DIGITAL ASSIGNMENT-2

LINEAR AND LOGISTIC REGRESSION

Practice Questions

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1. Importing Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score, roc_curve, classification_report

import warnings
warnings.filterwarnings('ignore')
```

2. Importing Dataset

```
bank_data = pd.read_csv(r'D:\Assignment ExcelR\Logistic Regression\bank-full.csv', delimiter=';')
bank_data.head()
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	po
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	u
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	u
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	u
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	u
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	u

3. Data Understanding

```
bank_data.shape
```

```
(45211, 17)
```

```
bank_data.columns
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'y'],
      dtype='object')
```

```
bank_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

```
bank_data.describe()
```

	age	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

```
bank_data.var()
```

```
age         1.127581e+02
balance     9.270599e+06
day         6.926361e+01
duration    6.632057e+04
campaign    9.597733e+00
pdays       1.002577e+04
previous    5.305841e+00
dtype: float64
```

```
bank_data.skew()
```

```
age          0.684818
balance      8.360308
day          0.093079
duration     3.144318
campaign     4.898650
pdays        2.615715
previous    41.846454
dtype: float64
```

```
bank_data.kurt()
```

```
age            0.319570
balance      140.751547
day           -1.059897
duration      18.153915
campaign      39.249651
pdays          6.935195
previous    4506.860660
dtype: float64
```

Missing Values

```
bank_data.isnull().sum()
```

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

Duplicated Values

```
bank_data[bank_data.duplicated()].shape
```

```
(0, 17)
```

Let's find how many discrete and continuous feature are their in our dataset by seperating them in variables

```
discrete_feature = [feature for feature in bank_data.columns if len(bank_data[feature].unique())<20 and feature]
print('Discrete Variables Count: {}'.format(len(discrete_feature)))
```

```
Discrete Variables Count: 10
```

```
continuous_feature = [feature for feature in bank_data.columns if bank_data[feature].dtype!='O' and feature not in discrete_feature]
print('Continuous Feature Count {}'.format(len(continuous_feature)))
```

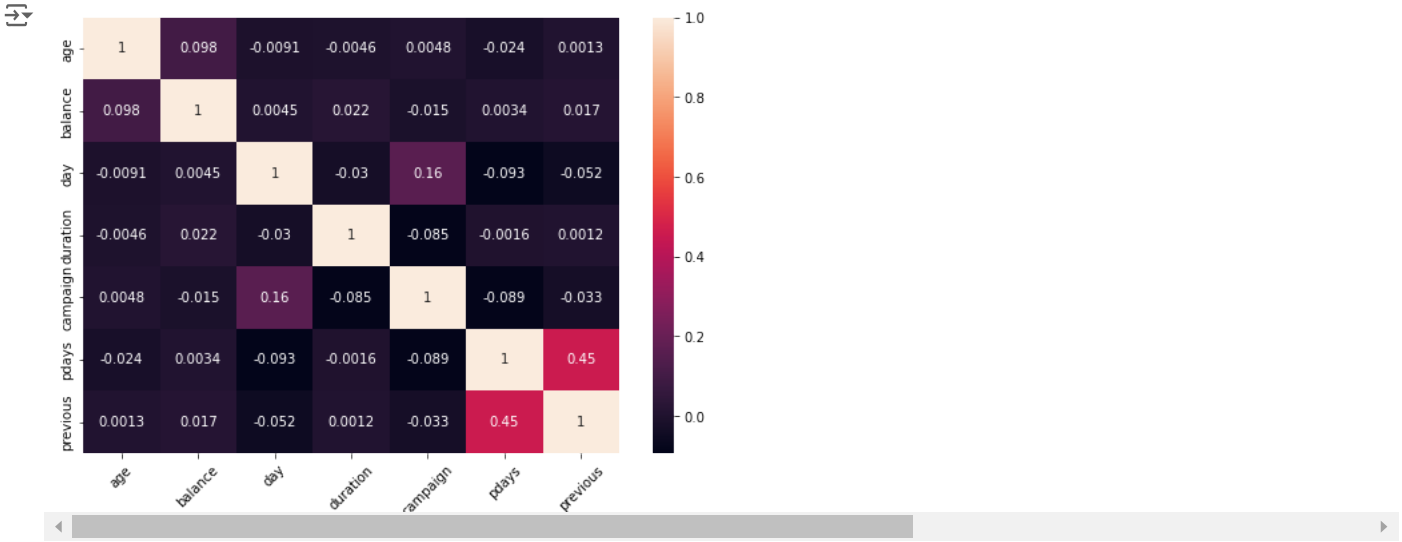
```
Continuous Feature Count 7
```

4. Exploratory Data Analysis

```
bank_data.corr()
```

	age	balance	day	duration	campaign	pdays	previous
age	1.000000	0.097783	-0.009120	-0.004648	0.004760	-0.023758	0.001288
balance	0.097783	1.000000	0.004503	0.021560	-0.014578	0.003435	0.016674
day	-0.009120	0.004503	1.000000	-0.030206	0.162490	-0.093044	-0.051710
duration	-0.004648	0.021560	-0.030206	1.000000	-0.084570	-0.001565	0.001203
campaign	0.004760	-0.014578	0.162490	-0.084570	1.000000	-0.088628	-0.032855
pdays	-0.023758	0.003435	-0.093044	-0.001565	-0.088628	1.000000	0.454820
previous	0.001288	0.016674	-0.051710	0.001203	-0.032855	0.454820	1.000000

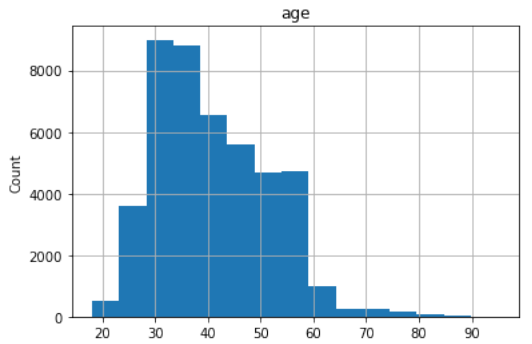
```
fig = plt.figure(figsize= (9,6))
sns.heatmap(bank_data.corr(), annot=True)
plt.xticks(rotation=45)
plt.show()
```

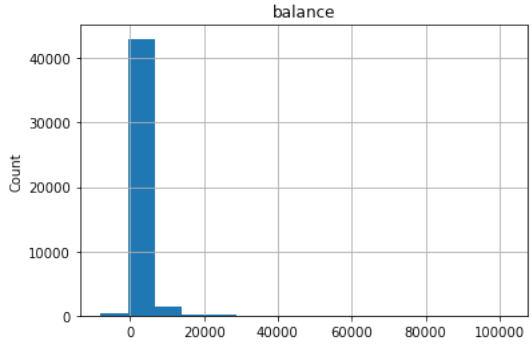


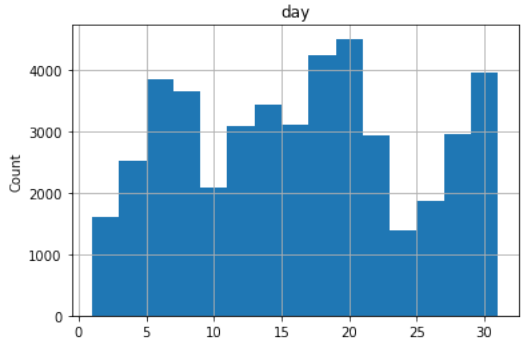
Lets analyze the continuous values by creating histograms to understand the distribution of the numerical features

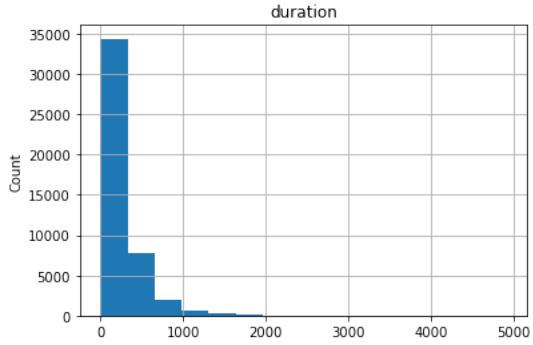
```
for feature in continuous_feature:
    bank_data1 = bank_data.copy()
    bank_data1[feature].hist(bins=15)
    plt.ylabel('Count')
    plt.title(feature)
    plt.show()
```

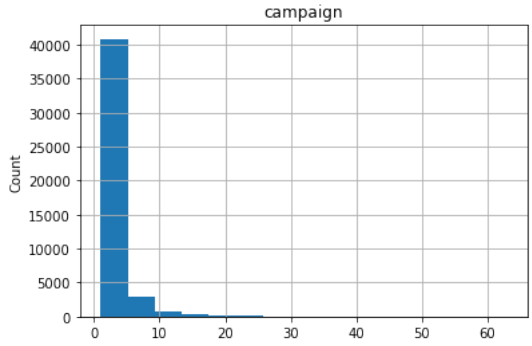
[+]

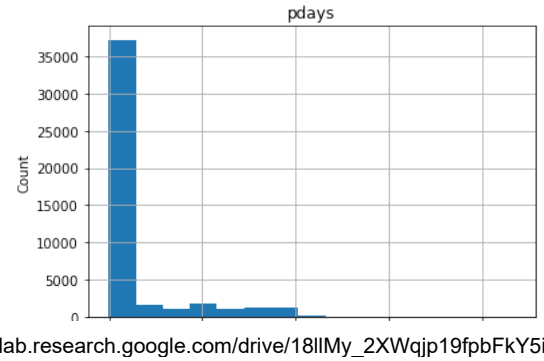

age
Count
0
2000
4000
6000
8000
20
30
40
50
60
70
80
90

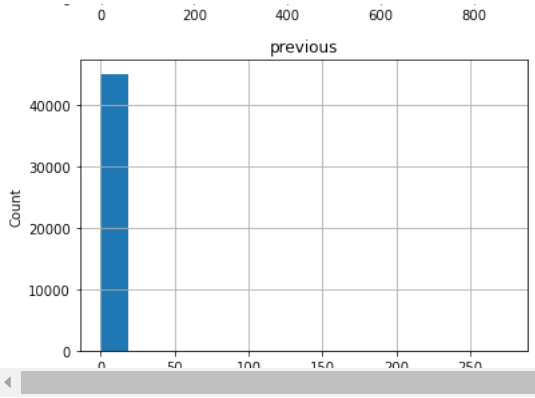

balance
Count
0
10000
20000
30000
40000
0
20000
40000
60000
80000
100000


day
Count
0
1000
2000
3000
4000
0
5
10
15
20
25
30


duration
Count
0
5000
10000
15000
20000
25000
30000
35000
0
1000
2000
3000
4000
5000

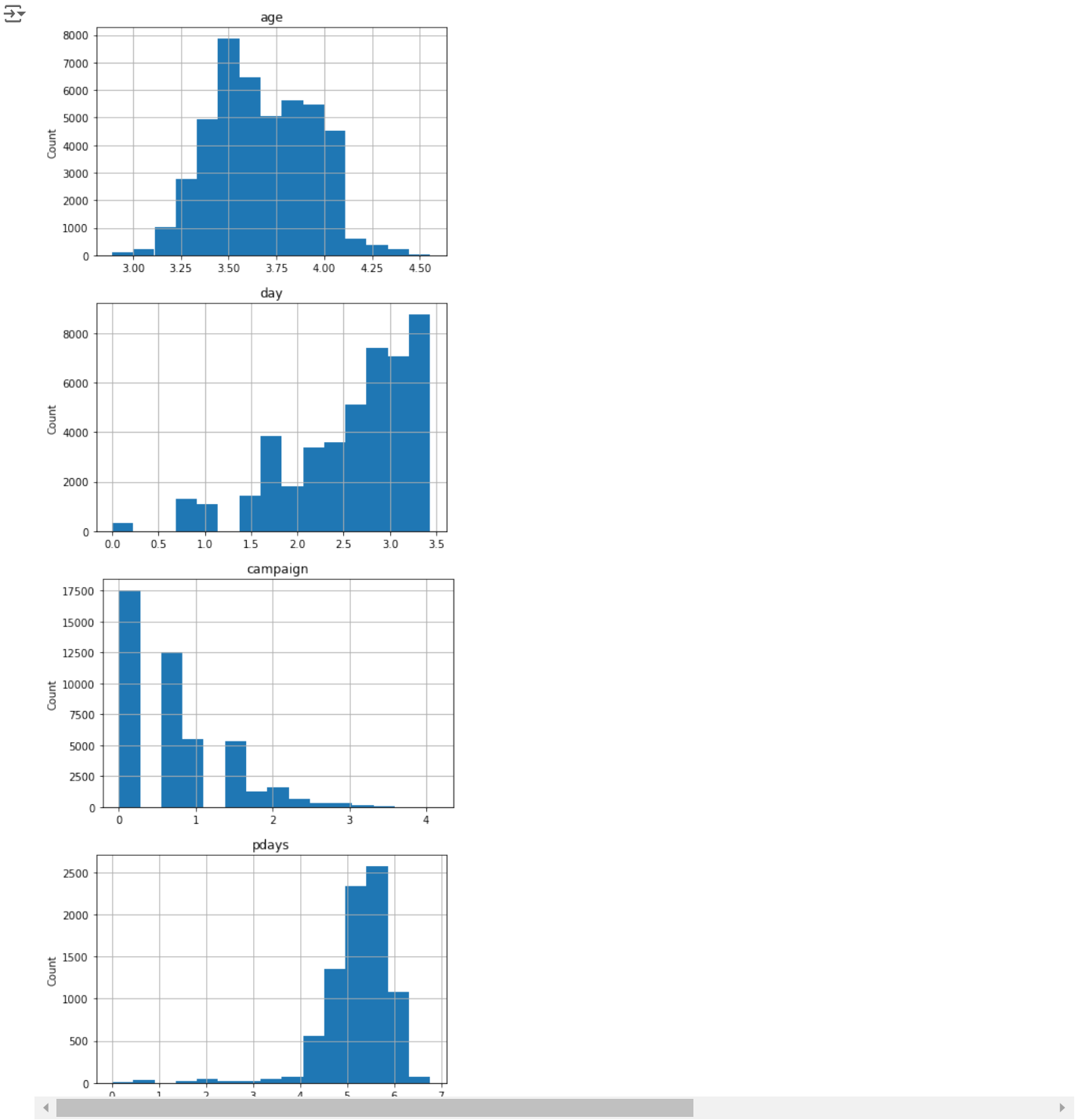

campaign
Count
0
5000
10000
15000
20000
25000
30000
35000
40000
0
10
20
30
40
50
60


pdays
Count
0
5000
10000
15000
20000
25000
30000
35000



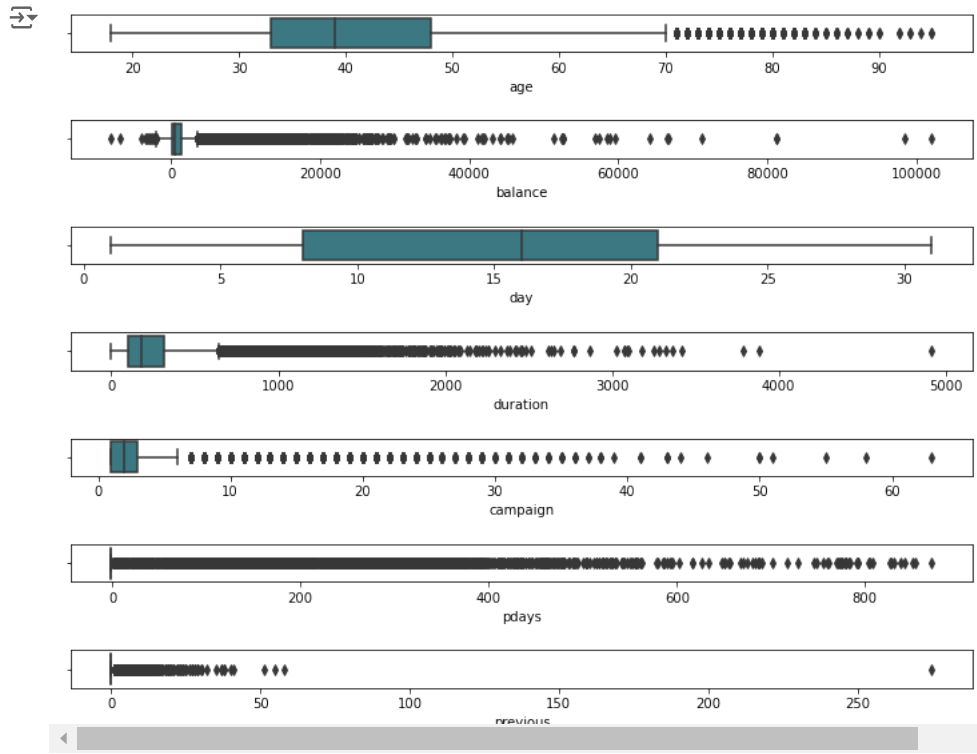
Log transformation

```
for feature in continuous_feature:
    bank_data2 = bank_data.copy()
    if 0 in bank_data2[feature].unique():
        pass
    else:
        bank_data2[feature] = np.log(bank_data2[feature])
        bank_data2[feature].hist(bins=15)
        plt.ylabel('Count')
        plt.title(feature)
        plt.show()
```



Outliers Detection

```
outlier = bank_data.copy()
fig, axes = plt.subplots(7,1,figsize=(10,8), sharex=False, sharey=False)
sns.boxplot(x='age',data=outlier,palette='crest',ax=axes[0])
sns.boxplot(x='balance',data=outlier,palette='crest',ax=axes[1])
sns.boxplot(x='day',data=outlier,palette='crest',ax=axes[2])
sns.boxplot(x='duration',data=outlier,palette='crest',ax=axes[3])
sns.boxplot(x='campaign',data=outlier,palette='crest',ax=axes[4])
sns.boxplot(x='pdays',data=outlier,palette='crest',ax=axes[5])
sns.boxplot(x='previous',data=outlier,palette='crest',ax=axes[6])
plt.tight_layout(pad=2.0)
```

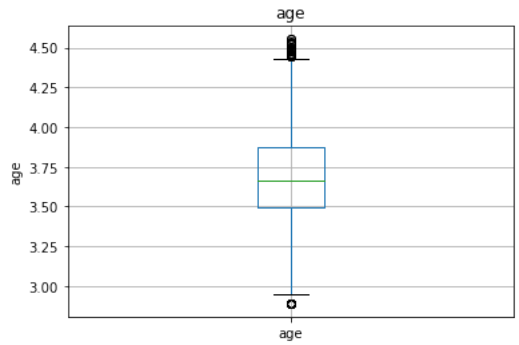


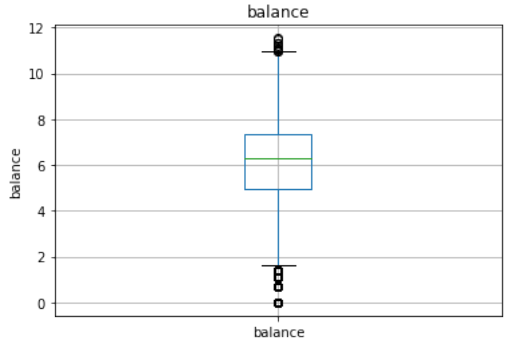
There are lot of outliers present in the dataframe but we can't drop them because they are present in a very large quantity and can be important for model building

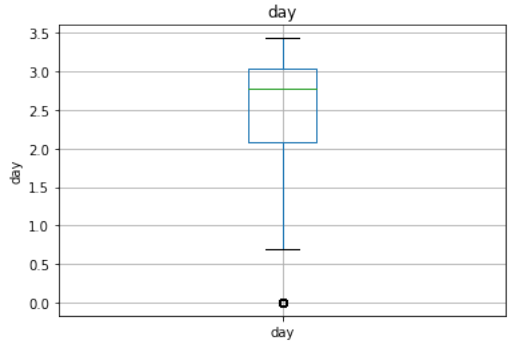
After Log-Transformation

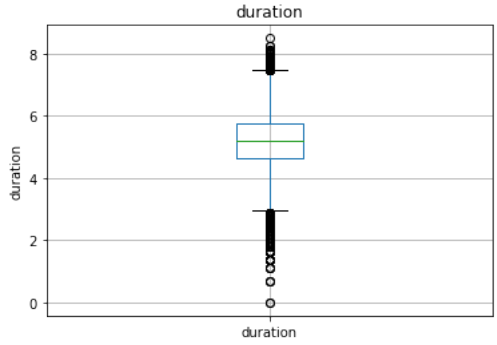
```
for feature in continuous_feature:
    bank_data3 = bank_data.copy()
    bank_data3[feature] = np.log(bank_data3[feature])
    bank_data3.boxplot(column=feature)
    plt.ylabel(feature)
    plt.title(feature)
    plt.show()
```

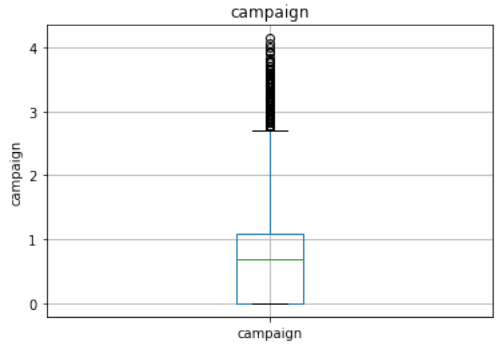
[+]

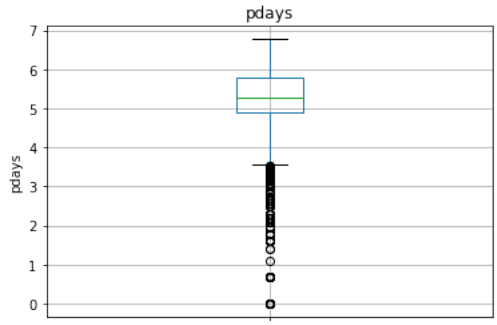

age
4.50
4.25
4.00
3.75
3.50
3.25
3.00
age
age

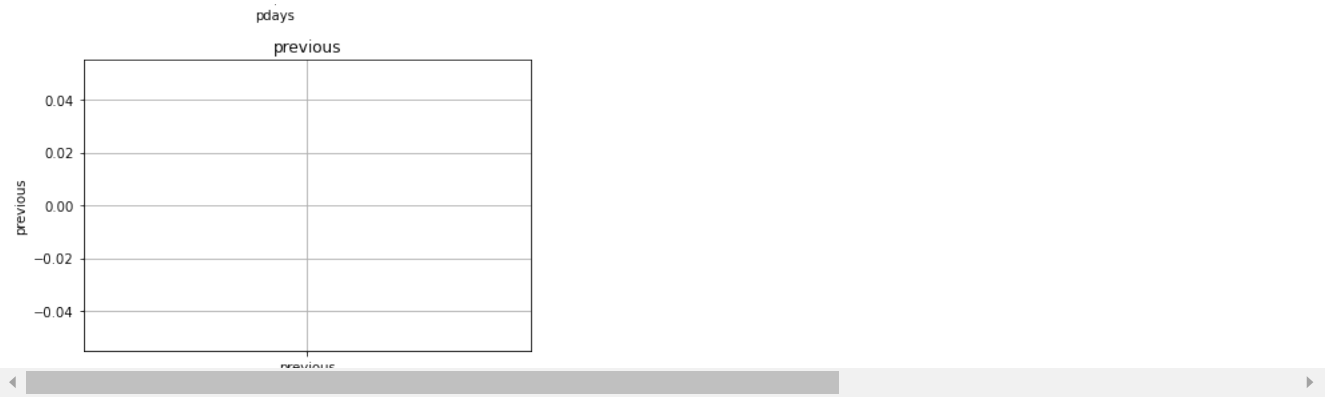

balance
12
10
8
6
4
2
0
balance
balance


day
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
day
day


duration
8
6
4
2
0
duration
duration


campaign
4
3
2
1
0
campaign
campaign


pdays
7
6
5
4
3
2
1
0
pdays



5. Data Preprocessing

```
bank_data[['job','marital','education','default','housing','loan','contact','poutcome','month','y']] = bank_data[
    ['job','marital','education','default','housing','loan','contact','poutcome','month','y']].astype('category')
bank_data_new = bank_data
```

```
bank_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  category
 2   marital    45211 non-null  category
 3   education  45211 non-null  category
 4   default    45211 non-null  category
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  category
 7   loan       45211 non-null  category
 8   contact    45211 non-null  category
 9   day        45211 non-null  int64
 10  month      45211 non-null  category
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  category
 16  y          45211 non-null  category
dtypes: category(10), int64(7)
memory usage: 2.8 MB
```

Label Encoding

```
bank_data_new['month'] = bank_data_new['month'].cat.codes
bank_data_new['job'] = bank_data_new['job'].cat.codes
bank_data_new['marital'] = bank_data_new['marital'].cat.codes
bank_data_new['education'] = bank_data_new['education'].cat.codes
bank_data_new['default'] = bank_data_new['default'].cat.codes
bank_data_new['housing'] = bank_data_new['housing'].cat.codes
bank_data_new['loan'] = bank_data_new['loan'].cat.codes
bank_data_new['contact'] = bank_data_new['contact'].cat.codes
bank_data_new['poutcome'] = bank_data_new['poutcome'].cat.codes
bank_data_new['y'] = bank_data_new['y'].cat.codes
```

6. Model Building

```
x1 = bank_data_new.drop('y', axis=1)
y1 = bank_data_new[['y']]
```

```
x1
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutc
0	58	4	1	2	0	2143	1	0	2	5	8	261	1	-1	0	
1	44	9	2	1	0	29	1	0	2	5	8	151	1	-1	0	
2	33	2	1	1	0	2	1	1	2	5	8	76	1	-1	0	
3	47	1	1	3	0	1506	1	0	2	5	8	92	1	-1	0	
4	33	11	2	3	0	1	0	0	2	5	8	198	1	-1	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
45206	51	9	1	2	0	825	0	0	0	17	9	977	3	-1	0	
45207	71	5	0	0	0	1729	0	0	0	17	9	456	2	-1	0	
45208	72	5	1	1	0	5715	0	0	0	17	9	1127	5	184	3	
45209	57	1	1	1	0	668	0	0	1	17	9	508	4	-1	0	
45210	37	2	1	1	0	2971	0	0	0	17	9	361	2	188	11	

45211 rows × 16 columns

```
y1
```

	y
0	0
1	0
2	0
3	0
4	0
...	...
45206	1
45207	1
45208	1
45209	0
45210	0

45211 rows × 1 columns

```
x_train, x_test, y_train, y_test = train_test_split(x1,y1,test_size=0.20,random_state=12)
print("Shape of X_train : ",x_train.shape)
print("Shape of X_test  : ",x_test.shape)
print("Shape of y_train : ",y_train.shape)
print("Shape of y_test  : ",y_test.shape)
```

```
Shape of X_train :  (36168, 16)
Shape of X_test  :  (9043, 16)
Shape of y_train :  (36168, 1)
Shape of y_test  :  (9043, 1)
```

```
logistic_model = LogisticRegression()
logistic_model.fit(x_train,y_train)
```

```
LogisticRegression()
```

```
logistic_model.coef_
```

```
array([[-2.56272589e-02,  1.39543529e-02, -1.09578144e-01,
        -1.57397743e-02, -5.33858503e-03,  3.04918356e-05,
        -2.19114435e-01, -6.58876024e-02, -2.24076246e-01,
        -1.79125869e-02, -5.54945378e-02,  3.45844766e-03,
        -3.08452326e-01, -3.68682383e-04,  1.22766131e-01,
        -2.09630796e-01]])
```

```
logistic_model.intercept_
```

```
array([-0.08435757])
```

MinMaxScaler

```
scalar = MinMaxScaler(feature_range= (0,1))
scalar.fit(bank_data_new)
scaled_x = scalar.transform(bank_data_new)
```

```
scaled_x
```

```
array([[0.51948052, 0.36363636, 0.5       , ..., 0.        , 1.        ,
        0.        ],
       [0.33766234, 0.81818182, 1.        , ..., 0.        , 1.        ,
        0.        ],
       [0.19480519, 0.18181818, 0.5       , ..., 0.        , 1.        ,
        0.        ],
       ...,
       [0.7012987 , 0.45454545, 0.5       , ..., 0.01090909, 0.66666667,
        1.        ],
       [0.50649351, 0.09090909, 0.5       , ..., 0.        , 1.        ,
        0.        ],
       [0.24675325, 0.18181818, 0.5       , ..., 0.04      , 0.33333333,
        0.        ]])
```

```
classifier1 = LogisticRegression()
classifier1.fit(scaled_x,y1)
```

```
LogisticRegression()
```

```
classifier1.coef_
```

```
array([[ 0.0870051 ,  0.04775924,  0.12651324,  0.16252677, -0.0576052 ,
         0.03974224, -0.34339486, -0.23072377, -0.46707242, -0.10404694,
         0.124258  ,  0.90757706, -0.1296082 ,  0.21393142,  0.01923177,
        -0.1480058 , 13.73203525]])
```

```
proba1 = classifier1.predict_proba(scaled_x)
proba1
```

```
array([[9.99760781e-01, 2.39218924e-04],
       [9.99762234e-01, 2.37766449e-04],
       [9.99832546e-01, 1.67453699e-04],
       ...,
       [1.67888481e-03, 9.98321115e-01],
       [9.99598875e-01, 4.01125023e-04],
       [9.99437111e-01, 5.62889153e-04]])
```

```
y_pred1 = classifier1.predict(scaled_x)
y_pred1
```

```
array([0, 0, 0, ..., 1, 0, 0], dtype=int8)
```

7. Model Testing || 8. Model Evaluation

Train Data

```
y_pred_train1 = logistic_model.predict(x_train)
```

```
print(confusion_matrix(y_train, y_pred_train1))
```

```
[[31344   585]
 [ 3502   737]]
```

```
print(classification_report(y_train,y_pred_train1))
```

```
              precision    recall  f1-score   support

           0       0.90      0.98      0.94     31929
           1       0.56      0.17      0.27      4239

    accuracy                           0.89     36168
   macro avg       0.73      0.58      0.60     36168
weighted avg       0.86      0.89      0.86     36168
```

```
accuracy_score(y_train,y_pred_train1)
```

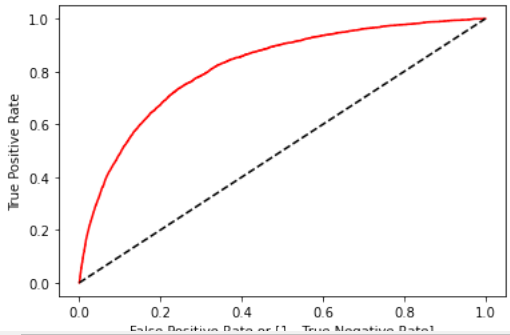
```
0.8869995576199956
```

```
fpr, tpr, thresholds = roc_curve(y_train,logistic_model.predict_proba (x_train)[:,1])

auc = roc_auc_score(y_train,logistic_model.predict_proba (x_train)[:,1])
print('AUC score : {:.2f}%'.format(auc*100))

plt.plot(fpr, tpr, color='red', label='logit model ( area  = %0.2f)'%auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
plt.ylabel('True Positive Rate')
plt.show()
```

```
AUC score : 81.67%
```




```
classification_report1 = classification_report(y_train,y_pred_train1)
print(classification_report1)
```

```
              precision    recall  f1-score   support

           0       0.90      0.98      0.94     31929
           1       0.56      0.17      0.27      4239

    accuracy                           0.89     36168
   macro avg       0.73      0.58      0.60     36168
weighted avg       0.86      0.89      0.86     36168
```

Test Data

```
y_pred_test1 = logistic_model.predict(x_test)
```