Machine Learning and Financial Security: Defining the Problem

This brief is part of an ongoing series on emerging technology and its role in improving financial security and opportunity for all Americans. Read our other briefs, Blockchain Technology and Financial Security & Machine Learning and Financial Security: Selecting and Using Data, to learn more.

Emerging technologies hold the potential to transform our financial services system in ways that could open up significant new opportunities for Americans making lower incomes. However, these technologies also come with new risks. The financial security field can influence the course of this technology toward positive social impact. In order to do so we must understand these developing technologies, their use cases (particularly for lower income Americans), and their potential challenges.

As part of Commonwealth's vision to make all Americans financially secure, we are engaging with emerging technologies that influence financial services. Commonwealth connected with machine learning experts Chip Baker, Co-Founder of Summit Path Partners, formerly Head of Strategy at Cinch Financial; and Jason Liu, AI architect at Savant Data Group, to understand the role machine learning can play in financial services, hear their thoughts on what financial institutions should consider in implementing this technology, and consider what the ecosystem as a whole can do to ensure these tools promote financial security.

What is machine learning?

Machine learning is a branch of artificial intelligence that uses computer systems to learn from data sets, identify patterns in the data, and make decisions and recommendations on future actions. Like the name implies, current popular and mature machine learning techniques involve giving a computer "training" data with inputs and outputs that allow it to find and learn trends in the data and predict future outputs.

Inputs are parameters that the model will consume about a specific individual or issue. Outputs are the recommendations that the model will produce. Without a set of true known scenarios from historical data, it is hard for a machine learning model to produce an accurate recommendation. The machine learning system can keep learning and adjusting its model as new data is added.

Machine learning is appealing to financial institutions because they can automate certain processes that previously had to be done by an employee, saving the financial institution time and money. For example, companies develop machine learning technologies that make recommendations on how a consumer should invest based on their age, income, assets, and historical trends.[1] Machine learning algorithms are able to analyze and find patterns in larger datasets than a human could, opening up the possibility for faster and more accurate recommendations in making decisions.

Still, machine learning, like any branch of artificial intelligence, has its limitations. Processing large data sets is time consuming and requires expert knowledge to ensure its accuracy. Also, without a clear set of goals the financial institution is trying to achieve, building a machine learning model can create incorrect outputs or major projects for a financial institution that lack a specific purpose. A machine learning model optimizes for certain parameters, such as minimized costs to the financial institution, or in the case of financial security, a measure like maximized credit score or minimized spending. Financial institutions need to be clear about what they are optimizing for and what the tradeoffs may be when building a model. Finally, these technologies also rely on their underlying data sources to make recommendations, risking that bias present in their training data carries into their outputs.

[1] *https://www.wired.com/2016/01/the-rise-of-the-artificially-intelligent-hedge-fund/*

What is the potential for machine learning in promoting financial security?

Machine learning has the potential to make financial security recommendations and analysis more efficient and scalable, but on its own is not a panacea to improving financial security. The tools are limited by the requirement for accurate input and output data. Machine learning tends to thrive when there is a large sample set of historical truth data- where the past inputs and outputs can be observed and confirmed- that can then be leveraged for training. A couple of examples where there is significant truth data that could be worth exploring further include:

- Leveraging credit data to assess a consumer's financial security compared to other financially secure consumers. Machine learning technology opens up possibilities to analyze large amounts of data about a consumer's account and payment history and compare them to other users to gain insight into potential markers of financial security or insecurity.

- Scaling human capital and time-intensive, employee-based financial security interventions that have proven successful. One instance of this could be financial coaching programs. One-on-one financial coaching has been effective, but having a human collect and process data, and make decisions, is expensive. Even if the AI-based workflow only handled data collection, processing, and part of the decision making, it can reduce the cost of the model.

What are the challenges in using machine learning to promote financial security?

Many fintechs and financial institutions have invested in designing tools to evaluate people's financial security and make recommendations to improve financial habits. While leveraging machine learning technology has great promise when it comes to delivering services at scale, current models may still struggle with having the right data to provide insights or evaluating what makes a recommendation effective.

Accounting for qualitative and quantitative metrics

Many machine learning algorithms use statistical averages, but will miss the complexities of some people's full financial situation. A variety of organizations have attempted to develop metrics to measure financial well-being. These can give us a better understanding of the many factors that contribute to one's financial security such as credit score, debt, and savings. Applying these methods to machine learning algorithms is complex and may need to be interpreted in a different way to ensure effective processing.

The complexity of measuring the human side

"A machine learning algorithm can mathematically optimize for a certain measure like credit score, but that loses the human side.

Two people may have the same income and living standards, but one lives on a farm and the other one lives in New York City. They are spending and saving in a different context. How do you define their financial security? We need to know data about the person, but also their environment." - Jason Liu

Financial decision-making is more nuanced than an algorithm may suggest.

Financial insecurity can be felt across the income spectrum. Moreover, our financial decisions are not always logical -for example, emotions may play a role in how people choose to spend or save. People need financial advice that accounts for priorities and values, unexpected circumstances, and individual desires. A machine learning tool is not necessarily able to make those allowances and tradeoffs. People also tend to have multiple financial goals. A machine learning program can weigh different preferences and priorities, but a consumer's individual priorities may be too nuanced for the technology alone to prioritize between them.

What should a financial institution consider when using these tools?

Have a clear problem to solve.

Even though machine learning is a popular topic and can attract internal investment, a financial institution still needs a specific objective to solve for in order to make an investment worth it.

Focus on data preparation.

Often the model gets most of the attention, but there is a huge risk of poor data inputs leading to poor recommendations. If a financial institution doesn't have enough data to train the model or data points from a wide enough range of consumers, the outputs will not be valuable even if the model is a good one. A financial institution that only has data from a certain target demographic or income level will only be able to make recommendations for that population. Using that data to make broad-based recommendations could lead to biased or unhelpful recommendations.

What can the ecosystem do to leverage these technologies more effectively?

Focus on underserved communities.

Financial products and tools focused on financial security have often not been designed specifically for underserved communities. Historically, it has been common to see products that take advantage of financial insecurity to charge higher interest rates or fees. Machine learning can provide tools to meet the needs of this community in a way that is also good for business. Entrepreneurs can research and design for these communities, and nonprofits already serving this community can share what works when it comes to improving a person's financial standing.

Subjectivity of financial decision making

"Machine learning algorithms can work like a GPS. They optimize variables to give you a path, and smarter ones can include statistical averages on things like traffic. But what is still missing is the trade-offs.

The GPS does not know your specific criteria in choosing a route. Maybe when I go home, I don't just want a direct route, I also want to enjoy the sunlight or the view. The GPS cannot know about secondary goals. It just gives the most optimized solution.

For financial situations we always have several goals, and not all of them are rational. Machine learning technology will struggle to decide between them." - Jason Liu

Consider new investment models.

The traditional VC-backed technology start up model's requirements for success, including the ability to scale quickly and turn a profit, make it incredibly difficult for companies to avoid falling into revenue traps, pushing products that don't meet consumer needs, and focusing on the mass affluent segments of the population. Venture capitalists and the fintech ecosystem broadly can work to build new funding models that take into account both the bottom line and a start up's social impact.

Invest in more academic research to forward the field.

More research on financial insecurity, the effectiveness and limitations of data, and comprehensive measurement standards are needed to develop new and impactful innovations.

What is next for machine learning?

Artificial intelligence and machine learning have captured the attention of the financial services industry. As financial institutions and financial technology companies make investments in this technology, it is imperative that we fully explore its potential use cases and determine where this technology is best applied.

For financially vulnerable consumers, this technology could offer unprecedented access to financial advice and services. In order to get there, efforts must also be made to understand the lives of financially vulnerable people. What financial goals are most important? What does financial security truly look like? Including financially vulnerable consumers into the discussion and answering these questions is necessary to leverage these technologies to set more Americans on a pathway to security.

What steps can we take to ensure that machine learning is strategically positioned to improve the financial security and opportunity of all Americans, especially those who are financially vulnerable? Contact us at info@buildcommonwealth.org to start a conversation.