##Gopaal ##AM.EN.U4CSE19364

Problem Definition

Credit default risk is the risk that a lender takes the chance that a borrower fails to make required payments of the loan.

Dataset

The training dataset used is from kaggle which is being used to train the models used in this project.

[https://www.kaggle.com/laotse/credit-risk-dataset (https://www.kaggle.com/laotse/credit-risk-dataset)](https://www.kaggle.com/laotse/credit-risk-dataset)

##Python packages

Numpy

NumPy, which stands for Numerical Python, is a library consisting of multidimensional array objects and a collection of routines for processing those arrays. Using NumPy, mathematical and logical operations on arrays can be performed.

Pandas

Pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language.

Matplotlib

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like wxPython, Qt, Tkinter.

Seaborn

Seaborn is a Python data visualization library based on matplotlib. Gives more attractive graphs than matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.

Scikit-Learn

Scikit-Learn (Sklearn) is the most useful and robust library for machine learning in Python. It provides a selection of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction via a consistence interface in Python.This library, which is largely written in Python, is built upon NumPy, SciPy and Matplotlib.

Data Loading

In [2]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import style
style.use("ggplot")
import os
import sys
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```python
from numpy import mean
from numpy import std
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import accuracy_score, f1_score, precision_sco
from sklearn.metrics import confusion_matrix
from mlxtend.plotting import plot_confusion_matrix
from sklearn import model_selection
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve
from sklearn.datasets import make_classification
from sklearn.model_selection import KFold
```

In [4]:
```python
# read data into a DataFrame
credit_df = pd.read_csv("credit_risk_dataset.csv")
```

In [5]:
```python
# check the data size
credit_df.shape
```

Out[5]: (32581, 12)

In [6]:
```
Nan_per = credit_df.isnull().sum()/credit_df.shape[0]*100
Nan_per.round(2)
```

Out[6]:
```
person_age                    0.00
person_income                 0.00
person_home_ownership         0.00
person_emp_length             2.75
loan_intent                   0.00
loan_grade                    0.00
loan_amnt                     0.00
loan_int_rate                 9.56
loan_status                   0.00
loan_percent_income           0.00
cb_person_default_on_file     0.00
cb_person_cred_hist_length    0.00
dtype: float64
```

In [7]:
```
# check the mode, median for the two features
print('person_emp_length mode {}'.format(credit_df['person_emp_leng
print('person_emp_length median {}'.format(credit_df['person_emp_le
print('loan_int_rate mode {}'.format(credit_df['loan_int_rate'].mod
print('loan_int_rate median {}'.format(credit_df['loan_int_rate'].m
```

```
person_emp_length mode 0.0
person_emp_length median 4.0
loan_int_rate mode 7.51
loan_int_rate median 10.99
```

In [8]:
```
# fill NaN with the mode
credit_df['person_emp_length'].fillna(credit_df['person_emp_length'
credit_df['loan_int_rate'].fillna(credit_df['loan_int_rate'].median
```

In [9]:
```
# check the nans are replaced
credit_df.isnull().sum()
```

Out[9]:
```
person_age                    0
person_income                 0
person_home_ownership         0
person_emp_length             0
loan_intent                   0
loan_grade                    0
loan_amnt                     0
loan_int_rate                 0
loan_status                   0
loan_percent_income           0
cb_person_default_on_file     0
cb_person_cred_hist_length    0
dtype: int64
```

In [10]:
```
# numerical varieblesnum_cols = pd.DataFrame(credit_df[credit_df.select_dtypes(include=[
# print the numerical variebles
num_cols.columns
```

Out[10]:
```
Index(['person_age', 'person_income', 'person_emp_length', 'loan_a
mnt',
       'loan_int_rate', 'loan_status', 'loan_percent_income',
       'cb_person_cred_hist_length'],
      dtype='object')
```

In [11]:
```
# clean the dataset and drop outliers
cleaned_credit_df = credit_df[credit_df['person_age']<=100]
cleaned_credit_df = cleaned_credit_df[cleaned_credit_df['person_emp
cleaned_credit_df = cleaned_credit_df[cleaned_credit_df['person_inc
```

In [12]:
```
# get the cleaned numberical variebles
cleaned_num_cols = pd.DataFrame(cleaned_credit_df[cleaned_credit_df
```

In [13]:
```
# get the categorical variebles
cat_cols = pd.DataFrame(cleaned_credit_df[cleaned_credit_df.select_
cat_cols.columns
```

Out[13]:
```
Index(['person_home_ownership', 'loan_intent', 'loan_grade',
       'cb_person_default_on_file'],
      dtype='object')
```

##Summarization

In [14]:
```
# decribe the dataset
credit_df.describe()
```

Out[14]:

	person_age	person_income	person_emp_length	loan_amnt	loan_int_rate	loa
count	32581.000000	3.258100e+04	32581.000000	32581.000000	32581.000000	3258
mean	27.734600	6.607485e+04	4.658114	9589.371106	11.009620	
std	6.348078	6.198312e+04	4.159669	6322.086646	3.081611	
min	20.000000	4.000000e+03	0.000000	500.000000	5.420000	
25%	23.000000	3.850000e+04	2.000000	5000.000000	8.490000	
50%	26.000000	5.500000e+04	4.000000	8000.000000	10.990000	
75%	30.000000	7.920000e+04	7.000000	12200.000000	13.110000	
max	144.000000	6.000000e+06	123.000000	35000.000000	23.220000	

In [15]:
```
encoded_cat_cols = pd.get_dummies(cat_cols)
cat_cols_corr = pd.concat([encoded_cat_cols, cleaned_credit_df['loa
corr = cat_cols_corr.corr().sort_values('loan_status', axis=1, asce
corr = corr.sort_values('loan_status', axis=0, ascending=True)
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask, k=1)] = True
```

In [16]:
```
# concat the numerical and one-hot encoded categorical variebles
cleaned_credit_df = pd.concat([cleaned_num_cols, encoded_cat_cols],
cleaned_credit_df.head()
```

Out[16]:

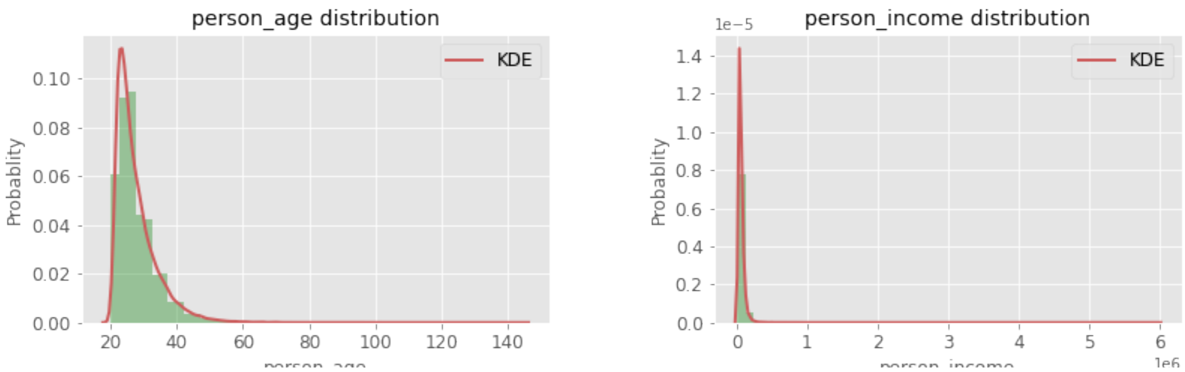
	person_age	person_income	person_emp_length	loan_amnt	loan_int_rate	loan_status	l
1	21	9600	5.0	1000	11.14	0	
2	25	9600	1.0	5500	12.87	1	
3	23	65500	4.0	35000	15.23	1	
4	24	54400	8.0	35000	14.27	1	
5	21	9900	2.0	2500	7.14	1	

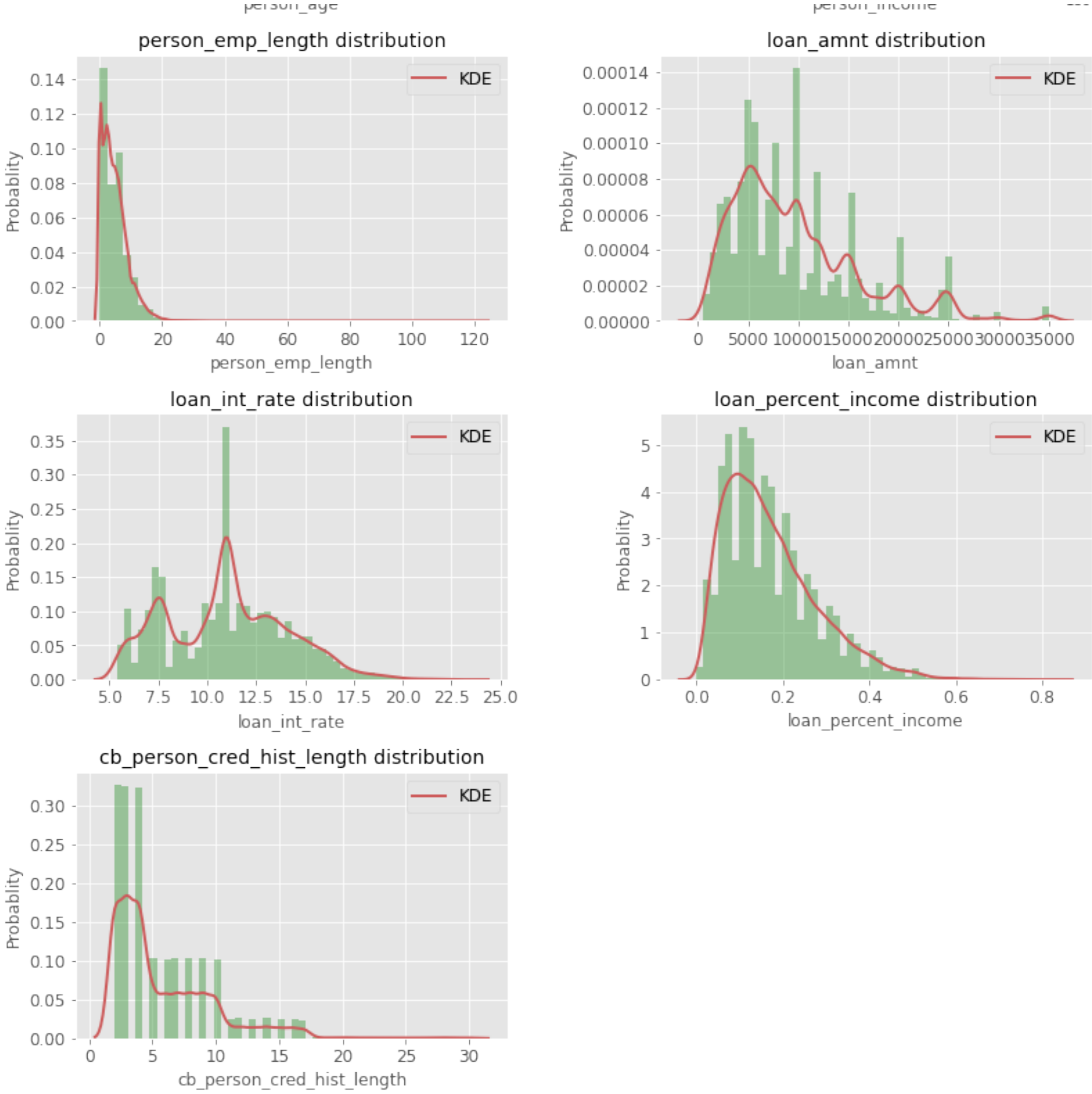
##Visualization

In [17]:
```
# drop the label column 'loan status' before visualization
num_cols_hist = num_cols.drop(['loan_status'], axis=1)
# visualize the distribution for each varieble
plt.figure(figsize=(12,16))

for i, col in enumerate(num_cols_hist.columns):
    idx = int('42'+ str(i+1))
    plt.subplot(idx)
    sns.distplot(num_cols_hist[col], color='forestgreen',
                 kde_kws={'color': 'indianred', 'lw': 2, 'label': 'l
    plt.title(col+' distribution', fontsize=14)
    plt.ylabel('Probablity', fontsize=12)
    plt.xlabel(col, fontsize=12)
    plt.xticks(fontsize=12)
    plt.yticks(fontsize=12)
    plt.legend(['KDE'], prop={"size":12})

plt.subplots_adjust(top=0.92, bottom=0.08, left=0.10, right=0.95, h
                    wspace=0.35)
plt.show()
```

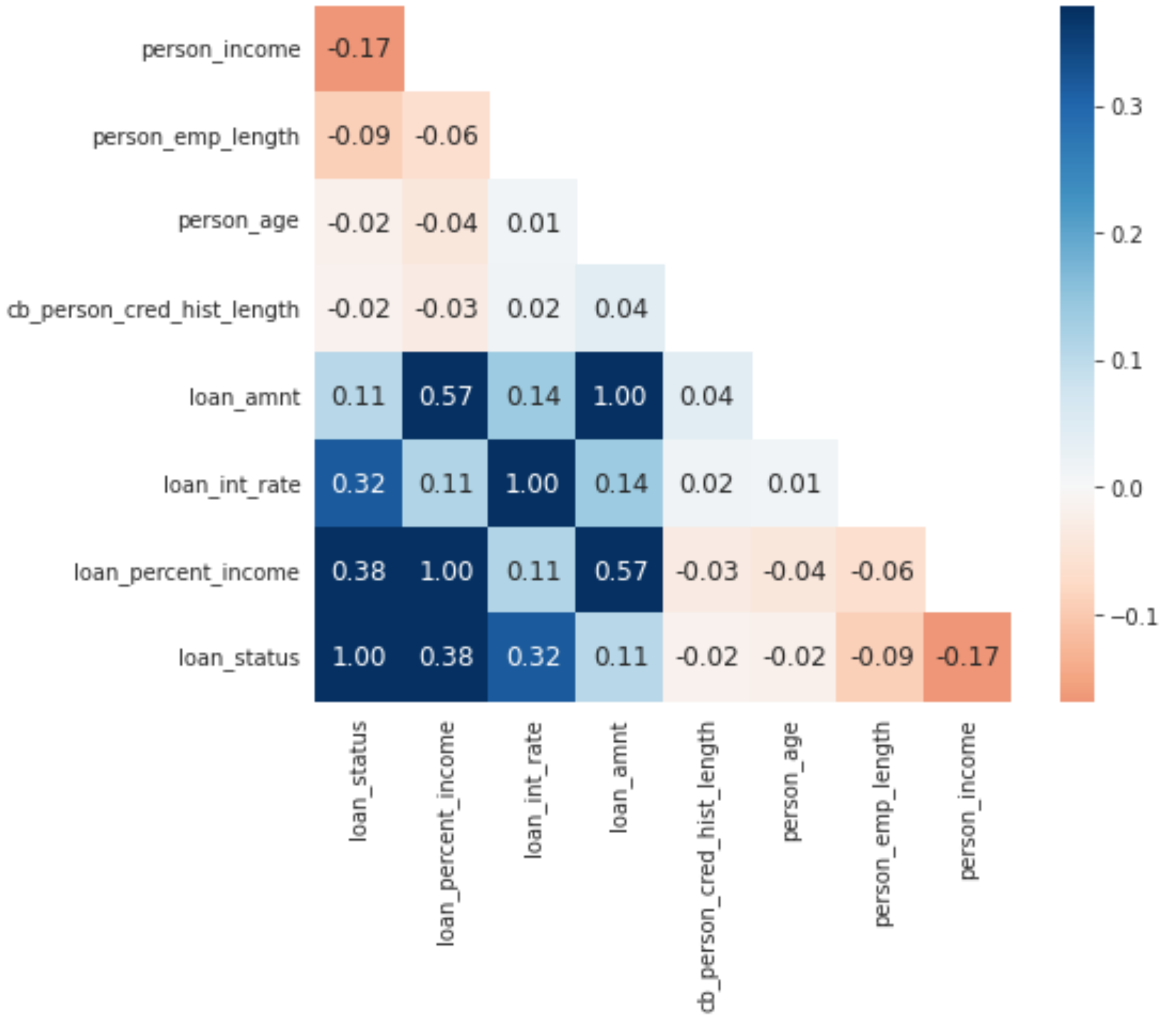




Observation: All of the distributions are positive skewed.

- `person_age` : Most people are 20 to 60 years old. In the following analysis, to be more general, people age > 100 will be droped.
- `person_emp_length` : Most people have less than 40 years of employment. People with employment > 60 years will be droped.
- `person_income` : It seems that there are outliers which has to be removed (> 4 million).
- For all other variables, the distribution is more uniform across the whole range, thus they will be kept.

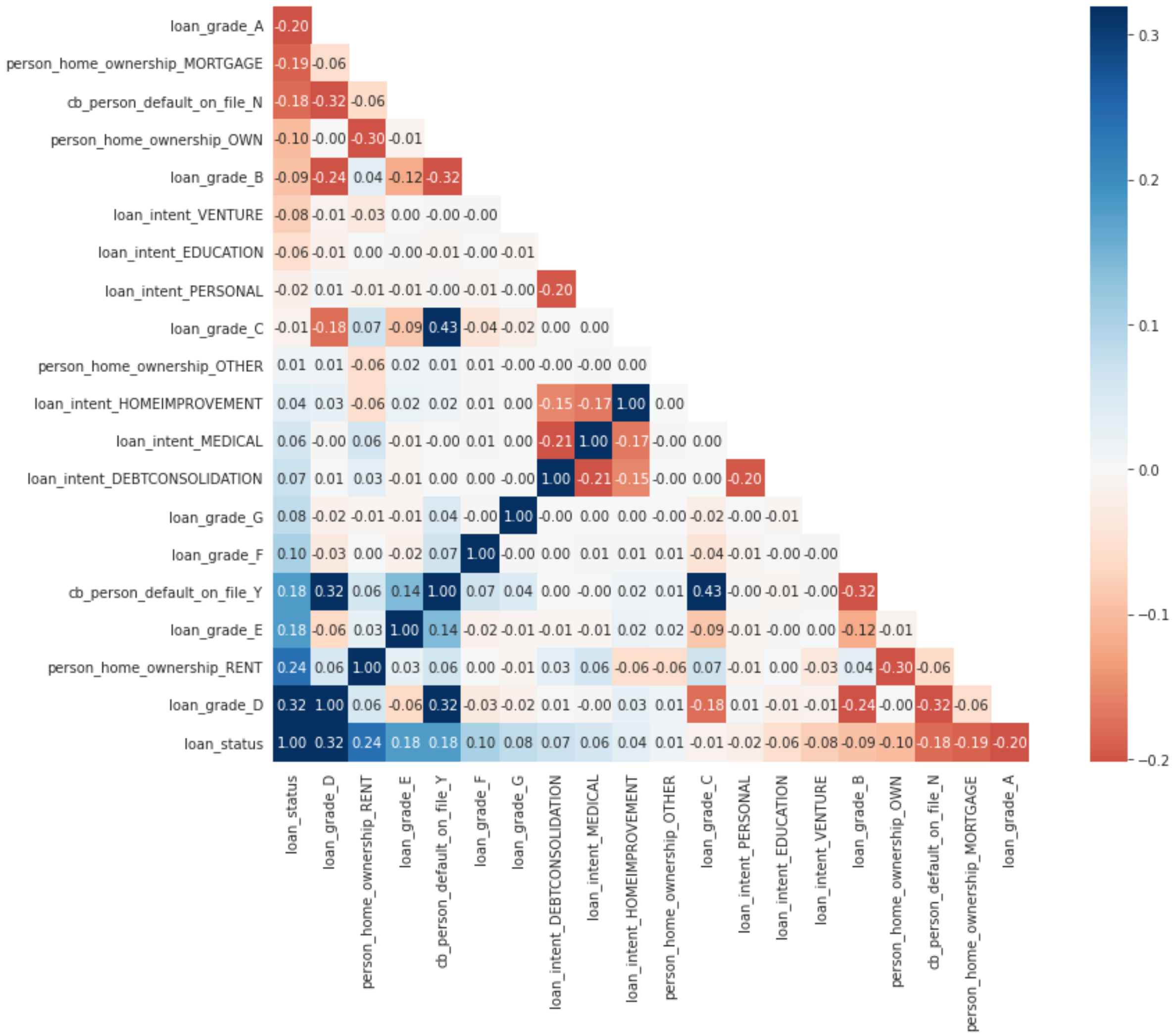
In [18]:
```python
corr = cleaned_num_cols.corr().sort_values('loan_status', axis=1, a
corr = corr.sort_values('loan_status', axis=0, ascending=True)
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask, k=1)] = True
with sns.axes_style("white"):
    f, ax = plt.subplots(figsize=(8, 6))
    ax = sns.heatmap(corr, mask=mask, vmin=corr.loan_status.min(),
                     vmax=corr.drop(['loan_status'], axis=0).loan_s
                     square=True, annot=True, fmt='.2f',
                     center=0, cmap='RdBu',annot_kws={"size": 12})
```



Observation:

- `person_income` , `person_emp_length` , and `person_age` : has negative effect on loan_status being default, which means the larger these variebles, the less likely the person is risky.
- `loan_percent_income` , `loan_int_rate` , and `loan_amnt` : has postive effect on loan_status being default, which means the larger these variebles, the more likely the person is risky.

In [19]:
```
# one-hot encode the catogorical variebles
encoded_cat_cols = pd.get_dummies(cat_cols)
cat_cols_corr = pd.concat([encoded_cat_cols, cleaned_credit_df['loa
corr = cat_cols_corr.corr().sort_values('loan_status', axis=1, asce
corr = corr.sort_values('loan_status', axis=0, ascending=True)
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask, k=1)] = True
with sns.axes_style("white"):
    f, ax = plt.subplots(figsize=(16, 10))
    ax = sns.heatmap(corr, mask=mask, vmin=corr.loan_status.min(),
                     vmax=corr.drop(['loan_status'], axis=0).loan_s
                     square=True, annot=True, fmt='.2f',
                     center=0, cmap='RdBu',annot_kws={"size": 10})
```



In [20]:
```
# check the cleaned dataset size
print ('The cleaned dataset has {} rows and {} columns'.format(clea
                                                                clea
print ('The cleaned dataset has {} numerical features and {} catego
      .format(len(cleaned_num_cols.columns)-1, len(encoded_cat_col
```

```
The cleaned dataset has 32574 rows and 27 columns
The cleaned dataset has 7 numerical features and 19 categorical fe
atures
```

##Data Interpretation

In [21]:
```
pd.read_csv("credit_risk_dataset.csv")
```

Out[21]:

	person_age	person_income	person_home_ownership	person_emp_length	
0	22	59000	RENT	123.0	
1	21	9600	OWN	5.0	
2	25	9600	MORTGAGE	1.0	
3	23	65500	RENT	4.0	
4	24	54400	RENT	8.0	
...	...	...	...	...	
32576	57	53000	MORTGAGE	1.0	
32577	54	120000	MORTGAGE	4.0	
32578	65	76000	RENT	3.0	HOMEIMP
32579	56	150000	MORTGAGE	5.0	
32580	66	42000	RENT	2.0	

32581 rows × 12 columns

##Generation of clean CSV

In [22]:
```
#Generating new csv for cleaned df
cleaned_credit_df.to_csv('Cleaned.csv')
```

In [23]:
```
label = cleaned_credit_df['loan_status'] # labels
features = cleaned_credit_df.drop('loan_status',axis=1) # features
x_train, x_test, y_train, y_test = model_selection.train_test_split

print('The train dataset has {} data\nThe test dataset has {} data'
      format(x_train.shape[0], x_test.shape[0]))
```

```
The train dataset has 22801 data
The test dataset has 9773 data
```

##Algorithms Implementation

Logistic Regression

In [24]:

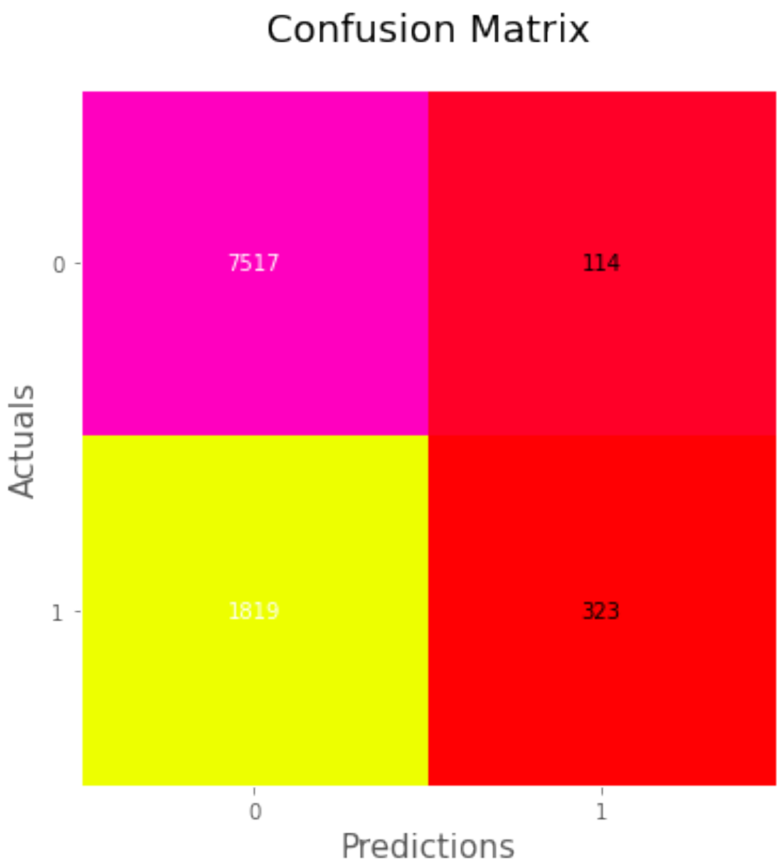
```
#Logistic Regression
lg = LogisticRegression(random_state=42)
lg.fit(x_train, y_train)
preds_lg = lg.predict(x_test)
preds_lg_proba = lg.predict_proba(x_test)
print('\n',classification_report(y_test, preds_lg))
print("Accuracy score = ",accuracy_score(y_test, preds_lg))
cm = confusion_matrix(y_test, preds_lg)
fig, ax = plot_confusion_matrix(conf_mat=cm, figsize=(6, 6), cmap="
plt.xlabel('Predictions', fontsize=15)
plt.ylabel('Actuals', fontsize=15)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.81      0.99      0.89      7631
           1       0.74      0.15      0.25      2142

    accuracy                           0.80      9773
   macro avg       0.77      0.57      0.57      9773
weighted avg       0.79      0.80      0.75      9773

Accuracy score =  0.8022101708789522
```



In [25]:
```
cmlr = confusion_matrix(y_test,preds_lg)
roclr =roc_auc_score(y_test, preds_lg)
acclr = accuracy_score(y_test,preds_lg)
preclr = precision_score(y_test, preds_lg)
reclr = recall_score(y_test, preds_lg)
f1lr = f1_score(y_test, preds_lg)
resultslr = pd.DataFrame([['Logistic Regression', acclr,preclr,recl
 columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score',

resultslr
```

Out[25]:

	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	Logistic Regression	0.80221	0.73913	0.150794	0.250485	0.567927

K-Nearest Neighbour

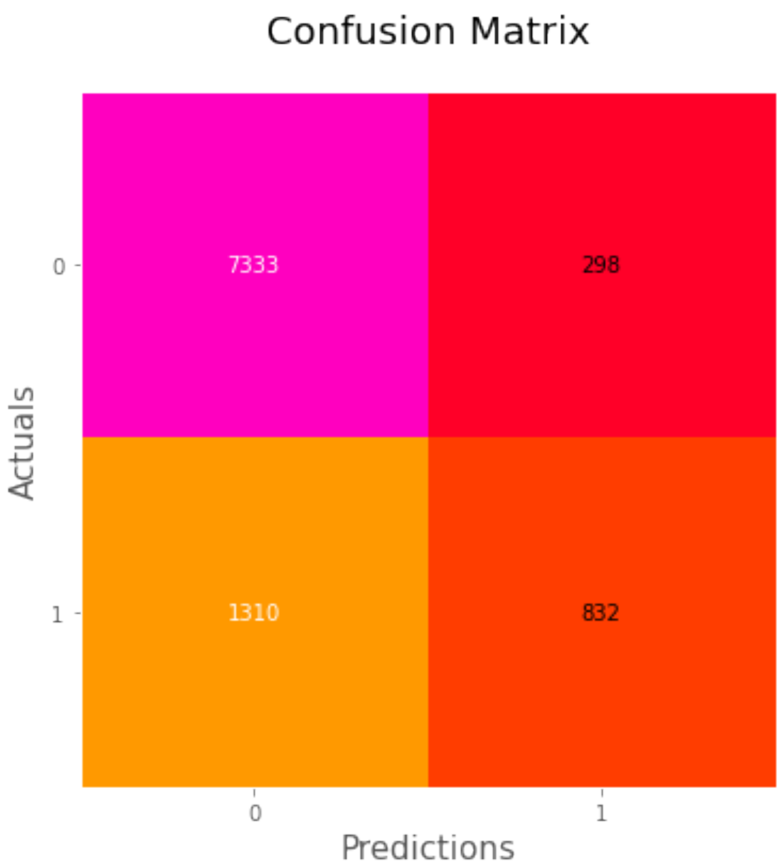
In [26]:
```
#KNN
knn = KNeighborsClassifier(n_neighbors=150)
knn.fit(x_train, y_train)
preds_knn = knn.predict(x_test)
preds_knn_proba = knn.predict_proba(x_test)
print('\n',classification_report(y_test, preds_knn))
print("Accuracy score = ",accuracy_score(y_test, preds_knn))
cm = confusion_matrix(y_test, preds_knn)
fig, ax = plot_confusion_matrix(conf_mat=cm, figsize=(6, 6), cmap="
plt.xlabel('Predictions', fontsize=15)
plt.ylabel('Actuals', fontsize=15)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.85      0.96      0.90      7631
           1       0.74      0.39      0.51      2142

    accuracy                           0.84      9773
   macro avg       0.79      0.67      0.70      9773
weighted avg       0.82      0.84      0.82      9773

Accuracy score =  0.8354650567891129
```



In [27]:
```
cmKNN = confusion_matrix(y_test,preds_knn)
rocKNN =roc_auc_score(y_test, preds_knn)
accKNN = accuracy_score(y_test,preds_knn)
precKNN = precision_score(y_test, preds_knn)
recKNN = recall_score(y_test, preds_knn)
f1KNN = f1_score(y_test, preds_knn)
resultsKNN = pd.DataFrame([['KNN', accKNN,precKNN,recKNN, f1KNN,roc
 columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score',

resultsKNN
```

Out[27]:

	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	KNN	0.835465	0.736283	0.388422	0.508557	0.674685

Decision trees

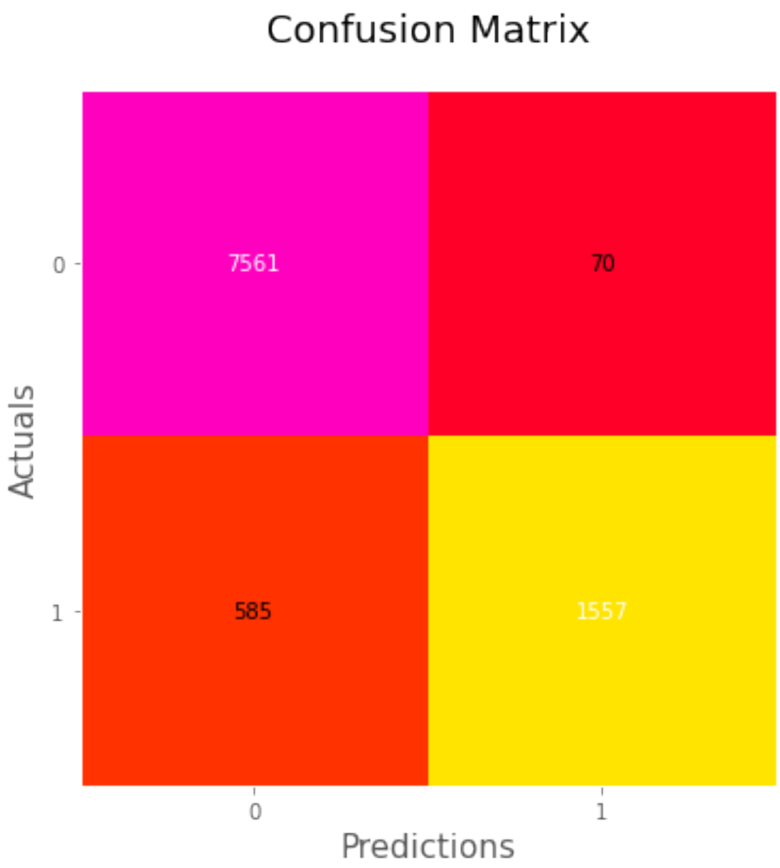
In [28]:
```python
# Decision trees
dt = DecisionTreeClassifier(max_depth=10, min_samples_split=2, min_
dt.fit(x_train, y_train)
preds_dt = dt.predict(x_test)
preds_dt_proba = dt.predict_proba(x_test)
print('\n',classification_report(y_test, preds_dt))
print("Accuracy score = ",accuracy_score(y_test, preds_dt))
cm = confusion_matrix(y_test, preds_dt)
fig, ax = plot_confusion_matrix(conf_mat=cm, figsize=(6, 6), cmap="
plt.xlabel('Predictions', fontsize=15)
plt.ylabel('Actuals', fontsize=15)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      7631
           1       0.96      0.73      0.83      2142

    accuracy                           0.93      9773
   macro avg       0.94      0.86      0.89      9773
weighted avg       0.93      0.93      0.93      9773

Accuracy score =  0.9329786145502916
```



In [29]:
```
cmdt = confusion_matrix(y_test,preds_dt)
rocdt =roc_auc_score(y_test, preds_dt)
accdt = accuracy_score(y_test,preds_dt)
precdt = precision_score(y_test, preds_dt)
recdt = recall_score(y_test, preds_dt)
f1dt = f1_score(y_test, preds_dt)
resultsdt = pd.DataFrame([['decision trees', accdt,precdt,recdt, f1
 columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score',

resultsdt
```

Out[29]:

	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	decision trees	0.932979	0.956976	0.726891	0.826214	0.858859

Gaussian Naive Bayes

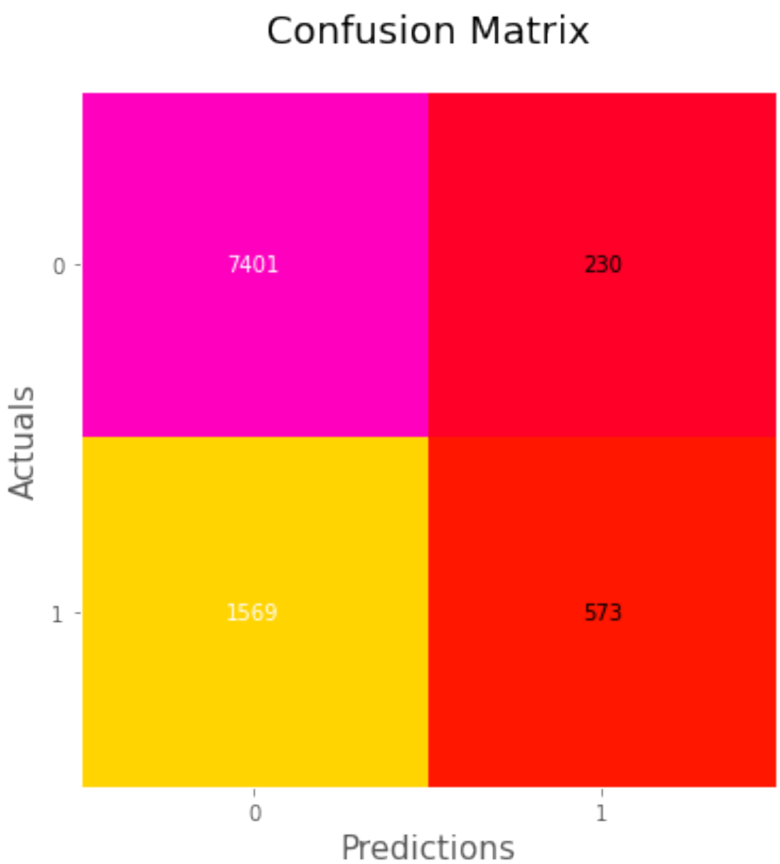
In [30]:
```
naive_bayes = GaussianNB()
naive_bayes.fit(x_train,y_train)
y_pred_nb =naive_bayes.predict(x_test)
roc=roc_auc_score(y_test, y_pred_nb)
acc = accuracy_score(y_test, y_pred_nb)
prec = precision_score(y_test, y_pred_nb)
rec = recall_score(y_test, y_pred_nb)
f1 = f1_score(y_test, y_pred_nb)
model= pd.DataFrame([['Gaussian Naive Bayes', acc,prec,rec, f1,roc]
columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score','
cm = confusion_matrix(y_test, y_pred_nb)
fig, ax = plot_confusion_matrix(conf_mat=cm, figsize=(6, 6), cmap="
print('\n',classification_report(y_test, y_pred_nb))
print("Accuracy score = ",accuracy_score(y_test, y_pred_nb))
plt.xlabel('Predictions', fontsize=15)
plt.ylabel('Actuals', fontsize=15)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.83      0.97      0.89      7631
           1       0.71      0.27      0.39      2142

    accuracy                           0.82      9773
   macro avg       0.77      0.62      0.64      9773
weighted avg       0.80      0.82      0.78      9773

Accuracy score =  0.8159214161465261
```



In [31]:
```
cmnb = confusion_matrix(y_test,y_pred_nb)
rocnb =roc_auc_score(y_test, y_pred_nb)
accnb = accuracy_score(y_test,y_pred_nb)
precnb = precision_score(y_test, y_pred_nb)
recnb = recall_score(y_test, y_pred_nb)
f1nb = f1_score(y_test, y_pred_nb)
resultsnb = pd.DataFrame([['Naive Bayes', accnb,precnb,recnb, f1nb,
 columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score',

resultsnb
```

Out[31]:

	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	Naive Bayes	0.815921	0.713574	0.267507	0.389134	0.618683

Random Forest Classification

In [32]:

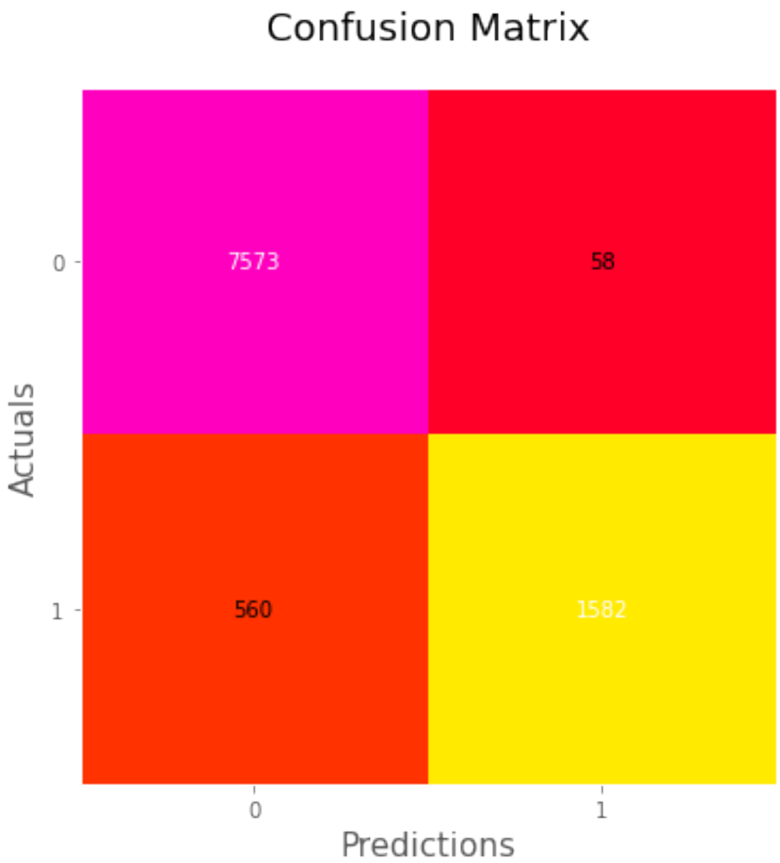
```
rf = RandomForestClassifier(n_estimators = 100,criterion = 'entropy
rf.fit(x_train,y_train)
y_pred_rf = rf.predict(x_test)
roc=roc_auc_score(y_test, y_pred_rf)
acc = accuracy_score(y_test, y_pred_rf)
prec = precision_score(y_test, y_pred_rf)
rec = recall_score(y_test, y_pred_rf)
f1 = f1_score(y_test, y_pred_rf)
model = pd.DataFrame([['Random Forest Classifier', acc,prec,rec, f1
columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score','
cm = confusion_matrix(y_test, y_pred_rf)
fig, ax = plot_confusion_matrix(conf_mat=cm, figsize=(6, 6), cmap="
print('\n',classification_report(y_test, y_pred_rf))
print("Accuracy score = ",accuracy_score(y_test, y_pred_rf))
plt.xlabel('Predictions', fontsize=15)
plt.ylabel('Actuals', fontsize=15)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.93      0.99      0.96      7631
           1       0.96      0.74      0.84      2142

    accuracy                           0.94      9773
   macro avg       0.95      0.87      0.90      9773
weighted avg       0.94      0.94      0.93      9773

Accuracy score =  0.936764555407756
```



In [33]:
```
cmrf = confusion_matrix(y_test,y_pred_rf)
rocrf =roc_auc_score(y_test, y_pred_rf)
accrf = accuracy_score(y_test,y_pred_rf)
precrf = precision_score(y_test, y_pred_rf)
recrf = recall_score(y_test, y_pred_rf)
f1rf = f1_score(y_test, y_pred_rf)
resultsrf = pd.DataFrame([['Random Forest', accrf,precrf,recrf, f1r
 columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score',

resultsrf
```

Out[33]:

	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	Random Forest	0.936765	0.964634	0.738562	0.836594	0.865481

##User Defined Implementation (Scratch Implementation)

In [34]:
```
# Logistic regression User Defined
class logistic_regression:
    def __init__(self,x,y):
        self.intercept = np.ones((x.shape[0], 1))
        self.x = np.concatenate((self.intercept, x), axis=1)
        self.weight = np.zeros(self.x.shape[1])
        self.y = y

    def sigmoid(self, x, weight):
        z = np.dot(x, weight)
        return 1 / (1 + np.exp(-z))

    def loss(self, h, y):
        return (-y * np.log(h) - (1 - y) * np.log(1 - h)).mean()

    def gradient_descent(self, X, h, y):
        return np.dot(X.T, (h - y)) / y.shape[0]

    def fit(self, lr , iterations):
        for i in range(iterations):
            sigma = self.sigmoid(self.x, self.weight)
            loss = self.loss(sigma,self.y)
            dW = self.gradient_descent(self.x , sigma, self.y)
            #Updating the weights
            self.weight -= lr * dW
        return print('Working successfully')
    def predict(self, x_new , treshold):
        x_new = np.concatenate((self.intercept, x_new), axis=1)
        result = self.sigmoid(x_new, self.weight)
        result = result >= treshold
        y_pred = np.zeros(result.shape[0])
        for i in range(len(y_pred)):
            if result[i].any() == True:
                y_pred[i] = 1
            else:
                continue

        return y_pred
```

In [35]:
```
regressor = logistic_regression(features,label)
regressor.fit(0.1 , 5000)
pred_lr = regressor.predict(features,0.5)
```

```
Working successfully
```

In [36]:

```
arr=np.asarray(label)
print(accuracy_score(arr, pred_lr))
cm = confusion_matrix(label, pred_lr)
fig, ax = plot_confusion_matrix(conf_mat=cm, figsize=(6, 6), cmap="
print('\n',classification_report(label, pred_lr))
print("Accuracy score = ",accuracy_score(label, pred_lr))
plt.xlabel('Predictions', fontsize=15)
plt.ylabel('Actuals', fontsize=15)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

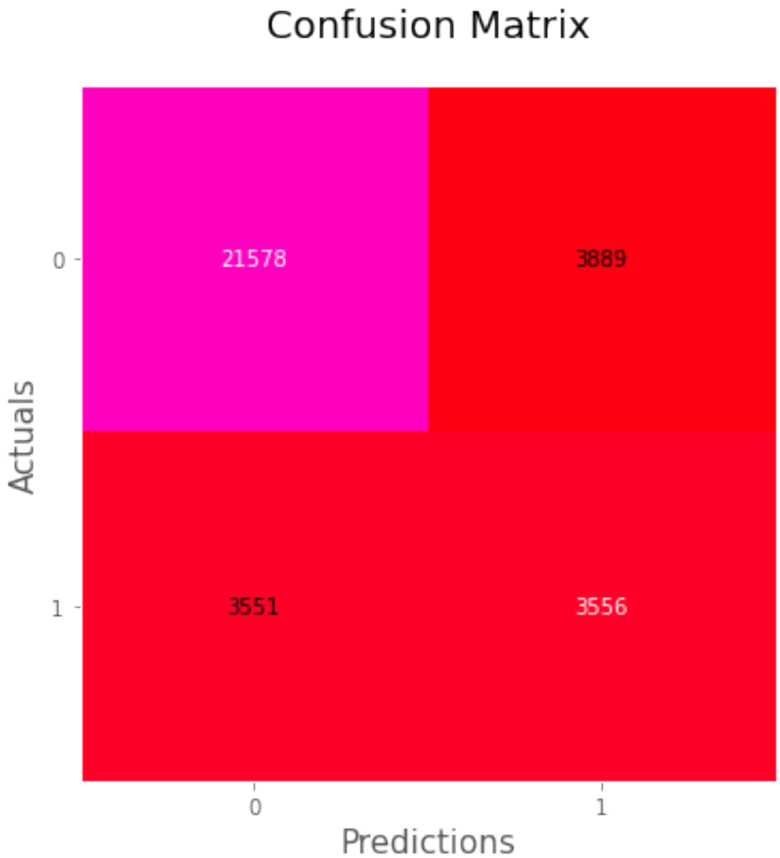
```
0.7715969791858538

              precision    recall  f1-score   support

           0       0.86      0.85      0.85     25467
           1       0.48      0.50      0.49      7107

    accuracy                           0.77     32574
   macro avg       0.67      0.67      0.67     32574
weighted avg       0.78      0.77      0.77     32574

Accuracy score =  0.7715969791858538
```



In [37]:

```
cmlg = confusion_matrix(label,pred_lr)
roclg =roc_auc_score(label, pred_lr)
acclg = accuracy_score(label,pred_lr)
preclg = precision_score(label, pred_lr)
reclg = recall_score(label, pred_lr)
f1lg = f1_score(label, pred_lr)
resultslg = pd.DataFrame([['Logistic Regression Manual', acclg,prec
 columns = ['Model', 'Accuracy', 'Precision', 'Recall', 'F1 Score',

resultslg
```

Out[37]:

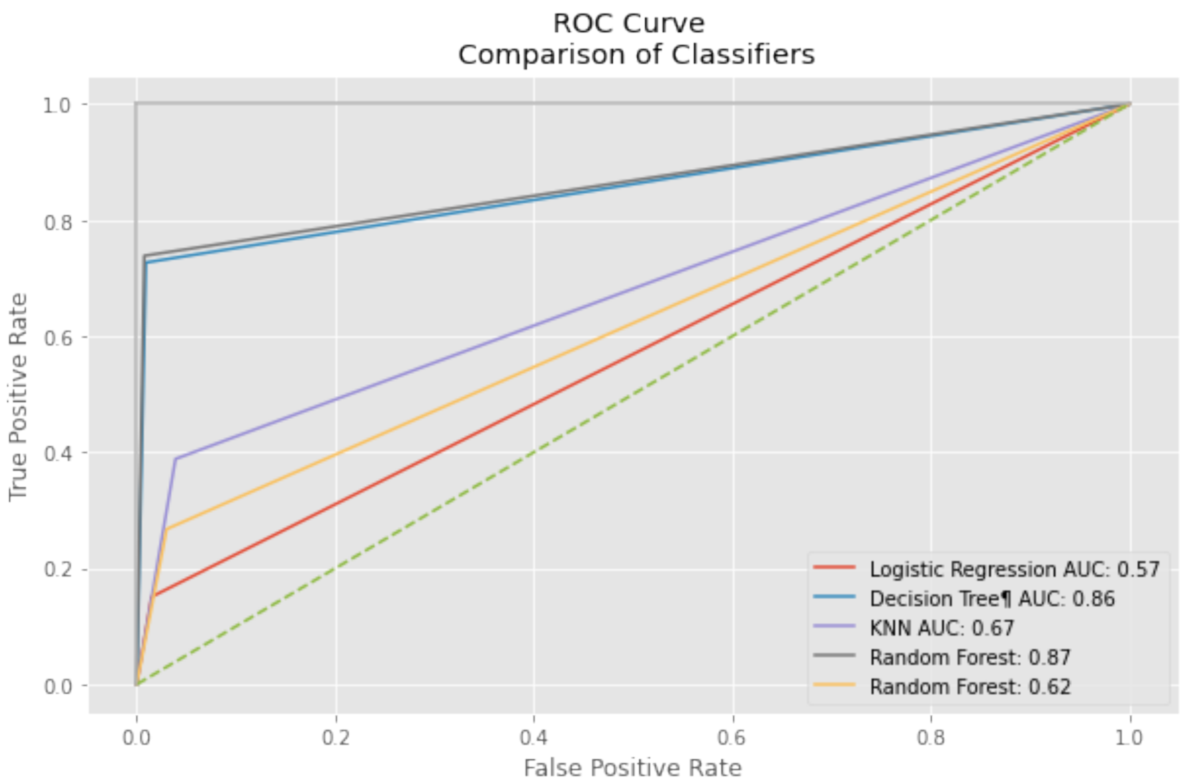
	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	Logistic Regression Manual	0.771597	0.477636	0.500352	0.48873	0.673822

In [42]:

```
log_fpr, log_tpr, log_threshold = roc_curve(y_test, preds_lg)
dt_fpr, rfc_tpr, rfc_threshold = roc_curve(y_test, preds_dt)
knn_fpr, knn_tpr, knn_threshold = roc_curve(y_test, preds_knn)
rf_fpr, rf_tpr, rf_threshold = roc_curve(y_test, y_pred_rf)
nb_fpr, nb_tpr, nb_threshold = roc_curve(y_test, y_pred_nb)
```

In [44]:
```
fig  = plt.figure(figsize=(10,6))
plt.title('ROC Curve \n Comparison of Classifiers')
plt.plot(log_fpr, log_tpr, label ='Logistic Regression AUC: {:.2f}'
plt.plot(dt_fpr, rfc_tpr, label ='Decision Tree¶ AUC: {:.2f}'.forma
plt.plot(knn_fpr, knn_tpr, label ='KNN AUC: {:.2f}'.format(roc_auc_
plt.plot(rf_fpr, rf_tpr, label ='Random Forest: {:.2f}'.format(roc_
plt.plot(nb_fpr, nb_tpr, label ='Random Forest: {:.2f}'.format(roc_

plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



In [45]:
```
frames = [resultslr ,resultsKNN , resultsrf , resultsdt, resultslg,
results = pd.concat(frames)

results
```

Out[45]:

	Model	Accuracy	Precision	Recall	F1 Score	ROC_AUC
0	Logistic Regression	0.802210	0.739130	0.150794	0.250485	0.567927
0	KNN	0.835465	0.736283	0.388422	0.508557	0.674685
0	Random Forest	0.936765	0.964634	0.738562	0.836594	0.865481
0	decision trees	0.932979	0.956976	0.726891	0.826214	0.858859
0	Logistic Regression Manual	0.771597	0.477636	0.500352	0.488730	0.673822
0	Naive Bayes	0.815921	0.713574	0.267507	0.389134	0.618683

Hence, we found that Random Forest is having the best accuracy.

Accuracy of the Random Forest is 93.6% which is the best accuracy when compared to the other 4 algorithms Logistic Regression, KNN, Decision Trees, Naive Bayes.