Multi-Stakeholder Recommendations: Case Studies, Methods and Challenges

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Tutorial at the 13th ACM Conference on Recommender Systems

Who am I

Yong Zheng, Assistant Professor at Illinois Tech, USA

Research

- Context-Aware Recommender Systems
- Multi-Criteria Recommender Systems
- Multi-Stakeholder Recommender Systems

Organization Committee

- ACM RecSys 2018
- ACM UMAP 2019 & 2018
- ACM IUI 2019 & 2018

Track on Recommender Systems @ ACM SAC 2020

- CFP Due: Sep 29, 2019. http://tiny.cc/recsys

Agenda

- Intro: Multi-Stakeholder Recommender System
- Research Problems & Methodologies
- Utility-Based MSRS with Case Studies
- Demo Based on MOEA Framework
- Challenges and Open Discussions

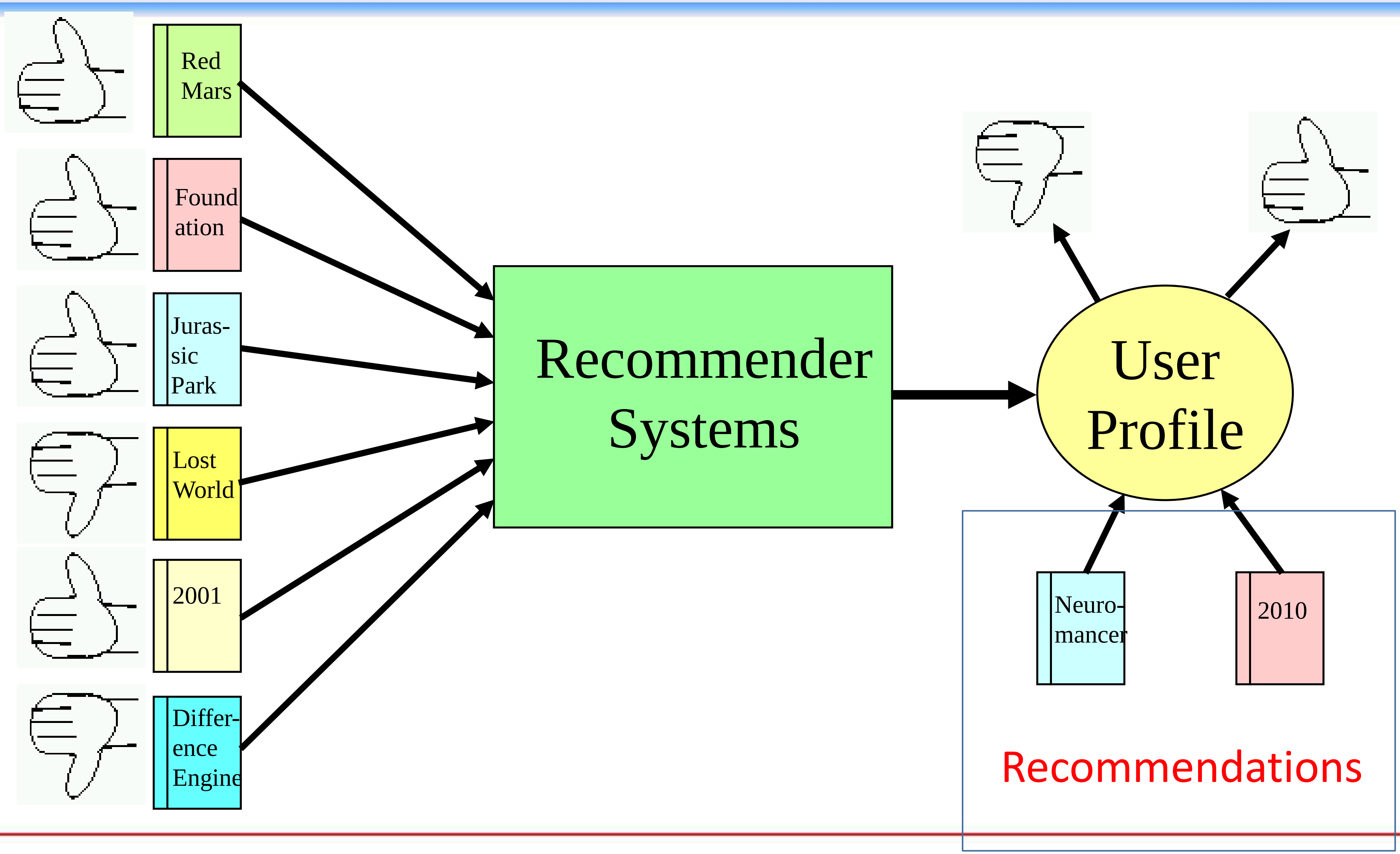
Agenda

- Intro: Multi-Stakeholder Recommender System
  - Recommender Systems
  - History of Multi-Stakeholder Recommendations
  - Why Multi-Stakeholder Recommendations?
  - Applications and Classifications
- Research Problems & Methodologies
- Utility-Based MSRS with Case Studies
- Demo Based on MOEA Framework
- Challenges and Open Discussions

Recommender Systems (RS)

- RS: item recommendations tailored to user preferences

How it works



Red Mars
Foundation
Jurassic Park
Lost World
2001
Difference Engine
Recommender Systems
User Profile
Neuromancer
2010
Recommendations

Different Types of Recommender Systems

- Context-Aware Recommender Systems
  consider context info, e.g., time, location, etc
- Multi-Criteria Recommender Systems
  consider ratings on different aspects of the items
- Group Recommender Systems
  produce recommendations to a group of users
- Cross-Domain Recommender Systems
  utilize preferences in different domains

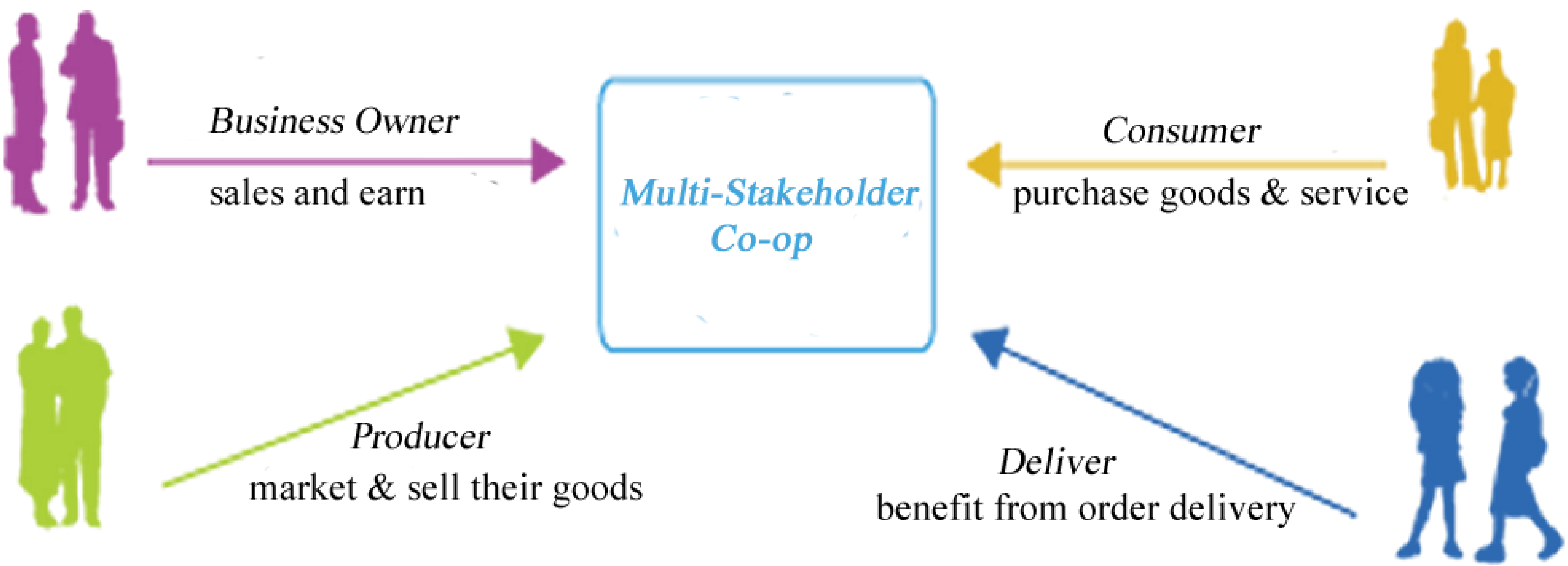
Recommender Systems (RS)

- In these RS, the end user is the only stakeholder

The only stakeholder is the receiver of recommendations

Recommender Systems (RS)

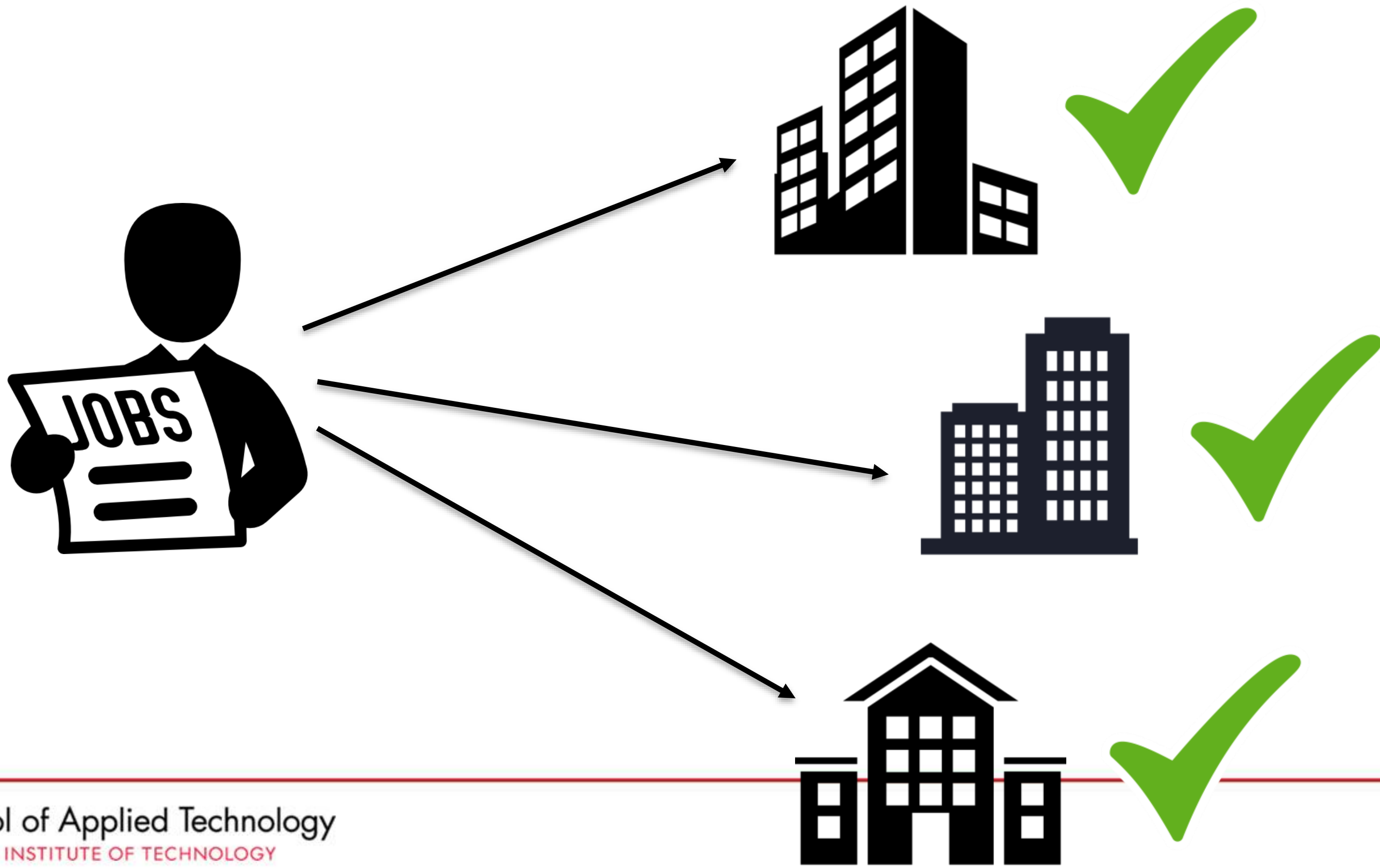
- In fact, there could be multiple stakeholders involved



History of MSRS

The notion is not that novel, we can find the trace

- Reciprocal Recommendations, e.g. job, dating



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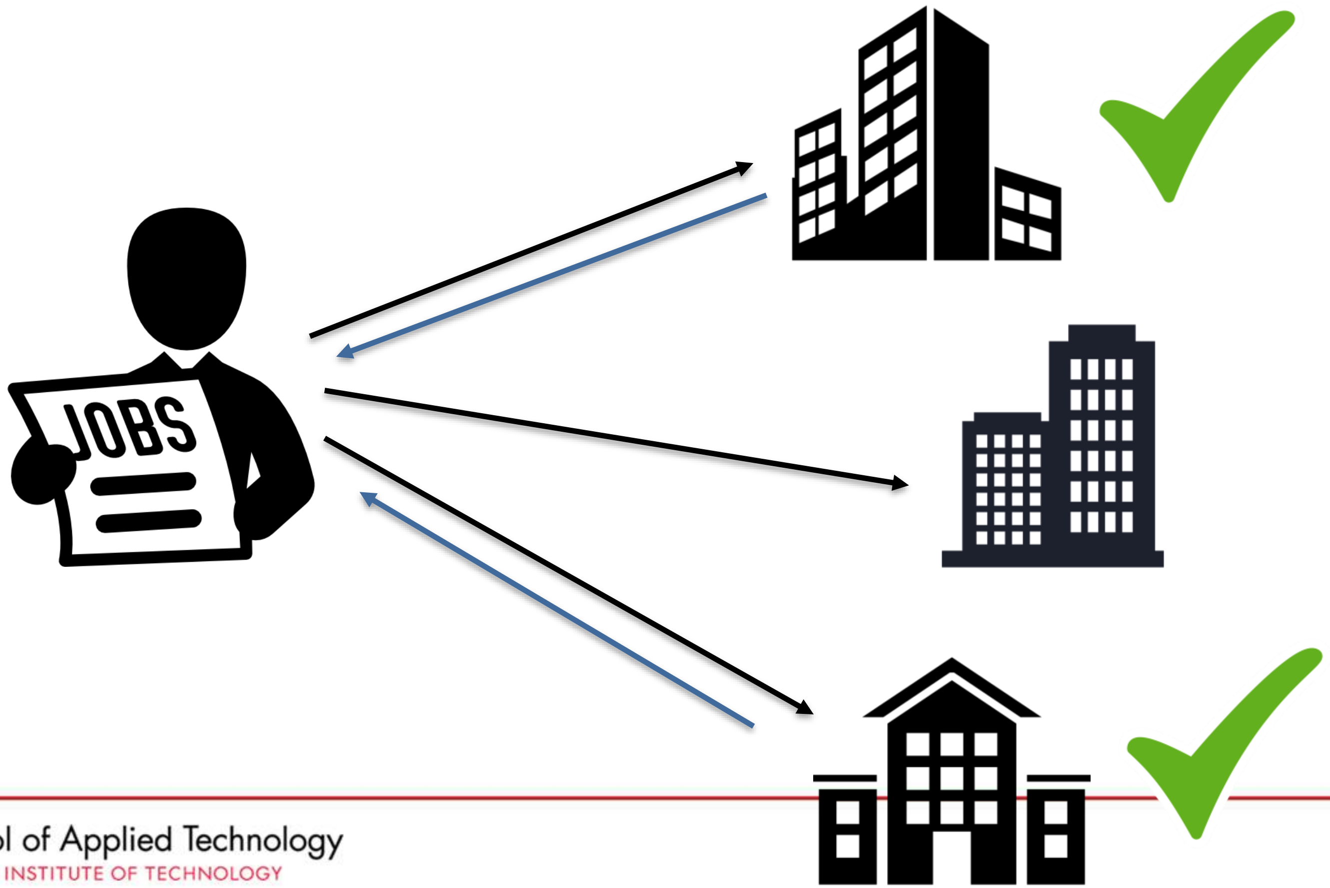


History of MSRS

The notion is not that novel, we can find the trace

- Multisided Platforms, e.g. auction and bidding

History of MSRS

The notion is not that novel, we can find the trace

- Group Recommendations

Aggregation Strategies

- Average
- Least Misery
- Most Happiness
- Most Respected Person
- …….

Strictly speaking, users are all consumers!
They are on the same side of transactions!

Multi-Stakeholder Recommender Systems (MSRS)

- We believe the perspective of other stakeholders may also be important
- MSRS try to produce the list of recommendations by balancing the needs of multiple stakeholders
- MSRS was formally proposed in 2016

  Burke, Robin D., Himan Abdollahpouri, Bamshad Mobasher, and Trinadh Gupta. "Towards Multi-Stakeholder Utility Evaluation of Recommender Systems." In UMAP (Extended Proceedings). 2016.

Multi-Stakeholder Recommender Systems (MSRS)

- VAMS Workshop at ACM RecSys 2017
- FairUMAP Workshop at ACM UMAP 2018
- FairUMAP Workshop at ACM UMAP 2019
- RMSE Workshop at ACM RecSys 2019

Why we need MSRS?

- On one hand, the perspectives or suggestions from other stakeholders are helpful
  - In learning material recommendations, not only the student preferences, but also the advices or suggestions by teachers (and/or parents) are important too.

Ekstrand, Michael D., Ion Madrazo Azpiazu, Katherine Landau Wright, and Maria Soledad Pera. "Retrieving and Recommending for the Classroom." ComplexRec 6, no. 2018 (2018): 14.

Why we need MSRS?

- On the other hand, there could be conflicting interests among multiple stakeholders
  - In multisided platforms, buyers vs sellers
    Sürer, Özge, Robin Burke, and Edward C. Malthouse. "Multistakeholder recommendation with provider constraints." ACM RecSys 2018.
  - In educations, students prefer easier projects, while instructors may suggest more challenging ones
    Zheng, Yong, Nastaran Ghane, and Milad Sabouri. "Personalized Educational Learning with Multi-Stakeholder Optimizations." FairUMAP@UMAP 2019

Why we need MSRS?

Some examples in the real-world applications

- Advertising
- ~~E-Commerce~~
- Hotels
- Movies
- ~~Educations~~

Maximizing the utility of one stakeholder may hurt other stakeholders!

Example: Advertising

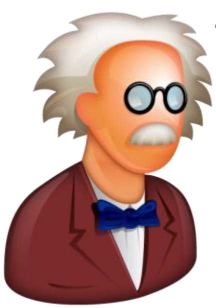
- **Different views**

Advertising Agency

"I wanna more clicks"

Car Producer

"I want users to buy the car"



End user/viewer

"I just like it"

Example: Advertising

- **Need a balance**

Advertising Agency

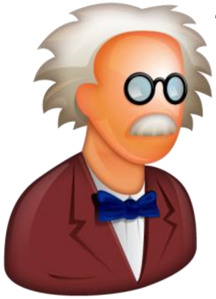
"I wanna more clicks"

End user/viewer

"I just like it"

Car Producer

"I want users to buy the car"



Kids are not customers
No capability to purchase

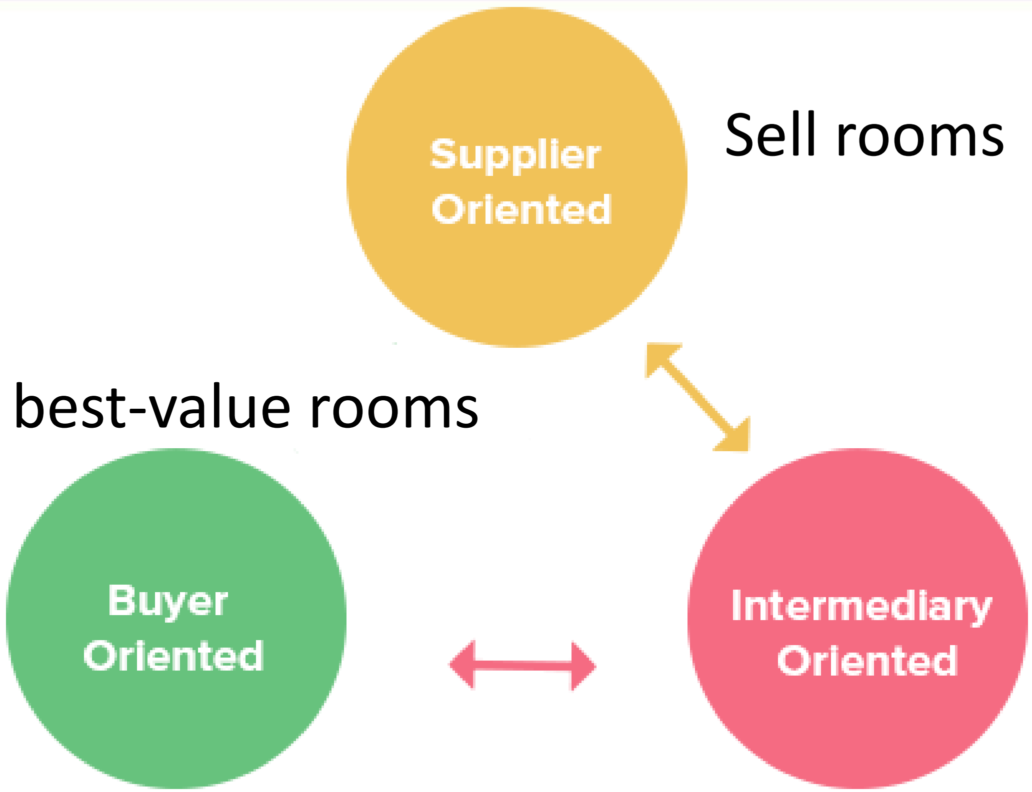
Kid

Kid

Example: Hotel Booking at Expedia

Sell rooms

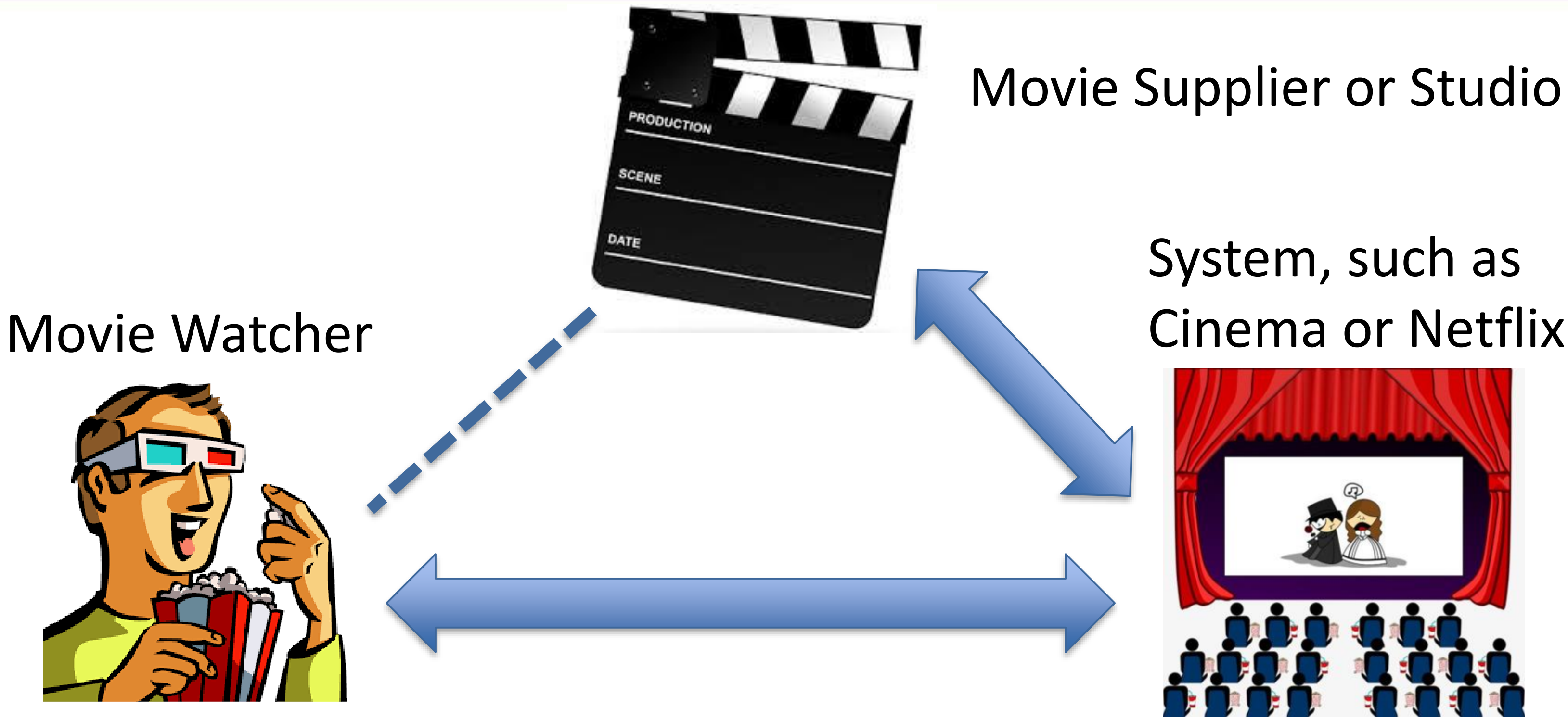
Find best-value rooms



Connect suppliers & buyers, and get commission fees

Nguyen, Phong, John Dines, and Jan Krasnodebski. "A multi-objective learning to re-rank approach to optimize online marketplaces for multiple stakeholders." VAMS Workshop @ ACM RecSys 2017.

Example: Movies



Burke, R. D., Abdollahpouri, H., Mobasher, B., & Gupta, T. (2016, July). Towards Multi-Stakeholder Utility Evaluation of Recommender Systems. In UMAP (Extended Proceedings).

Stakeholders and Classifications

- Burke, et al. claimed that the stakeholders could be categorized into 3 classes: consumer, provider, system.
- Take the advertising case for example
  - Ad viewer → consumer
  - Producer → provider
  - Advertising Agency → the system or platform

Burke, Robin, and Himan Abdollahpouri. "Patterns of Multistakeholder Recommendation." VAMS Workshop @ ACM RecSys 2017
Abdollahpouri, Himan, Robin Burke, and Bamshad Mobasher. "Recommender systems as multistakeholder environments." UMAP 2017

Stakeholders and Classifications

C = Consumer
P = Provider

Sub n = ignore
Sub p = satisfy

Sup + = Active
Sup - = Passive

		Passive (-)		Active (+)	
		P_n^-	P_p^-	P_n^+	P_p^+
Passive (-)	C_n^-	Most Popular		Featured Items	
	C_p^-	Standard	Reciprocal	Paid placement	Online display advertising
Active (+)	C_n^+	Query		Search engine advertising	
	C_p^+	Personalized Search			

Burke, Robin, and Himan Abdollahpouri. "Patterns of Multistakeholder Recommendation." VAMS Workshop @ ACM RecSys 2017

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Research on MSRS

- Research Problems
  - Data Sets
  - Personalization
  - Evaluations
  - FAT (Fairness, Accountability, and Transparency)
    - Tutorial @ ACM RecSys 2019, “Fairness and Discrimination in Recommendation and Retrieval”

MSRS: Data Sets

- The number of data sets available for MSRS research is limited.
  - Some data available for reciprocal recommendations https://www.kaggle.com/annavictoria/speed-dating-experiment

    Zheng, Yong, Tanaya Dave, Neha Mishra, and Harshit Kumar. "Fairness in reciprocal recommendations: A speed-dating study." FairUMAP workshop @ ACM UMAP 2018

MSRS: Data Sets

- The number of data sets available for MSRS research is limited.
  - MovieLens (+ IMDB) data

    Users as consumers

    Movie studios as providers

    Burke, R. D., Abdollahpouri, H., Mobasher, B., & Gupta, T. (2016, July). Towards Multi-Stakeholder Utility Evaluation of Recommender Systems. In UMAP (Extended Proceedings).

    Sürer, Özge, Robin Burke, and Edward C. Malthouse. "Multistakeholder recommendation with provider constraints." ACM RecSys 2018

MSRS: Data Sets

- The number of data sets available for MSRS research is limited.
  - Multisided Platforms: E-Commerce/Retails/Hotels
    They use cost, revenue and profit as objectives
    They are not available for public research
    Nguyen, Phong, John Dines, Jan Krasnodebski. "A multi-objective learning to re-rank approach to optimize online marketplaces for multiple stakeholders." VAMS Workshop @ ACM RecSys 2017.

    Louca, R., Bhattacharya, M., Hu, D., & Hong, L. Joint Optimization of Profit and Relevance for Recommendation Systems in E-commerce. RMSE workshop @ ACM RecSys 2019

MSRS: Data Sets

- The number of data sets available for MSRS research is limited.
  - Educational Data: Student Projects
    We make it available in the demo

    Yong Zheng, Nastaran Ghane, and Milad Sabouri. "Personalized Educational Learning with Multi-Stakeholder Optimizations." FairUMAP at ACM UMAP 2019.

    Yong Zheng. "Multi-Stakeholder Personalized Learning with Preference Corrections." IEEE ICALT 2019.

Research on MSRS

- Research Problems
  - Data Sets
  - Personalization
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MSRS: Personalization

- Stakeholders: consumers, providers, systems
- Interests: consistent or conflicting interests
- Objectives: multiple
- Target: top-N recommendations to consumers
- Goal: balance the needs of multiple stakeholders

MSRS: Personalization

Major challenges

- Define objectives or build utility functions
- Find the balance via multi-objective learning

MSRS: Personalization

Major challenges

- Define objectives or build utility functions
  - Simulations, Burke, et al., UMAP 2016
    consumer gain = relevant movies suggested in L
    provider gain = own movies included in L
  - Build utility functions, Zheng, FairUMAP 2018&2019
    similarity = sim (expectation vector, rating vector)
  - Use business metrics directly, Nguyen, VAMS 2017
    revenue, profit, margin, and so on…
- Find the balance via multi-objective learning

MSRS: Personalization

Major challenges

- Define objectives or build utility functions
- Find the balance via multi-objective learning
  - Combine multiple objectives into a single one
  - Constraint-based learning
  - Pareto Optimal for multi-objective learning

MSRS: Personalization

Major challenges

- Define objectives or build utility functions
- Find the balance via multi-objective learning
  - Combine multiple objectives into a single one

    Nguyen, Phong, et, al. "A multi-objective learning to re-rank approach to optimize online marketplaces for multiple stakeholders." VAMS Workshop @ ACM RecSys 2017.

$$\max_{\alpha,\beta} \mathcal{L}(\mathbf{m}|\mathbf{u}) = \sum_{i=1}^{n} \underbrace{\log(u_i)}_{\text{consumer}} + \alpha \underbrace{\log(p_i)}_{\text{supplier}} + \beta \underbrace{\log(m_i/p_i)}_{\text{Intermediary/agency}}$$

MSRS: Personalization

Major challenges

- Define objectives or build utility functions
- Find the balance via multi-objective learning
  - Constraint-based learning

    Optimize a single objective, set others as constraints

    Özge Sürer, et, al. "Multistakeholder recommendation with provider constraints." ACM RecSys 2018.

$$\max_x \sum_{j \in U} \sum_{r \in R} \sum_{i \in I_r} \hat{u}_{ij} x_{ij},$$

subject to

$$\sum_{r \in R} \sum_{i \in I_r} x_{ij} = k \qquad \forall j \in U, \qquad (1)$$

$$\frac{\sum_{j \in U} \sum_{i \in I_r} x_{ij}}{\sum_{j \in U} \sum_{r \in R} \sum_{i \in I_r} x_{ij}} \geq \alpha_r p_r \qquad \forall r \in R, \qquad (2)$$

$$x_{ij} \in \{0, 1\} \qquad \forall i \in I, j \in U, \qquad (3)$$

MSRS: Personalization

Major challenges

- Define objectives or build utility functions
- Find the balance via multi-objective learning
  - Pareto Optimal for multi-objective learning

    Yong Zheng, Nastaran Ghane, and Milad Sabouri. "Personalized Educational Learning with Multi-Stakeholder Optimizations." FairUMAP at ACM UMAP 2019.

  We will give more details in the case studies later.

Research on MSRS

- Research Problems
  - Data Sets
  - Personalization
  - Evaluations
  - FAT (Fairness, Accountability, and Transparency)
    - Tutorial @ ACM RecSys 2019, “Fairness and Discrimination in Recommendation and Retrieval”

MSRS: Evaluations

- Offline Evaluations
  - Produce solutions by proposed models
  - Setup baselines – methods consider consumers only
  - Observe the gain/loss for different stakeholders
- Online Studies or A/B Test
  - Most research papers claim that online user studies or A/B test are necessary
  - However, no such work yet

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Utility-Based MSRS Framework (UBMSRS)

It is a general framework which defines a workflow

- Define stakeholders
- Build utility functions for each stakeholder
- Apply multi-objective optimizer (MOO)
- Search for the best solution
- Evaluations (Offline vs Online)

UBMSRS: An Educational Case Study

It is a general framework which defines a workflow

- Define stakeholders
- Build utility functions for each stakeholder
- Apply multi-objective optimizer (MOO)
- Search for the best solution
- Evaluations (Offline vs Online)

Our case study

- Utilize multi-criteria ratings to build utility functions
- Use Pareto Optimal as MOO
- Offline evaluations only (working on user studies…)

Educational Setting and Data Set

- Educational Setting
  - Students are required to work on projects in data analytics/data science classes
  - They should find data sets on Kaggle.com, figure out research problems and use data analytics to solve the problems
  - The project is used to train and examine students
    - Brainstorming – figure out ideas by themselves
    - Problem solving – figure out appropriate solutions
    - Practical skills – work on experiments and evaluations
    - Writing skills – complete a final report

Educational Setting and Data Set

- Two stakeholders
  - Students: some may prefer to work on easy projects, while some others may prefer more challenging projects
  - Instructors: encourage students to work on more challenging ones, but it is NOT mandatory

Educational Setting and Data Set

- Grading will consider at least two components
  - The degree of difficulty of the selected projects or data
  - How well they completed the projects

    It is similar to high diving in Olympic Games

Data Collections

- Questionnaire: Student Part
  - We randomly selected 70 Kaggle data sets
  - Students selected at least 3 liked and disliked projects
  - Students gave overall ratings to these projects
  - In addition, there are multi-criteria ratings
    - App: how the student likes to application or domain of the data
    - Data: how easy it is in data processing
    - Ease: the general or overall ease of the projects
  - All ratings are in scale 1 to 5

Data Collections

- Questionnaire: Instructor Part
  - We only have one instructor
  - The instructor have no requirements on “App”
  - Instructor was asked to give rating to “Data” and “Ease” for all 70 items
  - These ratings are NOT instructors’ tastes, but his evaluations on the ease of the data sets as projects from the perspective of instructors

Data Collections

- Data Sets
  - 269 students, 1 instructor
  - 3,306 rating entries by 269 students on 70 items
  - Each rating is associated with overall and multi-criteria ratings

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
...	...	...	...	...	...

Utility-Based Multiple Stakeholder Recommendation

- Notations
  - Student, s
  - Instructor or Professor, p
  - Item, t
  - Utility of item from perspective of student, $U_{s,t}$
  - Utility of item from perspective of instructor, $U_{p,t}$
  - Given a recommendation list, L
    - $U_{s,L}$ = average $U_{s,t}$ in the list L
    - $U_{p,L}$ = average $U_{p,t}$ in the list L

Utility-Based Multiple Stakeholder Recommendation

- General Ideas
  - Build utility functions by using multi-criteria ratings
  - Balance the utilities from the perspective of multiple stakeholders
  - Use multi-objective learning to seek optimal solutions

Utility-Based Multiple Stakeholder Recommendation

- Components
  - Student ratings, $R_{s,t}$ = <App, Data, Ease>
    Instructor ratings, $R_{p,t}$ = <Data, Ease>
  - Assume there are student & instructor expectations
    Student Expectation, E_s = <App, Data, Ease>
    Instructor Expectation, E_p = <Data, Ease>
  - There are 269 students and 1 instructor
    We decide to learn E_s
    Acquire E_p from instructor = <4, 4>, and it is minimal requirements = students cannot select easier projects than <Data, Ease> = <4, 4>, e.g. <5, 5> is not suggested

Utility-Based Multiple Stakeholder Recommendation

- More about the expectation vector
  - The ratings in this vector are not “full-stack”
  - Take hotel booking on TripAdvisor for example

User	Hotel	Rating	Location	Cleanliness	Size	Service

The expectation vector is not always <5, 5, 5, 5> due to some limitations, e.g., budget

Utility-Based Multiple Stakeholder Recommendation

- Components
  - The utility function is defined as similarity between the rating vector and expectation vector
    - $U_{s,t}$ = similarity ($E_{s,}$, $R_{s,t}$)
    - $U_{p,t}$ = dissimilarity (E_p , $R_{p,t}$), it is dissimilarity because E_p is considered as the minimal requirement
  - Ranking score = $\alpha \times U_{s,t} + (1 - \alpha) \times U_{p,t}$
    - α is a weight factor, [0, 1]
    - The ranking score is used to rank items
    - α is not always 0.5, due to distributions of $U_{s,t}$ and $U_{p,t}$

Utility-Based Multiple Stakeholder Recommendation

- Multi-Objective Optimization (MOO)
  - Objectives
    - $U_{s,L}$ = the utility of top-N recommendation list, L, from the perspective of students = average utility of the top-N items from the perspective of students
    - $U_{p,L}$ = the utility of top-N recommendation list, L, from the perspective of instructors= average utility of the top-N items from the perspective of instructors
    - The difference between $U_{s,L}$ and $U_{p,L}$
    - The recommendation performance, we use F-1 measure and NDCG in this paper

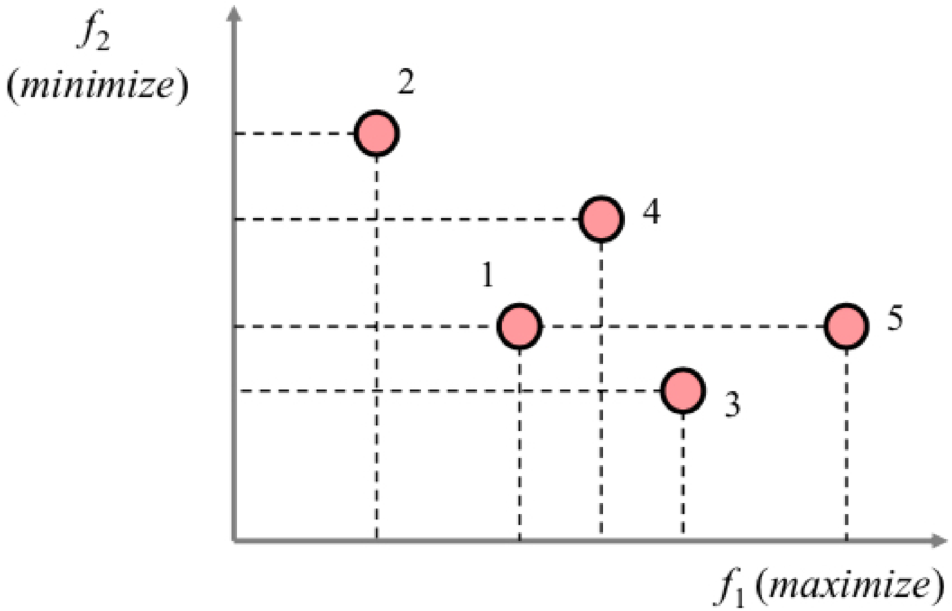
Maximizing Minimizing

Utility-Based Multiple Stakeholder Recommendation

- Multi-Objective Optimization (MOO)
  - Parameters to be learned
    - The student expectations for each student, E_s
    - The optimal value, α
  - We use MOEA library, http://moeaframework.org
  - Workflow
    - Two-Stage
      Learn E_s in advance by UBRec, then learn α by MOO
      UBRec ranks items by $U_{s,t}$ and maximizes NDCG
    - One-Stage
      Learn E_s and α together by MOO

Pareto Optimal

– Pareto optimal set is a set of optimal solutions in which no single objective can be further improved without hurting others



Solution 1 dominates Solution 2
Solution 5 dominates Solution 4

Pareto optimal set = a set of non-dominated solutions

Select a Single Solution from Pareto Optimal Set

- There are no unique ways to select a single solution
- We can set cut-off values
- We can use some strategies
  Least Misery, "A Pareto-Efficient Algorithm for Multiple Objective Optimization in E-Commerce Recommendation“, ACM RecSys 2019
- We can combine these objectives together

Select a Single Solution from Pareto Optimal Set

– We use a metric, Loss

$$Loss_1 = \frac{1}{3}\left(\frac{maxU_{s,L} - U_{s,L}}{maxU_{s,L}} + \frac{maxU_{p,L} - U_{p,L}}{maxU_{p,L}} + \frac{1}{2}\left(\frac{maxF_1 - F_1}{maxF_1} + \frac{maxNDCG - NDCG}{maxNDCG}\right)\right)$$

3 components

$$Loss_2 = \frac{1}{2}\left(\frac{maxU_{p,L} - U_{p,L}}{maxU_{p,L}} + \frac{1}{2}\left(\frac{maxF_1 - F_1}{maxF_1} + \frac{maxNDCG - NDCG}{maxNDCG}\right)\right)$$

2 components

– The max values above are from baseline methods

- UBRec: recommend items by $U_{s,t}$ only
- $Rank_p$: recommend items by $U_{p,t}$ only

Issues and Solutions

- Issue 1: Over-/Under-Expectations
  – We simply use similarity or distance measures to calculate the utilities
  – However, there may be over-/under-expectations
    For example, student expectation = <2, 2, 2>
    Rating vector for item T1 = <1, 1, 1>
    Rating vector for item T2 = <3, 3, 3>
    If we use Manhattan distance, T1 and T2 have the same distance to the student expectation, which one is preferred?

Issues and Solutions

- Solution: Over-/Under-Expectations
  - Filtering Strategy (domain-specific)
    Define rules, e.g., filter out items if over expectations
    Zheng, Yong, Nastaran Ghane, and Milad Sabouri. "Personalized Educational Learning with Multi-Stakeholder Optimizations." FairUMAP @ ACM UMAP 2019.
  - Learn a "penalty"
    learn a penalty if it is Over-/Under-Expectations
    Penalty is positive => this is a bonus!
    Penalty is negative => penalize the item

Issues and Solutions

- Issue 2: Different Perceptions
  - An easy project in view of instructors may be difficult from the perspective of students
  - We use a weighted linear combination of rating vectors <Data, Ease> associated with students and instructors to adjust the ratings

  Zheng, Yong. "Multi-Stakeholder Personalized Learning with Preference Corrections." IEEE ICALT 2019.

Experimental Results

- Results based on 5-fold cross validation

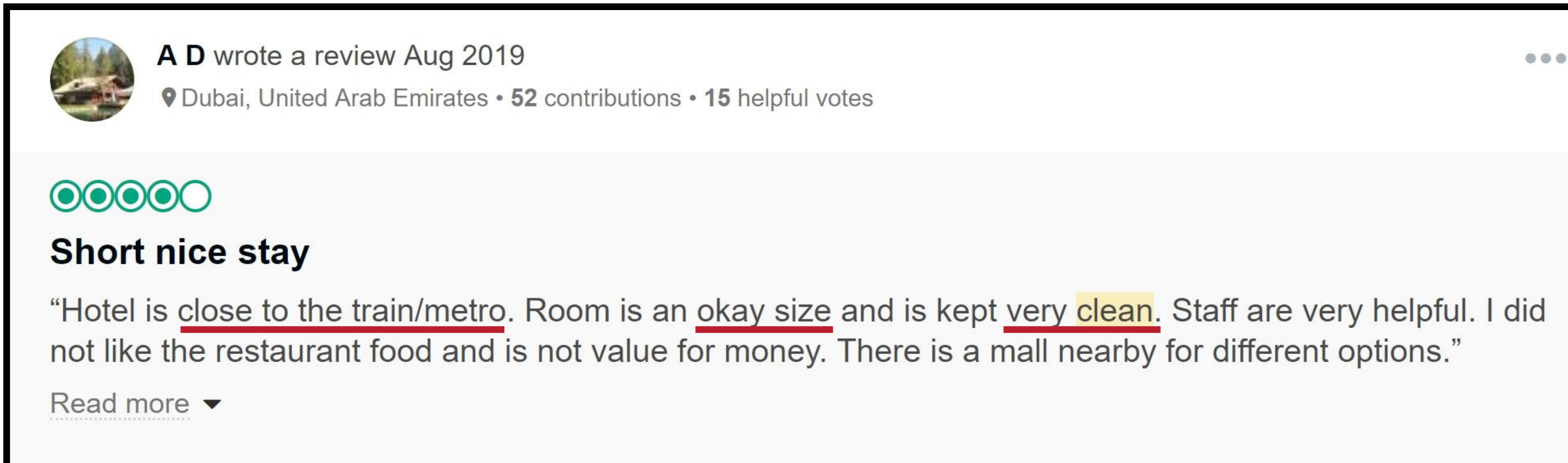
		$U_{s,L}$	$U_{p,L}$	F_1	NDCG	$Loss_1$	$Loss_2$
Baseline	UBRec	0.181	0.134	0.085	0.126	0.180	0.270
	$Rank_p$	0.072	0.298	0.027	0.039	0.425	0.336
MSRS	One-Stage	0.199	0.251	0.074	0.107	0.063	0.144
	Two-Stage	0.161	0.239	0.062	0.092	0.189	0.228

Yellow cells = max values as baselines, Green cells = best performing in Loss

- We can find better solutions if we consider the solutions for over-/under-expectations and the issue of different perceptions

Weaknesses

- What if we do not have multi-criteria ratings?
  – Learn multi-criteria ratings through review mining



A D wrote a review Aug 2019

Dubai, United Arab Emirates • **52** contributions • **15** helpful votes

Short nice stay

“Hotel is close to the train/metro. Room is an okay size and is kept very clean. Staff are very helpful. I did not like the restaurant food and is not value for money. There is a mall nearby for different options.”

Read more

  – Map the rating from low-dimension to high dimension by using kernel functions?

Weaknesses

- Is it always good to have smaller loss?
  - A small loss may also infer that we may need further balance the needs of stakeholders
  - What are the right cut-off thresholds?
    We may need user studies to learn them.
    such as the tolerance of the utility loss from the perspective of different stakeholders

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- Challenges and Open Discussions

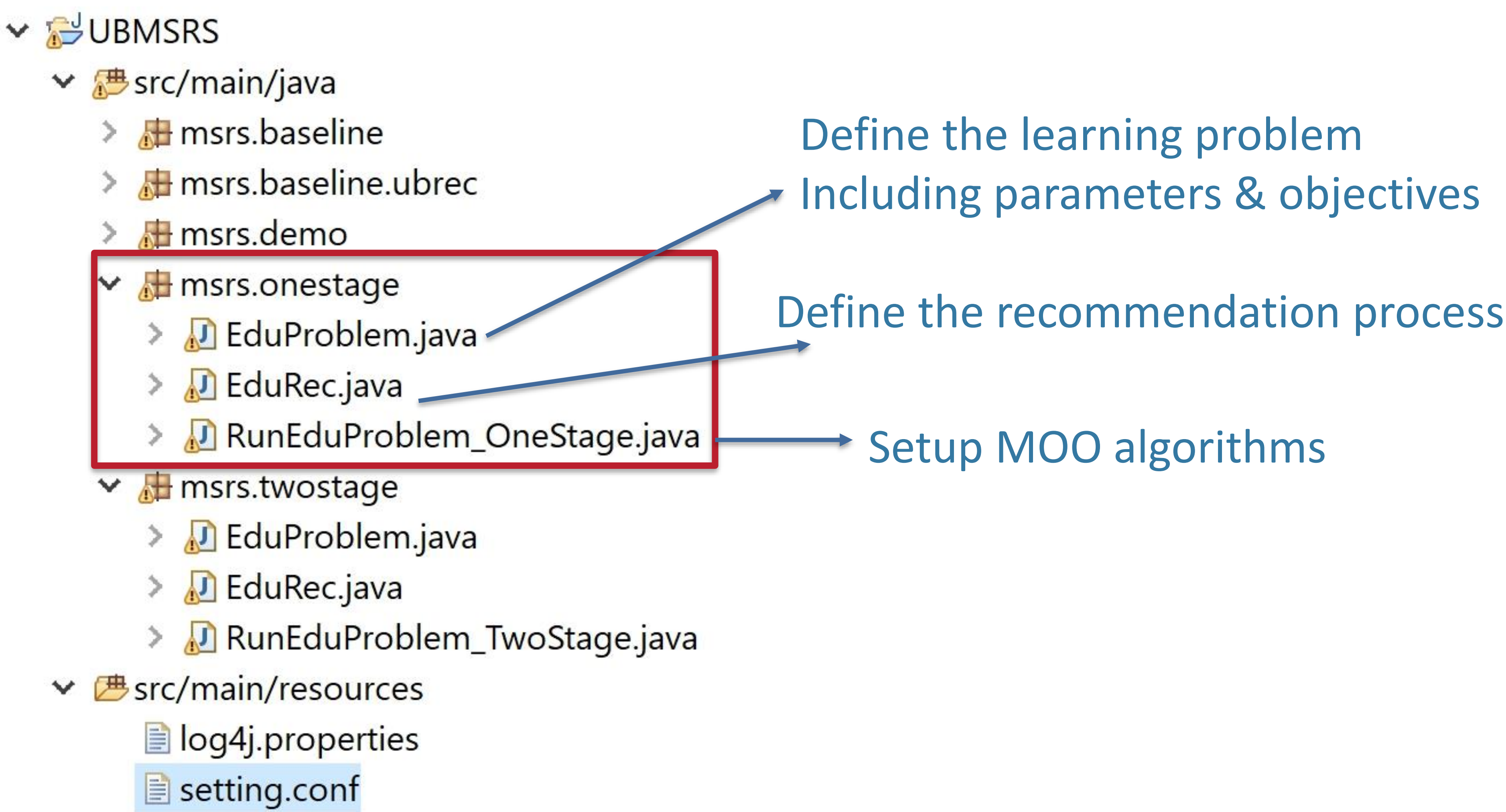
Demo

- Demo, https://github.com/irecsys/Tutorial_MSRS
- Setting and Running
  - JRE 8+
  - “java –jar UBMSRS.jar –c setting.conf”
  - Just change the configuration file setting.conf
- Features
  - Baseline UBRec and $Rank_p$
  - One-stage and two-stage MSRS
- Data: The case study of educational data set

MOEA

- MOEA, http://moeaframework.org
- A Free and Open Source Java Framework for Multi-objective Optimization
- It has the largest collection of EAs and MOEAs of any library. In addition to these pre-defined algorithms, new algorithms can be easily constructed using existing components. http://moeaframework.org/features.html

Implement MSRS Based on MOEA



Agenda

- Intro: Multi-Stakeholder Recommender System
- Research Problems & Methodologies
- Utility-Based MSRS with Case Studies
- Demo Based on MOEA Framework
- Challenges and Open Discussions

Challenges and Open Discussions

- Data Sets
- Evaluations by User Studies
  - A/B test to examine the recommendations
  - Learn the cut-off, e.g., tolerance of the utility loss
  - FAT (Fairness, Accountability, and Transparency)
  - User studies for each type of stakeholders
- Optimizations
  - Other optimization methods? Game theory?
  - Better ways to select the single optimal solution?

Stay Tuned….

https://tutorialcikm.github.io/

Multi-Stakeholder Recommendations: Case Studies, Methods and Challenges

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Tutorial at the 13th ACM Conference on Recommender Systems

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