Libraries

In [2]:
```
# ---------------------------------------------------------------
# System utilities
# ---------------------------------------------------------------
import os
import joblib

# ---------------------------------------------------------------
# Data manipulation libraries
# ---------------------------------------------------------------
import pandas as pd  # Data manipulation and analysis
import numpy as np   # Support for large, multi-dimensional arrays and matrices

# ---------------------------------------------------------------
# Data visualization libraries
# ---------------------------------------------------------------
import matplotlib.pyplot as plt  # 2D plotting library
import seaborn as sns            # Statistical data visualization built on top of M
import plotly.express as px      # Interactive visualizations for data exploration
import plotly.graph_objects as go  # Low-level interface for creating more complex

# ---------------------------------------------------------------
# Machine learning models and metrics from scikit-learn
# ---------------------------------------------------------------
from sklearn.preprocessing import MinMaxScaler, StandardScaler  # Feature scaling m
from sklearn.model_selection import train_test_split, GridSearchCV, cross_validate,
from sklearn.linear_model import LogisticRegression  # Logistic regression model
from sklearn.ensemble import RandomForestClassifier  # Random Forest classifier
from sklearn.tree import DecisionTreeClassifier      # Decision Tree classifier
from sklearn.metrics import (                        # Model evaluation metrics
    classification_report, confusion_matrix,
    roc_curve, roc_auc_score,
    mean_squared_error, mean_absolute_error, r2_score,
    accuracy_score, precision_score, recall_score, f1_score,
    make_scorer)

# ---------------------------------------------------------------
# Libraries for handling imbalanced datasets
# ---------------------------------------------------------------
from imblearn.over_sampling import SMOTE  # Synthetic Minority Over-sampling Techni
from imblearn.pipeline import Pipeline    # Pipeline for combining steps in model t

# ---------------------------------------------------------------
# Advanced visualization utilities for interactive plots
# ---------------------------------------------------------------
from plotly.subplots import make_subplots  # Create complex multi-plot visualizatio
```

In [3]:
```
# Get the current working directory
directorio_actual = os.getcwd()

# Specify the relative path from the current directory
ruta_csv_relativa = os.path.join('..','data','03_primary','3.spotify.csv')
```

```
# Load the CSV file
spotify = pd.read_csv(ruta_csv_relativa)
```

In [4]:
```
spotify
```

Out[4]:

	duration_ms_scaled	popularity_scaled	speechiness_scaled	acousticness_scaled	inst
0	0.461947	0.920689	0.494433	0.751530	
1	0.387347	0.849624	0.328098	0.994567	
2	0.446450	0.858572	0.244770	0.887294	
3	0.439024	0.913703	0.131397	0.993063	
4	0.436375	0.949954	0.229607	0.945470	
...	...	...	...	...	
113794	0.550216	0.611400	0.171275	0.967978	
113795	0.550216	0.622734	0.157759	0.999854	
113796	0.490010	0.622734	0.170017	0.989957	
113797	0.497723	0.776273	0.078262	0.930424	
113798	0.470088	0.622734	0.314571	0.972473	

113799 rows × 15 columns

Classification Model

Predictor sets

Four sets of predictors were created, which will be trained by multiple classification models.

In [8]:
```
# Predictor sets
predictors_essential = ['danceability_scaled', 'energy_scaled', 'loudness_scaled',
predictors_simplified = ['loudness_scaled', 'intensity', 'speechiness_scaled']
predictors_moderate = ['danceability_scaled', 'energy_scaled', 'loudness_scaled', '
predictors_complete = ['danceability_scaled', 'energy_scaled', 'loudness_scaled', '
                       'liveness_scaled', 'valence_scaled', 'intensity']
```

Train Model

In [5]:
```
def train_multiple_baseline_models(X, y):
    """
```

```
    This function trains multiple classification models with default parameters (ba
    and displays performance metrics for each model, including the ROC curve and AU

    Parameters:
    - X: Feature set.
    - y: Target labels.

    Return:
    - results: List of dictionaries containing model performance metrics.
    """
    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random

    # Models to be trained
    models = {
        'Logistic Regression': LogisticRegression(max_iter=1000),
        'Random Forest': RandomForestClassifier(random_state=42),
        'Decision Tree': DecisionTreeClassifier(random_state=42),
    }

    # Store results for ROC curves
    roc_curves = []

    # Iterate over the models and train each one
    results = []
    for model_name, model in models.items():
        print(f"\nTraining and evaluation: {model_name}")

        # Train the model
        model.fit(X_train, y_train)

        # Make predictions
        y_pred = model.predict(X_test)

        # Predict probabilities for ROC curve (if the model supports it)
        if hasattr(model, "predict_proba"):
            y_prob = model.predict_proba(X_test)[:, 1] # Probability of the positiv
        else:
            y_prob = None # For models without predict_proba (e.g, SVM with Linear

        # Calculate metrics
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred, average='weighted')
        recall = recall_score(y_test, y_pred, average='weighted')
        f1 = f1_score(y_test, y_pred, average='weighted')
        confusion_mtx = confusion_matrix(y_test, y_pred)

        # Calculate ROC curve and AUC if probabilities are available
        if y_prob is not None:
            fpr, tpr, _ = roc_curve(y_test, y_prob)
            auc = roc_auc_score(y_test, y_prob)

            # Store the ROC curve results
            roc_curves.append((fpr, tpr, model_name, auc))

        else:
```

```
            auc = 'N/A'

        # Save the results
        results.append({
            'model': model_name,
            'accuracy': accuracy,
            'precision': precision,
            'recall': recall,
            'f1_score': f1,
            'confusion_matrix': confusion_mtx,
            'AUC': auc
        })

        # Display the metrics
        print(f"Accuracy: {accuracy:.4f}")
        print(f"Precision: {precision:.4f}")
        print(f"Recall: {recall:.4f}")
        print(f"F1 Score: {f1:.4f}")
        print(f"AUC: {auc}")
        print("Confusion Matrix:")
        print(confusion_mtx)

    # Plot all ROC curves at the end
    plt.figure()
    for fpr, tpr, model_name, auc in roc_curves:
        plt.plot(fpr, tpr, label=f'{model_name} (AUC = {auc:.2f})')

    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')  # Diagonal reference li
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate (FPR)')
    plt.ylabel('True Positive Rate (TPR)')
    plt.title('ROC Curves')
    plt.legend(loc="lower right")
    plt.show()

    return results
```

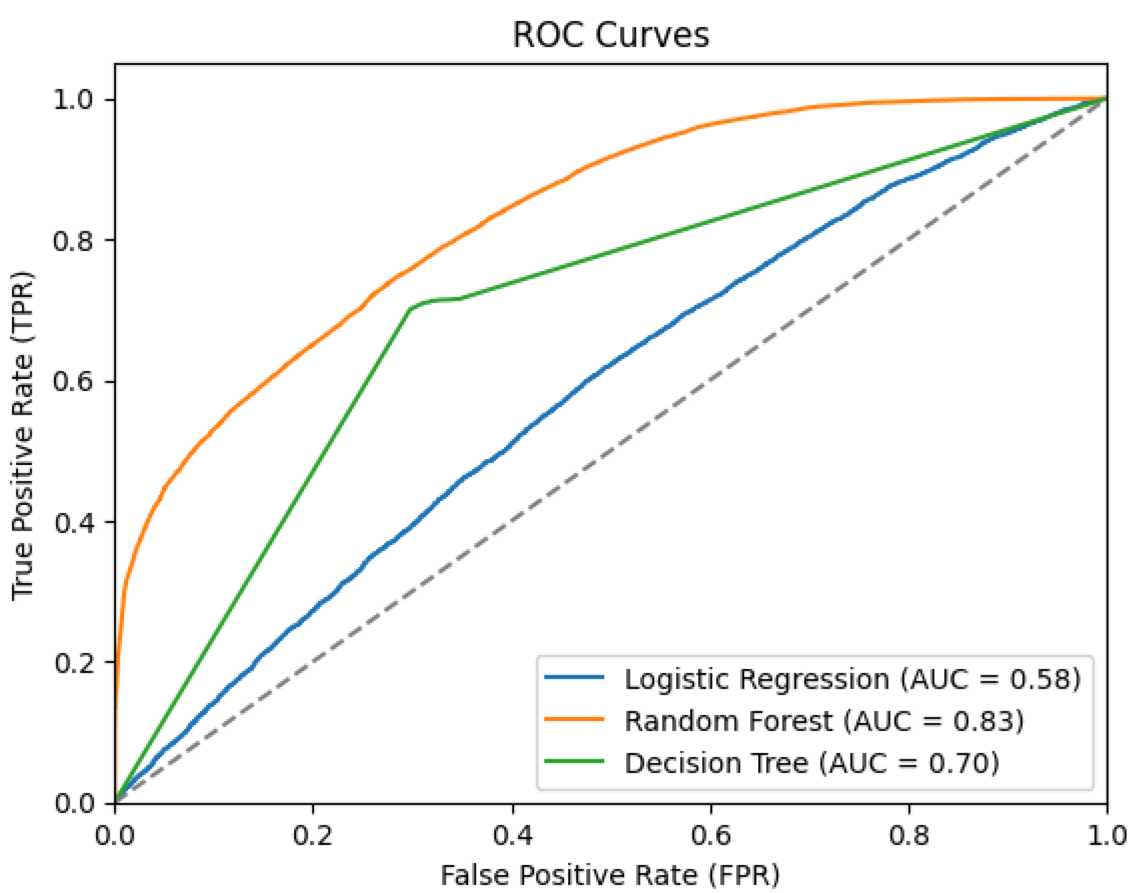
Models

predictors_essential

In [6]:

```
# Example usage
# X and y are your data (X: features, y: labels)
X = spotify[predictors_essential]  # Your features
y = spotify['popularity_class']    # Your label or target variable

results = train_multiple_baseline_models(X, y)
```

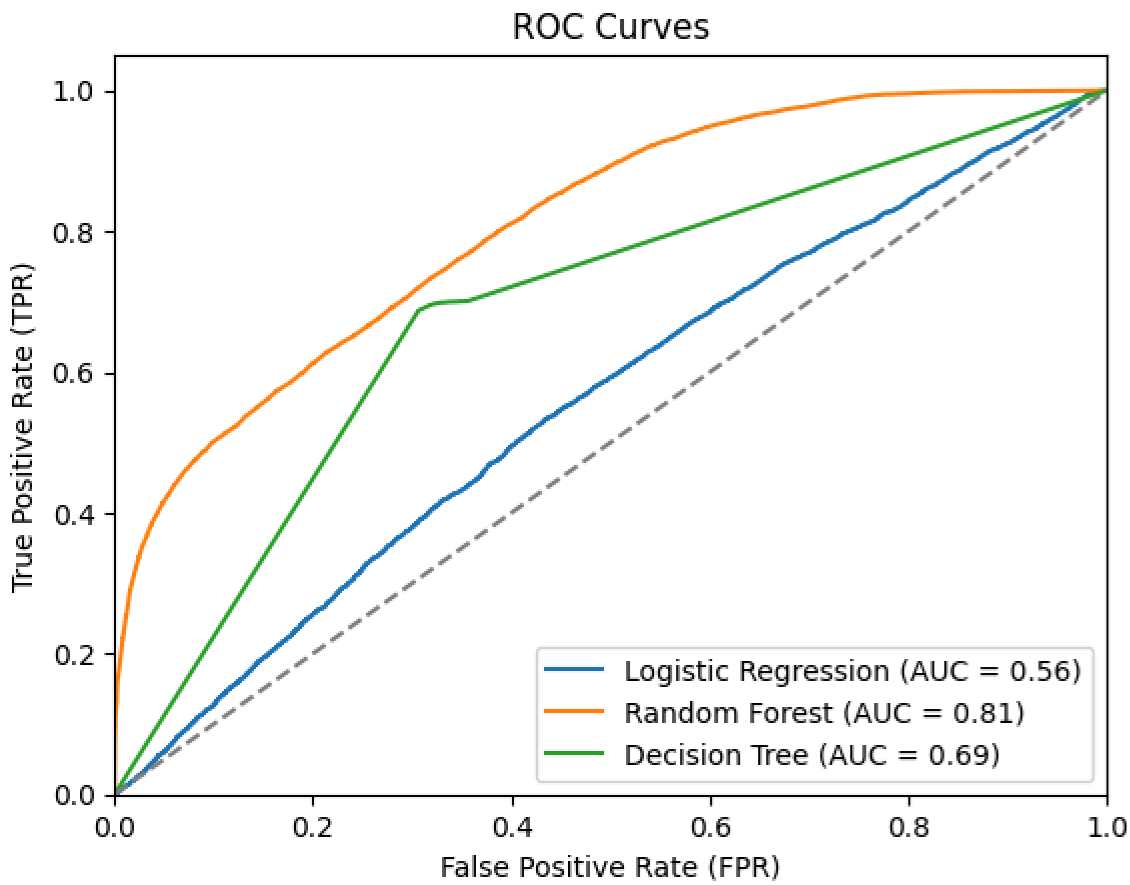
```
Training and evaluation: Logistic Regression
Accuracy: 0.5577
Precision: 0.5556
Recall: 0.5577
F1 Score: 0.5524
AUC: 0.5809036012628297
Confusion Matrix:
[[7889 4041]
 [6026 4804]]

Training and evaluation: Random Forest
Accuracy: 0.7305
Precision: 0.7314
Recall: 0.7305
F1 Score: 0.7306
AUC: 0.8314641464250911
Confusion Matrix:
[[8635 3295]
 [2839 7991]]

Training and evaluation: Decision Tree
Accuracy: 0.7009
Precision: 0.7015
Recall: 0.7009
F1 Score: 0.7010
AUC: 0.6992302899570363
Confusion Matrix:
[[8350 3580]
 [3228 7602]]
```



predictors_simplified

In [7]:
```
X = spotify[predictors_simplified]
y = spotify['popularity_class']

results = train_multiple_baseline_models(X, y)
```

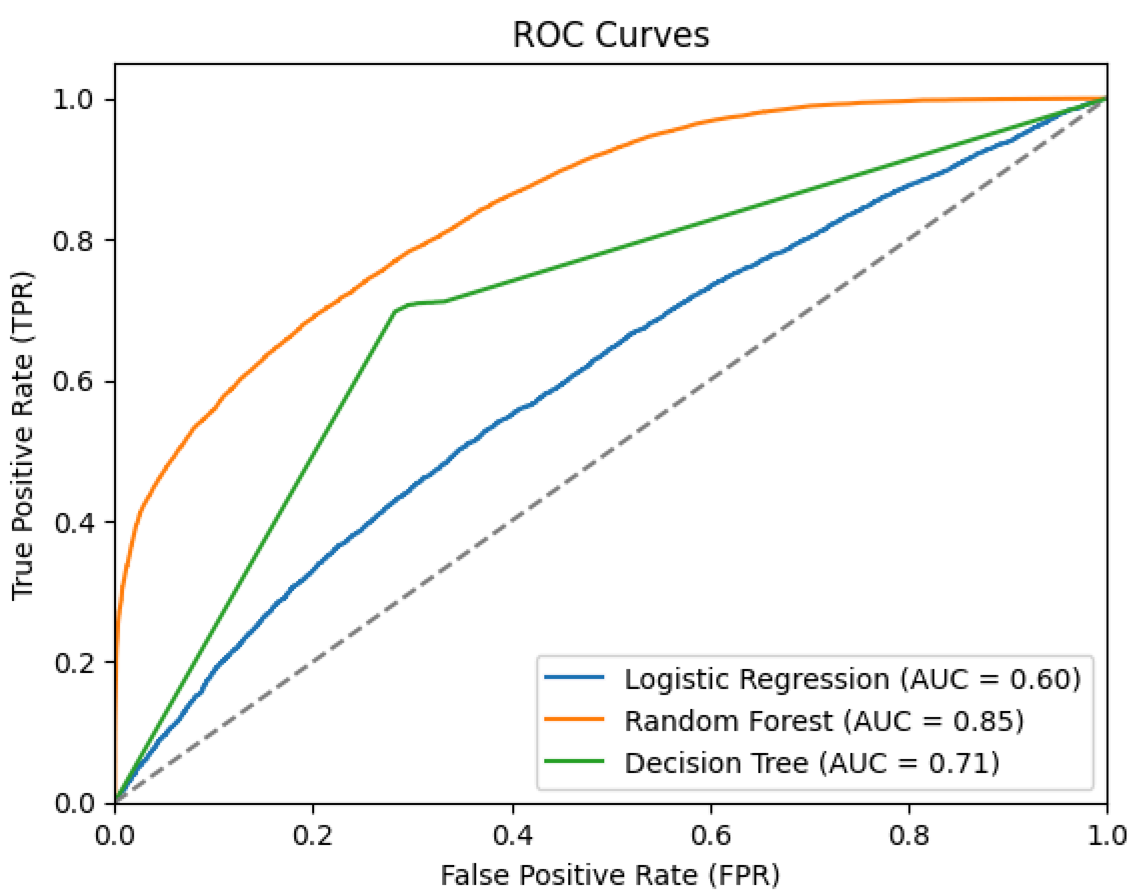
```
Training and evaluation: Logistic Regression
Accuracy: 0.5486
Precision: 0.5460
Recall: 0.5486
F1 Score: 0.5381
AUC: 0.5580833718389591
Confusion Matrix:
[[8252 3678]
 [6595 4235]]

Training and evaluation: Random Forest
Accuracy: 0.7055
Precision: 0.7061
Recall: 0.7055
F1 Score: 0.7057
AUC: 0.8099754067084153
Confusion Matrix:
[[8410 3520]
 [3182 7648]]

Training and evaluation: Decision Tree
Accuracy: 0.6901
Precision: 0.6907
Recall: 0.6901
F1 Score: 0.6902
AUC: 0.6875314759303075
Confusion Matrix:
[[8241 3689]
 [3365 7465]]
```



predictors_moderate

In [8]:
```
X = spotify[predictors_moderate]
y = spotify['popularity_class']

results = train_multiple_baseline_models(X, y)
```

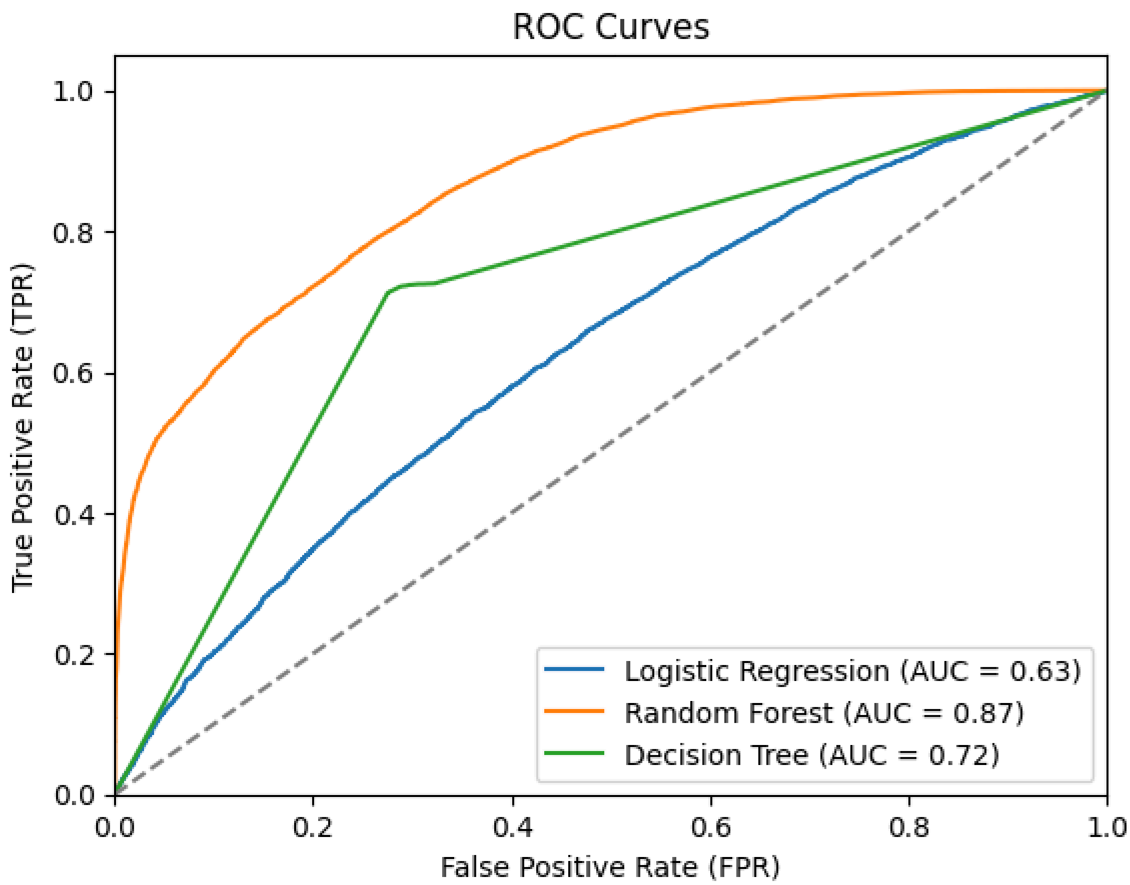
```
Training and evaluation: Logistic Regression
Accuracy: 0.5790
Precision: 0.5777
Recall: 0.5790
F1 Score: 0.5741
AUC: 0.601860777589184
Confusion Matrix:
[[8105 3825]
 [5758 5072]]

Training and evaluation: Random Forest
Accuracy: 0.7442
Precision: 0.7446
Recall: 0.7442
F1 Score: 0.7443
AUC: 0.845620702946319
Confusion Matrix:
[[8878 3052]
 [2771 8059]]

Training and evaluation: Decision Tree
Accuracy: 0.7072
Precision: 0.7075
Recall: 0.7072
F1 Score: 0.7073
AUC: 0.7050543258264776
Confusion Matrix:
[[8525 3405]
 [3258 7572]]
```



predictors_complete

In [9]:
```
X = spotify[predictors_complete]
y = spotify['popularity_class']

results = train_multiple_baseline_models(X, y)
```

```
Training and evaluation: Logistic Regression
Accuracy: 0.5906
Precision: 0.5895
Recall: 0.5906
F1 Score: 0.5884
AUC: 0.6266213964345726
Confusion Matrix:
[[7877 4053]
 [5264 5566]]

Training and evaluation: Random Forest
Accuracy: 0.7630
Precision: 0.7634
Recall: 0.7630
F1 Score: 0.7631
AUC: 0.8655014554739522
Confusion Matrix:
[[9085 2845]
 [2550 8280]]

Training and evaluation: Decision Tree
Accuracy: 0.7184
Precision: 0.7188
Recall: 0.7184
F1 Score: 0.7185
AUC: 0.7168112117546258
Confusion Matrix:
[[8612 3318]
 [3091 7739]]
```



Comparando los 4 modelos y sus predictores, el mejor modelo encontrado es el modelo de bosque aleatorio con el conjunto predictors_complete. Este modelo se ejecutará a través de Hyperparameters para mejorar sus métricas.

Hyperparameter - GridSerachCV

In [10]:
```
def optimize_simple_model(model, param_grid, X, y, test_size, scoring):
    """
    This function optimizes a model's hyperparameters using GridSearchCV and return

    Parameters:
    - model: The model to be trained (e.g., RandomForestClassifier()).
    - param_grid: A dictionary of hyperparameters for GridSearchCV.
    - X: Feature set.
    - y: Target labels (dependent variable).
    - test_size: Proportion of data for the test set (default is 0.2).
    - scoring: Metric to optimize (default is 'accuracy').

    Returns:
    - best_model: The model with the best hyperparameters.
    - metrics: A dictionary containing performance metrics (accuracy, precision, re
    """

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size,
```

```
    # Create GridSearchCV
    grid_search = GridSearchCV(model, param_grid, cv=5, scoring=scoring, n_jobs=-1)

    # Train the model with the training data
    grid_search.fit(X_train, y_train)

    # Get the best model
    best_model = grid_search.best_estimator_

    # Make predictions on the test set
    y_pred = best_model.predict(X_test)

    # Calculate the metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    # Create a dictionary with the metrics
    metrics = {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1_score': f1,
        'confusion_matrix': confusion_matrix(y_test, y_pred)
    }

    # Display results
    print(f"Best hyperparameters: {grid_search.best_params_}")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1 Score: {f1:.4f}")
    print("Confusion Matrix:")
    print(metrics['confusion_matrix'])

    return best_model, metrics
```

Train Hyperparameter

In [11]:

```
# Example usage:
# Parameters to optimize for RandomForest
param_grid_rf = {
    'n_estimators': [100, 150],
    'max_depth': [None, 10],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2]
}

# Assume you already have your features (X) and target variable (y)
X = spotify[predictors_complete]  # Your features -- predictors_complete
y = spotify['popularity_class']   # Your target variable

# Call the function to optimize the model
best_model_rf, metrics_rf = optimize_simple_model(
```

```
    RandomForestClassifier(random_state=50),
    param_grid_rf,
    X,
    y,
    test_size=0.2,
    scoring='accuracy'
)
```

```
Best hyperparameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_spli
t': 2, 'n_estimators': 150}
Accuracy: 0.7660
Precision: 0.7666
Recall: 0.7660
F1 Score: 0.7662
Confusion Matrix:
[[9101 2829]
 [2496 8334]]
```

As the model has not performed as expected, the SMOTE library will be tested to balance the data with its hyperparameters.

SMOTE with Hyperparameter

In [12]:
```
def optimize_model_smote(model, param_grid, X, y, model_path, test_size=0.2, scorin
    """
    This function optimizes a model's hyperparameters using GridSearchCV and SMOTE,
    returning the best model with its metrics and saving it to a file.

    Parameters:
    - model: The model to be trained (e.g., RandomForestClassifier()).
    - param_grid: A dictionary of hyperparameters for GridSearchCV.
    - X: Feature set.
    - y: Target labels (dependent variable).
    - model_path: File path where the best model will be saved (default is 'best_mo
    - test_size: Proportion of data for the test set (default is 0.2).
    - scoring: Metric to optimize (default is 'accuracy').

    Returns:
    - best_model: The model with the best hyperparameters.
    - metrics: A dictionary containing performance metrics (accuracy, precision, re
    """

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size,

    # Create a pipeline that applies SMOTE and then trains the model
    pipeline = Pipeline([
        ('smote', SMOTE(random_state=42)),  # Apply SMOTE to the training set
        ('model', model)  # The model to be optimized
    ])

    # Create GridSearchCV on the pipeline
    grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring=scoring, n_jobs=
```

```
    # Train with the training data
    grid_search.fit(X_train, y_train)

    # Get the best model
    best_model = grid_search.best_estimator_

    # Make predictions on the test set
    y_pred = best_model.predict(X_test)

    # Calculate the metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    # Create a dictionary with the metrics
    metrics = {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1_score': f1,
        'confusion_matrix': confusion_matrix(y_test, y_pred)
    }

    # Display results
    print(f"Best hyperparameters: {grid_search.best_params_}")
    print(f"Accuracy: {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall: {recall:.4f}")
    print(f"F1 Score: {f1:.4f}")
    print("Confusion Matrix:")
    print(metrics['confusion_matrix'])

    # Save the model to a file
    try:
        joblib.dump(best_model, model_path)
        print(f"Model saved at: {model_path}")
    except Exception as e:
        print(f"Error saving the model: {e}")

    return best_model, metrics
```

Train SMOTE with Hyperparameter

In [ ]:

```
# Call the function to optimize and save the model
best_model, metrics = optimize_model_smote(
    model = RandomForestClassifier(random_state=42),
    param_grid = {
    'model__n_estimators': [100, 150],
    'model__max_depth': [None, 10],
    'model__min_samples_split': [2, 5],
    'model__min_samples_leaf': [1, 2]
    },
    X = X,
    y = y,
```

```
    model_path='../data/06_models/random_forest_model.pkl'
)
```

The results were not as expected, so it was decided to continue working with the base model, as this way the execution will be much faster than with the hyperparameters.

Random Forest Model

In [9]:
```
# Define features (predictors_complete) and the target (popularity_class)
X = spotify[predictors_complete]  # Your features
y = spotify['popularity_class']   # Your target variable

# Split into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Train a model (RandomForestClassifier)
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Define the path to save the model
model_path = '../data/06_models/simple_random_forest_model.pkl'

# Save the trained model
joblib.dump(rf, model_path)
print(f"Model saved as {model_path}")
```

```
Model saved as ../data/06_models/simple_random_forest_model.pkl
```

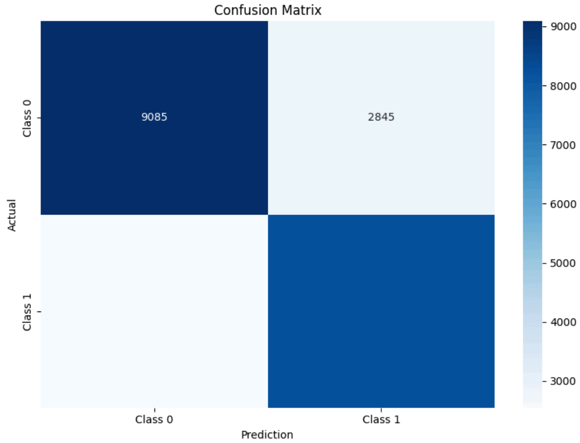
The model is stored so that it can be used without the need for continuous training.

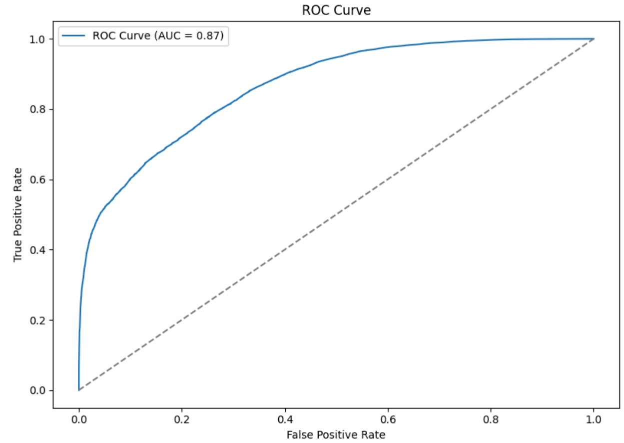
simple_random_forest_model metrics

In [10]:
```
# Load the saved model
rf = joblib.load('../data/06_models/simple_random_forest_model.pkl')
print("Model loaded successfully")

# Make predictions on the test set
y_pred = rf.predict(X_test)

# 1. Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")

# 2. Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# 3. Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```python
# 4. ROC-AUC (For binary classification)
if len(set(y_test)) == 2:
    y_pred_proba = rf.predict_proba(X_test)[:, 1]  # Probability of the positive cl
    roc_auc = roc_auc_score(y_test, y_pred_proba)
    print(f"ROC-AUC: {roc_auc:.4f}")

    # Get ROC curve values
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)

    # Create subplots to show the confusion matrix and ROC curve together
    fig, ax = plt.subplots(1, 2, figsize=(16, 6))

    # Subplot 1: Confusion Matrix
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class
    ax[0].set_xlabel('Prediction')
    ax[0].set_ylabel('Actual')
    ax[0].set_title('Confusion Matrix')

    # Subplot 2: ROC Curve
    ax[1].plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc:.2f})')
    ax[1].plot([0, 1], [0, 1], linestyle='--', color='gray')
    ax[1].set_xlabel('False Positive Rate')
    ax[1].set_ylabel('True Positive Rate')
    ax[1].set_title('ROC Curve')
    ax[1].legend(loc='best')

    # Show both plots
    plt.tight_layout()
    plt.show()
```

```
Model loaded successfully
Accuracy: 0.7630
Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.76      0.77     11930
           1       0.74      0.76      0.75     10830

    accuracy                           0.76     22760
   macro avg       0.76      0.76      0.76     22760
weighted avg       0.76      0.76      0.76     22760

Confusion Matrix:
[[9085 2845]
 [2550 8280]]
ROC-AUC: 0.8655
```





The performance of the model will be evaluated using cross-validation, k-fold cross-validation and stratified cross-validation techniques.

CROOS VALIDATION

In [29]:
```
def evaluate_model(model, X, y, cv_folds, metrics=['accuracy', 'precision', 'recall
    """
    Function that takes a model, features (X), target (y), and evaluates it using c

    Parameters:
    - model: The machine learning model (e.g., RandomForestClassifier()).
    - X: Input features.
    - y: Target or dependent variable.
    - metrics: List of metrics to evaluate (default: 'accuracy', 'precision', 'reca
    - cv_folds: Number of folds for cross-validation (default: 5).

    Returns:
    - Cross-validation results: Averages of metrics and timing information.
    """
    # Scale the features
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    # Apply cross-validation
    cv_results = cross_validate(model, X_scaled, y, cv=cv_folds, scoring=metrics, r

    # Display the results of the metrics and timing
    print("Cross-validation results:")

    for metric in metrics:
        print(f"Mean {metric.capitalize()}: {cv_results[f'test_{metric}'].mean():.4

    print(f"Mean Training Time: {cv_results['fit_time'].mean():.4f} seconds")
    print(f"Mean Prediction Time: {cv_results['score_time'].mean():.4f} seconds")

    return cv_results
```

Train cross validation

In [23]:
```
# Example usage
# Define features and target
X = spotify[predictors_complete]
y = spotify['popularity_class']

# Define the model
rf = RandomForestClassifier(n_estimators=100, random_state=42)

# Number of folds to train
cv_folds = 10  # 5 - 10

# Call the function to evaluate the model
results = evaluate_model(rf, X, y, cv_folds)
```

```
Cross-validation results:
Mean Accuracy: 0.7112
Mean Precision: 0.6835
Mean Recall: 0.7306
Mean Roc_auc: 0.8071
Mean Training Time: 30.4785 seconds
Mean Prediction Time: 0.4289 seconds
```

K-FOLD CROSS VALIDATION

In [13]:
```
def perform_k_fold_cv(model, X, y, cv=5, scoring=None):
    """
    This function performs K-Fold Cross-Validation on a given model and returns the

    Parameters:
    - model: The model to be evaluated (e.g., RandomForestClassifier()).
    - X: Feature set.
    - y: Target labels (dependent variable).
    - cv: Number of folds for K-Fold Cross-Validation (default is 5).
    - scoring: A dictionary of metrics to evaluate (optional).

    Returns:
    - results: A dictionary with the average metrics obtained.
    """
    # If no scoring metrics are specified, we use accuracy, precision, recall, and
    if scoring is None:
        scoring = {
            'accuracy': 'accuracy',
            'precision': make_scorer(precision_score, average='weighted'),
            'recall': make_scorer(recall_score, average='weighted'),
            'f1': make_scorer(f1_score, average='weighted')
        }

    # Perform cross-validation with the specified model
    results = cross_validate(model, X, y, cv=cv, scoring=scoring, n_jobs=-1, return

    # Display the metrics for each fold
    for i in range(cv):
        print(f"Fold {i + 1}:")
        for metric in scoring.keys():
```

```
            print(f"    {metric.capitalize()}: {results[f'test_{metric}'][i]:.4f}")
        print(f"    Training Time: {results['fit_time'][i]:.4f} seconds")
        print(f"    Prediction Time: {results['score_time'][i]:.4f} seconds")
        print()

    # Calculate and display the average metrics
    metrics_avg = {metric: results[f'test_{metric}'].mean() for metric in scoring}
    metrics_avg['mean_training_time'] = results['fit_time'].mean()
    metrics_avg['mean_prediction_time'] = results['score_time'].mean()


    print("Average metrics:")
    for metric, avg in metrics_avg.items():
        print(f"{metric.replace('_', ' ').capitalize()} average: {avg:.4f} seconds"

    return metrics_avg
```

Train K-FOLD

In [14]:
```
# Load the saved model
loaded_model = joblib.load('../data/06_models/simple_random_forest_model.pkl')

# Assume you already have your X and y data defined
# Call the cross-validation function with the loaded model
average_results = perform_k_fold_cv(loaded_model, X, y, cv=10)
```

```
Fold 1:
    Accuracy: 0.7236
    Precision: 0.7236
    Recall: 0.7236
    F1: 0.7236
    Training Time: 45.4336 seconds
    Prediction Time: 0.3058 seconds

Fold 2:
    Accuracy: 0.6787
    Precision: 0.6802
    Recall: 0.6787
    F1: 0.6790
    Training Time: 44.1614 seconds
    Prediction Time: 0.3301 seconds

Fold 3:
    Accuracy: 0.7530
    Precision: 0.7538
    Recall: 0.7530
    F1: 0.7531
    Training Time: 45.4748 seconds
    Prediction Time: 0.3368 seconds

Fold 4:
    Accuracy: 0.7200
    Precision: 0.7215
    Recall: 0.7200
    F1: 0.7202
    Training Time: 44.4743 seconds
    Prediction Time: 0.2905 seconds

Fold 5:
    Accuracy: 0.7098
    Precision: 0.7129
    Recall: 0.7098
    F1: 0.7098
    Training Time: 45.2535 seconds
    Prediction Time: 0.3622 seconds

Fold 6:
    Accuracy: 0.7053
    Precision: 0.7121
    Recall: 0.7053
    F1: 0.7048
    Training Time: 44.8763 seconds
    Prediction Time: 0.3018 seconds

Fold 7:
    Accuracy: 0.6871
    Precision: 0.6889
    Recall: 0.6871
    F1: 0.6873
    Training Time: 45.6988 seconds
    Prediction Time: 0.3109 seconds
```

```
Fold 8:
    Accuracy: 0.7487
    Precision: 0.7487
    Recall: 0.7487
    F1: 0.7487
    Training Time: 44.0519 seconds
    Prediction Time: 0.3161 seconds

Fold 9:
    Accuracy: 0.7126
    Precision: 0.7201
    Recall: 0.7126
    F1: 0.7120
    Training Time: 43.8782 seconds
    Prediction Time: 0.3051 seconds

Fold 10:
    Accuracy: 0.6736
    Precision: 0.6756
    Recall: 0.6736
    F1: 0.6738
    Training Time: 44.0454 seconds
    Prediction Time: 0.3227 seconds

Average metrics:
Accuracy average: 0.7112
Precision average: 0.7137
Recall average: 0.7112
F1 average: 0.7112
Mean training time average: 44.7348 seconds
Mean prediction time average: 0.3182 seconds
```

STRATIFIED K-FOLD CROSS VALIDATION

In [27]:

```
def evaluate_stratified_model(model, X, y, cv_folds, metrics=['accuracy', 'precisio
    """
    Function that takes a model, features (X), target (y), and evaluates it using s

    Parameters:
    - model: The machine learning model.
    - X: Input features.
    - y: Target or dependent variable.
    - metrics: List of metrics to evaluate (default: 'accuracy', 'precision', 'reca
    - cv_folds: Number of folds for cross-validation (default: 5).

    Returns:
    - Stratified cross-validation results: Averages of metrics and timing informati
    """
    # Scale the features
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    # Define stratified cross-validation
    strat_kfold = StratifiedKFold(n_splits=cv_folds, shuffle=True, random_state=42)
```

```
    # Apply stratified cross-validation
    cv_results = cross_validate(model, X_scaled, y, cv=strat_kfold, scoring=metrics

    # Display the results of the metrics and timing
    print("Stratified cross-validation results:")

    for metric in metrics:
        print(f"Mean {metric.capitalize()}: {cv_results[f'test_{metric}'].mean():.4

    print(f"Mean Training Time: {cv_results['fit_time'].mean():.4f} seconds")
    print(f"Mean Prediction Time: {cv_results['score_time'].mean():.4f} seconds")

    return cv_results
```

Train stratiefied

In [28]:

```
# Example usage with a pre-defined model
# Define features and target
X = spotify[predictors_complete]
y = spotify['popularity_class']

# Load or use the model already trained or configured
rf = RandomForestClassifier(n_estimators=100, random_state=42)

cv_folds = 5  # 5 - 10
# Call the function to evaluate the model using stratified cross-validation
stratified_results = evaluate_stratified_model(rf, X, y, cv_folds)
```

```
Stratified cross-validation results:
Mean Accuracy: 0.7641
Mean Precision: 0.7454
Mean Recall: 0.7629
Mean Roc_auc: 0.8626
Mean Training Time: 31.2205 seconds
Mean Prediction Time: 0.9431 seconds
```

The best model in terms of performance is the one using Stratified Cross-Validation, with an average accuracy of 76% and training time 31 seconcs.