CS 179g Final report

Team 8:

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Our dataset:

Link for the Shared Folder: Metacritic Movies Data

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- Part 2 Spark data processing and store in MySQL (with addressed comments)
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Part 1 - Data collection

Requirements

Collecting around 1GB of data from one of the followings:

- Crawl the web using Scrapy from website: <u>metacritic.com</u>

TA comments to address:

- How many reviews did you get in total?

We got 575057 reviews in total

- What's the min/max/average # reviews per movie?

We are not sure how to answer this question. According to metacritic.com, there are always a couple critic reviews for each movie, and some movies may not have any user reviews. Some popular movies can have hundreds of reviews.

- You may also include the movie description, release date, countries, languages. I think these are important as well.

We have included movie descriptions (summary) and release dates. We do not include countries and languages because they are not available for all movies.

Design

We want to get movie data from the website <u>metacritic.com</u>. We used a seed url to crawl all the links in the website to gather information about all the movies listed in the website (about 14488 movies). We also crawled another dataset for the review: user and critics reviews (about 575057 reviews), which we want to analyze to find out the user sentiment using a model.

Implementation

Using scrapy to crawl data about movies such as title, ratings, release date, distributer, reviews, actors, meta scores, user scores, positive scores, negative scores and so on.

We implement two scrapy crawlers to crawl the detailed information of each movie, and the critic and user reviews of all the movies. The data format are two JSON files: *movies.json* and *reviews.json*

- Movie spider: crawls through a list of movies (100 items) per page. We follow the movie detail link for each movie to get its metadata including (title, ratings, release date, actors, etc...)

- Review spider: traverse through the list of movies on the site, we follow through its critic and user review pages to get all the rating score, distribution of ratings, and comment of each movie.

Evaluation

Overall we are satisfied with the data we got for each movie so far. However, since the data is compact and in text format. We Are able to get roughly ~ 1GB of data from the entire collection of movies in metacritic.com.

Properties of data:

- 1. Movies data:
 - Title, id, rating, scores (user and meta), actors, genre, distributor, runtime, etc.
- 2. Reviews data: (both critic and user reviews)
 Author of user reviews, rating score, given review, etc.

Performance:

- Runtime: The crawler to crawl the movies data along with the critic reviews took 36657.27 seconds. Since we have set a delay of approximately 1-5 seconds in between requests to avoid getting blocked from the site, a longer runtime will be expected.
- Successes/misses: There are a total of 14482 movies on the site, we are able to crawl 14471 items, the overall success rate is 99.92% with the missing rate of 0.08%.
- 'retry/count': 947
- 'retry/max reached': 7
- 'retry/reason_count/429 Unknown Status': 89
- 'retry/reason count/504 Gateway Time-out': 858

Challenges:

- It gets difficult to avoid rejected requests for data and the websites block the crawling bots.
- All of our data is text, so it is not easy to gather 2GB of data.
- Using a delay to send requests makes the crawling process very long to be able to gather data.
- Websites tend to have many different layouts and designs which makes it difficult to crawl and get the same type of data we want, this adds a huge overhead in the cleaning process.

Screenshots

Figure: Movie data

```
▼ root: [] 14488 items

▼ 0:

1d: 6

title: "Three Colors: Red"
distributor: "Miramax"
date: "November 23, 1994"

▼ starring: [] 2 items

0: "Trème Jacob"
1: "Jean-Louis Trintignant"
summary: "Krysztof Kieslowski closes his Three Colors trilogy in grand fashion, with an incandescent meditation on fate and composed in Geneva whose life dramatically intersects with that of a bitter retired judge, played by Jean-Louis Trintignant. Red alousy and betrayal unfolds. Red is an intimate look at forged connections and a splendid final statement from a remarkable of the discrete of the discre
```

Figure: Critics review data

```
▼ 5700006:
review_type: "Critic Review"
release_date: "December 6, 2019"
movie_name: "Portrait of a Lady on Fire"
meta_score: "95"
review_crone: "96"
review: "4 film in which everything feels stunningly fresh, raw and new."
▼ 5700000:
review_crone: "86"
review_crone: "66"
revie
```

Figure: User review data

Figure: Crawling Result

Contribution

Movies data - Yanjun Zhu, Yongfeng Liang, Hongan Zhang, Mahdi Aouchiche Critic reviews - Yanjun Zhu, Hongan Zhang, Yongfeng Liang, Mahdi Aouchiche User reviews - Yongfeng Liang, Yanjun Zhu, Hongan Zhang, Mahdi Aouchiche Jupyter Lab setup - Yanjun Zhu, Yongfeng Liang, Hongan Zhang, Mahdi Aouchiche Brainstorm design - Yanjun Zhu, Yongfeng Liang, Hongan Zhang, Mahdi Aouchiche Preparing reports - Yanjun Zhu, Yongfeng Liang, Hongan Zhang, Mahdi Aouchiche Checking data results - Yanjun Zhu, Yongfeng Liang, Hongan Zhang, Mahdi Aouchiche

Part 2 - Spark Data Processing and store in MySQL Report

Requirements

Collect, clean, and analyze data and store it in SQL databases.

Design

Movies Rating Analysis:

By obtaining data from web crawlers, these original data (movies.json and reviews.json) are further cleaned to retain the desired analysis data. For example, MetaSore, UserScore, PostiveScore, NegativeScore and MixedScore are obtained after cleaning the scoring data of movies(Clean_New_Data.json). The data after cleaning is analyzed. First, Weight values of PostiveScore, NegativeScore and MixedScore are processed by implementing Spark. Next, normalization of Metascore and Userscore is performed by using pyspark. Finally, all standardized data are input into the model to calculate the movie recommendation score. By referring to the recommendation score, we can get the popularity of each film or recommend it to the audience.

Content-based filtering:

There are 14,488 movies in the dataset, one of the attributes we found common are the genres. Since there are 27 unique genres in the dataset. We use tf-idf to quantify the importance of a genre and construct a feature vector for each movie. Next, we use cosine similarity to compute a movie with every other movie in the database to get a list of top 10 similar movies.

Review Sentiment Analysis:

There are a total of 575,057 approximate reviews which include critic and user reviews. We want to analyze the sentiment of each text by calculating its polarity score. The polarity score is a float within the range [-1.0, 1.0].

Implementation

This portion is for the movies.json file cleaning and analysis

There was not much to clean in this file but we used Spark to store the data in a dataframe and then normalize the columns that contain the scores (the user score is on the scale of 0 to 10, and the critics score is on a scale of 0 to 100). We then store the cleaned data into a JSON file. Then, we use pyspark dataframe to further process and analyze the data with operations such as join, remove duplicate, and drop. Some data needs to be normalized. When we got all the data which we needed, we stored the data in the database by using SQL tables finally. Since there are a large number of reviews, we use spark to load the data into a dataframe and for each individual review we calculate the polarity score to further determine if the review has a positive, neutral or

negative sentiment. We generate the bar chart to explore the frequency of each genre in the data (see figure below) to discover distributions of different genres for the movie recommendations.

```
from pyspark.sql.functions import col

df = (sparkdf
    .withColumn('ID',col('ID').cast('int'))
    .withColumn("Metascore", col("Metascore").cast("float"))
    .withColumn("Userscore", col("Userscore").cast("float"))
    .withColumn("UserScorePositive", col("UserScorePositive").cast("float"))
    .withColumn("UserScoreMixed", col("UserScoreMixed").cast("float"))
    .withColumn("UserScoreNegative", col("UserScoreNegative").cast("float"))
    .dropna()
    )
}
```

Figure: Using pyspark to cast data type

```
dfPosi=Posi.drop('UserScorePositive', 'UserScoreMixed', 'UserScoreNegative', 'Sum', 'date')
dfPosi.show()
| ID|
                 title
                                  genres | Metascore | Userscore |
                                                                   Positive
      Three Colors: Red|[Drama, Mystery, ...|
                                            100.0
                                                      8.6 | 0.9212121212121213 |
            Casablanca|[Drama, Romance, ...| 100.0|
                                                      8.9 0.9448818897637795
  3 |
           Rear Window| [Mystery, Thriller]| 100.0|
                                                      8.8 0.9358974358974359
           Intolerance
                          [Drama, History]
 12
                                            99.0
                                                      7.4 0.72222222222222
           City Lights | [Drama, Comedy, R...|
                                                      8.9 | 0.9622641509433962 |
 10
                                             99.0
  9| Singin' in the Rain|[Comedy, Romance,...|
                                            99.0
                                                      8.7 0.9037433155080213
             Notorious | [Drama, Thriller,... | 100.0 |
 8
                                                      8.0 0.8648648648648649
       Some Like It Hot
                         [Comedy, Romance]
 18
                                           98.0
                                                      8.4 0.9032258064516129
 16 The Treasure of t... [Adventure, Drama...]
                                            98.0
                                                      8.5 | 0.9207920792079208 |
                        [Drama, Mystery]
                                           100.0
 1
         Citizen Kane
                                                      8.4 0.872093023255814
                                            94.0
100
              Lady Bird
                         [Drama, Comedy]
                                                      7.6 0.7915407854984894
99
         We Were Here
                            [Documentary]
                                             94.0
                                                      6.9 0.6428571428571429
 98
        The Gunfighter
                                [Western]
                                             94.0
                                                      97
         Apocalypse Now [Action, Drama, War]
                                             94.0
                                                      8.8 | 0.917037037037037|
```

Figure: Using pyspark to drop columns which is unnecessary for processing data

Math model to calculate recommendation scores

The weight value of user score and Meta score is calculated based on the weighted average, and the recommendation score is calculated based on the weighted sum of user score, Meta score and average of sum of Mixed, Positive and Negative. Because the results of the two scores are considered comprehensively, the recommendation score is more reasonable.

Recommendation scores = (MetaScore * 0.5 weighted) + (UserScore * 0.5 weighted) + {(Mixed) * 0.1 weighted + Positive * 0.1 weighted + Negative * 0.1 weighted)/3}

This portion is for the reviews json file cleaning and analysis

In "clean_the_reviews.py" file we used spark to clean the reviews.json file, we extracted review_clean as tokens without punctuation and removed stop words from the raw reviews. The first table is the output file which we used to populate the mysql database. We also used to compare the sentiment score with the overall critic and user scores. The second and the 3rd tables represent the critic reviews and user reviews respectively. The row count, max, min, and average values are calculated using spark functions. The results are displayed at the bottom of the tables. The sentiment score calculated does not match each review score but overall we are happy with the result using the raw reviews to calculate the sentiment score, which is very similar to using the clean reviews column.

release	date	movie nam	+ ne revi	ew type	+ reviewer name	+ review score	reviev	-+ v review clear	+ sentiment scor
			+		+	+		<u>-</u>	÷
		The Shop Around t						. one best stylish . one great movies	
		The Shop Around t Summer of Soul (. easily one best m	
		Summer of Soul (gets dvd release	
		Summer of Soul (one wordwow time	
y showing	top 5	rows	+		+	+		.+	+
	.,.	, .,							
 M cleaned	criti +	c reviews with sent	iments 		+	+		.+	+
release_	date	movie_name	revi	ew_type	reviewer_name	review_score	review	v review_clear	sentiment_scor
nuary 17,	1940	Gone with the Wind	Critic	Review	null	100	A towering landma	towering landmark	0.56
		Gone with the Wind						well even essenti	
		Gone with the Wind						one truly great f	
		Gone with the Wind						elements seem gro	
nuary 17, 	1940	Gone with the Wind	Critic	Review	null	100 +	To see Gone With	see gone wind big	0. +
y showing	top 5	rows							
w cleaned	user	reviews with sentim	ments						
release_	date	movie_nam	ne revi	ew_type	reviewer_name	review_score	review	v review_clear	sentiment_scor
nuary 12,	1940	The Shop Around t	User	Review	Unchartedhero	10	One of the best s	one best stylish	0.37
		The Shop Around t						one great movies	
		Summer of Soul (easily one best m	
		Summer of Soul (gets dvd release	
Tulv 2	2021	Summer of Soul (. User	Review	churchman58	10	One wordWOW!	one wordwow time	0.21

This results in this part are processed using 2 spark threads:

```
Total crawled reviews = 575057
Total cleaned reviews = 575057
Total critic reviews = 258238
Total user reviews = 316819

Min sentiment score = -1.0
Max sentiment score = 1.0
Average sentiment score = 0.14253025363970745

Min critics score = 0.0
Max critics score = 100.0
Average critics score = 62.49895832526584

Min user score = 0.0
Max user score = 10.0
Average user score = 6.589424876664594

SPARK using 2 threads:

Spark data cleaning time = 42.917057037353516 seconds
Spark calculation time = 334.89447498321533 seconds
Total time for spark processing = 377.81153202056885 seconds
```

