In-Class Assignment: Document Clustering

DATA 5420/6420

Name: Dallin Moore

In this in-class assignment we will utilize the same `TMDB movies dataset` as we did in the previous activity, however, we will now group movies together based off of different clustering methods. We will examine the pros and cons of these different methods and consider the different ways that they group together movies of similar taglines and overviews.

We begin as always by loading our required dependencies, loading in the dataset, and performing some cleaning/preporcessing steps.

```
import pandas as pd
import nltk
import re
import numpy as np

nltk.download('stopwords')
nltk.download('punkt')

!pip install kneed
from kneed import KneeLocator

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.cluster import AffinityPropagation

from scipy.cluster.hierarchy import ward, dendrogram
import matplotlib.pyplot as plt

from collections import Counter
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
Requirement already satisfied: kneed in /usr/local/lib/python3.10/dist-packages (0.8.5)
Requirement already satisfied: numpy>=1.14.2 in /usr/local/lib/python3.10/dist-packages (from kneed) (1.25.2)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from kneed) (1.11.4)
```

```
df = pd.read_csv("/content/tmdb_5000_movies.csv") # read in dataset
df.info() # check for missing observations
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4802 entries, 0 to 4801
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   budget                4802 non-null   int64  
 1   genres                4802 non-null   object 
 2   homepage              1712 non-null   object 
 3   id                    4802 non-null   int64  
 4   keywords              4802 non-null   object 
 5   original_language     4802 non-null   object 
 6   original_title        4802 non-null   object 
 7   overview              4799 non-null   object 
 8   popularity            4802 non-null   float64
 9   production_companies  4802 non-null   object 
 10  production_countries  4802 non-null   object 
 11  release_date          4801 non-null   object 
 12  revenue               4802 non-null   int64  
 13  runtime               4800 non-null   float64
 14  spoken_languages      4802 non-null   object 
 15  status                4802 non-null   object 
 16  tagline               3958 non-null   object 
 17  title                 4802 non-null   object 
 18  vote_average          4802 non-null   float64
 19  vote_count            4802 non-null   int64  
dtypes: float64(3), int64(4), object(13)
memory usage: 750.4+ KB
```

```
df = df[['title', 'tagline', 'overview', 'genres', 'popularity']]
df.tagline.fillna('', inplace=True)
df['description'] = df['tagline'].map(str) + ' ' + df['overview']
df.dropna(inplace=True)
```

```
<ipython-input-4-26d2589c0cc6>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
  df.tagline.fillna('', inplace=True)
<ipython-input-4-26d2589c0cc6>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
  df['description'] = df['tagline'].map(str) + ' ' + df['overview']
<ipython-input-4-26d2589c0cc6>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
  df.dropna(inplace=True)
```

```
stop_words = nltk.corpus.stopwords.words('english')

def normalize_document(doc):
    doc = re.sub(r'[^a-zA-Z0-9\s]', '', doc, re.I|re.A)                          # lower case and remove special characters\whi
    doc = doc.lower()
    doc = doc.strip()
    tokens = nltk.word_tokenize(doc)                                              # tokenize document
    filtered_tokens = [token for token in tokens if token not in stop_words]     # filter stopwords out of document
    doc = ' '.join(filtered_tokens)                                               # re-create document from filtered tokens
    return doc

normalize_corpus = np.vectorize(normalize_document)

norm_corpus = normalize_corpus(list(df['description']))
len(norm_corpus)
```

```
4799
```

```
norm_corpus[0:3]
```

```
array(['enter world pandora 22nd century paraplegic marine dispatched moon pandora unique mission becomes torn following orders
protecting alien civilization',
       'end world adventure begins captain barbossa long believed dead come back life headed edge earth turner elizabeth swann nothing
quite seems',
       'plan one escapes cryptic message bonds past sends trail uncover sinister organization battles political forces keep secret
service alive bond peels back layers deceit reveal terrible truth behind spectre'],
      dtype='<U803')
```

1) Cluster Similar Movies - K-Means Clustering Analysis

We first begin with clustering movies via KMeans, a type of partition-based clustering. The pipeline for performing this analysis includes:

- Feature Engineering
- Clustering using Kmeans algorithm
- Find an optimal value for K
- Preparing movie clusters

Similarity analysis was one way of grouping together movies, clustering analysis serves as a different approach. Let's see how these methods differ...

> ### A) Feature Engineering - TF-IDF

```
stop_words = stop_words + ['one', 'two', 'get']
tv = TfidfVectorizer(ngram_range=(2,2), min_df=2, max_df=0.7, stop_words=stop_words) # apply countvectorizer to norm_corpus, unigrams and bi
tv_matrix = tv.fit_transform(norm_corpus)
tv_matrix.shape
```

```
(4799, 8710)
```

Let's talk through some of these parameters in our TfidfVectorizer method...

Because movie descriptions contain lots of bigrams that describe the plot (ex. 'high school'), we will just focus of bigrams to keep the nubmer of features lower. For this dataset, 'one', 'two', and 'get' are all common stop words not included in our normal stop words list, so they will be added.

B) Clustering using KMeans

K must be user defined, and it can be difficult to know where to start in terms of the number of clusters. We'll try k = 3 first, then utilize a more empirical method of determining the optimal number of clusters.

```
km = KMeans(n_clusters=3,
            max_iter=10000,
            n_init= 50,
            random_state = 42).fit(tv_matrix)
Counter(km.labels_)
```

```
Counter({0: 4629, 2: 72, 1: 98})
```

What is the distribution of movie clusters looking like?

With 3 clusters, the first cluster contains a lot of the movies, arguably too many. To even them out we will probably just need to increase the number of clusters, which will find using the elbow rule.

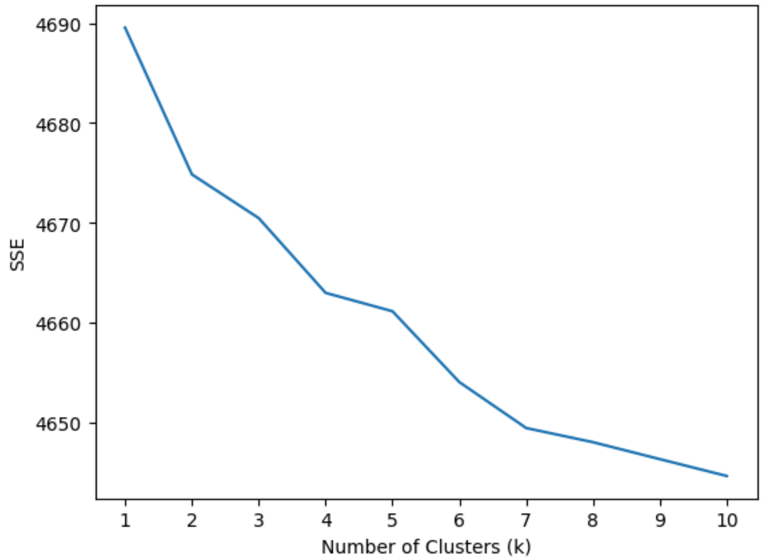
C) Find the optimal value for K - Elbow rule

We started off with 6 clusters, but perhaps there is a more optimal number. Let's examine a range of k values and use the Elbow rule method using the `KneeLocator` method to guide our selection of k.

```
kmeans_kwargs = {       # create a kmeans initialization dictionary
    "init": "random",
    "n_init": 10,
    "max_iter": 300,
    "random_state": 42,
}

sse = []                # create empty list for SSE values
for k in range(1,11):   # create loop to fit kmeans clustering analysis of k of size 1-11, add SSE values for each model to the list
  kmeans = KMeans(n_clusters=k, **kmeans_kwargs)
  kmeans.fit(tv_matrix)
  sse.append(kmeans.inertia_)


# create elbow plot
plt.plot(range(1,11), sse)
plt.xticks(range(1,11))
plt.xlabel("Number of Clusters (k)")
plt.ylabel("SSE")
plt.show()
```




```
kl = KneeLocator(range(1,11), sse, curve = 'convex', direction = 'decreasing')
kl.elbow
```

```
6
```

Now let's rerun our Kmeans with the optimal number of clusters...

```
km = KMeans(n_clusters=6,
            max_iter=10000,
            n_init= 50,
            random_state = 42).fit(tv_matrix)
Counter(km.labels_)
```

```
Counter({0: 4260, 5: 191, 1: 180, 2: 104, 3: 15, 4: 49})
```

D) Prepare Movie Clusters

Now let's get an idea of the characteristics of each cluster by pulling popular examples of movies within each of the clusters...

```
df['kmeans_cluster'] = km.labels_                                                  # assign cluster labels to new column in df

movie_clusters = (df[['title', 'kmeans_cluster', 'popularity']]                   # great a movie clusters df from title, cluster, and pop
                  .sort_values(by=['kmeans_cluster', 'popularity'],               # sort in descending order of cluster and popularity
                               ascending=False)
                  .groupby('kmeans_cluster').head(20))                            # group by cluster, show top 20 movies
movie_clusters = movie_clusters.copy(deep=True)
movie_clusters
```

	title	kmeans_cluster	popularity
238	Teenage Mutant Ninja Turtles	5	143.350376
362	Pixels	5	140.849495
2731	The Godfather: Part II	5	105.792936
298	The Wolf of Wall Street	5	95.007934
1366	The Devil Wears Prada	5	83.893257
...	...	...	...
124	Frozen	0	165.125366
9	Batman v Superman: Dawn of Justice	0	155.790452
0	Avatar	0	150.437577
662	Fight Club	0	146.757391
12	Pirates of the Caribbean: Dead Man's Chest	0	145.847379

115 rows × 3 columns

Next steps: View recommended plots

```
feature_names = tv.get_feature_names_out()
topn_features = 15
ordered_centroids = km.cluster_centers_.argsort()[:, ::-1]


for cluster_num in range(0,6):
    key_features = [feature_names[index]
                        for index in ordered_centroids[cluster_num, :topn_features]]
    movies = movie_clusters[movie_clusters['kmeans_cluster'] == cluster_num]['title'].values.tolist()
    print('CLUSTER #'+str(cluster_num+1))
    print('Key Features:', key_features)
    print('Popular Movies:', movies)
    print('-'*80)
```

```
CLUSTER #1
Key Features: ['world war', 'small town', 'young man', 'best friend', 'young woman', 'war ii', 'united states', 'along way', 'tells stor
Popular Movies: ['Minions', 'Interstellar', 'Deadpool', 'Guardians of the Galaxy', 'Mad Max: Fury Road', 'Jurassic World', 'Pirates of t
--------------------------------------------------------------------------------
CLUSTER #2
Key Features: ['high school', 'los angeles', 'school seniors', 'school student', 'best friend', 'angeles police', 'school senior', 'scho
Popular Movies: ['Terminator Genisys', 'Blade Runner', 'The Amazing Spider-Man 2', 'Spider-Man', 'Grease', 'Chronicle', 'Nerve', 'The It
--------------------------------------------------------------------------------
CLUSTER #3
Key Features: ['true story', 'based true', 'world war', 'incredible true', 'amazing true', 'extraordinary true', 'drama based', 'based i
Popular Movies: ["Schindler's List", '12 Years a Slave', 'The Pursuit of Happyness', 'Catch Me If You Can', 'The Conjuring 2', 'Apollo 1
--------------------------------------------------------------------------------
CLUSTER #4
Key Features: ['order save', 'save beloved', 'save daughter', 'save world', 'monkey king', 'taking place', 'man obsessed', 'named mr', '
Popular Movies: ['Pompeii', 'Ghost Rider', 'Epic', "My Sister's Keeper", 'Conspiracy Theory', 'Your Highness', 'Spy Kids: All the Time i
--------------------------------------------------------------------------------
CLUSTER #5
Key Features: ['falls love', 'quickly falls', 'singer falls', 'man falls', 'high society', 'working class', 'like anything', 'new york',
Popular Movies: ['The Girl Next Door', 'Ponyo', 'Scott Pilgrim vs. the World', "Singin' in the Rain", 'Meet Joe Black', 'Annie Hall', 'A
--------------------------------------------------------------------------------
CLUSTER #6
Key Features: ['new york', 'york city', 'party new', 'streets new', 'set new', 'family new', 'travel new', 'los angeles', 'upstate new',
Popular Movies: ['Teenage Mutant Ninja Turtles', 'Pixels', 'The Godfather: Part II', 'The Wolf of Wall Street', 'The Devil Wears Prada',
--------------------------------------------------------------------------------
```

How might you (briefly) describe each of these clusters based on their key features and the top popular movies within them?

- Cluster 1: Blockbusters Action Films
- Cluster 2: High School Drama
- Cluster 3: True Story Drama
- Cluster 4: Epic Adventures
- Cluster 5: Romantic & Whimsical
- Cluster 6: New York City Life

2) Affinity Propagation

Now let's try out a different clustering method, affinity propagation. Remember that this method does not require the user to specify the number of clusters; it does this automatically by finding exemplar observations that can well represent other data points in their cluster.

Because affinity propagation can often lead to the creation of many clusters, we will only examine the top 10 most common (largest) clusters...

A) First we will convert our tv_matrix into consine similarity values

```
# get cosine similarity features from tv_matrix
cosine_sim_features = cosine_similarity(tv_matrix)
```

B) Fit the Model to the features

Keep in mind that one of the downsides of Affinity Propagation is that its computationally expensive, so it runs pretty slow. It took mine over 2 minutes to execute.

```
# fit affinity propagation for 1000 iterations
%%time
ap = AffinityPropagation(max_iter=500)
ap.fit(cosine_sim_features)
res = Counter(ap.labels_)
res.most_common(10)
```

```
CPU times: user 2min 28s, sys: 2.15 s, total: 2min 30s
Wall time: 2min 47s
[(3, 3858),
 (34, 50),
 (117, 28),
 (98, 27),
 (119, 26),
 (144, 23),
 (64, 18),
 (58, 18),
 (112, 17),
 (60, 16)]
```

Wow that's a lot of different clusters! How might this impact the interpretability/usefulness of the clustering analysis? Are there benefits to having a larger number of small clusters vs. a small number of large clusters?

For this dataset and how we are using it (labeling the clusters ourselves, etc.), fewer clusters is definitely advantageous. However, if we just wanted to recommend a group of movies to watch after watching one movie, this could be useful. The clusters would be smaller and the movies more similar making it better to recommend the whole cluster.

C) Produce the most popular movies per top 10 clusters

```
df['affprop_cluster'] = ap.labels_
filtered_clusters = [item[0] for item in res.most_common(8)] # top 8 most common clusters
filtered_df = df[df['affprop_cluster'].isin(filtered_clusters)]
movie_clusters = (filtered_df[['title', 'affprop_cluster', 'popularity']]
                  .sort_values(by=['affprop_cluster', 'popularity'],
                               ascending=False)
                  .groupby('affprop_cluster').head(20))
movie_clusters = movie_clusters.copy(deep=True)

# get exemplars
exemplars = df.loc[ap.cluster_centers_indices_]['title'].values.tolist() # the top movies for each cluster

# get movies belonging to each cluster
for cluster_num in filtered_clusters:
    movies = movie_clusters[movie_clusters['affprop_cluster'] == cluster_num]['title'].values.tolist()
    exemplar_movie = df[df.index == ap.cluster_centers_indices_[cluster_num]]['title'].values[0]
    print('CLUSTER #'+str(cluster_num))
    print('Exemplar:', exemplar_movie)
    print('Popular Movies:', movies)
    print('-'*80)
```

```
CLUSTER #3
Exemplar: The Great Gatsby
Popular Movies: ['Minions', 'Interstellar', 'Deadpool', 'Guardians of the Galaxy', 'Mad Max: Fury Road', 'Jurassic World', 'Pirates of t
--------------------------------------------------------------------------------
CLUSTER #34
Exemplar: Morning Glory
Popular Movies: ['Teenage Mutant Ninja Turtles', 'I Am Legend', 'Taxi Driver', 'How to Be Single', 'The Mortal Instruments: City of Bone
--------------------------------------------------------------------------------
CLUSTER #117
Exemplar: Gone with the Wind
Popular Movies: ['Apollo 13', 'GoodFellas', 'The Big Short', 'Black Mass', 'Into the Wild', 'The Blair Witch Project', '50/50', 'The Ins
--------------------------------------------------------------------------------
CLUSTER #98
Exemplar: The Devil's Rejects
Popular Movies: ['Terminator Genisys', 'Blade Runner', 'The Italian Job', 'Speed', 'The Big Lebowski', 'Inherent Vice', 'Fear and Loathi
--------------------------------------------------------------------------------
CLUSTER #119
Exemplar: In Cold Blood
Popular Movies: ['The Imitation Game', 'Fury', 'Inglourious Basterds', 'The Notebook', 'Hellboy', 'The Thin Red Line', 'Valkyrie', 'The
--------------------------------------------------------------------------------
CLUSTER #144
Exemplar: Mad Hot Ballroom
Popular Movies: ['Pixels', 'King Kong', "Madagascar 3: Europe's Most Wanted", 'Whatever Works', 'Runaway Bride', 'The Siege', 'Synecdoch
--------------------------------------------------------------------------------
CLUSTER #64
Exemplar: Max
Popular Movies: ['No Strings Attached', 'Master and Commander: The Far Side of the World', 'Hairspray', 'Ben-Hur', 'Bridesmaids', 'Max',
--------------------------------------------------------------------------------
CLUSTER #58
Exemplar: Footloose
Popular Movies: ['The Iron Giant', 'Groundhog Day', 'Gremlins', 'Seven Samurai', 'A Nightmare on Elm Street', 'Footloose', 'Rock of Ages
--------------------------------------------------------------------------------
```

This is of course a larger number of clusters than we developed using KMeans, but what are some interesting differences in the way that these two algorithms grouped similar movies?

The way that some movies are grouped is still surprising, and possibly different than how a human would do it. However, by looking at the exemplar movie and reviewing the description, it lends some insight into why it represents the other movies. I think that this could again be an excellent way to recommend similar movies that the viewer might like.

3) Ward's Hierarchical Clustering

Finally we apply a hiearchical clustering method using cosine distance as our similarity metric and Ward as our linkage function. We will take the following steps in generating a hierarchy of similar movie clusters:

- A) Convert our cosine similarity features to a cosine distance matrix
- B) Calculte a linkage_matrix using `ward` to apply the Ward's linkage criterion
- C) Plot the hierarchical structure of clusters as a dendrogram

> ### A & B) Convert the cosine similarity features to cosine distance matrix and calculate linkage matrix

```
def ward_hierarchical_clustering(feature_matrix):
    cosine_distance = 1 - cosine_similarity(feature_matrix)
    linkage_matrix = ward(cosine_distance)
    return linkage_matrix

linkage_matrix = ward_hierarchical_clustering(tv_matrix)
```

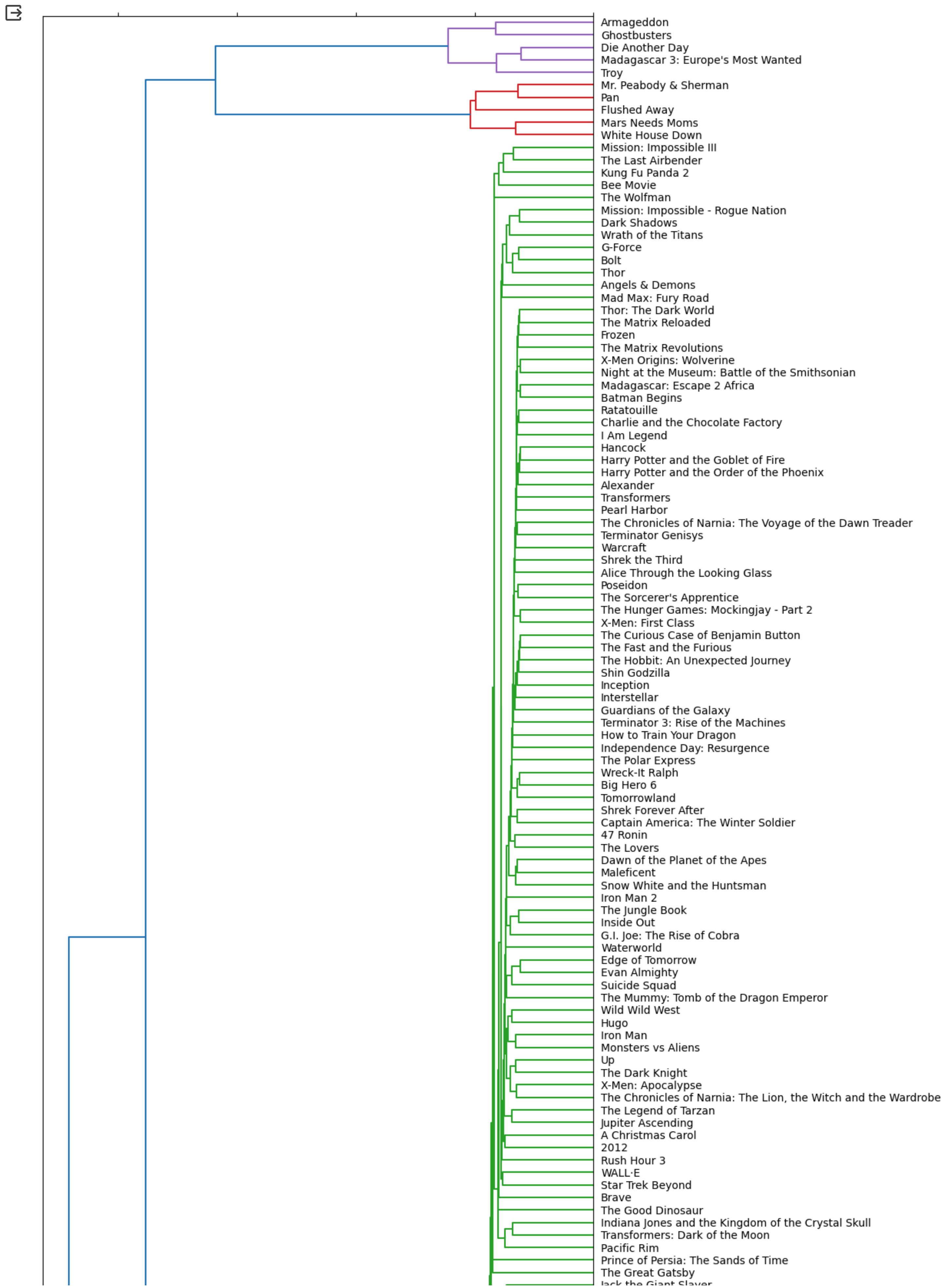
```
linkage_matrix
```

```
array([[4.90000000e+01, 1.57000000e+02, 0.00000000e+00, 2.00000000e+00],
       [1.77000000e+02, 4.79900000e+03, 0.00000000e+00, 3.00000000e+00],
       [2.08000000e+02, 4.80000000e+03, 0.00000000e+00, 4.00000000e+00],
       ...,
       [9.57000000e+03, 9.58000000e+03, 1.58976462e+01, 1.67000000e+02],
       [9.59300000e+03, 9.59400000e+03, 1.88459628e+01, 4.63600000e+03],
       [9.58500000e+03, 9.59500000e+03, 2.20775609e+01, 4.79900000e+03]])
```

C) Plot Hierarchical Structure of Movies as a Dendrogram

```
def plot_hierarchical_clusters(linkage_matrix, movie_data, p=100, figure_size=(8,12)):
    fig, ax = plt.subplots(figsize=figure_size)
    movie_titles = movie_data['title'].values.tolist()
    R = dendrogram(linkage_matrix, orientation="left", labels=movie_titles,
                   truncate_mode='lastp',
                   p=p,
                   no_plot=True)
    temp = {R["leaves"][ii]: movie_titles[ii] for ii in range(len(R["leaves"]))}
    def llf(xx):
        return "{}".format(temp[xx])
    ax = dendrogram(
            linkage_matrix,
            truncate_mode='lastp',
            orientation="left",
            p=p,
            leaf_label_func=llf,
            leaf_font_size=10.,
            )
    plt.tick_params(axis= 'x',
                   which='both',
                   bottom='off',
                   top='off',
                   labelbottom='off')
    plt.tight_layout()
    plt.savefig('movie_hierachical_clusters.png', dpi=200)
```

```
plot_hierarchical_clusters(linkage_matrix,
                           p = 150,
                           movie_data = df,
                           figure_size=(12,25))
```


Armageddon
Ghostbusters
Die Another Day
Madagascar 3: Europe's Most Wanted
Troy
Mr. Peabody & Sherman
Pan
Flushed Away
Mars Needs Moms
White House Down
Mission: Impossible III
The Last Airbender
Kung Fu Panda 2
Bee Movie
The Wolfman
Mission: Impossible - Rogue Nation
Dark Shadows
Wrath of the Titans
G-Force
Bolt
Thor
Angels & Demons
Mad Max: Fury Road
Thor: The Dark World
The Matrix Reloaded
Frozen
The Matrix Revolutions
X-Men Origins: Wolverine
Night at the Museum: Battle of the Smithsonian
Madagascar: Escape 2 Africa
Batman Begins
Ratatouille
Charlie and the Chocolate Factory
I Am Legend
Hancock
Harry Potter and the Goblet of Fire
Harry Potter and the Order of the Phoenix
Alexander
Transformers
Pearl Harbor
The Chronicles of Narnia: The Voyage of the Dawn Treader
Terminator Genisys
Warcraft
Shrek the Third
Alice Through the Looking Glass
Poseidon
The Sorcerer's Apprentice
The Hunger Games: Mockingjay - Part 2
X-Men: First Class
The Curious Case of Benjamin Button
The Fast and the Furious
The Hobbit: An Unexpected Journey
Shin Godzilla
Inception
Interstellar
Guardians of the Galaxy
Terminator 3: Rise of the Machines
How to Train Your Dragon
Independence Day: Resurgence
The Polar Express
Wreck-It Ralph
Big Hero 6
Tomorrowland
Shrek Forever After
Captain America: The Winter Soldier
47 Ronin
The Lovers
Dawn of the Planet of the Apes
Maleficent
Snow White and the Huntsman
Iron Man 2
The Jungle Book
Inside Out
G.I. Joe: The Rise of Cobra
Waterworld
Edge of Tomorrow
Evan Almighty
Suicide Squad
The Mummy: Tomb of the Dragon Emperor
Wild Wild West
Hugo
Iron Man
Monsters vs Aliens
Up
The Dark Knight
X-Men: Apocalypse
The Chronicles of Narnia: The Lion, the Witch and the Wardrobe
The Legend of Tarzan
Jupiter Ascending
A Christmas Carol
2012
Rush Hour 3
WALL·E
Star Trek Beyond
Brave
The Good Dinosaur
Indiana Jones and the Kingdom of the Crystal Skull
Transformers: Dark of the Moon
Pacific Rim
Prince of Persia: The Sands of Time
The Great Gatsby
Jack the Giant Slayer