ABSTRACT
We started this project in 2020 to help demystify intelligence. We observed confusion and a general overuse of the term, so we explored the fundamental concepts. Technology has advanced significantly during this short period to compel us to create a 3rd Edition. These fast advancements in Artificial Intelligence may mark the start of a new human-triggered Anthropocene era, similar to the Atomic age due to the Trinity Atomic Bomb or the Industrial Revolution age due to the invention of the Newcomen Atmospheric Engine. Does Artificial Intelligence open another Pandora’s box [69]? Ethical concerns are on the rise as Artificial Intelligence increases in capability, which brings us back to our original question what is intelligence?

Intelligence is a fundamental part of all living things and the foundation for Artificial Intelligence. In this primer, we explore the ideas associated with intelligence and, by doing so, understand the implications and constraints of future systems. Today Artificial Intelligence, in the form of Machine Learning, has significantly impacted our lives and will continue to do so for the foreseeable future.

As an exploration, we journey into essential domains of intelligence. We hope that people find this helpful in determining the future. Also, during the exploration, we hope to create new thought-provoking questions. Intelligence is not a single weighable quantity but a subject that spans Biology, Physics, Philosophy, Cognitive Science, Neuroscience, Psychology, and Computer Science.

The historian Yuval Noah Harari pointed out that engineers and scientists in the future will have to broaden their understandings to include disciplines such as Psychology, Philosophy, and Ethics. Fiction writers have long portrayed engineers and scientists as deficient in these areas. Today, in modern society, the emergence of Artificial Intelligence and legal requirements act as forcing functions to push these broader subjects into the foreground.

We start with an introduction to intelligence and move quickly to more profound thoughts and ideas. We call this a Life, the Universe, and Everything [2] primer, after the famous science fiction book by Douglas Adams. Forty-two may be the correct answer, but what are the questions?

CCS CONCEPTS
• Theory of computation → Machine learning theory.

KEYWORDS
intelligence, machine learning, philosophy, future, evolution, consciousness, reasoning

1 INTRODUCTION
We start with an introduction to human intelligence as we currently understand it and then explore Artificial Intelligence. This section covers the complexities of defining intelligence and ends with some fundamental concepts. Think of each subject as a level down from the title, as they are distinctly different ideas but universally connected. The entire journey takes us from total confusion, see Figure 1, to playing with some wrong numbers, and in the process, we hope to transfer some exciting thoughts.

There is a never-ending debate on whether a system under study can be entirely and self-consistently understood. The biochemist Efraim Racker eloquently put it “anyone who is not thoroughly confused doesn’t understand the subject”. Intelligence is complicated and not in a small way. We suffer from introspection, where the system under study and the observer are the same. This introspection causes hubris when it comes to an explanation.

As discussed, intelligence is complex due to our deep involvement. To help put this into some form of perspective, we use a scenario introduced by Plato in his work called The Republic.
The scenario is called *Plato’s Cave* [57], see Figure 2. The scene, outlined in the concept, describes a cave with a set of prisoners. Each prisoner’s existence involves facing forward in one direction, distanced apart, shackled to one another, and without communication. Behind them shines a bright candle. From their perspective, the entire world consists of silhouettes of themselves. Their world and realization of self are narrow and distorted as people outside the cave view them. Intelligence suffers from the same problem since we consider the subject from our perspective with our biases. We do not have the luxury of viewing intelligence objectively, which forces introspection —also known as the $n = 1$ problem, where the only example is ourselves [23].

When we discuss intelligence, what are we trying to understand? Is it finding the purpose of intelligence? What components make up the intelligence? How can it be applied? Discover the limitations? Measure the capability? How to build it? Or even how to control it? Each question is essential and complicated. But the question we should probably start with is *why should we care?*

**Why should we care?**

Apart from the fact that intelligence increases the likelihood of *survival*, it also empowers humans to handle abstract thoughts. One such thought is “*why has something occurred*?”, explaining the cause of a situation. We will discuss the idea of *cause-and-effect* throughout this primer, as it touches on many concepts associated with intelligence. Another reason to care is that artificial versions can augment or even replace our intelligence, e.g., extend our sensory capabilities such as eyesight, hearing, and data processing. We can use intelligence to push the boundaries of knowledge and exploration. Lastly, in theory, intelligence brings resilience, higher reliability, and, hopefully, better decision-making.

**Creativity**

We use creativity to solve problems by understanding the environment and problem domain to find a novel solution. We would have already created the most advanced intelligent system if we viewed intelligence as carrying out tasks. Even with traditional rule-based systems, we can effectively repeat complicated tasks. The challenge is handling new problems and new situations. Handling new cases is why creativity comes into the equation. It is one of the significant attributes that sets animal species apart. It is also how we solve new problems which are either fully or partially visible.

Creativity can be in many forms: playing football, painting, composing music, solving mathematical equations, or designing new User Interfaces. The list is endless. There are many cultural and social aspects associated with creativity. An essential factor is moving humans beyond primary survival objectives to other subjects such as art, music, and aesthetics. In other words, the secondary reasons, not just the primary goals of life, are sought.

It is arguable whether or not creativity exists in other animals. For example, is a bird song creative? Is it an expression of bird-self? Or is it simply a prescribed sequence of musical notes that a bird uses to maximize its chances of mating? Does a bird song purely satisfy the functional purpose of optimizing the effect of mating or mimicking? Are humans alone in creativity?

What is creativity? *Margaret Boden*, a Research Professor of Cognitive Science, broke down creativity into three useful mechanisms [7], namely *exploration* —playing within the rules, *combination* —applying one set of rules to another domain, and *transformation*
—rewriting the rules by removing a critical constraint. For intelligence, exploration creativity is risk-averse and limited, and at the other end of the scale, transformation creativity has the highest risk with novelty.

Humans can achieve all three levels. By contrast, current Artificial Intelligence struggles with anything beyond exploratory; it never ventures beyond the original programming. If Artificial Intelligence is going to be part of our society, does it need to be creative? Do we want it to be creative? For now, creativity serves as a distinct difference between human-level intelligence and machine intelligence.

**Are we living in a trusted simulator?**

Are we? Maybe. Rene Descartes (circa 1637) struggled with this question and went to enormous lengths to create an answer, culminating in the famous line, from *Discourse on Method*, “Cogito, ergo sum”, or translated to “I think, therefore I am”. Regardless of the answer, intelligence plays the same role in the real and the simulated. A simulation can replace everything in the world, and the underlying decision processes of the individual would remain unchanged. Simulation is critical if we want to mimic intelligence. We will return to this subject in Section 8 & 14 on Consciousness and Wrong Numbers respectively.

We can only trust our ability to think; everything else (i.e., inputs from our environment) is considered untrustworthy. Untrust places skepticism into the forefront of intelligence and a tendency for solipsism. Artificial Intelligence skepticism is a valuable quality, and it encourages the developer to reduce potential errors by having more sensors, either of different types or the same type, to reduce the concerns and possible errors. Simultaneous correlation of dispersed sensors is one of the best reasons for the Internet of Things.

**Alan M. Turing**

Alan Turing can be said to be one of the founders of modern Artificial Intelligence. He contributed to our understanding of natural and Artificial Intelligence, earning him an important place in history. He covered the fundamental operations of computing, provided a measurement for intelligence, and described his ideas on how to build said intelligence. These achievements occurred in an era where the available hardware was significantly limited.

On the fundamental operations of computing, he devised a theoretical machine called the Turing Machine (TM), where digital computation is a small set of essential functions. It is also worth mentioning biological organisms use a variant of the Turing Machine called a Random Access Machine (RAM). The significant difference between Turing Machines and Random Access Machines is that a RAM-based system can access arbitrary tape locations. Turing Machines can convert to Random Access Machines, but this is not bidirectional; not all Random Access Machines convert to a Turing Machine. Also, it is worth noting that in biology, the hardware is numerous (there are many different types of neurons). The software is the same (DNA genome), whereas in digital computers, the hardware tends to be limited (only a few types of digital neurons), and the software provides uniqueness. Both biological hardware and mutation-crossover provide the variation in organisms.

In *Computing machinery and intelligence* [71], released in 1950, Turing explored the idea of creating Artificial Intelligence. He determined that a system will require an ability to make errors/mistakes, i.e., allow for creativity, and must include some form of randomness as a critical component.

Finally, Turing envisaged a test that can gauge whether Artificial Intelligence has been achieved, either by a system mimicking or with actual intelligence. See Section 6, titled Measuring Intelligence for more details.

**Induction, correlation, and causality**

We must introduce three fundamental terms to help understand the rest of the primer. The first is *induction*. Induction takes what came before as a reference to what occurs in the future. Mathematics uses this technique to prove equations; for example, if we can prove $f(0)$, $f(1)$, then in theory, we can prove $f(n)$ and $f(n+1)$. Using this proof mechanism, we can determine whether a recursive function converges to a solution or diverges away from a solution. This method is called *proof by induction*. We use this technique to justify future actions because the past has shown that these actions produce known results. This form of intelligence uses historical patterns to predict the future. It is worth noting that the philosopher David Hume spent significant effort thinking about *The Problems of Induction* [28].

Humans spend a significant amount of time correlating information. We take known inputs and attempt to pattern match. The pattern may be an image, a sound, or a feeling. These correlations can be very sophisticated such as face recognition or partial recognition, where only some information is visible. This ability to correlate comes with the added feature of learning new patterns.

Machine learning, particularly the concept of Deep Learning, has progressed by leaps and bounds in recent years. After years of quietness, the Artificial Neural Network (ANN) field suddenly became a subject of intense research. Geoffrey Hinton, a Cognitive Psychologist and Computer scientist, co-authored a famous paper in 2012 *ImageNet Classification with Deep Convolutional Neural Networks* [36]. Hinton et al. showed a route for Artificial Neural Networks to mimic, if not exceed, the human ability to correlate —the ability to exceed marked the start of the Deep Learning era. Using lots of training data, an Artificial Neural Network can be just as good at identifying patterns as a human. This Deep Learning approach was superior to all other methods when AlexNet won the 2012 ImageNet (LSVRC-2012) competition.

The last important concept is *causality* in *The Book of Why: The New Science of Cause and Effect* (2018) [54] by Judea Pearl et al., Pearl conjectured that humans are better at cause-and-effect than statistics-and-probability. They went on to point out that causality differs significantly from correlation. Correlation is mapping input data to an output via a known pattern recognizer. In contrast, the cause is about determining why. The mathematics around causality involves creating a unique model. The model connects data to a set of actions. The relationships predict the future by testing counterfactual arguments. A counterfactual argument contradicts facts in a hypothetical future world or state. Best described in a statement if $X$ then $Y$, where the conditional clause $X$ is false.
Recommended reading
- *The Republic*, by Plato
- *The Book of Why*, by Judea Pearl Et al.
- *The Creativity Code*, by Marcus Du Sautoy
- *Introduction to Philosophy*, by John Perry Et al.

