DEVELOPING A RECOMMENDER SYSTEM FOR PRICING CONTEMPORARY FINE ART

by

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ABSTRACT

LAUREL BOYKIN POWELL. Developing a Recommender System for Pricing Contemporary Fine Art. (Under the direction of DR. ZBIGNIEW W. RAS)

The art market is a large and growing part of the global economy. However, uncertainty about prices, which can be problematic for many shareholders, can inhibit the growth of this market. This work discusses methods for the development of a knowledge based recommender system that will price contemporary fine art. Artworks are unique and often rare purchases. This makes a knowledge based system particularly suitable for that problem area. To the knowledge of this researcher, there are no knowledge based recommender systems for artwork pricing currently available.

In this dissertation, I will discuss past research in the field of art analytics, and the competing factors which drive art prices. I will also discuss the dataset that has been collected for use on this project. I will then discuss the development of both visual and textual features for this recommender system. Methods for the clustering of artists using visual features will be discussed. This work will also include an exploration of the development of personalized models based on these artist clusters and discuss their impact on the efficacy of the models built.

Lastly, this work will discuss a final structure for a recommender system and how it could be created moving forward.

DEDICATION

To my Mom, Dad, Hannah and Rachel, I could not have done this without you.

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CHAPTER 1: INTRODUCTION

Art, as an area of research in computing regarding commercial and business concerns, has been largely neglected. There have been a number of works dedicated to tasks such as classifying artworks by period or identifying specific artists based on visual features. However, these works are focused on archetypal works by great masters, and not on the large scale classification of contemporary works. The contemporary art market is a large and growing sector of the global economy. However, problems of consumer insecurity over prices has the potential to limit growth.

It is necessary here to address the difference between pricing contemporary works and non-contemporary works. This work focuses exclusively on contemporary works in the primary market. Contemporary artists in this context are artists working in or near the present day. When attempting to price works for artists of the past, there is a significant body of records and provenance that can be used to set a price. When pricing, for example, a work created 200 years ago the work has likely sold before. Even if it has not, there are a number of records of other works by like artists or the same artist that provide a strong basis for pricing. When dealing with works on the secondary art market or works created in the past, the value comes not just from the work or the artist but from the historical significant of the period and from the past owners. This creates a very different problem than the one faced by artists and collectors in the primary art market of today.

Customers entering this environment are challenged with a market that floods them with information while telling them very little. The online market allows artists to reach customers that they would not have previously had access to, but it creates a problem of potential customers that are not educated in the art market not knowing markers of quality and being uncertain about the validity of the prices that they are shown.

This work discusses the problem area of the contemporary art market and the challenge of developing an effective pricing model. Further, this work will review past works on recommender systems, and works on art analytics to discuss how these techniques could be applied in this context. One critical challenge to developing a recommender system is the development of a meaningful suite of features. Contemporary artists without a significant sales record frequently use simple metrics such as the size of the work and the cost of materials. In order for a recommender system to move beyond that, it must consider features that are less obvious to the artist. This work will discuss the features that have already been developed and propose other features to be explored at a later time.

Artists often provide biographical information about themselves and text descriptions of the work. These features, along with images and tags, are often all a potential customer has to go on when making an online purchase. However, the biography and description take the form of unstructured text. This work discusses the use of sentiment analysis and text clustering by using document vectors in order to transform this unstructured data into features.

This work will also discuss the development of features based on the visual attributes of the image. These include features developed from the number of edges in the image, and the dominant colors in the work. Features will also be developed that attempt to predict the dominant emotions conveyed by the image. These will be determined from the primary colors of the image tying into their base characteristics.

This work will also discuss how action rules could be developed to aid artists in the creation of profiles that would be more advantageous when displaying their work for the contemporary art market. This work will discuss features and attributes used in the development of these action rules and will address some of the challenges necessary for the creation of valid rules.

Lastly, this work will discuss using personalization to build models using two stages. The first stage will be the act of clustering artists based on their similarity. Once an artist has been placed in the appropriate cluster, a model built for that cluster will be used to place that artists work in price category. The models for each cluster will be trained exclusively on works belonging to artists within that cluster. This will give artists results that are more personalized.

A recommender system for prices can provide artists and consumers with information needed to price their work correctly or to feel secure in their purchases.

CHAPTER 2: STATE OF THE ART IN COMPUTING AND ART

This work discusses the challenge of pricing a work of fine art, and more broadly the issue of bringing something as complex and subjective as fine art into the realm of computing. Attempts at quantifying art, and even defining it, have proved challenging for many writers in the past. As said in [1],

> In a market that has to reconcile a fierce opposition between commercial and artistic values, and that has to commodify goods whose essence is considered to be non-commodifiable, dealers, artists, and collectors find ways to express and share non-economic values through the economic medium of pricing.

How is the price of a work of fine art determined? The art market has been described as an exception established economic theories throughout history [1, 2]. The price of a work of art is more complex than just the materials used, it is more than the number of hours the artist spent holding a brush, researching or planning. To further complicate things, buyers are not just purchasing the materials, they are purchasing a part of an artist's body of work. Buyers are interested in a work not just for its value today, but its future value.

To address these questions, theories have been developed to address the challenge of pricing fine art. This chapter will address some of the established methods and perspectives for price setting in fine art. This chapter focuses on contemporary fine art, rather than older works. This chapter will also discuss how prices and price setting create problems and inhibit growth in today's contemporary art market.

2.1 State of the Modern Market

The art market is a significant force in the global economy. In 2017, the global art market grew to 63.7 billion USD [3]. According to [4], the turnover from auction sales accounted for 8.45 billion USD. However, it is interesting to note that among collectors surveyed, many have never sold a work and approximately 40% did not know the value of their collections [3]. However, art has strong potential for financial returns,

> In the longer term, Contemporary Art and Post-War Art are honourable rivals of financial markets. Since 2000, the indices of these two periods have posted an overall gain equal to that of the S&P 500.[4]

The market itself, who buys art and how they do so is changing. In contrast to the market of 2008, in 2018, more art galleries closed than opened [3]. However, online sales now make up 29% of total gallery sales for a value of 4.22 billion USD which is a dramatic increase from 1.5 billion in 2013[5]. The aggregate value of the art sold as well as the number of works sold are both increasing, but the value is increasing more rapidly than the volume[6]. China is gaining an increasingly prominent role in the market relative to the leading markets of the United States and Europe [6]. There are still obstacles to widespread adoption of online sales, such as consumers that are attracted to the interaction with the artistic community which is lost online [7]. Concerns over prices are another big obstacle. In the Hiscox 2018 trade report on the market they wrote,

> Although existing collectors are used to secrecy and non-transparency when it comes to pricing, this is an aspect which clearly doesn't sit comfortably with new buyers. In this year's survey, 90% of new buyers and 92% of small spenders said that price transparency was a key consideration when buying art online. [5]

A consumer without an art dealer or investment expert advising them only has limited information on a work of art's place in the market particularly when buying online. The reputation of the artist is a key part of making a buyer feel comfortable with their purchase and assured as to its quality [2]. This leads to the question of how an uninformed buyer can make an intelligent purchasing decision in a complex market.

> The average upper-middle-class consumer with enough disposable income and cultural capital to value buying original art would be totally at a loss to explain why one watercolor painting is worth $300, another 3,000, and a third $30,000 while the size, shape, quality of materials, and other visual attributes may not vary significantly. None of the pieces would have the public-auction record to establish their investment quality. How is a buyer to know why this large watercolor of flowers in a vase on the dining room table is a bargain at $25,000 while this practically identical work on paper is overpriced at one-tenth the cost? I define this market of identity producers and confused consumers as a local art market. It is composed of an enormous number of producers relative to their actual sales and a relatively tiny number of consumers daring enough to enter the market. [8]

To add to the challenge, providing gallery sales prices or past auction records does not give potential collectors enough context to understand the pricing situation [9]. Even when examining auctions with reserve prices set by experts, the authors of [10] concluded that unexpected price fluctuations occur frequently. These fluctuations are tied to sales rates, and may be used to measure large scale changes in the market[10]. This makes the situations even more complex for the consumer. Information about art sales is becoming increasingly available, but the use of these simple 'thin' valuation methods is creating issues between consumers using these methods and stakeholders in the art market that use 'thick' complex valuation methods [9]. Some stakeholders show concern that the rigidity of using simple metrics, such as auction results, will create problems, especially due to the volatile and trend driven nature of auction results [9].

2.2 Understanding Art Prices

The forces that drive artwork prices are complex, and there are a number of theories that address the interplay of forces that influence the prices for works. Auctions are an important part of the price ecosystem and a number of models exist explaining buyer behaviors.

In [1], the author argues that prices are not just about commodity exchange but are a means of conveying cultural information. Prices are bound to narratives that give information about how the artist, buyer and dealer see themselves [1]. This creates situations where prices are driven by the stage of the artists career and ideas about what the price should be from the artists and dealers rather than purely economic decision making [1]. From an economic perspective, art has gained increasing attention as an investment for wealthy collectors [11]. In [11], the researchers found that art has a worse ‘risk-return profile’ than financial assets. In [11] they wrote when finding that the shifts of the art market were difficult to model:

> This may be because the fundamental value of art, as defined before, is hard to grasp. Combined with the impossibility of short-selling, this uncertainty implies a potential role for art buyer sentiment, which could be defined as unjustified optimism (or pessimism) about future resale values.

However, as discussed in [12], the value of an artwork to its owner is more than just its investment potential but the pleasure of having it. They propose that there are three types of art buyers: ‘collectors’ who are willing to pay a large amount and are generally unwilling to auction their collections, ‘flippers’ who are unwilling to pay high prices and frequently resell their collections without waiting for advantageous conditions, and ‘investors’ that are generally willing to pay less than collectors more than investors and will resell their works when market conditions are good [12]. It is interesting to note that some collector practices, such as rapidly ’flipping’ an art collection, have received backlash from other players within the art contemporary art market [13].

Another influence on pricing is the presence of ‘superstars’ [14]. A large number of sales comes from an increasingly small number of artists and galleries [14]. McAndrew points to the idea that inexperienced consumers, attempting to reduce risks or avoid spending time seeking information, often first look for works by artists with well known names from well established sources, which leads to a small subset of well known artists becoming more well known and their prices rising accordingly [14]. This idea about the behavior of ‘superstars’ was put forward in [15], who discussed how small variations in the talents of individuals and the quality of their work become magnified relative to the price of their work when examining the top price levels.

To add to the confusion, online auctions have their own unique behaviors and the number of works available has increased dramatically in recent years. For example, ’On September 8, 2000, within the category "antiques and art," eBay had a total of 14,103 active auctions in its "silver" and "silverplate" subcategories.’ [16] By comparison, on March 15, 2020, there were over 35,000 active auctions in the "silver antiques" category of "antiques" and over 600,000 items listed for sale [17]. More relevantly, there are over 40,000 active auctions in the "art paintings" subcategory of the "art" category and over 725,000 items listed for sale [17]. In [16], the authors explored how different factors of the auction format, such as the presence or absence of reserve price, impacted the results of Ebay auctions. Interestingly, this work uses reviews as a substitute for seller experience, as they theorize that sellers that receive a significant number of negative reviews tend to leave [16]. They concluded that some factors, such as the reputation of the seller and shipping charges, had no bearing on the outcome of the auction [16]. However, even these conclusions are not indisputable, as [18], determined that shipping cost does have an impact on whether an item will receive an above average bid.

There is not a single unified model for artwork prices, just a number of competing perspectives and theories. There are many factors that impact the prices of works and what actors in the art market believe that prices should be. A purely supply and demand oriented perspective is not enough to explain the emotional factors that influence buying behaviors.

CHAPTER 3: BACKGROUND

This chapter discusses relevant literature and background information in computing and art analytics. This chapter also discusses some of the methods used in later chapters for feature construction.

3.1 Recommender Systems

At their core, recommender systems are systems that form connections between a user and items that the user prefers [19]. A user may express what items they prefer directly, through ratings or likes or they may do so indirectly through behavior such as consuming certain products or browsing on certain topics [20, 19]. With the vast amount of data that the modern internet generates, a customer's preferences and product interests can be assessed [20]. This assessment grants users content that is more closely targeted to their interests. In many contexts, the array of options available can be overwhelming for a decision maker, so an automated system which filters out unlikely options is a benefit to the consumer [21].

Most recommender systems are designed to satisfy the preferences of a single individual, but recommender systems have been developed that are meant to provide aid for a group of users [22]. There are a number of potential application areas for this type of system such as project stakeholders, customers considering a group purchase or public displays [22]. Traditional recommendation algorithms, such as collaborative filtering, can be applied to a group environment [22].

3.1.1 Methods of Deriving a Recommendation

One method of classifying recommender systems is by using how they generate recommendations for users. There are five major methodologies for determining the recommendation for the user. These are discussed in more detail below.

- Collaborative Filtering
- Content Based or Content Filtering
- Demographic
- Knowledge Based
- Hybrid

3.1.1.1 Collaborative Filtering

Collaborative filtering is the earliest form of recommender system [23]. The earliest recommender systems used collaborative filtering to make recommendations to users [21]. The basic intuition for the system is that if two users have both liked similar things in the past, then if one of them likes a new item, then the other probably will also enjoy that item [24]. One of the most important limitations to collaborative filtering is that without ratings no recommendations can be made [21]. This can cause significant problems if there are few users or if new unique items are added too frequently. The inability to generate a recommendation without ratings is referred to as the 'coldstart' problem [21]. Collaborative filtering also has an inherent tendency to highly rate items that have been in the system longer and have been interacted with many times, popularity creates popularity [21].

3.1.1.2 Content Filtering

A recommender system that filters based on content will make recommendations based on their similarity to other items that the user has interacted with previously [24]. A content based system relies on analysis of the content to make recommendations [21]. This makes it well suited for recommending text or other content with a large amount of contextual information [19]. One major advantage of content oriented systems over collaborative systems is the independence of users, this allows for a user with a well developed profile to be given quality recommendations without regard to the number of other active users [21]. However, it does have notable drawbacks in that users without through profiles cannot be given good recommendations and that the system has a tendency to lock users into the interests described in their profiles [21].

3.1.1.3 Demographic Filtering

Demographic filtering uses demographic 'niches' to recommend items to users [24]. This method uses the idea that users of the same sex, nationality, age, etc, will share opinions about items [19]. A demographic recommender system is often not as useful as a more targeted system, but can be paired with one to improve its effectiveness by providing greater context [20]. An argument can be made that demographic recommender systems are a subset of collaborative recommender systems [25].

3.1.1.4 Knowledge Based Systems

A knowledge based system relies on domain knowledge in an area to make its recommendations [24]. When an environment is very complex, with a wide variety of options or a tendency to change over time, a knowledge based recommender system has a unique advantage [20]. With unique or high value items with complex sets of characteristics obtaining enough information to use content based on collaborative filtering becomes problematic [20]. Users may also want to be able to explicitly provide complex set of requirements [25, 20]. A primary distinction between knowledge based systems and other methods is that rely more on direct requirements from a user [20]. Knowledge based systems are often more useful than the other types early in their lifecycle but can lose utility if there is no learning component [24].

There are two main types of knowledge based recommender systems, constraint based systems and similarity based systems [20, 25]. The two primary approaches for the development of a knowledge based recommender system are 'constraint based' and 'case based' [20, 25]. In constraint based systems users specify constraints and often some constraints are given based on domain oriented rules [20]. In contrast, a case based system seeks a similar result to one defined by a user [25, 20]. In both cases, the system attempts to fulfill the requirements, and if it cannot the user must interactively modify their specifications [25, 20].

3.1.1.5 Hybrid Systems

A hybrid recommender system uses some combination of the methods to make a new system that is hopefully more robust than either would be alone [24]. For example, system which combines collaborative filtering with content filtering can overcome some of the shortcomings of both. Hybrid systems often combine methods of different types, but there is no requirement that models of the same type cannot be combined [20]. Hybrid systems can vary widely in design. Some systems take multiple models and merge them into a single whole, these are sometimes called 'monolithic' systems [20, 25]. Other design methods are either 'parallel' or 'sequential' which is also called 'pipeline' [20, 25]. Parallel designs have multiple independent recommender systems that are then merged, while a sequential design has one recommender feeding into another in order [20, 25]. Hybrid systems can also present multiple outputs to the users rather than combining them creating a 'mixed' system [20].

3.1.2 Recommender Systems for Art

A small number of systems have been developed that utilize recommender systems to address different issues in the art domain. While systems to recommend works of art exist, there is still considerable potential for the development of new systems in this application area.

The problem of developing a system that can recommend similar artworks to users was addressed in [26]. They attempted to classify artworks based on artistic style, genre and artist [26]. They extracted raw image features and then used them to train a similarity metric which was used for classification [26].

The challenge of recommending desirable visual artworks to a user was explored in [27]. Using a dataset of purchased artworks, they attempted to predict customer purchases using features that they had developed[27]. They experimented with metadata, which consisted of manually selected tags, explicit visual features as well as visual features derived using neural networks and concluded that metadata was the least useful for predicting purchases and visual features derived from neural networks performed best of all [27]. This work was followed up on in [28], where they continued to explore the problem of feature engineering for predicting what artworks a user will purchase.

In [29], the researchers developed a system to predict which art items a user would interact with on a website. This site hosts both creators and users and as the same individuals create as interact with content, this leads to unique behavior as users may break their preferences to interact with the works of artists that they support [29]. They used temporal as well as social and visual features to develop their models for predicting user actions and had highly positive results.

In [30], a recommender system for pricing works of contemporary art was explored. However, this system had a limited dataset of only approximately 20,000 best selling works. Additionally, the pricing intervals are large, and the recommendation method is largely limited to using medium and size as predictors. This features of this system were a notable influence on the ones discussed in chapter 4.

Existing systems do not use data analytics but human experts to evaluate fine art pieces and make recommendations. For instance, MutualArt (`https://www.mutualart.com/artappraisal`) has the world's most comprehensive database of past sale results but the number of features describing these sales is quite small. Its advisors are assigning price tags to new pieces of art by comparing them with similar pieces in the MutualArt database. The charge for a single service (one piece of art) is $49 and the waiting time to get recommendation is 72 hours. FINDARTINFO (http://www.findartinfo.com/english.html) is a similar free art appraisal service which contains information about 438,003 artists and 3,775,762 art prices. With this art appraisal tool, artist can value his/her fine art by comparing it with recent auction prices of similar pieces. There are also websites providing free art appraisal hints. For instance, wikiHow (https://www.wikihow.com/Value-Your-Art) helps to value artworks. There are professional art appraisers available, but they charge $300+ for a single service and the waiting time to get price recommendations is still relatively long.

3.1.3 Recommender Systems for Pricing

While a significant number of recommender systems have been focused on suggesting items that will be most appealing to a consumer, some systems attempt to integrate a business perspective as well[31]. For example, the system can take a users price preferences into account in order to maximize the likelihood of making a sale [31].

As prices are an important part of any commercial project, attempts have been made to develop recommender systems that can address this area. Some systems, such as the ones discussed in [32], have attempted to remove human involvement from price setting entirely. However, this technique is not without its own set of drawbacks. The authors begin by discussing some of the problems which can occur when these systems are left to run without any human involvement. They divide these algorithms into two groups, 'first generation' which use rules and 'second generation' which do not[32]. Rule based algorithms are quite simple and often set the prices based off of the seller's competitors [32]. Second generation algorithms are centered around maximizing profits and are designed to 'learn' [32].

In [33], the researchers developed a recommender system that would measure a buyer's willingness to pay for a product to recommend items to them. They analyzed the customer's past buying history on Ebay and modeled their willingness to pay for a product along with the emphasis that customer places on the reputation of a given Ebay seller [33]. One aspect of online sales that has been explored in some depth is the impact of factors such as review score on buyer willingness. Factors influencing buyer willingness were also explored in [34]. In [34], the author seeks to reconcile the seeming contradiction of how reviews do not always have a consistent impact on a potential buyers interest in a purchase. They propose that the consumer's perspective on purchasing risk determines how the reviews, which serve to mitigate risk, and price impact their willingness to pay [34].

3.2 Current Research in Art Analytics

While recommender systems targeted at art has been largely ignored, a significant amount of works have been dedicated to the task of classifying images or artworks automatically. Some of these techniques are specifically designed for tasks such as the automated tagging of works of fine art, while others are centered around the problem of discovering image features.

One interesting classification challenge was developed in 2014 by using part of the online collection for the Rijksmuseum [35]. The researchers sought to develop an automated system that could categorize by artist, material, type (such as separating paintings from prints) and year automatically [35]. They developed a feature vector from the image to describe the work for classification [35].

3.2.1 Tagging Fine Art

Tagging collections of fine art with automated methods has received some attention from the research community in recent years. A number of different approaches and objectives have been explored. The objectives of image retrieval based on emotion, similarity or an artistic description have been addressed by researchers.

In [36], the researchers developed an artwork retrieval system based on artistic concepts of color. Their can retrieve images that fit categories such as ‘Painting in warm colors’ or ‘Temperature contrast in the center’ [36]. This allows the works retrieved to be described in artistic terms and may be put to use when classifying works based on era or artist [36]. Some researchers have focused on categorizing works based on specific artistic periods, such as the work done in [37], [38], [39] and [40]. The features used varied widely, from the color focused domain oriented approach of [39] which emphasized that the reasoning of the system must be comprehensible to humans to the system developed by [40] that specifically avoids using prior domain knowledge. While the approaches differed, the emphasis on transforming visual attributes of a work for the goal of automated classification was consistent.

Another widely explored topic is the goal of tagging images or artworks with emotional labels automatically. A number of approaches have been considered. In [41], the researchers attempted to map images to one of eight emotional categories. The researchers classified photographs and a small selection of abstract paintings based on emotions [41]. They developed a set of visual features, such as the brightness of the image, an assortment of color based features, the presence or absence of human faces and compositional features [41]. In contrast, [42] used color exclusively to classify artworks based on their associated emotions. They used psychology theories to map specific colors to emotions and used applied these to the artworks in their collection [42].

3.3 Background on Features Constructed

A number of features were developed for use in the analysis discussed in the following chapters. The following section discusses background information on the features developed in later chapters.

3.3.1 Text Analytics

Text analytics, which is sometimes called text mining or machine learning from text, can be defined as 'the extraction of useful insights from text with various types of statistical algorithms' [43]. Mining text has its own unique set of challenges distinct from other topic spaces.

3.3.1.1 Document Vectors

A text document can be converted into a representative vector using the Paragraph2Vec algorithm [44]. This process, which is also called the "Distributed Memory Model of Paragraph Vectors (PV-DM)" or Paragraph Vector, was developed to expand on the original Word2Vec algorithm developed in [45]. Both of these algorithms use trained neural networks to make vector representations of text.

The original Word2Vec algorithm, which was developed by Mikolov et. al., uses neural networks and relies on the Skip-gram model. The Skip-gram model, which was originally developed in [46], predicts which word will next appear in a given sequence of words using a neural network. "The training objective of the Skip-gram model is to find word representations that are useful for predicting the surrounding words in a sentence or a document." [45]

Paragraph2Vec is fundamentally similar to Word2Vec. Paragraph2Vec extends the original idea of Word2Vec by adding another component which functions as a tag for the subject of the paragraph [44]. Paragraph Vector can take a document of any length and return a fixed length vector representation. This makes it remarkably useful for tasks such as determining document similarity.

One method of determining document similarity is by converting the documents into vectors and measuring their proximity in a multi-dimensional space. This was used in chapter 4 to develop classification features for text.

3.3.1.2 Determining Sentiment Polarity

Sentiment analysis, which can also be referred to as ‘opinion mining’ focuses on extracting a user’s opinion on some topic [43]. Attempting to judge the opinion of a user on some topic is a frequently appearing problem in sentiment analysis. One widely discussed technique is to determine the polarity of the sentiment [47]. This places the text into either positive and negative, or in some cases positive, negative and neutral categories [47]. Vader, the ‘Valence Aware Dictionary for sEntiment Reasoning’ is a model that uses a combination of rules and lexical features to assign polarity to text. It is used in chapters 4 and 5 to develop classification features.

3.3.2 Image Processing for Feature Extraction

A number of features were explored based on the prominent visual features of the artworks. These features are largely focused on using color, edges and the interplay of light and dark in a work to draw conclusions about how a work will be perceived by an audience.

As an example, three sample works will be used to as a visual illustration of how various methods would function.

3.3.2.1 Basic Colors

In order to quantify the colors discussed, the concept of universal basic colors was explored. This idea was originally put forward in [48]. While this work has been extensively challenged due to biases and limitations in the original study [49, 50], the concept of fundamental colors for comparison is useful for the purposes of analysis. This work uses eleven basic reference colors based on those given in [48]. They are as follows with the RGB values, other than brown, are taken from [51] and the brown comes from [52]: white (R 255, G 255, B 255), gray (R 128, G 128, B 128), black (R 0, G 0, B 0), red (R 255, G 0, B 0), orange (R 255, G 128, B), yellow (R 255, G 255, B 0), green (R 0, G 255, B 0), blue (R 0, G 0, B 255), purple (R 128, G 0, B 128),

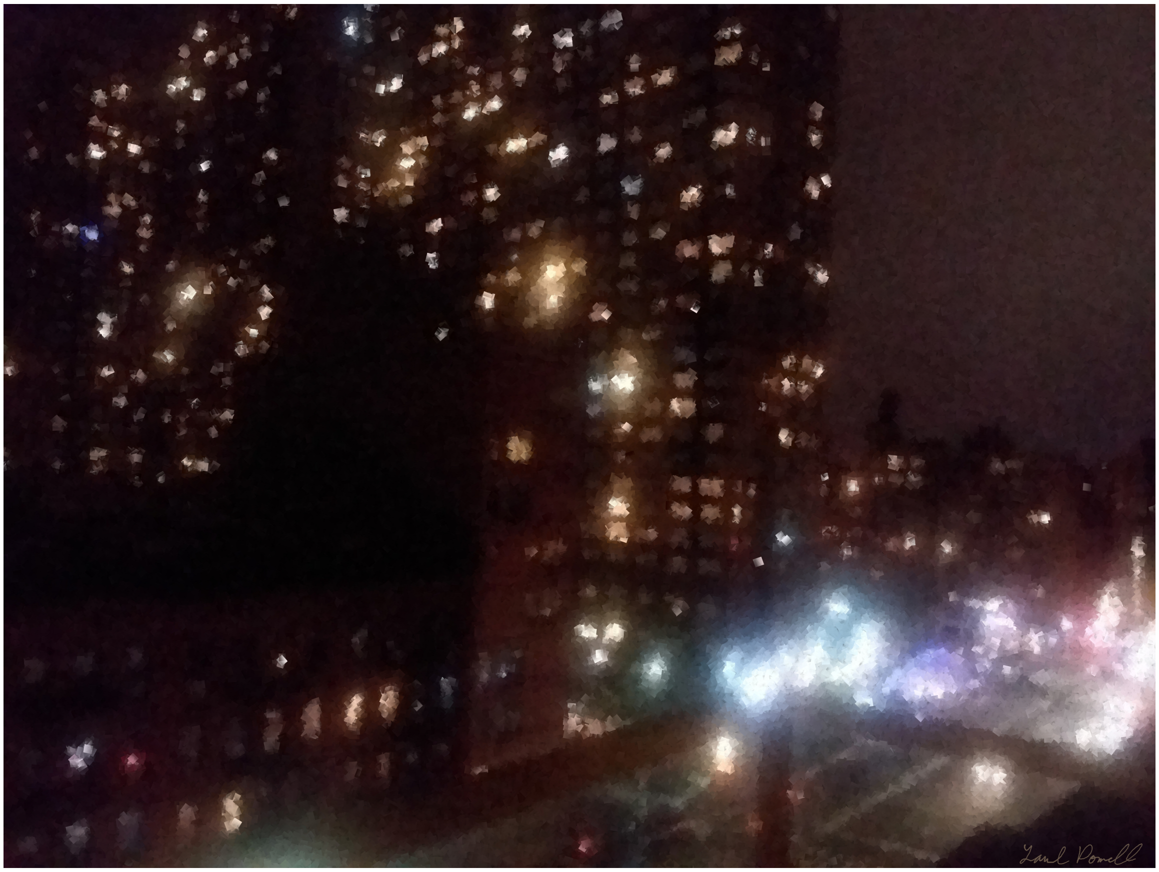

Figure 3.1: The Original Image of a City Scene

Figure 3.2: The Original Image of a Tree

Figure 3.3: The Original Image of a Floral Design

Figure 3.4: The city scene after being reduced to 10 colors

pink (R 255, G 192.0, B 203), and brown (R 63.8, G 47.9, B 31.9).

In chapters 4 and 5, these basic colors are used as features for classification and rule extraction. This is performed by utilizing k-means to determine the 10 colors that appear most often in the work. Using the Open Computer Vision library, each pixel in the work is positioned in an RGB space and clusters are found [53]. The centroids of these clusters are then tested against the reference colors using the [54] implementation of the CIEDE2000 color difference formula [55]. See figures 3.4, 3.5, and 3.6. Note that in 3.4, almost all color variation in the lights is lost, and how in 3.5 and 3.6 all subtle color shifts in the sky and plants are removed.

Figure 3.5: The tree after being reduced to 10 colors

Figure 3.6: The floral design after being reduced to 10 colors

3.3.2.2 Color and Emotion

Developing clear links between specific colors and specific emotions has been long term focus of many researchers. In this work, two different scales are used in order to quantify the emotions evoked by specific colors.

The Pleasure, Arousal, and Dominance Scale

The first method discussed is the pleasure, arousal and dominance scale, referred to as the PAD [56, 57, 58]. In [58], the author found relationships between the brightness of a color and the saturation of a color and its placement in the PAD matrix. The PAD matrix exists as a three dimensional space with independent axes for pleasure, arousal and dominance [56]. Pleasure ranges from extreme pain or unhappiness to extreme pleasure, arousal ranges from the lethargy or sleep to extreme excitement, and dominance ranges from extreme powerlessness to total situational control [57, 56]. In [56], specific emotional terms, such as "joyful", "fascinated", or "despairing", are linked to specific combinations of values on the PAD scale.

Valdez's work focuses on developing relationships between the dimensions of the PAD scale and specific aspects of color [58]. Over multiple controlled studies, participants were asked to rate colors based on their impact on their emotions [58]. A number of patterns emerged from the study, including that pleasure was strongly tied to the brightness and saturation of a color, arousal has a linear relationship with saturation and a more complex relationship with brightness, and dominance increases as saturation grows more stronger and decreases as a color brightens to a point [58]. Some of these relationships change after a certain threshhold of brightness is passed [58]. Interestingly, these findings map well to traditionally held opinions about "warm" and "cool" colors and their impact on the excitement of a viewer [58]. In order to quantify the relationships, Valdez found the equations reproduced below using regression [58].

$$Pleasure = 0.69Brightness + 0.22Saturation \tag{3.1}$$

$$Arousal = -0.31Brightness + 0.60Saturation \tag{3.2}$$

$$Dominance = -0.76Brightness + 0.32Saturation \tag{3.3}$$

Interestingly, hue had a very different impact on emotion in the studies. Hue had weaker findings on emotional impact and was largely limited to the pleasure dimension [58]. Valdez proposed that some of the traditionally held beliefs about hue and excitement might be due to improperly controlled for secondary factors such as the brightness of the samples [58].

This analysis takes influence from the analysis of emotion in photographs put forth in the work of [59], which also used the PAD scale. This also has similarities to [60], which also uses k-means clustering to find the most prominent color in an image and combines it with the PAD scale. In this analysis, PAD score of each of the representative colors was found using its brightness and saturation. In this work, the hsv scale was used, with value substituting for brightness. The percentage of the work that a specific color represents was used as a weight for the score. The scores were combined to provide an overall emotional score for the viewer.

The Activity, Weight, and Heat Scale

An alternative method for developing defined links between color and emotion was developed in [61]. This work examines multiple methodologies for quanitifying the impact of color on emotion and derives three factors termed: "colour activity", "colour weight", and "colour heat" [61].

After examining a number of other methodologies, the authors generated ten different scales for linking color and emotion and used data from British and Chinese subjects to generate three factors to describe an individual's emotional reactions to color [61]. The first factor, which was labeled as "colour activity", represents their original scales of "active-passive, fresh-stale, clean-dirty, and modern-classical" [61]. This factor was also tied to their scale of "tense-relaxed" however, that feature had significant variations across cultures and was discarded [61]. Their second factor combined their scales of "hard-soft, masculine-feminine, and heavy-light" to make "colour weight" [61]. Lastly, they developed the 'colour heat' factor which only used the "warm-cool" scale after discarding the "like-dislike" feature for excessive cultural variation [61].

These values are calculated using the equations reproduced below [61]. These use the CIELab values to define color known as L*, C*, h, a* and b*.

$$Coloractivity = -2.1 + 0.06\left[(L* - 50)^2 + (a* - 3)^2 + \left(\frac{b* - 17}{1.4}\right)^2\right]^{1/2} \quad (3.4)$$

$$Colorweight = -1.8 + 0.04(100 - L*) + 0.45\cos(h - 100°) \quad (3.5)$$

$$Colorheat = -0.5 + 0.02(C*)^{1.07}\cos(h - 50°) \quad (3.6)$$

For each of the extracted colors, the their scores on the activity, weight and heat scales were determined. Then, the percentage of the overall work that each color represents was used as a weight.

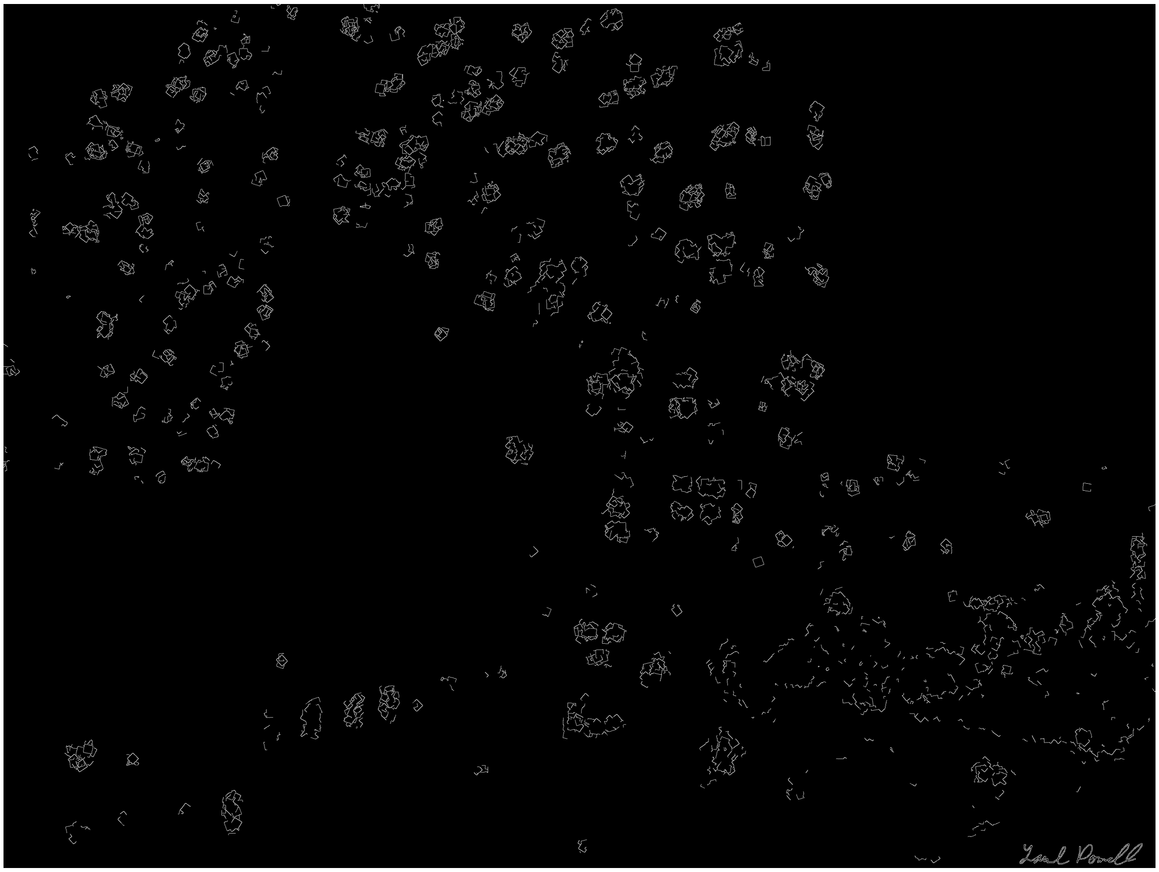

Figure 3.7: The city scene after edge detection is used

3.3.3 Edge Detection

The number of edges in an image can be utilized as a measure of the level of complexity of the image. The number of edges was calculated using the Canny edge detection method [62]. Canny edge detection uses the amount of variation in the colors surrounding a given pixel to determine if the pixel should be considered an edge pixel [62]. To use it as a feature, the number of edge and non-edge pixels in the image were counted and the percentage of edge pixels in the total image was determined. The OpenCV [53] set of tools was used for the calculation. Figures 3.4

3.3.4 Block Clustering

In [63], one method of quantifying aspects of an artwork is dividing it into nine equally sized blocks. These can then be used to quantify aspects of that work. This

Figure 3.8: The tree after edge detection is used

Figure 3.9: The floral design after edge detection is used

work uses this approach for two separate features. First, the idea of simply examining which portion of the work contains the highest average color value. The grayscale and red, green and blue channels were used for this. This could be taken to represent the brightest part of the artwork.

However, this was also used for a more complex process. By partitioning artworks into blocks, this allows for more direct comparisons between works. First, all works by a single artist were broken into blocks. The aggregate brightness and, using Canny edge detection, percentage of edges for a single work was calculated for each block. Then all works by the same artist were aggregated using the blocks. For example, all uppermost left blocks were combined. This allows for a visual representation of an artist's posted body of work. These values were then clustered, which placed artists with some measure of visual similarity in the same clusters. This was then used to develop personalized models based on artist clusters.

3.4 Action Rules

Action rules were originally developed as a method of changing the classification of objects from one category to another through changes to a specific set of attributes labeled as "flexible" [64]. Flexible attributes are attributes that can be considered subject to change by an involved individual. In contrast, "stable" attributes are attributes that cannot be easily changed. These rules while first proposed for business purposes, as in [64], they have been utilized in many other subject areas such as medical care [65].

Significant work has been done since the original proposal of action rules, and two aspects are of particular note for this work. First, the principle of the cost of an action rule is relevant to the selection of flexible attributes. This concept, which was first proposed in [66] and discussed further in [67], indicates how much it would cost to move one of the flexible attributes from one category to another. The flexible attributes discussed in the later portion of this work were selected to have a low cost for artists.

While there are multiple methods of generating action rules, this work focuses on the GUHA method [68]. This method, implemented in Lisp-Miner [69] and discussed in [70], constructs action rules by building contingency tables from a objects resembling association rules [68]. This method uses a pair of these objects with matching stable attributes. One of these objects has stable and flexible attributes matching the initial state of the relevant tuple and the other has stable and flexible attributes matching the desired state. The resulting rules are termed as "antecedent" and "succedent" [68]. These are then used to form G-Action rules [68].

CHAPTER 4: PRELIMINARY DATASET DEVELOPMENT AND FEATURE CONSTRUCTION

4.1 Development of the Original Dataset

The initial dataset was constructed from artworks extracted from Artfinder.com [71] using webscraping tools. Python was the primary language used for the writing the scraper, Javascript was processed with Apache Selenium [72], and Beautiful Soup [73] served as the primary text parser. Works on Artfinder.com are sold by the artists themselves or by their representatives. This places Artfinder in the primary art market. The secondary art market processes its own set of complexities which should be addressed in other works. Artfinder has a broad cross section of works, representing many different art styles, artist nationalities, mediums and subjects. In the dataset used here, approximately 3300 artists spread across 60 countries appear.

Information such as the medium of the work, it's size, and its subject was found on the artwork profile page. For the sake of searchability on their website, a number of features, such as the medium and style of the work were provided by the artist.

Artists also have about pages, which contain biographical information, as well as sections for social media. Most have a general biography, and their are optional sub-sections for education, awards and events. These categories are not strictly enforced or required by Artfinder, which leads to a general lack of structure. Often, artists have reviews posted for their works as well. However, reviews cannot be solely relied on as a predictive feature. Artfinder restricts posting reviews to past customers, and does not directly tie the review to a specific purchase. Comments are optional, but all reviewers provide a 'star rating' on a 5 point scale. Many artists, especially artists that have not been on Artfinder long enough to accumulate a large number of sales, often do not have reviews. Approximately 45% of the artists in the dataset referenced here have visible reviews. In this dataset, the prices for works of art range between a 12.97 USD to 1,000,000 USD. However, approximately 85% of the works have a USD of 1000 or less. Most art sales online are for works less than 1,500 USD [74]. The price distribution, omitting works priced at greater than 10,000 USD for reasons of scale, is reproduced in figure 4.1. For much of the work discussed in the following chapter, the price feature was discretized to a set of intervals as listed here: (0 - 105), (105 - 205), (205 - 405), (405 - 605), (605 - 810), (810 - 1030), (1030 - 1445), (1445 - 1825), (1825 - 2455), (2455 - 3855), (3855 - 5000), (5000 - 10,000), (> 10000). This discretization was developed by examining the range of prices for intervals with a relatively small number of works. Splits were placed in these 'gaps'. However, the number of gaps found was excessively large because prices for works tended to cluster around multiples of 50. Therefore, several smaller intervals were combined to create the above set of discrete prices.

A set of basic features was created to be used for comparisons. This list of features used takes cues from the features developed in [30]. All these attributes are discrete or were discretized. Other attributes discussed are extensions of or in some cases improvements to this basic set of features.

- artistID - A unique identifier for an artist. It may or may not be their legal name and serves as their username on the site.
- artistCountry - The artist's current country of residence as listed on their profile
- artwork_height - The height of the artwork in inches.
- artwork_width - The width of the artwork in inches.
- authentication - Artist provided method of authenticating the work.

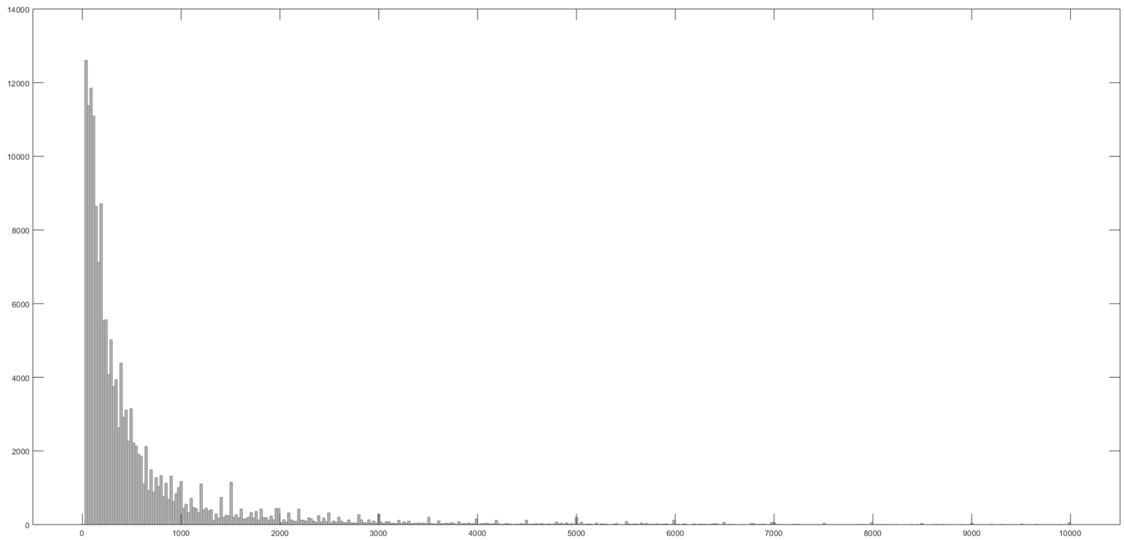

Figure 4.1: Price Distribution

- percent_five_stars - The percentage of five star reviews out of the total number of reviews.
- percent_four_stars - The percentage of four star reviews out of the total number of reviews.
- percent_three_stars - The percentage of three star reviews out of the total number of reviews.
- percent_two_stars - The percentage of two star reviews out of the total number of reviews.
- percent_one_star - The percentage of one star reviews out of the total number of reviews.
- medium - Artist provided medium of the artwork.
- style - Artist provided style of the artwork.
- subject - Artist provided subject of the artwork.

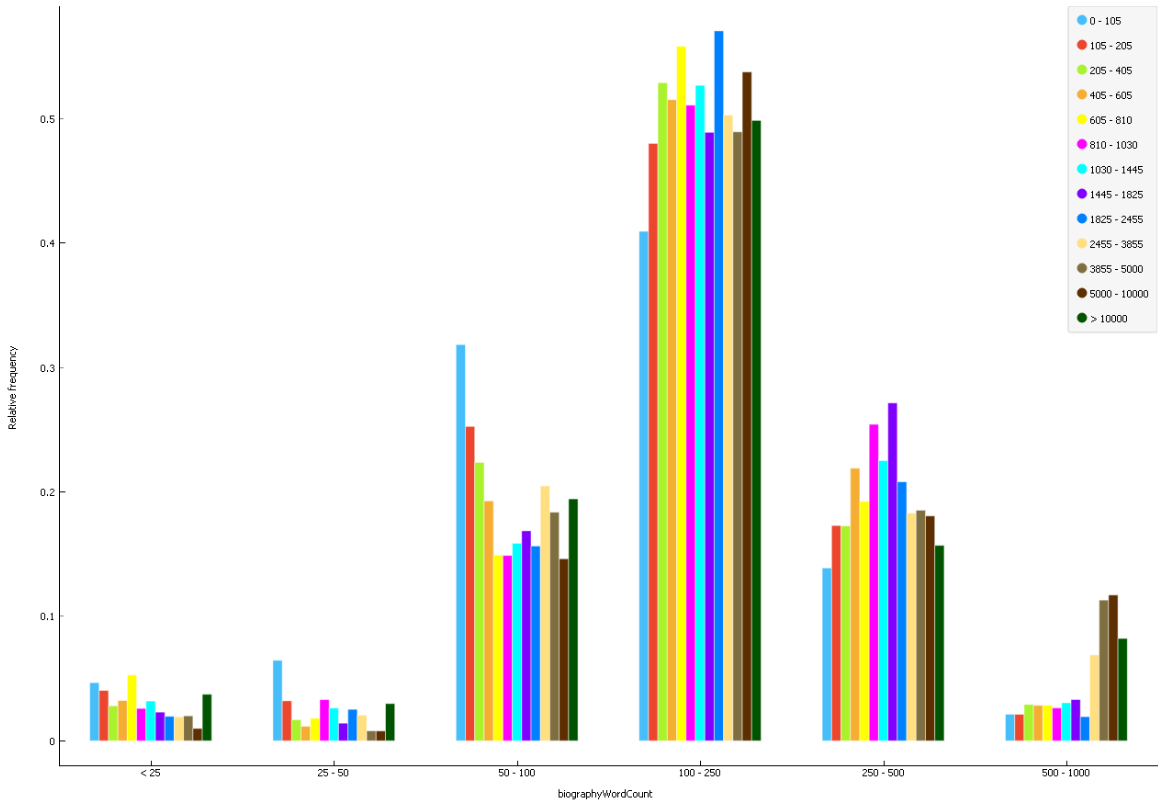

Figure 4.2: Word Count Frequency in Biography

4.2 Feature Construction

Text extracted from the artist about pages and the artwork description pages was analyzed. Every work had a title and brief text description. Artists have brief about pages with optional short biographies and sections about their awards, events, and education. An artist can have all of these sections or none of them.

One very primitive, but useful, application of this text was simple word count. Interestingly, the word count of the biography of the artist and the description of the artwork together were demonstrated to have some predictive power. This makes some intuitive sense, because their may be a link between the types of description used or the length of the artist's biography and their accomplishments. The distribution of word counts in the descriptions and biographies divided by prices is in figures 4.2 and 4.3.

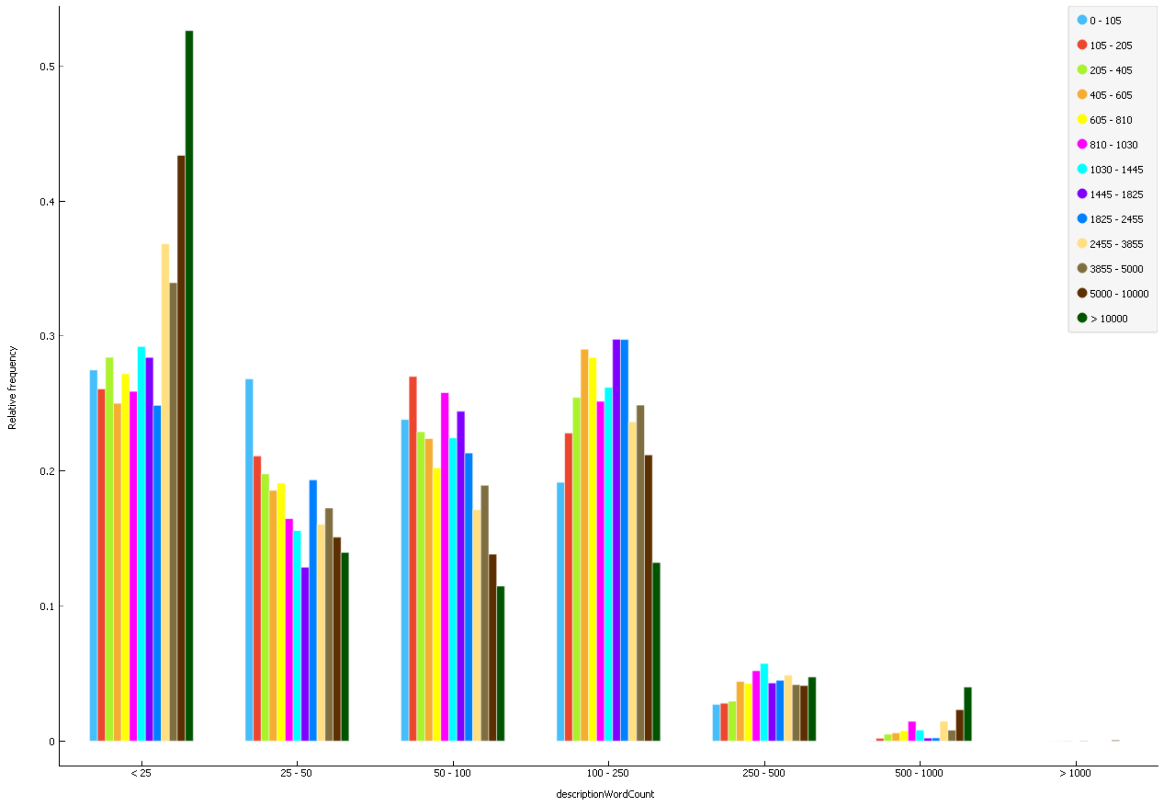

Figure 4.3: Word Count Frequency in Description

The length of and word choice in a product description has been found to have an impact on pricing [75]. When analyzing the prices of eBay sellers, the researchers found that descriptions between 40 and 55 words in length had a positive impact [75]. However, [76], would counter that by claiming descriptions should be between 350 and 400 words. This discrepancy may be due to the platform used. This creates an interesting challenge for sellers attempting to place their work to its best advantage.

Another interesting feature explored here is the presence or absence of the artist on social media. Artists can include links to locations they are available on the web in a designated space on their profile. In this work, the text their was checked for the presence of the words ‘facebook’, ‘twitter’, and ‘instagram’. This was then converted into a Boolean variable and used for classification. The distribution of these variables divided by price levels are found in figures 4.4, 4.5, and 4.6.

Doc2Vec, which is the implementation in Gensim [77] of Paragraph2Vec, was used

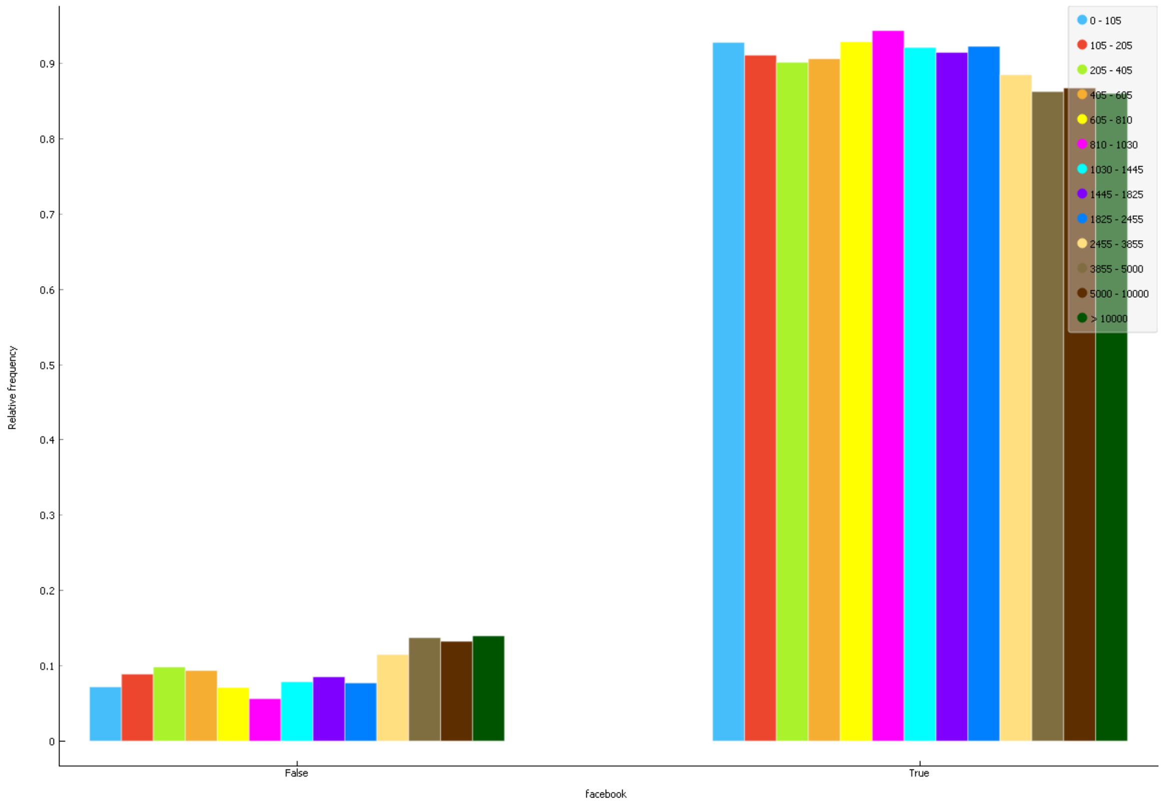

Figure 4.4: Facebook Frequency

to develop the document vector features [44]. A Gensim Paragraph2Vec model was trained on the artist biographies, their education sections, their events sections and their awards sections, as well as the titles and descriptions of the artworks. The text was preprocessed using the Gensim basic text preprocessing package. The Paragraph2Vec model was used to create vectors for each piece of training text. The vector could be of any length, and vectors of length 20 and length 100 were tested in this work. These vectors were then used to assign the text to clusters. The Sci-Kit Learn Library implementation of K-Means was used for the clustering [78].

Lastly, the polarity of the titles, artist biographies and artwork descriptions was determined and used as an extension to the base feature set. This was derived using ‘Valence Aware Dictionary for sEntiment Reasoning’, abbreviated to VADER, which uses a combination of rules and an opinion lexicon [79]. This was determined using human raters.

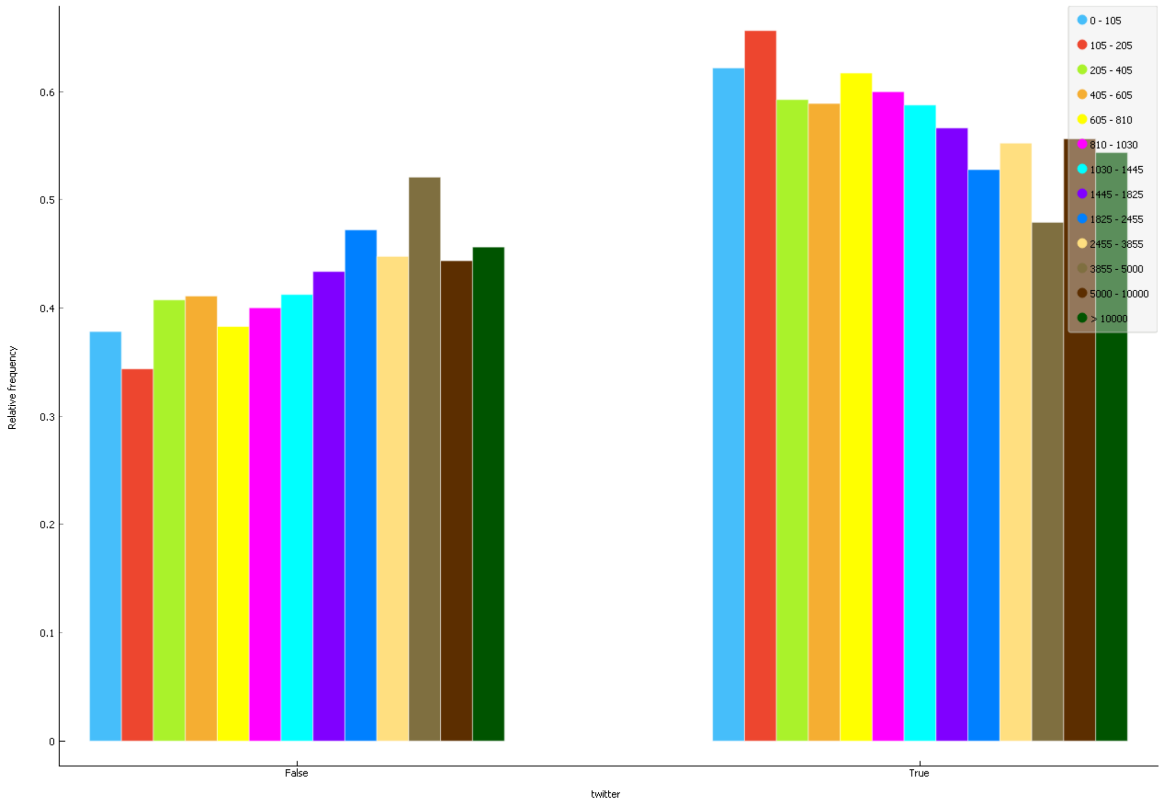

Figure 4.5: Twitter Frequency

The levels of sentiment in 150,000 of the descriptions can be found in figures 4.7, 4.8, and 4.9 and the sentiments of the biographies is in figures 4.10, 4.11, and 4.12. The titles display similar patterns to the descriptions. There is very little negative sentiment evident, and only small amounts of positive sentiment.

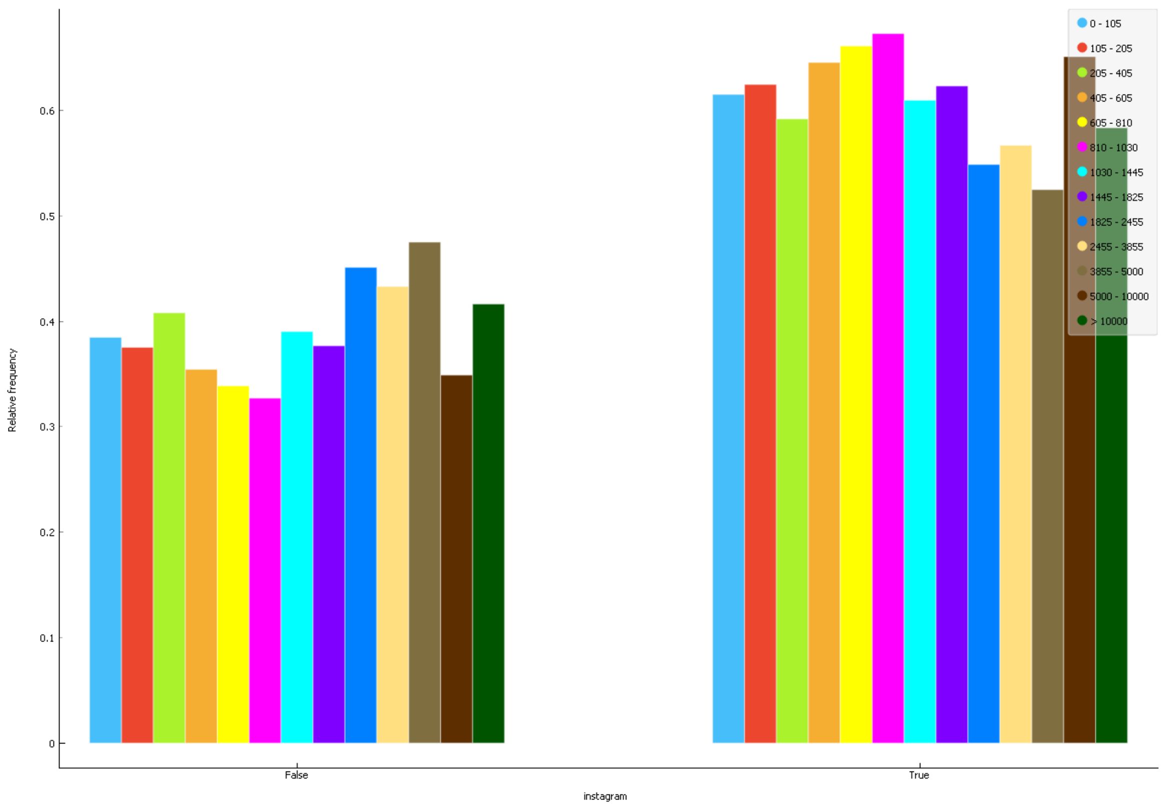

Figure 4.6: Instagram Frequency

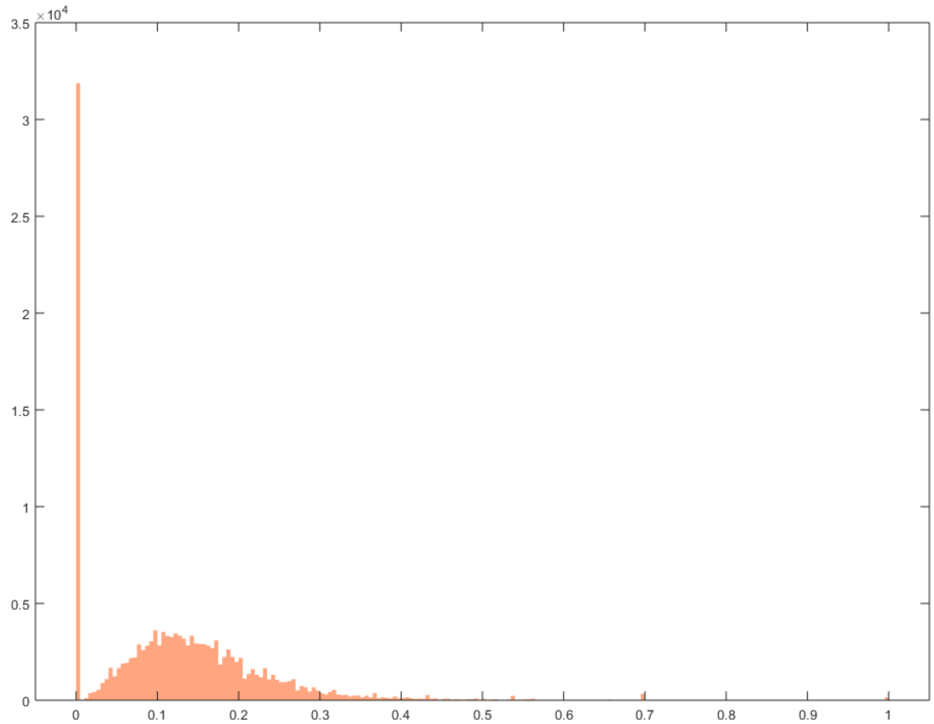

Figure 4.7: Positive Description Score

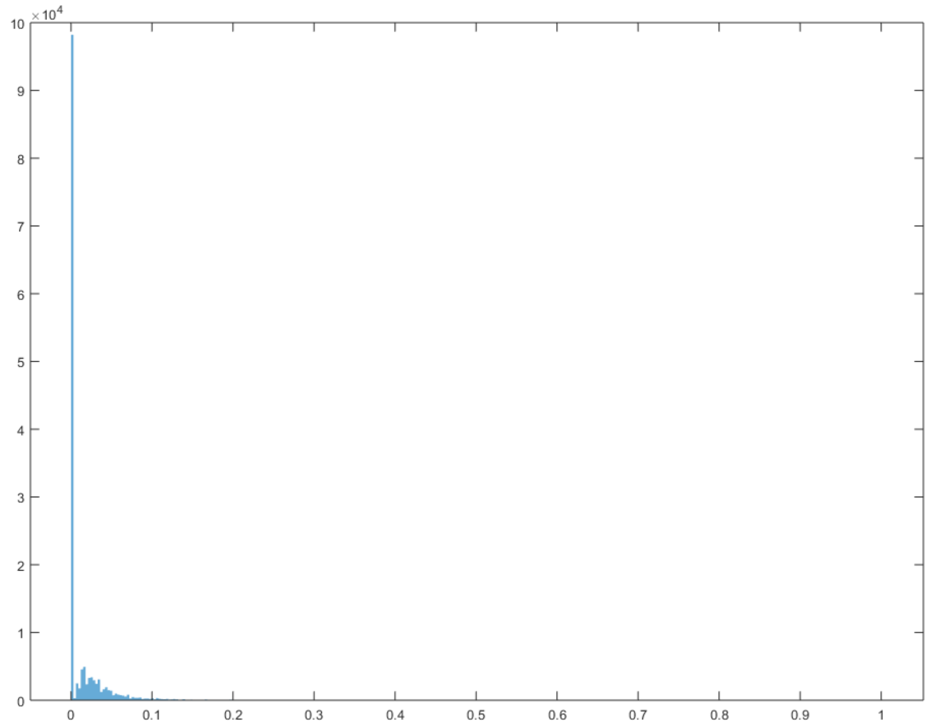

Figure 4.8: Negative Description Score

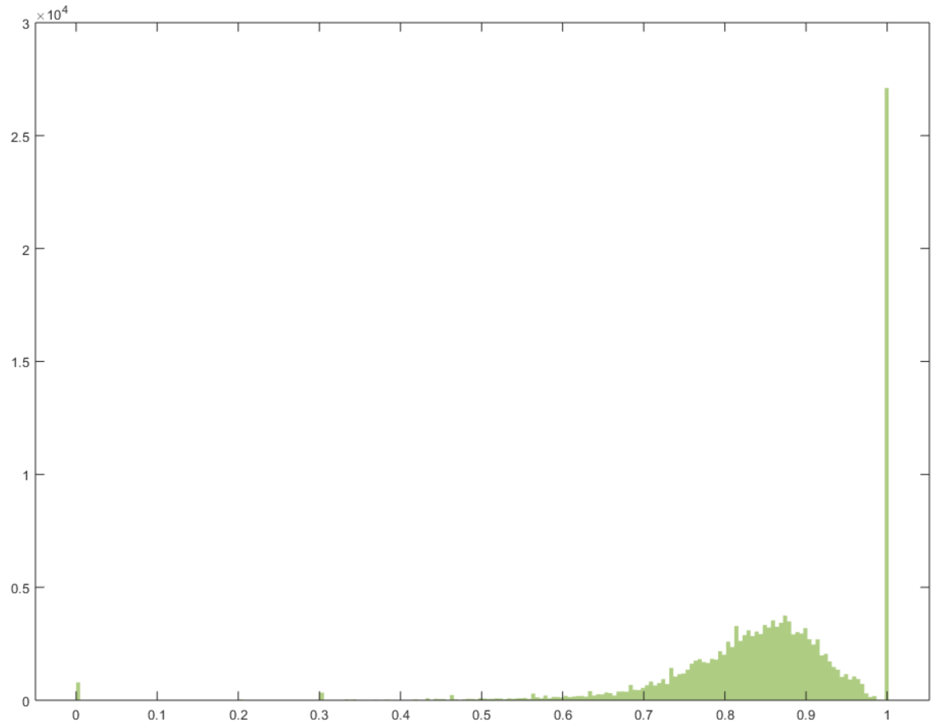

Figure 4.9: Neutral Description Score

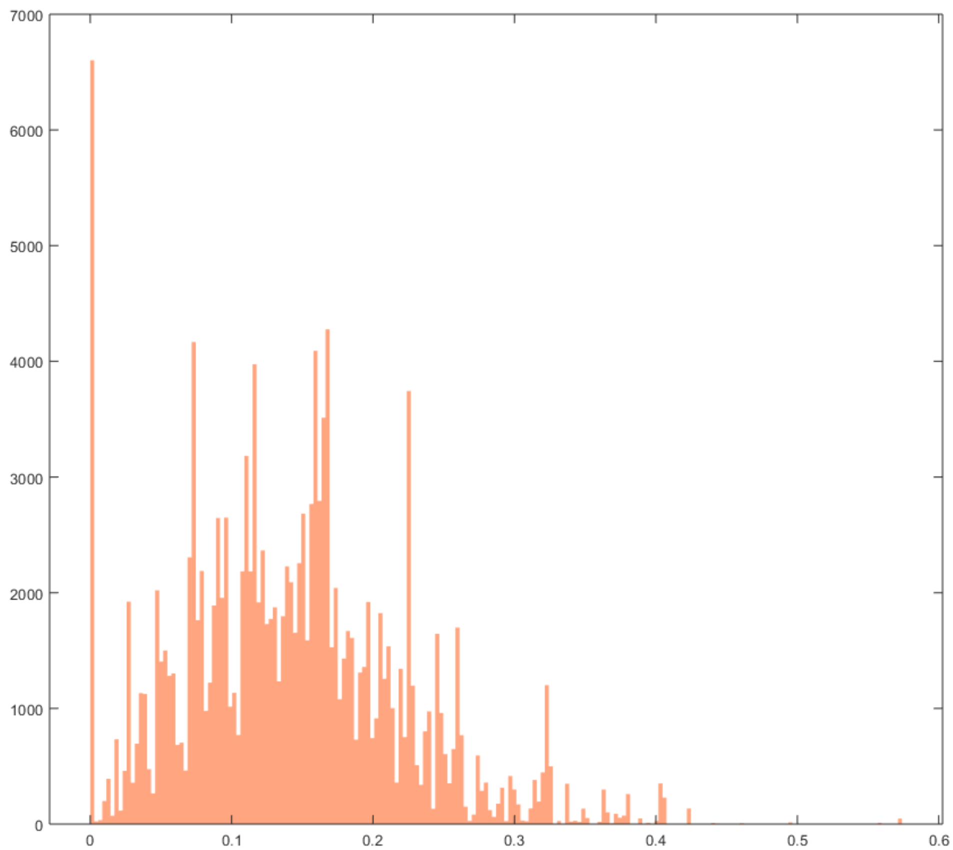

Figure 4.10: Positive Biography Score

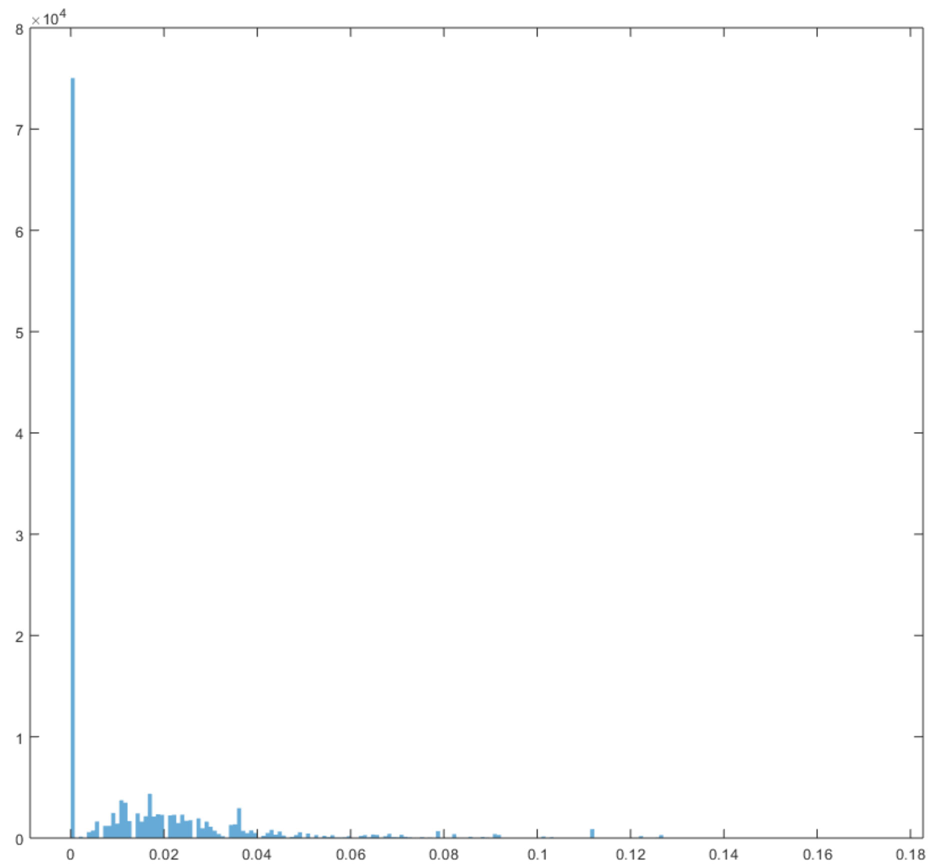

Figure 4.11: Negative Biography Score

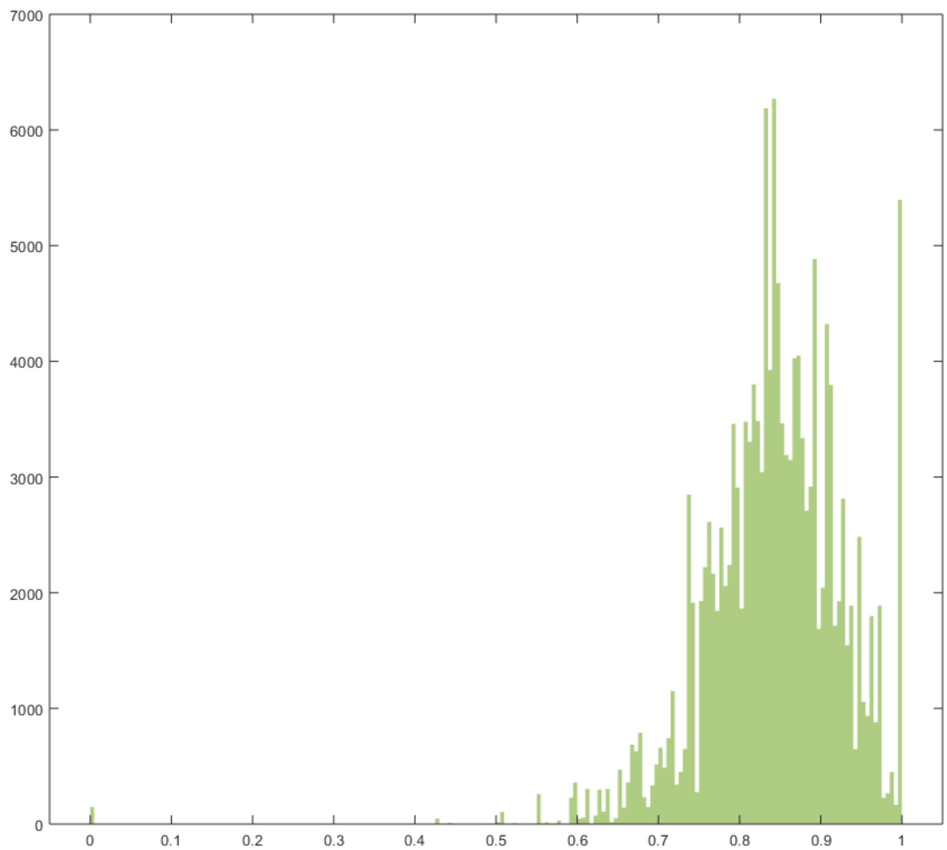

Figure 4.12: Neutral Description Score

CHAPTER 5: RESULTS

5.0.1 Inital Feature Exploration

The tables below show the inital results of testing the vector derived features, the word count features, the social media features and sentiment features on a random subset of 150,000 data points. The model used the random forest algorithm with 100 trees and was tested using 10-fold cross validation. The word counts of the artwork title, description and artist biography were used as an extension to the base feature set. The results are shown in table 5.1. The biography and description word counts have some value as predictive features.

The features developed from the use of social media have limited value as price predictors. This may be due to their widespread use across all price levels as seen in figures 4.4, 4.5 and 4.6. The results of testing them can be found in table 5.2.

As can be seen in figures 5.3, 5.4, and 5.5, the number of clusters used does not have a significant impact on the accuracy of the classifier. However, there is a notable link between the accuracy of the resulting model and which textual features were clustered. Clustering the biography, awards section, education section, or events section has a notable impact on the accuracy of the classifier. Interestingly, clustering the artwork description or title does not have a notable impact. This may be due to the vast number of titles and descriptions which creates an excessive amount of diversity in a cluster.

The sentiment of the text, in particular the sentiment of the artwork description has an interesting impact on the accuracy of the classifier. The full results can be found in figure 5.6. The combination of the scores for positive sentiment for all three examined features had a comparatively strong impact on the classifier.

Table 5.1: Results with Word Counts

	AUC	CA	F1	Precision	Recall
Base Features	0.938	0.667	0.664	0.663	0.667
Base Features and Biography Word Count	0.939	0.67	0.667	0.665	0.67
Base Features and Description Word Count	0.94	0.674	0.67	0.669	0.674
Base Features and Title Word Count	0.938	0.668	0.664	0.663	0.668
Base Features, Biography Word Count and Description Word Count	0.941	0.677	0.673	0.672	0.676
Base Features, Biography Word Count and Title Word Count	0.939	0.671	0.668	0.666	0.671
Base Features, Description Word Count and Title Word Count	0.94	0.674	0.67	0.669	0.674
Base Features, Biography Word Count, Description Word Count and Title Word Count	0.941	0.677	0.673	0.672	0.677

Table 5.2: Results with Social Media

	AUC	CA	F1	Precision	Recall
Base Features	0.938	0.667	0.664	0.663	0.667
Base Features and Facebook	0.938	0.667	0.663	0.662	0.667
Base Features and Twitter	0.938	0.668	0.665	0.664	0.668
Base Features and Instagram	0.938	0.669	0.665	0.664	0.669
Base Features, Facebook and Twitter	0.939	0.669	0.666	0.665	0.669
Base Features, Facebook and Instagram	0.939	0.669	0.665	0.664	0.669
Base Features, Twitter and Instagram	0.939	0.669	0.666	0.665	0.669
Base Features, Facebook, Twitter and Instagram	0.9339	0.67	0.667	0.665	0.67

Some of the features discussed above have a stronger impact when combined. This can be seen in table 5.7. Features such as the cluster of the biography and the level of positive sentiment in the description continue to have a positive impact on the overall efficacy of the classifier.

Table 5.3: Results with 10 Clusters

	AUC	CA	F1	Precision	Recall
Base Features (BF)	0.938	0.667	0.664	0.663	0.667
BF and Awards Cluster (Cl)	0.938	0.669	0.665	0.664	0.669
BF and Biography (Bio) Cl	0.939	0.671	0.668	0.667	0.671
BF and Description (Desc) Cl	0.936	0.662	0.658	0.657	0.662
BF and Education (Edu) Cl	0.939	0.67	0.667	0.666	0.67
BF and Events Cl	0.939	0.669	0.666	0.665	0.669
BF and Title Cl	0.934	0.656	0.652	0.651	0.656
BF, Awards Cl, Bio Cl, Desc Cl, Edu Cl, Events Cl, and Title Cl	0.939	0.667	0.663	0.662	0.667

Table 5.4: Results with 25 Clusters

	AUC	CA	F1	Precision	Recall
Base Features (BF)	0.938	0.667	0.664	0.663	0.667
BF and Awards Cluster (Cl)	0.939	0.669	0.666	0.665	0.669
BF and Biography (Bio) Cl	0.939	0.671	0.668	0.667	0.671
BF and Description (Desc) Cl	0.936	0.664	0.66	0.659	0.664
BF and Education (Edu) Cl	0.939	0.6	0.667	0.665	0.67
BF and Events Cl	0.939	0.67	0.667	0.665	0.67
BF and Title Cl	0.935	0.659	0.655	0.654	0.659
Base Features, Awards, Bio, Desc, Edu, Events, Title Clusters	0.941	0.672	0.668	0.667	0.672

Table 5.5: Results with 50 Clusters

	AUC	CA	F1	Precision	Recall
Base Features (BF)	0.938	0.67	0.666	0.665	0.67
BF and Awards Cluster (Cl)	0.939	0.672	0.669	0.667	0.672
BF and Biography (Bio) Cl	0.94	0.674	0.671	0.669	0.674
BF and Description (Desc) Cl	0.937	0.667	0.663	0.662	0.667
BF and Education (Edu) Cl	0.939	0.672	0.669	0.668	0.672
BF and Events Cl	0.939	0.672	0.669	0.667	0.672
BF and Title Cl	0.936	0.66	0.656	0.655	0.66
Base Features, Awards, Bio, Desc, Edu, Events, Title Clusters	0.942	0.676	0.672	0.671	0.676

Table 5.6: Results with Sentiment Features

	AUC	CA	F1	Precision	Recall
Base Features (BF)	0.938	0.668	0.665	0.663	0.668
BF and Biography Positive Sentiment (BioPos)	0.939	0.671	0.667	0.666	0.671
BF and Biography Negative Sentiment (BioNeg)	0.939	0.67	0.667	0.665	0.67
BF and Biography Neutral Sentiment (BioNeu)	0.939	0.671	0.668	0.667	0.671
BF and Description Positive Sentiment (DescPos)	0.94	0.679	0.676	0.675	0.679
BF and Description Negative Sentiment (DescNeg)	0.939	0.676	0.673	0.672	0.676
BF and Description Neutral Sentiment (DescNeu)	0.94	0.678	0.675	0.674	0.678
BF and Title Positive Sentiment (TitlePos)	0.938	0.668	0.664	0.663	0.668
BF and Title Negative Sentiment (TitleNeg)	0.938	0.668	0.665	0.663	0.668
BF and Title Neutral Sentiment (TitleNeu)	0.937	0.668	0.664	0.663	0.668
BF, BioPos, DescPos, TitlePos	0.941	0.682	0.679	0.678	0.682
BF, BioNeg, DescNeg, TitleNeg	0.94	0.679	0.675	0.674	0.679
BF, BioNeu, DescNeu, TitleNeu	0.941	0.682	0.679	0.678	0.682
BF, BioPos, BioNeg, BioNeu	0.94	0.673	0.669	0.668	0.673
BF, DescPos, DescNeg, DescNeu	0.942	0.682	0.678	0.677	0.682
BF, TitlePos, TitleNeg, TitleNeu	0.938	0.668	0.664	0.663	0.668
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu	0.944	0.687	0.683	0.683	0.687

Table 5.7: Results with Combined Features

	AUC	CA	F1	Precision	Recall
Base Features (BF)	0.938	0.667	0.664	0.663	0.667
BF, Facebook (FB), Twitter (TWT), Instagram (INST), Biography Word Count (BWC), Description Word Count (DWC), Title Word Count (TWC)	0.942	0.681	0.677	0.676	0.681
BF, FB, TWT, INST, BWC, DWC, TWC, Awards Cluster (10 Clusters)	0.943	0.682	0.678	0.677	0.682
BF, FB, TWT, INST, BWC, DWC, TWC, Biography Cluster (10 Clusters)	0.943	0.683	0.679	0.678	0.683
BF, FB, TWT, INST, BWC, DWC, TWC, Description Cluster (10 Clusters)	0.941	0.677	0.673	0.672	0.677
BF, FB, TWT, INST, BWC, DWC, TWC, Education Cluster (10 Clusters)	0.943	0.682	0.679	0.678	0.682
BF, FB, TWT, INST, BWC, DWC, TWC, Events Cluster (10 Clusters)	0.943	0.682	0.678	0.677	0.682
BF, FB, TWT, INST, BWC, DWC, TWC, Title Cluster (10 Clusters)	0.941	0.674	0.67	0.669	0.674
BF, FB, TWT, INST, BWC, DWC, TWC, Awards, Biography, Description, Education, Events, Title Clusters (10 Clusters)	0.943	0.678	0.674	0.674	0.678
BF, FB, TWT, INST, Awards Cluster (25 Clusters)	0.939	0.672	0.669	0.667	0.672
BF, FB, TWT, INST, Biography Cluster (25 Clusters)	0.94	0.674	0.671	0.669	0.674
BF, FB, TWT, INST, Description Cluster (25 Clusters)	0.938	0.668	0.664	0.663	0.668

Table 5.7: Results with Combined Features

	AUC	CA	F1	Precision	Recall
BF, FB, TWT, INST, Education Cluster (25 Clusters)	0.94	0.673	0.67	0.668	0.673
BF, FB, TWT, INST, Events Cluster (25 Clusters)	0.94	0.673	0.67	0.668	0.673
BF, FB, TWT, INST, Title Cluster (25 Clusters)	0.937	0.662	0.658	0.657	0.662
BF, FB, TWT, INST, BWC, DWC, TWC, Awards Cluster (25 Clusters)	0.943	0.683	0.679	0.678	0.683
BF, FB, TWT, INST, BWC, DWC, TWC, Biography Cluster (25 Clusters)	0.943	0.683	0.6679	0.679	0.683
BF, FB, TWT, INST, BWC, DWC, TWC, Description Cluster (25 Clusters)	0.941	0.677	0.672	0.672	0.677
BF, FB, TWT, INST, BWC, DWC, TWC, Education Cluster (25 Clusters)	0.942	0.683	0.68	0.679	0.683
BF, FB, TWT, INST, BWC, DWC, TWC, Events Cluster (25 Clusters)	0.942	0.683	0.679	0.678	0.683
BF, FB, TWT, INST, BWC, DWC, TWC, Title Cluster (25 Clusters)	0.941	0.674	0.67	0.669	0.674
BF, FB, TWT, INST, BWC, DWC, TWC, Awards, Biography, Description, Education, Events, Title Clusters (25 Clusters)	0.944	0.68	0.676	0.675	0.68
BF, FB, TWT, INST, BWC, DWC, TWC, Awards Cluster (50 Clusters)	0.943	0.683	0.679	0.678	0.683
BF, FB, TWT, INST, BWC, DWC, TWC, Bio Cluster (50 Clusters)	0.943	0.684	0.681	0.679	0.684
BF, FB, TWT, INST, BWC, DWC, TWC, Desc Cluster (50 Clusters)	0.941	0.677	0.673	0.672	0.677
BF, FB, TWT, INST, BWC, DWC, TWC, Edu Cluster (50 Clusters)	0.943	0.683	0.68	0.679	0.683

Table 5.7: Results with Combined Features

	AUC	CA	F1	Precision	Recall
BF, FB, TWT, INST, BWC, DWC, TWC, Events Cluster (50 Clusters)	0.943	0.684	0.68	0.679	0.684
BF, FB, TWT, INST, BWC, DWC, TWC, Title Cluster (50 Clusters)	0.941	0.677	0.672	0.672	0.677
BF, FB, TWT, INST, BWC, DWC, TWC, Awards, Biography, Description, Education, Events, Title Clusters (50 Clusters)	0.945	0.683	0.679	0.678	0.683
BF, FB, TWT, INST, BioPos, DescPos, TitlePos	0.943	0.687	0.684	0.683	0.687
BF, FB, TWT, INST, BioNeg, DescNeg, TitleNeg	0.941	0.681	0.678	0.677	0.681
BF, FB, TWT, INST, BioNeu, DescNeu, TitleNeu	0.942	0.685	0.681	0.68	0.685
BF, FB, TWT, INST, BioPos, BioNeg, BioNeu	0.941	0.675	0.672	0.671	0.675
BF, FB, TWT, INST, DescPos, DescNeg, DescNeu	0.943	0.686	0.682	0.681	0.686
BF, FB, TWT, INST, TitlePos, TitleNeg, TitleNeu	0.939	0.672	0.668	0.667	0.672
BF, FB, TWT, INST, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu	0.945	0.689	0.685	0.684	0.689
BF, BWC, DWC, TWC, BioPos, DescPos, TitlePos	0.944	0.686	0.682	0.682	0.686
BF, BWC, DWC, TWC, BioNeg, DescNeg, TitleNeg	0.942	0.683	0.68	0.679	0.683
BF, BWC, DWC, TWC, BioNeu, DescNeu, TitleNeu	0.944	0.686	0.682	0.682	0.686

Table 5.7: Results with Combined Features

	AUC	CA	F1	Precision	Recall
BF, BWC, DWC, TWC, BioPos, BioNeg, BioNeu	0.943	0.683	0.68	0.679	0.683
BF, BWC, DWC, TWC, descPos, descNeg, descNeu	0.944	0.686	0.681	0.681	0.686
BF, BWC, DWC, TWC, TitlePos, TitleNeg, TitleNeu	0.941	0.678	0.674	0.674	0.678
BF, BWC, DWC, TWC, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu	0.946	0.69	0.685	0.685	0.69
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Awards Cl (50)	0.945	0.688	0.684	0.684	0.688
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Bio Cl (50)	0.945	0.69	0.686	0.685	0.69
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Desc Cl (50)	0.946	0.688	0.684	0.684	0.688
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Edu Cl (50)	0.945	0.689	0.686	0.685	0.689
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Events Cl (50)	0.946	0.693	0.689	0.689	0.689

Table 5.7: Results with Combined Features

	AUC	CA	F1	Precision	Recall
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Title Cl (50)	0.944	0.682	0.677	0.677	0.682
BF, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Awards Cl (50), Bio Cl (50), Desc Cl (50), Edu Cl (50), Events Cl (50), Title Cl (50)	0.946	0.688	0.683	0.683	0.688
BF, FB, TWT, INST, BWC, DWC, TWC, BioPos, BioNeg, BioNeu, DescPos, DescNeg, DescNeu, TitlePos, TitleNeg, TitleNeu, Awards Cl (50), Bio Cl (50), Desc Cl (50), Edu Cl (50), Events Cl (50), Title Cl (50)	0.947	0.69	0.685	0.685	0.69

5.0.2 Initial Conclusions

This chapter discusses past work in price prediction for works of fine art. The primary focus of those works was on determining if various textual features could be utilized for price prediction. The text that an artist chooses to share about themselves and their work can be utilized as a predictive feature. It is interesting that the tone of the words can function as a predictive feature.

The features created from the word counts of an artist's biography, description and title do have value as predictive features. Their use increases when combined with other features. Their value may be explained by more experienced artists having longer or more detailed biographies. However, this will require further exploration as a feature.

Features based on the presence or absence of linked social media pages are of limited importance as predictors. The simple act of linking to a page does not indicate that the artist actively maintains it or has an active following. Additionally, with social media pages being present at roughly equal levels across all price points, this diminishes their predictive value.

The text clustering features do have value as predictors. However, the most positive impact came from the biography, education, awards and events segments. There are a significantly smaller number of these compared to the titles and descriptions, so it may be the unsupervised classifier is placing titles and descriptions into categories too vague to be adequate features.

Lastly, the sentiment of the text had an unexpectedly significant impact on the accuracy of the classifer. A feature that measures the positive sentiment of the text improve accuracy notably. Interestingly, the title features have no impact alone, possibly due to the lack of sentiment in the titles.

The sets of features discussed here demonstrate the potential of textual features as price predictors.

5.1 Development of Action Rules for Artwork Price Development

5.1.1 Initial Exploration

LISp-Miner [69] was used to develop a set of action rules for artwork prices. The listed asking price of one of the artworks was chosen as the decision feature and is treated as a flexible attribute in the following section. The set of flexible attributes center primarily on relatively low cost changes to how an artist presents themselves and their work to the public. The LISp-Miner discretiztion tools were used to partition the price attribute into ten sections each containing an approximately equal set of records. In the following section, these will be referred to as levels one through ten.

The chosen set of flexible attributes are tied to the concept of consumer perception. They are all easily modified by an artist attempting to improve their sales. This makes them low cost for an interested artist so that they can easily experiment with the recommended rules. As discussed previously, the word counts of the artist's biography and artwork description have value as predictive features. Similarly, the presence of social media links are also used for predictive purposes. While largely neutral, the sentiment of the descriptions and biographies were determined and added as features. All the flexible features used for building the antecedent of the rules are listed below. All features were discretized using the Lisp-Miner discretization tools.

- Positive Sentiment Level of Biography (Bio. Ps.)
- Negative Sentiment Level of Biography (Bio. Ng.)
- Positive Sentiment Level of Artwork Description (Desc. Ps.)
- Negative Sentiment Level of Artwork Description (Desc. Ng.)
- Word Count of the Artist Biography (Bio. WC)
- Word Count of the Artwork Description (Desc. WC)

- Social Media (Considered Together as SM)

  Artist Listed a Facebook Profile

  Artist Listed a Twitter Profile

  Artist Listed an Instagram Profile

The chosen set of stable attributes describe the work of art. These are used in constructing the antecedent portion of the G-Action rule. Taking cues from [30], features such as the size of the work as well as features tagged by the artist are used as stable features. The size of the work has been discretized into five categories with an approximately equal number of tuples using the Lisp-Miner discretization tools [69]. The subject of the work and its style are used as stable attributes along with the medium of the work. Due to the diversity of mediums, the number of mediums was reduced to seven broad categories and one NA category. Whether or not an artist had reviews visible to potential customers was also used as a binary stable attribute. As some amount of activity on the platform is required for a review to appear, this could be viewed as a marker of the amount of time or interest the artist has received. Finally, Canny edge detection [62], which was implemented in OpenCV [53], was used to calculate the percentage of edges in the primary image. While an artist may post multiple images, only the primary one was used for this analysis. A small number of works had errors during retrieval of the photograph, so these works were not considered. This can be seen as a rough representation of the detail level in the work, and was discretized into five partitions. Lastly, using Open-CV [53], the pixels in the work were clustered to determine the most prominent single color and that was used as a stable attribute. The full list of attributes is listed below.

- Artistic Style

- Artistic Subject

- Medium
- Height
- Width
- Artist Has Visible Reviews
- Percentage of the Artwork Representing Edges

Sets of rules were generated for combinations of prices and flexible attributes. These were all generated using the LISp-Miner Ac4ft-Miner tool. The list of stable attributes listed above was used throughout for comparison purposes. Rules that move from one price level to the next higher price level were the only ones considered in the analysis discussed below. The partitions used are as given here: (<12.97 - 58.28), (58,28 - 95.90), (95.90 - 130.04), (130.04 - 188.13), (188.13 - 250), (250 - 350), (350 - 490), (490 - 742), (742 - 1351.24), (1351.24 - >1,000,000). Minimum thresholds for the support and confidence of each of the two component rules were required. In order for a rule to be considered, it must have a support of at least two for the before rule, representing the initial state, and after rule, representing the final state, and a confidence of at least 60%. Rules were also restricted in length to one stable attribute and one flexible attribute.

Table 5.8: Coverage of Rules Generated using Base Stable Features

	SM	**Bio.WC**	**Desc.WC**	**Bio.Ps**	**Desc.Ps**	**Bio.Ng**	**Desc.Ng**
1->2	19.24	38.89	30.26	37.05	26.56	35.86	19.45
2->3	4.31	16.35	13.03	17.04	11.97	9.70	5.04
3->4	3.60	11.91	9.52	11.42	9.40	7.78	3.52
4->5	2.51	7.87	5.80	8.02	5.67	4.41	2.35
5->6	2.21	7.31	5.91	7.82	5.54	5.18	1.64
6->7	1.30	8.20	6.91	7.96	5.77	3.41	3.54
7->8	1.34	7.28	4.80	6.34	4.41	3.47	1.54
8->9	1.94	7.79	6.59	8.91	6.03	5.14	2.05
9->10	4.77	14.25	12.18	13.17	10.87	11.35	5.21

As seen in figure 5.8, the level of coverage of the rules is highly variable. Some attributes, such as social media, have a markedly lesser impact on the level of coverage. Attributes that impact an artist's biography had a more pronounced impact on the level of coverage of the resulting rule sets. This is particularly apparent when comparing the coverage when the negativity or positivity of the biography with the same feature of the description. The coverage levels tend to be lower in the middle price ranges. This may be due to the increasingly large price changes needed to move artworks from one category to another.

To expand on this, the main color feature was then added to the dataset as a stable attribute. As with the rules created above, 100,000 records were examined and rules were only considered if they had a support of at least two for the before and after rules and a confidence of at least 60%. The rules were discretized using Lisp-Miner in both cases. More rules were generated at each price point, and the coverage and confidence tended to be higher. The pattern of which flexible attributes had the most notable impact was repeated, and as before the best coverage was with the lowest price points. For the full coverage, see figure 5.9.

Table 5.9: Coverage of Rules Generated using Base Stable Features and Main Color

	SM	**Bio.WC**	**Desc.WC**	**Bio.Ps**	**Desc.Ps**	**Bio.Ng**	**Desc.Ng**
1->2	25.45	55.11	47.57	54.12	44.77	48.22	26.05
2->3	8.93	26.44	22.25	25.33	21.92	17.04	8.05
3->4	5.62	20.50	17.12	18.83	15.88	12.03	7.27
4->5	5.09	13.57	12.66	14.68	11.66	7.89	5.64
5->6	3.81	14.71	11.52	13.42	11.15	7.75	3.77
6->7	4.21	14.38	12.30	15.09	10.65	8.16	5.20
7->8	4.08	13.76	11.53	13.66	11.03	7.04	4.22
8->9	4.94	16.46	13.41	17.09	14.57	10.16	5.01
9->10	12.51	27.51	26.67	27.37	23.80	21.58	11.51

To expand on this concept further, more rule sets were generated using Lisp-Miner. There were several changes made to the rule generation process to improve the results. First, more variations in stable attributes were explored. Rules were generated using various visual features of the artworks as stable attributes. The pleasure, arousal and dominance scale as well as the activity, weight, and heat scales were considered as stable attributes. The average brightness of the image as a whole and the standard deviation of that brightness were also considered as stable attributes. The average red, green and blue values were examined, referred to as RGB mean, as were the standard deviations of these values. Taking a cue from the improvement shown in figure 5.9, a second color was also considered. Lastly, the work was divided into 9 equal sized blocks and the brightest and darkest blocks were used as stable attributes. This could be seen as an attempt to determine the approximate location of the focal point of the work.

The requirements for support and confidence were unchanged. Discretization was again performed using the Lisp-Miner tools. The stable attribute medium was expanded from seven broad categories and NA to ten with an NA category. The number of tuples was restricted to 50,000. Lastly, longer rules with up to two stable attributes and two flexible attributes were included. The full coverage for these features is visible in figure 5.10. The activity, weight, heat scores (abbreviated as AWH), pleasure, arousal, dominance scores (abbreviated as PAD), the identity of the single most prominent color out of ten (1 Color), the identity of the two most prominent colors out of ten (2 Color), the average brightness and standard deviation of the pixels in the image reduced to grayscale (Gray Mn Sd), the average intensity of the red, green and blue channels (RGB Mn), the standard deviation of the pixels in the red, green and blue channels (RGB Sd) and the position, when the image is divided into a three by three grid, of the brightest and darkest portion of the image reduced to grayscale (Min9Max9) were considered as additional stable attributes.

Table 5.10: Coverage with new attributes

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGBMn**	**RGB Sd**
1->2	64.05033	64.94907	65.36848	66.30717	67.98482	64.60955	65.96765	64.80927	65.08888
2->3	22.94918	24.02961	24.12965	25.29012	28.31132	24.02961	26.23049	24.2497	24.26971
3->4	19.35936	20.58058	20.34034	21.6016	23.4034	19.93994	22.16216	20.48048	20.84084
4->5	11.37271	11.99122	11.95132	13.50758	15.04389	11.67199	13.7071	11.85156	12.27055
5->6	9.482759	9.963913	10.14435	11.64796	13.47233	9.703288	10.70569	10.06415	9.983962
6->7	8.96	9.78	9.52	11.06	13.18	9.48	9.98	9.66	9.68
7->8	10.03799	10.5179	10.9978	11.87762	13.81724	10.17796	11.09778	10.55789	10.45791
8->9	10.94438	11.40456	11.48459	13.46539	15.42617	11.26451	11.94478	11.72469	11.28451
9->10	23.2	23.96	24.44	26.42	28.92	23.84	25.24	24.12	24.02

It is notable that the same pattern of middle partitions having particularly low coverage is repeated. Adding two color stable attributes or adding the blocks of the brightest and darkest portion of the work, improves the coverage marginally, but no stable attribute has a dramatically higher coverage rate than any of the others consistently. Many rules were generated, over 3,000 were created using only the base feature set moving from price 1 to price 2. An example of one of these rules is 'Artistic_style(Surrealistic) & Width(very low) && Bio_pos(very high) & Desc_pos(lower) -> Price(1), Artistic_style(Surrealistic) & Width(very low) && Bio_pos(avg) & Desc_pos(higher) -> Price(2)'.

In an attempt to further improve the accuracy of the models and gain higher coverage, artists with visual similarities were grouped. Artists were clustered by aggregating their works into a single representation of their style. These aggregations were then clustered. Two sets of attributes were used for clustering the edges of an artist's works in general and the aggregate brightness of it's pixels also in general.

Ten clusters were formed, but they varied significantly in size. The largest cluster contained 1759 artists, and the smallest was a significant outlier with only one artist with many works. In the following figures, the maximum number of works considered was 50,000, but fewer would be used if only a smaller number of works in that cluster exist.

As is evident from examining the coverage of the rules, this level of personalization significantly improves the coverage of the rule sets. However, some such as cluster six when based on edges have a very low coverage due to the small number, only four, artists represented. This prevents many rules from being generated. Some, such as cluster four based on edges which represents 415 artists, have excellent coverage levels. It is notable that even with the clusters, the patterns of lesser coverage in the middle price ranges and the lack of dramatic changes in coverage when adding new stable attributes is consistent.

These clusters were also used to generate predictive models as was performed in 5.0.1. These models displayed similar patterns precision and recall to those discussed previously. The full results of these models are displayed in Appendix A.

Table 5.11: Coverage of Cluster 0 Gray

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	39.17666	40.70338	42.33915	41.41221	41.46674	41.52126	40.07634	39.69466	41.41221
2->3	37.48271	37.92531	38.53389	38.31259	38.42324	38.2296	37.787	37.95297	39.00415
3->4	11.58254	11.58254	12.02146	12.14338	12.2653	11.58254	11.89954	11.68008	11.63131
4->5	7.946618	7.946618	7.946618	8.55323	8.674553	7.946618	8.03761	8.067941	7.946618
5->6	12.05332	12.05332	12.30856	12.73398	12.7907	12.19512	12.42201	12.42201	12.05332
6->7	9.324583	10.36369	9.351928	9.70741	9.871479	9.351928	10.74651	10.22696	9.433962
7->8	4.96963	4.96963	5.27333	5.438984	5.797902	4.96963	5.85312	5.024848	5.190502
8->9	9.744716	9.744716	9.772166	10.59566	10.62311	9.881965	10.89761	11.03486	10.89761
9->10	23.52295	24.12751	24.84199	25.99615	26.21599	24.45727	24.15499	24.23743	24.29239

Table 5.12: Coverage of Cluster 1 Gray

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	96.8254	97.8836	97.61905	97.08995	97.3545	97.3545	97.61905	97.3545	97.61905
2->3	81.86667	89.33333	92.8	86.93333	88	88.8	88.26667	90.66667	86.4
3->4	68.99225	85.52972	78.29457	71.05943	73.38501	75.71059	78.29457	80.62016	75.96899
4->5	77.98913	84.23913	83.69565	79.8913	82.6087	82.6087	84.78261	83.15217	81.52174
5->6	78.04233	89.94709	87.56614	80.68783	82.27513	87.03704	87.83069	89.68254	90.21164
6->7	70.7124	85.22427	83.64116	74.40633	79.15567	81.00264	81.53034	83.37731	81.7942
7->8	69.64286	85.45918	83.67347	73.72449	76.53061	78.31633	80.10204	80.10204	82.90816
8->9	62.7451	83.19328	76.19048	68.90756	75.07003	74.22969	76.7507	74.78992	76.7507
9->10	71.28205	90.76923	86.66667	76.92308	86.66667	82.82051	86.66667	85.89744	83.33333

Table 5.13: Coverage of Cluster 2 Gray

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	82.36469	84.54164	85.42041	84.22209	85.42041	83.84262	85.30058	85.1408	85.06091
2->3	47.30072	48.43111	49.61996	50.26311	52.19256	48.2557	50.02923	48.76242	48.68447
3->4	32.30457	33.80711	34.39594	35.06599	37.72589	33.96954	35.65482	34.61929	33.3401
4->5	24.47948	25.4902	25.87427	27.37012	29.99798	25.04548	26.50091	25.65191	25.40934
5->6	19.4761	21.17576	21.35573	21.83563	24.05519	21.25575	21.35573	21.89562	20.29594
6->7	16.67995	17.85572	17.73615	18.65285	21.12395	17.59665	18.03507	17.73615	17.57672
7->8	22.42558	23.20998	23.12953	24.55752	26.87047	23.02896	24.15527	23.16975	23.02896
8->9	18.34367	18.88378	18.94379	21.30426	23.88478	18.66373	20.024	19.34387	18.84377
9->10	38.11426	40.41151	41.39033	41.80983	45.04594	39.87215	41.88973	40.55134	40.37155

Table 5.14: Coverage of Cluster 3 Gray

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	75.96154	75.96154	78.84615	75.96154	75.96154	77.88462	77.88462	80.76923	77.88462
2->3	35.52632	46.05263	40.78947	35.52632	35.52632	35.52632	43.42105	43.42105	43.42105
3->4	84.61538	86.81319	84.61538	85.71429	85.71429	84.61538	86.81319	85.71429	86.81319
4->5	42.30769	45.19231	59.61538	45.19231	49.03846	50	53.84615	45.19231	42.30769
5->6	23.17073	28.04878	35.36585	23.17073	24.39024	31.70732	31.70732	32.92683	34.14634
6->7	27.58621	29.88506	29.88506	28.73563	29.88506	27.58621	32.18391	28.73563	29.88506
7->8	46.06742	57.30337	52.80899	53.93258	53.93258	50.5618	58.42697	47.19101	55.05618
8->9	47.77778	68.88889	57.77778	50	57.77778	60	55.55556	57.77778	65.55556
9->10	90.42553	96.80851	92.55319	91.48936	91.48936	95.74468	95.74468	91.48936	95.74468

Table 5.15: Coverage of Cluster 4 Gray

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	85.67335	89.68481	92.26361	85.95989	86.81948	89.11175	90.25788	89.39828	89.97135
2->3	64.33333	70.66667	71.33333	66.33333	68.66667	69	70.66667	70	71.66667
3->4	62.22222	72.22222	72.96296	65.55556	69.62963	71.11111	65.92593	71.85185	77.77778
4->5	35.44304	49.05063	47.1519	39.55696	42.08861	47.46835	44.62025	48.41772	46.83544
5->6	46.61922	59.4306	56.58363	49.82206	54.4484	53.73665	59.4306	54.80427	59.78648
6->7	52.05047	65.9306	67.82334	55.5205	59.30599	66.56151	61.82965	67.82334	64.35331
7->8	62.54417	74.91166	74.20495	65.72438	71.02473	69.61131	72.43816	75.61837	73.49823
8->9	75.38941	85.04673	83.4891	77.25857	78.19315	80.99688	82.55452	83.80062	84.42368
9->10	80.4878	90.59233	88.85017	83.62369	86.75958	85.36585	87.45645	88.50174	87.80488

Table 5.16: Coverage of Cluster 5 Gray

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	97.91667	100	100	97.91667	97.91667	99.30556	100	100	98.61111
2->3	57.93651	70.63492	72.22222	61.90476	65.87302	65.87302	76.19048	69.04762	79.36508
3->4	81.61765	88.23529	84.55882	83.82353	85.29412	88.23529	86.76471	87.5	88.23529
4->5	54.19847	75.57252	84.73282	62.59542	67.93893	70.99237	67.93893	76.33588	70.99237
5->6	29.62963	57.77778	57.03704	37.77778	42.96296	51.11111	45.18519	49.62963	49.62963
6->7	58.51852	75.55556	75.55556	62.96296	70.37037	73.33333	68.14815	74.81481	71.11111
7->8	28.24427	58.77863	52.67176	35.87786	45.80153	50.38168	54.96183	54.96183	54.96183
8->9	43.62416	51.67785	57.04698	47.65101	50.33557	57.71812	57.71812	54.36242	57.71812
9->10	90.90909	96.69421	95.86777	92.56198	92.56198	90.90909	95.04132	94.21488	93.38843

Table 5.17: Coverage of Cluster 6 Gray

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	96.64537	97.28435	97.36422	96.88498	97.20447	97.60383	97.76358	97.44409	97.36422
2->3	86.71329	90.98679	91.14219	87.95649	89.12199	90.05439	90.52059	90.83139	90.59829
3->4	83.0033	87.70627	87.45875	84.48845	85.89109	87.0462	87.54125	88.0363	87.21122
4->5	61.56926	70.77662	66.45316	64.3715	67.17374	64.85188	69.65572	67.09367	68.3747
5->6	47.99035	54.74277	52.97428	50.24116	55.7074	51.44695	59.80707	52.73312	52.65273
6->7	34.54686	41.82804	43.14485	41.59566	45.39117	41.98296	44.3842	43.6096	45.77847
7->8	70.81616	78.23578	77.90602	74.44353	76.66941	77.41138	78.56554	78.23578	75.59769
8->9	60.48896	64.03785	67.66562	64.58991	68.45426	67.0347	72.55521	67.50789	67.90221
9->10	82.90323	87.98387	88.06452	84.83871	86.6129	87.09677	88.46774	86.69355	86.93548

Table 5.18: Coverage of Cluster 7 Gray

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	21.31148	27.86885	39.34426	27.86885	29.5082	29.5082	31.14754	27.86885	37.70492
2->3	10	10	30	10	10	10	10	10	10
3->4	0	0	0	0	0	0	0	0	0
4->5	41.37931	58.62069	48.27586	41.37931	48.27586	44.82759	44.82759	44.82759	48.27586
5->6	35.29412	47.05882	47.05882	35.29412	47.05882	52.94118	52.94118	35.29412	52.94118
6->7	46.42857	50	50	46.42857	46.42857	46.42857	60.71429	50	50
7->8	30.76923	38.46154	38.46154	42.30769	42.30769	42.30769	34.61538	46.15385	42.30769
8->9	38.09524	42.85714	38.09524	38.09524	38.09524	38.09524	42.85714	47.61905	38.09524
9->10	45	50	50	45	55	55	50	60	55

Table 5.19: Coverage of Cluster 8 Gray

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	80.09592	81.03517	81.53477	81.19504	82.19424	80.93525	81.77458	80.97522	81.33493
2->3	37.22745	38.66773	39.40788	40.76815	43.68874	38.40768	40.44809	39.34787	38.36767
3->4	30.02	31.6	32.02	33.18	35.36	31.06	32.8	31.92	31.7
4->5	23.35127	24.34748	24.62642	25.9215	27.95378	23.92907	26.33991	24.78581	24.98506
5->6	25.89841	26.5007	26.72154	27.74543	29.41176	26.82192	27.36398	27.00261	26.62116
6->7	13.89111	14.67174	14.97198	16.05284	18.43475	14.45156	15.53243	14.47158	14.69175
7->8	14.5465	15.19985	15.39201	16.54497	18.17832	15.04612	16.4681	15.1422	15.0269
8->9	16.87097	17.59817	17.59817	19.55122	21.56659	17.55662	19.01101	17.95138	18.8448
9->10	29.01544	31.12091	30.23862	33.62743	36.29437	29.83758	31.4618	30.63966	30.11831

Table 5.20: Coverage of Cluster 9 Gray

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	86.93467	90.36851	90.20101	87.52094	88.1072	89.94975	90.61977	90.20101	89.44724
2->3	61.01541	68.72167	68.08704	66.18314	68.90299	69.26564	70.35358	68.72167	68.81233
3->4	56.7216	61.23157	62.27233	60.97138	64.35386	63.3131	65.0477	62.53252	65.74154
4->5	44.007	50.65617	50.65617	47.94401	52.66842	48.29396	50.83115	51.61855	50.56868
5->6	44.31138	53.72113	53.63559	52.78015	56.11634	52.43798	55.43199	53.63559	52.18135
6->7	48.49558	53.45133	53.36283	52.92035	55.04425	53.00885	55.84071	53.27434	54.15929
7->8	46.98276	55.60345	54.05172	52.15517	56.55172	53.27586	57.75862	55.17241	53.53448
8->9	60.89631	67.39895	68.89279	65.64148	68.98067	65.9051	70.73814	68.27768	67.31107
9->10	81.15183	85.95113	86.64921	83.76963	86.64921	84.99127	87.87086	86.82373	85.86387

Table 5.21: Coverage of Cluster 0 Edges

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	79.26708	80.22306	80.64131	80.68114	81.49771	80.84047	80.58156	80.50189	80.95997
2->3	35.20449	36.50762	36.7482	38.63272	41.4996	36.64796	38.31195	36.48757	36.56776
3->4	24.91018	26.16766	27.44511	27.32535	30.6986	26.28743	28.34331	26.62675	26.08782
4->5	14.63757	15.65879	15.95915	16.84021	19.0829	15.37845	16.98038	15.73889	15.35843
5->6	22.09302	22.71451	23.27586	24.37851	25.66159	23.43625	23.81716	23.07538	23.4162
6->7	15.14303	15.88318	15.94319	17.38348	18.82376	15.68314	16.26325	15.76315	16.12322
7->8	10.28362	12.40594	10.9782	12.75323	15.89813	11.11325	13.29346	11.15184	12.27089
8->9	20.57238	21.89963	21.85815	23.33057	26.00581	21.40191	22.56325	21.67151	21.56781
9->10	32.35001	34.40303	33.96452	36.31652	39.06717	33.86486	35.29998	34.00439	34.02432

Table 5.22: Coverage of Cluster 1 Edges

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	75.7764	81.36646	77.76398	77.01863	77.26708	83.35404	78.13665	81.49068	83.10559
2->3	62.45772	75.64825	78.01578	64.48703	65.27621	69.33484	70.23675	74.6336	76.09921
3->4	50.78219	60.89049	64.01925	52.1059	53.06859	64.13959	56.55836	63.05656	55.35499
4->5	45.12894	60.31519	53.4384	46.5616	49.5702	54.01146	57.02006	56.16046	51.2894
5->6	58.38084	66.93273	65.56442	61.8016	63.85405	64.0821	66.70468	64.76625	67.04675
6->7	71.05624	82.4417	86.6941	73.3882	75.58299	78.46365	84.49931	83.67627	83.81344
7->8	79.01235	88.39506	85.18519	80.61728	83.95062	82.71605	87.90123	85.4321	82.83951
8->9	88.0289	91.95046	92.15686	89.88648	90.91847	93.08566	91.74407	93.70485	93.39525
9->10	94.47077	96.68246	96.99842	95.7346	96.52449	96.36651	96.84044	96.52449	96.36651

Table 5.23: Coverage of Cluster 2 Edges

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	37.87879	37.87879		37.87879	37.87879	37.87879	37.87879	37.87879	37.87879
2->3	62.5	70.83333		62.5	62.5	66.66667	66.66667	66.66667	62.5
3->4	60.86957	63.04348		60.86957	60.86957	67.3913	69.56522	69.56522	65.21739
4->5	54.54545	72.72727		54.54545	59.09091	68.18182	63.63636	72.72727	72.72727
5->6	5.263158	10.52632		5.263158	12.2807	15.78947	8.77193	22.80702	5.263158
6->7	26.47059	47.05882		29.41176	32.35294	44.11765	41.17647	47.05882	38.23529
7->8	44.44444	68.88889		55.55556	75.55556	57.77778	53.33333	71.11111	64.44444
8->9	61.70213	68.08511		72.34043	72.34043	72.34043	63.82979	85.10638	63.82979
9->10	83.33333	90.47619		88.09524	88.09524	85.71429	85.71429	85.71429	85.71429

Table 5.24: Coverage of Cluster 3 Edges

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	95.0495	96.45215	96.36964	95.46205	96.28713	95.54455	96.61716	96.94719	95.70957
2->3	79.25926	84.60905	83.7037	83.45679	84.77366	81.893	85.18519	83.6214	81.7284
3->4	66.97248	73.4779	72.72727	72.06005	74.47873	73.72811	75.81318	74.72894	71.97665
4->5	69.60133	74.58472	73.25581	72.59136	75.08306	72.59136	76.24585	72.92359	74.25249
5->6	54.25268	59.04211	61.84971	58.62923	61.43683	60.28076	59.28984	62.18002	60.19818
6->7	47.35099	53.39404	53.97351	51.07616	54.55298	51.15894	58.19536	53.64238	51.65563
7->8	49.29694	54.42514	56.57568	55.33499	58.39537	53.68073	60.29777	55.74855	55.99669
8->9	60.42174	66.18005	67.39659	66.34225	69.82968	63.74696	73.80373	66.01784	67.5588
9->10	84.92129	88.40099	89.56089	87.98674	88.81524	88.40099	89.72659	89.80944	88.40099

Table 5.25: Coverage of Cluster 4 Edges

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	92.83128	95.11224	95.11224	93.66401	94.49674	94.64156	95.43809	94.67777	95.00362
2->3	65.48705	68.44217	69.6826	68.51514	70.63116	67.71251	71.1784	68.40569	69.75556
3->4	48.41883	52.07309	52.91637	52.14336	54.88405	51.33521	55.72734	51.19466	51.6163
4->5	35.25424	38.7194	38.45574	37.28814	40.30132	37.70245	40.33898	38.64407	37.43879
5->6	31.67747	32.93737	33.62131	33.6933	35.96112	33.29734	35.20518	33.54932	33.00936
6->7	26.79017	30.49519	30.88707	29.99644	32.91771	29.14143	30.60207	31.10082	29.56893
7->8	29.36775	32.43547	33.07146	33.07146	36.28881	31.94912	34.71755	32.99663	32.09877
8->9	34.43636	38.03636	37.27273	38.29091	40.8	36.83636	39.70909	37.74545	36.8
9->10	59.67213	64.29872	64.99089	64.33515	67.35883	63.06011	69.43534	64.66302	63.13297

Table 5.26: Coverage of Cluster 5 Edges

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	96.42857	99.4898	99.23469	96.68367	98.46939	98.97959	98.97959	99.23469	98.46939
2->3	52.92517	58.63946	57.95918	55.10204	56.87075	57.0068	56.32653	58.91156	56.73469
3->4	39.28571	46.42857	53.57143	39.28571	46.42857	46.42857	64.28571	60.71429	46.42857
4->5	69.89529	86.12565	85.07853	71.98953	78.01047	77.74869	83.76963	81.15183	81.41361
5->6	62.2739	79.32817	77.51938	70.54264	74.677	75.1938	78.29457	78.03618	77.77778
6->7	68.86076	80	83.29114	74.93671	79.74684	82.53165	80.50633	77.97468	84.55696
7->8	76.42487	81.86528	83.16062	78.49741	81.60622	81.34715	84.19689	82.64249	83.67876
8->9	74.02062	76.70103	76.90722	76.08247	78.5567	78.14433	77.1134	79.38144	77.52577
9->10	72.83951	81.48148	83.64198	75.61728	78.39506	79.62963	78.7037	78.08642	82.40741

Table 5.27: Coverage of Cluster 6 Edges

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	65	66.66667	77.5	65	66.66667	65	71.66667	66.66667	69.16667
2->3	0	0	0	0	0	0	0	0	0
3->4	0	0	0	0	0	0	0	0	0
4->5	0	5.714286	0	0	0	1.428571	0	5.714286	0
5->6	3.703704	9.259259	3.703704	3.703704	3.703704	3.703704	3.703704	12.96296	3.703704
6->7	0	0	0	0	0	0	0	0	0
7->8	0	0	0	0	0	0	0	0	0
8->9	8.163265	10.20408	8.163265	8.163265	8.163265	8.163265	8.163265	10.20408	12.2449
9->10	73.58491	75.4717	77.35849	73.58491	73.58491	77.35849	75.4717	73.58491	73.58491

Table 5.28: Coverage of Cluster 7 Edges

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	63.15789	63.15789	68.42105	63.15789	63.15789	68.42105	63.15789	76.31579	63.15789
2->3	75	82.5	87.5	77.5	80	77.5	77.5	85	77.5
3->4	41.17647	64.70588	58.82353	52.94118	67.64706	47.05882	55.88235	58.82353	58.82353
4->5	41.66667	50	52.77778	41.66667	41.66667	47.22222	47.22222	44.44444	41.66667
5->6	5	10	17.5	5	5	15	5	15	10
6->7	0	5	0	0	0	2.5	2.5	5	2.5
7->8	46.42857	64.28571	67.85714	57.14286	64.28571	64.28571	64.28571	64.28571	60.71429
8->9	65.71429	74.28571	71.42857	74.28571	74.28571	80	71.42857	77.14286	71.42857
9->10	55.31915	70.21277	65.95745	59.57447	63.82979	57.44681	59.57447	65.95745	63.82979

Table 5.29: Coverage of Cluster 8 Edges

	BF	AWH	PAD	1 Color	2 Colors	Gray Mn Sd	Min9Max9	RGB Mn	RGB Sd
1->2	98.58491	99.5283	99.0566	98.58491	99.0566	99.0566	99.0566	99.0566	99.0566
2->3	42.27941	52.57353	55.51471	42.64706	48.52941	50.73529	53.30882	52.94118	50.73529
3->4	21.46597	23.03665	23.56021	23.03665	25.65445	29.84293	23.56021	21.98953	35.07853
4->5	47.12644	56.89655	54.5977	53.44828	55.74713	51.72414	55.17241	54.5977	52.87356
5->6	23.64532	36.4532	46.30542	54.18719	66.00985	53.69458	33.00493	69.45813	39.40887
6->7	20.81633	30.61224	29.38776	23.26531	26.12245	27.7551	26.93878	31.02041	29.38776
7->8	29.31937	44.50262	43.4555	30.89005	40.31414	38.74346	42.93194	42.40838	46.0733
8->9	13.43284	17.91045	15.9204	13.93035	15.42289	13.93035	15.9204	14.92537	15.42289
9->10	28.77358	43.86792	41.50943	32.07547	34.43396	35.37736	35.37736	36.32075	34.43396

Table 5.30: Coverage of Cluster 9 Edges

	BF	**AWH**	**PAD**	**1 Color**	**2 Colors**	**Gray Mn Sd**	**Min9Max9**	**RGB Mn**	**RGB Sd**
1->2	67.35306	67.77289	68.05278	68.93243	69.05238	68.15274	68.69252	68.69252	68.93243
2->3	24.36119	24.36119	24.39962	26.60903	26.83958	24.36119	24.97598	24.41883	24.45725
3->4	9.531535	9.592375	9.592375	10.38329	10.66721	9.714054	9.612655	9.774894	9.531535
4->5	13.63994	13.67925	14.34748	14.44575	14.62264	13.75786	13.77752	13.85613	13.77752
5->6	13.32919	13.4743	13.72305	14.86318	15.11194	13.32919	13.66086	13.51575	13.74378
6->7	13.09956	13.09956	13.26078	13.88553	14.65135	13.09956	13.36155	13.13986	13.18017
7->8	5.162448	5.162448	5.18238	6.159059	6.976281	5.162448	5.222244	5.222244	5.162448
8->9	4.467147	4.467147	4.507212	5.168269	5.829327	5.008013	5.088141	5.068109	4.467147
9->10	22.95509	23.73697	23.55654	25.96231	26.12269	24.4988	26.72414	24.27827	23.83721

CHAPTER 6: CONCLUSIONS

What ultimately controls the price for a work of fine art? It is not as simple as concluding the most beautiful work will be the most expensive. What can this work tell us about the factors that indicated the price of a work of fine art? It is clear that how a work and an artist are perceived by a consumer impacts the potential sales price of the work. This is one of the reasons for the vital importance of artist biographies and artwork descriptions when modeling artwork prices. Even seemingly irrelevant features such as the overall sentiment of the text has a role in an artist's attempt to connect with a consumer and persuade them that this work is special and should be purchased.

