

THE CHINESE UNIVERSITY OF HONG KONG, SHENZHEN

CSC 3170

DATABASE SYSTEM

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## Group 26 Report: Rotten Potatoes

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# 1 Introduction

As an art and commercial work, movies have become pursuits of many people and generated tremendous value. Currently, there are two types of online movie platforms. On the one hand, platforms including Rotten Tomatoes and Douban gives people rich information regarding movies. On the other hand, sites like Netflix offers precise, personalized recommendation to users. Such a recommendation strategy allows users to discover more films they enjoy and attracts more users to the platform.

However, currently, no site combines the strengths of the mentioned movie sites. Besides, existing popular movie websites are full of quarrels and controversies from the perspective of the community environment. The movie recommendations are influenced deeply by the advertising, not the quality of films. Therefore, to satisfy the real requirements of movie lovers, we built a movie database called **Rotten Potatoes**, based on which, users can talk about their reviews of the movie freely. It also offers plenty of searching functions and personalized recommendations from the platform.

We use python packages **Requests** and **BeautifulSoup** to obtain the required data from IMDB, store it in a MySQL database. Then we build our searching functions and personalized movie recommendations on those data. We also build a user-friendly web using **amis** as the frontend and **express** as the backend.

# 2 Design

In this section, we focus on the design of the Entity-Relationship Model, the reduction from ER diagram into relational schemas, constraints and index.

## 2.1 Entity-Relationship Model

As shown in the [ER diagram](#), there are 5 entities and 3 relationships.

### 2.1.1 Entities

- **Entity “crew”** The crew participating in shooting movies. Each crew has identifying id, name, photo URL, introduction and birth date. The entity “crew” is a generalization of entity “directors” and “actors”.
  - **Entity “directors”** The directors that direct movies. A specification of entity “crew”. Each director has the same attributes as the crew.
  - **Entity “actors”** The actors that act in movies. A specification of entity “crew”. Each actor has the same attributes as the crew.
- **Entity “users”** The users of our movie website. Each user has identifying id, name, avatar URL and password.
- **Entity “movies”** The movie information. Each movie has identifying id, name, cover URL, introduction, release year and genres, where genres is a multivalued attribute.

### 2.1.2 Relationships

- **Relationship “direct”** Directors direct movies. A many-to-one relationship between entity “movies” and “directors”, which means a director can direct multiple movies while a movie can only be directed by one director, in our assumption.
- **Relationship “act”** Actors act in movies. A many-to-many relationship between entity “movies” and “actors”. An actor acts in a movie as a character with an attribute character name.
- **Relationship “comment”** Users comment movies. A many-to-many relationship between entity “movies” and “users”. A user comments a movie by a comment with attributes comment date, rate and content.

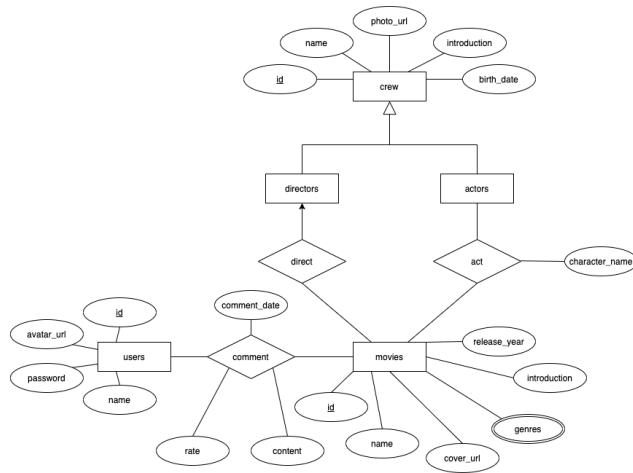


Figure 1: ER Diagram

## 2.2 Relational Schema

As shown in the [relational schema diagram](#), there are 7 schemas.

The following reductions are made:

- The attribute “genres” in entity “movies” is reduced to schema “genres” with attributes “genres\_name” and “movie\_id” as a foreign key referencing “id” of “movies”. Both of the attributes form a primary key to make sure no redundant genres in a movie.
- The relationship “direct” is reduced to attribute “director\_id” as a foreign key referencing “movies” for the many-to-one relationship.
- The relationship “act” is reduced to schema “characters”. Except for attribute “character\_name”, extra attributes “movie\_id” as a foreign key referencing “movies” and “actor\_id” as a foreign key referencing “actors” are added for the many-to-many relationship. Attribute “id” is also added to allow an actor to act as multiple characters in the same movie.
- The relationship “comment” is reduced to schema “comments”. Except for attributes “comment\_date”, “rate” and “content”, extra attributes “movie\_id” as a foreign key referencing

“movies” and “user\_id” as a foreign key referencing “users” are added for the many-to-many relationship. Attribute “id” is also added to allow a user to make multiple comments on the same movies.

- All identifying “id”s are reduced to the primary keys.

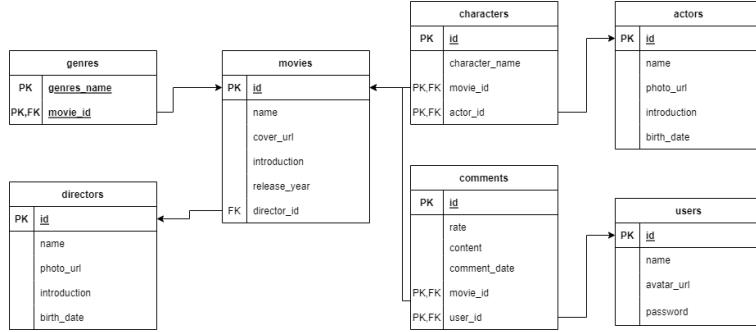


Figure 2: Relational Schema Diagram

## 2.3 Constraint

3 types of constraints are further added:

### Not Null Constraints

- All “id” attributes as they are primary key and thus automatically becoming not null.
- “name” attribute of schema “movies”.
- “name” and “director\_id” attributes of schema “directors”, as a movie is directed by exactly one director.
- “name” attribute of schema “actors”.
- “name” and “password” attributes of schema “users”.
- “actor\_id”, “movie\_id” and “character\_name” attributes of schema “characters”, as it is a weak entity of schemas “actors” and “movies”.
- “user\_id”, “movie\_id”, “rate”, “content” and “comment\_date” attributes of schema “comments”, as it is a weak entity of schemas “users” and “movies”.
- “genres\_name”, “movie\_id” attributes of schema “genres”, as it is a multivariate attribute of schema “movies”.

**Unique Constraint** A unique constraint is added to the “name” attribute of schema “users” as by our assumption there should be no repeating user names.

**Check Constraint** A check constraint is added to the “rate” attribute of schema “comments” to make sure the rate is from 0 to 10.

## 2.4 Index

The following attributes are indexed to make searching faster:

- “name” and “release\_year” attributes of schema “movies”.
- “name” and “birth\_date” attributes of schema “directors”.
- “name” and “birth\_date” attributes of schema “actors”.
- “name” attribute of schema “users”.

## 3 Implementation

In this section, we will introduce the implementation of our movie website. All codes of this project can be accessed from <https://github.com/warin2020/rotten-potatoes>.

### 3.1 Frontend

The frontend of our project is constructed using *amis*, a low-code frontend framework. It can generate a website using JSON configurations, which is suitable for developing a lightweight and agile application like this project. We constructed the following pages:

- Movie: a list of all the movies with their name and posters. Each movie is a ”Card” widget linking to the movie detail page.
- Actor: a list of all the actors/actresses, also implemented using the ”Card” widget, containing links to the detailed information.
- Director: a list of all the directors implemented similarly to the **Actor** page
- Comment: this page contains the latest comments that users release.
- Me: a portal for users to edit their information. Including updating avatar, name and password. This page also contains a list of movies recommended to the user.
- Search: to search for movies/actors/users, we implemented three different pages. The details will be discussed in the **Sample Queries** section.

Since our application is user-oriented, the UI of our website is very concise and user-friendly. Screenshots of our UI can be found in the appendix.

### 3.2 Backend

**Connect to MySQL in Nodejs** The query functions in our database are written in javascript language. They can be found in the corresponding files in the **services** folder. To maximize reusability, we wrote a template query function in **query.js** using the *mysql* module of Node.JS. The template function will first access the **.env** file for database configuration(e.g., the port on which the MySQL server is running, the logging username and password). Then, instead of establishing and closing connections to the database on every execution, the template creates a connection pool. Requests from the frontend will pass the query as a rest parameter to the template function, which will then issue the query and return the results (and errors, if any) back to the frontend.

**Provide API by Express Router** We use the `express` library to provide APIs for frontend users. All the routers are written in the `router/index.js`. Whenever users access a certain page, it will match a router in the file, which triggers the corresponding handler function. For example, after logging in, the user will see the *Movie* page, which contains a list of movies in the database. When the user clicks on any of the movie poster, the frontend will request for page `./movie/detail/<movie_id>`, matching a router in index.js (line 26). The router then calls the corresponding handler function, in this case, the `getMovieDetail()` function in `movie.js`, which directs the user to the corresponding movie detail page.

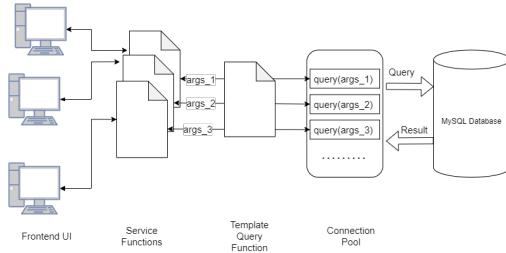


Figure 3: Database connection flowchart

**Access Control by jsonwebtoken** Based on `jsonwebtoken` package, in `auth/auth.js` using the key in `.env` file `SECRET_KEY` we implemented 2 functions `signToken` and `verifyToken`, by which, in `services/auth.js`, the routing function `login` returns a token to frontend and the middleware function `auth` checks whether the token from frontend is correct and not outdated.

### 3.3 Web Crawler

### 3.3.1 Basic Workflow

To populate our database with real-world data, we wrote a web crawler to scrap information from IMDB's Top 250 Movie Chart. The crawler is written in Python. It uses the [Requests](#) library to send HTTPS requests. The desired fields are acquired through parsing the page using [BeautifulSoup](#) library. The detailed process is shown in this flowchart:

1. Access the Top 250 Chart, where all the URLs to the detailed movie pages are located
  2. Traverse through the chart. For every movie on the chart:
    - (a) Access the detailed movie page, where information regarding the movie can be found.
    - (b) From the detailed movie page, we access the casting information.
      - For the director:
        - For directors yet to be recorded, access the detailed director page, where information regarding the director can be found.
      - For the actors/actresses who cast in this movie:
        - Access the detailed actor/actress page and find detailed information if their details are yet to be recorded.
    - (c) The comment section locates at the bottom of the movie page. We collect the rating, comments from this section.
    - (d) For each comment, we acquire the user information by accessing their homepage.

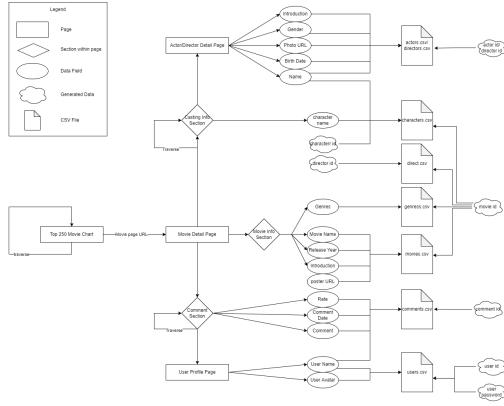


Figure 4: Web crawler flowchart

### 3.3.2 Encountered Problems and Solutions

During the scrapping process, we encountered some issues.

- The same director or actor/actress can participate in different movies. Therefore, we keep a mapping relationship and check whether we have recorded the same person's information. This step is done through hashing the person's name, which takes  $O(1)$  complexity.
- We do not have access to each user's password, so we randomly generate a password for each user we scrapped from IMDB. The password is a random combination of 5 to 10 numbers and characters.
- Some actors' birth dates cannot be achieved from their detailed page. We leave them as NULL.
- The gender of the movie stars is not explicitly listed on their detail page. However, by seeking their role in the movie (i.e, actor/actress), we can acquire their gender.

## 3.4 Sample Queries

### 3.4.1 User account & the Portal

**User registration** When a user tries to create his own account, he needs to specify his user name. In our system, every user must have a unique account name. Therefore, before granting a registration, we will first query the inputted user name in the **users** table. If the name already exists, the registration will not be accepted and the user should input a new user name. Otherwise, the user name, as well as user password, will be inserted into the user table, with a user ID generated automatically.

**User login** When a user log in, password will be queried from the user table, with the user name as the search key. Then, the correct password will be checked using jsonwebtoken, as mentioned in the [access control section](#)

**The Portal** User can modify his avatar, user name and password. This is achieved by updating a record in the **users** table.

```

        INSERT INTO users ( name password )
                      value
                      (
SELECT *                                inp_name,
FROM   users                                inp_psw
WHERE  NAME = register_na
)                                     SELECT *
                                         FROM   users
                                         WHERE  NAME = login_name

```

Figure 5: User registration verification  
Figure 6: User registration verification insert

```

UPDATE users          UPDATE users
SET    NAME = new_name SET    avatar_url = new_url
WHERE   id = user_id WHERE   id = user_id

```

Figure 8: Update avatar

```

SELECT password
FROM   users
WHERE  id = user_id;
UPDATE users
SET    password = new_password
WHERE   id = user_id

```

Figure 9: Update user name

Figure 10: Update user password

**Delete user** In our system, a user account can be deleted, while the comments on movies he made will be kept even after the account is deleted. This is achieved by associating the comments to a padding user before deleting the user account.

```

UPDATE comments
SET    user_id = 0
WHERE  user_id = user_id;

DELETE FROM users
WHERE  id = user_id

```

Figure 11: Delete user

### 3.4.2 CRUD on movies, actors and directors

**Information listing** Movies, actors and directors are listed on our web page. Basic information is selected from the corresponding table.

**Detail information** To show detailed information movies, actors and directors, we need to join several tables. **Actors** table is joined with the **characters** table to get all characters played by an actor, while **directors** table is joined with **movies** table to select all movies directed by the director. For the detail page of movies, 4 table joins are needed to acquire all necessary data. **Movies** table is joined with **characters** table to get all characters in a specific movie. Joining the **directors** table is also necessary to find the director of a specific movie. All comments and genres of the movie are obtained by joining the **movies** table with the **comments** table and **genres** table, respectively. Figure 16 displays the query used to generate actor details:

**Search movies** Movies can be searched using their names. Aside from directly searching, we also support filtering movies by their release time, movie rate and movie genres. We also added support for ordering (in ascending or descending order) the result by name, release year and rating.

```

SELECT id,
       name,
       photo_url
  FROM actors
 ORDER BY id
LIMIT 10 offset page_num

```

Figure 12: Listing actor

```

SELECT id,
       name,
       photo_url
  FROM directors
 ORDER BY id
LIMIT 10 offset page_num

```

Figure 13: Listing directors

```

SELECT id,
       name,
       cover_url
  FROM movies
 ORDER BY id
LIMIT 10 offset page_num

```

Figure 14: Listing movies

```

SELECT a.id,
       a.NAME,
       a.photo_url,
       c.character_name
  FROM actors AS a
 INNER JOIN characters AS c
    ON a.id = c.actor_id
 WHERE c.movie_id = movie_id

```

Figure 15: Actor detail

```

WITH search_name AS
(
    SELECT      m.NAME,
                m.id,
                m.cover_url,
                m.release_year,
                Round(Avg(c.rate),1) AS rate
        FROM      movies          AS m
    INNER JOIN comments      AS c
        ON      c.movie_id = m.id
        WHERE     NAME LIKE Concat('%', ?, '%')
        GROUP BY m.id
)
SELECT      NAME,
            id,
            cover_url,
            release_year,
            rate
  FROM      search_name
 WHERE     release_year BETWEEN ? AND ?
    AND     rate BETWEEN ? AND ?
 ORDER BY
            CASE
                WHEN ?=1 THEN ??
            end asc,
            CASE
                WHEN ?=0 THEN ??
            END DESC

```

Figure 16: Movies search

**Search actors** Similar to movies, actors are searched by their name, and filtered by their birth date. Also, ordering is supported on the birth date and name.

**Search user** For user searching, only name search is supported.

### 3.4.3 Comments

**List comments** Join the **comments** table and the **users** table to match the sender of each comment. After joining, all tuples are shown.

```

SELECT m.NAME AS movie_name,
       m.cover_url,
       c.movie_id,
       c.rate,
       c.content,
       c.comment_date,
       c.user_id,
       u.NAME AS user_name,
       u.avatar_url
  FROM movies AS m
    INNER JOIN comments AS c
      ON m.id = c.movie_id
    INNER JOIN users AS u
      ON u.id = c.user_id
 ORDER BY c.id

```

Figure 17: Comments list

**Delete comments** Comments deletion is achieved by deleting the corresponding tuples comment table.

**Add comments** Comment addition is achieved by inserting it into the comment table.

## 3.5 Data Analysis

### 3.5.1 Recommendation System with Restricted Boltzmann Machines

In 2007, Hinton showed that Restricted Boltzmann Machines (RBMs) can be successfully applied to the Netflix dataset and do personalized movie recommendations (Hinton et al., 2007). This paper was given in a DDA course project, but that project requires only the basic RBM without biases, conditional RBM and neighborhood. We reproduce [the model proposed by Hinton](#) in this project to do recommendations. We use Contrastive Divergence (CD) to approximate the maximum likelihood of the parameters by Gibbs sampling. The notions for the following procedure can be found in [the model](#).

1. Acquire the visible movie ratings  $\mathbf{V}$  of the user, each  $\mathbf{v}$  is  $K$  binary vector where  $v^k = 1$  if the rating is  $k$ , otherwise 0.
2. Sample the hidden units  $\mathbf{h}$  to binary numbers by probability given by  

$$p(h_j = 1 | \mathbf{V}, \mathbf{r}) = \sigma(c_j + \sum_{i=1}^m \sum_{k=1}^K v_i^k W_{ij}^k + \sum_{i=1}^M r_i D_{ij}),$$
 where  $\sigma(x) = \frac{1}{1+e^{-x}}.$

3. Reconstruct the visible units by  $p(v_i^k = 1 | \mathbf{h}) = \text{softmax}(b_i^k + \sum_{j=1}^F h_j W_{ij}^k)$ , where  $\text{softmax}(x_k) = \frac{e^{x_k}}{\sum_{l=1}^K e^{x_l}}$ . Notice that we only reconstruct the movies the user has rated.
4. Update the parameters by the origin data and reconstructed data. For example,  $\Delta W_{ij}^k = \epsilon(< v_i^k h_j >_{\text{data}} - < v_i^k h_j >_T)$ , where  $T$  represents the number of runs we do Gibbs sampling.
5. Prediction is much the same as doing Gibbs sampling except that we can reconstruct (predict) missing ratings.

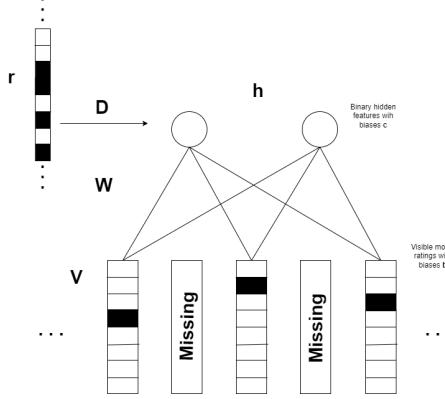


Figure 18: Conditional RBM

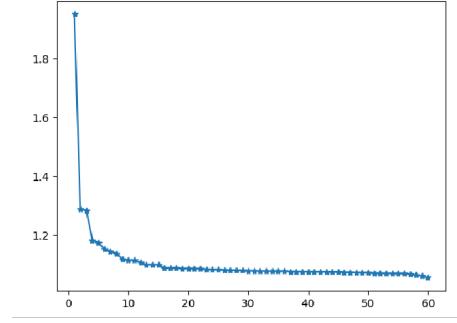


Figure 19: Train RMSE vs. Epochs

Figure above shows the evolution of Root Mean Squared Error (RMSE) during training. We achieve an RMSE of 1.04. Every time the user enters the **Me** page on our website, the system will automatically predict the ratings overall movies and recommend the top 8 movies to the user in **Guess you like** module. An example on the webpage is shown in figure below.

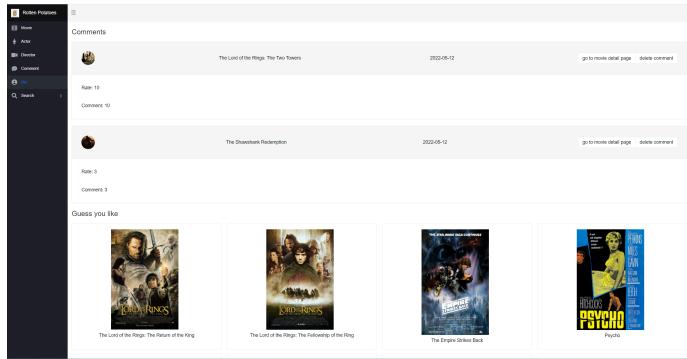


Figure 20: Personalized Movie Recommendation

### 3.5.2 Neighbourhood Model

Users have their preferences and tend to give similar ratings to movies of the same kind. In other words, movies are correlated and we can utilize this property to improve our predictions  $\hat{R}$ :

- Define an error matrix by  $\tilde{R} = R - \hat{R}$
- Define similarity between two movies by their column features (user ratings):  $d_{AB} = \frac{\tilde{r}_A^T \tilde{r}_B}{\|\tilde{r}_A\|_2 \|\tilde{r}_B\|_2}$

- Predict the error of one movie through the errors of its neighbours:  $\hat{r}_{iA} = \frac{1}{\sum_{B \in S} |d_{AB}|} \sum_{B \in S} d_{AB} \tilde{r}_{iB}$ , where  $S$  is the set of neighbours (with high absolute similarities) of  $A$ .
- Improve our RBM predictions by  $R_{um}^* = \hat{R}_{um} + \hat{r}_{um}$  for each  $(user, movie)$  pair desired.

We improve the RMSE from 1.04 to 1.02. The improvement is not high because our matrix is sparse. In our data set, many users only give one rating, so it is hard to construct a well defined similarity matrix. The other reason is that we crawl high-rating movies and the biases are not large to give a performance boost. However, we are still able to leverage the data and get some insight into the movie ratings.

For example, *The Godfather: part II* has a high similarity(0.9999) with *The Godfather*(based on the difference between real rating and predicted rating), which is expected. However, the similarity between *The Godfather* and the two sequels of *The Lord of the Rings* diverge. *The Fellowship of the Ring* has a similarity of 0.9999 with *The Godfather*, while its sequel *The Return of the King* has a similarity of -0.9999. This is counterintuitive and we should look into the data. We have three users giving ratings to both *The Godfather* and *The Lord of the Rings: The Return of the King*. The ratings are (10, 10), (10, 10) and (8, 10), respectively. For *The Godfather* and *The Lord of the Rings: The Fellowship of the Ring*, the rating pairs are all (10, 10). A rating of 8 is a relatively low rating in our dataset, hence the algorithm concludes that they are negatively correlated.

## 4 Result

The website can be accessed through URL <http://10.20.9.99:3000>. This server can only be accessed within the CUHK(SZ) campus network. In case of access failure, please contact our group member Tianhao SHI (120090472), who is in charge of server maintenance. You can also find the source code on our [Github repository](#). Snapshots of our website can be found in the appendix.

## 5 Conclusion

In this project, we build a movie database based on large-scale data collected from **IMDB**. Additional attention is paid to assure a **BCNF** form is kept for every schema in our database, thus the redundancy part is eliminated. We also **implement useful functions** for our users to search for the movies, casts or other users using name, time information, rate(only movies) and genres(only movies) as the keyword.

To improve user experience and replace the complex database operations with a few simple mouse clicks from users, we build a user-friendly website. Based on that, abundant **personalized interaction behaviors** can be achieved, which serves our users more conveniently. We hold an integral process of account management for users. Users can add comments to a movie and rate it as well as discover their appreciated reviews or users.

It is common for a movie database to recommend movies that the users have a potential interest in. However, how to make a personalized recommendation list of high quality is always a problem. We use a lot of techniques in the data analysis to satisfy the needs of users. We build a **Restricted Boltzmann Machines** with **Neighbourhood model** and get gratifying results.

## 6 Self Evaluation

In this part, we evaluate the advantages and disadvantages of our project.

### 6.1 What we have achieved

- Build a database conforming to the low redundancy paradigm
- Implement and optimize many necessary searching functions
- Create a user-friendly website to lower the bar of use
- Feed the database with a suitable amount of data and design a proper data analysis algorithm to satisfy personalized requirements

### 6.2 Future Improvements

- More information about movies, directors and actors can be added to the database. For example, for actors we may add their nationality and Oscar nominations; for movies, we may add their budget and the classification (PG13, NC17).
- More interaction functions can be added, like “like” a movie or “subscribe” a user. We can also add functions like “want to watch” a movie or “watched” a movie without commenting on it. This information can be utilized in conditional RBM to provide better recommendations (Hinton et al, 2007). Currently, we have the algorithm implemented but the information is unknown.
- In the future, we plan to distinguish the users of our platform. We will allow a common user to upgrade as an administrator, which will reduce the effort to maintain and supervise the comments other users post.
- Currently, the web crawler is implemented using synced requests, which reduced its performance. In the future, we will write the crawler using async requests to speed up the crawling performance and acquire more data for our database.

## 7 Contribution

Each of us contributed 20% to the whole project.

- 郑时飞: Web Craweler, Create table, relationship and webpage about directors
- 朱伯源: Construct initial code of frontend, backend and crawler, repository owner, work distributor
- 李易
- 施天昊: Web Crawler, Sorting queries, Server Deployment and Maintenence
- 汪明杰: Recommendation system and webpage about recommendation.

## 8 References

Salakhutdinov, R., Mnih, A., & Hinton, G. (2007). Restricted boltzmann machines for collaborative filtering. Proceedings of the 24th International Conference on Machine Learning - ICML '07. <https://doi.org/10.1145/1273496.1273596>

## 9 Appendix

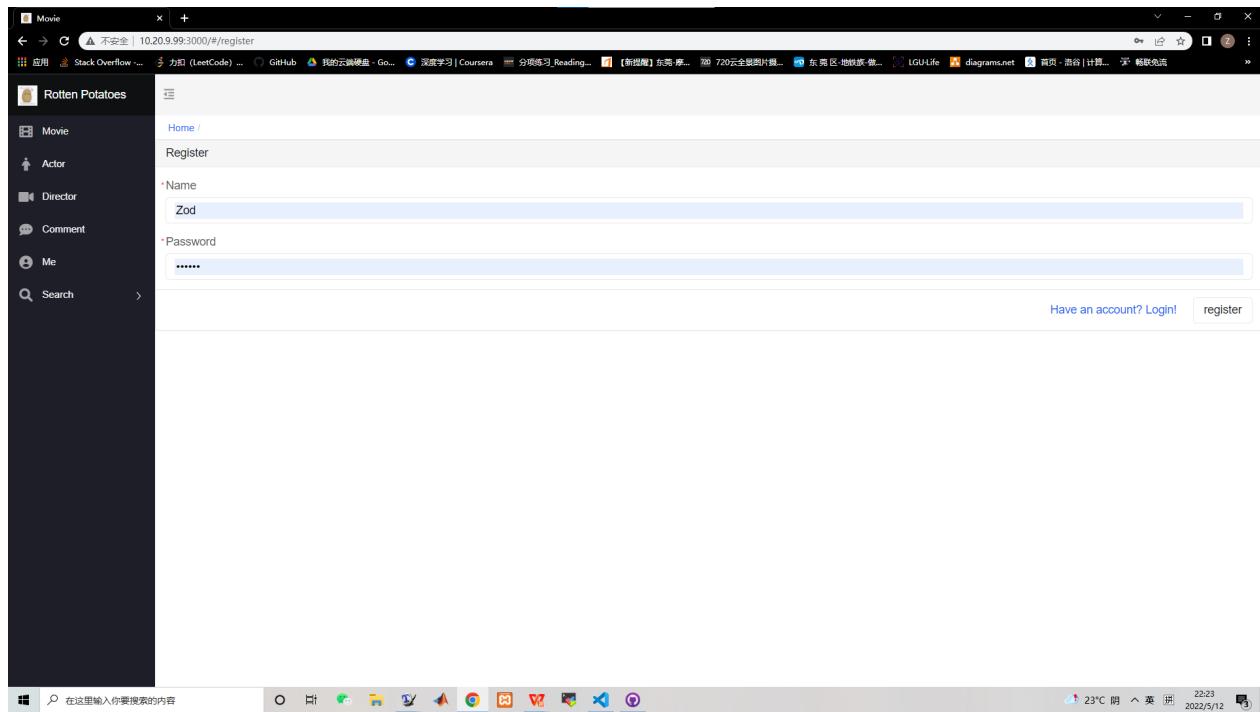


Figure 21: Register page

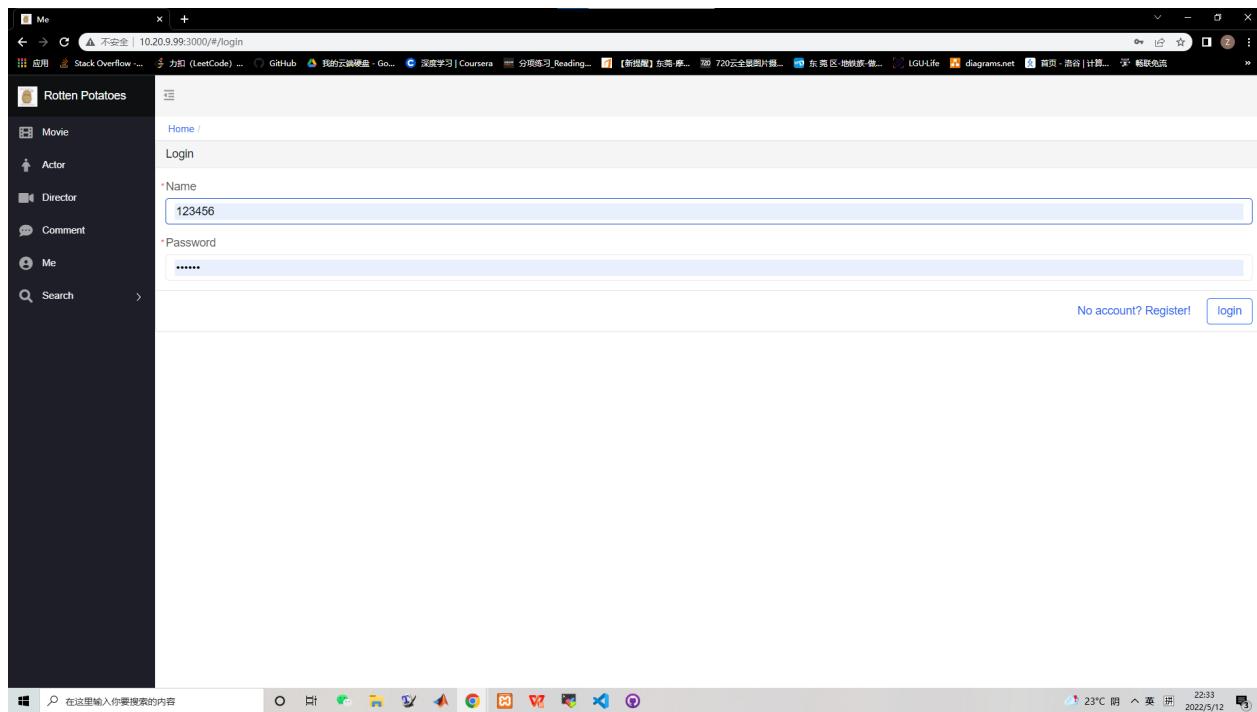


Figure 22: Login page

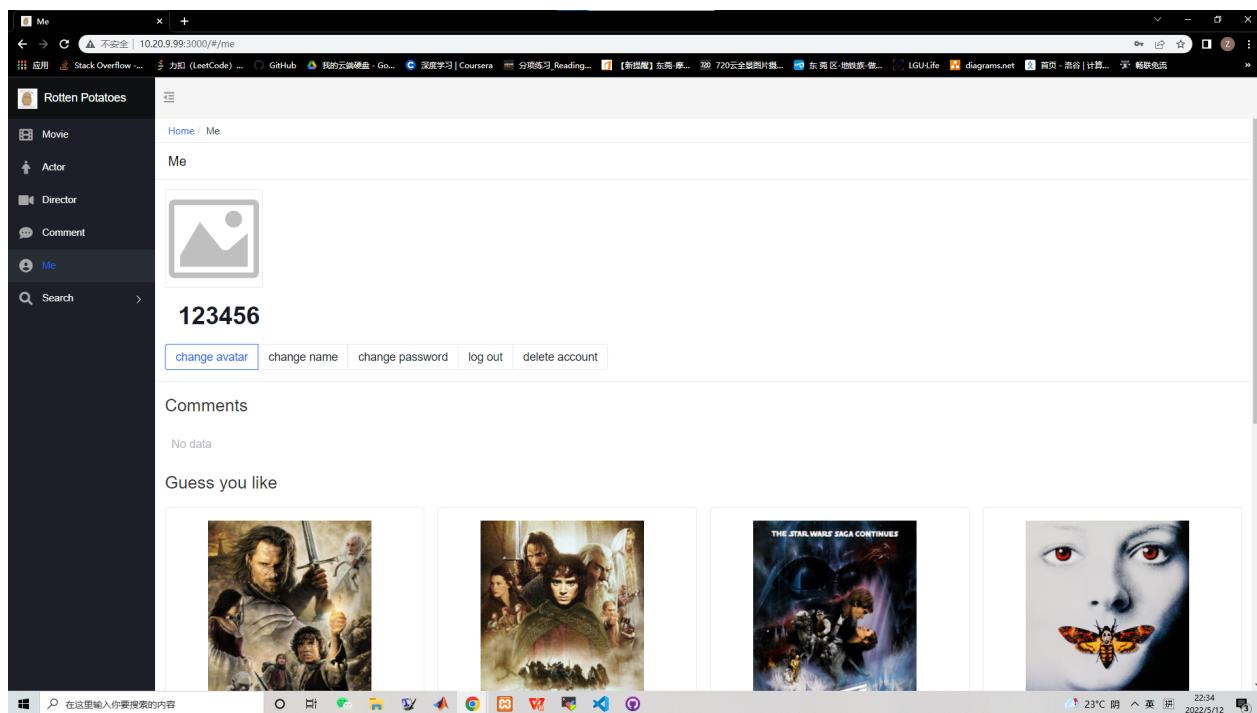


Figure 23: Personal center

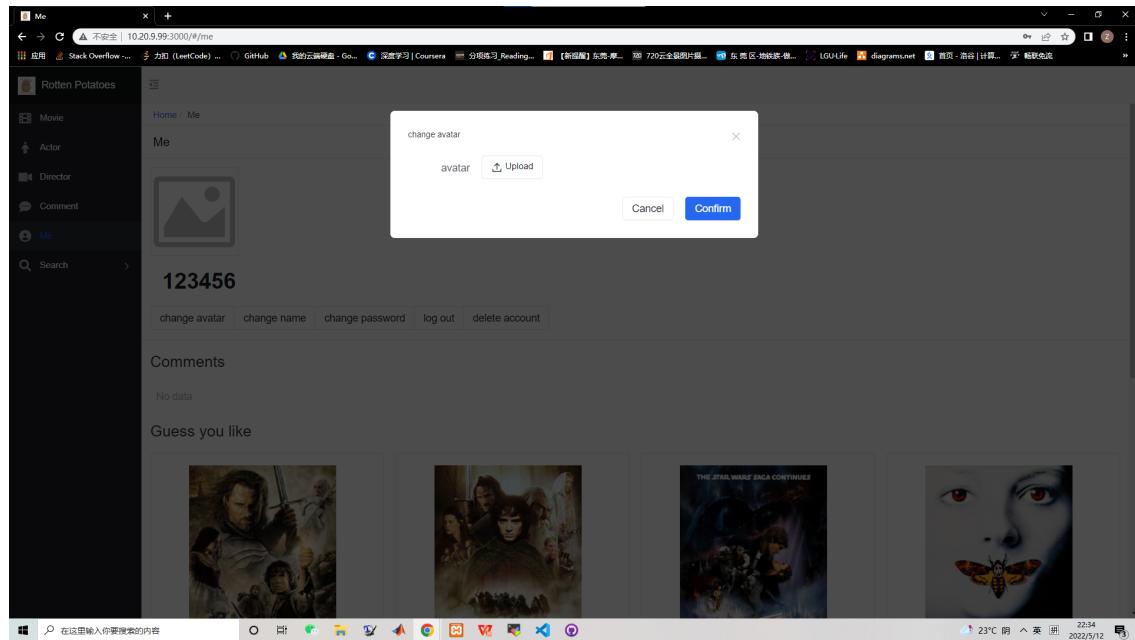


Figure 24: Before chaning avatar

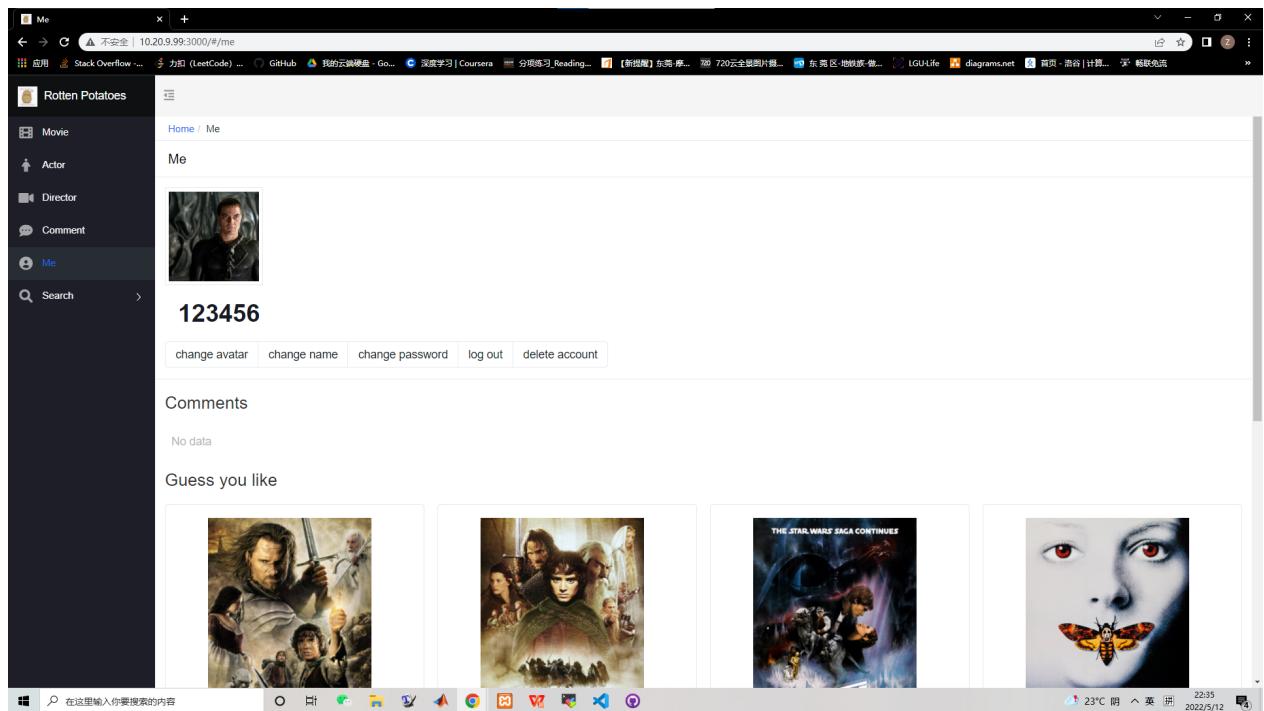


Figure 25: After chaning avatar

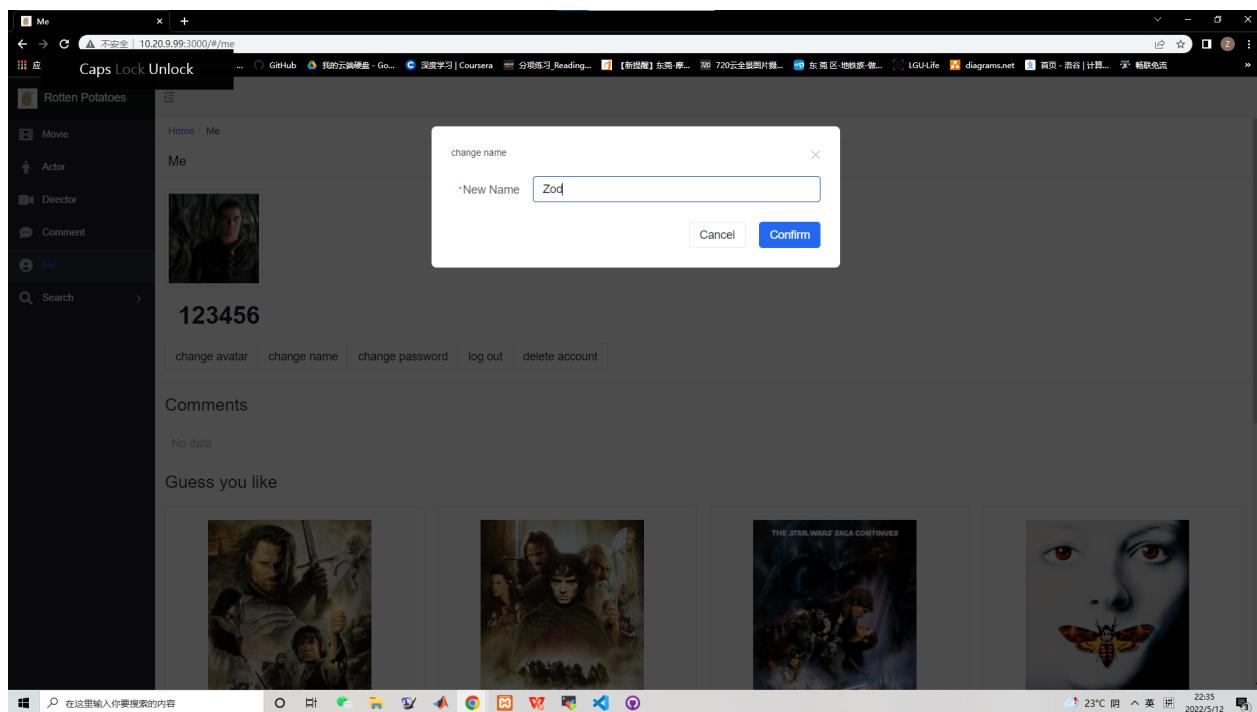


Figure 26: Before chaning name

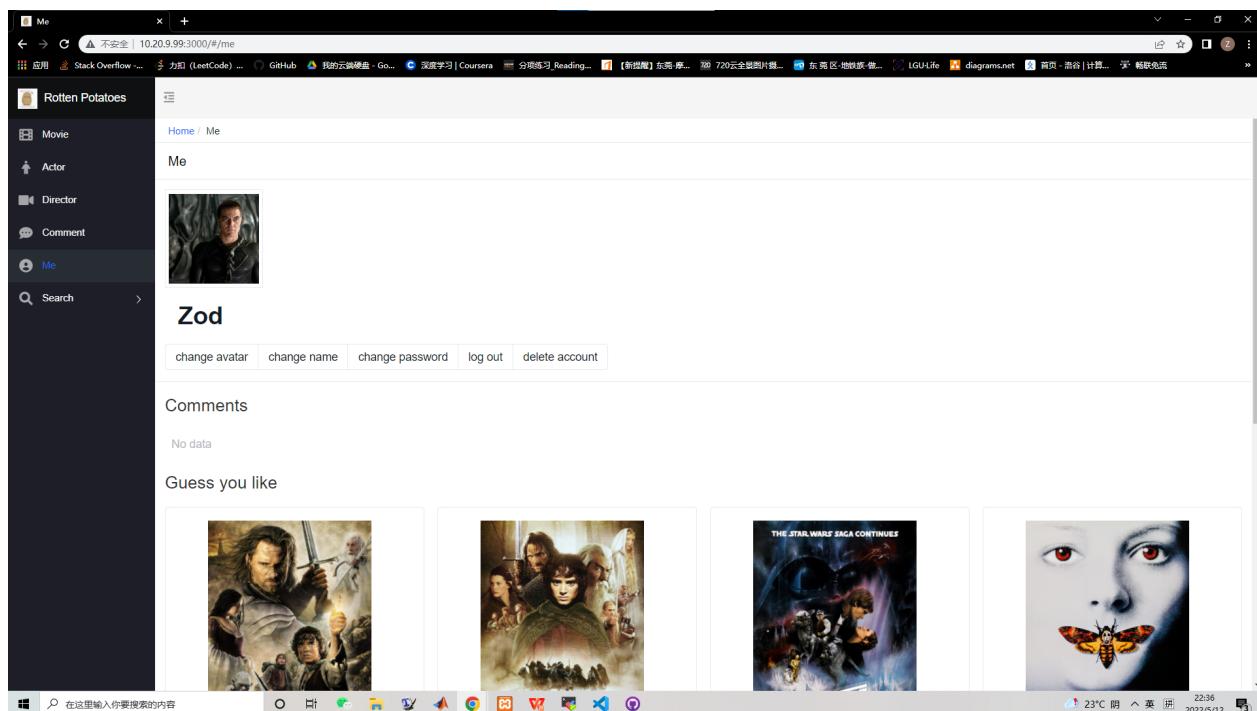


Figure 27: After chaning name

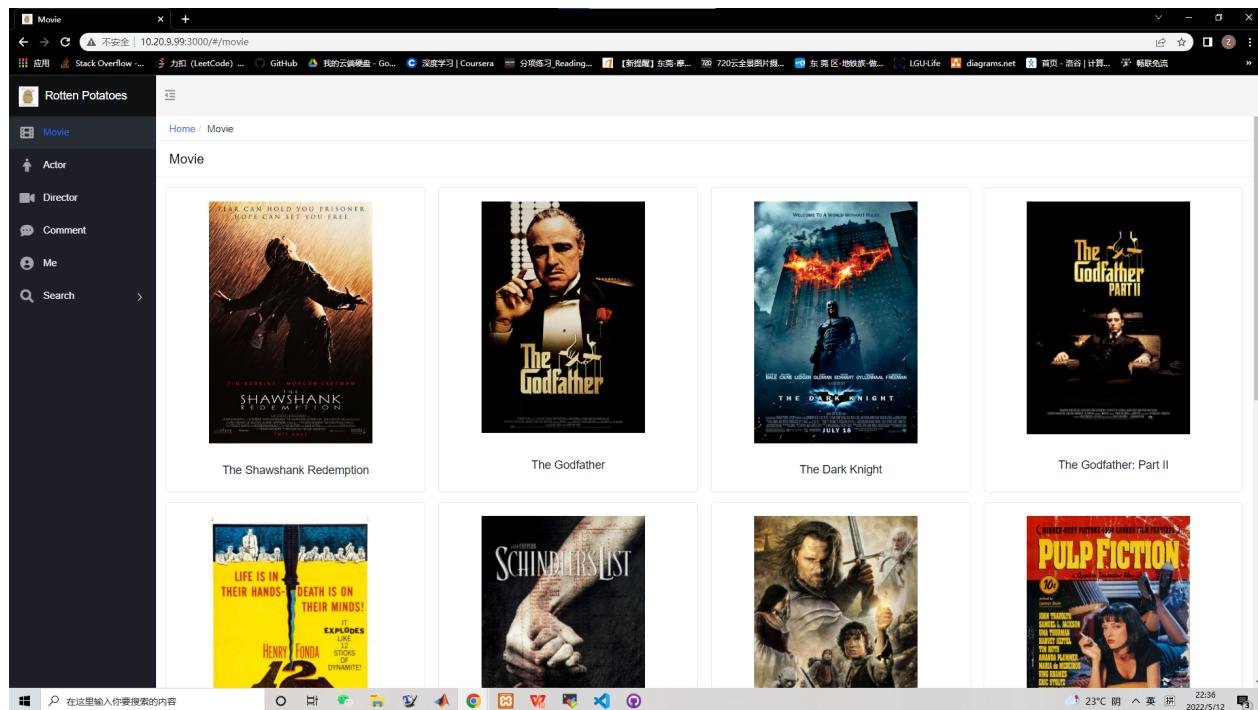


Figure 28: Movie list page

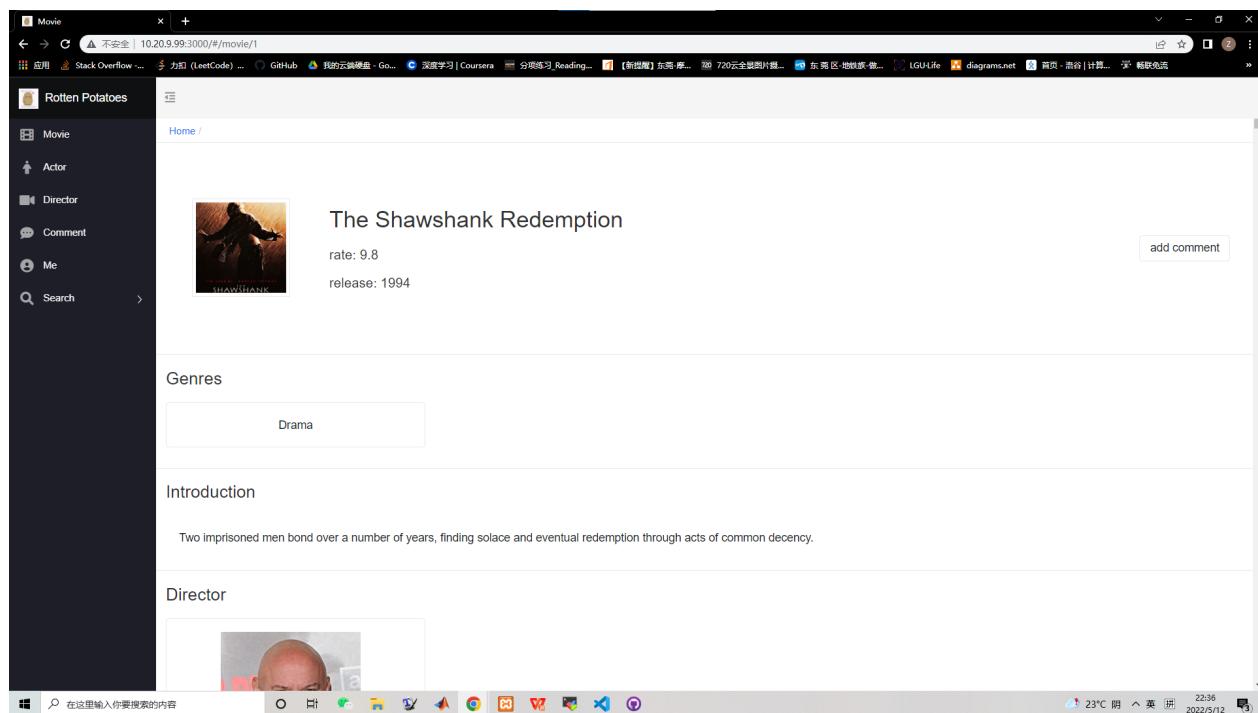


Figure 29: Movie detail page

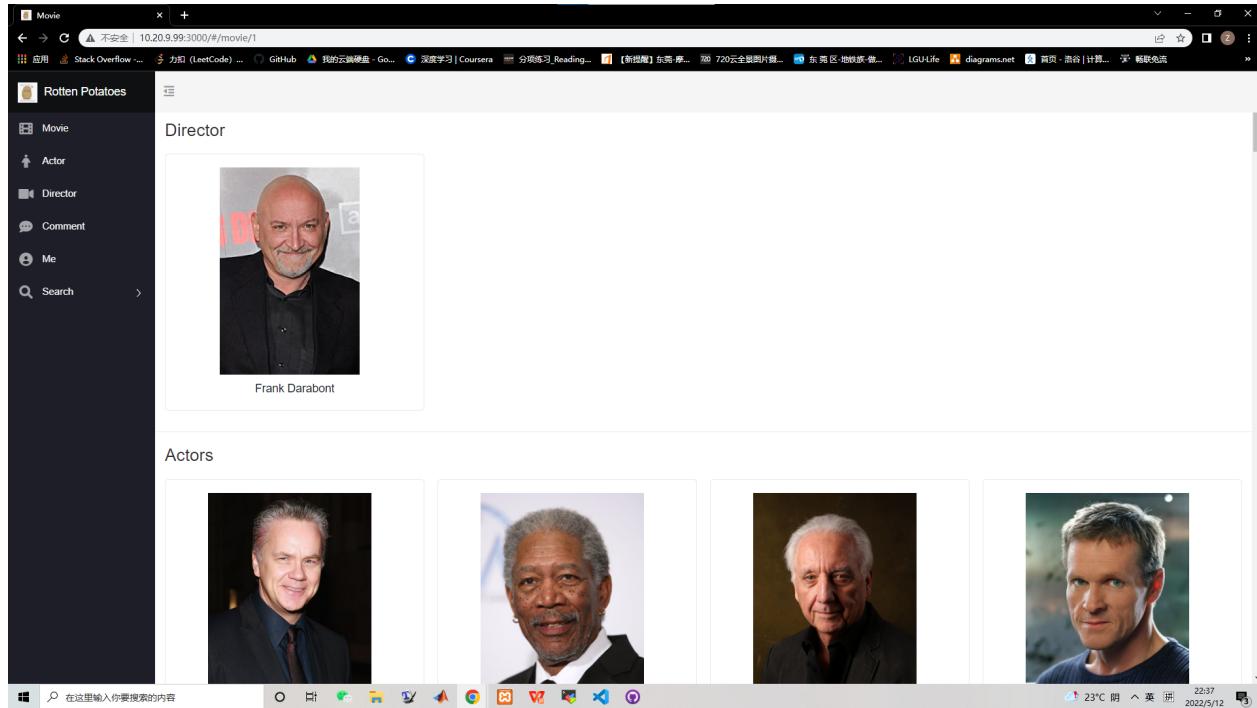


Figure 30: Movie detail page

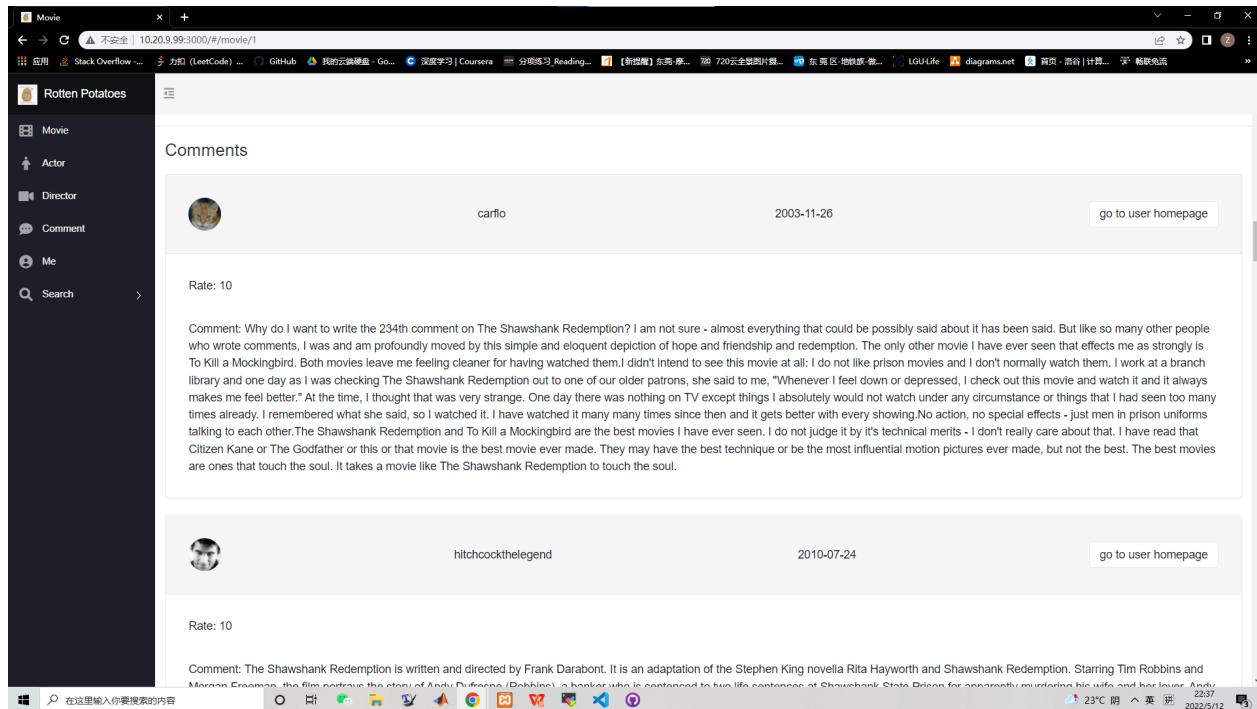


Figure 31: Movie detail page

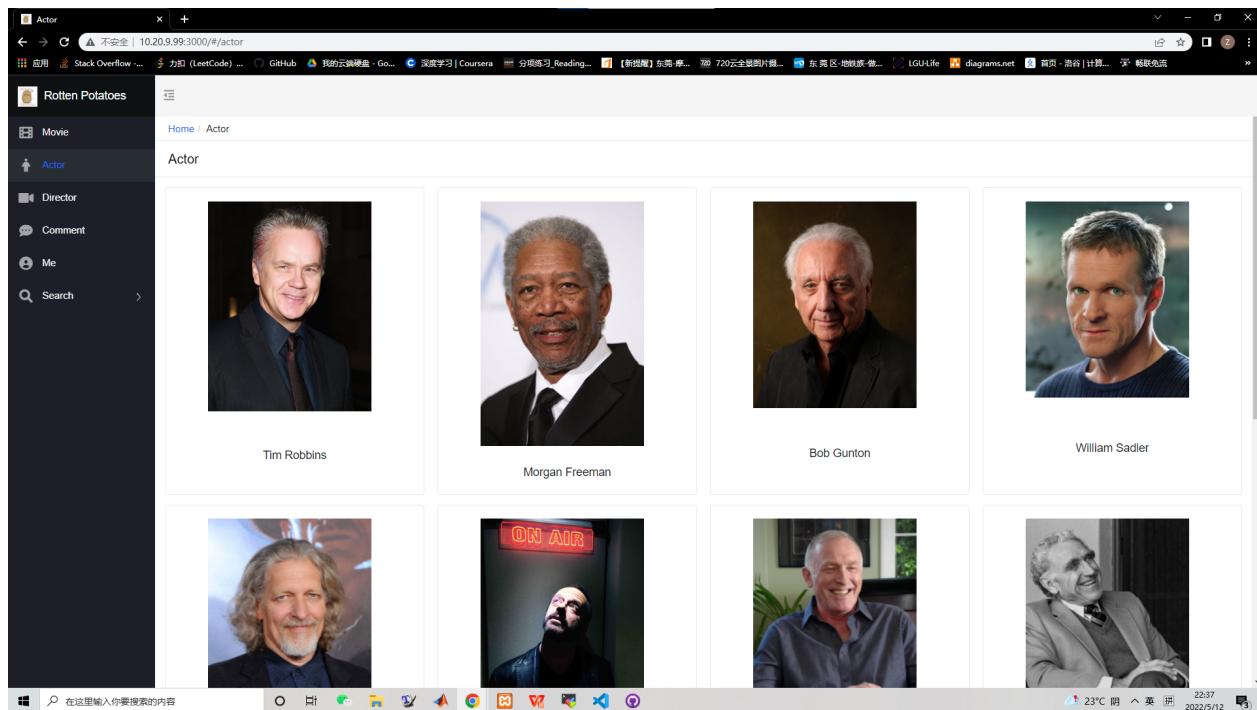


Figure 32: Actor list page

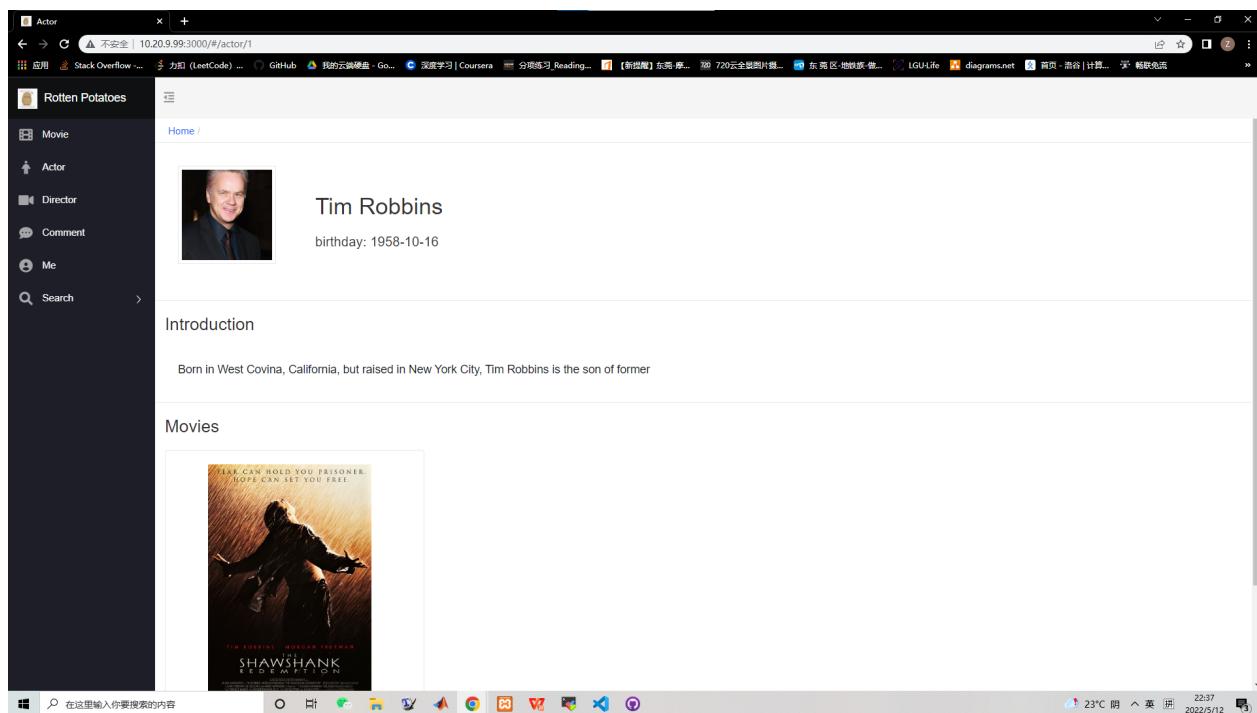


Figure 33: Actor detail page

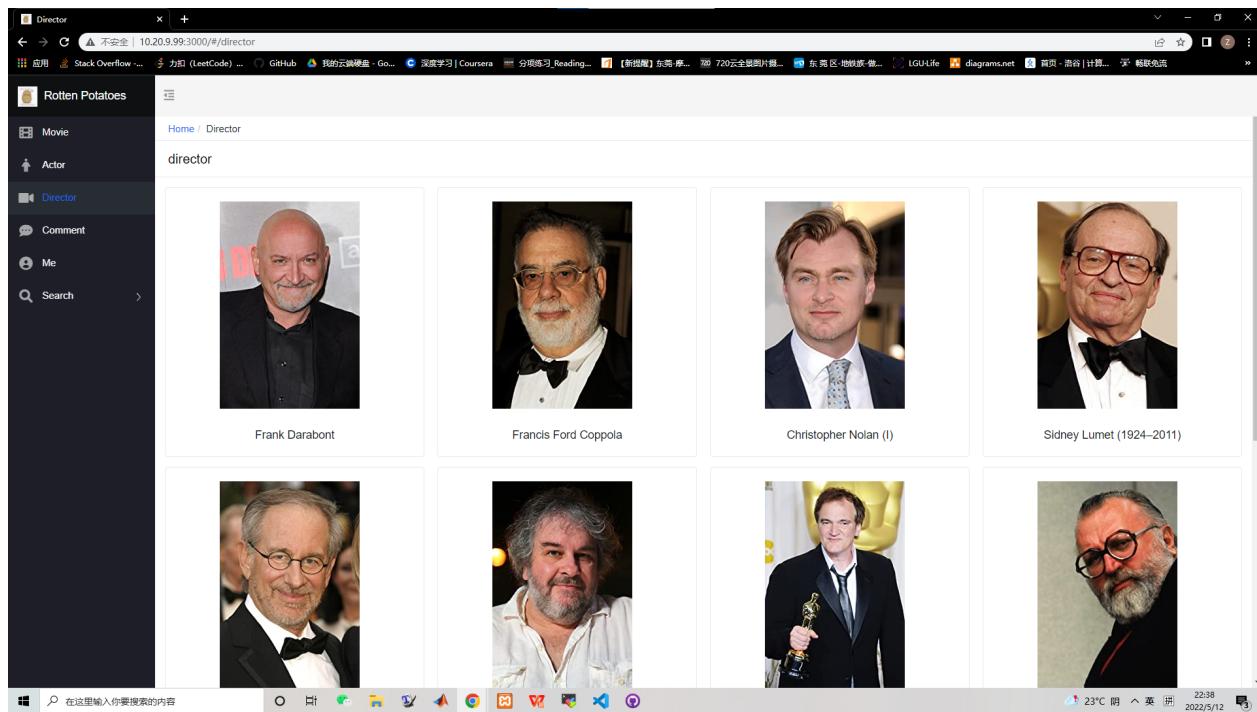


Figure 34: Director list page

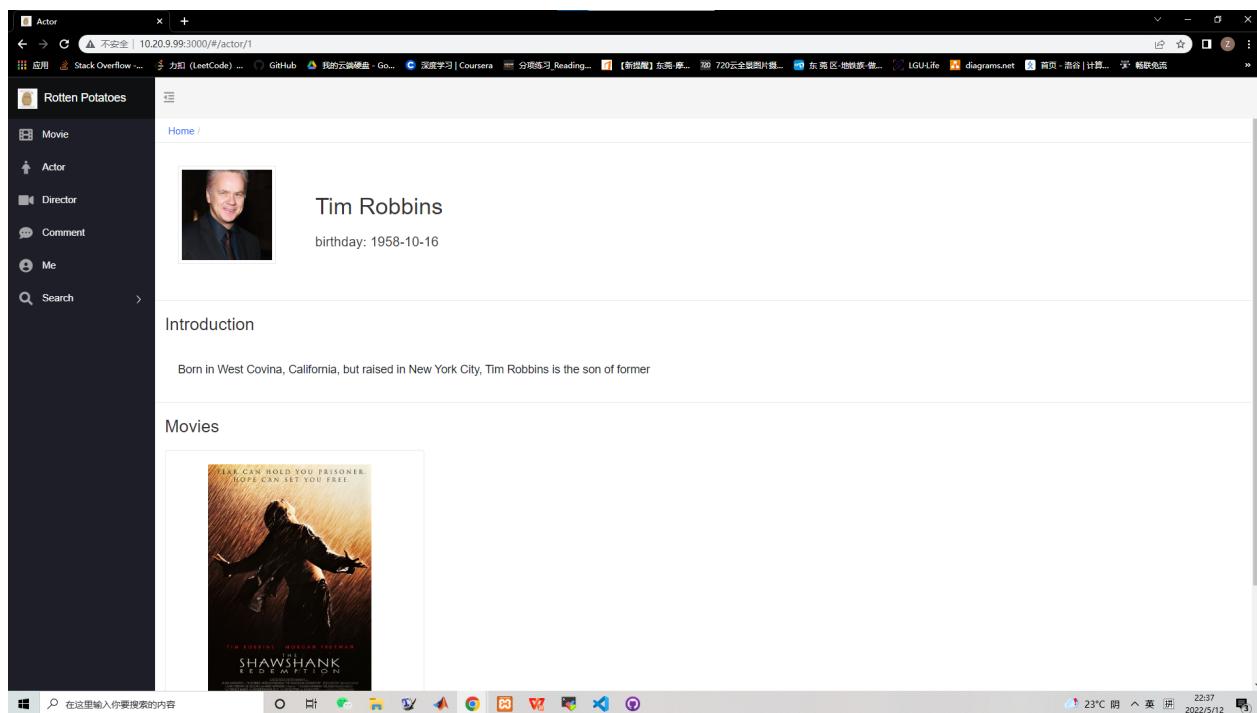


Figure 35: Director detail page

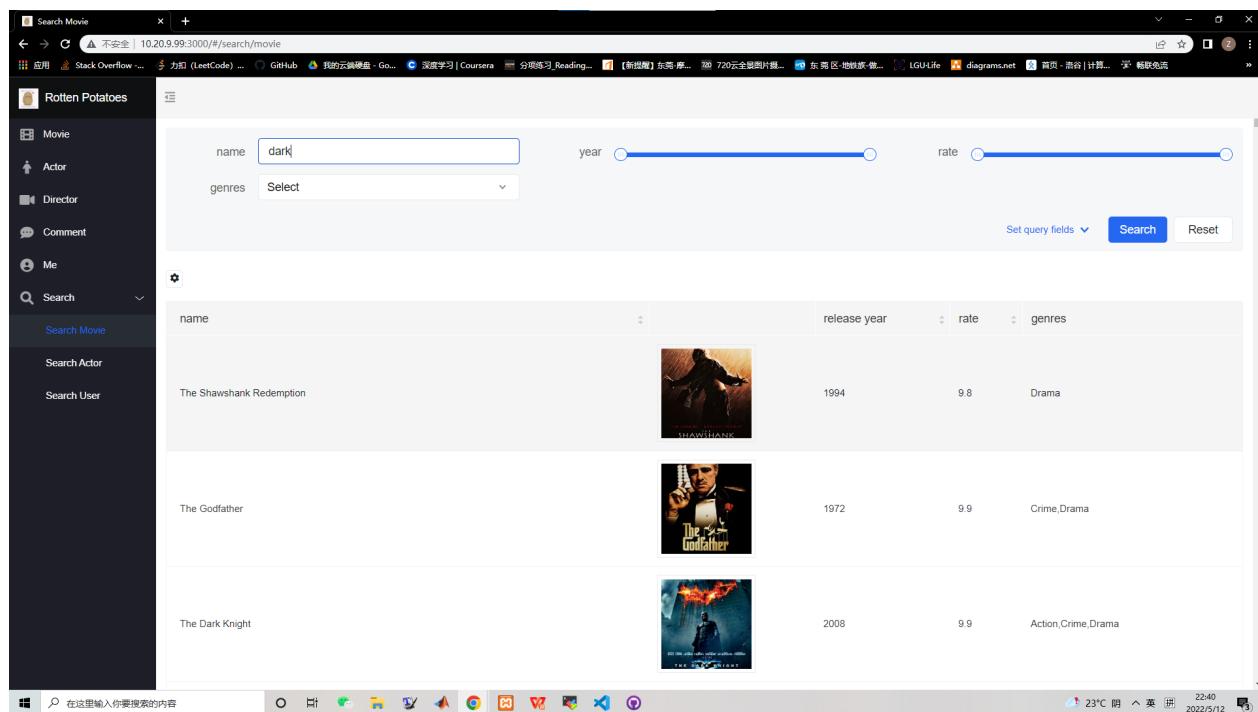


Figure 36: Movie search page

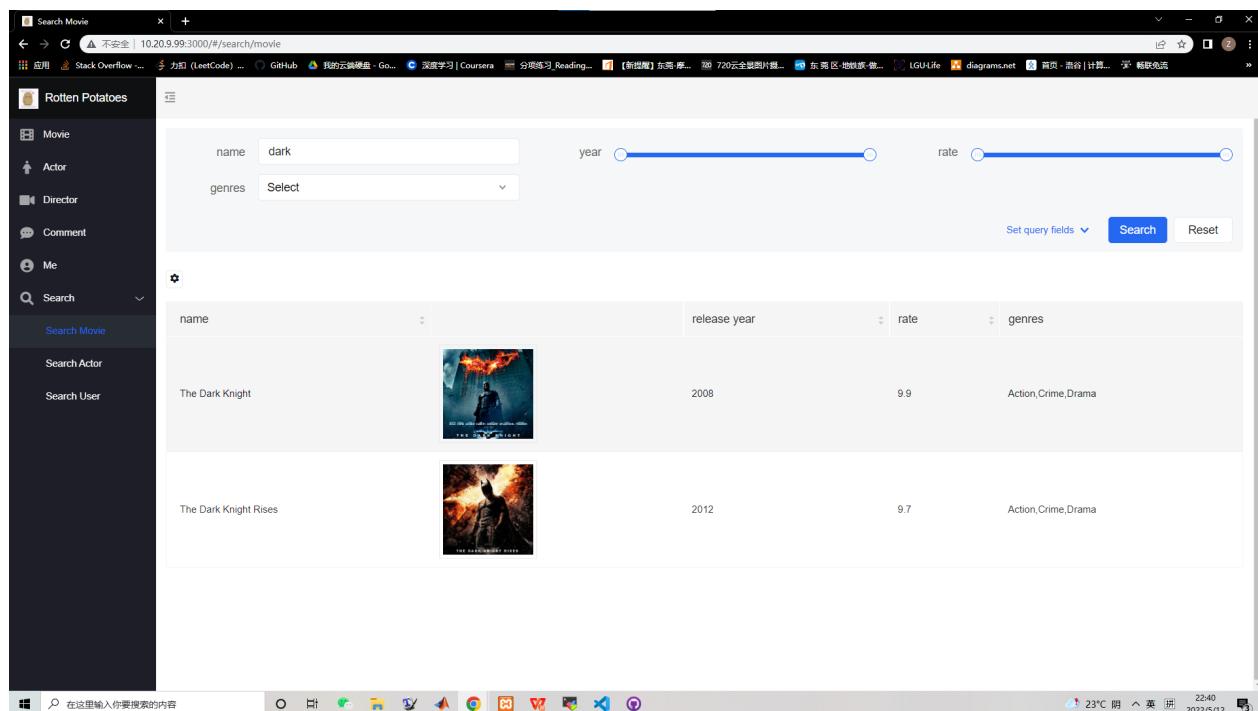


Figure 37: Search movie by name

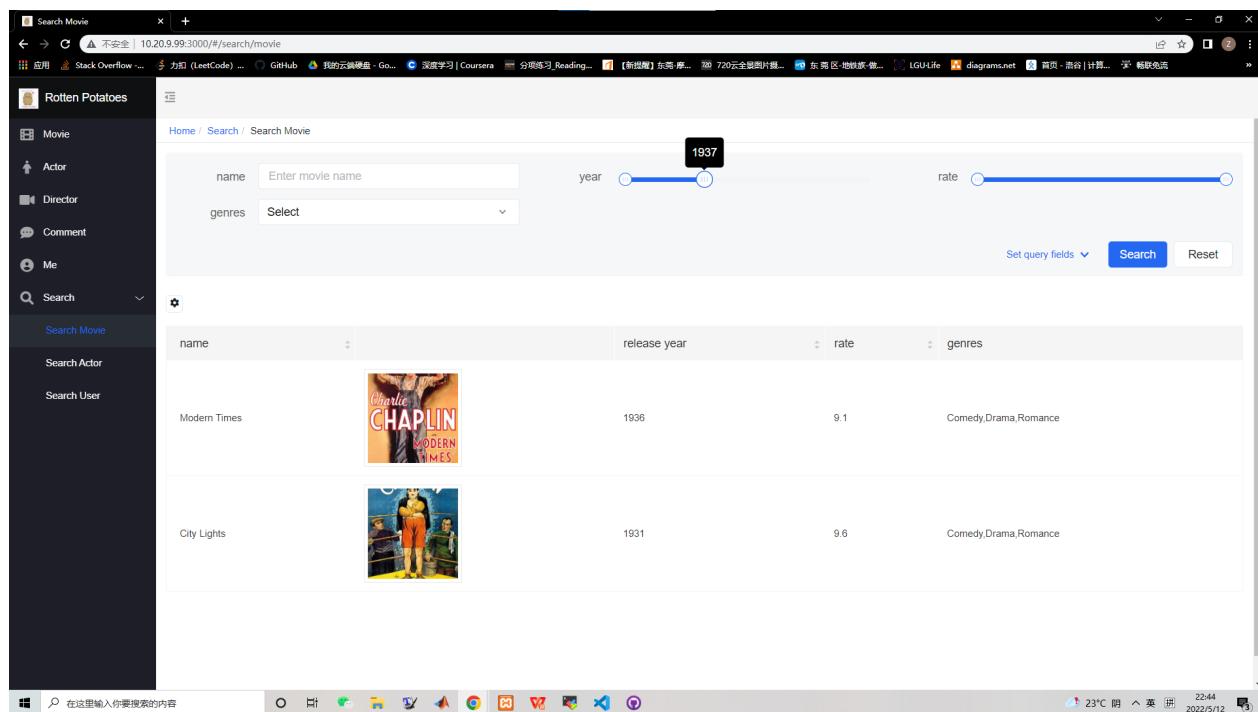


Figure 38: Filter movie by release date

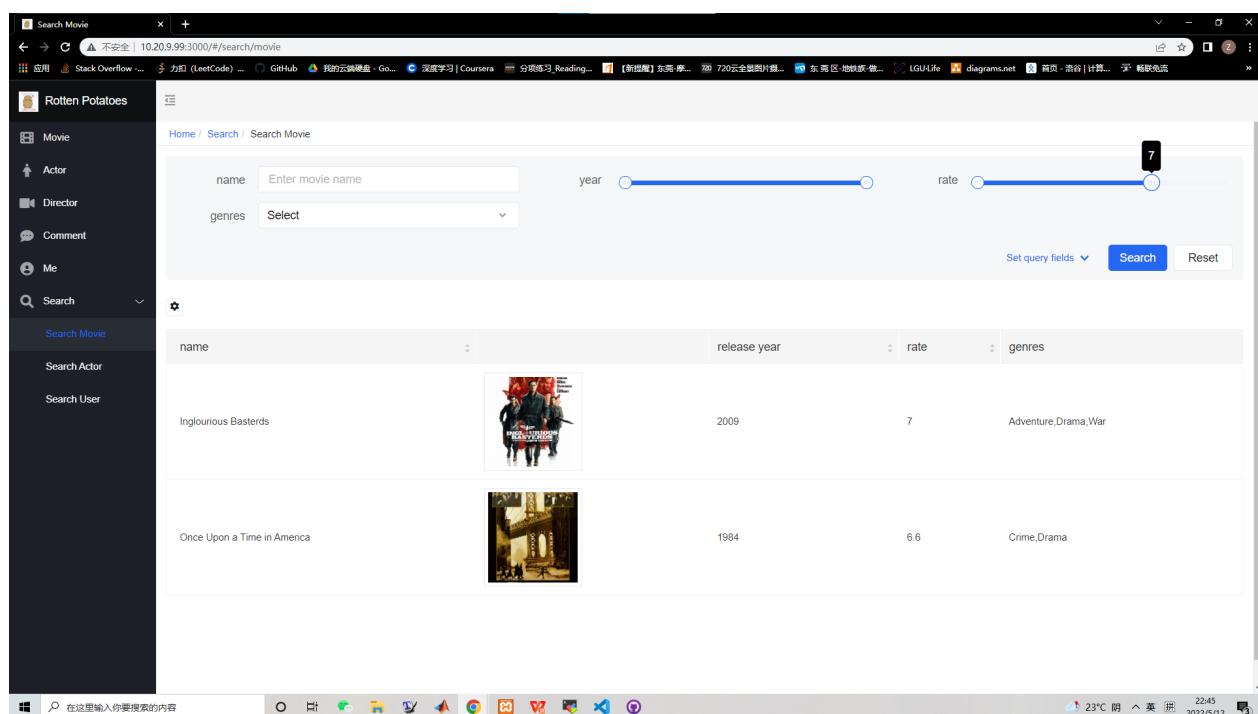


Figure 39: Filter movie by rate

The screenshot shows a web-based movie search application titled "Search Movie". On the left, there is a sidebar with navigation links: Home, Movie, Actor, Director, Comment, Me, Search (with sub-options: Search Movie, Search Actor, Search User), and a search bar placeholder "在这里输入你要搜索的内容". The main content area has a breadcrumb trail: Home / Search / Search Movie. It features search filters for name, year (range slider from 1960 to 2020), rate (range slider from 0 to 10), and genres (dropdown currently set to Action and Crime). Below the filters is a table displaying movie results:

name	release year	rate	genres
The Dark Knight	2008	9.9	Action,Crime,Drama
Léon	1994	9.3	Action,Crime,Drama
The Dark Knight Rises	2012	9.7	Action,Crime,Drama

The table includes columns for name, release year, rate, and genres. The first two rows are highlighted in light gray, indicating they are selected or active.

Figure 40: Filter movie by genres

This screenshot is identical to Figure 40, showing the same movie search interface and results. The only difference is the order of the movies in the table, which is now sorted by release year. The table rows are ordered as follows: Léon (1994), The Dark Knight (2008), and The Dark Knight Rises (2012).

Figure 41: Order movie by release date

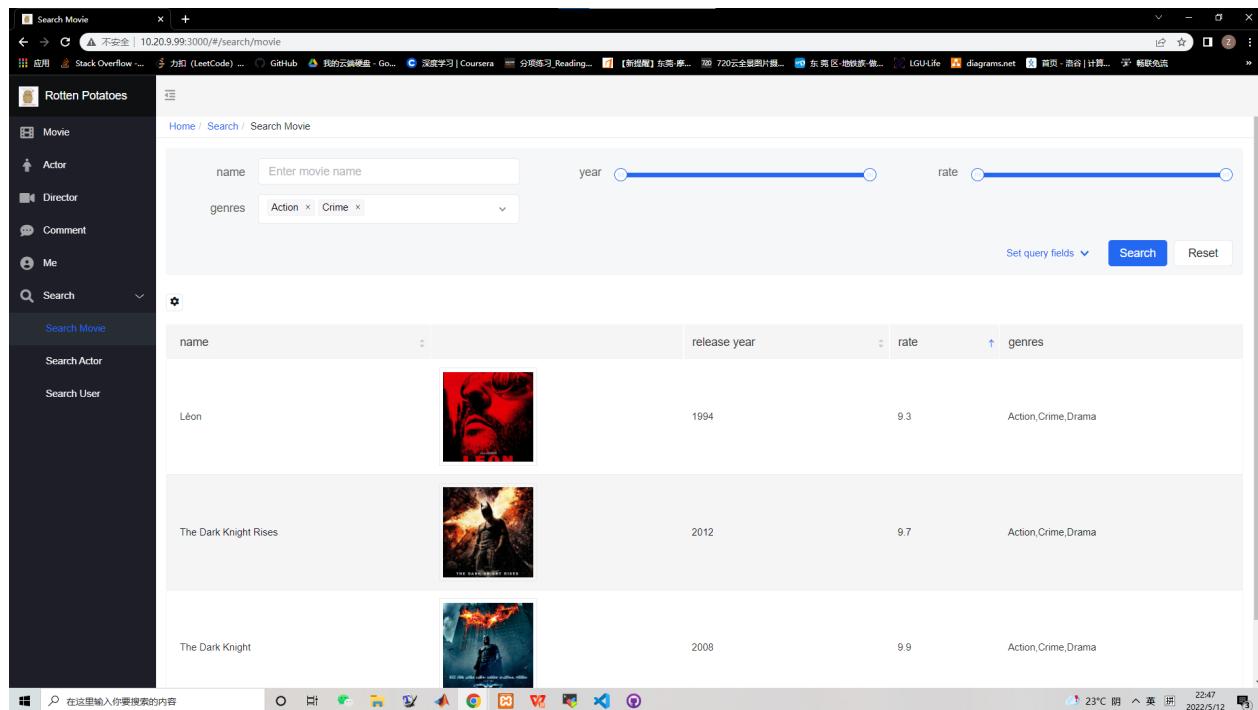


Figure 42: Order movie by rate

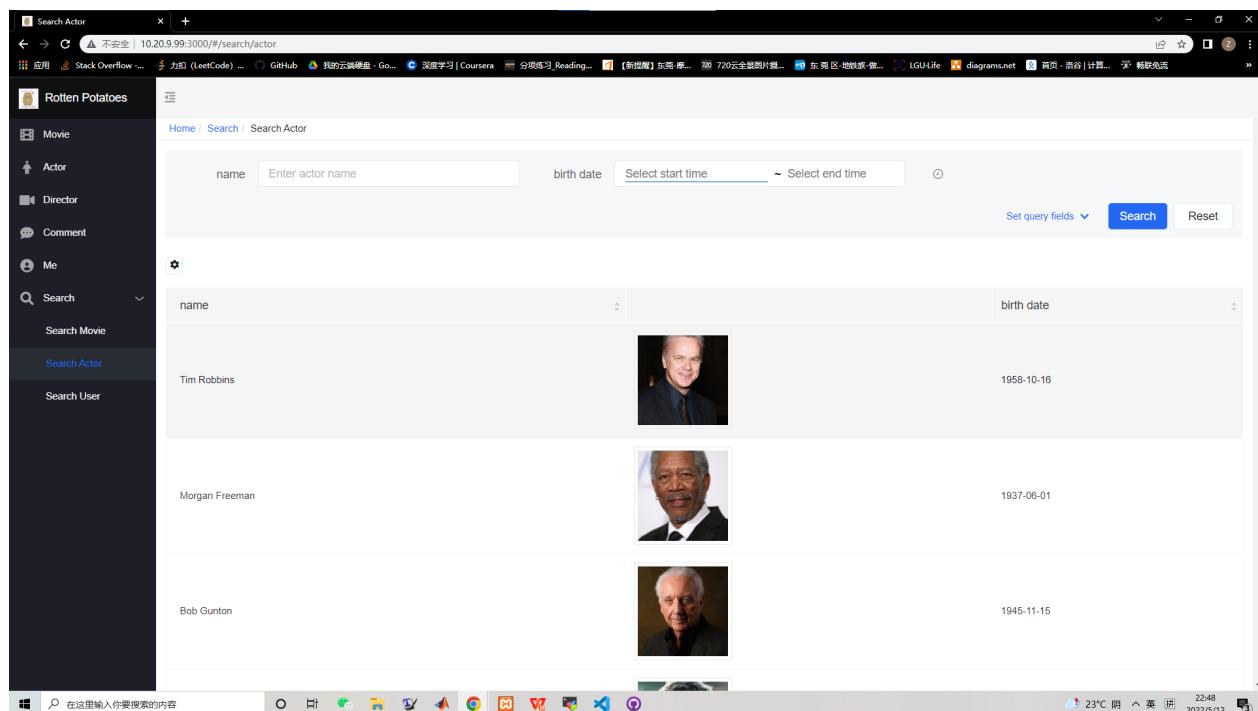


Figure 43: Actor search page

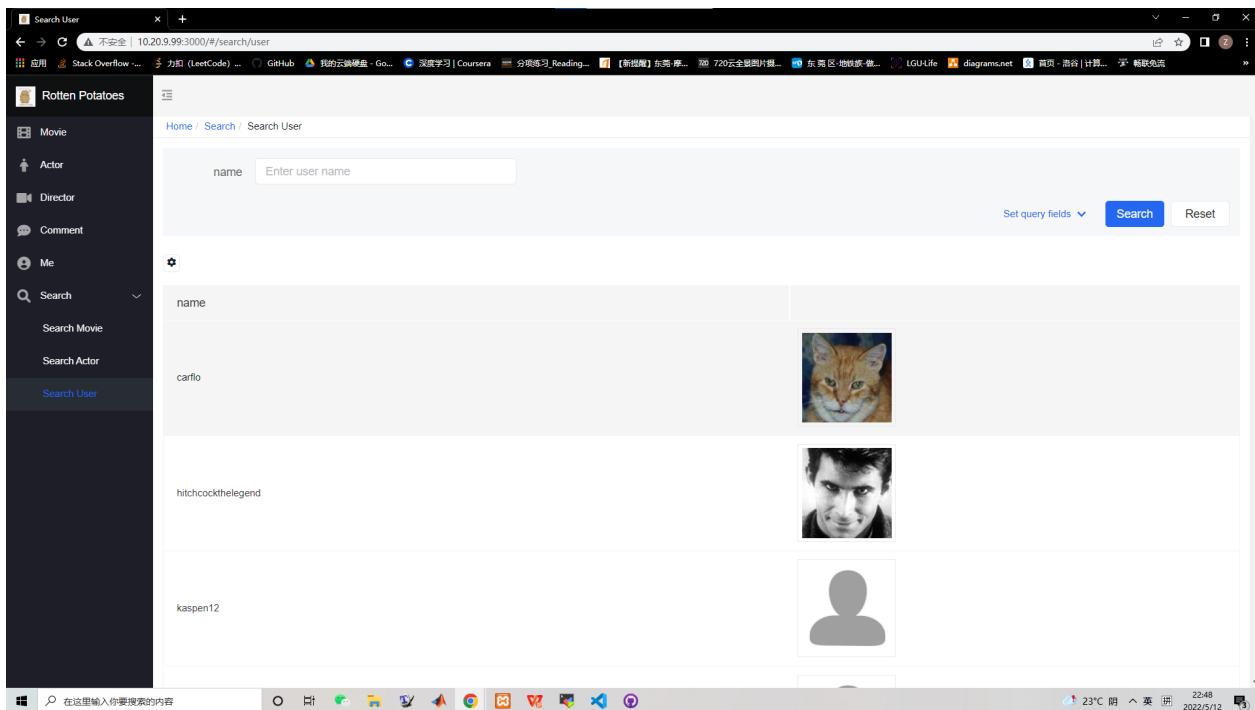


Figure 44: User search page

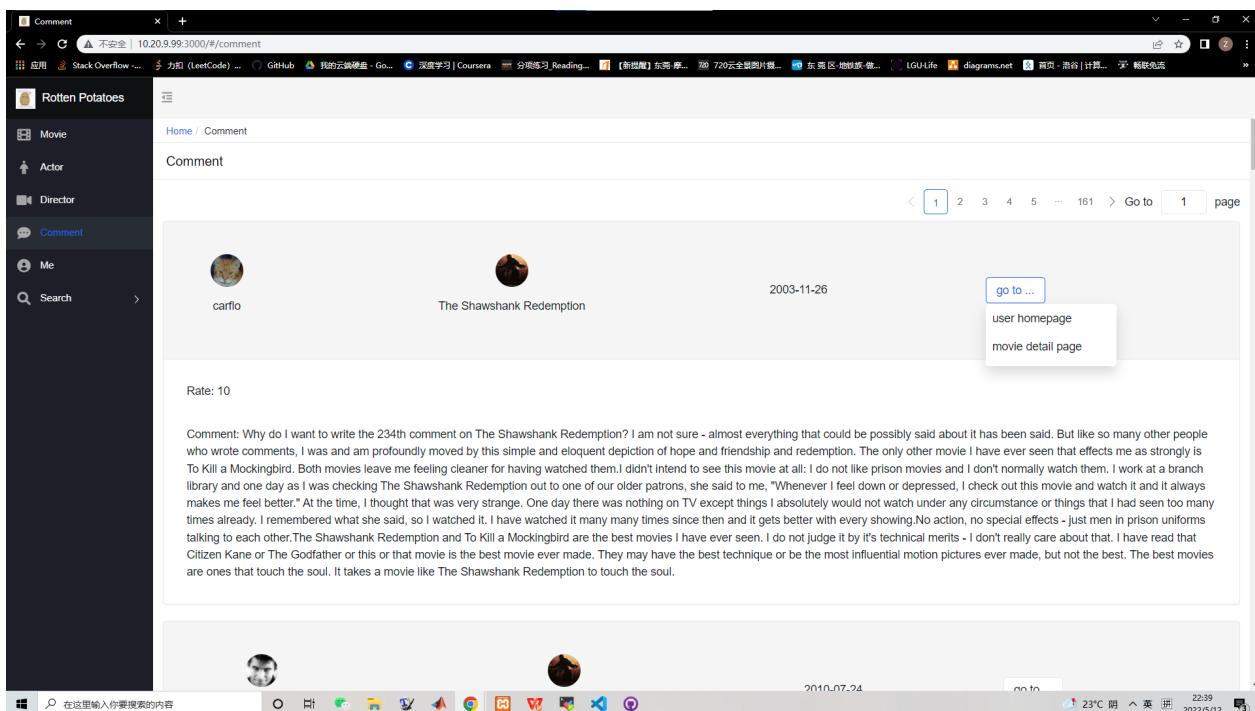


Figure 45: Comment list

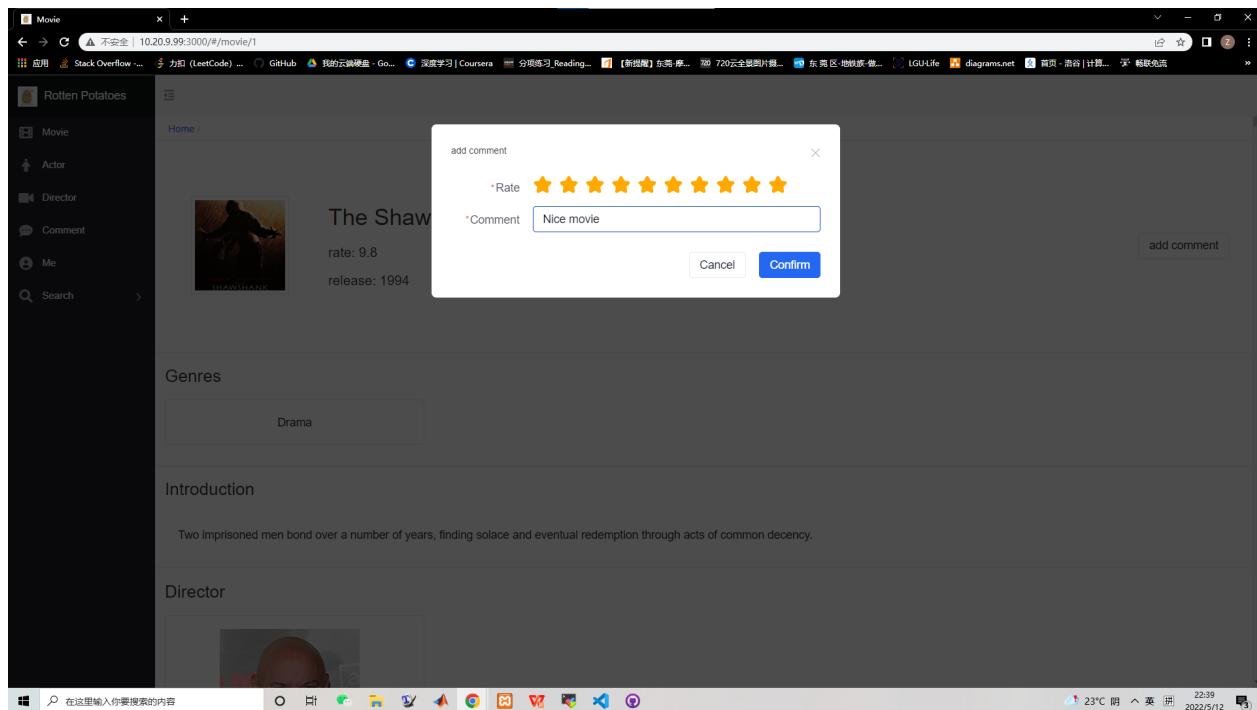


Figure 46: Add comment

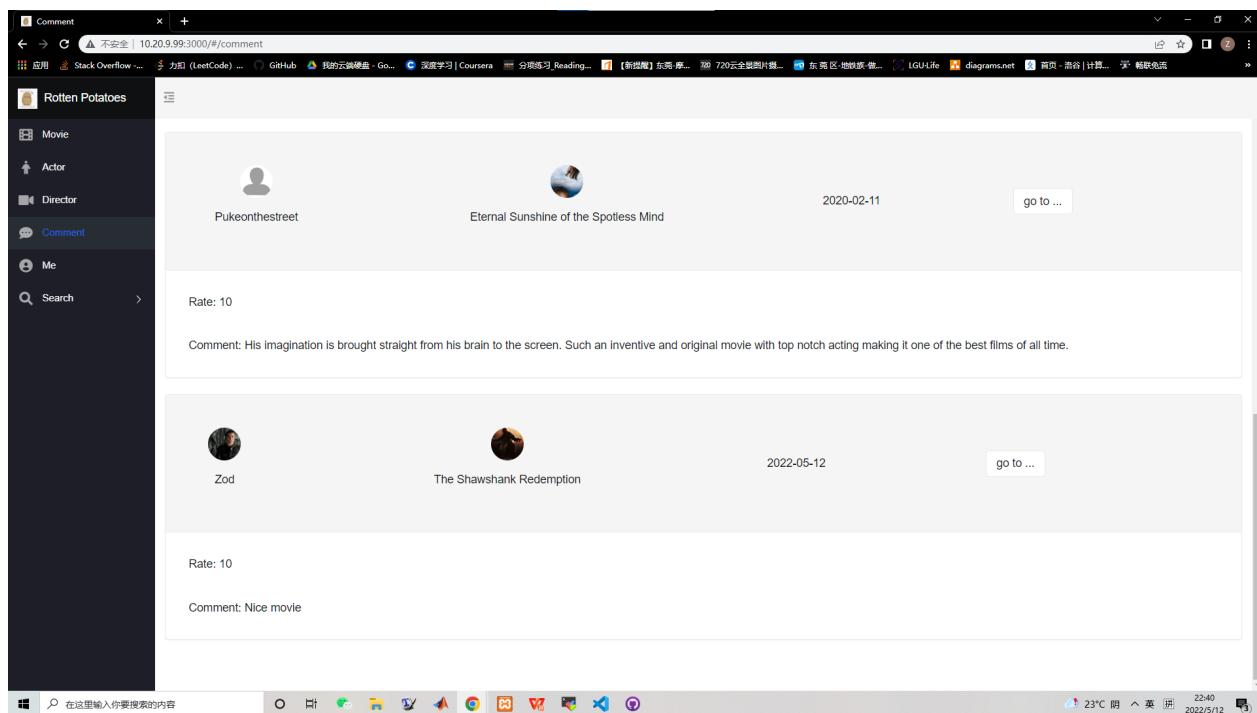


Figure 47: Comment before deleting user account

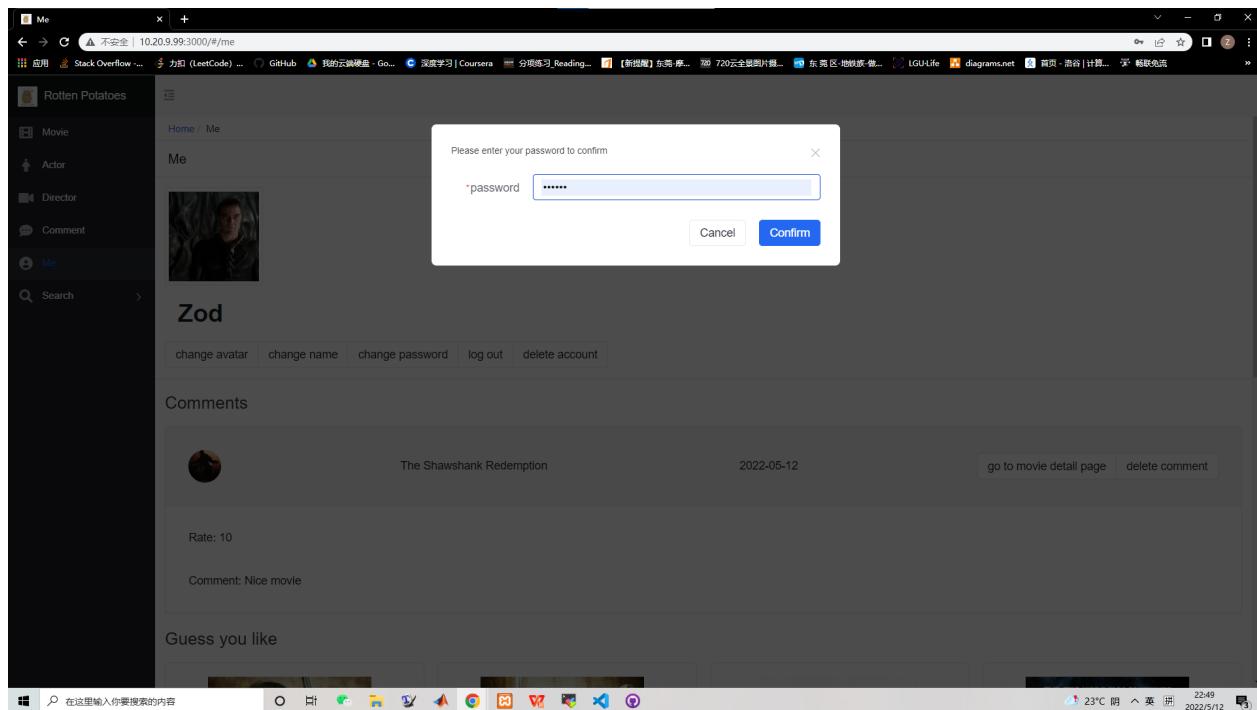


Figure 48: Delete user account

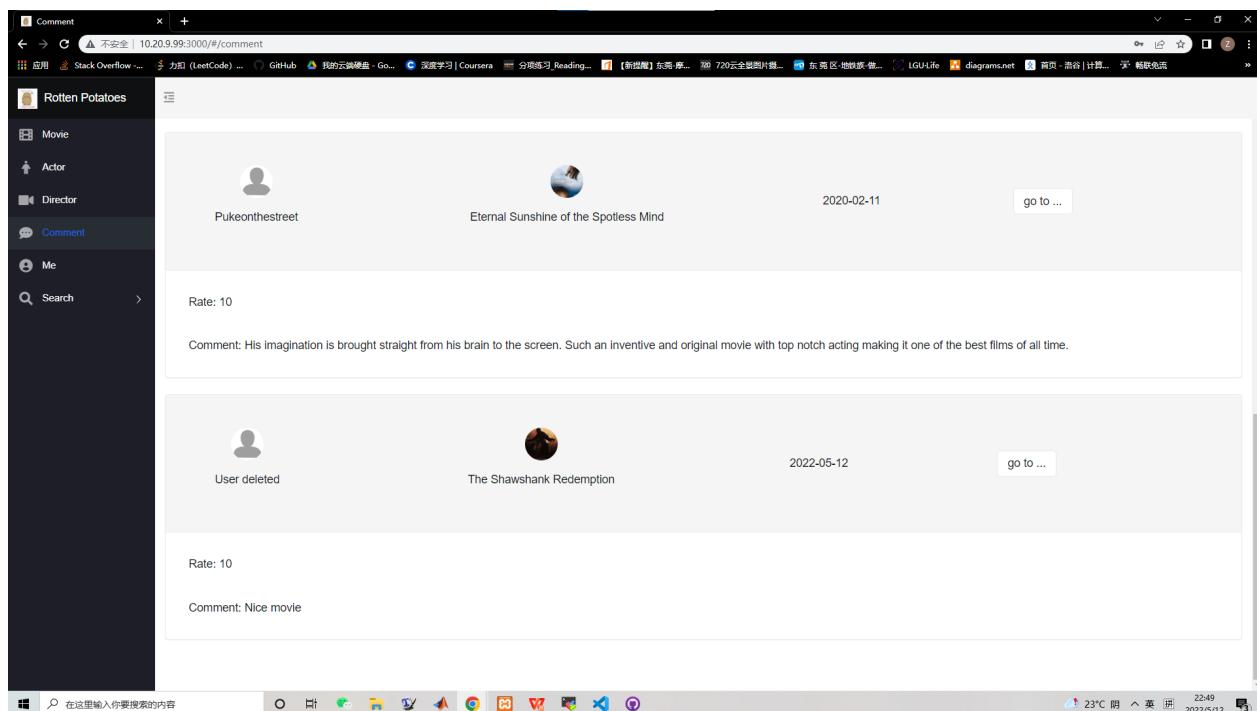


Figure 49: Comment after deleting user account