

# Investopedia

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# Agenda

- Problem Statement
- Scope of the Project
- System Requirements
- Process Flow
- Application
- Contribution of each member



# Problem Statement

- The stock market appears in the news every day. You hear about it every time it reaches a new high or a new low. The rate of investment and business opportunities in the Stock market can increase if an efficient algorithm could be devised to predict the short term price of an individual stock.





# Scope of the Project

At the present time there are lots of applications available which can predict gold, house, shares, etc. So, instead of building different applications to predict these stock we are making an application which can predict all these within a single application. This saves the user more memory in their devices and also the user return to the application is maintained.



# Requirements



## Software

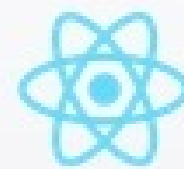
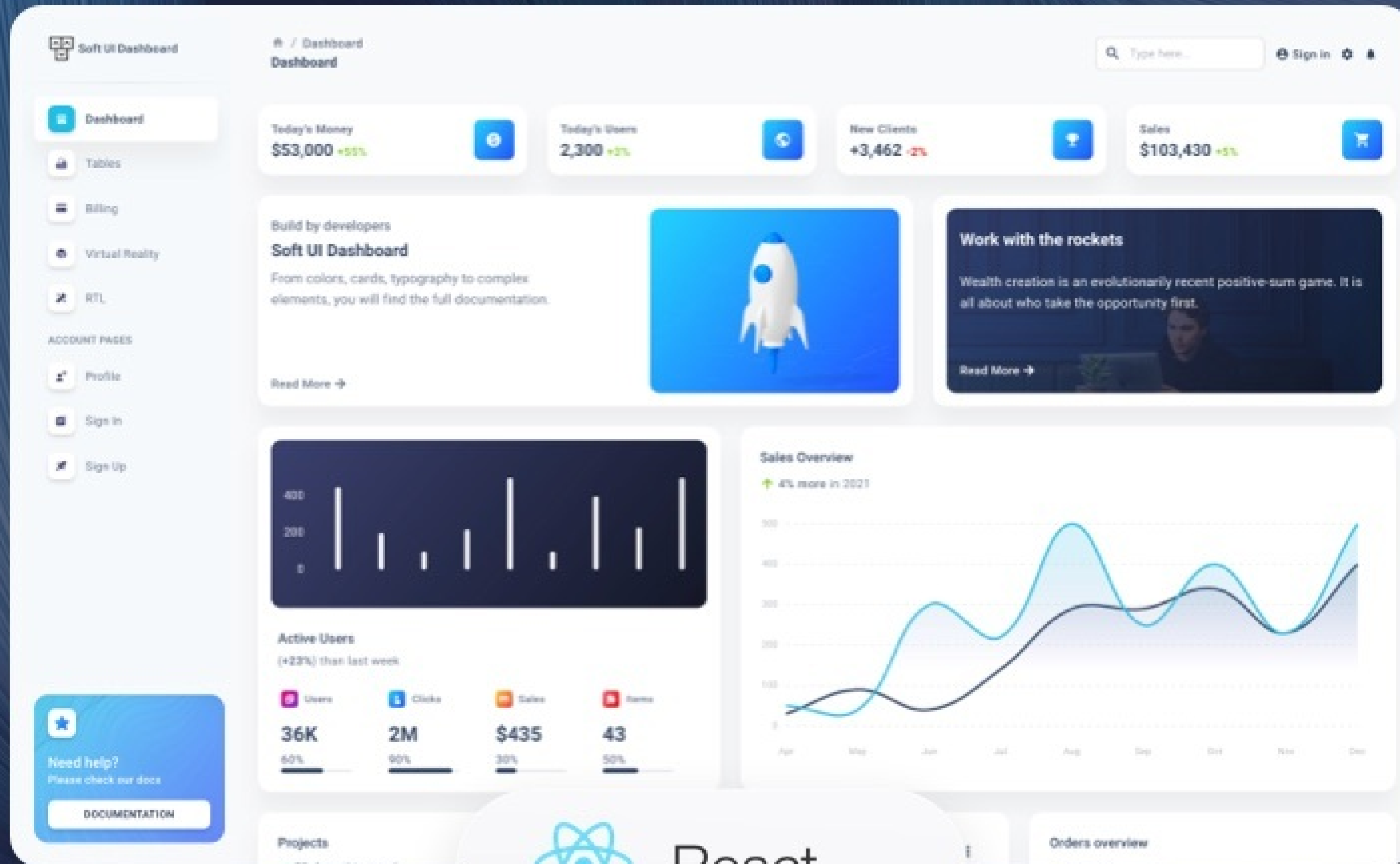
- IDE:
  - Google Colab (Backend)
  - VS code (Frontend)
- Python:
  - TensorFlow/Keras
  - Scikit Learn
- ReactJs:
  - ES6 Modules
  - Bootstrap
  - Tensorflow.js + React.js
- CLI

---

## Hardware

- Laptop
- RAM: 8GB
- Graphic card:
  - Given by Google Colab (K80 GPU and 12 GB of RAM)

# UX Design



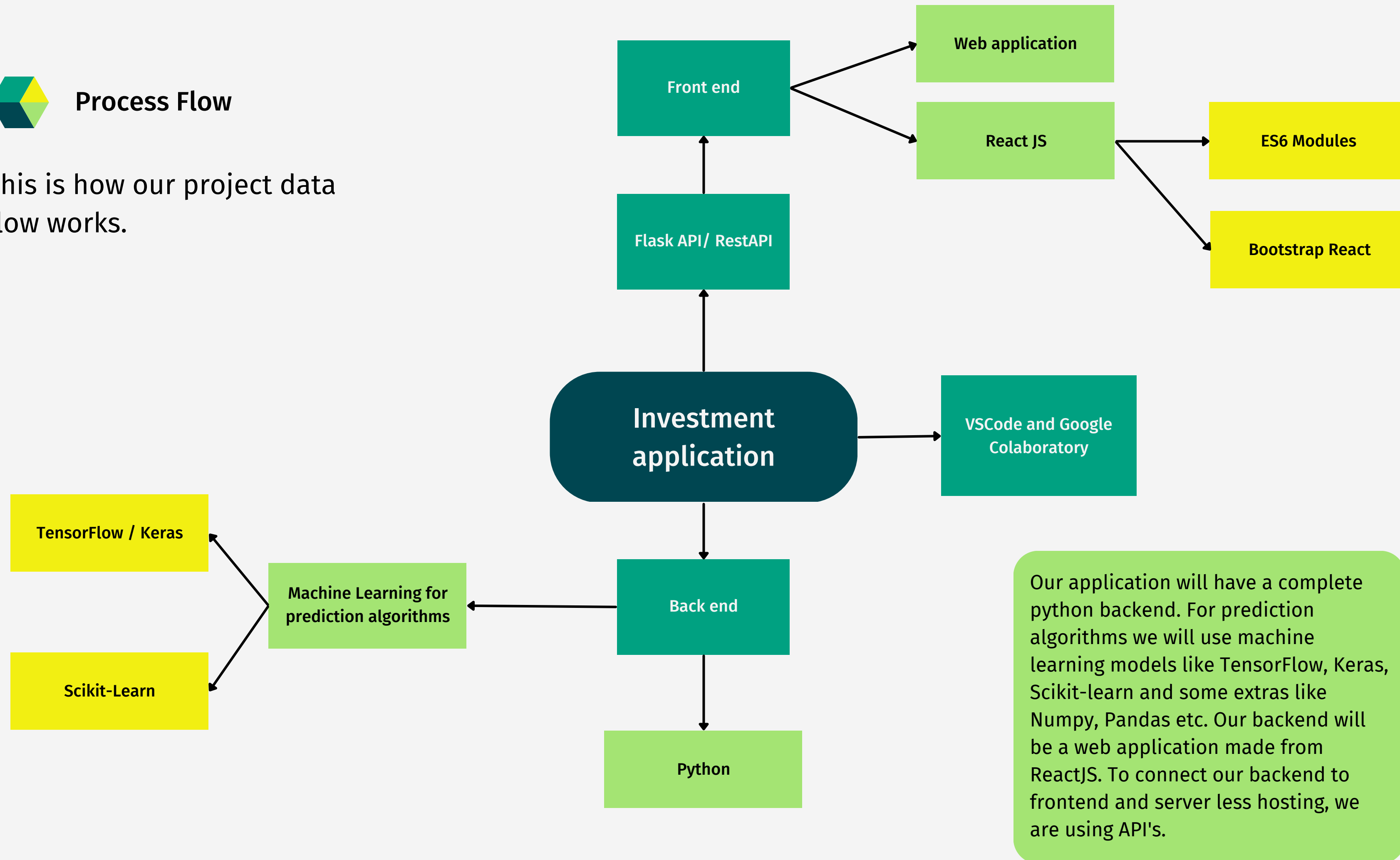
React





## Process Flow

This is how our project data flow works.



# Usability

- This application has a major usability criteria. We have loads and loads of new businesses everyday and there are new people in the market everyday looking for investment opportunities. Our application gives them a platform where majority users can find the opportunities to get the highest return from their investments. Using our prediction algorithm, customers can get all of the most common and low stake asset market predictions.
- This product will cover majority of the population as everyone wants to invest in the market nowadays.
- Many companies also have an issue of returning users. This means that how many people return to the application daily. Many apps start strong but soar down as they go forward. With more than 1 types of assets, we will have different users who like to invest in different markets. This maintains our returning users issue and keeps the application alive.



# **Review 2**

# Stock Prediction Model

Step 1: Import the modules

```
1  import pandas as pd
2  from sklearn.linear_model import LinearRegression
3  from sklearn.model_selection import train_test_split
4  import matplotlib.pyplot as plt
```

## Step 2: Defining Variables

```
6  # Load the stock data
7  df = pd.read_csv('NFTY.csv')
8
9  # Extract the closing price as the target variable
10 y = df['close']
11
12 # Extract the features
13 x = df[['open', 'high', 'low', 'volume']]
14
```

## Step 3: Training the model

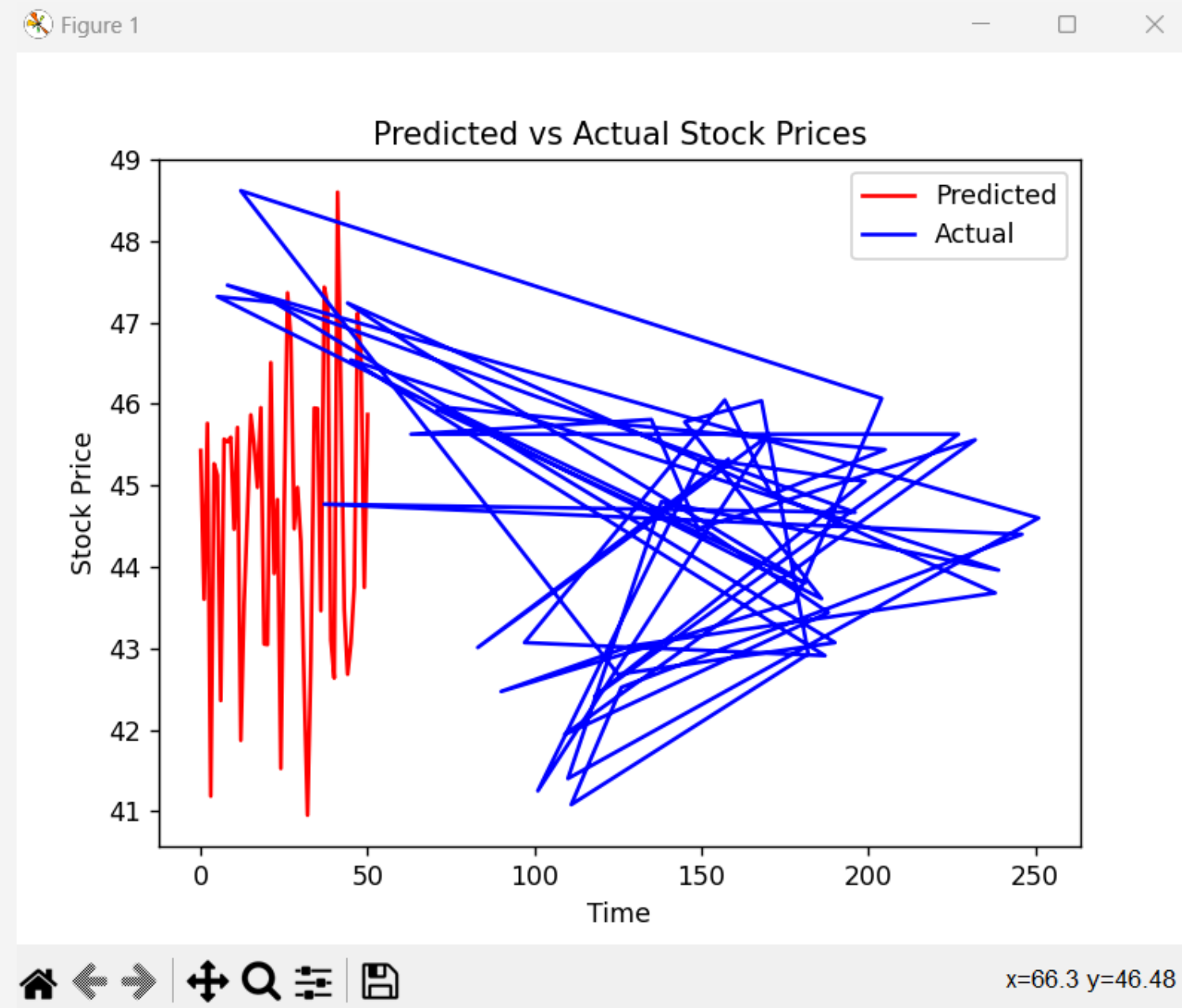
```
15 # Split the data into training and test sets
16 X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)
17
18 # Train the linear regression model
19 regressor = LinearRegression()
20 regressor.fit(X_train, y_train)
21
22 # Predict the stock prices
23 y_pred = regressor.predict(X_test)
```

## Step 4: Plotting the graph

```
26 # Plot the predicted stock prices
27 plt.plot(y_pred, color='red', label='Predicted')
28 # Plot the actual stock prices
29 plt.plot(y_test, color='blue', label='Actual')
30 # Add labels and a title
31 plt.xlabel('Time')
32 plt.ylabel('Stock Price')
33 plt.title('Predicted vs Actual Stock Prices')
34 plt.legend()
35 # Show the plot
36 plt.show()
```



# Output



Note: that the plot of the actual stock prices in this code may appear messy. This is because the `plt.plot()` function is being used to plot the `y_test` data, which is a series of individual stock prices over time. Since there are a large number of data points, the plot may appear cluttered and difficult to interpret.

# Stock Prediction Model (Updated)

```
NFTY.py X
Models > NFTY.py > ...
1 import pandas as pd
2 import numpy as np
3 from sklearn.model_selection import train_test_split
4 import matplotlib.pyplot as plt
5 import tensorflow as tf
6 from tensorflow import keras
7
8 # Load the stock data
9 df = pd.read_csv('NFTY.csv')
10 df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y')
11
12 # Extract the closing price as the target variable
13 y = df['close'].values
14
15 # Extract the features
16 x = df[['Open', 'High', 'Low', 'Volume']].values
17
18 # Split the data into training and test sets
19 X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)
20
21 # Create a sequential model
22 model = keras.Sequential()
23
24 # Add a dense layer
25 model.add(keras.layers.Dense(1, input_shape=(X_train.shape[1],)))
26
27 # Compile the model
28 model.compile(optimizer='adam', loss='mean_squared_error')
29
30 # Train the model
31 model.fit(X_train, y_train, epochs=100, batch_size=32)
32
33 # Predict the stock prices
34 y_pred = model.predict(X_test)
35
36 model.save('NFTY.h5')
37
```

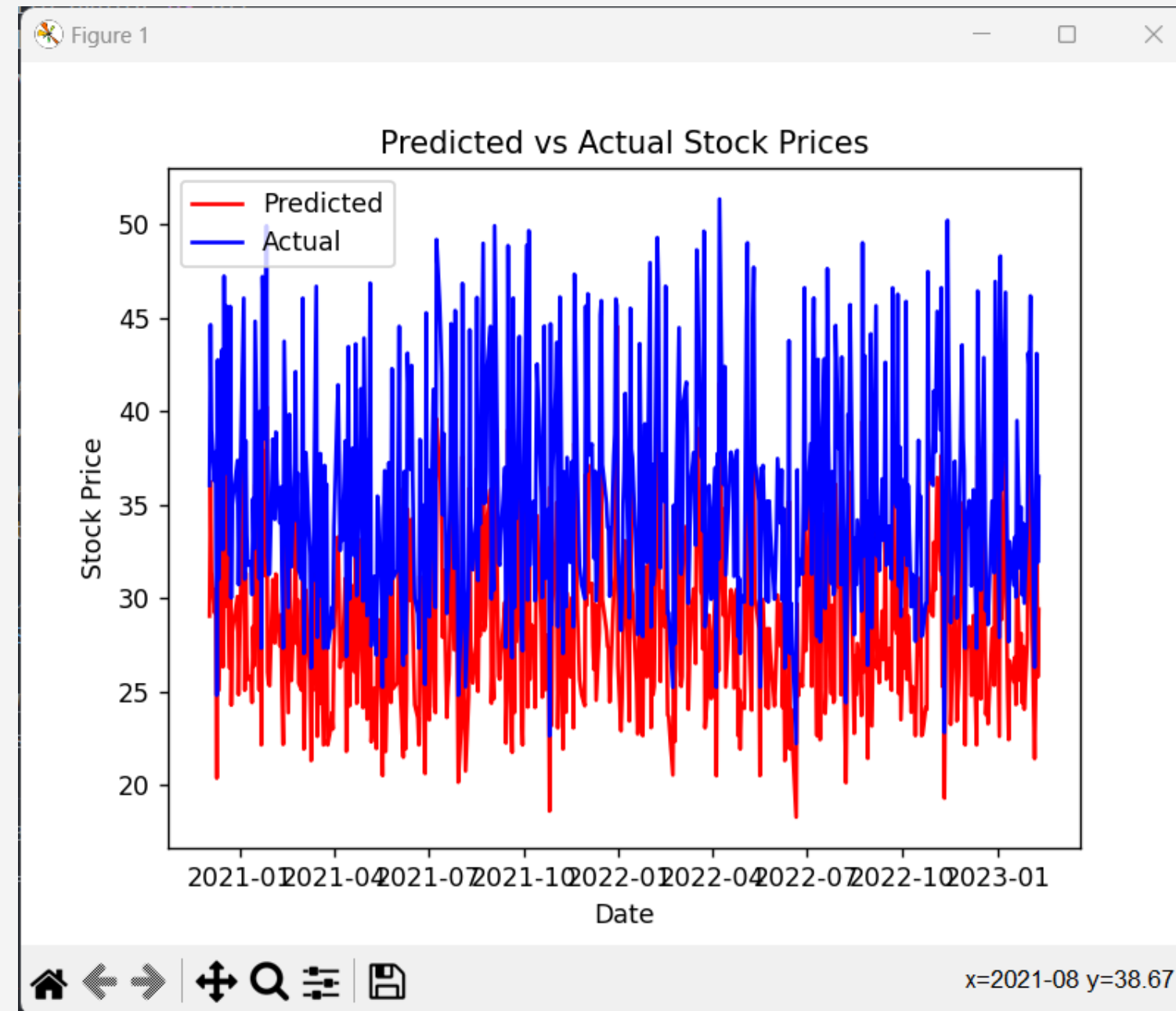
NFTY.py X

Models > NFTY.py > ...

```
38 # Plot the predicted stock prices
39 plt.plot(df['Date'][len(X_train):], y_pred, color='red', label='Predicted')
40 # Plot the actual stock prices
41 plt.plot(df['Date'][len(X_train):], y_test, color='blue', label='Actual')
42 # Add labels and a title
43 plt.xlabel('Date')
44 plt.ylabel('Stock Price')
45 plt.title('Predicted vs Actual Stock Prices')
46 plt.legend()
47 # Show the plot
48 plt.show()
49
50 def predict_price(date):
51     # convert the date string to a datetime object
52     date = pd.to_datetime(date, format='%d-%m-%Y')
53     # find the index of the date in the dataframe
54     index = df[df['Date'] == date].index[0]
55     # use the index to retrieve the features for the date
56     features = X[index].reshape(1, -1)
57     # use the model to predict the stock price for the date
58     price = model.predict(features)[0][0]
59     return price
60
61 date = '10-02-2023'
62 price = predict_price(date)
63 print(f'The predicted stock price for {date} is {price:.2f}')
```



# Output



Note: that the plot of the actual stock prices in this code may appear messy. This is because the `plt.plot()` function is being used to plot the `y_test` data, which is a series of individual stock prices over time. Since there are a large number of data points, the plot may appear cluttered and difficult to interpret.

# Gold prediction model

```
import pandas as pd
import numpy as np
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
```

Modules used

```
df = pd.read_csv("gold_price.csv", parse_dates=True, index_col='Date')
```

```
df.head()
```

```
df['Return'] = df['USD (PM)'].pct_change() * 100
df['Lagged_Return'] = df.Return.shift()
df = df.dropna()
train = df['2001':'2018']
test = df['2019']
# Create train and test sets for dependent and independent variables
X_train = train["Lagged_Return"].to_frame()
y_train = train["Return"]
X_test = test["Lagged_Return"].to_frame()
y_test = test["Return"]
```

```
model = LinearRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

## Training the model

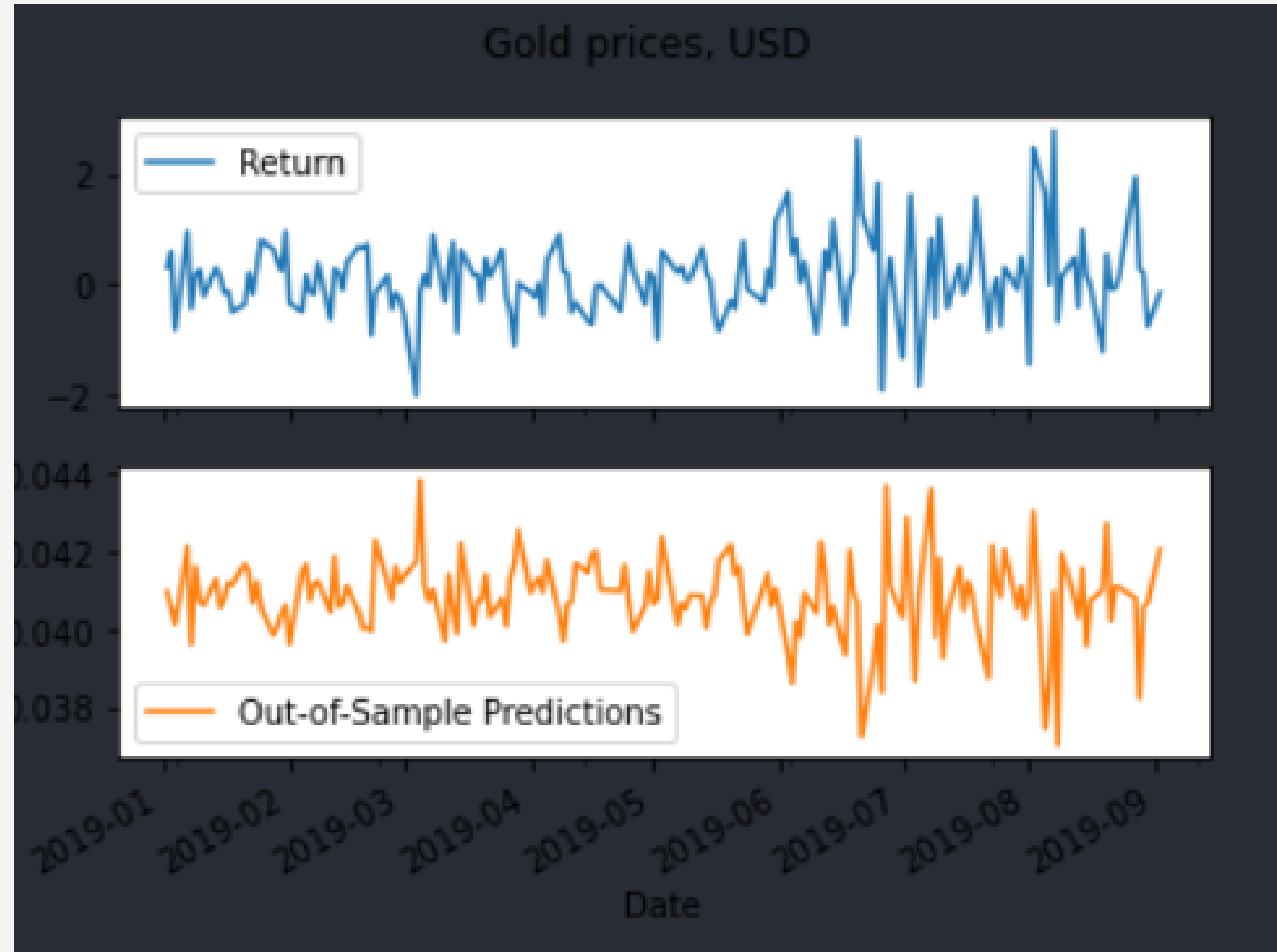
```
model = LinearRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

Saving the model  
checkpoints and  
printing the graph

```
import matplotlib.pyplot as plt
out_of_sample_results = y_test.to_frame()
```

```
out_of_sample_results["Out-of-Sample Predictions"] = model.predict(X_test)
out_of_sample_results.plot(subplots=True, title='Gold prices, USD')
plt.show()
```

## Output



# **Review 3**

```
<!DOCTYPE html>
<html>

  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1">
  <link rel="stylesheet" href="stylesheet.css">
  <link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/4.7.0/css/font-awesome.min.css">
  <link rel="preconnect" href="https://fonts.gstatic.com">
  <link href="https://fonts.googleapis.com/css2?family=Fredoka+One&family=Play&display=swap" rel="stylesheet">

<body>
  <nav class="nav">
    <div class="container">
      <div class="logo">
        <a href="#"></a>
      </div>
      <div id="mainListDiv" class="main_list">
        <ul class="navlinks">
          <li><a href="home.html">Home</a></li>
          <li><a href="google.html">Google</a></li>
          <li><a href="NFTY.html">NFTY</a></li>
          <li><a href="Microsoft.html">Microsoft</a></li>
          <li><a href="Apple.html">Apple</a></li>
          <li><a href="Gold.html">Gold</a></li>
          <li><a href="Housing.html">Housing</a></li>
        </ul>
      </div>
      <span class="navTrigger">
        <i></i>
        <i></i>
        <i></i>
      </span>
    </div>
  </nav>

  <section class="home">
  </section>
  <div style="height: 1000px">
    <!-- just to make scrolling effect possible -->
    <h2 class="myH2">Welcome to INVESTOPEDIA</h2>
    <p class="myP">This is an all in one website for investors.</p>
    <p class="myP">We have a collection of the predictions of the most common stocks people invest in and other assets such as |
    <br>
    <br>
    <br>
    <br>
    <p class="myP">Wondering how to use our platform? Here's how you can understand our product:</p>
    <p></p>
    <br>
    <br>
    <ol class="myP">
      <li>We have a range of assets available in our website. Nowadays the most common stocks that people are investing in are
      <li>Choose anyone of the following stocks and go to their respective webpage. There you will see a graph of past prices
      <li>Our model predicts the prices of tomorrow and gives you a recommendation of whether to invest or not. If it is red, |
      <li>Once you see the eye opening predictions, you can read through the small jist or reasoning as to why or why not inv
      <li>SEE!! ITS THAT EASY!!</li>
    </ol>
```

```

    <br>
    <br>
    <br>
    <p class="myP">WE HOPE YOU FIND THIS USEFULL</p>
    <p class="myP"></p>
    <p class="myP">
  </div>

  <!-- JQuery needed -->
  <script src="https://ajax.googleapis.com/ajax/libs/jquery/3.1.1/jquery.min.js"></script>
  <script src="js/scripts.js"></script>

  <!-- Function used to shrink nav bar removing paddings and adding black background -->
  <script>
    $(window).scroll(function() {
      if ($(document).scrollTop() > 50) {
        $('.nav').addClass('affix');
        console.log("OK");
      } else {
        $('.nav').removeClass('affix');
      }
    });
  </script>

  <footer>
    <div class="footer">
      <div class="row">
        <a href="#"><i class="fa fa-facebook"></i></a>
        <a href="#"><i class="fa fa-instagram"></i></a>
        <a href="#"><i class="fa fa-youtube"></i></a>
        <a href="#"><i class="fa fa-twitter"></i></a>
      </div>

      <div class="row">
        <ul>
          <li><a href="#">Contact us</a></li>
          <li><a href="#">Our Services</a></li>
          <li><a href="#">Privacy Policy</a></li>
          <li><a href="#">Terms & Conditions</a></li>
          <li><a href="#">Our product</a></li>
        </ul>
      </div>

      <div class="row">
      </div>
    </div>
  </footer>

</body>
</html>
```

Home  
webpage



```

    footer {
      text-align: center;
      padding: 3px;
      background-color: black;
      color: white;
    }

    body{
      margin:0;
      overflow-x:hidden;
    }

    .footer{
      background:black;
      padding:1px 0px;
      font-family: 'Play', sans-serif;
      text-align:center;
    }

    .footer .row{
      width:100%;
      margin:1% 0%;
      padding:0.6% 0%;
      color:gray;
      font-size:0.8em;
    }

    .footer .row a{
      text-decoration:none;
      color:gray;
      transition:0.5s;
    }

    .footer .row a:hover{
      color:white;
    }

    .footer .row ul{
      width:100%;
    }

    .footer .row ul li{
      display:inline-block;
      margin:0px 30px;
    }

    .footer .row a i{
      font-size:2em;
      margin:0% 1%;
    }

    @media (max-width:720px){
      .footer{
        text-align:left;
        padding:5%;
      }

      .footer .row ul li{
        display:block;
        margin:10px 0px;
        text-align:left;
      }

      .footer .row a i{
        margin:0% 3%;
      }
    }

    .myH2 {
      text-align:center;
      font-size: 4rem;
      color: white;
      font-size: 80px;
    }

    .myP {
      text-align: center;
      padding-left:15%;
      padding-right:15%;
      font-size: 25px;
      color: white;
    }

    .myP2 {
      text-align: center;
      padding-left:15%;
      padding-right:15%;
      font-size: 20px;
      font-weight: bold;
      color: white;
    }

    @media all and (max-width:700px){
      .myP {
        padding:2%;
      }
    }

    form {
      padding: 20px;
      display: flex;
      flex-direction: column;
      align-items: center;
      text-align: center;
    }

    label {
      margin-top: 10px;
    }

    input[type="file"] {
      margin-top: 10px;
      padding: 10px;
      border: 1px solid lightgray;
      border-radius: 5px;
      display: inline-block;
    }

    button[type="submit"] {
      margin-top: 20px;
      padding: 10px 20px;
      background-color: green;
      color: white;
      border: none;
      border-radius: 5px;
      cursor: pointer;
    }

    .imgcenter {
      display: block;
      margin-left: auto;
      margin-right: auto;
      height: 500px;
      width: 950px;
      border-radius: 3%;
    }

    @keyframes outT {
      0% {
        transform: translateY(0px) rotate(0deg);
      }
      50% {
        transform: translateY(9px) rotate(0deg);
      }
      100% {
        transform: translateY(9px) rotate(135deg);
      }
    }

    @-webkit-keyframes inBtm {
      0% {
        -webkit-transform: translateY(0px) rotate(0deg);
      }
      50% {
        -webkit-transform: translateY(-9px) rotate(0deg);
      }
      100% {
        -webkit-transform: translateY(-9px) rotate(135deg);
      }
    }

    @keyframes inBtm {
      0% {
        transform: translateY(0px) rotate(0deg);
      }
      50% {
        transform: translateY(-9px) rotate(0deg);
      }
      100% {
        transform: translateY(-9px) rotate(135deg);
      }
    }

    @-webkit-keyframes outBtm {
      0% {
        -webkit-transform: translateY(0px) rotate(0deg);
      }
      50% {
        -webkit-transform: translateY(-9px) rotate(0deg);
      }
      100% {
        -webkit-transform: translateY(-9px) rotate(135deg);
      }
    }

    @keyframes outBtm {
      0% {
        transform: translateY(0px) rotate(0deg);
      }
      50% {
        transform: translateY(-9px) rotate(0deg);
      }
      100% {
        transform: translateY(-9px) rotate(135deg);
      }
    }

    .affix {
      padding: 0;
      background-color: #111;
    }

    @keyframes inM {
      50% {
        transform: rotate(0deg);
      }
      100% {
        transform: rotate(45deg);
      }
    }

    @-webkit-keyframes outM {
      50% {
        -webkit-transform: rotate(0deg);
      }
      100% {
        -webkit-transform: rotate(45deg);
      }
    }

    @keyframes outM {
      50% {
        transform: rotate(0deg);
      }
      100% {
        transform: rotate(45deg);
      }
    }

    @-webkit-keyframes inT {
      0% {
        -webkit-transform: translateY(0px) rotate(0deg);
      }
      50% {
        -webkit-transform: translateY(9px) rotate(0deg);
      }
      100% {
        -webkit-transform: translateY(9px) rotate(135deg);
      }
    }

    @keyframes inT {
      0% {
        transform: translateY(0px) rotate(0deg);
      }
      50% {
        transform: translateY(9px) rotate(0deg);
      }
      100% {
        transform: translateY(9px) rotate(135deg);
      }
    }

    @-webkit-keyframes outT {
      0% {
        -webkit-transform: translateY(0px) rotate(0deg);
      }
      50% {
        -webkit-transform: translateY(9px) rotate(0deg);
      }
      100% {
        -webkit-transform: translateY(9px) rotate(135deg);
      }
    }

    @import url('https://fonts.googleapis.com/css?family=Quicksand:400,500,700');
    html,
    body {
      margin: 0;
      padding: 0;
      box-sizing: border-box;
      font-family: "Quicksand", sans-serif;
      font-size: 62.5%;
      font-size: 10px;
      background: linear-gradient(to top right, transparent 49%, #000080 49%, #000080 51%, #000000 51%, #000000 53%, #000000 55%, #000000 57%, #000000 59%, #000000 61%, #000000 63%, #000000 65%, #000000 67%, #000000 69%, #000000 71%, #000000 73%, #000000 75%, #000000 77%, #000000 79%, #000000 81%, #000000 83%, #000000 85%, #000000 87%, #000000 89%, #000000 91%, #000000 93%, #000000 95%, #000000 97%, #000000 99%, #000000 100%);
      background: radial-gradient(circle, #000000 0%, #000000 0.39, 194, 1);
    }

    /*-- Inspiration taken from abdo steif -->
    /* --> https://codepen.io/abdosteif/pen/bRoyMb?editors=1100*/

    /* Navbar section */

    .nav {
      width: 100%;
      height: 65px;
      position: fixed;
      line-height: 65px;
      text-align: center;
    }

    .nav div.logo {
      float: left;
      width: auto;
      height: auto;
      padding-left: 3rem;
    }

    .nav div.logo a {
      text-decoration: none;
      color: white;
      font-size: 2.5rem;
    }

    .nav div.logo a:hover {
      color: #c5fad5;
    }

    .nav div.main_list {
      height: 65px;
      float: right;
    }

    .nav div.main_list ul {
      width: 100%;
      height: 65px;
      display: flex;
      list-style: none;
      margin: 0;
      padding: 0;
    }

    .nav div.main_list ul li {
      width: auto;
      height: 65px;
      padding: 0;
      padding-right: 3rem;
    }

    .nav div.main_list ul li a {
      text-decoration: none;
      color: white;
      line-height: 65px;
      font-size: 2.4rem;
    }
  
```

CSS file for  
our webpage

```

from sklearn.datasets import load_boston
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
df = load_boston()
dataset = pd.DataFrame(df.data)
dataset.head()
dataset.shape
target = df.target
target.shape
dataset.isnull().sum()
dataset.columns = df.feature_names
dataset["Price"] = target
X = dataset.loc[:, : 'LSTAT']    # independent features
y = dataset.loc[:, 'Price']      # dependent features
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score    # Cross Validation
lin_regression = LinearRegression()
mse = cross_val_score(lin_regression, X, y, scoring='neg_mean_squared_error', cv=5)
print(type(mse))
mse = np.mean(mse)    # we will get the five values, then we calculate the mean
print(mse)
#ridge regression
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV    # to find the value of 'lambda'

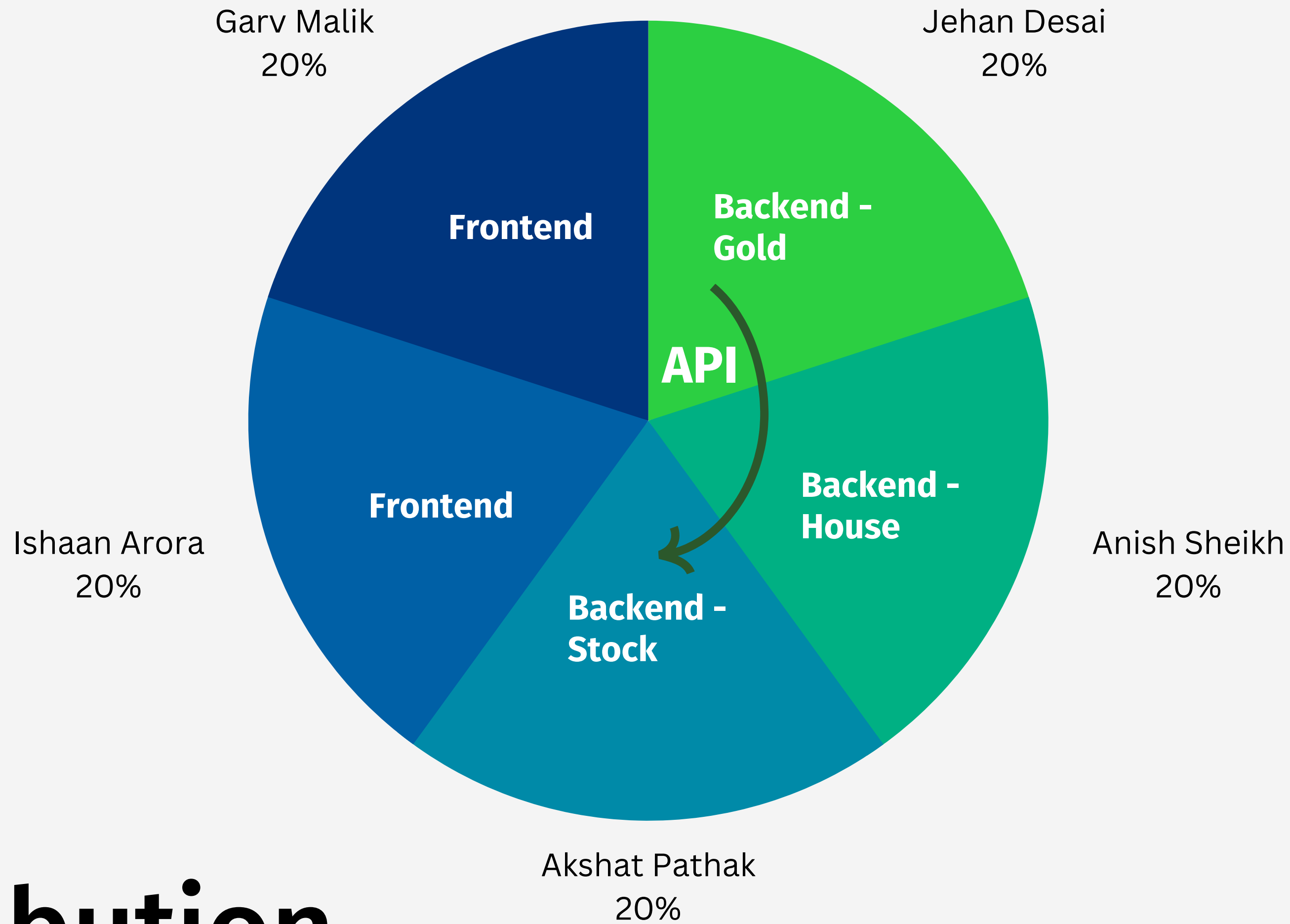
ridge = Ridge()
parameters = {'alpha': [1e-15, 1e-10, 1e-8, 1e-3, 1e-2, 1, 5, 10, 20, 30, 35, 40, 45, 50, 55, 100]}
ridge_regressor = GridSearchCV(ridge, parameters, scoring='neg_mean_squared_error', cv=5)
ridge_regressor.fit(X, y)
#Lasso regression
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV

lasso = Lasso()
parameters = {'alpha': [1e-15, 1e-10, 1e-8, 1e-3, 1e-2, 1, 5, 10, 20, 30, 35, 40, 45, 50, 55, 100]}
lasso_regressor = GridSearchCV(lasso, parameters, scoring='neg_mean_squared_error', cv=5)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
prediction_lasso = lasso_regressor.predict(X_test)
prediction_ridge = ridge_regressor.predict(X_test)

```

## House prediction model using 3 different regressions

1. Linear regression
2. Ridge regression
3. Lasso regression



# Contribution

**THANK YOU**

