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# Recommendation for Multi-Stakeholders and through Neural Review Mining

Muthusamy Chelliah (Flipkart, India), Yong Zheng  
(Illinois Tech, USA), Sudeshna Sarkar (IIT Kharagpur),  
Vishal Kakkar (Flipkart, India)



# Tutorial Schedule

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- **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>

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# 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](https://github.com/irecsys/Tutorial_MSRS)

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# 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](https://github.com/irecsys/Tutorial_MSRS)



# Agenda

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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

# Agenda

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- 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

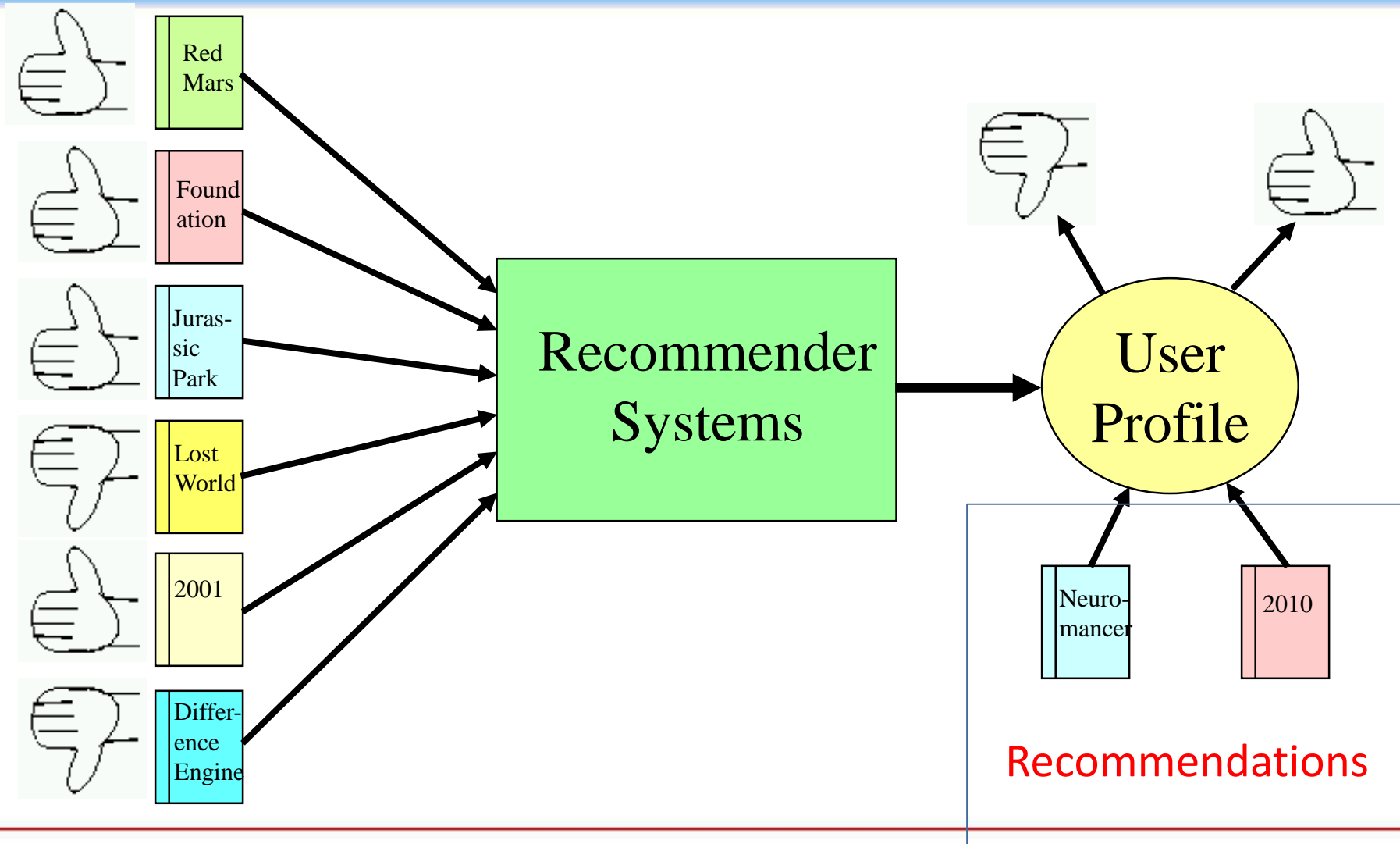


# Recommender Systems (RS)

- RS: item recommendations tailored to user preferences



# How it works





# Different Types of Recommender Systems

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- **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)

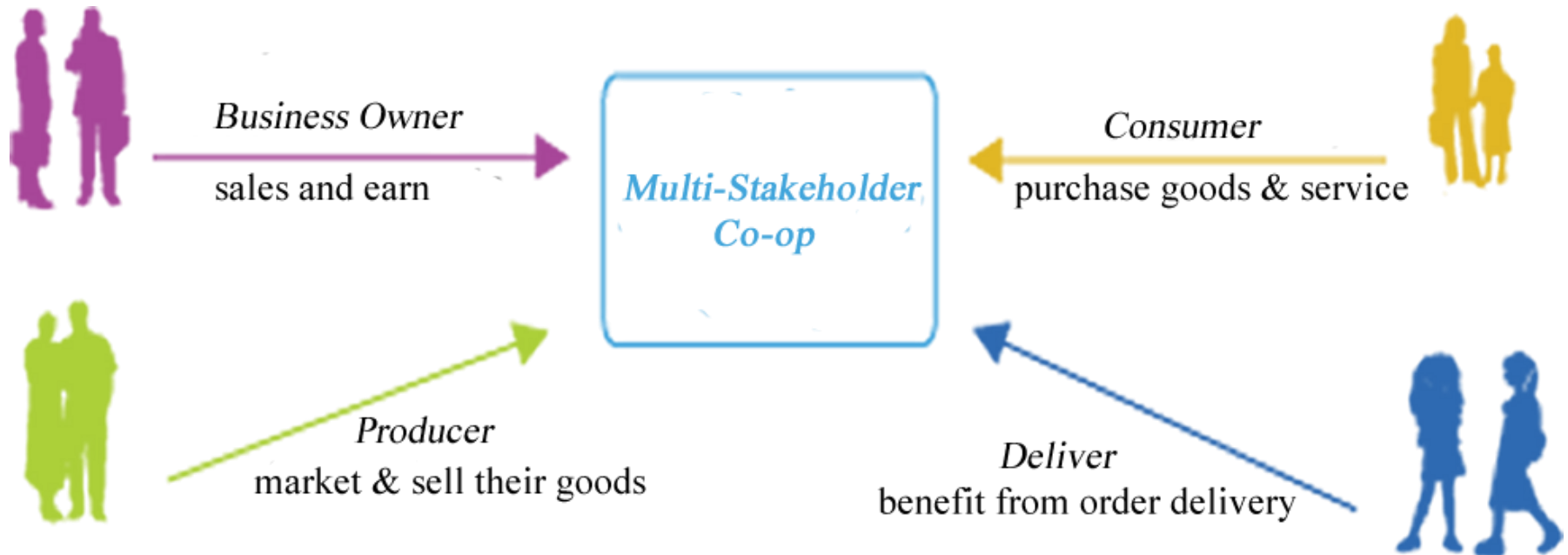
- In these RS, the end user is the only stakeholder



The only stakeholder is the receiver of recommendations

# Recommender Systems (RS)

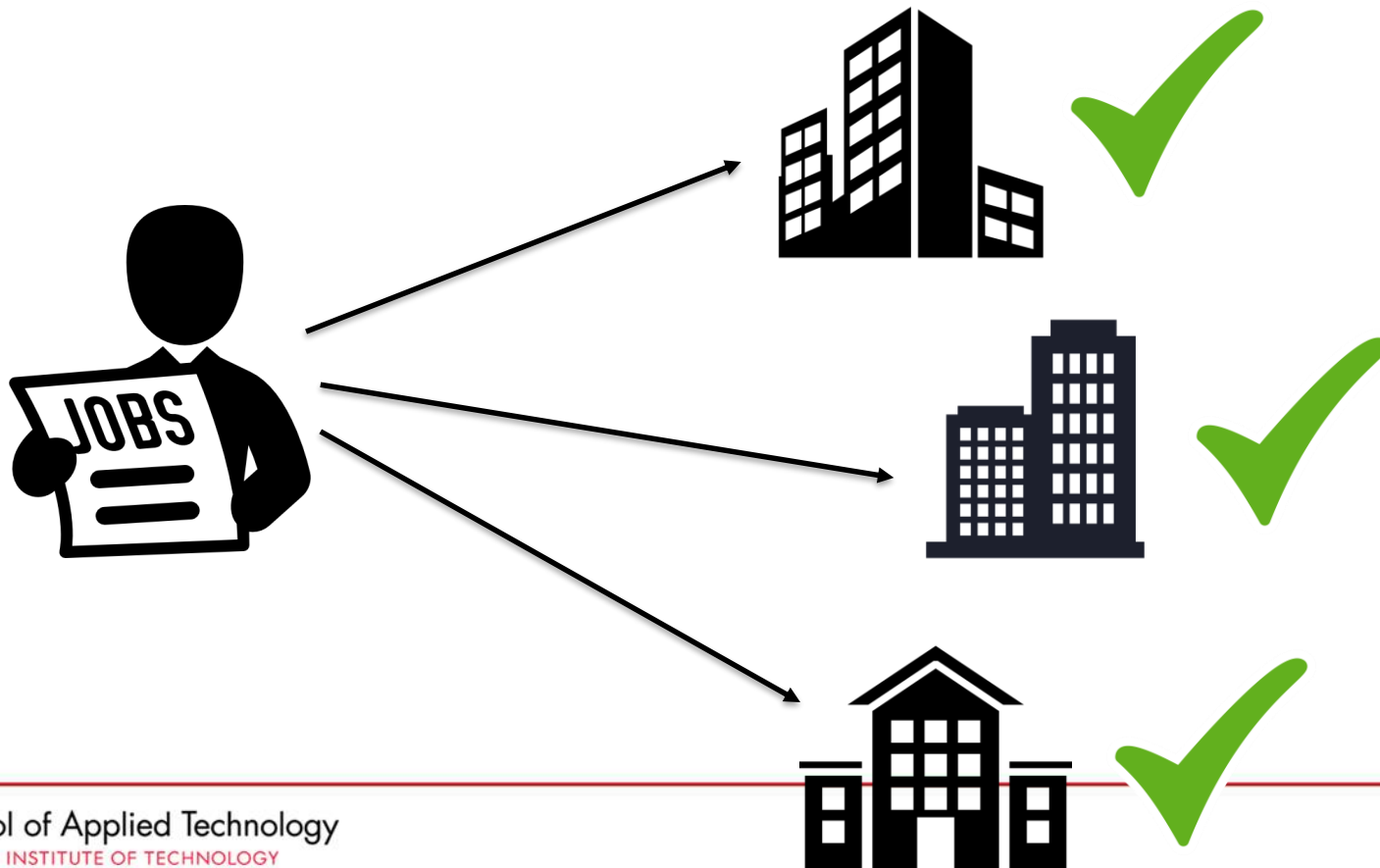
- In fact, there could be multiple stakeholders involved



# History of MSRS

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

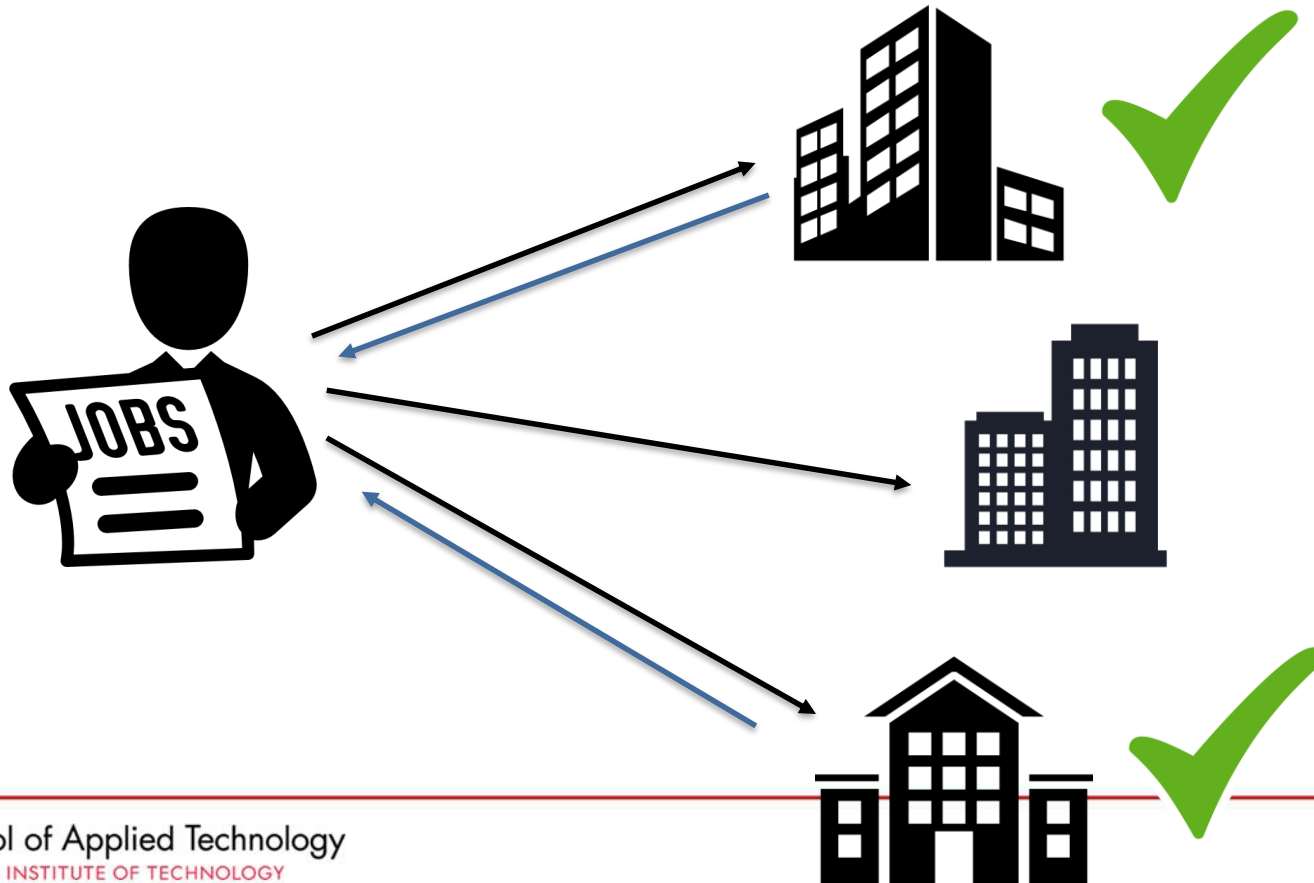
- Reciprocal Recommendations, e.g. job, dating



# History of MSRS

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

- Reciprocal Recommendations, e.g. job, dating



# 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)

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- 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)

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- 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!

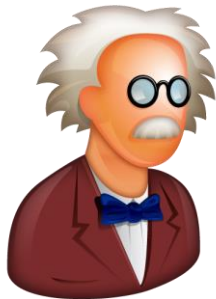
# Example: Advertising

- 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”

Kids are not customers  
No capability to purchase

End user/viewer

“I just like it”

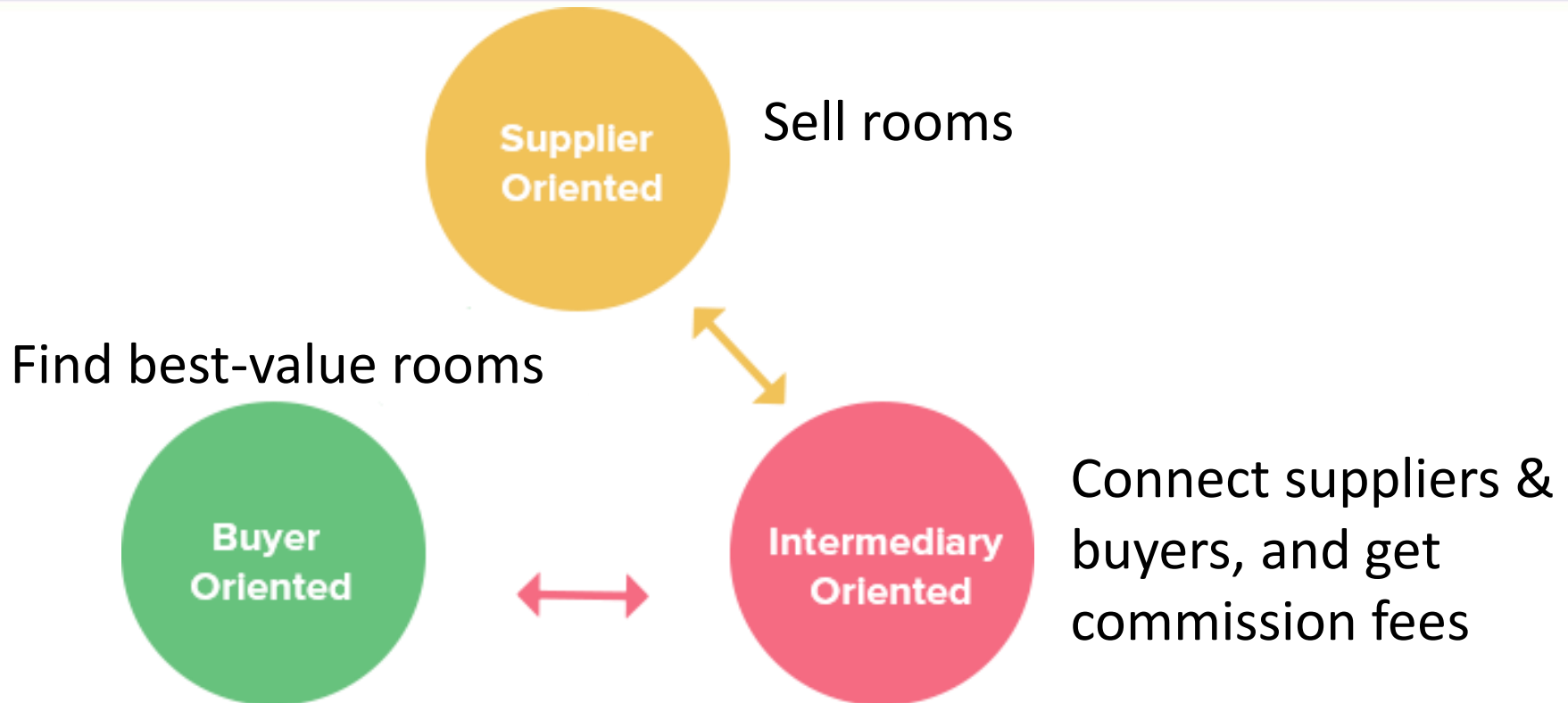


Kid

Kid



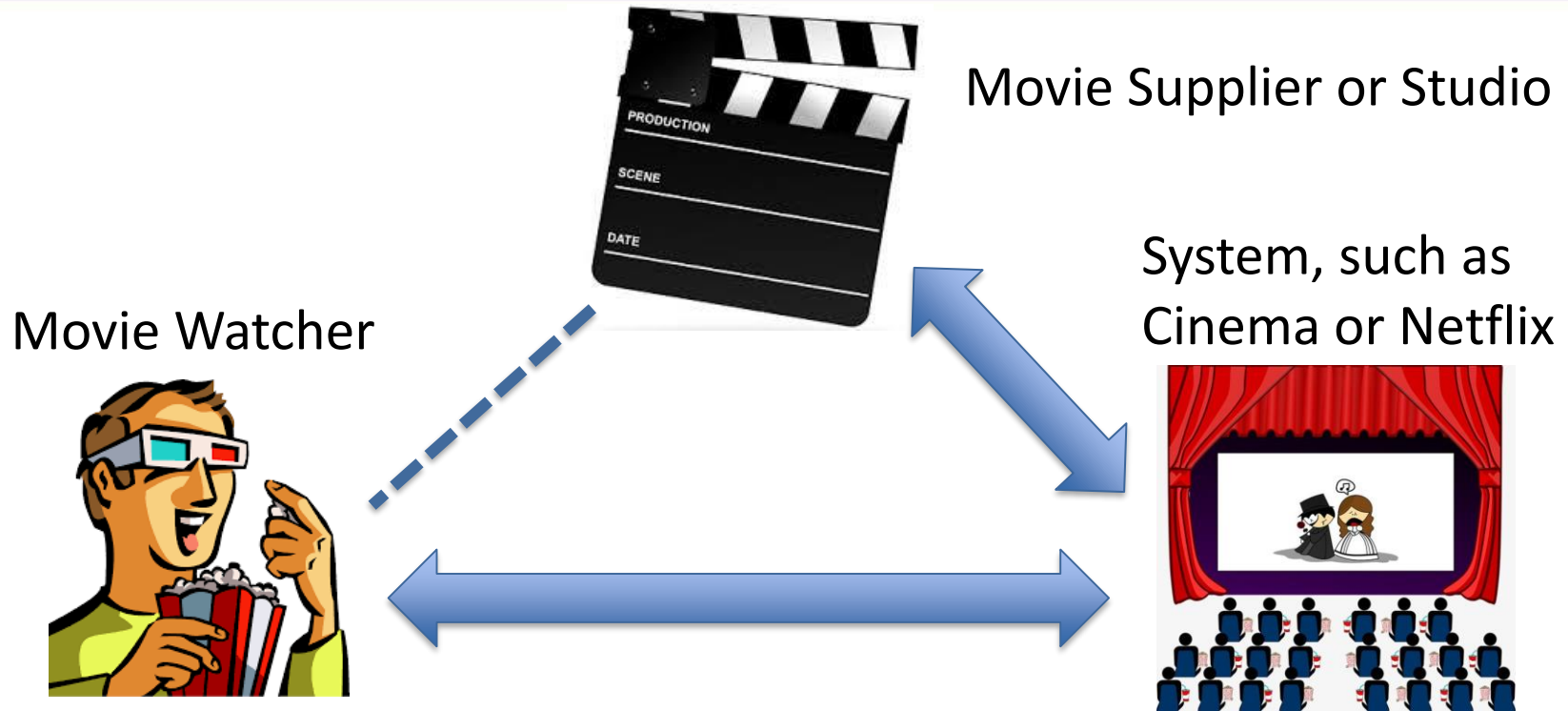
# Example: Hotel Booking at Expedia



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			

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Burke, Robin, and Himan Abdollahpour. "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



# Agenda

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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

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- 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](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

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



# MSRS: Personalization

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- 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

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## 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

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## 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.

$$\begin{aligned} & \max_x \sum_{j \in U} \sum_{r \in R} \sum_{i \in I_r} \hat{u}_{ij} x_{ij}, \\ & \text{subject to} \\ & \sum_{r \in R} \sum_{i \in I_r} x_{ij} = k \quad \forall j \in U, \quad (1) \end{aligned} \quad \left| \quad \begin{aligned} & \frac{\sum_{j \in U} \sum_{i \in I_r} x_{ij}}{\sum_{j \in U} \sum_{r \in R} \sum_{i \in I_r} x_{ij}} \geq \alpha_r p_r \quad \forall r \in R, \quad (2) \\ & x_{ij} \in \{0, 1\} \quad \forall i \in I, j \in U, \quad (3) \end{aligned}$$

# 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

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

# MSRS: Evaluations

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- 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

# Agenda

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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

# Utility-Based MSRS Framework (UBMSRS)

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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

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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

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- 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

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- 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

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- 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

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- 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

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- 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,  $R_{s,t} = \langle \text{App}, \text{Data}, \text{Ease} \rangle$   
Instructor ratings,  $R_{p,t} = \langle \text{Data}, \text{Ease} \rangle$
  - Assume there are student & instructor expectations  
Student Expectation,  $E_s = \langle \text{App}, \text{Data}, \text{Ease} \rangle$   
Instructor Expectation,  $E_p = \langle \text{Data}, \text{Ease} \rangle$
  - There are 269 students and 1 instructor  
We decide to learn  $E_s$   
Acquire  $E_p$  from instructor =  $\langle 4, 4 \rangle$ , and it is minimal  
requirements = students cannot select easier projects  
than  $\langle \text{Data}, \text{Ease} \rangle = \langle 4, 4 \rangle$ , e.g.  $\langle 5, 5 \rangle$  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  $\langle 5, 5, 5, 5 \rangle$  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 =  $\alpha \times U_{s,t} + (1 - \alpha) \times U_{p,t}$ 
    - $\alpha$  is a weight factor,  $[0, 1]$
    - The ranking score is used to rank items
    - $\alpha$  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



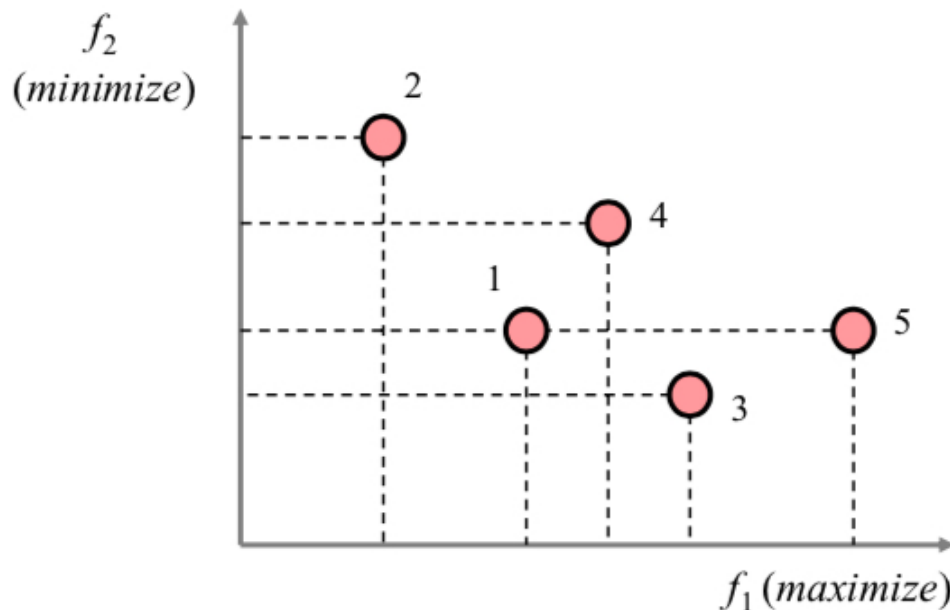
Minimizing

# Utility-Based Multiple Stakeholder Recommendation

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

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- 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

$$Loss_1 = \frac{1}{3} \left( \frac{\max U_{s,L} - U_{s,L}}{\max U_{s,L}} + \frac{\max U_{p,L} - U_{p,L}}{\max U_{p,L}} \right)$$

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

$$+ \frac{1}{2} \left( \frac{\max F_1 - F_1}{\max F_1} + \frac{\max NDCG - NDCG}{\max NDCG} \right)$$

---

$$Loss_2 = \frac{1}{2} \left( \frac{\max U_{p,L} - U_{p,L}}{\max U_{p,L}} \right)$$

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

$$+ \frac{1}{2} \left( \frac{\max F_1 - F_1}{\max F_1} + \frac{\max NDCG - NDCG}{\max NDCG} \right)$$

- The max values above are from baseline methods

- UBRec: recommend items by  $U_{s,t}$  only
- Rank<sub>p</sub>: 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 =  $\langle 2, 2, 2 \rangle$   
Rating vector for item T1 =  $\langle 1, 1, 1 \rangle$   
Rating vector for item T2 =  $\langle 3, 3, 3 \rangle$   
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

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- 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  $\langle \text{Data}, \text{Ease} \rangle$  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 <sub>p</sub>	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

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- 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



# Agenda

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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



# Demo

- Demo, [https://github.com/irecsys/Tutorial\\_MSRS](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<sub>p</sub>
  - 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

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- 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

## ▼ UBMSRS

### ▼ src/main/java

> msrs.baseline

> msrs.baseline.ubrec

> msrs.demo

#### ▼ msrs.onestage

> EduProblem.java

> EduRec.java

> RunEduProblem\_OneStage.java

#### ▼ msrs.twostage

> EduProblem.java

> EduRec.java

> RunEduProblem\_TwoStage.java

### ▼ src/main/resources

log4j.properties

setting.conf

Define the learning problem  
Including parameters & objectives

Define the recommendation process

Setup MOO algorithms

# Agenda

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# Challenges and Open Discussions

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- 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?





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# Section I: Multi-Stakeholder Recommender Systems



**ANY QUESTIONS?**

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Yong Zheng

Illinois Institute of Technology

Chicago, Illinois, USA

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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](https://github.com/vishalkakkar/CIKM_Tutorial)

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