Certificate Program in Python for Finance —Algorithmic Trading, Computational Finance, and Asset Management

Introduction & Overview

Dr. Yves J. Hilpisch







AGENDA

- Introduction
- The Program
- Quant Platform 2.0
- Mathematics Basics
- Python for Finance Basics
- Crypto Basics
- Finance with Python
- Tools and Skills
- Financial Packages
- Python for Financial Data Science
- Python for Excel
- Python for Databases

- Natural Language Processing
- Artificial Intelligence in Finance
- Reinforcement Learning for Finance
- Python for Algorithmic Trading
- Python for Computational Finance
- Python for Asset Management
- Case Studies & Demos
- Study Plans for the Programs
- Guiding Principles
- Reviews, Exercises & Test Projects
- User Forum (Technical Support)
- Discord Server (Realtime Chat)

Introduction







Dr. Yves J. Hilpisch is the founder and CEO of **The Python Quants** (http://tpq.io), a group focusing on the use of 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):

- * Finance 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)

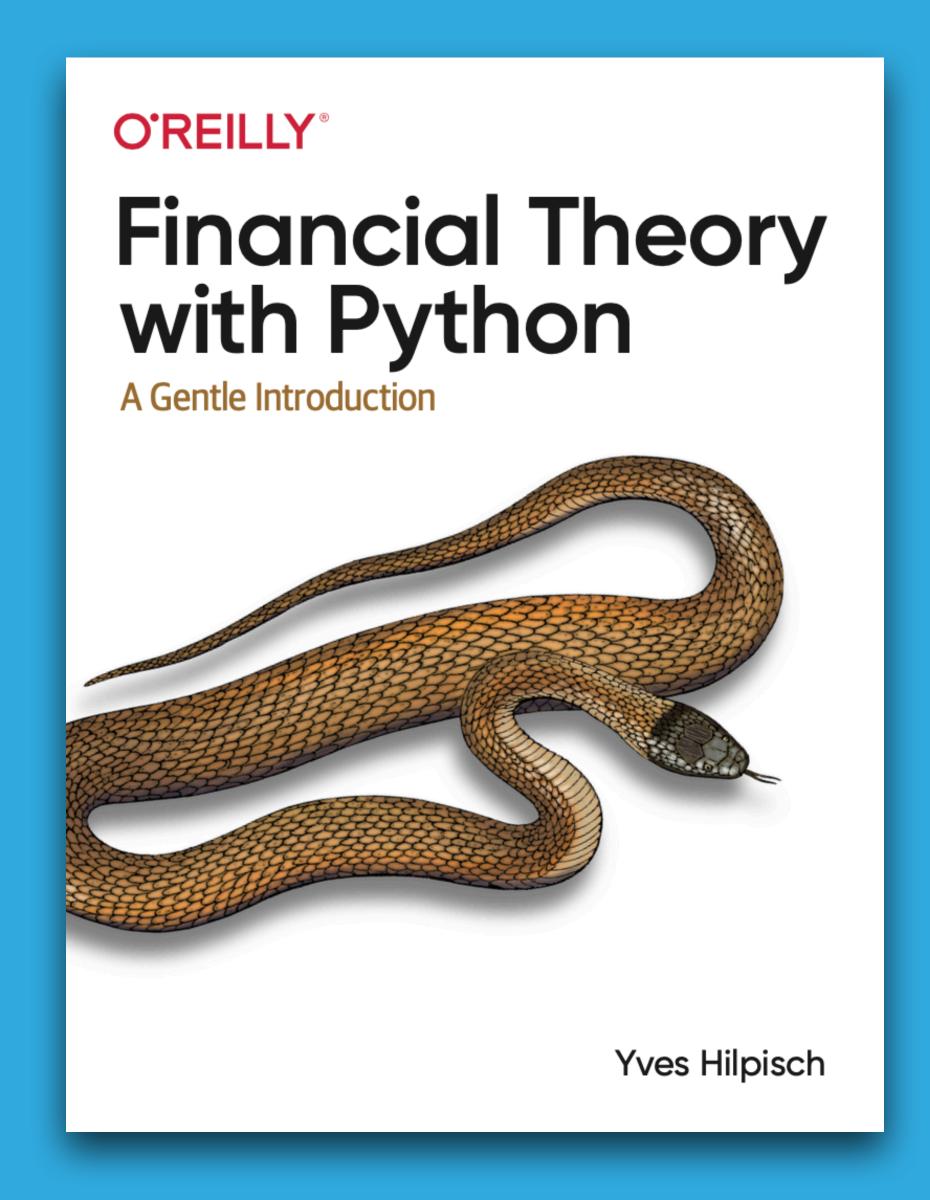


Yves is the director of the first online training program leading to University Certificates in Python for Algorithmic Trading (https://home.tpq.io/certificates/pyalgo), Computational Finance (https://home.tpq.io/certificates/compfin), and Asset Management (https://home.tpq.io/certificates/compfin). He also lectures on computational finance, machine learning, and algorithmic trading at the CQF Program (http://cqf.com).

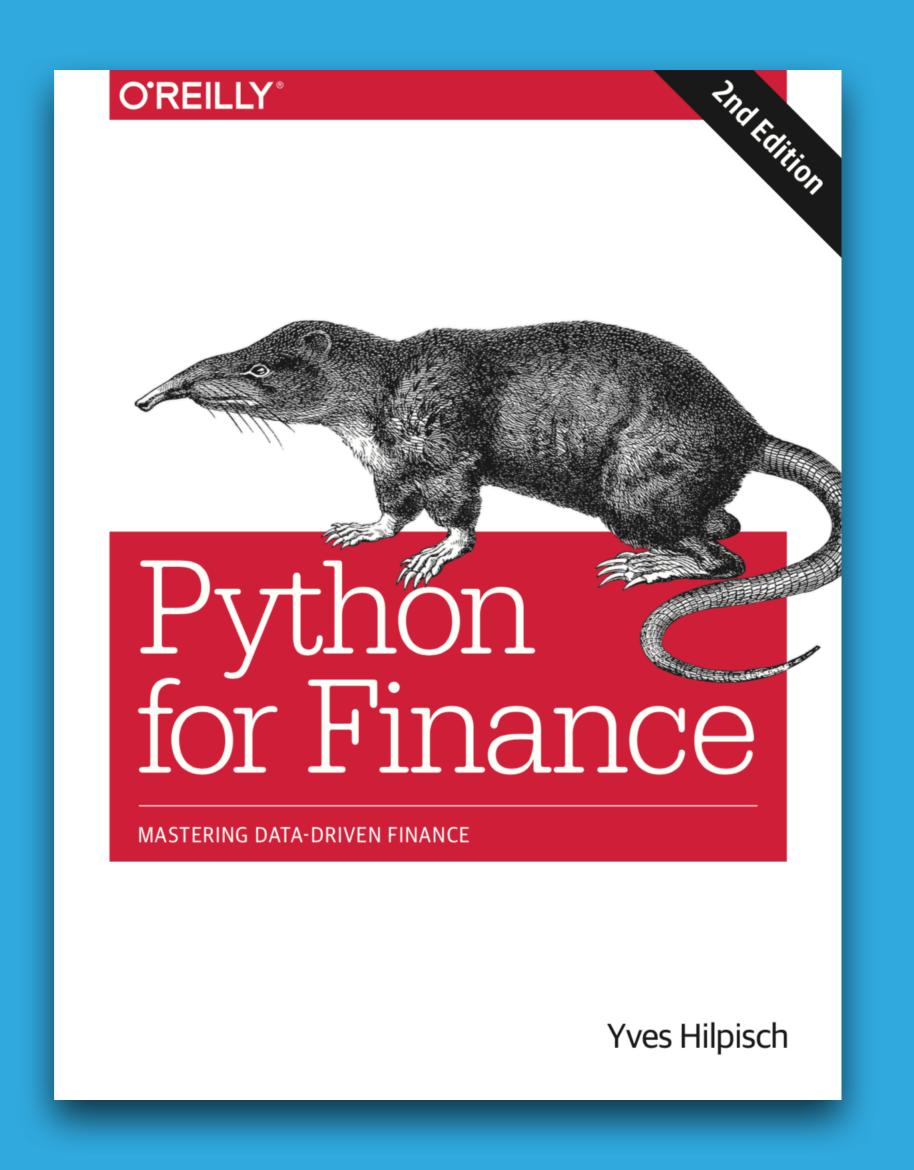
Yves is the originator of the financial analytics library **DX Analytics** (http://dx-analytics.com) and organizes Meetup group **events**, **conferences**, **and bootcamps** about Python, artificial intelligence and algorithmic trading in London (http://pqf.tpq.io), New York (http://aifat.tpq.io), Frankfurt,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

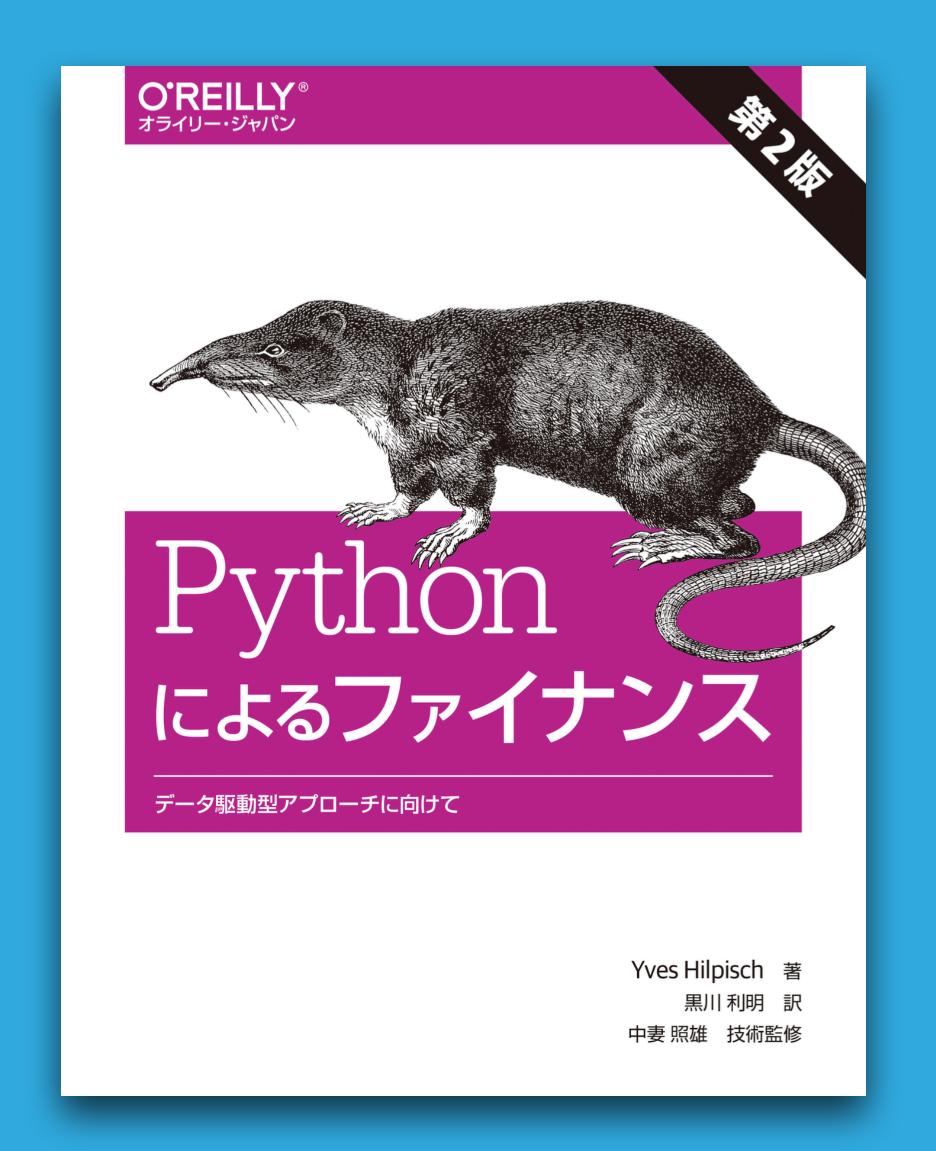
http://hilpisch.com

Financial Theory with Python

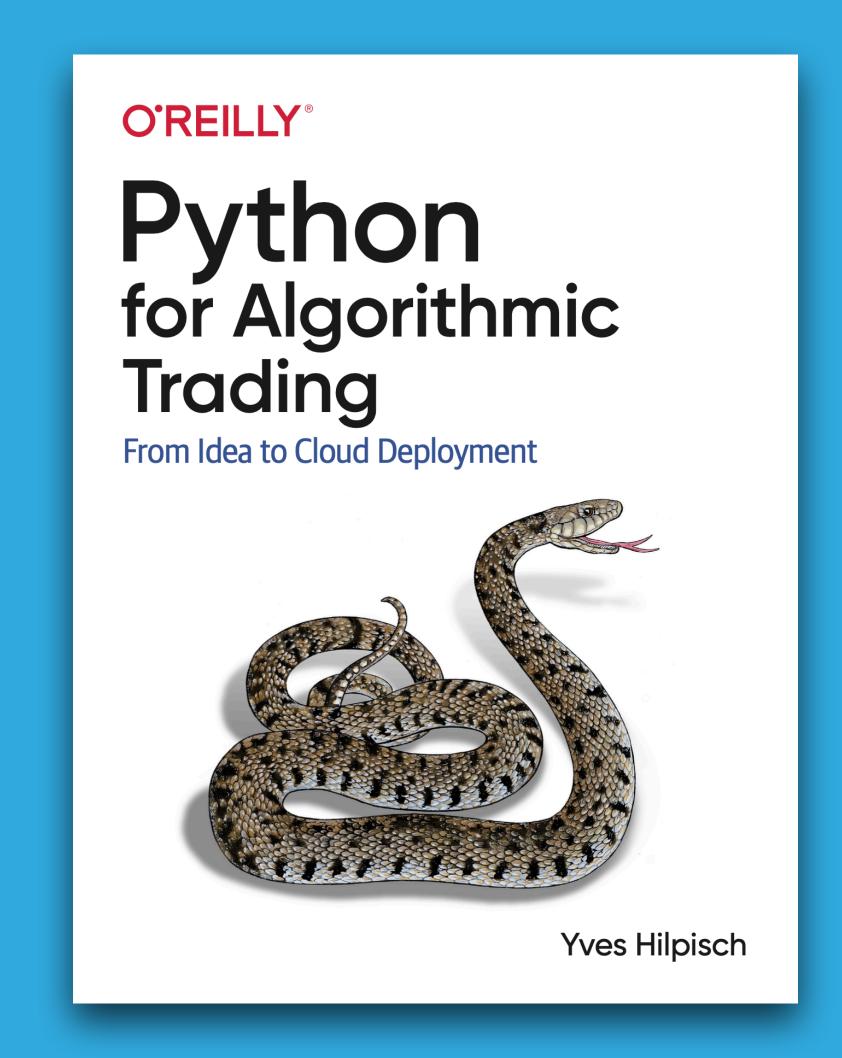


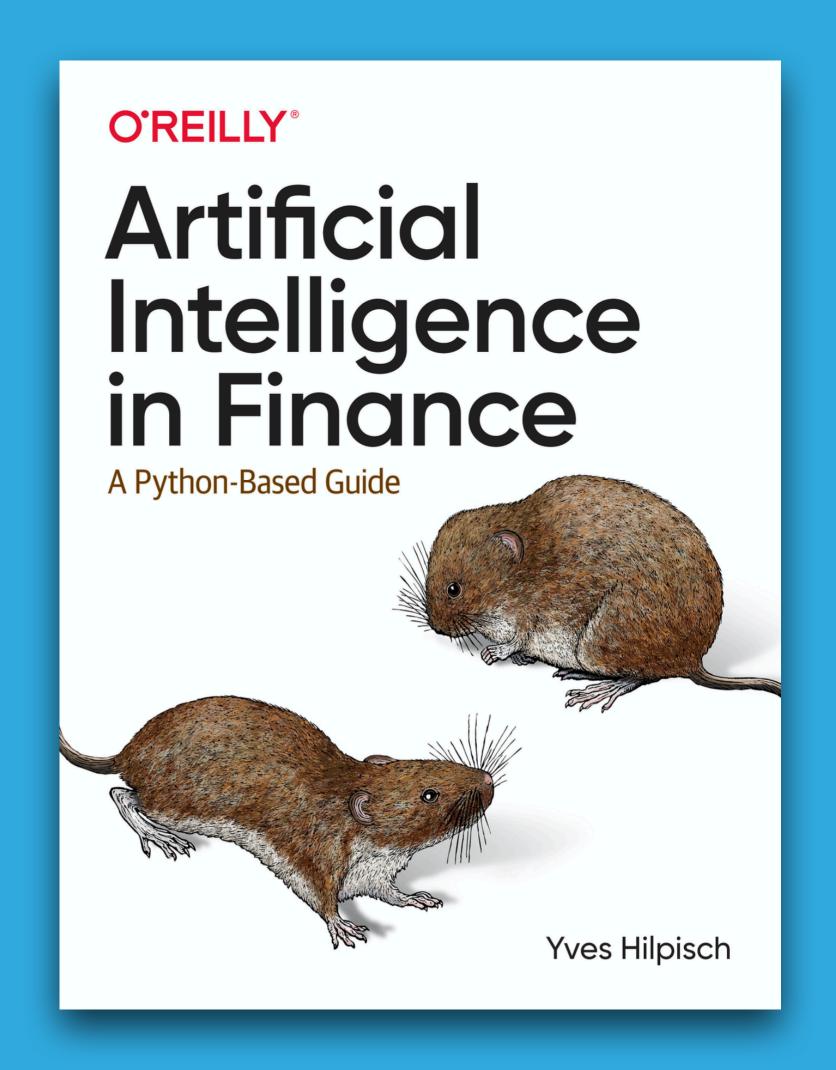
Python for Finance



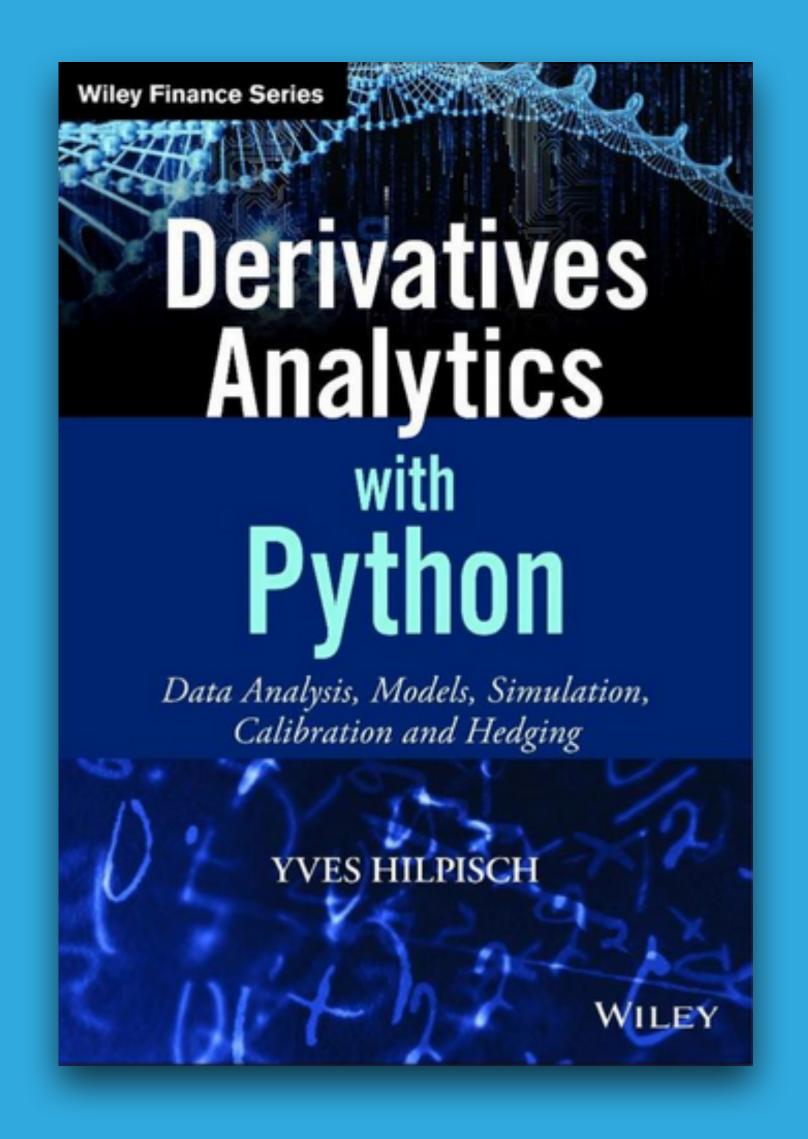


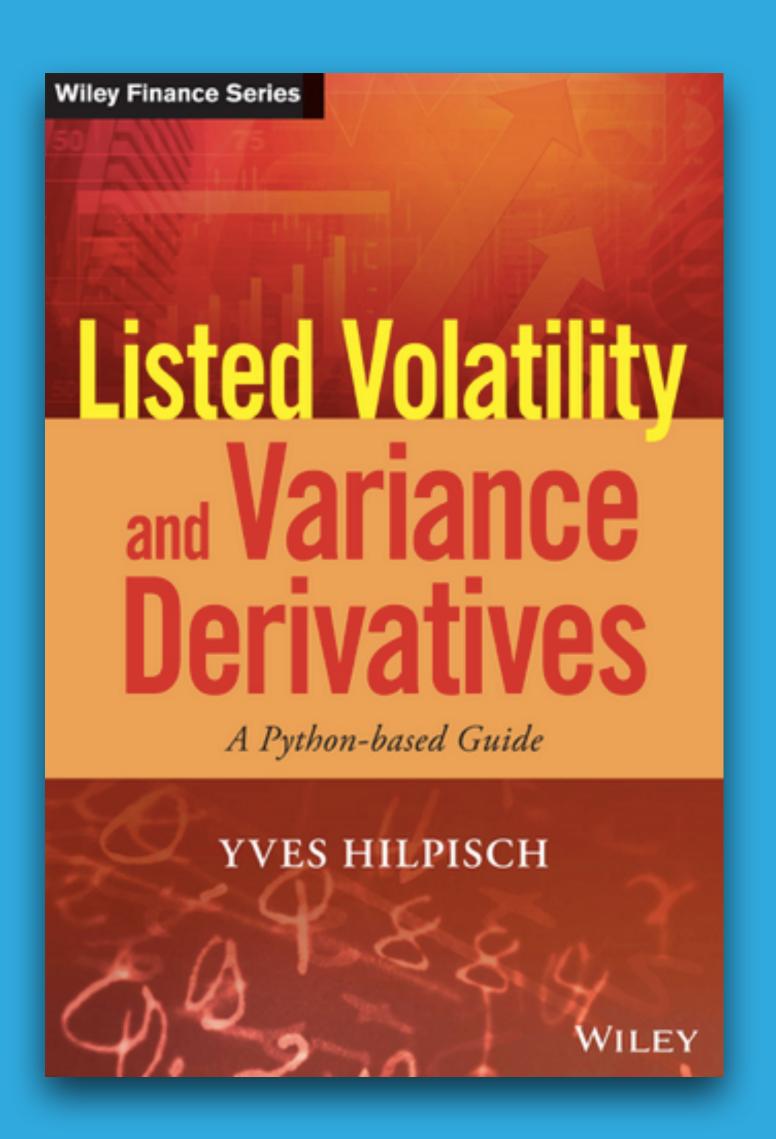
Python & AI for Finance & Trading





Quant Finance with Python



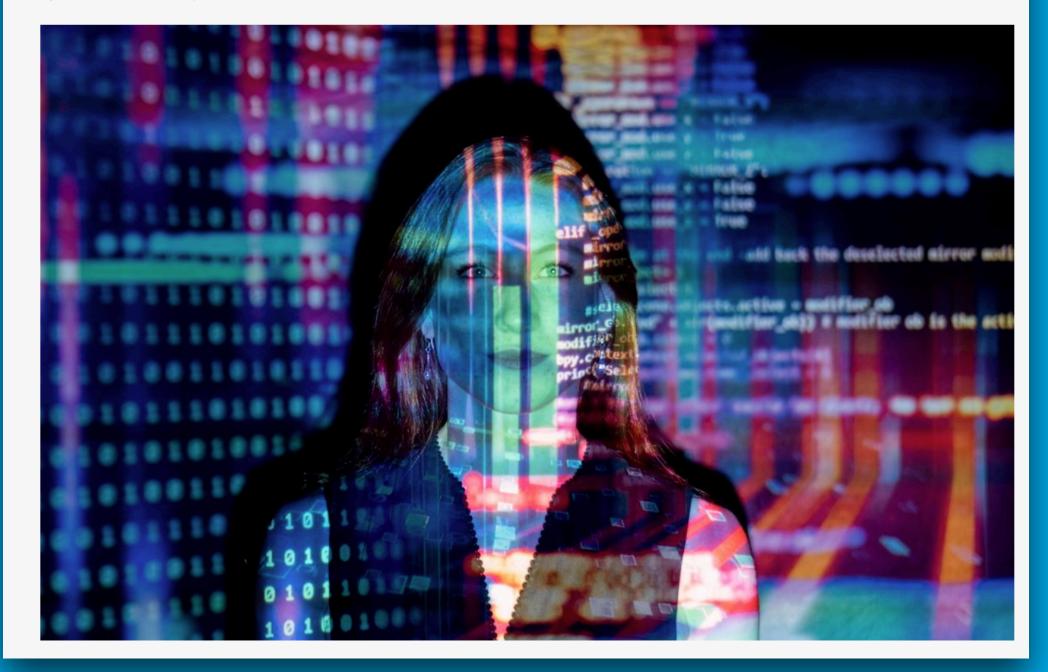


The Program



"If you want a banking job now, you need to code in Python"

by Mia Holmes 01 September 202

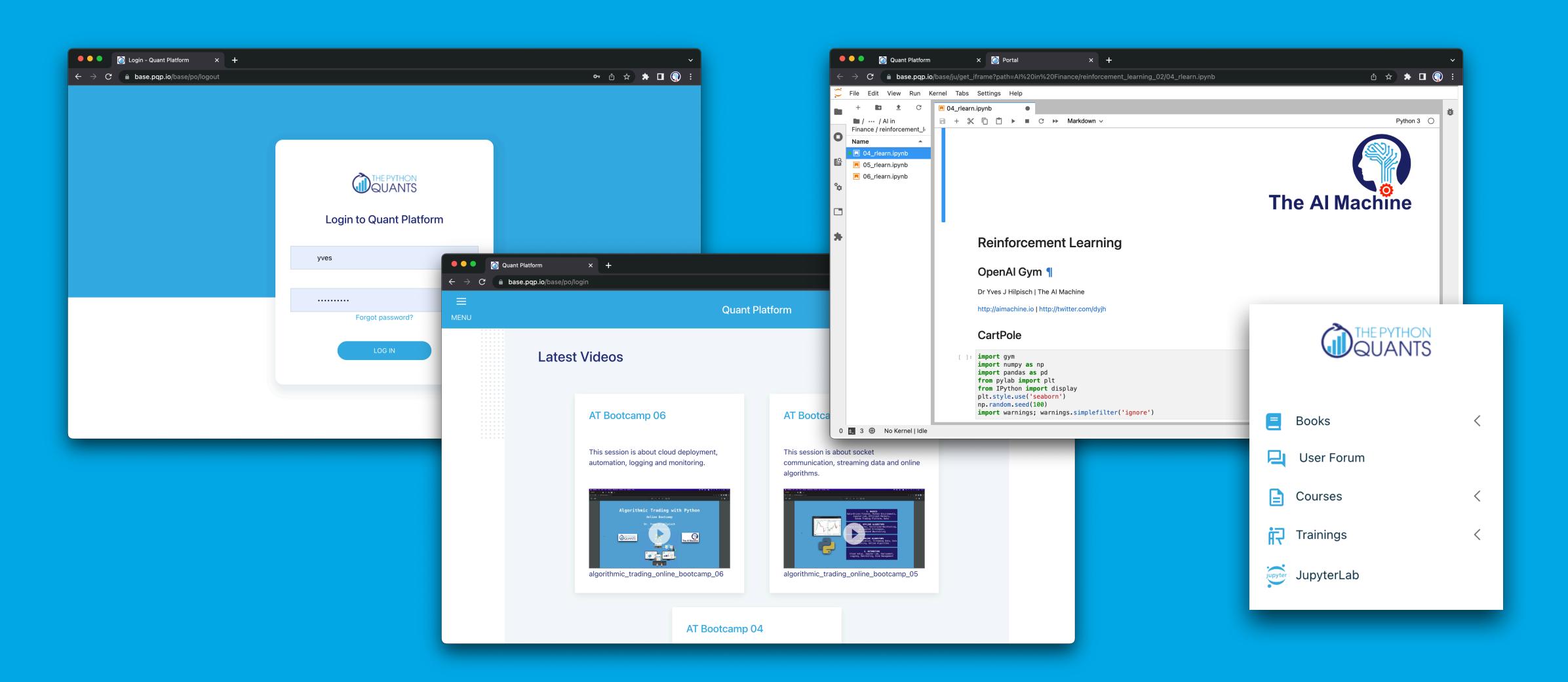


Therefore, if you're trying to get into banking now, Python is the skill that's needed. Python will get you a job across the banking industry - in anything from sales and trading to portfolio management or risk. It's the one skill that really differentiates applicants in the recruitment process.

Quant Platform 2.0

Quant Platform

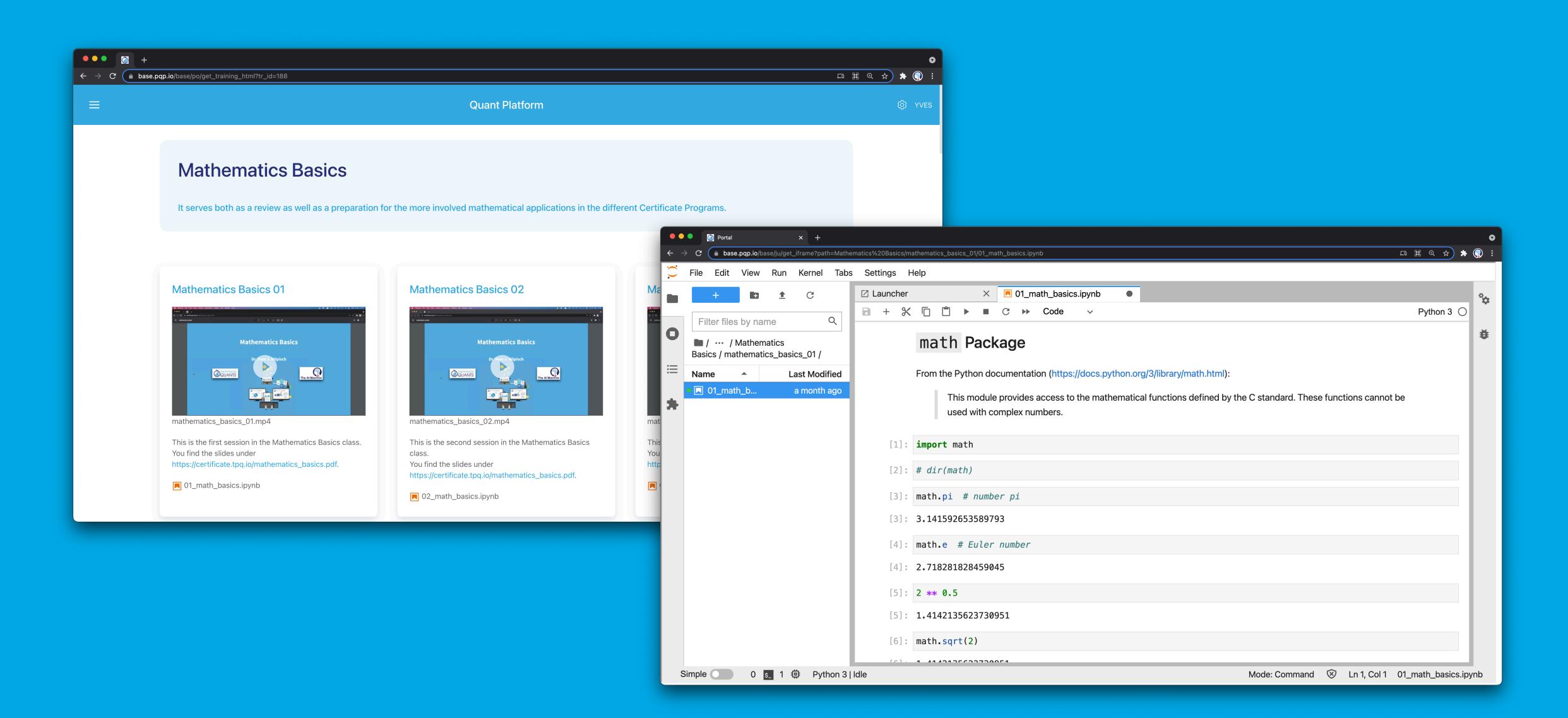
Your central content and code execution platform.



Mathematics Basics

Mathematics Basics

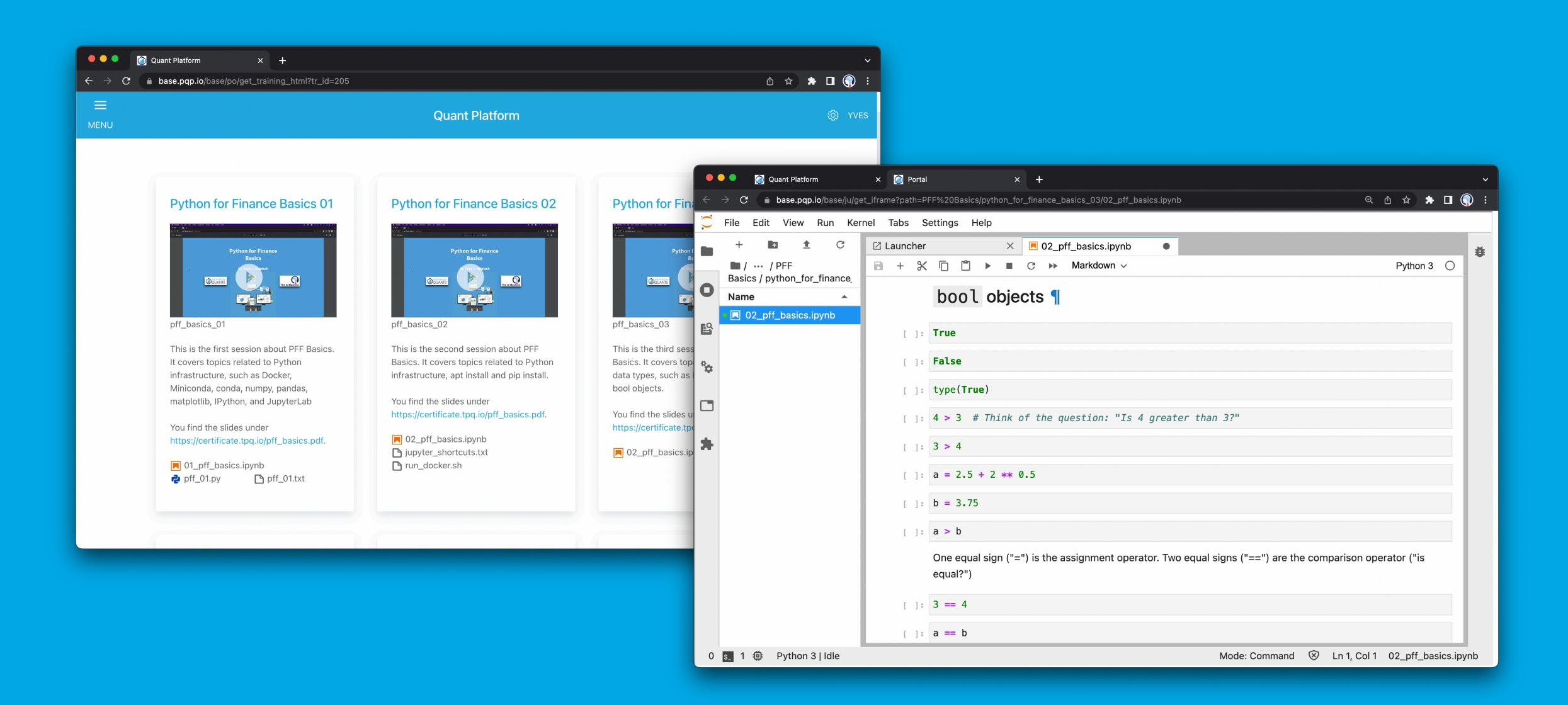
Reviewing fundamental mathematics concepts based on simple Python code.



Python for Fiance Basics

Python for Finance Basics

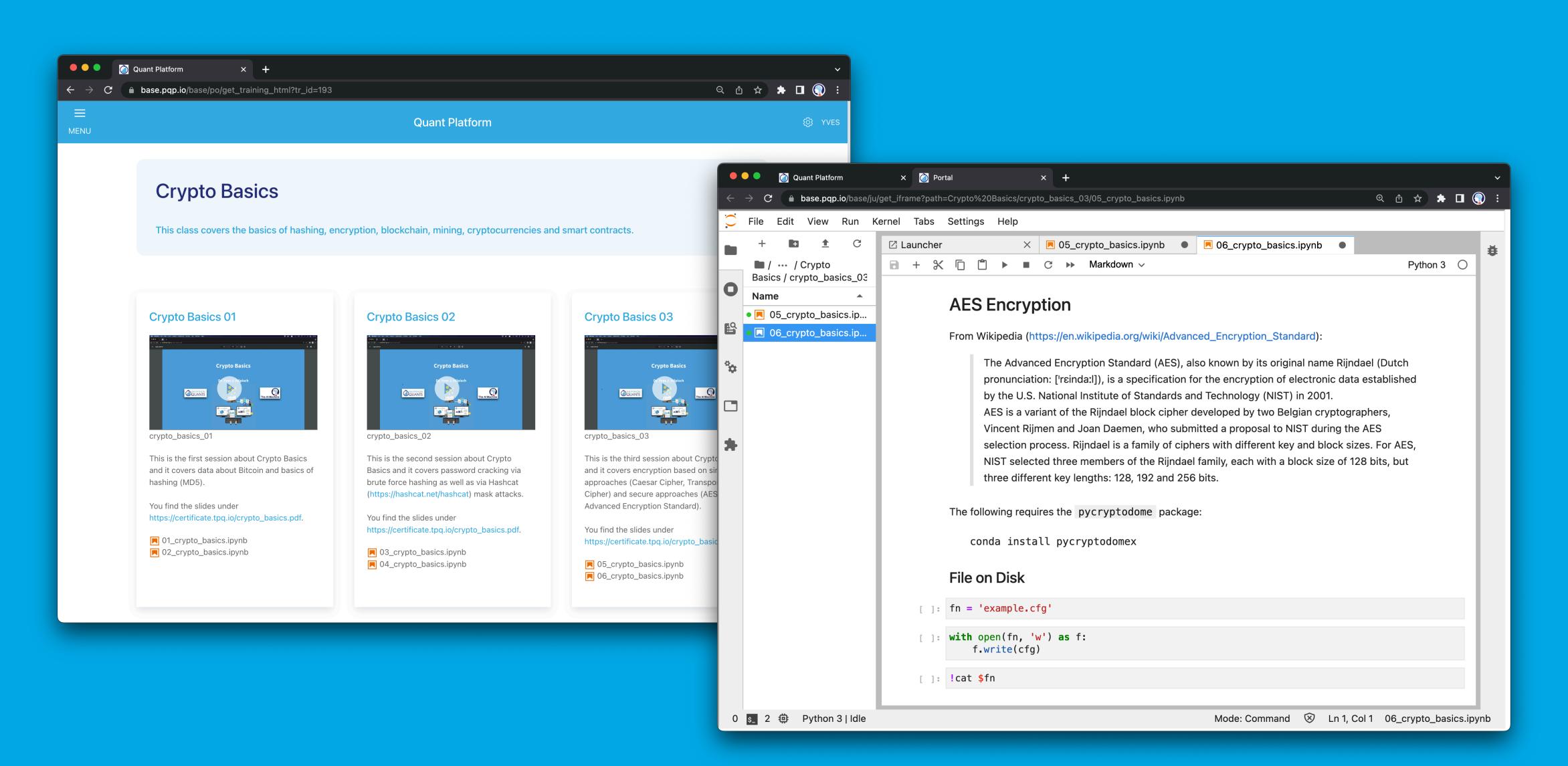
Introducing fundamental Python programming idioms and concepts.



Crypto Basics

Crypto Basics

Mastering the basic building blocks of the crypto space.



Finance with Python

O'REILLY® Financial Theory with Python A Gentle Introduction Yves Hilpisch

Finance with Python

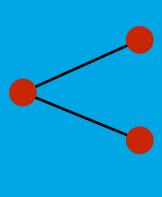
A gentle introduction to Finance, Python and the combination of both.

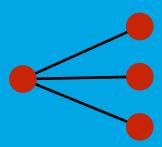
static two state economy fundamental theorem of asset pricing

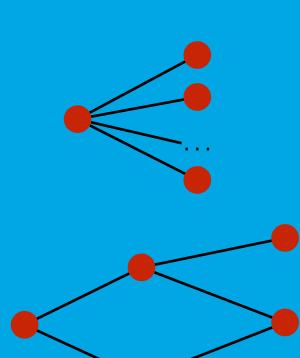
static three state economy dealing with market incompleteness

static multi state economy generalizing the state space

dynamic economies modeling uncertainty over time

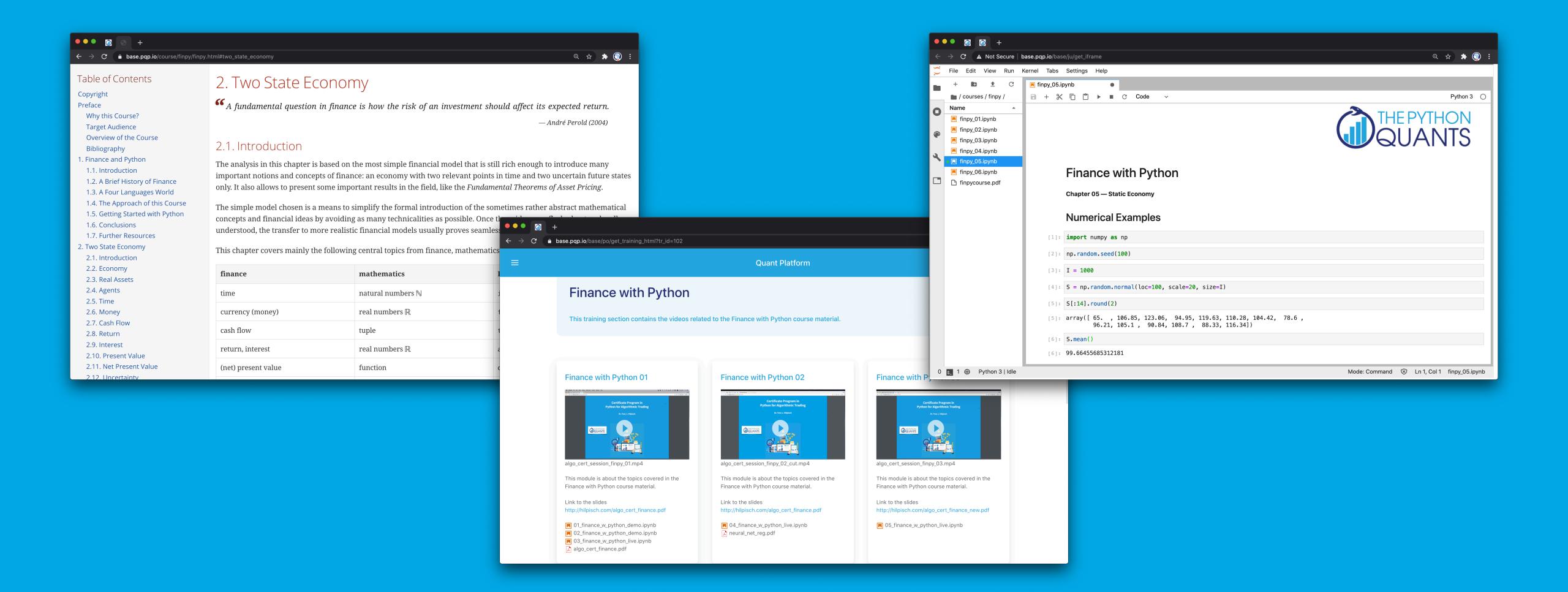






Finance with Python

A gentle introduction to Finance, Python and the combination of both.



Learning to use modern and proven tools for Python development and deployment.

BASICS	DEVELOPMENT	DISTRIBUTION
Python Installation & Environments on Mac & Linux on Windows	Code Editing with Vim	Python Packaging
Docker Usage Jupyter Notebook on Mac & Linux on Windows	Screen + Vim + q (editing, logging, debugging)	Documentation
Cloud Usage on Mac & Linux on Windows	Doctest & Unittest	Code Hosting (eg Github)
Basic Linux Tools & Shell Basics	Git Version Control	Case Study

Learning to use modern and proven tools for Python development and deployment.



cloud instances ("virtual servers") from a low as 5 USD per month, to really big instances

https://m.do.co/c/fbe512dd3dac



Docker containers to have separated OS run-times, packages and files
— on Mac OS, Linux & Windows



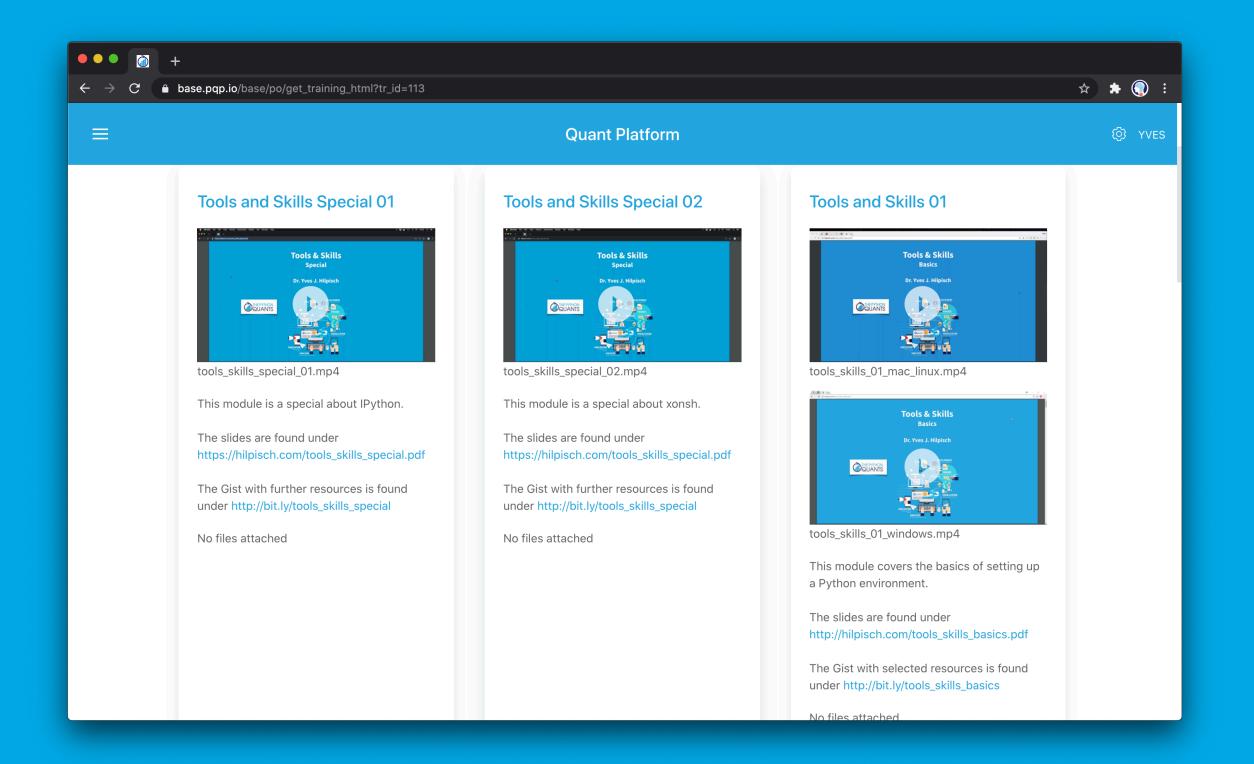
Python interpreter, packages, tools, environments

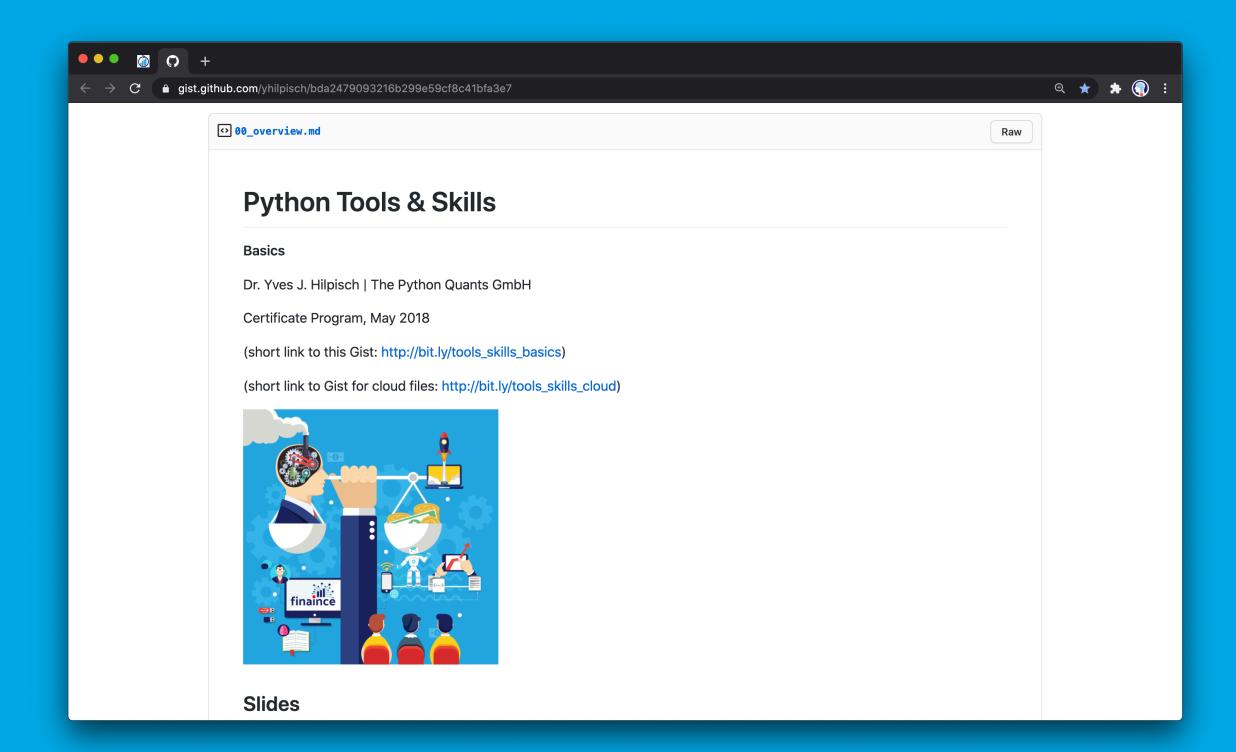
— via conda



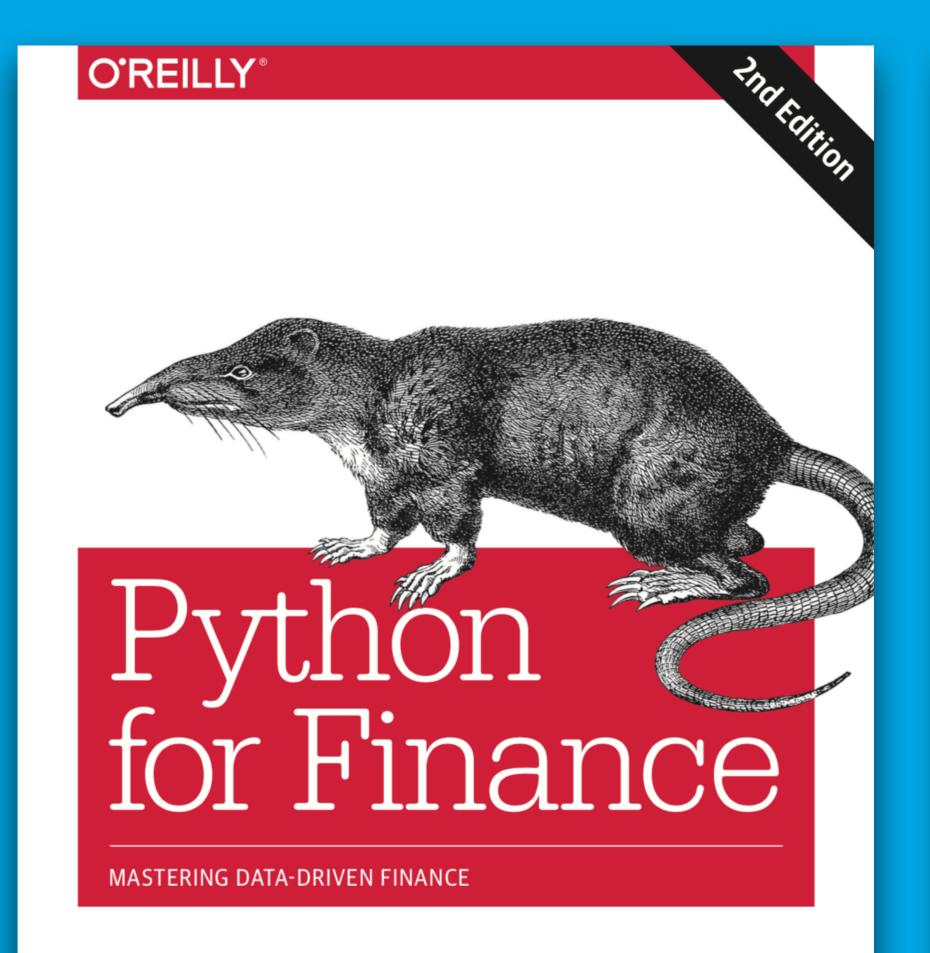
Jupyter Notebooks, terminal, editor,
IPython & Vim
— on every infrastructure

Learning to use modern and proven tools for Python development and deployment.

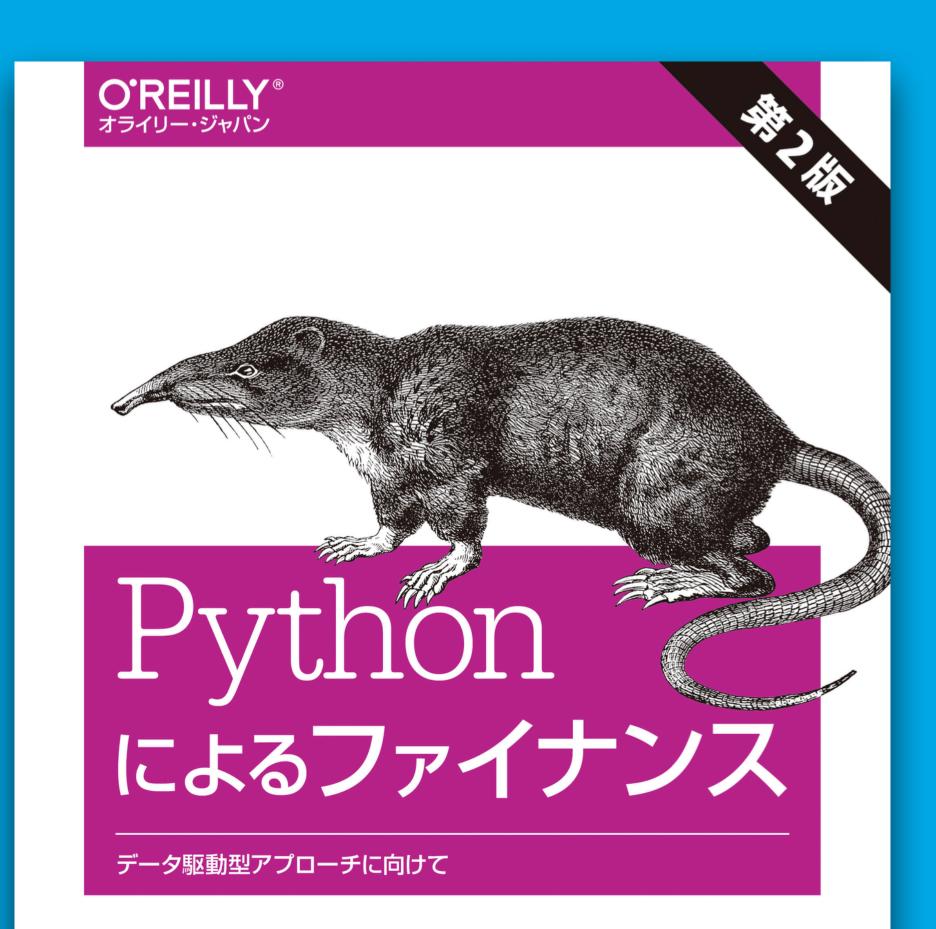




Python for Financial Data Science



Yves Hilpisch



Yves Hilpisch 著 黒川 利明 訳 中妻 照雄 技術監修

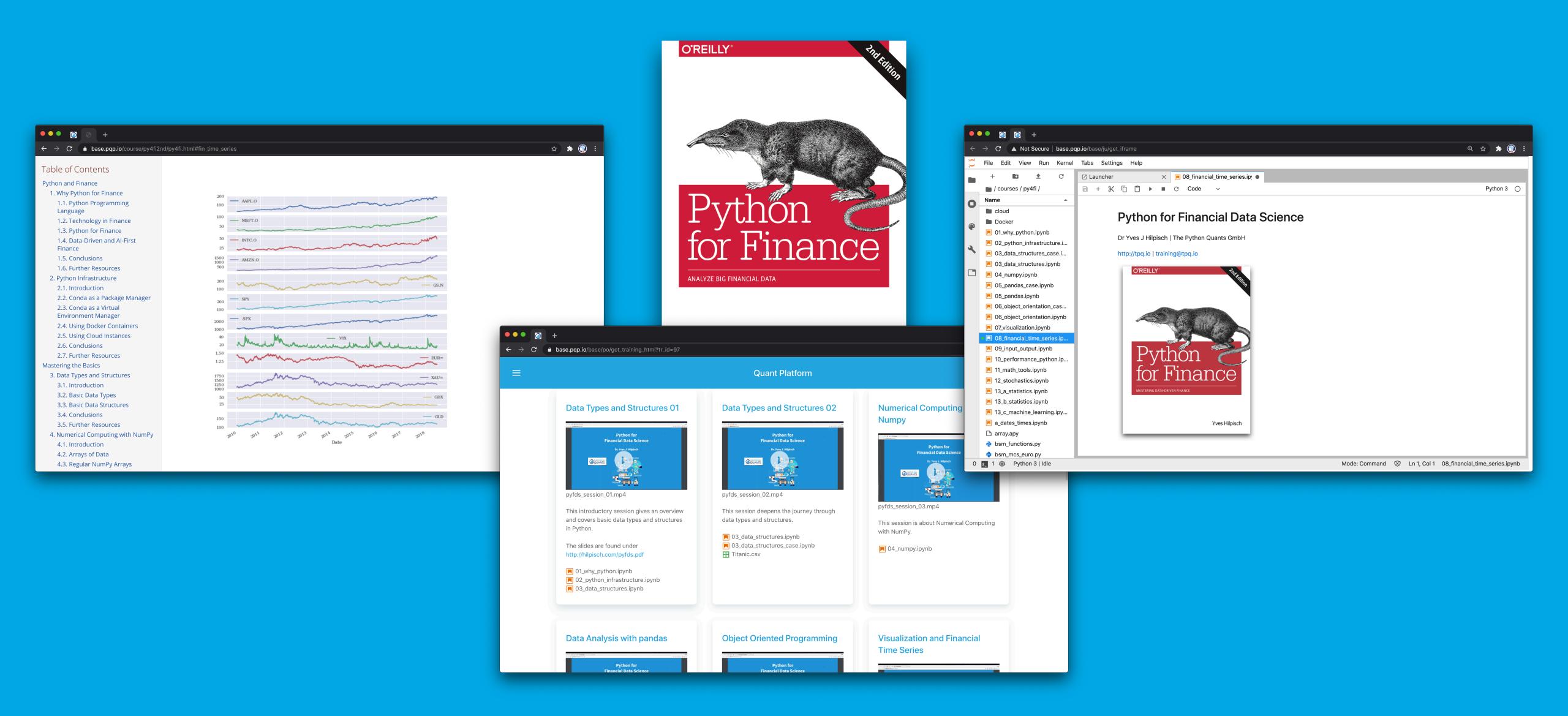
Python for Financial Data Science

Covering the most important Python idioms, techniques and packages for finance.

BASICS	DATA SCIENCE	MATHEMATICS
Python Data Types & Structures	Visualization	Mathematical Tools
Numerical Computing with NumPy	Financial Time Series	Stochastics
Data Analysis with pandas	Input-Output Operations	Statistics & Machine Learning
Object Oriented Programming	Performance Python	Special: Dates & Times

Python for Financial Data Science

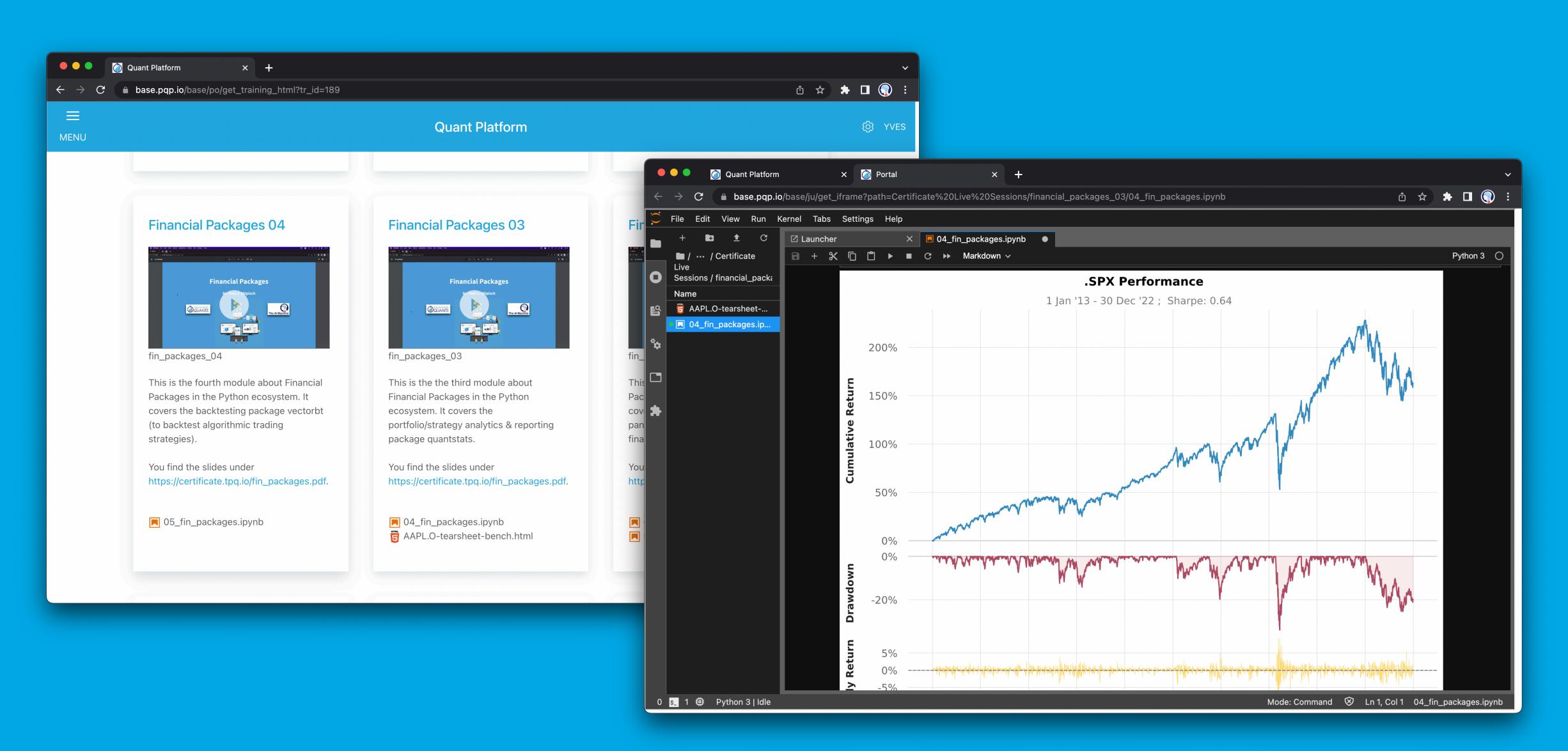
Covering the most important Python idioms, techniques and packages for finance.



Financial Packages

Financial Packages

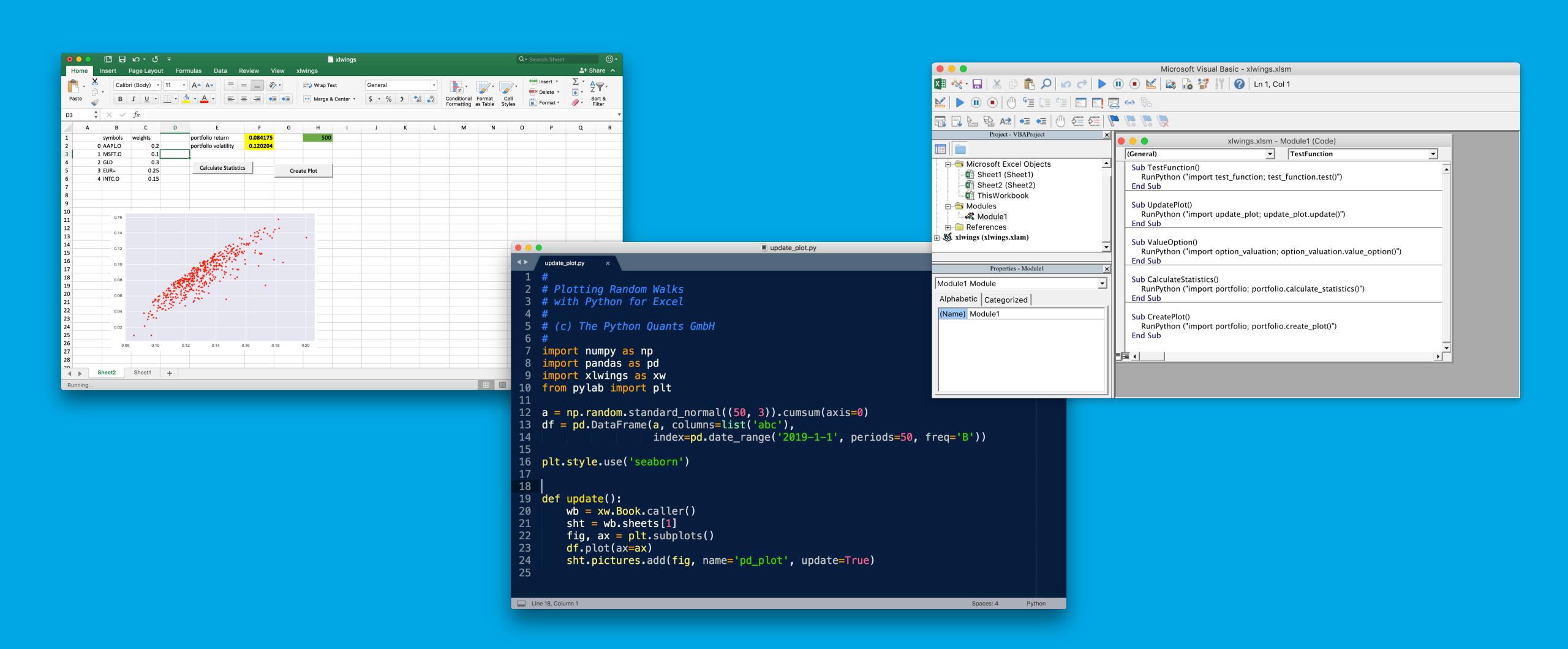
Efficient and powerful Python packages for finance.



Python for Excel

Python for Excel

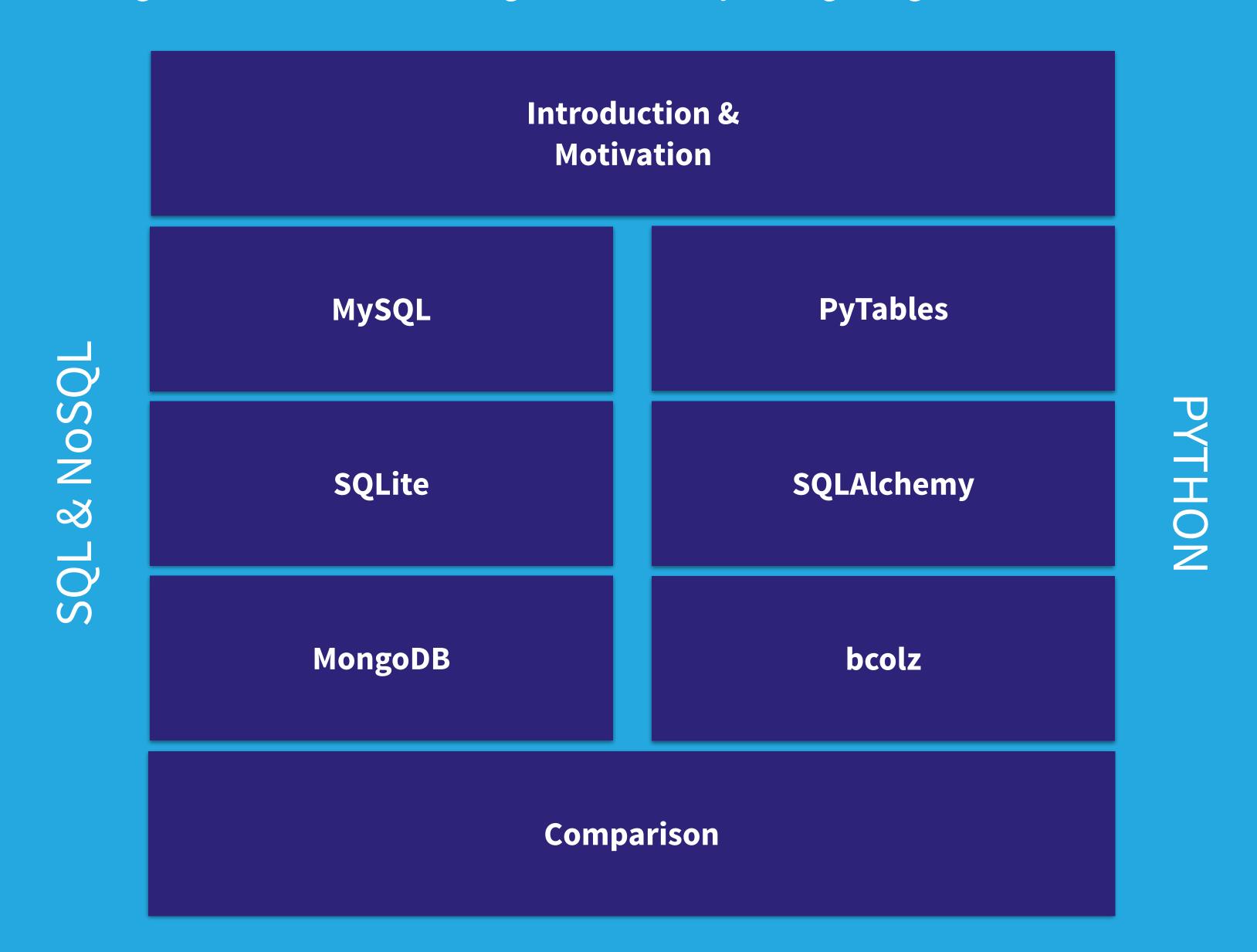
Combining Excel with the analytics power of Python.



Python for Databases

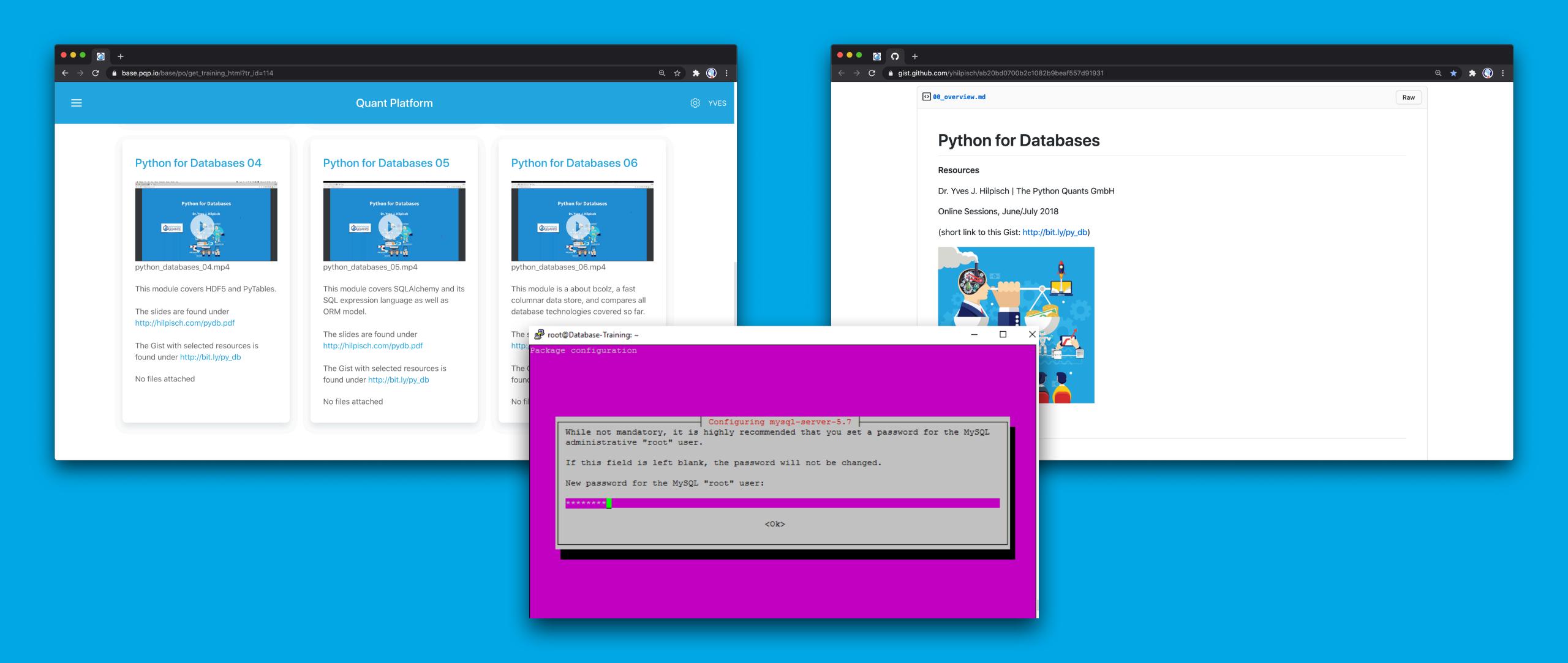
Python for Databases

Making use of database technologies to efficiently manage (large) financial data sets.



Python for Databases

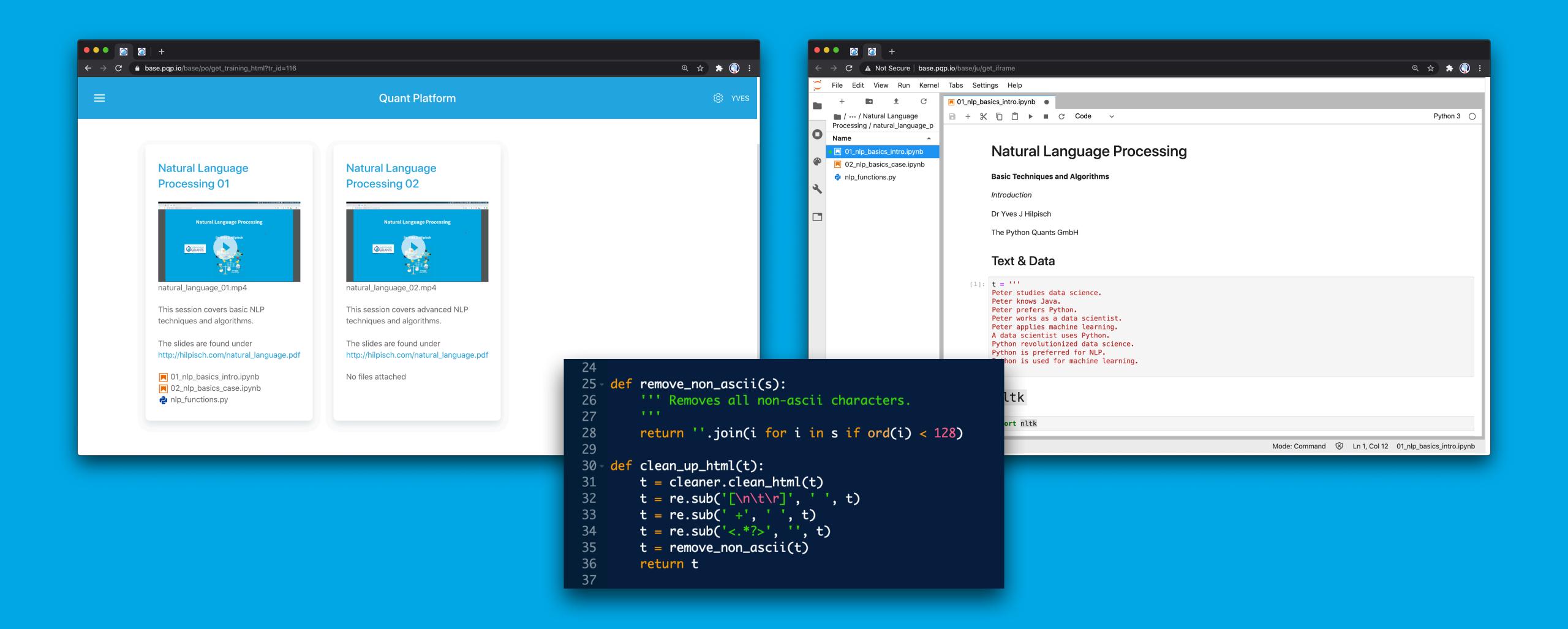
Making use of database technologies to efficiently manage (large) financial data sets.



Natural Language Processing

Natural Language Processing

Being able to process unstructured data sources such as news, texts, etc. at scale with Python.



Artificial Intelligence in Finance

Superintelligence

This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away.

—Silver et al. (2016)

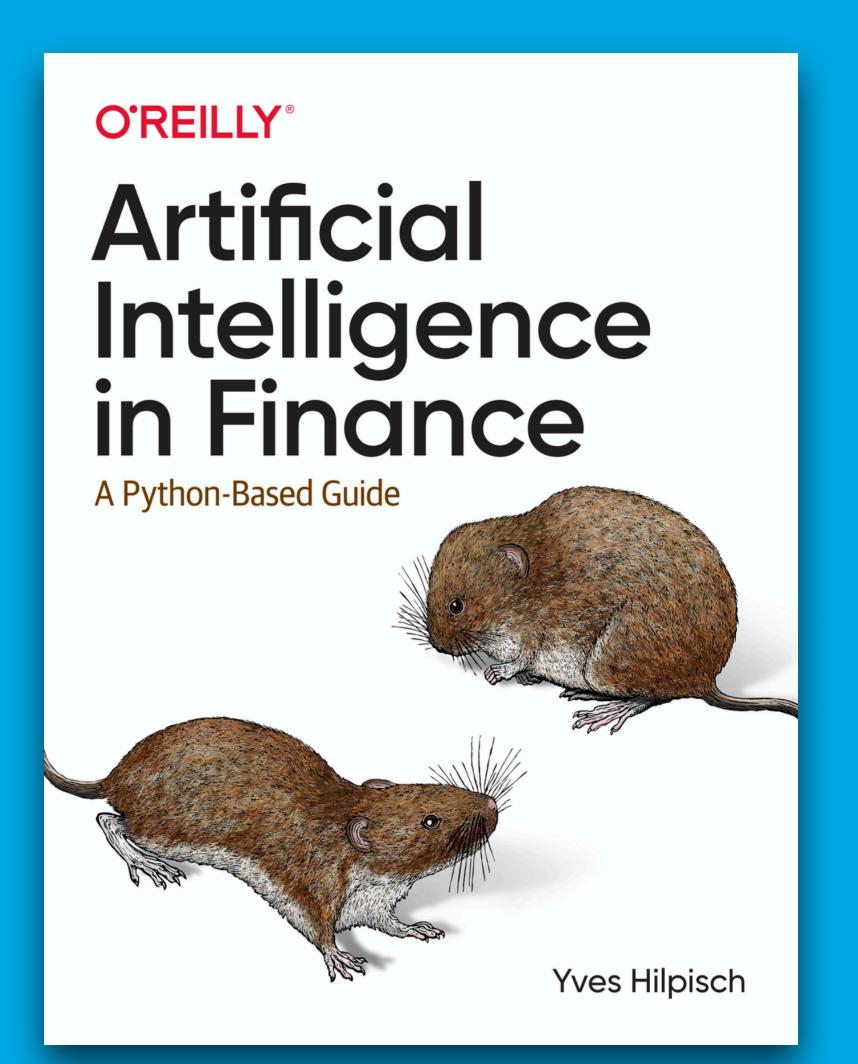
There are multiple definitions for the term *technological singularity*. Its use dates back at least to the article by Vinge (1993), which the author provocatively begins like this:

Within thirty years, we will have the technological means to create superhuman intelligence. Shortly after, the human era will be ended.

—Vinge (1993)

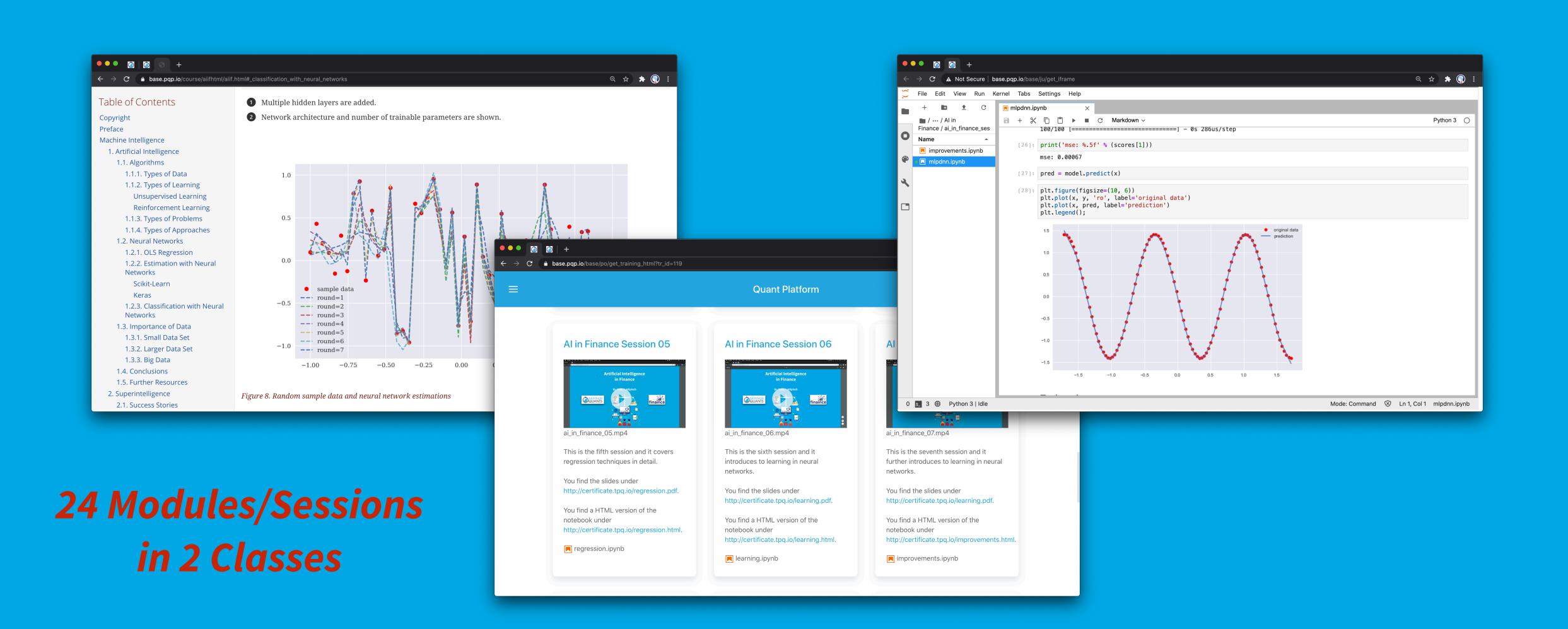
For the purposes of this chapter and book, *technological singularity* refers to a point in time at which machines can achieve superhuman intelligence or superintelligence — this is mostly in line with the original idea of Vinge (1993). The idea and concept was further popularized by the widely read and cited book Kurzweil (2005). Barrat (2013) has a wealth of historical and anecdotal information around the topic. Shanahan (2015) provides an informal introduction and overview of its central aspects. The expression *technological singularity* itself has its origin in a the concept of a *singularity* in physics. It refers to the center of a black hole where mass is highly concentrated, gravitation becomes infinite and traditional laws of physics break down. The beginning of the universe, the so-called Big Bang, is also referred to as a singularity.

Although the general ideas and concepts of the technological singularity and of superintelligences might not have an obvious and direct relationship to AI applied to finance, a better understanding of their background, related problems, and potential consequences are beneficial. The insights gained are important in a narrower context as well, such as AI in finance, and that they help in guiding the discussion about how AI might reshape finance in the near and long term.



Artificial Intelligence in Finance

Replacing normative finance by data-driven, AI-first finance



Reinforcement Learning for Finance

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih Koray Kavukcuoglu David Silver Alex Graves Ioannis Antonoglou

Daan Wierstra Martin Riedmiller

DeepMind Technologies

{vlad, koray, david, alex.graves, ioannis, daan, martin.riedmiller} @ deepmind.com

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.

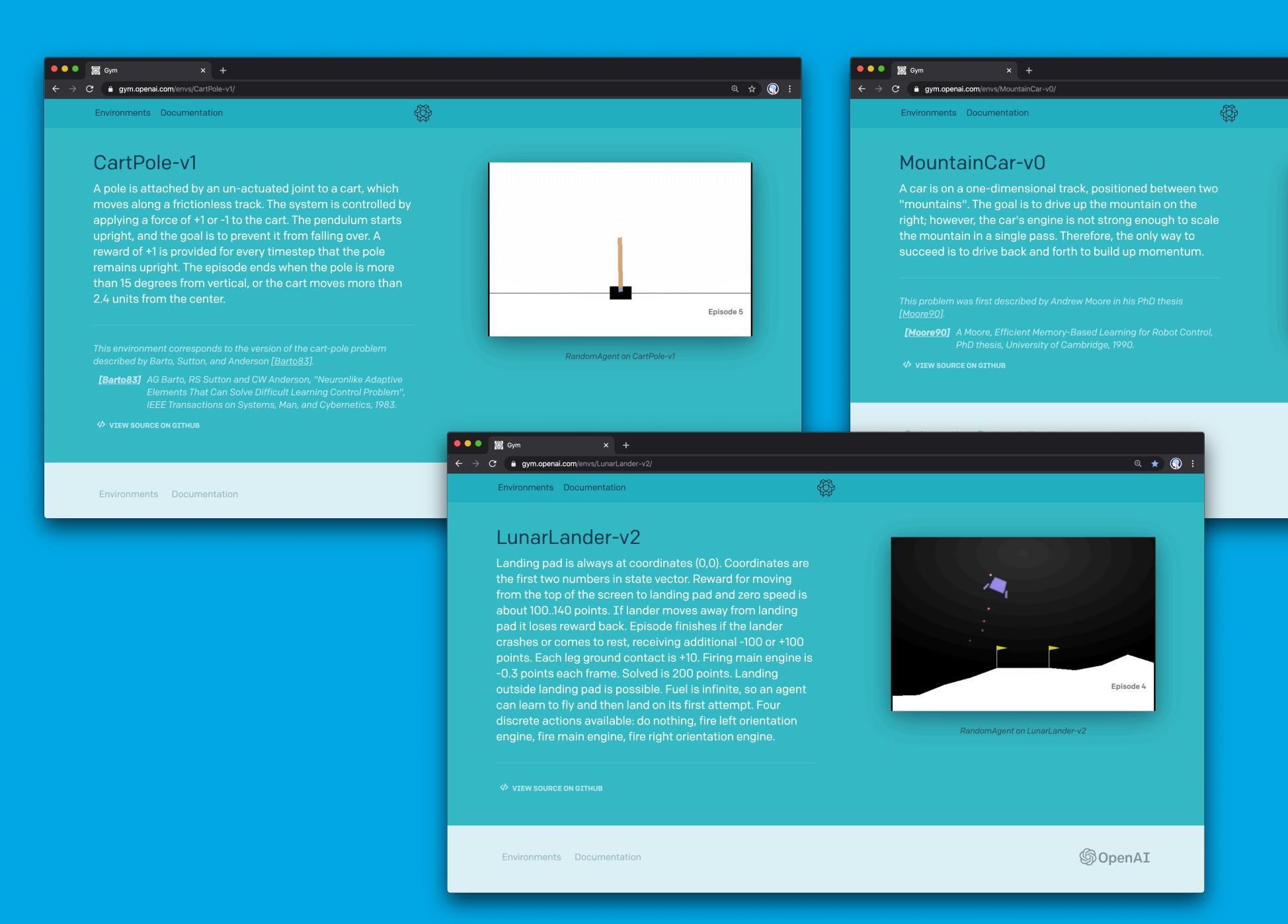
Recent advances in deep learning have made it possible to extract high-level features from raw sensory data, leading to breakthroughs in computer vision [11, 22, 16] and speech recognition [6, 7]. These methods utilise a range of neural network architectures, including convolutional networks, multilayer 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.

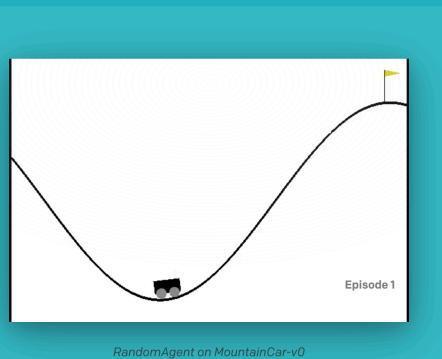
However reinforcement learning presents several challenges from a deep learning perspective. Firstly, most successful deep learning applications to date have required large amounts of hand-labelled training data. RL algorithms, on the other hand, must be able to learn from a scalar reward signal that 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

ained with a variant of the Q-learning [26] algorithm, with stochastic gradient descent to upda

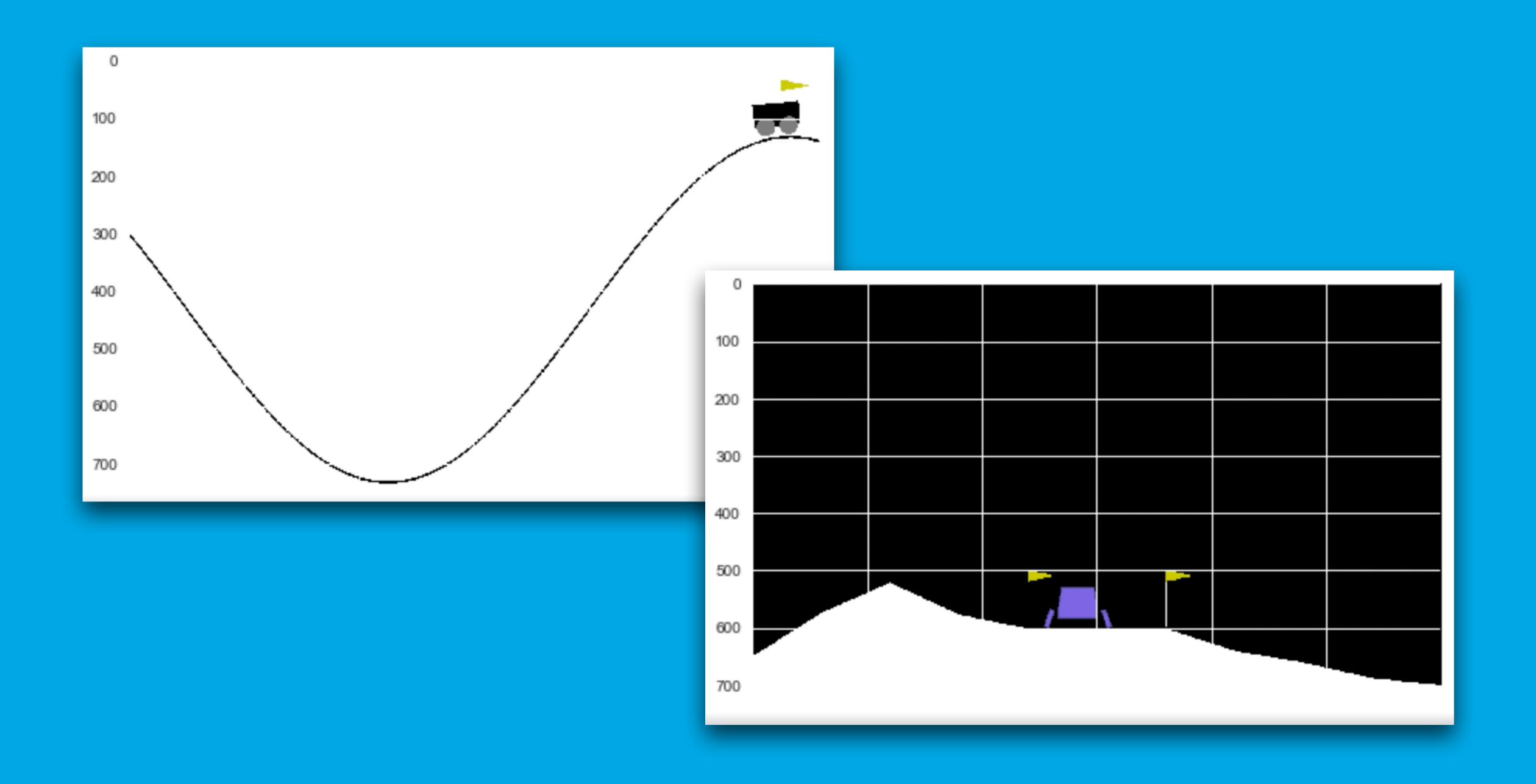






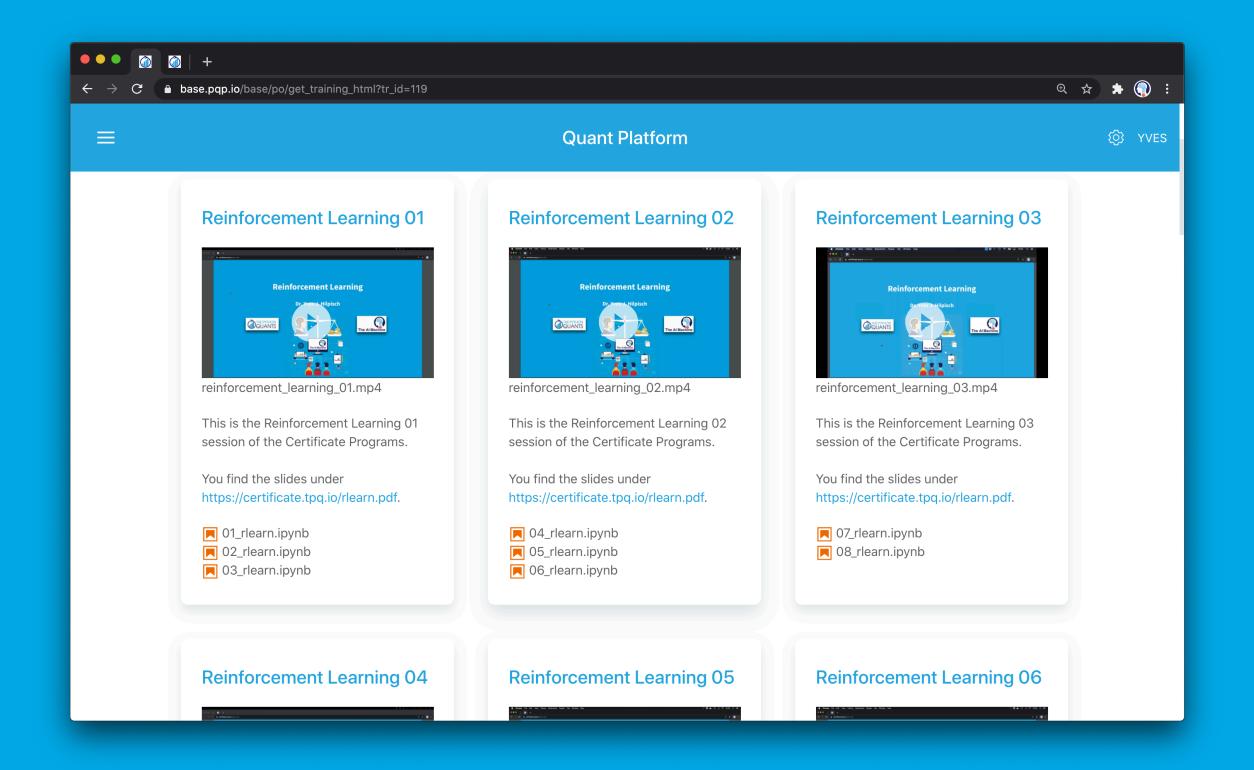
SOpenAI

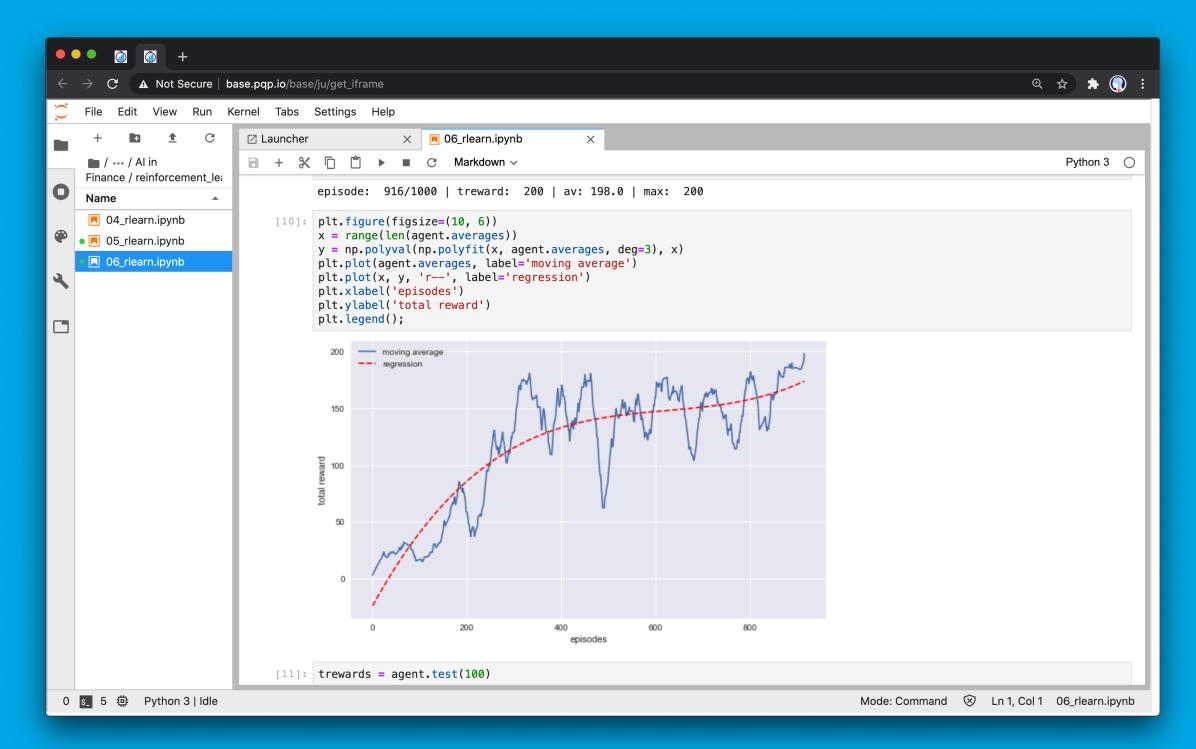
⊕ ★ **(**



Reinforcement Learning for Finance

From playing games to trading in the financial markets



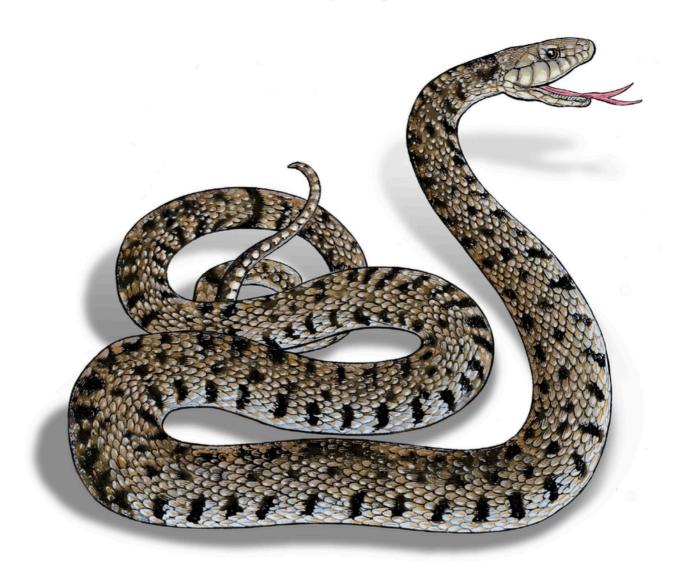


Python for Algorithmic Trading

O'REILLY®

Python for Algorithmic Trading

From Idea to Cloud Deployment



Yves Hilpisch

FOUNDATIONS	STRATEGIES	ALGO TRADING	EXPERIENCE	
Finance with Python	Vectorized Backtesting	Real-Time Data & Streaming	Practice Module 1	
01–02		Oanda Trading Platform	("own strategy")	
Finance with Python	Prediction-Based Trading	FXCM Trading Platform	Practice Module 2 ("deployment")	
03–04		Interactive Brokers Trading Platform		
Financial	Event-Based Backtesting	Gemini Trading Platform	Final Project ("research paper")	
Data Science		Automation & Review		

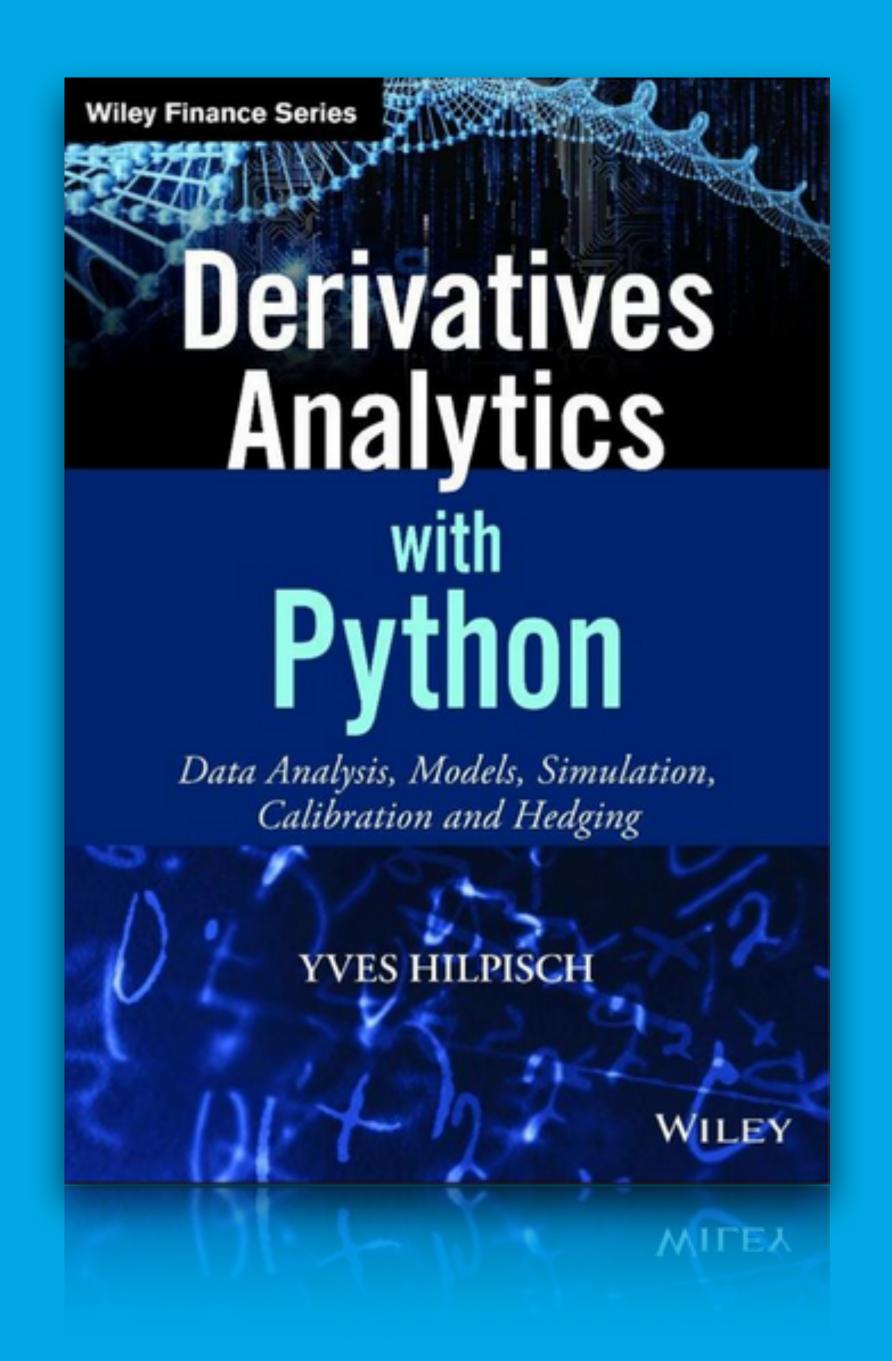
automation
trading code
connecting code
backtesting code
strategy code
financial data
infrastructure

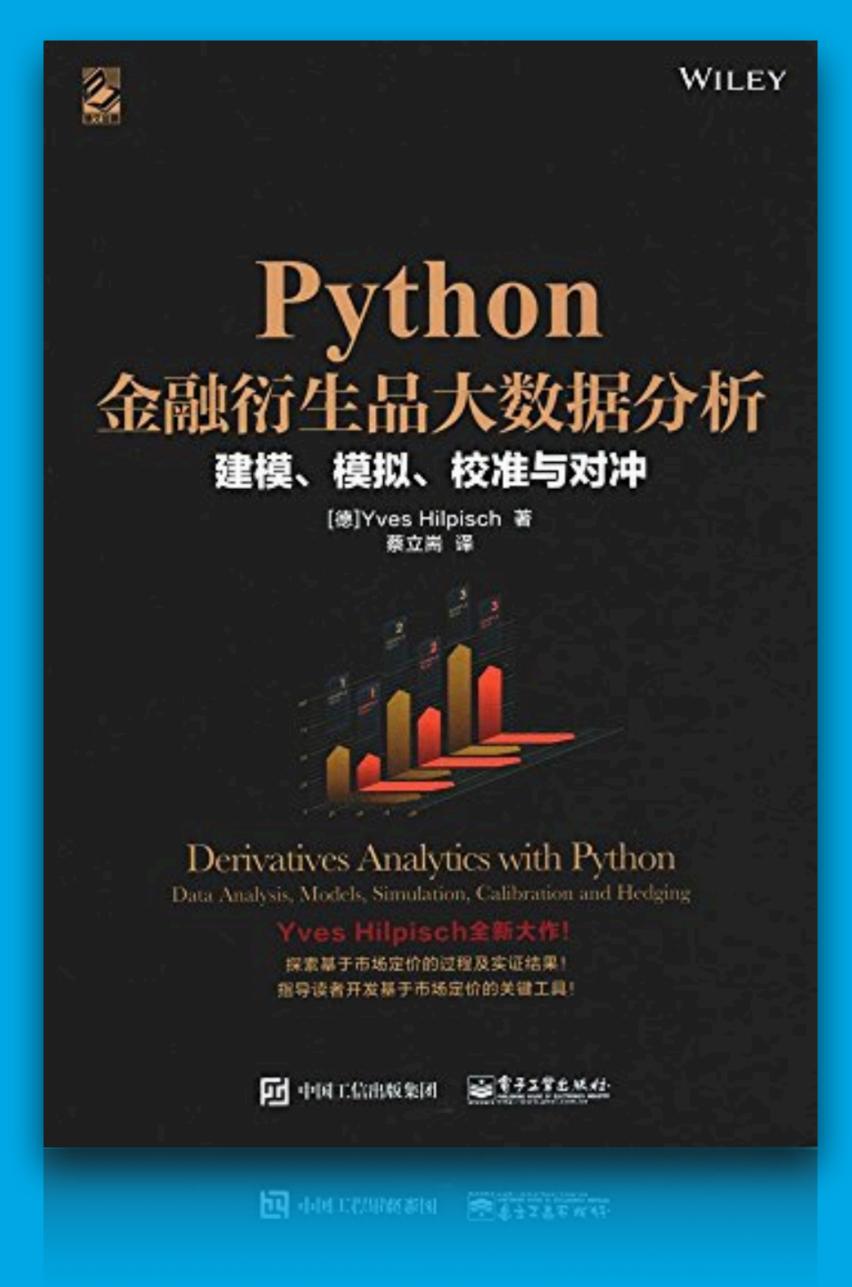


The Al Machine



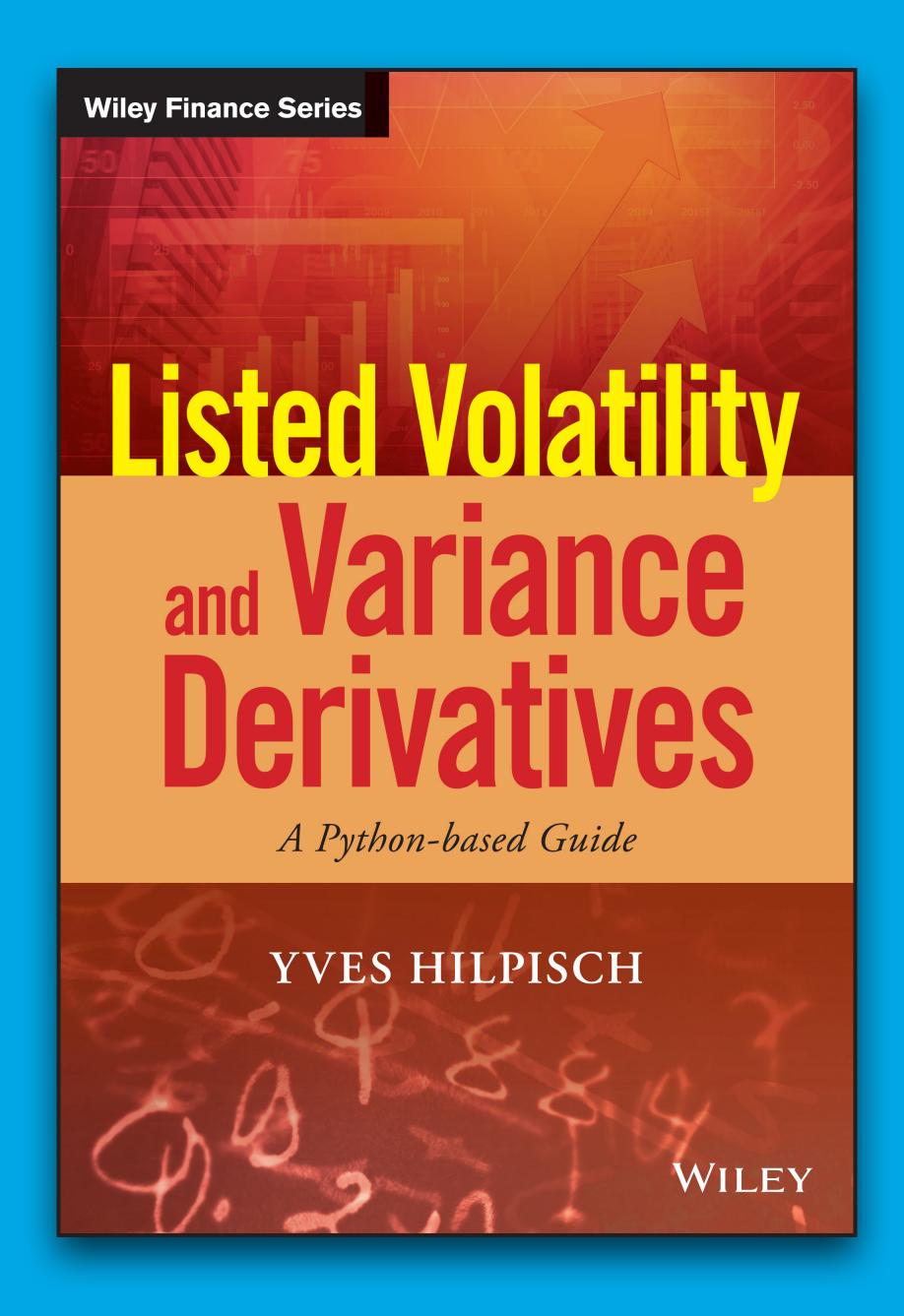
Python for Computational Finance





Computational Finance

BASICS	ADVANCED	APPLICATIONS
Market-Based Valuation	Fourier Pricing Applications	Calibration
Complete Market Models	American Options	Hedging
Risk-Neutral Valuation	General Market Model	Review
Fourier Pricing Theory	Monte Carlo Simulation	Practice



Listed Volatility & Variance Derivatives

Trading Volatility & Variance as an Asset Class

INTRODUCTION	VOLATILITY	VARIANCE	DX Analytics	ADDON
Derivatives, Volatility and Variance	Data Analysis & Strategies	Realized Variance & Variance Swaps	An Overview	Introduction to Python
Model-Free Replication of Variance	VSTOXX Index	Variance Futures at Eurex	Square-Root Diffusion	Volatility: Terms of the VSTOXX and its Derivatives
	Valuing Volatility Derivatives		Square-Root Jump Diffusion	Variance: Trading & Settlement
	Advanced Modelling of the VSTOXX Index			

DX Analytics

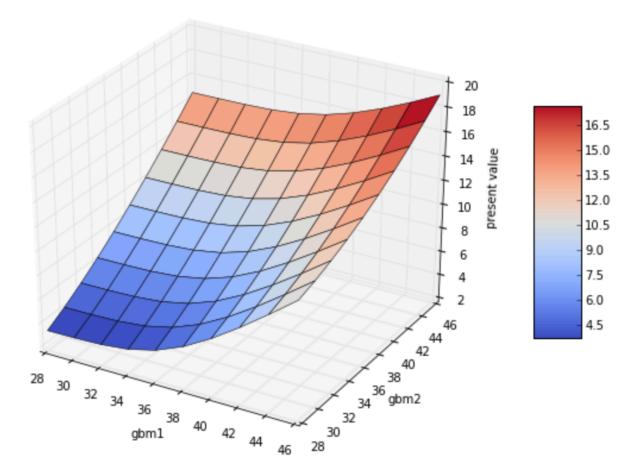
DX Analytics is a **Python-based financial analytics library** which allows the modeling of rather complex derivatives instruments and portfolios. Make sure to fully understand what you are using this Python package for and how to apply it. Please also read the license text and disclaimer.

Basic Philosophy

DX Analytics is a Python-based financial analytics library that mainly implements what is sometimes called the **global** valuation of (complex portfolios of) derivatives instruments (cf.

http://www.riskcare.com/files/7314/0360/6145/LowResRiskcare_Risk_0510_2.pdf). The major characteristic of this approach is the **non-redundant modeling** of all components needed for the valuation (e.g. risk factors) and the **consistent simulation and valuation** of all relevant portfolio components (e.g. correlated risk factors, multi-risk derivatives and portfolios themselves).

With DX Analytics you can, for instance, model and risk manage multi-risk derivatives instruments (e.g. American maximum call option) and generate 3-dimensional **present value surfaces** like this one:





Navigation

- 1. Quickstart
- 1.1. Risk Factor Models
- 1.2. Valuation Models
- 1.3. Excursion: SABR Model
- 1.4. Options Portfolio
- 2. Framework Classes and
- Functions
- 3. Model Classes
- 4. Single-Risk Derivatives Valuation
- 5. Multi-Risk DerivativesValuation
- 6. Multi-Risk Derivatives
 Portfolios
- 7. Parallel Valuation of
- Large Portfolios
- 8. Derivatives Portfolio
- **Risk Statistics**
- 9. Fourier-based Option
 Pricing
- 10. Implied Volatilities
- and Model Calibration
- 11. Interest Rate Swaps
- 12. Mean-Variance
- Portfolio Class
- 13. Stochastic Short Rates
- 14. Quite Complex
- Portfolios

Quick search

1. Quickstart

This brief first part illustrates—without much explanation—the usage of the DX Analytics library. It models two risk factors, two derivatives instruments and values these in a portfolio context.

```
[1]: import dx
import datetime as dt
import pandas as pd
from pylab import plt
plt.style.use('seaborn')
```

1.1. Risk Factor Models

The first step is to define a **model for the risk-neutral discounting**.

```
[2]: r = dx.constant_short_rate('r', 0.01)
```

We then define a **market environment** containing the major parameter specifications needed,

```
[3]: me_1 = dx.market_environment('me', dt.datetime(2016, 1, 1))

me_1.add_constant('initial_value', 100.)
    # starting value of simulated processes
me_1.add_constant('volatility', 0.2)
    # volatiltiy factor
me_1.add_constant('final_date', dt.datetime(2017, 6, 30))
    # horizon for simulation
me_1.add_constant('currency', 'EUR')
    # currency of instrument
me_1.add_constant('frequency', 'W')
    # frequency for discretization
me_1.add_constant('paths', 10000)
    # number of paths
me_1.add_curve('discount_curve', r)
    # number of paths
```

Next, the model object for the **first risk factor**, based on the geometric Brownian motion (Black-Scholes-Merton (1973) model).

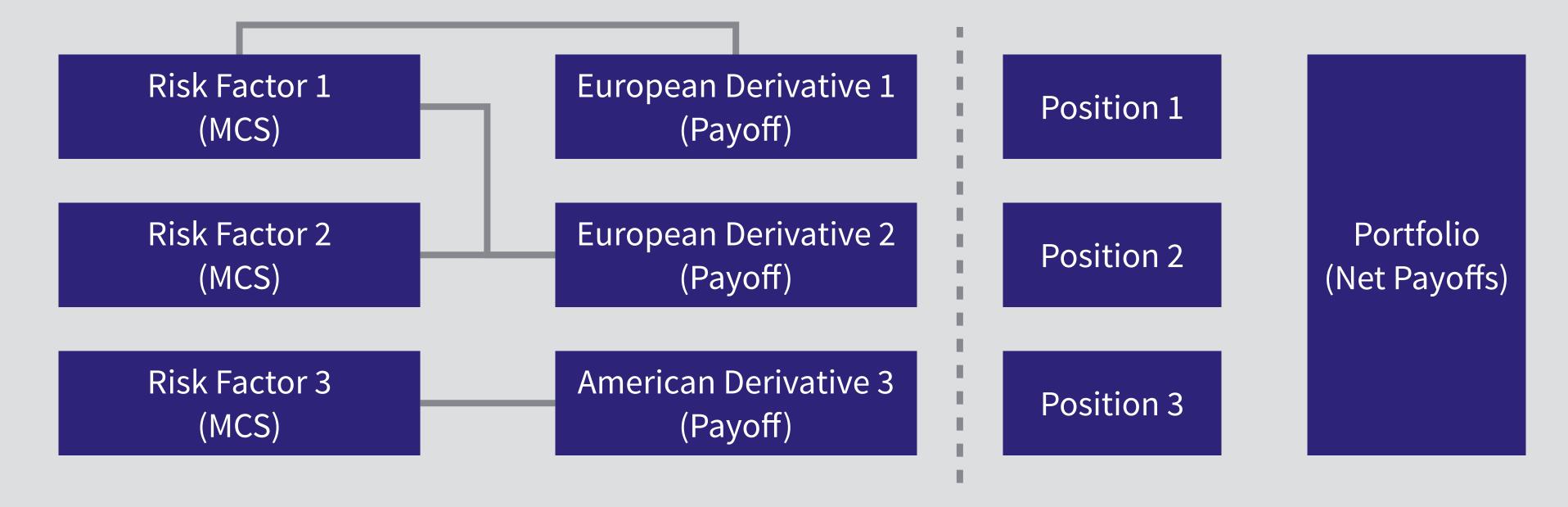
DX Analytics

BASICS	ADVANCED	SPECIAL
Quick Start	Fourier Pricing	Multi-Risk Derivatives
Framework & Model Simulation	American Valuation	Implied Volatilities & Calibration
European Valuation	Stochastic Short Rates	Hedging
Derivatives Portfolios	Derivatives Portfolios	Complex Portfolios

Risk-Neutral Present Values & Greeks for Instruments, Positions & Portfolios



Optimal Exercise Policy and Risk-Neutral Discounting



Risk-Neutral Discount Curve | Constant, Deterministic, Stochastic

hedging
market valuation
calibration
Fourier pricing
simulation
models
financial data
infrastructure

Python for Asset Management

Python for Asset Management

Basics of Risk and Return in Finance

Mean-Variance Portfolio Theory

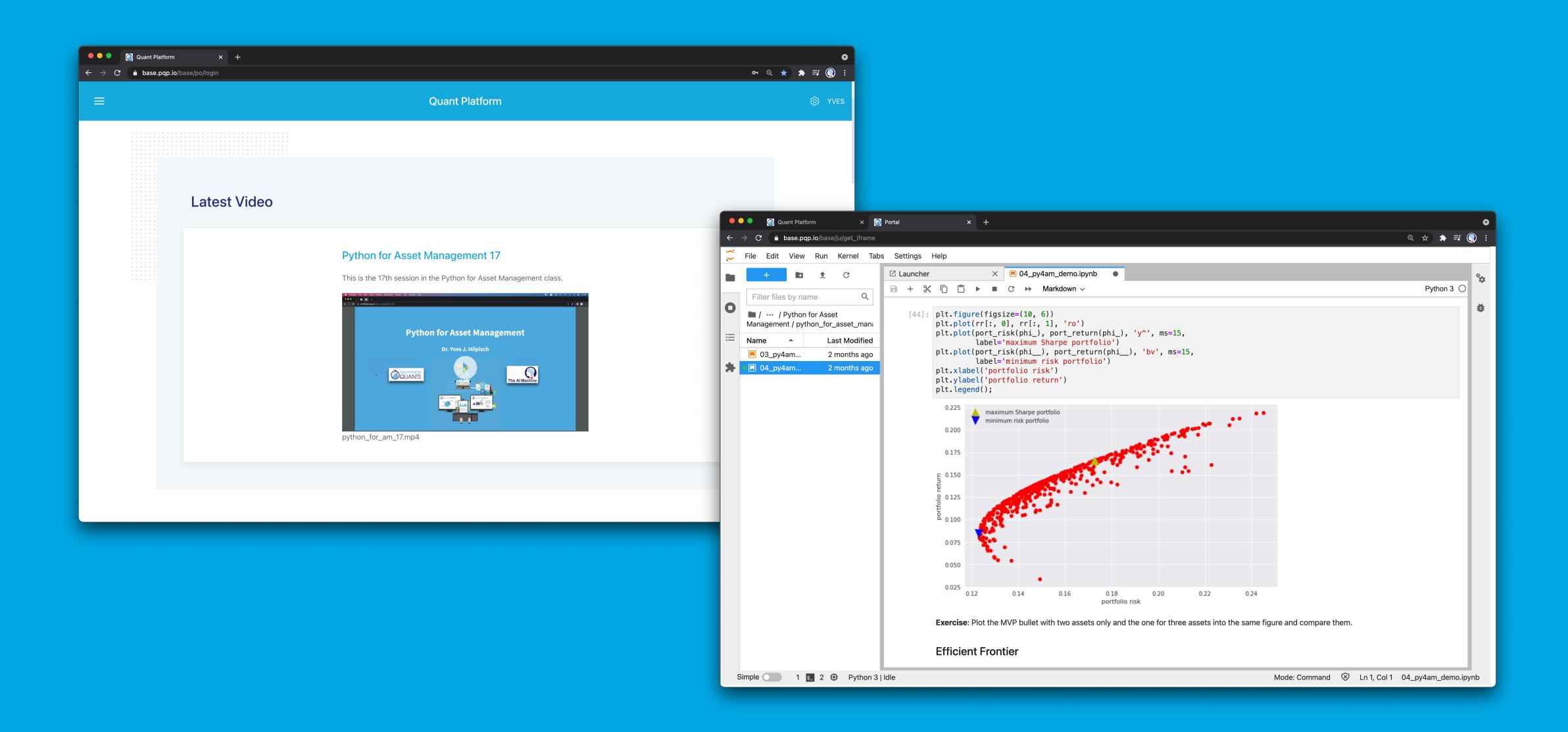
Capital Market Theory (CAPM, APT)

Alternatives to MVP Theory (e.g. Risk Budgeting/Parity)

Al and Machine Learning for Asset Management

Python for Asset Management

From traditional Mean-Variance Portfolio Theory to AI for Asset Management



The first stage starts with observation and experience and ends with beliefs about the future performances of available securities. The second stage starts with the relevant beliefs about future performances and ends with the choice of portfolio. This paper is concerned with the second stage. We first consider the rule that the investor does (or should) maximize discounted expected, or anticipated, returns. This rule is rejected both as a hypothesis to explain, and as a maximum to guide investment behavior. We next consider the rule that the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing. This rule has many sound points, both as a maxim for, and hypothesis about, investment behavior. We illustrate geometrically relations between beliefs and choice of portfolio according to the "expected returns—variance of returns" rule.

One type of rule concerning choice of portfolio is that the investor does (or should) maximize the discounted (or capitalized) value of future returns. Since the future is not known with certainty, it must be "expected" or "anticipated" returns which we discount. Variations of this type of rule can be suggested. Following Hicks, we could let "anticipated" returns include an allowance for risk. Or, we could let the rate at which we capitalize the returns from particular securities vary with risk.

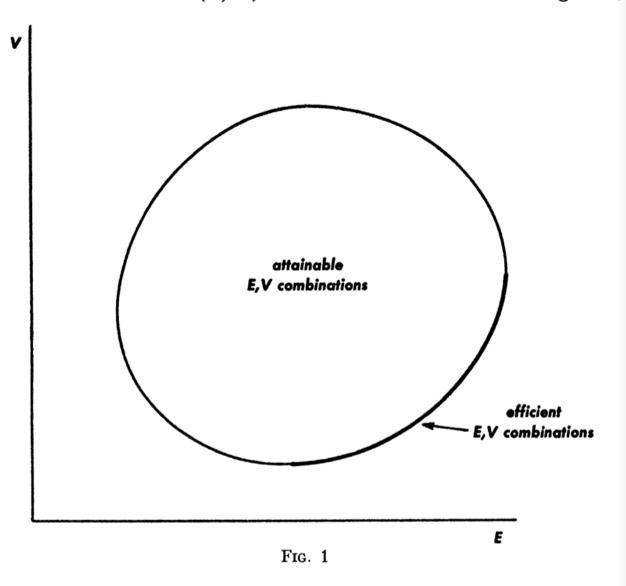
The hypothesis (or maxim) that the investor does (or should) maximize discounted return must be rejected. If we ignore market imperfections the foregoing rule never implies that there is a diversified portfolio which is preferable to all non-diversified portfolios. Diversification is both observed and sensible; a rule of behavior which does not imply the superiority of diversification must be rejected both as a hypothesis and as a maxim.

- * This paper is based on work done by the author while at the Cowles Commission for Research in Economics and with the financial assistance of the Social Science Research Council. It will be reprinted as Cowles Commission Paper, New Series, No. 60.
- 1. See, for example, J. B. Williams, *The Theory of Investment Value* (Cambridge, Mass.: Harvard University Press, 1938), pp. 55-75.
- 2. J. R. Hicks, Value and Capital (New York: Oxford University Press, 1939), p. 126. Hicks applies the rule to a firm rather than a portfolio.

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For fixed probability beliefs (μ_i, σ_{ij}) the investor has a choice of various combinations of E and V depending on his choice of portfolio X_1, \ldots, X_N . Suppose that the set of all obtainable (E, V) combinations were as in Figure 1. The E-V rule states that the investor would (or should) want to select one of those portfolios which give rise to the (E, V) combinations indicated as efficient in the figure; i.e., those with minimum V for given E or more and maximum E for given V or less.

There are techniques by which we can compute the set of efficient portfolios and efficient (E, V) combinations associated with given μ_i



and σ_{ij} . We will not present these techniques here. We will, however, illustrate geometrically the nature of the efficient surfaces for cases in which N (the number of available securities) is small.

The calculation of efficient surfaces might possibly be of practical use. Perhaps there are ways, by combining statistical techniques and the judgment of experts, to form reasonable probability beliefs (μ_i, σ_{ij}) . We could use these beliefs to compute the attainable efficient combinations of (E, V). The investor, being informed of what (E, V) combinations were attainable, could state which he desired. We could then find the portfolio which gave this desired combination.

Two conditions—at least—must be satisfied before it would be practical to use efficient surfaces in the manner described above. First, the investor must desire to act according to the E-V maxim. Second, we must be able to arrive at reasonable μ_i and σ_{ij} . We will return to these matters later.

Let us consider the case of three securities. In the three security case our model reduces to

$$1) \qquad E = \sum_{i=1}^{3} X_i \mu_i$$

2)
$$V = \sum_{i=1}^{3} \sum_{j=1}^{3} X_{i} X_{j} \sigma_{ij}$$

$$\sum_{i=1}^{3} X_i = 1$$

4)
$$X_i \ge 0$$
 for $i = 1, 2, 3$.

From (3) we get

$$X_3 = 1 - X_1 - X_2$$

If we substitute (3') in equation (1) and (2) we get E and V as functions of X_1 and X_2 . For example we find

1')
$$E = \mu_3 + X_1 (\mu_1 - \mu_3) + X_2 (\mu_2 - \mu_3)$$

The exact formulas are not too important here (that of V is given below). We can simply write

$$E = E(X_1, X_2)$$

$$V = V(X_1, X_2)$$

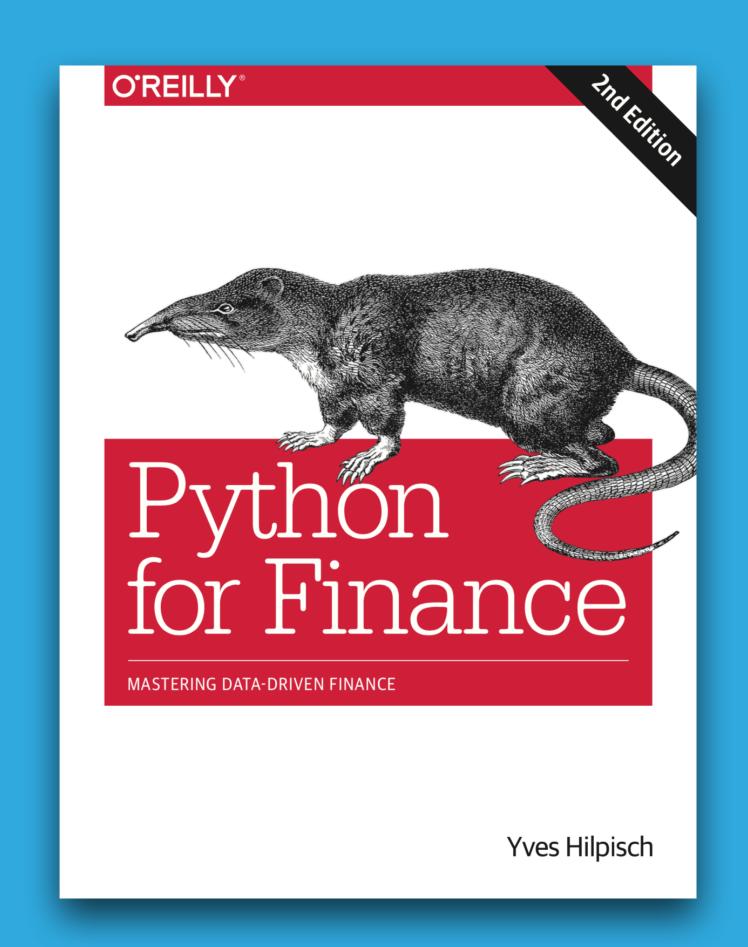
c)
$$X_1 \geqslant 0, X_2 \geqslant 0, 1 - X_1 - X_2 \geqslant 0$$

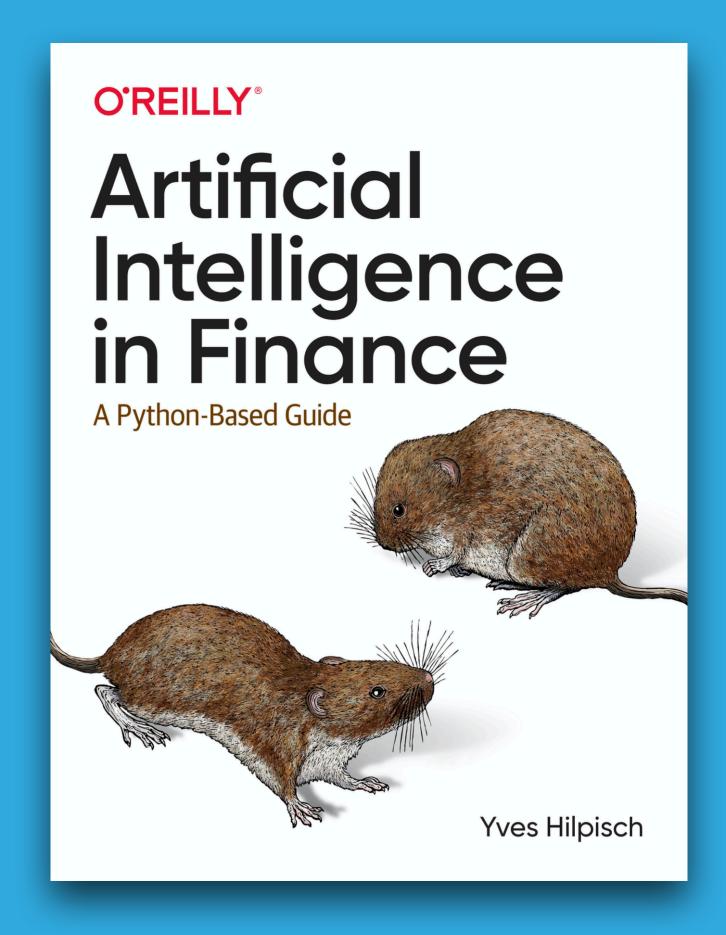
By using relations (a), (b), (c), we can work with two dimensional geometry.

The attainable set of portfolios consists of all portfolios which satisfy constraints (c) and (3') (or equivalently (3) and (4)). The attainable combinations of X_1 , X_2 are represented by the triangle \overline{abc} in Figure 2. Any point to the left of the X_2 axis is not attainable because it violates the condition that $X_1 \ge 0$. Any point below the X_1 axis is not attainable because it violates the condition that $X_2 \ge 0$. Any

8.
$$V = X_1^2(\sigma_{11} - 2\sigma_{13} + \sigma_{33}) + X_2^2(\sigma_{22} - 2\sigma_{23} + \sigma_{33}) + 2X_1X_2(\sigma_{12} - \sigma_{13} - \sigma_{23} + \sigma_{33}) + 2X_1(\sigma_{13} - \sigma_{33}) + 2X_2(\sigma_{23} - \sigma_{33}) + \sigma_{33}$$

Thierry Roncalli Introduction to Risk Parity and Budgeting Chapman & Hall/CRC FINANCIAL MATHEMATICS SERIES



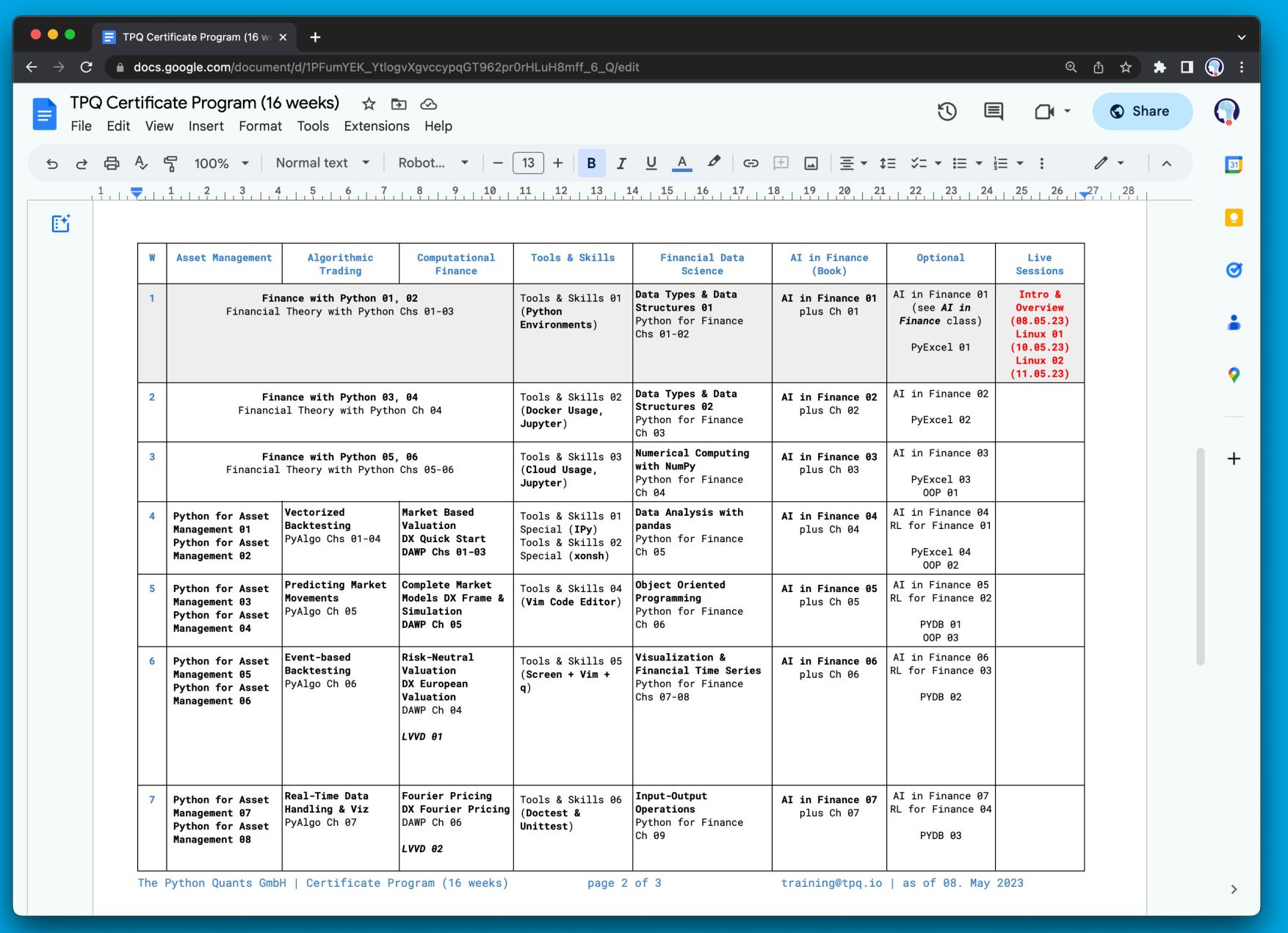


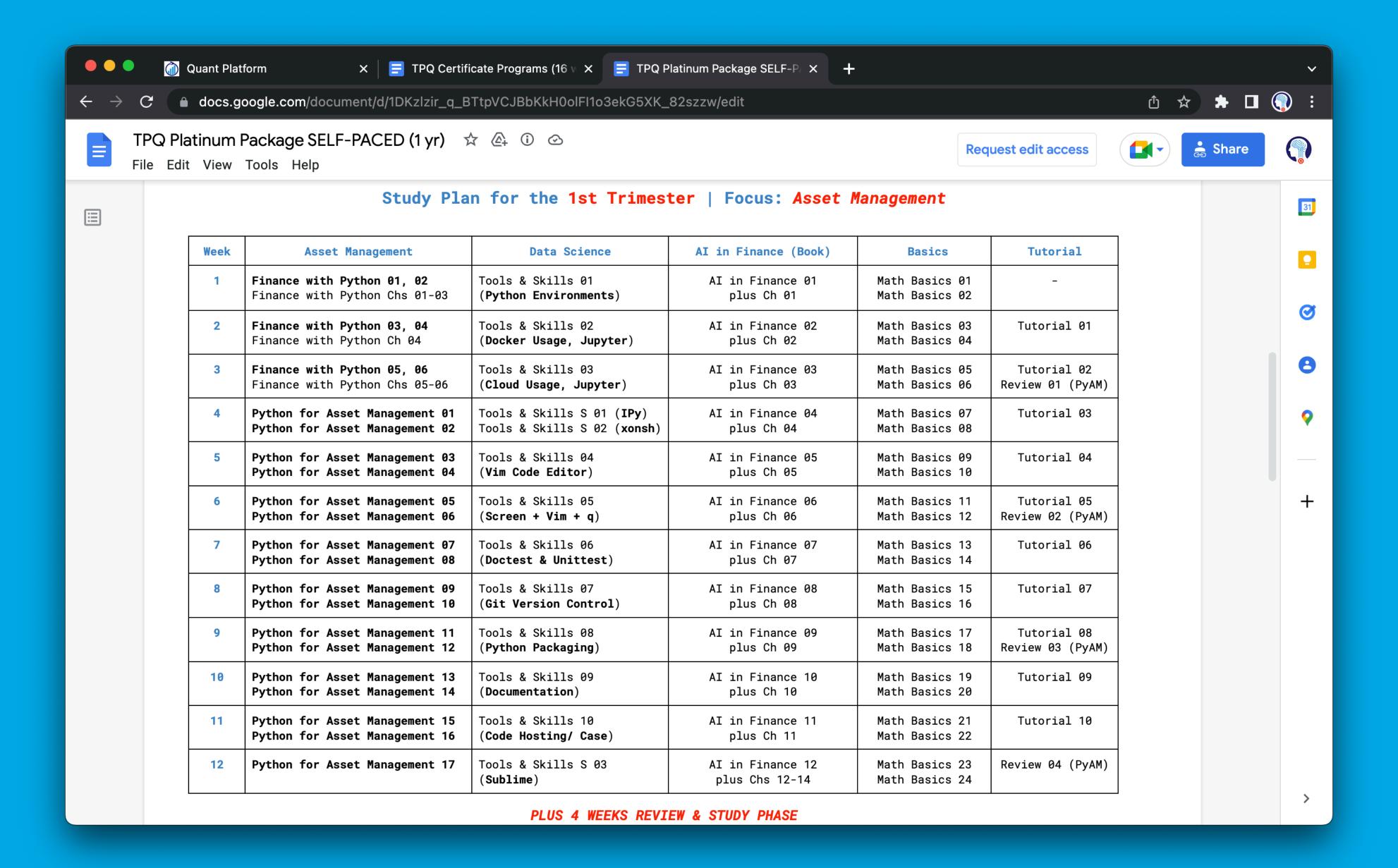
CASE STUDIES & DEMOS

- 1. Financial Packages
- 2. Model Calibration
- 3. Market Prediction
- 4. Oanda Trading Platform

Link to Gist: http://bit.ly/cert_intro

Study Plans for the Programs





Guiding Principles

Guiding Principles

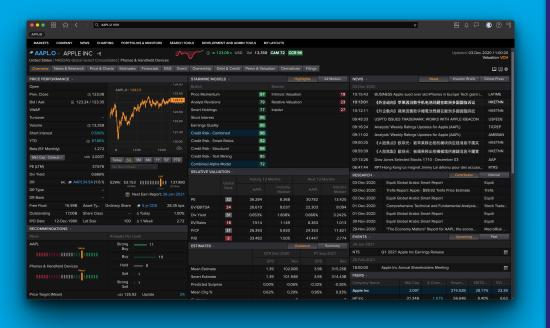


Python First

Coding and implementation are the focus, rather than theory or practical considerations.

Specific

Algorithms used & examples shown are specific in nature and not meant to provide an exhaustive overview.

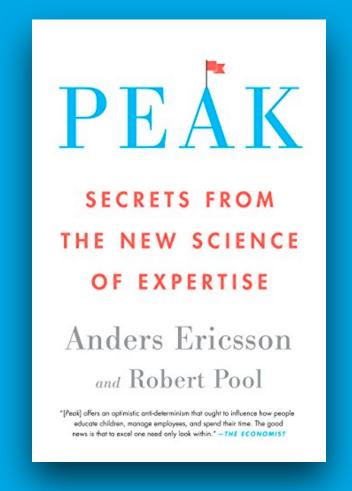


Reproducible

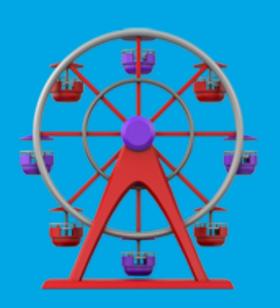
All examples are based on static data sets to allow for reproducibility of results.

Practical

To acquire coding and other practical skills is the main goal. Therefore skill acquisition is indispensable.



Might also be noteworthy ...



Different Levels

The classes and sessions will be easy for some and difficult for others.

Delegates might be beginners or experts.



Most classes are done on MacOS and should be straightforward to implement on Linux. With small adjustments also on Windows.





Sometimes Opportunistic

The classes and sessions sometimes do not provide a comprehensive, systematic treatment of the topics touched upon.

Delayed Rewards

Delegates should not only expect "immediate rewards". Often, it's better to follow closely, to digest, and revisit the materials later.



Review Questions, Exercises & Test Projects



Certificate Program in Python for Algorithmic Trading

Review Questions Weeks 01, 02, & 03

With regard to the topics covered in the first three weeks, you might review the materials based on the following questions. The review questions focus mainly on the **big picture**.

• Python in General

- Which data types did you learn about?
- What basic data structures provides Python you with?
- What is the basic syntax of a "for loop"?
- What is the syntax of a list comprehension? (make an example)
- Why is OOP a useful programming paradigm?

• Finance with Python

- Name three approaches to price a (European) option in a complete market model.
- Why is (freedom of) arbitrage such a strong argument in the context of financial pricing?
- What is a martingale measure and how can it be used to price options?
- What is the expected utility approach all about and how does it model decision making under uncertainty?
- What problems arise in the context of an incomplete market (model)?
- Explain the difference between a static and a dynamic financial model (for pricing purposes).

page 1 of 3

Tools & Skills

- Which dual role does the tool conda play?
- Why does it make sense to work with Python environments?
- How do you create an environment with conda?
- How do you install Python packages to such an environment?
- How do you delete a Python environment?
- Why is Docker a helpful, platform-independent technology?
- How does it help you with managing Python installations?
- What are the benefits of a cloud-based Python installation compared to a local one?
- Why, do you think, a cloud infrastructure is indispensable when running algorithmic trading strategies in automated fashion?

Financial Data Science

- What are typical real world problems that you face with regard to (financial) data sets?
- What are basic approaches to process CSV files with Python?
- Why is NumPy such a helpful package for numerical computing and financial analytics in particular?
- Explain the benefits of specialized data structures (eg ndarray object) as compared to more general ones (eg list object).
- What are vectorized operations (with NumPy) and what are the benefits of this programming paradigm?
- How do you generate random numbers with NumPy?

Al in Finance

- What do people understand under the Technological Singularity (TS)?
- What basic paths consider researchers possible to reach the TS?
- Do you personally believe a TS is possible and why or why not?
- What do people understand under the Financial Singularity and how might it be achieved technologically?
- What is meant by data-driven finance and which technological advances drive it?

page 2 of 3

How does it enable AI-first finance and what do you understand when you hear this expression?

What is the difference between a normative and a positive approach to finance?

How does it relate to the history of financial economics and to an AI-first future of finance?

Name three financial theories that might be considered elegant but not realistic (given empirical support).

page 3 of 3

Finance with Python

Arbitrage Pricing

Assume two traded assets are given, a risky one (stock) and a risk-less one (bond), with prices $S_0 = 10$, $S_0 = 1$. Their future payoffs are:

$$S_1 = \begin{pmatrix} 15 \\ 5 \end{pmatrix}$$

$$B_1 = \left(\begin{array}{c} 1.01\\ 1.01 \end{array}\right)$$

A European put option is introduced to the market with payoff:

$$P_1 = \begin{pmatrix} 0 \\ 3 \end{pmatrix}$$

Questions:

- What is the strike price of the put option?
- Which portfolio replicates the put option payoff perfectly?
- Is there a difference when using OLS regression for the replication?
- How can a learning algorithm be used to replicate the payoff?
- How can a learning algorithm be used to replicate the payoff?
- Is there a difference when using OLS regression for the replication?
- Which portfolio replicates the put option payoff perfectly?

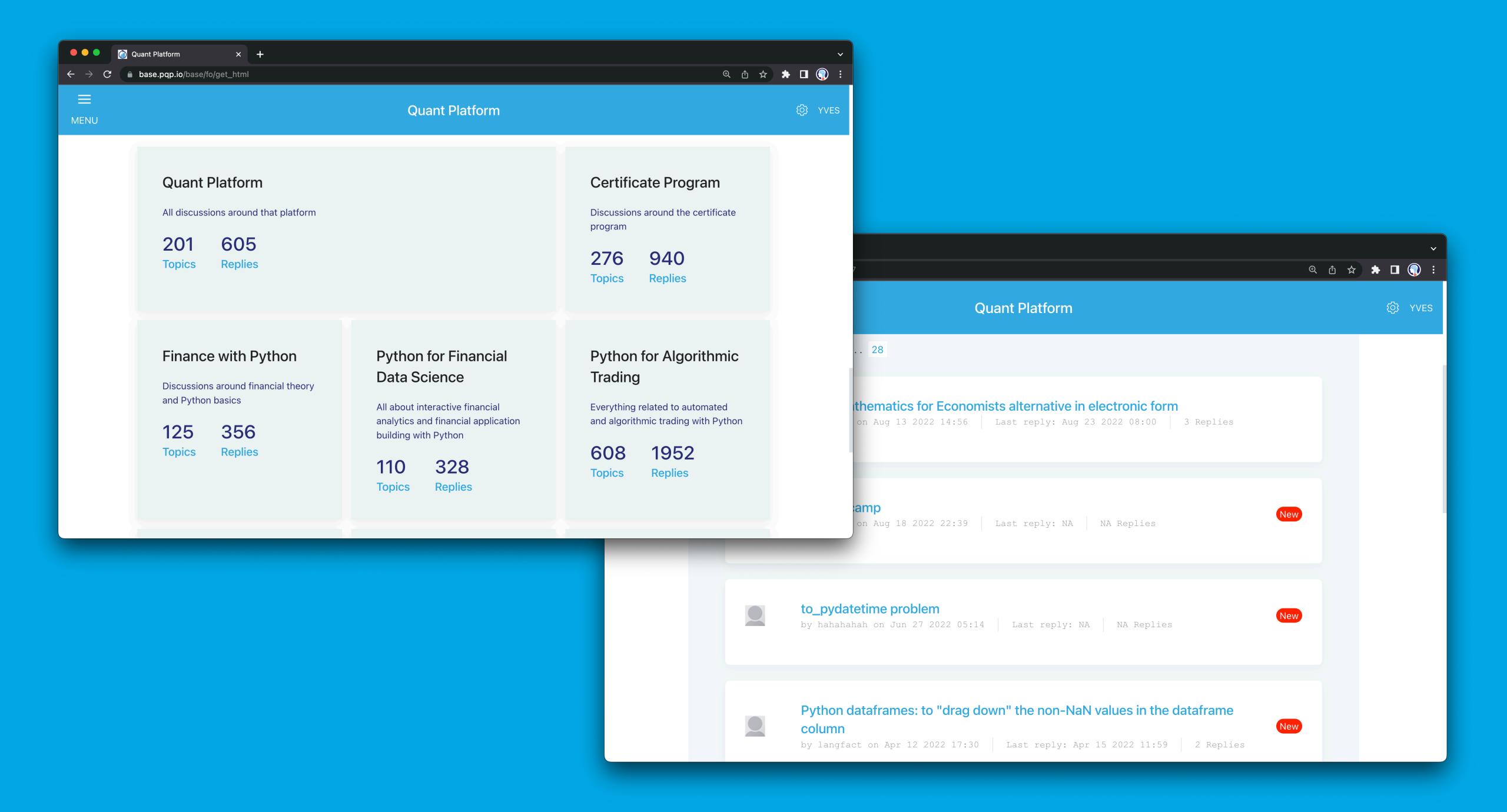
Test Project

Implement the following game:

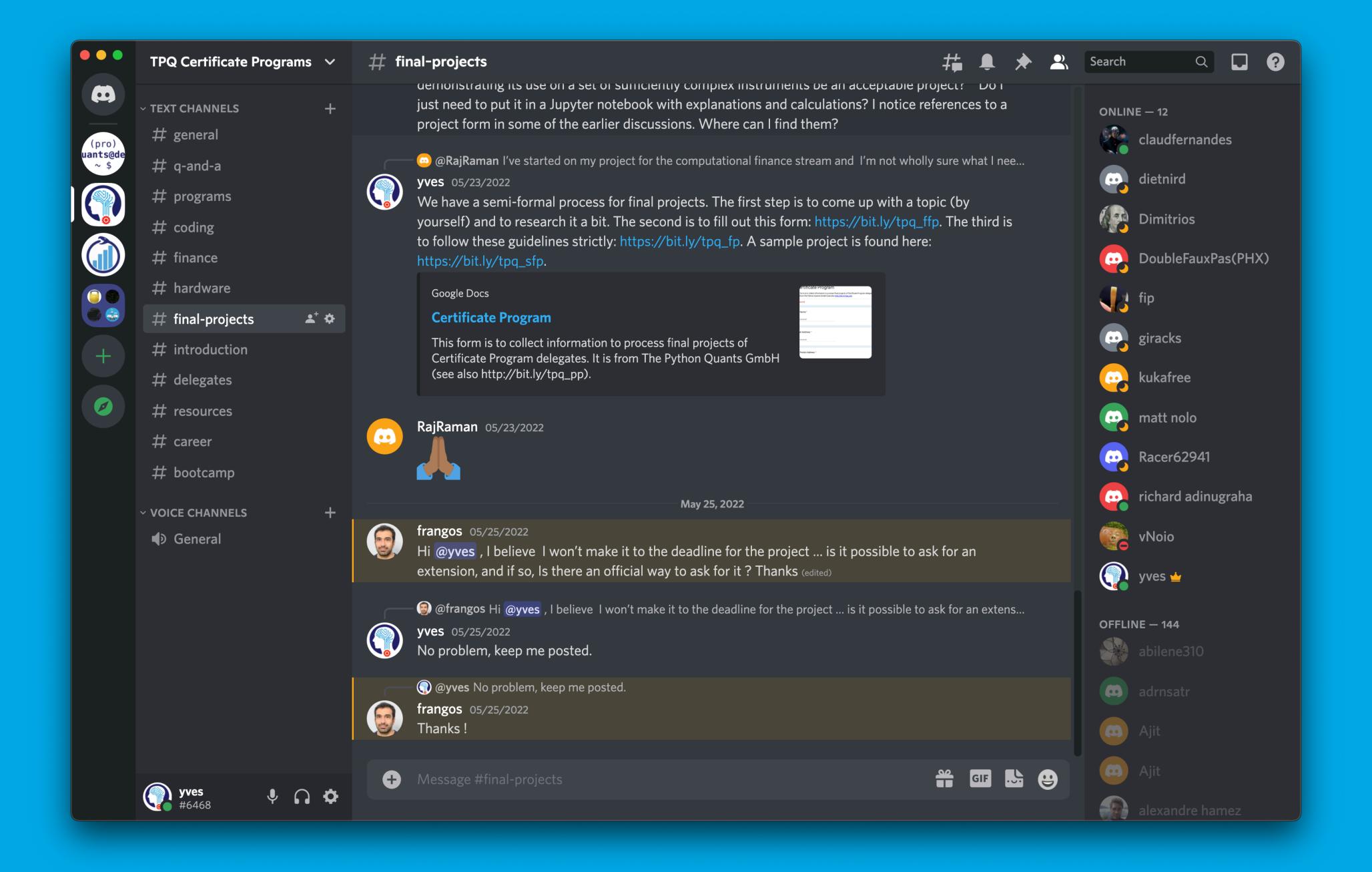
- a random number is drawn between 1 and 100
- the user is asked to provide a guess for the number
- it is checked whether the number is too low, too high or exactly right
- the user is provided with feedback about the result
- the game ends when the user has come up with the correct number
- the user is informed about the number of guesses needed

the user is informed about the number of guesses needed

User Forum



Discord Server



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