Final Project Proposal

Course: Business 35137
Group 8: Helen Du, Frank Wang, Trent Potter
Project Title: Modeling of Implied Volatility Surfaces Using IPCA and Neural Networks

Research Question

We'd like to investigate the structure and dynamics of the implied volatility (IV) surface across major equity and ETF options. Specifically, we aim to:

- **Explain the cross-sectional variation** in IV surfaces using observable characteristics (e.g., underlying returns, macro indicators, lagged IV PCs).
- **Predict the time-series evolution** of IV surfaces using both linear and non-linear models.

We ask:

- To what extent can equity-level and macro factors explain the daily variation in IV surface shapes?
- How well can these features predict next-day IV surfaces using a low-rank representation (simple principal components)?
- How do nonlinear NN models compare to a linear IPCA benchmark?

Data

We will use pre-computed daily implied volatilities via OptionMetrics for the following assets:

- Large-cap equities:
  - AAPL, NVDA, GOOG
- Index ETFs:
  - SPY (S&P 500), QQQ (Nasdaq 100), IWM (Russell 2000)
- Alternative/commodity ETFs:
  - TLT (long-term Treasuries), GLD (gold), IBIT (Bitcoin ETF)

Covariates

- 1-day, 5-day, 25-day log returns of the underlying and total-market-index
- 1-day, 5-day, 25-day changes in implied volatility principal components
- VIX index level and changes (proxy for 30-day SPX volatility)
- Fed-Funds and 10y yields and changes
- Additional ideas: realized underlying moments, trading volume, accounting-measures, corporate event indicators

Methods

Dimensionality Reduction

Use PCA on the standardized IV surface to extract the top K components (5-10) to explain 99%+ of variance in the full surface.

Linear Model: IPCA

Implement Instrumented PCA (Kelly et al., 2019) to identify latent factors that explain variation in IV PCs using observable lagged characteristics (Docs). Hold IPCA factors fixed for 1-period prediction.

Nonlinear Model: Neural Network

A simple feedforward NN will be trained to predict the IV PCs. Sample design w/ ChatGPT's help:

- **Architecture**: 1–2 hidden layers with ReLU activations and 32–64 units per layer
- **Regularization**: dropout (p=0.2–0.5), batch normalization, and L2 weight decay
- **Training regime**:
    - Early stopping based on validation RMSE
    - Adam optimizer with learning rate decay
    - Training with a rolling window to test robustness

Alternative architectures to consider if time permits:

- Shallow residual MLP (skip connections for better gradient flow)
- Factor-wise networks (one head per IV PC)
  Multi-task learning (joint modeling across assets)

Results

- **R^2 / RMSE / MAE** for IV PCs and reconstructed surfaces, both cross-sectional and predictive
- **Vega-weighted R^2 / RMSE / MAE**: calibrate to economically meaningful parts of the surface (down-weighting wings)
- **Model comparison**: between IPCA and neural models in both explanatory and predictive tasks
- **Sharpe:** Time-permitting, simple delta-hedged portfolio allocations in proportion to predicted vega-weighted volatility changes. (Questions & concerns here about MVE portfolio construction)