STATS/CSE 780 - Homework Assignment 2

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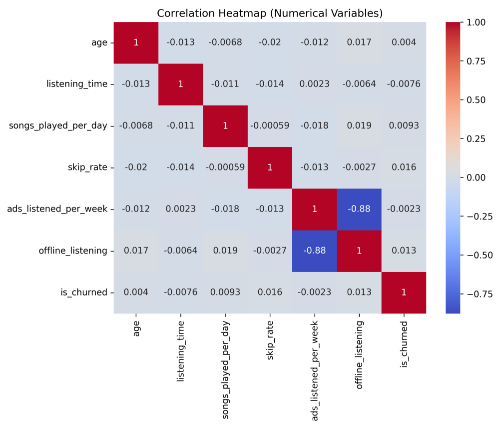
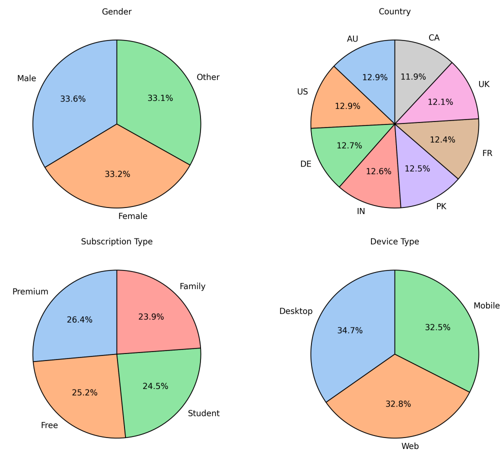
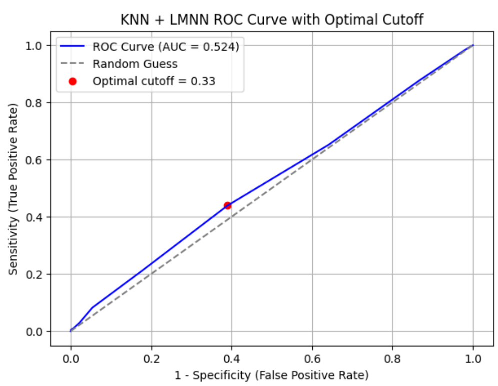
Supplemental Material

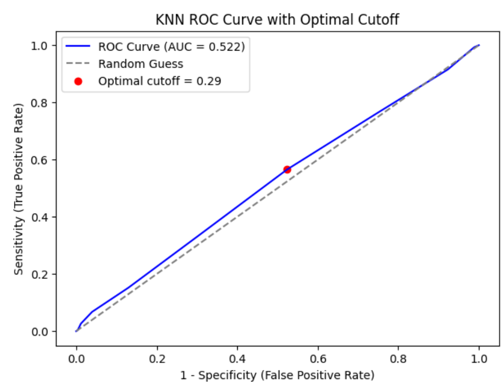
- Note: GitHub Copilot was used to assist with code generation and error handling.

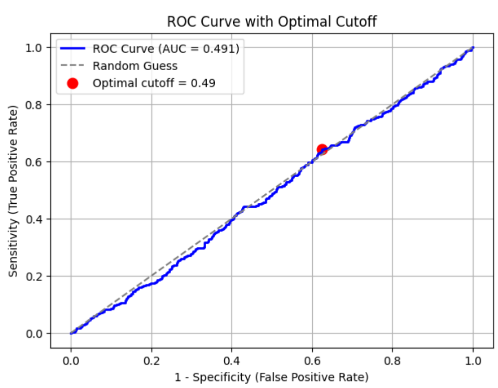
Plots

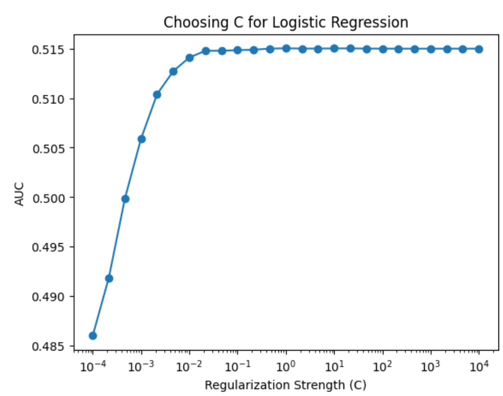


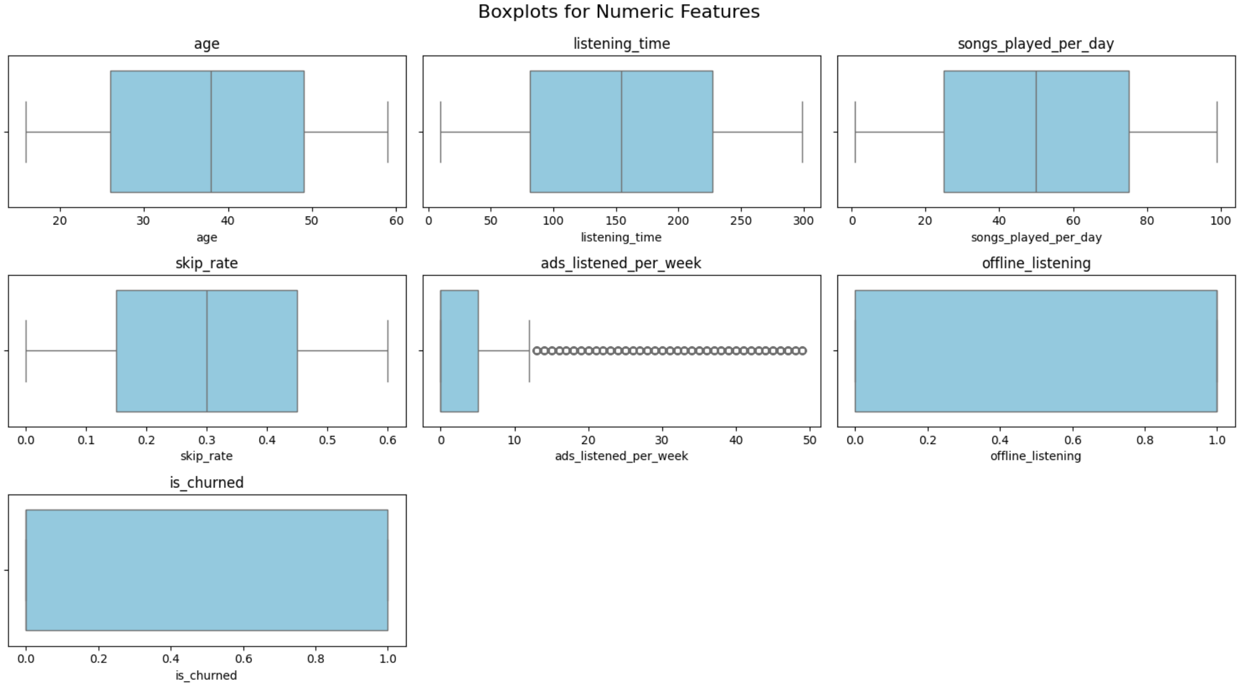












Imports

```
# Core
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore")

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Preprocessing & Splitting
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder, OneHotEncoder

# Models
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from metric_learn import LMNN  # Metric learning, optional
```

```python
# Metrics & Evaluation
from sklearn.metrics import (
    accuracy_score,
    f1_score,
    precision_score,
    recall_score,
    confusion_matrix,
    classification_report,
    roc_curve,
    roc_auc_score
)
```

```python
df = pd.read_csv("spotify_churn_dataset.csv")
df = df.drop(columns=['user_id'])
```

Exploratory Data analysis

```python
df.isna().sum()
df.shape
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8000 entries, 0 to 7999
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   gender                8000 non-null   object
 1   age                   8000 non-null   int64
 2   country               8000 non-null   object
 3   subscription_type     8000 non-null   object
 4   listening_time        8000 non-null   int64
 5   songs_played_per_day  8000 non-null   int64
 6   skip_rate             8000 non-null   float64
 7   device_type           8000 non-null   object
 8   ads_listened_per_week 8000 non-null   int64
 9   offline_listening     8000 non-null   int64
 10  is_churned            8000 non-null   int64
dtypes: float64(1), int64(6), object(4)
```

memory usage: 687.6+ KB

	age	listening_time	songs_played_per_day	skip_rate	ads_listened_per_week	offline_listening	is_ch
count	8000.000000	8000.000000	8000.000000	8000.000000	8000.000000	8000.000000	8000.
mean	37.662125	154.068250	50.127250	0.300127	6.943875	0.747750	0.258
std	12.740359	84.015596	28.449762	0.173594	13.617953	0.434331	0.438
min	16.000000	10.000000	1.000000	0.000000	0.000000	0.000000	0.000
25%	26.000000	81.000000	25.000000	0.150000	0.000000	0.000000	0.000
50%	38.000000	154.000000	50.000000	0.300000	0.000000	1.000000	0.000
75%	49.000000	227.000000	75.000000	0.450000	5.000000	1.000000	1.000
max	59.000000	299.000000	99.000000	0.600000	49.000000	1.000000	1.000

```
# Select categorical columns
categorical_cols = df.select_dtypes(include=['object', 'category']).columns

# Plot pie charts in 2x2 grids
for i in range(0, len(categorical_cols), 4):
    plt.figure(figsize=(10, 8))
    for j, col in enumerate(categorical_cols[i:i+4], 1):
        plt.subplot(2, 2, j)
        df[col].value_counts().plot(
            kind='pie',
            autopct='%1.1f%%',
            startangle=90,
            colors=sns.color_palette("pastel"),
            wedgeprops={'edgecolor': 'k'}
        )
        plt.title(col.replace("_", " ").title(), fontsize=10)
        plt.ylabel('')
    plt.tight_layout()
    plt.savefig("pie.png", dpi=300, bbox_inches='tight')
    plt.show()
```

```
plt.figure(figsize=(8,6))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap (Numerical Variables)")
plt.savefig("corr.png", dpi=300, bbox_inches='tight')
plt.show()
```

```python
# ----- Missing Values -----
print("Missing Values Summary:\n")
print(df.isnull().sum())
```

```
Missing Values Summary:

gender                  0
age                     0
country                 0
subscription_type       0
listening_time          0
songs_played_per_day    0
skip_rate               0
device_type             0
ads_listened_per_week   0
offline_listening       0
is_churned              0
dtype: int64
```

```python
# ----- Boxplots for Outliers -----
# Select only numeric columns
numeric_cols = df.select_dtypes(include=['number']).columns

# Create boxplots for each numeric column
plt.figure(figsize=(15, 8))
for i, col in enumerate(numeric_cols, 1):
    plt.subplot((len(numeric_cols) + 2)//3, 3, i)
    sns.boxplot(x=df[col], color='skyblue')
    plt.title(col)
    plt.tight_layout()

plt.suptitle("Boxplots for Numeric Features", fontsize=16, y=1.03)
plt.show()
```

Data Splitting

```python
y = df['is_churned']

# Features: drop the target
```

```python
X = df.drop(columns=['is_churned'])

# Optional: check the shapes
print("X shape:", X.shape)
print("y shape:", y.shape)
```

```
X shape: (8000, 10)
y shape: (8000,)
```

```python
# First, spliting off the test set (20%)
X_temp, X_test, y_temp, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Then, spliting the remaining 80% into training and validation (75% train, 25% val → 60/20 overall)
X_train, X_val, y_train, y_val = train_test_split(
    X_temp, y_temp, test_size=0.25, random_state=42, stratify=y_temp
)

print("Training size:", X_train.shape[0])
print("Validation size:", X_val.shape[0])
print("Test size:", X_test.shape[0])
```

```
Training size: 4800
Validation size: 1600
Test size: 1600
```

Scalling and Encoding

```python
# 3. One-hot encode categorical variables directly (returns DataFrame)
X_train_final = pd.get_dummies(X_train, dtype=int, columns=X_train.select_dtypes
                               (include=['object']).columns, drop_first=False)
X_val_final = pd.get_dummies(X_val, dtype=int,columns=X_val.select_dtypes
                             (include=['object']).columns, drop_first=False)
X_test_final = pd.get_dummies(X_test, dtype=int,columns=X_test.select_dtypes
                              (include=['object']).columns, drop_first=False)

# 4. Align columns (in case some categories are missing in val/test)
X_val_final = X_val_final.reindex(columns=X_train_final.columns, fill_value=0)
```

```python
X_test_final = X_test_final.reindex(columns=X_train_final.columns, fill_value=0)

# 5. Shapes
print("X_train:", X_train_final.shape)
print("X_val:", X_val_final.shape)
print("X_test:", X_test_final.shape)
```

```
X_train: (4800, 24)
X_val: (1600, 24)
X_test: (1600, 24)
```

```python
# Columns you want to scale
scale_cols = ['age', 'listening_time', 'songs_played_per_day', 'skip_rate']

scaler = StandardScaler()

# Copy so we don't overwrite original data
X_train_scaled = X_train_final.copy()
X_val_scaled   = X_val_final.copy()
X_test_scaled  = X_test_final.copy()

# Fit on train only
X_train_scaled[scale_cols] = scaler.fit_transform(X_train_final[scale_cols])
X_val_scaled[scale_cols]   = scaler.transform(X_val_final[scale_cols])
X_test_scaled[scale_cols]  = scaler.transform(X_test_final[scale_cols])
```

KNN

```python
# Range of k values to try
k_values = range(1, 21)  # try k from 1 to 20
val_accuracies = []

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_scaled, y_train)
    y_val_pred = knn.predict(X_val_scaled)
    acc = accuracy_score(y_val, y_val_pred)
    val_accuracies.append(acc)
```

```python
# Find best k
best_k = k_values[np.argmax(val_accuracies)]
print("Best k based on validation set:", best_k)
```

```
Best k based on validation set: 17
```

```python
plt.plot(k_values, val_accuracies, marker='o')
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Validation Accuracy")
plt.title("Choosing k using Validation Set")
plt.xticks(k_values)
plt.show()
```

```python
# --- Train best KNN on combined train+val and test it ---
best_k = 14  # selected from validation performance
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(np.vstack((X_train_scaled, X_val_scaled)), np.hstack((y_train, y_val)))
y_test_prob = knn.predict_proba(X_test_scaled)[:, 1]

# --- ROC and optimal cutoff ---
fpr, tpr, thresholds = roc_curve(y_test, y_test_prob)
optimal_idx = (tpr - fpr).argmax()
optimal_cutoff = thresholds[optimal_idx]
print(f"Optimal probability cutoff: {optimal_cutoff:.3f}")

# --- Plot ROC curve ---
plt.figure(figsize=(7,5))
plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc_score(y_test, y_test_prob):.3f})', color='blue')
plt.plot([0, 1], [0, 1], '--', color='gray', label='Random Guess')
plt.scatter(fpr[optimal_idx], tpr[optimal_idx], color='red', label=f'Optimal cutoff = {optimal_cutoff:.2f}')
plt.title("KNN ROC Curve with Optimal Cutoff")
plt.xlabel("1 - Specificity (False Positive Rate)")
plt.ylabel("Sensitivity (True Positive Rate)")
plt.legend()
plt.show()

# --- Apply optimal cutoff and compute metrics ---
y_test_pred = (y_test_prob >= optimal_cutoff).astype(int)
cm = confusion_matrix(y_test, y_test_pred)
tn, fp, fn, tp = cm.ravel()
```

```python
print("Confusion Matrix:")
print(cm)

accuracy = (tp + tn) / (tp + tn + fp + fn)
precision = precision_score(y_test, y_test_pred)
misclassification_error = 1 - accuracy
recall = recall_score(y_test, y_test_pred)  # Sensitivity
specificity = tn / (tn + fp)
f1 = f1_score(y_test, y_test_pred)
auc = roc_auc_score(y_test, y_test_prob)
```

```python
print(f"\nAccuracy: {accuracy:.3f}")
print(f"Precision: {precision:.3f}")
print(f"Misclassification Error: {misclassification_error:.3f}")
print(f"Sensitivity (Recall): {recall:.3f}")
print(f"Specificity: {specificity:.3f}")
print(f"F1-Score: {f1:.3f}")
print(f"AUC: {auc:.3f}")
```

```
Accuracy: 0.499
Precision: 0.274
Misclassification Error: 0.501
Sensitivity (Recall): 0.565
Specificity: 0.476
F1-Score: 0.369
AUC: 0.522
```

Logistic Regression

```python
C_values = np.logspace(-4, 4, 25)
accs, f1s, aucs = [], [], []

for C in C_values:
    clf = LogisticRegression(C=C, solver='liblinear', class_weight='balanced', max_iter=1000)
    clf.fit(X_train_scaled, y_train)
    y_val_prob = clf.predict_proba(X_val_scaled)[:,1]  # if binary
    y_val_pred = (y_val_prob >= 0.5).astype(int)
```

```
    accs.append(accuracy_score(y_val, y_val_pred))
    f1s.append(f1_score(y_val, y_val_pred, average='binary'))  # change average for multiclass
    try:
        aucs.append(roc_auc_score(y_val, y_val_prob))
    except Exception:
        aucs.append(np.nan)

# report best by different metrics
best_acc = C_values[np.nanargmax(accs)]
best_f1  = C_values[np.nanargmax(f1s)]
best_auc = C_values[np.nanargmax(aucs)]

print("Best C (acc):", best_acc, max(accs))
print("Best C (f1):", best_f1, max(f1s))
print("Best C (auc):", best_auc, max(aucs))
```

```
Best C (acc): 0.1 0.5225
Best C (f1): 0.00046415888336127773 0.35294117647058826
Best C (auc): 1.0 0.5150345007372649
```

```
import matplotlib.pyplot as plt

plt.semilogx(C_values, aucs, marker='o')
plt.xlabel("Regularization Strength (C)")
plt.ylabel("AUC")
plt.title("Choosing C for Logistic Regression")
plt.show()
```

```
# Train a final model (use best C or just C=1)
clf = LogisticRegression(C=1, solver='liblinear', class_weight='balanced', max_iter=1000)
clf.fit(X_train_scaled, y_train)

# Predict probabilities on validation or test set
y_test_prob = clf.predict_proba(X_test_scaled)[:, 1]

# Compute ROC curve values
fpr, tpr, thresholds = roc_curve(y_test, y_test_prob)
auc = roc_auc_score(y_test, y_test_prob)
```

```python
# Find optimal cutoff index
optimal_idx = (tpr - fpr).argmax()
optimal_cutoff = thresholds[optimal_idx]

# Plot ROC curve
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {auc:.3f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--', label='Random Guess')

# Mark optimal point
plt.scatter(fpr[optimal_idx], tpr[optimal_idx], color='red', s=80,
            label=f'Optimal cutoff = {optimal_cutoff:.2f}')

# Labels and legend
plt.xlabel('1 - Specificity (False Positive Rate)')
plt.ylabel('Sensitivity (True Positive Rate)')
plt.title('ROC Curve with Optimal Cutoff')
plt.legend()
plt.grid(True)
plt.show()

# Classify based on cutoff
y_test_pred = (y_test_prob >= 0.49).astype(int)

# Confusion matrix and performance metrics
cm = confusion_matrix(y_test, y_test_pred)
tn, fp, fn, tp = cm.ravel()

accuracy = accuracy_score(y_test, y_test_pred)
error_rate = 1 - accuracy
sensitivity = tp / (tp + fn)
specificity = tn / (tn + fp)
```

```python
print("\n=== Logistic Regression Test Performance ===")
print(f"Accuracy: {accuracy:.3f}")
print(f"Misclassification Error: {error_rate:.3f}")
print(f"Sensitivity (TPR): {sensitivity:.3f}")
print(f"Specificity (TNR): {specificity:.3f}")
print("Confusion Matrix:\n", cm)
```

```
=== Logistic Regression Test Performance ===
Accuracy: 0.459
Misclassification Error: 0.541
Sensitivity (TPR): 0.589
Specificity (TNR): 0.414
Confusion Matrix:
 [[491 695]
 [170 244]]
```

```
coef_df = pd.DataFrame({
    'Feature': X_train_scaled.columns,
    'Coefficient': clf.coef_.ravel()
})
coef_df['AbsCoefficient'] = np.abs(coef_df['Coefficient'])
coef_df.sort_values('AbsCoefficient', ascending=False)[0:3]
```

	Feature	Coefficient	AbsCoefficient
10	country_CA	-0.165776	0.165776
18	subscription_type_Free	-0.144746	0.144746
12	country_FR	0.135067	0.135067

KNN using LMNN

```
# Train LMNN on training data ---
lmnn = LMNN(k=5, learn_rate=1e-6, max_iter=200)
lmnn.fit(X_train_scaled, y_train)

# Transform train, val, test sets ---
X_train_lmnn = lmnn.transform(X_train_scaled)
X_val_lmnn   = lmnn.transform(X_val_scaled)
X_test_lmnn  = lmnn.transform(X_test_scaled)

# Select best k using validation accuracy ---
k_values = range(1, 21)
val_accuracies = []

for k in k_values:
```

```python
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train_lmnn, y_train)
    y_val_pred = knn.predict(X_val_lmnn)
    acc = accuracy_score(y_val, y_val_pred)
    val_accuracies.append(acc)

best_k = k_values[np.argmax(val_accuracies)]
print("Best k (with LMNN) based on validation set:", best_k)

# Plot validation accuracy vs k ---
plt.plot(k_values, val_accuracies, marker='o')
plt.xlabel("Number of Neighbors (k)")
plt.ylabel("Validation Accuracy (LMNN)")
plt.title("Choosing k using Validation Set (after LMNN)")
plt.xticks(k_values)
plt.show()
```

```python
# Train final KNN (best_k) on combined train+val and test it ---
knn = KNeighborsClassifier(n_neighbors=12)
knn.fit(np.vstack((X_train_lmnn, X_val_lmnn)), np.hstack((y_train, y_val)))

# Predict probabilities on test set ---
y_test_prob = knn.predict_proba(X_test_lmnn)[:, 1]

# ROC curve and optimal cutoff ---
fpr, tpr, thresholds = roc_curve(y_test, y_test_prob)
auc = roc_auc_score(y_test, y_test_prob)
optimal_idx = (tpr - fpr).argmax()
optimal_cutoff = thresholds[optimal_idx]
print(f"AUC (LMNN + KNN): {auc:.3f}")
print(f"Optimal probability cutoff: {optimal_cutoff:.3f}")

# Confusion matrix using optimal cutoff ---
y_test_pred = (y_test_prob >= optimal_cutoff).astype(int)
cm = confusion_matrix(y_test, y_test_pred)
print("Confusion Matrix (LMNN + KNN):")
print(cm)

# Compute performance metrics ---
```

```python
tn, fp, fn, tp = cm.ravel()

accuracy = (tp + tn) / (tp + tn + fp + fn)
misclassification_error = 1 - accuracy
precision = tp / (tp + fp) if (tp + fp) != 0 else 0
recall = tp / (tp + fn) if (tp + fn) != 0 else 0  # Sensitivity
specificity = tn / (tn + fp) if (tn + fp) != 0 else 0
f1_score_val = 2 * (precision * recall) / (precision + recall) if (precision + recall) != 0 else 0
auc_val = roc_auc_score(y_test, y_test_prob)

# Print metrics ---
print(f"\nAccuracy: {accuracy:.3f}")
print(f"Misclassification Error: {misclassification_error:.3f}")
print(f"Precision: {precision:.3f}")
print(f"Sensitivity (Recall): {recall:.3f}")
print(f"Specificity: {specificity:.3f}")
print(f"F1-Score: {f1_score_val:.3f}")
print(f"AUC: {auc_val:.3f}")
```

```
AUC (LMNN + KNN): 0.524
Optimal probability cutoff: 0.333
Confusion Matrix (LMNN + KNN):
[[723 463]
 [232 182]]

Accuracy: 0.566
Misclassification Error: 0.434
Precision: 0.282
Sensitivity (Recall): 0.440
Specificity: 0.610
F1-Score: 0.344
AUC: 0.524
```