Against the singularity hypothesis

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Abstract

The *singularity hypothesis* is a hypothesis about the future of artificial intelligence on which self-improving artificial agents will quickly become orders of magnitude more intelligent than the average human. Despite the ambitiousness of its claims, the singularity hypothesis has been defended at length by leading philosophers and artificial intelligence researchers. In this paper, I argue that the singularity hypothesis rests on undersupported growth assumptions. I show how leading philosophical defenses of the singularity hypothesis (Chalmers 2010, Bostrom 2014) fail to overcome the case for skepticism. I conclude by drawing out philosophical and policy implications of this discussion.

1 Introduction

The Association for the Advancement of Artificial Intelligence recently convened a panel to discuss the long-term future of artificial intelligence. That panel lamented "a tendency ... to dwell on *radical* long-term outcomes of AI research, while overlooking the broad spectrum of opportunities and challenges" raised by artificial intelligence (Horvitz and Selman 2012, p. 302). Rather than focusing on extreme scenarios involving murderous androids or superhuman planners, we might concentrate on better-evidenced issues such as bias (Fazelpour and Danks 2021), transparency (Creel 2020) and labor market distortions (Korinek and Stiglitz 2019).

One hypothesis in particular drew the panel's ire. The *singularity hypothesis* begins with the supposition that artificial agents will gain the ability to improve their own intelligence. From there, it is claimed that the intelligence of artificial agents will grow at a rapidly accelerating rate, producing an *intelligence explosion* in which artificial agents quickly become orders of magnitude more intelligent than their human creators. The result will be a singularity, understood as a fundamental discontinuity in human history beyond which our fate depends largely on how we interact with artificial agents.

Despite the ambitiousness of its claims, the singularity hypothesis has found no shortage of advocates. The singularity hypothesis has been defended at length by philosophers such as David Chalmers (2010; 2012) and Nick Bostrom (2014). Similar defenses have been penned by foundational figures in the history of artificial intelligence, including I.J. Good (1966), Ray Solomonoff (1985) and Stuart Russell (2019). The singularity hypothesis is endorsed by a nontrivial minority of contemporary artificial intelligence researchers.[1] It has been the subject of a special issue of the *Journal of Consciousness Studies* (Awret 2012) and several volumes of essays (Eden et al. 2012; Callaghan et al. 2017). The singularity hypothesis has become intertwined with philosophical debates about consciousness (Dennett 2012), digital minds (Dreyfus 2012), and philanthropic giving (Greaves et al. forthcoming). And the hypothesis attracts continued interdisciplinary discussion (Armstrong et al. 2016; Yampolskiy 2016).

These efforts have had a major impact on societal conceptions of artificial intelligence. The singularity hypothesis entered the public consciousness through popular works by Vernor Vinge (1993) and Ray Kurzweil (2005). It has been a primary subject of research at institutes such as the Singularity Institute for Artificial Intelligence and the Singularity University (Yudkowsky 2013).[2] And we will see in Section 6 that the singularity hypothesis had a significant effect on philanthropy through the effective altruism movement, contributing to a shift of philanthropic giving away from causes such as global health and development aid towards *longtermist* causes such as the prevention of existential catastrophe from self-improving artificial intelligence (Bales et al. 2024; MacAskill 2022; Greaves et al. forthcoming; Ord 2020).

Despite ongoing academic and public support for the singularity hypothesis, I argue

[1]See Baum et al. (2011); Grace et al. (2016); Müller and Bostrom (2016); Stein-Perlman et al. (2022) and Zhang et al. (2022) for surveys and discussion.

[2]The singularity hypothesis has also influenced discussions of existential risk from artificial intelligence at institutes such as the Future of Humanity Institute and the Center for the Governance of AI at Oxford, the Center for the Study of Existential Risk and Leverhulme Centre for the Future of Intelligence at Cambridge, the Center for Human-Compatible Artificial Intelligence and Existential Risk Initiative at Berkeley, the Center for AI Safety, Alignment Research Center, AI impacts, Anthropic, and Redwood Research. Note that the Singularity Institute has since been renamed to the Machine Intelligence Research Institute.

that the balance of evidence tells the other way. Here is the plan. Section 2 works towards a rigorous statement of the singularity hypothesis. Section 3 gives five reasons to think that the growth assumptions underlying the singularity hypothesis are too ambitious. Sections 4-5 consider recent philosophical arguments for the singularity hypothesis by Chalmers (2010) and Bostrom (2014), showing how these arguments do not sufficiently support the hypothesis' growth assumptions. Section 6 concludes by drawing out philosophical and policy implications of this discussion.

2 Formulating the singularity hypothesis

The term 'singularity hypothesis' has come to be understood in a variety of ways. Following Ammon Eden and colleagues (2012), I will assume that a singularity hypothesis has three components. First, it specifies a quantity. Second, it claims that this quantity will experience accelerated growth. And third, it claims that accelerated growth will lead to a discontinuity in human history. Specifying each of these components in detail will identify the version of the singularity hypothesis that interests me.[3]

2.1 Which quantity?

The quantity that I am interested in is *intelligence*. More specifically, I am interested in the claim that the general intelligence of artificial agents will grow through processes of recursive self-improvement. This is perhaps the best-known form of the singularity hypothesis, introduced to philosophers by I.J. Good:

> Let an ultraintelligent machine be defined as a machine that can far surpass all the intellectual activities of any man however clever. Since the design of machines is one of these intellectual activities, an ultraintelligent machine

[3]In particular, it is important to separate this version of the singularity hypothesis from a variety of weaker economic claims that, while highly contentious, merit serious consideration. See Nordhaus (2021) for discussion.

> could design even better machines; there would then unquestionably be an 'intelligence explosion,' and the intelligence of man would be left far behind (Good 1966, p. 33).

Good's claim is most naturally understood by assuming that there is an unambiguous concept of general intelligence and that this concept can be coherently applied to artificial agents. The claim is then that we should expect accelerating growth in the general intelligence of self-improving machines.

There is much more to be said here. A number of commentators have raised doubts about the cogency of the concept of general intelligence (Nunn 2012; Prinz 2012), or the likelihood of artificial systems acquiring meaningful levels of general intelligence (Dreyfus 2012; Landgrebe and Smith 2022; Lucas 1964; Plotnitsky 2012).[4] These concerns are well taken.[5][6] But these responses are controversial: many artificial intelligence researchers are happy to speak of general intelligence and express optimism about the likelihood of achieving human-level artificial intelligence within this century.[7] By contrast, I think that the falsity of the singularity hypothesis should be uncontroversial (though others may disagree). Hence I am prepared to grant, for the sake of argument, both the cogency of the concept of general intelligence and the supposition that the general intelligence of artificial agents may meaningfully approach human intelligence.

My skepticism will concentrate instead on the singularity hypothesis' ambitious growth assumptions, with one exception. At some points in the argument, we will consider very

[4]One might also wonder whether increases in general intelligence would imply increases in moral reasoning ability, putting pressure on the Orthogonality Hypothesis and Instrumental Convergence Thesis to be discussed in Section 6, given suitable moral motivation on behalf of artificial agents. Thanks to Eli Aleinikoff for this suggestion.

[5]However, it may be possible to reformulate arguments for the singularity hypothesis without appeal to the concept of general intelligence (Chalmers 2010).

[6]Relatedly, some readers may think that only suitably sophisticated systems can be described as intelligent.

[7]For example, the median respondent to Grace et al (2016) gave a 50% chance of human-level artificial intelligence within 40 years, and a 90% chance within 100 years. Similarly, the median respondent to Müller and colleagues' (2016) survey of top-cited AI researchers gave a 50% chance of human-level intelligence by 2050 and a 90% chance by 2070. As always, there is some difficulty in interpreting this data, and in particular Grace and colleagues found moderate sensitivity to the manner in which the question is framed.

strong claims about artificial intelligence, for example that the intelligence of artificial agents has grown by a factor of thirty three million in the past fifty years (Section 3.5). Here I think it may be appropriate to ask for clarification of the relevant notion of intelligence, such that claims of this magnitude can be both true and able to do the work that advocates of the singularity hypothesis need them to do.[8] I will return to this issue in Section 3.5.

2.2 Accelerating growth

The singularity hypothesis posits a sustained period of accelerating growth in the general intelligence of artificial agents. This is a strong assumption, but the strength of the assumption turns on how growth rates are measured. Typically, growth rates refer to *relative growth*, the percentage change of a quantity over time, so that for example a change from 1 to 2 units of intelligence represents the same growth rate as a change from 2 to 4 units of intelligence. More rarely, growth rates refer to the weaker concept of *absolute growth*, the unscaled change in magnitude of a quantity over time, so that for example a change from 1 to 2 units of intelligence represents the same growth rate as a change from 2 to 3 units of intelligence.

On both absolute and relative understandings, to say that artificial intelligence grows at an accelerating rate is to rule out many familiar types of growth, such as logarithmic growth (Figure 1a) and linear growth (Figure 1b). But these understandings differ on what they say about exponential growth (Figure 1c). Sustained exponential growth is a very strong growth assumption, but even so, exponential growth only represents an accelerating growth rate on the weaker understanding that growth rates track absolute growth. And in fact, as fast as exponential growth may be, it is often not fast enough to produce the qualitative behavior demanded of an intelligence explosion. For example,

[8]One way to quantify intelligence might be to adopt François Chollet's (2019) understanding of intelligence as skill-acquisition efficiency over a scope of tasks with respect to priors, experience, and generalization difficulty, perhaps benchmarked as Chollet suggests over the Abstraction and Reasoning Corpus (ARC) dataset. However, readers who prefer other operationalizations of intelligence are welcome to read this paper with those views in mind

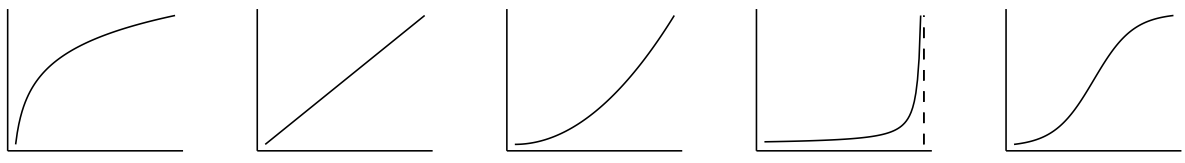
if intelligence grew exponentially at a rate of 2 percent per year, then it would take almost 350 years for intelligence to grow three orders of magnitude. Even if intelligence doubled every two years, it would take twenty years for intelligence to grow three orders of magnitude. For this reason, although some authors model an intelligence explosion using exponential growth (Chalmers 2010), most authors have understood the intelligence explosion to involve still faster modes of growth.

The most common model of an intelligence explosion involves hyperbolic growth (Figure 1d), which approaches a vertical asymptote in finite time (Bostrom 2014; Solomonoff 1985). Hyperbolic growth does constitute accelerating growth on both relative and absolute understandings, and precisely for this reason it is difficult to overstate just how strong a growth assumption is made by hyperbolic models. For example, on Bostrom's (2014) model intelligence doubles in 7.5 months, grows a thousandfold within 17.9 months, and approaches infinity at 18 months. In some ways, these numbers may still be too conservative. Bostrom defines a 'fast' takeoff of artificial intelligence as one occurring within minutes, hours or days, and a 'moderate' takeoff as occurring in months or years. Bostrom argues that a fast or moderate takeoff is highly likely to occur. These are strong growth assumptions, and they will need a correspondingly strong argument to ground them.

It is important to note that the singularity hypothesis posits a *sustained* period of hyperbolic or exponential growth. This is important, because many quantities grow rapidly for some time, but then revert to calmer growth modes such as logistic growth (Figure 1e). If we project forward past trends of accelerating growth, we risk neglecting the likelihood that growth will flatten out (Modis 2012). For example, economic models suggest that world population grew exponentially or even hyperbolically for much of the

Figure 1: Growth modes: Intelligence over time

(a) Logarithmic (b) Linear (c) Exponential (d) Hyperbolic (e) Logistic

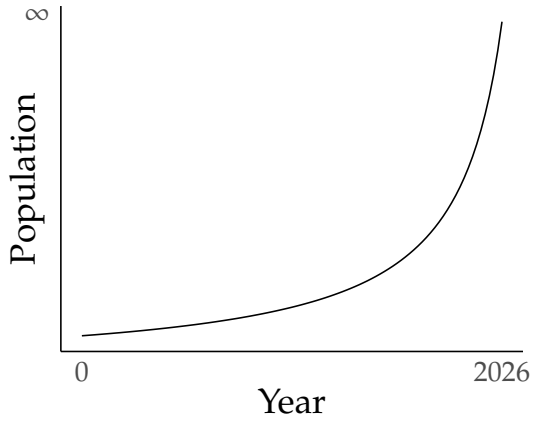


twentieth century, rising from 1.6 billion in 1900 to 4 billion in 1975 (Figure 2a). One famous model from this period held that continued hyperbolic growth would lead to an infinite population by 2026 (Von Foerster et al. 1960). But it would have been a Malthusian mistake to project continued hyperbolic population growth. World population is now projected to flatten out at around 11 billion people by 2100 (Figure 2b) and perhaps even to decrease thereafter (United Nations 2019). In the end, what began as a period of sharply accelerating growth will end with a relatively modest effect on total population.

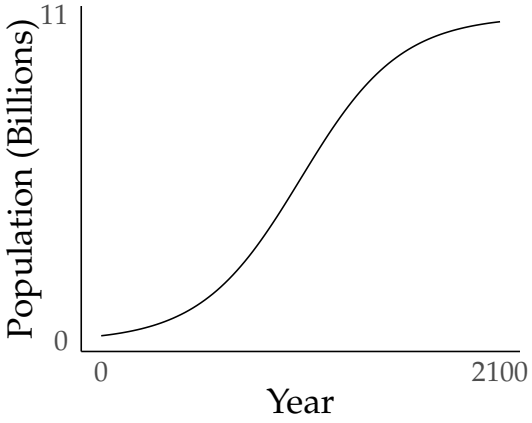
The case of population growth reveals the importance of the assumption that high growth rates will be sustained, even as intelligence grows by many orders of magnitude. The assumption of sustained growth cannot be grounded by projecting current growth rates indefinitely into the future, for as our discussion of population growth reveals, rapid growth rates often calm over time. Advocates of the singularity hypothesis must argue not only that the intelligence of artificial agents is now growing at an exponential or hyperbolic rate, but also that high rates of growth will continue as intelligence grows by many orders of magnitude. That is a much stronger claim. The strength of this claim can be brought out by considering the magnitude of the discontinuity in human history that accelerated growth is meant to bring about.

Figure 2: Population growth

(a) Hyperbolic model



(b) Current projection



2.3 Discontinuity

How long must this period of accelerated growth continue? The singularity hypothesis posits that growth will continue at least until a radical discontinuity in history is reached. If all goes well, it is held that artificial systems may become capable enough to upload copies of all living humans as full-fledged digital simulations of ourselves (Chalmers 2010). Humanity would then live on in digital form. And if all goes badly, artificial agents are predicted to become powerful enough to render humanity extinct, impotent or irrelevant at will (Bostrom 2014). We will discuss these implications in more detail in Section 6, but for now, just how much intelligence growth would be required to bring these developments about?

Opinions vary, but most advocates of the singularity hypothesis envision a machine several orders of magnitude more intelligent than the average human. For example, Richard Loosemore and Ben Goertzel take as their minimum target "a level of general intelligence 2-3 orders of magnitude greater than the human level" (Loosemore and Goertzel 2012, p. 86), and Chalmers considers a machine "at least as far beyond the most intelligent human as the most intelligent human is beyond a mouse" (Chalmers 2010, p. 11). The envisioned future is not one in which artificial agents grow to match humans, but one in which artificial agents leave unmodified humans far behind.

Summing up, the singularity hypothesis posits a period of sustained growth in the general intelligence of self-improving artificial agents. Intelligence growth will occur at an accelerating rate, yielding prolonged exponential or even hyperbolic growth. This growth will continue until a fundamental discontinuity in human history is reached and human destiny is firmly in control of artificial agents orders of magnitude more intelligent than ourselves.

These are strong claims, and they should require a correspondingly strong argument to ground them. In Sections 4-5, I argue that two leading philosophical defenses of the singularity hypothesis do not lend significant plausibility to the singularity hypothesis. My response in each case will focus on reasons for skepticism about the singularity

hypothesis' growth claims. For this reason, my first project (Section 3) is to draw out five reasons to be skeptical of the singularity hypothesis' growth claims, reasons which will be instrumental to my negative project in Sections 4-5. These reasons for skepticism will not imply that the singularity hypothesis is physically impossible, but will instead place a burden on advocates of the singularity hypothesis to produce strong arguments in favor of the hypothesis, and I argue in Sections 4-5 that this burden has not yet been met.

3 The case for skepticism

Existing responses to the singularity hypothesis often pursue one of two strategies. First, they push on the cogency of the concept of general intelligence or its applicability to the case at hand (Nunn 2012; Heylighen 2012; Prinz 2012). Second, they deny that artificial systems will reach human-level intelligence any time soon (Dreyfus 2012; Landgrebe and Smith 2022; Lucas 1964; Plotnitsky 2012). I want to explore a different source of resistance to the singularity hypothesis: questioning its growth assumptions. In this section, I give five reasons to be skeptical of the rate of intelligence growth needed to ground the singularity hypothesis. Then in Sections 4-5, I argue that leading philosophical defenses of the singularity hypothesis do not overcome the case for skepticism about growth rates.

3.1 Extraordinary claims require extraordinary evidence

The singularity hypothesis posits a sustained period of exponential or hyperbolic growth in the intelligence of artificial agents, continuing at least until machines exceed humans in intelligence by as much as humans exceed mice. These are extraordinary claims, and they should require correspondingly extraordinary evidence.[9] It is not enough to show that sustained periods of hyperfast growth are physically possible, fail to be ruled out by our evidence, or are supported by a few suggestive considerations. To lend credence to their

[9]On my understanding, to say that a claim is extraordinary is to say that it is implausible, which is to say that it has low prior probability. To say that extraordinary claims require extraordinary evidence is to say that implausible claims must be supported by strong evidence to acquire significant credibility.

growth claims, advocates of the singularity hypothesis owe us many excellent reasons to suspect that, despite the unusual nature of the growth rates they posit, these growth rates do in fact describe the future growth of artificial intelligence. Until this evidential burden is met, it is appropriate to place low credence in the singularity hypothesis because of the extraordinary nature of its growth claims.

3.2 Good ideas become harder to find

Suppose you are fishing without replacement from a deep pond. At first, catching fish is easy. The fish you catch dwell in shallow waters and are easily fooled into biting. But as time goes on, the time between catches grows longer. Now the fish left in the pond are shrewder and dwell deeper underwater. Catching a fish goes from a matter of minutes to a matter of hours, days, or weeks.

Many social scientists think that beyond a point, nearly all idea-generating processes behave like fishing. As low-hanging fruit is plucked, good ideas become harder to find (Bloom et al. 2020; Kortum 1997; Gordon 2016). Research productivity, understood as the amount of research input needed to produce a fixed output, falls with each subsequent discovery. While research productivity may initially remain constant, or even increase, the received view is that most idea-generating processes encounter diminishing research productivity as they progress.[10]

By way of illustration, the number of FDA-approved drugs per billion dollars of inflation-adjusted research expenditure decreased from over forty drugs per billion in the 1950s to less than one drug per billion in the 2000s (Scannell et al. 2012). And in the twenty years from 1971 to 1991, inflation-adjusted agricultural research expenditures in developed nations rose by over sixty percent, yet growth in crop yields per acre dropped by fifteen percent (Alston et al. 2000). The problem was not that researchers became

[10]To suggest that artificial agents will encounter diminishing research productivity is compatible with enumerating cognitive advantages that artificial agents may possess, such as increased intelligence, greater memory and learning speed, and decreased specialization of labor. Diminishing research productivity is not a claim about the research inputs supplied by artificial agents, but rather a claim about the rate at which fixed research inputs produce increases in machine intelligence.

lazy, poorly educated or overpaid. It was rather that good ideas became harder to find. Researchers in earlier decades identified many promising drugs and improvements to farming techniques, leaving later researchers to scrounge for more complex interventions. As good ideas became harder to find, research productivity declined.

Could the problem of improving artificial agents be an exception to the rule of diminishing research productivity? Recent history suggests otherwise. Consider Moore's law, a historically observed doubling of hardware capacities every two years.[11] A recent economic review singles out Moore's law as a prime example of declining research productivity: between 1971 and 2014, Moore's law was sustained across an eighteen-fold drop in semiconductor research productivity by astronomical increases in the amount of labor and capital devoted to semiconductor research (Bloom et al. 2020). This situation is unsustainable: many forecasters think that Moore's law will end in this decade, and most of the rest think it has already ended (Mack 2011; Shalf 2020; Theis and Wong 2017; Waldrop 2016). The declining pace of hardware growth is another piece of evidence for the relevance of declining research productivity to self-improving artificial intelligence.

Even if there is nothing special about the *problem* of improving artificial agents, could there be something special about the researchers we put this problem to? Perhaps diminishing research productivity afflicts human researchers, but not artificial agents. There is a sliver of truth to this objection: one cause of diminishing research productivity is the difficulty of maintaining large knowledge stocks (Jones 2009), a problem at which artificial agents excel. However, the underlying problem of fishing-out is a feature of problems, not agents, and as such it cannot be eliminated by enlisting artificial agents as researchers. After a while, any sensible investigatory process will have made more than its share of the easiest discoveries, and subsequent discoveries will become harder. Past that point, research productivity will diminish. Even many arguments for the singularity hypothesis concede this point, building diminishing research productivity directly into their models

[11] Moore's law is standardly operationalized by counting the number of transistors on a dense integrated circuit. However, there are other ways to operationalize Moore's law.

of intelligence growth (Davidson 2021; Roodman 2020).

Diminishing research productivity may not pose a severe threat to research processes that take us a hop, skip or a jump beyond current knowledge, but it does threaten research processes which seek to carry artificial intelligence many orders of magnitude beyond its current bounds. Even a relatively small rate of diminishing research productivity, compounded over many cycles of self-improvement, would become very large, exerting substantial downward pressure on the rate of intelligence growth.

3.3 Bottlenecks

Growth processes often slow down because they hit bottlenecks: single obstacles which hinder further improvement until they can be overcome. Just one bottleneck is enough to slow growth.

One way of pressing the point is due to Philippe Aghion and colleagues (Aghion et al. 2019).[12] Algorithms consist of various components such as search, computation and storage processes. These processes, in turn, break into subcomponents such as more elementary computations. It is an unalterable mathematical fact that an algorithm can run no more quickly than its slowest component. If nine-tenths of the component processes can be sped up, but the remaining processes cannot, then the algorithm can only be made ten times faster. This creates the opportunity for bottlenecks unless every single process can be sped up at once.

One reason to expect bottlenecks is that it is unclear how much room we have to improve various software and hardware components. Beginning with software, computer scientists and mathematicians have been working on algorithms such as search and architectures such as neural networks for a very long time. While there is doubtless room for improvement, if algorithms and architectures are already in sight of the best-achievable performance, then there is only so much we can do to make them faster.

[12]There may also be a good analogy to the O-ring model of economic development on which the components of growth enter the production function multiplicatively rather than additively (Kremer 1993).

Turning next to hardware, one reason to expect bottlenecks is that many of the physical resource constraints to be discussed in Section 3.4 take time to overcome. Improving hardware requires mining key materials, constructing manufacturing plants, building capital equipment, and generating and distributing large amounts of energy. We may well be able to speed up these processes, but it is not plausible to expect them all to be made thousands of times more efficient overnight. And if even one process resists being sped up, the whole system of recursive self-improvement may be delayed.

To posit a fast and sustained process of recursive self-improvement requires the strong assumption that all major bottlenecks to self-improvement may be overcome. If, as is likely, some bottlenecks remain, then the process of recursive self-improvement will slow.

3.4 Physical constraints

One reason why rapid growth processes in nature come to a halt is that they run up against physical constraints, such as finite resources and physical laws. To see the point in context, consider why most experts think that Moore's law is coming to an end. Why is it unlikely that the number of transistors per circuit will continue to double biannually?

