AI with Artificial X-rays

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While it is undeniable that AI has opened up a <u>wealth of promising opportunities</u>, it has also led to the emergence of a mindset that can be best described as "AI solutionism". [24]

Intel's Gadi Singer believes his most important challenge is his latest: using artificial intelligence (AI) to reshape scientific exploration. [23]

Artificial intelligence is astonishing in its potential. It will be more transformative than the PC and the Internet. Already it is poised to solve some of our biggest challenges. [22]

In the search for extraterrestrial intelligence (SETI), we've often looked for signs of intelligence, technology and communication that are similar to our own. [21]

Call it an a-MAZE-ing development: A U.K.-based team of researchers has developed an artificial intelligence program that can learn to take shortcuts through a labyrinth to reach its goal. In the process, the program developed structures akin to those in the human brain. [20]

And as will be presented today at the 25th annual meeting of the Cognitive Neuroscience networks to enhance their understanding of one of the most elusive intelligence systems, the human brain. [19]

U.S. Army Research Laboratory scientists have discovered a way to leverage emerging brain-like computer architectures for an age-old number-theoretic problem known as integer factorization. [18]

Now researchers at the Department of Energy's Lawrence Berkeley National Laboratory (Berkeley Lab) and UC Berkeley have come up with a novel machine learning method that enables scientists to derive insights from systems of previously intractable complexity in record time. [17]

Quantum computers can be made to utilize effects such as quantum coherence and entanglement to accelerate machine learning. [16]

Neural networks learn how to carry out certain tasks by analyzing large amounts of data displayed to them. [15]

Who is the better experimentalist, a human or a robot? When it comes to exploring synthetic and crystallization conditions for inorganic gigantic molecules, actively learning machines are clearly ahead, as demonstrated by British Scientists in an experiment with polyoxometalates published in the journal Angewandte Chemie. [14]

Machine learning algorithms are designed to improve as they encounter more data, making them a versatile technology for understanding large sets of photos such as those accessible from Google Images. Elizabeth Holm, professor of materials science and engineering at Carnegie Mellon University, is leveraging this technology to better understand the enormous number of research images accumulated in the field of materials science. [13]

With the help of artificial intelligence, chemists from the University of Basel in Switzerland have computed the characteristics of about two million crystals made up of four chemical elements. The researchers were able to identify 90 previously unknown thermodynamically stable crystals that can be regarded as new materials. [12]

The artificial intelligence system's ability to set itself up quickly every morning and compensate for any overnight fluctuations would make this fragile technology much more useful for field measurements, said co-lead researcher Dr Michael Hush from UNSW ADFA. [11]

Quantum physicist Mario Krenn and his colleagues in the group of Anton Zeilinger from the Faculty of Physics at the University of Vienna and the Austrian Academy of Sciences have developed an algorithm which designs new useful quantum experiments. As the computer does not rely on human intuition, it finds novel unfamiliar solutions. [10]

Researchers at the University of Chicago's Institute for Molecular Engineering and the University of Konstanz have demonstrated the ability to generate a quantum logic operation, or rotation of the qubit, that - surprisingly—is intrinsically resilient to noise as well as to variations in the strength or duration of the control. Their achievement is based on a geometric concept known as the Berry phase and is implemented through entirely optical means within a single electronic spin in diamond. [9]

New research demonstrates that particles at the quantum level can in fact be seen as behaving something like billiard balls rolling along a table, and not merely as the probabilistic smears that the standard interpretation of quantum mechanics suggests. But there's a catch - the tracks the particles follow do not always behave as one would expect from "realistic" trajectories, but often in a fashion that has been termed "surrealistic." [8]

Quantum entanglement—which occurs when two or more particles are correlated in such a way that they can influence each other even across large distances—is not an all-or-nothing phenomenon, but occurs in various degrees. The more a quantum state is entangled with its partner, the better the states will perform in quantum information applications. Unfortunately, quantifying entanglement is a difficult process involving complex optimization problems that give even physicists headaches. [7]

A trio of physicists in Europe has come up with an idea that they believe would allow a person to actually witness entanglement. Valentina Caprara Vivoli, with the University of Geneva, Pavel Sekatski, with the University of Innsbruck and Nicolas Sangouard, with the University of Basel, have together written a paper describing a scenario where a human subject would be able to witness an instance of entanglement—they have uploaded it to the arXiv server for review by others. [6]

The accelerating electrons explain not only the Maxwell Equations and the Special Relativity, but the Heisenberg Uncertainty Relation, the Wave-Particle Duality and the electron's spin also, building the Bridge between the Classical and Quantum Theories.

The Planck Distribution Law of the electromagnetic oscillators explains the electron/proton mass rate and the Weak and Strong Interactions by the diffraction patterns. The Weak Interaction changes the diffraction patterns by moving the electric charge from one side to the other side of the diffraction pattern, which violates the CP and Time reversal symmetry.

The diffraction patterns and the locality of the self-maintaining electromagnetic potential explains also the Quantum Entanglement, giving it as a natural part of the relativistic quantum theory.

Contents

Author: George Rajna

Preface

Physicists are continually looking for ways to unify the theory of relativity, which describes largescale phenomena, with quantum theory, which describes small-scale phenomena. In a new proposed experiment in this area, two toaster-sized "nanosatellites" carrying entangled condensates orbit around the Earth, until one of them moves to a different orbit with different gravitational field strength. As a result of the change in gravity, the entanglement between the

condensates is predicted to degrade by up to 20%. Experimentally testing the proposal may be possible in the near future. [5]

Quantum entanglement is a physical phenomenon that occurs when pairs or groups of particles are generated or interact in ways such that the quantum state of each particle cannot be described independently – instead, a quantum state may be given for the system as a whole. [4]

I think that we have a simple bridge between the classical and quantum mechanics by understanding the Heisenberg Uncertainty Relations. It makes clear that the particles are not point like but have a dx and dp uncertainty.

Training artificial intelligence with artificial X-rays

Artificial intelligence (AI) holds real potential for improving both the speed and accuracy of medical diagnostics. But before clinicians can harness the power of AI to identify conditions in images such as X-rays, they have to 'teach' the algorithms what to look for.

Identifying rare pathologies in medical images has presented a persistent challenge for researchers, because of the scarcity of images that can be used to train AI systems in a supervised learning setting.

Professor Shahrokh Valaee and his team have designed a new approach: using machine learning to create computer generated X-rays to augment AI training sets.

"In a sense, we are using machine learning to do machine learning," says Valaee, a professor in The Edward S. Rogers Sr. Department of Electrical & Computer Engineering (ECE) at the University of Toronto. "We are creating simulated X-rays that reflect certain rare conditions so that we can combine them with real X-rays to have a sufficiently large database to train the neural networks to identify these conditions in other X-rays."

Valaee is a member of the Machine Intelligence in Medicine Lab (MIMLab), a group of physicians, scientists and engineering researchers who are combining their expertise in image processing, artificial intelligence and medicine to solve medical challenges. "AI has the potential to help in a myriad of ways in the field of medicine," says Valaee. "But to do this we need a lot of data—the thousands of labelled images we need to make these systems work just don't exist for some rare conditions."

To create these artificial X-rays, the team uses an AI technique called a deep convolutional generative adversarial network (DCGAN) to generate and continually improve the simulated images. GANs are a type of algorithm made up of two networks: one that generates the images and the other that tries to discriminate synthetic images from real images. The two networks are trained to the point that the discriminator cannot differentiate real images from synthesized ones. Once a sufficient number of artificial X-rays are created, they are combined with real X-rays to train a deep convolutional neural network, which then classifies the images as either normal or identifies a number of conditions.

"We've been able to show that artificial data generated by a deep convolutional GANs can be used to augment real datasets," says Valaee. "This provides a greater quantity of data for training and improves the performance of these systems in identifying rare conditions."
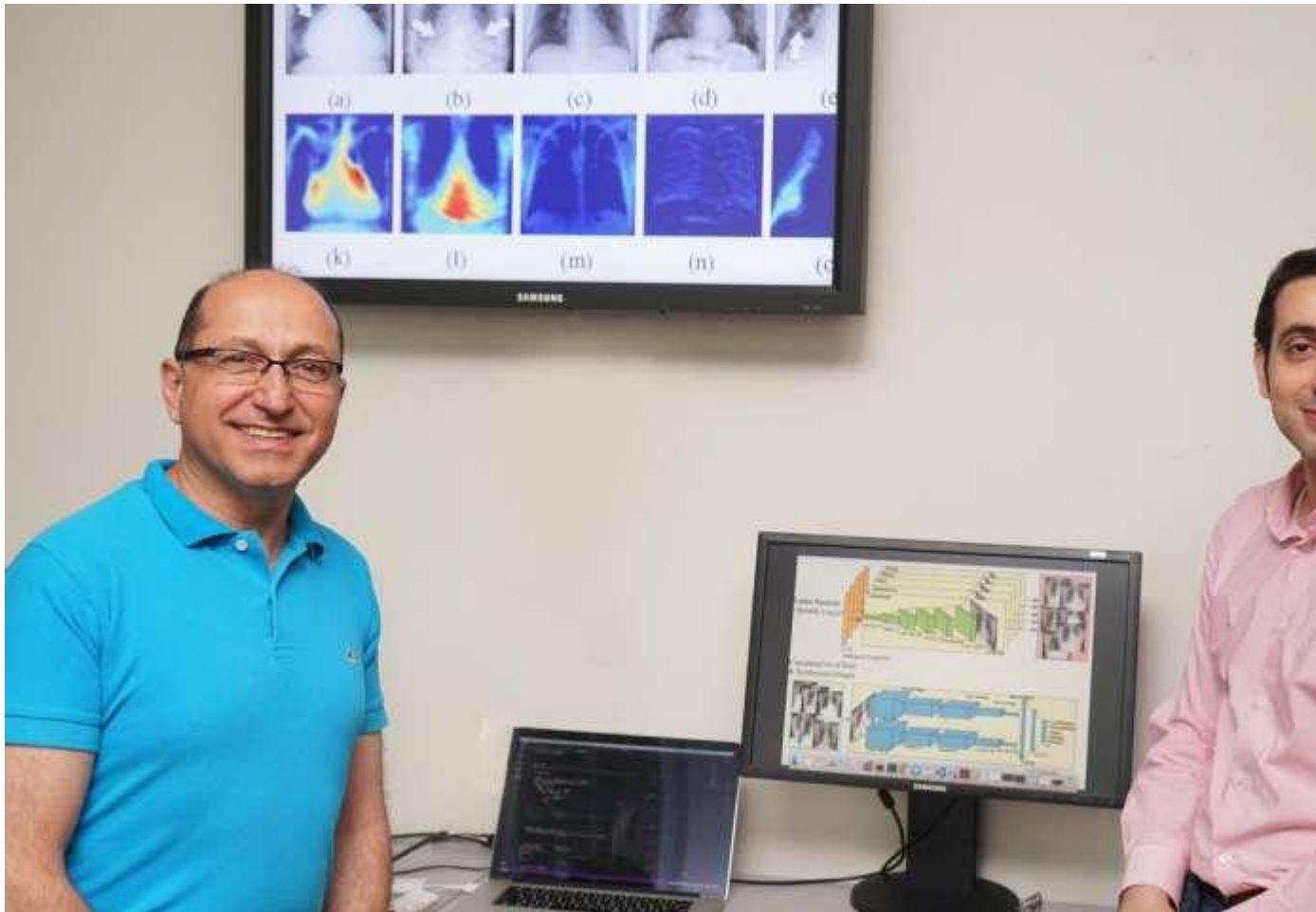
Professor Shahrokh Valaee (ECE, at left) and PhD candidate Hojjat Salehinejad are using machine learning to create simulated chest X-ray images to train AI systems to identify rare pathologies. Credit: Jessica MacInnis

The MIMLab compared the accuracy of their augmented dataset to the original dataset when fed through their AI system and found that classification accuracy improved by 20 per cent for common conditions. For some rare conditions, accuracy improved up to about 40 per cent—and because the synthesized X-rays are not from real individuals the dataset can be readily available to researchers outside the hospital premises without violating privacy concerns.

"It's exciting because we've been able to overcome a hurdle in applying artificial intelligence to medicine by showing that these augmented datasets help to improve classification accuracy," says Valaee. "Deep learning only works if the volume of training data is large enough and this is one way to ensure we have neural networks that can classify images with high precision." [26]

Less biased facial recognition? Microsoft touts improvement, IBM offering help

If a picture paints a thousand words, facial recognition paints two: It's biased.

You might remember a few years ago that Google Photos automatically tagged images of black people as "gorillas," or Flickr (owned by Yahoo at the time) doing the same and tagging people as "apes" or "animals."

Earlier this year, the *New York Times* reported on a study by Joy Buolamwini, a researcher at the MIT Media Lab, on artificial intelligence, algorithms and bias: She found that facial recognition is most accurate for white men, and least accurate for darker-skinned people, especially women.

Now—as facial recognition is being considered for use or is being used by police, airports, immigration officials and others—Microsoft says it has improved its facial-recognition technology to the point where it has reduced error rates for darker-skinned men and women by up to 20 times. For women alone, the company says it has reduced error rates by nine times.

Microsoft made improvements by collecting more data and expanding and revising the datasets it used to train its AI.

From a recent company blog post: "The higher error rates on females with darker skin highlights an industrywide challenge: Artificial intelligence technologies are only as good as the data used to train them. If a facial recognition system is to perform well across all people, the training dataset needs to represent a diversity of skin tones as well as factors such as hairstyle, jewelry and eyewear."

In other words, the company that brought us Tay, the sex-crazed and Nazi-loving chatbot, wants us to know it is trying, it's really trying. (You might also remember that Microsoft took its AI experiment Tay offline in 2016 after she quickly began to spew crazy and racist things on Twitter, reflecting the stuff she learned online. The company blamed a "coordinated attack by a subset of people" for Tay's corruption.)

In related news, IBM announced that it will release the world's largest facial dataset to technologists and researchers, to help in studying bias. It's actually releasing two datasets this fall: one that has more than 1 million images, and another that has 36,000 facial images equally distributed by ethnicity, gender and age.

Big Blue also said it improved its Watson Visual Recognition service for facial analysis, decreasing its error rate by nearly tenfold, earlier this year.

"AI holds significant power to improve the way we live and work, but only if AI systems are developed and trained responsibly, and produce outcomes we trust," IBM said in a blog post. "Making sure that the system is trained on balanced data, and rid of biases, is critical to achieving such trust." [25]

Why AI can't solve everything

The hysteria about the future of artificial intelligence (AI) is everywhere. There seems to be no shortage of sensationalist news about how AI could cure diseases, accelerate human innovation and improve human creativity. Just looking at the media headlines, you might think that we are already living in a future where AI has infiltrated every aspect of society.

While it is undeniable that AI has opened up a wealth of promising opportunities, it has also led to the emergence of a mindset that can be best described as "AI solutionism". This is the philosophy that, given enough data, machine learning algorithms can solve all of humanity's problems.

But there's a big problem with this idea. Instead of supporting AI progress, it actually jeopardises the value of machine intelligence by disregarding important AI safety principles and setting unrealistic expectations about what AI can really do for humanity.

AI solutionism

In only a few years, AI solutionism has made its way from the technology evangelists' mouths in Silicon Valley to the minds of government officials and policymakers around the world. The pendulum has swung from the dystopian notion that AI will destroy humanity to the utopian belief that our algorithmic saviour is here.

We are now seeing governments pledge support to national AI initiatives and compete in a technological and rhetorical arms race to dominate the burgeoning machine learning sector. For example, the UK government has vowed to invest £300m in AI research to position itself as a leader in the field. Enamoured with the transformative potential of AI, the French president Emmanuel Macron committed to turn France into a global AI hub. Meanwhile, the Chinese government is increasing its AI prowess with a national plan to create a Chinese AI industry worth US$150 billion by 2030. AI solutionism is on the rise and it is here to stay.

Neural networks – easier said than done

While many political manifestos tout the transformative effects of the looming "AI revolution", they tend to understate the complexity around deploying advanced machine learning systems in the real world.

One of the most promising varieties of AI technologies are neural networks. This form of machine learning is loosely modelled after the neuronal structure of the human brain but on a much smaller scale. Many AI-based products use neural networks to infer patterns and rules from large volumes of data. But what many politicians do not understand is that simply adding a neural network to a problem will not automatically mean that you'll find a solution. Similarly, adding a neural network to a democracy does not mean it will be instantaneously more inclusive, fair or personalised.

Challenging the data bureaucracy

AI systems need a lot of data to function, but the public sector typically does not have the appropriate data infrastructure to support advanced machine learning. Most of the data remains stored in offline archives. The few digitised sources of data that exist tend to be buried in bureaucracy. More often than not, data is spread across different government departments that each require special permissions to be accessed. Above all, the public sector typically lacks the

human talent with the right technological capabilities to fully reap the benefits of machine intelligence.

For these reasons, the sensationalism over AI has attracted many critics. Stuart Russell, a professor of computer science at Berkeley, has long advocated a more realistic approach that focuses on simple everyday applications of AI instead of the hypothetical takeover by super-intelligent robots. Similarly, MIT's professor of robotics, Rodney Brooks, writes that "almost all innovations in robotics and AI take far, far, longer to be really widely deployed than people in the field and outside the field imagine".

One of the many difficulties in deploying machine learning systems is that AI is extremely susceptible to adversarial attacks. This means that a malicious AI can target another AI to force it to make wrong predictions or to behave in a certain way. Many researchers have warned against the rolling out of AI without appropriate security standards and defence mechanisms. Still, AI security remains an often overlooked topic.

Machine learning is not magic

If we are to reap the benefits and minimise the potential harms of AI, we must start thinking about how machine learning can be meaningfully applied to specific areas of government, business and society. This means we need to have a discussion about AI ethics and the distrust that many people have towards machine learning.

Most importantly, we need to be aware of the limitations of AI and where humans still need to take the lead. Instead of painting an unrealistic picture of the power of AI, it is important to take a step back and separate the actual technological capabilities of AI from magic.

For a long time, Facebook believed that problems like the spread of misinformation and hate speech could be algorithmically identified and stopped. But under recent pressure from legislators, the company quickly pledged to replace its algorithms with an army of over 10,000 human reviewers.

The medical profession has also recognised that AI cannot be considered a solution for all problems. The IBM Watson for Oncology programme was a piece of AI that was meant to help doctors treat cancer. Even though it was developed to deliver the best recommendations, human experts found it difficult to trust the machine. As a result, the AI programme was abandoned in most hospitals where it was trialled.

Similar problems arose in the legal domain when algorithms were used in courts in the US to sentence criminals. An algorithm calculated risk assessment scores and advised judges on the sentencing. The system was found to amplify structural racial discrimination and was later abandoned.

These examples demonstrate that there is no AI solution for everything. Using AI simply for the sake of AI may not always be productive or useful. Not every problem is best addressed by applying machine intelligence to it. This is the crucial lesson for everyone aiming to boost investments in national AI programmes: all solutions come with a cost and not everything that can be automated should be. [24]

How is artificial intelligence changing science?

Intel's Gadi Singer believes his most important challenge is his latest: using artificial intelligence (AI) to reshape scientific exploration.

In a Q&A timed with the first Intel AI DevCon event, the Intel vice president and architecture general manager for its Artificial Intelligence Products Group discussed his role at the intersection of science—computing's most demanding customer—and AI, how scientists should approach AI and why it is the most dynamic and exciting opportunity he has faced.

Q. How is AI changing science?

Scientific exploration is going through a transition that, in the last 100 years, might only be compared to what happened in the '50s and '60s, moving to data and large data systems. In the '60s, the amount of data being gathered was so large that the frontrunners were not those with the finest instruments, but rather those able to analyze the data that was gathered in any scientific area, whether it was climate, seismology, biology, pharmaceuticals, the exploration of new medicine, and so on.

Today, the data has gone to levels far exceeding the abilities of people to ask particular queries or look for particular insights. The combination of this data deluge with modern computing and deep learning techniques is providing new and many times more disruptive capabilities.

Q. What's an example?

One of them, which uses the basic strength of deep learning, is the identification of very faint patterns within a very noisy dataset, and even in the absence of an exact mathematical model of what you're looking for.

Think about cosmic events happening in a far galaxy, and you're looking for some characteristics of the phenomena to spot them out of a very large dataset. This is an instance of searching without a known equation, where you are able to give examples, and through them, let the deep learning system learn what to look for and ultimately find out a particular pattern.

Q. So you know what you're looking for, but you don't know how to find it?

You can't define the exact mathematical equation or the queries that describe it. The data is too large for trial-and-error and previous big-data analytics techniques do not have enough defined features to successfully search for the pattern.

You know what you're looking for because you tagged several examples of it in your data, and you can generally describe it. Deep learning can help you spot occurrences from such a class within a noisy multidimensional dataset.

Q. Are there other ways AI can change the scientific approach?

Another example is when you do have a mathematical model, like a set of accurate equations. In this case you can use AI to achieve comparable results in 10,000 times less time and computing.

Say you have a new molecular structure and you want to know how it's going to behave in some environment for pharma exploration. There are very good predictive models on how it will behave. The problem is that those models take a tremendous amount of computation and time—it might take you weeks to try just one combination.

More: Intel AI VP Gadi Singer on One Song to the Tune of Another (The Next Platform) | Intel AI DevCon (Press Kit) | Artificial Intelligence at Intel (Press Kit) | More Intel Explainers

In such a case, you can use a deep learning system to shadow the accurate system of equations. You iteratively feed sample cases to this system of equations, and you get the results days later. The deep learning network learns the relationship between the input and the output, without knowing the equation itself. It just tracks it. It was demonstrated in multiple cases that, after you train the deep learning system with enough examples, it shows excellent ability to predict the result that will be given by the exact model. This translates to an efficiency that could turn hours or days into second.

Granted, sometimes the full computation will be required for ultimate model accuracy. However, that would only be needed for a small subset of cases. The fact that you can generate an accurate result so much faster with a fraction of the power and the time allows you to explore the potential solution space much faster.

In the last couple years, new machine learning methods have emerged for "learning how to learn." These technologies are tackling an almost-endless realm of options—like all the possible mutations in human DNA—and are using exploration and meta-learning techniques to identify the most relevant options to evaluate.

Q. What's the big-picture impact to the scientific method or just the approach that a scientist would take with AI?

Scientists need to partner with AI. They can greatly benefit from mastering the tools of AI, such as deep learning and others, in order to explore phenomena that are less defined, or when they need faster performance by orders of magnitude to address a large space. Scientists can partner with machine learning to explore and investigate which new possibilities have the best likelihood of breakthroughs and new solutions.

Q. I'm guessing you could retire if you wanted to. What keeps you going now?

Well, I'm having a great time. AI at Intel today is about solving the most exciting and most challenging problems the industry and science are facing. This is an area that moves faster than anything I've seen in my 35 years at Intel, by far.

The other aspect is that I'm looking at it as a change that is brewing in the interaction between humans and machines. I want to be part of the effort of creating this new link. When I talk about partnership of science and AI, or autonomous vehicles and other areas, there's a role here for a broader thinking than just how to give the fastest processor for the task. This newly forged interaction between people and AI is another fascinating part of this space. [23]

The U.S. needs a national strategy on artificial intelligence

China, India, Japan, France and the European Union are crafting bold plans for artificial intelligence (AI). They see AI as a means to economic growth and social progress. Meanwhile, the U.S. disbanded its AI taskforce in 2016. Without an AI strategy of its own, the world's technology leader risks falling behind.

The U.S. technology sector has long been a driver of global economic growth. From the PC to the Internet, the greatest advancements of the past 50 years were spawned in the U.S. This country's unique approach to limited regulation combined with public-private partnerships creates an environment for innovation generally unmatched in the free world. A national AI strategy can build on this history of economic and technological leadership.

Artificial intelligence is astonishing in its potential. It will be more transformative than the PC and the Internet. Already it is poised to solve some of our biggest challenges. As examples, AI has been used to more precisely detect and diagnose cancer, treat depression, improve crop yields, save energy, increase supply chain efficiencies and protect our financial systems. These are remarkable successes for such a young technology.

Governments can and should help build on these successes. A national strategy for AI will provide the necessary guideposts that enable industry and academia to innovate. When the regulatory environment is known and understood, businesses and government researchers can maximize their impact by pursuing the same goals.

In this context, it will also be important to address concerns about AI's impact on individuals. Privacy, cybersecurity, ethics and potential employment impact are all worthy of careful analysis. Governments and industry can and should work together to better understand these concerns before any new regulation is enacted.

As evidenced by their AI plans, governments around the world see AI as a catalyst for economic growth and a means to improve the lives of their citizens. They are prioritizing research and development and the establishment of a strong and diverse ecosystem to bring AI to fruition.

China's plan, for example, includes measurable objectives and detailed direction on specific areas of focus. This is backed by significant public-private funding commitments as well as industry-government alignment on direction.

The EU's strategy provides deliberate direction to avoid regulation while investing in R&D. It offers a clear focus on greater investment, preparation for socio-economic changes, and formation of an ethical and legal framework. Japan, India, France and others are adopting similar strategies.

Industry has partnered with many of these governments to develop their plans; we stand ready to work with the U.S. government in the same way. A good model for success is the semiconductor sector, where industry and the U.S. government partnered in the early 1980s to build the vast ecosystem that is considered the North Star for technology success today. AI can be history's greatest economic engine. Governments can – and should – help make this real.

Before disbandment, the U.S. Artificial Intelligence Research and Development Taskforce defined seven strategic objectives and two specific recommendations for AI. This report called on the government to develop a more detailed AI R&D plan, and study the creation of an AI R&D workforce. These recommendations can be the starting point for a definitive U.S. national strategy for AI.

This is not a call for a swarm of new laws and regulations. Rather, a U.S. national strategy can provide the structure for researchers and industry to follow as they develop artificial intelligence. Such direction provides operating certainty that lessens risk.

A national strategy therefore should aim to foster innovation across the industry and academia, and prepare society for changes to come. It can also provide operating clarity that lessens business risk. Two areas of focus should be prioritized: government funding of R&D to augment the great work being done by industry and the availability of government data for innovators to use in developing artificial intelligence capabilities. AI needs data to learn, and there are ways to do this without compromising privacy and security.

AI is too big for one company – or one country – to realize alone. The transformative potential of AI has been likened to electricity and the steam engine. Ensuring a role for the U.S. in this global revolution is critical to not just the U.S. economic engine but that of our entire world. [22]

Can artificial intelligence help find alien intelligence?

In the search for extraterrestrial intelligence (SETI), we've often looked for signs of intelligence, technology and communication that are similar to our own.

But as astronomer and SETI trailblazer Jill Tarter points out, that approach means searching for detectable technosignatures, like radio transmissions, not searching for intelligence.

Now scientists are considering whether artificial intelligence (AI) could help us search for alien intelligence in ways we haven't even thought of yet.

'Decoding' intelligence

As we think about extraterrestrial intelligence it's helpful to remember humans are not the only intelligent life on Earth.

Chimpanzees have culture and use tools, spiders process information with webs, cetaceans have dialects, crows understand analogies and beavers are great engineers. Non-human intelligence, language, culture and technology are all around us.

Alien intelligence could look like an octopus, an ant, a dolphin or a machine —or be radically different from anything on Earth.

We often imagine extraterrestrial life relative to our ideas about difference, but those ideas aren't even universal on Earth and are unlikely to be universal across interstellar space.

If some of us have only recently recognized non-human intelligence on Earth, what could we be missing when we imagine extraterrestrial life?

In early 2018, astronomers, neuroscientists, anthropologists, AI researchers, historians and others gathered for a "Decoding Alien Intelligence" workshop at the SETI Institute in Silicon Valley. Astrobiologist Nathalie Cabrol organized the workshop around her 2016 paper "Alien mindscapes," where she calls for a new SETI road map and a long-term vision for "the search for life as we do not know it."

In her paper, Cabrol asks how SETI can move past "looking for other versions of ourselves" and think "outside of our own brains" to imagine truly different extraterrestrial intelligence.

Thinking differently

Silicon Valley is famous for valuing "disruptive" thinking and this culture intersects with SETI research. Ever since the U.S. government stopped funding SETI in the mid-1990s, Silicon Valley ideas, technology and funding have been increasingly important.

A capuchin (Sapajus libidinosus) using a stone tool (T. Falótico). An octopus (Amphioctopus marginatus) carrying shells as shelter (N. Hobgood). (Wikimedia/Tiago Falótico, Nick Hobgood), CC BY-NC-SA

For example, the SETI Institute's Allen Telescope Array is named after Microsoft co-founder Paul Allen, who contributed over US$25 million to the project. And, in 2015, technology investor Yuri Milner announced Breakthrough Listen, a 10-year US$100 million SETI initiative.

Now, the SETI Institute, NASA, Intel, IBM and other partners are tackling space science problems through an AI research and development program called the Frontier Development Lab.

Lucianne Walkowicz, the Astrobiology Chair at the Library of Congress, described one AI-based method as "signal agnostic searching" at Breakthrough Discuss in 2017.

Walkowicz explained that this means using machine learning methods to look at any set of data without predetermined categories and instead let that data cluster into their "natural categories." The software then lets us know what stands out as outliers. These outliers could then be the target of additional investigations.

It turns out that SETI researchers think AI might be useful in their work because they believe machine learning is good at spotting difference.

But its success depends on how we —and the AI we create —conceptualize the idea of difference.

Smarter than slime mould?

Thinking outside our brains also means thinking outside our scientific, social and cultural systems. But how can we do that?

AI has been used to look for simulations of what researchers imagine alien radio signals might look like, but now SETI researchers hope it can find things we aren't yet looking for.

Graham Mackintosh, an AI consultant at the SETI Institute workshop, said extraterrestrials might be doing things we can't even imagine, using technologies so different we don't even think to look for them. AI, he proposed, might be able to do that advanced thinking for us.

We may not be able to make ourselves smarter, but perhaps, Mackintosh suggested, we can make machines that are smarter for us.

In a keynote at this year's Breakthrough Discuss conference, astrophysicist Martin Rees shared a similar hope, that AI could lead to "intelligence which surpasses humans as much as we intellectually surpass slime mould."

Parts of the Armillaria ostoyae organism include the mushrooms, the black rhizomorphs and the white mycelial felts. Credit: USDA/Forest Service/Pacific Northwest Region

First contact

If we met extraterrestrial slime mould, what could we assume about its intelligence? One challenge of SETI is that we don't know the limits of life or intelligence, so we need to be open to all possible forms of difference.

We might find intelligence in forms that Euro-American science has historically disregarded: Microbial communities, insects or other complex systems like the symbiotic plant-fungus relationships in mycorrhizal networks that learn from experience.

Intelligence might appear in atmospheres or geology at a planetary scale, or as astrophysical phenomena. What appears to be a background process in the universe, or just part of what we think of as nature, could turn out to be intelligence.

Consider that the largest living thing on Earth may be an *Armillaria ostoyae* fungus in Eastern Oregon's Blue Mountains, which extends to 10 square kilometres and is between 2,000 and 9,000 years old.

While this fungus may not be what most people think of as intelligence, it reminds us to think about the unexpected when searching for life and intelligence, and of what we might be missing right under our feet.

Thinking differently about intelligence means understanding that anything we encounter could be first contact with intelligent life. This might include our first encounter with artificial general intelligence (AGI), also called Strong AI, something closer to the sentient computer HAL 9000 from *2001: A Space Odyssey* or Data from *Star Trek: The Next Generation*.

As we work with machine learning to expand the SETI search, we also need social sciences to understand how our ideas shape the future of AI —and how AI will shape the future of our ideas.

Interdisciplinary futures

To avoid a human-centred point of view in SETI we need to consider how we encode ideas about difference into AI and how that shapes the outcomes. This is vital for finding and recognizing intelligence as we don't yet know it.

Some of the methods used in anthropology can help us identify ideas about difference that we've naturalized —concepts so familiar they seem invisible, like the divides many still see between nature and culture or biology and technology, for example.

Recent research on algorithms reveals how our naturalized ideas shape the technology we create and how we use it. And Microsoft's infamous AI chat bot Tay reminds us the AI we create can easily reflect the worst of those ideas.

We may never entirely stop building bias into search engines and search strategies for SETI, or coding it into AI. But through collaborations between scientists and social scientists we can think critically about how we conceptualize difference.

A critical, interdisciplinary approach will help us understand how our ideas about difference impact lives, research and possibilities for the future both here on Earth and beyond. [21]

Scientists make a maze-running artificial intelligence program that learns to take shortcuts

Call it an a-MAZE-ing development: A U.K.-based team of researchers has developed an artificial intelligence program that can learn to take shortcuts through a labyrinth to reach its goal. In the process, the program developed structures akin to those in the human brain.

The emergence of these computational "grid cells," described in the journal *Nature*, could help scientists design better navigational software for future robots and even offer a new window through which to probe the mysteries of the mammalian brain.

In recent years, AI researchers have developed and fine-tuned deep-learning networks—layered programs that can come up with novel solutions to achieve their assigned goal. For example, a

deep-learning network can be told which face to identify in a series of different photos, and through several rounds of training, can tune its algorithms until it spots the right face virtually every time.

These networks are inspired by the brain, but they don't work quite like them, said Francesco Savelli, a neuroscientist at Johns Hopkins University who was not involved in the paper. So far, AI systems don't come close to emulating the brain's architecture, the diversity of real neurons, the complexity of individual neurons or even the rules by which they learn.

"Most of the learning is thought to occur with the strengthening and weakening of these synapses," Savelli said in an interview, referring to the connections between neurons. "And that's true of these AI systems too—but exactly how you do it, and the rules that govern that kind of learning, might be very different in the brain and in these systems."

Regardless, AI has been really useful for a number of functions, from facial recognition to deciphering handwriting and translating languages, Savelli said. But higher-level activities—such as navigating a complex environment—have proved far more challenging.

One aspect of navigation that our brains seem to perform without conscious effort is path integration. Mammals use this process to recalculate their position after every step they take by accounting for the distance they've traveled and the direction they're facing. It's thought to be key to the brain's ability to produce a map of its surroundings.

Interview with Caswell Barry about grid cells. Credit: DeepMind

Among the neurons associated with these "cognitive maps": place cells, which light up when their owner is in some particular spot in the environment; head-direction cells, which tell their owner what direction they're facing; and grid cells, which appear to respond to an imaginary hexagonal grid mapped over the surrounding terrain. Every time a person steps on a "node" in this grid, the neuron fires.

"Grid cells are thought to endow the cognitive map with geometric properties that help in planning and following trajectories," Savelli and fellow Johns Hopkins neuroscientist James Knierim wrote in a commentary on the paper. The discovery of grid cells earned three scientists the 2014 Nobel Prize in physiology or medicine.

Humans and other animals seem to have very little trouble moving through space because all of these highly specialized neurons work together to tell us where we are and where we're going.

Scientists at DeepMind, which is owned by Google and University College London, wondered whether they could develop a program that could also perform path integration. So they trained the network with simulations of paths used by rodents looking for food. They also gave it data for a rodent's movement and speed as well as feedback from simulated place cells and head-direction cells.

During this training, the researchers noticed something strange: The simulated rodent appeared to develop patterns of activity that looked remarkably like grid cells—even though grid cells had not been part of their training system.

