Educational Recommender Systems

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AIED TOKYO 2023
24th INTERNATIONAL CONFERENCE ON ARTIFICIAL INTELLIGENCE IN EDUCATION

Schedule

- Part I. EdRec: An Overview
  - Time: July 3rd, 2023 | 09:00 AM – 10:30 AM + QA
  - Location: Hitotsubashi Hall, Room 203
- Part II. EdRec: Case Studies
  - Time: July 3rd, 2023 | 11:00 AM – 12:30 PM + QA
  - Location: Hitotsubashi Hall, Room 203

Case Studies

- Case Studies
  - Case Studies: EdRec Specialized to Education
    Characteristics: these RecSys were built for education domains only
    Example: Book/Course/Pathway EdRec
    Goals: learn how edu challenges handled in EdRec
  - Case Studies: General RecSys with Practice in Education
    Characteristics: these models may also be applied to other domains
    Example: context-aware/group/multi-criteria/multi-stakehold RecSys
    Goals: learn possible opportunities in EdRec

Schedule: Part II

- Case Studies: EdRec Specialized to Education (continued)
  - EdRec using pedagogical features
- Case Studies: General RecSys with Practice in Education
  - Context-Aware EdRec
  - ITM-Rec Data Set
  - Multi-Criteria EdRec, Group EdRec
  - Personality-Based EdRec
  - Multi-stakeholder EdRec, Multi-task EdRec, Multi-objective EdRec
  - EdRec: Fairness, Transparency, Explanations
- Challenges and Future Work
- QA and Open Discussions

Case Studies: EdRec with Pedagogical Features

- EdRec with Pedagogical Features
  - Pedagogical Features are unique resources in EdRec
    - instructional rules
    - pre/post requisites
    - knowledge level
    - learning history
    - learning style
    - educational standards
    - ……

Case Studies: EdRec with Pedagogical Features

- EdRec with Pedagogical Features
  - Unfortunately, limited research utilized these features in EdRec
  - Usage of Pedagogical Features in EdRec

    1). Rules or Requisites as constraints

    - ❑ Uddin, I., Imran, A. S., Muhammad, K., Fayyaz, N., & Sajjad, M. (2021). A systematic mapping review on MOOC recommender systems. IEEE Access, 9, 118379-118405.

    2). Pedagogical features as additional user info/item features/contexts in RecSys

    - ❑ Thongchotchat, V., Kudo, Y., Okada, Y., & Sato, K. (2023). Educational Recommendation System Utilizing Learning Styles: A Systematic Literature Review. IEEE Access.

    3). Knowledge level or learning styles to group learners

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    - They can be used as filters, e.g., filtering out irrelevant items
    - They can be used as rules to build structure or algorithms, e.g., the directed edges in graphs
    - They can be used as constraints in optimization algorithms, e.g., conditions as feasible solutions

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    - Help find user neighborhood
    - Formulate regularization terms/penalties in model-based collaborative filtering
    - Use as contexts in pre-/post-filtering or contextual modeling

Case Studies: EdRec with Pedagogical Features

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    3). Knowledge level or learning styles to group learners

    - Group or cluster learners for analysis
    - Alleviate sparsity preferences by groups
      - » Produce recommendations to group of learners
      - » Find patterns (e.g., association rules) from group of learners

Schedule: Part II

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Case Studies: Context-Aware EdRec

- In context-aware RecSys, we assume that user preferences may change from contexts to contexts
  - Restaurant
    Lunch alone ==> Fast-food restaurant
    Dinner together ==> Formal restaurant
  - Video watching
    Weekday ==> short videos
    Weekend ==> long movies
    Good bandwidth ==> 1080P videos
    Low bandwidth ==> 360P or 480P videos

Case Studies: Context-Aware EdRec

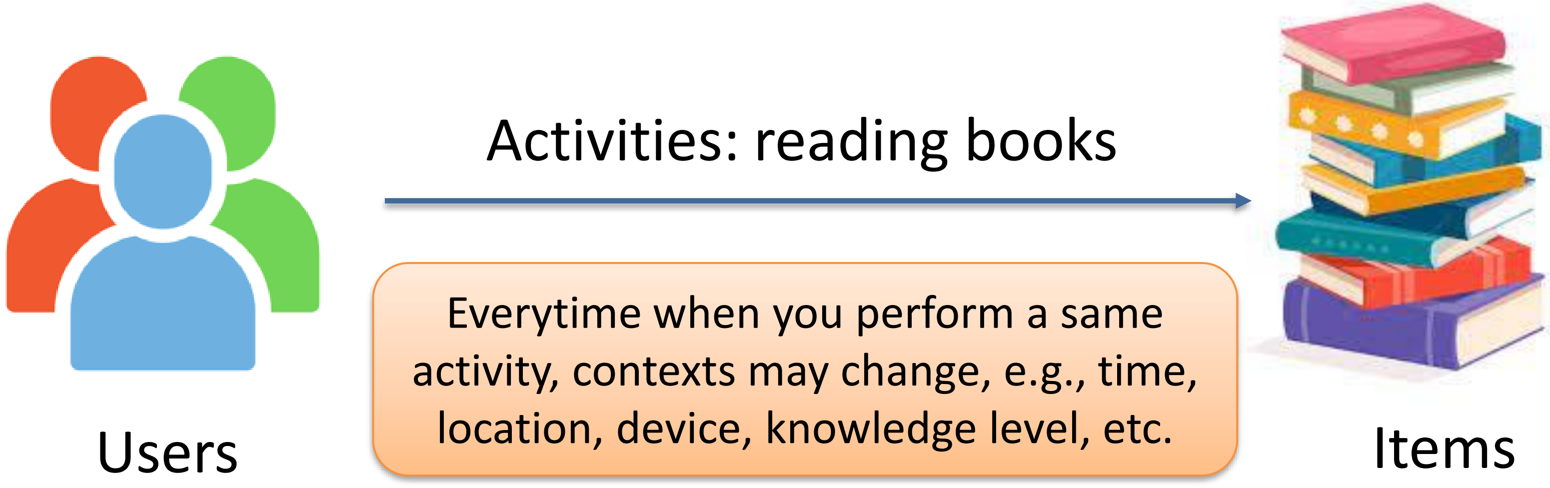
- What are the context variables?
  - Time and Location
  - User intent or purpose
  - User emotional states
  - Others: companion, weather, budget, etc

Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., & Duval, E. (2012). Context-aware recommender systems for learning: a survey and future challenges. *IEEE transactions on learning technologies*, *5*(4), 318-335.

- Contexts vary from domains to domains. In education domain,
  - All the factors above
  - Device, WIFI connections, Bandwidth, lighting, noise level
  - Learner's knowledge level, learning style, etc….

Case Studies: Context-Aware EdRec

- What are the context variables?
  - ➢ Dynamic attributes from users, e.g., emotions
  - ➢ Attributes of the activities



Case Studies: Context-Aware EdRec

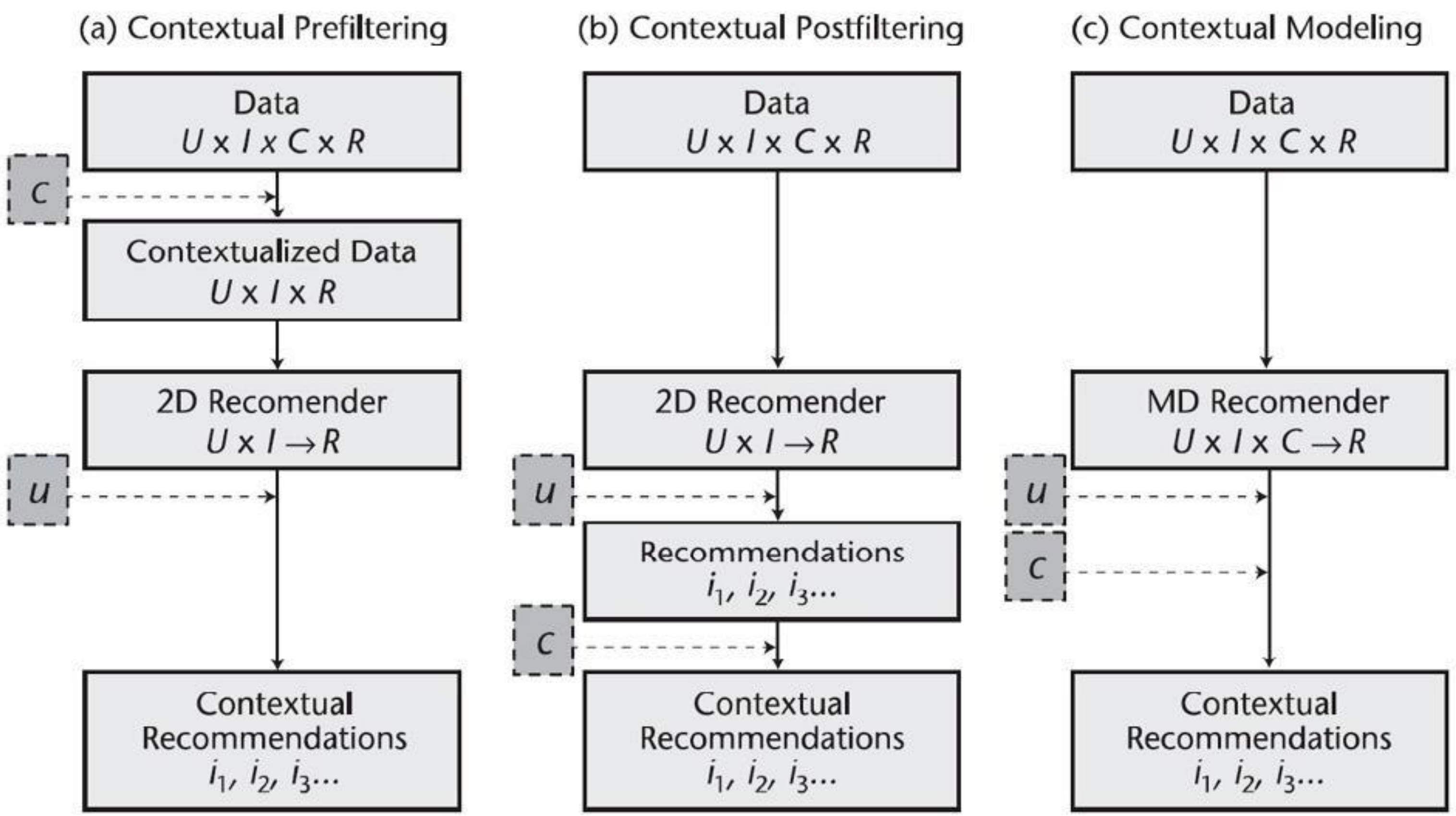
- Example of Rating Matrix for Context-Aware RecSys
  - ➢We have users' ratings on items along with context information

User	Item	Rating	Time	Location	Companion
U1	T1	3	Weekend	Home	Kids
U1	T2	5	Weekday	Home	Partner
U2	T2	2	Weekend	Cinema	Partner
U2	T3	3	Weekday	Cinema	Family
U1	T3	?	Weekend	Cinema	Kids

  - ➢This is context-aware rating data with explicit context information

Case Studies: Context-Aware EdRec

- Context-Aware RecSys with explicit context information



Case Studies: Context-Aware EdRec

- Challenges in context-aware EdRec, such as mobile learning
  - ➢We may not have user preferences on items in different contexts

User	Item	Rating	Time	Location	Companion
U1	T1	3	Weekend	Home	Kids
U1	T2	5	Weekday	Home	Partner
U1	T3	?	Weekend	Cinema	Kids

  - ➢Context-aware pervasive computing is more common in EdRec
    - ➢The system defines built-in rules and executes specific actions

    Example: when Internet connection speed is lower, reduce video resolution accordingly

Case Studies: Context-Aware EdRec

- Examples: Context-Aware EdRec
  - *Context-Aware Peer recommendations*

    Lonsdale, P., Baber, C., et al. (2005). Context awareness for MOBIlearn: creating an engaging learning experience in an art museum. *Mobilelearning anytimeeverywhere*, *115*.

    Location is acquired from mobile devices, and the system can recommend learning peers or partners according to proximity

Case Studies: Context-Aware EdRec

- Examples: Context-Aware EdRec
  - *Recommendation rules are predefined in learning models*

    Cui, Y., & Bull, S. (2005). Context and learner modelling for the mobile foreign language learner. System, 33(2)

    They ask learners to input location, concentration level, and frequencies of interruption, and recommend materials based on predefined models

Conditions (context model + user model)	Interactions (recommended options by the system)
Model = 1	Normal study (tutorials, exercises, revision)
Model = 2	One topic tutorial with full exercise
Model = 3	One topic tutorial with short exercise
Model = 4	One topic tutorial

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ITM-Rec Data Set

- ITM-Rec: An Open Data Set for Educational Recommender Systems https://www.kaggle.com/datasets/irecsys/itmrec
- It was collected from user questionnaires filled out by graduate students who enrolled in data science programs
  - Students need to select a real-world data set to complete data analytics or data science tasks as their final projects in the class
  - We randomly select 70 Kaggle data sets or topics, and asked students to give ratings to them

ITM-Rec Data Set

- Information Collected from the questionnaire
  - Student demographic info, e.g., age, gender, etc.
  - Student personality traits by answering a 10-question study
    Personality traits will be represented by BigFive personality frame
    Note: personality traits were not released in the ITM-Rec data
  - Students must select 3 preferred items and 3 disliked items

ITM-Rec Data Set

- Collected Rating Data
  - Individual ratings
    - Overall rating on the selected items
    - Ratings on multi-criteria of the items, e.g., App, Data, Ease

	Overall Rating			App					Data					Ease				
	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Credit Card Fraud Detection	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Congress Trump Score	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Homicide Reports	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

  - Group ratings
    - If students worked in a group for final projects, each group must select items and give overall & multi-criteria ratings to represent group's perspective.

ITM-Rec Data Set

- Final Data (individual ratings)
  - **users.csv**
    columns: UserID, Gender, Age, Married
    description: Meta data about students
  - **items.csv**
    columns: Item, Title, URL, Descriptions (texts or texts crawled from URL)
    description: Meta data about the topics of projects
  - **ratings.csv**
    columns: UserID, Item, Rating, App, Data, Ease, Class, Semester, Lockdown
    description: Students' individual ratings on items, including the overall rating and multi-criteria ratings, as well as three contextual variables, e.g., class, semester, lockdown periods (pre, dur, pos)
    statistics: 5,230 ratings given by 476 students on 70 items, sparsity: 84.30%

UserID	*ItemID*	*Rating*	*App*	*Data*	*Ease*	*Course*	*Semester*	*Lockdown*
1173	28	5	4	4	4	DA	Fall	PRE
1175	41	5	4	4	4	DS	Spring	POS
...	...	...	...	...	...	...	...	...

ITM-Rec Data Set

- Final Data (Group ratings)
  - **group.csv**
    columns: GroupID, UserID
    description: the compositions of groups
  - **group_size.csv**
    columns: GroupID, Size
    description: the number of students in each group
    statistics: group size: {2: 88, 3: 42, 4: 9, 5: 4}
  - **group_ratings.csv**
    columns: GroupID, Item, Rating, App, Data, Ease, Class, Semester, Lockdown
    description: Ratings on items given by groups, rather than individuals
    statistics: 1,117 ratings given by 143 groups on 70 items , sparsity: 88.84%

https://www.kaggle.com/datasets/irecsys/itmrec

ITM-Rec Data Set

- ITM-Rec data bring several recommendation opportunities
  - Context-aware Rec
  - Multi-criteria Rec
  - Group Rec
  - Multi-objective Rec
  - Multi-stakeholder Rec
  - Multi-task Rec
  - ....

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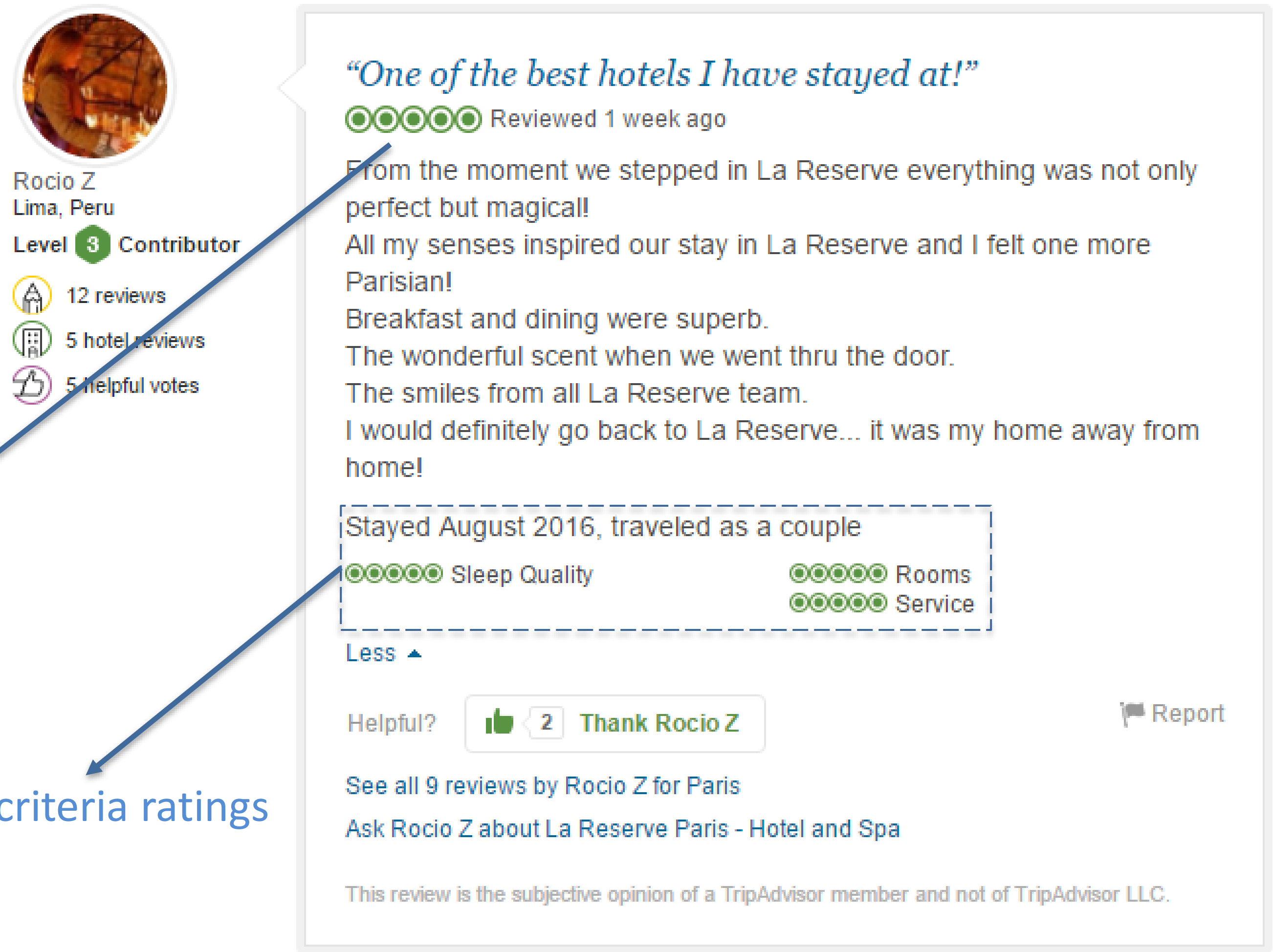
Case Studies: Multi-Criteria EdRec

- Multi-Criteria RecSys
  - In addition to users' overall ratings on the items, we also have multi-criteria ratings on the items



Overall rating

Multi-criteria ratings

Case Studies: Multi-Criteria EdRec

- Multi-Criteria RecSys
  - Example of multi-criteria rating data sets

Table 1. Example of Rating Data from TripAdvisor

User	Item	Rating	Room	Check-in	Service
U_1	T_1	3	3	4	3
U_2	T_2	4	4	4	5
U_3	T_1	?	?	?	?

Case Studies: Multi-Criteria EdRec

- Multi-Criteria RecSys
  - Example of multi-criteria rating in the ITM-Rec Data

UserID	*ItemID*	*Rating*	*App*	*Data*	*Ease*	*Course*	*Semester*	*Lockdown*
1173	28	5	4	4	4	DA	Fall	PRE
1175	41	5	4	4	4	DS	Spring	POS
...	...	...	...	...	...	...	...	...

Overall Ratings — Multi-Criteria Ratings — Context Variables

Case Studies: Multi-Criteria EdRec

- Multi-Criteria RecSys
  - Most multi-criteria RecSys models are composed of two stages:

User	Item	Rating	Food	Service	Ambience	Value
U_1	T_3	4	4	3	4	4
U_2	T_2	3	3	3	3	3
U_3	T_1	?	?	?	?	?

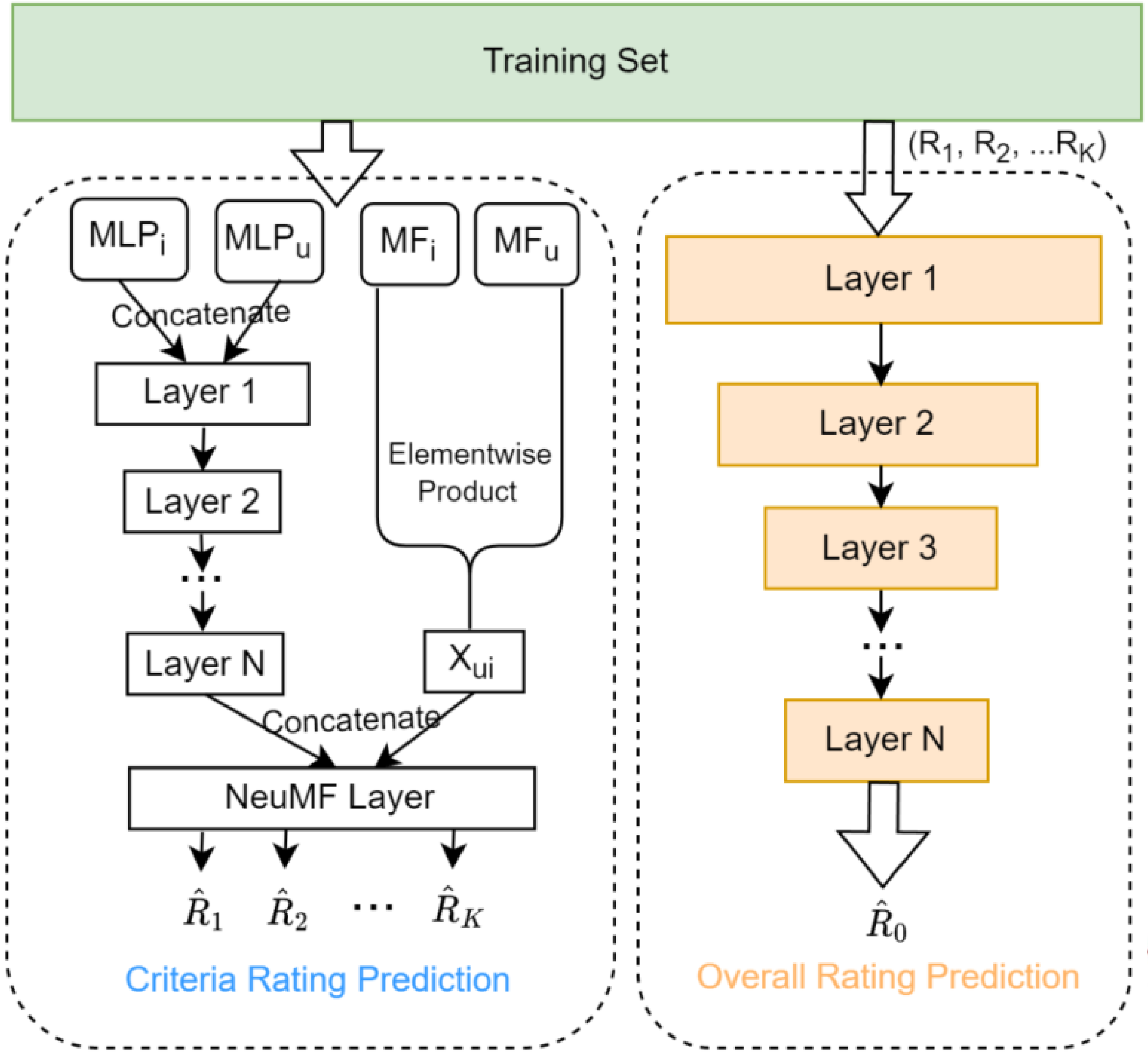
1) Multi-criteria rating predictions
Given a user and an item, predict the ratings in multiple criteria

2) Aggregations
Aggregate the predicted multi-criteria ratings to a single score as either overall rating or overall ranking score

Case Studies: Multi-Criteria EdRec

- Multi-Criteria RecSys
  - Example: Multi-Output Neural Matrix Factorization

Nassar, N., Jafar, A., & Rahhal, Y. (2020). Multi-criteria collaborative filtering recommender by fusing deep neural network and matrix factorization.
Journal of Big Data, 2020



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Case Studies: Group EdRec

- Group RecSys
  - Group RecSys: item recommendations to a group of users
    Example: group dinner/travel/studies/project
  - Challenges
    - Individuals may have different tastes
    - Conflicting tastes within a group
    - Group preferences are not available, or very limited
    - Group members are always changing

Case Studies: Group EdRec

- Group RecSys: Aggregate Individual Tastes to Represent Groups
  - Group RecSys usually aggregate individual preferences to estimate group preferences by multiple aggregation strategies
  - The aggregation strategies can also be viewed as the approach to represent group preferences from individual tastes.

> ❑ Masthoff, J. (2010). Group recommender systems: Combining individual models. In Recommender systems handbook (pp. 677-702). Boston, MA: Springer US.

Case Studies: Group EdRec

- Group RecSys: Aggregation Strategies
  Average or Summation

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_1	8	10	7	10	9	8	10	6	3	6
u_2	7	10	6	9	8	10	9	4	4	7
u_3	5	1	8	6	9	10	3	5	7	10
Group	20	21	21	25	26	28	22	15	14	23

Case Studies: Group EdRec

- Group RecSys: Aggregation Strategies

  Multiplication

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_1	8	10	7	10	9	8	10	6	3	6
u_2	7	10	6	9	8	10	9	4	4	7
u_3	5	1	8	6	9	10	3	5	7	10
Group	280	100	336	540	648	800	270	120	84	420

Case Studies: Group EdRec

- Group RecSys: Aggregation Strategies
  Least Misery

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_1	8	10	7	10	9	8	10	6	3	6
u_2	7	10	6	9	8	10	9	4	4	7
u_3	5	1	8	6	9	10	3	5	7	10
Group	5	1	6	6	8	8	3	4	3	6

Case Studies: Group EdRec

- Group RecSys: Aggregation Strategies
  Most Pleasure

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_1	8	10	7	10	9	8	10	6	3	6
u_2	7	10	6	9	8	10	9	4	4	7
u_3	5	1	8	6	9	10	3	5	7	10
Group	8	10	8	10	9	10	10	6	7	10

Case Studies: Group EdRec

- Group RecSys: Aggregation Strategies
  Average without Misery
  Example: ignore ratings < a threshold (e.g., 4)

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_1	8	10	7	10	9	8	10	6	3	6
u_2	7	10	6	9	8	10	9	4	4	7
u_3	5	1	8	6	9	10	3	5	7	10

Case Studies: Group EdRec

- Group RecSys: Aggregation Strategies

  Most Respected Person

  Example: assume u1 is the most respected person

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_1	8	10	7	10	9	8	10	6	3	6
u_2	7	10	6	9	8	10	9	4	4	7
u_3	5	1	8	6	9	10	3	5	7	10
Group	8	10	7	10	9	8	10	6	3	6

Case Studies: Group EdRec

- Example 1: Identify member roles in the group
  - General Idea: identify member roles in a group (i.e., dominators and followers) first, then apply aggregations by ignoring the contributions from the followers (e.g., calculating average by excluding followers)
    - Method 1: Utilize personality traits to distinguish dominators and followers

❑ Zheng, Y. (2018, March). Identifying Dominators and Followers in Group Decision Making based on The Personality Traits. In the HUMANIZE Workshop at ACM IUI 2018.

Dominators: higher values in openness and extraversion
Followers: higher values in agreeableness

Case Studies: Group EdRec

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    - Method 2: Learn a binary role (1 = dominator, 0 = follower) for each group member by using evolutionary optimization

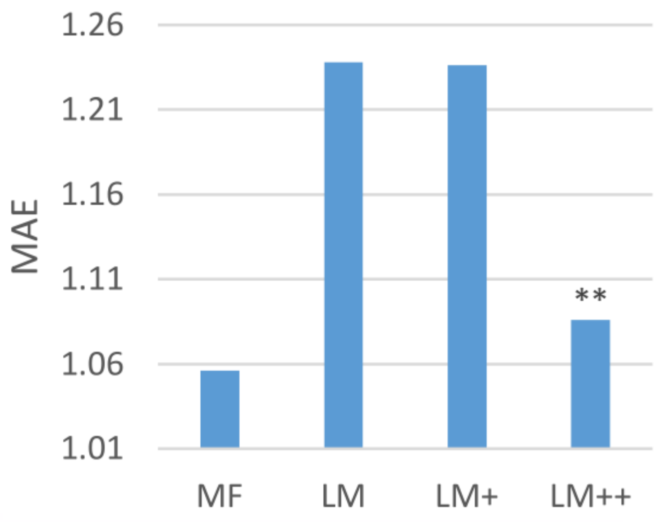
❑ Zheng, Y. (2018). Exploring user roles in group recommendations: A learning approach. In the HAAPIE workshop at ACM UMAP 2018.

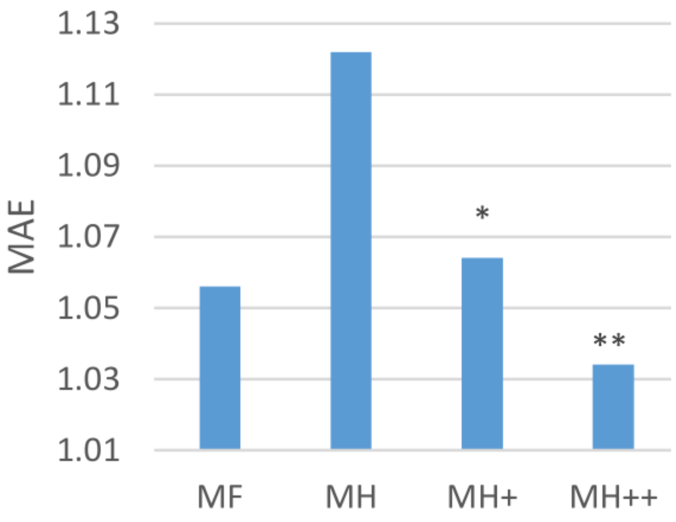
At the beginning, we assign random 1/0 to users
Then we learn discrete 1/0 values by using evolutionary algorithm towards maximizing the recommendation performance

Case Studies: Group EdRec

- Example 1: Identify member roles in the group
  - Results based on the ITM-Rec data

❑ Zheng, Y. (2018). Exploring user roles in group recommendations: A learning approach. In the HAAPIE workshop at ACM UMAP 2018.





LM: Least Misery
MH: Most Happiness

Method 1: +
Method 2: ++

Case Studies: Group EdRec

- Example 2: Maximize individual and group satsifaction
  - General Idea: use multi-objective optimization of individual and group

❑ Xiao, L., et al. (2017). Fairness-aware group recommendation with pareto-efficiency. In ACM RecSys, 2017

Individual satisfaction $U(u, I) = \frac{1}{K \times rel_{max}} \sum_{i \in I} rel(u, i)$

I = a set of K recommended items
u = a member in the group g

Objective 1: average individual satisfaction

$$SW(g, I) = \frac{1}{|g|} \sum_{u \in g} U(u, I), \forall g, I$$

Objective 2: group fairness

$$Least\ Misery: \ F_{LM}(g, I) = \min\{U(u, I), \forall u \in g\}$$

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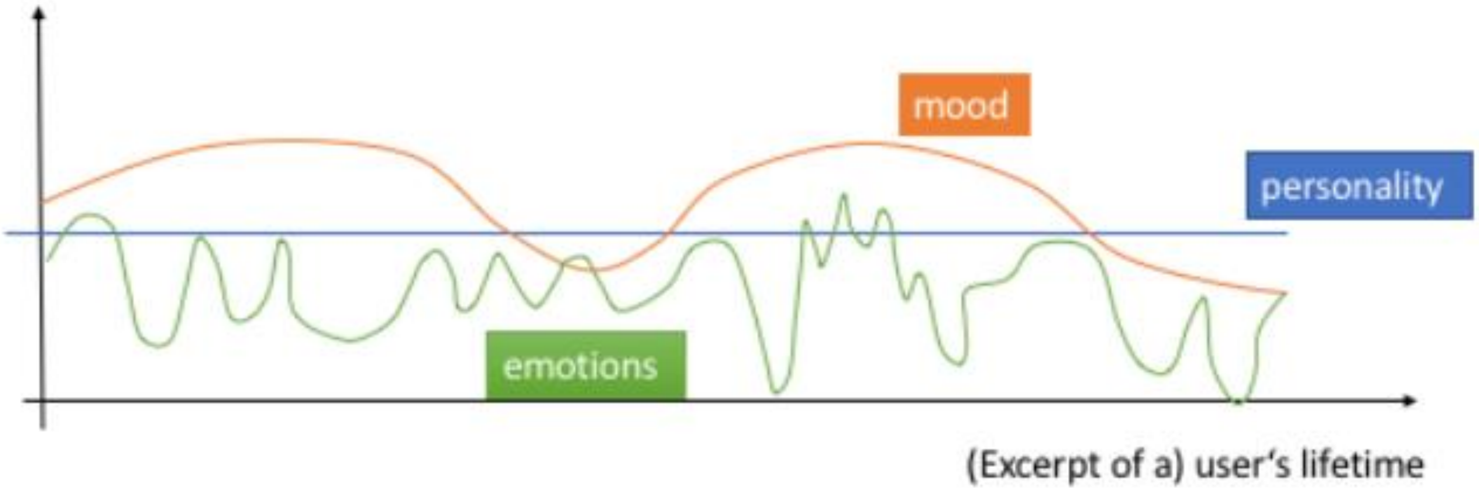
Case Studies: Personality-Based EdRec

- Personality and Personality traits
  - Personality is a subset of human factors
  - Personality is usually static, while emotions may be dynamic



Case Studies: Personality-Based EdRec

- Personality and Personality traits
  - Effects by personality can be easily observed in education
  - Users with different personality or culture background may present different user behaviors
    - For example, students from Asia may be shy to ask questions in the class, in comparison with students from America or Europe → culture issue
    - But some students from India prefer to ask questions in the class too → personality issue

Case Studies: Personality-Based EdRec

- Personality and Personality traits
  - Personality traits are used to represent human personalities.
  - There are several frameworks to collect personality traits by using questionnaires.
  - The most popular one is the BigFive personality framework

Trait	Description
Openness	Curious, original, intellectual, creative, and open to new ideas.
Conscientiousness	Organized, systematic, punctual, achievement oriented, and dependable.
Extraversion	Outgoing, talkative, sociable, and enjoys being in social situations.
Agreeableness	Affable, tolerant, sensitive, trusting, kind, and warm.
Neuroticism	Anxious, irritable, temperamental, and moody.

Case Studies: Personality-Based EdRec

- Personality and Personality traits
  - Ten-Item Personality Inventory (TIPI) used to calculate BigFive personality
    - I see myself as extraverted, enthusiastic.
    - I see myself as critical, quarrelsome.
    - I see myself as dependable, self-disciplined.
    - I see myself as anxious, easily upset.
    - I see myself as open to new experiences, complex.
    - I see myself as reserved, quiet.
    - I see myself as sympathetic, warm.
    - I see myself as disorganised, careless.
    - I see myself as calm, emotionally stable.
    - I see myself as conventional, uncreative.

Gosling, S. D., Rentfrow, P. J., & Swann Jr, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in personality*, *37*(6), 504-528.

Case Studies: Personality-Based EdRec

- There are several ways to utilize personality traits in RecSys
  – Consider them as one type of user demographic information
    - Being used to calculate user-user similarities
    - Being used to group/cluster users
    - Being used to solve cold-start problems
    - Being used as penalties/regularization terms in collaborative filtering
  – Use personality traits in item splitting
    - Treat a same item as “different ones” along with a specific personality info

Zheng, Y., & Subramaniyan, A. (2021). “Personality-aware recommendations: an empirical study in education”. *International Journal of Grid and Utility Computing*, *12*(5-6), 524-533.

Case Studies: Personality-Based EdRec

- There are several ways to utilize personality traits in RecSys
  - Results based on the ITM-Rec Data

	MAE	*Precision*	*Recall*	*NDCG*
$\text{UBCF}_{\gamma=1}$	1.133	0.082	0.394	0.242
$\text{UBCF}_{\gamma=0}$	1.123	0.087	0.411	0.283
$\text{UBCF}_{\gamma=0.4}$	**1.108**	**0.093**	**0.438**	**0.291**
MF	1.176	0.077	0.367	0.235
MF_p	**1.067**	0.081	0.371	0.246
MF_{reg}	1.106	0.080	0.370	0.241
MF_{p+reg}	**1.067**	**0.086**	**0.400**	**0.248**
iSplitting	**1.067**	**0.087**	**0.410**	**0.255**

Zheng, Y., & Subramaniyan, A. (2021). "Personality-aware recommendations: an empirical study in education". *International Journal of Grid and Utility Computing*, *12*(5-6), 524-533.

Schedule: Part II

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  - EdRec using pedagogical features
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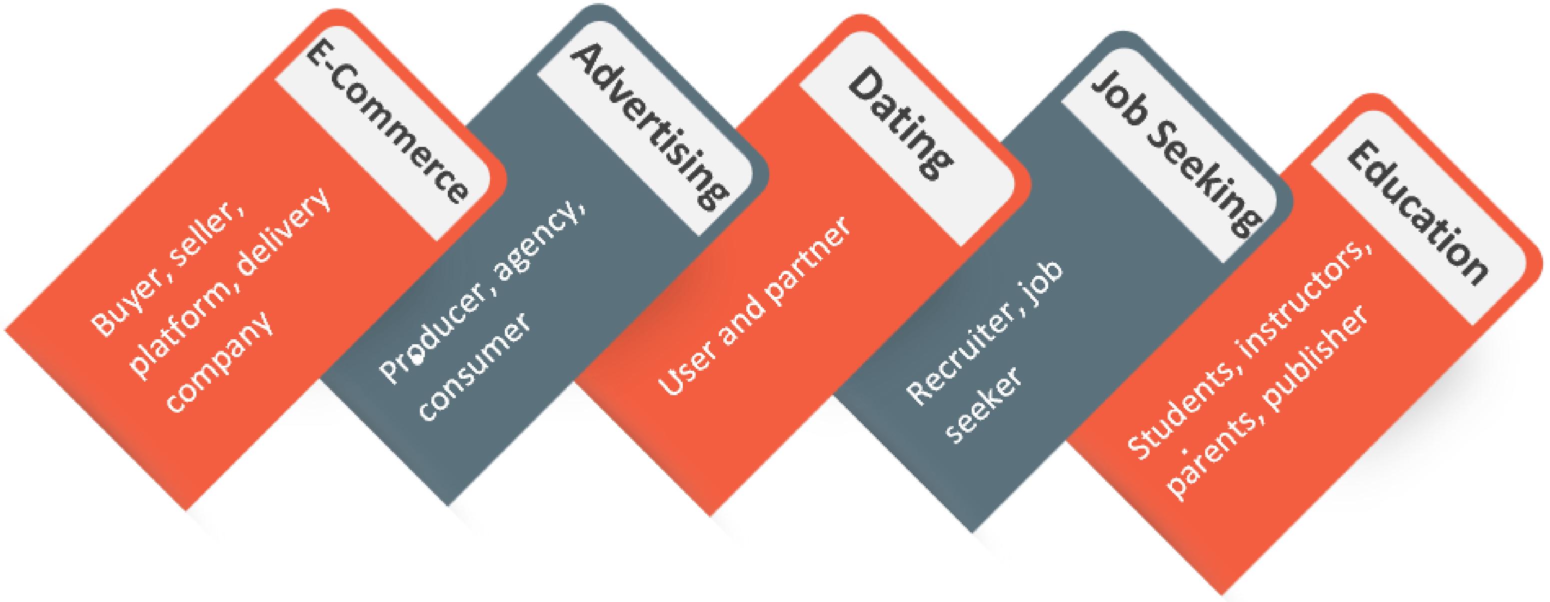
- QA and Open Discussions

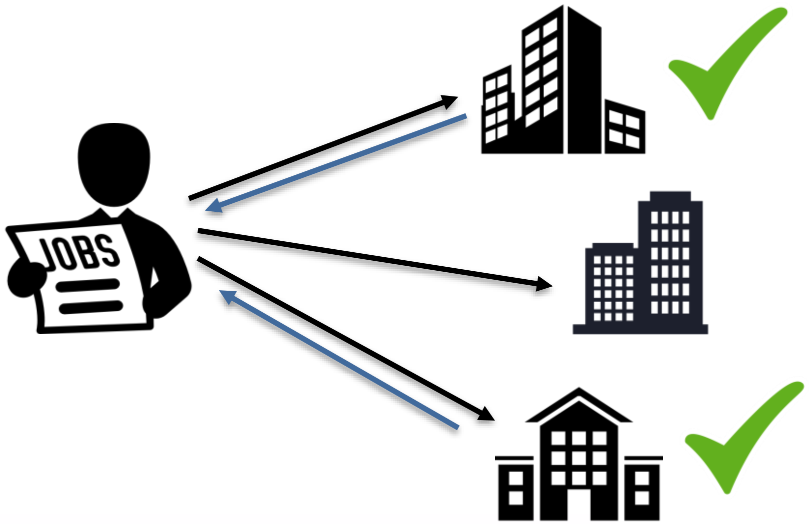
Case Studies: Multi-Stakeholder EdRec

- Multi-Stakeholder RecSys
  - The receiver of the recommendation is not the only stakeholder



Case Studies: Multi-Stakeholder EdRec

- Multi-Stakeholder RecSys
  - Maximizing utility of the items from one stakeholder may hurt the benefits of other stakeholders
  - Example 1: Job recommendations (reciprocal recommendation)



A good job RecSys should consider
- Whether the job seeker likes the job
- Whether the recruiter wants to hire the job seeker

Case Studies: Multi-Stakeholder EdRec

- Multi-Stakeholder RecSys
  - Maximizing utility of the items from one stakeholder may hurt the benefits of other stakeholders
  - Example 2: Book recommendations
    - Student: each student may have their own interests
    - Parents: parents may be worried about whether the books are appropriate for kids’ current age
    - Teachers: teachers may want students to read something helpful for classes
    - Publishers: publishers want to get more sales

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data

Instructor

Projects

Students

❑ Zheng, Y., Ghane, N., & Sabouri, M. (2019). Personalized educational learning with multi-stakeholder optimizations. In Adjunct Publication of the 27th Conference on User Modeling, Adaptation and Personalization (pp. 283-289).

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  - Example: Recommending Kaggle data sets as topics of final projects in a data mining and machine learning class
    - Students are required to complete a final project in the data science class
    - Students should select a data set from Kaggle.com, and analyze data in projects
    - There are two stakeholders
      - Students: they (most of them) want to select easy data set for easy projects
      - Instructors: they want students to select more challenging ones

❑ Zheng, Y., Ghane, N., & Sabouri, M. (2019). Personalized educational learning with multi-stakeholder optimizations. In Adjunct Publication of the 27th Conference on User Modeling, Adaptation and Personalization (pp. 283-289).

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  - The utility of items from the perspective of students

    Utility-based MCRS model is used to learn student expectations

    Zheng, Y. (2019, April). Utility-based multi-criteria recommender systems. In *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing* (pp. 2529-2531).

Table 1: Example of The Educational Data

User	Item	Overall Rating	App	Data	Ease
10	41	4	4	4	4
10	60	2	2	2	2
12	21	4	4	5	4
...	...	...	...	...	...

Table 2: User Expectation Data

User	App	Data	Ease
10	5	4	3
12	4	4	4
...	...	...	...

Utility can be denoted by similarity between multi-criteria rating vector (R) and expectation vectors (E)

Student, $U_{s,t}$ = similarity ($E_{s,}$, $R_{s,t}$)

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  - The utility of items from the perspective of instructors

    We ask instructor to give multi-criteria ratings ($R_{p,t}$) to these items too

    Instructor, $U_{p,t}$ = dissimilarity (E_p, $R_{p,t}$)

    E_p is the multi-criteria rating vector represents minimal requirements

    For example, <App, Data, Ease> = <3, 3, 3>

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  - The utility function of a recommendation list

$$\boxed{\text{Ranking score to sort items} = \alpha \times U_{s,t} + (1 - \alpha) \times U_{p,t}}$$

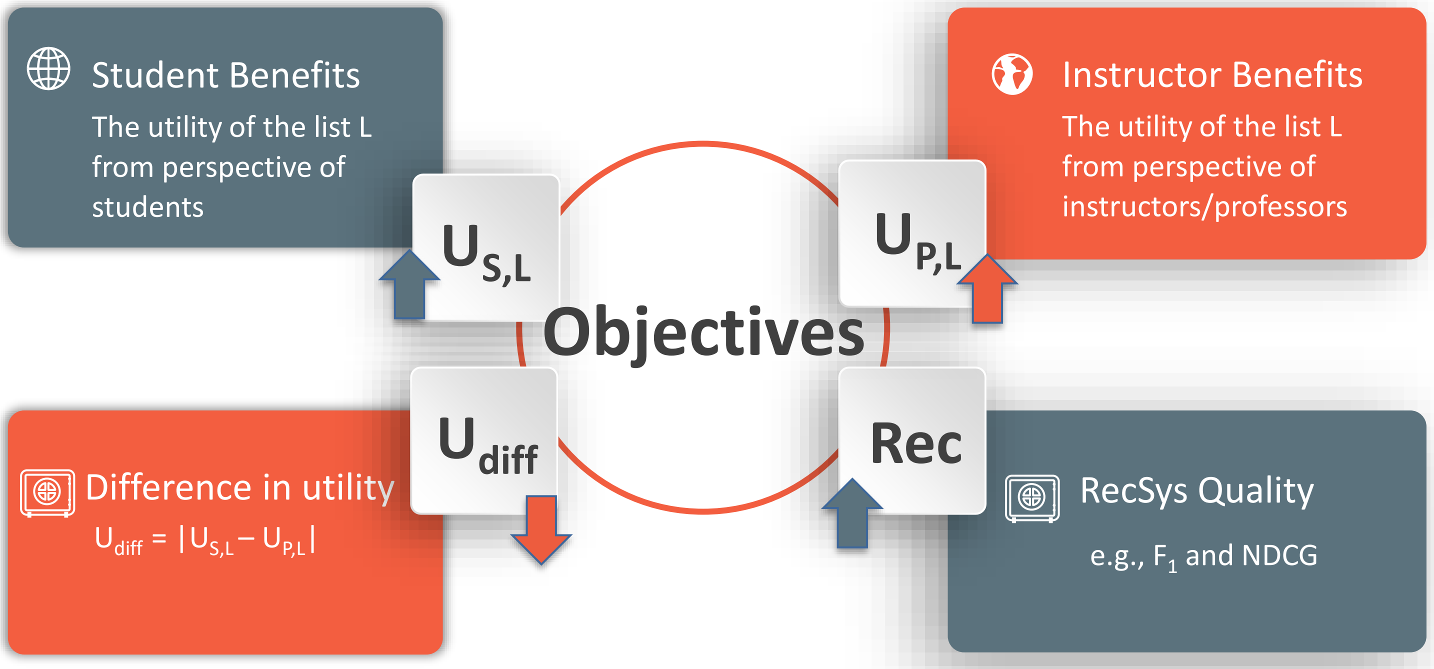
We use this ranking score to rank items to produce top-N list, L

$U_{p,L}$ = the summation of $U_{p,t}$ in the list L

$U_{s,L}$ = the summation of $U_{s,t}$ in the list L

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  – Setup objectives in the model



Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  - Multi-objective optimization process
    - Using MOEA as the multi-objective optimizer
      - Open-Source MOEA, http://moeaframework.org
      - Demo, https://github.com/irecsys/Tutorial_MSRS
    - MOEA will produce a Pareto set
    - Select the single best solution based on TOPSIS
      - Calculate the maximal objectives by using single-objective recommendation model, e.g. maximizing recommendation qualities by considering students/instructors only
      - Then calculate the average loss of the objectives
      - The solution with minimal loss is the best one

Case Studies: Multi-Stakeholder EdRec

- Case Study: Multi-Stakeholder EdRec based on the ITM-Rec Data
  - Results
    - Balancing the needs of instructors and students at a small loss at recommendations (NDCG & F_1)

	$U_{S,L}$	$U_{P,L}$	F_1	NDCG	Loss
UBRec	0.181	0.134	0.085	0.126	0.180
$Rank_p$	0.072	0.298	0.027	0.039	0.425
MSRS	0.199	0.251	0.074	0.107	0.063

    - UBRec: the best model considering students only
      $Rank_p$: the best model considering instructors only

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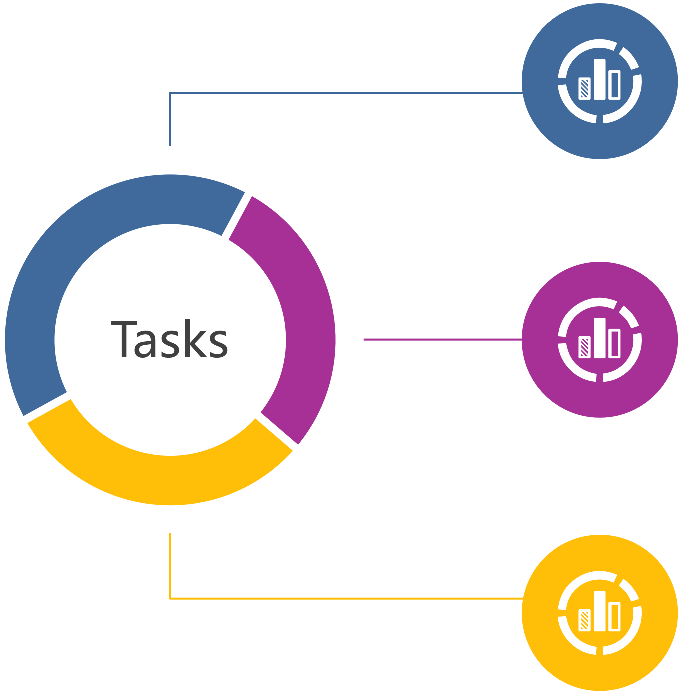
Case Studies: Multi-Task EdRec

- Multi-task RecSys
  - Multi-task RecSys refer to the recommender systems which optimize multiple tasks by a joint learning process
  - Joint learning is not novel, but multi-task RecSys usually share some common representations
    - Latent factors
    - Feature spaces
    - Neural network layers
    - …..

Case Studies: Multi-Task EdRec

- Multi-task RecSys
  - What are the tasks that can be fused with RecSys models?



Multiple Recommendation Tasks

e.g., rating prediction task and ranking task

Multiple Feedbacks or User Behaviors

e.g., Click-through, View-through, # of purchases, etc

RecSys Task + Non-RecSys Task

Text Generations: reviews, tips, opinions, explanations

Others: classifications, regressions, etc

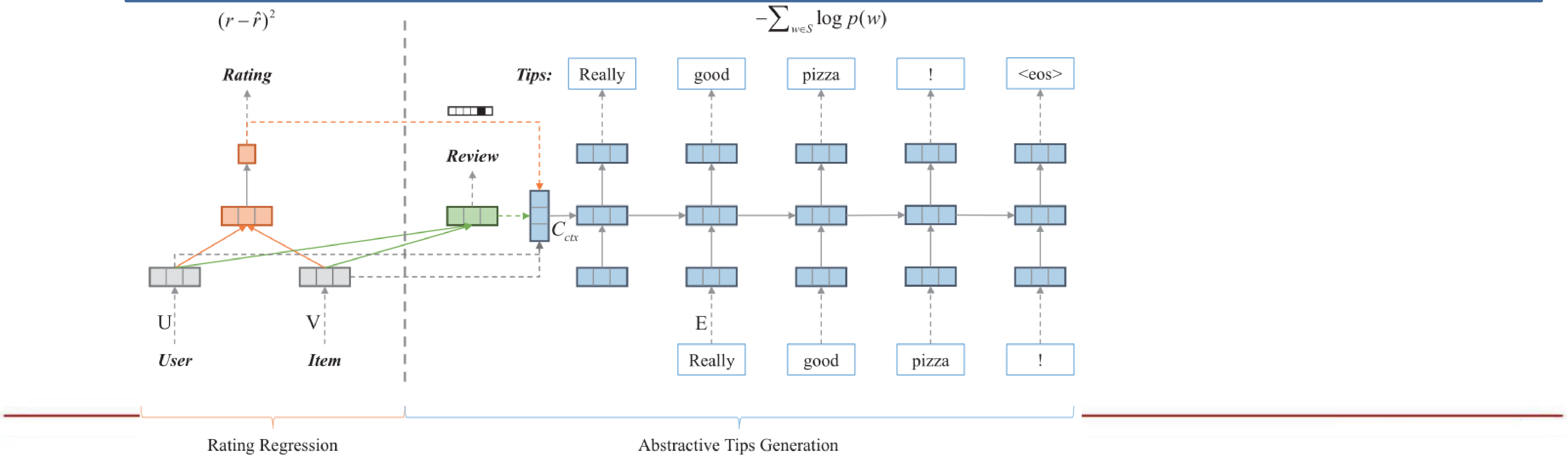
Case Studies: Multi-Task EdRec

- Multi-task RecSys
  - Multi-task RecSys can be used for "one-more-step" goals
    - Recommending "relevant" items are not enough!
    - Will users click more? View more? Buy more?
  - Multi-task RecSys can be also be used in education, e.g., recommendation task + learning outcomes (e.g., grade predictions)
    - Unfortunately, there are no existing work in EdRec now

Case Studies: Multi-Task EdRec

- Multi-task RecSys
  - Example 1: RecSys + Tip Generation

❑ Li, P., et al. (2017). Neural rating regression with abstractive tips generation for recommendation. In SIGIR 2017.



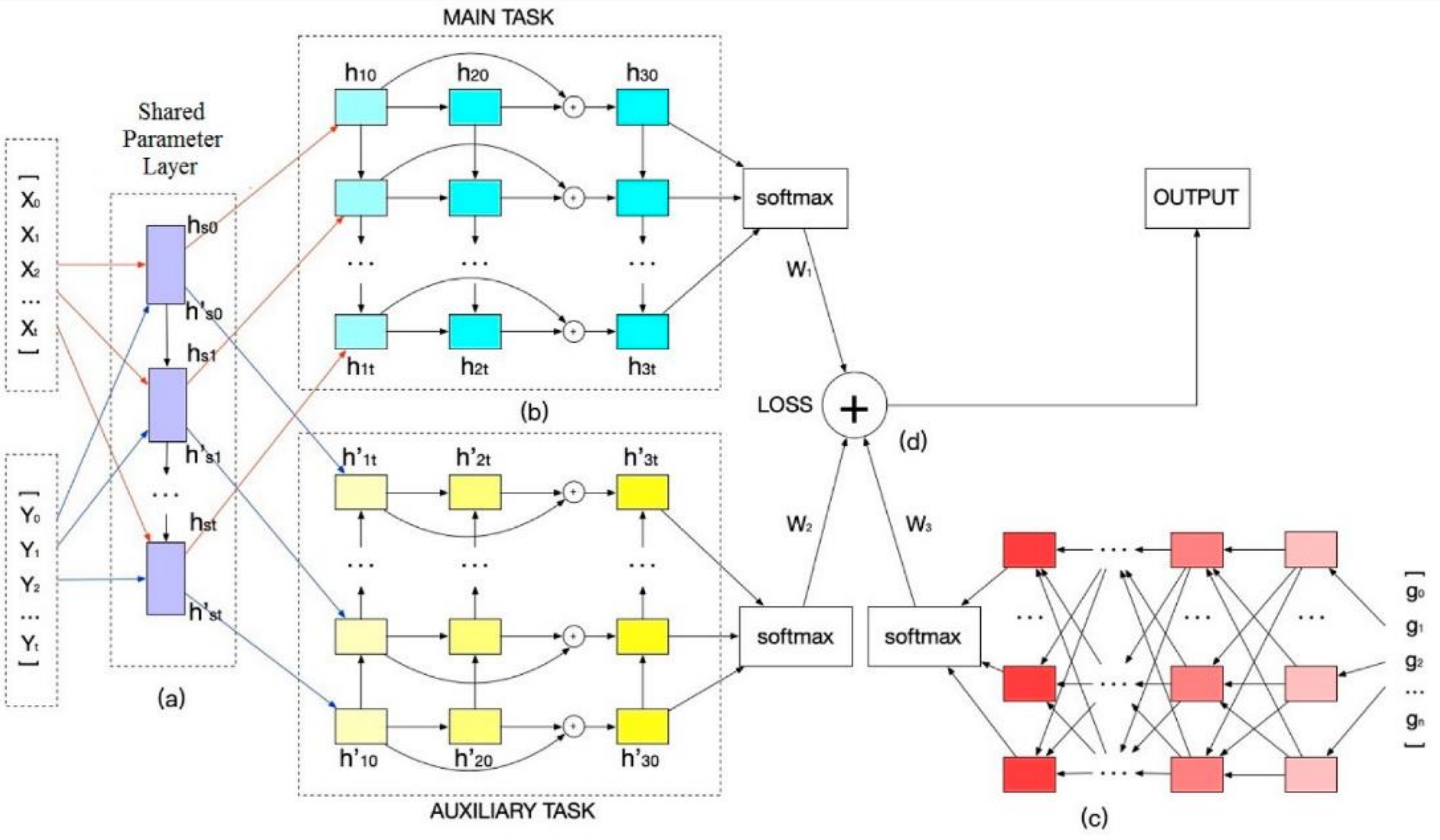
Case Studies: Multi-Task EdRec

- Multi-task RecSys
  - Example 2: Joint learning

❑ Shaojie Qu, et al. Predicting Student Performance and Deficiency in Mastering Knowledge Points in MOOCs Using Multi-Task Learning. Entropy 2019, 21, 1216.

X: assignments in sequence
Y: knowledge points in sequence
Task 1: performance of assignments
Task 2: performance on knowledge points
Task 3: predictions from extracted features rather than from sequential assignments

Figure 1. Proposed framework. (**a**) Shared parameters layer, (**b**) multi-task part with multi-layer LSTM. (**c**) multi-layer perceptron (MLP) using comprehensive features, and (**d**) attention mechanism.



ILLINOIS

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Case Studies: Multi-Objective EdRec

- Multi-Objective RecSys (MORS)
  - MORS is RecSys with multi-objective optimization

Case Studies: Multi-Objective EdRec

- Multi-Objective RecSys and EdRec
  - Many of the previous examples belong to multi-objective RecSys e.g., multi-stakeholder and multi-task RecSys
  - Multi-objective optimization (MOO) has been well studies. We just need to transform a RecSys problem to be solved by MOO
    - Scalarization method, e.g., weighted sum
      Transforming a multi-objective to a single-objective problem
    - Multi-objective evolutionary algorithms, e.g., MO genetic algorithms
      Directly produce a Pareto set which is a set of non-dominated optimal solutions

Case Studies: Multi-Objective EdRec

- Multi-Objective RecSys and EdRec
  - More details about MOO and MORS
    - Zheng, Y., & Wang, D. X. (2022). A survey of recommender systems with multi-objective optimization. *Neurocomputing*, *474*, 141-153.
    - Our tutorial@KDD 2021, https://moorecsys.github.io/KDD2021/index.html

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Case Studies: Fairness, Transparency, Explanations in EdRec

- EdRec with FAT (Fairness, Accountability and Transparency)
  - Fairness: reduce algorithmic biases with respective to specific attributes, e.g., age, gender, race, nationality, etc.
    Example: Gómez, E., et al. (2021). The winner takes it all: geographic imbalance and provider (un) fairness in educational recommender systems. In SIGIR 2021.
  - Transparency: explanation of the models and outputs to enhance trust
    Example: Zheng, Y., & Toribio, J. R. (2021). The role of transparency in multi-stakeholder educational recommendations. User modeling and user-adapted interaction, 31, 513-540.
  - Accountability: responsible outputs, responsible AI
    Example: Dignum, V. (2019). Responsible artificial intelligence: how to develop and use AI in a responsible way (p. 59). Cham: Springer.

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 1: EdRec with Fairness

  Gómez, E., et al. (2021). The winner takes it all: geographic imbalance and provider (un) fairness in educational recommender systems. In SIGIR 2021.

  – Scenario: study if imbalance in the country of teachers might affect the opportunities from certain regions to offer their services (e.g., MOOC)

  – Two groups were studies according to the popularity of locations in MOOC platforms – teachers <u>from USA</u>, teachers <u>from other countries</u>.

$$\mathcal{R}_C(G) = |G|/|C| \quad (1)$$

$$\mathcal{R}_R(G) = |\{r_{uc} : c \in G\}|/|R| \quad (2)$$

C = set of courses

G = set of courses belong to a group G

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 1: EdRec with Fairness

  Gómez, E., et al. (2021). The winner takes it all: geographic imbalance and provider (un) fairness in educational recommender systems. In SIGIR 2021.

  – Group Representations, i.e., amount and rating levels

$$\mathcal{R}_C(G) = |G|/|C| \qquad (1)$$

$$\mathcal{R}_R(G) = |\{r_{uc} : c \in G\}|/|R| \qquad (2)$$

C = set of courses
G = set of courses belong to a group G

  – Fairness Factors

$$\Delta\mathcal{V}(G) = \frac{1}{|U|}\sum_{u \in U} \frac{|\{\hat{r}_{uc} : c \in \hat{R}_G\}|}{|\hat{R}|} - \mathcal{R}_*(G)$$

Visibility: Diff of the proportion of items associated with a group in rec list

$$\Delta\mathcal{E}(G) = \frac{1}{|U|}\sum_{u \in U} \frac{\sum_{pos=1}^{k} \frac{1}{log_2(pos+1)}, \forall c \in \hat{R}_G}{\sum_{pos=1}^{k} \frac{1}{log_2(pos+1)}} - \mathcal{R}_*(G)$$

Exposure: Diff of the exposure obtained by the group in rec list

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 1: EdRec with Fairness

  Gómez, E., et al. (2021). The winner takes it all: geographic imbalance and provider (un) fairness in educational recommender systems. In SIGIR 2021.

  – Findings: underrepresented groups have lower visibility and exposure

Algorithm	NDCG	$\Delta\mathcal{V}_C$	$\Delta\mathcal{E}_C$	$\Delta\mathcal{V}_R$	$\Delta\mathcal{E}_R$
MostPop	0.0193	-0.3091	-0.2117	-0.2447	-0.1473
RandomG	0.0006	**0.0000**	**-0.0001**	0.0644	0.0643
UserKNN	0.0372	-0.0402	-0.1457	0.0242	-0.0813
ItemKNN	**0.2068**	-0.0862	-0.0783	-0.0218	-0.0139
BPR	0.1401	-0.0715	-0.0658	**-0.0071**	**-0.0014**
BiasedMF	0.0007	-0.1065	-0.0949	-0.0421	-0.0305
SVD++	0.0044	-0.0534	-0.0543	0.0110	0.0101

The authors proposed a re-ranking method to alleviate this issue. See more details in the paper

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 2: EdRec with Transparency
  - Transparency is able to let users understand how the recommendations were generated, which results in user trusts
  - Transparency can be realized by different ways:
    - Explanation of the outputs (e.g., recommended items/list)
    - Explanation of key parameters in the algorithms
    - Explanation by visualizations

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 2: EdRec with Transparency

  Zheng, Y., & Toribio, J. R. (2021). The role of transparency in multi-stakeholder educational recommendations. User modeling and user-adapted interaction, 31, 513-540.

  – This is the multi-stakeholder EdRec based on the ITM-Rec data

  – There is a parameter, alpha, which represents weights of students/teachers

  $$\boxed{\text{Ranking score to sort items} = \alpha \times U_{s,t} + (1 - \alpha) \times U_{p,t}}$$

  – We performed user studies to observe the effects of student satisfaction with vs. without explanations of alpha

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 2: EdRec with Transparency

  Zheng, Y., & Toribio, J. R. (2021). The role of transparency in multi-stakeholder educational recommendations. User modeling and user-adapted interaction, 31, 513-540.

Alpha: 0.3

TOP	TITLE	URL
1	Circadian Rhythm in the Brain	https://www.kaggle.com/kmader/circadian-rhythm-in-the-brain
2	European Soccer Database	https://www.kaggle.com/hugomathien/soccer
3	Getting Real about Fake News	https://www.kaggle.com/mrisdal/fake-news
4	The Bachelor contestants	https://www.kaggle.com/brianbgonz/the-bachelor-contestants
5	Iris Species	https://www.kaggle.com/uciml/iris

Case Studies: Fairness, Transparency, Explanations in EdRec

- Example 2: EdRec with Transparency

  Zheng, Y., & Toribio, J. R. (2021). The role of transparency in multi-stakeholder educational recommendations. User modeling and user-adapted interaction, 31, 513-540.

  – We let students change the alpha on the slider bar

  – For each alpha value (0, 0.1, …, 1.0), we gave a different list of items

  – Students need to select the best alpha according to satisfaction on items

    - Scenario 1: without explaining what does alpha mean
    - Scenario 2: with explanation of alpha

  – Findings: with explanations, students selected the recommendation list with more fairness (i.e., balance between students and instructors)

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EdRec: Challenges & Future Work

- There are a couple of challenges in EdRec
  - First, EdRec has same challenges from general RecSys
    - Sparsity issue: limited user preferences
    - Cold-start issues: zero history about a user or an item
    - Grey-Sheep users: users with unusual tastes
    - Novelty and Diversity issues
    - Offline vs Online evaluations
    - ……

EdRec: Challenges & Future Work

- There are a couple of challenges in EdRec
  - EdRec has same pedagogical or domain-specific challenges
    - How to better incorporate pedagogical features
    - How to adapt to learners’ knowledge levels, since they always change over time
    - How to capture and adapt to interest drifts
    - How to take advantage of EdRec by going beyond resource recommendations
    - ….

EdRec: Challenges & Future Work

- There are a couple of challenges in EdRec
  - EdRec has challenges in evaluations
    - Offline vs online evaluations
    - Short-term vs long-term evaluations
    - Evaluations based on recommendation metrics vs learning effectiveness
    - …

EdRec: Challenges & Future Work

- There are a couple of challenges in EdRec
  - User privacy, transparency and explanations
    - EdRec needs more data to build better models
    - How to let users trust us
    - How to provide explanations of the models/outputs
    - How to better visualize the outputs and explanations
    - How to improve transparency when it comes to multiple stakeholders

EdRec: Challenges & Future Work

- There are a couple of challenges in EdRec
  - Multi-task models and better evaluations
    - Evaluate models from more perspectives, not only recommendation quality, but the potentials to improve teaching and learning outcomes
    - Build multi-task models to optimize models by a joint learning of recommendations and educational objectives (e.g., learning outcomes)

EdRec: Challenges & Future Work

- There are a couple of challenges in EdRec
  - Other challenges
    - Limited open data sets for research
      ITM-Rec: An Open Data Set for Educational Recommender Systems
      https://www.kaggle.com/datasets/irecsys/itmrec
    - Challenges and opportunities by large language model (LLM), e.g., ChatGPT
    - Responsible AI

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Educational Recommender Systems

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