AN ARGUMENT FOR THE USE OF COMPUTER SIMULATED MODELS IN PHILOSOPHY

by

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A thesis submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Master of Arts in
Ethics and Applied Philosophy

Charlotte

2015

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ABSTRACT

JASON RUSSELL RINES. An argument for the use of computer simulated models in philosophy. (Under the direction of DR. MARVIN CROY)

This thesis will attempt to show how computer simulated models can act as a tool for philosophers. To accomplish this goal, this thesis will be broken down into six sections. The first three sections will go into more detail regarding the nature of the term 'computer simulated model.' They will discuss the history of computer simulated models, outline the process of constructing computer simulated models, and give context for the current use of computer simulated models in science. These sections will rely heavily on the work of Eric Winsberg to give a proper understanding of the functions of computer simulated models. The forth section will give a historical overview of different philosophical methods, including the dialectical method, Conceptual Analysis, and the work of Paul Churchland with Artificial Neural Networks. This section will also attempt to show how these philosophical methods relate to computer simulated models. The fifth section will discuss how American Pragmatism provides a positive framework for the utilization of computer simulated models by philosophers, specifically pulling from the works of Charles Peirce, William James, and John Dewey. The sixth and final section will address the notion that computer simulated models are reliable without seeking truth and use that notion to tie together the argument that computer simulated models can serve as a tool for philosophers.

DEDICATION

To my wonderful wife Olivia, my family, and my best friend Charlie. I also dedicate this thesis to the remembrance of Alan Turing and Jules Bianchi.

ACKNOWLEDGMENTS

I would like to thank my committee for their support and guidance throughout this process. First, I would like to thank my committee chair, Dr. Marvin Croy, for being a mentor not only throughout this thesis process but also throughout my academic career here at UNC Charlotte. He has gone out of his way to help me from the moment I declared philosophy as my major through the completion of my Master's Degree. His mentoring and support has opened many doors and led me to discover new avenues for success within philosophy. Second, I would also like to thank Dr. Mark Sanders for all of his help in advising me throughout the thesis process, as well as for introducing me to Pragmatism. His class on American Philosophy has influenced my perspectives within philosophy and help to shape the philosopher I am today. Third, I would like to thank Dr. Trevor Pearce. His advice and suggestions helped to shape and strengthen this thesis. His knowledge was an essential part of this thesis, and his feedback was overwhelmingly appreciated. Last, I would like to thank the entire philosophy department at UNC Charlotte. This department has shaped me both as a student and also as a person. Without the help of my committee as well as the philosophy department, I could not have made it this far.

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INTRODUCTION

This thesis will attempt to show how computer simulated models can act as a tool for philosophers. To accomplish this goal, this thesis will be broken down into six sections. The first three sections will go into detail regarding the nature of the term 'computer simulated model.' This will involve describing the process used to create these models, as well as some of their current uses. These sections will also show how these models are currently viewed as a reliable tool within the sciences. Specifically, the work of Eric Winsberg will be used to show how and why computer simulated models act as reliable tools for exploring the world around us. In describing computer simulated models as such, this thesis will address some of the concerns that philosophers have had about computer simulated models in regards to both their role in science and the prospect of using them for philosophy. The third section will also address some possible objections to the idea of philosophers using computer simulated models as a philosophical tool.

The fourth section will attempt to show the parallels between the construction of computer simulated models and well established methods within philosophy. This will be done by deconstructing two methods within philosophy and showing how the process and goals of these methods can be seen in the building and exploring of computer simulated models. This section will explain the role of Conceptual Analysis in philosophy and the goals Conceptual Analysis attempts to achieve. This will be done by considering the works of Bertrand Russell and Ludwig Wittgenstein and attempting to explain the setting in which Conceptual Analysis emerged and developed. This will be followed up by an explanation of how the aims of Conceptual Analysis can be replicated within the process of creating and using computer simulated models. Next, the emergence of experimental philosophy will be explained. Examples of philosophers such as Paul Churchland, who are already using computer simulated models within their experimental work, show how computer simulated models fit within the confines of philosophy.

The fifth section will show how American Pragmatism provides a positive framework for the utilization of computer simulated models by philosophers. Through a number of arguments, this examination will explore the core features of American Pragmatism and show how the application of computer simulated models by philosophers is consistent with the spirit of American Pragmatism as presented by Charles Peirce, William James, and John Dewey. First, it will be argued that the pragmatic construction of truth is consistent with and supported by the knowledge produced by computer simulated models. This argument will tie in with the notion that computer simulated models favor reliability over truth. Subsequently, this section will emphasize how computer simulated models have the ability to be a practical tool that is capable of solving not only abstract problems but also concrete ones. This idea stresses the importance for philosophers to be concerned with everyday problems and not just abstract ones. The fifth section will conclude with the argument that computer simulated models can be used as a tool for reflection and will consider how the iterative nature of computer simulated models echoes Dewey's emphasis of reflection within the process of inquiry.

The last section will address the notion that computer simulated models are reliable without seeking truth. This idea comes from Eric Winsberg but is supported through the work of pragmatists such as Dewey. As a whole, this thesis hopes to paint a detailed picture of the role computer simulated models can play as a tool for philosophers and argue that these models can be valuable to philosophers. Most importantly, this thesis hopes to show how American Pragmatism gives support for the use of computer simulated models by philosophers.

It should be noted that this idea of merging computers, science, and philosophy has been attempted before. Aaron Sloman wrote about this in detail in his book: *The Computer Revolution in Philosophy*. In that text, Sloman attempts to show how computers can help to revolutionize philosophy. Sloman also attempts to show the places where science and philosophy can overlap.[1] Sloman covers many of the same topics that will be addressed in this thesis. Sloman devotes a whole chapter to Conceptual Analysis.[2] In it, he argues for a more applied approach within science[3] and against computers simply being "number crunchers".[4] He believes that computers, science, and philosophy can all work together. Where this paper differs from the work of Sloman is in the application of computers to philosophy. Sloman argues for artificial intelligence (AI) to be the location where philosophy and computers overlap. While he is not wrong, this thesis will focus on the use of computer simulated models, instead of AI, within philosophy. As such, this thesis can be seen as a supportive argument, using new examples, for the integration of computer simulated models within philosophy.

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[1] Sloman, Aaron. *The Computer Revolution in Philosophy: Philosophy, Science and Models of Mind*. Hassocks: The Harvester Press, (1978):80-81
[2] Ibid: 84
[3] Ibid:16
[4] Ibid: 103

WHAT IS A COMPUTER SIMULATED MODEL?

In order to explain how computer simulated models can act as a philosophical tool, it must first be explained what is meant by the term ‘computer simulated model.’ It should be clear that the use of the term ‘computer simulated models’ refers not only to the models themselves but also to the entire process by which a computer simulated model is created and used. This includes any modification that might happen to the computer simulated model over time. It is important to focus on computer simulated models as a process since their usefulness to philosophers exists within this process and does not stem solely from the creation or use of a computer simulated model. It is also within this process that computer simulated models can be seen to have two connected yet separate processes. The first process is the creation and building of a computer model; the second is the simulation and analysis of the data. This distinction relies on the difference between simulation and modeling, as will be discussed later in this paper. While both of these steps are performed either by or on a computer, they represent different actions. The importance lies in how they work together to create the end result: the computer simulated model.

Historically, computer simulation has been a method used to supplement the solution of difficult mathematical problems. One of the earliest cases of computer simulation is the Monte Carlo method. The Monte Carlo Method is a means of computing the volume of irregularly shaped figures and was developed during the Manhattan Project in the nineteen forties by Stanislaw Ulam and John von Neuman. Often, these figures cannot be calculated using traditional methods. This calculation is completed by placing the figure inside of a cube of known volume and then trying to computationally come up with a ratio between the volume of the figure and the cube. The computer randomly chooses points within the cube and determines whether that point exists as a part of the figure or not. After repeating this action thousands of times, the computer can determine the ratio of the figure to the cube and therefore determine the volume of the figure. It is important to point out here that computer simulation is not just a method of quickly solving mathematical equations. Often, computer simulations are used to solve problems that have no traditional mathematic solution to them, such as in the Monte Carlo Method above.[5]

An important distinction must be made between a computer simulation and a numerical calculation. If computer simulation is thought of as an advanced calculator, the real value of computer simulation is not fully realized. As in the example above, computer simulations are able to solve mathematical problems in ways that are not possible using traditional analytical methods. This is often due to the ability of computers to store large volumes of data at any single moment. A computer is capable of keeping track of thousands of variables at any single moment. Sloman makes this same point when he points out the common misconception that computers are simply a tool with which to complete numerical calculations.[6] In the Monte Carlo example above, the computer is able to run the simple operation of determining if the point within the cube that it has selected is or is not a part of the desired figure being measured. With each step, the computer simply registers either a success or failure, where a success is a point

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[5] Lenhard, Johannes, Kuppers, Gunter, and Terry Shinn. "Computer Simulation: Practice, Epistemology, and Social Dynamics." *In Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 3-22. Dordrecht: Springer, (2006): 9

[6] Sloman, Aaron. *The Computer Revolution in Philosophy: Philosophy, Science and Models of Mind*. Hassocks: The Harvester Press, (1978): 103

that is within the figure and a failure is a point outside of the figure. While this simple process is nothing spectacular, the computer is able to complete this simple operation thousands of times to determine an accurate ratio of success points to failure points and therefore determine the volume of the figure.

If we now ask ourselves what in this example is the computer simulation, we find that the act being simulated is the act of choosing a point within the cube and determining whether that point exists as a part of the figure or not. To be clear, the computer is not simulating a purely mathematical calculation. This sentiment is echoed by Küppers, Lenhard, and Shinn, who state that "computer simulations are not numerical solutions of a theoretical model; rather, they employ a generative mechanism to imitate the dynamic behavior of the underlying process".[7] The simulation aspect of computer simulated models considers the simulation of time and the processes that are affected by time. The model aspect focuses on the representation of objects, as well as the dynamics of behavior that might exist between different objects within the model.