The first challenge involves resource constraints. Packing more transistors into a fixed area has led to massive increases in the amount of energy that must be fed through circuits during computation (Mack 2011). These energy demands are not only expensive, but also unsafe. There is only so much energy we can push through a circuit without overheating it given current technology. In addition to energy, we are also running out of capital (Waldrop 2016). The cost of new semiconductor plants has ballooned into the billions of dollars, and it is becoming increasingly difficult to continue meeting hardware targets by throwing more money at them.

In addition to resource constraints, we are also running up against basic laws of physics. For example, our best circuits use transistors whose diameter is only ten times that of a typical atom (Yeap et al. 2019). As transistor size takes a nosedive towards the subatomic, it becomes increasingly hard to manufacture and interact with shrinking transistors, and

previously irrelevant quantum uncertainty phenomena arise as potential limitations on the size of transistors.

The demise of Moore's law holds an important lesson for the progress of self-improving artificial intelligence. Any viable path to improving artificial intelligence will eventually run up against resource constraints and laws of physics in ways that are not easily surmountable. In some cases, it may be possible to find new resources or methods which circumvent existing physical constraints. But while we do so, and perhaps even thereafter, we have good reason to expect that growth will slow.

3.5 Sublinearity of intelligence growth from accessible improvements

One reason why the singularity hypothesis might seem plausible is that recent years have seen rapid improvements in quantities such as processing speed, memory and search depth. If intelligence grows proportionally to these quantities, then exponential growth in intelligence should require no more than a continuation of current trends. But that is not the case: the relevant notion of intelligence grows sublinearly in underlying quantities such as processing speed that have been the targets of recent growth.

One way to see the point is to consider performance metrics that might plausibly correlate with intelligence. Here the story is strikingly consistent. Across almost any metric we care to measure, sustained exponential growth in computer capacities has led at best to linear growth in performance.[13] For example, Neil Thompson and colleagues (2022) survey performance gains in computer game-play (Chess, Go) as well as three tasks that are highly dependent on sophisticated computation: protein folding, weather prediction, and modeling underground oil reservoirs. In each domain, Thompson and colleagues find exponential increases in the amount of compute power applied over time, but merely linear gains across metrics such as Chess and Go ELO rating, ability to solve protein folding problems, or to predict weather patterns and oil reserves. Across domains,

[13] Relatedly, see Lohn and Musser (2022) on the unsustainability of increases in compute power as drivers of artificial intelligence progress.

the lesson seems to be that exponential increases in underlying computer capacities lead at best to linear improvements in intelligence-related tasks.[14]

Natural objections to the argument from performance metrics do little to improve the situation. Perhaps advocates of the singularity hypothesis might object that all of the metrics in question correlate only imperfectly with intelligence. But in that case, they are welcome to supply alternative metrics which show consistent patterns of exponential increase. So far, no plausible metrics have been provided. Or perhaps it might be objected that the slow pace of performance increase is due to unrelated factors such as the increasing difficulty of successive improvements (Section 3.2). But even if that were true, it would merely relocate the problem, not solve it.[15]

Another reason to think that intelligence grows sublinearly in underlying capacities draws on Moore's law. In the past 50 years, the number of transistors in our best circuits increased from 3,500 in 1972 to 114 billion in 2022, and other hardware capacities showed similar growth. If we thought that intelligence grew linearly as a function of hardware capacity, we would have to say that computers have become 33 million times more intelligent over this period.

Many readers may find this claim implausible. Perhaps more carefully, if advocates of the singularity hypothesis want to make such claims, they need to do two things. First,

[14]Another lens on intelligence improvement comes from discussions of scaling laws, which ask how improvements in inputs such as model parameters, dataset size, or compute steps affect the loss of deep learning models (Bahri et al. 2021; Hernandez et al. 2021; Kaplan et al. 2020). The first thing to say about these models is that they project a power-law relationship between inputs and test loss, which falls short not only of hyperbolic growth, but on leading parameterizations even of the proportionality required by Chalmers to ground his argument for exponential growth. However, it is also important to emphasize that even most authors in the scaling law tradition are skeptical of projecting forward current growth trends, which are likely to slow. Finally, a careful look at scaling laws may reinforce aspects of the case against the singularity hypothesis: for example, leading scaling laws (Kaplan et al. 2020) allow many key inputs to serve as bottlenecks to growth. Thanks to an anonymous referee for pressing me to address the scaling law literature.

[15]Instead of the smooth growth predicted by scaling laws, some authors might expect sharp, gappy transitions characteristic of emergent abilities (Wei et al. 2022). While emergence is a genuine empirical phenomenon, more needs to be done to generate an argument from the potential for emergence to a nontrivial probability assignment to the singularity hypothesis. It is, of course, theoretically possible that one or a series of sharp leaps could quickly take us to superintelligence, but until more is said, it may be harder to appreciate whether the possibility of emergence goes significantly beyond the existing case for the singularity hypothesis or circumvents existing reasons to doubt the singularity hypothesis.

they need to clarify the relevant notion of intelligence on which it makes sense to speak of an intelligence increase on this scale having occurred. And second, they need to explain how the relevant notion of intelligence can do the work that their view demands. For example, they need to explain why we should expect increases in intelligence to lead to proportional increases in the ability to design intelligent agents (Section 4) and why we should attribute impressive and godlike powers to agents several orders of magnitude more intelligent than the average human (Section 6).

If, instead, the relevant notion of intelligence grows sublinearly in underlying computing capacities, then exponential growth in intelligence would require superexponential growth in underlying capacities. And hyperbolic growth? Don't ask.

3.6 Summarizing the case against the singularity hypothesis

The singularity hypothesis posits a sustained period of explosive growth in artificial intelligence. In this section, we have met five reasons to be skeptical of the hypothesis' growth claims. First, the singularity hypothesis makes an extraordinary claim which should require correspondingly extraordinary evidence. Second, as time goes on ideas for further improvement will become harder to find. Third, even a single bottleneck to growth would be enough to halt an intelligence explosion. Fourth, a number of physical constraints including resource limitations will close off likely avenues for growth. And finally, rapid growth in artificial intelligence might well require unfathomably fast growth in underlying quantities such as memory and computational speed.

Defenders of the singularity hypothesis owe us strong reasons to accept their growth claims in light of the obstacles that those claims have to overcome. In the next two sections, I survey leading philosophical defenses of the singularity hypothesis. I argue that these defenses are too weak to overcome skepticism about the singularity hypothesis' growth claims.

4 The observational argument

Chalmers argues for the singularity hypothesis by proposing the *proportionality thesis*: "increases in intelligence ... always lead to proportionate increases in the ability to design intelligent systems" (Chalmers 2010, p. 21). If the proportionality thesis is true, then each successive AI system should represent at least as much of an improvement as its successor, leading to an intelligence explosion as long as these improvements can be brought about quickly enough.

Section 3 suggested that growth rates are likely to diminish, which in this context means that increases in artificial intelligence should eventually produce less-than-proportionate increases in the ability to design artificial systems. Chalmers must deny that growth rates will diminish, at least until many iterations of self-improvement have elapsed. Given the reasons for skepticism on this front, one might expect an extended argument against diminishing growth. Chalmers' argument is a bit more compressed:

> If anything, 10% increases in intelligence-related capacities are likely to lead to all sorts of intellectual breakthroughs, leading to next-generation increases in intelligence that are significantly greater than 10%. Even among humans, relatively small differences in design capacities (say, the difference between Turing and an average human) seem to lead to large differences in the systems that are designed (say, the difference between a computer and nothing of importance). (Chalmers 2010, p. 27).

The first sentence is a restatement of the proportionality thesis, putting the burden of the argument on the second sentence. In that sentence, Chalmers uses a single observational data point, the difference between Turing and an average human, to defend the proportionality thesis across the board. Call this the *observational argument*.

The observational argument faces two challenges. First, it is local rather than global. It points to a single moment in the history of artificial intelligence and argues that, at this local point, increases in the intelligence of machine designers led to a greater-than-proportional

increase in the intelligence of resulting systems. The problem with local arguments is that they cannot demonstrate the possibility of sustained rates of high growth, because they only sample growth rates at a single point on a curve. Skeptics of the singularity hypothesis do not deny that there was *any* point in the history of artificial intelligence at which the proportionality thesis held. What we deny is that the proportionality thesis will continue to hold through long processes of recursive self-improvement. A single local observation about growth rates does not constitute evidence that these rates will continue indefinitely (Dreyfus 2012).

