

PROOF OF WORKING  
AND  
PROOF OF UNDERSTANDING

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## SQL

The sql files that belong to this are:

- Summary.sql
- title.sql
- Starring.sql

The output that belongs to this are:

- top50recommendationssummary.csv
- top50recommendationtitle.csv
- top50recommendationsstarring.csv

My favorite movie from the past are Mean Girls and Legally Blonde. The output for Mean Girls was better, so I chose to go for Mean girls.

I put comments in before the commands in the sql files to tell what I am doing. For all the recommender systems, I set the threshold at 0.01. I played with this, but if I wanted to get 50 recommendations, the threshold must be set at 0.01.

### Output: top 50 recommendations

1	mean-girls	1
2	bratz	0.856911
3	broken-bridges	0.808341
4	fatima	0.751072
5	morris-from-america	0.745188
6	high-school-musical-3-senior-year	0.700713
7	horses-of-god	0.693255
8	the-secret-world-of-arrietty	0.690641
9	blue-is-the-warmest-color	0.687022
10	laggies	0.686125

Above, a screenshot of the top 10 recommendations is shown. Originally, Mean Girls is a movie for teen girls so the output (bratz and high school musical for example) looks logical to me.

# PYTHON

The python file that belong here is:

- recommender.py

The output file that belongs here is:

- recommendationbasedonmetascore.csv

Also, for the Python part, I chose the movie Mean Girls.

### Output: top 50 recommendations

	A	B	C	D
1	movieName	Metascore_w	Author	AuthorHref
2	eragon	10	kitty	
3	alex-rider-operation-stormbreaker	10	kitty	
4	the-lake-house	10	kitty	
5	serenity	10	kitty	
6	i-robot	10	kitty	
7	the-da-vinci-code	10	kitty	
8	the-x-files	10	kitty	
9	titan-ae	10	kitty	
10	the-mummy	10	kitty	
11	galaxy-quest	10	kitty	
12	all-is-lost	10	warrenworld	/user/warrenworld
13	the-godfather-part-ii	10	warrenworld	/user/warrenworld
14	the-dark-knight-rises	10	warrenworld	/user/warrenworld
15	star-wars-episode-i---the-phantom-menace	9	kitty	
16	anchorman-2-the-legend-continues	9	warrenworld	/user/warrenworld
17	the-artist	9	warrenworld	/user/warrenworld
18	indiana-jones-and-the-kingdom-of-the-crystal-skull	9	warrenworld	/user/warrenworld
19	pitch-perfect	9	warrenworld	/user/warrenworld
20	gods-not-dead	9	warrenworld	/user/warrenworld

```

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movieName Metascore_w Author ... InteractionsThumbDown rel_inc abs_inc
81150 eragon 10 kitty ... NaN inf 10
81953 alex-rider-operation-stormbreaker 10 kitty ... NaN inf 10
84622 the-lake-house 10 kitty ... NaN inf 10
95308 serenity 10 kitty ... NaN inf 10
100862 i-robot 10 kitty ... NaN inf 10
110399 the-da-vinci-code 10 kitty ... NaN inf 10
113105 the-x-files 10 kitty ... NaN inf 10
134813 titan-ae 10 kitty ... NaN inf 10
136705 the-mummy 10 kitty ... NaN inf 10
138636 galaxy-quest 10 kitty ... NaN inf 10
14143 all-is-lost 10 warrenworld ... 0.0 inf 10
16220 the-godfather-part-ii 10 warrenworld ... 0.0 inf 10
183717 the-dark-knight-rides 10 warrenworld ... 1.0 inf 10
128454 star-wars-episode-i--the-phantom-menace 9 kitty ... NaN inf 9
31548 anchorman-2-the-legend-continues 9 warrenworld ... 0.0 inf 9
47572 the-artist 9 warrenworld ... 0.0 inf 9
147457 indiana-jones-and-the-kingdom-of-the-crystals... 9 warrenworld ... 0.0 inf 9
72455 pitch-perfect 9 warrenworld ... 0.0 inf 9
183497 gods-not-dead 9 warrenworld ... 6.0 inf 9
133432 cloverfield 8 kitty ... NaN inf 8
149786 pulp-fiction 8 warrenworld ... 0.0 inf 8
166715 fast-five 8 warrenworld ... 0.0 inf 8
45464 the-three-stooges 7 warrenworld ... 0.0 inf 7
10035 dolphins-tale 7 warrenworld ... 0.0 inf 7
133361 national-treasure-book-of-secrets 7 warrenworld ... 0.0 inf 7
118682 mr-deeds 6 kitty ... NaN inf 6
41764 here-comes-the-boom 6 warrenworld ... 0.0 inf 6
148222 true-romance 6 warrenworld ... 1.0 inf 6
43183 end-of-watch 5 warrenworld ... 0.0 inf 5
5394 bernie 5 warrenworld ... 0.0 inf 5
128408 father-of-the-brid-part-ii 5 warrenworld ... 0.0 inf 5
185674 the-amazing-spider-man-2 3 warrenworld ... 10.0 inf 3
39618 safe-haven 2 warrenworld ... 0.0 inf 2
42393 the-twilight-saga-breaking-dawn---part-2 1 warrenworld ... 0.0 inf 1
54985 vampires-suck 1 warrenworld ... 0.0 inf 1
146053 trainspotting 1 warrenworld ... 7.0 inf 1
145084 underwater 1 warrenworld ... 3.0 inf 1
178193 a-good-day-to-die-hard 1 warrenworld ... 0.0 inf 1
93287 war-of-the-worlds 10 patrickd ... NaN 2.0

```

This output is based on the metascore the authors gave on my favorite movie. To make this, Python is used. I did not have any experience with Python so, it took some effort to understand this. But thanks to Google and classmates who helped me out and explained it, I manage to get the outcome and understand the steps I made.

The steps I did:

1. Import the dataset with all the reviews.
2. Made a subset of my favorite movie Mean Girls.
3. Printed the subset so I saw how many reviews there are on Mean Girls.
4. Then with the `data.columns.tolist()`, I created the same variables for the subset as the `userReviews.csv`
5. Then I created the recommender dataframe (called `recommendation`). We want to make a RS based on the Author and the Metascore he or she gave. So first, I used the `iterrows()` to loop over the subset and create the filters `author` and `metascore`.
6. The filters 1 and 2 are made so the recommender dataframe has the movies in it where the same authors gave a higher metascore than on Mean Girls.
7. I made a new dataframe (`possible_recommendations`) with the outcome of `filter1` & `filter2` and added the relative increase and abstract increase of the metascores.
8. After that, I appended the `possible_recommendations` to the `recommendation` (final recommender dataframe).
9. In the end, I made a top 50 of the recommendations and copied this to a new csv file: `recommendationsbasedonmetascore.csv`.

