Creating Cohorts of Songs

Creating Cohorts of Songs – Course-end Project 2

Simplilearn AI & ML PGP | Spotify Rolling Stones Dataset

Objective: Perform exploratory data analysis and cluster analysis to create cohorts of songs and understand the factors that define each cohort for better song recommendations.

1]:
```python
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
sns.set_style('whitegrid')
print("Libraries loaded successfully.")
```

```
Libraries loaded successfully.
```

1. Load Data & Data Dictionary

Load the Rolling Stones Spotify dataset and (optionally) the data dictionary for column definitions.

[3]:
```python
# Load dataset
df = pd.read_csv('rolling_stones_spotify.csv')
# Remove unnamed index column if present
if df.columns[0].startswith('Unnamed') or df.columns[0] == '':
    df = df.iloc[:, 1:]
print("Dataset shape:", df.shape)
print("\nColumns:", list(df.columns))
df.head()
```

```
Dataset shape: (1610, 17)

Columns: ['name', 'album', 'release_date', 'track_number', 'id', 'uri', 'acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness', 'loudness', 'speechiness', 'tempo', 'valence', 'popular
ity', 'duration_ms']
```

[3]:

	name	album	release_date	track_number	id	uri	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popular
0	Concert Intro Music - Live	Licked Live In NYC	2022-06-10	1	2IEkywLJ4ykbhi1yRQvmsT	spotify:track:2IEkywLJ4ykbhi1yRQvmsT	0.0824	0.463	0.993	0.996000	0.932	-12.913	0.1100	118.001	0.0302	
1	Street Fighting Man - Live	Licked Live In NYC	2022-06-10	2	6GVgVJBKkGJoRfarYRvGTU	spotify:track:6GVgVJBKkGJoRfarYRvGTU	0.4370	0.326	0.965	0.233000	0.961	-4.803	0.0759	131.455	0.3180	
2	Start Me Up - Live	Licked Live In NYC	2022-06-10	3	1Lu761pZ0dBTGpzxaQoZNW	spotify:track:1Lu761pZ0dBTGpzxaQoZNW	0.4160	0.386	0.969	0.400000	0.956	-4.936	0.1150	130.066	0.3130	
3	If You Can't Rock Me - Live	Licked Live In NYC	2022-06-10	4	1agTQzOTUnGNggyckEqiDH	spotify:track:1agTQzOTUnGNggyckEqiDH	0.5670	0.369	0.985	0.000107	0.895	-5.535	0.1930	132.994	0.1470	
4	Don't Stop - Live	Licked Live In NYC	2022-06-10	5	7piGJR8YndQBQWVXv6KtQw	spotify:track:7piGJR8YndQBQWVXv6KtQw	0.4000	0.303	0.969	0.055900	0.966	-5.098	0.0930	130.533	0.2060	

[6]:
```python
# Load and display Data Dictionary (column definitions)
try:
    data_dict = pd.read_excel('Data Dictionary - Creating cohorts of songs.xlsx')
    print("Data Dictionary - Creating cohorts of songs:")
    display(data_dict)
except Exception as e:
    print("Data dictionary not loaded:", e)
    print("Spotify audio features: acousticness, danceability, energy, instrumentalness,")
    print("liveness, loudness, speechiness, tempo, valence, popularity, duration_ms")
```

```
Data dictionary not loaded: Missing optional dependency 'openpyxl'.  Use pip or conda to install openpyxl.
Spotify audio features: acousticness, danceability, energy, instrumentalness,
liveness, loudness, speechiness, tempo, valence, popularity, duration_ms
```

2. Data Quality Checks

Check for missing values and basic statistics of numeric features used for clustering.

[9]:
```python
# Data quality - missing values
print("Missing values per column:")
print(df.isnull().sum())
print("\nTotal missing:", df.isnull().sum().sum())
print("\nData types:\n", df.dtypes)
# Numeric features (Spotify audio features) for clustering
feature_cols = ['acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness',
               'loudness', 'speechiness', 'tempo', 'valence', 'popularity', 'duration_ms']
df_numeric = df[feature_cols].copy()
print("\nBasic statistics of clustering features:")
df_numeric.describe()
```

```
Missing values per column:
name                0
album               0
release_date        0
track_number        0
id                  0
uri                 0
acousticness        0
danceability        0
energy              0
instrumentalness    0
liveness            0
loudness            0
speechiness         0
tempo               0
valence             0
popularity          0
duration_ms         0
dtype: int64

Total missing: 0

Data types:
 name                 object
album               object
release_date        object
track_number         int64
id                  object
uri                 object
acousticness       float64
danceability       float64
energy             float64
instrumentalness   float64
liveness           float64
loudness           float64
speechiness        float64
tempo              float64
valence            float64
popularity           int64
duration_ms          int64
dtype: object

Basic statistics of clustering features:
```

Basic statistics of clustering features:

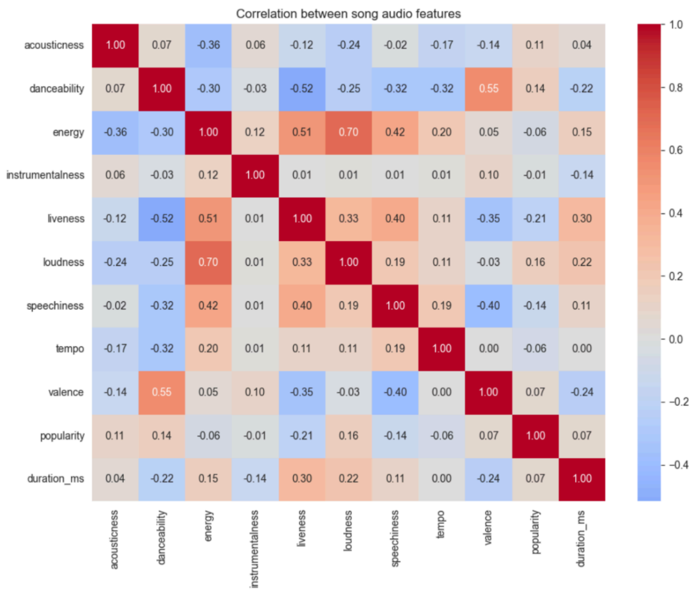
[9]:

	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popularity	duration_ms
count	1610.000000	1610.000000	1610.000000	1610.000000	1610.00000	1610.000000	1610.000000	1610.000000	1610.000000	1610.000000	1610.000000
mean	0.250475	0.468860	0.792352	0.164170	0.49173	-6.971615	0.069512	126.082033	0.582165	20.788199	257736.488199
std	0.227397	0.141775	0.179886	0.276249	0.34910	2.994003	0.051631	29.233483	0.231253	12.426859	108333.474920
min	0.000009	0.104000	0.141000	0.000000	0.02190	-24.408000	0.023200	46.525000	0.000000	0.000000	21000.000000
25%	0.058350	0.362250	0.674000	0.000219	0.15300	-8.982500	0.036500	107.390750	0.404250	13.000000	190613.000000
50%	0.183000	0.458000	0.848500	0.013750	0.37950	-6.523000	0.051200	124.404500	0.583000	20.000000	243093.000000
75%	0.403750	0.578000	0.945000	0.179000	0.89375	-4.608750	0.086600	142.355750	0.778000	27.000000	295319.750000
max	0.994000	0.887000	0.999000	0.996000	0.99800	-1.014000	0.624000	216.304000	0.974000	80.000000	981866.000000

3. Exploratory Data Analysis

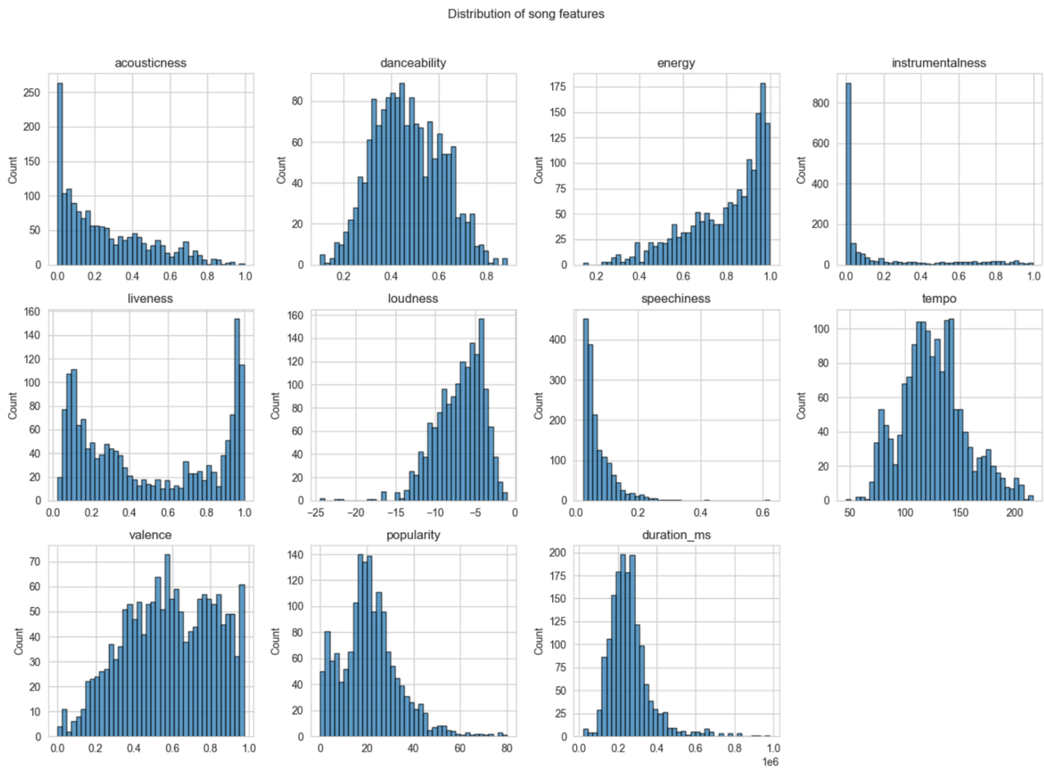
Understand distributions and relationships among audio features that will define song cohorts.

[12]:
```python
# Correlation heatmap of numeric features
plt.figure(figsize=(10, 8))
corr = df_numeric.corr()
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm', center=0)
plt.title('Correlation between song audio features')
plt.tight_layout()
plt.show()
```

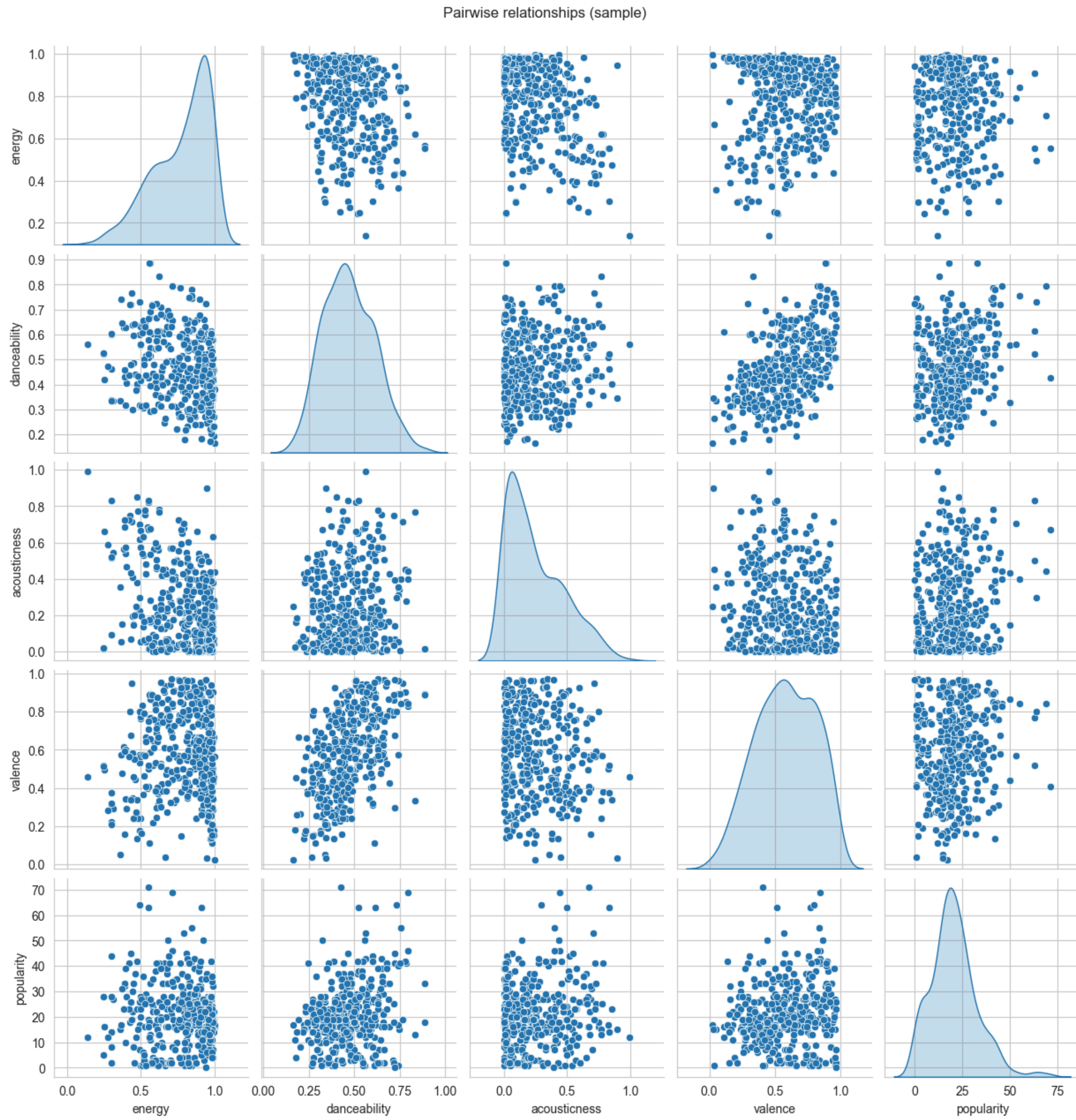


[14]:

```
# Distributions of key features
fig, axes = plt.subplots(3, 4, figsize=(14, 10))
axes = axes.flatten()
for i, col in enumerate(feature_cols):
    axes[i].hist(df_numeric[col].dropna(), bins=40, edgecolor='black', alpha=0.7)
    axes[i].set_title(col)
    axes[i].set_ylabel('Count')
axes[-1].axis('off')
plt.suptitle('Distribution of song features', y=1.02)
plt.tight_layout()
plt.show()
```



[16]:
```
# Pairplot of a subset of features (sample for speed)
sample = df_numeric.sample(min(400, len(df_numeric)), random_state=42)
sns.pairplot(sample[['energy', 'danceability', 'acousticness', 'valence', 'popularity']], diag_kind='kde')
plt.suptitle('Pairwise relationships (sample)', y=1.02)
plt.show()
```



4. Cluster Analysis – Creating Cohorts of Songs

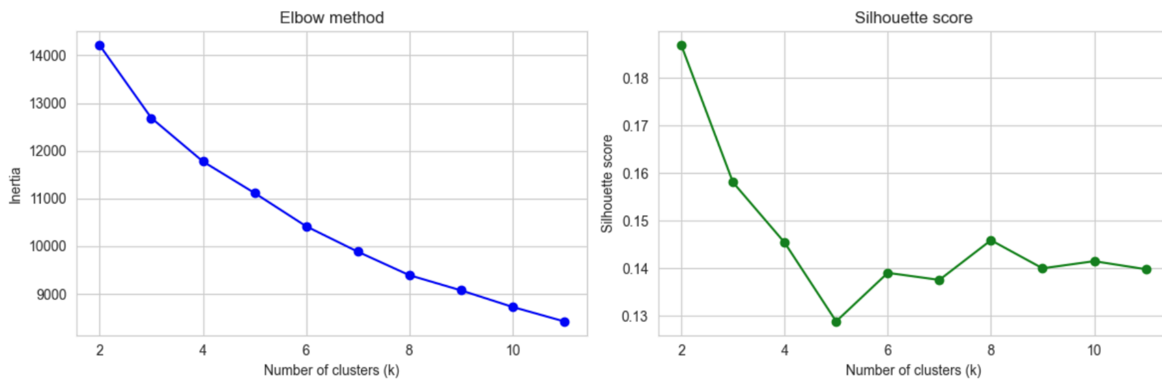
Scale features and apply K-Means. Use elbow method and silhouette score to choose number of cohorts (k).

[19]:
```
# Handle any missing values and scale features
X = df_numeric.dropna()
if len(X) < len(df_numeric):
    print("Dropped rows with missing values:", len(df_numeric) - len(X))
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print("Scaled feature matrix shape:", X_scaled.shape)
```

```
Scaled feature matrix shape: (1610, 11)
```

[37]:

```
# Elbow method and silhouette score for optimal k
inertias = []
silhouettes = []
K_range = range(2, 12)
for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_scaled)
    inertias.append(kmeans.inertia_)
    silhouettes.append(silhouette_score(X_scaled, kmeans.labels_))
fig, axes = plt.subplots(1, 2, figsize=(12, 4))
axes[0].plot(K_range, inertias, 'bo-')
axes[0].set_xlabel('Number of clusters (k)')
axes[0].set_ylabel('Inertia')
axes[0].set_title('Elbow method')
axes[1].plot(K_range, silhouettes, 'go-')
axes[1].set_xlabel('Number of clusters (k)')
axes[1].set_ylabel('Silhouette score')
axes[1].set_title('Silhouette score')
plt.tight_layout()
plt.show()
print("Silhouette scores:", dict(zip(K_range, [round(s, 3) for s in silhouettes])))
```




```
Silhouette scores: {2: 0.187, 3: 0.158, 4: 0.145, 5: 0.129, 6: 0.139, 7: 0.138, 8: 0.146, 9: 0.14, 10: 0.141, 11: 0.14}
```

[23]:

```
# Fit final K-Means with chosen k (e.g. k=5 for interpretable cohorts; adjust based on elbow/silhouette)
n_clusters = 5
kmeans_final = KMeans(n_clusters=n_clusters, random_state=42, n_init=10)
cluster_labels = kmeans_final.fit_predict(X_scaled)
# Attach cluster to dataframe for interpretation
df_clustered = X.copy()
df_clustered['cohort'] = cluster_labels
print("Cohort (cluster) sizes:")
print(df_clustered['cohort'].value_counts().sort_index())
print("\nSilhouette score for k=%d:" % n_clusters, round(silhouette_score(X_scaled, cluster_labels), 3))
```

```
Cohort (cluster) sizes:
cohort
0    381
1    253
2    252
3    369
4    355
Name: count, dtype: int64

Silhouette score for k=5: 0.129
```

5. Cohort Profiles – Factors That Define Each Cohort

Compare mean feature values across cohorts to interpret what type of songs each cohort represents.

[26]:

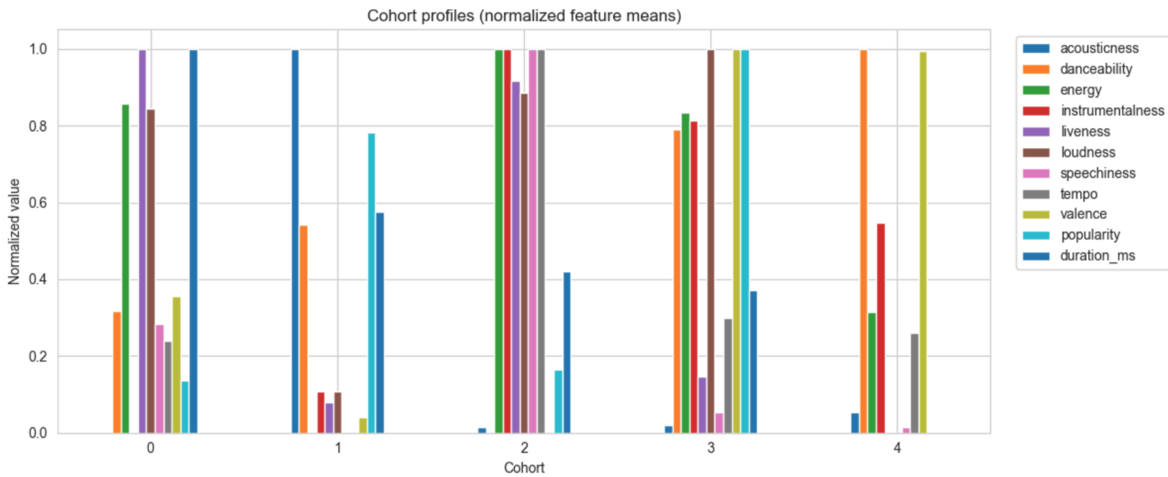
```
# Cohort profiles (mean of each feature per cohort)
cohort_profiles = df_clustered.groupby('cohort')[feature_cols].mean()
cohort_profiles.round(3)
```

[26]:

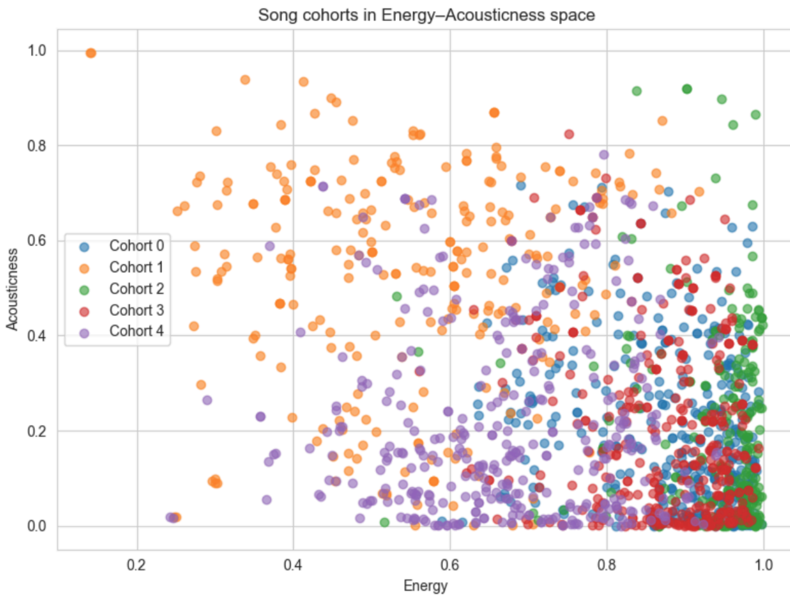
cohort	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popularity	duration_ms
0	0.193	0.402	0.887	0.057	0.851	-5.683	0.074	122.365	0.511	17.005	338533.780
1	0.521	0.464	0.545	0.081	0.274	-9.339	0.046	113.292	0.389	25.953	272789.585
2	0.198	0.315	0.944	0.280	0.799	-5.476	0.144	151.019	0.373	17.381	248718.056
3	0.199	0.531	0.878	0.239	0.316	-4.908	0.052	124.561	0.761	28.951	241231.341
4	0.210	0.589	0.670	0.179	0.225	-9.873	0.048	123.066	0.758	15.101	183851.538

[28]:

```
# Visualize cohort profiles (radar/bar)
cohort_profiles_plot = cohort_profiles.copy()
# Normalize for comparison (0–1 scale per feature for display)
for c in cohort_profiles_plot.columns:
    min_v, max_v = cohort_profiles_plot[c].min(), cohort_profiles_plot[c].max()
    if max_v > min_v:
        cohort_profiles_plot[c] = (cohort_profiles_plot[c] - min_v) / (max_v - min_v)
cohort_profiles_plot.plot(kind='bar', figsize=(12, 5))
plt.title('Cohort profiles (normalized feature means)')
plt.xlabel('Cohort')
plt.ylabel('Normalized value')
plt.legend(bbox_to_anchor=(1.02, 1), loc='upper left')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



[30]:
```python
# 2D visualization: project cohorts by two important features (e.g. energy vs acousticness)
df_clustered['cohort'] = cluster_labels
plt.figure(figsize=(8, 6))
for i in range(n_clusters):
    subset = df_clustered[df_clustered['cohort'] == i]
    plt.scatter(subset['energy'], subset['acousticness'], label=f'Cohort {i}', alpha=0.6)
plt.xlabel('Energy')
plt.ylabel('Acousticness')
plt.title('Song cohorts in Energy–Acousticness space')
plt.legend()
plt.tight_layout()
plt.show()
```



6. Summary – Factors That Create Cohorts of Songs

Based on EDA and cluster analysis:

[33]:
```python
# Summary: key differentiators per cohort (top 3 features above/below overall mean)
overall_mean = df_clustered[feature_cols].mean()
print("Factors that create distinct song cohorts (vs overall mean):\n")
for cohort_id in range(n_clusters):
    cohort_mean = cohort_profiles.loc[cohort_id]
    diff = (cohort_mean - overall_mean).reindex(cohort_mean.index)
    diff = diff.reindex(diff.abs().sort_values(ascending=False).index)
    top = diff.head(3)
    print("Cohort %d: " % cohort_id, " | ".join(["%s=%.2f" % (k, v) for k, v in top.items()]))
print("\nInterpretation: Cohorts are driven by energy, acousticness, danceability, valence,")
print("instrumentalness, tempo, and popularity. Use these profiles to recommend similar songs within each cohort.")
```

```
Factors that create distinct song cohorts (vs overall mean):

Cohort 0:  duration_ms=80797.29 | popularity=-3.78 | tempo=-3.72
Cohort 1:  duration_ms=15053.10 | tempo=-12.79 | popularity=5.16
Cohort 2:  duration_ms=-9018.43 | tempo=24.94 | popularity=-3.41
Cohort 3:  duration_ms=-16505.15 | popularity=8.16 | loudness=2.06
Cohort 4:  duration_ms=-73884.95 | popularity=-5.69 | tempo=-3.02

Interpretation: Cohorts are driven by energy, acousticness, danceability, valence,
instrumentalness, tempo, and popularity. Use these profiles to recommend similar songs within each cohort.
```