# Slide 1: Title Slide

## Title: Stock Price Prediction in the Presence of High Volatility, Missing Data, and Extreme Events

## Subtitle: Evaluating the Performance of Different Prediction Models and Data Preparation Techniques Your Name Date

# Slide 2: Challenges in Stock Price Prediction with High Volatility, Missing Data, and Outliers

## Brief Overview:

### • Addressing challenges in stock price prediction

### • Exploring the impact of high volatility, missing data, and outliers on time series prediction models

### • Importance of robustness and risk mitigation

### Challenges in stock price prediction:

#### • Impact of external factors (news, economic events, market sentiment)

#### • Noise in high-frequency data

#### • Heteroskedasticity in return distributions

### Significance of addressing challenges:

#### • Greater prediction accuracy for trading systems

#### • Robustness to fluctuations in price

#### • Improved risk mitigation

## Research questions:

### How does high volatility impact time series prediction models?

### What are effective methods for handling missing data and outliers?

### How do pre-processing techniques influence prediction performance?

### How does data imputation impact prediction accuracy?

### Can outlier detection techniques improve model robustness?

### How can relationships between price series be leveraged for better predictions?

# Research objective: investigate suitable approach for prediction when there is high volatility missing data and outliers due to extreme events

## Research questions:

## How does high volatility impact the accuracy of traditional time series prediction models, and which models are most robust to high volatility, missing data, and outliers?

## What are the most effective methods for handling missing data (e.g., linear interpolation, rolling mean) and outliers in stock price prediction with high volatility and extreme events?

## How do different pre-processing techniques, such as data imputation or outlier removal, affect the performance of prediction models in volatile stock price data?

## What are the main challenges in predicting stock prices for the given dataset, and can existing prediction methods address these challenges, or is there a need for new methods?

## How can outlier detection techniques be integrated into the stock price prediction process to enhance model robustness and improve overall predictive performance?

## How can relationships between price series be leveraged for improved predictions, including cross-series prediction and exploiting common trends and patterns?

# Slide 3: Data Description

## Dataset overview:

### • Source: Unknown (two unnamed price series)

### • Potential type: Futures data (trading begins early Sunday evening)

### • Time period: 5 years (2008-2013)

### • Frequency: 2-minute intervals

## Data characteristics:

### • 24-hour price data (excluding Saturdays)

### • Missing values and non-uniform distribution of time gaps

### • Shorter time gaps more common; longer time gaps less frequent

### • Presence of outliers (e.g., holidays, market closed days)

### • Significant number of missing values (not all likely to be holidays)

### • Wide range of time gaps (Time Series 1: avg. 17.67 min, max. 5,718 min; Time Series 2: avg. 168.24 min, max. 2,838 min)

## Data irregularities:

### • Skewness in time gap distribution

### • Long tails indicating significant deviations from expected 2-minute intervals

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# Slide 4: Exploratory Data Analysis

## Characteristics of the data:

### • Stationary price returns series

#### • ADF test: p-value = 0, stationary time series

#### • KPSS test: p-value = 0.1, stationary around deterministic trend

### • Nonlinear upwards trend

### • No seasonal components in hourly, daily, or weekly frequencies

### • Periodic components in daily and weekly frequencies

### • Non-normal distributions with heteroskedasticity and volatility clustering

## Seasonal decomposition:

### Time Series 1 (ts1):

#### • Strong correlation between price and trend

#### • Possible seasonality in monthly time frame

#### • Residuals strongly correlated (underlying structure not captured)

### Time Series 2 (ts2):

#### • More likely to be seasonal at higher timescales

#### • Strong upward trend across all timescales

#### • Residuals strongly correlated (underlying structure not captured)

## Periodogram analysis:

### • Both time series show seasonality or periods in intra-day timescale and daily (2 hours, 16 hours, 48 hours)

### • Significant lags in hourly and daily frequencies indicate serial correlation

Daily/Weekly

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# Slide 3: Data Description

## Key observations:

### • Extreme market events visually identified

### • Outliers: Focused on extreme market events (e.g., 2008)

### • Noise assumed to be inherent in data (not due to measurement error)

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## Logarithmic returns:

### not normally distributed (Kolmogorov-Smirnov test p-value = 0.0)

### Skewness and kurtosis: evidence of non-normality

#### • ts1: skewness ≈ 0, kurtosis = 138.45

#### • ts2: skewness = 0.99, kurtosis significantly different from 3

### Mean values close to zero, variances small but different between ts1 and ts2

### Covariance between ts1 and ts2: negative, but small magnitude

### Non-normal behaviour: heavy tails, high likelihood of extreme values

### Rolling mean and standard deviation (window size: 4 hours)

### Squared and absolute returns: periods of high volatility

### Heteroskedasticity present in time series

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# Slide: Modelling Outline

## Research goal: Develop suitable predictions for price returns, accounting for volatility, extreme events, and missing values

## Hypotheses:

### • H1: ts1 can predict ts1

### • H2: ts2 can predict ts2

### • H3: ts1 can predict ts2

### • H4: ts2 can predict ts1

## Motivation: Investigate relationships between time series and predictability; impact of imputation and feature engineering on uncertainty