Moreover, the local point which Chalmers sampled has been chosen to maximally downplay the possibility of diminishing growth rates. By considering growth rates in the very early history of computing, Chalmers samples a point before low-hanging fruit is likely to have been used up, resources depleted, or bottlenecks encountered, avoiding many of the best arguments for diminishing growth. We can readily grant that early-stage research often exhibits constant or increasing growth while retaining substantial confidence that growth rates will later fall.

A second worry for the observational argument is that it equivocates between intelligence and design capacities. The datum cited is that a small difference in *design capacities* between Turing and an average human led to large differences in the *intelligence* of the system designed. This is not an innocent slip, for we would not want to deny that many of Turing's contemporaries were more intelligent than Turing, but much less capable of designing intelligent systems. Therefore, it is not clear that the right thing to conclude from this discussion is that increases in intelligence lead to proportionate increases in the capacity to design intelligent systems. Otherwise, we would have to explain why many people more intelligent than Turing lacked Turing's capacity to design such systems.

Now as Chalmers notes, he could do equally well if all mentions of intelligence were replaced by some other term. So it would be enough to take the example as one in which a small difference in design capacities between Turing and an average human led to large differences in the *design capacities* of the system designed. But this inference fails on both

ends. It is not obvious that the systems designed by Turing had any design capacities at all. Nor is it obvious that the difference in design capacities between Turing and an average human are aptly described as small. Indeed, one might rightly take Turing's design efforts as evidence that his design capacities far outstripped those of an average contemporary.

In this section, we considered an argument for the singularity hypothesis based on the proportionality thesis that increases in intelligence always lead to proportionate increases in the ability to design intelligent systems. We considered Chalmers' observational argument for the proportionality thesis, which cites Turing's early progress as a historical example in which the proportionality thesis held. However, we saw that this argument struggles on two fronts: it is local rather than global, and it equivocates between intelligence and design capacities. Hence Chalmers' observational argument does not vindicate the singularity hypothesis.

5 Recalcitrance and optimization power

Bostrom (2014) argues that the rate of change of artificial intelligence will be driven by two quantities. The first is the amount of *optimization power*, or quality-weighted design effort applied to improving artificial systems. The second quantity is the *recalcitrance* of intelligence growth, the amount of optimization power that must be applied to produce a unit change in intelligence at the current margin. With this understanding of optimization power and recalcitrance, intelligence grows fractionally in optimization power and recalcitrance:

$$\text{Rate of intelligence change} = \frac{\text{Optimization power}}{\text{Recalcitrance}}.$$

If a high amount of optimization power is applied throughout a sustained period of low recalcitrance, the result will be an intelligence explosion.

A welcome feature of Bostrom's treatment is that Bostrom presents a number of specific reasons to expect low recalcitrance and high optimization power to obtain. This allows us

to examine Bostrom's proposal in detail. But the devil is in the details, and in this section I argue that Bostrom's empirical case for low recalcitrance and high optimization power is insufficient.[16]

More specifically, I argue that the details offered by Bostrom break into three categories. The first and largest class consists of mundane but plausible descriptions of how the future might develop which have been over-interpreted to support the possibility of intelligence explosion. The second class consists of thinly detailed restatements of the core hope behind the singularity hypothesis. And the third class consists of factually mistaken interpretations of past historical trends. I conclude that despite the rich detail in which his argument is made, Bostrom fails to provide adequate support for a sustained period of high optimization power combined with low recalcitrance.

5.1 Plausible but over-interpreted scenarios

Bostrom offers five reasons to think that recalcitrance will remain low throughout a period of sustained intelligence growth. Three of these suggestions are within the realm of plausibility, but do not lend significant support to the possibility of intelligence explosion. First, suppose that artificial intelligence is reached through whole-brain emulation, so that the first human-level artificial intelligence is a computer emulation of a single human brain.[17] En route to the first emulation, we may experience high recalcitrance as we struggle to adjust software and to meet hardware demands. But once the first emulation is produced, recalcitrance may drop as we make a series of rapid improvements. For example, we might simplify the algorithm by coarse-graining neural representations, allowing it to run more quickly. Or we might emulate the brains of distinct individuals, increasing the stock of artificial agents we can draw on.

This is our first example of a detailed and not-entirely-implausible scenario that has

[16]To the best of my knowledge, this section surveys every detailed suggestion from Chapter 4 of *Superintelligence* in support of low recalcitrance and high optimization power.

[17]For skepticism about this route to superintelligence, see Mandelbaum (2022).

been overinterpreted to support the possibility of a sustained period of low recalcitrance. There is no doubt that whole-brain emulations, like any new technology, can be improved once they are introduced. Nor is there any doubt that the first improvements may proceed rapidly by exploiting low-hanging fruit. But we have not been given any reason to think that these improvements would be rapid, powerful and sustained enough to bring about a powerful superintelligence. Indeed, Bostrom himself concedes that improvements to emulation technologies may soon hit a period of diminishing returns.

A second example of how artificial intelligence may be improved is through what Bostrom terms *content* improvements, improvements to software that go beyond changes to core algorithms. Bostrom offers the example of increased knowledge stocks: an agent trained on a small database may be improved by training it on large data sets, such as the entire Library of Congress. Here again we have a detailed and relatively plausible scenario for improvement, but one with limited implications for the growth of artificial intelligence. Bostrom is quite right that there is a trend towards training agents on larger datasets, and that improving datasets is a good tool for improving the capabilities of artificial agents. But as impactful as such improvements are, we are given no reason to suspect that absorbing even the entire Library of Congress would result in the sudden emergence of superintelligence. Indeed, there is some reason for doubt on this score. After all, the Library of Congress is already part of the collective knowledge stock of humanity, but this knowledge has only taken us so far.

A third example of how artificial intelligence may be improved is by improving hardware: we may run artificial agents on faster, more powerful or more numerous hardware systems. Here we encounter a third and final example of something that is likely to pass, but unlikely to ground an intelligence explosion. We saw in Section 3 that artificial systems have already experienced a sustained period of rapid hardware growth, but that this growth alone did not produce astronomical gains, for example because intelligence grows sublinearly in hardware capacities. We also saw that many experts expect the pace of hardware growth to slow rather than accelerate, so an appeal to growing hardware capac-

ities is unlikely to provide convincing evidence for an increase in the speed of intelligence growth.

5.2 Restating the core hope

Bostrom offers two further reasons to think that recalcitrance will remain low during a period of sustained intelligence growth. First, Bostrom suggests that artificial intelligence may be produced in a single leap by a clever software insight. If we are only one leap of programming away from superintelligence, then a single programmer in a basement may one day initiate and complete the intelligence explosion. And second, Bostrom suggests, an intelligence explosion may result from a shift in modes of processing. It may be that right now, artificial agents progress primarily by improving their domain-general reasoning capacities, and that as the domain-general reasoning capacities of artificial agents begin to predominate, artificial agents will be able to turn those domain-general reasoning capacities towards the problem of their own improvement, resulting in rapid intelligence growth.

Both of these suggestions express optimistic hopes that, without further evidence, go little beyond the core claim of the singularity hypothesis. It is of course possible that a single software insight could produce superintelligence. It is also possible that artificial agents, once they reach a certain level of domain-general reasoning ability, could improve themselves through one or a series of rapid software insights. But to take these claims from bare possibility to scientific plausibility, we need to provide evidence for thinking that they are likely to come to pass. And so far, Bostrom has not provided any evidence for either claim.

5.3 Mis-interpreting history

How low would the recalcitrance of intelligence improvement have to be in order to generate an intelligence explosion? Bostrom asks us to suppose that optimization power

increases linearly in the intelligence of an artificial systems, so that a system which doubles in intelligence doubles in optimization power. This seems at first like a more plausible version of Chalmers' proportionality thesis, since it removes the assumption of constant recalcitrance. However, Bostrom notes that with these assumptions in place, even constant recalcitrance combined with a linear relationship between intelligence and optimization power would produce only exponential intelligence growth, and under many assumptions the rate of exponential growth might be quite modest.

To generate hyperbolic growth, Bostrom makes a stronger modeling assumption than Chalmers: that recalcitrance varies inversely with the level I of an agent's current intelligence, so that recalcitrance is equal to $1/I$. On this model, we do indeed get an intelligence explosion: the more intelligent an agent becomes, the easier it gets to make further progress, leading to hyperbolic growth in artificial intelligence.

However, the assumption of rapidly decreasing recalcitrance is a surprising claim in need of justification. Here, Bostrom appeals to Moore's law:

> Suppose that the optimization power applied to the system is roughly constant ... prior to the system becoming capable of contributing substantially to its own design, and that this leads to the system doubling in capacity every 18 months. (This would be roughly in line with historical improvement rates from Moore's law combined with software advances.) This rate of improvement, if achieved by means of roughly constant optimization power, entails recalcitrance declining as the inverse of system power. (Bostrom 2014, p. 76).

In this passage, Bostrom asks us to imagine two things: that the intelligence of artificial agents has been doubling every eighteen months, and that this doubling has taken place without an increase in the optimization power applied to improving them. These assumptions would entail that historical rates of recalcitrance have been decreasing inversely in the intelligence of artificial agents, and if we project the trend forwards in time the argument for hyperbolic growth goes through.

However, each of Bostrom's assumptions mis-interprets historical data. Regarding the doubling time of intelligence, we saw in Section 3 that intelligence grows sublinearly in hardware capacities, so that for example from the fact that transistor counts grew thirty-three-millionfold over fifty years we cannot conclude that the intelligence of artificial agents grew millions-fold over the same period. We also saw in Section 3 that historical increases in hardware capacities were not achieved by a constant exertion of optimization power. Leading economic models suggest an eighteen-fold increase in the quality-weighted research effort needed to produce a doubling of hardware capacities over this period (Bloom et al. 2020). Hence the historical evidence does not support the assumptions of rapidly-doubling intelligence against constant optimization power that are needed to ground an intelligence explosion. Rather, the evidence suggests increasing recalcitrance of hardware gains, and thus strongly increasing recalcitrance of intelligence gains, since intelligence does not grow in lockstep with hardware. On Bostrom's model, these assumptions would not even ground exponential intelligence growth.

In this section, we considered Bostrom's argument for an intelligence explosion. This argument claimed that increasing amounts of optimization power will be applied during a period of constant or falling recalcitrance, leading to rapid growth in artificial intelligence. We saw that the considerations marshaled in support of Bostrom's conclusion fall into three categories. The first category consists of detailed descriptions of moderately plausible future scenarios, which have been wrongly interpreted as supporting an intelligence explosion. The second category consists of undetailed future scenarios that amount to thinly veiled assertions of the core hope behind the singularity hypothesis. And the final category consists of a mis-interpretation of historical growth trends which, once corrected, would tell against rather than in favor of intelligence explosion. Taken together, these considerations do not lend substantial support to the singularity hypothesis.

6 Philosophical implications

The singularity hypothesis posits a sustained period of accelerating growth in the general intelligence of artificial agents brought about by recursive processes of self-improvement. This growth is hypothesized to continue until artificial agents have become orders of magnitude more intelligent than their human designers, leading to a fundamental discontinuity in human history.

We saw in Section 3 that there are good reasons to be skeptical of the singularity hypothesis. The singularity hypothesis makes an extraordinary claim which should require correspondingly extraordinary evidence. As time goes on ideas for further improvement will become harder to find. Like most growth processes, the growth of artificial intelligence is likely to be stalled by bottlenecks. Over time, physical limitations such as finite resources and the laws of physics will constrain the pace of improvement. And rapid growth in artificial intelligence might well require unfathomably fast growth in underlying quantities such as memory and computational speed.

Sections 4-5 surveyed two leading philosophical arguments for the singularity hypothesis: Chalmers' observational argument and Bostrom's argument for a sustained period of low recalcitrance combined with high optimization power. We saw that each argument falls short of vindicating the singularity hypothesis. If that is right, then it would be inappropriate at this time to place substantial confidence in the singularity hypothesis.

In this section, I discuss philosophical and policy consequences of diminished confidence in the singularity hypothesis. These consequences depend heavily on the nature of the envisioned post-singularity future, so I split my discussion across optimistic (Section 6.1) and pessimistic (Section 6.2) views before exploring directions for future research (Section 6.3).

6.1 Optimistic views

Many advocates of the singularity hypothesis have had optimistic expectations for what a post-singularity future might bring. For example, Ray Kurzweil holds that after the singularity:

> Human aging and illness will be reversed; pollution will be stopped; world hunger and poverty will be solved. Nanotechnology will make it possible to create virtually any physical product using inexpensive information processes and will ultimately turn even death into a soluble problem. (Kurzweil 2005).

In a similar vein, a young Eliezer Yudkowsky founded the Singularity Institute with the express purpose of bringing about the singularity sooner, declaring "reaching the Singularity as fast as possible to be the Interim Meaning of Life," because it promised a solution to many of the world's greatest ills (Yudkowsky 2001).

On an optimistic vision of post-singularity life, the singularity hypothesis has important philosophical and practical consequences. Casting doubt on the singularity hypothesis will then tend to temper those consequences. In this section, I focus on consequences involving mental uploading and transformative economic growth.

Optimistic versions of the singularity hypothesis have promised a world in which it becomes possible for humans to upload our consciousness in digital form, cheating death by becoming very long-lived digital versions of ourselves (Chalmers 2010; Kurzweil 2005; Yudkowsky 1996). The possibility of mental uploading raises what may be one of the most consequential decisions of our lives: whether to preserve our consciousness through technologies such as brain scanning and cryonic freezing. Both interventions are offered by companies today, but in addition to their potentially life-extending benefits they have very real costs and risks. At a minimum, preservation is expensive, and the longer it takes for a singularity to be achieved, the more likely it is that existing forms of preservation will fail or be superseded, or that the companies preserving our consciousness will simply go out of business. The stakes are raised for those who think that higher-quality preservation

could be achieved on the bodies of those still alive, since brain scanning and cryonic freezing are both fatal processes. Optimists about a post-singularity world who expect rapid growth in artificial intelligence may think that a singularity is near enough to make the benefits of preservation outweigh the costs, even perhaps opting to be preserved while still alive, whereas those optimists who expect less rapid intelligence growth will find it more difficult to justify the costs of consciousness preservation today.

Another consequence arises from the observation that on leading theories of economic growth, rapid technological growth due to progress in artificial intelligence leads to runaway economic growth (Aghion et al. 2019; Roodman 2020). Without intervention, the benefits of growth would be concentrated among a few technology companies, who would quickly come to control the vast majority of the global economy, and human laborers could well lose the ability to demand even subsistence-level wages in a market dominated by artificial laborers. In answer to these threats, some authors have proposed implementing windfall clauses on which technology companies are bound to redistribute windfall profits above a certain level (O'Keefe et al. 2020). If the singularity hypothesis is correct, then extreme runaway profits are among the very most important policy issues facing humanity today, and herculean efforts should be devoted today to the implementation of windfall clauses. By contrast, as we come to expect slower or less dramatic developments in artificial intelligence, windfall clauses remain important proposals, but the urgency and value of passing them will tend to recede.

So far, we have examined what optimistic visions of the post-singularity future predict, with an eye to policy-relevant consequences of reduced confidence in the singularity hypothesis. What follows on more pessimistic visions of the post-singularity future? I address this question below.

6.2 Pessimistic views

Some advocates of the singularity hypothesis have had more pessimistic visions of what a post-singularity future might bring. In particular, some claim that rapid progress in

artificial intelligence may bring about an *existential catastrophe* for humanity, involving "the premature extinction of Earth-originating intelligent life or the permanent and drastic destruction of its potential for desirable future development" (Bostrom 2013, p. 15).

The best-known argument for existential risk from artificial intelligence is due to Nick Bostrom (2014) and Eliezer Yudkowsky (2013). This argument draws on three key claims. The first is the singularity hypothesis on which accelerating growth in self-improving artificial systems leads to the rapid emergence of artificial superintelligence. For example, we saw in Section 1 that Bostrom (2014) argues it is most likely that superintelligence will emerge on a 'fast' timescale of minutes, hours or days, or a 'moderate' timescale of months or years. Bostrom argues that on this timescale, a single project is likely to gain a decisive strategic advantage, quickly emerging to global dominance. At this point, the superintelligence will possess a range of 'cognitive superpowers' sufficient to allow it to form a singleton, "a world order in which there is at the global level a single decision-making agency" (Bostrom 2014, p. 78).

Given its cognitive superpowers and global dominance, the superintelligent singleton will then be in a position to enforce its will on humanity, so the remaining question is what a superintelligent agent would want to do. Two further premises, the Orthogonality Thesis and Instrumental Convergence Thesis (Bostrom 2012) are used to suggest that artificial agents may well have problematic motivations. From this, the Bostrom-Yudkowsky argument concludes that absent significant corrective measures, humanity may soon suffer existential catastrophe at the hands of artificial superintelligence.

There are many ways to push back against the Bostrom-Yudkowsky argument. But an under-appreciated line of resistance involves questioning the singularity hypothesis. Putting pressure against the singularity hypothesis puts pressure against the rapid emergence of superintelligence which Bostrom uses to argue for the likelihood of a singleton. Questioning the singularity hypothesis also puts pressure against the extent of 'cognitive superpowers' that superintelligent agents are likely to possess, suggesting that further work is needed to show not only that superintelligent agents would want to cause an

existential catastrophe, but also that they would be able to do so.

Some recent authors have set out to construct arguments for existential risk from artificial agents which do not rely on the singularity hypothesis (Carlsmith 2021; Cotra 2020; Ngo and Bales forthcoming). If I am right that the singularity hypothesis is improbable, then these efforts are in general to be commended. However, without the singularity hypothesis, these efforts face three hurdles not confronted by the original Bostrom-Yudkowsky argument.

First, insofar as these arguments envision slower emergence of powerful artificial agents, they will need to work harder to motivate the idea that artificial agents will be in a position to form a singleton. As Bostrom acknowledges, slower emergence of superintelligence provides more time for other initiatives to compete for power, and more time for humanity to learn about and react to the growth of artificial systems.

Second, insofar as these arguments envision less radically powerful agents, devoid of Bostromian 'cognitive superpowers', they will need to work harder to motivate the idea that artificial agents will be capable of causing existential catastrophe. For example, a recent argument by Joseph Carlsmith (2021) replaces Bostrom's cognitive superpowers with more mundane abilities such as hacking ability, financial resources, coordination, social influence, and destructive capacity generated by access to weapons systems. Demonstrating how these capabilities could lead to existential catastrophe will require much more sustained and detailed argument than has been presently provided.[18] Here it may be important to recall the enormity of the catastrophe which is being predicted. It is increasingly agreed that even the deliberately omnicidal misuse of all existing nuclear weapons would likely fall far short of causing existential catastrophe (Ord 2020). What this reminds us is that it is not enough to show that rogue artificial systems may cause financial disasters, manipulate humans, or misfire weapons. What needs to be demonstrated is that artificial systems will be powerful enough to destroy humanity or permanently curtail

[18]For example, Carlsmith does not argue extensively for his claim that these powers would give artificial agents the ability to permanently disempower humanity by the year 2070 (see Thorstad (2023), Section 4).

our potential. That is not an easy task.

Third, insofar as these arguments envision more temporally distant threats, they will need to work harder to motivate the urgency of acting today to study and prevent existential catastrophe. Pushing timelines too far into the future raises the concern that studies and safety proposals developed in response to today's technologies may be largely irrelevant to future paradigms in artificial intelligence, just as safety technologies developed for logic-based expert systems might be largely irrelevant for today's deep learning systems. Pushing timelines further into the future also raises the possibility of postponing action for future generations, who will be better-informed and more financially able to support risk mitigation efforts, and who will, if all goes well, have fewer urgent problems such as extreme poverty to solve instead.

Summing up, denying the singularity hypothesis is a promising strategy for combatting the Bostrom-Yudkowsky argument for existential risk from artificial agents. Emerging arguments have sought to reduce the reliance of existential risk claims on the singularity hypothesis. While this is a commendable development, it also raises new challenges which emerging arguments must work to overcome.

6.3 Future directions

So far, we have seen that denying the singularity hypothesis has important philosophical and policy implications across optimistic and pessimistic visions of what the post-singularity future might bring. It might be productive for future work to explore further implications of the singularity hypothesis. For example, what can reflection on the singularity hypothesis teach us about the nature and possibility of artificial intelligence (Dreyfus 2012)? What are the most plausible routes through which artificial general intelligence might eventually be reached (Mandelbaum 2022)? And how is the singularity hypothesis connected to more traditional ethical questions raised by growth in artificial intelligence? But as for the singularity hypothesis itself, I hope to have shown that the growth assumptions underlying the hypothesis are less plausible than its advocates suppose.

References

Aghion, Philippe, Jones, Benjamin, and Jones, Charles. 2019. "Artificial intelligence and economic growth." In Ajay Agrawal, Joshua Gans, and Avi Goldfarb (eds.), *The economics of artificial intelligence: An agenda*, 237–90. University of Chicago Press.

Alston, Julian, Chan-Kang, Connie, Marra, Michele, Pardey, Philip, and Wyatt, TJ. 2000. *A meta-analysis of rates of return to agricultural R&D*. International Food Policy Research Institute, https://www.ifpri.org/publication/meta-analysis-rates-return-agricultural-r-d.

Armstrong, Stuart, Bostrom, Nick, and Shulman, Carl. 2016. "Racing to the precipice: A model of artificial intelligence development." *AI and Society* 31:201–6.

Awret, Uziel. 2012. "Introduction." *Journal of Consciousness Studies* 19:7–15.

Bahri, Yasaman et al. 2021. "Explaining neural scaling laws." arXiv 2102.06701, https://arxiv.org/abs/2102.06701.

Bales, Adam, D'Alessandro, William, and Kirk-Giannini, Cameron Domenico. 2024. "Artificial intelligence: Arguments for catastrophic risk." *Philosophy Compass* 19:e12964.

Baum, Seth, Goertzel, Ben, and Goertzel, Ted. 2011. "How long until human-level AI? Results from an expert assessment." *Technological Forecasting and Social Change* 78:185–95.

Bloom, Nicholas, Jones, Charles, Van Reenen, John, and Webb, Michael. 2020. "Are ideas getting harder to find?" *American Economic Review* 110:1104–44.

Bostrom, Nick. 2012. "The superintelligent will: Motivation and instrumental rationality in advanced artificial agents." *Minds and Machines* 22:71–85.

—. 2013. "Existential risk prevention as a global priority." *Global Policy* 4:15–31.

—. 2014. *Superintelligence*. Oxford University Press.

Callaghan, Victor, Miller, James, Yampolskiy, Roman, and Armstrong, Stuart (eds.). 2017. *The technological singularity: Managing the journey*. Springer.

Carlsmith, Joseph. 2021. "Is power-seeking AI an existential risk?" Technical report, Open Philanthropy.

Chalmers, David. 2010. "The singularity: A philosophical analysis." *Journal of Consciousness Studies* 17:7–65.

—. 2012. "The singularity: A reply to commentators." *Journal of Consciousness Studies* 7-8:141–67.

Chollet, François. 2019. "On the measure of intelligence." arXiv 1911.01547, https://arxiv.org/pdf/1911.01547.pdf.

Cotra, Ajeya. 2020. "Forecasting TAI with biological anchors." https://www.alignmentforum.org/posts/KrJfoZzpSDpnrv9va/draft-report-on-ai-timelines.

Creel, Kathleen. 2020. "Transparency in complex computational systems." *Philosophy of Science* 87:568–89.

Davidson, Tom. 2021. "Could advanced AI drive explosive economic growth?" Technical report, Open Philanthropy, https://www.openphilanthropy.org/research/could-advanced-ai-drive-explosive-economic-growth/.

Dennett, Daniel. 2012. "The mystery of David Chalmers." *Journal of Consciousness Studies* 19:86–95.

Dreyfus, Hubert. 2012. "A history of first step fallacies." *Minds and Machines* 22:87–99.

Eden, Amnon, Moor, James, Søraker, Johnny, and Steinhart, Eric (eds.). 2012. *Singularity hypotheses: A scientific and philosophical assessment*. Springer.

Fazelpour, Sina and Danks, David. 2021. "Algorithmic bias: Senses, sources, solutions." *Philosophy Compass* 16:e12760.

Good, I.J. 1966. "Speculations concerning the first ultraintelligent machine." *Advances in Computers* 6:31–88.

Gordon, Robert. 2016. *The rise and fall of American growth*. Princeton University Press.

Grace, Katja, Salvatier, John, Zhang, Baobao, and Evans, Owain. 2016. "2016 Expert survey on progress in AI." AI Impacts, aiimpacts.org/2016-expert-survey-on-progress-in-ai.

Greaves, Hilary, Thorstad, David, and Barrett, Jacob (eds.). forthcoming. *Essays on longtermism*. Oxford University Press.

Hernandez, Danny et al. 2021. "Scaling laws for transfer." arXiv 2102.01293, https://arxiv.org/abs/2102.01293.

Heylighen, Francis. 2012. "A brain in a vat cannot break out: Why the singularity must be extended, embedded and embodied." *Journal of Consciousness Studies* 17:126–42.

Horvitz, Eric and Selman, Bart. 2012. "Interim report from the panel chairs: AAAI presidential panel on long-term AI futures." In Amnon Eden, James Moor, Johnny Søraker, and Eric Steinhart (eds.), *Singularity hypotheses: A scientific and philosophical assessment*, 301–6. Springer.

Jones, Benjamin. 2009. "The burden of knowledge and the 'Death of the renaissance man': Is innovation getting harder?" *Review of Economic Studies* 76:283–317.

Kaplan, Jared et al. 2020. "Scaling laws for neural language models." arXiv 2001.08361, https://arxiv.org/pdf/2001.08361.pdf

Korinek, Anton and Stiglitz, Joseph. 2019. "Artificial intelligence and its implications for income distribution and unemployment." In Ajay Agrawal, Joshua Gans, and Avi Goldfarb (eds.), *The economics of artificial intelligence: An agenda*, 349–90. University of Chicago Press.

Kortum, Samuel. 1997. "Research, patenting, and technological change." *Econometrica* 65:1389–1419.

Kremer, Michael. 1993. "The O-ring theory of economic development." *Quarterly Journal of Economics* 108:551–75.

Kurzweil, Ray. 2005. *The singularity is near: When humans transcend biology*. Viking.

Landgrebe, Jobst and Smith, Barry. 2022. *Why machines will never rule the world: Artificial intelligence without fear*. Routledge.

Lohn, Andrew and Musser, Micah. 2022. "AI and compute: How much longer can computing power drive artificial intelligence process?" CSET Issue Brief, https://doi.org/10.51593/2021CA009.

Loosemore, Richard and Goertzel, Ben. 2012. "Why an intelligence explosion is probable." In Amnon Eden, James Moor, Johnny Søraker, and Eric Steinhart (eds.), *Singularity hypotheses: A scientific and philosophical assessment*, 83–96. Springer.

Lucas, J.R. 1964. "Minds, machines and Gödel." In A.R. Anderson (ed.), *Minds and Machines*, 43–59. Prentice Hall.

MacAskill, William. 2022. *What we owe the future*. Basic books.

Mack, Chris. 2011. "Fifty years of Moore's Law." *IEEE Transactions on Systems Science and Cybernetics* 24:202–7.

Mandelbaum, Eric. 2022. "Everything and more: The prospects of whole brain emulation." *Journal of Philosophy* 119:444–59.

Modis, Theodore. 2012. "Why the singularity cannot happen." In Amnon Eden, James Moor, Johnny Søraker, and Eric Steinhart (eds.), *Singularity hypotheses: A scientific and philosophical assessment*, 311–40. Springer.

Müller, Vincent and Bostrom, Nick. 2016. "Future progress in artificial intelligence: A survey of expert opinion." In Vincent Müller (ed.), *Fundamental issues of artificial intelligence*, 555–72. Springer.

Ngo, Richard and Bales, Adam. forthcoming. "Deceit and power: Machine learning and misalignment." In Hilary Greaves, David Thorstad, and Jacob Barrett (eds.), *Essays on longtermism*, forthcoming. Oxford University Press.

Nordhaus, William. 2021. "Are we approaching an economic singularity? Information technology and the future of economic growth." *American Economic Journal: Macroeconomics* 13:299–332.

Nunn, Chris. 2012. "More splodge than singularity?" *Journal of Consciousness Studies* 19:57–60.

O'Keefe, Cullen, Cihon, Peter, Garfinkel, Ben, Flynn, Carrick, Leung, Jade, and Dafoe, Allan. 2020. "The windfall clause: Distributing the benefits of AI for the common good." Center for the Governance of AI Research Report, https://www.fhi.ox.ac.uk/windfallclause/.

Ord, Toby. 2020. *The precipice*. Bloomsbury.

Plotnitsky, Arkady. 2012. "The singularity wager: A response to David Chalmers." *Journal of Consciousness Studies* 7-8:61–76.

Prinz, Jesse. 2012. "Singularity and inevitable doom." *Journal of Consciousness Studies* 19:77–86.

Roodman, David. 2020. "On the probability distribution of long-term changes in the growth rate of the global economy: An outside view." Technical report, Open Philanthropy, https://www.openphilanthropy.org/sites/default/files/Modeling-the-human-trajectory.pdf.

Russell, Stewart. 2019. *Human compatible: Artificial intelligence and the problem of control*. Viking.

Scannell, Jack, Blanckley, Alex, Boldon, Helen, and Warrington, Brian. 2012. "Diagnosing the decline in pharmeceutical R&D efficiency." *Nature Reviews Drug Discovery* 11:191–200.

Shalf, John. 2020. "The future of computing beyond Moore's law." *Philosophical Transactions of the Royal Society A* 378:20190061.

Solomonoff, Ray. 1985. "The time scale of artificial intelligence: Reflections on social effects." *Human Systems Management* 5:149–53.

Stein-Perlman, Zach, Weinstein-Raun, Benjamin, and Grace, Katja. 2022. "2022 Expert Survey on Progress in AI." AI Impacts, 3 Aug 2022, https://aiimpacts.org/2022-expert-survey-on-progress-in-ai/.

Theis, Thomas and Wong, H.S. Philip. 2017. "The end of Moore's Law: A new beginning for information technology." *Computing in Science and Engineering* 19:41–50.

Thompson, Neil, Ge, Shuning, and Manso, Gabriel. 2022. "The importance of (exponentially more) computing power." ArXiv, https://arxiv.org/abs/2206.14007.

Thorstad, David. 2023. "Exaggerating the risks, Part 8: Carlsmith wrap-up." Reflective Altruism, https://ineffectivealtruismblog.com/2023/06/03/exaggerating-the-risks-part-8-carlsmith-wrap-up/.

United Nations, Population Division, Department of Economic and Social Affairs. 2019. "World Population Prospects 2019."

Vinge, Vernor. 1993. "The coming technological singularity: How to survive in the post-human era." *Whole Earth Review* 81:88–95.

Von Foerster, Heinz, Mora, Patricia, and Amiot, Lawrence. 1960. "Doomsday: Friday, 13 November, A.D. 2026." *Science* 132:1291–5.

Waldrop, Mitchell. 2016. "The chips are down for Moore's law." *Nature* 530:144.

Wei, Jason et al. 2022. "Emergent abilities of large language models." arXiv 2206.07682, https://arxiv.org/abs/2206.07682.

Yampolskiy, Roman. 2016. *Artificial superintelligence: A futuristic approach*. Chapman and Hall.

Yeap, Goffrey et al. 2019. "5nm CMOS Production Technology Platform featuring full-fledged EUV, and High Mobility Channel FinFETs with densest 0.021μm^2 SRAM cells for Mobile SoC and High Performance Computing Applications." *2019 IEEE International Electron Devices Meeting (IEDM)* 36.7.1–36.7.4.

Yudkowsky, Eliezer. 1996. "Staring into the singularity 1.2.5." http://yudkowsky.net/obsolete/singularity.html.

—. 2001. "The low beyond." https://web.archive.org/web/20070613184827/http://yudkowsky.net/singularity.html.

—. 2013. "Intelligence explosion microeconomics." Technical Report 2013-1, Machine Intelligence Research Institute, http://intelligence.org/files/IEM.pdf.

Zhang, Baobao, Dreksler, Noemi, Anderljung, Markus, Kahn, Lauren, Giattino, Charlie, Dafoe, Allan, and Horowitz, Michael C. 2022. "Forescasting AI progress: Evidence from a survey of machine learning researchers." Https://doi.org/10.48550/arXiv.2206.04132.