Many factors touch how an artwork is perceived by a potential customer, ranging from the artist's biography to the number of words in the artwork's title. These factors all influence how a consumer understands an artwork and what they are willing to pay for it.

As discussed here, it is difficult to say with certainty what will influence a customer to make a purchase and how an artist must change their display to be more commercially viable. When developing action rules, it is clear that personalized rule sets have a dramatically higher coverage than randomly selecting tuples for rule generation. The personalization method focused on reflecting an artist's posted body of work, rather than simply addressing a feature of an individual artwork. This allows for a level of breadth and allows the clusters to reflect the tendencies of an artist, rather than the tendencies on an artwork. The positive influence this has on the coverage of rule sets and the accuracy of predictive models is notable, and indicates that developing highly personalized models for artwork price prediction is an important step.

A major development for the future is the further exploration of potential methods of grouping artists for personalized models and rule sets. This work focused exclusively on the use of visual features to cluster artists, however, integrating details of an artist's background or sales record may serve the same purpose.

The role of features in the pricing of artwork is more complex. While some are clearly relevant, such as features relating the wording of the artist's biography, others show only small changes to the accuracy of the models or none at all. The price level explored here may be a factor in feature selection as well. Exploration of other visual aspects such as alignment with current design trends may be a good next step. This is made more complex with the addition of personalized models, because with this addition the most relevant feature is no longer consistent across all clusters.

Therefore, a system with multiple tiers for classification would be advantageous for a recommender system. As discussed previously, the artist plays a key role in the price of an artwork. The price of a work is not just related to the work itself, but also the artist that created it. Whether this tie comes from the social cues of prices, or from the assurance of the artists future career, the value of the artwork is undeniably reliant on the associated artist.

As was developed here, this system should first cluster artists based on their similarity. Artists with similar traits and similar prices should be placed together. In this work, the focus of the similarity was on visual features, but other methods could be utilized for more complete clustering.

As was discussed in chapter 5, the dataset could be then partitioned in order to train personalized models for each cluster. This improved the coverage of the rules and the accuracy of the models. More exploration is necessary to determine the best method of clustering artists.

Once a new artist is placed in a cluster, the model that was developed for pricing the works of artists in this cluster can be queried. This model will only be trained on artworks made by artists that are similar to the new artist. By selecting which model should be used to price an artist by what cluster that artist sits in, this creates a level of personalization in the system. If the cluster for an artist is reevaluated throughout his or her career, an artist can move from one cluster to another allowing the system to accommodate a developing career.

All of these factors indicate the scope of the work remaining in this area. Personalization is a key component to developing rule sets and models. This work puts forth a viable method for developing this personalization, however, future work may be vital to developing the ideal configuration of features for grouping artists and for each artist group.

REFERENCES

[1] O. Velthuis, *Talking Prices: Symbolic Meanings of Prices on the Market for Contemporary Art.* Princeton University Press, 2005.

[2] J. Beckert and J. Rössel, "THE PRICE OF ART: Uncertainty and reputation in the art field," *European Societies*, vol. 15, pp. 178–195, May 2013.

[3] N. Freeman, "The Art Market Grew to $63.7 Billion in 2017, and Other Key Takeaways from Art Basel Report," *Artsy*, Mar. 2018.

[4] "H1 2018 - Global Art Market Report, by Artprice.com," tech. rep., 2018.

[5] "The Hiscox Online Art Trade Report 2018," tech. rep., ArtTactic, 2018.

[6] J. Bialynicka-Birula, "Changes in the global art market," *Oeconomia Copernicana*, vol. 9, no. 4, pp. 695,705I, 2018-12-01.

[7] D. Evans, *The current and future influence of online art sales on the art market.* PhD Thesis, 2015.

[8] S. Plattner, "A Most Ingenious Paradox: The Market for Contemporary Fine Art," *American Anthropologist*, vol. 100, pp. 482–493, June 1998.

[9] E. Coslor, "Transparency in an opaque market: Evaluative frictions between "thick" valuation and "thin" price data in the art market," *Accounting, Organizations and Society*, vol. 50, pp. 13–26, Apr. 2016.

[10] O. Ashenfelter and K. Graddy, "Sale rates and price movements in art auctions," *American Economic Review*, vol. 101, no. 3, pp. 212,216, 2011-05-01.

[11] L. Renneboog and C. Spaenjers, "Buying Beauty: On Prices and Returns in the Art Market," *Management Science*, vol. 59, pp. 36–53, Jan. 2013.

[12] S. Lovo and C. Spaenjers, "A Model of Trading in the Art Market," *American Economic Review*, vol. 108, pp. 744–774, Mar. 2018.

[13] A. Luther, "Artist-run galleries - differentiating three models in current contemporary art markets," *Journal for Art Market Studies*, vol. 2, no. 1, 2018.

[14] C. McAndrew, "Why the "Superstar Economics" of the Art Market Is Its Biggest Threat," Nov. 2018.

[15] S. Rosen, "The Economics of Superstars," *The American Economic Review*, vol. 71, no. 5, pp. 845–858, 1981.

[16] J. H. Gilkeson and K. Reynolds, "Determinants of internet auction success and closing price: An exploratory study," *Psychology and Marketing*, vol. 20, no. 6, pp. 537,566, 2003-06.

[17] ““ebay.com”,” 2020.

[18] J. Baker and J. Song, “Exploring decision rules for sellers in business-to-consumer(b2c) internet auctions,” *International Journal of E-Business Research (IJEBR)*, vol. 4, no. 1, pp. 1–21, 2008.

[19] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutièrrez, “Recommender systems survey,” *Knowledge-Based Systems*, vol. 46, pp. 109–132, July 2013.

[20] C. C. Aggarwal, *Recommender Systems The Textbook.* Cham: Springer, 2016. OCLC: 1060650280.

[21] G. Kembellec, G. Chartron, and I. Saleh, eds., *Recommender systems.* Information systems, web and pervasive computing series, London: ISTE, 2014. OCLC: ocn898753060.

[22] A. Felfernig, L. Boratto, M. Stettinger, and M. TkalÄiÄ, “Decision Tasks and Basic Algorithms,” in *Group Recommender Systems*, pp. 3–26, Cham: Springer International Publishing, 2018.

[23] G. Chartron and G. Kembellec, *General Introduction to Recommender Systems*, ch. 1, pp. 1–23. John Wiley Sons, Ltd, 2014.

[24] F. Ricci, L. Rokach, and B. Shapira, “Recommender Systems: Introduction and Challenges,” in *Recommender Systems Handbook* (F. Ricci, L. Rokach, and B. Shapira, eds.), pp. 1–34, Boston, MA: Springer US, 2015.

[25] D. Jannach, M. Zanker, A. Felfernig, and G. Friedrich, *Recommender Systems: An Introduction.* Cambridge: Cambridge University Press, 2010.

[26] B. Saleh and A. Elgammal, “Large-scale Classification of Fine-Art Paintings: Learning The Right Metric on The Right Feature,” *arXiv:1505.00855 [cs]*, May 2015. arXiv: 1505.00855.

[27] P. Messina, V. Dominguez, D. Parra, C. Trattner, and A. Soto, “Exploring Content-based Artwork Recommendation with Metadata and Visual Features,” *arXiv:1706.05786 [cs]*, June 2017. arXiv: 1706.05786.

[28] P. Messina, V. Dominguez, D. Parra, C. Trattner, and A. Soto, “Content-based artwork recommendation: integrating painting metadata with neural and manually-engineered visual features,” *User Modeling and User-Adapted Interaction*, July 2018.

[29] R. He, C. Fang, Z. Wang, and J. McAuley, “Vista: A Visually, Socially, and Temporally-aware Model for Artistic Recommendation,” in *Proceedings of the 10th ACM Conference on Recommender Systems - RecSys ’16*, (Boston, Massachusetts, USA), pp. 309–316, ACM Press, 2016.

[30] C. Pawlowski, A. Gelich, and Z. W. Raś, "Can We Build Recommender System for Artwork Evaluation?," in *Intelligent Methods and Big Data in Industrial Applications* (R. Bembenik, \. Skonieczny, G. Protaziuk, M. Kryszkiewicz, and H. Rybinski, eds.), pp. 41–52, Cham: Springer International Publishing, 2019.

[31] D. Jannach and G. Adomavicius, "Price and Profit Awareness in Recommender Systems," *arXiv:1707.08029 [cs]*, July 2017. arXiv: 1707.08029.

[32] D. Popescu, "Repricing Algorithms in E-Commerce," 2016.

[33] A. Greenstein-Messica and L. Rokach, "Personal price aware multi-seller recommender system: Evidence from eBay," *Knowledge-Based Systems*, vol. 150, pp. 14–26, June 2018.

[34] J. Wu and E. A. A. Gaytán, "The role of online seller reviews and product price on buyers' willingness-to-pay: a risk perspective," *European Journal of Information Systems*, vol. 22, pp. 416–433, July 2013.

[35] T. Mensink and J. v. Gemert, "The Rijksmuseum Challenge: Museum-Centered Visual Recognition," in *ACM International Conference on Multimedia Retrieval (ICMR)*, 2014.

[36] M. Yelizaveta, Chua Tat-Seng, and A. Irina, "Analysis and Retrieval of Paintings Using Artistic Color Concepts," in *2005 IEEE International Conference on Multimedia and Expo*, (Amsterdam, The Netherlands), pp. 1246–1249, IEEE, 2005.

[37] L. Shamir, T. Macura, N. Orlov, D. M. Eckley, and I. G. Goldberg, "Impressionism, expressionism, surrealism: Automated recognition of painters and schools of art," *ACM Transactions on Applied Perception*, vol. 7, pp. 1–17, Feb. 2010.

[38] I. A. for Pattern Recognition and I. C. Society, eds., *2012 21st International Conference on Pattern Recognition (ICPR 2012): Tsukuba, Japan, 11 - 15 November 2012*. Piscataway, NJ: IEEE, 2012.

[39] Z. Falomir, L. Museros, I. Sanz, and L. Gonzalez-Abril, "Categorizing paintings in art styles based on qualitative color descriptors, quantitative global features and machine learning (QArt-Learn)," *Expert Systems with Applications*, vol. 97, pp. 83–94, May 2018.

[40] E. Gultepe, T. Edward. Conturo, and M. Makrehchi, "Predicting and grouping digitized paintings by style using unsupervised feature learning," *Journal of Cultural Heritage*, vol. 31, pp. 13–23, May 2018.

[41] J. Machajdik and A. Hanbury, "Affective image classification using features inspired by psychology and art theory," in *Proceedings of the international conference on Multimedia - MM '10*, (Firenze, Italy), p. 83, ACM Press, 2010.

[42] D. Kang, H. Shim, and K. Yoon, "A method for extracting emotion using colors comprise the painting image," *Multimedia Tools and Applications*, vol. 77, pp. 4985–5002, Feb. 2018.

[43] C. C. Aggarwal, *Machine Learning for Text.* Cham: Springer International Publishing, 2018.

[44] Q. V. Le and T. Mikolov, "Distributed Representations of Sentences and Documents," May 2014. arXiv: http://arxiv.org/abs/1405.4053v2.

[45] T. Mikolov, I. Sutskever, K. Chen, G. Corrado, and J. Dean, "Distributed Representations of Words and Phrases and their Compositionality," Oct. 2013. arXiv: http://arxiv.org/abs/1310.4546v1.

[46] T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient Estimation of Word Representations in Vector Space," Jan. 2013. arXiv: http://arxiv.org/abs/1301.3781v3.

[47] A. Montoyo, P. Martínez-Barco, and A. Balahur, "Subjectivity and sentiment analysis: An overview of the current state of the area and envisaged developments," *Decision Support Systems*, vol. 53, pp. 675–679, Nov. 2012.

[48] B. Berlin and P. Kay, *Basic color terms: their universality and evolution.* Berkeley: University of California Press, 1969.

[49] D. T. Lindsey and A. M. Brown, "Universality of color names," *Proceedings of the National Academy of Sciences*, vol. 103, pp. 16608–16613, Oct. 2006.

[50] D. Roberson and J. Hanley, "Color vision: Color categories vary with language after all," *Current Biology*, vol. 17, no. 15, pp. R605 – R607, 2007.

[51] "Color by name."

[52] L. I. Labrecque and G. R. Milne, "Exciting red and competent blue: the importance of color in marketing," *Journal of the Academy of Marketing Science*, vol. 40, pp. 711–727, Sept. 2012.

[53] O. Team, "OpenCV," Oct. 2017.

[54] G. Taylor, "python-colormath," 2014.

[55] G. Sharma, W. Wu, and E. N. Dalal, "The CIEDE2000 color-difference formula: Implementation notes, supplementary test data, and mathematical observations," *Color Research & Application*, vol. 30, no. 1, pp. 21–30, 2004.

[56] J. A. Russell and A. Mehrabian, "Evidence for a three-factor theory of emotions," *Journal of Research in Personality*, vol. 11, no. 3, pp. 273–294, 1977.

[57] A. Mehrabian, "Measures of individual differences in temperament," *Educational and Psychological Measurement*, vol. 38, pp. 1105–1117, dec 1978.

[58] P. Valdez and A. Mehrabian, “Effects of color on emotions.,” *Journal of Experimental Psychology: General*, vol. 123, no. 4, pp. 394–409, 1994.

[59] J. Machajdik and A. Hanbury, “Affective image classification using features inspired by psychology and art theory,” in *Proceedings of the international conference on Multimedia - MM ’10*, ACM Press, 2010.

[60] E. Kim and H.-J. Suk, “Hue extraction and tone match: generating a theme color to enhance the emotional quality of an image,” in *ACM SIGGRAPH 2015 Posters*, SIGGRAPH ’15, pp. 1–1, ACM, 2015.

[61] L. Ou, M. R. Luo, A. Woodcock, and A. Wright, “A study of colour emotion and colour preference. part i: Colour emotions for single colours,” *Color Research Application*, vol. 29, no. 3, pp. 232–240, 2004.

[62] J. Canny, “A Computational Approach to Edge Detection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, pp. 679–698, Nov. 1986.

[63] T. E. Lombardi, *The classification of style in fine-art painting*. PhD thesis, 2005. Copyright - Database copyright ProQuest LLC; ProQuest does not claim copyright in the individual underlying works; Last updated - 2020-02-21.

[64] Z. W. Ras and A. Wieczorkowska, “Action-rules: How to increase profit of a company,” in *Principles of Data Mining and Knowledge Discovery* (D. A. Zighed, J. Komorowski, and J. Żytkow, eds.), (Berlin, Heidelberg), pp. 587–592, Springer Berlin Heidelberg, 2000.

[65] A. Hajja, “Object-driven and temporal action rules mining,” 2013.

[66] A. A. Tzacheva and Z. W. RaÅ, “Action rules mining,” *International Journal of Intelligent Systems*, vol. 20, pp. 719–736, July 2005.

[67] A. A. Tzacheva, A. Bagavathi, and L. Ayila, “Discovery of Action Rules at Lowest Cost in Spark,” in *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*, (New Orleans, LA), pp. 87–94, IEEE, Nov. 2017.

[68] J. Rauch and M. Šimůnek, “Action rules and the guha method: Preliminary considerations and results,” in *Foundations of Intelligent Systems* (J. Rauch, Z. W. Raś, P. Berka, and T. Elomaa, eds.), (Berlin, Heidelberg), pp. 76–87, Springer Berlin Heidelberg, 2009.

[69] J. Rauch, M. Šimůnek, P. Berka, Z. Ĉerný, P. Dolejší, T. Karban, M. Kejkula, V. Lin, P. Máša, P. Spáčil, P. Strossa, M. Šebek, J. Šlesinger, M. Šubrt, E. Turunen, and F. Vanžura, “LISp-Miner,” Oct. 2019.

[70] V. Nekvapil, “Using the ac4ft-miner procedure in the medical domain [online],” 2009 [cit. 2020-01-03].

[71] "Artfinder.com," 2020.

[72] "Selenium."

[73] "Beautiful Soup."

[74] M. S. Fischer, "Online Art Sales Gathers Steam Among Buyers," *ThinkAdvisor*, Apr. 2015.

[75] C. Rawlins and P. Johnson, "SELLING ON EBAY: PERSUASIVE COMMUNICATION ADVICE BASED ON ANALYSIS OF AUCTION ITEM DESCRIPTIONS.," *Journal of Strategic E-commerce*, vol. 5, no. 1&2, pp. 75 – 81, 2007.

[76] S. Parish, "Product Description Word Counts: Why Length Matters."

[77] R. Řehůřek and P. Sojka, "Software Framework for Topic Modelling with Large Corpora," in *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, (Valletta, Malta), pp. 45–50, ELRA, May 2010.

[78] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[79] C. Hutto and E. Gilbert, "VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text," in *Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014*, 2015.

APPENDIX A: MODEL RESULTS

Notes:

- Control - 50,000 artworks randomly selected from all available artists
- Gray 0 - 36,410 artworks randomly selected from 568 possible artists
- Gray 1 - 3,769 artworks randomly selected from 39 possible artists
- Gray 2 - 50,000 artworks randomly selected from 913 possible artists
- Gray 3 - 905 artworks randomly selected from 20 possible artists
- Gray 4 - 3,024 artworks randomly selected from 29 possible artists
- Gray 5 - 1,341 artworks randomly selected from 30 possible artists
- Gray 6 - 12,489 artworks randomly selected from 159 possible artists
- Gray 7 - 240 artworks randomly selected from 1 possible artist
- Gray 8 - 50,000 artworks randomly selected from 1,399 possible artists
- Gray 9 - 11,481 artworks randomly selected from 187 possible artists
- Edge 0 - 50,000 artworks randomly selected from 1,759 possible artists
- Edge 1 - 8,043 artworks randomly selected from 73 possible artists
- Edge 2 - 450 artworks randomly selected from 12 possible artists
- Edge 3 - 12,077 artworks randomly selected from 212 possible artists
- Edge 4 - 27,509 artworks randomly selected from 425 possible artists
- Edge 5 - 3,906 artworks randomly selected from 57 possible artists
- Edge 6 - 530 artworks randomly selected from 4 possible artists

- Edge 7 - 365 artworks randomly selected from 12 possible artists
- Edge 8 - 2,103 artworks randomly selected from 13 possible artists
- Edge 9 - 50,000 artworks randomly selected from 778 possible artists

Table A.1: Cluster Models Control Group

	F1	Precision	Recall
Bio Ng, Bio Ps Bio WC, Desc WC	0.542	0.54	0.545
Bio Ng, Bio Ps Facebook, Twitter, Instagram	0.525	0.524	0.528
Bio Ng, Bio Neu, Bio Ps	0.519	0.517	0.522
Bio WC, Desc WC Facebook, Twitter, Instagram	0.513	0.512	0.517
Bio Ng, Bio Ps	0.507	0.506	0.511
Bio Ng, Bio Ps, Dominance	0.502	0.5	0.505
Bio Ng, Bio Ps, Gray Mn	0.501	0.499	0.504
Bio Ng, Bio Ps, Weight	0.501	0.499	0.505
Bio Ng, Bio Ps, Gray Sd	0.5	0.498	0.503
Bio Ng, Bio Ps, Color1	0.5	0.498	0.504
Bio Ng, Bio Ps, Arousal	0.5	0.498	0.504
Bio Ng, Bio Ps, Activity	0.5	0.498	0.504
Bio Ng, Bio Ps, Gray Mn, Gray Sd	0.499	0.498	0.503
Bio Ng, Bio Ps, Pleasure	0.499	0.497	0.503
Bio Ng, Bio Ps, Heat	0.498	0.496	0.502
Bio Ng, Bio Ps, Color1-2	0.496	0.494	0.5

Table A.1: Cluster Models Control Group

	F1	**Precision**	**Recall**
Bio Ng, Bio Ps, Min 9 Max 9	0.496	0.494	0.5
Bio Ng, Bio Ps, Min 16 Max 16	0.495	0.493	0.499
Bio Word Count, Desc Word Count	0.491	0.489	0.494
Bio Ng, Bio Ps, PAD	0.491	0.489	0.495
Bio Ng, Bio Ps, RGB Sd	0.491	0.489	0.495
Bio Ng, Bio Ps, Color1-3	0.491	0.489	0.495
Bio Neg, Bio Ps, RGB Mn	0.49	0.488	0.495
Bio Ng, Bio Ps, AWH	0.488	0.486	0.492
Bio Ng, Bio Ps, Color1-4	0.487	0.485	0.491
Bio WC, Desc WC, Activity	0.486	0.484	0.49
Bio Ng, Bio Ps, Gray Mn, RGB Mn	0.485	0.483	0.489
Bio Ng, Bio Ps, Color1-5	0.485	0.483	0.49
Bio WC, Desc WC, Gray Mn	0.485	0.483	0.49
Bio WC, Desc WC, Dominance	0.485	0.484	0.49
Bio WC, Desc WC, Weight	0.484	0.482	0.488
Bio WC, Desc WC, Heat	0.484	0.483	0.489

Table A.1: Cluster Models Control Group

	F1	Precision	Recall
Bio Ng, Bio Ps, Gray Sd, RGB Sd	0.483	0.481	0.488
Bio WC, Desc WC, Gray Sd	0.483	0.481	0.487
Bio WC, Desc WC, Color1	0.483	0.481	0.487
Bio WC, Desc WC, Pleasure	0.483	0.481	0.487
Bio WC, Desc WC, Arousal	0.483	0.481	0.487
Bio WC, Desc WC, Color Gray Mn, Color Gray Sd	0.481	0.48	0.486
Bio WC, Desc WC, Min 9 Max 9	0.48	0.478	0.484
Bio Ng, Bio Ps, Color1-6	0.479	0.477	0.484
Bio WC, Desc WC, Min 16 Max 16	0.479	0.477	0.483
Bio WC, Desc WC, Color1-2	0.478	0.476	0.483
Bio Ng, Bio Ps, RGB Mn, RGB Sd	0.477	0.475	0.482
Bio WC, Desc WC, Color1-3	0.476	0.474	0.481
Bio WC, Desc WC, PAD	0.475	0.473	0.48
Bio Ng, Bio Ps, Color1-7	0.474	0.472	0.479
Bio WC, Desc WC, AWH	0.473	0.471	0.478
Bio WC, Desc WC, RGB Mn	0.471	0.469	0.476

Table A.1: Cluster Models Control Group

	F1	**Precision**	**Recall**
Bio Ng, Bio Ps, Color1-8	0.47	0.468	0.476
Bio WC, Desc WC, RGB Sd	0.47	0.468	0.475
Bio Ng, Bio Ps, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.468	0.466	0.473
Bio WC, Desc WC, Gray Mn, RGB Mn	0.467	0.465	0.472
Bio WC, Desc WC, Color1-4	0.467	0.465	0.472
Bio Ng, Bio Ps, Color1-9	0.466	0.464	0.472
Bio WC, Desc WC, Color1-5	0.466	0.464	0.471
Bio Ng, Bio Ps, Color1-10	0.465	0.463	0.471
Bio WC, Desc WC, Gray Sd, RGB Sd	0.465	0.463	0.471
Bio WC, Desc WC, Color RGB Mn, Color RGB Sd	0.458	0.457	0.464
Bio WC, Desc WC, Color1-6	0.458	0.456	0.464
Bio WC, Desc WC, Color1-7	0.452	0.45	0.458
Bio WC, Desc WC, Color1-8	0.452	0.45	0.458
Bio WC, Desc WC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.449	0.447	0.455
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.448	0.446	0.453
Facebook, Twitter, Instagram	0.447	0.445	0.45

Table A.1: Cluster Models Control Group

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Gray Mn	0.447	0.445	0.451
Facebook, Twitter, Instagram, Gray Sd	0.447	0.444	0.451
Facebook, Twitter, Instagram, Dominance	0.447	0.445	0.451
Bio WC, Desc WC, Color1-9	0.445	0.443	0.451
Facebook, Twitter, Instagram, Color1	0.445	0.443	0.449
Facebook, Twitter, Instagram, Color1-2	0.445	0.442	0.449
Facebook, Twitter, Instagram, Activity	0.445	0.443	0.45
Bio WC, Desc WC, Color1-10	0.444	0.442	0.45
Facebook, Twitter, Instagram, Min 16 Max 16	0.444	0.442	0.449
Facebook, Twitter, Instagram, Pleasure	0.444	0.442	0.449
Facebook, Twitter, Instagram, Arousal	0.444	0.442	0.448
Facebook, Twitter, Instagram, PAD	0.442	0.44	0.447
Facebook, Twitter, Instagram, Weight	0.442	0.44	0.446
Desc Ng, Desc Neu, Desc Ps	0.442	0.439	0.446
Facebook, Twitter, Instagram, Color1-3	0.441	0.439	0.446
Facebook, Twitter, Instagram, Heat	0.44	0.438	0.444

Table A.1: Cluster Models Control Group

	F1	Precision	Recall
Desc Ng, Desc Ps	0.439	0.437	0.444
Facebook, Twitter, Instagram, Min 9 Max 9	0.439	0.437	0.444
Facebook, Twitter, Instagram, AWH	0.438	0.436	0.443
Facebook, Twitter, Instagram, RGB Mn	0.438	0.436	0.444
Facebook, Twitter, Instagram, Color1-4	0.437	0.435	0.443
Facebook, Twitter, Instagram, RGB Sd	0.435	0.433	0.44
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.434	0.432	0.439
Facebook, Twitter, Instagram, Color1-5	0.433	0.431	0.439
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.431	0.428	0.436
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.43	0.428	0.436
Facebook, Twitter, Instagram, Color1-6	0.429	0.427	0.435
Facebook, Twitter, Instagram, Color1-7	0.425	0.423	0.432
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.423	0.421	0.43
Facebook, Twitter, Instagram, Color1-8	0.421	0.419	0.428
Facebook, Twitter, Instagram, Color1-9	0.42	0.418	0.427
Facebook, Twitter, Instagram, Color1-10	0.414	0.412	0.422

Table A.1: Cluster Models Control Group

	F1	Precision	Recall
Title WC	0.409	0.406	0.414
Gray Mn, Gray Sd	0.4	0.397	0.406
Gray Mn	0.399	0.397	0.404
Gray Sd	0.397	0.394	0.402
Color1-2	0.397	0.395	0.403
Color1-3	0.397	0.394	0.402
Arousal	0.397	0.395	0.402
Dominance	0.397	0.394	0.402
Activity	0.397	0.395	0.402
Pleasure, Arousal, Dominance	0.396	0.393	0.402
Activity, Weight, Heat	0.396	0.393	0.402
RGB Mn	0.396	0.393	0.403
Color1	0.396	0.393	0.4
Color1-4	0.396	0.394	0.403
Max 16	0.396	0.394	0.401
Min 9 Max 9	0.396	0.393	0.402

Table A.1: Cluster Models Control Group

	F1	**Precision**	**Recall**
Min 16 Max 16	0.396	0.393	0.401
Weight	0.396	0.393	0.401
Max 9	0.395	0.392	0.4
Min 16	0.395	0.393	0.401
Base Features	0.394	0.391	0.398
Pleasure	0.394	0.391	0.399
Heat	0.394	0.391	0.399
RGB Mn, RGB Sd	0.393	0.39	0.4
Color1-5	0.393	0.39	0.399
Min 9	0.393	0.39	0.398
Gray Mn, RGB Mn	0.391	0.388	0.397
RGB Sd	0.391	0.388	0.397
Gray Sd, RGB Sd	0.389	0.386	0.395
Color1-6	0.388	0.385	0.396
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.387	0.384	0.394
Color1-7	0.386	0.383	0.394

Table A.1: Cluster Models Control Group

	F1	**Precision**	**Recall**
Color1-8	0.384	0.381	0.392
Color1-9	0.38	0.378	0.389
Color1-10	0.379	0.376	0.388

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
BioNg, BioPs BioWC, DescWC	0.63	0.63	0.631
BioWC, DescWC Facebook, Twitter, Instagram	0.62	0.619	0.62
BioNg, BioPs Facebook, Twitter, Instagram	0.612	0.611	0.613
BioNg, BioNeu, BioPs	0.609	0.609	0.611
Bio Word Count, Desc Word Count	0.604	0.604	0.605
BioWC, DescWC, Color1	0.602	0.601	0.603
BioWC, DescWC, Pleasure	0.602	0.602	0.604
BioNg, BioPs, Color1	0.601	0.6	0.602
BioWC, DescWC, Dominance	0.601	0.6	0.602
BioWC, DescWC, Gray Sd	0.6	0.599	0.601
BioWC, DescWC, Color1-2	0.6	0.599	0.601
BioNg, BioPs, Arousal	0.6	0.599	0.601
BioWC, DescWC, Arousal	0.6	0.6	0.602
BioWC, DescWC, Activity	0.6	0.6	0.602
BioNg, BioPs	0.599	0.599	0.601
BioNg, BioPs, Gray Mn	0.599	0.599	0.601

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-2	0.599	0.598	0.6
BioWC, DescWC, Gray Mn	0.599	0.599	0.6
BioWC, DescWC, Min 16 Max 16	0.599	0.598	0.6
BioNg, BioPs, Pleasure	0.599	0.598	0.6
BioWC, DescWC, Weight	0.599	0.599	0.6
BioWC, DescWC, Heat	0.599	0.598	0.6
BioNg, BioPs, Dominance	0.598	0.597	0.599
BioNg, BioPs, Activity	0.598	0.597	0.599
BioNg, BioPs, Gray Mn, Gray Sd	0.597	0.597	0.599
BioNg, BioPs, Min 16 Max 16	0.597	0.596	0.598
BioWC, DescWC, Min 9 Max 9	0.597	0.596	0.598
BioNg, BioPs, Weight	0.597	0.597	0.599
BioNg, BioPs, PAD	0.596	0.595	0.597
BioNg, BioPs, AWH	0.596	0.595	0.597
BioNg, BioPs, Gray Sd	0.596	0.596	0.598
BioWC, DescWC, RGB Mn	0.596	0.595	0.597

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.596	0.596	0.598
BioWC, DescWC, Color1-3	0.596	0.596	0.598
BioNg, BioPs, Min 9 Max 9	0.596	0.595	0.597
BioNeg, BioPs, RGB Mn	0.595	0.594	0.596
BioNg, BioPs, Color1-3	0.595	0.595	0.597
BioNg, BioPs, Color1-4	0.595	0.594	0.596
BioWC, DescWC, AWH	0.595	0.594	0.597
BioNg, BioPs, Heat	0.595	0.594	0.596
BioNg, BioPs, RGB Sd	0.594	0.593	0.596
BioWC, DescWC, PAD	0.594	0.594	0.596
BioWC, DescWC, RGB Sd	0.594	0.593	0.595
BioWC, DescWC, Color1-4	0.594	0.593	0.596
BioNg, BioPs, RGB Mn, RGB Sd	0.592	0.592	0.594
BioNg, BioPs, Color1-5	0.592	0.591	0.594
BioNg, BioPs, Gray Mn, RGB Mn	0.591	0.59	0.592
BioWC, DescWC, Gray Sd, RGB Sd	0.591	0.59	0.593

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
BioNg, BioPs, Gray Sd, RGB Sd	0.59	0.59	0.592
BioWC, DescWC, Gray Mn, RGB Mn	0.59	0.59	0.592
BioWC, DescWC, Color1-5	0.59	0.589	0.592
BioNg, BioPs, Color1-6	0.589	0.589	0.591
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.588	0.588	0.59
BioWC, DescWC, Color1-6	0.587	0.587	0.589
BioNg, BioPs, Color1-7	0.586	0.585	0.588
BioWC, DescWC, Color1-7	0.586	0.586	0.588
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.585	0.584	0.587
BioNg, BioPs, Color1-8	0.584	0.583	0.586
BioNg, BioPs, Color1-9	0.583	0.583	0.586
BioWC, DescWC, Color1-8	0.583	0.582	0.585
BioNg, BioPs, Color1-10	0.582	0.581	0.584
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.58	0.579	0.582
BioWC, DescWC, Color1-9	0.58	0.579	0.582
Facebook, Twitter, Instagram, Heat	0.577	0.556	0.558

Table A.2: Cluster Models Gray 0

	F1	Precision	Recall
BioWC, DescWC, Color1-10	0.576	0.576	0.579
DescNg, DescNeu, DescPs	0.569	0.569	0.571
DescNg, DescPs	0.565	0.564	0.567
Facebook, Twitter, Instagram, Color1	0.564	0.563	0.565
Facebook, Twitter, Instagram, Color1-2	0.563	0.563	0.565
Facebook, Twitter, Instagram, Gray Mn	0.562	0.561	0.563
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.561	0.56	0.562
Facebook, Twitter, Instagram, Color1-3	0.561	0.56	0.562
Facebook, Twitter, Instagram, Weight	0.561	0.56	0.562
Facebook, Twitter, Instagram	0.56	0.559	0.562
Facebook, Twitter, Instagram, PAD	0.56	0.559	0.561
Facebook, Twitter, Instagram, AWH	0.56	0.559	0.562
Facebook, Twitter, Instagram, Color1-4	0.56	0.559	0.562
Facebook, Twitter, Instagram, Pleasure	0.56	0.559	0.562
Facebook, Twitter, Instagram, Arousal	0.56	0.559	0.561
Facebook, Twitter, Instagram, RGB Mn	0.559	0.558	0.561

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Dominance	0.559	0.558	0.561
Facebook, Twitter, Instagram, Activity	0.559	0.558	0.56
Facebook, Twitter, Instagram, Gray Sd	0.558	0.557	0.559
Facebook, Twitter, Instagram, Min 9 Max 9	0.558	0.557	0.56
Facebook, Twitter, Instagram, Min 16 Max 16	0.558	0.557	0.56
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.557	0.556	0.559
Facebook, Twitter, Instagram, Color1-5	0.556	0.555	0.559
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.554	0.553	0.556
Facebook, Twitter, Instagram, RGB Sd	0.554	0.553	0.555
Facebook, Twitter, Instagram, Color1-6	0.554	0.553	0.556
Facebook, Twitter, Instagram, Color1-7	0.552	0.551	0.554
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.55	0.55	0.552
Facebook, Twitter, Instagram, Color1-8	0.549	0.548	0.552
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.548	0.548	0.551
Facebook, Twitter, Instagram, Color1-9	0.547	0.546	0.549
Facebook, Twitter, Instagram, Color1-10	0.545	0.544	0.548

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
Title WC	0.543	0.542	0.545
Color1-3	0.527	0.526	0.529
Color1	0.526	0.525	0.528
Color1-2	0.526	0.525	0.528
Gray Mn	0.525	0.524	0.526
Gray Mn, Gray Sd	0.525	0.524	0.527
Color1-4	0.524	0.523	0.526
Pleasure, Arousal, Dominance	0.523	0.522	0.525
Activity, Weight, Heat	0.523	0.522	0.526
Min 16 Max 16	0.523	0.522	0.525
Arousal	0.523	0.522	0.524
RGB Mn	0.522	0.521	0.525
Min 9 Max 9	0.522	0.521	0.524
Color1-5	0.521	0.52	0.524
Min 9	0.521	0.52	0.523
Pleasure	0.521	0.52	0.523

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
Weight	0.521	0.52	0.522
RGB Mn, RGB Sd	0.52	0.519	0.523
Dominance	0.52	0.519	0.522
Gray Mn, RGB Mn	0.519	0.518	0.521
Gray Sd	0.519	0.518	0.521
RGB Sd	0.519	0.518	0.522
Min 16	0.519	0.518	0.521
Activity	0.519	0.518	0.521
Max 16	0.518	0.517	0.52
Base Features	0.517	0.516	0.519
Color1-6	0.517	0.516	0.52
Max 9	0.517	0.516	0.519
Gray Sd, RGB Sd	0.516	0.515	0.518
Color1-7	0.516	0.515	0.519
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.515	0.514	0.518
Color1-8	0.515	0.514	0.518

Table A.2: Cluster Models Gray 0

	F1	**Precision**	**Recall**
Heat	0.515	0.514	0.517
Color1-9	0.513	0.512	0.516
Color1-10	0.509	0.508	0.512

Table A.3: Cluster Models Gray 1

	F1	Precision	Recall
BioWC, DescWC Facebook, Twitter, Instagram	0.65	0.651	0.651
BioNg, BioPs BioWC, DescWC	0.644	0.646	0.645
BioWC, DescWC, Gray Mn	0.639	0.64	0.639
Bio Word Count, Desc Word Count	0.638	0.639	0.639
BioWC, DescWC, Color1	0.637	0.638	0.638
BioWC, DescWC, Min 16 Max 16	0.636	0.638	0.637
BioWC, DescWC, Arousal	0.635	0.636	0.636
BioWC, DescWC, Activity	0.635	0.636	0.636
BioWC, DescWC, RGB Mn	0.634	0.636	0.635
BioWC, DescWC, Gray Sd	0.634	0.635	0.635
BioWC, DescWC, Color1-2	0.634	0.636	0.635
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.633	0.635	0.634
BioWC, DescWC, Pleasure	0.633	0.634	0.634
BioWC, DescWC, Min 9 Max 9	0.632	0.634	0.633
BioWC, DescWC, Heat	0.629	0.63	0.63
BioNg, BioPs Facebook, Twitter, Instagram	0.629	0.629	0.63

Table A.3: Cluster Models Gray 1

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-4	0.628	0.63	0.629
BioWC, DescWC, Weight	0.628	0.629	0.629
BioWC, DescWC, Dominance	0.627	0.628	0.627
BioWC, DescWC, RGB Sd	0.626	0.627	0.628
BioWC, DescWC, AWH	0.625	0.627	0.627
BioNg, BioPs, Arousal	0.625	0.626	0.626
BioNg, BioPs, Activity	0.625	0.626	0.627
DescNg, DescNeu, DescPs	0.625	0.627	0.626
BioWC, DescWC, PAD	0.624	0.626	0.626
BioWC, DescWC, Color1-3	0.624	0.626	0.625
BioWC, DescWC, Color1-5	0.624	0.625	0.625
BioNg, BioPs, Gray Mn	0.623	0.624	0.625
BioWC, DescWC, Gray Mn, RGB Mn	0.623	0.625	0.624
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.623	0.625	0.625
Facebook, Twitter, Instagram, Min 16 Max 16	0.623	0.624	0.625
BioWC, DescWC, Gray Sd, RGB Sd	0.622	0.623	0.624

Table A.3: Cluster Models Gray 1

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Heat	0.622	0.622	0.632
BioNg, BioPs, Gray Sd	0.621	0.622	0.623
BioNg, BioPs, Gray Mn, Gray Sd	0.621	0.621	0.622
BioWC, DescWC, Color1-8	0.621	0.624	0.623
Facebook, Twitter, Instagram, Gray Mn	0.621	0.621	0.622
Facebook, Twitter, Instagram, Gray Sd	0.621	0.622	0.623
Facebook, Twitter, Instagram, RGB Sd	0.621	0.622	0.623
BioNg, BioPs, Min 16 Max 16	0.621	0.621	0.622
BioNg, BioNeu, BioPs	0.621	0.621	0.623
BioNg, BioPs	0.62	0.62	0.621
BioNg, BioPs, Color1-6	0.62	0.623	0.621
BioWC, DescWC, Color1-6	0.62	0.621	0.621
DescNg, DescPs	0.619	0.621	0.62
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.619	0.621	0.621
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.619	0.62	0.62
BioNg, BioPs, Min 9 Max 9	0.619	0.62	0.621

Table A.3: Cluster Models Gray 1

	F1	Precision	Recall
Facebook, Twitter, Instagram, Arousal	0.619	0.62	0.62
BioNeg, BioPs, RGB Mn	0.618	0.619	0.619
BioNg, BioPs, RGB Sd	0.618	0.619	0.62
BioNg, BioPs, Color1-5	0.618	0.619	0.62
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.618	0.619	0.62
Facebook, Twitter, Instagram, Min 9 Max 9	0.618	0.619	0.619
BioNg, BioPs, Heat	0.618	0.619	0.62
Facebook, Twitter, Instagram, Pleasure	0.618	0.619	0.62
Facebook, Twitter, Instagram	0.617	0.617	0.618
BioNg, BioPs, Weight	0.617	0.618	0.619
BioNg, BioPs, Color1-2	0.616	0.616	0.618
Facebook, Twitter, Instagram, AWH	0.616	0.617	0.617
BioNg, BioPs, PAD	0.615	0.616	0.617
BioNg, BioPs, Gray Mn, RGB Mn	0.615	0.616	0.617
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.615	0.617	0.617
BioNg, BioPs, RGB Mn, RGB Sd	0.615	0.616	0.617

Table A.3: Cluster Models Gray 1

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-3	0.615	0.616	0.616
Facebook, Twitter, Instagram, Color1-4	0.615	0.617	0.616
BioNg, BioPs, Pleasure	0.615	0.616	0.617
Facebook, Twitter, Instagram, Activity	0.615	0.615	0.616
BioNg, BioPs, AWH	0.614	0.616	0.616
BioNg, BioPs, Color1-4	0.614	0.616	0.616
BioWC, DescWC, Color1-9	0.614	0.617	0.616
Facebook, Twitter, Instagram, Color1-5	0.614	0.615	0.616
BioNg, BioPs, Gray Sd, RGB Sd	0.613	0.614	0.615
BioNg, BioPs, Color1	0.613	0.613	0.615
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.612	0.613	0.614
BioWC, DescWC, Color1-7	0.611	0.614	0.613
BioWC, DescWC, Color1-10	0.611	0.614	0.613
BioNg, BioPs, Dominance	0.611	0.611	0.613
Facebook, Twitter, Instagram, Dominance	0.611	0.611	0.612
Facebook, Twitter, Instagram, PAD	0.61	0.611	0.612

Table A.3: Cluster Models Gray 1

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.609	0.61	0.611
Facebook, Twitter, Instagram, Color1-7	0.609	0.61	0.611
BioNg, BioPs, Color1-10	0.608	0.611	0.61
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.608	0.609	0.611
Facebook, Twitter, Instagram, Color1-2	0.608	0.609	0.609
Facebook, Twitter, Instagram, Color1-3	0.608	0.609	0.61
Facebook, Twitter, Instagram, Color1-8	0.608	0.61	0.609
BioNg, BioPs, Color1-8	0.607	0.61	0.61
BioNg, BioPs, Color1-7	0.606	0.608	0.608
Facebook, Twitter, Instagram, Color1-9	0.606	0.608	0.608
Facebook, Twitter, Instagram, Color1-10	0.606	0.608	0.609
Facebook, Twitter, Instagram, Weight	0.606	0.606	0.608
BioNg, BioPs, Color1-9	0.605	0.607	0.607
Facebook, Twitter, Instagram, RGB Mn	0.605	0.605	0.607
Facebook, Twitter, Instagram, Color1	0.605	0.605	0.606
Facebook, Twitter, Instagram, Color1-6	0.605	0.607	0.608

Table A.3: Cluster Models Gray 1

	F1	Precision	Recall
Title WC	0.605	0.605	0.606
Gray Mn, Gray Sd	0.604	0.604	0.606
Gray Mn	0.603	0.604	0.605
Max 16	0.601	0.601	0.602
Gray Sd	0.6	0.601	0.602
Arousal	0.599	0.599	0.601
Activity	0.599	0.599	0.6
Base Features	0.597	0.598	0.598
Activity, Weight, Heat	0.597	0.598	0.599
RGB Mn	0.595	0.595	0.597
Min 16 Max 16	0.595	0.596	0.597
Heat	0.595	0.595	0.597
Min 9	0.594	0.595	0.595
Max 9	0.594	0.595	0.596
Pleasure	0.594	0.594	0.596
Gray Sd, RGB Sd	0.593	0.593	0.595

Table A.3: Cluster Models Gray 1

	F1	**Precision**	**Recall**
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.592	0.593	0.595
Min 16	0.592	0.593	0.594
Color1-2	0.591	0.592	0.591
Color1-6	0.591	0.592	0.593
Color1-3	0.59	0.59	0.592
Min 9 Max 9	0.59	0.591	0.592
RGB Sd	0.589	0.589	0.591
Color1-7	0.589	0.59	0.592
Color1-5	0.588	0.589	0.59
Weight	0.588	0.587	0.589
Color1	0.587	0.588	0.588
Color1-4	0.587	0.588	0.588
Color1-8	0.587	0.588	0.59
Gray Mn, RGB Mn	0.585	0.585	0.588
Dominance	0.585	0.585	0.586
Pleasure, Arousal, Dominance	0.583	0.583	0.586

Table A.3: Cluster Models Gray 1

	F1	**Precision**	**Recall**
RGB Mn, RGB Sd	0.582	0.583	0.585
Color1-10	0.581	0.582	0.585
Color1-9	0.58	0.581	0.582

Table A.4: Cluster Models Gray 2

	F1	Precision	Recall
BioNg, BioPs BioWC, DescWC	0.644	0.644	0.646
BioWC, DescWC Facebook, Twitter, Instagram	0.63	0.629	0.631
BioNg, BioPs Facebook, Twitter, Instagram	0.627	0.626	0.628
BioNg, BioNeu, BioPs	0.62	0.62	0.621
BioNg, BioPs	0.612	0.611	0.613
BioNg, BioPs, Gray Sd	0.612	0.611	0.614
BioNg, BioPs, Gray Mn, Gray Sd	0.612	0.611	0.614
BioNg, BioPs, Arousal	0.612	0.611	0.613
BioNg, BioPs, Color1-2	0.611	0.61	0.613
BioNg, BioPs, Pleasure	0.611	0.61	0.612
BioNg, BioPs, Gray Mn	0.61	0.61	0.612
BioNg, BioPs, Color1	0.61	0.609	0.611
BioNg, BioPs, Dominance	0.61	0.609	0.612
BioWC, DescWC, Gray Mn	0.609	0.608	0.611
BioNg, BioPs, Activity	0.609	0.608	0.611
BioNg, BioPs, Color1-3	0.608	0.607	0.61

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
BioNg, BioPs, Min 9 Max 9	0.608	0.607	0.61
BioNg, BioPs, Weight	0.608	0.608	0.61
Bio Word Count, Desc Word Count	0.607	0.605	0.608
BioNg, BioPs, PAD	0.607	0.606	0.609
BioNg, BioPs, Heat	0.607	0.606	0.608
BioWC, DescWC, Arousal	0.607	0.606	0.609
BioNg, BioPs, RGB Sd	0.606	0.605	0.608
BioNg, BioPs, Color1-4	0.606	0.606	0.608
BioWC, DescWC, Color1	0.606	0.605	0.609
BioNg, BioPs, Min 16 Max 16	0.606	0.605	0.608
BioWC, DescWC, Dominance	0.606	0.605	0.608
BioWC, DescWC, Activity	0.606	0.605	0.608
BioWC, DescWC, Weight	0.606	0.605	0.608
BioNg, BioPs, AWH	0.605	0.604	0.607
BioNeg, BioPs, RGB Mn	0.605	0.604	0.607
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.605	0.604	0.607

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
BioWC, DescWC, Heat	0.605	0.604	0.607
BioWC, DescWC, Gray Sd	0.604	0.603	0.606
BioWC, DescWC, Color1-2	0.604	0.603	0.606
BioNg, BioPs, RGB Mn, RGB Sd	0.603	0.602	0.605
BioWC, DescWC, Pleasure	0.603	0.602	0.605
BioNg, BioPs, Color1-5	0.602	0.601	0.604
BioNg, BioPs, Gray Mn, RGB Mn	0.601	0.6	0.603
BioNg, BioPs, Gray Sd, RGB Sd	0.601	0.6	0.603
BioNg, BioPs, Color1-6	0.6	0.599	0.603
BioWC, DescWC, Color1-3	0.6	0.599	0.603
BioWC, DescWC, Min 16 Max 16	0.6	0.599	0.602
BioWC, DescWC, PAD	0.599	0.598	0.601
BioWC, DescWC, RGB Mn	0.599	0.598	0.601
BioWC, DescWC, Min 9 Max 9	0.599	0.598	0.601
BioWC, DescWC, AWH	0.597	0.596	0.599
BioWC, DescWC, RGB Sd	0.597	0.596	0.599

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.596	0.595	0.599
BioNg, BioPs, Color1-7	0.596	0.596	0.599
BioNg, BioPs, Color1-8	0.596	0.595	0.599
BioWC, DescWC, Color1-4	0.596	0.594	0.598
BioWC, DescWC, Gray Mn, RGB Mn	0.594	0.592	0.596
BioWC, DescWC, Gray Sd, RGB Sd	0.593	0.592	0.595
BioNg, BioPs, Color1-9	0.592	0.591	0.595
BioWC, DescWC, Color1-5	0.592	0.591	0.594
BioWC, DescWC, Color1-6	0.592	0.591	0.594
BioNg, BioPs, Color1-10	0.591	0.59	0.594
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.591	0.59	0.594
BioWC, DescWC, Color1-8	0.587	0.586	0.59
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.586	0.585	0.589
BioWC, DescWC, Color1-7	0.585	0.584	0.588
BioWC, DescWC, Color1-9	0.579	0.578	0.583
BioWC, DescWC, Color1-10	0.579	0.578	0.582

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1-2	0.563	0.562	0.565
Facebook, Twitter, Instagram, Arousal	0.563	0.562	0.565
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.562	0.561	0.564
Facebook, Twitter, Instagram, Gray Mn	0.561	0.56	0.563
Facebook, Twitter, Instagram, Color1	0.561	0.56	0.563
Facebook, Twitter, Instagram, Dominance	0.561	0.56	0.563
Facebook, Twitter, Instagram, Gray Sd	0.56	0.559	0.562
Facebook, Twitter, Instagram	0.559	0.559	0.561
Facebook, Twitter, Instagram, Color1-3	0.559	0.558	0.561
Facebook, Twitter, Instagram, RGB Mn	0.558	0.557	0.56
Facebook, Twitter, Instagram, Pleasure	0.558	0.557	0.56
Facebook, Twitter, Instagram, Activity	0.558	0.557	0.56
Facebook, Twitter, Instagram, Min 16 Max 16	0.557	0.556	0.559
DescNg, DescPs	0.556	0.555	0.558
Facebook, Twitter, Instagram, PAD	0.556	0.555	0.558
Facebook, Twitter, Instagram, RGB Sd	0.556	0.555	0.558

Table A.4: Cluster Models Gray 2

	F1	Precision	Recall
Facebook, Twitter, Instagram, Min 9 Max 9	0.556	0.555	0.559
Facebook, Twitter, Instagram, Weight	0.556	0.555	0.558
Facebook, Twitter, Instagram, AWH	0.555	0.554	0.558
Facebook, Twitter, Instagram, Color1-4	0.555	0.554	0.558
DescNg, DescNeu, DescPs	0.555	0.554	0.558
Facebook, Twitter, Instagram, Color1-5	0.554	0.553	0.556
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.553	0.552	0.556
Facebook, Twitter, Instagram, Heat	0.553	0.552	0.555
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.552	0.551	0.554
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.55	0.549	0.552
Facebook, Twitter, Instagram, Color1-6	0.549	0.548	0.552
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.548	0.547	0.551
Facebook, Twitter, Instagram, Color1-7	0.547	0.546	0.55
Facebook, Twitter, Instagram, Color1-8	0.545	0.544	0.548
Facebook, Twitter, Instagram, Color1-9	0.542	0.541	0.545
Facebook, Twitter, Instagram, Color1-10	0.538	0.536	0.541

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
Title WC	0.526	0.525	0.529
Gray Mn, Gray Sd	0.513	0.512	0.516
Color1-2	0.512	0.511	0.515
Color1	0.51	0.508	0.512
Pleasure, Arousal, Dominance	0.509	0.508	0.512
Gray Mn	0.509	0.508	0.512
Color1-3	0.509	0.507	0.512
Arousal	0.509	0.508	0.512
Min 9 Max 9	0.508	0.506	0.511
Dominance	0.508	0.507	0.511
RGB Mn	0.506	0.505	0.51
RGB Mn, RGB Sd	0.506	0.505	0.51
Base Features	0.505	0.503	0.507
Gray Sd	0.505	0.503	0.508
Color1-4	0.505	0.504	0.509
Max 9	0.505	0.504	0.508

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
Pleasure	0.505	0.504	0.508
Activity	0.505	0.504	0.508
Activity, Weight, Heat	0.504	0.503	0.507
Color1-5	0.504	0.502	0.507
Min 16	0.504	0.503	0.507
Max 16	0.504	0.502	0.507
Min 16 Max 16	0.504	0.502	0.507
Weight	0.504	0.503	0.507
Gray Mn, RGB Mn	0.503	0.502	0.506
Min 9	0.503	0.502	0.506
RGB Sd	0.502	0.501	0.506
Color1-6	0.502	0.5	0.506
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.501	0.5	0.505
Color1-7	0.5	0.499	0.504
Gray Sd, RGB Sd	0.499	0.497	0.502
Heat	0.498	0.497	0.501

Table A.4: Cluster Models Gray 2

	F1	**Precision**	**Recall**
Color1-8	0.496	0.494	0.5
Color1-9	0.493	0.492	0.498
Color1-10	0.492	0.491	0.496

Table A.5: Cluster Models Gray 3

	F1	Precision	Recall
BioWC, DescWC Facebook, Twitter, Instagram	0.744	0.749	0.744
BioWC, DescWC, Pleasure	0.74	0.747	0.739
BioNg, BioPs BioWC, DescWC	0.738	0.743	0.738
BioWC, DescWC, Color1	0.735	0.739	0.735
Bio Word Count, Desc Word Count	0.733	0.738	0.734
BioWC, DescWC, Gray Sd	0.733	0.738	0.734
BioWC, DescWC, Arousal	0.732	0.739	0.731
BioWC, DescWC, Heat	0.73	0.735	0.73
BioWC, DescWC, Color1-3	0.728	0.736	0.728
BioWC, DescWC, Weight	0.728	0.735	0.728
BioWC, DescWC, PAD	0.725	0.733	0.725
BioWC, DescWC, Gray Mn	0.724	0.729	0.724
BioWC, DescWC, RGB Mn	0.723	0.731	0.724
BioWC, DescWC, Color1-4	0.723	0.731	0.724
BioWC, DescWC, Color1-2	0.721	0.728	0.722
BioWC, DescWC, Activity	0.721	0.728	0.722

Table A.5: Cluster Models Gray 3

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Mn, RGB Mn	0.72	0.726	0.72
BioWC, DescWC, Min 16 Max 16	0.72	0.729	0.72
BioWC, DescWC, Dominance	0.72	0.727	0.719
BioWC, DescWC, RGB Sd	0.718	0.726	0.719
BioWC, DescWC, Min 9 Max 9	0.718	0.725	0.718
BioWC, DescWC, Color1-5	0.716	0.724	0.716
BioWC, DescWC, Gray Sd, RGB Sd	0.713	0.719	0.714
BioWC, DescWC, Color1-6	0.713	0.724	0.713
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.712	0.721	0.713
BioWC, DescWC, AWH	0.711	0.718	0.712
BioWC, DescWC, Color1-10	0.705	0.714	0.705
BioWC, DescWC, Color1-7	0.703	0.713	0.704
BioWC, DescWC, Color1-8	0.703	0.712	0.703
BioNg, BioPs Facebook, Twitter, Instagram	0.703	0.705	0.704
BioNg, BioPs, Gray Sd	0.699	0.704	0.699
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.699	0.707	0.698

Table A.5: Cluster Models Gray 3

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-9	0.697	0.708	0.696
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.696	0.703	0.696
DescNg, DescPs	0.695	0.702	0.696
DescNg, DescNeu, DescPs	0.695	0.7	0.697
Title WC	0.694	0.699	0.695
BioNg, BioPs, Gray Mn	0.693	0.699	0.694
Facebook, Twitter, Instagram, Gray Sd	0.693	0.697	0.694
BioNg, BioNeu, BioPs	0.693	0.696	0.695
Facebook, Twitter, Instagram, Dominance	0.692	0.695	0.692
BioNg, BioPs, Min 9 Max 9	0.691	0.697	0.691
BioNg, BioPs, Pleasure	0.691	0.696	0.692
Facebook, Twitter, Instagram, Pleasure	0.691	0.695	0.691
BioNg, BioPs	0.69	0.692	0.691
BioNg, BioPs, Heat	0.69	0.696	0.69
Gray Sd	0.689	0.695	0.69
Facebook, Twitter, Instagram	0.689	0.692	0.69

Table A.5: Cluster Models Gray 3

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-5	0.689	0.693	0.691
Facebook, Twitter, Instagram, Color1	0.688	0.69	0.688
Facebook, Twitter, Instagram, Arousal	0.688	0.691	0.69
Facebook, Twitter, Instagram, RGB Mn	0.687	0.69	0.687
BioNeg, BioPs, RGB Mn	0.686	0.69	0.687
BioNg, BioPs, Color1-6	0.685	0.693	0.686
Facebook, Twitter, Instagram, Gray Mn	0.685	0.688	0.686
Facebook, Twitter, Instagram, Color1-3	0.685	0.688	0.686
Arousal	0.685	0.688	0.686
Min 9	0.684	0.689	0.685
Pleasure	0.684	0.689	0.684
Color1-3	0.683	0.69	0.684
Color1-5	0.683	0.69	0.684
BioNg, BioPs, Color1	0.683	0.686	0.684
Facebook, Twitter, Instagram, Color1-2	0.683	0.687	0.683
Facebook, Twitter, Instagram, Color1-5	0.683	0.69	0.684

Table A.5: Cluster Models Gray 3

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Min 16 Max 16	0.683	0.69	0.684
RGB Mn	0.682	0.687	0.683
Max 9	0.682	0.685	0.683
Min 16	0.682	0.687	0.683
Dominance	0.682	0.687	0.682
Base Features	0.681	0.684	0.682
Color1	0.681	0.684	0.682
Facebook, Twitter, Instagram, AWH	0.681	0.687	0.681
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.681	0.687	0.682
Facebook, Twitter, Instagram, Heat	0.681	0.684	0.682
Gray Mn, RGB Mn	0.68	0.686	0.681
BioNg, BioPs, Arousal	0.68	0.682	0.682
Color1-4	0.679	0.686	0.68
Facebook, Twitter, Instagram, Min 9 Max 9	0.679	0.685	0.68
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.678	0.685	0.678
BioNg, BioPs, Dominance	0.678	0.682	0.678

Table A.5: Cluster Models Gray 3

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-2	0.677	0.682	0.677
BioNg, BioPs, Color1-7	0.677	0.684	0.678
BioNg, BioPs, Color1-8	0.677	0.685	0.677
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.677	0.679	0.678
Min 9 Max 9	0.677	0.684	0.677
Facebook, Twitter, Instagram, Activity	0.677	0.683	0.676
Facebook, Twitter, Instagram, Color1-6	0.676	0.682	0.677
BioNg, BioPs, Activity	0.676	0.68	0.676
BioNg, BioPs, AWH	0.675	0.679	0.675
BioNg, BioPs, Color1-3	0.675	0.681	0.675
BioNg, BioPs, Weight	0.675	0.676	0.676
RGB Sd	0.674	0.679	0.675
Color1-6	0.674	0.681	0.675
BioNg, BioPs, Gray Mn, Gray Sd	0.674	0.68	0.675
BioNg, BioPs, Min 16 Max 16	0.674	0.681	0.674
Color1-2	0.673	0.677	0.673

Table A.5: Cluster Models Gray 3

	F1	Precision	Recall
BioNg, BioPs, PAD	0.673	0.679	0.674
BioNg, BioPs, Color1-4	0.673	0.677	0.674
Facebook, Twitter, Instagram, RGB Sd	0.673	0.676	0.674
Facebook, Twitter, Instagram, PAD	0.672	0.677	0.672
Activity	0.672	0.677	0.672
BioNg, BioPs, Gray Sd, RGB Sd	0.671	0.677	0.673
Facebook, Twitter, Instagram, Color1-7	0.671	0.678	0.671
Gray Mn	0.67	0.674	0.671
BioNg, BioPs, Gray Mn, RGB Mn	0.67	0.676	0.672
Heat	0.67	0.675	0.671
Pleasure, Arousal, Dominance	0.669	0.677	0.67
Gray Sd, RGB Sd	0.669	0.672	0.671
Color1-7	0.669	0.677	0.669
BioNg, BioPs, RGB Sd	0.669	0.674	0.671
Facebook, Twitter, Instagram, Color1-8	0.669	0.679	0.669
Facebook, Twitter, Instagram, Weight	0.669	0.671	0.67

Table A.5: Cluster Models Gray 3

	F1	Precision	Recall
Min 16 Max 16	0.667	0.676	0.669
Max 16	0.666	0.673	0.667
Gray Mn, Gray Sd	0.665	0.67	0.666
BioNg, BioPs, Color1-9	0.665	0.673	0.666
Facebook, Twitter, Instagram, Color1-4	0.665	0.669	0.665
Facebook, Twitter, Instagram, Color1-10	0.663	0.669	0.665
BioNg, BioPs, Color1-10	0.662	0.673	0.664
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.661	0.664	0.664
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.661	0.664	0.663
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.66	0.665	0.662
Activity, Weight, Heat	0.659	0.663	0.66
BioNg, BioPs, RGB Mn, RGB Sd	0.659	0.663	0.662
Weight	0.659	0.665	0.661
Color1-10	0.658	0.667	0.66
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.656	0.66	0.657
RGB Mn, RGB Sd	0.655	0.658	0.657

Table A.5: Cluster Models Gray 3

	F1	**Precision**	**Recall**
Color1-8	0.655	0.662	0.657
Color1-9	0.655	0.662	0.656
Facebook, Twitter, Instagram, Color1-9	0.654	0.661	0.656

Table A.6: Cluster Models Gray 4

	F1	Precision	Recall
BioNg, BioPs BioWC, DescWC	0.674	0.673	0.676
Bio Word Count, Desc Word Count	0.672	0.671	0.674
BioWC, DescWC Facebook, Twitter, Instagram	0.67	0.67	0.672
BioWC, DescWC, Gray Mn	0.667	0.667	0.67
BioWC, DescWC, Pleasure	0.667	0.666	0.67
BioWC, DescWC, Activity	0.666	0.665	0.669
BioWC, DescWC, Color1	0.663	0.663	0.666
BioWC, DescWC, Gray Sd	0.662	0.661	0.665
BioWC, DescWC, Dominance	0.662	0.661	0.665
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.661	0.661	0.664
BioWC, DescWC, Arousal	0.66	0.659	0.663
BioWC, DescWC, RGB Mn	0.659	0.659	0.662
BioWC, DescWC, Heat	0.659	0.658	0.662
BioWC, DescWC, PAD	0.657	0.657	0.661
BioWC, DescWC, Min 9 Max 9	0.657	0.657	0.66
BioWC, DescWC, Weight	0.657	0.657	0.66

Table A.6: Cluster Models Gray 4

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Mn, RGB Mn	0.656	0.656	0.66
BioWC, DescWC, Color1-2	0.656	0.655	0.659
BioWC, DescWC, Color1-3	0.655	0.655	0.658
BioWC, DescWC, Min 16 Max 16	0.652	0.652	0.655
BioWC, DescWC, AWH	0.65	0.65	0.653
BioWC, DescWC, RGB Sd	0.648	0.647	0.651
BioWC, DescWC, Color1-5	0.648	0.648	0.652
BioNg, BioPs, Min 9 Max 9	0.646	0.645	0.649
BioNg, BioPs, Pleasure	0.646	0.645	0.649
BioNg, BioPs, Gray Sd	0.645	0.644	0.647
BioWC, DescWC, Color1-4	0.645	0.645	0.649
BioNg, BioPs, Min 16 Max 16	0.645	0.645	0.648
BioNg, BioPs, Weight	0.645	0.644	0.648
BioWC, DescWC, Gray Sd, RGB Sd	0.644	0.645	0.647
BioNg, BioPs, Activity	0.644	0.643	0.646
BioNg, BioNeu, BioPs	0.644	0.643	0.646

Table A.6: Cluster Models Gray 4

	F1	**Precision**	**Recall**
BioNg, BioPs, RGB Sd	0.643	0.642	0.646
BioNg, BioPs, Arousal	0.643	0.642	0.645
BioNg, BioPs Facebook, Twitter, Instagram	0.643	0.642	0.645
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.642	0.643	0.646
DescNg, DescPs	0.641	0.64	0.645
BioNg, BioPs, PAD	0.641	0.641	0.643
BioNg, BioPs, Gray Mn	0.64	0.639	0.643
BioNg, BioPs, Heat	0.64	0.64	0.643
BioNg, BioPs, Color1	0.639	0.639	0.642
BioNg, BioPs, Dominance	0.639	0.638	0.642
BioNeg, BioPs, RGB Mn	0.638	0.639	0.641
BioWC, DescWC, Color1-6	0.638	0.638	0.642
BioNg, BioPs	0.637	0.635	0.639
BioNg, BioPs, RGB Mn, RGB Sd	0.637	0.638	0.641
BioNg, BioPs, Color1-2	0.637	0.637	0.64
BioWC, DescWC, Color1-7	0.637	0.638	0.642

Table A.6: Cluster Models Gray 4

	F1	Precision	Recall
BioNg, BioPs, Gray Mn, RGB Mn	0.636	0.636	0.639
BioNg, BioPs, Color1-3	0.636	0.636	0.639
BioWC, DescWC, Color1-8	0.636	0.637	0.64
BioNg, BioPs, Gray Sd, RGB Sd	0.635	0.635	0.639
BioWC, DescWC, Color1-9	0.635	0.636	0.641
DescNg, DescNeu, DescPs	0.635	0.634	0.639
BioNg, BioPs, AWH	0.634	0.634	0.637
BioNg, BioPs, Gray Mn, Gray Sd	0.634	0.635	0.636
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.634	0.635	0.639
BioNg, BioPs, Color1-5	0.632	0.632	0.635
BioNg, BioPs, Color1-9	0.631	0.631	0.635
BioNg, BioPs, Color1-4	0.63	0.629	0.633
BioNg, BioPs, Color1-8	0.629	0.63	0.633
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.628	0.63	0.632
BioNg, BioPs, Color1-7	0.627	0.628	0.631
BioWC, DescWC, Color1-10	0.627	0.629	0.632

Table A.6: Cluster Models Gray 4

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-6	0.626	0.627	0.63
BioNg, BioPs, Color1-10	0.624	0.626	0.629
Facebook, Twitter, Instagram, Color1-2	0.612	0.611	0.616
Facebook, Twitter, Instagram, Min 9 Max 9	0.612	0.61	0.617
Facebook, Twitter, Instagram, Arousal	0.612	0.61	0.616
Facebook, Twitter, Instagram, Pleasure	0.611	0.609	0.614
Facebook, Twitter, Instagram, Weight	0.611	0.609	0.615
Facebook, Twitter, Instagram, Gray Mn	0.61	0.608	0.613
Facebook, Twitter, Instagram, Gray Sd	0.61	0.609	0.614
Facebook, Twitter, Instagram, Dominance	0.609	0.608	0.612
Facebook, Twitter, Instagram	0.606	0.604	0.609
Facebook, Twitter, Instagram, Min 16 Max 16	0.605	0.604	0.61
Facebook, Twitter, Instagram, RGB Mn	0.604	0.604	0.608
Facebook, Twitter, Instagram, RGB Sd	0.604	0.604	0.609
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.604	0.603	0.607
Facebook, Twitter, Instagram, AWH	0.603	0.603	0.607

Table A.6: Cluster Models Gray 4

	F1	Precision	Recall
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.601	0.601	0.605
Facebook, Twitter, Instagram, PAD	0.6	0.599	0.604
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.6	0.601	0.605
Facebook, Twitter, Instagram, Color1	0.6	0.598	0.604
Facebook, Twitter, Instagram, Activity	0.6	0.599	0.604
Facebook, Twitter, Instagram, Heat	0.6	0.598	0.604
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.599	0.598	0.604
Facebook, Twitter, Instagram, Color1-5	0.598	0.598	0.603
Facebook, Twitter, Instagram, Color1-3	0.596	0.594	0.6
Facebook, Twitter, Instagram, Color1-4	0.596	0.595	0.601
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.594	0.595	0.6
Facebook, Twitter, Instagram, Color1-7	0.593	0.593	0.598
Title WC	0.591	0.591	0.595
Facebook, Twitter, Instagram, Color1-6	0.588	0.588	0.593
Facebook, Twitter, Instagram, Color1-8	0.587	0.587	0.592
Arousal	0.585	0.583	0.589

Table A.6: Cluster Models Gray 4

	F1	**Precision**	**Recall**
Min 9	0.583	0.582	0.587
Pleasure	0.583	0.582	0.588
Heat	0.582	0.58	0.586
Gray Sd	0.581	0.579	0.586
Color1-2	0.581	0.579	0.585
Max 16	0.581	0.578	0.585
Min 9 Max 9	0.581	0.579	0.586
Gray Mn, Gray Sd	0.58	0.578	0.585
Color1	0.58	0.578	0.585
Base Features	0.579	0.577	0.584
Pleasure, Arousal, Dominance	0.578	0.577	0.583
Dominance	0.578	0.576	0.582
Weight	0.578	0.576	0.582
RGB Sd	0.577	0.575	0.582
Min 16 Max 16	0.577	0.575	0.583
Facebook, Twitter, Instagram, Color1-9	0.576	0.576	0.583

Table A.6: Cluster Models Gray 4

	F1	Precision	Recall
Color1-3	0.575	0.573	0.58
Facebook, Twitter, Instagram, Color1-10	0.575	0.575	0.581
Min 16	0.575	0.572	0.579
Gray Mn	0.573	0.57	0.577
Max 9	0.573	0.57	0.577
Activity	0.573	0.572	0.579
Gray Sd, RGB Sd	0.572	0.571	0.577
RGB Mn	0.571	0.569	0.575
RGB Mn, RGB Sd	0.571	0.57	0.577
Color1-4	0.57	0.568	0.575
Activity, Weight, Heat	0.569	0.568	0.575
Gray Mn, RGB Mn	0.568	0.567	0.572
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.564	0.563	0.57
Color1-5	0.564	0.563	0.569
Color1-6	0.563	0.562	0.569
Color1-8	0.563	0.563	0.569

Table A.6: Cluster Models Gray 4

	F1	**Precision**	**Recall**
Color1-7	0.562	0.562	0.568
Color1-9	0.558	0.556	0.565
Color1-10	0.551	0.55	0.558

Table A.7: Cluster Models Gray 5

	F1	**Precision**	**Recall**
BioNg, BioPs, Arousal	0.608	0.607	0.61
BioWC, DescWC, Color1-2	0.601	0.6	0.604
BioWC, DescWC Facebook, Twitter, Instagram	0.598	0.597	0.6
BioNg, BioPs, Color1-3	0.597	0.597	0.598
BioNg, BioPs, Activity	0.597	0.596	0.598
BioNg, BioPs Facebook, Twitter, Instagram	0.597	0.598	0.598
BioNg, BioPs, PAD	0.596	0.596	0.598
BioNg, BioPs, Color1	0.596	0.596	0.597
BioWC, DescWC, PAD	0.596	0.595	0.599
BioWC, DescWC, Pleasure	0.596	0.596	0.598
Facebook, Twitter, Instagram, Arousal	0.596	0.595	0.597
BioNg, BioPs, Dominance	0.595	0.595	0.597
BioWC, DescWC, Weight	0.595	0.594	0.597
BioWC, DescWC, Arousal	0.594	0.594	0.597
Facebook, Twitter, Instagram, Pleasure	0.594	0.593	0.596
Facebook, Twitter, Instagram, Dominance	0.594	0.593	0.596

Table A.7: Cluster Models Gray 5

	F1	**Precision**	**Recall**
BioNg, BioPs, Gray Sd, RGB Sd	0.593	0.593	0.594
BioNg, BioPs, Color1-2	0.593	0.591	0.595
BioWC, DescWC, Color1	0.593	0.593	0.596
BioNg, BioPs, Weight	0.593	0.593	0.595
BioNg, BioPs, RGB Sd	0.592	0.591	0.594
DescNg, DescPs	0.591	0.59	0.593
BioWC, DescWC, Color1-3	0.591	0.591	0.594
BioNg, BioPs BioWC, DescWC	0.591	0.591	0.594
BioNg, BioPs, Gray Sd	0.59	0.59	0.591
BioNg, BioPs, Gray Mn, Gray Sd	0.59	0.589	0.592
Facebook, Twitter, Instagram, Color1-4	0.59	0.588	0.592
BioNg, BioPs, Pleasure	0.59	0.59	0.59
BioNg, BioPs, Min 16 Max 16	0.589	0.589	0.591
BioNg, BioPs, Heat	0.589	0.588	0.591
BioWC, DescWC, Activity	0.589	0.589	0.591
BioNeg, BioPs, RGB Mn	0.588	0.588	0.59

Table A.7: Cluster Models Gray 5

	F1	Precision	Recall
BioNg, BioPs, Color1-4	0.588	0.588	0.59
Facebook, Twitter, Instagram, PAD	0.588	0.587	0.591
Facebook, Twitter, Instagram, Gray Sd	0.588	0.588	0.59
Title WC	0.588	0.588	0.589
Bio Word Count, Desc Word Count	0.587	0.585	0.588
BioWC, DescWC, Color1-6	0.587	0.586	0.591
BioNg, BioPs, Min 9 Max 9	0.587	0.587	0.588
BioNg, BioNeu, BioPs	0.587	0.587	0.588
DescNg, DescNeu, DescPs	0.587	0.586	0.59
Facebook, Twitter, Instagram	0.586	0.585	0.588
BioNg, BioPs	0.586	0.586	0.587
BioWC, DescWC, Gray Sd	0.586	0.585	0.589
Facebook, Twitter, Instagram, RGB Sd	0.586	0.586	0.588
Facebook, Twitter, Instagram, Color1	0.586	0.585	0.588
Facebook, Twitter, Instagram, Activity	0.586	0.585	0.587
BioNg, BioPs, Gray Mn, RGB Mn	0.585	0.586	0.586

Table A.7: Cluster Models Gray 5

	F1	**Precision**	**Recall**
BioWC, DescWC, RGB Sd	0.585	0.585	0.585
BioNg, BioPs, Gray Mn	0.584	0.584	0.585
BioNg, BioPs, Color1-6	0.584	0.584	0.585
BioWC, DescWC, AWH	0.583	0.582	0.585
BioWC, DescWC, RGB Mn	0.583	0.581	0.586
BioWC, DescWC, Gray Sd, RGB Sd	0.583	0.584	0.585
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.583	0.582	0.585
BioWC, DescWC, Dominance	0.583	0.582	0.586
Facebook, Twitter, Instagram, AWH	0.582	0.581	0.583
Facebook, Twitter, Instagram, Color1-2	0.582	0.581	0.585
Facebook, Twitter, Instagram, Color1-3	0.581	0.58	0.585
BioWC, DescWC, Min 9 Max 9	0.581	0.581	0.584
Arousal	0.581	0.581	0.584
Facebook, Twitter, Instagram, Weight	0.581	0.58	0.583
Facebook, Twitter, Instagram, Gray Mn	0.58	0.579	0.582
Facebook, Twitter, Instagram, RGB Mn	0.58	0.58	0.582

Table A.7: Cluster Models Gray 5

	F1	Precision	Recall
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.58	0.58	0.582
BioWC, DescWC, Min 16 Max 16	0.58	0.58	0.584
BioWC, DescWC, Heat	0.58	0.579	0.582
Facebook, Twitter, Instagram, Heat	0.58	0.579	0.581
BioNg, BioPs, AWH	0.579	0.58	0.582
BioWC, DescWC, Gray Mn	0.579	0.578	0.582
Color1	0.578	0.578	0.58
BioNg, BioPs, Color1-5	0.578	0.577	0.58
BioWC, DescWC, Gray Mn, RGB Mn	0.578	0.577	0.581
Gray Sd	0.577	0.576	0.579
Color1-2	0.577	0.577	0.581
Base Features	0.576	0.575	0.578
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.576	0.577	0.579
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.576	0.574	0.579
Facebook, Twitter, Instagram, Color1-8	0.576	0.575	0.58
BioWC, DescWC, Color1-4	0.575	0.575	0.578

Table A.7: Cluster Models Gray 5

	F1	Precision	Recall
BioWC, DescWC, Color1-5	0.575	0.574	0.579
BioWC, DescWC, Color1-9	0.575	0.573	0.579
Activity	0.575	0.574	0.576
Pleasure, Arousal, Dominance	0.574	0.574	0.576
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.574	0.573	0.577
RGB Mn	0.573	0.572	0.576
Facebook, Twitter, Instagram, Color1-5	0.573	0.572	0.575
Color1-3	0.572	0.571	0.575
BioNg, BioPs, Color1-8	0.572	0.572	0.574
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.572	0.571	0.576
Facebook, Twitter, Instagram, Min 16 Max 16	0.572	0.571	0.574
BioNg, BioPs, RGB Mn, RGB Sd	0.571	0.57	0.573
BioNg, BioPs, Color1-10	0.57	0.569	0.573
Facebook, Twitter, Instagram, Color1-6	0.57	0.568	0.574
Min 9	0.57	0.568	0.572
Max 16	0.57	0.569	0.572

Table A.7: Cluster Models Gray 5

	F1	**Precision**	**Recall**
Dominance	0.57	0.569	0.573
Gray Mn	0.569	0.567	0.571
BioNg, BioPs, Color1-7	0.569	0.568	0.57
BioNg, BioPs, Color1-9	0.569	0.568	0.572
BioWC, DescWC, Color1-8	0.569	0.569	0.573
Facebook, Twitter, Instagram, Min 9 Max 9	0.569	0.569	0.572
Pleasure	0.569	0.568	0.571
RGB Sd	0.568	0.568	0.57
BioWC, DescWC, Color1-10	0.568	0.568	0.572
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.568	0.566	0.571
Facebook, Twitter, Instagram, Color1-7	0.568	0.565	0.572
Heat	0.568	0.567	0.57
Gray Sd, RGB Sd	0.567	0.568	0.569
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.567	0.566	0.569
Weight	0.567	0.566	0.57
Gray Mn, Gray Sd	0.565	0.564	0.568

Table A.7: Cluster Models Gray 5

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-7	0.565	0.563	0.569
Min 9 Max 9	0.565	0.564	0.568
Gray Mn, RGB Mn	0.564	0.563	0.566
Max 9	0.564	0.563	0.566
Min 16 Max 16	0.564	0.563	0.567
Activity, Weight, Heat	0.562	0.56	0.565
Color1-4	0.561	0.56	0.565
Color1-6	0.56	0.559	0.564
Facebook, Twitter, Instagram, Color1-9	0.56	0.558	0.565
Min 16	0.559	0.557	0.562
RGB Mn, RGB Sd	0.558	0.557	0.56
Color1-5	0.557	0.556	0.561
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.556	0.555	0.559
Color1-7	0.554	0.554	0.557
Color1-10	0.554	0.553	0.559
Facebook, Twitter, Instagram, Color1-10	0.554	0.553	0.558

Table A.7: Cluster Models Gray 5

	F1	**Precision**	**Recall**
Color1-8	0.547	0.546	0.552
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.546	0.545	0.549
Color1-9	0.542	0.54	0.547

Table A.8: Cluster Models Gray 6

	F1	**Precision**	**Recall**
BioNg, BioPs BioWC, DescWC	0.69	0.69	0.69
BioWC, DescWC Facebook, Twitter, Instagram	0.685	0.686	0.686
BioWC, DescWC, Arousal	0.681	0.681	0.682
Bio Word Count, Desc Word Count	0.678	0.679	0.679
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.678	0.678	0.679
BioWC, DescWC, Dominance	0.678	0.678	0.679
BioWC, DescWC, Pleasure	0.677	0.677	0.678
BioWC, DescWC, Gray Mn	0.676	0.676	0.677
BioWC, DescWC, PAD	0.674	0.675	0.675
BioWC, DescWC, Gray Sd	0.674	0.674	0.675
BioWC, DescWC, Color1-3	0.674	0.675	0.676
BioWC, DescWC, Color1-4	0.674	0.676	0.675
BioWC, DescWC, Min 9 Max 9	0.674	0.675	0.676
BioWC, DescWC, Activity	0.674	0.674	0.675
BioWC, DescWC, Weight	0.674	0.675	0.675
BioWC, DescWC, AWH	0.673	0.674	0.674

Table A.8: Cluster Models Gray 6

	F1	Precision	Recall
BioWC, DescWC, Color1-2	0.673	0.674	0.675
BioNg, BioPs Facebook, Twitter, Instagram	0.673	0.673	0.675
BioNg, BioPs, Gray Sd	0.672	0.672	0.673
BioWC, DescWC, RGB Mn	0.672	0.672	0.673
BioNg, BioPs, Activity	0.672	0.672	0.673
BioNg, BioPs, Weight	0.672	0.673	0.673
BioWC, DescWC, Heat	0.672	0.673	0.673
BioNg, BioPs, PAD	0.671	0.672	0.673
BioNg, BioPs, Color1-2	0.671	0.671	0.672
BioNg, BioPs, Color1-3	0.671	0.671	0.673
BioNg, BioPs, Color1-4	0.671	0.672	0.673
BioWC, DescWC, Color1	0.671	0.671	0.672
BioNg, BioPs, Arousal	0.671	0.671	0.672
BioNg, BioNeu, BioPs	0.671	0.671	0.672
BioNg, BioPs, AWH	0.67	0.671	0.672
BioNg, BioPs, Gray Mn	0.67	0.671	0.672

Table A.8: Cluster Models Gray 6

	F1	Precision	Recall
BioNg, BioPs, Gray Mn, Gray Sd	0.67	0.67	0.672
BioWC, DescWC, RGB Sd	0.67	0.671	0.672
BioWC, DescWC, Min 16 Max 16	0.67	0.671	0.672
BioNg, BioPs	0.669	0.668	0.67
BioNg, BioPs, RGB Sd	0.669	0.669	0.67
BioNg, BioPs, Color1-5	0.669	0.67	0.671
BioWC, DescWC, Gray Mn, RGB Mn	0.669	0.67	0.671
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.669	0.67	0.671
BioNg, BioPs, Min 9 Max 9	0.669	0.669	0.67
BioNeg, BioPs, RGB Mn	0.668	0.668	0.67
BioNg, BioPs, Gray Sd, RGB Sd	0.668	0.669	0.67
BioNg, BioPs, Color1	0.668	0.668	0.67
BioNg, BioPs, Dominance	0.668	0.668	0.669
BioWC, DescWC, Color1-6	0.667	0.668	0.669
BioNg, BioPs, Pleasure	0.667	0.667	0.669
BioWC, DescWC, Gray Sd, RGB Sd	0.666	0.667	0.668

Table A.8: Cluster Models Gray 6

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-5	0.666	0.667	0.668
BioNg, BioPs, Heat	0.666	0.666	0.667
BioNg, BioPs, RGB Mn, RGB Sd	0.665	0.665	0.667
BioNg, BioPs, Color1-7	0.665	0.666	0.667
BioWC, DescWC, Color1-7	0.665	0.666	0.667
BioNg, BioPs, Min 16 Max 16	0.665	0.665	0.666
BioNg, BioPs, Gray Mn, RGB Mn	0.664	0.665	0.666
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.663	0.665	0.665
BioNg, BioPs, Color1-6	0.662	0.663	0.664
BioNg, BioPs, Color1-9	0.661	0.663	0.663
BioWC, DescWC, Color1-9	0.661	0.663	0.663
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.66	0.661	0.662
BioNg, BioPs, Color1-8	0.66	0.661	0.662
BioWC, DescWC, Color1-10	0.66	0.661	0.662
BioNg, BioPs, Color1-10	0.659	0.66	0.661
BioWC, DescWC, Color1-8	0.657	0.659	0.659

Table A.8: Cluster Models Gray 6

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Gray Sd	0.649	0.649	0.65
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.648	0.648	0.649
Facebook, Twitter, Instagram, Color1	0.648	0.648	0.649
Facebook, Twitter, Instagram, Arousal	0.648	0.647	0.649
Facebook, Twitter, Instagram, Activity	0.648	0.648	0.649
Facebook, Twitter, Instagram, Pleasure	0.646	0.646	0.647
Facebook, Twitter, Instagram, Weight	0.646	0.647	0.648
DescNg, DescPs	0.645	0.644	0.646
Facebook, Twitter, Instagram, Gray Mn	0.645	0.645	0.646
Facebook, Twitter, Instagram, Color1-3	0.645	0.645	0.646
Facebook, Twitter, Instagram, Dominance	0.645	0.645	0.647
Facebook, Twitter, Instagram, PAD	0.644	0.644	0.646
Facebook, Twitter, Instagram, AWH	0.644	0.645	0.646
Facebook, Twitter, Instagram, Color1-2	0.644	0.644	0.646
Facebook, Twitter, Instagram	0.643	0.643	0.644
Facebook, Twitter, Instagram, RGB Mn	0.643	0.643	0.644

Table A.8: Cluster Models Gray 6

	F1	Precision	Recall
Facebook, Twitter, Instagram, Color1-4	0.643	0.643	0.645
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.642	0.642	0.643
Facebook, Twitter, Instagram, Min 9 Max 9	0.642	0.642	0.644
DescNg, DescNeu, DescPs	0.641	0.641	0.644
Facebook, Twitter, Instagram, RGB Sd	0.64	0.64	0.642
Facebook, Twitter, Instagram, Color1-6	0.64	0.641	0.642
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.639	0.639	0.641
Facebook, Twitter, Instagram, Color1-5	0.638	0.639	0.64
Facebook, Twitter, Instagram, Min 16 Max 16	0.638	0.638	0.64
Facebook, Twitter, Instagram, Heat	0.638	0.638	0.639
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.637	0.638	0.639
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.637	0.638	0.639
Facebook, Twitter, Instagram, Color1-7	0.636	0.637	0.638
Facebook, Twitter, Instagram, Color1-9	0.635	0.636	0.637
Facebook, Twitter, Instagram, Color1-8	0.633	0.634	0.635
Facebook, Twitter, Instagram, Color1-10	0.632	0.634	0.635

Table A.8: Cluster Models Gray 6

	F1	**Precision**	**Recall**
Title WC	0.625	0.625	0.627
Gray Mn	0.62	0.619	0.622
Activity	0.619	0.619	0.621
Activity, Weight, Heat	0.618	0.617	0.62
Gray Mn, Gray Sd	0.618	0.618	0.62
Dominance	0.618	0.618	0.62
Arousal	0.617	0.616	0.619
Gray Sd	0.616	0.615	0.618
Color1	0.616	0.615	0.618
Color1-2	0.616	0.616	0.619
Pleasure	0.616	0.615	0.618
Weight	0.616	0.615	0.618
Pleasure, Arousal, Dominance	0.615	0.615	0.618
Base Features	0.614	0.613	0.616
Color1-3	0.614	0.613	0.616
Color1-4	0.613	0.612	0.615

Table A.8: Cluster Models Gray 6

	F1	Precision	Recall
Color1-5	0.613	0.614	0.616
Min 9	0.612	0.612	0.614
Max 9	0.612	0.611	0.614
Min 16 Max 16	0.612	0.612	0.614
RGB Mn	0.611	0.61	0.613
Color1-6	0.61	0.61	0.612
Max 16	0.61	0.61	0.612
Gray Mn, RGB Mn	0.609	0.608	0.611
Gray Sd, RGB Sd	0.609	0.609	0.612
RGB Mn, RGB Sd	0.609	0.609	0.612
Min 16	0.608	0.608	0.61
Min 9 Max 9	0.608	0.608	0.61
RGB Sd	0.607	0.607	0.61
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.606	0.606	0.609
Heat	0.606	0.606	0.608
Color1-7	0.604	0.604	0.607

Table A.8: Cluster Models Gray 6

	F1	Precision	Recall
Color1-8	0.601	0.601	0.604
Color1-10	0.601	0.601	0.605
Color1-9	0.599	0.599	0.603

Table A.9: Cluster Models Gray 7

	F1	Precision	Recall
DescNg, DescNeu, DescPs	0.658	0.66	0.662
BioNg, BioPs BioWC, DescWC	0.643	0.648	0.646
BioNg, BioPs, Dominance	0.642	0.65	0.646
Facebook, Twitter, Instagram, Weight	0.642	0.642	0.646
Dominance	0.636	0.643	0.642
Gray Mn, Gray Sd	0.634	0.64	0.637
DescNg, DescPs	0.634	0.635	0.637
BioWC, DescWC, Gray Sd	0.634	0.642	0.637
BioWC, DescWC, RGB Sd	0.634	0.645	0.637
BioWC, DescWC, Pleasure	0.634	0.641	0.637
Facebook, Twitter, Instagram, Dominance	0.633	0.64	0.637
Facebook, Twitter, Instagram, Activity	0.632	0.633	0.637
BioWC, DescWC Facebook, Twitter, Instagram	0.631	0.64	0.633
BioWC, DescWC, Activity	0.63	0.646	0.633
BioNg, BioPs	0.629	0.631	0.633
BioWC, DescWC, Gray Sd, RGB Sd	0.628	0.633	0.633

Table A.9: Cluster Models Gray 7

	F1	**Precision**	**Recall**
BioNg, BioPs, Activity	0.628	0.639	0.633
BioWC, DescWC, Heat	0.627	0.631	0.633
Bio Word Count, Desc Word Count	0.626	0.631	0.629
BioWC, DescWC, PAD	0.626	0.632	0.629
Base Features	0.625	0.628	0.629
Gray Sd	0.625	0.631	0.629
BioWC, DescWC, Gray Mn	0.623	0.63	0.625
BioWC, DescWC, Color1	0.622	0.637	0.629
Facebook, Twitter, Instagram, Gray Mn	0.621	0.63	0.625
Facebook, Twitter, Instagram, Gray Sd	0.621	0.628	0.625
Min 9 Max 9	0.621	0.628	0.625
Gray Sd, RGB Sd	0.62	0.626	0.625
Min 9	0.62	0.632	0.625
Pleasure	0.62	0.622	0.625
Weight	0.62	0.621	0.625
Facebook, Twitter, Instagram, Color1	0.619	0.63	0.625

Table A.9: Cluster Models Gray 7

	F1	Precision	Recall
BioWC, DescWC, Weight	0.617	0.62	0.621
Title WC	0.617	0.621	0.621
Pleasure, Arousal, Dominance	0.616	0.627	0.621
BioNg, BioPs, Weight	0.616	0.621	0.621
BioWC, DescWC, Dominance	0.615	0.622	0.621
BioWC, DescWC, Min 9 Max 9	0.614	0.617	0.617
BioWC, DescWC, Arousal	0.614	0.619	0.617
Facebook, Twitter, Instagram, Pleasure	0.614	0.619	0.621
BioWC, DescWC, AWH	0.609	0.613	0.613
BioNg, BioPs, Min 9 Max 9	0.609	0.614	0.613
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.608	0.611	0.613
Arousal	0.608	0.618	0.608
Facebook, Twitter, Instagram	0.607	0.611	0.613
BioNg, BioPs, Gray Sd, RGB Sd	0.607	0.618	0.613
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.606	0.61	0.613
BioNg, BioPs, RGB Sd	0.605	0.609	0.608

Table A.9: Cluster Models Gray 7

	F1	**Precision**	**Recall**
BioNg, BioPs Facebook, Twitter, Instagram	0.605	0.613	0.608
BioNg, BioNeu, BioPs	0.605	0.611	0.608
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.604	0.607	0.608
Facebook, Twitter, Instagram, RGB Mn	0.604	0.614	0.608
Min 16	0.604	0.609	0.608
Heat	0.604	0.61	0.608
BioWC, DescWC, Gray Mn, RGB Mn	0.603	0.621	0.613
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.603	0.614	0.608
BioWC, DescWC, Min 16 Max 16	0.603	0.616	0.608
BioNg, BioPs, Gray Mn, Gray Sd	0.602	0.603	0.608
Activity	0.602	0.607	0.608
RGB Sd	0.601	0.605	0.604
Facebook, Twitter, Instagram, PAD	0.601	0.603	0.608
BioNg, BioPs, Gray Sd	0.6	0.605	0.604
BioNg, BioPs, Pleasure	0.6	0.609	0.604
BioNg, BioPs, AWH	0.599	0.599	0.608

Table A.9: Cluster Models Gray 7

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-2	0.599	0.609	0.604
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.599	0.603	0.604
Max 9	0.599	0.61	0.604
Gray Mn, RGB Mn	0.598	0.598	0.604
BioNg, BioPs, PAD	0.598	0.604	0.604
Facebook, Twitter, Instagram, Min 9 Max 9	0.597	0.605	0.6
BioNg, BioPs, Heat	0.597	0.601	0.604
Gray Mn	0.596	0.6	0.604
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.596	0.604	0.604
Facebook, Twitter, Instagram, Min 16 Max 16	0.596	0.61	0.604
Facebook, Twitter, Instagram, Arousal	0.595	0.598	0.6
BioNg, BioPs, Arousal	0.594	0.605	0.6
BioWC, DescWC, RGB Mn	0.593	0.601	0.6
BioNg, BioPs, Min 16 Max 16	0.593	0.608	0.596
Facebook, Twitter, Instagram, Color1-2	0.592	0.599	0.596
BioNg, BioPs, Gray Mn, RGB Mn	0.591	0.6	0.6

Table A.9: Cluster Models Gray 7

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1	0.591	0.593	0.596
BioWC, DescWC, Color1-8	0.591	0.613	0.596
Facebook, Twitter, Instagram, Heat	0.59	0.593	0.596
BioNg, BioPs, Gray Mn	0.589	0.594	0.596
Min 16 Max 16	0.589	0.592	0.592
Color1	0.588	0.595	0.592
BioWC, DescWC, Color1-4	0.588	0.59	0.592
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.586	0.594	0.596
BioWC, DescWC, Color1-3	0.586	0.591	0.592
BioNeg, BioPs, RGB Mn	0.585	0.589	0.592
BioWC, DescWC, Color1-2	0.584	0.591	0.588
Facebook, Twitter, Instagram, Color1-7	0.584	0.597	0.592
Activity, Weight, Heat	0.581	0.588	0.588
Facebook, Twitter, Instagram, Color1-9	0.581	0.603	0.588
BioWC, DescWC, Color1-5	0.58	0.595	0.583
Facebook, Twitter, Instagram, AWH	0.58	0.584	0.588

Table A.9: Cluster Models Gray 7

	F1	Precision	Recall
Color1-2	0.578	0.587	0.583
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.578	0.581	0.583
RGB Mn	0.577	0.579	0.588
Facebook, Twitter, Instagram, RGB Sd	0.577	0.582	0.583
RGB Mn, RGB Sd	0.576	0.583	0.583
BioNg, BioPs, Color1-3	0.576	0.582	0.583
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.575	0.583	0.579
Color1-4	0.574	0.578	0.579
BioWC, DescWC, Color1-6	0.574	0.594	0.579
BioNg, BioPs, Color1-4	0.572	0.587	0.579
BioNg, BioPs, RGB Mn, RGB Sd	0.571	0.584	0.579
BioNg, BioPs, Color1-5	0.57	0.576	0.575
Max 16	0.57	0.576	0.575
Color1-9	0.569	0.58	0.579
Facebook, Twitter, Instagram, Color1-5	0.567	0.579	0.575
BioNg, BioPs, Color1-6	0.566	0.576	0.575

Table A.9: Cluster Models Gray 7

	F1	**Precision**	**Recall**
Color1-10	0.565	0.581	0.575
Facebook, Twitter, Instagram, Color1-3	0.565	0.572	0.571
BioNg, BioPs, Color1-7	0.562	0.57	0.571
Color1-8	0.56	0.586	0.571
Facebook, Twitter, Instagram, Color1-10	0.56	0.575	0.571
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.558	0.571	0.567
Facebook, Twitter, Instagram, Color1-6	0.558	0.565	0.562
BioWC, DescWC, Color1-9	0.555	0.573	0.562
Facebook, Twitter, Instagram, Color1-8	0.555	0.568	0.567
Color1-7	0.554	0.573	0.567
Color1-5	0.553	0.558	0.558
BioWC, DescWC, Color1-10	0.553	0.565	0.562
BioWC, DescWC, Color1-7	0.552	0.562	0.562
BioNg, BioPs, Color1-10	0.548	0.563	0.558
Color1-3	0.547	0.555	0.55
Color1-6	0.543	0.547	0.554

Table A.9: Cluster Models Gray 7

	F1	Precision	Recall
Facebook, Twitter, Instagram, Color1-4	0.541	0.551	0.546
BioNg, BioPs, Color1-8	0.536	0.551	0.546
BioNg, BioPs, Color1-9	0.532	0.551	0.546

Table A.10: Cluster Models Gray 8

	F1	Precision	Recall
BioNg, BioPs BioWC, DescWC	0.614	0.613	0.616
BioNg, BioPs Facebook, Twitter, Instagram	0.602	0.601	0.603
BioWC, DescWC Facebook, Twitter, Instagram	0.598	0.597	0.599
BioNg, BioNeu, BioPs	0.595	0.594	0.597
BioNg, BioPs, Pleasure	0.586	0.585	0.588
BioNg, BioPs, Arousal	0.586	0.585	0.588
BioNg, BioPs	0.585	0.584	0.587
BioNg, BioPs, Gray Mn	0.585	0.584	0.587
BioNg, BioPs, Dominance	0.585	0.584	0.587
BioNg, BioPs, Weight	0.585	0.584	0.586
BioNg, BioPs, Gray Sd	0.584	0.583	0.585
BioNg, BioPs, Color1	0.584	0.583	0.586
BioNg, BioPs, Activity	0.583	0.582	0.585
BioNg, BioPs, Gray Mn, Gray Sd	0.582	0.581	0.584
BioNg, BioPs, Min 16 Max 16	0.582	0.58	0.584
BioNg, BioPs, Color1-2	0.581	0.58	0.583

Table A.10: Cluster Models Gray 8

	F1	Precision	Recall
BioNg, BioPs, Min 9 Max 9	0.581	0.58	0.583
BioNg, BioPs, Heat	0.581	0.58	0.583
BioNg, BioPs, PAD	0.578	0.577	0.581
BioNeg, BioPs, RGB Mn	0.578	0.577	0.58
BioNg, BioPs, Color1-3	0.578	0.577	0.58
BioNg, BioPs, AWH	0.577	0.576	0.579
BioNg, BioPs, Color1-4	0.577	0.576	0.579
BioNg, BioPs, Gray Mn, RGB Mn	0.575	0.574	0.577
Bio Word Count, Desc Word Count	0.574	0.573	0.576
BioNg, BioPs, RGB Sd	0.574	0.573	0.576
BioWC, DescWC, Pleasure	0.573	0.572	0.575
BioWC, DescWC, Activity	0.573	0.572	0.575
BioNg, BioPs, Color1-5	0.572	0.571	0.574
BioWC, DescWC, Color1	0.572	0.571	0.574
BioWC, DescWC, Arousal	0.572	0.571	0.574
BioWC, DescWC, Dominance	0.572	0.571	0.575

Table A.10: Cluster Models Gray 8

	F1	**Precision**	**Recall**
BioNg, BioPs, Gray Sd, RGB Sd	0.571	0.57	0.573
BioNg, BioPs, RGB Mn, RGB Sd	0.571	0.57	0.574
BioNg, BioPs, Color1-6	0.571	0.57	0.574
BioWC, DescWC, Gray Mn	0.571	0.57	0.573
BioWC, DescWC, Gray Sd	0.571	0.57	0.573
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.57	0.569	0.572
BioWC, DescWC, Weight	0.57	0.569	0.572
BioWC, DescWC, Min 16 Max 16	0.569	0.568	0.571
BioWC, DescWC, Heat	0.569	0.567	0.571
BioWC, DescWC, Color1-2	0.568	0.567	0.571
BioNg, BioPs, Color1-7	0.566	0.565	0.569
BioWC, DescWC, Color1-3	0.566	0.564	0.568
BioWC, DescWC, Min 9 Max 9	0.565	0.563	0.567
BioWC, DescWC, PAD	0.564	0.562	0.566
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.563	0.562	0.566
BioNg, BioPs, Color1-8	0.563	0.562	0.566

Table A.10: Cluster Models Gray 8

	F1	**Precision**	**Recall**
BioWC, DescWC, AWH	0.563	0.562	0.566
BioWC, DescWC, RGB Mn	0.563	0.562	0.566
BioWC, DescWC, Gray Mn, RGB Mn	0.561	0.56	0.563
BioWC, DescWC, RGB Sd	0.561	0.559	0.563
BioWC, DescWC, Color1-4	0.56	0.559	0.563
BioNg, BioPs, Color1-9	0.559	0.558	0.562
BioNg, BioPs, Color1-10	0.559	0.558	0.562
BioWC, DescWC, Color1-5	0.558	0.557	0.561
BioWC, DescWC, Gray Sd, RGB Sd	0.556	0.554	0.558
BioWC, DescWC, Color1-6	0.554	0.553	0.557
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.552	0.551	0.555
BioWC, DescWC, Color1-7	0.549	0.548	0.552
BioWC, DescWC, Color1-8	0.548	0.547	0.551
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.547	0.546	0.55
BioWC, DescWC, Color1-9	0.544	0.542	0.547
BioWC, DescWC, Color1-10	0.538	0.537	0.542

Table A.10: Cluster Models Gray 8

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1	0.532	0.53	0.534
Facebook, Twitter, Instagram, Gray Mn	0.531	0.53	0.534
Facebook, Twitter, Instagram, Dominance	0.531	0.53	0.534
Facebook, Twitter, Instagram, Color1-2	0.53	0.528	0.532
Facebook, Twitter, Instagram, Gray Sd	0.529	0.527	0.531
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.529	0.527	0.532
Facebook, Twitter, Instagram, Arousal	0.529	0.527	0.531
Facebook, Twitter, Instagram, Weight	0.529	0.527	0.532
Facebook, Twitter, Instagram, Pleasure	0.528	0.527	0.531
Facebook, Twitter, Instagram, Activity	0.527	0.526	0.53
Facebook, Twitter, Instagram	0.526	0.525	0.528
Facebook, Twitter, Instagram, PAD	0.526	0.525	0.53
Facebook, Twitter, Instagram, Color1-3	0.526	0.524	0.529
Facebook, Twitter, Instagram, RGB Mn	0.525	0.524	0.528
Facebook, Twitter, Instagram, Min 9 Max 9	0.525	0.523	0.528
Facebook, Twitter, Instagram, Min 16 Max 16	0.524	0.522	0.527

Table A.10: Cluster Models Gray 8

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, AWH	0.523	0.522	0.526
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.522	0.52	0.525
Facebook, Twitter, Instagram, Color1-4	0.522	0.521	0.525
Facebook, Twitter, Instagram, Heat	0.522	0.52	0.524
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.521	0.519	0.525
Facebook, Twitter, Instagram, Color1-5	0.521	0.519	0.524
Facebook, Twitter, Instagram, RGB Sd	0.519	0.517	0.522
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.518	0.517	0.522
DescNg, DescNeu, DescPs	0.518	0.517	0.521
DescNg, DescPs	0.516	0.514	0.519
Facebook, Twitter, Instagram, Color1-6	0.516	0.514	0.52
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.513	0.512	0.517
Facebook, Twitter, Instagram, Color1-7	0.513	0.512	0.517
Facebook, Twitter, Instagram, Color1-8	0.511	0.51	0.516
Facebook, Twitter, Instagram, Color1-9	0.507	0.505	0.511
Facebook, Twitter, Instagram, Color1-10	0.504	0.503	0.509

Table A.10: Cluster Models Gray 8

	F1	Precision	Recall
Title WC	0.49	0.488	0.493
Gray Mn, Gray Sd	0.48	0.478	0.483
Color1-2	0.48	0.478	0.482
RGB Mn	0.478	0.476	0.481
Color1-3	0.477	0.476	0.48
Pleasure, Arousal, Dominance	0.475	0.473	0.478
Gray Mn	0.475	0.473	0.478
RGB Mn, RGB Sd	0.475	0.473	0.479
Dominance	0.475	0.473	0.478
Gray Sd	0.474	0.472	0.477
Color1	0.474	0.473	0.477
Color1-4	0.474	0.472	0.477
Weight	0.474	0.473	0.477
Activity, Weight, Heat	0.473	0.472	0.477
Gray Mn, RGB Mn	0.473	0.471	0.476
Pleasure	0.473	0.471	0.476

Table A.10: Cluster Models Gray 8

	F1	**Precision**	**Recall**
Activity	0.472	0.47	0.475
Color1-5	0.471	0.469	0.475
Max 16	0.471	0.469	0.474
Min 16 Max 16	0.471	0.469	0.474
Arousal	0.471	0.469	0.474
Color1-6	0.47	0.468	0.474
Max 9	0.47	0.468	0.473
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.469	0.467	0.473
Min 16	0.469	0.468	0.472
Min 9	0.468	0.466	0.471
Min 9 Max 9	0.468	0.466	0.471
Base Features	0.467	0.465	0.469
Color1-7	0.467	0.465	0.471
RGB Sd	0.466	0.464	0.47
Gray Sd, RGB Sd	0.464	0.462	0.468
Color1-8	0.464	0.462	0.468

Table A.10: Cluster Models Gray 8

	F1	**Precision**	**Recall**
Heat	0.464	0.462	0.466
Color1-9	0.46	0.458	0.464
Color1-10	0.459	0.457	0.464

Table A.11: Cluster Models Gray 9

	F1	Precision	Recall
BioNg, BioPs BioWC, DescWC	0.612	0.61	0.614
BioWC, DescWC Facebook, Twitter, Instagram	0.604	0.603	0.606
BioWC, DescWC, Gray Mn	0.599	0.598	0.601
BioNg, BioPs Facebook, Twitter, Instagram	0.599	0.597	0.601
BioNg, BioPs, Color1	0.598	0.597	0.6
BioNg, BioPs, Min 16 Max 16	0.598	0.597	0.6
BioWC, DescWC, Activity	0.598	0.598	0.6
BioNg, BioPs, Gray Mn	0.597	0.596	0.6
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.597	0.597	0.599
BioNg, BioPs, Min 9 Max 9	0.597	0.596	0.599
BioNg, BioPs, Activity	0.597	0.597	0.6
BioWC, DescWC, Heat	0.597	0.597	0.599
BioNg, BioNeu, BioPs	0.597	0.596	0.599
Bio Word Count, Desc Word Count	0.596	0.595	0.598
BioNg, BioPs, PAD	0.596	0.595	0.599
BioNg, BioPs, Color1-2	0.596	0.595	0.599

Table A.11: Cluster Models Gray 9

	F1	**Precision**	**Recall**
BioWC, DescWC, Min 16 Max 16	0.596	0.597	0.599
BioWC, DescWC, Arousal	0.596	0.595	0.598
BioWC, DescWC, Dominance	0.596	0.596	0.598
BioNeg, BioPs, RGB Mn	0.595	0.594	0.598
BioNg, BioPs, Gray Mn, Gray Sd	0.595	0.598	0.598
BioWC, DescWC, Gray Sd	0.595	0.594	0.597
BioNg, BioPs, Arousal	0.595	0.594	0.598
BioNg, BioPs, Heat	0.595	0.594	0.597
BioNg, BioPs, RGB Sd	0.594	0.594	0.597
BioNg, BioPs, RGB Mn, RGB Sd	0.594	0.593	0.596
BioNg, BioPs, Dominance	0.594	0.593	0.596
BioWC, DescWC, Pleasure	0.594	0.594	0.597
BioNg, BioPs	0.593	0.592	0.595
BioNg, BioPs, AWH	0.593	0.593	0.596
BioNg, BioPs, Gray Sd	0.593	0.592	0.595
BioWC, DescWC, AWH	0.593	0.594	0.596

Table A.11: Cluster Models Gray 9

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1	0.593	0.593	0.595
BioWC, DescWC, Color1-2	0.593	0.593	0.595
BioWC, DescWC, Min 9 Max 9	0.593	0.593	0.595
BioNg, BioPs, Pleasure	0.593	0.591	0.595
BioNg, BioPs, Weight	0.593	0.592	0.595
BioWC, DescWC, Color1-3	0.592	0.592	0.594
BioWC, DescWC, Weight	0.592	0.591	0.594
BioNg, BioPs, Gray Sd, RGB Sd	0.591	0.59	0.594
BioNg, BioPs, Color1-4	0.591	0.59	0.593
BioNg, BioPs, Color1-5	0.591	0.591	0.594
BioWC, DescWC, RGB Mn	0.591	0.591	0.593
BioNg, BioPs, Color1-3	0.59	0.59	0.593
BioWC, DescWC, Gray Mn, RGB Mn	0.59	0.59	0.592
BioWC, DescWC, Color1-4	0.59	0.591	0.593
BioWC, DescWC, Color1-5	0.59	0.591	0.593
BioWC, DescWC, PAD	0.589	0.589	0.592

Table A.11: Cluster Models Gray 9

	F1	**Precision**	**Recall**
BioWC, DescWC, RGB Sd	0.589	0.59	0.591
BioNg, BioPs, Gray Mn, RGB Mn	0.588	0.587	0.591
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.588	0.589	0.59
BioNg, BioPs, Color1-6	0.587	0.587	0.59
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.586	0.586	0.589
BioNg, BioPs, Color1-7	0.586	0.586	0.589
BioWC, DescWC, Gray Sd, RGB Sd	0.584	0.584	0.586
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.584	0.585	0.587
BioNg, BioPs, Color1-8	0.582	0.582	0.585
BioNg, BioPs, Color1-10	0.582	0.582	0.585
BioNg, BioPs, Color1-9	0.581	0.58	0.584
BioWC, DescWC, Color1-7	0.581	0.582	0.584
BioWC, DescWC, Color1-8	0.581	0.582	0.584
BioWC, DescWC, Color1-6	0.58	0.58	0.583
BioWC, DescWC, Color1-10	0.576	0.577	0.579
BioWC, DescWC, Color1-9	0.574	0.575	0.577

Table A.11: Cluster Models Gray 9

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1	0.573	0.572	0.575
Facebook, Twitter, Instagram, Dominance	0.57	0.57	0.572
Facebook, Twitter, Instagram, Activity	0.57	0.569	0.572
Facebook, Twitter, Instagram, AWH	0.569	0.569	0.571
Facebook, Twitter, Instagram, Gray Mn	0.569	0.569	0.572
Facebook, Twitter, Instagram, Gray Sd	0.569	0.568	0.571
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.569	0.569	0.571
Facebook, Twitter, Instagram, Min 16 Max 16	0.569	0.569	0.571
Facebook, Twitter, Instagram, Arousal	0.569	0.568	0.571
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.568	0.568	0.571
Facebook, Twitter, Instagram, Weight	0.568	0.567	0.57
DescNg, DescPs	0.567	0.567	0.569
Facebook, Twitter, Instagram, RGB Mn	0.567	0.567	0.569
Facebook, Twitter, Instagram, Color1-2	0.566	0.566	0.569
Facebook, Twitter, Instagram, Color1-3	0.566	0.566	0.568
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.565	0.565	0.568

Table A.11: Cluster Models Gray 9

	F1	Precision	Recall
Facebook, Twitter, Instagram, Min 9 Max 9	0.565	0.565	0.568
DescNg, DescNeu, DescPs	0.565	0.565	0.567
Facebook, Twitter, Instagram	0.564	0.563	0.566
Facebook, Twitter, Instagram, PAD	0.564	0.564	0.566
Facebook, Twitter, Instagram, Pleasure	0.564	0.564	0.567
Facebook, Twitter, Instagram, Heat	0.564	0.564	0.567
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.563	0.563	0.566
Facebook, Twitter, Instagram, RGB Sd	0.563	0.563	0.565
Facebook, Twitter, Instagram, Color1-5	0.562	0.562	0.564
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.561	0.562	0.564
Facebook, Twitter, Instagram, Color1-4	0.561	0.561	0.563
Facebook, Twitter, Instagram, Color1-7	0.56	0.561	0.562
Facebook, Twitter, Instagram, Color1-8	0.56	0.561	0.563
Facebook, Twitter, Instagram, Color1-6	0.557	0.558	0.56
Facebook, Twitter, Instagram, Color1-10	0.554	0.555	0.557
Facebook, Twitter, Instagram, Color1-9	0.553	0.554	0.556

Table A.11: Cluster Models Gray 9

	F1	**Precision**	**Recall**
Title WC	0.546	0.546	0.548
Gray Mn, Gray Sd	0.543	0.544	0.545
Activity, Weight, Heat	0.542	0.543	0.544
Color1-2	0.542	0.542	0.544
Max 16	0.542	0.542	0.543
RGB Mn	0.541	0.542	0.543
Color1	0.541	0.54	0.543
Gray Mn	0.54	0.541	0.542
Color1-3	0.54	0.541	0.542
Arousal	0.54	0.54	0.542
Activity	0.54	0.54	0.543
Min 16 Max 16	0.539	0.539	0.541
Dominance	0.539	0.539	0.541
RGB Mn, RGB Sd	0.538	0.54	0.541
Pleasure, Arousal, Dominance	0.537	0.538	0.539
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.537	0.538	0.539

Table A.11: Cluster Models Gray 9

	F1	Precision	Recall
Max 9	0.537	0.537	0.539
Min 16	0.537	0.538	0.539
Gray Mn, RGB Mn	0.536	0.537	0.538
Gray Sd	0.536	0.536	0.539
Base Features	0.535	0.535	0.537
RGB Sd	0.535	0.535	0.536
Weight	0.535	0.535	0.537
Color1-4	0.534	0.535	0.536
Color1-5	0.534	0.536	0.536
Color1-6	0.534	0.535	0.536
Min 9 Max 9	0.534	0.534	0.536
Gray Sd, RGB Sd	0.533	0.534	0.535
Color1-7	0.533	0.535	0.536
Min 9	0.533	0.534	0.535
Pleasure	0.532	0.532	0.534
Heat	0.532	0.533	0.535

Table A.11: Cluster Models Gray 9

	F1	**Precision**	**Recall**
Color1-8	0.531	0.533	0.533
Color1-9	0.527	0.529	0.53
Color1-10	0.524	0.526	0.526

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
BioNg, BioPs, Arousal	0.733	0.698	0.772
BioWC, DescWC, Dominance	0.732	0.695	0.774
BioWC, DescWC, Activity	0.729	0.691	0.773
BioWC, DescWC, Pleasure	0.728	0.69	0.77
BioWC, DescWC, Arousal	0.728	0.689	0.773
BioWC, DescWC, Weight	0.726	0.688	0.769
BioWC, DescWC, Heat	0.725	0.684	0.77
Facebook, Twitter, Instagram, Dominance	0.718	0.682	0.758
Facebook, Twitter, Instagram, Arousal	0.708	0.671	0.75
Facebook, Twitter, Instagram, Pleasure	0.707	0.671	0.748
Facebook, Twitter, Instagram, Activity	0.707	0.67	0.749
Facebook, Twitter, Instagram, Heat	0.707	0.673	0.746
Facebook, Twitter, Instagram, Weight	0.702	0.667	0.741
BioNg, BioPs BioWC, DescWC	0.6	0.599	0.602
BioNg, BioPs Facebook, Twitter, Instagram	0.586	0.585	0.588
BioWC, DescWC Facebook, Twitter, Instagram	0.583	0.581	0.585

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
BioNg, BioNeu, BioPs	0.576	0.575	0.578
BioNg, BioPs	0.567	0.565	0.569
BioNg, BioPs, Color1	0.565	0.563	0.567
BioNg, BioPs, Dominance	0.564	0.562	0.566
BioNg, BioPs, Pleasure	0.563	0.561	0.565
BioNg, BioPs, Gray Mn	0.562	0.561	0.565
BioNg, BioPs, Gray Sd	0.562	0.561	0.565
BioNg, BioPs, Color1-2	0.561	0.559	0.564
BioNg, BioPs, Activity	0.561	0.56	0.564
BioNg, BioPs, Weight	0.561	0.56	0.564
BioNg, BioPs, Gray Mn, Gray Sd	0.56	0.558	0.562
BioNg, BioPs, Heat	0.559	0.558	0.562
BioNg, BioPs, Min 16 Max 16	0.558	0.557	0.561
BioNg, BioPs, PAD	0.557	0.555	0.56
BioNg, BioPs, Color1-3	0.557	0.556	0.56
BioNg, BioPs, Min 9 Max 9	0.557	0.555	0.56

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
Bio Word Count, Desc Word Count	0.556	0.555	0.559
BioNg, BioPs, AWH	0.556	0.554	0.559
BioNeg, BioPs, RGB Mn	0.556	0.555	0.559
BioNg, BioPs, RGB Sd	0.553	0.552	0.556
BioNg, BioPs, Color1-4	0.553	0.551	0.556
BioWC, DescWC, Gray Mn	0.552	0.551	0.555
BioWC, DescWC, Color1	0.552	0.551	0.555
BioNg, BioPs, Gray Mn, RGB Mn	0.551	0.549	0.553
BioWC, DescWC, Gray Sd	0.551	0.55	0.554
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.551	0.55	0.554
BioWC, DescWC, Color1-2	0.549	0.547	0.552
BioNg, BioPs, Gray Sd, RGB Sd	0.548	0.547	0.551
BioNg, BioPs, Color1-5	0.548	0.547	0.552
BioNg, BioPs, RGB Mn, RGB Sd	0.547	0.545	0.55
BioNg, BioPs, Color1-6	0.547	0.545	0.55
BioWC, DescWC, Min 16 Max 16	0.546	0.545	0.55

Table A.12: Cluster Models Edge 0

	F1	Precision	Recall
BioWC, DescWC, PAD	0.545	0.543	0.548
BioWC, DescWC, Min 9 Max 9	0.545	0.544	0.548
BioWC, DescWC, Color1-3	0.543	0.542	0.546
BioWC, DescWC, RGB Mn	0.542	0.541	0.546
BioWC, DescWC, Color1-4	0.542	0.541	0.546
BioNg, BioPs, Color1-7	0.541	0.54	0.545
BioWC, DescWC, AWH	0.54	0.539	0.544
BioWC, DescWC, Gray Mn, RGB Mn	0.539	0.537	0.542
BioNg, BioPs, Color1-8	0.538	0.536	0.542
BioWC, DescWC, RGB Sd	0.538	0.536	0.541
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.537	0.535	0.541
BioNg, BioPs, Color1-9	0.535	0.534	0.539
BioWC, DescWC, Gray Sd, RGB Sd	0.535	0.534	0.539
BioWC, DescWC, Color1-5	0.534	0.532	0.538
BioNg, BioPs, Color1-10	0.533	0.532	0.537
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.532	0.531	0.536

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-6	0.531	0.53	0.535
BioWC, DescWC, Color1-7	0.529	0.527	0.533
BioWC, DescWC, Color1-8	0.524	0.522	0.528
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.523	0.521	0.527
BioWC, DescWC, Color1-9	0.521	0.519	0.525
BioWC, DescWC, Color1-10	0.518	0.517	0.533
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.512	0.51	0.515
Facebook, Twitter, Instagram, Gray Mn	0.511	0.509	0.514
Facebook, Twitter, Instagram, Color1	0.511	0.51	0.514
Facebook, Twitter, Instagram	0.509	0.507	0.511
Facebook, Twitter, Instagram, Gray Sd	0.509	0.507	0.512
Facebook, Twitter, Instagram, PAD	0.508	0.506	0.511
Facebook, Twitter, Instagram, Color1-2	0.508	0.506	0.511
Facebook, Twitter, Instagram, RGB Mn	0.506	0.504	0.509
Facebook, Twitter, Instagram, Color1-3	0.506	0.504	0.509
Facebook, Twitter, Instagram, Min 16 Max 16	0.505	0.504	0.509

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, AWH	0.504	0.502	0.508
Facebook, Twitter, Instagram, Min 9 Max 9	0.504	0.502	0.507
Facebook, Twitter, Instagram, Color1-4	0.503	0.502	0.507
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.501	0.499	0.504
DescNg, DescNeu, DescPs	0.501	0.499	0.505
Facebook, Twitter, Instagram, RGB Sd	0.499	0.497	0.502
Facebook, Twitter, Instagram, Color1-5	0.499	0.497	0.503
DescNg, DescPs	0.497	0.496	0.501
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.497	0.495	0.501
Facebook, Twitter, Instagram, Color1-6	0.495	0.493	0.499
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.493	0.491	0.497
Facebook, Twitter, Instagram, Color1-7	0.492	0.49	0.496
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.49	0.488	0.494
Facebook, Twitter, Instagram, Color1-8	0.49	0.488	0.494
Facebook, Twitter, Instagram, Color1-9	0.487	0.485	0.492
Facebook, Twitter, Instagram, Color1-10	0.484	0.482	0.489

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
Title WC	0.469	0.467	0.472
Gray Mn, Gray Sd	0.46	0.458	0.464
Pleasure, Arousal, Dominance	0.458	0.456	0.461
Gray Mn	0.457	0.455	0.461
Color1	0.456	0.454	0.459
Pleasure	0.456	0.454	0.459
RGB Mn	0.455	0.453	0.458
Color1-2	0.455	0.453	0.459
Color1-3	0.455	0.453	0.459
Dominance	0.455	0.453	0.459
Max 16	0.454	0.451	0.457
Gray Sd	0.453	0.451	0.456
Color1-4	0.453	0.45	0.457
Min 16 Max 16	0.453	0.451	0.457
Arousal	0.453	0.451	0.457
Weight	0.453	0.451	0.457

Table A.12: Cluster Models Edge 0

	F1	Precision	Recall
Max 9	0.452	0.45	0.456
Activity	0.452	0.45	0.456
Activity, Weight, Heat	0.451	0.449	0.455
Gray Mn, RGB Mn	0.451	0.449	0.455
Base Features	0.45	0.448	0.453
RGB Mn, RGB Sd	0.45	0.448	0.455
Min 16	0.45	0.448	0.454
Min 9 Max 9	0.45	0.448	0.454
Color1-5	0.449	0.447	0.454
Color1-6	0.447	0.445	0.452
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.446	0.444	0.451
Gray Sd, RGB Sd	0.445	0.443	0.449
RGB Sd	0.445	0.443	0.449
Color1-7	0.445	0.443	0.45
Heat	0.445	0.443	0.449
Color1-8	0.442	0.44	0.447

Table A.12: Cluster Models Edge 0

	F1	**Precision**	**Recall**
Color1-9	0.44	0.438	0.446
Color1-10	0.437	0.435	0.443
Min 9	0.0449	0.447	0.452

Table A.13: Cluster Models Edge 1

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Mn	0.658	0.658	0.66
BioWC, DescWC, PAD	0.657	0.657	0.659
BioWC, DescWC, Weight	0.657	0.657	0.659
BioWC, DescWC, Arousal	0.656	0.656	0.658
DescNg, DescNeu, DescPs	0.656	0.656	0.658
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.655	0.654	0.657
BioWC, DescWC, Dominance	0.655	0.655	0.656
BioWC, DescWC, AWH	0.653	0.653	0.655
BioWC, DescWC, RGB Mn	0.653	0.653	0.654
BioWC, DescWC, Color1	0.653	0.653	0.655
BioWC, DescWC, Min 9 Max 9	0.653	0.653	0.655
BioWC, DescWC, Pleasure	0.653	0.653	0.655
BioNg, BioPs BioWC, DescWC	0.653	0.653	0.655
BioWC, DescWC Facebook, Twitter, Instagram	0.653	0.652	0.654
BioWC, DescWC, Min 16 Max 16	0.652	0.652	0.654
BioWC, DescWC, Activity	0.652	0.652	0.654

Table A.13: Cluster Models Edge 1

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Mn, RGB Mn	0.651	0.651	0.653
BioWC, DescWC, Color1-2	0.651	0.651	0.653
Bio Word Count, Desc Word Count	0.65	0.649	0.651
BioWC, DescWC, Gray Sd	0.649	0.649	0.651
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.649	0.65	0.651
BioWC, DescWC, RGB Sd	0.648	0.648	0.65
BioWC, DescWC, Color1-3	0.648	0.647	0.65
BioWC, DescWC, Heat	0.648	0.648	0.649
BioWC, DescWC, Color1-4	0.647	0.647	0.65
BioWC, DescWC, Color1-5	0.646	0.646	0.648
DescNg, DescPs	0.644	0.644	0.645
BioWC, DescWC, Gray Sd, RGB Sd	0.643	0.643	0.646
BioWC, DescWC, Color1-6	0.643	0.643	0.645
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.642	0.643	0.644
BioWC, DescWC, Color1-7	0.642	0.641	0.644
BioWC, DescWC, Color1-8	0.642	0.643	0.645

Table A.13: Cluster Models Edge 1

	F1	**Precision**	**Recall**
BioNg, BioPs, PAD	0.641	0.641	0.643
BioWC, DescWC, Color1-9	0.641	0.642	0.644
BioNg, BioPs, Dominance	0.641	0.641	0.643
BioNg, BioPs, Gray Mn, Gray Sd	0.64	0.639	0.641
BioNg, BioPs, Min 9 Max 9	0.64	0.639	0.642
BioNeg, BioPs, RGB Mn	0.639	0.639	0.641
BioNg, BioPs, Arousal	0.637	0.637	0.639
BioNg, BioPs, Min 16 Max 16	0.636	0.636	0.638
BioNg, BioPs, Activity	0.636	0.635	0.638
BioNg, BioPs, Color1	0.635	0.634	0.637
Title WC	0.635	0.634	0.636
BioNg, BioPs, Gray Mn	0.634	0.633	0.635
BioNg, BioPs, Gray Sd	0.634	0.634	0.636
BioWC, DescWC, Color1-10	0.634	0.635	0.637
BioNg, BioPs, RGB Sd	0.633	0.632	0.635
BioNg, BioPs, RGB Mn, RGB Sd	0.633	0.633	0.635

Table A.13: Cluster Models Edge 1

	F1	Precision	Recall
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.633	0.633	0.635
BioNg, BioPs, Weight	0.633	0.633	0.635
Facebook, Twitter, Instagram, Arousal	0.633	0.632	0.634
BioNg, BioPs, Color1-2	0.632	0.631	0.634
Facebook, Twitter, Instagram, Gray Mn	0.632	0.631	0.633
Facebook, Twitter, Instagram, Min 9 Max 9	0.632	0.631	0.634
BioNg, BioPs, Heat	0.632	0.632	0.634
BioNg, BioNeu, BioPs	0.632	0.631	0.634
BioNg, BioPs, AWH	0.631	0.63	0.633
BioNg, BioPs, Gray Mn, RGB Mn	0.631	0.631	0.633
Facebook, Twitter, Instagram, PAD	0.631	0.631	0.633
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.631	0.631	0.633
BioNg, BioPs, Color1-4	0.63	0.63	0.633
Facebook, Twitter, Instagram, Pleasure	0.63	0.629	0.632
BioNg, BioPs, Color1-5	0.629	0.629	0.632
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.629	0.629	0.631

Table A.13: Cluster Models Edge 1

	F1	**Precision**	**Recall**
BioNg, BioPs, Pleasure	0.629	0.628	0.63
Facebook, Twitter, Instagram, Activity	0.629	0.629	0.631
BioNg, BioPs Facebook, Twitter, Instagram	0.629	0.628	0.631
BioNg, BioPs	0.628	0.627	0.629
BioNg, BioPs, Gray Sd, RGB Sd	0.628	0.628	0.63
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.628	0.628	0.63
Facebook, Twitter, Instagram, RGB Mn	0.628	0.628	0.63
Facebook, Twitter, Instagram, Color1	0.628	0.628	0.63
Facebook, Twitter, Instagram, Min 16 Max 16	0.628	0.628	0.63
Facebook, Twitter, Instagram, Dominance	0.628	0.628	0.63
BioNg, BioPs, Color1-7	0.627	0.627	0.63
Facebook, Twitter, Instagram, Weight	0.627	0.627	0.629
BioNg, BioPs, Color1-3	0.626	0.625	0.628
BioNg, BioPs, Color1-6	0.626	0.627	0.629
BioNg, BioPs, Color1-10	0.626	0.626	0.629
Facebook, Twitter, Instagram, Gray Sd	0.626	0.626	0.628

Table A.13: Cluster Models Edge 1

	F1	Precision	Recall
BioNg, BioPs, Color1-8	0.625	0.625	0.628
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.625	0.626	0.627
BioNg, BioPs, Color1-9	0.624	0.624	0.627
Facebook, Twitter, Instagram, RGB Sd	0.624	0.624	0.626
Facebook, Twitter, Instagram, Color1-3	0.624	0.624	0.627
Facebook, Twitter, Instagram, Color1-5	0.624	0.624	0.627
Facebook, Twitter, Instagram, AWH	0.623	0.623	0.626
Facebook, Twitter, Instagram, Color1-2	0.623	0.623	0.626
Facebook, Twitter, Instagram, Color1-6	0.623	0.623	0.626
Facebook, Twitter, Instagram	0.622	0.621	0.624
Facebook, Twitter, Instagram, Color1-7	0.622	0.622	0.624
Facebook, Twitter, Instagram, Color1-4	0.621	0.621	0.624
Facebook, Twitter, Instagram, Color1-9	0.621	0.622	0.624
Facebook, Twitter, Instagram, Heat	0.621	0.62	0.623
Facebook, Twitter, Instagram, Color1-8	0.62	0.62	0.623
Gray Mn, Gray Sd	0.617	0.618	0.62

Table A.13: Cluster Models Edge 1

	F1	Precision	Recall
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.617	0.617	0.619
Facebook, Twitter, Instagram, Color1-10	0.617	0.618	0.621
Arousal	0.617	0.617	0.619
Min 9 Max 9	0.616	0.616	0.619
Pleasure, Arousal, Dominance	0.615	0.615	0.618
Gray Mn	0.615	0.615	0.617
Max 9	0.615	0.615	0.618
Dominance	0.615	0.614	0.617
RGB Mn	0.614	0.614	0.616
Min 9	0.614	0.613	0.616
Max 16	0.614	0.613	0.616
Color1	0.613	0.612	0.615
Min 16	0.613	0.612	0.615
Weight	0.612	0.611	0.614
Color1-2	0.611	0.61	0.613
Min 16 Max 16	0.611	0.611	0.614

Table A.13: Cluster Models Edge 1

	F1	**Precision**	**Recall**
Pleasure	0.611	0.61	0.614
Activity	0.611	0.611	0.614
Gray Sd	0.61	0.61	0.612
Activity, Weight, Heat	0.609	0.608	0.611
RGB Sd	0.609	0.609	0.611
RGB Mn, RGB Sd	0.609	0.61	0.612
Color1-3	0.609	0.608	0.611
Base Features	0.608	0.606	0.61
Gray Mn, RGB Mn	0.608	0.608	0.611
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.605	0.605	0.607
Color1-4	0.605	0.605	0.608
Color1-5	0.605	0.606	0.608
Color1-8	0.605	0.606	0.609
Color1-6	0.604	0.605	0.607
Color1-7	0.604	0.605	0.607
Heat	0.604	0.603	0.606

Table A.13: Cluster Models Edge 1

	F1	**Precision**	**Recall**
Color1-9	0.602	0.603	0.606
Gray Sd, RGB Sd	0.601	0.601	0.604
Color1-10	0.601	0.602	0.605

Table A.14: Cluster Models Edge 2

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1-2	0.656	0.663	0.658
BioNg, BioPs, Color1-5	0.654	0.67	0.658
Facebook, Twitter, Instagram, Color1-3	0.651	0.664	0.653
BioNg, BioPs, Color1-2	0.65	0.66	0.651
BioNg, BioPs, Color1-3	0.648	0.665	0.649
Color1-3	0.647	0.659	0.651
BioNg, BioPs, Color1-6	0.642	0.662	0.644
Facebook, Twitter, Instagram, Color1-4	0.64	0.652	0.642
Color1-6	0.634	0.653	0.638
BioWC, DescWC, Color1-2	0.634	0.643	0.636
BioWC, DescWC, Color1-7	0.632	0.647	0.636
Color1-2	0.631	0.638	0.633
Color1-4	0.629	0.645	0.633
Facebook, Twitter, Instagram, Color1-5	0.629	0.644	0.633
BioWC, DescWC, Color1-6	0.628	0.645	0.633
Facebook, Twitter, Instagram, Color1	0.628	0.634	0.633

Table A.14: Cluster Models Edge 2

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1-7	0.628	0.645	0.636
Facebook, Twitter, Instagram, Pleasure	0.628	0.636	0.633
BioWC, DescWC, Color1-4	0.627	0.643	0.631
Facebook, Twitter, Instagram, Color1-6	0.626	0.644	0.631
BioNg, BioPs, Dominance	0.626	0.634	0.629
Color1-5	0.625	0.647	0.629
BioNg, BioPs, Color1-4	0.624	0.636	0.627
BioWC, DescWC, Color1	0.624	0.627	0.629
BioWC, DescWC, Color1-9	0.624	0.653	0.633
Color1-9	0.623	0.641	0.629
BioNg, BioPs, Color1	0.623	0.629	0.627
BioNg, BioPs, Pleasure	0.623	0.63	0.627
BioNg, BioPs, Color1-9	0.621	0.641	0.627
BioWC, DescWC, Color1-5	0.621	0.644	0.627
BioNg, BioPs, Color1-10	0.62	0.637	0.627
BioWC, DescWC, Color1-3	0.62	0.633	0.624

Table A.14: Cluster Models Edge 2

	F1	**Precision**	**Recall**
BioWC, DescWC, Dominance	0.62	0.63	0.624
BioWC, DescWC, Gray Mn	0.619	0.628	0.62
Facebook, Twitter, Instagram, Color1-8	0.619	0.633	0.624
BioNg, BioPs, AWH	0.617	0.625	0.622
Facebook, Twitter, Instagram, Color1-9	0.616	0.632	0.624
BioNg, BioPs, Gray Mn, RGB Mn	0.615	0.625	0.618
BioWC, DescWC, Activity	0.615	0.62	0.618
BioWC, DescWC, Weight	0.615	0.62	0.618
BioWC, DescWC, PAD	0.614	0.622	0.618
BioNg, BioPs, Color1-7	0.613	0.631	0.616
Pleasure, Arousal, Dominance	0.612	0.617	0.618
Bio Word Count, Desc Word Count	0.612	0.616	0.613
BioNg, BioPs, Gray Mn	0.612	0.618	0.613
BioWC, DescWC, RGB Mn	0.612	0.626	0.616
Facebook, Twitter, Instagram, Dominance	0.612	0.619	0.616
Title WC	0.611	0.616	0.613

Table A.14: Cluster Models Edge 2

	F1	Precision	Recall
Gray Mn	0.61	0.616	0.613
Color1-10	0.61	0.625	0.618
BioNeg, BioPs, RGB Mn	0.61	0.615	0.613
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.61	0.625	0.616
BioNg, BioPs, Weight	0.61	0.614	0.613
BioWC, DescWC, Gray Mn, RGB Mn	0.609	0.62	0.611
Facebook, Twitter, Instagram, Gray Mn	0.609	0.618	0.611
Facebook, Twitter, Instagram, RGB Mn	0.609	0.614	0.613
Dominance	0.609	0.615	0.611
Weight	0.609	0.614	0.613
Pleasure	0.608	0.616	0.613
Gray Mn, RGB Mn	0.607	0.612	0.611
Facebook, Twitter, Instagram, PAD	0.607	0.612	0.616
Facebook, Twitter, Instagram, Color1-10	0.607	0.624	0.616
Color1-7	0.606	0.619	0.613
BioWC, DescWC, AWH	0.606	0.615	0.611

Table A.14: Cluster Models Edge 2

	F1	Precision	Recall
BioWC, DescWC, Color1-8	0.606	0.617	0.611
BioWC, DescWC Facebook, Twitter, Instagram	0.606	0.609	0.609
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.605	0.614	0.609
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.605	0.61	0.609
BioNg, BioPs, PAD	0.604	0.613	0.607
BioNg, BioPs, Gray Sd	0.604	0.613	0.607
BioNg, BioPs, Min 9 Max 9	0.604	0.611	0.607
BioWC, DescWC, Min 9 Max 9	0.604	0.614	0.607
Color1	0.603	0.608	0.609
BioWC, DescWC, Pleasure	0.603	0.609	0.609
BioWC, DescWC, Heat	0.602	0.609	0.604
Facebook, Twitter, Instagram, Weight	0.602	0.606	0.607
Facebook, Twitter, Instagram, Heat	0.602	0.61	0.604
BioNg, BioPs BioWC, DescWC	0.602	0.605	0.604
BioNg, BioPs, Color1-8	0.601	0.614	0.609
Activity, Weight, Heat	0.6	0.603	0.604

Table A.14: Cluster Models Edge 2

	F1	Precision	Recall
BioNg, BioPs, RGB Mn, RGB Sd	0.6	0.617	0.607
Facebook, Twitter, Instagram, AWH	0.6	0.605	0.604
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.6	0.611	0.607
DescNg, DescNeu, DescPs	0.6	0.606	0.6
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.599	0.605	0.607
BioNg, BioPs, Arousal	0.599	0.606	0.6
BioNg, BioPs, Heat	0.599	0.604	0.6
BioWC, DescWC, Arousal	0.599	0.606	0.602
RGB Mn	0.598	0.605	0.602
BioWC, DescWC, Min 16 Max 16	0.598	0.605	0.6
BioNg, BioNeu, BioPs	0.598	0.603	0.6
Facebook, Twitter, Instagram, Gray Sd	0.597	0.602	0.6
Heat	0.597	0.601	0.6
BioNg, BioPs, Activity	0.597	0.598	0.6
BioWC, DescWC, Gray Sd, RGB Sd	0.595	0.612	0.602
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.595	0.607	0.6

Table A.14: Cluster Models Edge 2

	F1	Precision	Recall
Min 9	0.595	0.6	0.6
BioWC, DescWC, Color1-10	0.594	0.614	0.604
Activity	0.594	0.6	0.6
Min 9 Max 9	0.593	0.601	0.598
Facebook, Twitter, Instagram, Activity	0.593	0.599	0.598
DescNg, DescPs	0.592	0.597	0.596
BioNg, BioPs, Gray Mn, Gray Sd	0.59	0.598	0.593
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.59	0.598	0.598
Arousal	0.59	0.595	0.593
BioNg, BioPs Facebook, Twitter, Instagram	0.59	0.593	0.591
BioNg, BioPs	0.589	0.592	0.591
Facebook, Twitter, Instagram, RGB Sd	0.589	0.596	0.593
Facebook, Twitter, Instagram, Arousal	0.589	0.593	0.593
Facebook, Twitter, Instagram, Min 9 Max 9	0.588	0.594	0.596
Max 9	0.586	0.592	0.589
RGB Mn, RGB Sd	0.585	0.594	0.596

Table A.14: Cluster Models Edge 2

	F1	**Precision**	**Recall**
Color1-8	0.585	0.602	0.596
Gray Mn, Gray Sd	0.584	0.592	0.589
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.583	0.592	0.589
Max 16	0.583	0.586	0.589
Facebook, Twitter, Instagram, Min 16 Max 16	0.583	0.592	0.587
Gray Sd, RGB Sd	0.582	0.589	0.589
BioNg, BioPs, RGB Sd	0.582	0.588	0.584
BioWC, DescWC, Gray Sd	0.582	0.59	0.587
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.582	0.588	0.589
Min 16	0.582	0.588	0.584
Facebook, Twitter, Instagram	0.581	0.583	0.584
RGB Sd	0.579	0.586	0.584
BioNg, BioPs, Gray Sd, RGB Sd	0.578	0.586	0.582
Min 16 Max 16	0.578	0.584	0.587
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.576	0.585	0.582
Gray Sd	0.575	0.584	0.58

Table A.14: Cluster Models Edge 2

	F1	**Precision**	**Recall**
BioWC, DescWC, RGB Sd	0.575	0.585	0.58
Base Features	0.572	0.575	0.576
BioNg, BioPs, Min 16 Max 16	0.57	0.577	0.576

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
BioNg, BioPs BioWC, DescWC	0.682	0.681	0.683
BioWC, DescWC Facebook, Twitter, Instagram	0.674	0.674	0.676
BioNg, BioNeu, BioPs	0.672	0.671	0.673
BioNg, BioPs Facebook, Twitter, Instagram	0.669	0.669	0.671
BioNg, BioPs, Color1	0.664	0.664	0.666
BioWC, DescWC, Gray Sd	0.664	0.664	0.666
BioNg, BioPs, Dominance	0.664	0.664	0.666
BioWC, DescWC, Color1	0.663	0.662	0.665
BioNg, BioPs	0.662	0.661	0.663
BioWC, DescWC, Pleasure	0.662	0.662	0.664
BioWC, DescWC, Arousal	0.662	0.661	0.664
Bio Word Count, Desc Word Count	0.661	0.66	0.662
BioWC, DescWC, Gray Mn	0.661	0.66	0.663
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.661	0.661	0.663
BioWC, DescWC, Dominance	0.661	0.661	0.663
BioWC, DescWC, Heat	0.661	0.66	0.662

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
BioNg, BioPs, Gray Mn	0.66	0.66	0.662
BioNg, BioPs, Gray Sd	0.66	0.659	0.662
BioWC, DescWC, AWH	0.66	0.66	0.662
BioNg, BioPs, Arousal	0.66	0.66	0.662
BioNg, BioPs, Activity	0.66	0.66	0.662
BioNg, BioPs, Weight	0.66	0.659	0.662
BioNg, BioPs, Heat	0.66	0.66	0.662
BioWC, DescWC, Activity	0.66	0.66	0.662
BioWC, DescWC, Weight	0.66	0.66	0.662
BioNg, BioPs, Gray Mn, Gray Sd	0.659	0.658	0.661
BioNg, BioPs, Color1-2	0.659	0.659	0.661
BioWC, DescWC, Color1-2	0.659	0.659	0.661
BioWC, DescWC, Min 16 Max 16	0.659	0.659	0.661
BioNg, BioPs, Color1-3	0.658	0.658	0.66
BioWC, DescWC, Color1-3	0.658	0.657	0.66
BioNg, BioPs, AWH	0.657	0.657	0.66

Table A.15: Cluster Models Edge 3

	F1	Precision	Recall
BioNg, BioPs, PAD	0.656	0.656	0.659
BioNeg, BioPs, RGB Mn	0.656	0.655	0.658
BioNg, BioPs, Color1-5	0.656	0.655	0.658
BioNg, BioPs, Min 9 Max 9	0.656	0.656	0.659
BioNg, BioPs, Min 16 Max 16	0.656	0.655	0.658
BioNg, BioPs, Pleasure	0.656	0.656	0.658
BioNg, BioPs, Color1-4	0.655	0.655	0.658
BioWC, DescWC, Color1-4	0.655	0.655	0.657
BioWC, DescWC, Min 9 Max 9	0.655	0.655	0.657
BioNg, BioPs, Gray Sd, RGB Sd	0.654	0.653	0.656
BioWC, DescWC, RGB Sd	0.654	0.654	0.656
BioNg, BioPs, Gray Mn, RGB Mn	0.653	0.653	0.656
BioNg, BioPs, RGB Mn, RGB Sd	0.653	0.653	0.655
BioWC, DescWC, PAD	0.653	0.653	0.656
BioWC, DescWC, RGB Mn	0.653	0.653	0.656
BioNg, BioPs, RGB Sd	0.652	0.652	0.654

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Mn, RGB Mn	0.651	0.651	0.653
BioWC, DescWC, Gray Sd, RGB Sd	0.651	0.651	0.653
BioWC, DescWC, Color1-5	0.651	0.651	0.653
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.65	0.65	0.652
BioNg, BioPs, Color1-6	0.649	0.649	0.651
BioNg, BioPs, Color1-10	0.647	0.647	0.65
BioNg, BioPs, Color1-7	0.646	0.646	0.649
BioWC, DescWC, Color1-6	0.646	0.646	0.648
BioNg, BioPs, Color1-8	0.645	0.645	0.647
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.644	0.644	0.647
BioNg, BioPs, Color1-9	0.643	0.643	0.645
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.643	0.644	0.646
BioWC, DescWC, Color1-8	0.639	0.639	0.642
BioWC, DescWC, Color1-7	0.638	0.638	0.641
BioWC, DescWC, Color1-9	0.637	0.638	0.64
Facebook, Twitter, Instagram	0.635	0.634	0.636

Table A.15: Cluster Models Edge 3

	F1	Precision	Recall
BioWC, DescWC, Color1-10	0.635	0.635	0.638
Facebook, Twitter, Instagram, Color1	0.635	0.635	0.637
Facebook, Twitter, Instagram, Gray Sd	0.634	0.634	0.636
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.633	0.633	0.635
Facebook, Twitter, Instagram, Arousal	0.633	0.633	0.635
Facebook, Twitter, Instagram, Pleasure	0.632	0.631	0.634
Facebook, Twitter, Instagram, Dominance	0.632	0.631	0.634
Facebook, Twitter, Instagram, Activity	0.632	0.631	0.633
Facebook, Twitter, Instagram, Gray Mn	0.631	0.631	0.633
Facebook, Twitter, Instagram, PAD	0.63	0.63	0.632
Facebook, Twitter, Instagram, Color1-2	0.63	0.629	0.632
Facebook, Twitter, Instagram, Weight	0.63	0.629	0.632
Facebook, Twitter, Instagram, Heat	0.63	0.629	0.632
Facebook, Twitter, Instagram, Color1-3	0.629	0.629	0.631
Facebook, Twitter, Instagram, Min 9 Max 9	0.629	0.628	0.631
Facebook, Twitter, Instagram, Min 16 Max 16	0.629	0.629	0.631

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, RGB Mn	0.628	0.628	0.63
Facebook, Twitter, Instagram, RGB Sd	0.628	0.628	0.63
Facebook, Twitter, Instagram, AWH	0.627	0.627	0.629
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.626	0.627	0.629
Facebook, Twitter, Instagram, Color1-4	0.626	0.626	0.629
Facebook, Twitter, Instagram, Color1-5	0.625	0.625	0.627
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.623	0.623	0.626
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.623	0.623	0.625
Facebook, Twitter, Instagram, Color1-6	0.619	0.618	0.621
DescNg, DescNeu, DescPs	0.617	0.616	0.619
DescNg, DescPs	0.616	0.616	0.618
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.616	0.616	0.618
Facebook, Twitter, Instagram, Color1-7	0.616	0.616	0.619
Facebook, Twitter, Instagram, Color1-8	0.613	0.613	0.615
Facebook, Twitter, Instagram, Color1-10	0.613	0.613	0.616
Facebook, Twitter, Instagram, Color1-9	0.612	0.612	0.615

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
Title WC	0.6	0.599	0.602
Color1	0.593	0.592	0.595
Color1-2	0.591	0.591	0.593
Pleasure	0.591	0.59	0.593
Gray Sd	0.589	0.588	0.591
Gray Mn, Gray Sd	0.589	0.589	0.592
Arousal	0.589	0.589	0.592
Dominance	0.589	0.589	0.592
Activity, Weight, Heat	0.587	0.587	0.59
Activity	0.587	0.586	0.589
Base Features	0.586	0.586	0.588
Gray Mn	0.586	0.586	0.588
RGB Mn	0.586	0.586	0.588
Max 16	0.586	0.586	0.589
Min 16 Max 16	0.586	0.586	0.589
Weight	0.586	0.586	0.588

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
RGB Sd	0.585	0.584	0.587
RGB Mn, RGB Sd	0.585	0.585	0.587
Color1-4	0.585	0.585	0.587
Pleasure, Arousal, Dominance	0.584	0.584	0.586
Gray Sd, RGB Sd	0.583	0.583	0.585
Min 16	0.583	0.583	0.585
Heat	0.583	0.582	0.585
Color1-3	0.582	0.582	0.585
Min 9	0.582	0.581	0.584
Min 9 Max 9	0.582	0.581	0.584
Color1-5	0.581	0.581	0.584
Max 9	0.581	0.58	0.583
Color1-6	0.577	0.577	0.58
Gray Mn, RGB Mn	0.576	0.576	0.579
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.576	0.577	0.58
Color1-7	0.574	0.574	0.577

Table A.15: Cluster Models Edge 3

	F1	**Precision**	**Recall**
Color1-8	0.567	0.568	0.57
Color1-9	0.566	0.566	0.569
Color1-10	0.566	0.566	0.569

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
BioNg, BioPs BioWC, DescWC	0.64	0.639	0.641
BioWC, DescWC Facebook, Twitter, Instagram	0.629	0.628	0.63
BioNg, BioPs Facebook, Twitter, Instagram	0.621	0.62	0.622
BioNg, BioNeu, BioPs	0.62	0.619	0.621
BioNg, BioPs, Gray Sd	0.615	0.614	0.616
BioNg, BioPs, Arousal	0.615	0.614	0.616
BioNg, BioPs, Gray Mn, Gray Sd	0.614	0.613	0.616
BioNg, BioPs, Color1-2	0.614	0.613	0.616
Bio Word Count, Desc Word Count	0.613	0.612	0.614
BioNg, BioPs, Color1	0.613	0.612	0.614
BioWC, DescWC, Gray Sd	0.613	0.612	0.614
BioWC, DescWC, Color1	0.613	0.612	0.614
BioNg, BioPs, Min 16 Max 16	0.613	0.612	0.614
BioWC, DescWC, Min 9 Max 9	0.613	0.613	0.615
BioNg, BioPs, Dominance	0.613	0.612	0.615
BioWC, DescWC, Activity	0.613	0.612	0.614

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
BioNg, BioPs	0.612	0.611	0.613
BioNg, BioPs, Gray Mn	0.612	0.612	0.614
BioWC, DescWC, Arousal	0.612	0.611	0.614
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.611	0.611	0.613
BioWC, DescWC, Color1-2	0.611	0.61	0.613
BioWC, DescWC, Min 16 Max 16	0.611	0.61	0.613
BioNg, BioPs, Weight	0.611	0.61	0.612
BioWC, DescWC, Pleasure	0.611	0.61	0.613
BioWC, DescWC, Dominance	0.611	0.61	0.612
BioWC, DescWC, Weight	0.611	0.61	0.613
BioNg, BioPs, RGB Sd	0.61	0.609	0.611
BioNg, BioPs, Color1-3	0.61	0.609	0.611
BioWC, DescWC, Gray Mn	0.61	0.609	0.612
BioNg, BioPs, Min 9 Max 9	0.61	0.609	0.612
BioNg, BioPs, Activity	0.61	0.609	0.612
BioNg, BioPs, PAD	0.609	0.608	0.61

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-3	0.609	0.608	0.611
BioNg, BioPs, Pleasure	0.609	0.608	0.61
BioWC, DescWC, Heat	0.609	0.608	0.611
BioNeg, BioPs, RGB Mn	0.608	0.607	0.609
BioWC, DescWC, PAD	0.608	0.607	0.61
BioWC, DescWC, RGB Mn	0.608	0.607	0.61
BioNg, BioPs, Gray Sd, RGB Sd	0.607	0.606	0.609
BioNg, BioPs, Color1-4	0.607	0.606	0.609
BioNg, BioPs, Heat	0.607	0.606	0.609
BioNg, BioPs, AWH	0.606	0.605	0.608
BioNg, BioPs, RGB Mn, RGB Sd	0.606	0.605	0.608
BioNg, BioPs, Color1-5	0.606	0.605	0.608
BioWC, DescWC, AWH	0.606	0.605	0.608
BioNg, BioPs, Color1-6	0.605	0.604	0.607
BioWC, DescWC, RGB Sd	0.605	0.605	0.607
BioNg, BioPs, Gray Mn, RGB Mn	0.604	0.602	0.605

Table A.16: Cluster Models Edge 4

	F1	Precision	Recall
BioWC, DescWC, Gray Mn, RGB Mn	0.604	0.603	0.606
BioWC, DescWC, Color1-4	0.604	0.603	0.606
BioNg, BioPs, Color1-7	0.603	0.602	0.605
BioWC, DescWC, Gray Sd, RGB Sd	0.602	0.601	0.605
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.601	0.6	0.604
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.6	0.599	0.602
BioNg, BioPs, Color1-8	0.599	0.598	0.602
BioNg, BioPs, Color1-9	0.599	0.598	0.601
BioWC, DescWC, Color1-5	0.599	0.598	0.602
BioWC, DescWC, Color1-6	0.597	0.596	0.599
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.596	0.595	0.598
BioWC, DescWC, Color1-7	0.595	0.594	0.598
BioNg, BioPs, Color1-10	0.594	0.593	0.597
BioWC, DescWC, Color1-8	0.594	0.593	0.596
BioWC, DescWC, Color1-10	0.592	0.591	0.594
BioWC, DescWC, Color1-9	0.589	0.589	0.592

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1	0.577	0.576	0.579
Facebook, Twitter, Instagram, Min 16 Max 16	0.577	0.575	0.579
Facebook, Twitter, Instagram, Dominance	0.577	0.576	0.579
Facebook, Twitter, Instagram, Gray Mn	0.576	0.574	0.578
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.576	0.575	0.579
Facebook, Twitter, Instagram, Color1-2	0.576	0.575	0.578
Facebook, Twitter, Instagram, Arousal	0.576	0.574	0.577
Facebook, Twitter, Instagram, Activity	0.576	0.574	0.578
Facebook, Twitter, Instagram, Gray Sd	0.575	0.574	0.577
Facebook, Twitter, Instagram, RGB Sd	0.575	0.573	0.577
Facebook, Twitter, Instagram, Min 9 Max 9	0.574	0.573	0.576
Facebook, Twitter, Instagram, PAD	0.573	0.572	0.575
Facebook, Twitter, Instagram, Color1-3	0.573	0.571	0.575
Facebook, Twitter, Instagram	0.572	0.57	0.574
Facebook, Twitter, Instagram, Weight	0.572	0.57	0.574
Facebook, Twitter, Instagram, AWH	0.571	0.57	0.573

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, RGB Mn	0.571	0.569	0.573
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.571	0.57	0.573
Facebook, Twitter, Instagram, Pleasure	0.571	0.57	0.573
Facebook, Twitter, Instagram, Color1-5	0.569	0.568	0.572
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.568	0.566	0.57
Facebook, Twitter, Instagram, Color1-4	0.568	0.567	0.571
Facebook, Twitter, Instagram, Heat	0.567	0.566	0.569
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.566	0.565	0.568
DescNg, DescNeu, DescPs	0.566	0.565	0.569
Facebook, Twitter, Instagram, Color1-6	0.565	0.563	0.568
DescNg, DescPs	0.564	0.563	0.566
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.563	0.562	0.566
Facebook, Twitter, Instagram, Color1-7	0.563	0.562	0.566
Facebook, Twitter, Instagram, Color1-8	0.563	0.562	0.566
Facebook, Twitter, Instagram, Color1-9	0.56	0.559	0.564
Facebook, Twitter, Instagram, Color1-10	0.557	0.556	0.56

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
Title WC	0.536	0.535	0.539
Gray Mn, Gray Sd	0.533	0.532	0.537
Color1-2	0.532	0.53	0.535
Pleasure, Arousal, Dominance	0.53	0.529	0.533
Gray Mn	0.53	0.528	0.532
Color1-3	0.53	0.529	0.533
Min 16 Max 16	0.529	0.528	0.532
Arousal	0.529	0.528	0.532
Dominance	0.529	0.527	0.531
RGB Sd	0.528	0.526	0.531
Color1	0.528	0.527	0.531
Color1-4	0.528	0.526	0.531
RGB Mn	0.527	0.525	0.53
Gray Sd	0.527	0.525	0.529
RGB Mn, RGB Sd	0.527	0.526	0.53
Color1-5	0.527	0.526	0.531

Table A.16: Cluster Models Edge 4

	F1	Precision	Recall
Min 9 Max 9	0.527	0.525	0.53
Min 16	0.525	0.523	0.527
Max 16	0.525	0.524	0.528
Weight	0.525	0.524	0.529
Activity, Weight, Heat	0.524	0.522	0.527
Color1-6	0.524	0.523	0.528
Activity	0.524	0.523	0.527
Gray Sd, RGB Sd	0.523	0.521	0.526
Max 9	0.523	0.522	0.526
Base Features	0.522	0.52	0.524
Gray Mn, RGB Mn	0.522	0.521	0.526
Color1-7	0.522	0.521	0.526
Min 9	0.522	0.521	0.525
Pleasure	0.522	0.52	0.524
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.52	0.519	0.524
Color1-8	0.518	0.516	0.522

Table A.16: Cluster Models Edge 4

	F1	**Precision**	**Recall**
Color1-10	0.516	0.515	0.52
Heat	0.516	0.515	0.519
Color1-9	0.515	0.513	0.519

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
BioNg, BioNeu, BioPs	0.729	0.73	0.729
BioNg, BioPs Facebook, Twitter, Instagram	0.728	0.729	0.728
BioNg, BioPs, Dominance	0.727	0.728	0.727
BioNg, BioPs, Gray Mn	0.725	0.726	0.725
BioNg, BioPs, Gray Mn, Gray Sd	0.725	0.726	0.725
BioNg, BioPs	0.724	0.725	0.725
BioNg, BioPs, Color1	0.724	0.726	0.725
BioNg, BioPs, Activity	0.724	0.725	0.724
BioNg, BioPs, Weight	0.724	0.726	0.724
BioWC, DescWC, Arousal	0.724	0.726	0.724
BioNeg, BioPs, RGB Mn	0.723	0.725	0.723
BioNg, BioPs, Gray Sd	0.723	0.724	0.723
BioNg, BioPs BioWC, DescWC	0.723	0.724	0.723
BioNg, BioPs, PAD	0.722	0.724	0.722
BioWC, DescWC, PAD	0.722	0.724	0.721
BioNg, BioPs, Arousal	0.722	0.724	0.722

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
BioNg, BioPs, Color1-2	0.721	0.722	0.721
BioWC, DescWC, Dominance	0.721	0.722	0.721
BioWC, DescWC, Heat	0.721	0.723	0.721
Facebook, Twitter, Instagram	0.72	0.72	0.72
BioNg, BioPs, Gray Mn, RGB Mn	0.72	0.722	0.72
BioNg, BioPs, RGB Sd	0.72	0.722	0.72
BioWC, DescWC, Gray Sd	0.72	0.722	0.72
BioWC, DescWC, RGB Sd	0.72	0.722	0.72
BioNg, BioPs, Pleasure	0.72	0.722	0.721
BioWC, DescWC, Activity	0.72	0.721	0.72
BioWC, DescWC Facebook, Twitter, Instagram	0.72	0.721	0.72
Bio Word Count, Desc Word Count	0.719	0.721	0.719
BioWC, DescWC, Gray Mn	0.719	0.721	0.719
BioWC, DescWC, Color1	0.719	0.721	0.719
BioWC, DescWC, Pleasure	0.719	0.721	0.719
BioNg, BioPs, Color1-5	0.718	0.721	0.718

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Sd, RGB Sd	0.718	0.721	0.718
BioNg, BioPs, Min 9 Max 9	0.718	0.72	0.718
BioNg, BioPs, AWH	0.717	0.719	0.717
BioNg, BioPs, Gray Sd, RGB Sd	0.717	0.719	0.717
BioNg, BioPs, RGB Mn, RGB Sd	0.717	0.719	0.717
BioNg, BioPs, Color1-3	0.717	0.718	0.717
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.717	0.719	0.716
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.717	0.72	0.717
BioWC, DescWC, Color1-2	0.717	0.718	0.717
Facebook, Twitter, Instagram, Dominance	0.717	0.718	0.718
BioWC, DescWC, AWH	0.716	0.719	0.716
BioWC, DescWC, RGB Mn	0.716	0.719	0.716
Facebook, Twitter, Instagram, Gray Mn	0.716	0.717	0.717
BioNg, BioPs, Min 16 Max 16	0.716	0.718	0.716
BioNg, BioPs, Color1-4	0.715	0.717	0.715
BioWC, DescWC, Color1-3	0.715	0.717	0.715

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1	0.715	0.716	0.716
Facebook, Twitter, Instagram, Color1-2	0.715	0.716	0.715
Facebook, Twitter, Instagram, Color1-3	0.715	0.716	0.716
BioWC, DescWC, Min 9 Max 9	0.715	0.717	0.714
BioWC, DescWC, Min 16 Max 16	0.715	0.717	0.715
BioNg, BioPs, Heat	0.715	0.717	0.715
BioWC, DescWC, Weight	0.715	0.717	0.715
Facebook, Twitter, Instagram, Weight	0.715	0.716	0.716
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.714	0.717	0.714
BioWC, DescWC, Color1-5	0.714	0.717	0.714
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.714	0.715	0.715
Facebook, Twitter, Instagram, Min 9 Max 9	0.714	0.715	0.715
BioNg, BioPs, Color1-6	0.713	0.716	0.714
BioWC, DescWC, Gray Mn, RGB Mn	0.713	0.715	0.712
Facebook, Twitter, Instagram, Gray Sd	0.713	0.714	0.714
Facebook, Twitter, Instagram, Arousal	0.713	0.714	0.713

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-4	0.712	0.715	0.712
BioWC, DescWC, Color1-6	0.712	0.716	0.712
BioWC, DescWC, Color1-7	0.712	0.715	0.712
BioWC, DescWC, Color1-9	0.712	0.715	0.712
Facebook, Twitter, Instagram, PAD	0.712	0.712	0.712
Facebook, Twitter, Instagram, RGB Sd	0.712	0.713	0.713
Facebook, Twitter, Instagram, Min 16 Max 16	0.712	0.713	0.713
Facebook, Twitter, Instagram, Pleasure	0.712	0.712	0.713
Facebook, Twitter, Instagram, Activity	0.712	0.713	0.712
BioNg, BioPs, Color1-10	0.711	0.714	0.711
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.711	0.714	0.711
BioWC, DescWC, Color1-10	0.711	0.714	0.71
Facebook, Twitter, Instagram, AWH	0.711	0.712	0.711
Facebook, Twitter, Instagram, Heat	0.71	0.711	0.711
BioNg, BioPs, Color1-7	0.709	0.712	0.709
BioNg, BioPs, Color1-8	0.709	0.712	0.709

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, RGB Mn	0.709	0.71	0.71
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.709	0.709	0.71
BioNg, BioPs, Color1-9	0.708	0.711	0.708
BioWC, DescWC, Color1-8	0.707	0.711	0.707
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.707	0.708	0.708
Facebook, Twitter, Instagram, Color1-4	0.707	0.708	0.708
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.706	0.707	0.707
Facebook, Twitter, Instagram, Color1-5	0.705	0.706	0.706
DescNg, DescPs	0.704	0.705	0.705
Facebook, Twitter, Instagram, Color1-7	0.704	0.706	0.705
Facebook, Twitter, Instagram, Color1-8	0.704	0.705	0.705
DescNg, DescNeu, DescPs	0.704	0.704	0.705
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.703	0.704	0.704
Facebook, Twitter, Instagram, Color1-9	0.7	0.701	0.701
Facebook, Twitter, Instagram, Color1-6	0.699	0.701	0.7
Base Features	0.696	0.696	0.697

Table A.17: Cluster Models Edge 5

	F1	Precision	Recall
Facebook, Twitter, Instagram, Color1-10	0.695	0.696	0.696
Title WC	0.693	0.693	0.694
Gray Mn	0.687	0.687	0.688
Gray Sd	0.687	0.687	0.688
Color1	0.686	0.687	0.687
Gray Mn, Gray Sd	0.685	0.685	0.686
Color1-2	0.685	0.685	0.685
Min 16	0.685	0.686	0.686
Min 9	0.684	0.683	0.685
Dominance	0.684	0.684	0.685
Max 9	0.683	0.683	0.684
Arousal	0.683	0.684	0.684
Activity	0.683	0.683	0.683
Gray Mn, RGB Mn	0.681	0.681	0.682
Color1-3	0.68	0.68	0.68
Max 16	0.68	0.681	0.681

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
RGB Mn	0.679	0.679	0.68
RGB Sd	0.679	0.679	0.68
Min 9 Max 9	0.679	0.679	0.68
Pleasure	0.679	0.679	0.68
Color1-5	0.678	0.678	0.679
Pleasure, Arousal, Dominance	0.677	0.677	0.678
Activity, Weight, Heat	0.677	0.677	0.678
Gray Sd, RGB Sd	0.677	0.677	0.678
RGB Mn, RGB Sd	0.677	0.677	0.678
Min 16 Max 16	0.677	0.678	0.678
Weight	0.677	0.677	0.678
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.675	0.676	0.677
Color1-7	0.674	0.674	0.675
Color1-8	0.673	0.674	0.674
Color1-6	0.671	0.671	0.672
Heat	0.671	0.671	0.672

Table A.17: Cluster Models Edge 5

	F1	**Precision**	**Recall**
Color1-4	0.67	0.671	0.672
Color1-10	0.668	0.67	0.67
Color1-9	0.666	0.666	0.667

Table A.18: Cluster Models Edge 6

	F1	**Precision**	**Recall**
BioWC, DescWC, Color1-5	0.501	0.507	0.519
BioWC, DescWC, Color1-6	0.497	0.502	0.511
BioWC, DescWC, Color1-4	0.495	0.492	0.509
BioWC, DescWC, Color1-3	0.487	0.484	0.5
BioNg, BioPs BioWC, DescWC	0.486	0.481	0.5
Bio Word Count, Desc Word Count	0.482	0.477	0.494
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.481	0.481	0.494
BioWC, DescWC Facebook, Twitter, Instagram	0.481	0.477	0.494
BioWC, DescWC, Color1	0.48	0.474	0.498
BioWC, DescWC, Pleasure	0.478	0.475	0.491
BioWC, DescWC, Color1-2	0.476	0.473	0.492
BioWC, DescWC, Dominance	0.476	0.472	0.492
BioWC, DescWC, PAD	0.475	0.475	0.492
BioWC, DescWC, RGB Sd	0.475	0.475	0.496
BioWC, DescWC, Min 9 Max 9	0.475	0.475	0.496
BioWC, DescWC, Weight	0.475	0.47	0.492

Table A.18: Cluster Models Edge 6

	F1	Precision	Recall
BioWC, DescWC, Gray Mn	0.473	0.464	0.491
BioWC, DescWC, Color1-10	0.471	0.481	0.491
BioWC, DescWC, Gray Sd, RGB Sd	0.47	0.473	0.491
BioWC, DescWC, Color1-7	0.47	0.47	0.487
BioWC, DescWC, Color1-8	0.469	0.469	0.491
BioWC, DescWC, Arousal	0.469	0.466	0.485
BioWC, DescWC, Gray Sd	0.467	0.464	0.483
BioWC, DescWC, Heat	0.465	0.462	0.475
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.462	0.463	0.485
BioWC, DescWC, Color1-9	0.462	0.468	0.483
BioWC, DescWC, AWH	0.461	0.464	0.479
BioWC, DescWC, Gray Mn, RGB Mn	0.461	0.461	0.483
BioWC, DescWC, Activity	0.457	0.452	0.475
BioWC, DescWC, RGB Mn	0.453	0.45	0.474
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.453	0.457	0.477
BioWC, DescWC, Min 16 Max 16	0.452	0.449	0.47

Table A.18: Cluster Models Edge 6

	F1	**Precision**	**Recall**
Color1-6	0.442	0.442	0.462
Title WC	0.44	0.434	0.453
DescNg, DescNeu, DescPs	0.438	0.434	0.455
Facebook, Twitter, Instagram, Color1-6	0.437	0.435	0.458
Color1-10	0.434	0.438	0.46
Color1-5	0.433	0.431	0.455
DescNg, DescPs	0.433	0.431	0.445
Facebook, Twitter, Instagram, Color1-9	0.433	0.442	0.457
Color1-7	0.432	0.433	0.455
Facebook, Twitter, Instagram, Color1-7	0.432	0.435	0.453
BioNg, BioPs, Color1-4	0.43	0.43	0.451
BioNg, BioPs, Color1-8	0.428	0.429	0.453
Color1-3	0.427	0.423	0.449
Facebook, Twitter, Instagram, AWH	0.425	0.422	0.443
BioNg, BioPs, Color1-2	0.424	0.419	0.445
Facebook, Twitter, Instagram, Color1-5	0.424	0.419	0.443

Table A.18: Cluster Models Edge 6

	F1	**Precision**	**Recall**
Color1-8	0.423	0.429	0.445
Color1-9	0.423	0.424	0.449
BioNg, BioPs, Color1-5	0.423	0.42	0.445
BioNg, BioPs, Color1-6	0.423	0.421	0.443
BioNg, BioPs, AWH	0.42	0.415	0.443
Facebook, Twitter, Instagram, Color1-4	0.42	0.416	0.442
Color1-4	0.419	0.415	0.442
Facebook, Twitter, Instagram, Color1-8	0.417	0.42	0.442
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.416	0.423	0.451
Facebook, Twitter, Instagram, Color1-3	0.416	0.413	0.436
Weight	0.416	0.409	0.434
BioNg, BioPs, Color1-9	0.415	0.424	0.442
BioNg, BioPs, Color1-7	0.413	0.413	0.436
RGB Mn	0.411	0.404	0.438
BioNg, BioPs, Color1-3	0.411	0.407	0.43
Color1-2	0.41	0.402	0.43

Table A.18: Cluster Models Edge 6

	F1	Precision	Recall
Activity, Weight, Heat	0.409	0.403	0.434
Facebook, Twitter, Instagram, RGB Mn	0.409	0.402	0.438
BioNg, BioPs, RGB Mn, RGB Sd	0.407	0.405	0.447
BioNg, BioPs, Color1-10	0.407	0.413	0.436
BioNg, BioPs, Pleasure	0.407	0.398	0.426
Facebook, Twitter, Instagram, Weight	0.407	0.399	0.425
RGB Sd	0.405	0.408	0.432
BioNg, BioPs, PAD	0.404	0.402	0.426
Pleasure	0.403	0.392	0.421
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.4	0.394	0.425
Facebook, Twitter, Instagram, RGB Sd	0.4	0.402	0.426
BioNg, BioPs Facebook, Twitter, Instagram	0.4	0.393	0.423
BioNg, BioPs	0.398	0.388	0.421
BioNeg, BioPs, RGB Mn	0.398	0.391	0.426
BioNg, BioPs, Gray Sd, RGB Sd	0.397	0.395	0.43
Facebook, Twitter, Instagram, Color1	0.396	0.391	0.421

Table A.18: Cluster Models Edge 6

	F1	**Precision**	**Recall**
Gray Mn, RGB Mn	0.395	0.392	0.423
Facebook, Twitter, Instagram, Color1-10	0.395	0.387	0.426
BioNg, BioPs, Gray Mn, RGB Mn	0.394	0.387	0.421
Facebook, Twitter, Instagram, PAD	0.394	0.389	0.419
Facebook, Twitter, Instagram, Color1-2	0.394	0.387	0.415
Min 16	0.394	0.386	0.415
Activity	0.393	0.384	0.417
Color1	0.392	0.384	0.417
BioNg, BioPs, Weight	0.392	0.383	0.409
Facebook, Twitter, Instagram, Pleasure	0.392	0.385	0.409
Facebook, Twitter, Instagram, Gray Mn	0.391	0.382	0.411
Max 16	0.391	0.384	0.415
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.39	0.386	0.415
Arousal	0.39	0.386	0.408
Facebook, Twitter, Instagram, Dominance	0.39	0.384	0.411
Base Features	0.389	0.383	0.413

Table A.18: Cluster Models Edge 6

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram	0.389	0.381	0.409
BioNg, BioPs, RGB Sd	0.389	0.388	0.419
BioNg, BioPs, Color1	0.389	0.381	0.411
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.388	0.386	0.423
Gray Sd, RGB Sd	0.386	0.384	0.419
Min 16 Max 16	0.386	0.378	0.413
Dominance	0.385	0.375	0.409
BioNg, BioNeu, BioPs	0.385	0.378	0.402
Gray Mn	0.384	0.371	0.408
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.384	0.38	0.415
Gray Sd	0.383	0.376	0.406
BioNg, BioPs, Activity	0.383	0.373	0.408
Facebook, Twitter, Instagram, Arousal	0.383	0.378	0.4
Pleasure, Arousal, Dominance	0.382	0.376	0.409
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.382	0.379	0.417
Heat	0.382	0.379	0.398

Table A.18: Cluster Models Edge 6

	F1	Precision	Recall
Gray Mn, Gray Sd	0.381	0.376	0.404
BioNg, BioPs, Min 16 Max 16	0.381	0.374	0.408
BioNg, BioPs, Heat	0.381	0.375	0.398
Facebook, Twitter, Instagram, Gray Sd	0.38	0.372	0.406
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.38	0.377	0.415
Facebook, Twitter, Instagram, Activity	0.379	0.372	0.402
RGB Mn, RGB Sd	0.378	0.372	0.417
BioNg, BioPs, Gray Sd	0.378	0.371	0.398
Facebook, Twitter, Instagram, Min 16 Max 16	0.376	0.371	0.402
BioNg, BioPs, Arousal	0.375	0.364	0.396
Facebook, Twitter, Instagram, Heat	0.375	0.369	0.394
Min 9 Max 9	0.374	0.366	0.402
BioNg, BioPs, Min 9 Max 9	0.374	0.365	0.406
BioNg, BioPs, Dominance	0.374	0.366	0.398
BioNg, BioPs, Gray Mn, Gray Sd	0.373	0.37	0.396
BioNg, BioPs, Gray Mn	0.372	0.36	0.392

Table A.18: Cluster Models Edge 6

	F1	**Precision**	**Recall**
Max 9	0.37	0.363	0.391
Min 9	0.365	0.353	0.389
Facebook, Twitter, Instagram, Min 9 Max 9	0.365	0.354	0.394

Table A.19: Cluster Models Edge 7

	F1	Precision	Recall
Gray Sd	0.578	0.59	0.586
BioNg, BioPs, Color1-2	0.576	0.592	0.586
Facebook, Twitter, Instagram, Color1-2	0.574	0.582	0.584
BioWC, DescWC, Gray Sd	0.57	0.584	0.581
Facebook, Twitter, Instagram, Gray Sd	0.569	0.585	0.578
BioWC, DescWC, Color1-2	0.568	0.585	0.578
BioNg, BioPs, Min 16 Max 16	0.563	0.573	0.573
BioNg, BioPs, Color1-3	0.562	0.577	0.575
BioWC, DescWC, Gray Sd, RGB Sd	0.561	0.58	0.57
BioWC, DescWC, Activity	0.561	0.574	0.573
BioNg, BioPs, Gray Sd	0.56	0.574	0.57
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.56	0.583	0.573
BioWC, DescWC, Color1-3	0.559	0.576	0.57
BioNg, BioPs BioWC, DescWC	0.559	0.57	0.567
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.558	0.582	0.57
BioNg, BioPs, RGB Mn, RGB Sd	0.555	0.581	0.567

Table A.19: Cluster Models Edge 7

	F1	Precision	Recall
BioWC, DescWC, Color1	0.555	0.563	0.564
Bio Word Count, Desc Word Count	0.553	0.562	0.562
BioWC, DescWC Facebook, Twitter, Instagram	0.552	0.563	0.559
BioNg, BioPs, RGB Sd	0.551	0.572	0.564
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.551	0.579	0.564
BioWC, DescWC, Weight	0.551	0.566	0.559
BioWC, DescWC, AWH	0.55	0.563	0.564
BioWC, DescWC, Min 16 Max 16	0.55	0.557	0.559
BioWC, DescWC, Heat	0.55	0.561	0.562
Color1-2	0.549	0.557	0.559
BioNg, BioPs	0.549	0.557	0.559
BioNg, BioPs, Gray Mn, Gray Sd	0.549	0.566	0.559
BioWC, DescWC, Color1-5	0.549	0.568	0.567
BioWC, DescWC, Arousal	0.549	0.563	0.556
BioWC, DescWC, RGB Sd	0.548	0.572	0.562
BioWC, DescWC, Pleasure	0.548	0.562	0.559

Table A.19: Cluster Models Edge 7

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, RGB Sd	0.546	0.561	0.559
Min 9	0.546	0.552	0.556
Min 16 Max 16	0.546	0.558	0.556
BioWC, DescWC, Min 9 Max 9	0.546	0.557	0.556
Facebook, Twitter, Instagram, Dominance	0.546	0.556	0.559
Gray Mn, Gray Sd	0.545	0.565	0.559
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.545	0.563	0.559
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.544	0.556	0.559
BioWC, DescWC, Color1-8	0.544	0.57	0.562
Gray Sd, RGB Sd	0.543	0.563	0.556
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.543	0.561	0.553
Weight	0.543	0.553	0.553
BioNg, BioPs, Activity	0.543	0.558	0.559
BioNg, BioPs, Color1-4	0.542	0.557	0.559
BioWC, DescWC, RGB Mn	0.542	0.57	0.556
BioWC, DescWC, Color1-7	0.542	0.562	0.556

Table A.19: Cluster Models Edge 7

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1	0.542	0.548	0.551
Facebook, Twitter, Instagram, Color1-4	0.542	0.552	0.553
Facebook, Twitter, Instagram, Color1-7	0.542	0.558	0.556
BioNg, BioPs, Color1-7	0.541	0.581	0.559
Facebook, Twitter, Instagram, Color1-3	0.541	0.548	0.553
Min 16	0.54	0.562	0.551
BioWC, DescWC, Dominance	0.54	0.556	0.551
Base Features	0.539	0.546	0.548
BioNg, BioPs, Color1	0.539	0.545	0.548
Facebook, Twitter, Instagram, Min 16 Max 16	0.539	0.549	0.548
BioNg, BioPs Facebook, Twitter, Instagram	0.539	0.547	0.548
BioNg, BioNeu, BioPs	0.539	0.544	0.548
Color1	0.537	0.539	0.551
BioWC, DescWC, Color1-10	0.537	0.571	0.553
BioNg, BioPs, Pleasure	0.537	0.547	0.553
Title WC	0.537	0.545	0.553

Table A.19: Cluster Models Edge 7

	F1	**Precision**	**Recall**
Color1-4	0.536	0.551	0.548
BioWC, DescWC, Color1-4	0.536	0.55	0.545
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.536	0.575	0.553
BioNg, BioPs, Gray Sd, RGB Sd	0.535	0.549	0.548
Max 9	0.535	0.542	0.545
Facebook, Twitter, Instagram, Min 9 Max 9	0.535	0.546	0.545
Facebook, Twitter, Instagram, Weight	0.535	0.545	0.548
RGB Sd	0.532	0.546	0.545
BioNg, BioPs, PAD	0.532	0.548	0.545
BioNg, BioPs, Gray Mn	0.532	0.543	0.545
BioNg, BioPs, Color1-8	0.532	0.563	0.551
BioWC, DescWC, PAD	0.532	0.553	0.542
Facebook, Twitter, Instagram, RGB Mn	0.532	0.551	0.542
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.532	0.557	0.542
Facebook, Twitter, Instagram, Color1-8	0.532	0.561	0.548
Min 9 Max 9	0.532	0.544	0.542

Table A.19: Cluster Models Edge 7

	F1	Precision	Recall
BioNg, BioPs, Min 9 Max 9	0.532	0.543	0.542
Heat	0.532	0.534	0.545
Max 16	0.531	0.539	0.542
RGB Mn, RGB Sd	0.53	0.554	0.542
DescNg, DescPs	0.53	0.536	0.545
BioWC, DescWC, Color1-6	0.53	0.546	0.542
Facebook, Twitter, Instagram, Pleasure	0.53	0.545	0.542
Facebook, Twitter, Instagram	0.529	0.535	0.537
Dominance	0.529	0.54	0.54
Activity	0.529	0.54	0.542
Facebook, Twitter, Instagram, Heat	0.529	0.533	0.542
DescNg, DescNeu, DescPs	0.529	0.535	0.54
Color1-8	0.528	0.54	0.548
BioWC, DescWC, Gray Mn	0.528	0.543	0.537
Facebook, Twitter, Instagram, AWH	0.528	0.537	0.548
Facebook, Twitter, Instagram, Color1-9	0.528	0.55	0.548

Table A.19: Cluster Models Edge 7

	F1	**Precision**	**Recall**
Color1-7	0.527	0.541	0.542
Facebook, Twitter, Instagram, Gray Mn	0.527	0.539	0.537
Color1-3	0.526	0.531	0.54
BioWC, DescWC, Gray Mn, RGB Mn	0.526	0.543	0.54
BioWC, DescWC, Color1-9	0.526	0.546	0.542
BioNeg, BioPs, RGB Mn	0.525	0.533	0.54
Facebook, Twitter, Instagram, PAD	0.524	0.535	0.54
Gray Mn	0.523	0.532	0.534
BioNg, BioPs, Dominance	0.523	0.529	0.532
Color1-9	0.522	0.539	0.54
BioNg, BioPs, AWH	0.522	0.532	0.542
Facebook, Twitter, Instagram, Color1-5	0.522	0.534	0.545
BioNg, BioPs, Heat	0.521	0.526	0.534
BioNg, BioPs, Color1-9	0.52	0.544	0.54
Pleasure	0.518	0.53	0.534
BioNg, BioPs, Gray Mn, RGB Mn	0.517	0.536	0.532

Table A.19: Cluster Models Edge 7

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1-10	0.517	0.536	0.542
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.515	0.546	0.534
BioNg, BioPs, Color1-6	0.515	0.527	0.54
RGB Mn	0.514	0.538	0.526
Color1-6	0.514	0.536	0.532
Facebook, Twitter, Instagram, Color1-6	0.514	0.534	0.534
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.512	0.531	0.526
Facebook, Twitter, Instagram, Arousal	0.512	0.52	0.526
Facebook, Twitter, Instagram, Activity	0.512	0.513	0.526
Pleasure, Arousal, Dominance	0.509	0.522	0.521
BioNg, BioPs, Arousal	0.509	0.517	0.518
BioNg, BioPs, Weight	0.509	0.514	0.523
BioNg, BioPs, Color1-10	0.507	0.524	0.526
BioNg, BioPs, Color1-5	0.505	0.514	0.526
Color1-10	0.504	0.516	0.521
Color1-5	0.5	0.504	0.523

Table A.19: Cluster Models Edge 7

	F1	Precision	Recall
Arousal	0.5	0.503	0.512
Gray Mn, RGB Mn	0.497	0.512	0.51
Activity, Weight, Heat	0.496	0.498	0.521

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
BioWC, DescWC, Pleasure	0.788	0.789	0.79
BioWC, DescWC, Min 16 Max 16	0.786	0.789	0.788
BioWC, DescWC, Arousal	0.786	0.787	0.787
BioWC, DescWC, Activity	0.784	0.785	0.786
DescNg, DescPs	0.783	0.785	0.785
BioWC, DescWC, Color1-2	0.783	0.786	0.786
BioWC, DescWC, Color1-6	0.783	0.785	0.786
BioWC, DescWC, Min 9 Max 9	0.783	0.784	0.786
BioWC, DescWC, Heat	0.782	0.783	0.784
Bio Word Count, Desc Word Count	0.781	0.783	0.783
BioWC, DescWC, Color1-5	0.781	0.782	0.783
BioWC, DescWC, Dominance	0.781	0.783	0.784
BioNg, BioPs BioWC, DescWC	0.781	0.781	0.782
BioWC, DescWC Facebook, Twitter, Instagram	0.781	0.782	0.782
BioWC, DescWC, Gray Mn, RGB Mn	0.78	0.781	0.782
DescNg, DescNeu, DescPs	0.78	0.782	0.782

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
BioWC, DescWC, Gray Mn	0.779	0.78	0.782
BioWC, DescWC, Color1-3	0.779	0.781	0.781
BioWC, DescWC, Weight	0.779	0.78	0.782
BioWC, DescWC, AWH	0.778	0.78	0.781
BioWC, DescWC, Gray Sd	0.778	0.779	0.78
BioWC, DescWC, RGB Sd	0.778	0.78	0.78
BioWC, DescWC, RGB Mn	0.777	0.778	0.779
BioWC, DescWC, Color1	0.777	0.779	0.779
BioWC, DescWC, Color1-4	0.776	0.777	0.778
BioWC, DescWC, PAD	0.775	0.776	0.777
BioWC, DescWC, Gray Sd, RGB Sd	0.774	0.776	0.776
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.774	0.775	0.776
BioWC, DescWC, Color1-8	0.774	0.776	0.777
BioWC, DescWC, Color1-7	0.772	0.773	0.774
BioNg, BioPs, Gray Mn	0.771	0.771	0.774
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.769	0.77	0.772

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
BioNg, BioPs	0.768	0.769	0.77
BioNg, BioPs, Min 9 Max 9	0.768	0.769	0.771
BioNg, BioPs, Pleasure	0.768	0.768	0.77
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.767	0.768	0.77
BioWC, DescWC, Color1-9	0.767	0.767	0.769
BioNg, BioPs, AWH	0.766	0.766	0.768
BioNg, BioPs, RGB Sd	0.766	0.767	0.769
BioWC, DescWC, Color1-10	0.766	0.769	0.769
BioNg, BioPs, Activity	0.766	0.766	0.768
Facebook, Twitter, Instagram, Pleasure	0.766	0.767	0.768
BioNg, BioPs, Gray Sd	0.765	0.766	0.768
BioNg, BioPs, Gray Mn, Gray Sd	0.765	0.765	0.768
BioNg, BioPs, Color1-3	0.765	0.766	0.768
BioNg, BioNeu, BioPs	0.765	0.764	0.767
BioNg, BioPs, Color1-2	0.764	0.765	0.766
BioNg, BioPs, Dominance	0.764	0.764	0.767

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
BioNg, BioPs, Min 16 Max 16	0.763	0.764	0.766
BioNg, BioPs, Arousal	0.763	0.763	0.766
BioNg, BioPs, Weight	0.763	0.764	0.766
Facebook, Twitter, Instagram	0.762	0.764	0.765
BioNg, BioPs, PAD	0.762	0.763	0.765
BioNg, BioPs, Color1-5	0.762	0.763	0.764
Facebook, Twitter, Instagram, Min 16 Max 16	0.762	0.764	0.765
BioNg, BioPs, Gray Sd, RGB Sd	0.761	0.761	0.764
BioNg, BioPs, Color1	0.761	0.761	0.764
BioNg, BioPs, Heat	0.761	0.761	0.763
BioNg, BioPs Facebook, Twitter, Instagram	0.761	0.762	0.763
BioNeg, BioPs, RGB Mn	0.76	0.761	0.762
Facebook, Twitter, Instagram, Weight	0.76	0.761	0.763
BioNg, BioPs, Gray Mn, RGB Mn	0.759	0.76	0.761
BioNg, BioPs, RGB Mn, RGB Sd	0.759	0.76	0.762
BioNg, BioPs, Color1-4	0.759	0.76	0.761

Table A.20: Cluster Models Edge 8

	F1	Precision	Recall
BioNg, BioPs, Color1-6	0.759	0.76	0.762
BioNg, BioPs, Color1-8	0.759	0.761	0.762
Facebook, Twitter, Instagram, AWH	0.758	0.759	0.761
Facebook, Twitter, Instagram, Arousal	0.758	0.759	0.761
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.757	0.759	0.76
Facebook, Twitter, Instagram, Color1-3	0.757	0.758	0.76
Facebook, Twitter, Instagram, Dominance	0.757	0.758	0.76
BioNg, BioPs, Color1-7	0.756	0.758	0.759
Facebook, Twitter, Instagram, Min 9 Max 9	0.756	0.757	0.759
Facebook, Twitter, Instagram, Activity	0.756	0.757	0.758
Facebook, Twitter, Instagram, Color1-8	0.755	0.758	0.759
BioNg, BioPs, Color1-9	0.754	0.755	0.757
Facebook, Twitter, Instagram, RGB Mn	0.754	0.756	0.757
Facebook, Twitter, Instagram, Color1-2	0.754	0.754	0.757
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.753	0.754	0.756
Facebook, Twitter, Instagram, Gray Sd	0.753	0.754	0.756

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, RGB Sd	0.753	0.755	0.757
Facebook, Twitter, Instagram, Color1	0.753	0.754	0.755
Facebook, Twitter, Instagram, PAD	0.752	0.753	0.755
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.752	0.753	0.756
Facebook, Twitter, Instagram, Color1-6	0.751	0.752	0.755
Facebook, Twitter, Instagram, Color1-7	0.751	0.753	0.755
Facebook, Twitter, Instagram, Heat	0.751	0.753	0.754
BioNg, BioPs, Color1-10	0.75	0.752	0.754
Facebook, Twitter, Instagram, Color1-9	0.75	0.752	0.754
Facebook, Twitter, Instagram, Gray Mn	0.749	0.75	0.752
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.749	0.751	0.752
Facebook, Twitter, Instagram, Color1-4	0.748	0.749	0.751
Facebook, Twitter, Instagram, Color1-5	0.748	0.75	0.752
Facebook, Twitter, Instagram, Color1-10	0.747	0.748	0.751
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.744	0.745	0.748
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.742	0.744	0.746

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
Pleasure	0.742	0.742	0.747
Weight	0.74	0.74	0.746
Min 9	0.739	0.739	0.744
Max 16	0.739	0.74	0.744
Arousal	0.739	0.739	0.745
Dominance	0.739	0.739	0.744
Base Features	0.738	0.738	0.742
Min 9 Max 9	0.737	0.738	0.742
Title WC	0.737	0.737	0.742
Gray Sd	0.736	0.736	0.74
Gray Mn, Gray Sd	0.736	0.735	0.74
Color1-2	0.736	0.736	0.742
Activity	0.736	0.736	0.741
Gray Mn	0.735	0.735	0.74
Activity, Weight, Heat	0.733	0.733	0.739
Max 9	0.733	0.732	0.738

Table A.20: Cluster Models Edge 8

	F1	Precision	Recall
Min 16	0.733	0.733	0.739
Pleasure, Arousal, Dominance	0.732	0.732	0.738
RGB Sd	0.732	0.731	0.738
Color1-6	0.732	0.732	0.739
Color1-7	0.732	0.732	0.738
Min 16 Max 16	0.732	0.732	0.738
Gray Mn, RGB Mn	0.73	0.73	0.735
Color1	0.729	0.728	0.734
Heat	0.729	0.729	0.734
Gray Sd, RGB Sd	0.728	0.728	0.734
Color1-3	0.728	0.728	0.735
RGB Mn, RGB Sd	0.727	0.727	0.734
Color1-4	0.727	0.728	0.733
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.725	0.725	0.732
RGB Mn	0.723	0.723	0.729
Color1-5	0.723	0.723	0.73

Table A.20: Cluster Models Edge 8

	F1	**Precision**	**Recall**
Color1-8	0.723	0.723	0.729
Color1-9	0.721	0.722	0.728
Color1-10	0.719	0.719	0.727

Table A.21: Cluster Models Edge 9

	F1	Precision	Recall
BioNg, BioPs BioWC, DescWC	0.631	0.63	0.632
BioWC, DescWC Facebook, Twitter, Instagram	0.62	0.62	0.622
BioNg, BioPs Facebook, Twitter, Instagram	0.613	0.612	0.614
BioNg, BioNeu, BioPs	0.609	0.608	0.611
BioNg, BioPs, Pleasure	0.601	0.6	0.603
BioNg, BioPs, Gray Mn	0.6	0.6	0.602
BioNg, BioPs, Gray Mn, Gray Sd	0.6	0.599	0.602
BioNg, BioPs, Color1	0.6	0.6	0.602
BioNg, BioPs, Color1-2	0.6	0.6	0.602
BioNg, BioPs, Arousal	0.6	0.599	0.601
BioNg, BioPs, Activity	0.6	0.599	0.602
BioNg, BioPs	0.599	0.599	0.601
BioNg, BioPs, Dominance	0.599	0.598	0.6
Bio Word Count, Desc Word Count	0.598	0.598	0.6
BioNg, BioPs, Gray Sd	0.598	0.598	0.6
BioWC, DescWC, Color1	0.598	0.597	0.6

Table A.21: Cluster Models Edge 9

	F1	Precision	Recall
BioNg, BioPs, Min 9 Max 9	0.598	0.597	0.6
BioNg, BioPs, Heat	0.598	0.597	0.599
BioWC, DescWC, Dominance	0.598	0.597	0.6
BioWC, DescWC, Activity	0.598	0.597	0.599
BioNg, BioPs, AWH	0.597	0.596	0.599
BioNg, BioPs, Min 16 Max 16	0.597	0.596	0.599
BioNg, BioPs, Weight	0.597	0.596	0.599
BioNg, BioPs, PAD	0.596	0.595	0.598
BioNg, BioPs, Color1-3	0.596	0.595	0.598
BioWC, DescWC, Gray Mn	0.596	0.595	0.598
BioWC, DescWC, Pleasure	0.596	0.595	0.598
BioWC, DescWC, Arousal	0.596	0.595	0.597
BioWC, DescWC, Weight	0.596	0.595	0.598
BioNg, BioPs, Gray Mn, RGB Mn	0.595	0.594	0.597
BioWC, DescWC, Gray Sd	0.595	0.595	0.597
BioWC, DescWC, Color1-2	0.595	0.595	0.597

Table A.21: Cluster Models Edge 9

	F1	**Precision**	**Recall**
BioWC, DescWC, Min 9 Max 9	0.595	0.594	0.597
BioWC, DescWC, Min 16 Max 16	0.595	0.594	0.597
BioNeg, BioPs, RGB Mn	0.594	0.593	0.596
BioNg, BioPs, RGB Sd	0.594	0.593	0.596
BioNg, BioPs, Color1-4	0.594	0.593	0.596
BioNg, BioPs, Color1-5	0.594	0.593	0.596
BioWC, DescWC, Color Gray Mn, Color Gray Sd	0.594	0.593	0.596
BioWC, DescWC, Color1-3	0.593	0.592	0.595
BioWC, DescWC, Heat	0.593	0.593	0.595
BioNg, BioPs, RGB Mn, RGB Sd	0.592	0.591	0.594
BioWC, DescWC, AWH	0.592	0.591	0.594
BioWC, DescWC, RGB Mn	0.592	0.591	0.594
BioWC, DescWC, PAD	0.591	0.59	0.593
BioNg, BioPs, Gray Sd, RGB Sd	0.59	0.589	0.592
BioWC, DescWC, RGB Sd	0.59	0.589	0.592
BioNg, BioPs, Color1-6	0.589	0.589	0.592

Table A.21: Cluster Models Edge 9

	F1	Precision	Recall
BioNg, BioPs, Color1-7	0.589	0.588	0.592
BioWC, DescWC, Color1-4	0.589	0.588	0.591
BioWC, DescWC, Color1-5	0.588	0.587	0.59
BioNg, BioPs, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.587	0.586	0.589
BioWC, DescWC, Gray Mn, RGB Mn	0.587	0.586	0.589
BioWC, DescWC, Gray Sd, RGB Sd	0.586	0.585	0.588
BioNg, BioPs, Color1-8	0.585	0.584	0.587
BioWC, DescWC, Color RGB Mn, Color RGB Sd	0.585	0.584	0.587
BioNg, BioPs, Color1-9	0.584	0.584	0.587
BioWC, DescWC, Color1-6	0.584	0.583	0.587
BioNg, BioPs, Color1-10	0.581	0.581	0.584
BioWC, DescWC, Color1-8	0.58	0.579	0.582
BioWC, DescWC, Color1-7	0.579	0.579	0.582
BioWC, DescWC, Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.577	0.576	0.58
BioWC, DescWC, Color1-9	0.576	0.575	0.579
BioWC, DescWC, Color1-10	0.572	0.571	0.575

Table A.21: Cluster Models Edge 9

	F1	**Precision**	**Recall**
Facebook, Twitter, Instagram, Color1	0.55	0.549	0.552
Facebook, Twitter, Instagram, Gray Mn	0.549	0.547	0.551
Facebook, Twitter, Instagram, Gray Mn, Gray Sd	0.549	0.547	0.551
Facebook, Twitter, Instagram, Color1-2	0.549	0.548	0.551
Facebook, Twitter, Instagram, Dominance	0.549	0.548	0.551
DescNg, DescNeu, DescPs	0.549	0.548	0.551
Facebook, Twitter, Instagram, Arousal	0.548	0.547	0.55
DescNg, DescPs	0.547	0.546	0.549
Facebook, Twitter, Instagram, PAD	0.547	0.546	0.549
Facebook, Twitter, Instagram, Color1-3	0.547	0.546	0.55
Facebook, Twitter, Instagram, Activity	0.547	0.546	0.55
Facebook, Twitter, Instagram	0.546	0.545	0.547
Facebook, Twitter, Instagram, Gray Sd	0.546	0.545	0.548
Facebook, Twitter, Instagram, Pleasure	0.546	0.545	0.548
Facebook, Twitter, Instagram, RGB Mn	0.545	0.544	0.548
Facebook, Twitter, Instagram, Min 16 Max 16	0.545	0.544	0.548

Table A.21: Cluster Models Edge 9

	F1	Precision	Recall
Facebook, Twitter, Instagram, AWH	0.543	0.542	0.546
Facebook, Twitter, Instagram, Color1-4	0.543	0.542	0.546
Facebook, Twitter, Instagram, Min 9 Max 9	0.543	0.542	0.546
Facebook, Twitter, Instagram, Weight	0.543	0.542	0.545
Facebook, Twitter, Instagram, RGB Sd	0.542	0.541	0.545
Facebook, Twitter, Instagram, RGB Mn, RGB Sd	0.542	0.541	0.546
Facebook, Twitter, Instagram, Heat	0.542	0.541	0.544
Facebook, Twitter, Instagram, Gray Mn, RGB Mn	0.541	0.54	0.544
Facebook, Twitter, Instagram, Color1-5	0.541	0.54	0.544
Facebook, Twitter, Instagram, Color1-6	0.54	0.539	0.543
Facebook, Twitter, Instagram, Gray Sd, RGB Sd	0.538	0.537	0.541
Facebook, Twitter, Instagram, Gray Mn, RGB Mn, Sd	0.536	0.535	0.54
Facebook, Twitter, Instagram, Color1-7	0.536	0.535	0.54
Facebook, Twitter, Instagram, Color1-8	0.533	0.532	0.536
Facebook, Twitter, Instagram, Color1-9	0.531	0.53	0.535
Facebook, Twitter, Instagram, Color1-10	0.53	0.529	0.533

Table A.21: Cluster Models Edge 9

	F1	**Precision**	**Recall**
Title WC	0.513	0.512	0.515
Gray Mn, Gray Sd	0.501	0.5	0.504
Color1-2	0.501	0.499	0.503
Color1	0.499	0.497	0.501
Pleasure, Arousal, Dominance	0.498	0.497	0.501
Gray Mn	0.498	0.497	0.501
RGB Mn, RGB Sd	0.498	0.496	0.502
Color1-3	0.498	0.497	0.501
Activity	0.498	0.497	0.5
Activity, Weight, Heat	0.496	0.495	0.499
RGB Mn	0.496	0.495	0.499
Color1-4	0.496	0.495	0.499
Arousal	0.496	0.495	0.499
Dominance	0.496	0.495	0.498
Min 16 Max 16	0.495	0.494	0.498
Gray Sd	0.494	0.492	0.496

Table A.21: Cluster Models Edge 9

	F1	**Precision**	**Recall**
Gray Mn, RGB Mn, Gray Sd, RGB Sd	0.494	0.493	0.498
Color1-5	0.494	0.493	0.497
Max 16	0.494	0.493	0.496
Gray Mn, RGB Mn	0.493	0.492	0.497
Min 9 Max 9	0.493	0.492	0.496
Base Features	0.492	0.491	0.495
Color1-6	0.492	0.491	0.496
Min 9	0.492	0.491	0.495
Max 9	0.492	0.491	0.495
Pleasure	0.492	0.491	0.495
RGB Sd	0.491	0.489	0.494
Min 16	0.491	0.489	0.493
Weight	0.491	0.49	0.494
Gray Sd, RGB Sd	0.489	0.488	0.493
Color1-7	0.489	0.488	0.493
Color1-8	0.488	0.487	0.492

Table A.21: Cluster Models Edge 9

	F1	**Precision**	**Recall**
Heat	0.487	0.486	0.49
Color1-10	0.484	0.483	0.489
Color1-9	0.483	0.482	0.488