Project: AI-Based Recommendation System For Australian Migrants

Week 2 Work Report

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Outline

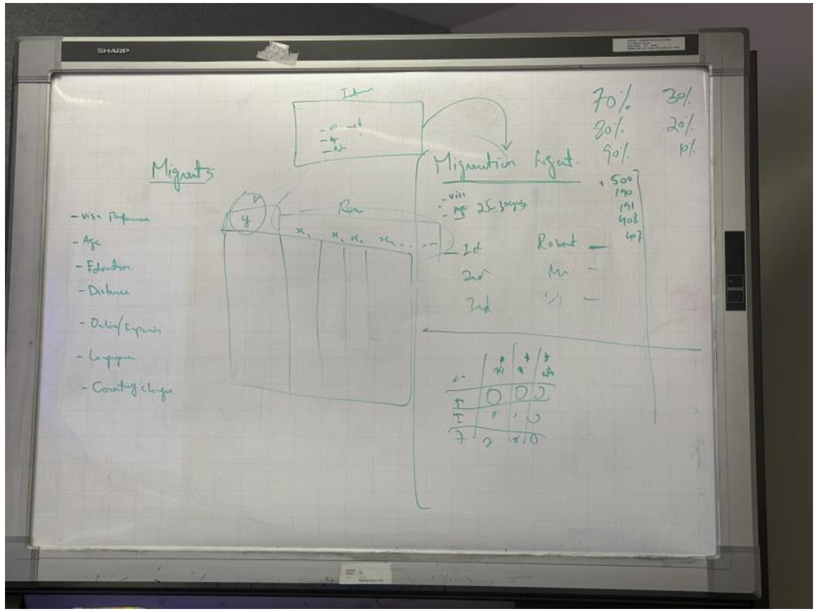
- Discussion in last week
- Requirement and outcome for this week(2 tables)
  - Top 3 popular recommendation models
    - Neural Collaborative Filtering(NCF)
    - Light Graph Convolution Network(LightGCN)
    - Deep Neural Networks for YouTube(YouTubeDNN)
  - Migrants' requirements/feature
- Discussion for next work and pitch presentation

Discussion in last week

- 5 group members collect 11 different models
  - Slides uploaded on GitHub

  Link: https://github.cs.adelaide.edu.au/MCI-Project-2025/HA1/tree/main/Docs/Report/Week%202

- A Project Sketch shown on the white board



- 2 tables required to finish in week 3
  - Top 3 popular recommendation models
    - Model name, brief description, reference, evaluation
  - Australian Migrants' requirements/feature
    - Requirements name, Why it is important

Top 3 popular recommendation models

Neural Collaborative Filtering(NCF)

- cited 7800+ times on google scholar
- Publish year: 2017
- Brief description：

  Neural Collaborative Filtering (NCF) is a deep learning-based approach that enhances recommendation systems by utilizing neural networks to model user-item interactions. Unlike traditional collaborative filtering methods, which rely on matrix factorization (MF) and use inner products to capture relationships, NCF replaces this operation with a neural network. This approach enables the model to learn more complex, non-linear patterns in user preferences, ultimately improving recommendation accuracy.

Top 3 popular recommendation models

Neural Collaborative Filtering(NCF)

- evaluation:
  - Hit Ratio (HR) @K

$$\mathrm{HR@K} = \frac{\text{Number of hits}}{\text{Total number of users}}$$

  - Normalized Discounted Cumulative Gain (NDCG) @K

$$\mathrm{NDCG@K} = \frac{\mathrm{DCG@K}}{\mathrm{IDCG@K}} \qquad \mathrm{DCG@K} = \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

IDCG(Ideal Discouted Cumulative Gain)

- Recall @K

$$Recall = \frac{|\{relevant\ items\} \cap \{retrieved\ items\}|}{|\{relevant\ items\}|}$$

Top 3 popular recommendation models

Light Graph Convolution Network(LightGCN)

- cited 4000+ times on google scholar
- Publish year: 2020
- Brief description ：

  LightGCN (Light Graph Convolutional Network) is a lightweight graph neural network model for recommendation systems. It is a simplified version of GNN (Graph Neural Network) in recommendation systems, inheriting the neighbor information aggregation idea of GCN (Graph Convolutional Network) and optimizing NGCF (Neural Graph Collaborative Filtering).

  Compared with traditional GCN and NGCF, LightGCN can achieve better performance in recommendation tasks while maintaining efficient computing (He et al. 2020).

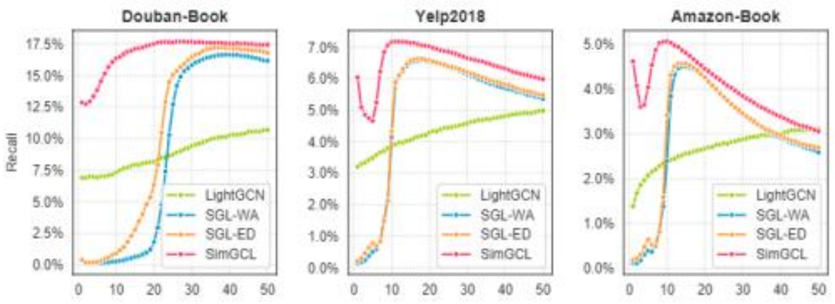
Top 3 popular recommendation models

Light Graph Convolution Network(LightGCN)

	Gowalla recall	Gowalla ndcg	Yelp2018 recall	Yelp2018 ndcg	Amazon-Book recall	Amazon-Book ndcg
MF	0.1291	0.1878	0.0317	0.0617	0.0250	0.0518
NeuMF	0.1326	0.1985	0.0331	0.0840	0.0253	0.0535
CMN	**0.1404**	**0.2129**	0.0364	0.0745	0.0267	0.0516
HOP-Rec	0.1399	0.2128	**0.0388**	**0.0857**	**0.0309**	**0.0606**
GC-MC	0.1395	0.1960	0.0365	0.0812	0.0288	0.0551
PinSage	0.1380	0.1947	0.0372	0.0803	0.0283	0.0545
NGCF	**0.1547***	**0.2237***	**0.0438***	**0.0926***	**0.0344***	**0.0630***
%Improv.	10.18%	5.07%	12.88%	8.05%	11.32%	3.96%
p-value	1.01e-4	5.38e-3	4.05e-3	2.00e-4	4.34e-2	7.26e-3

This figure shows the performance comparison of NGCF with other popular models (Wang et al. 2019)

Method	**Douban-Book Time (s)**	**Yelp2018 Time (s)**	**Amazon-Book Time (s)**
LightGCN	3.6	13.6	41.5
SGL-WA	4.4 (1.2x)	16.3 (1.2x)	47.0 (1.1x)
SGL-ED	13.3 (3.7x)	62.3 (4.6x)	235.3 (5.7x)
SimGCL	6.1 (1.7x)	27.9 (2.1x)	98.4 (2.4x)



This figure shows the performance comparison of LightGCN and other GNN models (Yu et al. 2021).

Top 3 popular recommendation models

Light Graph Convolution Network(LightGCN)

- evaluation:
  - According to Wu et al. (2022), LightGCN uses Recall and NDCG as evaluation metrics to measure its performance in recommendation tasks.
  - Recall: focuses on how many items in the recommendation list the user is actually interested in, regardless of the order of the recommendations (Wu et al. 2022).

$$Recall@K = \frac{\text{Number of relevant items in the recommendation list}}{\text{Total number of relevant items for the user}}$$

  - NDCG (Normalized Discounted Cumulative Gain): It not only considers the correctness of the recommendation (like Recall), but also the order of recommendation (Wu et al. 2022).

$$\mathbf{NDCG}@K = \frac{1}{|\mathcal{U}|} \Sigma_{u \in \mathcal{U}} \frac{\Sigma_{k=1}^{K} \frac{I(R_k^K(u) \in T(u))}{\log(k+1)}}{\Sigma_{k=1}^{K} \frac{1}{\log(k+1)}},$$

Top 3 popular recommendation models

Deep Neural Networks for YouTube(YouTube DNN)

- cited 4000+ times on google scholar
- Publish year: 2016
- Brief description ：

  DNN (Deep Neural Network) for YouTube, the system consists of two neural networks, one for candidate generation and one for sequencing. Quadric Polynomial Regression (QPR) is combined to avoid inaccurate results due to pretreatment of missing values. The accuracy of the model can be improved by input rich feature sets and normalization of these features to distinguish candidates with high recall rates.

Top 3 popular recommendation models

Deep Neural Networks for YouTube(YouTube DNN)

- evaluation:
  - MAE and RMSE

$$MAE = \frac{1}{N}\sum_{i,j}|R_{ij} - \hat{R}_{ij}|,$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i,j}(R_{ij} - \hat{R}_{ij})^2},$$

  - Recall
  - Precision
  - F1-measure

$$R = \frac{n_{rs}}{n_s} \qquad P = \frac{n_{rs}}{n_s} \qquad F1 = \frac{2 * P * R}{P + R}$$

Migrants' requirements/feature

Data Crawler and Data generation

Delimiter: ,

	Age	Nationality	Marital Status	Education Level	Studied in Australia	Occupation	Years of Experience	ıstralian Work Experi
1	24	China	Single	Bachelor	No	Software Engineer	18	
2	37	USA	Married	Master	No	Nurse	6	
3	46	Canada	Single	Master	No	Nurse	19	
4	32	USA	Married	Master	No	Electrician	5	
5	28	Germany	Single	Bachelor	No	Chef	0	
6	25	Canada	Married	Master	Yes	Accountant	16	
7	46	Canada	Single	Master	No	Chef	10	
8	38	UK	Married	Bachelor	No	Chef	17	
9	24	Canada	Single	PhD	Yes	Nurse	16	
10	43	USA	Married	Bachelor	No	Chef	6	
11	36	Canada	Married	Master	Yes	Software Engineer	16	
12	40	UK	Married	Master	Yes	Nurse	19	
13	28	UK	Single	Bachelor	Yes	Software Engineer	8	
14	28	Germany	Married	PhD	Yes	Accountant	16	
15	41	USA	Single	Master	No	Nurse	19	
16	38	India	Married	Master	No	Accountant	7	
17	21	India	Single	Master	No	Nurse	16	
18	25	Canada	Married	Bachelor	No	Electrician	6	
19	41	Germany	Single	Master	No	Chef	0	
20	20	China	Single	PhD	No	Electrician	12	
21	39	Canada	Married	Master	Yes	Accountant	18	
22	38	Germany	Single	Master	No	Chef	18	
23	19	USA	Single	PhD	Yes	Nurse	16	
24	41	USA	Married	Master	No	Chef	12	
25	29	USA	Single	Bachelor	Yes	Software Engineer	15	
26	47	USA	Single	Bachelor	No	Chef	7	
27	23	USA	Single	Bachelor	No	Software Engineer	18	
28	19	Germany	Married	PhD	Yes	Chef	17	
29	49	Germany	Single	Master	Yes	Software Engineer	0	
30	45	UK	Married	Bachelor	No	Accountant	13	
31	38	India	Single	PhD	Yes	Electrician	18	
32	18	USA	Single	Master	No	Nurse	14	

root [] 127 items
0
category "Visitor visas "
visa_name "Electronic Travel Authority (subclass 601)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/electronic-travel-authority-601"
1
category "Visitor visas "
visa_name "eVisitor (subclass 651)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/evisitor-651"
2
category "Visitor visas "
visa_name "Transit visa (subclass 771)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/transit-771"
3
category "Visitor visas "
visa_name "Visitor (subclass 600)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/visitor-600"
4
category "Visitor visas "
visa_name "Work and Holiday visa (subclass 462)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/work-holiday-462"
5
category "Visitor visas "
visa_name "Working Holiday visa (subclass 417)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/work-holiday-417"
6
category "Studying and training visas"
visa_name "Student visa (subclass 500)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/student-500"
7
category "Studying and training visas"
visa_name "Student Guardian visa (subclass 590)"
visa_url "https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/student-590"
8

Visitor visas [] 6 items
Studying and training visas [] 3 items
Family and partner visas [] 23 items
Working and skilled visas [] 22 items
Refugee and humanitarian visas [] 6 items
Other visas [] 13 items
Repealed visas [] 54 items

Migrants' requirements/feature

Research Methodology

- Official documentation analysis
- Comparative visa category study
- Real case cross-referencing
- Three-stage analytical process

Continuing Top 10:

6. English Proficiency
7. Skills Assessment
8. Age

Requirements Priority Ranking

1. **Visa Type**
2. **Health Requirements**
3. **Character Requirements**
4. Occupation
5. Work Experience

Priority determined by impact analysis and application process sequence

Final Two Tables Show

Top 3 Popular Recommendation System models				
model name	**brief description**	**reference**	**evaluation**	**note**
Neural Collaborative Filtering(NCF)	Neural Collaborative Filtering (NCF) is a deep learning-based approach that enhances recommendation systems by utilizing neural networks to model user-item interactions. Unlike traditional collaborative filtering methods, which rely on matrix factorization (MF) and use inner products to capture relationships, NCF replaces this operation with a neural network. This approach enables the model to learn more complex, non-linear patterns in user preferences, ultimately improving recommendation accuracy.	Ferrari Dacrema, M., Cremonesi, P. and Jannach, D. (2019) "Are we really making much progress? A worrying analysis of recent neural recommendation approaches: A worrying analysis of recent neural recommendation approaches," in Proceedings of the 13th ACM Conference on Recommender Systems. New York, NY, USA: ACM. He, X. et al. (2017) "Neural Collaborative Filtering," in Proceedings of the 26th International Conference on World Wide Web. Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee. Liang, D. et al. (2018) "Variational Autoencoders for Collaborative Filtering," arXiv [stat.ML]. Available at: http://arxiv.org/abs/1802.05814. Ong, K., Haw, S.-C. and Ng, K.-W. (2019) "Deep learning based-recommendation system: An overview on models, datasets, evaluation metrics, and future trends," in Proceedings of the 2019 2nd International Conference on Computational Intelligence and Intelligent Systems. New York, NY, USA: ACM. Rendle, S. et al. (2020) "Neural collaborative filtering vs. Matrix factorization revisited," in Fourteenth ACM Conference on Recommender Systems. New York, NY, USA: ACM. Wang, X. et al. (2019) "Neural graph collaborative filtering," in Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. New York, NY, USA: ACM.	Hit Ratio(HR), Normalized Discounted Cumulative Gain (NDCG) Recall	cited 7800+ times on google scholar
Light Graph Convolution Network(LightGCN)	LightGCN (Light Graph Convolutional Network) is a lightweight graph neural network model for recommendation systems. It is a simplified version of GNN (Graph Neural Network) in recommendation systems, inheriting the neighbor information aggregation idea of GCN (Graph Convolutional Network) and optimizing NGCF (Neural Graph Collaborative Filtering). Compared with traditional GCN and NGCF, LightGCN can achieve better performance in recommendation tasks while maintaining efficient computing (He et al. 2020).	He, X, Deng, K, Wang, X, Li, Y, Zhang, Y & Wang, M 2020, 'LightGCN: Simplifying and Powering Graph Convolution Network for Recommendation', arXiv (Cornell University), Cornell University. Wang, X, He, X, Wang, M, Feng, F & Chua, T-S 2019, 'Neural Graph Collaborative Filtering', Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. Wu, S, Sun, F, Zhang, W, Xie, X & Cui, B 2022, 'Graph Neural Networks in Recommender Systems: A Survey', ACM Computing Surveys. Yu, J, Yin, H, Xia, X, Chen, T, Cui, L & Hung 2021, 'Are Graph Augmentations Necessary? Simple Graph Contrastive Learning for Recommendation', arXiv (Cornell University), Cornell University.	Recall; NDCG (Normalized Discounted Cumulative Gain)	cited 4000+ times on google scholar
Deep Neural Networks for YouTube(YouTubeDNN)	DNN (Deep Neural Network) for YouTube, the system consists of two neural networks, one for candidate generation and one for sequencing. Quadric Polynomial Regression (QPR) is combined to avoid inaccurate results due to pretreatment of missing values. The accuracy of the model can be improved by input rich feature sets and normalization of these features to distinguish candidates with high recall rates.	Covington, P., Adams, J. and Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. Proceedings of the 10th ACM Conference on Recommender Systems - RecSys '16, [online] pp.191–198. doi:https://doi.org/10.1145/2959100.2959190. Shashi Shekhar, Singh, A. and Avadhesh Kumar Gupta (2022). A Deep Neural Network (DNN) Approach for Recommendation Systems. Lecture notes in networks and systems, pp.385–396. doi:https://doi.org/10.1007/978-981-16-9756-2_37. Zhang, L., Luo, T., Zhang, F. and Wu, Y. (2018). A Recommendation Model Based on Deep Neural Network. IEEE Access, 6, pp.9454–9463. doi:https://doi.org/10.1109/access.2018.2789866.	MAE,RMSE, Recall, Precision, F1-measure	cited 4000+ times on google scholar

Final Two Tables Show

Australian Migrants Requirements		
NO.	**Requirements name**	**Why it is important**
1	Visa Type	Different visa categories (skilled, family, investment, etc.) have completely different application conditions and assessment criteria, determining which immigration pathway an applicant should pursue
2	Health Requirements	Medical examinations are required to protect Australia's public health system, prevent the spread of infectious diseases, and ensure immigrants do not burden the healthcare system
3	Character Requirements	Applicants must pass character checks including police clearance certificates to ensure they do not pose a threat to the Australian community
4	Occupation	The list of occupations varies by category, Some occupations may have different requirements for immigration
5	Work experience	Professional history directly impacts eligibility for skilled migration visas and affects points calculation in the points-based system
6	English Proficiency	Different visas have different requirements for language scores; proficiency directly impacts points calculation and determines threshold eligibility for many visa types
7	Skills Assessment	Many visa categories require a skills assessment from relevant authorities to verify that the applicant's skills and qualifications meet Australian standards
8	Age	Different immigration conditions have different age requirements
9	Education	If you have completed more than 2 years of study in Australia, you can apply for a 485 graduate work visa and get extra points in skilled immigration.
10	Financial Capacity	Different immigration routes require different financial support.

（Continue in next slide）

Final Two Tables Show

Australian Migrants Requirements		
NO.	**Requirements name**	**Why it is important**
11	Regional Migration Restrictions	Some visas require applicants to live and work in specific regions for a period of time to promote regional development and balanced population distribution
12	Dependents	Conditions regarding whether an applicant's dependents can apply together, which is important for those planning to migrate with family
13	Residence History	Applications for permanent residence or citizenship typically require meeting certain residence requirements, demonstrating ongoing commitment and ties to Australia
14	Health Insurance	Some visa categories require applicants to maintain adequate health insurance during their stay in Australia to reduce the burden on the public healthcare system
15	Marital status	Being married or single may affect the form of application and whether a spouse can be a subsidiary applicant
16	Preferred State	Immigration policies are different in each city, for example in remote areas and in the capital
17	Nationality	People from different countries have different cultural backgrounds, so recommending an agent of the same nationality will be more convenient for communication and trust
18	Prior Visa Compliance	History of compliance with previous Australian or other country visa conditions affects eligibility, showing the applicant is trustworthy

Discussion for next work and pitch presentation

- How can we access the database?
- How many samples could we have?
- Should we follow the method shown in the research totally?
- When do we need to build a prototype?
- What do we need to prepare for the pitch presentation?

Reference

Covington, P., Adams, J. and Sargin, E. (2016). Deep Neural Networks for YouTube Recommendations. *Proceedings of the 10th ACM Conference on Recommender Systems - RecSys '16*, [online] pp.191–198. doi:https://doi.org/10.1145/2959100.2959190.

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