SC1015 MINI PROJECT

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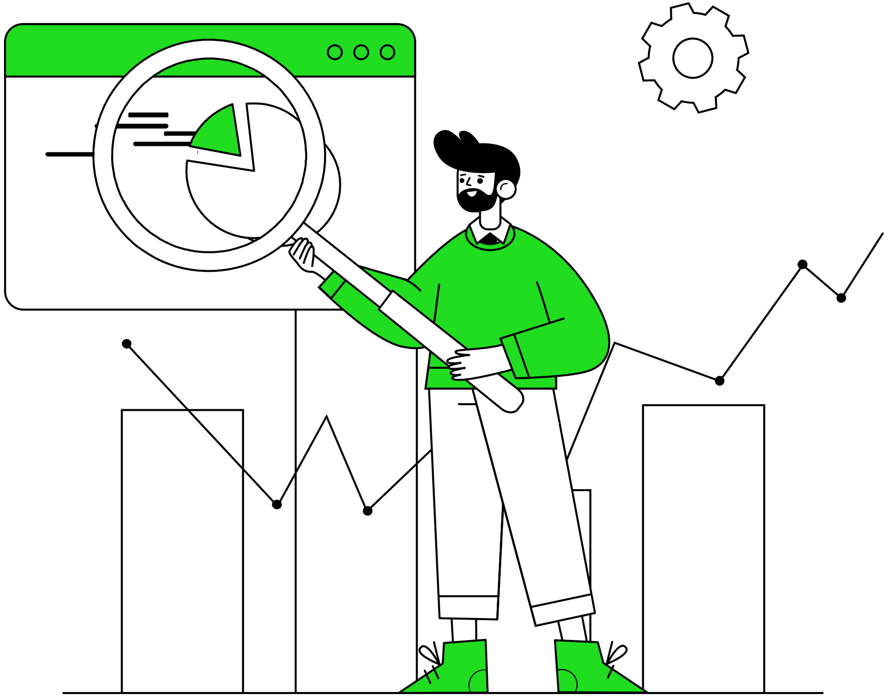
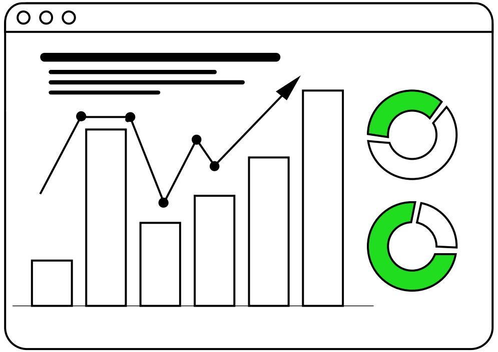


BACKGROUND OF MUSIC INDUSTRY

AS OF 2021, THERE ARE **1.2 MILLION ARTISTS** STREAMING ON SPOTIFY.



THIS IS A GROWING PLATFORM, AS OBSERVED FROM THE ENTRY OF **150,000 ARTISTS** ONTO SPOTIFY IN 2020.

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02 DATA PREPARATION & CLEANING

03 EDA & VISUALISATION

04 MACHINE LEARNING

05 CONCLUSION

PRACTICAL MOTIVATION

- ASSIST NEW ARTISTS TO INCREASE THEIR LIKELIHOOD OF RELEASING A HIT SONG
- ASSIST ESTABLISHED ARTISTS TO REPLICATE THEIR PREVIOUS HIT SONGS

PROBLEM DEFINITION

OUR GROUP INTENDS TO INVESTIGATE THE RELATIONSHIP BETWEEN AUDIO FEATURES AND POPULARITY OF SPOTIFY TRACKS.

02

DATA PREPARATION AND CLEANING

DATA PREPARATION

ACCESSING TO THE SPOTIFY'S API

```
import spotipy
from spotipy.oauth2 import SpotifyClientCredentials
cid = '6b2418c9674f4f7c9f5e2809aa2b3678'
secret = '781801fad3b646c6b7844583a170957c'
client_credentials_manager = SpotifyClientCredentials(client_id=cid, client_secret=secret)
sp = spotipy.Spotify(client_credentials_manager
=
client_credentials_manager)
```

EXTRACTING RELEVANT DATA FROM THE API

```
for yr in range(20):
    for i in range(20):
        track_results = sp.search(q='year:{}'.format(years[yr]), type='track', limit=50,offset=i*50)
        print(track_results)
        for i, t in enumerate(track_results['tracks']['items']):
            artist_name.append(t['artists'][0]['name'])
            track_name.append(t['name'])
            track_id.append(t['id'])
            popularity.append(t['popularity'])
```

DATA PREPARATION

EXTRACTING AUDIO FEATURES BASED ON TRACK_ID

```
ls = list(df['track_id'])
audio_features = []
for ids in range(0, 19400, 100):
    audio_features.append(sp.audio_features(ls[ids:ids+100]))

audio_features.append(sp.audio_features(ls[19400:19419]))
```

```
for i in range(0, 194):
    for j in range(100):
        if audio_features[i][j] != None:
            danceability.append(audio_features[i][j]['danceability'])
            energy.append(audio_features[i][j]['energy'])
            key.append(audio_features[i][j]['key'])
            loudness.append(audio_features[i][j]['loudness'])
            mode.append(audio_features[i][j]['mode'])
            speechiness.append(audio_features[i][j]['speechiness'])
            acousticness.append(audio_features[i][j]['acousticness'])
            instrumentalness.append(audio_features[i][j]['instrumentalness'])
            liveness.append(audio_features[i][j]['liveness'])
```


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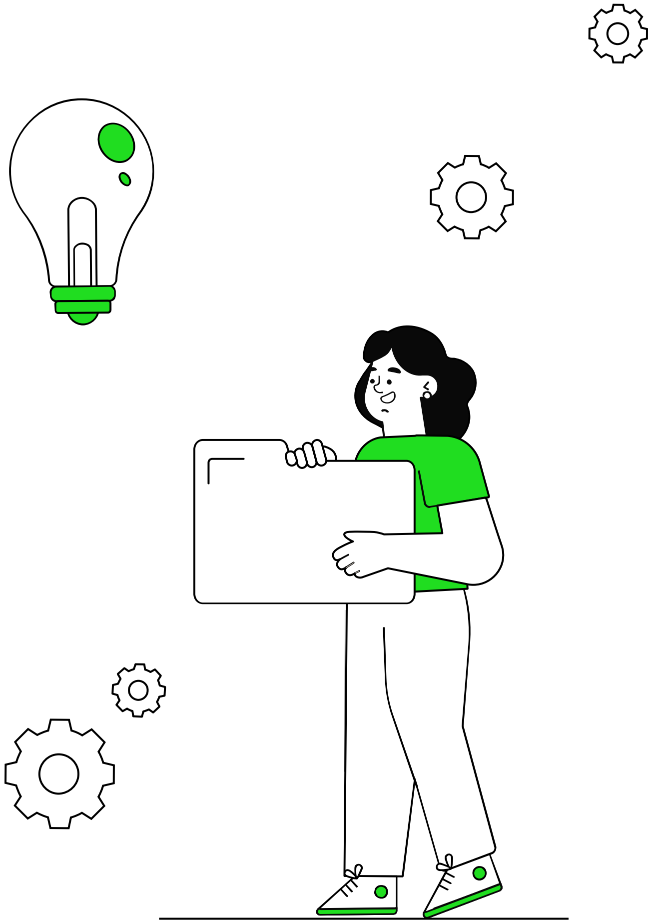
CLEANING

- REMOVING DUPLICATES
  - SAME TRACK_ID
- REMOVAL OF NONE VALUES FOR AUDIO FEATURES DATA
  - REPLACE NONE VALUES WITH EXTREME VALUE FOR EASE OF REMOVAL WHEN COMBINED WITH FINAL DATA SET
- EXPORTING THEM INTO A CSV FILE FOR FURTHER EDA

03 EDA AND VISUALISATION



RESPONSE VARIABLE

POPULARITY : BASED ON THE TOTAL NUMBER OF PLAYS THE TRACK HAS HAD AND HOW RECENT THOSE PLAYS ARE

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PREDICTOR VARIABLES (NUMERIC)

DANCEABILITY : HOW SUITABLE A TRACK IS FOR DANCING

ENERGY : MEASURE OF INTENSITY AND ACTIVITY

LOUDNESS : THE OVERALL LOUDNESS OF A TRACK IN DECIBELS.

SPEECHINESS : PRESENCE OF SPOKEN WORDS IN A TRACK.

ACOUSTICNESS : MEASURE OF WHETHER THE TRACK IS ACOUSTIC.

INSTRUMENTALNESS : PREDICTS WHETHER A TRACK CONTAINS NO VOCALS.

LIVENESS : DETECTS THE PRESENCE OF AN AUDIENCE IN THE RECORDING.

TEMPO : OVERALL ESTIMATED TEMPO OF A TRACK IN BEATS PER MINUTE

DURATION : DURATION OF THE TRACK IN MINUTES

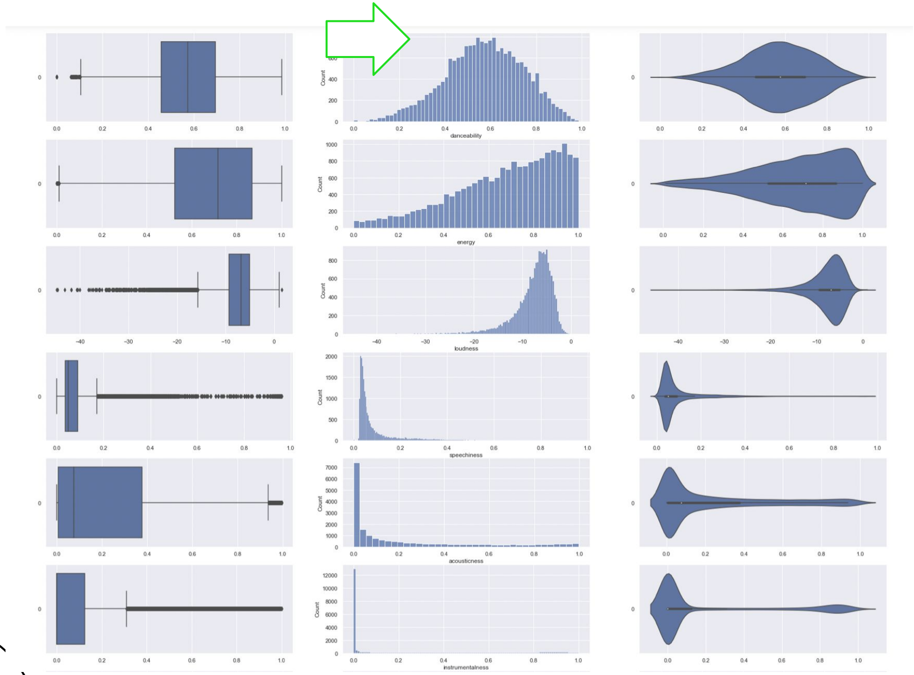
PREDICTOR VARIABLES (CATEGORICAL)

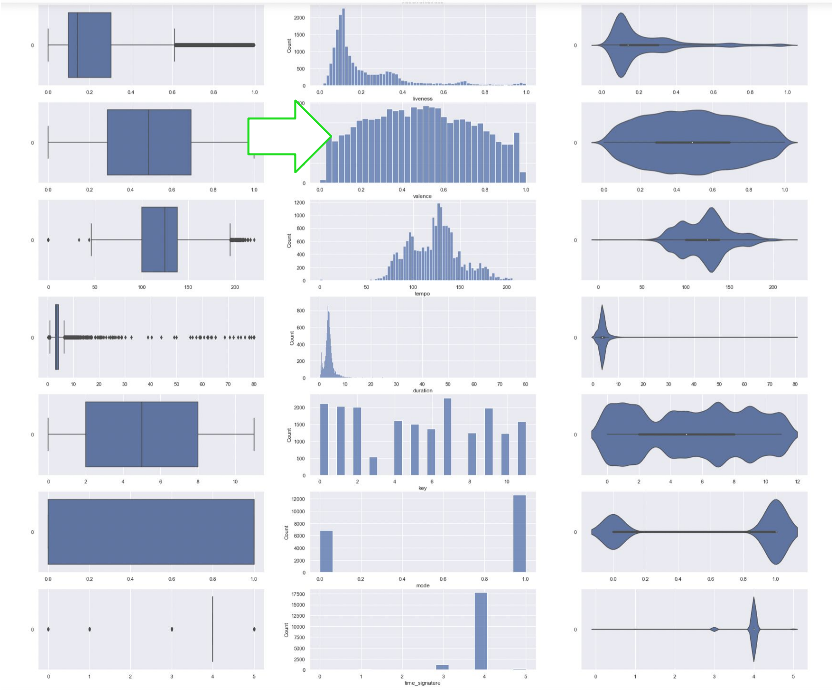
MODE : MAJOR (1) OR MINOR (0) SCALE

KEY : THE KEY THE TRACK IS IN

TIME SIGNATURE : AN ESTIMATION OF HOW MANY BEATS PER BAR

DISTRIBUTION OF ALL VARIABLES (NUMERIC & CATEGORICAL)





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SUMMARY STATISTICS (NUMERIC)

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	liveness	valence	tempo	duration
count	19416.000000	19416.000000	19416.000000	19416.000000	19416.000000	19416.000000	19416.000000	19416.000000	19416.000000	19416.000000
mean	0.570222	0.674815	-7.838767	0.090111	0.230815	0.177834	0.229087	0.490992	122.719028	3.953030
std	0.169750	0.233090	4.320179	0.105160	0.297112	0.325169	0.201796	0.252063	27.946602	3.010822
min	0.000000	0.000020	-44.761000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.290000
25%	0.458000	0.525000	-9.351500	0.036100	0.005130	0.000000	0.098300	0.287000	100.253250	3.030000
50%	0.575000	0.716000	-6.844500	0.049900	0.074900	0.000087	0.141000	0.487000	124.893000	3.690000
75%	0.694000	0.868000	-5.080000	0.090700	0.378000	0.124250	0.304000	0.693000	138.056000	4.410000
max	0.985000	1.000000	1.526000	0.961000	0.996000	1.000000	0.996000	0.998000	220.099000	80.000000

CORRELATION BETWEEN NUMERIC VARIABLES AND POPULARITY

	danceability	energy	loudness	speechiness	acousticness	instrumentalness	liveness	valence	tempo	duration	popularity
danceability	1.000	0.014	0.194	0.157	-0.109	-0.163	-0.195	0.409	-0.119	-0.034	0.061
energy	0.014	1.000	0.699	0.038	-0.698	0.004	0.129	0.267	0.204	-0.035	-0.004
loudness	0.194	0.699	1.000	-0.001	-0.543	-0.341	-0.047	0.264	0.138	-0.046	0.063
speechiness	0.157	0.038	-0.001	1.000	0.010	-0.115	0.132	0.030	0.011	-0.009	0.028
acousticness	-0.109	-0.698	-0.543	0.010	1.000	0.013	-0.001	-0.124	-0.174	-0.008	-0.032
instrumentalness	-0.163	0.004	-0.341	-0.115	0.013	1.000	0.058	-0.194	0.020	0.059	-0.057
liveness	-0.195	0.129	-0.047	0.132	-0.001	0.058	1.000	-0.050	-0.019	0.019	-0.036
valence	0.409	0.267	0.264	0.030	-0.124	-0.194	-0.050	1.000	0.046	-0.138	-0.007
tempo	-0.119	0.204	0.138	0.011	-0.174	0.020	-0.019	0.046	1.000	-0.012	0.004
duration	-0.034	-0.035	-0.046	-0.009	-0.008	0.059	0.019	-0.138	-0.012	1.000	-0.003
popularity	0.061	-0.004	0.063	0.028	-0.032	-0.057	-0.036	-0.007	0.004	-0.003	1.000

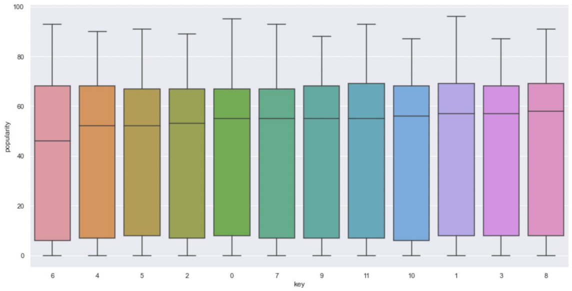
INSIGHTS: NONE OF THE NUMERIC VARIABLES HAVE A STRONG LINEAR RELATIONSHIP WITH POPULARITY.

SUMMARY STATISTICS (CATEGORICAL)

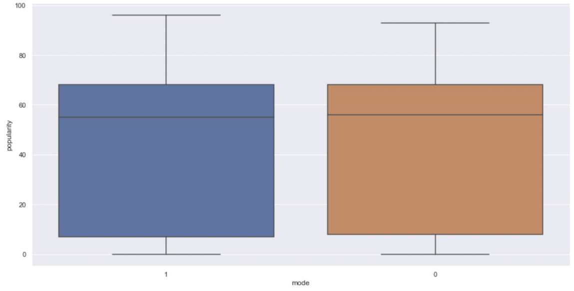
	key	mode	time_signature
count	19416.000000	19416.000000	19416.000000
mean	5.297384	0.648795	3.929440
std	3.555519	0.477359	0.367445
min	0.000000	0.000000	0.000000
25%	2.000000	0.000000	4.000000
50%	5.000000	1.000000	4.000000
75%	8.000000	1.000000	4.000000
max	11.000000	1.000000	5.000000

DISTRIBUTION OF CATEGORICAL VARIABLES AGAINST POPULARITY

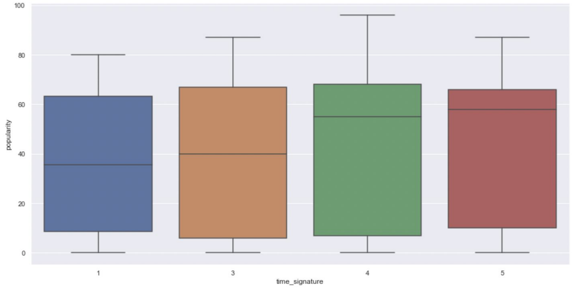
Key



Mode



Time Signature



INSIGHTS: ONLY **TIME SIGNATURE** INDICATE A **RELATIONSHIP** WITH POPULARITY.

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REMOVAL OF OUTLIERS USING ISOLATION FOREST

- UNSUPERVISED LEARNING ALGORITHM THAT CAN ISOLATE OUTLIERS FROM A MULTI-DIMENSIONAL DATASET EFFECTIVELY.
- EXPLOITS THE NATURE THAT ANOMALIES ARE "FEW AND DIFFERENT".

```
from sklearn.ensemble import IsolationForest

iForest = IsolationForest(n_estimators = 100, contamination = 0.05)

# fit model
iForest.fit(variables)

# predict on data
anomaly_mask = iForest.predict(variables) #anomalies will be masked as -1 in the array
print("number of anomalies identified:",anomaly_mask.tolist().count(-1)) #number of anomalies marked

temp = pd.concat([variables, popularity],axis=1).reindex(variables.index)

temp_wo = temp[(anomaly_mask != -1)].reset_index(drop=True)
print("new shape:",temp_wo.shape) # check the shape
```

```
number of anomalies identified: 970
new shape: (18446, 14)
```

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MACHINE LEARNING

RATIONALE

Since response variable is numeric, we decided to carry out machine learning using multivariate linear regression model.

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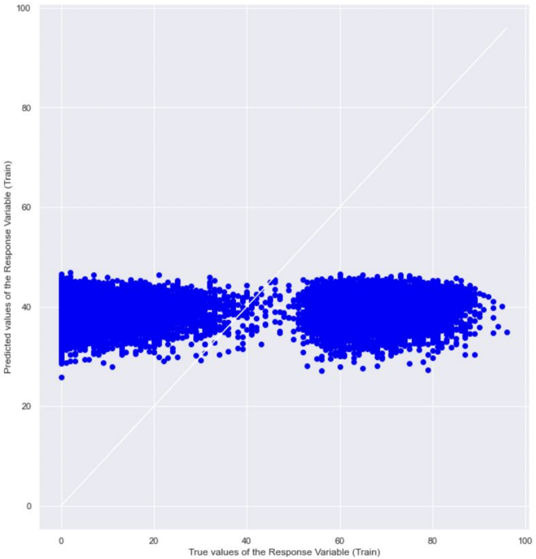
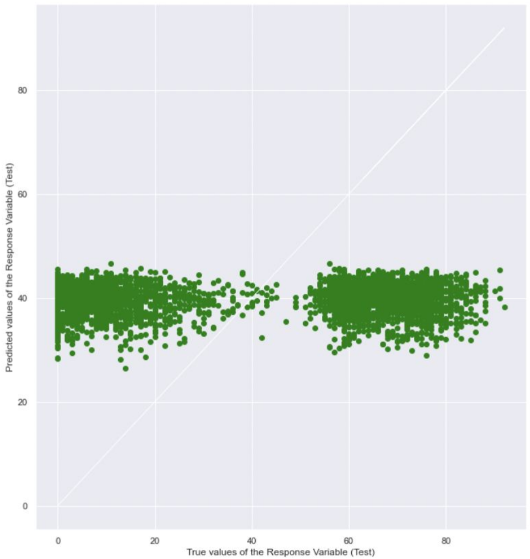
LINEAR REGRESSION MODEL I

Using top 6 numeric predictor variables



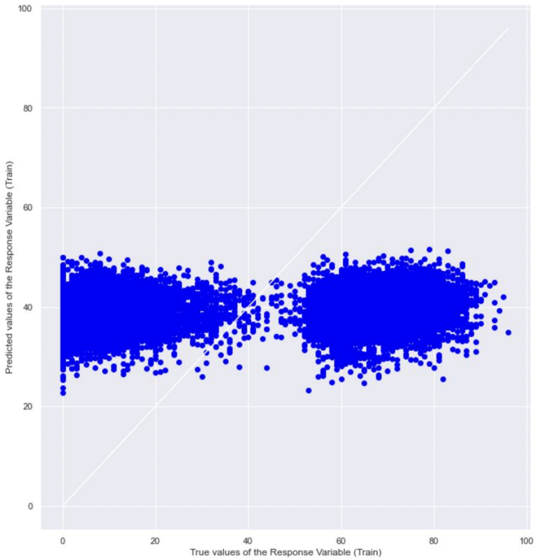


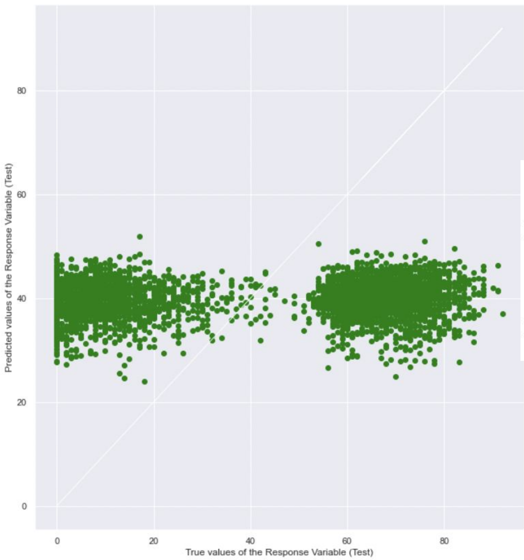

```
Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.00890941434677417
Mean Squared Error (MSE)        : 930.8169774377343

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.007092094933129012
Mean Squared Error (MSE)        : 931.3923985052814
```

LINEAR REGRESSION MODEL II

Using all numeric predictor variables






```
Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.013959366651487 67
Mean Squared Error (MSE)        : 926.074140195082

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.013783324417184883
Mean Squared Error (MSE)        : 925.1157234518339
```

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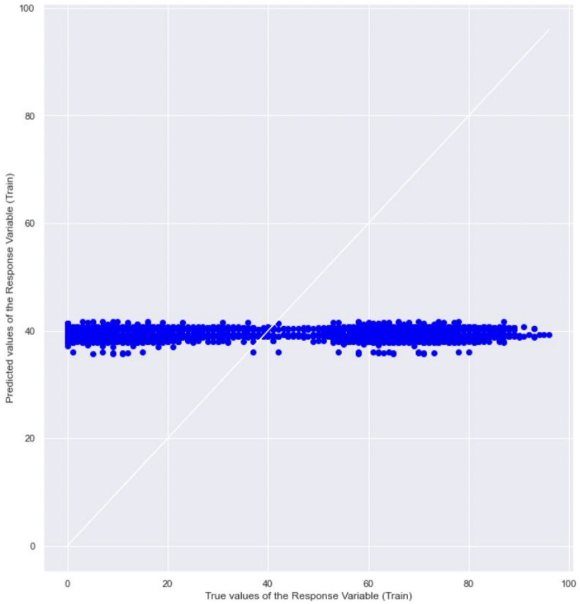
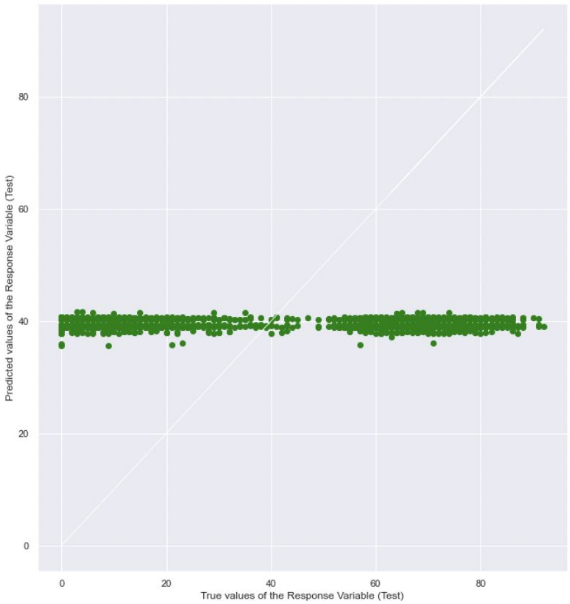
LINEAR REGRESSION MODEL III

Using all categorical predictor variables






```
Goodness of Fit of Model          Train Dataset
Explained Variance (R^2)          : 0.0005557844880001994
Mean Squared Error (MSE)          : 938.6625776364816

Goodness of Fit of Model          Test Dataset
Explained Variance (R^2)          : -0.00040441568143712026
Mean Squared Error (MSE)          : 938.424463580089
```

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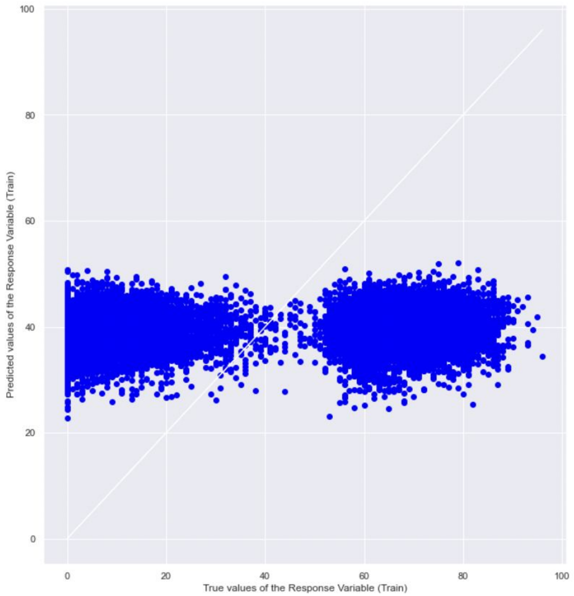
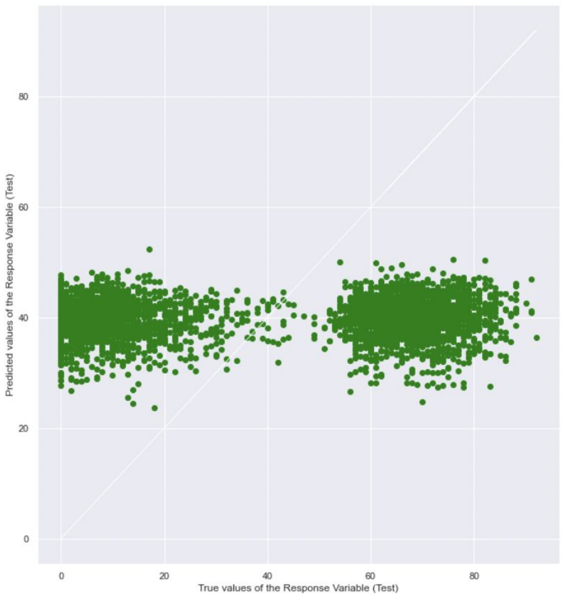
LINEAR REGRESSION MODEL IV

Using all (numeric and categorical) variables






```
Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.014332770138969608
Mean Squared Error (MSE)        : 925.723445404299

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.013995427438606649
Mean Squared Error (MSE)        : 924.9167612511666
```

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RESULTS ANALYSIS (LINEAR REGRESSION)

	EXPLAINED VARIANCE		MEAN SQUARED ERROR	
	TRAIN	TEST	TRAIN	TEST
MODEL I	0.0089	0.0071	930.82	931.39
MODEL II	0.0140	0.0138	926.07	925.12
MODEL III	0.0006	-0.0004	936.66	938.42
MODEL IV	0.0143	0.0140	925.72	924.92

OUR INSIGHTS

PERFORMANCE OF MODELS: MODEL 4 = MODEL 2 > MODEL 1 > MODEL 3

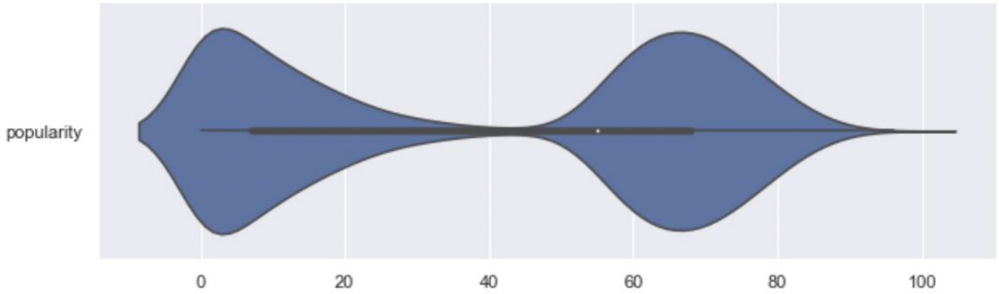
- SINCE ALL VARIABLES DO NOT EXHIBIT STRONG CORRELATION WITH THE POPULARITY VARIABLE

THE USAGE OF MORE VARIABLES GIVES A MORE ACCURATE PREDICTION.

- INTERESTING: THE DIFFERENCE IN EXPLAINED VARIANCE FOR MODEL 4 AND MODEL 2 IS NEGLIGIBLE

CATEGORICAL VARIABLES IN THE PREDICTION OF POPULARITY IS INCONSEQUENTIAL IN LINEAR REGRESSION.

EXPLORING OTHER MODELS



- GIVEN THE BIMODAL DISTRIBUTION ABOVE, WE CLASSIFY POPULARITY INTO TWO CLASSES:
  - TRUE: POPULARITY >= 50
  - FALSE: POPULARITY < 50

- NO CLASS IMBALANCE

RATIONALE

SINCE RESPONSE VARIABLE IS NOW CATEGORICAL, WE DECIDED TO CARRY OUT MACHINE LEARNING USING DECISION TREES/LOGISTIC REGRESSION MODEL.

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ONE-HOT ENCODING

- AS THE CATEGORICAL VARIABLES MAY NOT BE *ORDINAL*, INTEGER ENCODING IS UNFEASIBLE.
- WE DECIDED TO ENCODE NOMINAL (UNORDERED) CATEGORICAL VARIABLES VIA ONE-HOT ENCODING

key_0	key_1	key_2	key_3	key_4	key_5	key_6	key_7	key_8	key_9	key_10	key_11	mode_0	mode_1	time_signature_1	time_signature_3	time_signa
0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	
0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	

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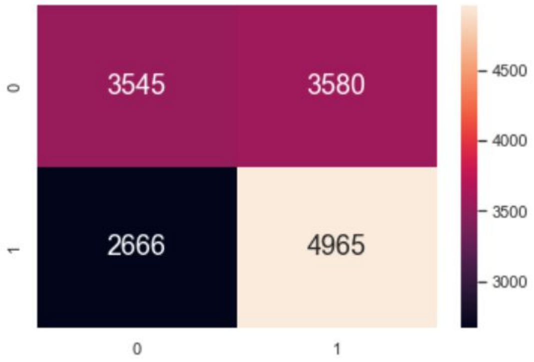
MODEL I: SINGLE DECISION TREE

```
Train Data
Accuracy  :       0.5767145567904581

TPR Train :       0.6506355654566898
TNR Train :       0.4975438596491228

FPR Train :       0.5024561403508772
FNR Train :       0.3493644345433102

<AxesSubplot:>
```




```
Test Data
Accuracy  :       0.5436314363143632

TPR Test :        0.631062951496388
TNR Test :        0.4469178082191781

FPR Test :        0.553082191780822
FNR Test :        0.368937048503612

<AxesSubplot:>
```

MODEL II: RANDOM FOREST (UNOPTIMISED)

```
Train Data
Accuracy  :       0.5984006505828138

TPR Train :       0.7282138645000655
TNR Train :       0.4593684210526316

FPR Train :       0.5406315789473685
FNR Train :       0.27178613549993447
```

<AxesSubplot:>


```
Test Data
Accuracy  :       0.5525745257452574

TPR Test :        0.6904024767801857
TNR Test :        0.4001141552511416

FPR Test :        0.5998858447488584
FNR Test :        0.30959752321981426
```

<AxesSubplot:>

ANALYSIS

- RANDOM FOREST USES MULTIPLE DECISION TREES THAT CHOOSES FEATURES RANDOMLY.
- IT DOES NOT RELY ON THE FEATURE IMPORTANCE EXHIBITED BY A SINGLE DECISION TREE.
- RANDOM FOREST CAN GENERALIZE OVER THE DATA IN A BETTER WAY.
- CLASSIFICATION ACCURACY, TPR AND TNR SLIGHTLY IMPROVED BY USING RANDOM FOREST

MODEL III: RANDOM FOREST (OPTIMISED HYPERPARAMETERS: MAX_DEPTH = 10, N_ESTIMATORS =900)

```
Train Data
Accuracy  :      0.7527785307671455

TPR Train :      0.8806185296815621
TNR Train :      0.615859649122807

FPR Train :      0.384140350877193
FNR Train :      0.11938147031843795

<AxesSubplot:>
```


```
Test Data
Accuracy  :      0.5598915989159892

TPR Test :       0.6847265221878225
TNR Test :       0.4218036529680365

FPR Test :       0.5781963470319634
FNR Test :       0.3152734778121775

<AxesSubplot:>
```

ANALYSIS

- THE MODEL'S ACCURACY ON THE TRAIN AND TEST SET HAS IMPROVED BASED ON THE OPTIMISED VALUES OF N_ESTIMATORS =900 AND MAX_DEPTH=10

- HOWEVER, THE ACCURACY OF THE TRAIN SET IS MUCH HIGHER THAN THAT OF THE TEST SET, WHICH PROVES THAT THE MODEL FAILS TO GENERALIZE TO THE TEST DATA.

- THIS PHENOMENON IS REFERRED TO AS 'OVERFITTING'.

MODEL IV: REGULARISED RANDOM FOREST (WITH OPTIMISED HYPERPARAMETERS + PRE-PRUNING)

- REGULARISATION TECHNIQUE: PRE-PRUNING
  - INVOLVES TUNING THE HYPERPARAMETERS OF THE RANDOM FOREST MODEL.
    - HYPERPARAMETERS: MIN_SAMPLES_LEAF, MIN_SAMPLES_SPLIT
    - THIS AIMS TO CONTROL THE COMPLEXITY OF THE MODEL, AND REDUCE OVERFITTING

- OPTIMISED PARAMETERS: MIN_SAMPLES_LEAF = 0.01, MIN_SAMPLES_SPLIT = 0.01

MODEL IV: RANDOM FOREST (WITH OPTIMISED HYPERPARAMETERS + PRE-PRUNING)

Train Data
Accuracy : 0.5939278937381404

TPR Train : 0.7102607784038789
TNR Train : 0.4693333333333333

FPR Train : 0.5306666666666666
FNR Train : 0.2897392215961211

<AxesSubplot:>

Test Data
Accuracy : 0.5509485094850949

TPR Test : 0.6687306501547987
TNR Test : 0.420662100456621

FPR Test : 0.579337899543379
FNR Test : 0.33126934984520123

<AxesSubplot:>

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05 CONCLUSION

ANALYSIS

- WITH PRE-PRUNING, CLASSIFICATION ACCURACY FOR TEST SET REMAINED RELATIVELY THE SAME, WHILE THAT FOR TRAIN SET DECREASED GREATLY.
  - OVERFITTING IS REDUCED, WHILE MAINTAINING CLASSIFICATION ACCURACY
- INSIGNIFICANT IMPROVEMENT IN TEST CLASSIFICATION ACCURACY MIGHT BE DUE TO THE UNRELATED NATURE OF OUR DATASET (BETWEEN POPULARITY AND AUDIO FEATURES)
- REGULARISATION ATTEMPT UNSUCCESSFUL

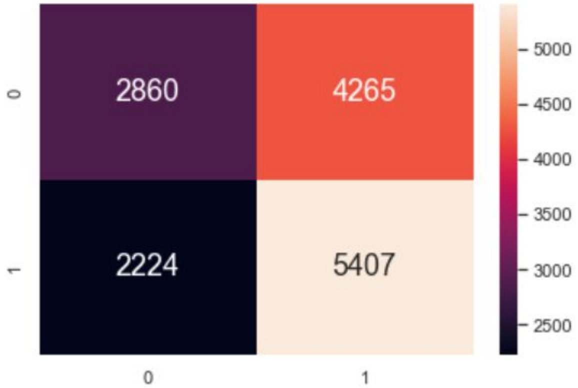
MODEL V: LOGISTIC REGRESSION CLASSIFICATION

```
Train Data
Accuracy  :       0.5602466793168881

TPR Train :       0.7085572008911021
TNR Train :       0.4014035087719298

FPR Train :       0.5985964912280701
FNR Train :       0.2914427991088979

<AxesSubplot:>
```




```
Test Data
Accuracy  :       0.5449864498644986

TPR Test  :       0.6878224974200207
TNR Test  :       0.386986301369863

FPR Test  :       0.613013698630137
FNR Test  :       0.31217750257997934

<AxesSubplot:>
```

ANALYSIS

- LOGISTIC REGRESSION IS A STATISTICAL ANALYSIS METHOD TO PREDICT A BINARY OUTCOME, SUCH AS YES OR NO, BASED ON PRIOR OBSERVATIONS OF A DATA SET
- LOGISTIC REGRESSION APPLIES REGULARISATION BY DEFAULT
- LOGISTIC REGRESSION MODEL PERFORMED SIMILAR TO PRE-PRUNED MODEL, WITH NO 'OVERFITTING'.

RESULTS ANALYSIS (CLASSIFICATION MODEL)

	CLASSIFICATION ACCURACY	
	TRAIN	TEST
MODEL I	0.5767	0.5436
MODEL II	0.5984	0.5526
MODEL III	0.7523	0.5599
MODEL IV	0.5939	0.5509
MODEL V	0.5602	0.5450

05 THE CONCLUSION

CONCLUSION

- OUT OF ALL CLASSIFICATION MODELS, LOGISTIC REGRESSION MODEL PERFORMS THE BEST.
    - THIS CAN BE OBSERVED BY REDUCTION IN 'OVERFITTING' AS WELL AS THE IMPROVEMENT IN ACCURACY FROM TRAIN SET TO TEST SET
- ADDITIONALLY, ALTHOUGH PRE-PRUNING WAS DONE TO REGULARISE THE DATA, IT WAS NOT A GOOD ATTEMPT BECAUSE THE ACCURACY ON THE TEST SET DID NOT IMPROVE

OUR THOUGHTS

NO PERFECT FORMULA

- VARIOUS GENRES EXISTS FOR A REASON
- POPULAR SONGS CHANGE OVERTIME ACCORDING TO DEMOGRAPHIC AND TASTE

EXTERNAL FACTORS

- MARKETING
- FUNDING
- EXPLOIT OF SPOTIFY POPULARITY ALGORITHM

RECOMMENDATIONS

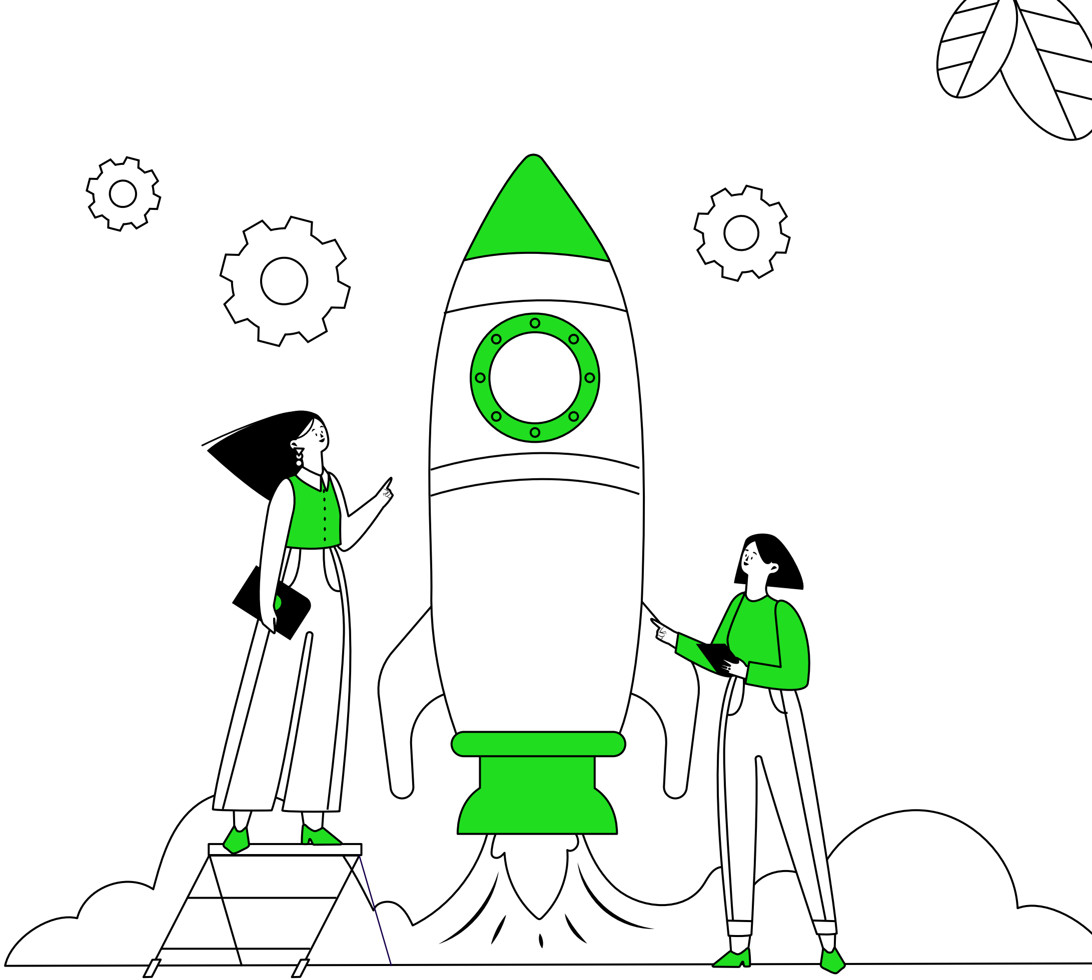
NARROW OUR SCOPE

- EXPLORE THE RELATIONSHIP IN THE SAME GENRE, RATHER THAN ACROSS MULTIPLE GENRES

DIFFERENT MACHINE LEARNING MODEL

- INCORPORATE DEEP LEARNING NEURAL NETWORKS TO BETTER STUDY THE RELATIONSHIP BETWEEN POPULARITY AND AUDIO VARIABLES

THANKS!



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SPOTIFY API - HTTPS://DEVELOPER.SPOTIFY.COM/DOCUMENTATION/WEB-API/