Predicting VIX Futures Direction Using Machine Learning

Financial Volatility Forecasting, Feature Engineering, and Model
Automation

Project Overview

• **Objective:** Forecast next-day VIX Futures direction using financial, technical, and sentiment-based indicators.

Scope:

- Machine learning modelling for financial volatility forecasting
- End-to-end automation of feature engineering, modelling, and evaluation
- Integration of economic and news sentiment factors with technical indicators
- Impact: Enhanced data-driven insights and predictive accuracy for volatility analysis in financial markets.

Key Contributions and Leadership

- Helped establish foundational data workflows, version control systems, reproducible analytic pipelines, reusable functions, technical documentations, and analytics best practices.
- Designed and developed the full machine learning infrastructure from scratch, including:
 - Automated Python pipelines for data ingestion, transformation, and modelling
 - Rolling window generation, evaluation, and reporting workflows
 - Internal Python packages for reusable feature engineering and model comparison
- Conducted research and experimentation on new methodologies and model types, ensuring continuous improvement.

Data and Feature Engineering

Data Sources:

- Historical financial and macroeconomic time-series
- News sentiment data and technical indicators (e.g. RSI, moving averages)

Feature Engineering:

- Engineered high-signal features combining technical, macro, and sentiment-based variables
- Enhanced predictive performance and robustness through careful feature selection and transformation
- Goal: Improve signal-to-noise ratio in volatility prediction.

Modelling Techniques

Models developed and tested:

- Time-series forecasting: ARIMA, GARCH, LSTM
- Classification and regression: XGBoost, Polynomial Logistic Regression, LightGBM

Approach:

- Combined statistical and machine learning approaches for short- and long-term prediction
- Integrated external economic and sentiment indicators into model frameworks
- Used iterative testing and validation to ensure generalisability and consistency

Automation and Infrastructure

- Built fully automated Python pipelines covering:
 - Data ingestion, cleaning, and transformation
 - Feature generation and versioning
 - Rolling model training and evaluation
 - Report generation and insights delivery
- Created a system for model versioning, accuracy tracking, and comparison using a metrics database.
- Later incorporated MLflow for model tracking and reproducibility.
- Ensured automation boosted development speed and improved reliability.

Evaluation and Validation

- Metrics: Accuracy, Precision, Recall, F1-Score, Balanced Accuracy, MCC. and ROC-AUC
- Validation:
 - Rolling time-window testing
 - Out-of-sample forecasting to simulate live performance
- Built an automated evaluation framework to compare model stability and feature importance across iterations.
- Developed reporting scripts to summarise findings and visualise performance trends.

Documentation and Knowledge Sharing

- Authored comprehensive internal technical documentation covering:
 - Financial time-series modelling and statistical assumptions
 - Model interpretability and feature importance
 - Evaluation metrics and model comparison
 - Best practices in reproducible ML pipelines
- Created detailed methodology and results reports, with interpretations, recommendations, and model limitations.
- Contributed to process transparency and knowledge sharing within a small, fast-moving team.

Results and Impact

- Improved predictive accuracy and interpretability across multiple models.
- Achieved consistent performance across testing periods with robust feature selection.
- Delivered actionable insights for volatility trend analysis and risk forecasting.
- Strengthened internal technical infrastructure and documentation culture.
- Supported early-stage growth by establishing reusable codebases and technical foundations.

Reflection and Learning

- Gained deep understanding of volatility dynamics and time-series forecasting challenges.
- Strengthened ability to balance innovation, interpretability, and reliability in model design.
- Enhanced automation, data engineering, and model management skills through end-to-end delivery.
- Developed a strong analytical mindset, problem-solving ability, and independent ownership in a fast-paced environment.

Thank you.