Using NLP Techniques to Predict Song Skip on Spotify based on sequential user and Acoustic data

Introduction

Music consumption habits have changed dramatically with the rise of streaming services like Spotify, Apple Music, and Tidal. The skip button plays a large role in the user's experience, as they are free to abandon songs as they choose. Music roviders are also incentivized to recommend songs that their users like in order to increase user experience and time spent on the platform.

Machine learning in the context of music often uses recommender system.There hasn't been much research on how a user's teraction with music over time can help recommend music to the use.

Team Introduction

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Preprocessing Data

Data preprocessing in Machine Learning is a crucial step that helps enhance the quality of data to promote the extraction of meaningful insights from the data. Data preprocessing in Machine Learning refers to the technique of preparing (cleaning and organizing) the raw data to make it suitable for a building and training Machine Learning models. In simple words, data preprocessing in Machine Learning is a data mining technique that transforms raw data into an understandable and readable format.

1.a. Data documentation

- **session log dataset**:

The schema for the session logs is given below. Each row corresponds to the playback of one track, and has the following fields, with corresponding values :

Field	Values
session_id	E.g. 65_283174c5-551c-4c1b-954b cb60ffcc2aec - unique identifier for the session that this row is a part of
session_position	{1-20} - position of row within session
session_length	{10-20} - number of rows in session
track_id_clean	E.g. t_13d34e4b-dc9b-4535-963d-419afa8332ec - unique identifier for the track played. This islinked with track_id in the track features and metadata table.

Field	Values
skip_1	Boolean indicating if the track was only played very briefly
skip_2	Boolean indicating if the track was only played briefly
skip_3	Boolean indicating if most of the track was played
not_skipped	Boolean indicating that the track was playedin its entirety
context_switch	Boolean indicating if the user changed context between the previous row and the current row. This could for example occur if the user switched from one playlist to another
no_pause_before_play	Boolean indicating if there was no pause between playback of the previous track andthis track
short_pause_before_play	Boolean indicating if there was a short pause between playback of the previous track and this track
long_pause_before_play	Boolean indicating if there was a long pause between playback of the previous track and this track
hist_user_behavior_n_seekfwd	Number of times the user did a seek forward within track
hist_user_behavior_n_seekback	Number of times the user did a seek back within track
hist_user_behavior_is_shuffle	Boolean indicating if the user encountered this track while shuffle mode was activated
hour_of_day	{0-23} - The hour of day
date	E.g. 2018-09-18 - The date
premium	Boolean indicating if the user was on premium or not. This has potential implications for skipping behavior.
context_type	E.g. editorial playlist - what type of context the playback occurred within
hist_user_behavior_reason_start	E.g. fwdbtn - the user action which led to the current track being played
hist_user_behavior_reason_end	E.g. trackdone - the user action which led to the current track playback ending

- **track features dataset**:

The schema for the track metadata and features is given below, each row has the following fields, with corresponding values:

Field	Values
track_id	E.g. t_13d34e4b-dc9b-4535-963d- 19afa8332ec- unique identifier for the track played. This is linked with track_id_clean in the session logs
duration	Length of track in seconds
release_year	Estimate of year the track was released
us_popularity_estimate	Estimate of the US popularity percentile of the track as of October 12, 2018
acousticness	See https://developer.spotify.com/documentation/ web-api/reference/tracks/get-audio-features/
beat_strength	See acousticness
bounciness	See acousticness
danceability	See acousticness
dyn_range_mean	See acousticness
energy	See acousticness
flatness	See acousticness

Field	Values
instrumentalness	See acousticness
key	See acousticness
liveness	See acousticness
loudness	See acousticness
mechanism	See acousticness
mode	See acousticness
organism	See acousticness
speechiness	See acousticness
time_signature	See acousticness
valence	See acousticness
acoustic_vector_0	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_1	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_2	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_3	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_4	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_5	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_6	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-
acoustic_vector_7	See http://benanne.github.io/2014/08/05/spotify-cnns.html and http://papers.nips.cc/paper/5004-deep-content-based-

1.a. Data wrangling

In [1]:

```
#importing necessary libarary and data
import pandas as pd
import numpy as np
track_data = pd.read_csv('tf_mini.csv')
session_data = pd.read_csv('log_mini.csv')
```

In [2]:

```
track_data.head()
```

Out[2]:

	track_id	duration	release_year	us_popularity_estimate	acousticness	beat_strength	bounciness	danceabi
0	t_a540e552-16d4-42f8-a185-232bd650ea7d	109.706673	1950	99.975414	0.458040	0.519497	0.504949	0.399

	track_id	duration	release_year	us_popularity_estimate	acousticness	beat_strength	bounciness	danceabi
1	t_67965da0-132b-4b1e-8a69-0ef99b32287c	187.693329	1950	99.969430	0.916272	0.419223	0.545530	0.491
2	t_0614ecd3-a7d5-40a1-816e-156d5872a467	160.839996	1951	99.602549	0.812884	0.425890	0.508280	0.491
3	t_070a63a0-744a-434e-9913-a97b02926a29	175.399994	1951	99.665018	0.396854	0.400934	0.359990	0.552
4	t_d6990e17-9c31-4b01-8559-47d9ce476df1	369.600006	1951	99.991764	0.728831	0.371328	0.335115	0.483

5 rows × 30 columns

In [3]:

```
session_data.head()
```

Out[3]:

	session_id	session_position	session_length	track_id_clean	skip_1	skip_2	skip_3	not_skipped	context_switch
0	0_00006f66-33e5-4de7-a324-2d18e439fc1e	1	20	t_0479f24c-27d2-46d6-a00c-7ec928f2b539	False	False	False	True	0
1	0_00006f66-33e5-4de7-a324-2d18e439fc1e	2	20	t_9099cd7b-c238-47b7-9381-f23f2c1d1043	False	False	False	True	0
2	0_00006f66-33e5-4de7-a324-2d18e439fc1e	3	20	t_fc5df5ba-5396-49a7-8b29-35d0d28249e0	False	False	False	True	0
3	0_00006f66-33e5-4de7-a324-2d18e439fc1e	4	20	t_23cff8d6-d874-4b20-83dc-94e450e8aa20	False	False	False	True	0
4	0_00006f66-33e5-4de7-a324-2d18e439fc1e	5	20	t_64f3743c-f624-46bb-a579-0f3f9a07a123	False	False	False	True	0

5 rows × 21 columns

In [4]:

```
#data assess
#we will start by combining the two datasets
#we will be merging on track id and track id clean
combined_data = session_data.merge(track_data,left_on='track_id_clean',right_on='track_id'
#we should check for inconsistent types
combined_data.dtypes
```

```
session_id                          object
```

Out[4]:
```
session_position                    int64
session_length                      int64
track_id_clean                     object
skip_1                               bool
skip_2                               bool
skip_3                               bool
not_skipped                          bool
context_switch                      int64
no_pause_before_play                int64
short_pause_before_play             int64
long_pause_before_play              int64
hist_user_behavior_n_seekfwd        int64
hist_user_behavior_n_seekback       int64
hist_user_behavior_is_shuffle        bool
hour_of_day                         int64
date                               object
premium                              bool
context_type                       object
hist_user_behavior_reason_start    object
hist_user_behavior_reason_end      object
track_id                           object
duration                          float64
release_year                        int64
us_popularity_estimate            float64
acousticness                      float64
beat_strength                     float64
bounciness                        float64
danceability                      float64
dyn_range_mean                    float64
energy                            float64
flatness                          float64
instrumentalness                  float64
key                                 int64
liveness                          float64
loudness                          float64
mechanism                         float64
mode                               object
organism                          float64
speechiness                       float64
tempo                             float64
time_signature                      int64
valence                           float64
acoustic_vector_0                 float64
acoustic_vector_1                 float64
acoustic_vector_2                 float64
acoustic_vector_3                 float64
acoustic_vector_4                 float64
acoustic_vector_5                 float64
acoustic_vector_6                 float64
acoustic_vector_7                 float64
dtype: object
```

we have the date column as a string so we will need to fix that

In [5]:
```
#checking for duplicates
combined_data.duplicated().sum()
```

Out[5]:
```
0
```

we have no duplicates in our dataset

In [6]:
```
#check for missing data
combined_data.isna().sum().sum()
```

Out[6]: 0

we have no missing data

since we found that our data is clean and consistent but for the date column we proceed to fix that column

In [7]:

```
#data clean
#we will transform the date column into days of week to figure out if skips are affected b
#whch day the tracks are played in
combined_data.date=pd.to_datetime(combined_data.date)
daysofweek =[]
for i in combined_data.date:
    daysofweek.append(pd.Timestamp(i).day_name())
combined_data['days_of_week']=daysofweek
combined_data.days_of_week
```

Out[7]:

```
0           Sunday
1           Sunday
2         Saturday
3           Sunday
4         Saturday
            ...
167875    Saturday
167876    Saturday
167877    Saturday
167878    Saturday
167879    Saturday
Name: days_of_week, Length: 167880, dtype: object
```

1.b. Data exploration

In [8]:

```
#importing important libararies
import matplotlib.pyplot as plt
import seaborn as sns
```

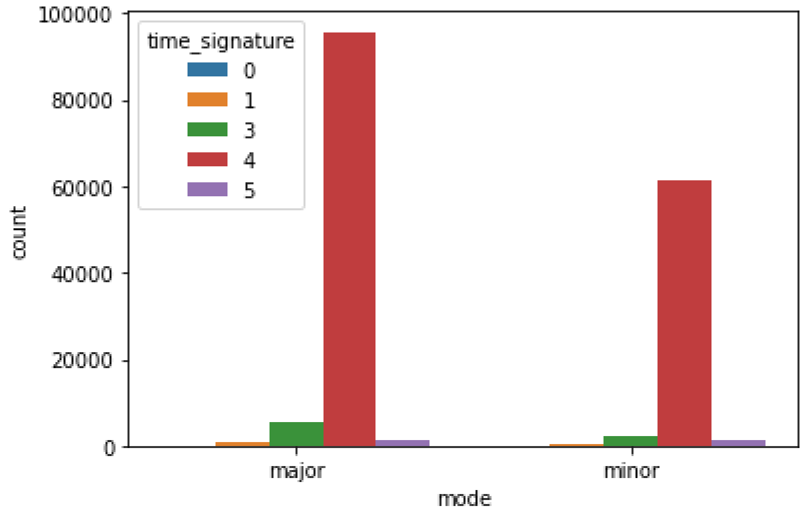
In [9]:

```
#EDA
#now we will start our exploratory analysis and figure out which data attributes are impor
#let us see how the timesignature is involved in making the mode
sns.countplot(combined_data['mode'],hue=combined_data.time_signature)
```

```
C:\Users\fahda\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

Out[9]:

```
<AxesSubplot:xlabel='mode', ylabel='count'>
```



most of tracks have a time signature of 4

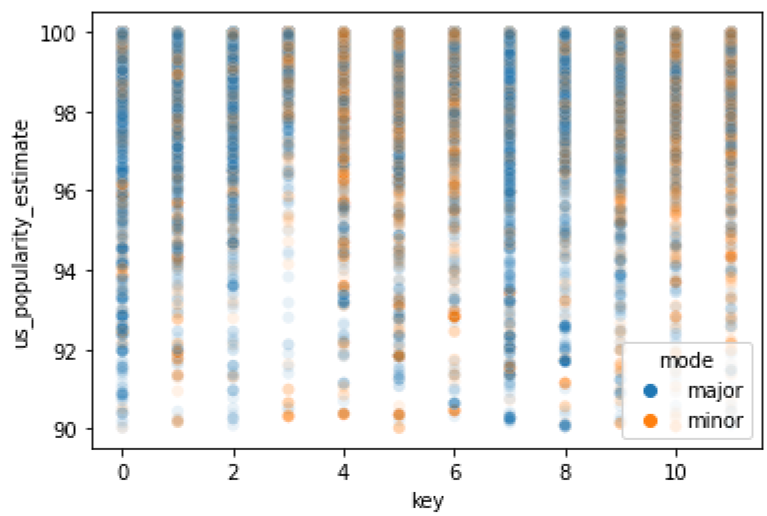
In [10]:

```
#what is the dominant modes in each key
sns.scatterplot(y= combined_data.us_popularity_estimate,x=combined_data.key,alpha=0.1,hue=
```

Out[10]:

```
<AxesSubplot:xlabel='key', ylabel='us_popularity_estimate'>
```

```
C:\Users\fahda\anaconda3\lib\site-packages\IPython\core\pylabtools.py:151: UserWarning: Cr
eating legend with loc="best" can be slow with large amounts of data.
  fig.canvas.print_figure(bytes_io, **kw)
```



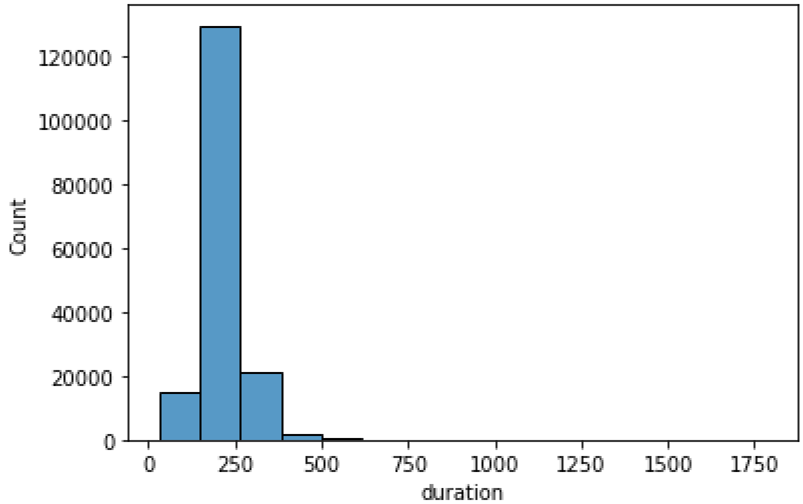
most minor mode are in key 4,5,6,9,10,11

In [11]:

```
#how does the track length affect the skip
sns.histplot(data=combined_data,x="duration",bins=15)
```

Out[11]:

```
<AxesSubplot:xlabel='duration', ylabel='Count'>
```



most from 200 to 300 seconds

In [12]:

```
#user behavior when he stops before the song
sns.countplot(combined_data.skip_2,hue=combined_data.short_pause_before_play)
```

```
C:\Users\fahda\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

Out[12]:

```
<AxesSubplot:xlabel='skip_2', ylabel='count'>
```

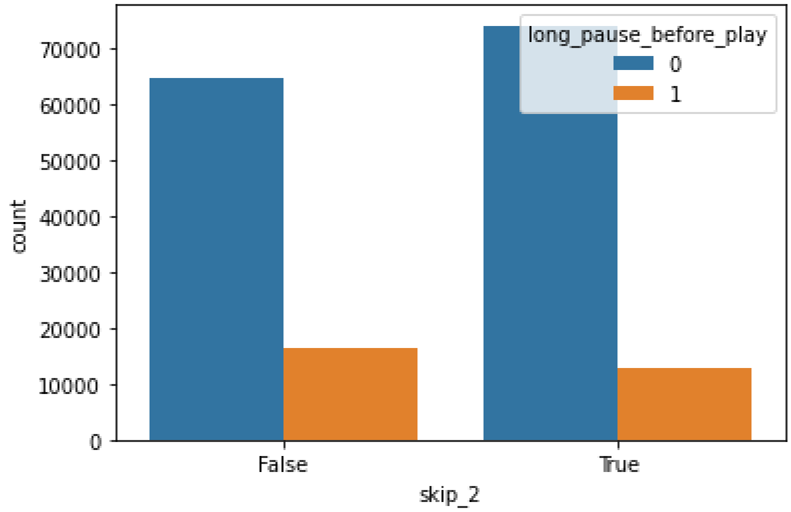
In [13]:

```
#does having a break before tracks afect whether or not you wi;; skip it
sns.countplot(combined_data.skip_2,hue=combined_data.long_pause_before_play)
```

```
C:\Users\fahda\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

Out[13]:

```
<AxesSubplot:xlabel='skip_2', ylabel='count'>
```

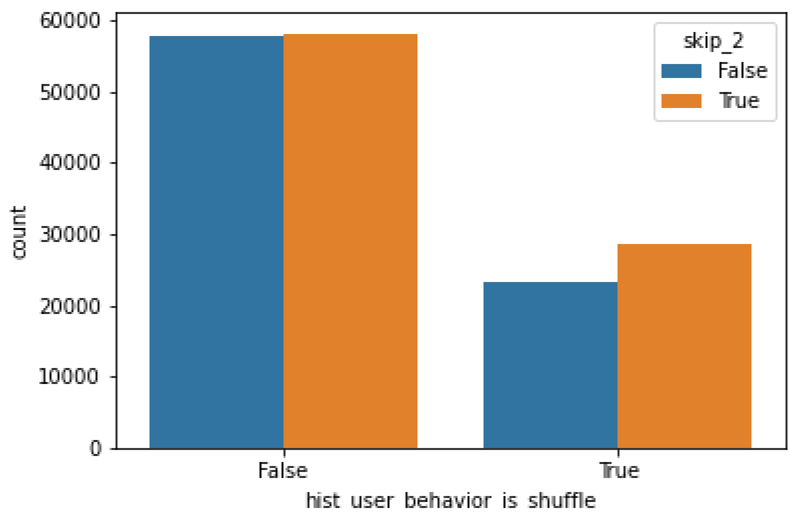


there is no effect whether the user stops a short or long or even does not stop so we will combine the three attributes into one

In [14]:
```
#lets see shuffle effect on the skip
sns.countplot(combined_data.hist_user_behavior_is_shuffle,hue=combined_data.skip_2)
```

```
C:\Users\fahda\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only valid positional a
rgument will be `data`, and passing other arguments without an explicit keyword will resul
t in an error or misinterpretation.
  warnings.warn(
```

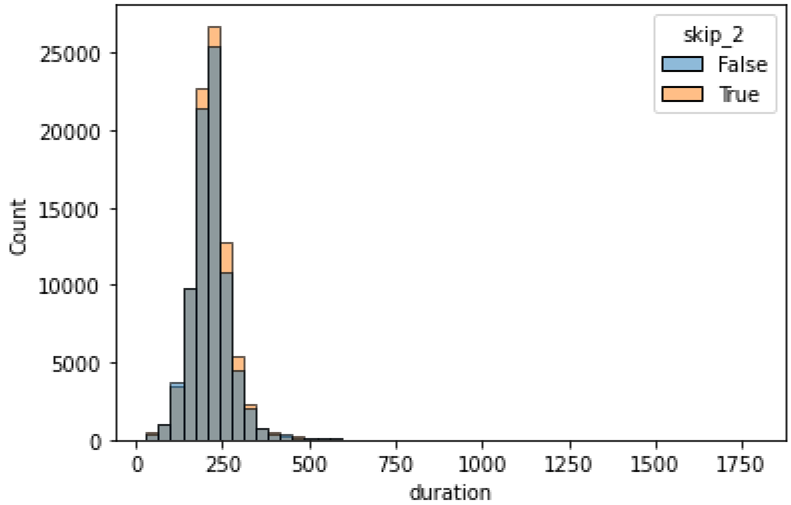
Out[14]:
```
<AxesSubplot:xlabel='hist_user_behavior_is_shuffle', ylabel='count'>
```



users who are on shuffle are more likely to skip

In [15]:
```
#will the time affect of the track the skip behavior
sns.histplot(x=combined_data.duration,bins=50,hue = combined_data.skip_2)
```

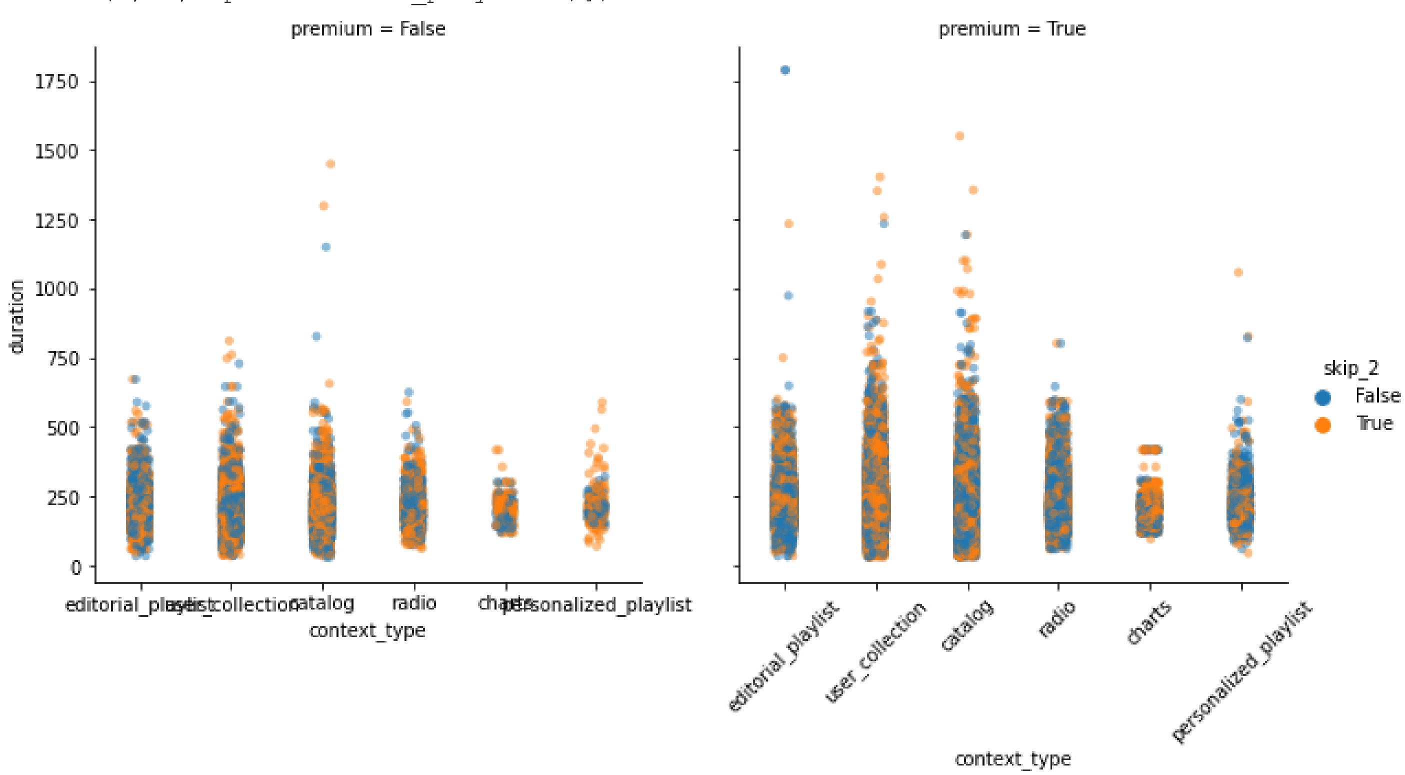
Out[15]:
```
<AxesSubplot:xlabel='duration', ylabel='Count'>
```



we see that skips tend to be alot when the track exceeds 200 seconds in length

In [16]:
```
#lets combine 4 attributes to see how does that affect the skip
sns.catplot(y='duration',x='context_type',data=combined_data,hue = 'skip_2',col='premium',
plt.xticks(rotation = 45)
```

Out[16]:
```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'editorial_playlist'),
  Text(1, 0, 'user_collection'),
  Text(2, 0, 'catalog'),
  Text(3, 0, 'radio'),
  Text(4, 0, 'charts'),
  Text(5, 0, 'personalized_playlist')])
```

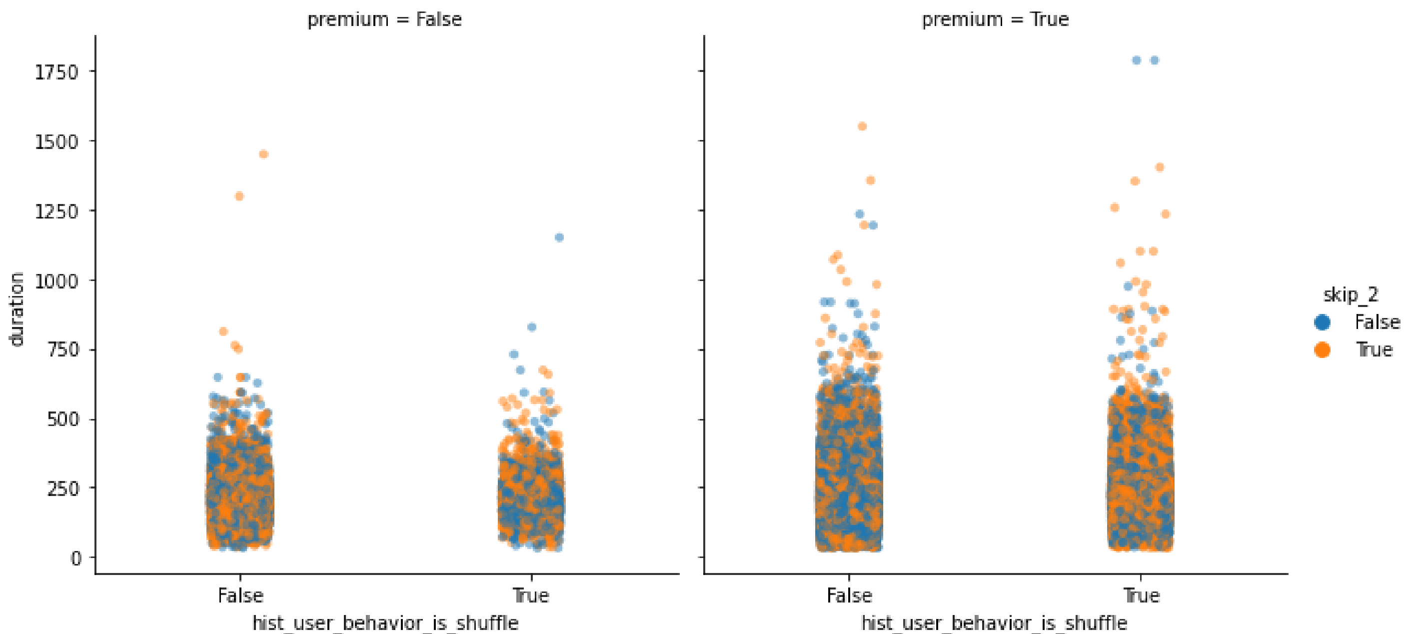


for premium users in the context type more skips happen in user collections and charts but less skips in editorial playlists,catalog and personalized playlist how ever for non preimium users more skips happen in catalog,radio and charts while less skips happen in editorial playlist user collection

In [17]:
```
#trying with diffrent attributes so we find more intersting insights
sns.catplot(y='duration',x='hist_user_behavior_is_shuffle',data=combined_data,hue = 'skip_
```

```
<seaborn.axisgrid.FacetGrid at 0x1f19e4fa310>
```

Out[17]:



for preumium users they tend to skip more on shuffle and less when not shuffling but for non premium usersthey tend to skip when they are not shuffling more than they re on shuffle

so far we have covered most of the important attributes in the next section we will improve our attributes and choose the most important of them because we have a lot of attributes and we do not want to risk overfitting

In [18]:
```
from sklearn.preprocessing import LabelEncoder
```

In [19]:
```
#feature engineering
# in this section we will try as much as we can to limit the number of our attributes

#we figure out that we dont need three skips so we drop them and revert the not skipped co
combined_data['is_skipped'] = ~combined_data.not_skipped
combined_data=combined_data.drop(['skip_1','skip_2','skip_3','not_skipped',
                                  'session_id','track_id_clean','track_id'],axis=1)

#converting boolen types into int
boolen_dtypes=['hist_user_behavior_is_shuffle','premium','is_skipped']
combined_data[boolen_dtypes]=combined_data[boolen_dtypes].astype(int)

#changing the relaese year into relaeased from
combined_data['released_from']=2022 - combined_data['release_year']

#combining the three pauses attributes into one
combined_data['is_paused_before_play']= ~(combined_data['no_pause_before_play']
                                           .astype(bool))
combined_data['is_paused_before_play']=combined_data['is_paused_before_play'].astype(int)
combined_data=combined_data.drop(['no_pause_before_play','short_pause_before_play',
                     'long_pause_before_play','release_year'],axis = 1)

# we have selected the most important features to train our model with and to ask as inou
selected_attributes =['context_switch','is_paused_before_play','hist_user_behavior_is_shu
              'hist_user_behavior_n_seekfwd','hist_user_behavior_n_seekback',
              'released_from','premium',"is_skipped",'session_length','session_position','
               'hist_user_behavior_reason_start','hist_user_behavior_reason_end',
               'hour_of_day']
final_data = combined_data[selected_attributes]
```

In [20]:
```
#lets take a look at the data
```

```
final_data.head()
```

Out[20]:

	context_switch	is_paused_before_play	hist_user_behavior_is_shuffle	hist_user_behavior_n_seekfwd	hist_user_behavio
0	0	1	1	0	
1	0	1	0	0	
2	0	1	0	0	
3	0	0	0	0	
4	0	1	1	0	

we need to extract the target attribute and to convert the three categorical variables

In [21]:

```
lencoder = LabelEncoder()

final_data['context_type'] = lencoder.fit_transform(final_data['context_type'])
final_data['hist_user_behavior_reason_start'] = lencoder.fit_transform(final_data['hist_us
final_data['hist_user_behavior_reason_end'] = lencoder.fit_transform(final_data['hist_user
```

```
C:\Users\fahda\AppData\Local\Temp\ipykernel_676\2598299921.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  final_data['context_type'] = lencoder.fit_transform(final_data['context_type'])
C:\Users\fahda\AppData\Local\Temp\ipykernel_676\2598299921.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  final_data['hist_user_behavior_reason_start'] = lencoder.fit_transform(final_data['hist_
user_behavior_reason_start'])
C:\Users\fahda\AppData\Local\Temp\ipykernel_676\2598299921.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  final_data['hist_user_behavior_reason_end'] = lencoder.fit_transform(final_data['hist_us
er_behavior_reason_end'])
```

In [22]:

```
target = combined_data.is_skipped
final_data.drop('is_skipped',axis = 1 ,inplace = True)
```

```
C:\Users\fahda\AppData\Local\Temp\ipykernel_676\902478284.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
ide/indexing.html#returning-a-view-versus-a-copy
  final_data.drop('is_skipped',axis = 1 ,inplace = True)
```

In [23]:

```
final_data.head()
```

Out[23]:

	context_switch	is_paused_before_play	hist_user_behavior_is_shuffle	hist_user_behavior_n_seekfwd	hist_user_behavio
0	0	1	1	0	

	context_switch	is_paused_before_play	hist_user_behavior_is_shuffle	hist_user_behavior_n_seekfwd	hist_user_behavio
1	0	1	0	0	
2	0	1	0	0	
3	0	0	0	0	
4	0	1	1	0	

Now our data is ready to be taken to the next step which is model implementation

2. Machine Learning modeling

Metrics considered for Model Evaluation

Accuracy: Accuracy simply measures how often the classifier correctly predicts. We can define accuracy as the ratio of the number of correct predictions and the total number of predictions.

2.a. Gradient Boosted Trees (LightGBM)

- LightGBM is a gradient boosting framework based on decision trees to increases the efficiency of the model and reduces memory usage.
- The main features of the LGBM model are as follows :
    - Higher accuracy and a faster training speed.
    - Low memory utilization
    - Comparatively better accuracy than other boosting algorithms and handles overfitting much better while working with smaller datasets.
    - Parallel Learning support.
    - Compatible with both small and large datasets

In [24]:

```
#importing important libararies
from lightgbm import LGBMClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report, f1_sc
```

In [25]:

```
#impelement model
X_train, X_test, y_train, y_test = train_test_split(final_data, target, test_size=0.2, rar
model_1 = LGBMClassifier(learning_rate=0.09,max_depth=-5,random_state=42)
model_1.fit(X_train, y_train)
y_pred = model_1.predict(X_test)
```

We have intialized our LGBM and trained it using test split

In [26]:

```
#model accuracy

score = model_1.score(X_test, y_test)
print("LGBM model Accuracy: " + str(score*100))
```

```
LGBM model Accuracy: 99.00226352156302
```

We have acheived 99% accuracy on the test set now lets move to the next model

2.b. RNN based Bi-LSTM

- **Bi-LSTM:(Bi-directional long short term memory):**
  - Bidirectional recurrent neural networks(RNN) are really just putting two independent RNNs together. This structure allows the networks to have both backward and forward information about the sequence at every time step.
  - Using bidirectional will run your inputs in two ways, one from past to future and one from future to past and what differs this approach from unidirectional is that in the LSTM that runs backward you preserve information from the future and using the two hidden states combined you are able in any point in time to preserve information from both past and future.

In [30]:

```
#importing important libararies
import tensorflow
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from keras.layers import Bidirectional
```

we will impelement our neural network from 1 input layer followed by 2 bidirectional layers followed by our output layer

In [ ]:

```
#impelement model
X_train, X_test, y_train, y_test = train_test_split(final_data,target,random_state =42)
input_shape = X_train.shape[1]
model_2=Sequential()
model_2.add(Bidirectional(LSTM(116,return_sequences=True),input_shape=(input_shape,1)))
model_2.add(Bidirectional(LSTM(116)))
model_2.add(Dense(1,activation = 'sigmoid'))
model_2.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
model_2.fit(X_train, y_train, epochs=1, batch_size=1000)

#prediction on test set
y_pred = model2.predict(X_test)
from numpy.ma.core import ceil, floor
predicitons =[]
for i in range(pred.shape[0]) :
  if pred[i] >0.5 :
    predicitons.append(int(ceil(pred[i])))
  else : predicitons.append(int(floor(pred[i])))
```

In [ ]:

```
#model accuracy
accuracy = accuracy_score(y_test,predicitons)
print("RNN based Bi-LSTM model Accuracy: " + str(score*100))
```

We have acheived 99% accuracy on the test set now lets move to deployment the models

3. Model Deployment

3.a Flask

Flask is a small and lightweight Python web framework that provides useful tools and features that make creating web applications in Python easier. It gives developers flexibility and is a more accessible framework for new developers since you can build a web application quickly using only a single Python file.

we started by bulding the model Bi-LSTM and then trained it on certain 14 features that we believe they are the most effictive and will help our model prediction reach the most.

After traning process we saved this model for pickle format so we can save the model with the trained wieghts.

we bulit after traning the HTML file that suits the project and give friendly user interface.

The last step was to build the slask application that consists of loading the model we built in the pickle formate and bulding prediction function and give an accurate result.

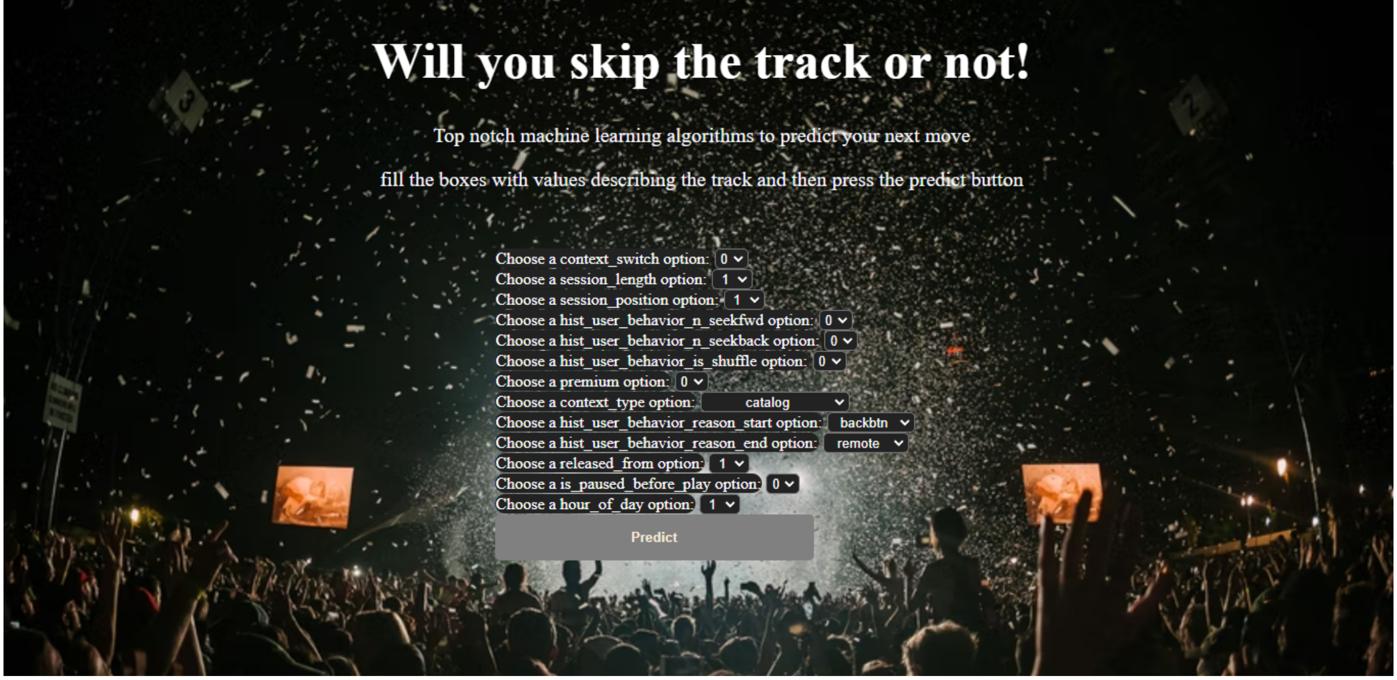
here is the flask app code :

In [ ]:

```
# import numpy as np
from flask import Flask,request ,jsonify,render_template
import pickle

# create flask
app = Flask(__name__)

# load pickle model
model = pickle.load(open('model.pkl','rb'))

# for haome page
@app.route("/")
def Home():
    return render_template("trial.html")

# for prediction from home page
@app.route("/predict",methods=['POST'])
def predict():
    float_feature = [float(x) for x in request.form.values()]
    features =[np.array(float_feature)]
    prediction = model.predict(features)
    if prediction > 0.5:
        assume = 'skipped'
    else: assume = 'not skipped'
    return render_template("trial.html",prediction_text ="The track will be {}".format(ass

if __name__ ==   "__main__":
    app.run(debug=True,use_reloader=False)
```

```
 * Serving Flask app "__main__" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: on
 * Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

And here is the result:



3.a Django

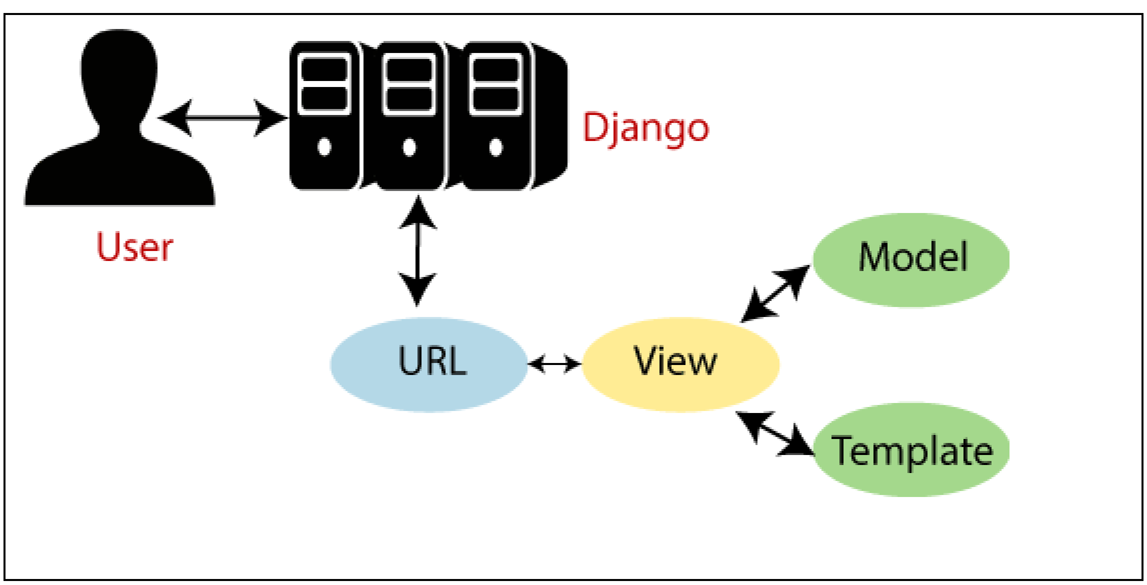
Django is a high-level Python web framework that enables rapid development of secure and maintainable websites. Built by experienced developers, Django takes care of much of the hassle of web development, so you can focus on writing your app without needing to reinvent the wheel

The Template is a presentation layer which handles User Interface part completely. The View is used to execute the business logic and interact with a model to carry data and renders a template.

Although Django follows MVC pattern but maintains it?s own conventions. So, control is handled by the framework itself.

There is no separate controller and complete application is based on Model View and Template. That?s why it is called MVT application.

See the following graph that shows the MVT based control flow. the django framework is based on the architechture Model-View-Template



Here, a user requests for a resource to the Django, Django works as a controller and check to the available resource in URL.

If URL maps, a view is called that interact with model and template, it renders a template.

Django responds back to the user and sends a template as a response.

In [ ]:
```

```