Gold Price Prediction

In [29]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
sns.set_style("darkgrid", {"grid.color": ".6",
                           "grid.linestyle": ":"})

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import Lasso

from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV
```

In [30]:
```
# read dataset using pndas function
# use parse_dates argument to change datetime dtype
dataset = pd.read_csv("gold_price_data.csv",
                      parse_dates=["Date"])
```

In [31]:
```
# information about the dataset
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2290 entries, 0 to 2289
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype         
---  ------   --------------  -----         
 0   Date     2290 non-null   datetime64[ns]
 1   SPX      2290 non-null   float64       
 2   GLD      2290 non-null   float64       
 3   USO      2290 non-null   float64       
 4   SLV      2290 non-null   float64       
 5   EUR/USD  2290 non-null   float64       
dtypes: datetime64[ns](1), float64(5)
memory usage: 107.5 KB
```

Data preprocessing - Missing Values/Null Values

Missing values have a very drastic effect on our model training. some of the models like LinearRegression do not fit the dataset which has missing values in it. However, there are some models which work well even with a missing dataset like RandomForest. But it is always a good practice to handle missing values first when working with the dataset.

Also, one thing to note is that when we load the data using pandas it automatically detects null values and replaces them with NAN.

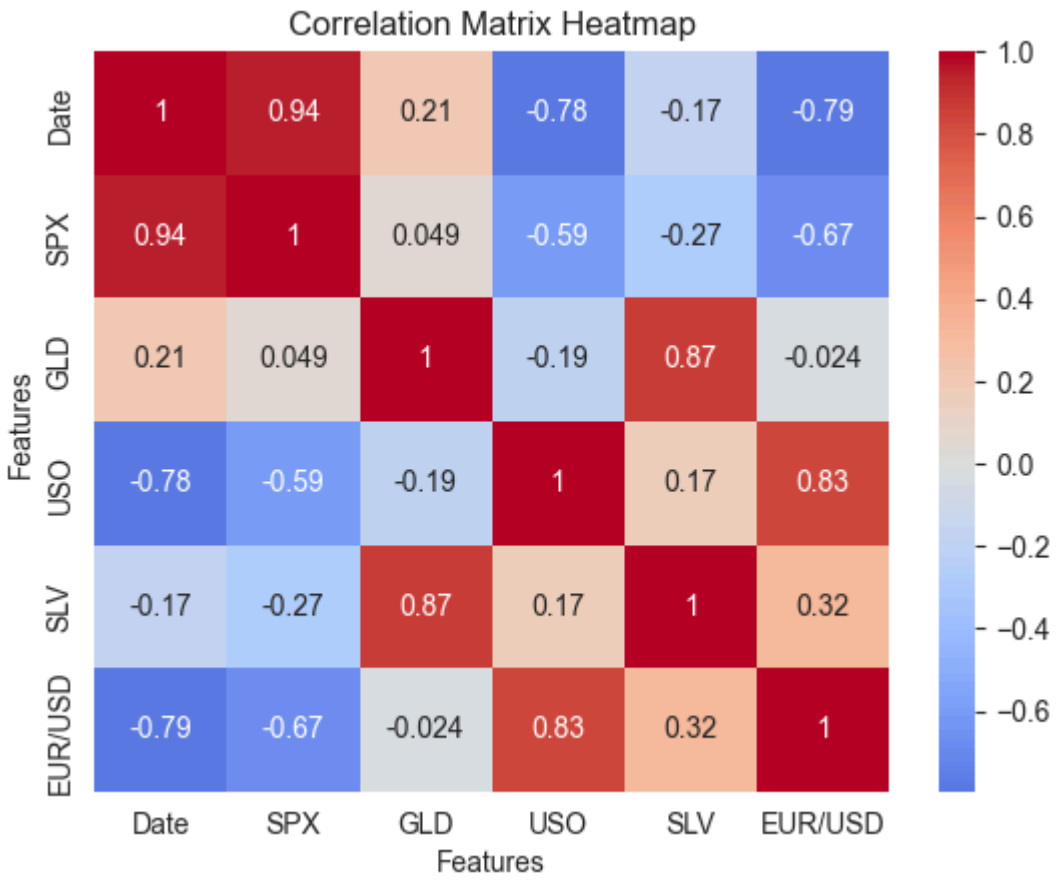
It will count the number of null values in each column of the dataset and display it in the notebook.

In [32]:
```
# Missing Values/Null Values Count
dataset.isna().sum().sort_values(ascending=False)
```

Out[32]:
```
Date       0
SPX        0
GLD        0
USO        0
SLV        0
EUR/USD    0
dtype: int64
```

Correlation Between Columns

In [33]:
```
# Calculate correlation matrix
correlation  = dataset.corr()

# Create heatmap
sns.heatmap(correlation, cmap='coolwarm',
            center=0, annot=True)

# Set title and axis labels
plt.title('Correlation Matrix Heatmap')
plt.xlabel('Features')
plt.ylabel('Features')

# Show plot
plt.show()
```



Here the two columns SLV and GLD are strongly correlated with each other compared to others, here we will drop SLV since GLD column also has a large correlation with our target column. Here We have used the pandas Drop function to drop the column along axis=1.

In [34]:
```
# drop SLV column
dataset.drop("SLV", axis=1,
             inplace=True)
```

Data Wrangling

Data wrangling is one of the main steps We use in a data science project to gain insight and knowledge from the data. We see data through every aspect and try to fetch most of the information from the dataframe.

We will first set the Date column as the index of the dataframe using the date as an index will add an advantage in plotting the data

In [35]:
```
# reset the index to date column
dataset.set_index("Date", inplace=True)
```

We will first observe the change in Gold price with each consecutive day throughout the year.

In [36]:
```
# plot price of gold for each increasing day
dataset["EUR/USD"].plot()
plt.title("Change in price of gold through date")
```

```
plt.xlabel("date")
plt.ylabel("price")
plt.show()
```

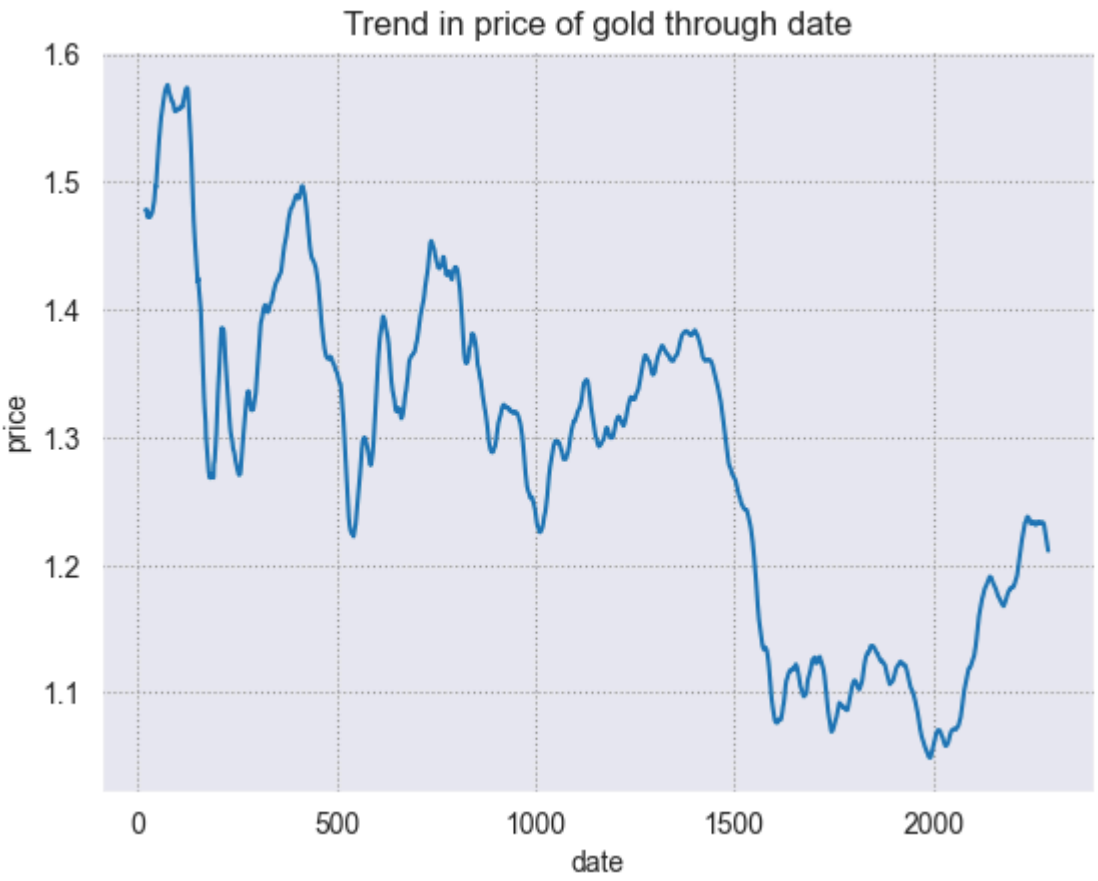
Through this graph, we are unable to find any good insight into the change in the price of gold. It looks very noisy, to see the trend in the data we have to make the graph smooth.

Trend in Gold Prices Using Moving Averages

To visualize the trend in the data we have to apply a smoothing process on this line which looks very noisy. There are several ways to apply to smooth. In our project, we will take an average of 20 previous data points using the pandas rolling function. This is also known as the Moving Average.

In [37]:
```
# apply rolling mean with window size of 3
dataset["price_trend"] = dataset["EUR/USD"]\
    .rolling(window=20).mean()

