# Generalization & Democratization of Artificial Intelligence & Machine Learning

## 1.1 - Introduction to Democratization

The world we wish to build for tomorrow remains highly dependent on our own individual experiences, backgrounds, development, culture, and our perception of our environments. In other words, two "different" people, more than likely, will approach a singular problem in very different ways. Their preconceptions of the problem itself may be enough to impact the process in a biased manner. These circumstances yield both positive and negative results towards the development of the human race and the condition of our societies. In many ways, the diversity of body and thought is extremely important to creating a broad set of solutions. While in other ways, this diversity can lead to inequality of outcome if only one homogenous group of individuals is working on fixing a problem.

## 1.2 - Democratization of Artificial Intelligence

An example of inequality, remains ever apparent in the development of artificial intelligence (AI) around the world. A shocking minority of the world's population has the training to work in artificial intelligence and artificial general intelligence (AGI). This number is around 10,000, and these people only come from seven countries (Shen, 2017). Additionally, the majority of this small group of individuals are heavily recruited into mega-corporations like Facebook and Google, or they are persuaded to teach at ivy-league universities. If this doesn't seem like a glaring issue, then there isn't much else to say. The future of the world shouldn't be planned by a handful of people with for-profit interests, government control, or large bank accounts. It should be planned by all people, and this is the issue that the democratization of artificial intelligence seeks to fix.

The paper "Distributed, Decentralized, and Democratized Artificial Intelligence" addresses this very issue of the unequal control and development of AI. Its authors label this future dystopia as a "technocracy" where "the most potent set of technologies in the history of humankind is spoken for by a small biased minority" (Montes & Goertzel, 2019). There is no doubt that these mega-corporations will eventually achieve a level of AGI, or an artificial agent which can learn anything that humans are capable of learning, because they have infinite resources. However, these researchers present their own solution to this seemingly impossible race to AGI — decentralization, or more specifically, SingularityNET.

## 1.3 - SingularityNET

SingularityNET is a decentralized self-organizing cooperative (DSOC) platform that is based on the same distributed ledger technology (DLT) that cryptocurrencies operate on. The platform allows for the buying and selling of AI services and cooperation between AI agents, packaged within a blockchain DLT (Montes & Goertzel, 2019). Blockchain technology ensures that the transaction between buyers, sellers, and artificial agents is verifiable, open to the public, and decentralized. Since blockchain payment relies on the real-time verification of information, there is no need for an intermediary between agents.

## 1.4 - A Decentralized Self-organizing Cooperative

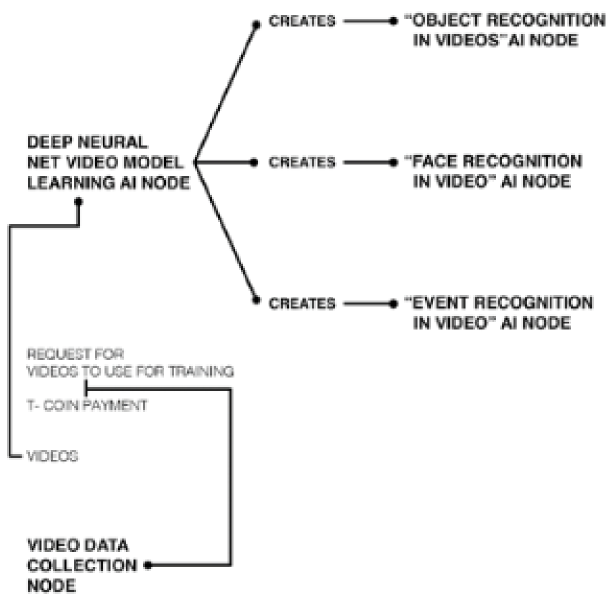
One of the major benefits to a platform such as SingularityNET includes the cooperation of a community. The structure of this platform depends on and is improved by the broad contribution of people from all over the world. In other words, anyone will be able to contribute which, historically, hasn't been the case in the bubble of Silicon Valley. The primary tech conglomerates like Facebook, Google, and Amazon won't be participating in a self-organized manner such as this. They are simply in a race to finish first and bring benefit and value to their shareholders and private interests. If these companies didn't value the development of AI or AGI for monetary purposes, then there wouldn't be any incentive. However, for communities who want to improve the lives of their loved ones or their fellow neighbors on this Earth, there isn't any greater incentive. This cooperation that exists within communities of people increases exponentially when it isn't only the people who have this sense of cooperation.

## 1.5 - Intelligent Agent Cooperation and Currency

A key feature of SingularityNET is its ability to allow artificial agents to communicate and cooperate amongst themselves. This community of agents would ultimately lead to a plethora of benefits including, but not limited to: "purchase new capabilities, monetize their assets, autonomously improve, coordinate functions, tackle new industries, develop emergent skills, outperform competitors, vastly improve accuracy, leverage newfound access, and boost processing power" (Montes & Goertzel, 2019). This level of automation would be unprecedented and this is why the race for the foundation of AGI should belong to the people who will be most affected by it. Additionally, as the authors state, this cooperation increases benefits to smaller business who need AI solutions and services, which in turn would extend the reach of the platform, "increasing the likelihood that a decentralized AI network would have market demand, traction, and thus impact" (Montes & Goertzel, 2019). Small businesses and researchers that would access the platform will have a much greater impact on the lives of the people they serve, than a company whose only allegiances are to the shareholders.

An additional core feature of the platform which separates it from other AI solution networks lies in the ability of two artificial actors to communicate with one another in order to realize the most effective solution for a vendor and to mass develop datasets for people to use. The researchers illustrate that two AIs will be involved in a matchmaking process which involves "cloud-based 'cognitive services' in exchange for micropayments" (Montes & Goertzel, 2019). Additionally, these artificial actors would help synergize massive datasets which have been traditionally controlled by large, tech corporations. These datasets would then be available to small companies or independent programmers who wish to create their own solutions without being tied to huge corporations who don't have their best interests in mind. Furthermore, the matchmaking service between individual AIs is complemented through the automated creation of specialized agents. For example, an agent which provides voice recognition services to the network is able to replicate another agent that specializes in a subtype of voice recognition. This features an unprecedented level of AI. If an efficient solution to a consumer's request doesn't exist, or the existing solution may be improved, the network of agents can communicate in order to provide a more tailored AI for this specific problem.

The exchanges between sellers and buyers would be maintained through a common currency which is unique to the platform. This ensures that if specific markets and economies are hit with a recession, then the platform will not be affected as greatly. Additionally, this protects against possible exploitation of the native currency through for-profit exchanges between external markets or the "manipulation by elites" (Montes & Goertzel, 2019). The authors posit that a reputation system would be beneficial towards the benevolence of the system through rewarding the good and punishing exploitative behavior. This not only incentivizes people to create valuable solutions and contribute to the development of AI in a proper manner, but it also prevents some "bad actors" from holding the platform hostage for a platitude of reasons. In order to further incentivize benevolent actions, there would be a "beneficial reserve" of tokens which would be allocated to people with high reputation or "external human-run organizations who are democratically judged to be beneficial to the network" (Montes & Goertzel, 2019).




- This model illustrates a simple example of how a request for an agent's assistance is made and additional AI nodes are created in regards to that request.
- The ability of the network to replicate specialized nodes resulted in the creation of three new nodes: object, face, and event recognition.

**Fig. 1.1: Agent Interaction** ((Montes & Goertzel, 2019))

Lastly, the authors mention the realized downsides to the fast development of AI in a democratic manner. They posit that democracy, in itself, is truly the best choice that humans have in terms of an equitable and majority-driven system of governance. The downside to this fact is that the votes of the majority will undoubtedly rule over the minority, whomever that may be. Furthermore, the rapid development of AI will create new solutions, but will also kill outdated ones in the process. Dr. Ben Goertzel states in a TEDx Talk that jobs such as truck drivers or cashiers are unfortunately, great examples of careers that will be overrun by the development of AI (TEDx Talks, 2019).

An AI or AGI  run with the purpose of improving the human condition through a decentralized, DLT network will ultimately lead "to a more ethically sound synthetic and biohybrid landscape" (Montes & Goertzel, 2019). The authors understand that the only ethical way to synthesize the foundation of AI and AGI with our world is to include all people who will be affected by this major transition in the span of human existence.

- ## Generalization of Artificial Intelligence

Kris Hammond, cofounder of Narrative Science and a professor of computer science defines artificial intelligence as a field “focused on developing computers that can do things people typically do” and adds that general AI (or AGI) are “systems that can engage in general reasoning” (Gobble, 2019). There is no artificial general intelligence as we define it currently, nor will there be one at all in the near future according to researchers with predictions of successful development ranging from 2030 to 2300 if it happens at all (de Berruti, F., Nel, P., & Whiteman, R., 2020). So why is AGI regularly referenced by researchers, technologists, and reporters as though it was coming soon?

Growing capabilities of digital devices and access to higher quality infrastructure like better internet speeds for the average individual and larger datasets that can be processed for more detailed and focused information about various topics has led to more focus on narrow AI to become ubiquitous. Speech recognition advancements made digital telephone agents and voice command assistants very common. Similarly computer vision advancements have made facial recognition and optical character recognition (OCR) powerful enough for systems to catalog entire albums of images tagging them with names to go with faces or keywords from documents with ease. Systems such as Watson, Deep Blue, and AlphaGo have shown that AI can beat world class individuals at their own specific games (Gobble, 2019).

All of these advancements in narrow AI has pushed the general idea that AGI should be feasible relatively soon. There are still many problem areas that need some sort of solution before AGI as we understand it to be defined can be achieved. Narrow AI can provide solutions within the problem set that it is developed to handle, however any sort of deviation outside of that area will cause those AI to fail (Gobble, 2019). However, AGI is supposed to be able to operate and learn in nearly any context that we can imagine a human operating in. While chatbot conversations are possible to be held at a level that a person could believe they are communicating with another person, there is currently no way to train an AI to engage in verbal dialogue to the same level due to the complexities of human language and emotion delivered through that language (Landgrebe, J., & Smith, B., 2019).

There are a number of potential areas of advancement that could lead to breakthroughs in getting closer to an AGI. Research toward improved or entirely new algorithms could work better to simulate human cognition. Quantum computing might also function as a drastic increase in capability to allow for algorithms to handle enough data for general intelligence simulation. Another area is for new and larger sets of data in the areas where current AI systems are weak such as a more comprehensive analysis of human speech, computer vision, and spatial movement (de Berruti, F., Nel, P., & Whiteman, R., 2020).

One area that is seeing more significant improvement is with AI surrounding more complex games that are real time and team based as well as exploring limiting the information that the AI has access to primarily limited to visual and/or auditory information that a human player would have access to. The overall idea is that the AI working in larger rules based games might lead to algorithmic improvements that would work for better generalization if the game is changed or in a context completely outside of games. The approaches in this area are varied based on the details of the specific game(s) that the AI are being developed for. One example uses a complex decision tree that is built up over the course of many cycles of learning and iteration which then defines a silo according to the first move of the game and identifies the potential good moves from the bad ones (Schofield, M., & Thielscher, M., 2019).

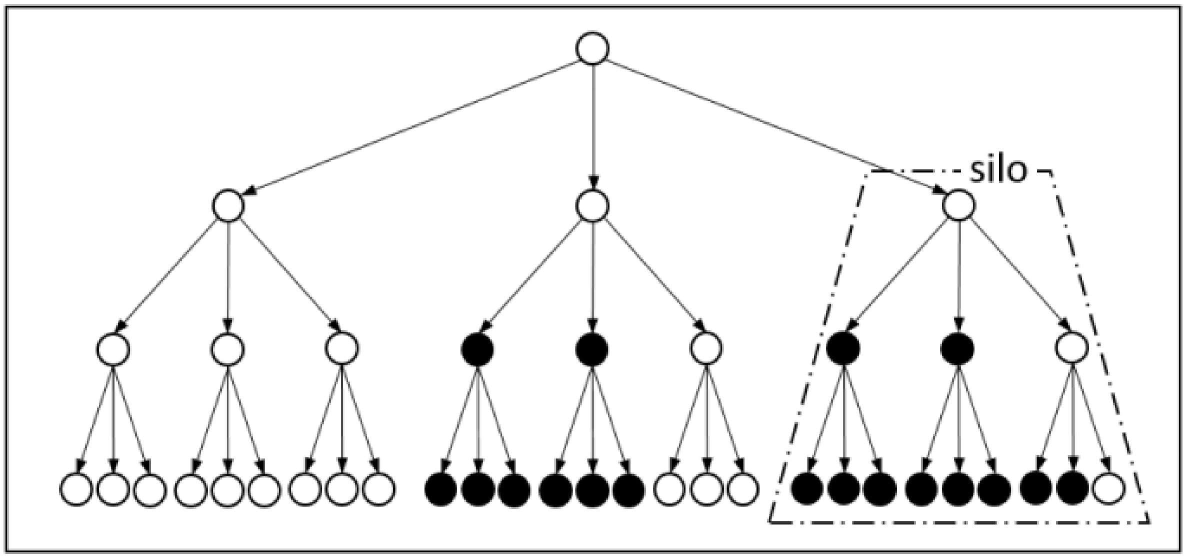



**Fig 1.2 Silo Based Decision Tree Model** ((Schofield, M., & Thielscher, M., 2019))

OpenAI is an AI research and development organization that has the specific goal of pursuing an AGI and has developed a number of notable projects like training a robot hand to solve a Rubik's Cube, using a game of hide-and-seek to develop AI agents, and developing a team of AI players that won multiple games against the highest ranked teams in the online battle arena game Dota 2. The core of the approach was deep reinforcement learning and had to overcome multiple problem areas related to using that approach on a system as complex as Dota 2 such as "long time horizons, partial observability, and high dimensionality of observation and action spaces" and the team managed to overcome the challenges with "thousands of GPUs over multiple months" (OpenAI, 2019).

Other organizations are taking the approach of simulating a human brain through hardware and software in order to develop an AGI. It is a process that takes JSON files as basic genome-like data structures and uses those structures to encode data to grow the model brain to respond to different stimuli such as character recognition of different styles, sizes, and clarity (Nadji-Tehrani, M., & Eslami, A., 2020).

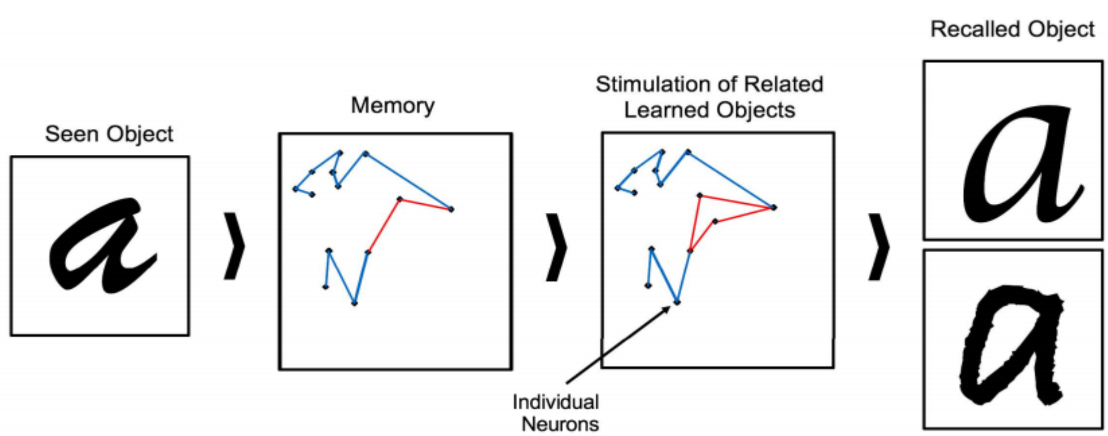
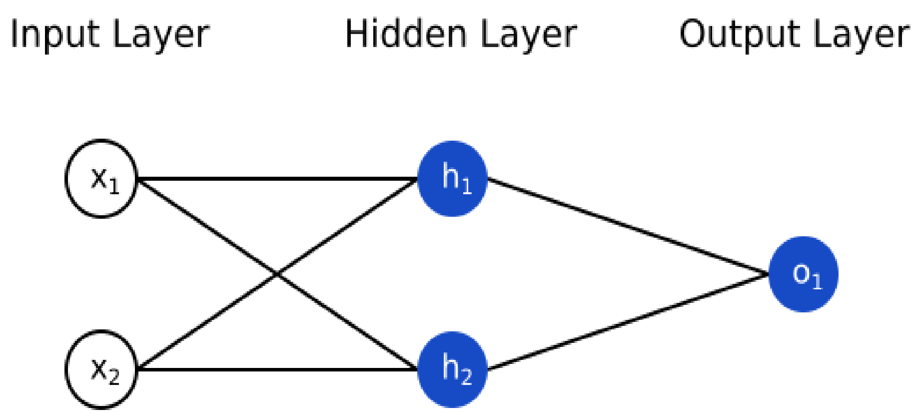



**Fig 1.3 Conceptual Model For Simulated Recall** ((Nadji-Tehrani, M., & Eslami, A., 2020))

- **Machine Learning Background**

Machine learning, a subset of artificial intelligence, is the ability of a computer program to learn and adjust itself based on data that it interprets. No human intervention is needed for this to occur, other than the initial training data which the computer needs to construct its base model. A very high-level understanding of machine learning could be achieved through a few core concepts involved with computer programming. For example, in traditional computing, most programmers "feed" a computer some input data, and then the computer does come calculations in order to produce some output data. Machine learning utilizes these same basic functions, however it uses them in a different way. In addition to some input data, a programmer gives the computer output data too, which it then uses to construct a model of understanding. In essence, the computer automatically reaches some conclusions based on the data that a programmer gives it, instead of the programmer telling the computer what to explicitly do.

---




- This image illustrates a very basic example of a neural network which serves as a model for machine learning.
- It is composed of the input layer, hidden layer (where the computer does some "magic," and the output layer.

**Fig. 1.4: Basic Neural Network** ((Zhou, 2019))

---

- **Examples of Machine Learning Generalization**

Machine learning is, in itself, a way of applying a limited form of artificial intelligence. There are several ways that machine learning is being utilized in our society. While we are far away from artificial intelligence as seen in fictional media, we are relatively close to a revolutionary change in the way we travel: self-driving cars. Tesla has been at the forefront of this technology and has already released cars with autopilot and auto-parking capabilities. The technology has come a long way since its infamous introduction in 2016 when, "Joshua Brown, an early adopter and Tesla enthusiast, died at the wheel of his car. The car failed to see a white truck that was crossing his path" (Stilgoe, 2).

A lot can change in four years. Tesla's autopilot technology uses machine learning to consistently and automatically improve its abilities. It has cameras and sensors that take pictures and record data so that it can better recognize things like road lanes, signs, and pedestrians.

**Fig. 1.5: Front-facing Portion of Tesla Autopilot System** ((Tesla, 2020))

Each Tesla vehicle is equipped with computer chips that run neural networks. These neural networks are what allows the self-driving capabilities to improve. They are algorithms that mimic the nervous system and can change based on the input. The newest Teslas contain FSD computers that can process "seven times" as much data than previous models (Tesla, 2019).

The ability of the machine learning software in Tesla's vehicles to generalize itself is key to improving the reliability and safety of the cars. Each Tesla vehicle is connected to a network that compiles all the data and images collected by the cars. The "fleet" of vehicles can then learn from each other and the machine learning process can be done much faster. Tesla employees can annotate certain footage that may contain rare or unique situations to make sure that it is learned correctly (Tesla, 2019). Overall, Tesla's machine learning technology is an excellent large-scale example of machine learning generalization.

- **Section Concise Summary: Democratization**

Researchers, educators, programmers, and corporations alike have become aware of the colossal challenge which is democratizing artificial intelligence. We all have witnessed the possible futures where AI belongs to a select few privileged individuals and where it belongs to the masses. The intentional decision that has been made by these individuals involves supporting the idea that an equitable, safe, and beneficial future is one which all people of the world have their stake in the next industrial revolution that is AI. A core issue of this revolution is that it's already here and most of us don't realize it. In a metaphorical sense, we are speeding towards the edge of a cliff with a blindfold on. As the previous sections demonstrate, we are capable of creating a beneficial future if we divert some of the speed of developing AI by creating a healthy culture of community cooperation, decentralized power, and intelligent regulation. SingularityNET serves as a great example of a platform which would lead to a much more beneficial future than the path we are on. Through its DSOC structure and democratic characteristics, this platform wouldn't discriminate over who has access to the most powerful tools humanity has created. Additionally, the innovative feature which allows artificial agents to collectively vote on the best solutions and even create new, specialized AIs will undoubtedly provide stakeholders with solutions that fit their needs. A common currency which is unique to the platform will protect the platform from external economic forces, and, as the authors state, “manipulation by elites” (Montes & Goertzel, 2019). The currency itself will be supported via Blockchain technology which remains extremely secure and decentralized. Lastly, the regulation of all AI platforms, including SingularityNET, should be done preemptively to protect against discrimination, inequality, and catastrophic events. In other words, “AI seatbelts” should be installed and developed before the car is ever put on the road. At a time in the history of human beings where injustice feels unyielding, one of our best solutions to the development and improvement of human life shouldn’t be excluded from the ruthless scrutiny of participating parties and developers. This powerful tool shouldn’t and will not belong to a select group of powerful individuals. The unbelievably beneficial possibilities of the development of artificial intelligence could not be more apparent, but we must not turn a blind eye to the possible detrimental effects as well.

## AI becoming Democratized

“If there is a need to democratize AI, how can it be put into practice? An instrumental approach to that question would first look at instances in which there are democratic choices and secondly at ways in which these decisions can be made” (Djeffal, 2019). This would bring about different types of democratic decisions that has their own types of advantages depending on the type of situation going on. Some of the decisions would be: “

- ordinary parliamentary processes to debate and regulate artificial intelligence
- use of specialized parliamentary committees to determine certain issues
- empowerment of experts to make certain decisions according to preconfigured principles
- direct involvement of citizens regarding certain questions through:
    - participatory methods
    - sortition: involving groups of randomly selected citizens in order to fulfil an office or make certain decisions
    - random sample voting: in order to vote on specific questions, a representative sample of the population is selected” (Djeffal, 2019)

There must be a decision that is made for a social and a technical layer for this method to work. Some of the decisions will not be made this way and will be made based of the technology that is available. Within the technical layer, you must be able to understand the type of technology that is suited for the situation. There are many design choices that could be made within this process. For a democratic type of standpoint, they are used to create the features of the technology that is used. “Understanding choices also requires a democratic mindset that is open to several possibilities without automatically preferring certain outcomes. Computer scientists especially, who are trained to achieve specific goals such as efficiency, regularly do not see behind the choices that maximize their preferred value” (Djeffal, 2019).

## Artificial Intelligence in Military History & Anthropology

As stated previously, machine learning and artificial intelligence are paramount to several industries around the world, and currently, industries are either trying to incorporate these systems within their prospective fields, or they are trying to implement a base-level system that can be built upon for the future. However, there are sometimes conflicts of interests among prospective fields as they may interfere with one another’s work or possibly create a moral conflict that goes deeper than just a technological issue, and this issue is most prevalent in technological applications in the fields of anthropology and military applications.

For example, anthropology is the study of humans and how humans have interacted since our beginnings. Applications of machine learning in anthropology are often that of interpreting prior familial relationships within certain established familial branches or even entire ancient tribes whose bloodlines lead back centuries (Cunningham, 1996).

Often, these machine learning applications help to divide familial and tribal relationships through various characteristics, such as marriage ties, common languages, average height and weight, etc (Cunningham, 1996). Often these systems are very complex and intake several centuries of data from various sources such as books, familial records, and even by word of mouth on rare occasions. However, these systems often do not consider the differences between relationships of the past and the taboos that were once accepted, but they are now viewed as forbidden by most of common society (Cunningham, 1996). For example, the practice of incestous relationships was more common practice during the middle ages and prior centuries, but these kinds of relationships are taboo now, so these AI machine learning systems must also take into account some family members may share more than one relation with one another (Cunningham, 1996).

This difference in relationship taboos is more than just an anthropological problem, as any implementations of this system may have to be unique depending on the family or even the culture as a whole, so allocation of prospective memory is a constant issue when implementing these systems as more memory may need to be allocated depending on the base group for which the system is studying. Another taboo that can be an issue is that of polygamy as several royal families and clans consisted of several marriages to one person, so the system must also be able to factor in the number of relationships for each person who may be represented in the system.

The issue extends further depending on the language of the prospective group as certain languages may not translate to another language exactly as sometimes there are words that exist in one language but not another, so either a base language for the system must be established, or the system must be capable of handling several unique languages. However, this is counterintuitive as some studied languages may not be widely available or even extinct, so it may be hard for the system to be programmed for that specific language, and as more languages become implemented within the system it starts to become cost-effective and can even hinder the system in the long run by taking up unnecessary resources (Cunningham, 1996). Up taking of resources can also lead to another issue in that not every anthropological study's data is 100 percent complete, or the data may even be incomplete since the data could have been lost to time or destroyed in some past incident.

The problem this causes is that of the system having an incomplete data state, so the system may cease to function until the issue is fixed, or the system may fail to function entirely (Cunningham, 1996). It is with all these issues that machine learning is currently being implemented in anthropology in slow and continuous intervals. As the continuous issues that plague these systems are being looked at under a close lens, so these implementations may be properly controlled and installed. If these systems are installed properly, the grand scale of the data may be properly maintained by the system, so that anthropologists can understand the data while also being allowed to focus on other proponents of their respective field without having to focus solely on the data that is being presented before them.

These applications and problems can also be seen within machine learning applications that are applied to military history. Military history data can be just as complex and if not more complex that certain pieces of anthropological data. As the data being taken in is not just familial relations, but it can also encompass data such as individual people, equipment, fatalities, and much more various kinds of data. However, anthropological data is often less technical than its military counterpart, so military data is often viewed as cold and mechanical compared to the more humanistic anthropology studies. This is where a conflict of interest can occur as depending on how the data is represented, certain military data may not tell the whole story of a conflict whereas the anthropological study may provide a more human element compared to the mathematical skew of the military data. To go more in depth, military data is often told from the viewpoint of the victors and losers (HAGSTRÖM, 2019), and it does not incorporate whom it may have affected during these prior conflicts. This is one of the many challenges that occurs when implementing an A.I. based machine learning system within a militarized field.

The data can often be skewed depending on where the data is received from or who is using the data and how it is being used (HAGSTRÖM, 2019). Data can also be neglected or misplaced within a system if the system's automation does not view it as significant data. This can lead to missing necessary data that may tell more of the history, but it may also lead to the system's automation having to be reprogrammed, thus creating additional costs in both man hours and additional monetary payments to both personnel and personnel managers (HAGSTRÖM, 2019).

Another issue is that of redundancy since the system is having to be implemented thus further affecting proper data retrieval and system automation (HAGSTRÖM, 2019). However, the problem is not just that of data, but it can also be a problem of the implemented system. For example, if the data implemented within the system is falsified or altered so it may be used for propaganda or to push a false narrative (HAGSTRÖM, 2019), this system can cause wide ranging consequences through various means, and it can also affect future data in other fields such as anthropology. So these problems must be viewed similarly as to how the anthropological system is viewed. Overall, these two systems are intertwined and have a bearing on the data for both systems, so these systems must be handled with proper care, and any subsequent problems must be handled properly and documented so that they can be dealt with in the future in case of problem renewal.

## Applying ML to Predict Student Performance

Now that the prospects of introducing AI into education has been discussed, where would Machine Learning fit into all of this? How would the AI teacher or tutor create specialized data for the individual student, and would the AI use ML techniques to solve this problem? Depending on the living situation of the individual student, the environment or family could affect the academic performance of the student. The students must always be aware of his or her performance in their

courses, and so ML algorithms could be used to predict the student performance. AI could use this data to provide the student a friendly UI human-computer interactive warning if the student falls behind and set an intervention date with the student. Later the AI could adjust specialized course material for the student to ensure a greater probability for academic success.
Such ML algorithms that are used to predict student performance are studied in one article and they are the following:

I. **Backpropagation (BP)**

A supervised neural network used for prediction and classification of data**.** A gradient-descent algorithm is used during learning and error is propagated back to change weights and reduce error value (Sekeroglu, Boran, et al., 2019).

II. **Support Vector Regression (SVR)**

Support Vector Machine prediction type that supports vectors so that features can be separated. The increment of classes may cause reduction of success rate in SVM in the classification stage, however (Sekeroglu, Boran, et al., 2019).

III. **Long-Short Term Memory (LSTM)**

Neural Network which performs exceptional results regarding the prediction in time-series, that depends on the memorization of previous inputs of neural networks (Sekeroglu, Boran, et al., 2019).

## Experiments Using ML Techniques

In the experiment of this research, two data sets were used: Student Performance Dataset (SPD) and Student Academic Performance Dataset (SAPD). SPD was used for prediction experiments, and SAPD was used for a classification experiment (Sekeroglu, Boran, et al., 2019). Data for both Math courses and Portuguese courses taken by students were based on 33 attributes relating to the students' parental status, home address, size of the family, etc. (Sekeroglu, Boran, et al., 2019). So, SPD predicts students' performances as output for Math and Portuguese courses while SAPD shares similar attributes but with only 21 of those, and it classifies three outputs as Good, Average, or Poor (Sekeroglu, Boran, et al., 2019).

In the two groups of prediction experiments for both Math Courses and Portuguese courses, BP, SVR, and LSTM algorithms were all used for 40% and 30% testing ratios of the instances. This means that some experiments were based on 40% of testing data of all instances and 60% of training data of all instances, with this same rule applying to the 30% testing ratio experiments. The primary indicators of success levels of the predicted results are evaluated by Mean Square Error (MSE), R^2 Score, and Explained Variance (EV) Score (Sekeroglu, Boran, et al., 2019).

In the two Math course prediction experiments, results were evaluated using the latter three criteria along with the three ML algorithms. For the 40% testing ratio experiment, SVR had the greatest degree of scores of MSE, R^2, and EV while BP had the lowest prediction rate for all evaluations (Sekeroglu, Boran, et al., 2019). Very similar results were found in the 30% testing ratio experiment were SVR has the best prediction results with BP having the lowest (Sekeroglu, Boran, et al., 2019).

In the two Portuguese course prediction experiments, results were evaluated in the very same way as in the Math course prediction experiments. Yet again overall, SVR has the highest prediction rate, with BP having the lowest for both 40% and 30% testing ratio experiments. However, LSTM shared very similar results with SVR in the 40% testing ratio experiment and even had the best rate over SVR (Sekeroglu, Boran, et al., 2019).

In the classification experiment, BP, Support Vector Machine, and Gradient Boosting Classifier algorithms are used in 40% and 30% testing ratios of SAPD and evaluation is done by an Accuracy formula (Sekeroglu, Boran, et al., 2019). According to the 40% testing ratio instances, BP, SVM, and GBC hit 80.91%, 79.38%, and 74.04% of classification rates, respectively. According to the 30% testing ratio instances, even better accuracy results were gathered for BP, SVM, and GBC that got 87.78%, 83.20%, and 82.44% respectively (Sekeroglu, Boran, et al., 2019).

Based on the results of all the prediction experiments, SVR had the least Mean Square Values and the highest R^2 and EV scores across the board compared to LSTM and BP. BP had the lowest scores for every R^2 and EV but had the highest MSE scores for all prediction experiments (Sekeroglu, Boran, et al., 2019). In the classification experiments, BP has the best results out of SVM and GBC with both 30% testing ratio and 40% testing ratio experiments having both 87.78% and 80.91% accuracy results, respectively (Sekeroglu, Boran, et al., 2019).

In conclusion, these results show that basically no matter what educational data is used, the data can be predicted or classified by ML algorithms, and results can improve depending on different data selection and ML algorithms used (Sekeroglu, Boran, et al., 2019). Applying this to AI in education, this would be a feasible solution for meeting the individual needs of the students if the AI were to incorporate ML that evaluates student performance predictions or classifications based on the varied dataset as it would account for parental status (single or married), in which area is the house is located (low-income neighborhood or high-income), and how large or small the size of the family is.

Going off of such a dataset, not only could the AI know the evaluated predictions of student and student academic performance, but based on these predictions, it could adjust course material depending on how well the student is doing in the course given personal and environmental circumstances. Perhaps AI could select better ML techniques that would yield greater accuracy and results in the prediction and classification of student and student academic performances.

## 4.2 - Section Concise Summary: Generalization

The generalization of artificial intelligence refers to the widespread adoption of technology that enables machinery to behave and think like humans. While this technology is still years away, most people are at least familiar with the idea of AI. Narrow AI currently exists, like Apple's Siri and the Google Assistant. They are capable of answering straight forward questions. The issue with implementing fully functional AI is expressing human emotion and other subjective elements.

## 4.3 - Section Concise Summary: Machine Learning

Machine learning is a component of AI. Humans are able to learn from their environment, so intelligent machines should be able to as well. Machine learning is already being implemented today, and a notable example is Tesla. They offer autopilot built-in to each vehicle. Their autopilot system is capable of gathering environment data that improves its self-driving capabilities.

## 5. Extended Resources

1. This TEDxTalk, given by Dr. Ben Goertzel, illustrates some of the most pressing issues of artificial intelligence in today's world. Dr. Goertzel, CEO of SingularityNET, details the importance of advancing and improving the human experience through a decentralized platform of artificial agents which may ultimately lead to the "singularity" of artificial general intelligence.
2. https://www.youtube.com/watch?v=r4manxX5U-0
3. Fig. 1.1: Agent Interaction. Montes, G. A., & Goertzel, B. (2019). Retrieved October 7, 2020.
4. Fig 1.2: Silo Based Decision Tree Model. Schofield, M., & Thielscher, M., (2019). Retrieved October 15, 2020.
5. Fig 1.3: Conceptual Model For Simulated Recall. Nadji-Tehrani, M., & Eslami, A. (2020). Retrieved October 15, 2020.
6. Fig. 1.4: Basic Neural Network. Zhou, V. (2019, March 3). Retrieved October, 13, 2020.
7. Another TEDxTalk, given by Karen Hao, details the catastrophic effects of artificial intelligence including: deep fakes, job-search discrimination, facial recognition, etc. Hao details the historical success of the improvement in car safety through the adoption and regulation of seatbelts and uses this example to show how the development of AI is outpacing its regulation. Hao proposes that regulation and the evaluation of the technology's impact should happen before the technology is released instead of after.
    a. https://www.youtube.com/watch?v=D28aL_5LH2Q
8. Podcast conversation discussing artificial general intelligence between Dr. Lex Fridman (MIT) and Dr. Ilya Sutskever (OpenAI). The discussion is around the current AI technologies that have seen advancements toward and possible next steps of technology needed to achieve AGI. There is also discussion of the concepts that define AGI such as intelligence, consciousness, and creativity. https://www.youtube.com/watch?v=i0UyKsAEaNI
9. Presentation by Dr. Danny Lange (Unity Technologies) about the role that modern game engines play in developing simulations to train AI. https://www.youtube.com/watch?v=BByWWTdNI0Y
10. Presentation by employees of Tesla, including Elon Musk, on Tesla vehicle autonomy
    a. https://www.youtube.com/watch?v=Ucp0TTmvqOE&t=8930s
11. Fig. 1.5: Front-facing Portion of Tesla Autopilot System. Tesla (2020). Retrieved October 15, 2020
12. . *AutoML* – Google Cloud AutoML product description:
13. https://cloud.google.com/automl/

14. *Azure* – Microsoft Azure product description:

15. https://azure.microsoft.com/en-us/services/machine-learning/

16. *ageMaker* – Amazon SageMaker product description:

17. https://aws.amazon.com/sagemaker/

18. The article reflects on varies ways of changing privacy within the concept of law and how it pertains to data protection with laws and its regulations. It also goes into how the law creates social developments with the use of technology.

19. https://link.springer.com/chapter/10.1007/978-3-476-04860-8_11

20. An article about current AI & ML during the current COVID pandemic.

21. https://federalnewsnetwork.com/open-first/2019/09/the-democratization-of-artificial-intelligence-and-machine-learning/

22. A video explaining some of the limitations and increasing deployment of AI https://www.youtube.com/watch?v=8cbxii7obvc

23. An Edureka session (Youtube video) that will help you understand the positive impact of Artificial Intelligence in the healthcare domain along with practical implementation in Python.
https://www.youtube.com/watch?v=j6EB9HO6acE

24. A short article on ML in healthcare
    i. https://intersog.com/blog/how-machine-learning-will-change-healthcare/

25. A research article that discusses many uses in which interpretable machine learning models are needed in healthcare and how they should be deployed.
    a. https://dl.acm.org/doi/abs/10.1145/3233547.3233667

26. A research article that provides more backgrounds and context to the DDS LANDS system.

    i. https://www.researchgate.net/publication/334363106_An_Agricultural_Prototype_DSS_LANDS_for_monitoring_the_main_crop_productions_in_Sardinia

## 6. References

de Berruti, F., Nel, P., & Whiteman, R. (2020). An executive primer on artificial general intelligence. McKinsey Insights, N.PAG.
Gobble, M. M. (2019). The Road to Artificial General Intelligence. Research Technology Management, 62(3), 55–59. doi.org:10.1080/08956308.2019.1587336
Landgrebe, J., & Smith, B. (2019). There is no Artificial General Intelligence.
Montes, G. A., & Goertzel, B. (2019). Distributed, decentralized, and democratized artificial intelligence. *Technological Forecasting and Social Change, 141*, 354-358. doi:10.1016/j.techfore.2018.11.010.

Shen, L., (2017). Former U.S. CTO: The "Robot Apocalypse" Could Happen. Here's How You Stop It. Retrieved September 10, 2020, from https://fortune.com/2017/11/14/megan-smith-cto-robot-apocalypse-elon-musk/

Stilgoe, J. (2017). *Seeing Like a Tesla: How Can We Anticipate Self-Driving Worlds?* Department of Science and Technology Studies University College London.

Tesla. (2019, April 22). *Tesla Autonomy Day* [Video file]. Retrieved from https://www.youtube.com/watch?v=Ucp0TTmvqOE&t=9777s

Zhou, V. (2019, March 3). Machine Learning for Beginners: An Introduction to Neural Networks. Retrieved October 13, 2020, from https://victorzhou.com/blog/intro-to-neural-networks/

Nadji-Tehrani, M., & Eslami, A. (2020). A Brain-Inspired Framework for Evolutionary Artificial General Intelligence. IEEE Transactions on Neural Networks and Learning Systems, PP. https://doi.org/10.1109/TNNLS.2020.2965567

Schofield, M., & Thielscher, M. (2019). General Game Playing with Imperfect Information. Journal of Artificial Intelligence Research, 66, 901–935.
OpenAI, Berner, C., Brockman, G., Chan, B., Cheung, V., Dębiak, P., Dennison, C., Farhi, D., Fischer, Q., Hashme, S., Hesse, C., Józefowicz, R., Gray, S., Olsson, C., Pachocki, J., Petrov, M., Pinto, H. P. d. O., Raiman, J., Salimans, T., Schlatter, J., ... Zhang, S. (2019). Dota 2 with Large Scale Deep Reinforcement Learning