As it was stated earlier, some computer models simply represent a mathematical relationship, while others represent actual objects in the world. This thesis will focus on the latter case. Three types of this latter case include Cellular Automata, Agent-Based Models, and Neural Networks. These three types do not rely on exact theoretical models.[8] Cellular Automata is the oldest of these types. This model works by dividing a two dimensional space into a grid. Each space on the grid should have eight neighbors or eight grid spaces surrounding it. Each grid space can be programed to have different

[7] Lenhard, Johannes, Kuppers, Gunter, and Terry Shinn. "Computer Simulation: Practice, Epistemology, and Social Dynamics." *In Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 3-22. Dordrecht: Springer, (2006): 11
[8] Ibid

behaviors depending on the states of its neighbors (the eight grid spaces surrounding it). With each step or movement in time, each grid space acts according to its assigned behavior. For example, say that there are two different behavior types, each with its own corresponding color. The first behavior type will change its color if more than five of its neighbors are the same color as it is. The second behavior type will change its color if less than two of its neighbors are the same color as it is. With every step, each grid space calculates its behavior and acts accordingly.

Agent-Based Models (ABM) try to exhibit Meta or global level phenomenon through the interaction of smaller autonomous agents. Unlike Cellular Automata, agent-based models are not confined to a grid structure. The agents in agent-based models can also be heterogeneous, with different classes of agents interacting in varying ways. This is the key advantage of agent-based-models over template-based models, such as Cellular Automata. Paul Humphreys describes this advantage well: “the fact that the agents are operating within an environment which is constantly changing, and the fact that an agent’s actions are reciprocally affected by the choices made by other agents”[9]- this is what makes agent-based models so useful. ABMs are able to model complex systems, in which agents affect and are affected by not only other agents but also a simulated environment. This ability makes agent-based models adept at modeling biological and social structures.[10] These models are also inherently bottom-up, where the focus of the model is on the interaction of agents and the environment. In this sense, no overarching

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[9] Humphreys, Paul. *Extending Ourselves: Computational Science, Empiricism, and Scientific Method*. New York: Oxford University Press, (2004): 130

[10] Lenhard, Johannes, Kuppers, Gunter, and Terry Shinn. *“Computer Simulation: Practice, Epistemology, and Social Dynamics.” In Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 3-22. Dordrecht: Springer, (2006): 12

structure is being assumed by the model. This will often lead to emergent phenomena at the macro level that are the result of the interactions of the micro-level agents. These phenomena cannot be predicted by simply analyzing the individual agents themselves.[11] Agent-based models lend themselves to the understanding of sufficient conditions for a given phenomenon. They can find their use in understanding the underlying mechanisms of known phenomenon, such as the behavior of birds flocking or the racial segregation of neighborhoods.[12] Normally, these mechanisms emerge from simple rules that are unrelated to the phenomenon itself.

Artificial Neural Networks are another example of a type of modeling that operates without the guidance of an overarching structure. Artificial Neural Networks operate with layers of 'neurons' that are connected to one another through links. All links have weights that are adjusted over time. The links and their weights determine how one layer affects another layer. One normally has an input layer of nodes on the bottom and an output layer on top. Unlike previous examples, neural networks function by creating a testing set of input and output pairs. The modeler will enter a set of input values for the network, and the system will adjust the weights that are attached to the links until the outputs of the network match the inputs given. This, in a sense, calibrates the network. Once this is done, one could ideally give the network a new input value, for which one might not have the corresponding output value, and the network will figure out what the output value should be. In this way, the network learns the pattern that the

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[11] Humphreys, Paul. *Extending Ourselves: Computational Science, Empiricism, and Scientific Method.* New York: Oxford University Press, (2004): 130

[12] Macy, Michael W, and Robert Willer. "From Factors to Actors: Computational Sociology and Agent-Based Modeling." Annual Review of Sociology 28, no. 1 (2002): 143-166.

modeler is attempting to find.[13] A more concrete example of this can be seen in neural networks that are used for facial recognition. For these networks, the input layer would be the number of pixels for a facial image. For this example, we will say that there are 64 pixels in each picture. The output layer might be the sex of the person in the picture. The input layer therefore has sixty four nodes or neurons, and the output layer will have two neurons (male and female). These two layers would be connected through middle layers of neurons. These middle layers can have a varying degree of nodes. It should be noted that each node in the first layer will be connected to each node in the layer above it. The network will be calibrated by giving it faces of known sex. For each iteration, one gives the network feedback. If the network properly assigns the correct sex to the picture, the weights of the links will strengthen; if the network assigns the wrong sex, the weights will be reduced. This happens over many iterations until the network is able to predict the correct sex at a high percentage rate (this percentage rate varies according to the needs of the modeler). With the network now trained, one can give the network a new face that it has not seen before and it should be able to assign the correct sex.[14] Models like these have been used by philosophers such as Paul Churchland within Philosophy of Mind to explore how high level concepts might emerge from lower level neural activity.[15]

All three of these model types avoid the usage of explicit mathematical equations to find their solutions. They also serve as examples of the differences between the

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[13] Lenhard, Johannes, Kuppers, Gunter, and Terry Shinn. "Computer Simulation: Practice, Epistemology, and Social Dynamics." In *Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 3-22. Dordrecht: Springer, (2006): 12

[14] Churchland, Paul M. *The Engine of Reason, the Seat of the Soul*. Cambridge: The MIT Press, (1995): 52-53

[15] I will go into more detail about Churchland and his mental models in a later section.

simulation aspect and modeling aspect. While the two terms are often used interchangeably, this thesis will attempt to make a distinction between them. While this is not a distinction shared by many, it serves a useful function. In order to appreciate the usefulness of computer simulated models to philosophy, one must understand how the process of creating and using computer simulated models involves the separate but connected aspects of computer simulation and computer modeling. The modeling side of computer simulated models includes the framework given to the model by the specific genre of computer simulated model it represents, such as the three types of models described above: Cellular Automata, Agent-Based Model, and Artificial Neural Networks. The modeling portion also involves the initial conditions of the model, as well as any rules of interaction between the different elements within the model. Artificial Neural Networks, in this regard, are limited in terms of the freedom the modeler has when it comes to varying any of these factors. All Artificial Neural Networks have a structure consisting of rows of neurons that are interconnected by weighted links. With Cellular Automata, the modeler has a few more freedoms, as the modeler can alter the rules by which the different grids interact with each other. The modeler, however, is stuck with the framework of grids. Agent-Based Models have the most freedoms in terms of the implementation of the model. The modeler has the ability to create n-number of agents, all with different rules for interaction, both with the environment and with other agents.

As stated before, computer simulation deals primarily with the element of time. For Cellular Automata, this means that what gets simulated is the interaction of each grid space at each discrete step. The simulation reveals how each grid space reacts given the state of its neighbors. Through simulation, one can see how patterns emerge and how the different rules for each grid space unfold. The simulation aspect of Agent-Based Models can reveal the occurrence of emergent phenomena. It is also what allows for the different behaviors and interactions of the individual agents to be realized. In Neural Networks, the simulation is both the calibration of the network through testing sets and the utilization of a trained network for the exploration of new instances. Some Artificial Neural Networks combine this into one step by having recurrent training networks built into the simulation. Simulation is also concerned with the data that is produced by the models. For Artificial Neural Networks, the data that is produced is normally just the output from the network, while Cellular Automata and Agent-Based Models can produce far more data, such as the state of different variables that the agents might have or the aggregate of the different states within a Cellular Automata.

A clearer example of this distinction can be seen in two more concrete examples. Considering the example of the Monte Carlo simulation, one can easily see the division between the modeling and simulating aspects. The model is the computer representation of the three dimensional shape of known volume and the three dimensional shape of unknown volume. The simulation is the computer choosing a spot within the three dimensional shape of known volume and then testing to see if that spot is also within the shape of unknown volume. The result of the simulation is a percentage that represents the volume of the shape of unknown volume to the volume of the shape of known volume. Another example would be if one were to create a computer simulated model of the universe. The model element would involve the space within which the universe exists, the basic particles that exist within this universe, and the laws of physics to determine how these particles will interact with each other. The simulation portion would be time. By running the simulation, it would reveal how all these particles interact over time. As it can be seen here, both elements are important to the overall function of the computer simulated model. Without the model, the simulation would have no rules to govern its behavior, and, without simulation, the model would not be able to produce any useful information. This distinction is also useful during any type of analysis that might be required due to unexpected results. Knowing if one's anomaly is part of the model or part of the simulation can help the modeler to better understand the nature of the anomaly and the phenomena being explored by the computer simulated model.

THE PROCESS OF COMPUTER SIMULATED MODELING

As was addressed in the previous section, it is important to think about computer simulated models as a process. This process spans from the conception of the computer simulated model all the way through the analysis of the results or output produced through the simulation. Embedded in this process is the value of computer simulated models to philosophers. In the first section, the difference between modeling and simulation was introduced. These two functions define the main division within the process of computer simulated modeling. This section will continue working within that division: the first part will focus on modeling and all of the steps involved in that process and second will consider simulation and all the parts involved in it. Included in the section on simulation will be the analysis of any output data from a model. By expanding on the process of computer simulated models, one can start to see the benefits that computer simulated models can bring to philosophy.

Most models are grounded in theory.[16] This theory can be based on mathematical principles, such Newtonian physics, or can simply be forged from empirical data that has yet to be reduced to a mathematical relationship. Weather forecasting fits into this second option. While large amounts of empirical weather data exists, the systems that are in play are too complicated to be described with an elegant mathematical equation. All models first start with a problem that is in need of solving. The nature of this problem can help the modeler answer the first question of modeling: what genre of computer simulated models should be used? As previously mentioned, there is a wide range of

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[16] Winsberg, Eric. *Science in the Age of Computer Simulation*. Chicago: The University of Chicago Press, (2010): 10-11

different computer simulated models, each with their own pros and cons. Understanding the nature of the problem can help inform the modeler of what type of computer simulated model would be the best option. For instance, Agent-Based Models are best suited for situations involving a heterogeneous set of agents. Artificial Neural Networks are suited to emulate the process of learning. The modeler must be aware of the limitations of each type of computer simulated model. This being said, it is possible for a person to model a specific phenomenon with different types of models. Take, for instance, a model of different tactics used in a prisoner's dilemma. The prisoner's dilemma is described as a scenario where what is best for the individual is not best for the group. *The Stanford Encyclopedia of Philosophy* describes it through a narrative:

> Tanya and Cinque have been arrested for robbing the Hibernia Savings Bank and placed in separate isolation cells. Both care much more about their personal freedom than about the welfare of their accomplice. A clever prosecutor makes the following offer to each. "You may choose to confess or remain silent. If you confess and your accomplice remains silent I will drop all charges against you and use your testimony to ensure that your accomplice does serious time. Likewise, if your accomplice confesses while you remain silent, they will go free while you do the time. If you both confess I get two convictions, but I'll see to it that you both get early parole. If you both remain silent, I'll have to settle for token sentences on firearms possession charges. If you wish to confess, you must leave a note with the jailer before my return tomorrow morning.[17]

As it can be seen, the prisoners dilemma is an example of a collective action problem, where the choice to work together to benefit the group (confessing) is in conflict with what is best for them individually (remaining silent).[18] There are many different formulations of this scenario, each with a different twist. The one this thesis will use is a twist on the original, where the prisoners complete multiple rounds and are aware of what

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[17] Kuhn, Steven, "Prisoner's Dilemma", *The Stanford Encyclopedia of Philosophy* (Fall 2014 Edition), Edward N. Zalta (ed.), www .plato.stanford.edu/archives/fall2014/entries/prisoner-dilemma.
[18] *Encyclopedia Britannica Online*, s. v. "collective action problem", accessed June 13, 2015, www .britannica.com/topic/collective-action-problem-1917157.

the other prisoner did in the last round. This allows for each prisoner to adjust his/her strategy based on what he/she thinks the other prisoner will do. Modeling this type of scenario has become a staple within computer simulated models. As such, it has been addressed using all three genres of computer simulated models that have been discussed. The key is to pick the type of model that is best suited for the modeler's needs.[19] Once the modeler has settled on the type of model he/she is going to use, he/she can move on to the second step in modeling.

The second step is to build the model inside of the computer environment. If one was to build an agent-based model of the prisoner's dilemma, one would have to decide how he/she is going to implement the different strategies. He/she would have to decide if he/she wanted the agent to be fixed to a specific strategy or if the agent might change strategies over time. He/she would have to determine how he/she is going to allow the different agents to engage with one another. Should the agents randomly interact with one another or should the modeler control the interactions in some way? How should the simulation keep track of the engagements? What variables should the modeler allow to be adjusted and which should the modeler keep constant? Which variables should even be considered? These types of question are just a few that must be addressed. All of these questions carry with them epistemological weight. How one chooses to implement these question has an effect on the end result and must be taken into consideration. It should also be noted that, within this process, one also has to consider that all of these questions must be translated into code that the computer can understand. This process

[19] It should be mentioned that the use of the prisoner's dilemma as an example is due only to the ease of description and is not a comment on the validity of the prisoner's dilemma as an evaluation of human rationality or decision making. The prisoner's dilemma is an exercise in game theory and not an empirical study of actual prisoners.

forces the modeler to make explicit all of the assumptions that he/she has implemented into this model. This can become tricky when trying to model behaviors that involve probability.

For instance, say that, empirically, we know that, when people are put into a prisoner's dilemma situation with multiple runs, twenty-five percent of people will adjust their strategy if they end up losing.[20] Now, if one was trying to exhibit this behavior in a model, he/she must now choose how to implement this behavior. One option would be to simply program twenty five percent of the agents to switch their strategy when they lose. Another option would be to give every agent a twenty five percent-chance of changing strategy when they lose. Since one of the advantages of agent based models is that they function as a bottom up process, maybe the modeler might choose to not program in the exact empirical percentage into the model at all. Maybe the modeler might choose to implement another strategy and see if the results match the empirically known statistics. This choice will often force the modeler to go back to the empirical data and consider which of these methods would best model the phenomena at hand. On the other hand, by running multiple computer simulated models, each with a different approach, the modeler might learn which method best fits the empirical data. In this sense, the process of building the model forces the modeler back to he/she original data and requires further inquiry into the theory or phenomena in question. In this way, the very processes of building the model can help to uncover more information about the nature of the phenomena being modeled.

[20] This is a hypothetical statement used to give an example of the process of model building.

After the model has been built, the next step in the process is to allow for the simulation process to run within the model. By running the simulation, one is putting into action all of the initial conditions along with all of the rules for interaction that were built into the model. Depending on the type of model, the act of simulation can take many forms. This is best expressed by comparing the simulation of an Artificial Neural Network to that of an agent based model. Most Artificial Neural Networks lack a graphical interface where the user can actually see the adjusting of weights during the simulation process. Because of this, the simulation process is simply useful for the data that it produces. With Artificial Neural Networks, the simulation process is involved with both the training of the network as well as the application of the network after it has been trained. With an agent-based model, the simulation takes a much different form. Most agent-based modeling programs, such as SWARM and NetLogo, utilize a graphical user interface that allows the modeler to see the movements and interaction of all of the agents in real time. Agent-based models can also produce large amounts of data that is normally exported into some type of database for further analysis.

Another important element of simulation is feedback. When simulating, it is normal for the program to run through the simulation multiple times before data is collected. This is due to the dynamic nature of computer simulated models. Each time the modeler runs the simulation, new data is produced. Due to the fact that events like probability and randomness are in play, each run has the ability to generate new data. This data is normally aggregated together, and, with the use of statistical measures, some type of conclusion is reached. With agent-based models it is normal for the modeler to intentionally vary the initial conditions in order to see how the changes affect the outcome. In the example of the prisoner's dilemma, the modeler might change the starting strategies or the amount of agents with each strategy. Changing these variables can have an effect on the outcome of the simulation. This is one of the benefits of computer simulated models: they have the ability to be adjusted quickly and analyzed in a relatively short amount of time. This also leads to the feedback loop that is key to the development of computer simulated models. With all computer simulated models, there is no real end to the development. Even after a model has been created and simulated, it is normal for the creator to go back and make changes either to the very structure of the model or to a single variable. Artificial Neural Networks can actually be built in a natural feedback loop that allows for the model to continue to make changes even after the model has been trained. This is the main reason to consider computer simulated models a process. It is a process that has the ability to generate new inquiries and hypotheses.

The continual reexamining and tweaking of computer simulated models is often the result of the fact that computer simulated models often generate more questions than answers. Through the process of building and then testing a computer simulated model, the modeler might uncover behavior of a phenomena inside of the model that might not match the empirical data from the world, even if the modeler thought he/she had properly represented it within the computer simulated model. This might cause the modeler to not only reexamine the code of the model to uncover any issues there but to also examine the phenomena in the world to see if he/she can find the cause of the discrepancy. This is similar to the way that new observations lead scientists to reconsider old theories. The output from computer simulated models can cause the designer to go back and adjust something or even to rethink the nature of his/her original question. The computer simulated model is a tool to create new ideas or perspectives. It is a rapid prototype device that can quickly be developed and deployed to generate new knowledge about a phenomena. Its value comes both from its ability to be flexible and adapt itself to a multitude of purposes as well as its computational power to represent complex and dynamic systems that until now were seen as unsolvable.[21]

[21] Lenhard, Johannes, Kuppers, Gunter, and Terry Shinn. "Computer Simulation: Practice, Epistemology, and Social Dynamics." In *Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 3-22. Dordrecht: Springer, (2006): 18

THE EPISTOMOLGY OF COMPUTER SIMULATED MODELS

Computer simulated models have found their home in a variety of disciplines, including economics, psychology, anthropology, biology, and chemistry. They are used because they serve as a scientific tool that allows researchers to investigate theories in ways that traditional methods cannot. Their widespread use in certain fields, specifically science, has led many philosophers of science to investigate their role, their inquiry being focused on the epistemology of computer simulated models as well as their relation to scientific theory and the process of experiment.

The relationship between scientific theory and scientific modeling is not as straightforward as one might think. While scientific models do find their grounding in scientific theory, it is not always the case that a model is derived directly from the theory. Winsberg states that "theory is at best guiding, rather than determining the choice of model."[22] He goes on to state three elements that are involved in the process of model creation: theory, physical intuition, and the considerations that are led from the limitations of computation.[23] So, while theory plays an important role in the creation of a scientific model, it is not the lone consideration. This led to one conception of the epistemology of computer simulated models: Verification and Validation.

Verification is the process of determining if the output of the computer simulated model approximates the solution to the original question that was being modeled. Validation is the process of determining if the model is a proper representation of the real world system being modeled. As Winsberg argues, "In validation you have to determine

[22] Winsberg, Eric. *Science in the Age of Computer Simulation*. Chicago: The University of Chicago Press, (2010): 16
[23] Ibid

whether you have chosen the right model […] in verification you have to determine whether you have found good solutions to that model".[24]

While verification and validation do provide a process for testing models against some type of empirical truth, there is some debate over whether actual computer simulated models in use really follow this model. This conception of computer simulated models attempts to place the results of the models against an empirical truth. Many models, however, serve a purpose that separates them from this type of framework. Winsberg proposes that, instead of utilizing the verification and validation epistemology, one should instead look to the epistemology of scientific experiments. Specifically, he believes that one can learn a good bit from how scientists come to view their experiments as rational. While there is no exhaustive list of the steps taken by scientists to find their experiments rational, simulationists do know that, over time and through the process of applying their experimental results to scientific problems, scientists do learn the best practices by which to evaluate their experiments.

It should also be stated that a rational belief in an experiment does not mean that the experiment guarantees the truth of the knowledge produced.[25] For those who would argue that simulations and experiments differ in their epistemological weight, specifically that experiments have a higher epistemological weight than simulations, this argument is highly determined by the context of the simulation. Emily Parke has argued that, in many ways, the privilege given to experiments over simulations is due to the inference that being more materially similar to the target phenomena leads to a better understanding of the phenomena. She argues that this inference might not be as sound as it first appears

[24] Ibid: 19
[25] Ibid: 20

and that in certain contexts simulations can have equal epistemological value to experiments.[26]

Michael Weisberg's notion of model construal might also help to better understand the relationship between a model and how it is to be interpreted. The construal of a model involves what Weisberg calls assignment and fidelity. Assignments are "explicit specifications of how parts of real or imagined target systems are to be mapped onto parts of the model".[27] Fidelity is "how similar the model must be to the world in order to be considered an adequate representation".[28] By articulating these two parts of a model, the researcher is able to express the bounds by which the model can be seen as useful. Fidelity, in particular, is useful for this discussion since it focuses on the tolerances that a model has. If a researcher states that this model needs to be within ten percent of the actual values, then one has a sort of benchmark by which to judge the model.[29]

By not attaching the success of a model to its ability to produce Truth, one allows for models to serve a more pragmatic role. It is in this vein that Winsberg argues that "A central conclusion that I would like to draw from what follows is that these strategies are best understood as being aimed at providing grounds for belief that a simulation provides reliable information about the real-world system being simulated."[30] This idea that computer simulated models are reliable is one that is essential to understanding the true value and purpose of computer simulated models. Winsberg defines reliability of models

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[26] Parke, Emily C. "Experiments, Simulations, and Epistemic Privilege." *Philosophy of Science 81*, no. 4 (2014): 516-536.
[27] Weisberg, Michael. *Simulation and similarity: Using Models to Understand the World*. Oxford University Press, (2012): 40
[28] Ibid: 41
[29] Ibid
[30] Ibid

by saying “I characterize reliability (for modeling principles) in terms of being able to produce results that fit well into the web of our previously accepted data, our observations, the results of our paper-and-pencil analyses, and our physical intuitions, and to make successful predictions or produce engineering accomplishments”.[31] This is the definition that this thesis will continue to refer to when describing a model as reliable.

In order to sanction a model as reliable, one must devise a way to test its reliability. This process involves both testing the reliability of the machines that are running the computer simulated model as well as testing the model itself. To test the accuracy of the machines, it is normal for the computer simulated model to be run on multiple computers, often with different components. This process is part of what Ryan Muldoon calls Robustness. The robustness of a computer simulated model comes from its ability to be confirmed through a community of users. Much like scientific experiments, which often must be verified by multiple labs to be considered confirmed, computer simulated models go through a similar process by being tested on different computers running different operating systems and using different components.[32] Another process normally done is called benchmarking. The process of benchmarking involves testing the outcomes of a computer simulated models against known data from the phenomena that is being modeled. Benchmarking a computer simulated model is similar to the process of calibrating a scientific tool.[33] The process normally tests the results of the model against already known data. While this data can come from a variety

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[31] Winsberg, Eric. *Science in the Age of Computer Simulation*. Chicago: The University of Chicago Press, (2010): 133
[32] Muldoon, Ryan. "Robust simulations." *Philosophy of Science 74*, no. 5 (2007): 873-883.
[33] Winsberg, Eric. *Science in the Age of Computer Simulation*. Chicago: The University of Chicago Press, (2010): 22

of places, the most useful data comes from empirical observations. For many computer simulated models, this is easily accomplished; that being said, an advantage that computer simulated models have over traditional experiments comes from their ability to produce data when empirical data is not easily obtained. For example, if one was to model how much damage a hurricane would cause if it hit a city, most would rather not allow a hurricane to hit a city in order to gather this data. This is often because the very motivation for figuring out what might happen is to prevent as much damage as possible.

To benchmark a computer simulated model of a hurricane hitting a city, one might first try and simulate the results of a hurricane that had already happened. Therefore, one would build a computer simulated model of a city that has been hit by a hurricane in the past as well as one of the hurricane that hit it. One would then run the simulation of the hurricane hitting the city and see if the known effects occur. If, after multiple runs, the computer simulated model is producing the effects expected from the simulation, it can then be said that the computer simulated model is reliably producing the phenomena. Of course, one would want to attempt this process multiple times with as many known examples as possible. If the computer simulated model properly exhibits all of the known events then one can say one has created a reliable computer simulated model of hurricanes hitting cities. With this model, one could now attempt to model a situation that has not happened, for instance a category 5 hurricane hitting New York City. With this model, one could generate predictions of the amount of damage and maybe even more specifically what type of damage would be done. This information could then be used to design a plan to prevent as much damage as possible. In this example, one can see how the computer simulated model is never disconnected from its practical purposes.

Benchmarking is normally the first step within the process of creating a reliable computer simulated model. Benchmarking can help one make sure that his/her model is properly representing the system in question. In science, though, nothing can be more supportive in the sanctioning of a model than its ability to properly predict future events. A good example of this is the discovery of the planet Neptune. The model in question here is the model of Newtonian physics, so it is a bit different than computer simulated models, though the similarity in the power of prediction holds true for both. In the case of Neptune, its discovery was first spurred on by irregularities in the orbit of Uranus. With only seven planets accounted for, Uranus was not following the correct orbit determined by gravitational forces. It was from this irregularity that it was predicted that another object must exist outside of the orbit of Uranus that was disturbing its orbit. Once the math was worked out and the scientists applied their new hypothesis to the known data, they were able to both predict where in space this object should be as well as an approximation of its mass. Sure enough, when they went to look for Neptune, it was exactly where it was expect to be. This ability to predict help build confidence in Newtonian physics as a reliable model by which to understand the universe.

It is important to see that computer simulated models are rarely in a state of being finished or complete. As stated earlier, computer simulated models are a process that is connected to a greater process: science or the process of human inquiry in general. As such, progress that is made in one area of inquiry can often have a positive effect on other areas. A historical example of this would be the influence of the Copernican model of the solar system on Bohr's model of the atom. It is easy to see how the representations from one area can help support a breakthrough in another area. This type of 'borrowing' can be seen in computer simulated models as well. There are many examples of a model being repurposed for another task. Humphrey's gives us some examples:

> Percolation theory (of which Ising models are a particular example) can be applied to phenomena as varied as the spread of fungal infections in orchards, the spread of forest fires, the synchronization of firefly flashing, and ferromagnetism. Agent-Based models are being applied to systems as varied as financial markets and biological systems developing under evolutionary pressures.[34]

As can be seen, computer simulated models are dynamic in their very nature. Even within a single instance of a model, it might be revised hundreds of times to either account for new empirical data or to have new uses added to it. At a more discrete level, it is common practice to utilize a segment of code from a model that is accomplishing a specific aim. For instance, in an agent-based model that is attempting to model the spread of AIDs, there might be a segment of code that accomplishes the act of finding a partner. It would be possible that another scientist looking at molecular bonding might utilize that same code segment, since the basic phenomena of finding a partner is similar enough to be accomplished by the same segment of code. In this way, it is hard to really measure the value of a computer simulated model, since even its discrete parts might find value outside of its original scope.

In this discussion, of the epistemology of computer simulated models, it is important to understand that this perspective comes from the pragmatic notion that views science as a process. This process is not guided towards the revealing of absolute truth but instead is focused on the ability to reliably solve problems that humans encounter. In

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[34] Humphreys, Paul. *Extending Ourselves: Computational Science, Empiricism, and Scientific Method.* New York: Oxford University Press, (2004): 70

this view of science, it is not the abstract or theoretical issues that move science but the practical ones. Theoretically, Copernicus's view of the solar system was much harder to support than Ptolemy's. The fact that Copernicus had to explain how it was possible for the earth to be spinning and yet have humans not experience this motion was almost impossible to explain without a robust theory of momentum and more importantly gravity. As such, it was not until Kepler and later Newton that the idea of a central sun and orbiting earth was theoretically explainable. That being said, Copernicus' theory was widely accepted long before the theoretical explanation was found.[35] What this example shows is that it is not absolute truth that guides science but its ability to solve practical problems. It is in this pragmatic structure that computer simulated models are developed.

The importance of taking a pragmatic perspective of science is due to a number of reasons that will be addressed formally in a later section; however, one specific reason that should be addressed now is the deemphasizing of computational power within computer simulated models. While increases in the computational power of computers has aided in are ability to solve problems that were previously unsolvable, the ability to compute complex problems is only one facet of computer simulated models. The concern with placing too much weight on the computational ability of computers (and therefore computer simulated models) is that one might abuse the ability to solve complex mathematical equations instead of searching for a different or maybe more robust yet simpler theory that would not require the same amount of computational power. Humphreys brings up this concern through the envisioning of what would have happened if Kepler had access to the computational power we have today. The fear is

[35] Kuhn, Thomas S. *The Copernican revolution: Planetary astronomy in the development of western thought.* Vol. 16. Harvard University Press, (1957): 261

that instead of searching for an elegant solution to the issue at hand, Kepler could have simply entered Tycho's data into a computer simulated model and found a model for the orbit of the planets while staying within the paradigm of epicycles used by both the Copernican and Ptolemaic models.[36] Just because computers have the power to solve complex problems does not mean that relying on these complex solutions as the basis of a scientific theory is a good idea. There has always been weight put behind the elegance of a theory. Occam's razor states that, when deciding between two theories, if all else is equal, the theory with the fewest required assumptions should be given more credence. In a similar vein, a theory that does not require the computational power of a computer to resolve its complexities should be given more weight than a theory that must rely on a computer. This is why computer simulated models that are not simply computational or mathematical but instead focus on the application of complex adaptive systems, such as Artificial Neural Networks and Agent-Based Models, are preferred.