# reset the index to date column
dataset.reset_index("Date", inplace=True)

# since we have used rolling method
# for 20 rows first 2 rows will be NAN
dataset["price_trend"].loc[20:].plot()

# set title of the chart
plt.title("Trend in price of gold through date")

# set x_label of the plot
plt.xlabel("date")
```

```
plt.ylabel("price")
plt.show()
```

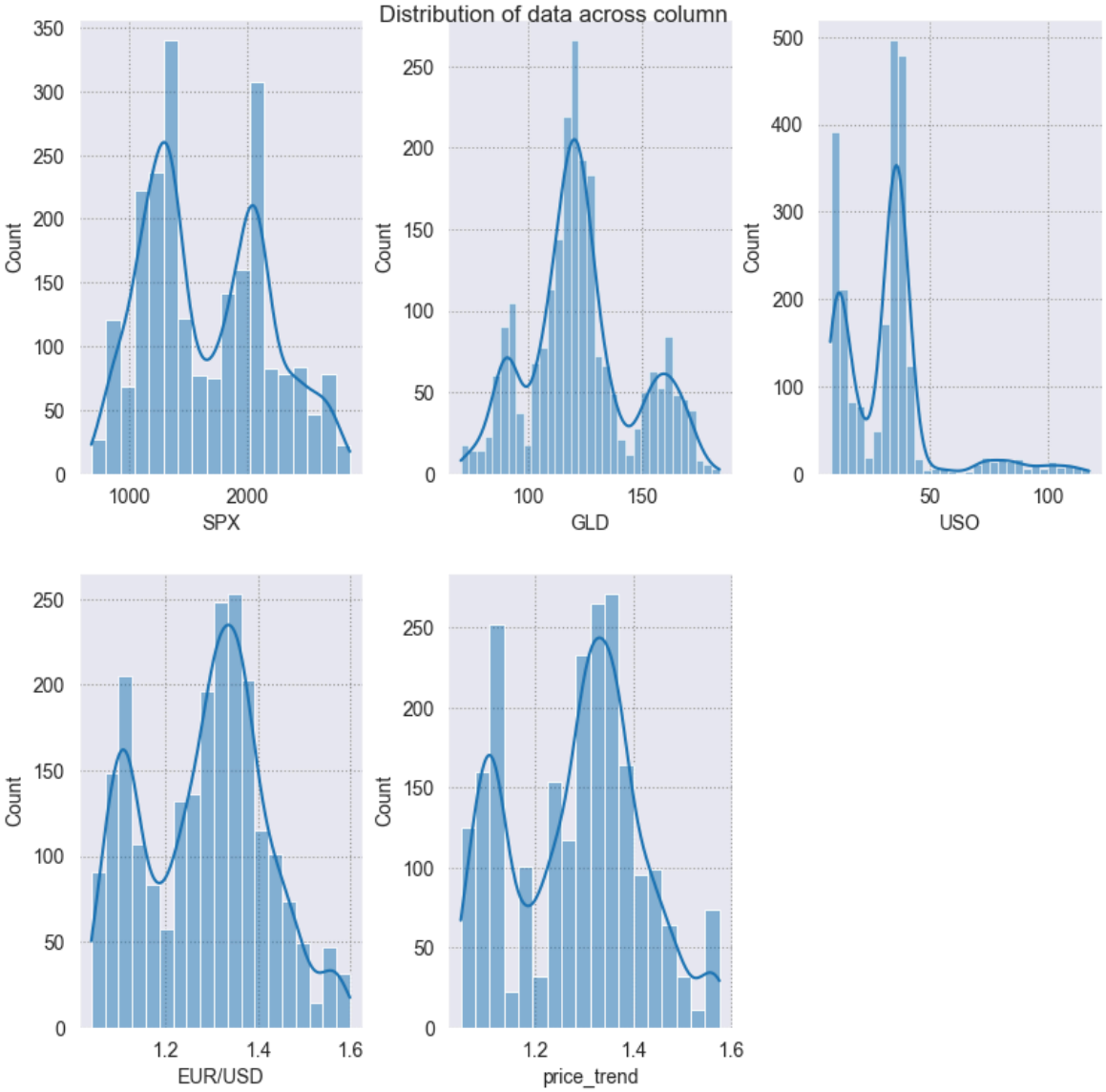


Now the graph looks less noisy and here we can analyze the trend in change in the gold price.

Distribution of Columns

To see the distribution of numerical columns we will plot the histogram of each column in one figure to do this we will use the Matplotlib subplot function.

In [38]:
```
fig = plt.figure(figsize=(8, 8))

# suptitle of the graph
fig.suptitle('Distribution of data across column')
temp = dataset.drop("Date", axis=1).columns.tolist()
for i, item in enumerate(temp):
    plt.subplot(2, 3, i+1)
    sns.histplot(data=dataset, x=item, kde=True)
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=2.0)
plt.show()
```



In [39]:
```
# skewness along the index axis
print(dataset.drop("Date", axis=1).skew(axis=0, skipna=True))

# This code is modified by Susobhan Akhuli
```

```
SPX            0.300362
GLD            0.334138
USO            1.699331
EUR/USD       -0.005292
price_trend   -0.029588
dtype: float64
```

Column USO has the highest skewness of 1.69, so here we will apply square root transformation on this column to reduce its skewness to 0. We can use different transformation functions to lower the skewness some are logarithmic transformation, inverse transformation, etc.

In [40]:
```
# apply saquare root transformation
# on the skewed dataset
dataset["USO"] = dataset["USO"]\
    .apply(lambda x: np.sqrt(x))
```

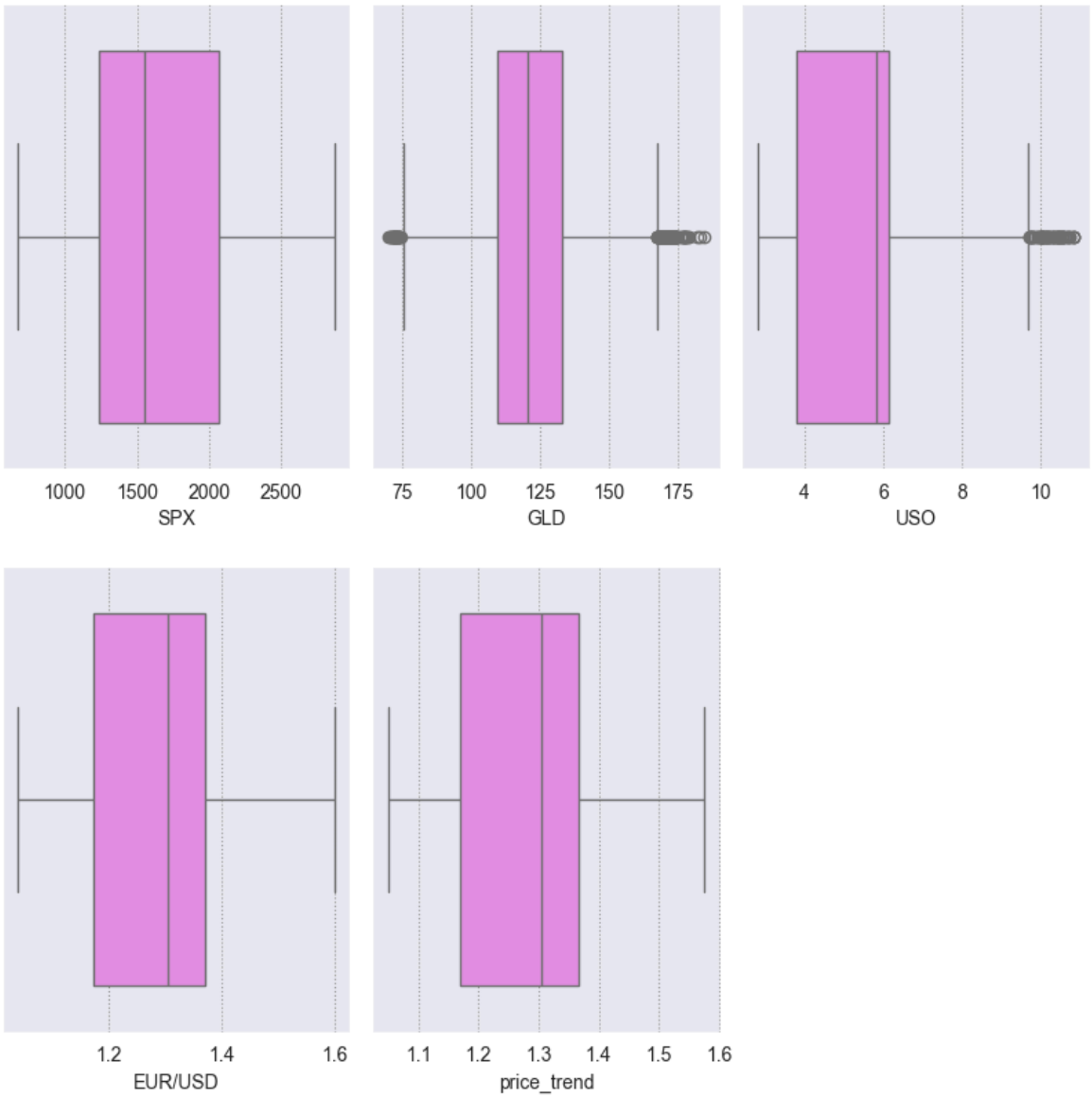
Handling Outliers

Outliers can have a very bad effect on our model like in linear regression if a data point is an outlier then it can add a very large mean square error. Removing outliers is a good process in EDA. Some models like Decisiontree and ensemble methods like RandomForests are not that much by outliers. However, it is always a good practice to handle the outlier.

Plotting Boxplot to Visualize the Outliers

Boxplots are very useful in plotting the spread and skewness of the data, it is also useful in plotting the individual's outlier data points, they consist of the box which represents points in the range of 25% to 75% quantiles. While the line in the middle of the box represents the median and the whisker at the end of the box shows the range of below 25 % and 75% excluding outliers.

In [41]:
```
fig = plt.figure(figsize=(8, 8))
temp = dataset.drop("Date", axis=1).columns.tolist()
for i, item in enumerate(temp):
    plt.subplot(2, 3, i+1)
    sns.boxplot(data=dataset, x=item, color='violet')
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=2.0)
plt.show()
```



It can be seen clearly that the column 'USO' has outliers present in the column, so we create a function to normalize the outlier present in the column.

In [42]:
```
def outlier_removal(column):
    # Capping the outlier rows with Percentiles
    upper_limit = column.quantile(.95)
    # set upper limit to 95percentile
    lower_limit = column.quantile(.05)
    # set lower limit to 5 percentile
    column.loc[(column > upper_limit)] = upper_limit
    column.loc[(column < lower_limit)] = lower_limit
    return column
```

Here We have set the upper limit of the column to 95 %of the data and the lower limit to the 5 %. that means that which are greater than 95% percentile of the data are normalized to the data 95% value same for the data points which are lower than 5% of the data.

In [43]:
```
# Normalize outliers in columns except Date

dataset[['SPX', 'GLD', 'USO', 'EUR/USD']] = \
    dataset[['SPX', 'GLD', 'USO', 'EUR/USD']].apply(outlier_removal)
```

Modeling the Data

Before We start modeling the data must divide the data into train and test, so that after training the data We can see how much our data is learning the pattern and generalizing on new data points. it is also a way to see that our model is not learning the noise in the data or say it is not overfitting the dataset.

In [44]:
```
# select the features and target variable
X = dataset.drop(['Date', 'EUR/USD'], axis=1)

y = dataset['EUR/USD']
# dividing dataset in to train test
x_train, x_test,\
    y_train, y_test = train_test_split(X, y,
                                       test_size=0.2)
```

Scaling the Data

Before we train the model on our data we should perform scaling on our data to normalize. After scaling the data our mean of each column becomes zero and their standard deviation becomes 1. It is also called z-score normalization since we subtract the mean of the column from each element and divide it by the standard deviation of the column. It brings all the columns to the same scale and directly comparable with one another.

It is always advisable to start fitting the data from a simple model and then move it to a complex one. One of the reasons for doing this is simple model takes less time and storage to train on the data. Also, many simple models work far better than complex ones and these models are also more interpretable than complex models.

In [45]:
```
# Create an instance of the StandardScaler
scaler = StandardScaler()

# Fit the StandardScaler on the training dataset
scaler.fit(x_train)

# Transform the training dataset
# using the StandardScaler
x_train_scaled = scaler.transform(x_train)
x_test_scaled = scaler.transform(x_test)
```

Lasso Regression

In this model, we have used linear regression with L1 Regularization, also with help of the make_pipeline object, we will use lasso regression with 2 degrees. We will also use the

GridSearch object in every model to get the best-performing hyperparameter and lower the variance.

In [46]:
```
# Impute missing values using SimpleImputer
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='mean') # Replace NaNs with the mean of each co

# Fit and transform the imputer on the scaled training data
x_train_scaled = imputer.fit_transform(x_train_scaled)

# Transform the scaled test data using the trained imputer
x_test_scaled = imputer.transform(x_test_scaled)

# Create a PolynomialFeatures object of degree 2
poly = PolynomialFeatures(degree=2)

# Create a Lasso object
lasso = Lasso()

# Define a dictionary of parameter
#values to search over
param_grid = {'lasso__alpha': [1e-4, 1e-3, 1e-2,
                                                    1e-1, 1, 5, 10,
                                                    20, 30, 40]}

# Create a pipeline that first applies
# polynomial features and then applies Lasso regression
pipeline = make_pipeline(poly, lasso)

# Create a GridSearchCV object with
#the pipeline and parameter grid
lasso_grid_search = GridSearchCV(pipeline,
                                                            param_grid,
                                                            scoring='r2', cv

# Fit the GridSearchCV object to the training data
lasso_grid_search.fit(x_train_scaled, y_train)

# Predict the target variable using
# the fitted model and the test data
y_pred = lasso_grid_search.predict(x_train_scaled)

# Compute the R-squared of the fitted model on the train data
r2 = r2_score(y_train, y_pred)

# Print the R-squared
print("R-squared: ", r2)

# Print the best parameter values and score
print('Best parameter values: ',
        lasso_grid_search.best_params_)
print('Best score: ',
        lasso_grid_search.best_score_)
```

```
R-squared:  0.9662038568977868
Best parameter values:  {'lasso__alpha': 0.0001}
Best score:  0.9652432688874927
```

Here we are fitting our multiple regression of degree, however, to use lasso regression with multiple regression we must use the pipeline method from sklearn. We will also use the grid search method for cross-validation and selecting the best-performing hyperparameter for the training data. Grid search is one of the best ways to find a model which does not overfit the training data.

We have used the R-squared evaluation matrix throughout our model. We have used this matrix since We want to compare our model and choose which is best performing.

RandomForestRegressor for Regression

In the second model, we will use the ensemble method to fit our training data. like in Random Forest it uses several decision trees to fit on the data, one thing to note is that in random forest regressor m number of rows are used for training which is always less than n. Where n is the total number of original columns present in the training dataset, also for row points random forest select these row's element.

In [47]:
```
# Insiate param grid for which to search
param_grid = {'n_estimators': [50, 80, 100],
              'max_depth': [3, 5, 7]}

# create instance of the Randomforest regressor
rf = RandomForestRegressor()

# Define Girdsearch with random forest
# object parameter grid scoring and cv
rf_grid_search = GridSearchCV(rf, param_grid, scoring='r2', cv=2)

# Fit the GridSearchCV object to the training data

rf_grid_search.fit(x_train_scaled, y_train)

# Print the best parameter values and score
print('Best parameter values: ', rf_grid_search.best_params_)
print('Best score: ', rf_grid_search.best_score_)
```

```
Best parameter values:  {'max_depth': 7, 'n_estimators': 80}
Best score:  0.976584358742346
```

Here We have used both RandomForest regressor and Gridsearchcv, The Gridsearch will help in selecting the best number of decision trees from 50,80,100. We have also specified the maximum depth of the tree as a parameter which can be 3,5 or 7.

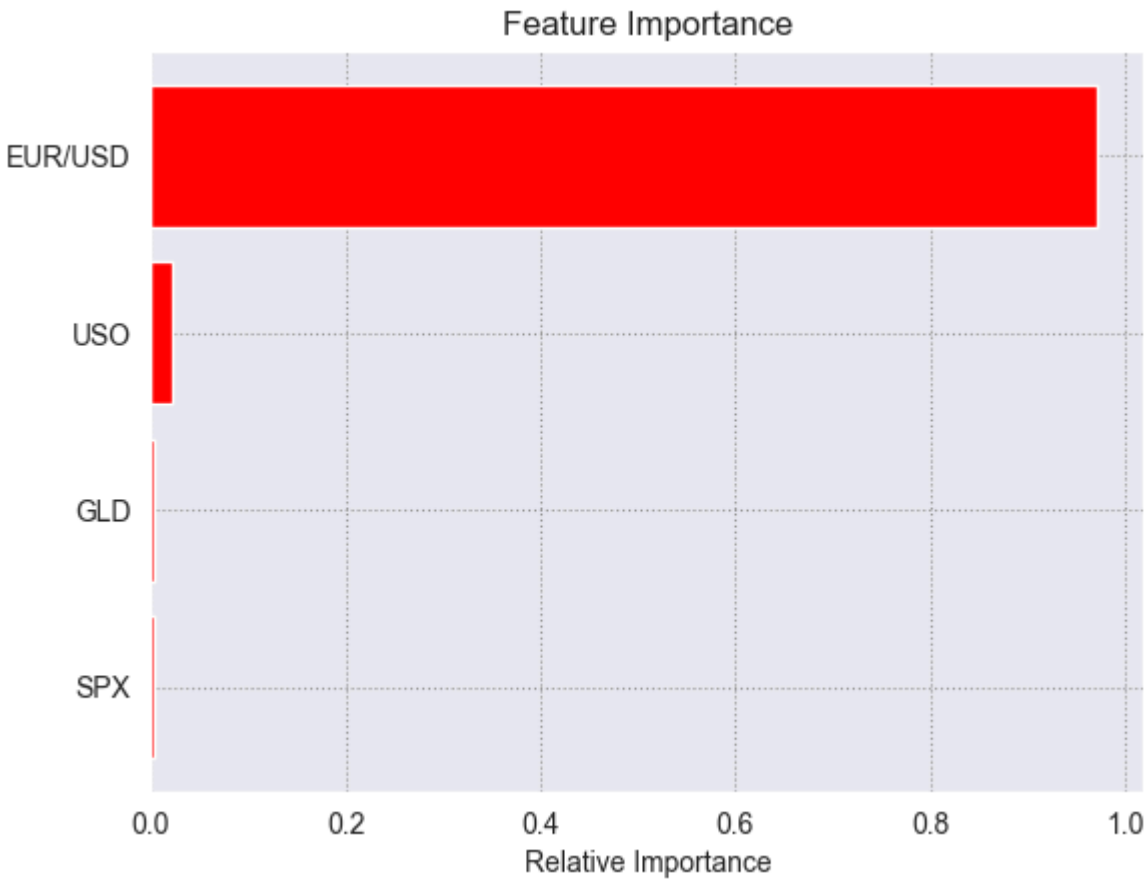
The best parameter value shows that the model gives the best result when it takes the average result of one hundred Decision trees having a maximum depth of 7.

In [48]:
```
# Compute the R-squared of the
# fitted model on the test data
r2 = r2_score(y_test,
              rf_grid_search.predict(x_test_scaled))

# Print the R-squared
print("R-squared:", r2)
```

```
R-squared: 0.9776720037484052
```

These models are called Black box models since We won't be able to visualize what is happening under the hood of the model however, we will plot the bar chart of the feature importance from the dataset.

In [49]:
```
features = dataset.drop("Date", axis=1).columns

# store the importance of the feature
importances = rf_grid_search.best_estimator_.\
    feature_importances_


indices = np.argsort(importances)

# title of the graph
plt.title('Feature Importance')

plt.barh(range(len(indices)),
         importances[indices],
         color='red',
         align='center')

# plot bar chart
plt.yticks(range(len(indices)),
           [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



XGBoost Model for Regression

In Boosting Technique the data is fitted in several sequential Weak learning algorithm models which are only slightly better than random guessing. In each next sequential model more Weights are given to the points are which are misclassified/regressed by previous models

In our models, we will use the XGBOOST model for fitting our training dataset.

In [50]:
```
# Create an instance of the XGBRegressor model
model_xgb = XGBRegressor()

# Fit the model to the training data
model_xgb.fit(x_train_scaled, y_train)

# Print the R-squared score on the training data
print("Xgboost Accuracy =", r2_score(
    y_train, model_xgb.predict(x_train_scaled)))
```

```
Xgboost Accuracy = 0.999499142996875
```

In [51]:
```
# Print the R-squared score on the test data
print("Xgboost Accuracy on test data =",
      r2_score(y_test,
               model_xgb.predict(x_test_scaled)))
```

```
Xgboost Accuracy on test data = 0.9822338244482082
```

In [52]:
```
import eli5 as eli
# weight of variables in xgboost model
# Get the names of the features
feature_names = x_train.columns.tolist()

# Explain the weights of the features using ELI5
eli.explain_weights(model_xgb,
                    feature_names=feature_names)
```

Out[52]:

Weight	Feature
0.9605	price_trend
0.0264	USO
0.0075	GLD
0.0056	SPX