## Experiments (4 data preparation methods):

### Original data, missing values removed, outliers not identified

### Original data, missing values removed, outliers identified

### Imputed data, outliers not identified

### Imputed data, outliers identified

## Model Performance Comparison:

### • Evaluate models on different dataset versions (original, imputed, with and without outlier identification)

### • Examine the impact of data imputation and outlier detection techniques on prediction accuracy and model robustness

Considerations:

• Choice of imputation technique: preservation of data structure, noise levels, model performance

• Accounting for extreme market conditions and black swan events

• Testing volatility-based models and deep learning models (e.g., LSTM) for robustness to outliers

* Imputation technique considerations: preservation of data structure and noise, impact on model performance
* Importance of accounting for extreme market conditions and black swan events

# Slide: Methodology - Data Preparation and Pre-processing

## Pre-processing steps:

## Imputation techniques considered:

### • Mean imputation

### • Linear interpolation

### • Median interpolation

## Imputation strategy:

### • Different methods for short gaps (< 4 hours) and long gaps

### • Preserve time series structure and stability

### • Rolling window of 4 hours for moving mean imputation

## Data used:

### • Original data including Saturdays

## Linear interpolation:

### • Least sensitive to underlying volatility

### • No artificial volatility introduced (unlike mean and median)

## Outlier detection:

### • Based on squared price returns series

### • Methods compared: Peak over Threshold and DBSCAN clustering

### • DBSCAN chosen: identifies outliers by cluster size relative to neighbours (epsilon=0.15,min cluster size = 2)

## Outlier observations:

### • Higher number of outliers in first series

### • Smaller number of common outliers, suggesting stock-specific factors have significant impact

# Outlier detection:

## extreme market events (e.g., 2008) and sensitivity analysis for model stability and prediction improvement

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## In general, the results suggest that the time series are stationary and do not exhibit any trend or structural change over time.

### Non-normality: consider alternative methods to filter extreme value outliers

# Slide: Data Resampling

## Rationale for resampling:

### • Capture potential daily and weekly periodicities

### • Reduce uncertainty in true value due to missing values clustering in shorter time frames

### • Improve computational efficiency

## Resampling methods:

### • Resampled to hourly and daily frequencies

### • Used mean of the original data for resampling

# Slide 5: Random Walk Simulation as a Benchmark

## Random walk :

### • Simple assumption of price series behaving like a random walk

### • Used for both univariate (H1H2) and multivariate (H3H4) cases

## Simulating unpredictability of stock prices:

### • Applied using the mean and standard deviation of the returns price series

### • Captures short-term unpredictability in stock prices

## Importance of comparison:

### • Helps determine if chosen models or modelling approach is appropriate for prediction

### • Indicates if series is inherently random or has underlying structure/pattern for forecasting purposes

### • Compare model performance against random walk RMSE

# Slide 7: Prediction Models

## Chosen prediction models:

### • KNN clustering

### • Random Forest

### • Decision Tree

### • Gradient Boosting Tree

### • Light Gradient Boosting Tree

### • Gaussian Process

## Key characteristics and rationale:

### • Non-linearity and fat-tailed distribution of price returns

### • Traditional models unable to account for heteroskedasticity (changing volatility over time)

### • Classical machine learning regression methods as a first approach

## Applying models to test hypotheses:

### • Models will be applied on four versions of the dataset

### • Evaluating performance and suitability for predicting price returns

# Slide 8: Evaluation Metrics and Validation

## Evaluation metrics:

### • RMSE: Root Mean Squared Error

### • Significance: Assess prediction accuracy and model performance

## Train and test sets:

### • Split at 31-12-2012 (4 years of training data, 1 year of test data)

## Cross-validation:

### • Walk forward cross-validation with grid search

### • Optimal number of splits: 30

### • Test forecast horizon: 7 days for daily resampled series, 24 hours for hourly resampled series

### • Prevents overfitting while including sufficient data for training

### • K-fold cross-validation for model tuning and hyperparameter optimization

### • Retrain the model on the complete training set after k-fold cross-validation

# Slide 11: Limitations and Future Research Avenues

## Limitations of the study:

### • Data limitations

### • Model assumptions

### • Parameter tuning

* Focus on risk management in forecasting

# Future Research Avenues:

## Missing values:

### • Kalman filter

### • Time-weighted imputation

### • Cluster methods

### • Distribution-based imputation

## Outlier detection:

### • Local order factor

### • Autoencoder

## Explore other prediction models:

### • Regime-switching models (Markov-switching, hidden Markov models)

### • Wavelet-based methods

### • Bayesian methods (Bayesian hierarchical models, Bayesian state-space models, Gaussian process regression)

### Adapt existing prediction methods or develop new ones for high-frequency data, extreme events, and non-normal return distributions

## Investigate the role of data granularity:

### • Impact on prediction method performance

### • Limitations of one-step forecasting for high-frequency or low-frequency data

Results