1. Business Understanding

Anime Classification

Crunchyroll and Funimation just merged their entire catalouges and now have money to burn, they are looking for the top rated anime for their streaming service and what makes the anime's top rated for their own original animes.

2. Data Understanding

The data im working with for this project comes from this <u>Kaggle dataset</u> (https://www.kaggle.com/datasets/marlesson/myanimelist-dataset-animes-profiles-reviews) from the year 2020. The target variable for this project is "Score X" which is the overall score for the animes which will be split into multiclass since value counts go from 1 through 10.

The making of the master dataset

```
In [123]:
              import pandas as pd
              import numpy as np
              from sklearn.model selection import train test split
              from sklearn.linear model import LogisticRegression
              from sklearn.pipeline import Pipeline
              from sklearn.compose import ColumnTransformer
              from sklearn.preprocessing import StandardScaler, OneHotEncoder
              from imblearn.over sampling import SMOTE
              from imblearn.pipeline import make pipeline
              from imblearn.pipeline import Pipeline as imbpipline
              from sklearn.dummy import DummyClassifier
              from sklearn.metrics import accuracy_score, precision_score, recall_score,\
              plot confusion matrix
              import matplotlib.pyplot as plt
              import seaborn as sns
              %matplotlib inline
              from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
  In [2]:
           reviewsdf = pd.read_csv('data/reviews.csv') # The three datasets
              profilesdf = pd.read csv('data/profiles.csv')
              animesdf = pd.read csv('data/animes.csv')
  In [3]:
           reviewsdf.columns #Seeing which columns I can use to combine the datasets
     Out[3]: Index(['uid', 'profile', 'anime_uid', 'text', 'score', 'scores', 'link'], d
              type='object')
```

▶ dfmerge = pd.DataFrame(data=mergedf1) In [7]:

Out[7]:

	uid	profile	anime_uid	text	score_x	scores	
0	255938	DesolatePsyche	34096.0	\n \n \n \n 	8.0	{'Overall': '8', 'Story': '8', 'Animation': '8	https://myanimelist.ne
1	255938	DesolatePsyche	34096.0	\n \n \n \n 	8.0	{'Overall': '8', 'Story': '8', 'Animation': '8	https://myanimelist.ne
2	259117	baekbeans	34599.0	\n \n \n \n 	10.0	{'Overall': '10', 'Story': '10', 'Animation':	https://myanimelist.ne
3	259117	baekbeans	34599.0	\n \n \n \n 	10.0	{'Overall': '10', 'Story': '10', 'Animation':	https://myanimelist.ne
4	253664	skrn	28891.0	\n \n \n \n 	7.0	{'Overall': '7', 'Story': '7', 'Animation': '9	https://myanimelist.ne
204577	27829	NaN	NaN	NaN	NaN	NaN	
204578	2649	NaN	NaN	NaN	NaN	NaN	
204579	8676	NaN	NaN	NaN	NaN	NaN	
204580	36043	NaN	NaN	NaN	NaN	NaN	

```
uid
                                   profile anime_uid text score_x
                                                                    scores
             204581
                      33082
                                     NaN
                                               NaN NaN
                                                            NaN
                                                                      NaN
             204582 rows × 18 columns
            dfmerge.isnull().sum().sum() #Checking for null values
In [8]:
    Out[8]: 2064198
In [9]:
            dfmerge.all()
    Out[9]: uid
                             True
             profile
                             True
             anime_uid
                             True
                             True
             text
             score_x
                            False
             scores
                             True
             link x
                             True
             title
                             True
             synopsis
                             True
                             True
             genre
             aired
                             True
             episodes
                             True
             members
                             True
                             True
             popularity
             ranked
                             True
                             True
             score_y
             img_url
                             True
             link_y
                             True
             dtype: bool
```

```
master_notebook - Jupyter Notebook
    In [10]:
                     cleandf = dfmerge.dropna()
                      cleandf #dropping null values
episodes
          members
                      popularity
                                  ranked score_y
                                                                                           img_url
     1.0
              360.0
                        11732.0
                                   8664.0
                                               5.90 https://cdn.myanimelist.net/images/anime/2/705...
                                                                                                      https://myanimelis
     1.0
              360.0
                        11732.0
                                   8664.0
                                               5.90 https://cdn.myanimelist.net/images/anime/2/705...
                                                                                                      https://myanimelis
     1.0
              100.0
                        15323.0 12764.0
                                               6.70 https://cdn.myanimelist.net/images/anime/2/745...
                                                                                                     https://myanimelist.
```

```
cleandf.isnull().sum().sum()
In [11]:
   Out[11]: 0
In [12]:
             allmerge = pd.merge(cleandf, profilesdf,
                                on='profile',
                                how='outer')
             print(allmerge) #repeating the process all over again
             100890
                               NaN
                                                                                    []
             100891
                               NaN
                                                                                    []
             100892
                                                                                    []
                               NaN
                                                                 link
                       https://myanimelist.net/profile/Slushpuppy282 (https://myanimel
             ist.net/profile/Slushpuppy282)
                       https://myanimelist.net/profile/Slushpuppy282 (https://myanimel
             ist.net/profile/Slushpuppy282)
                       https://myanimelist.net/profile/Slushpuppy282 (https://myanimel
             ist.net/profile/Slushpuppy282)
                       https://myanimelist.net/profile/Slushpuppy282 (https://myanimel
             3
             ist.net/profile/Slushpuppy282)
                         https://myanimelist.net/profile/ParaParaJMo (https://myanimel
             ist.net/profile/ParaParaJMo)
             100888
                          https://myanimelist.net/profile/daniel1302 (https://myanimel
             ist.net/profile/daniel1302)
             100889
                          https://myanimelist.net/profile/bridgesams (https://myanimel
             ist.net/profile/bridgesams)
```

Out[13]:

uid		profile	anime_uid	text	score_x	scores		^
0	29323.0	Slushpuppy282	7588.0	\n \n \n \n 	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	https://myanimelist.ne	;
1	29323.0	Slushpuppy282	7588.0	\n \n \n \n 	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	https://myanimelist.ne	;
2	29323.0	Slushpuppy282	7588.0	\n \n \n \n 	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	https://myanimelist.ne	;
3	29323.0	Slushpuppy282	7588.0	\n \n \n \n 	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	https://myanimelist.ne	;
4	30968.0	ParaParaJMo	1253.0	\n \n \n \n 	9.0	{'Overall': '9', 'Story': '9', 'Animation': '9	https://myanimelist.ne	;
100888	NaN	daniel1302	NaN	NaN	NaN	NaN		
100889	NaN	bridgesams	NaN	NaN	NaN	NaN		
100890	NaN	Officer_Anime	NaN	NaN	NaN	NaN		
100891	NaN	Yuez	NaN	NaN	NaN	NaN		
100892	NaN	srry4apologizng	NaN	NaN	NaN	NaN		
100893 r	ows × 22	2 columns						~
4							•	

In [14]: ► allmergedf.isnull().sum().sum()

Out[14]: 1347096

```
In [15]:
             mergeddf = allmergedf.dropna()
             mergeddf['scores'].value counts().sum()
   Out[15]: 18429
          ▶ | mergeddf.isnull().sum().sum()
In [16]:
   Out[16]: 0
In [17]:
          #mergeddf
                                         . . .
          ▶ | mergeddf.columns
In [18]:
   Out[18]:
             Index(['uid', 'profile', 'anime_uid', 'text', 'score_x', 'scores', 'link_
             х',
                    'title', 'synopsis', 'genre', 'aired', 'episodes', 'members',
                    'popularity', 'ranked', 'score_y', 'img_url', 'link_y', 'gender',
                    'birthday', 'favorites_anime', 'link'],
                   dtype='object')
In [19]:
          # #mergeddf.info()
             <class 'pandas.core.frame.DataFrame'>
             Int64Index: 18429 entries, 0 to 25780
             Data columns (total 22 columns):
              #
                  Column
                                   Non-Null Count
                                                   Dtype
                  _____
                                   _____
              0
                  uid
                                   18429 non-null float64
              1
                  profile
                                   18429 non-null object
              2
                  anime_uid
                                   18429 non-null float64
              3
                                   18429 non-null object
                  text
              4
                                   18429 non-null float64
                  score x
              5
                                   18429 non-null object
                  scores
              6
                  link x
                                   18429 non-null object
              7
                  title
                                   18429 non-null object
              8
                  synopsis
                                   18429 non-null object
              9
                  genre
                                   18429 non-null
                                                   object
              10
                  aired
                                   18429 non-null
                                                   object
              11
                                   18429 non-null float64
                  episodes
              12
                  members
                                   18429 non-null float64
              13
                  popularity
                                   18429 non-null float64
              14
                  ranked
                                   18429 non-null float64
              15
                  score y
                                   18429 non-null
                                                   float64
              16
                  img url
                                   18429 non-null object
              17
                  link y
                                   18429 non-null object
              18
                  gender
                                   18429 non-null object
              19
                  birthday
                                   18429 non-null
                                                   object
                 favorites_anime 18429 non-null
              20
                                                   object
              21
                 link
                                   18429 non-null
                                                   object
             dtypes: float64(8), object(14)
             memory usage: 3.2+ MB
```

In [21]: ▶ mergeddf #checking to see if the columns are dropped

Out[21]:

uid		profile	anime_uid	score_x	scores	title	synopsis	
0	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	[י;
1	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	יין
2	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	יין
3	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	יין
4	30968.0	ParaParaJMo	1253.0	9.0	{'Overall': '9', 'Story': '9', 'Animation': '9	Kokoro no Catchball	An educational anime about the importance of h	'(
25775	29103.0	Samurai_Wolf337	8676.0	9.0	{'Overall': '9', 'Story': '9', 'Animation': '9	Tanoshii Sansuu	Music video for a song about arithmetic by Sei	['
25776	13167.0	meri_nicole	5060.0	9.0	{'Overall': '9', 'Story': '8', 'Animation': '7	Zoobles!	The Candy Factory is a place where all Zoobles	
25777	22745.0	samurai_gaz25	5060.0	10.0	{'Overall': '10', 'Story': '10', 'Animation':	Brothers Conflict: Setsubou	Ema finds a special lamp that her father left	['ŀ 'Ron 'S
25778	22745.0	samurai_gaz25	5060.0	10.0	{'Overall': '10', 'Story': '10', 'Animation': 	Brothers Conflict: Setsubou	Ema finds a special lamp that her father left	['ŀ 'Ron 'S

	uid	profile	anime_uid	score_x	scores	title	synopsis	
25780	34734.0	Akuteru	2593.0	9.0	{'Overall': '9', 'Story': '10', 'Animation': '	Minami Kamakura Koukou Joshi Jitenshabu: Kita	Unaired episode included with the special edit	[': 'S 'Sh:
18429	rows × 17	columns						
4								•

Feature Engineering

Using the "Scores" and extracting the scores from story to enjoyment since overall has the same value as the target column that is being used for the classification model

```
▶ mergeddf.scores[0]
In [22]:
    Out[22]: "{'Overall': '7', 'Story': '7', 'Animation': '6', 'Sound': '9', 'Characte
              r': '6', 'Enjoyment': '0'}"

    def scoreExtractor(df):

In [23]:
                  Story = [string.split(',')[1].split(':')[1].replace("'",'') for string in
                  Animation = [string.split(',')[2].split(':')[1].replace("'",'') for string.
                  Sound = [string.split(',')[3].split(':')[1].replace("'",'') for string in
                  Character = [string.split(',')[4].split(':')[1].replace("'",'') for string.split(',')[4].split(':')[1].replace("'",'')
                  Enjoyment = [string.split(',')[5].split(':')[1].replace("'",'').replace("
                  df['Story score'] = pd.Series(Story)
                  df['Animation score'] = pd.Series(Animation)
                  df['Sound score'] = pd.Series(Sound)
                  df['Character score'] = pd.Series(Character)
                  df['Enjoyment score'] = pd.Series(Enjoyment)
                  return df
```

Out[24]:

	uid profi		anime_uid	score_x	scores	title	synopsis	genre	ai
0	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
1	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
2	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
3	29323.0	Slushpuppy282	7588.0	7.0	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
4	30968.0	ParaParaJMo	1253.0	9.0	{'Overall': '9', 'Story': '9', 'Animation': '9	Kokoro no Catchball	An educational anime about the importance of h	['Kids', 'Sports']	2

5 rows × 22 columns

```
In [25]:
             \#mergeddf.info() \#seeing that there are missing values in the new columns I \#
             <class 'pandas.core.frame.DataFrame'>
             Int64Index: 18429 entries, 0 to 25780
             Data columns (total 22 columns):
              #
                  Column
                                   Non-Null Count Dtype
                  -----
                                   _____
              0
                  uid
                                   18429 non-null float64
              1
                  profile
                                   18429 non-null
                                                  obiect
                                   18429 non-null float64
              2
                  anime uid
              3
                                   18429 non-null float64
                  score x
              4
                  scores
                                   18429 non-null object
              5
                  title
                                   18429 non-null object
              6
                  synopsis
                                   18429 non-null object
              7
                  genre
                                   18429 non-null
                                                   object
              8
                                   18429 non-null
                  aired
                                                   object
              9
                  episodes
                                   18429 non-null float64
              10
                  members
                                   18429 non-null float64
                                   18429 non-null float64
              11
                  popularity
              12
                  ranked
                                   18429 non-null float64
                  score y
                                   18429 non-null
              13
                                                   float64
                 gender
              14
                                   18429 non-null object
              15
                  birthday
                                   18429 non-null object
                 favorites_anime 18429 non-null object
              16
                  Story score
                                   13359 non-null
              17
                                                   object
                  Animation score 13359 non-null
                                                   object
              19
                                   13359 non-null
                                                   object
                  Sound score
              20 Character score 13359 non-null
                                                   object
                  Enjoyment score 13359 non-null
                                                   object
             dtypes: float64(8), object(14)
             memory usage: 3.9+ MB
```

Using the median of each column to fill in nan values

In [28]:

```
#mergeddf.info()
  <class 'pandas.core.frame.DataFrame'>
  Int64Index: 18429 entries, 0 to 25780
  Data columns (total 22 columns):
   #
       Column
                        Non-Null Count
                                       Dtype
       -----
                        -----
   0
       uid
                        18429 non-null float64
   1
       profile
                        18429 non-null object
                        18429 non-null float64
   2
       anime uid
   3
                        18429 non-null float64
       score x
   4
       scores
                        18429 non-null object
   5
       title
                        18429 non-null object
   6
       synopsis
                        18429 non-null object
   7
       genre
                        18429 non-null
                                       object
   8
       aired
                        18429 non-null
                                       object
   9
       episodes
                        18429 non-null float64
   10
       members
                        18429 non-null float64
                        18429 non-null float64
   11
       popularity
   12
       ranked
                        18429 non-null float64
       score_y
                        18429 non-null int32
   13
   14
       gender
                        18429 non-null object
   15
       birthday
                        18429 non-null object
       favorites_anime 18429 non-null object
       Story score
                        18429 non-null
   17
                                       int32
       Animation score 18429 non-null int32
   19
                        18429 non-null int32
       Sound score
   20 Character score 18429 non-null int32
       Enjoyment score 18429 non-null int32
  dtypes: float64(7), int32(6), object(9)
  memory usage: 3.4+ MB
```

Creating target for model

```
mergeddf['score_x'].value_counts() #Checking the
In [29]:
    Out[29]:
             10.0
                      4684
              9.0
                      4617
              8.0
                      3362
                      2358
              7.0
              6.0
                      1373
              5.0
                       837
              4.0
                       436
              3.0
                       411
              2.0
                       223
              1.0
                       128
             Name: score_x, dtype: int64
             mergeddf['score_x'] = mergeddf['score_x'].astype(int)
In [30]:
             #Turning the column into integers to get rid of float values
```

In [31]: ▶ mergeddf.head()

Out[31]:

	uid profile		anime_uid	score_x	scores	title	synopsis	genre	a i
0	29323.0	Slushpuppy282	7588.0	7	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
1	29323.0	Slushpuppy282	7588.0	7	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
2	29323.0	Slushpuppy282	7588.0	7	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
3	29323.0	Slushpuppy282	7588.0	7	{'Overall': '7', 'Story': '7', 'Animation': '6	Oyaji no, Imo no Kamisama.	A man wanders into a liquor store and sees a f	['Slice of Life']	2
4	30968.0	ParaParaJMo	1253.0	9	{'Overall': '9', 'Story': '9', 'Animation': '9	Kokoro no Catchball	An educational anime about the importance of h	['Kids', 'Sports']	2
5 r	ows × 22	columns							
4									•

Target assignment

- Target 1 for ratings 8 through 10
- Target 2 for ratings 5 through 7
- Target 3 for ratings 1 through 4

```
mergeddf['score x'].value counts()
In [32]:
    Out[32]:
              10
                     4684
                     4617
              8
                     3362
              7
                     2358
              6
                     1373
              5
                      837
              4
                      436
              3
                      411
              2
                      223
              1
                      128
              Name: score x, dtype: int64
              mergeddf['target'] = [1 if x >= 8 else 3 if x <= 4 else 2 for x in <math>mergeddf['target']
In [33]:
              mergeddf['target'].value counts()
In [34]:
    Out[34]:
              1
                    12663
              2
                     4568
              3
                     1198
              Name: target, dtype: int64
```

EDA

In [35]:

now that the data set is cleaned it is the perfect time for EDA

10721.000000

```
Out[35]:
                                                                   episodes
                                                                                               popularity
                             uid
                                     anime_uid
                                                     score_x
                                                                                 members
            count 18429.000000
                                  18429.000000
                                                18429.000000
                                                               18429.000000
                                                                             1.842900e+04
                                                                                            18429.000000 1
                   16430.223723
                                   2426.388410
                                                     8.018286
                                                                  13.640241
                                                                             4.360289e+04
                                                                                             7067.585762
            mean
                                                                                             4780.629512
                   14126.427760
                                   2753.329957
                                                     1.952897
                                                                  39.844532
                                                                             1.210216e+05
               std
                                      1.000000
                                                                             2.600000e+01
                                                                                                1.000000
              min
                        1.000000
                                                     1.000000
                                                                   1.000000
              25%
                     2460.000000
                                    295.000000
                                                     7.000000
                                                                   1.000000
                                                                             4.550000e+02
                                                                                             2846.000000
              50%
                    11275.000000
                                   1535.000000
                                                     9.000000
                                                                   2.000000
                                                                             3.773000e+03
                                                                                             6442.000000
              75%
                    31772.000000
                                   3306.000000
                                                    10.000000
                                                                  13.000000
                                                                             2.511800e+04
                                                                                            11209.000000
```

10.000000

3057.000000

1.871043e+06

mergeddf.describe() #seems animation, character and simply enjoying the anime

40849.000000

16314.000000 1

```
In [36]:
           | # Distribution graphs (histogram/bar graph) of column data
              def plotPerColumnDistribution(df, nGraphShown, nGraphPerRow):
                  nunique = df.nunique()
                  df = df[[col for col in df if nunique[col] > 1 and nunique[col] < 50]] #</pre>
                  nRow, nCol = df.shape
                  columnNames = list(df)
                  nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow
                  plt.figure(num = None, figsize = (6 * nGraphPerRow, 8 * nGraphRow), dpi =
                  for i in range(min(nCol, nGraphShown)):
                      plt.subplot(nGraphRow, nGraphPerRow, i + 1)
                      columnDf = df.iloc[:, i]
                      if (not np.issubdtype(type(columnDf.iloc[0]), np.number)):
                          valueCounts = columnDf.value_counts()
                          valueCounts.plot.bar()
                      else:
                          columnDf.hist()
                      plt.ylabel('Distribution')
                      plt.xticks(rotation = 90)
                      plt.title(f'{columnNames[i]} (column {i})')
                  plt.tight layout(pad = 1.0, w pad = 1.0, h pad = 1.0)
                  plt.show()
           #plotPerColumnDistribution(mergeddf, 25 ,3)
In [37]:
              #The average rating looks between 7 through 8
In [38]:

    def partial heatmap(data, start, stop):

                  y = data['target']
                  df = data.iloc[:, start:stop]
                  sns.heatmap(df.corr(), annot=True, fmt='.2f')
                  plt.show() #Heat map for correlation
In [39]:
           partial heatmap(mergeddf, 10, 40)
              anime pop = mergeddf[mergeddf.popularity!=0].sort values(by='ranked').head(10
In [131]:
              anime_pop.head() # Checking the
In [42]:
              anime genre = mergeddf.genre
              anime genre.head(100)
                                           . . .
```

```
In [43]:

    genre list = []

            genre_splited = []
            for i in anime genre.index:
               for j in anime_genre[i].split(", "):
                   genre splited.append(j)
                   if j not in genre list:
                      genre list.append(j)
In [44]:

■ genre_list[0:100]

In [82]:
         plt.figure(figsize=(15,10))
            sns.barplot(x=anime_genres_count.index.tolist(), y=anime_genres_count.tolist(
            plt.xlabel('Genres')
            plt.ylabel('Anime Count')
            plt.title('The Most Popular Genres In The Anime Industry (Regarded all Multi-
           plt.xticks(rotation= 100, fontsize=20)
            plt.show() #Comedy seems to be the most common genre in the dataset
```

Extracting every genre from the genre column

In [84]: mergeddf['Action'] = [1 if 'Action' in genre else 0 for genre in mergeddf['ge mergeddf['Adventure'] = [1 if 'Adventure' in genre else 0 for genre in merged mergeddf['Ai'] = [1 if 'Ai' in genre else 0 for genre in mergeddf['genre']] mergeddf['Arts'] = [1 if 'Arts' or 'Martial' in genre else 0 for genre in mer mergeddf['Cars'] = [1 if 'Cars' in genre else 0 for genre in mergeddf['genre'] mergeddf['Comedy'] = [1 if 'Comedy' in genre else 0 for genre in mergeddf['ge mergeddf['Dementia'] = [1 if 'Dementia' in genre else 0 for genre in mergeddf mergeddf['Demons'] = [1 if 'Demons' in genre else 0 for genre in mergeddf['ge mergeddf['Drama'] = [1 if 'Drama' in genre else 0 for genre in mergeddf['genr mergeddf['Ecchi'] = [1 if 'Ecchi' in genre else 0 for genre in mergeddf['genr mergeddf['Fantasy'] = [1 if 'Fantasy' in genre else 0 for genre in mergeddf[' mergeddf['Game'] = [1 if 'Game' in genre else 0 for genre in mergeddf['genre' mergeddf['Harem'] = [1 if 'Harem' in genre else 0 for genre in mergeddf['genr mergeddf['Historical'] = [1 if 'Historical' in genre else 0 for genre in merg mergeddf['Horror'] = [1 if 'Horror' in genre else 0 for genre in mergeddf['ge mergeddf['Josei'] = [1 if 'Josei' in genre else 0 for genre in mergeddf['genr mergeddf['Kids'] = [1 if 'Kids' in genre else 0 for genre in mergeddf['genre' mergeddf['Life'] = [1 if 'Life' or 'Slice' or 'of' in genre else 0 for genre mergeddf['Magic'] = [1 if 'Magic' in genre else 0 for genre in mergeddf['genr mergeddf['Mecha'] = [1 if 'Mecha' in genre else 0 for genre in mergeddf['genr mergeddf['Military'] = [1 if 'Military' in genre else 0 for genre in mergeddf mergeddf['Music'] = [1 if 'Music' in genre else 0 for genre in mergeddf['genr mergeddf['Mystery'] = [1 if 'Mystery' in genre else 0 for genre in mergeddf[' mergeddf['Parody'] = [1 if 'Parody' in genre else 0 for genre in mergeddf['ge mergeddf['Police'] = [1 if 'Police' in genre else 0 for genre in mergeddf['ge mergeddf['Power'] = [1 if 'Power' or 'Super' in genre else 0 for genre in mer mergeddf['Psychological'] = [1 if 'Psychological' in genre else 0 for genre i mergeddf['Romance'] = [1 if 'Romance' in genre else 0 for genre in mergeddf[' mergeddf['Samurai'] = [1 if 'Samurai' in genre else 0 for genre in mergeddf[' mergeddf['School'] = [1 if 'School' in genre else 0 for genre in mergeddf['ge mergeddf['Sci-Fi'] = [1 if 'Sci-Fi' in genre else 0 for genre in mergeddf['ge mergeddf['Seinen'] = [1 if 'Seinen' in genre else 0 for genre in mergeddf['ge mergeddf['Shouju'] = [1 if 'Shouju' in genre else 0 for genre in mergeddf['ge mergeddf['Shounen'] = [1 if 'Shounen' in genre else 0 for genre in mergeddf[' mergeddf['Space'] = [1 if 'Space' in genre else 0 for genre in mergeddf['genr mergeddf['Sports'] = [1 if 'Sports' in genre else 0 for genre in mergeddf['ge mergeddf['Supernatural'] = [1 if 'Supernatural' in genre else 0 for genre in mergeddf['Thriller'] = [1 if 'Thriller' in genre else 0 for genre in mergeddf mergeddf['Vampire'] = [1 if 'Vampire' in genre else 0 for genre in mergeddf['

In [165]: ▶ #mergeddf.info() #checking to see if the values have any nulls

OHE and SMOTE

one hot encoding object columns and using smote for the imbalanace of the target column

```
▶ # Defined a OneHotEncoder function for ease of access
In [53]:
             def OHE(X train, categories):
                 onehot = OneHotEncoder(sparse=False, handle unknown = 'ignore')
                 x train cat = pd.DataFrame(onehot.fit transform(X train[categories]))
                 x train cat.columns = onehot.get feature names(categories)
                 # Reset indices to avoid merging conflicts
                 x train cat.reset index(drop=True, inplace=True)
                 X train.reset index(drop=True, inplace=True)
                 # Joined the OHE dataframe to the dataframe that is passed into the funct
                 x_train_df = X_train.drop(categories, axis = 1).join(x_train_cat)
                 return x train df
             def confusion and metrics(model, X test, y test):
                 # Accuracy Score
                 print(f"Accuracy Score: {model.score(X_test, y_test):.3f}")
                 # Plot confusion matrix for visualization
                 plot confusion matrix(model, X test, y test);
             # Defined a function to take in column name and output log-odds coefficient a
             def print odds(dataframe, column name):
                 # Prints out the name of the column and it's original log odds value
                 print(f"{column name}: {dataframe[column name][0]}")
                 # Prints out the odds value of the column
                 print(f"Odds: {np.exp(dataframe[column name][0])}")
          X = mergeddf.drop(['target', 'profile','clean_genre', 'birthday','uid', 'genr
In [54]:
             y = mergeddf['target']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, ran
In [55]:
```

```
In [56]: # Called the OHE function we made and assigned new dataframe variables
    train_ohe = OHE(X_train, ['gender'])
    test_ohe = OHE(X_test, ['gender'])
    train_ohe
```

Out[56]:

	episodes	members	popularity	ranked	score_y	Story score	Animation score	Sound score	Character score
0	23.0	98110.0	1115.0	2921.0	7	10	8	9	9
1	12.0	2611.0	7330.0	8649.0	5	8	9	8	9
2	6.0	22001.0	3043.0	3668.0	7	8	8	8	7
3	1.0	176401.0	619.0	459.0	8	9	10	10	10
4	14.0	2425.0	7480.0	3872.0	6	8	9	8	9
13816	72.0	2148.0	7834.0	637.0	7	8	8	7	9
13817	1.0	200.0	13386.0	11640.0	5	10	10	10	10
13818	1.0	243.0	12779.0	9733.0	5	8	7	9	7
13819	1.0	77.0	15805.0	14574.0	5	7	10	9	7
13820	1.0	50882.0	1881.0	854.0	7	10	10	8	9

13821 rows × 53 columns

```
In [57]:  ▶ train ohe.columns
    Out[57]: Index(['episodes', 'members', 'popularity', 'ranked', 'score_y', 'Story sco
              re',
                       'Animation score', 'Sound score', 'Character score', 'Enjoyment scor
              е',
                      'Action', 'Adventure', 'Ai', 'Arts', 'Cars', 'Comedy', 'Dementia',
                      'Demons', 'Drama', 'Ecchi', 'Fantasy', 'Game', 'Harem', 'Historica
              1',
                      'Horror', 'Josei', 'Kids', 'Life', 'Magic', 'Martial', 'Mecha',
                      'Military', 'Music', 'Mystery', 'Parody', 'Police', 'Power',
                      'Psychological', 'Romance', 'Samurai', 'School', 'Sci-Fi', 'Seinen', 'Shouju', 'Shounen', 'Space', 'Sports', 'Supernatural', 'Thriller',
                      'Vampire', 'gender_Female', 'gender_Male', 'gender_Non-Binary'],
                     dtype='object')
In [59]: ▶ | y_test.value_counts() #class imbalance
    Out[59]: 1
                    3174
              2
                    1143
```

291

Name: target, dtype: int64

3

warnings.warn("Pass {} as keyword args. From version 0.9 "

Dummy Model

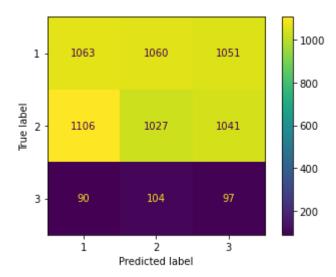
Counter({1: 9489, 2: 3425, 3: 907}) Counter({1: 3174, 2: 3174, 3: 291})

```
In [61]: # Created Dummy Classifier model to look at simple accuracy score
    from sklearn.dummy import DummyClassifier
    dummy = DummyClassifier(strategy='uniform')
    dummy.fit(X_train, y_train)
    y_pred = dummy.predict(X_train)
    y_test_pred = dummy.predict(X_test)
    y_pred_df = pd.DataFrame(y_pred)
    dummy.score(X_test, y_test)
```

Out[61]: 0.3352864583333333

In [62]: ▶ confusion_and_metrics(dummy, X_test_smote, y_test_smote) #Accuracy score from

Accuracy Score: 0.326



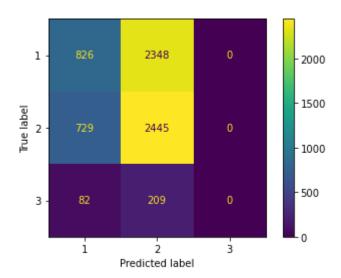
Accuracy score printed out is 32% which isn't the best we can do

First model

Out[167]: 0.49269468293417684

In [168]: ► confusion_and_metrics(model, X_test_smote, y_test_smote)

Accuracy Score: 0.493



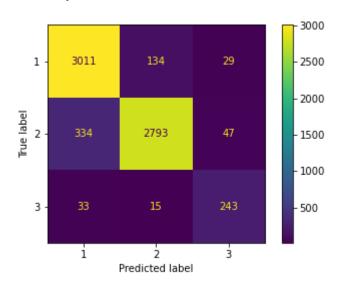
The Logistic Regression accuracy score went up 17% from the dummy classifier

Second model

Out[169]: 0.9108299442687152

```
In [170]: ▶ confusion_and_metrics(dt, X_test_smote, y_test_smote)
```

Accuracy Score: 0.911



The best score so far from a decision tree being 91%

```
In [71]:  # Feature columns
    X = X_smote
    # Target column - H1N1 Knowledge
    y = y_smote

from sklearn.ensemble import ExtraTreesClassifier
    import matplotlib.pyplot as plt

# Instantiate model
    modelfeatures = ExtraTreesClassifier()
    modelfeatures.fit(X,y)
    print(modelfeatures.feature_importances_) # use built in class 'feature_import # Plot graph of feature importances for better visualization
    feat_importances = pd.Series(modelfeatures.feature_importances_, index=X.colu feat_importances.nlargest(10).plot(kind='barh')
    plt.show()
```

In [110]:

```
df new.value counts() #Looking at the distribution of the action genre and th
   Out[110]: Action target
                                 9364
                      1
                      2
                                 3518
              1
                      1
                                 3299
                      2
                                 1050
              0
                      3
                                  942
                      3
                                  256
              dtype: int64
In [112]:
           ▶ plt.figure(figsize=(15,10))
              sns.barplot(x=df_new['target'], y=df_new['Action'])
              plt.xlabel('Genres')
              plt.ylabel('Anime Count')
              plt.title('The Most Popular Genres In The Anime Industry (Regarded all Multi-
              plt.xticks(rotation= 100, fontsize=20)
              plt.show() #graphing the distribution to see the overall ratings are
                                           . . .
In [114]:
           ▶ plt.figure(figsize=(15,10))
              sns.barplot(x=mergeddf['target'], y=mergeddf['gender'])
              plt.xlabel('Genres')
              plt.ylabel('Anime Count')
              plt.title('The Most Popular Genres In The Anime Industry (Regarded all Multi-
              plt.xticks(rotation= 100, fontsize=20)
              plt.show() #Looking at the scores distributed by gender
                                           . . .
In [74]:

    import datetime

In [75]:
           Husing the Birthday column to get the age of the user ratings
              mergeddf['birthday'] = pd.to datetime(mergeddf['birthday'], errors = 'coerce'
              mergeddf=mergeddf[mergedd#.notn]
              birth date = mergeddf.birthday
              gender = mergeddf.gender
              #spent = users.user days spent watching
              age = []
              for each in birth_date:
                  age.append(round((datetime.datetime.now()-each).days/365.25,1))
In [76]:
              mergeddf['age'] = age #appears to be missing values
              #mergeddf.info()
                                           . . .
```

```
In [166]:
              mergeddf[['age']] = mergeddf[['age']].fillna(mergeddf[['age']].median()).asty
              mergeddf['age'].value_counts() #Using fillna to replace it with the median
              #also seems to be extreme outliers
                                            . . .
           genres with comedy = [] #Comedy being the most relevant genre in anime seeing
In [121]:
              for i in anime genre.index:
                  if anime_genre[i].find('Comedy') > -1:
                       for j in anime genre[i].split(", "):
                           if j != 'Comedy':
                               genres with comedy.append(j)
In [124]:
                   genres with comedy count = pd.Series(genres with comedy).value counts().
                1
                2
                3
                   fig = {
                4
                     "data": [
                5
                6
                         "values": genres_with_comedy_count.tolist(),
                7
                         "labels": genres with comedy count.index.tolist(),
                         "domain": {"x": [0, .8]},
                8
                         "name": "Number Of Students Rates",
                9
                         "hoverinfo": "label+percent+name",
               10
                         "hole": .4,
               11
                         "type": "pie"
               12
               13
                       },],
               14
                     "layout": {
                           "title": "Top 10 Multi-label Tags With Comedy"
               15
               16
                       }
               17
               18
                   iplot(fig)
```

Conclusion

Overall the best model was the Decision tree classifier it had the best accuracy score it correctly identified ratings being from ranges 1-4 for 3 being not a good rating, 5-7 being average scoring, and 8-10 being a great rating. The logistic regression only correctly identifying the target 49% of the time. For more accurate scores and using different evaluation methods more feature engingeering can be done and more predictors for the logistic regression since it can be even more powerful.

Recommendations

I recommend that Crunchyroll:

- · To license popular animes that their competitors don't have the rights to
- · When making their own original animes to focus on the soundtrack
- To start off with comedy multi labels for the genre for their original animes

Future considerations

Next steps to do for Crunchyroll

- Look into ROI when buying the rights to the animes
- Model NLP for sentiment analysis on twitter

[n []: ► H	A.I.		
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