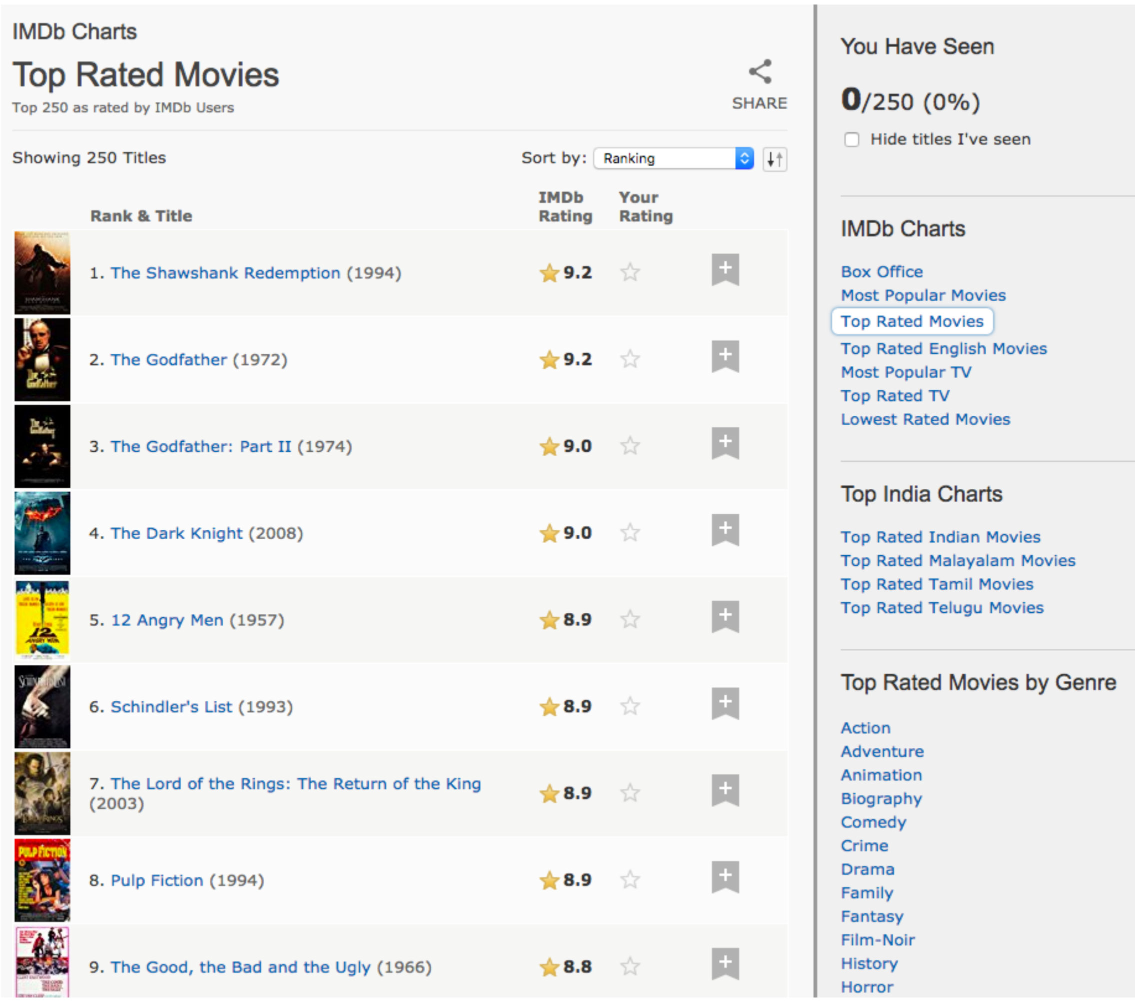
Lab 3: Building an IMDB Top 250 Clone with Pandas

The **Internet Movie Database** (**IMDB**) maintains a chart called the IMDB Top 250, which is a ranking of the top 250 movies according to a certain scoring metric. All the movies in this list are non-documentary, theatrical releases with a runtime of at least 45 minutes and over 250,000 ratings:



This chart can be considered the simplest of recommenders. It doesn't take into consideration the tastes of a particular user, nor does it try to deduce similarities between different movies. It simply calculates a score for every movie based on a predefined metric and outputs a sorted list of movies based on that score.

In this lab, we will be covering the following:

- Building a clone of the IMDB Top 250 chart (henceforth referred to as the simple recommender).
- Taking the functionalities of the chart one step further and building a knowledge-based recommender. This model takes user preferences with regards to genre, timeframe, runtime, language, and so on, and recommends movies that satisfy all conditions.

The simple recommender

The first step in building our simple recommender is setting up our workspace. Let's create a new directory named [Lab3]. Create a Jupyter Notebook in this directory named [Simple Recommender] and open it in the browser.

Let's now load the dataset we used in the previous lab into our notebook.

In case you have not downloaded it already, the dataset is available at
https://www.kaggle.com/rounakbanik/the-movies-dataset/downloads/movies_metadata.csv/7.

```
import pandas as pd
import numpy as np

#Load the dataset into a pandas dataframe
df = pd.read_csv('../data/movies_')

#Display the first five movies in the dataframe
df.head()
```

Upon running the cell, you should see a familiar table-like structure output in the notebook.

Building the simple recommender is fairly straightforward. The steps are as follows:

1. Choose a metric (or score) to rate the movies on
2. Decide on the prerequisites for the movie to be featured on the chart
3. Calculate the score for every movie that satisfies the conditions
4. Output the list of movies in decreasing order of their scores

The metric

The metric is the numeric quantity based on which we rank movies. A movie is considered to be better than another movie if it has a higher metric score than the other movie. It is very important that we have a robust and a reliable metric to build our chart upon to ensure a good quality of recommendations.

The prerequisties

The variable **m** in the IMDb weighted rating formula sets a threshold for movie popularity, ensuring that only films with a certain number of votes are considered for the rankings. It is defined as the number of votes of the 80th percentile movie in the dataset, meaning that only movies with more votes than 80% of other films qualify.

The choice of **m** can be adjusted to control the balance between popularity and score quality. A higher value of **m** makes the rankings more selective, focusing on well-known films, while a lower value allows more movies to be considered, including lesser-known titles. Experimenting with different values helps optimize the recommender's performance.

Let us now calculate the value of *m*:

```
#Calculate the number of votes garnered by the 80th percentile movie
m = df['vote_count'].quantile(0.80)
m

OUTPUT:
50.0
```

We can see that only 20% of the movies have gained more than 50 votes. Therefore, our value of *m* is [50].

Another prerequisite that we want in place is the runtime. We will only consider movies that are greater than [45 minutes] and less than [300 minutes] in length. Let us define a new DataFrame, [q_movies], which will hold all the movies that qualify to appear in the chart:

```
#Only consider movies longer than 45 minutes and shorter than 300 minutes
q_movies = df[(df['runtime'] >= 45) & (df['runtime'] <= 300)]

#Only consider movies that have garnered more than m votes
q_movies = q_movies[q_movies['vote_count'] >= m]

#Inspect the number of movies that made the cut
q_movies.shape

OUTPUT:
(8963, 24)
```

We see that from our dataset of 45,000 movies approximately 9,000 movies (or 20%) made the cut.

Calculating the score

The final value that we need to discover before we calculate our scores is *C*, the mean rating for all the movies in the dataset:

```
# Calculate C
C = df['vote_average'].mean()
C

OUTPUT:
5.6182072151341851
```

We can see that the average rating of a movie is approximately 5.6/10. It seems that IMDB happens to be particularly strict with their ratings. Now that we have the value of *C*, we can go about calculating our score for each movie.

First, let us define a function that computes the rating for a movie, given its features and the values of *m* and *C*:

```
# Function to compute the IMDB weighted rating for each movie
def weighted_rating(x, m=m, C=C):
    v = x['vote_count']
    R = x['vote_average']
    # Compute the weighted score
    return (v/(v+m) * R) + (m/(m+v) * C)
```

Next, we will use the familiar [apply] function on our [q_movies] DataFrame to construct a new feature score. Since the calculation is done for every row, we will set the axis to [1] to denote row-wise operation:

```
# Compute the score using the weighted_rating function defined above
q_movies['score'] = q_movies.apply(weighted_rating, axis=1)
```

Sorting and output

There is just one step left. We now need to sort our DataFrame on the basis of the score we just computed and output the list of top movies:

	title	vote_count	vote_average	score	runtime
10309	Dilwale Dulhania Le Jayenge	661.0	9.1	8.855148	190.0
314	The Shawshank Redemption	8358.0	8.5	8.482863	142.0
834	The Godfather	6024.0	8.5	8.476278	175.0
40251	Your Name.	1030.0	8.5	8.366584	106.0
12481	The Dark Knight	12269.0	8.3	8.289115	152.0
2843	Fight Club	9678.0	8.3	8.286216	139.0
292	Pulp Fiction	8670.0	8.3	8.284623	154.0
522	Schindler's List	4436.0	8.3	8.270109	195.0
23673	Whiplash	4376.0	8.3	8.269704	105.0
5481	Spirited Away	3968.0	8.3	8.266628	125.0
2211	Life Is Beautiful	3643.0	8.3	8.263691	116.0
1178	The Godfather: Part II	3418.0	8.3	8.261335	200.0
1152	One Flew Over the Cuckoo's Nest	3001.0	8.3	8.256051	133.0
1176	Psycho	2405.0	8.3	8.245381	109.0
351	Forrest Gump	8147.0	8.2	8.184252	142.0
1184	Once Upon a Time in America	1104.0	8.3	8.183804	229.0
1154	The Empire Strikes Back	5998.0	8.2	8.178656	124.0
18465	The Intouchables	5410.0	8.2	8.176357	112.0
289	Leon: The Professional	4293.0	8.2	8.170276	110.0
3030	The Green Mile	4166.0	8.2	8.169381	189.0
1170	GoodFellas	3211.0	8.2	8.160414	145.0
2216	American History X	3120.0	8.2	8.159278	119.0
1161	12 Angry Men	2130.0	8.2	8.140785	96.0
9698	Howl's Moving Castle	2049.0	8.2	8.138499	119.0
2884	Princess Mononoke	2041.0	8.2	8.138264	134.0

And voila! You have just built your very first recommender. Congratulations!

We can see that the Bollywood film *Dilwale Dulhania Le Jayenge* figures at the top of the list. We can also see that it has a noticeably smaller number of votes than the other Top 25 movies. This strongly suggests that we should probably explore a higher value of *m*. This is left as an exercise for the reader; experiment with different values of *m* and observe how the movies in the chart change.

The knowledge-based recommender

In this section, we are going to go ahead and build a knowledge-based recommender on top of our IMDB Top 250 clone. This will be a simple function that will perform the following tasks:

1. Ask the user for the genres of movies he/she is looking for
2. Ask the user for the duration
3. Ask the user for the timeline of the movies recommended
4. Using the information collected, recommend movies to the user that have a high weighted rating (according to the IMDB formula) and that satisfy the preceding conditions

The data that we have has information on the duration, genres, and timelines, but it isn't currently in a form that is directly usable. In other words, our data needs to be wrangled before it can be put to use to build this recommender.

In our [Lab3] folder, let's create a new Jupyter Notebook named [Knowledge Recommender]. This notebook will contain all the code that we write as part of this section.

As usual, let us load our packages and the data into our notebook. Let's also take a look at the features that we have and decide on the ones that will be useful for this task:

```
import pandas as pd
import numpy as np

df = pd.read_csv('../data/movies_metadata.csv')

#Print all the features (or columns) of the DataFrame
df.columns

OUTPUT:
Index(['adult', 'belongs_to_collection', 'budget', 'genres', 'homepage', 'id',
       'imdb_id', 'original_language', 'original_title', 'overview',
       'popularity', 'poster_path', 'production_companies',
       'production_countries', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'status', 'tagline', 'title', 'video',
       'vote_average', 'vote_count'],
      dtype='object')
```

From our output, it is quite clear which features we do and do not require. Now, let's reduce our DataFrame to only contain features that we need for our model:

```
#Only keep those features that we require
df = df[['title','genres', 'release_date', 'runtime', 'vote_average', 'vote_count']]

df.head()
```

Next, let us extract the year of release from our [release_date] feature:

```
#Convert release_date into pandas datetime format
df['release_date'] = pd.to_datetime(df['release_date'], errors='coerce')

#Extract year from the datetime
df['year'] = df['release_date'].apply(lambda x: str(x).split('-')[0] if x != np.nan
else np.nan)
```

Our [year] feature is still an [object] and is riddled with [NaT] values, which are a type of null value used by Pandas. Let's convert these values to an integer, [0], and convert the datatype of the [year] feature into [int].

To do this, we will define a helper function, [convert_int], and apply it to the [year] feature:

```
#Helper function to convert NaT to 0 and all other years to integers.
def convert_int(x):
    try:
        return int(x)
    except:
        return 0

#Apply convert_int to the year feature
df['year'] = df['year'].apply(convert_int)
```

We do not require the [release_date] feature anymore. So let's go ahead and remove it:

```
#Drop the release_date column
df = df.drop('release_date', axis=1)

#Display the dataframe
df.head()
```

The [runtime] feature is already in a form that is usable. It doesn't require any additional wrangling. Let us now turn our attention to [genres].

Genres

Upon preliminary inspection, we can observe that the genres are in a format that looks like a JSON object (or a Python dictionary). Let us take a look at the [genres] object of one of our movies:

```
#Print genres of the first movie
df.iloc[0]['genres']

OUTPUT:
"[{'id': 16, 'name': 'Animation'}, {'id': 35, 'name': 'Comedy'}, {'id': 10751, 'name':
'Family'}]"
```

We can observe that the output is a stringified dictionary. In order for this feature to be usable, it is important that we convert this string into a native Python dictionary. Fortunately, Python gives us access to a function called [literal_eval] (available in the [ast] library) which does exactly that. [literal_eval] parses any string passed into it and converts it into its corresponding Python object:

```
#Import the literal_eval function from ast
from ast import literal_eval

#Define a stringified list and output its type
a = "[1,2,3]"
print(type(a))

#Apply literal_eval and output type
b = literal_eval(a)
print(type(b))

OUTPUT:
```

```
<class 'str'>
<class 'list'>
```

We now have all the tools required to convert the *genres* feature into the Python dictionary format.

Also, each dictionary represents a genre and has two keys: [id] and [name]. However, for this exercise (as well as all subsequent exercises), we only require the [name]. Therefore, we shall convert our list of dictionaries into a list of strings, where each string is a genre name:

```
#Convert all NaN into stringified empty lists
df['genres'] = df['genres'].fillna('[]')

#Apply literal_eval to convert to the list object
df['genres'] = df['genres'].apply(literal_eval)

#Convert list of dictionaries to a list of strings
df['genres'] = df['genres'].apply(lambda x: [i['name'] for i in x] if isinstance(x,
list) else [])

df.head()
```

Printing the head of the DataFrame should show you a new [genres] feature, which is a list of genre names. However, we're still not done yet. The last step is to [explode] the genres column. In other words, if a particular movie has multiple genres, we will create multiple copies of the movie, with each movie having one of the genres.

For example, if there is a movie called *Just Go With It* that has *romance* and *comedy* as its genres, we will [explode] this movie into two rows. One row will be *Just Go With It* as a *romance* movie. The other will be a *comedy* movie:

```
#Create a new feature by exploding genres
s = df.apply(lambda x: pd.Series(x['genres']),axis=1).stack().reset_index(level=1,
drop=True)

#Name the new feature as 'genre'
s.name = 'genre'

#Create a new dataframe gen_df which by dropping the old 'genres' feature and adding
the new 'genre'.
gen_df = df.drop('genres', axis=1).join(s)

#Print the head of the new gen_df
gen_df.head()
```

	title	runtime	vote_average	vote_count	year	genre
0	Toy Story	81.0	7.7	5415.0	1995	animation
0	Toy Story	81.0	7.7	5415.0	1995	comedy
0	Toy Story	81.0	7.7	5415.0	1995	family
1	Jumanji	104.0	6.9	2413.0	1995	adventure
1	Jumanji	104.0	6.9	2413.0	1995	fantasy

You should be able to see three *Toy Story* rows now; one each to represent *animation*, *family*, and *comedy*. This [gen_df] DataFrame is what we will use to build our knowledge-based recommender.

The build_chart function

We are finally in a position to write the function that will act as our recommender. We cannot use our computed values of *m* and *C* from earlier, as we will not be considering every movie just the ones that qualify. In other words, these are three main steps:

1. Get user input on their preferences
2. Extract all movies that match the conditions set by the user
3. Calculate the values of *m* and *C* for only these movies and proceed to build the chart as in the previous section

Therefore, the [build_chart] function will accept only two inputs: our [gen_df] DataFrame and the percentile used to calculate the value of *m*. By default, let's set this to 80%, or [0.8]:

```
def build_chart(gen_df, percentile=0.8):
    #Ask for preferred genres
    print("Input preferred genre")
    genre = input()

    #Ask for lower limit of duration
    print("Input shortest duration")
    low_time = int(input())

    #Ask for upper limit of duration
    print("Input longest duration")
    high_time = int(input())

    #Ask for lower limit of timeline
    print("Input earliest year")
    low_year = int(input())

    #Ask for upper limit of timeline
    print("Input latest year")
    high_year = int(input())

    #Define a new movies variable to store the preferred movies. Copy the contents of
gen_df to movies
    movies = gen_df.copy()

    #Filter based on the condition
    movies = movies[(movies['genre'] == genre) &
                    (movies['runtime'] >= low_time) &
                    (movies['runtime'] <= high_time) &
                    (movies['year'] >= low_year) &
                    (movies['year'] <= high_year)]

    #Compute the values of C and m for the filtered movies
    C = movies['vote_average'].mean()
    m = movies['vote_count'].quantile(percentile)
```

```
    #Only consider movies that have higher than m votes. Save this in a new dataframe
q_movies
    q_movies = movies.copy().loc[movies['vote_count'] >= m]

    #Calculate score using the IMDB formula
    q_movies['score'] = q_movies.apply(lambda x: (x['vote_count']/(x['vote_count']+m)
* x['vote_average'])
                                       + (m/(m+x['vote_count']) * C)
                                       ,axis=1)

    #Sort movies in descending order of their scores
    q_movies = q_movies.sort_values('score', ascending=False)

    return q_movies
```

Time to put our model into action!

We want recommendations for animated movies between 30 minutes and 2 hours in length, and released anywhere between 1990 and 2005. Let's see the results:

```
In [114]: #Generate the chart for top animation movies and display top 5.
          build_chart(gen_df).head()

          Input preferred genre
          animation
          Input shortest duration
          30
          Input longest duration
          120
          Input earliest year
          1990
          Input latest year
          2005

Out[114]:
```

	title	runtime	vote_average	vote_count	year	genre	score
9698	Howl's Moving Castle	119.0	8.2	2049.0	2004	animation	7.994823
359	The Lion King	89.0	8.0	5520.0	1994	animation	7.926672
0	Toy Story	81.0	7.7	5415.0	1995	animation	7.637500
6232	Finding Nemo	100.0	7.6	6292.0	2003	animation	7.549423
546	The Nightmare Before Christmas	76.0	7.6	2135.0	1993	animation	7.460500

We can see that the movies that it outputs satisfy all the conditions we passed in as input. Since we applied IMDB's metric, we can also observe that our movies are very highly rated and popular at the same time. The top 5 also includes *The Lion King*, which is my favorite animated movie of all time! I, for one, would be very happy with the results of this list.

Summary

In this lab, we built a simple recommender, which was a clone of the IMDB Top 250 chart. We then proceeded to build an improved knowledge-based recommender, which asked the user for their preferred genres, duration, and time. In the process of building these models, we also learned to perform some advanced data wrangling with the Pandas library.