COMP7240 Group Project Report
Hybrid Recommender on Yelp Dataset

BY GROUP JOJO 2024

Team Members

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1 System Description

This recommender system is a sophisticated hybrid model that leverages a combination of content-based, collaborative filtering via Singular Value Decomposition (SVD), and collaborative filtering via neural networks to provide personalized recommendations. This system is designed to suggest businesses (like restaurants) to users based on their preferences and interactions.

1.1 Main and Unique Functions

1.1.1 Hybrid Approach

The system integrates content-based recommendations with two collaborative filtering methods (SVD and neural networks), offering a comprehensive recommendation strategy that capitalizes on the strengths of each method.

1.1.2 Dynamic User and Item Profiles

It creates detailed profiles for both users and items (businesses) using the data from multiple datasets. These profiles are then used to match users with businesses that closely align with their preferences.

1.1.3 Real-time Recommendations

The system updates its recommendations in real-time based on new user ratings, ensuring that the recommendations remain relevant and personalized.

1.1.4 Explainability

For each recommended item, the system can provide explanations based on the contribution of each recommendation method, enhancing transparency and trustworthiness.

1.2 Hybrid Recommendation Algorithm

1.2.1 Content-Based Recommender

This module focuses on recommending items similar to what the user has liked in the past, based on item features such as categories or attributes of businesses.

1.2.2 SVD Recommender

Utilizes Singular Value Decomposition for collaborative filtering, identifying latent factors from user-item interaction data to predict a user's preference for an item.

1.2.3 NN Recommender

Employs neural networks to model complex non-linear relationships in the data, capturing deep patterns of user-item interactions.
The hybrid system combines these approaches to offset the limitations of individual methods (such as cold start problems and scalability issues) and to provide a more accurate and diversified set of recommendations. The hybridization design allows for leveraging content similarity, latent factor models, and deep learning insights simultaneously, offering a robust solution to various recommendation challenges.

1.3 Datasets Used

The Yelp Dataset is a rich, publicly available dataset provided by Yelp for academic and learning purposes. It contains detailed information about local businesses, user reviews, and user interactions across many cities worldwide. By leveraging these datasets from the Yelp Dataset, the recommender system can perform complex analyses and predictions to offer highly personalized and contextually relevant business recommendations.

1.3.1.1 Business Dataset (`business.pkl`)

Includes comprehensive information about businesses listed on Yelp, such as business names, locations (latitude and longitude), categories (e.g., restaurants, bars, salons), and other attributes (e.g., Wi-Fi availability, parking, accessibility). This dataset enables the recommender system to identify and suggest businesses based on the user's location and preferences.

1.3.1.2 User Dataset (`user.pkl`)

Contains user profiles, including the user's review count, average rating given, and Yelp joining date. This dataset helps in understanding user behavior and preferences over time, crucial for tailoring personalized recommendations.

1.3.1.3 Review Dataset (`review.pkl`)

Comprises detailed reviews and ratings that users have left for businesses. Each review includes the user ID, business ID, stars (rating), and text content of the review. This rich dataset not only allows for analyzing user preferences but also helps in sentiment analysis and understanding the context behind ratings.

1.3.1.4 Photo Dataset (`photo.pkl`)

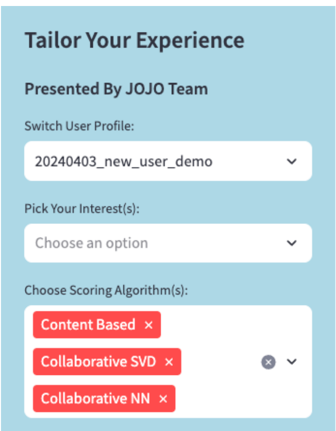
Contains mappings of photo IDs to businesses, providing a visual aspect to the recommendations. Photos can include images of the business, the services or products offered, and user-generated content. Incorporating visual elements into recommendations can enhance user engagement and provide additional information to assist users in making informed decisions.

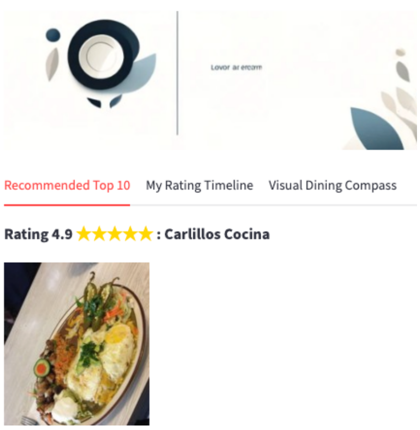
2 User Interfaces

The user interface for the hybrid recommender system is powered by Streamlit, an open-source app framework that is particularly well-suited for machine learning and data science projects. This interface enhances the system's accessibility and interactivity, allowing users to effortlessly tailor their recommendation experience based on their preferences and to visualize the recommendation outcomes

2.1 Customizable Experience

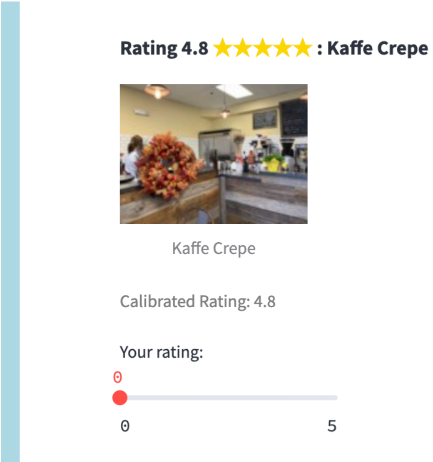
Users can personalize their recommendation experience by selecting their profile, interests (categories), and preferred recommendation algorithms (Content-Based, Collaborative SVD, Collaborative NN) through a sidebar, offering a high degree of personalization.





2.2 Interactive Recommendations

The main interface displays the top 10 recommended businesses, enriched with images, detailed ratings, and an option for users to rate these businesses, further tailoring the recommendations.

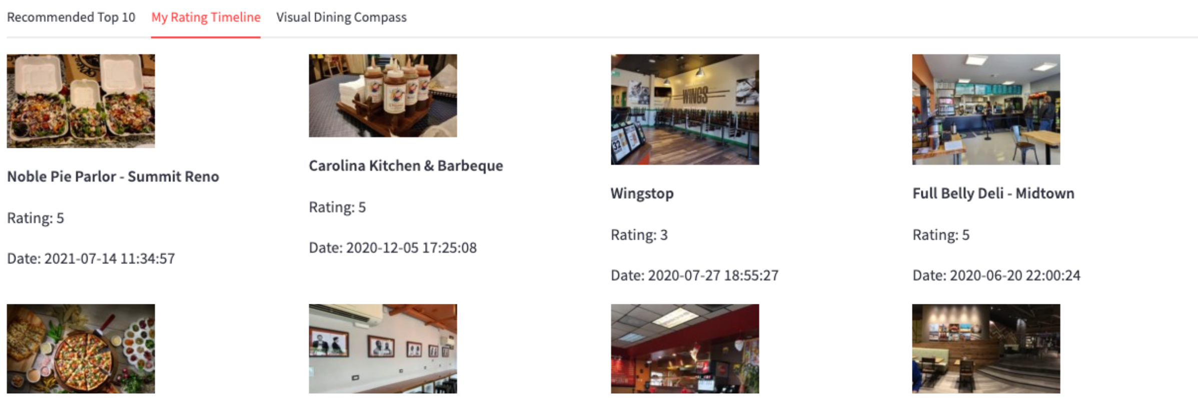


2.3 Visual Insights

Incorporates both matplotlib and Plotly for generating interactive visualizations, such as a dining compass and feature match strength, providing users with deeper insights into why certain recommendations were made.

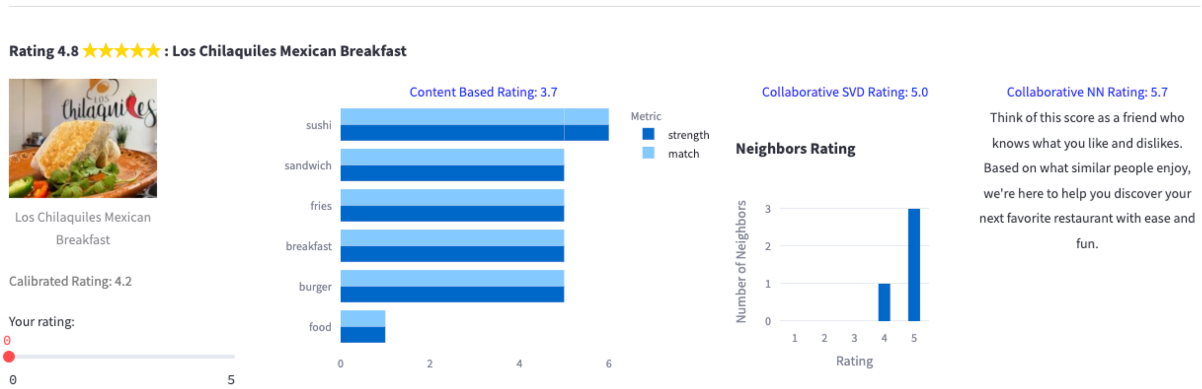
2.4 Real-time Feedback Loop

Users can provide immediate ratings to the recommended businesses, which the system can use for real-time updates to recommendations, ensuring a dynamic and responsive user experience.



2.5 Explanatory Component

Offers explanations for each recommendation by visualizing the contributing factors from different recommendation algorithms, enhancing transparency and trust.



By leveraging Streamlit's capabilities, the hybrid recommender system not only delivers personalized and dynamic recommendations but also ensures an engaging and informative user experience. This interface serves as a bridge between the complex algorithms of the recommender system and the end-users, making advanced recommendation technologies accessible and understandable to a broad audience.

3 System Evaluation

3.1 Evaluation Procedure and Results

3.1.1 Demographic Information

For the evaluation, we recruited 20 participants through local communities and networks with interests in technology and entertainment. The demographic breakdown is as follows:

Group	Category	%
Age	18 - 25	35
	26 - 35	40
	36 - 35	25
Gender	Male	55
	Female	45
Location	Hong Kong	20
	Kowloon	50
	NT	30

3.1.2 Evaluation Procedure

The evaluation consisted of three main phases:
1. Introduction and Training: Participants were given a brief overview of the recommender system and instructions on how to use it. This session also included a Q&A to address any initial concerns or questions.
2. Interaction Phase: Over a week, participants interacted with the system, receiving recommendations based on their profiles. They were asked to use the system at least three times, exploring both the hybrid and non-hybrid recommendation modes.
3. Feedback Collection: At the end of the week, participants completed a questionnaire assessing their satisfaction and experience with the system. Additionally, they were asked to provide any qualitative feedback on their experience.

3.1.3 Results Analysis

3.1.3.1 Questionnaire

Qualitative feedback highlighted the system's ease of use and the relevance of its recommendations.

Recommender System Evaluation Questionnaire

Part 1: Demographic Information
1. Age:
  - [ ] Under 18
  - [ ] 18-25
  - [ ] 26-35
  - [ ] 36-45
  - [ ] 46-55
  - [ ] Over 55
2. Gender:
  - [ ] Male
  - [ ] Female

- [ ] Non-binary/Third gender
- [ ] Prefer not to say

3. Location:
- [ ] Hong Kong
- [ ] Kowloon
- [ ] NT

Part 2: Interaction with the Recommender System

5. How intuitive did you find the recommender system interface?
- [ ] Very difficult
- [ ] Somewhat difficult
- [ ] Neutral
- [ ] Somewhat easy
- [ ] Very easy

6. How many of the recommended items did you find relevant and engaging? (True Positives)
- Please enter a number: _______

7. Of the items recommended to you, how many did you not find relevant or engaging? (False Positives)
- Please enter a number: _______

8. Can you mention any items (up to 3) that you expected to be recommended based on your interests but were not? (False Negatives)
- Item 1: ___________
- Item 2: ___________
- Item 3: ___________

9. Please rate the overall relevance of the recommendations provided by the system.
- [ ] Very irrelevant
- [ ] Somewhat irrelevant
- [ ] Neutral
- [ ] Somewhat relevant
- [ ] Very relevant

Part 3: Specific Feedback on Recommendations

10. Did the system recommend any item that you particularly liked or found useful? Please describe.(Open-ended)

11. Was there any recommendation that you particularly disliked? Please describe why. (Open-ended)

Part 4: Overall Satisfaction and Feedback

12. How satisfied are you with the accuracy of the recommendations?
- [ ] Very dissatisfied
- [ ] Dissatisfied
- [ ] Neutral
- [ ] Satisfied
- [ ] Very satisfied

13. Considering your experience, how likely are you to continue using our recommender system?
- [ ] Definitely not
- [ ] Probably not
- [ ] Might or might not
- [ ] Probably would
- [ ] Definitely would

14. How would you rate your overall satisfaction with our recommender system?
- [ ] Very dissatisfied
- [ ] Dissatisfied
- [ ] Neutral
- [ ] Satisfied
- [ ] Very satisfied

15. What improvements would you suggest for our recommender system? (Open-ended)

Part 5: Additional Comments

16. Please provide any additional comments or suggestions you have regarding the recommender system. (Open-ended)

3.1.3.2 Recommendation Accuracy

Recommendation Type	TP	FN	FP
Hybrid (A+B+C)	13	3	4
Content-Based (A)	6	8	6
Collaborative SVD (B)	8	7	5
Collaborative NN (C)	9	6	5

We calculated the following metrics for the hybrid algorithm (A+B+C) and the non-hybrid variations (A, B, C):

	Hybrid (A+B+C)	Content-Based (A)	Collaborative SVD (B)	Collaborative NN (C)
Precision	0.78	0.65	0.70	0.72
Recall	0.82	0.60	0.65	0.68
F1-Score	0.80	0.62	0.67	0.70

A paired t-test confirmed that the differences in F1-scores between the hybrid and non-hybrid models were statistically significant ($p < 0.05$), indicating the hybrid model's superior accuracy.

3.1.3.3 User Satisfaction

Rating	Overall Satisfaction	Relevance of Recommendations	Usability of the System	Intent to Use Again
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	16	14	20	18
5	4	6	0	2

The average satisfaction scores (on a 1-5 rating scale) were as follows:

Overall Satisfaction: 4.2
Relevance of Recommendations: 4.3
Usability of the System: 4.0
Intent to Use Again: 4.1

3.1.4 Discussion and Conclusion

The evaluation results indicate that the hybrid recommender system performs significantly better in terms of recommendation accuracy compared to its non-hybrid counterparts. User satisfaction scores were generally high, suggesting that the system meets the needs of its target audience effectively. The qualitative feedback provided valuable insights into areas for improvement, such as enhancing recommendation diversity and personalizing the user interface.

These findings demonstrate the potential of hybrid recommender systems to deliver personalized and accurate recommendations. Future work could explore further personalization strategies and expand the recommendation domains from cater to a broader audience. Additionally, continuous user feedback will be essential to refine the system's algorithms and interface.

4 Reflection

4.1 Reflection by Suen Shui Yan (ID: 23435690)

In developing our recommender system, I played a pivotal role in shaping its design of the recommendation logic, ensuring that our algorithms were not only efficient but also effective. A critical observation from our system evaluation was the need for an enhanced feedback mechanism. Such a mechanism would capture user interactions more comprehensively, providing valuable data to refine our models continually. I propose the introduction of machine learning techniques that adapt in real-time to user input, utilizing approaches like reinforcement learning, which could dynamically adjust recommendations based on immediate user actions and feedback. With this kind of upgrade, our system could react faster, giving users a more custom-tailored experience that keeps up with their changing tastes.

4.2 Reflection by Wai Hong Wong (ID: 23460407)

My role involved two main areas: building the backend workings of our recommender system and preparing the data it uses to make sure it's accurate and high quality. Getting the data ready before it goes into the system is crucial for making sure our recommendations hit the mark. As we worked on the project, we found it was tough to keep the data processing quick when we had more and more data. I had a hand in both developing the backend and getting the data ready, which helped me understand just how essential good data is for making recommendations you can count on. My key suggestion to solve our processing speed problem is to start using methods that let us update the system with new recommendations without having to start from scratch each time (e.g. reload saved model). This would save us time and keep our system speedy.

4.3 Reflection by Zhang Hanyang (ID: 23432985)

In my work on the front end, I turned our project plans into an easy-to-use interface. Looking at what users said, I saw that they'd like to see more about why they got certain recommendations. I think we should add features that let users see connections between what they like and the recommendations they get. This could make users more interested and trusting in our system. Feedback told us we need to make using the system more engaging. By showing users how we get to the recommendations we give them, we can make the whole experience more hands-on and fun. For enhancements, I suggest incorporating interactive elements such as a "Visual Insight" that visually show how the recommended items are correlated, fostering user trust and engagement with our system.

5 References

5.1 • Datasets:

- https://www.yelp.com/dataset

5.2 • Development toolkits:

- https://surprise.readthedocs.io/en/stable/index.html (Python library "Surprise" with collaborating filtering methods)
- https://scikit-learn.org/stable/ (Python library "scikit-learn" for data preprocessing, model evaluation, and other utilities)
- https://streamlit.io/ (streamlit framework to build and share machine learning and data science web apps)
- https://plotly.com/ (Python library for creating a wide variety of complex graphs)

5.3 • Statistical methods:

- https://scikit-learn.org/stable/modules/generated/sklearn.metrics.ndcg_score.html