Using Artificial Intelligence to Augment Human Intelligence

By creating user interfaces which let us work with the representations inside machine learning models, we can give people new tools for reasoning.

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What are computers for?

Historically, different answers to this question – that is, different visions of computing – have helped inspire and determine the computing systems humanity has ultimately built. Consider the early electronic computers. ENIAC, the world's first general-purpose electronic computer, was commissioned to compute artillery firing tables for the United States Army. Other early computers were also used to solve numerical problems, such as simulating nuclear explosions, predicting the weather, and planning the motion of rockets. The machines operated in a batch mode, using crude input and output devices, and without any real-time interaction. It was a vision of computers as number-crunching machines, used to speed up calculations that would formerly have taken weeks, months, or more for a team of humans.

In the 1950s a different vision of what computers are for began to develop. That vision was crystallized in 1962, when Douglas Engelbart proposed that computers could be used as a way of [1]. In this view, computers weren't primarily tools for solving number-crunching problems. Rather, they were real-time interactive systems, with rich inputs and outputs, that humans could work with to support and expand their own problem-solving process. This vision of intelligence augmentation (IA) deeply influenced many others, including researchers such as Alan Kay at Xerox PARC, entrepreneurs such as Steve Jobs at Apple, and led to many of the key ideas of modern computing systems. Its ideas have also deeply influenced digital art and music, and fields such as interaction design, data visualization, computational creativity, and human-computer interaction.

Research on IA has often been in competition with research on artificial intelligence (AI): competition for funding, competition for the interest of talented researchers. Although there has always been overlap between the fields, IA has typically focused on building systems which put humans and machines to work together, while AI has focused on complete outsourcing of intellectual tasks to machines. In particular, problems in AI are often framed in terms of matching or surpassing human performance: beating humans at chess or Go; learning to recognize speech and images or translating language as well as humans; and so on.

This essay describes a new field, emerging today out of a synthesis of AI and IA. For this field, we suggest the name *artificial intelligence augmentation* (AIA): the use of AI systems to help develop new methods for intelligence augmentation. This new field introduces important new fundamental questions, questions not associated to either parent field. We believe the principles and systems of AIA will be radically different to most existing systems.

Our essay begins with a survey of recent technical work hinting at artificial intelligence augmentation, including work on *generative interfaces* – that is, interfaces which can be used to explore and visualize generative machine learning models. Such interfaces develop a kind of cartography of generative models, ways for humans to explore and make meaning from those models, and to incorporate what those models "know" into their creative work.

Our essay is not just a survey of technical work. We believe now is a good time to identify some of the broad, fundamental questions at the foundation of this emerging field. To what extent are these new tools enabling creativity? Can they be used to generate ideas which are truly surprising and new, or are the ideas cliches, based on trivial recombinations of existing ideas? Can such systems be used to develop fundamental new interface primitives? How will those new primitives change and expand the way humans think?

Using generative models to invent meaningful creative operations

Let's look at an example where a machine learning model makes a new type of interface possible. To understand the interface, imagine you're a type designer, working on creating a new font [1] . After sketching some initial designs, you wish to experiment with bold, italic, and condensed variations. Let's examine a tool to generate and explore such variations, from any initial design. For reasons that will soon be explained the quality of results is quite crude; please bear with us.

Of course, varying the bolding (i.e., the weight), italicization and width are just three ways you can vary a font. Imagine that instead of building specialized tools, users could build their own tool merely by choosing examples of existing fonts. For instance, suppose you wanted to vary the degree of serifing on a font. In the following, please select 5 to 10 sans-serif fonts from the top box, and drag them to the box on the left. Select 5 to 10 serif fonts and drag them to the box on the right. As you do this, a machine learning model running in your browser will automatically infer from these examples how to interpolate your starting font in either the serif or sans-serif direction:

In fact, we used this same technique to build the earlier bolding italicization, and condensing tool. To do so, we used the following examples of bold and non-bold fonts, of italic and non-italic fonts, and of condensed and non-condensed fonts:

To build these tools, we used what's called a *generative model*; the particular model we use was trained by [2]. To understand generative models, consider that *a priori* describing a font appears to require a lot of data. For instance, if the font is 64 by 64 pixels, then we'd expect to need $64 \times 64 = 4,096$ parameters to describe a single glyph. But we can use a generative model to find a much simpler description.

We do this by building a neural network which takes a small number of input variables, called *latent variables*, and produces as output the entire glyph. For the particular model we use, we have 40 latent space dimensions, and map that into the $4,096$-dimensional space describing all the pixels in the glyph. In other words, the idea is to map a low-dimensional space into a higher-dimensional space:

The generative model we use is a type of neural network known as a [3]. For our purposes, the details of the generative model aren't so important. The important thing is that by changing the latent variables used as input, it's possible to get different fonts as output. So one choice of latent variables will give one font, while another choice will give a different font:

You can think of the latent variables as a compact, high-level representation of the font. The neural network takes that high-level representation and converts it into the full pixel data. It's remarkable that just 40 numbers can capture the apparent complexity in a glyph, which originally required $4,096$ variables.

The generative model we use is learnt from a training set of more than 50 thousand fonts [4] scraped from the open web. During training, the weights and biases in the network are adjusted so that the network can output a close approximation to any desired font from the training set, provided a suitable choice of latent variables is made. In some sense, the model is learning a highly compressed representation of all the training fonts.

In fact, the model doesn't just reproduce the training fonts. It can also generalize, producing fonts not seen in training. By being forced to find a compact description of the training examples, the neural net learns an abstract, higher-level model of what a font is. That higher-level model makes it possible to generalize beyond the training examples already seen, to produce realistic-looking fonts.

Ideally, a good generative model would be exposed to a relatively small number of training examples, and use that exposure to generalize to the space of all possible human-readable fonts. That is, for any conceivable font – whether existing or perhaps even imagined in the future – it would be possible to find latent variables corresponding exactly to that font. Of course, the model we're using falls far short of this ideal – a particularly egregious failure is that many fonts generated by the model omit the tail on the capital "Q" (you can see this in the examples above). Still, it's useful to keep in mind what an ideal generative model would do.

Such generative models are similar in some ways to how scientific theories work. Scientific theories often greatly simplify the description of what appear to be complex phenomena, reducing large numbers of variables to just a few variables from which many aspects of system behavior can be deduced. Furthermore, good scientific theories sometimes enable us to generalize to discover new phenomena.

As an example, consider ordinary material objects. Such objects have what physicists call a *phase* – they may be a liquid, a solid, a gas, or perhaps something more exotic, like a superconductor or Bose-Einstein condensate. *A priori*, such systems seem immensely complex, involving perhaps 10^{23} or so molecules. But the laws of thermodynamics and statistical mechanics enable us to find a simpler description, reducing that complexity to just a few variables (temperature, pressure, and so on), which encompass much of the behavior of the system. Furthermore, sometimes it's possible to generalize, predicting unexpected new phases of matter. For example, in 1924, physicists used thermodynamics and statistical mechanics to predict a remarkable new phase of matter, Bose-Einstein condensation, in which a collection of atoms may all occupy identical quantum states, leading to surprising large-scale quantum interference effects. We'll come back to this predictive ability in our later discussion of creativity and generative models.

Returning to the nuts and bolts of generative models, how can we use such models to do example-based reasoning like that in the tool shown above? Let's consider the case of the bolding tool. In that instance, we take the average of all the latent vectors for the user-specified bold fonts, and the average for all the user-specified non-bold fonts. We then compute the difference between these two average vectors:

We'll refer to this as the *bolding vector*. To make some given font bolder, we simply add a little of the bolding vector to the corresponding latent vector, with the amount of bolding vector added controlling the boldness of the result [2]:

This technique was introduced by [5], and vectors like the bolding vector are sometimes called *attribute vectors*. The same idea is use to implement all the tools we've shown. That is, we use example fonts to creating a bolding vector, an italicizing vector, a condensing vector, and a user-defined serif vector. The interface thus provides a way of exploring the latent space in those four directions.

The tools we've shown have many drawbacks. Consider the following example, where we start with an example glyph, in the middle, and either increase or decrease the bolding (on the right and left, respectively):

Examining the glyphs on the left and right we see many unfortunate artifacts. Particularly for the rightmost glyph, the edges start to get rough, and the serifs begin to disappear. A better generative model would reduce those artifacts. That's a good long-term research program, posing many intriguing problems. But even with the model we have, there are also some striking benefits to the use of the generative model.

To understand these benefits, consider a naive approach to bolding, in which we simply add some extra pixels around a glyph's edges, thickening it up. While this thickening perhaps matches a non-expert's way of thinking about type design, an expert does something much more involved. In the following we show the results of this naive thickening procedure versus what is actually done, for Georgia and Helvetica:

As you can see, the naive bolding procedure produces quite different results, in both cases. For example, in Georgia, the left stroke is only changed slightly by bolding, while the right stroke is greatly enlarged, but only on one side. In both fonts, bolding doesn't change the height of the font, while the naive approach does.

As these examples show, good bolding is *not* a trivial process of thickening up a font. Expert type designers have many heuristics for bolding, heuristics inferred from much previous experimentation, and careful study of historical examples. Capturing all those heuristics in a conventional program would involve immense work. The benefit of using the generative model is that it automatically learns many such heuristics.

For example, a naive bolding tool would rapidly fill in the enclosed negative space in the enclosed upper region of the letter "A". The font tool doesn't do this. Instead, it goes to some trouble to preserve the enclosed negative space, moving the A's bar down, and filling out the interior strokes more slowly than the exterior. This principle is evident in the examples shown above, especially Helvetica, and it can also be seen in the operation of the font tool:

The heuristic of preserving enclosed negative space is not *a priori* obvious. However, it's done in many professionally designed fonts. If you examine examples like those shown above it's easy to see why: it improves legibility. During training, our generative model has automatically inferred this principle from the examples it's seen. And our bolding interface then makes this available to the user.

In fact, the model captures many other heuristics. For instance, in the above examples the heights of the fonts are (roughly) preserved, which is the norm in professional font design. Again, what's going on isn't just a thickening of the font, but rather the application of a more subtle heuristic inferred by the generative model. Such heuristics can be used to create fonts with properties which would otherwise be unlikely to occur to users. Thus, the tool expands ordinary people's ability to explore the space of meaningful fonts.

The font tool is an example of a kind of cognitive technology. In particular, the primitive operations it contains can be internalized as part of how a user thinks. In this it resembles a program such as *Photoshop* or a spreadsheet or 3D graphics programs. Each provides a novel set of interface primitives, primitives which can be internalized by the user as fundamental new elements in their thinking. This act of internalization of new primitives is fundamental to much work on intelligence augmentation.

The ideas shown in the font tool can be extended to other domains. Using the same interface, we can use a generative model to manipulate images of human faces using qualities such as expression, gender, or hair color. Or to manipulate sentences using length, sarcasm, or tone. Or to manipulate molecules using chemical properties:

Images from *Sampling Generative Networks* by [6] .

Sentence from *Pride and Prejudice* by Jane Austen. Interpolated by the authors. Inspired by experiments done by the novelist [7]

Images from *Automatic chemical design using a data-driven continuous representation of molecules* by [8] .

Such generative interfaces provide a kind of cartography of generative models, ways for humans to explore and make meaning using those models.

We saw earlier that the font model automatically infers relatively deep principles about font design, and makes them available to users. While it's great that such deep principles can be inferred, sometimes such models infer other things that are wrong, or undesirable. For example, [6] the addition of a smile vector in some face models will make faces not just smile more, but also appear more feminine. Why? Because in the training data more women than men were smiling. So these models may not just learn deep facts about the world, they may also internalize prejudices or erroneous beliefs. Once such a bias is known, it is often possible to make corrections. But to find those biases requires careful auditing of the models, and it is not yet clear how we can ensure such audits are exhaustive.

More broadly, we can ask why attribute vectors work, when they work, and when they fail? At the moment, the answers to these questions are poorly understood.

For the attribute vector to work requires that taking any starting font, we can construct the corresponding bold version by adding the *same* vector in the latent space. However, *a priori* there is no reason using a single constant vector to displace will work. It may be that we should displace in many different ways. For instance, the heuristics used to bold serif and sans-serif fonts are quite different, and so it seems likely that very different displacements would be involved:

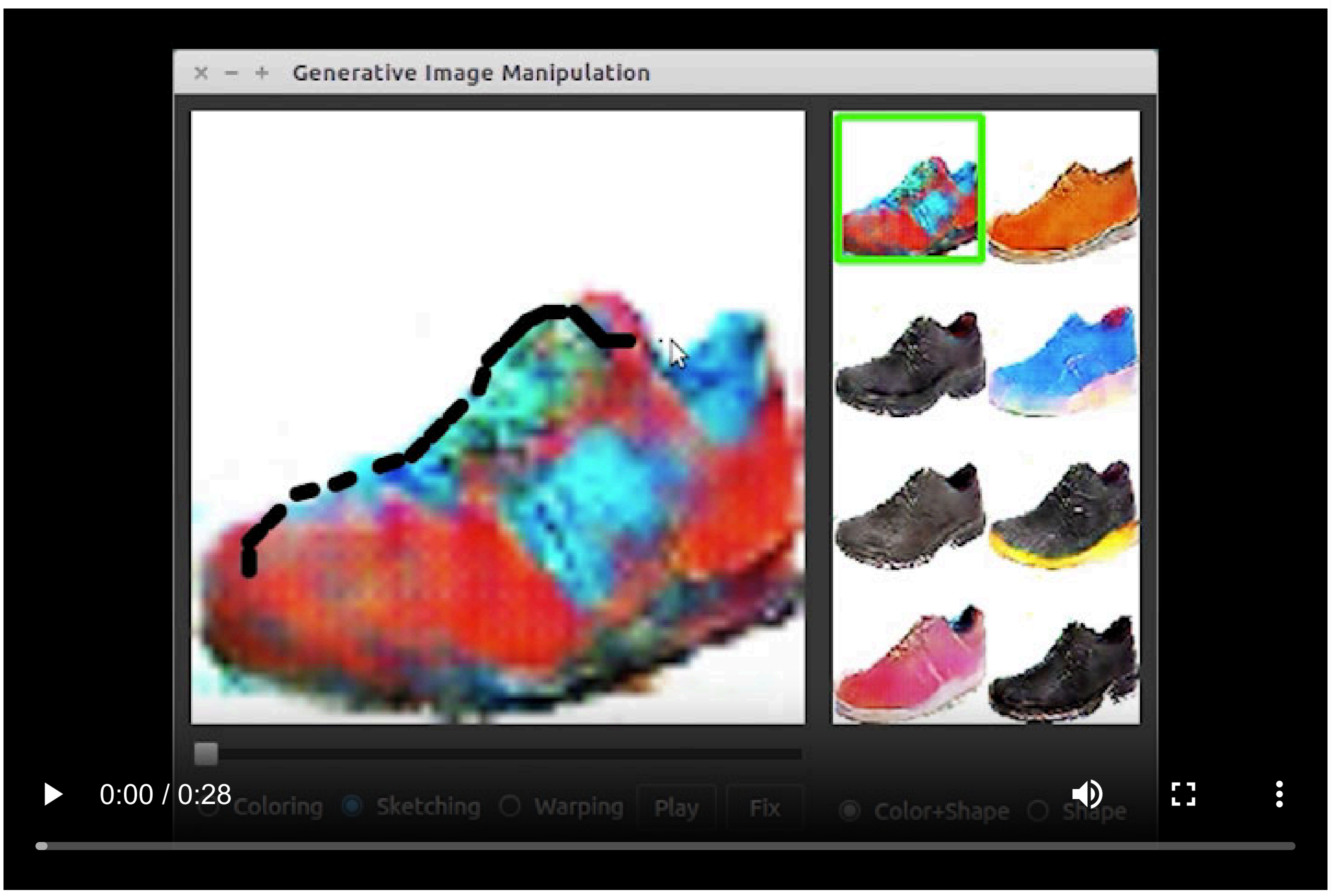
Of course, we could do something more sophisticated than using a single constant attribute vector. Given pairs of example fonts (unbold, bold) we could train a machine learning algorithm to take as input the latent vector for the unbolded version and output the latent vector for the bolded version. With additional training data about font weights, the machine learning algorithm could learn to generate fonts of arbitrary weight. Attribute vectors are just an extremely simple approach to doing these kinds of operation.

For these reasons, it seems unlikely that attribute vectors will last as an approach to manipulating high-level features. Over the next few years much better approaches will be developed. However, we can still expect interfaces offering operations broadly similar to those sketched above, allowing access to high-level and potentially user-defined concepts. That interface pattern doesn't depend on the technical details of attribute vectors.

Interactive Generative Adversarial Models

Let's look at another example using machine learning models to augment human creativity. It's the interactive generative adversarial networks, or iGANs, introduced by [9] in 2016.

One of the examples of Zhu *et al* is the use of iGANs in an interface to generate images of consumer products such as shoes. Conventionally, such an interface would require the programmer to write a program containing a great deal of knowledge about shoes: soles, laces, heels, and so on. Instead of doing this, Zhu *et al* train a generative model using 50 thousand images of shoes, downloaded from Zappos. They then use that generative model to build an interface that lets a user roughly sketch the shape of a shoe, the sole, the laces, and so on:

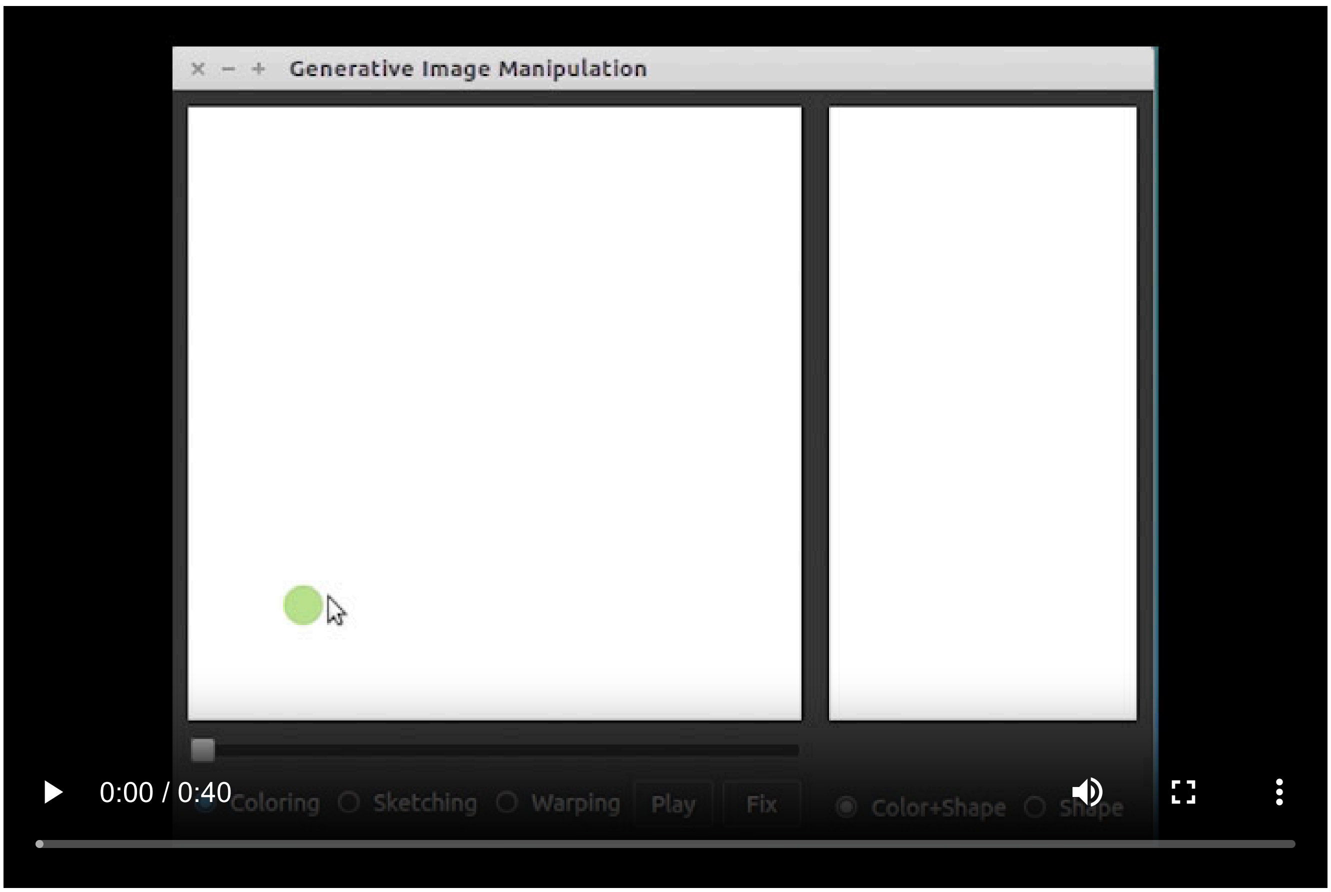


Excerpted from [9].

The visual quality is low, in part because the generative model Zhu *et al* used is outdated by modern (2017) standards – with more modern models, the visual quality would be much higher.

But the visual quality is not the point. Many interesting things are going on in this prototype. For instance, notice how the overall shape of the shoe changes considerably when the sole is filled in – it becomes narrower and sleeker. Many small details are filled in, like the black piping on the top of the white sole, and the red coloring filled in everywhere on the shoe's upper. These and other facts are automatically deduced from the underlying generative model, in a way we'll describe shortly.

The same interface may be used to sketch landscapes. The only difference is that the underlying generative model has been trained on landscape images rather than images of shoes. In this case it becomes possible to sketch in just the colors associated to a landscape. For example, here's a user sketching in some green grass, the outline of a mountain, some blue sky, and snow on the mountain:



Excerpted from [9].

The generative models used in these interfaces are different than for our font model. Rather than using variational autoencoders, they're based on [10]. But the underlying idea is still to find a low-dimensional latent space which can be used to represent (say) all landscape images, and map that latent space to a corresponding image. Again, we can think of points in the latent space as a compact way of describing landscape images.

Roughly speaking, the way the iGANs works is as follows. Whatever the current image is, it corresponds to some point in the latent space:

Suppose, as happened in the earlier video, the user now sketches in a stroke outlining the mountain shape. We can think of the stroke as a constraint on the image, picking out a subspace of the latent space, consisting of all points in the latent space whose image matches that outline:

The way the interface works is to find a point in the latent space which is near to the current image, so the image is not changed too much, but also coming close to satisfying the imposed constraints. This is done by optimizing an objective function which combines the distance to each of the imposed constraints, as well as the distance moved from the current point. If there's just a single constraint, say, corresponding to the mountain stroke, this looks something like the following:

We can think of this, then, as a way of applying constraints to the latent space to move the image around in meaningful ways.

The iGANs have much in common with the font tool we showed earlier. Both make available operations that encode much subtle knowledge about the world, whether it be learning to understand what a mountain looks like, or inferring that enclosed negative space should be preserved when bolding a font. Both the iGANs and the font tool provide ways of understanding and navigating a high-dimensional space, keeping us on the natural space of fonts or shoes or landscapes. As Zhu *et al* remark:

> *[F]or most of us, even a simple image manipulation in Photoshop presents insurmountable difficulties… any less-than-perfect edit immediately makes the image look completely unrealistic. To put another way, classic visual manipulation paradigm does not prevent the user from "falling off" the manifold of natural images.*

Like the font tool, the iGANs is a cognitive technology. Users can internalize the interface operations as new primitive elements in their thinking. In the case of shoes, for example, they can learn to think in terms of the difference they want to apply, adding a heel, or a higher top, or a special highlight. This is richer than the traditional way non-experts think about shoes ("Size 11, black" *etc*). To the extent that non-experts do think in more sophisticated ways – "make the top a little higher and sleeker" – they get little practice in thinking this way, or seeing the consequences of their choices. Having an interface like this enables easier exploration, the ability to develop idioms and the ability to plan, to swap ideas with friends, and so on.

Two models of computation

Let's revisit the question we began the essay with, the question of what computers are for, and how this relates to intelligence augmentation.

One common conception of computers is that they're problem-solving machines: "computer, what is the result of firing this artillery shell in such-and-such a wind [and so on]?"; "computer, what will the maximum temperature in Tokyo be in 5 days?"; "computer, what is the best move to take when the Go board is in this position?"; "computer, how should this image be classified?"; and so on.

This is a conception common to both the early view of computers as number-crunchers, and also in much work on AI, both historically and today. It’s a model of a computer as a way of outsourcing cognition. In speculative depictions of possible future AI, this *cognitive outsourcing* model often shows up in the view of an AI as an oracle, able to solve some large class of problems with better-than-human performance.

But a very different conception of what computers are for is possible, a conception much more congruent with work on intelligence augmentation.

To understand this alternate view, consider our subjective experience of thought. For many people, that experience is verbal: they think using language, forming chains of words in their heads, similar to sentences in speech or written on a page. For other people, thinking is a more visual experience, incorporating representations such as graphs and maps. Still other people mix mathematics into their thinking, using algebraic expressions or diagrammatic techniques, such as Feynman diagrams and Penrose diagrams.

In each case, we’re thinking using representations invented by other people: words, graphs, maps, algebra, mathematical diagrams, and so on. We internalize these cognitive technologies as we grow up, and come to use them as a kind of substrate for our thinking.

For most of history, the range of available cognitive technologies has changed slowly and incrementally. A new word will be introduced, or a new mathematical symbol. More rarely, a radical new cognitive technology will be developed. For example, in 1637 Descartes published his “Discourse on Method”, explaining how to represent geometric ideas using algebra, and vice versa:

This enabled a radical change and expansion in how we think about both geometry and algebra.

Historically, lasting cognitive technologies have been invented only rarely. But modern computers are a meta-medium enabling the rapid invention of many new cognitive technologies. Consider a relatively banal example, such as *Photoshop*. Adept *Photoshop* users routinely have formerly impossible thoughts such as: “let’s apply the clone stamp to the such-and-such layer.”. That’s an instance of a more general class of thought: “computer, [new type of action] this [new type of representation for a newly imagined class of object]”. When that happens, we’re using computers to expand the range of thoughts we can think.

It’s this kind of *cognitive transformation* model which underlies much of the deepest work on intelligence augmentation. Rather than outsourcing cognition, it’s about changing the operations and representations we use to think; it’s about changing the substrate of thought itself. And so while cognitive outsourcing is important, this cognitive transformation view offers a much more profound model of intelligence augmentation. It’s a view in which computers are a means to change and expand human thought itself.

Historically, cognitive technologies were developed by human inventors, ranging from the invention of writing in Sumeria and Mesoamerica, to the modern interfaces of designers such as Douglas Engelbart, Alan Kay, and others.

Examples such as those described in this essay suggest that AI systems can enable the creation of new cognitive technologies. Things like the font tool aren't just oracles to be consulted when you want a new font. Rather, they can be used to explore and discover, to provide new representations and operations, which can be internalized as part of the user's own thinking. And while these examples are in their early stages, they suggest AI is not just about cognitive outsourcing. A different view of AI is possible, one where it helps us invent new cognitive technologies which transform the way we think.

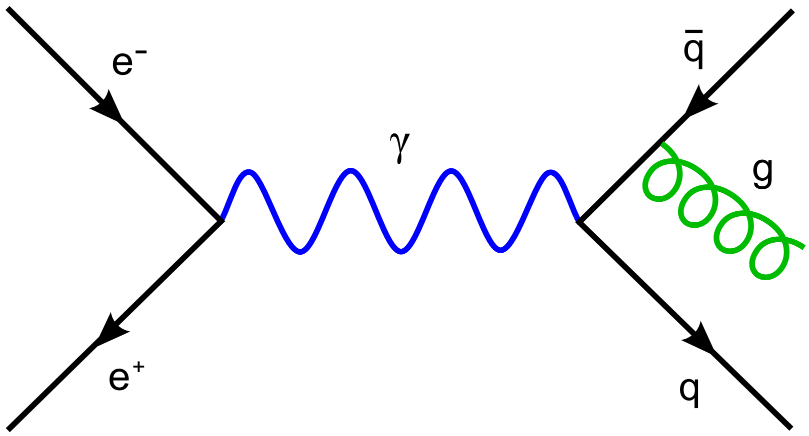
In this essay we've focused on a small number of examples, mostly involving exploration of the latent space. There are many other examples of artificial intelligence augmentation. To give some flavor, without being comprehensive: the [11], for neural network assisted drawing; the [12], which enables users to rapidly build new musical instruments and artistic systems; [13], for developing animations by exploring latent spaces; machine learning models for designing [14]; and a generative model which enables interpolation between [15]. In each case, the systems use machine learning to enable new primitives which can be integrated into the user's thinking. More broadly, artificial intelligence augmentation will draw on fields such as [16] and [17].

Finding powerful new primitives of thought

We've argued that machine learning systems can help create representations and operations which serve as new primitives in human thought. What properties should we look for in such new primitives? This is too large a question to be answered comprehensively in a short essay. But we will explore it briefly.

Historically, important new media forms often seem strange when introduced. Many such stories have passed into popular culture: the near riot at the premiere of Stravinsky and Nijinksy's "Rite of Spring"; the consternation caused by the early cubist paintings, leading *The New York Times* [18]: "What do they mean? Have those responsible for them taken leave of their senses? Is it art or madness? Who knows?"

