Capstone Project:
Recommendations Models for Films

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CONTENTS

OVERVIEW

The original intention of this project was to develop a movie recommendations engine, similar to those employed by Netflix, or YouTube, but with a focus on colour and mood as aspects or features of films that have yet to be explored in the realm of traditional recommendations systems.

In thinking about how to define “colour” in the context of the model, there a variety of approaches that could be taken. We can analyze colour as the average hue of a single frame of a movie, and then express this average hue in terms of blocks of time. For example, we could take the average hues of the all the frames that make up the first minute of the movie, and define the average colour of each minute of the movie based on this logic. It is also possible to find the average hue of all the frames throughout the runtime of the film, and then add this average hue as a colour dimension to our movie metadata.

There were attempts to locate sources that could provide any data at all on the subject of colour in films, with some being identified as useful enough to be considered for future projects, most notably The Colors of Motion (thecolorsofmotion.com) and HappyCoding.io. It quickly became evident, however, that there would be a need to independently acquire movie files and conduct processing and analysis in order to develop a large enough dataset to be considered for this project. As such, it was decided that this aspect of the model would be scrapped.

The mood of a film can similarly be analyzed in a variety of ways. For the scope of this project, the idea was always to utilize a text-based emotion classification system, considering text data gathered from movie overviews/ descriptions/plot summaries, and review data published by regular movie-goers as well as film review publications. This data did end up being included in the project, albeit the initial prototype does not use this emotion classification as a feature in the model. This document does describe the intention and plan to incorporate this data in a future release, in order to develop a more robust model that is closer to the original project and business goals.

DATA DESCRIPTION

👉 Movie Data

The movie related data used to build the models can be divided into 2 categories:

1. Movie metadata

The MovieLens 25M dataset, published by GroupLens (https://grouplens.org/datasets/movielens/25m/), contains over 25 million rows of ratings data assigned to over 62,000 unique titles. We will specifically be using the *ratings.csv* and *movies.csv* files, with the latter representing movie metadata. The raw structure of the movie metadata can be seen in the sample below:

movieId	title	genres
1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	Jumanji (1995)	Adventure|Children|Fantasy
3	Grumpier Old Men (1995)	Comedy|Romance
4	Waiting to Exhale (1995)	Comedy|Drama|Romance
5	Father of the Bride Part II (1995)	Comedy

For the purpose of this project, we will not be using the genres data; both because the current prototype does not consider this in calculating recommendations, but also because this data is captured in the IMDb data - which should be a more robust set of metadata that can be worked into future updates to the engine.

The raw IMDb dataset (https://www.imdb.com/interfaces/) contains 8,999,075 rows of data; each corresponding to a different film, television episode, or other type of media as described below:

```
array(['short', 'movie', 'tvEpisode', 'tvSeries', 'tvShort', 'tvMovie',
       'tvMiniSeries', 'tvSpecial', 'video', 'videoGame', 'tvPilot'],
      dtype=object)
```

However, because the scope of this project only includes movies, we can already see that a significant number of titles will be dropped from the final dataset. The structure of can be seen in this sample:

	tconst	titleType	primaryTitle	originalTitle	isAdult	startYear	endYear	runtimeMinutes	genres
0	tt0000001	short	Carmencita	Carmencita	0	1894	\N	1	Documentary,Short
1	tt0000002	short	Le clown et ses chiens	Le clown et ses chiens	0	1892	\N	5	Animation,Short
2	tt0000003	short	Pauvre Pierrot	Pauvre Pierrot	0	1892	\N	4	Animation,Comedy,Romance
3	tt0000004	short	Un bon bock	Un bon bock	0	1892	\N	12	Animation,Short
4	tt0000005	short	Blacksmith Scene	Blacksmith Scene	0	1893	\N	1	Comedy,Short

Feature	Description
tconst	Unique IMDb ID used to identify the title
titleType	The category of content type to which the title belongs
primaryTitle	The title of the content as is commonly known
originalTitle	The original title of the content, in its original language
isAdult	A binary value indicating whether the content is an adult film; 0: non-adult, 1: adult
startYear	Corresponds to the year of release
endYear	For tv series, this indicates the year the series ended. For movies, this value is \N.
runtimeMinutes	The runtime of the content in minutes
genres	The genres to which the title belongs

The primary fields we'll be using from this dataset are *tconst*, *primaryTitle*, and *startYear*. For future models, the remaining features may be useful.

2. Ratings/feedback data

The entirety of this data comes from the *reviews.csv* portion of the MovieLens dataset. This file contains 25,000,095 rows consisting of ratings assigned to a particular movie by a single user, as well as the timestamp at which the rating was submitted. See sample below:

userId	movieId	rating	timestamp
1	296	5.0	1147880044
1	306	3.5	1147868817
1	307	5.0	1147868828
1	665	5.0	1147878820
1	899	3.5	1147868510

Feature	Description
userId	Unique MovieLens ID used to identify user associated with rating
movieId	Unique MovieLens ID used to identify movie associated with rating. Foreign key of *movies.csv*.
rating	Value from 1.0 to 5.0 with increments of 0.5 corresponding to rating submitted by a user for a particular title
timestamp	Seconds since UTC corresponding to submission time of rating

It may be interesting to analyze how a user's rating of a movie may change overtime using the timestamp dimension, however, for the scope of this project, we will not be using timestamp data.

👉 Emotion Data

The data concerning the training of the text-based emotion classification model can divided into 2 categories:

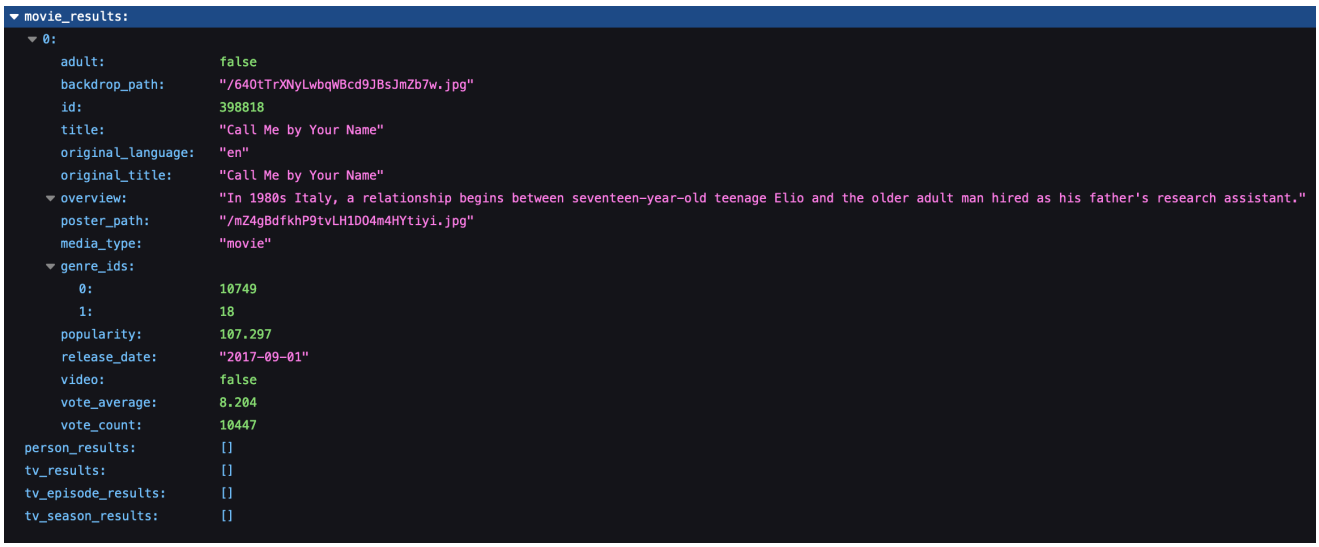
1. Training data

Though there exists public datasets of full-length movie reviews labeled for sentiment analysis, these datasets exclusively categorize review texts by binary sentiment (i.e. positive or negative). Because the aim of this project is to analyze films in more specific categories of emotion, the training set for our model is based on the Emotions dataset as published by Hugging Face (https://huggingface.co/datasets/emotion). This dataset contains 20,000 labelled text strings, each assigned to one of six classes: anger, fear, joy, love, sadness, and surprise. A sample of this dataset is provided below:

Text	Emotion
im feeling rather rotten so im not very ambiti...	sadness
im updating my blog because i feel shitty	sadness
i never make her separate from me because i do...	sadness
i left with my bouquet of red and yellow tulip...	joy
i was feeling a little vain when i did this one	sadness

2. Movie description/overview data

Movie descriptions/overviews are retrieved from TMDB (https://www.themoviedb.org/) using their API. We need the IMDb ID of the desired movie in order to fetch its data; this requires a bridge between the MovieLens and IMDb datasets which we will explore later on. The TMDB API provides a find method to search by external id. See an example call: https://api.themoviedb.org/3/find/tt5726616?api_key=85fc3c49845e51a05cbaadc87fa820a8&language=en-US&external_source=imdb_id



EXPLORATORY DATA ANALYSIS/CLEANING & PRE-PROCESSING

👉 Movie Data

movies.csv contains the full titles (and release year) of all films represented in *ratings.csv*. No null values are present in the movies.csv data. We will drop the genre field, leaving us with just movieId, and title. The number of unique values by feature is as follows:

movieId	62423
title	62325

The movieId field ranges from 1 to 62,423, while there are 62,325 unique entries in title, meaning there are 98 duplicated movie titles. Upon further inspection, it was found that these duplicate titles refer to the same film but with slightly different values for the associated genres. The inclusion of the year of release in parentheses in the title field removes ambiguity in dealing with films that have identical titles but different years.

ratings.csv comprises the bulk of the data that we will be working with. It is related to *movies.csv* through movieId, and contains 25,000,095 rows of data. As previously stated, we will not be using the timestamp dimension for the purposes of this project. This leaves us with the following number of unique values for each feature:

userId	162541
movieId	59047
rating	10

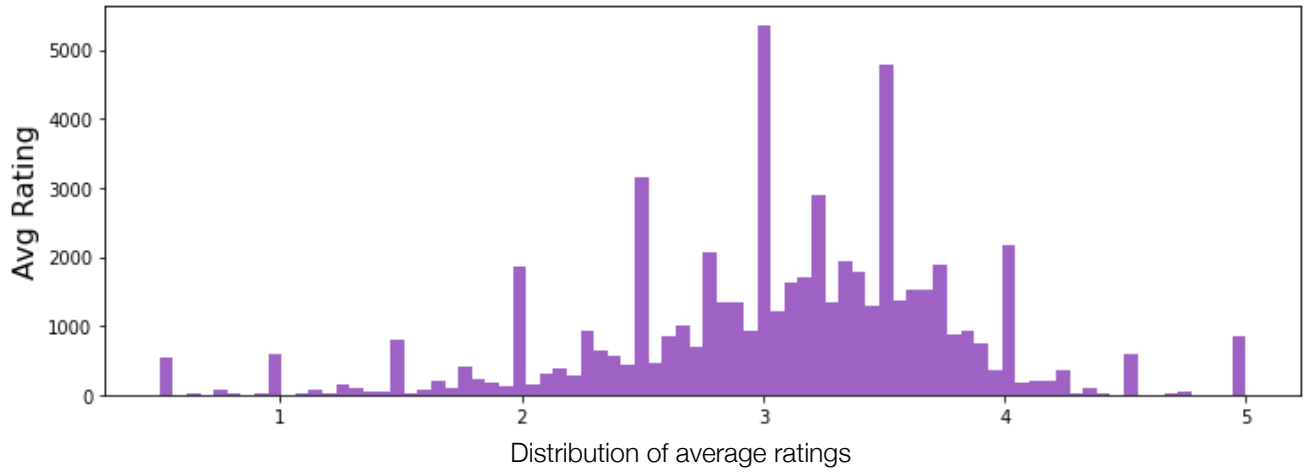
The 10 different classes of ratings include decimal numbers between range 1.0 and 5.0, with 0.5 increments in between values. movieId only returns 59,047 unique values, indicating that there are titles in *movies.csv* that have no ratings.

Perform a right-inner merge of *movies.csv* and *ratings.csv* on movieId.

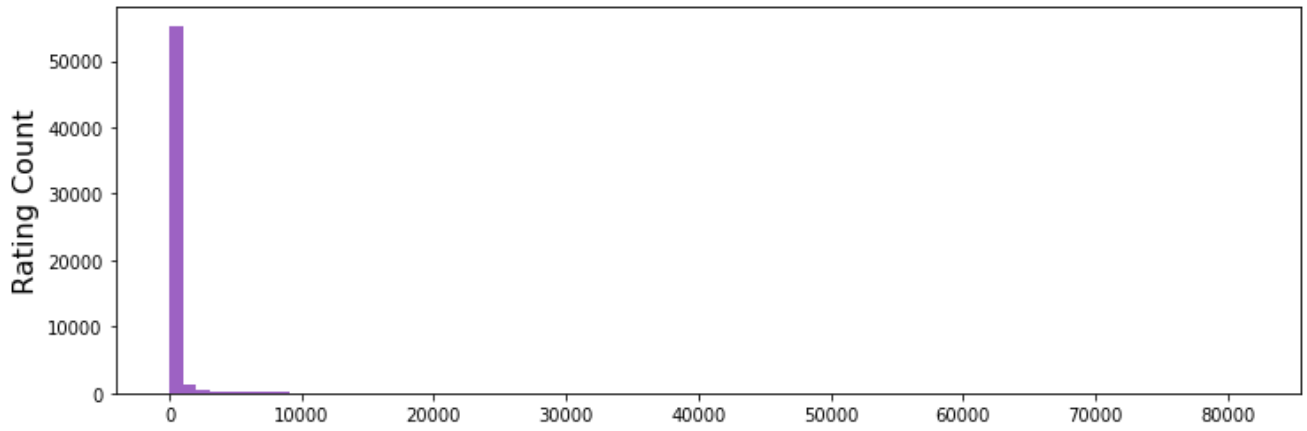
userId	movieId	rating	title
1	296	5.0	Pulp Fiction (1994)
1	306	3.5	Three Colors: Red (Trois couleurs: Rouge) (1994)
1	307	5.0	Three Colors: Blue (Trois couleurs: Bleu) (1993)
1	665	5.0	Underground (1995)
1	899	3.5	Singin' in the Rain (1952)

We continue by finding the average rating, and total number of ratings for each title, and generating a new data frame object as below:

movieId	AvgRating	CountRating
1	3.893708	57309
2	3.251527	24228
3	3.142028	11804
4	2.853547	2523
5	3.058434	11714



Distribution of average ratings



Distribution of total ratings

The distribution of average ratings appears fairly normal. The distribution of total ratings or ratings counts, however, is heavily skewed right. In order to effectively deal with noisy data and to truncate the current dataset to a more manageable size, we will only consider those users with at least 100 different rating submissions, and then take a random sample of 30,000 user IDs. These 30,000 user IDs will be used to filter the full ratings dataset.

```
# Calculate how many movies each user has submitted a rating for. This will be
# used later to filter out users with a low number of ratings
user_ratings_df = ratings_df.groupby('userId')['rating'].count().reset_index()
user_ratings_df.rename(columns={'rating':'NoMoviesRated'}, inplace=True)

user_list = user_ratings_df[user_ratings_df.NoMoviesRated>=100]['userId'].
to_list()
user_list = random.sample(user_list, 30000)
```

userId	NoMoviesRated
1	70
2	184
3	656
4	242
5	101

Data frame of users and total ratings submitted

We will then only consider those films with at least 100 submitted ratings. After merging the aggregated ratings data with the main ratings data frame, we get something like looks like this:

userId	movieId	rating	title	AvgRating	CountRating
93864	356	5.0	Forrest Gump (1994)	4.048011	81491
66019	356	4.0	Forrest Gump (1994)	4.048011	81491
4039	356	4.0	Forrest Gump (1994)	4.048011	81491
16649	356	5.0	Forrest Gump (1994)	4.048011	81491
57276	356	4.5	Forrest Gump (1994)	4.048011	81491

This cleaned data frame represents 10,326 unique titles and 30,000 unique users.

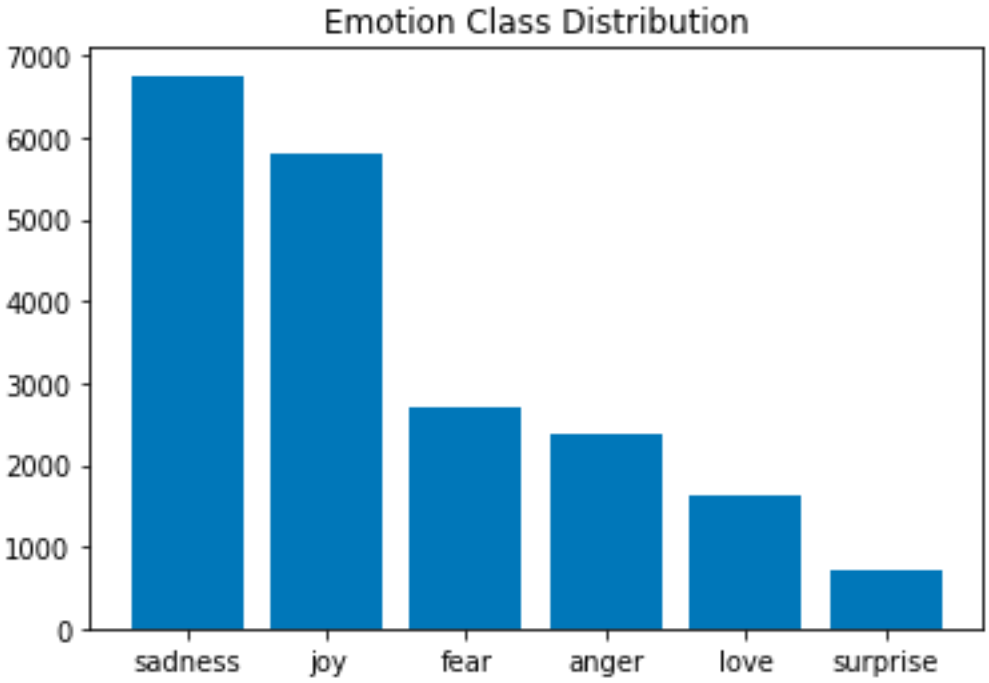
This data frame will then be transformed to produce the following matrix of user IDs, movie IDs, and ratings:

userId	13	18	19	23	43	46	69	76	86	89	...
movieId											
1	4.0	3.0	0.0	0.0	4.0	0.0	3.0	0.0	5.0	0.0	...
2	0.0	0.0	3.5	0.0	3.5	0.0	0.0	0.0	3.0	3.0	...
3	0.0	1.5	0.0	5.0	0.0	0.0	0.0	0.0	0.0	4.0	...
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
5	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
...	...	...	...	...	...	...	...	...	...	...	...
203519	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
204352	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
204542	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
204698	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
205383	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

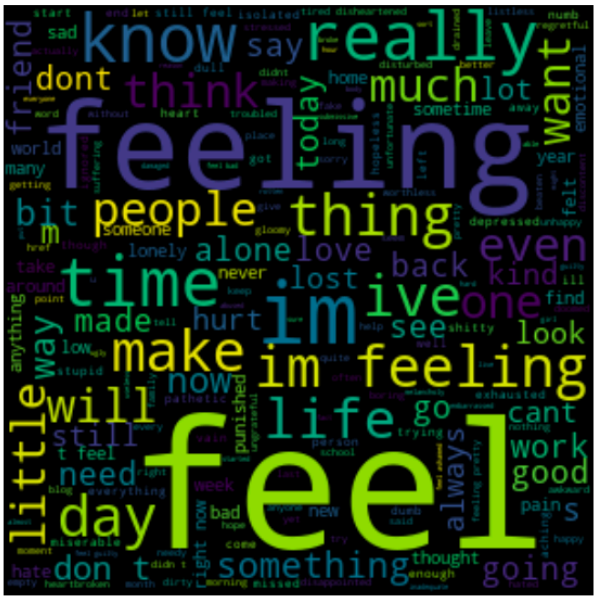
This matrix will eventually be fitted on our K-Nearest Neighbors model. The data frame used to produce the matrix will be used to train our singular value decomposition (SVD) model.

👉 Emotion Data

The emotion data set consists of 20,000 tweet-sized strings of text with associated emotion labels from the following classes: sadness, joy, fear, anger, love, and surprise. A label encoder object is used to transform these six classes to numerical type for further work.



sadness Word Cloud



fear Word Cloud

The word “feel” and its derivatives appear frequently in the data set. We will deal with this noise shortly, but first, we will divide our data into training, validation, and testing subsets. The original file download from Hugging Face already splits the data into these categories in the ratio 16000:2000:2000, but we will go ahead and randomly select data from the full 20,000 records following these ratios for our model.

Working with the Keras library, we will use a tokenizer object to vectorize the training set text corpus. With the assistance of the Natural Language Toolkit (NLTK) and Regular Expressions (RE) libraries, we will clean the texts by removing common stop words, stemming the words to their root forms, etc.

After processing the training, validation, and test text data, the output results in this type of data structure:

```
array([[    0,     0,     0, ...,  6737, 12724,  5015],
       [    0,     0,     0, ...,  6484,  3089,  4430],
       [    0,     0,     0, ..., 11511,  6075,  8546],
       ...,
       [    0,     0,     0, ...,  6484,  6371, 14260],
       [    0,     0,     0, ..., 11878,  8186, 13585],
       [    0,     0,     0, ...,  9706,  2504, 14504]], dtype=int32)
```

Each line or nested array represent cleaned text strings.

MODELS

3 separate models will be built; 2 based on the ratings data, and 1 based on the emotions data. The intention is for the final recommendation engine to incorporate suggestions from all 3 models. However, the initial prototype deployment does not have a robust recommendations system that is built on the emotion data. We will first discuss the 3 models and then outline how they have been brought together in the initial prototype, and how they are planned to be used in future versions of the product.

👉 Memory-based Collaborative Filtering with KNN

There are two broad categories of recommendations systems: content-based, and collaborative-based. The former returns suggested content based on the similarity of the content itself to other pieces of content, whereas the latter suggests content based on what users with similar preferences have consumed. This project is built on user ratings/preferences data, meaning we are using the collaborative approach.

Memory-based approaches use simple measures such as cosine similarity to calculate the distance between two vectors. In this context, our KNN model will utilize cosine similarity to calculate the distance between a given movie and all other movies in the data set based on the ratings users have submitted for each movie. We take the matrix of user IDs, movie IDs, and ratings, and transform the data frame object to a scipy sparse matrix. The KNN object is instantiated, and then fitted with the sparse matrix. We can then pass an example movie title to the kneighbors method of the model, specify the number of nearest neighbors (or recommendations) we want, and it returns those movies that are shortest in distance to the inputted movie title.

```
recommend('inception')
```

```
Inception (2010)
```

	Title	Distance
0	Dark Knight, The (2008)	0.217647
1	Interstellar (2014)	0.277964
2	Dark Knight Rises, The (2012)	0.278636
3	Inglourious Basterds (2009)	0.282665
4	Shutter Island (2010)	0.287717

👉 Model-based Collaborative Filtering SVD

In the model-based approach, we use an SVD algorithm to predict the ratings a particular user would assign to a movie based on the data set of ratings, movie IDs, and user IDs. The Surprise library provides easy-to-use algorithms and methods for training and evaluating recommendation system models. We split the data in a 75:25 ratio of training to test, and then instantiate the SVD model object and fit it with the training set. We then test the model by comparing the predicted ratings calculated by the model to actual ratings submitted by users.

```
RMSE: 0.6991

0.6991493234777875
```

Evaluating the model, we see an RMSE of 0.6991, indicating very good performance.

We define a function to return the top-N recommendations per user based on predicted ratings (in this case, we'll use N=5). Save these recommendations as a pandas series object along with a series for associated user IDs. This new data frame will be saved and loaded during deployment.

uid	movieId	predictedRating
118670	356	5.000000
118670	457	4.977576
118670	527	4.931338
118670	1246	4.869925
118670	1198	4.796270

👉 Emotion Classification Model

Instantiate a Keras RNN model object and add the following layers and compile:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 300, 200)          3048800

 dropout (Dropout)           (None, 300, 200)          0

 lstm (LSTM)                 (None, 128)               168448

 dropout_1 (Dropout)         (None, 128)               0

 dense (Dense)               (None, 64)                8256

 dropout_2 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 6)                 390

=================================================================
Total params: 3,225,894
Trainable params: 3,225,894
Non-trainable params: 0
_________________________________________________________________
```

Fit the model with our training sets and the following parameters:

```
callback = EarlyStopping(
    monitor='val_loss',
    patience=2,
    restore_best_weights=True
    )

# Fit model
history = model.fit(X_train,
                    y_train,
                    validation_data=(X_val, y_val),
                    verbose=1,
                    batch_size=64,
                    epochs=10,
                    callbacks=[callback]
                   )
```

Train the model:

```
Epoch 1/10
250/250 [==============================] - 179s 709ms/step - loss: 1.4526 -
accuracy: 0.4238 - val_loss: 0.9367 - val_accuracy: 0.6840
Epoch 2/10
250/250 [==============================] - 177s 709ms/step - loss: 0.5691 -
accuracy: 0.8182 - val_loss: 0.4344 - val_accuracy: 0.8590
Epoch 3/10
250/250 [==============================] - 182s 728ms/step - loss: 0.2810 -
accuracy: 0.9061 - val_loss: 0.3347 - val_accuracy: 0.8845
Epoch 4/10
250/250 [==============================] - 193s 770ms/step - loss: 0.1822 -
accuracy: 0.9396 - val_loss: 0.3016 - val_accuracy: 0.8900
Epoch 5/10
250/250 [==============================] - 214s 855ms/step - loss: 0.1287 -
accuracy: 0.9555 - val_loss: 0.3303 - val_accuracy: 0.8860
Epoch 6/10
250/250 [==============================] - 205s 821ms/step - loss: 0.1107 -
accuracy: 0.9613 - val_loss: 0.3608 - val_accuracy: 0.8805
```

After 6 epochs, we stop as the validation accuracy has declined twice since the 4th epoch. We keep the best weights, and evaluate the model against the validation and test sets:

```
model.evaluate(X_val, y_val, verbose=1)
```

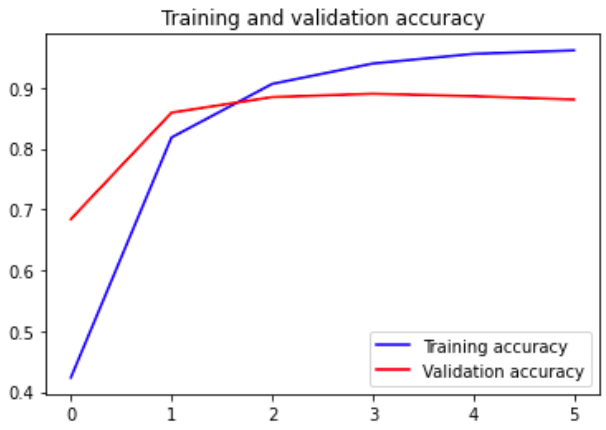
✓ 11.7s

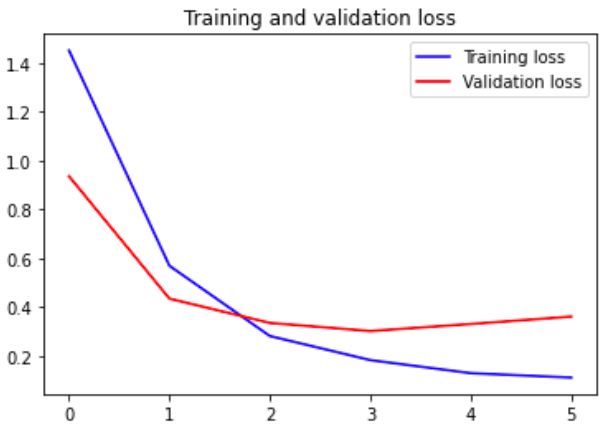
```
63/63 [==============================] - 11s 177ms/step - loss: 0.3016 -
accuracy: 0.8900

[0.30155712366104126, 0.8899999856948853]
```

```
model.evaluate(X_test, y_test, verbose=1)
```

✓ 11.8s

```
63/63 [==============================] - 12s 183ms/step - loss: 0.2763 -
accuracy: 0.9000

[0.2763170003890991, 0.8999999761581421]
```





Testing the emotion classification model with sample texts:

```
He was speechles when he found out he was accepted to this new job
1/1 [==============================] - 0s 92ms/step
1/1 [==============================] - 0s 38ms/step
joy : 0.4717341661453247


This is outrageous, how can you talk like that?
1/1 [==============================] - 0s 41ms/step
1/1 [==============================] - 0s 47ms/step
anger : 0.8275076150894165


I feel like im all alone in this world
1/1 [==============================] - 0s 61ms/step
1/1 [==============================] - 0s 40ms/step
sadness : 0.989284098148346


He is really sweet and caring
1/1 [==============================] - 0s 61ms/step
1/1 [==============================] - 0s 42ms/step
love : 0.7478350400924683
```

DEPLOYMENT

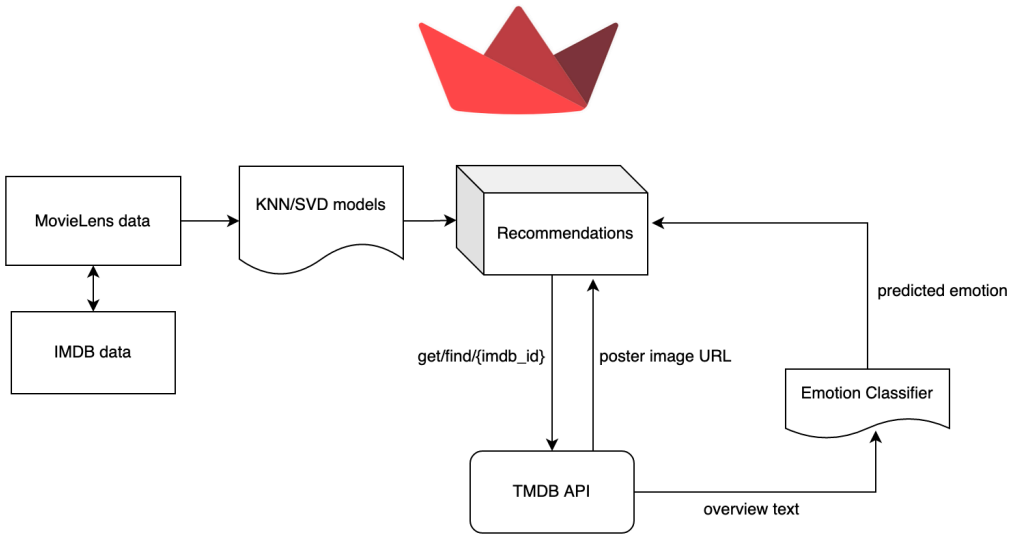
👉 Deployment Strategy for v1 of App

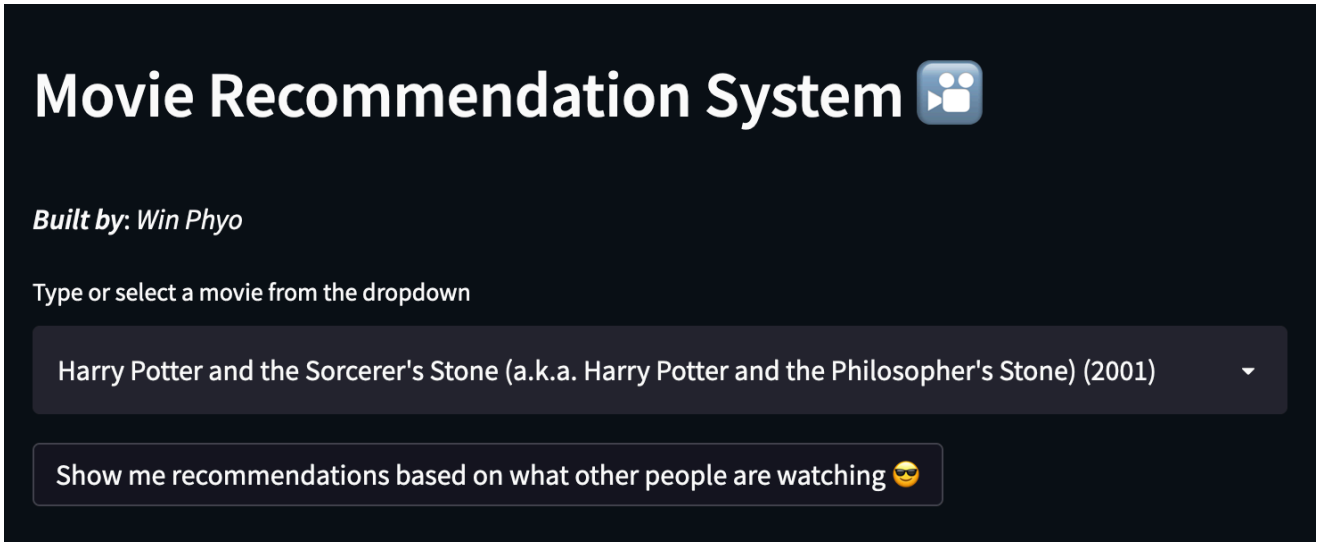
The v1 prototype of the movie recommendations app will host both the KNN and SVD model on separate web pages. We will take advantage of the Streamlit library to build out the front-end for our app. We need to save a few important objects relating to each of the 3 models:

- For the memory-based KNN approach, we need the model itself, the scipy sparse matrix object, and the main data frame with the aggregated ratings, movie title, and movie ID.
- For the model-based SVD approach, we save the top 10 predictions for each user in a data frame object, and then load this data frame when running the app. This is a good-enough solution at present, as it does not appear to introduce any significant strain on loading times or resource usage.
- Additionally, for the emotion classification model we need to load the model itself, as well download the NLTK English stop words

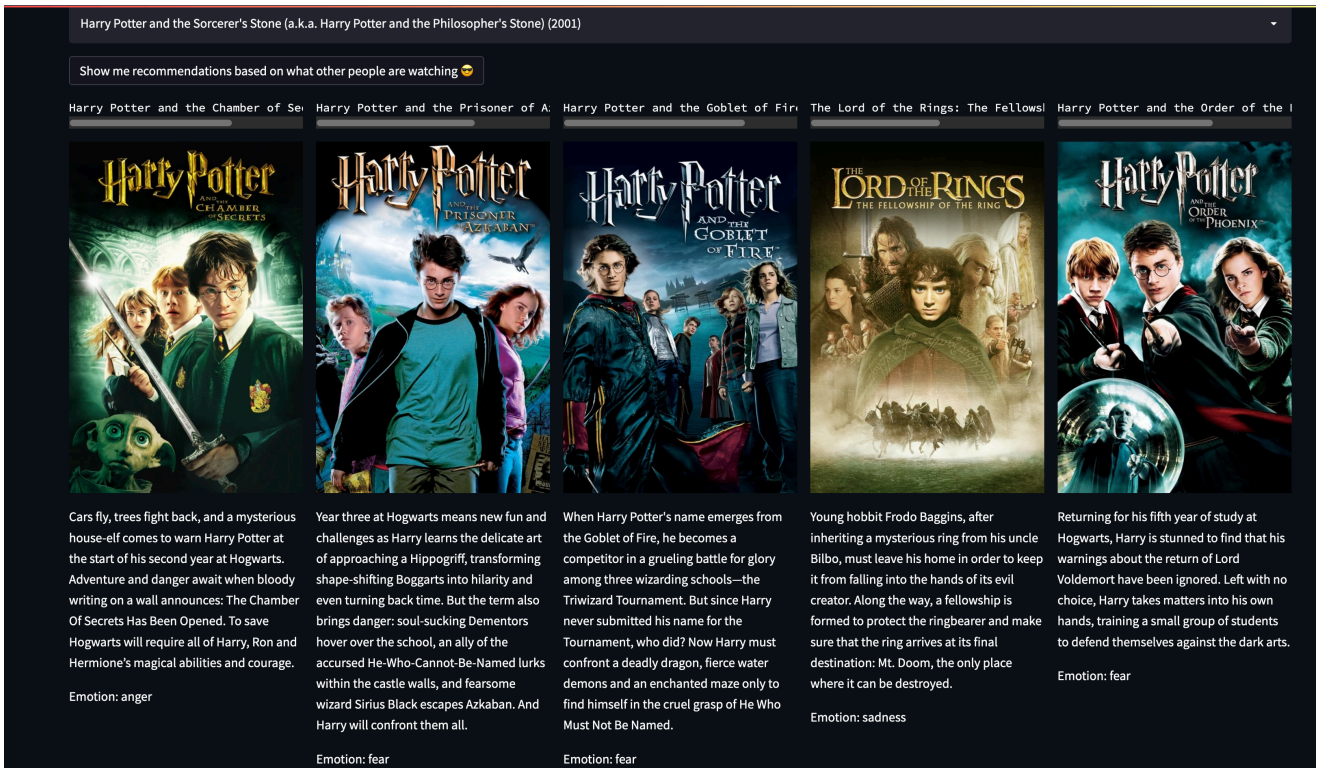
For both ratings-based models, we will need to define a relationship between the MovieLens proprietary movie ID and the corresponding IMDb ID for suggested titles. The IMDb ID is a parameter for the call to the TMBD API using the get/find/{external_id} method (https://developers.themoviedb.org/3/find/find-by-id). This response object contains the overview text and URL for the associated movie poster. The IMDb dataset contains the IMDb ID that we need, the title of the movie, as well the year of release. It is necessary to produce a clean text string that includes the year of release in a format that is consistent across both IMDb and MovieLens data. Following this, we can merge on movie title in order to get the IMDb ID needed for the API call.

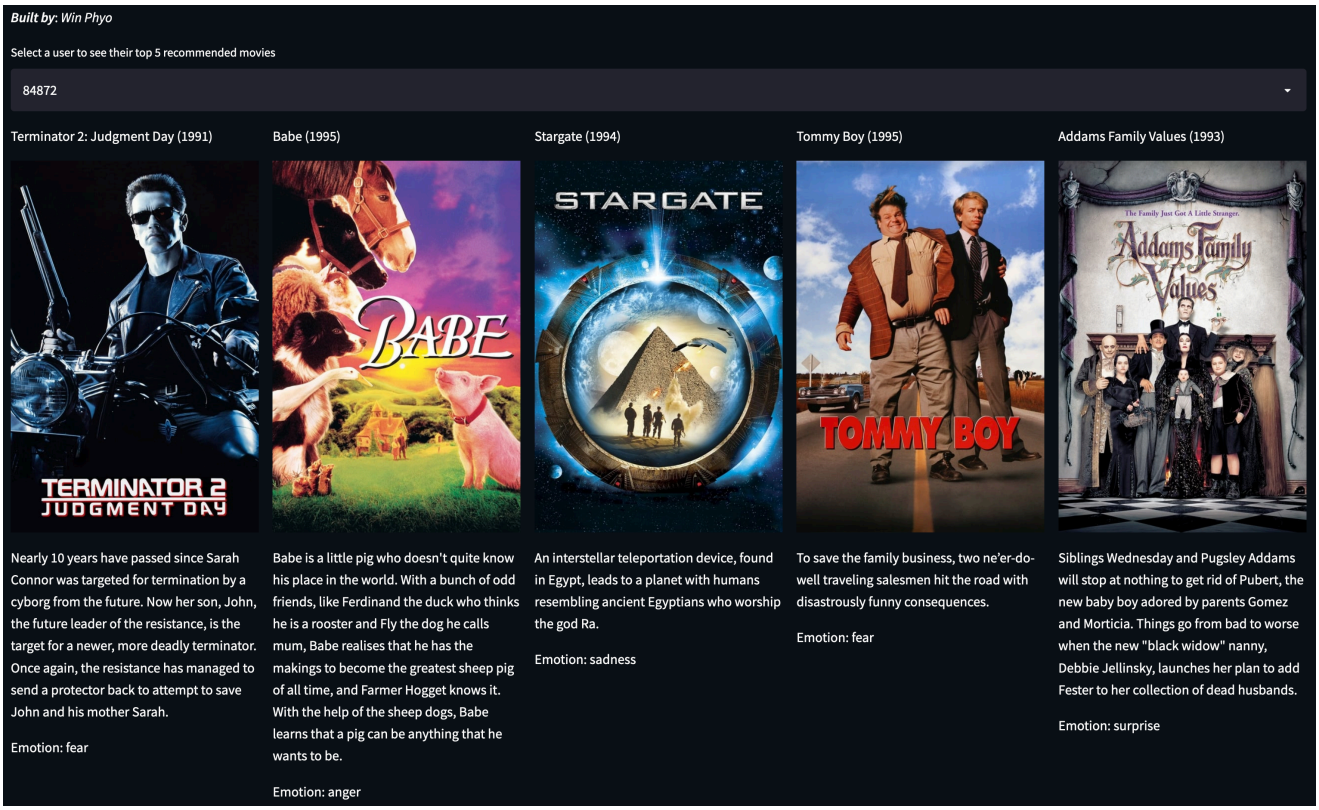
This API call and subsequent application of the emotion classifier to the overview text occurs after the app user submits input. For the memory-based KNN, the input is a movie title (chosen from a drop-down list of the 10,326 unique movie titles after cleaning the dataset). For the SVD model, the input is a user ID of one of the MovieLens users with at least 100 ratings submitted.





Main page of KNN-model based recommendation system. The model finds those titles with the lowest distance between them and the user-submitted movie in terms of cosine similarity, and returns the top 5. The IMDb IDs of the resulting recommendations are passed to the TMDB API call; from the response, the URL to the movie poster and overview text is extracted and the emotion classification function applied to it. The final result are 5 movies, posters, overviews, and the predicted emotion from the overview text.





Main page of the SVD-model based recommendation system. The model takes a particular user ID as input and returns the top 5 movies with the highest predicted ratings for that user. In exactly the same process as above, the app makes requests to the TMBD API to fetch overview and movie poster data, and the emotion classifier is applied to the overview text.

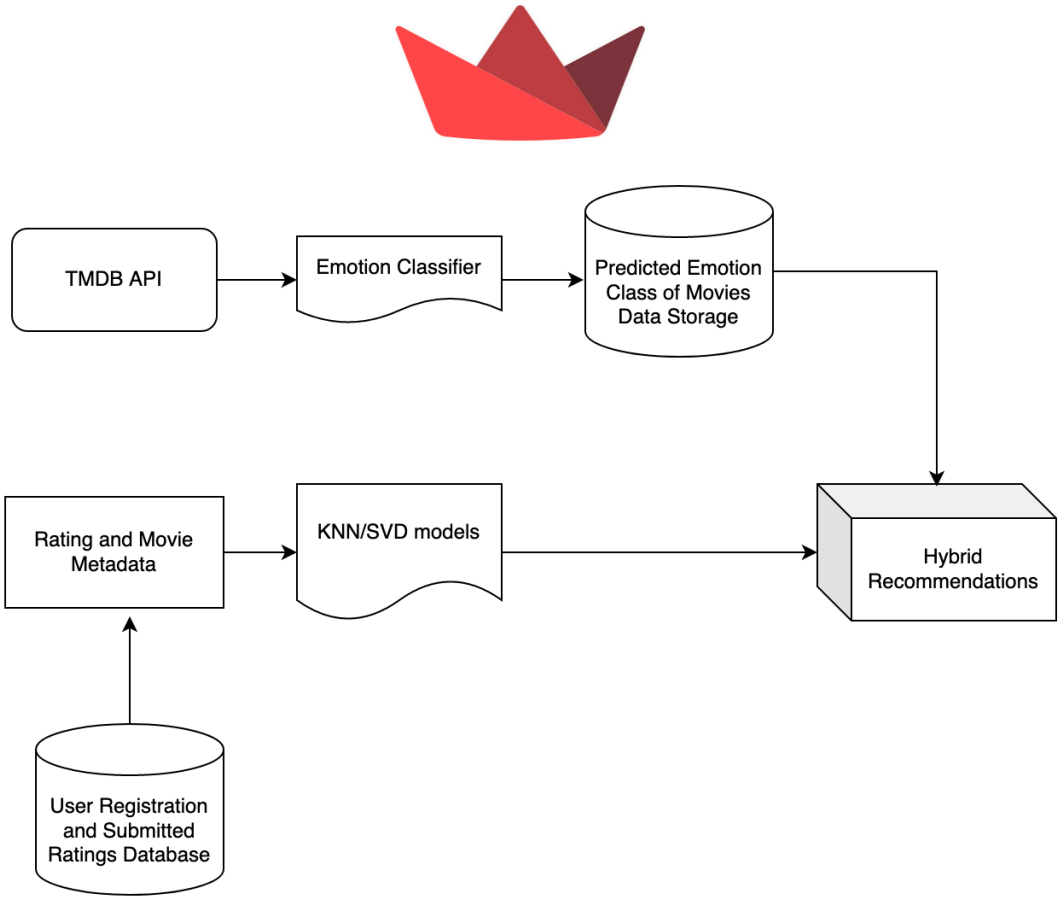
👉 Deployment Strategy for v2 of App

The primary flaws of the current prototype version of the app are: its failure to adequately incorporate emotion data in the recommendations themselves, instead simply providing the user with a predicted emotion of the recommendations generated solely through ratings data; and the inability to add new data points in the form of new users or new ratings submissions.

To address the first issue, it is planned to build a hybrid recommendation engine that returns recommendations from the ratings-based models as well as a new emotion-based model. This new model will be built using the overview texts from the TMBD API response, and the current emotion classifier. The idea is to provide content suggestions entirely based on similarity in terms of predicted emotion class. As the current model is capable of providing both a class and a probability, the simplest deployment of this would be to, given a movie title:

- find those movies of the same class,
- among those movies, select those with the closest probability to that of the given movie.

There also is a need to build out a registration feature. For this to be possible, we need to provision a database that holds user data including ratings, and allow the user to submit ratings for films.



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Streamlit - https://streamlit.io/

GitHub Repository - https://github.com/wkphyo/capstone-project