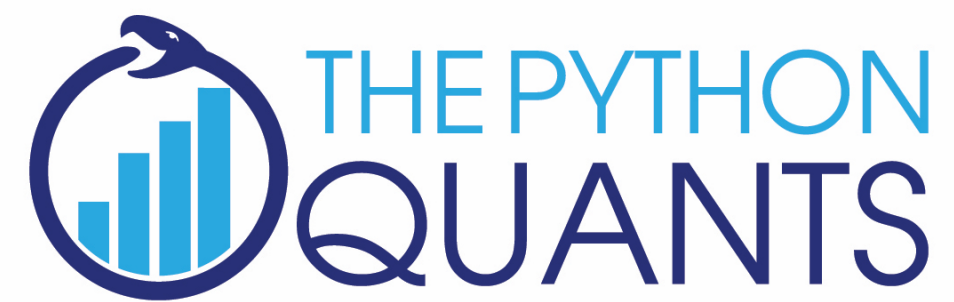


Python & AI for Algorithmic Trading

Dr. Yves J. Hilpisch

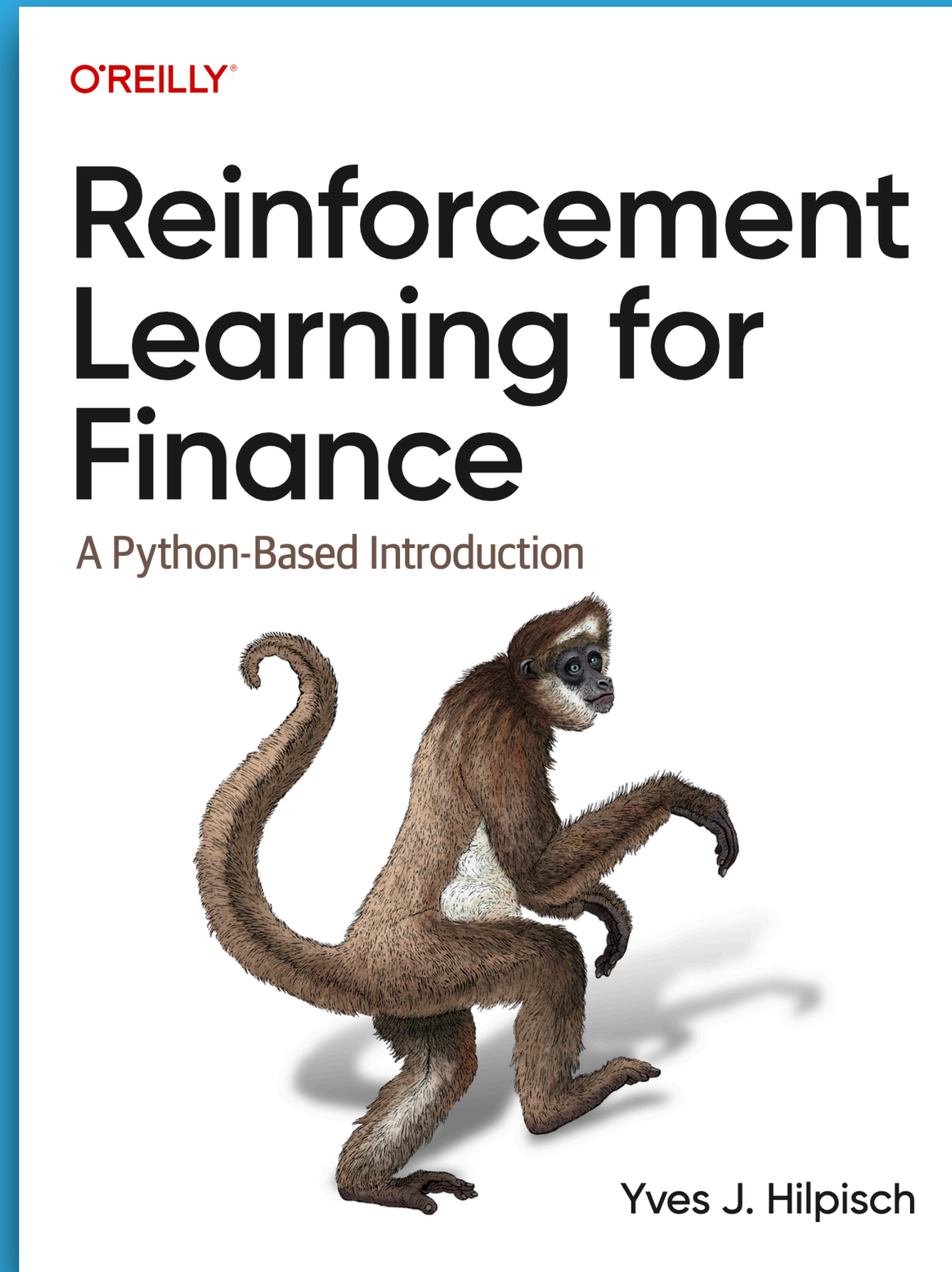
Online Bootcamp, November 13–15, 2024



Introduction

RL for Finance

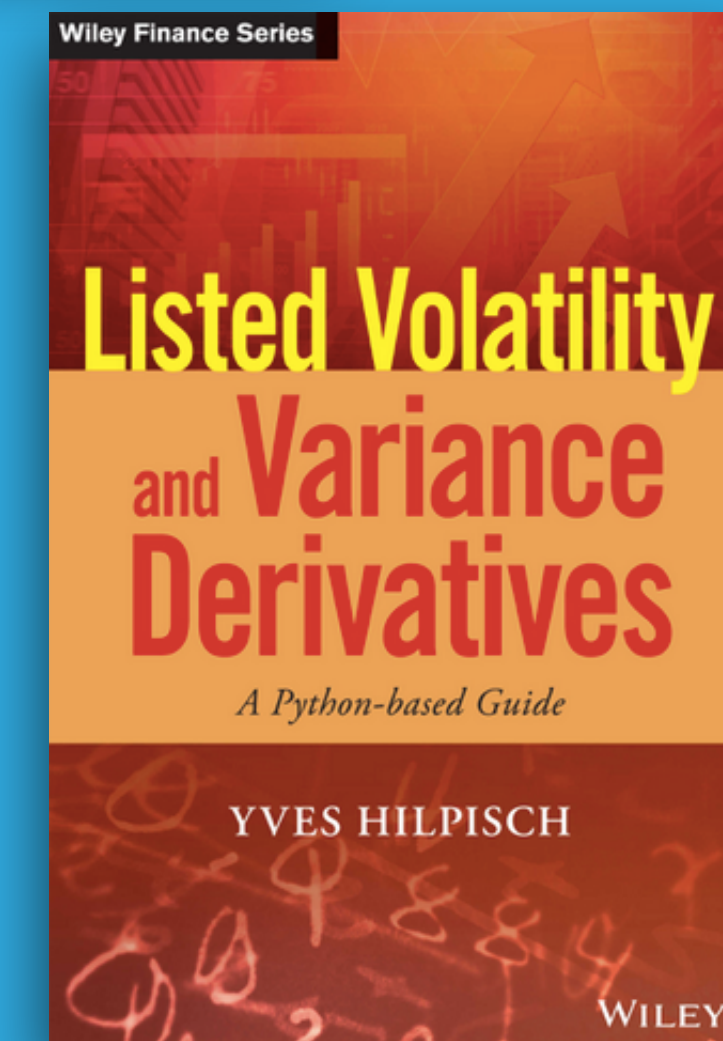
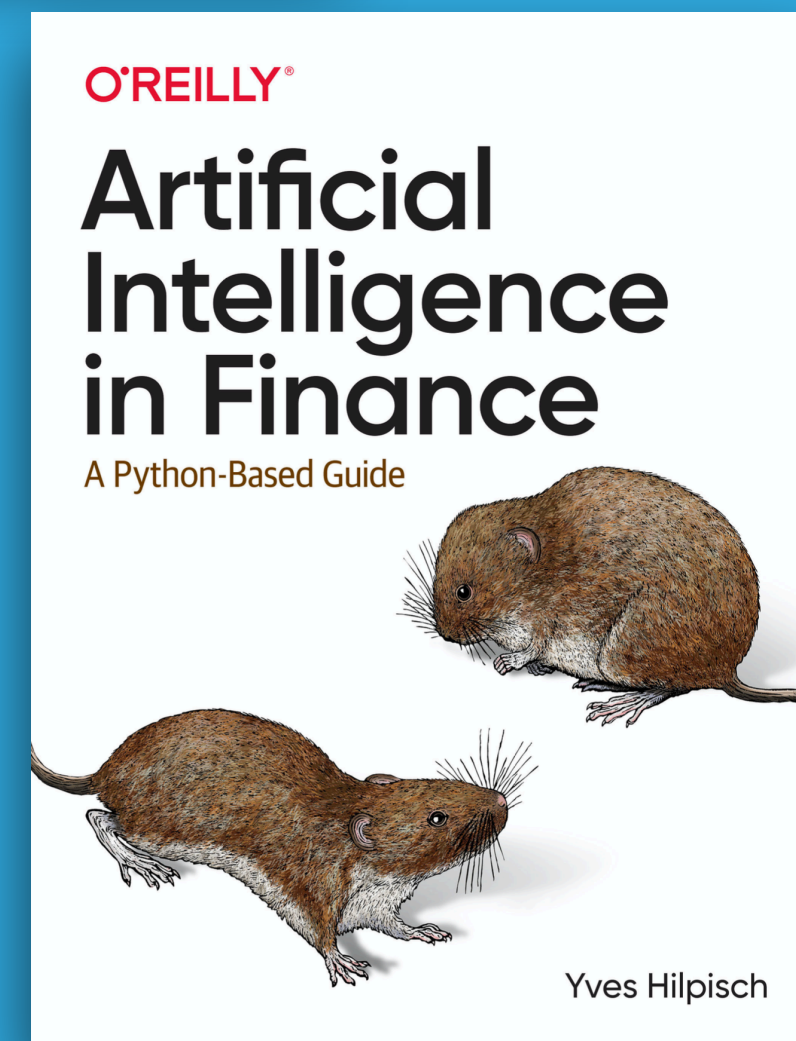
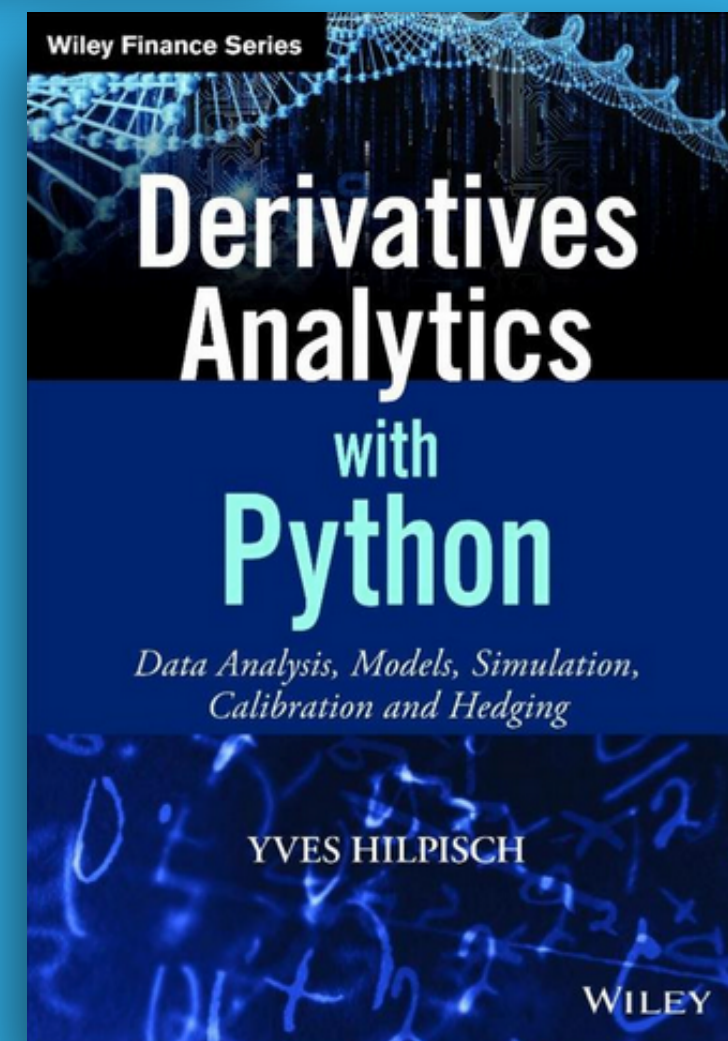
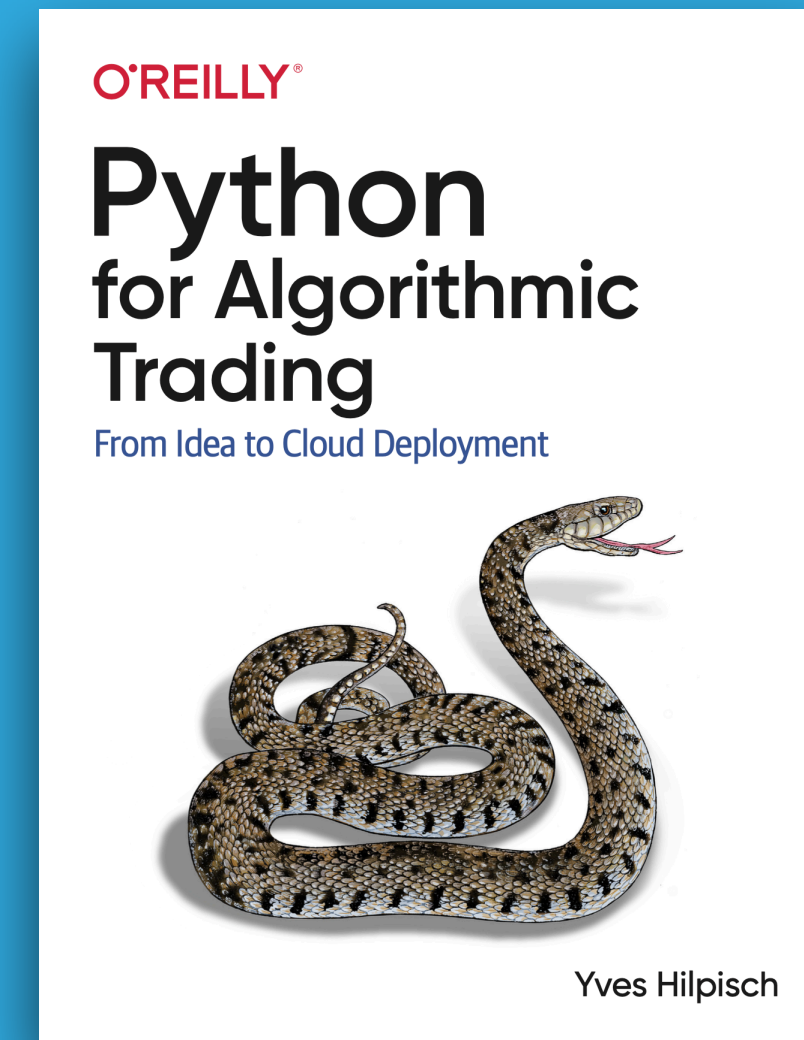
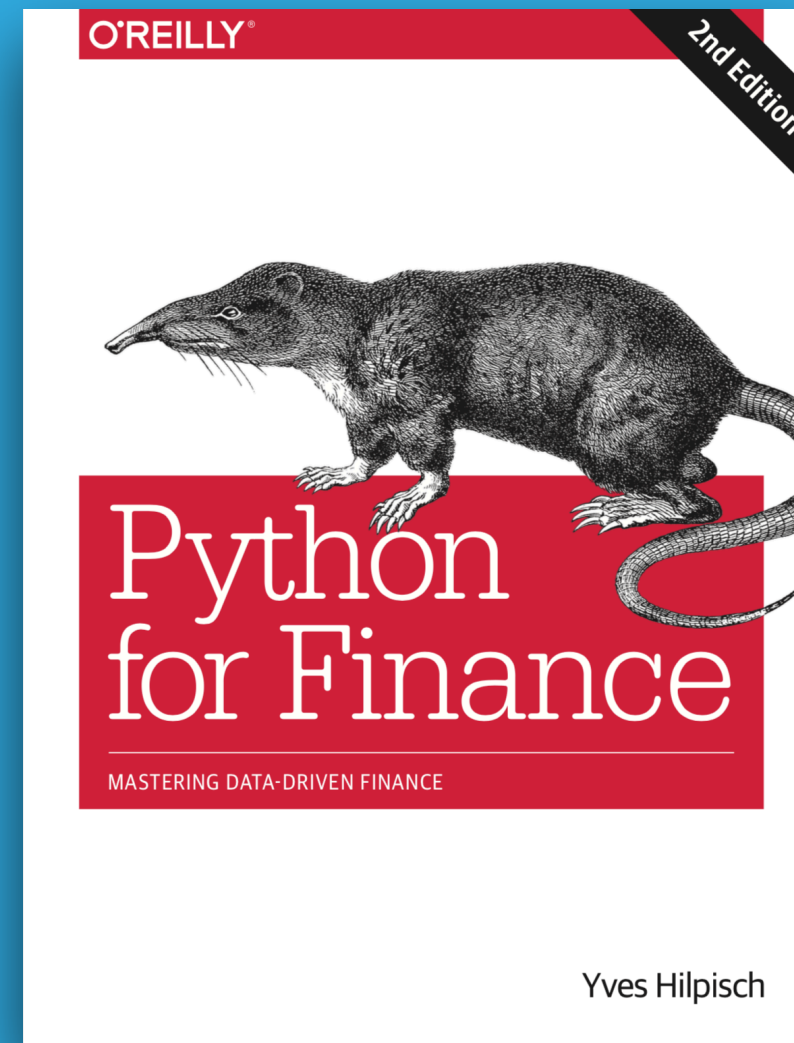
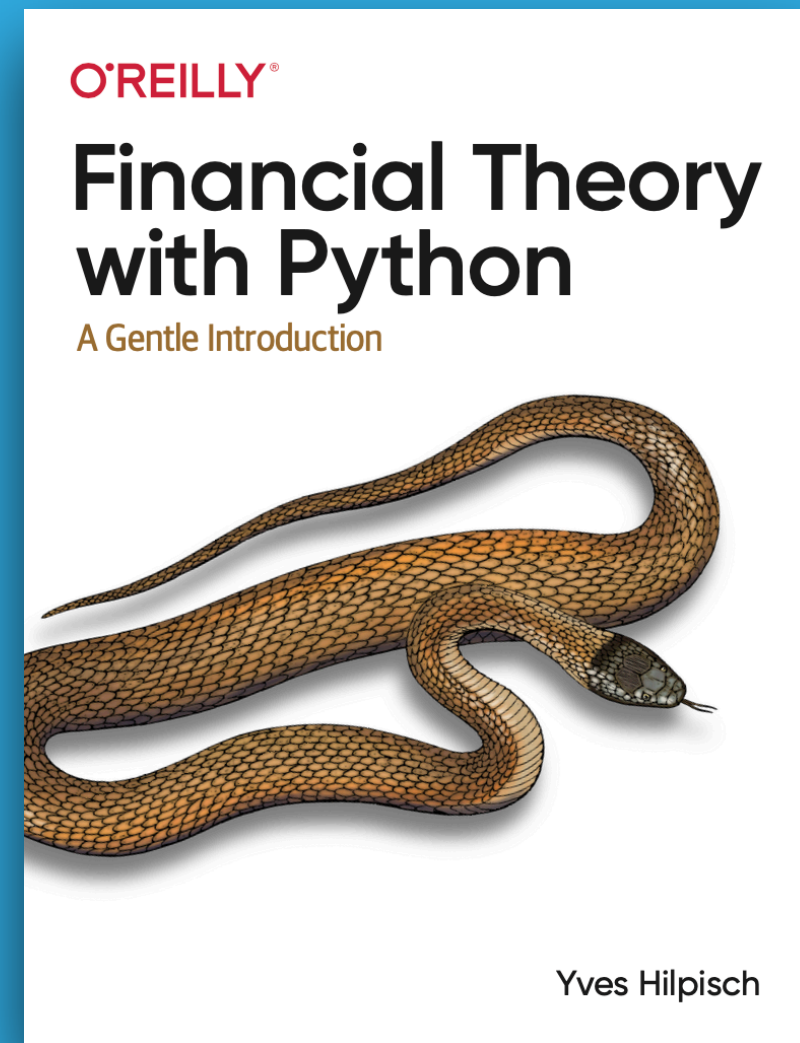
A Python-based introduction with different applications.



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Peter Mueller, CFA

(born February 22, 1995)

June 19, 2023

Dr. Yves J. Hilpisch
CEO & Program Director



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(live or self-paced)**

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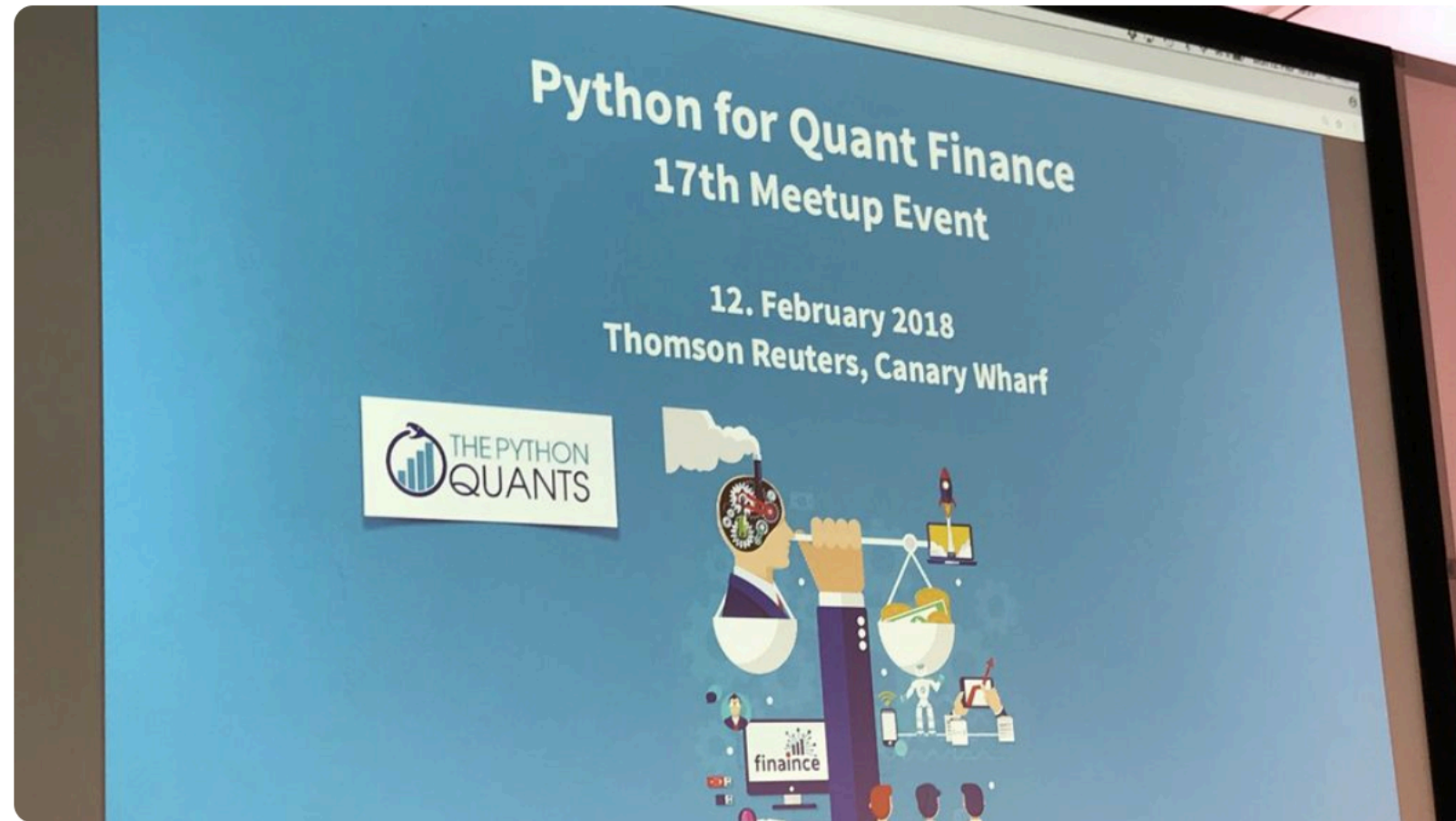
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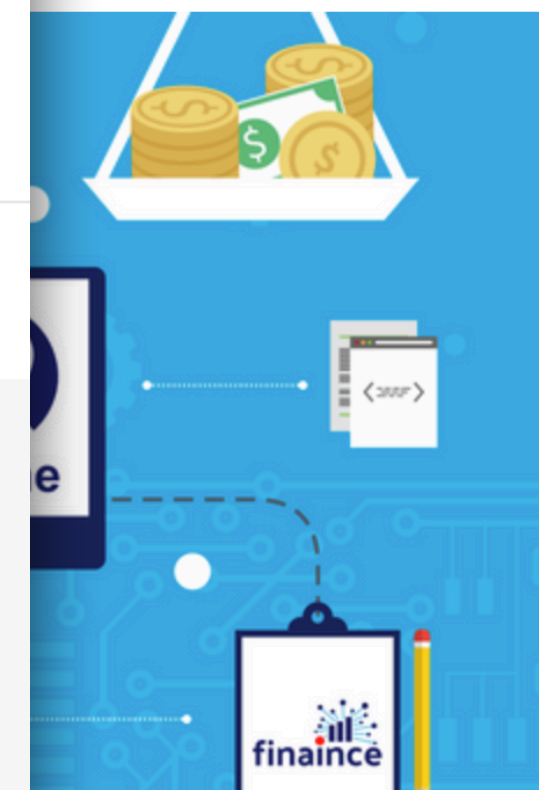
What we're about

This group is about the use of Python & AI for Quantitative Financial Applications, Algorithmic Trading and Interactive Financial Analytics.

Organizers



Yves H. and 2 others
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Artificial Intelligence in Finance & Algorithmic Trading

📍 New York, NY
👤 345 members · Public group [?]
👤 Organized by **Yves Hilpisch**

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What we're about

This Meetup group is concerned with data-driven and AI-first finance in general and algorithmic trading in particular. Its events cover the latest...

Organizer



Yves Hilpisch
[Message](#)

Dr. Yves J. Hilpisch is the founder and CEO of **The Python Quants** (<http://tpq.io>), a group focusing on the use of Python and open source technologies for financial data science, artificial intelligence, algorithmic trading, and computational finance. He is also the founder and CEO of **The AI Machine** (<http://aimachine.io>), a company focused on AI-powered algorithmic trading based on a proprietary strategy execution platform.

Yves has a Diploma in Business Administration, a Ph.D. in Mathematical Finance, and is Adjunct Professor for Computational Finance.

Yves is the author of six books (<https://home.tpq.io/books>):

- * Reinforcement Learning for Finance (2024, O'Reilly)
- * Financial Theory with Python (2021, O'Reilly)
- * Artificial Intelligence in Finance (2020, O'Reilly)
- * Python for Algorithmic Trading (2020, O'Reilly)
- * Python for Finance (2018, 2nd ed., O'Reilly)
- * Listed Volatility and Variance Derivatives (2017, Wiley Finance)
- * Derivatives Analytics with Python (2015, Wiley Finance)



Yves is the director of the online training program leading to the **Certificates in Python for Finance** (<https://cpf.tpq.io>). He also lectures on computational finance, reinforcement learning, and algorithmic trading at the **CQF Program** (<http://cqf.com>).

Yves is the originator of the financial analytics library **DX Analytics** (<http://dx-analytics.com>) and organizes Meetup group **events, conferences, and bootcamps** about Python, artificial intelligence and algorithmic trading in London (<http://pqf.tpq.io>) and New York (<http://aifat.tpq.io>). He has given **keynote speeches** at technology conferences in the United States, Europe, and Asia.

Gist with Code Resources

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Overview

Online Bootcamp

DAY 1

The Basics

(Python, Simple Strategies, Vectorized Backtesting)

DAY 2

The Platform

(Trading Platform, AI-Based Strategies)

DAY 3

The Deployment

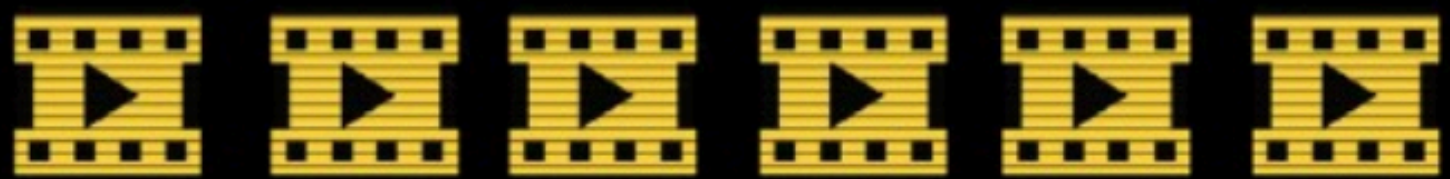
(Cloud Provider, Tool Chain, Deployment)

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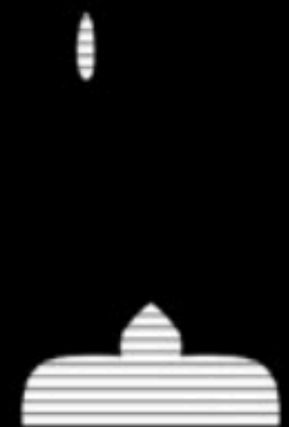
1. AI Success Stories
2. Physics Envy &
The Beauty Myth
3. Efficient Markets
4. Data-Driven Finance
5. AI-First Finance
6. DAYS 1-3 Bootcamp

AI Success Stories

SEAN GERRISH 



MACHINES THINK

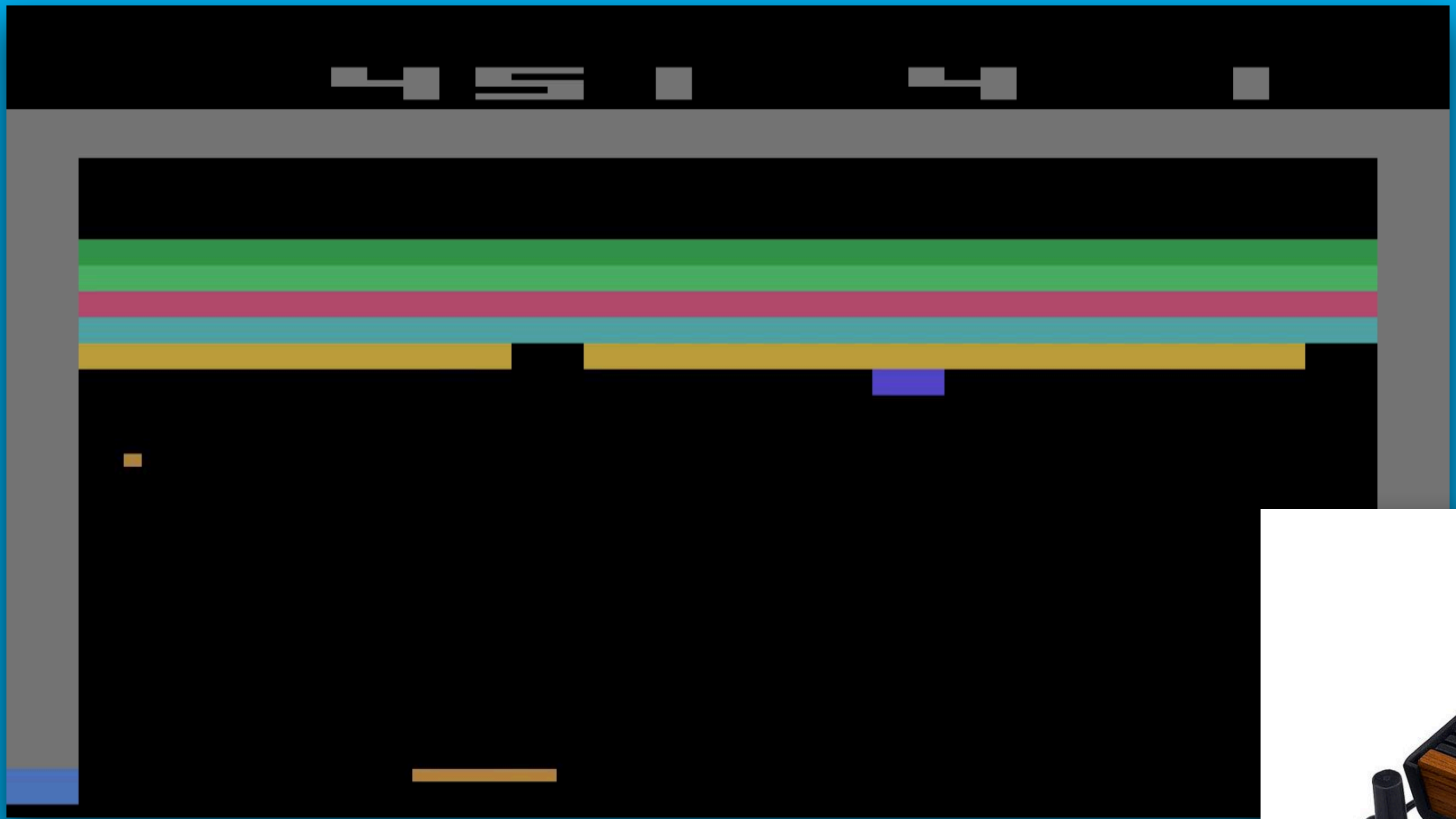


Success Stories about Deep Learning and Deep Reinforcement Learning:

- Self-Driving Cars
- Recommendation Engines
- Playing Atari Games
- Image Recognition & Classification
- Speech Recognition
- Playing the Game of Go

AI Success Stories

–Atari Games and Reinforcement Learning



“We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.”

Mnih, V. (2013): “Playing Atari with Deep Reinforcement Learning”. <https://arxiv.org/pdf/1312.5602v1.pdf>

arXiv:1312.5602v1 [cs.LG] 19 Dec 2013

Playing Atari with Deep Reinforcement Learning

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Daan Wierstra Martin Riedmiller
DeepMind Technologies
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Abstract

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

1 Introduction

Learning to control agents directly from high-dimensional sensory inputs like vision and speech is one of the long-standing challenges of reinforcement learning (RL). Most successful RL applications that operate on these domains have relied on hand-crafted features combined with linear value functions or policy representations. Clearly, the performance of such systems heavily relies on the quality of the feature representation.

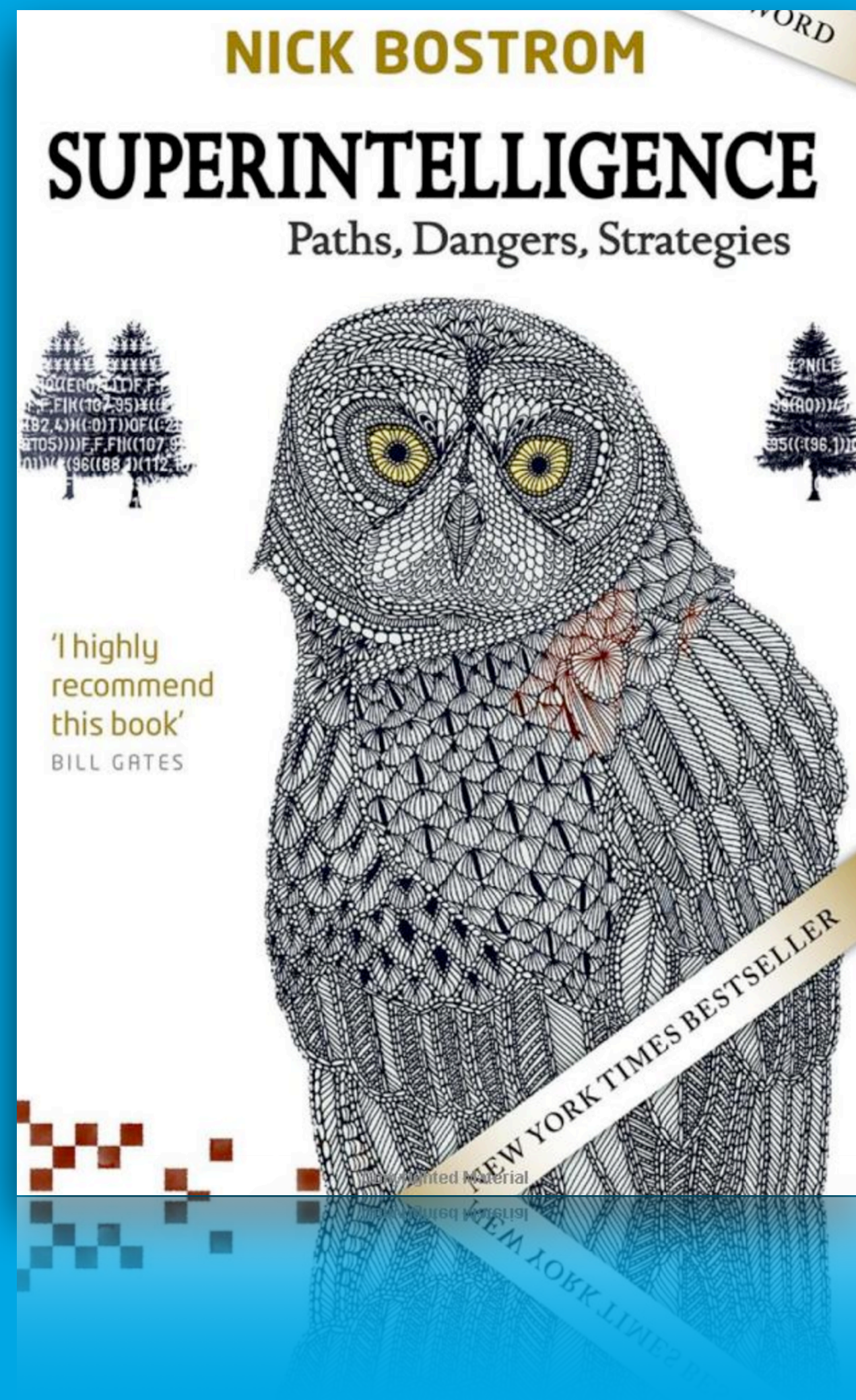
Recent advances in deep learning have made it possible to extract high-level features from raw sensory data, leading to breakthroughs in computer vision [11, 22, 16] and speech recognition [6, 7]. These methods utilise a range of neural network architectures, including convolutional networks, multilayer perceptrons, restricted Boltzmann machines and recurrent neural networks, and have exploited both supervised and unsupervised learning. It seems natural to ask whether similar techniques could also be beneficial for RL with sensory data.

However reinforcement learning presents several challenges from a deep learning perspective. Firstly, most successful deep learning applications to date have required large amounts of hand-labelled training data. RL algorithms, on the other hand, must be able to learn from a scalar reward signal that is frequently sparse, noisy and delayed. The delay between actions and resulting rewards, which can be thousands of timesteps long, seems particularly daunting when compared to the direct association between inputs and targets found in supervised learning. Another issue is that most deep learning algorithms assume the data samples to be independent, while in reinforcement learning one typically encounters sequences of highly correlated states. Furthermore, in RL the data distribution changes as the algorithm learns new behaviours, which can be problematic for deep learning methods that assume a fixed underlying distribution.

This paper demonstrates that a convolutional neural network can overcome these challenges to learn successful control policies from raw video data in complex RL environments. The network is trained with a variant of the Q-learning [26] algorithm, with stochastic gradient descent to update the weights. To alleviate the problems of correlated data and non-stationary distributions, we use

AI Success Stories

—Go and AlphaGo



“Go-playing programs have been improving at a rate of about 1 dan/year in recent years. If this rate of improvement continues, they might beat the human world champion in about a decade.”

Nick Bostrom (2014): Superintelligence.

The story of AlphaGo so far

AlphaGo is the first computer program to defeat a professional human Go player, the first program to defeat a Go world champion, and arguably the strongest Go player in history.

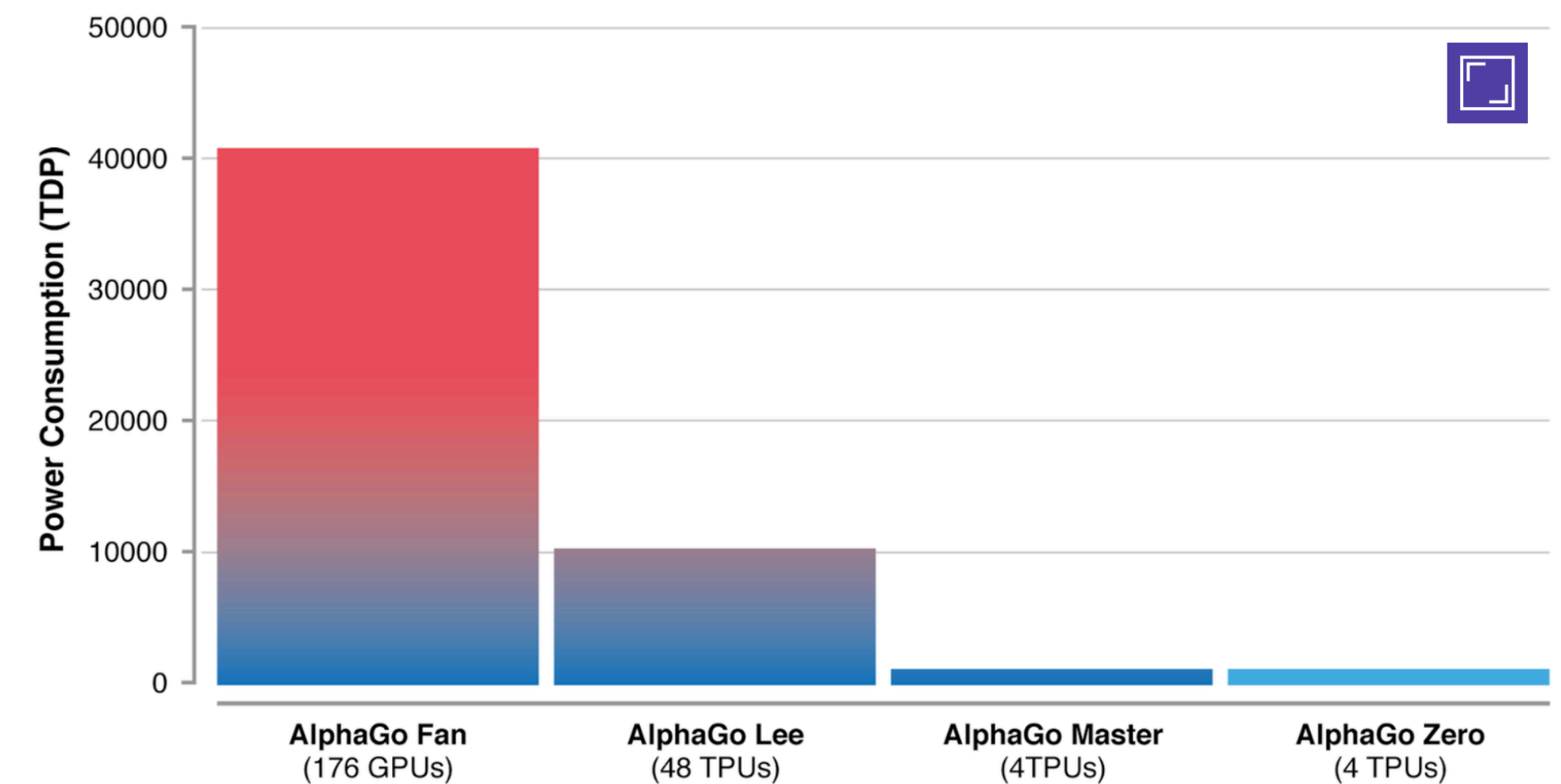
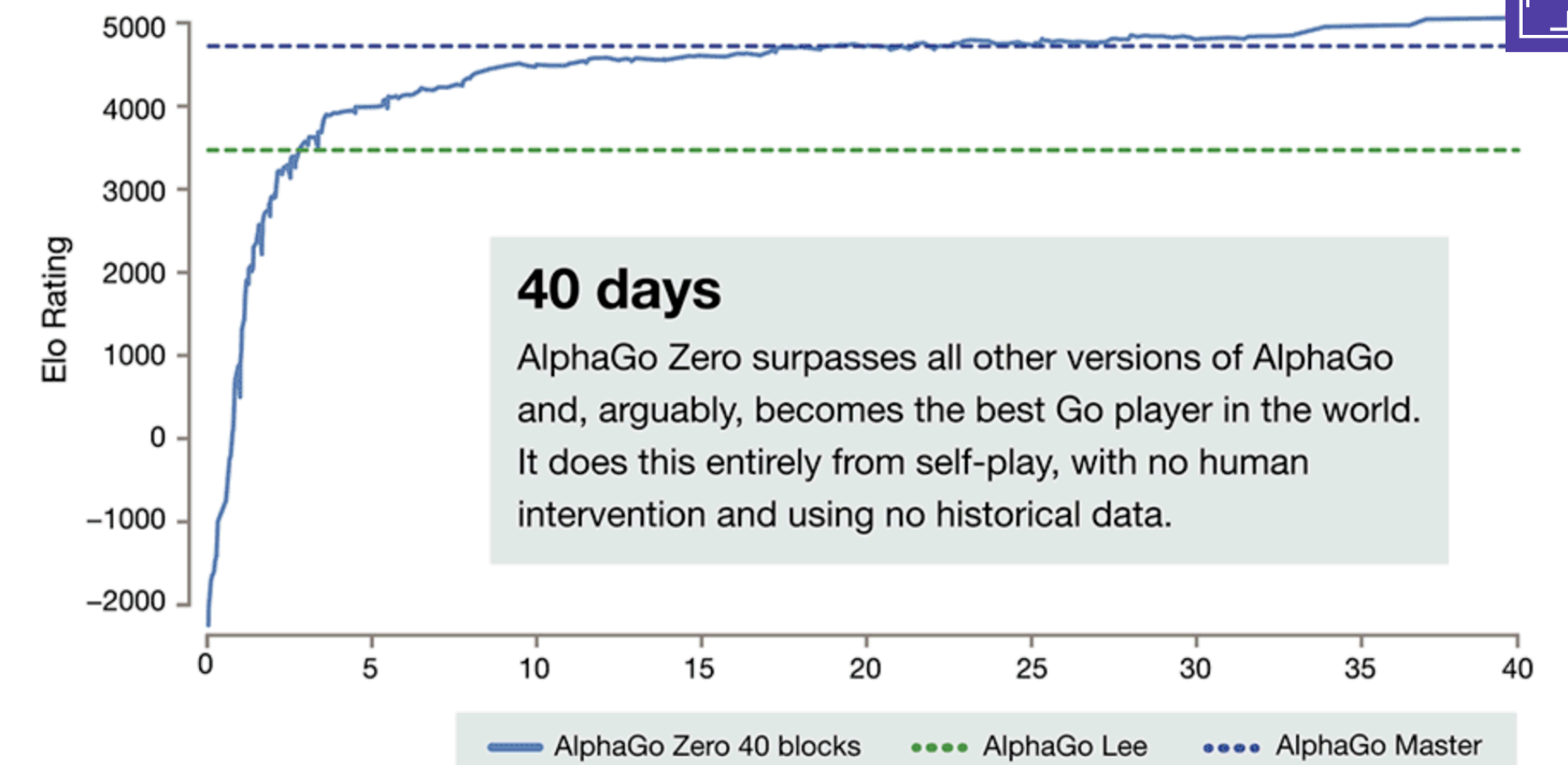
AlphaGo's first formal match was against the reigning 3-times European Champion, Mr Fan Hui, in October 2015. Its 5-0 win was the first ever against a Go professional, and the results were published in full technical detail in the international journal, [Nature](#). AlphaGo then went on to compete against legendary player Mr Lee Sedol, winner of 18 world titles and widely considered to be the greatest player of the past decade.

AlphaGo's 4-1 victory in Seoul, South Korea, in March 2016 was watched by over 200 million people worldwide. It was a landmark achievement that experts agreed was a decade ahead of its time, and earned AlphaGo a 9 dan professional ranking (the highest certification) - the first time a computer Go player had ever received the accolade.

During the games, AlphaGo played a handful of [highly inventive winning moves](#), several of which - including move 37 in game two - were so surprising they overturned hundreds of years of received wisdom, and have since been examined extensively by players of all levels. In the course of winning, AlphaGo somehow taught the world completely new knowledge about perhaps the most studied and contemplated game in history.

contemplated game in history

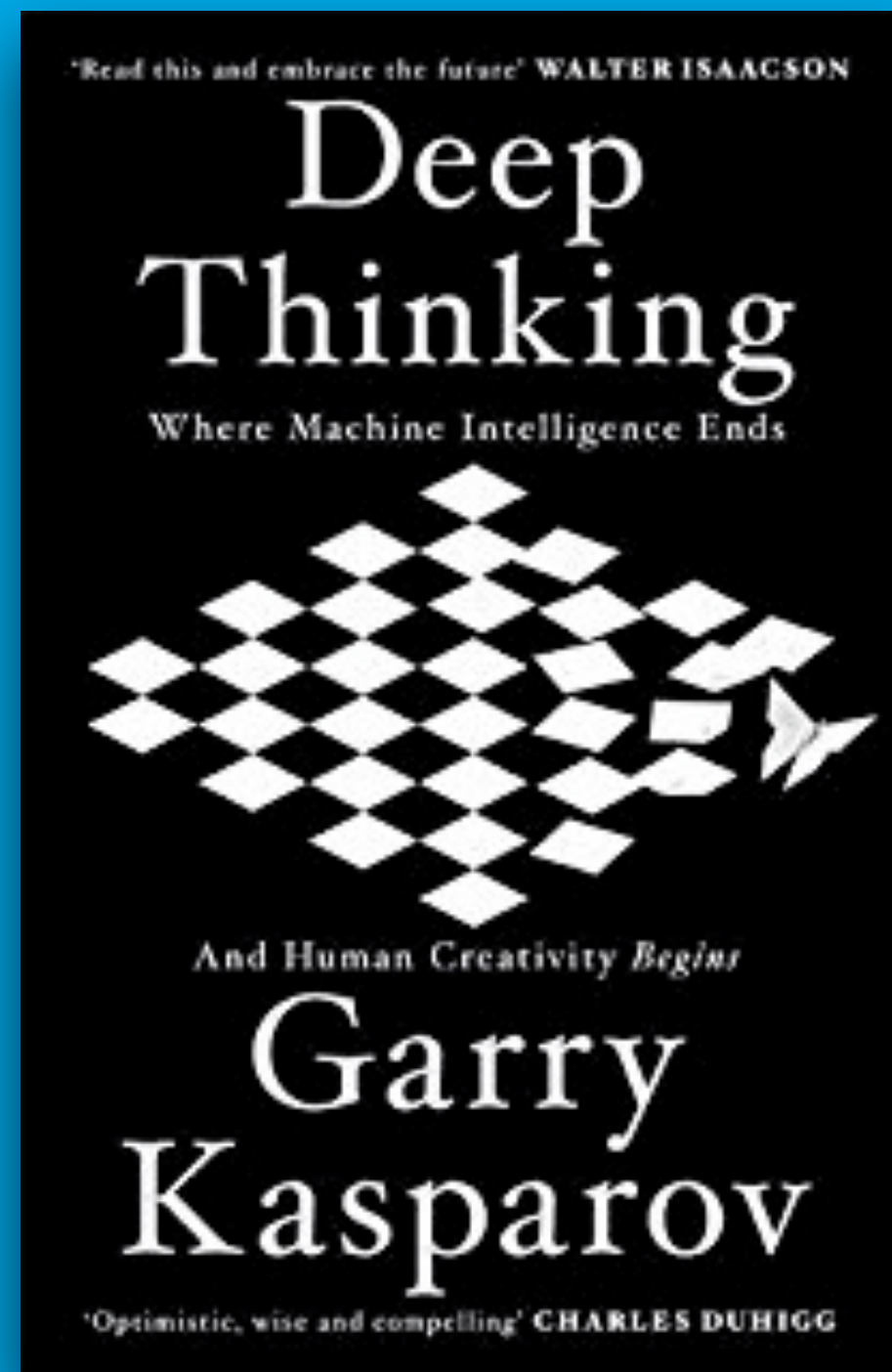
taught the world completely new knowledge about perhaps the most studied and extensively played games of all levels in the course of winning



AlphaGo has become progressively more efficient thanks to hardware gains and more recently algorithmic advances

AI Success Stories

–Chess, Deep Blue & AlphaZero



“It was a pleasant day in Hamburg in June 6, 1985, ... Each of my opponents, all thirty-two of them, was a computer. ... it didn't come as much of a surprise, ..., when I achieved a perfect 32-0 score.”

“Twelve years later I was in New York City fighting for my chess life. Against just one machine, a \$10 million IBM supercomputer nicknamed 'Deep Blue'.”

“Jump forward another 20 years to today, to 2017, and you can download any number of free chess apps for your phone that rival any human Grandmaster.”

A close-up photograph of a chessboard with several chess pieces. The board is dark with light-colored squares. Pieces include a king, queen, rook, bishop, knight, and pawns. The text is overlaid on this image.

AlphaZero: Shedding new light on the grand games of chess, shogi and Go

“Traditional chess engines – including the world computer chess champion Stockfish and IBM’s ground-breaking Deep Blue – rely on **thousands of rules and heuristics handcrafted by strong human players** that try to account for every eventuality in a game. ...

AlphaZero takes a totally different approach, replacing these hand-crafted rules with a **deep neural network and general purpose algorithms** that know nothing about the game beyond the basic rules.”

“The amount of **training** the network needs depends on the style and complexity of the game, taking **approximately 9 hours for chess**, 12 hours for shogi, and 13 days for Go.”

“In Chess, for example, it searches **only 60 thousand positions** per second in chess, compared to roughly 60 million for Stockfish.”

Source: <http://deepmind.com>

AI Success Stories

—GPT o1, ChatGPT & LLMs

Sparks of Artificial General Intelligence: Early experiments with GPT-4

Sébastien Bubeck Varun Chandrasekaran Ronen Eldan Johannes Gehrke
Eric Horvitz Ece Kamar Peter Lee Yin Tat Lee Yuanzhi Li Scott Lundberg
Harsha Nori Hamid Palangi Marco Tulio Ribeiro Yi Zhang

Microsoft Research

Abstract

Artificial intelligence (AI) researchers have been developing and refining large language models (LLMs) that exhibit remarkable capabilities across a variety of domains and tasks, challenging our understanding of learning and cognition. The latest model developed by OpenAI, GPT-4 [Ope23], was trained using an unprecedented scale of compute and data. In this paper, we report on our investigation of an early version of GPT-4, when it was still in active development by OpenAI. We contend that (this early version of) GPT-4 is part of a new cohort of LLMs (along with ChatGPT and Google’s PaLM for example) that exhibit more general intelligence than previous AI models. We discuss the rising capabilities and implications of these models. We demonstrate that, beyond its mastery of language, GPT-4 can solve novel and difficult tasks that span mathematics, coding, vision, medicine, law, psychology and more, without needing any special prompting. Moreover, in all of these tasks, GPT-4’s performance is strikingly close to human-level performance, and often vastly surpasses prior models such as ChatGPT. Given the breadth and depth of GPT-4’s capabilities, we believe that it could reasonably be viewed as an early (yet still incomplete) version of an artificial general intelligence (AGI) system. In our exploration of GPT-4, we put special emphasis on discovering its limitations, and we discuss the challenges ahead for advancing towards deeper and more comprehensive versions of AGI, including the possible need for pursuing a new paradigm that moves beyond next-word prediction. We conclude with reflections on societal influences of the recent technological leap and future research directions.

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How can I implement the Black-Scholes option pricing formula for a European call option in concise Python code?



You can implement the Black-Scholes option pricing formula for a European call option in a more concise manner using Python and the `scipy.stats` library as shown below:



python

Copy code

```
import numpy as np
from scipy.stats import norm

def black_scholes_call(S, K, T, r, sigma):
    d1 = (np.log(S / K) + (r + 0.5 * sigma**2) * T) / (sigma * np.sqrt(T))
    d2 = d1 - sigma * np.sqrt(T)
    return S * norm.cdf(d1) - K * np.exp(-r * T) * norm.cdf(d2)

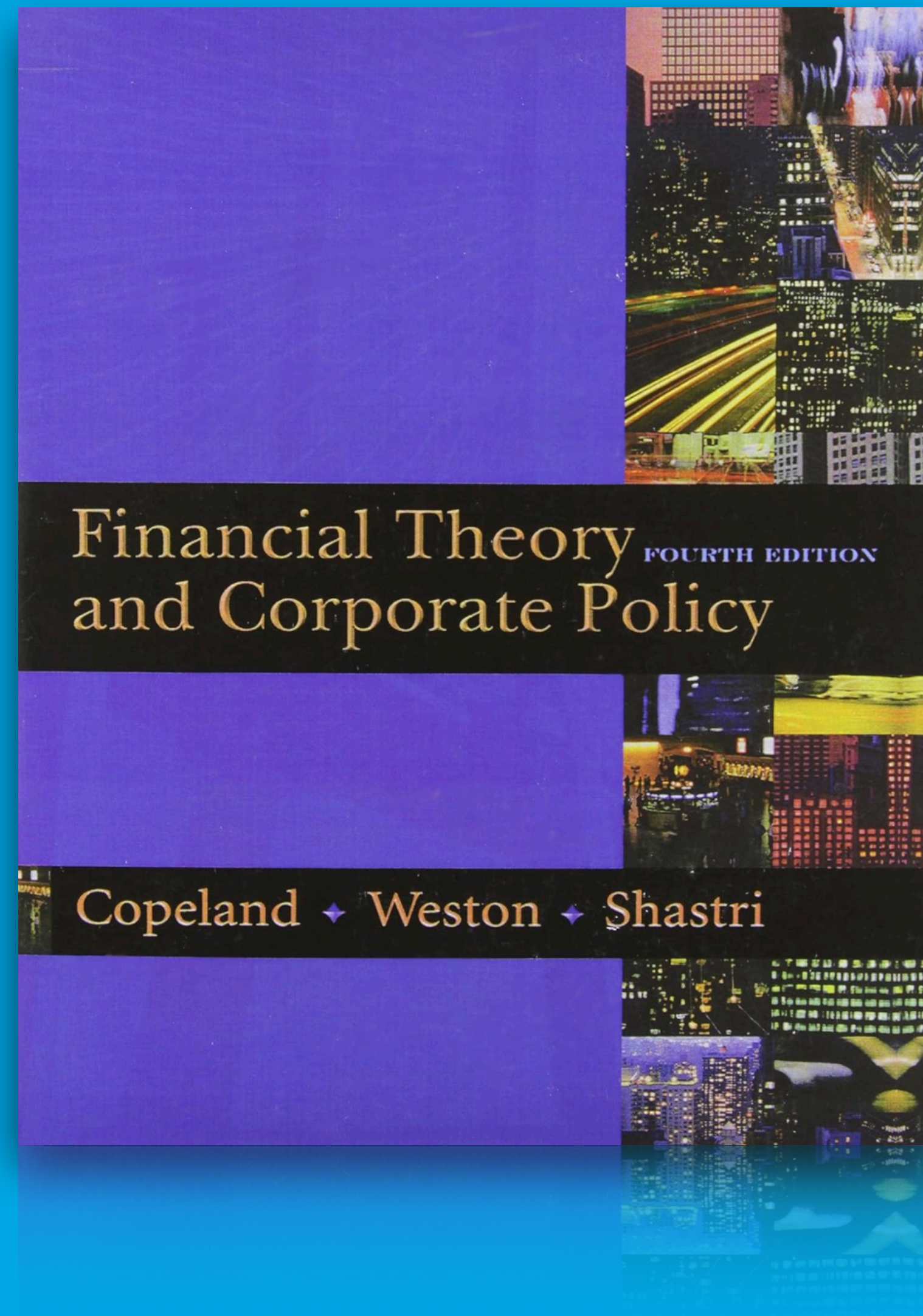
S, K, T, r, sigma = 100, 110, 1, 0.05, 0.25
print("Call price:", black_scholes_call(S, K, T, r, sigma))
```

This implementation calculates the price of a European call option using the Black-Scholes formula in a more concise way. The function `black_scholes_call` takes the same input parameters as before (stock price, strike price, time to maturity, risk-free interest rate, and stock volatility) and returns the option price. The example usage demonstrates how to call this function and print the resulting call price.

Physics Envy & The Beauty Myth

Traditional Finance

Not all cornerstones of traditional finance have stood the test of time.



Cornerstones of Finance

A. Expected Utility (x)

B. Equilibrium Theory (x)

C. Normal Distributions (x)

D. Linear Relationships (x)

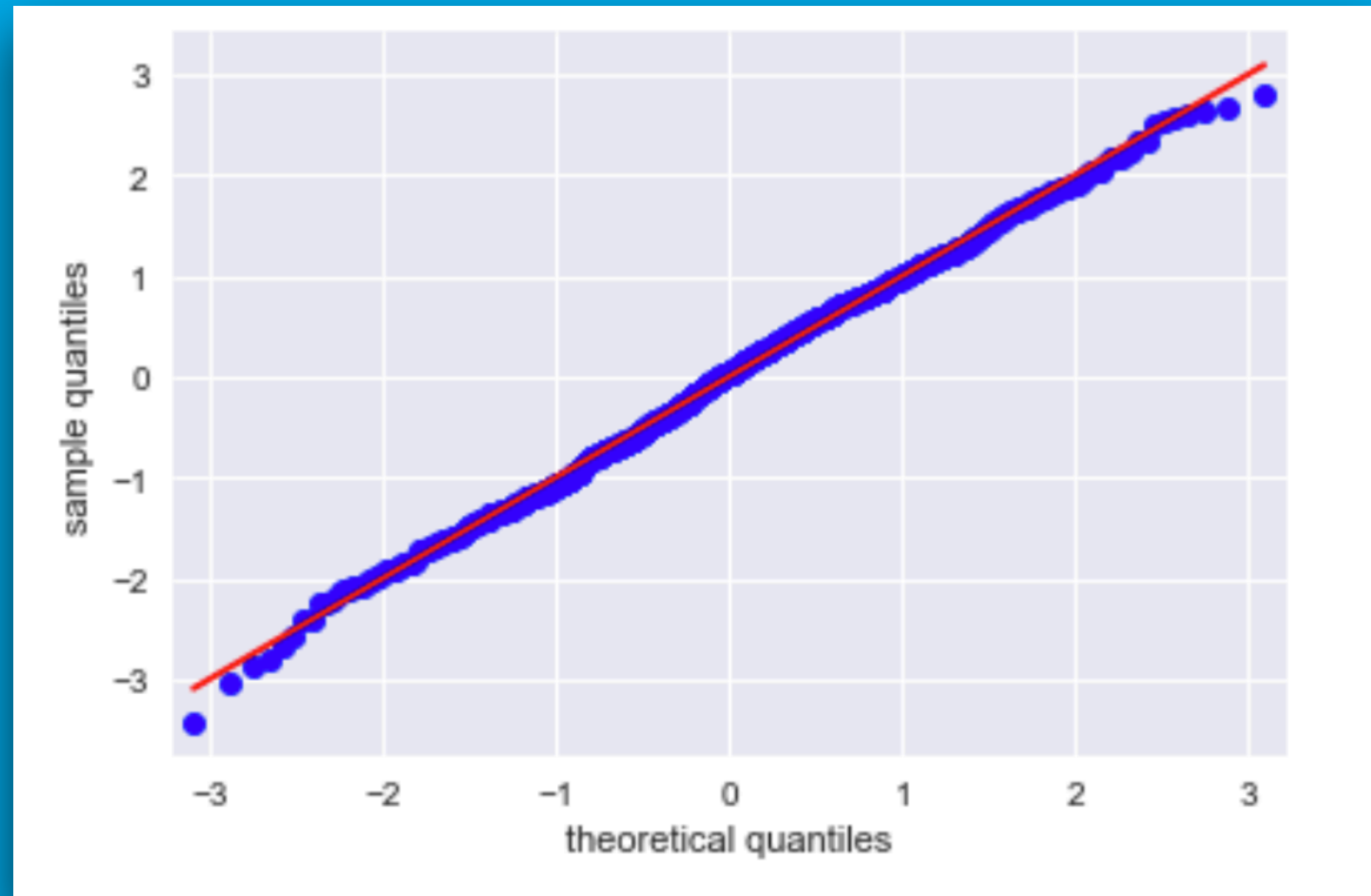
E. Efficient Markets (✓)

F. Arbitrage Pricing (✓)

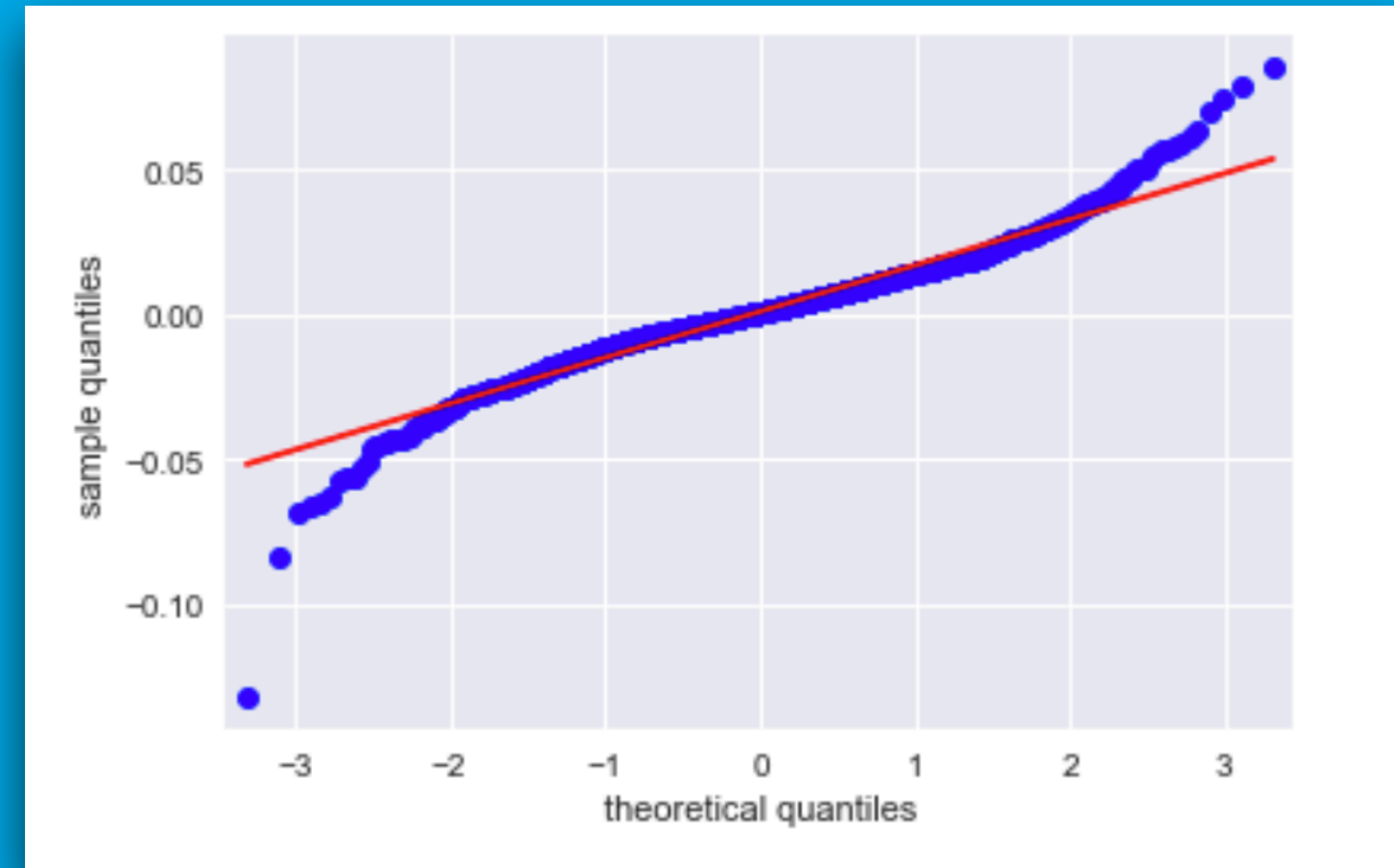
Normal Distributions

Easy to handle mathematically, often found in physics, but almost never in finance.

Theory



Reality



Linear Relationships

Easy to understand, intuitively appealing, and straightforward to manage.

The Journal of FINANCE

VOL. XIX

SEPTEMBER 1964

No. 3

CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK*

WILLIAM F. SHARPE†

I. INTRODUCTION

ONE OF THE PROBLEMS which has plagued those attempting to predict the behavior of capital markets is the absence of a body of positive micro-economic theory dealing with conditions of risk. Although many useful insights can be obtained from the traditional models of investment under conditions of certainty, the pervasive influence of risk in financial transactions has forced those working in this area to adopt models of price behavior which are little more than assertions. A typical classroom explanation of the determination of capital asset prices, for example, usually begins with a careful and relatively rigorous description of the process through which individual preferences and physical relationships interact to determine an equilibrium pure interest rate. This is generally followed by the assertion that somehow a market risk-premium is also determined, with the prices of assets adjusting accordingly to account for differences in their risk.

A useful representation of the view of the capital market implied in such discussions is illustrated in Figure 1. In equilibrium, capital asset prices have adjusted so that the investor, if he follows rational procedures (primarily diversification), is able to attain any desired point along a *capital market line*.¹ He may obtain a higher expected rate of return on his holdings only by incurring additional risk. In effect, the market presents him with two prices: the *price of time*, or the pure interest rate (shown by the intersection of the line with the horizontal axis) and the *price of risk*, the additional expected return per unit of risk borne (the reciprocal of the slope of the line).

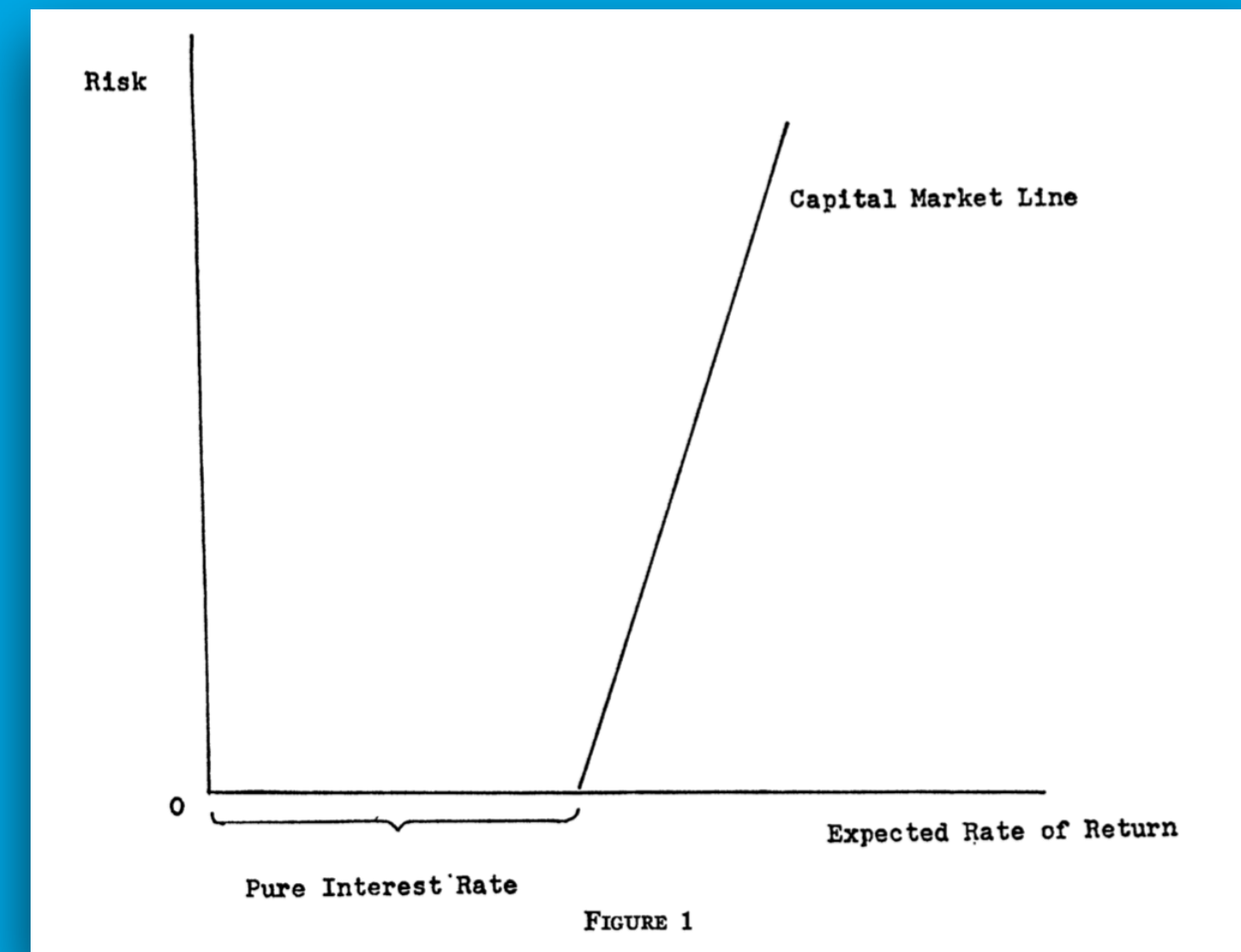
* A great many people provided comments on early versions of this paper which led to major improvements in the exposition. In addition to the referees, who were most helpful, the author wishes to express his appreciation to Dr. Harry Markowitz of the RAND Corporation, Professor Jack Hirshleifer of the University of California at Los Angeles, and to Professors Yoram Barzel, George Brabb, Bruce Johnson, Walter Oi and R. Haney Scott of the University of Washington.

† Associate Professor of Operations Research, University of Washington.

1. Although some discussions are also consistent with a non-linear (but monotonic) curve.

$$\mu_i = r + \beta_i(\mu_M - r)$$

“Market Risk”
“Idiosyncratic Risk”



Lacking Empirical Support

CAPM is still popular both in theory and practice although it lacks empirical support.

DETERMINING THE COST OF CAPITAL IS THEREFORE A MATERIAL
COMPONENT OF COMPANY VALUATIONS

Determination of beta factors and cost of capital

The cost of capital is the interest rate used to discount the cash flows relevant to the valuation. The determination of the cost of capital is thus an essential component of business valuations. For the determination of cost of capital, the valuation standard IDW S1 explicitly refers to the capital market-based Capital Asset Pricing Model (CAPM or Tax-CAPM), according to which the cost of equity can basically be broken down into a base interest rate, a beta factor and a market risk premium. The beta represents the company-specific risk and measures the price fluctuation of the individual value (the individual value risk) in relation to the market (market risk).

The beta factor is determined on the basis of a linear regression of returns. In practice, a valuer is regularly faced with a challenge in this process: in the case of unlisted companies, the derivation must be made via the returns of suitable listed comparable companies (peer group).

“The attraction of the CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk.”

“The version of the CAPM developed by Sharpe (1964) and Lintner (1965) has never been an empirical success. ... The problems are serious enough to invalidate most applications of the CAPM.”

Fama and French (2004):
“The Capital Asset Pricing Model: Theory and Evidence.”

Prices are Predictions

Prices embody predictions about future cash flows discounted to today.

1.1 Prices are Predictions

Modern analysis of financial markets centers on the following definition of a price, derived from the generic optimality condition of an investor:

$$P_{i,t} = E[M_{t+1}X_{i,t+1}|\mathcal{I}_t]. \quad (1.1)$$

In words, the prevailing price of an asset, $P_{i,t}$, reflect investors' valuation of its future payoffs, $X_{i,t+1}$. These valuations are discounted based on investors' preferences, generically summarized as future realized marginal rates of substitution, M_{t+1} . The price is then determined by investor expectations of these objects given their conditioning information $\mathcal{I}_t$. In other words, prices are predictions—they reflect investors' best guesses for the (discounted) future payoffs shed by an asset.

for the (discounted) future payoffs shed by an asset.

other words, prices are predictions—they reflect investors' best guesses

Source: Kelly and Xiu (2023)

Prediction Fails

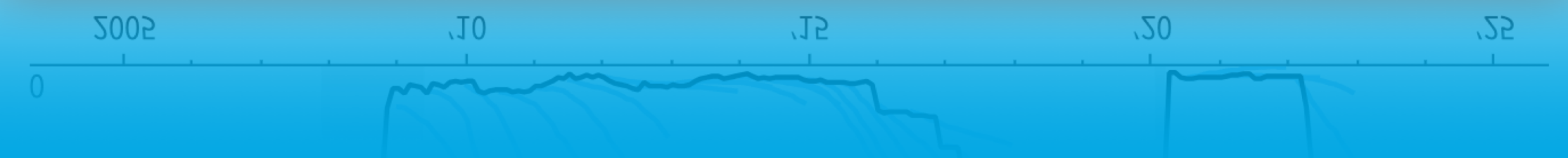
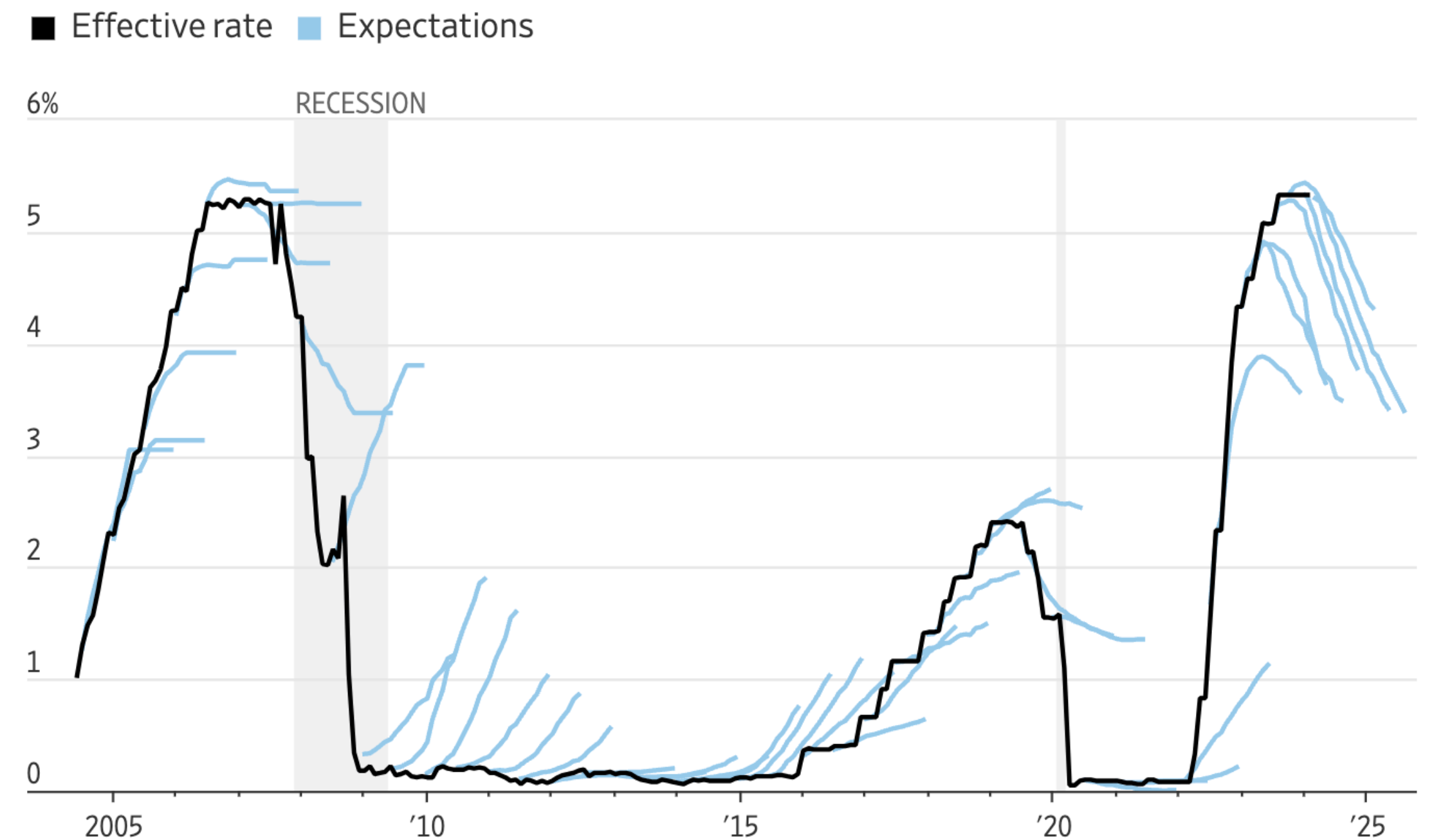
Empirically, finance has a pretty bad track record in predicting prices

10-year U.S. Treasury yield, market expectations vs. realized



Note: Expectations based on average consensus from the Philadelphia Fed's quarterly survey of professional forecasters.
Source: Clocktower Group

Federal-funds rate, market expectations vs. realized



Source: wsj.com

Physics Envy

Finance might have been driven for too long by quest for the most simple models.

WARNING: Physics Envy May Be Hazardous To Your Wealth!*

Andrew W. Lo[†] and Mark T. Mueller[‡]

This Draft: March 19, 2010

Abstract

The quantitative aspirations of economists and financial analysts have for many years been based on the belief that it should be possible to build models of economic systems—and financial markets in particular—that are as predictive as those in physics. While this perspective has led to a number of important breakthroughs in economics, “physics envy” has also created a false sense of mathematical precision in some cases. We speculate on the origins of physics envy, and then describe an alternate perspective of economic behavior based on a new taxonomy of uncertainty. We illustrate the relevance of this taxonomy with two concrete examples: the classical harmonic oscillator with some new twists that make physics look more like economics, and a quantitative equity market-neutral strategy. We conclude by offering a new interpretation of tail events, proposing an “uncertainty checklist” with which our taxonomy can be implemented, and considering the role that quants played in the current financial crisis.

Keywords: Quantitative Finance; Efficient Markets; Financial Crisis; History of Economic Thought.

JEL Classification: G01, G12, B16, C00

*The views and opinions expressed in this article are those of the authors only, and do not necessarily represent the views and opinions of AlphaSimplex Group, MIT, or any of their affiliates and employees. The authors make no representations or warranty, either expressed or implied, as to the accuracy or completeness of the information contained in this article, nor are they recommending that this article serve as the basis for any investment decision—this article is for information purposes only. Research support from AlphaSimplex Group and the MIT Laboratory for Financial Engineering is gratefully acknowledged. We thank Jerry Chafkin, Peter Diamond, Arnout Eikeboom, Doyne Farmer, Gifford Fong, Jacob Goldfield, Tom Imbo, Jakub Jurek, Amir Khandani, Bob Lockner, Paul Mende, Robert Merton, Jun Pan, Roger Stein, Tina Vandersteel for helpful comments and discussion.

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[‡]Senior Lecturer, MIT Sloan School of Management, and Visiting Scientist, MIT Department of Physics, Center for Theoretical Physics, 77 Massachusetts Avenue, Cambridge, MA 02142–1347, mark.t.mueller@mac.com (email).

arXiv:1003.2688v3 [q-fin.RM] 20 Mar 2010

Efficient Markets

Efficient Markets

Markets appear to be efficient, meaning that traditional prediction methods are ineffectual.

1965–1974

Random Walks in Stock Market Prices

Eugene F. Fama

For many years economists, statisticians, and teachers of finance have been interested in developing and testing models of stock price behavior. One important model that has evolved from this research is the theory of random walks. This theory casts serious doubt on many other methods for describing and predicting stock price behavior—methods that have considerable popularity outside the academic world. For example, we shall see later that if the random walk theory is an accurate description of reality, then the various “technical” or “chartist” procedures for predicting stock prices are completely without value.

In general the theory of random walks raises challenging questions for anyone who has more than a passing interest in understanding the behavior of stock prices. Unfortunately, however, most discussions of the theory have appeared in technical academic journals and in a form which the non-mathematician would usually find incomprehensible. This article describes, briefly and simply, the theory of random walks and some of the important issues it raises concerning the work of market analysts. To preserve brevity some aspects of the theory and its implications are omitted. More complete (and also more technical) discussions of the theory of random walks are available elsewhere; hopefully the introduction provided here will encourage the reader to examine one of the more rigorous and lengthy works listed at the end of this article.

COMMON TECHNIQUES FOR PREDICTING STOCK MARKET PRICES

In order to put the theory of random walks into perspective we first discuss, in brief and general terms, the two approaches to predicting stock prices that are commonly espoused by market professionals. These are (1) “chartist” or “technical” theories and (2) the theory of fundamental or intrinsic value analysis.

The basic assumption of all the chartist or technical theories is that history tends to repeat

itself, i.e., past patterns of price behavior in individual securities will tend to recur in the future. Thus the way to predict stock prices (and, of course, increase one’s potential gains) is to develop a familiarity with past patterns of price behavior in order to recognize situations of likely recurrence.

Essentially, then, chartist techniques attempt to use knowledge of the past behavior of a price series to predict the probable future behavior of the series. A statistician would characterize such techniques as assuming that successive price changes in individual securities are dependent. That is, the various chartist theories assume that the *sequence* of price changes prior to any given day is important in predicting the price change for that day.¹

The techniques of the chartist have always been surrounded by a certain degree of mysticism, however, and as a result most market professionals have found them suspect. Thus it is probably safe to say that the pure chartist is relatively rare among stock market analysts. Rather the typical analyst adheres to a technique known as fundamental analysis or the intrinsic value method. The assumption of the fundamental analysis approach is that at any point in time an individual security has an intrinsic value (or in the terms of the economist, an equilibrium price) which depends on the earning potential of the security. The earning potential of the security depends in turn on such fundamental factors as quality of management, outlook for the industry and the economy, etc.

Through a careful study of these fundamental factors the analyst should, in principle, be able to determine whether the actual price of a security is above or below its intrinsic value. If actual prices tend to move toward intrinsic values, then attempting to determine the intrinsic value of a security is equivalent to making a prediction of its future price; and this is the essence of the predictive procedure implicit in fundamental analysis.

THE THEORY OF RANDOM WALKS

Chartist theories and the theory of fundamental analysis are really the province of the market

“This theory casts serious doubt on many other methods for describing and predicting stock price behavior – methods that have considerable popularity outside the academic world. For example, we shall see later that, if the random-walk theory is an accurate description of reality, then the various “technical” or “chartist” procedures for predicting stock prices are completely without value.”

→ In a least-squares sense, the best predictor of tomorrow’s stock price is today’s stock price.

Reprinted from Financial Analysts Journal (September/October 1965):55–59.

Efficient Markets—Simple Illustration

If a stock price follows a (simple) random walk (no drift & normally distributed returns), then it rises and falls with the same probability of 50% (“toss of a coin”).

In such a case, the best predictor of tomorrow's stock price – in a least-squares sense – is today's stock price.

Data-Driven Finance

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Yves Hilpisch

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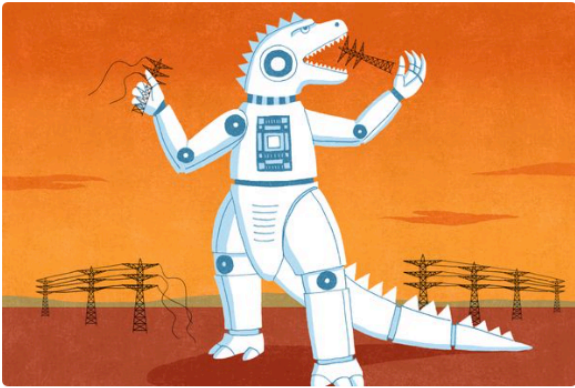
EXCLUSIVE

Activision Blizzard to Pay More Than \$50 Million to Settle Lawsuit That Spurred Takeover

California's Civil Rights Department sued Activision in 2021, alleging its leadership ignored numerous employee complaints of sexual harassment, discrimination and pay disparity.

By Sarah E. Needleman and Kirsten Grind

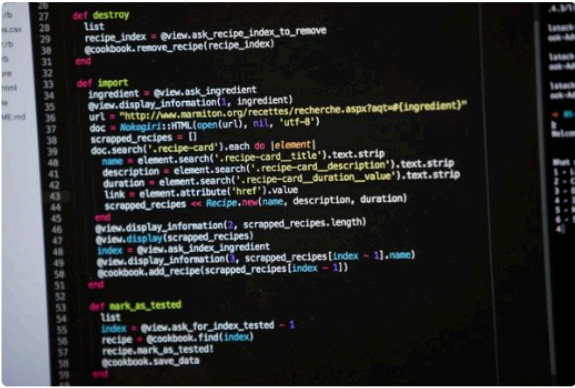
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KEYWORDS

AI Is Ravenous for Energy. Can It Be Satisfied?

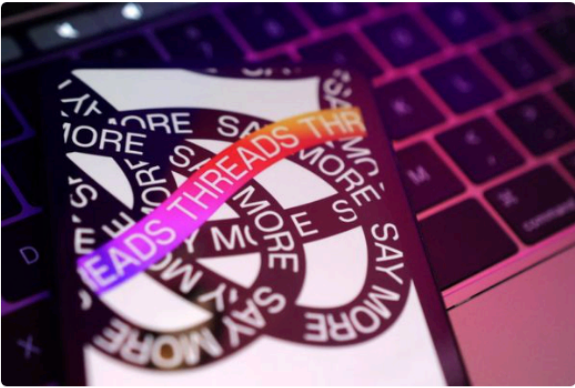
The revolution in artificial intelligence may soon require more electricity than all



PRO CYBER NEWS

Intelligence Researchers to Study Computer Code for Clues to Hackers' Identities

The government program will explore if



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APPLE INC

United States | NASDAQ Global Select Consolidated | Phones & Handheld Devices

197.57 c USD -0.54 -0.2726 % Vol 128,538,401 CAM 40 CCR 96

Updated: 16-Dec-2023 10:25:18

Summary SOV

Overview News & Research Price & Charts Estimates Financials ESG Event Ownership Debt & Credit Peers & Valuation Derivatives

BUSINESS SUMMARY

Apple Inc. designs, manufactures and markets smartphones, personal computers, tablets, wearables and accessories, and sells a variety of related services. The Company's product categories include iPhone, Mac, iPad, and Wearables, Home and Accessories. Its software platforms include iOS, iPadOS, macOS, watchOS and tvOS. Its services include advertising, AppleCare, cloud services, digital content and payment services. It operates various platforms, including the App Store, that allow customers to discover and download applications and digital content, such as books, music, video, games and podcasts. It also offers digital content through subscription-based services, including Apple Arcade, Apple Fitness+, Apple Music, Apple News+ and Apple TV+. The Company's products include iPhone 15 Pro, iPhone 15, iPhone 14, iPhone 13, MacBook Air, MacBook Pro, iMac, Mac mini, Mac Studio, Mac Pro, iPad Pro, iPad Air, iPad, iPad mini, Apple Watch Series 9, AirPods, AirPods Pro, AirPods Max and HomePod.

NEWS

16-Dec-2023

04:32:00

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RTRS

02:31:46

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Apple reportedly facing expansion of China ban

SEECOM

15-Dec-2023

23:07:44

UPDATE 1-China's ban on Apple's iPhone accelerates- Bloomberg News

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Apple workers deserve iDorms as good as the technology

FT

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China's ban on Apple's iPhone accelerates- Bloomberg News

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CHINA'S IPHONE BAN ACCELERATES ACROSS GOVERNMENT AND STATE FIRMS- BLO...

RTRS

20:46:29

Government issues advisory regarding various vulnerabilities in Apple products

HINDUT

EVENTS

UPCOMING

PAST

31-Jan-2024

AMC

Q1 2024 Apple Inc Earnings Release

PRICE PERFORMANCE

Open

197.53

Prev. Close

198.11

Bid / Ask

196.56 / 196.6

VWAP

197.581529

Turnover

USD 25.40B

Volume

128,538,401

Short Interest

0.70%

YTD

52.06%

Beta (5Y Monthly)

1.30

Mkt Cap - Default

USD 3.07T

PE (LTM)

32.21

Div Yield

0.48%

DR

BRL AAPL34.SA (1:0.05)

DR Type

--

DR Bank

--

Free Float

15.54B

Asset

Outstanding

15.55B

Share

IPO Date

12-Dec-1980

Lot Si

FUNDAMENTALS

AAPL.O, .SPX, AMZN.O C...

WS

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AAPL.O

COMPARE

TEMPLATES

Rebasing / Price Return

Daily

RESET

APPLE INC 52.06%

S&P 500 INDEX 22.91%

AMAZON COM 78.54%

Asset	Return (%)
Apple Inc. (AAPL.O)	+52.06%
S&P 500 INDEX	+22.91%
Amazon.com (AMZN.O)	+78.54%

2023

Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

1D 5D 10D 1M 3M 6M YTD 1Y 2Y 3Y 5Y 10Y 20Y Max

30-Dec-2022 - 15-Dec-2023

... to the Terminal ...

Minute Bars

```
[11]: %%time
data = ek.get_timeseries(symbols,
                        start_date='2023-12-15',
                        end_date='2023-12-16',
                        interval='minute',
                        fields='*')

CPU times: user 26.5 ms, sys: 2.22 ms, total: 28.7 ms
Wall time: 800 ms
```

```
[12]: data.loc['2023-12-15 15:30:00':
              '2023-12-15 15:34:00']
```

[12]:

	AAPL.O	HIGH	LOW	OPEN	CLOSE	COUNT	VOLUME
Date							
2023-12-15 15:30:00	198.24	198.02	198.16	198.0398	2668	131027	
2023-12-15 15:31:00	198.16	198.035	198.04	198.1199	2543	112091	
2023-12-15 15:32:00	198.15	198.06	198.105	198.1012	2486	95976	
2023-12-15 15:33:00	198.16	198.05	198.107	198.065	2573	114239	
2023-12-15 15:34:00	198.109	198.0	198.07	198.005	2497	119302	

2023-12-15 15:34:00	198.109	198.0	198.07	198.005	2497	119302
2023-12-15 15:33:00	198.16	198.05	198.107	198.065	2573	114239
2023-12-15 15:32:00	198.15	198.06	198.105	198.1012	2486	95976

Tick Data

```
[13]: %%time
data = ek.get_timeseries('AAPL.O',
                        start_date='2023-12-15 15:00:00',
                        end_date='2023-12-15 15:15:00',
                        interval='tick',
                        fields=['*'])
```

CPU times: user 103 ms, sys: 7.09 ms, total: 110 ms
Wall time: 1.74 s

```
[14]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 36176 entries, 2023-12-15 15:00:00.009000 to 2023-12-15 15:14:59.991000
Data columns (total 2 columns):
#   Column  Non-Null Count  Dtype
---  ---
0   VALUE   36137 non-null    Float64
1   VOLUME  36176 non-null    Int64
dtypes: Float64(1), Int64(1)
memory usage: 918.5 KB
```

```
[15]: data.tail()
```

[15]:

	AAPL.O	VALUE	VOLUME
Date			
2023-12-15 15:14:59.579	198.16		3
2023-12-15 15:14:59.609	198.151		53
2023-12-15 15:14:59.613	198.15		200
2023-12-15 15:14:59.858	198.155		40
2023-12-15 15:14:59.991	198.15		16

2023-12-15 15:14:59.991	198.15		16
2023-12-15 15:14:59.858	198.155		40
2023-12-15 15:14:59.613	198.15		200

... to powerful APIs.

Financial News

Apple Event on 30. October 2023 (<https://www.apple.com/events>).

```
[18]: headlines = ek.get_news_headlines(query='R:AAPL.0 macbook m3',
                                       count=5,
                                       date_from='2023-10-29',
                                       date_to='2021-10-31')
```

```
[19]: headlines
```

```
[19]:
```

	versionCreated		text	storyId	sourceCode
	2023-10-28 12:33:37.872	2023-10-28 12:33:39.512000+00:00	Apple Scary Fast event: MacBook Pro with M3 Ma...	urn:newsml:newswire.refinitiv.com:20231028:nNR...	NS:MINTNE
	2023-10-28 09:15:46.319	2023-10-28 09:50:37.924000+00:00	Apple Scary Fast event: MacBook M2 with M3 Max...	urn:newsml:newswire.refinitiv.com:20231028:nNR...	NS:MINTNE
	2023-10-28 09:16:16.240	2023-10-28 09:38:53.757000+00:00	Apple Scary Fast event: MacBook Pro with M3 Ma...	urn:newsml:newswire.refinitiv.com:20231028:nNR...	NS:MINTNE
	2023-10-05 11:31:39.137	2023-10-05 11:43:42.534000+00:00	MacBook Air M1 at just Rs 52,999: Amazon Great...	urn:newsml:newswire.refinitiv.com:20231005:nNR...	NS:INDIAE
	2023-10-01 14:01:05.453	2023-10-01 14:01:13.513000+00:00	Amazon unveils Apple deals for Great Indian Fe...	urn:newsml:newswire.refinitiv.com:20231001:nNR...	NS:INDIAE

```
[20]: story = headlines.iloc[0]
```

```
[21]: story
```

```
[21]: versionCreated      2023-10-28 12:33:39.512000+00:00
text      Apple Scary Fast event: MacBook Pro with M3 Ma...
storyId    urn:newsml:newswire.refinitiv.com:20231028:nNR...
sourceCode      NS:MINTNE
Name: 2023-10-28 12:33:37.872000, dtype: object
```

```
[22]: news_text = ek.get_news_story(story['storyId'])
```

```
[25]: ugm2_fexf = ek.get_ugm2_story(story_id, story_idq,)
```

```
name: 2023-10-28 12:33:39.512000+00:00 qfbb: object
sourceCode
```

```
NS:MINTNE
```

... to powerful APIs.

```
[23]: from IPython.display import HTML
```

```
[24]: HTML(news_text)
```

[24]: New Delhi

New Delhi, Oct. 28 -- Apple is all set to unveil new devices at the company's annual October event, which has been dubbed 'Scary Fast' because it takes place on the eve of Halloween at 5:00 PM PT/5:30 AM IST. The tech giant had earlier unveiled the latest iPhone 15 range at the Wonderlust event in September.

Also Read| Apple Scary Fast event: MacBook Air, MacBook Air Pro, iMac and everything expected

The highlight of the new Apple event is expected to be the launch of the new M3 chipset, which will run on 3-nanometer processors and bring significant improvements over the M2 lineup that was released in June 2022, Bloomberg reported.

Bloomberg's Mark Gurnman reported that Apple is likely to unveil two new MacBook Pros, codenamed J514 and J516, powered by the M3 Pro and M3 Max processors.

Apple is reportedly testing different versions of the 12-core M3 Pro processor, which will include six high-performance cores and six efficiency cores. Another M3 Pro chipset could have 14 main cores, including 10 high-performance cores, 4 efficiency cores and 20 graphics cores.

Meanwhile, a top-of-the-range M3 Max chipset could come with 16 main cores, including 12 high-performance cores, 4 efficiency cores and 40 graphics cores. The iPhone maker is also planning to offer more upgraded RAM variants, including a 24GB and 48GB options.

The Bloomberg report notes that while the specifications for the M3 chipsets that will ship with the new MacBook Pro lineup are not clear, the Cupertino company is likely to offer improved gaming capabilities similar to the much-touted prowess of the A 17 chip in the iPhone 15 Pro.

Recent media reports had hinted at the possibility of Apple expanding its iPad line-up, with announcements expected at recent events. However, Gurnman noted that Apple will not be unveiling any new iPads at this year's event. Published by HT Digital Content Services with permission from MINT. For any query with respect to this article or any other content requirement, please contact Editor at contentservices@htlive.com

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... to powerful APIs.

AI-First Finance

“It doesn't matter how beautiful your theory is, it doesn't matter how smart you are. If it doesn't agree with experiment, it's wrong.”

Richard Feynman

“It ain’t what you don’t know that gets you into trouble. It’s what you know for sure that just ain’t so.”

Marc Twain

Scientific Method

The scientific method involves the refutation of models that lack empirical support.

Dictionary

Definitions from [Oxford Languages](#) · [Learn more](#)



sci·en·tif·ic meth·od

/ˌsɪənˌtɪfɪk ˈmeθəd/

noun

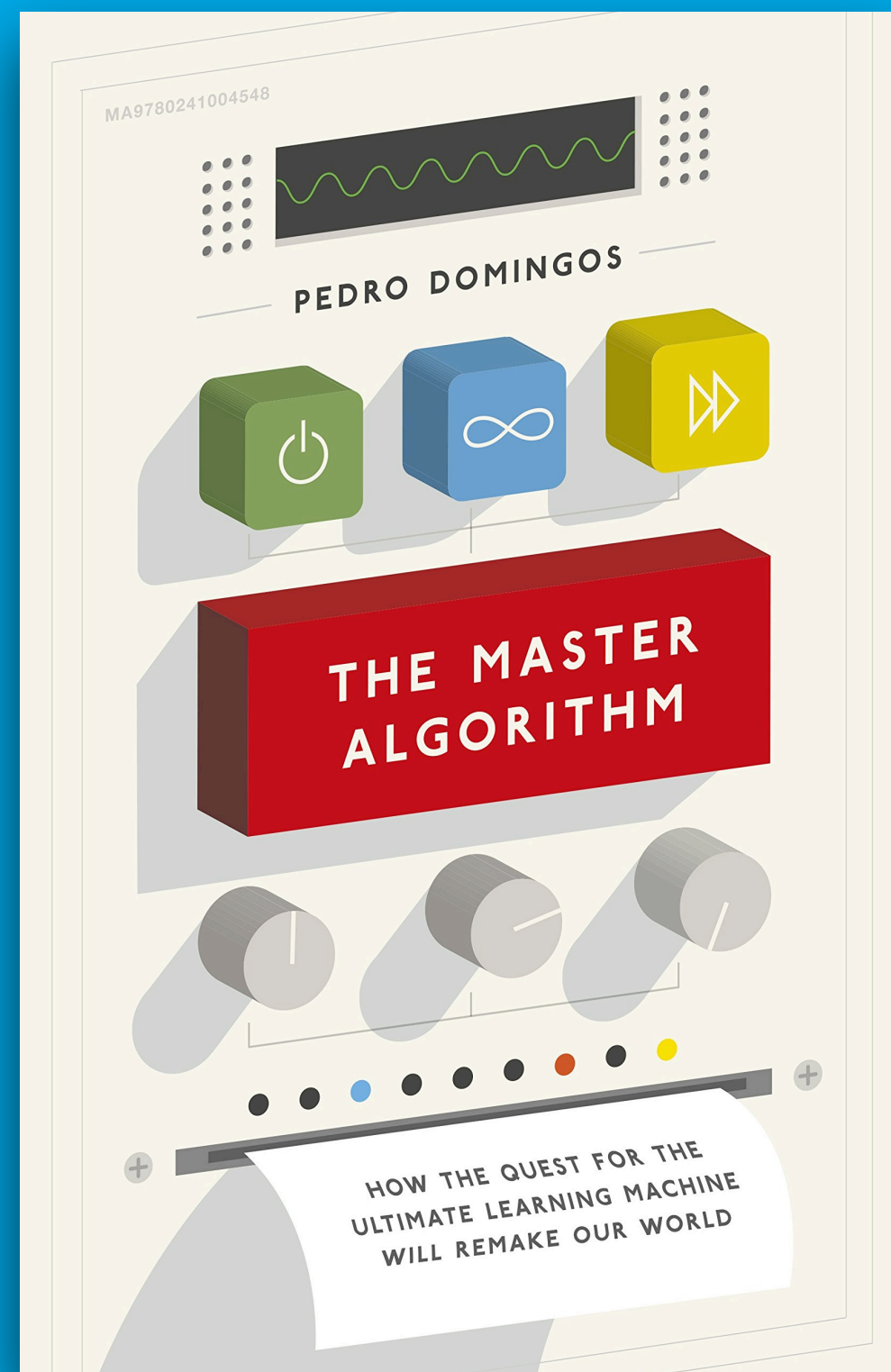
a method of procedure that has characterized natural science since the 17th century, consisting in systematic observation, measurement, and experiment, and the formulation, testing, and modification of hypotheses.

"criticism is the backbone of **the scientific method**"

"criticism is the backbone of **the scientific method**"
of hypotheses.

Machine Learning

Machines effortlessly test and refute thousands of different hypotheses.



“Machine learning is the scientific method on steroids. It follows the same process of generating, testing, and discarding or refining hypotheses. But while a scientist may spend his or her whole life coming up with and testing a few hundred hypotheses, a machine-learning system can do the same in a second. Machine learning automates discovery. It’s no surprise then that it’s revolutionizing science as much as it’s revolutionizing business.”

Efficient Markets

New technologies and methods have changed the thinking about efficient markets.

Jensen (1978): “Some Anomalous Evidence Regarding Market Efficiency.”:

“A market is efficient with respect to an information set S if it is impossible to make economic profits by trading on the basis of information set S .”



Timmermann and Granger (2004): “Efficient Market Hypothesis and Forecasting.”:

“A market is efficient with respect to the information set, $S(t)$, search technologies, $T(t)$, and forecasting models, $M(t)$, if it is impossible to make economic profits by trading on the basis of signals produced from a forecasting model in $M(t)$ defined over predictor variables in the information set $S(t)$ and selected using a search technology in $T(t)$.”

ML-Based Asset Pricing

Machine learning methods can easily encompass a large number of predictor variables.

Empirical Asset Pricing via Machine Learning*

Shihao Gu

Booth School of Business, University of Chicago

Bryan Kelly

Yale University, AQR Capital Management, and NBER

Dacheng Xiu

Booth School of Business, University of Chicago

We perform a comparative analysis of machine learning methods for the canonical problem of empirical asset pricing: measuring asset risk premiums. We demonstrate large economic gains to investors using machine learning forecasts, in some cases doubling the performance of leading regression-based strategies from the literature. We identify the best-performing methods (trees and neural networks) and trace their predictive gains to allowing nonlinear predictor interactions missed by other methods. All methods agree on the same set of dominant predictive signals, a set that includes variations on momentum, liquidity, and volatility. (*JEL* C52, C55, C58, G0, G1, G17)

“..., the collection of candidate conditioning variables for the risk premium is large. The profession has accumulated a staggering list of predictors that various researchers have argued possess forecasting power for returns. The number of stock-level predictive characteristics reported in the literature numbers in the hundreds and macroeconomic predictors of the aggregate market number in the dozens. Additionally, predictors are often close cousins and highly correlated. Traditional prediction methods break down when the predictor count approaches the observation count or predictors are highly correlated. With an emphasis on variable selection and dimension reduction techniques, machine learning is well suited for such challenging prediction problems by reducing degrees of freedom and condensing redundant variation among predictors.”

Adding Complexity

Like Natural Language Processing, finance might need to go bigger & embrace complexity.



EXPERT OPINION

Contact Editor: **Brian Brannon**, bbrannon@computer.org

The Unreasonable Effectiveness of Data

Alon Halevy, Peter Norvig, and Fernando Pereira, Google

Eugene Wigner's article "The Unreasonable Effectiveness of Mathematics in the Natural Sciences"¹ examines why so much of physics can be neatly explained with simple mathematical formulas

such as $f = ma$ or $e = mc^2$. Meanwhile, sciences that involve human beings rather than elementary particles have proven more resistant to elegant mathematics. Economists suffer from physics envy over their inability to neatly model human behavior. An informal, incomplete grammar of the English language runs over 1,700 pages.² Perhaps when it comes to natural language processing and related fields, we're doomed to complex theories that will never have the elegance of physics equations. But if that's so, we should stop acting as if our goal is to author extremely elegant theories, and instead embrace complexity and make use of the best ally we have: the unreasonable effectiveness of data.

One of us, as an undergraduate at Brown University, remembers the excitement of having access to the Brown Corpus, containing one million English words.³ Since then, our field has seen several notable corpora that are about 100 times larger, and in 2006, Google released a trillion-word corpus with frequency counts for all sequences up to five words long.⁴ In some ways this corpus is a step backwards from the Brown Corpus: it's taken from unfiltered Web pages and thus contains incomplete sentences, spelling errors, grammatical errors, and all sorts of other errors. It's not annotated with carefully hand-corrected part-of-speech tags. But the fact that it's a million times larger than the Brown Corpus outweighs these drawbacks. A trillion-word corpus—along with other Web-derived corpora of millions, billions, or trillions of links, videos, images, tables, and user interactions—captures even very rare aspects of human

behavior. So, this corpus could serve as the basis of a complete model for certain tasks—if only we knew how to extract the model from the data.

Learning from Text at Web Scale

The biggest successes in natural-language-related machine learning have been statistical speech recognition and statistical machine translation. The reason for these successes is not that these tasks are easier than other tasks; they are in fact much harder than tasks such as document classification that extract just a few bits of information from each document. The reason is that translation is a natural task routinely done every day for a real human need (think of the operations of the European Union or of news agencies). The same is true of speech transcription (think of closed-caption broadcasts). In other words, a large training set of the input-output behavior that we seek to automate is available to us *in the wild*. In contrast, traditional natural language processing problems such as document classification, part-of-speech tagging, named-entity recognition, or parsing are not routine tasks, so they have no large corpus available in the wild. Instead, a corpus for these tasks requires skilled human annotation. Such annotation is not only slow and expensive to acquire but also difficult for experts to agree on, being bedeviled by many of the difficulties we discuss later in relation to the Semantic Web. The first lesson of Web-scale learning is to use available large-scale data rather than hoping for annotated data that isn't available. For instance, we find that useful semantic relationships can be automatically learned from the statistics of search queries and the corresponding results⁵ or from the accumulated evidence of Web-based text patterns and formatted tables,⁶ in both cases without needing any manually annotated data.

"Eugene Wigner's article "The Unreasonable Effectiveness of Mathematics in the Natural Sciences" examines why so much of physics can be neatly explained with simple mathematical formulas such as $f = ma$ or $e = mc^2$.

Meanwhile, sciences that involve human beings rather than elementary particles have proven more resistant to elegant mathematics. Economists suffer from physics envy over their inability to neatly [and successfully] model human behavior.

An informal, incomplete grammar of the English language runs over 1,700 pages. Perhaps when it comes to natural language processing and related fields, we're doomed to complex theories that will never have the elegance of physics equations. But if that's so, we should stop acting as if our goal is to author extremely elegant theories, and instead embrace complexity and make use of the best ally we have: the unreasonable effectiveness of data."

AI as Technology

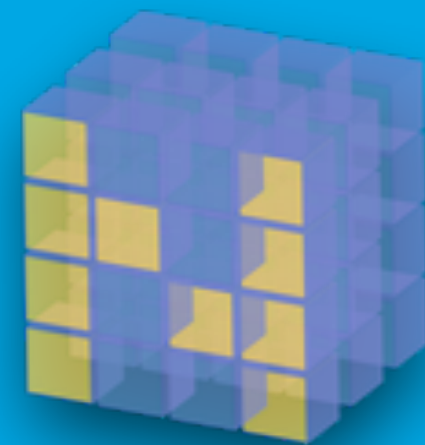
The case for AI as a key technology is driven by two major aspects of modern finance.

Ever-increasing volume, variety, and velocity of financial data.

Non-linear, high dimensional, and changing relationships in finance.

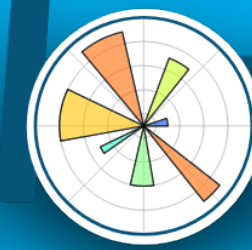


IP[y]:
IPython

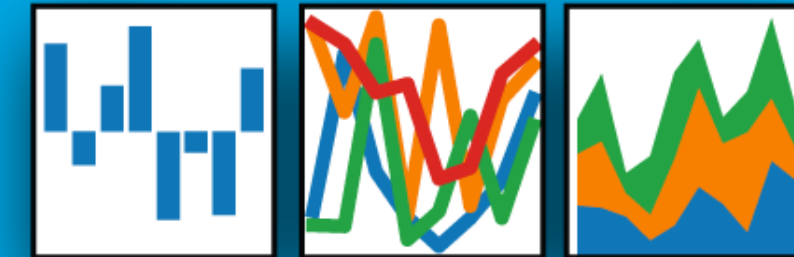


NumPy

matplotlib



pandas
 $y_i t = \beta' x_{it} + \mu_i + \epsilon_{it}$



Keras

Online Bootcamp

DAY 1

The Basics

(Python, Simple Strategies, Vectorized Backtesting)

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MacBook Pro 14 Inch, M1, 16GB,
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MacMini, M1-8 Cores, 8GB, 256 GB



MacMini, i7-6 Cores, 32GB, 512 GB



MacMini, M1 Max,
32GB, 512 GB





MacMini, M4, 16GB, 256GB

<https://digitalocean.com>



The Python Quants GmbH

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