Another example comes from physics. In the 1940s, different formulations of the theory of quantum electrodynamics were developed independently by the physicists Julian Schwinger, Shin'ichirō Tomonaga, and Richard Feynman. In their work, Schwinger and Tomonaga used a conventional algebraic approach, along lines similar to the rest of physics. Feynman used a more radical approach, based on what are now known as Feynman diagrams, for depicting the interaction of light and matter:



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Initially, the Schwinger-Tomonaga approach was easier for other physicists to understand. When Feynman and Schwinger presented their work at a 1948 workshop, Schwinger was immediately acclaimed. By contrast, Feynman left his audience mystified. As James Gleick put it in his [19]:

> *It struck Feynman that everyone had a favorite principle or theorem and he was violating them all… Feynman knew he had failed. At the time, he was in anguish. Later he said simply: "I had too much stuff. My machines came from too far away."*

Of course, strangeness for strangeness's sake alone is not useful. But these examples suggest that breakthroughs in representation often appear strange at first. Is there any underlying reason that is true?

Part of the reason is because if some representation is truly new, then it will appear different than anything you've ever seen before. Feynman's diagrams, Picasso's paintings, Stravinsky's music: all revealed genuinely new ways of making meaning. Good representations sharpen up such insights, eliding the familiar to show that which is new as vividly as possible. But because of that emphasis on unfamiliarity, the representation will seem strange: it shows relationships you've never seen before. In some sense, the task of the designer is to identify that core strangeness, and to amplify it as much as possible.

Strange representations are often difficult to understand. At first, physicists preferred Schwinger-Tomonaga to Feynman. But as Feynman's approach was slowly understood by physicists, they realized that although Schwinger-Tomonaga and Feynman were mathematically equivalent, Feynman was more powerful. As Gleick puts it:

> *Schwinger's students at Harvard were put at a competitive disadvantage, or so it seemed to their fellows elsewhere, who suspected them of surreptitiously using the diagrams anyway. This was sometimes true… Murray Gell-Mann later spent a semester staying in Schwinger's house and loved to say afterward that he had searched everywhere for the Feynman diagrams. He had not found any, but one room had been locked…*

These ideas are true not just of historical representations, but also of computer interfaces. However, our advocacy of strangeness in representation contradicts much conventional wisdom about interfaces, especially the widely-held belief that they should be “user friendly”, i.e., simple and immediately useable by novices. That most often means the interface is cliched, built from conventional elements combined in standard ways. But while using a cliched interface may be easy and fun, it’s an ease similar to reading a formulaic romance novel. It means the interface does not reveal anything truly surprising about its subject area. And so it will do little to deepen the user’s understanding, or to change the way they think. For mundane tasks that is fine, but for deeper tasks, and for the longer term, you want a better interface.

Ideally, an interface will surface the deepest principles underlying a subject, revealing a new world to the user. When you learn such an interface, you internalize those principles, giving you more powerful ways of reasoning about that world. Those principles are the diffs in your understanding. They’re all you really want to see, everything else is at best support, at worst unimportant dross. The purpose of the best interfaces isn’t to be user-friendly in some shallow sense. It’s to be user-friendly in a much stronger sense, [20] about the world, making them the working conditions in which users live and create. At that point what once appeared strange can instead becomes comfortable and familiar, part of the pattern of thought [3].

What does this mean for the use of AI models for intelligence augmentation?

Aspirationally, as we’ve seen, our machine learning models will help us build interfaces which reify deep principles in ways meaningful to the user. For that to happen, the models have to discover deep principles about the world, recognize those principles, and then surface them as vividly as possible in an interface, in a way comprehensible by the user.

Of course, this is a tall order! The examples we’ve shown are just barely beginning to do this. It’s true that our models do sometimes discover relatively deep principles, like the preservation of enclosed negative space when bolding a font. But this is merely implicit in the model. And while we’ve built a tool which takes advantage of such principles, it’d be better if the model automatically inferred the important principles learned, and found ways of explicitly surfacing them through the interface. (Encouraging progress toward this has been made by [21], which use information-theoretic ideas to find structure in the latent space.) Ideally, such models would start to get at true explanations, not just in a static form, but in a dynamic form, manipulable by the user. But we’re a long way from that point.

Do these interfaces inhibit creativity?

It’s tempting to be skeptical of the expressiveness of the interfaces we’ve described. If an interface constrains us to explore only the natural space of images, does that mean we’re merely doing the expected? Does it mean these interfaces can only be used to generate visual cliches? Does it prevent us from generating anything truly new, from doing truly creative work?

To answer these questions, it’s helpful to identify two different modes of creativity. This two-mode model is over-simplified: creativity doesn’t fit so neatly into two distinct categories. Yet the model nonetheless clarifies the role of new interfaces in creative work.

The first mode of creativity is the everyday creativity of a craftsperson engaged in their craft. Much of the work of a font designer, for example, consists of competent recombination of the best existing practices. Such work typically involves many creative choices to meet the intended design goals, but not developing key new underlying principles.

For such work, the generative interfaces we've been discussing are promising. While they currently have many limitations, future research will identity and fix many deficiencies. This is happening rapidly with GANs: the original GANs [10] had many limitations, but models soon appeared that were better adapted to images [22], improved the resolution, reduced artifacts [4], and so on. With enough iterations it's plausible these generative interfaces will become powerful tools for craft work.

The second mode of creativity aims toward developing new principles that fundamentally change the range of creative expression. One sees this in the work of artists such as Picasso or Monet, who violated existing principles of painting, developing new principles which enabled people to see in new ways.

Is it possible to do such creative work, while using a generative interface? Don't such interfaces constrain us to the space of natural images, or natural fonts, and thus actively prevent us from exploring the most interesting new directions in creative work?

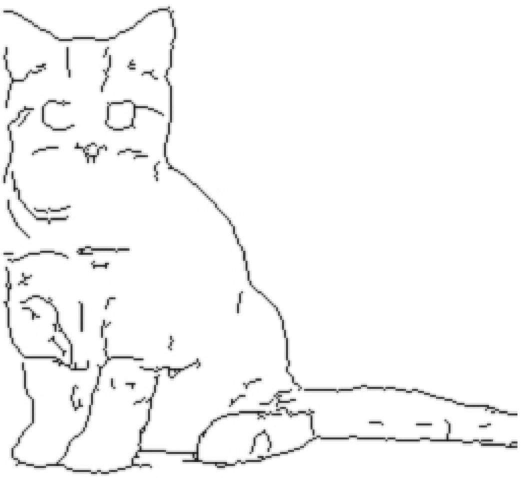
The situation is more complex than this.

In part, this is a question about the power of our generative models. In some cases, the model can only generate recombinations of existing ideas. This is a limitation of an ideal GAN, since a perfectly trained GAN generator will reproduce the training distribution. Such a model can't directly generate an image based on new fundamental principles, because such an image wouldn't look anything like it's seen in its training data.

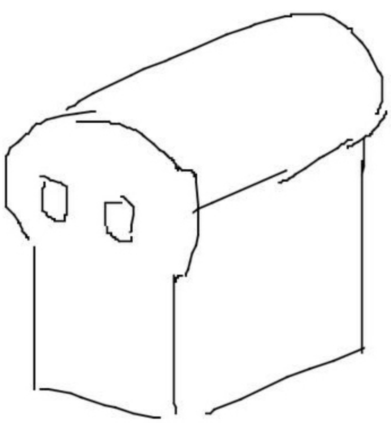
Artists such as Mario Klingemann and Mike Tyka are now using GANs to create interesting artwork. They're doing that using "imperfect" GAN models, which they seem to be able to use to explore interesting new principles; it's perhaps the case that bad GANs may be more artistically interesting than ideal GANs. Furthermore, nothing says an interface must only help us explore the latent space. Perhaps operations can be added which deliberately take us out of the latent space, or to less probable (and so more surprising) parts of the space of natural images.

Of course, GANs are not the only generative models. In a sufficiently powerful generative model, the generalizations discovered by the model may contain ideas going beyond what humans have discovered. In that case, exploration of the latent space may enable us to discover new fundamental principles. The model would have discovered stronger abstractions than human experts. Imagine a generative model trained on paintings up until just before the time of the cubists; might it be that by exploring that model it would be possible to discover cubism? It would be an analogue to something like the prediction of Bose-Einstein condensation, as discussed earlier in the essay. Such invention is beyond today's generative models, but seems a worthwhile aspiration for future models.

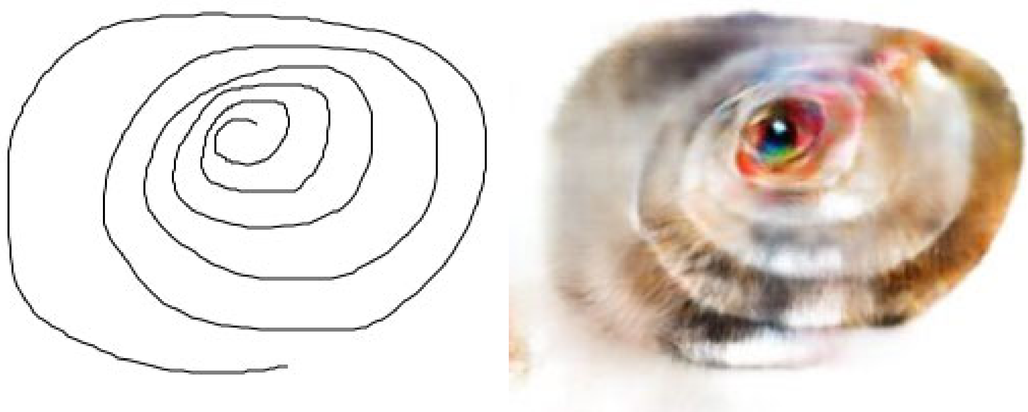
Our examples so far have all been based on generative models. But there are some illuminating examples which are not based on generative models. Consider the pix2pix system developed by [23]. This system is trained on pairs of images, e.g., pairs showing the edges of a cat, and the actual corresponding cat. Once trained, it can be shown a set of edges and asked to generate an image for an actual corresponding cat. It often does this quite well:

INPUT	OUTPUT	
		Live demo by Christopher Hesse

When supplied with unusual constraints, pix2pix can produce striking images:

		Bread cat by Ivy Tsai

Cat beholder by Marc Hesse



Spiral cat

This is perhaps not high creativity of a Picasso-esque level. But it is still surprising. It's certainly unlike images most of us have ever seen before. How does pix2pix and its human user achieve this kind of result?

Unlike our earlier examples, pix2pix is not a generative model. This means it does not have a latent space or a corresponding space of natural images. Instead, there is a neural network, called, confusingly, a generator – this is not meant in the same sense as our earlier generative models – that takes as input the constraint image, and produces as output the filled-in image.

The generator is trained adversarially against a discriminator network, whose job is to distinguish between pairs of images generated from real data, and pairs of images generated by the generator.

While this sounds similar to a conventional GAN, there is a crucial difference: there is no latent vector input to the generator [5]. Rather, there is simply an input constraint. When a human inputs a constraint unlike anything seen in training, the network is forced to improvise, doing the best it can to interpret that constraint according to the rules it has previously learned. The creativity is the result of a forced merger of knowledge inferred from the training data, together with novel constraints provided by the user. As a result, even relatively simple ideas – like the bread- and beholder-cats – can result in striking new types of images, images not within what we would previously have considered the space of natural images.

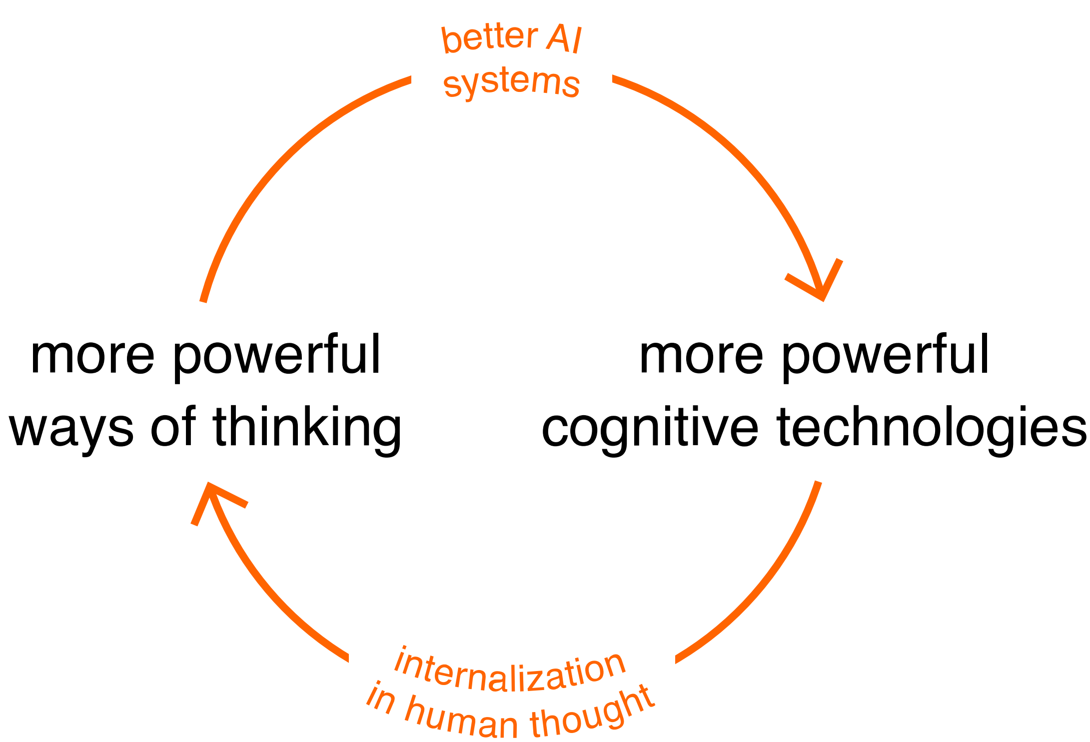
Conclusion

It is conventional wisdom that AI will change how we interact with computers. Unfortunately, many in the AI community greatly underestimate the depth of interface design, often regarding it as a simple problem, mostly about making things pretty or easy-to-use. In this view, interface design is a problem to be handed off to others, while the hard work is to train some machine learning system.

This view is incorrect. At its deepest, interface design means developing the fundamental primitives human beings think and create with. This is a problem whose intellectual genesis goes back to the inventors of the alphabet, of cartography, and of musical notation, as well as modern giants such as Descartes, Playfair, Feynman, Engelbart, and Kay. It is one of the hardest, most important and most fundamental problems humanity grapples with.

As discussed earlier, in one common view of AI our computers will continue to get better at solving problems, but human beings will remain largely unchanged. In a second common view, human beings will be modified at the hardware level, perhaps directly through neural interfaces, or indirectly through whole brain emulation.

We've described a third view, in which AIs actually change humanity, helping us invent new cognitive technologies, which expand the range of human thought. Perhaps one day those cognitive technologies will, in turn, speed up the development of AI, in a virtuous feedback cycle:



It would not be a Singularity in machines. Rather, it would be a Singularity in humanity's range of thought. Of course, this loop is at present extremely speculative. The systems we've described can help develop more powerful ways of thinking, but there's at most an indirect sense in which those ways of thinking are being used in turn to develop new AI systems.

Of course, over the long run it's possible that machines will exceed humans on all or most cognitive tasks. Even if that's the case, cognitive transformation will still be a valuable end, worth pursuing in its own right. There is pleasure and value involved in learning to play chess or Go well, even if machines do it better. And in activities such as story-telling the benefit often isn't so much the artifact produced as the process of construction itself, and the relationships forged. There is intrinsic value in personal change and growth, apart from instrumental benefits.

The interface-oriented work we've discussed is outside the narrative used to judge most existing work in artificial intelligence. It doesn't involve beating some benchmark for a classification or regression problem. It doesn't involve impressive feats like beating human champions at games such as Go. Rather, it involves a much more subjective and difficult-to-measure criterion: is it helping humans think and create in new ways?

This creates difficulties for doing this kind of work, particularly in a research setting. Where should one publish? What community does one belong to? What standards should be applied to judge such work? What distinguishes good work from bad?

We believe that over the next few years a community will emerge which answers these questions. It will run workshops and conferences. It will publish work in venues such as Distill. Its standards will draw from many different communities: from the artistic and design and musical communities; from the mathematical community's taste in abstraction and good definition; as well as from the existing AI and IA communities, including work on computational creativity and human-computer interaction. The long-term test of success will be the development of tools which are widely used by creators. Are artists using these tools to develop remarkable new styles? Are scientists in other fields using them to develop understanding in ways not otherwise possible? These are great aspirations, and require an approach that builds on conventional AI work, but also incorporates very different norms.

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Author contribution

Authors are listed alphabetically in the byline. Michael drafted the text of the essay, but the ideas of the essay were developed jointly in conversation with Shan. Shan developed the interactive diagrams, with considerable input from Michael.

Footnotes

1. We shall egregiously abuse the distinction between a font and a typeface. Apologies to any type designers who may be reading. [↩]
2. In practice, sometimes a slightly different procedure is used. In some generative models the latent vectors satisfy some constraints – for instance, they may all be of the same length. When that's the case, as in our model, a more sophisticated "adding" operation must be used, to ensure the length remains the same. But conceptually, the picture of adding the bolding vector is the right way to think. [↩]
3. A powerful instance of these ideas is when an interface reifies general-purpose principles. An example is an interface [20] developed based on the principle of conservation of energy. Such general-purpose principles generate multiple unexpected relationships between the entities of a subject, and so are a particularly rich source of insights when reified in an interface. [↩]
4. So much work has been done on improving resolution and reducing artifacts it seems unfair to single out any small set of papers, and to omit the many others. [↩]
5. Actually, Isola *et al* experimented with adding such a latent vector to the generator, but found it made little difference to the resulting images. [↩]

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