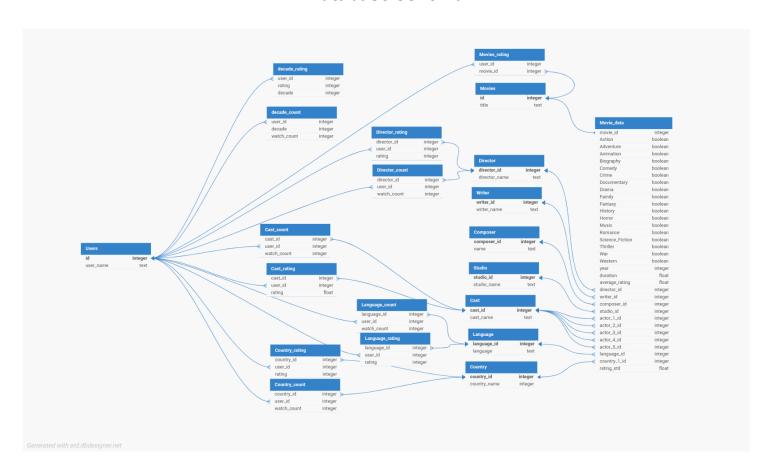
In The Name Of GOD

Datascience Prject: Phase 2

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Database schema



Link: https://dbdesigner.page.link/QQwD3K8r53MfD5P17

Queries On Database

1. A simple one:

```
SELECT movie_id, rating
FROM Movies_ratings;
```

This query gets the ratings of each movie from ratings table. Result:

	movie_id	rating
1237	186	3.0
1238	186	4.0
1239	186	4.0
1240	451	4.5
1241	451	2.5
1242	451	5.0
1243	451	5.0
1244	451	3.0
1245	451	5.0
1246	451	4.0
1247	451	3.0
1248	451	5.0

2. Selecting the movies with highest rates using filtering and sorting:

```
SELECT movie_id, AVG(rating) as avg_rating
FROM Movies_ratings
GROUP BY movie_id
HAVING AVG(rating) > 4.0
ORDER BY avg_rating DESC;
```

Result:

	movie_id	avg_rating
1	335	5.0
2	190	5.0
3	153	4.89285714285714
4	218	4.75
5	523	4.71875
6	724	4.70909090909091
7	163	4.69495091164095
8	649	4.67362924281984
9	303	4.62686567164179
10	598	4.62570888468809
11	517	4.6216814159292
12	429	4.61979166666667

3. Joining movies and ratings tables:

```
SELECT m.movie_id, m.movie_title, m.genre, AVG(r.rating) AS avg_rating
FROM Movies m

JOIN Movies_ratings r ON m.movie_id = r.movie_id

GROUP BY m.movie_id

ORDER BY avg_rating DESC;
```

Result:

	movie_id	title	avg_rating
1	335	Children of Heaven	5.0
2	190	12th Fail	5.0
3	153	The Grapes of Wrath	4.89285714285714
4	218	Das Boot	4.75
5	523	The Best Years of Our Lives	4.71875
6	724	The General	4.70909090909091
7	163	12 Angry Men	4.69495091164095
8	649	Parasite	4.67362924281984

4. Counting the number of movies each user's seen:

```
SELECT user_id, COUNT(DISTINCT movie_id) AS num_movies_rated
FROM Movies_ratings
GROUP BY user_id
ORDER BY num_movies_rated DESC;
```

Result:

	user_id	num_movies_rated
2	296	711
3	147	710
4	603	705
5	653	698
6	277	696
7	847	694
8	826	694
9	727	694
10	537	694
11	561	693
12	343	693
13	272	693

5. Selecting the movies based which were released after 2010:

```
SELECT movie_id, title, year
FROM Movies
WHERE year > 2010;
```

Result:

	movie_id	title	year
1	2	Ant-Man	2015
2	3	Jai Bhim	2021
3	4	The Nice Guys	2016
4	5	Aftersun	2022
5	6	The Cabin in the Woods	2011

Feature Engineering

For this part we added some new features which rationally will help the model recommend better. We tried to consider the logic behind what the model will do and give it some useful extra information about how each movie or each user are.

1. Favorite Genre For Each User:

According to the ratings we have we found the average rating of each genre given by each user and then we assigned the genre with the maximum rating for each user.

2. Ratings STD For Each Movie:

We know that the movies which have more variated ratings might help the model categorize and recommend users to each other better. So using the ratings we found the STD of the ratings for each movie and assigned it as a feature of movies.

3. Analyzing Each Person's Personality:

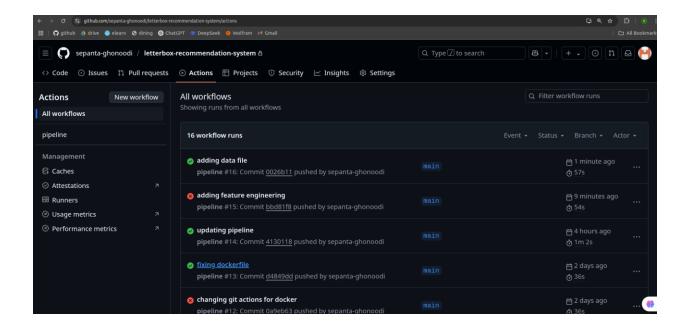
It is possible to find a person's characteristics by the movies they've seen! Using the big five model we tried to define a new one hot encoded feature for users which determines the five personality traits for each user according to the genres they like.



For each personality trait inside each user we calculated the average rating of the genres that trait might be related to. Then we assigned a threshold(3.5) for the ratings to know whether a person likes that genre or not. If a person likes all the genres of a trait, the one hot feature of that trait will be equal to 1.

We normalized the numerical features using sklearn and removed the null data. About removing unuseful features, because each feature is an independent feature from the others and we've concluded that there might be no irrelevant feature and no correlation between them. So we decided to keep all the features.

CI/CD Implementation



MLOps

Docker file:

Docker build:

```
-/D/IS4/DSC/letterbox-project (main*) » docker build --network=host -t phase_2 image .

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Docker run:

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```