The next result is the same file run again using only 1 thread:

```
Total crawled reviews = 575057
Total cleaned reviews = 575057
Total critic reviews = 258238
Total user reviews = 316819

Min sentiment score = -1.0
Max sentiment score = 1.0
Average sentiment score = 0.14253025363970745

Min critics score = 0.0
Max critics score = 100.0
Average critics score = 62.49895832526584

Min user score = 0.0
Max user score = 10.0
Average user score = 6.589424876664594

SPARK using 1 thread:

Spark data cleaning time = 44.57609152793884 seconds
Spark calculation time = 341.2775456905365 seconds
Total time for spark processing = 385.85363721847534 seconds
```

In our case the data is not big enough to illustrate a large gap in the run time between spark using 2 threads or 1 thread, which is usually the case. For both our runs it took approximately 6 min and 45 seconds to clean and process the data.

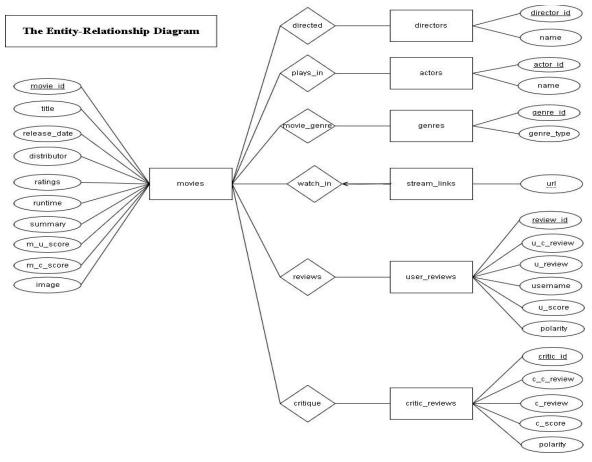
Evaluation

By calculating the recommendation score output by the model, we can see that it is generally consistent with user score and Meta score, but not very accurate with each review. The recommendation score calculated by the model is more reasonable, mainly because the weight of input value is taken into comprehensive consideration. The weight value of user score and Meta score is calculated based on the weighted average, and the recommendation score is calculated based on the weighted sum of user score and Meta score. Because the results of the two scores are considered comprehensively, the recommendation score is more reasonable.

Screenshots

SQL relational diagram:

We designed the database to be able to handle all the crawled data and the different attributes for each movie. Each movie has a different amount of its attributes and so we had to make many tables to accommodate the queries for the user interface. The database is created and populated by the "Create_SQL_Database.py" which deletes the existing tables when the file is run and creates them fresh again and then populated. The cs179g mysql database contains 12 tables in total as shown in the diagram below which has 1 weak entity "stream links".



The MySQL database creation took approximately 22 min to download, some attributes such as the number of actors, directors, movies and reviews are displayed below.

```
Total time to create MySQL DB = 1288.4311833381653 s

Number of actors = 33654

Number of directors = 7680

Number of genres = 27

Number of user reviews = 316731

Number of critic reviews = 257758

Number of total reviews = 600523

Number of movies = 14488

Number of movies w/o release date = 89

(your_venv) ubuntu@ip-172-31-20-178:~/users/maouc001$
```

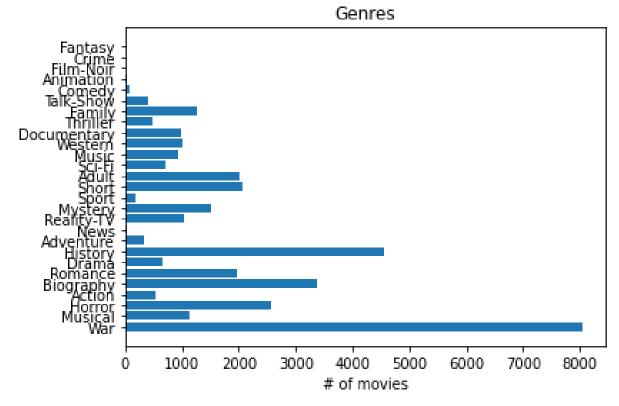


Figure: The frequency of Each Genre in the data

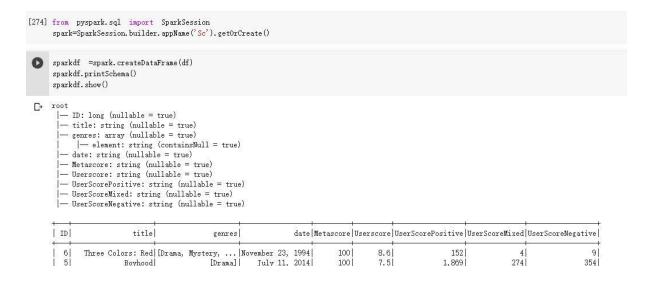


Figure: Using pyspark to implement data

3 Rear Window	[Mystery, Thriller] Se		1054	100	8.81	365	15	10
	[Drama, Thriller,			100	9.2	3, 293	93	115
2 Ine Godfather				991	7.4	3, 293 13	1	4
Intolerance Moonlight		october 21,		99	7.1	1, 244	175	317
	[Drama, Comedy, R			99	8.9	102	1101	31
	[Comedy, Romance,			99	8.7	169	13	51
	[Drama, Thriller, Se			100	8.0	641	7	3
	[Comedy, Romance]			981	8.4	140	iil	4
	[Drama, Mystery, De			98	8.7	2, 414	188	150
6 The Treasure of t				98	8.5	93	6	2
1 Citizen Kane				100	8.4	600	52	36
00 Lady Bird	[Drama, Comedy] I			94	7.6	786	117	90
9 We Were Here				94	6.9	27	6	9
8 The Gunfighter	[Western]	June 23,		94	7.4	8	1	ől
	[Action, Drama, War]			94	8.8	619	35	21
The second second second	[Drama, Comedy, R	June 15,		94	8.8	40	ol	1
5 Meet Me in St. Louis				94	6.0	21	21	11
olmeet me in St. Louis	[DIama, Comedy, R	January 1,	1010	71	0.01	-1	41	-1
y showing top 20 rows m pyspark.sql.function = (sparkdf	s import col	nt'))						

Figure: Display Normalized Mata scores and User Scores

Part 3 - Web Page Frontend

Requirements

Build Web interface using a web programming framework (Django) to explore the preprocessed or analyzed data. For other front-end related web design techniques, we used HTML as well.

Design

The web interface will have a Home page. It has a Home button, a search button, a reset button, 2 drop down menus and a text input box. The goal of this home page is to ask the user to select a category of movie search between movie name, actor, distributor, genre, and director that they want to search from. They can choose to order the movies by the release date (default display) or descending order by user or critic score. Then, enter the keyword(s) in the input box and hit the search button. This will redirect the user to a search result page.

In the result page, There is a home button on top that redirects back to the home page. Below it is a text that tells how many results are returned. All the relevant movies are displayed in rows. It shows the information of each movie including the image, title, metascore, user score, summary, genre, distributor, etc. Additionally, there is a button under each movie's title called "Show more info". Once the user clicks on any of those buttons it will redirect to the movie's detailed page.

In the movie's detailed page, more information is shown in addition to the result page. The user can see the stream links, critic reviews, user reviews and the recommended similar movies in this page.

Implementation

First, we follow the TA's steps to set up Django, start the web interface project, and modify some of the files.

Next, we create a home page using the template provided by the TA. Then, we modify the HTML code to add a background image, a few buttons, and inputs.

Finally in the views.py, we create two functions: search and more that correspond to two web pages. The home page calls the search function and the search function calls the more function. The structure of these two functions are similar to lab8's which composes MySQL queries and input these queries to the MySQL database. We hardcode most of the HTML codes in strings as well as to organize and display the results returned from the database. We then return the complete HTML code to Django to form a webpage.

Evaluation

The data are directly retrieved from the database tables to display to the front end which can reduce the time to load the webpage. The overall time to road the search result page... seconds

The search using some non alphabetic and non numeric characters still creates the issue of SQL injection is still an issue, we tried to overcome it by checking the user input in the search using a regex to eliminate some characters and display an error message to the user. We also tried to take advantage of the Django csrf Middleware parameter and the {% csrf_token %} after a user input to catch some of the sql injection types.

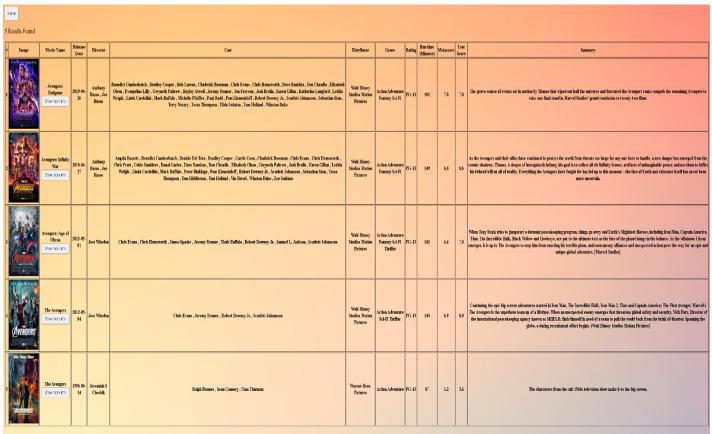
The search by each category works fine and returns correct results. Ideally we wanted to display the available movie genre available when searching by the genre, but we did not implement this option, so the user has to type all or part of the movie genre to get results which is the same as all other searches.

Screenshots

Home page with various of searching options:

Home	THE PARTY NAMED IN
LAZZ: Search Movies	
Powered by Metacritic.com	
Search from: Movie Name Please enter a keyword: Search	Display by: Newly Released
Search Reset	

Result of the search displayed by release date in descending order: (if none selected it is used by default)



Result of the search displayed by user score in descending order:

Home											
5 Results Found											
# Image	Movie Nume	Release Date	Director	Cast	Distributor	Genre	Rating	Run time (Misutes)		User Score	Summery
Arranga	Avengers: Infinity War Show more into	2018-04- 27	Anthony Russo , Joe Russo	Angale Bassel, Bosselis Camberhock, Benkin Jud Hee, Brodhy Couper, Carrie Cene, Chabrick Bassena, Chin Denn, Chin Humseeth, Chin Frant, Chile Smallers, Dona Guirley, Dove Bastlini, Don Chesle, Elizabed Ches, Geyand Faltwe, Jeak Brodh, Kares Gillas, Leitin Wilgit, Linda Cuelellid, Mark Enfals, Perer Bibling, Pon Elezanderf, Eshert Denney Jr., Serviert Johanson, Eshartan Sun, Tessa Thompson, Jim Höldertm, Jim Hölderd, Vh. Birsel, Wheren Duley, Zuc Stalman.	Walt Disney Studios Motion Pictures	Action Adventure Fantasy Sci-Fi	PG-13	149	6.8	8.4	As the Averages and this data have customed to protect the world from threat two large for any one lower to build, a new denges has energed from the consist students. Thomas. A depost of the regulation for furnity, the goal is no reflect all the finding's Stans, sufficient of entimetically deposite power, and one them to the little like volume of the order of the summer. The fore of Farsh and externor hard flass severe been never uncertain.
AVENDERS	The Avengers Show more into	2012-05- 04	Joss Whedon	Clefa Kvans , Jersey Renner , Robert Develoy Jr. Scarbest Johannan	Walt Disney Studies Motion Pictures	Action Adventure Sci-Fi Thriller	PG-13	143	6.9	8.0	Conducting the spic life serves adverses stated in Iron Man, The Internabile Hall, Fron Man 2. There and Capatile Souriers: The First Avenages in the serves appeared to the serves of the Serves of the International procedure of International Processing Serves on SIRICAD, Enable Internal International Processing Serves of International Processing Serves of International Processing Serves on SIRICAD, Enable International Contract Co
	Avengers: Endgame Show race (nf)	2019-04- 26	Anthony Rusco , Joe Russo	Benedici Camberbards, Frankry Cupper, Refs. Larvon, Chabrield Barsman, Chife Krum, Chris Hemrewch, Drus Bartiers, Dan Chaselle, Hitaberle Chen, Krumphin Lilly, Groyant Patters, Highey Adved, Jerseny Stemer, Am Forence, John Bredts, Exers Gilles, Kreisrien Langford, Leitin Wright, Linds Cardellini, Mark Enfales, Michelle Freifer, Paul Bold, Don Domentielli, Edwict Downey, &c., Scarlett Johnsonse, Sebestian Stan, Terry Notery, Tessa Thompson, 13th Solution, Dan Helmed, Wheten Dade	Walt Disney Studies Motion Pictures	Action Adventure Fantasy Sci-Fi	PG-13	181	7.8	7.8	The grow curve of events set is median by Thanes that wipord our helf the universe and fracture of the Avengers coulds compels the remaining Avengers to take one find stand in Morvel Stadios' great conclusion to twenty two fittes.
Armans	Avergers: Age of Ultron Show more into	2015-05- 01	Joss Whedon	Chris Evans , Chris Hemwerth , James Spader , Jervary Renner , Mark Raffolz , Robert Devney Jr. , Samuel L. Juckson , Scarlett Johanson	Walt Disney Studies Motion Pictures	Action Adventure Fantasy Sci-Fi Thrifler		141	6.6	7.0	Weer Twy Stark, tries to Jumpatur a dormout peecele-eping program, things go very and Furth's Nightiest Herees, beholing from Man, Capatin America. The: The herealite Field, Back Where and Healeys, we appet so the obligator free as the fact of the jalance large in the balance. As the Mildown Dress ownerspec, It is up to The Aveogree to stop bins from easieting his travelly least, and not measury allience and unexpected action pives the way for me sple and unique global solventore. [Marvel Studies]
a vanda	The Avengers Show more info	1998-05-	Jeremisth S Chechik	Rohh Plenser , Stan Connery , Una Thurann	Warner Bres. Pictures	Action Adventure	PG-13	87	1.2	2.6	The characters from the cult 1960s television show make it to the hig serven.

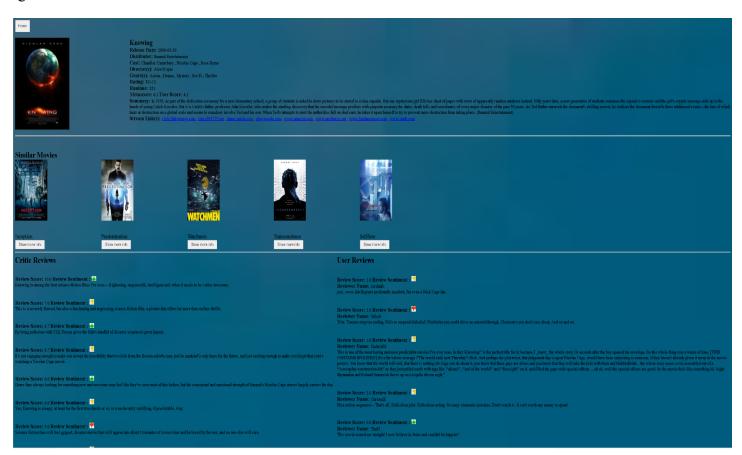
Result of the search displayed by metacritics score in descending order:

Home											
5 Results Found											
# Image	Movie Name	Releuse Date	Director	Cast	Distributor	Geure	Rating	Run time (Minutes)	Mecasco	User Score	Sumacy
	Avengers: Endgame Shos more nb	2019-04- 26	Anthony Russo , Joe Russo	Benridd Cushorbarid, Brushy Cupper, Bet Larons, Chabrick Bursons, Chit Neus, Chit Stenewech, Dres Bentier, Duc Chadle, Hindred Cline, Evaquine Lilly, Greyant Delaws; Highey Abrell, Jerony Romer, Am Forces, John Benti, Saver Gilles, Liecheine Laugherl, Leititz Weigle, Linds Cardellid, Mack Raffals, Mikeder Früffer, Paul Bold, Tem Exementiff, Rabert Dewey, Je., Seutert Johnston, Sebestian Stan, Derry Meney, Treas Bungson, Tills Seltons, Tem Hadnad, Whenta Dale	Walt Disney Studies Motion Pictures	Action Adventure Funtacy Sci Fl		181	7.8	7.8	The grove course of events set in motion by Thunes that wiped out half the underset and fundament the Avengers could compels the remaining Avengers to take one find stand in Marvel Studies' ground conclusion to twenty (see films.
2 (Avenuens	The Avengers Show more info	2012-05- 04	Joss Whedon	Chris Evans , Jersmy Renner , Robert Devezey da , Scarbeit Johnsson	Walt Disney Studios Motion Pictures	Action Adventure Sci-Fi Thriller		143	6.9	8.0	Continuing the epic big surrow obveniers started in Iron Man, The Incredible Hall, Iron Man 2, Thur and Capatals America. The Past Averages Sub- The Averages Sub-superform team up of a lifetime. When an ansequent omany emerges that theretoes global startey and accessity, Mol. Farg. Biberton as the International parachersping agency known as SHIELD, thou Manuford haved of a ranse up this twood has for the bright of disasters Spanning the globa, a facing verminous effect beginn. (Vol. Elson y Sonday Melsian Persure)
	Avengers: Infinity War Show more rule	2018-04- 27	Anthony Russo , Joe Russo	Angels Rissort, Rosseller Cunderheite, Stadels Dei Yere, Rosseller Caspe, Carrie Cean, Calcite Rissonan, Carle Teuns, Chris Homeswelt, Chris Perri, Code Smiddere, Donal Curies, Done Bundies, Don Claude, Elizabels Cleas, Geynold Schwer, Josh Fedin, Kern Gillas, Leitin Weigle, Lidata Carbellini, Mark Edfilas, Feter Bildage, Pon Domeniell', Robert Demoy Jr., Scriptick Johnsona, Edwinius Stan, Texas Thompson, Ton Bildheiton, Tem Helmed, Vin Direct, Winston Daler, Zee Sadana.	Walt Désney Studies Merion Pictures	Action Adventure Funtany Sci-H		149	6.8	8.6	As the Averages and their diffus hears continued to preser the most of two threats can long for any one here to knowle, a new denger has energed from the content data for the content of the limitary States, statistics of minocipately preser, and not have to diffuse the content of the content of the content of the limitary States, statistics of minocipately preser, and not not to diffuse the limitary States, statistics of minocipately preser, and not not to diffuse the limitary States, statistics of minocipately preserved from the limitary States, statistics of the limitary States, and the limitary States of the l
Amous	Avengers: Age of Ultrou Sinco more nito	2015-05 01	Joss Wheden	Cleis Evans , Cleis Hensevorth , James Spader , Jersney Renner , Mark Buffsår , Rebert Devnay Jr. , Samed L. Jackson , Scraint Johansson	Walt Disney Studies Motion Pictures	Action Advesture Fantacy Sci-H Thriller		141	6.6	7.0	When long Sork kine to jumpeler a document providency large me, thing up over your Earth's Mighted Heroes, including two Man, Copiels known. The The Incomplete Hills, Hilles Wilder and Howkeys over put in the delinear tere on the fine of the planet image in the belones, skets williamon three energies, it is up to The Averagers to step him from energies like revitle plans, and some money allineous and surveyered action pave the way for an epile or delined adversors. [Moved Smither]
	The Avengers Show more into	1998-48- 14	Jerendah S Chochlik	Holph Finners, from Connery , Cuss Thormus	Warner Bros. Pictures	Action Adventure	e PG-13	87	1.2	2.6	The characters from the cult 1966 (electricins show make it to the Vig serven.

Selecting a movie from the search results using the 'show more info' button will display the info page below which contains the complete info for the selected movie. It also displays up to 5 recommended movies based on the genres of the selected movie. After the recommended movies, the info page displays the reviews given by the critics (on the left) and the users (on the right). Each review displays its score if available, otherwise N/A is displayed. Next to the review score, we display the sentiment analysis of the reviews in 3 categories. Positive reviews are represented by a thumbs up, sentiment polarity is in range: [0.3, 1.0]. Neutral reviews are represented by a neutral thumb, sentiment polarity is in range: [-0.3, +0.3]. Negative reviews are represented by a thumb down, sentiment polarity is in range: [-1.0, -0.3].

The available stream links to watch the movie are provided as the website where to watch the movie, clicking on the preferred website will pop a new tab where the user is directed to watch the movie.

The recommended movies also have a show more button which will display the movie info and stream links on this page if the user chooses a recommended movie. And in turn it will populate other movie recommendations again and the selected movie critic and user reviews information with scores and sentiments.



Challenges:

_ The time is limited to only display a number of movies and a number of reviews, So we implemented the option to show all the movies returned by the search and all the movie reviews, the user can scroll down to see everything that is requested.

Contribution

Store analyzed data in MySQL: Mahdi Aouchiche, Yongfeng Liang, Hongan Zhang, Yanjun Zhu Web Interface Design: Mahdi Aouchiche, Yongfeng Liang, Hongan Zhang, Yanjun Zhu Web Interface Implementation: Mahdi Aouchiche, Yongfeng Liang, Hongan Zhang, Yanjun Zhu

To run the project:

Go to the directory: cd final_submit/part3/mysite

Run the commends: python3 manage.py migrate

python3 manage.py runserver 0.0.0.0:8080

Then open a web browser: http://cs179g-fall-2021-08.cs.ucr.edu:8080/