UNIVERSITÄT KLAGENFURT

Recommender Systems in Finance: Methods and Business Value

Dietmar Jannach, University of Klagenfurt, Austria
dietmar.jannach@aau.at

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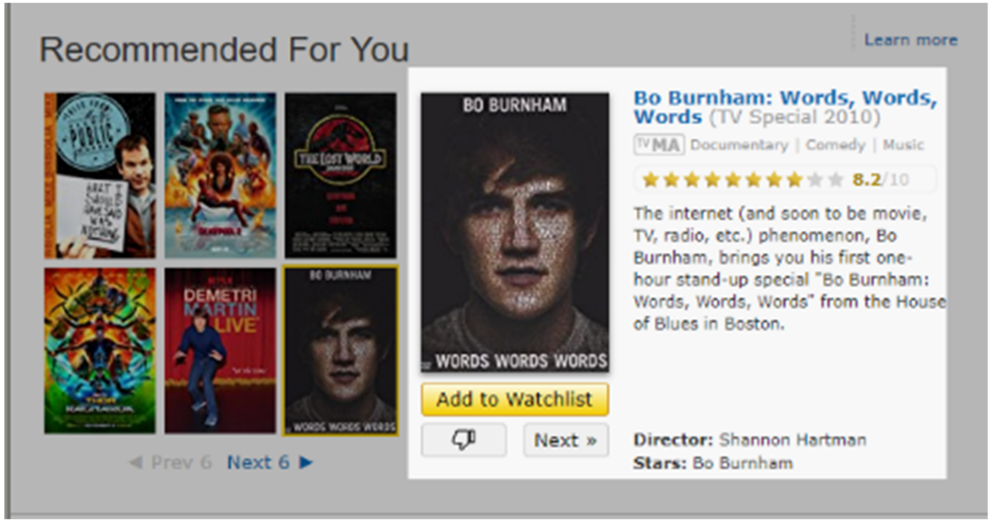
Recommender Systems (RS)

- A pervasive part of our daily online user experience
- One of the most widely used applications of machine learning / artificial intelligence

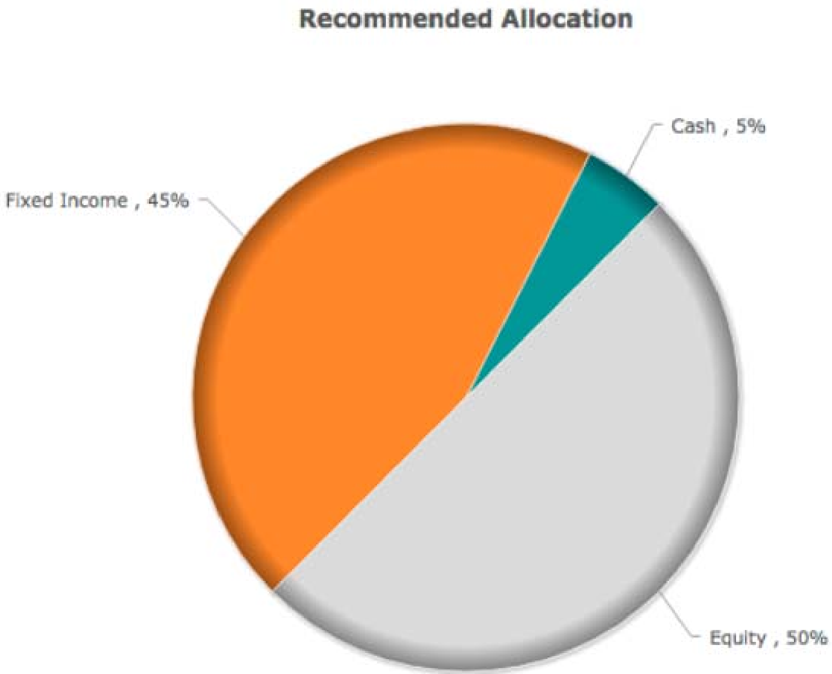


Applications

- News
- Books
- Videos
- Music
- Games
- Shopping goods
- Friends
- Groups
- Jobs
- Apps
- Restaurants
- Hotels
- Deals
- Partners
- …
- Cigars
- Software code, code reviewers
- …

Applications

- Where's Finance?
- Recommendations obviously play a role in Finance



Recommender Systems in Finance

- Some activity happening in academia

- But far from being mainstream

Outline

- Understand the potential values of recommender systems
- Learn how we they are built
- [Understand the needs in the financial domain]

Who benefits?

- Why should we use recommender systems?
  - Recommenders can have value both for consumers and the providers of the recommendations
  - There can be even more stakeholders:
    - e.g.: consumers, trader, product provider

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

Potential value for the consumer

- Examples:
  - Help users find objects that match their long-term preferences (information filtering)
  - Help users explore the item space and improve decision making
  - Make contextual recommendations, e.g.,
    - Show alternatives
    - Show accessories
  - Remind users of what they liked in the past
  - Actively notify consumers of relevant content

Potential value for the provider

- Examples:
  - Change user behavior in desired directions
  - Create additional demand
  - Increase (short term) business success
  - Enable item "discoverability"
  - Increase activity on the site and user engagement
  - Provide a valuable add-on service
  - Learn more about the customers

Multi-stakeholder considerations

- When goals are fully aligned
  - Better recommendations can lead to more satisfied, returning customers who find what they need
- When there can be a goal conflict
  - Not all recommendable items may have the same business value
  - From a business perspective, it might be better to recommend items with a higher sales margin
    - As long as the recommendations are still reasonable

What's the business value?

- Typical quotes about value

"35% of Amazon.com's revenue is generated by its recommendation engine."

"We think the combined effect of personalization and recommendations save us more than $1B per year."

"Netflix says 80 percent of watched content is based on algorithmic recommendations"

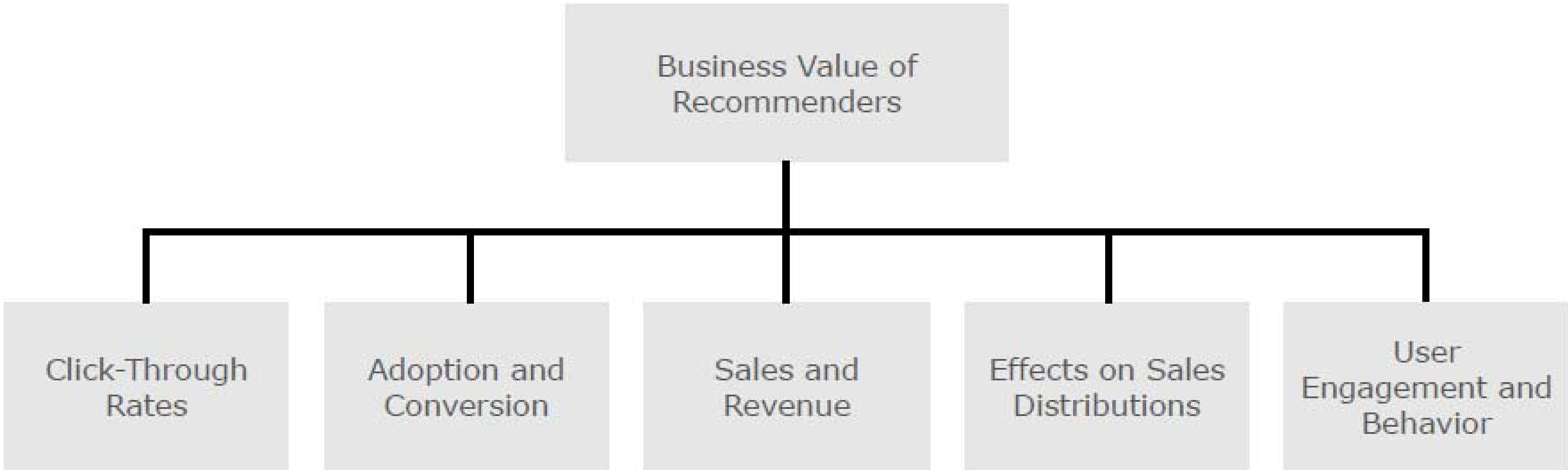
Carlos A. Gomez-Uribe and Neil Hunt. 2015. The Netflix Recommender System: Algorithms, Business Value, and Innovation. ACM Trans. Manage. Inf. Syst. 6, 4, Article 13

Measuring the business value

- Measuring the business value can be difficult
  - What does it tell us that 80% of the watched content comes from the recommendations?
  - Where do the said savings come from?
- The used measures often largely depend on
  - The business model of the provider
  - The intended effects of the recommendations
  - Assumptions about consumer value

What is often measured?

- Considering both the impact and value perspective



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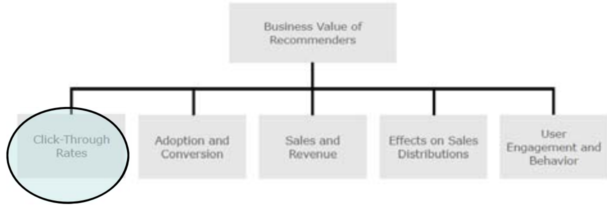
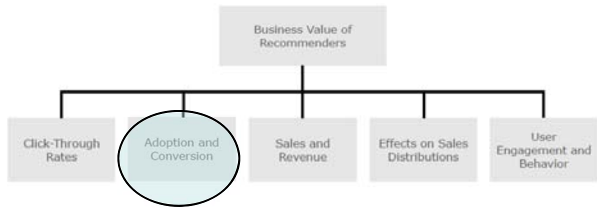
Click-Through Rates



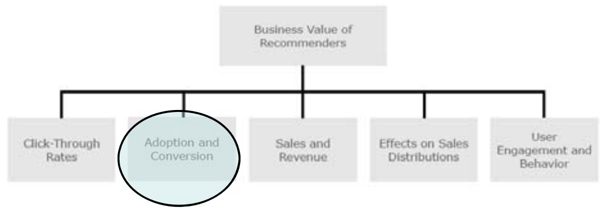
- Measures how many clicks are garnered by recommendations
  - Popular in the news recommendation domain
    - Google News: 38% more clicks compared to popularity-based recommendations
    - Forbes: 37% improvement through better algorithm compared to time-decayed popularity based method
    - swissinfo.ch: Similar improvements when considering only short-term navigation behavior
  - YouTube: Almost 200% improvement through co-visitation method (compared to popular recommendations)

Adoption and Conversion Rates



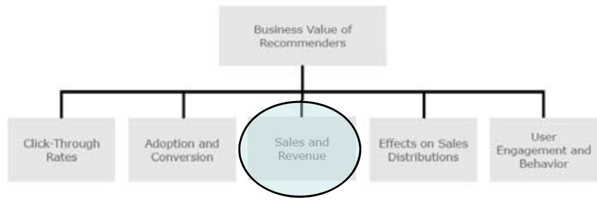
- CTR usually not the ultimate measure
  - Cannot know if users actually liked/purchased what they clicked on (consider also: click bait)
- Therefore
  - Various, domain-specific adoption measures common
- YouTube, Netflix: “Long CTR”/ “Take rate”
  - only count click if certain amount of video was watched

Adoption and Conversion Rates



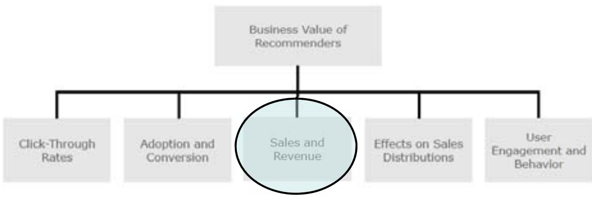
- Alternatives when items cannot be viewed/read:
- eBay:
  - "purchase-through-rate", "bid-through-rate"
- Other:
  - LinkedIn: Contact with employer made
  - Paper recommendation: "link-through", "cite-through"
  - E-Commerce marketplace: "click-outs"
  - Online dating: "open communications", "positive contacts per user"

Sales and Revenue



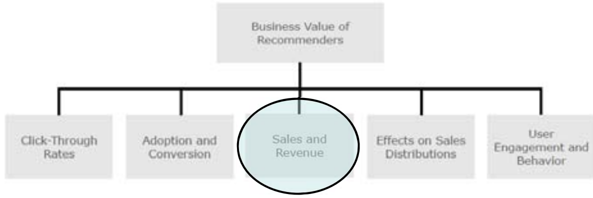
- CTR and adoption measures are good indicators of relevant recommendations
- However:
  - Often unclear how this translates into business value
  - Users might have bought an item anyway
  - Substantial increases might be not relevant for business when starting from a very low basis
- In addition:
  - Problem of measuring effects with flat-rate subscription models (e.g., Netflix).

Sales and Revenue



- Only a few studies, some with limitations
  - Video-on-demand study: 15% sales increase after introduction (no A/B test, could be novelty effect)
  - DVD retailer study:
    - 35% lift in sales when using purchased-based recommendation method compared to “no recommendations”
    - Almost no effects when recommendations were based on view statistics
    - Choice of algorithm matters a lot

Sales and Revenue

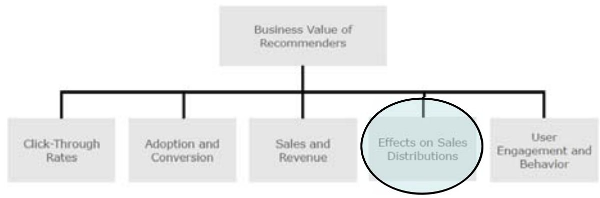


- e-grocery studies:
  - 1.8 % direct increase in sales in one study
  - 0.3 % direct effects in another study
  - However:
    - Up to 26% indirect effects, e.g., where customers were pointed to other categories in the store
    - "Inspirational" effect also observed in music recommendation in our own work
- eBay:
  - 6 % increase for similar item recommendations through largely improved algorithm
  - (500 % increase in other study for specific area)

Sales and Revenue

- Book store study:
  - 28 % increase with recommender compared with "no recommender"; could be seasonal effects
  - Drop of 17 % after removing the recommender
- Mobile games (own study)
  - 3.6 % more purchases through best recommender
  - More is possible

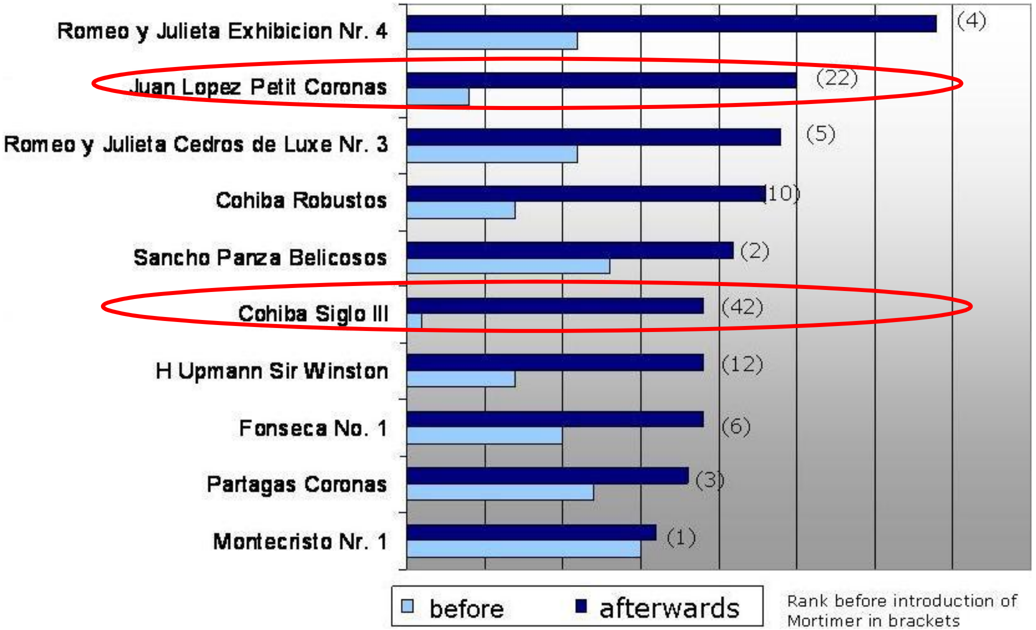
Effects on Sales Distributions



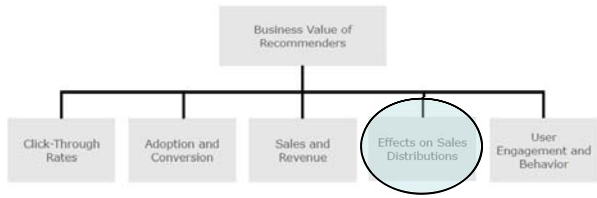
- Goal is maybe not to sell *more* but *different* items
- Influence sales behavior of customers
  - stimulate cross-sales
  - sell off on-stock items
  - promote items with higher margin
  - long-tail recommendations

Effects on Sales Distributions

- Premium cigars study:
  - Interactive advisory system installed
  - Measurable shift in terms of what is sold
    - e.g., due to better-informed customers

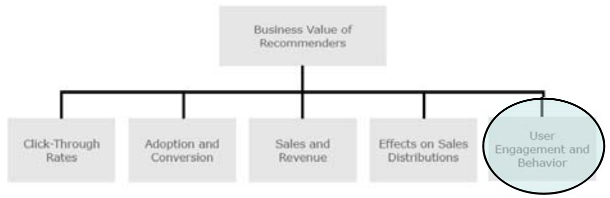


Effects on Sales Distributions



- Netflix:
  - Measure the "effective catalog size", i.e., how many items are actually (frequently) viewed
  - Recommenders lead users away from blockbusters
    - Could also be beneficial in terms of license costs
- Online retailer study:
  - Comparison of different algorithms on sales diversity
  - Outcomes
    - Recommenders tend to **decrease** the overall diversity
    - Might increase diversity at individual level though

User Behavior and Engagement



- Assumption:
  - Higher engagement leads to higher re-subscription rates (e.g., at Spotify)
- News domain studies:
  - 2.5 times longer sessions, more sessions when there is a recommender
- Music domain study:
  - Up to 50% more user activity
- LinkedIn:
  - More clicks on job profiles after recommender introduced

Discussion & challenges

- General
  - No doubt about huge business potential of RS
- Challenges, e.g.:
  - Direct financial impact sometimes difficult to measure (e.g., Netflix)
  - User activity and clicks might not be indicative of consumer value and business success
  - Long-term effects often difficult to measure
  - **Know what to measure**

What to measure?

- Some underlying questions:
  - What is the intended purpose of the system?
  - What kind of value should it create?
  - How can we assess (and balance) the value for the different stakeholders?

Abdollahpouri, H., Adomavicius, G., Burke, R., Guy, I., Jannach, D., Kamishima, T., Krasnodebski, J. and Pizzato, L.: "Multistakeholder Recommendation: Survey and Research Directions". User Modeling and User-Adapted Interaction, Vol. forthcoming. 2020

A conceptual framework

- Should help to decide what and how to measure (both in academia and industry)
- Layered structure – strategic to operational
- Considers two viewpoints

Overarching goal of the system, strategic value

Recommendation purpose / Intended utility

System (algorithm) task

Computational metrics

Framework overview

		Consumer's Viewpoint	Provider's Viewpoint
Strategic Perspective	Overarching Goal	"Personal Utility": Happiness, Satisfaction, Knowledge, ...	"Organizational Utility": Profit, Revenue, Growth, ...
	Recommendation Purpose	• Help users find objects that match the user's long-term preferences • Show alternatives • Help users explore or understand the item space • ...	• Change user behavior in desired directions • Create additional demand • Increase activity on the site • ...
Operational Perspective	System Task	• Annotate in context (i.e., estimate preference of a given item) • Find good items • Create diverse set of alternatives • Find suitable accessories • Retrieve novel but relevant items • ...	
	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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Summary of value considerations

- Demonstrated business value of recommenders in many domains
- Size of impact however depends on many factors like baselines, domain specifics etc.
- Measuring impact is generally not trivial
  - Choice of the evaluation measure matters a lot
  - CTR can be misleading
- "Metric-Task-Purpose-Fit" to be considered

Methods

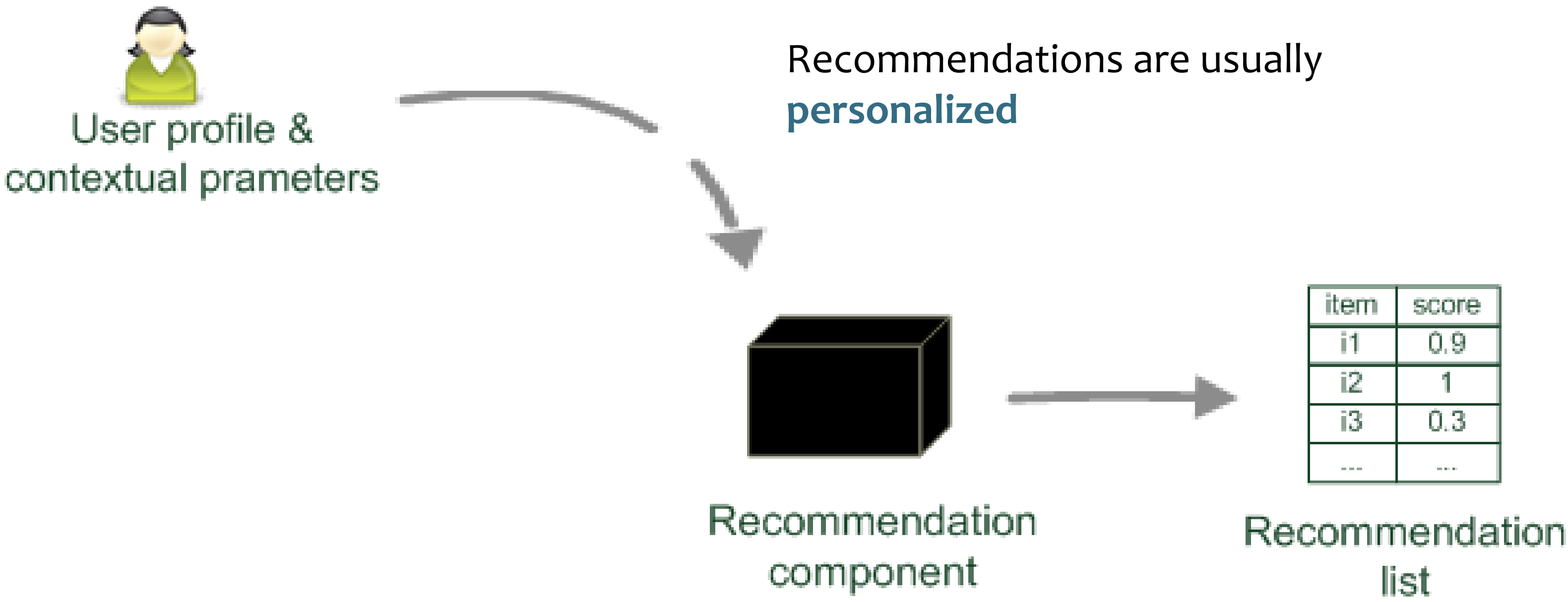
Outline

- Content-based Filtering
- Collaborative Filtering
- Hybrid Systems
- Knowledge-based Systems

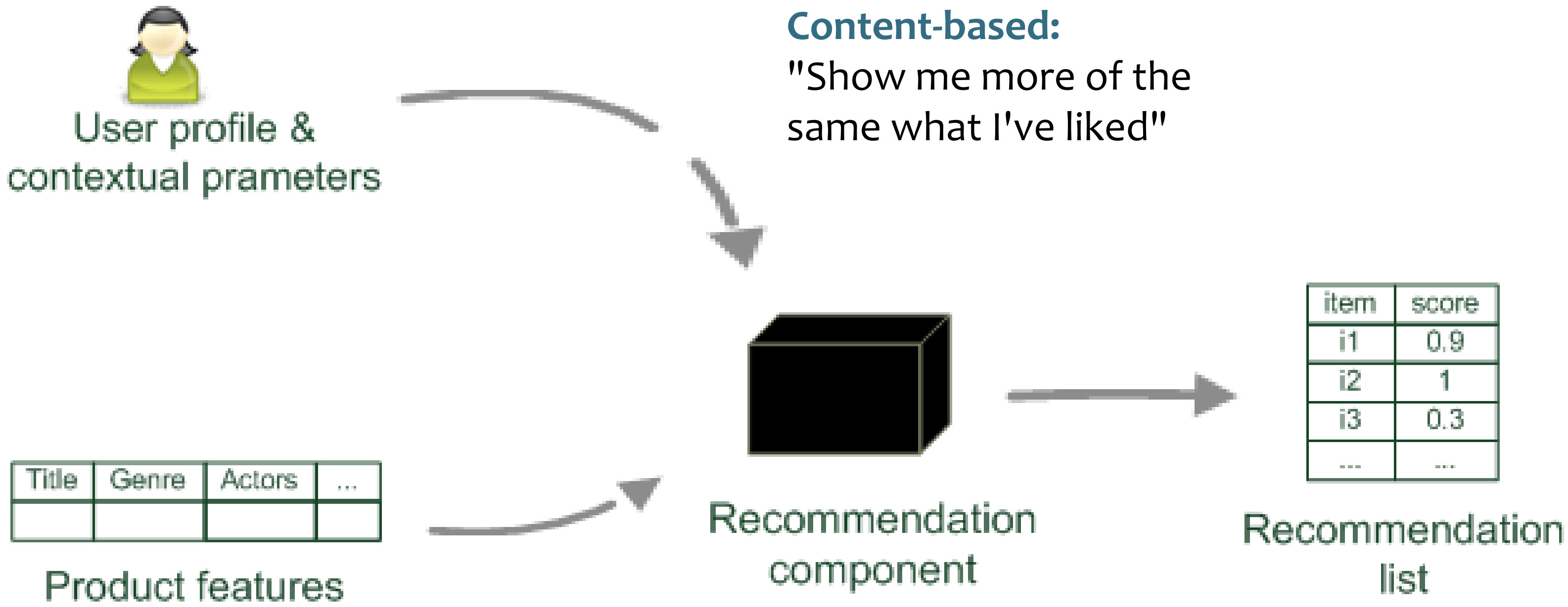
- Interactive Recommendation

Recommendation Principles

Recommendations are usually **personalized**

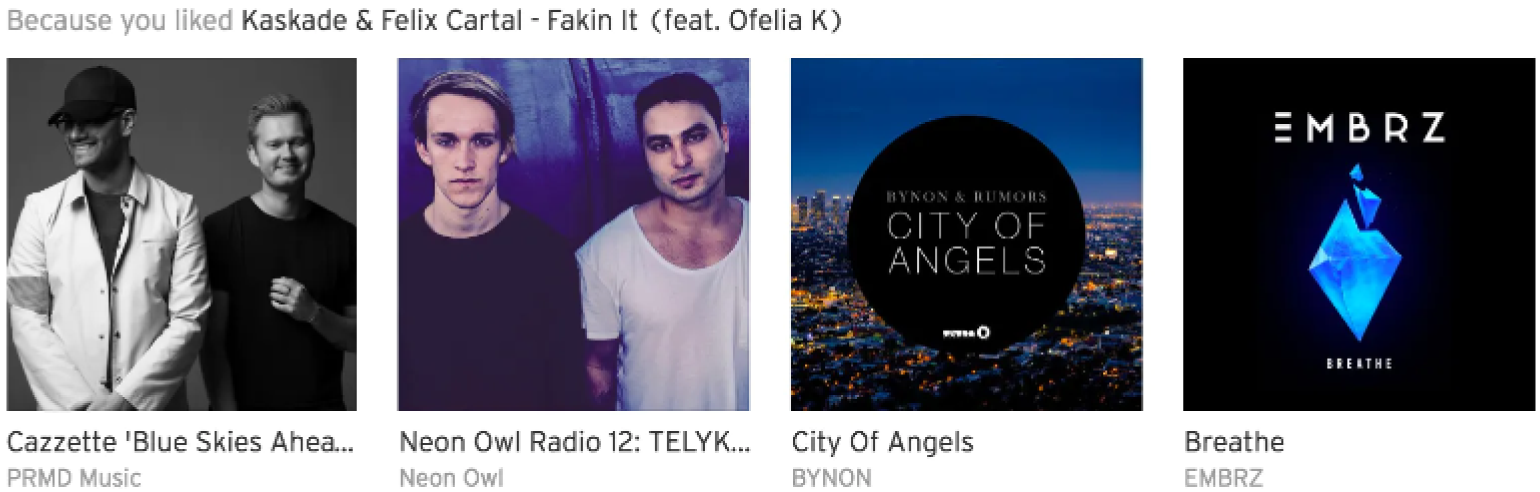


Content-based Filtering



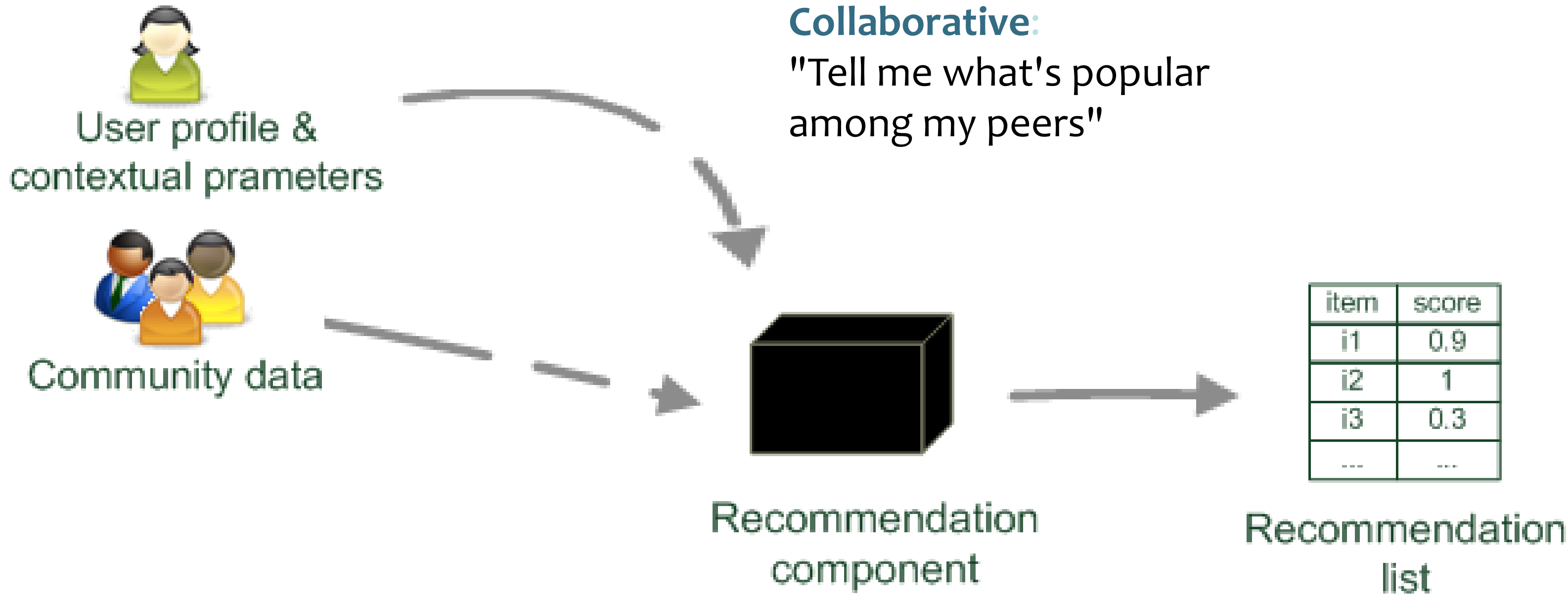
Content-based:
"Show me more of the same what I've liked"

Because you liked



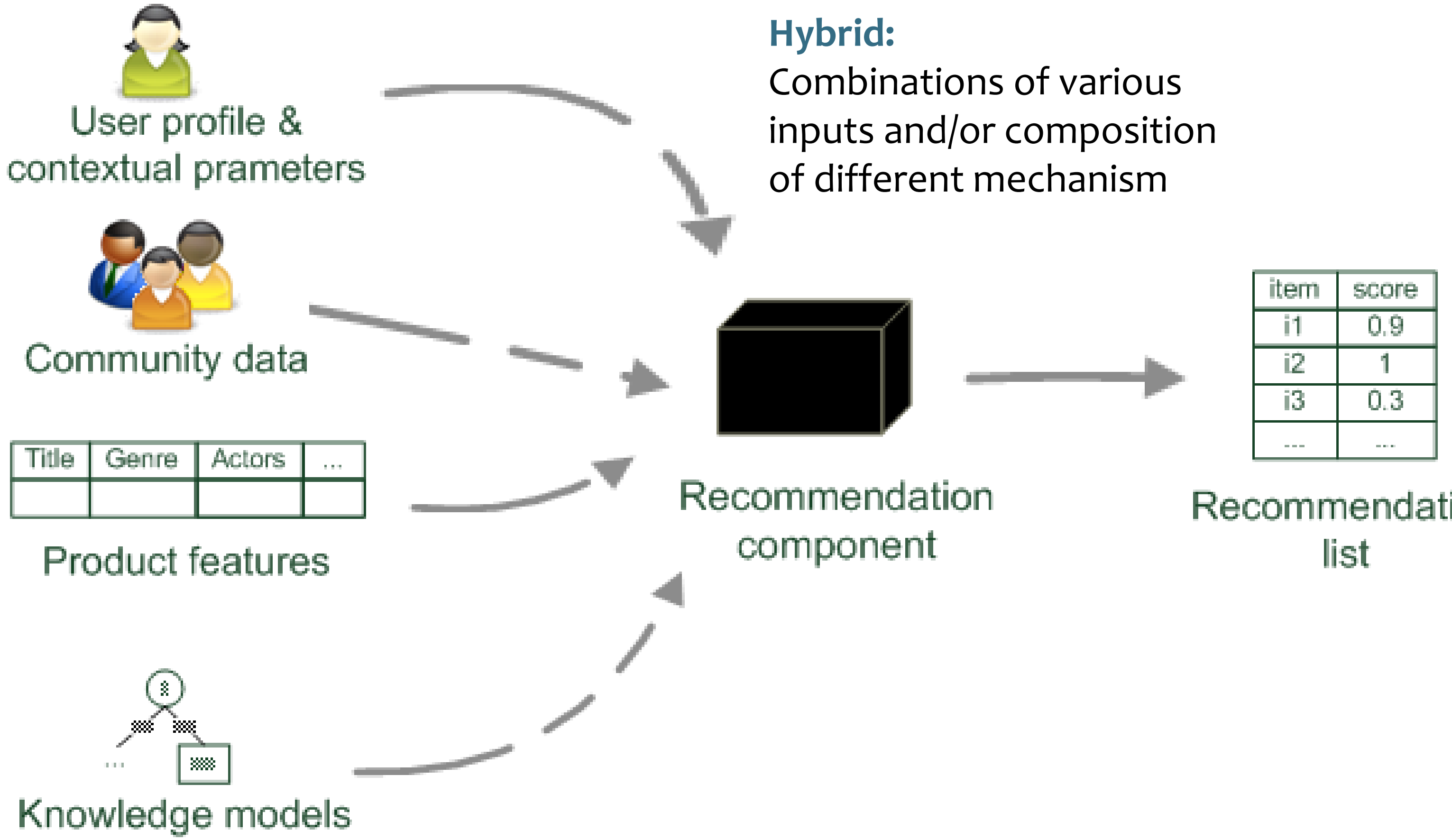
Collaborative Filtering

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



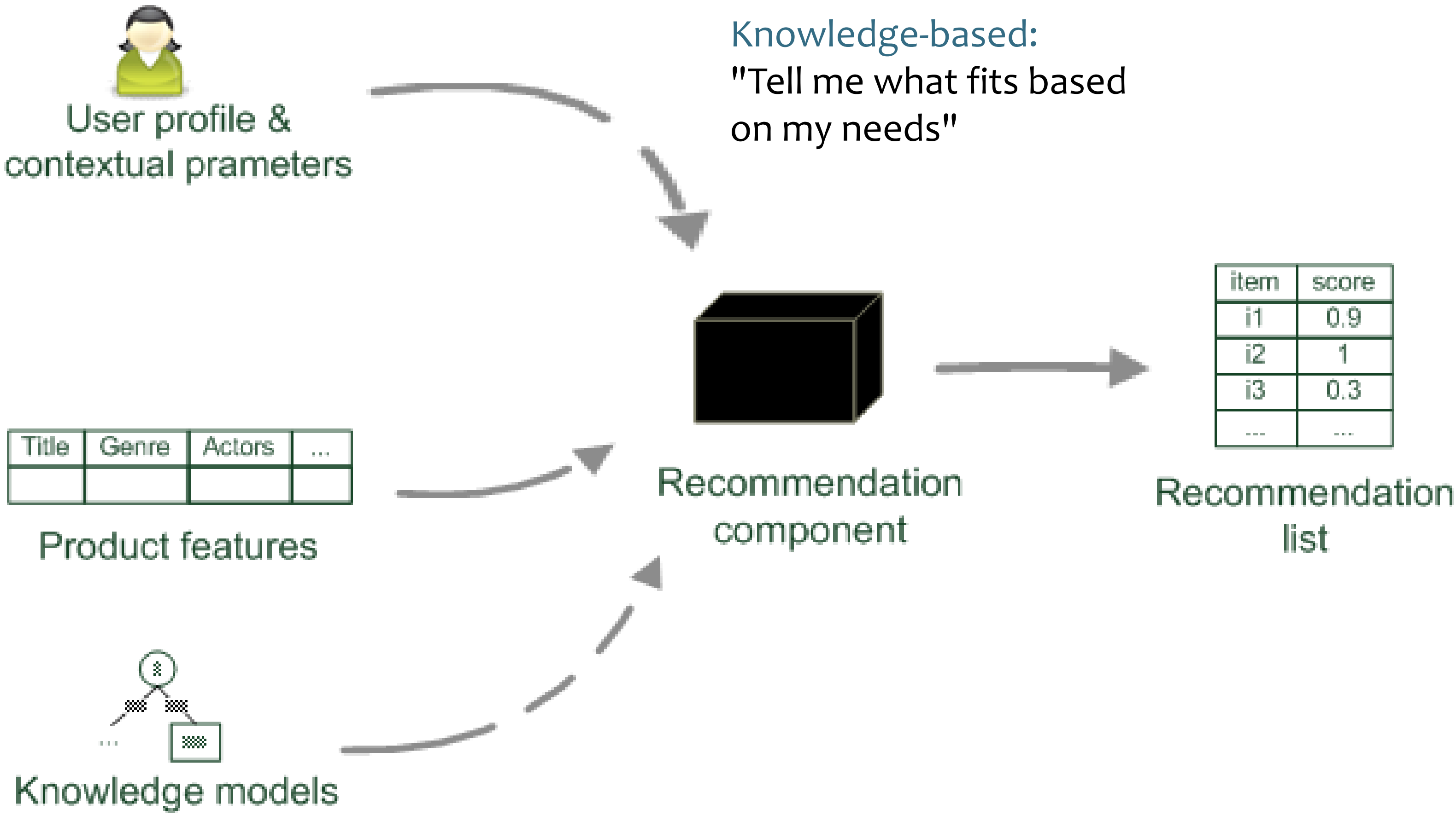
Customers who bought …

Hybrid Recommendation Approach



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

Knowledge-based Systems

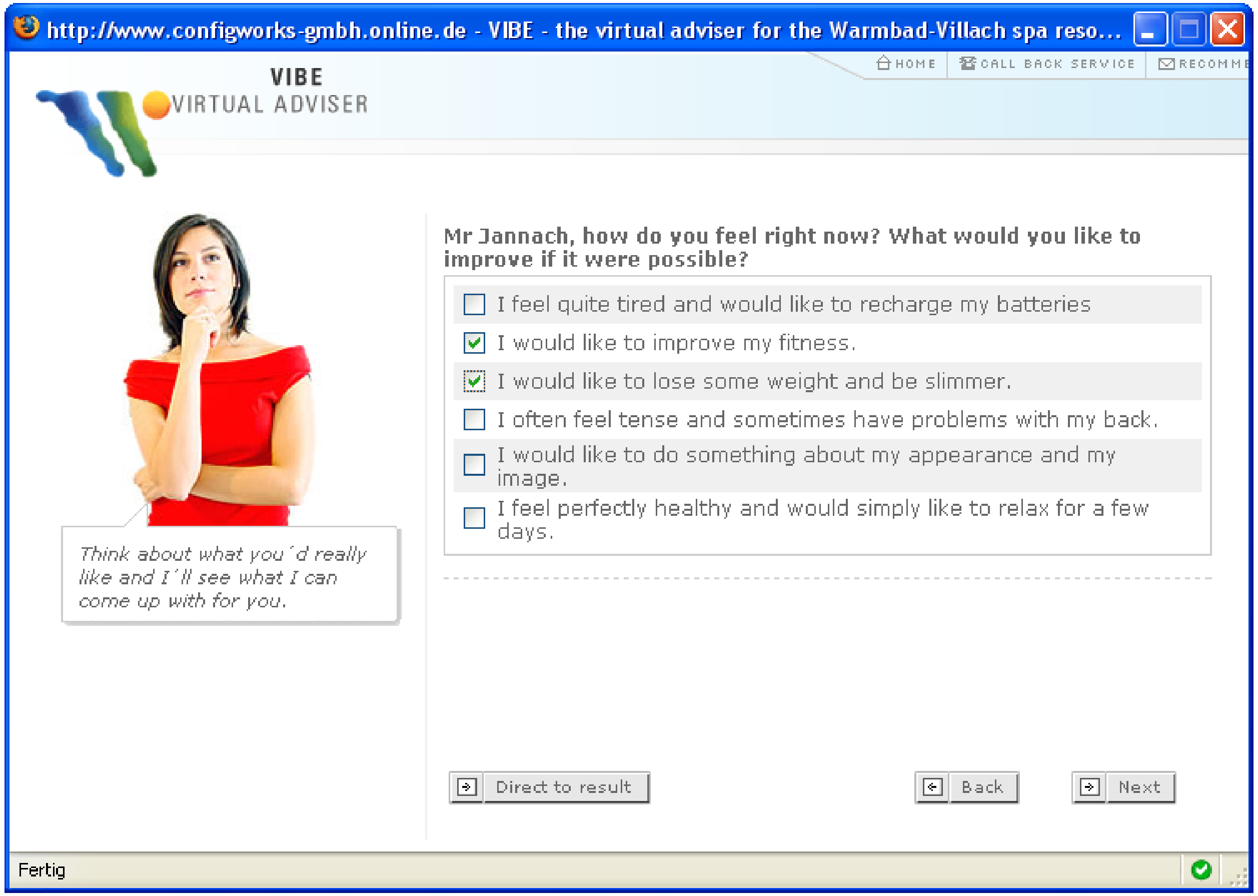


Knowledge-based:
"Tell me what fits based on my needs"

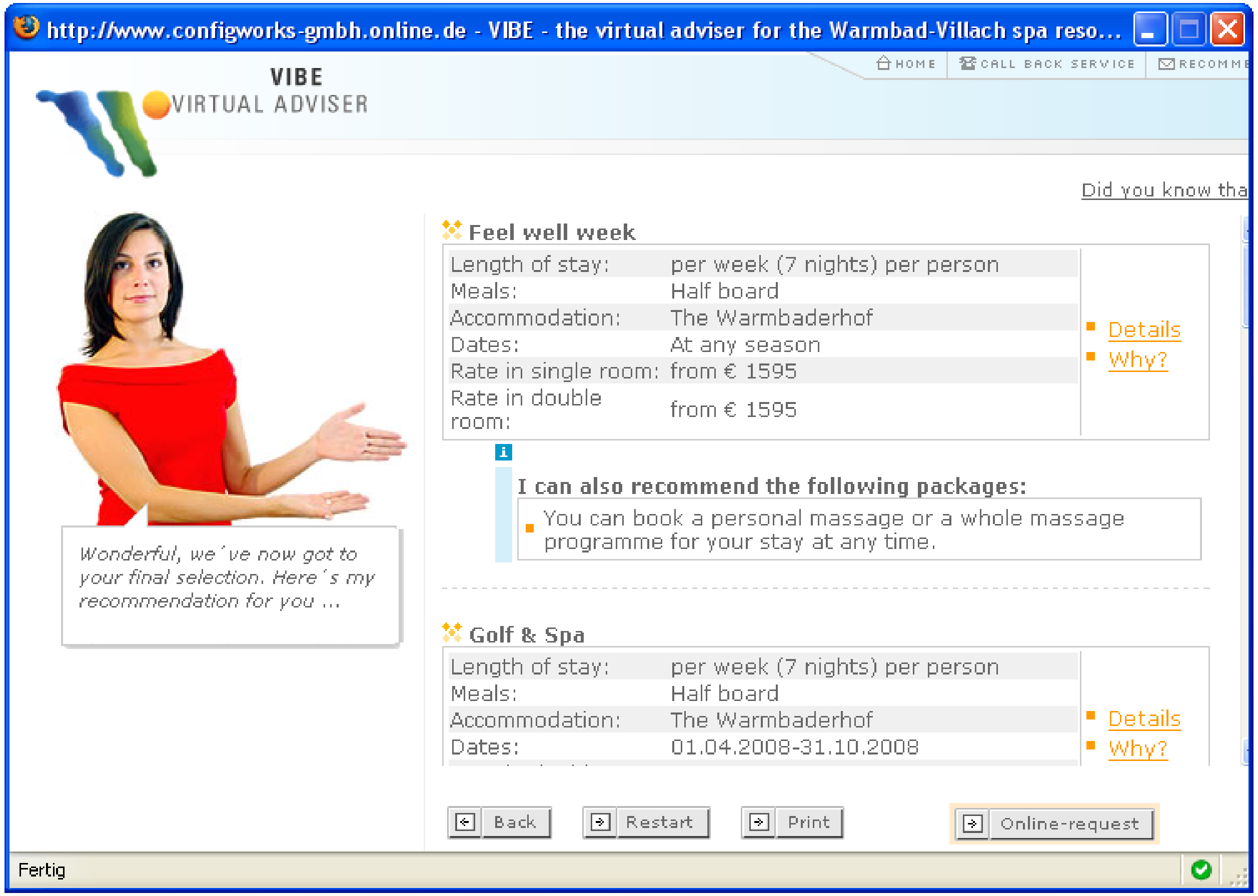
Knowledge-based Systems

- Hybrid collaborative and content-based systems are highly successful in practice
  - And do not require knowledge engineering
- Why do we need knowledge-based systems?
  - Often low number of past interactions (purchases)
  - Often explicit customer requirements are relevant
  - Longer time spans between purchases

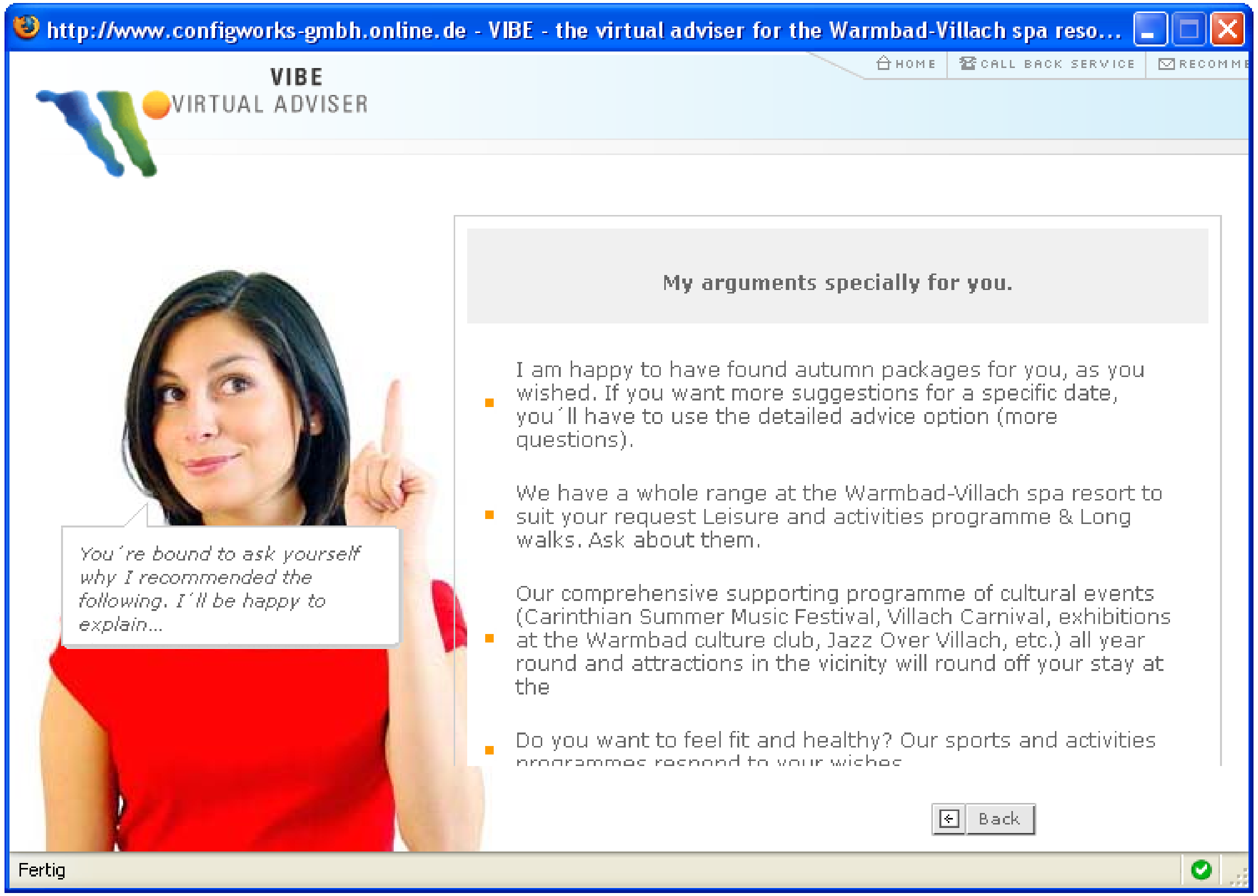

An interactive travel recommender



An interactive travel recommender



An interactive travel recommender



A financial advisory system

- Built for an Austrian bank in mid-2000s
- Provides multi-step interactive needs acquisition
  - personalized according to preferences
- Generates tailored set of recommendations
- Is able to explain recommendations
- Points consumers to inconsistencies with respect to their expectations

Financial advisor demo (German)

Hypo Veranlagungsplaner

Allgemeine Informationen

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Hypo Veranlagungsplaner

Der Weg zu Ihrer ganz persönlichen Vermögens-anlage.

Weiter

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Discussion

- Successful application in practice (own startup)
  - Built more solutions, e.g. for Hungarian bank or Austrian insurance company
- Mimics behavior of experienced sales advisor
  - Automated documentation of advisory process
- Solutions based on expert knowledge
  - Comprehensive tooling, automated generation of application
  - No learning component

Discussion

- In 2020:
  - Chatbots have become popular in 2016
  - Enormous advances in natural language technology
- Challenges:
  - Limitations of pure learning approaches for conversational recommendation
  - Certain amounts of knowledge engineering required
    - Predictability of recommendations is an issue

Examples of other applications

- Content / Case-based Recommendation
  - Look up similar past customers

Personalized finance advisory through case-based recommender systems and diversification strategies

CrossMark

Cataldo Musto [a,*], Giovanni Semeraro [a], Pasquale Lops [a], Marco de Gemmis [a], Georgios Lekkas [b]

[a] *Universita degli Studi di Bari "Aldo Moro", Department of Computer Science, Italy*
[b] *Objectway Financial Software, Italy*

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A B S T R A C T

Recommendation of financial investment strategies is a complex and knowledge-intensive task. Typically, *financial advisors* have to discuss at length with their wealthy clients and have to sift through several *investment proposals* before finding one able to completely meet investors' needs and constraints. As a consequence, a recent trend in wealth management is to improve the advisory process by exploiting recommendation technologies. This paper proposes a framework for recommendation of asset allocation strategies which combines *case-based reasoning* with a novel diversification strategy to support financial advisors in the task of proposing diverse and personalized investment portfolios. The performance of the framework has been evaluated by means of an experimental session conducted against 1172 real users, and results show that the yield obtained by recommended portfolios overcomes that of portfolios proposed by human advisors in most experimental settings while meeting the preferred risk profile. Furthermore, our diversification strategy shows promising results in terms of both diversity and average yield.

Case-based recommendation

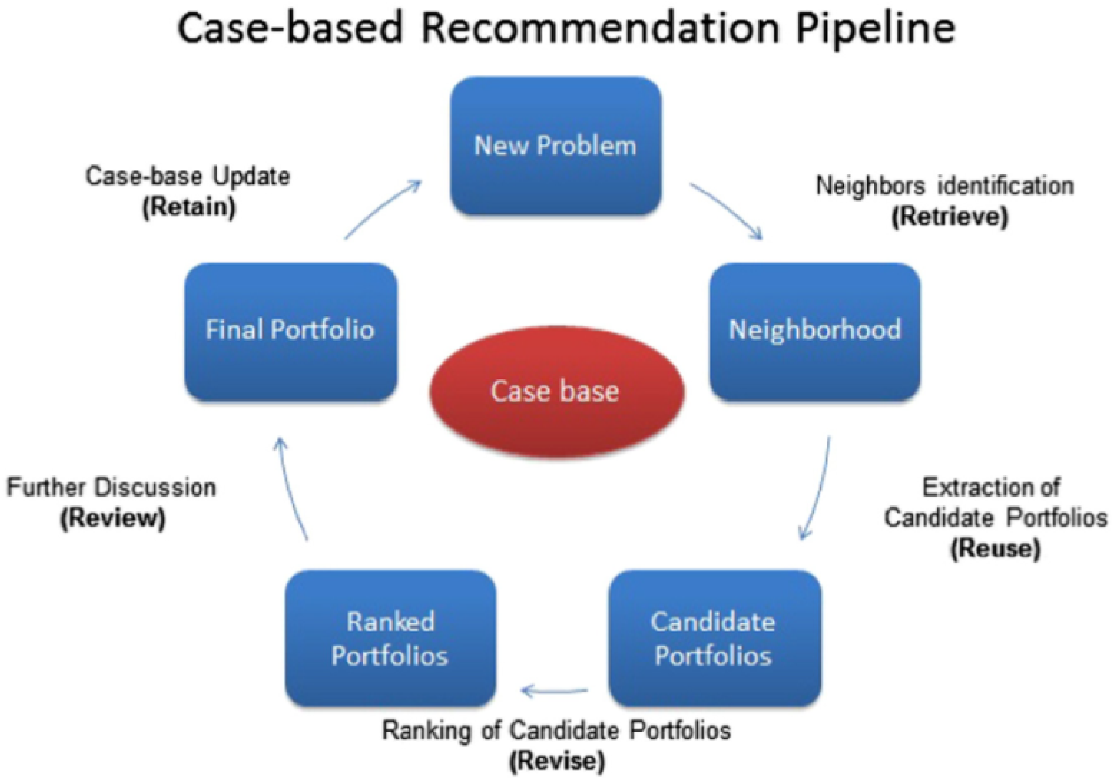

Fig. 2. Our case-based recommendation pipeline.

Examples of other applications

- A number of portfolio advisory approaches
  - Mostly knowledge-intensive

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PB-ADVISOR: A private banking multi-investment portfolio advisor

Israel Gonzalez-Carrasco, Ricardo Colomo-Palacios, Jose Luis Lopez-Cuadrado, Ángel García-Crespo, Belén Ruiz-Mezcua

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Abstract

Private banking is a business area in which the investor requires tailor-made advice. Because of the current market situation, investors are requiring answers to difficult questions and looking for assurance from wealth managers. Private bankers need to have deep knowledge about an innumerable list of products and their characteristics as well as the suitability of each product for the client's characteristics to be able to offer an optimal portfolio according to client expectations. Client and portfolio diversity calls for new recommendation and advice systems focused on their specific characteristics. This paper presents PB-

Examples of other applications

- Equity funds selection
  - Collaborative content-based hybrid
  - Multi-criteria decision making

New Hybrid Recommender Approaches: An Application to Equity Funds Selection

Nikolaos F. Matsatsinis and Eleftherios A. Manarolis

Department of Production Engineering and Management Decision Support Systems Laboratory, Technical University of Crete, Crete, Greece
{nikos,manarolis}@ergasya.tuc.gr

Abstract. Recommender Systems and Multicriteria Decision Analysis remain two separate scientific fields in spite of their similarity in supporting the decision making process and reducing information overload. In this paper we present a novel algorithmic framework, which combines features from Recommender Systems literature and Multicriteria Decision Analysis to alleviate the sparsity problem and the absence of multidimensional correlation measures. We apply the introduced framework for recommending Greek equity funds to a set of simulation generated investors. The proposed framework treats MCDA's algorithm UTADIS as a content - based recommendation technique which, in conjunction with collaborative filtering results in two Hybrid Recommendation approaches. The resulting approaches manage to outperform the separate application of the UTADIS and collaborative filtering methods in terms of recommendation accuracy.

Keywords: Hybrid Recommender, Collaborative Filtering, UTADIS, equity funds.

Discussion

- Undisputed success of recommender systems in many domains
- Ways forward in the financial domain
  - Financial recommendations Amazon style?
    - Customers who bought …
  - Conversational recommendation?
  - Specific applications?
    - e.g., portfolio or investment recommendations
  - Mostly data analytics?
    - forecasting – also a sort of decision-support and recommendation

- Thank you for your attention
- dietmar.jannach@aau.at

- https://tinyurl.com/finrec2020