While this thesis is focused on computer simulated models as a tool for philosophers and this section has focused on computer simulated models in regards to their effect on science, their usefulness is something that can transcend these two disciplines. If one takes the perspective that allows for science and philosophy to both be seen as different human enterprises of inquiry, both with the similar aim of addressing the concerns and ambitions of humans, then one can start to see how the acceptance and usefulness of computer simulated models in science might apply to their ability to be useful for philosophers. Some possible arguments against this point could include: science and computer simulated models are reductionist and philosophy has aimed at a

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[36] Humphreys, Paul. *Extending Ourselves: Computational Science, Empiricism, and Scientific Method.* New York: Oxford University Press, (2004): 134

more holistic perspective; computer simulated models could only be used in specific areas of philosophy, such as philosophy of science and philosophy of mind; and the time it would take to train a philosopher to learn how to use computer simulated models would be prohibitive.

In regards to the first of these arguments against computer simulated models in philosophy, it can be agreed that, at times, science has been reductionist. In physics, for instance, there is a race to find the smallest particles in hopes that, by understanding the building blocks of the universe, we can explain the phenomena that we experience. In the same regard, computer simulated models can also exhibit reductionist tendencies. Agent-Based Models are often built through the modeling of the smallest agents in order to explain meta-level phenomena. The fear that some philosophers might have with this approach is that it can lead to the ignoring of important meta-level phenomena. For instance, we know that emotions are caused by electro-chemical processes in the brain. It can be argued that, by understanding these processes, we can better understand human emotions. The issue is that we already have useful knowledge of emotions through psychology and the qualitative studies of behavior. We should not throw out this knowledge just because a study of the biochemical reactions is more fundamental.

While the fear of reductionism is valid and should not be ignored, it is false to claim that computer simulated models are innately reductionist. One of the benefits of computer simulated models is their ability to model emergent properties. With computer simulated models, modelers have the opportunity to study both the elemental and the meta-level interaction of the systems chosen. With computer simulated models, the goal has always been to understand systems as a whole and to not focus simply on the least common denominator. It is for this reason that computer simulated models can aid philosophers. They are some of the first scientific tools that are able to model and represent the complex types of phenomena in which philosophers have always been interested.

To respond to the argument that computer simulated models are only applicable in certain fields of philosophy, such as philosophy of science and philosophy of mind, Agent-based models have been used in many fields, including sociology and anthropology. There have been political models built using computer simulated models to study voter behavior and segregation. The example of the prisoner's dilemma has been used in cellular automata to investigate ethical decision making and choices. Just because the majority of models built have been done so for scientific purposes does not mean that the platform is limited to science. The real need is to get these tools into the hands of non-scientists and see what they can come up with. This leads into the last argument.

Many people might argue that the learning curve to understanding how to program and then use computer simulated models is quite high. This step learning curve might discourage philosophers from picking up these new tools and applying them to their work. Most philosophers spend decades learning how to hone their craft in the traditional methods that are taught within philosophy. Many do not have the time to learn how to program and use these new computer simulated models. The response to this line of thinking is that, while computer simulated models are new and unorthodox to many philosophers, the learning curve is neither more nor less steep than the learning curve for more traditional philosophical methods. With programs like NetLogo, Matlab, and

Swarm, which focus on being simple to use and learn and are full of detailed tutorials, the barrier to entry is slowing coming down. More importantly, as this thesis has articulated, the process of learning how to model itself can be as useful as the final product. This thesis is not aimed at replacing any traditional philosophical methods but instead augmenting said methods. By using mixed methods and utilizing the benefits of computer simulated models while retaining the traditional methods, philosophers have more options in regards to how they approach philosophical problems.

The next section will go into more detail concerning exactly how computer simulated models relate to methods with which philosophers are already familiar. The key point to remember is that computer simulated models are a process that exists within the larger process of human inquiry a place where both philosophy and science reside.

PAST AND CURRENT PHILOSOPHICAL METHODS

In order to properly articulate how computer simulated models can aid philosophers, it is important to understand what philosophers have attempted to accomplish. By taking a look at the methods of past philosophers, as well as an example of a current philosopher who is already using computer simulated models as a part of his philosophical method, one might have a better understanding of what philosophers aim to achieve. In analyzing philosophical methods, the focus will be on the aim of the method as well as the method itself.

The first method to look at is that of Plato within the Socratic dialogues. Specifically at the Euthyphro, to uncover what Socrates attempts to accomplish within that text. In the Euthyphro, Socrates asks the question: what is Piety? Socrates approaches Euthyphro, a priest, in hopes of uncovering what Piety is. This is being spurred on by the fact that Socrates is being charged with being impious. In order to argue against this claim, Socrates hopes that in finding out the meaning of Piety he might be better able to address the charge against him. The Dialectical Method is applied through a dialogue where specific questions are asked in hope of revealing a robust definition or concept. In the example of the Euthyphro, the aim is to uncover what it means to be pious. With each exchange, the implicit contradictions that existed within Euthyphro's understanding of Piety become explicit. During the dialogue, Euthyphro gives multiple definitions for what is pious and with each new definition Socrates finds it to be inadequate or inconsistent with the previous understandings that Euthyphro had given. It should be noted Socrates found them inadequate because none of the definitions gave him what he is looking for: An understanding of Piety that can be applied to different actions to categorize them as either pious or impious. While the analysis of the concept of Piety might seem theoretical in nature for Socrates, this was, in fact, a quite practical endeavor. In the Euthyphro, Socrates is preparing to clear his name by showing that the actions he performed do not fit within the concept of impiety. The Dialectical Method's aim is to reveal the inadequacies and inconsistencies of the concepts that one holds. Through this one becomes more aware of what is not known or more specifically why one does not know what one thought one might know.

Moving forward in time to the twentieth century, one of the dominate methods in philosophy is Conceptual Analysis. The basic idea of Conceptual Analysis is to break down and analyze the language one uses in hopes of creating a better understanding of the meaning of the words one says. This basic premise has been applied in a multitudes of ways by different philosophers throughout the twentieth century. As mentioned earlier in this thesis, Sloman brings up Conceptual Analysis as one of the areas that can see overlap of science, philosophy, and computers.[37] Sloman argues that, "Every science will have at its frontiers concepts which are to some extent in need of analysis and possibly improvement".[38]

One of the first philosophers to discuss the method of Conceptual Analysis was Bertrand Russell. Russell is one of the philosophers who argues for an Ideal Language. What Russell wanted was a language built for the purpose of logic and philosophy that would remove the philosophical defects that can be found in ordinary language.[39] The

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[37] Sloman, Aaron. *The Computer Revolution in Philosophy: Philosophy, Science and Models of Mind*. Hassocks: The Harvester Press, (1978): 100
[38] Ibid: 99-100
[39] Black, Max. "Russell's Philosophy of Language." In *The Linguistic Turn*, edited by Richard M. Rorty, 136-146. Chicago: The University of Chicago Press, (1992): 138-139

philosophical defects being ambiguities and contradictions within ordinary language. This is normally accomplished through the translation of ordinary language. The aim being that through translation from ordinary language to an ideal language we can reveal the true meaning of the statement. This translation can also reveal any contradictions or metaphysical dilemmas that might have existed in the ordinary language.[40] Russell's Ideal Language is also atomistic in its nature. The aim is to break down language to its smallest parts in order to better understand the whole. Similar to the Dialectic Method, the aim of Russell's Conceptual Analysis is to uncover the meaning of the concepts that one uses. The difference is that the Dialectic Method works through dialogue and asking questions while Conceptual Analysis deals with breaking down language and sentences.

Russell's Conceptual Analysis focused on the creation of an ideal language. Other philosophers have argued against the need for an ideal language and instead feel that ordinary language is robust enough to be analyzed on its own. One of these philosophers is Wittgenstein. While early in his life Wittgenstein did argue for an ideal language… later in his life Wittgenstein changed his position. Wittgenstein introduces the idea of a language game in his work titled *Philosophical Investigations*. The language game shows how ordinary language is able to avoid the pitfalls that Russell believed existed within it. Wittgenstein states that if one thinks about all of the activities that one calls games: what do they all have in common? He believes the answer is not something specific to all of them but they do share similarities across the board. He refers to this phenomena as family resemblance.[41] For Wittgenstein, all games share a

[40] Ibid
[41] Wittgenstein, Ludwig. *Philosophical Investigations*, 4th ed., trans. G. E. M. Anscombe, P. M. S. Hacker, and Joachim Schulte. New York: Wiley-Blackwell, (2009):36

family resemblance. While they are all different they do share some characteristics in common with one another. It is in this state of similarities that our language exists. Games like language have rules and we learn these rules in order to properly play the game. While all games have rules they do not all share the same rules. Part of understanding the game is to understand the rules. It is in cases where the rules are misinterpreted that confusion exists. This is the same for language. It is not the structure of ordinary language that causes confusion but lack of understanding of the specific “language game” that causes confusion. Wittgenstein believes there are a number of different “language games” that exist. Wittgenstein articulates this point by stating:

> But how many kinds of sentence are there? Say assertion, question, and command?—there are countless kinds: countless different kinds of use of what we call "symbols", "words", "sentences". And this multiplicity is not something fixed, given once for all; but new types of language, new language-games, as we may say, come into existence, and others become obsolete and get forgotten. (We can get a rough picture of this from the changes in mathematics.) Here the term "language-game" is meant to bring into prominence the fact that the speaking of language is part of an activity, or of a form of life.[42]

It is through these language games that ordinary language is able to have its meaning. By understanding the language game at work, one can then understand the meaning of an utterance. This removes the need to create an ideal language. While the focus is no longer on the creation of an ideal language, the focus remains on the ability to extract meaning from a sentence. In language games the meaning of a word is relative to the language game that it is associated with. One is no longer attached to the idea that a single word or concept must have a single meaning.[43]

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[42] Ibid: 14-15
[43] Ibid: 41-42

Up to this point all of the methods that have been discussed center around the need to uncover the true meaning of a concept. While they do this in different ways, each is attempting to uncover a truth about the world. This is something that these method do not have in common with computer simulated models. Computer simulated models attempt to capture a reliable understanding of the world but not the absolute understanding. They do, however, have in common the goal of uncovering hidden meaning and understanding. In the process of programming a computer simulated model, the programmer must articulate the phenomena in a way that the computer can recognize. Computers function through the use of symbolic representations. Most programming languages extensively use expressions such as ‘if and only if’, ‘or’, ‘and’, ‘while’, etc. These are all acceptable ways of expressing a relationship to a computer. This type of language, it could be argued, is a form of ideal language. Computer languages cannot handle ambiguity. Not only is the language of computer simulated models similar in form to the type of ideal language Russell was after, but the process of converting ideas into code can have the same revealing nature. Often times, when a programmer is forced to represent a phenomena in code, it forces the programmer to be aware of all assumptions and deviations from the ideal that must be made. As stated earlier, often times a computer simulated model is only partially reliant on the underlying theory. Assumptions or approximations must be made for practical purposes.

The metaphysical assumptions of the philosophical methods that were discussed differ from the metaphysical assumptions of computer simulated models. While that is true for the examples that were given, not all philosophers believe that Conceptual

Analysis must lead to an understanding of anything real. Rorty believed that the work of Davidson helped to free the analysis of language from this metaphysical bond.

> The term “experience” as used by philosophers Kant and Dewey, was, like Locke’s term “idea,” ambiguous between “sense-impression” and “belief.” The term “sentence,” used by philosophers in the Fregean tradition, lacks this ambiguity. Once the philosophy of language was freed from what Quine and Davidson call “the dogmas of empiricism” with which Russell, Carnap, and Ayer (though not Frege) had entangled it, sentences were no longer thought of as expressions of experience nor as representations of extra-experiential reality. Rather, they were thought of as strings of marks and noises used by human beings in the development and pursuit of social sciences—practices which enabled people to achieve their ends, ends which do not include “representing reality as it is in itself”.[44]

Rorty’s understanding of language now fits nicely with the epistemology that is consistent with what computer simulated models aim to do. Both Conceptual Analysis and computer simulated models are aimed at providing humans with a better understand of the world, not so to uncover any Truth, but to help achieve specific and practical goals.

While most philosophers have not applied computer simulated models to their philosophical method, there are some who have. Paul Churchland has applied Artificial Neural Networks to further his philosophical claims about the nature of the human mind. Churchland uses Artificial Neural Networks, which are one type of Computer Simulated Models. Artificial Neural Networks attempt to model the functional behavior of our own neurons.

Neurons function by having both inputs and outputs. Our brain is estimated to have around 100 billion neurons and 100 trillion synaptic connections.[45] The neuron has three main components: the dendrites, which receive the electrical signals from other

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[44] Rorty, Richard M. “Twenty-five Years After.” In *The Linguistic Turn*, edited by Richard M. Rorty, 371-374. Chicago: The University of Chicago Press, 1992.

[45] Churchland, Paul M. *The Engine of Reason, the Seat of the Soul*. Cambridge: The MIT Press, (1995):

neurons; the cell body; and the axon, which is what connects the output of the neuron to the inputs of other neurons. When the neuron receives stimulus through its dendrites, it sums up this signal and then sends out a corresponding stimulus through the axon to other neurons. This creates a chain reaction which one experiences as cognitive activity. Artificial Neural Networks attempt to mimic this behavior. They also have inputs and outputs and are interconnected. The connections between nodes have weights attached to them. This represents the activation levels that neurons exhibit. Churchland's argument is: By developing a system that can functionally mimic the brain, one is better able to understand how it is that the brain can form concepts, morals, memories, and any other cognitive phenomena. It should be note that this is a bottom-up approach to cognition. Churchland believes that all human cognition can be explained through the bottom-up process of network formation.[46] This idea is at odds with Chomsky's Nativism. The Nativist perspective holds that many human functions are top-down in nature and exist from birth.

For Churchland, Artificial Neural Networks are simply a tool that allows one to see how the brain works at an elementary level. The Artificial Neural Networks provide a model to work with and build from. Many of the claims that Churchland makes cannot be currently performed with actual human minds it also serves a practical purpose. So when Churchland is able to see the emergence of concepts from the output of the Artificial Neural Networks he is able to state that perhaps the human mind creates categories in a similar way. The functional relationship between the Artificial Neural Network and our actual brain allows for a two way street of influence. Not only can we

[46] Ibid

apply what is learned from Artificial Neural Networks to our own minds but we can also take theories that we have about how the brain works and test them through the Artificial Neural Networks.

One example of a philosophical debate about the nature of the mind that can be investigated using Artificial Neural Networks is the argument over Nativism versus Empiricism. This argument revolves around what concepts, if any, people are born with. A Nativist would argue that one is born with the most basic concepts and from there are able to learn more about the world. An Empiricist believes that one is born with simply the ability to learn and from there is able to acquire all of the required skills. This debate is commonly used to discuss the nature of human language.

Churchland considers himself an Empiricist and believes that Artificial Neural Networks can give an example of how humans can learn without needing innate concepts or abilities. Up until this point all of the Artificial Neural Networks that have been discussed use a training set and backpropagation in order to learn. This method is inadequate for explaining how humans can learn without innate abilities. Churchland agrees with this but believes that another type of training, called Hebbian learning, might be the answer. Churchland states:

> In biological creatures the process of experience-dependent long-term adjustment of the brain's synaptic connections is defiantly not governed by the supervised back-propagation-of-errors technique widely used to train up our computer-modeled artificial networks. That brute force artificial technique requires that the 'correct behavior' for a mature network be known in advance of any learning activity, in order that subsequent synaptic changes can be steered by the explicit goal of reducing the degree of error that separates the student network's actual behavior from the optimal behavior that this supervised technique seeks, stepwise, to impose upon it. But biological creatures have no such advance access to "the right answers," and they have no means of applying such information, to each synapse one-by-one, in any case. Synaptic change in biological creatures is

> apparently driven, instead by a process called *Hebbian learning*, in honor of the psychologist Donald O. Hebb, who first described the process.[47]

The Hebbian process is achieved by strengthening the synaptic connection between neurons that tend to fire together. Churchland uses the example of " Roughly, whichever subset of synapses happen to 'sing' *together*, when and if they do sing, subsequently have their individual 'voices' made permanently louder".[48] Here the neurons that sing together are the ones that fire together.

With Hebbian learning it is possible to build Artificial Neural Networks that are able to learn without the need of outside training. Churchland creates an example of an Artificial Neural Network trained using a Hebbian learning method that is able to predict the next instance in a sequence. This means the network has learned to identify simple patterns through a Hebbian process. While this is not conclusive evidence for Empiricism, this type of work can help support an Empiricist claim that it is possible for the mind to learn basic rules and concepts that might otherwise be thought of as native through a process similar to the Hebbian networks. As such this serves as an example of how computer simulated models can aid in philosophical issues.

While Churchland serves as a great example of a philosopher using computer simulated models he claims to be a scientific realist. Churchland seems, at first, to serve as a counter-example for the case that will be made about pragmatism being a useful foundation for computer-simulated models within philosophy. If we look closer, however, at the works of Churchland, we can find that he can actually help to show the importance of pragmatism to computer simulated models.

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[47] Churchland, Paul M. *Plato's Camera*. Cambridge: The MIT Press, (2012): 157
[48] Ibid: 158

Churchland's argument for scientific realism over pragmatism stems from his belief that "If, on the other hand, we choose to *define* "truth" or "representational virtue" directly in terms of pragmatic success - as in "the true is what works"-we deny ourselves all access to an evidently rich domain of potential explanations".[49] What Churchland believes is lost is the ability to understand "the world of things-in-themselves".[50] His dismissal of pragmatism hangs on his belief that we actually do conceptualize reality.

The method by which humans are able to represent reality is through the convergence of what Churchland calls our "High Dimensional Mental Maps".[51] Churchland describes this process:

> First, and *pro tem*, we can take the integrity of our current maps for granted, and then seek to understand and evaluate the cognitive strategies, tactics, and maps of other creatures like ourselves, both biological and artificial. Second, and lifting the *pro tem* assumptions just mentioned, we can play our several native cognitive maps off against one another in their areas of mutual overlap, progressively modifying each map in response to the need to maintain consistency and consilience across the form of our scientific theories, maps that get fleetingly indexed by measuring instruments above and beyond the humble biological senses bequeathed to us by the human genome. These theories can also be evaluated for representational accuracy, both by unfolding quality of the pragmatic world-navigation that they make possible, and by the straightforward comparison of several distinct but overlapping maps with one another, in pursuit of mutual criticism, modification, and potential unification.[52]

Churchland is saying that, by comparing one's overlapping cognitive maps, one somehow converges on reality. An objection to that point is that one's mental maps are still cognitive in nature. While different people's maps might overlap with one another the overlap is still cognitive in nature. Churchland still has yet to show that our cognitive

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[49] Ibid: 134
[50] This is referring to the Kantian notion of a "thing in itself"
[51] Mental maps are akin to our cognitive concepts. Churchland argued that neural networks can cause a bottom up process that results in the emergence of concepts. He refers to this process as the creation of mental maps.
[52] Ibid: 137-138

maps represent or “map on” to real objects. With that important detail missing, his claim looks to be pragmatic. Churchland himself states “Its cartographical metaphors withstanding, the reader will recognize in this inescapable lesson the familiar Pragmatist’s criterion for the evaluation of our cognitive commitments”.[53]

All philosophical methods have the aim of better understanding the world around us. Whether it is understanding the meaning of a concept like Piety, or understanding the meaning of a sentence, or understanding the workings of our minds, all philosophical methods hope to aid in our understanding of the world. Computer simulated models have been built to continue this endeavor. Some believe that our better understanding comes from actually uncovering some underlying truth about the world. If however, we do not go down the path of realism, but instead focus our efforts on the reliability of our ideas and not the Truth of them, computer simulated models might prove to be a useful companion to philosophers.

[53] Ibid: 128

PRAGMATISM AS A FRAMEWORK FOR PHILOSOPHY AND SCIENCE

In order to see the value of computer simulated models to philosophers, it helps that one holds certain views on truth and the role of science. These views are best articulated by pragmatists such as William James, Charles Peirce, and John Dewey. James helped to define pragmatism as a method and developed a robust understanding of truth that was dynamic and temporal.[54] James, however, does not go into detail about the application of science and its methods to be everyday lives. It is Dewey who better articulates how science comes to affect our lives and how we use science as a tool to better our lives.

William James was the first to really outline in detail what pragmatism meant. He gave credit to Charles Peirce as the first to introduce pragmatism to philosophy. James continually cites Peirce and it is clear that much of James' interpretation of pragmatism is due to his understanding of Peirce. That said, it was James who defined what it meant to solve a problem pragmatically. The key for James was that we must interpret the practical consequences of metaphysical problems.[55] James states that "it is astonishing to see how many philosophical disputes collapse into insignificance the moment you subject them to this simple test of tracing a concrete consequence. There can be no difference anywhere that doesn't make a difference elsewhere." He goes on to comment that the aim of philosophy is to identify how practical consequences affect the lives of ordinary people.[56]

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[54] James, Williams. *Pragmatism*. Los Angeles: Indo-European Publishing, (2010): 20
[55] Ibid: 22
[56] Ibid: 23

For James, science can now play an important role in explaining the phenomena that exists around us. A scientific realist might argue that eventually one might resolve the metaphysical questions that one has about the world. The goal would be to uncover some absolute reality. This idea is absurd to James. He thought that, with science, one would no longer search for some absolute reality but instead simply attempt to understand the world as it exists today. James believes scientific theories are instruments, not answers. They are tools that aid in our progress forward toward better understandings.[57]

James not only gives a new method with which to approach philosophy, but he also redefines truth in pragmatic terms. James says, "True ideas are those that we can assimilate, validate, corroborate and verify. False ideas are those that we cannot… the truth of an idea is not a stagnant property inherent in it. Truth happens to an idea. It becomes true, is made true by events. Its verity is in fact an event, a process: the process namely of its verifying itself, its verification. Its validity is the process of its validation".[58] This conception of truth is one that is better equipped to deal with the dynamic nature of the world we live in and more specifically the dynamic nature that computer simulated models fit into. James' construction of truth also goes one step further. James makes the claim that what is useful is true and what is true is useful.[59]

James uses the terms verification and validation in reference to the process that truth finds itself within. It should be noted that those same terms are used to test computer simulated models. As mentioned in an earlier section, Verification for

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[57] Ibid
[58] Ibid: 87
[59] Ibid: 88

computer simulated models refers to how the model represents the world it is modeling and Validation refers to the mathematical foundation the model is built upon. James holds a different meaning for these terms. A meaning that actually might be more useful within the modeling community than the one we currently use. For James: truth, verification, and validity are intertwined with one another. James states, “True is the name for whatever idea starts the verification-process, useful is the name for its completed function in experience”.[60] From this perspective, it can be seen that verification is the process that leads from an idea to its eventual point of becoming useful. Here verification is not simply a test for correspondence between two representations but is a process that has at its end the aim of creating a useful understanding. This is what computer simulated models accomplish when they are verified. A verified model should be seen as a useful tool for understanding whatever phenomena it was built to explore. Validity for James is simply the process of verifying an idea. It does not attach itself to the analytical understanding used within the modeling community, of having proper mathematical equations, but is again involved in the process of truth.

Detaching validity and validation from absolutes enables them to become more in line with the function of computer simulated models. Computer simulated models are processes themselves and do not aim to come to an absolute understanding of the world but instead simply aim to help mankind solve specific problems. If one views computer simulated models as tools or instruments that aid in solving problems then their true value can be realized. This is an idea that is best articulated by John Dewey. In fact, in many ways, it is Dewey’s interpretation of pragmatism that allows for the best understanding of

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[60] Ibid

the role computer simulated models can play in the aiding of both science and philosophy.

Dewey used the term Instrumentalism to refer to his philosophy. Instrumentalism involves putting ideas to work and using them like instruments to solve genuine problems.[61] One of the areas that Dewey focused on was the act of inquiry. Dewey constructed a view of inquiry that began with the encountering of a practical problem, a perplexing situation, or general conflict and leads to the resolution of said problem. Inquiry was focused on addressing indeterminate situations and making them determinate.[62] Inquiry is also a process that seems to never end. This sentiment is drawn from Peirce's doctrine of Fallibilism. Fallibilism is "that all beliefs, no matter how certain they may seem, are subject to revision as a consequence of the results of further inquiry".[63] It can be said that all three pragmatists: Peirce, Dewey, and James; share in the idea that inquiry is a process that exists in time. It is a process that is ongoing and focuses specifically on the issues that affect people in the moment. While inquiry spans across all time in discrete moments, it is grounded in the endeavors of humans for that moment.[64] This idea fits nicely with computer simulated models since they too are caught within a process with no predetermined end. A computer simulated model has the ability to be modified over time and adapted to either new empirical information found or even

[61] Hahn, Lewis E. "Dewey's Philosophy and Philosophic Method." In *Guide to the Works of John Dewey*, edited by Jo Ann Boydston, 15-60. Carbondale: Southern Illinois University Press, (1970): 22

[62] Dewey, John. *Logic: The Theory of Inquiry*. New York: Saerchinger Press, 2007.

[63] Peirce, Charles Sanders. "How to make our ideas clear." *The Nature of Truth: Classic and Contemporary Perspectives* (2001): 193-209.).

[64] Hahn, Lewis E. "Dewey's Philosophy and Philosophic Method." In *Guide to the Works of John Dewey*, edited by Jo Ann Boydston, 15-60. Carbondale: Southern Illinois University Press, (1970): 85

to an entirely new application. It is able to adapt to the constant change that inquiry, as pragmatically constructed, brings.

Dewey claimed the aims of philosophy were to “render ordinary life-experiences and their predicaments more significant and luminous to us and make our dealings with them more fruitful”.[65] Not only does Dewey expand on the process of inquiry but he redefines the aim of philosophy and science and places them more in touch with the aims of ordinary people. In regard to science, Dewey sees the activity of science not as acts done by any one individual scientist but as the acts done by a community of scientists. The key being that the scientific method works because it can be repeated and tested multiple time by multiple scientists, and only when a consensus is reached can it be said that we have knowledge. This conception of the scientific method works nicely with computer simulated models since they are designed to be run and rerun. They work by aggregating data over multiple runs. They also are designed to be easily picked up by other scientist and tested themselves. Just as Dewey argues that knowledge is only reached through a consensus of people, the value of computer simulated models comes from a similar consensus that is reached over time, as the model justifies itself through the production of useful data. This also refers back to the notion of robust models. As Muldoon argues, the robustness of a computer simulated model is gain through the widespread use of them within a community.[66] Dewey also comments on the distinction between pure and applied sciences.

The pure sciences are often thought of as being higher or more prestigious. A realist might even claim that they aim to understand reality at its core. Applied sciences,

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[65] Dewey, John. *Experience and Nature*. New York: Dover Publications, Inc., (1958): 7
[66] Muldoon, Ryan. "Robust simulations." *Philosophy of Science* 74, no. 5 (2007): 883

such as engineering or medicine, deal with the immediate problems of a practical nature. They deal with solving the problems of humanity and not uncovering the workings of the universe. It has been known that applied sciences often deal with terms such as "best practices". They deal with tolerances and approximations that intentionally shy away from absolutely precise understandings. That is not to say that they don't care about precision but instead that they care more about the practical implications then the theoretical implications. For example, a civil engineer building a bridge might intentionally build the bridge to withstand a load higher than it will ever encounter. This is because the risk of the bridge collapsing is greater in value than whatever cost savings they could gain from using less material. While some people would say that engineering is less of a science than physics, Dewey argues the opposite.

> What is sometimes termed "applied" science, may then be more truly science than what is conventionally called pure science. For it is directly concerned with not just instrumentalities, but instrumentalities at work in effecting modifications of existence in behalf of conclusions that are reflectively preferred. Thus conceived the characteristic subject-matter of knowledge consists of fulfilling objects, which as fulfillments are connected with a history to which they give character. Thus conceived, knowledge exists in engineering, medicine and the social arts more adequately than it does in mathematics and physics. Thus conceived, history and anthropology are scientific in a sense in which bodies of information that stop short with general formulae are not.[67]

This point is key because computer simulated models are traditionally seen as an applied method of science. Sloman would also support this claim as he said: "the pure scientist needs to behave like an engineer: designing and testing working theories. The more complex the process studies, the closer the two must become. Pure and applied science merge. And philosophers need to join in".[68] By taking Dewey's point to heart, we see

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[67] Dewey, John. *Experience and Nature*. New York: Dover Publications, Inc., (1958): 161-162
[68] Sloman, Aaron. *The Computer Revolution in Philosophy: Philosophy, Science and Models of Mind*. Hassocks: The Harvester Press, (1978): 16

that, in many ways, the applied methods are more valuable to man than the theoretical methods. Computer simulated model's value to philosophy is best realized by defining science and the role of philosophy as Dewey does. By taking an Instrumentalist approach to computer simulated models, we can clearly see how interpreting them as practical tools is more beneficial than trying to interpret them as truth-seeking representations. A point that is further supported by Winsberg's claim that simulations seek reliability without seeking truth.

