Computer simulations as a technological singularity in the empirical sciences

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Summary: In this paper, I discuss the conditions necessary for computer simulations to qualify as a technological singularity in the empirical sciences. A technological singularity encompasses two claims: a) the enhancement of human cognitive capacities by the computer, and b) their displacement from the center of the production of knowledge. For computer simulations to be a technological singularity, then, they must fulfill points a) and b) above. Although point a) is relatively unproblematic, point b) needs further analysis. In particular, in order to show that humans could be displaced from the center of the production of knowledge, it is necessary to establish the reliability of computer simulations. That is, I need to show that computer simulations are reliable processes that render, most of the time, valid results. To be a reliable process, in turn, means that simulations accurately represent the target system and carry out error-free computations. I therefore analyze verification and validation methods as the grounds for such representation accuracy and error-free computations. Since the aim is to entrench computer simulations as a technological singularity, the entire analysis must be careful to keep human agents out of the picture.

1 Introduction

To talk of a 'singularity' evokes the idea of a natural occurrence beyond which the course of humanity has changed in significant ways. The Big Bang is one good example of such a singularity that affects our future on physical and existential levels.

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Now, to talk of a 'technological singularity' seems to evoke something else, something related to an occurrence that is the byproduct of human activity. Philosophers have not yet come to an agreement on the notion of a technological singularity. What seems to be common ground, however, is the idea that in order to speak of a technological singularity, humans must somehow be displaced from the center of the production of knowledge. Much of current literature asserts that the origin of such a displacement is related to the introduction of computers and their pervasive use in our modern life. Either by means of the emergence and evolution of super-intelligent machines [6, 14], or by means of powerful computers that enhance human cognitive capacities [10], computers are changing the way we gather and organize information about our world. Thus understood, the notion of technological singularity is intended to underscore the existence of an epistemological barrier beyond which humans cannot trespass, and where computers become the center of the epistemological endeavor.[1]

The specialized literature has mainly focused on problems of singularity stemming from the philosophy of mind [13], philosophy of economics [11], and ethics [9], just to mention a few. This paper, instead, centers on the junction between the philosophy of science and the still young but vigorous philosophy of computer simulations. Concretely, I am interested in refocusing on the problem of technological singularity from the viewpoint of computer simulations and their pervasive use in the empirical sciences. The general question that is being posed here is: under what conditions can computer simulations be considered a technological singularity in the empirical sciences?

In this context, we should first note that I am assuming that at least some computer simulations do qualify as a technological singularity. This fact is, to my mind, uncontroversial. It should not take much effort to find a case in current scientific practice where a computer simulation advanced the general scientific knowledge of a target system. However, to assume that some computer simulations qualify as a technological singularity presupposes an understanding of what a technological singularity entails. Allow me, then, to begin by drawing a minimal working characterization of what makes a computer simulation qualify as a technological singularity.

> A computer simulation is a technological singularity if humans have been displaced from the center of production of knowledge, and if such knowledge is reliable to the extent of being usable without further sanctioning.

Although this characterization needs clarification, it provides the first basic intuitions on the issue. To begin with, displacing humans from the production of knowledge is necessary, although not sufficient, for considering computer simulations a singularity, as is demonstrated by the use of computer simulations for 'face recognition.' Although such a simulation displaces humans in some clear respects, such as in simulating how the human brain would analyze the large amount of data required for face recognition, it does not render better information (e.g., the computer simulation could not recognize a human face as fast and as accurate as a human

[1] Since the context is clear, from now on I will use the terms 'technological singularity' and 'singularity' interchangeably.

could). Conversely, a computer simulation could provide knowledge of an empirical target system without necessitating the displacement of humans from the center of production of knowledge. A simple example of this is a simulation of an orbiting satellite using Newtonian mechanics. Humans have been calculating these orbits for many years and there are no good reasons for thinking that a simulation necessarily displaces humans from such simple calculations. As for demanding a reliable production of knowledge, it is straightforward that such a claim is needed for entrenching the idea of singularity. Although still in rough form, these intuitions concede the existence of conditions under which computer simulations qualify as a technological singularity. Could we evaluate more precisely what these conditions are?

In 2009 Paul Humphreys wrote a cogent paper defending the novelty of computer simulations in the philosophical arena. In that work, he introduced the notion of 'anthropocentric predicament' as the question about "how we, as humans, can understand and evaluate computationally based scientific methods that transcend our own abilities" [7, 617]. At first glance, the anthropocentric predicament aims at fathoming the methods used by scientists for the evaluation of computer simulations. Under this interpretation, the anthropocentric predicament is tailored to human cognitive capacities, and therefore to an anthropocentric epistemology. But Humphreys' intentions are precisely the opposite. To his mind, computer simulations come to take the place of humans in the production of knowledge and, as such, "an exclusively anthropocentric epistemology is no longer appropriate because there now exist superior, non-human, epistemic authorities" [7, 617].

Understood in this second sense, the anthropocentric predicament is the route to considerations about computer simulations as a technological singularity in the empirical sciences. However, as presented, it is silent on the conditions under which a simulation produces knowledge of an empirical target system that is as reliable as a human. This paper, then, draws from the anthropocentric predicament and addresses what I believe are the basic conditions for considering computer simulations as a technological singularity. I begin by showing how, under the correct epistemological and methodological conditions, computer simulations are reliable producers of simulation results about the empirical world. For this, I propose to revisit the anthropocentric predicament as elaborated by Humphreys and argue, following the author, that an exclusively anthropocentric epistemology is no longer appropriate in a context where reliable knowledge is also delivered by computer simulations. This first part of the paper shows in what sense the anthropocentric predicament is key for understanding computer simulations as a technological singularity. A second and more extended part assimilates the previous outcomes and deals with the problem of reliability at face value. For this, I rely on Alvin Goldman's work on *process reliabilism*. The core idea is that under the right epistemological and methodological conditions, computer simulations are reliable processes that produce knowledge about the empirical target system. The challenge in this second part is to show what those conditions are and why we are justified in believing in the reliability of computer simulations. I then propose to approach this issue by firstly adopting a representationalist viewpoint, where a computer simulation is a reliable process if it correctly represents the target system (and, as I will also argue, correctly computes the simulation model). Thus understood, this approach greatly reduces the number of computer simulations capable of qualifying as a technological singularity. This outcome, although correct, seems to be at odds with some uses of computer simulations in daily scientific practice. In effect, there are concrete cases where computer simulations do provide reliable knowledge, even when the implemented simulation model does not fully represent the empirical target system. The conceptual shift, then, is to consider the many 'epistemic functions' that computer simulations perform and allow them to qualify as a technological singularity. Good examples of such epistemic functions are prediction and exploratory strategies. Due to lack of space, however, I will leave unanswered the question of whether a non-representationalist computer simulation qualifies (and, if so, under what conditions) as a technological singularity in the empirical sciences.

2 The anthropocentric predicament

In 2009, Roman Frigg and Julian Reiss warned us of the growth of overemphasized and generally unwarranted claims about the philosophical importance of computer simulations. This growth was reflected in the increasing number of philosophers convinced that the philosophy of science, nourished by computer simulations, required an entirely new epistemology, a revised ontology, and novel semantics. Although the authors admit the importance that computer simulations have in contemporary theoretical and practical science, they believe that computer simulations hardly call into question the basic philosophical principles of understanding science and conceptualizing reality [4, 594-595]. I share with Frigg and Reiss the puzzlement on this issue. It is hard to sustain that a new scientific method (instrument, mechanism, etc.), however powerful and novel it might be, could all by itself imperil the current state of philosophy of science. It is still an open question, however, whether or not Frigg and Reiss have correctly interpreted the underlying claims of the authors they criticize.

An important consequence of the article was the reactions that arose within the philosophical community. Paul Humphreys, for instance, directly engaged Frigg and Reiss with an answer. He claimed that Frigg and Reiss' assertions obscured the challenges that computer simulations pose for the philosophy of science. The core of Humphreys' reply was to recognize that the question about the novelty of computer simulations has two sides: one side which focuses on how traditional philosophy illuminates the philosophical study of computer simulations (e.g., through a philosophy of models and a philosophy of experiment, as Frigg and Reiss claim); and another side which exclusively focuses on aspects of computer simulations in and of themselves, that is, philosophical questions stemming from the very object of study regardless of any clarification from a more familiar philosophy. It is this second way of looking at the issue that gives philosophical importance to computer simulations.

Humphreys, then, elaborates on a set of novelties ascribed to computer simulations that constitute distinctively new methods in the scientific and philosophical arena. This set includes, among others, the 'epistemic opacity' of computer simulations relative to a cognitive agent, that is, the impossibility of knowing all the epistemically relevant constituents acting during a simulation. In short, being epistemically opaque means that, due to the complexity and speed of the computational process, no cognitive agent could follow the entire simulation. A second novelty that chimes with epistemic opacity is the 'temporal dynamics' of computer simulations. This concept has two possible interpretations. Either it refers to the necessary computer-time to solve the simulation model, or it stands for the temporal development of the target system as represented in the simulation model. A good example of both interpretations of temporal dynamics is a simulation implementing a model of the dynamics of the atmosphere that takes, say, 100 days to compute.

These two novelties nicely illustrate what is typical of computer simulations, namely, their inherent complexity, as the case of epistemic opacity and the first interpretation of temporal dynamics reveals; and the inherent complexity of the target systems, as the case of the second interpretation of temporal dynamics shows. Now, what is common between these two novelties is, in turn, that they both entrench computers as the main epistemic authority by displacing humans from the center of the production of knowledge. Indeed, either because the process of computing is too complex for us to follow or because the target system is too complex for us to comprehend, computers become the exclusive source for gathering information about the world.

Humphreys called this feature the *anthropocentric predicament*, which refers to the idea of understanding the world from a non-human perspective by representational intermediaries tailored to human cognitive capacities [7, 617]. The anthropocentric predicament, then, gets its support from the view that scientific practice only progresses because new methods are available for handling large amounts of information. In former times, the amount of information collected by a given discipline was, to a certain extent, manageable for the scientists. The astronomers could keep their books and stellar maps, and even perform many different kinds of calculations by controlling every step of the process. Today's scientific practice, however, handles enormous amount of information that are virtually impossible to manage without the aid of technology. A good example of this is the Diffuse Infrared Background Experiment on the NASA Cosmic Background Explorer satellite which produces 160 million measurements per twenty-six week period [15, 231]. The new technology which Humphreys has in mind is, surely, the digital computer. An equally important aspect of the anthropocentric predicament is that it requires computer simulations to represent an empirical target system. Such a requirement seems to be a natural consequence of the issue at stake, for displacing humans from the center of production of knowledge requires that knowledge to be grounded in the structure of the target system.

Thus understood, the anthropocentric predicament is the route to entrenching computer simulations as a technological singularity in the empirical sciences. Nevertheless, in order to be a singularity, it is not enough for computer simulations to simply set humans apart from the epistemic enterprise, it also requires the simulation results to be epistemically on *a par* with the data that could have been produced by a human agent. Indeed, a computer simulation that represents a sophisticated Ptolemaic model could displace humans from the center of knowledge insofar as it produces accurate results that, other things being equal, humans could not produce by themselves. However, such a computer simulation could not be counted as a reliable source of information about the planetary movement, and therefore it could not seriously be considered as a reliable producer of knowledge. Computer simulations are not epistemic leverage that turns any implemented model into insight about the empirical world, nor can they simply displace human agents from the center of production of knowledge by representing inherently complex systems and readily producing results of intricate models. In order to be a singularity, computer simulations must produce results that effectively lead to knowledge about their empirical target systems. To this end, computer simulations must be conceptualized as reliable processes in a specific sense yet to be determined. It is in this precise sense that the anthropocentric predicament fails to ground computer simulations as a singularity, remaining silent on the conditions under which they are reliable producers of knowledge about the empirical world.

The following section addresses the conditions for a reliable computer simulation. To my mind, a reliable computer simulation is one that renders, most of the time, valid simulation results about the empirical target system. A reliable computer simulation, then, provides the justification that our beliefs about the simulation results are, most of the time, true rather than false of that empirical system, leading to knowledge about such a target system. The question about singularity, then, is subsumed into the question of what it means to have a reliable computer simulation.

Let it be noted that singularity entails reliability, although the converse is not necessarily true. Many computer simulations are reliable in the sense just given, although they do not qualify as a singularity. The reason for this is fairly simple. A computer simulation can be reliable even when it is sanctioned *after* the computation of the simulation results. For instance, Ian Jenkins et al. [8] present a simulation of self-assembling DNA-coated spheres. The unusual feature of this simulation is that it has thousands of configurations that are as energetically favorable as the real experiment. Only expert knowledge can determine which simulation is more accurate than others. It follows that the simulation results are sanctioned *after* the computation of the simulation, and therefore the simulation cannot be considered a singularity. In the face of this, let me call the juncture of all methods that collectively grant reliability to the simulation *before* its execution on the computer, and therefore *before* obtaining the simulation results, the *pre-computed reliability stage*. There is also a *post-computed reliability stage*, which refers to methods for sanctioning the simulation results *after* they have been obtained and, therefore, requiring the intervention of an agent. Since singularity is only concerned with the pre-computed reliability stage of a computer simulation, there is no need to address issues related to post-computed reliable stages. Allow me now to discuss in more detail what entails a pre-computed reliability stage.

3 The reliability of computer simulations

Epistemologists have taught us that questions about knowledge have their roots in the notion of truth and epistemic justification. While it is widely agreed that what is false cannot be known, there is less consent on what it means to say that we know something and why we are justified in believing so. In this paper I am only interested in analyzing the justification of believing that the simulation results are valid of a target system. To be a *valid simulation result* is to match, with more or less accuracy, the (theoretically) measured and observed values of the empirical target system. With these notions in mind, allow me to address the philosophical importance of epistemic justification for the singularity hypothesis. Let me begin by asking in what specific sense are we justified in believing that a computer simulation renders knowledge about the empirical world? A suitable answer is to consider the computer simulation as a belief-forming process, that is, as a process capable of producing results that are, most of the time, valid of the empirical target system. If such results can be produced, then we can say that we are justified in believing the simulation results and, as such, in claiming for knowledge of the empirical target system. In plain words, if the simulation results are acceptably close or similar to real-world measurements, observations, or even pen-and-paper calculations, then we are entitled to claim empirical knowledge of that target system.

In epistemology, such an account is known as *process reliabilism*, where one of the major contributors and theorist has been Alvin Goldman. In its simplest form, reliabilism says that we know if our beliefs are justified by a reliable process, where 'reliable' here means a process that produces, most of the time, truths [5, cf.]. For instance, we know that '2 + 2 = 4' because the reasoning process involved in addition is, under normal circumstances and within a limited set of operations, a reliable process. According to Goldman, then, there is nothing accidental in knowledge that is produced by a reliable process. Reinterpreting process reliabilism for computer simulations, we can say that a simulation is a reliable process if it produces results that are, most of the time, valid of the target system. Following Goldman, there is nothing accidental about believing that a computer simulation produces valid results of a target system (provided that certain conditions are fulfilled -and yet to be specified) and, consequently, about the claim that we obtain knowledge of that target system. Thus understood, process reliability is resolved as the belief-forming process that renders simulation results as valid for the intended empirical target system. This point can be easily illustrated by considering CS_R as the simulation results and RW_D as the data of its target system. According to reliabilism, then, we are justified in believing the results of the computer simulation if $|CS_R - RW_R| \cong 0$, that is, if the simulation results approximate the real data measured, observed, or computed. To put the same ideas in a rather different form, the reliability of computer simulations is built on the quantitatively assessed accuracy of its results. Such accuracy is obtained by two sources, namely, the representational capacity of the simulation and a relatively error-free computation. The question about the reliability of computer simulations and therefore of knowledge is now shifted to understanding these two sources.

Let me motivate this issue by briefly enumerating which computer simulations could not be regarded as reliable.

1. Cases of misrepresenting computer simulations:

    a. Any computer simulation that implements a known false model (e.g., the Ptolemaic model of the solar system) could not be expected to render knowledge of planetary movement.
    b. Any computer simulation that has no representational underpinning of the target system, such as heuristic simulations. (e.g. the Oregonator is a simulation for exploring the limits of the Belousov chemical reaction. Such a simulation implements a model whose system of equations is *stiff* and therefore it might lead to qualitatively erroneous results [3, 1880]). A particular case of this is:
        i. Any computer simulation that renders *unrealistic simulated results*, that is, results that cannot represent an empirical target system (e.g., a computer simulation implementing a Newtonian model setting the gravitational force to $G = 1m^3kg^{-1}s^{-2}$).[2] Such simulations violate the laws of nature and cannot be considered empirically accurate.

2. Cases of miscalculating computer simulations:

    a. A computer simulation that miscalculates due to large round-off errors, large truncation errors, and other kinds of artifacts in the calculation, such as ill-programmed algebraic modules and libraries. Such software errors cannot stand for valid simulation results of the target system.
    b. A computer that miscalculates due to physical errors, such as an ill-programmed computer module or a malfunctioning hardware component. Similar to (2.a) above, these types of errors warrant invalid simulation results and, as such, do not render knowledge of the target system.

