# Recommender Systems: Beyond the Algorithms

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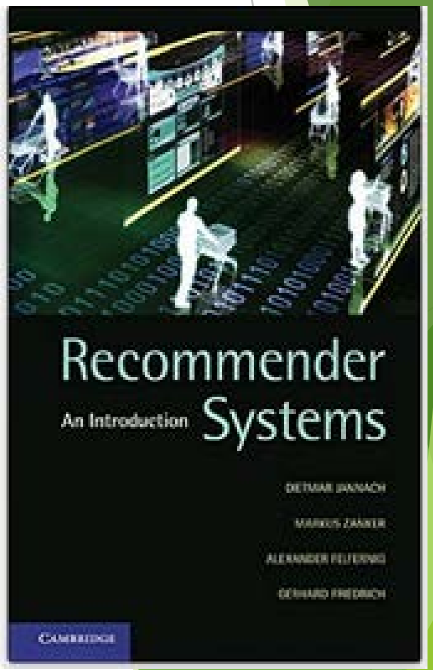
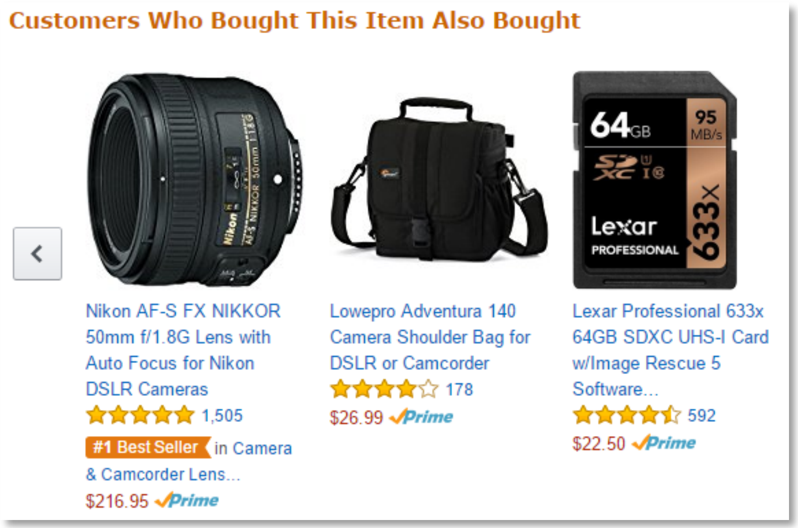
# About me

- Professor of Computer Science at TU Dortmund, Germany
  - On the move to Alpen-Adria-Universität Klagenfurt, Austria
- Research interests
  - Recommender Systems
    - E-Commerce applications, business value of recommenders
    - Interactive advisory systems
  - Artificial Intelligence
    - Model-based Diagnosis, Constraints
  - Software Engineering
    - Debugging of Spreadsheets



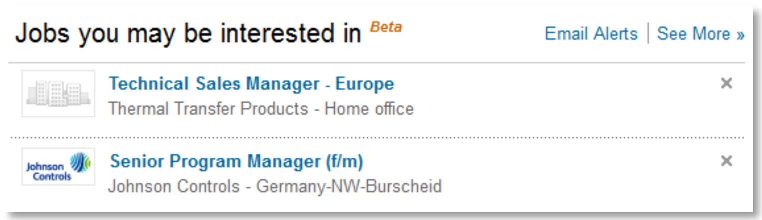
# Recommender Systems

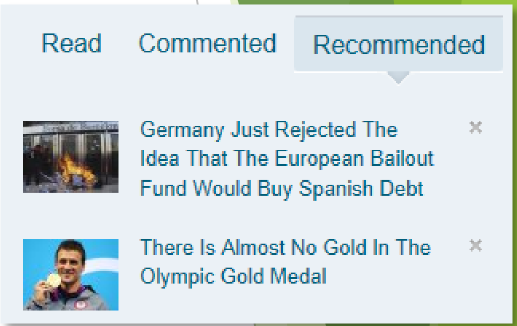
- Automated recommendations
  - A pervasive part of our online user experience
  - Explicitly recommend us shopping items, movies, music, news, friends, jobs, groups or people to follow, restaurants, hotels…
  - Silently select and rank the items to present
    - News feeds, ads (in some sense)

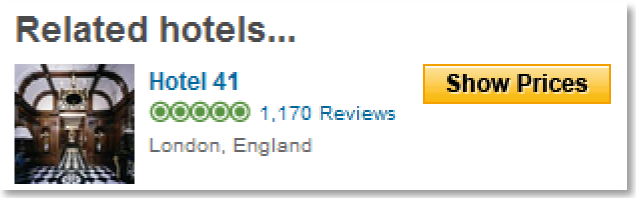


# Recommender Systems

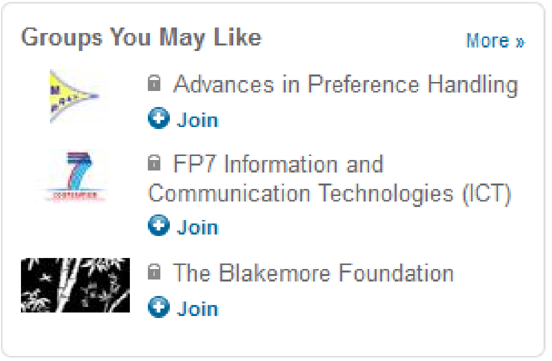
- Once you see them, they are everywhere





# This summer school

- Mostly focuses on a computer science oriented perspective, e.g.,
  - Algorithms to process past user actions to predict the relevance of an item for a certain user
  - Information sources that be fed into our algorithms
  - Ways to make our algorithms scale to millions of users and items
  - Methods of measuring that our algorithms are better than previous ones
  - UI mechanisms to acquire user preferences and to present the recommendations
- Algorithm help us predict to which extent an item is generally relevant for an individual user
  - Which is a central question

# But there is more

- Recommender systems research is not only about algorithms and application design
- Automated recommendations have an effect on recommendation consumers and providers
  - They change the consumer behavior
  - They have an effect on the business
- Some challenges
  - These effects are not always easily predictable
  - There might be conflicting goals
  - Some effects are based on psychological effects
  - And may depend on a variety of other factors, including user trust or website credibility

# In this talk

- We will briefly review the history of recommender systems
- We will outline challenges when adopting a purely algorithmic-oriented research perspective
- We sketch a purpose-oriented framework for the design and evaluation of recommender systems


Jannach, D., Resnick, P., Tuzhilin, A. and Zanker, M.: "*Recommender Systems - Beyond Matrix Completion*". Communications of the ACM, Vol. 59(11). Association for Computing Machinery (ACM), 2016, pp. 94-102

Jannach, D. and Adomavicius, G.: "*Recommendations with a Purpose*". In: Proceedings of the 10th ACM Conference on Recommender Systems (RecSys 2016). Boston, Massachusetts, USA, 2016, pp. 7-10

# A bit of history

- Recommender systems have their roots in various fields
  - e.g., Information Retrieval, Machine Learning, Human Computer Interaction
- Their design can furthermore be influenced by insights from more distant fields
  - e.g., Consumer behavior, psychology, marketing
- Typical goals:
  - Avoid information overload (filtering)
  - Active promotion of content
- Personalization often as a central concept

# Information Filtering roots

- Information Filtering
  - Systems that filter incoming streams of information in a personalized way
  - Dates back to the late 1960s
  - Early systems use explicitly stated preferences regarding topics or keywords
  - Later on, automated content analysis and user profiling
- Today:
  - "Content-based Filtering" recommender techniques
  - Personalized Information Retrieval

# Leveraging the opinions of others

- 1982: ACM president complained about email junk
  - Envisioned a set of "trusted authorities" that assess the quality of the messages
- 1987: Information Lens
  - Based on manual filters, but could also specify people whose opinions they value
- 1992: Tapestry – "Collaborative Filtering"
  - Continued Information Lens ideas, introduced idea of considering ratings, but still a manual process
- 1994: GroupLens and others
  - System automatically predicted ratings of users, based on "matrix filling" (completion) setup

# Collaborative Filtering booms

- The Matrix Completion problem
  - Became established as a standard way of operationalizing research
  - Problem of predicting missing ratings
  - Evaluate algorithms
    - Prediction error, rank measures

| | Item1 | Item2 | Item3 | Item4 | Item5 |
|---|---|---|---|---|---|
| Alice | 5 | ? | 4 | 4 | ? |
| User1 | 3 | 1 | 2 | 3 | 3 |
| User2 | 4 | 3 | 4 | 3 | 5 |
| User3 | 3 | 3 | 1 | 5 | 4 |
| User4 | 1 | 5 | 5 | 2 | 1 |

# Collaborative Filtering (CF) booms

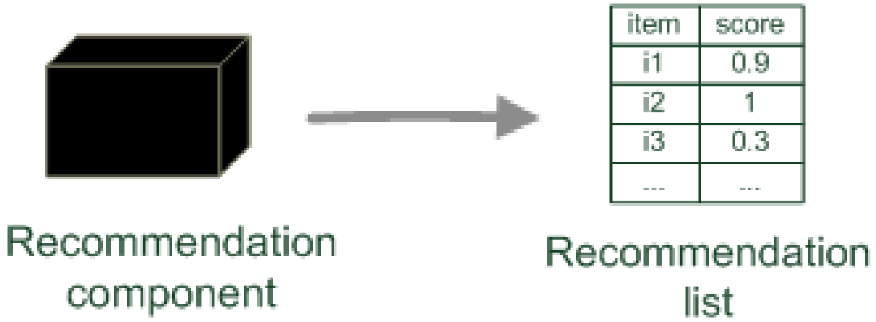
- 1998:
  - Dimensionality reduction for CF, clustering
  - Collaborative/Content-based Hybrids
- 1999: It works in e-commerce!
  - First reports on successful applications in practice (e-commerce, music, video)
- 2000:
  - Item-to-item collaborative filtering
- 2003: Amazon.com
  - Report on the successful use of recommendations at Amazon.com using item-to-item filtering
  - Today, many algorithms, many non-personalized ones as well

# The Netflix Prize

- Netflix announced a 1 million $ prize in 2006
  - For beating their system by 10% in terms of the prediction error
  - Provided at that time huge dataset
- Effects
  - Further boosted research on the matrix completion problem
- Contest ended in 2009, some winning ingredients
  - Matrix factorization (not using exact SVD)
  - Ensemble methods
- Today
  - Collaborative Filtering as a standard method in industry

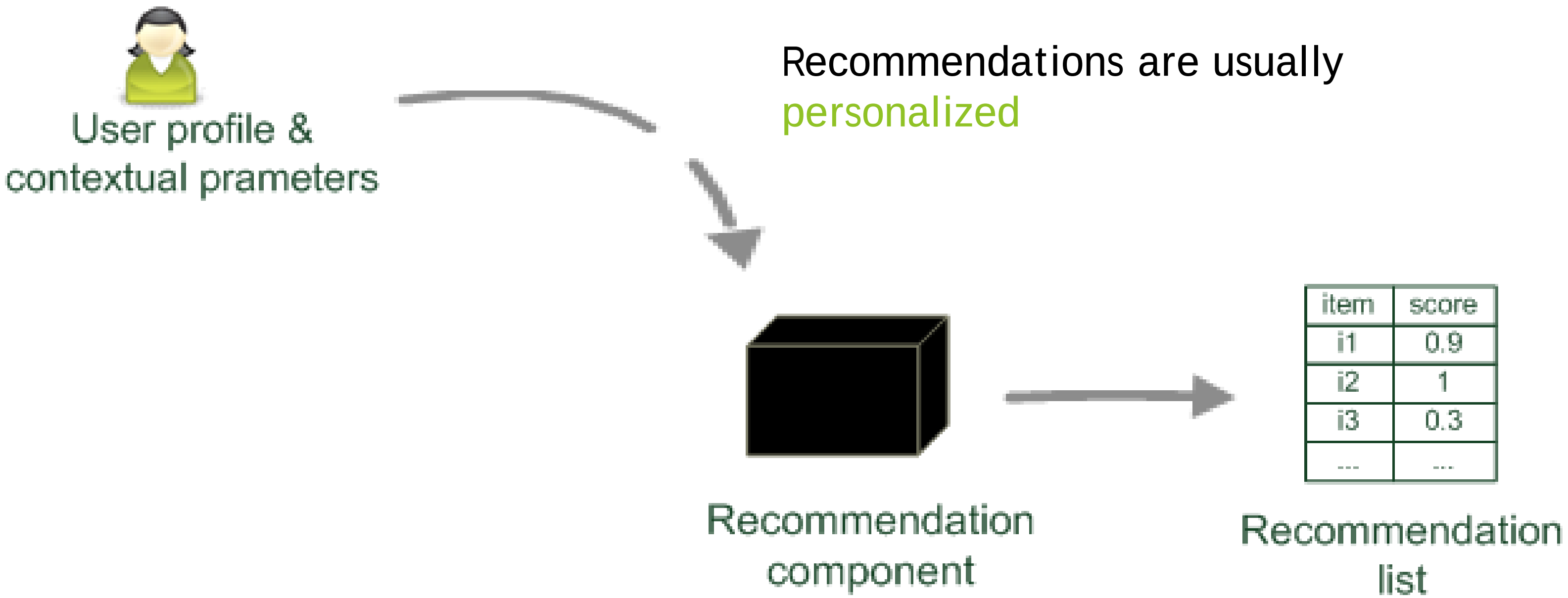
# Recommendation Paradigms

Recommender systems reduce information overload by estimating relevance

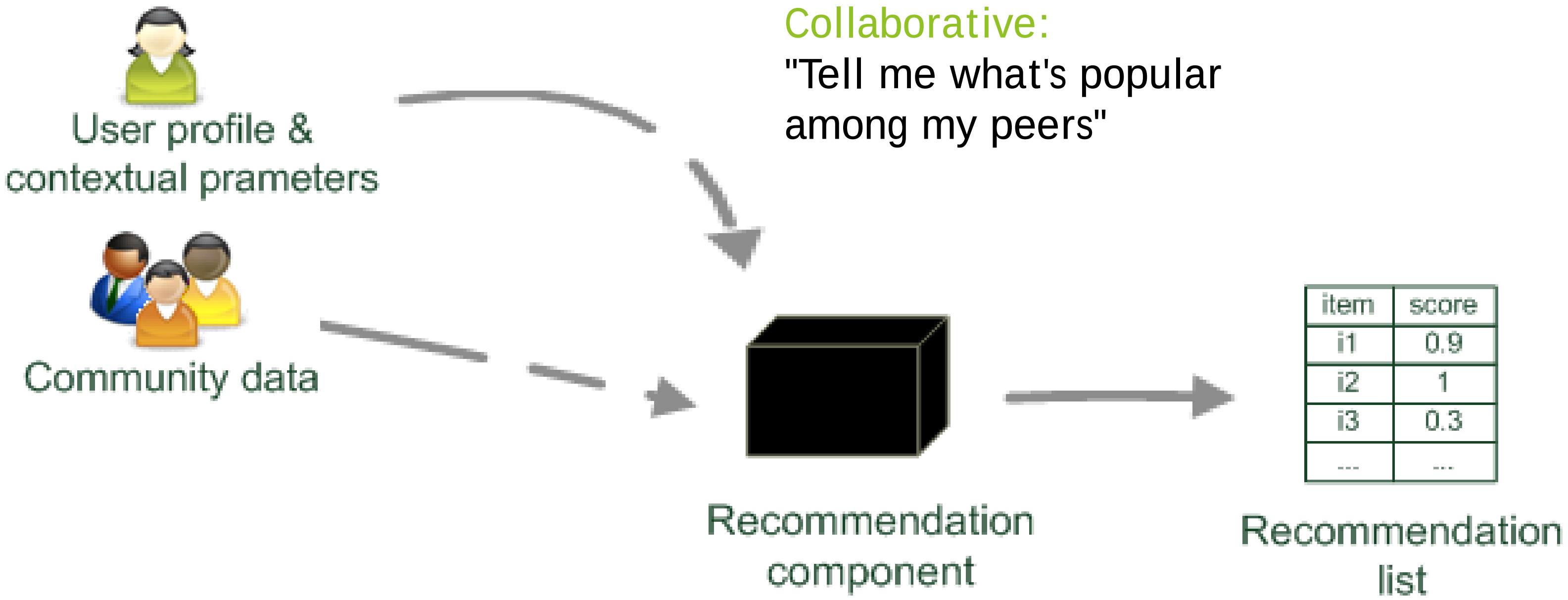


# Recommendation Paradigms

Recommendations are usually personalized



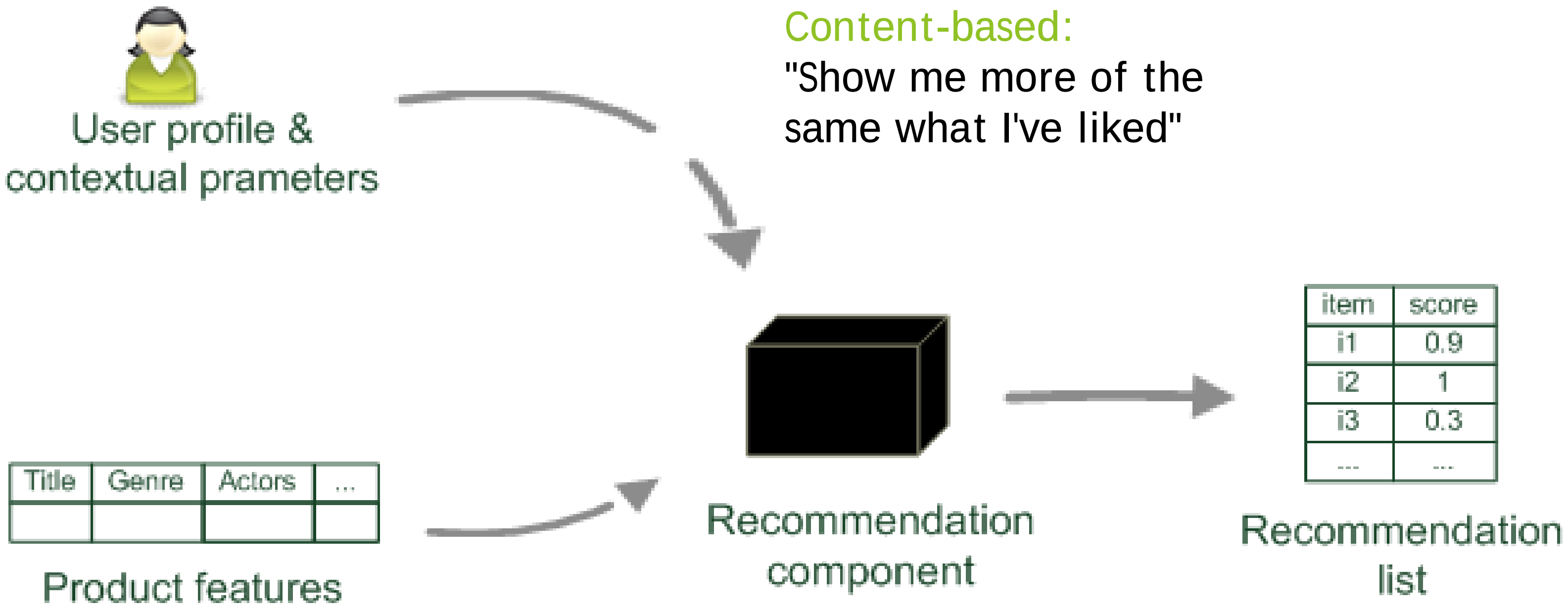
# Recommendation Paradigms




Collaborative:
"Tell me what's popular among my peers"

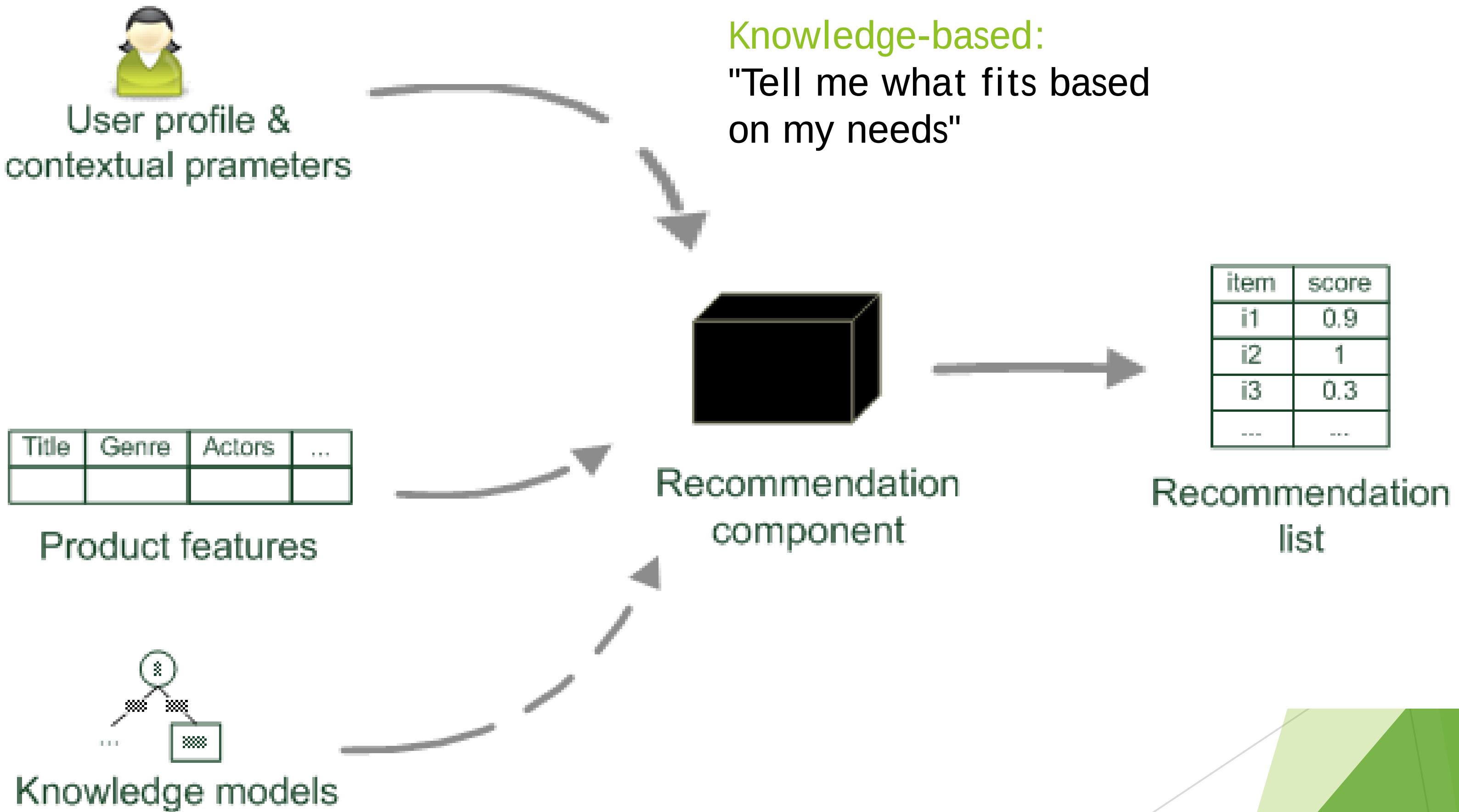
# Recommendation Paradigms

Content-based:
"Show me more of the same what I've liked"

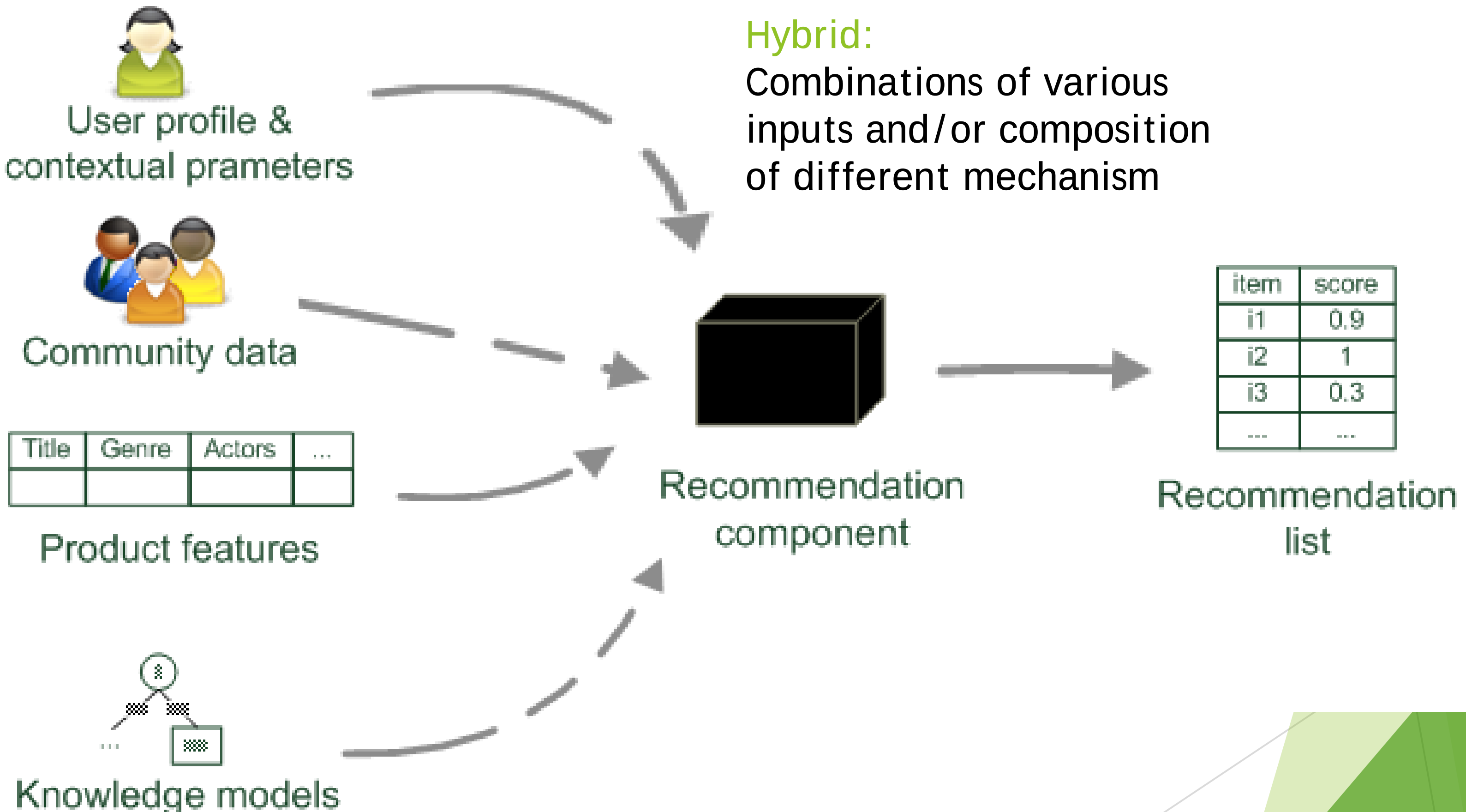


# Recommendation Paradigms

Knowledge-based:
"Tell me what fits based on my needs"



# Recommendation Paradigms




Hybrid:
Combinations of various inputs and/or composition of different mechanism

# Beyond matrix completion

- Research based on the matrix completion problem formulation still predominant today
  - An established and domain-independent problem abstraction
  - Established evaluation procedures
  - Allows for reproducibility, in theory
  - Hundreds of papers published each year
  - Plethora of technical approaches, many of them comparably complex
- The problem formulation however has its limitations

# Matrix completion setup limitations

- “Post-diction” is not prediction
  - Users do not rate items at random
  - Algorithm optimization and evaluation procedures however only considers the rated items
  - Models optimized for known ratings might not work best in the real world
  - More and more field tests (A/B tests) done, often confirming this issue
- Public datasets
  - Help us compare our methods
  - But how important is movie recommendation?
  - How do the findings generalize?

# Matrix completion setup limitations

- Rating prediction not often relevant in practice
  - Item ranking more important
  - Learning-to-rank methods important in recent years
- Evaluation focused on finding good items
  - Avoiding “bad” recommendations might also be important
  - Accurately predicting the 1-star or 2-star ratings might be of limited value
- “Bad” research practice
  - Many different accuracy measures and evaluation protocol variants
  - Non-public datasets or data sampling
  - No source code provided

# Matrix completion setup limitations

- There is at most one preference signal per user and item
  - In reality there are a lot of implicit signals over time
  - Implicit feedback based algorithms often use the matrix completion setup as well
- Reminding users of known items not in the scope
  - Even though it might be relevant in practice
  - Recent log analysis from e-commerce shop
    - 40% of "successful" recommendations were viewed before by the user
  - Recent field test with reminders
    - Reminding can be helpful also for the business

Lerche, L., Jannach, D. and Ludewig, M.: *"On the Value of Reminders within E-Commerce Recommendations"*. In: Proceedings UMAP 2016. Halifax, Canada, 2016.

# Prediction accuracy addiction

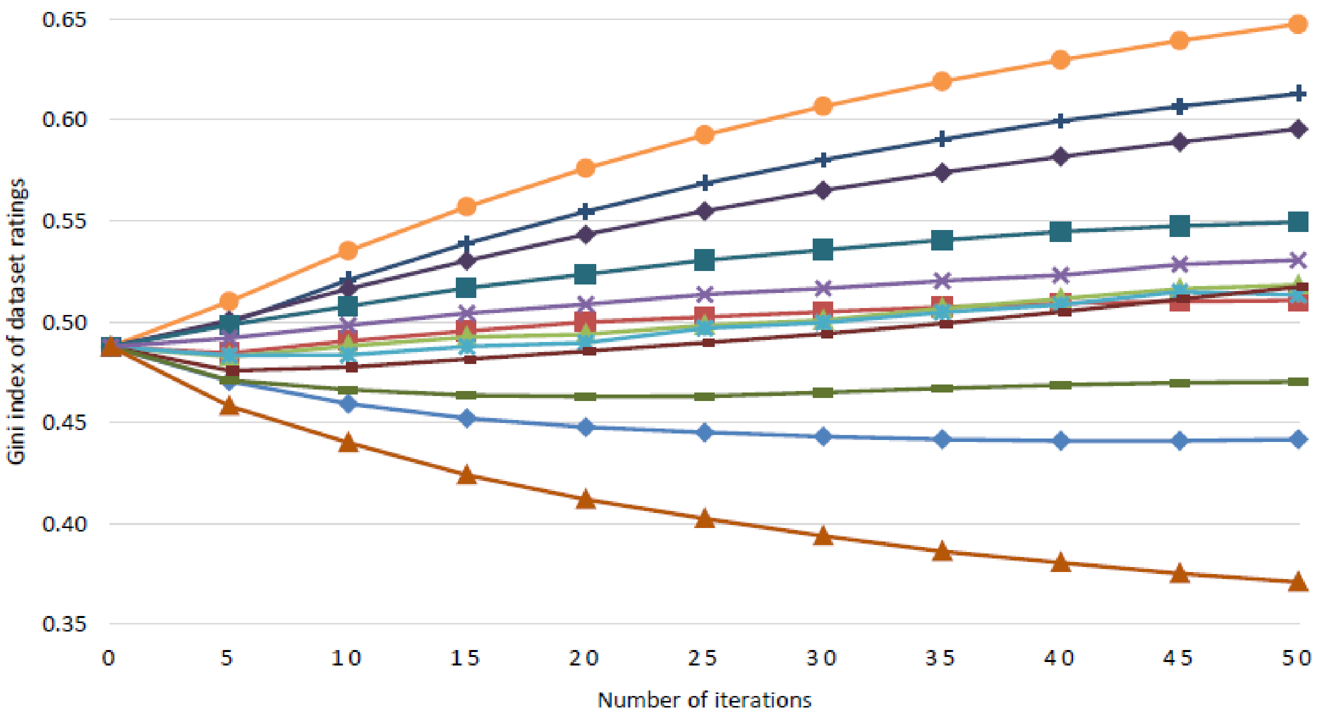
- Prediction and ranking accuracy
  - Predicting the (relative) relevance of unseen items as the main focus of algorithmic works still today
  - However, researchers for many years know that prediction accuracy is often not enough
- Other components of utility
  - Diversity, novelty, and serendipity
    - But how much of it (in a given domain)?
  - Utility for the consumer
    - Recommending the obvious might be accurate but pointless
  - Utility for the provider
    - Business value (see also later)

Jugovac, M., Jannach, D. and Lerche, L.: *"Efficient Optimization of Multiple Recommendation Quality Factors According to Individual User Tendencies"*. Expert Systems With Applications, 2017

# Prediction accuracy addiction

- Additional undesired biases can exist
  - Focus mostly on popular items (popularity bias)
    - Leads to high precision and recall, but limited value
    - Can lead to "rich-get-richer-effect
  - Focus on a small set of items (concentration bias)
    - Limited catalog coverage
- Some algorithms lead to similar accuracy values but to largely different recommendations
- Undesired Long-term effects

# Rich-get-richer simulation




Jannach, D., Lerche, L., Kamehkhosh, I. and Jugovac, M.: *"What recommenders recommend: an analysis of recommendation biases and possible countermeasures"*. User Modeling and User-Adapted Interaction, Vol. 25(5). Springer Nature, 2015, pp. 427-491.

# Context matters

- Which items are relevant can depend on the context
  - With whom I watch a video, my mood, environmental parameters
- Traditional matrix completion setups do not consider the user context
  - A number of technical approaches developed in recent years
  - Still, a lack of datasets to do research on
- Long-term and short-term interests
  - Users may have a diverse profile, but arrive at the site with a specific shopping intent

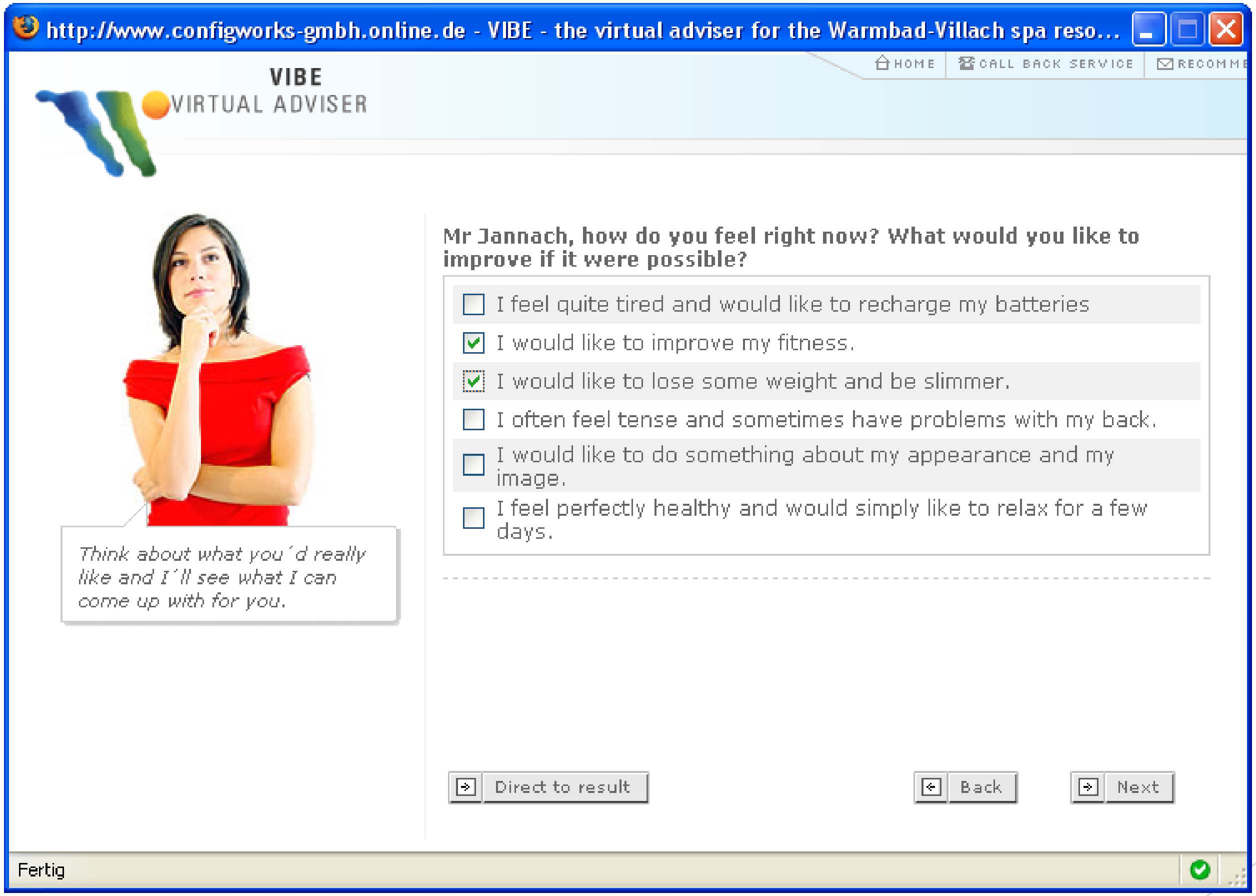
Jannach, D., Lerche, L. and Jugovac, M.: *"Adaptation and Evaluation of Recommendations for Short-term Shopping Goals"*. In: Proceedings RecSys 2015. Vienna, Austria, 2015, pp. 211-218

# Interacting with users

- How the user can interact with the system can significantly impact their effectiveness
- Much less research on UI/UX-related issues than on algorithmic approaches
- Questions, e.g.,:
  - How do we acquire the preferences?
  - How do we present the results?
  - Are there any ways to convince or persuade a user?
  - How should the system explain its recommendations?
  - When should recommendations be presented?

Jugovac, M. and Jannach, D.: *"Interacting with Recommenders – Overview and Research Directions"*. ACM Transactions on Intelligent Interactive Systems (ACM TiiS). forthcoming

# Is this even a recommender?



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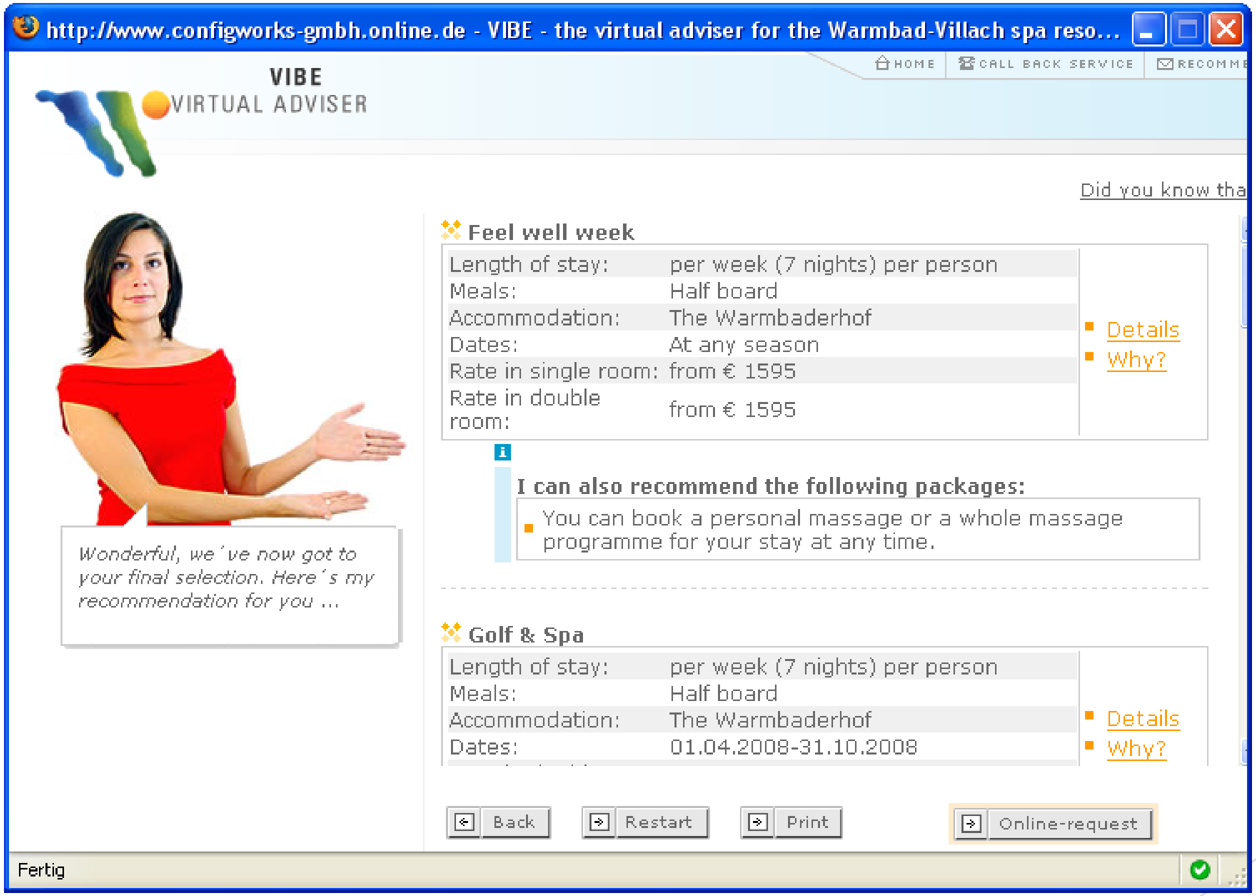

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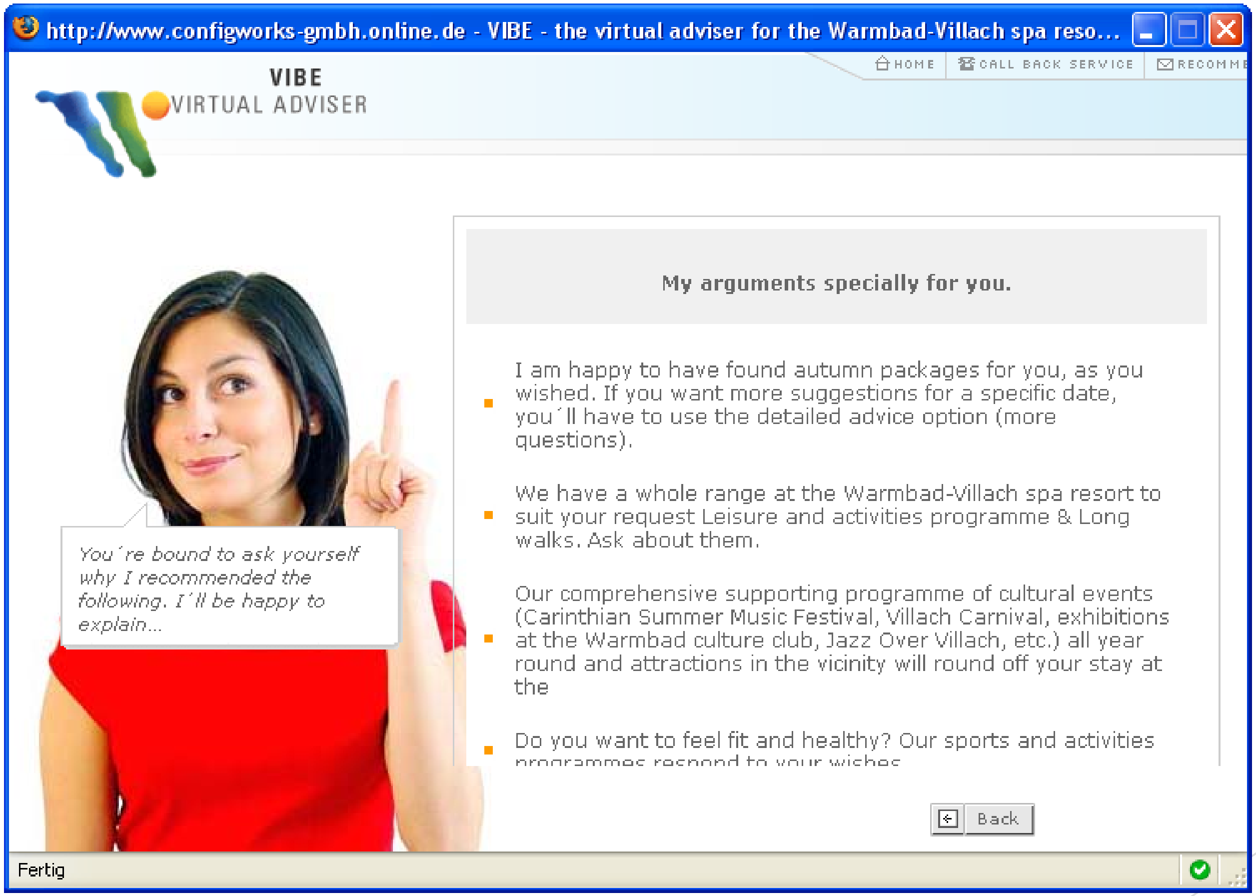

# User control

- Recommenders are mostly a black box to users
- How do we help users change their profiles and "correct" the system's assumptions?


Jannach, D., Naveed, S. and Jugovac, M.: *"User Control in Recommender Systems: Overview and Interaction Challenges"*. In: EC-Web 2016. Porto, Portugal, 2016

# In the long run

- Trust and loyalty
  - Key targets in the long run from the provider perspective
- Trust needs repeated positive experiences
  - Continuously persuading the user to take a non-optimal decision can be detrimental for the service
  - Balance between provider and consumer benefit must be found
- Explanations maybe a key factor
  - Transparency as an important trust-enabling factor

Nilashi, M., Jannach, D., bin Ibrahim, O., Esfahani, M. D. and Ahmadi, H.: *"Recommendation quality, transparency, and website quality for trust-building in recommendation agents"*. Electronic Commerce Research and Applications, Vol. 19. Elsevier BV, 2016, pp. 70-84

# A purpose-oriented approach

- A central, but often not-addressed question

  What is a good recommender system?

- Some possible answers
  - One that achieves a low RMSE on historical data?
  - One that produces diverse item lists?
  - One that leads to high click-through-rates?

    ...
- Or:

  One that creates some form of utility

# Utility for whom

- Value for the customer
  - RS helps user find things that are interesting
  - RS helps user narrow down the set of choices
  - RS helps user explore the space of options
  - RS helps user discover new things, entertainment
  - ...
- Value for the provider
  - Increased sales, click trough rates, conversion etc.
  - Increased trust and customer loyalty
  - More opportunities for promotion, persuasion
  - More knowledge about customers
  - ...

# It all depends

- Recommendations can serve different purposes
  - Whether a recommendation is good nor not depends on the intended purpose and the perspective
  - The purpose can very specific for a domain or application

- In academia:
  - we often abstract from such domain-specifics

# In the literature

- Set of abstract, computational tasks
  1. Find (all or some) good items
  2. Predict the relevance of unseen items ("annotate in context")
  3. Recommend sequence
  4. Just browsing

# Current research practice

- Operationalization of the research problem
  - Limited set of tasks, mostly relevance prediction
  - Abstract, domain-independent performance measures
- Plus:
  - Standard evaluation schemes
  - Public datasets
- Benefits:
  - Well-defined problem
  - Continuous improvement
  - Comparability & reproducibility

# Some dangers

- Do we over-simplify or over-generalize things?
  - High diversity might be good in some domains, but not in others
  - What a "good item" is, depends on the viewpoint and purpose
  - How do we know that our abstract measures reflect either viewpoint?
- Time to re-assess our research practice
  - Re-visit the fundamental goals & tasks of recommenders and how we evaluate such systems
  - Is our approach too narrow – can we cover more than what we are currently do today?

# A conceptual framework

- Goals
  - For a structured discussion of goals and purposes
  - To point out areas of future research
  - Consider provider and consumer side
- Structure – 4 layers

| |
|---|
| Overarching goal of the system, strategic value |
| Recommendation purpose / Intended utility |
| System (algorithm) task |
| Computational metrics |

| | | Consumer's Viewpoint | Provider's Viewpoint |
|---|---|---|---|
| Strategic Perspective | Overarching Goal | "Personal Utility": Happiness, Satisfaction, Knowledge, Entertainment, Benefit | "Organizational Utility": Profit, Revenue, Return on Investment, Growth, Customer Retention |
| | Recommendation Purpose | • Help users find objects that match the user's long-term preferences<br>• Show alternatives<br>• Help users explore or understand the item space, … | • Change user behavior in desired directions<br>• Create additional demand<br>• Help users discover new artists, directors, genres<br>• Increase activity on the site<br>• . . . |
| Operational Perspective | System Task | • Annotate in context (i.e., estimate preference of a given item)<br>• Find good items<br>• Create diverse set of alternatives<br>• Find mix of familiar and relevant unknown items<br>• Find suitable accessories<br>• … | |
| | Computational Metric | Predictive accuracy (e.g., RMSE, MAE), classification accuracy (e.g., Precision, Recall, AUC), ranking and top-n accuracy (e.g., rank correlation, MRR, NDCG, etc.), item discoverability (diversity, novelty, or serendipity measures), recommendation biases (e.g., concentration or popularity biases) and blockbuster effects, survey-based user satisfaction scores, business- and domain-specific measures (e.g., conversion rates or click-through-rates), . . . | |

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| | Recommendation Purpose | • Help users find objects that match the user's long-term preferences<br>• Show alternatives<br>• Help users explore or understand the item space, ... | • Change user behavior in desired directions<br>• Create additional demand<br>• Help users discover new artists, directors, genres<br>• Increase activity on the site<br>• . . . |
| **Operational Perspective** | System Task | • Annotate in context (i.e., estimate preference of a given item)<br>• Find good items<br>• Create diverse set of alternatives<br>• Find mix of familiar and unknown items<br>• Find suitable accessories<br>• ... | |
| | Computational Metric | Predictive accuracy (e.g., RMSE, MAE), classification accuracy (e.g., Precision, Recall, AUC), ranking and top-n accuracy (e.g., rank correlation, MRR, NDCG, etc.), item discoverability (diversity, novelty, or serendipity measures), recommendation biases (e.g., concentration or popularity biases) and blockbuster effects, survey-based user satisfaction scores, business- and domain-specific measures (e.g., conversion rates or click-through-rates), . . . | |

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| Operational Perspective | System Task | • Annotate in context (i.e., estimate preference of a given item)<br>• Find good items<br>• Create diverse set of alternatives for item of interest with a focus on high-margin items<br>• Find mix of familiar and relevant new items<br>• Find suitable accessories<br>• ... | |
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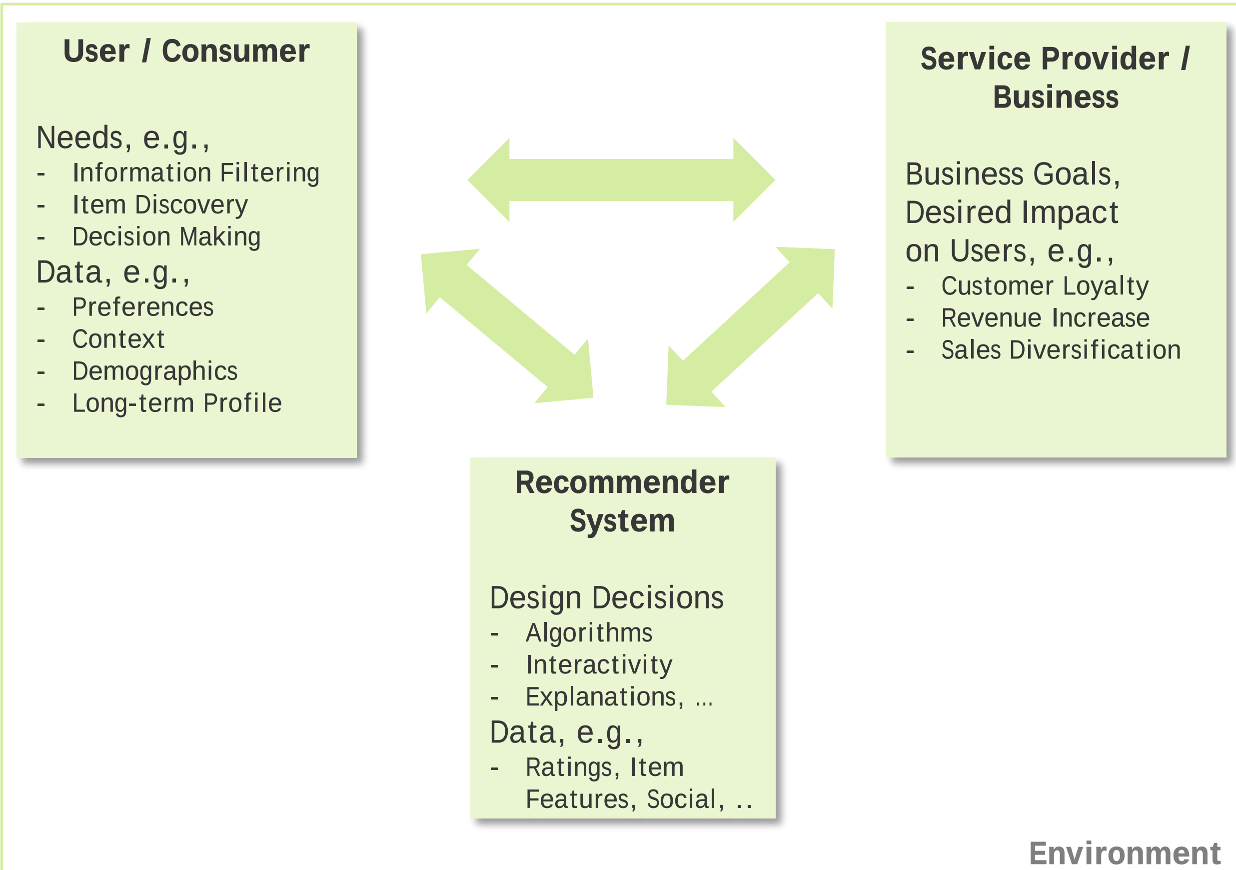
# Immediate challenges

- Defining new tasks and metrics
  - Next-item recommendation as a candidate
  - Consider metric-purpose-fit
- Multi-metric evaluations, understanding trade-offs
- Data and protocol issues
- Moving beyond computer science (RECO-nomics)

# From Algorithms to Systems

- For a more comprehensive research approach, need to move beyond computer science
  - Often, too much focus on abstract accuracy measures (in machine learning based research)
  - Question of the purpose of the system seldom asked
    - What to measure and where to be good at depends on the purpose
- Research in Information Systems literature
  - Not much visibility in CS literature
  - Accuracy only one of many factors for RS success
- Putting the user back in the loop

# A more comprehensive picture



# Summary

- Sketched importance of recommenders
- Discussed history of recommender systems
- Outlined challenges of current research practice
  - Recommendation is not (only) a machine learning problem
  - And it is not solved
- Reviewed a conceptual framework to the design and evaluation of recommender systems

# Outlook

- Need to address problem (more often) with an interdisciplinary approach
  - Focus on problems other than algorithms
  - Develop a richer repertoire of research methods
    - Many of them are already out there
- "Standardize" research operationalization of relevant practical problems
  - E.g., next-item recommendation, session-based recommendation, usage of multiple recommendation lists, ….
- Need to better understand real-world implications of research results
  - Do a real-world check, consider specific purposes or our systems, consider the stakeholder's roles
  - Several studies show that the most accurate methods in offline experiments lead to the best user perception or business success

- Thank you for your attention

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