"The emergence of grid-like units is an impressive example of deep learning doing what it does best: inventing an original, often unpredicted internal representation to help solve a task," Savelli and Knierim wrote.

Interview with Matt Botvinick about neuroscience and AI. Credit: DeepMind

Grid cells appear to be so useful for path integration that this faux-rodent came up with a solution eerily similar to a real rodent brain. The researchers then wondered: Could grid cells also be useful in another crucial aspect of mammal navigation?

That aspect, called vector-based navigation, is basically the ability to calculate the straight-shot, "as the crow flies" distance to a goal even if you originally took a longer, less-direct route. That's a useful skill for finding shortcuts to your destination, Savelli pointed out.

To test this, researchers challenged the grid-cell-enabled faux-rodent to solve a maze, but blocked off most of the doorways so the program would have to take the long route to its goal. They also modified the program so it was rewarded for actions that brought it closer to the goal. They trained the network on a given maze and then opened shortcuts to see what happened.

Sure enough, the simulated rodent with grid cells quickly found and used the shortcuts, even though those pathways were new and unknown. And it performed far better than a faux-rodent whose start point and goal point were tracked only by place cells and head-direction cells. It even beat out a "human expert," the study authors said.

The findings eventually could prove useful for robots making their way through unknown territory, Savelli said. And from a neuroscientific perspective, they could help researchers better understand how these neurons do their job in the mammalian brain.

Of course, this program was highly simplified compared to its biological counterpart, Savelli pointed out. In the simulated rodent, the "place cells" didn't change—even though place cells and grid cells influence each other in complex ways in real brains.

"By developing the network such that the place-cell layer can be modulated by grid-like inputs, we could begin to unpack this relationship," Savelli and Knierim wrote.

Developing this AI program further could help scientists start to understand all the complex relationships that come into play in living neural systems, they added.

But whether they want to hone the technology or use it to understand biology, scientists will have to get a better handle on their own deep-learning programs, whose solutions to problems are often hard to decipher even if they consistently get results, scientists said.

"Making deep-learning systems more intelligible to human reasoning is an exciting challenge for the future," Savelli and Knierim wrote. [20]

Dissecting artificial intelligence to better understand the human brain

In the natural world, intelligence takes many forms. It could be a bat using echolocation to expertly navigate in the dark, or an octopus quickly adapting its behavior to survive in the deep ocean. Likewise, in the computer science world, multiple forms of artificial intelligence are emerging - different networks each trained to excel in a different task. And as will be presented today at the 25th annual meeting of the Cognitive Neuroscience Society (CNS), cognitive neuroscientists increasingly are using those emerging artificial networks to enhance their understanding of one of the most elusive intelligence systems, the human brain.

"The fundamental questions cognitive neuroscientists and computer scientists seek to answer are similar," says Aude Oliva of MIT. "They have a complex system made of components - for one, it's called neurons and for the other, it's called units - and we are doing experiments to try to determine what those components calculate."

In Oliva's work, which she is presenting at the CNS symposium, neuroscientists are learning much about the role of contextual clues in human image recognition. By using "artificial neurons" - essentially lines of code, software - with neural networkmodels, they can parse out the various elements that go into recognizing a specific place or object.

"The brain is a deep and complex neural network," says Nikolaus Kriegeskorte of Columbia University, who is chairing the symposium. "Neural network models are brain-inspired models that are now state-of-the-art in many artificial intelligence applications, such as computer vision."

In one recent study of more than 10 million images, Oliva and colleagues taught an artificial network to recognize 350 different places, such as a kitchen, bedroom, park, living room, etc. They expected the network to learn objects such as a bed associated with a bedroom. What they didn't expect was that the network would learn to recognize people and animals, for example dogs at parks and cats in living rooms.

The machine intelligence programs learn very quickly when given lots of data, which is what enables them to parse contextual learning at such a fine level, Oliva says. While it is not possible to dissect human neurons at such a level, the computer model performing a similar task is entirely transparent. The artificial neural networks serve as "mini-brains that can be studied, changed, evaluated, compared against responses given by human neural networks, so the cognitive neuroscientists have some sort of sketch of how a real brain may function."

Indeed, Kriegeskorte says that these models have helped neuroscientists understand how people can recognize the objects around them in the blink of an eye. "This involves millions of signals emanating from the retina, that sweep through a sequence of layers of neurons, extracting semantic information, for example that we're looking at a street scene with several people and a dog," he says. "Current neural network models can perform this kind of task using only computations that biological neurons can perform. Moreover, these neural network models can predict to some extent how a neuron deep in the brain will respond to any image."

Using computer science to understand the human brain is a relatively new field that is expanding rapidly thanks to advancements in computing speed and power, along with neuroscience imaging

tools. The artificial networks cannot yet replicate human visual abilities, Kriegeskorte says, but by modeling the human brain, they are furthering understanding of both cognition and artificial intelligence. "It's a uniquely exciting time to be working at the intersection of neuroscience, cognitive science, and AI," he says.

Indeed, Oliva says; "Human cognitive and computational neuroscience is a fast-growing area of research, and knowledge about how the human brain is able to see, hear, feel, think, remember, and predict is mandatory to develop better diagnostic tools, to repair the brain, and to make sure it develops well." [19]

Army's brain-like computers moving closer to cracking codes

U.S. Army Research Laboratory scientists have discovered a way to leverage emerging brain-like computer architectures for an age-old number-theoretic problem known as integer factorization.

By mimicking the brain functions of mammals in computing, Army scientists are opening up a new solution space that moves away from traditional computing architectures and towards devices that are able to operate within extreme size-, weight-, and power-constrained environments.

"With more computing power in the battlefield, we can process information and solve computationally-hard problems quicker," said Dr. John V. "Vinnie" Monaco, an ARL computer scientist. "Programming the type of devices that fit these criteria, for example, brain-inspired computers, is challenging, and cracking crypto codes is just one application that shows we know how to do this."

The problem itself can be stated in simple terms. Take a composite integer N and express it as the product of its prime components. Most people have completed this task at some point in grade school, often an exercise in elementary arithmetic. For example, 55 can be expressed as 5*11 and 63 as 3*3*7. What many didn't realize is they were performing a task that if completed quickly enough for large numbers, could break much of the modern day internet.

Public key encryption is a method of secure communication used widely today, based on the RSA algorithm developed by Rivest, Shamir, and Adleman in 1978. The security of the RSA algorithm relies on the difficulty of factoring a large composite integer N, the public key, which is distributed by the receiver to anyone who wants to send an encrypted message. If N can be factored into its prime components, then the private key, needed to decrypt the message, can be recovered. However, the difficulty in factoring large integers quickly becomes apparent.

As the size of N increases by a single digit, the time it would take to factor N by trying all possible combinations of prime factors is approximately doubled. This means that if a number with ten digits takes 1 minute to factor, a number with twenty digits will take about 17 hours and a number with 30 digits about two years, an exponential growth in effort. This difficulty underlies the security of the RSA algorithm.

Challenging this, Monaco and his colleague Dr. Manuel Vindiola, of the lab's Computational Sciences Division, demonstrated how brain-like computers lend a speedup to the currently best known algorithms for factoring integers.

The team of researchers have devised a way to factor large composite integers by harnessing the massive parallelism of novel computer architectures that mimic the functioning of the mammalian brain. So called neuromorphic computers operate under vastly different principles than conventional computers, such as laptops and mobile devices, all based on an architecture described by John von Neumann in 1945.

In the von Neumann architecture, memory is separate from the central processing unit, or CPU, which must read and write to memory over a bus. This bus has a limited bandwidth, and much of the time, the CPU is waiting to access memory, often referred to as the von Neumann bottleneck.

Neuromorphic computers, on the other hand, do not suffer from a von Neumann bottleneck. There is no CPU, memory, or bus. Instead, they incorporate many individual computation units, much like neurons in the brain.

These units are connected by physical or simulated pathways for passing data around, analogous to synaptic connections between neurons. Many neuromorphic devices operate based on the physical response properties of the underlying material, such as graphene lasers or magnetic tunnel junctions. Because of this, these devices consume orders of magnitude less energy than their von Neumann counterparts and can operate on a molecular time scale. As such, any algorithm capable of running on these devices stands to benefit from their capabilities.

The speedup acquired by the ARL researchers is due to the formulation of a method for integer factorization with the help of a neuromorphic co-processor. The current fastest algorithms for factoring integers consist primarily of two stages, sieving and a matrix reduction, and the sieving stage comprises most of the computational effort.

Sieving involves searching for many integers that satisfy a certain property called B-smooth, integers that don't contain a prime factor greater than B. Monaco and Vindiola were able to construct a neural network that discovers B-smooth numbers quicker and with greater accuracy than on a von Neumann architecture. Their algorithm leverages the massive parallelism of brain-inspired computers and the innate ability of individual neurons to perform arithmetic operations, such as addition. As neuromorphic architectures continue to increase in size and speed, not limited by Moore's Law, their ability to tackle larger integer factorization problems also grows. In their work, it's estimated that 1024-bit keys could be broken in about a year, a task once thought to be out of reach. For comparison, the current record, a 232 decimal digit number (RSA-768) took about 2,000 years of computing time over the course of several years.

From a broader perspective, this discovery pushes us to question how a shift in computing paradigm might affect some of our most basic security assumptions. As emerging devices shift to incorporate massive parallelism and harness material physics to compute, the computational hardness underlying some security protocols may be challenged in ways not previously imagined. This work also opens the door to new research areas of emerging computer architectures, in terms of

algorithm design and function representation, alongside low-power machine learning and artificial intelligence applications.

"Encrypted messages in warfare often have an expiration date, when their contents become un-actionable," Monaco said. "There is an urgency to decrypt enemy communications, especially those at the field level, since these expire the quickest, compared to communication at higher echelons. In field conditions, power and connectivity are extremely limited. This is a strong motivating factor for using a brain-inspired computer for such a task where conventional computers are not practical." [18]

Teaching computers to guide science: Machine learning method sees forests and trees

While it may be the era of supercomputers and "big data," without smart methods to mine all that data, it's only so much digital detritus. Now researchers at the Department of Energy's Lawrence Berkeley National Laboratory (Berkeley Lab) and UC Berkeley have come up with a novel machine learning method that enables scientists to derive insights from systems of previously intractable complexity in record time.

In a paper published recently in the *Proceedings of the National Academy of Sciences* (*PNAS*), the researchers describe a technique called "iterative Random Forests," which they say could have a transformative effect on any area of science or engineering with complex systems, including biology, precision medicine, materials science, environmental science, and manufacturing, to name a few.

"Take a human cell, for example. There are 10^{170} possible molecular interactions in a single cell. That creates considerable computing challenges in searching for relationships," said Ben Brown, head of Berkeley Lab's Molecular Ecosystems Biology Department. "Our method enables the identification of interactions of high order at the same computational cost as main effects - even when those interactions are local with weak marginal effects."

Brown and Bin Yu of UC Berkeley are lead senior authors of "Iterative Random Forests to Discover Predictive and Stable High-Order Interactions." The co-first authors are Sumanta Basu (formerly a joint postdoc of Brown and Yu and now an assistant professor at Cornell University) and Karl Kumbier (a Ph.D. student of Yu in the UC Berkeley Statistics Department). The paper is the culmination of three years of work that the authors believe will transform the way science is done. "With our method we can gain radically richer information than we've ever been able to gain from a learning machine," Brown said.

The needs of machine learning in science are different from that of industry, where machine learning has been used for things like playing chess, making self-driving cars, and predicting the stock market.

"The machine learning developed by industry is great if you want to do high-frequency trading on the stock market," Brown said. "You don't care why you're able to predict the stock will go up or down. You just want to know that you can make the predictions."

But in science, questions surrounding why a process behaves in certain ways are critical. Understanding "why" allows scientists to model or even engineer processes to improve or attain a desired outcome. As a result, machine learning for science needs to peer inside the black box and understand why and how computers reached the conclusions they reached. A long-term goal is to use this kind of information to model or engineer systems to obtain desired outcomes.

