Deep Learning and Financial Stability

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Abstract

The financial sector is entering a new era of rapidly advancing data analytics as deep learning models are adopted into its technology stack. A subset of Artificial Intelligence, deep learning represents a fundamental discontinuity from prior analytical techniques, providing previously unseen predictive powers enabling significant opportunities for efficiency, financial inclusion, and risk mitigation. Broad adoption of deep learning, though, may over time increase uniformity, interconnectedness, and regulatory gaps. This paper maps deep learning's key characteristics across five possible transmission pathways exploring how, as it moves to a mature stage of broad adoption, it may lead to financial system fragility and economy-wide risks. Existing financial sector regulatory regimes - built in an earlier era of data analytics technology - are likely to fall short in addressing the systemic risks posed by broad adoption of deep learning in finance. The authors close by considering policy tools that might mitigate these systemic risks.

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Introduction

Financial history is rich with transformative analytical innovations that improve the pricing and allocation of capital and risk. These innovations date back to antiquity including the earliest forms of ledgers, the development of the present value formulas by Leonardo Bonacci (aka Fibonacci)[3] in the 13th century, and the invention of the Fisher Black, Robert Merton, and Myron Scholes options pricing model in the 1960s.

Deep learning, a subfield of AI, is a general-purpose computation tool particularly adept at prediction and classification tasks. The technology relies on neural networks conceptually inspired by the structure of the brain. Its models iterate repeatedly to optimize for the best approximation function between inputs and outputs. The advent of deep learning builds upon previous technologies but may represent a significant discontinuity from prior data analytic techniques used within the financial sector.

Still in early stages of adoption, deep learning is already being used in finance for fraud detection, regulatory compliance, market surveillance, and administration. It is starting to be used in trading, asset management, risk management, credit underwriting, and insurance underwriting. Further, through natural language processing (NLP) applications, deep learning is beginning to transform user interfaces, client onboarding, and insurance claims processing. While these applications are not yet truly dominant in finance the way they are in vision or speech, deep learning still comes out on top, after careful tuning, in many tasks. It is likely, even if one assumes only today's modest benefits, that much broader adoption is yet to come. With further advancements in the technology, it is likely that deep learning will gain significant traction in critical finance functions of credit allocation, insurance underwriting, internal risk management, and trading.

Presenting potential benefits of increased efficiency, greater financial inclusion, enhanced user experience, optimized returns, and better risk management, we hypothesize that deep learning, as it moves to a more mature stage of broad adoption, also may lead to increased systemic risk of the financial sector.

In this paper, we tell the story of deep learning and financial stability in three acts. In Act 1, we introduce our protagonist, deep learning, describing where it lives within finance, and identifying its nine key characteristics that, taken together, make it a novel advancement. In Act 2, we introduce a major environmental challenge for deep learning in finance - systemic risk and channels of fragility. In Act 3, we accompany our main actor along five journeys, exploring whether when mature deep learning might awaken systemic risks' stormy clouds, whose thunderstorms threaten bystanders far and wide.

[3] Goetzmann, "Fibonacci and the Financial Revolution."

Like many dramas, our main character may appear to be living in equilibrium until dramatic events reveal underlying vulnerabilities. A Coda concludes our story, reviewing policy considerations and providing a path forward for deep learning and financial stability.

Act 1 of our story establishes the ways in which deep learning represents a significant discontinuity when compared to previous advances in data analytics. We started our research exploring what might distinguish deep learning - specific characteristics - from traditional data analytic tools used within finance. This was critical to our assessment of the potential effects deep learning might have on the fragility of the financial sector.

We found nine key characteristics of deep learning relevant to our analysis of financial stability. These characteristics include five intrinsic features of deep learning, hyper-dimensionality, non-linearity, non-determinism, dynamism, and complexity; three heightened challenges of limited explainability, fairness, and robustness; and an insatiable hunger for data. While some of these characteristics might be said to be incremental, taken together they represent a significant departure from existing technologies.

Act 2 examines the relationship between deep learning and systemic risk - the likelihood that the failure of one actor, firm, or model may propagate out to negatively affect the rest of the financial system and economy at large. From the extensive academic literature and public sector regulatory perspectives on systemic risk, we explore our hypothesis through three relevant channels of systemic risk propagation: monocultures and herding, network interconnectedness, and regulatory gaps.

Financial crises often arise in one sector, region, or market. History is replete with shocks emanating from one corner of finance in which the pulling of one thread undoes the financial knitting across an economy. Consider the 2008 financial crisis, the epicenter of which was the U.S. subprime mortgage market. Thus, deep learning may not need to bring uniformity, network interconnectedness, or regulatory gaps to all sectors. An increase in systemic risk through even one sector may position deep learning as a central actor in the after-action reports of the crisis of 2027 or 2037.

Thus, begins Act 3, where journey with deep learning along five potential pathways - data, model design, regulatory, algorithmic coordination, and user interface - through which it may heighten systemic risk. We consider not just the state of deep learning now, but where it may end up when more mature.

In the data pathway we propose that the economics of data aggregation will, over time, lead to an increase in concentrated, single-source providers, adding risk via both the herding channel and network interconnectedness channel. Additionally, the exponential growth and usage of alternative data - generally with short time series - introduces significant potential uniformity of out of series tail risk.

Along the model design pathway, we investigate how the development of industry, expert, and academic consensus on optimal model type selection, inductive bias, and hyperparameter selection, may lead to uniformity, what might be called “mono-models.” The emergence of AI-as-a-Service providers - particularly those providing specific models - also may increase network interconnectedness. Along this pathway, deep learning also may raise model stability and tail risks given its combination of non-linearity, hyper-dimensionality, and complexity as well as its reliance on short time-horizon data sets.

In the regulatory pathway we explore how challenges of explainability, fairness, and robustness may lead to regulatory gaps as well as how regulatory design may promote homogeneity in deep learning models. Early stage technologies often outpace the development of requisite monitoring capabilities leading to periods of regulation gaps. Regulatory approaches to address these challenges inadvertently may lead to model uniform.

Along the algorithmic coordination pathway, we explore how the characteristics of deep learning may enable both intentional and unintentional algorithmic collusion.

In the user interface (UI) pathway, we highlight the potential for UI software providers to become concentrated, as well as how the economies of scale of natural language processing models are likely to lead to uniformity and network interconnectedness in the sector. There also is risk that advice provided by each virtual assistant becomes standardized and commoditized, causing herding of client decision making.

While deep learning is still in an early stage of adoption within much of the financial sector, our analysis is focused on how its key characteristics may increase systemic risk as the technology moves to a broader mature stage of adoption. Early stage technologies often see a great deal of diversity due to high levels of experimentation by entrepreneurs and developers. History and economics have shown that following early phases of competitive diversity, finance often recedes to more technological uniformity with concentrated actors and interconnected systems.

In the Coda, we consider policy levers that might mitigate the potential systemic risks identified in Act 3. Current model risk management guidance - written prior to this new wave of data analytics - will need to be updated. It will not be sufficient, though, to address the increased risks of herding, network interconnectedness or future regulatory gaps likely to arise with deep learning. Model risk management tools, while lowering overall risk, primarily address firm-level or so-called micro-prudential risks. Many of the challenges to financial stability which deep learning may pose in the future - uniformity of data, monocultures of model design, network interconnectedness with data aggregators and AI-as-a-Service providers, regulatory gaps in the face of limited explainability, and possible algorithmic coordination - will require new thinking on system-wide or macro-prudential policy interventions. Additional micro-prudential policy levers considered include internal mapping, firm buffers, and regulatory diversity. Macro-prudential policy levers considered include external mapping, material external dependencies, horizontal reviews, and network buffers. Finally, there may be a need for additional ex-post and crisis management tools for when problems do materialize.

Our contributions in this paper are fourfold. Foremost, we propose a framework by which to assess the effect of deep learning on financial stability. Secondly, within that framework, we build out and define the key characteristics of deep learning which distinguish it from earlier financial data analytics. Thirdly, through five potential pathways, we assess deep learning's impact on financial fragility. Lastly, we consider both micro and macro prudential policies to potentially mitigate the future challenges deep learning may pose to systemic risk.

Existing Literature

Others have considered how the adoption of deep learning might affect financial system fragility. Much of that work focuses on how the limited explainability of deep learning models may create "black-boxes," whose opaque inner-workings mask how inputs relate to outputs.[4] This literature discusses how unexplainable results may lead to a decrease in the ability of developers, boardroom executives, and regulators to anticipate model vulnerabilities. The Financial Stability Board (FSB) raised concerns specifically about the use of AI in stress testing: a lack of explainability could mean systemic risks are not spotted in time.[5] Zetzsche et. al. propose a framework with which to address some of "black-box" challenges, including "regulatory approaches which bring the human into the loop."[6]

There is a smaller selection of work that examines how deep learning augments some of key systemic risk transmission channels. Lin notes that "wider adoption of financial artificial intelligence can amplify certain systemic risks for the financial system relating to size, speed, and linkage."[7] Danielsson, Macrae, et al. focus on the rise of monocultures in the financial system due to agents optimizing using the same metrics.[8] Similarly, Mark Carney highlights the likelihood of increased procyclicality in the financial sector due to uniformity.[9] Larry Wall and the World Economic Forum raise the risk that economies of

4 Knight, "The Financial World Wants to Open AI's Black Boxes."

5 FSB, "Artificial Intelligence and Machine Learning in Financial Services."

6 Zetzsche et al., "Artificial Intelligence in Finance."

7 Lin, "Artificial Intelligence, Finance, and the Law."

8 Danielsson, Macrae, and Uthemann, "Artificial Intelligence and Systemic Risk."

9 Carney, "The Promise of FinTech - Something New Under the Sun?"

scale in data aggregation will concentrate data sources, perhaps also leading to additional herding behavior.[10] The FSB and Buckley et. al. describe the potential risk due to new systemically important third-party providers and infrastructure.[11] Speaking more generally on the digital transformation of finance, Genberg discusses the rise of big data and how big tech may soon operate as financial institutions, but outside of the regulatory framework.[12]

We build on the work of this existing literature, proposing a new framework by which to assess the effect of deep learning on financial stability. Within that framework, we identify key characteristics of deep learning distinguishing it from traditional financial data analytics and explore how these characteristics may affect systemic risk along five potential pathways. Further, we raise some new micro and macro prudential policy considerations that might lessen these risks.

Act 1

AI in Finance

Finance, technology, and data analytics have long existed in symbiosis. Artificial Intelligence (AI) and more specifically deep learning are just the most recent innovations in data analytics to be leveraged by the financial sector. Deep learning builds upon a significant period of transition which brought the internet, mobile phones, cloud computing, and more recently the open banking movement into the financial sector's technology stack. The introduction of deep learning, with its data processing capacity and its predictive prowess, builds on top of and leverages these existing technologies.

While traditional quantitative tools are still the mainstay of financial sector data analytics and predictive decision making, deep learning is beginning to be used in a variety of applications across finance.[13] And though deep learning models currently used in finance are not yet all that deep,[14] they are used to help identify fraudulent transactions as well as detect cyber attacks and potential security vulnerabilities. They streamline administrative tasks including check and document processing. Deep learning is being used in customer marketing - predicting behavior, attrition, churn rates, and reaction to ads.

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[10] Wall, "Some Financial Regulatory Implications of Artificial Intelligence."; "World Economic Forum, "Navigating Uncharted Waters."

[11] FSB, "Financial Stability Implications from FinTech."; Buckley et al., "The Dark Side of Digital Financial Transformation."

[12] Genberg, "Digital Transformation."

[13] Dixon, Halperin, and Bilokon, *Machine Learning in Finance*.

[14] Dixon and Halperin, "The Four Horsemen of Machine Learning in Finance."

It is used in asset management to improve operational efficiency, conduct sentiment analysis, and enhance investment returns.[15] It is starting to be used to improve credit risk management and underwriting decisions.[16] Along with new alternative data sources, it may become the foundation for alternative credit scoring systems to Fair Isaac Corporation (FICO) scores.[17] It is beginning to be used by insurance companies to improve the pricing and targeting of services to customers. Some institutions have explored the use of deep learning models to help comply with stress testing, liquidity, and capital regulations.

Traders have often been at the cutting edge of model experimentation, looking for marginal improvements in speed and predictive power. Deep learning is starting to be adopted in the capital markets by AI-based hedge funds, high frequency traders and the large asset management platforms. It is being used - along with alternative data - to generate so-called 'smart beta' factors for investing. It is used to predict buy-sell interest, securities lending and capital raising interest.[18] Deep learning also is starting to be used to help monitor markets for manipulation.[19]

Customer interfaces and interactions have been transformed by the deep learning subfield of NLP. It has been key to more intelligent and responsive chatbots and automated call centers, enabling more efficient and possibly more effective customer service. Robo-advisors and virtual assistants have become abundant, using NLP to interview customers, understand their investing preferences, and make trades in the market on their behalf.

These applications are not yet as dominant in finance as they have become in vision recognition or language processing. Having said that, deep learning is still likely to enjoy widespread adoption. After careful tuning, in many tasks it already comes out on top. Investing in the market - or playing blackjack against the house - using a tool that helps win 51% of the time can lead to significant profits. In time, with enhancements in computational power and model development, it is likely to demonstrate growing advantages vs. traditional analytics leading. It is likely then, even if one assumes only today's benefits, that much broader adoption is yet to come.

Deep learning models used by companies are both developed internally and sourced externally. AI-as-a-Service is a rising sector, with companies providing out-of-the-box, deep learning insights. In the insurance area, Cape Analytics[20] uses geospatial data to

[15] Tech at Bloomberg, "Bloomberg - Are You a Robot?"
[16] Caron, "The Transformative Effect of AI on the Banking Industry."
[17] Berg et al., "On the Rise of FinTechs – Credit Scoring Using Digital Footprints."
[18] Emerson et al., "Trends and Applications of Machine Learning in Quantitative Finance."
[19] van Liebergen, "Machine Learning: A Revolution in Risk Management and Compliance?"
[20] Business Wire, "Cape Analytics Secures Investment From State Farm Ventures."

provide deep learning powered real estate property valuations while Tractable[21] uses deep learning to automatically assess car accident damages and estimate repair costs. There are deep learning driven search engines like AlphaSense[22] that inform investment decisions as well as companies such as ZestAI[23] using deep learning models for credit underwriting. AI-as-a-Service providers are not just finance specific. Large tech incumbents such as Google, Baidu, Amazon, and Microsoft as well as early stage companies like OpenAI[24] offer plug-and-play deep learning services to finance companies to assist in everything from chatbots to document scanning.

Regulators have also begun to explore deep learning tools. Some agencies are using them to better detect system-level market manipulation and money laundering. Others are eyeing the technology to aid in automating model risk management oversight.[25]

Deep learning is still in the early stages of its penetration into the financial system. Some companies, specifically amongst FinTech start-ups and hedge funds, have centered their entire business model around it, while others, such as many community banks, brokers, and smaller asset managers have yet to adopt it over more traditional techniques. Promising automated predictive power at speed, though, it is likely that deep learning will grow to become a critical tool within most aspects of the financial system. Appropriate understanding of the technology with an informed view of its benefits and risks will be critical to the success of this new economy.

Deep Learning

Deep learning, a subfield of AI, first theorized in the mid-1950s, has truly established itself in the last 5 to 10 years. This is in part due to widespread advancements in processing power, the mass digitization and availability of big data, and fundamental conceptual innovations from theoretical computer scientists.

Deep learning relies on neural networks conceptually inspired by the structure of the brain. Figure 1 is a simple example of a neural network using nodes and edges to enhance computational power. Each node is represented by a circle, each edge connecting nodes is represented by a black line, and each layer is distinguished by a unique color. For each edge a weight is calculated that scales the data passing from one node to another. Each

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[21] Lomas, "Tractable Claims $25M to Sell Damage-Assessing AIs to More Insurance Giants."

[22] AlphaSense, "AlphaSense Partners With Leading Investment Banks To Provide Corporations With Broad Access To Wall Street Research."

[23] Zest AI, "Zest AI Secures Investment From Insight Partners To Accelerate Adoption Of Fairer And More Transparent Credit Underwriting Software Across Enterprise-Grade Lending Operations."

[24] Hao, "The Messy, Secretive Reality behind OpenAI's Bid to Save the World."

[25] Woodall, "Model Risk Managers Eye Benefits of Machine Learning."

node also has a bias, or offset, term added to it's inputs. Taken together, the weights and bias terms of a neural network - computed by the model - are called its parameters.

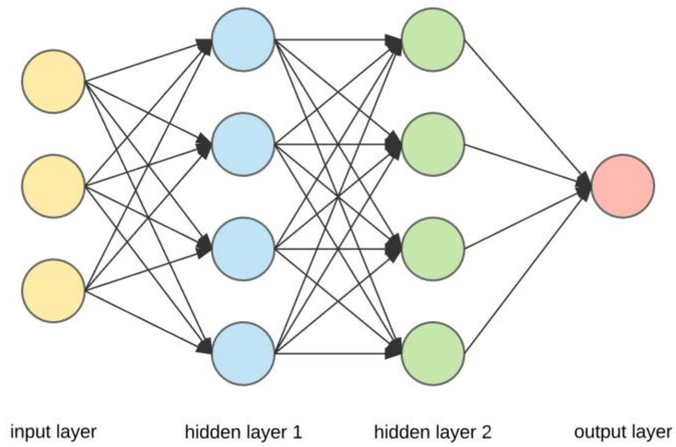

Figure 1. A diagram of a simple neural network. (Ognjanovski, "Everything You Need to Know about Neural Networks and Backpropagation — Machine Learning Made Easy….")

Through numerous iterations, a deep learning model adjusts parameters (the weights of the connections) to create the best approximation function between inputs and outputs. This process involves optimizing an objective function, often a reward function or a loss function, searching for the objective function's global minimum. As the size, dimensions, and complexity of the feature space grows, there emerge computational limitations that make locating the global minimum impossible. This leads to a need for regularization techniques to help the model generalize better and lessen the chance it becomes stuck in a local minima within the data set.

Despite the highly automated nature of neural networks, there is still much human involvement in the modeling process. Developers set what are known as the 'hyperparameters' including the number of layers, the number of nodes in each layer, the nodes' activation functions, data normalization techniques, and regularization techniques, amongst others. These hyperparameters are adjusted based on the problem class and computational resource trade-offs. Setting hyperparameters creates inductive bias, priming models before seeing data.

One of the fundamental hyperparameters is the selection of overall model type, such as deciding to use supervised learning, unsupervised learning, or reinforcement learning - each one suited to different problem types. Supervised learning - which utilizes labeled datasets - is best at prediction tasks such as calculating an individual's credit score. For classification problems such as identifying distinct clusters of customers for marketing purposes, unsupervised learning - using unlabeled datasets - is often used. Finally, reinforcement learning helps solve problems that can be modeled as games with rules and incentive structures. The human-beating chess machines and Google DeepMind's Alpha-

Go rely on reinforcement learning models.[26] Reinforcement learning may have particular usefulness for capital market trading and investing. After all, there may be no bigger multi-party competition in the world than the global stock and debt markets.

Key Characteristics

We now turn to exploring what might distinguish deep learning from traditional data analytic tools used within finance. These will be critical to our assessment of the potential effects deep learning might have on the fragility of the financial sector.

We find that nine key characteristics of deep learning - some of which might be said to be incremental - when taken together represent a significant departure from previous data analytics tools.

Five inherent characteristics:

- Hyper-dimensionality
- Nonlinearity
- Non-determinism
- Dynamism
- Complexity

Three existing challenges exacerbated by deep learning:

- Limited Explainability
- Bias
- Lack of Robustness

One overarching characteristic:

- Insatiable demand for data.

Inherent Characteristics of Deep Learning

We start with a review of five characteristics inherent to the design and structure of neural networks and deep learning.

Hyper-dimensionality

The hyper-dimensionality of deep learning both makes exploration for global minima both more difficult and computationally expensive and leads to model overfitting and instability concerns.

[26] Silver et al., "A General Reinforcement Learning Algorithm That Masters Chess, Shogi, and Go through Self-Play."

The parameter space of deep learning is exponentially larger than that of previous data analytics. As described above, the parameters of neural networks include the weights along the edges connecting nodes as well as the bias terms. Linear regression model parameters scale in number linearly with the number of variables included in the model. In neural networks, as the network grows in width (number of nodes in each layer) and depth (number of layers), the number of parameters grows exponentially. A simple multiple linear model with three input variables will have four parameters - one for each explanatory variable and one for the y-intercept constant. The neural network shown in Figure 1 despite also having three input variables has 37 parameters. GPT-3, the natural language generator engine of OpenAI, has 175 billion parameters.[27] The cutting edge of finance neural networks are not as deep as GPT-3, but can still have thousands to millions of parameters. More modeling parameters increases the likelihood that a model overfits, especially when there are orders of magnitude more parameters than input data points to train on.

Deep learning models also are able to use significantly more variables in their predictions than previous data analytics. As a result, deep learning experiences the curse of dimensionality - as the dimensionality increases, the volume of the feature space increases so fast that the available data becomes sparsely distributed. The space becomes larger, more complex, and diffuse, making clustering observations more difficult and locating global minima computationally impossible.

Nonlinearity

Nonlinearity of neural networks enables incredible predictive flexibility while also adding to complexity and the potential of overfitting predictive outcomes to data.

While some forms of traditional data analytics involve nonlinearity, for neural networks it is central to its design. Each node in a neural network has a nonlinear function called an activation function. The result or prediction of a neural network is a combination of the outputs of these nonlinear functions at each node. It is this nonlinearity that enables neural networks to map any relationship between inputs and outputs. Formally, this concept is known as the Universal Approximation theorem. Universal approximation is what allows deep learning to surpass previous modeling methods - there is no analog for prior techniques. At the same time, universal approximation also can lead to model overfitting. Regularization - a process of applying constraints to a model to encourage generalization and avoid overfitting - addresses this concern but also decreases accuracy.

Further, non-linearity can cause non-convex prediction spaces (which make exploration more difficult and the likelihood of settling in a local minima higher) and can increase

[27] Brown et al., “Language Models Are Few-Shot Learners.”; Chen and Chokshi, “16 Minutes on the News #37.”

complexity and reduce explainability, obfuscating the relationship between individual features and outcomes.

Non-determinism

Like Forrest Gump reaching into his box of chocolates, each time a neural network is trained, the developer does not know what they are going to get. The neural network may have a different set of parameters, thus a different algorithm, each time. For most previous statistical analysis tools, a particular modeling technique applied to a dataset would be deterministic - producing an identical decision algorithm every time it is trained. The impact of hyper-dimensionality and nonlinearity on the input space of deep learning makes calculating a single, global minimum computationally intractable. The input space is too large and complex to fully explore. In theory, with unlimited computational power, deep learning models could be deterministic. Instead, deep learning models rely on stochastic (random) elements in their optimization processes. One additional source of non-determinism emerges when the probabilistic output of one neural network is fed as an input into another neural network.

Dynamism

Deep learning models automatically and dynamically adapt, continuously optimizing themselves or 'learning', both before and after deployment. Each deep learning model has an optimization process to evaluate its performance while training and adjust its parameters to compensate for weaknesses.

Some types of deep learning such as reinforcement learning are specially designed to be dynamic, others optimize by interacting adversarially with other models. Many previous quantitative analysis tools would be effectively set after training, their algorithm and parameters unchanging. Some would be updated daily by modelers given the most recent batch of data. Going further than each of these, many deep learning models automatically rebuild themselves, what is known as 'continuous learning.' They adjust their parameters given more recent data and feedback without any human oversight, and automatically re-deploy to production.

Post-deployment optimization is particularly relevant for predicting financial data. Markets are dynamic systems with millions of actors continuously making millions of decisions, pricing and allocating risk and capital. Models that continually rebuild themselves against the latest relevant data, re-optimizing their parameters, adjusting their decision algorithm, and automatically deploying to production decisioning systems, are able to predict at higher accuracies.

Complexity

Neural networks are far more complex and intricate than previous quantitative analytics. While the math of neural networks to some is not necessarily complicated, the design features, hyper-dimensionality, and non-linearity of neural networks lead to a greater overall complexity.

Financial institutions compound the rising degree of complexity by linking together the decisions and predictions of many hundreds of their internal models. These models may feed directly into each other and or may use observations from other models to adjust their behavior.

Existing Challenges Exacerbated by Deep Learning

The following three characteristics – limited explainability, bias, and robustness - are challenges that arise from the previous five characteristics. These challenges are not new, existing already in previous methods of data analysis. But they are greatly accentuated by deep learning.

Limited Explainability

Deep learning models' decisions and outcomes are often unexplainable. Though lacking a universally accepted definition, explainability generally captures the notion that decisions and outcomes of a model can be explained to customers, management, and regulators. For example, model operators could give reasons why the model qualified one person for a loan while it recommended rejecting another.

But if deep learning predictions were explainable, they wouldn't be used in the first place. Instead, we would use linear models, table lookups, if-then statements, fixed rules and other, simpler approaches. The insights that come out of deep networks should inherently be challenging to interpret in terms accessible to humans. The system is learning its own latent representation of the data which may not align with a human mental model. This lack of traditional explainability poses diverse challenges at various levels within organizations and regulatory bodies. Human agency and traditional intervention approaches may be lost as a consequence of lack of model explainability and transparency. Current, post-hoc explainable AI techniques including LIME, SHAP, and ELI-5 have been devised to try to gain insight into how the models work, but they are each limited in their capabilities.[28] Regulatory responses to this limited explainability will need to consider the tradeoffs between the benefits of enhanced predictive power and the need for sufficient explainability.

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[28] OnClick360, "Interpretable Machine Learning with Lime+ELI5+SHAP+InterpretML."

Bias and Lack of Fairness

Fairness, the principle that every person will have equal access to financial services without discrimination on accord of race, color, religion, national origin, sex, marital status, or age, is a critical societal goal. It is key to financial inclusion, economic opportunity, individual dignity, societal cohesion, and trust in the financial system. Deep learning, however, may make it more difficult to ensure for such fairness. The outcomes of its predictive algorithms may be based on data reflecting historical biases as well as latent features which may inadvertently be proxies for protected characteristics. Further, the challenges of explainability, may mask underlying systemic racism and bias in deep learning predictive models. While not the subject of this paper, these are very important challenges for deep learning which will need significant work going forward.[29]

Problems associated with data analytics, finance and bias unfortunately are not new. In the 1960s, the civil rights movement and concerns about new financial technologies such as general merchant credit cards and related consumer credit data analytics as pioneered by FICO, led to new U.S. laws designed to ensure equal access, including the Fair Housing Act,[30] Fair Credit Reporting Act,[31] and Equal Credit Opportunity Act.[32] Subsequent regulation interpreting and enforcing these laws require various pre-process, in-process, and post-process checks. Pre-process validation requires direct intervention in the data to remove discriminatory variables and ensure the data is well distributed and representative. In-process techniques impose restrictions into and onto the model. Post-process review requires correcting a model after training, if it becomes clear it is biased.

Technical and regulatory approaches to the challenges of bias have yet to fully emerge for deep learning models. Considerations may raise tradeoffs between predictive accuracy and fairness. A deep learning model that is thought to be accurate also may bring with it more bias, capturing and cementing historic inequities amongst protected groups. Addressing fairness likely will require context specific considerations, as the tradeoffs may vary in consequence along the spectrum of deep learning applications.

Lack of Robustness

The ability of neural networks to extract latent features from datasets is both a source of incredible predictive power and a potential source of weakness. These latent features are often unobservable, but highly predictive. Even after being uncovered, their impact on predictions remains difficult for human modelers to understand.[33] Small perturbations

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[29] Johnson, Pasquale, and Chapman, "Artificial Intelligence, Machine Learning, and Bias in Finance."
[30] "Fair Housing Act."
[31] "Fair Credit Reporting Act."
[32] Kreiswirth and Tabor, "What You Need to Know about the Equal Credit Opportunity Act and How It Can Help You."
[33] Ilyas et al., "Adversarial Examples Are Not Bugs, They Are Features."

to these latent input features can result in dramatically different, high-confidence model predictions[34] and interpretations[35] that are later deemed incorrect under human scrutiny. Well-targeted latent feature perturbations are also known to be easily transferable between models,[36] introducing interconnectedness concerns, as well as opening a potential avenue for adversarial or cyber attack. A lack of robustness may also emerge from overfitting, a natural consequence of the incredible approximation capability of deep learning models. Research from Tsipras and Madry, et. al. suggests that addressing these concerns may involve an inherent tradeoff between robustness and accuracy.[37]

Overarching Characteristic

The eight characteristics just discussed - five intrinsic to neural networks and three challenges accentuated by neural networks - contribute to a ninth characteristic - deep learning's insatiable demand for data.

Demand for Data

As the size of a training data set increases, deep learning accuracy increases as a power law.[38] Deep learning models' insatiable demand for data is a consequence of their hyper-dimensionality and the techniques necessary for enhancing explainability, reducing bias, and increasing robustness. It is fed by the explosion of big data and alternative data sources.

Alternative data isn't new - when Galileo Galilei presented his telescope to the Venetian Senate in 1609, it provided a new way to see inbound ships and helped merchants get an early glimpse of what might change market prices.[39] Four centuries later the Internet, the digital economy, smartphones, wearables, telematics, and the global positioning system (GPS) similarly allow financial market actors to see data sooner and get a jump on emerging risks. Datasets are growing exponentially in height and width - both the number of variables and the number of observations.

Act 2

Systemic Risk

Now in Act 2, we turn to consider a major environmental challenge for deep learning - systemic risk and channels of fragility in the financial system. Systemic risk is the risk

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34 Nguyen, Yosinski, and Clune, "Deep Neural Networks Are Easily Fooled."
35 Ghorbani, Abid, and Zou, "Interpretation of Neural Networks Is Fragile."
36 Goodfellow, Shlens, and Szegedy, "Explaining and Harnessing Adversarial Examples."
37 Tsipras et al., "Robustness May Be at Odds with Accuracy."
38 Hestness et al., "Deep Learning Scaling Is Predictable, Empirically."
39 Fowler, "Galileo and the Telescope."

that events or failures involving one actor, either a firm or individual, or one market sector propagate out to negatively affect the broader financial system and the economy at large. Time and time again, economies around the globe have witnessed such events when weaknesses in the banking or financial sector spill out to hurt the general public - with millions of bystanders losing their jobs, homes and savings.

Throughout the nineteenth and early twentieth century numerous economic crises emerged from the financial sector. Modern risk management, financial regulation, deposit insurance and central bank backstops have addressed many of the earlier sources of such systemic risk. The basic fundamentals of finance, however, remain - from time to time risks internally built up and concentrated within the financial sector harmfully spill out to the rest of an economy. Most recently we witnessed the devastating ramifications of the 2008 financial crisis, with millions of people losing their jobs and homes, in the USA and around the globe.

The real-world consequences of the periodic crises have motivated rigorous research on systemic risk and underlying firm-level risk sensitivities from both the academic and regulatory communities. Many regulatory organizations around the globe have focused on classifying the attributes of firms that may make their failure more likely to propagate widely. Established by the Dodd-Frank Act in 2010, the Financial Stability Oversight Council (FSOC) viewed the systemic risk of an institution through three channels: the exposure transmission channel, the asset liquidation transmission channel, and the critical function or service transmission channel.[40] Federal Reserve Governor Daniel Tarullo in 2011, identified four ways that distress at one firm can propagate to the rest of the system, in what he called: 'domino effect', 'fire-sale effect', 'contagion effect', and 'discontinuity of critical function' effect.[41] The European Systemic Risk Board (ESRB) intermediate objectives of macro-prudential policy around (i) excessive credit and leverage; (ii) excessive maturity mismatch and market illiquidity; (iii) direct and indirect exposure concentration; (iv) systemic impact of misaligned incentives; and (v) resilience of infrastructure.[42] The Financial Stability Board (FSB), a group representing the G20 nations, identified five broad categories by which to evaluate institutions that may materially impact systemic risk: "size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global (cross-jurisdictional) activity, and complexity."[43] Building upon these five categories, the Basel Committee of Banking Supervision identifies thirteen underlying indicators for assessing systemic risk.[44]

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[40] Leydier et al., "Sullivan & Cromwell Discusses FSOC Changes to Nonbank SIFI-Designation Guidance."

[41] Tarullo, "Regulating Systemic Risk."

[42] The European Systemic Risk Board, "Recommendation of the European Systemic Risk Board of 4 April 2013 on Intermediate Objectives and Instruments of Macro-Prudential Policy."

[43] FSB, "Guidance to Assess the Systemic Importance of Financial Institutions."

[44] Basel Committee on Banking Supervision, "Global Systemically Important Banks."

There also is a very extensive and important body of academic research concerning systemic risk within the financial sector which generally categorizes sources of fragility into one of three primary channels. The first is about uniformity or monocultures, including that which arise from herding.[45] The second relates to interconnectedness.[46] The third concerns the effect of gaps in the regulatory frameworks themselves.

The academic and regulatory categorizations are different in some ways, but similar in most ways. For the purposes of this research, we've organized our exploration of deep learning's effect on financial stability through the three broad channels proposed by the academic literature that encapsulate the perspectives from both camps.

Herding

Herding is characterized by multiple individual actors making similar decisions, either rational or behavioral, resulting in a monoculture. Uniformity in finance can also arise when many actors in the financial sector rely on a centralized dataset or model.[47] Most recently herding developed in the subprime mortgage market was observed prior to the 2008 financial crisis. This is not a new problem, though. For example, the 1970s Latin debt crisis exposed herding behavior in lending to Latin American countries and the intervening four decades featured other crises induced by herding including the U.S. Savings and Loan crisis of the late 1980s, the dot-com bubble, and the quant crisis of 2007. Outside the U.S., both Japan and Scandinavia suffered banking crises due to credit bubbles that burst.

Network Interconnectedness

Network interconnectedness refers to either the emergence of a dependency on some concentrated infrastructure, data, or operational service provider or an intricate web of firm-to-firm relationships, contractual, financial and otherwise, which propagates risk across a system. In 2009, Andrew Haldane, the former head of Financial Stability at the Bank of England, described the financial system as a complex, adaptive network with similarities to both tropical rainforests and populations during the spread of disease. According to Haldane, such networks can be both fragile and robust at the same time with feedback mechanisms adding to fragility during times of stress.[48] The 2008 subprime mortgage crisis had aspects of both of these categories of connectedness - a central dependency developed around credit rating agencies, as well as a rise in network

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[45] For example, Bikhchandani and Sharma, "Herd Behavior in Financial Markets."; Gennaioli and Shleifer, *A Crisis of Beliefs*.

[46] For example, Acemoglu, Ozdaglar, and Tahbaz-Salehi, "Systemic Risk and Stability in Financial Networks."; Yellen, "Interconnectedness and Systemic Risk: Lessons from the Financial Crisis and Policy Implications."

[47] Kremer and Nautz, "Causes and Consequences of Short-Term Institutional Herding."

[48] Haldane, "Rethinking the Financial Network."

interconnectedness in the derivatives market, resulting in rapid spreading of failures. The Euro area debt crisis, peaking in 2012, saw government debt problems in Greece trigger similar problems in Portugal, Spain, Cyprus, and other member countries.

Regulatory Gaps

On multiple occasions, gaps in regulatory frameworks have allowed systemic risks to build up and spill out to the broader economy. These gaps can arise when innovations outpace updates in regulatory regimes; when firms conduct financial activities outside of established regulatory perimeters; and when policy makers reform rules or fail to enforce those which are on the books in an effort to lessen regulatory burdens.

The 2008 financial crisis was a product of numerous regulatory gaps. Technological advancements in asset securitizations such as collateralized debt obligations (CDOs), derivatives such as credit default swaps (CDS), faulty credit ratings processes, and weakened mortgage underwriting standards outpaced legal constraints, obscuring risks in the housing, derivatives, and mortgage markets. Risks also built up within sectors which were either lightly regulated, such as state licensed finance companies or hedge funds, or unregulated, such as the swaps markets. Earlier U.S. crises, from the Great Depression to the Savings and Loan crisis, also involved regulatory gaps.

Act 3

Transmission Pathways

We now turn in Act 3 to investigate our hypothesis that broad adoption of deep learning in finance is likely to threaten financial stability in meaningful ways. To explore whether the growing maturity of deep learning might awaken systemic risks' stormy clouds, we accompany the technology along five pathways:

- Data
- Model Design
- Regulatory
- Algorithmic Coordination
- User Interface

For each pathway, we examine how the nine key characteristics of deep learning may lead to increased systemic risk through underlying firm-level risk sensitivities and the channels of herding, network interconnectedness, and regulatory gaps. We also explore how systemic risks may manifest differently in developing economies with less advanced technology, finance, and regulation.

We conclude that deep learning is likely to increase systemic risks, though possibly not equally along each of these transmission pathways. The data, model, and regulatory pathways pose more readily evident risks. The algorithmic coordination and user interface pathways less so, though each may develop fragility challenges with time.

It is our hope that this framework can help the public sector, private sector, policy community, and academia evaluate appropriate trade-offs and mitigate the risks that deep learning poses to financial and economic stability.

Data Pathway

Deep learning may lead to increased financial instability and systemic risk through a data pathway. The insatiable demand for data by deep learning models is likely to lead to both increased uniformity and network interconnectedness through reliance on concentrated data aggregators, increased sensitivity from the growing use of alternative data with short sample sizes, and potential exposure to latent feature risks.

The tendency towards concentrated data sets with sometimes dominant influence is due in large part to data economies of scale, scope, and network effects.[49] Whether in the resource intensiveness of gathering, cleaning, and labeling large datasets or the advantages which accrue to a platform at the center of a network or market ecosystem, the spoils in data aggregation often goes to the few. If, as it is said, 'data is the new oil', then it might be said that there are many in the finance and tech industries aspiring to be this era's John D Rockefeller and Standard Oil.

There are many such examples throughout financial history - whether the 15th century Medici Bank,[50] J.P. Morgan of the late 19th century, or FICO at the center of consumer credit data in the late 20th and early 21st century. Finance presently has a number of such aggregators as well. In the payment and credit space FinTech start-ups such as Plaid (agreed to be acquired by Visa)[51] and Credit Karma (agreed to be acquired by Intuit)[52] built multi-billion dollar valuations based on data aggregation. At the time of this writing, however, it has been reported that both of these potential mergers are being closely reviewed by Department of Justice officials for antitrust considerations.

Intercontinental Exchange (ICE), a leading exchange company as well as data provider, recently acquired Ellie Mae for $11 billion.[53] Ellie Mae is said to be the "leading cloud-

[49] Carriere-Swallow and Haksar, "The Economics and Implications of Data."

[50] De Roover, *The Rise and Decline of the Medici Bank*.

[51] Rudegeair, "WSJ News Exclusive | Visa's Planned Purchase of Plaid Faces Antitrust Scrutiny at the Justice Department."

[52] LaComb, "Elimination of Digital DIY Tax Prep Disrupter Should Concern Antitrust Law Enforcers."

[53] ICE, "Intercontinental Exchange Enters Definitive Agreement to Acquire Ellie Mae from Thoma Bravo."

based platform provider for the mortgage finance industry."[54] ICE already owns Simplifile[55], the largest mortgage e-record company in the US, and MERS, which has a national registry of over 75% of the US mortgage market.[56] It has been reported that ICE now has a single system of record for close to half of the U.S. mortgage market.[57]

Internationally, WeChat Pay and AliPay are highly concentrated payment processing and financial services platforms, each servicing over 800 million consumers.[58] They each also leverage payment data for a broad range of non-financial services. In what is yet another reminder of the significant potential value of data networks, Ant Group, parent to Ant Financial and AliPay, announced the world's largest initial public offering in October 2020, valuing the company at over $300 billion.[59] While these data aggregators became dominant prior to broad adoption of deep learning, their advantages will continue to compound as deep learning models demand more and more data.

Multiple sectors deploying deep learning have already seen coalescence around large, critical datasets. ImageNet is a dominant dataset for academic research in the field of vision recognition research. Google Maps, Google Earth and their affiliate Waze dominate the route optimization business and related traffic datasets.[60] In the field of autonomous vehicles there are the Waymo and Level 5 datasets, among others.[61] Breast cancer researchers often use the Breast Cancer Wisconsin (Diagnostic) Data Set.[62] NLP models for text processing and generation commonly use Common Crawl, a dataset with snapshots of all websites from the last 20 years - effectively representing all of the text on the internet.[63]

Firms recognize that controlling a proprietary dataset can provide competitive advantages. In the credit card industry, for instance, detailed consumer data is closely guarded. Even if in the future there still exist many firm based proprietary datasets, there are likely to be both shared underlying datasets as well as actors who have been able build concentrated dominant datasets.

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54 "Ellie Mae® Digital Lending Platform™ Named 2020 Finovate Finalist for 'Best Digital Mortgage Platform' | Ellie Mae."

55 Content Solutions Team, "Simplifile Provides a Standardized Platform to Connect Lenders, Settlement Agents, Notaries and Counties."

56 Meyer, "ICE Makes Its Move in $15tn US Mortgage Market."

57 Seeking Alpha, "Intercontinental Exchange - A Look Post Ellie Mae."

58 Zhai and Zhu, "China's Central Bank Urges Antitrust Probe into Alipay, WeChat Pay - Sources."

59 Zhong, "Ant Group Set to Raise $34 Billion in World's Biggest I.P.O."

60 Copeland, "Google Parent's Stock Soars on Gangbuster Earnings."

61 Choudhury, "Top 10 Popular Datasets For Autonomous Driving Projects."

62 Ak, "A Comparative Analysis of Breast Cancer Detection and Diagnosis Using Data Visualization and Machine Learning Applications."

63 Jayson, "Extracting Data from Common Crawl Dataset."

Some jurisdictions are moving towards nationally coordinated, highly concentrated datasets and data driven decision making. WeChat and AliPay in China, for example, have each built dominant concentrated datasets.[64] China has also created a social credit scoring system that aggregates granular data on a wide array of activity from payment transaction details to geographical movement data and dating profile information. While this may lead to better price discovery and efficient exchange, it may also lead to "the view" of "the economy in a box."

The European Commission has proposed common "data spaces" to aggregate data from industry and other sources - hand delivering data concentration.[65] For many developing nations, concentration is likely to emerge because there are a limited number of companies with the economic and data resources capable of building robust deep learning models. First movers may grow disproportionately large in the data space.

The likely concentration of data - either by data providers or within dominant financial sector participants - adds both uniformity and network interconnectedness risks. Models built on the same datasets are likely to generate highly correlated predictions that proceed in lockstep, causing crowding and herding. The risk of uniformity - and thus systemic risk - increases as the data provider moves further up the value chain, from simply providing raw data; to standardized, normalized, and regularized data; to summarized data; to analytics and insights generated from the data. Highly concentrated data providers, similar to cloud storage companies, are a source of network interconnectedness risk - new single points of failure to the network.

Exploring the data pathway also highlights systemic risk arising from the growing use of alternative data with short sample sizes - thus engendering uniform risk of many firms being exposed to out of sample risk. Alternative data sources used to feed deep learning predictive models, including our social media engagement, Internet use, wearable data, telematics data, and GPS and smartphone data simply do not have long enough time horizons to cover even a single, complete financial cycle. With these datasets, it is not as if firms can go back and digitize old data - most of these new data simply went unrecorded. Models built using these datasets may be fragile due to their reliance on limited time series datasets.[66]

Further, deep learning models have a propensity to rely on latent - as opposed to observable - features. This makes it difficult to identify the features and variables driving predictive decisions. Not knowing which features are driving predictive outcomes makes it challenging to ensure that the dataset is sufficiently representative of those particular

[64] Zhai and Zhu, "China's Central Bank Urges Antitrust Probe into Alipay, WeChat Pay - Sources."
[65] European Commission, "Data Sharing in the EU – Common European Data Spaces (New Rules)."
[66] Wall, "Machines Learning Finance."

features. This limited explainability is further aggravated by the out of sample risks discussed above.

Model Design Pathway

A review of historical examples from financial crises demonstrates that models can lead to systemic risks through the uniformity channel, the network interconnectedness channel, as well as due to regulatory gaps. As hypothesized by Khandani and Lo, the 2007 quant crisis was a consequence of model herding.[67] Quantitative investing funds unknowingly developed highly similar optimization functions, leading to crowding in the sector and an eventual collapse. The 2008 crisis exposed the over-reliance of the financial sector on the three main credit agencies Standards & Poor's (S&P), Moody's, and Fitch to underwrite collateral debt obligations (CDOs).[68] These agencies used models with similar methodologies and evaluations of mortgage debt, all of which proved to be faulty. It is hypothesized that herding and crowding in high frequency algorithmic trading is partially responsible for causing flash crashes, highly volatile days with rapid breaks in security pricing. [69]

Initially, in deep learning's complex and non-deterministic model environment, differences in initializing models and hyperparameters may lead to a greater diversity of outcomes. Further, finance being less transparent may make it less likely that model design converges rapidly. As the financial sector gains more experience, though, and deep learning becomes more fully adopted, there may emerge academic and industry consensus on hyperparameter selection, such as for the type of learning model, the size and shape of the network, and the loss function. Online deep learning competitions hosted by Kaggle have already demonstrated a preference for Stochastic Gradient Boosted Trees (SGBT), CNN, RNN, and, increasingly, Transformers.[70] There may also be a human factor contributing to model design uniformity. There simply are not that many people trained to build and manage these models, and they tend to have fairly similar backgrounds. In addition, there are strong affinities among people who trained together: the so-called apprentice effect. For all of these reasons, the inductive bias of models may become more uniform over time.

There may also emerge model uniformity due to standardization of regulatory requirements addressing the challenges of explainability, fairness, and robustness. This could be particular fairness formulas to obey or hyperparameter settings that enable greater explainability. Additionally, as evidenced by the quant crisis of 2007, a more

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67 Khandani and Lo, "What Happened to the Quants in August 2007?"

68 Hill, "Why Did Rating Agencies Do Such a Bad Job Rating Subprime Securities?"

69 Lo, "Moore's Law vs. Murphy's Law in the Financial System."; Kirilenko and Lo, "Moore's Law versus Murphy's Law."

70 "Kaggle."

intractable source of uniformity can arise when institutions operating in the same sector optimize for similar profit functions.[71] This may result in herding of behavior without any of the model design overlap described above. Any of these sources of consensus would result in a loss of model diversity.

A combination of uniformity and network interconnectedness is likely to arise from a dependency on external service providers for models or model design. Whether at the lowest or highest ends of technological sophistication, from basic programming language access to full back office support software, there is a growing reliance on external software providers. There are software packages to make building custom deep learning models easier including Kubeflow, TensorFlow, and Keras. In addition, the AI-as-a-Service sector has expanded, providing both fully trained and deployable deep learning models as well as deep learning generated insights. These providers include traditional technology hub services firms such as BlackRock's Aladdin,[72] newer risk analytics firms such as Two Sigma's Venn,[73] or AI research startups such as OpenAI. There are significant economies of scale to deep learning due to the significant computational power needed to train large, dense networks. Large institutions - whether Big Finance or Big Tech - may be able to afford the resources necessary to build their own custom models from the ground up. Smaller financial institutions, however, are likely to find that their own economics lead them to use an AI-as-a-Service provider, as they cannot afford to build and train all of their own models. This is likely to result in concentrated AI-as-a-Service providers, heightening the chance of uniform approaches to model development and potential uniformity in predictive decisions.

Model uniformity is not new. For instance, it is well known that most financial market participants have come to rely on Black-Scholes-Merton option pricing model. Using deep learning models may lead users to implicitly believe that they have a differentiated edge, though it may not be true in particular sectors due to uniform reliance on third-party model frameworks. This may create yet another form of potential fragility to the financial system.

Model uniformity may be an even more acute problem in developing economies. The pool of computer scientists for building in-house models may be limited, leading to an increased reliance on third-party service providers and FinTech services. Widespread third-party model dependence also may not be appropriate for the countries they are being deployed in, as the data they were trained on may be of limited relevance.

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71 Litterman, "Robert Litterman, Sussman Award Lecture: Part 3, September 2013 - YouTube."

72 Henderson and Walker, "BlackRock's Black Box: The Technology Hub of Modern Finance."

73 Orr, "Two Sigma Built an Invite-Only Competitor to BlackRock's Aladdin. Now, Any Institution Can Get It."

Additional systemic risk emerges from the inherent characteristics of deep learning. The non-linearity and hyper-dimensionality of deep learning models make them likely to be more sensitive within a certain input range, but less likely to perform well outside of that range. These models will also often be trained on short data sets related to alternative data. Thus, deep learning models may more frequently end up in local minima and have larger out of range tails, leading to so-called "fat tails" and a higher prominence of "black swan" events.[74] Furthermore, deep learning models' inherent challenges of robustness may accentuate existing systemic risks related to adversarial or cyber attacks.

Lastly, it is likely that regulatory gaps have emerged and may grow significantly with the greater adoption of deep learning in finance. Deep learning has developed rapidly, and regulators have yet to update regulatory regimes for the use and management of this new technology. This is evidenced in the U.S. by the fact that the most relevant comprehensive model risk management guidance was published in 2011. Even when regulators update model risk management guidance, it is entirely possible that the inherent characteristics of deep learning, including challenges of explainability, complexity, and robustness would leave significant gaps for regulators using insufficient tools - akin to using foggy wave glasses - to supervise these models' behavior.

The use of deep learning models for capital, liquidity, and firm-wide risk management may be particularly challenging. Adequate and appropriate capital, liquidity and risk management underpins the safety and soundness of the entire financial system. To the extent that firms are permitted to use deep learning for these critical risk measures, an inherently hard to explain technology may underpin how much capital and liquidity is maintained by systemically important institutions. This would reduce regulators' understanding of the risks in the financial system they are responsible for overseeing.

Regulatory Pathway

We now turn to consider how deep learning may heighten financial fragility through regulatory frameworks or possible gaps. These gaps could emerge from how regulatory requirements are internalized in deep learning models, regulatory arbitrage by which activities migrate to less regulated actors, and as a result of how regulators use deep learning models in their supervision process.

It is possible that the manner in which deep learning models internalize regulatory requirements leads to greater standardization and uniformity. As with any new technology, the public sector is grappling with how to ensure for deep learning's responsible use in critical applications. Given the significance of the deep learning challenges - explainability, fairness, and robustness - and its growing adoption in critical

[74] Taleb, *The Black Swan*.

areas of finance, financial regulators will be called upon to help set standards for its use. Such standards may risk being uniformly internalized by model developers.

Network interconnectedness may arise from a concentration of vendors providing applications to satisfy legal and regulatory compliance for explainability, fairness, and robustness challenges. This could lead to monomodels and a central dependency on a service provider. In a similar manner to how many asset management companies have become reliant on BlackRock's Aladdin, it is possible that firms, particularly FinTech startups, come to rely on a small selection of outside vendors to comply with regulatory standards.

The adoption of deep learning in finance is also likely to be uneven, with some FinTech startups or AI-as-a-Service firms - both generally less regulated - moving quite quickly. Large regulated financial institutions moving with pace, yet possibly more focused on the challenges of explainability, fairness and robustness. Smaller, community institutions - not having the resources to independently adopt deep learning - may move more slowly. Over time, such tiered adoption between regulated and less regulated firms and between large and small firms may lead to regulatory arbitrage by which certain activities within the financial sector migrate to less regulated actors. Furthermore, financial stability may be affected by this bifurcation, with large parts of the financial sector outside of a core system that is more deep learning enabled.

Regulators also are actively investigating how to adopt deep learning for their own purposes in supervising institutions. Uses may eventually include fraud detection, anti-money lending detection, stress testing, and macroprudential monitoring. Regulatory deep learning models may unknowingly promote uniformity in the agents they regulate.[75] The regulatory models may struggle to account for nuance, penalizing unusual approaches by agents with higher capital requirements or more stringent oversight. Regulatory deep learning models will be exposed to similar challenges of explainability, bias, and robustness as models for producing credit and insurance provision predictions. Robustness concerns are likely to be particularly significant. If a regulatory oversight model is perturbed or fooled, it could cause an outsize risk to the system. It also may be possible for adversaries to intentionally distort these regulatory models.

Algorithmic Coordination Pathway

Deep learning systems adapt to new data patterns. Given the wealth of market signals within finance - prices, rates, volumes, bids, offers - by design one firm's models are going to be adapting to the signals from other firm's models. This is, by nature, coordinating

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75 Danielsson et al., "Model Risk of Risk Models."

with other market participants behaviors. Models may add fragility through an invisible, machine-based, form of coordination and possible collusion.

The OECD describes how the risk of collusion in a market is affected by the number of firms in the market, the barrier to entry for a firm, the transparency of the market, and the frequency of interactions in the market.[76] Deep learning models are less explainable, more complex, and more dynamic than other models. Accordingly, market transparency is likely to decrease, due to both explainability and complexity challenges. The frequency of interactions is likely to rise, as deep learning models are more dynamic than previous data analytics, constantly learning from recent events.

There is the possibility that algorithmic coordination would lead to both increased network interconnectedness due to models at different financial firms communicating with each other, as well as leading to a uniformity in behavior - herding or crowding. These models can process more data than previous analytics due to their hyper-dimensionality and insatiable demand for data. Therefore, they can incorporate data streams concerning their competitors actions and model their behavior. Certain deep learning model types such as reinforcement models and generative adversarial networks (GANs) may be particularly well suited to this task. A variety of research already exists to suggest these risks presently exist. Some research has found that Q-learning models, a type of reinforcement learning, are capable of developing a strategy for ensuring supra-competitive pricing in a controlled experimental setting.[77] Other work demonstrates that in a market driven by algorithmic traders, "even a high degree of attention to overfitting on the part of traders is unlikely to entirely eliminate destabilizing speculation."[78] Evidence exists that high frequency trading algorithms manipulate the order book with unexecuted orders (possibly related to "ghost liquidity" and "spoofing") as a form of messaging between agents.[79] The financial system is in essence one of the largest "games" in the world, with a constant flow of information and a built-in reward system. It is likely given the attributes of the financial system and deep learning, that these models, whether intentionally or unintentionally, will coordinate and communicate with each other to better optimize their results in this "game."

Deep learning also may expose a regulatory gap in that supervision tools used to monitor for algorithmic coordination amongst previous data analytics may not be able to discern deep learning coordination until after the fact. Without the ability to understand and

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76 OECD, "Algorithms and Collusion: Competition Policy in the Digital Age."

77 Klein, "Autonomous Algorithmic Collusion."; Calvano et al., "Artificial Intelligence, Algorithmic Pricing and Collusion."

78 Georges and Pereira, "Market Stability with Machine Learning Agents."

79 Kirilenko and Lo, "Moore's Law versus Murphy's Law."

explain the inputs and outputs of the deep learning models, regulators will be at a disadvantage to discover and counteract algorithmic coordination.

User Interface Pathway

Deep learning NLP-based UI has led to many platforms providing automated advice and recommendations for investing, lending, and insurance offerings. This can concentrate views, judgments, decisions, and actions which could create systemic risk.

Deep learning is used widely in the UI and customer interaction space. This spans from uses as benign as check and document processing all the way to highly consequential processes, with chatbots providing investment advice. Bank of America,[80] Capital One,[81] and JP Morgan Chase[82] have each rolled out proprietary virtual assistants while Fidelity and Vanguard[83] have started to adopt robo-advisory services. Many FinTech startups, such as Betterment, Ellevest, Sofi, and Wealthfront rely heavily on such chatbots and virtual assistants.[84] Future research is needed to explore the potential effects of uniformity in virtual assistant software and other user interface applications further up the decision-making value chain. There also is risk that advice provided by each virtual assistant becomes standardized and commoditized, causing herding of client decision making, at least within a firm, but potentially across an entire asset class or sector.

As virtual assistant software and advanced NLP software continues to improve, they may increase network interconnectedness and concentration. Already Google, Baidu, Amazon, Ant, and OpenAI have some of the most advanced chatbots, virtual assistants, and textual analysis tools on the market. Widespread adoption of these services may create a new system dependency and source of systemic risk.

Coda

Policy Considerations

We've explored in this paper how broad adoption of deep learning within the financial system is likely to lead to greater fragility by increasing uniformity, network interconnectedness, and regulatory gaps. We mapped nine key characteristics of deep learning - hyper-dimensionality, nonlinearity, non-determinism, dynamism, complexity, limited explainability, bias, lack of robustness, and demand for data - against these

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80 "Bank of America Offers Clients a More Complete, Personalized View of Their Financial Relationship Through Enhanced Mobile App Experience."

81 Streeter, "Capital One Doubles Down on Chatbot with New Features and Marketing."

82 Jones, "Are Consumers Ready for Conversational Digital Banking Experiences?"

83 Snel, "Fidelity, Vanguard at Top of Robo Heap."

84 Meola, "Top Robo Advisors in 2020."

channels through five pathways. Now we turn to considering how one might mitigate the systemic risks that our hypothesis suggests will emerge from greater adoption of deep learning models.

While current model risk management guidance - generally written prior to this new wave of data analytics - will need to be updated, it will not be sufficient to address risks of herding, network interconnectedness, or potential future regulatory gaps. These model risk management tools, along with many other regulations, primarily address firm level or so-called micro-prudential risks. Many of the challenges to financial stability that deep learning may pose will require new thinking on system wide or macro-prudential policy interventions. Policy interventions may need to be tailored to context, as the financial activity to which deep learning is applied will have an important bearing on the systemic risks possibly emanating from such use as well as the tools appropriate in the policy tool kit. Moreover, there may be a need to plan in advance for potential ex post, crisis management interventions.

Micro-Prudential Risk Mitigation

Internal Mapping

For financial institutions and regulators, a mapping of institution-wide dependencies on internal data and software may be a productive first step. While each model is currently subject to model risk guidance, financial institutions are often running hundreds if not thousands of models. These models often connect directly to other models and use the same internal datasets and the same latent features. This mapping process may help reveal concentrated dependencies within each financial institution.

Model Hygiene

Next, as some other researchers have recommended, regulators should update the existing framework for model risk management within the financial sector to better capture deep learning models.[85] The U.S.'s model risk management guidance, SR 11-7, from 2011,[86] ECB's TRIM from 2017,[87] and Canada's E-23[88] from 2017, among others, were drafted with previous linear modeling techniques less dependent upon hyper-dimensionality, dynamism and complexity. The Monetary Authority of Singapore released principals for the use of "AI and Data Analytics."[89]

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85 McPhail and McPhail, "Machine Learning Implications for Banking Regulation."; Richman, von Rummell, and Wuthrich, "Believing the Bot - Model Risk in the Era of Deep Learning."

86 Parkinson, "SR 11-7: Guidance on Model Risk Management."

87 European Central Bank, "Guide for the Targeted Review of Internal Models (TRIM)."

88 CRISIL, "Canada Aligns."

89 Bertholon-Lampiris and Nadège Grennepois, "Building a Robust Model Risk Management Framework in Financial Institutions."

Existing model risk management guidance generally speaks to model design, governance, and external verifiability. Deep learning models, however, are less explainable, dynamic after deployment, and overwhelmingly complex. Existing model hygiene regulation is quite focused on documentation of the development process, in contrast to model outcomes. Regulators may wish to look into more technical ways of managing risk, such as adversarial model stress testing or outcome-based metrics focusing less on how the model arrives at its prediction and more on model behavior once deployed.

Additionally, the heightened challenges of robustness with deep learning models in comparison to linear modeling may suggest regulators pay particular attention to these new risks.

Firm Buffers

Another conceptual framework for managing risk in the financial system which prescribes buffers for such use. There is usually a quantity of loss absorbing capital - equity - determined by regulators and set aside depending on the particular risks assumed. Banks have minimum capital ratios expressed in percent of (risk-weighted and unweighted) assets, while insurers and pension funds have required solvency ratios. Regulations such as loan-to-value (LTV) limits for mortgages, margin for derivatives, and minimum "haircuts" on collateral for repos provide loss-absorbing buffers.

Policymakers might wish to consider these frameworks in light of the use of deep learning models in different financial activities. Deep learning models used for administrative or document processing tasks are not as risky as deep learning models used to commit capital, underwrite credit or insurance or use balance sheet assets. Regulators might consider if changes to loss absorbing buffers might be appropriate for banks and insurance companies using deep learning for particular activities within credit or insurance underwriting, and capital market trading. Further, authorities might consider add-on or minimum buffers - building in some margin of error - if banks were to determine risk weights or capital based upon deep learning algorithms. The U.K., Belgian, Finnish and other authorities have recently done so for traditional model-based risk weights for mortgages.[90]

Currently, many financial firms run their deep learning models in parallel with linear models as a proxy for explainability, a form of a buffer. Regulators might consider requiring that financial institutions continue running such back-up models and processes that do not rely on deep learning in case the models fail or act in unexpected ways. There also may need to be consideration how best to prepare the system for the eventuality of a deep learning model failing due to a lack of explainability.

[90] Regulatory News, "PRA Proposes to Amend SS11/13 on Internal Ratings-Based Approaches."

Regulatory Diversity

We also have discussed how regulations can lead to certain types of uniformity in model design. Regulations meant to address explainability, fairness, and robustness concerns - even if written to be technologically neutral - may lead to uniformity. The rise of neural networks, and the various ways they may add fragility to the system, highlights the trade-offs of uniformity vs. possibly actively promoting diversity. Regulators might address this tradeoff when crafting regulation by proposing multiple ways to internalize regulations while remaining compliant with guidance.

Macro-Prudential Risk Mitigation

Having considered possible mitigations at the micro-prudential level, we now consider possible interventions to address market or system-wide uniformity, network interconnectedness or regulatory gaps.

External Mapping

To help mitigate systemic risks a mapping of each firm's external dependencies on data and software providers could be quite an important initiative. This would involve each institution investigating their own material dependencies, including but not limited to data, software, AI-as-a-Service and cloud providers. The results of such mapping could be shared with firm-wide senior risk managers, firm boards, and regulators. Once aggregated and viewed from the network level, such external mappings could provide a better - though likely still incomplete - picture of systemic dependencies and complex interconnections of the system. Further, regulators could coordinate stress tests in which different institutions simulate actual transactions to understand how deep learning algorithms might interact under plausible adverse market scenarios.

Material External Dependencies

Material or system wide dependencies on third party AI-as-a-Service providers, such as Google, OpenAI, and others, may call for requirements that such external models comply with updated financial system model risk management regulation. Similarly, material or system wide dependencies on data aggregators may suggest bringing such data aggregators within transparency, cybersecurity, and credit reporting agency requirements. The risk management and transparency of external providers can be affected either: 1) indirectly through regulating the material contractual arrangements between financial institutions and such third party providers; or 2) directly by bringing the third party providers into some regulatory fold.

Financial regulators have grappled with similar challenges related to dependencies on cloud computing. These new dependencies, though, could be even more significant.

Cloud computing, at its base, provides storage and possible additional software capabilities. AI-as-a-Service can provide full end-to-end automated decision making.

In addition, to the extent that concentration develops, competition (antitrust) officials may wish to consider appropriate policy interventions, including close reviews of significant mergers and anti-competitive behavior.

Horizontal Reviews

A framework of horizontal reviews could be helpful to assess the extent to which there may develop uniform decision making across the network. In the U.S. there are currently at least two horizontal risk monitoring programs. The Shared National Credit (SNC) program, established in 1977, was designed to capture the largest loans (over $100 million) held across multiple financial institutions.[91] Bi-annual reports are publicly released regarding trends within these loans and regulators have on occasion used the data to modify supervisory guidance. Additionally, regulators in the U.S.[92] and a number of other countries use horizontal reviews of risk management practices and capital planning as part of supervisory activities and periodic stress tests.

Additional horizontal reviews related to deep learning models use, predictive decision making, and outcomes by financial institutions, could reveal herding amongst market participants or network interconnectedness to material external dependencies.

Network Buffers

When material uniform risk exposures or external dependencies on data aggregators or AI-as-a Service providers emerge across a financial system regulators could consider using available policy levers to address such systemic risks. Regulators could consider policy levers, from writing public economic reports concerning findings, changing supervisory guidance, reforming regulations, or reassessing capital buffers regarding such shared holdings or dependencies.

There could be a requirement that financial institutions continue running back-up traditional data analytics models in case the models fail or act in unexpected ways. Where deep learning is used widely in trading and asset management, regulators could coordinate stress tests and war games in which different institutions simulate actual trading through their test systems under various plausible adverse scenarios. This could help understand how deep learning algorithms might interact to an actual market shock.

Developing World

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[91] Office of the Comptroller of the Currency, "Shared National Credit Report."
[92] Board of Governors of the Federal Reserve System, "Supervision and Regulation Report."

The systemic risk and financial fragility challenges of deep learning adoption in finance are likely to be more acute in developing countries as it is more likely that there will be dependencies on concentrated service providers. Thus, this may be an area to which the international community wants to pay closer attention, working to assist countries in preventing potential problems early. Possible macro-prudential policy interventions also may be guided within the purview of the International Monetary Fund and the World Bank.

Ex-post Interventions

Furthermore, policymakers may wish to consider how best to plan in advance for potential ex-post, crisis management interventions. Such considerations might include some form of circuit-breakers, so-called "kill switches," and the ability to recover. Central banks may wish to consider in which circumstances deep learning model shocks might lead them to use their lender or market maker of last resort. Lastly, it may be appropriate to call for certain material AI-as-a-Service providers to the financial sector to maintain recovery and resolution plans for their models.

Call to Action

The micro and macro prudential approaches considered above, even if implemented in total, may be insufficient to the task of addressing uniformity, network interconnectedness, and potential regulatory gaps. The dedication and ingenuity of academia, public officials, and the private sector will be needed to best understand the magnitude and scope of potential challenges that broad adoption of deep learning may pose to systemic risk as well as to frame appropriate tools for mitigating said challenges.

Conclusion

This paper explored the use of deep learning in the financial sector and its possible effects on financial stability at future stages of adoption. It reviewed key characteristics of deep learning - features of hyper-dimensionality, non-linearity, non-determinism, dynamism, and complexity; challenges of explainability, bias, and robustness; and an insatiable hunger for data. The advent of deep learning – which combines these nine characteristics together – marks a fundamental discontinuity enabling significant opportunities for enhanced efficiency, financial inclusion, and risk mitigation. Over time, however, broad adoption of deep learning may also increase uniformity, interconnectedness, and regulatory gaps, leaving the financial system more fragile. Existing financial sector regulatory regimes - built in an earlier era of data analytics technology - are likely to fall short in addressing the risks posed by deep learning. Adequately mitigating such risks will require additional research and discussion. We hope that the framework we have developed might help contribute to such dialogue.

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