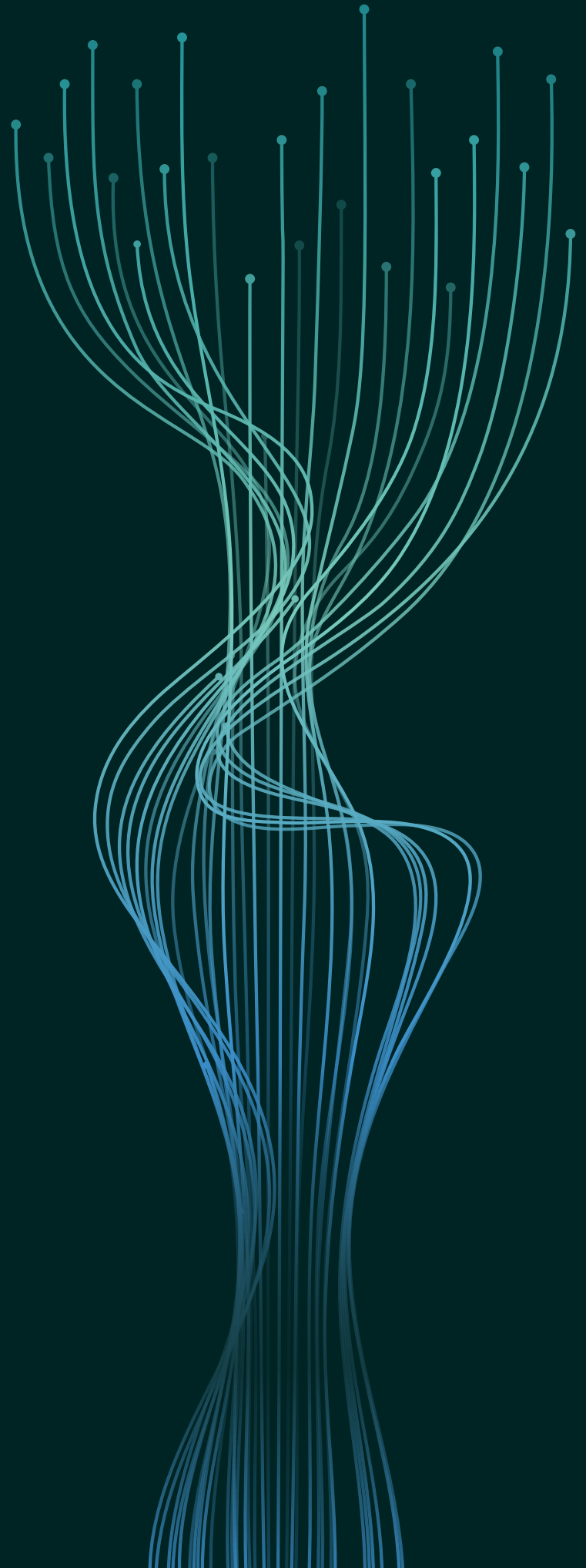




Stanford University
Human-Centered
Artificial Intelligence



OCTOBER 2021
INDUSTRY BRIEF

An initiative of the HAI Corporate Members Program

AI and Financial Services



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INDUSTRY BRIEF

Introduction

The financial impact of COVID-19 rippled through all levels of society. Record unemployment spikes jeopardized the ability of many to provide for their families' basic needs. The economic toll of the pandemic's first year counted roughly 200,000 permanent establishment closures above normal levels.¹ The federal government enacted over \$4 trillion in relief packages to stave off the worst of an economic fallout. This disruption to business-as-usual challenged the foundations of our financial infrastructure, and in doing so, accelerated increased technology adoption not only in response to the current crisis, but in anticipation of the next. Some have identified this as a pivotal turning point: fintech investing has surged to a record high of 1,280 deals totaling \$39 billion in 2021, up from 1,078 deals and \$20.4 billion invested in all of 2020.²

Looking ahead, there remain many transformative opportunities to embed AI-enhanced capabilities in current and new systems — across credit assessment, risk management, portfolio optimization, financial health, government service administration, and customer engagement. In this brief, we highlight some of the latest Stanford research pointing to potential avenues for further innovation in these areas. We also introduce some of the ongoing efforts to ensure the responsible development of these nascent technologies. We hope that industry practitioners will find this information helpful in their efforts to build a more robust, inclusive, and resilient financial infrastructure.

HAI's mission is to advance AI research, education, policy and practice to improve the human condition. To learn more about HAI, visit hai.stanford.edu

[1] Crane, L., Decker, R.A., Flaaen, A.B., Hamins-Puertolas, A., & Kurz, C. (2020). Business Exit During the COVID-19 Pandemic: Non-Traditional Measures in Historical Context. *Social Science Research Network*, 2020, 1-43.

[2] Kocalitcheva, K. (2021, October 18). Fintech's record year. *Axios*.