In highly complex systems - whether it's a single cell, the human body, or even an entire ecosystem - there are a large number of variables interacting in nonlinear ways. That makes it difficult if not impossible to build a model that can determine cause and effect. "Unfortunately, in biology, you come across interactions of order 30, 40, 60 all the time," Brown said. "It's completely intractable with traditional approaches to statistical learning."

The method developed by the team led by Brown and Yu, iterative Random Forests (iRF), builds on an algorithm called random forests, a popular and effective predictive modeling tool, translating the internal states of the black box learner into a human-interpretable form. Their approach allows researchers to search for complex interactions by decoupling the order, or size, of interactions from the computational cost of identification.

"There is no difference in the computational cost of detecting an interaction of order 30 versus an interaction of order two," Brown said. "And that's a sea change."

In the PNAS paper, the scientists demonstrated their method on two genomics problems, the role of gene enhancers in the fruit fly embryo and alternative splicing in a human-derived cell line. In both cases, using iRF confirmed previous findings while also uncovering previously unidentified higher-order interactions for follow-up study.

Brown said they're now using their method for designing phased array laser systems and optimizing sustainable agriculture systems.

"We believe this is a different paradigm for doing science," said Yu, a professor in the departments of Statistics and Electrical Engineering & Computer Science at UC Berkeley. "We do prediction, but we introduce stability on top of prediction in iRF to more reliably learn the underlying structure in the predictors."

"This enables us to learn how to engineer systems for goal-oriented optimization and more accurately targeted simulations and follow-up experiments," Brown added.

In a PNAS commentary on the technique, Danielle Denisko and Michael Hoffman of the University of Toronto wrote: "iRF holds much promise as a new and effective way of detecting interactions in a variety of settings, and its use will help us ensure no branch or leaf is ever left unturned." [17]

Rise of the quantum thinking machines

Quantum computers can be made to utilize effects such as quantum coherence and entanglement to accelerate machine learning.

Although we typically view information as being an abstract or virtual entity, information, of course, must be stored in a physical medium. Information processing devices such as computers and phones are therefore fundamentally governed by the laws of physics. In this way, the fundamental physical limits of an agent's ability to learn are governed by the laws of physics. The best known theory of physics is quantum theory, which ultimately must be used to determine the absolute physical limits of a machine's ability to learn.

A quantum algorithm is a stepwise procedure performed on a quantum computer to solve a problem such as searching a database. Quantum machine learning software makes use of quantum algorithms to process information in ways that classical computers cannot. These quantum effects open up exciting new avenues which can, in principle, outperform the best known classical algorithms when solving certain machine learning problems. This is known as quantum enhanced machine learning.

Machine learning methods use mathematical algorithms to search for certain patterns in large data sets. Machine learning is widely used in biotechnology, pharmaceuticals, particle physics and many other fields. Thanks to the ability to adapt to new data, machine learning greatly exceeds the ability of people. Despite this, machine learning cannot cope with certain difficult tasks.

Quantum enhancement is predicted to be possible for a host of machine learning tasks, ranging from optimization to quantum enhanced deep learning.

In the new paper published in Nature, a group of scientists led by Skoltech Associate Professor Jacob Biamonte produced a feasibility analysis outlining what steps can be taken for practical quantum enhanced machine learning.

The prospects of using quantum computers to accelerate machine learning has generated recent excitement due to the increasing capabilities of quantum computers. This includes a commercially available 2000 spin quantum accelerated annealing by the Canada-based company D-Wave Systems Inc. and a 16 qubit universal quantum processor by IBM which is accessible via a (currently free) cloud service.

The availability of these devices has led to increased interest from the machine learning community. The interest comes as a bit of a shock to the traditional quantum physics community, in which researchers have thought that the primary applications of quantum computers would be using quantum computers to simulate chemical physics, which can be used in the pharmaceutical industry for drug discovery. However, certain quantum systems can be mapped to certain machine learning models, particularly deep learning models. Quantum machine learning can be used to work in tandem with these existing methods for quantum chemical emulation, leading to even greater capabilities for a new era of quantum technology.

"Early on, the team burned the midnight oil over Skype, debating what the field even was—our synthesis will hopefully solidify topical importance. We submitted our draft to Nature, going forward subject to significant changes. All in all, we ended up writing three versions over eight months with nothing more than the title in common," said lead study author Biamonte. [16]

A Machine Learning Systems That Called Neural Networks Perform Tasks by Analyzing Huge Volumes of Data

Neural networks learn how to carry out certain tasks by analyzing large amounts of data displayed to them. These machine learning systems continually learn and readjust to be able to carry out the task set out before them. Understanding how neural networks work helps researchers to develop better applications and uses for them.

At the 2017 Conference on Empirical Methods on Natural Language Processing earlier this month, MIT researchers demonstrated a new general-purpose technique for making sense of neural networks that are able to carry out natural language processing tasks where they attempt to extract data written in normal text opposed to something of a structured language like database-query language.

The new technique works great in any system that reads the text as input and produces symbols as the output. One such example of this can be seen in an automatic translator. It works without the need to access any underlying software too. Tommi Jaakkola is Professor of Electrical Engineering and Computer Science at MIT and one of the authors on the paper. He says, "I can't just do a simple randomization. And what you are predicting is now a more complex object, like a sentence, so what does it mean to give an explanation?"

As part of the research, Jaakkola, and colleague David Alvarez-Melis, an MIT graduate student in electrical engineering and computer science and first author on the paper, used a black-box neural net in which to generate test sentences to feed black-box neural nets. The duo began by teaching the network to compress and decompress natural sentences. As the training continues the encoder and decoder get evaluated simultaneously depending on how closely the decoder's output matches up with the encoder's input.

Neural nets work on probabilities. For example, an object-recognition system could be fed an image of a cat, and it would process that image as it saying 75 percent probability of being a cat, while still having a 25 percent probability that it's a dog. Along with that same line, Jaakkola and Alvarez-Melis' sentence compressing network has alternative words for each of those in a decoded sentence along with the probability that each is correct. So, once the system has generated a list of closely related sentences they're then fed to a black-box natural language processor. This then allows the researchers to analyze and determine which inputs have an effect on which outputs.

During the research, the pair applied this technique to three different types of a natural language processing system. The first one inferred the way in which words were pronounced; the second was a set of translators, and the third was a simple computer dialogue system which tried to provide adequate responses to questions or remarks. In looking at the results, it was clear and pretty obvious that the translation systems had strong dependencies on individual words of both the input and output sentences. A little more surprising, however, was the identification of gender

biases in the texts on which the machine translation systems were trained. The dialogue system was too small to take advantage of the training set.

"The other experiment we do is in flawed systems," says Alvarez-Melis. "If you have a black-box model that is not doing a good job, can you first use this kind of approach to identify problems? A motivating application of this kind of interpretability is to fix systems, to improve systems, by understanding what they're getting wrong and why." [15]

Active machine learning for the discovery and crystallization of gigantic polyoxometalate molecules

Who is the better experimentalist, a human or a robot? When it comes to exploring synthetic and crystallization conditions for inorganic gigantic molecules, actively learning machines are clearly ahead, as demonstrated by British Scientists in an experiment with polyoxometalates published in the journal Angewandte Chemie.

Polyoxometalates form through self-assembly of a large number of metal atoms bridged by oxygen atoms. Potential uses include catalysis, electronics, and medicine. Insights into the self-organization processes could also be of use in developing functional chemical systems like "molecular machines".

Polyoxometalates offer a nearly unlimited variety of structures. However, it is not easy to find new ones, because the aggregation of complex inorganic molecules to gigantic molecules is a process that is difficult to predict. It is necessary to find conditions under which the building blocks aggregate and then also crystallize, so that they can be characterized.

A team led by Leroy Cronin at the University of Glasgow (UK) has now developed a new approach to define the range of suitable conditions for the synthesis and crystallization of polyoxometalates. It is based on recent advances in machine learning, known as active learning. They allowed their trained machine to compete against the intuition of experienced experimenters. The test example was $Na(6)[Mo(120)Ce(6)O(366)H(12)(H(2)O)(78)]\cdot 200\ H(2)O$, a new, ring-shaped polyoxometalate cluster that was recently discovered by the researchers' automated chemical robot.

In the experiment, the relative quantities of the three necessary reagent solutions were to be varied while the protocol was otherwise prescribed. The starting point was a set of data from successful and unsuccessful crystallization experiments. The aim was to plan ten experiments and then use the results from these to proceed to the next set of ten experiments - a total of one hundred crystallization attempts.

Although the flesh-and-blood experimenters were able to produce more successful crystallizations, the far more "adventurous" machine algorithm was superior on balance because it covered a significantly broader domain of the "crystallization space". The quality of the prediction of whether an experiment would lead to crystallization was improved significantly more by the machine than the human experimenters. A series of 100 purely random experiments resulted in no improvement. In addition, the machine discovered a range of conditions that led to crystals which would not have been expected based on pure intuition. This "unbiased" automated method makes the discovery of

novel compounds more probably than reliance on human intuition. The researchers are now looking for ways to make especially efficient "teams" of man and machine. [14]

Using machine learning to understand materials

Whether you realize it or not, machine learning is making your online experience more efficient. The technology, designed by computer scientists, is used to better understand, analyze, and categorize data. When you tag your friend on Facebook, clear your spam filter, or click on a suggested YouTube video, you're benefitting from machine learning algorithms.

Machine learning algorithms are designed to improve as they encounter more data, making them a versatile technology for understanding large sets of photos such as those accessible from Google Images. Elizabeth Holm, professor of materials science and engineering at Carnegie Mellon University, is leveraging this technology to better understand the enormous number of research images accumulated in the field of materials science. This unique application is an interdisciplinary approach to machine learning that hasn't been explored before.

"Just like you might search for cute cat pictures on the internet, or Facebook recognizes the faces of your friends, we are creating a system that allows a computer to automatically understand the visual data of materials science," explains Holm.

The field of materials science usually relies on human experts to identify research images by hand. Using machine learning algorithms, Holm and her group have created a system that automatically recognizes and categorizes microstructural images of materials. Her goal is to make it more efficient for materials scientists to search, sort, classify, and identify important information in their visual data.

"In materials science, one of our fundamental data is pictures," explains Holm. "Images contain information that we recognize, even when we find it difficult to quantify numerically."

Holm's machine learning system has several different applications within the materials science field including research, industry, publishing, and academia. For example, the system could be used to create a visual search of a scientific journal archives so that a researcher could find out whether a similar image had ever been published. Similarly, the system can be used to automatically search and categorize image archives in industries or research labs. "Big companies can have archives of 600,000 or more research images. No one wants to look through those, but they want to use that data to better understand their products," explains Holm. "This system has the power to unlock those archives."

Holm and her group have been working on this research for about three years and are continuing to grow the project, especially as it relates to the metal 3-D printing field. For example, they are beginning to compile a database of experimental and simulated metal powder micrographs in order to better understand what types of raw materials are best suited for 3-D printing processes.

Holm published an article about this research in the December 2015 issue of Computational Materials Science titled "A computer vision approach for automated analysis and classification of microstructural image data." [13]

Artificial intelligence helps in the discovery of new materials

With the help of artificial intelligence, chemists from the University of Basel in Switzerland have computed the characteristics of about two million crystals made up of four chemical elements. The researchers were able to identify 90 previously unknown thermodynamically stable crystals that can be regarded as new materials.

They report on their findings in the scientific journal Physical Review Letters.

Elpasolite is a glassy, transparent, shiny and soft mineral with a cubic crystal structure. First discovered in El Paso County (Colorado, USA), it can also be found in the Rocky Mountains, Virginia and the Apennines (Italy). In experimental databases, elpasolite is one of the most frequently found quaternary crystals (crystals made up of four chemical elements). Depending on its composition, it can be a metallic conductor, a semi-conductor or an insulator, and may also emit light when exposed to radiation.

These characteristics make elpasolite an interesting candidate for use in scintillators (certain aspects of which can already be demonstrated) and other applications. Its chemical complexity means that, mathematically speaking, it is practically impossible to use quantum mechanics to predict every theoretically viable combination of the four elements in the structure of elpasolite.

Machine learning aids statistical analysis

Thanks to modern artificial intelligence, Felix Faber, a doctoral student in Prof. Anatole von Lilienfeld's group at the University of Basel's Department of Chemistry, has now succeeded in solving this material design problem. First, using quantum mechanics, he generated predictions for thousands of elpasolite crystals with randomly determined chemical compositions. He then used the results to train statistical machine learning models (ML models). The improved algorithmic strategy achieved a predictive accuracy equivalent to that of standard quantum mechanical approaches.

ML models have the advantage of being several orders of magnitude quicker than corresponding quantum mechanical calculations. Within a day, the ML model was able to predict the formation energy – an indicator of chemical stability – of all two million elpasolite crystals that theoretically can be obtained from the main group elements of the periodic table. In contrast, performance of the calculations by quantum mechanical means would have taken a supercomputer more than 20 million hours.

Unknown materials with interesting characteristics

An analysis of the characteristics computed by the model offers new insights into this class of materials. The researchers were able to detect basic trends in formation energy and identify 90 previously unknown crystals that should be thermodynamically stable, according to quantum mechanical predictions.

On the basis of these potential characteristics, elpasolite has been entered into the Materials Project material database, which plays a key role in the Materials Genome Initiative. The initiative was launched by the US government in 2011 with the aim of using computational support to accelerate the discovery and the experimental synthesis of interesting new materials.

Some of the newly discovered elpasolite crystals display exotic electronic characteristics and unusual compositions. "The combination of artificial intelligence, big data, quantum mechanics and supercomputing opens up promising new avenues for deepening our understanding of materials and discovering new ones that we would not consider if we relied solely on human intuition," says study director von Lilienfeld. [12]

Physicists are putting themselves out of a job, using artificial intelligence to run a complex experiment

The experiment, developed by physicists from The Australian National University (ANU) and UNSW ADFA, created an extremely cold gas trapped in a laser beam, known as a Bose-Einstein condensate, replicating the experiment that won the 2001 Nobel Prize.

"I didn't expect the machine could learn to do the experiment itself, from scratch, in under an hour," said co-lead researcher Paul Wigley from the ANU Research School of Physics and Engineering.

"A simple computer program would have taken longer than the age of the Universe to run through all the combinations and work this out."

Bose-Einstein condensates are some of the coldest places in the Universe, far colder than outer space, typically less than a billionth of a degree above absolute zero.

They could be used for mineral exploration or navigation systems as they are extremely sensitive to external disturbances, which allows them to make very precise measurements such as tiny changes in the Earth's magnetic field or gravity.

The artificial intelligence system's ability to set itself up quickly every morning and compensate for any overnight fluctuations would make this fragile technology much more useful for field measurements, said co-lead researcher Dr Michael Hush from UNSW ADFA.

"You could make a working device to measure gravity that you could take in the back of a car, and the artificial intelligence would recalibrate and fix itself no matter what," he said.

"It's cheaper than taking a physicist everywhere with you."

The team cooled the gas to around 1 microkelvin, and then handed control of the three laser beams over to the artificial intelligence to cool the trapped gas down to nanokelvin.

Researchers were surprised by the methods the system came up with to ramp down the power of the lasers.

"It did things a person wouldn't guess, such as changing one laser's power up and down, and compensating with another," said Mr Wigley.

"It may be able to come up with complicated ways humans haven't thought of to get experiments colder and make measurements more precise.

The new technique will lead to bigger and better experiments, said Dr Hush.

"Next we plan to employ the artificial intelligence to build an even larger Bose-Einstein condensate faster than we've seen ever before," he said.

The research is published in the Nature group journal Scientific Reports. [11]

Quantum experiments designed by machines

The idea was developed when the physicists wanted to create new quantum states in the laboratory, but were unable to conceive of methods to do so. "After many unsuccessful attempts to come up with an experimental implementation, we came to the conclusion that our intuition about these phenomena seems to be wrong. We realized that in the end we were just trying random arrangements of quantum building blocks. And that is what a computer can do as well - but thousands of times faster", explains Mario Krenn, PhD student in Anton Zeilinger's group and first author research.

After a few hours of calculation, their algorithm - which they call Melvin - found the recipe to the question they were unable to solve, and its structure surprised them. Zeilinger says: "Suppose I want build an experiment realizing a specific quantum state I am interested in. Then humans intuitively consider setups reflecting the symmetries of the state. Yet Melvin found out that the most simple realization can be asymmetric and therefore counterintuitive. A human would probably never come up with that solution."

The physicists applied the idea to several other questions and got dozens of new and surprising answers. "The solutions are difficult to understand, but we were able to extract some new experimental tricks we have not thought of before. Some of these computer-designed experiments are being built at the moment in our laboratories", says Krenn.

Melvin not only tries random arrangements of experimental components, but also learns from previous successful attempts, which significantly speeds up the discovery rate for more complex solutions. In the future, the authors want to apply their algorithm to even more general questions in quantum physics, and hope it helps to investigate new phenomena in laboratories. [10]

Moving electrons around loops with light: A quantum device based on geometry

Researchers at the University of Chicago's Institute for Molecular Engineering and the University of Konstanz have demonstrated the ability to generate a quantum logic operation, or rotation of the qubit, that - surprisingly—is intrinsically resilient to noise as well as to variations in the strength or duration of the control. Their achievement is based on a geometric concept known as the Berry phase and is implemented through entirely optical means within a single electronic spin in diamond.

Their findings were published online Feb. 15, 2016, in Nature Photonics and will appear in the March print issue. "We tend to view quantum operations as very fragile and susceptible to noise, especially when compared to conventional electronics," remarked David Awschalom, the Liew Family Professor of Molecular Engineering and senior scientist at Argonne National Laboratory,

who led the research. "In contrast, our approach shows incredible resilience to external influences and fulfills a key requirement for any practical quantum technology."

Quantum geometry

When a quantum mechanical object, such as an electron, is cycled along some loop, it retains a memory of the path that it travelled, the Berry phase. To better understand this concept, the Foucault pendulum, a common staple of science museums helps to give some intuition. A pendulum, like those in a grandfather clock, typically oscillates back and forth within a fixed plane. However, a Foucault pendulum oscillates along a plane that gradually rotates over the course of a day due to Earth's rotation, and in turn knocks over a series of pins encircling the pendulum.

The number of knocked-over pins is a direct measure of the total angular shift of the pendulum's oscillation plane, its acquired geometric phase. Essentially, this shift is directly related to the location of the pendulum on Earth's surface as the rotation of Earth transports the pendulum along a specific closed path, its circle of latitude. While this angular shift depends on the particular path traveled, Awschalom said, it remarkably does not depend on the rotational speed of Earth or the oscillation frequency of the pendulum.

"Likewise, the Berry phase is a similar path-dependent rotation of the internal state of a quantum system, and it shows promise in quantum information processing as a robust means to manipulate qubit states," he said.

A light touch

In this experiment, the researchers manipulated the Berry phase of a quantum state within a nitrogen-vacancy (NV) center, an atomic-scale defect in diamond. Over the past decade and a half, its electronic spin state has garnered great interest as a potential qubit. In their experiments, the team members developed a method with which to draw paths for this defect's spin by varying the applied laser light. To demonstrate Berry phase, they traced loops similar to that of a tangerine slice within the quantum space of all of the potential combinations of spin states.

"Essentially, the area of the tangerine slice's peel that we drew dictated the amount of Berry phase that we were able to accumulate," said Christopher Yale, a postdoctoral scholar in Awschalom's laboratory, and one of the co-lead authors of the project.

This approach using laser light to fully control the path of the electronic spin is in contrast to more common techniques that control the NV center spin, through the application of microwave fields. Such an approach may one day be useful in developing photonic networks of these defects, linked and controlled entirely by light, as a way to both process and transmit quantum information.

A noisy path

A key feature of Berry phase that makes it a robust quantum logic operation is its resilience to noise sources. To test the robustness of their Berry phase operations, the researchers intentionally added noise to the laser light controlling the path. As a result, the spin state would travel along its intended path in an erratic fashion.

However, as long as the total area of the path remained the same, so did the Berry phase that they measured.

"In particular, we found the Berry phase to be insensitive to fluctuations in the intensity of the laser. Noise like this is normally a bane for quantum control," said Brian Zhou, a postdoctoral scholar in the group, and co-lead author.

"Imagine you're hiking along the shore of a lake, and even though you continually leave the path to go take pictures, you eventually finish hiking around the lake," said F. Joseph Heremans, co-lead author, and now a staff scientist at Argonne National Laboratory. "You've still hiked the entire loop regardless of the bizarre path you took, and so the area enclosed remains virtually the same."

These optically controlled Berry phases within diamond suggest a route toward robust and faulttolerant quantum information processing, noted Guido Burkard, professor of physics at the University of Konstanz and theory collaborator on the project.

"Though its technological applications are still nascent, Berry phases have a rich underlying mathematical framework that makes them a fascinating area of study," Burkard said. [9]

Researchers demonstrate 'quantum surrealism'

In a new version of an old experiment, CIFAR Senior Fellow Aephraim Steinberg (University of Toronto) and colleagues tracked the trajectories of photons as the particles traced a path through one of two slits and onto a screen. But the researchers went further, and observed the "nonlocal" influence of another photon that the first photon had been entangled with.

The results counter a long-standing criticism of an interpretation of quantum mechanics called the De Broglie-Bohm theory. Detractors of this interpretation had faulted it for failing to explain the behaviour of entangled photons realistically. For Steinberg, the results are important because they give us a way of visualizing quantum mechanics that's just as valid as the standard interpretation, and perhaps more intuitive.

"I'm less interested in focusing on the philosophical question of what's 'really' out there. I think the fruitful question is more down to earth. Rather than thinking about different metaphysical interpretations, I would phrase it in terms of having different pictures. Different pictures can be useful. They can help shape better intuitions."

At stake is what is "really" happening at the quantum level. The uncertainty principle tells us that we can never know both a particle's position and momentum with complete certainty. And when we do interact with a quantum system, for instance by measuring it, we disturb the system. So if we fire a photon at a screen and want to know where it will hit, we'll never know for sure exactly where it will hit or what path it will take to get there.

The standard interpretation of quantum mechanics holds that this uncertainty means that there is no "real" trajectory between the light source and the screen. The best we can do is to calculate a "wave function" that shows the odds of the photon being in any one place at any time, but won't tell us where it is until we make a measurement.

Yet another interpretation, called the De Broglie-Bohm theory, says that the photons do have real trajectories that are guided by a "pilot wave" that accompanies the particle. The wave is still probabilistic, but the particle takes a real trajectory from source to target. It doesn't simply "collapse" into a particular location once it's measured.

In 2011 Steinberg and his colleagues showed that they could follow trajectories for photons by subjecting many identical particles to measurements so weak that the particles were barely disturbed, and then averaging out the information. This method showed trajectories that looked similar to classical ones - say, those of balls flying through the air.

But critics had pointed out a problem with this viewpoint. Quantum mechanics also tells us that two particles can be entangled, so that a measurement of one particle affects the other. The critics complained that in some cases, a measurement of one particle would lead to an incorrect prediction of the trajectory of the entangled particle. They coined the term "surreal trajectories" to describe them.

In the most recent experiment, Steinberg and colleagues showed that the surrealism was a consequence of non-locality - the fact that the particles were able to influence one another instantaneously at a distance. In fact, the "incorrect" predictions of trajectories by the entangled photon were actually a consequence of where in their course the entangled particles were measured. Considering both particles together, the measurements made sense and were consistent with real trajectories.

Steinberg points out that both the standard interpretation of quantum mechanics and the De Broglie-Bohm interpretation are consistent with experimental evidence, and are mathematically equivalent. But it is helpful in some circumstances to visualize real trajectories, rather than wave function collapses, he says. [8]

Physicists discover easy way to measure entanglement—on a sphere
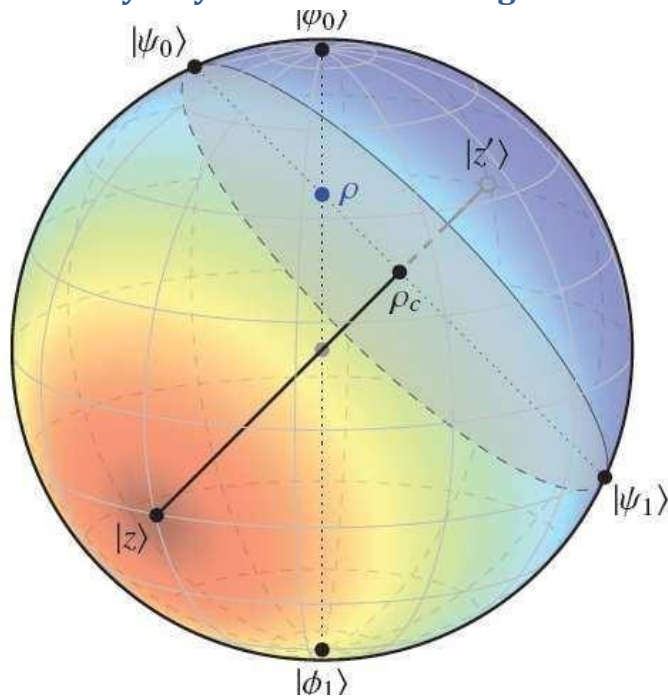
Entanglement on a sphere: This Bloch sphere shows entanglement for the one-root state ρ and its radial state ρ_c. The color on the sphere corresponds to the value of the entanglement, which is determined by the distance from the root state z, the point at which there is no entanglement. The

closer to z, the less the entanglement (red); the further from z, the greater the entanglement (blue). Credit: Regula and Adesso. ©2016 American Physical Society

Now in a new paper to be published in Physical Review Letters, mathematical physicists Bartosz Regula and Gerardo Adesso at The University of Nottingham have greatly simplified the problem of measuring entanglement.

To do this, the scientists turned the difficult analytical problem into an easy geometrical one. They showed that, in many cases, the amount of entanglement between states corresponds to the distance between two points on a Bloch sphere, which is basically a normal 3D sphere that physicists use to model quantum states.

As the scientists explain, the traditionally difficult part of the math problem is that it requires finding the optimal decomposition of mixed states into pure states. The geometrical approach completely eliminates this requirement by reducing the many possible ways that states could decompose down to a single point on the sphere at which there is zero entanglement. The approach requires that there be only one such point, or "root," of zero entanglement, prompting the physicists to describe the method as "one root to rule them all."

The scientists explain that the "one root" property is common among quantum states and can be easily verified, transforming a formidable math problem into one that is trivially easy. They demonstrated that the new approach works for many types of two-, three- and four-qubit entangled states.

"This method reveals an intriguing and previously unexplored connection between the quantum features of a state and classical geometry, allowing all one-root states to enjoy a convenient visual representation which considerably simplifies the study and understanding of their properties," the researchers explained.

The simple way of measuring a state's entanglement could have applications in many technological areas, such as quantum cryptography, computation, and communication. It could also provide insight into understanding the foundations of thermodynamics, condensed matter physics, and biology. [7]

An idea for allowing the human eye to observe an instance of entanglement
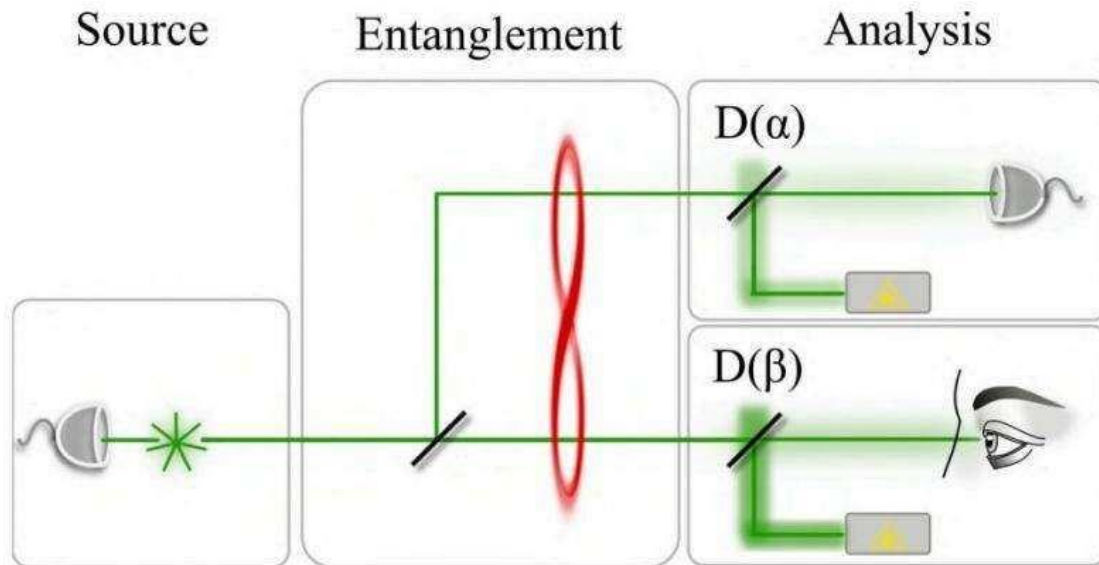
Scheme of the proposal for detecting entanglement with the human eye. Credit: arXiv:1602.01907

Entanglement, is of course, where two quantum particles are intrinsically linked to the extent that they actually share the same existence, even though they can be separated and moved apart. The idea was first proposed nearly a century ago, and it has not only been proven, but researchers routinely cause it to occur, but, to date, not one single person has every actually seen it happen—they only know it happens by conducting a series of experiments. It is not clear if anyone has ever actually tried to see it happen, but in this new effort, the research trio claim to have found a way to make it happen—if only someone else will carry out the experiment on a willing volunteer.

The idea involves using a beam splitter and two beans of light—an initial beam of coherent photons fired at the beam splitter and a secondary beam of coherent photons that interferes with the photons in the first beam causing a change of phase, forcing the light to be reflected rather than transmitted. In such a scenario, the secondary beam would not need to be as intense as the first, and could in fact be just a single coherent photon—if it were entangled, it could be used to allow a person to see the more powerful beam while still preserving the entanglement of the original photon.

The researchers suggest the technology to carry out such an experiment exists today, but also acknowledge that it would take a special person to volunteer for such an assignment because to prove that they had seen entanglement taking place would involve shooting a large number of photons in series, into a person's eye, whereby the resolute volunteer would announce whether they had seen the light on the order of thousands of times. [6]

Quantum entanglement
Measurements of physical properties such as position, momentum, spin, polarization, etc.

performed on entangled particles are found to be appropriately correlated. For example, if a pair of particles is generated in such a way that their total spin is known to be zero, and one particle is found to have clockwise spin on a certain axis, then the spin of the other particle, measured on the same axis, will be found to be counterclockwise. Because of the nature of quantum measurement, however, this behavior gives rise to effects that can appear paradoxical: any measurement of a property of a particle can be seen as acting on that particle (e.g. by collapsing a number of superimposed states); and in the case of entangled particles, such action must be on the entangled system as a whole. It thus appears that one particle of an entangled pair "knows" what measurement has been performed on the other, and with what outcome, even though there is no known means for such information to be communicated between the particles, which at the time of measurement may be separated by arbitrarily large distances. [4]

The Bridge

The accelerating electrons explain not only the Maxwell Equations and the Special Relativity, but the Heisenberg Uncertainty Relation, the wave particle duality and the electron's spin also, building the bridge between the Classical and Quantum Theories. [1]

Accelerating charges

The moving charges are self maintain the electromagnetic field locally, causing their movement and this is the result of their acceleration under the force of this field. In the classical physics the charges will distributed along the electric current so that the electric potential lowering along the current, by linearly increasing the way they take every next time period because this accelerated motion. The same thing happens on the atomic scale giving a dp impulse difference and a dx way difference between the different part of the not point like particles.

Relativistic effect

Another bridge between the classical and quantum mechanics in the realm of relativity is that the charge distribution is lowering in the reference frame of the accelerating charges linearly: ds/dt = at (time coordinate), but in the reference frame of the current it is parabolic: s = a/2 t^2 (geometric coordinate).

Heisenberg Uncertainty Relation

In the atomic scale the Heisenberg uncertainty relation gives the same result, since the moving electron in the atom accelerating in the electric field of the proton, causing a charge distribution on delta x position difference and with a delta p momentum difference such a way that they product is about the half Planck reduced constant. For the proton this delta x much less in the nucleon, than in the orbit of the electron in the atom, the delta p is much higher because of the greater proton mass.

This means that the electron and proton are not point like particles, but has a real charge distribution.

Wave – Particle Duality

The accelerating electrons explains the wave – particle duality of the electrons and photons, since the elementary charges are distributed on delta x position with delta p impulse and creating a wave packet of the electron. The photon gives the electromagnetic particle of the mediating force of the electrons electromagnetic field with the same distribution of wavelengths.

Atomic model

The constantly accelerating electron in the Hydrogen atom is moving on the equipotential line of the proton and it's kinetic and potential energy will be constant. Its energy will change only when it is changing its way to another equipotential line with another value of potential energy or getting free with enough kinetic energy. This means that the Rutherford-Bohr atomic model is right and only that changing acceleration of the electric charge causes radiation, not the steady acceleration. The steady acceleration of the charges only creates a centric parabolic steady electric field around the charge, the magnetic field. This gives the magnetic moment of the atoms, summing up the proton and electron magnetic moments caused by their circular motions and spins.

The Relativistic Bridge

Commonly accepted idea that the relativistic effect on the particle physics it is the fermions' spin - another unresolved problem in the classical concepts. If the electric charges can move only with accelerated motions in the self maintaining electromagnetic field, once upon a time they would reach the velocity of the electromagnetic field. The resolution of this problem is the spinning particle, constantly accelerating and not reaching the velocity of light because the acceleration is radial. One origin of the Quantum Physics is the Planck Distribution Law of the electromagnetic oscillators, giving equal intensity for 2 different wavelengths on any temperature. Any of these two wavelengths will give equal intensity diffraction patterns, building different asymmetric constructions, for example proton - electron structures (atoms), molecules, etc. Since the particles are centers of diffraction patterns they also have particle – wave duality as the electromagnetic waves have. [2]

The weak interaction

The weak interaction transforms an electric charge in the diffraction pattern from one side to the other side, causing an electric dipole momentum change, which violates the CP and time reversal symmetry. The Electroweak Interaction shows that the Weak Interaction is basically electromagnetic in nature. The arrow of time shows the entropy grows by changing the temperature dependent diffraction patterns of the electromagnetic oscillators.

Another important issue of the quark model is when one quark changes its flavor such that a linear oscillation transforms into plane oscillation or vice versa, changing the charge value with 1 or -1.

This kind of change in the oscillation mode requires not only parity change, but also charge and time changes (CPT symmetry) resulting a right handed anti-neutrino or a left handed neutrino.

The right handed anti-neutrino and the left handed neutrino exist only because changing back the quark flavor could happen only in reverse, because they are different geometrical constructions, the u is 2 dimensional and positively charged and the d is 1 dimensional and negatively charged. It needs also a time reversal, because anti particle (anti neutrino) is involved.

The neutrino is a 1/2spin creator particle to make equal the spins of the weak interaction, for example neutron decay to 2 fermions, every particle is fermions with ½ spin. The weak interaction changes the entropy since more or less particles will give more or less freedom of movement. The entropy change is a result of temperature change and breaks the equality of oscillator diffraction intensity of the Maxwell–Boltzmann statistics. This way it changes the time coordinate measure and
makes possible a different time dilation as of the special relativity.

The limit of the velocity of particles as the speed of light appropriate only for electrical charged particles, since the accelerated charges are self maintaining locally the accelerating electric force. The neutrinos are CP symmetry breaking particles compensated by time in the CPT symmetry, that is the time coordinate not works as in the electromagnetic interactions, consequently the speed of neutrinos is not limited by the speed of light.

The weak interaction T-asymmetry is in conjunction with the T-asymmetry of the second law of thermodynamics, meaning that locally lowering entropy (on extremely high temperature) causes the
weak interaction, for example the Hydrogen fusion.

Probably because it is a spin creating movement changing linear oscillation to 2 dimensional oscillation by changing d to u quark and creating anti neutrino going back in time relative to the proton and electron created from the neutron, it seems that the anti neutrino fastest then the velocity of the photons created also in this weak interaction?

A quark flavor changing shows that it is a reflection changes movement and the CP- and T-symmetry breaking!!! This flavor changing oscillation could prove that it could be also on higher level such as atoms, molecules, probably big biological significant molecules and responsible on the aging of the life.

Important to mention that the weak interaction is always contains particles and antiparticles, where the neutrinos (antineutrinos) present the opposite side. It means by Feynman's interpretation that these particles present the backward time and probably because this they seem to move faster than the speed of light in the reference frame of the other side.

Finally since the weak interaction is an electric dipole change with ½ spin creating; it is limited by the velocity of the electromagnetic wave, so the neutrino's velocity cannot exceed the velocity of light.

The General Weak Interaction

The Weak Interactions T-asymmetry is in conjunction with the T-asymmetry of the Second Law of Thermodynamics, meaning that locally lowering entropy (on extremely high temperature) causes for example the Hydrogen fusion. The arrow of time by the Second Law of Thermodynamics shows the increasing entropy and decreasing information by the Weak Interaction, changing the temperature dependent diffraction patterns. A good example of this is the neutron decay, creating more particles with less known information about them.

The neutrino oscillation of the Weak Interaction shows that it is a general electric dipole change and it is possible to any other temperature dependent entropy and information changing diffraction pattern of atoms, molecules and even complicated biological living structures.

We can generalize the weak interaction on all of the decaying matter constructions, even on the biological too. This gives the limited lifetime for the biological constructions also by the arrow of time. There should be a new research space of the Quantum Information Science the 'general neutrino oscillation' for the greater then subatomic matter structures as an electric dipole change. There is also connection between statistical physics and evolutionary biology, since the arrow of time is working in the biological evolution also.

The Fluctuation Theorem says that there is a probability that entropy will flow in a direction opposite to that dictated by the Second Law of Thermodynamics. In this case the Information is growing that is the matter formulas are emerging from the chaos. So the Weak Interaction has two directions, samples for one direction is the Neutron decay, and Hydrogen fusion is the opposite direction.

Fermions and Bosons

The fermions are the diffraction patterns of the bosons such a way that they are both sides of the same thing.

Van Der Waals force

Named after the Dutch scientist Johannes Diderik van der Waals – who first proposed it in 1873 to explain the behaviour of gases – it is a very weak force that only becomes relevant when atoms and molecules are very close together. Fluctuations in the electronic cloud of an atom mean that it will have an instantaneous dipole moment. This can induce a dipole moment in a nearby atom, the result being an attractive dipole–dipole interaction.

Electromagnetic inertia and mass

Electromagnetic Induction

Since the magnetic induction creates a negative electric field as a result of the changing acceleration, it works as an electromagnetic inertia, causing an electromagnetic mass. [1]

Relativistic change of mass

The increasing mass of the electric charges the result of the increasing inductive electric force acting against the accelerating force. The decreasing mass of the decreasing acceleration is the result of the inductive electric force acting against the decreasing force. This is the relativistic mass

change explanation, especially importantly explaining the mass reduction in case of velocity decrease.

The frequency dependence of mass

Since $E = hv$ and $E = mc^2$, $m = hv /c^2$ that is the m depends only on the v frequency. It means that the mass of the proton and electron are electromagnetic and the result of the electromagnetic induction, caused by the changing acceleration of the spinning and moving charge! It could be that the m_o inertial mass is the result of the spin, since this is the only accelerating motion of the electric charge. Since the accelerating motion has different frequency for the electron in the atom and the proton, they masses are different, also as the wavelengths on both sides of the diffraction pattern, giving equal intensity of radiation.

Electron – Proton mass rate

The Planck distribution law explains the different frequencies of the proton and electron, giving equal intensity to different lambda wavelengths! Also since the particles are diffraction patterns they have some closeness to each other – can be seen as a gravitational force. [2]

There is an asymmetry between the mass of the electric charges, for example proton and electron, can understood by the asymmetrical Planck Distribution Law. This temperature dependent energy distribution is asymmetric around the maximum intensity, where the annihilation of matter and antimatter is a high probability event. The asymmetric sides are creating different frequencies of electromagnetic radiations being in the same intensity level and compensating each other. One of these compensating ratios is the electron – proton mass ratio. The lower energy side has no compensating intensity level, it is the dark energy and the corresponding matter is the dark matter.

Gravity from the point of view of quantum physics

The Gravitational force

The gravitational attractive force is basically a magnetic force.

The same electric charges can attract one another by the magnetic force if they are moving parallel in the same direction. Since the electrically neutral matter is composed of negative and positive charges they need 2 photons to mediate this attractive force, one per charges. The Bing Bang caused parallel moving of the matter gives this magnetic force, experienced as gravitational force.

Since graviton is a tensor field, it has spin = 2, could be 2 photons with spin = 1 together.

You can think about photons as virtual electron – positron pairs, obtaining the necessary virtual mass for gravity.

The mass as seen before a result of the diffraction, for example the proton – electron mass rate Mp=1840 Me. In order to move one of these diffraction maximum (electron or proton) we need to intervene into the diffraction pattern with a force appropriate to the intensity of this diffraction maximum, means its intensity or mass.

The Big Bang caused acceleration created radial currents of the matter, and since the matter is composed of negative and positive charges, these currents are creating magnetic field and attracting forces between the parallel moving electric currents. This is the gravitational force experienced by the matter, and also the mass is result of the electromagnetic forces between the charged particles. The positive and negative charged currents attracts each other or by the magnetic forces or by the much stronger electrostatic forces!?

The gravitational force attracting the matter, causing concentration of the matter in a small space and leaving much space with low matter concentration: dark matter and energy.
There is an asymmetry between the mass of the electric charges, for example proton and electron, can understood by the asymmetrical Planck Distribution Law. This temperature dependent energy distribution is asymmetric around the maximum intensity, where the annihilation of matter and antimatter is a high probability event. The asymmetric sides are creating different frequencies of electromagnetic radiations being in the same intensity level and compensating each other. One of these compensating ratios is the electron – proton mass ratio. The lower energy side has no compensating intensity level, it is the dark energy and the corresponding matter is the dark matter.

The Higgs boson

By March 2013, the particle had been proven to behave, interact and decay in many of the expected ways predicted by the Standard Model, and was also tentatively confirmed to have + parity and zero spin, two fundamental criteria of a Higgs boson, making it also the first known scalar particle to be discovered in nature, although a number of other properties were not fully proven and some partial results do not yet precisely match those expected; in some cases data is also still awaited or being analyzed.

Since the Higgs boson is necessary to the W and Z bosons, the dipole change of the Weak interaction and the change in the magnetic effect caused gravitation must be conducted. The Wien law is also important to explain the Weak interaction, since it describes the T_{max} change and the diffraction patterns change. [2]

Higgs mechanism and Quantum Gravity

The magnetic induction creates a negative electric field, causing an electromagnetic inertia. Probably it is the mysterious Higgs field giving mass to the charged particles? We can think about the photon as an electron-positron pair, they have mass. The neutral particles are built from negative and positive charges, for example the neutron, decaying to proton and electron. The wave – particle duality makes sure that the particles are oscillating and creating magnetic induction as an inertial mass, explaining also the relativistic mass change. Higher frequency creates stronger magnetic induction, smaller frequency results lesser magnetic induction. It seems to me that the magnetic induction is the secret of the Higgs field.

In particle physics, the Higgs mechanism is a kind of mass generation mechanism, a process that gives mass to elementary particles. According to this theory, particles gain mass by interacting with the Higgs field that permeates all space. More precisely, the Higgs mechanism endows gauge bosons in a gauge theory with mass through absorption of Nambu–Goldstone bosons arising in spontaneous symmetry breaking.

The simplest implementation of the mechanism adds an extra Higgs field to the gauge theory. The spontaneous symmetry breaking of the underlying local symmetry triggers conversion of components of this Higgs field to Goldstone bosons which interact with (at least some of) the other fields in the theory, so as to produce mass terms for (at least some of) the gauge bosons. This mechanism may also leave behind elementary scalar (spin-0) particles, known as Higgs bosons.

In the Standard Model, the phrase "Higgs mechanism" refers specifically to the generation of masses for the $W^{\pm}$, and Z weak gauge bosons through electroweak symmetry breaking. The Large Hadron Collider at CERN announced results consistent with the Higgs particle on July 4, 2012 but stressed that further testing is needed to confirm the Standard Model.

What is the Spin?
So we know already that the new particle has spin zero or spin two and we could tell which one if we could detect the polarizations of the photons produced. Unfortunately this is difficult and neither ATLAS nor CMS are able to measure polarizations. The only direct and sure way to confirm that the particle is indeed a scalar is to plot the angular distribution of the photons in the rest frame of the centre of mass. A spin zero particles like the Higgs carries no directional information away from the original collision so the distribution will be even in all directions. This test will be possible when a much larger number of events have been observed. In the mean time we can settle for less certain indirect indicators.

The Graviton
In physics, the graviton is a hypothetical elementary particle that mediates the force of gravitation in the framework of quantum field theory. If it exists, the graviton is expected to be massless (because the gravitational force appears to have unlimited range) and must be a spin-2 boson. The spin follows from the fact that the source of gravitation is the stress-energy tensor, a second-rank tensor (compared to electromagnetism's spin-1 photon, the source of which is the four-current, a first-rank tensor). Additionally, it can be shown that any massless spin-2 field would give rise to a force indistinguishable from gravitation, because a massless spin-2 field must couple to (interact with) the stress-energy tensor in the same way that the gravitational field does. This result suggests that, if a massless spin-2 particle is discovered, it must be the graviton, so that the only experimental verification needed for the graviton may simply be the discovery of a massless spin-2 particle. [3]

The Secret of Quantum Entanglement
The Secret of Quantum Entanglement that the particles are diffraction patterns of the electromagnetic waves and this way their quantum states every time is the result of the quantum state of the intermediate electromagnetic waves. [2] When one of the entangled particles wave function is collapses by measurement, the intermediate photon also collapses and transforms its

state to the second entangled particle giving it the continuity of this entanglement. Since the accelerated charges are self-maintaining their potential locally causing their acceleration, it seems that they entanglement is a spooky action at a distance.

Conclusions

The accelerated charges self-maintaining potential shows the locality of the relativity, working on the quantum level also.

The Secret of Quantum Entanglement that the particles are diffraction patterns of the electromagnetic waves and this way their quantum states every time is the result of the quantum state of the intermediate electromagnetic waves.

One of the most important conclusions is that the electric charges are moving in an accelerated way and even if their velocity is constant, they have an intrinsic acceleration anyway, the so called spin, since they need at least an intrinsic acceleration to make possible they movement .

The bridge between the classical and quantum theory is based on this intrinsic acceleration of the spin, explaining also the Heisenberg Uncertainty Principle. The particle – wave duality of the electric charges and the photon makes certain that they are both sides of the same thing. Basing the gravitational force on the accelerating Universe caused magnetic force and the Planck Distribution Law of the electromagnetic waves caused diffraction gives us the basis to build a Unified Theory of the physical interactions.

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