CONCLUDING THOUGHTS: INSTRUMENTALISM AS RELIABILITY WITHOUT TRUTH

As mentioned at the end of the last section, the thought that computer simulated models seek reliability, and not truth, helps to show their true value.[69] When combined with a pragmatic framework, understanding computer simulated models as reliable tools describes their usefulness to both scientists and philosophers. For Winsberg, this notion of reliability without truth is the key to understanding the place of computer simulated models within the scope of inquiry. He states, "Despite their mixed ancestries, many of these simulations are trusted in making predictions and building representations of phenomena, and they are often successfully used in engineering applications".[70] This echoes what Dewey thought should be the aim of science: to be able to produce useful predictions and to aid in concrete understandings of the world.

Winsberg believes that computer simulated models gain this reliability through the process of model-building itself. "I have argued that the credibility of a simulation model must come not only from the credentials supplied to it by its theoretical ancestors, but also from the antecedently established credentials of the model-building techniques employed in its construction".[71] The credibility of a model is not judged alone but in connection to all other models and the technique of model building itself. This again recalls Dewey in "the method of science requires, then, the establishment of a continuum of inquiry, and a continuum of inquiry which is adequate to the purpose of a community of inquiries… The objectivity of those results depends upon the fact that the method used

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[69] Winsberg, Eric. *Science in the Age of Computer Simulation*. Chicago: The University of Chicago Press, (2010): 132
[70] Ibid: 120
[71] Ibid

are public and can be repeated."[72] Again, the idea that a method is found to be useful through the process of producing reliable understandings is something supported both by Dewey and Winsberg.

The bridge between these two philosophers can be seen through the comments of Arthur Fine. Fine's defense of Instrumentalism over Realism helps to bridge the gap between the Instrumentalism of Dewey and the interpretation of computer simulations in science by Winsberg. Fine states:

> Instrumentalism takes reliability as its fundamental concept and differs from realism only in this: Where the realist goes for truth in the sense of a correspondence with reality, the instrumentalist goes for general reliability… Where the realist says that science does (or should) aim at the truth, the instrumentalist says that science does (or should) aim at reliability… The realist cannot win this game since whatever points to the truth, realist style, will also point to reliability.[73]

This echoes the same point that was made about Churchland in a previous section. When Churchland refuses to accept the pragmatic element of his theory and instead sticks to realism, Churchland does himself a disservice, since the same claims can be made pragmatically without having to bind yourself to the commitments that realism requires.

This leads to the finishing thoughts of this thesis. The aim of this thesis has been to explain and describe the process of computer simulated models and then to show how they are capable of being used as aids to philosophers. Firstly, by defining the term computer simulated model as a process that involves two distinct yet connected steps of modeling and simulating, we gain a better understanding of the many uses that computer

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[72] Hahn, Lewis E. "Dewey's Philosophy and Philosophic Method." In *Guide to the Works of John Dewey*, edited by Jo Ann Boydston, 15-60. Carbondale: Southern Illinois University Press, (1970): 82

[73] Fine, Arthur. *The shaky game: Einstein, realism, and the quantum theory*. Vol. 2. Chicago: University of Chicago Press, (1996): 183

simulated models have already accomplished within the discipline of science. Once it is seen how computer simulated models have aided in the progress of science over time, we can see the validity of them as tools of inquiry. Secondly, by relating those to traditional methods of philosophy, such as Conceptual Analysis, we can start to see how computer simulated methods are able to accomplish the goals that philosophers have often set out to accomplish: namely, to gain a better understanding of the meaning that exists within the numerous phenomena that exists around us. Lastly, the usefulness of computer simulated models is aided even more by adopting a pragmatic perspective of philosophy. By adopting a pragmatic understanding of both philosophy and science, we can see how these seemingly separate methods actually overlap by both being methods aimed at the human endeavor of general inquiry. Pragmatism also allows us to accept that computer simulated models do not aim to uncover any absolute truth about the world, but instead aim to provide reliable understandings and predictions for the concrete and daily problems that plague the lives of people.

REFERENCES

Black, Max. "Russell's Philosophy of Language." In *The Linguistic Turn*, edited by Richard M. Rorty, 136-146. Chicago: The University of Chicago Press, 1992.

Churchland, Paul M. *The Engine of Reason, the Seat of the Soul*. Cambridge: The MIT Press, 1995.

Churchland, Paul M. *Plato's Camera*. Cambridge: The MIT Press, 2012.

Dewey, John. *Experience and Nature*. New York: Dover Publications, Inc., 1958.

Dewey, John. *How We Think*. Lexington: Renaissance Classics, 2012.

Dewey, John. *Logic: The Theory of Inquiry*. New York: Saerchinger Press, 2007.

Dewey, John. *The Later Works, 1925-1953, Volume 4: 1929*, edited by Jo Ann Boydson. Carbondale: Southern Illinois University Press, 2008.

Encyclopedia Britannica Online, s. v. "collective action problem", accessed June 13, 2015, www .britannica.com/topic/collective-action-problem-1917157.

Epstein, Brian. "Agent-Based Modeling and the Fallacies of Individualism." In *Models, Simulations, and Representations*, edited by Paul Humphreys and Cyrille Imbert, 115-144. New York: Routledge, 2011.

Fine, Arthur. *The shaky game: Einstein, realism, and the quantum theory*. Vol. 2. Chicago: University of Chicago Press, 1996.

Frigg, Roman, and Julian Reiss. "The Philosophy of Simulation: Hot New Issues or Same Old Stew?" *Synthese* 169, no. 3 (2009): 593-613.

Hahn, Lewis E. "Dewey's Philosophy and Philosophic Method." In *Guide to the Works of John Dewey*, edited by Jo Ann Boydston, 15-60. Carbondale: Southern Illinois University Press, 1970.

Hebb, Donald Olding. *The organization of behavior: A neuropsychological theory*. Psychology Press, 2005.

Humphreys, Paul. *Extending Ourselves: Computational Science, Empiricism, and Scientific Method*. New York: Oxford University Press, 2004.

Humphreys, Paul. "The Philosophical Novelty of Computer Simulation Methods." *Synthese: An International Journal for Epistemology, Methodology and Philosophy of Science* 169, no. 3 (2009): 615-626.

Ihde, Don. “Models, Models Everywhere.” In *Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 79-86. Dordrecht: Springer, 2006.

James, Williams. *Pragmatism*. Los Angeles: Indo-European Publishing, 2010.

Kennedy, Gail. “Dewey’s Logic and Theory of Knowledge.” In *Guide to the Works of John Dewey*, edited by Jo Ann Boydston, 61-98. Carbondale: Southern Illinois University Press, 1970.

Kuhn, Steven, "Prisoner's Dilemma." *The Stanford Encyclopedia of Philosophy*. www .plato.stanford.edu/archives/fall2014/entries/prisoner-dilemma/.

Kuhn, Thomas S. *The Copernican revolution: Planetary astronomy in the development of western thought*. Vol. 16. Harvard University Press, 1957.

Kuorikoski, Jaakko. “Simulation and the Sense of Understanding.” In *Models, Simulations, and Representations*, edited by Paul Humphreys and Cyrille Imbert, 115-144. New York: Routledge, 2011.

Lenhard, Johannes, Kuppers, Gunter, and Terry Shinn. “Computer Simulation: Practice, Epistemology, and Social Dynamics.” In *Simulation: Pragmatic Construction of Reality*, edited by Johannes Lenhard, Gunter Kuppers, and Terry Shinn, 3-22. Dordrecht: Springer, 2006.

Macy, Michael W, and Robert Willer. “From Factors to Actors: Computational Sociology and Agent-Based Modeling.” *Annual Review of Sociology* 28, no. 1 (2002): 143-166.

Muldoon, Ryan. "Robust simulations." *Philosophy of Science* 74, no. 5 (2007): 873-883.

Parke, Emily C. “Experiments, Simulations, and Epistemic Privilege.” *Philosophy of Science* 81, no. 4 (2014): 516-536.

Peirce, Charles Sanders. "How to make our ideas clear." *The Nature of Truth: Classic and Contemporary Perspectives* (2001): 193-209.

Rorty, Richard. “Representation, Social Practice, and Truth.” *Philosophical Studies: An International Journal for Philosophy in the Analytic Tradition* 54, no. 2 (1988): 215-228.

Rorty, Richard M. “Twenty-five Years After.” In *The Linguistic Turn*, edited by Richard M. Rorty, 371-374. Chicago: The University of Chicago Press, 1992.

Shapere, Dudley. “Philosophy and the Analysis of Language.” In *The Linguistic Turn*, edited by Richard M. Rorty, 271-283. Chicago: The University of Chicago Press, 1992.

Sloman, Aaron. *The Computer Revolution in Philosophy: Philosophy, Science and Models of Mind*. Hassocks: The Harvester Press, 1978.

Weisberg, Michael. *Simulation and similarity: Using models to understand the world*. Oxford: Oxford University Press, 2012.

Weisberg, Michael. “Three Kinds of Idealization.” *The Journal of Philosophy* 104, no. 12 (2007): 639-659.

Weisberg, Michael. “Who is a Modeler?” *The British Journal for the Philosophy of Science* 58, no. 2 (2007): 207-233.

Winsberg, Eric. “Computer Simulation and the Philosophy of Science.” *Philosophy Compass* 4, no. 5 (2009): 835-845.

Winsberg, Eric. “Sanctioning Models: The Epistemology of Simulation.” *Science in Context* 12, no. 2 (1999): 275-292.

Winsberg, Eric. *Science in the Age of Computer Simulation*. Chicago: The University of Chicago Press, 2010.

Wittgenstein, Ludwig. *Philosophical Investigations*, 4th ed., trans. G. E. M. Anscombe, P. M. S. Hacker, and Joachim Schulte. New York: Wiley-Blackwell, 2009.