

# Courses in this Machine Learning series

1. Introduction to Trading with Machine Learning on Google Cloud (**this course**)
2. Using Machine Learning in Trading and Finance
3. Reinforcement Learning for Trading Strategies

# Recommended target audience

- Data analysts, data scientists, and machine learning engineers that want to learn how to apply their knowledge to financial use cases, specifically trading, using Google Cloud
- Financial advisors and traders who are interested in applying Machine Learning for trading strategies and decision making. These individuals will need to have previous knowledge of the foundational concepts of ML.

# Module Overview: Intro to Trading with Machine Learning on Google Cloud

- Machine Learning in Finance and your first model using Google Cloud
- Trading Fundamentals: Quant Theory, Arbitrage, and Back-testing
- Supervised Learning with BigQuery ML and ARIMA models
- Introduction to Neural Networks and Deep Learning

# Specific Qwiklabs you will complete in this intro course

- **Building a Regression Model in AI Platform Notebooks with Python**
  - Load data from BigQuery into a Pandas DataFrame
  - Build a linear regression model in Scikit-Learn
- **Building a Regression Model in BigQuery ML for AAPL Stock Data**
  - Use SQL and BigQuery ML to build and evaluate AAPL stock model
- **Building an ARIMA Model for a Financial Dataset**
  - Pull data from Google Cloud Storage into a Pandas dataframe
  - Learn how to prepare raw stock closing data for an ARIMA model
  - Apply the Dickey-Fuller test
  - Build an ARIMA model using the statsmodels library

# Lab environment will be actual Google Cloud accounts

Each lab provides you a real Google Cloud project for a limited time

You will have two browser windows:

- One with a lab walkthrough,
- Another is Google Cloud at [console.cloud.google.com](https://console.cloud.google.com)

← Building an ARIMA Model for a Financial Dataset

End Lab 01:29:51

[Open Google Console](#)

**Caution:** When you are in the console, do not deviate from the lab instructions. Doing so may cause your account to be blocked. [Learn more.](#)

**Username**  
student-04-4fb5705bbfb5@qwiklabs.net

**Password**  
9t4N3NbC

**GCP Project ID**  
qwiklabs-gcp-04-21cf2a46433d

1 hour 30 minutes 1 Credit ★★★★★ [Rate Lab](#)

## Building an ARIMA Model for a Financial Dataset

### Overview

In this lab, you will build an ARIMA model for AAPL stock closing prices using the statsmodels library in

Overview

Set up your environment

Launch AI Platform Not

Clone Course Repo within your AI

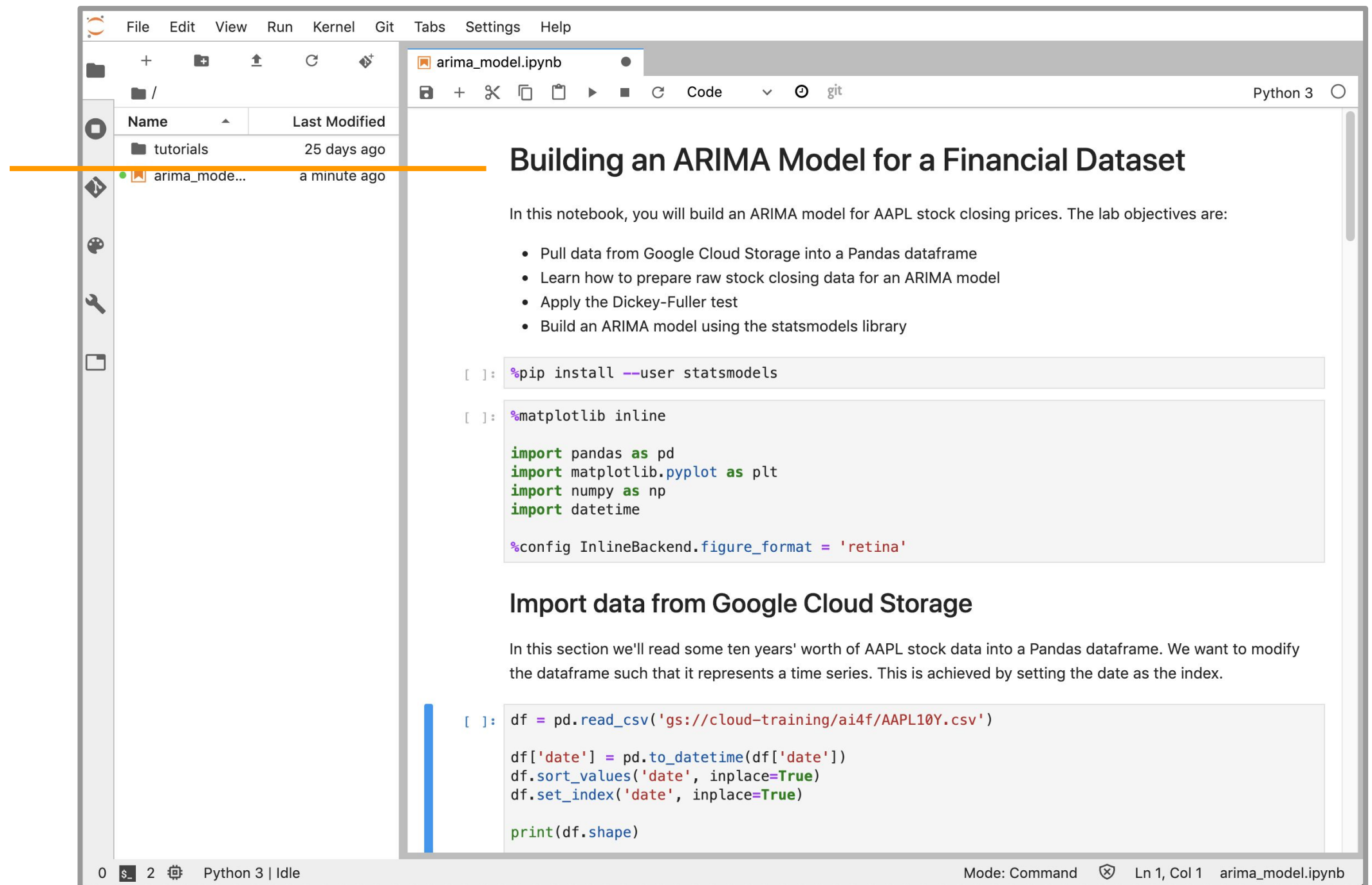
Chat

# We will use Python3 in Jupyter Notebooks on AI Platform

Each lab corresponds to a public .ipynb file that you will work through

All lab instructions and code are publicly available:

<https://github.com/GoogleCloudPlatform/training-data-analyst/tree/master/courses/ai-for-finance>



The screenshot displays a Jupyter Notebook environment. On the left, a file explorer shows a directory structure with 'tutorials' and 'arima\_model.ipynb'. The main area shows the notebook content, which includes a title, objectives, and code cells. The code cells contain the following Python code:

```
[ ]: %pip install --user statsmodels

[ ]: %matplotlib inline

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import datetime

%config InlineBackend.figure_format = 'retina'

Import data from Google Cloud Storage

In this section we'll read some ten years' worth of AAPL stock data into a Pandas dataframe. We want to modify the dataframe such that it represents a time series. This is achieved by setting the date as the index.

[ ]: df = pd.read_csv('gs://cloud-training/ai4f/AAPL10Y.csv')

df['date'] = pd.to_datetime(df['date'])
df.sort_values('date', inplace=True)
df.set_index('date', inplace=True)

print(df.shape)
```

# What is *not* covered in this intro course

- **Building and implementing the next highly-profitable DJIA futures high-frequency trading algorithm**
- **Modeling with TensorFlow 2.X → That is course #2 in this series**
- **Advanced ML and data science topics → courses #2 and #3**
  - Hyperparameter tuning
  - LSTM time-series models
  - Reinforcement learning models
- **Prerequisites**
  - Python basics → See References links
  - Machine learning 101 (what are features etc.) → See References links





# A Brief History of Machine Learning in Quantitative Trading and Finance



# Learning Objectives

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- Distinguish between the three types of data-driven analysis
- Identify the major use cases for ML in trading, investment and finance
- Identify applications with the highest growth potential for ML and AI

# Agenda

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Evolution of quantitative modeling techniques

Machine learning history and use cases

Where is the use of ML likely to grow the most?

# Early approaches use static data models and statistics

1. Financial markets are simple, relatively static, data generating processes
2. Use historical data and a statistical algorithm to identify features and loadings that approximate this process
3. Integrate the model into an order-execution strategy
4. Monitor PnL and shut down if loss exceeds tolerance
5. Start creating a new market model

# Modern approaches use Machine Learning to model fluid market behaviors and complexity

1. Financial markets are a dynamic, evolving collection of behaviors
2. Use historical data to train a model and adjusts features and loadings to improve predictive power
3. Integrate the model into an order-execution strategy
4. Retrain and retest continually with new data to capture the market's current state

# Reinforcement Learning attempts to mimic human intelligence

1. Financial markets are a dynamic, evolving collection of behaviors
2. Use historical data to create a set of policies for an agent that distinguishes good from bad decisions in all market states
3. Allow the agent to automatically adjust strategy based on previous experience and the market's current state
4. Monitor PnL and shut down if exceeds loss tolerance



Google Cloud



# Agenda

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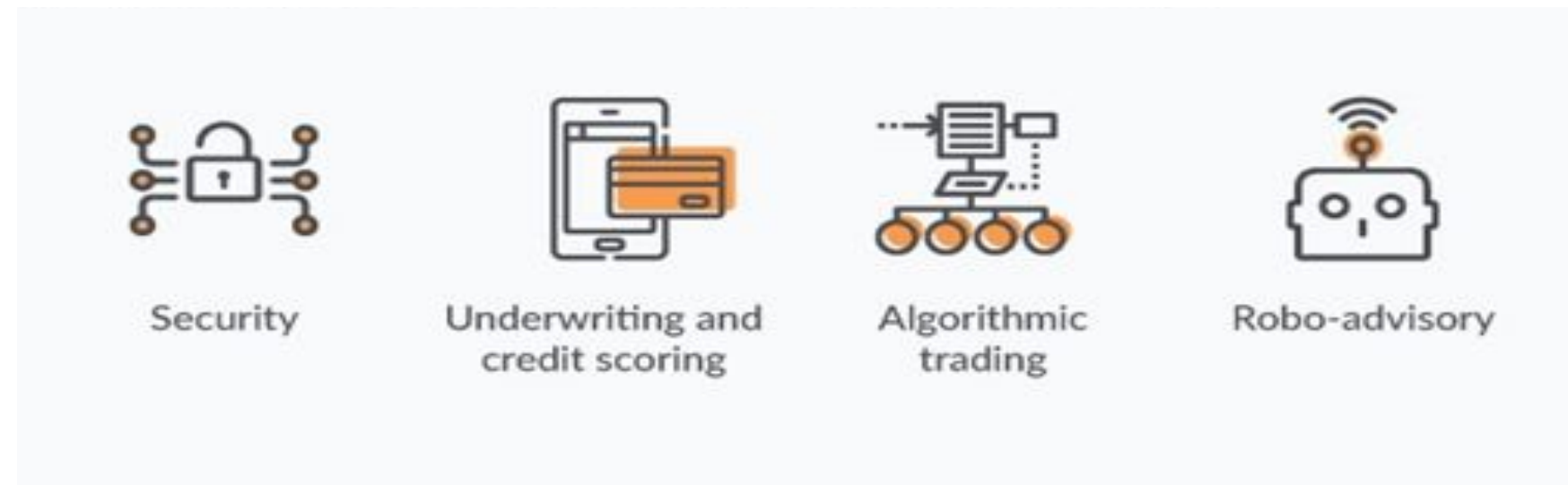
Evolution of quantitative modeling techniques

Machine learning history and use cases

Where is the use of ML likely to grow the most?

# Machine Learning Use Cases

- Algorithmic trading
- Portfolio management
- Loan underwriting
- Fraud detection





# AI and ML in Algorithmic Trading

- Pattern Formation
- Predictive Trading
- Increased Trading Speed (HFT)

# Use of AI and ML in Algorithmic Trading Timeline

- 1982 James Simons starts quant investment firm Renaissance Technologies
- 1987 Black Monday 22% one-day crash in S&P 500 caused by automated “program trading”
- 1988 David Shaw founds D.E. Shaw and is an early adopter of AI among its hedge funds
- 2010 Flash Crash occurs on May 6. In 36 minutes, the S&P crashed 8%, before a rebound
- 2012 Knight Capital loses \$440 million in 45 minutes after deploying unverified trading software
- 2017 Two Sigma hedge fund which uses ML, crosses the \$50 billion in assets under management
- 2018 Renaissance Technologies, citing reduced profitability, reduces the use of pattern-based strategies for futures trading in its Renaissance Institutional Diversified Alpha (RIDA) fund by more than 60%

# Portfolio Management

- Robo advisors
- User created profiles
- Tailored portfolio allocations for the mass market
- Lower fees

# Loan Underwriting

- Individual borrower credit data
- Demographic clusters and trends
- Constant recalibration of credit allocations and interest rates
- Require large historical and current data sets

# Fraud Detection

- Growing number of transactions and users
- Require detailed user transaction history
- Real time fraud prevention
- Loss minimization

# Agenda

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Evolution of quantitative modeling techniques

Machine learning history and use cases

Where is the use of ML likely to grow the most?

# High Potential ML Use Cases

- Financial products recommendation (Robo-advising)
- Sentiment analysis
- Security



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# ML Potential Downsides

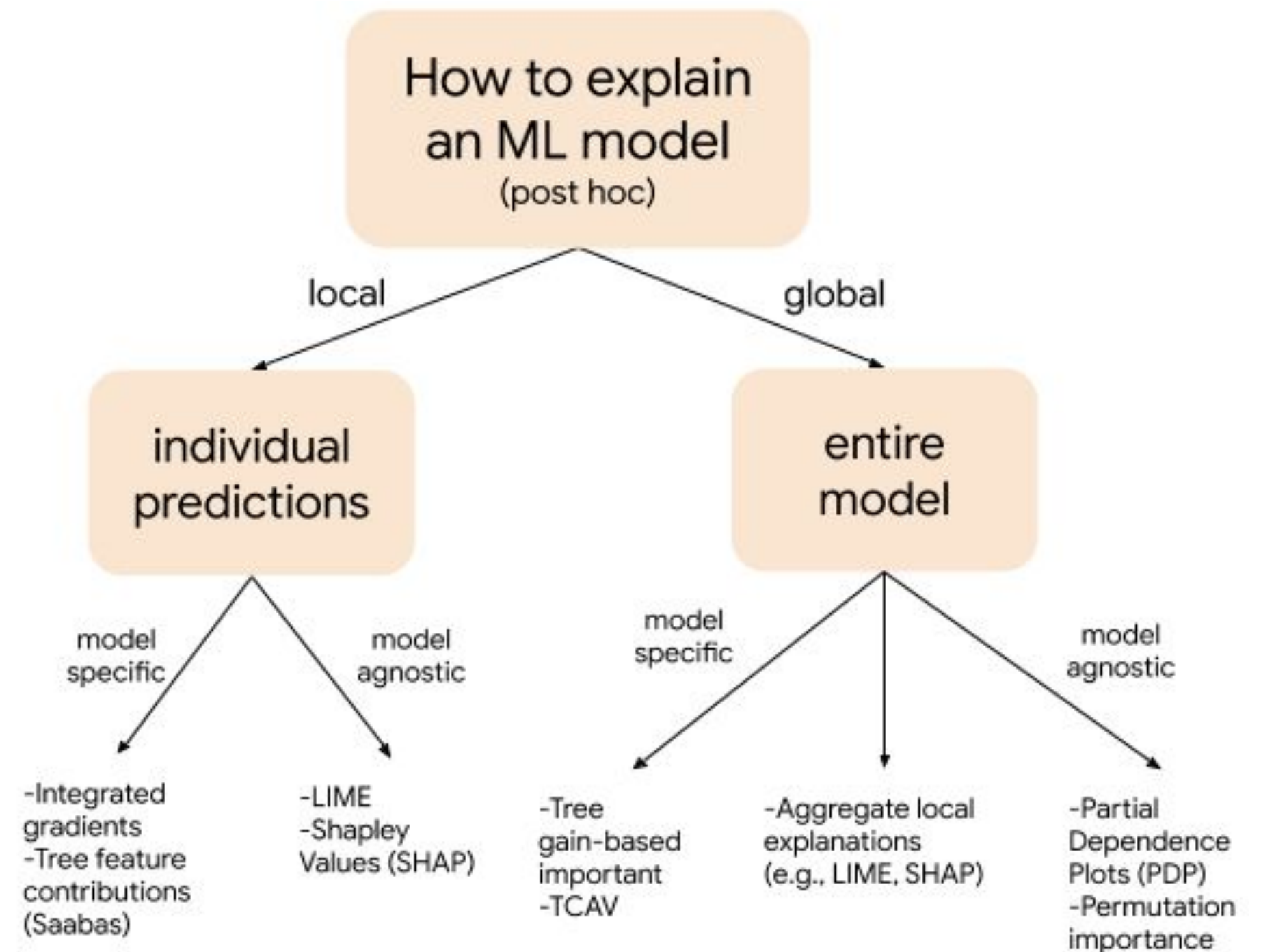
- ML models are difficult to interpret
- Relationship between predictions and factors is unclear
- Lending decisions can't be tied to specific borrower credit data
- Possible discrimination based on prohibited criteria

# Improving ML Model Interpretability

- Unlocking the black box
- Relating individual predictions to entire model
- Explainable AI

[How to deploy interpretable models on Google Cloud Platform](#)

[Explainable AI code](#)



# Recap

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- Choosing what to model depends on what your goal is and what data you have available
- Exogenous = fundamental data on performance and competitiveness
- Endogenous = historical share price price and trading volume
- Trading Fundamentals: Quant Theory, Arbitrage, and Back-testing
- Supervised Learning with BigQuery ML and ARIMA models

# Preview of Future Topics

- Building models with TensorFlow 2.X
- LSTM models for time-series prediction