Recommendation for Multi-Stakeholders and through Neural Review Mining

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Tutorial Schedule

- Section I: Multi-Stakeholder Recommendations
  - Time: 1:30 PM to 3:00 PM
  - Presenter: Yong Zheng (Illinois Tech, USA)
- Coffee Break: 3:00 PM to 3:30 PM
- Section II: Neural Review Mining
  - Time: 3:30 PM to 5:00 PM
  - Presenter: Muthusamy Chelliah (Flipkart, India), Sudeshna Sarkar (IIT Kharagpur)
- Website: https://tutorialcikm.github.io

Section I: Multi-Stakeholder Recommender Systems

Yong Zheng

Illinois Institute of Technology, USA

Time: 1:30 PM to 3:00 PM

https://github.com/irecsys/Tutorial_MSRS

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

Tutorial Materials

- https://github.com/irecsys/Tutorial_MSRS

Agenda

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

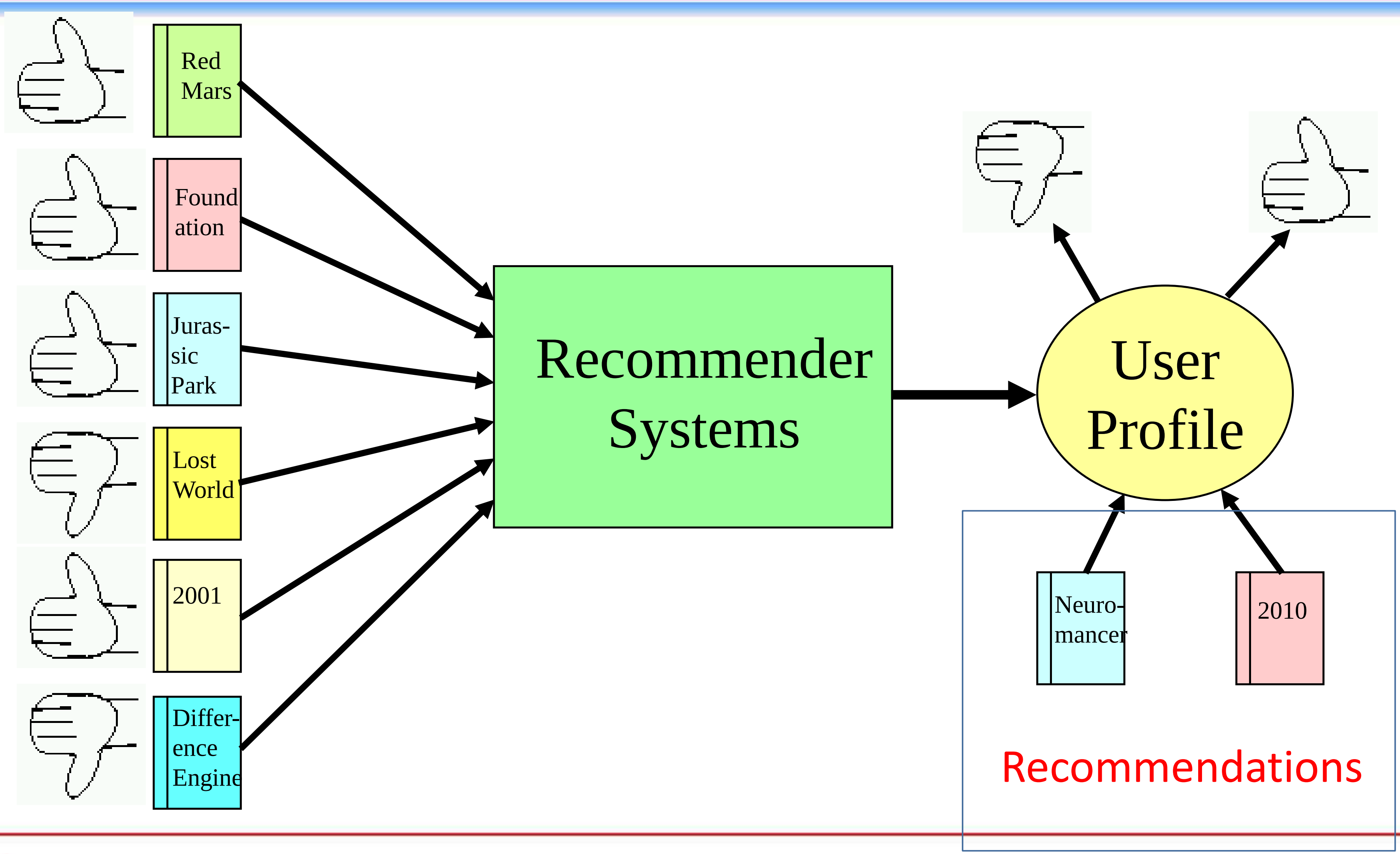
Agenda

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

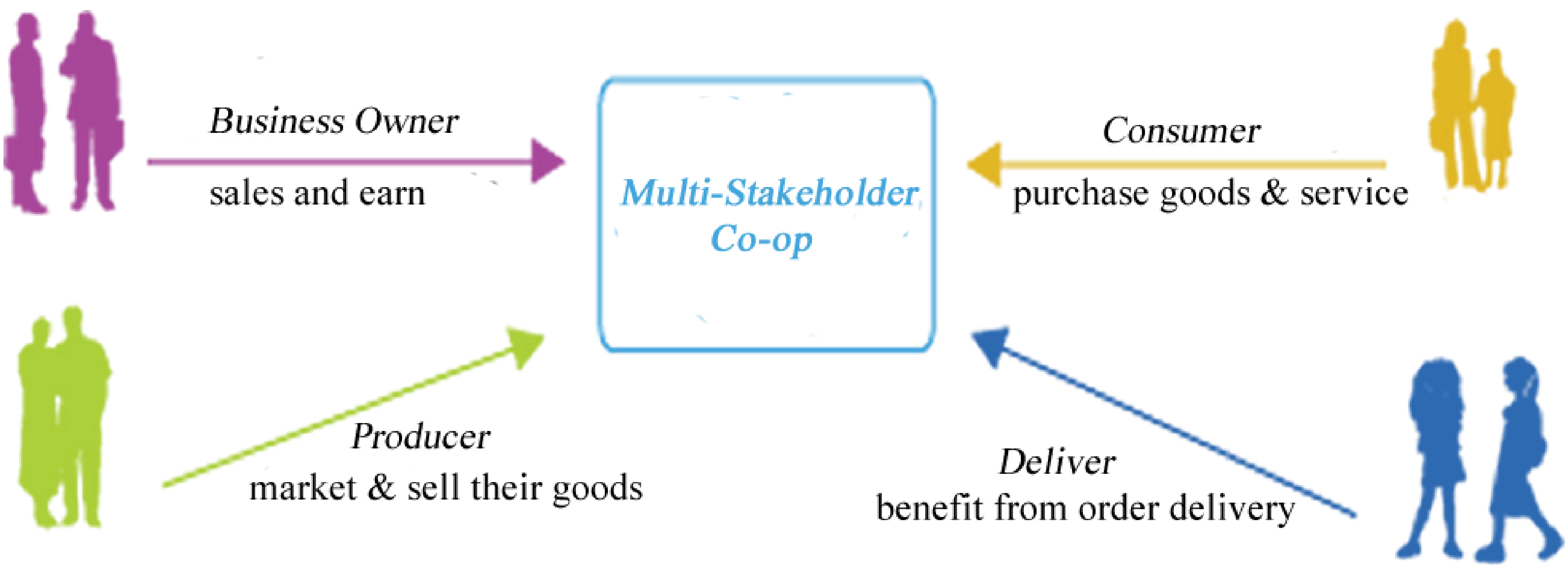
Recommender Systems (RS)

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

The only stakeholder is the receiver of recommendations

Recommender Systems (RS)

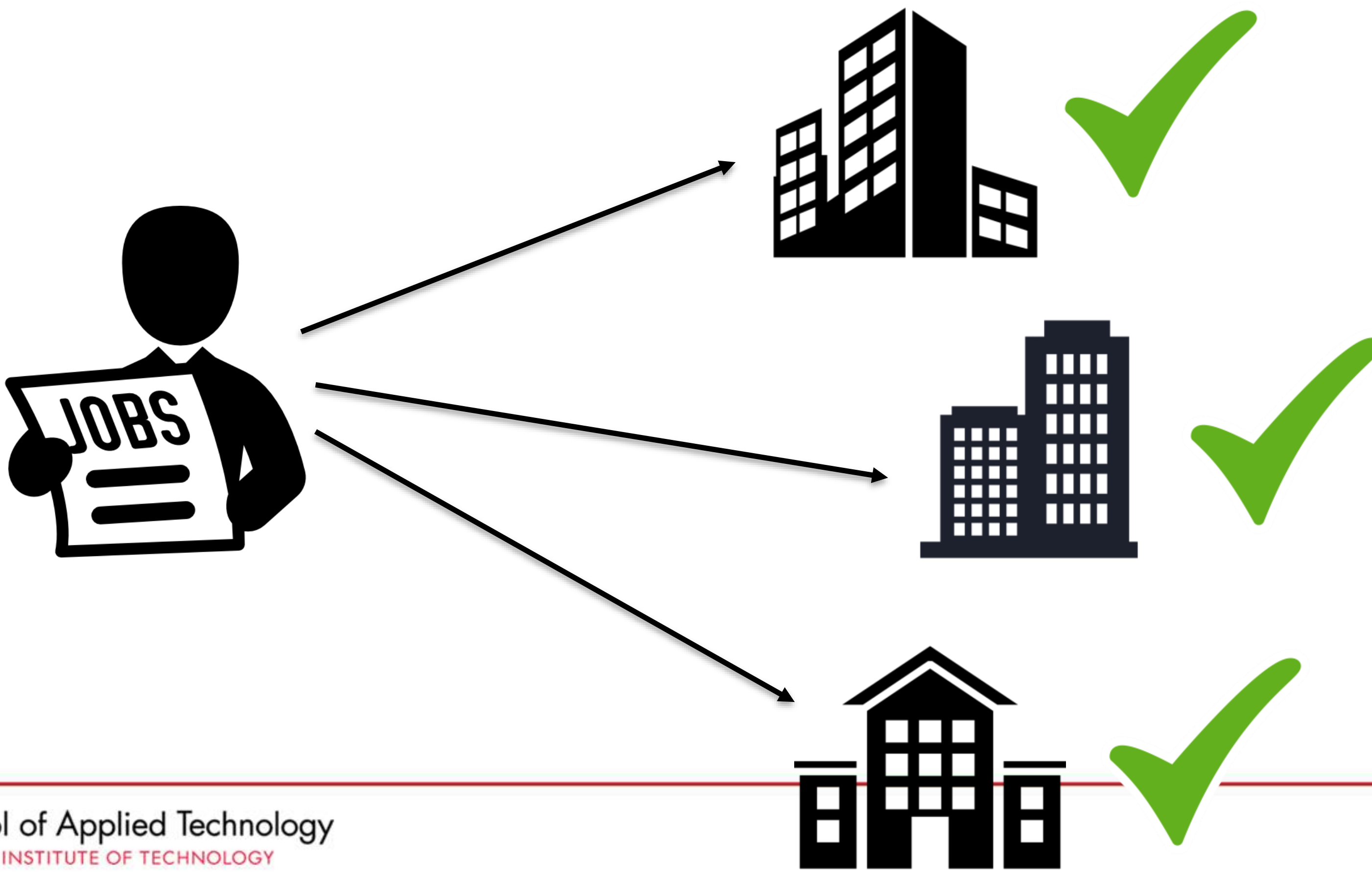
- In fact, there could be multiple stakeholders involved



History of MSRS

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

- Reciprocal Recommendations, e.g. job, dating



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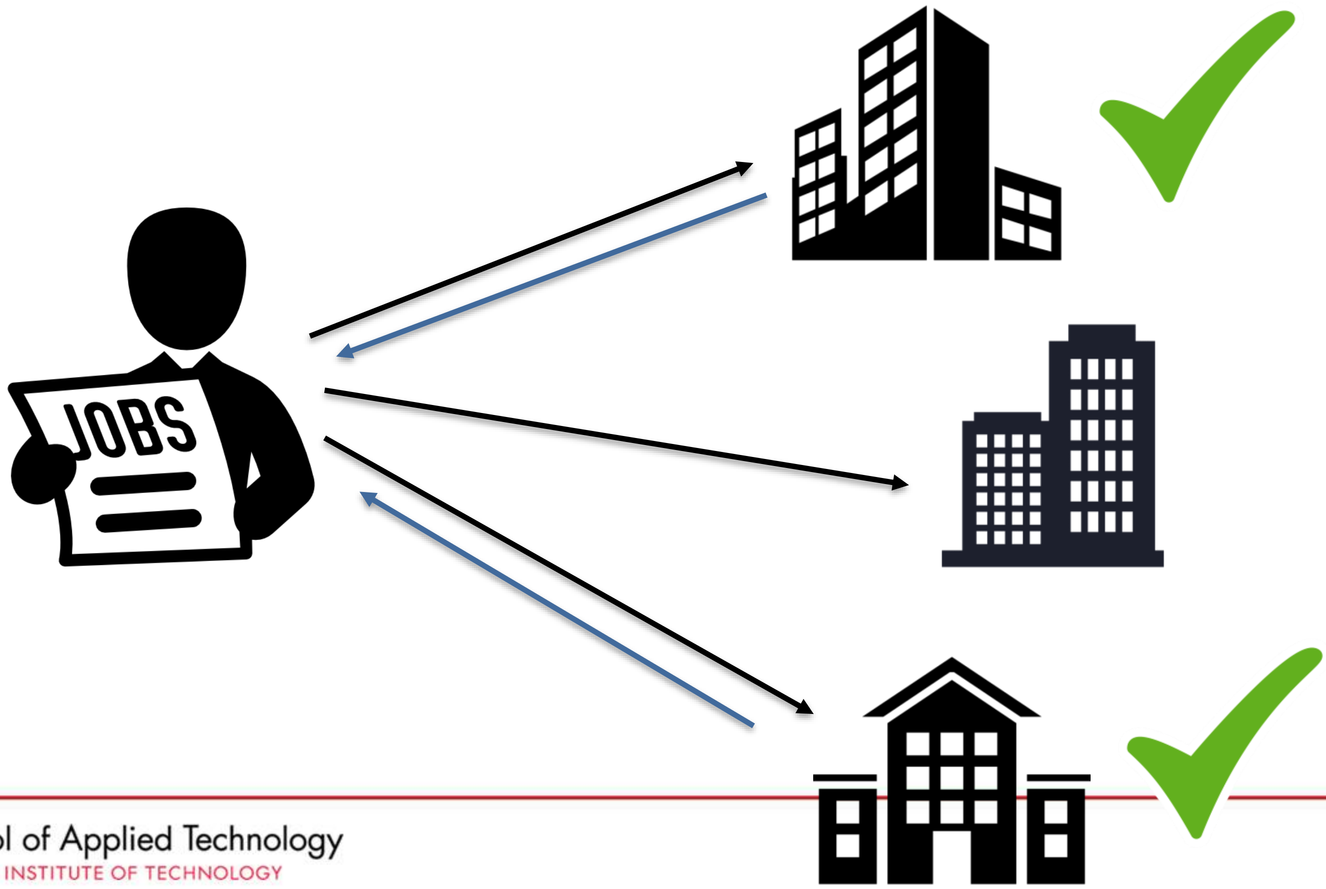


History of MSRS

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

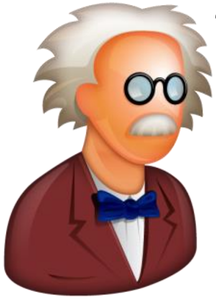
- **Different views**

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

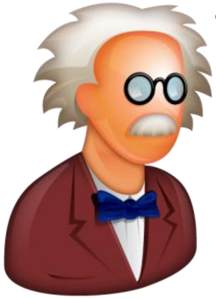
“I wanna more clicks”

Car Producer

“I want users to buy the car”

End user/viewer

“I just like it”



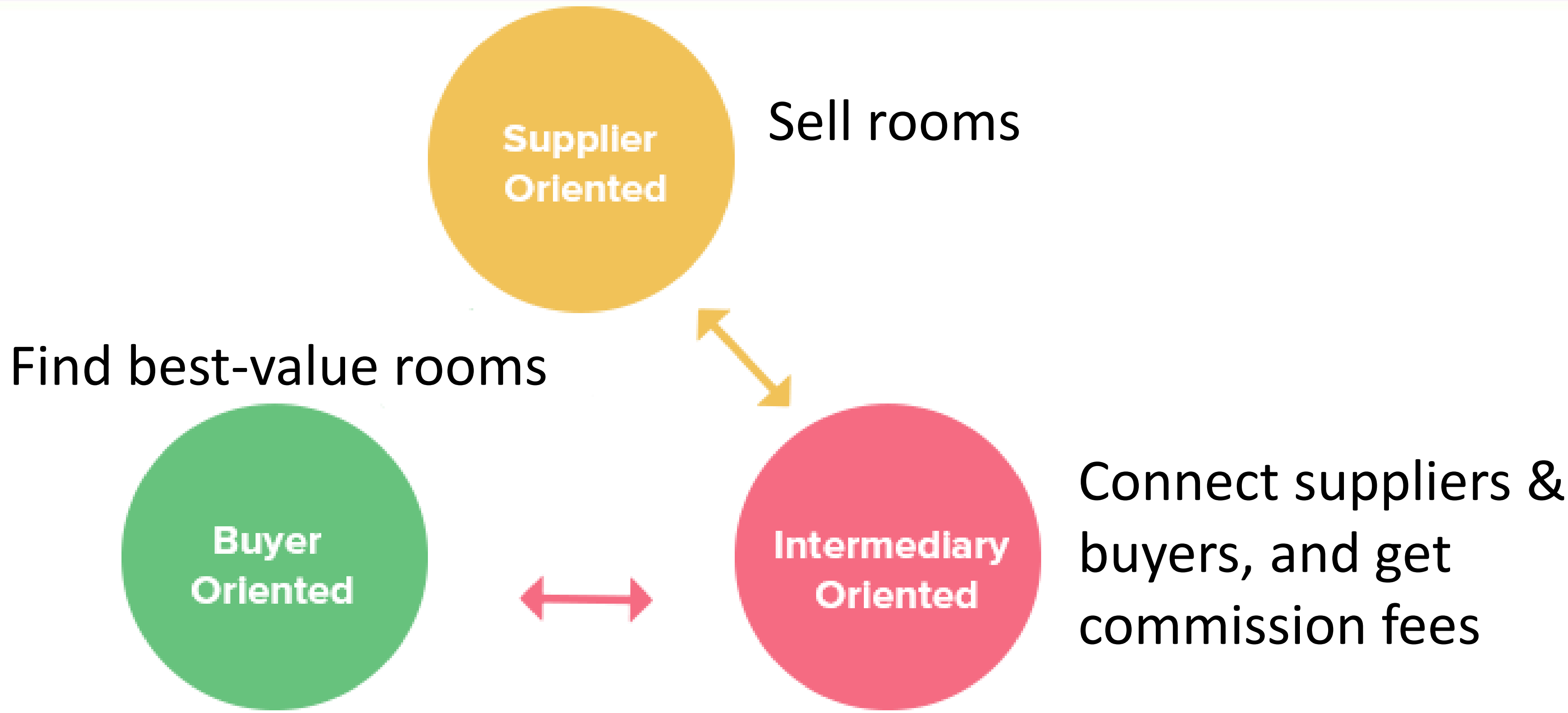
Kids are not customers

No capability to purchase

Kid

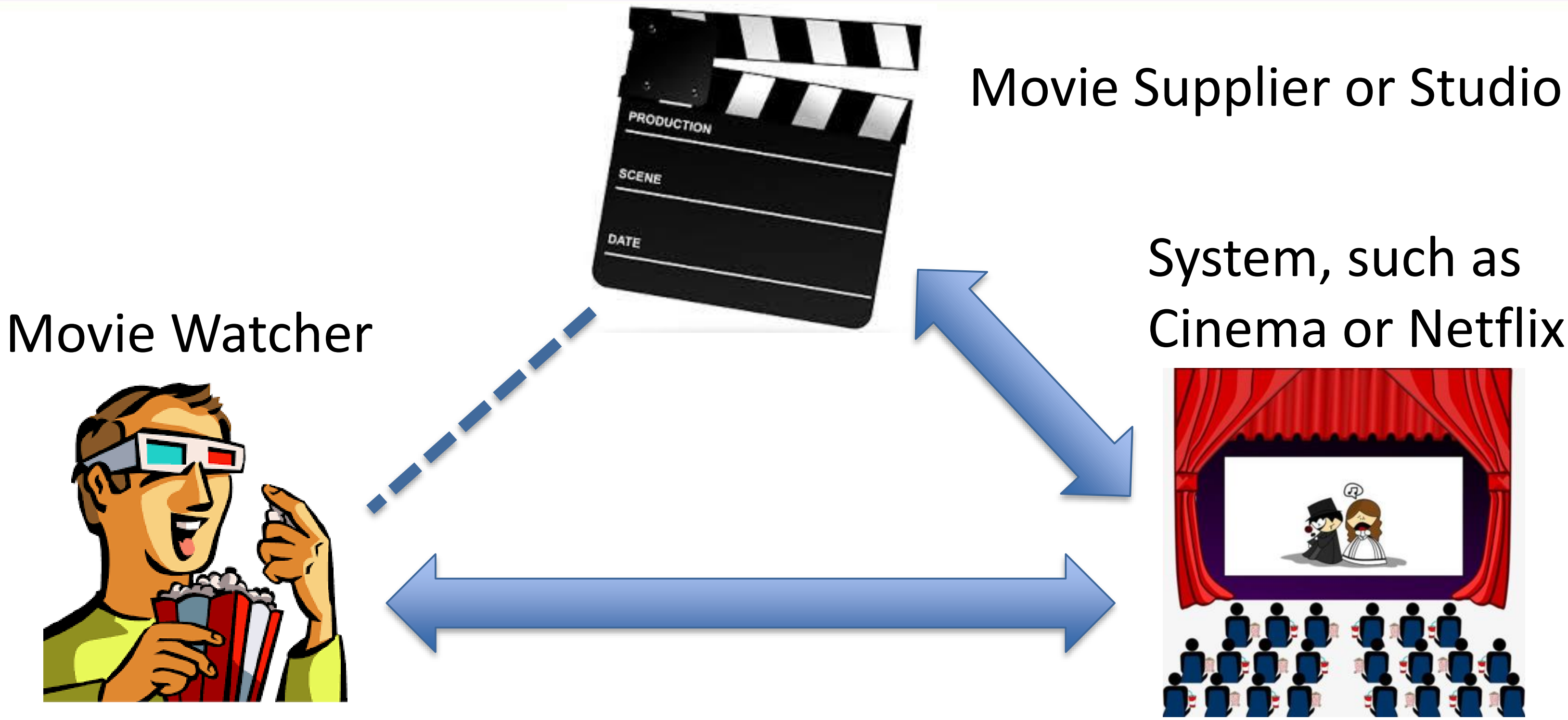
Kid

Example: Hotel Booking at Expedia



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 = non-personalized
Sub p = Personalized

Sup + = Active with query
Sup - = Passive without query

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

MSRS Applications

- The list of multiple stakeholders and the usefulness of MSRS is a domain-specific problem
- MSRS is useful in the following context
  - Advertising
  - Diversity of item providers
  - Conflicting interests
    - Bidding
    - Cost vs profits, loss vs gains
    - Recommendation performance vs profits

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

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
    URL: https://github.com/irecsys/Tutorial_MSRS

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

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

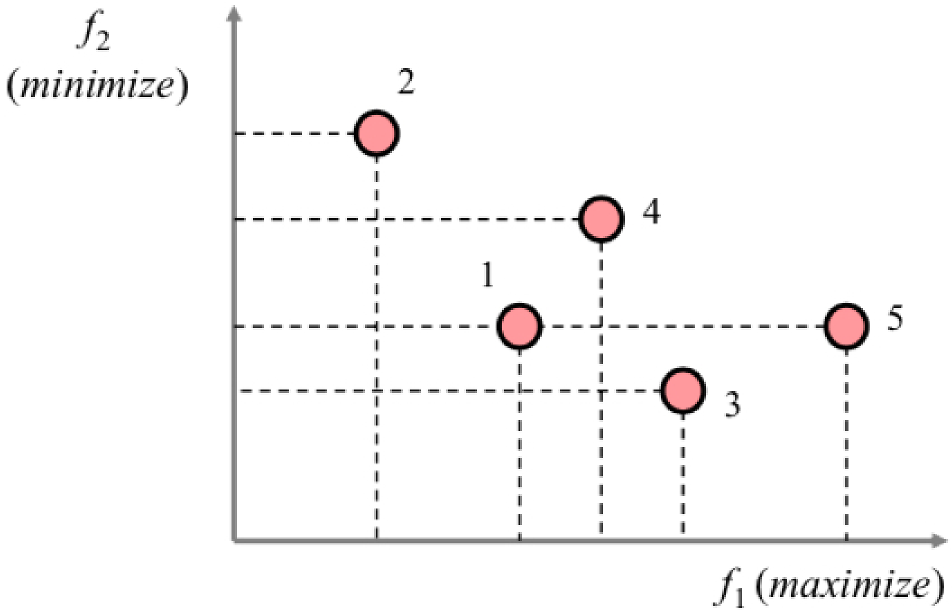
Maximizing Minimizing

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: $U_{s,L}$, $U_{p,L}$, rec

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

2 components: $U_{p,L}$, rec

– 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

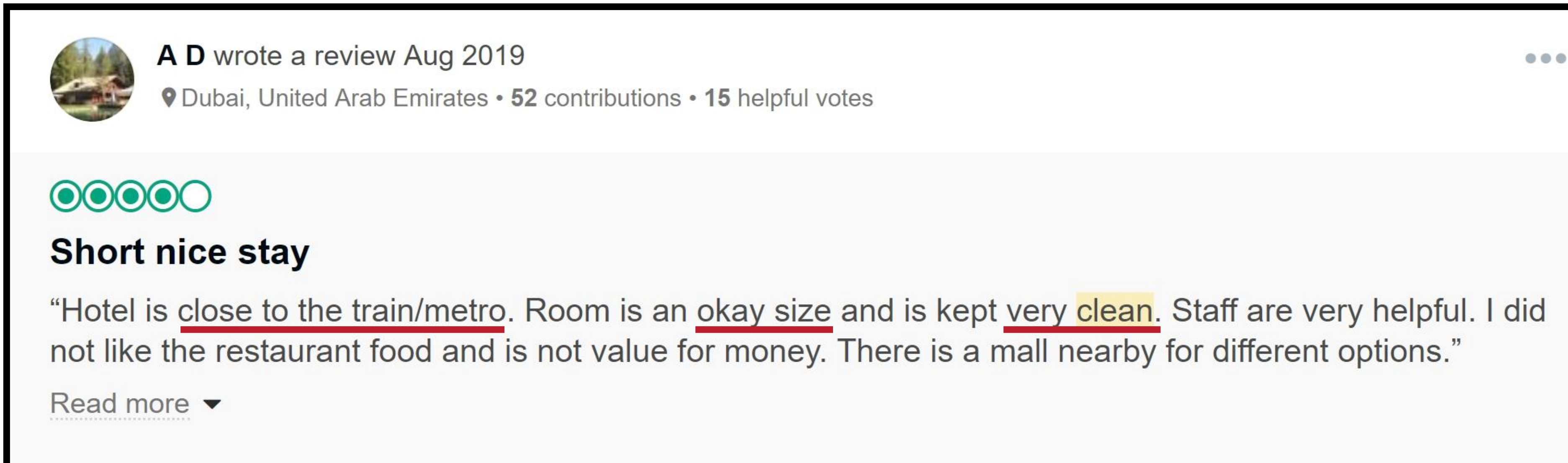
		$U_{s,L}$	$U_{p,L}$	F_1	NDCG	$Loss_1$	$Loss_2$
Baseline	UBRec	0.181	0.134	0.085	0.126	0.180	0.270
	$Rank_p$	0.072	0.298	0.027	0.039	0.425	0.336
MSRS	One-Stage	0.199	0.251	0.074	0.107	0.063	0.144
	Two-Stage	0.161	0.239	0.062	0.092	0.189	0.228

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**



  - 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

Generalized Utility-Based Models

- How to extend the model to general cases?
  - The idea behind utility-based multi-stakeholder recommendations is general
  - The major challenge is building utility functions
  - It is not necessary to have multi-criteria ratings, as able you are able to calculate the utility of the item from the perspective of each stakeholder
  - In terms of the multi-criteria based setting, it is not necessary to let different stakeholders rate the items in the same criteria

Agenda

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

Configuration: Setting.conf

```
# setup the path or the folder
# just put all the data in this folder
data.path.wins=d:\\data\\
data.path.lins=/home/user/

# turn on learning student expectations
# the demo will load expectations if you turn off learning
expectation.learn=off

# the demo will run baseline approaches first if you turn on it
runbaseline=on
```

Configuration: Setting.conf

```
expectation.filename=expectations_student_learned_
by_UBRec_NDCG_0.214.csv

# how many items the system will recommend
topN=10

# maximal number of evaluations
maxeval=5000

# max metrics from UBRec and Rankp
# they are used to calculate the loss
maxf1=0.107
maxndcg=0.214
maxutil_instructor=0.241
maxutil_student=0.745
```

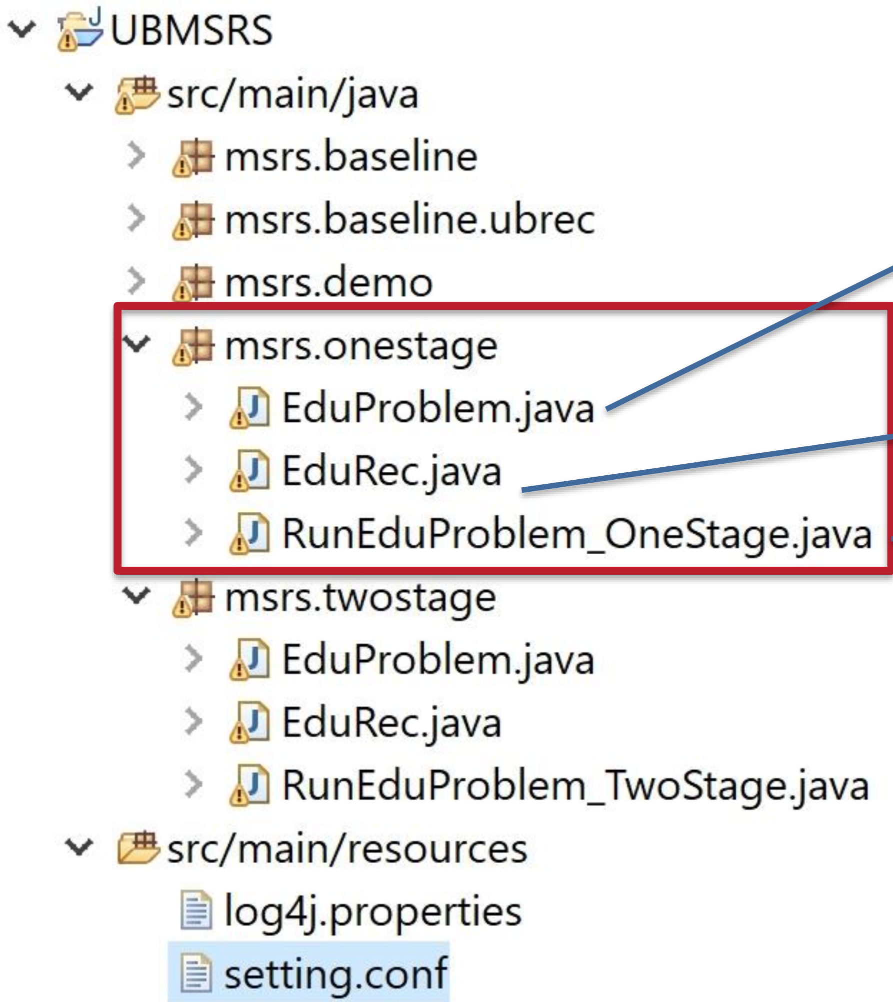
Example of Outputs

- In “data” folder
  - Sample of Outputs_OneStage.txt
  - Sample of Outputs_TwoStage.txt

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



Define the learning problem
Including parameters & objectives

Define the recommendation process

Setup MOO algorithms

Agenda

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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?

Section I: Multi-Stakeholder Recommender Systems

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Illinois Institute of Technology

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Section II: Neural Review Mining

Muthusamy Chelliah (Flipkart, India)
Sudeshna Sarkar (IIT Kharagpur)

Time: 3:30 PM – 5:00 PM

https://github.com/vishalkakkar/CIKM_Tutorial