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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: Should I cite the yfinance package here?

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: Should I mention the implementation details of the data collection script?

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].

3.2 Data Analysis

Data analysis is a critical step in understanding the underlying quality, patterns, and characteristic 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.

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.)

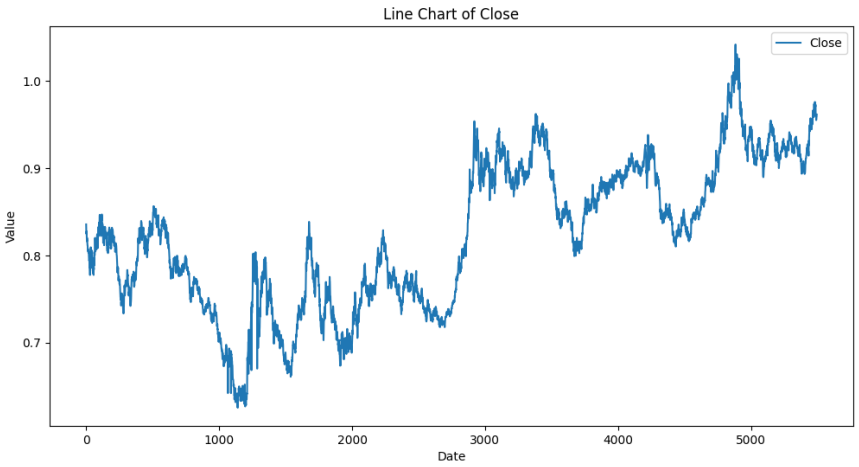

Figure 3.1: Line Chart of the USDEUR Exchange Rate (The Primary Dataset)

3.2.3 Stationarity Testing

Stationarity testing is an important process in time series analysis. A stationary time series has constant statistical properties (mean, variance, autocorrelation) over time. Testing for stationarity helps make decision, such as if differencing or detrending are necessary.

3.2.3.1 Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test is a widely-used statistical test to assess the presence of a unit root in a time series sample. It operates under the following principles:

- **Null Hypothesis (H_0):** The time series has a unit root, which means it is non-stationary.
- **Alternative Hypothesis (H_1):** The time series is stationary.
- **Mechanism:** The ADF test augments the standard Dickey-Fuller test by including lagged difference terms to account for higher order autoregressive processes. If the test statistic is significantly lower than

the critical values, we reject the null hypothesis and conclude that the series is stationary. Otherwise, we fail to reject the null hypothesis.

3.2.3.2 Kwiatkowski-Phillips-Schmidt-Shin Test

The Kwiatkowski-Phillips-Schmidt-Shin(KPSS) test complements the ADF test by taking the opposite approach:

- **Null Hypothesis (H_0):** The time series is stationary around a deterministic trend (or level stationary).
- **Alternative Hypothesis (H_1):** The time series is non-stationary.
- **Mechanism:** The KPSS test evaluates the null hypothesis by estimating the variance of a random walk component in the series. If the test statistic exceeds the critical value, we reject the null hypothesis and conclude that the series is non-stationary. Otherwise, we fail to reject the null hypothesis. This test is particularly useful because it provides a different perspective on stationarity compared to the ADF test.

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