01_churn_prediction

October 23, 2025

1 Task 1: Customer Churn Prediction for a Telecom Company

Task Overview Objective: Build a machine learning model to predict customer churn using historical data.

Deliverables:

- Exploratory Data Analysis (EDA)
- Feature engineering
- Train/test split and model selection (Logistic Regression, XGBoost, etc.)
- Performance metrics (confusion matrix, AUC-ROC)
- Final report with visualizations

[205]:
```python
# Mock Data (Python):

import pandas as pd
import numpy as np

np.random.seed(42)

n = 10000

data = pd.DataFrame({
    'CustomerID': np.arange(n),
    'Gender': np.random.choice(['Male', 'Female'], size=n),
    'SeniorCitizen': np.random.choice([0, 1], size=n),
    'Tenure': np.random.randint(1, 72, size=n),
    'MonthlyCharges': np.round(np.random.uniform(20, 120, size=n), 2),
    'TotalCharges': lambda df: df['Tenure'] * df['MonthlyCharges'],
    'Contract': np.random.choice(['Month-to-month', 'One year', 'Two year'],␣
 ↪size=n),
    'PaymentMethod': np.random.choice(['Electronic check', 'Mailed check', 'Bank␣
 ↪transfer', 'Credit card'], size=n),
    'Churn': np.random.choice([0, 1], size=n, p=[0.73, 0.27])
})

data['TotalCharges'] = (data['Tenure'] * data['MonthlyCharges']).round(2)
```

[206]:
```python
data.head()
```

```
[206]:    CustomerID  Gender  SeniorCitizen  Tenure  MonthlyCharges  TotalCharges  \
       0           0    Male              0      55          111.88       6153.40
       1           1  Female              1      36           58.70       2113.20
       2           2    Male              0      37          118.86       4397.82
       3           3    Male              1      14           96.14       1345.96
       4           4    Male              1      27           28.05        757.35

                Contract     PaymentMethod  Churn
       0        Two year      Mailed check      0
       1        Two year  Electronic check      0
       2        One year  Electronic check      0
       3  Month-to-month      Mailed check      1
       4        Two year      Mailed check      0
```

```
[207]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   CustomerID      10000 non-null  int64
 1   Gender          10000 non-null  object
 2   SeniorCitizen   10000 non-null  int64
 3   Tenure          10000 non-null  int64
 4   MonthlyCharges  10000 non-null  float64
 5   TotalCharges    10000 non-null  float64
 6   Contract        10000 non-null  object
 7   PaymentMethod   10000 non-null  object
 8   Churn           10000 non-null  int64
dtypes: float64(2), int64(4), object(3)
memory usage: 703.2+ KB
```

```
[216]: data['Churn'].value_counts()
```

```
[216]: Churn
       0    7330
       1    2670
       Name: count, dtype: int64
```

```
[209]: X = data[['Gender', 'SeniorCitizen', 'Tenure', 'MonthlyCharges',␣
        ↪'TotalCharges', 'Contract', 'PaymentMethod']]
       y = data['Churn']
```

```
[ ]: from sklearn.preprocessing import LabelEncoder, StandardScaler

     le = LabelEncoder()
```

```
X.loc[:, 'Gender'] = le.fit_transform(X['Gender'])
X.loc[:, 'Contract'] = le.fit_transform(X['Contract'])
X.loc[:, 'PaymentMethod'] = le.fit_transform(X['PaymentMethod'])

# preprocess the data
scalar = StandardScaler()
X.loc[:, ['Tenure', 'MonthlyCharges', 'TotalCharges']] = scalar.
 ↪fit_transform(X[['Tenure', 'MonthlyCharges', 'TotalCharges']])
X.loc[:, ['Contract', 'PaymentMethod']] = scalar.fit_transform(X[['Contract',␣
 ↪'PaymentMethod']])
```

[211]:

```
X.sample(n=5)
```

[211]:

```
      Gender  SeniorCitizen    Tenure  MonthlyCharges  TotalCharges  Contract  \
1780       0              1 -0.339256       -1.705627     -1.026792 -0.013227
4401       1              0  0.099753       -0.153487     -0.017785 -0.013227
5129       0              0 -0.436814        0.388431     -0.178860 -0.013227
3968       0              1 -0.534371       -0.649094     -0.665083 -1.249411
9678       0              1 -1.119716       -0.761763     -1.017518 -1.249411

     PaymentMethod
1780     -1.340355
4401      1.344651
5129      0.449649
3968      0.449649
9678      0.449649
```

[212]:

```
from sklearn.model_selection import train_test_split

# train test split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)
```

[213]:

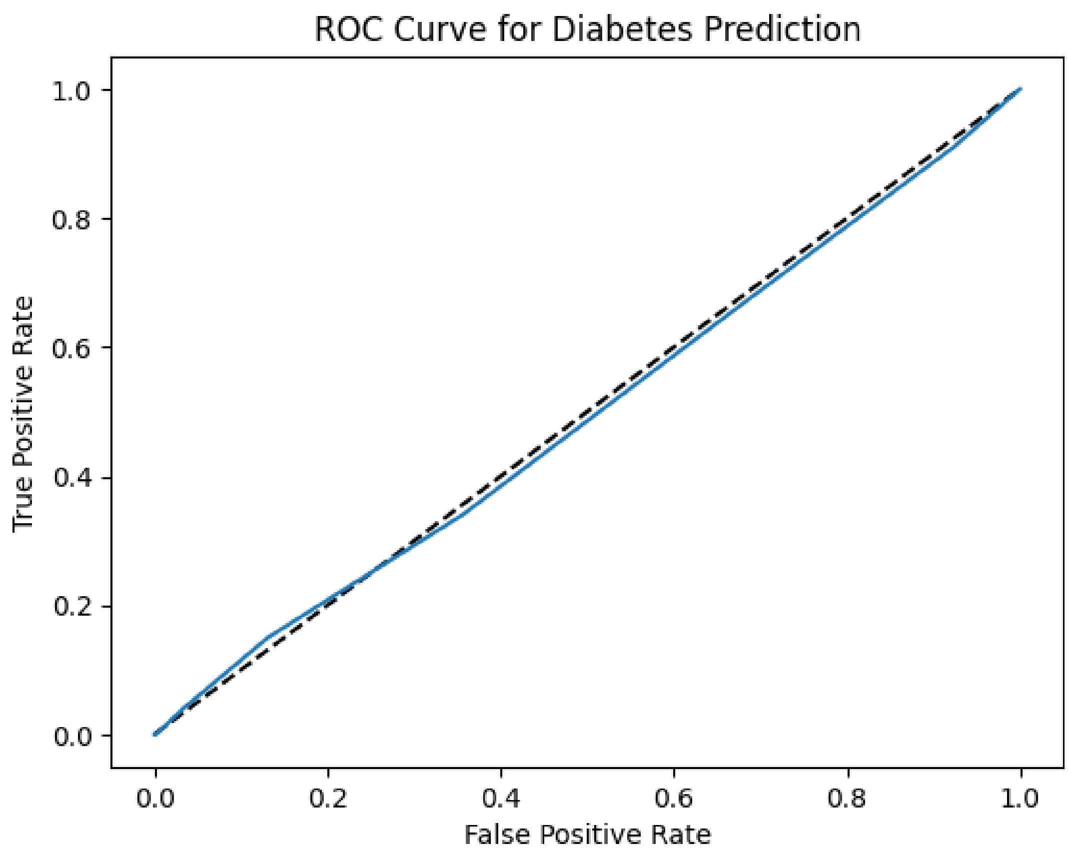
```
from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=8)
model.fit(X_train, y_train)

# predict the model
y_pred = model.predict(X_test)
```

[214]:

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, roc_auc_score

# Predict probabilities
y_probs = model.predict_proba(X_test)
```

```
print("Probabilities of being True Negative and True Positive: ")
print(y_probs[:5])

y_pred_probs = y_probs[:, 1] # Picked 2nd column which contains␣
↪Predicted-Yes(True Positive) values. and 1st column contains␣
↪Predicted-No(True Negative) values
print("Probabilities of being True Positive: ", y_pred_probs[:5])

# Generate ROC curve values: fpr, tpr, thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_pred_probs)
plt.plot([0, 1], [0, 1], 'k--')

# Plot tpr against fpr
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Diabetes Prediction')
plt.show()

################################
print(roc_auc_score(y_test, y_pred_probs)) # Calculate roc_auc_score
```

```
Probabilities of being True Negative and True Positive:
[[0.875 0.125]
 [0.875 0.125]
 [0.75  0.25 ]
 [0.625 0.375]
 [0.75  0.25 ]]
Probabilities of being True Positive:  [0.125 0.125 0.25  0.375 0.25 ]
```

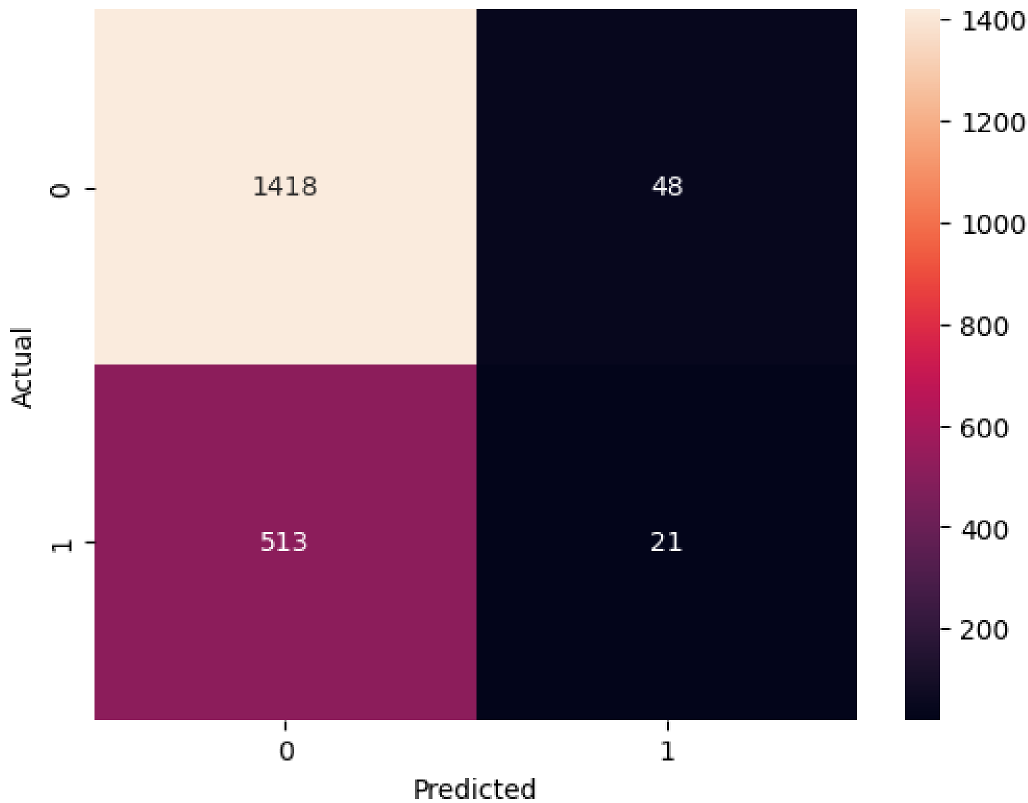



```
0.4934373898247927
```

[215]:
```python
from sklearn.metrics import confusion_matrix, classification_report

# evaluate the model
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

# plot confusion matrix
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
[[1418   48]
 [ 513   21]]
              precision    recall  f1-score   support

           0       0.73      0.97      0.83      1466
           1       0.30      0.04      0.07       534
```

accuracy			0.72	2000
macro avg	0.52	0.50	0.45	2000
weighted avg	0.62	0.72	0.63	2000



1.1 REPORT:

The model is evaluated on a dataset of 2000 samples. The results are as follows:

- Our model is predicting 72% accurately.
- The model performs well on `Class 0`, achieving high recall (0.97), meaning it correctly identifies most of the `Class 0` samples.
- For `Class 1`, performance is very poor, with recall only 0.04. This shows the model is failing to detect `Class 1` cases.

The model is biased toward `Class 0` and struggles with detecting `Class 1`