Financial Machine Learning: An Engineering Problem

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Objectives

- Financial Engineering is a well-established research field, with a long history in academic programs at leading universities in the U.S., U.K., France, etc.
  - Thousands of students enroll in financial engineering courses, and receive Masters and PhD degrees in Financial Engineering worldwide
- However, Financial Engineer is not (yet) developed in some countries as a university degree or a professional career
- In this seminar, we
  - define Financial Engineering as a separate research field
  - provide examples of how sophisticated institutional investors use Financial Engineering every day
  - illustrate the value of Financial Engineering outside of Finance

Financial Engineering is a mature field of research and an established professional practice, distinct from applied mathematics, statistics, econometrics, or computer science.

How I Have Used Financial Engineering

Science

BERKELEY LAB

ADIA ¦ Lab

CORNELL UNIVERSITY FOUNDED A.D. 1865

RCC.HARVARD.EDU
Real Colegio Complutense
ñRCC

Industry

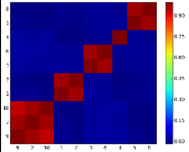
ADIA
جهـاز أبـوظـبـي للاسـتـثـمـار
Abu Dhabi Investment Authority

GUGGENHEIM

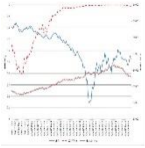
CITADEL

UBS

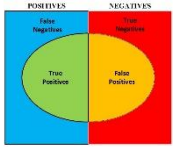
Innovations



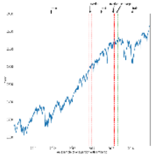
HRP|NCO



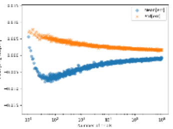
VPIN|OEH



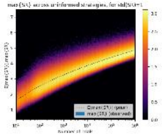
Corrective AI



CPCV

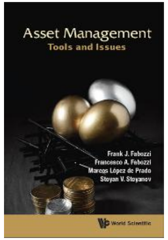


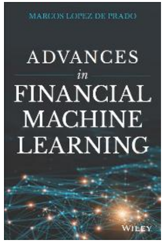
False Strat Theorem

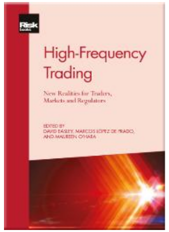


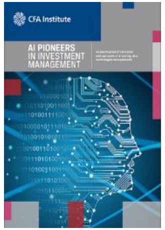
PSR|DSR

Publications









Govt Policy

UNITED STATES CONGRESS

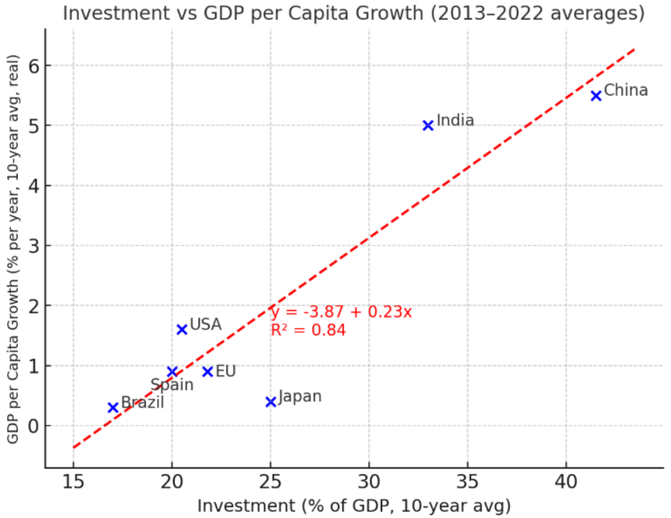
COMMODITY FUTURES TRADING COMMISSION 1975

CONFIDENTIAL

The Fundamental Problem of Investing

Why Investing Matters

- **Investing** is the allocation of scarce resources (time, money, effort, capital) today toward projects, assets, or activities with the *expectation* of future benefits (cash flows, utility, productivity)
  - Allocation decisions are made subject to high uncertainty
- **Efficient investing** is essential to a prosperous, self-reliant and sustainable society
  - Supports national security and sovereignty
  - Delivers stable job creation and social harmony
  - Is the foundation for economic competitiveness and innovation leadership
- In an increasingly multi-polar world, efficient investing is a competitive advantage



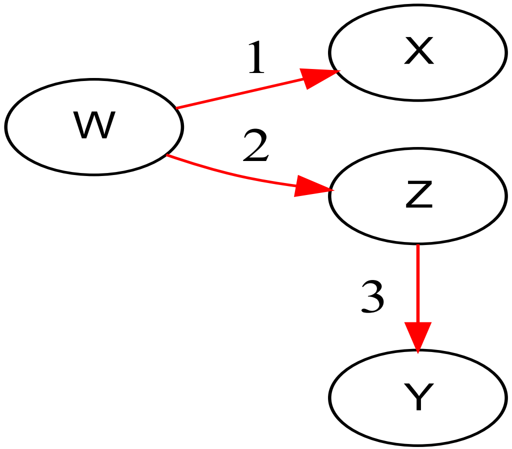
Higher investment supports stronger GDP/capital growth. However, as the plot shows, not all investments are equally efficient (e.g., USA vs EU or Japan). The discipline of investing can help Governments and private institutions achieve superior outcomes.

Investing has become a Data Science Problem

	Before 1950	1950–2000	2000–2015	2015–
Conditions	Investing is largely driven by speculation, due to • no financial theories • no computers • simplistic math models • limited data	Academics formalize the concepts of diversification, risk-premia and valuation • MPT, CAPM, APT, risk factors, Black-Scholes, market microstructure	Technological advances in • data storage • supercomputing • networking Math models become more sophisticated	The explosion in alternative data shifts research objectives, from valuation and forecasting, towards nowcasting (direct estimation)
	Technical analysis	Fundamental analysis, econometrics	Market microstructure, HFT	Machine learning, causal inference
Rationale	Investment decisions are motivated by stories or themes	Investment decisions rely on financial analysis of specific opportunities	Investment decisions increasingly rely on research and technology. Some of the best performing funds are quant-driven	
Training	Investment professionals do not receive a formal education	During this period, CFA is the gold standard of financial accreditation	Firms hire STEM grads for research and software engineering roles	High demand for data scientists and automation experts

However, Accurate Forecasting is Not Enough

- Making investment decisions requires a **causal attribution** of premia to risk factors
  - Without this attribution, investors are exposed to unrewarded risks
- Investing is not a forecasting problem
  - Accurate forecasts are not enough in investing
- This causal attribution must be done under uncertainty
  - What are the premia? (expected returns)
  - What are the risk factors? (risk model)
  - What risk causes a particular premium? (attribution)
  - What are the interactions across risk factors (joint effects)

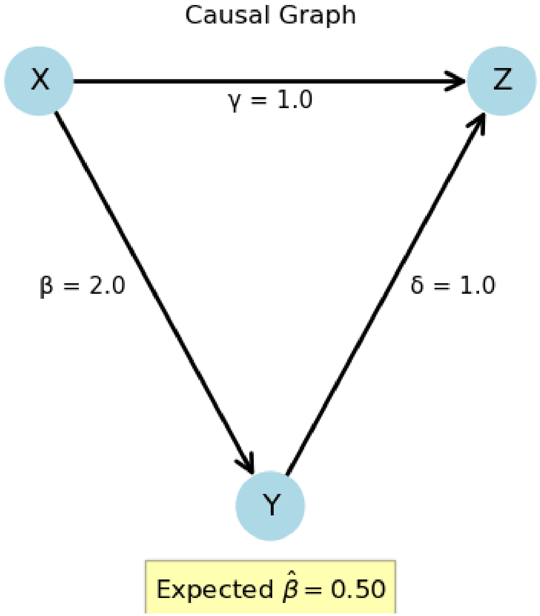


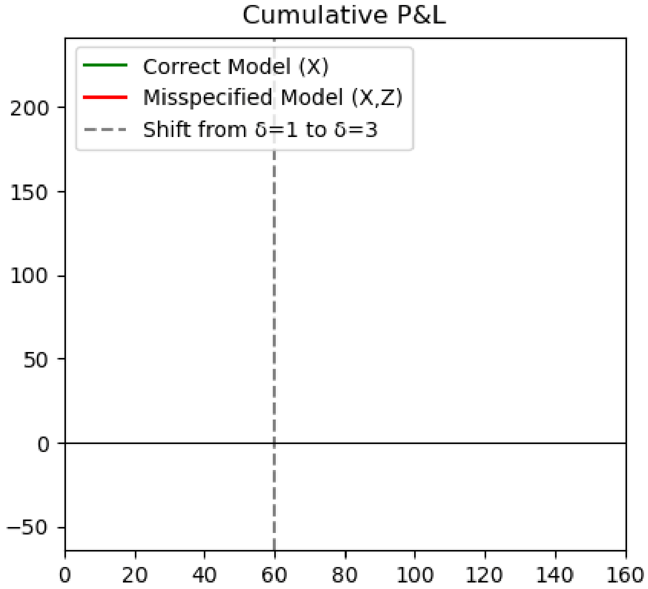
Two variables can be associated without one causing the other. For example, weather (W) influences ice cream sales (X) and the number of swimmers (Z), hence the number of drownings (Y).

An AI algorithm can use X to predict Y, however investing requires estimating the effect of X on Y.

Example: Causal Factor Investing

The causal graph shows that: (a) factor X (the cause) influences variable Y (the target) with factor loading $\beta = 2$ (the effect), and (b) that variable Z is influenced by variables X and Y, thus Z is a collider.





Applying causal discovery tools, a researcher will exclude Z as a control. The green line shows that the correctly specified factor strategy is equally profitable regardless of the effect size of Y on Z ($\delta = 1$ or $\delta = 3$).

When $\delta = 1$, then $E\left[\hat{\beta}|X, Z\right] = 0.5$, and the misspecified strategy still performs well (see red line before the dashed vertical line), because the estimated $\hat{\beta}$ has the correct sign. However, if the value of δ changes from $\delta = 1$ to $\delta = 3$, then $E\left[\hat{\beta}|X, Z\right] = -0.5$, and the misspecified strategy yields systematic losses (see red line after the dashed vertical line), because an investor seeking exposure to X will sell securities that should be bought and vice versa.

What Makes Investing an Engineering Problem?

Problem #1: Barriers to Experimentation

- Scientists propose causal theories to explain phenomena (observed associations)
  - A theory that cannot be falsified empirically, is not scientific
    - Note: Not scientific does not mean false
- Association does not imply causation
  - X is associated with Y iff $P[Y,X] \neq P[X]P[Y]$
  - X causes Y iff $P\big[Y|do[X]\big] > P[Y]$
- In the natural sciences, causal theories are falsified through randomized controlled experiments
- Controlled financial experiments are rarely possible
  - E.g., we cannot repeat the Flash Crash of 2010 controlling for some market participants
  - Instead, researchers engage in uncontrolled multiple testing

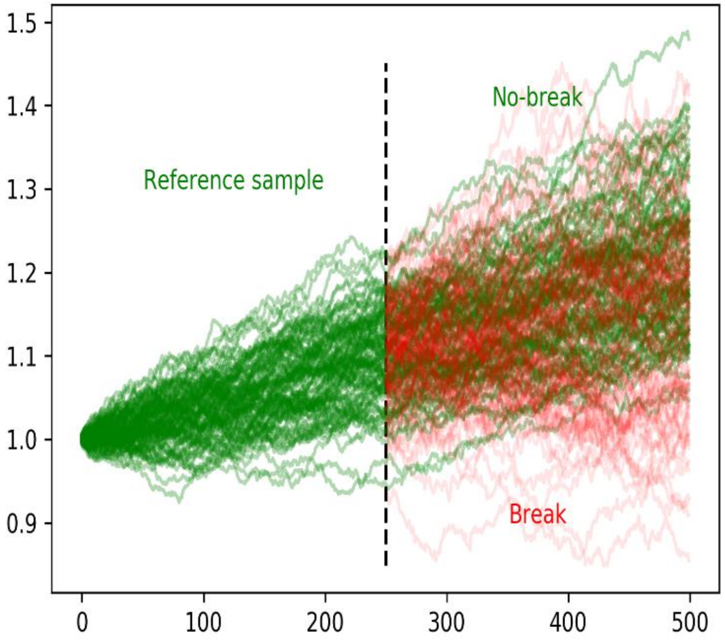
In the 1930s, Ronald Fisher popularized randomized experiments as a way to de-confound variables.

The first published RCT appeared in 1948. Today, well-blinded RCTs are considered the gold standard in experimental research.

Instead of RCTs, financial researchers often compute backtests (historical *simulations*).

Problem #2: Non-Stationarity

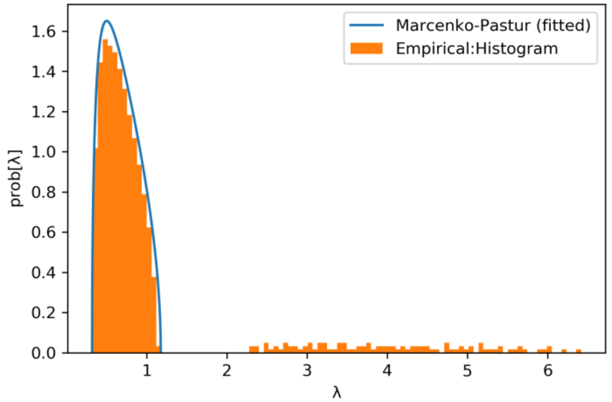
- Time series analysis relies on two key assumptions
  - **Ergodicity**: Observations span the entire support for the stochastic process
  - **Stationarity**: The unconditional joint probability distribution is time invariant
- Ergodicity can be recovered by combining non-ergodic processes
  - E.g., investing in diversified indices, rather than in an individual company that may go bankrupt
- Financial systems are non-stationary due to
  - structural breaks (e.g., changes in regulations)
  - drift in parameters that characterize the data-generating process (e.g., competition)

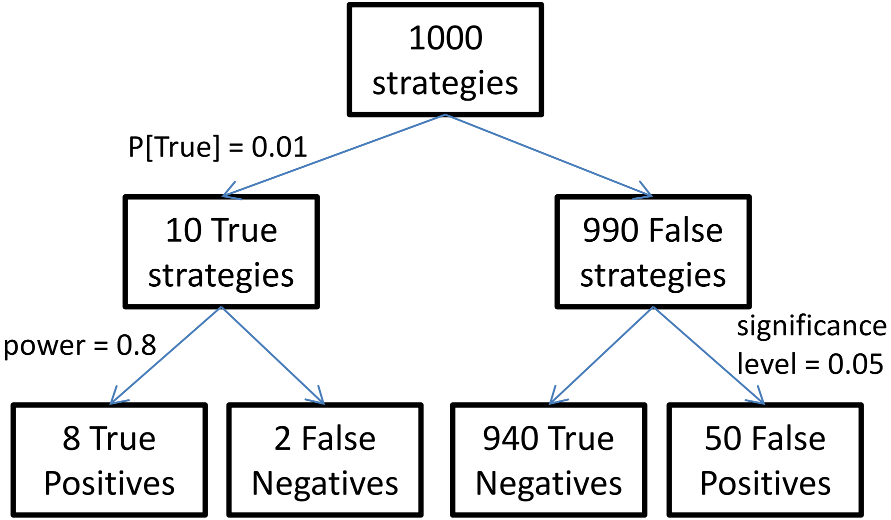


After 250 observations, a structural break takes place with probability 0.5. The problem is to detect the break as soon as possible, with high precision and high recall. See [ADIA Lab Data Science Tournament](#).

Problem #3: Low Signal-to-Noise Ratio

[Strict competition](#) among investment managers lowers the signal-to-noise ratio. For example, almost all the information contained in a factor covariance matrix (e.g., Barra) can be associated with noise rather than signal. As a result, the probability of finding a profitable investment strategy is extremely low, and alpha decays quickly.

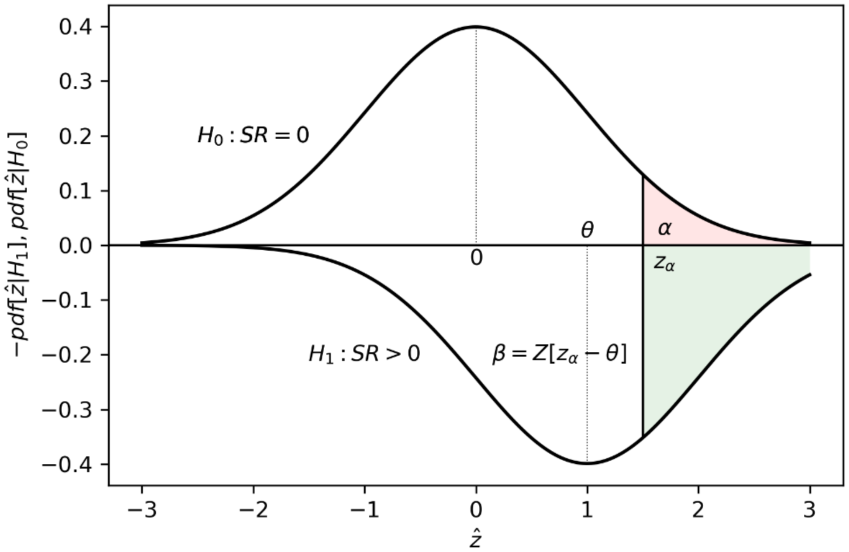




Suppose that the probability of a backtested strategy being profitable is 1%.
Then, at the standard thresholds of 5% significance and (optimistic) 80% power, researchers are expected to make 58 discoveries out of 1000 trials, where 8 are true positives and 50 are false positives. Under these circumstances, **a *p*-value of 5% implies that at least 86% of the discoveries are false!**

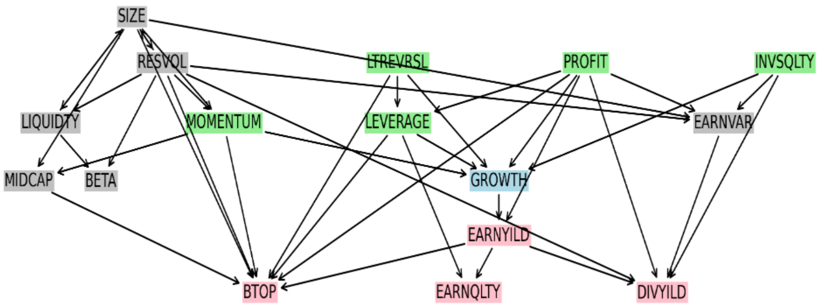
Problem #4: Small Samples

- Financial datasets often exhibit
  - Short time series, few variables
  - Highly cross-dependent variables
  - Highly serially-dependent variables
- Financial researchers often must produce inference from small samples
  - Strong train-set overfitting
  - Strong test-set overfitting
- At standard confidence levels, statistical tests on financial datasets have low power
  - High proportion of false negatives
  - High false discovery rate



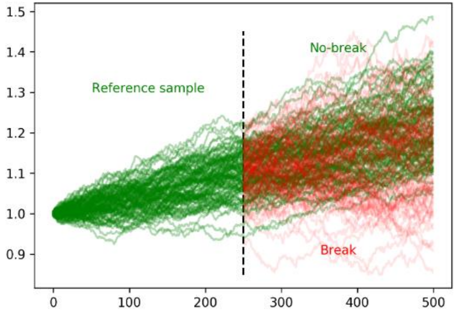
Sample size strongly influences the power of a test. As the sample size decreases, the standard deviation of the test's statistic increases. To keep constant the false positive rate (red area), the critical value shifts rightwards, thus decreasing the test's power (green area).

Investing Requires a New Type of AI

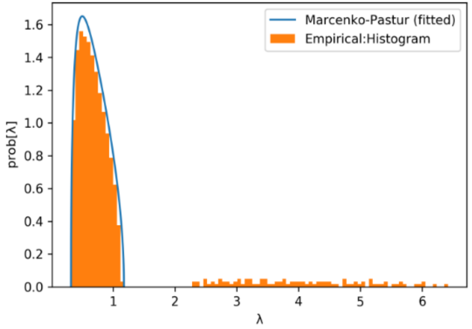


Investing is a causal problem

Barriers to experimentation



Non-stationarity, due to structural breaks and parameter shift



Low signal-to-noise ratio, due to intense competition

$$N \gg T$$

The number of variables (N) greatly exceeds the number of observations per variable (T)

What is Financial Engineering?

A Working Definition

- **Financial Engineering** is an interdisciplinary research field that develops **engineering solutions to financial problems**, where either the problem is mathematically intractable, or its closed-form mathematical solution relies on unrealistic assumptions
- Financial Engineering solutions often share one or more of the following features
  - Computationally intensive: Use of numerical methods, algorithms, Monte Carlo experiments, etc.
  - Pragmatic: Tolerance for the use of heuristics and approximations in order to solve real problems
  - Safety Factor: Robust to the violation of assumptions
- As a research field, Financial Engineering is related to, but distinct from
  - **Mathematical Finance / Financial Mathematics**: The research field that provides mathematical solutions to *tractable* financial problems, e.g. the celebrated Black-Scholes option pricing formula
    - However, Black-Scholes results differ from real-world prices because of the model's simplifying assumptions!
  - **Financial Econometrics**: The research subfield (within mathematical finance) that develops statistical methods to solve financial problems, e.g. Engle's GARCH model

Financial Engineering Map

LAYER	USE CASE	TECHNOLOGY
Data	Market & Economic Data	Bloomberg Feeds; Macroeconomic Indicators
	Alternative Data	Satellite Images; Transaction Data; ESG Metrics
	Insurance & Credit Data	Claims Histories; Borrower Profiles
	Data Collection & Ingestion	APIs; Web Scraping; Point-in-Time
	Extraction, Transformation & Loading (ETL)	Apache Airflow; Spark; dbt; Informatica
	Data Cleaning & Quality Control	Outlier Detection; Imputation; Structural Break tests
	Data Structuration	Databases; Knowledge Graphs
	Feature Engineering	Factor Construction; Autoencoders, LLMs
	Nowcasting	Dynamic Factor Models; Mixed-Frequency Models
Theory	Asset Pricing Theory	No-Arbitrage Models; Utility Maximization
	Derivative Pricing	Black-Scholes-Merton; SDE Solvers; PDE Methods
	Causal Discovery	PC algorithm, FCI, GES, NOTEARS
	Risk Modeling	Monte Carlo; Extreme Value Theory
	Portfolio Theory	Mean-Variance; Risk Budgeting
	Insurance Pricing	Actuarial Models; Credibility Theory
	Credit Risk Models	Merton Models; Default Intensity Models
	Asset-Liability Management (ALM)	Immunization; Duration Matching

LAYER	USE CASE	TECHNOLOGY
Prediction	Machine Learning Models	Random Forests; Deep Nets
	Natural Language Processing	Transformers; Sentiment Analysis
	High-Frequency Analytics	Order Flow Prediction; Anomaly Detection
	Behavioral Prediction	Churn Models; Investor Sentiment
	Default & Claims Prediction	XGBoost; Severity/Frequency Models
	Fraud Detection	Graph ML; Anomaly Detection
	Time-Series Forecasting Models	ARIMA; VAR; GARCH; LSTMs
Validation	Statistical Testing	Hypothesis Tests; Factor Validation
	Econometric Diagnostics & Tests	Unit-Root Tests; Cointegration Tests
	Causal Inference	IV/2SLS; Causal Forests
	Forecast Evaluation	Backtesting; Out-of-Sample Tests
	Stress Testing	Historical; Hypothetical
	Hedging Effectiveness Testing	Hedge Ratios
	Regulatory Capital Models	Basel III; EIOPA Frameworks
Production	Portfolio Construction & Optimization	Convex Optimization; Graph-based methods
	Risk Management Systems	VaR; CVaR Dashboards
	Trading & Execution	Optimal Execution; Multi-Agent RL
	Product Structuring	ETFs; Structured Notes
	Insurance & Pension Products	Cat Bonds; Longevity Swaps
	Enterprise Risk Management (ERM)	ORSA Dashboards

The "Alpha Assembly Line" Paradigm

Function	RESEARCH			TESTING	PRODUCTION		
Role	Data Curation	Feature Analysis	Strategy Development	Testing	Deployment	Portfolio Oversight	Portfolio Implementation
Question	Can we structure this dataset as (X, y)?	Has X predicted y in the past?	Why should X predict y going forward?	What's the false positive probability?	What's the most efficient deployment of the prototype?	Does the strategy perform as expected?	How can we achieve the target positions with minimal shortfall?
Popperian Cycle	Problem Situation (PS_n)		Tentative Theory (TT_n)	Error Elimination (EE_n)			
	Phase Trials 1 & 2 (Proto-squad, Prioritization, Squad)			**Phase 3 Trials** (Testing & Deployment)		**Phase 4 Trials** (Embargo & Decay)	

Strategy metadata ($n \leftarrow n + 1$) (meta-labeling)

For a description of the assembly line stations, read https://ssrn.com/abstract_id=3104847

Top Engineering Schools with Financial Programs

COLUMBIA ENGINEERING

CORNELL UNIVERSITY FOUNDED A.D. 1865

CornellEngineering

THE UNIVERSITY OF CALIFORNIA BERKELEY 1868

Imperial College London

NYU

TANDON SCHOOL OF ENGINEERING

DAUPHINE UNIVERSITÉ PARIS

EPFL

THE CITY UNIVERSITY OF NEW YORK

STEVENS INSTITUTE OF TECHNOLOGY 1870

THE UNIVERSITY OF CALIFORNIA UCLA

Use Case: Portfolio Construction

The Mathematical Solution (1/3)

- Consider an investment universe with N assets, where the expected value of returns is represented by an array μ, and the covariance of returns is represented by the matrix V
- We would like to minimize the variance of a portfolio with allocations ω, measured as $\omega' V \omega$, subject to achieving a target $\omega' a = \bar{a}$, where a characterizes the optimal solution
- The problem can be stated as

$$\min_{\omega} \frac{1}{2} \omega' V \omega$$
$$\text{s.t.:}\ \omega' a = \bar{a}$$

The Mathematical Solution (2/3)

- This problem can be expressed in Lagrangian form as

$$L[\omega, \lambda] = \frac{1}{2}\omega' V \omega - \lambda(\omega' a - \bar{a})$$

with first order conditions

$$\frac{\partial L[\omega,\lambda]}{\partial \omega} = V\omega - \lambda a; \frac{\partial L[\omega,\lambda]}{\partial \lambda} = \omega' a - \bar{a}$$

- Setting the first order (necessary) conditions to zero, we obtain that $V\omega - \lambda a = 0 \Longrightarrow \omega = \lambda V^{-1} a$, and $\omega' a = a' \omega = \bar{a} \Longrightarrow \lambda a' V^{-1} a = \bar{a} \Longrightarrow \lambda = \frac{\bar{a}}{a' V^{-1} a}$, thus

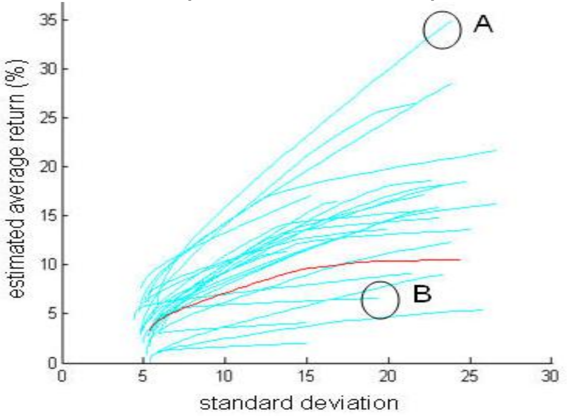
$$\omega^* = \bar{a}\frac{V^{-1} a}{a' V^{-1} a}$$

- The sufficient condition is that the Hessian is positive definite
  - In this case, the Hessian is the covariance matrix V, hence the sufficient condition is verified

The Mathematical Solution (3/3)

- This solution is mathematically correct only if a and V are known (…unrealistic)
- *Financial Mathematicians* estimate ω^* as

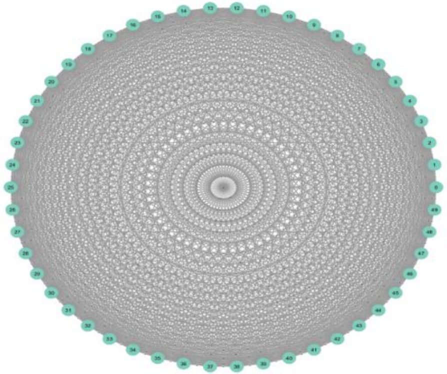
$$\widehat{\omega}^* = \bar{a}\frac{\hat{V}^{-1}\hat{a}}{\hat{a}'\hat{V}^{-1}\hat{a}}$$

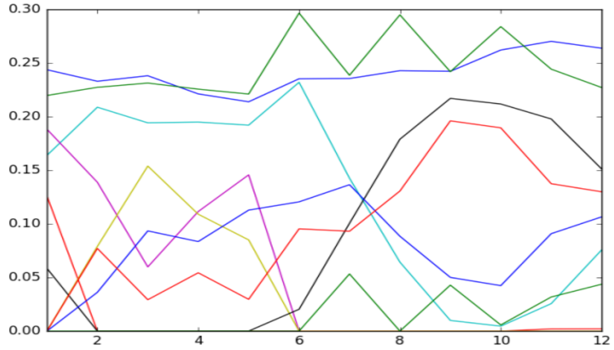


where $\hat{V}$ is the estimated V, and $\hat{a}$ is the estimated a.

- However, replacing each variable with its estimate will lead to unstable solutions, i.e. solutions where a small change in the inputs will cause extreme changes in $\widehat{\omega}^*$
- This is problematic, because in many practical applications there are material costs associated with the re-allocation from one solution to another (noise trading)
- Next, let us see how *Financial Engineers* solved this problem

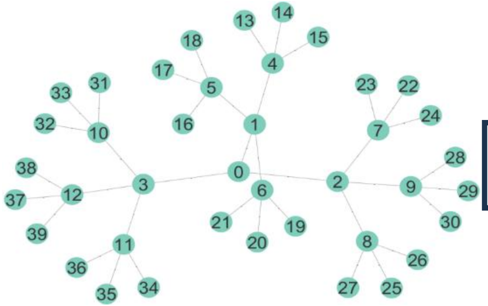
Engineering Solution 1: Hierarchical Risk Parity (HRP)

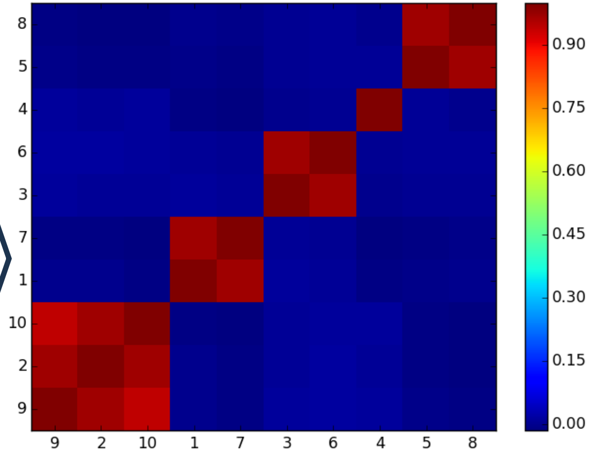


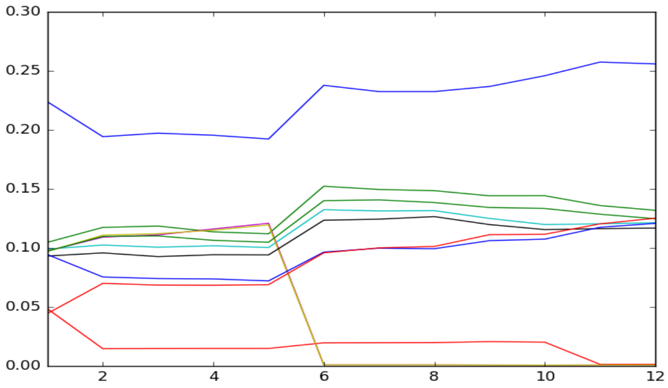


$$\sigma^2_{CLA} = .1157$$

$$\sigma^2_{HRP} = .0671$$

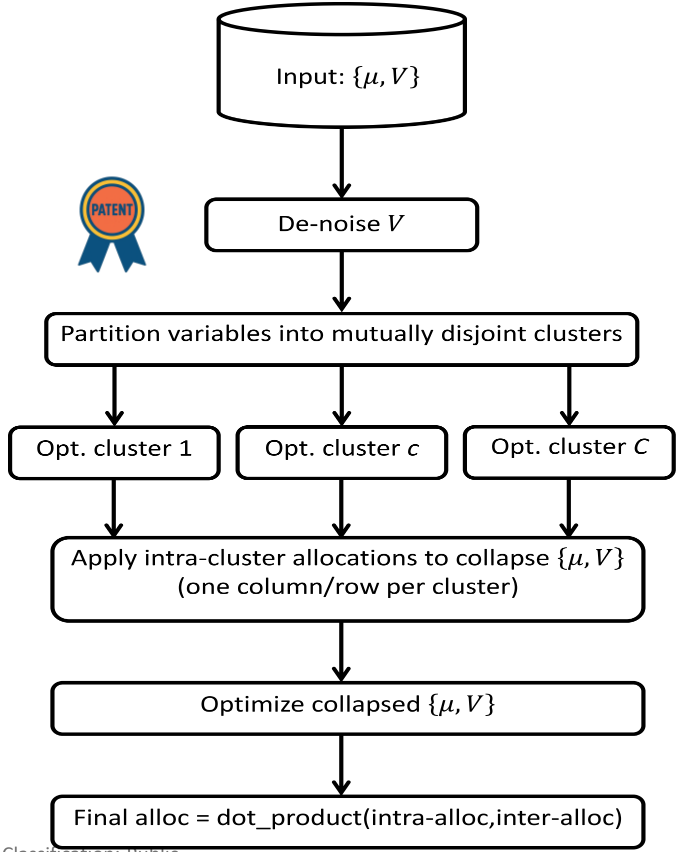






Classification: Public

Engineering Solution 2: Nested Cluster Optimal (NCO)



	Markowitz	NCO
Raw	7.02E-02	3.17E-02
Shrunk	6.54E-02	5.72E-02

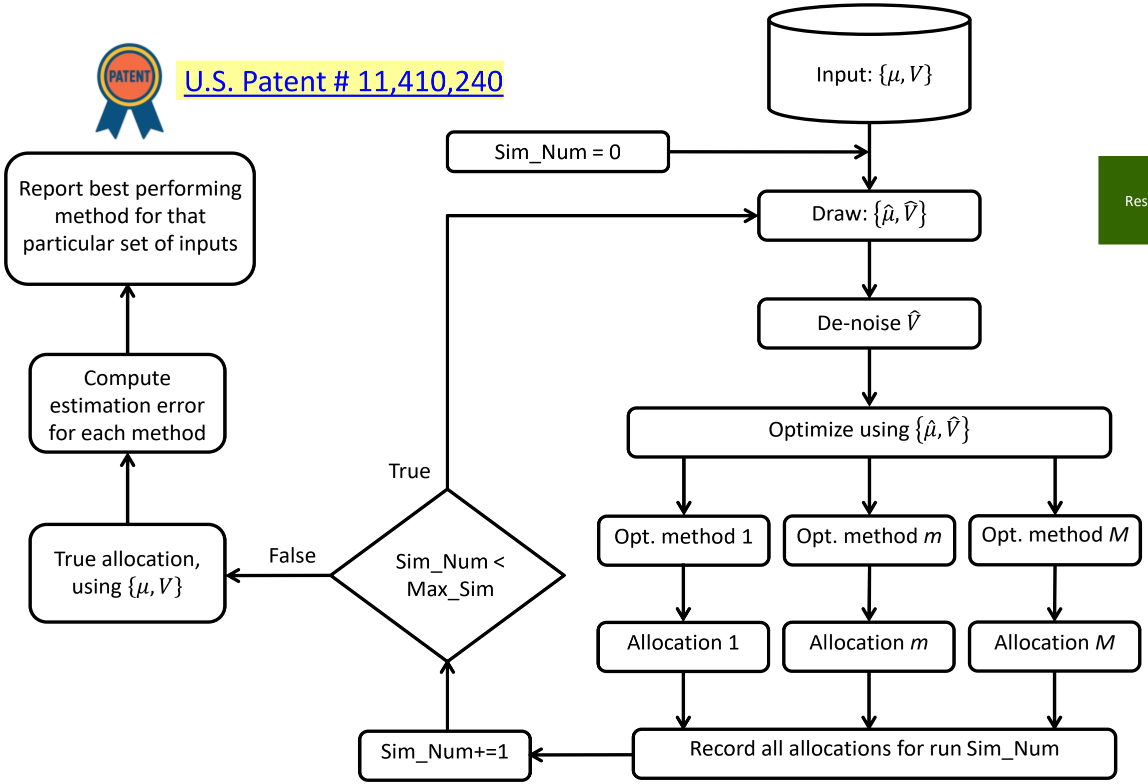
Why does NCO beat Markowitz?

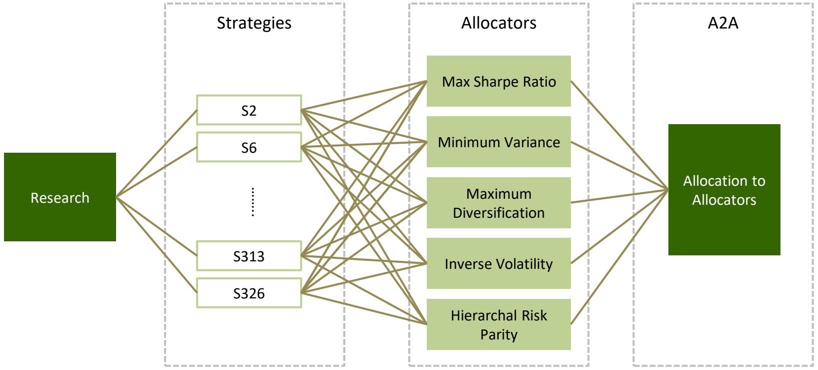
By construction, the reduced covariance matrix is close to a diagonal matrix, and the optimization problem is close to the ideal Markowitz case.

In other words, the clustering and intra-cluster optimization steps have allowed us to transform a "Markowitz-cursed" problem ($|\rho| \gg 0$) into a well-behaved problem ($\rho \approx 0$).

Engineering Solution 3: Allocation To Allocators (A2A)

U.S. Patent # 11,410,240



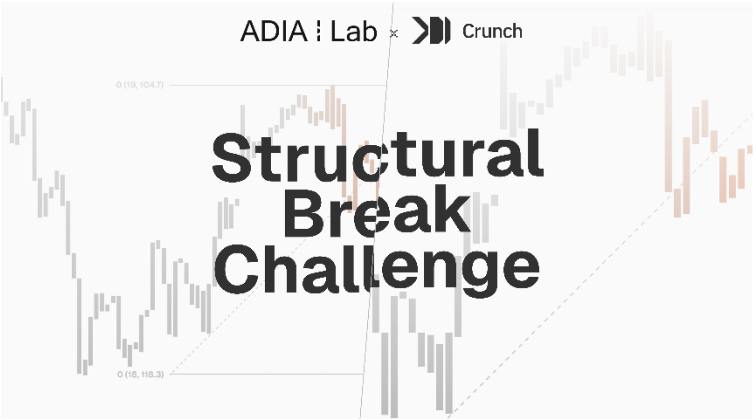


- An ensemble approach to diversify model risks (avoidance of single point of failure)
- Each base allocator is designed to achieve certain performance related goal
- The base allocators are then aggregated based on a robustness criterion
- A meta-allocation model is used to determine the final allocation from the base allocation

Applications Beyond Finance

Engineering Decision-Making Under Uncertainty

- Financial Engineering demonstrates the power of engineering to answer complex questions
- Many important societal problems share similar characteristics to financial decision-making
  - Barriers to experimentation
  - Non-stationarity
  - Low signal-to-noise ratio
  - Small samples
- In 2022, ADIA established ADIA Lab as an independent research institute dedicated to apply computational and data sciences to solving critical societal problems



Scientific disciplines often deal with idealized or narrowly-defined problems. Engineering approaches can be well-suited to solve complex problems that are mathematically intractable or where mathematical solutions make unrealistic assumptions. For example, ADIA Lab's 2025 Structural Break Challenge crowdsources the development of algorithms for detecting structural breaks.

Engineering Decision-Making Under Uncertainty

- ADIA Lab's 2024 Data Science Challenge called for the application of AI methods to the discovery of causal relations
- The challenge was designed in collaboration with:
  - **Prof. Guido Imbens – Nobel Prize 2021**
  - **Prof. Miguel Hernan – Rousseeuw 2022**
- The competition attracted 1,904 teams worldwide, who contributed 3,343 solutions
- The winning teams received a cash prize of $100,000
  - The winning solutions are state-of-the-art

ADIA Lab Causal Discovery Challenge

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Abstract. This paper describes the ADIA Lab Causal Discovery Challenge conducted in 2024. The challenge focused on causal discovery, the task of inferring causal relationships from observational data, with an emphasis on the classification of variables according to their causal roles. Participants were tasked with identifying eight causal categories (Confounder, Collider, Mediator, Independent, Cause of X, Consequence of X, Cause of Y, and Consequence of Y) using a large synthetic database generated using known causal graphs. The competition attracted significant global participation, with 1,904 registered users submitting 3,343 solution attempts. We analyze the methodological approaches

ADIA Lab Research Verticals & Key Projects (1/2)

Climate Science

1. Techno-economic Assessment of Unconventional Water Sources
2. Using AI and Large Language Models (LLM) for explaining and demonstrating climate simulations
3. Promoting interoperability and interdisciplinary in Climate Science: improve access to data, enhance communication between systems, and foster inter-disciplinary collaboration

Health Sciences

1. Quantifying Economic Value for Health
2. Federated Data Tools for Secure Health Data Sharing
3. Redesign Healthcare Delivery
4. Adoption of AI Technologies by Health Professionals
5. Causal AI for the Generation of Real-World Evidence
6. Impact of Diversity on deployment of precision medicine in the UAE

Materials Science

1. AI-Guided Discovery of Advanced Materials for Extreme Environments
2. Accelerated Simulation Platforms for Materials Design and Testing
3. Development of Sustainable and Recyclable Materials for Industrial Use
4. Integration of Quantum Computing for Predictive Materials Modeling
5. Autonomous Laboratory Systems for Rapid Materials Innovation

ADIA Lab Research Verticals & Key Projects (2/2)

Digital Economy

1. Trusted digital contract framework for the digital economy
2. Labor and Capital Mobility in the Production Network
3. Phygital Asset Integration Framework: Creating and Securing Digital Representations of Physical Assets

Trustworthy AI

1. Robust and Transparent AI Models for High-Stakes Decision-Making
2. Bias Mitigation and Fairness Evaluation in Machine Learning Systems
3. Causality, Explainability and Interpretability in AI Models
4. Adversarial Robustness and Security in AI Pipelines
5. Certification and Auditing Frameworks for AI Systems

Supercomputing

1. Development of Exascale Computing Capabilities for Scientific Discovery
2. Energy-Efficient Algorithms for Large-Scale Simulation and Modeling
3. AI-Accelerated High-Performance Computing Workflows
4. Advanced Architectures for Quantum-Classical Hybrid Systems
5. Benchmarking and Optimization of HPC Infrastructure

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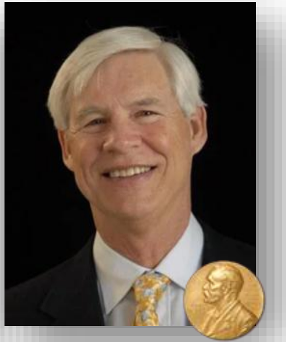

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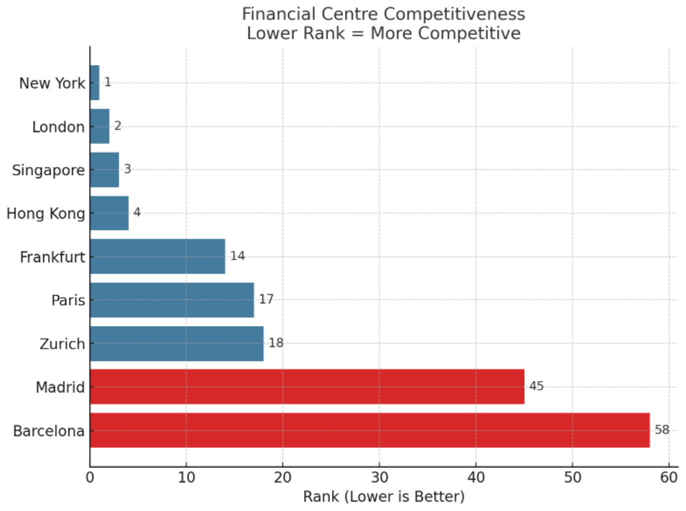
Conclusiones

El Coste de Oportunidad (1/2)

- **Subrepresentación en centros de decisión globales**
  - España tiene escasa presencia en instituciones financieras líderes, hedge funds, bancos de inversión y fondos soberanos, donde los ingenieros financieros tienen un papel clave
  - Sesgo negativo en la asignación de capital a España
- **Desventaja en innovación financiera y pérdida de competitividad**
  - La ausencia de este perfil limita la capacidad del país para desarrollar productos financieros innovadores, algoritmos de inversión o infraestructuras de mercado competitivas
  - Pérdida de capital nacional en favor de entidades extranjeras
- **Ineficiencia en la gestión de recursos financieros**
  - La escasez de expertos con formación rigurosa lleva a decisiones subóptimas en la gestión de recursos públicos y privados



Source: Global Financial Centres Index 37 (Z/Yen Group, March 2025)

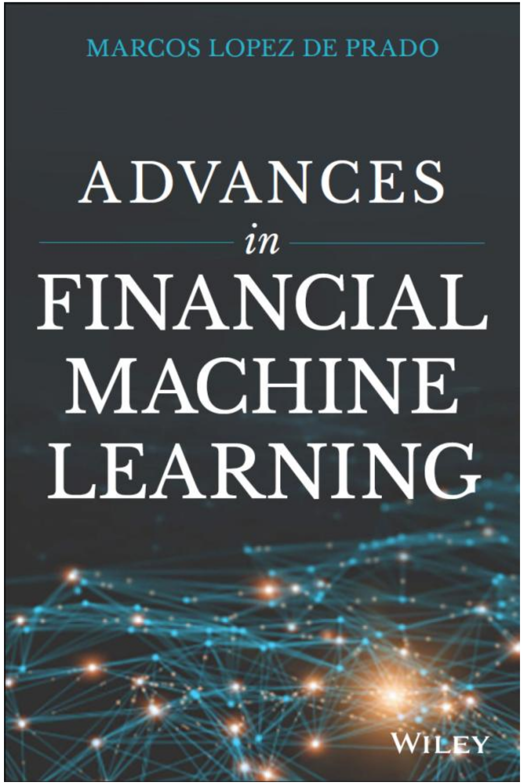
España ocupa posiciones bajas en los rankings the competitividad financiera. Para atraer y retener inversiones, es necesario que España eduque ingenieros especializados en proveer soluciones a problemas financieros.

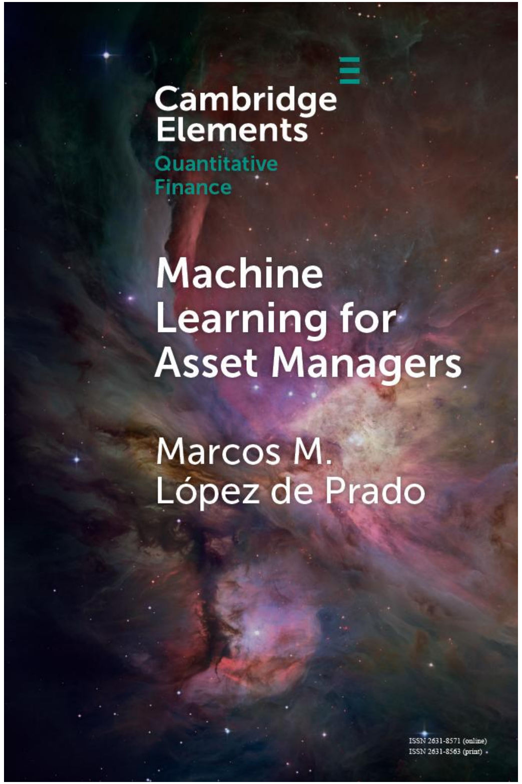
El Coste de Oportunidad (2/2)

- **Dependencia de talento extranjero**
  - España recurre a profesionales extranjeros o a consultoras internacionales, lo que implica mayores costes y menor PIB
  - La claudicación de la soberanía digital implica la pérdida de infraestructura estratégica, propiedad intelectual, privacidad, …
- **Fuga de talento matemático y técnico**
  - Estudiantes y profesionales españoles migran al extranjero para formarse y trabajar en ingeniería financiera, lo que representa una pérdida neta de capital humano altamente cualificado
- **Desalineación con los estándares internacionales**
  - Las universidades de referencia mundial (Columbia, Cornell, Berkeley, Imperial, etc.) ofrecen programas de ingeniería financiera; la falta de oferta en España excluye a nuestro país de esta importante red global de investigación

La ingeniería financiera es un pilar esencial para el desarrollo competitivo de la **economía digital**, en particular en el ámbito Fintech, gestión de activos, y mercados de capitales. **Para no quedarse atrás, España necesita seguir el ejemplo de otros países de la OCDE**.

For Additional Details





The first wave of quantitative innovation in finance was led by Markowitz optimization. Machine Learning is the second wave and it will touch every aspect of finance. López de Prado's Advances in Financial Machine Learning is essential for readers who want to be ahead of the technology rather than being replaced by it.
— Prof. **Campbell Harvey**, Duke University. Former President of the American Finance Association.

Financial problems require very distinct machine learning solutions. Dr. López de Prado's book is the first one to characterize what makes standard machine learning tools fail when applied to the field of finance, and the first one to provide practical solutions to unique challenges faced by asset managers. Everyone who wants to understand the future of finance should read this book.
— Prof. **Frank Fabozzi**, Johns Hopkins University. Editor of The Journal of Portfolio Management.

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