
Recommendation for Multi-Stakeholders and through Neural Review Mining

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(Illinois Tech, USA), Sudeshna Sarkar (IIT Kharagpur),
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BEIJING CHINA
November 03-07, 2019

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)



Section I: Multi-Stakeholder Recommender Systems

Yong Zheng

Illinois Institute of Technology

Chicago, Illinois, USA

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

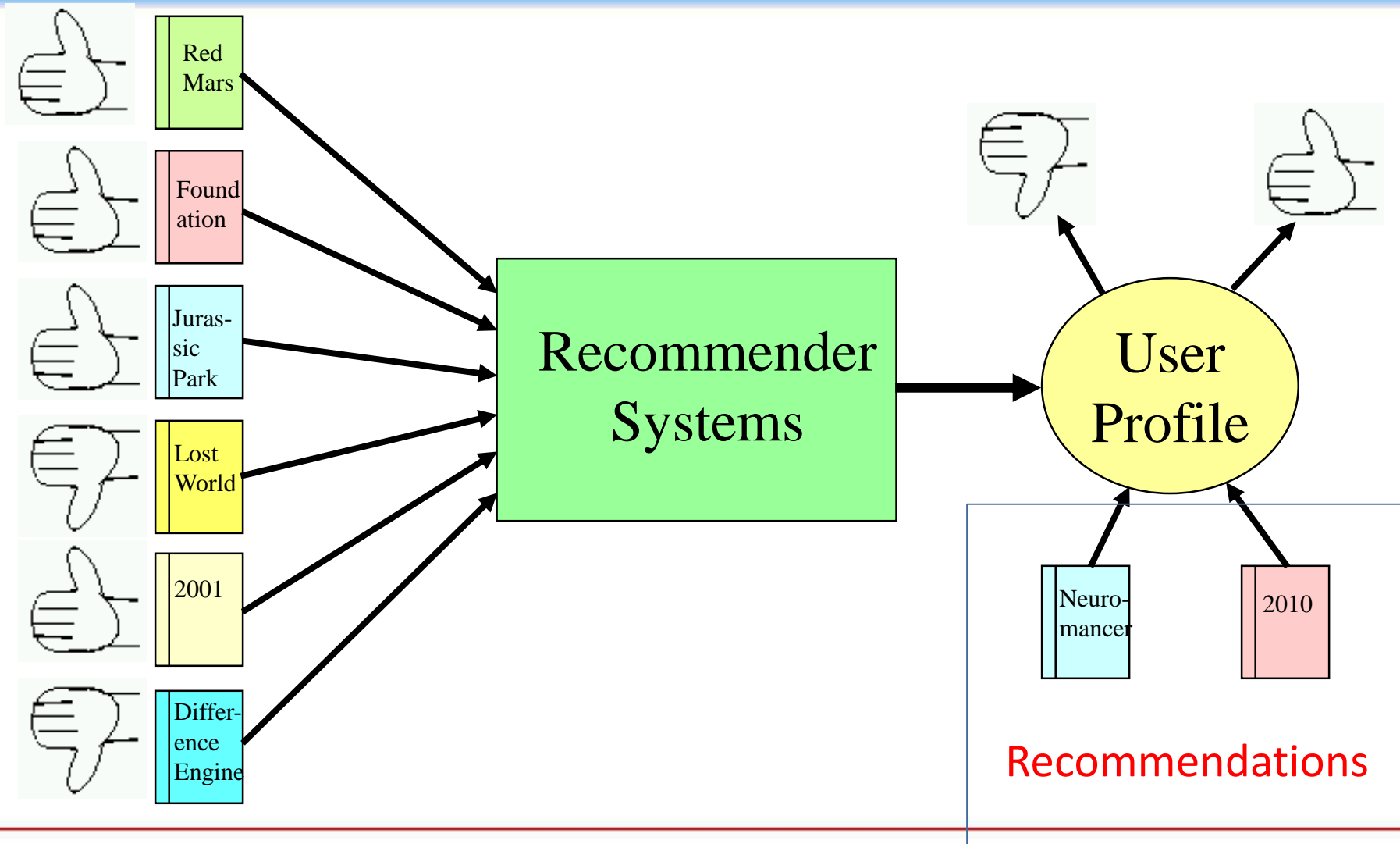


Recommender Systems (RS)

- RS: item recommendations tailored to user preferences



How it works



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)

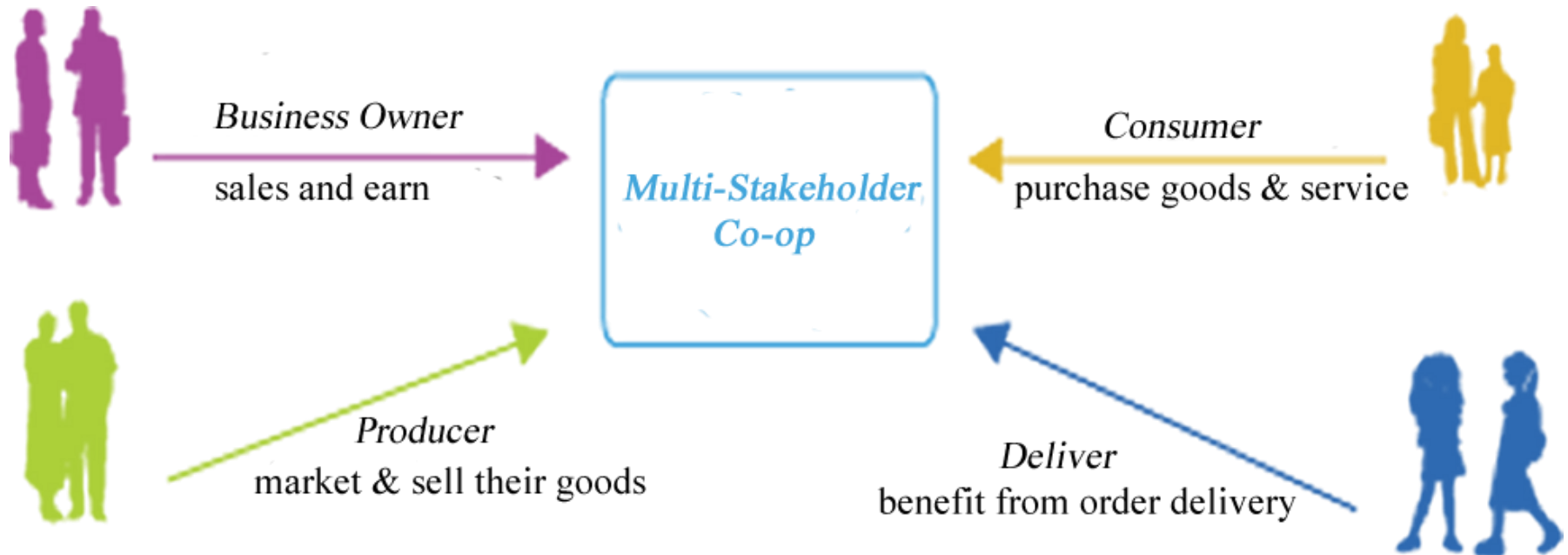
- In these RS, the end user is the only stakeholder



The only stakeholder is the receiver of recommendations

Recommender Systems (RS)

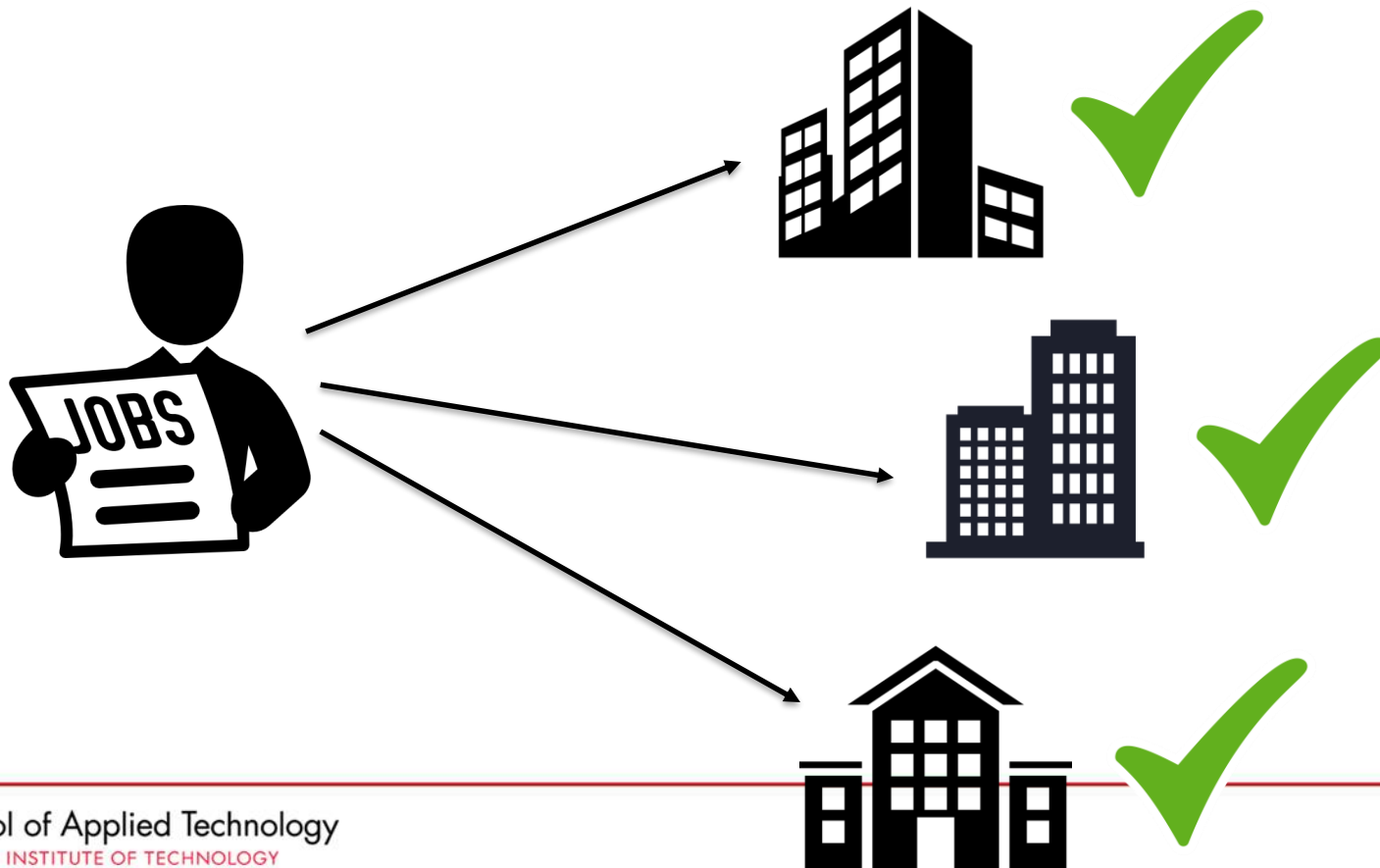
- In fact, there could be multiple stakeholders involved



History of MSRS

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

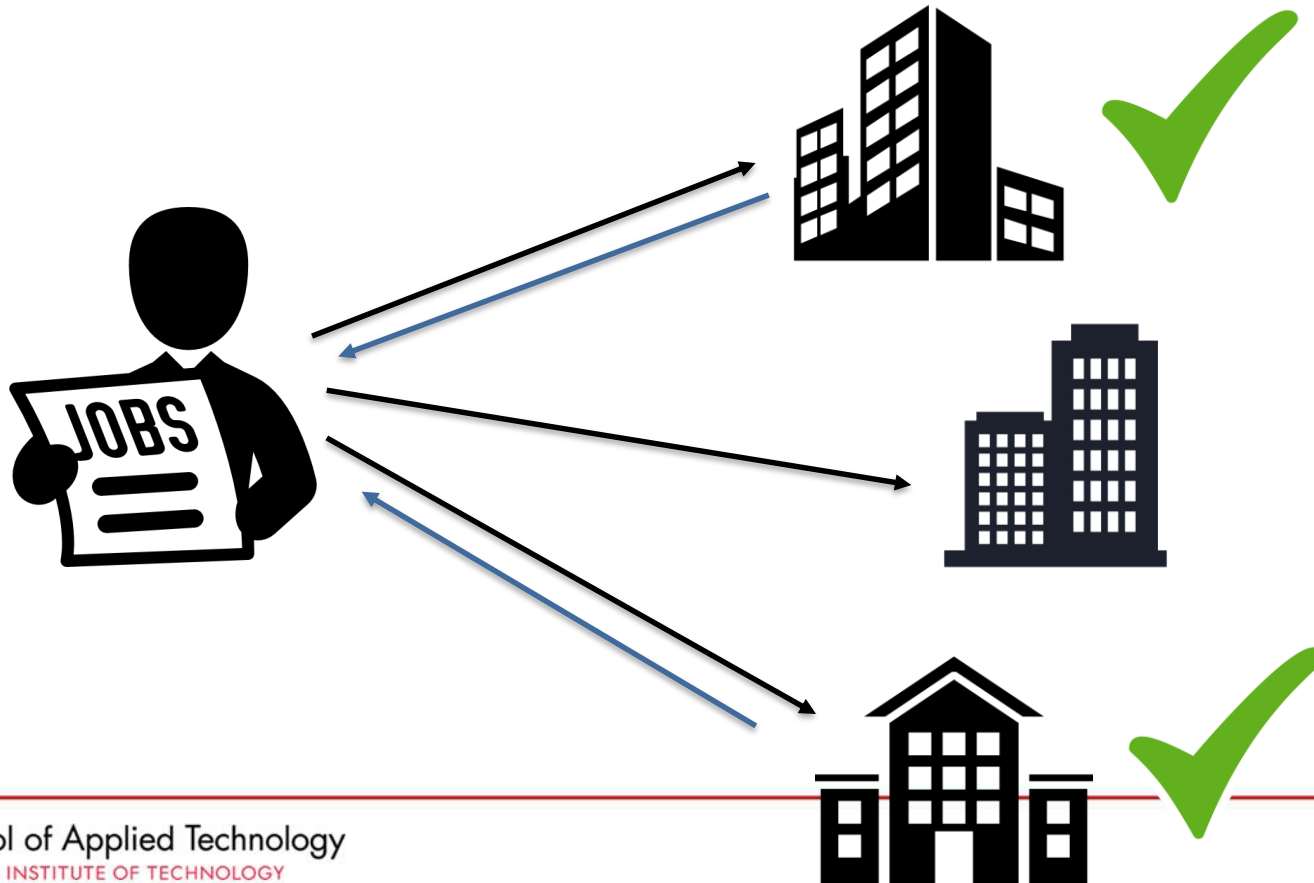
- Reciprocal Recommendations, e.g. job, dating



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)

- 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!

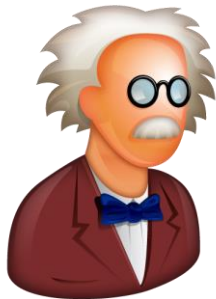
Example: Advertising

- Different views



Advertising Agency

“I wanna more clicks”



Car Producer

“I want users to buy the car”



End user/viewer

“I just like it”



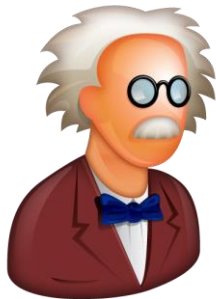
Example: Advertising

- Need a balance



Advertising Agency

“I wanna more clicks”



Car Producer

“I want users to buy the car”

Kids are not customers
No capability to purchase

End user/viewer

“I just like it”

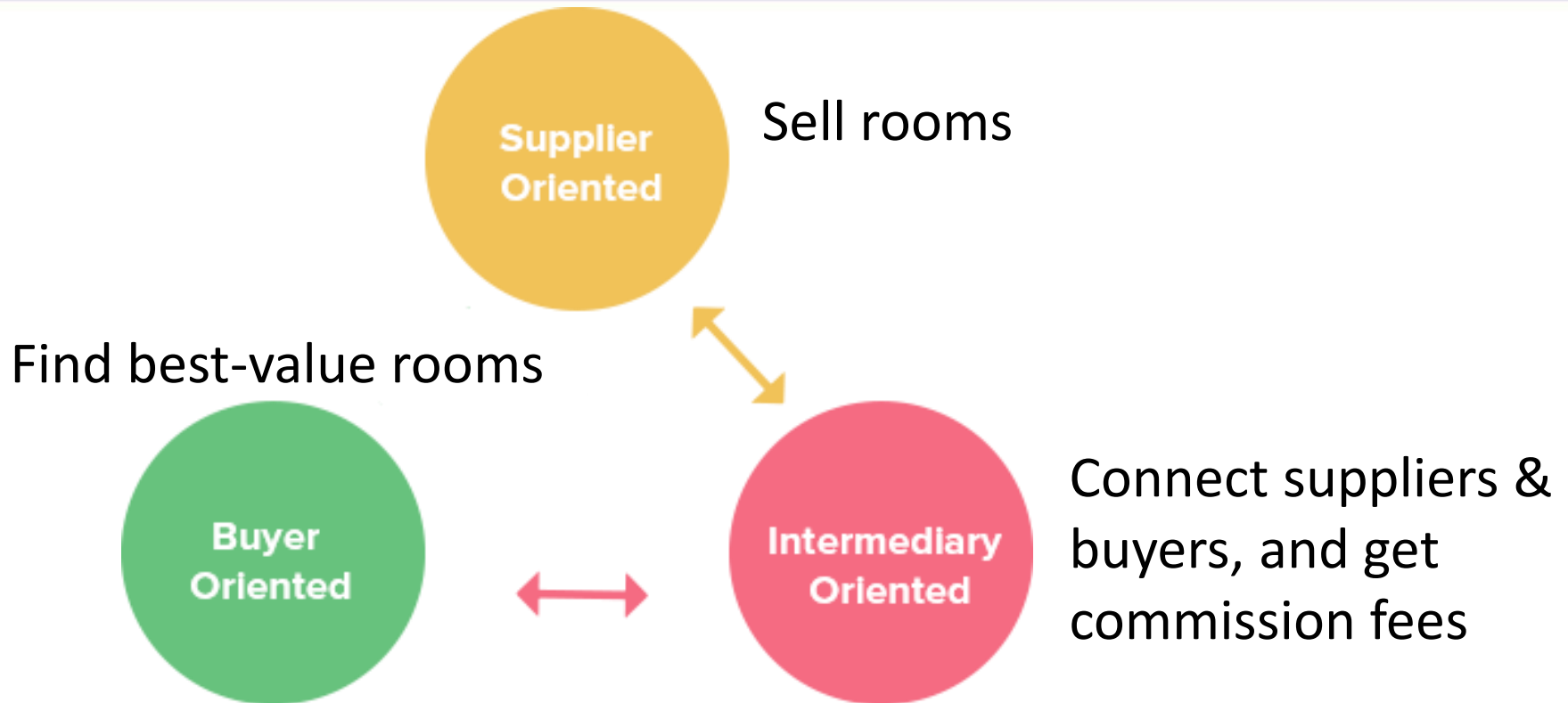


Kid

Kid

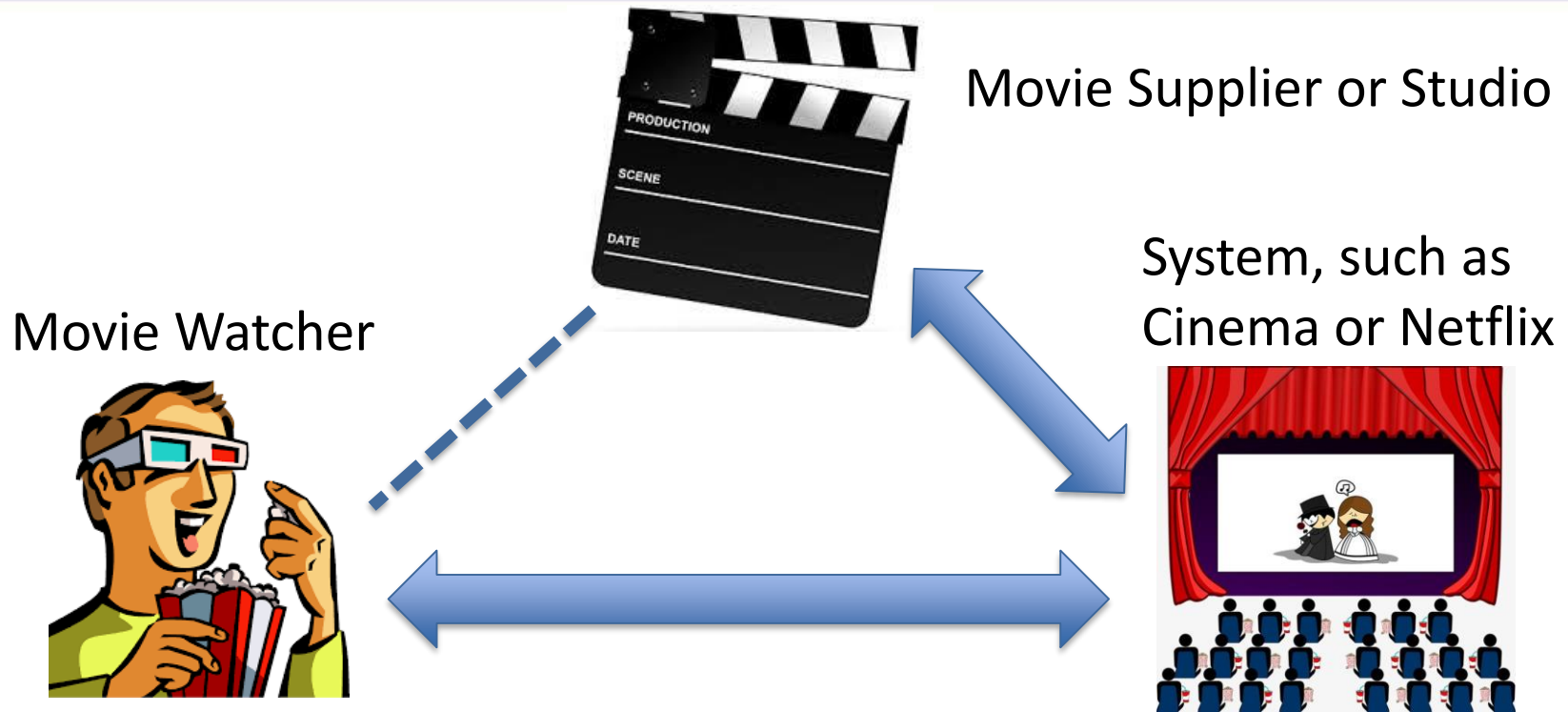


Example: Hotel Booking at Expedia



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			

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

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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

- 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
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 - 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.

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

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



Agenda

- 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)

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 projectsIt 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, $R_{s,t} = \langle \text{App}, \text{Data}, \text{Ease} \rangle$
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 = $\alpha \times U_{s,t} + (1 - \alpha) \times U_{p,t}$
 - 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



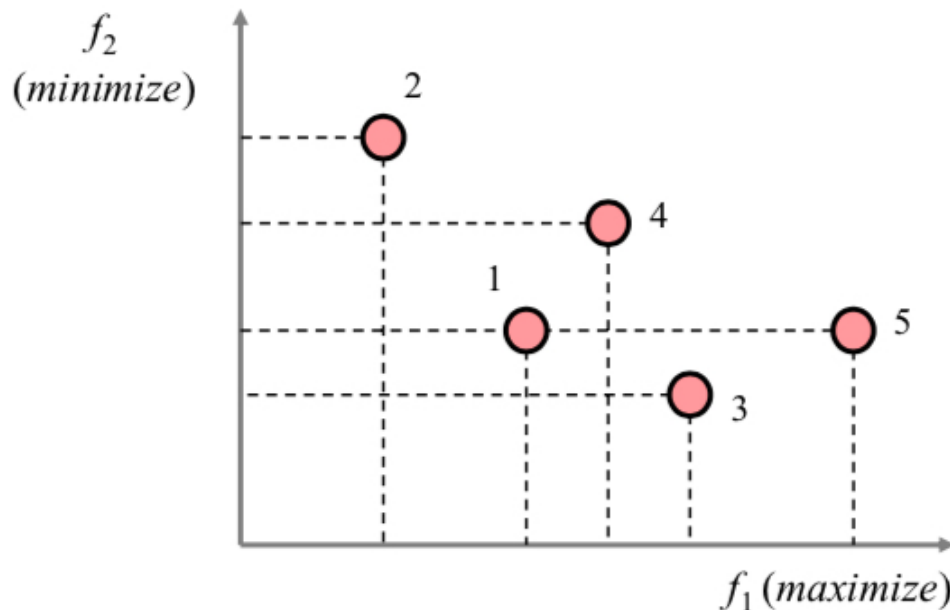
Minimizing

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

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

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

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

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 = $\langle 2, 2, 2 \rangle$
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

- 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 _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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- 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

▼ 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

- Intro: Multi-Stakeholder Recommender System
- Research Problems & Methodologies
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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



ANY QUESTIONS?

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Section II: Neural Review Mining

Muthusamy Chelliah (Flipkart, India)

Sudeshna Sarkar (IIT Kharagpur)

Time: 3:30 PM – 5:00 PM
