DATA EXPLORATION & PREPROCESSING A data exploration and preprocessing notebook or report that analyzes the dataset, handles missing values, and prepares the data for modeling

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid')
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import (accuracy_score, precision_score,
recall_score, f1_score,
                             roc_auc_score, classification_report,
confusion_matrix)
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
import joblib

from imblearn.over_sampling import SMOTE



# 1.1 Load data & quick overview

df = pd.read_csv(r"C:\Users\Pravallika\Downloads\Customerdata.csv")
print("Shape:", df.shape)
display(df.head())
display(df.info())
display(df.describe(include='all').T)

# Target check (example: 'Churn' column with Yes/No)
print(df['Churn'].value_counts(dropna=False))
sns.countplot(x='Churn', data=df)
plt.title('Churn Distribution'); plt.show()
```

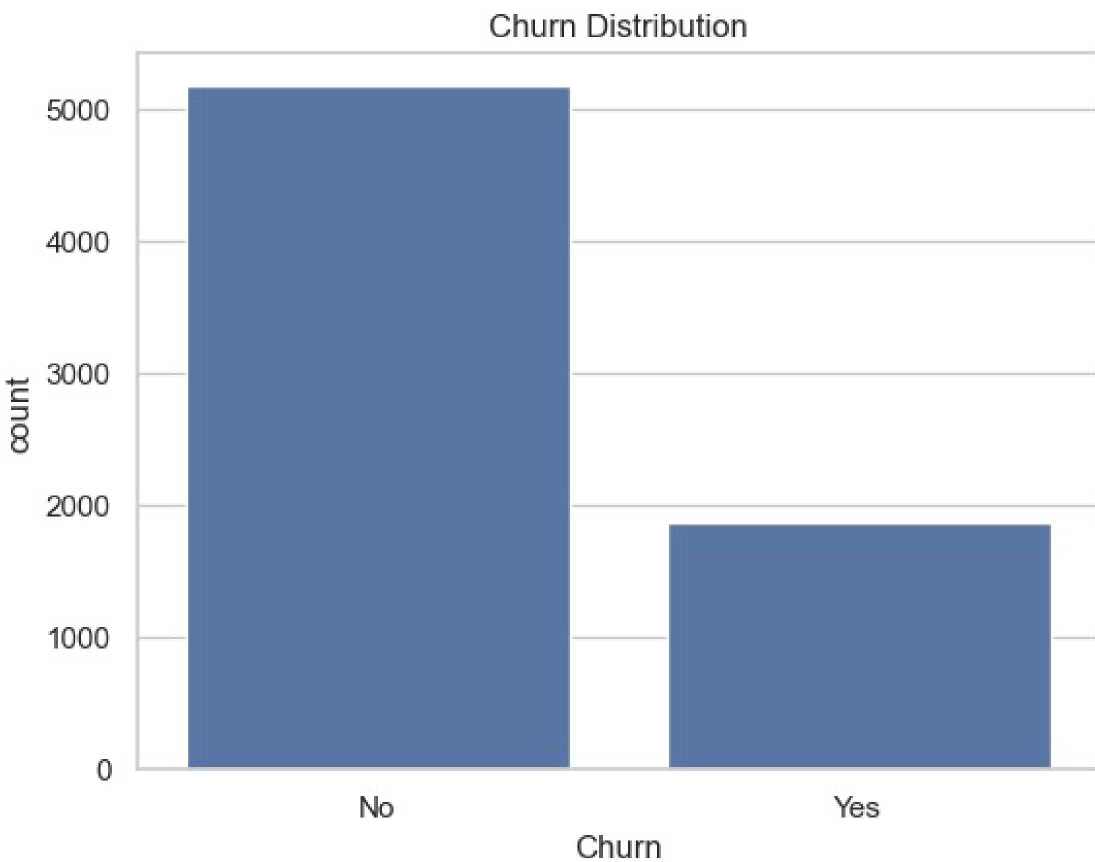
```
Shape: (7043, 21)

   customerID  gender  SeniorCitizen Partner Dependents  tenure
PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1
No
1  5575-GNVDE    Male              0      No         No      34
Yes
2  3668-QPYBK    Male              0      No         No       2
Yes
3  7795-CFOCW    Male              0      No         No      45
```

```
No
4  9237-HQITU  Female              0      No         No       2
Yes

      MultipleLines InternetService OnlineSecurity  ...
DeviceProtection  \
0  No phone service             DSL             No  ...
No
1                No             DSL            Yes  ...
Yes
2                No             DSL            Yes  ...
No
3  No phone service             DSL            Yes  ...
Yes
4                No     Fiber optic             No  ...
No

  TechSupport StreamingTV StreamingMovies        Contract
PaperlessBilling  \
0          No          No              No  Month-to-month
Yes
1          No          No              No        One year
No
2          No          No              No  Month-to-month
Yes
3         Yes          No              No        One year
No
4          No          No              No  Month-to-month
Yes

               PaymentMethod MonthlyCharges  TotalCharges  Churn
0           Electronic check          29.85         29.85     No
1               Mailed check          56.95       1889.50     No
2               Mailed check          53.85        108.15    Yes
3  Bank transfer (automatic)          42.30       1840.75     No
4           Electronic check          70.70        151.65    Yes

[5 rows x 21 columns]

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
```

```
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB

None

                  count unique             top  freq
mean  \
customerID         7043   7043      3186-AJIEK     1            NaN

gender             7043      2            Male  3555            NaN

SeniorCitizen    7043.0    NaN             NaN   NaN       0.162147

Partner            7043      2              No  3641            NaN

Dependents         7043      2              No  4933            NaN

tenure           7043.0    NaN             NaN   NaN      32.371149

PhoneService       7043      2             Yes  6361            NaN

MultipleLines      7043      3              No  3390            NaN

InternetService    7043      3     Fiber optic  3096            NaN

OnlineSecurity     7043      3              No  3498            NaN

OnlineBackup       7043      3              No  3088            NaN

DeviceProtection   7043      3              No  3095            NaN

TechSupport        7043      3              No  3473            NaN

StreamingTV        7043      3              No  2810            NaN

StreamingMovies    7043      3              No  2785            NaN
```

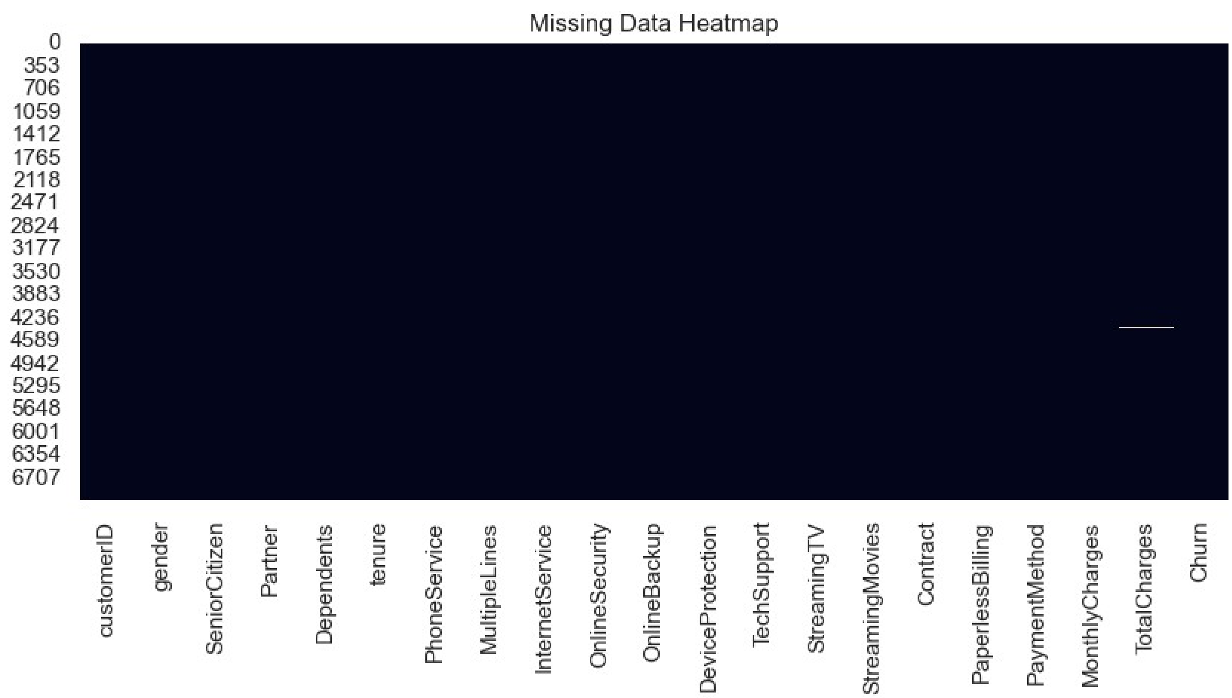
```
Contract              7043       3    Month-to-month  3875           NaN
PaperlessBilling      7043       2               Yes  4171           NaN
PaymentMethod         7043       4  Electronic check  2365           NaN
MonthlyCharges      7043.0     NaN               NaN   NaN     64.761692
TotalCharges        7032.0     NaN               NaN   NaN   2283.300441
Churn                 7043       2                No  5174           NaN

                          std    min     25%       50%         75%
max
customerID                NaN    NaN     NaN       NaN         NaN
NaN
gender                    NaN    NaN     NaN       NaN         NaN
NaN
SeniorCitizen        0.368612    0.0     0.0       0.0         0.0
1.0
Partner                   NaN    NaN     NaN       NaN         NaN
NaN
Dependents                NaN    NaN     NaN       NaN         NaN
NaN
tenure              24.559481    0.0     9.0      29.0        55.0
72.0
PhoneService              NaN    NaN     NaN       NaN         NaN
NaN
MultipleLines             NaN    NaN     NaN       NaN         NaN
NaN
InternetService           NaN    NaN     NaN       NaN         NaN
NaN
OnlineSecurity            NaN    NaN     NaN       NaN         NaN
NaN
OnlineBackup              NaN    NaN     NaN       NaN         NaN
NaN
DeviceProtection          NaN    NaN     NaN       NaN         NaN
NaN
TechSupport               NaN    NaN     NaN       NaN         NaN
NaN
StreamingTV               NaN    NaN     NaN       NaN         NaN
NaN
StreamingMovies           NaN    NaN     NaN       NaN         NaN
NaN
Contract                  NaN    NaN     NaN       NaN         NaN
NaN
PaperlessBilling          NaN    NaN     NaN       NaN         NaN
NaN
```

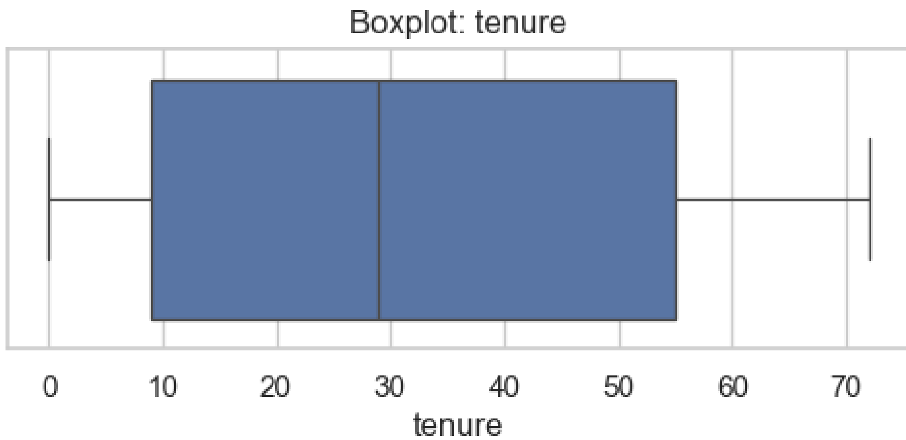
```
PaymentMethod                  NaN     NaN      NaN        NaN          NaN
NaN
MonthlyCharges           30.090047   18.25     35.5      70.35        89.85
118.75
TotalCharges           2266.771362    18.8   401.45   1397.475    3794.7375
8684.8
Churn                          NaN     NaN      NaN        NaN          NaN
NaN

Churn
No     5174
Yes    1869
Name: count, dtype: int64
```

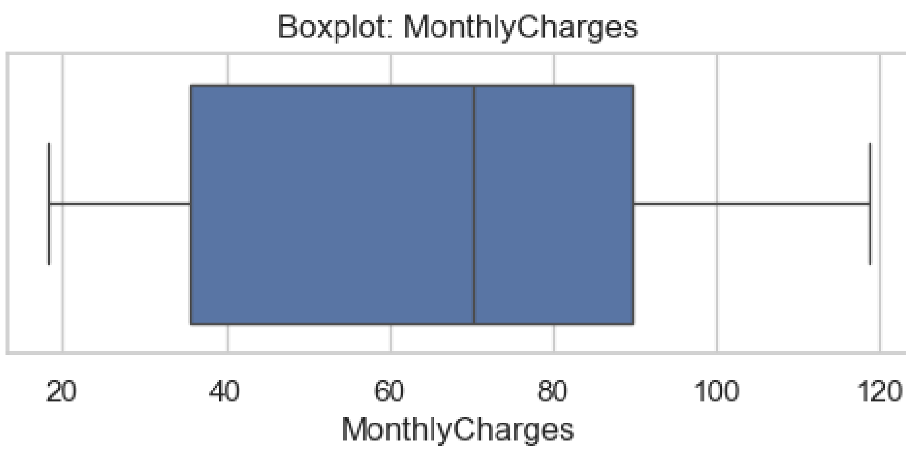


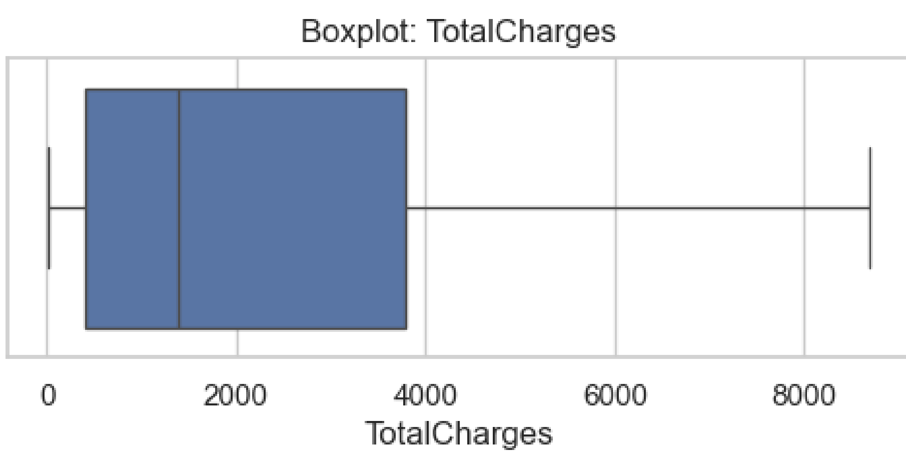

```python
# Missing values
missing = df.isnull().sum().sort_values(ascending=False)
print("Missing values per column:\n", missing[missing>0])

# Visual missingness
plt.figure(figsize=(10,4))
sns.heatmap(df.isnull(), cbar=False)
plt.title('Missing Data Heatmap'); plt.show()
```

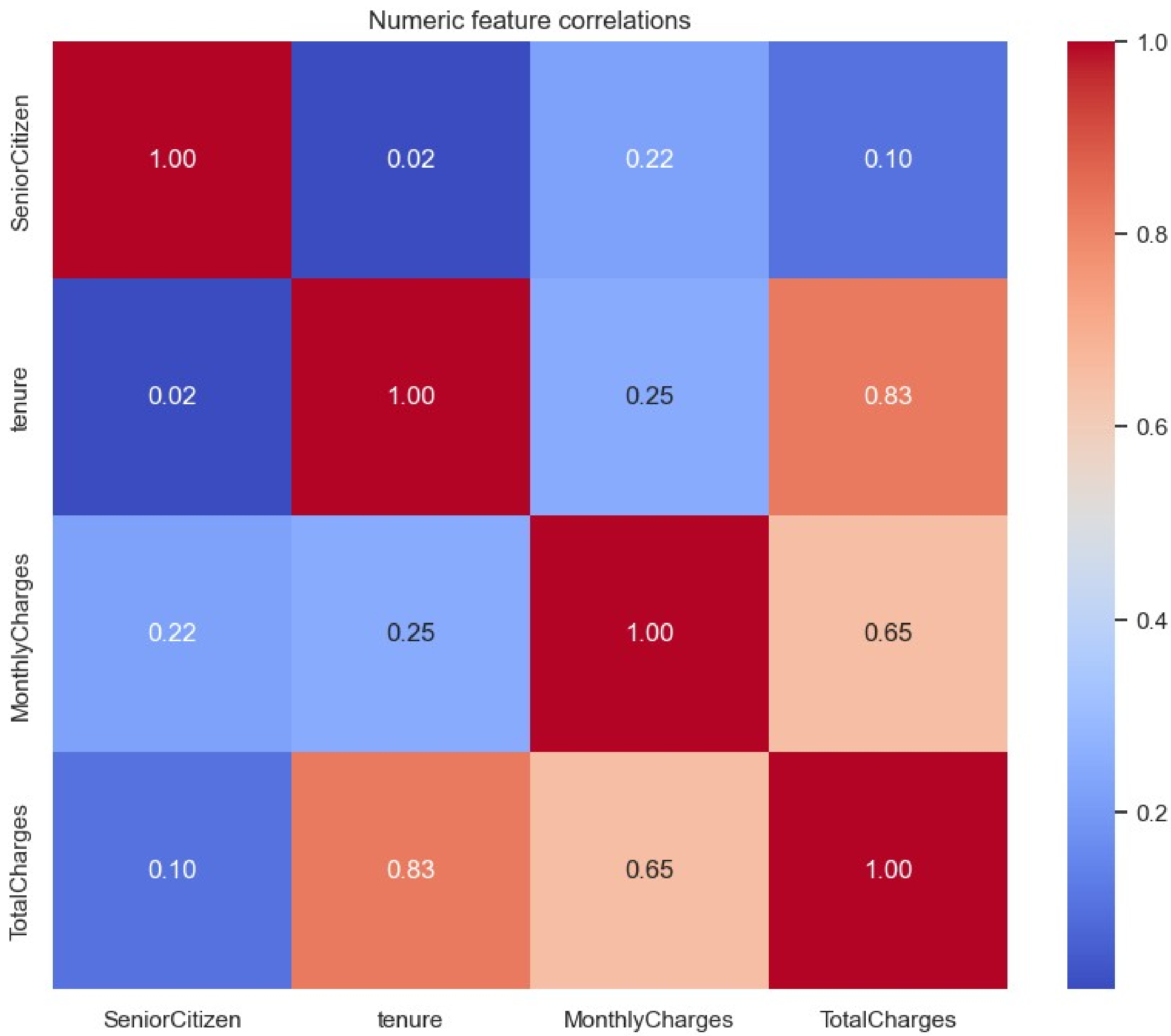
```
# Price/charge-like columns: outlier check example
for col in ['tenure', 'MonthlyCharges', 'TotalCharges']:
    if col in df.columns:
        plt.figure(figsize=(6,2))
        sns.boxplot(x=df[col])
        plt.title(f'Boxplot: {col}')
        plt.show()

# Correlation heatmap for numeric features
plt.figure(figsize=(10,8))
sns.heatmap(df.select_dtypes(include=[np.number]).corr(), annot=True,
fmt=".2f", cmap='coolwarm')
plt.title('Numeric feature correlations'); plt.show()

Missing values per column:
 TotalCharges    11
dtype: int64
```




Boxplot: tenure
0
10
20
30
40
50
60
70
tenure


Boxplot: MonthlyCharges
20
40
60
80
100
120
MonthlyCharges


Boxplot: TotalCharges
0
2000
4000
6000
8000
TotalCharges




```python
# 1.2 Cleaning & Feature Engineering

if 'TotalCharges' in df.columns and df['TotalCharges'].dtype ==
'object':
    df['TotalCharges'] = pd.to_numeric(df['TotalCharges'],
errors='coerce')

# Impute missing values
num_cols =
df.select_dtypes(include=['int64','float64']).columns.tolist()
cat_cols =
df.select_dtypes(include=['object','category']).columns.tolist()
# remove target from cat_cols
if 'Churn' in cat_cols:
    cat_cols.remove('Churn')
```

```
num_imputer = SimpleImputer(strategy='median')
cat_imputer = SimpleImputer(strategy='most_frequent')

df[num_cols] = pd.DataFrame(num_imputer.fit_transform(df[num_cols]),
columns=num_cols)
df[cat_cols] = pd.DataFrame(cat_imputer.fit_transform(df[cat_cols]),
columns=cat_cols)

# Feature engineering examples:
if 'tenure' in df.columns:
    df['tenure_group'] = pd.cut(df['tenure'], bins=[-
1,3,12,24,48,120], labels=['0-3','4-12','13-24','25-48','49+'])

# Create a numeric indicator for multi-service usage example
service_cols = [c for c in df.columns if
c.lower().startswith(('internet','online','tech','stream'))]
if service_cols:
    df['num_services'] = df[service_cols].apply(lambda row:
sum(row=='Yes') if row.dtype=='O' else np.nan,
axis=1).fillna(0).astype(int)

for c in cat_cols:
    df[c] = df[c].replace(' ', np.nan).fillna(df[c].mode()[0])
```

A machine learning model capable of predicting customer churn

```
# Prepare X, y

target = 'Churn'
y = df[target].map({'Yes':1,'No':0}) if df[target].dtype=='object'
else df[target]
X = df.drop(columns=[target])

# Identify column types for transformer
numeric_features =
X.select_dtypes(include=[np.number]).columns.tolist()
categorical_features =
X.select_dtypes(include=['object','category']).columns.tolist()

# Preprocessing pipelines
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
```

```
    ('onehot', OneHotEncoder(handle_unknown='ignore',
sparse_output=False))

])

preprocessor = ColumnTransformer(transformers=[
    ('num', numeric_transformer, numeric_features),
    ('cat', categorical_transformer, categorical_features)
], remainder='drop')

#Train/validation/test split

X_trainval, X_test, y_trainval, y_test = train_test_split(X, y,
test_size=0.20, random_state=42, stratify=y)
X_train, X_val, y_train, y_val = train_test_split(X_trainval,
y_trainval, test_size=0.1875, random_state=42, stratify=y_trainval)
print("Shapes -> Train:", X_train.shape, "Val:", X_val.shape, "Test:",
X_test.shape)
```

```
Shapes -> Train: (4577, 22) Val: (1057, 22) Test: (1409, 22)
```

```
# We'll build pipelines that include SMOTE after preprocessing; use
imblearn Pipeline
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)



# Logistic Regression (interpretable baseline)
pipe_lr = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', smote),
    ('clf', LogisticRegression(max_iter=1000,
class_weight='balanced'))
])
pipe_lr.fit(X_train, y_train)

# Random Forest (powerful, interpretable via importances)
pipe_rf = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', smote),
    ('clf', RandomForestClassifier(random_state=42,
class_weight='balanced', n_jobs=-1))
])
param_grid_rf = {
    'clf__n_estimators': [100, 200],
    'clf__max_depth': [None, 10, 20]
}
grid_rf = GridSearchCV(pipe_rf, param_grid_rf, cv=3, scoring='f1',
```

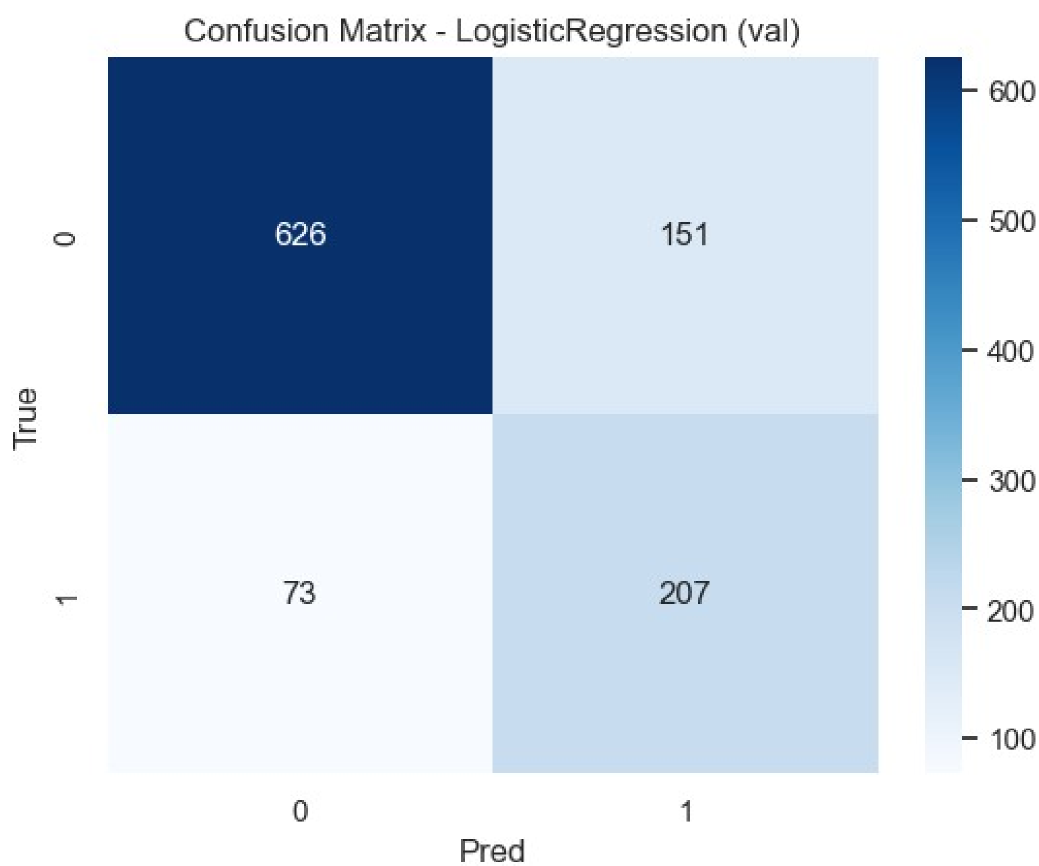
```
n_jobs=-1)
grid_rf.fit(X_train, y_train)

# XGBoost (often best performance)
pipe_xgb = ImbPipeline(steps=[
    ('preprocessor', preprocessor),
    ('smote', smote),
    ('clf', XGBClassifier(eval_metric='logloss', random_state=42))
])
param_grid_xgb = {
    'clf__n_estimators': [100, 200],
    'clf__max_depth': [3,6]
}
grid_xgb = GridSearchCV(pipe_xgb, param_grid_xgb, cv=3, scoring='f1',
n_jobs=-1)
grid_xgb.fit(X_train, y_train)

print("Best RF params:", grid_rf.best_params_)
print("Best XGB params:", grid_xgb.best_params_)
```

Model Evaluation An evaluation of model performance using appropriate metrics such as accuracy, precision, recall, F1 score, etc.

```
# Utility to evaluate and print metrics
def evaluate_model(name, model, X, y):
    preds = model.predict(X)
    probs = model.predict_proba(X)[:,1] if hasattr(model,
"predict_proba") else None
    acc = accuracy_score(y, preds)
    prec = precision_score(y, preds)
    rec = recall_score(y, preds)
    f1 = f1_score(y, preds)
    roc = roc_auc_score(y, probs) if probs is not None else None
    print(f"--- {name} ---")
    print(f"Accuracy: {acc:.4f}  Precision: {prec:.4f}  Recall:
{rec:.4f}  F1: {f1:.4f}  ROC-AUC: {roc:.4f}")
    print(classification_report(y, preds))
    cm = confusion_matrix(y, preds)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
    plt.title(f'Confusion Matrix - {name}'); plt.xlabel('Pred');
plt.ylabel('True'); plt.show()
    return
{'accuracy':acc,'precision':prec,'recall':rec,'f1':f1,'roc':roc}

# Evaluate on validation to choose best model
res_lr = evaluate_model("LogisticRegression (val)", pipe_lr, X_val,
y_val)
res_rf = evaluate_model("RandomForest (val)", grid_rf.best_estimator_,
```

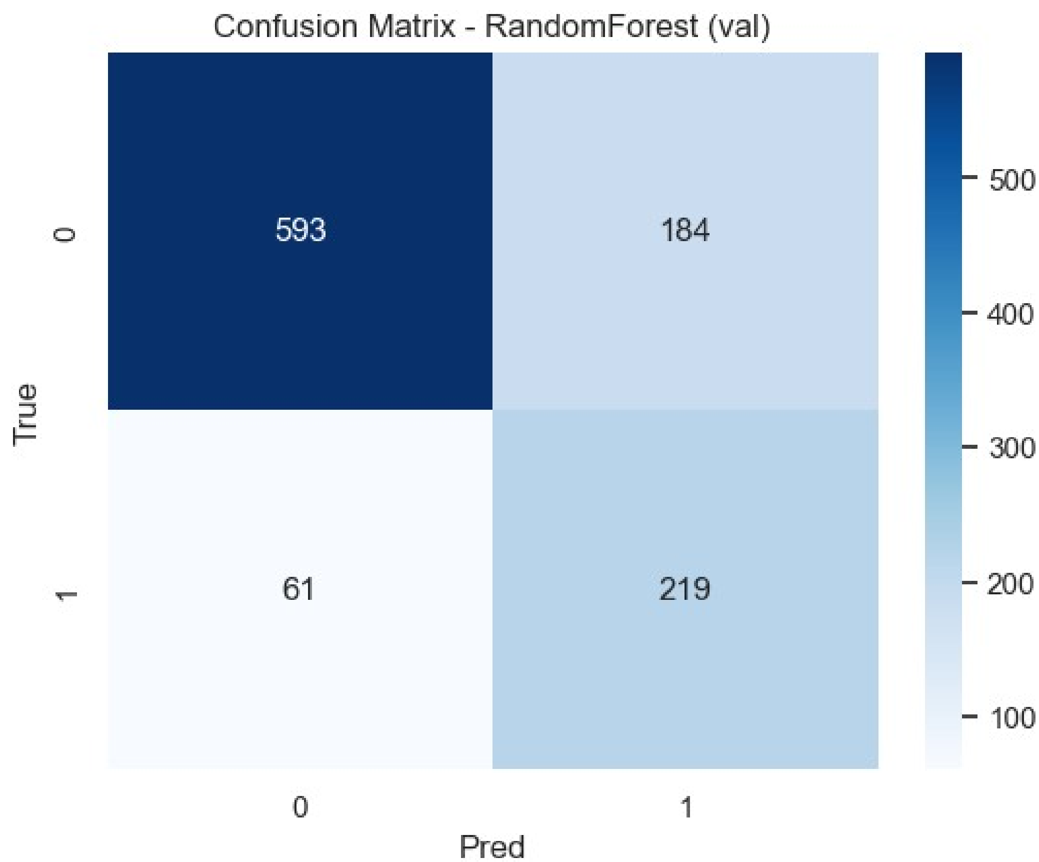
```
X_val, y_val)
res_xgb = evaluate_model("XGBoost (val)", grid_xgb.best_estimator_,
X_val, y_val)
```

```
--- LogisticRegression (val) ---
Accuracy: 0.7881  Precision: 0.5782  Recall: 0.7393  F1: 0.6489  ROC-
AUC: 0.8556
              precision    recall  f1-score   support

           0       0.90      0.81      0.85       777
           1       0.58      0.74      0.65       280

    accuracy                           0.79      1057
   macro avg       0.74      0.77      0.75      1057
weighted avg       0.81      0.79      0.80      1057
```




```
--- RandomForest (val) ---
Accuracy: 0.7682  Precision: 0.5434  Recall: 0.7821  F1: 0.6413  ROC-
AUC: 0.8505
              precision    recall  f1-score   support

           0       0.91      0.76      0.83       777
```

```
           1       0.54      0.78      0.64       280

    accuracy                           0.77      1057
   macro avg       0.73      0.77      0.74      1057
weighted avg       0.81      0.77      0.78      1057
```




```
--- XGBoost (val) ---
Accuracy: 0.8193  Precision: 0.6894  Recall: 0.5786  F1: 0.6291  ROC-AUC: 0.8514
              precision    recall  f1-score   support

           0       0.86      0.91      0.88       777
           1       0.69      0.58      0.63       280

    accuracy                           0.82      1057
   macro avg       0.77      0.74      0.75      1057
weighted avg       0.81      0.82      0.81      1057
```

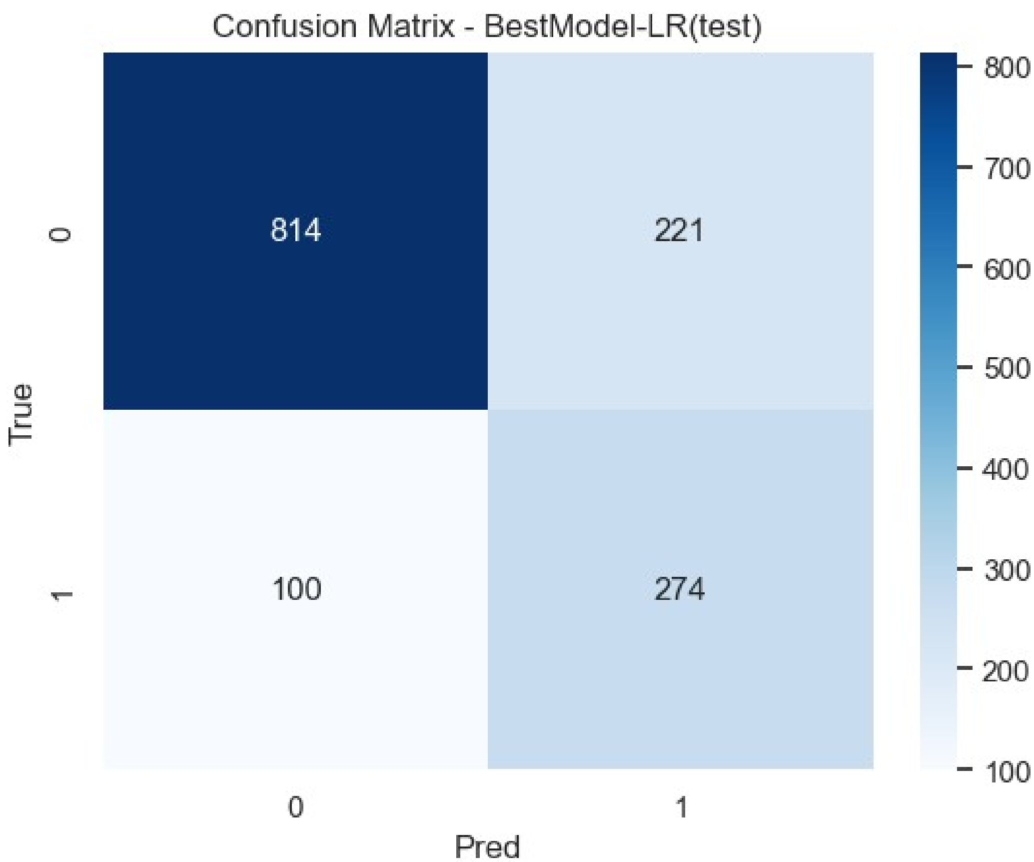

```
val_scores = {'LR':res_lr['f1'], 'RF':res_rf['f1'],
'XGB':res_xgb['f1']}
best_key = max(val_scores, key=val_scores.get)
best_model = {'LR':pipe_lr, 'RF':grid_rf.best_estimator_,
'XGB':grid_xgb.best_estimator_}[best_key]
print("Best model selected:", best_key, "with F1:",
val_scores[best_key])
```

```
Best model selected: LR with F1: 0.6489028213166145
```

```
#Evaluate on test set
res_test = evaluate_model(f"BestModel-{best_key}(test)", best_model,
X_test, y_test)
```

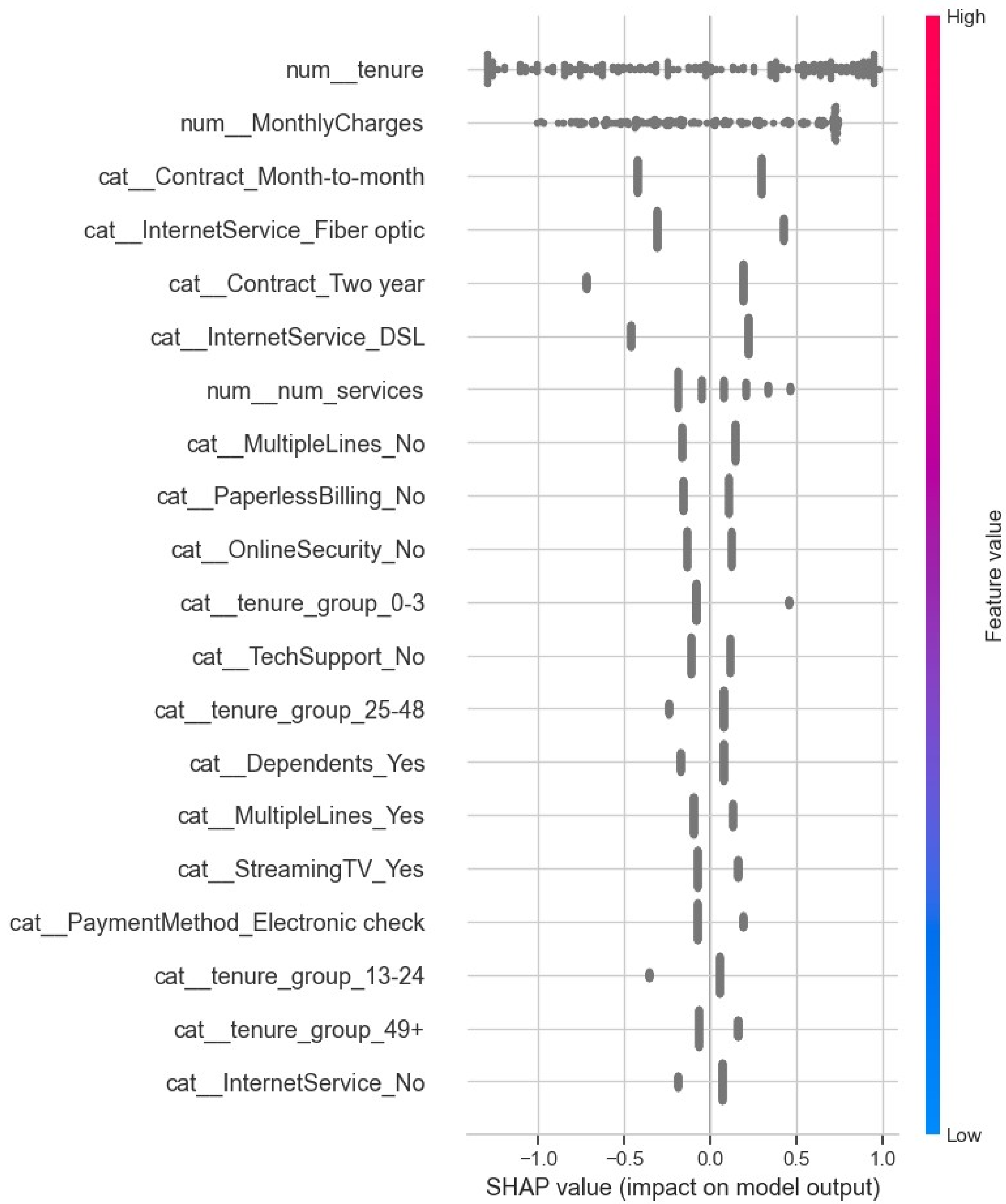
```
--- BestModel-LR(test) ---
Accuracy: 0.7722  Precision: 0.5535  Recall: 0.7326  F1: 0.6306  ROC-
AUC: 0.8452
              precision    recall  f1-score   support

           0       0.89      0.79      0.84      1035
```

```
           1       0.55      0.73      0.63       374

    accuracy                           0.77      1409
   macro avg       0.72      0.76      0.73      1409
weighted avg       0.80      0.77      0.78      1409
```




```
# I
def get_feature_names(column_transformer):
    # numeric features
    num = column_transformer.transformers_[0][2]
    cat = column_transformer.transformers_[1][2]
    # onehot feature names
    ohe = 
column_transformer.named_transformers_['cat'].named_steps['onehot']
    cat_names = 
ohe.get_feature_names_out(column_transformer.transformers_[1][2])
    return list(num) + list(cat_names)
```

```
if best_key in ['RF','XGB']:
    # extract preprocessor from pipeline
    pre = best_model.named_steps['preprocessor']
    feat_names = list(numeric_features) +
list(best_model.named_steps['preprocessor'].named_transformers_['cat']
.named_steps['onehot'].get_feature_names_out(categorical_features))
    importances = best_model.named_steps['clf'].feature_importances_
    feat_imp = pd.Series(importances,
index=feat_names).sort_values(ascending=False).head(20)
    plt.figure(figsize=(8,6))
    sns.barplot(x=feat_imp.values, y=feat_imp.index)
    plt.title('Top 20 Feature Importances'); plt.show()

import shap

X_background =
best_model.named_steps['preprocessor'].transform(X_train.sample(200))
explainer =
shap.LinearExplainer( model=best_model.named_steps['clf'],masker=X_bac
kground)
X_to_explain = X_background
shap_values = explainer.shap_values(X_to_explain)
feat_names =
best_model.named_steps['preprocessor'].get_feature_names_out()
shap.summary_plot(shap_values, X_to_explain, feature_names=feat_names)
```




```
# Save best model
joblib.dump(grid_rf.best_estimator_, 'best_churn_model.joblib')
# Assuming grid_rf is the best model
```

```python
# Predict function for new raw dataframe (must have same columns)
def predict_new(df_new, model_path='best_churn_model.joblib'):
    model = joblib.load(model_path)
    preds = model.predict(df_new)
    # Check if the model has predict_proba before accessing it
    probs = model.predict_proba(df_new)[:,1] if hasattr(model,
'predict_proba') else None
    return preds, probs

# Example usage:
# Assuming X_test is a raw dataframe before preprocessing
new_df = X_test.iloc[[0]] # raw (not preprocessed) row
p, pr = predict_new(new_df)
print('Pred:', p, 'Prob:', pr)
```

```
Pred: [0] Prob: [0.18218309]
```