Modern Challenges in Machine Learning and Artificial Intelligence

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Abstract. The usage and development of Machine Learning models along with the advancement and popularization of Artificial Intelligence, naturally leads to new challenges in multiple levels in the field. In one hand the trust in the field of AI needs to be boosted in order to increase the adoption rate, on the other hand the usage of AI has been largely abused by those who decided to adopt the term in their line of work. A clear line of what is expected from AI and what AI is, must be drawn so that the trust, acceptance and adoption of AI can be increased. These, and other data related problems are the primary subject of this paper.

Keywords: Machine Learning, Artificial Intelligence, AI Acceptance, Bias in Data.

1 Introduction

Artificial Intelligence (AI) has been around for several decades. In the last 3-5 years the development and usage of AI related technologies experienced a massive worldwide expansion due to the advancement of many of the Machine Learning (ML) algorithm implementations that became also freely available for everyone to use. This last factor alone was enough to boost the advancement in the field and to make companies completely revamp the way they operate. In fact, the investment in the field in the last 5 years is also booming as evident from the following charts provided by (Shanhong Liu, 2021) and shown here in figures 1 and 2 here. Given the fast growth in the area, it comes natural for many companies to be lacking behind the ability to adopt new technologies and to fully conform with the new AI defined trends. On the other hand, companies need to keep the hype and investor's interest and therefore are doing the best efforts to associate their business with anything related to AI. In fact, these efforts are too ambitious to be fruitful and very often AI becomes a ground for speculations.

In Figure 1 we see the AI corporate investment between 2015-2020 (Shanhong Liu, 2021). In Figure 2, we see that 84% of enterprises believe investing in AI will lead to greater competitive advantages (Louis Columbus, 2018).

AI challenges in adoption and development lay in different levels and have various nature. The most typical challenge is posed in business management to determine the ever so complex analysis *buy vs. build*. This is deeply rooted in the companies' strategical course of action and is tightly connected to *building trust in AI* technologies. Many are reluctant in using AI because of *data privacy* concerns. Not in the last place are the burning questions of *ethics* and *equality in AI* technologies. We clearly have a plethora of problems to address when it comes to popularizing the new way forward through AI as the stakes are extremely high. Most of the effort by far is concentrated in the business models and management and all the rest of these challenges are lacking behind and still need further improvement.

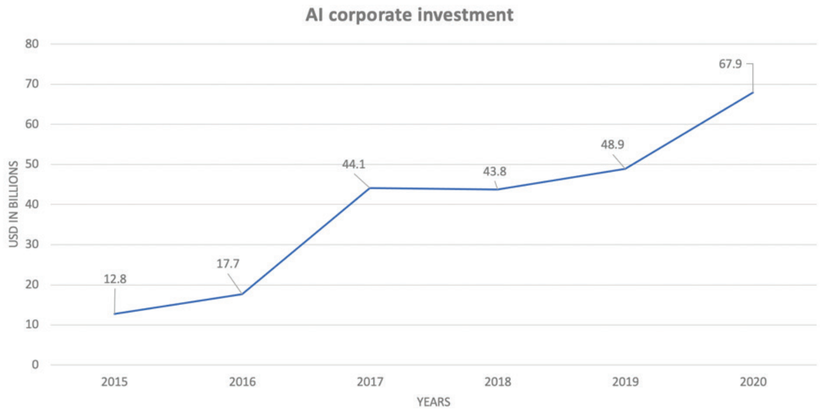

Fig. 1. Artificial Intelligence corporate investment from 2015 to 2020 (Shanhong Liu, 2021)

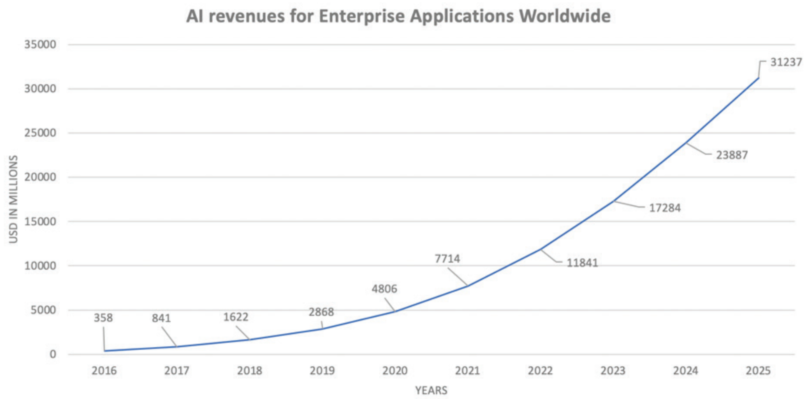

Fig. 2. Revenues from AI Enterprise technologies in the world market (Louis Columbus, 2018)

Looking at the popular AI issues from a slightly different prospective, we observe another interesting phenomenon. Many companies that are working with sophisticated data analytics while using well known machine learning methods are also declaring that they work with AI, where in fact this is not the case. AI became a standard synonym for any algorithm that performs an analysis of any kind, which I refer to as an "AI pandemic". A clear distinction of what AI truly stands for needs to be made. The rules of AI development, adoption and usage must be clarified so that any AI speculation or scare from using AI technologies should be cleared. This is needed not only to be fair to all AI users, but to boost the trust of true AI adoption by both companies and consumers.

2 Challenges in AI Acceptance and Adoption

Although AI is the natural way forward for all developers of modern technology, the field still suffers from wide acceptance by many. There are different reasons for this outcome depending on the recipient using these types of technologies. There are two main types of recipients: on one hand we have *companies* and on the other hand we have the end users or *consumers*. As for the first kind, it is evident from the *Annual MIT Sloan Management Review – Boston Consulting Group*, companies that tend to treat AI as a sequence of algorithms or simply as a type of technology rather than a new way of thinking, while largely ignoring the human behind the technology, suffer from failure in the field (BCG, 2020). In addition, many companies are declaring that they use AI because, since it is the new hype, but they are not conforming to the most common AI requirements, as proven by *Fortune.com* (Jonathan Vanian, 2019). Furthermore, companies that are getting some value from their investments view AI to upend and change current business practices like sales, rather than simply buying an AI tool from a vendor. Another key point is that companies that are successful in AI adoption and usage are those that create a mini-IT departments that are dedicated in developing and improving AI technologies as a core initiative. AI in general will prove more successful if it is viewed like a vehicle to improve specific business models rather than being implemented in isolation to a specific product. On the other hand, consumers are still very skeptical in accepting AI with open arms. Some fear that AI will replace their jobs and they will suffer from the 'rise of the machines'. Furthermore, reports like the one posted by *huffingtonpost.ca* that quotes Dell Technologies stating "*85% of the jobs in 2030 are not even created yet*" contribute to the problem (Daniel Tencer, 2017). This however means that the types of jobs people will do in the future will be of different nature, and it doesn't mean that we will be left without work. Other people resent new technologies simply on the grounds of data sharing as they fear they will lose their privacy. All these factors simply show that there is plenty to be done in the field to gain wider acceptance not only by companies, but also by end-consumer. More information and education need to be disseminated to gain wider acceptance and adoption of this inevitable turn in technological advancement we call AI.

3 Data Bias and How to Deal with It

One of the main challenges when it comes to applying advanced ML models is dealing with the data itself. It is well known that most of the work we do in ML and AL system design is directly connected to working with the data. That includes collecting, understanding, labeling, cleaning, reducing, balancing, normalizing, and formatting the data to a unique batch that is ready for processing. All these operations have their challenges and in most cases they can be automated. But data can be tricky not only from management and processing prospective, but also by its nature. Some studies point of gender imbalance in image recognition systems for example (Schwemmer, et al., 2020). Others also lead to biased classifiers from imbalanced data in medical images (Larrazabal, Nieto, Peterson, Milone, & Ferrante, 2020). Data can be unbalanced based on how it is collected. There are different ways of handling this kind of data. If we have an abundance of data observations, we can consider using only an equal amount of data points from each class thus easily solving the bias in this regard. On the other hand, we might not have the luxury of disregarding data samples since our datasets may not be as plentiful. This of course is tightly connected to the number of feature points or attributes per observation vector. It reminds us of the "*curse of dimensionality*", where the larger the feature vector is, the exponentially larger the data observations must be. In the cases, where data points are scarce, we can either try using techniques of *data expansion* or at least use *stratification* so that we make sure that all classes are equally represented in our training and validation sets. In the case of data expansion, we can also include *data augmentation* where we meaningfully change one part of the dataset to gain healthy variations considered as new and possible observations. An example would be to flip images left to right in a small image dataset, then add the resulting batch to the main dataset. This way we can essentially double the number of observations. In another case we could consider pre-filtering the dataset in specific ways: *images* with color filters where a specific color is treated as feature, and *audio* with specific band-pass/stop filers that emphasize on specific sound characteristics.

But these are the obvious ways of dealing with uneven data in the pre-processing stage. Some bias is deeply hidden in the data samples. Going back to the specific gender imbalance in image recognition systems type of bias introduced in (Schwemmer, et al., 2020), there is a way of identifying and correcting the batch in a two-step procedure. In the specific case we can identify those labels that hold the highest representation of a specific gender, assigned by the image recognition algorithm. For that purpose, we can use the Pearson's chi-square test statistics χ^2, with an addition of the Yates correction, or:

$$\chi^2_{corrected} = \sum_{i=1}^{N} \frac{(|O_i - E_i| - 0.5)^2}{E_i}$$

where, O_i represents the observed label, E_i signifies the expected label, and 0.5 is the Yates correction on the labels returned by the *Google Cloud Vision* (GCV), which could also be returned by the *Amazon Rekognition* (AR) or *Microsoft Azure Vision* (MAV). AR is a cloud-based system that can extract metadata from images and video files, which may include image objects, text snippets, etc. The purpose of MAV is similar. In the specific case the labels are of different genders for either men or woman. The reason for using the 0.5 coefficient introduced by Frank Yates is to correct the continuity in the Persons formula.

The second step as suggested in (Schwemmer, et al., 2020) is to use a negative binomial regression to obtain the expected counts of GCV labels for all men and women.

We can expand on a Poisson Regression Model (PRM), which assumes that the count for observation i is drawn from a PRM distribution with mean μ_i that represents the rate of occurrence of an event that will occur over a given period. In our case we can use the factor rate of change, or:

$$\mu_i = E(y_i|\boldsymbol{x}, x_k) = e^{\beta_0} e^{\beta_1 x_1} e^{\beta_2 x_2} e^{\beta_3 x_3} \ldots$$

If we assume that x_k changes by δ, then we can expand, such that:

$$\mu_i = E(y_i|\boldsymbol{x}, x_k + \delta) = e^{\beta_0} e^{\beta_1 x_1} e^{\beta_2 x_2} e^{\beta_2 \delta} e^{\beta_3 x_3} \ldots$$

Then the factor change in our regression model can be represented as:

$$\frac{E(y|\boldsymbol{x}, x_k + \delta)}{E(y|\boldsymbol{x}, x_k)} = \frac{e^{\beta_0} e^{\beta_1 x_1} e^{\beta_2 x_2} e^{\beta_2 \delta} e^{\beta_3 x_3}}{e^{\beta_0} e^{\beta_1 x_1} e^{\beta_2 x_2} e^{\beta_3 x_3}} = e^{\beta_2 \delta} = \exp \beta_k \delta$$

where for a given change δ in variable x_k, the expected count of different gender labels in a specific category, increases by a factor of exp $\beta_k \delta$, while holding all other variables constant. The reason for using a negative binomial distribution is because it gives us the ability to model count variables whilst correcting for overdispersion of the count outcome. This can happen when the conditional variance surpasses the conditional mean of the distribution.

So far, we have identified one main type of bias in raw data that was gender based. But data bias can spin off around any kind of data based on historical learning as well. For example, since most successful businessmen in the past were white male, the system would be biased towards this kind of decision for any future predictions. The same could be said for people with specific degree, race, ethnicity, marital status, specific area of living or even specific name. If we train a system mostly on green apples, red ones would be less likely to be detected later in the testing stage. So, because of all these phenomena we are responsible to make sure to study our raw data well and do best efforts to eliminate or minimize it before we enter the learning stage of our ML and subsequently AI system.

4 DeepOnet Leering through Universal Approximation

In the business world, undoubtedly AI is the next big thing that will drive revenue and will lead to many success stories for the many years to come. To the scientific community, AI is still a hot topic for research and development. As the demand and expectations grow, the complexity of nonlinear problems also grows and with that the computational complexity of algorithms also experiences a huge rise. The demand for faster hardware and more efficient algorithms is always high. Improving today's ML models that will carry the next AI generation of smart systems also need a closer look. Some algorithms are looking into new mathematical modeling then estimating the weights at the very beginning of a Artificial Neural Network (ANN) rather than calculating the

Partial Derivative Equations (PDEs) in the conventional backpropagation stage in a Feed Forward type of network (FFN) such as Convolutional Neural Networks (CNNs) (Ananthaswamy, 2021). CNNs can be either *shallow*, when containing a single hidden layer, or *deep* when constructed with two or more hidden layers. Regardless, the conventional way of solving these types of networks is through exhaustively calculating their PDEs through multiple epochs to achieve training, also known as 'learning'. These networks are designed to be good approximators to specific nonlinear problems and they use the conventional way of getting closer to the ground truth. In some cases, PDEs can be rather complex and universal analytic solution cannot be offered through using them. In fact, not every time there is a mathematical solution that exist for some of these complex problems. On the other hand, even when a solution can be found using the conventional way of solving the PDEs, a huge computational cost tag is attached to these systems and more advanced and expensive multi-core hardware is needed for these types of cases. The need for novel solution is evidently growing. In connection, there is a new school of thought that suggests a much faster approximation of the results. It is a rather unconventional way of delivering such type of solution through faster approximation of the desirable outcome. In this new solution, after accepting some boundary conditions, and instead of finding the solution analytically, we convert the PDEs into a set of 'tractable algebraic equations', which represents the result derived in different time of the process (Ananthaswamy, 2021). In doing so we represent the problem in short time interval snippets rather than offering an exact mathematical solution. The advancement in the field was proposed through the DeepOnet system offered by George Karniadakis et al. (Lu, Pengzhan, & Karniadakis, 2019). As an example, the authors claim that for a conventional problem that usually takes 18 hours to compute, through the usage of DeepOnet the same problem can be approximated in 2.5 seconds.

5 How to Design a Modern AI System

As we already established, if you are doing advanced statics, machine learning, or deep learning, that does not make your model an AI model. There are several factors that need to be taken into consideration when designing an AI centered system. The three most important requirements for an AI system are as follows:

1. The first major and most important requirement is that the system should be designed with the human in mind, or should be *human-centered*. This means that the system should be designed using key points from *social science* as it will best select the most relevant information for self-improvement. This also goes if the system should be choosing an algorithm or technology for the users, something studied by interacting with other people or systems.
2. The system should use *prescriptive analytics* and should be able to take action or suggest the best course to move forward based on the underlying ML model.
3. The last major requirement is that the system should be able to learn from its mistakes and to *self-improve* as a result. That is usually done through a sophisticated reward system.

All these points will make an AI system flexible and scalable, which are the most important final goals for making a modern AI system. AI is much more than nicely executed ML algorithms together. It is a very philosophical endeavor if one wants to design an AI system with the goal of serving its true purpose. In this regard AI designers may greatly benefit from *phenomenology*, which is given as "*the study of structures of consciousness as experienced from the first-person point of view*" (Smith, 2013). The philosophical topic of phenomenology deals directly with reason, logic, and ethics. All these fields are extremely relevant when it comes to alleviating the effects of bias hence increasing AI adoption.

6 Conclusions

With the rise of ML usage worldwide and the development of various AI smart systems, our responsibility in society rises immensely as to introduce these technologies in the right way to guarantee ethical and moral equality to increase AI acceptance and adoption. There are different types of bias that need to be handled with caution to guarantee fairness. In addition, there are different instruments that could be used to pre-process raw data and to deliver well balanced data for designing a fair AI system.

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