In [80]:

```
import pandas as pd
import quandl
import math, datetime
import numpy as np
from sklearn import preprocessing, model_selection ,svm
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
from matplotlib import style
import random
```

In [79]:

```
style.use('ggplot')
```

with preprocessing we can keep our features between -1 to +1

In [3]:

```
df=quandl.get("WIKI/GOOGL")
```

In [4]:

```
df.head()
```

Out[4]:

	Open	High	Low	Close	Volume	Ex-Dividend	Split Ratio	Adj. Open	Adj. High	Adj. Low	Adj. Close	Adj. Volume
Date												
2004-08-19	100.01	104.06	95.96	100.335	44659000.0	0.0	1.0	50.159839	52.191109	48.128568	50.322842	44659000.0
2004-08-20	101.01	109.08	100.50	108.310	22834300.0	0.0	1.0	50.661387	54.708881	50.405597	54.322689	22834300.0
2004-08-23	110.76	113.48	109.05	109.400	18256100.0	0.0	1.0	55.551482	56.915693	54.693835	54.869377	18256100.0
2004-08-24	111.24	111.60	103.57	104.870	15247300.0	0.0	1.0	55.792225	55.972783	51.945350	52.597363	15247300.0
2004-08-25	104.76	108.00	103.88	106.000	9188600.0	0.0	1.0	52.542193	54.167209	52.100830	53.164113	9188600.0

In [6]:

```
df.columns
```

Out[6]:

```
Index(['Open', 'High', 'Low', 'Close', 'Volume', 'Ex-Dividend', 'Split Ratio',
       'Adj. Open', 'Adj. High', 'Adj. Low', 'Adj. Close', 'Adj. Volume'],
      dtype='object')
```

Discarding the irrerelevant features

In [7]:

```
df=df[['Adj. Open', 'Adj. High', 'Adj. Low', 'Adj. Close', 'Adj. Volume']]
```

In [8]:

```
df["HL_PCT"]= (df["Adj. High"]  - df["Adj. Close"])/ df["Adj. Close"]*100 #calculating the high-low
```

```
percentage
```

In [9]:

```
df["PCT_change"]= (df["Adj. Close"]  - df["Adj. Open"])/ df["Adj. Open"]*100 #calculating the high-
low percentage
```

In [10]:

```
df=df[["Adj. Close","HL_PCT", "PCT_change","Adj. Volume" ]]
```

In [11]:

```
df.head()
```

Out[11]:

	Adj. Close	HL_PCT	PCT_change	Adj. Volume
Date				
2004-08-19	50.322842	3.712563	0.324968	44659000.0
2004-08-20	54.322689	0.710922	7.227007	22834300.0
2004-08-23	54.869377	3.729433	-1.227880	18256100.0
2004-08-24	52.597363	6.417469	-5.726357	15247300.0
2004-08-25	53.164113	1.886792	1.183658	9188600.0

In [12]:

```
forecast_col='Adj. Close'
```

In [13]:

```
df.fillna(-9999 , inplace= True) #to fill the nan values with some outlier value instead of
removing the values because removing them will be expensive
```

In [39]:

```
forecast_out= int(math.ceil(0.1*len(df))) #math.ceil will round-off the value to the nearest
integer greater than then the value
#say 0.2 then math.ceil will give 1.0
#ceil will return the float value and we will convert it in integer with int
print(forecast_out)
```

```
31
```

so when we make predictions we are make predictions 31days ahead

In [27]:

```
df['label']= df[forecast_col].shift(-forecast_out)
#shifting the column negatively or shifted up so this way our adjusted close will be 0.1 or 10days
into the future
```

In [28]:

```
df.head()
```

Out[28]:

	Adj. Close	HL_PCT	PCT_change	Adj. Volume	label
Date					

Date	Adj. Close	HL_PCT	PCT_change	Adj. Volume	label
2004-08-19	50.322842	3.712563	0.324968	44659000.0	67.739104
2004-08-20	54.322689	0.710922	7.227007	22834300.0	69.399229
2004-08-23	54.869377	3.729433	-1.227880	18256100.0	68.752232
2004-08-24	52.597363	6.417469	-5.726357	15247300.0	69.639972
2004-08-25	53.164113	1.886792	1.183658	9188600.0	69.078238

In [29]:

```
df.dropna(inplace=True)
df.tail()
```

Out[29]:

Date	Adj. Close	HL_PCT	PCT_change	Adj. Volume	label
2016-09-22	815.95	0.381151	0.734568	1759290.0	781.10
2016-09-23	814.96	0.250319	-0.022082	1411673.0	802.03
2016-09-26	802.65	0.925684	-0.885382	1472732.0	811.98
2016-09-27	810.73	0.340434	1.109961	1367271.0	805.59
2016-09-28	810.06	0.023455	0.743707	1470280.0	780.29

Now we will define our X(features) and y(output)

In [33]:

```
X=np.array(df.drop(["label"],1))
y=np.array(df["label"])
```

In [34]:

```
X=preprocessing.scale(X)
```

In [35]:

```
print(len(X), len(y))
```

```
3050 3050
```

Split the data into training and testing

In [36]:

```
X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0.2)
```

In [41]:

```
clf_lr=LinearRegression()
clf_lr.fit(X_train, y_train)
```

Out[41]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [44]:

```
accuracy_lr=clf_lr.score(X_test,y_test)
#squared error
```

In [43]:

```
clf_svm=svm.SVR()
clf_svm.fit(X_train, y_train)
```

```
C:\Users\aksha\Anaconda3\lib\site-packages\sklearn\svm\base.py:196: FutureWarning: The default val
ue of gamma will change from 'auto' to 'scale' in version 0.22 to account better for unscaled feat
ures. Set gamma explicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[43]:

```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1,
  gamma='auto_deprecated', kernel='rbf', max_iter=-1, shrinking=True,
  tol=0.001, verbose=False)
```

In [45]:

```
accuracy_svm=clf_svm.score(X_test,y_test)
```

In [46]:

```
print("linear regression ={} ". format(accuracy_lr))
print("SVM ={} ". format(accuracy_svm))
```

```
linear regression =0.9695933982702092
SVM =0.7918039566109623
```

Predicting values for which we don't have the y values

In [58]:

```
X = np.array(df.drop(['label'],1))
```

In [59]:

```
X = np.array(df.drop(['label'],1))
```

In [60]:

```
X_lately = X[-forecast_out:] #upto 90%
```

In [61]:

```
X = X[-forecast_out:]#last 10%
```

In [64]:

```
len(X)
```

Out[64]:

```
3019
```

In [69]:

```
df.dropna(inplace=True)
y=np.array(df["label"])
y=y[0:3019]
```

In [70]:

```
len(y)
```

Out[70]:

```
3019
```

In [71]:

```
X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y, test_size=0.2)
```

In [72]:

```
clf=LinearRegression()
clf.fit(X_train, y_train)
```

Out[72]:

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [73]:

```
accuracy=clf.score(X_test,y_test)
```

In [75]:

```
forecast_set = clf.predict(X_lately)
```

In [77]:

```
print(forecast_set, accuracy, forecast_out)
```

```
[807.84919588 811.78337695 809.09471022 806.35732311 803.77813483
 803.25365316 800.01663704 797.77448941 799.00721255 802.18568035
 797.93615083 796.60231093 798.1827586  803.59571512 813.12815412
 814.40289289 808.99118864 793.87402178 803.84105016 794.79120267
 796.08054125 806.46076953 804.52705022 801.39504342 806.26472336
 811.34220972 821.40097552 821.34079018 808.83487464 816.12873079
 816.18642379] 0.9656120261075334 31
```

In [80]:

```
df["forecast"]=np.nan
```

In [81]:

```
last_date=df.iloc[-1].name
last_unix =last_date.timestamp()
one_day=86400
next_unix= last_unix+ one_day
```

In [92]:

```
for i in forecast_set:
    next_date= datetime.datetime.fromtimestamp(next_unix)
    next_unix += one_day
    df.loc[next_date]= [np.nan for _ in range(len(df.columns)-1)]+ [i]

df.tail()
```

Out[92]:

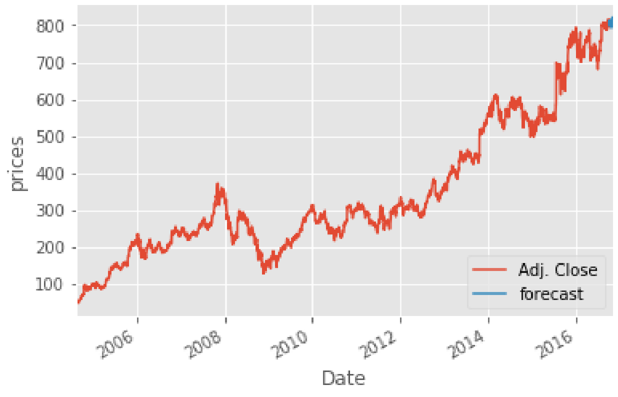
	Adj. Close	HL_PCT	PCT_change	Adj. Volume	label	forecast
Date						
2016-11-25 05:30:00	NaN	NaN	NaN	NaN	NaN	821.400976
2016-11-26 05:30:00	NaN	NaN	NaN	NaN	NaN	821.340790

Date	Adj. Close	HL_PCT	PCT_change	Adj. Volume	label	forecast
2016-11-27 05:30:00	NaN	NaN	NaN	NaN	NaN	808.894875
2016-11-28 05:30:00	NaN	NaN	NaN	NaN	NaN	816.128731
2016-11-29 05:30:00	NaN	NaN	NaN	NaN	NaN	816.186424

The above snippet says we will get the loc of index of the data-frame i.e our df index is a time stamp value so we are referencing to the index of the dataframe with loc[next*date] so if the index doesnt exist it will create it but if it did exist it will just replace it on the rhs side i.e [np.nan for* in range(len(df.columns)-1)]+ [i] we are just getting the list of values where the columns value is nan which can be seen when we print out the last few values

In [91]:

```
df['Adj. Close'].plot()
df["forecast"].plot()
plt.legend(loc=4) #4 means in the 4th axis
plt.xlabel("Date")
plt.ylabel("prices")
plt.show()
```



Pickling and Scaling

pickling is a way of saving a file so one advantage of using pickling is that we want to save our classifiers so that we have huge value of data say gb's then we don't want to train our data with every predictions because that we will be computationally expensive so with the pickle we will just save the classifer and when we want to make predictions we will just restore then classifer and make predictions

In [93]:

```
import pickle
```

In [94]:

```
clf=LinearRegression()
clf.fit(X_train, y_train)


with open('linearregression.pickle', 'wb') as f:
    pickle.dump(clf,f) #this will save the classifer clf in f
```

In [95]:

```
#now when we want to open it then
pickle_in=open('linearregression.pickle' , 'rb')
clf=pickle.load(pickle_in)
```

Linear Regression in depth

In linear regression we apply the formula y=mx + b to get the line of best find , so considering if we have values of x, m and b we will

In linear regression we apply the formula y=mx + b to get the line of best find.. so considering if we have values of x, m and b we will easily calculate the y- values

Now, x is the x coordinates

m is the slope of the line which is given by ((mean of x)(mean of y)- (mean of xy))/(square of mean of x - mean of x^2)

b is the y-intercept which is given by mean of y - slope(m)* mean of x

In [40]:

```
from statistics import mean
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import style
```

In [41]:

```
style.use('fivethirtyeight')
```

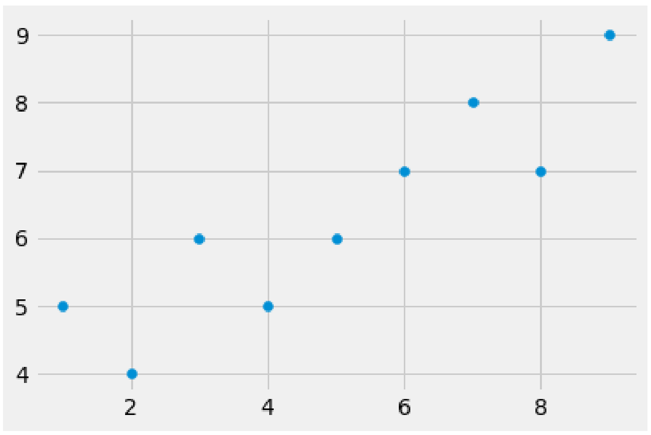
Building a toy data on our own

In [44]:

```
#xs= np.array([1, 4, 3, 2, 5 ,8 ,6, 4 , 8 ,7], dtype= np.float64)

#ys= np.array([2, 5, 4, 1, 3 ,6 ,5, 3 , 9 ,6], dtype= np.float64)

xs= np.array([1, 2 ,3 ,4 ,5 ,6 ,7 , 8, 9], dtype= np.float64)

ys= np.array([5,4,6,5,6,7 ,8, 7 ,9], dtype= np.float64)
```

In [45]:

```
plt.scatter(xs,ys) #scatter plot
plt.show()
```



Now we will create a function to caluclate the slope of the line of best fit

In [46]:

```
def best_slope(xs,ys):
    x_bar = mean(xs)
    y_bar = mean(ys)
    m= (((x_bar * y_bar) - mean(xs*ys)) /
        ((x_bar* x_bar) - mean(xs * xs)))

    return m

#PEMDAS
```

In [47]:

```
m=best_slope(xs , ys)
```

```
m=best_slope(xs , ys)
print(m)
```

```
0.5166666666666674
```

In [48]:

```
def best_intercept(xs , ys):
    y_bar= mean(ys)
    x_bar = mean(xs)
    m=best_slope(xs ,ys)

    b=(y_bar - (m*x_bar))
    return b
```

In [49]:

```
b=best_intercept(xs,ys)
print(b)
```

```
3.749999999999996
```

In [76]:

```
def squared_error(ys , ys_line):
    """We calculate the square error by finding the square of the difference between the y_points
and the regression line"""
    return sum((ys_line - ys)**2)
```

In [77]:

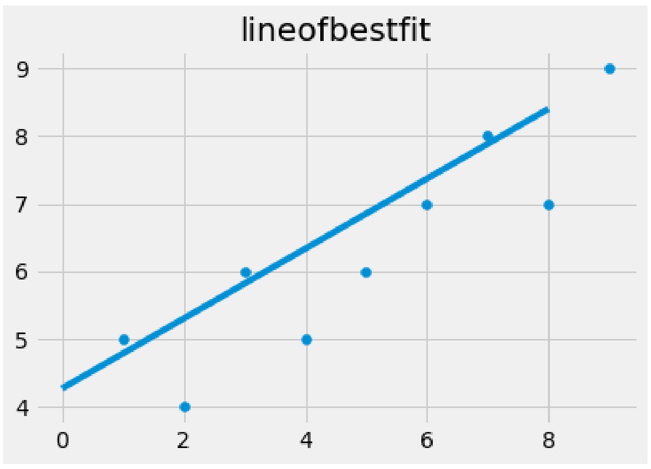
```
def coeff_of_deter(ys , ys_line):
    #print(ys_orig)
    y_mean_line = [mean(ys) for y in ys]
    squared_error_reg = squared_error(ys , ys_line)
    squared_error_y_mean = squared_error(ys , y_mean_line)
    return 1-(squared_error_reg/squared_error_y_mean)
```

In [78]:

```
#finding the regression line

reg_line = [ (m*x) +b for x in xs]
```

In [69]:

```
plt.scatter(xs, ys)
plt.plot(reg_line)
plt.title("lineofbestfit")
plt.show()
```



Now this our model predicting the line of best fit and if we have test data then let's how it pans out

In [70]:

```
predict_x= 10
#now with the formula y=mx+b we will predict y
predict_y = (m*predict_x + (b))
```

In [79]:

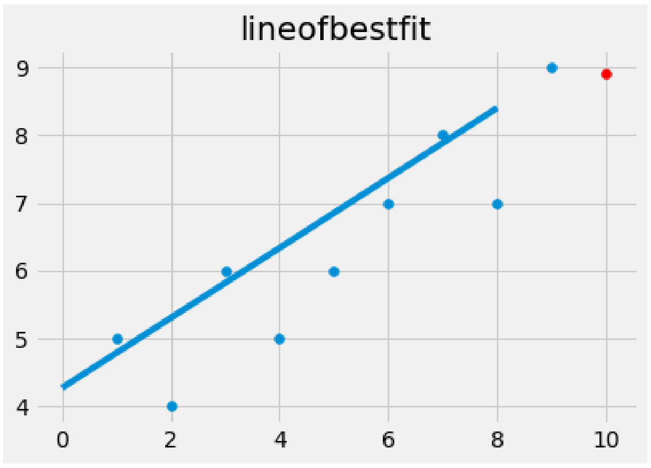
```
r_sq= coeff_of_deter(ys, reg_line)
print(r_sq)
```

```
0.8008333333333333
```

r^2 = 0.8 then we save that SEy_hat/SE mean(y) =0.2 which means only 2% values are incorrect predictions

In [54]:

```
plt.scatter(xs, ys)
plt.scatter(predict_x, predict_y , color= 'r')
plt.plot(reg_line)
plt.title("lineofbestfit")
plt.show()
```



The red value is the predicted value

But one question arises is the line of best fit is really a "line of best fit" i.e. how accuracte is the line of best fit

Calculating the accuracy of the best fit (R-squared or coefficient of Determination)

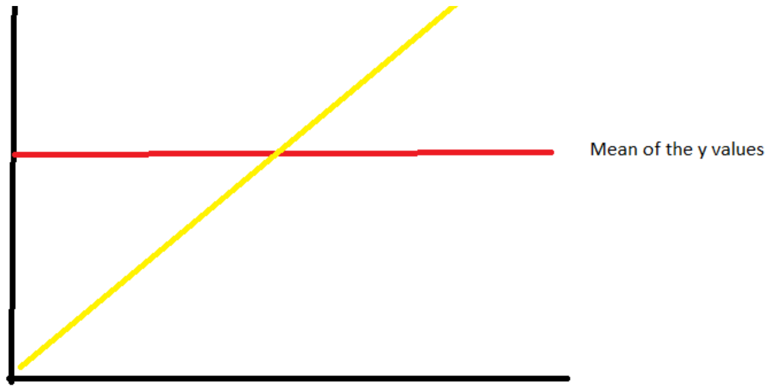
We calculate this error by finding how above and below our datapoints are from the line of best fit and then square the distance.

Why the reason of squaring :

1. to eliminate the negative and positive distance clashes. But we can also use absolute error to overcome the negative and positive distances because we want to penalise the outliers.
2. Higher powers of r could result in complex optimation operations.

r^2 = (1 - SEy_hat/SE mean(y))

where SE means squared error y_hat =regression line or line of best fit



So what r^2 really does is that it compares the accuracy of the line of means of ys and the accuracy of our regression line.

So we have values of r^2 lying between 0-1 and we want to have r values as high as possible or as close as possible to 1

Testing our assumptions we have made above

Creating our sample dataset

In [85]:

```
def dataset(hm, variance , step=2 , correlation= False):
    """hm : how many datapoints should be there in our dataset
        variance : how variable or different we want our dataset to be
        step= 2 : default value of 2 , steps means how far the y-values should be there from one a
nother
        correlation : whether we want our dataset to be positive or negative or none correlation
    """
    val=1 #first value of y is 1
    ys= []
    for i in range(hm):
        y= val+ random.randrange(-variance , variance)
        ys.append(y)
    if correlation and correlation == 'pos':
        val += step

    elif correlation and correlation == 'neg':
        val -= step

    xs=[ i for i in range(len(ys))]

    return np.array(xs, dtype= np.float64) , np.array(ys, dtype= np.float64)
```

Q-> if correlation and correlation == 'pos': why do we mention the same variable twice ? Isn't just if correlation == 'pos': enough ?

Ans-> he used it for the default value, for example if the user didn't input, a correlation value, its default is False, so the condition if correlation and correlation (False and False) wouldn't be true, so it would skip the condition, just for that

In [161]:

```
#dataset(hm, variance , step=2 , correlation= False)
xs , ys =dataset(50 , 50 , step=2 , correlation ="pos")
```

In [162]:

```
m=best_slope(xs , ys)
print(m)
```

```
-0.047298919567827134
```

In [163]:

```
b=best_intercept(xs,ys)
print(b)
```

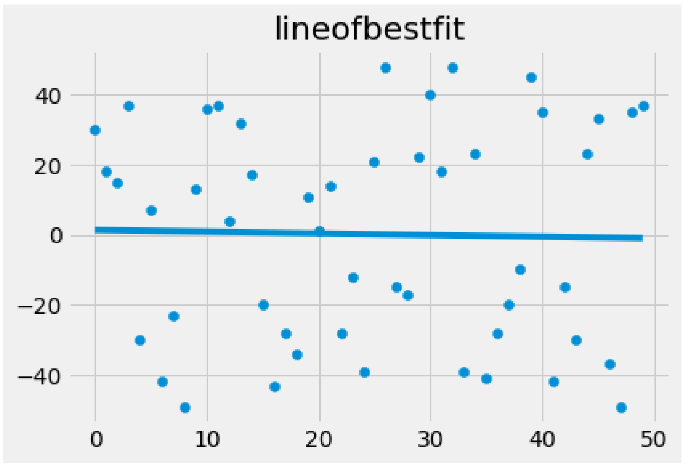
```
1.3388235294117647
```

In [164]:

```
reg_line = [ (m*x) +b for x in xs]
```

In [165]:

```
plt.scatter(xs, ys)
plt.plot(reg_line)
plt.title("lineofbestfit")
plt.show()
```



In [166]:

```
r_sq= coeff_of_deter(ys, reg_line)
print(r_sq)
```

```
0.0004989724382056249
```

our r-sq values in 0.00049 so that we can conclued that we have non-linear data

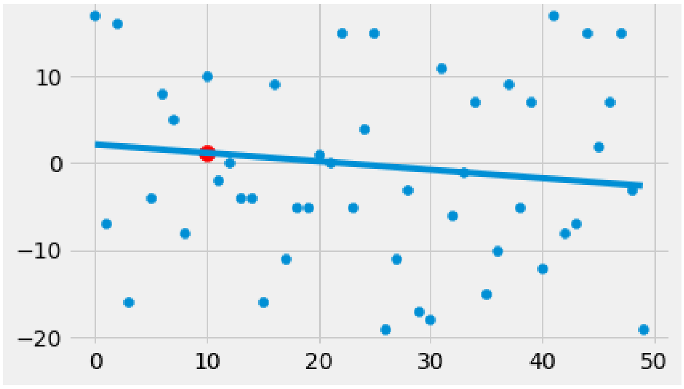
As the variance increases the r^sq values get closer to 0 and as it decreases the points comes closer and closer and therefore r-sq gets closer to 1 and we will fail to perform any linear regression task

In [142]:

```
predict_x= 10
#now with the formula y=mx+b we will predict y
predict_y = (m*predict_x + (b))
```

In [143]:

```
plt.scatter(xs, ys)
plt.scatter(predict_x, predict_y ,s=100, color= 'r') #s=100 will increase the size of the
datapoint
plt.plot(reg_line)
plt.title("lineofbestfit")
plt.show()
```



```
In [ ]:
```