NLP Section - Movies recommendation system (Capstone project)

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```
#!pip install ydata-profiling
```

```
import pandas as pd
import numpy as np

#EDA Profiling library
#from ydata_profiling import ProfileReport
```

```
# load movie dataset from Google Drive using pandas

from google.colab import drive
drive.mount('/content/drive')

# Load CSV file
df = pd.read_csv('/content/drive/MyDrive/Capstone_Project/movies.csv')

df.head(3)
```

```
Mounted at /content/drive
```

	budget	genres	homepage	id	keywords	original_language	original_title	overview	popularity	production_companies	production_countries	release_date	revenue	runtime	spoken_languages	status	tagline	title	vote_average	vote_count
0	237000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	http://www.avatarmovie.com/	19995	[{"id": 1463, "name": "culture clash"}, {"id":...	en	Avatar	In the 22nd century, a paraplegic Marine is di...	150.437577	[{"name": "Ingenious Film Partners", "id": 289...	[{"iso_3166_1": "US", "name": "United States o...	2009-12-10	2787965087	162.0	[{"iso_639_1": "en", "name": "English"}, {"iso...	Released	Enter the World of Pandora.	Avatar	7.2	11800
1	300000000	[{"id": 12, "name": "Adventure"}, {"id": 14, "...	http://disney.go.com/disneypictures/pirates/	285	[{"id": 270, "name": "ocean"}, {"id": 726, "na...	en	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	139.082615	[{"name": "Walt Disney Pictures", "id": 2}, {"...	[{"iso_3166_1": "US", "name": "United States o...	2007-05-19	961000000	169.0	[{"iso_639_1": "en", "name": "English"}]	Released	At the end of the world, the adventure begins.	Pirates of the Caribbean: At World's End	6.9	4500
2	245000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	http://www.sonypictures.com/movies/spectre/	206647	[{"id": 470, "name": "spy"}, {"id": 818, "name...	en	Spectre	A cryptic message from Bond’s past sends him o...	107.376788	[{"name": "Columbia Pictures", "id": 5}, {"nam...	[{"iso_3166_1": "GB", "name": "United Kingdom"...	2015-10-26	880674609	148.0	[{"iso_639_1": "fr", "name": "Fran\u00e7ais"},...	Released	A Plan No One Escapes	Spectre	6.3	4466

```
df.dtypes
```

	0
budget	int64
genres	object
homepage	object
id	int64
keywords	object
original_language	object
original_title	object
overview	object
popularity	float64
production_companies	object
production_countries	object
release_date	object
revenue	int64
runtime	float64
spoken_languages	object
status	object
tagline	object
title	object
vote_average	float64
vote_count	int64

dtype: object

```
# I created this function after the initial trainings as I realized a json string is not a good strategy, JSON needs to be parse for better results
import ast

# clean function for genre and keyword fields
def extract_names(json_str):
    try:
        items = ast.literal_eval(json_str)
        return " ".join([item['name'] for item in items if 'name' in item])
    except (ValueError, SyntaxError):
        return ""
```

```
profile = ProfileReport(df, title="Pandas Profiling Report", explorative=True)
profile.to_notebook_iframe()
```

Recommendation Models Section : TF-IDF , BERT and LSTM

TERM Frequency-Inverse Document Frequency Recommendation system using the following logic:

- Combining features like genres, keywords, and overview text into a single string for each movie.
- Converting text into vectors using this techniques: TF-IDF (Term Frequency-Inverse Document Frequency) and CountVectorizer.
- Calculating similarity between movies using cosine similarity.
- Returning the top-N most similar movies for a given input movie.

```
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import nltk
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import MinMaxScaler

nltk.download('stopwords')
stop_words = set(stopwords.words('english'))
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
df_clean = df[['title', 'overview', 'genres', 'keywords', 'popularity', 'release_date']].dropna()

# format JSON strings from genre and keyboards
df_clean['genres'] = df_clean['genres'].apply(extract_names)
df_clean['keywords'] = df_clean['keywords'].apply(extract_names)

# Get the from each
df_text = df_clean[['title', 'overview', 'genres', 'keywords']]
df_text.dropna(inplace=True)
```

```
/tmp/ipython-input-23-227816985.py:9: 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-copy
  df_text.dropna(inplace=True)
```

```
df_text.head()
```

	title	overview	genres	keywords
0	Avatar	In the 22nd century, a paraplegic Marine is di...	Action Adventure Fantasy Science Fiction	culture clash future space war space colony so...
1	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	Adventure Fantasy Action	ocean drug abuse exotic island east india trad...
2	Spectre	A cryptic message from Bond’s past sends him o...	Action Adventure Crime	spy based on novel secret agent sequel mi6 bri...
3	The Dark Knight Rises	Following the death of District Attorney Harve...	Action Crime Drama Thriller	dc comics crime fighter terrorist secret ident...
4	John Carter	John Carter is a war-weary, former military ca...	Action Adventure Science Fiction	based on novel mars medallion space travel pri...

```
# Combine text into a single feature
def combine_features(row):
    return f"{row['overview']} {row['genres']} {row['keywords']}"
```

```
df_text['combined_text'] = df_text.apply(combine_features, axis=1)
```

```
/tmp/ipython-input-25-851857547.py:5: 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-copy
  df_text['combined_text'] = df_text.apply(combine_features, axis=1)
```

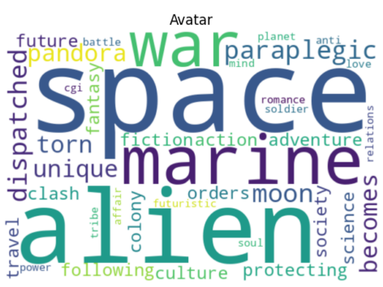
```
df_text.head()
```

	title	overview	genres	keywords	combined_text
0	Avatar	In the 22nd century, a paraplegic Marine is di...	Action Adventure Fantasy Science Fiction	culture clash future space war space colony so...	In the 22nd century, a paraplegic Marine is di...
1	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	Adventure Fantasy Action	ocean drug abuse exotic island east india trad...	Captain Barbossa, long believed to be dead, ha...
2	Spectre	A cryptic message from Bond’s past sends him o...	Action Adventure Crime	spy based on novel secret agent sequel mi6 bri...	A cryptic message from Bond’s past sends him o...
3	The Dark Knight Rises	Following the death of District Attorney Harve...	Action Crime Drama Thriller	dc comics crime fighter terrorist secret ident...	Following the death of District Attorney Harve...
4	John Carter	John Carter is a war-weary, former military ca...	Action Adventure Science Fiction	based on novel mars medallion space travel pri...	John Carter is a war-weary, former military ca...

```
df_text['combined_text'][0]
```

```
'In the 22nd century, a paraplegic Marine is dispatched to the moon Pandora on a unique mission, but becomes torn between following orders and protecting an alien civilization. Action Adventure Fantasy Science Fiction culture clash future space war space colony society space travel futuristic romance space alien tribe alien planet cgi marine soldier battle love affai
r anti war power relations mind and soul 3d'
```

```
# Remove stop words and Word Cloud for 5 movies (reference purposes only)
def clean_text(text):
    tokens = text.lower().split()
    return " ".join([word for word in tokens if word not in stop_words and word.isalpha()])

df_text['clean_text'] = df_text['combined_text'].apply(clean_text)

# Generate word cloud for first 5 movies
for i in range(5):
    wc = WordCloud(width=600, height=400, background_color='white').generate(df_text['clean_text'].iloc[i])
    plt.figure(figsize=(6, 4))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis('off')
    plt.title(df['title'].iloc[i])
    plt.show()
```



Clean text to vectors using TF-IDF

```
vectorizer = TfidfVectorizer(max_features=5000)
tfidf_matrix = vectorizer.fit_transform(df_text['clean_text'])
```

```
tfidf_matrix.indices
```

```
array([2699, 1279, 2891, ..., 1298, 1332,  617], dtype=int32)
```

```
df_clean.head()
```

Show hidden output

```
df_clean['release_date'] = pd.to_datetime(df_clean['release_date'], errors='coerce').dt.year
df_clean['release_year'] = df_clean['release_date'].fillna(0).astype(int)
df_clean['popularity'] = pd.to_numeric(df_clean['popularity'], errors='coerce').fillna(0)
# metadata: release year and popularity
metadata = df_clean[['release_year', 'popularity']].fillna(0)
```

```
metadata.head()
```

	release_year	popularity
0	2009	150.437577
1	2007	139.082615
2	2015	107.376788
3	2012	112.312950
4	2012	43.926995

```
# normalize the metadata
scaler = MinMaxScaler()
normalized_metadata = scaler.fit_transform(metadata[['release_year', 'popularity']])
```

```
# combine TF-IDF vectors with metadata (This steps needs a GPU otherwise it takes significant time)
tfidf_dense = tfidf_matrix.toarray()
```

```
# stack features
hybrid_features_tfidf = np.hstack([tfidf_dense, normalized_metadata])
```

```
# Compute Cosine Similarity
#cosine_sim = cosine_similarity(tfidf_matrix, tfidf_matrix)
cosine_sim = cosine_similarity(hybrid_features_tfidf)
```

```
cosine_sim
```

```
array([[1.        , 0.47510747, 0.48491201, ..., 0.47165521, 0.46307268,
        0.44450296],
       [0.47510747, 1.        , 0.48764759, ..., 0.46499235, 0.45806016,
        0.43968479],
       [0.48491201, 0.48764759, 1.        , ..., 0.49289385, 0.48047999,
        0.46117052],
       ...,
       [0.47165521, 0.46499235, 0.49289385, ..., 1.        , 0.48515064,
        0.46441463],
       [0.46307268, 0.45806016, 0.48047999, ..., 0.48515064, 1.        ,
        0.45930899],
       [0.44450296, 0.43968479, 0.46117052, ..., 0.46441463, 0.45930899,
        1.        ]])
```

```
# compute similarity matrix for the hybrid TF-IDF + metadata model
similarity_matrix = cosine_similarity(hybrid_features_tfidf)
```

Functions to call recommendations, sim-scores, genre the TMDB API (queryposters and cast)

```
import requests
from IPython.display import Image, display

# API key
api_key = "b400409e22d456acb002b98fa90b2c2d" # I got this key by registering on TMDB website

# get poster URL from TMDb
def get_poster_url(movie_title):
    try:
        url = f"https://api.themoviedb.org/3/search/movie?api_key={api_key}&query={movie_title}"
        response = requests.get(url)
        data = response.json()
        if data["results"] and data["results"][0].get("poster_path"):
            poster_path = data["results"][0]["poster_path"]
            return f"https://image.tmdb.org/t/p/w300{poster_path}"
    except Exception as e:
        print(f"Error fetching poster for {movie_title}: {e}")
    return None
```

```
# Recommendation function with poster display
def recommend_movies(title, top_n=5):
    idx = df_clean[df_clean['title'].str.lower() == title.lower()].index
    if len(idx) == 0:
        print("Movie not found.")
        return

    idx = idx[0]
    sim_scores = list(enumerate(similarity_matrix[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)[1:top_n+1]
    movie_indices = [i[0] for i in sim_scores]

    recommendations = df_clean[['title', 'genres', 'keywords', 'overview']].iloc[movie_indices].copy()
    recommendations['similarity_score'] = [sim[1] for sim in sim_scores]

    # Display posters and details
    for _, row in recommendations.iterrows():
        title = row['title']
        poster_url = get_poster_url(title)
        print(f"\n {title} (Similarity Score: {row['similarity_score']:.3f})")
        print(f"Genres: {row['genres']}")
        print(f"Keywords: {row['keywords']}")
        if poster_url:
            display(Image(url=poster_url))
        else:
            print("Poster not found.")

    return recommendations.sort_values(by='similarity_score', ascending=False)
```

```
def explain_recommendation(input_title, recommended_df):
    input_row = df_clean[df_clean['title'].str.lower() == input_title.lower()].iloc[0]
    input_genres = set(input_row['genres'].split(','))
    input_keywords = set(input_row['keywords'].split(','))

    explanations = []

    for _, row in recommended_df.iterrows():
        rec_genres = set(row['genres'].split(','))
        rec_keywords = set(row['keywords'].split(','))
        common_genres = input_genres.intersection(rec_genres)
        common_keywords = input_keywords.intersection(rec_keywords)
```

```
        explanation = {
            'title': row['title'],
            'similarity_score': row['similarity_score'],
            'shared_genres': ', '.join(common_genres),
            'shared_keywords': ', '.join(common_keywords)
        }
        explanations.append(explanation)

    return pd.DataFrame(explanations)
```

```
recs = recommend_movies("Superman", top_n=5)
explanations = explain_recommendation("Superman", recs)
display(explanations)
```

```
 Superman Returns (Similarity Score: 0.593)
Genres: Adventure Fantasy Action Science Fiction
Keywords: saving the world dc comics invulnerability sequel superhero based on comic book kryptonite super powers superhuman strength lex luthor
```


```
 Man of Steel (Similarity Score: 0.569)
Genres: Action Adventure Fantasy Science Fiction
Keywords: saving the world dc comics superhero based on comic book superhuman alien invasion reboot super powers dc extended universe
```


```
 X-Men: Apocalypse (Similarity Score: 0.550)
Genres: Science Fiction
Keywords: mutant supernatural powers marvel comic superhero based on comic book superhuman apocalypse superhero team world domination aftercreditsstinger 1980s
```


```
 Superman IV: The Quest for Peace (Similarity Score: 0.541)
Genres: Action Adventure Science Fiction
Keywords: saving the world dc comics mountains nuclear missile u.s. army alter ego sequel superhero laboratory convertible catholic school newspaper editor nuclear weapons disarmament volcanic eruption great wall of china super powers superhuman strength
```


```
 Batman v Superman: Dawn of Justice (Similarity Score: 0.540)
Genres: Action Adventure Fantasy
Keywords: dc comics vigilante superhero based on comic book revenge super powers clark kent bruce wayne dc extended universe
```

	title	similarity_score	shared_genres	shared_keywords
0	Superman Returns	0.593078		
1	Man of Steel	0.568557	Action Adventure Fantasy Science Fiction	
2	X-Men: Apocalypse	0.549582		
3	Superman IV: The Quest for Peace	0.540714		
4	Batman v Superman: Dawn of Justice	0.540101		

Movie Clustering

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
```

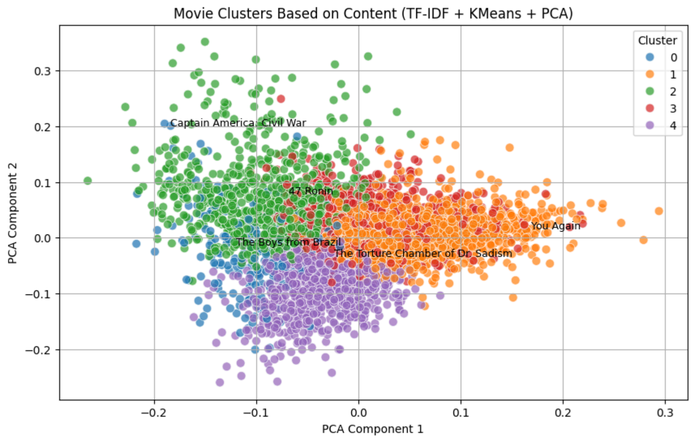
```
vectorizer = TfidfVectorizer(stop_words='english', max_features=5000)
X = vectorizer.fit_transform(df_text['combined_text'])
```

```
num_clusters = 5  # We can try less or more depending how we want to present this on the project
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
df_text['cluster'] = kmeans.fit_predict(X)
```

```
pca = PCA(n_components=2, random_state=42)
reduced = pca.fit_transform(X.toarray())

df_text['pca1'] = reduced[:, 0]
df_text['pca2'] = reduced[:, 1]
```

```
plt.figure(figsize=(10, 6))
sns.scatterplot(
    x="pca1", y="pca2", hue="cluster", palette="tab10", data=df_text, s=60, alpha=0.7
)
# For refence, I'm adding labels for some sample movies
sample_titles = df_text.groupby('cluster').apply(lambda x: x.sample(1, random_state=42))
for _, row in sample_titles.iterrows():
    plt.text(row['pca1'], row['pca2'], row['title'], fontsize=9)
plt.title("Movie Clusters Based on Content (TF-IDF + KMeans + PCA)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend(title="Cluster")
plt.grid(True)
plt.show()
```

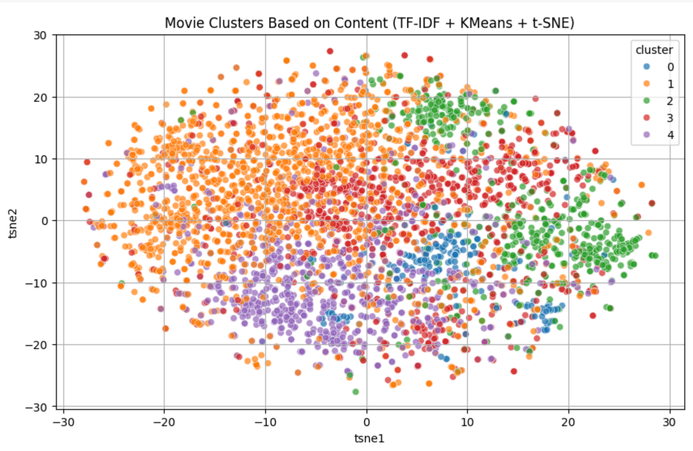
```
/tmp/ipython-input-48-212090144.py:6: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this w
  sample_titles = df_text.groupby('cluster').apply(lambda x: x.sample(1, random_state=42))
```




```
from sklearn.feature_extraction.text import TfidfVectorizer

# Re-use your TF-IDF vectorizer
terms = vectorizer.get_feature_names_out()
order_centroids = kmeans.cluster_centers_.argsort()[:, ::-1]

print("\nTop terms per cluster:")
for i in range(num_clusters):
    print(f"\nCluster {i}:")
    for j in range(10):
        print(f"  {terms[order_centroids[i, j]]}")
```

```
  secret
  agent
  action
  thriller
  cia
  comic
  spy
  superhero
  adventure
  fbi

Cluster 1:
  comedy
  drama
  romance
  love
  film
  life
  woman
  school
  new
  music

Cluster 2:
  war
  science
  fiction
  action
  world
  space
  alien
  adventure
  thriller
  dystopia

Cluster 3:
  family
  father
  comedy
  adventure
  animation
  fantasy
  son
  relationship
  drama
  young

Cluster 4:
  crime
  thriller
  murder
  police
  action
  drama
  drug
  mystery
  killer
  horror
```

```
from sklearn.manifold import TSNE

tsne = TSNE(n_components=2, perplexity=50, n_iter=300, random_state=42)
X_embedded = tsne.fit_transform(X.toarray())

df_text['tsne1'], df_text['tsne2'] = X_embedded[:,0], X_embedded[:,1]

# Plot with t-SNE
plt.figure(figsize=(10,6))
sns.scatterplot(x='tsne1', y='tsne2', hue='cluster', data=df_text, palette='tab10', alpha=0.7)
plt.title("Movie Clusters Based on Content (TF-IDF + KMeans + t-SNE)")
plt.grid(True)
plt.show()
```



Hybrid Approach - BERT

This next section will combine multiple text and numeric features:

- Textual features (overview, keywords)
- Metadata (genre, release year, cast)
- Ratings / popularity scores

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics.pairwise import cosine_similarity
from sentence_transformers import SentenceTransformer
import warnings
warnings.filterwarnings("ignore")
```

```
import torch
print(torch.cuda.is_available())
```

```
True
```

```
df_clean = df[['title', 'overview', 'genres', 'keywords', 'popularity', 'release_date']].dropna()

# format JSON strings from genre and keyboards
df_clean['genres'] = df_clean['genres'].apply(extract_names)
df_clean['keywords'] = df_clean['keywords'].apply(extract_names)

# Get the from each
df_text = df_clean[['title', 'overview', 'genres', 'keywords']]
df_text.dropna(inplace=True)
```

```
df_clean.head()
```

	title	overview	genres	keywords	popularity	release_date	combined_text	release_year
0	Avatar	In the 22nd century, a paraplegic Marine is di...	Action Adventure Fantasy Science Fiction	culture clash future space war space colony so...	150.437577	2009	In the 22nd century, a paraplegic Marine is di...	2009
1	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	Adventure Fantasy Action	ocean drug abuse exotic island east india trad...	139.082615	2007	Captain Barbossa, long believed to be dead, ha...	2007
2	Spectre	A cryptic message from Bond’s past sends him o...	Action Adventure Crime	spy based on novel secret agent sequel mi6 bri...	107.376788	2015	A cryptic message from Bond’s past sends him o...	2015
3	The Dark Knight Rises	Following the death of District Attorney Harve...	Action Crime Drama Thriller	dc comics crime fighter terrorist secret ident...	112.312950	2012	Following the death of District Attorney Harve...	2012
4	John Carter	John Carter is a war-weary, former military ca...	Action Adventure Science Fiction	based on novel mars medallion space travel pri...	43.926995	2012	John Carter is a war-weary, former military ca...	2012

```
# text fields for BERT input
df_clean['combined_text'] = df['overview'] + " " + df['genres'] + " " + df['keywords']

# release date to year
#df_clean['release_date'] = pd.to_datetime(df['release_date'], errors='coerce').dt.year.fillna(0).astype(int)
df_clean['release_date'] = pd.to_datetime(df_clean['release_date'], errors='coerce').dt.year
df_clean['release_year'] = df_clean['release_date'].fillna(0).astype(int)
df_clean['popularity'] = pd.to_numeric(df_clean['popularity'], errors='coerce').fillna(0)
# metadata: release year and popularity
metadata = df_clean[['release_year', 'popularity']].fillna(0)
```

```
# load BERT model
model = SentenceTransformer('all-MiniLM-L6-v2', device='cuda')
```

```
modules.json: 100%                                                  349/349 [00:00<00:00, 10.2kB/s]
config_sentence_transformers.json: 100%                             116/116 [00:00<00:00, 5.53kB/s]
README.md:         10.5k/? [00:00<00:00, 450kB/s]
sentence_bert_config.json: 100%                                     53.0/53.0 [00:00<00:00, 3.26kB/s]
config.json: 100%                                                   612/612 [00:00<00:00, 41.8kB/s]
model.safetensors: 100%                                             90.9M/90.9M [00:02<00:00, 55.1MB/s]
tokenizer_config.json: 100%                                         350/350 [00:00<00:00, 18.6kB/s]
vocab.txt:         232k/? [00:00<00:00, 11.5MB/s]
tokenizer.json:         466k/? [00:00<00:00, 13.5MB/s]
special_tokens_map.json: 100%                                       112/112 [00:00<00:00, 4.05kB/s]
config.json: 100%                                                   190/190 [00:00<00:00, 11.8kB/s]
```

```
# Due to previous errors, I will replace NaN or non-string values with an empty string
df_clean['combined_text'] = df_clean['combined_text'].fillna('').astype(str)
# encode combined text
bert_embeddings = model.encode(df_clean['combined_text'].tolist(), show_progress_bar=True)
```

```
Batches: 100%  150/150 [00:12<00:00, 20.55it/s]
```

```
# movies numerical metadata
#metadata = df_clean[['release_date', 'popularity']].fillna(0)

# normalize
scaler = MinMaxScaler()
normalized_metadata = scaler.fit_transform(metadata)

# BERT + Metadata
hybrid_features = np.hstack([bert_embeddings, normalized_metadata])
```

```
# computer similirity cosine
similarity_matrix = cosine_similarity(hybrid_features)
```

