Check In #1:

Goal: Predicting the genre of a track

Our team has chosen the Hugging Face Spotify Tracks dataset.

The key features we have decided to study are popularity, duration, danceability, energy, key, loudness, speechiness, acousticness, instrumentalness, liveness, valence, tempo, track genre(for training) because these would be most useful for genre prediction.

In [1]: %pip install datasets
%pip install plotly
%pip install matplotlib
%pip install seaborn
%pip install datascience
%pip install scikit-learn

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Requirement already satisfied: datasets in c:\users\windows\appdata\local\programs\python\python39\lib\site-packages (3.0.2)
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       Note: you may need to restart the kernel to use updated packages.
In [2]: import pandas as pd
        df = pd.read csv("hf://datasets/maharshipandya/spotify-tracks-dataset/dataset.csv")
       c:\Users\WINDOWS\AppData\Local\Programs\Python\Python\Python39\lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
        from .autonotebook import tqdm as notebook_tqdm
In [3]: from datascience import *
        import numpy as np
        import pandas as pd
        import plotly.express as px
        import matplotlib.pyplot as plt
In [4]: df.columns
Out[4]: Index(['Unnamed: 0', 'track_id', 'artists', 'album_name', 'track_name',
                 'popularity', 'duration_ms', 'explicit', 'danceability', 'energy',
                'key', 'loudness', 'mode', 'speechiness', 'acousticness',
                'instrumentalness', 'liveness', 'valence', 'tempo', 'time_signature',
                'track_genre'],
              dtvpe='object')
In [5]: df.sample(10)
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ut[5]:	Unn	amed: 0	track_id	artists	album_name	track_name p	opularity du	uration_ms	explicit	danceability energy	loudnes	s mode sp	eechiness	acousticness	instrumentalness	liveness	/alence te	mpo time_signature	tra	ack_genre
6	66552	66552 3	Xh4kaQAumTW993ETAdACB	Ray Remesch	EFlashApps Nursery Rhymes, Vol. 3	English Spanish Color Song	26	67010	False	0.716 0.3490	-8.00	7 1	0.0330	0.690000	0.000000	0.1770	0.645 121	1.973 4		kids
1	6534	16534 7	HnAXewQTDWHRZ2FNrVlZY	Michael Harrison	Revelation F	Revelation: Music in Pure Intonation: Night Vi	45	187960	False	0.329 0.0130	-33.238	3 0	0.0486	0.994000	0.919000	0.0671	0.285 71	1.608 4		classical
7	6735	76735	3fOkhpPPYDD5sydEM1a2uV Ge	orges Bizet;Elisabeth Vidal;Michel Plasson;W	Bizet : Carmen C	Carmen, Act III, No.20 Trio: Mêlons! Coupons!	21	185760	False	0.468 0.0984	-19.09	1 1	0.0618	0.982000	0.000002	0.1820	0.156 120).414 4		opera
3	6145	36145	55HsZ3r9G0G58AYWZFY5VI	YL	RAP MUSCULATION RENTRÉE 2022	Niya	0	180120	True	0.753 0.7590	-7.848	3 0	0.0669	0.157000	0.000000	0.1020	0.514 105	5.015 3		french
	5013	5013	0cSkn2l67csUljEy0EEBPn	LiSA	炎	炎	67	275000	False	0.477 0.6850	-4.554	1 1	0.0325	0.105000	0.000000	0.2770	0.308 152	2.040 4		anime
6	7266	67266	4pJUzyPGGBdV2yKlqYLNTN	Jhayco;Anuel AA	Frescura y Perreo	Ley Seca	0	263666	False	0.759 0.8430	-3.718	3 1	0.0913	0.127000	0.000000	0.1140	0.560 105	5.016 4		latin
	6801	6801	049SQ7EJTypWBZFhqBDuhC	I AM	Life Through Torment	Face of Death	18	125000	True	0.236 0.9620	-5.760) 1	0.1280	0.000004	0.048600	0.5070	0.420 95	5.121 4	bl	lack-metal
9	6098	96098	6Q4no26EaF80ttkl9HEWME	Casuarina	Roda de Samba do Casuarina e Convidados	Canto de Ossanha	47	264533	False	0.435 0.7080	-8.022	2 0	0.0375	0.649000	0.002100	0.7410	0.729 95	5.750 4		samba
8	3338	83338	DF9fZwEu2cWSgqoRWzAtAS	ARTY;Griff Clawson	Live For	Live For	63	171433	False	0.552 0.9100	-3.226	5 1	0.0385	0.224000	0.000014	0.1340	0.369 126	5.007 4	progressi	ive-house
1	8853	18853	DBd1WeTf27JqYQLQJPWKRo	Tom Papa	Calm, Cool, and Collected	Uncle Tom	20	76493	False	0.479 0.7970	-9.380	0	0.8530	0.801000	0.000000	0.8440	0.819 94	1.891 1		comedy

10 rows × 21 columns

The one missing row might be because the name and artists are in Korean since it is a k-pop genre song.

```
In [6]: missing_prop = df.isna().sum() / len(df.index)
missing_prop.sort_values()
           missing_rows = df[df.isna().any(axis=1)]
           print("Number of missing data rows:", len(missing_rows))
           print("Missing data rows:")
           print(missing_rows)
          Number of missing data rows: 1
         Missing data rows:
         Unnamed: 0 track_id artists album_name track_name \
65900 65900 1kR4gIb7nGxHPI3D2ifs59 NaN NaN NaN
                  popularity duration_ms explicit danceability energy ... loudness \backslash 0 0 False 0.501 0.583 ... -9.46
          65900
                  mode speechiness acousticness instrumentalness liveness valence \backslash 0 0.0605 0.69 0.00396 0.0747 0.734
          65900 0 0.0605
                     tempo time_signature track_genre
          65900 138.391
         [1 rows x 21 columns]
In [7]: # List of number of tracks (rows) in each unique track_genre
for genre in df['track_genre'].unique():
    print(f"{genre}: {len(df[df['track_genre'] == genre])}")
```

acoustic: 1000 afrobeat: 1000 alt-rock: 1000 alternative: 1000 ambient: 1000 anime: 1000 black-metal: 1000 bluegrass: 1000 blues: 1000 brazil: 1000 breakbeat: 1000 british: 1000 cantopop: 1000 chicago-house: 1000 children: 1000 chill: 1000 classical: 1000 club: 1000 comedy: 1000 country: 1000 dance: 1000 dancehall: 1000 death-metal: 1000 deep-house: 1000 detroit-techno: 1000 disco: 1000 disney: 1000 drum-and-bass: 1000 dub: 1000 dubstep: 1000 edm: 1000 electro: 1000 electronic: 1000 emo: 1000 folk: 1000 forro: 1000 french: 1000 funk: 1000 garage: 1000 german: 1000 gospel: 1000 goth: 1000 grindcore: 1000 groove: 1000 grunge: 1000 guitar: 1000 happy: 1000 hard-rock: 1000 hardcore: 1000 hardstyle: 1000 heavy-metal: 1000 hip-hop: 1000 honky-tonk: 1000 house: 1000 idm: 1000 indian: 1000 indie-pop: 1000 indie: 1000 industrial: 1000 iranian: 1000 j-dance: 1000 j-idol: 1000 j-pop: 1000 j-rock: 1000 jazz: 1000 k-pop: 1000 kids: 1000 latin: 1000 latino: 1000 malay: 1000 mandopop: 1000 metal: 1000 metalcore: 1000 minimal-techno: 1000 mpb: 1000 new-age: 1000 opera: 1000 pagode: 1000 party: 1000 piano: 1000 pop-film: 1000 pop: 1000 power-pop: 1000 progressive-house: 1000

psych-rock: 1000 punk-rock: 1000 punk: 1000 r-n-b: 1000 reggae: 1000 reggaeton: 1000 rock-n-roll: 1000 rock: 1000 rockabilly: 1000 romance: 1000 sad: 1000 salsa: 1000 samba: 1000 sertanejo: 1000 show-tunes: 1000 singer-songwriter: 1000 ska: 1000 sleep: 1000 songwriter: 1000 soul: 1000 spanish: 1000 study: 1000 swedish: 1000 synth-pop: 1000 tango: 1000 techno: 1000 trance: 1000 trip-hop: 1000 turkish: 1000 world-music: 1000

Data Cleaning:

There is only 1 row missing some values, so we are removing this row.

```
In [8]: df = df.dropna()
    missing_prop = df.isna().sum() / len(df.index)
    missing_prop.sort_values()
    missing_rows = df[df.isna().any(axis=1)]

    print("Number of missing data rows:", len(missing_rows))
    print("Missing data rows:")
    print(missing_rows)

Number of missing data rows: 0
    Missing data rows: 0
    Missing data rows: Empty DataFrame
```

Columns: [Unnamed: 0, track_id, artists, album_name, track_name, popularity, duration_ms, explicit, danceability, energy, key, loudness, mode, speechiness, acousticness, instrumentalness, liveness, valence, tempo, time_signature, track_genre]

[0 rows x 21 columns]

Index: []

Exploratory Data Analysis:

Average popularity per Genre

```
In [9]: avg_popularity_per_genre = df.groupby('track_genre')['popularity'].mean().reset_index()
avg_popularity_per_genre.columns = ["Genre", "Avg Popularity"]
avg_popularity_per_genre = avg_popularity_per_genre.sort_values(by='Avg Popularity', ascending=False)
avg_popularity_per_genre
```

Out[9]:		Genre	Avg Popularity
	81	pop-film	59.283000
	65	k-pop	56.952953
	15	chill	53.651000
	94	sad	52.379000
	44	grunge	49.594000

	13	chicago-house	12.339000
	24	detroit-techno	11.174000
	67	latin	8.297000
	93	romance	3.245000
	59	iranian	2 210000

114 rows × 2 columns

Average Danceability Per Genre Table:

```
In [10]:
avg_dance_per_genre = df.groupby('track_genre')['danceability'].mean().reset_index()
avg_dance_per_genre.columns = ["Genre", "Avg Danceability"]
avg_dance_per_genre_sorted = avg_dance_per_genre.sort_values(by='Avg Danceability', ascending=True)
pd.set_option('display.max_rows', None)
print(avg_dance_per_genre_sorted)
```

Genre Avg Danceability	101 sleep 0.167923	101			
42 grindcore 6 0.271854 6 black-metal 0.296411 59 iranian 0.306686 76 opera 0.313563 75 new-age 0.343655 4 ambient 0.367867 12 death-metal 0.368411 6 classical 0.381923 113 world-music 0.414572 72 metalcore 0.423800 50 heavy-metal 0.428500 93 romance 0.432133 79 piano 0.455098 44 grunge 0.457662 6 disney 0.462874 98 show-tunes 0.46273 11 metal 0.464288 14 groupe 0.473410 14 goth 0.478875 14 hard-rock 0.482250 15 punk 0.49978 11 british 0.501276 84 psych-rock 0.502554 85 punk 0.49978 11 british 0.501276 84 psych-rock 0.502554 15 punk 0.597329 15 punk 0.527837 58 industrial 0.50416 15 punk 0.527837 58 industrial 0.50416 16 punk 0.527837 59 punk 0.52847 59 punk 0.527837 59 punk 0.52	42 grindcore 6 0.271854 6 black-metal 0.296411 59 iranian 0.306086 76 opera 0.313563 75 new-age 0.348455 4 ambient 0.367867 22 death-metal 0.368411 6 classical 0.368411 6 classical 0.368411 6 classical 0.414572 72 metalcore 0.423800 50 heavy-metal 0.428500 93 romance 0.432133 79 piano 0.455098 44 grunge 0.457062 6 disney 0.462874 84 grunge 0.457062 6 disney 0.462874 85 power-pop 0.473410 41 goth 0.478875 47 hard-rock 0.482250 38 garage 0.484264 85 punk 0.49778 11 british 0.501276 84 psych-rock 0.502554 85 punk 0.499778 11 british 0.501276 84 psych-rock 0.502554 9 dubstep 0.518087 39 german 0.524338 54 idd 0.527837 58 industrial 0.530416 2 alt-rock 0.534493 57 bluegrass 0.534862 49 hardstyle 0.539229 77 drum-and-bass 0.534861 9.537451 108 tango 0.537851 108 tango 0.537862 9 guitar 0.537451 108 tango 0.537861 9 prock 0.546593 9 graman 0.544393 9 graman 0.544393 9 graman 0.544393 10 pianodopo 0.537862 9 dubstep 0.530416 2 alt-rock 0.534493 10 pianodopo 0.537861 108 tango 0.537861 108 tango 0.537861 108 tango 0.537862 9 prockabilly 0.539229 109 cockabilly 0.539229 109 cockabilly 0.559229 100 mandopop 0.546532 12 cantopop 0.546532 12 cantopop 0.546593 12 country 0.55524 13 alternative 0.559927 9 brazil 0.550802 19 cockabilly 0.559229 100 sangwriter 0.56202 19 singer-songwriter	42 grindcore 6 black-metal 0.296411 59 iranian 0.306086 76 opera 0.313563 75 new-age 0.348455 4 ambient 0.367867 22 death-metal 0.368411 16 classical 0.381923 113 world-music 0.414572 72 metalcore 0.423800 93 romance 0.432133 79 piano 0.455098 44 grunge 0.457062 26 disney 0.462874 84 grunge 0.462874 84 groupe 0.462878 85 pwh-rook 0.478875 47 hard-rock 0.482256 38 garage 0.484264 85 punk 0.497778 11 british 0.501276 84 psych-rock 0.502554 85 punk 0.499778 11 british 0.501276 84 psych-rock 0.502554 85 punk 0.499778 11 british 0.501276 84 psych-rock 0.502554 85 punk 0.493778 11 british 0.501276 84 psych-rock 0.502554 85 punk 0.497781 10 british 0.501276 86 punk-rock 0.5032554 87 punk 0.59339 89 german 0.524338 11 dm 0.527837 58 industrial 0.530416 2 alt-rock 0.534493 59 german 0.534662 49 hardstyle 0.539229 27 drum-and-bass 0.534686 5 anime 0.537451 108 tango 0.537862 49 hardstyle 0.539229 45 guitar 0.540307 46 happy 0.552647 47 om amadopop 0.5467909 46 hardstyle 0.539229 47 cantopop 0.546532 48 hardcore 0.546411 90 acoustic 0.549593 91 rock-n-roll 0.550302 92 rockabilly 0.55922 93 drum-and-bass 0.53669 94 brazil 0.550802 95 singer-songwriter 0.562022 99 singer-songwriter 0.562022 90 songwriter 0.562022 91 pagode 0.577723 100 ska 0.59321 101 trance 0.583409 102 songwriter 0.562022 103 songwriter 0.562022 104 spanish 0.590413 105 scandopop 0.574088 105 spanish 0.604310 17 club 0.603154 104 spanish 0.604310 17 club 0.603154 105 spanish 0.604310 17 club 0.603154 104 spanish 0.604310 17 club 0.603354 105 spanish 0.604310 107 synth-pop 0.632935 108 progressive-house 0.632935 109 opon 6.304411 100 club 0.603154 110 trance 0.583409 110 club 0.603154 1110 trance 0.583409 11110 trance 0.583409 11110 trance 0.583409 11110 trance 0.583409 11110 trance 0.583409 111110 trance 0.583409 111110 trance 0.633641 111111111111111111111111111111111			
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77 pagode 0.577723 100 ska 0.580676 110 trance 0.583409 43 groove 0.583409 56 indie 0.587272 106 swedish 0.590413 97 sertanejo 0.591647 55 indian 0.592273 81 pop-film 0.597146 33 emo 0.599321 103 soul 0.600112 17 club 0.603354 104 spanish 0.604310 57 indie-pop 0.604370	77 pagode 0.577723 100 ska 0.580676 110 trance 0.583409 43 groove 0.583409 56 indie 0.587272 100 swedish 0.590413 97 sertanejo 0.591647 55 indian 0.592273 81 pop-film 0.597146 33 emo 0.599321 103 soul 0.600112 17 club 0.603354 104 spanish 0.604310 57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616677 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.638441	77 pagode 0.577723 100 ska 0.580676 110 trance 0.583409 43 groove 0.583409 43 groove 0.583910 56 indie 0.587272 100 sertanejo 0.591647 55 indian 0.592273 81 pop-film 0.592143 33 emo 0.599211 103 soul 0.600112 17 club 0.603354 104 spanish 0.604310 57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.638441			
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55 indian 0.592273 81 pop-film 0.597146 33 emo 0.599321 103 soul 0.600112 17 club 0.603354 104 spanish 0.604310 57 indie-pop 0.604370	55 indian 0.592273 81 pop-film 0.597146 33 emo 0.599321 103 soul 0.600112 17 club 0.603354 104 spanish 0.604310 57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.630441	55 indian 0.592273 81 pop-film 0.597146 33 emo 0.599321 103 soul 0.600112 17 club 0.603354 104 spanish 0.604310 57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 6.638441			
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104 spanish 0.604310 57 indie-pop 0.604370	104 spanish 0.604310 57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616977 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.638441	104 spanish 0.604310 57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.638441			
57 indie-pop 0.604370	57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.639441	57 indie-pop 0.604370 87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.630441			
	87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.628663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.638441	87 r-n-b 0.614388 112 turkish 0.616077 107 synth-pop 0.629663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.639441	57		
	107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.630441	107 synth-pop 0.620663 83 progressive-house 0.623935 69 malay 0.628617 80 pop 0.630441		r-n-b	
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	80 pop 0.630441	80 pop 0.630441			
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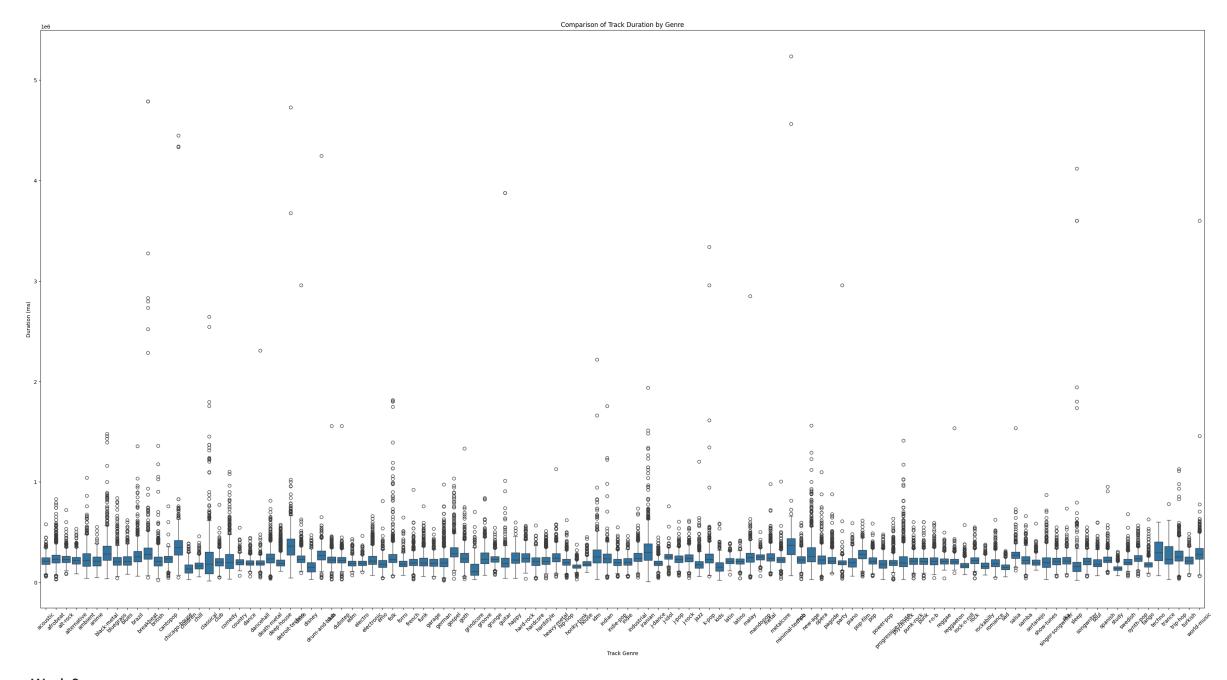
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            french
                         0.651468
                         0.651749
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15
             chill
                         0.664346
78
                         0.667191
             party
                         0.668288
95
             salsa
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            disco
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            techno
                         0.684348
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                         0.758521
13
      chicago-house
                         0.766176
                         0.778906
```

Average Energy Value Per Genre Table:

```
In [11]: avg_energy_per_genre = df.groupby('track_genre')['energy'].mean().reset_index()
avg_energy_per_genre.columns = ['Genre', 'Average Energy']
avg_energy_per_genre_sorted = avg_energy_per_genre.sort_values(by='Average Energy', ascending=True)
pd.set_option('display_max_rows', None)
print(avg_energy_per_genre_sorted)
```

	Genre	Average Energy
16 75	classical new-age	0.189827 0.214501
4	ambient	0.237162
93	romance	0.294304
26	disney	0.302519
76 79	opera piano	0.317054 0.320103
45	guitar	0.324999
101	sleep	0.342072
64 52	jazz honky-tonk	0.352954 0.366957
108	tango	0.372828
98	show-tunes	0.398742
105	study	0.410658
15 102	chill songwriter	0.426723 0.434188
99	singer-songwriter	0.434188
0	acoustic	0.435368
12	cantopop	0.461696
94 14	sad children	0.462470 0.494645
70	mandopop	0.498434
11	british	0.507127
91 7	rock-n-roll	0.526615 0.530280
39	bluegrass german	0.531718
113	world-music	0.532987
103	soul	0.533873
34 59	folk iranian	0.545807 0.545846
54	idm	0.555399
56	indie	0.556192
57	indie-pop	0.561140
84 55	psych-rock indian	0.561503 0.567121
40	gospel	0.576256
69	malay	0.578397
74 8	mpb blues	0.579787
36	french	0.581878 0.594990
19	country	0.596805
81	pop-film	0.604562
80 112	pop turkish	0.606437 0.609804
66	kids	0.613129
9	brazil	0.620721
106	swedish	0.622003
111 37	trip-hop funk	0.622363 0.632999
87	r-n-b	0.638130
92	rockabilly	0.659372
31 33	electro emo	0.665000 0.669967
96	samba	0.672644
5	anime	0.674108
65 90	k-pop	0.675747 0.679071
62	rock j-pop	0.679604
73	minimal-techno	0.680272
51	hip-hop	0.682530
21 32	dancehall electronic	0.685262 0.694752
18	comedy	0.699934
1	afrobeat	0.702812
60 104	j-dance	0.703755 0.707777
20	spanish dance	0.708583
97	sertanejo	0.710391
24	detroit-techno	0.710512
77 107	pagode synth-pop	0.712123 0.713135
28	dub	0.714817
3	alternative	0.720030
17	club	0.721734
95 88	salsa reggae	0.724518 0.725791
67	latin	0.727080
68	latino	0.731797
13	chicago-house	0.733215
25 89	disco reggaeton	0.737565 0.738728
41	goth	0.740970
23	deep-house	0.741855

```
38
                                0.744350
                    garage
       109
                                 0.746413
                    techno
                   alt-rock
                                 0.754173
       53
                     house
                                 0.755083
       30
                       edm
                                 0.756196
       29
                    dubstep
                                 0.758969
       63
                    j-rock
                                 0.760684
                                0.763622
                     groove
                                0.789526
       35
                     forro
       100
                                0.793134
                      ska
       47
                                0.795039
                  hard-rock
       82
                  power-pop
                                0.801688
       44
                    grunge
                                0.803290
       85
                                 0.809673
                  punk-rock
                                0.809980
       83 progressive-house
                                0.813359
      71
                                 0.840273
                     metal
                                0.842453
       48
                   hardcore
       110
                    trance
                                0.845272
       10
                  breakbeat
                                0.853275
       58
                 industrial
                                 0.861745
       61
                    j-idol
                                 0.868677
       78
                     party
                                0.871237
                 heavy-metal
                                0.874003
                                0.874897
                black-metal
      27
                                0.876635
              drum-and-bass
       49
                  hardstyle
                                0.901246
       46
                     happy
                                0.910971
       72
                  metalcore
                                0.914485
       42
                  grindcore
                                0.924201
                death-metal
                                0.931470
In [12]: %matplotlib inline
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
        # Set the plot size
        plt.figure(figsize=(40, 20))
        # Create a box plot
        sns.boxplot(x='track_genre', y='duration_ms', data = df)
        # Set labels and title
        plt.title('Comparison of Track Duration by Genre')
        plt.xlabel('Track Genre')
        plt.ylabel('Duration (ms)')
        # Rotate x labels for better readability if there are many genres
        plt.xticks(rotation=45)
        # Show the plot
        plt.show()
```



Week 3

```
# first split the dataset into 70% training and 30% temp
         train_data, temp_data = train_test_split(df, test_size=0.3, random_state=42)
         # then split the temp dataset into 15% testing and 15% validation
         test_data, val_data = train_test_split(temp_data, test_size=0.5, random_state=42)
         print(f'Training data shape: {train_data.shape}')
         print(f'Testing data shape: {test_data.shape}')
         print(f'Validation data shape: {val_data.shape}')
         # If need to remake these datasets, uncomment to create new CSV files
         # train_data.to_csv('csv/train_data.csv', index=False)
         # test_data.to_csv('csv/test_data.csv', index=False)
         # val_data.to_csv('csv/val_data.csv', index=False)
        Training data shape: (79799, 21)
        Testing data shape: (17100, 21)
        Validation data shape: (17100, 21)
In [14]: # for consistency, everyone should use the same datasets by reading the same csv files
         train_data = pd.read_csv("./csv/train_data.csv")
         test_data = pd.read_csv("./csv/test_data.csv")
         val_data = pd.read_csv("./csv/val_data.csv")
In [15]: from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         X_scaled = []
         y = []
         for d in [train_data, test_data, val_data]:
             non_numeric_cols = d.select_dtypes(include=['object']).columns
             # print(non_numeric_cols)
             X = d.drop(columns=['popularity', 'track_id', 'track_name', 'album_name', 'artists', 'track_genre'])
             y.append(d['popularity'])
             # for Lasso:
             scaler = StandardScaler()
             X_scaled.append(scaler.fit_transform(X))
In [16]: # training data
X_train = X_scaled[0]
         y_{train} = y[0]
         # testing data
         X_test = X_scaled[1]
         y_{test} = y[1]
         # validation data
         X_{val} = X_{scaled[2]}
         y_val = y[2]
```

Regularization

We are using lasso regression (L1 Regularization)

```
In [17]: from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error

lasso = Lasso(alpha=0.1) # try changing alpha to make it better!

lasso fit(X_train, y_train)

y_val_pred = lasso.predict(X_val)
mesc

wisc
val_mes = mean_squared_error(y_val, y_val_pred)
print(f'validation MSE; (val_mse)")

lasso_coefficients = lasso.coef_
feature_names = X.columns
# feature_names = A.farop(columns=/'popularity', 'track_id', 'track_name', 'album_name', 'artists', 'track_genee']).columns
important_features = ([feature, coef] for feature, coef in zip(feature_names, lasso_coefficients) if coef |= 0]

print("Important Features: orted(important_features)
for feature, coef in important_features:
print(f''[feature]) {coeff')"}
```

```
Validation MSE: 482.86028217945733
Important Features:
instrumentalness: -2.414702875009987
valence: -2.2671419290598616
speechiness: -1.418747157755636
danceability: 1.2105724310109753
explicit: 0.8757417797762873
Unnamed: 0: 0.4617996878219175
time signature: 0.4068828297359902
tempo: 0.30046698670147104
mode: -0.2540433439760859
loudness: 0.2540127477409079
energy: -0.178837834347387
acousticness: -0.09365770338322728
duration_ms: -0.09162713619712619
liveness: 0.022333228072016768
```

Based on these lasso regression results to find the most important predictors of popularity, we have decided to use Danceability as our predictors of popularity so we can apply linear regression.

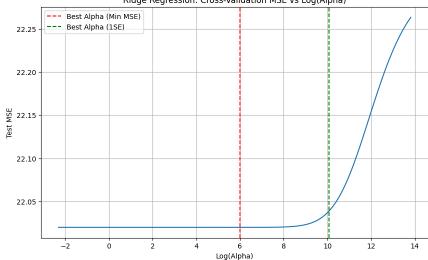
One question we have: we are a bit confused about why valence is a big negative predictor of popularity. Some of the lasso regression results were did not exactly align with our own assumptions of what they should be.

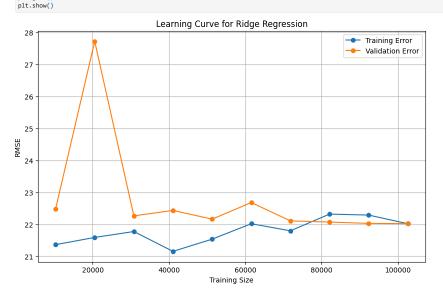
```
In [18]: #Linear and LAD Regression Models
         from sklego.linear_model import LADRegression
         from sklearn.linear_model import LinearRegression
         lad_fit = LADRegression()
         lad_fit.fit(X_train, y_train)
         ls_fit = LinearRegression()
         ls_fit.fit(X_train,y_train)
         print("Intercept: ", ls_fit.intercept_)
print("Coefficients: ", ls_fit.coef_[0])
        Intercept: 33.2653007519
        Coefficients: 0.556606970401
In [19]: import plotly.graph_objects as go
         # plot both the LS and LAD lines on top of the scatterplot of gr_liv_area against sale_price
         fig = px.scatter(train_data, x='danceability', y='popularity')
         fig.add_trace(
             go.Scatter(x=train_data['danceability'],
                          y=lad_fit.intercept_ + train_data['danceability'] * lad_fit.coef_[0],
                          mode='lines'.
                          name='LAD',
                          line={'dash': 'dash',
                               'color': 'red'})
                          # L1 model
         fig.add_trace(
             go.Scatter(x=train_data['danceability'],
                          y=ls_fit.intercept_ + train_data['danceability'] * ls_fit.coef_[0],
                          mode='lines',
                          name='LS',
                          line={'dash': 'solid',
                                'color': 'black'})
                          # L2 modeL
         fig.update_traces(marker=dict(size=2))
```

Not great for visualization, let's try a different form of regression.

```
# compute the rMSE, MAE, MAD, correlation and R2 of true value with predictions
         print('LS rMSE:', np.sqrt(mean_squared_error(pred_val_df['true'], pred_val_df['ls_pred'])))
         print('LS MAE:', mean_absolute_error(pred_val_df['true'], pred_val_df['ls_pred']))
         print('LS MAD:', np.median(np.abs(pred_val_df['true'] - pred_val_df['ls_pred'])))
         print('LS correlation:', np.corrcoef(pred_val_df['true'], pred_val_df['ls_pred'])[0, 1])
         print('LS R2:', r2_score(pred_val_df['true'], pred_val_df['ls_pred']))
        LS rMSE: 22.0393643843
        LS MAE: 18.378427291
        LS MAD: 15.9652304617
        LS correlation: 0.161013356635
        LS R2: 0.02592530101480972
        LS rMSE: 21.9695910058
        LS MAE: 18.3143020336
        LS MAD: 15.8762158042
        LS correlation: 0.157469512411
        LS R2: 0.02470036472170345
         Applying Ridge Regression
In [21]: # for ridge regression
         X = df.drop(columns=['popularity', 'track_id', 'track_name', 'album_name', 'artists', 'track_genre'])
         y = df['popularity']
In [22]: from sklearn.linear_model import Ridge
          from sklearn.model_selection import KFold, cross_validate, learning_curve
         scaler = StandardScaler()
         X_scaled = scaler.fit_transform(X)
         print(X_scaled.shape)
         alphas = np.logspace(-1, 6, 100)
         kf = KFold(n_splits=10, shuffle=True, random_state=42)
         ridge_cv_scores = []
          for alpha in alphas:
           ridge = Ridge(alpha=alpha)
           ridge_cv = cross_validate(estimator=ridge,
                                       X=X_scaled,
                                       cv=kf,
                                       scoring='neg_root_mean_squared_error')
           ridge_cv_scores.append({'alpha': alpha,
                                      'log_alpha': np.log(alpha),
                                      'test_mse': -np.mean(ridge_cv['test_score'])})
          ridge_cv_scores_df = pd.DataFrame(ridge_cv_scores)
          px.line(ridge_cv_scores_df,
                 x='log_alpha',
                 y='test_mse',
                 title='Ridge')
          #find best alpha
          ridge\_alpha\_min = ridge\_cv\_scores\_df.sort\_values(by='test\_mse').head(1).alpha.values[0]
          mse_se_ridge = ridge_cv_scores_df['test_mse'].std() / np.sqrt(10)
         mse_min_ridge = ridge_cv_scores_df['test_mse'].min()
          ridge_alpha_1se = ridge_cv_scores_df[(ridge_cv_scores_df['test_mse'] <= mse_min_ridge + mse_se_ridge) &</pre>
                                              (ridge_cv_scores_df['test_mse'] >= mse_min_ridge - mse_se_ridge)].sort_values(by='alpha', ascending=False).head(1).alpha.values[0]
         print('Ridge (min): ', ridge_alpha_min)
         print('Ridge (1SE): ', ridge_alpha_1se)
         ridge_min_fit = Ridge(alpha=ridge_alpha_min).fit(X=X_scaled, y=y)
         ridge_1se_fit = Ridge(alpha=ridge_alpha_1se).fit(X=X_scaled, y=y)
        (113999, 15)
        Ridge (min): 403.70172586
Ridge (1SE): 23644.8941265
In [23]: plt.figure(figsize=(10, 6))
         plt.plot(ridge_cv_scores_df['log_alpha'], ridge_cv_scores_df['test_mse'])
         plt.title('Ridge Regression: Cross-Validation MSE vs Log(Alpha)')
         plt.xlabel('Log(Alpha)')
         plt.ylabel('Test MSE')
         plt.axvline(x=np.log(ridge_alpha_min), color='r', linestyle='--', label='Best Alpha (Min MSE)')
         plt.axvline(x=np.log(ridge_alpha_1se), color='g', linestyle='--', label='Best Alpha (1SE)')
         plt.legend()
         plt.grid()
         plt.show()
```

Ridge Regression: Cross-Validation MSE vs Log(Alpha)





Overfitting or Underfitting?

This graph shows that from 20000 to about 30000 (training size), the training error and validation error gap being really big means the model is overfitting, meaning the model isn't good at generalizing at this smaller size. Then the error gap decreases after 40000 and continues to improve.

WEEK 4

Logistic Regression

In [25]: import numpy as np
import pandas as pd

We are choosing mode as our response variable for logistic regression.

```
import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LogisticRegression
         from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
         from sklearn.metrics import roc_curve, roc_auc_score
          from sklearn.metrics import precision_recall_curve
In [26]: non_numeric_cols = df.select_dtypes(exclude=[np.number]).columns.tolist()
         print(non_numeric_cols)
         numeric_df = df.select_dtypes(include=[np.number])
         correlation_matrix = numeric_df.corr()
         mode_correlation = correlation_matrix['mode'].sort_values(ascending=False)
         print(mode_correlation)
          fig = px.imshow(correlation_matrix, text_auto=True)
         fig.update_layout(title='Correlation Matrix')
         fig.show()
        ['track_id', 'artists', 'album_name', 'track_name', 'explicit', 'track_genre']
        mode
                            1.000000
        acousticness
                            0.095568
        valence
                            0.021964
        liveness
                            0.014004
        Unnamed: 0
                           0.005110
                           0.000572
        tempo
        popularity
                           -0.013948
        time signature
                          -0.024090
                           -0.035581
        duration_ms
        loudness
                           -0.041768
        speechiness
                           -0.046535
        instrumentalness -0.049961
        danceability
                          -0.069224
        energy
                           -0.078365
                           -0.135911
        Name: mode, dtype: float64
         Although none of the variables show a particularly strong correlation with mode, we will be using key, acousticness, and energy as they still were the most correlated. Another option we could have chosen to perform logistic regression on was the "explicit" variable, but there was too large of a class imbalance so we chose mode instead.
In [27]: response = df['mode']
In [28]: X = df[['acousticness', 'energy', 'key']]
         y = df['mode']
In [29]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=22)
In [30]: model = LogisticRegression()
         model.fit(X_train, y_train)
Out[30]: V LogisticRegression
          LogisticRegression()
```

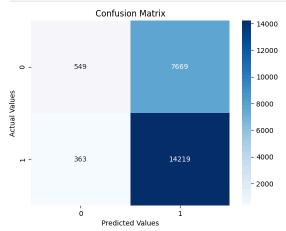
Prediction Accuracy: 64.77% Prediction Error: 35.23%

In [31]: # prediction accuracy and error
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Prediction Accuracy: {accuracy * 100:.2f}%")
print(f"Prediction Error: {(1-accuracy) * 100:.2f}%")

```
In [32]: # confusion matrix
             # confusion matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix")
              plt.ylabel("Actual Values")
              plt.xlabel("Predicted Values")
              plt.show()
```

plt.figure(figsize=(8, 6))

plt.show()



plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc:.2f})', color='darkorange')

plt.plot(tpr, tpr, label="'RUC Curve (AUC = {roc_auc:.zf})",
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold = thresholds[optimal_idx] print('optimal_threshold: ', optimal_threshold)

```
In [33]: # True positive and negative rate
truePositiveRate = cm[1,1] / (cm[1,1] + cm[1,0])
            falsePositiveRate = cm[0,1] / (cm[0,1] + cm[0,0])
            print(f"True Positive Rate: {truePositiveRate:.2f}")
           print(f"True Negative Rate: {falsePositiveRate:.2f}")
          True Positive Rate: 0.98
          True Negative Rate: 0.93
In [34]: # ROC Curve
           y_prob = model.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
            roc_auc = roc_auc_score(y_test, y_prob)
```


optimal_threshold: 0.649974884131

```
In [35]; from sklearn.model_selection import cross_val_score

# **-Fold Cross-Validation

# **-We'll use the previously selected features for this exercise (or all features if you haven't done feature selection yet)

X_cv = X

Y_cv = Y

# Initialize the logistic regression model

model_cv = logistic regression()

# Perform 5-Fold Cross-Validation

cv_scores = cross_val_score(model_cv, X_cv, y_cv, cv=5)

# Output the cross-validation scores for each fold

# Modify the printed scores to the acutal cv_scores

print(**Cross-Validation Scores for each fold (cv_scores)*)

print(**Cross-Validation Accuracy: (np.mean(cv_scores) = 100:.2F)%**)

Cross-Validation Scores for each fold (cv_scores) ** 100:.4531759]
```

5. To choose a threshold for positive predictions, we examined the ROC curve and which showed how true positive rate (FPR) and false positive rate (FPR) and we used the AUC score as a measure of overall model performance. We selected a threshold of 0.65 from calculating the optimal threshold where where (TPR - FPR) is maximized.

If we want to improve the ROC and AUC, we can convert one of the numerical variables to a categorical one, and perform logistic regression on that.

Week 5

Applying KNN for the energy feature:

Mean Cross-Validation Accuracy: 64.50%

In [36]:
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import LabelEncoder

To split the energy feature into a binary feature, we are specifying the threshold to be the 75th percentile. So the top 25% of tracks will be "high", and everything else is "low".

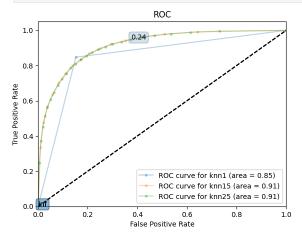
```
In [38]: df_copy = df.copy()
threshold = df_copy['energy'].median()

df_copy["energy_level"] = df_copy['energy'].apply(lambda x: "high" if x>=threshold else "low")

#encode as 0 or 1 (1 = high, 0 = Low)
le = LabelEncoder()
df_copy['energy_level'] = le.fit_transform(df_copy['energy_level'])
```

```
# dropping energy_level, and the non numerical features
X = df_copy[['loudness', 'acousticness']]
         y = df_copy['energy_level']
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
In [39]: knn1 = KNeighborsClassifier(n_neighbors=1)
         knn15 = KNeighborsClassifier(n_neighbors=15)
         knn25 = KNeighborsClassifier(n_neighbors=25)
In [40]: knn1.fit(X_train, y_train)
         knn15.fit(X_train, y_train)
         knn25.fit(X_train, y_train)
Out[40]: v KNeighborsClassifier
         KNeighborsClassifier(n_neighbors=25)
In [41]: y_pred1 = knn1.predict(X_test)
         y_pred15 = knn15.predict(X_test)
         y_pred25 = knn25.predict(X_test)
In [42]: accuracy1 = accuracy_score(y_test, y_pred1)
         accuracy15 = accuracy_score(y_test, y_pred15)
         accuracy25 = accuracy_score(y_test, y_pred25)
         print(accuracy1)
         print(accuracy15)
         print(accuracy25)
        0.8476608187134503
        0.8319005847953216
        0.8300292397660819
In [43]: from sklearn.metrics import confusion_matrix, accuracy_score, f1_score
         model_cv.fit(X_train, y_train)
         \# this function may help to manually make confusion table from a different threshold
         def t_repredict(model_cv, t, X_train):
             probs = model_cv.predict_proba(X_train)
             p0 = probs[:,0]
             p1 = probs[:,1]
             ypred = (p1 > t)*1
             return ypred
         # default threshold
         y_pred_train = t_repredict(model_cv, 0.5, X_train)
         # Our decided threshold
         y_pred_train = t_repredict(model_cv, threshold, X_train)
         conf_matrix_train = confusion_matrix(y_train, y_pred_train)
         TN, FP, FN, TP = conf_matrix_train.ravel() # Extract TN, FP, FN, TP from the matrix
         # Prediction Accuracy
         accuracy = accuracy_score(y_train, y_pred_train)
         # Prediction Error (1 - accuracy)
         error = 1 - accuracy
         # True Positive Rate (Sensitivity / Recall)
         true_positive_rate = TP / (TP + FN)
         # True Negative Rate (Specificity)
         true_negative_rate = TN / (TN + FP)
         f1 = f1_score(y_train, y_pred_train)
         # Display results
         print("Confusion Matrix:\n", conf_matrix_train)
         print("Prediction Accuracy:", accuracy)
         print("Prediction Error:", error)
         print("True Positive Rate (Recall/Sensitivity):", true_positive_rate)
         print("True Negative Rate (Specificity):", true_negative_rate)
print("F1 Score:", f1)
```

```
Confusion Matrix:
        [[36557 3401]
        [13300 26541]]
        Prediction Accuracy: 0.7907116630534218
        Prediction Error: 0.20928833694657822
        True Positive Rate (Recall/Sensitivity): 0.666173037825
        True Negative Rate (Specificity): 0.914885629911
        F1 Score: 0.760672370061
In [44]: from sklearn.metrics import roc_curve, auc
         # a function to make 'pretty' ROC curves for this model
         def make_roc(name, clf, ytest, xtest, ax=None, labe=5, proba=True, skip=0):
             initial=False
             if not ax:
                ax=plt.gca()
                initial=True
             if proba:#for stuff like logistic regression
                fpr, tpr, thresholds=roc_curve(ytest, clf.predict_proba(xtest)[:,1])
             else:#for stuff Like SVM
                fpr, tpr, thresholds=roc_curve(ytest, clf.decision_function(xtest))
             roc_auc = auc(fpr, tpr)
             if skip:
                l=fpr.shape[0]
                ax.plot(fpr[0:1:skip], tpr[0:1:skip], '.-', alpha=0.3, label='ROC curve for %s (area = %0.2f)' % (name, roc_auc))
                ax.plot(fpr, tpr, '.-', alpha=0.3, label='ROC curve for %s (area = %0.2f)' % (name, roc_auc))
             label_kwargs = {}
             label_kwargs['bbox'] = dict(
                boxstyle='round,pad=0.3', alpha=0.2,
             if labe!=None:
                 for k in range(0, fpr.shape[0],labe):
                    threshold = str(np.round(thresholds[k], 2))
                    ax.annotate(threshold, (fpr[k], tpr[k]), **label_kwargs)
             if initial:
                ax.plot([0, 1], [0, 1], 'k--')
                 ax.set_xlim([0.0, 1.0])
                 ax.set_ylim([0.0, 1.05])
                 ax.set_xlabel('False Positive Rate')
                 ax.set_ylabel('True Positive Rate')
                ax.set_title('ROC')
             ax.legend(loc="lower right")
             return ax
         make_roc("knn1", knn1, y_test, X_test, ax=None, labe=20, proba=True, skip=1);
         make_roc("knn15", knn15, y_test, X_test, ax=None, labe=20, proba=True, skip=1);
         make_roc("knn25", knn25, y_test, X_test, ax=None, labe=20, proba=True, skip=1);
```



```
X_cv = X
 y_cv = y
 # Perform 5-Fold Cross-Validation
 cv_scores_knn1 = cross_val_score(knn1, X_cv, y_cv, cv=5)
 cv_scores_knn15 = cross_val_score(knn15, X_cv, y_cv, cv=5)
 cv_scores_knn25 = cross_val_score(knn25, X_cv, y_cv, cv=5)
 # Output the cross-validation scores for each fold
 * Output the cross-volution scores for each fold for knn1: {cv_scores_knn1}")
 print(f"Mean Cross-Validation Accuracy for knn1: {np.mean(cv_scores_knn1) * 100:.2f}%")
 print(f"Cross-Validation Scores for each fold for knn15: {cv_scores_knn15}")
 print(f"Mean Cross-Validation Accuracy for knn15: {np.mean(cv_scores_knn15) * 100:.2f}%")
 print(f"Cross-Validation Scores for each fold for knn25: {cv_scores_knn25}")
print(f"Mean Cross-Validation Accuracyfor knn25: {np.mean(cv_scores_knn25) * 100:.2f}%")
Cross-Validation Scores for each fold for knn1: [ 0.82263158  0.8120614  0.84184211  0.85837719  0.7959121 ]
Mean Cross-Validation Accuracy for knn1: 82.62%
Cross-Validation Scores for each fold for knn15: [ 0.8247807  0.79622807  0.84065789  0.845
                                                                                                    0.79288565]
Mean Cross-Validation Accuracy for knn15: 81.99%
Cross-Validation Scores for each fold for knn25: [ 0.82412281 0.79342105 0.84052632 0.84315789 0.79082416]
Mean Cross-Validation Accuracyfor knn25: 81.84%
```