Researched Position on Industry Issue

James Taylor

University of Maryland University College

**Introduction**

Emerging technologies have been adored and loathed through all of history. Bicycles were called unsafe and impractical in the early 1900’s; actors thought people wouldn’t want movies with talking audio (Edwards, 2015). Technologies have always had their detractors, and sometimes they were right. For new technology to become adapted widely, the costs of introducing it have to outweigh the benefit of using it.

Artificial intelligence has continued its march into the business world. There are trust and practicality issues that have come up as more places look to use its capabilities. Executives won’t utilize automation if it can’t fit into the business and regulatory requirements. If Data Science is to continue its projected growth, the industry needs to deliver software that operates within the current business standards and practices.

**Practical Examples**

A large part of being an accountant is to audit the business, tracking bills, payments and debts. The classification problem of receiving a document, determining if it is a bill or payment, and delivering the value of said item is one artificial intelligence can handle. Algorithms that can handle invoices, financial statements, contract agreements and other accountancy documents is really an enticing tool because it takes away lots of man-hours of reading.

As machine learning is trained on examples, only the larger accounting institutions have the amount of data needed to train these models (Vetter, 2018). As an example, KPMG uses an IBM tool to keep their leasing company clients in accordance to IFRS 16 standards (Vetter, 2018).

There is not much room for errors in handling finances. Paying bills and managing sales revenue is what every business must do to operate. There are plenty of tax and financial documents that every business needs to produce to stay within regulations. Documents need to be signed before an action can be done, like large transfers of money. Companies want tools that can help them with these tasks. They will buy it if it saves them money, keeps them legal and produces a paper-trail to track where and how money is spent.

Artificial intelligence has created a new challenge for regulators. Where people could be held liable for their mistakes, software is now capable of making determinations. What fundamentally separates these algorithms from previous software is its ability to change overtime. The more the algorithm is used the more data it has experienced, thus making it more effective. What an algorithm does today may be deferent later from now even in the same exact situation.

The Food and Drug Administration (FDA) is attempting to grapple with the algorithm paradigm. They approve drugs and biotechnology for human use, so it is difficult to greenlight a therapy dependent on software that will change as time goes on. On such technology uses algorithms to detect breast cancer in mammograms and improves its ability and confidence of detection as it is exposed to more mammograms (Ross, 2019).

Scott Gottlieb, the former FDA Commissioner, wrote a paper addressing the challenges the FDA faces when overseeing the artificial intelligence wave into medicine. He fretted about the need for the new technology offering potentially large improvements in medicine, and ability to maintain oversight over safe practices (Ross, 2019). A team won a cancer detection competition touting a 97% detection rate of lung and breast cancer in 2016, which beats the human detection rate handedly (Towers-Clark, 2019).

Data scientists and regulators need to meet in the middle. Government officials want reliable products that are well understood and examinable to ensure using it will not cause harm. As of today, the models that make the best predictions are normally the ones least understood. These two goals are at odds with each other. One solution the FDA has approved are ‘locked algorithms’, where the technology uses machine learning but it does not take in more data as it is used (Ross, 2019). One could call this a naïve algorithm because it does not change as it is used more. The downside to this regulated approach is the model won’t see as many observations, so it will take more time increase its accuracy. Data scientists need to heed to regulators concerns for safety if breaking into heavily regulated markets.

Banking is heavily regulated market were algorithms are disrupting. Determining someone’s credit risk has been a touchstone for lawmakers attempting to help disadvantaged ethnic groups. Thus, banks have had their boundaries to determine one’s likelihood to pay a loan back drawn for them. If a bank is found to loan money to people differently based on things like race, gender and neighborhood of residency, they could pay heavy fines for illegal discriminatory lending practices.

How an algorithm would become biased against gender or races would be through proxy discrimination (Towers-Clark, 2019). As an example, imagine people are paying for a credit card online. The algorithm that determines if a person should receive a card has discovered people that apply from certain parts of a state are at a higher risk of defaulting on their credit debt. In this example, those parts of the state are areas with higher minority populations. The algorithm found a statistical correlation between area of applicant and ability to repay debt, but by doing that it became biased against minority populations. Traditional statistical techniques would have been able to parse out these variables, but big data may have more of an issue doing this (Towers-Clark, 2019).

Based on federal law a lender must disclose why they denied someone credit. This creates a dataset that can be inspected to look for discriminatory practices. This explanation requirement gives an added layer of complexity to an algorithm making these determinations Towers-Clark, 2019). Artificial intelligence explaining its decision is a developing ability not perfected yet.

In the pursuit of more accuracy, data scientist will want to include as much data as possible to accept or deny applications. There may be strange but effective variables that correlate to paying back a loan. This new big data may cause interactions that cause the proxy discrimination mentioned earlier. For instance, an algorithm may scan an applicant’s social media posts, and associate credit risk with certain spelling and diction styles. Different ethnic groups may communicate differently with word choice, like minorities using more slang. This is encroaching on determining a person’s credit worthiness by ethnicity. Data scientists and lawmakers need to coordinate how to best adapt to big data making determinations in the grey-area of the law.

**Conclusion**

Technology has been disrupting the status quo since the first stone tool was invented millions of years ago. Today’s economy is infused with regulations on how to conduct business whether you agree with the rules or not. Data scientists are producing tools that have great potential benefits but operate in ambiguous legal territory. This is not the first time in modern history this has occurred. Data scientists would be wise to approach the status quo of practices and regulations as partners and not obstructionists. It will take effort on both sides to deliver tools that are legal and practical, allowing more people to benefit from the technological improvements.

References

Edwards, P. (2015, June). 7 world-changing inventions people thought were dumb fads. Retrieved from <https://www.vox.com/2015/2/9/8004661/fads-inventions-changed-world>

Klein, A. (2019, April). Credit denial in the age of AI. The Brookings Institution. Retrieved from <https://www.brookings.edu/research/credit-denial-in-the-age-of-ai/>

Ross, C. (2019, April). FDA developing new rules for artificial intelligence in medicine. STAT. Retrieved from <https://www.statnews.com/2019/04/02/fda-new-rules-for-artificial-intelligence-in-medicine/>

Towers-Clark, C. (2019, April). The cutting-edge of AI in cancer detection. Retrieved from <https://www.forbes.com/sites/charlestowersclark/2019/04/30/the-cutting-edge-of-ai-cancer-detection/#3194ff717336>

Vetter, A. (2018, October). What CPAs should know about machine learning vs. deep learning. Association of International Certified Professional Accountants. Retrieved from <https://www.journalofaccountancy.com/newsletters/2018/oct/artificial-intelligence-terminology.html>