```
# updated recommendation movies w/ similarity scores, genre and keywords
def recommend_movies(title, top_n=10):
    idx = df_clean[df_clean['title'].str.lower() == title.lower()].index
    if len(idx) == 0:
        print("Movie not found.")
        return

    idx = idx[0]
    sim_scores = list(enumerate(similarity_matrix[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)[1:top_n+1]
    movie_indices = [i[0] for i in sim_scores]

    recommendations = df_clean[['title', 'release_year', 'genres', 'keywords', 'overview']].iloc[movie_indices].copy()
    recommendations['similarity_score'] = [sim[1] for sim in sim_scores]

    for _, row in recommendations.iterrows():
        movie_title = row['title']
        release_year = row['release_year']
        print(f"\n {movie_title} ({release_year}) — Similarity Score: {row['similarity_score']:.3f}")
        print(f"Genres: {row['genres']}")
        print(f"Keywords: {row['keywords']}")
        poster_url = get_poster_url(movie_title)
        if poster_url:
            display(Image(url=poster_url))
        else:
            print("Poster not found.")
        print("—" * 60)

    return recommendations.sort_values(by='similarity_score', ascending=False)
```

```
import requests
from IPython.display import Image, display

# API key
api_key = "b400409e22d456acb002b98fa90b2c2d" # I got this key by registering on TMDB website
```

```
# get poster URL from TMDb
def get_poster_url(movie_title):
    try:
        url = f"https://api.themoviedb.org/3/search/movie?api_key={api_key}&query={movie_title}"
        response = requests.get(url)
        data = response.json()
        if data["results"] and data["results"][0].get("poster_path"):
            poster_path = data["results"][0]["poster_path"]
            return f"https://image.tmdb.org/t/p/w300{poster_path}"
    except Exception as e:
        print(f"Error fetching poster for {movie_title}: {e}")
    return None
```

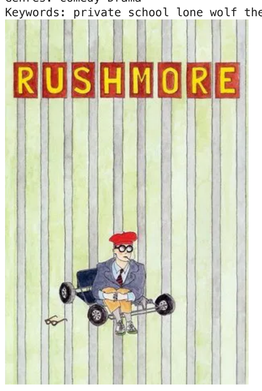
```
recommend_movies("Toy Story", top_n=5)
```

```
 Toy Story 3 (2010) — Similarity Score: 0.935
Genres: Animation Family Comedy
Keywords: hostage college toy barbie animation escape day care teddy bear duringcreditsstinger toy comes to life personification inanimate objects coming to life toy story
```


```
------------------------------------------------------------

 Toy Story 2 (1999) — Similarity Score: 0.928
Genres: Animation Comedy Family
Keywords: museum prosecution identity crisis airplane flea market collector teamwork friendship rescue team garage sale duringcreditsstinger toy comes to life personification inanimate objects coming to life
```


```
------------------------------------------------------------

 CJ7 (2008) — Similarity Score: 0.898
Genres: Comedy Drama Family Fantasy Science Fiction
Keywords: little boy ufo extraterrestrial
```


```
------------------------------------------------------------

 Rushmore (1998) — Similarity Score: 0.878
Genres: Comedy Drama
Keywords: private school lone wolf theatre play theatre group theatre director independent film
```




```
------------------------------------------------------------

 Jimmy Neutron: Boy Genius (2001) — Similarity Score: 0.878
Genres: Action Adventure Animation Comedy Family Fantasy Science Fiction
Keywords: showdown gi villain genius alien rescue miniaturization robot battle laser gun spear boy genius
```


```
------------------------------------------------------------
```

	title	release_year	genres	keywords	overview	similarity_score
42	Toy Story 3	2010	Animation Family Comedy	hostage college toy barbie animation escape da...	Woody, Buzz, and the rest of Andy's toys haven...	0.935133
343	Toy Story 2	1999	Animation Comedy Family	museum prosecution identity crisis airplane fl...	Andy heads off to Cowboy Camp, leaving his toy...	0.928273
2262	CJ7	2008	Comedy Drama Family Fantasy Science Fiction	little boy ufo extraterrestrial	Ti, a really poor construction worker that str...	0.897503
3023	Rushmore	1998	Comedy Drama	private school lone wolf theatre play theatre ...	When a beautiful first-grade teacher arrives a...	0.878488
1825	Jimmy Neutron: Boy Genius	2001	Action Adventure Animation Comedy Family Fanta...	showdown gi villain genius alien rescue miniat...	Jimmy Neutron is a boy genius and way ahead of...	0.878079

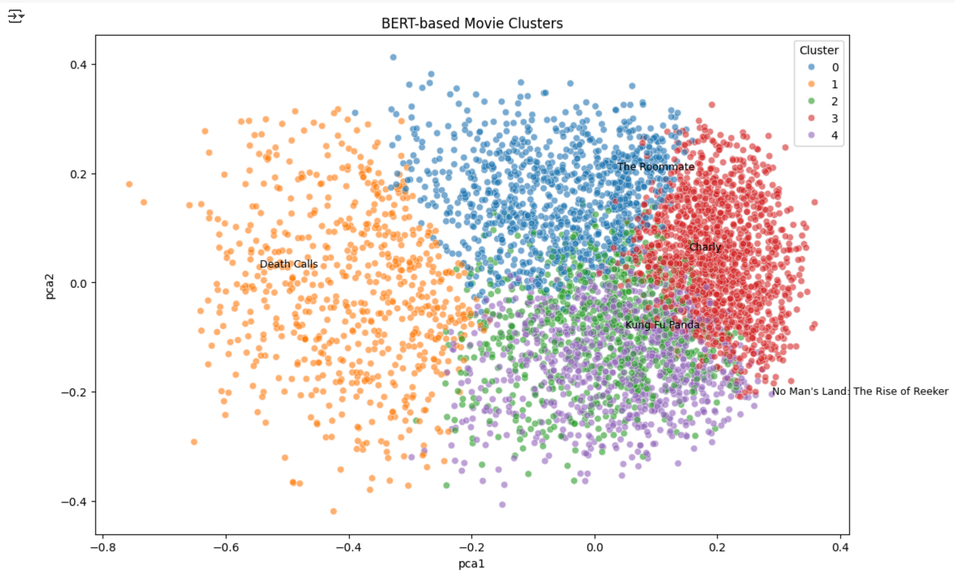
K-meamns clustering for Bert recommendation system

```
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
```

```
n_clusters = 5
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
df['cluster'] = kmeans.fit_predict(bert_embeddings)
```

```
pca = PCA(n_components=2)
pca_result = pca.fit_transform(bert_embeddings)
df['pca1'] = pca_result[:, 0]
df['pca2'] = pca_result[:, 1]
```

```
plt.figure(figsize=(12, 8))
sns.scatterplot(data=df, x='pca1', y='pca2', hue='cluster', palette='tab10', alpha=0.6)

# Add labels for a few example movies (1 per cluster)
sample_titles = df.groupby('cluster').apply(lambda x: x.sample(1, random_state=11)).reset_index(drop=True)
for _, row in sample_titles.iterrows():
    plt.text(row['pca1'], row['pca2'], row['title'], fontsize=9)

plt.title("BERT-based Movie Clusters")
plt.legend(title='Cluster')
plt.show()
```




```
print("\nTop representative movies per BERT-based cluster:")
for i in range(n_clusters):
    print(f"\nCluster {i}:")

    # get indices of items in this cluster
    cluster_indices = df[df['cluster'] == i].index

    # get the centroid of the cluster
    centroid = kmeans.cluster_centers_[i].reshape(1, -1)

    # compute cosine similarity to the centroid
    cluster_embeddings = bert_embeddings[cluster_indices]
    sims = cosine_similarity(cluster_embeddings, centroid).flatten()

    # get top 5 most representative movies
    top_indices = cluster_indices[np.argsort(sims)[-5:][::-1]]
    for idx in top_indices:
        print(f"  {df.loc[idx, 'title']} - {df.loc[idx, 'genres']}")
```

```
Top representative movies per BERT-based cluster:

Cluster 0:
  Stepmom - [{"id": 18, "name": "Drama"}, {"id": 10749, "name": "Romance"}]
  Submarine - [{"id": 18, "name": "Drama"}, {"id": 35, "name": "Comedy"}, {"id": 10749, "name": "Romance"}]
  To Die For - [{"id": 14, "name": "Fantasy"}, {"id": 18, "name": "Drama"}, {"id": 35, "name": "Comedy"}, {"id": 53, "name": "Thriller"}]
  Somewhere - [{"id": 35, "name": "Comedy"}, {"id": 18, "name": "Drama"}]
  Down to You - [{"id": 35, "name": "Comedy"}, {"id": 18, "name": "Drama"}, {"id": 10751, "name": "Family"}, {"id": 10749, "name": "Romance"}]

Cluster 1:
  Kung Pow: Enter the Fist - [{"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}]
  An Alan Smithee Film: Burn, Hollywood, Burn - [{"id": 35, "name": "Comedy"}]
  The Black Dahlia - [{"id": 18, "name": "Drama"}]
  Movie 43 - [{"id": 35, "name": "Comedy"}]
  Sympathy for Lady Vengeance - [{"id": 18, "name": "Drama"}, {"id": 53, "name": "Thriller"}]

Cluster 2:
  I, Frankenstein - [{"id": 27, "name": "Horror"}, {"id": 53, "name": "Thriller"}]
  Planet of the Apes - [{"id": 53, "name": "Thriller"}, {"id": 878, "name": "Science Fiction"}, {"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}]
  Minions - [{"id": 10751, "name": "Family"}, {"id": 16, "name": "Animation"}, {"id": 12, "name": "Adventure"}, {"id": 35, "name": "Comedy"}]
  Final Fantasy: The Spirits Within - [{"id": 12, "name": "Adventure"}, {"id": 28, "name": "Action"}, {"id": 16, "name": "Animation"}, {"id": 14, "name": "Fantasy"}, {"id": 878, "name": "Science Fiction"}, {"id": 53, "name": "Thriller"}]
  The Iron Giant - [{"id": 12, "name": "Adventure"}, {"id": 16, "name": "Animation"}, {"id": 10751, "name": "Family"}, {"id": 14, "name": "Fantasy"}, {"id": 878, "name": "Science Fiction"}]

Cluster 3:
  The Shipping News - [{"id": 18, "name": "Drama"}, {"id": 10749, "name": "Romance"}]
  In the Name of the King: A Dungeon Siege Tale - [{"id": 12, "name": "Adventure"}, {"id": 14, "name": "Fantasy"}, {"id": 28, "name": "Action"}, {"id": 18, "name": "Drama"}]
  The Lovely Bones - [{"id": 14, "name": "Fantasy"}, {"id": 18, "name": "Drama"}]
  The Village - [{"id": 18, "name": "Drama"}, {"id": 9648, "name": "Mystery"}, {"id": 53, "name": "Thriller"}]
  A Mighty Heart - [{"id": 18, "name": "Drama"}, {"id": 53, "name": "Thriller"}]

Cluster 4:
  The Fugitive - [{"id": 12, "name": "Adventure"}, {"id": 28, "name": "Action"}, {"id": 53, "name": "Thriller"}, {"id": 80, "name": "Crime"}, {"id": 9648, "name": "Mystery"}]
  The Client - [{"id": 18, "name": "Drama"}, {"id": 53, "name": "Thriller"}, {"id": 80, "name": "Crime"}, {"id": 9648, "name": "Mystery"}]
  Taken 3 - [{"id": 53, "name": "Thriller"}, {"id": 28, "name": "Action"}]
  Killer Joe - [{"id": 80, "name": "Crime"}, {"id": 18, "name": "Drama"}, {"id": 53, "name": "Thriller"}]
  A Low Down Dirty Shame - [{"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}, {"id": 80, "name": "Crime"}]
```

Unsupervised LSTM Model (recommendation system).

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, LSTM, Dense, Concatenate
from sklearn.metrics.pairwise import cosine_similarity
```

```
# Load dataframe (df) from google drive running the top cells

# clean and combine text features as with TF-IDF and BERT
df_clean = df[['title', 'overview', 'genres', 'keywords', 'popularity', 'release_date']].dropna()

# combine text fields into one
df_clean['combined_text'] = df_clean['title'] + " " + df_clean['overview'] + " " + df_clean['genres'] + " " + df_clean['keywords']

# normalize popularity and release date
df_clean['release_date'] = pd.to_datetime(df_clean['release_date'], errors='coerce').dt.year.fillna(0).astype(int)
scaler = MinMaxScaler()
df_clean[['popularity', 'release_date']] = scaler.fit_transform(df_clean[['popularity', 'release_date']])
```

```
# example of combined_text for reference purposes
df_clean['combined_text'][1]
```

```
'Pirates of the Caribbean: At World\'s End Captain Barbossa, long believed to be dead, has come back to life and is headed to the edge of the Earth with Will Turner and Elizabeth Swann. But nothing is quite as it seems. [{"id": 12, "name": "Adventure"}, {"id": 14, "name": "Fantasy"}, {"id": 28, "name": "Action"}] [{"id": 270, "name": "ocean"}, {"id": 726, "name": "drug abuse"}, {"id": 911, "name": "exotic island"}, {"id": 1319, "name": "east india trading company"}, {"id": 2038, "name": "love of one\'s life"}, {"id": 2052, "name": "traitor"}, {"id": 2580, "name": "shipwreck"}, {"id": 2660, "name": "strong woman"}, {"id": 3799, "name": "ship"}, {"id": 5740, "name": "alliance"}, {"id": 5941, "name": "calypso"}, {"id": 6155, "name": "afterlife"}, {"id": 6211, "name": "fighter"}, {"id": 12988, "name": "pirate"}, {"id": 157186, "name": "swashbuckler"}, {"id": 179430, "name": "aftercreditsstinger"}]'
```

```
df_clean.head()
```

	title	overview	genres	keywords	popularity	release_date	combined_text
0	Avatar	In the 22nd century, a paraplegic Marine is di...	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	[{"id": 1463, "name": "culture clash"}, {"id":...	0.171814	0.920792	Avatar In the 22nd century, a paraplegic Marin...
1	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	[{"id": 12, "name": "Adventure"}, {"id": 14, "...	[{"id": 270, "name": "ocean"}, {"id": 726, "na...	0.158846	0.900990	Pirates of the Caribbean: At World's End Capta...
2	Spectre	A cryptic message from Bond’s past sends him o...	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	[{"id": 470, "name": "spy"}, {"id": 818, "name...	0.122634	0.980198	Spectre A cryptic message from Bond’s past sen...
3	The Dark Knight Rises	Following the death of District Attorney Harve...	[{"id": 28, "name": "Action"}, {"id": 80, "nam...	[{"id": 849, "name": "dc comics"}, {"id": 853,...	0.128272	0.950495	The Dark Knight Rises Following the death of D...
4	John Carter	John Carter is a war-weary, former military ca...	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	[{"id": 818, "name": "based on novel"}, {"id":...	0.050169	0.950495	John Carter John Carter is a war-weary, former...

```
# format JSON strings from genre and keyboards
df_clean['genres'] = df_clean['genres'].apply(extract_names)
df_clean['keywords'] = df_clean['keywords'].apply(extract_names)
```

```
df_clean.head()
```

	title	overview	genres	keywords	popularity	release_date	combined_text
0	Avatar	In the 22nd century, a paraplegic Marine is di...	Action Adventure Fantasy Science Fiction	culture clash future space war space colony so...	0.171814	0.920792	Avatar In the 22nd century, a paraplegic Marin...
1	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	Adventure Fantasy Action	ocean drug abuse exotic island east india trad...	0.158846	0.900990	Pirates of the Caribbean: At World's End Capta...
2	Spectre	A cryptic message from Bond’s past sends him o...	Action Adventure Crime	spy based on novel secret agent sequel mi6 bri...	0.122634	0.980198	Spectre A cryptic message from Bond’s past sen...
3	The Dark Knight Rises	Following the death of District Attorney Harve...	Action Crime Drama Thriller	dc comics crime fighter terrorist secret ident...	0.128272	0.950495	The Dark Knight Rises Following the death of D...
4	John Carter	John Carter is a war-weary, former military ca...	Action Adventure Science Fiction	based on novel mars medallion space travel pri...	0.050169	0.950495	John Carter John Carter is a war-weary, former...

```
# text preprocessing and tokenization
tokenizer = Tokenizer(num_words=10000, oov_token="<OOV>")
tokenizer.fit_on_texts(df_clean['combined_text'])

sequences = tokenizer.texts_to_sequences(df_clean['combined_text'])
padded_sequences = pad_sequences(sequences, maxlen=100, padding='post', truncating='post')

# metadata as additional input
metadata_features = df_clean[['popularity', 'release_date']].values
```

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, LSTM, Dense, Concatenate

# inputs for the model
text_input = Input(shape=(100,), name="text_input")
meta_input = Input(shape=(2,), name="meta_input")

# LSTM on text
embedding = Embedding(input_dim=10000, output_dim=64, input_length=100)(text_input)
lstm_out = LSTM(64)(embedding)

# combine LSTM and metadata
merged = Concatenate()([lstm_out, meta_input])
dense = Dense(64, activation='relu')(merged)
output = Dense(32, activation='relu')(dense)  # This becomes the embedding vector for recommendations

# define model
model = Model(inputs=[text_input, meta_input], outputs=output)
model.compile(optimizer='adam', loss='mse')
model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just remove it.
  warnings.warn(
```

Model: "functional_2"

Layer (type)	Output Shape	Param #	Connected to
text_input (InputLayer)	(None, 100)	0	–
embedding_1 (Embedding)	(None, 100, 64)	640,000	text_input[0][0]
lstm_1 (LSTM)	(None, 64)	33,024	embedding_1[0][0]
meta_input (InputLayer)	(None, 2)	0	–
concatenate_1 (Concatenate)	(None, 66)	0	lstm_1[0][0], meta_input[0][0]
dense_1 (Dense)	(None, 64)	4,288	concatenate_1[0]…
dense_2 (Dense)	(None, 32)	2,080	dense_1[0][0]

Total params: 679,392 (2.59 MB)
Trainable params: 679,392 (2.59 MB)
Non-trainable params: 0 (0.00 B)

```
# dummy output to learn identity (FYI each movie vector is like a label)
X_text = padded_sequences
X_meta = metadata_features

# random targets for training embeddings
y = np.random.rand(len(df_clean), 32)

# train the model
model.fit([X_text, X_meta], y, epochs=100, batch_size=32)
```

```
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 40ms/step - loss: 0.0144
Epoch 73/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 11s 43ms/step - loss: 0.0144
Epoch 74/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 5s 36ms/step - loss: 0.0142
Epoch 75/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 42ms/step - loss: 0.0139
Epoch 76/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 43ms/step - loss: 0.0138
Epoch 77/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 39ms/step - loss: 0.0146
Epoch 78/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 40ms/step - loss: 0.0144
Epoch 79/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 11s 42ms/step - loss: 0.0135
Epoch 80/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 43ms/step - loss: 0.0131
Epoch 81/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 37ms/step - loss: 0.0131
Epoch 82/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 43ms/step - loss: 0.0131
Epoch 83/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - loss: 0.0126
Epoch 84/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 37ms/step - loss: 0.0127
Epoch 85/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 42ms/step - loss: 0.0127
Epoch 86/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 37ms/step - loss: 0.0126
Epoch 87/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 42ms/step - loss: 0.0123
Epoch 88/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 42ms/step - loss: 0.0131
Epoch 89/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 40ms/step - loss: 0.0133
Epoch 90/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 39ms/step - loss: 0.0123
Epoch 91/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 40ms/step - loss: 0.0122
Epoch 92/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 39ms/step - loss: 0.0118
Epoch 93/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 41ms/step - loss: 0.0119
Epoch 94/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 39ms/step - loss: 0.0117
Epoch 95/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 39ms/step - loss: 0.0114
Epoch 96/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 7s 44ms/step - loss: 0.0118
Epoch 97/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 6s 38ms/step - loss: 0.0115
Epoch 98/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 7s 43ms/step - loss: 0.0117
Epoch 99/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 10s 44ms/step - loss: 0.0115
Epoch 100/100
150/150 ━━━━━━━━━━━━━━━━━━━━ 11s 48ms/step - loss: 0.0112
<keras.src.callbacks.history.History at 0x7ee7543f4990>
```

```
# Get learned embeddings for all movies
movie_embeddings = model.predict([X_text, X_meta])

from sklearn.metrics.pairwise import cosine_similarity

def recommend_lstm(movie_title, top_n=5):
    idx = df_clean[df_clean['title'].str.lower() == movie_title.lower()].index
    if len(idx) == 0:
        print("Movie not found.")
        return

    idx = idx[0]
    query_embedding = movie_embeddings[idx]
    sim_scores = cosine_similarity([query_embedding], movie_embeddings)[0]
    top_indices = np.argsort(sim_scores)[::-1][1:top_n+1]

    recommendations = df_clean.iloc[top_indices][['title', 'genres', 'keywords', 'overview']].copy()
    recommendations['similarity_score'] = sim_scores[top_indices]

    return recommendations.sort_values(by='similarity_score', ascending=False)
```

```
150/150 ━━━━━━━━━━━━━━━━━━━━ 2s 13ms/step
```

```
recommend_lstm("Superman")
```

	title	genres	keywords	overview	similarity_score
79	Iron Man 2	Adventure Action Science Fiction	malibu marvel comic superhero based on comic b...	With the world now aware of his dual life as t...	0.926549
987	Dream House	Drama Thriller Mystery	house fire extension ladder last day on job	Publisher, Will Atenton quits a lucrative job ...	0.918319
3356	Flirting with Disaster	Comedy Romance	lsd looking for birth parents half-brother in...	Adopted as a child, new father Mel Colpin (Ben...	0.899952
3716	Lilya 4-ever	Crime Drama	suicide sex sweden underground nightclub nudit...	Lilya lives in poverty and dreams of a better ...	0.897716
1473	The Astronaut's Wife	Drama Science Fiction Thriller	wife husband relationship space travel space m...	When astronaut Spencer Armacost returns to Ear...	0.891503

GLOVE + LSTM Model w/ additional numeric features (Supervised training)

1st load the df from the top df code / google drive

```
import re
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
# combine text fields
df['combined_text'] = df['overview'].fillna('') + " " + \
                      df['genres'].fillna('') + " " + \
                      df['keywords'].fillna('')
```

```
# function to clean text
def clean_text(text):
    text = re.sub(r'[^a-zA-Z0-9\s]', '', text)
    return text.lower()

#apply to the combined text
df['combined_text'] = df['combined_text'].apply(clean_text)
```

```
#  text tokenize
tokenizer = Tokenizer(num_words=10000)
tokenizer.fit_on_texts(df['combined_text'])
sequences = tokenizer.texts_to_sequences(df['combined_text'])
X_text = pad_sequences(sequences, maxlen=300)
```

```
# normalizing all nmerical features
df['release_year'] = pd.to_datetime(df['release_date'], errors='coerce').dt.year.fillna(0).astype(int)
df[['popularity', 'vote_average', 'vote_count', 'runtime']] = df[['popularity', 'vote_average', 'vote_count', 'runtime']].fillna(0)
numerical = df[['release_year', 'popularity', 'vote_average', 'vote_count', 'runtime']]
scaler = MinMaxScaler()
X_num = scaler.fit_transform(numerical)
```

```
# language encoding
df['original_language'] = df['original_language'].fillna('unknown')
le = LabelEncoder()
X_lang = le.fit_transform(df['original_language']).reshape(-1, 1)

# numerical + language
X_meta = np.hstack((X_num, X_lang))

# input for LSTM
X_final = [X_text, X_meta]
```

```
X_final
```

```
[array([[   0,    0,    0, ...,  407,    1,  346],
        [   0,    0,    0, ...,  223,    1,  224],
        [   0,    0,    0, ...,    1,  508,  868],
        ...,
        [   0,    0,    0, ...,    2,    1, 1046],
        [   0,    0,    0, ..., 1555,   25, 4935],
        [   0,    0,    0, ...,    1,  298,  130]], dtype=int32),
 array([[9.96033713e-01, 1.71814515e-01, 7.20000000e-01, 8.58057010e-01,
         4.79289941e-01, 7.00000000e+00],
        [9.95042142e-01, 1.58846031e-01, 6.90000000e-01, 3.27225131e-01,
         5.00000000e-01, 7.00000000e+00],
        [9.99008428e-01, 1.22634857e-01, 6.30000000e-01, 3.24752763e-01,
         4.37869822e-01, 7.00000000e+00],
        ...,
        [9.98016857e-01, 1.64973372e-03, 7.00000000e-01, 4.36300175e-04,
         3.55029586e-01, 7.00000000e+00],
        [9.97521071e-01, 9.78787458e-04, 5.70000000e-01, 5.09016870e-04,
         2.89940828e-01, 7.00000000e+00],
        [9.94050570e-01, 2.20411627e-03, 6.30000000e-01, 1.16346713e-03,
         2.66272189e-01, 7.00000000e+00]])]
```

```
from sklearn.metrics.pairwise import cosine_similarity

# similarity scores based on vote average
vote_scores = df['vote_average'].values.reshape(-1, 1)
y_similarity = cosine_similarity(vote_scores)
```

```
# download GloVe embeddings
!wget http://nlp.stanford.edu/data/glove.6B.zip
!unzip glove.6B.zip -d /content/
```

Show hidden output

```
# Glove embedding
embedding_index = {}
with open('/content/glove.6B.100d.txt', encoding='utf-8') as f:
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embedding_index[word] = coefs

embedding_dim = 100
word_index = tokenizer.word_index
embedding_matrix = np.zeros((10000, embedding_dim))

for word, i in word_index.items():
    if i >= 10000:
        continue
    embedding_vector = embedding_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

```
from keras.models import Model
from keras.layers import Input, Embedding, LSTM, Dense, Concatenate, Dropout

# text input
text_input = Input(shape=(300,))
embed = Embedding(input_dim=10000, output_dim=100, weights=[embedding_matrix], input_length=300, trainable=False)(text_input)
lstm_out = LSTM(64)(embed)

# metadata input
meta_input = Input(shape=(X_meta.shape[1],))
meta_dense = Dense(32, activation='relu')(meta_input)

# combine
combined = Concatenate()([lstm_out, meta_dense])
combined = Dropout(0.3)(combined)
output = Dense(1, activation='sigmoid')(combined)

model = Model(inputs=[text_input, meta_input], outputs=output)
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just remove it.
  warnings.warn(
```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 300)	0	–
embedding (Embedding)	(None, 300, 100)	1,000,000	input_layer[0][0]
input_layer_1 (InputLayer)	(None, 6)	0	–
lstm (LSTM)	(None, 64)	42,240	embedding[0][0]
dense (Dense)	(None, 32)	224	input_layer_1[0]…
concatenate (Concatenate)	(None, 96)	0	lstm[0][0], dense[0][0]
dropout (Dropout)	(None, 96)	0	concatenate[0][0]
dense_1 (Dense)	(None, 1)	97	dropout[0][0]

Total params: 1,042,561 (3.98 MB)
Trainable params: 42,561 (166.25 KB)
Non-trainable params: 1,000,000 (3.81 MB)

```
# sample dummy labels (1 if vote_average diff < 0.5 else 0)
labels = np.where(abs(df['vote_average'].values - df['vote_average'].values.mean()) < 0.5, 1, 0)

model.fit(X_final, labels, epochs=50, batch_size=32, validation_split=0.2)
```

```
Epoch 1/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 10s 24ms/step - accuracy: 0.5123 - loss: 0.7565 - val_accuracy: 0.7190 - val_loss: 0.6117
Epoch 2/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.5333 - loss: 0.7263 - val_accuracy: 0.6556 - val_loss: 0.6552
Epoch 3/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step - accuracy: 0.5507 - loss: 0.6861 - val_accuracy: 0.6837 - val_loss: 0.6523
Epoch 4/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 6s 33ms/step - accuracy: 0.5682 - loss: 0.6853 - val_accuracy: 0.5442 - val_loss: 0.6790
Epoch 5/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 4s 24ms/step - accuracy: 0.5869 - loss: 0.6715 - val_accuracy: 0.6961 - val_loss: 0.6286
Epoch 6/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 4s 16ms/step - accuracy: 0.6078 - loss: 0.6592 - val_accuracy: 0.5411 - val_loss: 0.6850
Epoch 7/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.6125 - loss: 0.6524 - val_accuracy: 0.5796 - val_loss: 0.6669
Epoch 8/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 15ms/step - accuracy: 0.6093 - loss: 0.6483 - val_accuracy: 0.6785 - val_loss: 0.6113
Epoch 9/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 16ms/step - accuracy: 0.6387 - loss: 0.6341 - val_accuracy: 0.5796 - val_loss: 0.6704
Epoch 10/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 20ms/step - accuracy: 0.6420 - loss: 0.6207 - val_accuracy: 0.5952 - val_loss: 0.6741
Epoch 11/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 18ms/step - accuracy: 0.6755 - loss: 0.6042 - val_accuracy: 0.5848 - val_loss: 0.6892
Epoch 12/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.6830 - loss: 0.5858 - val_accuracy: 0.6129 - val_loss: 0.6603
Epoch 13/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 13ms/step - accuracy: 0.6854 - loss: 0.5723 - val_accuracy: 0.5911 - val_loss: 0.6913
Epoch 14/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 13ms/step - accuracy: 0.7272 - loss: 0.5365 - val_accuracy: 0.5786 - val_loss: 0.6944
Epoch 15/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.7499 - loss: 0.5101 - val_accuracy: 0.5827 - val_loss: 0.7042
Epoch 16/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 20ms/step - accuracy: 0.7804 - loss: 0.4661 - val_accuracy: 0.5421 - val_loss: 0.7766
Epoch 17/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 18ms/step - accuracy: 0.7845 - loss: 0.4615 - val_accuracy: 0.5973 - val_loss: 0.7270
Epoch 18/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 13ms/step - accuracy: 0.8129 - loss: 0.4157 - val_accuracy: 0.5411 - val_loss: 0.7856
Epoch 19/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.8250 - loss: 0.3895 - val_accuracy: 0.5879 - val_loss: 0.8023
Epoch 20/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step - accuracy: 0.8632 - loss: 0.3238 - val_accuracy: 0.5505 - val_loss: 0.9786
Epoch 21/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.8683 - loss: 0.3152 - val_accuracy: 0.5463 - val_loss: 1.0111
Epoch 22/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 19ms/step - accuracy: 0.8881 - loss: 0.2662 - val_accuracy: 0.5515 - val_loss: 1.1158
Epoch 23/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 19ms/step - accuracy: 0.9079 - loss: 0.2358 - val_accuracy: 0.5494 - val_loss: 1.1637
Epoch 24/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 15ms/step - accuracy: 0.9293 - loss: 0.1755 - val_accuracy: 0.5786 - val_loss: 1.1221
Epoch 25/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step - accuracy: 0.9425 - loss: 0.1556 - val_accuracy: 0.5557 - val_loss: 1.2033
Epoch 26/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 14ms/step - accuracy: 0.9575 - loss: 0.1217 - val_accuracy: 0.5359 - val_loss: 1.4716
Epoch 27/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step - accuracy: 0.9629 - loss: 0.1100 - val_accuracy: 0.5494 - val_loss: 1.3650
Epoch 28/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 2s 20ms/step - accuracy: 0.9631 - loss: 0.1116 - val_accuracy: 0.5245 - val_loss: 1.6538
Epoch 29/50
121/121 ━━━━━━━━━━━━━━━━━━━━ 3s 20ms/step - accuracy: 0.9707 - loss: 0.0847 - val_accuracy: 0.5317 - val_loss: 1.5598
```

```
from keras.models import Model
from sklearn.metrics.pairwise import cosine_similarity

# xtract features from the penultimate layer
feature_extractor = Model(inputs=model.input, outputs=model.get_layer(index=-2).output)

# feature embeddings for all movies
movie_embeddings = feature_extractor.predict(X_final, batch_size=32)
```

```
151/151 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step
```

```
# compute pairwise cosine similarity between all movies
similarity_matrix = cosine_similarity(movie_embeddings)
```

```
def recommend_movies_lstm(title, top_n=5):
    # find movie index
    idx = df[df['title'].str.lower() == title.lower()].index
    if len(idx) == 0:
        print("Movie not found.")
        return
    idx = idx[0]

    # Get similarity scores for the movie
    sim_scores = list(enumerate(similarity_matrix[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

    # Skip the movie itself (first match) and select top-N
    sim_scores = sim_scores[1:top_n + 1]
    movie_indices = [i[0] for i in sim_scores]

    print(f"\nTop {top_n} similar movies to: {df.iloc[idx]['title']}")
    for i in movie_indices:
        title = df.iloc[i]['title']
        score = sim_scores[movie_indices.index(i)][1]
        print(f"{title} — Similarity Score: {score:.3f}")
```

```
recommend_movies_lstm("Transformers", top_n=5)
```

```
Top 5 similar movies to: Transformers
Spider-Man 2 — Similarity Score: 0.929
Left Behind — Similarity Score: 0.926
Dragonball Evolution — Similarity Score: 0.916
Cars — Similarity Score: 0.914
Dinner for Schmucks — Similarity Score: 0.911
```

```
# Clustering
from sklearn.cluster import KMeans

# cluster into 5 groups
num_clusters = 5
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
df['cluster'] = kmeans.fit_predict(movie_embeddings)
```

```
# 5 movies per cluster for inspection
for i in range(num_clusters):
    print(f"\nCluster {i}:")
    sample_movies = df[df['cluster'] == i].sample(5, random_state=42)
    for title in sample_movies['title']:
        print(f"  - {title}")
```

```
Cluster 0:
  - Wyatt Earp
  - You've Got Mail
  - 1408
  - Stuart Little
  - Sweet November

Cluster 1:
  - Away We Go
  - 127 Hours
  - Dancer in the Dark
  - Persepolis
  - Queen of the Damned

Cluster 2:
  - Kill Bill: Vol. 1
  - Network
  - The French Connection
  - The Brain That Wouldn't Die
  - Dolphin Tale

Cluster 3:
  - Ramanujan
  - Central Station
  - Dragon Nest: Warriors' Dawn
  - Cries and Whispers
  - Coming Home

Cluster 4:
  - I Don't Know How She Does It
  - Fifty Shades of Grey
  - Frozen River
  - Isn't She Great
  - I Am Love
```

```
from sklearn.metrics.pairwise import cosine_similarity
import numpy as np

print("\nTop representative movies per LSTM-based cluster:")
for i in range(num_clusters):
    print(f"\nCluster {i}:")

    # Get indices of items in this cluster
    cluster_indices = df[df['cluster'] == i].index

    # Get the centroid of the cluster
    centroid = kmeans.cluster_centers_[i].reshape(1, -1)

    # Compute cosine similarity to the centroid
    cluster_embeddings = movie_embeddings[cluster_indices]
    sims = cosine_similarity(cluster_embeddings, centroid).flatten()

    # Get top 5 most representative movies
    top_indices = cluster_indices[np.argsort(sims)[-5:][::-1]]
    for idx in top_indices:
        print(f"  {df.loc[idx, 'title']} - {df.loc[idx, 'genres']}")
```

```
Top representative movies per LSTM-based cluster:

Cluster 0:
  The Brothers Grimm - [{"id": 12, "name": "Adventure"}, {"id": 14, "name": "Fantasy"}, {"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}, {"id": 53, "name": "Thriller"}]
  Cellular - [{"id": 28, "name": "Action"}, {"id": 12, "name": "Adventure"}, {"id": 80, "name": "Crime"}, {"id": 53, "name": "Thriller"}]
  Madagascar: Escape 2 Africa - [{"id": 10751, "name": "Family"}, {"id": 16, "name": "Animation"}]
  Hotel for Dogs - [{"id": 35, "name": "Comedy"}, {"id": 10751, "name": "Family"}]
  The Other Guys - [{"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}, {"id": 80, "name": "Crime"}]

Cluster 1:
```

```
    Undercover Brother - [{"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}]
    Insomnia - [{"id": 80, "name": "Crime"}, {"id": 9648, "name": "Mystery"}, {"id": 53, "name": "Thriller"}]
    Guess Who - [{"id": 35, "name": "Comedy"}, {"id": 10749, "name": "Romance"}]
    Hesher - [{"id": 18, "name": "Drama"}]
    The Boxtrolls - [{"id": 16, "name": "Animation"}, {"id": 35, "name": "Comedy"}, {"id": 10751, "name": "Family"}, {"id": 14, "name": "Fantasy"}]

  Cluster 2:
    Dinner for Schmucks - [{"id": 35, "name": "Comedy"}]
    Coraline - [{"id": 16, "name": "Animation"}, {"id": 10751, "name": "Family"}]
    Meet the Spartans - [{"id": 35, "name": "Comedy"}]
    Texas Chainsaw 3D - [{"id": 27, "name": "Horror"}, {"id": 53, "name": "Thriller"}]
    Glengarry Glen Ross - [{"id": 80, "name": "Crime"}, {"id": 18, "name": "Drama"}, {"id": 9648, "name": "Mystery"}]

  Cluster 3:
    Dragon Nest: Warriors' Dawn - [{"id": 12, "name": "Adventure"}, {"id": 10751, "name": "Family"}, {"id": 14, "name": "Fantasy"}, {"id": 16, "name": "Animation"}]
    A Woman, a Gun and a Noodle Shop - [{"id": 35, "name": "Comedy"}, {"id": 18, "name": "Drama"}, {"id": 53, "name": "Thriller"}]
    Shinjuku Incident - [{"id": 18, "name": "Drama"}, {"id": 28, "name": "Action"}, {"id": 53, "name": "Thriller"}, {"id": 80, "name": "Crime"}]
    Crazy Stone - [{"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}]
    Hero - [{"id": 18, "name": "Drama"}, {"id": 12, "name": "Adventure"}, {"id": 28, "name": "Action"}, {"id": 36, "name": "History"}]

  Cluster 4:
    Sympathy for Lady Vengeance - [{"id": 18, "name": "Drama"}, {"id": 53, "name": "Thriller"}]
    The 41-Year-Old Virgin Who Knocked Up Sarah Marshall and Felt Superbad About It - [{"id": 35, "name": "Comedy"}]
    ABCD (Any Body Can Dance) - [{"id": 18, "name": "Drama"}, {"id": 10402, "name": "Music"}]
    Clerks II - [{"id": 35, "name": "Comedy"}]
    The Spy Next Door - [{"id": 28, "name": "Action"}, {"id": 35, "name": "Comedy"}, {"id": 10751, "name": "Family"}]
```

```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import seaborn as sns

# Reduce to 2D using PCA
pca = PCA(n_components=2)
reduced_embeddings = pca.fit_transform(movie_embeddings)

# Add PCA components to the DataFrame
df['pca1'] = reduced_embeddings[:, 0]
df['pca2'] = reduced_embeddings[:, 1]
df['cluster'] = kmeans.labels_

# Plot the clusters
plt.figure(figsize=(12, 8))
palette = sns.color_palette("hsv", len(df['cluster'].unique()))
sns.scatterplot(data=df, x='pca1', y='pca2', hue='cluster', palette=palette, alpha=0.7)

# Optional: Add movie titles for a few representative samples per cluster
sample_titles = df.groupby('cluster').apply(lambda x: x.sample(1, random_state=42))
for _, row in sample_titles.iterrows():
    plt.text(row['pca1'], row['pca2'], row['title'], fontsize=8)

plt.title("LSTM-based Movie Clusters (PCA Projection)")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.legend(title="Cluster")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-36-1686716481.py:20: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this
  sample_titles = df.groupby('cluster').apply(lambda x: x.sample(1, random_state=42))
```