assignment_2

February 9, 2021

[5]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
data = pd.read_csv("./EURUSD=X.csv")
```

Step 1: Examine the dataset

[6]:

```python
print(data.dtypes)
data.head(3)
```

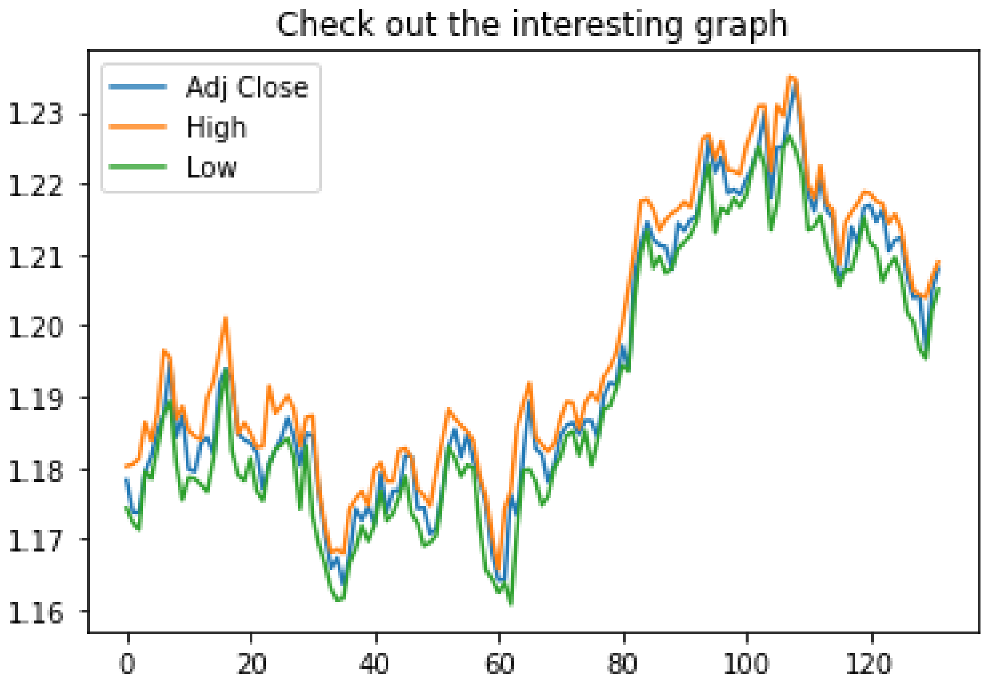
```
Date           object
Open          float64
High          float64
Low           float64
Close         float64
Adj Close     float64
Volume          int64
dtype: object
```

[6]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2020-08-10	1.178245	1.180200	1.174300	1.178273	1.178273	0
1	2020-08-11	1.173764	1.180498	1.172319	1.173778	1.173778	0
2	2020-08-12	1.173985	1.181265	1.171303	1.173654	1.173654	0

[18]:

```python
plt.plot(range(len(data["Date"])), data["Adj Close"], label = "Adj Close")
plt.plot(range(len(data["Date"])), data["High"], label = "High")
plt.plot(range(len(data["Date"])), data["Low"], label = "Low")
plt.title('Check out the interesting graph')
plt.legend()
plt.show()
```



Step 2: Linear Regression, Gradient Descent, Self Implemented

derivation Let cost function be: $c = \sum_{k=1}^{M} \|y_k - w^T x_k\|_2^2$, then getting it in the matrix form, such that: $X = [\vec{f}_1, ..., \vec{f}_N, \vec{1}]$ where f_i are feature vectors. In this case we have that:

$$c = (X\vec{w} - \vec{t})^T(X\vec{w} - \vec{t}) = \vec{w}^T X^T X\vec{w} - \vec{w}^T X^T t - \vec{t}^T X\vec{w} + \vec{t}^T\vec{t}$$

$$= \vec{w}^T X^T X\vec{w} - 2\vec{w}^T X^T t + \vec{t}^T\vec{t}$$

Again taking gradient, we see that: $D_{\vec{w}}c = 2(X^T X\vec{w} - X^T\vec{t})$. We will adopt the simplest descent algorithm.

[79]:
```
class regressor:
    def __init__(self):
        self.w = None

    def train(self, dtrain, labels, n_epochs, gamma):
        if dtrain.shape[0] != labels.shape[0]:
            print("Erorr: training set and label set must have same length")
            return

        if n_epochs <= 0:
            print("enter training rounds at least 1")
            return

        if gamma > 1 or gamma <= 0:
```

```
            print("please enter the correct learning rate")
            return

        w = np.zeros(dtrain.shape[1])
        X = dtrain
        y = labels
        for _ in range(n_epochs):
            w = w - (2 * gamma) * (np.dot(np.dot(X.T, X), w) - np.dot(X.T, y))

        self.w = w

    def predict(self, dtest):
        if not dtest:
            return
```

Step 3: Split training and testing set

[136]:
```
labels = data["Adj Close"].values
print(labels.shape, type(labels))
```

```
(132,) <class 'numpy.ndarray'>
```

[137]:
```
dtrain = [[i] for i in range(len(data["Date"]))]
dtrain = np.asarray(dtrain)
dtrain = np.append(dtrain, np.ones((len(data["Date"]), 1)), axis = 1)
print("Shape of training data is: {}".format(dtrain.shape))
print(dtrain[:3,:])
```

```
Shape of training data is: (132, 2)
[[0. 1.]
 [1. 1.]
 [2. 1.]]
```

[141]:
```
X_train = dtrain
y_train = labels
print(X_train.shape, y_train.shape)
```

```
(132, 2) (132,)
```

Step4: Build the model and start the training

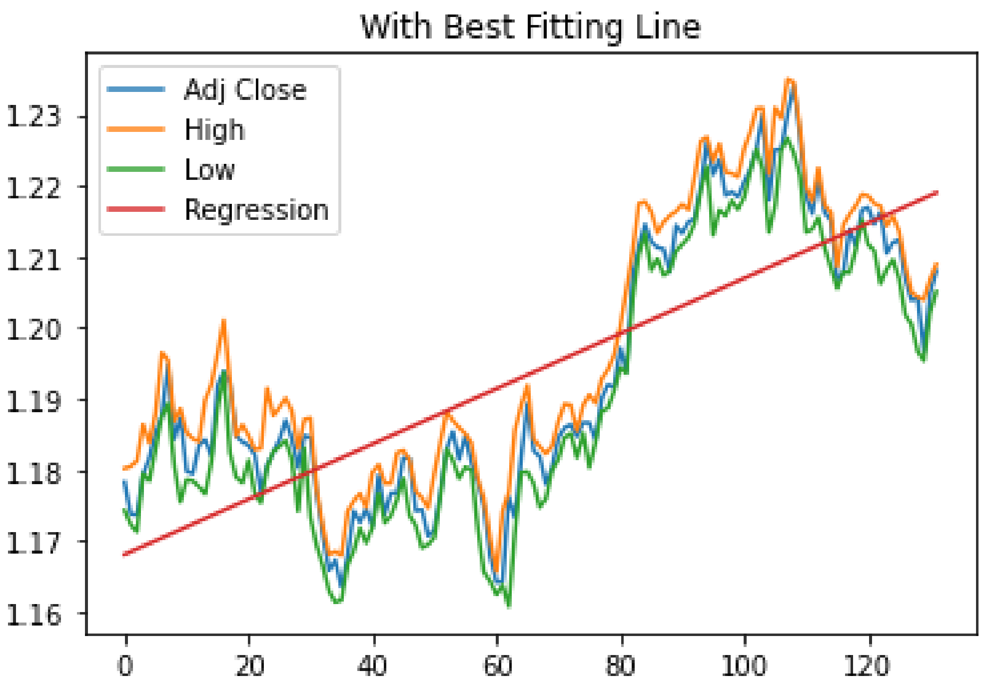
[142]:
```
n_epochs = 100000
gamma = 1e-6
model = regressor()
model.train(X_train, y_train, n_epochs, gamma)
```

[144]:
```
w = model.w
```

Step5: Draw the graphs

[147]:
```
preds = [(x * w[0]) + w[1] for x in range(len(data["Date"]))]
```

[148]:
```
plt.plot(range(len(data["Date"])), data["Adj Close"], label = "Adj Close")
plt.plot(range(len(data["Date"])), data["High"], label = "High")
plt.plot(range(len(data["Date"])), data["Low"], label = "Low")
plt.plot(range(len(data["Date"])), preds, label = "Regression")
plt.title('With Best Fitting Line')
plt.legend()
plt.show()
```



0.1 DISCLAIMER:

Some version of gradient disappearence occurs. In normal regresison we'll probably scale the feature vectors within a sphere, but this is kind of tricky with time as our features. The usual way to deal with this is to use time series techniques.