

Multistakeholder Recommendation

Part 1

Objectives

- ▶ You should come away from this part of the session
 - ▶ Knowing what multistakeholder recommendation is
 - ▶ Being able to identify multistakeholder issues that might arise in an application
 - ▶ Understanding a range of approaches for implementing and evaluating MSR

Who am I

- ▶ Recommender systems researcher since the mid-90s (before “recommender systems” was the accepted term)
- ▶ Currently: Professor in the Department of Information Science, University of Colorado, Boulder
 - ▶ Director of That Recommender Systems Lab (that-recsys-lab.net)
- ▶ Formerly: DePaul University in Chicago (2002-2018)
 - ▶ Co-led the Web Intelligence Lab with Bamshad Mobasher
- ▶ Current chair of the Steering Committee for the RecSys conference
- ▶ Organizing the Recommendation in Multistakeholder Environments workshop (RMSE 2019)
 - ▶ next week

We are looking for new PhD students!

There's also a diversity-focused post-doc at CU Boulder

Raise your hand if

- ▶ Have prior exposure to the concept of multistakeholder recommendation?
- ▶ Have prior exposure to the concept of fairness-aware recommendation?
- ▶ Have used a multistakeholder recommender system?
- ▶ Have used the Amazon.com web site?
- ▶ Have used Facebook?

Outline of these sessions

- ▶ Session I: Multistakeholder recommendation
 - ▶ Definitions
 - ▶ Challenges
 - ▶ Evaluation
 - ▶ Algorithms
- ▶ Session II: Fairness-aware recommendation
 - ▶ Definitions
 - ▶ Challenges
 - ▶ Evaluation
 - ▶ Algorithms

Stakeholder (definition)

- ▶ Comes from the literature on business management
 - ▶ A stakeholder in an organization is (by definition) any group or individual who can affect or is affected by the achievement of the organization's objectives.
 - ▶ (Freeman, 2010)
- ▶ For recommender systems, my definition
 - ▶ A recommendation stakeholder is any group or individual who can affected or is affected by the delivery of recommendations to users.
- ▶ Normally in recommender systems research
 - ▶ We consider only the user as a stakeholder
 - ▶ Optimize recommendations for "user satisfaction"

Multistakeholder recommendation environment

- ▶ An environment / application where the requirements for recommendation generation
 - ▶ Include the perspectives of multiple parties
 - ▶ Not just the user
 - ▶ Example: computational advertising
 - ▶ User ~~wants~~ might respond to ads meeting their interests
 - ▶ Advertisers want users within an audience segment
 - ▶ Publishers want to maximize ad revenues

Isn't this bad?

- ▶ “Recommendation should be all about the user”
- ▶ Two answers
 - ▶ This is already the case in many e-commerce settings
 - ▶ Filter out products that are out-of-stock
 - ▶ Optimize for time on site (do users really want that?)
 - ▶ Promote “house brands”
 - ▶ Promote new sellers / new items to overcome cold-start
 - ▶ Explore-exploit
 - ▶ Better to be transparent about the considerations
 - ▶ Without recognition of the multistakeholder nature of business
 - ▶ We can get into trouble: unfairness, bias, filter bubbles
 - ▶ Why not make these constraints explicit in our systems
 - ▶ Not something tacked on after the fact

Business Roundtable

- ▶ Recent report from the US Business Roundtable organization re-defining the role of a corporation:
- ▶ *"While each of our individual companies serves its own corporate purpose, we share a fundamental commitment to **all of our stakeholders**. We commit to:*
 - ▶ *Delivering value to our customers...*
 - ▶ *Investing in our employees...*
 - ▶ *Dealing fairly and ethically with our suppliers...*
 - ▶ *Supporting the communities in which we work...*
 - ▶ *Generating long-term value for shareholders...*
- ▶ *Each of our stakeholders is essential. **We commit to deliver value to all of them, for the future success of our companies, our communities and our country.**"*
- ▶ Signed by 180 CEOs
 - ▶ Including Amazon, Apple, Oracle, SAP, etc.

Multistakeholder recommendation

- ▶ A multistakeholder recommender system is one in which the objectives of multiple parties, in addition to objectives attributed to the user, are considered in the computation of recommendations,
 - ▶ Especially a system in which such parties lie on different sides of the recommendation interaction.

Multisided platforms (MSPs)

- ▶ *Especially a system in which such parties lie on different sides of the recommendation interaction.*
- ▶ “Multisided platforms are technologies, products or services that create value primarily by enabling direct interactions between two or more customer or participant groups.” (Hagiu, 2014)



What questions so far?



Example

- ▶ Out of school time activities
- ▶ Wide range of options
 - ▶ entire summer
 - ▶ regular after-school
 - ▶ one-time events
- ▶ Wide range of providers
 - ▶ schools
 - ▶ non-profits
 - ▶ museums
 - ▶ sports clubs
- ▶ Audience: teens



Exercise

- ▶ Form groups of three or four
- ▶ Consider a system that recommends such activities
- ▶ List stakeholder groups
 - ▶ 15 minutes
- ▶ Be prepared to discuss your stakeholder groups

Possible confusion

- ▶ Isn't it just the system designer / owner?
- ▶ People who are building the system decide what objectives to optimize
 - ▶ aren't they the only stakeholders?
- ▶ The idea of a stakeholder is about impact, not about control

Distinction

▶ Evaluation

- ▶ A recommender system implementer can apply a metric that evaluates the impact of its recommendations on different stakeholders
- ▶ To understand how different stakeholders are affected

▶ Optimization

- ▶ An implementer can incorporate objectives related to different stakeholders as part of system optimization
- ▶ Tuning the system to achieve particular stakeholder impact

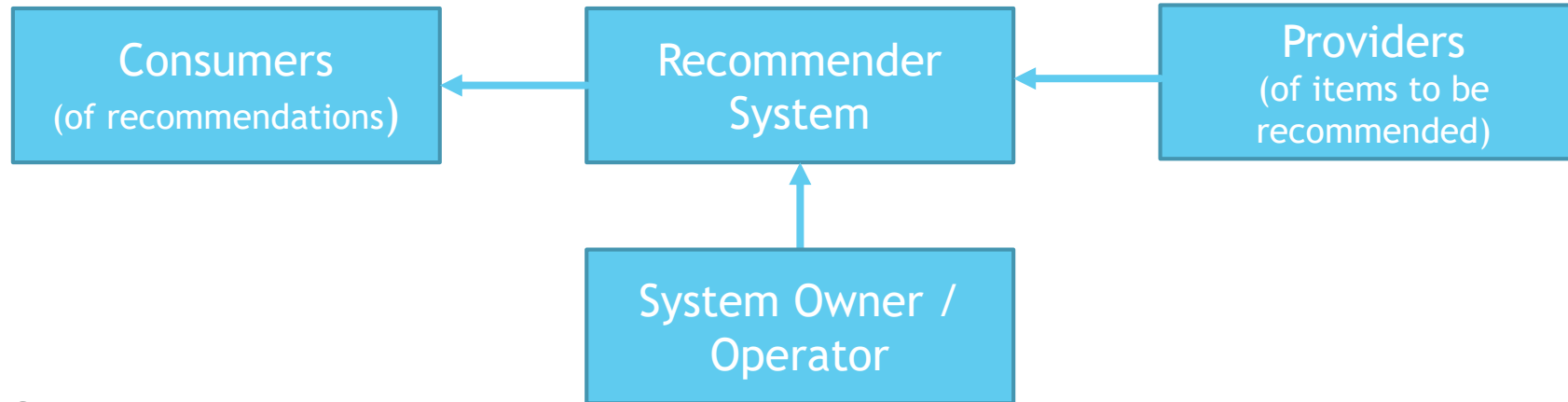
▶ Involvement

- ▶ An implementer can incorporate multiple stakeholders in the design of the system itself and the tradeoffs between different objectives

Related areas

- ▶ Group recommendation
 - ▶ Long history in recommender systems
 - ▶ Multiple parties receive the same recommendation
- ▶ Multistakeholder analysis of businesses
- ▶ Multisided platforms
- ▶ Matching markets
 - ▶ Reciprocal recommendation
- ▶ Computational advertising
- ▶ Non-accuracy methods in recommendation
 - ▶ long-tail
 - ▶ diversity

Key stakeholders



- ▶ Consumers
 - ▶ Individuals who get recommendations
- ▶ Providers
 - ▶ Entities who supply items that the system recommends
 - ▶ could be multiple parties on this side, depending on type of item
- ▶ System
 - ▶ Entity that operates the recommender system
- ▶ May also be "side stakeholders"
 - ▶ Example: different delivery services for items

Provider considerations

- ▶ Entities whose items are being recommended
 - ▶ maybe this is the system itself, not often not
- ▶ Types of objectives
 - ▶ Neutral: no related objective
 - ▶ We don't care how providers fare
 - ▶ Personalized: specific objectives for providers
 - ▶ Who are the "good" consumers?
- ▶ Types of interactions
 - ▶ Passive interaction: implicit feedback
 - ▶ Who does the provider accept?
 - ▶ Active interaction: provider specifies
 - ▶ Who does the provider want?

Examples

- ▶ AirBnB hosts
 - ▶ A host can decide whether or not to accept a potential guest
 - ▶ The system could learn from that as part of matching with users
 - ▶ passive
- ▶ On-line dating
 - ▶ The user specifies the type of match they are seeking
 - ▶ The system uses this information to match with users
 - ▶ active

Consumer considerations

- ▶ Objective will be personalized
 - ▶ otherwise not really a recommender system
 - ▶ "popular items"
- ▶ Types of interactions
 - ▶ Passive
 - ▶ "Welcome back! Here are some recommendations"
 - ▶ Active
 - ▶ User specifies a context, query or other information
 - ▶ Recommendations tailored to the input
 - ▶ Example:
 - ▶ search for Spanish restaurants, but the list is ordered in a personalized manner

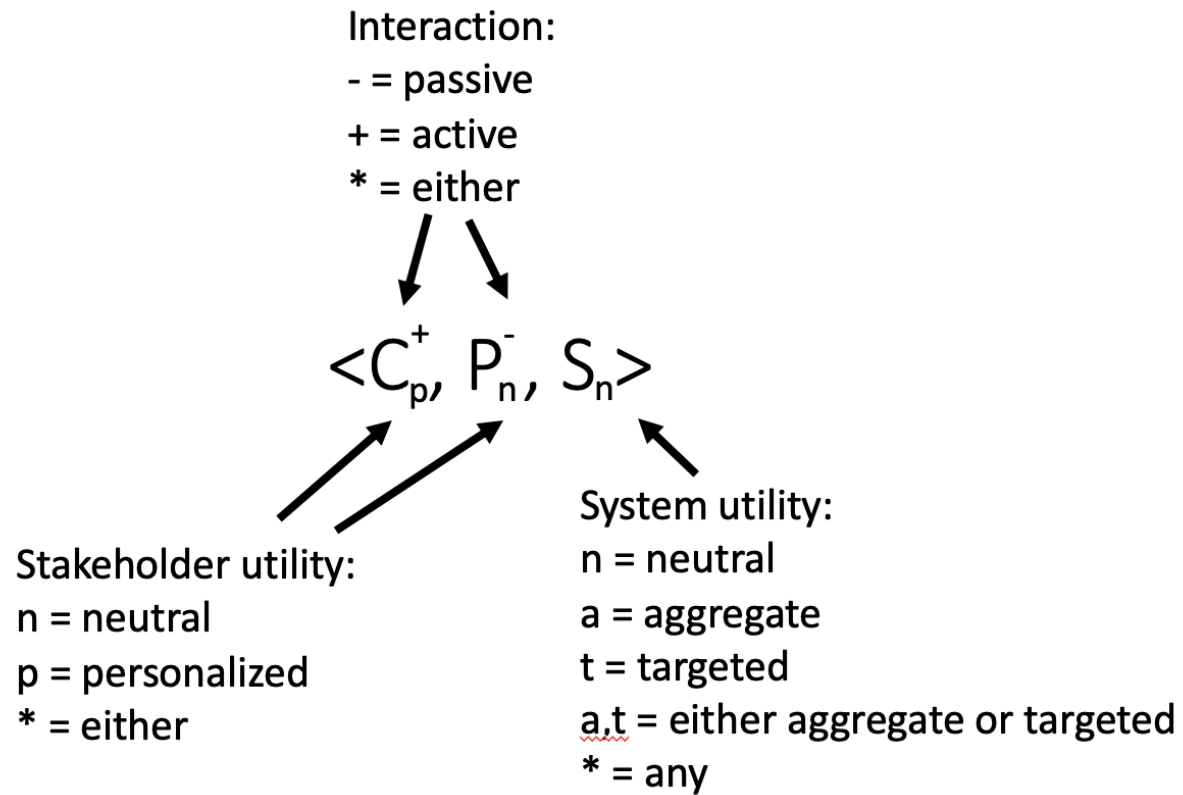
Aside: interaction semantics

- ▶ Technical distinction between recommendation and personalized search
 - ▶ not much
 - ▶ many fielded systems have both characteristics
- ▶ Difference largely in user's mental model
 - ▶ what does the user think they are getting
 - ▶ answers to a question
 - ▶ suggestions based on history
- ▶ Much of this discussion applies regardless

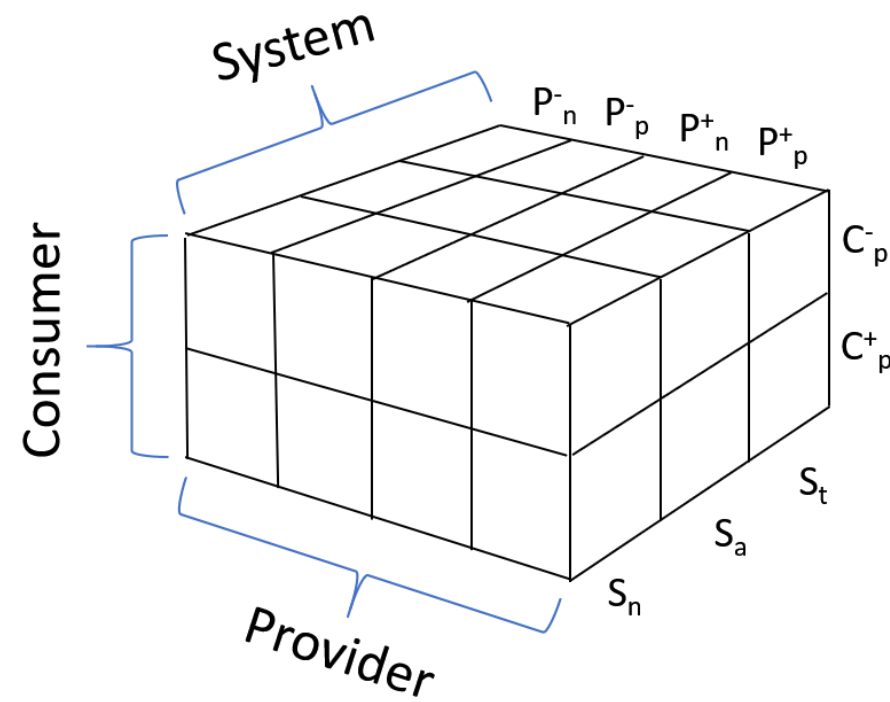
System

- ▶ How does the system gain from recommendation interactions?
 - ▶ and does that depend on specific interactions?
- ▶ Neutral
 - ▶ the system doesn't care what is recommended and to whom as long as users are satisfied
 - ▶ Think MovieLens
- ▶ Aggregate
 - ▶ the system specifically gains from recommendations in some aggregate way
 - ▶ for example, a commission on sales
- ▶ Targeted
 - ▶ the system has its own objectives about what is recommended and to whom
 - ▶ and those objectives might not be shared by other participants
 - ▶ Example: fairness (more later)

Some notation



Design space



Examples

- ▶ On-line dating (reciprocal recommendation)
 - ▶ $\langle C_p^+, P_p^+, S_n \rangle$
- ▶ Display advertising
 - ▶ $\langle C_p^-, P_p^+, S_a \rangle$
- ▶ Social network recommendation (ala Daley et al. 2010)
 - ▶ $\langle C_p^-, P_p^-, S_t \rangle$

The point

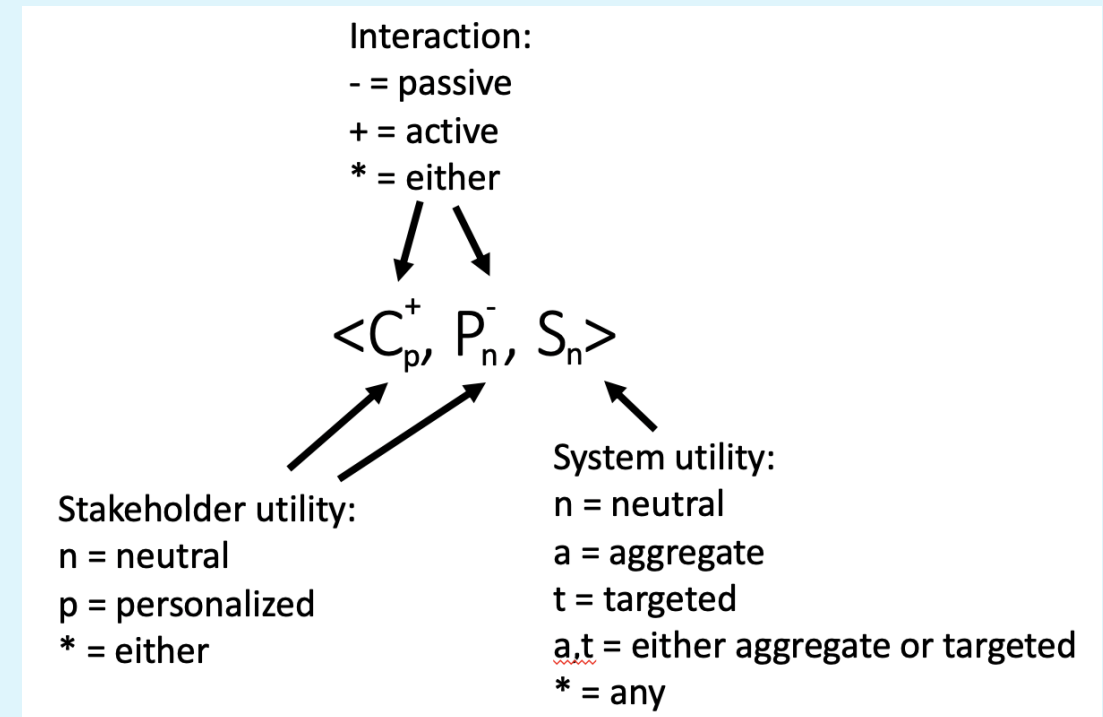
- ▶ There are a lot of different multistakeholder configurations
 - ▶ Not all solutions are applicable to every configuration
- ▶ Example
 - ▶ If you can model system utility as an aggregate of provider utility
 - ▶ via commission, for example
 - ▶ Then you don't have to worry about separate system objectives

What questions so far?



Exercise

- ▶ Consider the configuration
- ▶ $\langle C_p^+, P_n^-, S_t \rangle$
- ▶ How does this map to the out-of-school activity recommender?
- ▶ Discuss



Implementations

- ▶ Multi-criteria optimization methods
- ▶ Re-ranking
- ▶ Note
 - ▶ Implementations often similar to techniques used for other non-accuracy metrics
 - ▶ diversity, coverage, etc.

Multi-criteria methods

- ▶ Combined optimization objective
 - ▶ Example: $\text{loss} = \alpha \text{obj1} + (1 - \alpha) \text{obj2}$
- ▶ Sequential optimization
 - ▶ $S_1 = \text{opt}(\text{obj1})$
 - ▶ $S_2 = \text{opt}(\text{obj2})$ but bound loss on obj1 (1% for example)

Combined objective

- ▶ Many examples
 - ▶ Recent one
 - ▶ Mehrotra et al. "Towards a Fair Marketplace", CIKM 2018
- ▶ Application: Playlist recommendation in Spotify
 - ▶ Stakeholders are users, artists
 - ▶ Users want accuracy recommendations
 - ▶ Artists want to be recommended

"Fair Marketplace", cont'd

- ▶ Algorithm: contextual bandit

- ▶ learns to maximize reward $s_u^* = \operatorname{argmax}_{s \in \mathcal{S}_u} ((1 - \beta) \phi(u, s) + \beta \psi(s))$

- ▶ where ϕ is the relevance and ψ is the fairness

- ▶ β controls the tradeoff

Regularization

- ▶ A combined objective
 - ▶ where the non-accuracy multistakeholder objective is treated as a regularization over the accuracy objective
 - ▶ We'll see an example when we talk about fairness

Sequential optimization

- ▶ Derive a solution for the accuracy objective
 - ▶ then solve for a second objective constraining the loss on the first
- ▶ Example
 - ▶ Agarwal, et al. "Click shaping to optimize multiple objectives", KDD 2011
- ▶ Application: content for the Yahoo! Front Page
 - ▶ Two different KPIs
 - ▶ click-through rate
 - ▶ time on site (stickiness)
 - ▶ These are both about the user (maybe?)
 - ▶ However, paper discusses other system stakeholder objectives such as site revenue

"Click shaping"

- ▶ Algorithm: Bayesian estimation of CTR
 - ▶ followed by constrained optimization of the time-spent metric
 - ▶ using linear programming

Multi-criteria methods

- ▶ Requires resolving some tricky tuning issues
- ▶ Combined objectives
 - ▶ require setting a weight on the outcomes for different stakeholders
- ▶ Regularization
 - ▶ distorts the optimization space, can cause significant accuracy loss
- ▶ Sequential optimization
 - ▶ have to decide what is an appropriate average accuracy loss
 - ▶ distributional control might be better

Re-ranking

- ▶ Produce recommendation lists in the usual way
 - ▶ optimized for user stakeholders
- ▶ Then re-rank to balance original ranking vs other stakeholders' objectives
- ▶ Example
 - ▶ Sürer, Özge, Robin Burke, and Edward C. Malthouse. "Multistakeholder recommendation with provider constraints". RecSys 2018.
- ▶ Application: Recommendation in a multi-supplier marketplace
 - ▶ User stakeholders
 - ▶ Suppliers want a share of recommendations delivered

"Multi-supplier"

- ▶ Algorithm: agnostic to initial algorithm
 - ▶ user-based algorithm computes all recommendation lists for all users
 - ▶ define desired optimal provider exposure as an integer programming problem
 - ▶ use a Lagrangian relaxation of IP to achieve scalability

Provider-side metrics

- ▶ Lots of literature on measuring outcomes for users
- ▶ How do we measure outcomes for provider?
 - ▶ application-specific
 - ▶ what matters to these folks?
- ▶ Several ideas
 - ▶ exposure: people see their products / items
 - ▶ audience: who sees their items
 - ▶ quality: prediction outcomes

Exposure

- ▶ Count the number of recommendations of the provider's items across some set of recommendation lists

- ▶ doesn't matter whether the user is interested

$$\sum_{L_i \in \mathcal{L}} \sum_{j \in L_i} \mathbb{1}(j \in I_p)$$

- ▶ Count the number of **Hits** (that is recommendations matching the test data)

- ▶ doesn't work so well for cold-start providers

$$\sum_{L_i \in \mathcal{L}} \sum_{j \in L_i} \mathbb{1}(j \in I_p \wedge r_{ij} \in T)$$

- ▶ Could normalize by

- ▶ the number of lists
- ▶ the size of provider's catalog

- ▶ Can also take rank into account

Audience

- ▶ Count how many users are reached by the provider's items; they see at least one item

- ▶ Quality of match not included

$$\sum_{L_i \in \mathcal{L}} \mathbb{1}(|I_p \cap L_i| > 0)$$

- ▶ Count how many users in some targeted group g see the recommendations

$$\sum_{L_i \in \mathcal{L}} \mathbb{1}(|I_p \cap L_i| > 0 \wedge g_p(i))$$

- ▶ Variants

- ▶ Use hits instead of just counts

Accuracy

- ▶ How accurate are the recommendations of the provider's items when they are given
 - ▶ Could use any metric: RMSE, nDCG, etc.
 - ▶ Might be deceptive if $|T_p|$ is small

$$\left[\sum_{r_{ij} \in T_p} m(r_{ij}, \hat{r}_{ij}) \right] / |T_p|$$

What questions so far?



Exercise

- ▶ Think back to our recommender for out of school activities
- ▶ What metric(s) would be appropriate for providers?
- ▶ If you think multiple metrics are appropriate,
 - ▶ how should tradeoffs between them be managed?

Conclusion

- ▶ **Multistakeholder recommendation**
 - ▶ the objectives of multiple parties are considered in making recommendations,
 - ▶ when the parties lie on different sides of the recommendation interaction.
- ▶ **Multistakeholder recommendation is a necessity in many applications**
 - ▶ It is not "bad" to incorporate the stakeholders other than the user
 - ▶ If a system has benefits for users, system viability is in their interest
- ▶ **Multistakeholder recommendation approaches**
 - ▶ Multi-criteria optimization
 - ▶ incl. regularization
 - ▶ Re-ranking

Open questions

- ▶ Transparency
 - ▶ How to surface / explain multistakeholder aspects of recommendation?
 - ▶ Esp. to consumers who might resist such aspects
- ▶ Tradeoffs
 - ▶ How to define and evaluate tradeoffs?
- ▶ Multistakeholder UX
 - ▶ How do different stakeholders interact with the system?

References

- ▶ Agarwal, et al. Click shaping to optimize multiple objectives. KDD 2011
- ▶ Business Roundtable, Statement on the Purpose of a Corporation. <https://opportunity.businessroundtable.org/wp-content/uploads/2019/08/BRT-Statement-on-the-Purpose-of-a-Corporation-with-Signatures.pdf>, August 2019
- ▶ Daly, E., Werner Geyer, and David R. Millen. The network effects of recommending social connections. RecSys 2010.
- ▶ Freeman, R. E. *Strategic management: A stakeholder approach*. Cambridge university press, 2010.
- ▶ Hagiu, A. *Strategic decisions for multisided platforms*. MIT, 2014.
- ▶ Mehrotra et al. Towards a Fair Marketplace: Counterfactual Evaluation of the trade-off between Relevance, Fairness & Satisfaction in Recommendation Systems. CIKM 2018
- ▶ Sürer, Ö et al. Multistakeholder recommendation with provider constraints. RecSys 2018.

Break

