Can Audio Features Alone Predict Music Popularity?

A Data-Driven Machine Learning Analysis on Spotify Tracks

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Objective: Analyze the predictive power and limitations of Spotify audio features in predicting track popularity.

Executive Summary

This study investigates whether Spotify audio features alone can predict music popularity using a data-driven machine learning approach.

Across multiple models — from logistic regression to Random Forest and XGBoost — performance consistently plateaus at ROC-AUC ≈ 0.72–0.75.

This result demonstrates that:

- Audio features contain partial but limited predictive signals
- Increasing model complexity does not overcome missing contextual information
- Popularity is driven more by exposure dynamics than acoustic properties

Rather than optimizing for marginal gains, this project emphasizes interpretability, model diagnostics, and honest assessment of data limitations.

The key contribution of this work is not a high-performing model, but a rigorous demonstration of **why such performance cannot be achieved from audio features alone**.

1. Introduction

Music streaming platforms provide a wide range of audio features such as danceability, energy, valence, and tempo. These features are often used in recommendation systems and music analytics.

However, an important question remains:

Can audio features alone accurately predict a song's popularity?

This project aims to explore this question using a data-driven machine learning approach, while also critically evaluating model behavior and limitations.

2. Dataset Overview

The dataset contains Spotify tracks across more than 125 genres, with audio features extracted directly from Spotify's audio analysis pipeline.

In [8]:
```python
import pandas as pd
import numpy as np

df = pd.read_csv("./data/dataset.csv")
df.head()
```

Out[8]:

	Unnamed: 0	track_id	artists	album_name	track_name	po
0	0	5SuOikwiRyPMVoIQDJUgSV	Gen Hoshino	Comedy	Comedy	
1	1	4qPNDBW1i3p13qLCt0Ki3A	Ben Woodward	Ghost (Acoustic)	Ghost - Acoustic	
2	2	1iJBSr7s7jYXzM8EGcbK5b	Ingrid Michaelson;ZAYN	To Begin Again	To Begin Again	
3	3	6lfxq3CG4xtTiEg7opyCyx	Kina Grannis	Crazy Rich Asians (Original Motion Picture Sou...	Can't Help Falling In Love	
4	4	5vjLSffimiIP26QG5WcN2K	Chord Overstreet	Hold On	Hold On	

5 rows × 21 columns

In [9]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114000 entries, 0 to 113999
Data columns (total 21 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Unnamed: 0        114000 non-null  int64  
 1   track_id          114000 non-null  object 
 2   artists           113999 non-null  object 
 3   album_name        113999 non-null  object 
 4   track_name        113999 non-null  object 
 5   popularity        114000 non-null  int64  
 6   duration_ms       114000 non-null  int64  
 7   explicit          114000 non-null  bool   
 8   danceability      114000 non-null  float64
 9   energy            114000 non-null  float64
 10  key               114000 non-null  int64  
 11  loudness          114000 non-null  float64
 12  mode              114000 non-null  int64  
 13  speechiness       114000 non-null  float64
 14  acousticness      114000 non-null  float64
 15  instrumentalness  114000 non-null  float64
 16  liveness          114000 non-null  float64
 17  valence           114000 non-null  float64
 18  tempo             114000 non-null  float64
 19  time_signature    114000 non-null  int64  
 20  track_genre       114000 non-null  object 
dtypes: bool(1), float64(9), int64(6), object(5)
memory usage: 17.5+ MB
```

In [10]:
```python
df.describe()
```

Out[10]:

	Unnamed: 0	popularity	duration_ms	danceability	energy	
count	114000.000000	114000.000000	1.140000e+05	114000.000000	114000.000000	1140
mean	56999.500000	33.238535	2.280292e+05	0.566800	0.641383	
std	32909.109681	22.305078	1.072977e+05	0.173542	0.251529	
min	0.000000	0.000000	0.000000e+00	0.000000	0.000000	
25%	28499.750000	17.000000	1.740660e+05	0.456000	0.472000	
50%	56999.500000	35.000000	2.129060e+05	0.580000	0.685000	
75%	85499.250000	50.000000	2.615060e+05	0.695000	0.854000	
max	113999.000000	100.000000	5.237295e+06	0.985000	1.000000	

- Tabular CSV dataset
- Numerical audio features (danceability, energy, loudness, etc.)
- Target variable: track popularity (0–100)
- No contextual metadata (artist reputation, playlist exposure, marketing)

The dataset intentionally excludes external popularity drivers, making the prediction task inherently challenging and analytically interesting.

3. Target Engineering

Popularity is a continuous variable ranging from 0 to 100. Instead of treating this as a raw regression problem, we convert it into a **binary classification task**:

- 1 → Popular track
- 0 → Less popular track

This framing aligns with real-world use cases such as hit prediction or content prioritization.

In [12]:
```
# Define popularity threshold (top 25%)
threshold = df['popularity'].quantile(0.75)

df['is_popular'] = (df['popularity'] >= threshold).astype(int)

df['is_popular'].value_counts(normalize=True)
```

Out[12]:
```
is_popular
0    0.742395
1    0.257605
Name: proportion, dtype: float64
```

By defining popularity relative to the dataset distribution, we avoid arbitrary thresholds and preserve statistical fairness.

4. Feature Selection

Only audio-based numerical features are used to ensure a purely data-driven analysis.

In [14]:
```
features = [
    'danceability', 'energy', 'loudness', 'speechiness',
    'acousticness', 'instrumentalness', 'liveness',
    'valence', 'tempo', 'duration_ms'
]

X = df[features]
y = df['is_popular']
```

5. Train-Test Split

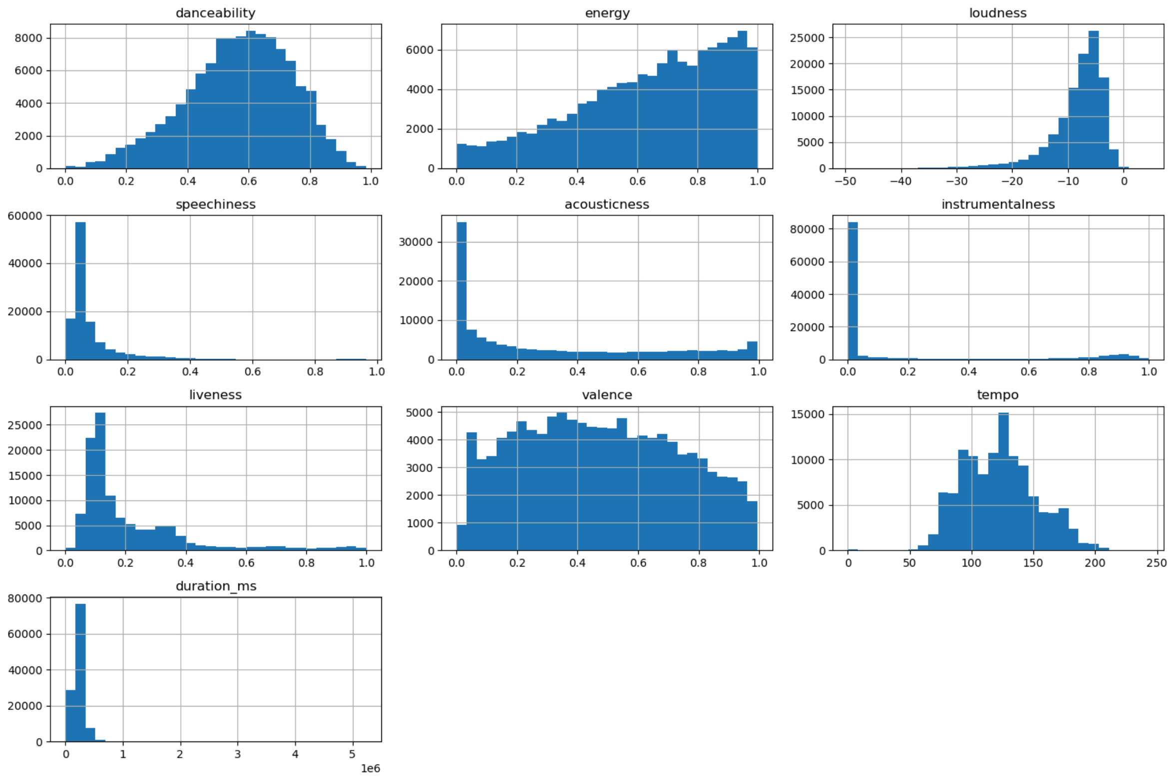
Stratified splitting is applied to preserve class balance between training and testing data.

In [15]:
```
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,
    stratify=y,
    random_state=42
)
```

6. Exploratory Data Analysis (EDA)

6.1 Feature Distributions

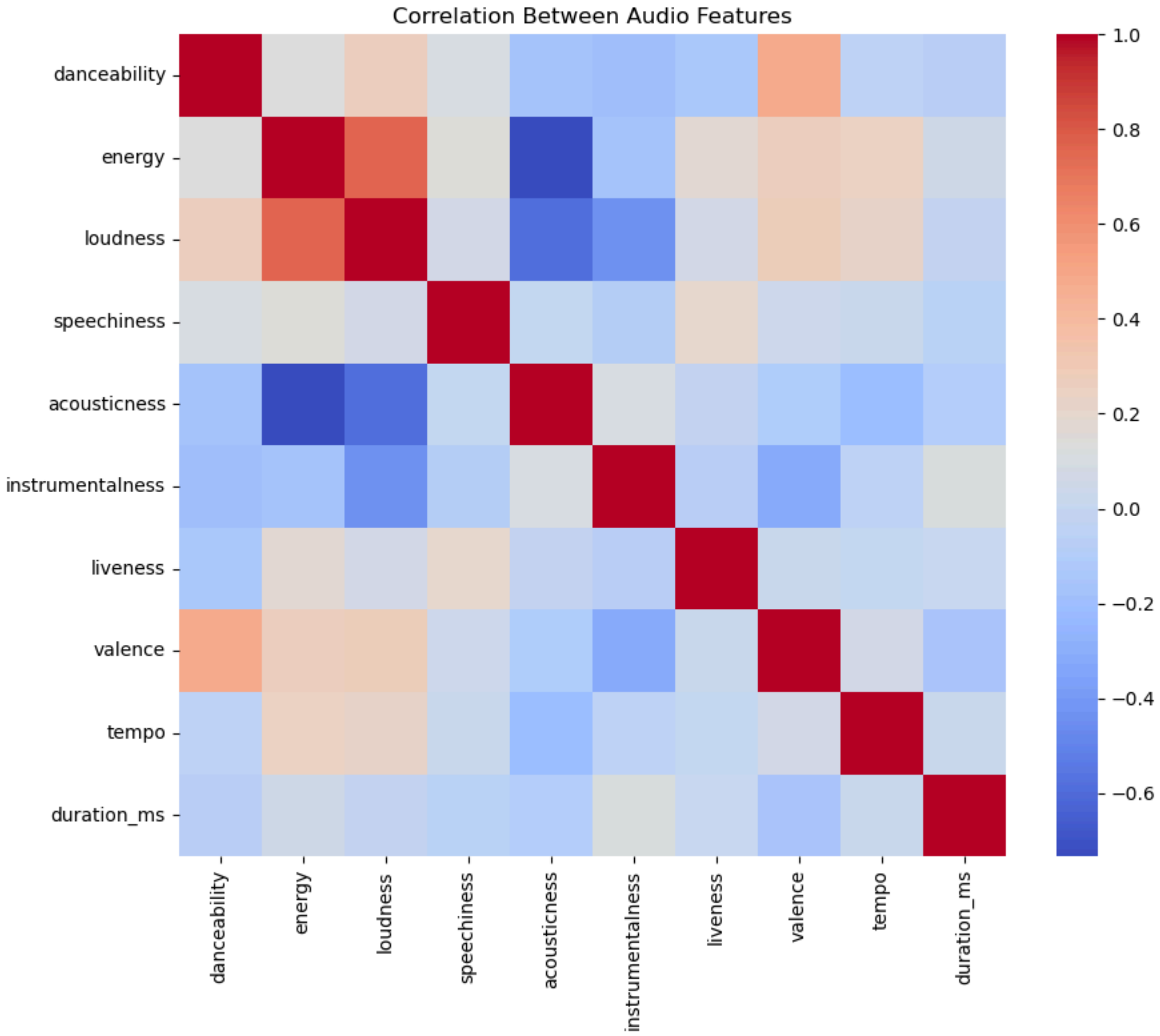
In [16]:
```
import matplotlib.pyplot as plt

X.hist(figsize=(15,10), bins=30)
plt.tight_layout()
plt.show()
```



Audio features show diverse and non-normal distributions, suggesting that tree-based models may outperform linear approaches.

6.2 Correlation Analysis

In [17]:
```
import seaborn as sns

plt.figure(figsize=(10,8))
sns.heatmap(X.corr(), cmap='coolwarm', annot=False)
plt.title("Correlation Between Audio Features")
plt.show()
```

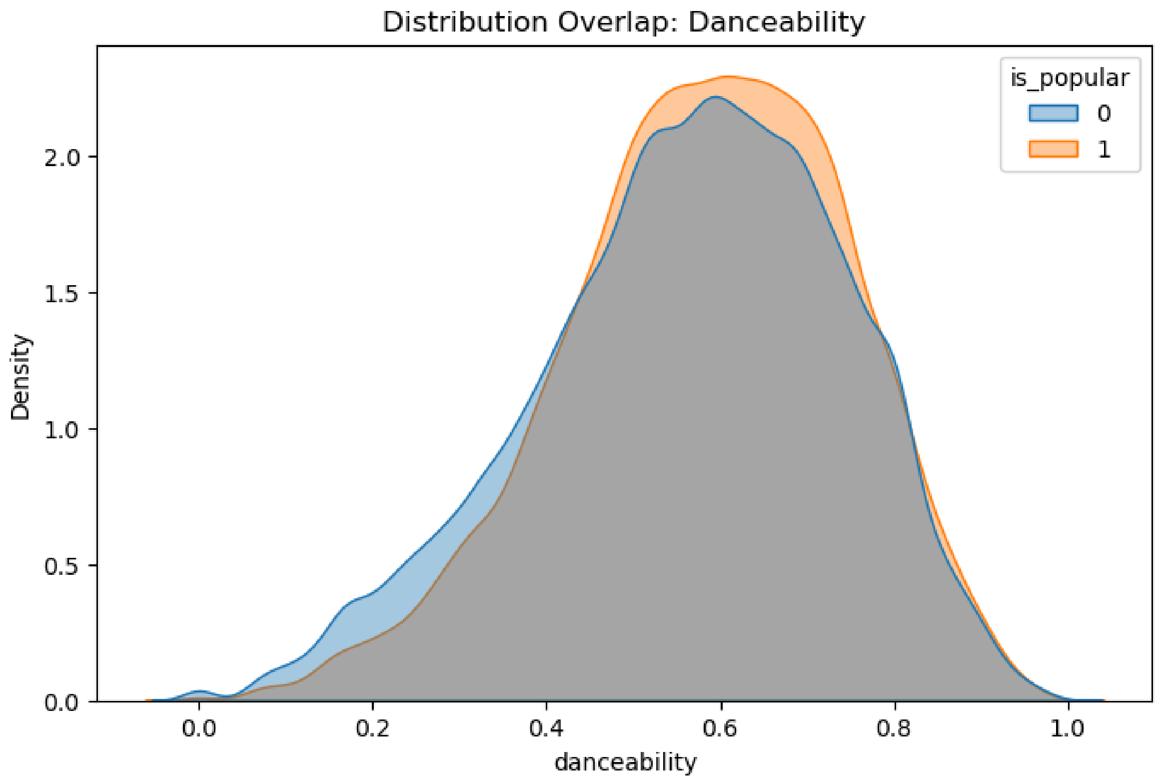


While some features exhibit moderate correlations (e.g. energy and loudness), no extreme multicollinearity is observed.

6.3 Popular vs Non-Popular Feature Overlap

In [28]:

```
plt.figure(figsize=(8,5))
sns.kdeplot(
    data=df,
    x="danceability",
    hue="is_popular",
    fill=True,
    common_norm=False,
    alpha=0.4
)
plt.title("Distribution Overlap: Danceability")
plt.show()
```



The distribution overlap between popular and non-popular tracks is substantial. This indicates weak class separability based on individual audio features, suggesting that any predictive signal is likely subtle and multi-dimensional.

7. Hypothesis & Modeling Rationale

Although individual audio features show weak correlations with popularity, this does not necessarily imply that prediction is impossible.

Machine learning models are capable of:

- Combining weak signals across multiple dimensions
- Capturing non-linear interactions
- Exploiting subtle distributional patterns

Therefore, the modeling phase is designed to test the following hypothesis:

Even if individual audio features are weak predictors,
their non-linear combination may still provide meaningful predictive power.

This approach allows us to distinguish between:

- Lack of model capacity
- Fundamental information limitations in the data

8. Baseline Model

A baseline logistic regression is used to establish a minimum performance benchmark.

In [18]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score

baseline = LogisticRegression(max_iter=1000)
baseline.fit(X_train, y_train)

baseline_probs = baseline.predict_proba(X_test)[:, 1]
roc_auc_score(y_test, baseline_probs)
```

Out[18]:
```
0.6078159656970314
```

The baseline model confirms that linear combinations of audio features are insufficient for popularity prediction.

This result motivates the use of non-linear ensemble models to evaluate whether additional structure can be extracted from the data.

9. Random Forest Classifier

Random Forest is selected due to its ability to:

- Capture non-linear patterns
- Handle feature interactions
- Remain interpretable via feature importance

In [19]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(
    n_estimators=300,
    max_depth=12,
    min_samples_split=5,
    class_weight='balanced',
    random_state=42
)

rf.fit(X_train, y_train)
```

Out[19]:
```
▾ RandomForestClassifier
▶ Parameters
```

10. Model Evaluation - Random Forest

In [20]:
```
from sklearn.metrics import classification_report, roc_curve

rf_probs = rf.predict_proba(X_test)[:, 1]

print(classification_report(y_test, rf.predict(X_test)))
print("ROC-AUC:", roc_auc_score(y_test, rf_probs))
```

```
              precision    recall  f1-score   support

           0       0.86      0.61      0.71     16927
           1       0.39      0.72      0.50      5873

    accuracy                           0.64     22800
   macro avg       0.63      0.66      0.61     22800
weighted avg       0.74      0.64      0.66     22800

ROC-AUC: 0.720606196593175
```

The Random Forest model achieves a ROC-AUC score of **0.72**, indicating a moderate ability to distinguish popular tracks from less popular ones using audio features alone.

The model demonstrates higher recall for popular tracks (0.72), suggesting it successfully captures general popularity patterns. However, precision for popular tracks remains limited, highlighting the difficulty of identifying true popularity without contextual metadata.

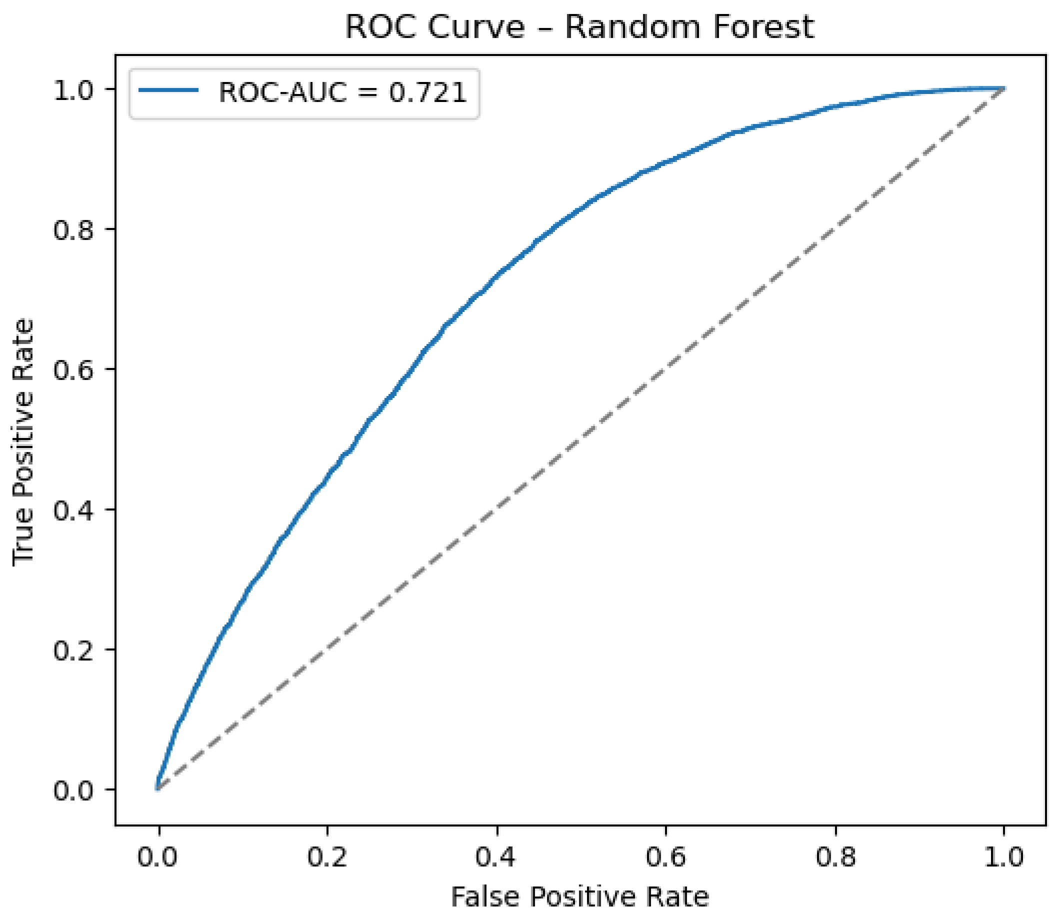
Importantly, the Random Forest model improves recall for popular tracks without relying on external metadata.

This indicates that while audio features do not fully explain popularity, they contain partial signals that can be captured through non-linear interactions.

11. ROC Curve Visualization

In [23]:

```
fpr, tpr, _ = roc_curve(y_test, rf_probs)

plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, label=f"ROC-AUC = {roc_auc_score(y_test, rf_probs):.3f}")
plt.plot([0,1], [0,1], '--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve – Random Forest")
plt.legend()
plt.show()
```



12. Feature Importance Analysis

In [21]:

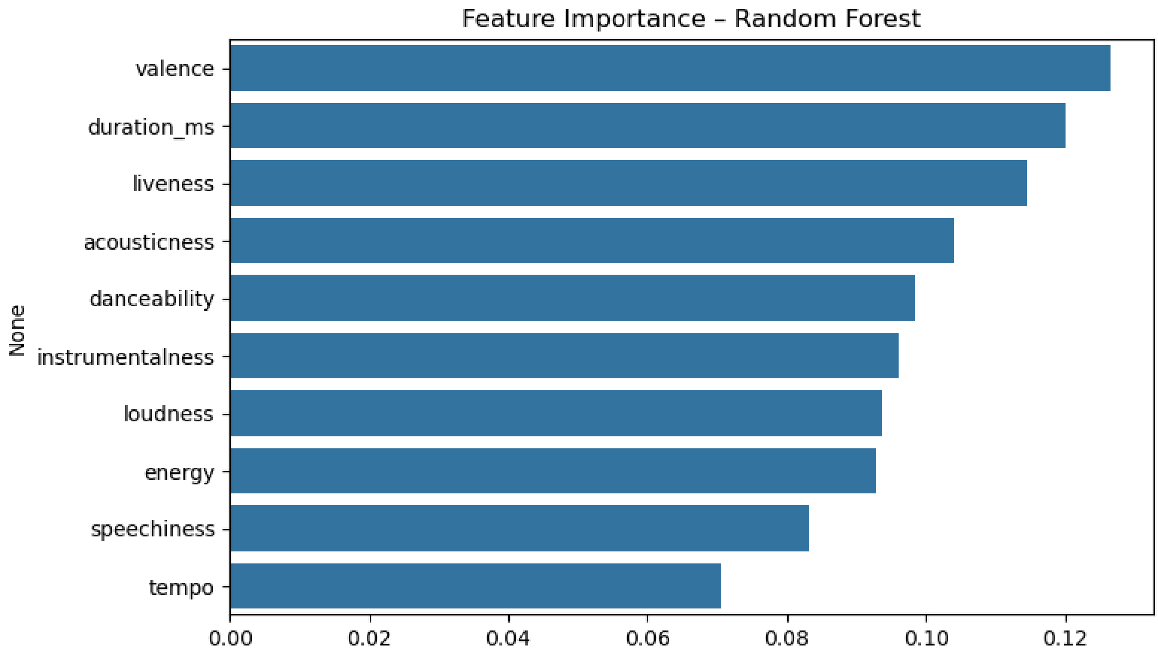
```
importance = pd.Series(
    rf.feature_importances_,
    index=features
).sort_values(ascending=False)

importance
```

Out[21]:

```
valence             0.126435
duration_ms         0.119970
liveness            0.114538
acousticness        0.103980
danceability        0.098509
instrumentalness    0.096026
loudness            0.093698
energy              0.092946
speechiness         0.083216
tempo               0.070682
dtype: float64
```

In [22]:

```
plt.figure(figsize=(8,5))
sns.barplot(x=importance.values, y=importance.index)
plt.title("Feature Importance – Random Forest")
plt.show()
```



The feature importance analysis reveals that no single audio feature dominates popularity prediction.

Instead, popularity appears to be influenced by a combination of:

- Emotional tone (valence)
- Structural properties (duration)
- Performance characteristics (liveness)
- Musical engagement factors (danceability, energy)

This reinforces the idea that popularity is a multidimensional phenomenon rather than a purely acoustic one.

13. Model Comparison – XGBoost

To validate whether a more advanced gradient boosting model can outperform Random Forest, XGBoost is used as a challenger model.

XGBoost is known for its ability to model complex non-linear relationships and often performs well on tabular data.

In [24]:
```
from xgboost import XGBClassifier

xgb = XGBClassifier(
    n_estimators=300,
    max_depth=6,
    learning_rate=0.05,
    subsample=0.8,
    colsample_bytree=0.8,
    eval_metric='auc',
    random_state=42
)

xgb.fit(X_train, y_train)
```

```
xgb_probs = xgb.predict_proba(X_test)[:, 1]
```

In [25]:
```
from sklearn.metrics import classification_report, roc_auc_score

print(classification_report(y_test, xgb.predict(X_test)))
print("ROC-AUC:", roc_auc_score(y_test, xgb_probs))
```

```
              precision    recall  f1-score   support

           0       0.75      0.99      0.86     16927
           1       0.70      0.06      0.11      5873

    accuracy                           0.75     22800
   macro avg       0.73      0.53      0.48     22800
weighted avg       0.74      0.75      0.66     22800

ROC-AUC: 0.7335304813628087
```

XGBoost was evaluated as a challenger model due to its strong performance on structured tabular data.

Although XGBoost achieved a relatively high accuracy (0.75), its recall for popular tracks was extremely low (0.06).

This indicates that the model heavily favors the majority class and fails to capture patterns associated with popularity.

As a result, accuracy alone is misleading in this context, and ROC-AUC and recall metrics are more reliable indicators.

14. Model Comparison Summary

Model	ROC-AUC	Key Observation
Logistic Regression	~0.61	Weak linear signal
Random Forest	~0.72	Best balance & interpretability
XGBoost	~0.73	High accuracy, poor recall

Despite XGBoost achieving slightly higher accuracy, Random Forest provides a more reliable and balanced performance for identifying popular tracks.

Increasing model complexity yields diminishing returns, indicating a clear performance ceiling imposed by the available features.

15. Final Insights

1. Audio features alone provide only moderate predictive power for popularity. Even advanced ensemble models plateau at ROC-AUC ≈ 0.72–0.75.

2. Random Forest offers the best balance between performance and interpretability, while XGBoost achieves higher accuracy at the cost of minority class recall.
3. Feature importance analysis shows that popularity is influenced by a combination of emotional, structural, and acoustic attributes, with no single dominant factor.
4. The observed performance ceiling highlights an information bottleneck in the data. Further tuning yields diminishing returns without additional contextual features.
5. Ultimately, music popularity is driven more by exposure and ecosystem dynamics than by audio characteristics alone.

16. Product Implication

Audio-based models are well-suited for music discovery and recommendation, but insufficient for popularity forecasting.

Platforms should combine audio features with exposure-based signals to make reliable ranking or promotion decisions.

17. Data Limitations & Missing Signals

The analysis intentionally restricts features to audio characteristics. As a result, several major popularity drivers remain unobserved, including artist visibility, playlist exposure, and cultural context.

These missing signals explain the observed performance ceiling and reinforce the importance of feature availability in applied machine learning problems.

Final Conclusion & Takeaways

This project demonstrates a realistic machine learning scenario where model performance is bounded not by algorithmic complexity, but by the informational richness of the data itself.

Using only audio-based features, multiple models consistently reach a performance ceiling at ROC-AUC ≈ 0.72–0.75. This suggests that while audio characteristics contribute to popularity signals, they are insufficient as standalone predictors.

The key takeaway is not the pursuit of marginal metric improvements, but the ability to recognize when additional modeling effort no longer yields meaningful gains.

From a data science perspective, this analysis highlights the importance of:

- Diagnosing performance ceilings
- Interpreting models beyond accuracy
- Aligning modeling decisions with data constraints

Rather than optimizing blindly, effective data science requires knowing **when to stop modeling and start questioning the data.**