Explainable FinTech

A Transdisciplinary Perspective

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THE THE STREET BULLETER

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Key Take Aways

- The software- and data-intensive nature of FinTech makes it an exciting domain for AI and software engineering research
- 2. FinTech research (at TU Delft) spans many disciplines and research groups
- 3. Future challenges in finance demand transdisciplinary collaboration

Software Engineering Research

[Empirical methods, theory building] Seek to understand the methods and techniques that collaborating people use to develop software systems that bring value to society





[Design science, interventions] Use this understanding to propose and evaluate novel software development methods and techniques



SE4AI: Adjust the software development process to the needs of AI-based systems

AI4SE: Augment the software development life cycle with artificial intelligence



The Financial Sector

- Data intensive
- Software intensive
- High stakes
- Highly regulated
- Long (system, data) lifetimes

High impact societal sector, with critical software engineering challenges



ING Bank

Global bank based in The Netherlands

Five-year collaboration with TU Delft:

- Explainable AI
- Human-AI decision making
- Data integration
- Incident management and AlOps
- Release planning
- Search-based testing and repair



Agile at Scale at ING

- ING Bank: 15,000 IT staff
- Self-organizing teams (5-9 developers)
- Short iterations (1-4 weeks)
- User stories, features, epics
- Delivered in releases (2-6 months)
- Quarterly planning of all releases



Elvan Kula et al IEEE TSE 2022

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Why is My Project Late?

What are factors affecting timely epic delivery?

• Let's ask!

How do these factors impact schedule deviation?

• Let's measure and model!

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Factors Affecting On-Time Delivery in Large-Scale Agile Software Development

Elvan Kula[®], *Member, IEEE*, Eric Greuter, Arie van Deursen[®], *Member, IEEE*, and Georgios Gousios[®]

Abstract—Late delivery of software projects and cost overruns have been common problems in the software industry for decades. Both problems are manifestations of deficiencies in effort estimation during project planning. With software projects being complex socio-technical systems, a large pool of factors can affect effort estimation and on-time delivery. To identify the most relevant factors and their interactions affecting schedule deviations in large-scale agile software development, we conducted a mixed-methods case study at ING: two rounds of surveys revealed a multitude of organizational, people, process, project and technical factors which were then quantified and statistically modeled using software repository data from 185 teams. We find that factors such as requirements refinement, task dependencies, organizational alignment and organizational ploitics are perceived to have the greatest impact on ontime delivery, whereas proxy measures such as project size, number of dependencies, historical alelivery performance and team familiarity can help explain a large degree of schedule deviations. We also discover hierarchical interactions among factors: organizational factors are perceived to interact with people factors, which in turn impact technical factors. We compose our findings in the form of a conceptual framework representing influential factors and their relationships to ontime delivery. Our results can help practitioners identify and manage delay risks in agile settings, can inform the design of automated tools to predict schedule overruns and can contribute towards the development of a relational theory of software project management.

Index Terms—Software engineering management, effort estimation, empirical studies, software companies

1 INTRODUCTION

T ATE delivery and cost overruns have been common prob-Lilems in the software industry for decades. On average, software projects run around 30 percent overtime [1]. This percentage does not seem to have decreased since the 1980s [2]. Even though effort estimation is at the heart of almost all industries, it is especially challenging in the software industry. This is mainly due to the fact that software development is a complex undertaking, affected by a varietv of social and technical factors. The overall perceived success of a software project depends heavily on meeting the time and cost estimates [3]. Improving effort estimation is therefore a critical goal for software organizations: it can help companies reduce delays and improve customer satisfaction, while enabling them to efficiently allocate resources, reduce costs and optimize delivery [4], [5]. In spite of the availability of many estimation methods and guidelines [6], [7], on-time delivery in software development remains a major challenge. Prior research identified a large number of factors that may influence the software development effort

- Eric Greuter is with the ING Tech, 1102, MG, Amsterdam, The Netherlands. E-mail: Eric.Greuter@ing.com.
- Arie van Deursen and Georgios Gousios are with the Delft University of Technology, 2628 Delft, The Netherlands. E-mail: (Arie.vanDeursen, G.Gousios)@tudelft.nl.

Manuscript received 14 Oct. 2020; revised 16 June 2021; accepted 13 July 2021. Date of publication 2 Aug. 2021; date of current version 19 Sept. 2022. (Corresponding author: Ebran Kula.) Recommended for acceptance by M. P. Robillard. Digital Object Identifier no. 01.109/TSE.2021.3101192 [8], but which factors have the most impact is not clear. We lack an understanding of the relationships between these factors and how they impact on-time delivery.

Effort estimation is also a major challenge in agile software development. Prior work [9] has found that around half of the agile projects run into effort overruns of 25 percent or more. In agile settings, software is incrementally developed through short iterations to enable a fast response to changing markets and customer demands. Agile projects leverage short-term, iterative planning in which effort estimates are progressively refined [10]. A particular challenge involves combining the flexible, short-term agile planning setting with the business needs for long term planning of availability of large pieces of functionality (often referred to as "epics" [11]). Most agile teams heavily rely on experts' subjective assessment of team- and project-related factors to arrive at an estimate [12], [13]. However, these factors remain largely unexplored [13]; further analysis is required to investigate influential factors and how they impact delays in agile projects.

By identifying and investigating influential factors, we can obtain valuable insights on what data and techniques are needed to become more predictable at delivering software in agile settings. An identification of the most influential factors can help software organizations increase the effectiveness and efficiency of scheduling strategies by concentrating measurement and risk management activities directly on those factors that have the greatest impact on on-time delivery. Such knowledge can also guide future research on building and evaluating software effort estimation techniques, methods and tools. Furthermore, a deeper understanding of the interactions between influential factors can help in identifying the root causes of delays, and developing tools and

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Timely Epic Delivery: *Perceived* Factors

Survey 1: Which factors?

- 289 responses
- 25 factors; 5 dimensions

Survey 2: Factor importance?

- 337 responses
- Rated impact level per factor

Factor top 10:

- 1. Requirements refinement
- 2. Task dependencies
- 3. Organizational alignment
- 4. Organizational politics
- 5. Geographic distribution
- 6. Technical dependencies
- 7. Agile maturity
- 8. Regular delivery
- 9. Team stability
- 10. Skills and knowledge

11

Measuring Delay: Balanced Relative Error

 If actual delivery date *after* estimated date ("late", pos%):

$$BRE = \frac{Act - Est}{Planned duration}$$

• If actual delivery date *before* estimated date ("early", neg%):

$$BRE = \frac{Act - Est}{Actual duration}$$

• Collected BRE from 3,771 epics (273 teams), for 3 years

13 Predictor Variables

- 35 metrics for 20 factors
- 13 metrics explain 67% of variation (MARS model,)
- Match with perception?
 - Underestimated: *size*
 - Agreed effect:
 dependencies, seniority, stability
 - Overestimated:

refinement, geography,

Agreed little effect:
 coverage, code smells, ...



Can we Predict Delay?

- Delay knowledge increases as epic unfolds (in milestones)
- Mobility literature: Delay adheres to <u>patterns</u>, which can be learned by clustering delay time series

- Is epic delay subject to patterns?
- Can patterns improve delay prediction?



Elvan Kula et al FSE 2023

Epic Delay Patterns



Dataset: 4,040 epics of at least 10 sprints from 270 teams, 2017-2022

| | Median | | | |
|------------------------------|--------|------|------|------|
| Predictor variable | C1 | C2 | C3 | C4 |
| nr-sprints | 13 | 15 | 14 | 11 |
| out-degree | 7 | 3 | 4 | 4 |
| hist-performance | 0.69 | 0.67 | 0.74 | 0.61 |
| dev-age-abc | 2.49 | 2.61 | 2.92 | 2.84 |
| team-existence | 1.30 | 1.53 | 1.29 | 1.42 |
| team-size | 8 | 7 | 6 | 7 |
| security-level | 0.56 | 0.77 | 0.53 | 0.36 |
| nr-unplanned-stories (ratio) | 0.11 | 0.16 | 0.10 | 0.08 |
| changed-leads | 3 | 2 | 3 | 2 |
| stability-ratio | 0.73 | 0.81 | 0.64 | 0.72 |
| nr-stories | 52 | 43 | 39 | 45 |
| nr-incidents | 8 | 12 | 8 | 6 |
| dev-workload-points | 15 | 12 | 10 | 8 |
| BRE | 0.23 | 0.17 | 0.11 | 0.09 |
| % epics in category: | 36% | 44% | 14% | 6% |

Delay Patterns Improve Delay Prediction

- Global - Global Iterative - Dynamic without patterns - Dynamic



Epic Conclusions

- There are measurable factors contributing to epic delay
 - Size, project dependencies, past performance
- Delay follows patterns
 - Largest pattern is timely at start with delay peak at end, due to security and incidents
- Factors + patterns predict delay, dynamically
 - Beats the global and iterative state-of-the-art baselines





turnover

- (¹) OJ C 343, 26.8.2021, p. 1.
 (²) OJ C 155, 30.4.2021, p. 38
- (*) Position of the European Parliament of 10 November 2022 (not yet published in 28 November 2022.

EU Digital Operational Resilience Act (DORA)

- Harmonized rules for safeguarding against ICT-related **incidents** in financial sector
- Insist on documented policies for protection, detection, containment, recovery, and repair
- All changes to be recorded, tested, assessed, approved, implemented, and verified in a controlled manner

Incident Management at ING

- "ITIL" process with four stages:
 - Incident logging;
 - Investigation & diagnosis;
 - Resolution
 - Verification & closure
- Compliance with DORA, PSD2, ...
- But does it work well?
 - Interview study with 15 ING experts

E. Kapel et al. "Enhancing Incident Management: Insights from a Case Study at ING". ACM/IEEE FinanSE 2024.



2024 IEEE/ACM Workshop on Software Engineering Challenges in Financial Firms (FinanSE)

Enhancing Incident Management

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 If Privi (Finance):
 RQ2: What are the main challenges when handling in dents: VLMA, Paper.
 RQ3: What are future opportunities for improvements the incident management process?
 Our study reveals eight one observations. The incident management

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"A client prefers receiving a very generic message quickly than waiting for 30 minutes for a detailed message." (P13)

"Even if we understand the chain today, it will be different in a month" (P9) "If you have long overdue incidents then you are not in control of your incident process and are at risk. Then we do not comply with the regulations of the European Bank that we should be in control." (P1)

Observations & Recommendations

- 1. Demonstrable regulatory compliance is key driver of process
- 2. Logged incidents often are duplicates or false alarms
- 3. Rapid evolution of bank's IT systems complicate diagnosis
- 4. Strict access rules hamper rapid incident resolution
- 5. Incident resolution is prioritized over structural fix creation
- 6. Communication across teams with all affected parties is key
- 7. Data-driven approaches (anomaly detection, pattern recognition, clustering) demand clean monitoring data and tight supervision
- 8. Incorporating human oversight is essential when implementing automated resolutions to support the incident management process

| Insights from a C | Enhancing Incident Management: Insights from a Case Study at ING | | |
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| Litera Kapel Edens Kapel Edens Kapel Brittenson NO Buak Antorlam, Nosel Holland, The Netherlands Domitalis Spiraellis dapatellingender And Dett, Zaiel Holland, The Netherlands ABSTRACT | Laise Gruty at Line Cruz Etwalfal Bell University of Technology Delt, Zaiel-Holland, The Netherlands Arie van Deutsten arie snadeunsengibuddit at Delt Diviserity of Technology Delt, Zaiel-Holland, The Netherlands 1 INTRODUCTION | | |
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Work in Progress: Tracing Incidents & Changes

Six months of change data:

| Change Records | | | |
|---------------------|--------|-------|--|
| Close code | Count | Perc. | |
| Closed successfully | 86,000 | 95% | |
| Cancelled | 4,000 | 4% | |
| Induced incident | 1,000 | 1% | |
| Total | 91,000 | 100% | |

On the Difficulty of Identifying Incident-Inducing Changes

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ABSTRACT

Effective change management is crucial for businesses heavily reliant on software and services to minimise incidents induced by changes. Unfortunately, in practice it is often difficult to effectively use artificial intelligence for IT Operations (AIOps) to enhance service management, primarily due to inadequate data quality. Es-tablishing reliable links between changes and the induced incidents is crucial for identifying patterns, improving change deployment, identifying high-risk changes, and enhancing incident response In this research, we investigate the enhancement of traceability between changes and incidents through AIOps methods. Our approach involves a close examination of incident-inducing changes, the replication of methods linking incidents to the changes that caused them, introducing an adapted method, and demonstrating its results using historical data and practical evaluations. Our findings reveal that incident-inducing changes exhibit different characteristics dependent on context. Furthermore, a significant disparity exists between assessments based on historical data and real-world observation, with an increased occurrence of false positives when identifying links between unlabeled changes and incidents. This study highlights the complex nature of identifying links between changes and incidents, emphasising the contextual influence on AlOps method effectiveness. While we are actively working on improving the quality of current data through AIOps approaches, it remains apparent that further measures are necessary to address

issues like data imbalances and promote a postmortem culture that

brings attention to the value of properly administrating tickets. A

better overview of change failure rates contributes to improved risk

- Software and its engineering \rightarrow Risk management; Software

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compliance and reliable change management.

post-development issues: Software reliability.

oi.org/10.1145/3639477.363975

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KEYWORDS change management, incident management, traceability

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1 INTRODUCTION

Nowadays, major businesses and industries, such as banking, health care and retail are increasingly reliant on software and related services, often referred to as software-defined businesses [1]. This approach emphasises an agile way of working, encouraging fast paced development and deployment of new features. While this offers many benefits, it also leads to a higher volume and faster pace of change deployment. In this context, changes are defined as mod ifications to existing applications, comprising additions, alterations and deletions [18].

Changes can occasionally trigger incidents, especially if they undergo inadequate testing or incorrect implementation. For instance, a software upgrade might lead to compatibility issues, resulting in an incident. The change management process aims to minimise change-related risks, thereby reducing the occurrence of incidents caused by changes. An incident is defined as an unplanned inter ruption to a service or a reduction in service quality at a specific time [18]. Incidents can lead to customer dissatisfaction, financial losses, and reputational damage; therefore, they must be prevented IT service changes are one of the leading contributors to outages accounting for about 70% of live system outages [5]. This is often referred to as the change failure rate, which measures the percentage of deployments causing a failure in production [15]. Other factors that contribute to the difficulty of identifying incident-inducing changes include the complex nature of large IT environments [6 the potential for seemingly successful changes to still induce inc dents [16, 38], the service where an incident begins may be different from the once that caused it [36], the necessity for engineers to sift through large amounts of heterogeneous data to identify the root cause [36], and the fact that incidents are often the result of

changes occurring hours or days before the incident [17]. To enable the application of Artificial Intelligence for IT Op erations (AIOps), which utilises big data, machine learning and advanced analytics to enhance IT operations [21], proper data quality is crucial to systemically learn from the past and ensure effective

E. Kapel et al. "On the Difficulty of Identifying Incident-Inducing Changes". ICSE SEIP 2024.



Riskier Changes in Weekend



Ratio between incident-inducing changes and non-incident inducing changes per day of the week.



Higher Upfront "risk-category" for Incident-Causing Changes





From Incident back to Change?

- Not all incidents related to change
- Links missing in many cases:
 - Focus on resolution, not on documentation
- Can we establish such links *automatically*?
 - Try data mining approach published by IBM
 - Time: most recent fix before incident?
 - Time with shared 'dimensions' (words, impact, type, group, doubles accuracy?
 - Correct change in top 5 in 56.9% of cases

| Original | | |
|-------------|-------|-------|
| Dimension | top 5 | top 1 |
| Time | 52% | 30% |
| All | 67% | 51% |
| Significant | 75% | 58% |

| Replication | | |
|-------------|-------|-------|
| Dimension | top 5 | top 1 |
| Time | 35.3% | 9.8% |
| All | 45.1% | 11.8% |
| Significant | 56.9% | 22.2% |



Current Quest: Incident Prediction



"Explanation in Artificial Intelligence: Insights from the Social Sciences"

(Tim Miller, Artificial Intelligence, 2018)

An explanation is an answer

to a why-question

Explanation in artificial intelligence: Insights from the social sciences

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Keywords: Explanation Explainability Interpretability Explainable Al Transparency There has been a recent resurgence in the area of explainable artificial intelligence as researchers and practitioners seek to provide more transparency to their algorithms. Much of this research is focused on explicitly explaining decisions or actions to a human observer, and it should not be controversial to say that looking at how humans explain to each other can serve as a useful starting point for explanation in artificial intelligence. However, it is fair to say that most work in explainable artificial intelligence uses only the researchers' intuition of what constitutes a 'good' explanation. There exist vast and valuable bodies of research in philosophy, psychology, and cognitive science of how people define, generate, select, evaluate, and present explanations, which argues that people employ certain cognitive biases and social expectations to the explanation process. This paper argues that the field of explanable artificial intelligence can build on this existing research, and reviews relevant papers from philosophy, cognitive psychology/science, and social psychology, which study these topics. It draws out some important findings, and discusses ways that these can be infused with work on explainable artificial intelligence.

1. Introduction

Recently, the notion of *explainable artificial intelligence* has seen a resurgence, after having slowed since the burst of work on explanation in expert systems over three decades ago; for example, see Chandrasekaran et al. [23], [168], and Buchanan and Shortliffe [14]. Sometimes abbreviated XAI (eXplainable artificial intelligence), the idea can be found in grant solicitations [32] and in the popular press [136]. This resurgence is driven by evidence that many AI applications have limited take up, or are not appropriated at all, due to ethical concerns [2] and a *lack of trust* on behalf of their users [166,101]. The running hypothesis is that by building more transparent, interpretable, or explainable systems, users will be better equipped to understand and therefore trust the intelligent agents [129,25,65].

While there are many ways to increase trust and transparency of intelligent agents, two complementary approaches will form part of many trusted autonomous systems: (1) generating decisions¹ in which one of the criteria taken into account during the computation is how well a human could understand the decisions in the given context, which is often called *interpretability* or *explainability*; and (2) explicitly explaining decisions to people, which we will call *explanation*. Applications of explanation are considered in many sub-fields of artificial intelligence, such as justifying autonomous agent behaviour [129,65], debugging of machine learning models [89], explaining medical decision-making [45], and explaining predictions of classifiers [157].

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¹ We will use *decision* as the general term to encompass outputs from AI systems, such as categorisations, action selection, etc.

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Explanations are *Contextual*

- **Contrastive**: compared to counterfactual alternative
- Selective: focusing on relevant parts of full causal chain
- Social: transferring knowledge, assuming prior knowledge



(Tim Miller, Artificial Intelligence, 2018)

Counterfactual Reasoning

 Factual: Model denies loan
 Counterfactual: Alternative inputs that would accept loan

 Algorithmic recourse:
 Change of behavior to get desired outcome



Patrick Altmeyer JuliaCon, 2022, 2023 IEEE SaTML, 2023 AAAI 2024



A Library for Generating Counterfactuals

- Possible, faithful, plausible, "close" to the factual, ...
- Gradient descent in feature space (with extra cost terms)
- Leverage 'energy' in input data seen during training
- Macro-effects after recourse adoption
- Rich library of Julia packages



https://github.com/JuliaTrustworthyAI

ING Bank

Global bank based in The Netherlands Five-year collaboration with TU Delft:

- Explainable AI
- Human-AI decision making
- Data integration
- Incident management and AlOps
- Release planning
- Search-based testing and repair





Step 1: The Compromise

- ByBit crypto exchange uses 3rd party "Safe Wallet"
 - This is the weak link that can be exploited.
- Hackers obtain credentials for Safe{Wallet} developer machine
 - API keys of safe.global leaked or compromised
- Upload malicious Javascript code for "Safe UI"
 - Targeting Ethereum multisig cold wallet of Bybit
 - Makes it appear that Bybit is signing a legitimate transaction, when in fact it is a malicious one.





can't verify it, don't sign it.

Unlock a new way of ownership

The most trusted decentralized custody protocol and collective asset management platform.



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Step 2: The Theft

- Two weeks later:
 - Routine transfer from Bybit's Ethereum cold wallet to hot wallet triggers the malicious code
- Bybit CEO unknowingly signs the malicious transaction
- Hackers able to move ~401,000 ETH to addresses under their control

Step 3: The Laundering

- Move stolen assets through a complex web of intermediary addresses.
- Swap stolen ETH for tokens including Bitcoin and DAI.
- Move assets across networks using:
 - Decentralized exchanges and cross-chain bridges
 - Instant swap service without "Know Your Customer" reqs
- Keep portion of stolen funds idle across various addresses
 - Delay laundering to outlast the heightened scrutiny





Bybit Implications

- Affects world peace: 1.5B for North-Korea
- Affects price of crypto-currencies
- Undermines societal trust in fintech
- Requires mix of prevention / remediation measures:
 - Strong cybersecurity, (incl. phishing)
 - Regulation (KYC, money laundering)
 - Forensics and traceability
 - While preserving privacy



Venkatesh Chandrasekar

The Delft Fintech Lab

- Bring together all
 TU Delft Fintech activities
- Research, education, innovation
- Launched May 2023
- 50 researchers in four faculties
- 25 commercial / societal partners

Delft Fintech Lab: Research Pillars

- Fraud detection, privacy preservation
- Algorithmic trading
- Risk management
- Engineering financial systems
- Decentralized finance



Selected Blockchain/Security Research

- Testing the protocol (Lead: Burcu Kulahcioglu Ozkan)
 - OOPSLA 2023: Randomized testing for Byzantine Fault Tolerance
 - ICSE SEIP 2023: Evolutionary testing of Ripple's consensus algorithm
 - Issues detected and reported;
 kointy received
- Testing smart contracts (Lead: Mitchell Olsthoorn)
 - ICSE Tool Demo 2022: Syntest-Solidity (https://www.syntest.org/)
 - ICSME 2022: Guiding tests through transaction-reverting statements



Anti-Money Laundering

- Pattern-based synthetic data set
 - > 100 million transactions
 - Varying levels of illicitness (1:1750)
- ML-based detection approach
 - Trained on synthetic data
 - Validated on Ethereum data

Kubilay Atasu, NeuRIPS'23, AAAI'24, ICAIF'24



(a) Fan-out (b) Fan-in (c) Gather-scatter (d) Scatter-gather (e) Simple cycle (f) Random (g) Bipartite (h) Stack



ML in Trading @ Delft

- Efficient and accurate algorithms to address trading in financial markets
- ML / math for valuation of financial derivatives
 - use of energy cost functions
 - domain knowledge (asymptotic option prices).
- Reinforcement learning for algorithmic trading and portfolio optimization
- Synthesis of implied volatility surfaces using diffusion models and auto-encoders.



Antonis Papapantoleon

| MANAGEMENT SCIENCE | |
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| Published Online: 28 Jun 2022 https://do | bi.org/10.1287/mnsc.2022.4456 |
| Abstract | |
| We consider derivatives written on multiple financial market, and we are interested in th upper and lower bounds for their arbitrage- completely realistic setting, in that we only prices for other single- and multi-asset deriv presence of bid-ask spread in these prices | underlyings in a one-period le computation of model-free free prices. We work in a assume the knowledge of traded vatives and even allow for the . We provide a fundamental |

prices for other single- and multi-asset derivatives and even allow for the presence of bid-ask spread in these prices. We provide a fundamental theorem of asset pricing for this market model, as well as a superhedging duality result, that allows to transform the abstract maximization problem over probability measures into a more tractable minimization problem wectors, subject to certain constraints. Then, we recast this problem into a linear semi-infinite optimization problem and provide two algorithms for its solution. These algorithms provide upper and lower bounds for the prices that are ε -optimal, as well as a characterization of the optimal pricing measures. These algorithms are efficient and allow the computation of bounds in high-dimensional scenarios (e.g., when d = 60). Moreover, these algorithms can be used to detect arbitrage opportunities and identify the corresponding arbitrage strategies. Numerical experiments using both synthetic and real market data showcase the efficiency of these algorithms, and they also allow understanding of the reduction of model risk by including additional information in the form of known derivative prices.

FinTech as "Convergence"

- Grand societal challenges demand blended expertise of technical and socio-economic sciences
- TU Delft is strengthening its partnership with Erasmus University Rotterdam.
- Pilot FinTech projects:
 - Synthetic data generation
 - Default prediction
 - Household financial distress





FinTech Education?

- Train future engineers who can
 - Design, build, evolve, and operate current and future financial systems
 - Assess and influence societal implications of new technological developments in the financial sector
- Exploring transdisciplinary master with intake from various disciplinary bachelor programs

ML in finance, anti-money laundering, robo-trading, distributed consensus, ...





Summary So Far

- The financial sector is a software factory
- Financial services need to be reliable, explainable, and secure
- Regulations help (DORA, KYC, AML)
- To move FinTech forward, we need to
 - Iook beyond our own disciplines ...
 - ... and train the next generation to do so

The Role of AI?

- Capabilities of **foundation models** are mind blowing
- This will affect many aspects of society, including finance and FinTech
- The ambitions of **Artificial General Intelligence** reach even higher
- Will (generative) AI solve our problems?



I V Large Language Models for Code



more readable source code-like representation. Still, reverse engineering is difficult and costly, involving considering effort in labelling code with helpful summaries. While the automated summarisation of decompiled code can help reverse engineers

For source code, methods exist to automatically generate of the code. mmaries from code [11, 12]. Source code summarisation

models for code are vulnerable to data extraction attacks, like their natural language counterparts. From the training data that was identified to be potentially extractable we were able to extract 47%

These abilities cannot be predicted by extrapolating scaling laws and only emerge at a certain critical model size threshold [50]. This makes it appealing to train ever-larger models, as canabilities as chain-of-thought promotion In

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Nothing Beats Good Data

- Finance has rich history of thorough data-driven research
 - Diffusion and auto-encoders add superpowers to your data
 - Use obtained understanding for synthetic data generation
- As Fintech 'organization', cherish, curate, your own data
- As research community, share data to drive research

Foundation Models for FinTech

- Endless, fascinating possibilities
- Your organization won't fit in a prompt
 - Explore agents, retrieval-augmentation, ...
 - Consider finetuning/training with own data
- A model will inherit the good and bad from the training data
 - "Alignment" is tricky and volatile
 - Secret training data impedes progress



Prompt: a picture for "Explainable Fintech: A Transdisciplinary perspective"



Al should be Focused

Timnit Gebru (SaTML 2023):

We should build smaller-scale systems (that are well-scoped and well-defined) for which we can provide specifications for expected behavior, tolerance and safety protocols.

https://x.com/NicolasPapernot/status/1623885641380425728

Earning and Keeping Societal Trust

- Financial systems must be dependable and trustworthy
- High complexity, volatility of crypto currencies, unreasonable profits, and excessive carbon emissions all undermine society's support for fintech.
- FinTech should be a 'fair game'



Eric Beinhocker Oxford

Fair Social Contracts for Large-Scale Collaboration



| Moral preferences | Dimension | Description |
|-------------------------|--------------|---|
| Relational fairness | Agency | I can choose to play the game and have choices within the game. |
| | Inclusion | I have an opportunity to play the game. I am not excluded. |
| | Dignity | If I play by the rules and contribute to the best of my abilities, I will be valued, respected, and have status. |
| Procedural fairness | Rule-based | I know the rules of the game and they are applied equally to everyone. |
| | Meritocratic | <i>I, and everyone else, will receive rewards and punishments in the game based on merit.</i> |
| | Security | If I play by the rules and contribute to the game, but suffer misfortune through no fault of my own, I will be protected. |
| Distributional fairness | Capabilities | I have the capabilities to play the game or the opportunity to acquire them. |
| | Reciprocity | If I play by the rules and contribute, others will reciprocate, and I will share in the game's rewards. |
| | Progress | If I play by the rules and contribute to the best of my abilities, my life and the lives of those I care about will improve. |



Green FinTech

- Fintech should *benefit* the climate
- Al-based Fintech needs Green Al
- Proof-of-work / Bitcoin mining is a terrible idea for the planet
- Lenders need collateral valuation over time *as climate changes*
- Finance is a domain that can steer society



Key Take Aways

- The software- and data-intensive nature of fintech makes it an exciting domain for Al and software engineering research
- Key challenges in FinTech include dependability, security, societal support, and sustainability
- Transdisciplinary research and education is needed to address such challenges in FinTech

Explainable FinTech

A Transdisciplinary Perspective

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