AI & Financial Services

1 Credit & Lending

4 Financial Health

2 Risk Management

5 Government & Policy

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Virtual Assistants & Conversational Interfaces

1 Engaging Interfaces

2 Efficient Learning

1 AI & FINANCIAL SERVICES CREDIT & LENDING



★ WHAT'S NEW?

Industry is exploring applications of machine learning to credit assessment and lending, in part motivated by the belief that such approaches can improve the efficiency, fairness, and inclusiveness of existing lending practices. In response, researchers have turned their attention to both the technical development of these algorithms as well as the responsible use and potential consequences--positive and negative--of their applications.

📌 WHY DOES THIS MATTER NOW?

During the COVID-19 pandemic, complaints to the Consumer Financial Protection Bureau (CFPB) reached record levels as both consumers and financial institutions grappled with the economic fallout. Consumers' top complaints concerned incorrect credit reporting and debt collection,¹ suggesting the challenge financial companies faced amidst disruption of their traditional customer data sources (e.g., debt and mortgage repayment rates). These events have prompted interest in algorithmic tools and alternative data sources (e.g., on education, employment, and rental longevity) to develop more robust decisioning strategies² as well as a call from industry for greater regulatory clarity on the use of AI and alternative data in underwriting to promote both innovation and financial inclusion.³

👁️ EYE ON CAMPUS

Researchers on campus are...

- Finding that predictive algorithms for credit scores are less accurate for minorities, based on the largest ever study of real-world mortgage data. They showed that lenders face more uncertainty when assessing default risk of historically underserved groups in US credit markets and that this information disparity is a quantitatively important driver of inefficient and unequal credit market outcomes.
- Evaluating emerging practices in lending to explain, document, and govern the responsible use of machine learning in credit underwriting. They seek to provide insights critical for firms looking to evaluate and adopt these tools and policymakers looking to establish governing standards and principles.

- Developing an algorithm for budget-constrained decision makers screening loan applicants that maximizes a standard measure of social welfare. Their approach applies beyond lending to other resource allocation contexts, such as assessing household wealth in order to target government subsidies.

- Identifying blind spots that might arise from unconscious bias and historical inequalities over the course of developing, deploying and operating AI systems that automate consumer lending processes. They explore issues such as discrimination by proxy, disparate impact, transparency and explainability, and control over personal data.

- Refuting the relationship between borrower search behavior and mortgage pricing predicted by standard search models and suggesting an alternative more suitable for consumer credit markets. One implication of their model is that if big data and AI allow lenders to screen and reject borrowers with more precision, such innovation could lead to a large redistribution from borrowers to lenders.



“In the financial sector, extensive legal and regulatory frameworks force consideration of questions about trustworthiness of AI/ML more holistically and at an earlier stage than may occur elsewhere. More research is urgently needed to understand how regulatory and legal frameworks need to adapt to an era where underwriting decisions are taken by AI/ML algorithms. In particular, we need to develop AI/ML governance tools that support compliance with fair lending and prudential risk management requirements, as well as the ability to provide accurate adverse action notices to consumers.”

-Laura Blattner,
Assistant Professor
of Finance;
HAI Faculty Affiliate

[1] U.S. Public Interest Research Group Education Fund. (2021, March). Consumers in Peril. [2] Brue, M. (2021, March 31). How Digital Finance Is Changing The Credit Game In The Covid-19 Era. Forbes. [3] NCRC. (2021, June 29). Statement on Request for Guidance on Implementation of Disparate Impact Rules under ECOA.



2 AI & FINANCIAL SERVICES RISK MANAGEMENT

★ WHAT'S NEW?

Researchers are developing methods that can help institutions understand and mitigate risk more effectively in response to unexpected events or shocks. Among their innovations are methods for generating data to model events in real time and for identifying factors in novel data sets explaining individual stock returns within a larger picture of systemic risk.

📌 WHY DOES THIS MATTER NOW?

In 2019, 60% of financial-services sector respondents to a McKinsey Global AI Survey reported embedding at least one AI capability (with 25% reporting leveraging machine learning to detect fraud and support underwriting and risk management).¹ Come 2020, a subsequent study found that COVID-19 had affected model reliability across all bank functions and operations. It explained, “Most models are almost by necessity designed to predict a stable future. In truth, the real failure is not that banks used models which failed in this crisis but rather that they did not have fallback plans to manage when the crisis did come.”² As financial institutions continue to embed more AI capabilities post-pandemic, they may wish to place greater emphasis on resilience in the face of instability, for example by building greater transparency into model outcomes or by supplementing existing data sources.

👁️ EYE ON CAMPUS

Researchers on campus are...

- Developing a way to study economic crashes, despite their rarity, by utilizing large-scale surveys of Vanguard clients and generating data in real time to understand the evolution of investor beliefs, trading, and markets. Their method enabled them to observe in almost real time the financial shock and sudden downturn in response to COVID-19 in early 2020.
- Using a novel high-frequency data set to shed light on factors that explain individual stock returns and contribute to our understanding of systematic risk. Their findings, including that there is sizeable risk compensation from exploiting the “reversal pattern” they document, may have direct implications for investment strategies.
- Developing efficient numerical methods for the analysis of large pools of loans and asset-backed securities backed by such pools. For a broad class of machine learning models of loan-level risk in discrete time, they prove a law of large numbers and a central limit theorem for the pool-level risk.

[1] McKinsey. (2021, May). Building the AI Bank of the Future. [2] Laurent, M., Plantefève, O., Tejada, M., & van Weyenbergh, F. (2020, September 16). Banking models after COVID-19: Taking model-risk management to the next level. McKinsey & Company.



“AI is rapidly gaining importance in risk management and investment as machine learning tools allow us to capture the complex dependencies of financial outcomes, for example asset prices, on high dimensional information sets. However, the low signal-to-noise ratio and only moderately large size of many financial data sets limit the use of off-the-shelf prediction methods. Successful tools for risk management and investment therefore must include economic constraints and subject specific knowledge in the machine learning methods. A carefully designed problem formulation can combine the best of both worlds: The flexibility and robustness of machine learning methods and the relevance of economic restrictions.”

-Markus Pelger, Assistant Professor of Management Science & Engineering



3 AI & FINANCIAL SERVICES CAPITAL MARKETS

★ WHAT'S NEW?

Researchers newly employ optimization techniques and more recently developed machine learning techniques to tackle challenges in the capital markets domain. On the one hand, machine learning approaches like deep learning seem a natural fit given the high dimensionality and complex functional dependencies of financial data. On the other hand, researchers are also finding that certain benefits of optimization methods (e.g., interpretability), already tested and found highly reliable in other domains, also make them highly suitable for real-world financial contexts.

📌 WHY DOES THIS MATTER NOW?

Banks were challenged during the COVID-19 pandemic to adequately respond to high volatility and uncertainty in financial markets. Many faced problems calculating value at risk across their asset classes and adjusting valuations.¹ More advanced models may help with providing more accurate and timely assessments in the future. Looking ahead, Insider Intelligence predicts that robo-advisors that automate the investing process by relying on algorithms and other data to build and manage portfolios will be managing \$4.6 trillion by 2022.² Building better AI capabilities now may make firms both more resilient in managing their own portfolios and prepared for future retail consumer demand.

👁️ EYE ON CAMPUS

Researchers on campus are...

- Illustrating how stratified models are interesting and useful in portfolio construction and finance as compared to neural networks. While such models can contain a large number of parameters, they are fully interpretable and auditable.
- Proposing a data-driven portfolio selection model that integrates side information (e.g., macro-economic factors, the company's financial statements, historical trading data), conditional estimation, and robustness using a flexible framework of distributionally robust optimization. They show that the distributionally robust portfolio allocation with side information problem can be reformulated as a finite-dimensional optimization problem.
- Proposing a unifying conceptual framework for statistical arbitrage and developing a novel deep learning solution, which identifies asset commonality and time-series patterns from large panels of returns and firm characteristics. Their optimal trading policy outperforms all benchmark approaches and is economically interpretable.
- Using deep neural networks to estimate an asset pricing model for individual stock returns. Their model uses an innovative no-arbitrage condition and outperforms out-of-sample all benchmark approaches in terms of Sharpe ratio, explained variation and pricing errors and identifies the key factors that drive asset prices.

[1] Applying machine learning in capital markets: Pricing, valuation adjustments, and market risk. (2020, November 2). McKinsey & Company. [2] Intelligence, I. (2021, July 30). Top 10 Best Robo Advisors in 2021. Insider Intelligence.



“AI, broadly interpreted to include machine learning, statistical modeling and simulation, optimization, and sequential decision making under uncertainty, has long been used in some areas of finance and capital markets such as portfolio construction for quantitative hedge funds. It is now poised to have large impact in many others. Research is needed to identify these application areas and to develop or adapt the methods to handle them.”

**-Stephen Boyd,
Samsung Professor
of Engineering;
Professor of Electrical
Engineering; HAI
Faculty Affiliate**



4 AI & FINANCIAL SERVICES FINANCIAL HEALTH



★ WHAT'S NEW?

Researchers are using AI and big data to help consumers make better financial decisions, researchers more effectively understand and target interventions at factors contributing to poverty, and policymakers evaluate the efficacy of relief programs. Their contributions demonstrate the potential for leveraging AI and the right data sets to effectively improve financial health across specific contexts such as retirement planning, health insurance selection, and debt management.

📌 WHY DOES THIS MATTER NOW?

Two-thirds of Americans are not financially healthy, according to the Financial Health Network.¹ Moreover, the gap between those who are financially health and those who are not is only widening:² Half of non-retired adults say that the economic impact of COVID-19 will make achieving their long-term financial goals harder.³ There is now both a great need and opportunity for financial technology to improve financial health outcomes for individuals.

👁️ EYE ON CAMPUS

Researchers on campus are...

- Using a dataset from Equifax of 20 million borrowers' credit scores, payment histories, delinquencies, deferrals, and geographic locations to quantify the magnitude of relief from debt forbearance during the COVID-19 pandemic. Their findings indicated that the relief went to those who truly needed it and that one-third of those who were given forbearance actually kept making payments, appearing to use the relief like a credit line to draw on if their situation became dire.
- Building a model to compute the optimal age to claim social security benefits. Their findings could help investment advisors and individuals make more optimal wealth management decisions in anticipation of retirement.
- Developing an algorithm that helps consumers make better decisions when it comes to their health insurance. Those who used their algorithm were 36% more likely to change to better prescription plans and reported more satisfaction with the process of choosing health insurance. Extrapolating their results to 25M people enrolled in Medicare Part D, savings could reach \$680M.
- Using machine learning to analyze the factors involved in poverty and some of its consequences, creating a fine-grained classification of kinds of poverty. The output of their analyses could contribute to predictive models that help target policies and interventions more precisely.



“During COVID-19, we rapidly mobilized to analyze the impact of financial relief on American households. Key to the effort was the ability to integrate large and diverse datasets — we drew from credit bureaus, the U.S. Census, Zillow, the Department of Labor, the IRS, the Small Business Administration, and other real-time data sources on employment rates, mobility patterns, and COVID case rates across geographies. This enabled a fine-grained study where we analyzed millions of households and identified the kinds of individuals that were helped by relief efforts as well as those that are still vulnerable. Effectively leveraging big data in real time can contribute to this kind of deeper understanding of the financial situation of households and firms, which can in turn inform better policy and product decisions.”

—Amit Seru, Steven
and Roberta Denning
Professor of Finance

[1] Financial Health Network. (2020, October). U.S. Financial Health Pulse. [2] 'A tale of two Americas': How the pandemic is widening the financial health gap. (2020, October 13). Fortune. [3] Horowitz, J. M., Brown, A., & Minkin, R. (2021, March 5). A Year Into the Pandemic, Long-Term Financial Impact Weighs Heavily on Many Americans. Pew Research Center's Social & Demographic Trends Project.



5 AI & FINANCIAL SERVICES GOVERNMENT & POLICY

★ WHAT'S NEW?

Researchers are developing algorithmic tools that may aid government policymakers, regulators, and administrators. Some of their findings can help inform financial policies by providing more accurate and robust financial estimations. One group explores how federal agencies can leverage AI to conduct audits or adjudicate benefits more efficiently and effectively. Others suggest an approach that can help authorities identify corruption from financial data.

Researchers are also examining how policies regulating the financial technology industry may impact big data-driven innovation in the space.

📌 WHY DOES THIS MATTER NOW?

Just at the IRS, federal funding cuts over the last decade have resulted in 14% fewer employees, 20% fewer enforcement staff, and the lowest level of individual and business audits in 10 years.¹ During COVID-19, many functions of government across healthcare regulatory entities, jobless benefit and small business agencies, and social service units were overwhelmed.² Compared to human attention and oversight, AI algorithms are significantly more scalable and computationally powerful. They thus have the potential to complement human teams and make existing strained operations more wide-reaching, productive, and effective. Firms may take inspiration from these applications for their own operations. They may also want to pay close attention to policies with downstream implications for the fintech ecosystem more generally.

👁️ EYE ON CAMPUS

Researchers on campus are...

- Working with the IRS to apply AI to tax collection. Specifically, they are developing an active-learning system to decide which tax returns to audit. The hope is that an algorithmically driven selection process will apply IRS resources more fairly and effectively than a random selection process.
- Examining how AI will transform government, starting with an analysis of the Social Security Administration's use of AI tools to adjudicate disability benefits cases and the Securities and Exchange Commission's use of AI tools to target enforcement efforts under federal securities law,

- Developing robust machine learning methods for better yield curve estimation, which is a foundation for central bank policy making. Their estimates outperform current benchmarks with lower pricing errors and yield fitting errors and they contribute a new benchmark data set.
- Documenting "disguised corruption" by Chinese banks attempting to influence local bureaucrats and evade regulators. Though their analysis is based on data on 185,000 credit card customers from a major Chinese bank, they suggest this issue could extend to other emerging economies as well.
- Using machine learning to analyze over 24,000 U.S. finance patents, finding a surge in innovation from information technology firms and others outside the financial sector. They also find that regulatory pressures may be shifting the geography of financial innovation.

[1] Waikar, S. (2020, June 8). How an Active Learning System Can Help Close the U.S. Tax Gap. Stanford HAI.
[2] Eggers, W., O'Leary, J., & Chew, B. (2020, April 16). Governments' response to COVID-19. Deloitte Insights.



"Government agencies are increasingly experimenting with AI to improve service delivery, ensure compliance, process claims, and inform policy. The government's use of AI will place particular emphasis on accountability, transparency, and explainability, and much research activity will go into ensuring that AI is adapted consistent with values of public governance."
—*Daniel Ho, William Benjamin Scott and Luna M. Scott Professor of Law; Professor of Political Science; Associate Director of HAI*



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Closer Look: Virtual Assistants & Conversational Interfaces

Any AI-first strategy for reimagining customer engagement must consider virtual assistants and conversational agents. Here, we take a closer look at some of the underlying research that could power these customer experiences.

1 VIRTUAL ASSISTANTS & CONVERSATIONAL INTERFACES: ENGAGING INTERFACES

★ WHAT'S NEW?

Researchers are exploring how to improve the human experience of virtual assistants and conversational interfaces from different angles across engagement and content generation. One team examines how the descriptive metaphors of such agents impact users' ultimate perceptions and interactions with them. Others investigate how to make such agents more human-like, for example by mimicking our ability to weave in factual content.

📌 WHY DOES THIS MATTER NOW?

Heading into 2020, just 4% of mid-size banks and credit unions had deployed a chatbot.¹ By the end of 2020, 13% had and another 16% intended to invest in chatbots in 2021.¹ At the same time, surveys have found that 86% of customers prefer to interact with a human agent and 71% would be less likely to use a brand if it didn't have customer service agents available.¹ Thus, although chatbot adoption is on the rise, the technology has yet to rival human agents. Further advances are likely needed to improve the experience of these technologies in practice.

👁️ EYE ON CAMPUS

Researchers on campus are...

- Studying how descriptions and metaphors shape user expectations in their experiences of conversational agents. They find that agents described as highly competent (e.g., “a record-breaking, five-time winner of the Turing Test”) are received negatively while those projecting warmth (e.g., “sympathetic ear”) elicit greater cooperation and positive engagement from users.
- Winning second place in the latest Amazon Alexa Prize Challenge for the “Chirpy Cardinal” chatbot. They highlight the potential for large-scale pre-trained neural generative models such as GPT-2 to enable more natural and engaging conversations.

- Developing algorithms to automatically detect and reduce “subjective bias”, which they define to occur when language that should be neutral and fair is skewed by feeling, opinion, or taste, consciously or unconsciously in text. The methods can provide insights for those seeking to mitigate the potential for bias in generated dialog.

- Developing agents that can weave factual content into conversations as naturally as humans. They develop a method for selecting responses that exhibit human-like acknowledgement of their counterpart’s utterances.

[1] Shevlin, R. (2021, June 28). Every Bank Needs A Chatbot (Or Two) For Its Digital Transformation. Forbes.



“In many industries, particularly ones like financial services, it is crucially important to have a good customer relationship. This spans everything from engendering trust to creating empathy and warmth. We believe that next generation dialog agents need to not only be able to accurately do tasks and transactions on your behalf but to provide engaging, sympathetic and responsive conversation. The challenge for industry will be in learning how to build and make use of the language and world knowledge and contextual understanding that will enable these conversational socialbots in specific applications.”

–*Christopher Manning, Thomas M. Siebel Professor in Machine Learning; Professor of Linguistics and of Computer Science; Associate Director of HAI*

2 VIRTUAL ASSISTANTS & CONVERSATIONAL INTERFACES: EFFICIENT LEARNING

★ WHAT'S NEW?

Researchers are developing new approaches for addressing the challenge of adapting existing large language models for customized contexts. They tackle problems across working with limited annotated datasets, enabling structured reasoning over broad ranges of knowledge, designing domain-specific language instructions, and enhancing performance with limited compute.

📌 WHY DOES THIS MATTER NOW?

In July 2020, OpenAI released GPT-3, the largest known language model of the time. GPT-3 impressed many for its ability to write uncannily human-like text without supervision. Its capabilities were estimated to be extensive, with potential applications to chatbots, text summarization, search, and code generation.¹ However, there are many documented limitations to repurposing such large language models in practice and they often require substantial engineering effort for specific commercial use cases.² Thus, while GPT-3 represents a recent and important technological milestone for language models, there is still significant progress to be made.

EYE ON CAMPUS

Researchers on campus are...

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- Launching a new Center for Research for Foundation Models (CRFM), an interdisciplinary initiative born out of HAI to advance the study, development, and deployment of foundation models (e.g., BERT, GPT-3, CLIP, Codex) -- models trained on broad data at scale that are highly adaptable to a number of downstream tasks, including virtual assistants.
- Building a general-purpose, interactive agent, RUSS, that can master web service tasks such as redeeming a gift card or resetting a user's password. They suggest web agents like RUSS can help individuals who are visually impaired, less technologically advanced, or otherwise preoccupied (e.g., with driving) in navigating the web.

- Proposing a new end-to-end model for question answering that combines pre-trained large language models and knowledge graphs. They address the challenge of enabling interpretable and structured reasoning over a broad range of knowledge.

HAI
RESEARCH

- Proposing a new pre-training task for language representation learning that results in better performance on downstream tasks compared to masked language modeling pre-training methods such as BERT. They see particularly strong gains with small models, finding that a model trained on one GPU for 4 days outperformed GPT (trained using 30x more compute) on the GLUE natural language understanding benchmark.

[1] Tamkin, A., & Ganguli, D. (2021, February 5). How Large Language Models Will Transform Science, Society, and AI. Stanford HAI. [2] Vincent, J. (2020, July 30). OpenAI's latest breakthrough is astonishingly powerful, but still fighting its flaws. The Verge.



“There is an emerging paradigm shift for building AI systems based on a general class of models we call foundation models (e.g., GPT-3, BERT). In just the last few years, their scale and scope have exploded. Their widespread deployment will inevitably transform AI applications across industries from finance to healthcare to law. Companies that can effectively leverage the impressive capabilities of foundation models – including processing different modalities, allowing for fast adaptation, and allowing for natural language interaction – are likely to gain significant competitive advantages. However, much remains to be understood about both the underlying technical principles and downstream societal impact of these models. Industry will thus have a critical role to play not only in realizing the commercial potential of foundation models, but also in joining the conversations shaping their responsible development and use.

–Percy Liang, Assistant Professor of Computer Science; HAI Faculty Affiliate



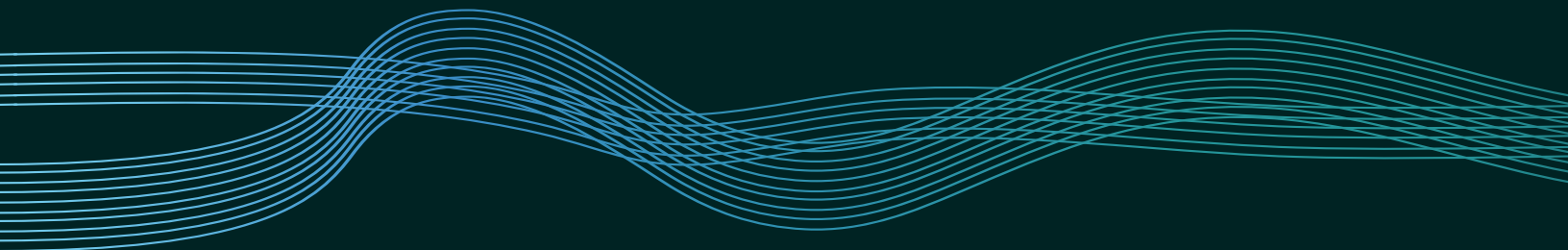
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Industry Take

Industry will play a critical role in scaling the applications of AI research. For this reason, it is a goal and privilege of HAI to convene stakeholders from industry in addition to those in academia, government, and civil society to address the technical and societal challenges posed by AI.

Leading venture investors, positioned at the frontlines of startup innovation, can provide a unique perspective on the impact and role of AI technologies in the financial services.





Industry Take



“We are particularly excited about fintech in emerging markets. In more mature markets, we have already seen huge successes in leveraging AI to democratize access to high-quality financial services. In emerging markets, however, adoption of digital payments or even basic banking services has lagged behind smartphone penetration and pervasive digital touchpoints. We see here a prime opportunity for innovators to start from ground zero and translate working solutions into AI-first financial infrastructures unencumbered by legacy systems.”

–*Elizabeth Yin, General Partner, Hustle Fund*



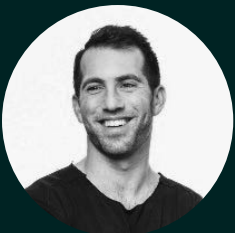
“AI has many financial services applications that bend the cost curve of various players along the value chain. From transaction fraud monitoring to regulatory compliance to credit underwriting, AI is enabling businesses to transact at lower marginal cost and therefore bring services to underserved populations. Given the scale of global monetary flows and profit pools, small movements in things like conversion and approval rates can drive large-scale change.”

–*Matt Heiman, Managing Director, Vetamer Capital*



“AI is quickly permeating every corner of fintech and will transform the way businesses and consumers make everyday financial decisions. We see AI impacting each vertical of fintech, from payments to lending to investing to insurance. AI models will soon overtake humans in tasks including underwriting borrowers, approving corporate expenses, detecting payments fraud, and pricing complex insurance products.”

–*Merritt Hummer, Partner, Bain Capital Ventures*



“Financial services exist to enable people and businesses to transact across space and time at scale. Historically, intermediaries are required to judge and price risk to facilitate transactions using imprecise models, high-level data, and human judgement. This process is prone to bias and inaccuracy, which leads to higher prices and limited access. AI and machine learning have the power to use source data to better price risk across lending, insurance, payments, and eventually investing, which, if deployed correctly, will increase access to historically underserved groups and significantly reduce intermediary fees, providing an accelerant to the entire economy.”

–*Seth Rosenberg, Investor, Greylock Partners*



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Corporate Engagement

Stanford HAI seeks corporate members who will enable it to lead with the unparalleled interdisciplinary breadth and excellence of Stanford University, and a laser focus on human-centered development and deployment of AI technology. We invite engagement from companies that share our mission to advance AI research, education, policy, and practice to improve the human condition.



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Are you prepared for the next wave of change? THINGS YOU SHOULD KNOW.

\$15.7T

in value will be added
by AI to the global
economy by 2030¹

\$341B

are forecasted to be
spent by companies on AI
solutions in 2021 alone²

52%

of Fortune 500 companies
were extinguished by
digital disruption between
2000 and 2014³

\$1.4B

in annualized value can
be gained by AI-led
transformation of a
Fortune 500 company⁴

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1 PwC's Global Artificial Intelligence Study: Sizing the prize. (n.d.) PricewaterhouseCoopers, Retrieved March 1, 2021.

2 IDC Forecasts Companies to Spend Almost \$342 Billion on AI Solutions in 2021. (2021, August 4). IDC: The Premier Global Market Intelligence Company.

3 Wang, R. (2014, February 18) "Research Summary: Sneak Peeks From Constellation's Futurist Framework And 2014 Outlook On Digital Disruption," Constellation Research.

4 Incorporate enterprise A.I. now or risk getting disrupted. (n.d.) Fortune + C3. Ai, Retrieved March 1, 2021.



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The potential annual value of AI and analytics is projected to be up to **\$1 trillion** for global banking.¹

Financial services leaders recognize this future, with **more than half** believing AI will create the biggest change in how financial services are delivered over the next two years.²

Does your organization have the vision and capacity to be an industry leader in this transformation?

[1] McKinsey & Company, Global Banking Practice. (2021, May 8). Building the AI Bank of the Future.

[2] PwC. (2019). Global Fintech Report 2019.



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Become a corporate member today.

50% of companies
are likely to miss the
window of opportunity.¹
Let's talk.

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Corporate Members Program
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Panos Madamopoulos,
Managing Director for Industry
Programs and Partnerships

¹ Jacques Bughin, "Wait-and-See Could Be a Costly AI Strategy," MIT Sloan Management Review, June 15, 2018.



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HAI CORPORATE AFFILIATE PROGRAM

JOIN THE INAUGURAL PROGRAM AREA: **FINANCIAL SERVICES & AI**

The upcoming HAI Corporate Affiliate Program, which launches this fall, brings industry together with Stanford faculty, research, policy and education for members who are interested in topics at the intersection of Financial Services & AI.

For the Financial Services Program Area, focus areas will include:



**AI-Augmented
Decision Making in
Financial Services -
Michael Bernstein**



**AI Governance
and Regulation in
Financial Services -
Laura Blattner &
Jann Spiess**



**Design and
Regulation of
Financial Markets -
Darrell Duffie**



**AI Augmented
Communication in
Financial Services -
Jeff Hancock**



**VR/AR Training
for Consumers
and Banks -
Jeremy Bailenson**



**Social Impact and
Financial Services -
Susan Athey**



**Optimization in
Financial Services -
Stephen Boyd &
Yinyu Ye**



**Digital Economy -
Erik Brynjolfsson**



**AI Safety -
Clark Barrett**



**AI in Investment,
Lending and Trading -
Markus Pelger &
Kay Giesecke**



**AI in Risk
Management
and Insurance -
Jose Blanchet**



**Cybersecurity
& Digital Risk
Management in
Financial Services -
Andrew Grotto**

The potential annual value of AI and analytics is projected up to **\$1 trillion** for global banking¹

More than half of Financial Services leaders believe artificial intelligence will create the **biggest change** in how financial services are delivered over the next two years²

According to the 2018 Growth Readiness Study, asset managers who are embracing big data and analytics are found to be growing their revenue **1.5 times** more quickly than the rest of financial services³

¹ <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/the-executives-ai-playbook?page=industries/banking/>

² <https://www.cbinsights.com/research/jpmorgan-chase-consumer-banking/>

³ <https://www.fisglobal.com/-/media/fisglobal/files/pdf/report/the-readiness-report-2018-the-pursuit-of-growth.pdf>



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LEVEL \$1M per year

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Appendix



Artificial Intelligence Definitions

Intelligence might be defined as the ability to learn and perform suitable techniques to solve problems and achieve goals, appropriate to the context in an uncertain, ever-varying world. A fully pre-programmed factory robot is flexible, accurate, and consistent but not intelligent.

Artificial Intelligence (AI), a term coined by emeritus Stanford Professor John McCarthy in 1955, was defined by him as “the science and engineering of making intelligent machines”. Much research has humans program software agents to behave in a clever way, like playing chess, but, today, we emphasize agents that can learn, as human beings navigating our changing world do.

Autonomous systems can independently plan and decide sequences of steps to achieve a specified goal without micro-management. A hospital delivery robot must autonomously navigate busy corridors to succeed in its task. In AI, autonomy doesn’t have the sense of being self-governing that is common in politics or biology.

Machine Learning (ML) is the part of AI studying how computer systems can improve their perception, knowledge, decisions, or actions based on experience or data. For this, ML draws from computer science, statistics, psychology, neuroscience, economics, and control theory.

In **supervised learning**, a computer learns to predict human-given labels, such as dog breed based on labeled dog pictures; **unsupervised learning** does not require labels, sometimes making its own prediction tasks such as trying to predict each successive word in a sentence; **reinforcement learning** lets an agent learn action sequences that optimize its total rewards,

such as winning games, without explicit examples of good techniques, enabling autonomy.

Deep Learning is the use of large multi-layer **(artificial) neural networks** that compute with continuous (real number) representations, a little like the hierarchically-organized neurons in human brains. It is currently the most successful ML approach, usable for all types of ML, with better generalization from small data and better scaling to big data and compute budgets.

An **algorithm** lists the precise steps to take, such as a person writes in a computer program. AI systems contain algorithms, but often just for a few parts like a learning or reward calculation method. Much of their behavior emerges via learning from data or experience, which is a sea change in system design that Stanford alumnus Andrej Karpathy dubbed **Software 2.0**.

Narrow AI is intelligent systems for particular tasks, e.g., **speech** or **facial recognition**. **Human-level AI**, or **Artificial General Intelligence (AGI)**, seeks broadly intelligent, context-aware machines. It is needed for effective, adaptable **social chatbots** or **human-robot interaction**.

Human-Centered Artificial Intelligence is AI that seeks to augment the abilities of, address the societal needs of, and draw inspiration from human beings. It researches and builds effective partners and tools for people, such as a robot helper and companion for the elderly.

Text by Professor Christopher Manning, v 1.1, November 2020

[Learn more at hai.stanford.edu](https://hai.stanford.edu)

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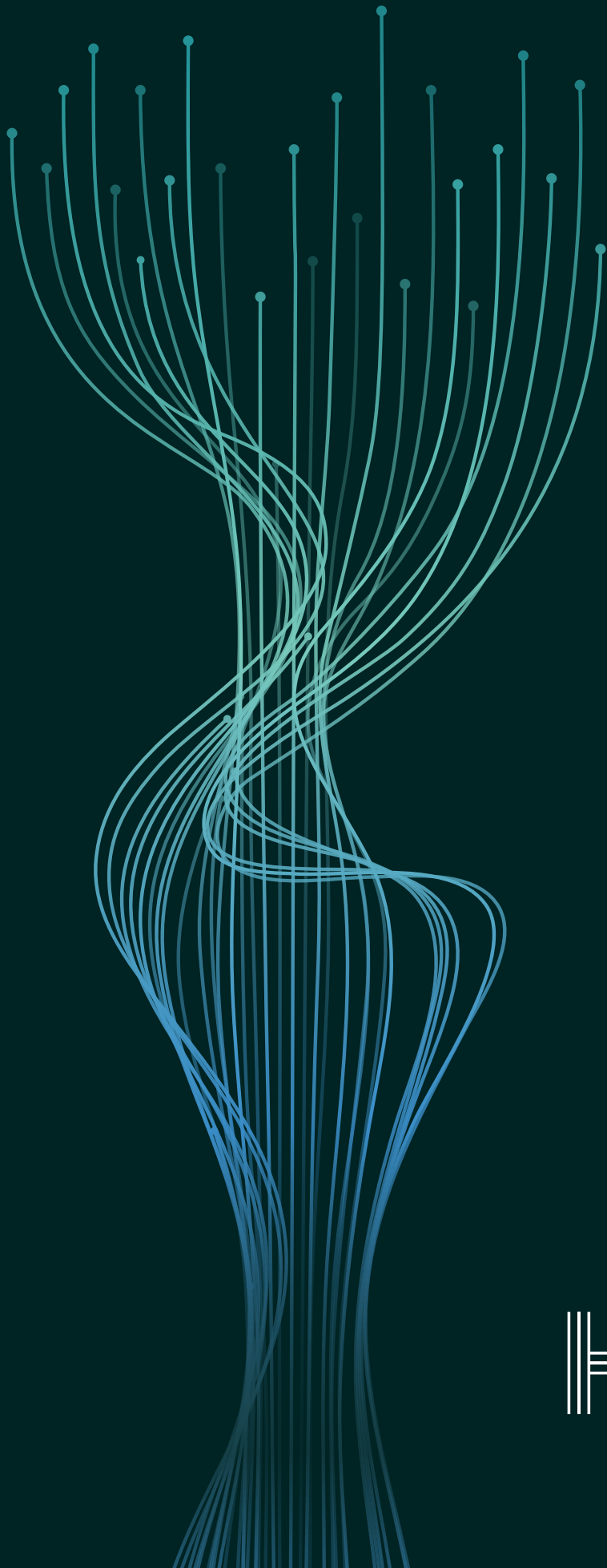


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INDUSTRY BRIEF

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