Code

January 10, 2024

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from pandas.plotting import scatter_matrix
import plotly.express as px
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
df = pd.read_csv('/Users/yiweihan/Desktop/bank-full.csv')
df.head()
```

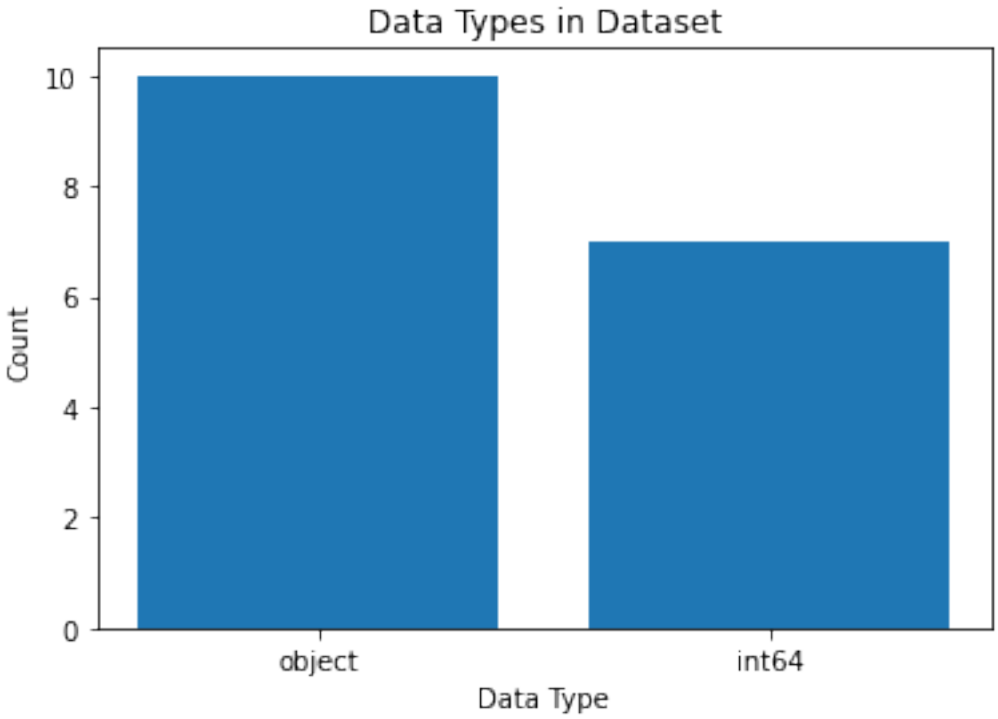
[2]:

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

[3]:
```
df.shape
```

[3]: (45211, 17)

[4]:
```
dtypes = df.dtypes.value_counts()

# Create a bar plot of the datatypes
plt.bar(dtypes.index.astype(str), dtypes.values)
plt.xlabel("Data Type")
plt.ylabel("Count")
plt.title("Data Types in Dataset")
plt.show()
```



1 Pre Processig

1.1 Unknown Data

[5]:
```
df.drop(df[df['job'] == 'unknown' ].index , inplace=True)
df.drop(df[df['education'] == 'unknown' ].index , inplace=True)
df.head()
```

[5]:

	age	job	marital	education	default	balance	housing	loan	\
0	58	management	married	tertiary	no	2143	yes	no	
1	44	technician	single	secondary	no	29	yes	no	
2	33	entrepreneur	married	secondary	no	2	yes	yes	

```
5   35    management  married   tertiary      no      231     yes   no
6   28    management   single   tertiary      no      447     yes  yes

   contact  day month  duration  campaign  pdays  previous poutcome Target
0  unknown    5   may       261         1     -1         0  unknown     no
1  unknown    5   may       151         1     -1         0  unknown     no
2  unknown    5   may        76         1     -1         0  unknown     no
5  unknown    5   may       139         1     -1         0  unknown     no
6  unknown    5   may       217         1     -1         0  unknown     no
```

[6]:
```
df.shape
```

[6]:
```
(43193, 17)
```

1.2 Numerical Data

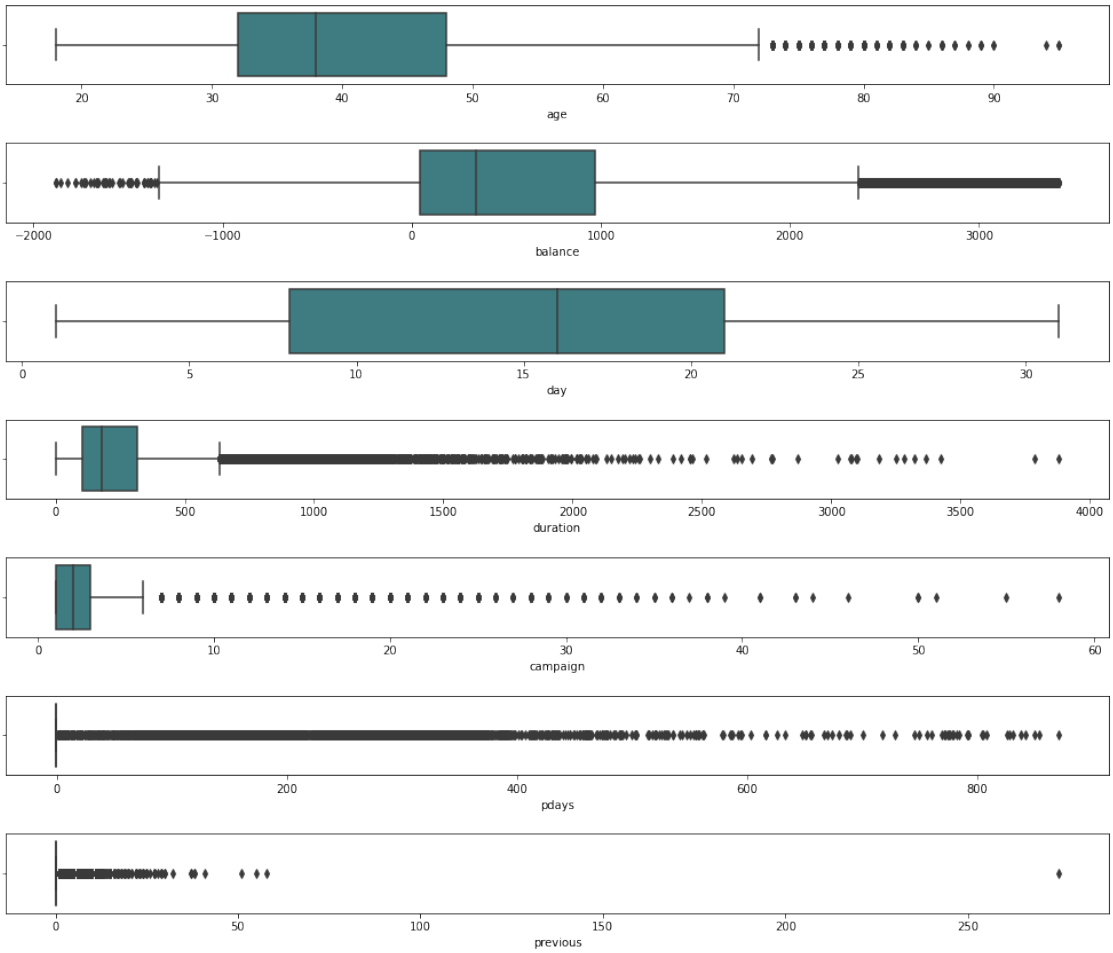
[7]:
```
Q1 = df['balance'].quantile(0.25)
Q3 = df['balance'].quantile(0.75)
IQR = Q3 - Q1
df = df[~((df['balance'] < (Q1 - 1.5 * IQR)) | (df['balance'] > (Q3 + 1.5 *␣
 ↪IQR)))]
```

[8]:
```
df.shape
```

[8]:
```
(38648, 17)
```

[9]:
```
cols=["age","duration","campaign","pdays","previous","balance"]
```

[10]:
```
ot=df.copy()
fig, axes=plt.subplots(7,1,figsize=(14,12),sharex=False,sharey=False)
sns.boxplot(x='age',data=ot,palette='crest',ax=axes[0])
sns.boxplot(x='balance',data=ot,palette='crest',ax=axes[1])
sns.boxplot(x='day',data=ot,palette='crest',ax=axes[2])
sns.boxplot(x='duration',data=ot,palette='crest',ax=axes[3])
sns.boxplot(x='campaign',data=ot,palette='crest',ax=axes[4])
sns.boxplot(x='pdays',data=ot,palette='crest',ax=axes[5])
sns.boxplot(x='previous',data=ot,palette='crest',ax=axes[6])
plt.tight_layout(pad=2.0)
```



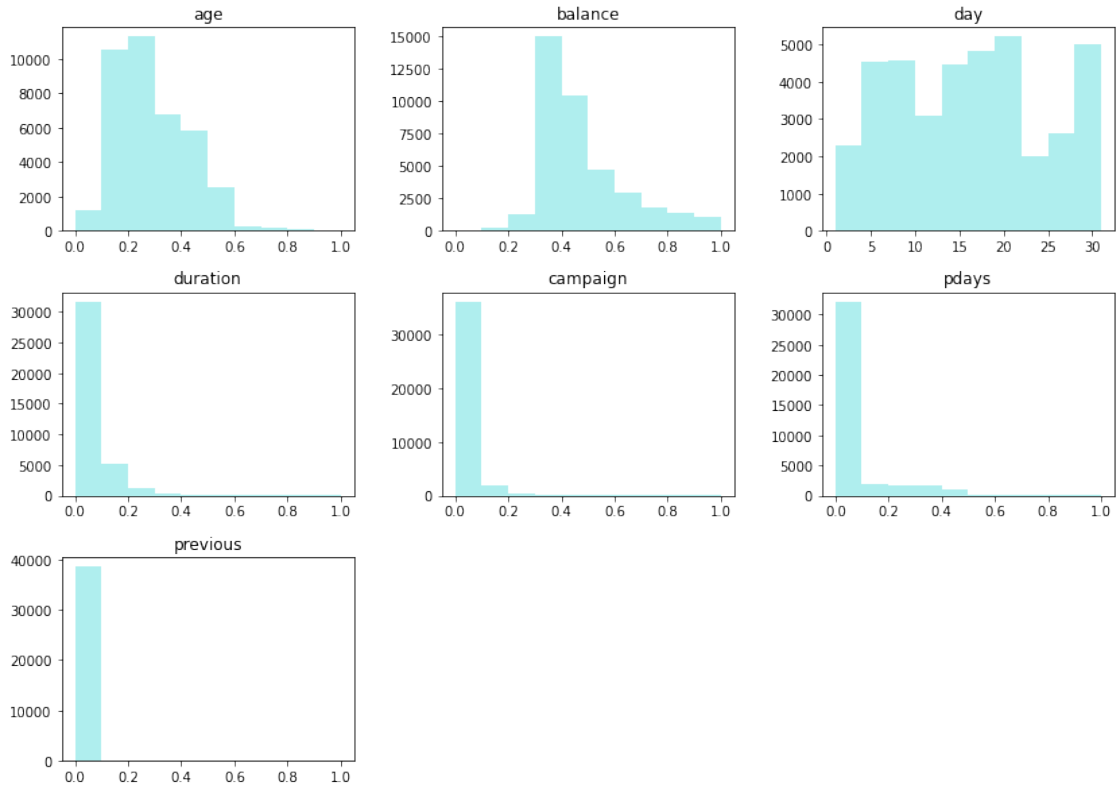
[11]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df['age'] = scaler.fit_transform(df[['age']])
df['balance'] = scaler.fit_transform(df[['balance']])
df['duration'] = scaler.fit_transform(df[['duration']])
df['campaign'] = scaler.fit_transform(df[['campaign']])
df['pdays'] = scaler.fit_transform(df[['pdays']])
df['previous'] = scaler.fit_transform(df[['previous']])
df.head()
```

[11]:

	age	job	marital	education	default	balance	housing	loan
0	0.519481	management	married	tertiary	no	0.758809	yes	no
1	0.337662	technician	single	secondary	no	0.360467	yes	no
2	0.194805	entrepreneur	married	secondary	no	0.355380	yes	yes
5	0.220779	management	married	tertiary	no	0.398530	yes	no
6	0.129870	management	single	tertiary	no	0.439231	yes	yes

	contact	day	month	duration	campaign	pdays	previous	poutcome	Target
0	unknown	5	may	0.067251	0.0	0.0	0.0	unknown	no
1	unknown	5	may	0.038907	0.0	0.0	0.0	unknown	no
2	unknown	5	may	0.019583	0.0	0.0	0.0	unknown	no
5	unknown	5	may	0.035816	0.0	0.0	0.0	unknown	no
6	unknown	5	may	0.055913	0.0	0.0	0.0	unknown	no

[12]:
```
df.hist(figsize=(14,10),color="paleturquoise",grid=False)
plt.show()
```



1.3 Binary Data

[13]:
```
from sklearn.preprocessing import LabelEncoder
lb = LabelEncoder()
df['housing'] = lb.fit_transform(df['housing'])
df['loan'] = lb.fit_transform(df['loan'])
df['default'] = lb.fit_transform(df['default'])
df['Target'] = lb.fit_transform(df['Target'])
df.head()
```

[13]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	Target
0	0.519481	management	married	tertiary	0	0.758809	1	0	unknown	5	may	0.067251	0.0	0.0	0.0	unknown	0
1	0.337662	technician	single	secondary	0	0.360467	1	0	unknown	5	may	0.038907	0.0	0.0	0.0	unknown	0
2	0.194805	entrepreneur	married	secondary	0	0.355380	1	1	unknown	5	may	0.019583	0.0	0.0	0.0	unknown	0
5	0.220779	management	married	tertiary	0	0.398530	1	0	unknown	5	may	0.035816	0.0	0.0	0.0	unknown	0
6	0.129870	management	single	tertiary	0	0.439231	1	1	unknown	5	may	0.055913	0.0	0.0	0.0	unknown	0

1.4 Ordinal Data

[14]:
```
df['education'] = np.where(df['education'] == 'primary', 1,
                  np.where(df['education'] == 'secondary', 2,
                  np.where(df['education'] == 'tertiary', 3, 0)))
df.head()
```

[14]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	Target
0	0.519481	management	married	3	0	0.758809	1	0	unknown	5	may	0.067251	0.0	0.0	0.0	unknown	0
1	0.337662	technician	single	2	0	0.360467	1	0	unknown	5	may	0.038907	0.0	0.0	0.0	unknown	0
2	0.194805	entrepreneur	married	2	0	0.355380	1	1	unknown	5	may	0.019583	0.0	0.0	0.0	unknown	0
5	0.220779	management	married	3	0	0.398530	1	0	unknown	5	may	0.035816	0.0	0.0	0.0	unknown	0
6	0.129870	management	single	3	0	0.439231	1	1	unknown	5	may	0.055913	0.0	0.0	0.0	unknown	0

```
6       0
```

[15]:
```
df['month'] = np.where(df['month'] == 'jan', 1,
                  np.where(df['month'] == 'feb', 2,
                  np.where(df['month'] == 'mar', 3,
                  np.where(df['month'] == 'apr', 4,
                  np.where(df['month'] == 'may', 5,
                  np.where(df['month'] == 'jun', 6,
                  np.where(df['month'] == 'jul', 7,
                  np.where(df['month'] == 'aug', 8,
                  np.where(df['month'] == 'sep', 9,
                  np.where(df['month'] == 'oct', 10,
                  np.where(df['month'] == 'nov', 11,12)))))))))))
df.head()
```

[15]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	Target
0	0.519481	management	married	3	0	0.758809	1	0	unknown	5	5	0.067251	0.0	0.0	0.0	unknown	0
1	0.337662	technician	single	2	0	0.360467	1	0	unknown	5	5	0.038907	0.0	0.0	0.0	unknown	0
2	0.194805	entrepreneur	married	2	0	0.355380	1	1	unknown	5	5	0.019583	0.0	0.0	0.0	unknown	0
5	0.220779	management	married	3	0	0.398530	1	0	unknown	5	5	0.035816	0.0	0.0	0.0	unknown	0
6	0.129870	management	single	3	0	0.439231	1	1	unknown	5	5	0.055913	0.0	0.0	0.0	unknown	0

1.5 Categorical Data

[16]:
```
one_hot = pd.get_dummies(df['marital'])
df = df.drop('marital', axis=1)
df = df.join(one_hot)
df.head()
```

[16]:

	age	job	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	Target	divorced	married	single
0	0.519481	management	3	0	0.758809	1	0	unknown	5	5	0.067251	0.0	0.0	0.0	unknown	0	0	1	0
1	0.337662	technician	2	0	0.360467	1	0	unknown	5	5	0.038907	0.0	0.0	0.0	unknown	0	0	0	1
2	0.194805	entrepreneur	2	0	0.355380	1	1	unknown	5	5	0.019583	0.0	0.0	0.0	unknown	0	0	1	0

```
5  0.220779    management          3        0  0.398530        1     0
6  0.129870    management          3        0  0.439231        1     1

   contact  day  month  duration  campaign  pdays  previous poutcome  Target  \
0  unknown    5      5  0.067251       0.0    0.0       0.0  unknown       0
1  unknown    5      5  0.038907       0.0    0.0       0.0  unknown       0
2  unknown    5      5  0.019583       0.0    0.0       0.0  unknown       0
5  unknown    5      5  0.035816       0.0    0.0       0.0  unknown       0
6  unknown    5      5  0.055913       0.0    0.0       0.0  unknown       0

   divorced  married  single
0     False     True   False
1     False    False    True
2     False     True   False
5     False     True   False
6     False    False    True
```

[17]:
```
one_hot = pd.get_dummies(df['job'])
df = df.drop('job', axis=1)
df = df.join(one_hot)
df.head()
```

[17]:
```
        age  education  default   balance  housing  loan  contact  day  month  \
0  0.519481          3        0  0.758809        1     0  unknown    5      5
1  0.337662          2        0  0.360467        1     0  unknown    5      5
2  0.194805          2        0  0.355380        1     1  unknown    5      5
5  0.220779          3        0  0.398530        1     0  unknown    5      5
6  0.129870          3        0  0.439231        1     1  unknown    5      5

   duration  …  blue-collar  entrepreneur  housemaid management  retired  \
0  0.067251  …        False         False      False       True    False
1  0.038907  …        False         False      False      False    False
2  0.019583  …        False          True      False      False    False
5  0.035816  …        False         False      False       True    False
6  0.055913  …        False         False      False       True    False

   self-employed  services  student  technician  unemployed
0          False     False    False       False       False
1          False     False    False        True       False
2          False     False    False       False       False
5          False     False    False       False       False
6          False     False    False       False       False

[5 rows x 29 columns]
```

[18]:
```
one_hot = pd.get_dummies(df['contact'])
df = df.drop('contact', axis=1)
```

```
df = df.join(one_hot)
df.head()
```

[18]:

	age	education	default	balance	housing	loan	day	month	\
0	0.519481	3	0	0.758809	1	0	5	5	
1	0.337662	2	0	0.360467	1	0	5	5	
2	0.194805	2	0	0.355380	1	1	5	5	
5	0.220779	3	0	0.398530	1	0	5	5	
6	0.129870	3	0	0.439231	1	1	5	5	

	duration	campaign	…	management	retired	self-employed	services	\
0	0.067251	0.0	…	True	False	False	False	
1	0.038907	0.0	…	False	False	False	False	
2	0.019583	0.0	…	False	False	False	False	
5	0.035816	0.0	…	True	False	False	False	
6	0.055913	0.0	…	True	False	False	False	

	student	technician	unemployed	cellular	telephone	unknown
0	False	False	False	False	False	True
1	False	True	False	False	False	True
2	False	False	False	False	False	True
5	False	False	False	False	False	True
6	False	False	False	False	False	True

[5 rows x 31 columns]

[19]:
```
df = df.drop('poutcome', axis=1)
df.head()
```

[19]:

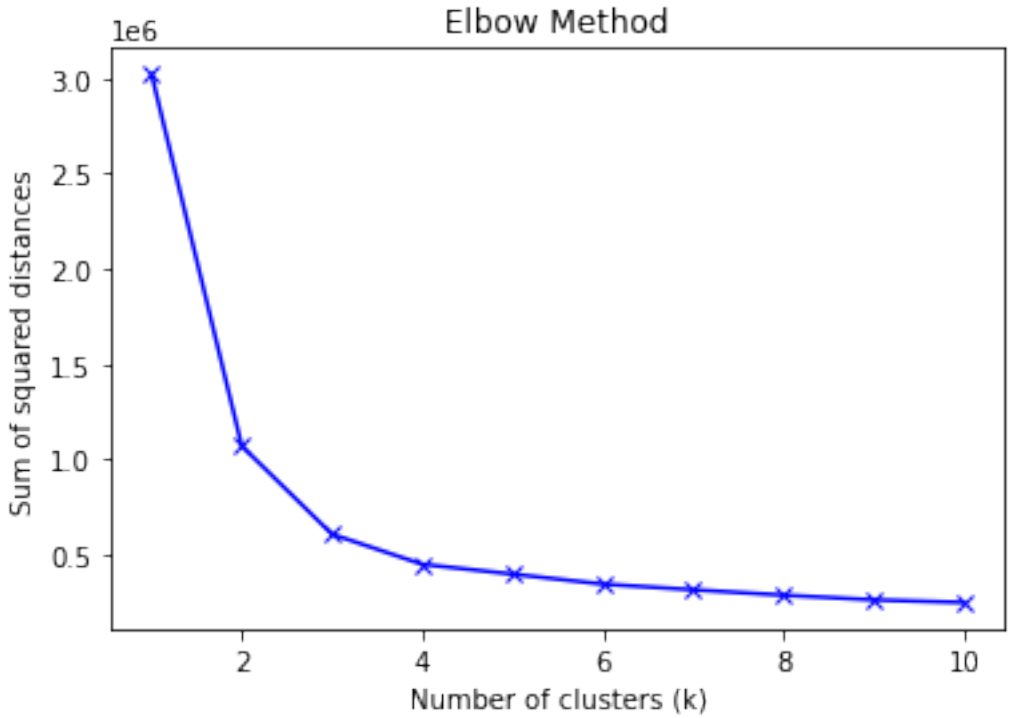
	age	education	default	balance	housing	loan	day	month	\
0	0.519481	3	0	0.758809	1	0	5	5	
1	0.337662	2	0	0.360467	1	0	5	5	
2	0.194805	2	0	0.355380	1	1	5	5	
5	0.220779	3	0	0.398530	1	0	5	5	
6	0.129870	3	0	0.439231	1	1	5	5	

	duration	campaign	…	management	retired	self-employed	services	\
0	0.067251	0.0	…	True	False	False	False	
1	0.038907	0.0	…	False	False	False	False	
2	0.019583	0.0	…	False	False	False	False	
5	0.035816	0.0	…	True	False	False	False	
6	0.055913	0.0	…	True	False	False	False	

	student	technician	unemployed	cellular	telephone	unknown
0	False	False	False	False	False	True
1	False	True	False	False	False	True
2	False	False	False	False	False	True

```
5    False       False       False     False      False     True
6    False       False       False     False      False     True

[5 rows x 30 columns]
```

[20]:
```
from sklearn.cluster import KMeans
ssd = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(df)
    ssd.append(kmeans.inertia_)

plt.plot(range(1, 11), ssd, 'bx-')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Sum of squared distances')
plt.title('Elbow Method')
plt.show()
```



2 Modeling

2.1 Model Preparation

2.1.1 Train Test Split

[21]:
```
X=df.drop('Target',axis=1)
y=df['Target']
from collections import Counter
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=1)
print('Original dataset shape %s' % Counter(y_train))
```

```
Original dataset shape Counter({0: 24072, 1: 2981})
```

2.1.2 SMOTE

[22]:
```
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_train, y_train = smote.fit_resample(X_train, y_train)
print('Resample dataset shape %s' % Counter(y_train))
```

```
Resample dataset shape Counter({0: 24072, 1: 24072})
```

2.2 Decision Tree

[23]:
```
from sklearn.tree import DecisionTreeClassifier
model1 = DecisionTreeClassifier()
model1.fit(X_train, y_train)
y_pred = model1.predict(X_test)
print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy score: 0.8630
```

[24]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model1, X, y, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.8148771  0.68214748 0.62949547 0.51403804 0.24556864]
```

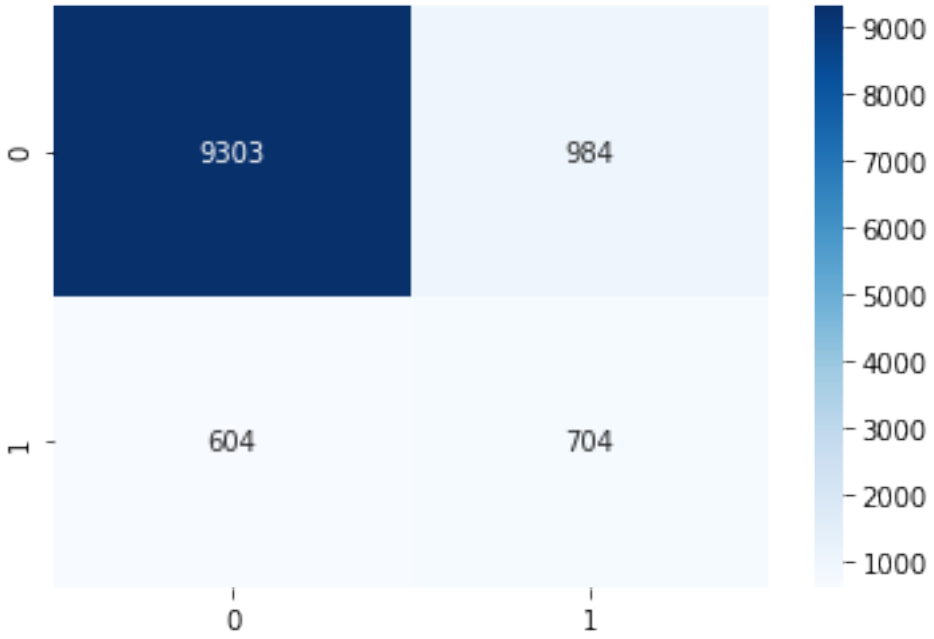
[25]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model1, X_train, y_train, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.80579499 0.91857929 0.91639838 0.91317894 0.9221022 ]
```

[26]:
```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(model1, X_test, y_test, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.8771022  0.8792583  0.88184562 0.87365244 0.87235878]
```

[27]:
```
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='0.0f', cmap =␣
↪'Blues');
```



[28]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.90      0.92     10287
           1       0.42      0.54      0.47      1308

    accuracy                           0.86     11595
   macro avg       0.68      0.72      0.70     11595
weighted avg       0.88      0.86      0.87     11595
```

[29]:
```
from sklearn.metrics import precision_score, recall_score, f1_score
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print('Precision: {0:0.4f}'.format(precision))
print('Recall: {0:0.4f}'.format(recall))
print('F1 score: {0:0.4f}'.format(f1))
```

```
Precision: 0.4171
Recall: 0.5382
F1 score: 0.4700
```

2.3 XG Boost

[30]:
```
import xgboost as xgb
model2 = xgb.XGBClassifier(random_state = 455)
model2.fit(X_train, y_train)
y_pred = model2.predict(X_test)
print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy score: 0.9053
```

[31]:
```
scores = cross_val_score(model2, X, y, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.89029754 0.70750323 0.72496766 0.47160047 0.32371588]
```

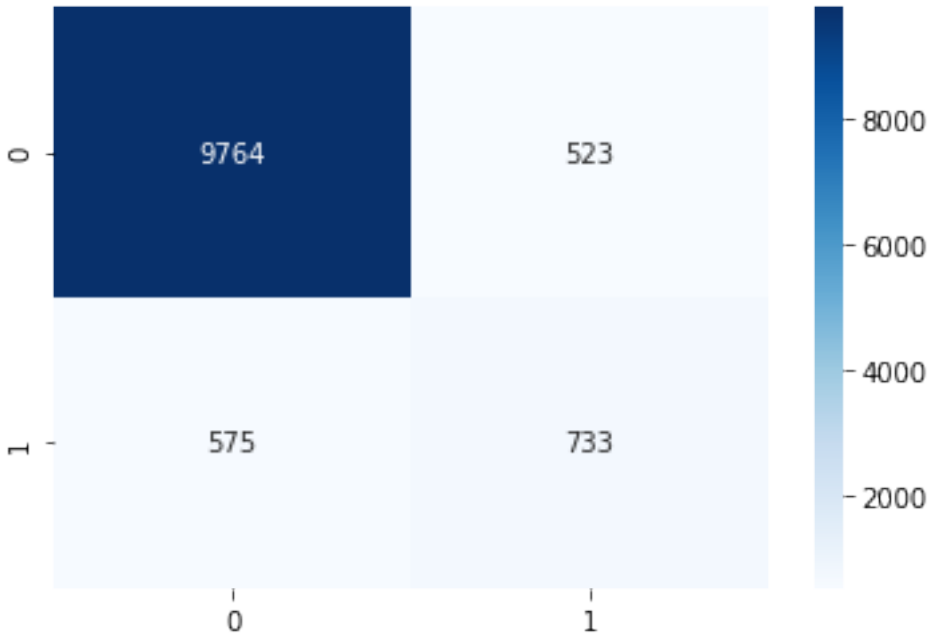
[32]:
```
scores = cross_val_score(model2, X_train, y_train, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.72364732 0.96728632 0.96572853 0.96323606 0.96780224]
```

[33]:
```
scores = cross_val_score(model2, X_test, y_test, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.89995688 0.90513152 0.90168176 0.90901251 0.91030617]
```

[34]:
```
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='0.0f', cmap =␣
↪'Blues');
```



[35]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.95      0.95     10287
           1       0.58      0.56      0.57      1308

    accuracy                           0.91     11595
   macro avg       0.76      0.75      0.76     11595
weighted avg       0.90      0.91      0.90     11595
```

[36]:
```
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print('Precision: {0:0.4f}'.format(precision))
print('Recall: {0:0.4f}'.format(recall))
print('F1 score: {0:0.4f}'.format(f1))
```

```
Precision: 0.5836
Recall: 0.5604
F1 score: 0.5718
```

2.4 Logistic Regression

[37]:
```
from sklearn.linear_model import LogisticRegression
model4 = LogisticRegression()
model4.fit(X_train, y_train)
y_pred = model4.predict(X_test)
print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy score: 0.8633
```

[38]:
```
scores = cross_val_score(model4, X, y, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.89896507 0.90582147 0.88408797 0.83024971 0.87048777]
```

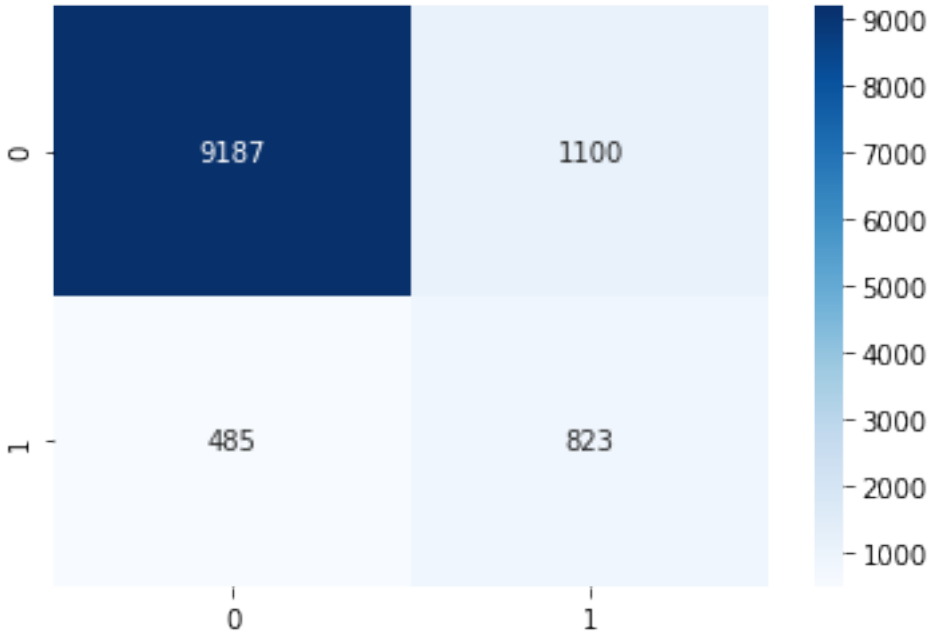
[39]:
```
scores = cross_val_score(model4, X_train, y_train, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.79696749 0.89666632 0.90040503 0.89469311 0.90029082]
```

[40]:
```
scores = cross_val_score(model4, X_test, y_test, cv = 5, scoring='accuracy')
print('Cross-validation scores:{}'.format(scores))
```

```
Cross-validation scores:[0.90168176 0.89650712 0.89435101 0.898232   0.89607589]
```

[41]:
```
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='0.0f', cmap =␣
↪'Blues');
```



[42]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.89      0.92     10287
           1       0.43      0.63      0.51      1308

    accuracy                           0.86     11595
   macro avg       0.69      0.76      0.72     11595
weighted avg       0.89      0.86      0.87     11595
```

[43]:
```
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print('Precision: {0:0.4f}'.format(precision))
print('Recall: {0:0.4f}'.format(recall))
print('F1 score: {0:0.4f}'.format(f1))
```

```
Precision: 0.4280
Recall: 0.6292
F1 score: 0.5094
```

2.5 Voting Classifier

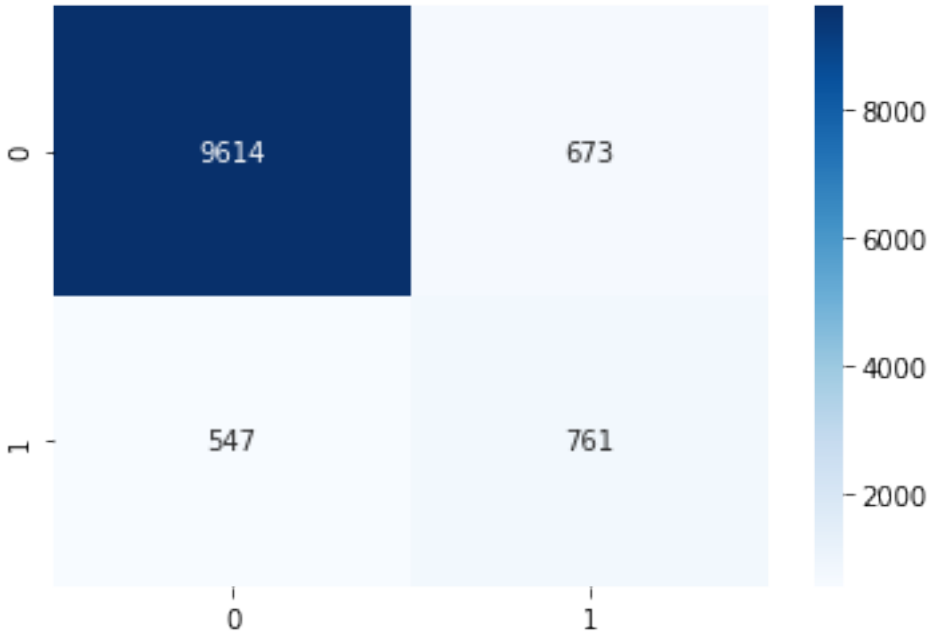
[44]:
```
from sklearn.metrics import log_loss, mean_squared_error
from sklearn.ensemble import  GradientBoostingClassifier, VotingClassifier
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
```

[54]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC

model_1 = LogisticRegression()
model_2 = XGBClassifier()
model_3 = KNeighborsClassifier()
model_4 = DecisionTreeClassifier()
model_5 = SVC(probability=True)
final_model = VotingClassifier(
    estimators=[('lr', model_1), ('xgb', model_2), ('knn', model_3), ('dt',␣
 ↪model_4), ('svm', model_5)],voting='soft')
final_model.fit(X_train, y_train)
pred_final = final_model.predict(X_test)

score = accuracy_score(y_test, pred_final)
```

[55]:
```
score
```

[55]:
```
0.8947822337214316
```

[56]:
```
sns.heatmap(confusion_matrix(y_test, pred_final), annot=True, fmt='0.0f', cmap␣
 ↪= 'Blues');
```

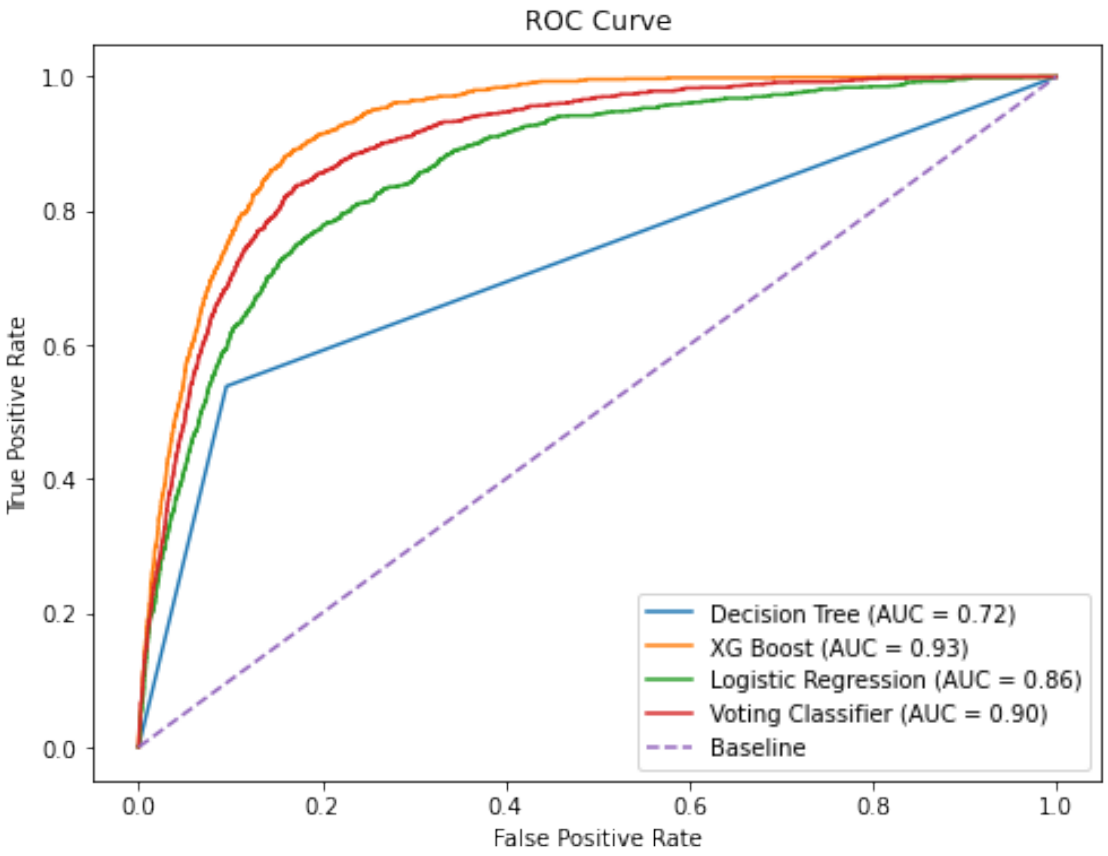


[57]:
```
precision = precision_score(y_test, pred_final)
recall = recall_score(y_test, pred_final)
f1 = f1_score(y_test, pred_final)

print('Precision: {0:0.4f}'.format(precision))
print('Recall: {0:0.4f}'.format(recall))
print('F1 score: {0:0.4f}'.format(f1))
```

```
Precision: 0.5307
Recall: 0.5818
F1 score: 0.5551
```

2.6 ROC Curve

[58]:
```
models = [model1, model2, model4,final_model]
model_names = ['Decision Tree', 'XG Boost', 'Logistic Regression','Voting␣
 ↪Classifier']

plt.figure(figsize=(8,6))
for i in range(len(models)):
    if i != 4:
        pred_prob = models[i].predict_proba(X_test)[:,1]
    else:
        pred_prob = models[i].predict_proba(X_test)
        pred_prob = pred_prob[:,1]
    fpr, tpr, thresholds = roc_curve(y_test, pred_prob)
    auc_score = roc_auc_score(y_test, pred_prob)
    plt.plot(fpr, tpr, label=model_names[i] + ' (AUC = {:.2f})'.
 ↪format(auc_score))
plt.plot([0, 1], [0, 1], linestyle='--', label='Baseline')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```


ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Decision Tree (AUC = 0.72)
XG Boost (AUC = 0.93)
Logistic Regression (AUC = 0.86)
Voting Classifier (AUC = 0.90)
Baseline

[ ]: