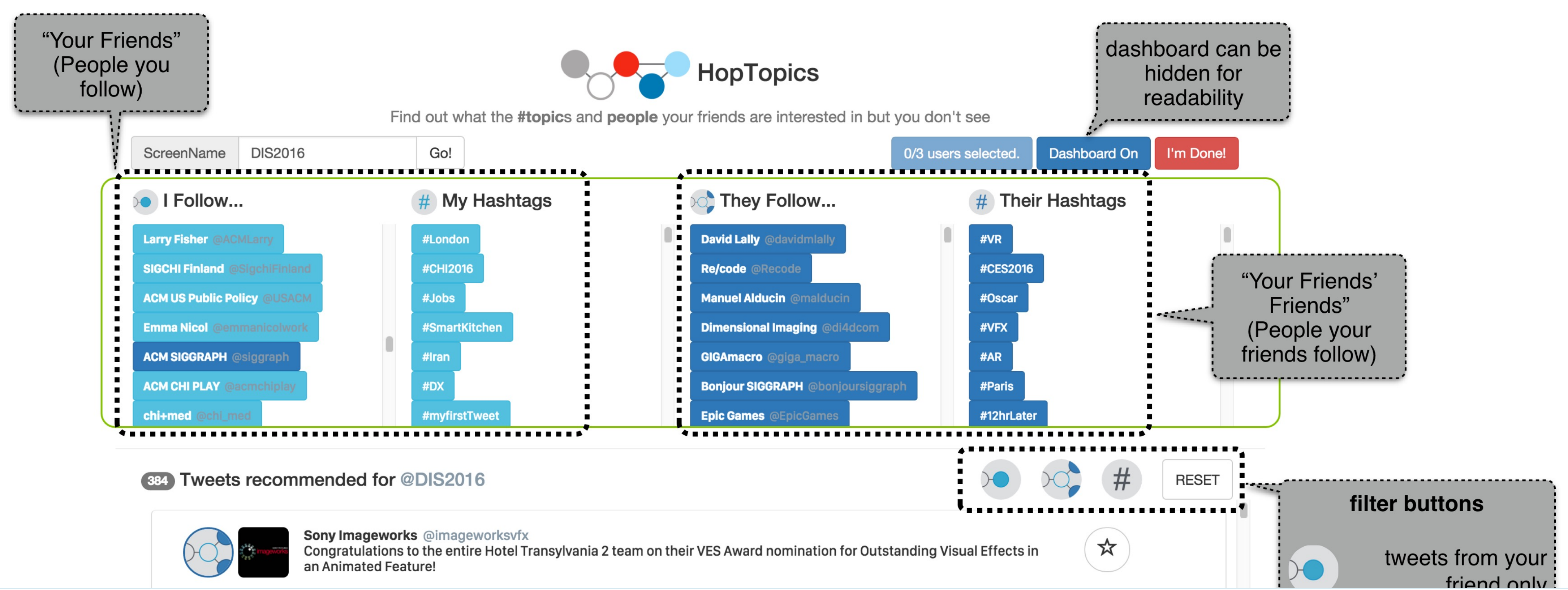


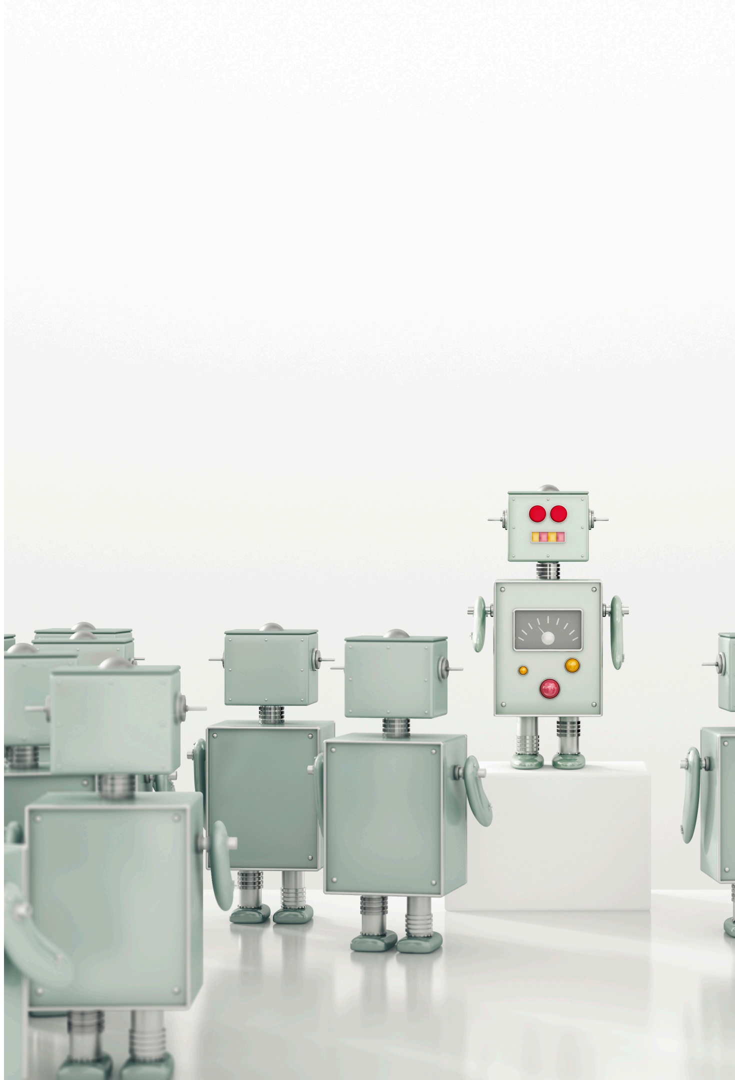
INTERACTIVE AND ADAPTIVE EXPLANATION INTERFACES FOR RECOMMENDER SYSTEMS

Professor Nava Tintarev
Department of Advanced Computing Sciences

Maastricht University
TU Delft Delft University of Technology

BROADER CONTEXT

- **There is a gap between what we can generate and what we need in applications.**
- **XAI methods (especially local explanations) are generally not robust**
  - Same instance results in different explanations. E.g., feature importance can change direction, rank etc
  - Different XAI methods also give different explanations
  - Vulnerable to adversarial attacks: different predicted classes, or again different explanations
- **Humans interpreting the results**
  - Cognitive limitations
  - (Cognitive) Biases e.g. anchoring, confirmation bias
  - Differing knowledge and skills sets



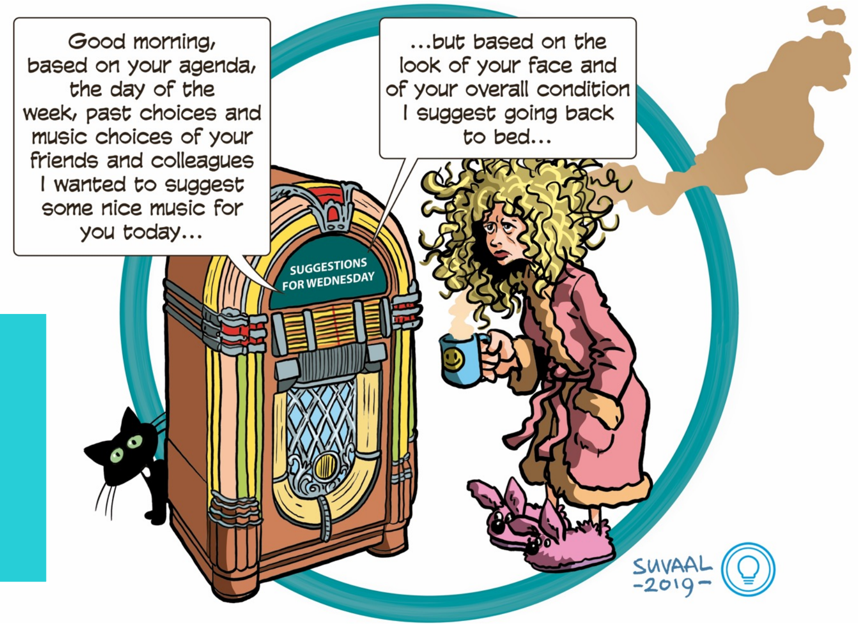
TAKE HOME PREVIEW

Explanations can serve different purposes

Different people need different explanations

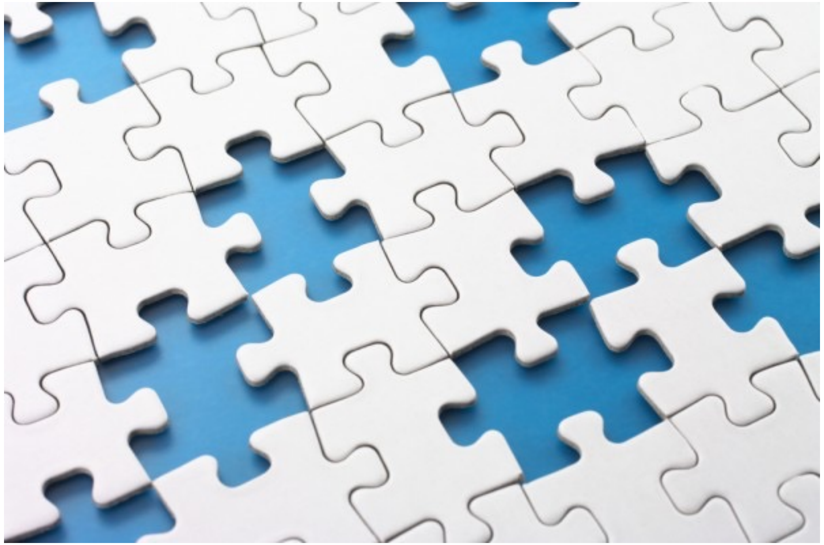
Different situations call for different explanations

There is a benefit in interactive explanations (especially for complex domains)

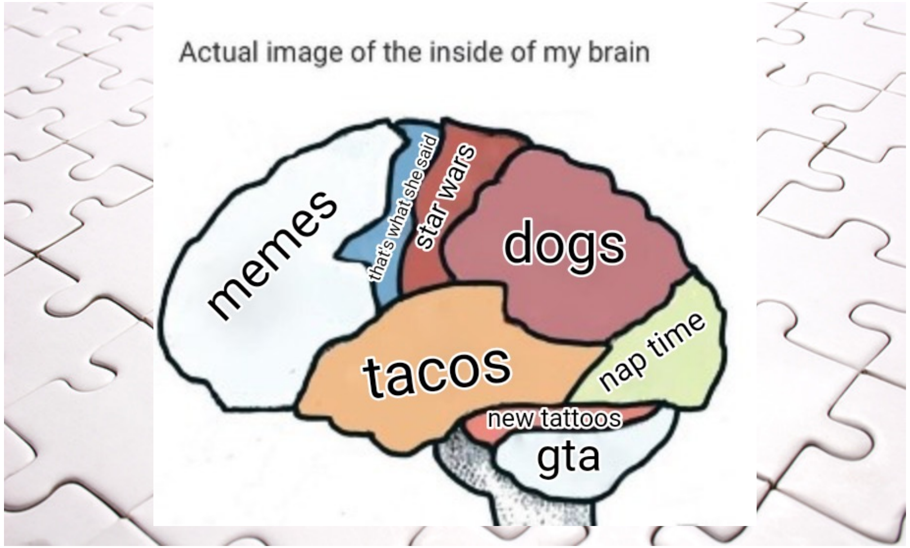


MOTIVATION

Computer



User



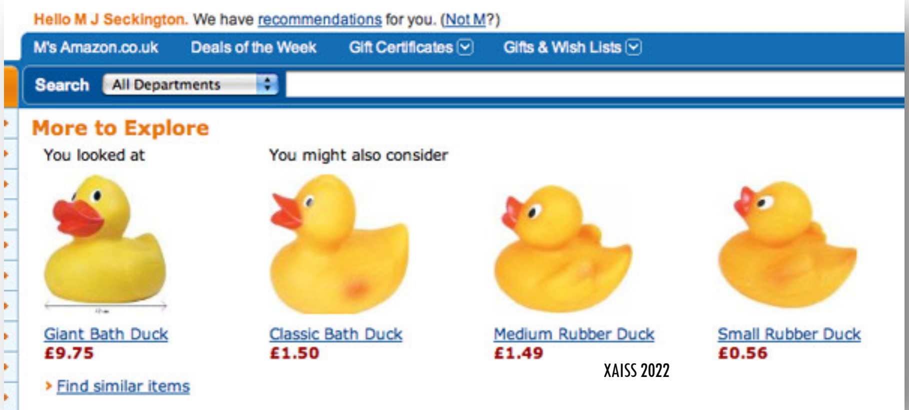
MOTIVATION

Interpretability is

the degree to which a <u>human</u> can understand the cause of a decision (Miller 2017)

the degree to which a <u>human</u> can consistently predict the model's result (Kim et al 2016)

To which extent the model and/or the prediction are <u>human-</u>understandable (Guidotti et al 2018, Amparore et al 2020)



MOTIVATION

More human (non-expert) and system collaborations.

Potential in leveraging joint strengths.

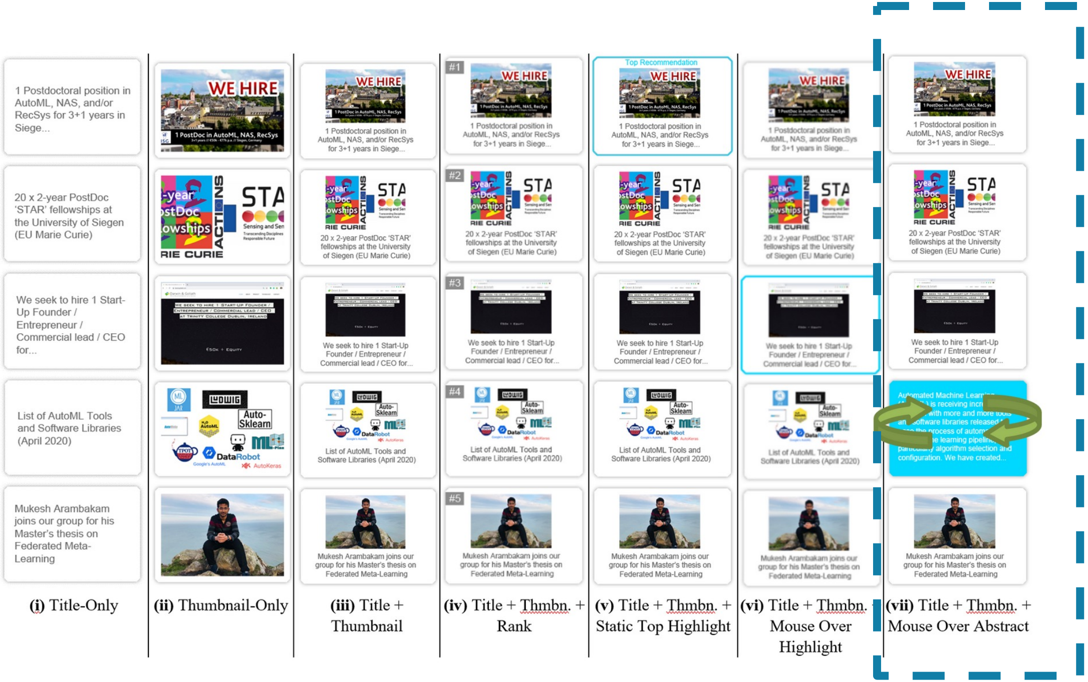
We might not accept advice from systems

- We do not know which information has been used,
- or if our opinion is considered…

Many barriers are not technical, but cognitive.

Explanations can help us make better decisions together with systems.

(Tintarev, 2016)



INTERFACE MATTERS (EXAMPLE 1)

Best variation is 66% more effective than the worst one (stat. sign.; $p<0.05$).

Measured clickthrough rate

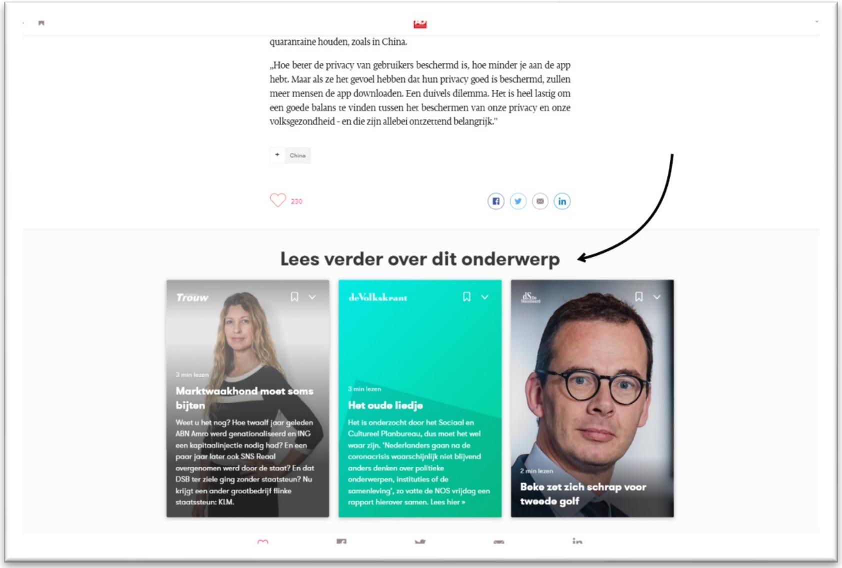
Title+thumbnail+abstract did best (vii)

Beel & Dixon UMAP'21

INTERFACE MATTERS (EXAMPLE 2)

Mats Mulder
MSc

Diversification of viewpoint on a Dutch news aggregator (Mulder et al, FACCT'21)



Oana Inel
postdoc

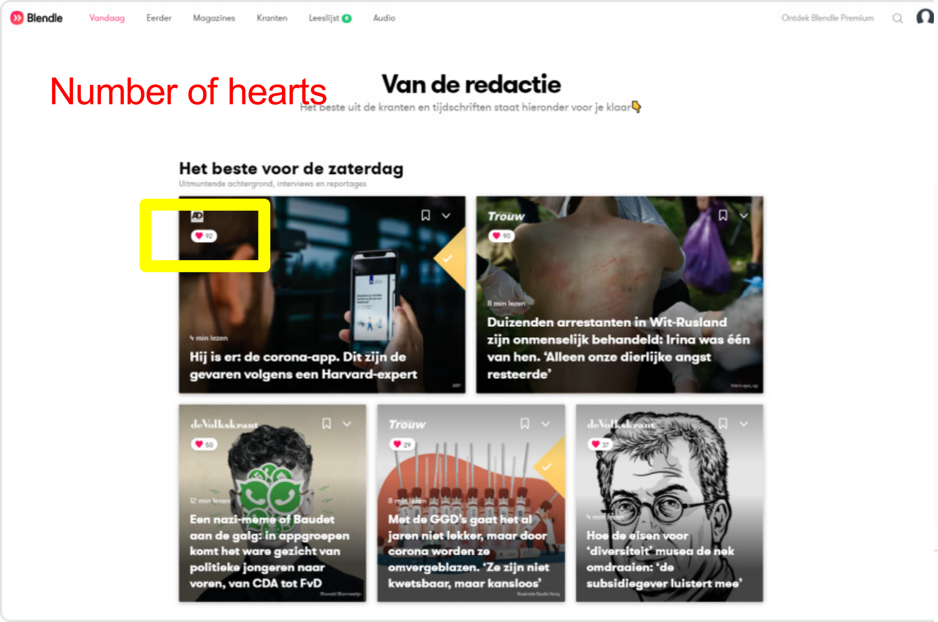
Jasper Oosterman
Blendle

Voor het hele verhaal Blendle

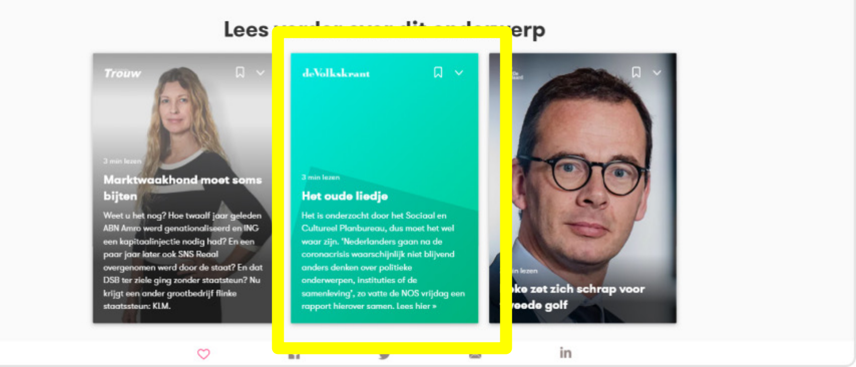
INTERFACE MATTERS!

Click-through rate for "diverse viewpoint" condition correlated with:

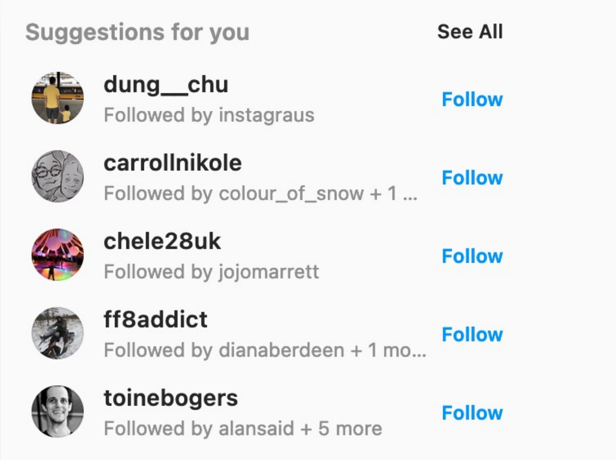
Number of hearts

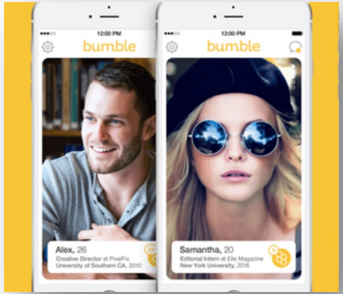


Thumbnail 3.1% more

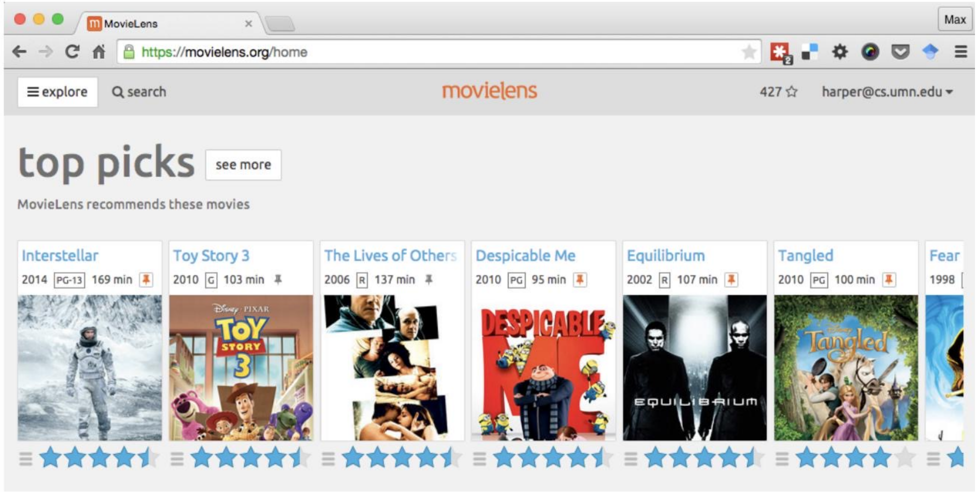


CONFESSION: I DON'T WORK IN ALL OF AI!





SEARCH VERSUS RECOMMENDATION



Search

Query

Help user find out what they want

Figure out intents

(not highly personalized)

More focused?

Recommendation

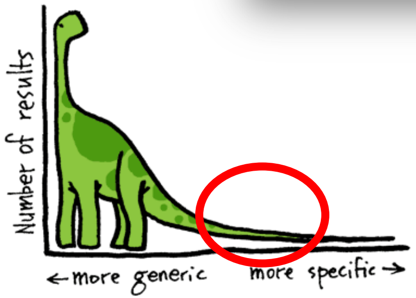
Previously rated items

Help user find more of what they like or relevant alternatives. E.g., give me something I like

Personalized

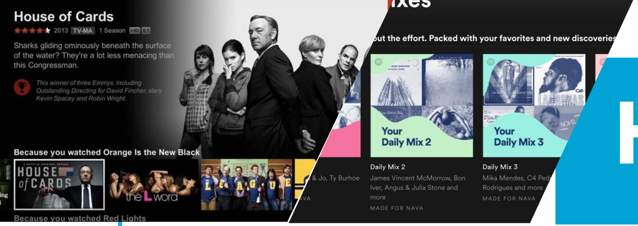
More exploratory?

When does a Recommender System (RS) do its job well?



- "Recommend widely unknown items that users might actually like!"
- 20% of items accumulate 74% of all positive ratings

HOW DOES A RECOMMENDER SYSTEM WORK?



HOW DOES A RS WORK?

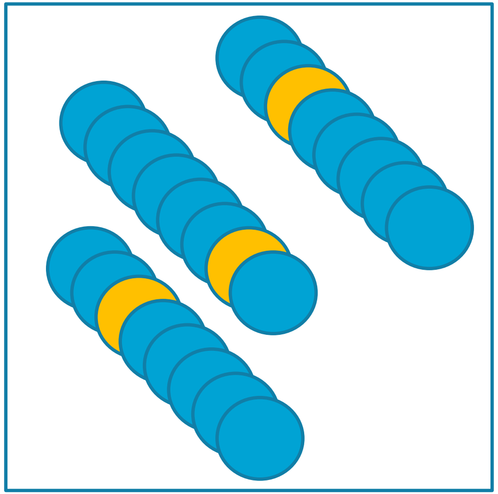
Systems that make personalized recommendations of goods, services, and people (Kautz)

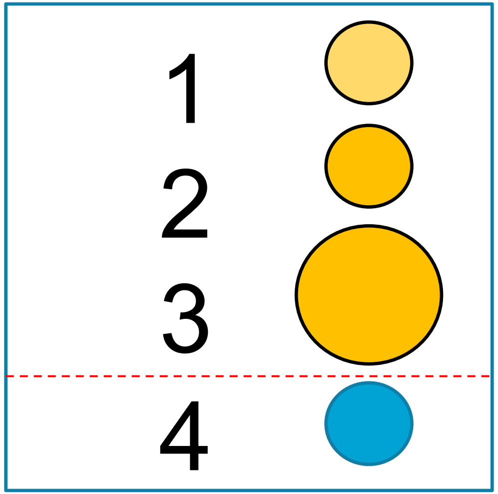
User identifies one or more objects as being of interest

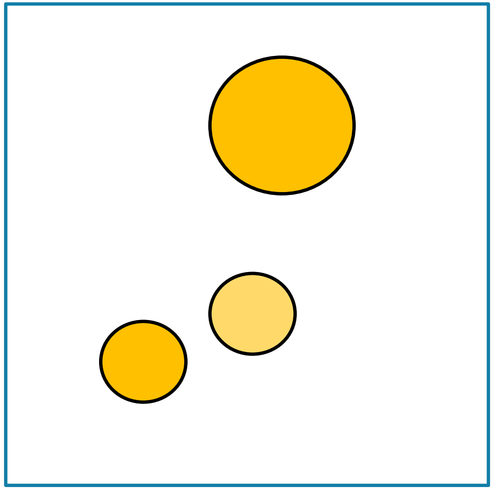
The recommender system suggests other objects that are similar (infers liking)

Ranking and filtering algorithm

- Ranks the options, filters out lower ranking options

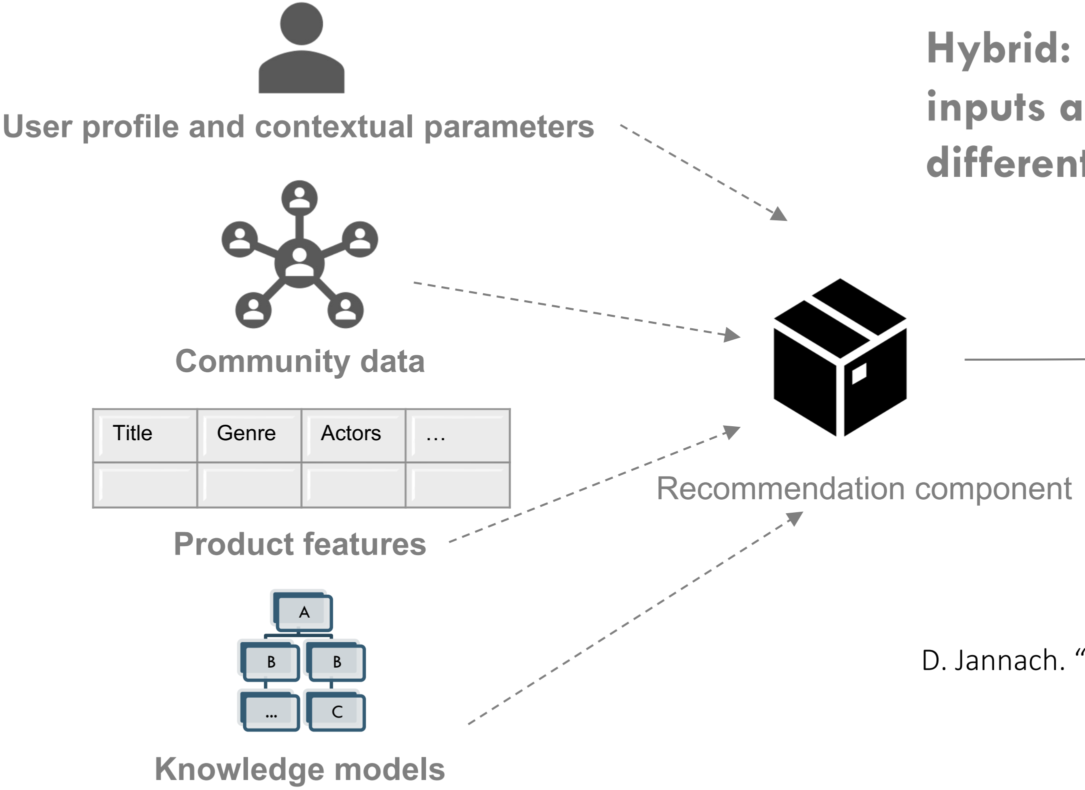






What could be "similar"?

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



Item	Score
$item_1$	0.9
$item_2$	1
$item_3$	0.3
…	…

Recommendation scores

D. Jannach. "Introduction to Recommender Systems"

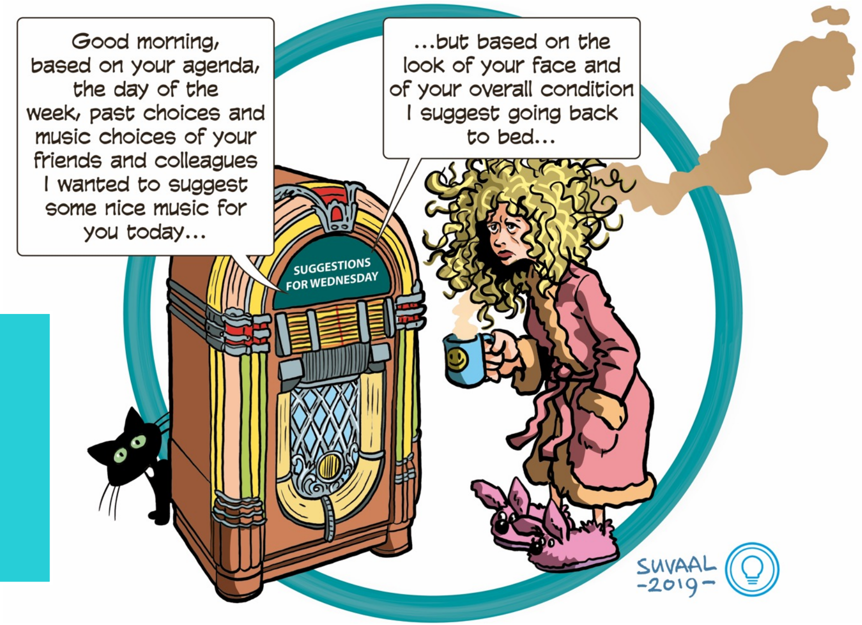
OVERVIEW

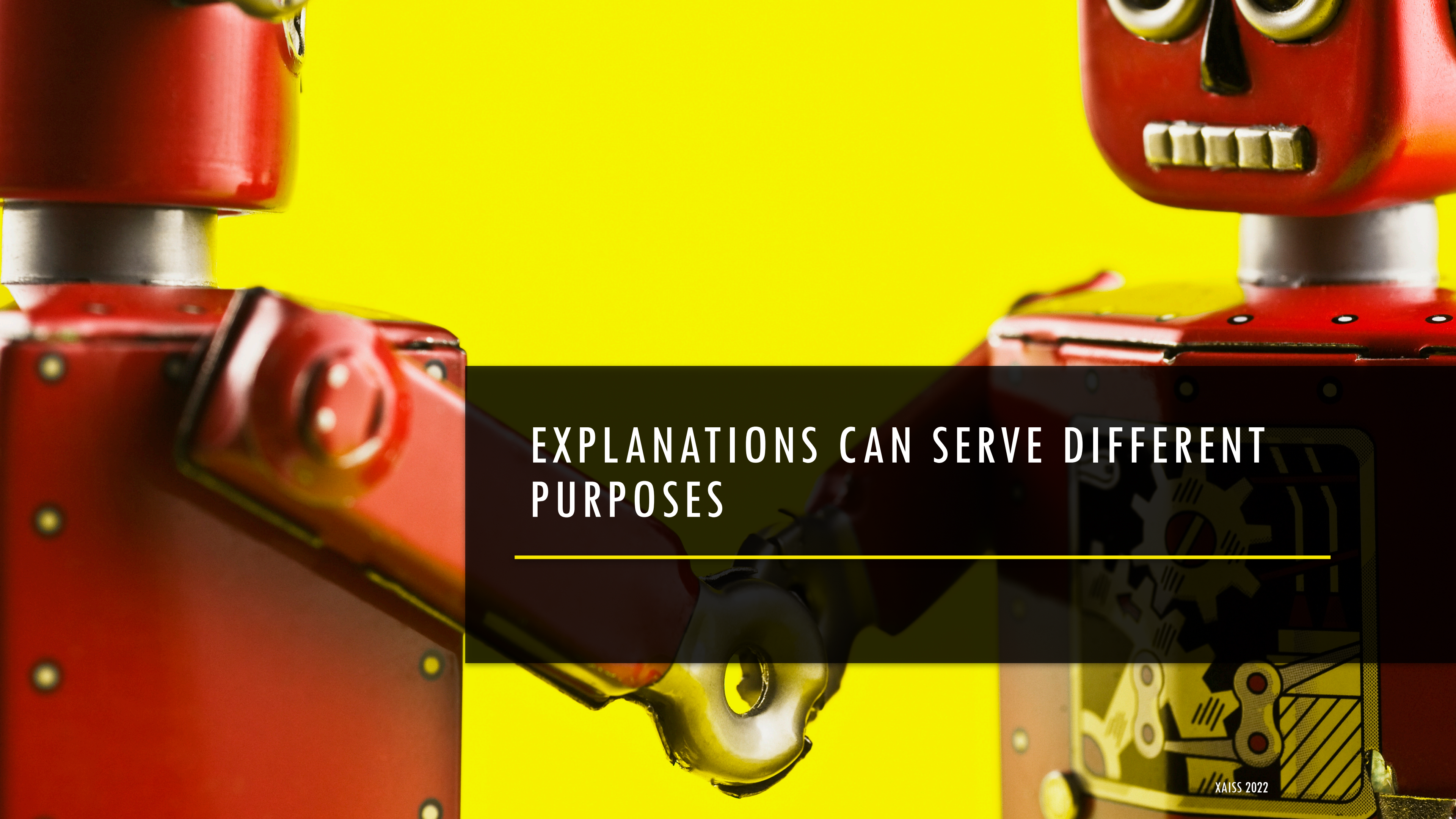
Explanations can serve different purposes

Different people need different explanations

Different situations call for different explanations

There is a benefit in interactive explanations (especially for complex domains)





EXPLANATIONS CAN SERVE DIFFERENT PURPOSES

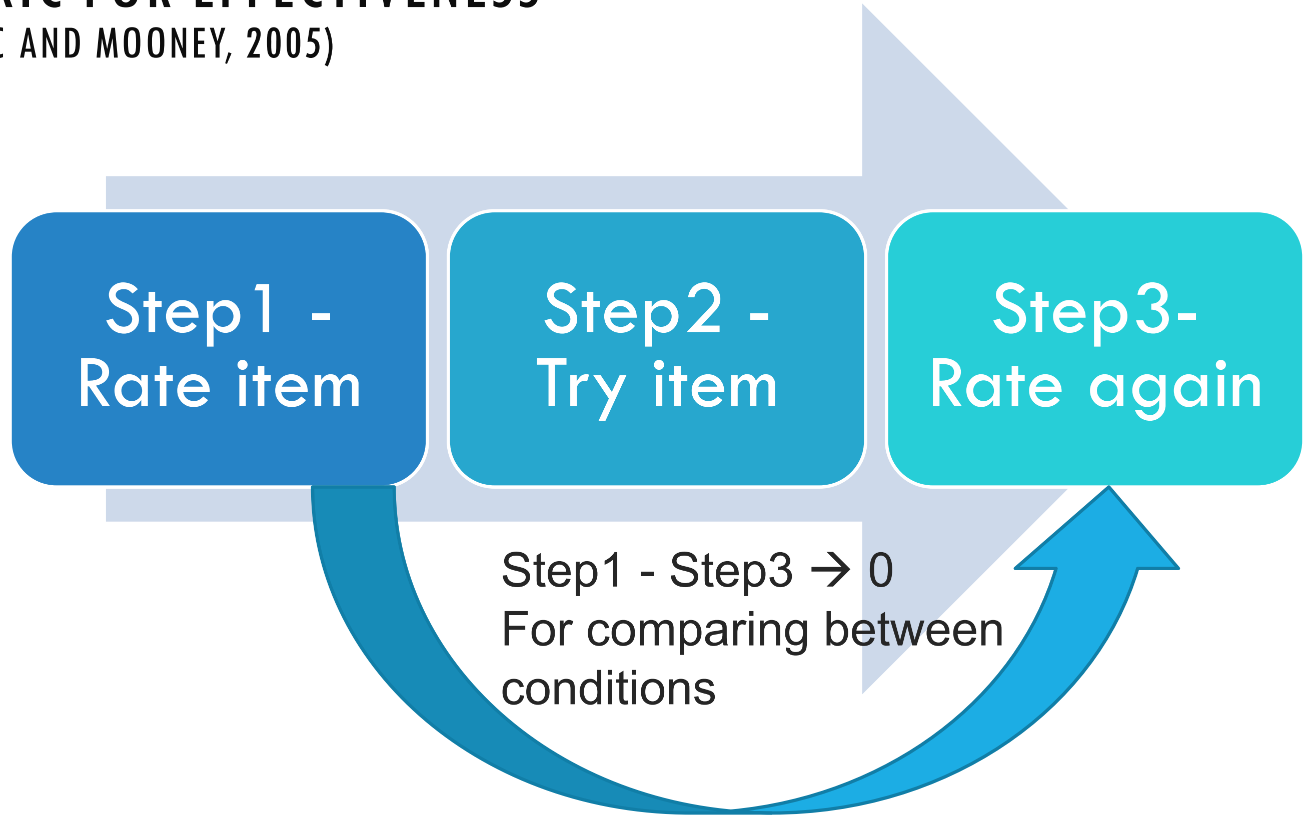
WHY EXPLAIN (RECSYS)

Purpose	Description
Transparency	**How** was this recommendation made?
Effectiveness	**Why** (not) this item?
Trust	Increase users' confidence in the system
Persuasiveness	Why **must** you buy this item?
Satisfaction	Increase the ease of use or enjoyment
Scrutability	Allow users to tell the system it is wrong
Efficiency	Help users make decisions faster

Trade-offs?

Tintarev and Masthoff, 2007 (more recent Tintarev and Masthoff 2022)

METRIC FOR EFFECTIVENESS
(BILGIC AND MOONEY, 2005)



PHD: PERSONALIZED EXPLANATIONS

(TINTAREV & MASTHOFF, 🏆 AH 2008)

Non-personalized: “This movie belongs to the genre(s): Action & Adventure and Comedy. On average other users rated this movie 4/5.0”

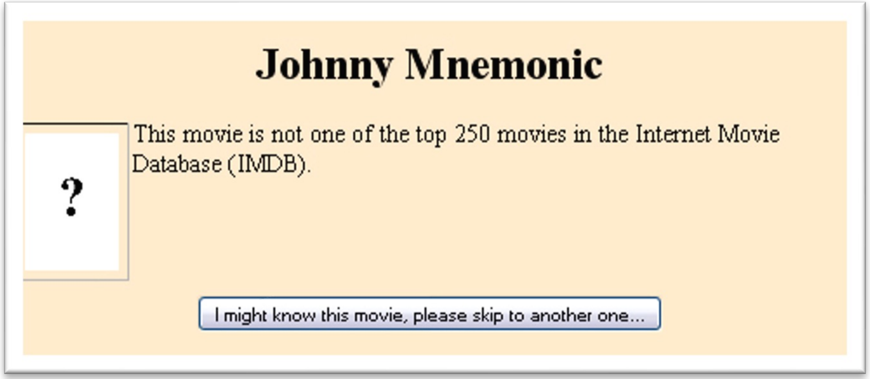
More …

effective?

persuasive?

satisfying?

Personalized:
“Unfortunately, this movie belongs to at least one genre you do not want to see: Action & Adventure. It also belongs to the genre(s): Comedy. This movie stars Jo Marr and Robert Redford.”



“PHD SUMMARY”

(TINTAREV & MASTHOFF, UMUAI 2012)

2 domains (cameras and movies)

4 experiments (personalization kept doing poorly!)

Personalized explanations worse for effectiveness, but people were more satisfied!

Change in opinion ok for baseline, but lots of cases where no opinion could be given.

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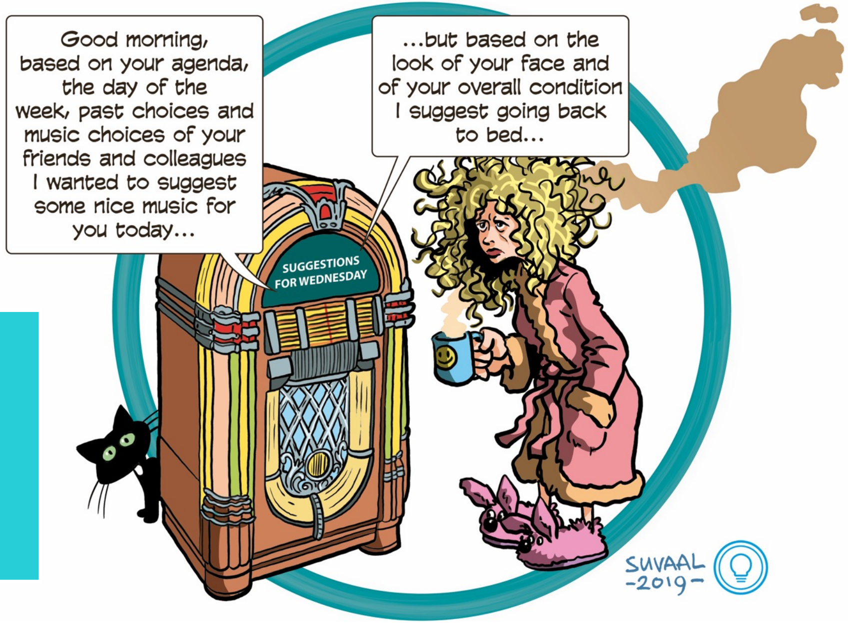
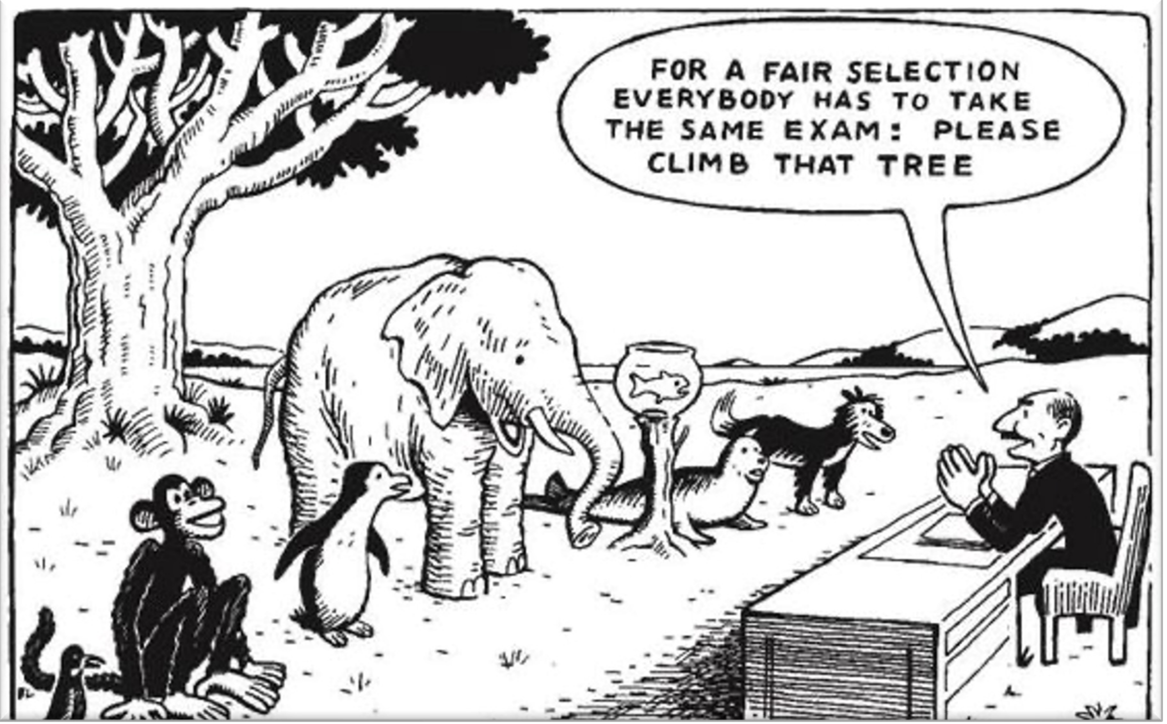
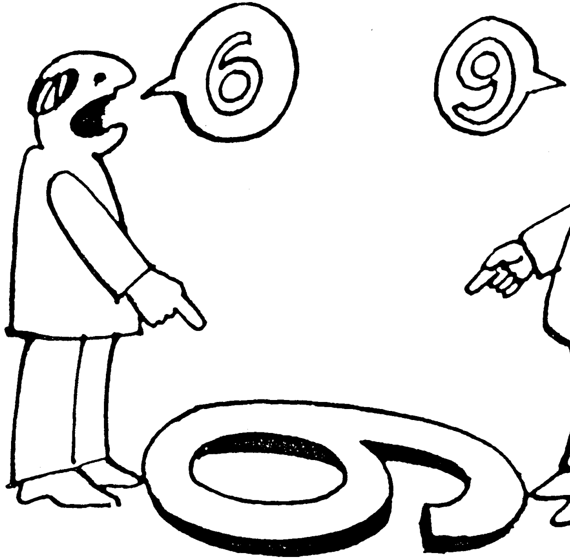






DIFFERENT PEOPLE NEED DIFFERENT EXPLANATIONS

INTELLIGENT USER INTERFACES

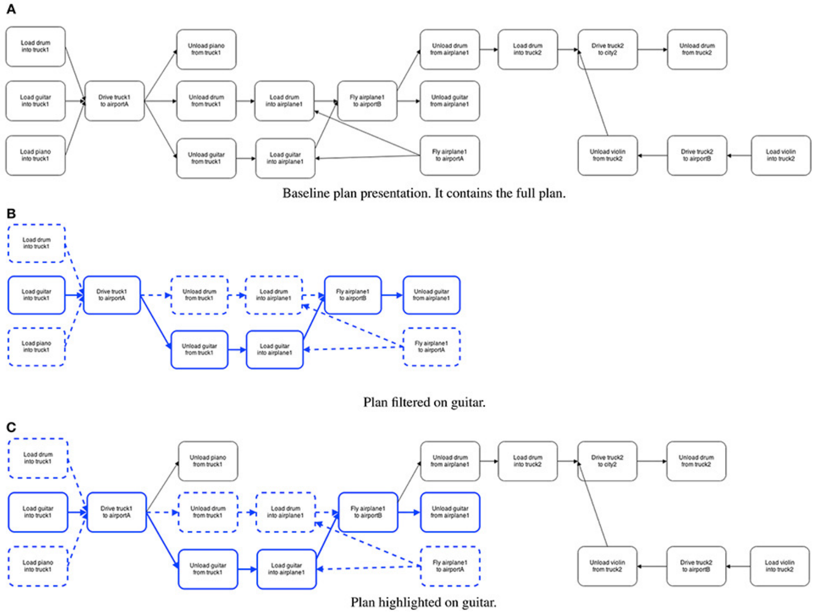
User interface – what the system shows of its internal state to a user, and allows the user to modify it to something resembling their internal model. NB: Includes chatbots!

Intelligent – Containing some measure of reasoning (human or artificial). Can be classification, recommendation, natural language processing, planning etc

In particular –

- **adaptive** systems which change their behavior in response to their environment,
- or **interactive** systems, which change their behavior to user interaction specifically.

ADAPTIVE INTERFACES (TINTAREV, MASTHOFF, 2016)



Modality

- E.g., text versus graphics

Layout

- E.g., horizontal timeline

Aggregation

- E.g., level of detail

Emphasis

- E.g. color or bold (see image)

Degree of Interactivity

PERSONALITY

Personality traits

- Personality ---``a person's nature or disposition; the qualities that give one's character individuality"
- Common model: OCEAN/FFM - Five Factor Model:
- Openness to Experience (O), Conscientiousness (C), Extroversion (E). Agreeableness (A), and Neuroticism (N)

Locus of Control

- The extent to which a person believes they can control events that affect them
- Internal LoC believe they can control their own fate, external LoC believes that their fate is determined by external forces

Resilience

- ``the ability to bounce back from stress"

EXPERTISE (1)

- Domain specific: often adapted to expert versus novice

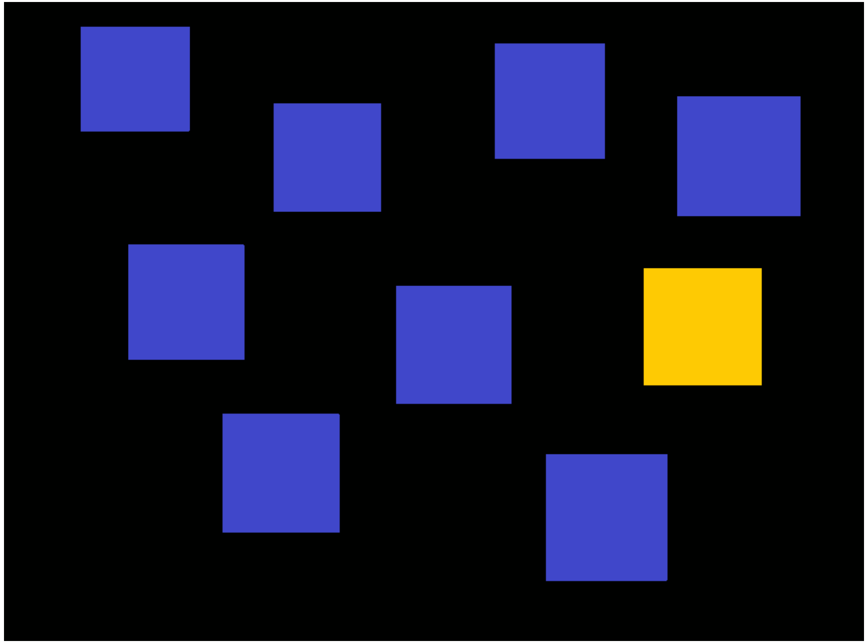
Example 1: 4th year student versus 1st year student

EXPERTISE (2)

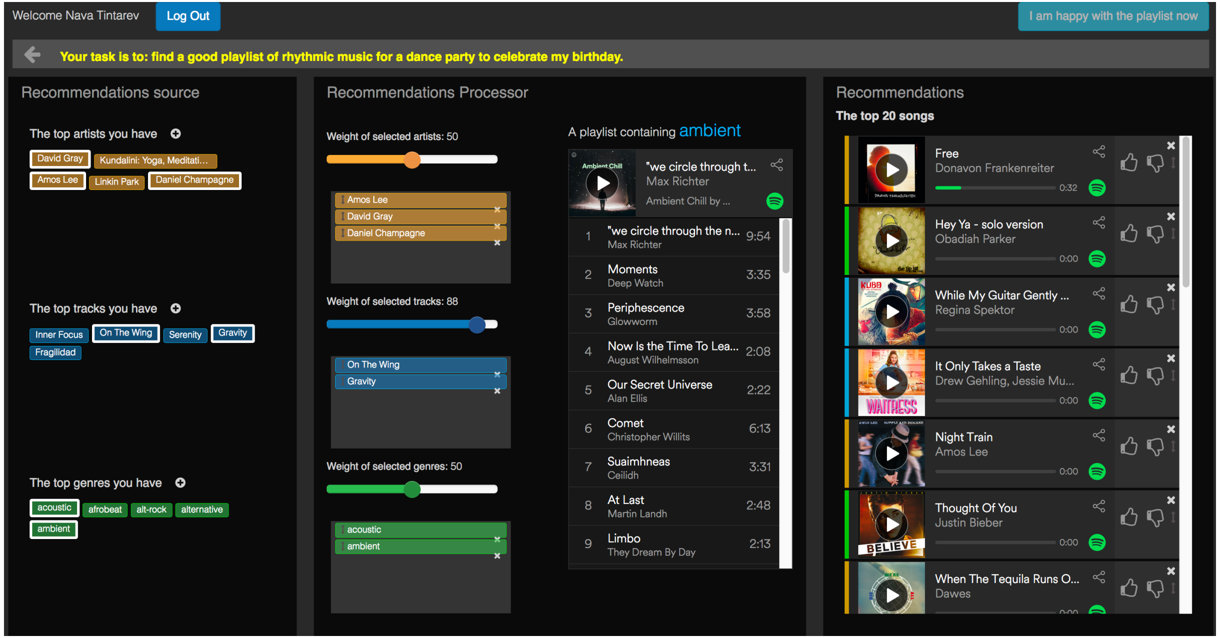
- Example 2: Goldsmith's Music sophistication Index:
  - Active Musical Engagement, e.g. how much time and money resources spent on music
  - Self-reported Perceptual Abilities, e.g. accuracy of musical listening skills
  - Musical Training, e.g. amount of formal musical training received
  - Self-reported Singing Abilities, e.g. accuracy of one's own singing
  - Sophisticated Emotional Engagement with Music, e.g. ability to talk about emotions that music expresses

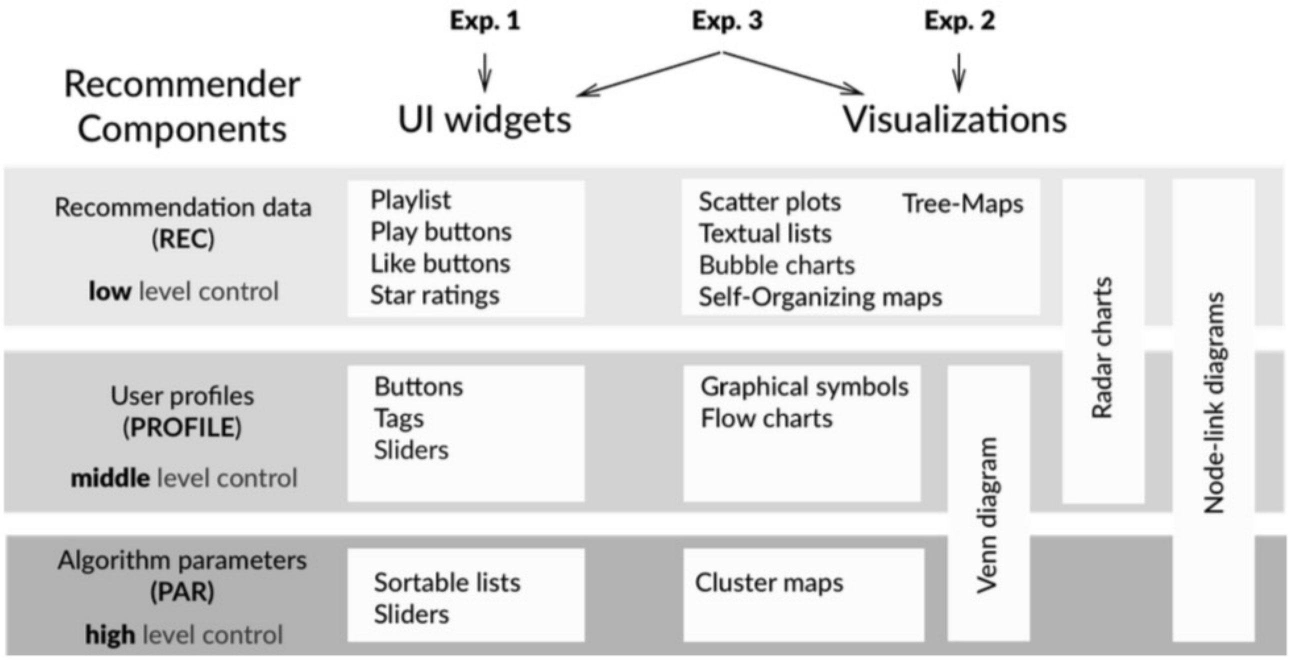
COGNITIVE TRAITS

- **Perceptual speed** - quickly and accurately compare letters, numbers, objects, pictures, or patterns
- **Verbal working memory** – temporary memory for words and **verbal** items
- **Visual working memory** – temporary memory for visual items



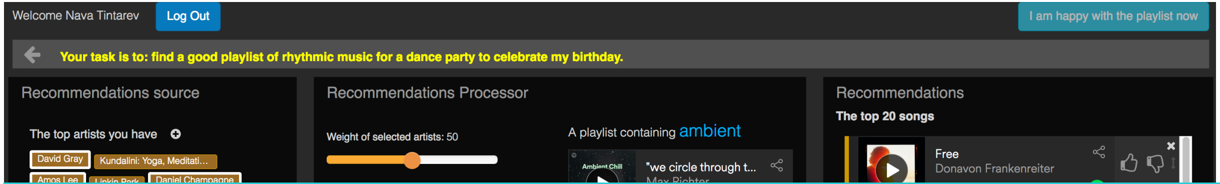
WHAT IS TOO COMPLEX?



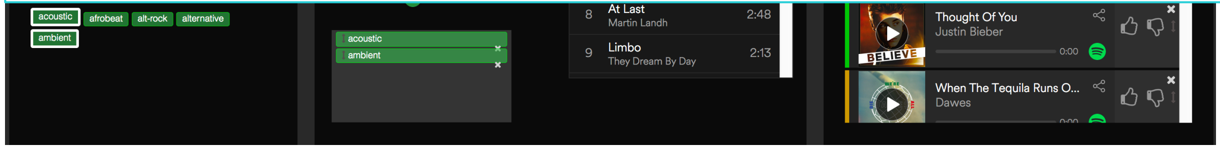

Exp. 1
Exp. 3
Exp. 2
Recommender Components
UI widgets
Visualizations
Recommendation data (REC)
low level control
Playlist
Play buttons
Like buttons
Star ratings
Scatter plots
Tree-Maps
Textual lists
Bubble charts
Self-Organizing maps
Radar charts
Node-link diagrams
User profiles (PROFILE)
middle level control
Buttons
Tags
Sliders
Graphical symbols
Flow charts
Venn diagram
Algorithm parameters (PAR)
high level control
Sortable lists
Sliders
Cluster maps

PERSONAL CHARACTERISTICS EXAMPLE 1

YUCHENG JIN ET AL, INTRS WORKSHOP@RECSYS'17



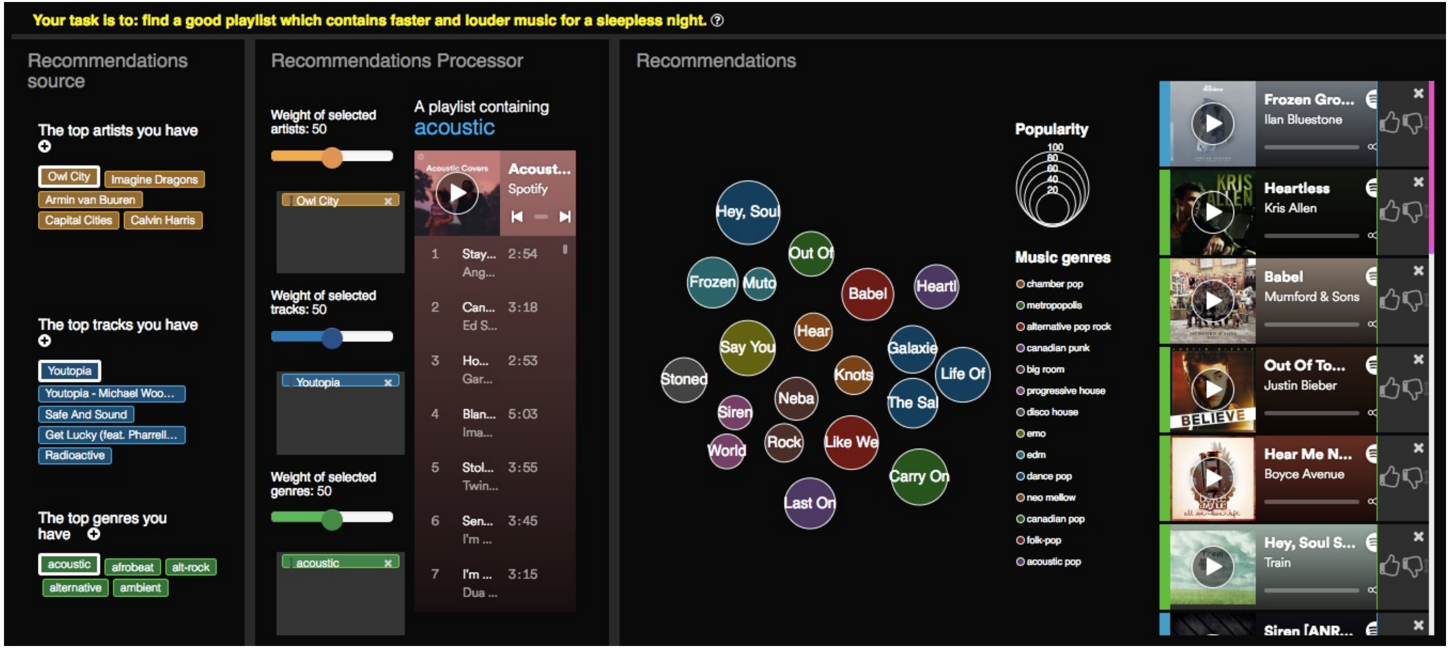
- Working memory did not influence cognitive load.
- Musical sophistication affected both acceptance and cognitive load.



Yucheng Jin

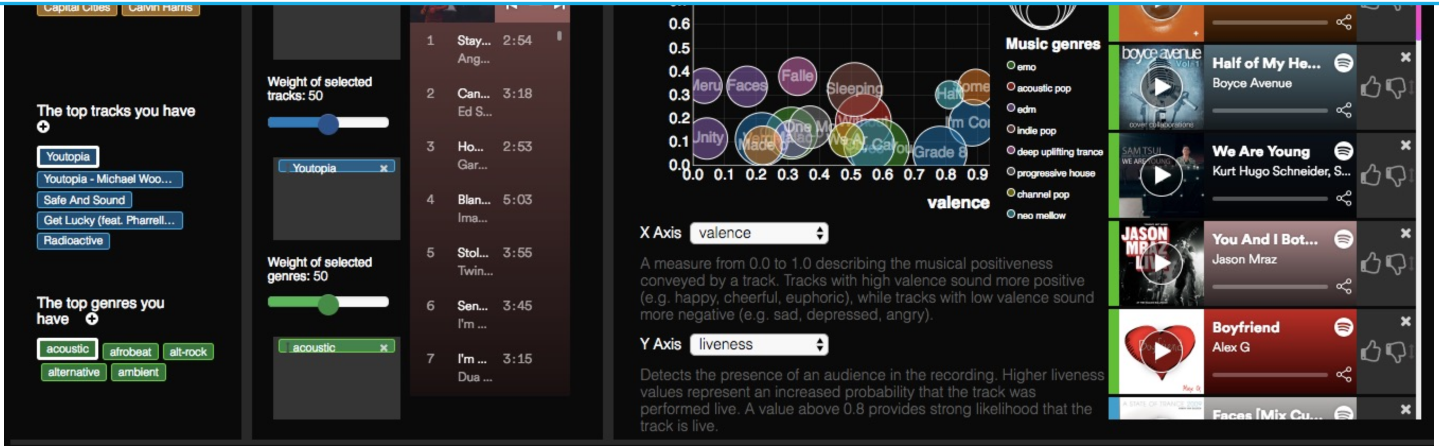
Katrien Verbert

EXAMPLE 2. CONTROL + SIMBUB



EXAMPLE 2. CONTROL + COMBUB

Perceptions of diversity differed between two visualizations for people with high musical sophistication. They also differed for people with high visual working memory.
→ Individual differences matter!



INDIVIDUAL DIFFERENCES

PC	**Experiment 1 User controls**	**Experiment 2 Visualizations**	**Expertiment 3 Controls + Vis.**
Visual memory (VM)	Acceptance (no) Diversity (no) Cognitive load (no)	Acceptance (no) Diversity (no) Cognitive load (no)	Acceptance (no) Diversity (no) Cognitive load (no)
Musical sophistication (MS)	**Acceptance (+)** Diversity (no) Cognitive load (no)	**Acceptance (+)** **Diversity (+)** Cognitive load (no)	**Acceptance (+)** **Diversity (+, m)** Cognitive load (no)

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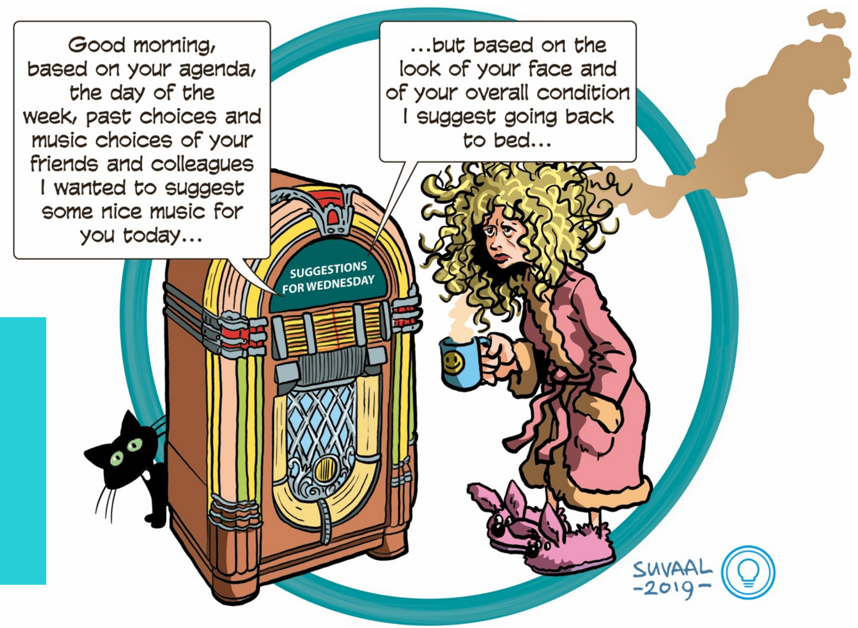

QUESTIONS?

TAKE HOME PREVIEW

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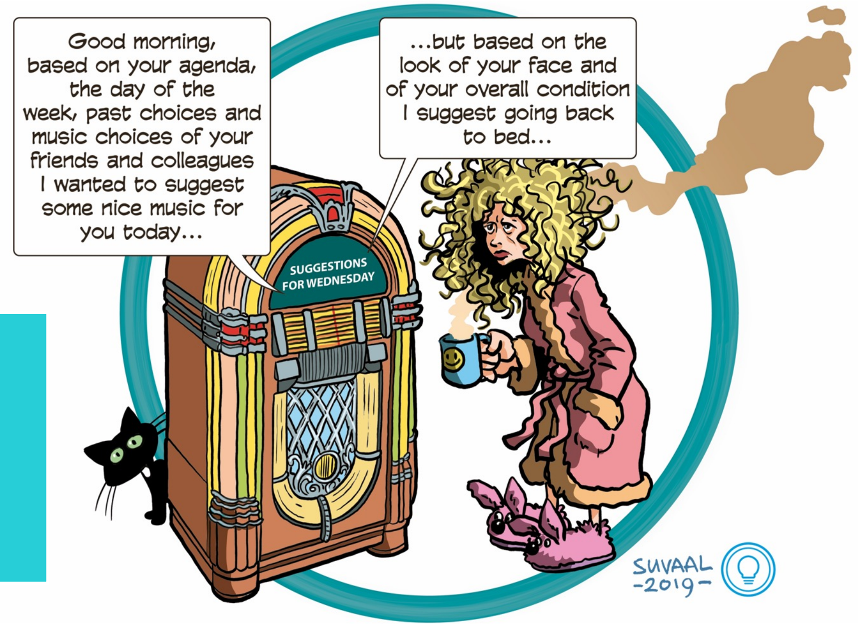


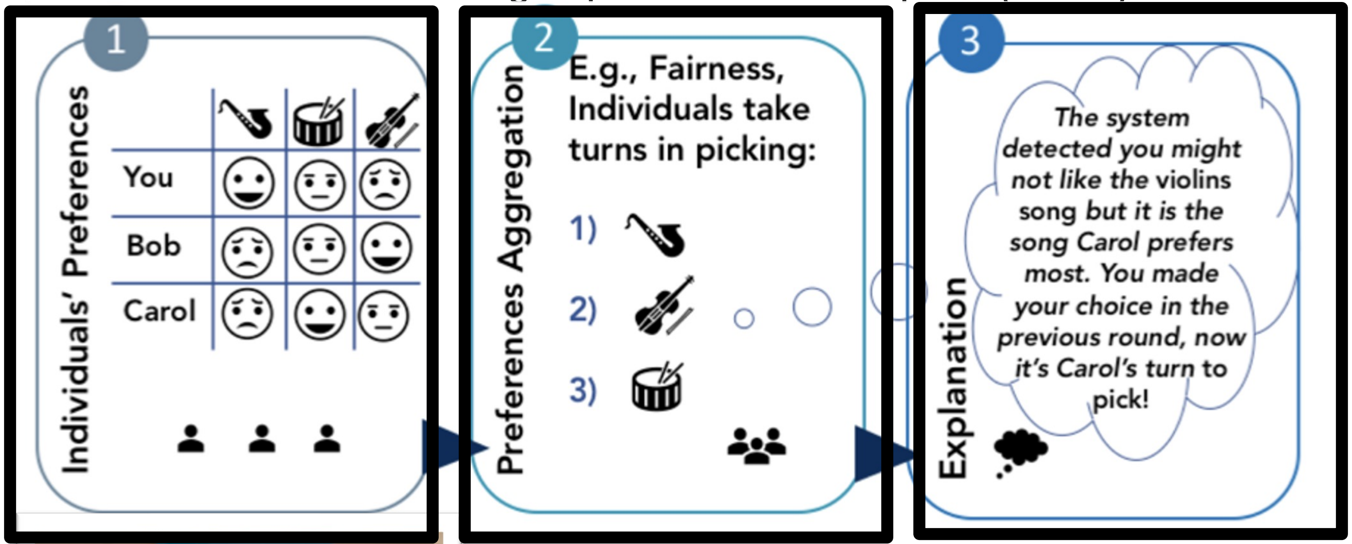
DIFFERENT SITUATIONS CALL FOR DIFFERENT EXPLANATIONS

Groups

Viewpoint diversity

ADAPTING TO CONTEXT: GROUPS

How to recommend items to groups when no best option (for all) exist?



(Najafian & Tintarev 2018, Najafian et al 2018)

PhD: Shabnam Najafian (Start Feb 2018)

EXPLANATIONS FOR GROUPS (NAJAFIAN ET AL, UMAP'21)

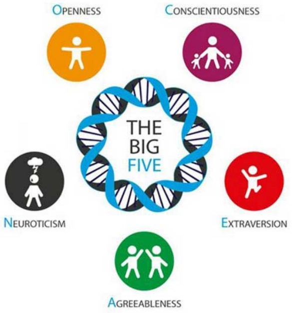
Relationship Type

Group Composition

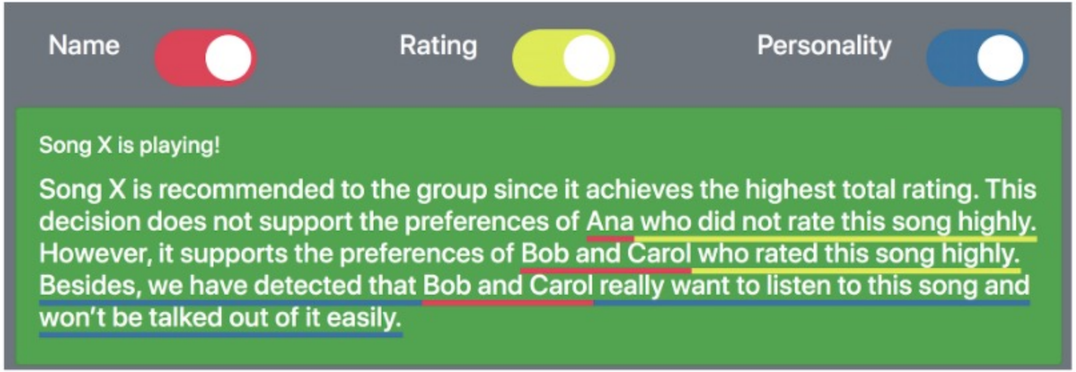
Perceived Transparency

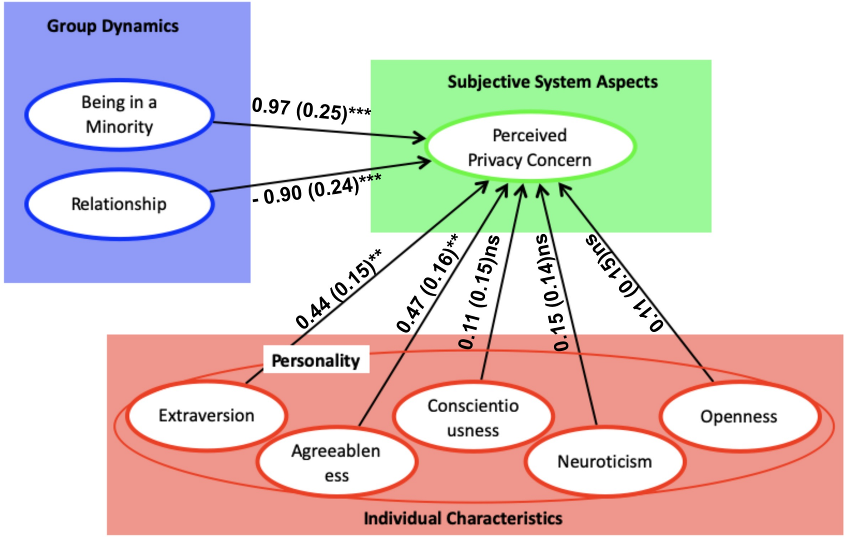
Perceived Privacy

Personality



Recommendation Outcome



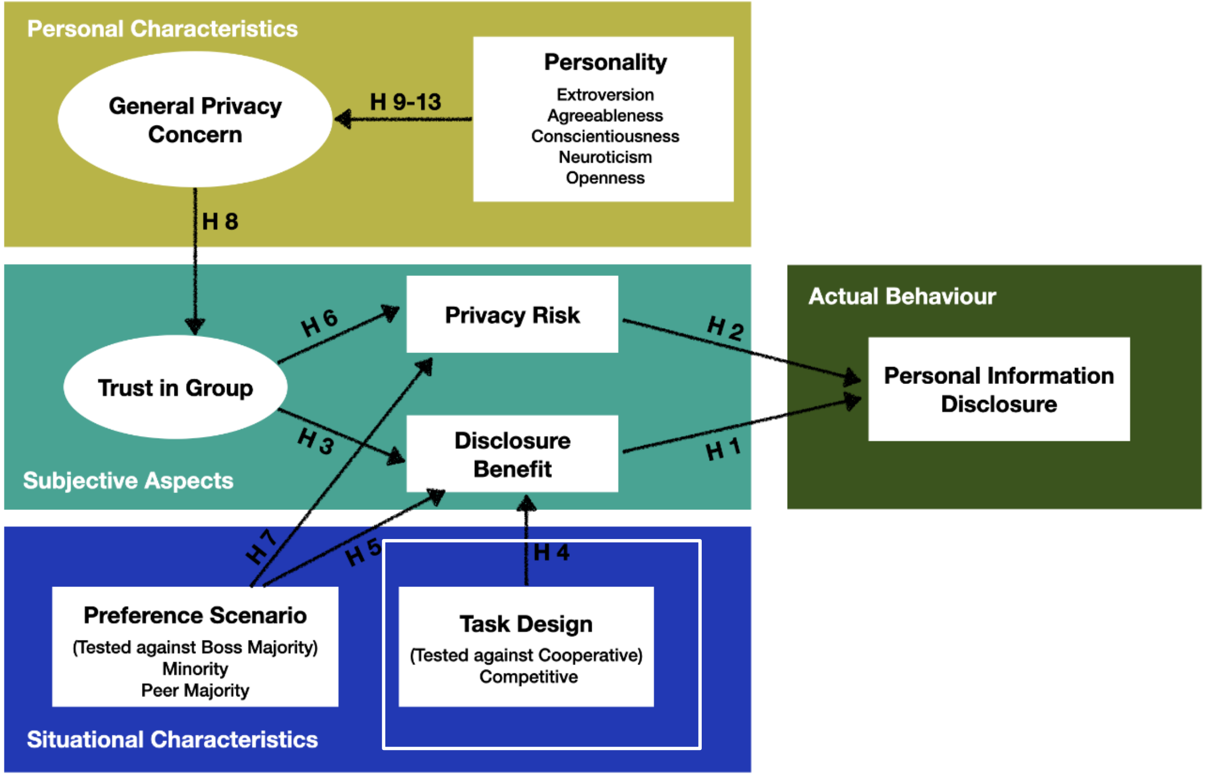


The "Bulldog coffeeshop" (cannabis store) has been recommended to your group since Carol will love it! The coffee-shop isn't the primary preference of Bob and John, but they are okay with it. Their preferences will be taken into account in the next recommendations.

Besides, Carol is feeling quite sad today, and we know that she really wants to visit the coffee-shop and won't be talked out of it easily. It's a good recommendation geographically – it is close to all three of you. Carol is at Vondelpark, only a minute's walk from the coffee-shop. Bob and John are at SoHo (LGBTQ+) bar, five minutes from the coffee-shop. You can all meet there in 10 minutes. Since you're all above 18 years in age, you can buy cannabis at the coffee-shop (Carol is 29, Bob is 28, and John is 35)."

Explainable Group Recommendations

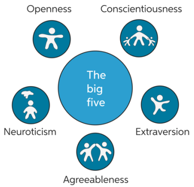
(Najafian et al, UMAP'21)



EXPLAINABLE GROUP RECOMMENDATIONS

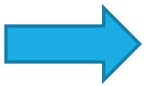
Francesco Barile,
Assistant Professor,
Explainable
Recommender Systems

Modeling individual satisfaction in a group context



Personality

Tie Strength



Group Context

Social choice-based explanations for Group Recommendations

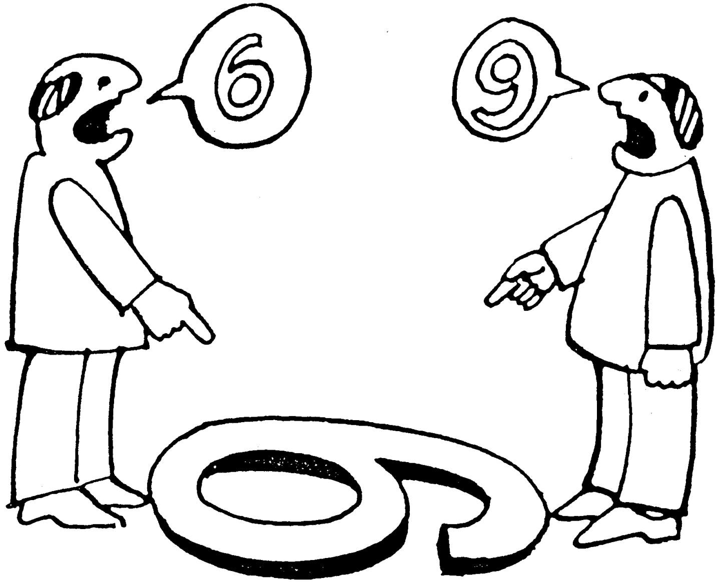
Effectiveness of social choice-based explanations in terms of fairness, consensus, and satisfaction

Complexity of rating scenario? Benefit of explanations?

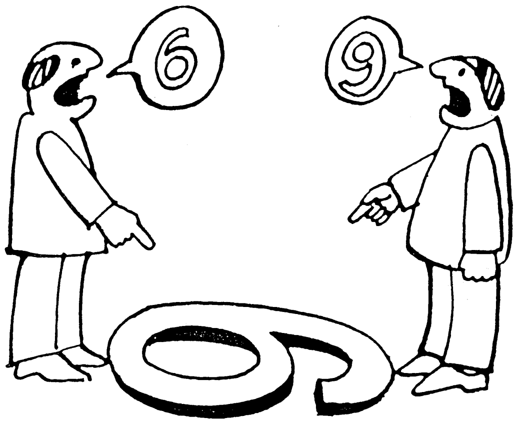
Barile et al. (2021). Toward Benchmarking Group Explanations: Evaluating the Effect of Aggregation Strategies versus Explanation.

Maastricht University

ADAPTING TO CONTEXT: VIEWPOINT DIVERSITY



ADAPTING TO CONTEXT: VIEWPOINT DIVERSITY



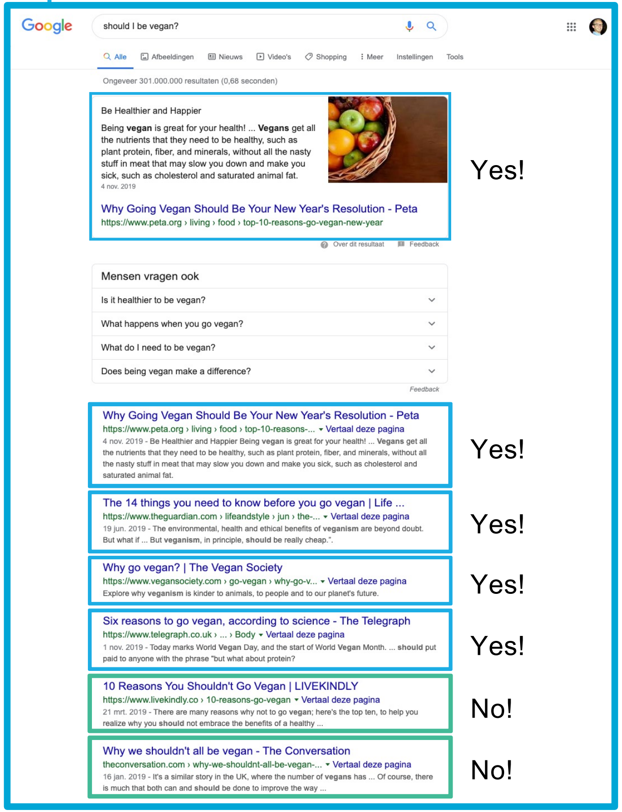
- Search results are biased, **no variety on viewpoint (different from topic or source).**

- Humans are highly influenced by search result rankings (SEME).
- During online information search, users tend to select search results that confirm pre-existing beliefs or values and ignore competing possibilities **(Confirmation bias)**
- → Potential harmful effects on individuals, businesses, and society.
  - e.g., by affecting individual health choices, important public debates, or election outcomes
- Recommendations need to be explained if we care about user perceptions!

EXPLANATION INTERFACES FOR BIAS MITIGATION?

MEASURING VIEWPOINT DIVERSITY

FOR WEB SEARCH ON DEBATED TOPICS



***Search Engine Manipulation Effect* (SEME):** when search results favor a particular viewpoint, users tend to adopt it

Our work (see website for papers)

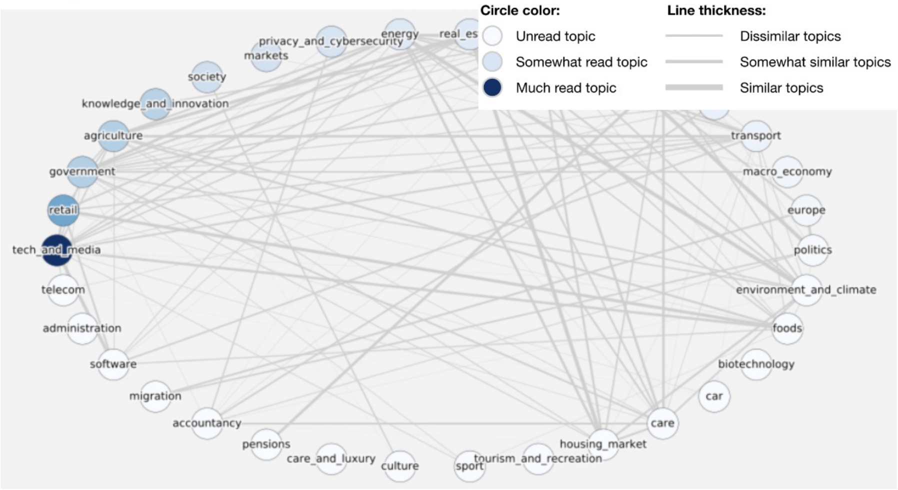
- Comprehensive viewpoint labels (SENTIRE 2020, 🏆 HCOMP 2021, 🏆 CHIIR 2022)
- Understanding algorithmic biases (BIAS 2020)
- Understanding cognitive biases of users (SIGIR 2021)

Tim Draws, PhD

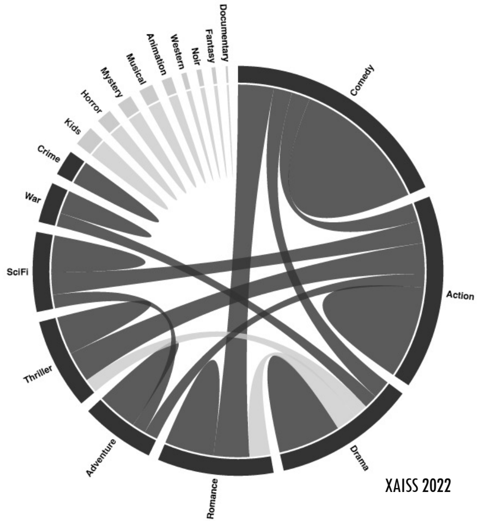
Delft University of Technology

EXPLANATION INTERFACES FOR BIAS MITIGATION?

Sullivan et al. Collaboration with FD Media @ICTwIndustry, *ExUm Workshop, UMAP*, 2019



Tintarev et al. *ACM Symposium On Applied Computing*, **2018**



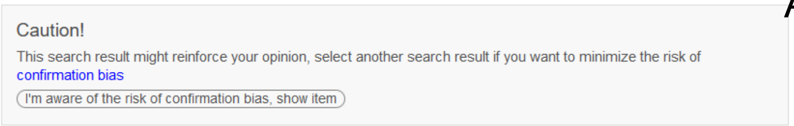
XAISS 2022

PRESENTING VIEWPOINT DIVERSE SEARCH RESULTS

Objective: Identify effective confirmation bias mitigation approaches during web interactions

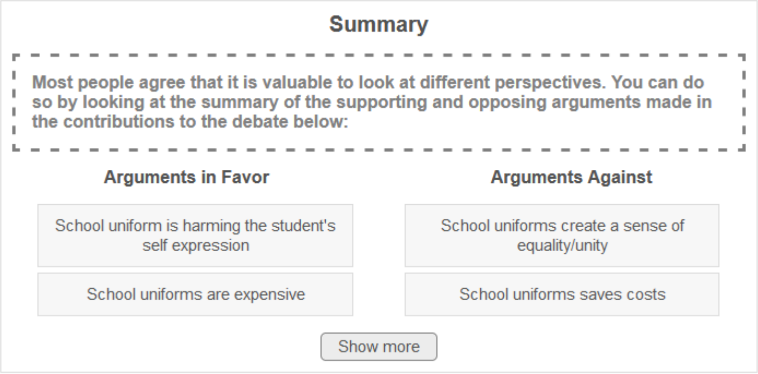
Approach: Language based nudging interventions (explanations, warnings) that prompt reflective choice and influence behavior (🏆HT2021)

Challenges: maintaining users' autonomy, adapting to different users, interactivity



User study 1: Confirmation bias mitigation during search on debated topics with obfuscations and warning labels

🏆 Rieger, A., Draws, T., Theune, M., & Tintarev, N. (2021, August). This Item Might Reinforce Your Opinion: Obfuscation and Labeling of Search Results to Mitigate Confirmation Bias. In *Proceedings of the 32nd ACM Conference on Hypertext and Social Media* (pp. 189-199).



User study 2: Confirmation bias mitigation during interactions with online debates with a summary and personalized persuasive suggestions. ExUM workshop at UMAP'22.

Alisa Rieger, PhD

NL4XAI

TU Delft Delft University of Technology

IIIA Institut d'Investigació en Intel·ligència Artificial

UNIVERSITY OF TWENTE.

wizenoze

Project, Secondment project partners

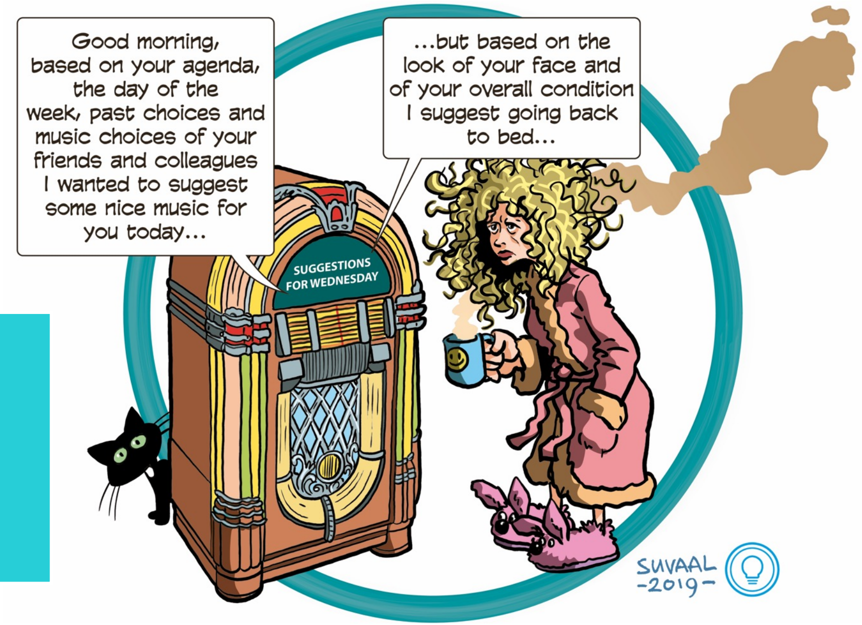
TAKE HOME PREVIEW

Explanations can serve different purposes

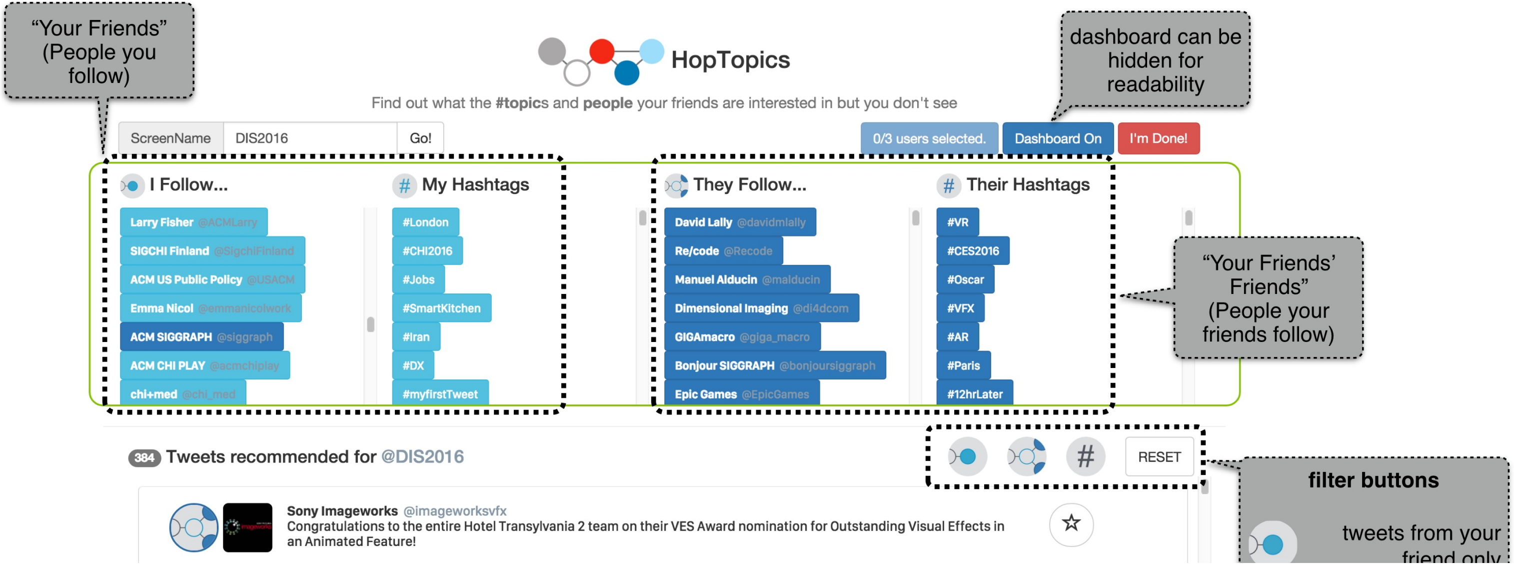
Different people need different explanations

Different situations call for different explanations

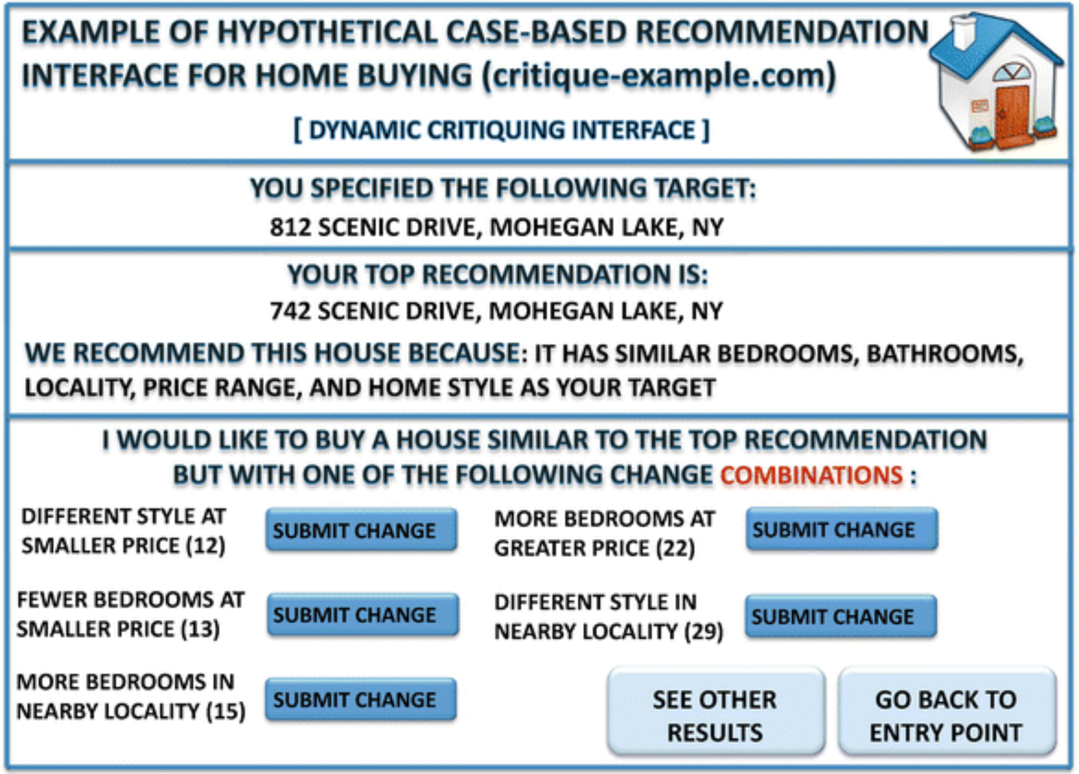
There is a benefit in interactive explanations (especially for complex domains)



THERE IS A BENEFIT IN INTERACTIVE EXPLANATIONS

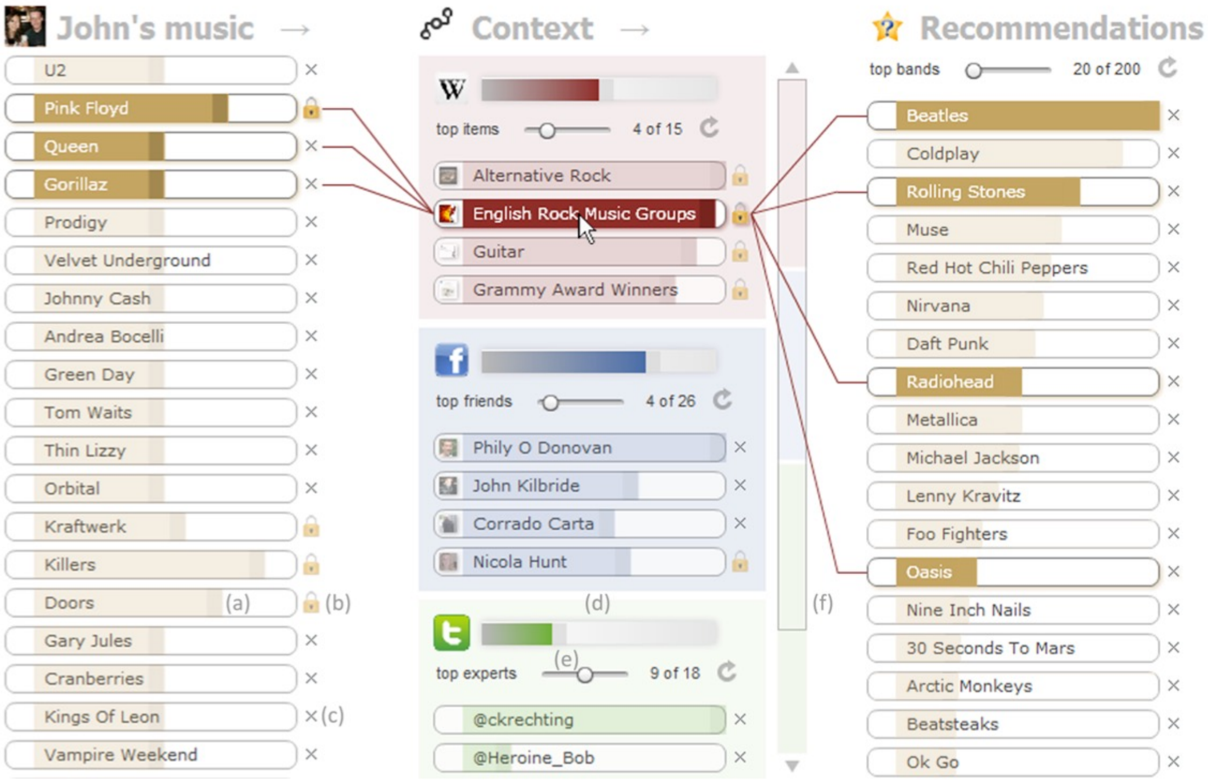


CRITIQUING


EXAMPLE OF HYPOTHETICAL CASE-BASED RECOMMENDATION INTERFACE FOR HOME BUYING (critique-example.com)
[DYNAMIC CRITIQUING INTERFACE]
YOU SPECIFIED THE FOLLOWING TARGET:
812 SCENIC DRIVE, MOHEGAN LAKE, NY
YOUR TOP RECOMMENDATION IS:
742 SCENIC DRIVE, MOHEGAN LAKE, NY
WE RECOMMEND THIS HOUSE BECAUSE: IT HAS SIMILAR BEDROOMS, BATHROOMS, LOCALITY, PRICE RANGE, AND HOME STYLE AS YOUR TARGET
I WOULD LIKE TO BUY A HOUSE SIMILAR TO THE TOP RECOMMENDATION BUT WITH ONE OF THE FOLLOWING CHANGE COMBINATIONS :
DIFFERENT STYLE AT SMALLER PRICE (12)
SUBMIT CHANGE
MORE BEDROOMS AT GREATER PRICE (22)
SUBMIT CHANGE
FEWER BEDROOMS AT SMALLER PRICE (13)
SUBMIT CHANGE
DIFFERENT STYLE IN NEARBY LOCALITY (29)
SUBMIT CHANGE
MORE BEDROOMS IN NEARBY LOCALITY (15)
SUBMIT CHANGE
SEE OTHER RESULTS
GO BACK TO ENTRY POINT

RELATED WORK: TASTEWEIGHTS

BOSTANDJIEV ET AL., 2012



MOVIE RECOMMENDATIONS

SCAFFER ET AL, 2015

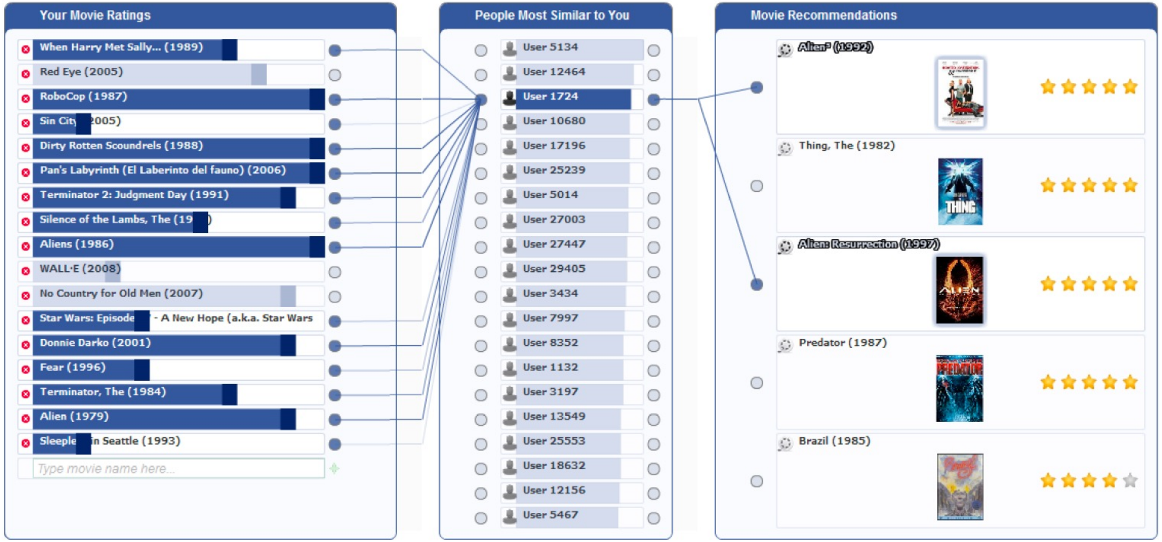
Left to right:

1) user's profile items

2) top-k similar users;

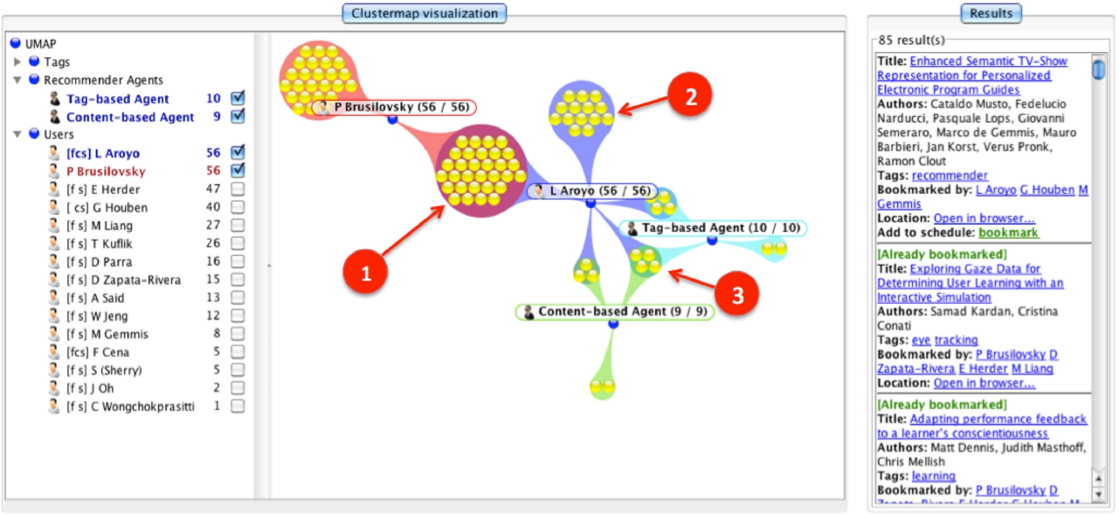
3) top-n recommendations.

Adds, deletes, or re-rates produce updated recommendations



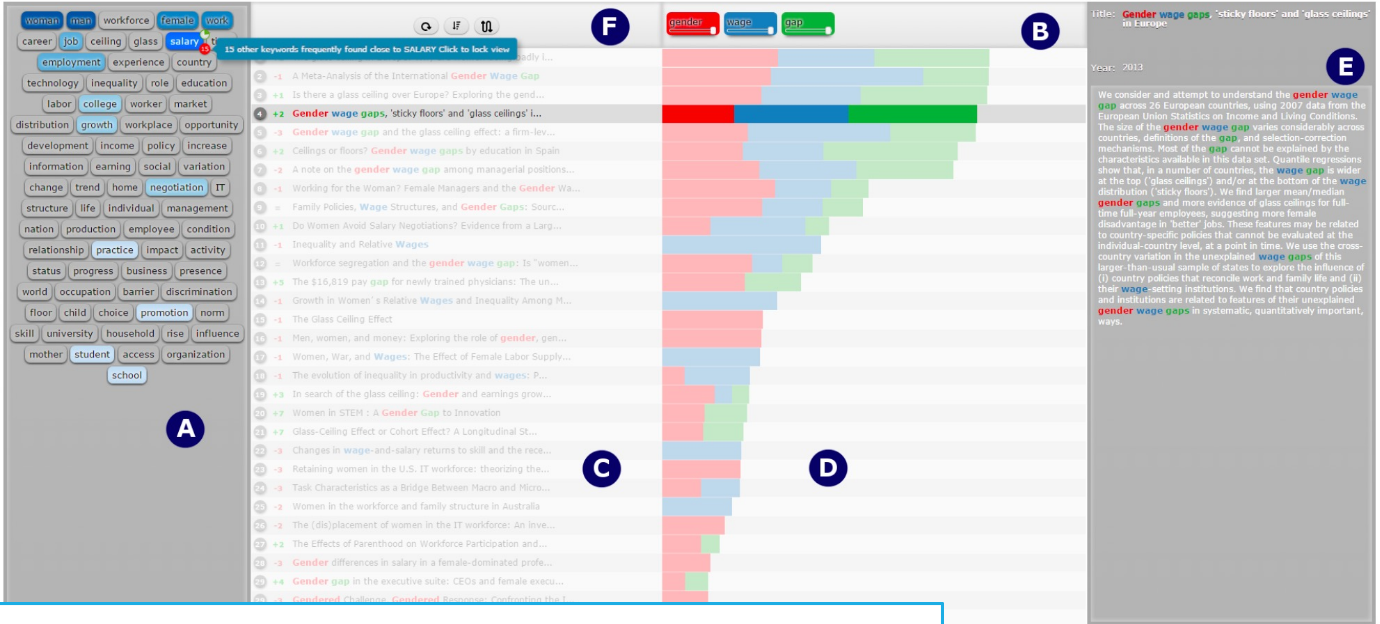
ACADEMIC TALKS VERBERT ET AL. 2013

1) Which of user's bookmarked papers are also bookmarked by user L. Aroyo
2) Which are bookmarked by L. Aroyo, but not recommended
3) Which are recommended by selected recommenders, and also bookmarked by L. Arroyo



ARTICLES URANK

Di Sciasco et al., 2016



A) Tag Box – keyword summary

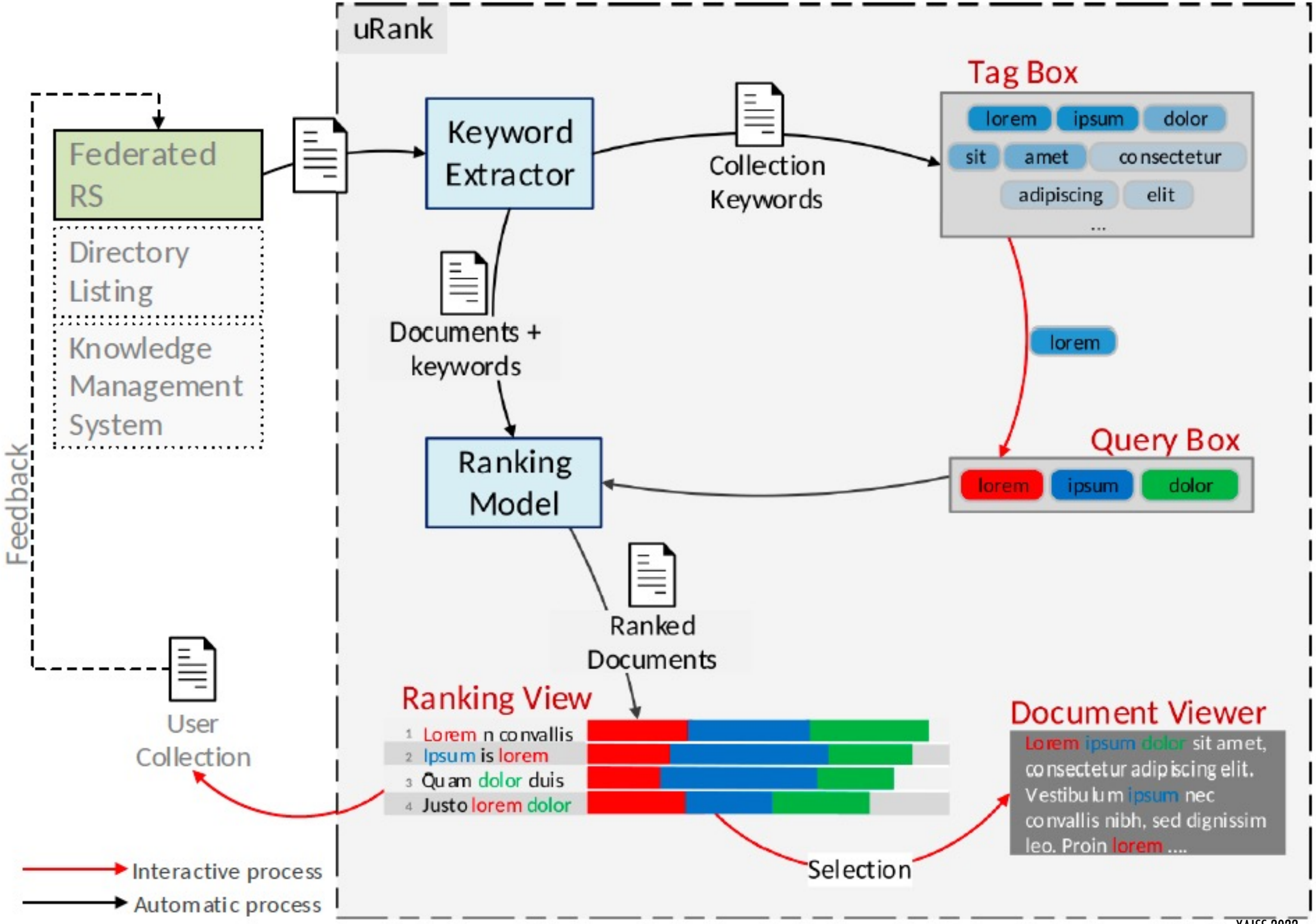
B) Query Box – Keywords that originated the current ranking state

C) Document List – Augmented document titles

D) Ranking View – relevance scores

E) Document Viewer – title, year, and snippet of document with augmented keywords

F) Ranking Controls – wrap buttons for ranking settings

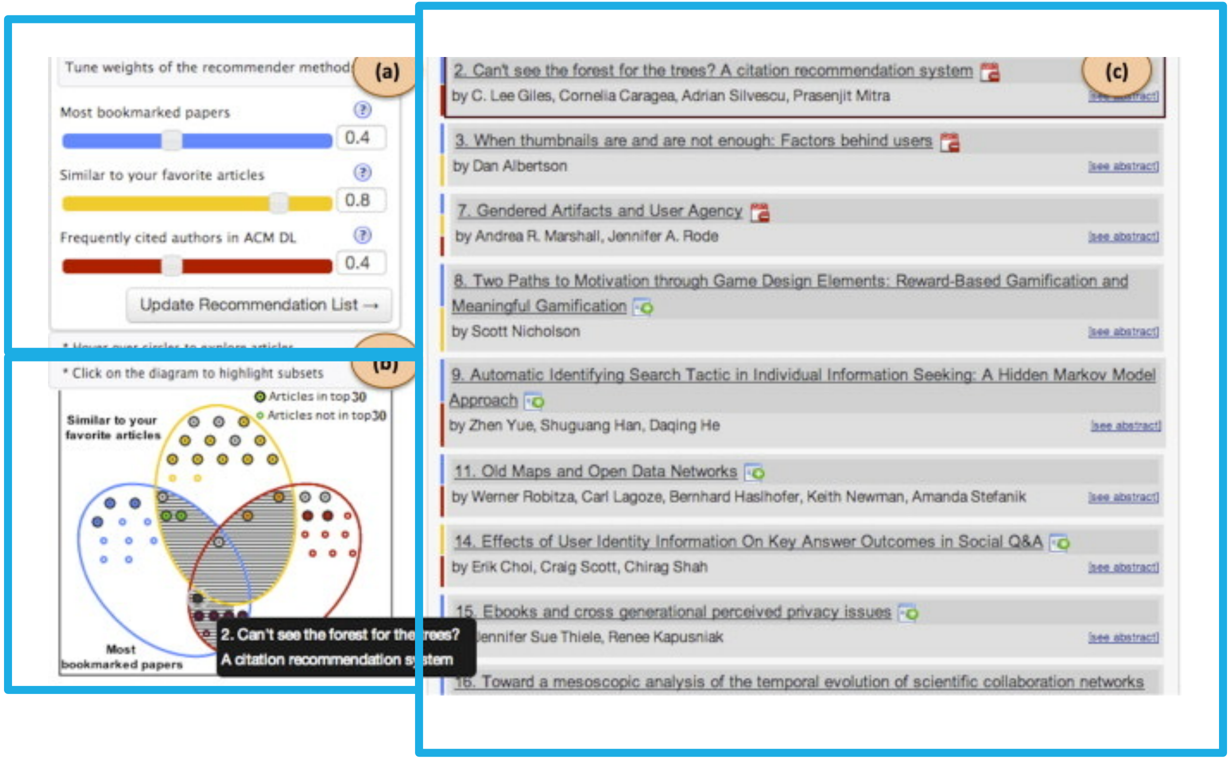


uRank
Federated RS
Directory Listing
Knowledge Management System
Feedback
Keyword Extractor
Collection Keywords
Tag Box
lorem
ipsum
dolor
sit
amet
consectetur
adipiscing
elit
...
Documents + keywords
lorem
Query Box
lorem
ipsum
dolor
Ranking Model
Ranked Documents
Ranking View
1 Lorem n convallis
2 Ipsum is lorem
3 Quam dolor duis
4 Justo lorem dolor
Document Viewer
Lorem ipsum dolor sit amet, consectetur adipiscing elit. Vestibulum ipsum nec convallis nibh, sed dignissim leo. Proin lorem ....
Selection
User Collection
Interactive process
Automatic process

SETFUSION PARRA & BRUSILOVSKY, 2015

Which items or people

Look at the intersections



Contribution to results (color-coded)

INTERSECTION EXPLORER CARDOSO ET AL. 2018

Resulting recs.

Choice of algorithm, user, content-features

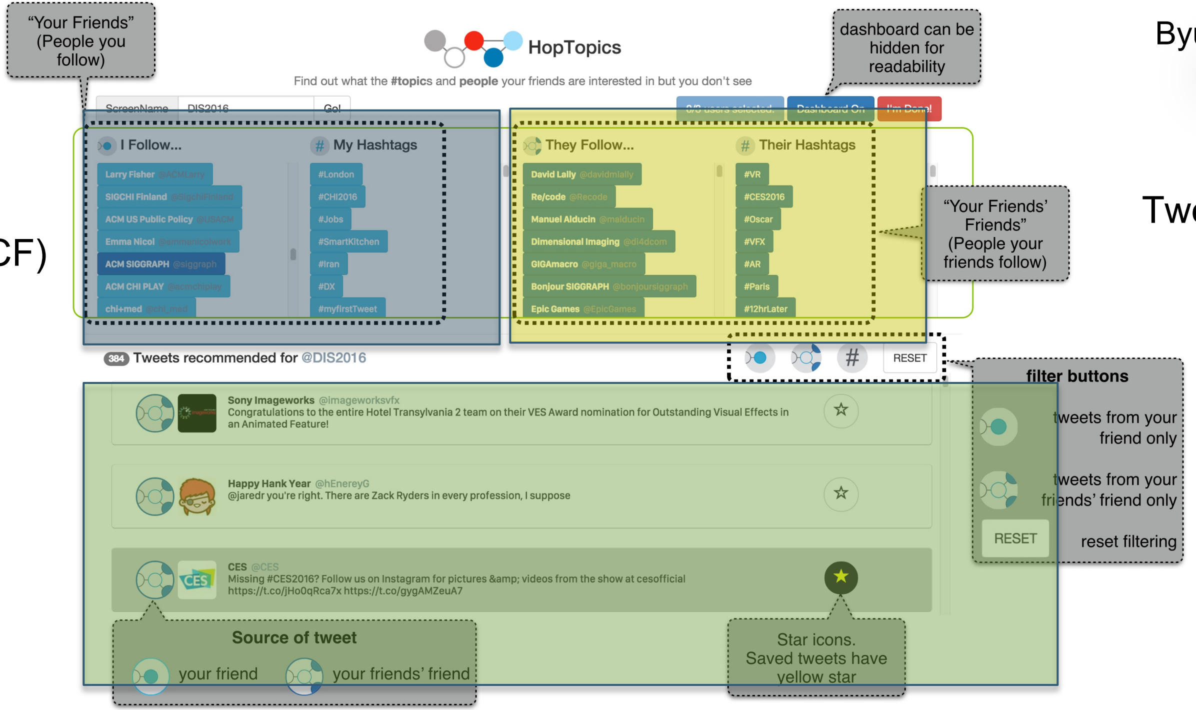
Which of the factors are used in the selection

HOPTOPICS

KANG ET AL 2016

Byungkyu (Jay) Kang

Person to person (CF)
Also content-based



Two "hops"

Can set 1 or two hops, or content-based

HOPTOPICS: SOCIAL CONTENT DISCOVERY

Better sense of control and transparency.

Poor mental model for the degree of novel content discovered for non-personalized data.

Perceptions (user-defined) of diversity (and relevance!) are important.

BENEFITS

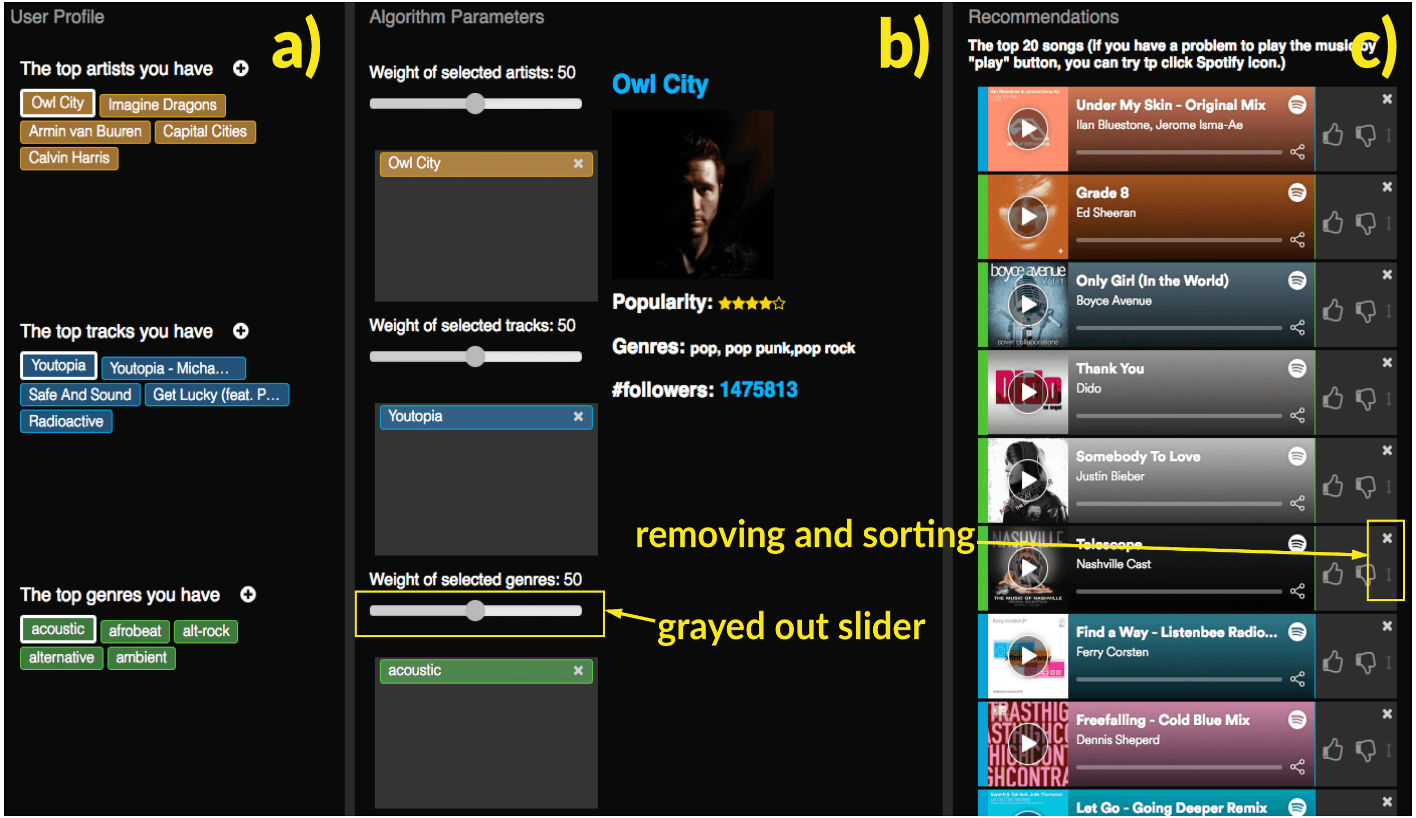
(i) dynamic feedback improves the effectiveness of profile updates,

(ii) when dynamic feedback is present, users can identify and remove items that contribute to poor recommendations,

(iii) profile update tasks improve perceived accuracy of recommendations and trust in the recommender, <u>regardless of actual recommendation accuracy</u>.

Sweet spot for cognitive load

User profile (PRO) | Algorithm parameters (PAR) | Recommendations (REC)



Jin et al. 2016

Spotify WEB API

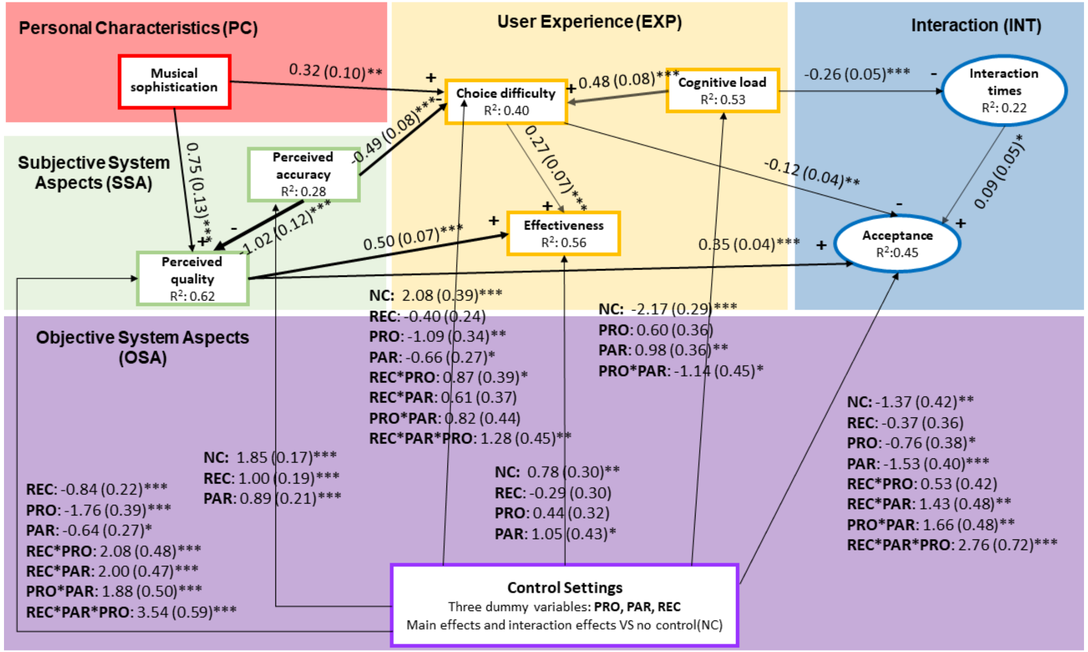
Between-subjects

Independent variable: settings of user control

	REC	PRO	PAR
Setting 1			
Setting 2	*		
Setting 3		*	
Setting 4			*
Setting 5	*	*	
Setting 6	*		*
Setting 7		*	*
Setting 8	*	*	*

Dependent variables:

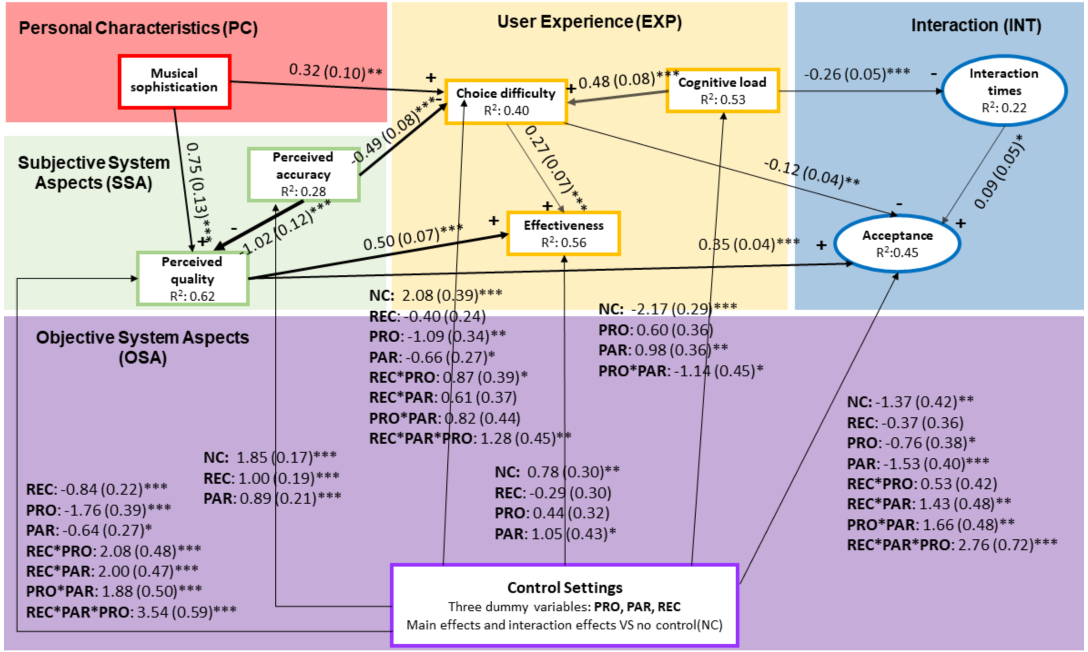
- Acceptance (ratings)
- Cognitive load (NASA-TLX), MS, VM
- Framework Knijnenburg et al.



The structured equation modeling (SEM) results. The number (thickness) on the arrows represents the β coefficients and standard error of the effect. Significance: *** $p < .001$, ** $p < .01$, * $p < .05$. R^2 is the proportion of variance explained by the model. Factors are scaled to have an SD of 1.

CFA - validity questions
Quality
Accuracy
Effectiveness
Choice difficulty
Diversity
Trust
Satisfaction

The fit of our SEM model
$X(2, 98) = 257.410$
$p < .001$
RMSEA= 0.083
CFI = 0.980
TLI = 0.968



The structured equation modeling (SEM) results. The number (thickness) on the arrows represents the β coefficients and standard error of the effect. Significance: *** p < .001, ** p < .01, * p < .05. R^2 is the proportion of variance explained by the model. Factors are scaled to have an SD of 1.

CFA - validity questions

Quality

Accuracy

Effectiveness

Choice difficulty

~~Diversity (low AVE value)~~

~~Trust (low AVE value)~~

~~Satisfaction (modification index)~~

The fit of our SEM model

X(2, 98) = 257.410

p <.001

RMSEA= 0.083

CFI = 0.980

TLI = 0.968

CONCLUSION

Main effects: REC has lowest cognitive load and highest acceptance

Two-way interaction: does not necessarily result in higher cognitive load. Adding an additional control component to PAR increases the acceptance. PRO*PAR has less cognitive load than PRO and PAR

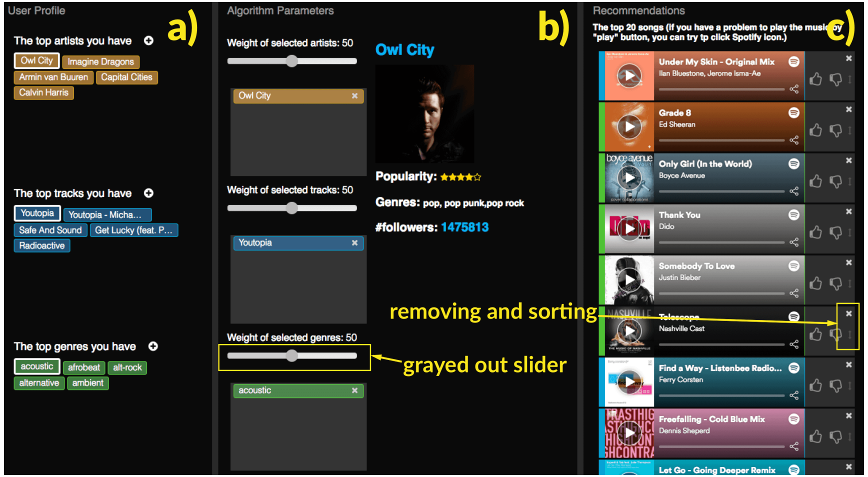
Three-way interaction: it increases acceptance, and does not lead to higher cognitive load. Increase interaction times and accuracy

High MS (expertise) corresponds w. higher quality, and thereby results in higher acceptance

User profile (PRO)

Algorithm parameters (PAR)

Recommendations (REC)



WHAT COULD THIS MEAN FOR THE REST OF XAI?

- Another way to study stability of explanations?
- Another way for the user to intuitively understand which factors change results (c.f., counterfactuals)?
- Need for longitudinal studies!

WHAT'S NEXT?

Ongoing

Twitter - conversational health: Mutual recognition, **viewpoint diversity**, incivilitiy, intolerance (UM) → June'22

EU Marie-Curie Training work on Natural language for Explainable AI (NL4XAI) (TUD) → Oct'23

IBM - Representing diverse views for polarized topics online (TUD) → Aug'23

Named collaborator (w. UvA/VU): Rethinking news recommender algorithms: Nudging users towards diverse news exposure → 2024

In progress

Long Term Program (10Y) in development (Co-I). ROBUST: Trustworthy AI-based Systems for Sustainable Growth. 25M NWO/95M total. 2 ICAI labs for UM.

- TAIM – Trustworthy AI in Media (RTL/UvA)
- TROIKA - Trustworthy Collaborative Knowledge Accelerator (BIOMAXX/TUD)
- Notification around November 2022

ERC Consolidator grant under review

- Modeling the Dynamics which Influence the eFfectiveness of Explanations for Recommended Online Content (MoDIFiER)

ICAI Innovation Center for Artificial Intelligence

NWO

European Commission

QUESTIONS?

References, including chapter on explanations in recommender systems on the next slides.

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MEASURING VIEWPOINT DIVERSITY IN TWITTER CONVERSATIONS

Maastricht University

Representation

- at conversation level, measures how the views expressed in a single conversation compares to the breadth of views expre

Fragmentation

- at user level, measures the extent to which the participants in a conversation are exposed to different viewpoints.

For the topic of **Immigration** on Twitter, conversations are **highly representative** of the underlying data, while most users have **low fragmentation** i.e. exposed to similar viewpoints. Further analysis reveals, anti-immigrant viewpoints occur in echo-chambers, while pro-immigrant viewpoints receive consistent pushback from anti-immigration.

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Research Assistant
Maastricht University
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Work done as a part of the Twitter project on Measuring Conversational Health. Collaborators: Amir Ebrahimi Fard, Sarah Sugars, Federico Bianchi, Patricia Rossini, Dirk Hovy, Rebekah Tromble and Nava Tintarev

SOCIAL SEARCH BROWSER

CHURCH ET AL. 2010