A generally valid principle in computer simulations is that there are no limits to the imagination of the scientists. This is precisely the reason why simulations are, one might argue, facilitating the shift from a traditional empirically-based scientific practice into a more rationally-based one. However, neither of the examples described above fit the conditions for a pre-computed reliable simulation. While simulations belonging to case (1.a) are insufficient for an accurate representation the empirical target system, those belonging to case (1.b) are highly contentious. The latter case, as is illustrated by the Oregonator example, is trusted only insofar as the results are subject to the subsequent acceptance by experts. Whenever this is the case, the simulation automatically fails to classify as pre-computed reliable and, therefore, violates the basic assumption of the singularity hypothesis. Although much of current scientific practice depends on these kinds of simulations, they do not comply with the minimal conditions for being a singularity, and therefore they inevitably fail to qualify as one.

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[2] Unrealistic results are not equivalent to erroneous results. In this case, the results are correct of the simulation model although they do not represent any known empirical system. As such, they are not going to be considered in this paper.

In the same manner, heuristic simulations must not necessarily render invalid results. For this reason, they are useful simulations for exploring the mathematical limits of the simulation model, as well as the consequences of an unrealistically constructed law of nature, among other uses. Such simulations facilitate the representation of counterfactual worlds, thought experiments, or simply fulfill propaedeutic purposes, but given our current conception of technological singularity, they do not qualify as such.

Besides their representational features, computer simulations are also part of the laboratory *instrumentarium*, and as such are inevitably exposed to miscalculations of different sorts. A first classification of errors divides them into *random errors*, such as a voltage dip during computation, or a careless laboratory member tripping over the power cord, and *systematic errors*, that is, errors that are inherently part of the simulation. Random errors have little philosophical value. Their low probability of occurrence, however, do make a small contribution (although negligible) to the frequency of a process of producing beliefs that are false rather than true. Systematic errors, on the other hand, can be subdivided into *logical errors* (i.e., errors in the programming of software, such as the errors illustrated in (2.a) above), and *hardware errors* (i.e., errors related to the malfunctioning of the physical component of the computer, exemplified in (2.b) above). This paper concedes that miscalculations do occur in the practice of computer simulations, but assumes that they are rare and rather negligible for the overall evaluation of the reliability of computer simulations. The reason is that over the years of technological advancement, computers have become less prone to suffer from failure. A host of recovering procedures such as duplication and redundancy mechanisms for critical components, functions, and data grant this dependability. Also, new techniques in the design and practice of programming, as well as the plethora of programming languages and expert knowledge at the programmers' disposal, among other aspects of computer software, facilitate the assertion that computers are relatively error-free and fail-safe instruments. As a working assumption, then, I take that computer simulations are stable instruments that, most of the time, do not incur calculation errors that might alter the simulation results (or, if they do, such errors are entirely negligible).

3.1 Verification and validation methods

The bluntly false and highly speculative examples used above constitute only a small portion of computer simulations used in scientific practice. For the most part, scientists interpret, design, and program the simulation of an intended target systems with remarkable representational accuracy and on stable instruments. This paper concedes this much. We must carefully distinguish, however, simulation results that require further epistemic sanctioning from results whose validity has been granted during a pre-computed reliability stage. An argument is advanced to the effect of addressing *verification* and *validation methods* applied during the pre-computed reliability stage that grant validity to simulation results.

Verification and validation methods are at the basis of claims about the reliability of computer simulations. They build on the confidence and credibility of simulation results, and in this respect, understanding their uses and limits is central for claims about singularity. While verification methods substantiate the scientist's belief that the mathematical model is correctly implemented and solved by the simulation, validation methods provide evidence that the simulation results match, with more or less accuracy, empirical data. Let us take a closer look at what comprises each method.

The American Society of Mechanical Engineers (ASME), along with other institutions, adopted the following definition of verification: "[t]he process of determining that a computational model accurately represents the underlying mathematical model and its solution" [2, 7]. Thus understood, verification could be obtained in two ways: by finding evidence that the algorithms are working correctly, and by measuring that the discrete solution of the mathematical model is accurate. The former method is called *code verification*, while the latter is known as *calculation verification*. The purpose of making these distinctions is to categorize the set of methods for the assessment of correctness of the computational model with respect to the mathematical model, as opposed to assessing the adequacy of the mathematical model with respect to the empirical system of interest. Code verification, then, seeks to remove programming and logic errors in the computer program, and as such it belongs to the design stages of the computational model. Calculation verification, on the other hand, seeks to determine the numerical errors due to discretization approximations, round-off errors, discontinuities, and the like. Both code verification and calculation verification, are guided by formal and deductive principles, as well as by empirical methods and intuitive practice (or by a combination of both).

Validation, on the other hand, has been defined as "[t]he process of determining the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model" [2, 7]. Validation, then, is somehow closer to the empirical system since it is concerned with the accuracy in the representation of such a model. Validation methods also make use of benchmarks or reference values that help establish the accuracy of the simulation results. Benchmarking is a technique used by computer scientists for measuring the performance of a computer system based on comparisons between simulation results and experimental data. The simplest way to obtain such data comes from performing traditional empirical experiments. Now, since the true value of the empirical target system cannot always be absolutely determined, it is an accepted practice to use a reference value obtained by traditional measurements and observational procedures. A different situation is when the value of the target system can be theoretically determined, as is the case in quantum mechanics where the value of the position of atoms are obtained by theoretical methods. In such cases, the simulation results can be validated with high accuracy. In the same vein, results from different but related simulations could also be used for validation purposes, as these results can be easily compared to the simulation results of interest. Validation, then, aims at providing proof of the accuracy of simulation results with respect to the empirical target system of interest. Thus understood, the appeal to validation methods as grounds for reliable processes brings out questions that lurk behind inductive processes. The general concern is that such methods only allow validation up to a certain number of results, that is, up to those of which we have previous data. Due to their comparative nature, these methods do not provide mechanisms for validating new, unknown results. It follows that validation is a method for assisting in the detection of errors, but not designed for detecting misrepresentations of the target system.

It should not be expected, however, that during an actual verification or validation process scientists decouple these methods. The multiple problems related to mathematical representation, mathematical correctness, algorithm correctness, and software implementation make the entire enterprise of verification and validation highly interwoven processes. Moreover, code verification by formal means is virtually impossible in complex and elaborated simulations. Let it also be noted that not all verification and validation methods are performed at the same stages of design and output of a simulation. Some verifications are only carried out during design stages, while others, such as *manufactured solutions*, depend on the intervention of an agent. Manufactured solutions are custom-designed verification methods for highly accurate numerical solutions to partial differential equations (PDEs). It consists in testing numerical algorithms and computer codes by finding solution functions that have altered the implemented PDEs, but which also satisfy such equations. As William Oberkampf and Timothy Trucano indicate, "[a manufactured solution] verifies many numerical aspects in the code, such as the mathematical correctness of the numerical algorithms, the spatial-transformation for the grid generation, the grid-spacing technique, and the absence of coding errors in the software implementation" [12, 723].

In a similar fashion, validation methods might focus on the design stages as well as on the output of a simulation. It is easier to devise validation methods requiring the intervention of an agent, for the construction and subsequent use of benchmarks requires such involvement. Examples of this abound in the literature and there is no need to discuss this point any further. One could always consult Oberkampf and Trucano's list for the documentation of benchmarks, all of which must be in place for successfully warranting accuracy of the computed results [12, 728].

4 Final words

In this paper I defended the idea that, under the right conditions, computer simulations are reliable processes that produce, most of the time, valid simulation results. Valid simulation results are taken as knowledge of the target system, facilitating the claim that computer simulations are a technological singularity. Now, in order to fully qualify as a technological singularity, such results must not be sanctioned by a human agent. On the face of it, the number of simulations that qualify as a technological singularity has been reduced to a few well established cases with representational underpinning and error-free computations. Such representation and error-free computations are grounded on verification and validations methods, as elaborated above.

One immediate consequence is that the universe of computer simulations has been significantly reduced. At first, this outcome might strike one as an undesirable and anti-intuitive consequence. One might think that many computer simulations are being used today as reliable processes producing valid results of a given empirical system, and that there is no special problem in doing so. The general trend nowadays is to overthrow humans as the ultimate epistemic authority, replacing them with computer simulations [16]. A good example of this is the simulation of the spread of influenza, as expounded by Ajelli et al. [1], where two different kinds of computer simulations provide knowledge of a hypothetical scenario. In some situations, in effect, no further sanctioning is needed and the information provided by these simulations is used as obtained. However, contrary to appearances, the vast majority of cases get their results sanctioned after they have been produced, undermining the possibilities of becoming a technological singularity. One might safely conclude that the number of computer simulations that qualify as a singularity are, indeed, limited.

Admittedly, much more needs to be said in both directions, namely, what grounds computer simulations as a technological singularity (especially regarding verification and validation methods) as well as how current scientific practice accommodates this philosophical view. Equally important is to elaborate on cases such as Ajelli et al., where the simulation seems to be a singularity if used in certain situations and fails to be one in some others.

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