

# **Project Report**

Statistics For Data Science

Semester — II

# **HDFC Bank Stock Prices**

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Git Hub Link: https://github.com/MahirMavani/sds-assignment

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#### Introduction

This project focuses on data analysis using Python, specifically on analyzing
historical stock data of HDFC Bank. It combines various data science techniques to
uncover insights from time series financial data using libraries like pandas,
matplotlib, and seaborn.

#### **Project Overview**

• The goal of the project is to load and analyze the stock market data of HDFC Bank, clean and preprocess the dataset, perform exploratory data analysis (EDA), and generate insightful visualizations. The data was sourced in CSV format and includes key information such as open, close, high, low prices, and trading volume over a period of time.

#### **Project Insights**

- A detailed understanding of the data types and structure of financial datasets.
- Visualization helped in identifying trends in stock prices and volumes over time.
- Correlation analysis revealed the relationships between different stock indicators like closing price, volume, and high-low range.

### **Project Challenges**

- Handling missing values and ensuring the dataset was clean for analysis.
- Choosing the right types of graphs and charts to visualize financial trends meaningfully.
- Managing large amounts of time-series data efficiently for smoother analysis.

#### **Project Goals**

- Develop proficiency in using Python for data analysis.
- Understand stock data behavior through visualization.
- Learn to summarize and interpret real-world financial datasets.
- Improve problem-solving skills using data science tools.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df=pd.read csv(r"D:\downloads\HDFCBANK.NS.csv")
df
            Date
                         0pen
                                      High
                                                     Low
                                                                Close \
                     3.030000
0
      1996-01-01
                                  3.030000
                                                2.925000
                                                             2.980000
1
      1996-01-02
                     2.980000
                                  3.025000
                                                2.950000
                                                             2.975000
2
                     2.975000
                                  2.995000
                                                2.950000
      1996-01-03
                                                             2.985000
```

```
3
      1996-01-04
                     2.985000
                                   2.980000
                                                2.940000
                                                              2.965000
4
      1996-01-05
                     2.965000
                                   2.980000
                                                2.950000
                                                              2.960000
. . .
6562 2022-01-17
                  1530.000000
                                1556.000000
                                             1519.150024
                                                          1521.500000
6563 2022-01-18
                  1533.000000
                                1550.900024
                                             1523.000000
                                                          1529.250000
6564 2022-01-19
                  1534.000000
                                                          1518.449951
                                1539.750000
                                             1513.349976
6565 2022-01-20
                  1528.449951
                                1528.500000
                                             1500.099976
                                                          1509.000000
6566 2022-01-21
                  1500.000000
                                1529.800049
                                             1485.599976
                                                          1521.599976
        Adj Close
                       Volume
         2.417746
0
                     350000.0
1
         2.413689
                     412000.0
2
         2.421803
                     284000.0
3
         2.405575
                     282000.0
4
         2.401519
                     189000.0
6562 1521.500000
                   11494686.0
6563 1529.250000
                    6170576.0
6564 1518.449951
                    7158813.0
6565
     1509.000000
                    7598923.0
6566 1521.599976
                    5768339.0
[6567 rows x 7 columns]
Check for missing values and data types
print('Missing values:')
print(df.isnull().sum())
print('\nData types:')
print(df.dtypes)
Missing values:
Date
              0
0pen
              0
High
              0
Low
              0
Close
              0
Adj Close
              0
Volume
Next_Close
dtype: int64
Data types:
Date
              datetime64[ns]
                     float64
0pen
High
                     float64
                     float64
Low
Close
                     float64
Adj Close
                     float64
Volume
                     float64
```

Next\_Close float64

dtype: object

# A brief descriptive statistics overview df.describe()

3 1996-01-04 2.985 2.980 2.940 2.965

4 1996-01-05 2.965 2.980 2.950 2.960

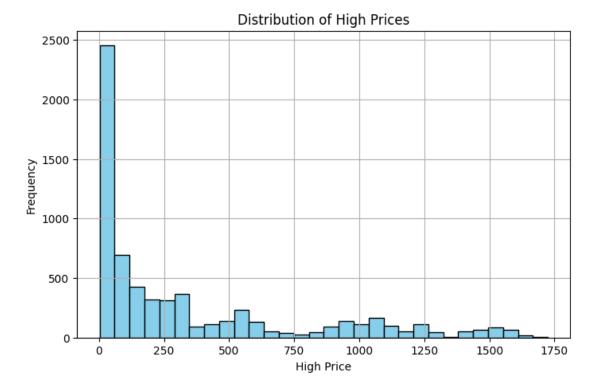
df.describe()								
				Da	te	0pen	High	Low
count mean min 25% 50% 75% max std	2008-1	199 200 200 201	:28:21. 6-01-01 2-04-10 8-09-22 5-06-04 2-01-20	0989012 00:00: 18:00: 12:00: 06:00:	48 33 00 2 00 2 00 13 00 51	2.000000 7.005717 2.435000 3.753749 3.282501 3.462509 5.000000 8.946730	6552.000000 340.404149 2.435000 24.090000 136.925003 518.424988 1725.000000 432.700515	6552.000000 333.226588 2.395000 23.303750 130.095001 509.062492 1671.000000 424.688284
Close Adj Close Volume Next_Close count 6552.000000 6552.000000 6.552000e+03 6552.000000 mean 336.894411 328.001586 4.941659e+06 337.122263 min 2.435000 1.975574 0.000000e+00 2.435000 25% 23.645000 20.435167 1.560665e+06 23.648750 50% 133.197502 121.573917 3.426695e+06 133.272499 75% 513.737488 495.121086 6.362624e+06 513.825012 max 1688.699951 1688.699951 2.011300e+08 1688.699951 std 428.701835 426.924740 5.714749e+06 428.930570  Convert 'Date' column to datetime df['Date'] = pd.to_datetime(df['Date']) df.head(5)								
0 1996- 1 1996- 2 1996- 3 1996- 4 1996- Sort by	-01-02 -01-03 -01-04 -01-05	Open 3.030 2.980 2.975 2.985 2.965	High 3.030 3.025 2.995 2.980 2.980	Low 2.925 2.950 2.950 2.940 2.950	Close 2.980 2.975 2.985 2.965 2.960	Adj Close 2.417746 2.413689 2.421803 2.405579 2.401519	350000.0 412000.0 3 284000.0 5 282000.0	
df.head	d(5) Date	0pen	High	Low	Close	Adj Close	e Volume	
0 1996- 1 1996- 2 1996-	-01-01 -01-02	3.030 2.980 2.975	3.030 3.025 2.995	2.925 2.950 2.950	2.980 2.975 2.985	2.417746 2.413689 2.421803	350000.0 412000.0	

2.405575 282000.0

2.401519 189000.0

#### Check basic info

```
print(df.info())
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6567 entries, 0 to 6566
Data columns (total 7 columns):
#
    Column Non-Null Count Dtype
---
    Date 6567 non-null
Open 6560 non-null
High 6560 non-null
                                datetime64[ns]
 0
                                float64
 1
                                float64
 2
 3
              6560 non-null
                                float64
    Low
    Close 6560 non-null float64
 4
 5
    Adj Close 6560 non-null
                                float64
    Volume
            6560 non-null float64
dtypes: datetime64[ns](1), float64(6)
memory usage: 359.3 KB
None
Visualizing the Data
Histogram of 'High' prices
import matplotlib.pyplot as plt
import pandas as pd
plt.figure(figsize=(8, 5))
plt.hist(df['High'], bins=30, color='skyblue', edgecolor='black')
plt.title("Distribution of High Prices")
plt.xlabel("High Price")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()
```

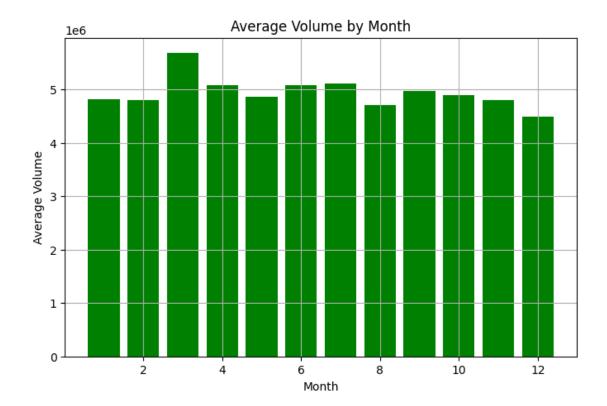


# Bar plot

```
# Convert Date to datetime
df['Date'] = pd.to_datetime(df['Date'])
df['Month'] = df['Date'].dt.month

# Average volume by month
monthly_avg = df.groupby('Month')['Volume'].mean()

# Bar plot
plt.figure(figsize=(8, 5))
plt.bar(monthly_avg.index, monthly_avg.values, color='green')
plt.title("Average Volume by Month")
plt.xlabel("Month")
plt.ylabel("Average Volume")
plt.grid(True)
plt.show()
```



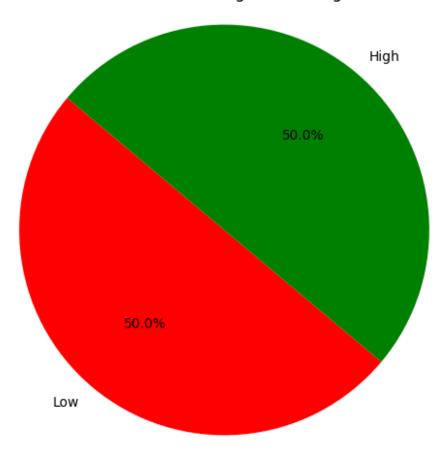
# Pie chart of categories

```
median_close = df['Close'].median()
df['Close_Category'] = df['Close'].apply(lambda x: 'High' if x > median_close
else 'Low')

counts = df['Close_Category'].value_counts()

plt.figure(figsize=(6, 6))
plt.pie(counts, labels=counts.index, autopct='%1.1f%%',
colors=['red','green'], startangle=140)
plt.title("Distribution of Closing Price Categories")
plt.axis('equal')
plt.show()
```

# Distribution of Closing Price Categories



#### **Creating a Box Plot**

FutureWarning:

```
# Convert date and extract month
df['Date'] = pd.to_datetime(df['Date'])
df['Month'] = df['Date'].dt.month

# Box plot: Close price distribution across months
plt.figure(figsize=(10, 6))
sns.boxplot(x='Month', y='Close', data=df, palette='Set3')
plt.title("Box Plot of Close Prices by Month")
plt.xlabel("Month")
plt.ylabel("Closing Price")
plt.grid(True)
plt.show()

C:\Users\Mahir\AppData\Local\Temp\ipykernel_32212\781908893.py:7:
```

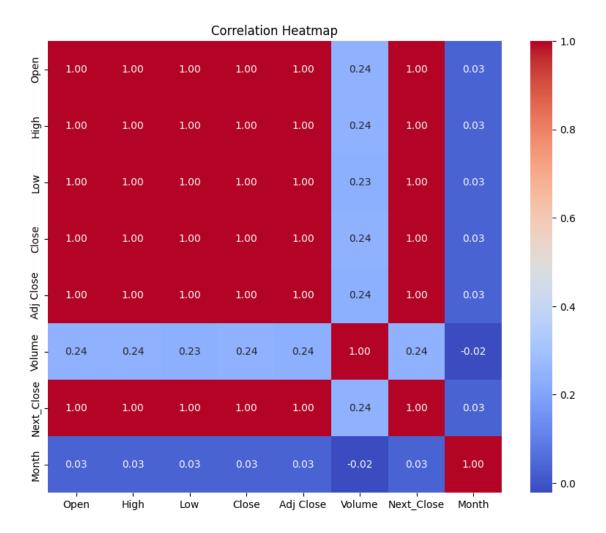
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

# sns.boxplot(x='Month', y='Close', data=df, palette='Set3')



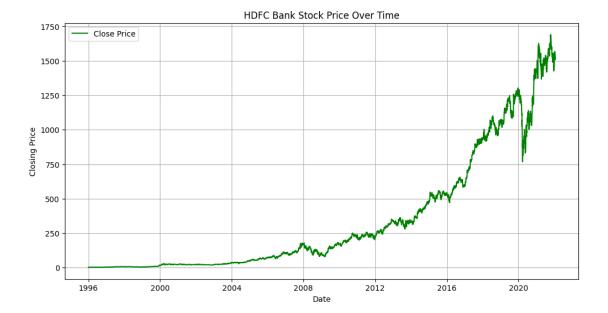
# **Creating a Correlation Heatmap**

```
if 'Date' in df.columns:
    df['Date'] = pd.to_datetime(df['Date'])
numeric_df = df.select_dtypes(include='number')
correlation_matrix = numeric_df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



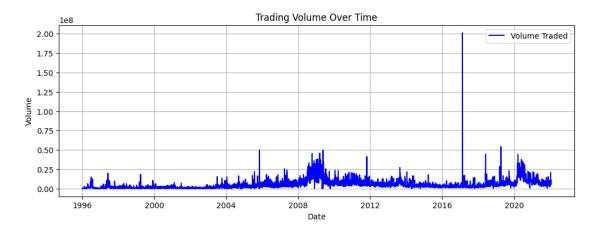
#### Plotting closing price over time

```
plt.figure(figsize=(12, 6))
plt.plot(df['Date'], df['Close'], label='Close Price', color='green')
plt.title("HDFC Bank Stock Price Over Time")
plt.xlabel("Date")
plt.ylabel("Closing Price")
plt.grid(True)
plt.legend()
plt.show()
```



# Displaying Volume trends over the time

```
plt.figure(figsize=(12, 4))
plt.plot(df['Date'], df['Volume'], label='Volume Traded', color='blue')
plt.title("Trading Volume Over Time")
plt.xlabel("Date")
plt.ylabel("Volume")
plt.grid(True)
plt.legend()
plt.show()
```



# **Creating log feature for prediction**

```
df['Next_Close'] = df['Close'].shift(-1)
df = df.dropna()
```

#### **Cretaing Features and target**

```
X = df[['Open', 'High', 'Low', 'Close', 'Volume']]
y = df['Next Close']
```

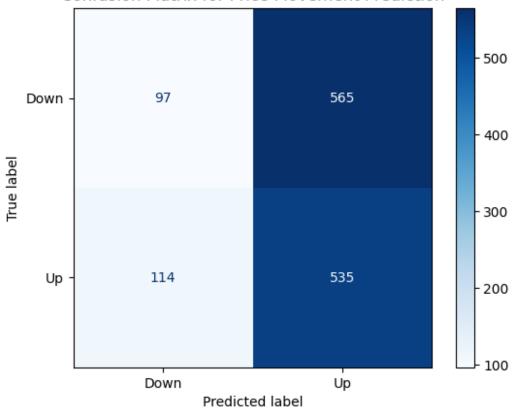
```
Train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
shuffle=False)
Training model
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
y pred = model.predict(X test)
Evaluating the model that is trained
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2 score(y test, y pred)
print(f"MAE: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
print(f"R2 Score: {r2:.2f}")
MAE: 11.52
RMSE: 17.31
R<sup>2</sup> Score: 1.00
Creating a Confusion Matrix for model Evaluation
from sklearn.model selection import train test split
from sklearn.linear model import LogisticRegression
from sklearn.metrics import confusion matrix, ConfusionMatrixDisplay
# Prepare data: classify price movement
df['Price_Up'] = (df['Close'].shift(-1) > df['Close']).astype(int) # 1 =
price went up next day
df = df.dropna() # drop last row with NaN target
# Features and target
X = df[['Open', 'High', 'Low', 'Close', 'Volume']]
y = df['Price_Up']
# Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
# Train Logistic regression model
model = LogisticRegression(max iter=1000)
model.fit(X_train, y_train)
# Predict
```

```
y_pred = model.predict(X_test)

# Confusion Matrix

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Down", "Up"])
disp.plot(cmap='Blues')
plt.title("Confusion Matrix for Price Movement Prediction")
plt.show()
```

# Confusion Matrix for Price Movement Prediction



#### **What I Learned from This Project**

- How to read and manipulate CSV files using pandas.
- Techniques to identify and handle missing or inconsistent data.
- How to create and interpret visualizations using matplotlib and seaborn.
- Understanding of stock market terms and indicators through hands-on analysis

#### **Conclusion**

• This project was an insightful introduction to financial data analysis using Python. It improved my data handling and visualization skills and deepened my understanding

of stock market trends. Working with real-world data presented unique challenges, which ultimately enhanced my analytical thinking and technical abilities.