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Methodology

This chapter presents the methodology used to achieve the project's objectives. It starts by describing the data collection process and analyzing the data collected, followed by an overview of the pre-processing techniques. The chapter then discusses the model building approach and the hyperparameter optimization strategy.

3.1 Data Collection

Data for this study were obtained from the Yahoo Finance platform using Python' s `yfinance` package. The data collection process was designed to support three main aspects of the research: (i) the primary dataset, (ii) supplementary features for multivariate modeling, and (iii) datasets for benchmarking against previous studies.

QUESTION: 我该不该引用yfinance的官方文档？

3.1.1 Primary Dataset

The primary dataset consists of the USDEUR exchange rate with a daily frequency, spanning from December 1, 2003 to January 31, 2025.

QUESTION: 我是否应该提及具体的数据收集的实施脚本

3.1.2 Supplementary Features for Multivariate Models

To build a robust multivariate model, additional financial indicators were collected. The supplementary data include:

- Crude Oil (WTI Futures)
- Gold Futures
- FTSE 100 Index
- US Dollar Index (DXY)

These datasets cover the period from January 1, 2000 until the present day. When used, they are aligned based on the corresponding currency pair's time base.

3.1.3 Benchmarking Datasets

For comparative analysis with prior research, additional datasets were collected to ensure that the time series forecasting results are directly comparable. Two sets of benchmarking data were collected:

1. A multi-currency dataset covering the period from December 18, 2017 to January 27, 2023. This dataset includes exchange rates for EUR/USD, GBP/USD, AUD/USD, and NZD/USD. For USD/JPY data, the script inverts the closing prices to derive the JPY/USD rate[1].

2. A focused subset for the EUR/USD pair spanning from January 1, 2013 to January 1, 2018[2].

写的很难受, 该不该写Data Analysis? 总觉得不对劲

3.2 Data Analysis

Data analysis is a critical step in understanding the underlying quality, patterns, and characteristics of the dataset.

3.2.1 Data Quality Check

Ensuring high data quality is a critical first step before any analysis. In this stage, the following checks are performed:

- **Missing Values:** Confirm that there are no missing entries, or if there are, decide on an appropriate imputation method.
- **Outliers:** Identify any extreme values using statistical methods (this project used IQR), or if there are any, determine if they need to be removed or capped.
- **Duplicates:** Check for duplicate records to prevent bias in analysis.
- **Consistency and Integrity:** Ensure data types, ranges, and formats are consistent across the dataset.

Results: All datasets collected via yfinance contain no missing values or duplicates, and no outliers were detected using the Interquartile Range (IQR) method. Data types are consistent, with the ‘Date‘ as an object and ‘Close‘ as float64.

3.2.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) involves summarizing the main characteristics of the dataset using visual and quantitative methods. This project includes the following EDA techniques:

- **Summary Statistics:** Compute mean, median, variance, and other descriptive measures to understand data distribution.

- **Line Chart for Long-Term Trends:** Plot the USDEUR exchange rate over time to reveal long-term trends and identify potential anomalies. (See Figure 3.1.)

- **Rolling Statistics for Volatility Analysis:** Compute the rolling mean and standard deviation of the USDEUR exchange rate using a 30-day window to assess volatility changes over time. (See Figure 3.2.)

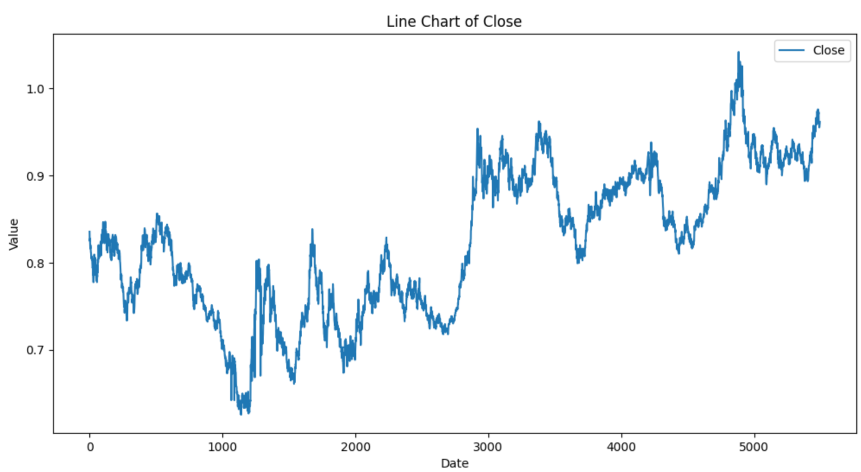

图 3.1: Line Chart of the USDEUR Exchange Rate (The Primary Dataset)

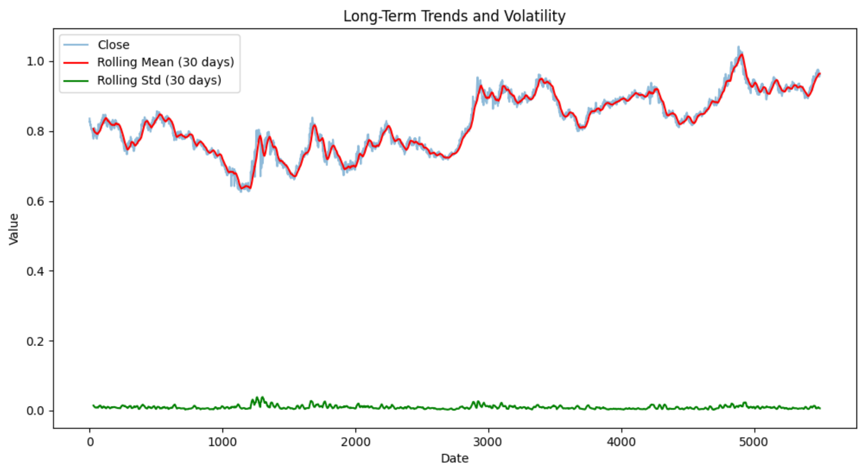

图 3.2: Rolling Mean and Standard Deviation of the USDEUR Exchange Rate (The Primary Dataset))

For the primary dataset, its summary statistics indicate that the mean exchange rate is approximately 0.823 with a standard deviation of 0.084, which reflects moderate variability. The line charts visually confirms this stability, which highlights long-term fluctuations without evident anomalies.

3.2.3 Stationarity Testing

Stationarity testing is an important process in time series analysis. A stationary time series has statistical properties that do not change over time.

3.2.3.1 Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test operates under the following principles:

- **Null Hypothesis (H_0):** The time series has a unit root (non-stationary).

- **Alternative Hypothesis (H_1):** The time series is stationary.

3.2.3.2 Kwiatkowski-Phillips-Schmidt-Shin Test

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test operates under these principles:

- **Null Hypothesis (H_0):** The time series is stationary around a deterministic trend (level stationary).

- **Alternative Hypothesis (H_1):** The time series is non-stationary.

Results: The ADF test failed to reject the null hypothesis of a unit root at the 1% significance level, while the KPSS test rejected the null hypothesis of stationarity at the 1% level. Together, these results provide strong evidence that the dataset is non-stationary, which suggests that further differencing is required to achieve stationarity.

QUESTION: multivariate的feature selection部分不放在这里有影响吗?

3.3 Data Pre-processing

3.3.1 Data Splitting using Sliding Windows

For time series forecasting, model's performance can differ significantly over different time periods. To ensure the robustness and predictive reliability of my models across different time intervals, this project designs a sliding window approach for data splitting. Rather than segmenting the dataset directly, the sliding window method ensures effective use of overlapping intervals, which is particularly useful for short time series data.

The dataset is divided into training, validation, and test sets within each sliding window. The training set fits predictive models, the validation set is for hyperparameter tuning, and the test set provides an unbiased evaluation of the model's performance.

Figure 3.3 illustrates the sliding window approach, which shows how overlapping data intervals effectively split the dataset and maximize data usage.

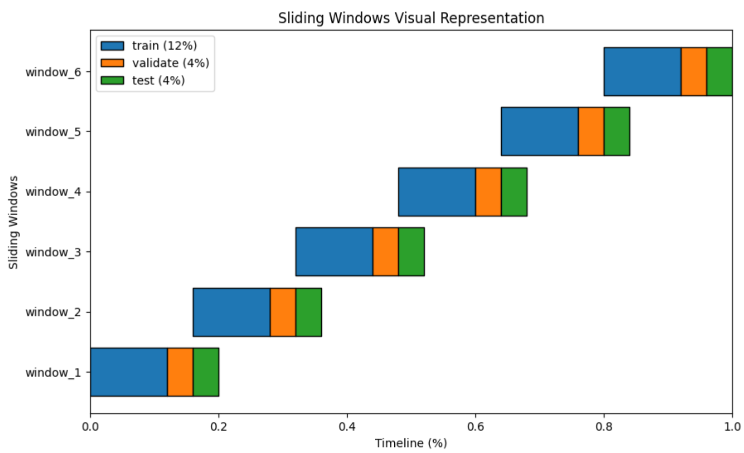

图 3.3: Sliding Window Data Splitting Strategy

3.3.2 Data Scaling and Normalization

Data scaling and normalization are important preprocessing techniques aimed at improving model performance, convergence speed, and stability.

3.3.2.1 Z-Scale Normalization:

Z-scale normalization is defined as:

$$z = \frac{x - \mu}{\sigma} \tag{3.1}$$

where x is a data point, μ is the mean, and σ is the standard deviation of the dataset.

3.3.2.2 Min-Max Scaling:

Min-max scaling rescales data to the range $[0, 1]$:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3.2}$$

Min-max scaling is particularly useful when data distribution is not normal.

3.3.3 Data Smoothing and Detrending

Time series data often exhibits trends that can negatively affect predictive modeling. Differencing is an effective technique to remove trends and improve the stationarity of time series data. Differencing involves computing the difference between consecutive observations:

$$x'_t = x_t - x_{t-1} \tag{3.3}$$

where x'_t is the differenced data at time t.

3.3.4 Sequence Transformation

Long Short-Term Memory (LSTM) models require data structured into sequences. This involves reshaping data into a three-dimensional array:

$$(\text{samples}, \text{timesteps}, \text{features}) \tag{3.4}$$

where samples represent the number of independent sequences in the dataset, timesteps represent the number of time intervals within each sample, and features represent the number of variables observed at each time step.

3.4 Model Building

3.4.1 LSTM Classifier

3.4.1.1 Structure

3.4.1.2 Data Smoothing and Detrending

3.4.1.3 Training

3.4.1.3.1 Optimizer

3.4.1.3.1.1 Adam

3.4.1.3.1.2 Nadam

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Chapter 4

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Chapter 5

Development

Chapter 6

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7.1 Achievements

7.2 Limitations

7.3 Future Work

参考文献

[1] Fernando García, Francisco Guijarro, Javier Oliver, and Rima Tamošiūnienė. Foreign exchange forecasting models: Arima and lstm comparison. *Engineering Proceedings*, 39(1):81, 2023.

[2] D.C. Yıldırım, I.H. Toroslu, and U. Fiore. Forecasting directional movement of forex data using lstm with technical and macroeconomic indicators. *Financial Innovation*, 7(1), 2021.