In [943…

```
import itertools
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import NullFormatter
import pandas as pd
import numpy as np
import matplotlib.ticker as ticker
from sklearn import preprocessing
import warnings
warnings.filterwarnings('ignore')
```

In [944…

```
df = pd.read_csv('loan_train.csv')
df.head()
```

Out[944…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educati
0	0	0	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	H Schoo Bel
1	2	2	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	Becha
2	3	3	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	colle
3	4	4	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	colle
4	6	6	PAIDOFF	1000	30	9/9/2016	10/8/2016	29	colle

In [945…

```
df.shape
```

Out[945…

```
(346, 10)
```

changing to date time object

In [946…

```
# changing both, effective date and due date' format.
df['effective_date'] = pd.to_datetime(df['effective_date'])
df['due_date'] = pd.to_datetime(df['due_date'])
df.head()
```

Out[946…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educa
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Scho E
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bec
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	cc
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	cc
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	cc

Data visualization and Pre-processing

In [947…

```
df['loan_status'].value_counts()
```

Out[947…

```
PAIDOFF       260
COLLECTION     86
Name: loan_status, dtype: int64
```

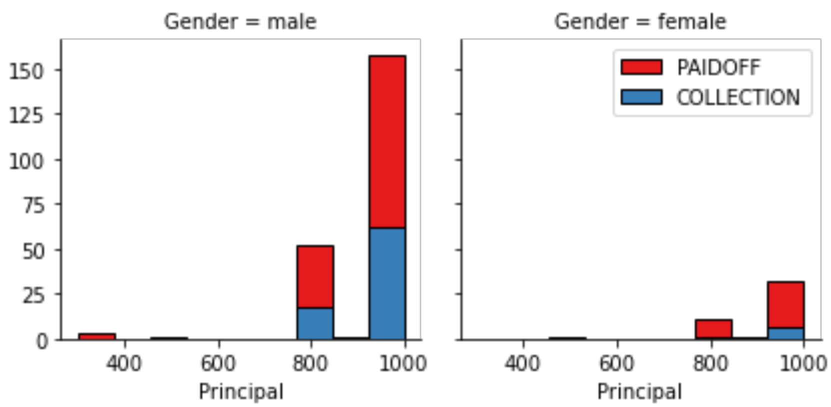
In [948…

```
### 260 out of 346 have been paid off with 86 sent into correction.
```

Lets plot some columns to better understand out data

In [949…

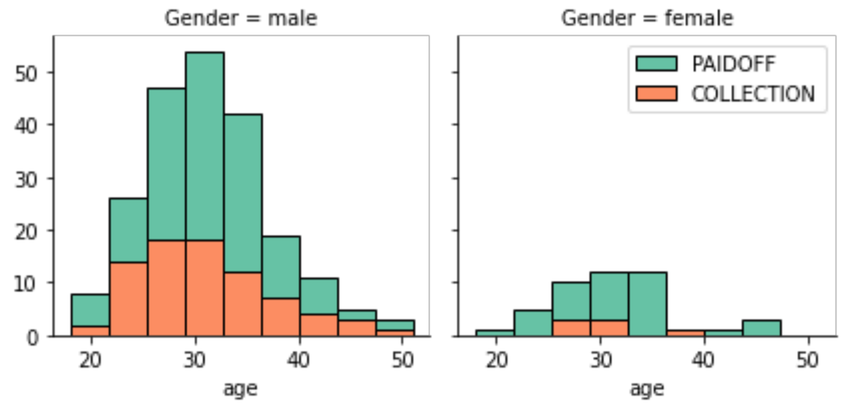
```
import seaborn as sns

bins = np.linspace(df.Principal.min(), df.Principal.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wr
g.map(plt.hist, 'Principal', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



Men seem to have higher rate of default compared to women.

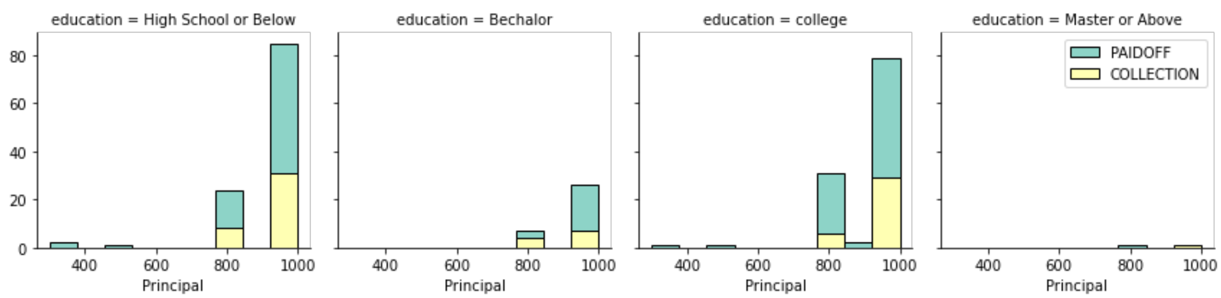
In [950…

```
bins = np.linspace(df.age.min(), df.age.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set2", col_wr
g.map(plt.hist, 'age', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



In [951…

```
bins = np.linspace(df.Principal.min(), df.Principal.max(), 10)
g = sns.FacetGrid(df, col="education", hue="loan_status", palette="Set3", col
g.map(plt.hist, 'Principal', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



lets look at relationship between day of week (effective date) and loan status

In [952…

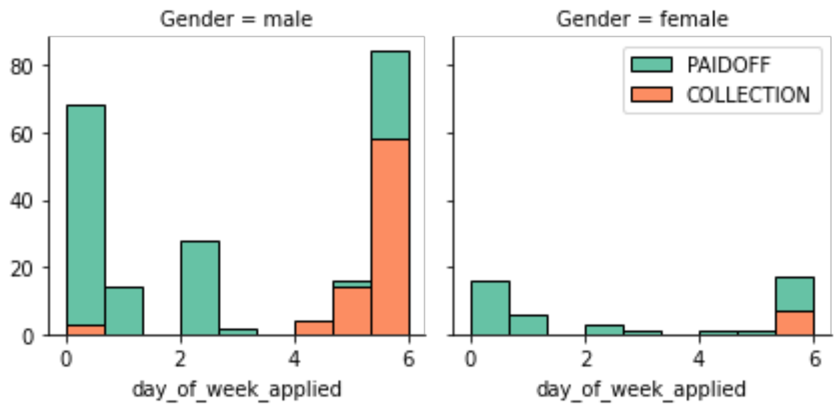
```
df['day_of_week_applied'] = df['effective_date'].dt.dayofweek
df.head()
```

Out[952…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educ
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Schc E
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bec
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	cc
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	cc
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	cc

In [953…

```
bins = np.linspace(df.day_of_week_applied.min(), df.day_of_week_applied.max()
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set2", col_wr
g.map(plt.hist, 'day_of_week_applied', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



It seems that when the effective date of loan is during the weekends, the loans tend to go into collection at a higher rate compared to weekdays

In [954…

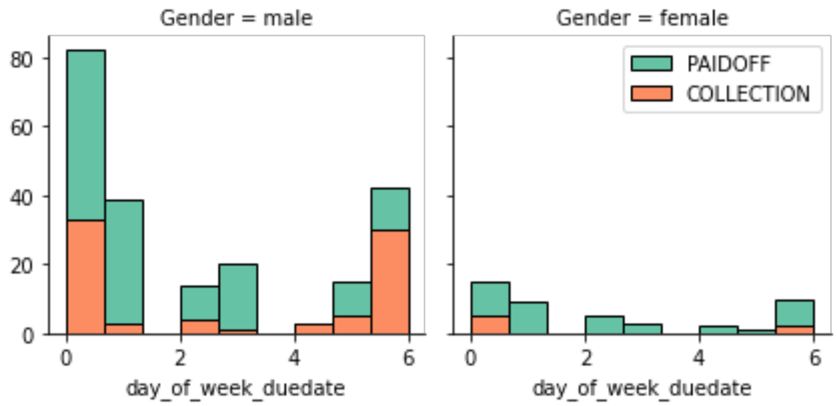
```
df['day_of_week_duedate'] = df['due_date'].dt.dayofweek
df.head()
```

Out[954…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educ
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Scho E
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bec
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	cc
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	cc
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	cc

In [955…

```
bins = np.linspace(df.day_of_week_duedate.min(), df.day_of_week_duedate.max()
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set2", col_wr
g.map(plt.hist, 'day_of_week_duedate', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



the rate of default seems high on Monday and Sunday (day 0 and 6) as per their due dates.

Pre-Processing and Extraction

lets create 2 new columns in our dataframe to help us better analyze the impact of days_of_week on defaults

In [956…

```
df['applied_weekend'] = df['day_of_week_applied'].apply(lambda x: 1 if (x > 3
df['due_on_0_6_day'] = df["day_of_week_duedate"].apply(lambda x: 1 if (x == 0
df.head()
```

Out[956…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educ
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Sch E
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bec
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	cc
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	cc
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	cc

In [957…

```
#converting categorical data into numerical date (Gender)
df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)
df.head()
```

Out[957…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educ
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	Sch E
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bec
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	cc
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	cc

Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educ

In [958…

```
Feature = df[['Principal','terms','age','Gender','applied_weekend','due_on_0_
Feature = pd.concat([Feature,pd.get_dummies(df['education'])], axis=1)


Feature.head()
```

Out[958…

	Principal	terms	age	Gender	applied_weekend	due_on_0_6_day	loan_status	Bechalor
0	1000	30	45	0	0	0	PAIDOFF	0
1	1000	30	33	1	0	0	PAIDOFF	1
2	1000	15	27	0	0	0	PAIDOFF	0
3	1000	30	28	1	1	0	PAIDOFF	0
4	1000	30	29	0	1	0	PAIDOFF	0

In [959…

```
#lets create a new column 'loan_status_01'to store numerical data about loan
Feature['loan_status_01'] = Feature['loan_status'].apply(lambda x:1 if (x ==
Feature.drop(['loan_status'], axis =1, inplace = True)
Feature.head()
```

Out[959…

	Principal	terms	age	Gender	applied_weekend	due_on_0_6_day	Bechalor	High School or Below	Maste o Abov
0	1000	30	45	0	0	0	0	1	
1	1000	30	33	1	0	0	1	0	
2	1000	15	27	0	0	0	0	0	
3	1000	30	28	1	1	0	0	0	
4	1000	30	29	0	1	0	0	0	

In [960…

```
targetx = Feature[['loan_status_01']].values
targetx[0:5]
```

Out[960…

```
array([[1],
       [1],
       [1],
       [1],
       [1]])
```

In [961…

```
Feature.drop(['loan_status_01'], axis = 1, inplace =True)
Feature.head()
```

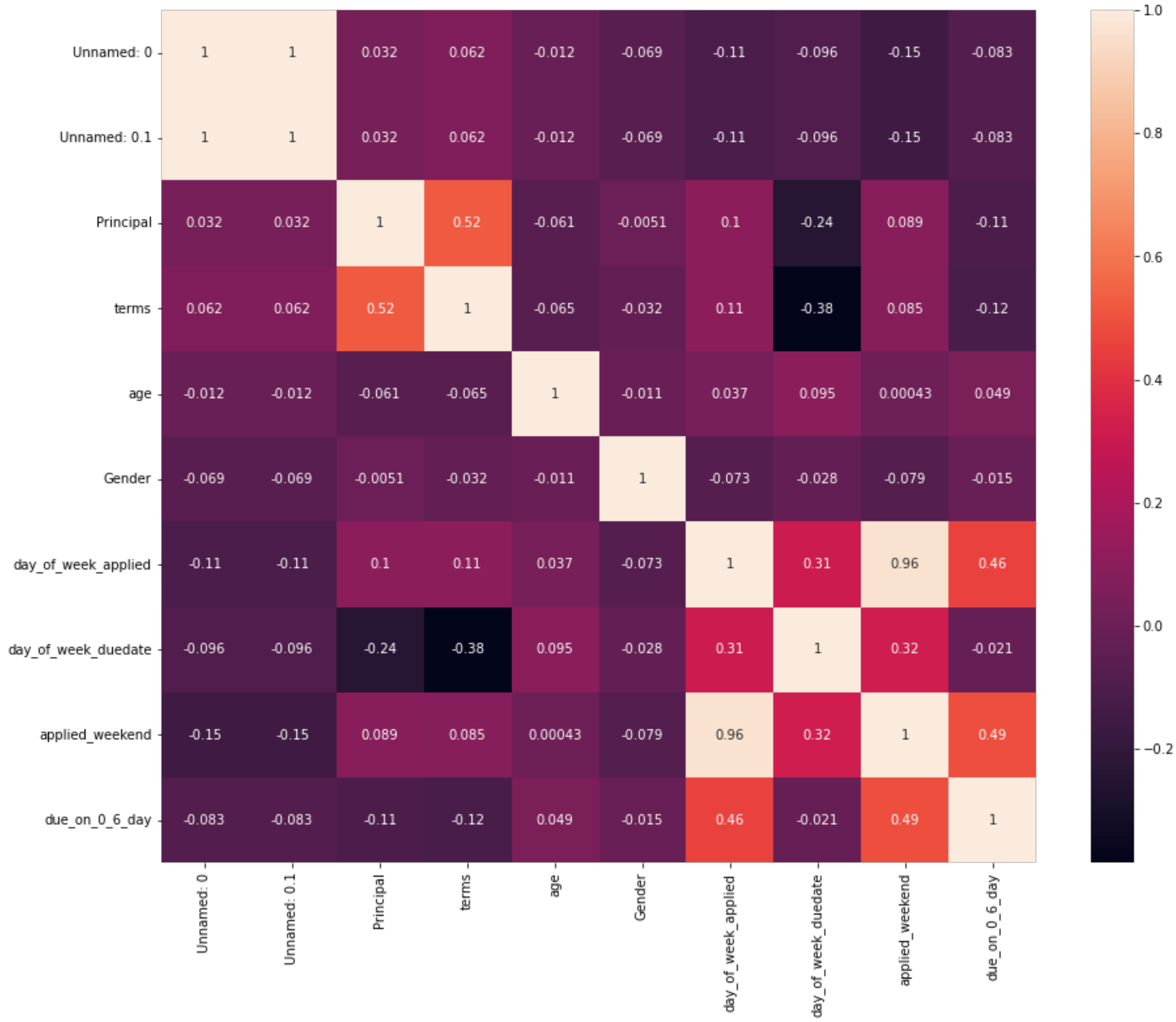
Out[961…

Principal	terms	age	Gender	applied_weekend	due_on_0_6_day	Bechalor	High School	Maste o

								or Below	Abov
0	1000	30	45	0	0	0	0	1	
1	1000	30	33	1	0	0	1	0	
2	1000	15	27	0	0	0	0	0	
3	1000	30	28	1	1	0	0	0	
4	1000	30	29	0	1	0	0	0	

In [962…

```
plt.figure(figsize=(15, 12))
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True)
plt.show()
```



lets define our feature sets, X and target Y:

In [963…

```
#getting a Numpy representation of the DF Feature
X = Feature.values
X[0:5]
```

Out[963…
```
array([[1000,   30,   45,    0,    0,    0,    0,    1,    0,    0],
       [1000,   30,   33,    1,    0,    0,    1,    0,    0,    0],
       [1000,   15,   27,    0,    0,    0,    0,    0,    0,    1],
       [1000,   30,   28,    1,    1,    0,    0,    0,    0,    1],
       [1000,   30,   29,    0,    1,    0,    0,    0,    0,    1]])
```

In [964…
```
y = targetx
y[0:5]
```

Out[964…
```
array([[1],
       [1],
       [1],
       [1],
       [1]])
```

Normalization of data

Since we have different CSV files for training and testing, we will not split the data, and use the entire 'loan_train.csv' for training models.

In [965…
```
X = preprocessing.StandardScaler().fit(X).transform(X.astype(float))
X[0:5]
```

Out[965…
```
array([[ 0.51578458,  0.92071769,  2.33152555, -0.42056004, -1.20577805,
        -1.31316772, -0.38170062,  1.13639374, -0.07624929, -0.86968108],
       [ 0.51578458,  0.92071769,  0.34170148,  2.37778177, -1.20577805,
        -1.31316772,  2.61985426, -0.87997669, -0.07624929, -0.86968108],
       [ 0.51578458, -0.95911111, -0.65321055, -0.42056004, -1.20577805,
        -1.31316772, -0.38170062, -0.87997669, -0.07624929,  1.14984679],
       [ 0.51578458,  0.92071769, -0.48739188,  2.37778177,  0.82934003,
        -1.31316772, -0.38170062, -0.87997669, -0.07624929,  1.14984679],
       [ 0.51578458,  0.92071769, -0.3215732 , -0.42056004,  0.82934003,
        -1.31316772, -0.38170062, -0.87997669, -0.07624929,  1.14984679]])
```

In [966…
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, ran
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (276, 10) (276, 1)
Test set: (70, 10) (70, 1)
```

Classification

Now, it is your turn, use the training set to build an accurate model. Then use the test set to report the accuracy of the model You should use the following algorithm:

K Nearest Neighbor(KNN) Decision Tree Support Vector Machine Logistic Regression

Notice:

You can go above and change the pre-processing, feature selection, feature-extraction, and so on, to make a better model. You should use either scikit-learn, Scipy or Numpy libraries for developing the classification algorithms. You should include the code of the

K Nearest Neighbor(KNN)

Notice: You should find the best k to build the model with the best accuracy.\ warning: You should not use the loan_test.csv for finding the best k, however, you can split your train_loan.csv into train and test to find the best k.

In [967…

```
#training
from sklearn.neighbors import KNeighborsClassifier

k = 3
neigh = KNeighborsClassifier(n_neighbors = k).fit(X_train,y_train.ravel())
```

In [968…

```
#predicitng (with k being 3)
knn_result = neigh.predict(X_test)
knn_result[0:5]
#y[0:5]
```

Out[968…

```
array([1, 1, 1, 1, 1])
```

In [969…

```
y_test[0:5]
```

Out[969…

```
array([[1],
       [1],
       [1],
       [1],
       [1]])
```

In [970…

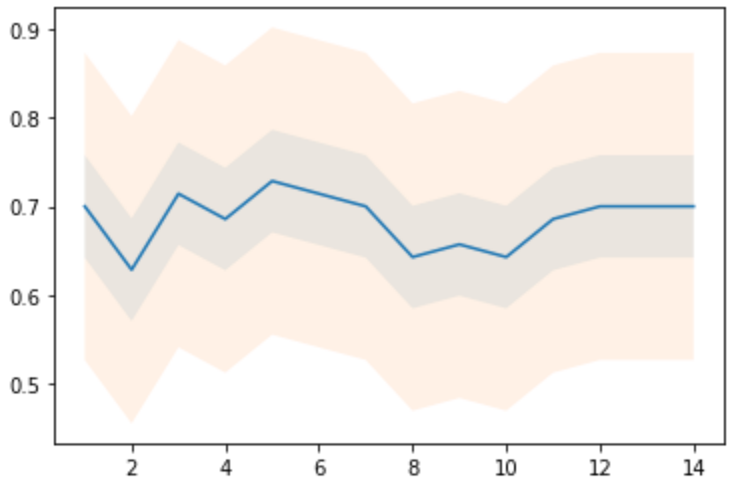
```
from sklearn import metrics
print("Train set Accuracy: ", metrics.accuracy_score(y_train, neigh.predict(X
print("Test set Accuracy: ", metrics.accuracy_score(y_test, knn_result))
```

```
Train set Accuracy:  0.8659420289855072
Test set Accuracy:  0.7142857142857143
```

In [971…

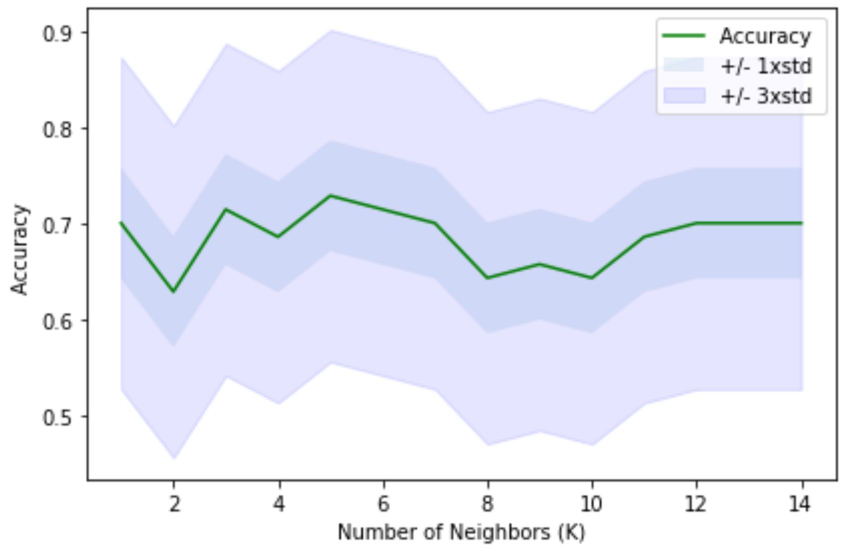
```
#lets find the best value for k and accuracy

Ks = 15
mean_acc = np.zeros((Ks-1))
std_acc = np.zeros((Ks-1))

for n in range(1,Ks):
    knn = KNeighborsClassifier(n_neighbors=n).fit(X_train, y_train.ravel())
    mean_acc[n-1] = metrics.accuracy_score(y_test, knn.predict(X_test))
    std_acc[n-1] = np.std(knn_result==y_test)/np.sqrt(knn_result.shape[0])

print(mean_acc)

plt.plot(range(1,Ks), mean_acc)
plt.fill_between(range(1,Ks),mean_acc - 1 * std_acc,mean_acc + 1 * std_acc, a
plt.fill_between(range(1,Ks),mean_acc - 3 * std_acc,mean_acc + 3 * std_acc, a

plt.show()
```

```
[0.7        0.62857143 0.71428571 0.68571429 0.72857143 0.71428571
 0.7        0.64285714 0.65714286 0.64285714 0.68571429 0.7
 0.7        0.7       ]
```



In [972…

```
#Plotting the model accuracy for the different number of neighbors.

plt.plot(range(1,Ks),mean_acc,'g')
plt.fill_between(range(1,Ks),mean_acc - 1 * std_acc,mean_acc + 1 * std_acc, a
plt.fill_between(range(1,Ks),mean_acc - 3 * std_acc,mean_acc + 3 * std_acc, a
plt.legend(('Accuracy ', '+/- 1xstd','+/- 3xstd'))
plt.ylabel('Accuracy ')
plt.xlabel('Number of Neighbors (K)')
plt.tight_layout()
plt.show()
print( "The best accuracy was ", mean_acc.max(), "with k=", mean_acc.argmax()
```




```
The best accuracy was  0.7285714285714285 with k= 5
```

In [973…

```
k = 5
neigh = KNeighborsClassifier(n_neighbors = k).fit(X_train,y_train.ravel())
#predicitng (with k being 5)
knn_result = neigh.predict(X_test)
knn_result[0:5]
#y[0:5]
```

Out[973…

```
array([1, 1, 1, 1, 1])
```

In [974…

```
print("Train set Accuracy: ", metrics.accuracy_score(y_train, neigh.predict(X
print("Test set Accuracy: ", metrics.accuracy_score(y_test, knn_result))
```

```
Train set Accuracy:  0.8442028985507246
Test set Accuracy:  0.7285714285714285
```

The best accuracy was 0.7285714285714285 with value of k = 5 (using the'loan_train.csv')

We will evaluate the models using loan_test.csv at the end

Decision Tree

In [975…

```
from sklearn.tree import DecisionTreeClassifier
```

In [976…

```
#model
drugTree = DecisionTreeClassifier(criterion="entropy")
drugTree.fit(X_train,y_train)
```

Out[976…

```
DecisionTreeClassifier(criterion='entropy')
```

In [977…

```
#prediction
tree_result = drugTree.predict(X_test)
print(tree_result[0:5])
print(y_test[0:5])
```

```
[1 1 1 1 1]
[[1]
 [1]
 [1]
 [1]
 [1]]
```

In [978…

```
metrics.accuracy_score(y_test, tree_result)
```

Out[978…

```
0.7142857142857143
```

Accuracy score is 0.7 using the using the'loan_train.csv'

Support Vector Machine

using kernel = rbf

In [979…

```
from sklearn import svm
from sklearn.metrics import classification_report, confusion_matrix, f1_score
clf = svm.SVC(kernel='rbf', random_state = 4)
clf.fit(X_train, y_train.ravel())
```

Out[979…

```
SVC(random_state=4)
```

In [980…

```
#predict

svm_predict = clf.predict(X_test)
print(svm_predict[0:5])
print(y_test[0:5])
```

```
[0 1 1 1 1]
[[1]
 [1]
 [1]
 [1]
 [1]]
```

In [981…

```
svm_result = metrics.accuracy_score(y_test,svm_predict)
svm_result
```

Out[981…

```
0.7714285714285715
```

using kernel = linear

In [982…

```
clf = svm.SVC(kernel='linear', random_state = 4)
clf.fit(X_train, y_train.ravel())

#predict
svm_predict = clf.predict(X_test)
print(svm_predict[0:5])
print(y_test[0:5])

svm_result = metrics.accuracy_score(y_test,svm_predict)
svm_result
```

```
[1 1 1 1 1]
[[1]
 [1]
 [1]
 [1]
 [1]]
```

Out[982…

```
0.7857142857142857
```

using kernel = poly

In [983…

```
clf = svm.SVC(kernel='poly', random_state = 4)
clf.fit(X_train, y_train.ravel())

#predict
svm_predict = clf.predict(X_test)
print(svm_predict[0:5])
print(y_test[0:5])

svm_result = metrics.accuracy_score(y_test,svm_predict)
svm_result
```

```
[1 1 1 1 1]
[[1]
 [1]
 [1]
 [1]
 [1]]
```

Out[983…

```
0.7857142857142857
```

using kernel = sigmoid

In [984…

```
clf = svm.SVC(kernel='sigmoid', random_state = 4)
clf.fit(X_train, y_train.ravel())

#predict
svm_predict = clf.predict(X_test)
print(svm_predict[0:5])
print(y_test[0:5])

svm_result = metrics.accuracy_score(y_test,svm_predict)
svm_result
```

```
[1 1 1 1 1]
```

```
[[1]
 [1]
 [1]
 [1]
```

Out[984…

```
0.7714285714285715
```

SVM model with kernel = linear and poly have highest accuracy level

Logistic Regression

In [985…

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(C=0.01, solver='liblinear').fit(X_train, y_train.rave
lr_predict = lr.predict(X_test)
print(lr_predict[0:5])
print(y_test[0:5])
```

```
[0 1 1 1 1]
[[1]
 [1]
 [1]
 [1]
 [1]]
```

In [986…

```
lr_result = metrics.accuracy_score(y_test,lr_predict)
lr_result
```

Out[986…

```
0.6571428571428571
```

In [987…

```
from sklearn.metrics import classification_report, confusion_matrix, f1_score
cnf_matrix = confusion_matrix(y_test, lr_predict)
f1_lr = f1_score(y_test, lr_predict, average='weighted')
cnf_matrix, f1_lr
```

Out[987…

```
(array([[ 4, 11],
        [13, 42]]),
 0.6646825396825397)
```

using solver = saga

In [988…

```
lr = LogisticRegression(C=0.01, solver='saga').fit(X_train, y_train.ravel())
lr_predict = lr.predict(X_test)
print(lr_predict[0:5])
print(y_test[0:5])
```

```
[1 1 1 1 1]
[[1]
 [1]
 [1]
 [1]
 [1]]
```

In [989…
```
lr_result = metrics.accuracy_score(y_test,lr_predict)
lr_result
```

Out[989…
```
0.7857142857142857
```

In [990…
```
cnf_matrix = confusion_matrix(y_test, lr_predict)
f1_lr = f1_score(y_test, lr_predict, average='weighted')
cnf_matrix, f1_lr
```

Out[990…
```
(array([[ 0, 15],
        [ 0, 55]]),
 0.6914285714285714)
```

Model Evaluation using Test set

In [991…
```
test_df = pd.read_csv('loan_test.csv')
test_df.head()
```

Out[991…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educat
0	1	1	PAIDOFF	1000	30	9/8/2016	10/7/2016	50	Becha
1	5	5	PAIDOFF	300	7	9/9/2016	9/15/2016	35	Master Abo
2	21	21	PAIDOFF	1000	30	9/10/2016	10/9/2016	43	H Schoo Bel
3	24	24	PAIDOFF	1000	30	9/10/2016	10/9/2016	26	colle
4	35	35	PAIDOFF	800	15	9/11/2016	9/25/2016	29	Becha

In [992…
```
test_df['effective_date'] = pd.to_datetime(test_df['effective_date'])
test_df['due_date'] = pd.to_datetime(test_df['due_date'])
test_df.head()
```

Out[992…

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	educa
0	1	1	PAIDOFF	1000	30	2016-09-08	2016-10-07	50	Bec
1	5	5	PAIDOFF	300	7	2016-09-09	2016-09-15	35	Mas A
2	21	21	PAIDOFF	1000	30	2016-09-10	2016-10-09	43	Scho E
3	24	24	PAIDOFF	1000	30	2016-09-10	2016-10-09	26	cc
4	35	35	PAIDOFF	800	15	2016-09-11	2016-09-25	29	Bec

In [993…

```
test_df.drop(['Unnamed: 0', 'Unnamed: 0.1'], axis = 1, inplace = True)
test_df['day_ofweek_applied'] = test_df['effective_date'].dt.dayofweek
test_df['day_ofweek_due'] = test_df['due_date'].dt.dayofweek
test_df['applied_weekend'] = test_df['day_ofweek_applied'].apply(lambda x :1
test_df['due_on_0_6_day'] = test_df['day_ofweek_due'].apply(lambda x:1 if (x

test_df['Gender'].replace(to_replace = ['male','female'], value = [0,1], inpl

edu_dummy = pd.get_dummies(test_df.education)
feature_test = pd.concat([test_df,edu_dummy], axis =1)


test_df.head()
```

Out[993…

	loan_status	Principal	terms	effective_date	due_date	age	education	Gender	day_ofw
0	PAIDOFF	1000	30	2016-09-08	2016-10-07	50	Bechalor	1	
1	PAIDOFF	300	7	2016-09-09	2016-09-15	35	Master or Above	0	
2	PAIDOFF	1000	30	2016-09-10	2016-10-09	43	High School or Below	1	
3	PAIDOFF	1000	30	2016-09-10	2016-10-09	26	college	0	
4	PAIDOFF	800	15	2016-09-11	2016-09-25	29	Bechalor	0	

In [994…

```
test_df.drop(['effective_date', 'due_date'], axis =1 , inplace = True)
target_test = test_df[['loan_status']]
test_df.head(), target_test.head()
```

Out[994…

```
(  loan_status  Principal  terms  age             education  Gender  \
 0     PAIDOFF       1000     30   50              Bechalor       1
 1     PAIDOFF        300      7   35        Master or Above       0
 2     PAIDOFF       1000     30   43  High School or Below       1
 3     PAIDOFF       1000     30   26               college       0
 4     PAIDOFF        800     15   29              Bechalor       0

    day_ofweek_applied  day_ofweek_due  applied_weekend  due_on_0_6_day
 0                   3               4                0               0
 1                   4               3                1               0
 2                   5               6                1               1
 3                   5               6                1               1
 4                   6               6                1               1   ,
   loan_status
 0     PAIDOFF
 1     PAIDOFF
 2     PAIDOFF
 3     PAIDOFF
 4     PAIDOFF)
```

In [995…

```
feature_test.head()
```

Out[995…

loan_status	Principal	terms	effective_date	due_date	age	education	Gender	day_ofw

0	PAIDOFF	1000	30	2016-09-08	2016-10-07	50	Bechalor	1
1	PAIDOFF	300	7	2016-09-09	2016-09-15	35	Master or Above	0
2	PAIDOFF	1000	30	2016-09-10	2016-10-09	43	High School or Below	1
3	PAIDOFF	1000	30	2016-09-10	2016-10-09	26	college	0
4	PAIDOFF	800	15	2016-09-11	2016-09-25	29	Bechalor	0

In [996…

```
Feature.head()
```

Out[996…

	Principal	terms	age	Gender	applied_weekend	due_on_0_6_day	Bechalor	High School or Below	Maste o Abov
0	1000	30	45	0	0	0	0	1	
1	1000	30	33	1	0	0	1	0	
2	1000	15	27	0	0	0	0	0	
3	1000	30	28	1	1	0	0	0	
4	1000	30	29	0	1	0	0	0	

In [997…

```
X_test = feature_test[['Principal','terms','age','Gender','applied_weekend','
X_test.head()
```

Out[997…

	Principal	terms	age	Gender	applied_weekend	due_on_0_6_day	Bechalor	High School or Below	Maste o Abov
0	1000	30	50	1	0	0	1	0	
1	300	7	35	0	1	0	0	0	
2	1000	30	43	1	1	1	0	1	
3	1000	30	26	0	1	1	0	0	
4	800	15	29	0	1	1	1	0	

In [998…

```
target_test['loan_status_01'] = test_df['loan_status'].apply(lambda x:1 if (x
y_test = target_test[['loan_status_01']]
```

In [999…

```
X_final = X_test.values
X[0:5]
```

Out[999…

```
array([[ 0.51578458,  0.92071769,  2.33152555, -0.42056004, -1.20577805,
```

```
        -1.31316772, -0.38170062,  1.13639374, -0.07624929, -0.86968108],
       [ 0.51578458,  0.92071769,  0.34170148,  2.37778177, -1.20577805,
        -1.31316772,  2.61985426, -0.87997669, -0.07624929, -0.86968108],
       [ 0.51578458, -0.95911111, -0.65321055, -0.42056004, -1.20577805,
        -1.31316772, -0.38170062, -0.87997669, -0.07624929,  1.14984679],
       [ 0.51578458,  0.92071769, -0.48739188,  2.37778177,  0.82934003,
        -1.31316772, -0.38170062, -0.87997669, -0.07624929,  1.14984679],
       [ 0.51578458,  0.92071769, -0.3215732 , -0.42056004,  0.82934003,
        -1.31316772, -0.38170062, -0.87997669, -0.07624929,  1.14984679]])
```

In [100…

```
y_final = y_test.values
y[0:5]
```

Out[100…

```
array([[1],
       [1],
       [1],
       [1],
       [1]])
```

In [100…

```
#Normalize the data
X_final = preprocessing.StandardScaler().fit(X_final).transform(X_final)
X_final[0:5]
```

Out[100…

```
array([[ 0.49362588,  0.92844966,  3.05981865,  1.97714211, -1.30384048,
        -1.03774904,  2.39791576, -0.79772404, -0.19611614, -0.86135677],
       [-3.56269116, -1.70427745,  0.53336288, -0.50578054,  0.76696499,
        -1.03774904, -0.41702883, -0.79772404,  5.09901951, -0.86135677],
       [ 0.49362588,  0.92844966,  1.88080596,  1.97714211,  0.76696499,
         0.96362411, -0.41702883,  1.25356634, -0.19611614, -0.86135677],
       [ 0.49362588,  0.92844966, -0.98251057, -0.50578054,  0.76696499,
         0.96362411, -0.41702883, -0.79772404, -0.19611614,  1.16095912],
       [-0.66532184, -0.78854628, -0.47721942, -0.50578054,  0.76696499,
         0.96362411,  2.39791576, -0.79772404, -0.19611614, -0.86135677]])
```

K Nearest Neighbor(KNN) test data evaluation

In [100…

```
from sklearn.metrics import jaccard_score
from sklearn.metrics import f1_score
from sklearn.metrics import log_loss
from sklearn import metrics
```

In [ ]:

```

```

In [100…

```
k = 5
knn = KNeighborsClassifier(n_neighbors=k).fit(X,y.ravel())
y_hat = knn.predict(X_final)
y_hat[0:5]
knn_f1 = f1_score(y_final, y_hat, average='weighted')
knn_jacc = jaccard_score(y_final, y_hat, pos_label=1) #label 1  == "PAIDOFF"
print(f" jaccard_score = {knn_jacc}")
print(f" f1_score = {knn_f1}")
print("Accuracy: ", metrics.accuracy_score(y_final, y_hat))
print(confusion_matrix(y_final, y_hat))
print(classification_report(y_final, y_hat))
```

```
 jaccard_score = 0.7446808510638298
 f1_score = 0.7719407963310403
Accuracy:  0.7777777777777778
[[ 7  7]
 [ 5 35]]
              precision    recall  f1-score   support

           0       0.58      0.50      0.54        14
           1       0.83      0.88      0.85        40

    accuracy                           0.78        54
   macro avg       0.71      0.69      0.70        54
weighted avg       0.77      0.78      0.77        54
```

Decision Tree test data evaluation

In [100…

```
drugTree1 = DecisionTreeClassifier(criterion="entropy")
drugTree1.fit(X,y)
#prediction
tree_result1 = drugTree1.predict(X_final)
```

In [100…

```
accu = metrics.accuracy_score(y_final, tree_result1)
tree_f1 = f1_score(y_final, tree_result1, average='weighted')
tree_jacc = jaccard_score(y_final, tree_result1, pos_label=1) #label 1  == "P
print(f" jaccard_score = {tree_jacc}")
print(f" f1_score = {tree_f1}")
print(f" Accuracy = {accu}")
print(confusion_matrix(y_final, tree_result1))
print(classification_report(y_final, tree_result1))
```

```
 jaccard_score = 0.6530612244897959
 f1_score = 0.6812985825331505
 Accuracy = 0.6851851851851852
[[ 5  9]
 [ 8 32]]
              precision    recall  f1-score   support

           0       0.38      0.36      0.37        14
           1       0.78      0.80      0.79        40

    accuracy                           0.69        54
```

```
   macro avg       0.58      0.58      0.58        54
weighted avg       0.68      0.69      0.68        54
```

Support Vector Machine test data evaluation

In [100…

```
clf1 = svm.SVC(kernel='linear', random_state = 4)
clf1.fit(X,y.ravel())

#predict
svm_predict1 = clf1.predict(X_final)
```

In [100…

```
accu2 = metrics.accuracy_score(y_final, svm_predict1)
svm_f1 = f1_score(y_final, svm_predict1, average='weighted')
svm_jacc = jaccard_score(y_final, svm_predict1, pos_label=1) #label 1  == "PA
print(f" jaccard_score = {svm_jacc}")
print(f" f1_score = {svm_f1}")
print(f" Accuracy = {accu2}")
print(confusion_matrix(y_final, svm_predict1))
print(classification_report(y_final, svm_predict1))
```

```
 jaccard_score = 0.7407407407407407
 f1_score = 0.6304176516942475
 Accuracy = 0.7407407407407407
[[ 0 14]
 [ 0 40]]
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        14
           1       0.74      1.00      0.85        40

    accuracy                           0.74        54
   macro avg       0.37      0.50      0.43        54
weighted avg       0.55      0.74      0.63        54
```

Logistic Regression test data evaluation

In [101…

```
lr1 = LogisticRegression(C=0.01, solver='saga').fit(X,y.ravel())
lr_predict1 = lr1.predict(X_final)

#log_loss
y_hat_prob = lr1.predict_proba(X_final)
lr_logloss = log_loss(y_final, y_hat_prob)
```

In [101…

```
accu3 = metrics.accuracy_score(y_final, lr_predict1)
lr_f1 = f1_score(y_final, lr_predict1, average='weighted')
lr_jacc = jaccard_score(y_final, lr_predict1, pos_label=1) #label 1  == "PAID
print(f" jaccard_score = {lr_jacc}")
print(f" f1_score = {lr_f1}")
print(f" Accuracy = {accu3}")
print(f" Log loss = {lr_logloss}")
print(confusion_matrix(y_final, lr_predict1))
print(classification_report(y_final, lr_predict1))
```

```
 jaccard_score = 0.7407407407407407
 f1_score = 0.6304176516942475
 Accuracy = 0.7407407407407407
 Log loss = 0.5169854741326203
[[ 0 14]
 [ 0 40]]
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        14
           1       0.74      1.00      0.85        40

    accuracy                           0.74        54
   macro avg       0.37      0.50      0.43        54
weighted avg       0.55      0.74      0.63        54
```

Report

In [102…

```
headings = ['Algorithm','Jaccard','F1-Score','Logloss']
results1 = [
    ['KNN',knn_jacc,knn_f1,'N/A'],
    ['Decision Tree',tree_jacc,tree_f1,'N/A'],
    ['SVM',svm_jacc,svm_f1,'N/A'],
    ['Logistic Regression',lr_jacc,lr_f1,lr_logloss]
]
res = pd.DataFrame(results1, columns = headings)
res
```

Out[102…

	Algorithm	Jaccard	F1-Score	Logloss
0	KNN	0.744681	0.771941	N/A
1	Decision Tree	0.653061	0.681299	N/A
2	SVM	0.740741	0.630418	N/A
3	Logistic Regression	0.740741	0.630418	0.516985

In [ ]: