Machine Learning Engineer Nanodegree

Capstone Project Report

Deepika Kothapalli

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Project Overview:

Banks contain huge information about the customers. They can use this data for several useful purposes. In order to have a good relationship with the customers and to market several other schemes. They will select a means of communication like phone call or SMS etc.
Sometimes Banks can use TV and other means to inform or market their offers and schemes. But customers may not pay a good interest in that. So, they use telephone as a medium where they can directly speak with the customer about the offers and clarify about certain things and know whether they are interested or not.
In this way they can get to know about the genuine feedback what they think of the certain offer. Through direct contact with the customer it is also possible to convince the customer about their ideas. This type of marketing product or service is called direct marketing which came into existence in 1960's.

Problem Statement:

- In this I want to determine whether the customer subscribe to the campaign or not. I want to classify the customers subscribed and unsubscribed to the campaign.
- There are certain features based on which I want to classify the data points like age, type of job, marital status, education, loan, housing, number of days before the bank contacted the customer etc.
- I decided to use several supervised learning classification algorithms like Decision trees, logistic regression etc. I will find

the best model among those using many performance metrics through which I can get good results.

- This project consists of several phases like Data Exploration, Data preprocessing, application of various classification algorithms, finding the best model etc.

Features and Description:

- age: age of the customer.
- Present: occupation of the customer ('admin', 'bluecollar', 'entrepreneur', 'housemaid', 'management', 'retired', 'self-employed', 'services', 'student', 'technician', 'unemployed', 'unknown')
- marital: Marital status of the customer ('single', 'married', 'divorced', 'unknown')
- default : whether the customer has a credit in default ('yes', 'no', 'unknown')
- balance: current balance in the account.
- housing: whether the customer has housing loan ('yes', 'no', 'unknown')
- loan: whether the customer has personal loan ('yes', 'no', 'unknown')
- contact : contact communication type ('cellular','telephone')
- day : days before which the customer is contacted
- month : last contact month of year ('jan', 'feb', 'mar', ..., 'nov', 'dec')
- duration : last contact duration, in seconds
- campaign : number of contacts performed during this campaign and for this client (numeric, includes last contact)
- pdays: number of days that passed by after the client was last contacted from a previous campaign
- ***previous***: number of contacts performed before this campaign and for this client
- poutcome: outcome of the previous contact('success','failure','unknown').

Metrics :

Accuracy : It determines the proportion of correct predicts among all the predictions

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

Precision :

$$Precision = \frac{(TP)}{(TP + FP)}$$

It determines among all the customers that are predicted as subscribed to the campaign who are actually subscribed.

Recall :

$$Recall = \frac{(TP)}{(TP + FN)}$$

Recall determines the proportion of subscribed customers correctly predicted among the actual subscribed customers.

F-Beta score :

F-beta score is the weighted harmonic mean of precision and recall.

$$F - beta = \frac{(1 + \beta 2) * Precision * recall}{\mathrm{\beta 2 * precision + recall}}$$

F-beta=(1+ β2) *precision *recall/(β2*precision+recall)

Data Exploration:

In this section I have calculated the total number of records, number of customers of the bank subscribed for the campaign, number of the customers who are unsubscribed for the campaign. Finally the percentage of customers subscribed for the campaign among all the customers.

```
Total number of records: 4521
The number of customers subscribed: 521
The number of customers does not subscribe: 4000
The percentage of customers subscribed: 11.5239991152%
```

From the exploration I found that the number of customers subscrib ed for the campaign are very few among all the customers of the bank.

data.describe()

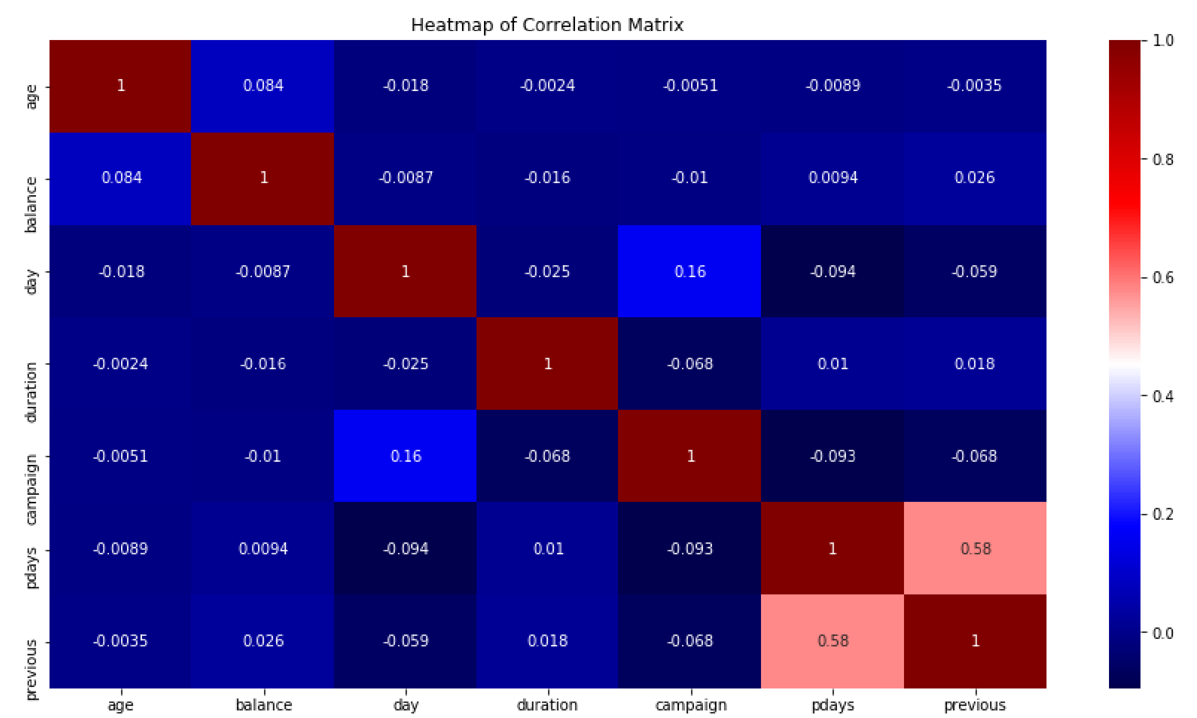
	age	balance	day	duration	campaign	pdays	previous
count	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000
mean	41.170095	1422.657819	15.915284	263.961292	2.793630	39.766645	0.542579
std	10.576211	3009.638142	8.247667	259.856633	3.109807	100.121124	1.693562
min	19.000000	-3313.000000	1.000000	4.000000	1.000000	-1.000000	0.000000
25%	33.000000	69.000000	9.000000	104.000000	1.000000	-1.000000	0.000000
50%	39.000000	444.000000	16.000000	185.000000	2.000000	-1.000000	0.000000
75%	49.000000	1480.000000	21.000000	329.000000	3.000000	-1.000000	0.000000
max	87.000000	71188.000000	31.000000	3025.000000	50.000000	871.000000	25.000000

data.head()

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	-1	0	unknown	no
1	33	services	married	secondary	no	4789	yes	yes	cellular	11	may	220	1	339	4	failure	no
2	35	management	single	tertiary	no	1350	yes	no	cellular	16	apr	185	1	330	1	failure	no
3	30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	-1	0	unknown	no
4	59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	-1	0	unknown	no

Visualization :

In Visualization first I plotted a heat matrix to determine the correlation between features. After plotting the heat matrix I found that the previous and pdays are highly correlated with the highest value 0.58.



Algorithms and Techniques :

I have used four algorithms for this model. They are: logistic regression, DecisionTreeClassifier, AdaBoostClassifier, GradientBoostClassifier.

Logistic Regression:

Logistic regression is a method of classification: the model outputs the probability of a categorical target variable Y belonging to a certain class.

The two possible dependent variable values are often labelled as "0" and "1", which represent outcomes such as pass/fail, win/lose, alive/dead or subscribed/unsubscribed.

The logistic model is a modification of linear regression that makes sure to output a probability between 0 and 1 by applying the sigmoid function, which, when graphed, looks like the characteristic S-shaped curve

$$S(x) = \frac{1}{1 + e^{-x}}$$

AdaBoostClassifier :

Ada-boost, like Random Forest Classifier is another ensemble classifier. (Ensemble classifier are made up of multiple classifier algorithms and whose output is combined result of output of those classifier algorithms).

Ada-boost classifier combines weak classifier algorithm to form strong classifier. A single algorithm may classify the objects poorly. But if we combine multiple classifiers with selection of training set at every iteration and assigning right amount of weight in final voting, we can have good accuracy score for overall classifier.

DecisionTreeClassifier:

In decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. As the name goes, it uses a tree-like model of decisions. Though a commonly used tool in data mining for deriving a strategy to reach a particular goal

A decision tree is drawn upside down with its root at the top. In the image on the left, the bold text in black represents a condition/internal node, based on which the tree splits into branches/ edges. The end of the branch that doesn't split anymore is the decision/leaf, in this case, whether the passenger died or survived, represented as red and green text respectively.

Growing a tree involves deciding on which features to choose and what conditions to use for splitting, along with knowing when to stop. As a tree generally grows arbitrarily, you will need to trim it down for it to look beautiful.

GradientBoostClassifier :

Gradient boosting is a machine learning technique
for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

It builds the model in a stage-wise fashion like
other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

Benchmark model :

Logistic regression is used as benchmark model. F-Beta score of benchmark model is reference and other model will be judging to perform better if their f-beta score will be greater than Logistic regression model. Accuracy, f-beta score and confusion matrix and will try to get better results in the ensemble learning models.

```
Accuracy score for logistic regression : 0.892817679558
f-score for logistic regression :0.663871260199
```

Data Preprocessing :

- As many values are categorical values, so we need to bring them to a scale.
- I have performed one hot encoding technique to convert the categorical data into numeric data

Code :

features_final = pd.get_dummies(features_log_minmax_transform)
target = target.map(lambda x : 0 if x == 'no' else 1)

features_final.head()

Output :

age	balance	day	duration	campaign	pdays	previous	job_admin.	job_blue-collar	job_entrepreneur	...	month_jun	month_mar	month_may	montl
0.295798	0.670258	0.830482	0.432841	0.000000	0.000000	0.000000	0	0	0	...	0	0	0	
0.358144	0.758455	0.646241	0.591474	0.000000	0.860896	0.493981	0	0	0	...	0	0	1	
0.396723	0.645175	0.771866	0.564558	0.000000	0.856934	0.212746	0	0	0	...	0	0	0	
0.295798	0.653156	0.250000	0.575887	0.282921	0.000000	0.000000	0	0	0	...	1	0	0	
0.741502	0.000000	0.396241	0.595656	0.000000	0.000000	0.000000	0	1	0	...	0	0	1	

- As there is skewness in the data I have normalized the numeric data by first applying logarithmic transformation and then scaled the data using MinmaxScaler
- I have splitted the data into 80% training data and 20% testing data using train_test_split()

Implementation :

Logistic Regression :

Logistic regression is a method of classification: the model outputs the probability of a categorical target variable Y belonging to a certain class.

I will import this model form sklearn.linear_model. I have random_state as a parameter to this classifier.

Code:

```
from sklearn import linear_model
l =  linear_model.LogisticRegression(random_state=20)
l_fit = l.fit(X_train,y_train)
l_pred = l_fit.predict(X_test)
score=accuracy_scorer(y_test,l_pred)
f_score = fbeta_scorer(y_test,l_pred)
print "Accuracy score for DecisionTreeClassifier :
{}".format(dec_score)
print "f-score for DecisionTreeClassifier :{}".format(dec_f_score)
```

Output:

```
Accuracy score for logistic regression : 0.892817679558
f-score for logistic regression :0.663871260199
```

AdaBoostClassifier :

Ada Boost is best used to boost the performance of any machine learning algorithm.

Ada-boost classifier combines weak classifier algorithm to form strong classifier. A single algorithm may classify the objects poorly. But if we combine multiple classifiers with selection of training set at every iteration and assigning right amount of weight in final voting

I have imported this model from sklearn. ensemble. I have passed only random_state as parameter to this classifier.

Code :

```
from sklearn.ensemble import AdaBoostClassifier
ada_clf=AdaBoostClassifier(random_state=20)
ada_fit=ada_clf.fit(X_train,y_train)
ada_pred=ada_fit.predict(X_test)
ada_score=accuracy_scorer(y_test,ada_pred)
ada_f_score=fbeta_scorer(y_test,ada_pred)
print "Accuracy score for AdaBoostClassifier : {}".format(ada_score)
print "f-score for AdaBoostClassifier:{}".format(ada_f_score)
```

Output :

```
Accuracy score for AdaBoostClassifier : 0.893922651934
f-score for AdaBoostClassifier:0.605031948882
```

DecisionTreeClassifier :

In decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. As the name goes, it uses a tree-like model of decisions. Though a commonly used tool in data mining for deriving a strategy to reach a particular goal

I have imported this model from sklearn.tree. I have passed random_state as parameter to this model.

Code :

from sklearn.tree import DecisionTreeClassifier

```
dec_clf = DecisionTreeClassifier(random_state=100)
dec_fit = dec_clf.fit(X_train,y_train)
dec_pred = dec_fit.predict(X_test)
dec_score = accuracy_scorer(y_test,dec_pred)
dec_f_score = fbeta_scorer(y_test,dec_pred)
print "Accuracy score for DecisionTreeClassifier : {}".format(dec_score)
print "f-score for DecisionTreeClassifier :{}".format(dec_f_score)
```

Output:

```
Accuracy score for DecisionTreeClassifier : 0.850828729282
f-score for DecisionTreeClassifier :0.392341842397
```

GradientBoostingClassifier :

Gradient boosting is a machine learning technique
for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

I have imported this model from sklearn.ensemble. I have passed random_state as parameter to this model.

Code :

```
from sklearn.ensemble import GradientBoostingClassifier
gbc_clf = GradientBoostingClassifier(random_state=20)
gbc_fit = gbc_clf.fit(X_train,y_train)
gbc_pred = gbc_clf.predict(X_test)
gbc_score = accuracy_scorer(y_test,gbc_pred)
gbc_f_score = fbeta_scorer(y_test,gbc_pred)
print "Accuracy score for GradientBoostingClassifier : {}".format(gbc_score)
print "f-score for GradientBoostingClassifier:{}".format(gbc_f_score)
```

Output :

```
Accuracy score for GradientBoostingClassifier : 0.891712707182
f-score for GradientBoostingClassifier:0.593955142232
```

Refinement :

First to improve the performance of all the models on the dataset I have removed some unnecessary features based on the ranking of RFE . So that It may produce some better results.

I have applied all the four models on the customers data. Benchmark model i.e., logistic regression has an accuracy score of 0.89 anf f-score of 0.66.

After that I have applied other algorithms I mentioned above to check the performance of those models when compared to the bench mark model.

Among all the models applied AdaBoostClassifier has the f-score and accuracy score better but less than the logistic regression.

I thought of optimizing the AdaBoostClassifier using GridSearch as it may perform better than the Benchmark model after optimization.

Grid-searching is the process of scanning the data to configure optimal parameters for a given model. Depending on the type of model utilized, certain parameters are necessary. Grid-searching does NOT only apply to one model type. Grid-searching can be applied across machine learning to calculate the best parameters to use for any given model. It is important to note that Grid-searching can be extremely computationally expensive and may take your machine quite a long time to run. Grid-Search will build a model on each parameter combination possible. It iterates through every parameter combination and stores a model for each combination.

Even after optimization of the AdaBoostClassifier the performance of it han't improved much. It's f-score is only increased at a very small rate i.e, from 0.60 to 0.61 but it is still less than the benchmark model.

So, I chose it as a best model and further optimized it using GridSearc
h. Then its performance is increased from 0.66 to 0.86 which is very h
igh improvement.

Results :

Model Evaluation and Validation :

After applying different algorithms on the data set the benchmark mo
del logistic regression is performing well when compared to all the m
odels with an accuracy score of 0.89 and f-score of 0.66.

After that I have tried to optimize the AdaBoostClassifier to check wh
ether its score will increase than the benchmark model as it is having
the next good accuracy and f-score after logistic regression.

But the score doesn't improved very much for AdaBoostClassifier eve
n after optimization using GridSearch.

Hence, I have finalized that logistic regression is the best model for th
is data set and optimized it for having better results.

The f-score of the best model i.e., logistic regression has improved a l
ot after optimization. It increased from 0.66 to 0.86 which is very high
.

```
GridSearchCV(cv=None, error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=20, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'C': [0.0001, 0.001, 0.01, 0.1]},
       pre_dispatch='2*n_jobs', refit=True,
       scoring=make_scorer(fbeta_score, beta=0.5), verbose=0)
LogisticRegression(C=0.1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=20, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

Justification:

The final model that I have chosen is the best model when compared to the other models I have tested as the f-score of the logistic regressi on is very high when compared to the other models. No other model even reached that f-score. AdaboostClassifier has some good f-score nearer to logistic regression with an f-score of 0.60 . But after optimiz ation its score han't gone beyond 0.61. Whereas after optimization f-score of logistic has become 0.86 which is very high.

Unoptimized model :

```
Accuracy score for logistic regression : 0.892817679558
f-score for logistic regression :0.663871260199
```

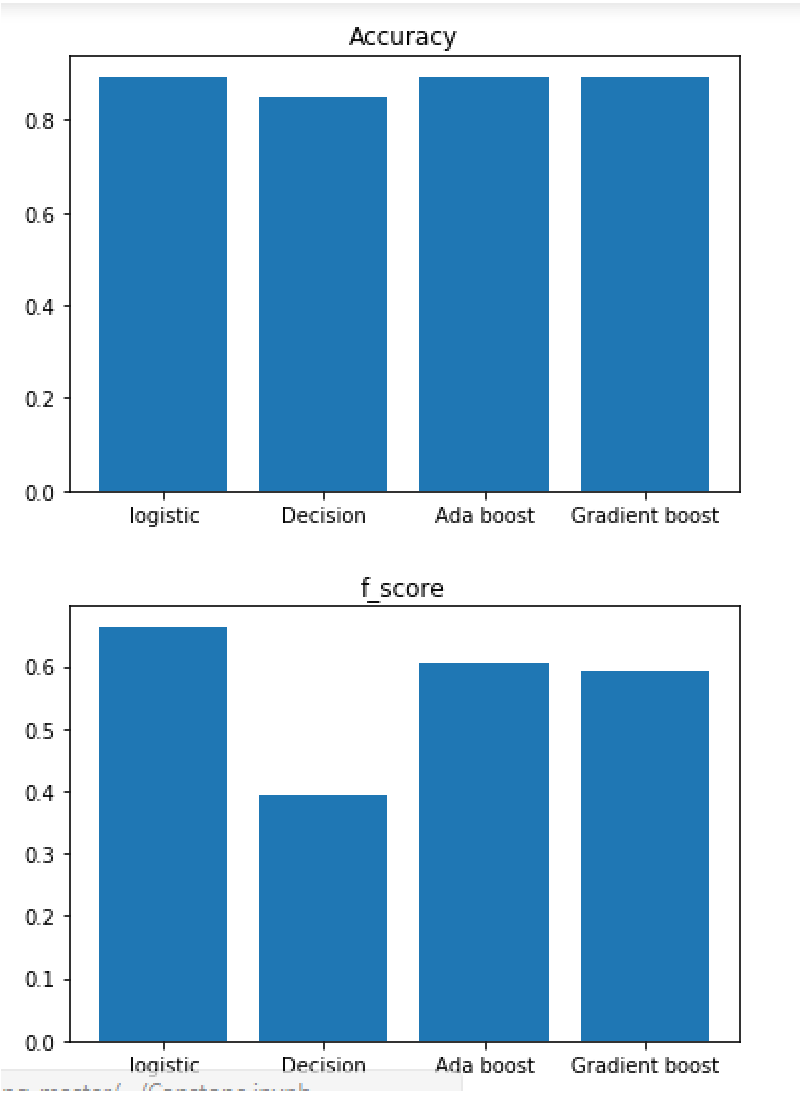
Optimized model :

```
The final accuracy of the best model is 0.889502762431
The final f-score of the best model is 0.868386243386
```

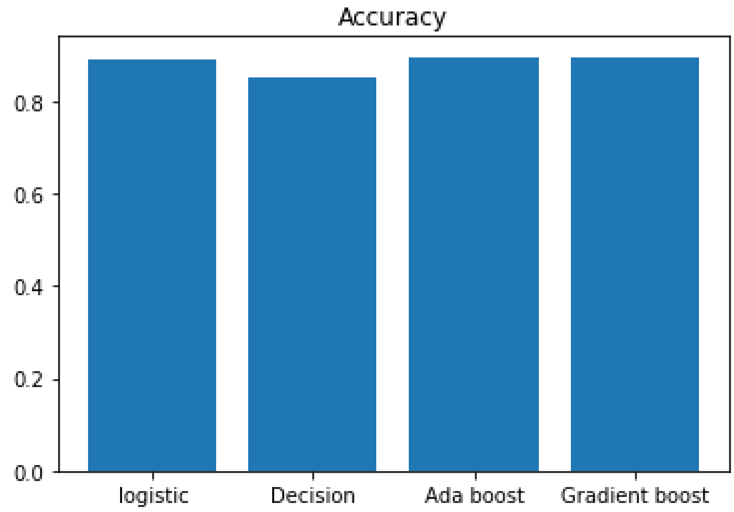
Free-Form Visualization :

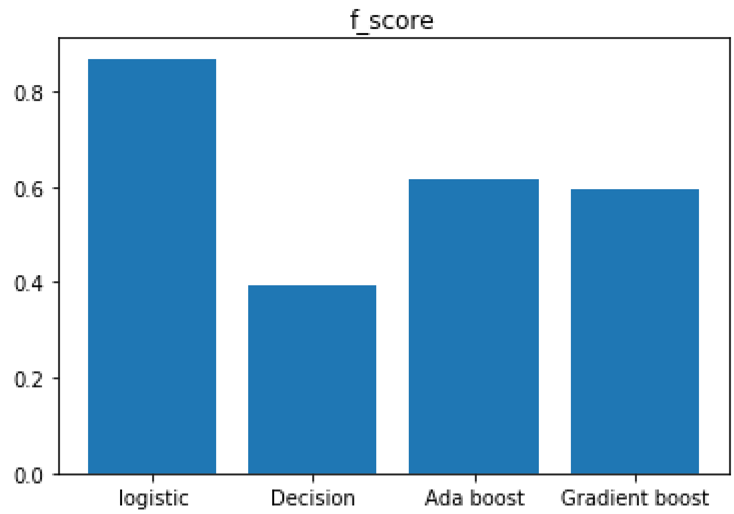
I have visualised the accuracy and f-score of all the models and deter mine the best model before and after the Optimization. Before and af ter the optimization f-score and accuracy score of the bench mark mo del is high when compared to the other models with an accuracy scor e of 0.89 , f-score- 0.66 before optimization and accuracy score -0.89, f-score -0.86 after optimization

Before optimization :



After optimization :





Reflection:

Initially I load the data from the bank.csv file using read_csv() . After that I started data exploration. I find the total number of records, number of customers who subscribed for the campaign, the customers who are not subscribed and the percentage of customers subscribed for the campaign.

After that I have plotted to histograms to determine the skewness of the data. After finding that the data is skewed, I started normalizing the data. I first applied logarithmic transformation and then performed minmaxscaling to scale down the data.

As there are more categorical features in the data, I have applied one hot encoding technique to convert the categorical data to numeric.

After that I removed some of the features that are not found essentia l for prediction by ranking the features using RFE.

After preprocessing I have splitted the data into 80% training and 20 % testing set and applied all the best algorithms on the data set.

I have used some evaluation metrics like Accuracy and f-score to fin d the best algorithm.

Finally I optimized the model using Grid search Which improved the p erformance of the best model logistic regression.

Improvements:

We can apply several more algorithms on this dataset So that we can obtain a more wise model which produces best results. We can also use some review metrics like log-loss to determine how quickly the model will be able to tune.

References:

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