Implement KNN classier and experiment with the following concepts

```
Check the performance of KNN with different distance measures
Check the performance of KNN with binary, categorical & numerical data
```

KNN is an algorithm that is useful for matching a point with its closest k neighbors in a multi-dimensional space. It can be used for data that are continuous, discrete, ordinal and categorical

Numerical

1. Euclidean distance Euclidean Distance represents the shortest distance between two points. It is used to calculate the distance between two rows of data that have numerical values, such a floating point or integer values.
2. Manhattan distance: Manhattan Distance is the sum of absolute differences between points across all the dimensions. It is a good measure to use if the input variables are not similar in type such as age, height, etc.

Binary

1. Euclidean distance: Euclidean Distance represents the shortest distance between two points. It is used to calculate the distance between two rows of data that have numerical values, such a floating point or integer values.
2. Jaccard distance:

Categorical

1. Hamming distance: Hamming Distance measures the similarity between two strings of the same length. The Hamming Distance between two strings of the same length is the number of positions at which the corresponding characters are different. It take all the categorical attributes and for each, count one if the value is not the same between two points. The Hamming distance is then the number of attributes for which the value was different.
2. Jaccard distance Jaccard distance can be used to measure when categorical variables are present in the data.

In [1]:
```
#Importing the Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

Numerical Data

In [2]:
```
#Reading the dataset (Gold dataset)
gold_dataset = pd.read_csv("gold_rate_history.csv", index_col='Date', header='infer', parse_dates=True, infer_da
```

In [3]:
```
gold_dataset.head()
```

Out[3]:

Date	Country	State	Location	Pure Gold (24 k)	Standard Gold (22 K)
2006-01-02	India	Tamilnadu	Chennai	768.0	711.0
2006-01-03	India	Tamilnadu	Chennai	770.5	713.0
2006-01-04	India	Tamilnadu	Chennai	784.5	726.0
2006-01-05	India	Tamilnadu	Chennai	782.5	725.0
2006-01-06	India	Tamilnadu	Chennai	776.0	719.0

Data Pre-Processing

1. Checking for missing values

In [4]:
```
gold_dataset.isna().sum()
```

Out[4]:
```
Country                 0
State                   0
Location                0
Pure Gold (24 k)        0
Standard Gold (22 K)    0
dtype: int64
```

2. Dropping the unnecessary columns

In [5]:
```
# Dropping Unwanted Columns
unwanted_cols = ['Country','State','Location']
gold_dataset.drop(unwanted_cols, axis=1, inplace=True)
gold_dataset.head()
```

Out[5]:

Date	Pure Gold (24 k)	Standard Gold (22 K)
2006-01-02	768.0	711.0
2006-01-03	770.5	713.0
2006-01-04	784.5	726.0
2006-01-05	782.5	725.0
2006-01-06	776.0	719.0

3. Renaming the columns

In [6]:
```
# Renaming Columns
gold_dataset.rename(columns={"Pure Gold (24 k)": "Pure_Gold_24k", "Standard Gold (22 K)": "Std_Gold_22k",},inpla
gold_dataset.head()
```

Out[6]:

Date	Pure_Gold_24k	Std_Gold_22k
2006-01-02	768.0	711.0
2006-01-03	770.5	713.0
2006-01-04	784.5	726.0
2006-01-05	782.5	725.0
2006-01-06	776.0	719.0

4. Data Scaling

In [7]:
```
#For Nnormalizing real-valued input and output variables
from sklearn.preprocessing import MinMaxScaler
cols = gold_dataset.columns
idx = gold_dataset.index
scaler = MinMaxScaler(feature_range=(0,1))

df_scaled = pd.DataFrame(scaler.fit_transform(gold_dataset), columns=cols, index=idx)
```

5. Feature Extraction

In [8]:
```
df_svr = df_scaled.copy()

# Converting Date Index to Column for Feature Extraction
df_svr.reset_index(level=0, inplace=True)

# Time Feature Extraction
df_svr['year']=df_svr['Date'].dt.year
df_svr['month']=df_svr['Date'].dt.month
df_svr['day']=df_svr['Date'].dt.day
df_svr['quarter']=df_svr['Date'].dt.quarter
df_svr['weekofyear']=df_svr['Date'].dt.weekofyear
df_svr['weekday']=df_svr['Date'].dt.weekday

# Dropping Date Column
df_svr.drop('Date',axis=1,inplace=True)

df_svr
```

Out[8]:

	Pure_Gold_24k	Std_Gold_22k	year	month	day	quarter	weekofyear	weekday
0	0.000000	0.000000	2006	1	2	1	1	0
1	0.000508	0.000425	2006	1	3	1	1	1
2	0.003354	0.003188	2006	1	4	1	1	2
3	0.002948	0.002976	2006	1	5	1	1	3
4	0.001626	0.001700	2006	1	6	1	1	4
...	...	...	...	...	...	...	...	...
4966	0.881277	0.881828	2020	10	6	4	41	1
4967	0.869689	0.870351	2020	10	7	4	41	2
4968	0.870705	0.871201	2020	10	8	4	41	3
4969	0.879244	0.879702	2020	10	9	4	41	4
4970	0.885546	0.886291	2020	10	10	4	41	5

4971 rows × 8 columns

Model Building and Model Evaluation

In [9]:
```
# Feature Engineering
features = ['year','month','day','quarter','weekofyear','weekday']
target = ['Pure_Gold_24k']
X = df_svr[features]
y = df_svr[target]

#Splitting the dataset
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, random_state=42)
```

Euclidean distance

In [10]:
```
from sklearn.neighbors import KNeighborsRegressor
knn1 = KNeighborsRegressor(n_neighbors=3, metric='euclidean')
knn1.fit(X_train, y_train.values.ravel())
y_pred1 = knn1.predict(X_test)
```

In [16]:
```
from sklearn import metrics as mt
rmse = mt.mean_squared_error(y_test,y_pred1)
r2_score = mt.r2_score(y_test,y_pred1)
print("Root Mean Square Error: ", rmse)
print("R Squared value: ", r2_score)
```

```
Root Mean Square Error:  0.003168466413739735
R Squared value:  0.9222175432735079
```

Conclusion: The root mean square error is 0.003 which indicated as better fit and the R squared value is 0.9222 which indicates that 92.22% of the data fits the model.

Manhattan distance

In [17]:
```
knn2 = KNeighborsRegressor(n_neighbors=3, metric='manhattan')
knn2.fit(X_train, y_train.values.ravel())
y_pred2 = knn2.predict(X_test)
```

In [18]:
```
rmse = mt.mean_squared_error(y_test,y_pred2)
r2_score = mt.r2_score(y_test,y_pred2)
print("Root Mean Square Error: ", rmse)
print("R Squared value: ", r2_score)
```

```
Root Mean Square Error:  0.0032969305166786157
R Squared value:  0.9190638871437093
```

Conclusion: The root mean square error is 0.003 which indicated as better fit and the R squared value is 0.9190 which indicates that 91.90% of the data fits the model.

Conclusion for numerical data

KNN with Euclidean distance measure gives the accuracy of 92.22% and KNN with Manhattan distance measure gives the accuracy of 91.90%. Therefore Euclidean distance measure gives a better accuracy. Hence it is a better KNN model as compared to KNN with Manhattan distance measure

Binary Data

In [20]:
```
#Reading the dataset (Loan dataset)
loan_dataset = pd.read_csv("train_u6lujuX_CVtuZ9i.csv")
```

In [21]:
```
loan_dataset.head()
```

Out[21]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	:
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	:
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	:
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	:
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	:

Data Pre-Processing

1. Checking for missing values

In [22]:
```
loan_dataset.isna().sum()
```

Out[22]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

2. Filling missing values

In [23]:
```
loan_dataset['Gender'] = loan_dataset['Gender'].fillna(loan_dataset['Gender'].mode().values[0])
loan_dataset['Married'] = loan_dataset['Married'].fillna(loan_dataset['Married'].mode().values[0])
loan_dataset['Dependents'] = loan_dataset['Dependents'].fillna(loan_dataset['Dependents'].mode().values[0])
loan_dataset['Self_Employed'] = loan_dataset['Self_Employed'].fillna(loan_dataset['Self_Employed'].mode().values
loan_dataset['LoanAmount'] = loan_dataset['LoanAmount'].fillna(loan_dataset['LoanAmount'].mean())
loan_dataset['Loan_Amount_Term'] = loan_dataset['Loan_Amount_Term'].fillna(loan_dataset['Loan_Amount_Term'].mode
loan_dataset['Credit_History'] = loan_dataset['Credit_History'].fillna(loan_dataset['Credit_History'].mode().val
```

3. Removing the Id column

In [24]:
```
loan_dataset.drop('Loan_ID', axis=1, inplace=True)
loan_dataset.head()
```

Out[24]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cred
0	Male	No	0	Graduate	No	5849	0.0	146.412162	360.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	128.000000	360.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	66.000000	360.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	120.000000	360.0	
4	Male	No	0	Graduate	No	6000	0.0	141.000000	360.0	

4. Feature Extraction

In [25]:
```
#Convert some object data type to int
gender = {"Female": 0, "Male": 1}
yes_no = {'No' : 0,'Yes' : 1}
dependents = {'0':0,'1':1,'2':2,'3+':3}
education = {'Not Graduate' : 0, 'Graduate' : 1}
property = {'Semiurban' : 0, 'Urban' : 1,'Rural' : 2}
output = {"N": 0, "Y": 1}

loan_dataset['Gender'] = loan_dataset['Gender'].replace(gender)
loan_dataset['Married'] = loan_dataset['Married'].replace(yes_no)
loan_dataset['Dependents'] = loan_dataset['Dependents'].replace(dependents)
loan_dataset['Education'] = loan_dataset['Education'].replace(education)
loan_dataset['Self_Employed'] = loan_dataset['Self_Employed'].replace(yes_no)
loan_dataset['Property_Area'] = loan_dataset['Property_Area'].replace(property)
loan_dataset['Loan_Status'] = loan_dataset['Loan_Status'].replace(output)

loan_dataset.head()
```

Out[25]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cred
0	1	0	0	1	0	5849	0.0	146.412162	360.0	
1	1	1	1	1	0	4583	1508.0	128.000000	360.0	
2	1	1	0	1	1	3000	0.0	66.000000	360.0	
3	1	1	0	0	0	2583	2358.0	120.000000	360.0	
4	1	0	0	1	0	6000	0.0	141.000000	360.0	

Model Building and Model Evaluation

In [26]:
```
# Drop "Loan_Status" and assign it to target variable.
X = loan_dataset.drop('Loan_Status', 1)
y = loan_dataset.Loan_Status

#Splitting the dataset into train and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
```

Euclidean distance

In [28]:
```
from sklearn.neighbors import KNeighborsClassifier
knn3 = KNeighborsClassifier(n_neighbors=3, metric='euclidean')
knn3.fit(X_train, y_train)
y_pred3 = knn3.predict(X_test)
```

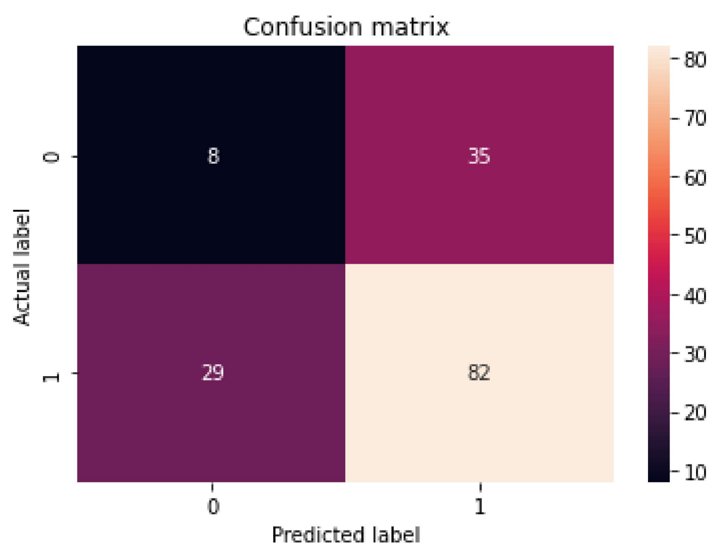
In [29]:
```
#Actual value and the predicted value
diff_knn3 = pd.DataFrame({'Actual value': y_test, 'Predicted value': y_pred3})
diff_knn3.head()
```

Out[29]:

	Actual value	Predicted value
454	1	1
52	0	1
536	1	1
469	0	1
55	1	1

In [27]:
```
#Confusion matrix
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(y_test, y_pred3)
p = sns.heatmap(pd.DataFrame(cm), annot=True ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')

print(classification_report(y_test, y_pred3))
```

```
              precision    recall  f1-score   support

           0       0.22      0.19      0.20        43
           1       0.70      0.74      0.72       111

    accuracy                           0.58       154
   macro avg       0.46      0.46      0.46       154
weighted avg       0.57      0.58      0.57       154
```



Conclusion: 154 (25%) of the records were given for testing out of which 61 records were misclassified

Jaccard distance

In [30]:
```
knn4 = KNeighborsClassifier(n_neighbors=3, metric='jaccard')
knn4.fit(X_train, y_train)
y_pred4 = knn4.predict(X_test)
```

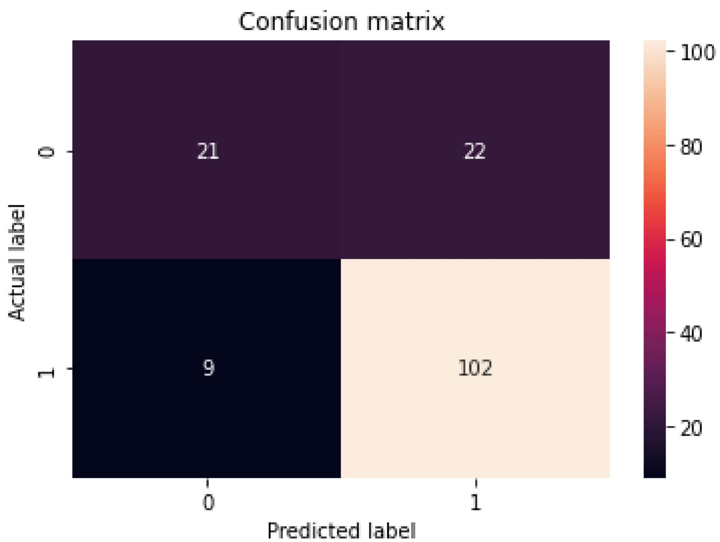
In [31]:
```
#Actual value and the predicted value
diff_knn4 = pd.DataFrame({'Actual value': y_test, 'Predicted value': y_pred4})
diff_knn4.head()
```

Out[31]:

	Actual value	Predicted value
454	1	1
52	0	1
536	1	1
469	0	1
55	1	1

In [32]:
```
#Confusion matrix and classification report
cm = confusion_matrix(y_test, y_pred4)
p = sns.heatmap(pd.DataFrame(cm), annot=True ,fmt='g')
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')

print(classification_report(y_test, y_pred4))
```

```
              precision    recall  f1-score   support

           0       0.70      0.49      0.58        43
           1       0.82      0.92      0.87       111

    accuracy                           0.80       154
   macro avg       0.76      0.70      0.72       154
weighted avg       0.79      0.80      0.79       154
```



Conclusion: 154 (25%) of the records were given for testing out of which 31 records were misclassified

Conclusion for binary data

KNN with Euclidean distance measure gives the accuracy of 58% and KNN with Jaccard distance measure gives the accuracy of 80%. Therefore Jaccard distance measure gives a better accuracy. Hence it is a better KNN model as compared to KNN with Euclidean distance measure

Categorical Data

In [33]:
```
#Reading the dataset (Black friday sale)
sales_dataset = pd.read_csv("black_friday_sale.csv", nrows = 20000)
```

In [34]:
```
sales_dataset.head()
```

Out[34]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Produc
0	1000001	P00069042	F	0-17	10	A	2	0	3	
1	1000001	P00248942	F	0-17	10	A	2	0	1	
2	1000001	P00087842	F	0-17	10	A	2	0	12	
3	1000001	P00085442	F	0-17	10	A	2	0	12	
4	1000002	P00285442	M	55+	16	C	4+	0	8	

Data Pre-Processing

1. Checking for missing values

In [35]:
```
sales_dataset.isna().sum()
```

Out[35]:
```
User_ID                           0
Product_ID                        0
Gender                            0
Age                               0
Occupation                        0
City_Category                     0
Stay_In_Current_City_Years        0
Marital_Status                    0
Product_Category_1                0
Product_Category_2             6397
Product_Category_3            13994
Purchase                          0
dtype: int64
```

2. Feature selection

In [36]:
```
sales_dataset = sales_dataset[['Occupation','Gender', 'Purchase']]
```

Model Building and Model Evaluation

In [49]:
```
x = sales_dataset.loc[:,sales_dataset.columns != 'Gender']
y = sales_dataset.loc[:,'Gender']

#Splitting the dataset
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2, random_state = 42)
```

Hamming distance

In [50]:
```
knn5 = KNeighborsClassifier(n_neighbors = 3, metric='hamming')
knn5.fit(x_train,y_train)
y_pred5 = knn5.predict(x_test)
```

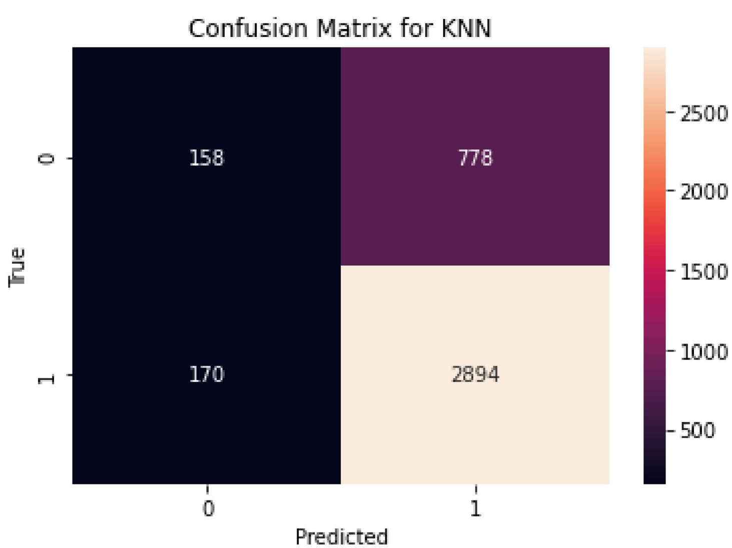
In [51]:
```
#Actual value and the predicted value
diff_knn5 = pd.DataFrame({'Actual value': y_test, 'Predicted value': y_pred5})
diff_knn5.head()
```

Out[51]:

	Actual value	Predicted value
10650	M	M
2041	M	M
8668	F	M
1114	F	M
13902	F	M

In [52]:
```
#Confusion matrix and classification report
con_mat = confusion_matrix(y_test, y_pred5)
print(con_mat)

sns.heatmap(con_mat, annot=True, fmt="d")
plt.title('Confusion Matrix for KNN')
plt.xlabel('Predicted')
plt.ylabel('True')

print(classification_report(y_test, y_pred5))
```

```
[[ 158  778]
 [ 170 2894]]
              precision    recall  f1-score   support

           F       0.48      0.17      0.25       936
           M       0.79      0.94      0.86      3064

    accuracy                           0.76      4000
   macro avg       0.63      0.56      0.55      4000
weighted avg       0.72      0.76      0.72      4000
```



Conclusion: 4000 (20%) of the records were given for testing out of which 948 records were misclassified

Jaccard distance

In [54]:
```
knn6 = KNeighborsClassifier(n_neighbors=3, metric='jaccard')
knn6.fit(x_train, y_train)
y_pred6 = knn6.predict(x_test)
```

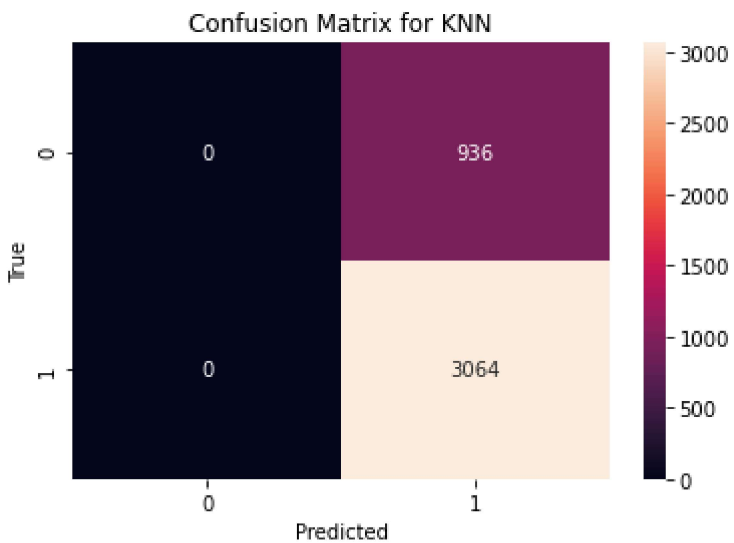
In [55]:
```
#Actual value and the predicted value
diff_knn6 = pd.DataFrame({'Actual value': y_test, 'Predicted value': y_pred6})
diff_knn6.head()
```

Out[55]:

	Actual value	Predicted value
10650	M	M
2041	M	M
8668	F	M
1114	F	M
13902	F	M

In [57]:
```
#Confusion matrix and classification report
con_mat = confusion_matrix(y_test, y_pred6)
print(con_mat)

sns.heatmap(con_mat, annot=True, fmt="d")
plt.title('Confusion Matrix for KNN')
plt.xlabel('Predicted')
plt.ylabel('True')

print(classification_report(y_test, y_pred6))
```

```
[[   0  936]
 [   0 3064]]
              precision    recall  f1-score   support

           F       0.00      0.00      0.00       936
           M       0.77      1.00      0.87      3064

    accuracy                           0.77      4000
   macro avg       0.38      0.50      0.43      4000
weighted avg       0.59      0.77      0.66      4000
```



Conclusion: 4000 (20%) of the records were given for testing out of which 936 records were misclassified

Conclusion for categorical data

KNN with Hamming distance measure gives the accuracy of 76% and KNN with Jaccard distance measure gives the accuracy of 77%. Therefore Jaccard distance measure gives a better accuracy. Hence it is a better KNN model as compared to KNN with Hamming distance measure