TIMESERIES PREDICTION - APPLICATIONS TO ADA AND BTC

Introduction

Cardano is a cryptocurrency network and open source project that aims to run a public blockchain platform for smart contracts. Cardano's internal cryptocurrency is called Ada. The development of the project is overseen and supervised by the Cardano Foundation based in Zug, Switzerland.

The platform began development in 2015 and was launched in 2017 by Charles Hoskinson, a co-founder of Ethereum and BitShares. According to Hoskinson, he had left Ethereum after a dispute over keeping Ethereum nonprofit. After leaving he co-founded IOHK, a blockchain engineering company, whose primary business is the development of Cardano, alongside the Cardano Foundation and Emurgo.The platform is named after Gerolamo Cardano and the cryptocurrency after Ada Lovelace.

The currency debuted with a market cap of 600 million dollars. By the end of 2017, it had a market cap of 10 billion dollars, and reached a value of 33 billion dollars briefly in 2018 before a general tightening of the crypto market dropped its value back to 10 billion dollars. According to Mashable, Cardano claims that it overcomes existing problems in the crypto market: mainly that Bitcoin is too slow and inflexible, and that Ethereum is not safe or scalable. Cardano is considered a third-generation cryptocurrency by its creators.

1 Understand the problem and import the more important libraries

I want to compare ADA with BTC (Bitcoin) which all of you should know. If not: https://en.wikipedia.org/wiki/Bitcoin

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

First of all I downloaded both datasets and import them to the project. I took data from Jan 2018 ultil Feb 2021.

In [2]:
```
#Load de data
cardano_hst = pd.read_csv('C:/Users/torre/OneDrive/Escritorio/PERSONAL/DATA SCIENCE/Ca
cardano_hst.head()
```

Out[2]:

	Date	Price	Open	High	Low	Vol.	Change %
0	Feb 20, 2021	1.149122	0.925955	1.176955	0.914190	1.80B	24.11%
1	Feb 19, 2021	0.925894	0.913695	0.945353	0.880769	839.10M	1.33%
2	Feb 18, 2021	0.913752	0.891719	0.956599	0.891719	904.68M	2.47%
3	Feb 17, 2021	0.891702	0.870390	0.897079	0.823855	750.02M	2.45%
4	Feb 16, 2021	0.870393	0.859853	0.905065	0.834791	929.87M	1.19%

We got the Closed attribute ase Price

In [3]:
```
bitcoin_hst = pd.read_csv('C:/Users/torre/OneDrive/Escritorio/PERSONAL/DATA SCIENCE/Ca
bitcoin_hst.head()
```

Out[3]:

	Date	Price	Open	High	Low	Vol.	Change %
0	Feb 20, 2021	55923.7	55922.0	57523.8	54124.1	127.85K	0.03%
1	Feb 19, 2021	55906.6	51590.1	56238.5	50816.8	139.43K	8.38%
2	Feb 18, 2021	51582.2	52094.5	52524.0	50941.6	94.35K	-0.95%
3	Feb 17, 2021	52079.2	49161.3	52577.7	49018.1	140.03K	5.92%
4	Feb 16, 2021	49169.7	47934.2	50515.8	47044.4	141.37K	2.57%

In [4]:
```
cardano_hst.shape
```

Out[4]:
```
(1148, 7)
```

In [5]:
```
bitcoin_hst.shape
```

Out[5]:
```
(1148, 7)
```

In [6]:
```
cardano_hst.describe()
```

Out[6]:

	Price	Open	High	Low
count	1148.000000	1148.000000	1148.000000	1148.000000
mean	0.133454	0.133274	0.140585	0.124751
std	0.160964	0.160209	0.173440	0.144590
min	0.023222	0.023225	0.026454	0.017774
25%	0.045895	0.045884	0.047424	0.044232
50%	0.081616	0.081616	0.084058	0.078212
75%	0.143326	0.143324	0.148790	0.137339
max	1.149122	1.180000	1.350000	1.050000

We can get from this data indicators that the historical maximum is 1.35 but never closed like that or even higher that 1.149122. Also we can see that the std (standard deviation) is higher on 'High' than in the other ones so that mean the cryptocurrency market fluctuate more on higher values.

In [7]:
```
bitcoin_hst.describe()
```

Out[7]:

	Price	Open	High	Low
count	1148.000000	1148.000000	1148.000000	1148.000000
mean	10023.177003	9985.070035	10278.126394	9684.443118
std	7313.543011	7186.251726	7540.971388	6895.392082
min	3228.700000	3228.600000	3282.300000	3177.000000
25%	6597.875000	6597.575000	6708.500000	6472.175000
50%	8544.700000	8544.800000	8743.650000	8243.850000
75%	10405.225000	10404.775000	10736.575000	10130.675000
max	55923.700000	55922.000000	57523.800000	54124.100000

2 Data Preparation

In [8]:
```
cardano_hst = cardano_hst.rename(columns={"Vol.": "Vol","Change %": "Change"})
bitcoin_hst = bitcoin_hst.rename(columns={"Vol.": "Vol","Change %": "Change"})
```

In [9]:
```
cardano_hst.head()
```

Out[9]:

	Date	Price	Open	High	Low	Vol	Change
0	Feb 20, 2021	1.149122	0.925955	1.176955	0.914190	1.80B	24.11%
1	Feb 19, 2021	0.925894	0.913695	0.945353	0.880769	839.10M	1.33%
2	Feb 18, 2021	0.913752	0.891719	0.956599	0.891719	904.68M	2.47%
3	Feb 17, 2021	0.891702	0.870390	0.897079	0.823855	750.02M	2.45%
4	Feb 16, 2021	0.870393	0.859853	0.905065	0.834791	929.87M	1.19%

In [10]:
```
import datetime

# Convert Date to datetime
cardano_hst['Date'] = pd.to_datetime(cardano_hst['Date'])
cardano_hst['Crypto'] = 'ADA'
bitcoin_hst['Date'] = pd.to_datetime(bitcoin_hst['Date'])
bitcoin_hst['Crypto'] = 'BTC'
```

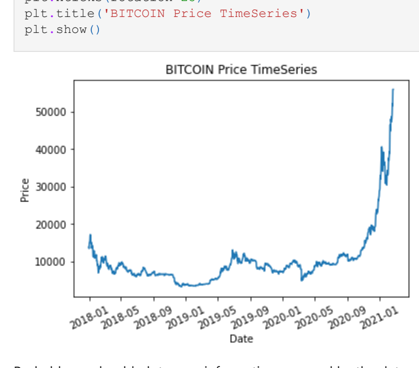
I'll probably want to concatenate both datasets so thats why I created the Crypto attribute to differentiate rows.

In [11]:
```
cardano_hst.head()
```

Out[11]:

	Date	Price	Open	High	Low	Vol	Change	Crypto
0	2021-02-20	1.149122	0.925955	1.176955	0.914190	1.80B	24.11%	ADA
1	2021-02-19	0.925894	0.913695	0.945353	0.880769	839.10M	1.33%	ADA
2	2021-02-18	0.913752	0.891719	0.956599	0.891719	904.68M	2.47%	ADA
3	2021-02-17	0.891702	0.870390	0.897079	0.823855	750.02M	2.45%	ADA
4	2021-02-16	0.870393	0.859853	0.905065	0.834791	929.87M	1.19%	ADA

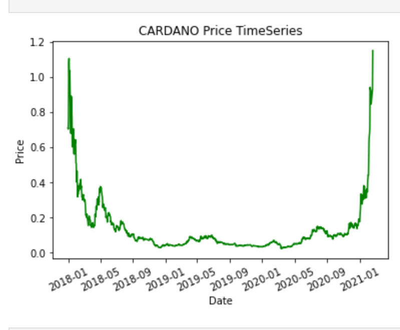
In [12]:
```
import seaborn as sns

sns.lineplot(x='Date', y='Price', data=bitcoin_hst)
plt.xticks(rotation=25)
plt.title('BITCOIN Price TimeSeries')
plt.show()
```



Probably we should plot some information grouped by the date sub-attributes so that's why the next code.

In [13]:
```
cardano_hst = cardano_hst.set_index('Date')

cardano_hst['Year'] = cardano_hst.index.year
cardano_hst['Month'] = cardano_hst.index.month
cardano_hst['Day'] = cardano_hst.index.day
```

In [14]:
```
sns.lineplot(x="Date", y="Price", data=cardano_hst, color='green')
plt.xticks(rotation=25)
plt.title('CARDANO Price TimeSeries')
plt.show()
```



In [15]:
```
bitcoin_hst['Change'] = bitcoin_hst['Change'].str.replace('%', '')
bitcoin_hst['Vol'] = bitcoin_hst['Vol'].str.replace('B', '000000000')
bitcoin_hst['Vol'] = bitcoin_hst['Vol'].str.replace('M', '000000')
bitcoin_hst['Vol'] = bitcoin_hst['Vol'].str.replace('K', '000')
bitcoin_hst['Vol'] = bitcoin_hst['Vol'].str.replace('.', '')
#bitcoin_hst = bitcoin_hst.drop(columns=['Date'])
```

```
<ipython-input-15-afd584413ff3>:5: FutureWarning: The default value of regex will chan
ge from True to False in a future version. In addition, single character regular expre
ssions will*not* be treated as literal strings when regex=True.
  bitcoin_hst['Vol'] = bitcoin_hst['Vol'].str.replace('.', '')
```

In [16]:
```
bitcoin_hst.head()
```

Out[16]:

	Date	Price	Open	High	Low	Vol	Change	Crypto
0	2021-02-20	55923.7	55922.0	57523.8	54124.1	12785000	0.03	BTC
1	2021-02-19	55906.6	51590.1	56238.5	50816.8	13943000	8.38	BTC
2	2021-02-18	51582.2	52094.5	52524.0	50941.6	9435000	-0.95	BTC
3	2021-02-17	52079.2	49161.3	52577.7	49018.1	14003000	5.92	BTC
4	2021-02-16	49169.7	47934.2	50515.8	47044.4	14137000	2.57	BTC

In [17]:
```
cardano_hst['Change'] = cardano_hst['Change'].str.replace('%', '')
cardano_hst['Vol'] = cardano_hst['Vol'].str.replace('B', '000000000')
cardano_hst['Vol'] = cardano_hst['Vol'].str.replace('M', '000000')
cardano_hst['Vol'] = cardano_hst['Vol'].str.replace('.', '')
#cardano_hst = cardano_hst.drop(columns=['Date'])
```

```
<ipython-input-17-9f8d90b4cd53>:4: FutureWarning: The default value of regex will chan
ge from True to False in a future version. In addition, single character regular expre
ssions will*not* be treated as literal strings when regex=True.
  cardano_hst['Vol'] = cardano_hst['Vol'].str.replace('.', '')
```

In [18]:
```
cardano_hst.head()
```

Out[18]:

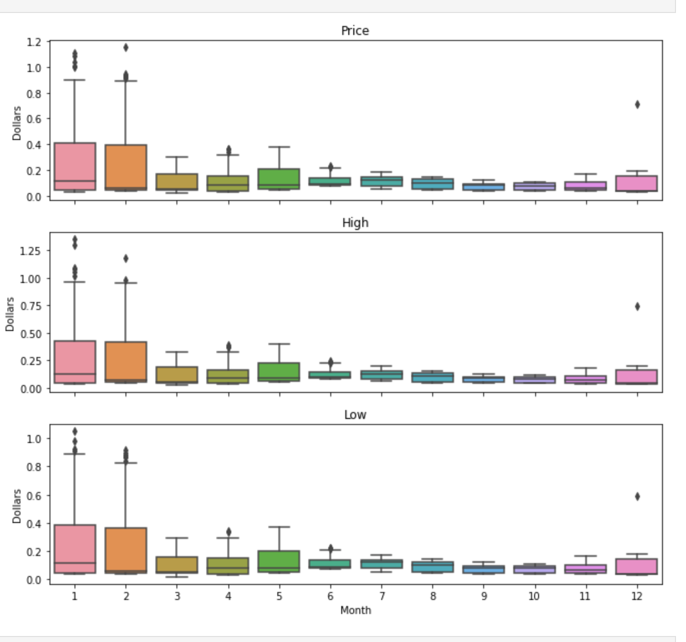
Date	Price	Open	High	Low	Vol	Change	Crypto	Year	Month	Day
2021-02-20	1.149122	0.925955	1.176955	0.914190	180000000000	24.11	ADA	2021	2	20
2021-02-19	0.925894	0.913695	0.945353	0.880769	83910000000	1.33	ADA	2021	2	19
2021-02-18	0.913752	0.891719	0.956599	0.891719	90468000000	2.47	ADA	2021	2	18
2021-02-17	0.891702	0.870390	0.897079	0.823855	75002000000	2.45	ADA	2021	2	17
2021-02-16	0.870393	0.859853	0.905065	0.834791	92987000000	1.19	ADA	2021	2	16

In [19]:
```
cardano_hst.isnull().any()
```

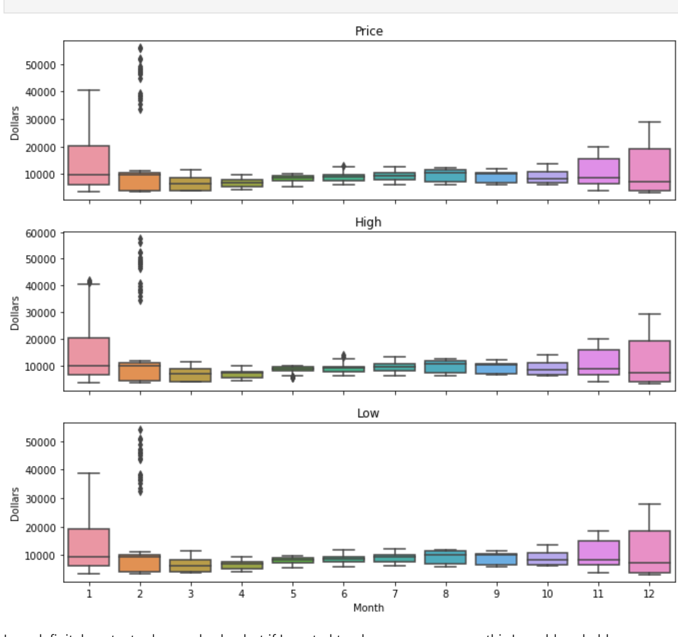
Out[19]:
```
Price     False
Open      False
High      False
Low       False
Vol       False
Change    False
Crypto    False
Year      False
Month     False
Day       False
dtype: bool
```

4 Data Analysis for ADA

In [20]:
```
cardano_hst['Month'] = cardano_hst.index.month

ig, axes = plt.subplots(3, 1, figsize=(11, 10), sharex=True)
for name, ax in zip(['Price', 'High', 'Low'], axes):
    sns.boxplot(data=cardano_hst, x='Month', y=name, ax=ax)
    ax.set_ylabel('Dollars')
    ax.set_title(name)
    # Remove the automatic x-axis label from all but the bottom subplot
    if ax != axes[-1]:
        ax.set_xlabel('')
```



In [21]:
```
bitcoin_hst = bitcoin_hst.set_index('Date')
bitcoin_hst['Month'] = bitcoin_hst.index.month

ig, axes = plt.subplots(3, 1, figsize=(11, 10), sharex=True)
for name, ax in zip(['Price', 'High', 'Low'], axes):
    sns.boxplot(data=bitcoin_hst, x='Month', y=name, ax=ax)
    ax.set_ylabel('Dollars')
    ax.set_title(name)
    # Remove the automatic x-axis label from all but the bottom subplot
    if ax != axes[-1]:
        ax.set_xlabel('')
```



I am definitely not a trader or a broker but if I wanted to play some money on this I would probably earn more money on January, February, May and December for ADA and the same for BTC but November instead of May.

In [22]:
```
cardano_hst.dtypes
```

Out[22]:
```
Price      float64
Open       float64
High       float64
Low        float64
Vol         object
Change      object
Crypto      object
Year         int64
Month        int64
Day          int64
dtype: object
```

In [23]:
```
print (cardano_hst[pd.to_numeric(cardano_hst.Vol, errors='coerce').isnull()])
```

```
               Price      Open      High       Low Vol Change Crypto  Year  \
Date
2021-01-14  0.311028  0.312734  0.324066  0.298576   -  -0.55    ADA  2021

            Month  Day
Date
2021-01-14      1   14
```

In [24]:
```
cardano_hst = cardano_hst[~cardano_hst.Vol.str.contains("-")]
```

In [25]:
```
print (cardano_hst[pd.to_numeric(cardano_hst.Change, errors='coerce').isnull()])
```

```
Empty DataFrame
Columns: [Price, Open, High, Low, Vol, Change, Crypto, Year, Month, Day]
Index: []
```

In [26]:
```
cardano_hst.loc['Vol'] = pd.to_numeric(cardano_hst['Vol'])
cardano_hst.loc['Change'] = pd.to_numeric(cardano_hst['Change'])
```

In [27]:
```
cardano_hst.dtypes
```

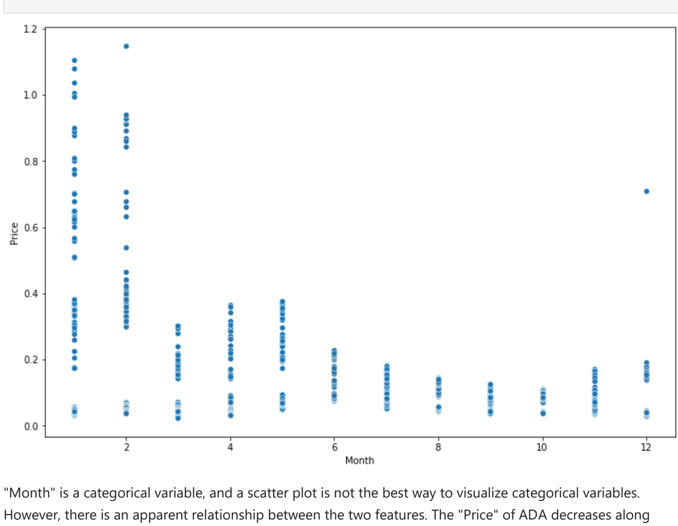
Out[27]:
```
Price      float64
Open       float64
High       float64
Low        float64
Vol         object
Change      object
Crypto      object
Year       float64
Month      float64
Day        float64
dtype: object
```

In [28]:
```
(cardano_hst.corr()**2)["Price"].sort_values(ascending = False)[1:]
```

Out[28]:
```
High     0.994051
Low      0.990196
Open     0.984712
Month    0.133492
Year     0.003404
Day      0.002516
Name: Price, dtype: float64
```

In [29]:
```
def customized_scatterplot(y, x):
        ## Sizing the plot.
    #style.use('fivethirtyeight')
    plt.subplots(figsize = (12,8))
    ## Plotting target variable with predictor variable(OverallQual)
    sns.scatterplot(y = y, x = x);
```

In [30]:
```
customized_scatterplot(cardano_hst.Price, cardano_hst.Month)
```



"Month" is a categorical variable, and a scatter plot is not the best way to visualize categorical variables. However, there is an apparent relationship between the two features. The "Price" of ADA decreases along the year. Let's check out some more features to determine the outliers.

4 Feature Engineering

I want to keep the "Month" attribute onto the training dataset so I'll convert it into dummy indicator/variable

In [31]:
```
# Read the data
train = cardano_hst
```

In [32]:
```
train.head()
```

Out[32]:

Date	Price	Open	High	Low	Vol	Change	Crypto	Year	Month	Day
2021-02-20 00:00:00	1.149122	0.925955	1.176955	0.914190	180000000000	24.11	ADA	2021.0	2.0	20.0
2021-02-19 00:00:00	0.925894	0.913695	0.945353	0.880769	83910000000	1.33	ADA	2021.0	2.0	19.0
2021-02-18 00:00:00	0.913752	0.891719	0.956599	0.891719	90468000000	2.47	ADA	2021.0	2.0	18.0
2021-02-17 00:00:00	0.891702	0.870390	0.897079	0.823855	75002000000	2.45	ADA	2021.0	2.0	17.0
2021-02-16 00:00:00	0.870393	0.859853	0.905065	0.834791	92987000000	1.19	ADA	2021.0	2.0	16.0

In [33]:
```
dummy = pd.get_dummies(train['Month'])
```

In [34]:
```
train = pd.concat([train, dummy], axis=1)
train.head()
```

Out[34]:

Date	Price	Open	High	Low	Vol	Change	Crypto	Year	Month	Day	...	3.0
2021-02-20 00:00:00	1.149122	0.925955	1.176955	0.914190	180000000000	24.11	ADA	2021.0	2.0	20.0	...	0
2021-02-19 00:00:00	0.925894	0.913695	0.945353	0.880769	83910000000	1.33	ADA	2021.0	2.0	19.0	...	0
2021-02-18 00:00:00	0.913752	0.891719	0.956599	0.891719	90468000000	2.47	ADA	2021.0	2.0	18.0	...	0
2021-02-17 00:00:00	0.891702	0.870390	0.897079	0.823855	75002000000	2.45	ADA	2021.0	2.0	17.0	...	0
2021-02-16 00:00:00	0.870393	0.859853	0.905065	0.834791	92987000000	1.19	ADA	2021.0	2.0	16.0	...	0

5 rows × 22 columns

In [35]:
```
print(train.columns)
```

```
Index([ 'Price',   'Open',   'High',    'Low',    'Vol', 'Change', 'Crypto',
         'Year',  'Month',    'Day',      1.0,      2.0,      3.0,      4.0,
            5.0,      6.0,      7.0,      8.0,      9.0,     10.0,     11.0,
           12.0],
      dtype='object')
```

Check for null rows values

In [36]:
```
train['Open'].isnull().values.any()
```

Out[36]:
```
True
```

In [84]:
```
#train['Low'].isnull().sum()
```

In [38]:
```
train.isnull().sum().sum()
```

Out[38]:
```
20
```

In [39]:
```
train = train.dropna()
```

In [ ]:

5 Time Series Forecasting using LinearRegression

In statistics, linear regression is a linear approach to modelling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called simple linear regression; for more than one, the process is called multiple linear regression. [https://en.wikipedia.org/wiki/Linear_regression]

In this first approach we just want to build a model with one predictor (simple). The most significant one is "Open" so lets have a look!

In [85]:
```
y = train.Price
predictor_col = ['Open']

# Create training predictors data
X = train[predictor_col]
```

In [86]:
```
X.head()
```

Out[86]:

Date	Open
2021-02-20 00:00:00	0.925955
2021-02-19 00:00:00	0.913695
2021-02-18 00:00:00	0.891719
2021-02-17 00:00:00	0.870390
2021-02-16 00:00:00	0.859853

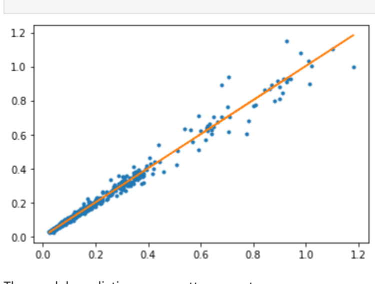
In [87]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size = .25, random_state
```

In [88]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error

## Call in the LinearRegression object
lin_reg = LinearRegression(normalize=True, n_jobs=-1)
## fit train and test data.
lin_reg.fit(X_train, y_train)
## Predict test data.
y_pred = lin_reg.predict(X_test)
#y_pred = lin_reg.predict(X_test)
```

In [91]:
```
from sklearn.metrics import mean_squared_error, r2_score

# The mean squared error
print('Mean squared error: %.2f'
      % mean_squared_error(y_test, y_pred).round(4))
# The coefficient of determination: 1 is perfect prediction
print('Coefficient of determination: %.2f'
      % r2_score(y_test, y_pred).round(4))
print('Train accuracy: %.2f'
      % lin_reg.score(X_train, y_train).round(4))
print('Test accuracy: %.2f'
      % lin_reg.score(X_test, y_test).round(4))
```

```
Mean squared error: 0.00
Coefficient of determination: 0.99
Train accuracy: 0.98
Test accuracy: 0.99
```

In [92]:
```
# Plot outputs
plt.plot(X.Open, y.values,'.')
plt.plot(X.Open, lin_reg.predict(X),'-')
plt.show()
```



The model predictions are pretty accurate

5 Time Series Forecasting using Ridge

In [ ]:
```
# pull data into target (y) and predictors (X)
y = train.Price
predictor_cols = ['Open']#, 'High', 'Low', 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, 9.

# Create training predictors data
X = train[predictor_cols]

#my_model = RandomForestRegressor()
#my_model.fit(train_X, train_y)
```

In [ ]:
```
#plt3d = plt.figure().gca(projection='3d')
#plt3d.view_init(azim=5)
#plt3d.plot_trisurf(X['Open'].values, X['High'].values, lin_reg.predict(X), alpha=0.7
```

This model solves a regression model where the loss function is the linear least squares function and regularization is given by the l2-norm. Also known as Ridge Regression or Tikhonov regularization. This estimator has built-in support for multi-variate regression (i.e., when y is a 2d-array of shape (n_samples, n_targets)).

Linear least squares with l2 regularization.

Minimizes the objective function:

||y - Xw||^2_2 + alpha * ||w||^2_2

In [149…
```
from sklearn.linear_model import Ridge

clf = Ridge(alpha=1.0)
## fit train and test data.
clf.fit(X_train, y_train)
## Predict test data.
y_pred_ridge = clf.predict(X_test)
```

In [154…
```
from sklearn.ensemble import RandomForestRegressor
```

In [ ]: