Shakar_Credit Approval Project

April 19, 2025

[1]:
```
import pandas as pd

# Read the data file
df = pd.read_csv('./crx.data', header=None, na_values="?")

# # Preview the data
# print(df.head())
# print(df)

# Assign columns A1 to A16
df.columns = [f"A{i+1}" for i in range(df.shape[1])]

# Rename the last column to 'A16 (Class)'
df.rename(columns={"A16": "A16 (Class)"}, inplace=True)

# # Preview data again
# print(df.head())

# Print value counts ONLY for categorical (string/object) columns
print("value counts for categorical (object) columns:")
categorical_preview_cols = df.select_dtypes(include=['object']).columns.tolist()

for col in categorical_preview_cols:
    print(f"\nColumn: {col}")
    print(df[col].value_counts(dropna=False))

## NOTE: we have no t's for A4 because they were probably MISSING values

# Strip and map only valid class values and map +/- into 1/0
df["A16 (Class)"] = df["A16 (Class)"].astype(str).str.strip().map({'+': 1, '-':␣
↪0})


print("\n",df.shape[0], "rows ×", df.shape[1], "columns")

df.head()
```

```
value counts for categorical (object) columns:
```

```
Column: A1
A1
b      468
a      210
NaN     12
Name: count, dtype: int64

Column: A4
A4
u      519
y      163
NaN      6
l        2
Name: count, dtype: int64

Column: A5
A5
g      519
p      163
NaN      6
gg       2
Name: count, dtype: int64

Column: A6
A6
c      137
q       78
w       64
i       59
aa      54
ff      53
k       51
cc      41
m       38
x       38
d       30
e       25
j       10
NaN      9
r        3
Name: count, dtype: int64

Column: A7
A7
v      399
h      138
bb      59
```

```
ff      57
NaN      9
j        8
z        8
dd       6
n        4
o        2
Name: count, dtype: int64

Column: A9
A9
t    361
f    329
Name: count, dtype: int64

Column: A10
A10
f    395
t    295
Name: count, dtype: int64

Column: A12
A12
f    374
t    316
Name: count, dtype: int64

Column: A13
A13
g    625
s     57
p      8
Name: count, dtype: int64

Column: A16 (Class)
A16 (Class)
-    383
+    307
Name: count, dtype: int64
```

690 rows × 16 columns

[1]:

```
  A1     A2     A3 A4 A5 A6 A7    A8 A9 A10  A11 A12 A13    A14  A15  \
0  b  30.83  0.000  u  g  w  v  1.25  t   t    1   f   g  202.0    0
1  a  58.67  4.460  u  g  q  h  3.04  t   t    6   f   g   43.0  560
2  a  24.50  0.500  u  g  q  h  1.50  t   f    0   f   g  280.0  824
3  b  27.83  1.540  u  g  w  v  3.75  t   t    5   t   g  100.0    3
```

```
4  b  20.17  5.625  u  g  w  v  1.71  t   f    0   f   s  120.0    0

   A16 (Class)
0            1
1            1
2            1
3            1
4            1
```

[2]:
```python
# Check for missing values
print(df.isna().sum())
```

```
A1             12
A2             12
A3              0
A4              6
A5              6
A6              9
A7              9
A8              0
A9              0
A10             0
A11             0
A12             0
A13             0
A14            13
A15             0
A16 (Class)     0
dtype: int64
```

[3]:
```python
# we only lose at most 13 out of 690 rows (about ~2%), so we drop them


df_clean = df.dropna()

df_clean.head()
```

[3]:
```
  A1     A2     A3 A4 A5 A6 A7    A8 A9 A10  A11 A12 A13    A14  A15  \
0  b  30.83  0.000  u  g  w  v  1.25  t   t    1   f   g  202.0    0
1  a  58.67  4.460  u  g  q  h  3.04  t   t    6   f   g   43.0  560
2  a  24.50  0.500  u  g  q  h  1.50  t   f    0   f   g  280.0  824
3  b  27.83  1.540  u  g  w  v  3.75  t   t    5   t   g  100.0    3
4  b  20.17  5.625  u  g  w  v  1.71  t   f    0   f   s  120.0    0

   A16 (Class)
0            1
1            1
2            1
```

```
3            1
4            1
```

[4]:
```
df = df_clean  # overwrite original df
print("\n",df.shape[0], "rows ×", df.shape[1], "columns")
df.head()
```

```
 653 rows × 16 columns
```

[4]:
```
  A1     A2     A3 A4 A5 A6 A7    A8 A9 A10  A11 A12 A13    A14  A15  \
0  b  30.83  0.000  u  g  w  v  1.25  t   t    1   f   g  202.0    0
1  a  58.67  4.460  u  g  q  h  3.04  t   t    6   f   g   43.0  560
2  a  24.50  0.500  u  g  q  h  1.50  t   f    0   f   g  280.0  824
3  b  27.83  1.540  u  g  w  v  3.75  t   t    5   t   g  100.0    3
4  b  20.17  5.625  u  g  w  v  1.71  t   f    0   f   s  120.0    0

   A16 (Class)
0            1
1            1
2            1
3            1
4            1
```

[5]:
```
# Find columns with categorical or non-numeric data types
categorical_cols = df.select_dtypes(include="object").columns.tolist()

# print("Categorical columns:", categorical_cols)

# for col in categorical_cols:
#     df[col] = pd.Categorical(df[col])  # Ensures pandas tracks all categories

# One hot encoding, turning categoricals into multiple columns based on their␣
 ↪respective non-numeric values and outputting True or False

# print(pd.get_dummies(df, columns=['A1']))

# df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)

# # print(df.columns, '\n\n')

# print(df["A4"].value_counts())


# One-hot encode all categorical columns, no dropping columns to avoid␣
 ↪collinearity as of yet
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=False)
print(df_encoded.columns)
```

```
## NOTE: A4_t must've been removed doing to missing values

print("\n",df_encoded.shape[0], "rows ×", df_encoded.shape[1], "columns")


df_encoded.head()
```

```
Index(['A2', 'A3', 'A8', 'A11', 'A14', 'A15', 'A16 (Class)', 'A1_a', 'A1_b',
       'A4_l', 'A4_u', 'A4_y', 'A5_g', 'A5_gg', 'A5_p', 'A6_aa', 'A6_c',
       'A6_cc', 'A6_d', 'A6_e', 'A6_ff', 'A6_i', 'A6_j', 'A6_k', 'A6_m',
       'A6_q', 'A6_r', 'A6_w', 'A6_x', 'A7_bb', 'A7_dd', 'A7_ff', 'A7_h',
       'A7_j', 'A7_n', 'A7_o', 'A7_v', 'A7_z', 'A9_f', 'A9_t', 'A10_f',
       'A10_t', 'A12_f', 'A12_t', 'A13_g', 'A13_p', 'A13_s'],
      dtype='object')

 653 rows × 47 columns
```

[5]:

```
      A2     A3    A8  A11    A14  A15  A16 (Class)   A1_a   A1_b   A4_l  …  \
0  30.83  0.000  1.25    1  202.0    0            1  False   True  False  …
1  58.67  4.460  3.04    6   43.0  560            1   True  False  False  …
2  24.50  0.500  1.50    0  280.0  824            1   True  False  False  …
3  27.83  1.540  3.75    5  100.0    3            1  False   True  False  …
4  20.17  5.625  1.71    0  120.0    0            1  False   True  False  …

    A7_z   A9_f  A9_t  A10_f  A10_t  A12_f  A12_t  A13_g  A13_p  A13_s
0  False  False  True  False   True   True  False   True  False  False
1  False  False  True  False   True   True  False   True  False  False
2  False  False  True   True  False   True  False   True  False  False
3  False  False  True  False   True  False   True   True  False  False
4  False  False  True   True  False   True  False  False  False   True

[5 rows x 47 columns]
```

[6]:

```
# import pandas as pd

# # Assume df is your cleaned, no-NaN dataset with A1-A15 and 'A16 (Class)'

# # Step 1: Find categorical columns (type 'object')
# categorical_cols = df.select_dtypes(include=['object', 'category']).columns.
 ↪tolist()

# # Step 2: Convert each to Categorical to retain observed categories
# for col in categorical_cols:
#     df[col] = pd.Categorical(df[col])

# # Step 3: One-hot encode with all categories (no drop)
# df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=False)
```

```
# df_encoded
```

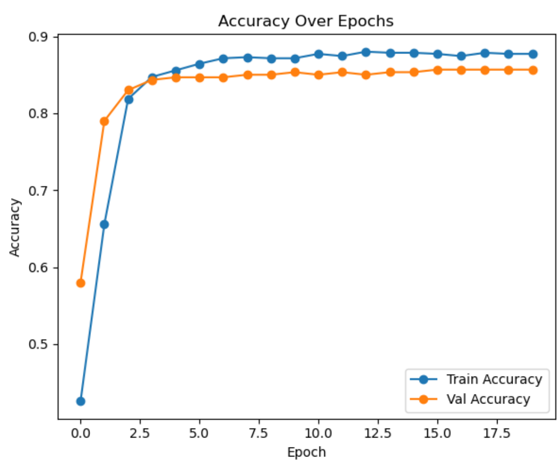
[7]:
```
# print("Original columns:", df.columns)
# print("Encoded columns:", df_encoded.columns)
```

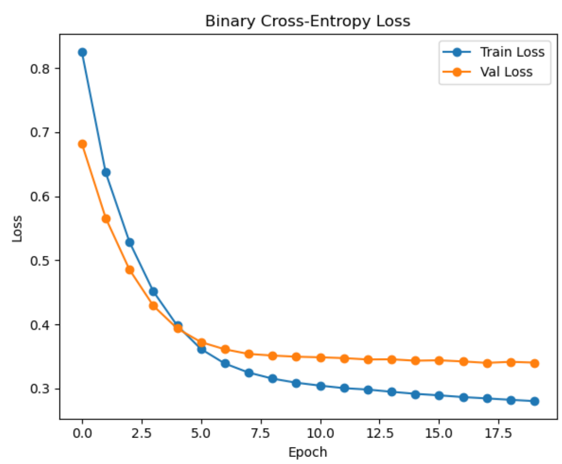
[8]:
```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification

# Step 1: Generate dummy binary classification data
X, y = make_classification(n_samples=1000, n_features=10, n_classes=2,␣
↪random_state=42)

# Step 2: Split into train/test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Step 3: Define a simple neural network
model = Sequential([
    Dense(32, activation='relu', input_shape=(X.shape[1],)),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')  # Output probability for binary␣
↪classification
])

# Step 4: Compile with binary_crossentropy (i.e., log loss)
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Step 5: Train and save history
history = model.fit(X_train, y_train, epochs=20, batch_size=32,␣
↪validation_data=(X_test, y_test))

# Step 6: Plot training vs validation accuracy and loss
plt.figure(figsize=(12, 5))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy', marker='o')
plt.plot(history.history['val_accuracy'], label='Val Accuracy', marker='o')
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
```

```python
plt.ylabel('Accuracy')
plt.legend()

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss', marker='o')
plt.plot(history.history['val_loss'], label='Val Loss', marker='o')
plt.title('Binary Cross-Entropy Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

```
Epoch 1/20
22/22 [==============================] - 0s 6ms/step - loss: 0.8254 - accuracy:
0.4257 - val_loss: 0.6822 - val_accuracy: 0.5800
Epoch 2/20
22/22 [==============================] - 0s 1ms/step - loss: 0.6371 - accuracy:
0.6557 - val_loss: 0.5662 - val_accuracy: 0.7900
Epoch 3/20
22/22 [==============================] - 0s 1ms/step - loss: 0.5287 - accuracy:
0.8186 - val_loss: 0.4855 - val_accuracy: 0.8300
Epoch 4/20
22/22 [==============================] - 0s 1ms/step - loss: 0.4516 - accuracy:
0.8471 - val_loss: 0.4292 - val_accuracy: 0.8433
Epoch 5/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3984 - accuracy:
0.8557 - val_loss: 0.3939 - val_accuracy: 0.8467
Epoch 6/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3618 - accuracy:
0.8643 - val_loss: 0.3725 - val_accuracy: 0.8467
Epoch 7/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3391 - accuracy:
0.8714 - val_loss: 0.3613 - val_accuracy: 0.8467
Epoch 8/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3250 - accuracy:
0.8729 - val_loss: 0.3540 - val_accuracy: 0.8500
Epoch 9/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3156 - accuracy:
0.8714 - val_loss: 0.3515 - val_accuracy: 0.8500
Epoch 10/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3092 - accuracy:
0.8714 - val_loss: 0.3497 - val_accuracy: 0.8533
Epoch 11/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3046 - accuracy:
0.8771 - val_loss: 0.3488 - val_accuracy: 0.8500
```

```
Epoch 12/20
22/22 [==============================] - 0s 1ms/step - loss: 0.3007 - accuracy:
0.8743 - val_loss: 0.3475 - val_accuracy: 0.8533
Epoch 13/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2985 - accuracy:
0.8800 - val_loss: 0.3454 - val_accuracy: 0.8500
Epoch 14/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2950 - accuracy:
0.8786 - val_loss: 0.3457 - val_accuracy: 0.8533
Epoch 15/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2918 - accuracy:
0.8786 - val_loss: 0.3435 - val_accuracy: 0.8533
Epoch 16/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2895 - accuracy:
0.8771 - val_loss: 0.3441 - val_accuracy: 0.8567
Epoch 17/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2868 - accuracy:
0.8743 - val_loss: 0.3424 - val_accuracy: 0.8567
Epoch 18/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2847 - accuracy:
0.8786 - val_loss: 0.3401 - val_accuracy: 0.8567
Epoch 19/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2825 - accuracy:
0.8771 - val_loss: 0.3418 - val_accuracy: 0.8567
Epoch 20/20
22/22 [==============================] - 0s 1ms/step - loss: 0.2804 - accuracy:
0.8771 - val_loss: 0.3405 - val_accuracy: 0.8567
```





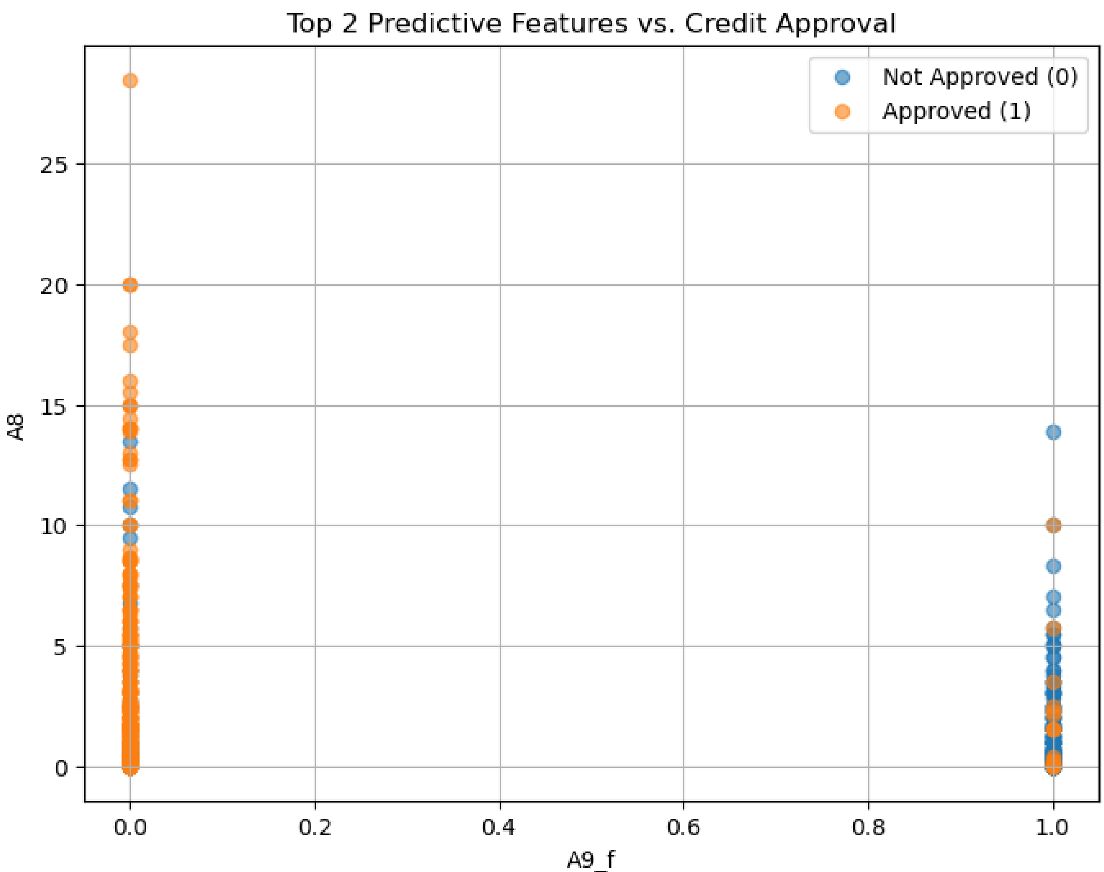
[9]:
```
from sklearn.ensemble import RandomForestClassifier

X = df_encoded.drop("A16 (Class)", axis=1)
```

```
y = df_encoded["A16 (Class)"]

model = RandomForestClassifier(random_state=42)
model.fit(X, y)

# Get top features
importances = pd.Series(model.feature_importances_, index=X.columns)
top_features = importances.sort_values(ascending=False)
print(top_features.head(10), '\n')

# # top 2 predictive features to use for our 2D classification model
# top_features = top_importances.head(2)
# print(top_features)


# Filter out dummy variables from same original group (e.g. avoid A9_f and A9_t␣
↪together)
for i in range(len(top_features)):
    for j in range(i + 1, len(top_features)):
        f1 = top_features.index[i]
        f2 = top_features.index[j]
        if f1.split('_')[0] != f2.split('_')[0]:  # not from same original␣
↪column
            print(f"Using features: {f1}, {f2}")
            break
    break
```

```
A9_f     0.189223
A9_t     0.147181
A8       0.081950
A11      0.080041
A3       0.063200
A14      0.060265
A15      0.060178
A2       0.053778
A10_t    0.041591
A10_f    0.035312
dtype: float64

Using features: A9_f, A8
```

[10]:
```
# Step 4: Scatter plot of the two features, colored by class
plt.figure(figsize=(8, 6))
plt.scatter(X[y == 0][f1], X[y == 0][f2], label='Not Approved (0)', alpha=0.6)
plt.scatter(X[y == 1][f1], X[y == 1][f2], label='Approved (1)', alpha=0.6)
plt.xlabel(f1)
plt.ylabel(f2)
```

```
plt.title('Top 2 Predictive Features vs. Credit Approval')
plt.legend()
plt.grid(True)
plt.show()
```



[11]:

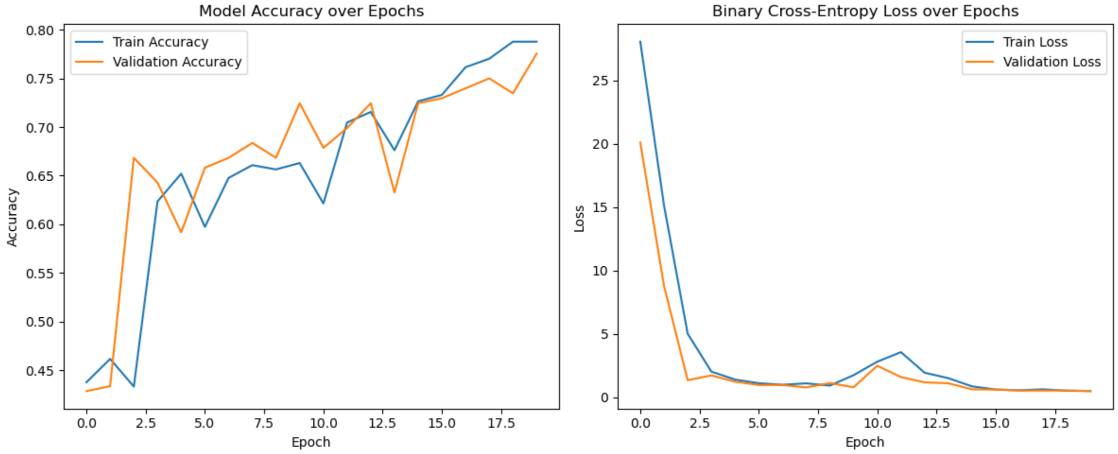
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam

# Step 5: Convert data to float32 for TensorFlow
X_np = X.values.astype(np.float32)
y_np = y.values.astype(np.float32)

# Step 6: Build and compile the neural network
model = Sequential([
    Dense(32, activation='relu', input_shape=(X.shape[1],)),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

```python
model.compile(optimizer=Adam(),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Step 7: Train the model
history = model.fit(X_np, y_np, validation_split=0.3, epochs=20, batch_size=32)

# Step 8: Plot accuracy and loss curves
plt.figure(figsize=(12, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Binary Cross-Entropy Loss over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```

```
Epoch 1/20
15/15 [==============================] - 0s 6ms/step - loss: 28.0632 - accuracy:
0.4376 - val_loss: 20.1059 - val_accuracy: 0.4286
Epoch 2/20
15/15 [==============================] - 0s 2ms/step - loss: 15.1503 - accuracy:
0.4617 - val_loss: 8.7991 - val_accuracy: 0.4337
Epoch 3/20
15/15 [==============================] - 0s 2ms/step - loss: 5.0137 - accuracy:
0.4333 - val_loss: 1.3460 - val_accuracy: 0.6684
Epoch 4/20
15/15 [==============================] - 0s 2ms/step - loss: 2.0202 - accuracy:
0.6236 - val_loss: 1.7200 - val_accuracy: 0.6429
```

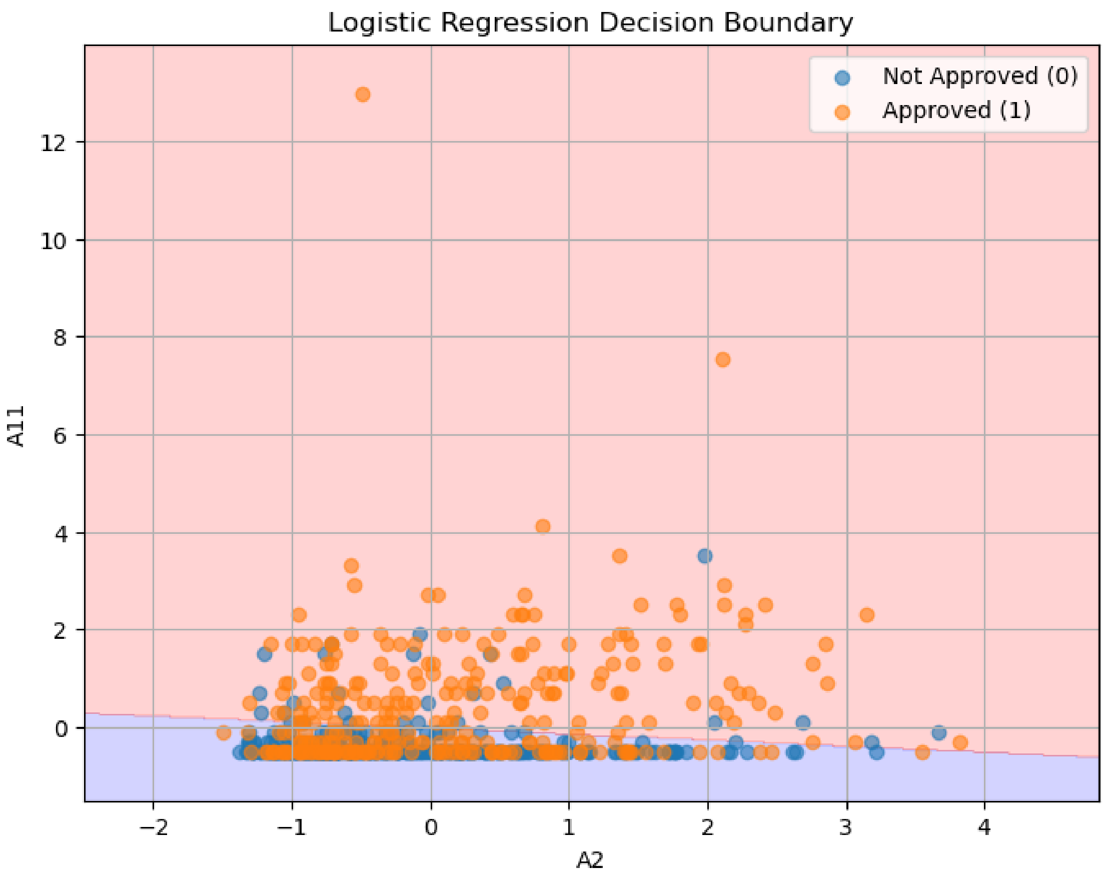
```
Epoch 5/20
15/15 [==============================] - 0s 2ms/step - loss: 1.3946 - accuracy:
0.6521 - val_loss: 1.2287 - val_accuracy: 0.5918
Epoch 6/20
15/15 [==============================] - 0s 2ms/step - loss: 1.1066 - accuracy:
0.5974 - val_loss: 0.9635 - val_accuracy: 0.6582
Epoch 7/20
15/15 [==============================] - 0s 2ms/step - loss: 0.9826 - accuracy:
0.6477 - val_loss: 0.9627 - val_accuracy: 0.6684
Epoch 8/20
15/15 [==============================] - 0s 2ms/step - loss: 1.0955 - accuracy:
0.6608 - val_loss: 0.7758 - val_accuracy: 0.6837
Epoch 9/20
15/15 [==============================] - 0s 1ms/step - loss: 0.9180 - accuracy:
0.6565 - val_loss: 1.1161 - val_accuracy: 0.6684
Epoch 10/20
15/15 [==============================] - 0s 1ms/step - loss: 1.7384 - accuracy:
0.6630 - val_loss: 0.7860 - val_accuracy: 0.7245
Epoch 11/20
15/15 [==============================] - 0s 2ms/step - loss: 2.8054 - accuracy:
0.6214 - val_loss: 2.4854 - val_accuracy: 0.6786
Epoch 12/20
15/15 [==============================] - 0s 2ms/step - loss: 3.5573 - accuracy:
0.7046 - val_loss: 1.5905 - val_accuracy: 0.6990
Epoch 13/20
15/15 [==============================] - 0s 2ms/step - loss: 1.9332 - accuracy:
0.7155 - val_loss: 1.1747 - val_accuracy: 0.7245
Epoch 14/20
15/15 [==============================] - 0s 1ms/step - loss: 1.5059 - accuracy:
0.6761 - val_loss: 1.1001 - val_accuracy: 0.6327
Epoch 15/20
15/15 [==============================] - 0s 1ms/step - loss: 0.8555 - accuracy:
0.7265 - val_loss: 0.6228 - val_accuracy: 0.7245
Epoch 16/20
15/15 [==============================] - 0s 1ms/step - loss: 0.6097 - accuracy:
0.7330 - val_loss: 0.6014 - val_accuracy: 0.7296
Epoch 17/20
15/15 [==============================] - 0s 1ms/step - loss: 0.5487 - accuracy:
0.7615 - val_loss: 0.5223 - val_accuracy: 0.7398
Epoch 18/20
15/15 [==============================] - 0s 1ms/step - loss: 0.6220 - accuracy:
0.7702 - val_loss: 0.5216 - val_accuracy: 0.7500
Epoch 19/20
15/15 [==============================] - 0s 1ms/step - loss: 0.5157 - accuracy:
0.7877 - val_loss: 0.5265 - val_accuracy: 0.7347
Epoch 20/20
15/15 [==============================] - 0s 1ms/step - loss: 0.4813 - accuracy:
0.7877 - val_loss: 0.4875 - val_accuracy: 0.7755
```



[12]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, log_loss
import matplotlib.pyplot as plt
import numpy as np

# Step 1: Select 2 good features (preferably numeric/continuous)
top_features = ['A2', 'A11']  # You can replace this with any 2 numeric columns

X_2d = df_encoded[top_features].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(int)

# Step 2: Standardize features for smoother decision boundary
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_2d)

# Step 3: Train logistic regression
clf = LogisticRegression()
clf.fit(X_scaled, y)

# Step 4: Predict and evaluate
y_pred = clf.predict(X_scaled)
y_prob = clf.predict_proba(X_scaled)

acc = accuracy_score(y, y_pred)
loss = log_loss(y, y_prob)

print(f"\n Logistic Regression Accuracy: {acc:.4f}")
print(f" Logistic Regression Log Loss: {loss:.4f}")

# Step 5: Plot decision boundary
```

```
x_min, x_max = X_scaled[:, 0].min() - 1, X_scaled[:, 0].max() + 1
y_min, y_max = X_scaled[:, 1].min() - 1, X_scaled[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))

grid = np.c_[xx.ravel(), yy.ravel()]
Z = clf.predict(grid).reshape(xx.shape)

plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, alpha=0.2, cmap='bwr')
plt.scatter(X_scaled[y == 0, 0], X_scaled[y == 0, 1], label='Not Approved (0)',␣
 ↪alpha=0.6)
plt.scatter(X_scaled[y == 1, 0], X_scaled[y == 1, 1], label='Approved (1)',␣
 ↪alpha=0.6)
plt.xlabel(top_features[0])
plt.ylabel(top_features[1])
plt.title('Logistic Regression Decision Boundary')
plt.legend()
plt.grid(True)
plt.show()
```

```
Logistic Regression Accuracy: 0.7458
Logistic Regression Log Loss: 0.5499
```



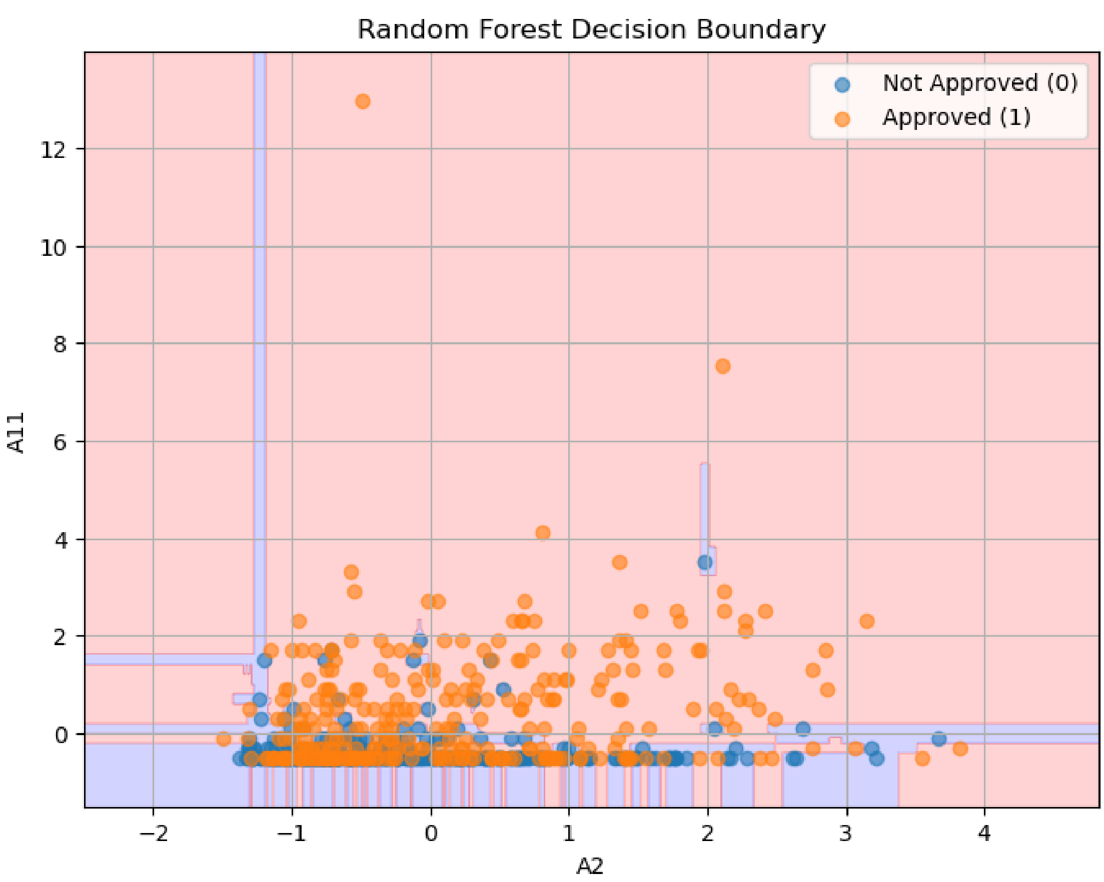
[13]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, log_loss
from sklearn.preprocessing import StandardScaler
import numpy as np

# Step 1: Select 2 features
top_features = ['A2', 'A11']
X_2d = df_encoded[top_features].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(int)

# Step 2: Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_2d)

# Step 3: Logistic Regression
log_reg = LogisticRegression()
log_reg.fit(X_scaled, y)
```

```python
y_pred_log = log_reg.predict(X_scaled)
y_proba_log = log_reg.predict_proba(X_scaled)

acc_log = accuracy_score(y, y_pred_log)
loss_log = log_loss(y, y_proba_log)

# Step 4: Random Forest
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_scaled, y)

y_pred_rf = rf_clf.predict(X_scaled)
y_proba_rf = rf_clf.predict_proba(X_scaled)

acc_rf = accuracy_score(y, y_pred_rf)
loss_rf = log_loss(y, y_proba_rf)

# Step 5: Print comparison
print("  Model Comparison (using features: A2, A11)")
print(f"  Logistic Regression Accuracy:     {acc_log:.4f}")
print(f"  Logistic Regression Log Loss:     {loss_log:.4f}")
print(f"  Random Forest Accuracy:           {acc_rf:.4f}")
print(f"  Random Forest Log Loss:           {loss_rf:.4f}")
```

```
Model Comparison (using features: A2, A11)
Logistic Regression Accuracy:     0.7458
Logistic Regression Log Loss:     0.5499
Random Forest Accuracy:           0.9464
Random Forest Log Loss:           0.1916
```

[14]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler

# Step 1: Choose same two numeric features (or try different ones)
top_features = ['A2', 'A11']
X_2d = df_encoded[top_features].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(int)

# Step 2: Standardize for smoother visualization (RF doesn't need this to train)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_2d)

# Step 3: Train random forest classifier
rf_clf = RandomForestClassifier(n_estimators=100, random_state=42)
rf_clf.fit(X_scaled, y)

# Step 4: Plot decision boundary
x_min, x_max = X_scaled[:, 0].min() - 1, X_scaled[:, 0].max() + 1
```

```
y_min, y_max = X_scaled[:, 1].min() - 1, X_scaled[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))

grid = np.c_[xx.ravel(), yy.ravel()]
Z = rf_clf.predict(grid).reshape(xx.shape)

plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, alpha=0.2, cmap='bwr')
plt.scatter(X_scaled[y == 0, 0], X_scaled[y == 0, 1], label='Not Approved (0)',␣
 ↪alpha=0.6)
plt.scatter(X_scaled[y == 1, 0], X_scaled[y == 1, 1], label='Approved (1)',␣
 ↪alpha=0.6)
plt.xlabel(top_features[0])
plt.ylabel(top_features[1])
plt.title('Random Forest Decision Boundary')
plt.legend()
plt.grid(True)
plt.show()
```

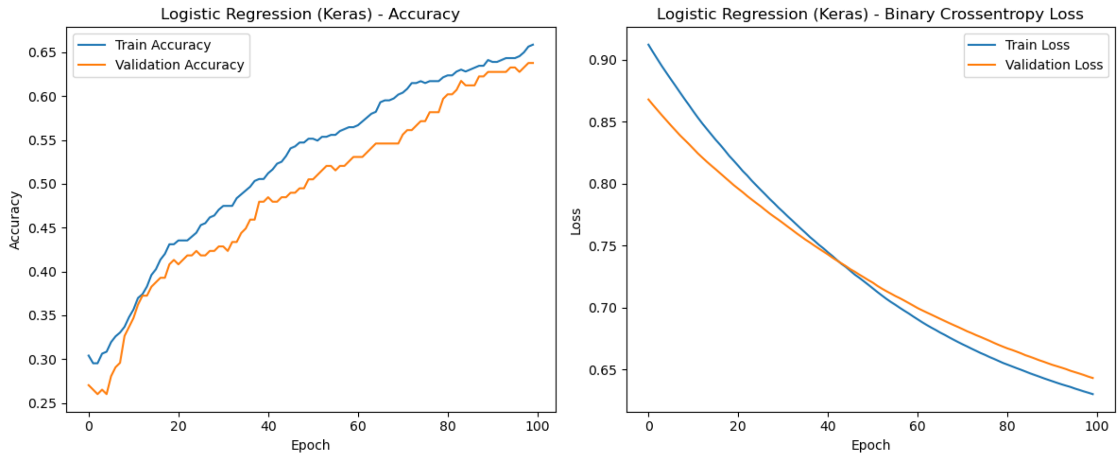


[15]:

```python
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam

# Step 1: Prepare data (same two features, scaled)
X_2d = df_encoded[["A2", "A11"]].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(np.float32)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_2d)

# Step 2: Build logistic regression model (Keras = 1-layer NN)
model = Sequential([
    Dense(1, activation='sigmoid', input_shape=(2,))
])

# model = Sequential([
#     Dense(8, activation='relu', input_shape=(2,)),  # NEW hidden layer
#     Dense(1, activation='sigmoid')
# ])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Step 3: Train the model
history = model.fit(X_scaled, y, validation_split=0.3, epochs=100,␣
 ↪batch_size=32, verbose=0)

# Step 4: Plot training and validation accuracy/loss
plt.figure(figsize=(12, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Logistic Regression (Keras) - Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
```

```
plt.title('Logistic Regression (Keras) - Binary Crossentropy Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

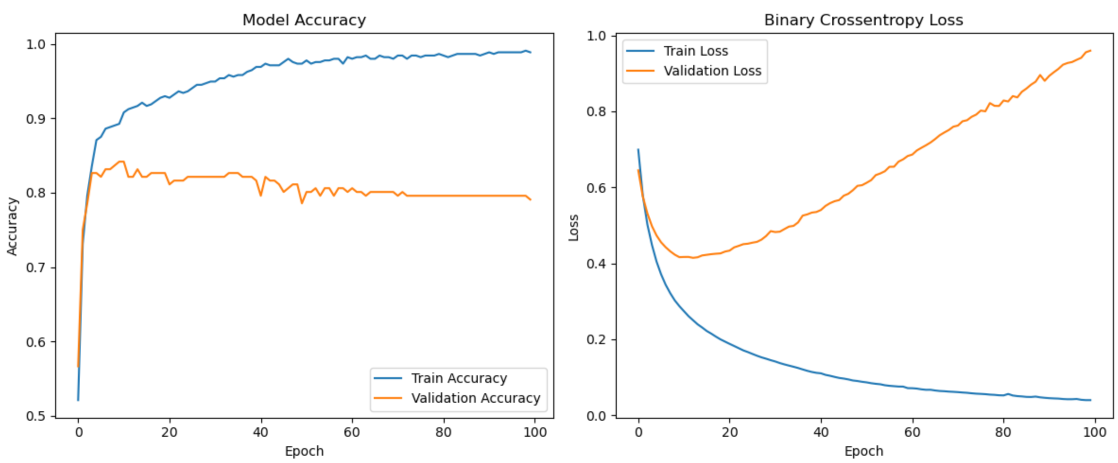
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



[16]:
```
X_full = df_encoded.drop("A16 (Class)", axis=1)
y_full = df_encoded["A16 (Class)"].astype(np.float32)

# Scale full features
scaler = StandardScaler()
X_scaled_full = scaler.fit_transform(X_full.values.astype(np.float32))


model = Sequential([
    Dense(32, activation='relu', input_shape=(X_scaled_full.shape[1],)),
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

```
history = model.fit(X_scaled_full, y_full, validation_split=0.3, epochs=100,␣
↪batch_size=32, verbose = 0)

# Plot accuracy and loss
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Binary Crossentropy Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



[17]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, log_loss
```

```python
# Features and target
X = df_encoded.drop("A16 (Class)", axis=1)
y = df_encoded["A16 (Class)"]

# Standardize
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train logistic regression
log_reg = LogisticRegression(max_iter=1000)
log_reg.fit(X_scaled, y)

# Predict
y_pred = log_reg.predict(X_scaled)
y_prob = log_reg.predict_proba(X_scaled)

# Evaluate
acc = accuracy_score(y, y_pred)
loss = log_loss(y, y_prob)

print(f" Logistic Regression Accuracy (Train): {acc:.4f}")
print(f" Logistic Regression Log Loss (Train): {loss:.4f}")
```

```
 Logistic Regression Accuracy (Train): 0.8913
 Logistic Regression Log Loss (Train): 0.2809
```

[18]:
```python
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(X_scaled, y, test_size=0.3,␣
 ↪random_state=42)

log_reg.fit(X_train, y_train)

y_pred_val = log_reg.predict(X_val)
y_proba_val = log_reg.predict_proba(X_val)

val_acc = accuracy_score(y_val, y_pred_val)
val_loss = log_loss(y_val, y_proba_val)

print(f" Logistic Regression Validation Accuracy: {val_acc:.4f}")
print(f" Logistic Regression Validation Log Loss: {val_loss:.4f}")
```

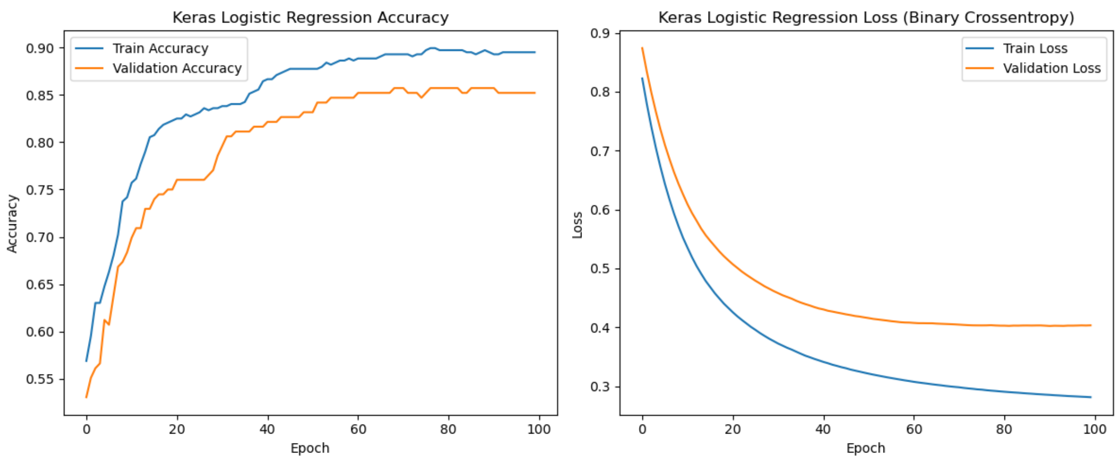
```
 Logistic Regression Validation Accuracy: 0.8520
 Logistic Regression Validation Log Loss: 0.3778
```

[19]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Step 1: Load and preprocess your data
X = df_encoded.drop("A16 (Class)", axis=1).values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(np.float32)

# Step 2: Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 3: Train/validation split
X_train, X_val, y_train, y_val = train_test_split(X_scaled, y, test_size=0.3,␣
↪random_state=42)

# Step 4: Define logistic regression model (1-layer, sigmoid output)
model = Sequential([
    Dense(1, activation='sigmoid', input_shape=(X_train.shape[1],))
])

# Step 5: Compile model with binary cross-entropy loss
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Step 6: Train the model
history = model.fit(X_train, y_train, validation_data=(X_val, y_val),␣
↪epochs=100, batch_size=32, verbose=0)

# Step 7: Plot accuracy and loss
plt.figure(figsize=(12, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Keras Logistic Regression Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
```

```
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Keras Logistic Regression Loss (Binary Crossentropy)')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

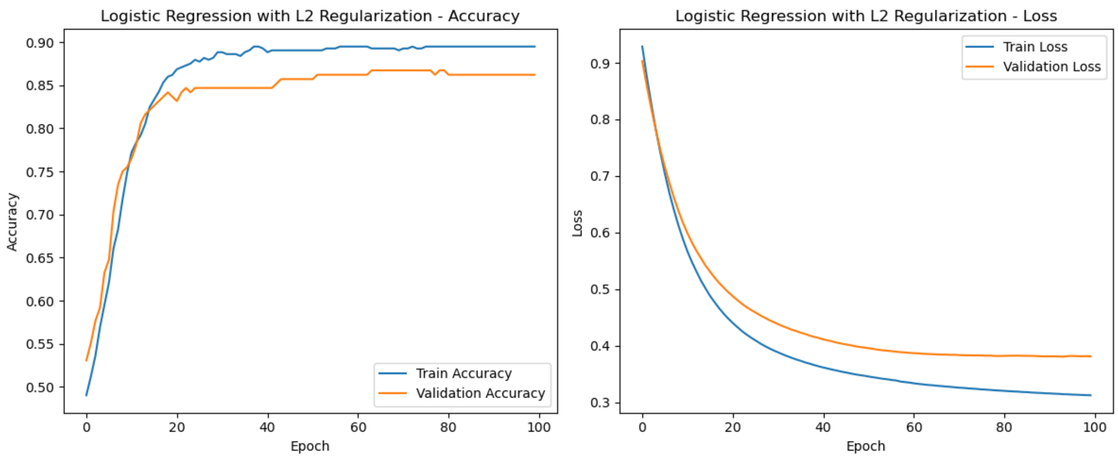
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



[20]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import numpy as np

# Data (use your preprocessed df_encoded)
X = df_encoded.drop("A16 (Class)", axis=1).values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(np.float32)

# Scale
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train/validation split
```

```
X_train, X_val, y_train, y_val = train_test_split(X_scaled, y, test_size=0.3,␣
↪random_state=42)

# Define logistic regression model with L2 regularization
model = Sequential([
    Dense(1, activation='sigmoid',
          input_shape=(X_train.shape[1],),
          kernel_regularizer=regularizers.l2(0.01))
])

# Compile
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Train
history = model.fit(X_train, y_train, validation_data=(X_val, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Plot accuracy and loss
plt.figure(figsize=(12, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Logistic Regression with L2 Regularization - Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Logistic Regression with L2 Regularization - Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```

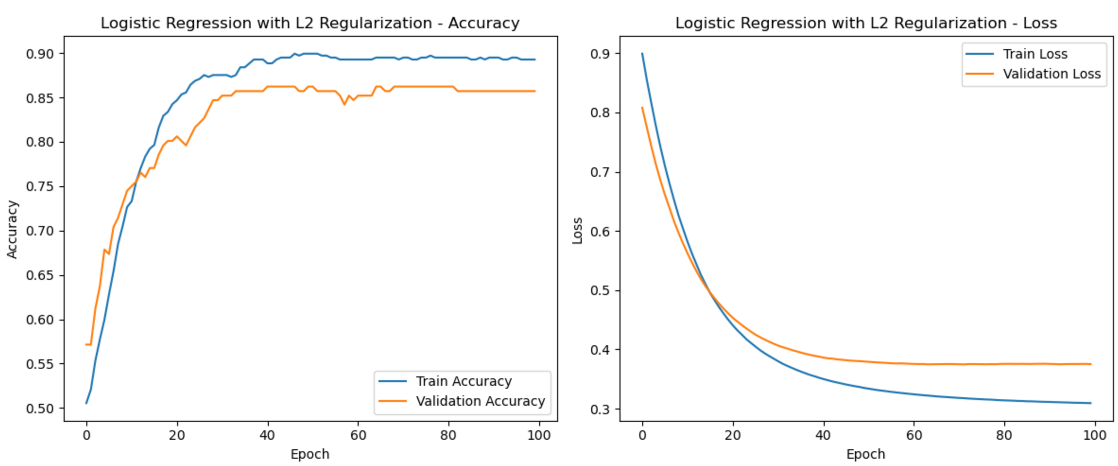


[21]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import numpy as np

# Data (use your preprocessed df_encoded)
X = df_encoded.drop("A16 (Class)", axis=1).values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(np.float32)

# Scale
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train/validation split
X_train, X_val, y_train, y_val = train_test_split(X_scaled, y, test_size=0.3,
↪random_state=42)

# Define logistic regression model with L2 regularization
model = Sequential([
    Dense(1, activation='sigmoid',
          input_shape=(X_train.shape[1],),
          kernel_regularizer=regularizers.l2(0.01))
])

# Compile
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
```

```
              metrics=['accuracy'])

# Train
history = model.fit(X_train, y_train, validation_data=(X_val, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Plot accuracy and loss
plt.figure(figsize=(12, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Logistic Regression with L2 Regularization - Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Logistic Regression with L2 Regularization - Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

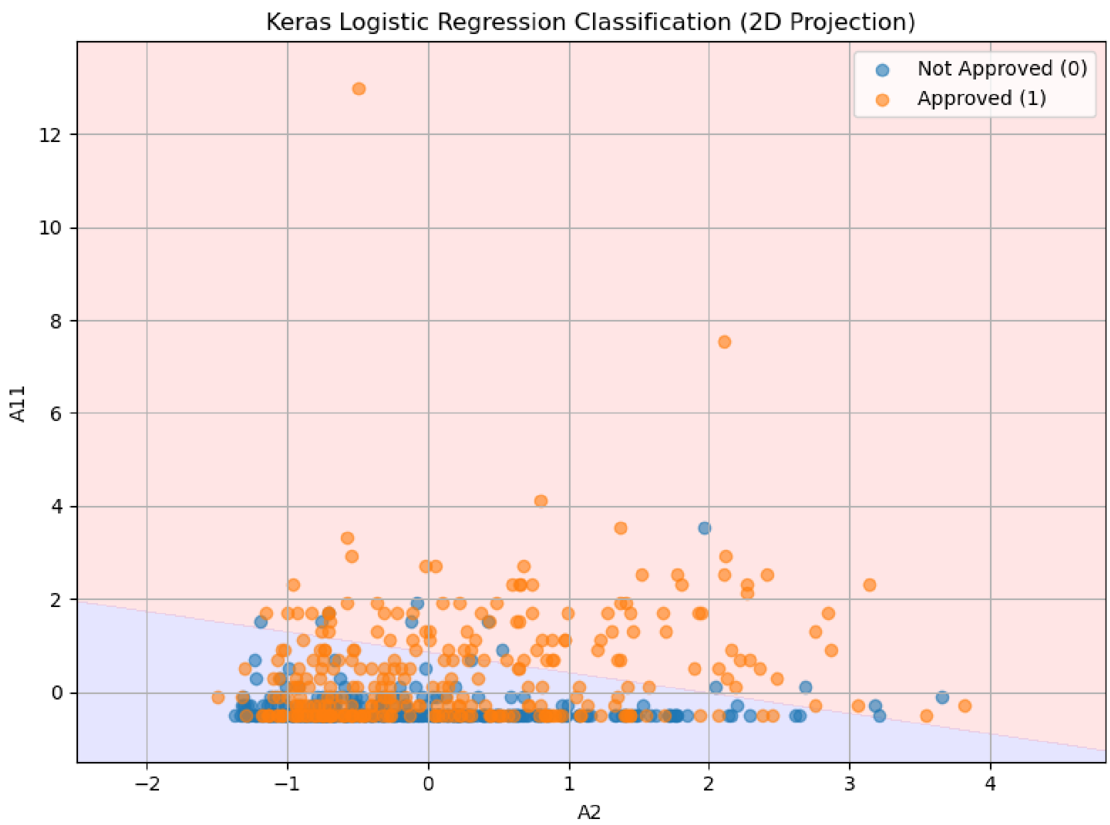
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



[22]:
```python
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler

# Step 1: Pick two numeric features
top_features = ['A2', 'A11']
X_2d = df_encoded[top_features].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(int)

# Step 2: Scale using the same logic
scaler = StandardScaler()
X_2d_scaled = scaler.fit_transform(X_2d)

# Step 3: Create meshgrid for plotting decision surface
x_min, x_max = X_2d_scaled[:, 0].min() - 1, X_2d_scaled[:, 0].max() + 1
y_min, y_max = X_2d_scaled[:, 1].min() - 1, X_2d_scaled[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))

grid = np.c_[xx.ravel(), yy.ravel()]
# Pad the rest of the input with 0s since the model expects full input length
X_grid_full = np.zeros((grid.shape[0], X_train.shape[1]), dtype=np.float32)

# Replace the two chosen features in the zeroed grid
f1_idx = df_encoded.columns.get_loc(top_features[0])
f2_idx = df_encoded.columns.get_loc(top_features[1])
X_grid_full[:, f1_idx] = grid[:, 0]
X_grid_full[:, f2_idx] = grid[:, 1]

# Predict using the full logistic regression model
Z = model.predict(X_grid_full).reshape(xx.shape)

# Step 4: Plot decision boundary and points
plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')

plt.scatter(X_2d_scaled[y == 0][:, 0], X_2d_scaled[y == 0][:, 1],
            label='Not Approved (0)', alpha=0.6)
plt.scatter(X_2d_scaled[y == 1][:, 0], X_2d_scaled[y == 1][:, 1],
            label='Approved (1)', alpha=0.6)

plt.xlabel(top_features[0])
plt.ylabel(top_features[1])
plt.title('Keras Logistic Regression Classification (2D Projection)')
```

```
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

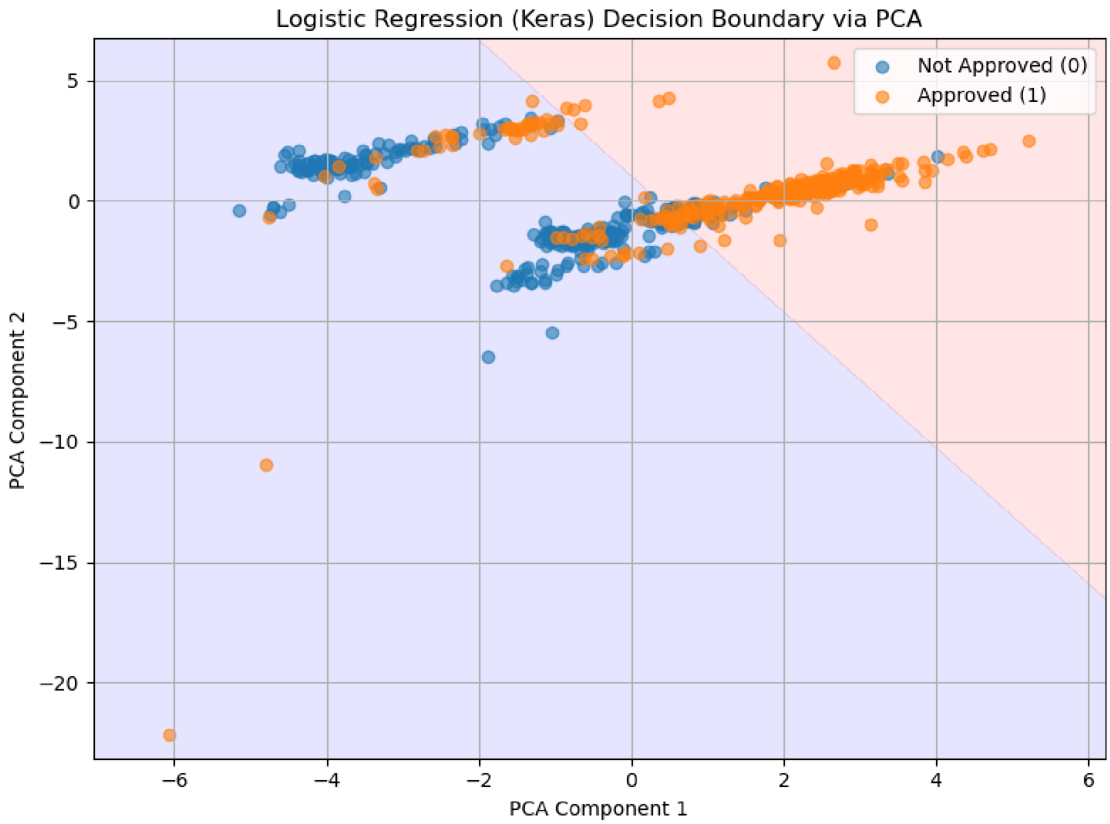
```
7813/7813 [==============================] - 3s 331us/step
```



[23]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import numpy as np

# Step 1: Standardize full data (if not already)
X = df_encoded.drop("A16 (Class)", axis=1).values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(int)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Step 2: Fit PCA and transform to 2D
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
```

```python
# Step 3: Create 2D grid in PCA space
x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))

grid_pca = np.c_[xx.ravel(), yy.ravel()]

# Step 4: Inverse-transform PCA → original feature space → predict
X_grid_original = pca.inverse_transform(grid_pca)  # shape (N, num_features)
Z = model.predict(X_grid_original).reshape(xx.shape)

# Step 5: Plot decision boundary + real data
plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')

plt.scatter(X_pca[y == 0][:, 0], X_pca[y == 0][:, 1], alpha=0.6, label='Not␣
 ↪Approved (0)')
plt.scatter(X_pca[y == 1][:, 0], X_pca[y == 1][:, 1], alpha=0.6,␣
 ↪label='Approved (1)')

plt.title('Logistic Regression (Keras) Decision Boundary via PCA')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
7813/7813 [==============================] - 3s 349us/step
```



[24]:

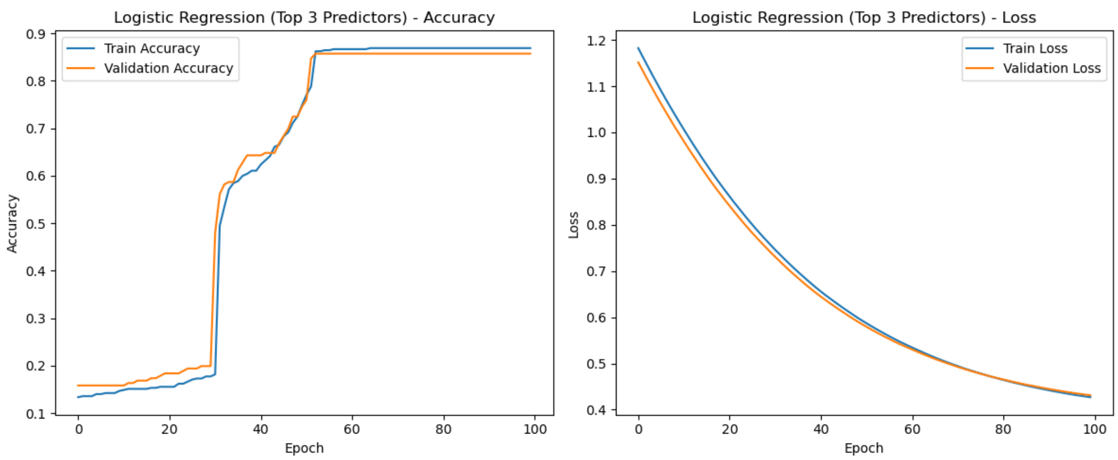
```
from sklearn.linear_model import LogisticRegression

# Standardize the full dataset
X = df_encoded.drop("A16 (Class)", axis=1)
y = df_encoded["A16 (Class)"]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train logistic regression (scikit-learn for coefficients)
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_scaled, y)

# Get top 3 features by absolute weight
coef_abs = np.abs(logreg.coef_[0])
top_3_indices = np.argsort(coef_abs)[-3:][::-1]
top_3_features = X.columns[top_3_indices].tolist()

print("  Top 3 predictive features:", top_3_features)
```

```
Top 3 predictive features: ['A15', 'A9_t', 'A9_f']
```

[25]:
```
# Subset X to just the top 3 features
X_top3 = df_encoded[top_3_features].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(np.float32)

# Standardize
scaler_top3 = StandardScaler()
X_top3_scaled = scaler_top3.fit_transform(X_top3)

# Train/test split
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(X_top3_scaled, y, test_size=0.
↪3, random_state=42)

# Define Keras logistic regression model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers

model = Sequential([
    Dense(1, activation='sigmoid', input_shape=(3,),
          kernel_regularizer=regularizers.l2(0.01))
])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Train
history = model.fit(X_train, y_train,
                    validation_data=(X_val, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Plot accuracy/loss
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Logistic Regression (Top 3 Predictors) - Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
```

```
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Logistic Regression (Top 3 Predictors) - Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

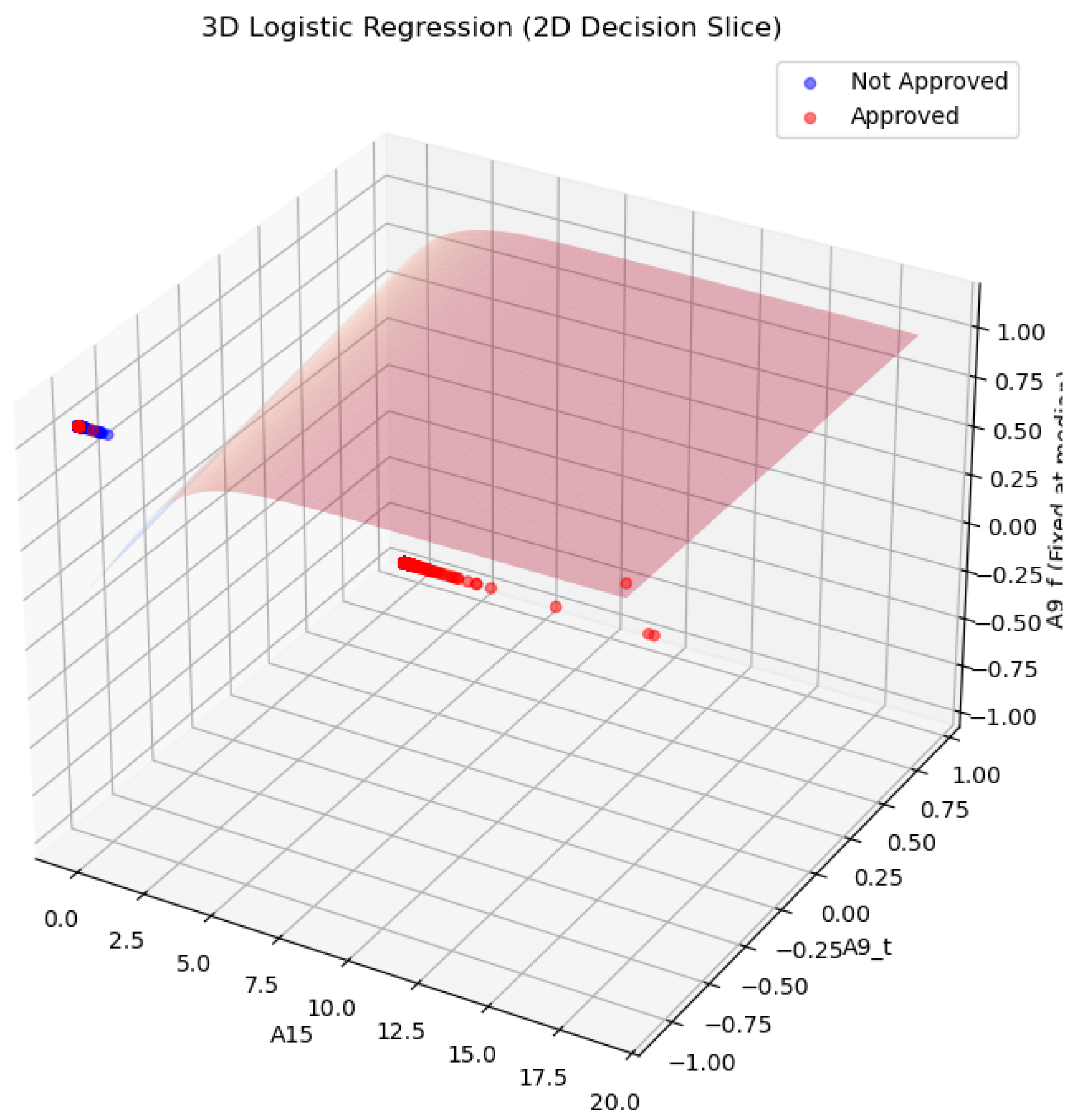
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



[26]:
```
from mpl_toolkits.mplot3d import Axes3D
from matplotlib import cm

# Step 1: Prepare 3D data again
X_3d = df_encoded[top_3_features].values.astype(np.float32)
y = df_encoded["A16 (Class)"].values.astype(int)
X_3d_scaled = scaler_top3.transform(X_3d)

# Step 2: Fix Z dimension and create meshgrid in X-Y plane
x_range = np.linspace(X_3d_scaled[:, 0].min(), X_3d_scaled[:, 0].max(), 100)
y_range = np.linspace(X_3d_scaled[:, 1].min(), X_3d_scaled[:, 1].max(), 100)
xx, yy = np.meshgrid(x_range, y_range)
zz_fixed = np.median(X_3d_scaled[:, 2])  # hold Z constant

# Step 3: Create full input grid (N, 3)
grid = np.c_[xx.ravel(), yy.ravel(), np.full(xx.ravel().shape, zz_fixed)]
Z = model.predict(grid).reshape(xx.shape)
```

```
# Step 4: Plot
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

# Data points
ax.scatter(X_3d_scaled[y == 0, 0], X_3d_scaled[y == 0, 1], X_3d_scaled[y == 0,␣
↪2],
           color='blue', label='Not Approved', alpha=0.5)
ax.scatter(X_3d_scaled[y == 1, 0], X_3d_scaled[y == 1, 1], X_3d_scaled[y == 1,␣
↪2],
           color='red', label='Approved', alpha=0.5)

# Decision boundary (2D surface in 3D space)
ax.plot_surface(xx, yy, Z, cmap='coolwarm', alpha=0.3)

# Labels
ax.set_xlabel(top_3_features[0])
ax.set_ylabel(top_3_features[1])
ax.set_zlabel(f"{top_3_features[2]} (Fixed at median)")
ax.set_title("3D Logistic Regression (2D Decision Slice)")
ax.legend()
plt.tight_layout()
plt.show()
```

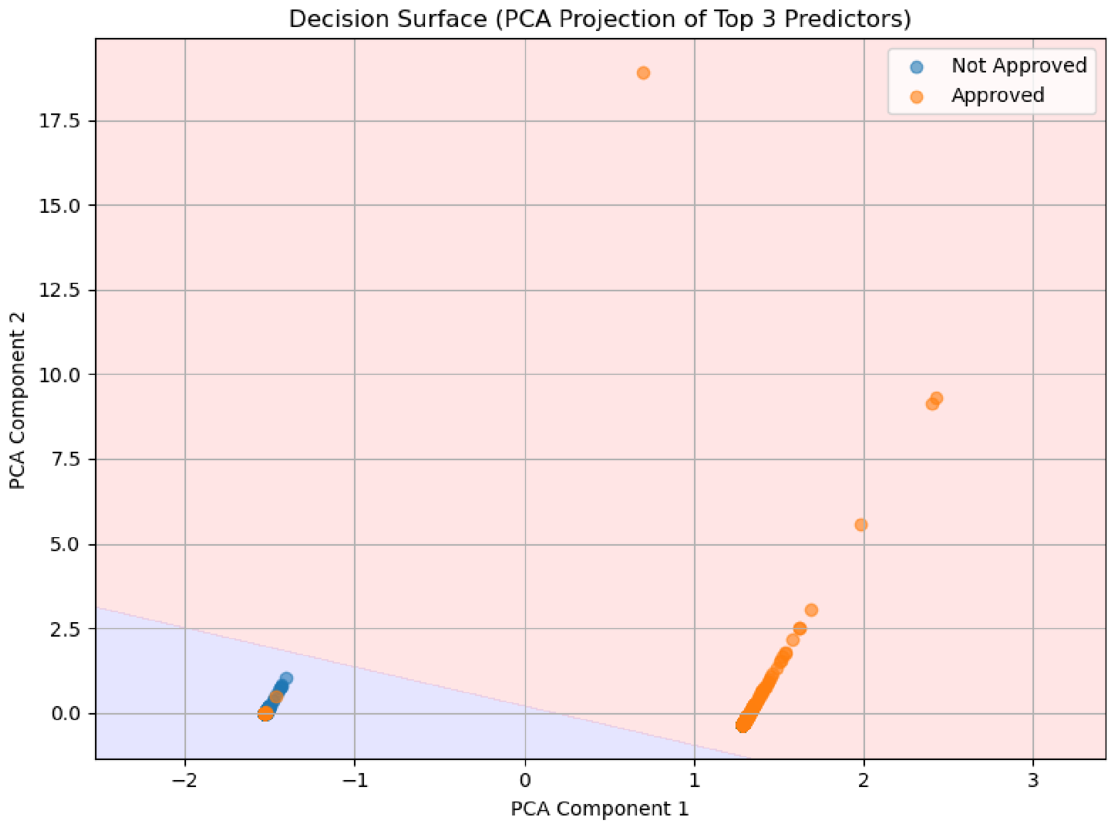
```
313/313 [==============================] - 0s 345us/step
```



[28]:
```
from sklearn.decomposition import PCA

# Step 1: PCA to 2D from 3 scaled features
pca = PCA(n_components=2)
X_pca_2d = pca.fit_transform(X_3d_scaled)

# Step 2: Meshgrid in PCA space
x_min, x_max = X_pca_2d[:, 0].min() - 1, X_pca_2d[:, 0].max() + 1
y_min, y_max = X_pca_2d[:, 1].min() - 1, X_pca_2d[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))
grid_2d = np.c_[xx.ravel(), yy.ravel()]
```

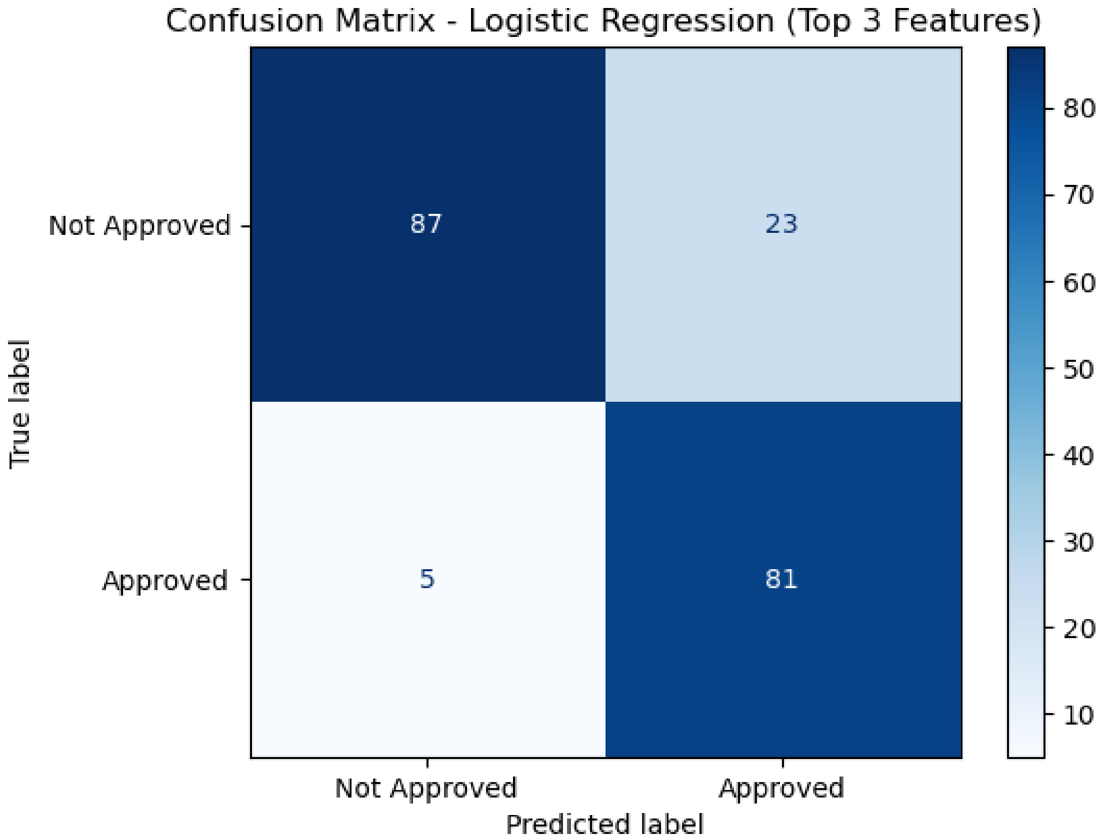
```
# Step 3: Inverse transform to 3D feature space
grid_3d = pca.inverse_transform(grid_2d)

# Step 4: Predict using model
Z = model.predict(grid_3d).reshape(xx.shape)

# Step 5: Plot
plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')
plt.scatter(X_pca_2d[y == 0, 0], X_pca_2d[y == 0, 1], label='Not Approved',␣
↪alpha=0.6)
plt.scatter(X_pca_2d[y == 1, 0], X_pca_2d[y == 1, 1], label='Approved', alpha=0.
↪6)

plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("Decision Surface (PCA Projection of Top 3 Predictors)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# print(f"Total number of points in plot: {X_all_pca.shape[0]}")
```

```
7813/7813 [==============================] - 3s 353us/step
```



[29]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪classification_report

# Predict on the validation set
y_pred_probs = model.predict(X_val)
y_pred = (y_pred_probs > 0.5).astype(int)

# Confusion matrix
cm = confusion_matrix(y_val, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not␣
↪Approved", "Approved"])
disp.plot(cmap='Blues')
plt.title("Confusion Matrix - Logistic Regression (Top 3 Features)")
plt.grid(False)
plt.show()

# Optional: Print precision/recall/F1 report
print("  Classification Report:")
print(classification_report(y_val, y_pred, target_names=["Not Approved",␣
↪"Approved"]))
```

```
7/7 [==============================] - 0s 622us/step
```




```
 Classification Report:
              precision    recall  f1-score   support

Not Approved       0.95      0.79      0.86       110
    Approved       0.78      0.94      0.85        86

    accuracy                           0.86       196
   macro avg       0.86      0.87      0.86       196
weighted avg       0.87      0.86      0.86       196
```

[30]:

```
# Step 1: Predict on validation set
y_pred_probs = model.predict(X_val)
y_pred = (y_pred_probs > 0.5).astype(int).flatten()

# Step 2: Identify misclassified indexes
misclassified_idx = np.where(y_pred != y_val)[0]
```

```
print(f"  Total misclassifications: {len(misclassified_idx)}")

# Step 3: Create Series for true and predicted
misclassified_true = pd.Series(y_val, index=np.arange(len(y_val))).
 ↪iloc[misclassified_idx]
misclassified_pred = pd.Series(y_pred[misclassified_idx],␣
 ↪index=misclassified_true.index, name="Predicted")

# Step 4: Recover original (unscaled) feature values
X_val_orig = pd.DataFrame(scaler_top3.inverse_transform(X_val),␣
 ↪columns=top_3_features)
misclassified_df = X_val_orig.iloc[misclassified_idx].copy()
misclassified_df["True Label"] = misclassified_true.values
misclassified_df["Predicted Label"] = misclassified_pred.values

# Step 5: Preview
misclassified_df.head(10)
```

```
7/7 [==============================] - 0s 861us/step
  Total misclassifications: 28
```

[30]:

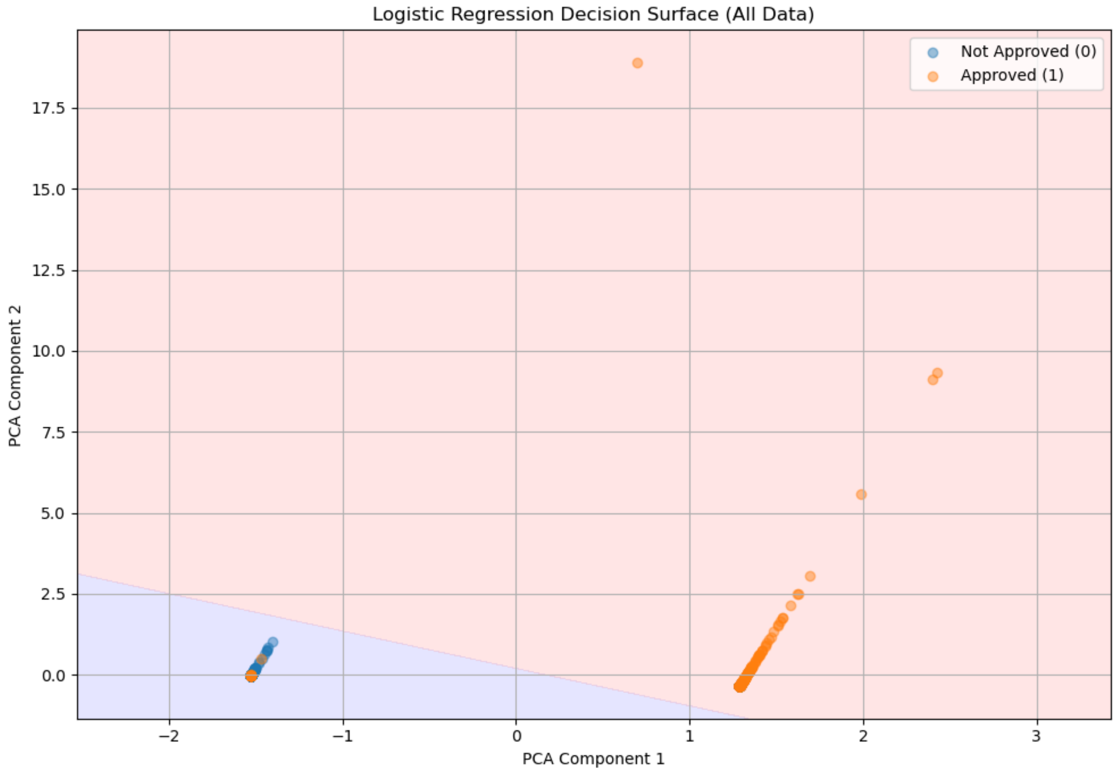
	A15	A9_t	A9_f	True Label	Predicted Label
0	209.999939	1.000000e+00	-1.282458e-08	0.0	1
6	-0.000006	1.000000e+00	-1.282458e-08	0.0	1
8	-0.000006	1.000000e+00	-1.282458e-08	0.0	1
11	-0.000006	1.000000e+00	-1.282458e-08	0.0	1
18	-0.000006	1.000000e+00	-1.282458e-08	0.0	1
23	0.999994	-1.697774e-08	1.000000e+00	1.0	0
28	-0.000006	-1.697774e-08	1.000000e+00	1.0	0
47	-0.000006	1.000000e+00	-1.282458e-08	0.0	1
60	-0.000006	1.000000e+00	-1.282458e-08	0.0	1
65	-0.000006	1.000000e+00	-1.282458e-08	0.0	1

[31]:

```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Step 1: Recombine the full dataset using the original top 3 features
X_all = df_encoded[top_3_features].values.astype(np.float32)
y_all = df_encoded["A16 (Class)"].values.astype(int)

# Step 2: Re-scale using the same scaler
X_all_scaled = scaler_top3.transform(X_all)

# Step 3: Fit PCA on all points and transform
pca_all = PCA(n_components=2)
X_all_pca = pca_all.fit_transform(X_all_scaled)
```

```
# Step 4: Create 2D meshgrid in PCA space
x_min, x_max = X_all_pca[:, 0].min() - 1, X_all_pca[:, 0].max() + 1
y_min, y_max = X_all_pca[:, 1].min() - 1, X_all_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 500),
                     np.linspace(y_min, y_max, 500))
grid_2d = np.c_[xx.ravel(), yy.ravel()]

# Step 5: Inverse-transform grid to original feature space (for prediction)
grid_3d = pca_all.inverse_transform(grid_2d)
Z = model.predict(grid_3d).reshape(xx.shape)

# Step 6: Plot decision surface + all data points
plt.figure(figsize=(10, 7))
plt.contourf(xx, yy, Z, levels=[0, 0.5, 1], alpha=0.2, cmap='bwr')

# Scatter all points
plt.scatter(X_all_pca[y_all == 0, 0], X_all_pca[y_all == 0, 1], label='Not␣
 ↪Approved (0)', alpha=0.45)
plt.scatter(X_all_pca[y_all == 1, 0], X_all_pca[y_all == 1, 1], label='Approved␣
 ↪(1)', alpha=0.45)

plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("Logistic Regression Decision Surface (All Data)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

print(f"Total number of points in plot: {X_all_pca.shape[0]}")
```

```
7813/7813 [==============================] - 4s 497us/step
```




```
Total number of points in plot: 653
```

1 Dropping Multi-Collinear variables

[32]:
```
# Load the newly uploaded data
df = pd.read_csv('./crx.data', header=None, na_values="?")
df.columns = [f"A{i+1}" for i in range(df.shape[1])]
df.rename(columns={"A16": "A16 (Class)"}, inplace=True)
df["A16 (Class)"] = df["A16 (Class)"].astype(str).str.strip().map({'+': 1, '-':
 ↪0})
df = df.dropna()

# One-hot encode categorical variables (keep all dummies)
df_encoded = pd.get_dummies(df, drop_first=False).astype(int)

# Recalculate the correlation matrix and find perfectly correlated columns
X = df_encoded.drop("A16 (Class)", axis=1)
corr_matrix = X.corr().abs()

# Identify perfectly correlated pairs (excluding self-correlation)
perfect_corr_pairs = []
for i in range(len(corr_matrix.columns)):
```

```
    for j in range(i + 1, len(corr_matrix.columns)):
        if corr_matrix.iloc[i, j] == 1.0:
            col1 = corr_matrix.columns[i]
            col2 = corr_matrix.columns[j]
            perfect_corr_pairs.append((col1, col2))

# Convert to DataFrame and display
perfect_corr_df = pd.DataFrame(perfect_corr_pairs, columns=["Feature 1",␣
 ↪"Feature 2"])
perfect_corr_df.head(20)
```

[32]:

	Feature 1	Feature 2
0	A1_a	A1_b
1	A4_l	A5_gg
2	A4_u	A5_g
3	A4_y	A5_p
4	A10_f	A10_t
5	A12_f	A12_t

2 Pairs like A1_a/A1_b, A10_f/A10_t, A12_f/A12_t make sense — these are two-value categorical features, so one-hot encoding gives two perfectly inverse columns

3 But A4_l A5_gg, and similar, looks suspicious — they're from different original features and should not be perfectly correlated under normal conditions

4 You may have a small number of rows with rare values — and by coincidence, A4_l = 1 always appears with A5_gg = 1, etc.

5 These are accidental correlations due to the small dataset.

[33]:

```
# Apply a broader set of drops to remove all known collinear features
cols_to_drop = [
    'A1_b', 'A4_y', 'A5_p', 'A6_q', 'A7_z', 'A9_f',
    'A10_t', 'A12_t', 'A13_s'
]
df_encoded_clean = df_encoded.drop(columns=cols_to_drop)

# Prepare X and y for statsmodels
X = df_encoded_clean.drop("A16 (Class)", axis=1)
y = df_encoded_clean["A16 (Class)"]

# Add intercept and fit with robust handling of convergence
```

```python
import statsmodels.api as sm
X_with_const = sm.add_constant(X)

try:
    logit_model = sm.Logit(y, X_with_const)
    result = logit_model.fit(disp=False)  # suppress fitting output
    summary_output = result.summary()
except Exception as e:
    summary_output = str(e)

summary_output
```

```
/opt/anaconda3/lib/python3.10/site-packages/statsmodels/base/model.py:607:
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check
mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

[33]:

Dep. Variable:	A16 (Class)	**No. Observations:**	653
Model:	Logit	**Df Residuals:**	617
Method:	MLE	**Df Model:**	35
Date:	Sat, 19 Apr 2025	**Pseudo R-squ.:**	0.5952
Time:	21:10:48	**Log-Likelihood:**	-182.07
converged:	False	**LL-Null:**	-449.77
Covariance Type:	nonrobust	**LLR p-value:**	7.743e-91

	coef	std err	z	P> |z|	[0.025	0.975]
const	-7.6708	2.778	-2.761	0.006	-13.116	-2.226
A2	0.0131	0.017	0.778	0.436	-0.020	0.046
A3	-0.0236	0.032	-0.744	0.457	-0.086	0.039
A8	0.0832	0.046	1.801	0.072	-0.007	0.174
A11	0.1293	0.060	2.157	0.031	0.012	0.247
A14	-0.0026	0.480	-0.005	0.996	-0.943	0.937
A15	0.0006	0.000	2.922	0.003	0.000	0.001
A1_a	0.0863	0.309	0.279	0.780	-0.520	0.692
A4_l	11.5034	nan	nan	nan	nan	nan
A4_u	0.4243	2.01e+08	2.11e-09	1.000	-3.95e+08	3.95e+08
A5_g	0.4243	2e+08	2.12e-09	1.000	-3.92e+08	3.92e+08
A5_gg	11.5034	nan	nan	nan	nan	nan
A6_aa	-0.3179	nan	nan	nan	nan	nan
A6_c	-0.0003	0.607	-0.000	1.000	-1.189	1.189
A6_cc	1.1207	nan	nan	nan	nan	nan
A6_d	0.4958	0.623	0.796	0.426	-0.724	1.716
A6_e	1.7674	1.306	1.353	0.176	-0.793	4.327
A6_ff	-4.1128	nan	nan	nan	nan	nan
A6_i	-0.6554	282.520	-0.002	0.998	-554.385	553.074
A6_j	-4.6186	2.135	-2.164	0.030	-8.803	-0.435
A6_k	-0.7126	0.580	-1.229	0.219	-1.850	0.424
A6_m	-0.1355	0.621	-0.218	0.827	-1.352	1.081
A6_r	-2.1723	4.475	-0.485	0.627	-10.943	6.598
A6_w	0.6166	0.493	1.251	0.211	-0.349	1.583
A6_x	2.4904	nan	nan	nan	nan	nan
A7_bb	3.5255	2.100	1.679	0.093	-0.591	7.641
A7_dd	2.5564	2.002	1.277	0.202	-1.367	6.480
A7_ff	5.8953	2.883	2.045	0.041	0.245	11.546
A7_h	4.0474	nan	nan	nan	nan	nan
A7_j	7.9775	3.067	2.601	0.009	1.967	13.988
A7_n	6.7767	nan	nan	nan	nan	nan
A7_o	-12.2295	1.38e+04	-0.001	0.999	-2.7e+04	2.7e+04
A7_v	3.8298	1.979	1.935	0.053	-0.049	7.708
A9_t	3.8640	nan	nan	nan	nan	nan
A10_f	-0.4274	0.381	-1.121	0.262	-1.175	0.320
A12_f	0.2480	116.480	0.002	0.998	-228.048	228.544
A13_g	0.0832	0.188	0.443	0.658	-0.285	0.451
A13_p	-9.7411	-0	inf	0.000	-9.741	-9.741

[34]:

```python
# Extract and organize summary table with p-values
summary_table = result.summary2().tables[1]  # Get the coefficient summary table
sorted_by_pval = summary_table.sort_values("P>|z|", ascending=True)
sorted_by_pval.head(20)
```

[34]:

```
          Coef.  Std.Err.         z     P>|z|    [0.025     0.975]
A13_p -9.741127 -0.000000       inf  0.000000 -9.741127 -9.741127
```

```
A15     0.000567  0.000194  2.921818  0.003480   0.000187   0.000947
const -7.670844  2.777977 -2.761306  0.005757 -13.115579  -2.226110
A7_j    7.977475  3.066774  2.601259  0.009288   1.966708  13.988242
A6_j   -4.618597  2.134723 -2.163558  0.030498  -8.802577  -0.434616
A11     0.129277  0.059942  2.156715  0.031028   0.011794   0.246760
A7_ff   5.895300  2.882907  2.044915  0.040863   0.244907  11.545693
A7_v    3.829783  1.978827  1.935381  0.052944  -0.048646   7.708212
A8      0.083151  0.046167  1.801099  0.071687  -0.007334   0.173636
A7_bb   3.525489  2.100033  1.678778  0.093195  -0.590500   7.641477
A6_e    1.767373  1.306137  1.353130  0.176014  -0.792608   4.327354
A7_dd   2.556423  2.001823  1.277047  0.201585  -1.367078   6.479923
A6_w    0.616577  0.492839  1.251070  0.210909  -0.349371   1.582524
A6_k   -0.712643  0.580065 -1.228556  0.219238  -1.849550   0.424264
A10_f -0.427426  0.381410 -1.120646  0.262439  -1.174977   0.320125
A6_d    0.495757  0.622526  0.796364  0.425821  -0.724372   1.715886
A2      0.013122  0.016858  0.778380  0.436345  -0.019919   0.046163
A3     -0.023593  0.031724 -0.743689  0.457064  -0.085771   0.038585
A6_r   -2.172289  4.474879 -0.485441  0.627364 -10.942891   6.598313
A13_g   0.083188  0.187662  0.443283  0.657561  -0.284624   0.450999
```

Keep (Significant predictors): | Feature | Coef | P>|z| | Notes | |———|———-|———|——-| | A13_p | -9.74 | 0.000 | Strong signal but suspicious (maybe very rare?) | A15 | +0.00057 | 0.00348 | Reliable small positive predictor | const | -7.67 | 0.00576 | Intercept (baseline log-odds) | A7_j | +7.98 | 0.00929 | Strong approval signal | A6_j | -4.62 | 0.03050 | Strong negative predictor | A11 | +0.13 | 0.03103 | More credit lines → approval | A7_ff | +5.90 | 0.04086 | Strong positive predictor

[35]:
```python
final_features = [
    'A15',
    'A7_j',
    'A6_j',
    'A11',
    'A7_ff'
]

# Optional extras:
# 'A7_v', 'A8'
```

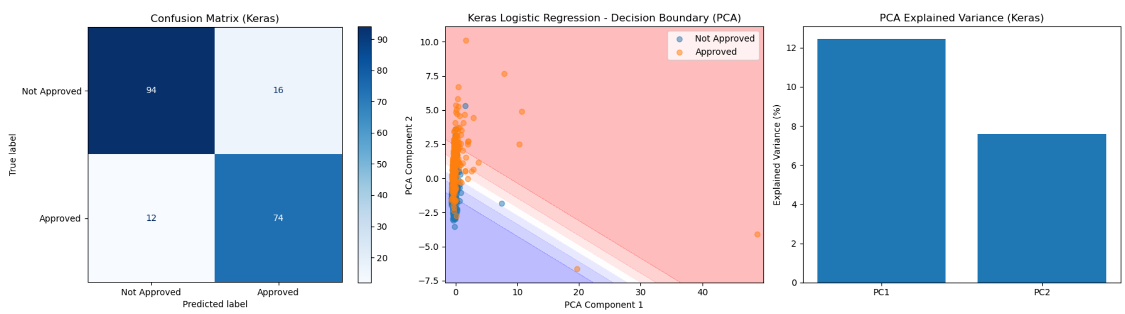
[36]:
```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers

# Reuse final features and data split
X_train_k, X_val_k, y_train_k, y_val_k = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

```python
# Scale
scaler_k = StandardScaler()
X_train_k_scaled = scaler_k.fit_transform(X_train_k)
X_val_k_scaled = scaler_k.transform(X_val_k)

# Define a Keras logistic regression model with L2 regularization
model = Sequential([
    Dense(1, activation='sigmoid', input_shape=(X_train_k_scaled.shape[1],),
          kernel_regularizer=regularizers.l2(0.01))
])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(X_train_k_scaled, y_train_k,␣
↪validation_data=(X_val_k_scaled, y_val_k),
                    epochs=100, batch_size=32, verbose=0)

# Predict for confusion matrix
y_val_pred_probs = model.predict(X_val_k_scaled)
y_val_pred_classes = (y_val_pred_probs > 0.5).astype(int)
cm_keras = confusion_matrix(y_val_k, y_val_pred_classes)

# PCA projection of the full dataset for decision boundary
X_all_k_scaled = scaler_k.transform(X)
pca_k = PCA(n_components=2)
X_pca_k = pca_k.fit_transform(X_all_k_scaled)

# Decision boundary
xx, yy = np.meshgrid(np.linspace(X_pca_k[:, 0].min() - 1, X_pca_k[:, 0].max() +␣
↪1, 300),
                     np.linspace(X_pca_k[:, 1].min() - 1, X_pca_k[:, 1].max() +␣
↪1, 300))
grid_pca_k = np.c_[xx.ravel(), yy.ravel()]
grid_orig_k = pca_k.inverse_transform(grid_pca_k)
Z_k = model.predict(grid_orig_k).reshape(xx.shape)

# Plot
fig, axs = plt.subplots(1, 3, figsize=(18, 5))

# 1. Confusion Matrix
ConfusionMatrixDisplay(confusion_matrix=cm_keras, display_labels=["Not␣
↪Approved", "Approved"]).plot(ax=axs[0], cmap='Blues')
axs[0].set_title("Confusion Matrix (Keras)")
```

```
# 2. PCA Decision Boundary
axs[1].contourf(xx, yy, Z_k, alpha=0.3, cmap='bwr')
axs[1].scatter(X_pca_k[y == 0, 0], X_pca_k[y == 0, 1], label='Not Approved',␣
 ↪alpha=0.5)
axs[1].scatter(X_pca_k[y == 1, 0], X_pca_k[y == 1, 1], label='Approved',␣
 ↪alpha=0.5)
axs[1].set_title("Keras Logistic Regression - Decision Boundary (PCA)")
axs[1].set_xlabel("PCA Component 1")
axs[1].set_ylabel("PCA Component 2")
axs[1].legend()

# 3. PCA Variance
axs[2].bar(["PC1", "PC2"], pca_k.explained_variance_ratio_ * 100)
axs[2].set_ylabel("Explained Variance (%)")
axs[2].set_title("PCA Explained Variance (Keras)")

plt.tight_layout()
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```

```
7/7 [==============================] - 0s 530us/step
2813/2813 [==============================] - 1s 410us/step
```

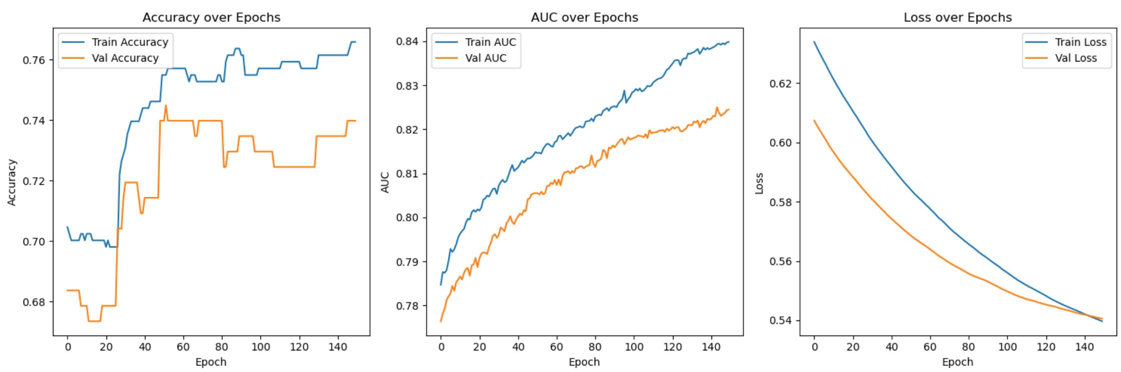


[37]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
from tensorflow.keras.metrics import AUC
```

```python
# === Final selected features ===
final_features = ['A15', 'A7_j', 'A6_j', 'A11', 'A7_ff', 'A7_v', 'A8']
X = df_encoded[final_features].values
y = df_encoded["A16 (Class)"].values

# === Split and scale ===
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# === Keras logistic model ===
model = Sequential([
    Dense(1, activation='sigmoid',
          input_shape=(X_train_scaled.shape[1],),
          kernel_regularizer=regularizers.l2(0.01))
])

model.compile(optimizer=Adam(learning_rate=0.0005),
              loss='binary_crossentropy',
              metrics=['accuracy', AUC(name='auc')])

# === Train ===
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=150,
                    batch_size=64,
                    verbose=0)

# === Plot metrics ===
plt.figure(figsize=(15, 5))

# Accuracy
plt.subplot(1, 3, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("Accuracy over Epochs")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

# AUC
plt.subplot(1, 3, 2)
plt.plot(history.history['auc'], label='Train AUC')
plt.plot(history.history['val_auc'], label='Val AUC')
plt.title("AUC over Epochs")
```

```
plt.xlabel("Epoch")
plt.ylabel("AUC")
plt.legend()

# Loss
plt.subplot(1, 3, 3)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("Loss over Epochs")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()
```

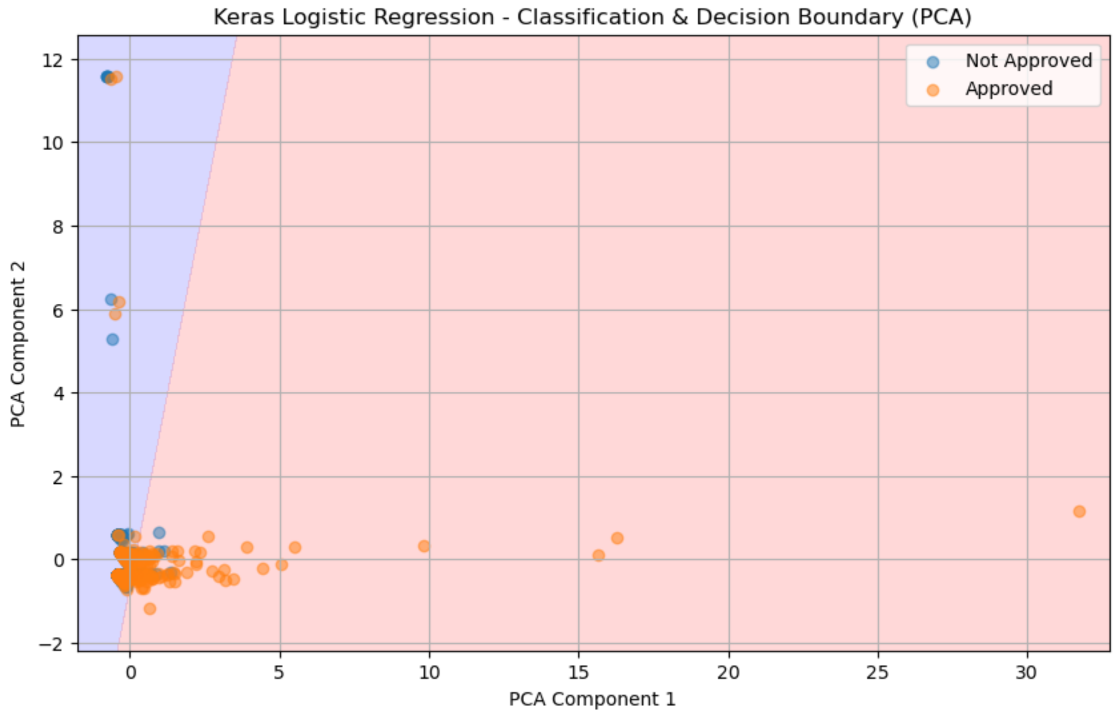
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



[40]:
```
from sklearn.decomposition import PCA

# Combine full dataset and scale
X_all_scaled = scaler.transform(X)
y_all = y  # already defined

# PCA for 2D projection
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_all_scaled)

# Predict probabilities across PCA space
xx, yy = np.meshgrid(np.linspace(X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1,
 ↪300),
```

```
                     np.linspace(X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1,␣
 ↪300))
grid_pca = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca.inverse_transform(grid_pca)
Z = model.predict(grid_original).reshape(xx.shape)

# Plot decision boundary + actual points
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, levels=[0, 0.5, 1], alpha=0.3, cmap='bwr')
plt.scatter(X_pca[y_all == 0, 0], X_pca[y_all == 0, 1], label="Not Approved",␣
 ↪alpha=0.5)
plt.scatter(X_pca[y_all == 1, 0], X_pca[y_all == 1, 1], label="Approved",␣
 ↪alpha=0.5)
plt.legend()
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("Keras Logistic Regression - Classification & Decision Boundary␣
 ↪(PCA)")
plt.grid(True)
plt.show()

# # Confusion Matrix
# cm = confusion_matrix(y_test, y_pred)
# ConfusionMatrixDisplay(cm, display_labels=["Not Approved", "Approved"]).
 ↪plot(cmap='Blues')
# plt.title("Random Forest - Confusion Matrix")
# plt.grid(False)
# plt.show()

# # Evaluate
# y_pred = rf.predict(X_test)
# accuracy = accuracy_score(y_test, y_pred)
# print(f" Random Forest Accuracy: {accuracy:.4f}")
```

```
2813/2813 [==============================] - 1s 426us/step
```

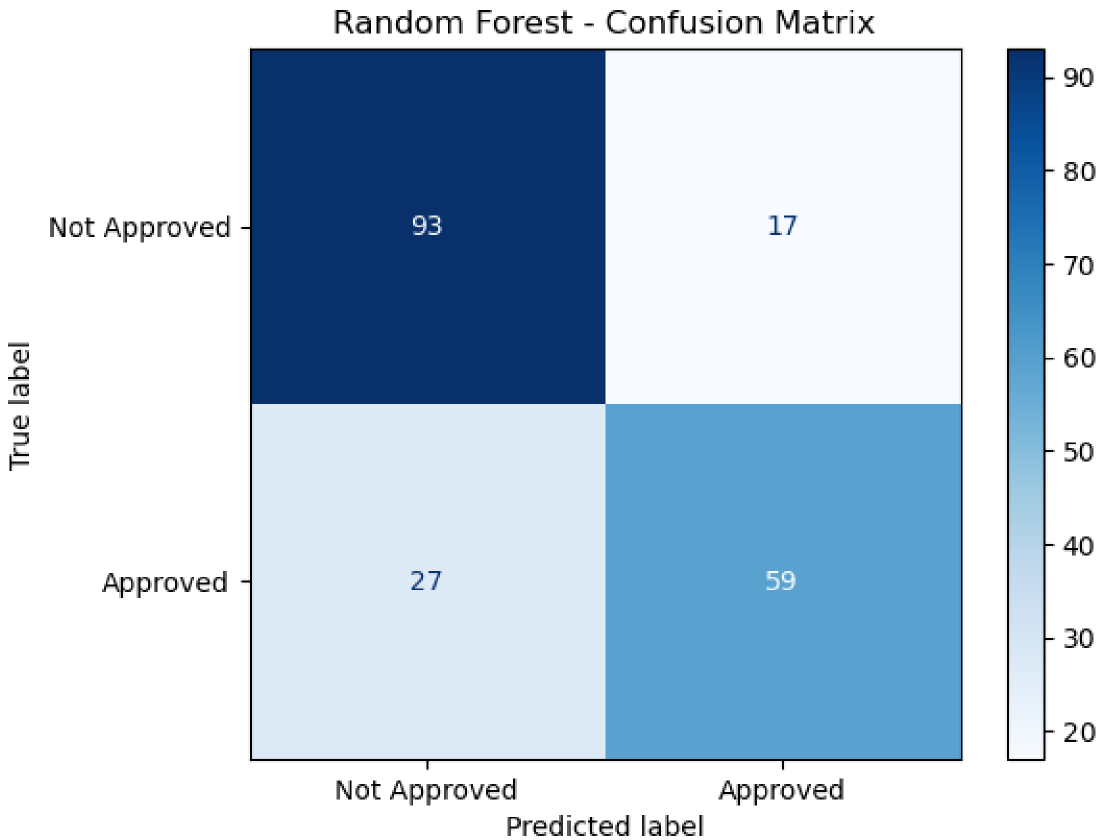


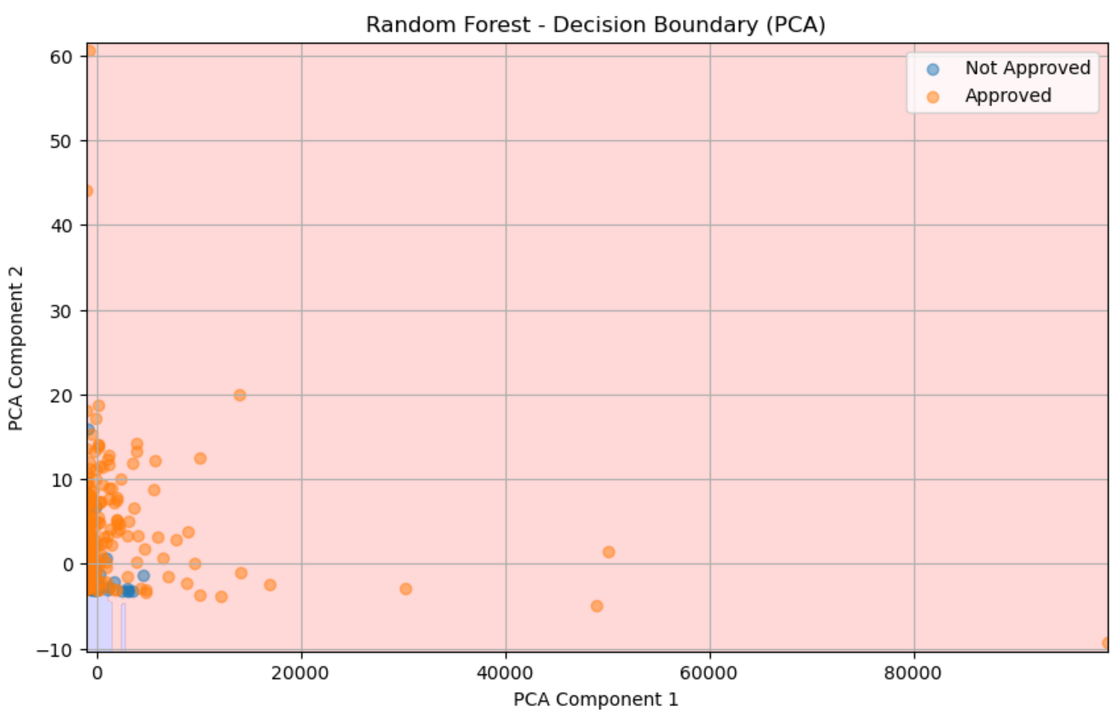
6 Random forest

[41]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪ConfusionMatrixDisplay
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np

# Final features
final_features = ['A15', 'A7_j', 'A6_j', 'A11', 'A7_ff', 'A7_v', 'A8']
X = df_encoded[final_features].values
y = df_encoded["A16 (Class)"].values

# Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Train Random Forest
rf = RandomForestClassifier(n_estimators=100, max_depth=6, random_state=42)
rf.fit(X_train, y_train)
```

```
# Evaluate
y_pred = rf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f" Random Forest Accuracy: {accuracy:.4f}")

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(cm, display_labels=["Not Approved", "Approved"]).
↪plot(cmap='Blues')
plt.title("Random Forest - Confusion Matrix")
plt.grid(False)
plt.show()

# PCA for 2D decision surface
X_all = np.vstack((X_train, X_test))
y_all = np.concatenate((y_train, y_test))
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_all)

# Grid for decision boundary
xx, yy = np.meshgrid(np.linspace(X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1,␣
↪300),
                     np.linspace(X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1,␣
↪300))
grid_pca = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca.inverse_transform(grid_pca)
Z = rf.predict(grid_original).reshape(xx.shape)

# Plot
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, levels=[0, 0.5, 1], alpha=0.3, cmap='bwr')
plt.scatter(X_pca[y_all == 0, 0], X_pca[y_all == 0, 1], label="Not Approved",␣
↪alpha=0.5)
plt.scatter(X_pca[y_all == 1, 0], X_pca[y_all == 1, 1], label="Approved",␣
↪alpha=0.5)
plt.title("Random Forest - Decision Boundary (PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend()
plt.grid(True)
plt.show()
```

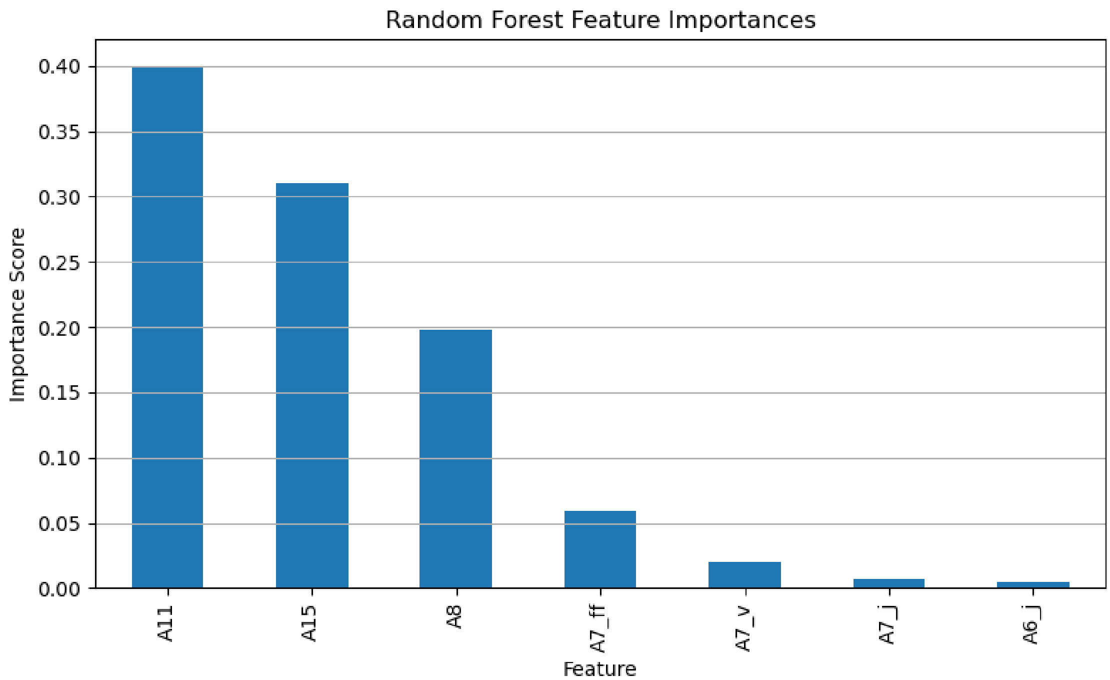
```
Random Forest Accuracy: 0.7755
```


Random Forest - Confusion Matrix
Not Approved
Approved
True label
93
17
27
59
Not Approved
Approved
Predicted label
90
80
70
60
50
40
30
20


Random Forest - Decision Boundary (PCA)
Not Approved
Approved
PCA Component 2
60
50
40
30
20
10
0
−10
0
20000
40000
60000
80000
PCA Component 1

Visualize feature importances

[42]:
```
importances = rf.feature_importances_
importance_series = pd.Series(importances, index=final_features).
↪sort_values(ascending=False)

# Plot feature importances
plt.figure(figsize=(8, 5))
importance_series.plot(kind='bar')
plt.title("Random Forest Feature Importances")
plt.ylabel("Importance Score")
plt.xlabel("Feature")
plt.grid(axis='y')
plt.tight_layout()
plt.show()

importance_series
```



[42]:
```
A11      0.400057
A15      0.310554
A8       0.198352
A7_ff    0.059286
```

```
A7_v      0.020307
A7_j      0.006526
A6_j      0.004918
dtype: float64
```

Feature Importance Meaning A11 0.400 Most influential — number of existing credit lines A15 0.311 High impact — likely monetary amount or duration A8 0.198 Useful — possibly credit history or guarantees

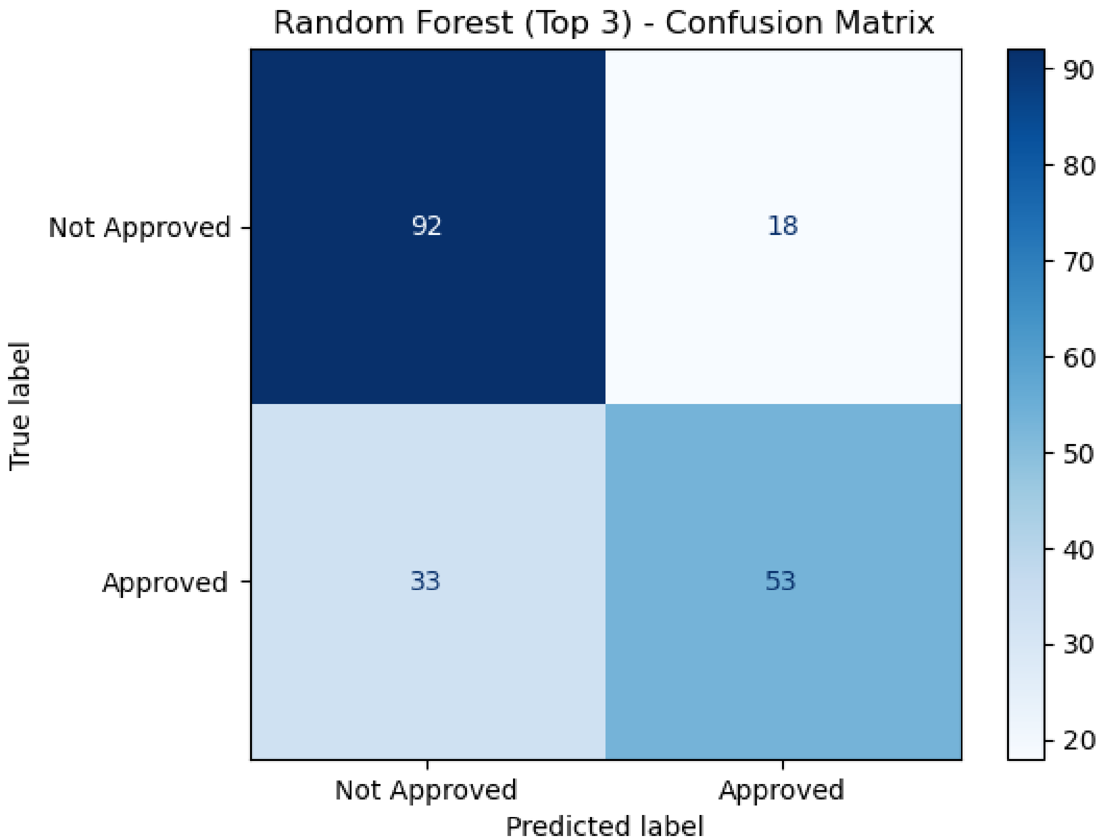
Others are minor

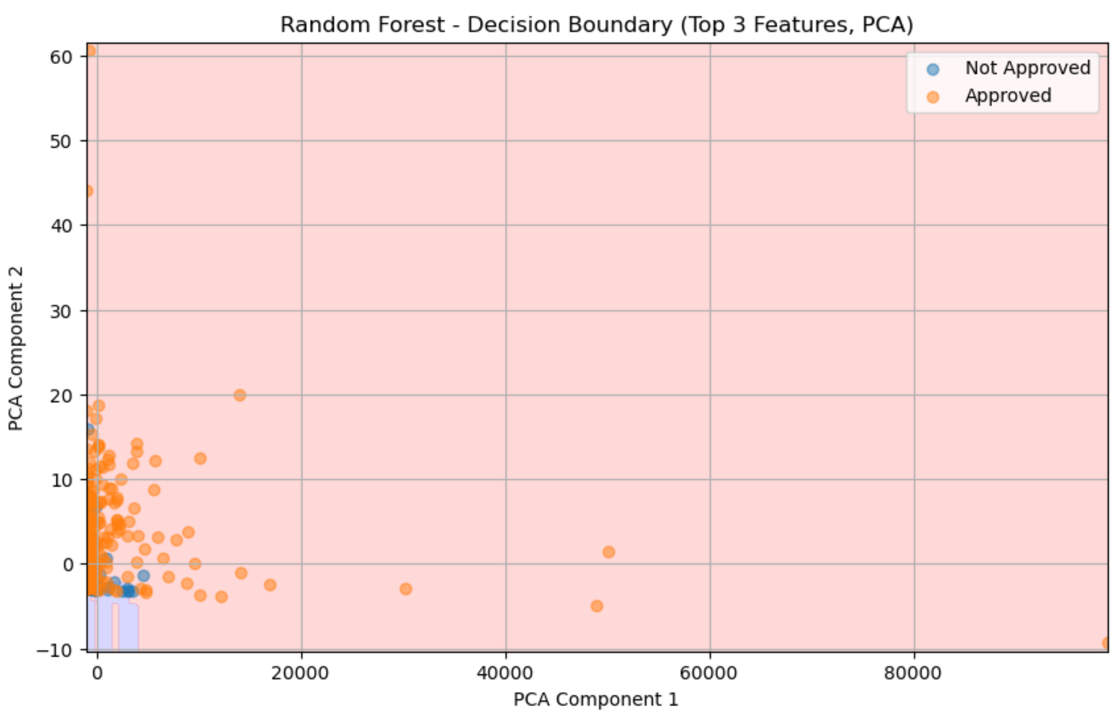
7 Random forest with 3 features

[43]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪ConfusionMatrixDisplay
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import numpy as np

# Use only the top 3 features
top3_features = ['A11', 'A15', 'A8']
X_top3 = df_encoded[top3_features].values
y_top3 = df_encoded["A16 (Class)"].values

# Train/test split
X_train_rf3, X_test_rf3, y_train_rf3, y_test_rf3 = train_test_split(X_top3,␣
↪y_top3, test_size=0.3, random_state=42)

# Train Random Forest
rf_top3 = RandomForestClassifier(n_estimators=100, max_depth=6, random_state=42)
rf_top3.fit(X_train_rf3, y_train_rf3)

# Predict and evaluate
y_pred_rf3 = rf_top3.predict(X_test_rf3)
accuracy_rf3 = accuracy_score(y_test_rf3, y_pred_rf3)
cm_rf3 = confusion_matrix(y_test_rf3, y_pred_rf3)

# Display accuracy and confusion matrix
print(f" Random Forest (Top 3 Features) Accuracy: {accuracy_rf3:.4f}")
ConfusionMatrixDisplay(confusion_matrix=cm_rf3, display_labels=["Not Approved",␣
↪"Approved"]).plot(cmap='Blues')
plt.title("Random Forest (Top 3) - Confusion Matrix")
plt.grid(False)
plt.show()
```

```
# PCA for decision boundary
X_all_rf3 = np.vstack((X_train_rf3, X_test_rf3))
y_all_rf3 = np.concatenate((y_train_rf3, y_test_rf3))
pca_rf3 = PCA(n_components=2)
X_pca_rf3 = pca_rf3.fit_transform(X_all_rf3)

# Create decision boundary
xx, yy = np.meshgrid(np.linspace(X_pca_rf3[:, 0].min() - 1, X_pca_rf3[:, 0].
 ↪max() + 1, 300),
                     np.linspace(X_pca_rf3[:, 1].min() - 1, X_pca_rf3[:, 1].
 ↪max() + 1, 300))
grid_pca_rf3 = np.c_[xx.ravel(), yy.ravel()]
grid_orig_rf3 = pca_rf3.inverse_transform(grid_pca_rf3)
Z_rf3 = rf_top3.predict(grid_orig_rf3).reshape(xx.shape)

# Plot decision boundary
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z_rf3, levels=[0, 0.5, 1], alpha=0.3, cmap='bwr')
plt.scatter(X_pca_rf3[y_all_rf3 == 0, 0], X_pca_rf3[y_all_rf3 == 0, 1],␣
 ↪label="Not Approved", alpha=0.5)
plt.scatter(X_pca_rf3[y_all_rf3 == 1, 0], X_pca_rf3[y_all_rf3 == 1, 1],␣
 ↪label="Approved", alpha=0.5)
plt.title("Random Forest - Decision Boundary (Top 3 Features, PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend()
plt.grid(True)
plt.show()
```

```
Random Forest (Top 3 Features) Accuracy: 0.7398
```

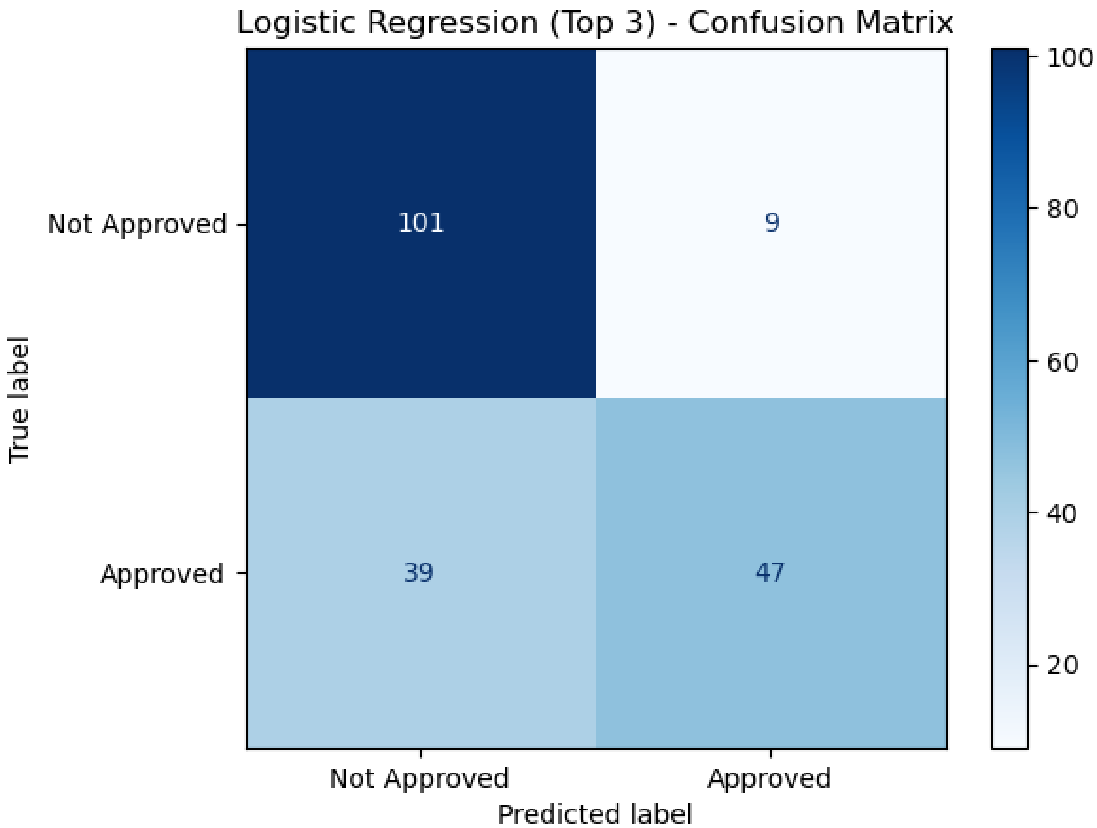

Random Forest (Top 3) - Confusion Matrix
Not Approved
Approved
True label
Predicted label
92
18
33
53
90
80
70
60
50
40
30
20


Random Forest - Decision Boundary (Top 3 Features, PCA)
Not Approved
Approved
PCA Component 1
PCA Component 2
0
20000
40000
60000
80000
60
50
40
30
20
10
0
−10

8 Logistic regression with 3 features

[44]:
```python
from sklearn.linear_model import LogisticRegression

# Train logistic regression using the same top 3 features
logreg_top3 = LogisticRegression()
logreg_top3.fit(X_train_rf3, y_train_rf3)

# Predict and evaluate
y_pred_logreg3 = logreg_top3.predict(X_test_rf3)
accuracy_logreg3 = accuracy_score(y_test_rf3, y_pred_logreg3)
cm_logreg3 = confusion_matrix(y_test_rf3, y_pred_logreg3)

# Display accuracy and confusion matrix
print(f" Logistic Regression (Top 3 Features) Accuracy: {accuracy_logreg3:.
↪4f}")
ConfusionMatrixDisplay(confusion_matrix=cm_logreg3, display_labels=["Not␣
↪Approved", "Approved"]).plot(cmap='Blues')
plt.title("Logistic Regression (Top 3) - Confusion Matrix")
plt.grid(False)
plt.show()
```

```
Logistic Regression (Top 3 Features) Accuracy: 0.7551
```

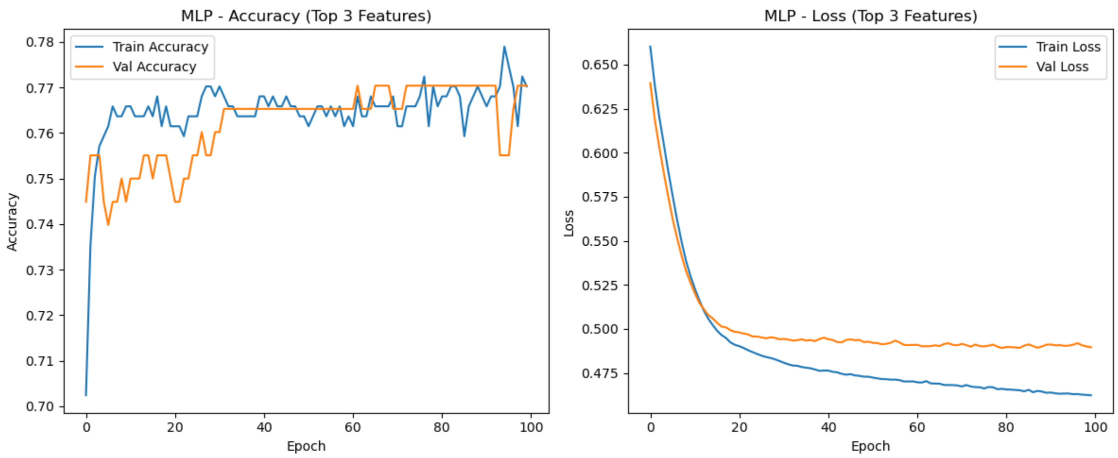


9 Multi-Layer Perceptron with 3 features (MLP)

[45]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam

# === Use top 3 predictors ===
top3_features = ['A11', 'A15', 'A8']
X = df_encoded[top3_features].values
y = df_encoded["A16 (Class)"].values

# === Split and scale ===
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
scaler = StandardScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# === Define the MLP ===
model = Sequential([
    Dense(16, activation='relu', input_shape=(X_train_scaled.shape[1],)),
    Dense(8, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])

# === Train ===
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=100, batch_size=32, verbose=0)

# === Plot accuracy and loss ===
plt.figure(figsize=(12, 5))

# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("MLP - Accuracy (Top 3 Features)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("MLP - Loss (Top 3 Features)")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```

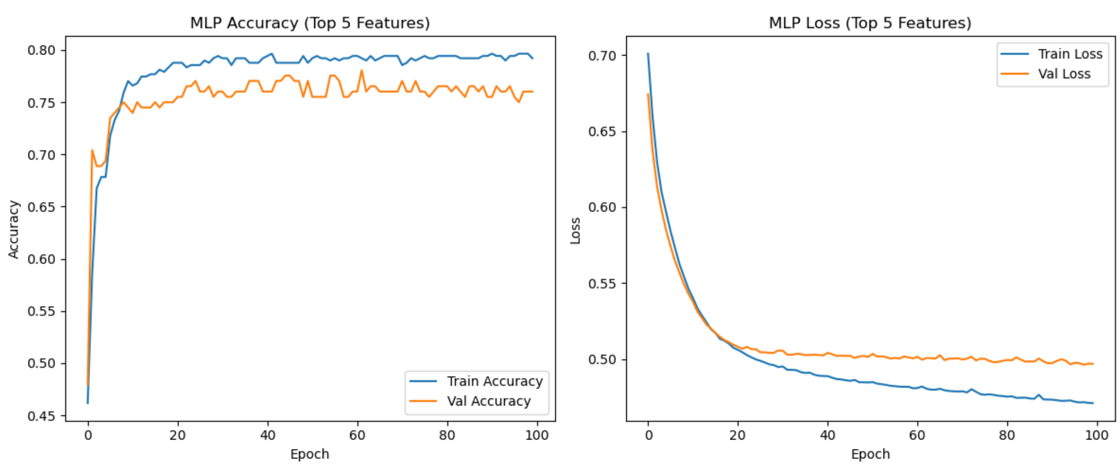


[46]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam

# Top 5 features from feature importance
top5_features = ['A11', 'A15', 'A8', 'A7_ff', 'A7_v']
X = df_encoded[top5_features].values
y = df_encoded["A16 (Class)"].values

# Split and scale
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Define MLP
model = Sequential([
    Dense(16, activation='relu', input_shape=(X_train_scaled.shape[1],)),
    Dense(8, activation='relu'),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

```python
# Train
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Plot Accuracy and Loss
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("MLP Accuracy (Top 5 Features)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("MLP Loss (Top 5 Features)")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```



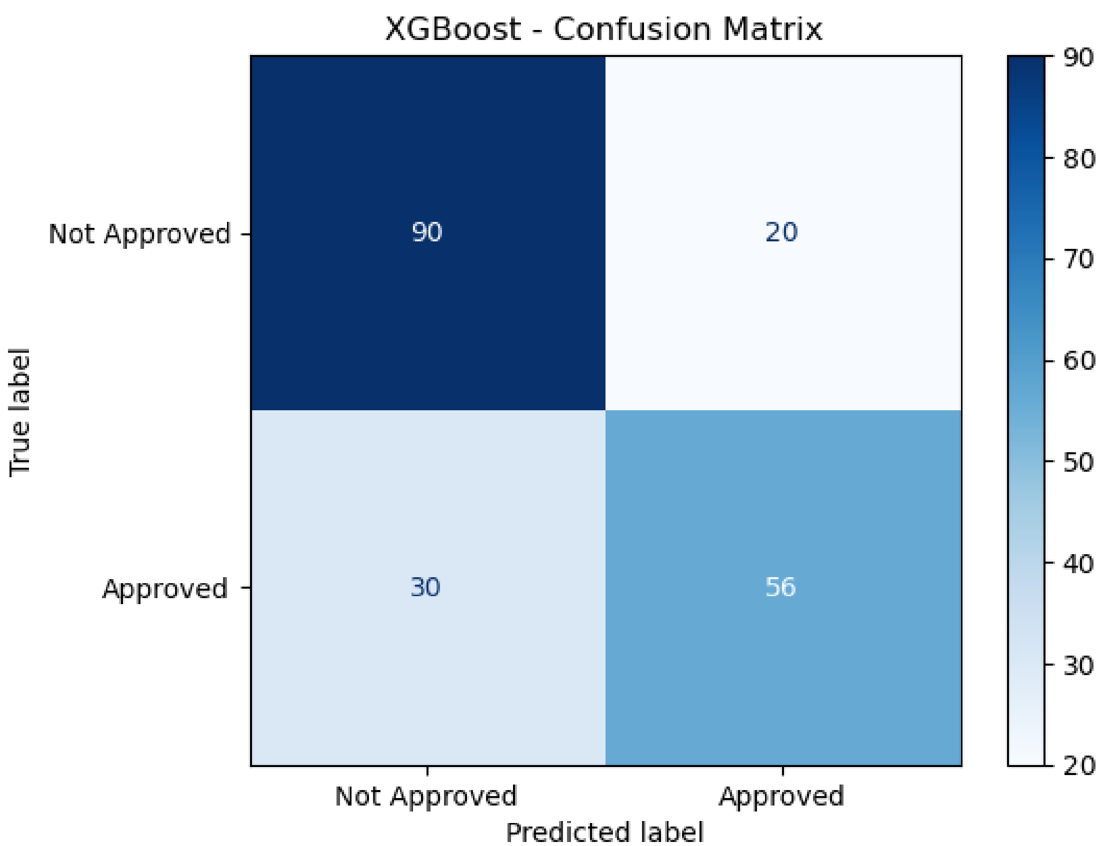
10 XGBoost

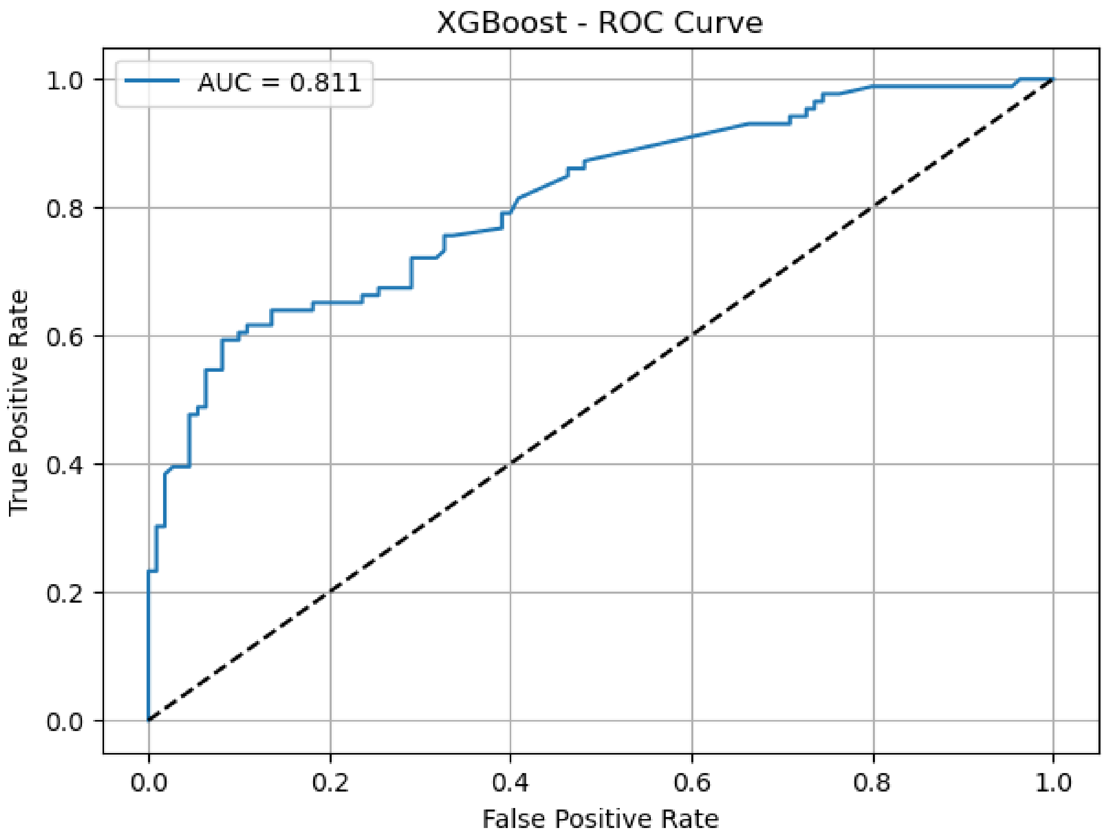
[47]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from xgboost import XGBClassifier, plot_importance
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪ConfusionMatrixDisplay, roc_auc_score, roc_curve

# === Select top 5 features ===
top5_features = ['A11', 'A15', 'A8', 'A7_ff', 'A7_v']
X = df_encoded[top5_features].values
y = df_encoded["A16 (Class)"].values

# === Train/test split ===
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# === Train XGBoost classifier ===
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
↪random_state=42)
xgb_model.fit(X_train, y_train)

# === Evaluate ===
y_pred = xgb_model.predict(X_test)
y_probs = xgb_model.predict_proba(X_test)[:, 1]
accuracy = accuracy_score(y_test, y_pred)
auc = roc_auc_score(y_test, y_probs)
cm = confusion_matrix(y_test, y_pred)

print(f"  XGBoost Accuracy: {accuracy:.4f}")
print(f"  XGBoost AUC: {auc:.4f}")

# === Confusion Matrix ===
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not Approved",␣
↪"Approved"]).plot(cmap='Blues')
plt.title("XGBoost - Confusion Matrix")
plt.grid(False)
plt.show()

# === ROC Curve ===
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label=f"AUC = {auc:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
```

```
plt.ylabel("True Positive Rate")
plt.title("XGBoost - ROC Curve")
plt.legend()
plt.grid(True)
plt.show()

# === Feature Importance ===
plt.figure(figsize=(8, 5))
plot_importance(xgb_model, importance_type='weight', max_num_features=10)
plt.title("XGBoost - Feature Importance (Top 5)")
plt.tight_layout()
plt.show()
```

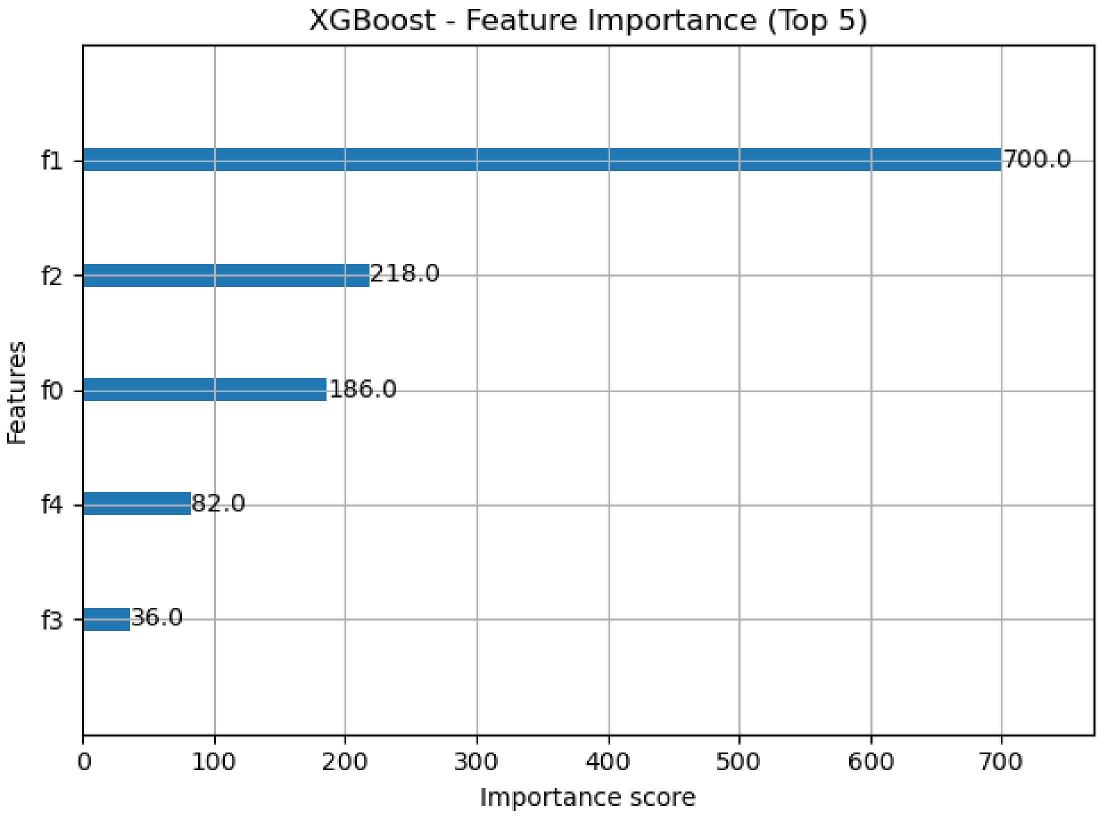
```
XGBoost Accuracy: 0.7449
XGBoost AUC: 0.8110
```

```
/opt/anaconda3/lib/python3.10/site-packages/xgboost/training.py:183:
UserWarning: [21:12:09] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```






```
<Figure size 800x500 with 0 Axes>
```



XGBoost Code:

f0 f1
f2
f3
f4

Real Feature:

A11 A15 A8 A7_ff A7_v

11 A11 (number of credit lines) is consistently your MVP across all models

12 A15 and A8 are reliable support features

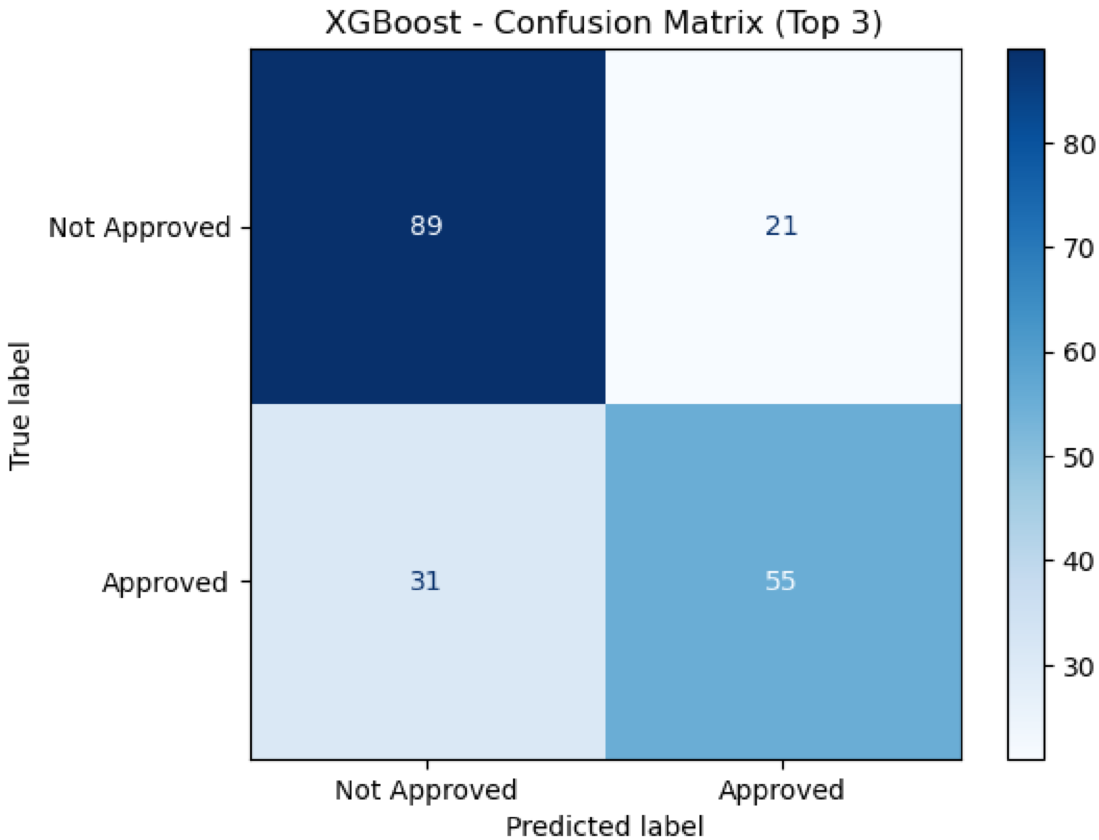
13 A7_ff and A7_v help marginally — dropping them likely won't hurt much

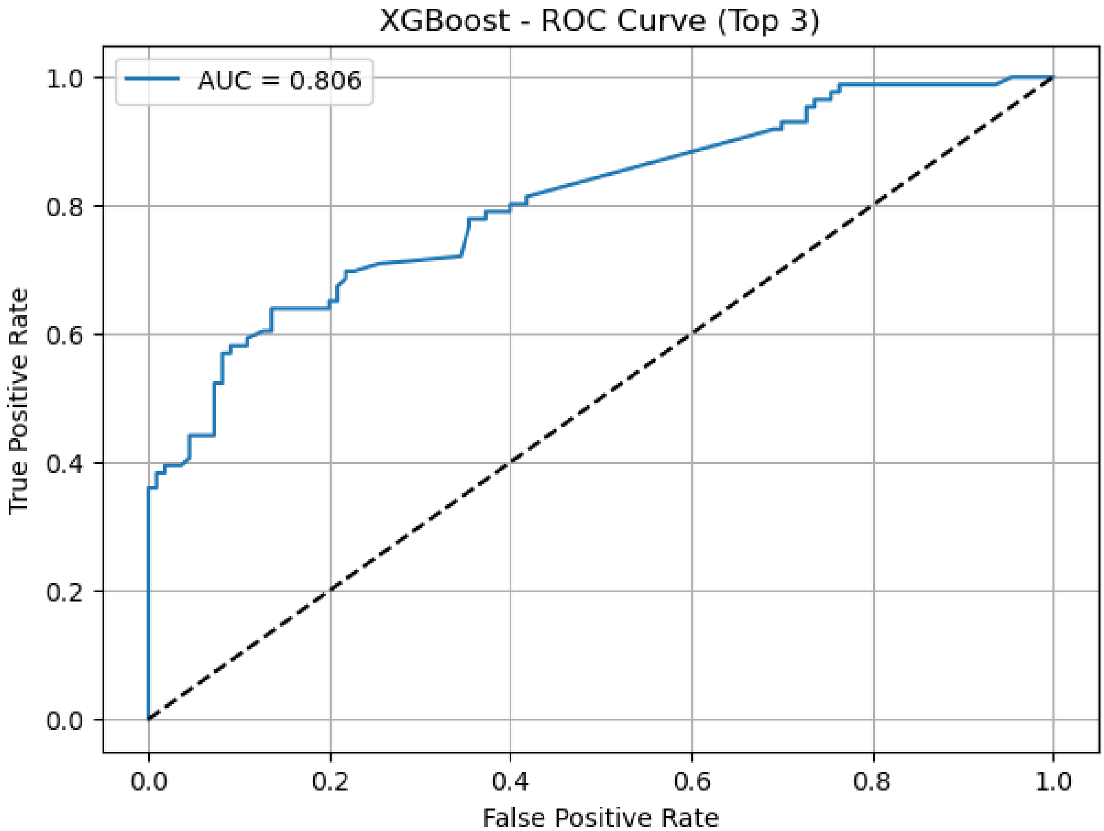
[49]:
```
from xgboost import XGBClassifier, plot_importance
from sklearn.metrics import roc_auc_score, confusion_matrix, accuracy_score,␣
↪ConfusionMatrixDisplay, roc_curve

# Top 3 most important features
top3_xgb_features = ['A11', 'A15', 'A8']
X_top3_xgb = df_encoded[top3_xgb_features].values
y_top3_xgb = df_encoded["A16 (Class)"].values

# Train/test split
X_train_3, X_test_3, y_train_3, y_test_3 = train_test_split(X_top3_xgb,␣
↪y_top3_xgb, test_size=0.3, random_state=42)

# Train XGBoost on top 3
xgb_top3 = XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
↪random_state=42)
xgb_top3.fit(X_train_3, y_train_3)

# Evaluate
y_pred_3 = xgb_top3.predict(X_test_3)
y_probs_3 = xgb_top3.predict_proba(X_test_3)[:, 1]
acc_3 = accuracy_score(y_test_3, y_pred_3)
auc_3 = roc_auc_score(y_test_3, y_probs_3)
cm_3 = confusion_matrix(y_test_3, y_pred_3)

# Display metrics and confusion matrix
print(f" XGBoost (Top 3) Accuracy: {acc_3:.4f}")
print(f" XGBoost (Top 3) AUC: {auc_3:.4f}")
ConfusionMatrixDisplay(cm_3, display_labels=["Not Approved", "Approved"]).
↪plot(cmap='Blues')
plt.title("XGBoost - Confusion Matrix (Top 3)")
plt.grid(False)
plt.show()

# ROC Curve
fpr_3, tpr_3, _ = roc_curve(y_test_3, y_probs_3)
plt.figure(figsize=(7, 5))
plt.plot(fpr_3, tpr_3, label=f"AUC = {auc_3:.3f}")
```

```python
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("XGBoost - ROC Curve (Top 3)")
plt.legend()
plt.grid(True)
plt.show()

# Feature Importance Plot
plt.figure(figsize=(8, 5))
plot_importance(xgb_top3, importance_type='weight', max_num_features=10)
plt.title("XGBoost - Feature Importance (Top 3)")
plt.tight_layout()
plt.show()
```

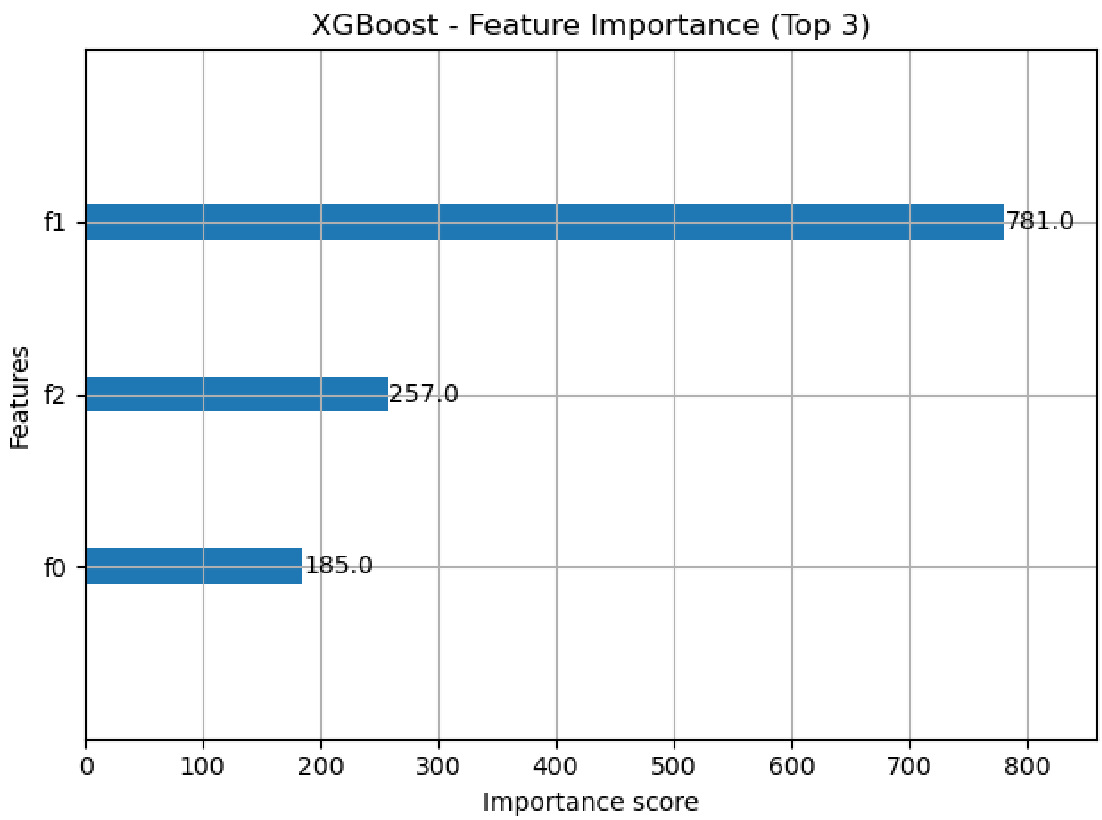
```
XGBoost (Top 3) Accuracy: 0.7347
XGBoost (Top 3) AUC: 0.8063
```

```
/opt/anaconda3/lib/python3.10/site-packages/xgboost/training.py:183:
UserWarning: [21:20:11] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```


XGBoost - Confusion Matrix (Top 3)
Not Approved
Approved
True label
89
21
31
55
Not Approved
Approved
Predicted label
80
70
60
50
40
30



<Figure size 800x500 with 0 Axes>

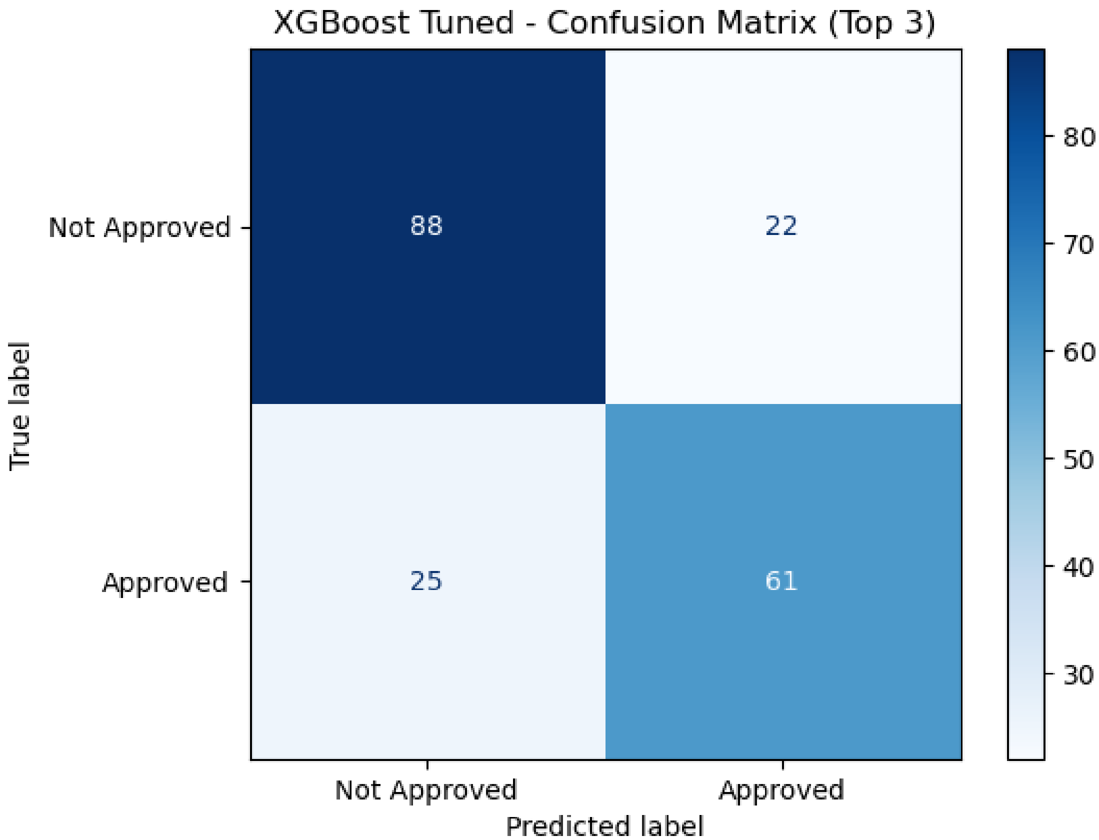


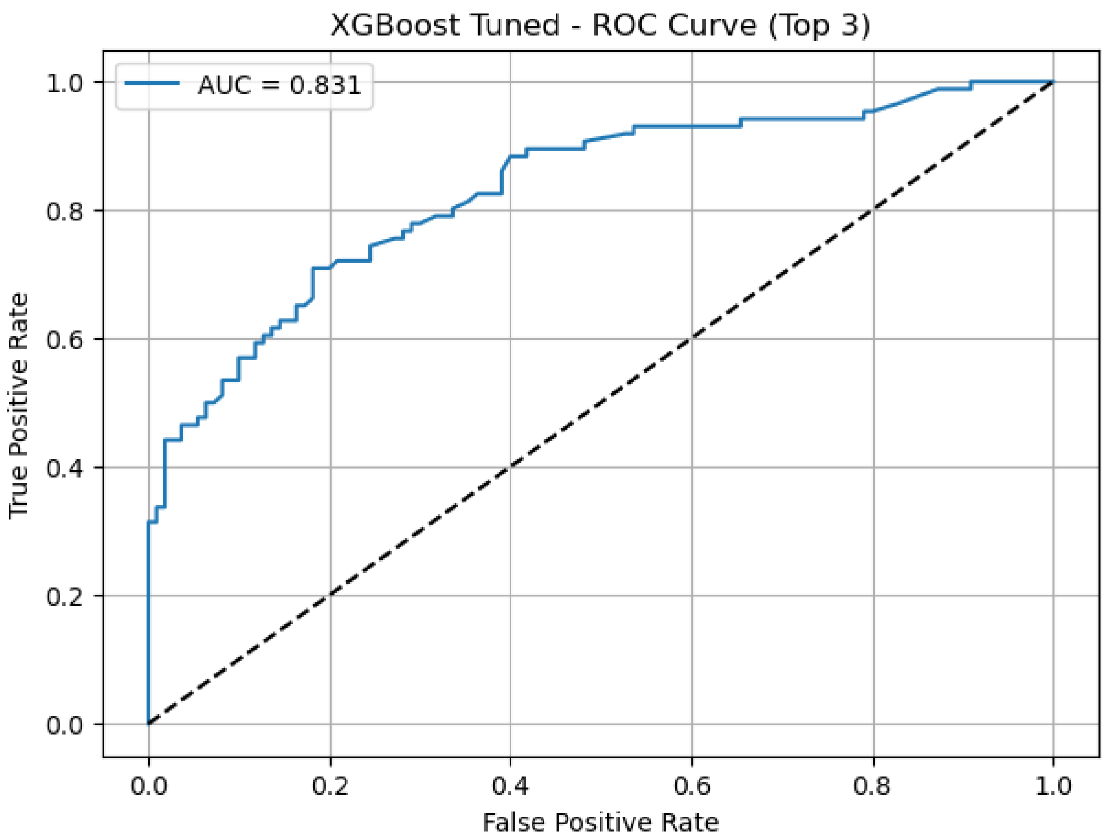
[60]:
```
# Reload and reprocess raw data from crx.data
df = pd.read_csv("./crx.data", header=None, na_values="?")
df.columns = [f"A{i+1}" for i in range(df.shape[1])]
df.rename(columns={"A16": "A16 (Class)"}, inplace=True)
df["A16 (Class)"] = df["A16 (Class)"].astype(str).str.strip().map({'+': 1, '-':
 ↪0})

# Drop missing
df.dropna(inplace=True)

# Identify categorical variables
categorical_cols = [col for col in df.columns if df[col].dtype == 'object' and
 ↪col != "A16 (Class)"]

# One-hot encode all categorical columns (without drop_first to retain all info)
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=False)

# Train XGBoost with top 3 features: A11, A15, A8
top3_features = ['A11', 'A15', 'A8']
X = df_encoded[top3_features].values
```

```
y = df_encoded["A16 (Class)"].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Train tuned XGBoost model
xgb_tuned = XGBClassifier(max_depth=8, learning_rate=0.05,␣
↪use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb_tuned.fit(X_train, y_train)

# Predict and evaluate
y_pred = xgb_tuned.predict(X_test)
y_probs = xgb_tuned.predict_proba(X_test)[:, 1]
acc = accuracy_score(y_test, y_pred)
auc = roc_auc_score(y_test, y_probs)
cm = confusion_matrix(y_test, y_pred)

# Show accuracy and AUC
print(f" XGBoost (Depth=8, LR=0.05) Accuracy: {acc:.4f}")
print(f" XGBoost (Depth=8, LR=0.05) AUC: {auc:.4f}")

# Confusion Matrix
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not Approved",␣
↪"Approved"]).plot(cmap='Blues')
plt.title("XGBoost Tuned - Confusion Matrix (Top 3)")
plt.grid(False)
plt.show()

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_probs)
plt.figure(figsize=(7, 5))
plt.plot(fpr, tpr, label=f"AUC = {auc:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("XGBoost Tuned - ROC Curve (Top 3)")
plt.legend()
plt.grid(True)
plt.show()
```

```
 XGBoost (Depth=8, LR=0.05) Accuracy: 0.7602
 XGBoost (Depth=8, LR=0.05) AUC: 0.8313
```

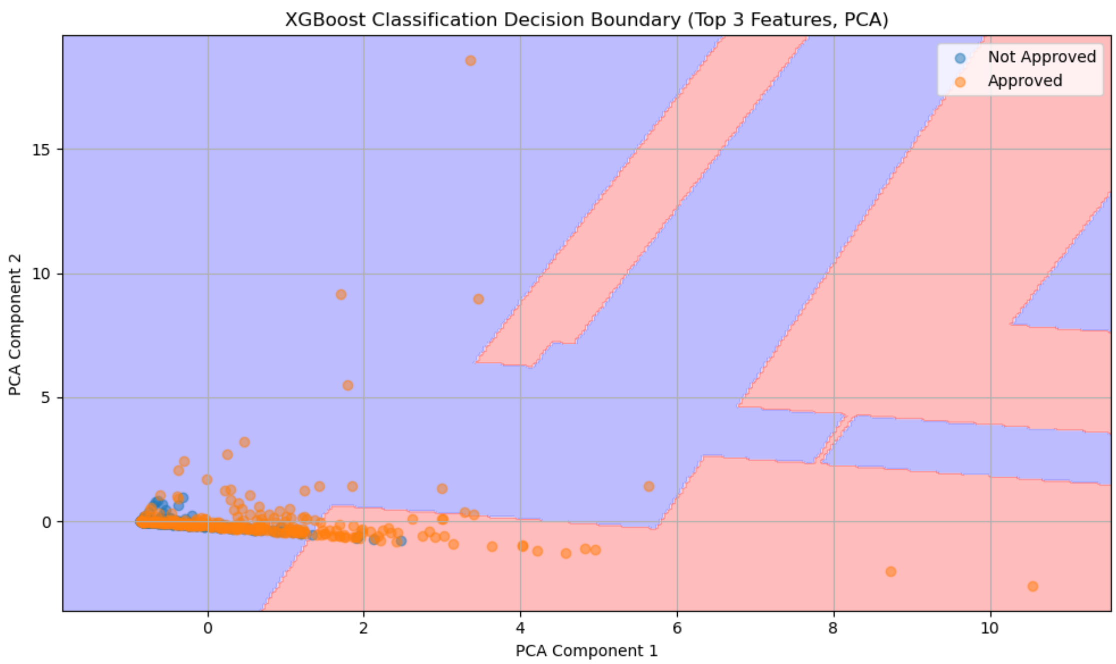
```
/opt/anaconda3/lib/python3.10/site-packages/xgboost/training.py:183:
UserWarning: [21:34:42] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```


XGBoost Tuned - Confusion Matrix (Top 3)
True label
Not Approved
Approved
88
22
25
61
Not Approved
Approved
Predicted label
80
70
60
50
40
30



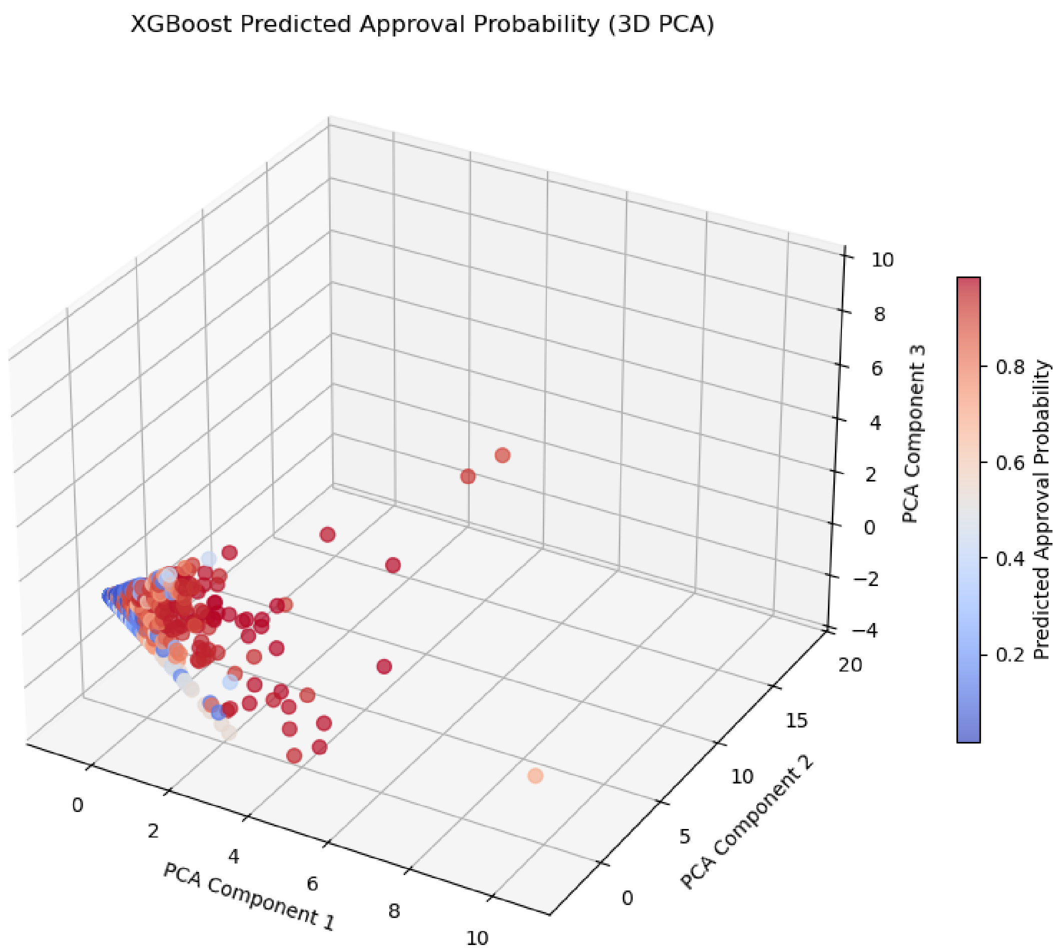
[61]:
```
from sklearn.decomposition import PCA

# Reduce to 2D using PCA for visualization
pca = PCA(n_components=2)
X_all_scaled = scaler_lr.fit_transform(X)  # scale full dataset
X_pca = pca.fit_transform(X_all_scaled)
y_all = y  # labels for the whole dataset

# Create meshgrid for decision boundary
x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
                     np.linspace(y_min, y_max, 300))
grid = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca.inverse_transform(grid)
grid_pred = xgb_tuned.predict(grid_original).reshape(xx.shape)

# Plot decision surface with data points
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, grid_pred, alpha=0.3, cmap='bwr')
```

```
plt.scatter(X_pca[y_all == 0, 0], X_pca[y_all == 0, 1], label="Not Approved",␣
    ↪alpha=0.5)
plt.scatter(X_pca[y_all == 1, 0], X_pca[y_all == 1, 1], label="Approved",␣
    ↪alpha=0.5)
plt.title("XGBoost Classification Decision Boundary (Top 3 Features, PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



[63]:
```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Top 3 features and labels
top3_features = ['A11', 'A15', 'A8']
X = df_encoded[top3_features].values
y = df_encoded["A16 (Class)"].values

# Scale before PCA
scaler = StandardScaler()
```

```python
X_scaled = scaler.fit_transform(X)

# 3D PCA
pca_3d = PCA(n_components=3)
X_pca_3d = pca_3d.fit_transform(X_scaled)

# Get predicted probabilities from XGBoost
y_probs = xgb_tuned.predict_proba(X)[:, 1]  # probability of approval

# 3D scatter plot colored by predicted probability
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
scatter = ax.scatter(
    X_pca_3d[:, 0], X_pca_3d[:, 1], X_pca_3d[:, 2],
    c=y_probs, cmap='coolwarm', s=50, alpha=0.7
)

ax.set_xlabel("PCA Component 1")
ax.set_ylabel("PCA Component 2")
ax.set_zlabel("PCA Component 3")
ax.set_title("XGBoost Predicted Approval Probability (3D PCA)")
cbar = fig.colorbar(scatter, ax=ax, shrink=0.5)
cbar.set_label("Predicted Approval Probability")

plt.tight_layout()
plt.show()
```

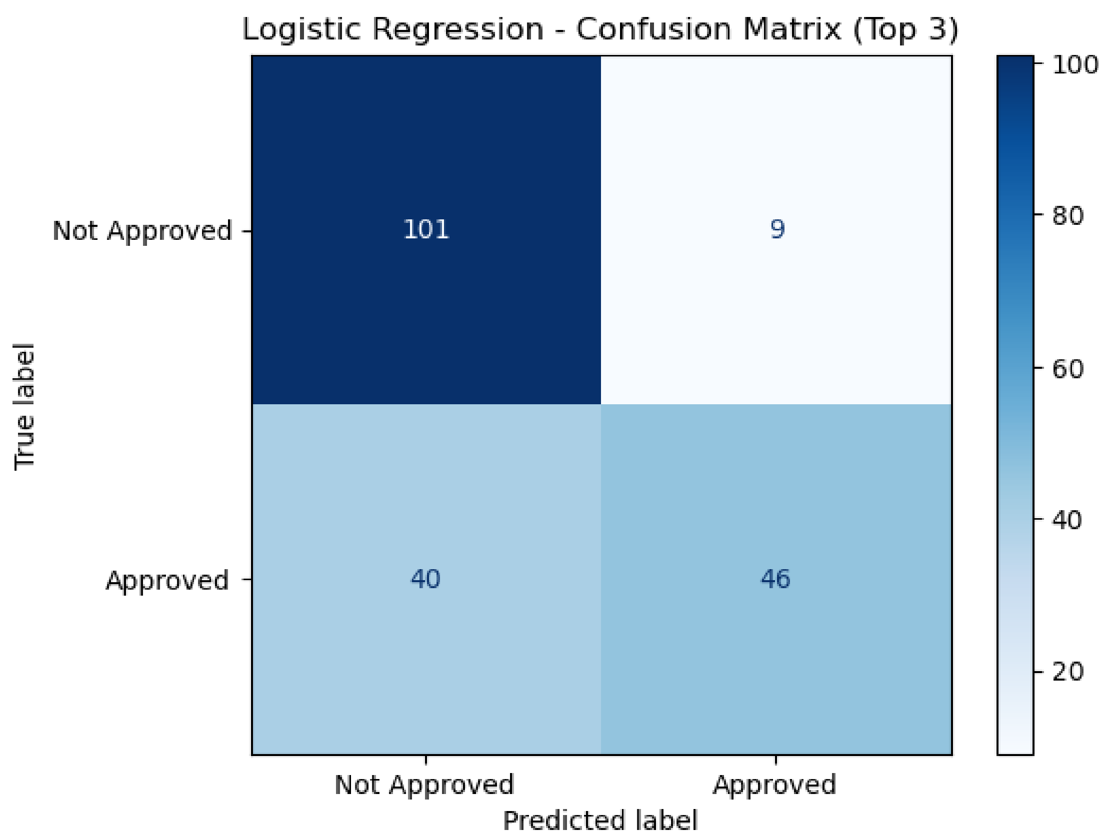


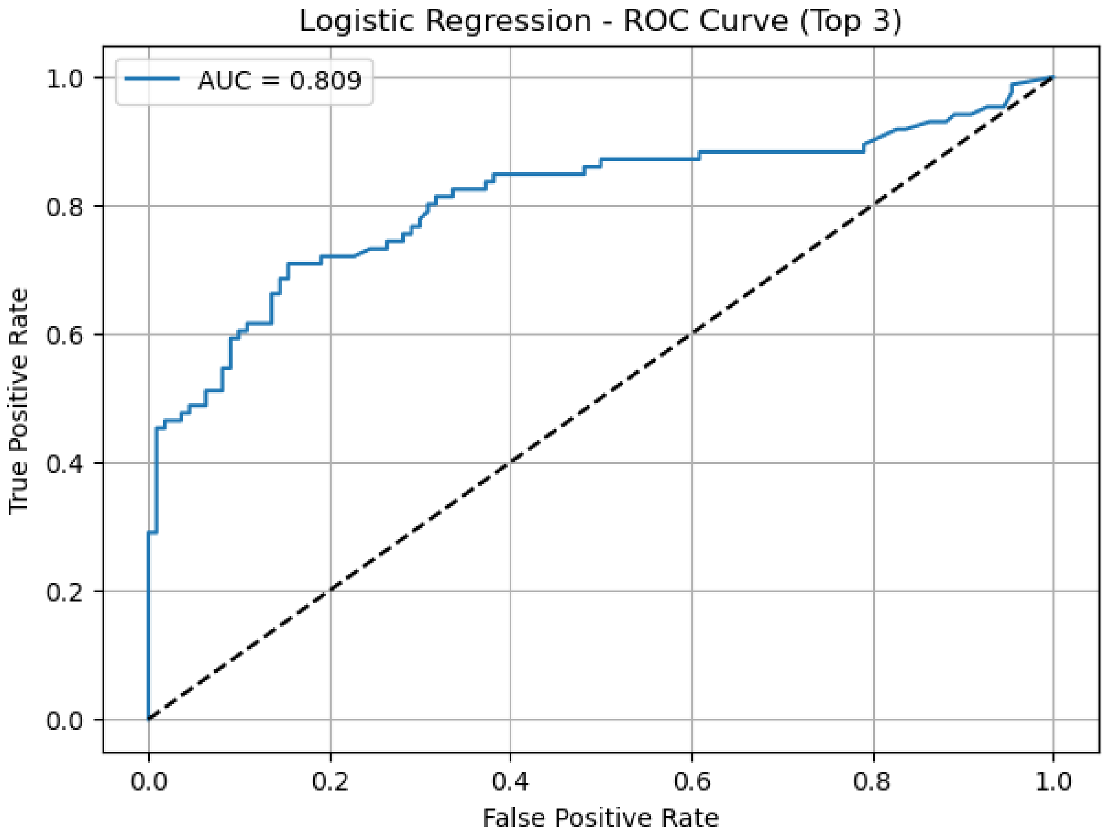
[71]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split


# Prepare top 3 features
top3_features = ['A11', 'A15', 'A8']
X = df_encoded[top3_features].values
y = df_encoded["A16 (Class)"].values
```

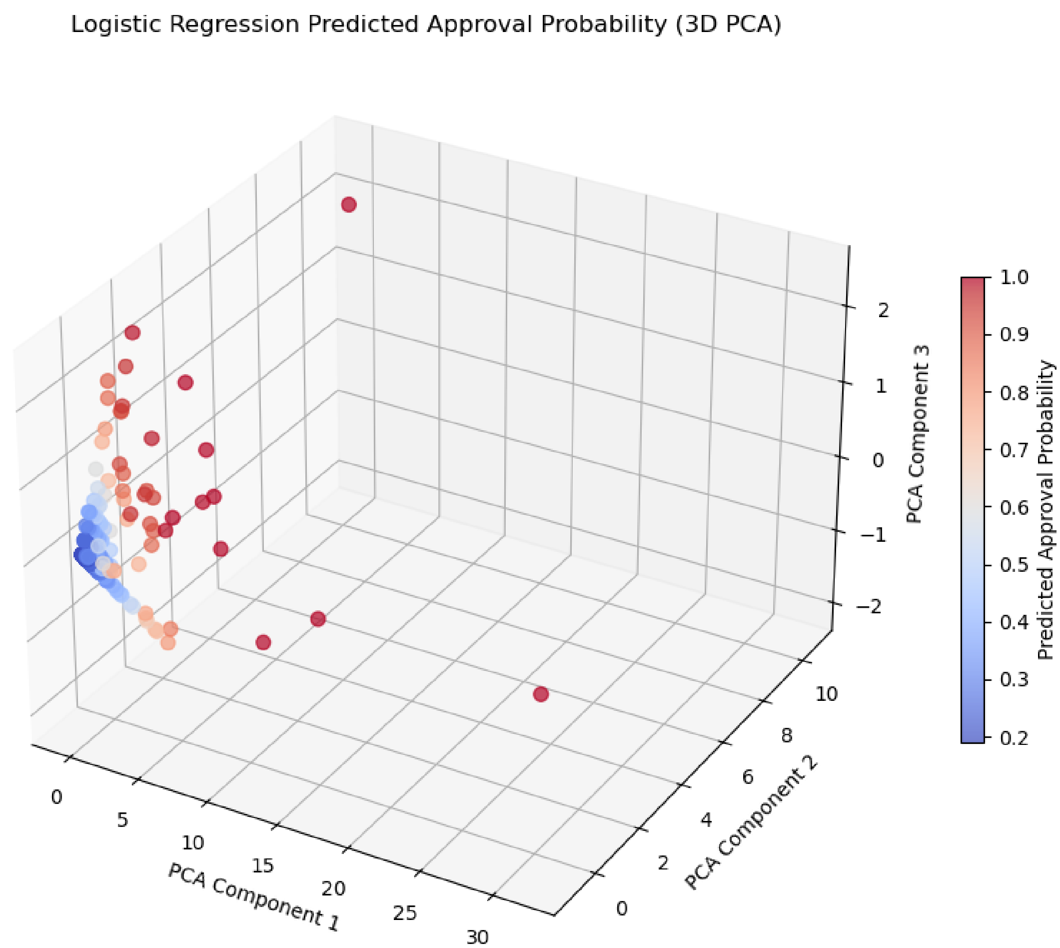
```python
# Split and scale
X_train_lr, X_test_lr, y_train_lr, y_test_lr = train_test_split(X, y,␣
 ↪test_size=0.3, random_state=42)
scaler_lr = StandardScaler()
X_train_lr_scaled = scaler_lr.fit_transform(X_train_lr)
X_test_lr_scaled = scaler_lr.transform(X_test_lr)

# Train logistic regression with L2 regularization
logreg = LogisticRegression(penalty='l2', C=1.0, solver='liblinear',␣
 ↪random_state=42)
logreg.fit(X_train_lr_scaled, y_train_lr)

# Predict and evaluate
y_pred_lr = logreg.predict(X_test_lr_scaled)
y_probs_lr = logreg.predict_proba(X_test_lr_scaled)[:, 1]
acc_lr = accuracy_score(y_test_lr, y_pred_lr)
auc_lr = roc_auc_score(y_test_lr, y_probs_lr)
cm_lr = confusion_matrix(y_test_lr, y_pred_lr)

# Print results
print(f" Logistic Regression Accuracy (Top 3): {acc_lr:.4f}")
print(f" Logistic Regression AUC (Top 3): {auc_lr:.4f}")

# Confusion Matrix
ConfusionMatrixDisplay(confusion_matrix=cm_lr, display_labels=["Not Approved",␣
 ↪"Approved"]).plot(cmap='Blues')
plt.title("Logistic Regression - Confusion Matrix (Top 3)")
plt.grid(False)
plt.show()

# ROC Curve
fpr_lr, tpr_lr, _ = roc_curve(y_test_lr, y_probs_lr)
plt.figure(figsize=(7, 5))
plt.plot(fpr_lr, tpr_lr, label=f"AUC = {auc_lr:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Logistic Regression - ROC Curve (Top 3)")
plt.legend()
plt.grid(True)
plt.show()

# === PCA 3D projection ===
pca = PCA(n_components=3)
X_pca = pca.fit_transform(X_test_lr_scaled)

# === Plot ===
```

```
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
scatter = ax.scatter(X_pca[:, 0], X_pca[:, 1], X_pca[:, 2],
                     c=y_probs_lr, cmap='coolwarm', s=50, alpha=0.7)

ax.set_xlabel("PCA Component 1")
ax.set_ylabel("PCA Component 2")
ax.set_zlabel("PCA Component 3")
ax.set_title("Logistic Regression Predicted Approval Probability (3D PCA)")
cbar = fig.colorbar(scatter, ax=ax, shrink=0.5)
cbar.set_label("Predicted Approval Probability")

plt.tight_layout()
plt.show()
```

```
Logistic Regression Accuracy (Top 3): 0.7500
Logistic Regression AUC (Top 3): 0.8094
```

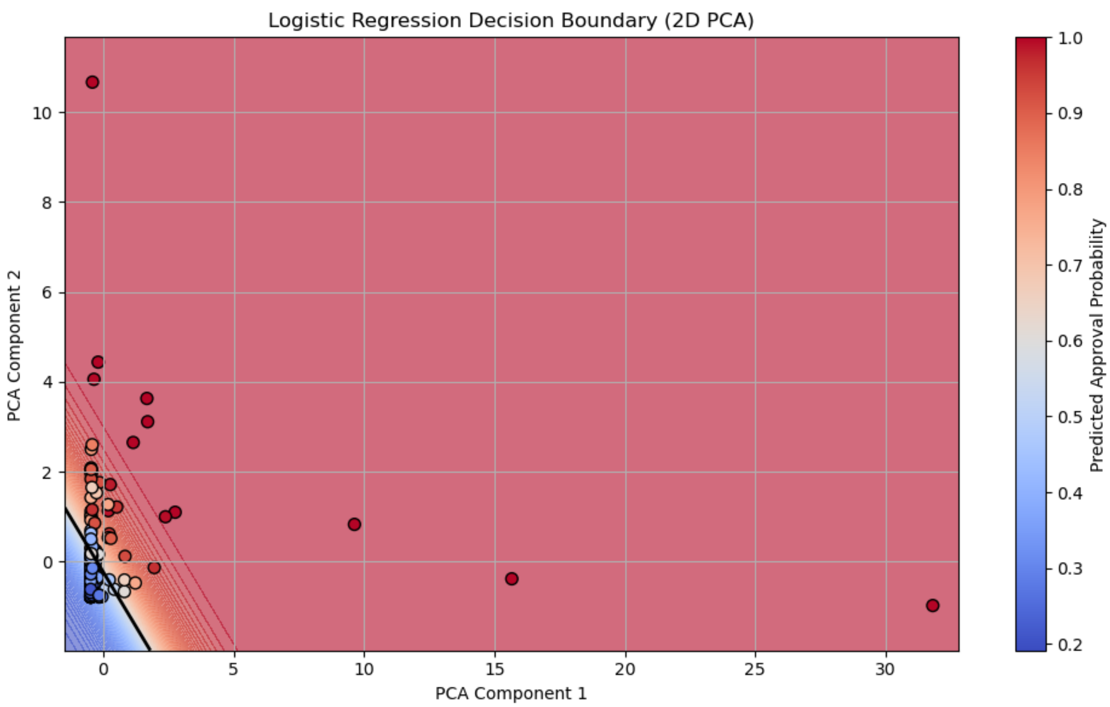



Logistic Regression - ROC Curve (Top 3)
AUC = 0.809
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



[74]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split


# === PCA (2D) ===
pca = PCA(n_components=2)
X_test_pca = pca.fit_transform(X_test_scaled)

# === Create meshgrid in PCA space ===
x_min, x_max = X_test_pca[:, 0].min() - 1, X_test_pca[:, 0].max() + 1
y_min, y_max = X_test_pca[:, 1].min() - 1, X_test_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
```

```
                     np.linspace(y_min, y_max, 300))
grid_pca = np.c_[xx.ravel(), yy.ravel()]

# === Inverse transform the grid to model feature space ===
grid_original = pca.inverse_transform(grid_pca)
Z = logreg.predict_proba(grid_original)[:, 1].reshape(xx.shape)

# === Plot ===
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)  # decision␣
↪boundary
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_probs, cmap='coolwarm',␣
↪s=50, edgecolors='k')
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("Logistic Regression Decision Boundary (2D PCA)")
cbar = plt.colorbar()
cbar.set_label("Predicted Approval Probability")
plt.grid(True)
plt.tight_layout()
plt.show()
```

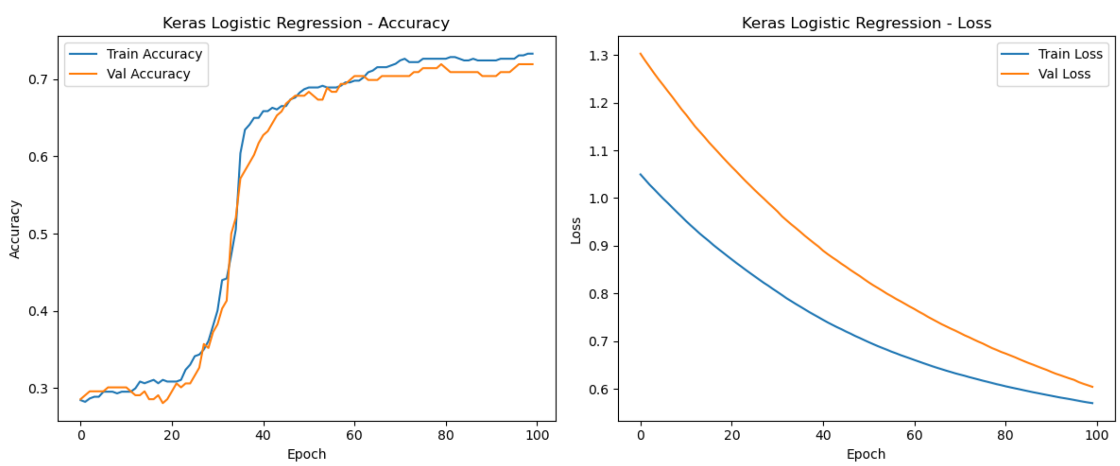


13.1 LOGISTIC REGRESSION

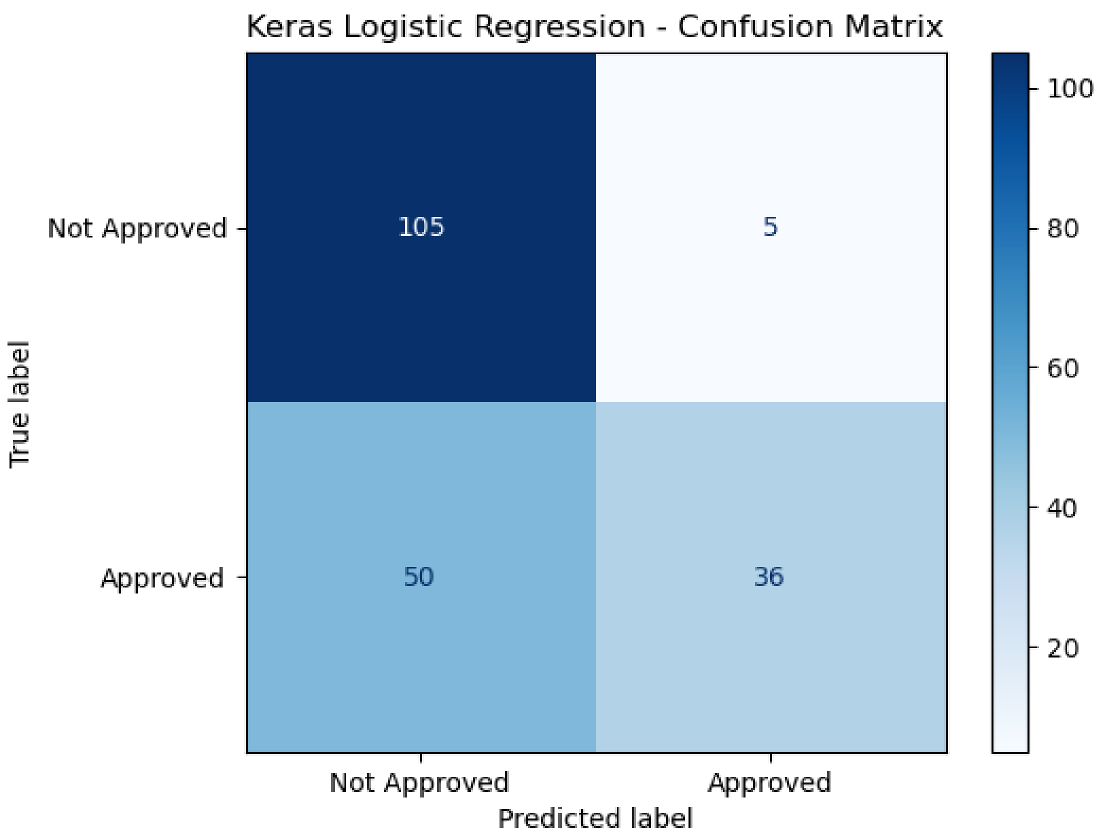
[75]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import AUC

# Load and preprocess your data
top3_features = ['A11', 'A15', 'A8']
X = df_encoded[top3_features].values
y = df_encoded["A16 (Class)"].values

# Train/val split
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Scale
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Keras model: logistic regression = 1-layer NN
model = Sequential([
    Dense(1, activation='sigmoid', input_shape=(X_train_scaled.shape[1],))
])

model.compile(optimizer=Adam(learning_rate=0.001),
              loss=BinaryCrossentropy(),
              metrics=['accuracy', AUC(name="auc")])

# Train
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Plot accuracy & loss
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
```

```
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("Keras Logistic Regression - Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("Keras Logistic Regression - Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()

# Confusion matrix
y_pred = (model.predict(X_val_scaled) > 0.5).astype(int)
cm = confusion_matrix(y_val, y_pred)
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not Approved",␣
↪"Approved"]).plot(cmap='Blues')
plt.title("Keras Logistic Regression - Confusion Matrix")
plt.grid(False)
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```

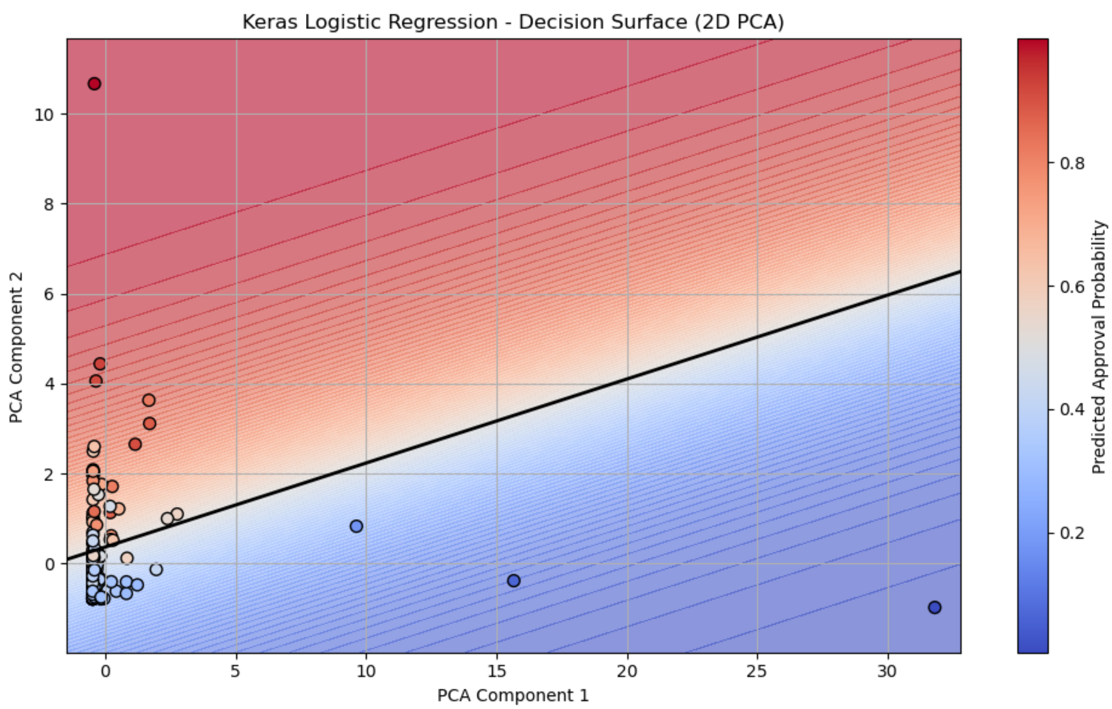



```
7/7 [==============================] - 0s 433us/step
```



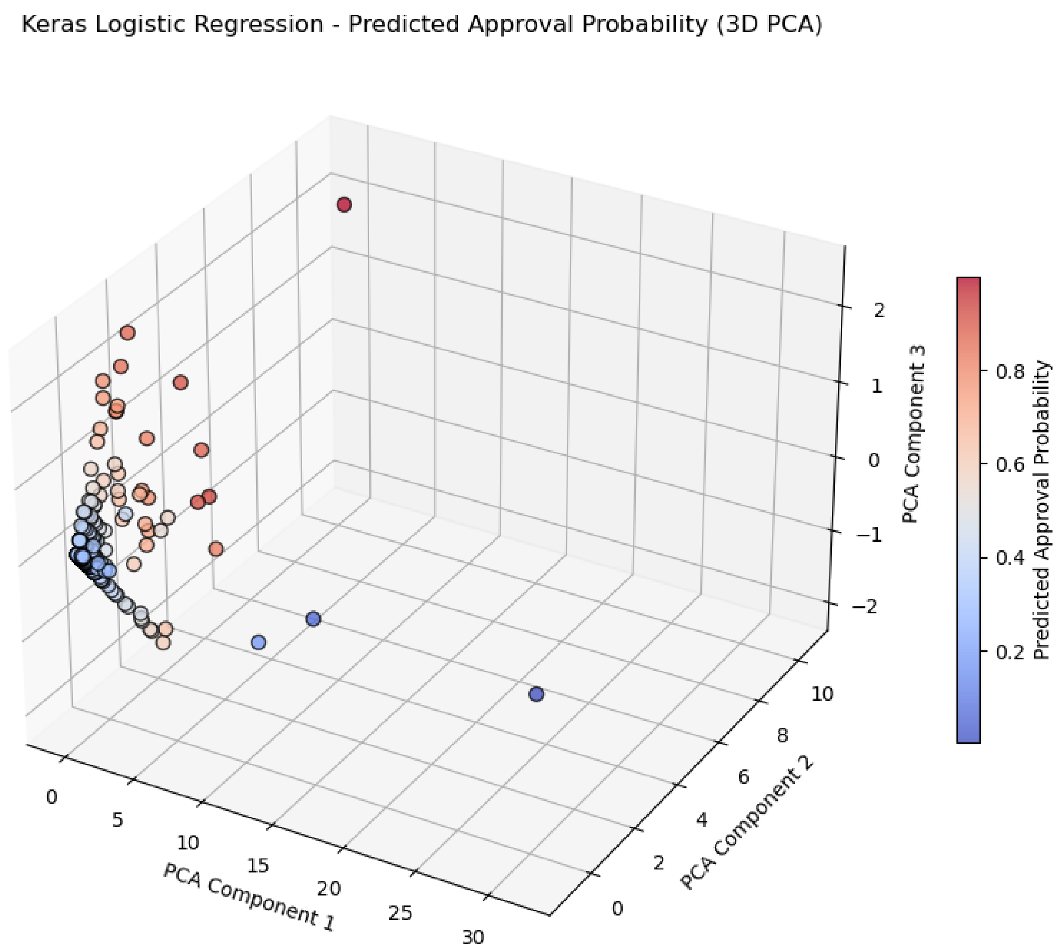
[76]:
```python
from sklearn.decomposition import PCA
import numpy as np
import matplotlib.pyplot as plt

# === 2D PCA projection of scaled test set ===
pca = PCA(n_components=2)
X_test_pca = pca.fit_transform(X_val_scaled)

# === Create meshgrid for PCA space ===
x_min, x_max = X_test_pca[:, 0].min() - 1, X_test_pca[:, 0].max() + 1
y_min, y_max = X_test_pca[:, 1].min() - 1, X_test_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
                     np.linspace(y_min, y_max, 300))
grid_pca = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca.inverse_transform(grid_pca)

# === Predict on grid to get decision surface ===
Z = model.predict(grid_original, verbose=0).reshape(xx.shape)

# === Predict on actual test points ===
```

```
y_probs = model.predict(X_val_scaled, verbose=0).flatten()

# === Plot ===
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)  # decision␣
    ↪boundary
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_probs, cmap='coolwarm',␣
    ↪s=50, edgecolor='k')
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.title("Keras Logistic Regression - Decision Surface (2D PCA)")
cbar = plt.colorbar()
cbar.set_label("Predicted Approval Probability")
plt.grid(True)
plt.tight_layout()
plt.show()
```



[77]:
```
from mpl_toolkits.mplot3d import Axes3D
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# === 3D PCA projection of scaled validation set ===
pca_3d = PCA(n_components=3)
```

```
X_val_pca_3d = pca_3d.fit_transform(X_val_scaled)

# === Predicted probabilities from Keras model ===
y_probs_keras = model.predict(X_val_scaled, verbose=0).flatten()

# === 3D scatter plot ===
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

scatter = ax.scatter(
    X_val_pca_3d[:, 0], X_val_pca_3d[:, 1], X_val_pca_3d[:, 2],
    c=y_probs_keras, cmap='coolwarm', s=50, alpha=0.75, edgecolor='k'
)

ax.set_xlabel("PCA Component 1")
ax.set_ylabel("PCA Component 2")
ax.set_zlabel("PCA Component 3")
ax.set_title("Keras Logistic Regression - Predicted Approval Probability (3D␣
 ↪PCA)")
cbar = fig.colorbar(scatter, ax=ax, shrink=0.5)
cbar.set_label("Predicted Approval Probability")

plt.tight_layout()
plt.show()
```



14 NONLINEAR REGRESSION

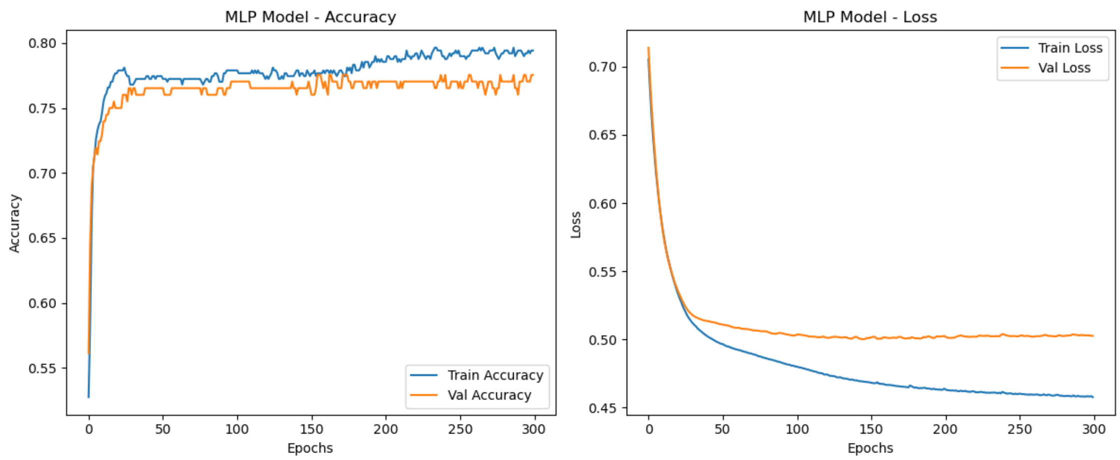
[107]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import AUC
from tensorflow.keras import regularizers
from tensorflow.keras.optimizers import RMSprop
```

```python
# === Use top 3 predictors ===
top3_features = ['A11', 'A15', 'A8']
X = df_encoded[top3_features].values
y = df_encoded["A16 (Class)"].values

# === Train/val split + scaling ===
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# # L2 Regularization
# Dense(16, activation='relu', kernel_regularizer=regularizers.l2(0.003))

# # === Build nonlinear model (MLP) ===
# model = Sequential([
#     Dense(16, activation='relu', input_shape=(X_train_scaled.shape[1],)),
#     Dense(8, activation='relu'),
#     Dense(1, activation='sigmoid')  # output layer for binary classification
# ])

# model.compile(optimizer=Adam(learning_rate=0.0005),
#               loss=BinaryCrossentropy(),
#               metrics=['accuracy', AUC(name="auc")])

# model.compile(optimizer = RMSprop(learning_rate=0.0005),
#               loss=BinaryCrossentropy(),
#               metrics=['accuracy', AUC(name="auc")])

model = Sequential([
    Dense(16, activation='relu', kernel_regularizer=regularizers.l2(0.001),␣
↪input_shape=(X_train.shape[1],)),
    Dense(8, activation='relu', kernel_regularizer=regularizers.l2(0.001)),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer=Adam(learning_rate=0.002),
              loss='binary_crossentropy',
              metrics=['accuracy'])



# === Train the model ===
history = model.fit(X_train_scaled, y_train,
```

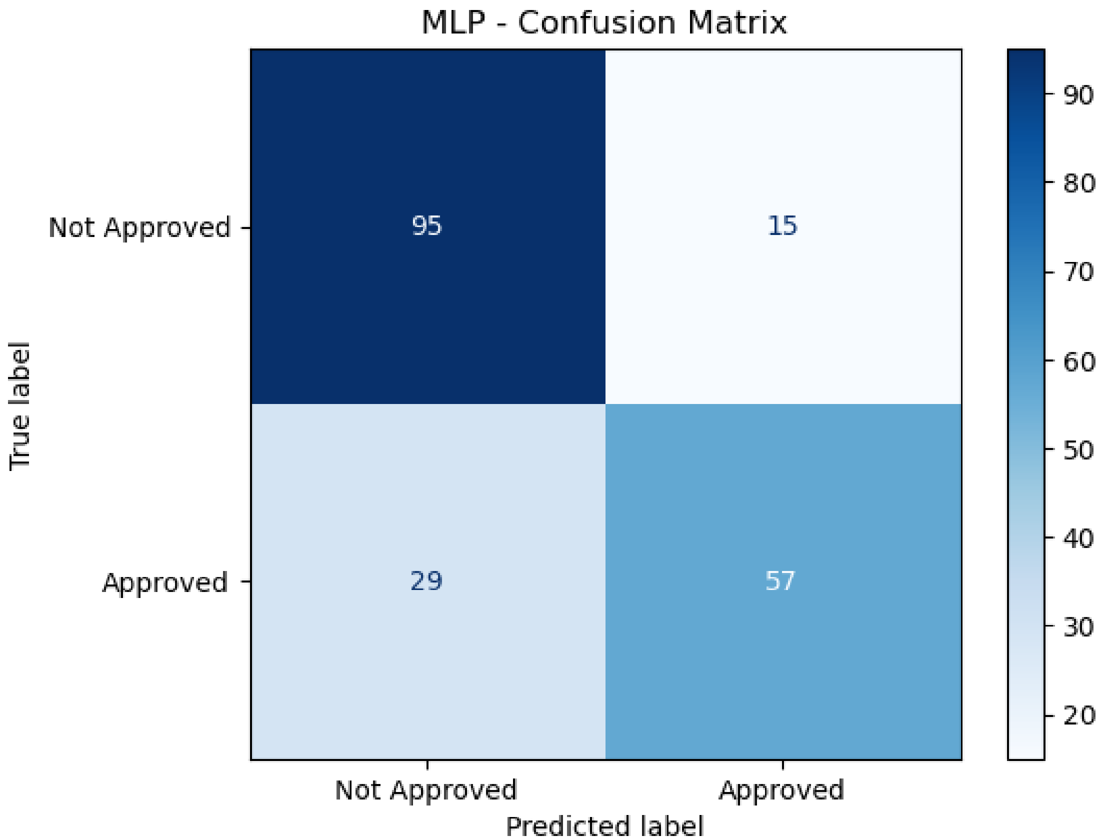
```
                    validation_data=(X_val_scaled, y_val),
                    epochs=300, batch_size=128, verbose=0)

# === Plot Accuracy and Loss ===
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("MLP Model - Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("MLP Model - Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()

# === Confusion Matrix ===
y_pred = (model.predict(X_val_scaled) > 0.5).astype(int)
cm = confusion_matrix(y_val, y_pred)
ConfusionMatrixDisplay(cm, display_labels=["Not Approved", "Approved"]).
 ↪plot(cmap='Blues')
plt.title("MLP - Confusion Matrix")
plt.grid(False)
plt.show()

# Predictions
y_probs = model.predict(X_val_scaled).flatten()
y_preds = (y_probs > 0.5).astype(int)



# ROC Curve
fpr, tpr, _ = roc_curve(y_val, y_probs)
auc_val = roc_auc_score(y_val, y_probs)
plt.figure()
plt.plot(fpr, tpr, label=f"AUC = {auc_val:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve")
```

```
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.legend()
plt.grid(True)
plt.show()
```

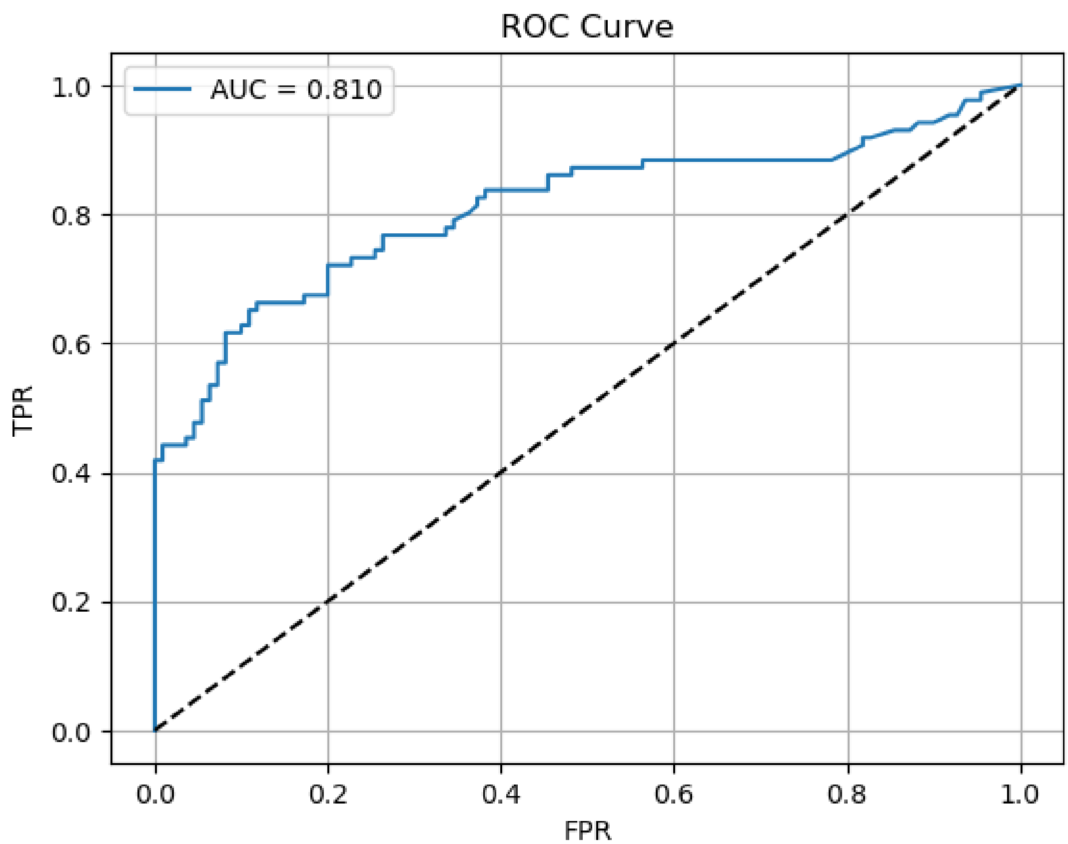
```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```




```
7/7 [==============================] - 0s 371us/step
```




```
7/7 [==============================] - 0s 366us/step
```



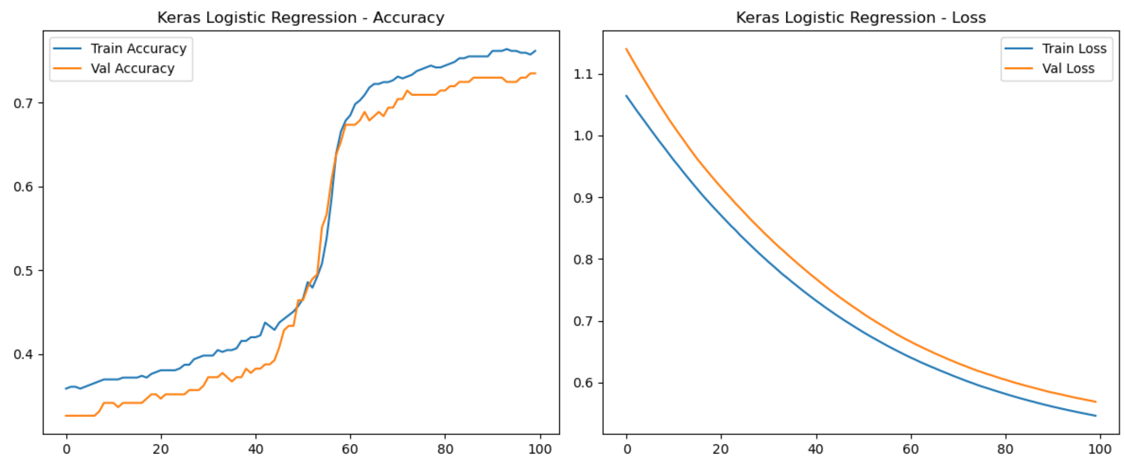
15 5 Features

[105]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪roc_curve, roc_auc_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import AUC
import matplotlib.pyplot as plt

# Features and target
top5_features = ['A11', 'A15', 'A8', 'A13_p', 'A7_ff']
X = df_encoded[top5_features].values
y = df_encoded["A16 (Class)"].values

# Train/test split and scaling
```

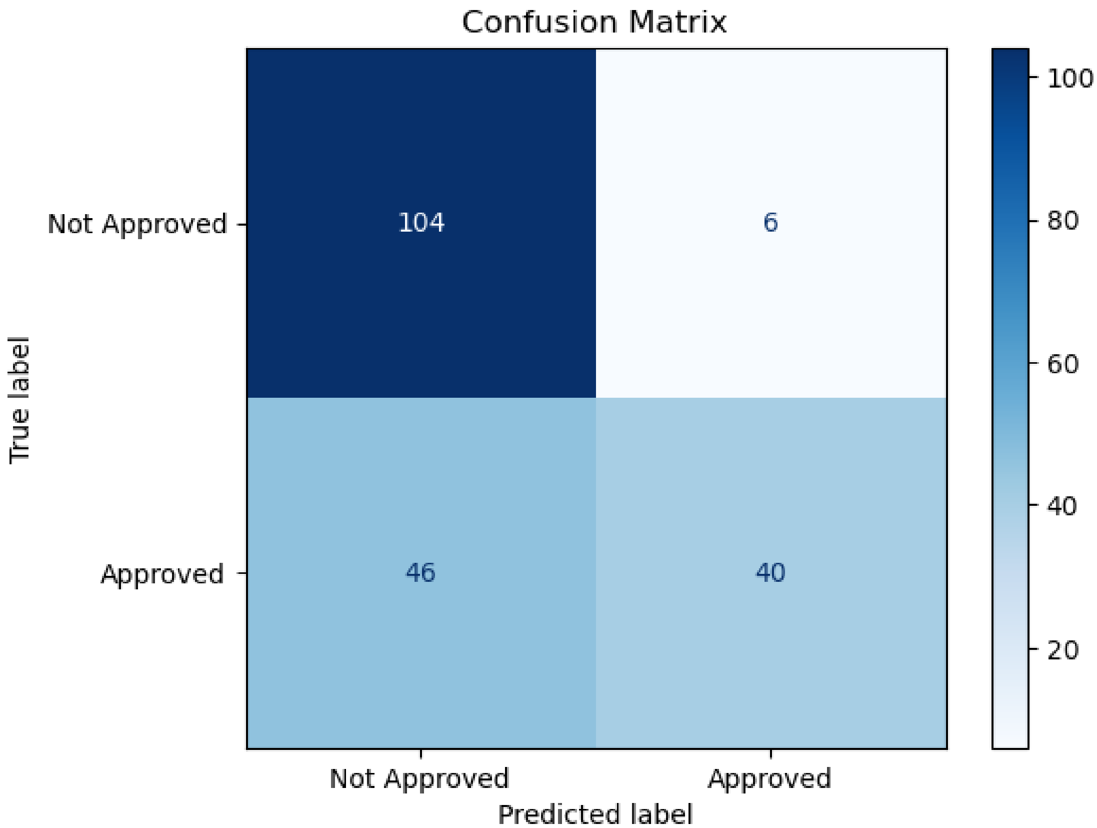
```
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Define model
model = Sequential([
    Dense(1, activation='sigmoid', input_shape=(X_train_scaled.shape[1],))
])
model.compile(optimizer=Adam(learning_rate=0.001),
              loss=BinaryCrossentropy(),
              metrics=['accuracy', AUC(name="auc")])

# Train
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Accuracy/Loss Plots
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("Keras Logistic Regression - Accuracy")
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("Keras Logistic Regression - Loss")
plt.legend()
plt.tight_layout()
plt.show()

# Predictions
y_probs = model.predict(X_val_scaled).flatten()
y_preds = (y_probs > 0.5).astype(int)

# Confusion Matrix
cm = confusion_matrix(y_val, y_preds)
ConfusionMatrixDisplay(cm, display_labels=["Not Approved", "Approved"]).
↪plot(cmap='Blues')
plt.title("Confusion Matrix")
plt.grid(False)
plt.show()

# ROC Curve
```

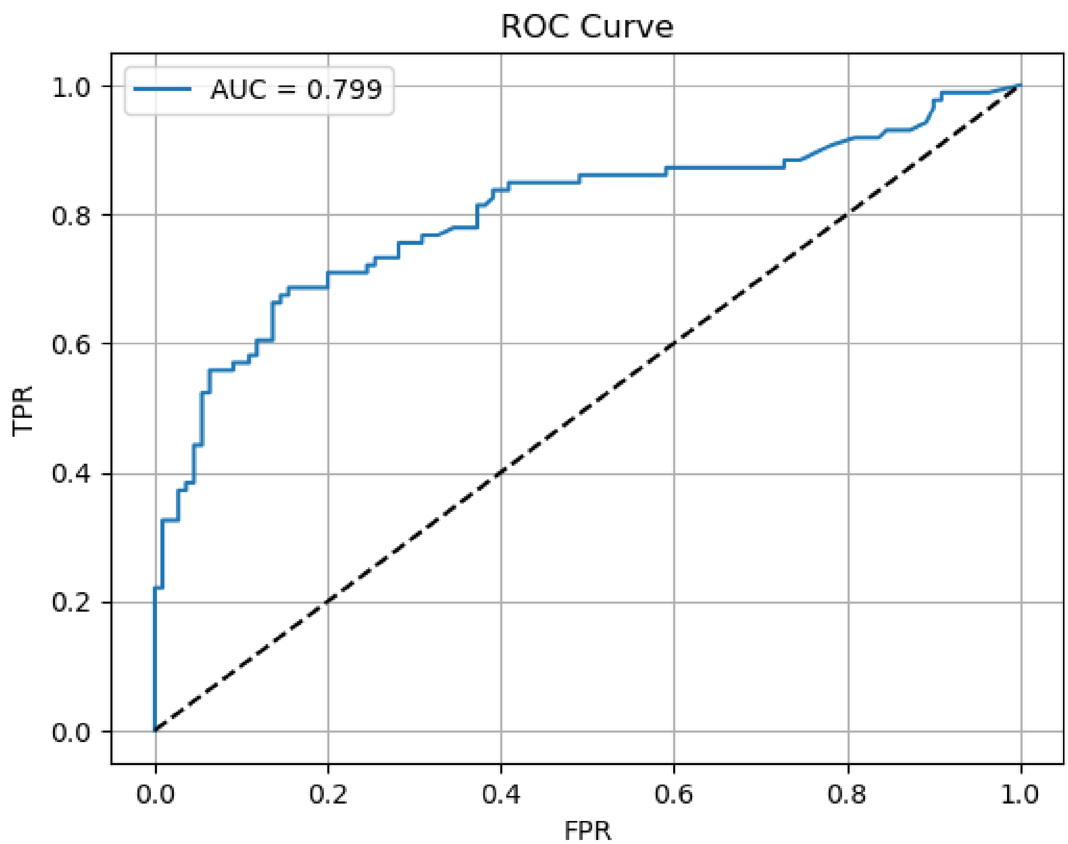
```python
fpr, tpr, _ = roc_curve(y_val, y_probs)
auc_val = roc_auc_score(y_val, y_probs)
plt.figure()
plt.plot(fpr, tpr, label=f"AUC = {auc_val:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("ROC Curve")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.legend()
plt.grid(True)
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```




```
7/7 [==============================] - 0s 430us/step
```


Confusion Matrix
Not Approved
Approved
True label
104
6
46
40
Not Approved
Approved
Predicted label
100
80
60
40
20

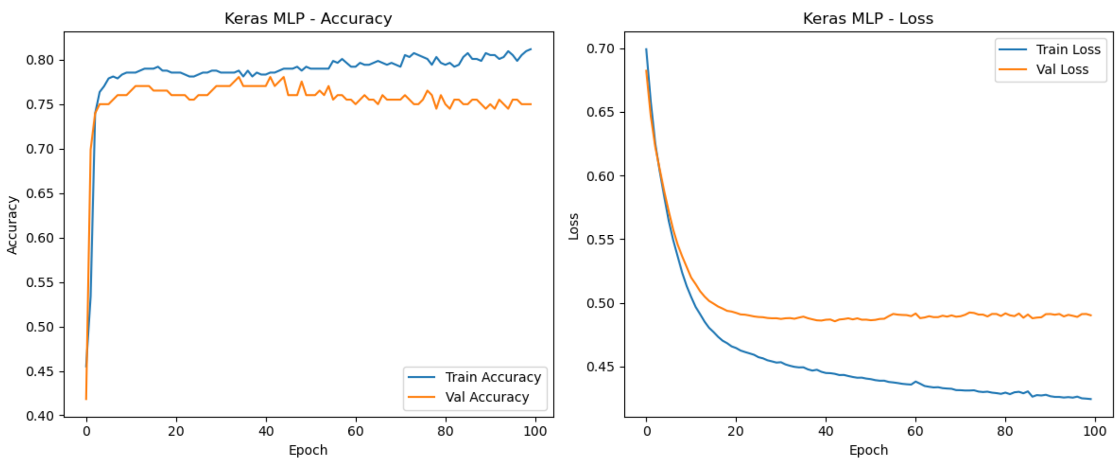


[108]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import AUC
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Features and target
top5_features = ['A11', 'A15', 'A8', 'A13_p', 'A7_ff']
X = df_encoded[top5_features].values
y = df_encoded["A16 (Class)"].values

# Train/test split and scaling
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

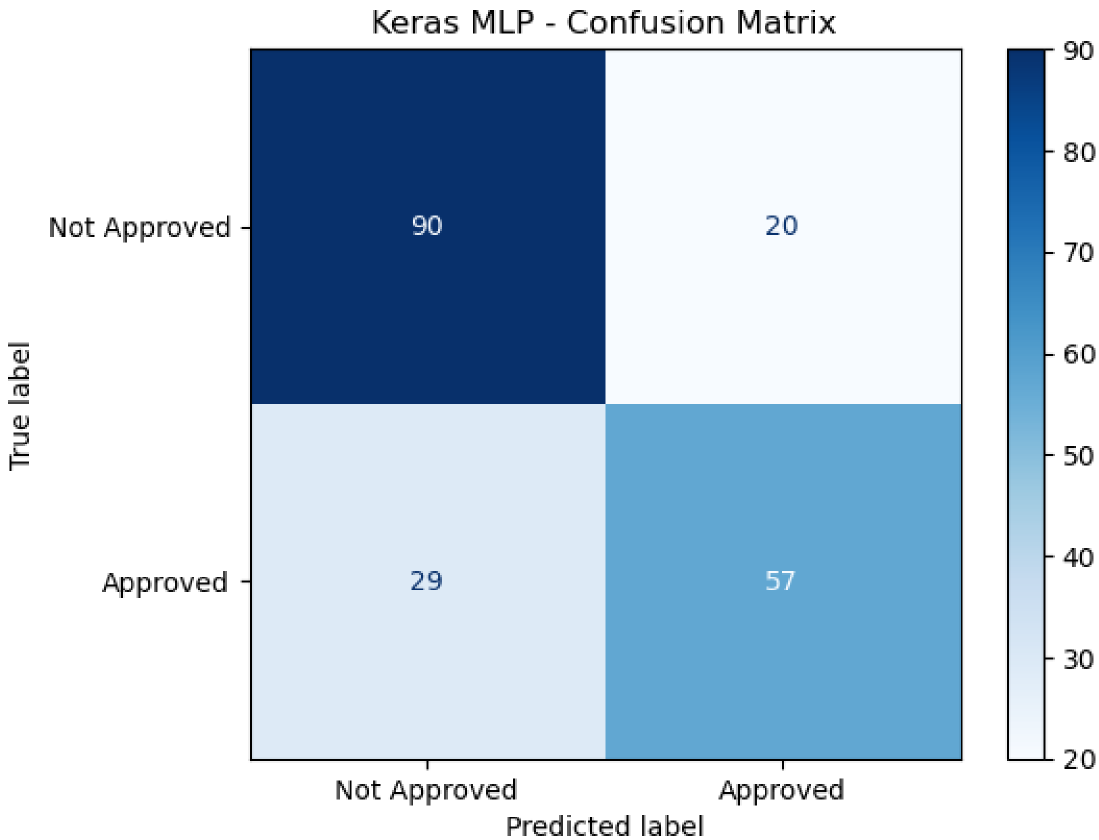
```python
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Define MLP model
model = Sequential([
    Dense(16, activation='relu', input_shape=(X_train_scaled.shape[1],)),
    Dense(8, activation='relu'),
    Dense(1, activation='sigmoid')
])
model.compile(optimizer=Adam(learning_rate=0.001),
              loss=BinaryCrossentropy(),
              metrics=['accuracy', AUC(name="auc")])

# Train model
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=100, batch_size=32, verbose=0)

# Plot accuracy and loss
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("Keras MLP - Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("Keras MLP - Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.tight_layout()
plt.show()

# Predict
y_probs = model.predict(X_val_scaled).flatten()
y_preds = (y_probs > 0.5).astype(int)

# Confusion Matrix
cm = confusion_matrix(y_val, y_preds)
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not Approved",␣
 ↪"Approved"]).plot(cmap='Blues')
plt.title("Keras MLP - Confusion Matrix")
```

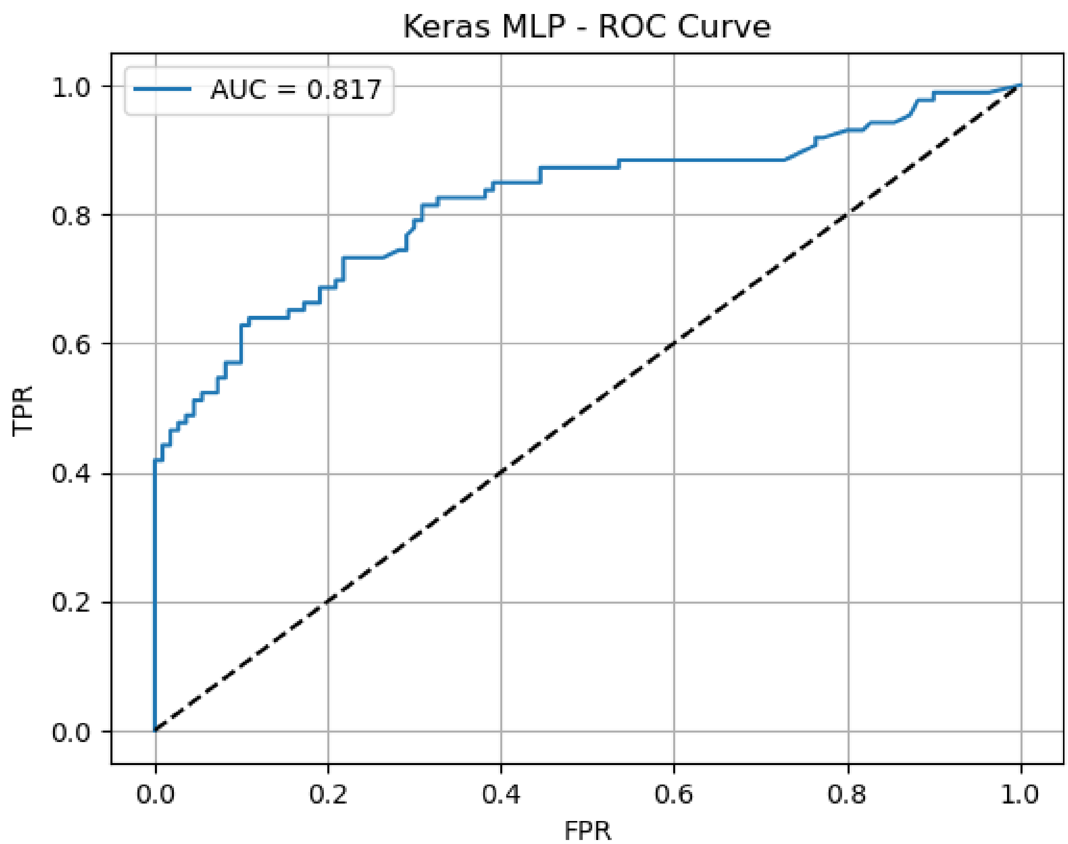
```python
plt.grid(False)
plt.show()

# ROC Curve
fpr, tpr, _ = roc_curve(y_val, y_probs)
auc_val = roc_auc_score(y_val, y_probs)
plt.figure()
plt.plot(fpr, tpr, label=f"AUC = {auc_val:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("Keras MLP - ROC Curve")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.legend()
plt.grid(True)
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```




```
7/7 [==============================] - 0s 602us/step
```

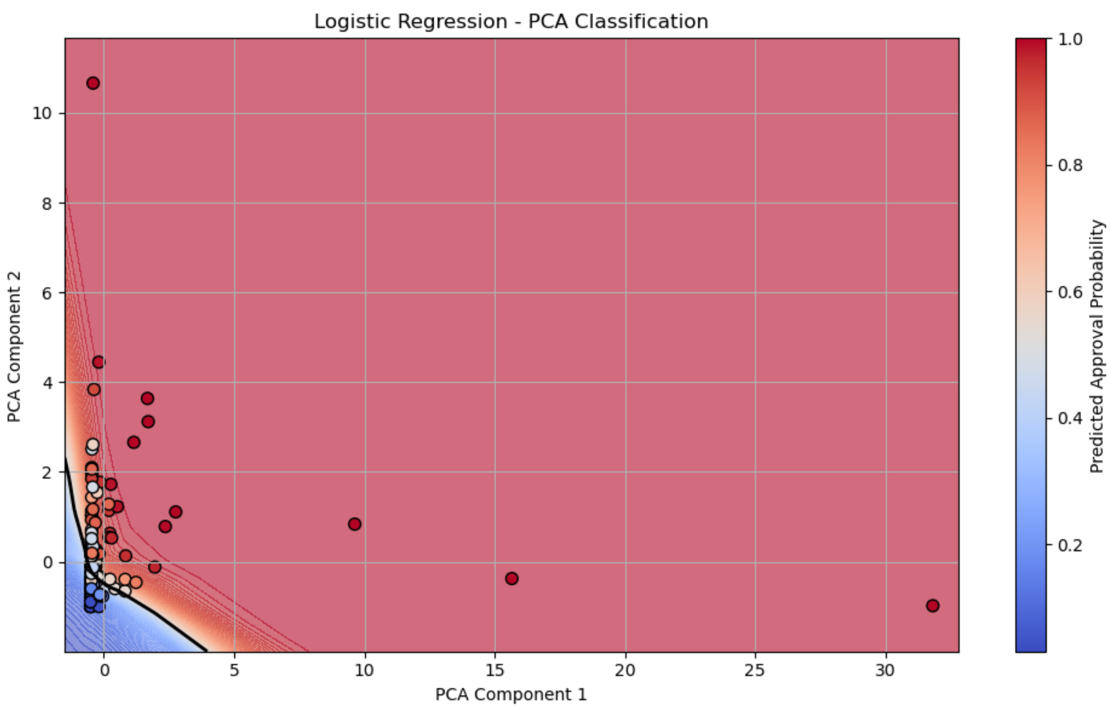

Keras MLP - Confusion Matrix
True label
Predicted label
Not Approved
Approved
Not Approved
Approved
90
20
29
57
90
80
70
60
50
40
30
20

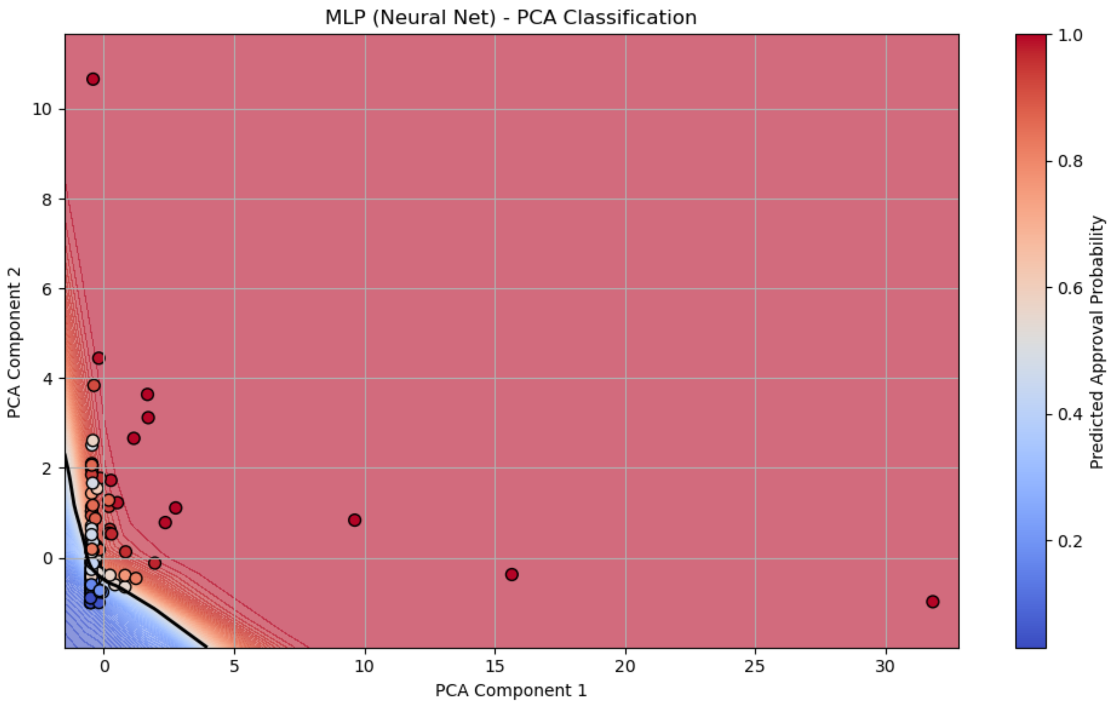


[109]:
```python
from sklearn.decomposition import PCA
import numpy as np
import matplotlib.pyplot as plt

def plot_pca_classification(model, X_val_scaled, y_probs, title):
    # PCA to 2D
    pca = PCA(n_components=2)
    X_pca = pca.fit_transform(X_val_scaled)

    # Create meshgrid in PCA space
    x_min, x_max = X_pca[:, 0].min() - 1, X_pca[:, 0].max() + 1
    y_min, y_max = X_pca[:, 1].min() - 1, X_pca[:, 1].max() + 1
    xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
                         np.linspace(y_min, y_max, 300))
    grid_pca = np.c_[xx.ravel(), yy.ravel()]
    grid_original = pca.inverse_transform(grid_pca)

    # Predict on grid
    Z = model.predict(grid_original, verbose=0).reshape(xx.shape)
```

```
    # Plot
    plt.figure(figsize=(10, 6))
    plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
    plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)  #␣
↪decision boundary
    plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y_probs, cmap='coolwarm', s=50,␣
↪edgecolor='k')
    plt.xlabel("PCA Component 1")
    plt.ylabel("PCA Component 2")
    plt.title(title)
    cbar = plt.colorbar()
    cbar.set_label("Predicted Approval Probability")
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

[110]:
```
# Logistic Regression
y_probs_logreg = model.predict(X_val_scaled, verbose=0).flatten()
plot_pca_classification(model, X_val_scaled, y_probs_logreg,
                        "Logistic Regression - PCA Classification")

# MLP
y_probs_mlp = model.predict(X_val_scaled, verbose=0).flatten()
plot_pca_classification(model, X_val_scaled, y_probs_mlp,
                        "MLP (Neural Net) - PCA Classification")
```



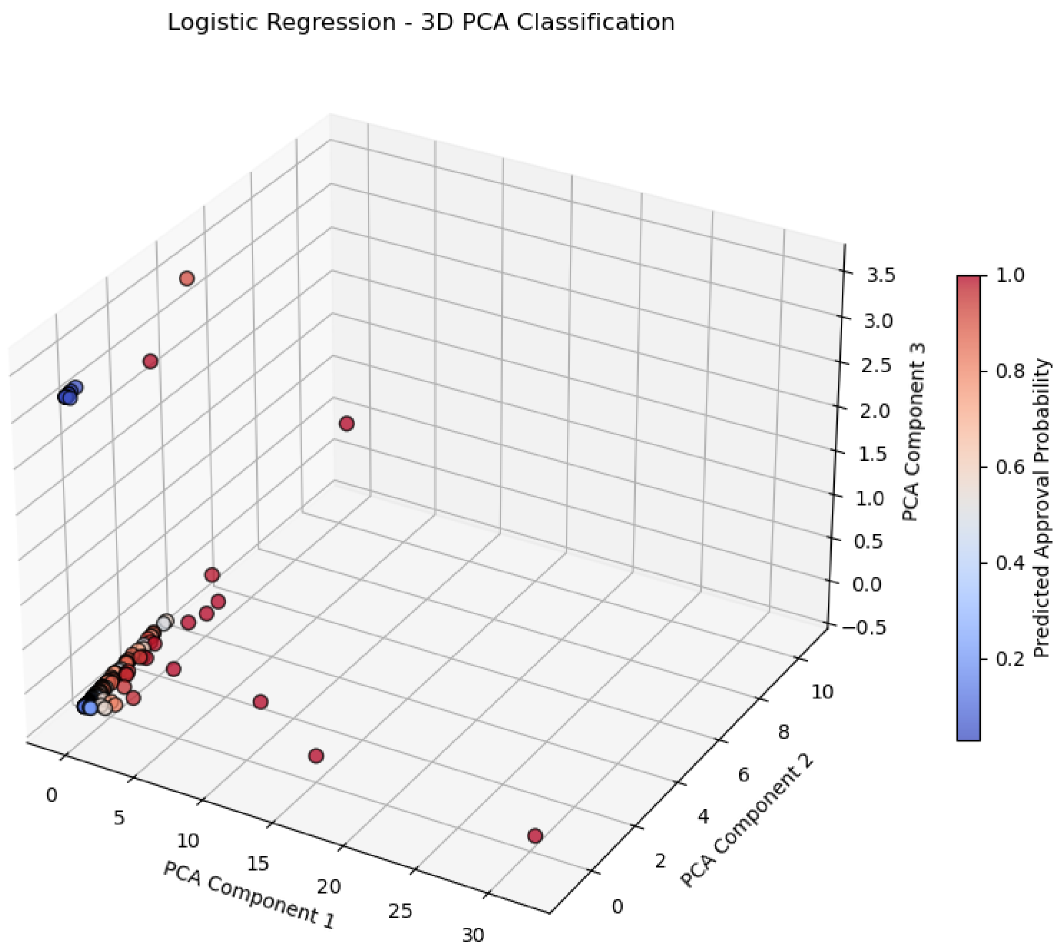


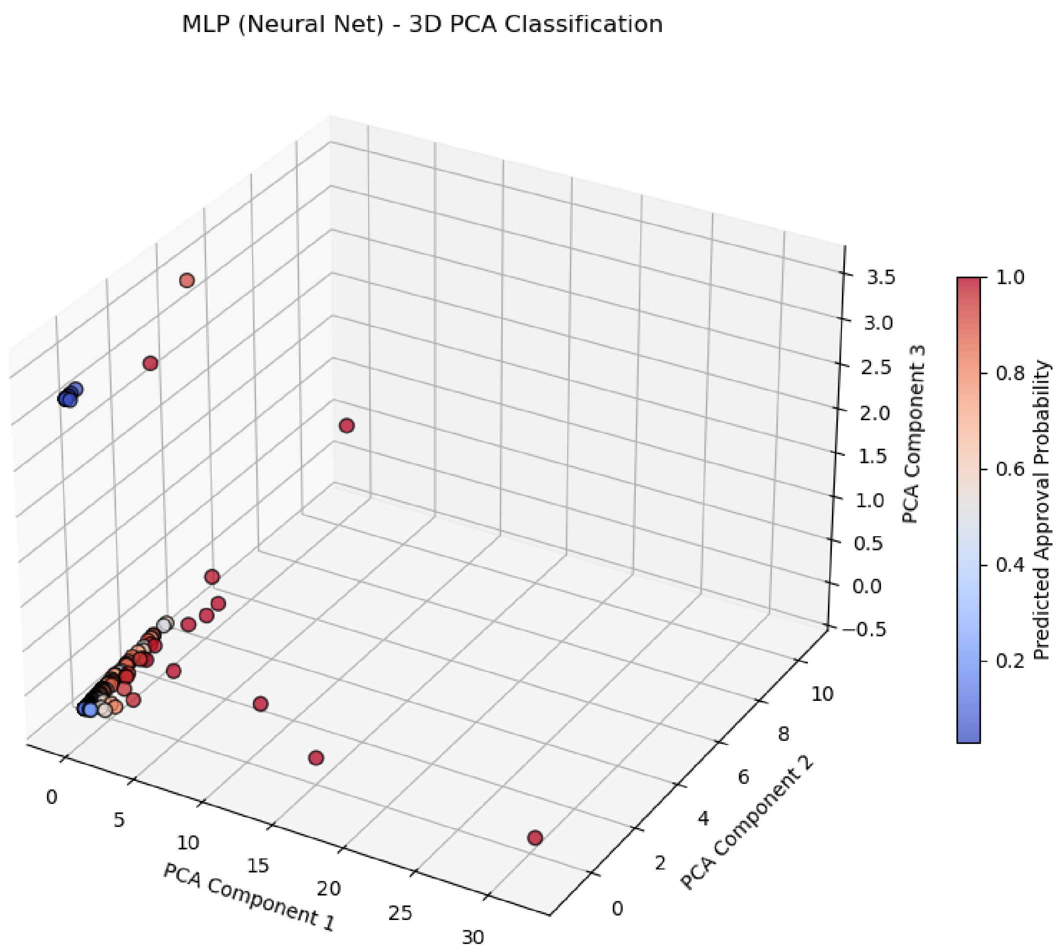
[111]:
```python
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

def plot_3d_pca_classification(model, X_val_scaled, y_probs, title):
    # 3D PCA projection
    pca = PCA(n_components=3)
    X_pca = pca.fit_transform(X_val_scaled)

    # Plot
    fig = plt.figure(figsize=(10, 7))
    ax = fig.add_subplot(111, projection='3d')
    scatter = ax.scatter(
        X_pca[:, 0], X_pca[:, 1], X_pca[:, 2],
        c=y_probs, cmap='coolwarm', s=50, alpha=0.75, edgecolor='k'
    )
    ax.set_xlabel("PCA Component 1")
    ax.set_ylabel("PCA Component 2")
    ax.set_zlabel("PCA Component 3")
    ax.set_title(title)
    cbar = fig.colorbar(scatter, ax=ax, shrink=0.5)
    cbar.set_label("Predicted Approval Probability")
    plt.tight_layout()
```

```
    plt.show()
```

[112]:

```
# Logistic Regression
y_probs_logreg = model.predict(X_val_scaled, verbose=0).flatten()
plot_3d_pca_classification(model, X_val_scaled, y_probs_logreg,
                           "Logistic Regression - 3D PCA Classification")

# MLP
y_probs_mlp = model.predict(X_val_scaled, verbose=0).flatten()
plot_3d_pca_classification(model, X_val_scaled, y_probs_mlp,
                           "MLP (Neural Net) - 3D PCA Classification")
```





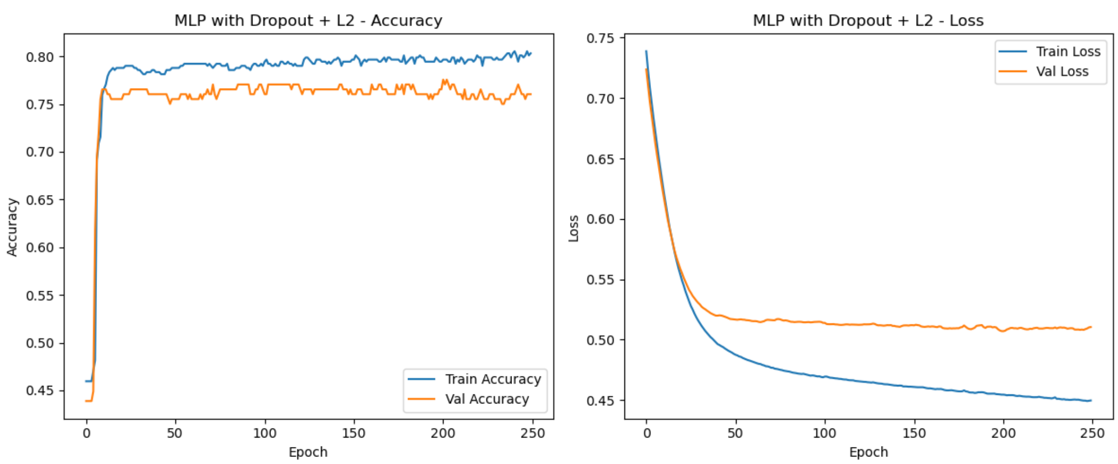
16 Dropout (removed) + L2 to MLP

[124]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.regularizers import l2
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from tensorflow.keras.metrics import AUC
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
 ↪roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Features and target
top5_features = ['A11', 'A15', 'A8', 'A13_p', 'A7_ff']
X = df_encoded[top5_features].values
```

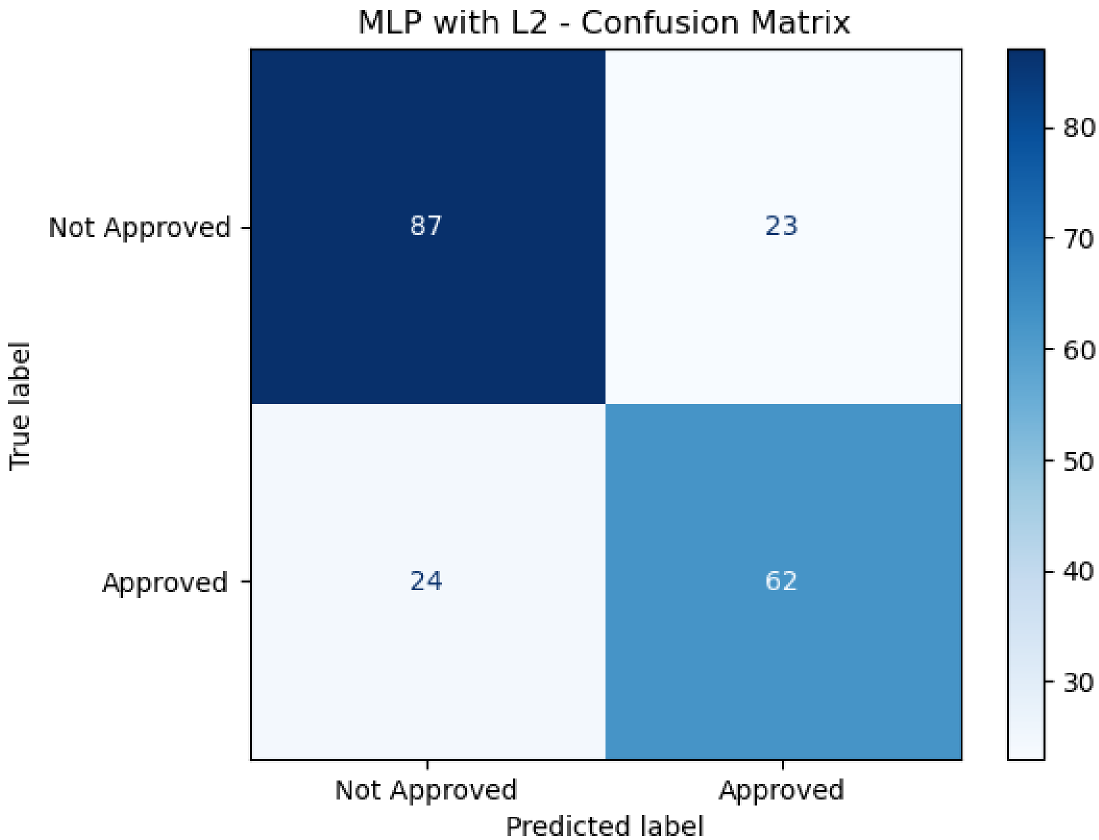
```
y = df_encoded["A16 (Class)"].values

# Train/test split and scaling
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)

# Build the model
model = Sequential([
    Dense(32, activation='relu', kernel_regularizer=l2(0.001),␣
↪input_shape=(X_train_scaled.shape[1],)),
    Dense(16, activation='relu', kernel_regularizer=l2(0.001)),
    Dense(1, activation='sigmoid')
])

model.compile(optimizer=Adam(learning_rate=0.0005),
              loss=BinaryCrossentropy(),
              metrics=['accuracy', AUC(name='auc')])

# Train the model
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_val_scaled, y_val),
                    epochs=250, batch_size=64, verbose=0)

# Plot accuracy and loss
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.title("MLP with Dropout + L2 - Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title("MLP with Dropout + L2 - Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.tight_layout()
plt.show()
```

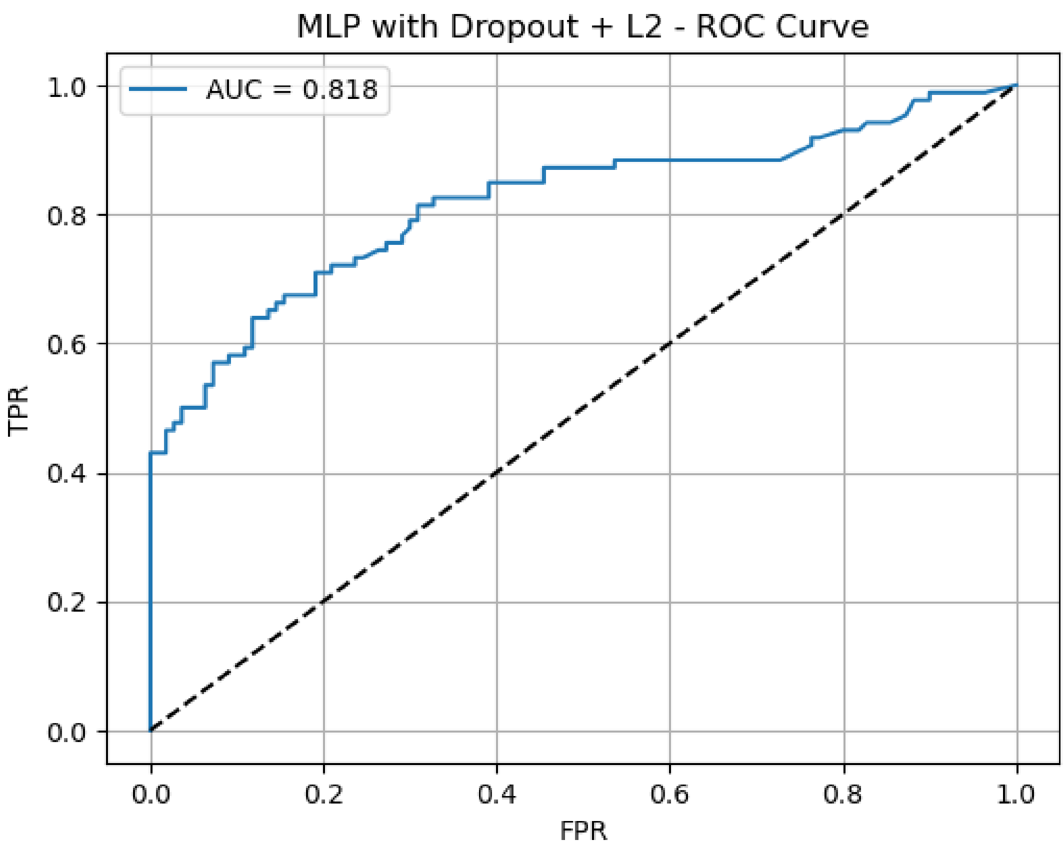
```python
# Evaluate predictions
y_probs = model.predict(X_val_scaled).flatten()
y_preds = (y_probs > 0.5).astype(int)

# Confusion Matrix
cm = confusion_matrix(y_val, y_preds)
ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Not Approved",␣
↪"Approved"]).plot(cmap='Blues')
plt.title("MLP with L2 - Confusion Matrix")
plt.grid(False)
plt.show()

# ROC Curve
fpr, tpr, _ = roc_curve(y_val, y_probs)
auc_val = roc_auc_score(y_val, y_probs)
plt.figure()
plt.plot(fpr, tpr, label=f"AUC = {auc_val:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("MLP with Dropout + L2 - ROC Curve")
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.legend()
plt.grid(True)
plt.show()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.
```




```
7/7 [==============================] - 0s 638us/step
```


MLP with L2 - Confusion Matrix
True label
Not Approved
Approved
87
23
24
62
Not Approved
Approved
Predicted label
80
70
60
50
40
30



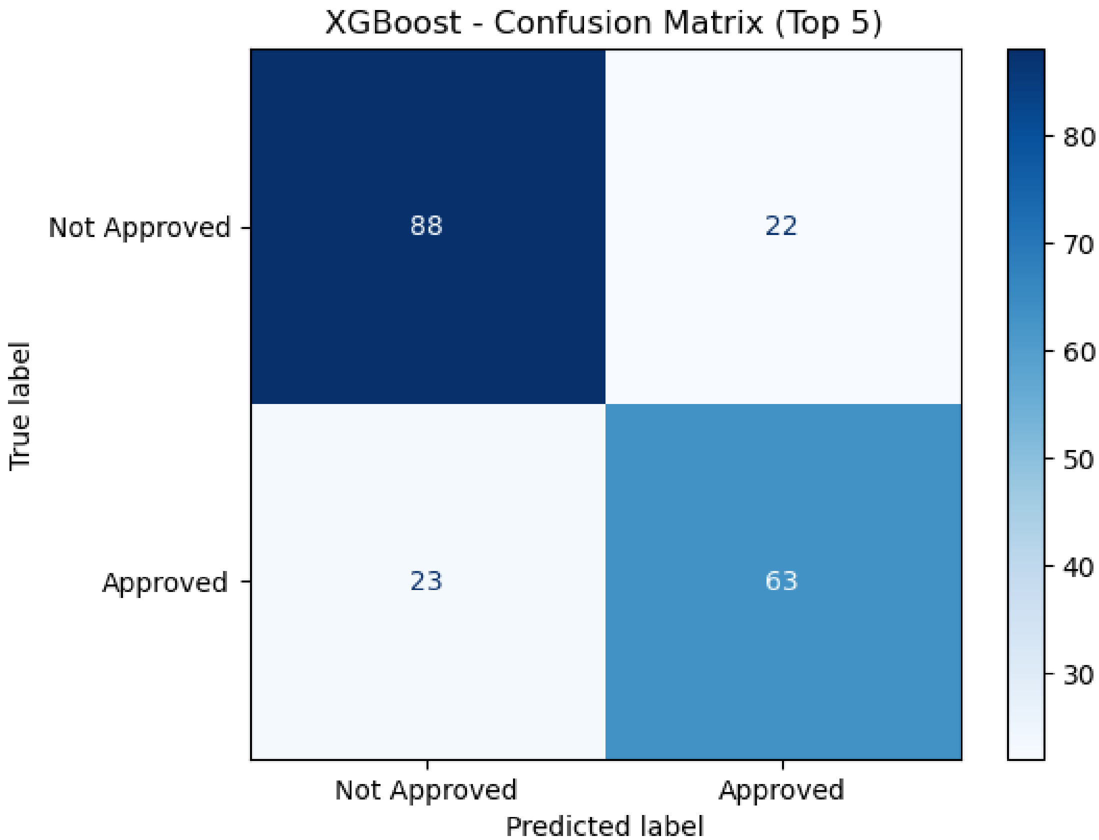
17 XGBoost

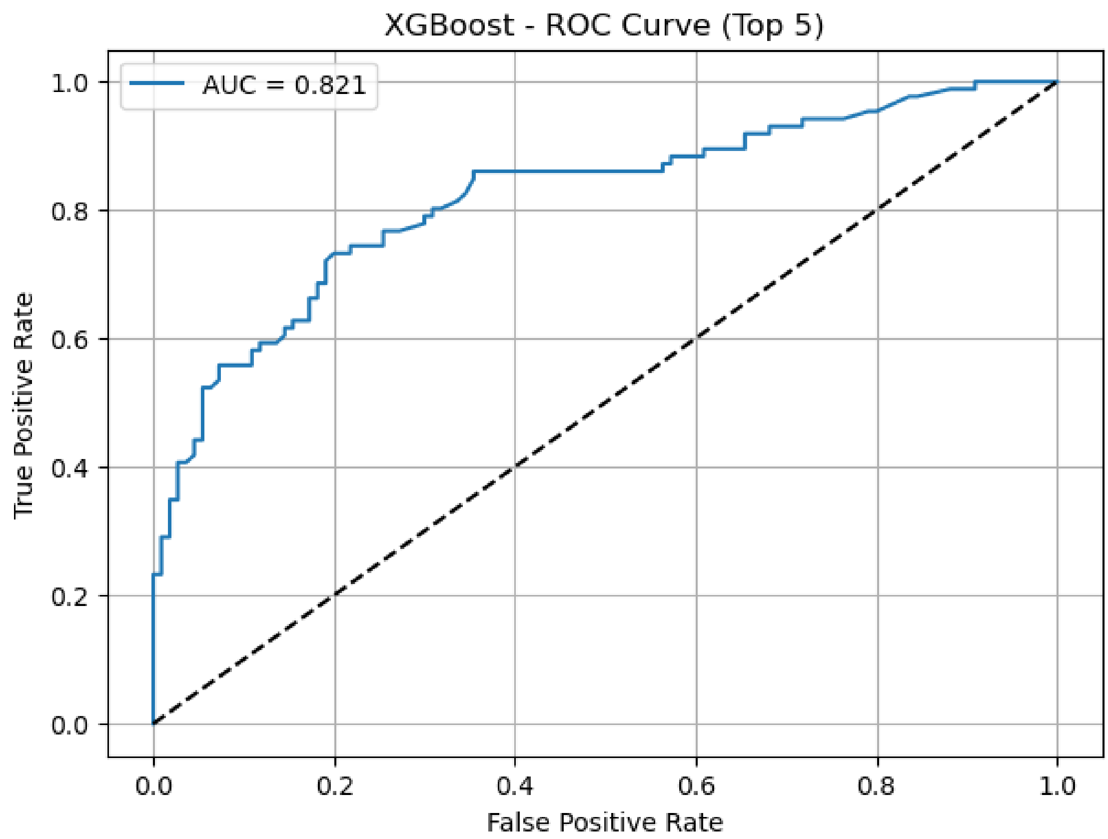
[160]:
```
import xgboost as xgb
from sklearn.metrics import accuracy_score, roc_auc_score, confusion_matrix,␣
↪ConfusionMatrixDisplay, roc_curve

# Prepare data for XGBoost
X = df_encoded[top5_features].values
y = df_encoded["A16 (Class)"].values
X_train_xgb, X_test_xgb, y_train_xgb, y_test_xgb = train_test_split(X, y,␣
↪test_size=0.3, random_state=42)

# Train XGBoost model
xgb_model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss',␣
↪random_state=42)
xgb_model.fit(X_train_xgb, y_train_xgb)


# Predictions
```

```
y_pred_xgb = xgb_model.predict(X_test_xgb)
y_probs_xgb = xgb_model.predict_proba(X_test_xgb)[:, 1]
y_train_pred = xgb_model.predict(X_train_xgb)


# Metrics
acc_xgb = accuracy_score(y_test_xgb, y_pred_xgb)
train_acc = accuracy_score(y_train_xgb, y_train_pred)
auc_xgb = roc_auc_score(y_test_xgb, y_probs_xgb)

# Print results
print(f" XGBoost Test Accuracy (Top 5): {acc_xgb:.4f}")
print(f" XGBoost Train Accuracy (Top 5): {train_acc:.4f}")
print(f" XGBoost AUC (Top 5): {auc_xgb:.4f}")

# Confusion Matrix
cm_xgb = confusion_matrix(y_test_xgb, y_pred_xgb)
ConfusionMatrixDisplay(cm_xgb, display_labels=["Not Approved", "Approved"]).
 ↪plot(cmap='Blues')
plt.title("XGBoost - Confusion Matrix (Top 5)")
plt.grid(False)
plt.show()

# ROC Curve
fpr_xgb, tpr_xgb, _ = roc_curve(y_test_xgb, y_probs_xgb)
plt.figure(figsize=(7, 5))
plt.plot(fpr_xgb, tpr_xgb, label=f"AUC = {auc_xgb:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("XGBoost - ROC Curve (Top 5)")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid(True)
plt.show()
```

```
 XGBoost Test Accuracy (Top 5): 0.7704
 XGBoost Train Accuracy (Top 5): 0.9431
 XGBoost AUC (Top 5): 0.8208
```

```
/opt/anaconda3/lib/python3.10/site-packages/xgboost/training.py:183:
UserWarning: [23:24:19] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

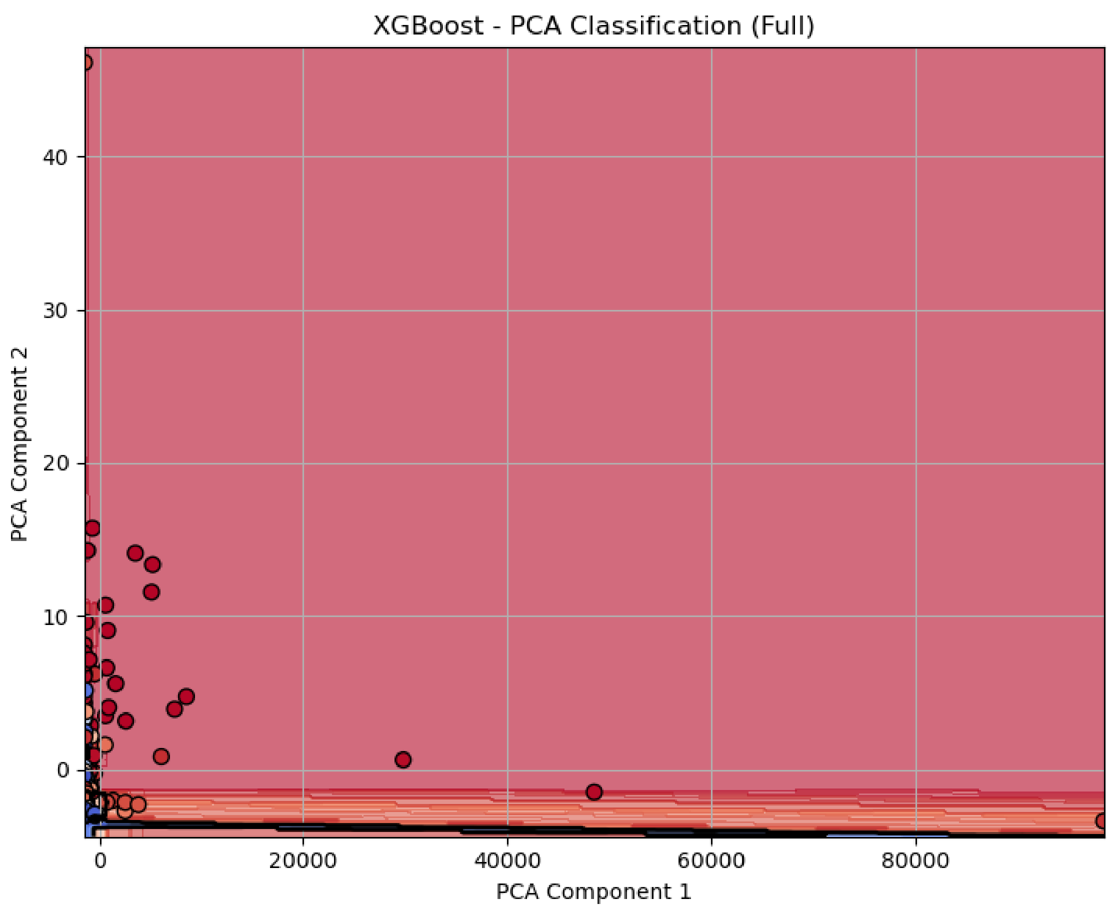

XGBoost - Confusion Matrix (Top 5)
True label
Not Approved
Approved
88
22
23
63
Predicted label
Not Approved
Approved
80
70
60
50
40
30



[133]:

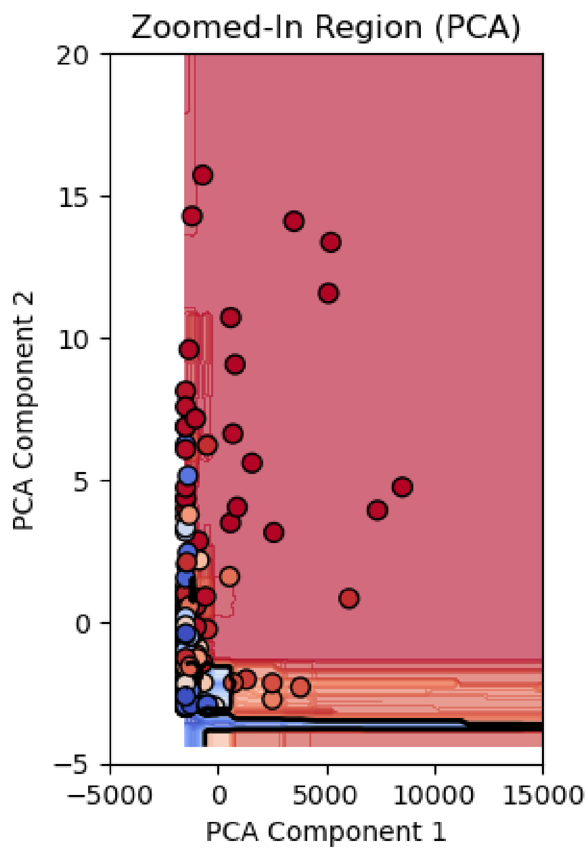
```
from sklearn.decomposition import PCA
import numpy as np
import matplotlib.pyplot as plt

# === 2D PCA Projection of Test Set ===
pca = PCA(n_components=2)
X_test_pca = pca.fit_transform(X_test_xgb)

# === Create meshgrid in PCA space ===
x_min, x_max = X_test_pca[:, 0].min() - 1, X_test_pca[:, 0].max() + 1
y_min, y_max = X_test_pca[:, 1].min() - 1, X_test_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
                     np.linspace(y_min, y_max, 300))

# === Inverse transform PCA space back to original feature space ===
grid_pca = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca.inverse_transform(grid_pca)

# === Predict on the grid using XGBoost ===
Z = xgb_model.predict_proba(grid_original)[:, 1]
```

```
Z = Z.reshape(xx.shape)

# === Plot ===
# Full PCA 2D mesh + predictions
plt.figure(figsize=(14, 6))

# --- Full view ---
plt.subplot(1, 2, 1)
plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_probs_xgb, cmap='coolwarm',␣
    ↪s=50, edgecolor='k')
plt.title("XGBoost - PCA Classification (Full)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.grid(True)

plt.tight_layout()
plt.show()
```



[147]:

```
# --- Zoomed-in view ---
plt.subplot(1, 2, 2)
plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_probs_xgb, cmap='coolwarm',␣
    ↪s=50, edgecolor='k')
plt.title("Zoomed-In Region (PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")

#  Adjust zoomed-in bounds manually (you can refine based on where 15,000 and␣
    ↪20 landed in PCA)
plt.xlim(-5000, 15000)
plt.ylim(-5, 20)
plt.show()
```

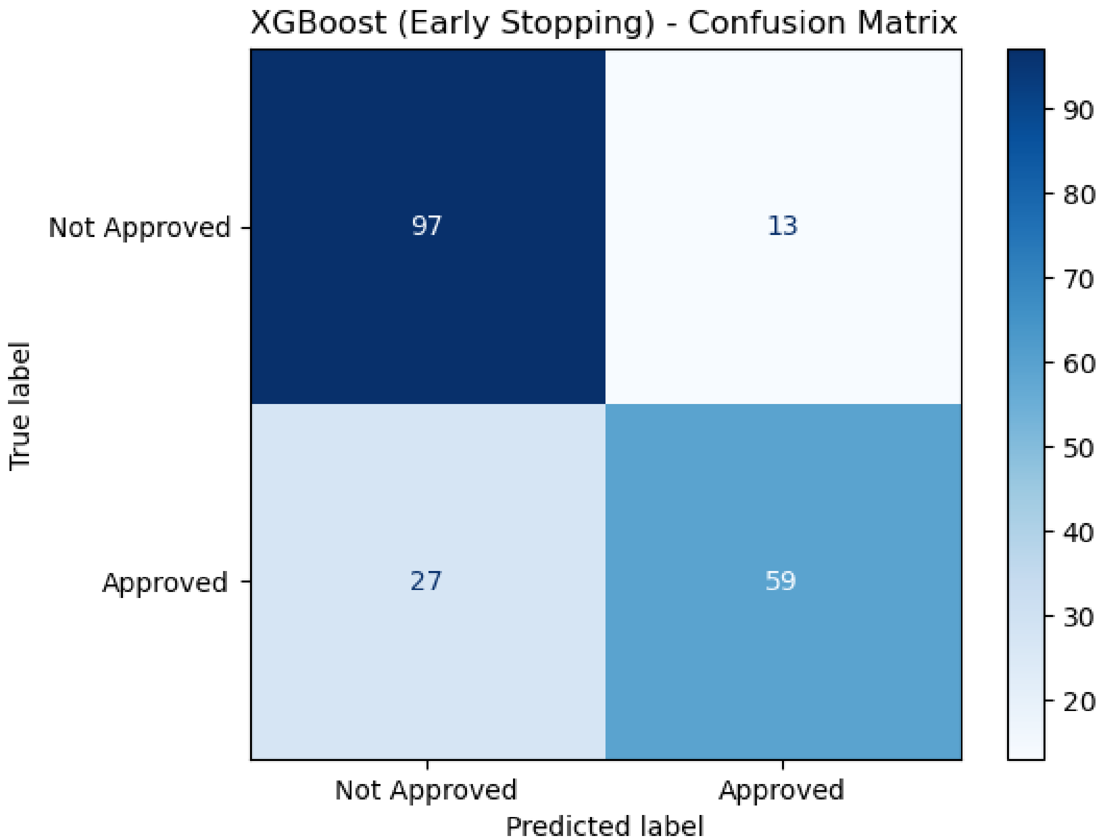


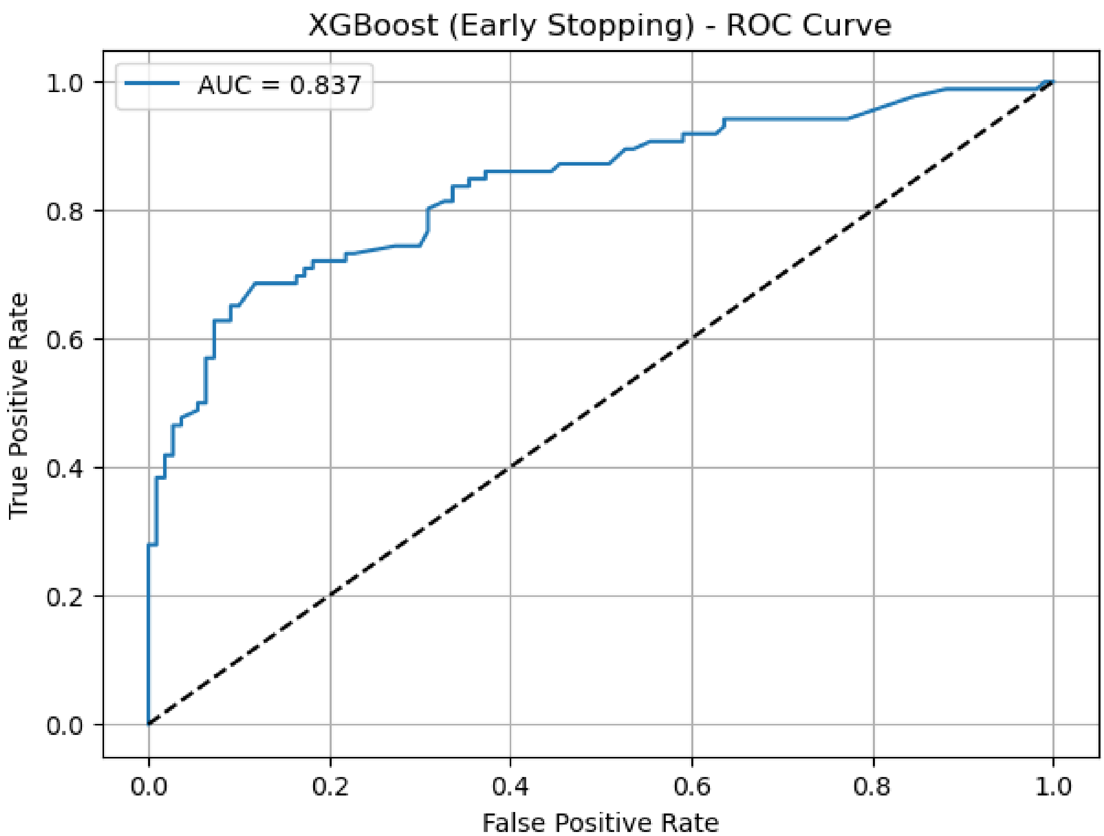
18 Less Over-fitted version of XGBoost (using early stopping)

[170]:
```
from sklearn.metrics import accuracy_score

# Full working XGBoost model with early stopping using version 3.0.0
xgb_model_es = xgb.XGBClassifier(
    max_depth=4,
    learning_rate=0.05,
    n_estimators=500,
    subsample=0.8,
    colsample_bytree=0.8,
    use_label_encoder=False,
    early_stopping_rounds=20,
    eval_metric=["logloss", "error"],
    callbacks=[],
    evals_result=evals_result,
    random_state=42
)

# Fit with early stopping
evals_result = {}
xgb_model_es.fit(
    X_train_xgb,
    y_train_xgb,
    eval_set = [(X_train_xgb, y_train_xgb), (X_test_xgb, y_test_xgb)],
    verbose=False,

)



# Predictions
y_pred_es = xgb_model_es.predict(X_test_xgb)
y_probs_es = xgb_model_es.predict_proba(X_test_xgb)[:, 1]

# Evaluation metrics
acc_es = accuracy_score(y_test_xgb, y_pred_es)
auc_es = roc_auc_score(y_test_xgb, y_probs_es)

# Confusion Matrix
cm_es = confusion_matrix(y_test_xgb, y_pred_es)
ConfusionMatrixDisplay(cm_es, display_labels=["Not Approved", "Approved"]).
 ↪plot(cmap='Blues')
plt.title("XGBoost (Early Stopping) - Confusion Matrix")
plt.grid(False)
plt.show()

# ROC Curve
```

```
fpr_es, tpr_es, _ = roc_curve(y_test_xgb, y_probs_es)
plt.figure(figsize=(7, 5))
plt.plot(fpr_es, tpr_es, label=f"AUC = {auc_es:.3f}")
plt.plot([0, 1], [0, 1], 'k--')
plt.title("XGBoost (Early Stopping) - ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.grid(True)
plt.show()

# Print accuracy and AUC
print(f" XGBoost Accuracy (with Early Stopping): {acc_es:.4f}")
print(f" XGBoost AUC (with Early Stopping): {auc_es:.4f}")


# Predict on training set
y_train_pred = xgb_model_es.predict(X_train_xgb)

# Calculate training accuracy
train_acc = accuracy_score(y_train_xgb, y_train_pred)
print(f" XGBoost Training Accuracy: {train_acc:.4f}")
```

```
/opt/anaconda3/lib/python3.10/site-packages/xgboost/callback.py:386:
UserWarning: [23:33:48] WARNING:
/Users/runner/work/xgboost/xgboost/src/learner.cc:738:
Parameters: { "evals_result", "use_label_encoder" } are not used.

  self.starting_round = model.num_boosted_rounds()
```


XGBoost (Early Stopping) - Confusion Matrix
Not Approved
Approved
True label
97
13
27
59
Not Approved
Approved
Predicted label
90
80
70
60
50
40
30
20

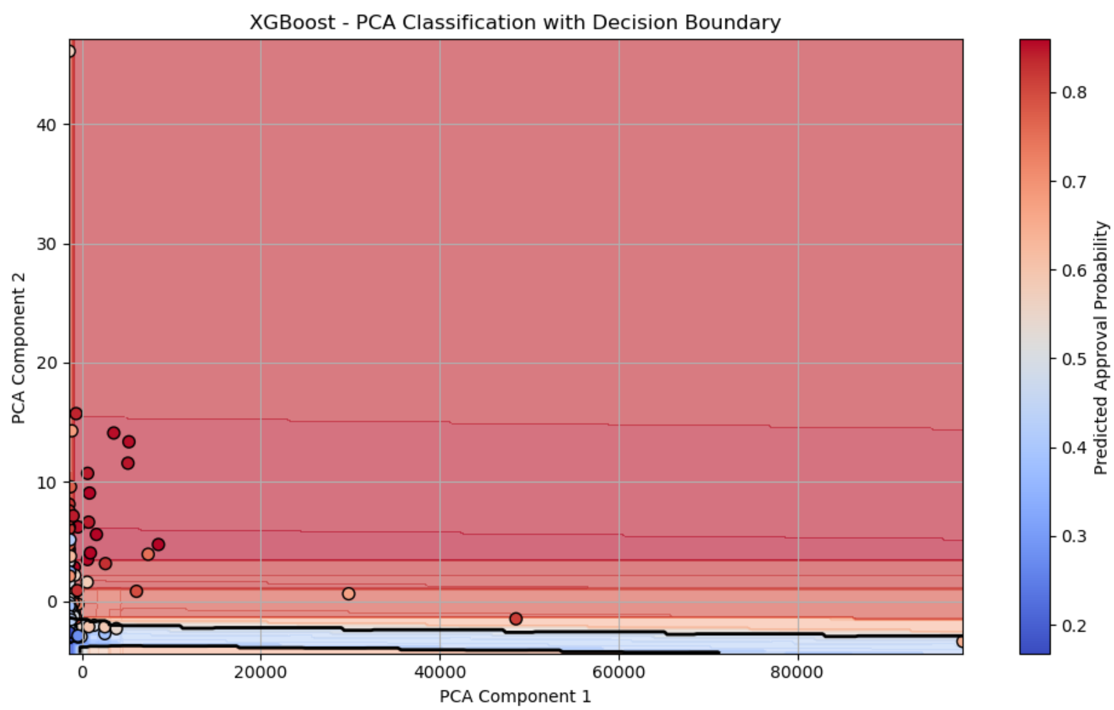



```
XGBoost Accuracy (with Early Stopping): 0.7959
XGBoost AUC (with Early Stopping): 0.8367
XGBoost Training Accuracy: 0.8446
```

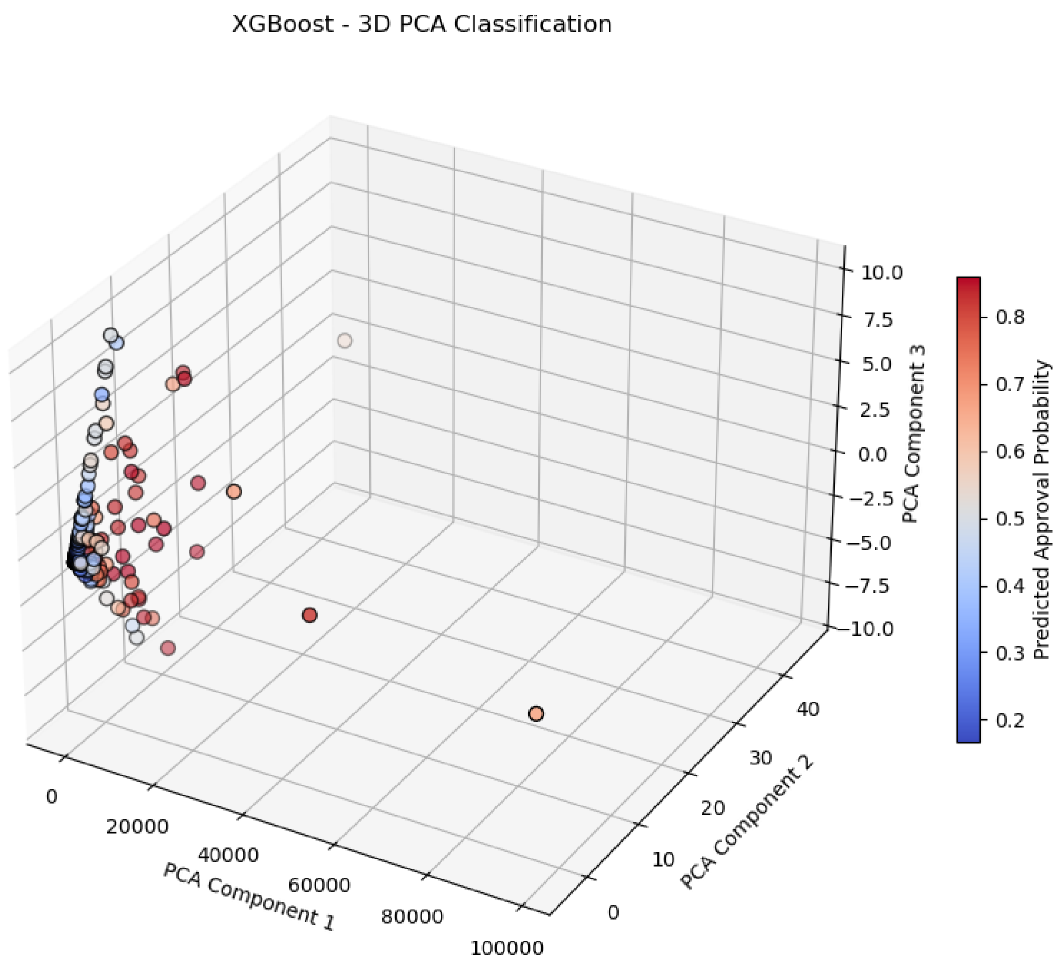
[172]:

```
from sklearn.decomposition import PCA
import numpy as np
import matplotlib.pyplot as plt

# Step 1: PCA Projection of Test Set
pca = PCA(n_components=2)
X_test_pca = pca.fit_transform(X_test_xgb)

# Step 2: Create a grid in PCA space
x_min, x_max = X_test_pca[:, 0].min() - 1, X_test_pca[:, 0].max() + 1
y_min, y_max = X_test_pca[:, 1].min() - 1, X_test_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
                     np.linspace(y_min, y_max, 300))

grid_pca = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca.inverse_transform(grid_pca)
```

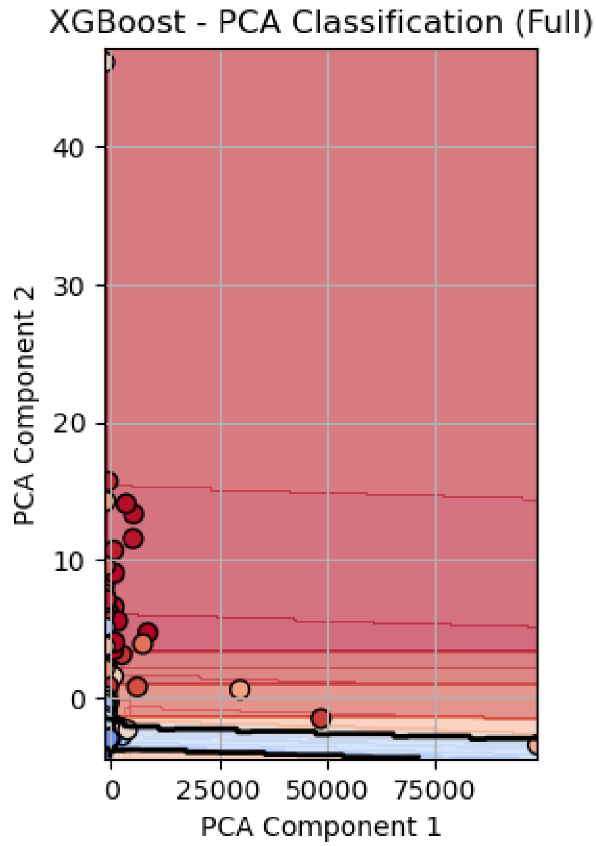
```
# Step 3: Predict on grid using trained XGBoost model
Z = xgb_model_es.predict_proba(grid_original)[:, 1]
Z = Z.reshape(xx.shape)

# Step 4: Predict on test set to get coloring
y_probs_test = xgb_model_es.predict_proba(X_test_xgb)[:, 1]

# Step 5: Plot
plt.figure(figsize=(10, 6))
plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_probs_test,␣
↪cmap='coolwarm', s=50, edgecolor='k')
plt.title("XGBoost - PCA Classification with Decision Boundary")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
cbar = plt.colorbar()
cbar.set_label("Predicted Approval Probability")
plt.grid(True)
plt.tight_layout()
plt.show()
```



[173]:
```python
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D

# 3D PCA Projection of Test Set
pca_3d = PCA(n_components=3)
X_test_pca_3d = pca_3d.fit_transform(X_test_xgb)

# Predicted probabilities for coloring
y_probs_test_3d = xgb_model_es.predict_proba(X_test_xgb)[:, 1]

# Plot 3D PCA Classification
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
scatter = ax.scatter(
    X_test_pca_3d[:, 0], X_test_pca_3d[:, 1], X_test_pca_3d[:, 2],
    c=y_probs_test_3d, cmap='coolwarm', s=50, edgecolor='k'
)
ax.set_xlabel("PCA Component 1")
ax.set_ylabel("PCA Component 2")
ax.set_zlabel("PCA Component 3")
ax.set_title("XGBoost - 3D PCA Classification")
cbar = fig.colorbar(scatter, ax=ax, shrink=0.5)
cbar.set_label("Predicted Approval Probability")
plt.tight_layout()
plt.show()
```

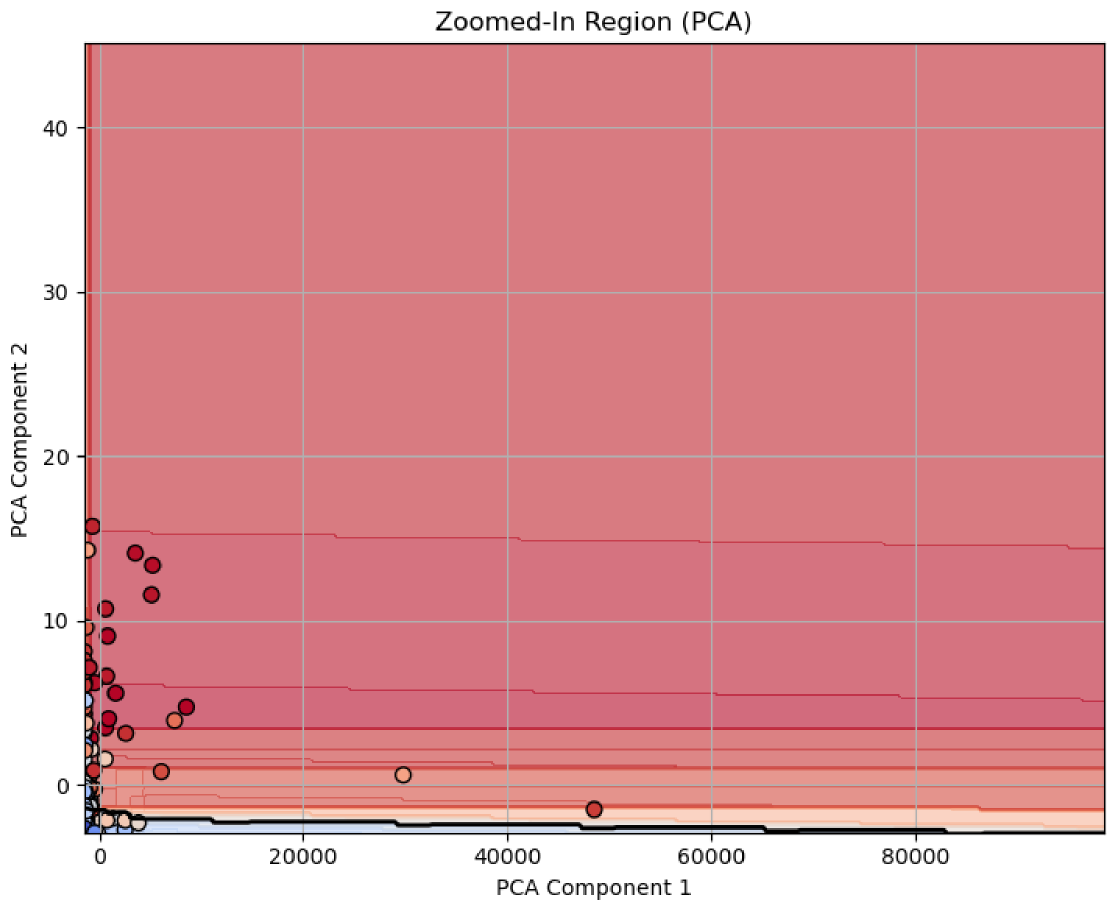


XGBoost - 3D PCA Classification
PCA Component 1
PCA Component 2
PCA Component 3
Predicted Approval Probability
0
20000
40000
60000
80000
100000
0
10
20
30
40
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−10.0
0.2
0.3
0.4
0.5
0.6
0.7
0.8



[174]:
```
# 2D PCA and Grid for Side-by-Side Zoom
pca_2d = PCA(n_components=2)
X_test_pca = pca_2d.fit_transform(X_test_xgb)

# Create grid
x_min, x_max = X_test_pca[:, 0].min() - 1, X_test_pca[:, 0].max() + 1
y_min, y_max = X_test_pca[:, 1].min() - 1, X_test_pca[:, 1].max() + 1
xx, yy = np.meshgrid(np.linspace(x_min, x_max, 300),
                     np.linspace(y_min, y_max, 300))
grid_pca = np.c_[xx.ravel(), yy.ravel()]
grid_original = pca_2d.inverse_transform(grid_pca)
Z = xgb_model_es.predict_proba(grid_original)[:, 1].reshape(xx.shape)

# Side-by-side plots
plt.figure(figsize=(14, 6))


# Zoomed-in view
plt.subplot(1, 2, 2)
plt.contourf(xx, yy, Z, levels=100, cmap='coolwarm', alpha=0.6)
```

```
plt.contour(xx, yy, Z, levels=[0.5], colors='black', linewidths=2)
plt.scatter(X_test_pca[:, 0], X_test_pca[:, 1], c=y_probs_test_3d,␣
  ↪cmap='coolwarm', s=50, edgecolor='k')
plt.title("Zoomed-In Region (PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.xlim(X_test_pca[:, 0].min() + 1.5, X_test_pca[:, 0].max() - 2)
plt.ylim(X_test_pca[:, 1].min() + 0.5, X_test_pca[:, 1].max() - 1)
plt.grid(True)

plt.tight_layout()
plt.show()
```



[ ]: