dsc-gamerengagement-classification

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1 Gamer Engagement Classification

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2 Overview

This project analyzes gamer engagement data to offer strategic business recommendations for a new game studio. We aim to train statistical models in order to predict the most engaging gaming genres and difficulties for game production. Gaming engagement is very correlated to profitability as more players tend to bring new players in and it also allows more people to purchase in game features or Downloadable Content (DLC), incresing the revenue. As result this project provides three business recommendations: what genres and dificulties should a future game have for a variety of gamer profiles.

2.1 Business Problem

The company is expanding its portfolio by investing in a new game studio. Launching a new game in today's competitive entertainment industry requires a solid understanding of what drives game success and attracts audiences. The game industry is known for its substantial risks and high capital demands. Recent successes in games with high investment and higher return rate such as the incredibly difficult role playing game (RPG) "Elden Ring" costing around $200 millions but selling over 25 million copies and the action/simulation game "Grand Theft Auto V" which similarly costed around $265 millions but is estimated to have sold almost $8 billions are certainly a good example of how successful this industry can be. However, bad investments also do exist, like the first person shooting game "Immortals of Aveum", which costed $125 millions but sold only around $2 millions, which caused massive layoffs on the studio.

Our project aims to analyze a gamer engagement dataset. By using data analysis techniques and statistical modelling, we seek to predict the best features that correlate with high player engagement. The goal is to provide three concrete business recommendations that maximize engagement and lower business risks, ensuring a strong entry into the market.

Questions we tried to answer with analysis: * What are the top features that correlate with gamer engagement? * How different are the audiences and their engagement choices? * What genres are most engaging for multiple audiences?

[1]:
```
#Importing used libraries for the project
import pandas as pd
import matplotlib.pyplot as plt
```

```python
import seaborn as sns
import numpy as np

from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import ConfusionMatrixDisplay, accuracy_score,␣
 ↪recall_score, precision_score, roc_curve,roc_auc_score, f1_score
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import GridSearchCV
```

[121]:
```python
#Read file with dataset
df = pd.read_csv('data/online_gaming_behavior_dataset.csv')
df.rename(columns={'GameGenre':'Genre','GameDifficulty':
 ↪'Difficulty','PlayerLevel':'Level','EngagementLevel':'Engagement'},␣
 ↪inplace=True)
df.tail()
```

[121]:
```
       PlayerID  Age  Gender Location       Genre  PlayTimeHours  \
40029     49029   32    Male      USA    Strategy      20.619662
40030     49030   44  Female    Other  Simulation      13.539280
40031     49031   15  Female      USA         RPG       0.240057
40032     49032   34    Male      USA      Sports      14.017818
40033     49033   19    Male      USA      Sports      10.083804

       InGamePurchases Difficulty  SessionsPerWeek  AvgSessionDurationMinutes  \
40029                0       Easy                4                         75
40030                0       Hard               19                        114
40031                1       Easy               10                        176
40032                1     Medium                3                        128
40033                0       Easy               13                         84

       Level  AchievementsUnlocked Engagement
40029     85                    14     Medium
40030     71                    27       High
40031     29                     1       High
40032     70                    10     Medium
40033     72                    39     Medium
```

[122]:
```python
#Obtain information about dataset and statistics
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40034 entries, 0 to 40033
Data columns (total 13 columns):
 #   Column                     Non-Null Count  Dtype
```

```
---  ------                   --------------  -----
 0   PlayerID                 40034 non-null  int64
 1   Age                      40034 non-null  int64
 2   Gender                   40034 non-null  object
 3   Location                 40034 non-null  object
 4   Genre                    40034 non-null  object
 5   PlayTimeHours            40034 non-null  float64
 6   InGamePurchases          40034 non-null  int64
 7   Difficulty               40034 non-null  object
 8   SessionsPerWeek          40034 non-null  int64
 9   AvgSessionDurationMinutes  40034 non-null  int64
 10  Level                    40034 non-null  int64
 11  AchievementsUnlocked     40034 non-null  int64
 12  Engagement               40034 non-null  object
dtypes: float64(1), int64(7), object(5)
memory usage: 4.0+ MB
```

[123]:
```
df['Location'].value_counts()
```

[123]:
```
Location
USA       16000
Europe    12004
Asia       8095
Other      3935
Name: count, dtype: int64
```

[124]:
```
df['Genre'].value_counts()
```

[124]:
```
Genre
Sports        8048
Action        8039
Strategy      8012
Simulation    7983
RPG           7952
Name: count, dtype: int64
```

[125]:
```
df['Gender'].value_counts()
```

[125]:
```
Gender
Male      23959
Female    16075
Name: count, dtype: int64
```

[126]:
```
df['Gender'].replace({'Male':0,'Female':1},inplace=True)
df.rename(columns={'Gender':'Female'},inplace=True)
```

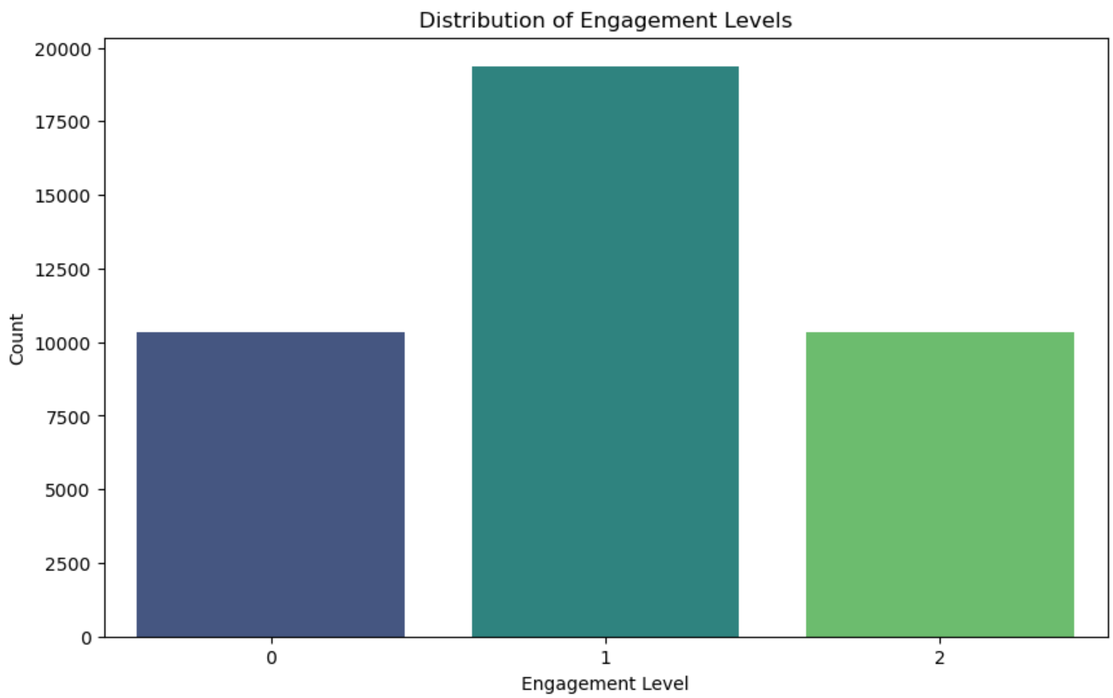
[127]:
```
df['Difficulty'].value_counts()
```

[127]:
```
Difficulty
Easy      20015
Medium    12011
Hard       8008
Name: count, dtype: int64
```

[128]:
```
df['Engagement'].value_counts()
```

[128]:
```
Engagement
Medium    19374
High      10336
Low       10324
Name: count, dtype: int64
```

[120]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='Engagement', data=df, palette='viridis')
plt.title('Distribution of Engagement Levels')
plt.xlabel('Engagement Level')
plt.ylabel('Count')
plt.show()
```



[114]:
```
#Replace ordinal target by integers

df['Engagement'].replace({'Low':0,'Medium':1,'High':2},inplace=True)
```

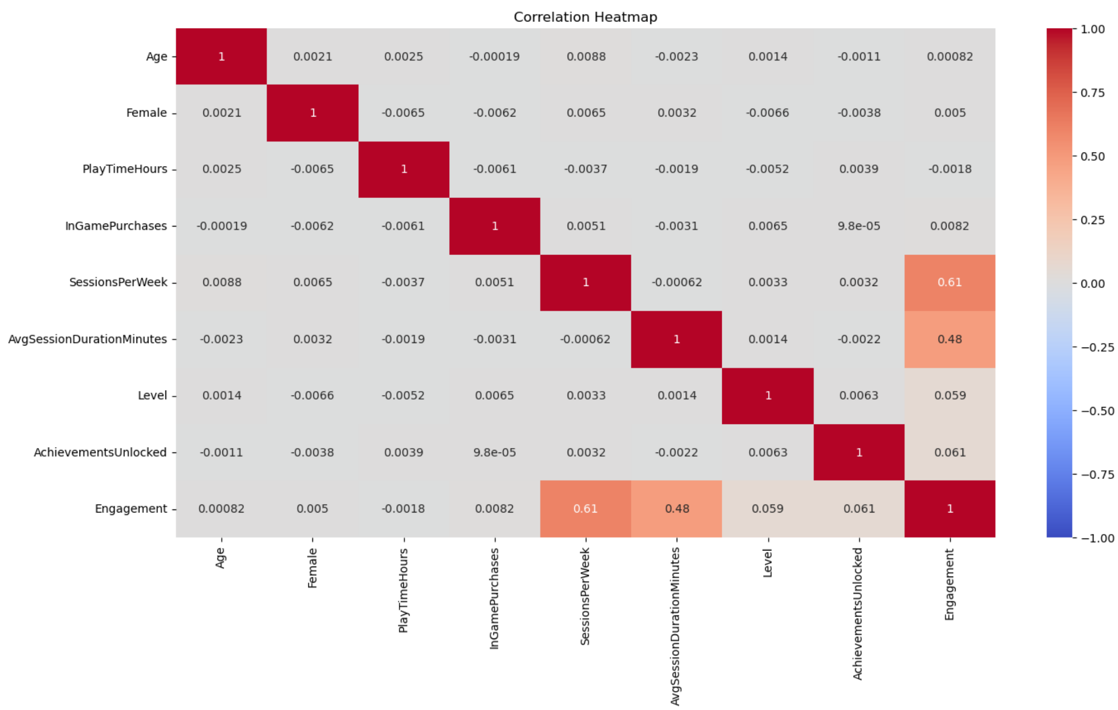
[117]:
```
df
```

[117]:
```
       PlayerID  Age  Female Location       Genre  PlayTimeHours  \
0          9000   43       0    Other    Strategy      16.271119
1          9001   29       1      USA    Strategy       5.525961
2          9002   22       1      USA      Sports       8.223755
3          9003   35       0      USA      Action       5.265351
4          9004   33       0   Europe      Action      15.531945
…           …   …     …      …        …           …
40029     49029   32       0      USA    Strategy      20.619662
40030     49030   44       1    Other  Simulation      13.539280
40031     49031   15       1      USA         RPG       0.240057
40032     49032   34       0      USA      Sports      14.017818
40033     49033   19       0      USA      Sports      10.083804

       InGamePurchases Difficulty  SessionsPerWeek  AvgSessionDurationMinutes  \
0                    0     Medium                6                        108
1                    0     Medium                5                        144
2                    0       Easy               16                        142
3                    1       Easy                9                         85
4                    0     Medium                2                        131
…                 …        …               …                        …
40029                0       Easy                4                         75
40030                0       Hard               19                        114
40031                1       Easy               10                        176
40032                1     Medium                3                        128
40033                0       Easy               13                         84

       Level  AchievementsUnlocked  Engagement
0         79                    25           1
1         11                    10           1
2         35                    41           2
3         57                    47           1
4         95                    37           1
…      …                   …         …
40029     85                    14           1
40030     71                    27           2
40031     29                     1           2
40032     70                    10           1
40033     72                    39           1

[40034 rows x 13 columns]
```

[118]:
```
#Find correlations between target variable and features and produca a heatmap
corr = df.drop(['PlayerID','Location','Genre','Difficulty'],axis=1).corr()
corr['Engagement'].sort_values(ascending=False)
```

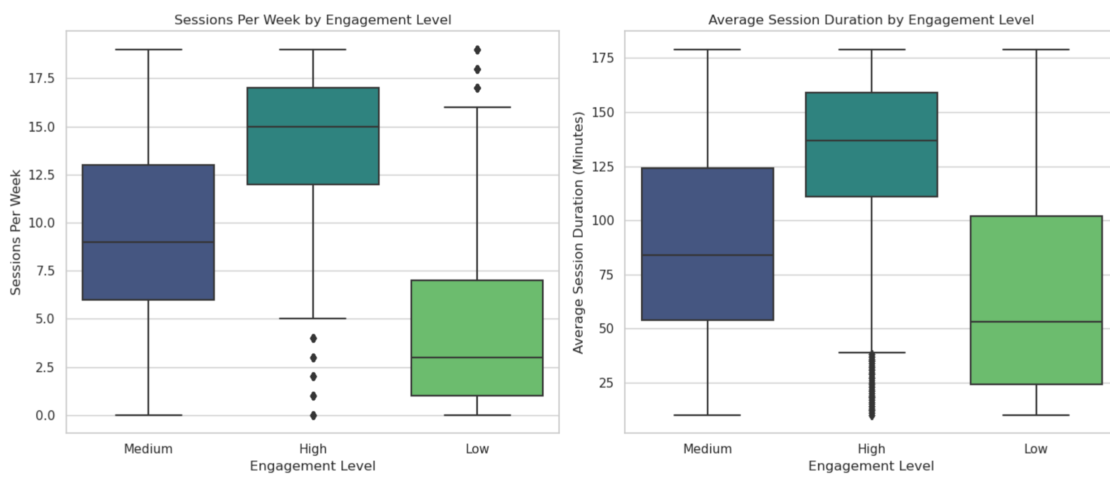
[118]:
```
Engagement                   1.000000
SessionsPerWeek              0.605996
AvgSessionDurationMinutes    0.476698
AchievementsUnlocked         0.060576
Level                        0.059315
InGamePurchases              0.008209
Female                       0.004978
Age                          0.000824
PlayTimeHours               -0.001849
Name: Engagement, dtype: float64
```

[119]:
```python
plt.figure(figsize=(16, 8))
sns.heatmap(corr, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Heatmap')
plt.show();
```



[131]:
```python
sns.set(style="whitegrid")

#Create a figure with subplots
plt.figure(figsize=(14, 6))

#Box plot for Sessions Per Week by Engagement Level
plt.subplot(1, 2, 1)
sns.boxplot(x='Engagement', y='SessionsPerWeek', data=df, palette='viridis')
```

```
plt.title('Sessions Per Week by Engagement Level')
plt.xlabel('Engagement Level')
plt.ylabel('Sessions Per Week')

#Box plot for Average Session Duration by Engagement Level
plt.subplot(1, 2, 2)
sns.boxplot(x='Engagement', y='AvgSessionDurationMinutes', data=df,␣
 ↪palette='viridis')
plt.title('Average Session Duration by Engagement Level')
plt.xlabel('Engagement Level')
plt.ylabel('Average Session Duration (Minutes)')

#Adjust layout for better spacing
plt.tight_layout()
plt.show()
sns.set(style="whitegrid")
```



With these box plots we can see that the players with higher engagement levels tend to play games more often and for longer durations.

[ ]:
```
# Replace ordinal difficulty by integers
df['Difficulty'].replace({'Easy':0,'Medium':1,'Hard':2},inplace=True)
```

[11]:
```
df
```

[11]:
```
   PlayerID  Age  Female Location     Genre  PlayTimeHours  \
0      9000   43       0    Other  Strategy      16.271119
1      9001   29       1      USA  Strategy       5.525961
2      9002   22       1      USA    Sports       8.223755
3      9003   35       0      USA    Action       5.265351
4      9004   33       0   Europe    Action      15.531945
```

```
…          …   …     …       …          …            …
40029      49029   32        0       USA    Strategy      20.619662
40030      49030   44        1     Other  Simulation      13.539280
40031      49031   15        1       USA         RPG       0.240057
40032      49032   34        0       USA      Sports      14.017818
40033      49033   19        0       USA      Sports      10.083804

       InGamePurchases  Difficulty  SessionsPerWeek  \
0                    0           1                6
1                    0           1                5
2                    0           0               16
3                    1           0                9
4                    0           1                2
…                  …           …                …
40029                0           0                4
40030                0           2               19
40031                1           0               10
40032                1           1                3
40033                0           0               13

       AvgSessionDurationMinutes  Level  AchievementsUnlocked  Engagement
0                            108     79                    25           1
1                            144     11                    10           1
2                            142     35                    41           2
3                             85     57                    47           1
4                            131     95                    37           1
…                            …    …                   …         …
40029                         75     85                    14           1
40030                        114     71                    27           2
40031                        176     29                     1           2
40032                        128     70                    10           1
40033                         84     72                    39           1

[40034 rows x 13 columns]
```

[12]:
```python
#Using OneHotEncoder to create new columns for categorical data
ohe = OneHotEncoder(drop='first',sparse=False)
```

[13]:
```python
nominal_columns = ['Location', 'Genre']
X_nom_trans = ohe.fit_transform(df[nominal_columns])
cols = ohe.get_feature_names_out()
X_nom = pd.DataFrame(X_nom_trans, columns=cols)
X_nom
```

```
/home/cayke/anaconda3/envs/learn-env/lib/python3.8/site-
packages/sklearn/preprocessing/_encoders.py:972: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
```

```
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

[13]:

```
       Location_Europe  Location_Other  Location_USA  Genre_RPG  \
0                  0.0             1.0           0.0        0.0
1                  0.0             0.0           1.0        0.0
2                  0.0             0.0           1.0        0.0
3                  0.0             0.0           1.0        0.0
4                  1.0             0.0           0.0        0.0
…                    …               …             …          …
40029              0.0             0.0           1.0        0.0
40030              0.0             1.0           0.0        0.0
40031              0.0             0.0           1.0        1.0
40032              0.0             0.0           1.0        0.0
40033              0.0             0.0           1.0        0.0

       Genre_Simulation  Genre_Sports  Genre_Strategy
0                   0.0           0.0             1.0
1                   0.0           0.0             1.0
2                   0.0           1.0             0.0
3                   0.0           0.0             0.0
4                   0.0           0.0             0.0
…                     …             …               …
40029               0.0           0.0             1.0
40030               1.0           0.0             0.0
40031               0.0           0.0             0.0
40032               0.0           1.0             0.0
40033               0.0           1.0             0.0

[40034 rows x 7 columns]
```

[14]:

```python
df = pd.concat([df.drop(['Location', 'Genre'],axis=1),X_nom],axis=1)
df
```

[14]:

```
       PlayerID  Age  Female  PlayTimeHours  InGamePurchases  Difficulty  \
0          9000   43       0      16.271119                0           1
1          9001   29       1       5.525961                0           1
2          9002   22       1       8.223755                0           0
3          9003   35       0       5.265351                1           0
4          9004   33       0      15.531945                0           1
…             …    …       …              …                …           …
40029     49029   32       0      20.619662                0           0
40030     49030   44       1      13.539280                0           2
40031     49031   15       1       0.240057                1           0
40032     49032   34       0      14.017818                1           1
40033     49033   19       0      10.083804                0           0
```

```
       SessionsPerWeek  AvgSessionDurationMinutes  Level  \
0                    6                        108     79
1                    5                        144     11
2                   16                        142     35
3                    9                         85     57
4                    2                        131     95
…                    …                          …      …
40029                4                         75     85
40030               19                        114     71
40031               10                        176     29
40032                3                        128     70
40033               13                         84     72

       AchievementsUnlocked  Engagement  Location_Europe  Location_Other  \
0                        25           1              0.0             1.0
1                        10           1              0.0             0.0
2                        41           2              0.0             0.0
3                        47           1              0.0             0.0
4                        37           1              1.0             0.0
…                         …           …                …               …
40029                    14           1              0.0             0.0
40030                    27           2              0.0             1.0
40031                     1           2              0.0             0.0
40032                    10           1              0.0             0.0
40033                    39           1              0.0             0.0

       Location_USA  Genre_RPG  Genre_Simulation  Genre_Sports  Genre_Strategy
0               0.0        0.0               0.0           0.0             1.0
1               1.0        0.0               0.0           0.0             1.0
2               1.0        0.0               0.0           1.0             0.0
3               1.0        0.0               0.0           0.0             0.0
4               0.0        0.0               0.0           0.0             0.0
…                 …          …                 …             …               …
40029           1.0        0.0               0.0           0.0             1.0
40030           0.0        0.0               1.0           0.0             0.0
40031           1.0        1.0               0.0           0.0             0.0
40032           1.0        0.0               0.0           1.0             0.0
40033           1.0        0.0               0.0           1.0             0.0

[40034 rows x 18 columns]
```

It seems like the best features that correlate the most with engagement are Sessions per Week and Avg Session Duration in Minutes, which makes a lot of sense.

[17]:
```python
X = df.drop(['PlayerID','Engagement'], axis=1)
y = df['Engagement']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=19)
```

[18]:
```
scaler_allfeats = StandardScaler()
X_train_scaled = scaler_allfeats.fit_transform(X_train)
X_test_scaled = scaler_allfeats.transform(X_test)
```

3 Baseline Model - Logistic regression with all features

In our first Baseline Model using Logistic Regression on all features with no penalty and with class weight balanced to account for different ratios in target class.

[19]:
```
logreg_baseline =␣
 ↪LogisticRegression(penalty=None,random_state=19,class_weight='balanced')
```

[20]:
```
logreg_baseline.fit(X_train_scaled,y_train)
```

[20]:
```
LogisticRegression(class_weight='balanced', penalty=None, random_state=19)
```

[21]:
```
logreg_baseline.score(X_train_scaled,y_train)
```

[21]:
```
0.7876103247293922
```

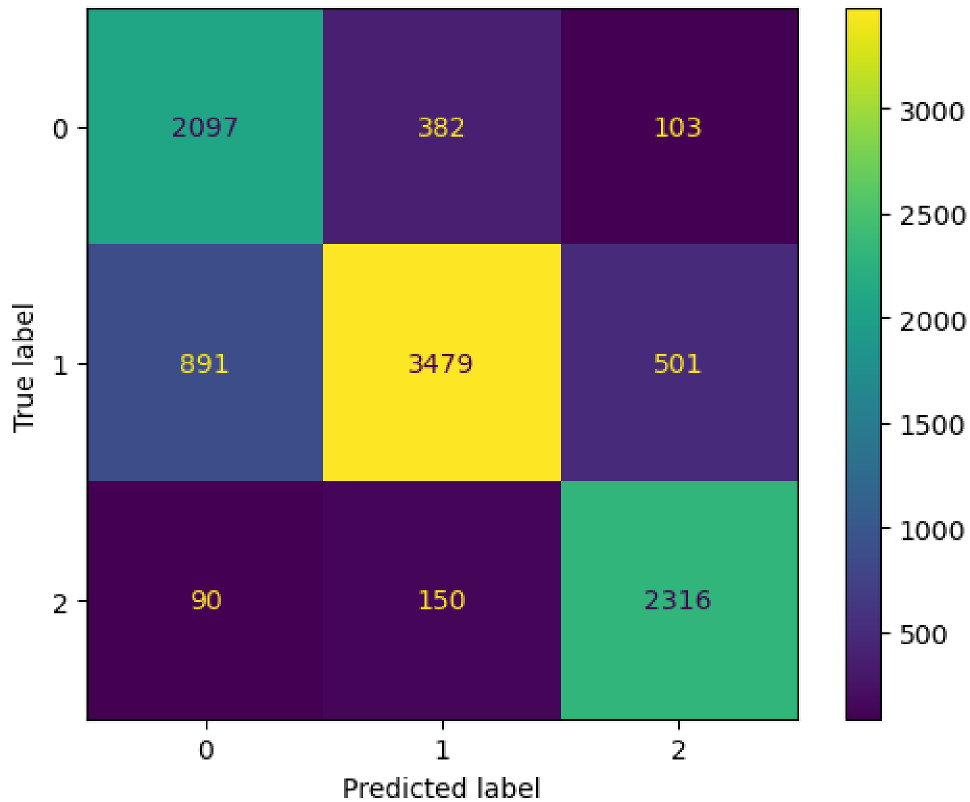
[22]:
```
y_baseline = logreg_baseline.predict(X_test_scaled)
```

[23]:
```
logreg_baseline.score(X_train_scaled,y_train)
```

[23]:
```
0.7876103247293922
```

[24]:
```
ConfusionMatrixDisplay.from_estimator(logreg_baseline,X_test_scaled,y_test)
```

[24]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7ed9ccfc3d00>
```



[25]:
```
accuracy_baseline, recall_baseline, precision_baseline, f1_baseline = accuracy_score(y_test,y_baseline), \
recall_score(y_test,y_baseline,average=None), \
precision_score(y_test,y_baseline,average=None),\
f1_score(y_test,y_baseline,average=None)
accuracy_baseline, recall_baseline, precision_baseline, f1_baseline
```

[25]:
```
(0.7884903586771905,
 array([0.81216112, 0.71422706, 0.90610329]),
 array([0.68128655, 0.86736475, 0.79315068]),
 array([0.7409894 , 0.78338212, 0.8458729 ]))
```

4 Model 2 - Logistic Regression with only the most correlated features

Using a model with the most correlated features can reduce noise or decrease accuracy.

[26]:
```
logreg_bestfeats =␣
↪LogisticRegression(penalty=None,random_state=19,class_weight='balanced')
```

[27]:
```
X_train_bestfeats, X_test_bestfeats, y_train, y_test =␣
↪train_test_split(X[['SessionsPerWeek','AvgSessionDurationMinutes']], y,␣
↪test_size=0.25, random_state=19)
```

[28]:
```
scaler_bestfeats = StandardScaler()
X_train_bestfeats_scaled_2 = scaler_bestfeats.fit_transform(X_train_bestfeats)
X_test_bestfeats_scaled_2 = scaler_bestfeats.transform(X_test_bestfeats)
```

[29]:
```
logreg_bestfeats.fit(X_train_bestfeats_scaled_2,y_train)
```

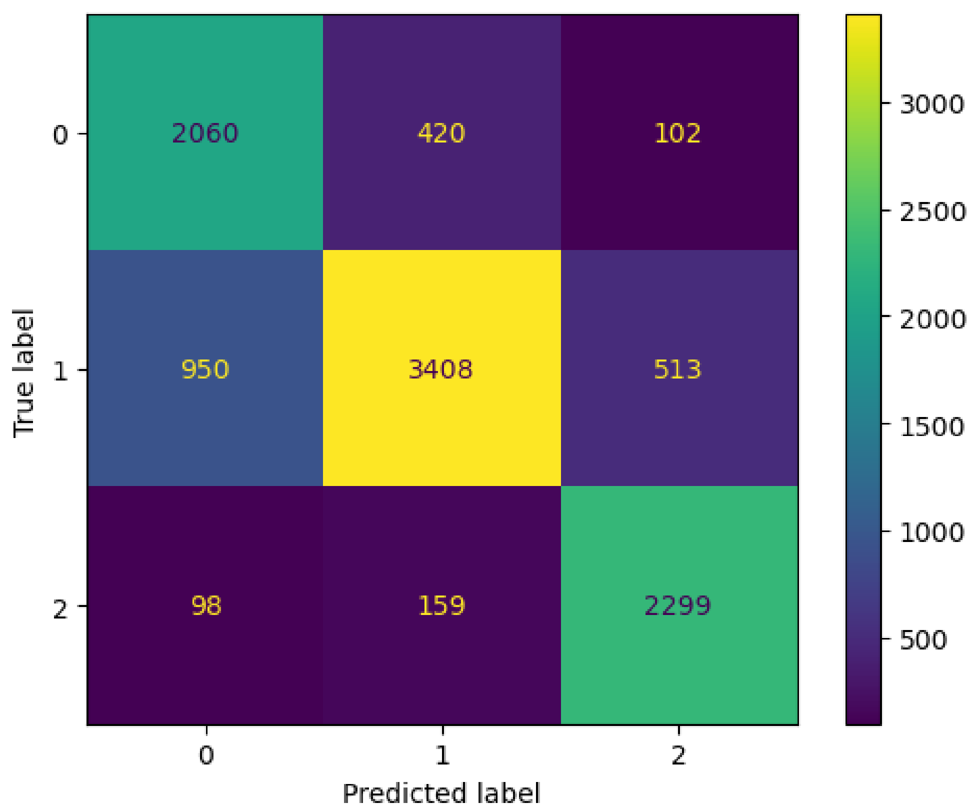
[29]:
```
LogisticRegression(class_weight='balanced', penalty=None, random_state=19)
```

[30]:
```
logreg_bestfeats.score(X_train_bestfeats_scaled_2,y_train)
```

[30]:
```
0.778684429641965
```

[31]:
```
y_bestfeats = logreg_bestfeats.predict(X_test_bestfeats_scaled_2)
```

[32]:
```
ConfusionMatrixDisplay.
↪from_estimator(logreg_bestfeats,X_test_bestfeats_scaled_2,y_test);
```



[33]:
```python
accuracy_bestfeats, recall_bestfeats, precision_bestfeats, f1_bestfeats = accuracy_score(y_test,y_bestfeats), \
    recall_score(y_test,y_bestfeats,average=None), \
    precision_score(y_test,y_bestfeats,average=None),\
    f1_score(y_test,y_bestfeats,average=None)
accuracy_bestfeats, recall_bestfeats ,precision_bestfeats, f1_bestfeats
```

[33]:
```
(0.7760015985612948,
 array([0.79783114, 0.699651  , 0.89945227]),
 array([0.66280566, 0.85477803, 0.7889499 ]),
 array([0.72407733, 0.76947392, 0.84058501]))
```

5 Model 3 - Decision Tree Classifier

[34]:
```python
dtc_notuning = DecisionTreeClassifier(random_state=19,class_weight='balanced')
```

[35]:
```python
dtc_notuning.fit(X_train_scaled,y_train)
```

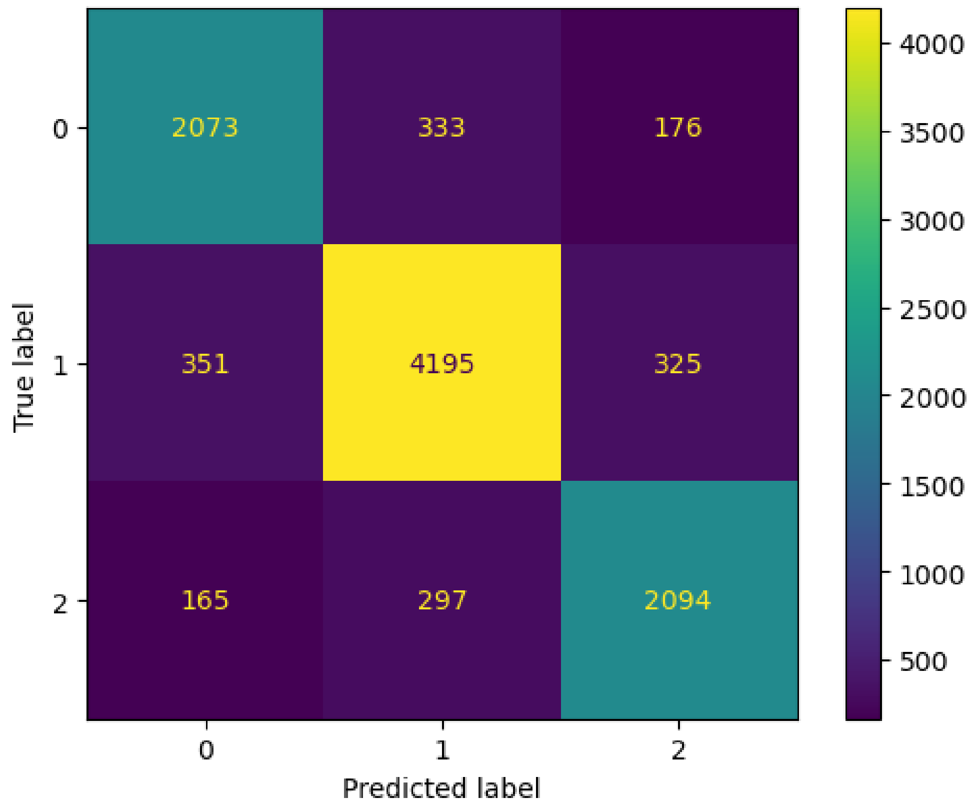
[35]:
```
DecisionTreeClassifier(class_weight='balanced', random_state=19)
```

[36]:
```python
dtc_notuning.score(X_train_scaled,y_train)
```

[36]:
```
1.0
```

[37]:
```python
y_dtc = dtc_notuning.predict(X_test_scaled)
```

[38]:
```python
ConfusionMatrixDisplay.from_estimator(dtc_notuning,X_test_scaled,y_test);
```



[39]:
```
accuracy_dtc, recall_dtc, precision_dtc, f1_dtc = accuracy_score(y_test,y_dtc),␣
↪\
                                                                                ␣
↪recall_score(y_test,y_dtc,average=None), \
                                                                                ␣
↪precision_score(y_test,y_dtc,average=None),\
                                                                                ␣
↪f1_score(y_test,y_dtc,average=None)
accuracy_dtc, recall_dtc ,precision_dtc, f1_dtc
```

[39]:
```
(0.8354480967129584,
 array([0.802866  , 0.86121946, 0.81924883]),
 array([0.80069525, 0.86943005, 0.80693642]),
 array([0.80177915, 0.86530528, 0.81304601]))
```

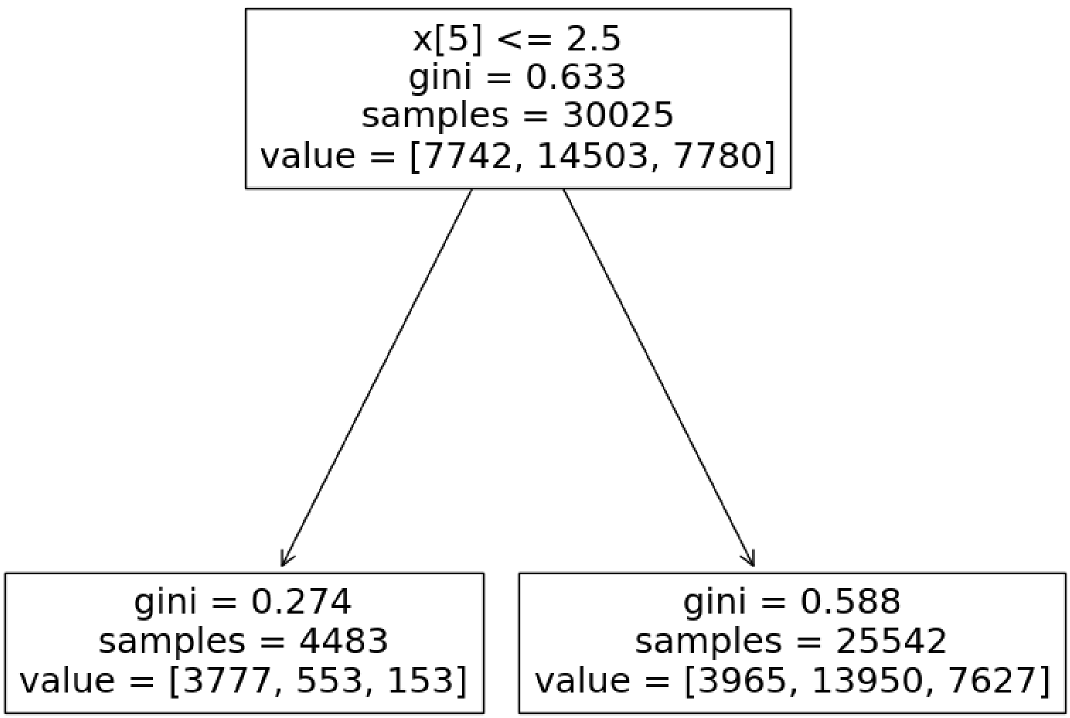
5.1 Using Decision Tree as a Feature Selector

[40]:
```
dtc_featselect = DecisionTreeClassifier(max_depth=1,random_state=19)
```

[41]:
```
dtc_featselect.fit(X_train,y_train)
```

[41]: DecisionTreeClassifier(max_depth=1, random_state=19)

[42]:
```
f, ax = plt.subplots(figsize=(10, 10))

plot_tree(dtc_featselect,ax=ax);
```



[43]:
```
X_train.columns[5]
```

[43]: 'SessionsPerWeek'

Decison tree classifier found that the most important feature to decide the engagement for a player tends to be the number of Sessions per Week. We divide the original dataset in 2 of them then and run different models for each.

6 Model 4 - 2 Logistic Regressions on Sessions Per Week

[44]:
```
df
```

[44]:
```
       PlayerID  Age  Female  PlayTimeHours  InGamePurchases  Difficulty  \
0          9000   43       0      16.271119                0           1
1          9001   29       1       5.525961                0           1
2          9002   22       1       8.223755                0           0
3          9003   35       0       5.265351                1           0
4          9004   33       0      15.531945                0           1
…             …    …       …              …                …           …
40029     49029   32       0      20.619662                0           0
40030     49030   44       1      13.539280                0           2
40031     49031   15       1       0.240057                1           0
40032     49032   34       0      14.017818                1           1
40033     49033   19       0      10.083804                0           0

       SessionsPerWeek  AvgSessionDurationMinutes  Level  \
0                    6                        108     79
1                    5                        144     11
2                   16                        142     35
3                    9                         85     57
4                    2                        131     95
…                    …                          …      …
40029                4                         75     85
40030               19                        114     71
40031               10                        176     29
40032                3                        128     70
40033               13                         84     72

       AchievementsUnlocked  Engagement  Location_Europe  Location_Other  \
0                        25           1              0.0             1.0
1                        10           1              0.0             0.0
2                        41           2              0.0             0.0
3                        47           1              0.0             0.0
4                        37           1              1.0             0.0
…                         …           …                …               …
40029                    14           1              0.0             0.0
40030                    27           2              0.0             1.0
40031                     1           2              0.0             0.0
40032                    10           1              0.0             0.0
40033                    39           1              0.0             0.0

       Location_USA  Genre_RPG  Genre_Simulation  Genre_Sports  Genre_Strategy
0               0.0        0.0               0.0           0.0             1.0
1               1.0        0.0               0.0           0.0             1.0
2               1.0        0.0               0.0           1.0             0.0
```

3	1.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0
…	…	…	…	…	…
40029	1.0	0.0	0.0	0.0	1.0
40030	0.0	0.0	1.0	0.0	0.0
40031	1.0	1.0	0.0	0.0	0.0
40032	1.0	0.0	0.0	1.0	0.0
40033	1.0	0.0	0.0	1.0	0.0

[40034 rows x 18 columns]

[45]:
```
X_more = df[df['SessionsPerWeek']>2.5].drop(['PlayerID','Engagement'],axis=1)
X_less = df[df['SessionsPerWeek']<=2.5].drop(['PlayerID','Engagement'],axis=1)

y1_more = df[df['SessionsPerWeek']>2.5]['Engagement']
y2_less = df[df['SessionsPerWeek']<=2.5]['Engagement']
```

[46]:
```
print(f'Shape of X matrix with more than 2.5 sessions per week is {X_more.
 ↪shape} which is \
{X_more.shape[0]/(X_more.shape[0]+X_less.shape[0]):.03f} of total.')
print(f'Shape of X matrix with less or equal than 2.5 sessions per week is␣
 ↪{X_less.shape} which is \
{X_less.shape[0]/(X_more.shape[0]+X_less.shape[0]):.03f} of total.')
```

```
Shape of X matrix with more than 2.5 sessions per week is (34069, 16) which is
0.851 of total.
Shape of X matrix with less or equal than 2.5 sessions per week is (5965, 16)
which is 0.149 of total.
```

[47]:
```
X_train_more = X_train[X_train['SessionsPerWeek']>2.5]
X_test_more = X_test[X_test['SessionsPerWeek']>2.5]

X_train_less = X_train[X_train['SessionsPerWeek']<=2.5]
X_test_less = X_test[X_test['SessionsPerWeek']<=2.5]
```

[48]:
```
y_train_more = y_train.loc[X_train_more.index]
y_test_more = y_test.loc[X_test_more.index]

y_train_less = y_train.loc[X_train_less.index]
y_test_less = y_test.loc[X_test_less.index]
```

[49]:
```
scaler_more = StandardScaler()
scaler_less = StandardScaler()

X_train_more_scaled = scaler_more.fit_transform(X_train_more)
X_test_more_scaled = scaler_more.transform(X_test_more)
```

```
X_train_less_scaled = scaler_less.fit_transform(X_train_less)
X_test_less_scaled = scaler_less.transform(X_test_less)
```

[50]:
```
logreg_more = LogisticRegression(penalty=None, random_state=19, max_iter=10000)
logreg_less = LogisticRegression(penalty=None, random_state=19, max_iter=10000)
```

[51]:
```
logreg_more.fit(X_train_more_scaled,y_train_more)
```

[51]:
```
LogisticRegression(max_iter=10000, penalty=None, random_state=19)
```

[52]:
```
logreg_less.fit(X_train_less_scaled,y_train_less)
```

[52]:
```
LogisticRegression(max_iter=10000, penalty=None, random_state=19)
```

[53]:
```
logreg_less.score(X_train_less_scaled,y_train_less)
```

[53]:
```
0.907651126477805
```

[54]:
```
logreg_more.score(X_train_more_scaled,y_train_more)
```

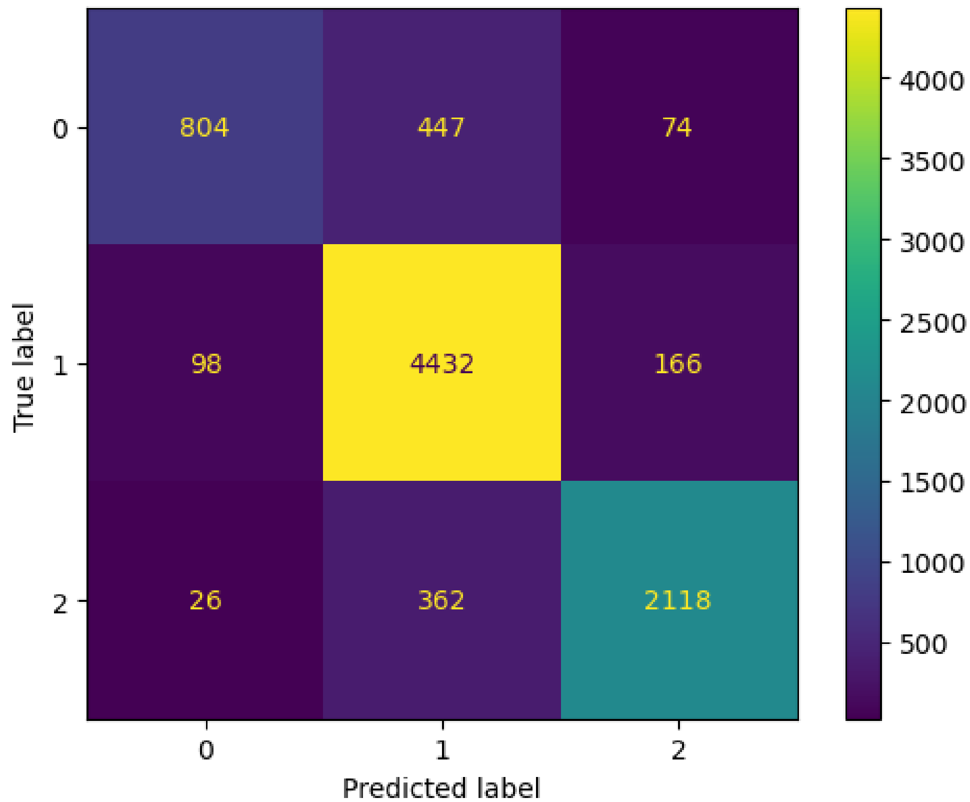
[54]:
```
0.8637146660402474
```

[55]:
```
ratio_more = len(X_train_more)/(len(X_train_more)+len(X_train_less))
ratio_less = len(X_train_less)/(len(X_train_more)+len(X_train_less))
ratio_more*logreg_more.score(X_train_more_scaled,y_train_more)␣
↪+ratio_less*logreg_less.score(X_train_less_scaled,y_train_less)
```

[55]:
```
0.8702747710241464
```

[56]:
```
y_pred_more = logreg_more.predict(X_test_more_scaled)
```

[57]:
```
ConfusionMatrixDisplay.
↪from_estimator(logreg_more,X_test_more_scaled,y_test_more);
```

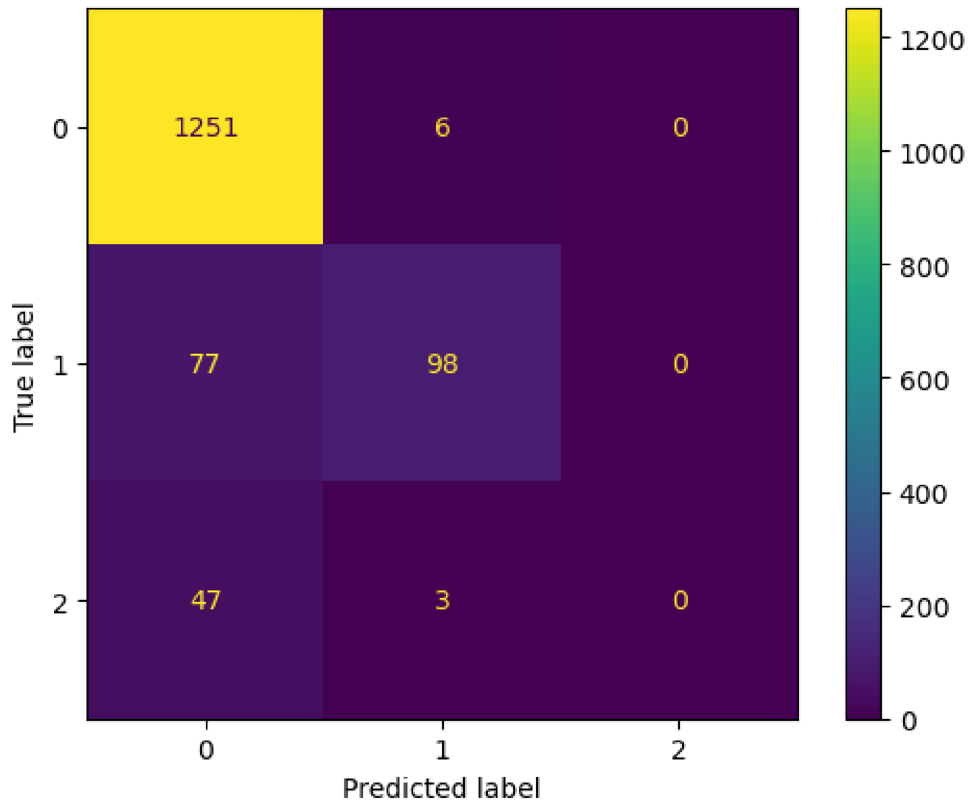


[58]:
```
accuracy_more, recall_more, precision_more, f1_more =␣
↪accuracy_score(y_test_more,y_pred_more), \
                                                                    ␣
↪recall_score(y_test_more,y_pred_more,average=None), \
                                                                    ␣
↪precision_score(y_test_more,y_pred_more,average=None),\
                                                                    ␣
↪f1_score(y_test_more,y_pred_more,average=None)
accuracy_more, recall_more ,precision_more, f1_more
```

[58]:
```
(0.8624369649349126,
 array([0.60679245, 0.94378194, 0.84517159]),
 array([0.86637931, 0.84564015, 0.89821883]),
 array([0.71371505, 0.89201972, 0.87088816]))
```

[59]:
```
y_pred_less = logreg_less.predict(X_test_less_scaled)
```

[60]:
```
ConfusionMatrixDisplay.
↪from_estimator(logreg_less,X_test_less_scaled,y_test_less);
```



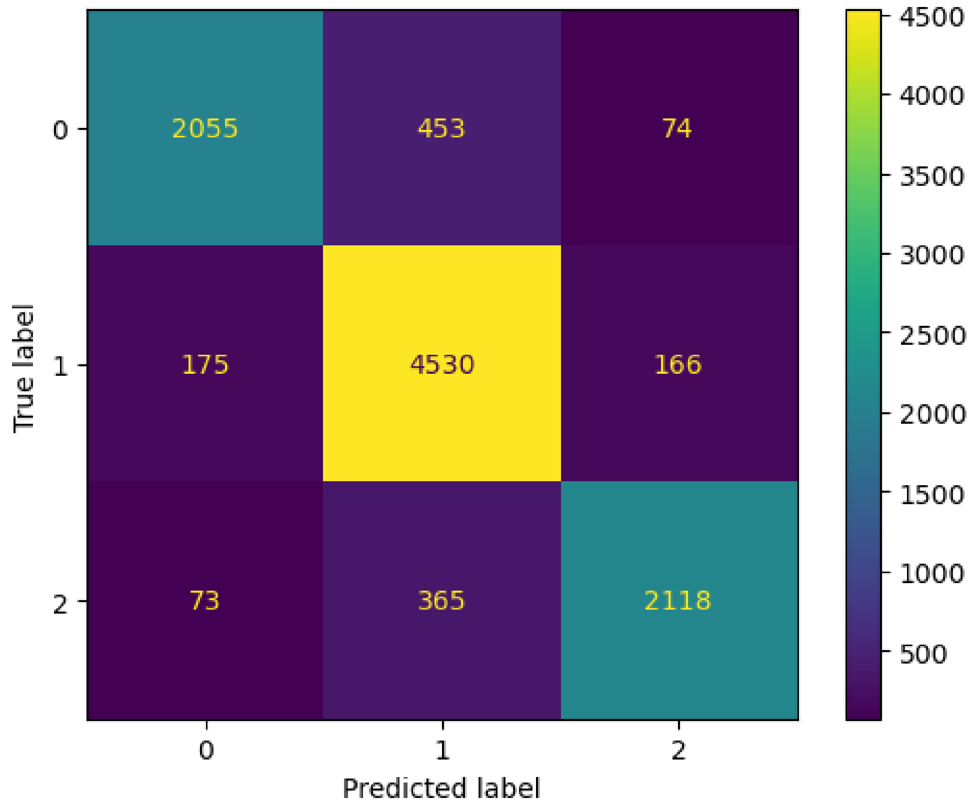
[61]:
```
accuracy_less, recall_less, precision_less, f1_less =␣
↪accuracy_score(y_test_less,y_pred_less), \
                                                                        ␣
↪recall_score(y_test_less,y_pred_less,average=None,zero_division=0), \
                                                                        ␣
↪precision_score(y_test_less,y_pred_less,average=None),\
                                                                        ␣
↪f1_score(y_test_less,y_pred_less,average=None)
accuracy_less, recall_less ,precision_less, f1_less
```

```
/home/cayke/anaconda3/envs/learn-env/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1469: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[61]:
```
(0.9102564102564102,
 array([0.99522673, 0.56      , 0.        ]),
 array([0.90981818, 0.91588785, 0.        ]),
 array([0.9506079 , 0.69503546, 0.        ]))
```

[62]:
```
y_test_2dfs = np.concatenate([y_test_more,y_test_less])
y_pred_2dfs = np.concatenate([y_pred_more,y_pred_less])
```

[63]:
```
ConfusionMatrixDisplay.from_predictions(y_test_2dfs,y_pred_2dfs);
```



[64]:
```
accuracy_2dfs, recall_2dfs, precision_2dfs, f1_2dfs =␣
↪accuracy_score(y_test_2dfs,y_pred_2dfs), \
                                                                   ␣
↪recall_score(y_test_2dfs,y_pred_2dfs,average=None,zero_division=0), \
                                                                   ␣
↪precision_score(y_test_2dfs,y_pred_2dfs,average=None),\
                                                                   ␣
↪f1_score(y_test_2dfs,y_pred_2dfs,average=None)
accuracy_2dfs, recall_2dfs ,precision_2dfs, f1_2dfs
```

[64]:
```
(0.8695174343091218,
 array([0.79589466, 0.92999384, 0.8286385 ]),
 array([0.89231437, 0.84704562, 0.89821883]),
 array([0.84135107, 0.88658381, 0.86202686]))
```

7 Model 5 - Hyperparameter Tuned Decision Tree

[65]:
```python
param = {
    'criterion':['gini', 'entropy', 'log_loss'],
    'splitter': ['best', 'random'],
    'max_depth': [None, 5, 10, 15, 20],
    'min_samples_split': [2, 3, 4, 5],
    'min_samples_leaf': [1, 2, 3, 4]
}
dtc_tuning = DecisionTreeClassifier(random_state=19,class_weight='balanced')

grid_search = GridSearchCV(estimator=dtc_tuning, param_grid=param,␣
 ↪scoring='precision_micro', cv=5, n_jobs=-1,
                           verbose=1,return_train_score=True)
```

[66]:
```python
grid_search.fit(X_train_scaled, y_train)
```

```
Fitting 5 folds for each of 480 candidates, totalling 2400 fits
```

[66]:
```
GridSearchCV(cv=5,
             estimator=DecisionTreeClassifier(class_weight='balanced',
                                              random_state=19),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy', 'log_loss'],
                         'max_depth': [None, 5, 10, 15, 20],
                         'min_samples_leaf': [1, 2, 3, 4],
                         'min_samples_split': [2, 3, 4, 5],
                         'splitter': ['best', 'random']},
             return_train_score=True, scoring='precision_micro', verbose=1)
```

[67]:
```python
best_params = grid_search.best_params_
best_estimator = grid_search.best_estimator_
```

[68]:
```python
best_params
```

[68]:
```
{'criterion': 'entropy',
 'max_depth': 10,
 'min_samples_leaf': 4,
 'min_samples_split': 2,
 'splitter': 'best'}
```

[69]:
```python
best_estimator.score(X_train_scaled,y_train)
```

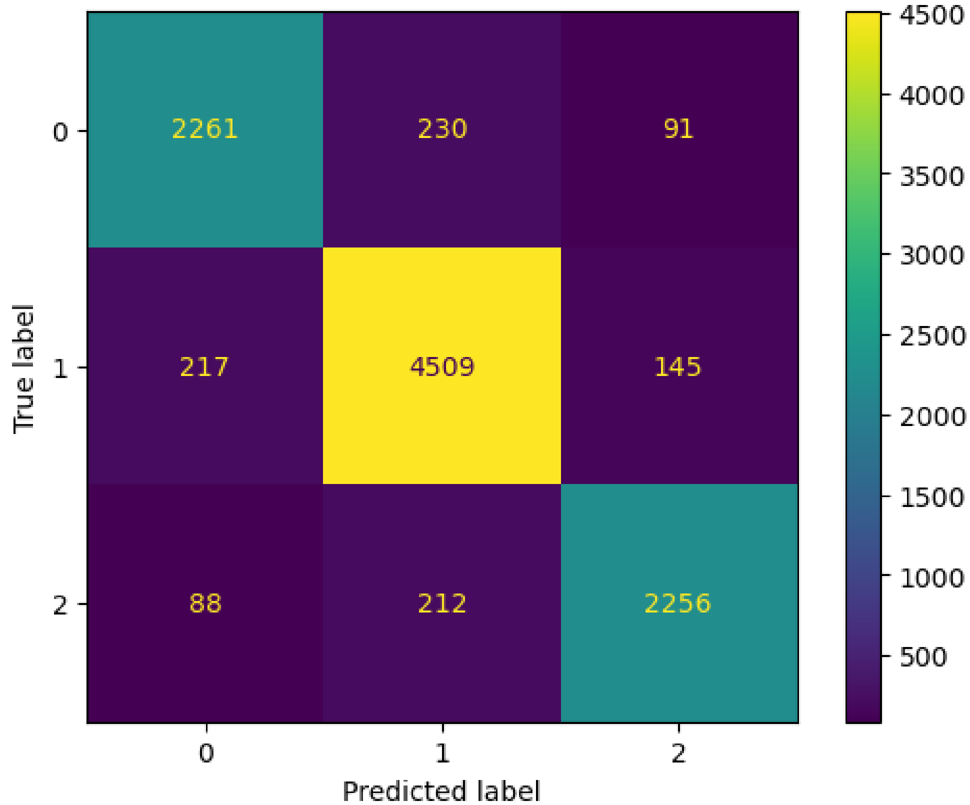
[69]:
```
0.9230308076602831
```

[70]:
```python
best_estimator
```

[70]: DecisionTreeClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=10, min_samples_leaf=4, random_state=19)

[71]:
```
y_pred_tuning = best_estimator.predict(X_test_scaled)
```

[72]:
```
ConfusionMatrixDisplay.from_estimator(best_estimator,X_test_scaled,y_test);
```



[73]:
```
accuracy_tuning, recall_tuning, precision_tuning, f1_tuning =␣
↪accuracy_score(y_test,y_pred_tuning), \
                                                                    ␣
↪recall_score(y_test,y_pred_tuning,average=None), \
                                                                    ␣
↪precision_score(y_test,y_pred_tuning,average=None),\
                                                                    ␣
↪f1_score(y_test,y_pred_tuning,average=None)
accuracy_tuning, recall_tuning ,precision_tuning, f1_tuning
```

[73]: (0.9017883904485963,
 array([0.87567777, 0.92568261, 0.88262911]),
 array([0.88113796, 0.91072511, 0.90529695]),

```
array([0.87839938, 0.91814294, 0.89381933]))
```

8 Model Selection

We used five models to try to make predictions about our target variable of engagement to find what factors were the most important.

Our first model was a baseline model with a score of 78% accuracy on both the train and test The second model was a logistic regression model with the most correlated features, it had a 77% accuracy on the train and test The third model was a decision tree classifier with a 100% accuracy on the train and 83% accuracy on the test The fourth used two logistic regression models based on first split from decision tree classifier (SessionsPerWeek). It scored 88% accuracy on the train and 86% accuracy on the test. The final model was a decision tree classifier with the hyperparameter tuned, it scored the best with a 92% accuracy on the train and 90% accuracy on the test.

8.1 Evaluation

Baseline model: The baseline model provides a benchmark to compare the performance of other models. It shows consistent performance on both train and test sets, indicating that more sophisticated models need to outperform this baseline to be considered effective.

Logistic Regression Model with Correlated Features: This model slightly underperforms compared to the baseline. It suggests that merely using the most correlated features may not capture the complexity of the data. The consistent accuracy on train and test sets indicates no overfitting but suggests room for improvement in feature selection or model complexity.

Decision Tree Classifier: The decision tree shows perfect accuracy on the training set but a significant drop in the test set, indicating overfitting. The model memorizes the training data but fails to generalize to unseen data. Pruning or tuning hyperparameters could help mitigate this overfitting.

Combined Logistic Regression Models (Split by SessionsPerWeek): This approach shows a substantial improvement over the baseline and the previous logistic regression model. The strategy of splitting the data based on a feature (SessionsPerWeek) and then applying logistic regression models enhances performance, indicating that handling subpopulations differently can be beneficial.

Hyperparameter Tuned Decision Tree Classifier: This model achieves the highest accuracy among all tested models, showing both high training and test accuracy, which indicates a good balance between bias and variance. Hyperparameter tuning effectively addresses the overfitting observed in the previous decision tree model, leading to better generalization.

9 Weighted Average Engagement

In order to predict a game's sucess we predict how different main features can achieve a better engagement from players . For that, we focus on the American market.

[74]:
```
df
```

[74]:
```
      PlayerID  Age  Female  PlayTimeHours  InGamePurchases  Difficulty  \
0         9000   43       0      16.271119                0           1
```

```
1        9001  29     1    5.525961          0        1
2        9002  22     1    8.223755          0        0
3        9003  35     0    5.265351          1        0
4        9004  33     0   15.531945          0        1
…           …     …     …          …              …         …
40029   49029  32     0   20.619662          0        0
40030   49030  44     1   13.539280          0        2
40031   49031  15     1    0.240057          1        0
40032   49032  34     0   14.017818          1        1
40033   49033  19     0   10.083804          0        0

       SessionsPerWeek  AvgSessionDurationMinutes  Level  \
0                    6                        108     79
1                    5                        144     11
2                   16                        142     35
3                    9                         85     57
4                    2                        131     95
…                  …                          …      …
40029                4                         75     85
40030               19                        114     71
40031               10                        176     29
40032                3                        128     70
40033               13                         84     72

       AchievementsUnlocked  Engagement  Location_Europe  Location_Other  \
0                        25           1              0.0             1.0
1                        10           1              0.0             0.0
2                        41           2              0.0             0.0
3                        47           1              0.0             0.0
4                        37           1              1.0             0.0
…                       …           …                …               …
40029                    14           1              0.0             0.0
40030                    27           2              0.0             1.0
40031                     1           2              0.0             0.0
40032                    10           1              0.0             0.0
40033                    39           1              0.0             0.0

       Location_USA  Genre_RPG  Genre_Simulation  Genre_Sports  Genre_Strategy
0               0.0        0.0               0.0           0.0             1.0
1               1.0        0.0               0.0           0.0             1.0
2               1.0        0.0               0.0           1.0             0.0
3               1.0        0.0               0.0           0.0             0.0
4               0.0        0.0               0.0           0.0             0.0
…             …          …                 …             …               …
40029           1.0        0.0               0.0           0.0             1.0
40030           0.0        0.0               1.0           0.0             0.0
40031           1.0        1.0               0.0           0.0             0.0
```

```
40032           1.0        0.0              0.0           1.0              0.0
40033           1.0        0.0              0.0           1.0              0.0

[40034 rows x 18 columns]
```

[75]:
```
df1 = df[df['Location_USA']==1].
 ↪drop(['PlayerID','Location_USA','Location_Europe','Location_Other'],axis=1)
df1
```

[75]:
```
       Age  Female  PlayTimeHours  InGamePurchases  Difficulty  \
1       29       1       5.525961                0           1
2       22       1       8.223755                0           0
3       35       0       5.265351                1           0
6       25       0       9.752716                0           2
10      17       0       4.829916                0           2
…     …     …            …            …          …
40028   36       0       1.020489                0           2
40029   32       0      20.619662                0           0
40031   15       1       0.240057                1           0
40032   34       0      14.017818                1           1
40033   19       0      10.083804                0           0

       SessionsPerWeek  AvgSessionDurationMinutes  Level  \
1                    5                        144     11
2                   16                        142     35
3                    9                         85     57
6                    1                         50     13
10                   8                         95     14
…                 …                        …    …
40028                4                         34     97
40029                4                         75     85
40031               10                        176     29
40032                3                        128     70
40033               13                         84     72

       AchievementsUnlocked  Engagement  Genre_RPG  Genre_Simulation  \
1                        10           1        0.0               0.0
2                        41           2        0.0               0.0
3                        47           1        0.0               0.0
6                         2           0        0.0               0.0
10                       12           2        0.0               0.0
…                      …         …       …              …
40028                    21           0        1.0               0.0
40029                    14           1        0.0               0.0
40031                     1           2        1.0               0.0
40032                    10           1        0.0               0.0
40033                    39           1        0.0               0.0
```

```
       Genre_Sports  Genre_Strategy
1               0.0             1.0
2               1.0             0.0
3               0.0             0.0
6               0.0             0.0
10              0.0             1.0
…               …               …
40028           0.0             0.0
40029           0.0             1.0
40031           0.0             0.0
40032           1.0             0.0
40033           1.0             0.0

[16000 rows x 14 columns]
```

[76]:

```
age_range = [20,31,43]
r_age_15_25 = len(df1[(df1['Age']>=15) & (df1['Age']<=25)])/len(df1)
r_age_26_36 = len(df1[(df1['Age']>=26) & (df1['Age']<=36)])/len(df1)
r_age_37_47 = len(df1[(df1['Age']>=37) & (df1['Age']<=47)])/len(df1)
r_age_range = [r_age_15_25,r_age_26_36,r_age_37_47]

gender_range = [0,1]
r_male = len(df1['Female']==0)/len(df1)
r_female = len(df1['Female']==1)/len(df1)
r_gender_range = [r_male,r_female]

playtime_range = [4,12,20]
r_playtime_0_8 = len(df1[df1['PlayTimeHours']<=8])/len(df1)
r_playtime_8_16 = len(df1[(df1['PlayTimeHours']>8) &␣
 ↪(df1['PlayTimeHours']<=16)])/len(df1)
r_playtime_16_24 = len(df1[df1['PlayTimeHours']>16])/len(df1)
r_playtime_range = [r_playtime_0_8, r_playtime_8_16, r_playtime_16_24]

purchase_range = [0,1]
r_nopurchases = len(df1[df1['InGamePurchases']==0])/len(df1)
r_purchases = len(df1[df1['InGamePurchases']==1])/len(df1)
r_purchase_range = [r_nopurchases,r_purchases]

difficulty_range = [0,1,2]
r_easy = len(df1['Difficulty']==0)/len(df1)
r_medium = len(df1['Difficulty']==1)/len(df1)
r_hard = len(df1['Difficulty']==2)/len(df1)
r_difficulty_range = [r_easy,r_medium,r_hard]

sessions_range = [3,9,15]
r_sessions_0_6 = len(df1[df1['SessionsPerWeek']<=6])/len(df1)
```

```
r_sessions_6_12 = len(df1[(df1['SessionsPerWeek']>6) &␣
 ↪(df1['SessionsPerWeek']<=12)])/len(df1)
r_sessions_12_18 = len(df1[df1['SessionsPerWeek']>12])/len(df1)
r_sessions_range = [r_sessions_0_6, r_sessions_6_12, r_sessions_12_18]

avgsessions_range = [38,94,150]
r_avgsessions_0_66 = len(df1[df1['AvgSessionDurationMinutes']<=66])/len(df1)
r_avgsessions_66_122 = len(df1[(df1['AvgSessionDurationMinutes']>66) &␣
 ↪(df1['AvgSessionDurationMinutes']<=122)])/len(df1)
r_avgsessions_122_178 = len(df1[(df1['AvgSessionDurationMinutes']>122) &␣
 ↪(df1['AvgSessionDurationMinutes']<=178)])/len(df1)
r_avgsessions_range = [r_avgsessions_0_66, r_avgsessions_66_122,␣
 ↪r_avgsessions_122_178]

level_range = [17,50,83]
r_lvl_1_33 = len(df1[df1['Level']<=33])/len(df1)
r_lvl_33_65 = len(df1[(df1['Level']>33) & (df1['Level']<=65)])/len(df1)
r_lvl_65_97 = len(df1[(df1['Level']>65) & (df1['Level']<=97)])/len(df1)
r_lvl_range = [r_lvl_1_33, r_lvl_33_65, r_lvl_65_97]

achievement_range = [9,25,41]
r_achiev_0_16 = len(df1[df1['Level']<=16])/len(df1)
r_achiev_16_32 = len(df1[(df1['Level']>16) & (df1['Level']<=32)])/len(df1)
r_achiev_32_48 = len(df1[(df1['Level']>32) & (df1['Level']<=48)])/len(df1)
r_achievement_range = [r_achiev_0_16,r_achiev_16_32,r_achiev_32_48]

rpg_range = [0,1]
r_norpg = len(df1['Genre_RPG']==0)/len(df1)
r_rpg = len(df1['Genre_RPG']==1)/len(df1)
r_rpg_range=[r_norpg,r_rpg]

sim_range = [0,1]
r_nosim = len(df1['Genre_Simulation']==0)/len(df1)
r_sim = len(df1['Genre_Simulation']==1)/len(df1)
r_sim_range = [r_nosim, r_sim]

sports_range = [0,1]
r_nosports = len(df1['Genre_Sports']==0)/len(df1)
r_sports = len(df1['Genre_Sports']==1)/len(df1)
r_sports_range = [r_nosports,r_sports]

strat_range = [0,1]
r_nostrat = len(df1['Genre_Strategy']==0)/len(df1)
r_strat = len(df1['Genre_Strategy']==1)/len(df1)
r_strat_range = [r_nostrat,r_strat]
```

9.1 Weighted Average Engagement - Comparing Age Groups

[77]:
```python
import warnings
warnings.filterwarnings("ignore")
norm1,norm2,norm3 = 0,0,0
total_engagement_age1,total_engagement_age2,total_engagement_age3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                    if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                    X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                    if  age==age_range[0]:
                                                        norm1 += total_prop
                                                        total_engagement_age1␣
 ↪+= total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                    elif age==age_range[1]:
                                                        norm2 += total_prop
```

```
                                                                total_engagement_age2␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                            else:
                                                                norm3 += total_prop
                                                                total_engagement_age3␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]


total_engagement_age1,total_engagement_age2,total_engagement_age3 =␣
↪total_engagement_age1/norm1,total_engagement_age2/
↪norm2,total_engagement_age3/norm3
```

[78]:
```
print(total_engagement_age1,total_engagement_age2,total_engagement_age3)
```

```
1.0651184364605106 1.0651184364605024 1.0651184364605129
```

Weighted Average Engagement for Age Groups are: - Ages between 15-25: 1.065 - Ages between 26-36: 1.065 - Ages between 37-47: 1.065

9.2 Weighted Average Engagement - Comparing Gender

[79]:
```
total_engagement_male,total_engagement_female = 0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
↪zip(strat_range,r_strat_range):
                                                    if␣
↪sum([rpg,sim,sports,strat])>1:
```

```
                                                    continue
                                                total_prop =␣
↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                X_topredict = np.
↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
↪reshape(1,-1)
                                                X_topredict_scaled =␣
↪scaler_allfeats.transform(X_topredict)
                                                if  ␣
↪gender==gender_range[0]:
                                                    norm1 += total_prop
                                                    total_engagement_male␣
↪+= total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                else:
                                                    norm2 += total_prop
                                                    total_engagement_female␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]

total_engagement_male,total_engagement_female = total_engagement_male/
↪norm1,total_engagement_female/norm2
```

[80]:
```
total_engagement_male,total_engagement_female
```

[80]:
```
(1.0651184364605024, 1.0651184364605024)
```

Weighted Average Engagement for Gender Groups are: - Males: 1.065 - Female: 1.065

9.3 Weighted Average Engagement - Comparing Playtime

[81]:
```
total_engagement_playtime1,total_engagement_playtime2,total_engagement_playtime3␣
↪= 0,0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
↪zip(level_range,r_lvl_range):
```

```
                                        for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                            for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                                for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                                    for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                        for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                            if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                                continue
                                                            total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                            X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                            X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                            if  ␣
 ↪playtime==playtime_range[0]:
                                                                norm1 += total_prop
                                                               ␣
 ↪total_engagement_playtime1 += total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
                                                            elif␣
 ↪playtime==playtime_range[1]:
                                                                norm2 += total_prop
                                                               ␣
 ↪total_engagement_playtime2 +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
                                                            else:
                                                                norm3 += total_prop
                                                               ␣
 ↪total_engagement_playtime3 +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]

total_engagement_playtime1,total_engagement_playtime2,total_engagement_playtime3␣
 ↪= total_engagement_playtime1/norm1,total_engagement_playtime2/
 ↪norm2,total_engagement_playtime3/norm3
```

[82]:
```
total_engagement_playtime1,total_engagement_playtime2,total_engagement_playtime3
```

[82]: (1.0651184364605293, 1.0651184364605044, 1.0651184364605135)

Weighted Average Engagement for Playtime Groups are: - Playtime between 0-8: 1.065 - Playtime between 8-16: 1.065 - Playtime between 16-24: 1.065

9.4 Weighted Average Engagement - Comparing InGamePurchases

[83]:
```
total_engagement_nopurchase,total_engagement_purchase = 0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                    if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                    X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                    if  ␣
 ↪purchase==purchase_range[0]:
                                                        norm1 += total_prop
                                                       ␣
 ↪total_engagement_nopurchase += total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
```

```
                                                    else:
                                                        norm2 += total_prop
                                                       ␣
 ↪total_engagement_purchase +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]

total_engagement_nopurchase,total_engagement_purchase =␣
 ↪total_engagement_nopurchase/norm1,total_engagement_purchase/norm2
```

[84]:
```
total_engagement_nopurchase,total_engagement_purchase
```

[84]: (1.0651184364605162, 1.065118436460508)

Weighted Average Engagement for InGamePurchase Groups are: - No In Game Purchases: 1.065 - In Game Purchases: 1.065

9.5 Weighted Average Engagement - Comparing Difficulty Groups

[85]:
```
import warnings
warnings.filterwarnings("ignore")

total_engagement_difficulty1,total_engagement_difficulty2,total_engagement_difficulty3␣
 ↪= 0,0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
```

```
                                                    if␣
↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
↪reshape(1,-1)
                                                    X_topredict_scaled =␣
↪scaler_allfeats.transform(X_topredict)
                                                    if  ␣
↪difficulty==difficulty_range[0]:
                                                        norm1 += total_prop
                                                       ␣
↪total_engagement_difficulty1 += total_prop*best_estimator.
↪predict(X_topredict_scaled)[0]
                                                    elif␣
↪difficulty==difficulty_range[1]:
                                                        norm2 += total_prop
                                                       ␣
↪total_engagement_difficulty2 +=total_prop*best_estimator.
↪predict(X_topredict_scaled)[0]
                                                    else:
                                                        norm3 += total_prop
                                                       ␣
↪total_engagement_difficulty3 +=total_prop*best_estimator.
↪predict(X_topredict_scaled)[0]

total_engagement_difficulty1,total_engagement_difficulty2,total_engagement_difficulty3␣
↪= total_engagement_difficulty1/norm1,total_engagement_difficulty2/
↪norm2,total_engagement_difficulty3/norm3
```

[86]:

```
print(total_engagement_difficulty1,total_engagement_difficulty2,total_engagement_difficulty3)
```

```
1.0651184364605113 1.0651184364605113 1.0651184364605113
```

Weighted Average Engagement for Difficulty Groups are: - Difficulty Easy: 1.065 - Difficulty Medium: 1.065 - Difficulty Hard: 1.065

9.6 Weighted Average Engagement - Comparing Number of Sessions Groups

[87]:

```
import warnings
warnings.filterwarnings("ignore")

total_engagement_sessions1,total_engagement_sessions2,total_engagement_sessions3␣
↪= 0,0,0
```

```
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                    if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                    X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                    if  ␣
 ↪sessions==sessions_range[0]:
                                                        norm1 += total_prop
                                                       ␣
 ↪total_engagement_sessions1 += total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
                                                    elif␣
 ↪sessions==sessions_range[1]:
                                                        norm2 += total_prop
                                                       ␣
 ↪total_engagement_sessions2 +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
```

```
                                                else:
                                                    norm3 += total_prop
                                                   ␣
 ↪total_engagement_sessions3 +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]

total_engagement_sessions1,total_engagement_sessions2,total_engagement_sessions3␣
 ↪= total_engagement_sessions1/norm1,total_engagement_sessions2/
 ↪norm2,total_engagement_sessions3/norm3
```

[88]:
```
print(total_engagement_sessions1,total_engagement_sessions2,total_engagement_sessions3)
```

```
0.4074577133914237 1.1458656146797594 1.6659122343769686
```

Weighted Average Engagement for Sessions Per Week Groups are: - Sessions 0-6: 0.40 - Sessions 6-12: 1.14 - Sessions 12-18: 1.66

9.7 Weighted Average Engagement - Comparing Average Session Duration in Minutes Groups

[89]:
```
import warnings
warnings.filterwarnings("ignore")

total_engagement_avgsessions1,total_engagement_avgsessions2,total_engagement_avgsessions3␣
 ↪= 0,0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
```

```
                                                    for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                        if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                            continue
                                                        total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                        X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                        X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                        if  ␣
 ↪avgsessions==avgsessions_range[0]:
                                                            norm1 += total_prop
                                                           ␣
 ↪total_engagement_avgsessions1 += total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
                                                        elif␣
 ↪avgsessions==avgsessions_range[1]:
                                                            norm2 += total_prop
                                                           ␣
 ↪total_engagement_avgsessions2 +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]
                                                        else:
                                                            norm3 += total_prop
                                                           ␣
 ↪total_engagement_avgsessions3 +=total_prop*best_estimator.
 ↪predict(X_topredict_scaled)[0]

total_engagement_avgsessions1,total_engagement_avgsessions2,total_engagement_sessions3␣
 ↪= total_engagement_avgsessions1/norm1,total_engagement_avgsessions2/
 ↪norm2,total_engagement_sessions3/norm3
```

[90]:
```
print(total_engagement_avgsessions1,total_engagement_avgsessions2,total_engagement_sessions3)
```

```
0.6464374999999846 1.069472716231037 0.36906213091441387
```

Weighted Average Engagement for Average Session in Minutes Groups are: - Average Session In Between 10-66min: 0.64 - Average Session In Between 66-122min: 1.06 - Average Session In Between 122-178min: 0.36

9.8 Weighted Average Engagement - Comparing Level Groups

[91]:
```
import warnings
warnings.filterwarnings("ignore")

total_engagement_level1,total_engagement_level2,total_engagement_level3 = 0,0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                    if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                    X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                    if  level==level_range[0]:
                                                        norm1 += total_prop
                                                        total_engagement_level1␣
 ↪+= total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                    elif level==level_range[1]:
                                                        norm2 += total_prop
```

```
                                                    total_engagement_level2␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                else:
                                                    norm3 += total_prop
                                                    total_engagement_level3␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]

total_engagement_level1,total_engagement_level2,total_engagement_level3 =␣
↪total_engagement_level1/norm1,total_engagement_level2/
↪norm2,total_engagement_level3/norm3
```

[92]:
```
print(total_engagement_level1,total_engagement_level2,total_engagement_level3)
```

```
0.996263689802591 1.0627962210614372 1.1397048109185937
```

Weighted Average Engagement for Level Groups are: - Level in Between 1-34: 0.99 - Level in Between 34-67: 1.06 - level in Between 67-99: 1.13

9.9 Weighted Average Engagement - Comparing Achievement Groups

[93]:
```
import warnings
warnings.filterwarnings("ignore")

total_engagement_achievement1,total_engagement_achievement2,total_engagement_achievement3␣
↪= 0,0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
↪zip(sports_range,r_sports_range):
```

```
                                                    for strat, strat_prop in zip(strat_range,r_strat_range):
                                                        if sum([rpg,sim,sports,strat])>1:
                                                            continue
                                                        total_prop = age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                        X_topredict = np.array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
reshape(1,-1)
                                                        X_topredict_scaled = scaler_allfeats.transform(X_topredict)
                                                        if  achievement==achievement_range[0]:
                                                            norm1 += total_prop
                                                            total_engagement_achievement1 += total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                        elif achievement==achievement_range[1]:
                                                            norm2 += total_prop
                                                            total_engagement_achievement2 +=total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                        else:
                                                            norm3 += total_prop
                                                            total_engagement_achievement3 +=total_prop*best_estimator.predict(X_topredict_scaled)[0]

total_engagement_achievement1,total_engagement_achievement2,total_engagement_achievement3 = total_engagement_achievement1/norm1,total_engagement_achievement2/norm2,total_engagement_achievement3/norm3
```

[94]:
```
print(total_engagement_achievement1,total_engagement_achievement2,total_engagement_achievement
```

```
0.9962636898025888 1.100582174688662 1.100582174688683
```

Weighted Average Engagement for Achievement Groups are: - Level in Between 0-16: 0.99 - Level in Between 16-32: 1.10 - level in Between 32-48: 1.10

9.10 Weighted Average Engagement - Comparing RPG

[95]:
```
total_engagement_norpg,total_engagement_rpg = 0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
 ↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
 ↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
 ↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
 ↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
 ↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
 ↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
 ↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
 ↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
 ↪zip(strat_range,r_strat_range):
                                                    if␣
 ↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
 ↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
 ↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
 ↪reshape(1,-1)
                                                    X_topredict_scaled =␣
 ↪scaler_allfeats.transform(X_topredict)
                                                    if  rpg==rpg_range[0]:
                                                        norm1 += total_prop
                                                        total_engagement_norpg␣
 ↪+= total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                    else:
                                                        norm2 += total_prop
                                                        total_engagement_rpg␣
 ↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]
```

```
total_engagement_norpg,total_engagement_rpg = total_engagement_norpg/
↪norm1,total_engagement_rpg/norm2
```

[96]:
```
total_engagement_norpg,total_engagement_rpg
```

[96]: (1.065118436460517, 1.0651184364605106)

Weighted Average Engagement for RPG Groups are: - No RPG: 1.065 - RPG: 1.065

9.11 Weighted Average Engagement - Comparing Simulation Games

[97]:
```
total_engagement_nosim,total_engagement_sim = 0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
↪zip(strat_range,r_strat_range):
                                                    if␣
↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
↪reshape(1,-1)
```

```
                                                    X_topredict_scaled =␣
↪scaler_allfeats.transform(X_topredict)
                                                    if   sim==sim_range[0]:
                                                        norm1 += total_prop
                                                        total_engagement_nosim␣
↪+= total_prop*best_estimator.predict(X_topredict_scaled)[0]
                                                    else:
                                                        norm2 += total_prop
                                                        total_engagement_sim␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]

total_engagement_nosim,total_engagement_sim = total_engagement_nosim/
↪norm1,total_engagement_sim/norm2
```

[98]:
```
total_engagement_nosim,total_engagement_sim
```

[98]: (1.065118436460517, 1.0651184364605106)

Weighted Average Engagement for Simulation Groups are: - No Simulation: 1.065 - Simulation: 1.065

9.12 Weighted Average Engagement - Comparing Sports Games

[99]:
```
total_engagement_nosports,total_engagement_sports = 0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
↪zip(sessions_range,r_sessions_range):
                        for avgsessions, avgsessions_prop in␣
↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
↪zip(sports_range,r_sports_range):
```

```
                                                for strat, strat_prop in␣
↪zip(strat_range,r_strat_range):
                                                    if␣
↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
↪reshape(1,-1)
                                                    X_topredict_scaled =␣
↪scaler_allfeats.transform(X_topredict)
                                                    if  ␣
↪sports==sports_range[0]:
                                                        norm1 += total_prop
                                                       ␣
↪total_engagement_nosports += total_prop*best_estimator.
↪predict(X_topredict_scaled)[0]
                                                    else:
                                                        norm2 += total_prop
                                                        total_engagement_sports␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]

total_engagement_nosports,total_engagement_sports = total_engagement_nosports/
↪norm1,total_engagement_sports/norm2
```

[100]:
```
total_engagement_nosports,total_engagement_sports
```

[100]: (1.065118436460517, 1.06511843646O5106)

Weighted Average Engagement for Sports Groups are: - No Sports: 1.065 - Sports: 1.065

9.13 Weighted Average Engagement - Comparing Strategy Games

[101]:
```
total_engagement_nostrat,total_engagement_strat = 0,0
norm1,norm2,norm3 = 0,0,0
for age,age_prop in zip(age_range,r_age_range):
    for gender, gender_prop in zip(gender_range,r_gender_range):
        for playtime, playtime_prop in zip(playtime_range, r_playtime_range):
            for purchase, purchase_prop in zip(purchase_range,r_purchase_range):
                for difficulty, difficulty_prop in␣
↪zip(difficulty_range,r_difficulty_range):
                    for sessions, sessions_prop in␣
↪zip(sessions_range,r_sessions_range):
```

```
                        for avgsessions, avgsessions_prop in␣
↪zip(avgsessions_range,r_avgsessions_range):
                            for level, level_prop in␣
↪zip(level_range,r_lvl_range):
                                for achievement,achievement_prop in␣
↪zip(achievement_range,r_achievement_range):
                                    for rpg,rpg_prop in␣
↪zip(rpg_range,r_rpg_range):
                                        for sim,sim_prop in␣
↪zip(sim_range,r_sim_range):
                                            for sports,sports_prop in␣
↪zip(sports_range,r_sports_range):
                                                for strat, strat_prop in␣
↪zip(strat_range,r_strat_range):
                                                    if␣
↪sum([rpg,sim,sports,strat])>1:
                                                        continue
                                                    total_prop =␣
↪age_prop*gender_prop*playtime_prop*purchase_prop*difficulty_prop*sessions_prop*avgsessions_

                                                    X_topredict = np.
↪array([age,gender,playtime,purchase,difficulty,sessions,avgsessions,level,achievement,0,0,1
↪reshape(1,-1)
                                                    X_topredict_scaled =␣
↪scaler_allfeats.transform(X_topredict)
                                                    if   strat==strat_range[0]:
                                                        norm1 += total_prop
                                                      ␣
↪total_engagement_nostrat += total_prop*best_estimator.
↪predict(X_topredict_scaled)[0]
                                                    else:
                                                        norm2 += total_prop
                                                        total_engagement_strat␣
↪+=total_prop*best_estimator.predict(X_topredict_scaled)[0]
total_engagement_nostrat,total_engagement_strat = total_engagement_nostrat/
↪norm1,total_engagement_strat/norm2
```

[102]:

```
total_engagement_nostrat,total_engagement_strat
```

[102]: (1.065118436460517, 1.0651184364605106)

Weighted Average Engagement for Strategy Groups are: - No Strategy: 1.065 - Strategy: 1.065

10 Business Recommendations

In order to create an engaging game, we have 3 different recommendations in descending order of importance: - More sessions are better: players with a larger amount of sessions per week engage much more with the game than with a low number of sessions. We recommend creating special events during different days of the week (dungeons, missions, bosses) with special rewards so players keep coming back multiple times per week. Engagement can increase by 1.26 for players who come back several times per week.

- Balance is everything: players with very large average session duration engage poorer than gamers with low duration. In order to prevent a decline in this behavior we suggest advising the gamer to take a break to stretch after a long time (~2h) which also increases the number of sessions. Playing the game in moderate amounts per session can increase engagement by 0.7.

- Feeling of achievement and progress is important: players with higher levels and more achievements engage better. The game should be able to allow the player to level up faster initially and unlock achievements that are meaningful. This can increase the average engagement by 0.14 for higher level players and 0.1 for more achievements.

[ ]:

```

```