Bias is present in every aspect of life, from how people's perceptions of someone are shaped by skin color or gender, to a person liking one food over the other because it is organic. Big data is not immune to bias. We like to think it is, because data is fact, it represents exactly what happened and how it happened. However, as Cathy O'Nieil discussed in her TED Talk, big data comes with the inherent biases surrounding the world and the subject at the time of its collection. When this data is used to train an algorithm with some goal in mind, the biases from the data can seep through the algorithm, producing a definition of success that is skewed in the direction of the biases. For example, an algorithm to determine if a job candidate is 'hirable'. If the training data has a very prevalent variable that is skewed in one direction (ie. male for gender), then the resulting algorithm could view being 'male' as an important quality to hire someone.

Algorithms are not scientific fact, they are not guaranteed to produce perfect results, and their definition of success is impacted not only by the data involved, but also the coder who wrote the algorithm. During Cathy O'Neils talk she says "algorithms are opinions embedded in code". This goes against what most people believe, they like to see algorithms as fact that nothing can disprove, however that is not the case. Algorithms are at the whim of their designer, they can use what features in the data the designer/client sees as more important, they can use as many and as little features as they want, and most importantly, they can choose a threshold of success (ie. a person is hirable). This is a very interesting fact, because it shows there are two sources of bias in algorithms, the designer and the data. This makes it difficult for data scientists to answer questions like, "should I hire this person", but also easy for private companies to abuse these biases and produce algorithms whose solutions favor the opinions of the client. Cathy O'Neil mentions the veil of secrecy that these companies use to protect their algorithms from being debunked or labeled inaccurate. This veil of secrecy helps these companies market their algorithms as truth and fact, but as Cathy O'Neil says, "algorithms can be interrogated", and we need to interrogate them so "we can fix them".

A specific example of an algorithm displaying bias is the former Amazon AI recruiting tool. Beginning in 2014 Amazon machine-learning engineers began building an algorithm with the goal of automating the recruiting and hiring process to gather the best candidates based on their résumés. The algorithm gave candidates between 1 and 5 stars, where if you put in 50 applications it would give you the top rated (5 star) candidates to hire (Iriondo). The pro of this algorithm is that it can find the best candidates faster, and can also remove bias from the person reviewing the résumés. However, the engineers discovered a very impactful flaw, for technical jobs, like a software engineer, the algorithm was rating men much higher than women at a disproportionate rate. This was caused by the training data used. The data was from a 10-year period and the algorithm would look for patterns in these résumés, however during those 10 years, the résumés were submitted primarily by men. Thus the patterns the algorithm was noting as successful and indicative of more stars, were ones with male keywords. The algorithm didn't just elevate male applicants, it actively downgraded female applicants. Since less applicants were women over those 10 years, the algorithm penalized applicants whose résumés included the word 'women', there were even cases where it penalized women who went to all-women's colleges (Reed). The engineers did try to fix the algorithm, however they canceled the project after realizing there was no guarantee the algorithm would not devise another gender-discriminatory sorting technique. This case is very important to look at because it shows an instance where the data was biased to the point it was unusable, which can be the case for a lot of data.

There are many pros and cons for using algorithms to make decisions. Algorithms can help make decisions faster and eliminate some bias from human-reviewers. However, algorithms cannot interpret data in context. Like in our case study, the algorithm could not determine that a "women's college" was equivalent to "college". I think the best way as a data scientist to combat this is to perform extensive tests on your data before you use it, with the goal to find the least-biased dataset, so you can create your algorithm to ignore this little bias.

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