Churn Customer Prediction

September 16, 2025

1 Customer Churn Prediction

This notebook demonstrates how to build a **supervised machine learning model** to predict customer churn, an online food ordering provider.

Why churn prediction matters? - Acquiring a new customer is 5–7 times more expensive than retaining an existing one. - By predicting churn, can target discounts, loyalty campaigns, or personalized offers to customers **before they leave**.

1.1 Step 1: Import Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.metrics import classification_report, confusion_matrix,␣
↪roc_auc_score, roc_curve

import warnings
warnings.filterwarnings('ignore')
```

1.2 Step 2: Create Sample Dataset

[2]:
```
# Simulated dataset
np.random.seed(42)
n = 10000

data = pd.DataFrame({
    'customer_id': range(1, n+1),
    'last_order_days_ago': np.random.randint(1, 365, n),
    'total_orders': np.random.poisson(10, n),
```

```
    'avg_order_value': np.random.uniform(5, 50, n),
    'complaints': np.random.binomial(5, 0.1, n),
    'discount_used': np.random.randint(0, 20, n),
    'churn': np.random.binomial(1, 0.3, n)  # 1 = churned, 0 = active
})

data.head()
```

[2]:

```
   customer_id  last_order_days_ago  total_orders  avg_order_value  \
0            1                  103            10        38.251680
1            2                  349             9        37.210404
2            3                  271             9        36.023084
3            4                  107             9        17.451155
4            5                   72             9        30.801515

   complaints  discount_used  churn
0           1              4      1
1           0             13      1
2           0              7      1
3           0             10      0
4           1             14      1
```

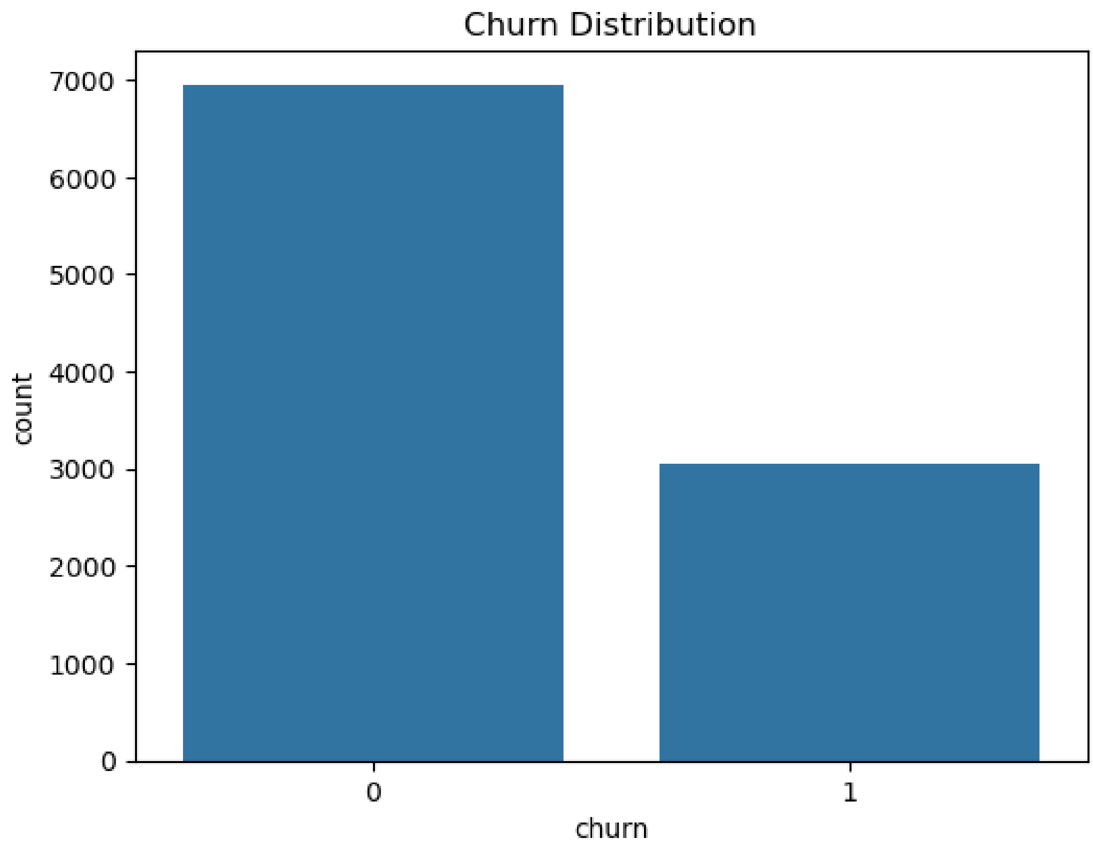
1.3 Step 3: Exploratory Data Analysis

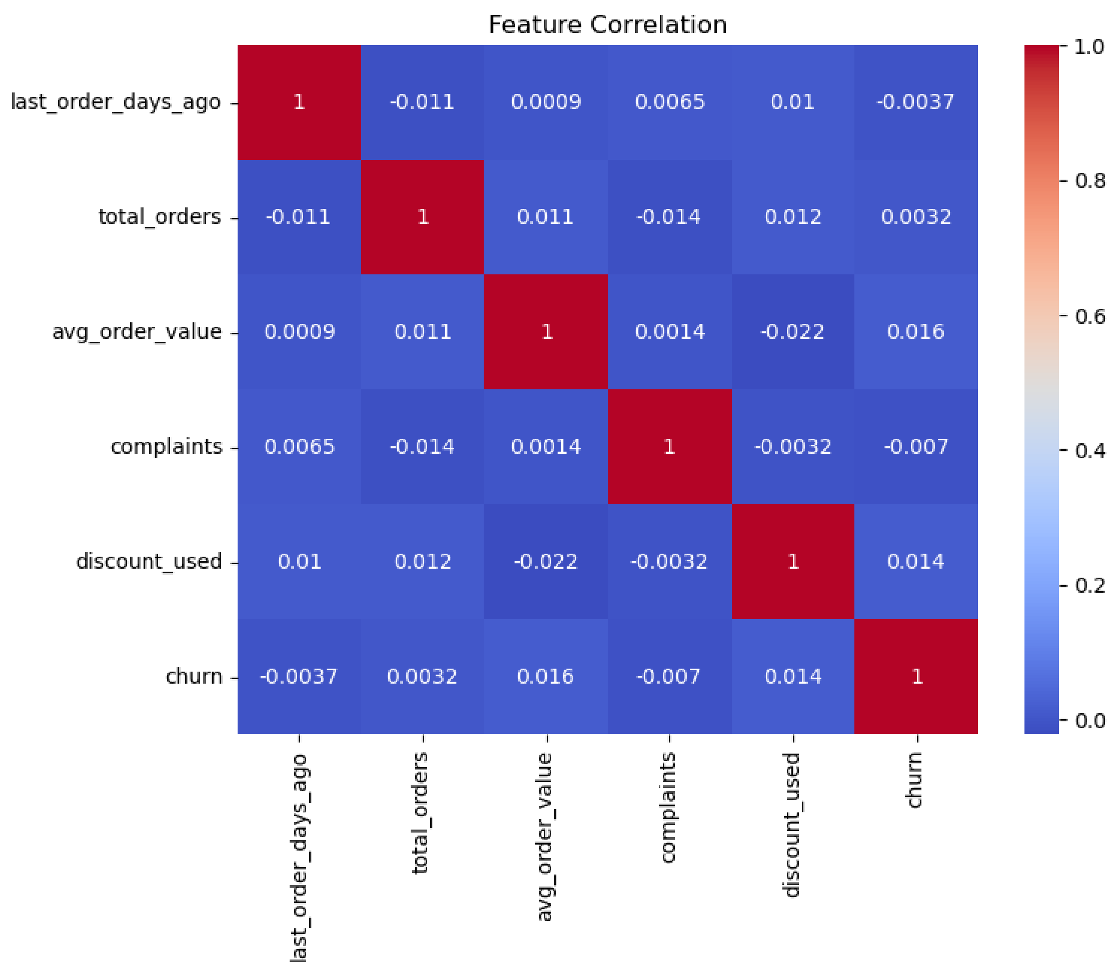
[3]:

```
# Basic statistics
print(data.describe())

# Churn distribution
sns.countplot(x='churn', data=data)
plt.title("Churn Distribution")
plt.show()

# Correlation heatmap
plt.figure(figsize=(8,6))
sns.heatmap(data.drop('customer_id', axis=1).corr(), annot=True,␣
 ↪cmap='coolwarm')
plt.title("Feature Correlation")
plt.show()
```

```
       customer_id  last_order_days_ago  total_orders  avg_order_value  \
count  10000.00000         10000.000000  10000.000000     10000.000000
mean    5000.50000           181.922300     10.042600        27.451422
std     2886.89568           104.853453      3.160472        13.000012
min        1.00000             1.000000      0.000000         5.009142
25%     2500.75000            93.000000      8.000000        16.280541
50%     5000.50000           181.000000     10.000000        27.375755
75%     7500.25000           273.000000     12.000000        38.774759
max    10000.00000           364.000000     23.000000        49.995486
```

	complaints	discount_used	churn
count	10000.000000	10000.000000	10000.000000
mean	0.499400	9.437900	0.305100
std	0.668763	5.735227	0.460473
min	0.000000	0.000000	0.000000
25%	0.000000	4.000000	0.000000
50%	0.000000	9.000000	0.000000
75%	1.000000	14.000000	1.000000
max	4.000000	19.000000	1.000000





1.4 Step 4: Data Preprocessing

[4]:
```
X = data.drop(['customer_id', 'churn'], axis=1)
y = data['churn']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42, stratify=y)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

1.5 Step 5: Train Models

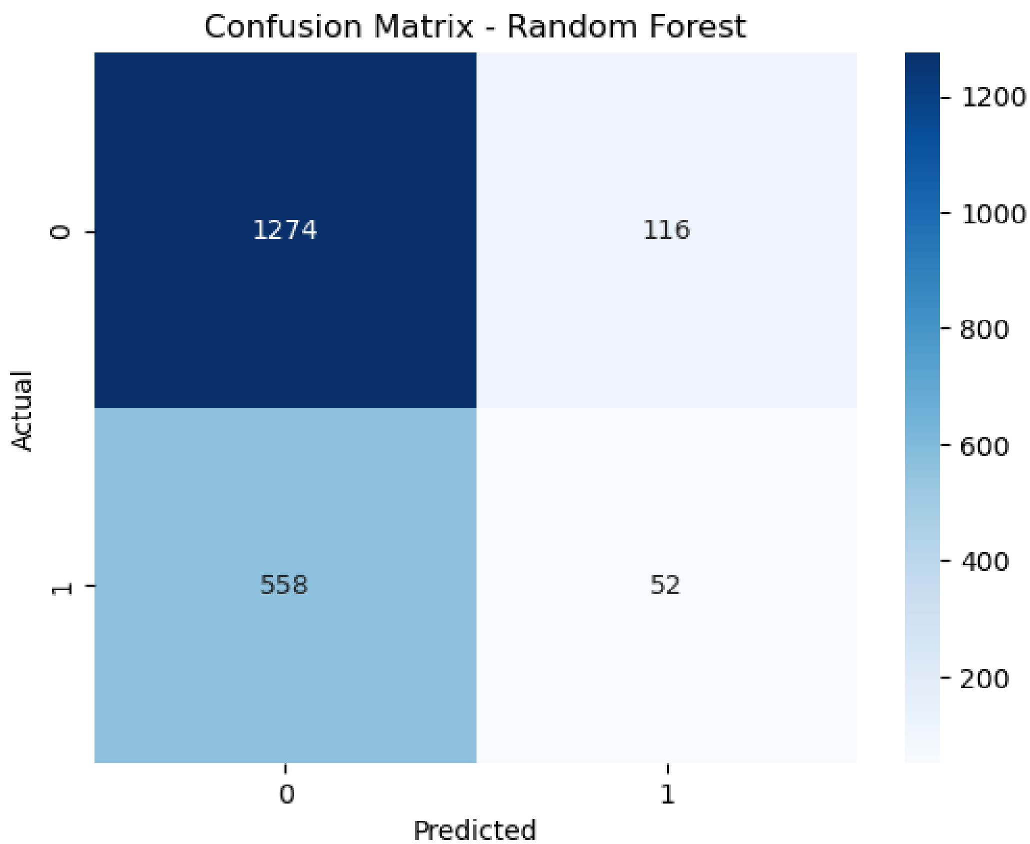
[5]:
```
# Logistic Regression
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_train_scaled, y_train)
y_pred_log = log_reg.predict(X_test_scaled)

# Random Forest
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)

# XGBoost
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
 ↪random_state=42)
xgb.fit(X_train, y_train)
y_pred_xgb = xgb.predict(X_test)
```

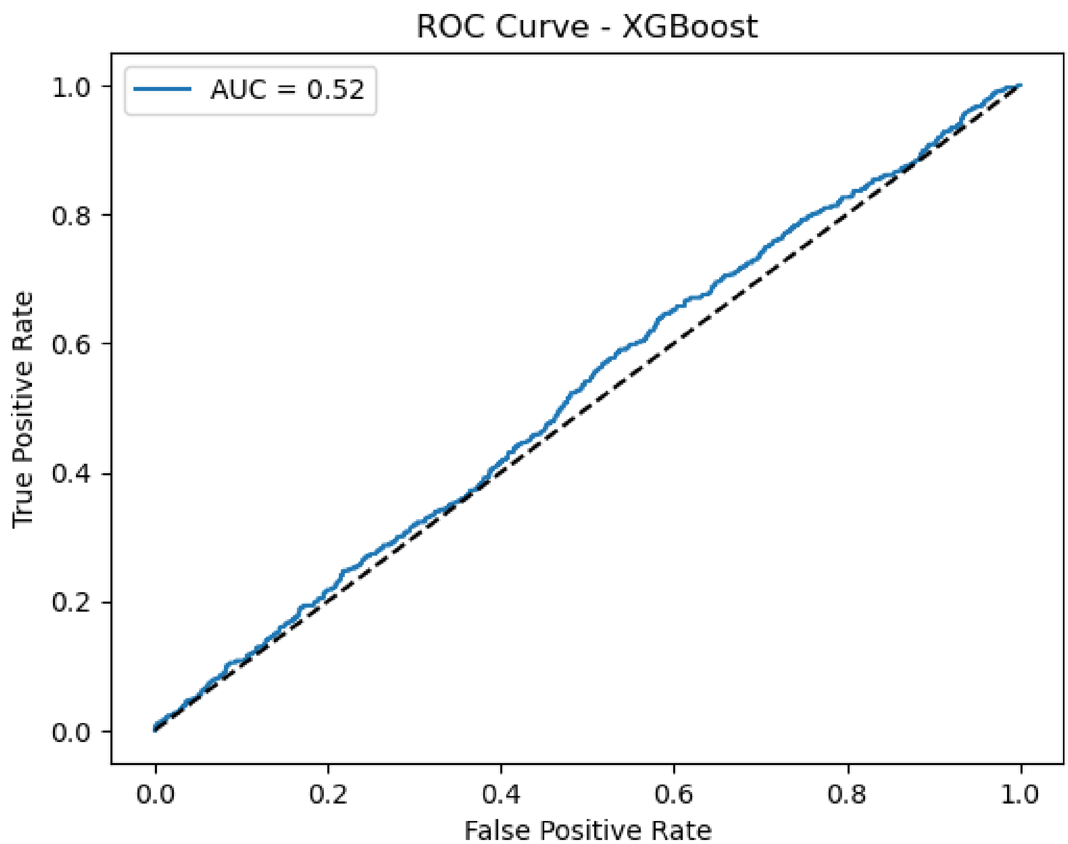
1.6 Step 6: Model Evaluation

[6]:
```
print("Logistic Regression:\n", classification_report(y_test, y_pred_log))
print("Random Forest:\n", classification_report(y_test, y_pred_rf))
print("XGBoost:\n", classification_report(y_test, y_pred_xgb))

# Confusion Matrix for Random Forest
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d',␣
 ↪cmap='Blues')
plt.title("Confusion Matrix - Random Forest")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# ROC Curve for XGBoost
y_probs = xgb.predict_proba(X_test)[:,1]
fpr, tpr, _ = roc_curve(y_test, y_probs)
plt.plot(fpr, tpr, label=f"AUC = {roc_auc_score(y_test, y_probs):.2f}")
plt.plot([0,1], [0,1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - XGBoost")
plt.legend()
plt.show()
```

```
Logistic Regression:
               precision    recall  f1-score   support

           0       0.69      1.00      0.82      1390
           1       0.00      0.00      0.00       610
```

```
    accuracy                           0.69      2000
   macro avg       0.35      0.50      0.41      2000
weighted avg       0.48      0.69      0.57      2000

Random Forest:
              precision    recall  f1-score   support

           0       0.70      0.92      0.79      1390
           1       0.31      0.09      0.13       610

    accuracy                           0.66      2000
   macro avg       0.50      0.50      0.46      2000
weighted avg       0.58      0.66      0.59      2000

XGBoost:
              precision    recall  f1-score   support

           0       0.70      0.89      0.78      1390
           1       0.32      0.12      0.17       610

    accuracy                           0.66      2000
   macro avg       0.51      0.50      0.48      2000
weighted avg       0.58      0.66      0.60      2000
```


Confusion Matrix - Random Forest
1274
116
558
52
Actual
Predicted
0
1
0
1
1200
1000
800
600
400
200

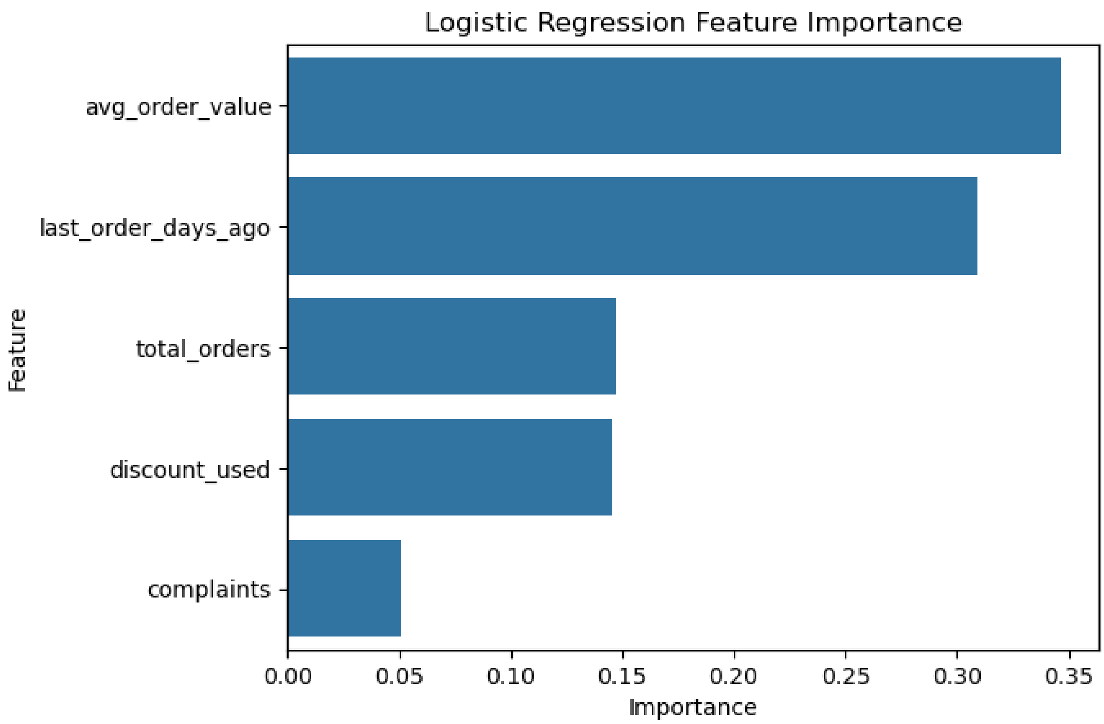


[7]:
```python
ex_data = [186, 8, 25.8733, 2, 11]

# Convert to numpy array and reshape to (1, n_features)
ex_data = np.array(ex_data).reshape(1, -1)

# Preprocessing by Standard Scaler
ex_data_scaled = scaler.transform(ex_data)

# Prediction By Algorithms:
ex_data_pred_log = log_reg.predict(ex_data_scaled)
ex_data_pred_rf = rf.predict(ex_data_scaled)
ex_data_pred_xgb = xgb.predict(ex_data_scaled)

print(f'Prediction by Logistic Regression is {ex_data_pred_log[0]}')
print(f'Prediction by Random Forest is {ex_data_pred_rf[0]}')
print(f'Prediction by XGBoost is {ex_data_pred_xgb[0]}')
```

```
Prediction by Logistic Regression is 0
Prediction by Random Forest is 1
Prediction by XGBoost is 0
```

1.7 Step 7: Feature Importance

[9]:
```
importances = rf.feature_importances_
feat_names = X.columns

feat_imp = pd.DataFrame({'Feature': feat_names, 'Importance': importances})
feat_imp.sort_values(by='Importance', ascending=False, inplace=True)

sns.barplot(x='Importance', y='Feature', data=feat_imp)
plt.title("Logistic Regression Feature Importance")
plt.show()
```



1.8 Step 8: Conclusion & Business Use Case

- The models give us a way to predict which customers are likely to churn.
- We can integrate this model into the CRM/marketing system:
  - Send targeted discounts to **high-risk churners**.
  - Recommend personalized meals to re-engage customers.
  - Monitor churn rates across restaurants and regions.

Next Steps: - Replace synthetic dataset with real customer order data.
- Regularly retrain the model with new data.

- Deploy as an API to integrate with the app.

```
[ ]:
```