2 HUMAN INTELLIGENCE

Animals are multimodal in that they can simultaneously cope with multiple activities while handling multiple stimuli—controlling movement, and analyzing vision, sound, taste, and smell simultaneously. For many species, this activity is mundane and happens continuously without interruption from day one to the final demise.

If intelligence were purely about brain size, then we would be ranked 4th on our planet, see Figure 3. Whales, elephants, and dolphins would be correspondingly 1st, 2nd, and 3rd place. Archaeological evidence shows that our brains were significantly larger around 15,000 years ago [43, 66], so our brains have shrunk during that time. One potential reason for this change is associated with society-based problem-solving, i.e., from isolated individuals to communicating individuals. We do not require the same brain size to solve each problem. In other words, we as humans have become a distributed system and solve problems in groups. See Section 5, titled *System design of intelligence* for more on distributed intelligence.

| Brain Feature | Measurement |
|---------------|-------------|
| Type          | Massively parallel |
| Volume        | 1400 cm³ (85 in³) |
| Neurons       | 86 Bn |
| Synapses (network) | > 100 Tn |
| Average adult weight | 1.5 kg (3.3 lb) |
| Processing capability | 1 exaFLOP |
| MIPS Performance | 100 Mn |
| Power Requirement | 15-20 Watts |
| Brain cell    | 0.07 volts at 1 nanoamp |

Figure 3: Human Brain Specification

Sophisticated language advancement has significantly contributed to the transition toward social problem-solving. We use language to coordinate complicated spatial-temporal problems, e.g., problem domains, creativity, courtship, causality, and abstraction. Language is a significant differentiator in social interaction between animals. It is also why the latest advancements in Machine Learning have the potential to be so important. Language has so much influence on our thoughts and experiences, i.e., *Sapir-Whorf* hypothesis [23].

This discussion brings us to the question: *How is Human intelligence organized?* The question is complicated. We will attempt to frame this with three filters: functional components, physical system design, and knowledge representation. These filters are not mutually exclusive; there are probably many more, but we will limit it to three. We decided to separate the concept of consciousness as a unique and separate subject.

When a brain is damaged or handles a new skill, the brain adapts using *neuroplasticity*. Neuroplasticity allows for modification, repair, and adaptation. The network of neurons changes, meaning human brains do not remain fixed. Current research focuses on the frequency of adaption. Artificially induced neuroplasticity can occur with carefully planned electrical stimulation at specific locations in the brain. When applied to stroke patients, the hope is to allow them to regain some dexterity.

What type of computational system is the brain? There has been much speculation between philosophers, neuroscientists, and computer scientists [40]. Is the brain a conventional classical machine, or is there something different? The University of Salzburg concluded there is insufficient energy to justify its capabilities [53, 67]. They speculate that the brain could be some form of classical/quantum hybrid computer. This hybrid would explain why it is so difficult to pin down and why our brains are energy efficient. We will return to quantum mechanics a few more times throughout this paper.

It is worth mentioning many systems in the human body are automatic and rely on reflexes, e.g., touching something scorching (electrical signal) or freezing (chemical signal). Many of these reactive systems are not under the mental control of the host. The heart is one of those systems that is isolated and self-contained.

Functional components

The human brain divides into two primary functional components for decision making: the hippocampus and the prefrontal lobe. Both parts carry out different operational tasks. The hippocampus stores memory, processes object recognition and even achieves simple decision-making. By comparison, the prefrontal lobe is much more complicated. It can assess complex problems and carry out advanced decision-making.

The main difference between the two functions is that the hippocampus cannot determine the ramifications of a decision. This limitation means the hippocampus can easily include irrational prejudices and biases without understanding the broader implications.

Early Machine Learning systems exhibited this characteristic, producing some notably embarrassing results. Today, engineers mitigate this issue by carefully selecting the training data used to create the models to reduce bad bias in the system. For humans, the prefrontal lobe acts as an override for the hippocampus. The override is achieved by understanding the implications of a decision and stopping anything flagged as having an untoward outcome. The prefrontal lobe achieves this by abstracting the ideas and understanding the ramifications.

For Machine Learning systems, the prefrontal lobe function is one of the desired capabilities. Today we rely on hippocampus-style processes with carefully selected training data, but tomorrow we want a higher-level capability that understands and perceives consequences.

Physical system design

Whether they control a bee or a human, brains exploit massive parallel processing to achieve intelligence based on a complicated network of biological neurons. These neurons, and the associated structures, differ in complexity between animals. A bee neuron is distinctly different from a human neuron. In some respects more advanced.
The human brain divides into two physical hemispheres, i.e., left and right. Each hemisphere has distinct characteristics that give humans uniqueness, such as being left or right-handed. There are famous controversies, such as the right hemisphere being artistic, creative, intuitive, and spatially aware [59]. By comparison, the left hemisphere is verbal, analytical, linguistic, and linear [59]. These ideas may be untrue generalization, but we can say that the right hemisphere controls the left-hand motor skills, and conversely, the left hemisphere controls the right-hand side and verbal response. These physical roles, like handedness, can be swapped for various medical reasons, with partial loss of dexterity, e.g., a left-handed person forced to write with their right hand.

Why do the left and right hemispheres matter for human intelligence? It matters because they are two co-dependent intelligent systems [34]. In *Homo Deus: A Brief History of Tomorrow* [26], Harari highlighted an important experiment in the 1960s. People with life-threatening epilepsy had the option of hemisphere separation, which cuts the physical communication channels between the brain’s left and right sides. These unique people allowed researchers to gain valuable data. One experiment involved a patient and a simple question “What do you want to be?”. First, because the question is verbal, the left hemisphere replied “a librarian”. The researchers placed a pen in the patient’s left hand and showed the same question as a written note. The right hemisphere responded, and replied “a racing car driver”.

The different answers enforce the notion that the human brain is, in fact, not one brain but two brains connected closely together. Each hemisphere has its desires and allocated control tasks. These observations make a human more than a single intelligent system but a combination of two distinctly different interconnected systems that require arbitration.

As well as the left and right hemispheres, there are three critical physical components, namely cerebrum, cerebellum, and brainstem [29]. The most significant part of the brain is the cerebrum, which goes across the hemispheres; it handles an array of functions, including touch, vision, speech, reasoning, emotions, learning, hearing, and precision motor control. The cerebellum is much smaller and coordinates muscle movement and balance. Finally, the brainstem connects to the cerebrum, cerebellum, and spinal cord. It handles the automatic reflex systems from breathing to swallowing.

**Knowledge representation**

*Stuart Russell*, Computer Scientist at the University of California Berkeley, wrote “Intelligence without knowledge is like an engine without fuel” [61]. Knowledge representation is at the heart of Artificial Intelligence and all forms of intelligence. Once the right representation is determined, a biological or digital algorithm can easily manipulate the system to create the desired result.

We pick one idea on human knowledge representation, which, if true, has a significant implication on intelligence. A research paper released in 2017 titled *Cliquies of Neurons Bound into Cavities Provide a Missing Link between Structure and Function* conjectured that there is a possibility that we think in up to 11 dimensions [58]. They used a technique called *Algebraic Topology* on neurons. The biological neurons appear to form clusters called cliques and spaces called cavities. These elements, in turn, create high-dimensional geometric objects. Biological neurons differ significantly from artificial neurons in that each neuron has extreme connectivity, i.e., connections. An average human brain contains about 86 billion neurons, with over 100 trillion connections, providing thought and consciousness.

Using this technique, the researchers observed that ideas appear in the brain as dynamic hills of shifting sand, rising up and then disappearing, with the potential of being up to 11 dimensions. Eleven dimensions are far greater than the four, three spatial plus a temporal, which we generally consider essential. Even today, if we look at the most complex Deep Learning systems, they operate at around six dimensions.

**What are we?**

*Christof Koch*, a neuroscientist at the Allen Institute for Brain Science and others, pointed out that we may be a glorified machine [25, 34]. Made from biological components, in essence, a device incapable of understanding its own programming [34]. From this worldview, the mind is a program that runs on a wet computer. This wet computer is unconventional compared with digital computers. It does not follow the standard von Neumann irreversible design rules. The wet computer also does not have a system-wide clock or communication bus. Built out of low-speed millisecond switches, combined compute plus memory, and mixed analog and digital signals. These all create a very different kind of machine. He also notes that, unlike the artificial equivalent, the human brain hardly uses any feed-forward for image processing.

The biological vision design allows humans to learn from a single example, whereas today’s Deep Learning systems require many samples to create a consistent visual model. The human vision system is more sophisticated and efficient than its artificial cousin.

Of course, biological systems follow billions of years of evolution, i.e., an endless repetition of natural selection, crossover, and mutation.

**Neuron view**

As mentioned previously, the biological system has many different hardware devices. For vision, there are about 100 different types of biological neurons. Koch notes that the cortical network feeds backward [34]. Roughly only 1 in 10 neurons have connections from a previous stage. Most obtain information from nearby neurons or neurons at a higher abstract level, i.e., feed-backward. The theorists do not know precisely why this is the case, but it allows the brain to learn from a single example. Today, the most successful Machine Learning systems rely solely on feed-forward. Each layer passes filter data to the next. We do not find feed-forward mechanisms in nature.

For future Machine Learning, *Recurrent Neural Networks* and *Neuromorphic Computing* show promise in feed-backward connections. These technologies, particularly the new hardware appearing in the Neuromorphic Computing space, are beginning to excite Neuroscientists as a possible solution for future artificial systems.

**Recommended reading**

- *The Feeling Of Life Itself*, by Christof Koch
- *Homo Deus: A Brief History of Tomorrow*, by Yuval Noah Harari
3 REASONING

Logical reasoning can be challenging for some people. What is often called common sense is probably more accurately described as social knowledge. Here, we refer to the capacity to conclude from external evidence. Reasoning is the act of going through a problem or situation systematically. As a method of introduction, we will define logical inference as being achieved using one of three methods, namely deductive, inductive, and abductive reasoning. Deductive reasoning involves making a statement or statements and inferring a conclusion, i.e., general-to-specific. Inductive and abductive reasoning takes the opposite approach and attempts to generalize from an instance, i.e., specific-to-general. In other words, the latter methods incorporate uncertainty or probability. Abductive reasoning differs in that it includes cause-and-effect. An important note: all three methods require the capacity for abstract thought, i.e., reasoning beyond what is apparent in the immediate physical environment and often involving multiple states.

Examples of the three reasoning methods:

- **Deductive reasoning**: “all adults were once children”, “Jenny is still alive and no longer a child”, so we can deduce “Jenny is an adult”.
- **Inductive reasoning**: “the first person I met this morning was happy”, so “everyone is happy this morning”.
- **Abductive reasoning**: “a soccer ball is flying towards us”, so “a football player on the opposite team must have kicked the ball”.

Reasoning is fundamental to intelligence. The masters of reason are considered the most intelligent in our society. Deductive reasoning is more mechanical, whereas inductive and abductive reasoning requires some form of inspirational jump, i.e., calculated uncertainty.

Within Computer Science, rule-based Expert Systems and languages such as Prolog have taken direct advantage of deductive reasoning —reasoning forward or backward. The example given of deductive reasoning above is a forward deduction example, but if we say, “Jenny is an adult”, we have the rules to backward-deduce that she was once a child. Machine Learning grapples with inductive and abductive reasoning. Both require some form of probability and potential randomness to land on a good enough or general solution.

**Other attributes**

**Observed/Non-observed**: Reasoning is entirely different when the problem is either fully or partially observable. An example of a situation that is altogether observable is the game of chess, where all the future moves can be calculated in advance using some form of search mechanism, e.g., an iterative deepening A* search. These are the realms in which computer intelligence outmatches even the most extraordinary human minds. IBM’s Deep Blue beat Garry Kasparov in Chess [18], and Google’s AlphaGo defeated the then grandmaster Lee Sedol in the game of Go [47]. Neither system uses human understanding or beliefs. They can break beliefs by using experimentation and logic.

**Easily defined systems** where programmers or mathematicians can represent all possible outcomes are a great showcase of brute-force computing. By contrast, partially observable or obscure problems are challenging. These problems require some form of a best guess. A good example is control systems for autonomous cars, where decisions are made based on a combination of partial observations and prior experiences, i.e., there are always going to be situations that are new and unknown.

It is worth pointing out that AlphaGo was trained with humans and took several weeks to become a grandmaster. Its successor, AlphaZero, learned by playing itself, and it only took a few days to equal and beat AlphaGo. Both used Reinforcement Learning, which is a reward-based system. AlphaGo uses innate knowledge approach, effectively starting from a known point of understanding. AlphaZero began with a clean slate (tabula rasa) [15]. The computational hardware required for AlphaZero is considerably less than for AlphaGo.

**Demonstrative/Non-demonstrative inference**: Demonstrative inference is one where the premises can directly form the conclusion. In other words, a decision is valid only if the premises are true. By comparison, the non-demonstrative inference is when the premises do not directly form the conclusion. The conclusion can be entirely false even though each premise is, in fact, true. The connections mean that truth-preserving only occurs in demonstrative inference and not in non-demonstrative inference [19].

**Ampliative/Non-ampliative inference**: The ampliative inference is frequently used in reasoning to mean “adding to that which is already known”. This extension occurs when the conclusion contains content that was not present “either explicitly or implicitly in the premise”. For example, in a murder mystery novel where the main focus is on two characters, A and B, as the main suspects, it is revealed, generally, on the last page, an unexpected character, C, who is the murderer [19].

Philosopher David Hume in An Enquiry Concerning Human Understanding [30], believed there are two forms of reasoning: relation of ideas and matter of fact. The relation of ideas is both demonstrative and non-ampliative inference. In contrast, the matter of fact is ampliative inference and not necessarily truth-preserving. We can make a true conclusion, even though the premises are false.

**Recommended reading**

- The Book of Why, by Judea Pearl Et al.
- The Creativity Code, by Marcus Du Sautoy
- Introduction to Philosophy, by John Perry Et al.

4 BIAS, PREJUDICE, AND INDIVIDUALITY

Bias shows favoritism for or against an object compared with another. That object can be a thing, person, or group. Generally speaking, it is a learned mechanism. The human experience occurs through perception. A significant amount of perception filtering takes place to focus on specific tasks. For example, a very good demonstration of this is an easy one to perform on ones self: simultaneously touch your nose and toes with each of your hands. The touch sensation happens simultaneously, but the neural distance
between a human’s nose and the brain is a fraction of the distance from their toes. Human biases exist to focus intelligence on specific goals and tasks. This is the way human brains define normal and non-normal.

While human bias does exhibit itself in destructive ways, it does serve a significant function in day-to-day intelligence by determining what is relevant at any given moment. In a way, it is a filter on the human mind to show what we care about most at the moment in time. Whether it is a walk to work in a city or our past selves gathering food in the forest, bias ignores the mundane information and focuses on the novel. In this case, the novelty is the task at hand, or more importantly, from a survival sense, danger.

We gain new knowledge if it is both relevant and salient in epistemological terms. In this context, human bias determines what is relevant to the individual, and prior experience determines salience. Therefore, humans learn more items only if the information is understandable and fits their interests and worldviews.

System designers attempt to converge a model for Machine Learning to a known norm, as in producing solutions that lack inspiration or excitement —technically perfect solutions without mistakes. Iris Murdoch, a philosopher, pointed out that by allowing editing, a writer will move text from the excitement of spontaneity to a more passive normative.

It is essential to note that in biology, bias defines individuals; there are no individuals without prejudice.

Good bias is when the system follows a specific path. By comparison, bad biasing is when a system exhibits non-intended biases. There are many examples of bad biasing in Machine Learning. One excellent example is Microsoft’s chatbot known as Tay [64]. The chatbot used information and interactions from Twitter to learn. Unfortunately, the chatbot learned all the wrong things, i.e., extreme human prejudice. The primary method to avoid lousy biasing is to select training data that reduces the possibilities of bad decision-making.

Two other methods that could help identify and potentially circumvent bad biasing are causality modeling as outlined by Judea Pearl [54] and understanding the decision with explainable Artificial Intelligence [61] (see Section 10).

5 SYSTEM DESIGN OF INTELLIGENCE

Intelligence has a vital physical component. The physical location determines performance, latency, and capability within the body or system. The physical location chooses the type and style of intelligence. Performance determines whether intelligence has the speed necessary to produce the desired outcome. Latency is about response times, i.e., having a perfect answer is no use if the answer is too late. For intelligence, response times can be strict or relaxed depending upon the problem domain, e.g., driving a car or designing an airplane wing. Finally, capability - does the intelligence have enough functional units to take in all the inputs and execute the rules to produce a solution? When is a system too limited or a problem too much to handle?

There are memory considerations along with computation and communication, i.e., short-term and long-term memory. Is the memory required to be in the foreground, or is there a background element? Is the memory longer-term, where it will be seldom required, or short-term instantly required? For animals, the combination of computation and memory occurs in a very non-von Neumann fashion and is inseparable.

Centralized and distributed intelligence

In nature, the organization of intelligence occurs in different ways. For instance, cephalopods [21] demonstrate intelligent actions based on problem-solving and memory. The evolution of its intelligence has created a unique structure. Rather than having a large centralized brain, an Octopus’s intelligence is distributed within the limbs; each limb resembles a distinct thinking entity that cooperates with the rest of the cephalopod body.

Another form of intelligence is in groups. Bees, Ants, soccer teams, and, more recently, military drones all exhibit what is called swarm intelligence: here, the system itself is the intelligence.

There are at least six distinct physical architectures or physical categories of intelligence. These categories occur in both natural forms of intelligence and artificial ones.

- **Centralized** intelligence requires one large brain to perform all tasks. All memory, knowledge, reasoning, and correlation occurs in this centralized location. All existing redundancy is localized.
- **Decentralized** intelligence has multiple brains, all remaining in a single entity. Knowledge, reasoning, and correlation are all duplicated throughout the entity. Decentralized means intelligence has distinct physical redundancy, and each unit can carry out similar tasks with high cooperation.
- **Distributed** means that the intelligence is part of a vast interconnected network, physically located away from one another, not necessarily part of the same single entity. A network potentially involves some form of hierarchy. Where the nodes can be heterogeneous, and redundancy occurs due to scale. In computing, this comes under N-version programming or Byzantine Algorithms.
- **Swarm** intelligence is similar to distributed intelligence, but the physical nodes are much more localized and act as one entity. The nodes within the swarm influence their neighbors. Redundancy occurs at the node level. If a node fails, the system can self-reconfigure.
- **Cloud model**, for only Artificial Intelligence, is an example of a hybrid structure. Where loosely coupled data centers have the failover capability, but at any given time, there is one dominant data center. Redundancy exists because each data center in the group can become a primary.
- **Embodied** intelligence includes some of the above examples but not the data center model. Embodied intelligence refers to the phenomenon of a greater capacity for understanding the world when the intelligence resides in a physical, sensing form, i.e., a system that exists and interacts with the world and understands it differently than isolated one. See Section 1 Are we living in a trusted simulator? in a jar hypothesis. This concept is similar to the dualist philosophical mind-body problem. Is the mind separate from the brain, or what impact do electro-chemical constructs affect the body’s decision-making? For the best working model of embodied intelligence in computers, see Reinforcement learning in Section 7.
As intelligent systems move out of a central location, coordination and communication latency become a significant bottleneck, i.e., scaling effects arise. Pressure occurs as the system needs to optimize at both edge nodes and the nodes dedicated to coordination. In particular, how knowledge is structured, disseminated, and eventually transferred between all system nodes becomes essential. Language, either written or spoken, plays a necessary function for humans. Scaled federated systems [16] (a specific form of distributed systems) can be an effective mechanism to create a higher order of intelligence.

**Artificial variables**

In designing a system, we must consider all the different constraints. Figure 4 shows three possible design variables, namely latency, energy, and sophistication. These design variables determine the type of problems tackled. These are separate constraints yet can be equally important. Specific issues will have additional limitations.

Latency is the required time to make a decision. For example, an autonomous car makes most decisions instantly, similar to when humans are driving.

Energy is also a constraint; the energy required to produce a decision may be much more than locally available. In these situations, system intelligence may have to be adopted. Computers are attached to a network; humans connect to society or political hierarchies. Alternatively, deciding the latency requirements might help reduce the energy requirements, i.e., high latency means less peak energy required.

Tim Palmer at Oxford University conjectured that human intelligence possibly has two energy levels [53], i.e., low and high. In the low-energy state, the computation is much more stochastic or dreaming-like. The low-energy state can explore more complex problems. The high-energy state is more about implementation and quick decision-making. The idea here is that the energy level determines the type of computation occurring.

Finally, the required sophistication makes a difference in how to organize intelligence. If the requirement is rule-based, then the system must be capable of executing a set of rules. In contrast, something more sophisticated, such as conscience (right or wrong), requires a more complicated structure and approach.

**6 MEASURING INTELLIGENCE**

One of the most critical questions we have to ask is how to measure intelligence? How do we know that someone, or something, is intelligent? As an example, is a rock intelligent? If not, why not? We have many controversial tools to determine human intelligence, but how about Artificial Intelligence? For Artificial Intelligence, the environment is essential, and Artificial Intelligent systems can seem super intelligent in highly constrained microworlds [62], e.g., the block world [76] being a good example.

Fundamentally, most measurements involve testing an agent, and testing involves having it complete some specific task. These tasks vary from reciting facts from memory to creating long-form answers to physical problems, e.g., puzzles. We will explore some of these tests next.

**Standardized testing**

Standardized testing has become ubiquitous for testing intelligence. From grade school to graduate school, testing is the most common way for students to show they can display intelligence.

Criticisms of standardized testing are due to not all children being able to learn in the same way or exhibit a specific intelligence. It also tends to ignore the creative aspects of intelligence, assuming that mathematics and reading comprehension are the only ways to exhibit intelligence. Standardized testing is based on the assumption that intelligence is standardized. As this paper hopefully shows, the problem is much more complicated.

The Allen Institute for Artificial Intelligence in 2019 announced that they created an Artificial intelligence system that could pass the standard 8th grade science test [45]. According to the New York Times, the system correctly answered over 90 percent of the questions on an 8th grade science test and over 80 percent on a 12th grade exam. Since we wrote this piece, OpenAI’s GPT-4 has passed medical, law, and business school exams [74]. It has also moved from passing with a minimum grade to passing with proficiency, opening up some exciting future possibilities, see Section 12.

**IQ test**

For many decades, the Intelligence Quotient test has become the de facto intelligence test, with a score of 100 being the average across the population. Scoring high points gets you a prestigious invitation to Mensa.

However, one’s IQ typically relates not to how much knowledge one has but one’s capacity for learning. Another way to look at this is how much water is in the glass versus what is the capacity of the glass. Are humans born intelligent, or do environmental effects make them wise (i.e., do pressure points make us more intelligent)? Or, more realistically, is it a bit of both?

Again, there are signs that IQ tests explicitly designed for Artificial Intelligence are starting to appear. Washington State University (WSU) claims to have created the first-ever IQ test for Artificial Intelligence [78], funded by Defense Advanced Research Projects Agency (DARPA). WSU made a test that measures real-world performance in novel and unknown environments that do not account for complexity. The end score considers the “accuracy, correctness, time taken, and the amount of data they need to perform”.

**Language as a measure of intelligence**

The Philosophy of Language is an endeavor categorizing how humans learn a language. The focus is on how the brain stores symbolic language and what are the primary concepts involved.

From a simple measurement perspective, the size of one’s vocabulary can measure intelligence. Shakespeare may have had a vocabulary of 40-60,000 words. The average English speaker has a vocabulary of 20-30,000 words. We can produce an intelligence scale from intermediate to high using these measurements.

Other aspects of language include the creation of natural language. Facebook had to shut down an Artificial intelligence system for creating a secret language [37]. The Facebook system aimed to explore the subject of negotiation, but the plan quickly went in a different direction. Once connected, two Artificial intelligence systems started learning from each other’s mistakes and quickly
developed a unique language. These systems started with basic English.

Large Language Models also represent this measure Section 12. Large refers to the size of the model, but it could also refer to the size of the corpus of its data. Large Language Models, like ChatGPT, appear intelligent due to the language model driving them.

**Turing test**

The Turing test has become infamous in the world of Artificial Intelligence. Proposed by Alan M. Turing in 1950 and originally called the *Imitation game* [71] describes a simple method to determine intelligence. The test focuses on a machine’s ability to exhibit intelligent behaviors indistinguishable from that of a human. A person interacts through an interface with an unknown entity. That entity can be another human or a machine. The machine has passed the Turing test if the person cannot distinguish which one is human or machine.

Only one Artificial Intelligence system has passed the Turing Test [63]. The passing is not without controversy. The Chatbot is called *Eugene Goostman* and acts like a 13-year-old Ukrainian boy. The chosen age and country of origin forced the judges to compensate for errors and awkward grammar. The Royal Society held the test in London in 2014. Eugene Goostman managed to convince 30% of the judges that it was human for 5 minutes during a typed conversation.

Efficiency: Back of an envelope calculation. Let us create an efficiency equation for passing the Turing Test 1.

\[
TTE_y = \frac{x}{y \times d \times h \times p}
\]  

Where \(x\) is what you are comparing with (human or artificial), \(y\) is years old, \(d\) is days per year (365), \(h\) hours in a day (24), and \(p\) is power consumption (for humans it is 20 Watts). Using an average graduate age of 21 years old, the Turing Test Efficiency 21 (TTE21) would have a divisor of 3.7 MWh (MegaWatt hours). This number crudely represents the training cost in Watt hours to pass the Turing Test.

\[
TTE_{21} = \frac{x}{3.7MWh}
\]

The quotient for another 21-year-old would be 1, compared to a 57-year-old, which is 2.7. Passing the Turing Test takes a 57-year-old 2.7 times more training energy than a 21-year-old. The higher the quotient, the more energy is required to pass the Turing Test. The quotient gives us a simple metric to determine the cost of attaining a level of intelligence indistinguishable from humans.

**Problem solving**

Measuring problem-solving ability is a way to measure reasoning capability without language. One of the best ways to do this is through Behavioral Psychology. Behavioral Psychology is a school of thought focused on observable and measurable intelligence. It assumes a blank slate (*tabula rasa*) and that all aspects of intelligence are due to a learning process. One’s intelligence is directly proportional to the complexity of the problem domain. In this case, problem-solving refers to a physical embodiment of deductive reasoning.

Pavlovian conditioning is the best example of Behavioral Psychology put into observable practice. By shaping the environment, specific actions can be co-related to understanding the world and capacity for intelligence. Since animals cannot speak or refuse to talk to humans, this is one of the first examples of being able to test an animal’s understanding.

Crows, primates, and cephalopods all can reason up to several steps in advance to solve problems. In some cases, crows can solve problems better than most 5-year-olds. Crows can retrieve objects floating in containers just out of beak reach by adding rocks [39].

Problem-solving as a measure shows some promise as a method to evaluate certain kinds of Artificial Intelligence. This method is especially true for systems that navigate changing environments or new problems to solve [12].
Measuring brain activity

Measuring brain’s electrical activity is vital to determine whether a non-responsive person is either in a vegetative state or suffering from locked-in syndrome. A vegetative state is when a person appears awake without awareness. By comparison, locked-in syndrome is a condition where a person is aware but cannot communicate. Some forms of stroke or head injury cause these situations.

This issue is where non-invasive Brain Computer Interfacing helps determine levels of consciousness. For example, one method to help discover the level of consciousness is called Zap and Zip [34]. A sensor cap fits onto a patient’s head. The sensors measure electroencephalogram or more commonly referred to as EEG. EEG is the activity occurring in the brain. First, a magnetic pulse “zap” is applied. The cap sensors pick up the EEG signals. The EEG data is a large amount of unstructured information. Then the zip compression algorithm is used to compress the data. The zip algorithm compresses common repeating patterns and leaves unique activities unchanged. As in no discarded information, the zip compression algorithm is called a lossless compression algorithm. The resulting file size is the measurement of consciousness. A small file size indicates that most brain systems are automatic. A large file leans toward the patient having consciousness but cannot communicate.

Artificial Intelligence has no consciousness, so there is no equivalent method.

Recommended reading

- The Feeling Of Life Itself, by Christof Koch
- Human Compatible, by Stuart Russell
- Artificial Intelligence: A Modern Approach, by Stuart Russell Et al.
- On the Measure of Intelligence, by François Chollet

7 MATHEMATICALLY MODELING INTELLIGENCE

In an attempt to make the world understandable, humans use mathematics. Mathematics is said to be either invented or naturally occurring. If we believe it is naturally occurring, it is a discipline of discovery rather than an invention of ingenuity. Immanuel Kant, the philosopher, said “that it was Nature herself, and not the mathematician, who brings mathematics into Natural philosophy” [65]. For our discussion, we choose the invention path.

Mathematics is a collection of rules that attempts to model and map the world about us. There is a vast number of techniques for algorithmically representing the world. It is a tool that is gaining in capability. Is it only a matter of time before we can model intelligence mathematically? The following are what we believe to be the most focused mathematical models for intelligence.

In many cases, these methodologies require an expert, in most cases a human, to assist in pointing out the correct from the incorrect. While reading this section, the essential element to remember is the George Box aphorism: “All models are wrong, but some are useful.”

We create models to generalize and abstract. We could make a model so complex that it reflects reality or so simple that it is easier to implement and train. Models are essential in Machine Learning. From the outside looking in, we need to train a model; the model itself has to have the ability to learn. In general, there are two main categories of learning, namely supervised and unsupervised. As the name implies, supervised learning requires an expert to dictate. The expert determines what is correct and what is incorrect. Unsupervised learning requires no domain expert to intervene. There are sub-categories, which include, for example, semi-supervised learning.

We will categorize each model by pairing it with one of the previously defined elements associated with intelligence and highlighting their unique biomimicry. Biomimicry is the emulation of processes found in nature. The point for this is two-fold. First, to put the methodology into perspective and second, to reinforce the notion that replication requires a detailed definition and a form of measurement.

Specialization vs generalization

Statistical modeling is all about optimizing based on some desired result. Engineers, researchers, and data scientists define the methods and the desired outcomes.

Chollet defines intelligence as “The intelligence of a system is a measure of its skill-acquisition efficiency over a scope of tasks, concerning priors, experience, and generalization difficulty;” [12]. This observation is helpful to remember as most, if not all, of these methodologies optimize for a specific task. Chollet points out that there is no quantifiable measure for the general. The more optimized a model is for a particular job, the more specialized it is, and the less general it will become.

Historically, we believed that specialized knowledge came from generalized knowledge. However, the following methods show how to obtain technical expertise without general knowledge. Each model has constraints, but all focus on optimizing a particular feature. For example, Reinforcement Learning (for now) optimizes along with one variable, defined by its reward function.

Bayesian probabilism

Biomimicry note: Paired with deductive reasoning and statistics

Bayesian probabilism is where the comparison between human and Machine Intelligence stops, as biological systems are generally weak at statistics. As mentioned previously, Judea Pearl believes humans are wrongly-wired or, more precisely intentionally wrongly wired for other evolutionary priorities [54]. Bayesian probability primarily lends itself to robotics and Simultaneous Localization and Mapping (SLAM). The reason for the popularity in these areas is because it seems to be the best method to mitigate multiple sources of information to establish a consensus of best known. For example, while a robot tracks its path, it always runs on minimal information and makes decisions based on statistical likelihood.

Bayes Theorem underpins Bayesian probability, a mathematical equation for how justified a specific belief is about the world.

Bayes Theorem is defined as:

\[ P(A|B) = \frac{P(B|A)P(A)}{P(B)} \] (3)
Bayes Theorem mathematically expresses classical logic, as far as the known is concerned. When dealing with the unknown, new variables need to be introduced. Entropy in probabilism refers to the amount of the problem space that remains unknown. As the equation expresses the probability that something is true, the amount known about the system must be recorded and categorized.

Deep learning

Biomimicry note: Paired with the physical nature of the human brain

Given the popularity of Deep Learning, there is a gamut of material available on the subject. Here we will briefly overview the biological basis and the mathematical functions that allow Deep Learning models to learn.

Artificial neurons. The fundamental building block of Deep Learning is the Artificial Neuron (AN), also commonly known as a perceptron. An Artificial Neuron imitates the same neurons found in the brain. A single biological neuron has input in the form of dendrites and outputs in the format of axons. The machine equivalent, the Artificial Neuron, is shown in Figure 5.

![Figure 5: Artificial Neuron (Wiki media Commons)](image)

Here we have a set of inputs, a transfer function, and an activation function. A threshold is also often referred to as the bias. In simplistic terms, a simple Artificial Neural Network (ANN) can consist of only a few neurons. An Artificial Neural Network typically consists of Artificial Neurons arranged in layers, each layer connecting to the next. Deep Learning is a very complex layer system of thousands of neurons. Through a mathematical function known as back-propagation and supervised learning, these weights and thresholds will slowly and carefully modify overtime to give the correct answer when given a set of inputs.

Generative Adversarial Networks

Biomimicry note: Paired with creativity

Generative Adversarial Networks, or GANs, are based on Deep Neural Networks (DNNs), where two networks compete with opposing goals on the same data set. Generative Adversarial Networks focus on generating images, video, or audio, i.e., everything from Deepdreams to Deepfakes. Creating a human face where no such person exists is an example of a Deepdream [32], whereas placing a known politician in a old pop music video is a Deepfake.

A Generative Adversarial Network consists of two networks: a generative network and a discriminative network. These are often called the creator and the critic. The critic, see Figure 6, is similar to a typical supervised network, trained to recognize specific cases. The creator’s role is to fool the critic through clever feature extraction. Over time and given enough samples, the creator can mimic the features found in the dataset. The critic network judges the creator’s network using the same training data as a comparison point. In this case, both networks train each other in a digital arms race, the creator becoming more capable of counterfeiting solutions and the critic becoming more discriminatory. Eventually, the creator becomes so good that the critic can no longer tell what is original.

A particular application of GANs is Deepfakes [81], which have grown in popularity over the last few years, thanks to the ease of creating them and potential applications—these range from political disinformation to blackmail and general amusement. While we stated growing concern and the potential for deepfakes to influence people’s decisions and viewpoints, this had yet to happen. Today, we have seen the start of genuine consequences, from kidnappers using Deepfake voices pretending to abduct a child [31] to Artificial Intelligent Chatbots designed specifically for malware purposes [72]. With as many ways to generate Deepfakes, we hope there are ways to identify their inaccuracy.

Reinforcement learning

Biomimicry note: Paired with problem-solving

Reinforcement Learning (or simply RL) is another subset of Machine Learning in which Neural Networks make up the building blocks of the algorithm. Hutter and Legg stated, [38], if “Intelligence
measures an agent’s ability to achieve goals in a wide range of environments”, Reinforcement Learning approaches this in baby steps, focusing on one environment at a time.

When looking at Reinforcement Learning, it is essential to remember that at its core, it is a Behavioral Model, similar to Pavlovian conditioning. Everything is an action-reward pair. For example, positive reinforcement dictates that a meaningful positive reward is received when a model creates the right action.

Figure 7: RL Agent (Wiki media Commons)

Figure 7 shows the Reinforcement Learning agent, environment, reward function.

Recommended reading
- The Emperor’s New Mind, by Roger Penrose
- The Book of Why, Judea Pearl Et al.
- Gödel, Escher, Bach: an Eternal Golden Braid, by D. Hofstadter
- On Growth and Form, by D’Arcy Wentworth Thompson

8 CONSCIOUSNESS

Consciousness is the ability to experience existence, the awareness of being [23]. Consciousness is the least understood and most intriguing aspect of intelligence. We can determine a level of intelligence, but consciousness is much more difficult. Philosophers and scientists have continuously argued about its definition [40]. In this section, we will explain the significant ideas. We start by determining how consciousness may differ from intelligence. One of the many complex questions is whether we can have unconscious intelligence. Can we separate true intelligence from consciousness? See Figure 8. This question is essential for artificial intelligence and humans. Harari put the importance into perspective, and he stated “Humans are in danger of losing their value because intelligence is decoupling from consciousness” [26].

What is the relationship between consciousness and intelligence? Inspired by Christof Koch, Figure 8 is an attempt at a visualization [34]. The diagram shows the relationship between the two concepts, with intelligence along the x-axis and consciousness represented by the y-axis. The points represent a best-guess level of consciousness and intelligence. A lot of poetic license was applied to show the progression required to attain human-level intelligence, symbolized by the label Us. This poetic license is why we, the authors, call this a wrong diagram on consciousness since it is our interpretation, e.g., it would be hard to prove whether compassion truly requires more consciousness than a premonition. All current Artificial Intelligence systems remain grounded on the x-axis. All animals, including humans, are on the x and y-axis. The space beyond human intelligence is labeled Singularity, see Section 9 for more details. The figure shows the large technology gap between current artificial systems and humans. It also hopefully highlights the importance of consciousness as compared with intelligence.

Traditionally, when discussing consciousness, philosophers have used the Mind-body problem. The mind-body problem defines the body as an objective physical system and the mind as a subjective system. This belief is called dualism. The question revolves around how the mind and body connect. This belief ultimately makes intelligence a combination of the physical and the mind (i.e., embodiment) and is inseparable [14]. These connections are why robotics has so much promise with the ability to emulate the mind and body.

Why is consciousness necessary? Say we have two devices called A and B. Externally, they exhibit the same characteristics. They take input data, process it, and finally output a result. These devices function the same. Device A is functionally correct, and device B is self-aware. The difference is B understands the data: it understands the meaning, cause, and implications for a particular conclusion. It is aware of its existence, i.e., not mindless but conscious. Consciousness requires a measurement method. ‘A’ is a philosophical zombie, in that it exhibits all the behavioral aspects of intelligence but none of the understanding.

To emphasize the differences between consciousness and intelligence, John Searle created the notion of the Chinese room [13, 27]. It poses a thought experiment as a counter-argument to the famous Turing Test [52]. The investigation requires that you imagine that you are in a room, and you get three batches of information: a set of symbols (‘a script’), ‘a story,’ and ‘questions.’ You give back a bunch of symbols that are answers to the questions. Also provided are a set of written rules in English, known as the ‘the program.’ You have no understanding of Chinese. Chinese characters pass into the room. You apply the rules mindlessly. Answers return in perfect Chinese. The people outside the room can only assume that the person inside speaks fluent Chinese, but the person inside knows nothing about the language.

Professor Paul Li, a Cognitive Scientist from U.C. Berkeley, in a talk at Stanford University, asked the question “what do we know, for sure, about consciousness?”. Computational-Representation Understanding Of Mind (CRUM) shows that it is most likely biological/neurological, electrical, and chemical. That is all we know, and it is not much.

Finally, the concept of other minds, if we understand our mind, can we understand other people? We can access our minds, but can we rationalize anything about anyone else’s mind? [17]. These are important questions. Can we rationalize consciousness?

Below are a subset of consciousness ideas:

- Functional basis: Consciousness occurs as a result of functional elements. By learning more about the brain, we will gain a better
understanding. In this concept, consciousness is viewed simply as a byproduct of functional execution. The Global Workspace Theory (GWT) [5, 6] is one concept that falls under the functional category. This theory is closely related to an old idea in Artificial Intelligence. Global Workspace Theory has a centralized blackboard (workspace) where ideas live. These living ideas are placed or taken from the blackboard; some ideas appear briefly. Ideas can be combined, processed, or ignored. Subsystems are available to handle low-level ideas. Consciousness, therefore, comes about through functional processes.

The functional approach also includes the notion that animals are physical “wet” computers, processing complex data. The main task today is to understand how these complicated biological systems interact and function as a complex system. High-level consciousness is a functional system, so the more we understand the functions, the closer we get to having the ability to understand and, in theory, create machines with consciousness.

- Universe basis: Galileo believed certain things have repeatable physical characteristics that obey mathematical laws [17], e.g., a ball rolling down a hill. Other concepts reside only in the conscious, e.g., smell, taste, and color. These qualities only exist in the mind. If people cease to exist, then these qualities evaporate. Meaning our physical laws are incapable of providing the complete story. Philip Goff put forward the concept of Panpsychism [22]. Panpsychism proposes that consciousness is a fundamental aspect of reality [17]. Meaning it is equivalent to mass or charge. The belief is that consciousness is inherent in the fabric of the universe and not limited to a brain. This belief comes about if we separate the substrate and the concept. Christof Koch stated that if true, the “cosmos is suffused with sentence” [35]. This idea leads to cosmopsychism that the universe itself is conscious. Panpsychism theory has difficulty explaining combination, i.e., how small consciousness combines to create a more significant form [17]. In other ideas such as Psychological ether theory, brains do not produce consciousness but use consciousness, i.e., consciousness existed before our brains existed.

- Experiences basis: Christof Koch defines consciousness as a set of experiences. The historical experiences differentiate humans from each other and machines [34]. Some humans are more disposed to experiences than others. Experiences are a form of causal action. Koch showed an exciting model, already introduced in Figure 8, to show the difference between consciousness and intelligence. In this figure, we have taken the liberty to show how we humans and Artificial Intelligence could map out. The driver for this figure is to provide two elements, the first is an abstract view of where we are in terms of intelligence, and the second is to highlight the importance of consciousness. Koch describes an experience in terms of the Integrated Information Theory (IIT) [70]:

  “consciousness is determined by the causal properties of any physical system acting upon itself. That is, consciousness is a fundamental property of any mechanism that has cause-effect power upon itself.”

  Christof Koch [34, 70]

Integrated Information Theory can be said to be a form of Panpsychism. Koch and others proposed that we may never replicate biological consciousness if the replication method is digital simulation. Consciousness requires causal powers to make consciousness conscious. For engineers and scientists, this is probably best illustrated as a simple equation; see Figure 9. Using the equation, we would need both simulated rules and the ability to store and create causal effects to make a conscious machine.

- Quantum basis: As an alternative thought, Roger Penrose, a mathematical physicist, believes that "whatever consciousness is,
As previously mentioned, many sub-areas of consciousness exist, in-cluding the physical self and the ability to contemplate what the physical is thinking or feeling, i.e., introspective. This self-awareness extends into self-evaluation and a sense of personal identity. Allowing an entity to assess how it interacts with the outside world. A related subject is mirror self-recognition, where only a few animals recognize that they are looking at themselves when using a mirror.

One last point on consciousness. There are ethical consequences to allowing artificial consciousness. Those consequences are around existential, sentient, and cognitive capacities. In other words, when is a thing, not a thing, but a sentient being with likes and dislikes? The question about sentience is difficult to answer but is essential if we need to go beyond basic intelligence. A necessary use for consciousness is enabling conscience, i.e., determining right or wrong. Does consciousness ultimately lead to emotion? What happens if a system gets angry or even happy?

Recommended reading

- The Feeling Of Life Itself, by Christof Koch
- Galileo’s Error, by Philip Goff
- Homo Deus: A Brief History of Tomorrow, by Yuval Noah Harari

9 AUGMENTING HUMAN INTELLIGENCE

In this section, we dive into how practical Artificial Intelligence applications are built and utilized alongside human operators. It is not a new concept, however, given the surge of Generative Artificial Intelligence (commonly known as Generative AI) and Large Language Model (LLM) (see Section 12), we see a much broader adoption. It is not just specific fields that are diving into the world of Artificial Intelligence, but everyone.

Extension of human intelligence

Fundamentally, it is best to think of current Artificial Intelligence and Machine Learning systems as extensions of human intelligence. They come from human observations, algorithm designs, and constructions. Effectively, a task-based copy. Rule-based systems are an excellent example, and new techniques are far superior. These tasks range from identifying cars to trading stocks, but none originate from anything separate from something a person has already done. In another way of thinking, Artificial Intelligence does not find new novel tasks that only it can complete.

This concept comes with a caveat. There are things that machines are better at than humans due to scale, whether it is a scale of speed (reacting in milliseconds), compute (shear power of cloud-based computing outways a single human’s computational power), or knowledge (machine recall is not subject to the same problems as human memory). An excellent example is LeanDojo, a Large Language Model-based approach to solving mathematical proofs [84].

Human In the Loop

An important human-machine interaction concept is Human-in-the-Loop. Human-in-the-loop refers to the development of the algorithm and deploying the algorithm for problem-solving [24, 79]. This process allows humans over-site to alter and audit the algorithm in real time. Consider the following interaction:

Imagine a system where a human doctor uses a machine-learning algorithm for detecting cancer in X-ray images. The algorithm churns through thousands of images faster than a doctor. However, it could be better. When the algorithm has low confidence, it flags the human doctor who checks its prediction. The check results are fed back into the system to improve the data set and the prediction model, i.e., a human-machine feedback loop.

In the past, humans have represented the expert, the position of auditor, or supervisor. Machine systems are good at taking in multiple channels of information or running through several tasks all at once, and the human is the one who subsequently takes that result and makes a decision. This configuration then combines one system’s strengths with another, forming a new type of intelligence, i.e., human-machine intelligence.

Centaurs

Il centauro in Italian translates to two things: centaur and motorcyclists. The concept is similar to what Native Americans experienced
at the re-introduction of horses to the Americas: two separate entities combined to harness the strengths of each. For a horseman and the horse, it’s the rider’s cunning and drive combined with the horse’s speed and stamina. For humans and machines, our imagination, creativity, and desire to produce combined with a machine’s speed and knowledge representation. This cooperation has become more prevalent in the last year thanks to the wide adoption and usage of Large Language Models (see Section 12). What we are witnessing with Large Language Models and Generative AI is not a replacement of human skills but an augmentation of everyone without those skills. A person who could not draw a cat before but could imagine and describe one can now generate an image. A person without writing skills can now create a sonnet (or an academic paper, special thanks to Grammerly). The output is nothing new; it comes from the combined skill of every author and content creator who went into developing the Large Language Model. These technologies are not replacing creatives but filling in deficits for the rest of us.

**Recommended reading**
- *Novacene*, by James Lovelock
- *ChatGPT*, by OpenAI

### 10 EXCEEDING HUMAN INTELLIGENCE

Up to this point, we have been discussing digital cloning; in this section, we discuss how to exceed our intelligence. This area comes with both optimism and concern. Surprisingly, it was *John von Neumann* who created the now infamous term *Technological Singularity* [73]. The belief is that once Singularity occurs, technology will reach an irreversible point that exceeds human capability; see Figure 10 —Singularity is achieved by constructing an artificial system or through augmentation. Specifically for intelligence, this is known as superintelligence and hyperintelligence. There are at least two other methods to exceed human intelligence, namely evolution or external influence. Evolution does not stop [10]; it continues. Humans are just an interlude in the process; assuming we are an endpoint would be an error. The fourth possibility is an external influencer, i.e., *extraterrestrial* [23]. Extraterrestrial is beyond this paper’s scope but raises some interesting questions about how we define life and, more precisely, how we define intelligent life, e.g., *Assembly Theory* [20].

There are always concerns. The primary problem with having superintelligence is having superintelligence with no consciousness, i.e., no awareness of implications. Harari describes an Artificial Intelligent system that takes over the world (and beyond), and its only objective is computing π [26]. It constantly pursues gaining resources and removes all obstacles, with no awareness of right or wrong; the system takes over the world by continuously consuming more and more resources to feed a pointless calculation. It has no evil intentions; it is too focused on its goal to consider other factors. It has no awareness of the self and the implications of its actions. Humans are secondary at best in this scenario.

*If some form of super Artificial Intelligence should emerge, will it occur by accident due to system complexity?* The system would attain sufficient complexity to allow intelligence to emerge. In other words, emergence would not be designed or manufactured but would form naturally through chaotic processes. This chaotic emergence would mean that intelligence would appear without the expected controls.

#### Superintelligence

There are at least two main methods to build a system capable of superintelligence [8]. The first method is to create a system so complex in knowledge and sophistication that intelligence hopefully appears. The other process involves transferring or copying an existing biological intelligence in the hope of jump-starting superintelligence. The jump-start consists of reading and copying neurons and synapses.

Koch pointed out that at the current rate of technological advancement, we should be capable of simulating a mouse brain within 2-years [34]. The *Blue Brain/Spinnaker* project is on course to achieve this goal with a massive parallel spiking neuron machine [46]. A device must simulate 100 million neurons even for this relatively simple task. As Koch also points out, this is merely a functional model with no consciousness or awareness, i.e., a *zombie* intelligence.

#### Hyperintelligence

Hyperintelligence is a concept where humans are augmented with technology to enhance their intelligence. James Lovelock, the originator of the *Gaia hypothesis* (i.e., the Earth is a self-regulating system), believes that increasing human intelligence is the only solution to global warming and world issues. The only way to improve intelligence is through augmentation [41].

In recent years, we have seen a rapid increase in the sophistication of *Brain Computer Interfacing* (BCI) in reading and writing. The intrusive devices are implanted directly into the brain, connecting
We have intelligence and multiple individual intelligence nodes, i.e., with the social etiquette of dogs. With older dogs. When dogs mature into adulthood, without this we do not comply, depending on severity, repercussions occur, e.g., warding obedience: more money, promotion, or high status. And, if humans end up co-existing with this new intelligence? Do humans become pets and end up in zoos? Do humans ascend to a higher plane of existence (we become the machine)? Or do humans eventually become extinct (for good or bad reasons)? Do government regulations slow down or speed up this process? Does energy/resources become the primary constraint and limiting factor?

What happens?

If we exceed human intelligence, where does this lead us [23]? Do humans end up co-existing with this new intelligence? Do humans become pets and end up in zoos? Do humans ascend to a higher plane of existence (we become the machine)? Or do humans eventually become extinct (for good or bad reasons)? Do government regulations slow down or speed up this process? Does energy/resources become the primary constraint and limiting factor?

11 CONTROL OF INTELLIGENCE

We have intelligence and multiple individual intelligence nodes, i.e., animals and artificial. How do we control these nodes to do something useful or ensure they behave correctly? Sometimes correct behavior is optional, overridden by basic survival requirements. In animal intelligence, survival tends to have the highest priority. Humans have religion, laws, ethics, morals, and social norms to ensure compliance with society. A selfish motivator is applied, rewarding obedience: more money, promotion, or high status. And, if we do not comply, depending on severity, repercussions occur, e.g., isolation of an animal from the pack.

For most animals, conformance training occurs when young, and more so for altricial species. For example, maturer dogs make sure the younger ones are in check. Dog owners are very familiar with this concept, so they introduce younger dogs to an environment with older dogs. When dogs mature into adulthood, without this social training, they lack some social skills, i.e., they do not comply with the social etiquette of dogs.

Constraining machine learning

The introduction mostly covered animal control, so what about Artificial Intelligence and Machine Learning? What are the control mechanisms available for artificial systems? What are the potential repercussions of non-control?

Machine Learning performs two significant tasks. The first is a pattern matcher using some form of correlation, i.e., deep learning. Second, Machine Learning strives toward an optimized goal utilizing some metric or reward, i.e., Reinforcement learning. Both are useful within narrow problem spaces. The exciting part is when the system changes from perception to decision-making. Perception is about determining an environment, e.g., the orange is in front of the pineapple, or the bed is in a hotel. Perception is relatively safe since the consequences tend to be limited. By contrast, decision-making is about interacting within the physical world (for example, autonomous vehicles). Decision-making is inherently more dangerous since there are human implications.

Stuart Russell in Human Compatible - Artificial Intelligence and the problem of Control, and others, have identified this transition as highly dangerous [49]. There is concern that unquestioning belief in reinforcement learning, with its endless pursuit of simple, attainable goals, might lead to problems. The real-world environment is much more complicated [77] since there are humans (other independent agents). For example, Russell [61] points out potential danger if the system identifies protecting its kill-switch as part of an optimizing metric.

What are the mechanisms to control Machine Learning?

- **Testing.** Vigorous testing is the easiest way to control a Machine Learning model. Corrections are made to the training data if the model goes awry. The disadvantage is that we cannot handle every test case and scenario—a strong linkage exists between testing and training data.
- **Boundary limitation.** We can set boundary limitations for the Machine Learning systems, i.e., no dialing volume to 11. These are simple mechanisms that narrow the operating range. The disadvantage of boundary limitations is that not all environments have a precise operating scope, and maybe there is a rare instance that requires setting something to “11”.
- **Parallel modeling** involves a simple duplicate functional model that checks the more complex Machine Learning model. If there is a noticeable difference, then a contention error is raised. By judging the contention, a decision on the right course of action can occur. The disadvantage of parallel modeling is that, like the previous two examples, it is only suitable for more straightforward problems with abundant computational resources.
- **Multiple Machine Learning systems** N-version programming may provide a control method. Either they are using the same input data or different input data. Each system votes on a final decision, and the majority wins. The voting method has resilience since it handles a wrongly trained model, i.e., a Byzantine-style algorithm.
- **Explainable AI.** Another method to help control Machine Learning systems is to have a strategy to understand them. This strategy is essential to determining how conclusions come about in a network. Explainability is vital to avoid bad biasing. As a counterpoint, Julian Miller, Computer Scientist at York University, stated that explainability might act against the goal of Artificial Intelligence. For example, we find it difficult to understand our decision-making, so why expect Artificial Intelligence to be explainable or understandable?
- **Inverse Reinforcement Learning.** As described by Russell, it is when you alter the reward mechanism to be more oriented

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**Recommended reading**

- *Superintelligence - Path, Dangers, Strategies*, by Nick Bostrom
- *The Major Transitions in Evolution Revisited*, by B. Calcott Et al.
- *Human compatible*, by Stuart Russell
- *Novacene*, by James Lovelock
- *The Feeling Of Life Itself*, by Christof Koch

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**Human Compatible - Artificial Intelligence and the problem of Control**, by Stuart Russell.
around humans. The reward is based on human preference to produce beneficial Artificial Intelligent systems. "... machines will need to learn more about what we want from observations of the choices we make and how we make them. Machines designed in this way will defer to humans; they will ask for permission; they will act cautiously when guidance is unclear, and they will allow themselves to be switched off" [61] —in other words, building mathematical models that can capture, understand, and work with human intent.

Today Artificial Intelligence and Machine Learning systems are comparatively basic, i.e., narrow. The next generation of systems will likely be much more capable, and with that capability comes the requirement for more control. At what resource cost are we willing to pay for explainability and control? Is it essential that Artificial Intelligent systems fall under human control mechanisms, e.g., ethics, laws, and religion?

**Explainability in Deep Learning**

Over the last few years, explainability has become the forefront of recent Deep Learning conversations. Not all Deep Learning architectures are the same; some are more explainable than others. Convolutional Neural Networks (CNN) are the worst in explainability but the most popular in terms of ease of development. These two factors go together.

Explainable AI refers to decoding the black box that is Deep Learning. The issue is that the architectures are so massive and removed from human involvement that they need more readable. There have been some methodologies to address this. Heat mapping is one aspect that highlights specific areas in the images of a dataset that co-relate to high-impact weights in Neural Networks.

Explainability has been one of the significant factors impacting the adoption of Deep Learning. Most Deep Learning models lack transparency, which means that any human-involved interaction will be complicated.

This difficulty is genuine in the medical industry. Two metrics help in explainability, at least in terms of performance. These are the sensitivity factors that are specific to any model. Sensitivity refers to the proportion of correctly diagnosed positives, e.g., people identified as having cancer who do, or correct negatives, e.g., people diagnosed as cancer-free who are. These metrics aid in the adoption process by highlighting the likelihood of the worst-case scenario in medicine, i.e., a false-negative answer.

**Recommended reading**

- Human Compatible, by Stuart Russell
- Homo Deus: A Brief History of Tomorrow, by Yuval Noah Harari
- Superintelligence - Path, Dangers, Strategies, by Nick Bostrom
- The Possibility of Life, Jaime Green

**12 LARGE LANGUAGE MODELS AND GENERATIVE AI**

Large Language Models (LLM) have become increasingly popular, raising excitement and concern. We can ask questions and receive near-perfect responses. The excitement comes from our desire to interact with computers using natural language, e.g., Star Trek’s voice computer. This desire can be traced back to the mid-1960s with programs such as ELIZA and DOCTOR [80], which provided primitive natural language interactions.

Over what appears to be a short period, Large Language Models can now pass professional exams in disciplines such as medicine [33] or accountancy [82]. Not just pass but pass at a high proficiency level. Let’s ask one a question, “Concisely, what is a Large Language Model?”. Below is the response from OpenAI ChatGPT-3.5 on Friday, July 28th, 2023, at 7:48 PM:

“A large language model is an artificial intelligence model that has been trained on vast amounts of text data to understand and generate human-like text. It uses a deep learning architecture called transformers to process and analyze language patterns, allowing it to answer questions, generate responses, perform language translation, and perform various natural language processing tasks. The term “large” refers to the extensive amount of training data and the size of the model’s parameters, which helps it achieve a higher level of language comprehension and generate more coherent and contextually relevant responses.”

OpenAI ChatGPT-3.5

If we did a traditional search, we could find a similar response, which would require reading various websites. This simple example shows some of the versatility of a Large Language Model. We next try a more challenging question. The question we asked is this “Concisely, what is a Large Language Model from Plato’s perspective?”. This question is much more challenging, even for a human. Below is the response from OpenAI ChatGPT-3.5 on Friday, July 28th, 2023 at 8:10 PM:

“A large language model is like a modern-day oracle of language. It is a vast and intricate system designed by humans, equipped with the wisdom of countless texts from the past. This machine can comprehend human language and generate responses that appear to be imbued with intelligence, even though it lacks true understanding or consciousness. It is a tool that can be harnessed for various purposes, acting as a virtual companion, advisor, or storyteller, but its capabilities are limited to the information it has been fed. As a result, while it may seem to possess knowledge and insight, it remains a creation of human ingenuity, not a sentient being with genuine wisdom.”

OpenAI ChatGPT-3.5

This second response provides much more insight into what a Large Language Model is and is not. It may not be true to Plato’s style, but the model exhibits adaptability.

Large Language Models use a technique called transformers. Transformers were described in Vaswani Et al. paper Attention Is All You Need [75]. They create general models that can transfer learning to specific areas. Pre-trained models focus on multiple tasks. We can view transformers as another form of sophisticated
search tool. Instead of receiving a list of web pages to be post-reviewed, we get an answer to the question. For more specialized searches, we can use a prompt template to help narrow the search and provide higher-quality responses.

Initial concerns
All increases in capability cause concern, these models have generated great excitement and worry. These concerns are not necessarily new, but because Large Language Models produce quality natural language responses, it magnifies the standard issues. Organizations such as OpenAI propose alleviating some of these concerns through self-regulation, e.g., through organizations such as the Frontier Model Forum [51].

The concerns:

• **Hallucinations**: Large Language Models trained on large data sets with incomplete or contrarian information. In response to some questions, the models can give potentially silly, inaccurate, or downright dangerous answers, i.e., garbage in, garbage out [50]. Human intelligence is not immune to such hallucinations.

• **Verification**: Requirement for verification is due to the hallucinations. Like all programs written by humans, we must verify the results. Assuming output from a Large Language Model to be correct would be dangerous, especially in cases where the results have consequences. For example, Medical Advise, even if the output from the model seems logical and friendlier than a human equivalent, it should be verified. Humans look for multiple sources for verification by comparing facts, opinions, and statements.

• **Resources**: A comment from Sajjad Moazeni, a University of Washington Assistant Professor of Electrical and Computer Engineering: "Overall, this can lead to up to 10 gigawatt-hour (GWh) power consumption to train a single large language model like ChatGPT-3. This is, on average, roughly equivalent to the yearly electricity consumption of over 1,000 U.S. households." [44]. Using the TTE21 equation 2 for efficiency, the Large Language Model would have an estimated inefficiency level of 2700. Passing the Turing Test takes 2700 times more energy than training a 21-year-old. Along with the power consumption, a model requires a large amount of water to cool the data center, estimated to be 185,000 gallons [3]. Resource consumption is an issue for these models. Intelligence relies on efficiency just as much as being intelligent. If we want to scale Large Languages Models, they must become efficient; otherwise, it is not sustainable.

• **Transparency**: How was the response created? What were the sources used? Just providing answers to questions does not mean that the logic is correct, i.e., sophistry. We are wary of untruths, biases, or made-up information without transparency. Also, plagiarism, copyright infringement, privacy, and intellectual property rely on transparency. Want transparency, but we could argue that humans do not provide transparency. Humans may do this because the act is too complex, do not know, or do not want to divulge.

• **Education**: Similar to any new tools in history, e.g., Slide Rule, Digital Calculator, Personal Computer, and Google Search. There is always concern about how Education adapts. Each new tool causes a rethink in teaching. Education is all about proof of learning. Intelligent systems (including humans) need to be able to learn.

• **Normalization**: We have a general tool that is so powerful it can create and summarize texts. If it is so good, then are we not at risk of normalizing the written language to the point of being obsolete? If we (humans) communicated in a normalized fashion, we would probably question the effectiveness and value of that communication. We would move away from individualism.

The above concerns are typical for all Artificial and Biological Intelligence, but are we expecting too much from these new models too soon? Considering that the models are derivatives of human-produced knowledge. After all, a Large Language Model is, at this point, a sophisticated search tool that responds with well-formed natural language answers.

An important variant of the Large Language Model is the Multi-modal Large Language Model (MLLM) [85]. As the name implies, it combines the capabilities of Large Language Models with the ability to converse in multiple modalities. Modalities are speech, images, audio, and many more. It allows for more human-like communication, potentially moving towards some form of Artificial General Intelligence.

Why are these models so significant? It is not because they consistently produce perfect results nor provide any progress towards consciousness, but they offer a method to explore what we already know. We want answers or, more importantly, good enough answers to ambiguous questions.

Using natural language is a significant achievement, so we should consider it a Trinity event. We see a path to a proper multimodal capable system handling voice, images, sound, and taste. Trinity was the name given to the first successful Atomic bomb experiment, a significant inflection point in history (for good or bad). There was a before and after time, and we may consider the emergence of this technology as equally significant. As of writing this section, we are only scratching the surface of understanding. The potential capabilities are just appearing. It is still early days.

**Recommended reading**
- ChatGPT, by OpenAI

**13 LEGAL IMPLICATIONS**
Most humans operate within some form of the legal system. The legal system is required to pass blame or exonerate an entity. The critical question is, what happens when artificial intelligence makes the wrong decision? Is artificial intelligence to blame? Is the operator or final integrator to blame? Is the person who switched on the system to blame? Is the engineer or data scientist to blame? Or, if in doubt, is the entire stack of people to blame?

These are fundamental questions for government regulators and insurance companies. For government regulators, it usually comes down to ensuring that the new systems do not act against society or hinder progress [9]. Insurance companies look at the problem of how best to protect their company from unnecessary costs. In other words, what does the insurance cover, and what does it not...
cover Artificial Intelligence technology introduce other problems for the legal world:

“A New York lawyer is facing a court hearing of his own after his firm used AI tool ChatGPT for legal research. A judge said the court was faced with an “unprecedented circumstance” after a filing was found to reference example legal cases that did not exist.”

**BBC News, May 2023** [4].

Other problems include taking knowledge and creating new versions. Copying biographies and selling those biographies online [68]. These new tools can take existing content and re-irritate the content into new forms. As Artificial Intelligence tackles evermore sophisticated problem spaces, the legal system must learn to adapt to these new challenges. We are making this a catch-up race, and the regulators and insurance companies need to catch up.

14 **WRONG NUMBERS**

We have finally got to the wrong numbers section, and this, in part, is inspired by a paper written by Roman V Yampolskiy, titled *Why We Do Not Evolve Software? Analysis of Evolutionary Algorithms* [83]. What are the crucial numbers if we want to build a human simulator from the ground up, using fundamental principles, i.e., *tabula rasa* or clean slate?

We start with a premise *p*′ (p prime). *p*′ states that “soon we will be able to create an intelligent machine with sufficient computational power to simulate all the evolutionary processes required to produce human intelligence”. *p*′ depends largely upon significant advancements in computing. Today’s technological advances must continue at a similar pace for the next coming decades. Now, the vital question to ask what is the perceived computational gaps between today’s computer systems and human-level intelligence?. To help answer that question, we start right from the beginning; see Figure 11.

| Quantity       | Measurement          |
|----------------|----------------------|
| Age of the Cosmos | 13.8 Billion years \(^1\) |
| Age of the Earth  | 3.5 Billion years     |
| Age of Life      | 3 Billion years       |
| Age of Humans    | 300 Thousand years    |

**Figure 11: Basic numbers**

The Earth and life is one giant supercomputer where intelligence emerged from biological processes. Figure 11, shows the basic cosmological and biological numbers. What are the following numbers of interest? The number of cell generations (generation every 20 minutes) from the dawn of life 3 billion years ago is estimated to be around \(9^{12}\). The total number of neurons worldwide can be estimated to be roughly \(10^{25}\) [83]. We can calculate the amount of computation for intelligent life to be from \(10^{31}\) to \(10^{44}\) Flops (Floating Point Operations per Second). The entire Earth’s DNA storage is around \(1.32 \times 10^{27}\) bytes. To help put this into perspective, a gram of DNA contains about 455 exabytes of data. The cellular transcribe (RNA transcribes genetic information from DNA to a ribosome) about \(10^{15}\) yottaNOPS. That is about \(10^{22}\) times that of the *Fujitsu Fugaku supercomputer*. Finally, we add an estimated computing time of roughly 3 billion years. These are all vast numbers.

Evolution plays with all these features using convergence (combining to know outcomes) and contingency (creating unexpected outcomes) [10]. The Earth is the only planet known to sustain intelligent life, making the probability of life a startlingly rare event, i.e., 1 in \(26.1 \times 10^{21}\).

The simulator will have to simulate neurons. A simple neuron is \(1 \times 10^{3}\) Flops, Hodgkin-Huxley (Electrophysiological model) is \(1,200 \times 10^{3}\) Flops, and the multi-compartmental model is \(1,200 \times 10^{6} - 10^{7}\) Flops. All at the scale of \(10^{25}\) neurons.

Currently, the fastest supercomputers range from 60 to 537 petaFlops [42]. The mobile phone network or cryptocurrency mining community may exceed this in raw floating-point performance. The current storage capacity required to run the simulation is \(10^{21}\) times that of the top 4 supercomputers in 2019.

If Moore’s law continues, it will take roughly 6.7 years to increase the computation by a power of 1. After 100 years, the gap will still be significant. Even if we created dedicated hardware accelerators and optimized software, it would only add a few more orders of magnitude.

From the evidence presented, traditional technology will fail to reach human level intelligence in the next 50 or 100 years. Other possibilities, such as *Quantum Evolutionary Computation*, may create an equivalent to human intelligence using brute force computation. Unfortunately, Quantum Evolutionary Computation is too new to predict its likelihood of success.

**Recommended reading**
- *The Major Transitions in Evolution Revisited*, by B. Calcott Et al.

15 **FINAL THOUGHTS**

It would be easy to conclude that intelligence is X or Y. We hope that we have shown intelligence is a highly complicated subject with no absolutes. Intelligence interweaves through human culture, language, and being. Many creative theories exist, but fundamental agreed-upon definitions and metrics are still required. An Artificial Intelligent system may seem intelligent in narrow problem spaces (e.g., mathematics, the block world, and image recognition). Still, predicting complex problems with only historical information may be out of reach.

Induction relies upon uniformity of nature, the law of nature. Even when considering our experiences, the past is seldom a good predictor of the future. Nature is just too complicated. The big question is whether an artificial model could fit into a universal law of regular causality, but more needs to be proven.

Figure 12 shows the various options for a landscape. It is based partly on a list provided by Stuart Russell [61]. Each problem maps onto the categories shown in the figure. These categories can be more or less challenging depending upon the system, i.e., artificial or biological.
• Start = Tabula rasa | Innate knowledge
• Action = Discrete | Continuous
• Predictability = Predictable | Unpredictable
• Quality = Precise | Good enough
• Observability = Full | Partial
• Agents = Others | Isolation
• Time = Constrained | Relaxed
• Flow = Feed-forward | Feed-backwards

Figure 12: Landscape, inspired by Stuart Russell’s list [61]

Applying to a landscape, we want intelligence to possess knowledge and be multi-modal. Both in a general sense and a more specialized one. Inherently logical with detailed reasoning, repeatability, and verification. It should gain experience by continuously learning and improving with minimal data requirements. Communication should be through natural mechanisms, e.g., voice, text, images, brain waves, and movement. We want intelligence to be conscious and empathetic, understanding the implications. We need it to be creative, solving problems using new ideas and solutions. With these new ideas, we want to predict what happens next and the causal path on how we got here. There is no point in having energy-inefficient intelligence; high Intelligence per Watt (IW) is a requirement. Finally, we want explanations and to be actively involved in the decision-making process.

Intelligence must adapt to changing environments; it must require only limited examples before full recognition can occur. The system should not require 10,000 hours of learning to become a grandmaster of pattern recognition.

If we mimic intelligence, is there a threshold we reach that makes it impossible to distinguish it from natural intelligence? Is the only solution to copy an existing high intelligence, i.e., innate knowledge? Or even build intelligence from the ground up from basic principles, i.e., tabular rasa? The more data, the more confusion. The root of confusion is self-references, and self-references lead to paradoxes. A paradox has no solution or conclusion.

Is intelligence even in the realm of our understanding and capability? Intelligence through 3 billion years of evolution. Or is it a set of quantum equations yet to be discovered?

Biological neurons operate mainly as feed-backward systems. Feed-backwards is different from most artificial systems that rely on feed-forward communication. For neuroscientists, neuromorphic technology allows building closer to biological systems, i.e., using feed-backward connections. Potentially opening up the chance to explore more complicated subjects such as consciousness.

There are so many topics not covered in this text. These include our favorites: Evolutionary Algorithms and Emergent Behaviors in analog robotics. However, hopefully, we did share enough to make clear two things:

1. There is a lot of research and philosophy on biological intelligence, and now equally as much is focused on artificial varieties.
2. There is much that we do not know. Focusing on one specialized subset of Artificial Intelligence should not mean we put blinders on to all other possibilities.

There is excitement in Deep Learning and other biomimetic systems, and there is still more to learn. However, it is possible that Artificial Intelligence can only become truly successful if it is understandable. If we only focus on answers, then we are missing the point of intelligence. Focusing on only one sub-field may not be the “correct” approach. Another problem is why we are trying to replicate something with many known flaws, such as Human Intelligence. It is akin to tape-recording a radio-broadcast [60].

We have many species on this planet that exhibit intelligent behavior, and we, for the most part, ignore them simply because we do not have established ways of communication [11].

“On the planet Earth, man had always assumed that he was more intelligent than dolphins because he had achieved so much – the wheel, New York, wars and so on – whilst all the dolphins had ever done was muck about in the water having a good time. But conversely, the dolphins had always believed that they were far more intelligent than man – for precisely the same reasons.”
Douglas Adams [1]

We cannot communicate with other biological intelligent forms, so how can we plan for a fundamentally different form of intelligence? More than likely, Artificial Intelligence will arrive slowly, be massively distributed, and will be unrecognizable. Before that happens, we have much time to practice communicating with other humans and biological intelligent forms.

In line with non-biomimicry, non-von Neumann machines, one topic worth diving into is the role of quantum physics in computers and consciousness. However, with quantum physics and minor variations of the observable within our thought processes, some deviation from pure causality could be called free-will. Quantum computing is still new enough that even if they have built a verified quantum computer, most companies do not know what to do with it. Quantum computing is an aspect that we think may genuinely unlock the potential of Artificial Intelligence. Quantum computers are one example of making intelligence that is radically different than our own.

Social and emotional intelligence is another aspect of intelligence that requires further research. We only briefly mentioned it. Some work is happening in Human-Machine Interaction groups, but most are through user interface design/behavioral style observation. The theory of mind, understanding non-verbal intent, and general conversational skills remain largely unexplored. That will likely be the next big step forward in Artificial Intelligence.

Lastly, is it possible to have intelligence without consciousness? Is this a safe path to take with the necessary safeguards? Ultimately, these systems will probably have to make conscious decisions involving conscience. Does this lead to problems — do we give Artificial Intelligence legal standing? Is it the same as a human or better? Responsible for its actions or not?

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**OPEN DASKALOS PROJECT SERIES: Lost in Algorithm (1st Edition), December 2022 by Andrew Sloss**

Algorithms are becoming more capable, and with that comes hic sunt dracones (here be dragons). The term symbolizes areas beyond our known maps. We use this term since we are stepping into an exciting, potentially dangerous, and unknown area with algorithms. Our curiosity to understand the natural world is driving our search for new methods. For this reason, we believe it is crucial to explore the subject of algorithms.

URL: https://arxiv.org/abs/2008.07324

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Algorithms are becoming more capable, and with that comes hic sunt dracones (here be dragons). The term symbolizes areas beyond our known maps. We use this term since we are stepping into an exciting, potentially dangerous, and unknown area with algorithms. Our curiosity to understand the natural world is driving our search for new methods. For this reason, we believe it is crucial to explore the subject of algorithms.

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