Educational Recommender Systems

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Intro

- Dr. Yong Zheng
- Assistant Professor at Illinois Tech, USA
- Research Interests
  - Recommender Systems (RecSys)
    - Context-Aware, Multi-Objective, Multi-Criteria RecSys
  - Technology-Enhanced Learning, EdRec

Intro

- Educational Recommender Systems (EdRec)
  - 2023 IEEE Global Engineering Education Conference (EDUCON)
    - Duration: 1 hr 30 min
    - Tutorial on EdRec:
      - Overviews (Intro, Characteristics, Development, Challenges)
  - 2023 International Conference on Artificial Intelligence in Education (AIED)
    - Duration: 3 hrs
    - Tutorial on EdRec:
      - Overviews (Intro, Characteristics, Development, Challenges)
      - More Case studies with technical details

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

Schedule: Part I

- Intro: Recommender Systems (RecSys)
- RecSys in Education vs in Other Domains
- Classifications of Educational Recommender Systems (EdRec)
- List of Available Data Sets
- Case Studies: EdRec Specialized to Education

Time: July 3rd, 2023 | 09:00 AM – 10:30 AM + QA
Location: Hitotsubashi Hall, Room 203

Schedule: Part II

- Case Studies: EdRec Specialized to Education (continued)
- Case Studies: General RecSys with Practice in Education
- Summary, Challenges, Future Work
- QA, Open Discussions

Time: July 3rd, 2023 | 11:00 AM – 12:30 AM + QA
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Part I. EdRec: An Overview

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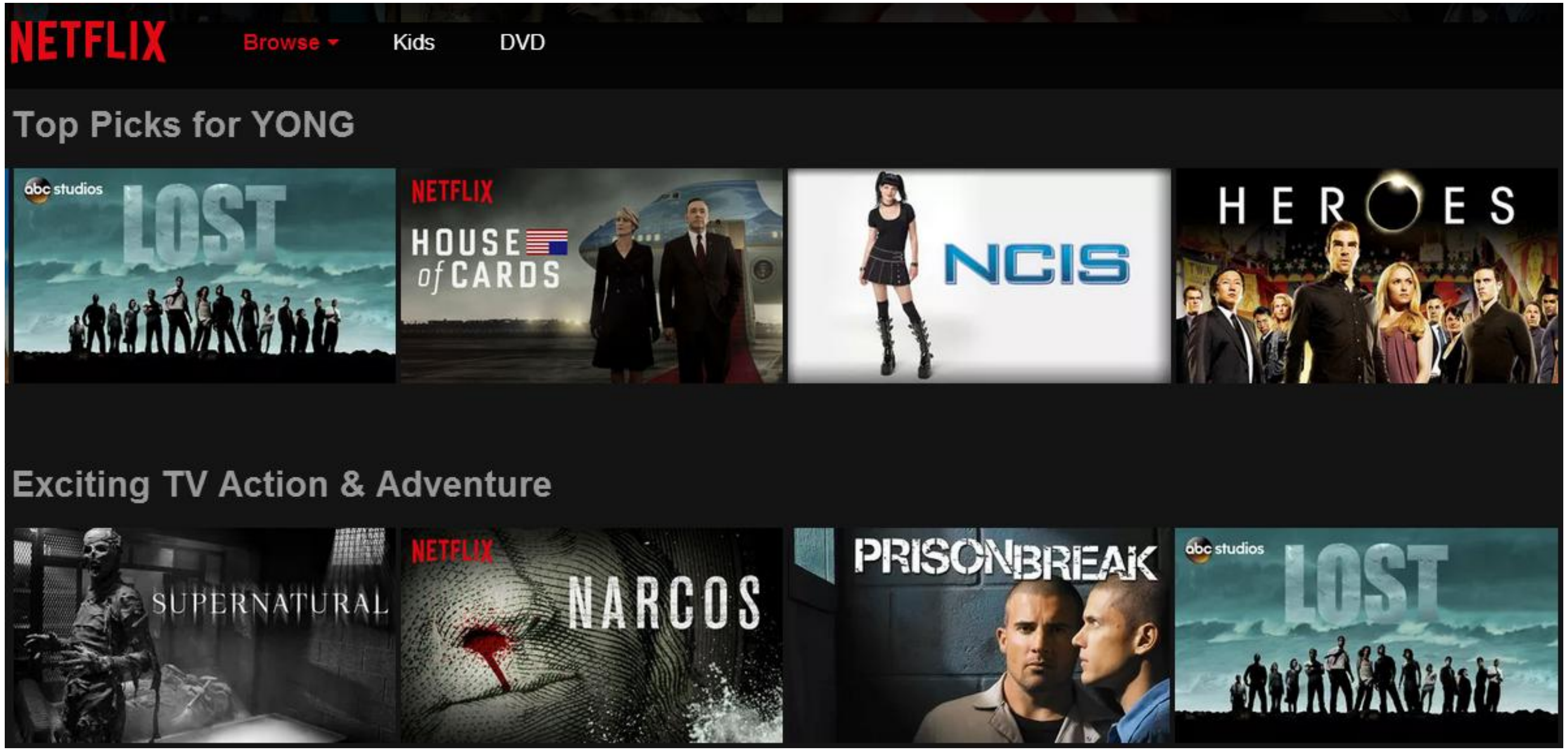
Recommender Systems (RecSys)

- Item recommendations tailored to user preferences

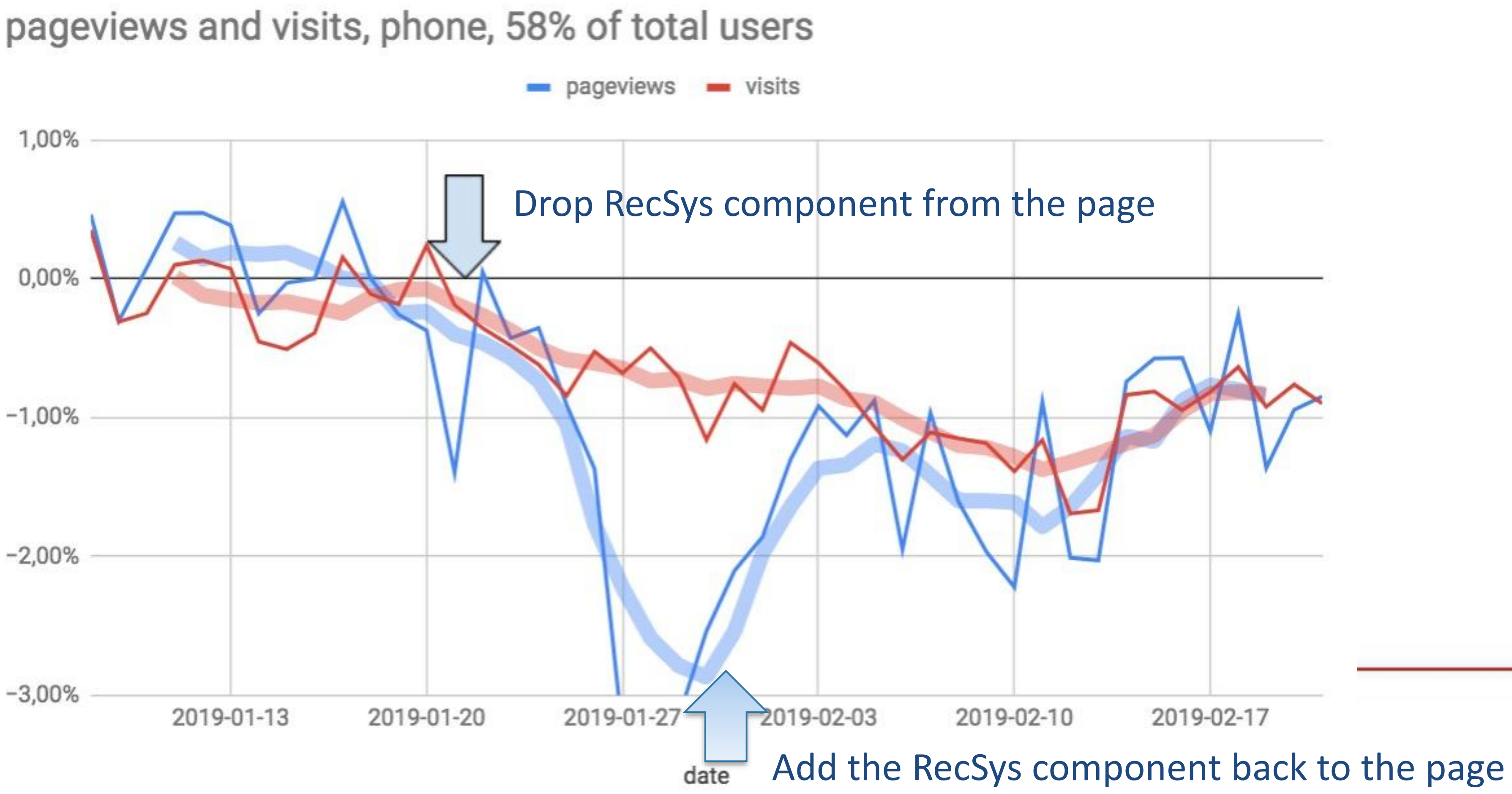
Recommender Systems (RecSys)

Example: Movie Recommendations on Netflix

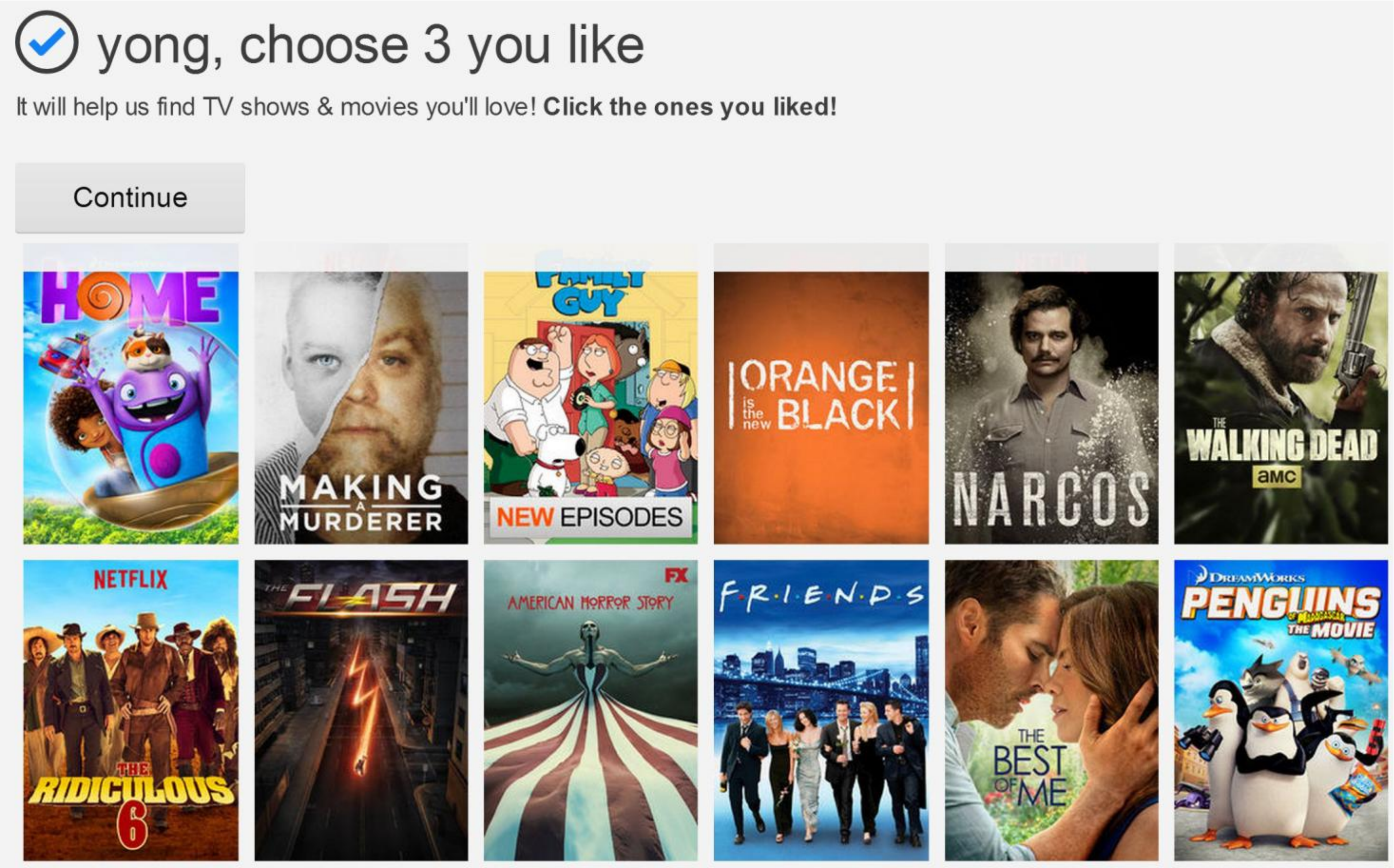


Why Recommender Systems?

- How about we remove RecSys components



How it works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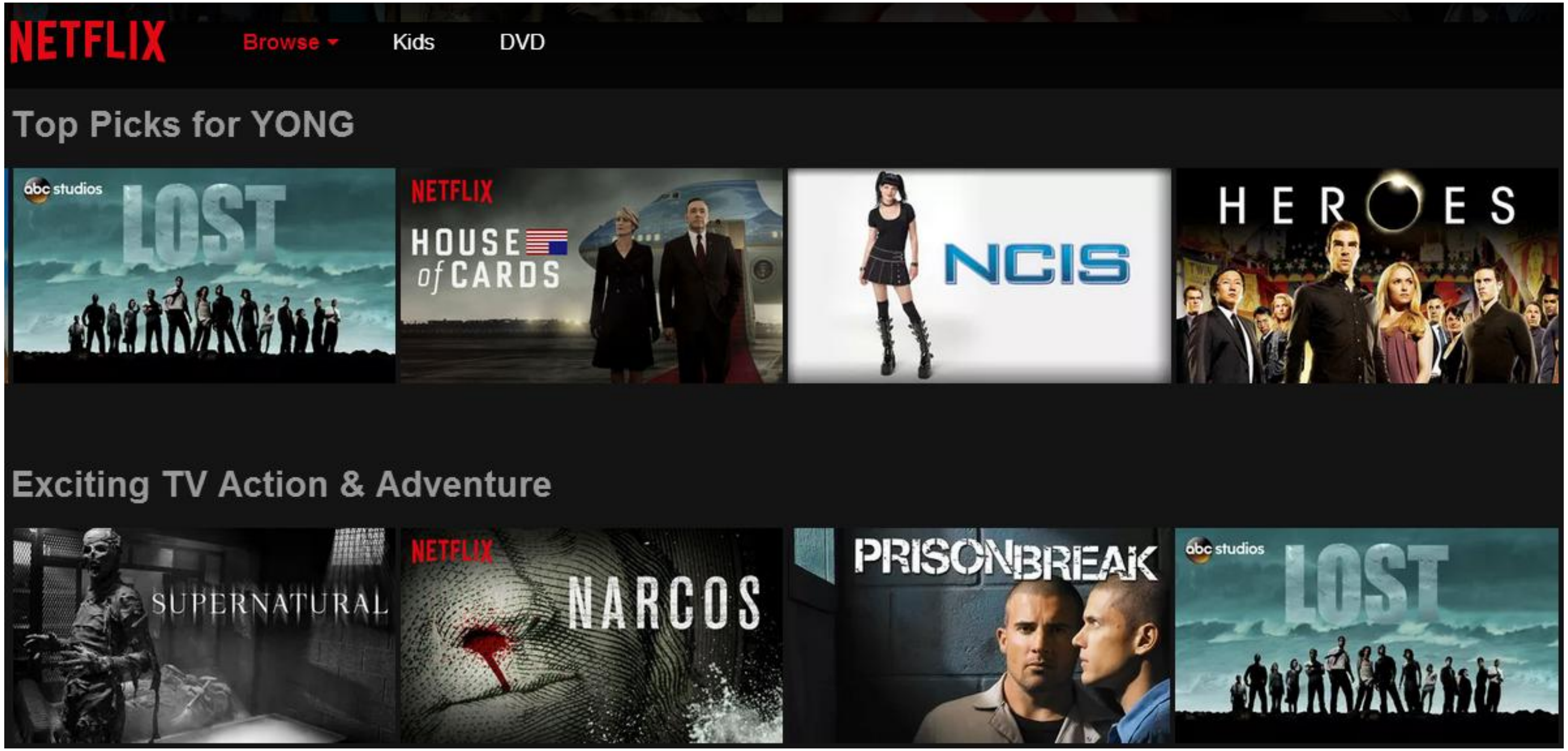
It will help us find TV shows & movies you'll love! Click the ones you liked!
Continue
HOME
MAKING A MURDERER
FAMILY GUY
NEW EPISODES
ORANGE is the new BLACK
NARCOS
THE WALKING DEAD
amc
NETFLIX
THE RIDICULOUS 6
THE FLASH
FX
AMERICAN HORROR STORY
F·R·I·E·N·D·S
THE BEST OF ME
DREAMWORKS
PENGUINS OF MADAGASCAR THE MOVIE

How it works


NETFLIX
Browse
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Top Picks for YONG
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LOST
NETFLIX
HOUSE of CARDS
NCIS
HEROES
Exciting TV Action & Adventure
SUPERNATURAL
NETFLIX
NARCOS
PRISONBREAK
abc studios
LOST

How it works

- User Preferences on the items

Ratings

Binary Feedback

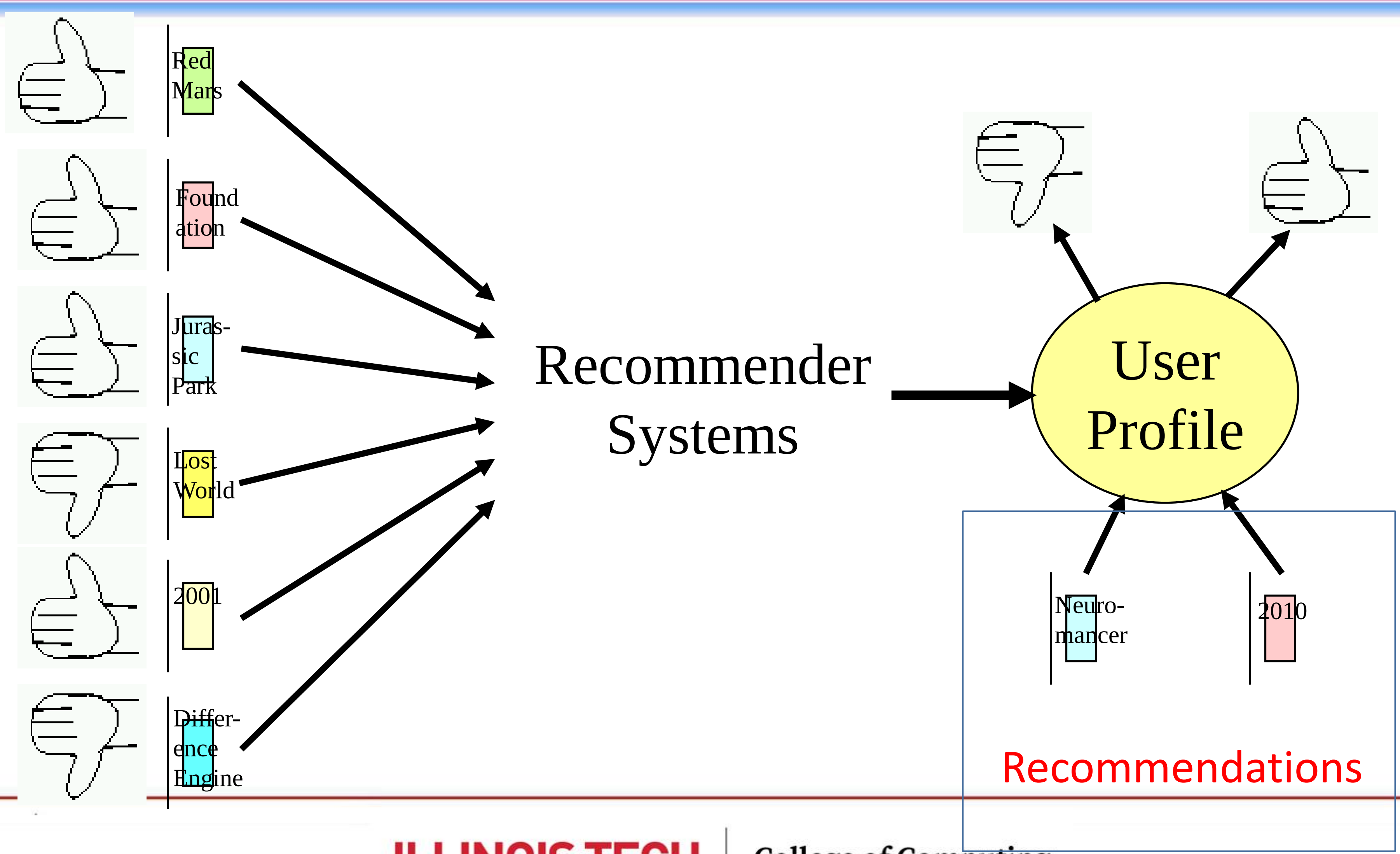
Reviews

Behaviors

Explicit

Implicit

How it works


Red Mars
Found ation
Juras- sic Park
Lost World
2001
Differ- ence Engine
Recommender Systems
User Profile
Neuro- mancer
2010
Recommendations

Traditional Recommender Systems

- User demographic information + Item features
- Users’ preferences on the items, i.e., rating matrix

- **Unknown ratings** as “empty” cells or ?
- **Known ratings** are either binary ones (1/0, thumb up/down) or real numbers (rating scale 1 to 5)

Recommendation Tasks

- Task 1: Rating Predictions
  – Given a user and an item, predict how the user likes the item
  – Evaluation metrics: prediction errors, e.g., MAE, RMSE, …
  – Example, evaluations on a sample of testing set

UserID	ItemID	Rating (real)	Rating (predicted)	Absolute Err
1	4	4	3.9	0.1
1	3	5	4.2	0.8
2	5	3	3.3	0.3
2	4	3	4	1.0
2	2	4	3.6	0.4

Mean Absolute Error, MAE = 2.6/5 = 0.52

Recommendation Tasks

- Task 2: Top-N recommendations
  - Given a user, recommend top-N items to this specific user
  - Evaluation metrics
    - Relevance metrics: precision, recall, F1, AUC
    - Ranking metrics: MAP, MRR, NDCG
  - An example from testing set

UserID	Relevance Items (rating >=3)	Top-5 Recommendation List	Precision@5	Recall@5
1	5, 9, 11, 14, 23, 58, 62, 77	5, 11, 15, 22, 33	2/5	2/8
2	1, 3, 6, 12, 29, 33, 38, 46, 59, 88	3, 12, 44, 56, 88	3/5	3/10

Recommendation Algorithms

- Collaborative filtering, e.g., rec items inferred from users with similar tastes
- Content-based algorithms, e.g., relying on content similarity
- Models utilizing demographic information, e.g., user clusters
- Utility-based recommendations, e.g., value function of items
- Knowledge-based models, e.g., rule-based recommendations
- Hybrid models

❑ Burke, Robin. "Hybrid recommender systems: Survey and experiments." User modeling and user-adapted interaction 12 (2002): 331-370.

Recommendation Algorithms

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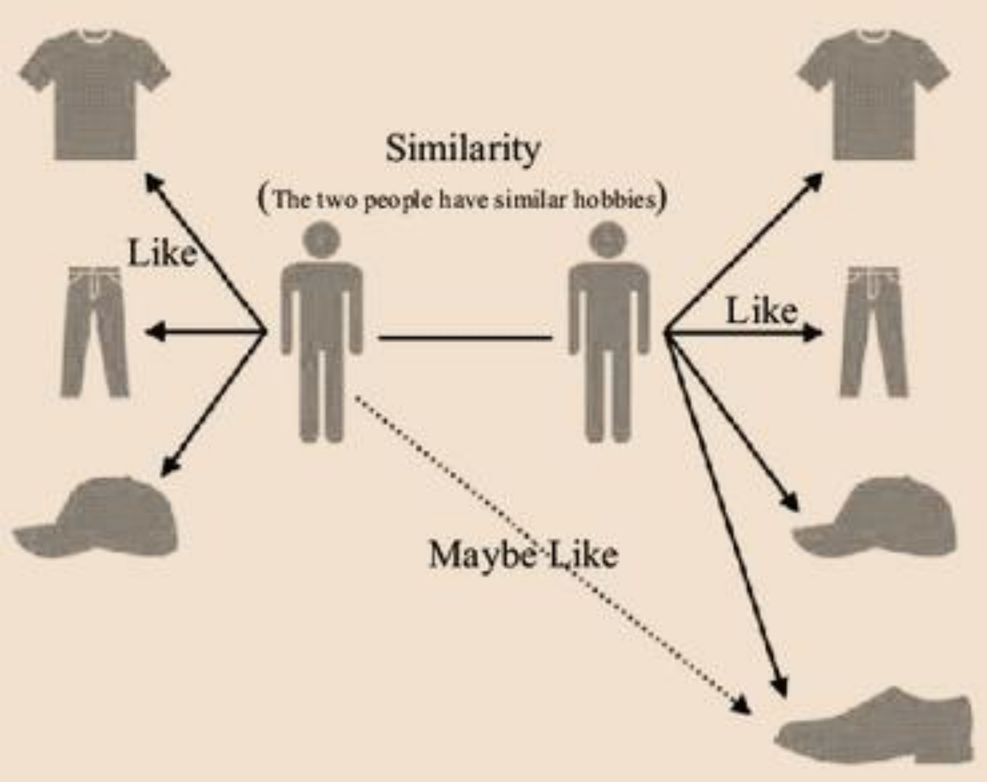

Well-known collaborative filtering (CF)

- User-based CF
- Item-base CF
- Matrix factorization
- Neural Collaborative Filtering
- Neural Matrix factorization

Recommendation Algorithms

- Content-based algorithms, e.g., relying on content similarity

  - User Profile: a list of items the user liked before, along with content features
  - Measure the similarity between an item and the bag of items in user profile
    - NLP techniques, e.g., vector-space models, semantic ontologies, LDA, word/text embeddings, etc.
  - Sort and rank items to be recommended to the user

Recommendation Algorithms

- Models utilizing demographic information, e.g., user clusters
  - It may only work well in specific domains, e.g., movie domains
  - User demographic information
    - Traditional Info: age, gender, nationality, marriage, education level, location, zip code, …
    - Psychology Info: personality traits
  - How to use them in RecSys
    - Rule-based models, e.g., males like action movies, while females prefer drama movies
    - User clustering, e.g., put users into clusters, and generate recommendations to each cluster
    - Demographic info used in CF: 1). Find better neighbors; 2). Assist regularizations

Recommendation Algorithms

- Utility-based recommendations, e.g., value function of items
  - Utility function can estimate a score for an item
  - The score could be an estimated overall rating or a ranking score
  - Rating prediction functions in RecSys can be viewed as utility functions
  - But there are many more other utility functions
    - Similarity functions
    - Distance functions
    - Utility functions from decision-making theories, e.g., multi-attribute utility functions

Recommendation Algorithms

- Knowledge-based models, e.g., rule-based recommendations
  - We can extract knowledge or patterns first, and then utilize them to produce top-N recommendations
  - Knowledge or patterns can be extracted from several techniques or resources, e.g., association rules, knowledge graphs, outlier detections, case-based reasoning, etc.
  - Example: how to use association rules in RecSys
    - Rules like, Book A -- > {Book B, Book C} [support = 0.6, confidence = 0.9]
    - Any users who are interested in Book A (e.g., viewed, added to carts, purchased, rated, …) will receive book recommendations of Book B and C

Recommendation Algorithms

- Hybrid models
  - They are different hybrid approaches to combine different models together in order to adapt RecSys in multiple scenarios
  - There are 7 different hybrid approaches
  - Example: switching method
    - For users that we have their preferences, we can utilize collaborative filtering
    - For cold-start users (e.g., new users in the system), we can utilize demographic based recommendation models

❑ Burke, Robin. "Hybrid recommender systems: Survey and experiments." User modeling and user-adapted interaction 12 (2002): 331-370.

Recommendation Algorithms

- Collaborative filtering, e.g., rec items inferred from users with similar tastes
- Content-based algorithms, e.g., relying on content similarity
- Models utilizing demographic information, e.g., user clusters
- Utility-based recommendations, e.g., value function of items
- Knowledge-based models, e.g., rule-based recommendations
- Hybrid models

- ❑ Burke, Robin. "Hybrid recommender systems: Survey and experiments." User modeling and user-adapted interaction 12 (2002): 331-370.

Different Types of Recommender Systems

- Traditional RecSys
  – Building models on traditional data (user, item, ratings, user/item info)
- Extended and Different Types of RecSys
  – Context-Aware RecSys
  – Group RecSys
  – Cross-Domain RecSys
  – Multi-Criteria RecSys
  – Multi-Stakeholder RecSys
  – Multi-Objective RecSys
  – …

Different Types of Recommender Systems

- Traditional RecSys
  - Building models on traditional data (user, item, ratings, user/item info)
- Extended and Different Types of RecSys (EdRec as Example)
  - **Context-Aware RecSys**
  - Group RecSys
  - Cross-Domain RecSys
  - Multi-Criteria RecSys
  - Multi-Stakeholder RecSys
  - Multi-Objective RecSys

Recommend lecture videos to a student in specific contexts (e.g., time, location, device, bandwidth, WIFI, etc.)

Different Types of Recommender Systems

- Traditional RecSys
  - Building models on traditional data (user, item, ratings, user/item info)
- Extended and Different Types of RecSys (EdRec as Example)
  - Context-Aware RecSys
  - **Group RecSys**
  - Cross-Domain RecSys
  - Multi-Criteria RecSys
  - Multi-Stakeholder RecSys
  - Multi-Objective RecSys

Recommend items to a group of learners, rather than a single user (e.g., group project)

Different Types of Recommender Systems

- Traditional RecSys
  - Building models on traditional data (user, item, ratings, user/item info)
- Extended and Different Types of RecSys (EdRec as Example)
  - Context-Aware RecSys
  - Group RecSys
  - **Cross-Domain RecSys**
  - Multi-Criteria RecSys
  - Multi-Stakeholder RecSys
  - Multi-Objective RecSys

Transfer knowledge from one domain to another, e.g., predicting user tastes in textbooks from their tastes in music

Different Types of Recommender Systems

- Traditional RecSys
  - Building models on traditional data (user, item, ratings, user/item info)
- Extended and Different Types of RecSys (EdRec as Example)
  - Context-Aware RecSys
  - Group RecSys
  - Cross-Domain RecSys
  - **Multi-Criteria RecSys**
  - Multi-Stakeholder RecSys
  - Multi-Objective RecSys

Improve recommendation quality by taking user preferences in multiple aspects of the textbooks (author reputation, shipping speed, quiz/answers, etc.)

Different Types of Recommender Systems

- Traditional RecSys
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- Extended and Different Types of RecSys (EdRec as Example)
  - Context-Aware RecSys
  - Group RecSys
  - Cross-Domain RecSys
  - Multi-Criteria RecSys
  - **Multi-Stakeholder RecSys**
  - Multi-Objective RecSys

Produce item recommendations by considering perspectives from multiple stakeholders (students, parents, instructors, publishers, etc.)

Different Types of Recommender Systems

- Traditional RecSys
  – Building models on traditional data (user, item, ratings, user/item info)
- Extended and Different Types of RecSys (EdRec as Example)
  – Context-Aware RecSys
  – Group RecSys
  – Cross-Domain RecSys
  – Multi-Criteria RecSys
  – Multi-Stakeholder RecSys
  – **Multi-Objective RecSys**

Produce item recommendations by considering multiple objectives, e.g., accuracy, diversity, novelty, etc.

Schedule: Part I

- Intro: Recommender Systems (RecSys)
- RecSys in Education vs in Other Domains
- Classifications of Educational Recommender Systems (EdRec)
- List of Available Data Sets
- Case Studies: EdRec Specialized to Education

RecSys: Education vs Other Domains

- RecSys can be built as long as we have user preference data
- So, what are the unique characteristics of EdRec?

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Heterogeneous Data
  - Diverse items
  - Not only relevance
  - User preferences by external factors
  - Level of personalization
  - Multiple context factors
  - Work together with other functions
  - Evaluation: real-life testing

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Heterogeneous Data
    - Movies: user ratings on movies, movie content info, user info
    - E-Commerce: ratings or implicit feedbacks, item features, user info
    - Education: ratings or implicit feedbacks from multiple resources, user/item info, pedagogical features (e.g., instructional rules, pre/post requisites, learning history/style/standards, etc.)

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Diverse items
    - What to be the “items” in item recommendations
      - Teaching/Learning materials
      - Formal/Informal learning objects
      - Peers or group partners
      - University/Course/Degree/Career
      - Learning Pathways
      - ….

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Not only relevance
    - Movies: relevance and rankings only
    - E-Commerce: relevance along with other objectives, e.g., click-through, purchases
    - Education: not only relevance, but also the actual effects on teaching/learning, such as learning outcomes/feedbacks, continuous learning

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - User preferences by external factors
    - User preferences may change due to emotions and contexts
    - In education, user preferences can be easily changed by external factors, such as teaching/learning objectives/standards, learning style, etc.

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RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Level of personalization
    - Most domains seek personalization at the level of individuals
    - In education, personalization at a group level is common, e.g., student groups (beginner/intermediate/advanced), user groups (teachers/students/course developers)

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Multiple context factors
    - Time and location are common contexts in other domains
    - The contextual variables in the education domain may include
      - Time, location
      - Device: mobile vs PC, WIFI vs wired Internet connection, Bandwidth, etc.
      - Companion: single learner vs group learners
      - Pedagogical features (e.g., rules, pre/post requisites, learning history, standards, 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.

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Work together with other functions/techniques (EDM/AIED/LA)
    - Assist course design, peer-matching, group formulation
    - Predicting student performance
    - Identify students with difficulties, detect misunderstandings
    - Find Patterns by association rule mining
    - …

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Evaluation: real-life testing
    - Offline recommendation evaluations: errors, relevance and ranking metrics
    - User studies or questionnaires to learn user satisfactions
    - Online A/B tests to compare different models
    - Real-life testing: actual effects on teaching and learning

RecSys: Education vs Other Domains

- The characteristics of EdRec
  - Heterogeneous Data
  - Diverse items
  - Not only relevance
  - User preferences by external factors
  - Level of personalization
  - Multiple context factors
  - Work together with other functions
  - Evaluation: real-life testing

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EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to recommendation opportunities/tasks
  - According to the receiver of recommendations
  - According to the number of stakeholders considered
  - According to the type of recommender systems
  - According to the type of recommendation algorithms
  - According to the educational specialities

EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to recommendation opportunities/tasks
    - Learning objects (e.g., resources, activities, hints, course) recommendations
    - Pathway (e.g., a sequence of items/resources) recommendations
    - Peer (e.g., teammate or learners with similar interests) recommendations
    - Non-recommendation tasks, e.g., predicting student performance

- Drachsler, H., Verbert, K., Santos, O. C., & Manouselis, N. (2015). Panorama of recommender systems to support learning. Recommender systems handbook, 421-451.
- Manouselis, N., Drachsler, H., Verbert, K., Duval, E., Manouselis, N., Drachsler, H., ... & Duval, E. (2013). Survey and analysis of TEL recommender systems. Recommender systems for learning, 37-61.

EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to the receiver of recommendations
    - EdRec for students/learners
    - EdRec for instructors
    - EdRec for course developers
    - EdRec for other stakeholders (e.g., parents, publishers, etc.)

EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to the number of stakeholders considered
    - EdRec with consideration of a single stakeholder (e.g., learner or instructor only)
    - EdRec with consideration of multiple stakeholders
      - Example: project recommendations to students
        - » Consider student preferences
        - » Consider instructors' expectations/requirements

❑ 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).

EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to the type of recommender systems
    - Traditional item recommendations
    - Context-aware RecSys
    - Group RecSys
    - Tag/Resource RecSys
    - Cross-domain RecSys
    - Multi-criteria RecSys
    - Multi-stakeholder RecSys
    - Multi-objective RecSys
    - RecSys with Human Factors (Personality, Emotions, Trust)
    - ……………………………

EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to the type of recommendation algorithms
    - Collaborative Filtering
    - Content-Based Approaches
    - Demographic-Based Algorithms
    - Utility-Based Models
    - Knowledge-Based Approaches
    - Hybrid Models

EdRec: Classifications

- There are multiple ways to classify EdRec.
  - According to the educational specialities
    - EdRec specifically related to Education, such as
      - EdRec built in educational info systems, such as Intelligent tutoring systems
      - EdRec utilizing pedagogical features
      - Book/course/citation recommendations
    - EdRec uses general RecSys models but as a practice in education, since
      - Easy to collect own data sets
      - Easy to collect special preferences, e.g., group preferences
      - Easy to perform user studies/AB tests

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Available Data for Research

- There are limited data sets available for research on EdRec, due to the following possible reasons
  - Complex features, e.g., pedagogical features
  - Data sensitivity and privacy issues
    - Personnel Privacy, e.g., students'/instructors' privacy
    - Organizer policy, e.g., organization of after-school programs
    - University policy, e.g., human-subject regulations
    - Platform/Information system securities, e.g., attributes in relational databases

Available Data for Research

- List of available data sets for EdRec
  - **dataTEL**: data challenge at dataTEL workshop, https://shorturl.at/zHJ36
  - **Mendeley's DataTEL Data**

    Download URL is not available. Mendeley provides API now

    Preferences: authors and their paper lists, readership, view logs, stars

    Jack, K., et al. (2012). Mendeley's open data for science and learning: a reply to the dataTEL challenge. *International Journal of Technology Enhanced Learning*, *4*(1-2), 31-46.
  - **A list of popular data in literature**

    However, most of the download URLs are not working now

    Verbert, K., Drachsler, H., et al. (2011, February). Dataset-driven research for improving recommender systems for learning. In *Proceedings of the 1st LAK conference.*

Available Data for Research

- List of available data sets for EdRec
  - **Data sets for BookRec**
    - GoodReads, https://cseweb.ucsd.edu/~jmcauley/datasets.html#goodreads
    - Book Crossing, http://www2.informatik.uni-freiburg.de/~cziegler/BX/
    - LibraryThing, https://cseweb.ucsd.edu/~jmcauley/datasets.html#social_data
  - **Data sets for CourseRec**
    - MoocData, http://moocdata.cn/data/course-recommendation
    - EdX Courses, https://www.kaggle.com/discussions/general/301320
    - MOOC enrolls from LinkedIn, https://parklize.blogspot.com/2016/04/umap2016ea.html

Available Data for Research

- List of available data sets for EdRec
  - **ITM-Rec**: multi-criteria rating data sets for project/data recommendations
    https://www.kaggle.com/datasets/irecsys/itmrec
    This is a small data set collected from student qustionnaires
    This data is available for building multiple types of RecSys, e.g.,
    Multi-Criteria RecSys
    Context-Aware RecSys
    Group RecSys
    Multi-objective RecSys
    ……………………………………
    We will discuss this data set later in tutorial Part II.

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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

Case Studies

- Case Studies: EdRec Specialized to Education
  - EdRec built in Educational Information Systems
  - EdRec: course recommendations
  - EdRec: book recommendations
  - EdRec: pathway recommendations
  - EdRec: peer matching
  - EdRec using pedagogical features

Case Studies

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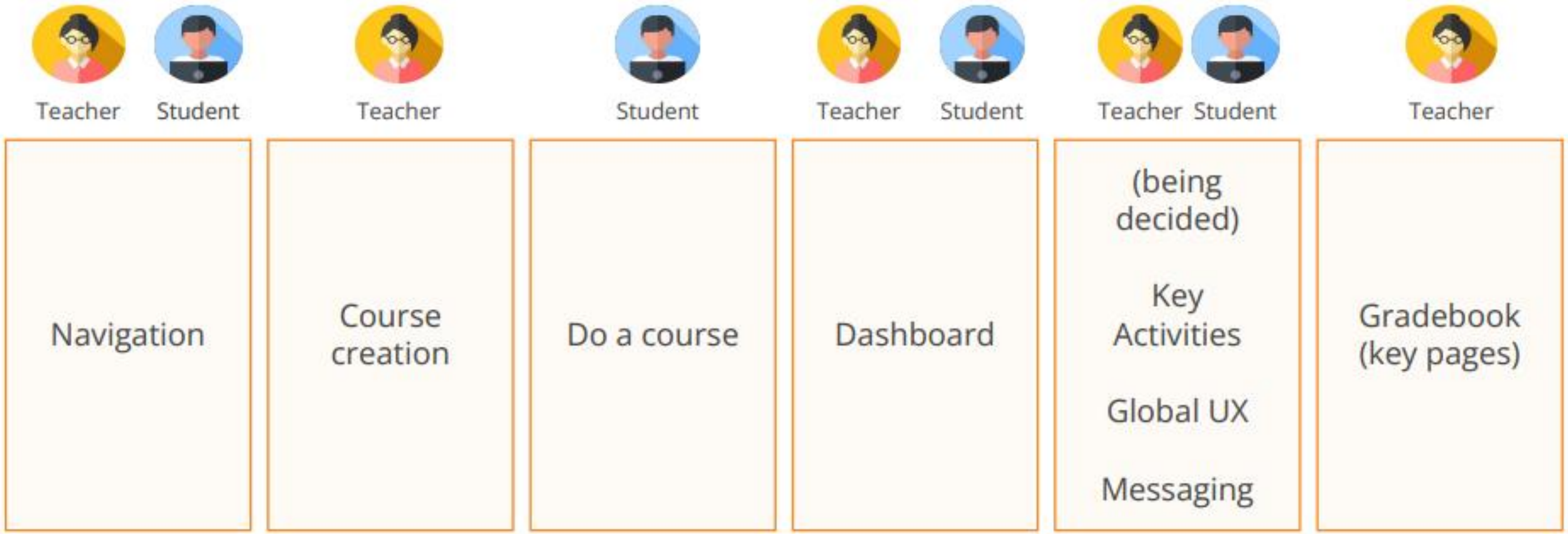
Case Studies: EdRec built in Edu Info Systems

- Educational info systems or learning management systems (e.g., ITS, Moodle, Blackboard) have enriched data related to student activities and preferences.
- EdRec can be built as a component in these systems, or be built based on the data collected from these systems

Case Studies: EdRec built in Edu Info Systems

- Example: CourseRec on Moodle

Moodle: <u>M</u>odular <u>O</u>bject-<u>O</u>riented <u>D</u>ynamic <u>L</u>earning <u>E</u>nvironment



Case Studies: EdRec built in Edu Info Systems

- Example: CourseRec on Moodle

  Aher, S. B., & Lobo, L. M. R. J. (2013). Combination of machine learning algorithms for recommendation of courses in E-Learning System based on historical data. *Knowledge-Based Systems*, *51*, 1-14.

  – User preferences: Student enrollments in courses

  – Technique: rule-based recommendations

$$Rule: X \Rightarrow Y$$

$$Support = \frac{frq(X,Y)}{N}$$

$$Confidence = \frac{frq(X,Y)}{frq(X)}$$

$$Lift = \frac{Support}{Supp(X) \times Supp(Y)}$$

Rule	Support	Confidence	Lift
$A \Rightarrow D$	2/5	2/3	10/9
$C \Rightarrow A$	2/5	2/4	5/6
$A \Rightarrow C$	2/5	2/3	5/6
$B\&C \Rightarrow D$	1/5	1/3	5/9

Case Studies: EdRec built in Edu Info Systems

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  – User preferences: Student enrollments in courses

  – Technique: rule-based recommendations

    - Association rules can be applied to courses or clusters of courses
    - Each rule is associated with minimal support and confidence

Best rules found:
1. Data_Structure_II =yes Data_Structure_I =yes conf:(0.93)
2. Data_Structure_II =yes Java_Programming =yes Data_Structure_I =yes conf:(0.93)
3. Data_Structure_II =yes Visual_Basic =yes Data_Structure_I =yes conf:(0.93)
4. Data_Structure_II =yes C_Programming =yes Data_Structure_I =yes conf:(0.92)

Case Studies

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  - EdRec built in Educational Information Systems
  - EdRec: course recommendations
  - EdRec: book recommendations
  - EdRec: pathway recommendations
  - EdRec: peer matching
  - EdRec using pedagogical features

Case Studies: Course Recommendations

- CourseRec may not be always useful at University level
  - Schools have mandatory and elective courses
  - Mandatory courses usually have their own pathways
  - RecSys may be only useful in elective courses. However, the number of elective courses is limited
  - The usefulness of CourseRec at Universities varies in institutions
- CourseRec is more popular in MOOC Recommendations
  - MOOC courses from a degree program in a University
  - MOOC courses have no relations with academic programs

Case Studies: Course Recommendations

- Challenges in CourseRec
  - Academic requirements, e.g., prerequistes
  - Not only student interests, but also career path
  - Sparse/limited student preferences or feedbacks
  - Cold-start issues, e.g., new courses released

Guruge, D. B., Kadel, R., & Halder, S. J. (2021). The state of the art in methodologies of course recommender systems—a review of recent research. *Data*, *6*(2), 18.

Case Studies: Course Recommendations

- Example: Pre-requisite recommendations

  Pang, Y., et al. (2018). Forgetting punished recommendations for MOOC. In *7th International Conference, CSoNet 2018, Springer Publishing*

  – Scenario: If a student failed to pass d1, the system can recommend prerequisites/learning objects to him/her

  – The authors introduced a forgetting function (based on time decays) to penalize the utility score of an item for a learner

Case Studies: Course Recommendations

- Example: Pre-requisite recommendations

Require: learner vectors $L\{l_1, l_2, \ldots, l_m\}$, the target learner r, unqualified location d_1;

Ensure: prerequisite recommendation result I_{pr};

1: get top similar d_1 qualified learner set $Ss_1, s_2, ..., s_{k1}$;

2: **for** EACH $s \in S$ **do**

3: **for** EACH $i \in s\{i_1, i_2, \ldots, i_{index(d_1)}\}$ **do**

4: $p_{ri} += sim_{sr} \times se_{si} \times q(i, d_1)$;

5: $dec_{ri} += sim_{sr} \times q(i, d_1)$;

6: $p_{ri} /= dec_{ri}$;

7: $p_{ri} += w_1 \times (100 - \underline{f(se_{ri}, dis(time(r, d_1), time(r, i))))} + w_2 \times (100 - se_{r,d_1}) + w_3 \times p_{ri}$;

8: select top k_2 p_{ri} for learner r, add i to I_{pr}

9: **return** I_{pr};

Utility score based on weighted average
q returns correlation between LO
sim returns similarity between two learners
se is learning score by learner s

Penalty by forgetting functions

Case Studies

- Case Studies: EdRec Specialized to Education
  - EdRec built in Educational Information Systems
  - EdRec: course recommendations
  - EdRec: book recommendations
  - EdRec: pathway recommendations
  - EdRec: peer matching
  - EdRec using pedagogical features

Case Studies: Book Recommendations

- Collaborative filtering, content-based approaches, and hybrid models are most popular solutions in BookRec
- Challenges in BookRec
  - Cold-start users/items
  - Balance among accuracy, novelty, diversity, etc.
  - Adapt to evolving user tastes
  - Missing perspectives of multiple-stakeholders
  - Multi-objective concerns, e.g., not only interests, but also career path, usefulness, etc.

Case Studies: Book Recommendations

- Example: Balancing multiple metrics

Accuracy

Relevance of recommendations
e.g., precision, recall, NDCG, etc

Novelty

Unknown to the user,
but potentially interested in

Diversity

Recommend something different,
e.g., different item categories

Coverage

User coverage & item coverage

Kaminskas, M., & Bridge, D. (2016). Diversity, serendipity, novelty, and coverage: a survey and empirical analysis of beyond-accuracy objectives in recommender systems. ACM TIIS, 7(1), 1-42.

Case Studies: Book Recommendations

- Example: Balancing multiple metrics

Kaminskas, M., & Bridge, D. (2016). Diversity, serendipity, novelty, and coverage: a survey and empirical analysis of beyond-accuracy objectives in recommender systems. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, *7*(1), 1-42.

Data: N; a set of candidate items C, s.t. $|C| > N$
Result: result list R, s.t. $|R| = N$

$R \longleftarrow [\,]$;
while $|R| < N$ **do**
  $i \longleftarrow \arg\max_{i \in C} f_{obj}(i, R)$;
  $R \longleftarrow R{+}{+}[i]$;
  $C \longleftarrow C \setminus \{i\}$;
end
return R;

A greedy re-ranking algorithm

$$f_{obj}(i, R) = \alpha \cdot \underbrace{rel(i)}_{\text{Objective 1: accuracy metric}} + \underbrace{(1-\alpha) \cdot \frac{1}{|R|} \sum_{j \in R} \mathrm{dist}(i, j)}_{\text{Objective 2: Diversity metric}}$$

Objective 1:
accuracy metric

Objective 2:
Diversity metric

Case Studies: Book Recommendations

- Example: Balancing multiple metrics
  - The nature of these problems is the multi-objective optimization
  - There are several other solutions, rather than the greedy re-ranking
  - You can refer to our survey paper about multi-objective RecSys
    - Zheng, Y., & Wang, D. X. (2022). A survey of recommender systems with multi-objective optimization. Neurocomputing, 474, 141-153
    - Our tutorial (ACM SIGKDD 2021 and IEEE ICDM 2022) about multi-objective RecSys, https://moorecsys.github.io/

Case Studies

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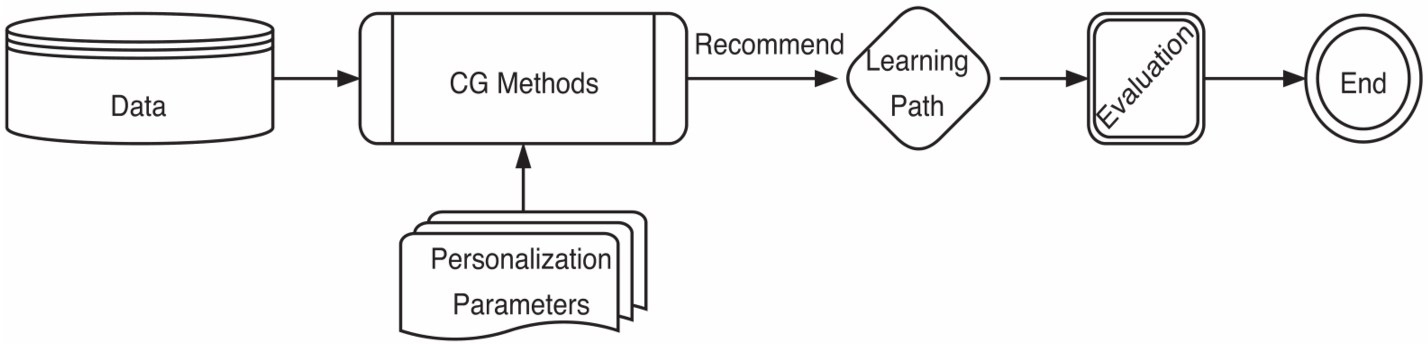
Case Studies: Pathway Recommendations

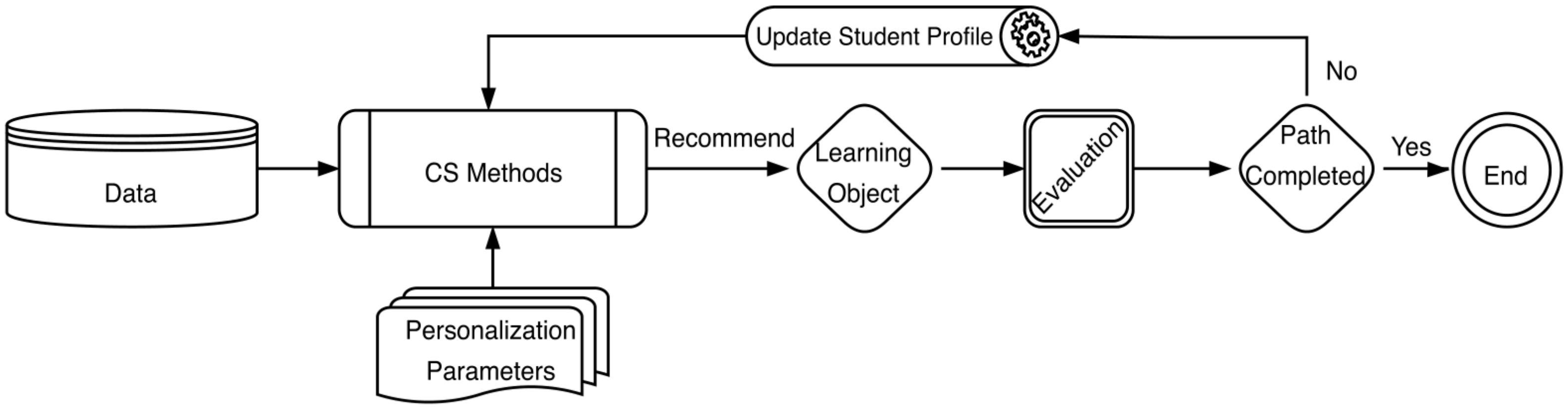
- Learning path = a sequence of learning objects for learning
- Challenges in PathRec
  - There are several personalization parameters to be considered, e.g., learning style, learning goals, student background, time span, etc.
  - How to produce a sequence of learning objects and evaluate them

Nabizadeh, A. H., Leal, J. P., Rafsanjani, H. N., & Shah, R. R. (2020). Learning path personalization and recommendation methods: A survey of the state-of-the-art. *Expert Systems with Applications*, *159*, 113596.

Case Studies: Pathway Recommendations

- PathRec: solutions in two categories
  - Course Generation (CG)
    - Produce a path
    - Evaluations after path completion
  - Course Sequence (CS)
    - Rec LO each step
    - Evaluation after LO completion
    - Then repeat





Case Studies: Pathway Recommendations

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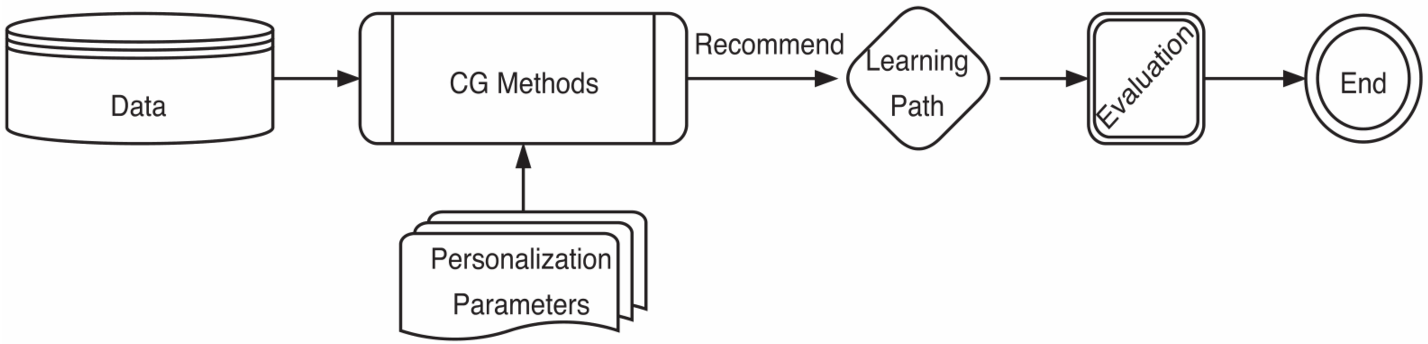

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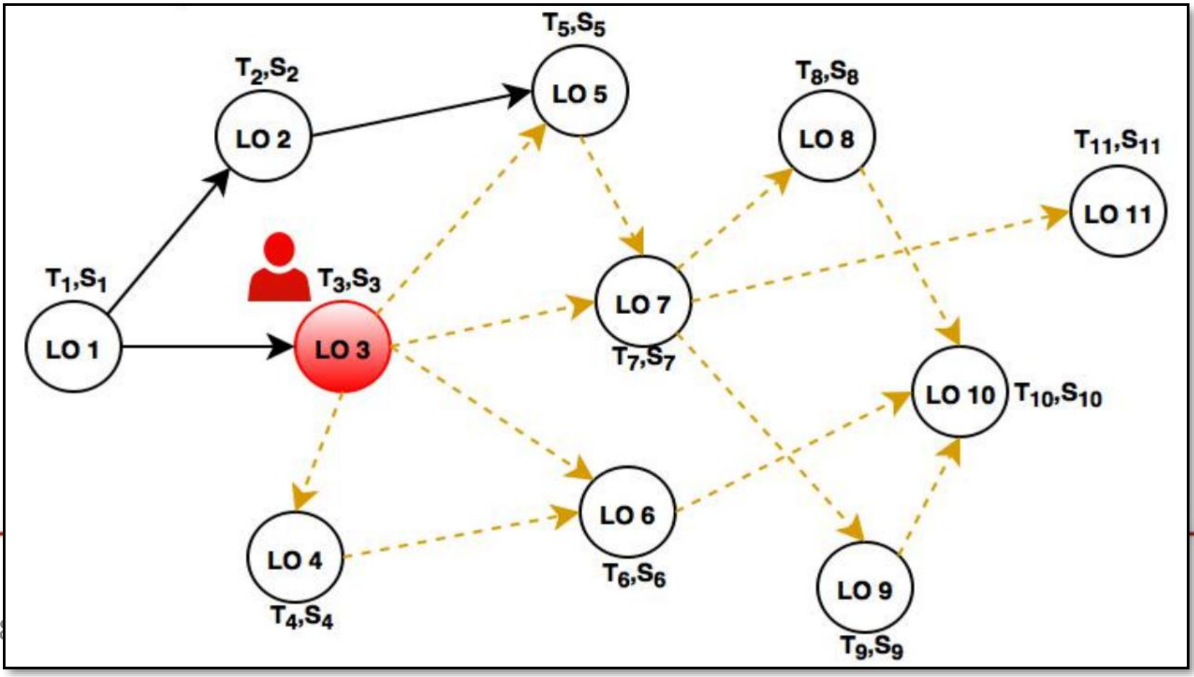
Case Studies: Pathway Recommendations

- Example 1: Course Generation (CG)

  Nabizadeh, A. H., Mário Jorge, A., & Paulo Leal, J. (2017). Rutico: Recommending successful learning paths under time constraints. In Adjunct publication of ACM UMAP conference, 2017

  – Given a learner's knowledge background (state on graph) and time restrictions, try to recommend a learning path which maximize the scores



Each node has two attributes: time and score
Edges indicate prerequisites relationships

Current learner is the RED node

- The learner has completed LO1, LO3
- Dashed lines are possible learning path

Case Studies: Pathway Recommendations

- Example 1: Course Generation (CG)

  Nabizadeh, A. H., Mário Jorge, A., & Paulo Leal, J. (2017). Rutico: Recommending successful learning paths under time constraints. In Adjunct publication of ACM UMAP conference, 2017

  – Depth-First search is applied from the node of learner to produce all possible learning path

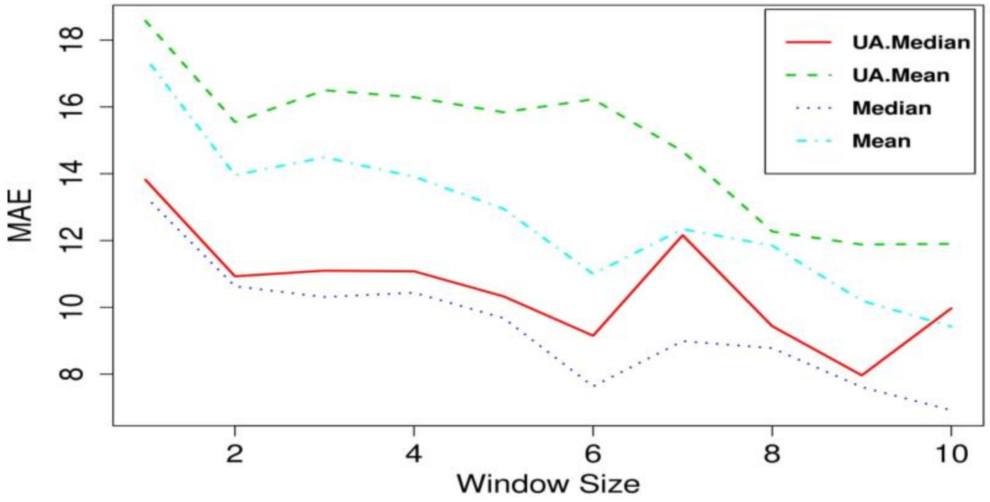
  – For each learning path, we can estimate learning time and possible scores, e.g., using median or mean methods

  – Finally, select the one which satisfies learner’s time restrictions and maximizes the possible scores

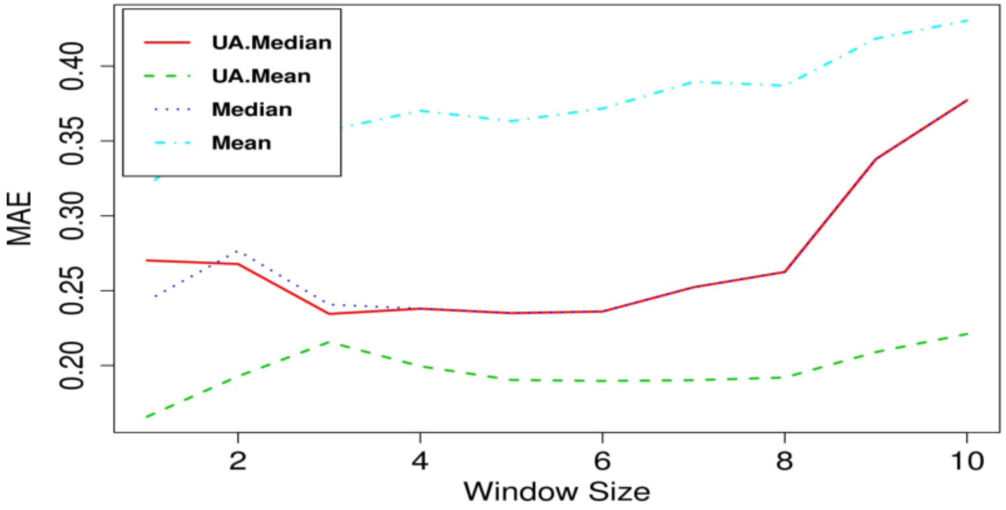
Case Studies: Pathway Recommendations

- Example 1: Course Generation (CG)

  Nabizadeh, A. H., Mário Jorge, A., & Paulo Leal, J. (2017). Rutico: Recommending successful learning paths under time constraints. In Adjunct publication of ACM UMAP conference, 2017



(a) Learning Time estimation. Timescale is in minutes.



(b) Learning Score estimation.

Window size refers to the number of unobserved LOs to be ignored

Case Studies: Pathway Recommendations

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    - Rec LO each step
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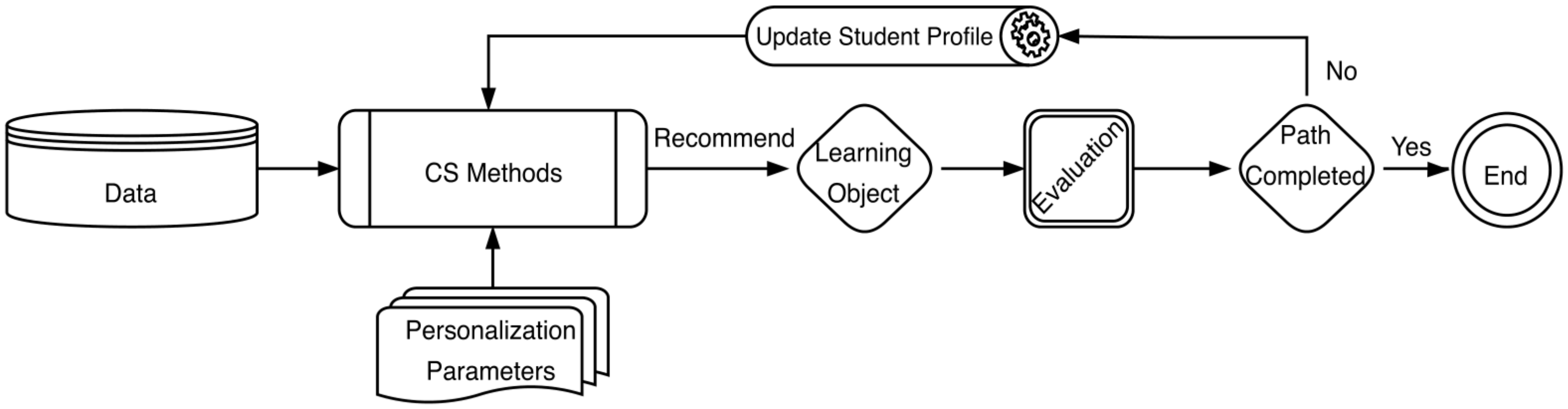
    - Then repeat

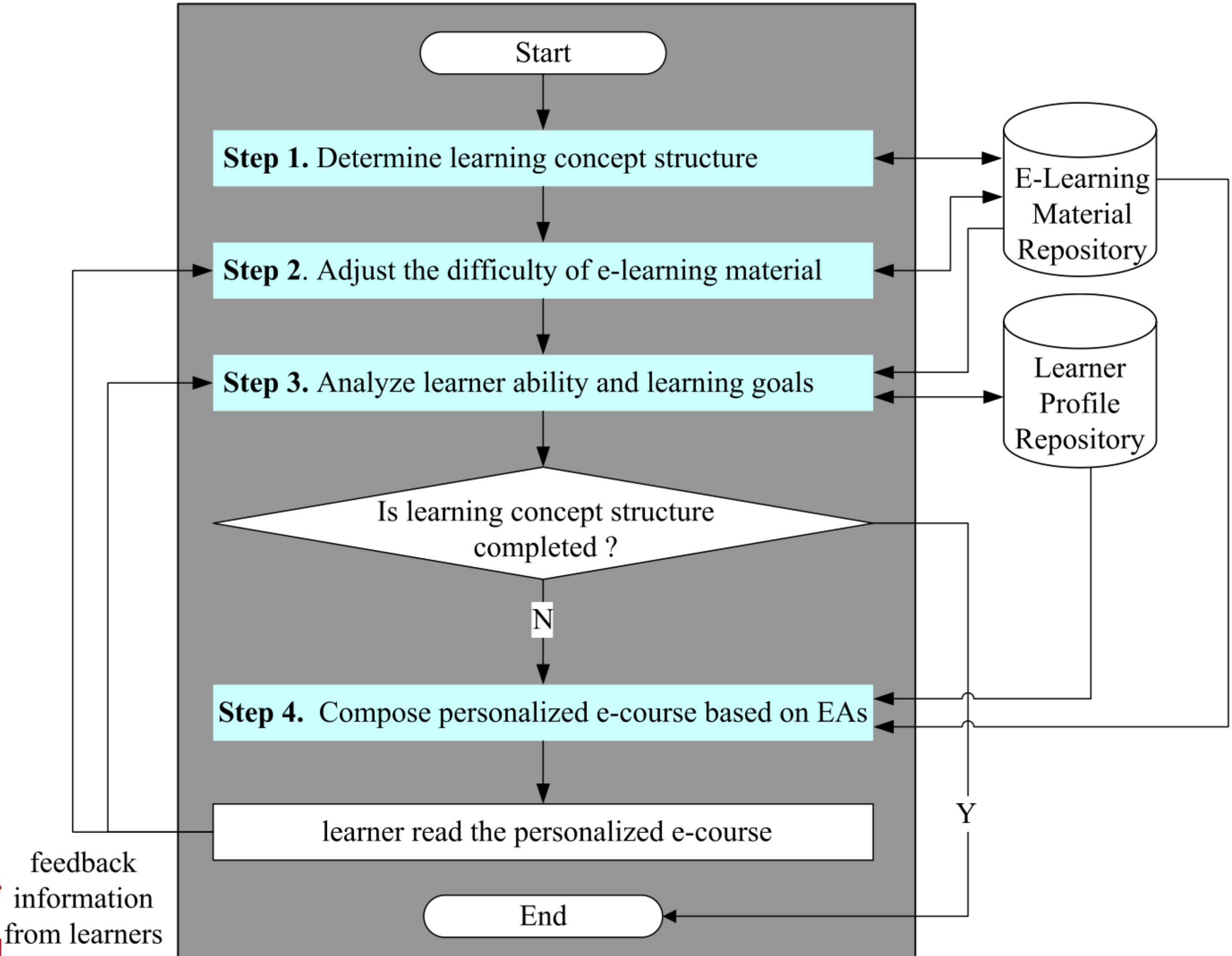


Case Studies: Pathway Recommendations

- Example 2: Course Sequence

Li, J.-W., Chang, Y.-C., Chu, C.-P., & Tsai, C.-C. (2012). A self-adjusting e-course generation process for personalized learning. Expert Systems with Applications, 39, 3223–3232.

  - Recommend an e-course in each step
  - Collect learner's feedbacks for
  - adjustments
  - Recommend next one
  - Repeat until a whole path is completed, i.e., learning concept structure completed



Self-adjusting E-course Generation Process

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Case Studies: Peer Recommendations

- PeerRec: find peers for learning
  - Goals: find peers in the same class or learning network
  - It can be considered as a process of reciprocal recommendations
    - ReciprocalRec is a special case of multi-stakeholder recsys
    - There are only two stakeholders, and we'd like to find matched
    - Examples: peer match in learning, job match in job seeking, dating, etc.
  - See more details about "multi-stakeholder EdRec" in tutorial Part II

Case Studies

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  - EdRec: peer matching
  - EdRec using pedagogical features

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
  - Multi-Criteria EdRec, Group EdRec
  - Personality-Based EdRec
  - Multi-stakeholder EdRec, Multi-task EdRec
  - EdRec: Fairness, Transparency, Explanations
- Challenges and Future Work
- QA and Open Discussions

11:00 AM – 12:30 PM + QA

Educational Recommender Systems

Dr. Yong Zheng
Illinois Institute of Technology, USA

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

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
  - Multi-Criteria EdRec, Group EdRec
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