QUIZ ASSESSMENT

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Question 1:

Importance of Activation Function in Neural Network

By generating a weighted total and then including bias with it, the activation function determines whether or not a neuron should be turned on. The activation function's objective is to add non-linearity to a neuron's output. It is utilized to determine the neural network's output, such as yes or no. The obtained values are mapped between 0 and 1 or -1 and 1, etc.

A neuron's activation status is determined by an activation function. By employing simpler mathematical procedures, it will determine whether or not the neuron's input to the network is significant during the prediction process. We are aware that neurons in neural networks behave in accordance with weight, bias, and their respective activation roles. The weights and biases of the neurons in a neural network would be updated based on the output error. Back-propagation is the name of this procedure. Back-propagation is made possible by activation functions since they provide the gradients and error needed to update the weights and biases.

The 3 types of activation functions in a neural network are:

1. ***Sigmoid or Logistic Activation Function***

   The Sigmoid Activation function, often known as the logistic function, has long been a favourite activation function for neural networks. The function converts the input into a number between 0.0 and 1.0. Values significantly lower than 0.0 are snapped to 0.0, and inputs substantially bigger than 1.0 are changed to the value 1.0. The function has an S-shape from zero up through 0.5 to 1.0 for all potential inputs. It was the standard activation used on neural networks for a considerable amount of time, up until the early 1990s.

2. ***Binary Step Function***

   Binary step function is a threshold-based activation function, meaning that once a specific threshold is reached, activation occurs, and below that point, deactivation occurs. The threshold is zero on the graph up top. As the name implies, this activation function can be utilized in binary classifications, but it cannot be employed when dealing with numerous classes.

3. ***Linear Activation Function***

   The Linear activation is proportionate to the input in a linear activation function, also referred to as "no activation" or the "identity function" (multiplied by 1.0). The function just spits out the value it was given, doing nothing to the weighted sum of the input.

Question 2:

Bagging Ensemble Method

Ensemble models (commonly referred to as "weak learners") are taught to tackle the same problem using the ensemble learning paradigm, which then combines the findings to produce better ones. The basic claim is that by properly combining weak models, we can produce more precise and/or reliable models.

This phenomenon occurs when all of the models are integrated to produce the best machine learning model. In such a way that we can use assistance from other models or combine assistance from all the models to produce the best hypothesis and outcomes when any one of the combined models begins to falter.

We fit the several learners separately from one another using parallel approaches, making it possible to train them simultaneously. The most well-known method of this type is "bagging," which stands for "bootstrap aggregating" and tries to create an ensemble model that is stronger than the individual models that make up it.

Whether we are working with a classification or regression problem, we receive a function during the training process that takes an input, returns an output, and is defined in relation to the training dataset. The fitted model is also subject to variability because of the theoretical variance of the training dataset (remember that a dataset is an observed sample coming from a genuine unknown underlying distribution); if another dataset had been observed, we would have received a different model.

The basic concept behind bagging is to fit a number of different models and "average" their forecasts to get a model with a lower variance. However, fitting totally independent models is not practical because it would necessitate

Procedure for Bagging are:

1. Consider a training set that contains m features and n observations. You must choose a random sample without replacement from the practice dataset.
2. Using sample data, a model is constructed using a subset of m features that is randomly selected.
3. The nodes are divided using the feature that offers the best split among all of them.
4. You have the best root nodes because the tree has matured.
5. Repeating the previous steps n times. To provide the most accurate prediction, it combines the results of various decision trees.

In [166]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import json
import datetime
import matplotlib.pyplot as plt
pd.set_option('display.max_columns', 40)
```

In [167]:
```
# Label Encoding and One-Hot Encoding Libraries
from sklearn.preprocessing import OneHotEncoder

from sklearn.model_selection import train_test_split

# Decision Tree Classifier
from sklearn.tree import DecisionTreeClassifier

# Metrics for understanding the model's performance
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
```

In [168]:
```
movie_df = pd.read_csv('/Users/HarshitGaur/Documents/Northeastern University/M
```

In [169]:
```
movie_df.head(5)
```

Out[169]:

	year	movie	movie_id	certificate	duration	genre	rate	metascore	syn
0	2001	Kate & Leopold	tt0035423	PG-13	118	Comedy|Fantasy|Romance	6.4	44.0	An E Duke 1 inadve c
1	2000	Chicken Run	tt0120630	G	84	Animation|Adventure|Comedy	7.0	88.0	W co appa flies ch
2	2005	Fantastic Four	tt0120667	PG-13	106	Action|Adventure|Family	5.7	40.0	A gro astro superp aft
3	2002	Frida	tt0120679	R	123	Biography|Drama|Romance	7.4	61.0	A biog of Frida k cha
4	2001	The Lord of the Rings: The Fellowship of the Ring	tt0120737	PG-13	178	Adventure|Drama|Fantasy	8.8	92.0	A Hobbi the and comp

5 rows × 119 columns

In [170]:
```
movie_df.dtypes
```

Out[170]:
```
year                                                     int64
movie                                                   object
movie_id                                                object
certificate                                             object
duration                                                 int64
                                                         ...
Los_Angeles_Film_Critics_Association_nominated_categories    object
release_date.year                                      float64
release_date.month                                     float64
release_date.day-of-month                              float64
release_date.day-of-week                               float64
Length: 119, dtype: object
```

In [171]:
```
movie_df[movie_df['Oscar_Best_Picture_won'] == 'Yes'][['year','movie']].value_
```

Out[171]:
```
year  movie
2000  Gladiator                                              1
2001  A Beautiful Mind                                       1
2016  Moonlight                                              1
2015  Spotlight                                              1
2014  Birdman or (The Unexpected Virtue of Ignorance)        1
2013  12 Years a Slave                                       1
2012  Argo                                                   1
2011  The Artist                                             1
2010  The King's Speech                                      1
2008  The Hurt Locker                                        1
      Slumdog Millionaire                                    1
2007  No Country for Old Men                                 1
2006  The Departed                                           1
2004  Million Dollar Baby                                    1
      Crash                                                  1
2003  The Lord of the Rings: The Return of the King          1
2002  Chicago                                                1
2017  The Shape of Water                                     1
dtype: int64
```

In [172]:
```
movie_df.info()
```

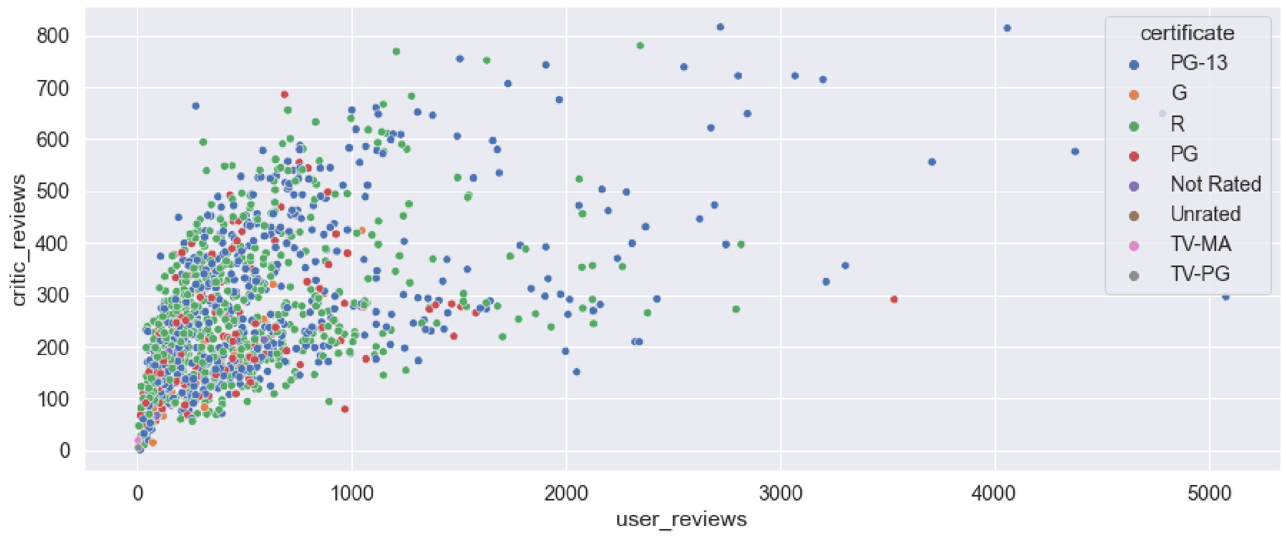
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1235 entries, 0 to 1234
Columns: 119 entries, year to release_date.day-of-week
dtypes: float64(10), int64(46), object(63)
memory usage: 1.1+ MB
```

Part 1: EDA

Q1. Scatterplot

Displaying a Scatter Plot to show the relationship between users' reviews and critics' reviews of each movie (data points) present in the data set.

In [173]:
```
sns.scatterplot(data = movie_df, x = "user_reviews", y = "critic_reviews", hue
plt.show()
```



From the above plot, we can find that there is kind of a linear relationship between users' reviews and critics' reviews. If we distinguish this distribution on basis of "certificate" of the movies, we can find some insights that "PG-13" and "R" certified movies have recieved more reviews from both parties.

Pearson's Correlation Coefficient

In [174]:
```
correlation = movie_df[['user_reviews', 'critic_reviews']].corr()

print("Pearson's Correlation Coefficient between Users' Reviews and Critics' R
print(correlation.loc['user_reviews', 'critic_reviews'])
```

```
Pearson's Correlation Coefficient between Users' Reviews and Critics' Review
s :
0.4958437616066603
```

Q2. Average Duration vs. Certificate

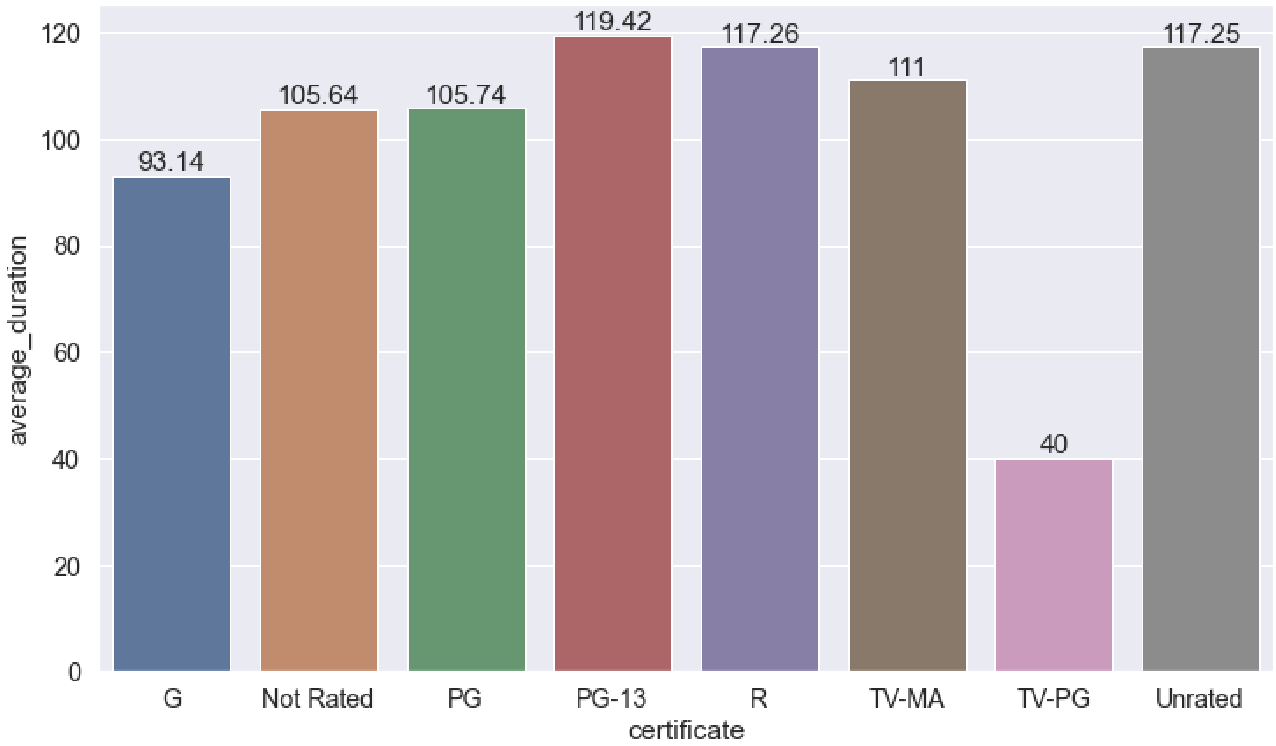
In [175]:
```
avgDuration_certificate = movie_df.groupby('certificate', as_index = False)['d
```

In [176]:
```
avgDuration_certificate['average_duration'] = round(avgDuration_certificate['a
avgDuration_certificate
```

Out[176]:

	certificate	average_duration
0	G	93.14
1	Not Rated	105.64
2	PG	105.74
3	PG-13	119.42
4	R	117.26
5	TV-MA	111.00
6	TV-PG	40.00
7	Unrated	117.25

In [177]:
```
plt.rcParams['figure.figsize'] = [12, 7]

bar_plt = sns.barplot(data = avgDuration_certificate, x = 'certificate', y = '

for i in bar_plt.containers:
    bar_plt.bar_label(i,)
```



The above bar plot signifies the "average duration" of movies in each of the "certificates" present in the movie industry.

We can find the below insights from the above graph:

1. 'PG-13' certified movies have the largest average duration of length with a value of around 119.42.
2. 'R' and 'Unrated' certified movies come next with average duration of about 117.26 and 117.25 respectively.
3. 'TV-PG' movies have the lowest average duration of 40 amongst all the certificates.

Q3. Genre split and histogram

Splitting the 'genre' column of the data set to retrieve the different genres every movie belong to.

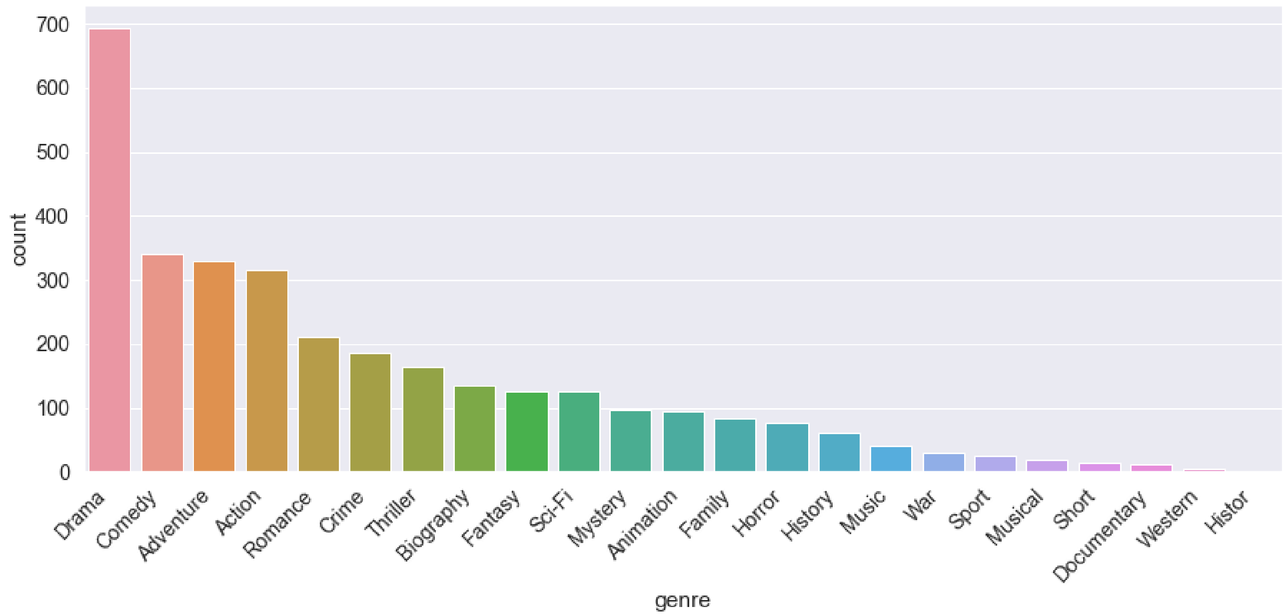
In [178]:
```
genre_movie_df = pd.DataFrame(movie_df['genre'].str.split('|', expand = False)
# genre_movie_df = movie_df['genre'].str.split('|', expand = False).explode().
# movie_df['genre'].str.split('|', expand = False).explode().value_counts()
```

In [179]:
```
genre_movie_df = genre_movie_df.reset_index()

genre_movie_df = genre_movie_df.rename(columns={'index':'genre', 'genre':'coun
genre_movie_df
```

Out[179]:

	genre	count
0	Drama	694
1	Comedy	341
2	Adventure	330
3	Action	315
4	Romance	211
5	Crime	186
6	Thriller	163
7	Biography	134
8	Fantasy	126
9	Sci-Fi	125
10	Mystery	97
11	Animation	94
12	Family	84
13	Horror	77
14	History	61
15	Music	41
16	War	30
17	Sport	26
18	Musical	19
19	Short	15
20	Documentary	11
21	Western	6
22	Histor	1

```
In [180]: plt.rcParams['figure.figsize'] = [15, 6]

hist_plot = sns.barplot(data = genre_movie_df, x = 'genre', y = 'count')
hist_plot.set_xticklabels(
    hist_plot.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



Plotting a histogram to check the frequency distribution of genres in the data set. We can find the below observations from the histogram:

1. 'Drama' genre has the highest frequency at around 694 which is more than twice the frequency of 2nd largest frequency of 341 belonging to 'Comedy' genre.
2. 'Histor' has the lowest frequency of 1 only. It means only one movie in the data set belongs to 'Histor' genre.

Part 2: Model Building

Q1. Removing "Oscar_Best_XXX_Won" except target variable. Keeping all except these.

```
In [181]: keep_columns = [
    "year", "movie", "movie_id", "certificate", "duration", "genre", "rate", ":
    "votes", "gross", "release_date", "user_reviews", "critic_reviews", "popul
    "awards_nominations", "Oscar_Best_Picture_won"
]

movie_df = movie_df[keep_columns]
```

In [182]:
```
movie_df.head(3)
```

Out[182]:

	year	movie	movie_id	certificate	duration	genre	rate	metascore	syno
0	2001	Kate & Leopold	tt0035423	PG-13	118	Comedy|Fantasy|Romance	6.4	44.0	An Eng Duke 187 inadvert dr
1	2000	Chicken Run	tt0120630	G	84	Animation|Adventure|Comedy	7.0	88.0	Wh cock appare flies ir chic
2	2005	Fantastic Four	tt0120667	PG-13	106	Action|Adventure|Family	5.7	40.0	A grou astron superpov afte

Q2. Convert Target Variable into Binary

In [183]:
```
movie_df['Oscar_Best_Picture_won'].value_counts()
```

Out[183]:
```
No      1217
Yes       18
Name: Oscar_Best_Picture_won, dtype: int64
```

In [139]:
```
movie_df['Oscar_Best_Picture_won'] = np.where(movie_df['Oscar_Best_Picture_won
movie_df['Oscar_Best_Picture_won'].value_counts()
```

Out[139]:
```
0    1217
1      18
Name: Oscar_Best_Picture_won, dtype: int64
```

Target Variable 'Oscar_Best_Picture_Won' has been converted with 0 and 1 values for 'No' and 'Yes' values resp.

Q3. Remove columns with high cardinality

In [184]:
```
movie_df.columns[ movie_df.nunique() / len(movie_df) > 0.70]
```

Out[184]:
```
Index(['movie', 'movie_id', 'synopsis', 'votes', 'gross', 'popularity'], dty
pe='object')
```

In [185]:
```
movie_df_mod = movie_df.drop(['movie', 'movie_id', 'synopsis', 'votes', 'gross
movie_df_mod.head(3)
```

Out[185]:

	year	certificate	duration	genre	rate	metascore	release_date	user_reviews	c
0	2001	PG-13	118	Comedy|Fantasy|Romance	6.4	44.0	2001-12-25	318.0	
1	2000	G	84	Animation|Adventure|Comedy	7.0	88.0	2000-06-23	361.0	
2	2005	PG-13	106	Action|Adventure|Family	5.7	40.0	2005-07-08	1008.0	

Features with high cardianlity (more than 70%) like 'movie', 'movie_id', 'synopsis', 'votes', 'gross', 'popularity' have been removed from the data set.

Q4. Test-Train Split

In [186]:
```
movie_df_mod['release_date'] = pd.to_datetime(movie_df_mod['release_date'])
```

In [187]:
```
movie_df_mod['release_year'] = movie_df_mod['release_date'].dt.year
```

Release Date has been used to extract the 'Year' of the movie.

In [188]:
```
movie_df_mod = movie_df_mod.drop(['year', 'release_date', 'genre', 'certificat
```

In [189]:
```
movie_df_mod.head(3)
```

Out[189]:

	duration	rate	metascore	user_reviews	critic_reviews	awards_wins	awards_nominations	Oscar_Bes
0	118	6.4	44.0	318.0	125.0	1	4	
1	84	7.0	88.0	361.0	186.0	5	11	
2	106	5.7	40.0	1008.0	278.0	0	0	

Checking NA values in the columns

In [190]:
```
movie_df_mod.isna().sum()
```

Out[190]:
```
duration                 0
rate                     0
metascore               29
user_reviews            14
critic_reviews          10
awards_wins              0
awards_nominations       0
Oscar_Best_Picture_won   0
release_year            30
dtype: int64
```

Dropping the NA values.

In [191]:
```
movie_df_mod = movie_df_mod.dropna()
movie_df_mod.isna().sum()
```

Out[191]:
```
duration                0
rate                    0
metascore               0
user_reviews            0
critic_reviews          0
awards_wins             0
awards_nominations      0
Oscar_Best_Picture_won  0
release_year            0
dtype: int64
```

In [192]:
```
train = movie_df_mod[movie_df_mod['release_year'] <= 2017]
test = movie_df_mod[movie_df_mod['release_year'] > 2017]
```

In [193]:
```
X_train = train.drop(['Oscar_Best_Picture_won'], axis = 1)
Y_train = train['Oscar_Best_Picture_won']

X_test = test.drop(['Oscar_Best_Picture_won'], axis = 1)
Y_test = test['Oscar_Best_Picture_won']
```

Q5 and Q6. Tree Based Model and Prediction --> Decision Tree Classifier

Converting 'release_date' into datetime field.

In [196]:
```
## Decision Tree Classifier
clf = DecisionTreeClassifier(criterion='entropy', max_depth = 5, min_samples_s
clf.fit(X_train, Y_train)
test_pred_decision_tree = clf.predict(X_test)
```

In [197]:
```
#get the confusion matrix
# confusion_matrix = confusion_matrix(Y_test, test_pred_decision_tree)

#turn this into a dataframe
# matrix_df = pd.DataFrame(confusion_matrix)
```

In [198]:
```
accuracy_score(Y_test, test_pred_decision_tree)
```

Out[198]:
```
0.9666666666666667
```

Observation - The accuracy of the training and the test set is almost similar, around 96%, indicating that the model is not over fitting.

In [201]:
```
labels = movie_df_mod['Oscar_Best_Picture_won']
```

In [202]:
```
#get the precision score
precision = precision_score(Y_test,
                            test_pred_decision_tree,
                            average=None)

#turn it into a dataframe
precision_results = pd.DataFrame(precision, index=labels.unique())

#rename the results column
precision_results.rename(columns={0:'precision'}, inplace =True)
precision_results
```

Out[202]:

	precision
No	1.0
Yes	0.0

In [203]:
```
recall = recall_score(Y_test, test_pred_decision_tree,
                              average =None)
recall_results = pd.DataFrame(recall, index= labels.unique())
recall_results.rename(columns ={0:'Recall'}, inplace =True)
recall_results
```

```
/Users/HarshitGaur/opt/anaconda3/lib/python3.8/site-packages/sklearn/metric
s/_classification.py:1248: UndefinedMetricWarning: Recall is ill-defined and
being set to 0.0 in labels with no true samples. Use `zero_division` paramet
er to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Out[203]:

	Recall
No	0.966667
Yes	0.000000

In [204]:
```
f1 = f1_score(Y_test, test_pred_decision_tree, average=None)
f1_results = pd.DataFrame(f1, index=labels.unique())
f1_results.rename(columns={0:'f1'}, inplace=True)
f1_results
```

Out[204]:

	f1
No	0.983051
Yes	0.000000