## Here we will be analyzing the sales records of company

```
In [387]: import numpy as np
          import pandas as pd
          import statsmodels.api as sm
          import statsmodels.formula.api as smf
          import seaborn as sns
          import altair as alt
          from sklearn.preprocessing import scale
          from sklearn.model selection import train test split, GridSearchCV, cro
          ss val score
          from sklearn.metrics import confusion matrix, accuracy score, classific
          ation report
          from sklearn.metrics import roc auc score,roc curve
          import statsmodels.formula.api as smf
          import matplotlib.pyplot as plt
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.discriminant analysis import LinearDiscriminantAnalysis
          from sklearn.linear model import LogisticRegression
          from sklearn.svm import SVC
          from sklearn.naive bayes import GaussianNB
          from sklearn import tree
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.ensemble import GradientBoostingClassifier
          from xqboost import XGBClassifier
          from lightgbm import LGBMClassifier
          from catboost import CatBoostClassifier
          from sklearn.neighbors import KNeighborsRegressor
          from warnings import filterwarnings
          from sklearn.metrics import r2 score, mean squared error
          from sklearn.ensemble import RandomForestRegressor
          from sklearn.linear model import LinearRegression
```

```
import numpy as np
import pandas as pd
import statsmodels.api as sm
import statsmodels.formula.api as smf
import seaborn as sns
from sklearn.preprocessing import scale
from sklearn.model_selection import train test split, GridSearchCV, cro
ss val score
from sklearn.metrics import confusion matrix, accuracy score, classific
ation report
from sklearn.metrics import roc auc score, roc curve
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant analysis import LinearDiscriminantAnalysis
from sklearn.linear model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive bayes import GaussianNB
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from lightqbm import LGBMClassifier
from catboost import CatBoostClassifier
from warnings import filterwarnings
filterwarnings('ignore')
filterwarnings('ignore')
```

### Introducing the data set and understanding variables

		Order ID	ProductName	DiscountRate	Sales\$	Profit	Amount	Category	SubCategory
	0	BN-2011- 7407039	Enermax Note Cards, Premium	0.5	45	-26	3	Office Supplies	Paper
	1	AZ-2011- 9050313	Dania Corner Shelving, Traditional	0.0	854	290	7	Furniture	Bookcases
	2	AZ-2011- 6674300	Binney & Smith Sketch Pad, Easy- Erase	0.0	140	21	3	Office Supplies	Art
	3	BN-2011- 2819714	Boston Markers, Easy-Erase	0.5	27	-22	2	Office Supplies	Art
	4	BN-2011- 2819714	Eldon Folders, Single Width	0.5	17	-1	2	Office Supplies	Storage
	Pro Dis Sal Pro Amo Cat Suk	oductName scountRa	te float64 int64 int64 int64 object	obj data_Shape		947, 8	3)}		
		ere we iriables	can have a	n initial id	d <mark>ea a</mark>	<mark>bou1</mark>	t the c	listribu	ution of
In [51]:	df	.describ	e().T						
Out[51]:			count mear	n std	min	25%	50% 75	% max	<b>.</b>

	count	mean	std	min	25%	50%	75%	max
DiscountRate	8047.0	0.110047	0.181773	0.0	0.0	0.0	0.1	0.85
Sales\$	8047.0	291.845657	485.212156	3.0	48.0	117.0	313.0	6517.00
Profit	8047.0	35.198211	178.125844	-3060.0	1.0	14.0	47.0	2476.00
Amount	8047.0	3.772089	2.203369	1.0	2.0	3.0	5.0	14.00

In [56]: df.describe(include="all").T

Out[56]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
Order ID	8047	4117	AZ- 2014- 7040665	11	NaN	NaN	NaN	NaN	NaN	NaN	NaN
ProductName	8047	1810	Eldon File Cart, Single Width	26	NaN	NaN	NaN	NaN	NaN	NaN	NaN
DiscountRate	8047	NaN	NaN	NaN	0.110047	0.181773	0	0	0	0.1	0.85
Sales\$	8047	NaN	NaN	NaN	291.846	485.212	3	48	117	313	6517
Profit	8047	NaN	NaN	NaN	35.1982	178.126	-3060	1	14	47	2476
Amount	8047	NaN	NaN	NaN	3.77209	2.20337	1	2	3	5	14
Category	8047	3	Office Supplies	5286	NaN	NaN	NaN	NaN	NaN	NaN	NaN
SubCategory	8047	17	Art	1152	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [52]: df.corr()

Out[52]:

	DiscountRate	Sales\$	Profit	Amount
DiscountRate	1.000000	-0.026350	-0.351328	0.003686
Sales\$	-0.026350	1.000000	0.441217	0.353441

```
DiscountRate
                                       Sales$
                                                 Profit Amount
                  Profit
                           -0.351328
                                     0.441217
                                             1.000000 0.098670
                Amount
                            0.003686
                                     0.353441
                                              0.098670 1.000000
In [55]: df.isnull().mean() # checking null value
Out[55]: Order ID
                             0.0
          ProductName
                             0.0
          DiscountRate
                             0.0
          Sales$
                             0.0
          Profit
                             0.0
          Amount
                             0.0
          Category
                             0.0
          SubCategory
                             0.0
          dtype: float64
          df.groupby(["DiscountRate","Category","SubCategory"]).agg({"Profit":"me
In [68]:
          an"}) ## This way of table shows the profitability
Out[68]:
                                                        Profit
           DiscountRate
                             Category SubCategory
                   0.00
                                                   213.420118
                             Furniture
                                       Bookcases
                                           Chairs
                                                   139.785714
                                      Furnishings
                                                    51.289963
                                           Tables
                                                   385.800000
                        Office Supplies
                                       Appliances
                                                   312.900990
                   0.65
                           Technology
                                                   -153.500000
                                         Machines
                                          Phones
                                                   -548.200000
                   0.70
                             Furniture
                                           Tables
                                                   -916.166667
```

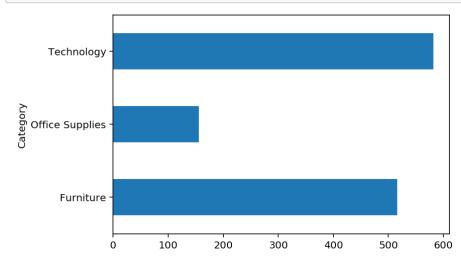
DiscountRate	Category	SubCategory	
0.80	Furniture	Furnishings	-142.000000
0.85	Furniture	Tables	-1925.000000

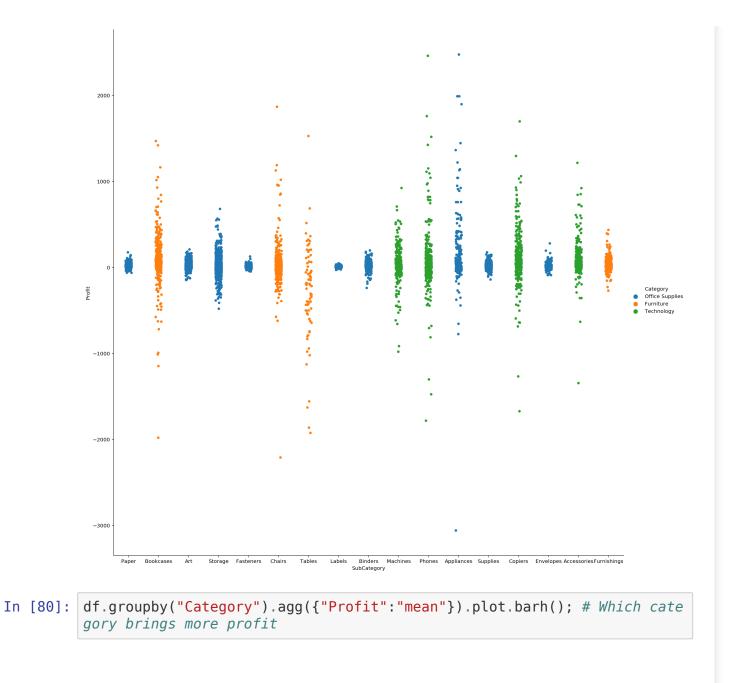
78 rows × 1 columns

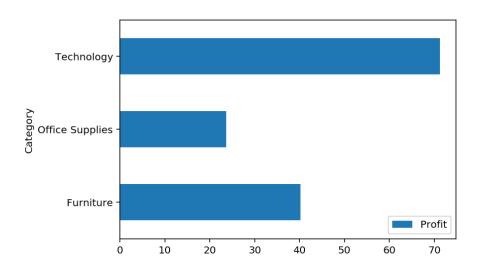
## Visualization

```
In [79]: %config InlineBackend.figure_format = 'retina'
df.groupby("Category").mean()["Sales$"].plot.barh();  # Which Categor
y brings more income
```

**Profit** 

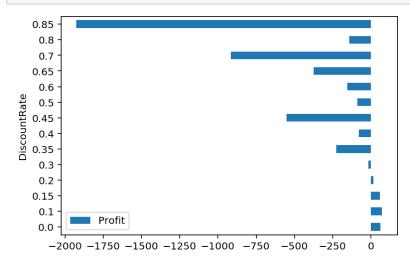






In [381]: %config InlineBackend.figure\_format = 'retina'

df.groupby("DiscountRate").agg({"Profit":"mean"}).plot.barh(); ## Here
 we are able to understand the profitability is increasing around 0,0-0,15 discount rate.



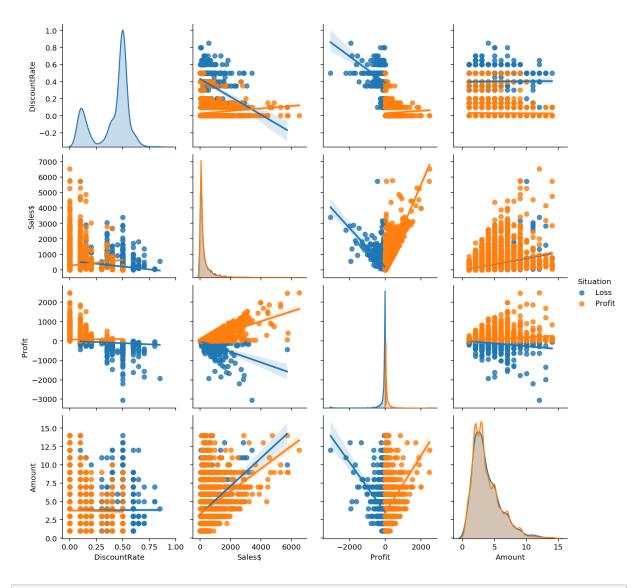
```
In [84]: def situation(profit):
    if profit >= 0:
```

```
return "Profit"
else:
    return "Loss"

In [85]: df["Situation"] = df["Profit"].apply(situation)

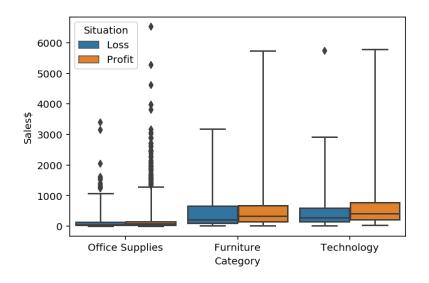
In [86]: sns.pairplot(df, vars= ["DiscountRate", "Sales$", "Profit", "Amount"], hue=
    "Situation", kind="reg") # Here we seperated the graphs according to si
    tuation

Out[86]: <seaborn.axisgrid.PairGrid at 0x21402d43b70>
```



In [379]: sns.boxplot(x='Category',y='Sales\$',hue = 'Situation', data = df,whis=1
0,width=.9) # The graph shows the relationship of Profit and Loss betwe
en Categories

Out[379]: <matplotlib.axes.\_subplots.AxesSubplot at 0x21441e82160>



# **Creating Machine Learning Model with KNN&RF&LogisticsRegression**

```
In [117]: def map_category(category):
    if category == 'Office Supplies':
        return 1
    elif category == 'Furniture':
        return 2
    elif category == 'Technology':
        return 3
In [119]: df1 = df.copy()
    df1["Category"] = df1["Category"].apply(map_category)

In [125]: X = df1.drop(["Order ID", "ProductName", "SubCategory", "Situation", "Profit"], axis = 1)
    y = df1.Profit
```

```
In [126]: X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.
          30,
                                                                       train size =
          0.70, random_state =0)
In [129]: knn model = KNeighborsRegressor().fit(X train, y train) # Building Mode
In [130]: knn model
Out[130]: KNeighborsRegressor(algorithm='auto', leaf size=30, metric='minkowski',
                               metric params=None, n jobs=None, n neighbors=5, p=
          2,
                               weights='uniform')
In [131]: y pred = knn model.predict(X test)
In [134]: np.sqrt(mean squared error(y test,y pred)) # Calculation the Error.
Out[134]: 167.31945028317594
In [139]: new data = [[0.5],[27],[2],[1]]
          new data = pd.DataFrame(new data).T
          knn model.predict(new data) ##Looks like model is predicting well, ho
          wever I will try to optimize the model by finding best hyperparameters.
Out[139]: array([-18.8])
In [285]: df.head(10)
Out[285]:
               Order
                     ProductName DiscountRate Sales$ Profit Amount Category SubCategory Situation
                 BN-
                     Enermax Note
                                                                 Office
                2011-
                          Cards,
                                        0.5
                                              45
                                                 -26
                                                                            Paper
                                                                                    Lo
                                                               Supplies
              7407039
                         Premium
```

	Order ID	ProductName	DiscountRate	Sales\$	Profit	Amount	Category	SubCategory	Situatio
1	AZ- 2011- 9050313	Dania Corner Shelving, Traditional	0.0	854	290	7	Furniture	Bookcases	Prc
2	AZ- 2011- 6674300	Binney & Smith Sketch Pad, Easy- Erase	0.0	140	21	3	Office Supplies	Art	Pro
3	BN- 2011- 2819714	Boston Markers, Easy-Erase	0.5	27	-22	2	Office Supplies	Art	Lo
4	BN- 2011- 2819714	Eldon Folders, Single Width	0.5	17	-1	2	Office Supplies	Storage	Lo
5	AZ- 2011- 617423	Binney & Smith Pencil Sharpener, Water Color	0.0	90	21	3	Office Supplies	Art	Prc
6	AZ- 2011- 617423	Sanford Canvas, Fluorescent	0.0	207	77	4	Office Supplies	Art	Pro
7	AZ- 2011- 2918397	Bush Floating Shelf Set, Pine	0.1	155	36	1	Furniture	Bookcases	Pro
8	AZ- 2011- 2918397	Accos Thumb Tacks, Assorted Sizes	0.0	33	2	3	Office Supplies	Fasteners	Pro
9	AZ- 2011- 2918397	Smead Lockers, Industrial	0.1	716	143	4	Office Supplies	Storage	Pro
4									<b></b>
RM	SE = []								
<pre>for k in range(10):     k = k+1</pre>									

In [140]:

```
knn \ model = KNeighborsRegressor(n \ neighbors = k).fit(X \ train, y \ train)
          in)
              y pred = knn model.predict(X train)
              rmse = np.sqrt(mean squared error(y train,y pred))
              RMSE.append(rmse)
              print("k=",k, "için RMSE value", rmse)
          k= 1 icin RMSE value 16.75974423995296
          k= 2 için RMSE value 105.8054451062587
          k= 3 için RMSE value 128.88901334867512
          k= 4 için RMSE value 136.43468708221639
          k= 5 için RMSE value 142.48292720692731
          k= 6 için RMSE value 146.39835367344085
          k= 7 için RMSE value 147.38190903606295
          k= 8 için RMSE value 149.31249818838532
          k= 9 için RMSE value 150.77108879815836
          k= 10 için RMSE value 152.88629418251864
In [141]: from sklearn.model selection import GridSearchCV
          knn params = {"n neighbors": np.arange(1,30,1)}
In [157]:
          knn =KNeighborsRegressor()
In [158]: knn cv model = GridSearchCV(knn,knn params, cv =10)
In [159]: knn cv model.fit(X train, y train)
Out[159]: GridSearchCV(cv=10, error_score=nan,
                       estimator=KNeighborsRegressor(algorithm='auto', leaf size=
          30,
                                                      metric='minkowski',
                                                      metric params=None, n jobs=N
          one,
                                                      n neighbors=5, p=2,
                                                      weights='uniform'),
                       iid='deprecated', n jobs=None,
                       param grid=\{'n neighbors': array([1, 2, 3, 4, 5, 6,
          7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,
```

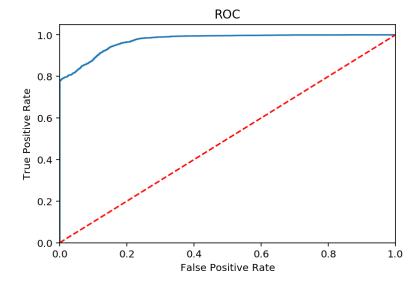
```
18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29])},
                       pre_dispatch='2*n_jobs', refit=True, return train score=Fa
          lse,
                       scoring=None, verbose=0)
In [160]: knn cv model.best params ["n neighbors"]
Out[160]: 23
In [152]: RMSE = []
          RMSE CV = []
          for k in range(10):
              k = k+1
              knn model = KNeighborsRegressor(n neighbors = k).fit(X train, y tra
          in)
              y pred = knn model.predict(X train)
              rmse = np.sqrt(mean squared error(y train,y pred))
              rmse cv = np.sqrt(-1*cross val score(knn model, X train, y train, cv=1
          0,
                                                  scoring = "neg mean squared err
          or").mean())
              RMSE.append(rmse)
              RMSE CV.append(rmse cv)
              print("k=",k, " RMSE value", rmse, "RMSE CV value:", rmse cv)
          k= 1 RMSE value 16.75974423995296 RMSE CV value: 222.1203644391432
          k= 2 RMSE value 105.8054451062587 RMSE CV value: 193.19605311150775
          k= 3 RMSE value 128.88901334867512 RMSE CV value: 184.9912315989125
          k= 4 RMSE value 136.43468708221639 RMSE CV value: 179.14293553569996
          k= 5 RMSE value 142.48292720692731 RMSE CV value: 176.14514879564152
          k= 6 RMSE value 146.39835367344085 RMSE CV value: 174.57388836995958
          k= 7 RMSE value 147.38190903606295 RMSE CV value: 171.90409750355903
          k= 8 RMSE value 149.31249818838532 RMSE CV value: 171.61344542445832
          k= 9 RMSE value 150.77108879815836 RMSE CV value: 171.99767331289104
          k= 10 RMSE value 152.88629418251864 RMSE CV value: 170.08631728475808
In [162]: knn tuned = KNeighborsRegressor(n neighbors = knn cv model.best params
```

```
["n neighbors"])
           knn tuned.fit(X train, y train)
Out[162]: KNeighborsRegressor(algorithm='auto', leaf size=30, metric='minkowski',
                                metric params=None, n jobs=None, n neighbors=23, p=
          2,
                                weights='uniform')
In [163]: np.sqrt(mean squared error(y test,knn tuned.predict(X test))) # Our mea
           n squared error has decreased from 167 to 151
Out[163]: 151,28093134200765
In [174]: new data = [[0.5],[116],[5],[1]]
           new data = pd.DataFrame(new data).T
           y pred1=knn tuned.predict(X)
In [177]: k t = pd.DataFrame({"Prediction": y pred1[0:10],
                                "Real vallue": y[0:10]})
           k_t
Out[177]:
              Prediction Real_vallue
              -4.173913
                              -26
           1 107.695652
                             290
           2 21.347826
                              21
              -2.739130
                              -22
              -2.869565
                              -1
              20.652174
                              21
             -20.086957
                              77
                              36
              28.521739
                               2
               7.739130
              81.130435
                             143
```

## LogisticRegression

```
In [216]: def situation num(profit):
              if profit >= 0:
                  return 1
              else:
                  return 0
In [221]: df2 = df1.copy()
In [222]: df2["Profit"] = df2["Profit"].apply(situation_num)
In [233]: X1 = df2.drop(["Order ID", "ProductName", "SubCategory", "Situation", "Prof
          it"], axis = 1)
          v1 = df2.Profit
In [240]: X1 train, X1 test, y1 train, y1 test = train test split(X1,y1, test siz
          e = 0.30,
                                                                     train size =
          0.70, random state =0)
In [248]: from sklearn.linear model import LogisticRegression
          loj = LogisticRegression(solver = "liblinear")
          loj model = loj.fit(X1 train,y1 train)
          #loi model.coef
In [249]: y pred = loj model.predict(X1)
In [250]: accuracy score(y1,y pred)
Out[250]: 0.9343854852740152
In [257]: logit roc auc = roc auc score(y1, loj model.predict(X1))
```

```
fpr, tpr, thresholds = roc_curve(y1, loj_model.predict_proba(X1)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='AUC (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([-0, 1.0])
plt.ylim([-0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
plt.show()
```



```
In [258]: cross_val_score(loj_model,X1_test,y1_test,cv=10).mean()
```

Out[258]: 0.9399660505469635

### **Random Forest**

```
In [353]: df3 = df1.copy()
x = df3.drop(["Order ID","ProductName","SubCategory","Situation","Profi
```

```
t"], axis = 1)
          y = df3.Profit
In [354]: x train, x test, y train, y test = train test split(x,y, test size = 0.
                                                                     train size =
          0.70, random state =0)
In [355]: forest = RandomForestRegressor(n estimators= 100,
                                       criterion= "mse",
                                       random state= 1,
                                       n jobs = -1
          forest.fit(x train,y train)
          forest train pred = forest.predict(x train)
          forest test pred = forest.predict(x test)
          print('MSE train data: %.3f, MSE test data: %.3f' % (
          mean squared error(y train, forest train pred),
          mean squared error(y test,forest test pred)))
          print('R2 train data: %.3f, R2 test data: %.3f' % (
          r2 score(y train, forest train pred),
          r2 score(y test, forest test pred)))
          MSE train data: 2218.922, MSE test data: 11646.519
          R2 train data: 0.934, R2 test data: 0.565
In [356]: import matplotlib.pyplot as pl
          pl.figure(figsize=(10,6))
          pl.scatter(forest train pred, forest train pred - y train,
                    c = 'black', marker = 'o', s = 35, alpha = 0.5,
                    label = 'Train data')
          pl.scatter(forest test pred, forest test pred - y test,
                    c = 'c', marker = 'o', s = 35, alpha = 0.7,
                    label = 'Test data')
          pl.xlabel('Predicted values')
          pl.ylabel('Tailings')
```

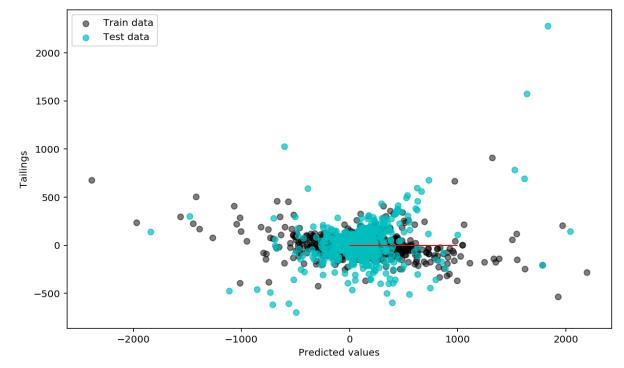
```
pl.legend(loc = 'upper left')
           pl.hlines(y = 0, xmin = 0, xmax = 1000, lw = 1, color = 'red')
           pl.show()
              2500
                       Train data
                       Test data
              2000
              1500
            Tailings
               500
              -500
                     -2000
                             -1500
                                     -1000
                                              -500
                                                               500
                                                                      1000
                                                                              1500
                                                                                       2000
                                                  Predicted values
In [357]: new_data = [[0.0],[854],[7],[2]]
           new data = pd.DataFrame(new data).T
           y pred2 = forest.predict(x)
In [358]: pd.DataFrame({"Prediction": y pred2[0:10],
                           "Real value": y[0:10]})
Out[358]:
               Prediction Real_value
              -19.991333
                               -26
                              290
            1 233.349476
```

	Prediction	Real_value
2	30.047036	21
3	-18.110399	-22
4	-5.982603	-1
5	23.482197	21
6	55.557492	77
7	29.007286	36
8	9.125724	2
9	217.410214	143

#### **OPTIMIZING THE RF MODEL**

```
Out[362]: GridSearchCV(cv=10, error_score=nan,
                       estimator=RandomForestRegressor(bootstrap=True, ccp alpha=
          0.0,
                                                       criterion='mse', max depth
          =None,
                                                       max features='auto',
                                                       max leaf nodes=None,
                                                       max samples=None.
                                                       min impurity decrease=0.0,
                                                       min impurity split=None,
                                                       min samples leaf=1,
                                                       min samples split=2,
                                                       min weight fraction leaf=
          0.0.
                                                       n estimators=100, n jobs=-
          1,
                                                       oob score=False, random st
          ate=1,
                                                       verbose=0, warm start=Fals
          e),
                       iid='deprecated', n jobs=None,
                       param grid={'n estimators': array([ 1, 2, 3, 4, 5, 6,
            7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,
                 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29])},
                       pre_dispatch='2*n_jobs', refit=True, return train score=Fa
          lse,
                       scoring=None, verbose=0)
In [366]: rf cv model.best params
Out[366]: {'n estimators': 27}
In [367]: rf tuned = RandomForestRegressor(n estimators= 27)
In [368]: rf tuned.fit(x train, y train)
Out[368]: RandomForestRegressor(bootstrap=True, ccp alpha=0.0, criterion='mse',
                                max depth=None, max features='auto', max leaf nod
```

```
es=None,
                                max samples=None, min impurity decrease=0.0,
                                min impurity split=None, min samples leaf=1,
                                min samples split=2, min weight fraction leaf=0.
          0,
                                n estimators=27, n jobs=None, oob score=False,
                                random state=None, verbose=0, warm start=False)
In [369]: rf tuned.score(x train,y train)
Out[369]: 0.9238740175820388
In [373]: np.sqrt(mean squared error(y test,forest.predict(x test)))
Out[373]: 107.91904137208944
In [372]: np.sqrt(mean squared error(y test,rf tuned.predict(x test))) # Comparin
           the MSE, we have little better result with optimized parameters.
Out[372]: 105.86392308133048
In [370]: rf tuned = RandomForestRegressor(n estimators= 27)
          rf tuned.fit(x train, y train)
          forest train pred = rf tuned.predict(x train)
          forest test pred = rf tuned.predict(x test)
          print('MSE train data: %.3f, MSE test data: %.3f' % (
          mean squared error(y train, forest train pred),
          mean squared error(y test,forest test pred)))
          print('R2 train data: %.3f, R2 test data: %.3f' % (
          r2 score(y train, forest train pred),
          r2 score(y test, forest test pred)))
          MSE train data: 2127.071, MSE test data: 11207.170
          R2 train data: 0.937, R2 test data: 0.581
In [371]: pl.figure(figsize=(10,6))
```



[My Linkedin link ] (https://www.linkedin.com/in/volkan-eymir-akcora/)

```
In [383]: ! jupyter nbconvert --to html OrdersProject.ipynb
```

