google-stock-prediction-1

[1]:
```
import pandas as pd
from matplotlib import pyplot
```

[2]:
```
from pandas import read_csv
data=pd.read_csv('C:\TSAdataset\GOOG_data.
 ↪csv',header=0,index_col=0,parse_dates=True,infer_datetime_format=True)
data.head()
```

[2]:

Date	Open_Price	Close_Price	Adj_Close_Price	Volume
2019-06-14	1086.420044	1085.349976	1085.349976	1111500
2019-06-17	1086.280029	1092.500000	1092.500000	941600
2019-06-18	1109.689941	1103.599976	1103.599976	1386700
2019-06-19	1105.599976	1102.329956	1102.329956	1338800
2019-06-20	1119.989990	1111.420044	1111.420044	1262000

1 Ploting data in time series format

[3]:
```
import plotly.express as px
figure=px.line(data,x=data.index,y="Close_Price",title="Time Series␣
 ↪Analysis(line plot)")
figure.show()
```

2 Extracting time series analysis component

[4]:
```
#De-Trend
```

[5]:
```
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

[6]:
```
df=pd.read_csv('C:\TSAdataset\GOOG_data.
 ↪csv',header=0,index_col=0,parse_dates=True,infer_datetime_format=True)
df.head()
```

[6]:

Date	Open_Price	Close_Price	Adj_Close_Price	Volume
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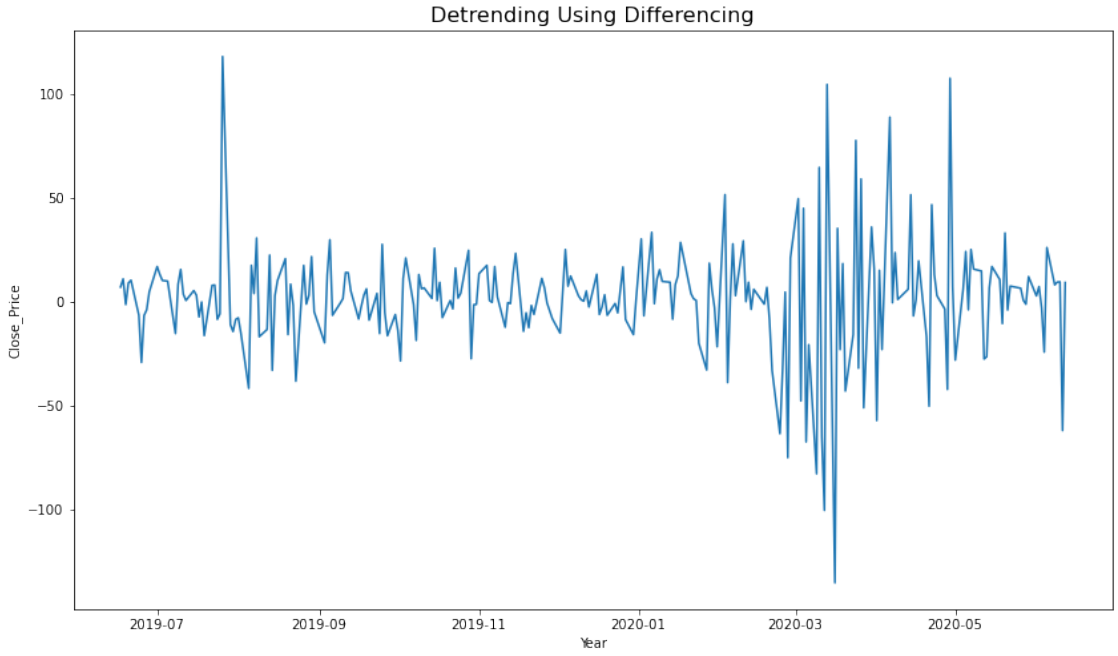
2019-06-20	1119.989990	1111.420044	1111.420044	1262000

[7]:
```
diff=df.Close_Price.diff()
```

[8]:
```
plt.figure(figsize=(14,8))
plt.plot(diff)
plt.title('Detrending Using Differencing',fontsize=16)
plt.xlabel('Year')
plt.ylabel('Close_Price')
plt.show()
```



[9]:
```
#De-Seasonality
```

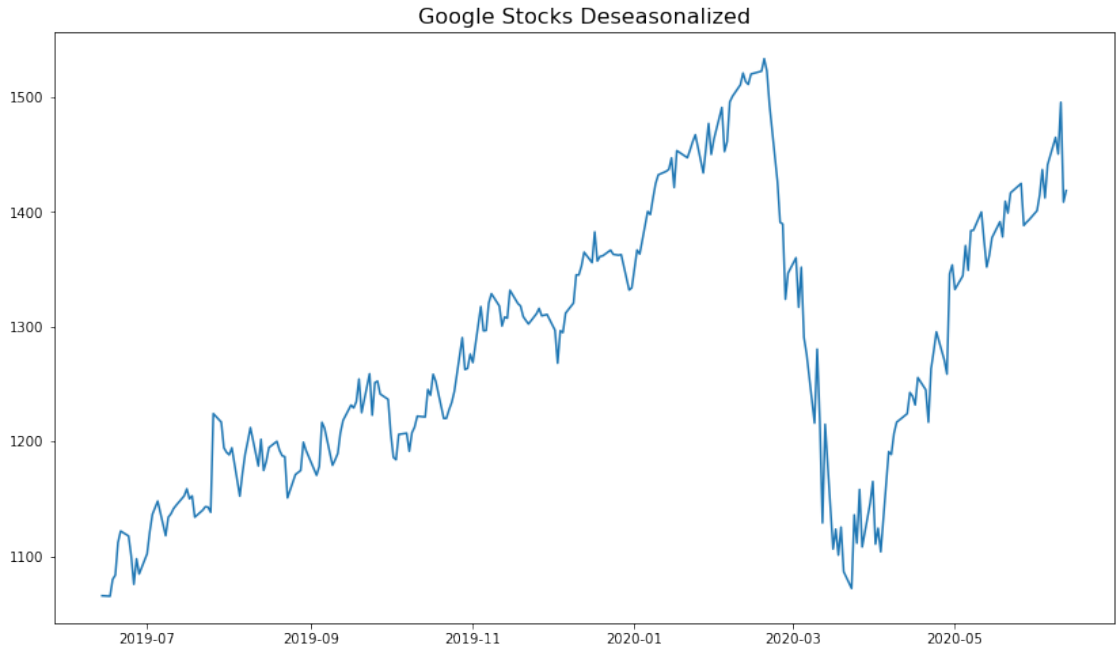
[10]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

[11]:
```
result_mul = seasonal_decompose(df['Close_Price'], model='multiplicative',␣
↪period=30)
```

[12]:
```
deseasonalized = df['Close_Price'].values / result_mul.seasonal
```

[13]:
```
plt.figure(figsize=(14,8))
plt.plot(deseasonalized)
plt.title('Google Stocks Deseasonalized', fontsize=16)
plt.plot()
```

[13]: []



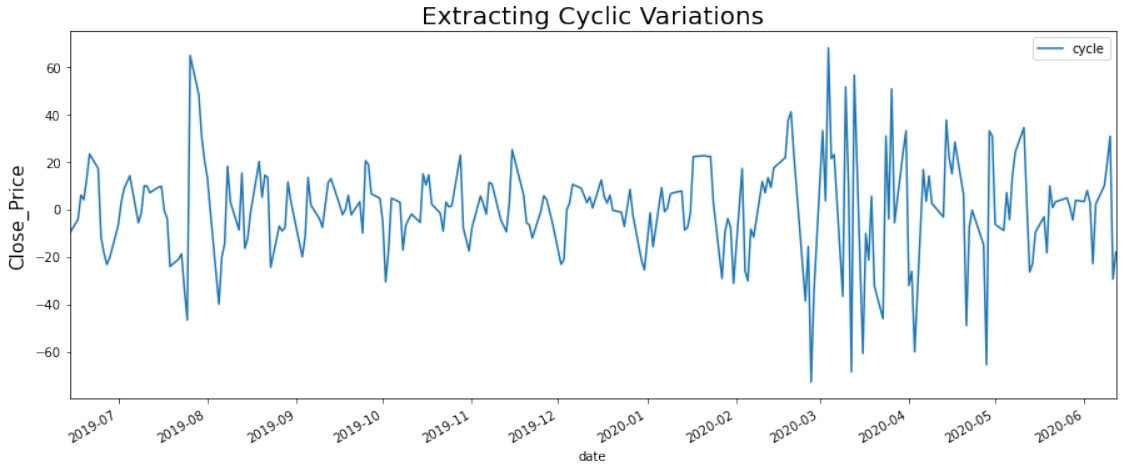
[14]:
```
#Detecting cyclic variations
```

[15]:
```
from statsmodels.tsa.filters.hp_filter import hpfilter
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

[16]:
```
df=pd.read_csv('C:\TSAdataset\GOOG_data.
 ↪csv',header=0,index_col=0,parse_dates=True,infer_datetime_format=True)
```

[17]:
```
GOOG_cycle,GOOG_trend = hpfilter(df['Close_Price'], lamb=100)
df['cycle'] =GOOG_cycle
df['trend'] =GOOG_trend
df[['cycle']].plot(figsize=(15,6)).autoscale(axis='x',tight=True)
plt.title('Extracting Cyclic Variations', fontsize=20)
plt.xlabel('date')
plt.ylabel('Close_Price', fontsize =15)
```

```
plt.show()
```



[18]:
```
# Detecting irregularities in GOOG_data
```

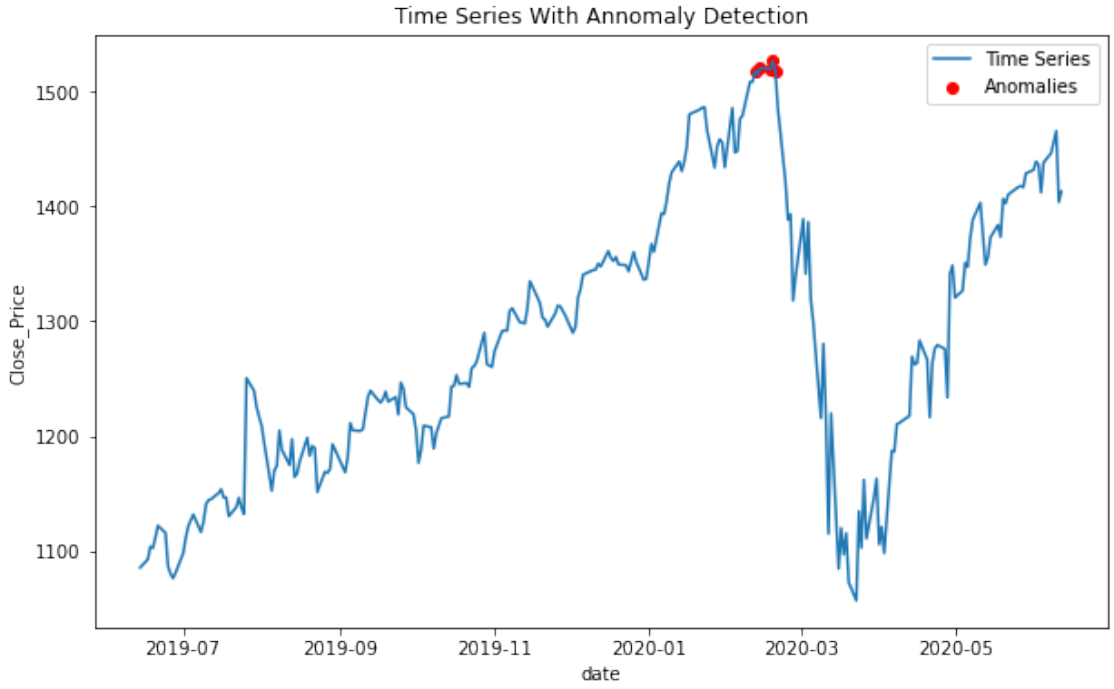
[19]:
```
#I have used Z-score method  to identify anomalies
# set threshold to 2
```

[20]:
```
z_scores = (df['Close_Price'] - df['Close_Price'].mean()) / df['Close_Price'].
 ↪std()
```

[21]:
```
z_score_threshold = 2.0
```

[22]:
```
anomalies=df[abs(z_scores) > z_score_threshold]
```

[23]:
```
plt.figure(figsize=(10,6))
plt.plot(df.index,df['Close_Price'],label='Time Series')
plt.scatter(anomalies.
 ↪index,anomalies['Close_Price'],color='red',label='Anomalies')
plt.xlabel('date')
plt.ylabel('Close_Price')
plt.title('Time Series With Annomaly Detection')
plt.legend()
plt.show()
```



3 Check whether data is stationary or non stationary

[24]:
```
from pandas import read_csv
from statsmodels.tsa.stattools import adfuller
```

[25]:
```
df=pd.read_csv('C:\TSAdataset\GOOG_data.
  ↪csv',header=0,index_col=0,parse_dates=True)
df.head()
df1=df.drop(['Volume', 'Open_Price','Adj_Close_Price'], axis=1)
```

[26]:
```
result=adfuller(df1)
```

[27]:
```
print('ADF statistic: %f'% result[0])
```

```
ADF statistic: -2.497410
```

[28]:
```
print('Critical values :')
for key,value in result[4].items():
    print('\t%s:% .3f' % (key,value))
```

```
Critical values :
        1%:-3.458
        5%:-2.874
        10%:-2.573
```

[29]:
```
if result[0]>result[4]["5%"]:
    print("reject H0 - Time Series Is Stationary")
else:
    print("failed to reject H0 - Time Series Is Non Stationary")
```

```
reject H0 - Time Series Is Stationary
```

4 Implement Auto Regressive model for time series

[30]:
```
from pandas import read_csv
from matplotlib import pyplot
from statsmodels.tsa.ar_model import AutoReg
from sklearn.metrics import mean_squared_error
from math import sqrt
```

[31]:
```
#load the dataset

df=pd.read_csv('C:\TSAdataset\GOOG_data.
 ↪csv',header=0,index_col=0,parse_dates=True,infer_datetime_format=True)
google_stock=df['Close_Price']
```

[32]:
```
#split data into training and testing sets

train_size = int(len(google_stock) * 0.8)
train, test = google_stock[:train_size], google_stock[train_size:]
```

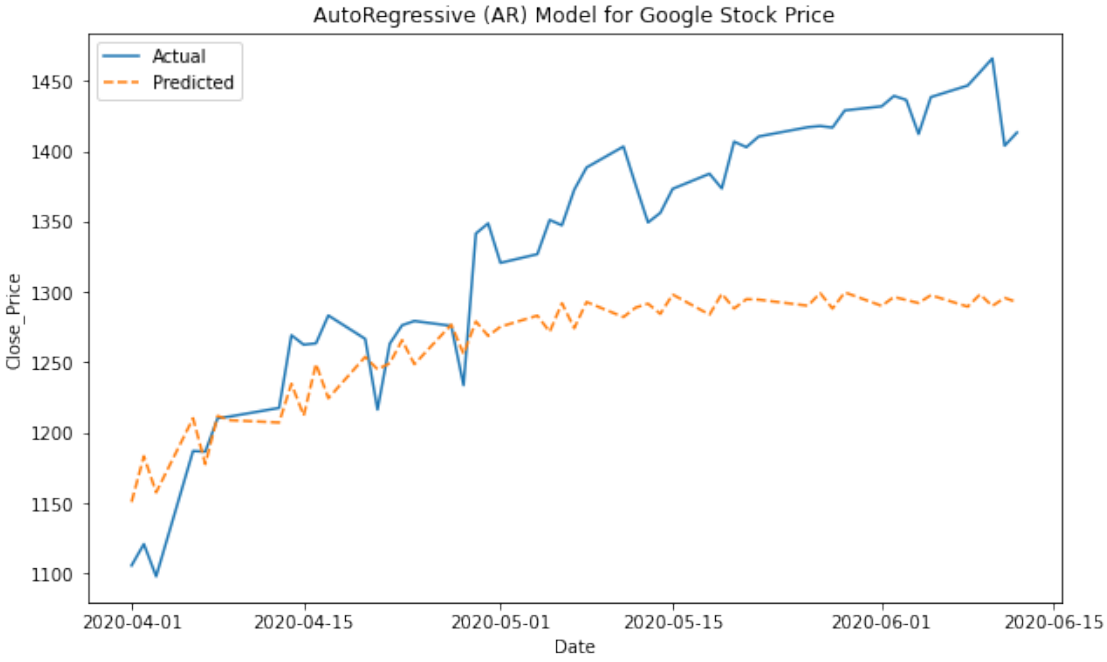
[33]:
```
#fit AR model

lags = 10
model = AutoReg(train, lags=lags)
model_fit = model.fit()
```

[34]:
```
#predict using the trained AR model

start = len(train)
end = len(train) + len(test) - 1
predictions = model_fit.predict(start=start, end=end, dynamic=False)
```

[35]:
```
#calculate mean squared error

mse = mean_squared_error(test, predictions)
print(f"Mean Squared Error: {mse}")
```

```
Mean Squared Error: 8215.914903466022
```

[36]:
```
#plot actual and predicted values

plt.figure(figsize=(10, 6))
plt.plot(test.index, test.values, label='Actual')
plt.plot(test.index, predictions, label='Predicted', linestyle='--')
plt.legend()
plt.title('AutoRegressive (AR) Model for Google Stock Price')
plt.xlabel('Date')
plt.ylabel('Close_Price')
plt.show()
```



5 Validate the model

[37]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import TimeSeriesSplit
from statsmodels.tsa.ar_model import AutoReg
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
```

[38]:
```
#load the dataset

df=pd.read_csv('C:\TSAdataset\GOOG_data.
 ↪csv',header=0,index_col=0,parse_dates=True,infer_datetime_format=True)
```

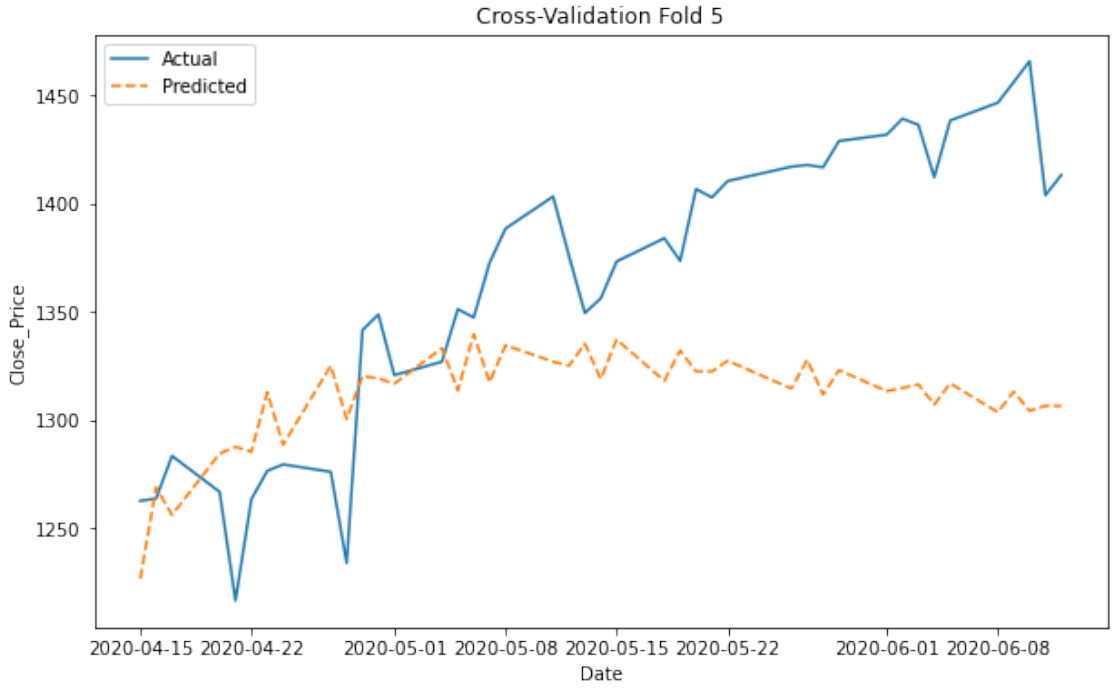
```
google_stock=df['Close_Price']
```

[39]:
```
#number of splits for cross validation

n_splits=5
```

[40]:
```
# Initialize TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=n_splits)
mse_scores = []                                  # To store Mean Squared Error␣
 ↪(MSE) scores
```

[41]:
```
#perform cross validation

for train_idx, test_idx in tscv.split(google_stock):
    train, test = google_stock.iloc[train_idx], google_stock.iloc[test_idx]

    lags = 10
    model = AutoReg(train, lags=lags)
    model_fit = model.fit()

    start = len(train)
    end = len(train) + len(test) - 1
    predictions = model_fit.predict(start=start, end=end)

    mse = mean_squared_error(test, predictions)
    mse_scores.append(mse)
```

[42]:
```
#Plot the actual and predicted values for the current fold

plt.figure(figsize=(10, 6))
plt.plot(test.index, test.values, label='Actual')
plt.plot(test.index, predictions, label='Predicted', linestyle='--')
plt.legend()
plt.title(f'Cross-Validation Fold {len(mse_scores)}')
plt.xlabel('Date')
plt.ylabel('Close_Price')
plt.show()
```



[43]:
```
# Calculate the average MSE across folds

average_mse = np.mean(mse_scores)
print(f"Average Mean Squared Error: {average_mse}")
```

```
Average Mean Squared Error: 30472.09208227747
```

6 Use the model to forecast future values

[44]:
```
import pandas as pd
from statsmodels.tsa.ar_model import AutoReg
import matplotlib.pyplot as plt
from datetime import datetime, timedelta
```

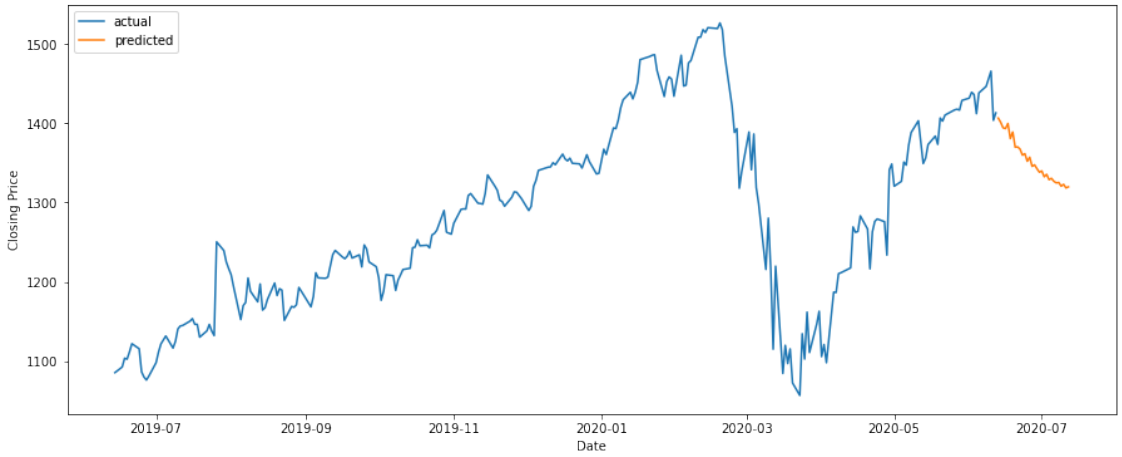
[45]:
```
df=pd.read_csv('C:\TSAdataset\GOOG_data.
  ↪csv',header=0,index_col=0,parse_dates=True,infer_datetime_format=True)
closing_prices=df['Close_Price']
```

[46]:
```
order = 10  # AR order (p)
model = AutoReg(closing_prices, lags=order)
model_fit = model.fit()
```

[47]:
```
forecast_periods = 30  # Number of future periods to forecast
```

```
forecast_index = pd.date_range(start=closing_prices.index[-1] +␣
  ↪timedelta(days=1), periods=forecast_periods, freq='D')
forecast = model_fit.forecast(steps=forecast_periods)
```

[48]:
```
plt.figure(figsize=(15,6))
plt.plot(closing_prices.index, closing_prices, label='Historical')
plt.plot(forecast_index, forecast, label='Forecast')
plt.xlabel('Date')
plt.ylabel('Closing Price')
plt.legend(["actual", "predicted"], loc ="upper left")
plt.show()
```



[ ]:

[ ]: