Type Detection on Amazon: Movie or TV Series?

This project aims to develop a machine learning model capable of automatically classifying products listed on Amazon as either movies or TV seasons. Leveraging a dataset of Amazon product titles and descriptions, we will employ natural language processing techniques and machine learning algorithms to predict the type of content each product represents. By automating this classification task, we aim to enhance the efficiency of content categorization, helping users easily find and purchase their desired movies and TV series on the platform.

Import Libraries

```
In [130]:
             import pandas as pd
              import numpy as np
              import matplotlib.pyplot as plt
              import seaborn as sns
              from wordcloud import WordCloud
              from sklearn.model selection import train test split
              from sklearn.feature extraction.text import CountVectorizer
              from sklearn.naive bayes import MultinomialNB
              from sklearn.svm import SVC
              from sklearn.metrics import accuracy_score, confusion_matrix, classification
              from sklearn.preprocessing import LabelEncoder
              from sklearn.ensemble import RandomForestClassifier
              from sklearn.neural network import MLPClassifier
              import nltk
              from nltk.corpus import stopwords
              from nltk.stem import PorterStemmer
              from nltk.stem import WordNetLemmatizer
              from nltk.tokenize import word tokenize
              import warnings
              warnings.filterwarnings('ignore')
```

Uploading CSV

uploading csy, storing in dataframe and displaying first 5 entries of dataframe

Out[131]:		show_id	type	title	director	cast	country	date_added	release_year	ratin
	0	s1	Movie	The Grand Seduction	Don McKellar	Brendan Gleeson, Taylor Kitsch, Gordon Pinsent	Canada	March 30, 2021	2014	Na
	1	s2	Movie	Take Care Good Night	Girish Joshi	Mahesh Manjrekar, Abhay Mahajan, Sachin Khedekar	India	March 30, 2021	2018	13
	2	s3	Movie	Secrets of Deception	Josh Webber	Tom Sizemore, Lorenzo Lamas, Robert LaSardo, R	United States	March 30, 2021	2017	Na
	3	s4	Movie	Pink: Staying True	Sonia Anderson	Interviews with: Pink, Adele, Beyoncé, Britney	United States	March 30, 2021	2014	Na
	4	s 5	Movie	Monster Maker	Giles Foster	Harry Dean Stanton, Kieran O'Brien, George Cos	United Kingdom	March 30, 2021	1989	Na
	4									•

.shape

returns a tuple representing the dimensions (number of rows and columns) of a pandas DataFrame.

```
In [132]: M df.shape
Out[132]: (9668, 12)
```

renaming and dropping

renaming column listen_in to genre and dropping column show_id.

Out[133]:

	type	title	director	cast	country	date_added	release_year	rating	duratio
0	Movie	The Grand Seduction	Don McKellar	Brendan Gleeson, Taylor Kitsch, Gordon Pinsent	Canada	March 30, 2021	2014	NaN	113 m
1	Movie	Take Care Good Night	Girish Joshi	Mahesh Manjrekar, Abhay Mahajan, Sachin Khedekar	India	March 30, 2021	2018	13+	110 m
2	Movie	Secrets of Deception	Josh Webber	Tom Sizemore, Lorenzo Lamas, Robert LaSardo, R	United States	March 30, 2021	2017	NaN	74 m
3	Movie	Pink: Staying True	Sonia Anderson	Interviews with: Pink, Adele, Beyoncé, Britney	United States	March 30, 2021	2014	NaN	69 m
4	Movie	Monster Maker	Giles Foster	Harry Dean Stanton, Kieran O'Brien, George Cos	United Kingdom	March 30, 2021	1989	NaN	45 m
4									•

.info

provides a concise summary of information about a pandas DataFrame, including data types, non-null counts, and memory usage.

```
In [134]:

    df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9668 entries, 0 to 9667
Data columns (total 11 columns):
                   Non-Null Count Dtype
 #
     Column
0
     type
                   9668 non-null
                                   object
 1
                                   object
     title
                   9668 non-null
 2
     director
                   7586 non-null
                                   object
 3
     cast
                   8435 non-null
                                   object
 4
     country
                   672 non-null
                                   object
 5
     date added
                   155 non-null
                                   object
 6
     release_year
                   9668 non-null
                                   int64
 7
                   9331 non-null
                                   object
     rating
 8
     duration
                   9668 non-null
                                   object
 9
     genre
                   9668 non-null
                                   object
    description
                   9668 non-null
                                   object
dtypes: int64(1), object(10)
```

memory usage: 831.0+ KB

features types

assinging and displaying features types.

```
In [135]:
           ▶ feature_types = {
                   'type': 'Nominal Categorical',
                   'title': 'Nominal Categorical',
                   'director': 'Nominal Categorical',
                   'cast': 'Nominal Categorical',
                   'country': 'Nominal Categorical',
                   'date_added': 'Nominal Categorical',
                   'release_year': 'Numerical',
                   'rating': 'Nominal Categorical',
                   'duration': 'Nominal Categorical',
                   'genre': 'Nominal Categorical',
                   'description': 'Nominal Categorical'
              }
              for column in df.columns:
                  if column in feature_types:
                       print(f"{column}: {feature_types[column]}")
                  else:
                      print(f"{column}: Not specified")
              type: Nominal Categorical
```

title: Nominal Categorical
director: Nominal Categorical
cast: Nominal Categorical
country: Nominal Categorical
date_added: Nominal Categorical
release_year: Numerical

rating: Nominal Categorical duration: Nominal Categorical genre: Nominal Categorical description: Nominal Categorical

missing data analysis

calculates and returns the count of missing (null) values for each column in a DataFrame, allowing for easy identification of data gaps.

```
In [136]:

    df.isnull().sum()

    Out[136]: type
                                    0
               title
                                    0
               director
                                 2082
               cast
                                 1233
               country
                                 8996
               date added
                                 9513
               release_year
                                    0
                                  337
               rating
               duration
                                    0
               genre
                                    0
               description
                                    0
               dtype: int64
```

dupliacted data analysis

calculates and returns the count of missing (null) values for each column in a DataFrame , helping to assess the impact of data removal on missing data patterns.

missing data percentage calculation

calculates and stores the percentage of missing (null) values for each column in a DataFrame (df). It divides the count of missing values by the total number of rows in the DataFrame and then rounds the result to two decimal places, providing insights into the proportion of missing data for each column.

```
In [138]:
              percentage = (df.isnull().sum() / df.shape[0] * 100).round(2)
              percentage
   Out[138]: type
                                0.00
              title
                                0.00
               director
                               21.53
                               12.75
               cast
               country
                               93.05
               date added
                               98.40
                                0.00
               release_year
                                3.49
               rating
                                0.00
               duration
                                0.00
               genre
               description
                                0.00
               dtype: float64
```

high-missing-value columns removal

columns_to_drop is a list of column names where the percentage of missing values exceeds 90%. These columns are then removed from the DataFrame df to create a new DataFrame

initial data preview

displays the top rows of the DataFrame, allowing a quick overview of its structure and content following the removal of high-missing-value columns.

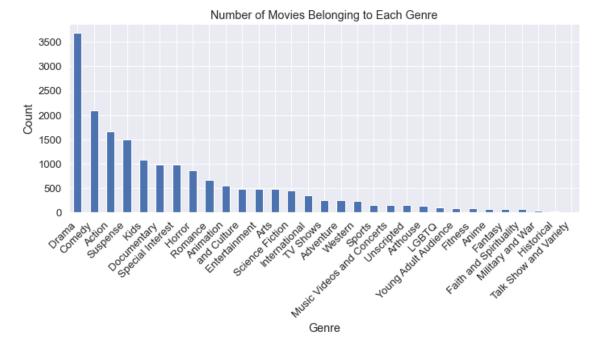
In [140]: df dropped.head() Out[140]: title type director cast release_year rating duration genre descri Brendan Α Gleeson. The f Don Taylor Comedy, Movie Grand 2014 NaN 113 min village McKellar Kitsch, Drama Seduction proc Gordon loc Pinsent Α Mahesh Take F Manjrekar, Care Girish Abhay Drama. decid Movie 2018 110 min 1 13+ Good Joshi Mahajan, International 1 Night Sachin Khedekar Cri Tom After a Sizemore, Action, Lorenzo disc Secrets of Josh 2 Movie 2017 NaN 74 min Lamas, Drama, his \ Deception Webber Robert Suspense cheati LaSardo, R... Interviews Pink b Pink: with: Pink, the Sonia Documentary Movie Staying Adele. 2014 NaN 69 min once a Anderson True Beyoncé. bringir Britney... Harry Te€ Dean Stanton, Monster Giles Drama, Ва Movie Kieran 1989 NaN 45 min Maker Foster Fantasy wa O'Brien, work George fa Cos...

missing value imputation

creates a new DataFrame by filling all missing values in the previous DataFrame with the string "unattainable," addressing missing data by replacing it with a specified placeholder value.

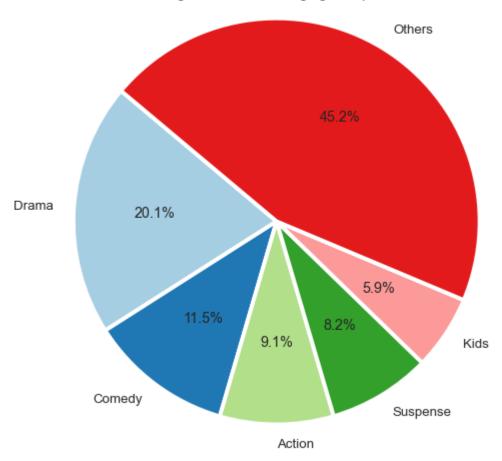
Visualizations

Genre Distribution of Movies



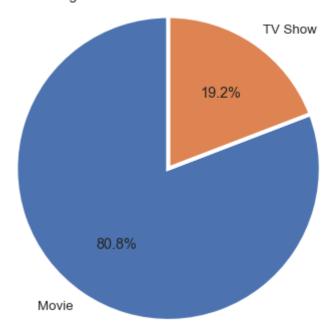
Top 4 Genre Distribution

Percentage of Movies Belonging to Top 4 Genres



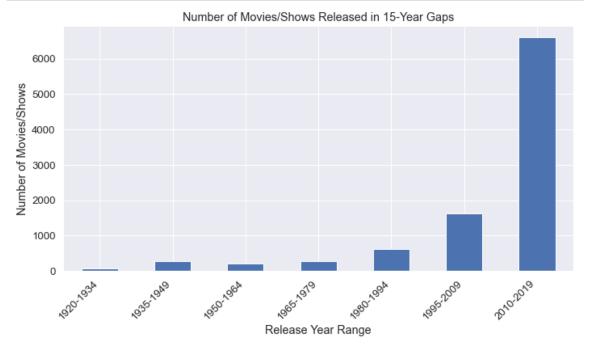
Percentage Distribution of Content Type

Percentage Distribution of Movies and TV Shows



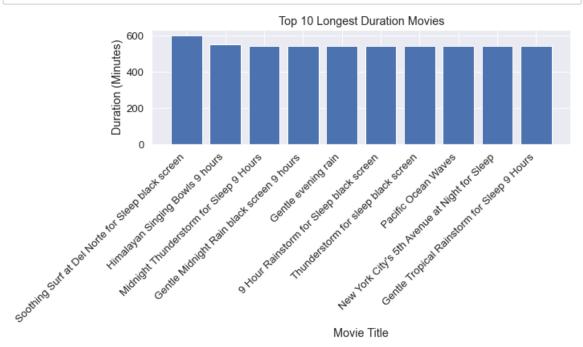
Number of Movies/Shows Released in 15-Year Intervals

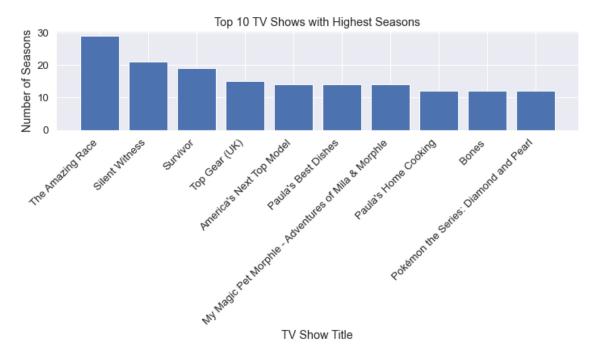
```
year gaps = range(min(df visualization['release year']), max(df visualizati
In [146]:
              labels = []
              for year in year_gaps:
                  if(year==2010):
                      labels.append(f"{year}-2019")
                  else:
                      labels.append(f"{year}-{year+14}")
              grouped_counts = df.groupby(pd.cut(df['release_year'], bins=[*year_gaps, f]
              plt.figure(figsize=(10, 6))
              grouped_counts.plot(kind='bar')
              plt.xlabel('Release Year Range')
              plt.ylabel('Number of Movies/Shows')
              plt.title('Number of Movies/Shows Released in 15-Year Gaps')
              plt.xticks(rotation=45, ha='right')
              plt.tight layout()
              plt.show()
```



Top 10 Longest Duration Movies and Top 10 TV Shows with Highest Seasons

```
In [147]:
             df visualization['num seasons'] = df visualization['duration'].str.extract(
             top 10 longest movies = df visualization[df visualization['type'] == 'Movie'
             top 10 highest seasons tv = df visualization[df visualization['type'] == '1
             plt.figure(figsize=(10, 6))
             plt.bar(top 10 longest movies['title'], top 10 longest movies['duration mir
             plt.xlabel('Movie Title')
             plt.ylabel('Duration (Minutes)')
             plt.title('Top 10 Longest Duration Movies')
             plt.xticks(rotation=45, ha='right')
             plt.tight layout()
             plt.show()
             plt.figure(figsize=(10, 6))
             plt.bar(top_10_highest_seasons_tv['title'], top_10_highest_seasons_tv['num]
             plt.xlabel('TV Show Title')
             plt.ylabel('Number of Seasons')
             plt.title('Top 10 TV Shows with Highest Seasons')
             plt.xticks(rotation=45, ha='right')
             plt.tight layout()
             plt.show()
             df_visualization.drop(['duration_minutes'], axis = 1, inplace = True)
             df_visualization.drop(['num_seasons'], axis = 1, inplace = True)
```





Most Common Words in Descriptions

Out[148]: <matplotlib.image.AxesImage at 0x1b887cccf40>

The Most Common Word in Description



label encoding for visualization

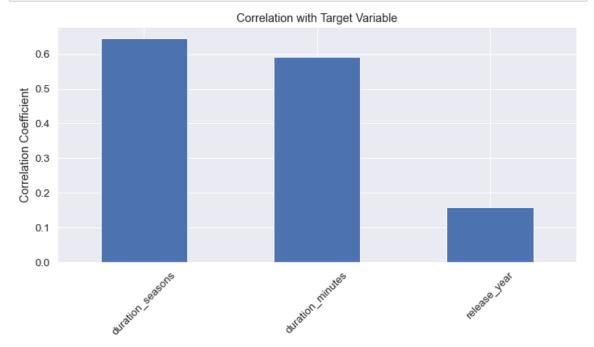
season duration transformation

```
#ransformation of TV show durations from 'duration' to 'duration minutes'
In [150]:
              average_season_duration = 400
              def seasons_to_minutes(row):
                  if 'Season' in row['duration']:
                      num seasons = int(row['duration'].split()[0])
                      return num_seasons * average_season_duration
                  return int(row['duration'].split()[0])
              def minutes_to_seasons(row):
                  if 'min' in row['duration']:
                      num minutes = int(row['duration'].split()[0])
                      return num minutes // average season duration
                  return int(row['duration'].split()[0])
              df_visualization['duration_minutes'] = df_visualization.apply(seasons_to_mi
              df_visualization['duration_seasons'] = df_visualization.apply(minutes_to_seasons')
              df_visualization.drop(['duration'], axis = 1, inplace = True)
```

Correlation Heatmap of Content Type, Release Year, and Duration



Correlation with Content Type



Data Preprocessing

Text Data Preprocessing Functions

These functions, text_preprocessing, remove_stop_words, stemming, and lemmatization, serve various text data preprocessing purposes:

- text_preprocessing: Tokenizes text, converts it to lowercase, and removes nonalphanumeric characters.
- 2. remove_stop_words: Removes common English stop words from the text.
- 3. stemming: Applies Porter stemming to reduce words to their root form.
- 4. lemmatization: Utilizes WordNet lemmatization to reduce words to their base or dictionary form.

```
In [154]:

    def text_preprocessing(text):

                  words = word tokenize(text)
                  words = [word.lower() for word in words]
                  words = [word for word in words if word.isalnum()]
                  return ' '.join(words)
              def remove stop words(text):
                  stop words = set(stopwords.words('english'))
                  words = word tokenize(text)
                  words = [word for word in words if word.lower() not in stop_words]
                  return ' '.join(words)
              def stemming(text):
                  stemmer = PorterStemmer()
                  words = word tokenize(text)
                  words = [stemmer.stem(word) for word in words]
                  return ' '.join(words)
              def lemmatization(text):
                  lemmatizer = WordNetLemmatizer()
                  words = word tokenize(text)
                  words = [lemmatizer.lemmatize(word) for word in words]
                  return ' '.join(words)
```

Text Data Vectorization and Integration

a CountVectorizer is used to convert text data from the column in the DataFrame into a numerical matrix title_matrix. The resulting matrix is then transformed into a DataFrame, with columns representing the unique words in the text. Finally, these word frequency features are concatenated with the original DataFrame before removing the previous column to create a consolidated dataset for further analysis.

One-Hot Encoding for Categorical Data

The apply_one_hot_encoding function is applied to the DataFrame for various categorical columns ('director', 'cast', 'rating', 'genre'). The process involves the following steps:

- 1. Adding an 'ID' column to uniquely identify rows.
- 2. Splitting the specified column by commas and creating multiple rows for each value using explode.
- 3. Creating one-hot encoded columns for each unique value in the exploded column.
- 4. Grouping by 'ID' and selecting the maximum value to consolidate the one-hot encoded data.
- 5. Dropping the original categorical column and the 'ID' column to obtain the final one-hot encoded representation for the specified column.

Model Preparing

Feature-Target Split

Train-Test Split

```
In [159]: ► X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rain_test_split(X, y, test_size=0.2,
```

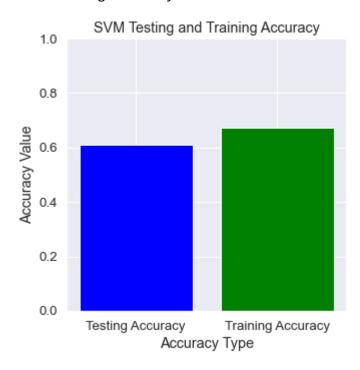
Model Training and Testing

Support Vector Machine (SVM) Classifier and Accuracy Visualization

A Support Vector Machine (SVM) classifier is trained and evaluated on the provided training and testing datasets (X_train, y_train, X_test, y_test). The classifier's accuracy on both the testing and training sets is calculated and displayed.

```
In [161]:
              svm_classifier = SVC(C=0.001)
              svm classifier.fit(X train, y train)
              svm preds = svm classifier.predict(X test)
              svm accuracy = accuracy score(y test, svm preds)
              svm train preds = svm classifier.predict(X train)
              svm_train_accuracy = accuracy_score(y_train, svm_train_preds)
              print(f"SVM Testing Accuracy: {svm_accuracy}")
              print(f"SVM Training Accuracy: {svm train accuracy}")
              categories = ['Testing Accuracy', 'Training Accuracy']
              values = [svm_accuracy, svm_train_accuracy]
              plt.bar(categories, values, color=['blue', 'green'])
              plt.xlabel('Accuracy Type')
              plt.ylabel('Accuracy Value')
              plt.title('SVM Testing and Training Accuracy')
              plt.ylim(0, 1) # Set the y-axis limits appropriately
              plt.show()
```

SVM Testing Accuracy: 0.61 SVM Training Accuracy: 0.6725

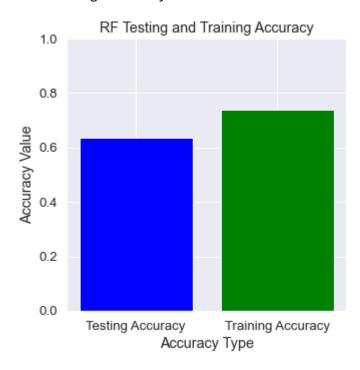


Random Forest Classification and Accuracy Visualization

A Random Forest classifier to the training data, calculates both testing and training accuracies, and then displays the results. It also visualizes the accuracies using a bar chart, illustrating the performance of the Random Forest model on the dataset.

```
In [162]:
          rf classifier.fit(X train, y train)
             rf preds = rf classifier.predict(X test)
             rf accuracy = accuracy score(y test, rf preds)
             rf_train_preds = rf_classifier.predict(X_train)
             rf_train_accuracy = accuracy_score(y_train, rf_train_preds)
             print(f"RF Testing Accuracy: {rf_accuracy}")
             print(f"RF Training Accuracy: {rf_train_accuracy}")
             categories = ['Testing Accuracy', 'Training Accuracy']
             values = [rf_accuracy, rf_train_accuracy]
             plt.bar(categories, values, color=['blue', 'green'])
             plt.xlabel('Accuracy Type')
             plt.ylabel('Accuracy Value')
             plt.title('RF Testing and Training Accuracy')
             plt.ylim(0, 1) # Set the y-axis limits appropriately
             plt.show()
```

RF Testing Accuracy: 0.635
RF Training Accuracy: 0.7375

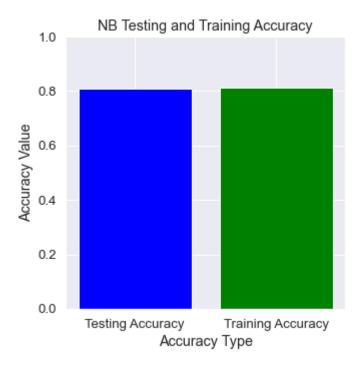


Naive Bayes Classification and Accuracy Visualization

A Multinomial Naive Bayes (NB) classifier with a specified alpha value is applied to the training data. It calculates and displays both testing and training accuracies for the NB model. The code also visualizes the accuracies using a bar chart, illustrating the performance of the NB model on the dataset.

```
▶ | nb_classifier = MultinomialNB(alpha=10)
In [164]:
              nb classifier.fit(X train, y train)
              nb preds = nb classifier.predict(X test)
              nb accuracy = accuracy score(y test, nb preds)
              nb train preds = nb classifier.predict(X train)
              nb_train_accuracy = accuracy_score(y_train, nb_train_preds)
              print(f"NB Testing Accuracy: {nb_accuracy}")
              print(f"NB Training Accuracy: {nb train accuracy}")
              categories = ['Testing Accuracy', 'Training Accuracy']
              values = [nb_accuracy, nb_train_accuracy]
              plt.bar(categories, values, color=['blue', 'green'])
              plt.xlabel('Accuracy Type')
              plt.ylabel('Accuracy Value')
              plt.title('NB Testing and Training Accuracy')
              plt.ylim(0, 1) # Set the y-axis limits appropriately
              plt.show()
```

NB Testing Accuracy: 0.81
NB Training Accuracy: 0.81375

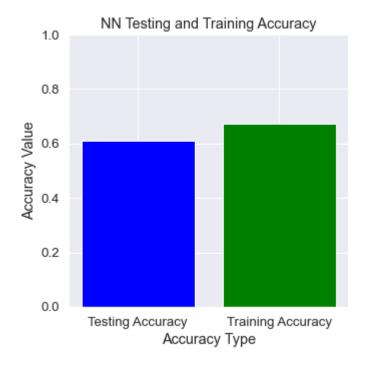


Neural Network Classification and Accuracy Visualization

A Multi-Layer Perceptron (MLP) classifier with specific hidden layer sizes and alpha value is applied to the training data. It calculates and displays both testing and training accuracies for the MLP model. Additionally, the code visualizes the accuracies using a bar chart, illustrating the performance of the Neural Network model on the dataset.

```
In [165]:
           ▶ nn classifier = MLPClassifier(hidden layer sizes=(64,32,16),alpha=1000)
              nn classifier.fit(X train, y train)
              nn preds = nn classifier.predict(X test)
              nn accuracy = accuracy score(y test, nn preds)
              nn_train_preds = nn_classifier.predict(X_train)
              nn_train_accuracy = accuracy_score(y_train, nn_train_preds)
              print(f"NN Testing Accuracy: {nn_accuracy}")
              print(f"NN Training Accuracy: {nn train accuracy}")
              categories = ['Testing Accuracy', 'Training Accuracy']
              values = [nn_accuracy, nn_train_accuracy]
              plt.bar(categories, values, color=['blue', 'green'])
              plt.xlabel('Accuracy Type')
              plt.ylabel('Accuracy Value')
              plt.title('NN Testing and Training Accuracy')
              plt.ylim(0, 1) # Set the y-axis limits appropriately
              plt.show()
```

NN Testing Accuracy: 0.61
NN Training Accuracy: 0.6725



In []: ▶