

"Your Friends"
(People you follow)



HopTopics

Find out what the #topics and people your friends are interested in but you don't see

ScreenName DIS2016

Go!

0/3 users selected.

Dashboard On

I'm Done!

I Follow...

Larry Fisher @ACMLarry
SIGCHI Finland @SigchiFinland
ACM US Public Policy @USACM
Emma Nicol @emmanicolwork
ACM SIGGRAPH @siggraph
ACM CHI PLAY @acmchoplay
chi+med @chi_med

My Hashtags

#London
#CHI2016
#Jobs
#SmartKitchen
#Iran
#DX
#myfirstTweet

They Follow...

David Lally @davidmlally
Re/code @Recode
Manuel Alducin @malduclin
Dimensional Imaging @di4dcom
GIGAMacro @giga_macro
Bonjour SIGGRAPH @bonjournsiggraph
Epic Games @EpicGames

Their Hashtags

#VR
#CES2016
#Oscar
#VFX
#AR
#Paris
#12hrLater

"Your Friends'
Friends"
(People your
friends follow)

384 Tweets recommended for @DIS2016



Sony Imageworks @imageworksvfx

Congratulations to the entire Hotel Transylvania 2 team on their VES Award nomination for Outstanding Visual Effects in an Animated Feature!

RESET



filter buttons

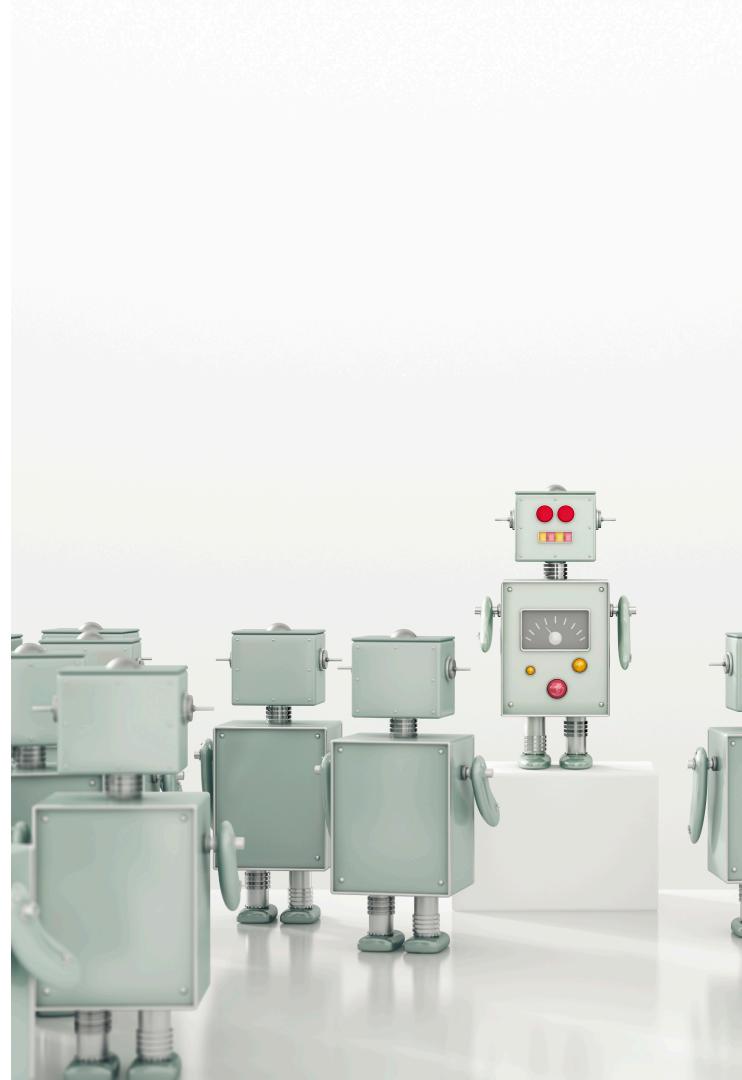
tweets from your
friend only

INTERACTIVE AND ADAPTIVE EXPLANATION INTERFACES FOR RECOMMENDER SYSTEMS

Professor Nava Tintarev
Department of Advanced
Computing Sciences

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



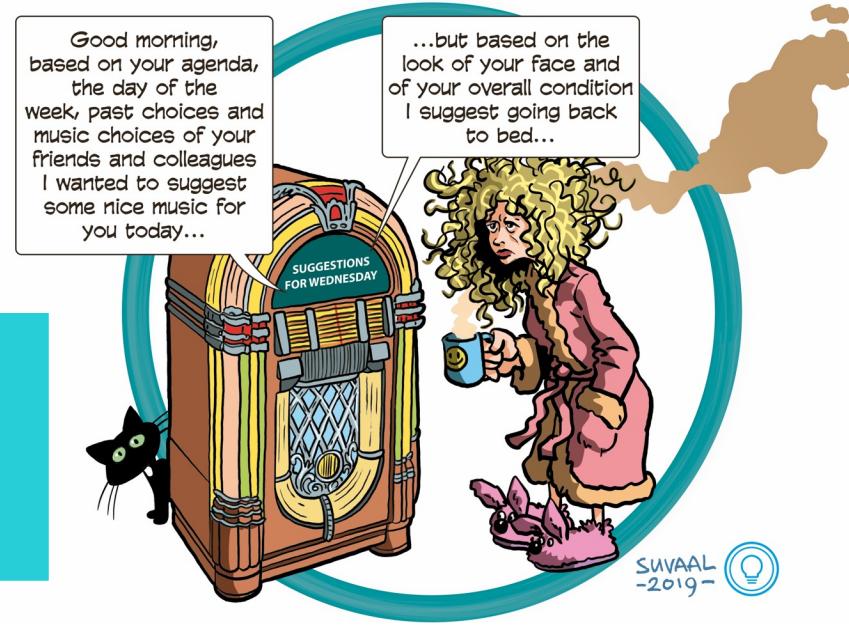
TAKE HOME PREVIEW

Explanations can serve different purposes

Different people need different explanations

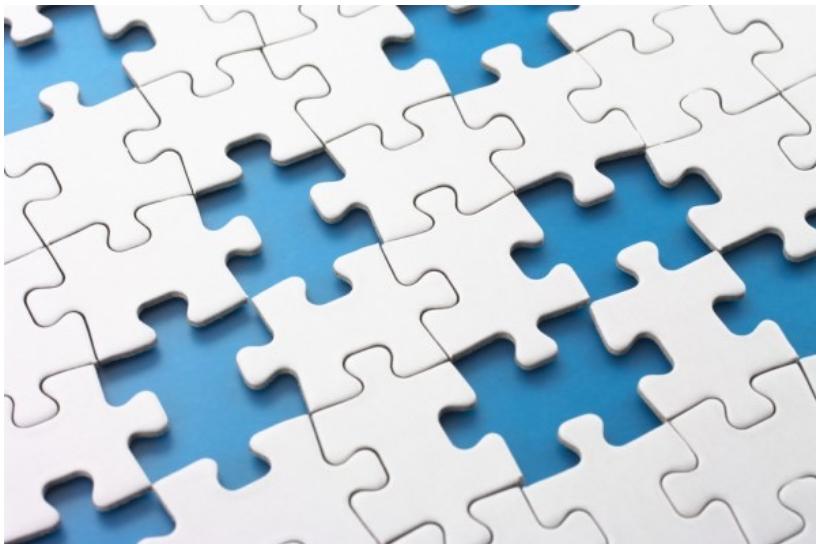
Different situations call for different explanations

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



MOTIVATION

Computer



User



MOTIVATION

Interpretability is

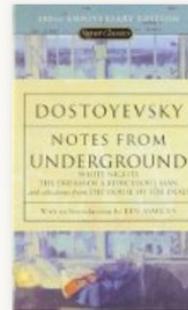
the degree to which a human can understand the cause of a decision
(Miller 2017)

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

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

RECOMMENDATIONS

Because you enjoyed Harry Potter and the Cursed Child - Parts One and Two (Harry Potter, #8):



Notes from Underground, White Nights, The Dream of a Ridiculous Man, and Selections from The House of the Dead
by Fyodor Dostoyevsky

★★★★★ 4.17 avg. rating

[Want to Read](#)

Hello M J Seckington. We have [recommendations](#) for you. (Not M?)

M's Amazon.co.uk Deals of the Week Gift Certificates ▾ Gifts & Wish Lists ▾

Search All Departments ▾

More to Explore

You looked at



Giant Bath Duck
£9.75

[Find similar items](#)

You might also consider



Classic Bath Duck
£1.50



Medium Rubber Duck
£1.49



Small Rubber Duck
£0.56

XAISS 2022

MOTIVATION

More human (non-expert) and system collaborations.

Potential in leveraging joint strengths.

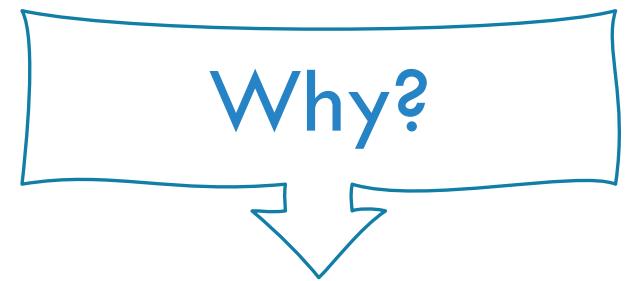
We might not accept advice from systems

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

Many barriers are not technical, but cognitive.

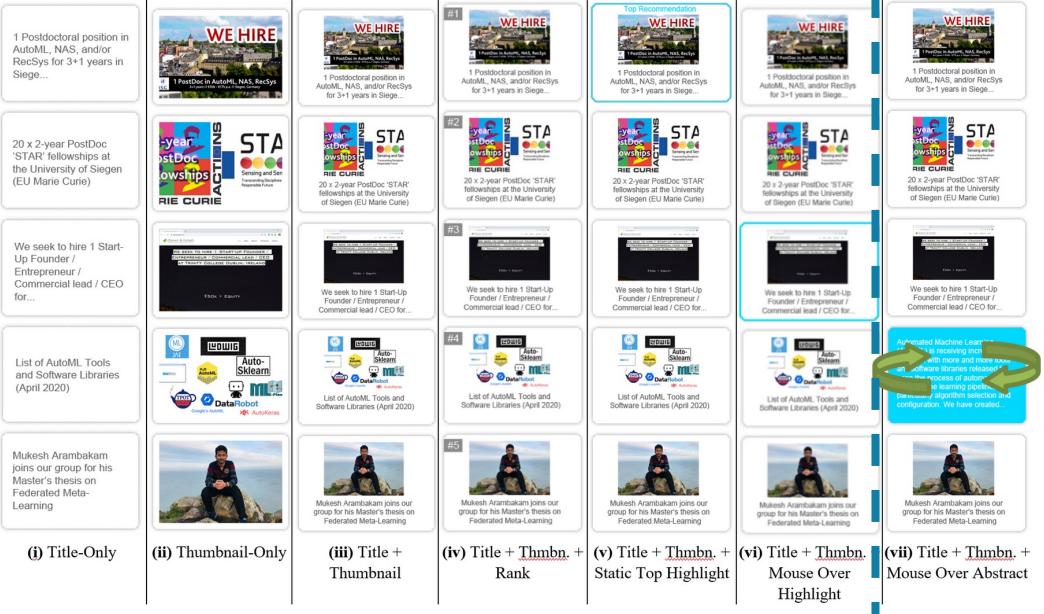
Explanations can help us make better decisions together with systems.

(Tintarev, 2016)



Meer aanbevelingen voor jou [Meer bekijken](#)

The interface displays three book covers as recommendations. From left to right: 1. 'DUNE' by Frank Herbert, featuring a desert landscape with the title in large blue letters. 2. 'ONE LINE A DAY: A FIVE-YEAR JOURNAL', with a colorful floral pattern on the cover. 3. A partially visible book cover with a red and white design. Above the books, the text 'Meer aanbevelingen voor jou' and a link 'Meer bekijken' are displayed.



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 1)

INTERFACE MATTERS (EXAMPLE 2)



Jasper Oosterman
Blendle

A screenshot of a web-based news aggregator. At the top, there is a single news article snippet with a small thumbnail, a title, and a brief summary. Below this, there is a call-to-action button labeled "Lees verder over dit onderwerp". A curved arrow points from this button to a row of three smaller news snippets at the bottom. Each snippet includes a thumbnail, a title, and a brief summary. The titles visible are "Marktwaakhond moet soms bijten", "Het oude liedje", and "Bekijk zet zich schrap voor tweede golf". The news sources mentioned are Trouw, de Volkskrant, and NOS.

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



Mats Mulder
MSc



Oana Inel
postdoc

Voor het hele verhaal



INTERFACE MATTERS!



Click-through rate for “diverse viewpoint” condition correlated with:

Blendle Vandaag Eerder Magazines Kranten Leeslijst Audio

Number of hearts

Van de redactie

Het beste uit de kranten en tijdschriften staat hieronder voor je klaar! 📰



Het beste voor de zaterdag

Uitmuntende achtergrond, interviews en reportages



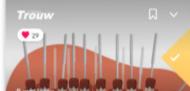
Hij is er: de corona-app. Dit zijn de gevaren volgens een Harvard-expert



Duizenden arrestanten in Wit-Rusland zijn onmenselijk behandeld: Irina was één van hen. 'Alleen onze dierlijke angst resteerde'



Een nazi-meme of Baudet aan de galg: in appgroepen komt het ware gezicht van politieke jongeren naar voren, van CDA tot FvD

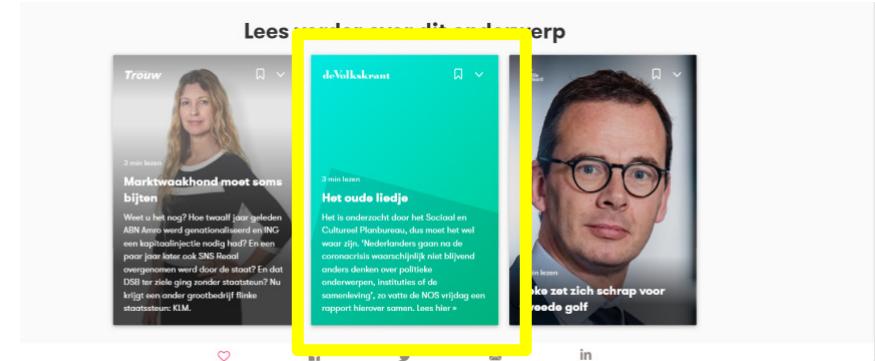


Met de GGD's goat het al jaren niet lekker, maar door corona worden ze omvergeblazen. 'Ze zijn niet kwetsbaar, maar kansloos'



Hoe de eisen voor 'diversiteit' musea de nek omdraaien: 'de subsidiegever luistert mee'

Thumbnail 3.1% more



Lees

3 min lezen

Trouw

Marktwaakhond moet soms bijten

Went u het nog? Hoe twintig jaar geleden ABN Amro werd genationaliseerd om ING een tegenovergewicht nodig had? En een paar jaar later ook SNS Raad meegemoedigen werd door die steed? En dat DSM ter ziele ging zonder staatssteun? Nu krijgt een ander grootbedrijf flinke staatssteun: KLM.

3 min lezen

deVolkskrant

Het oude lieidje

Went u het nog? Hoe twintig jaar geleden ABN Amro werd genationaliseerd om ING een tegenovergewicht nodig had? En een paar jaar later ook SNS Raad meegemoedigen werd door die steed? En dat DSM ter ziele ging zonder staatssteun? Nu krijgt een ander grootbedrijf flinke staatssteun: KLM.

3 min lezen

deVolkskrant

De oudste golf

Wie zet zich schrap voor de oude golf

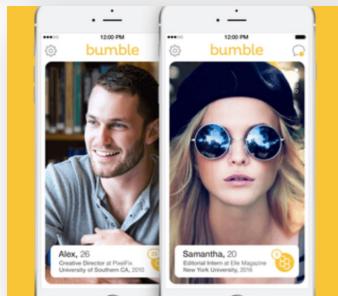
CONFESSTION: I DON'T WORK IN ALL OF AI!

Band of Brothers
2001 R 705 min 评分

Casablanca
1942 PG 102 min 评分

One Flew Over the Cuckoo's Nest
1975 R 133 min 评分

...
5 stars 5 stars 5 stars



Trends for you

Trending in Netherlands

#Gino

3,953 Tweets

...

#TheBoysTV 🎬

Eén onoverwinnelijke man. Bekijk #TheBoysTV op 3 juni op Prime Video.

☒ Promoted by Prime Video NL

...

Trending in Netherlands

Turken

...

Trending in Netherlands

#ikwokevanjou

...

Trending in Netherlands

#vaccinatieplicht

1,103 Tweets

...

Trending in Netherlands

Ginny

2,076 Tweets

...

Trending in Netherlands

Veluwe

...



Suggestions for you

See All



dung_chu

Followed by instagraus

Follow



carrollnikole

Followed by colour_of_snow + 1 more

Follow



chele28uk

Followed by jojomarrett

Follow



ff8addict

Followed by dianaberdeen + 1 more

Follow



toinebogers

Followed by alansaid + 5 more

Follow

SEARCH VERSUS RECOMMENDATION

Search

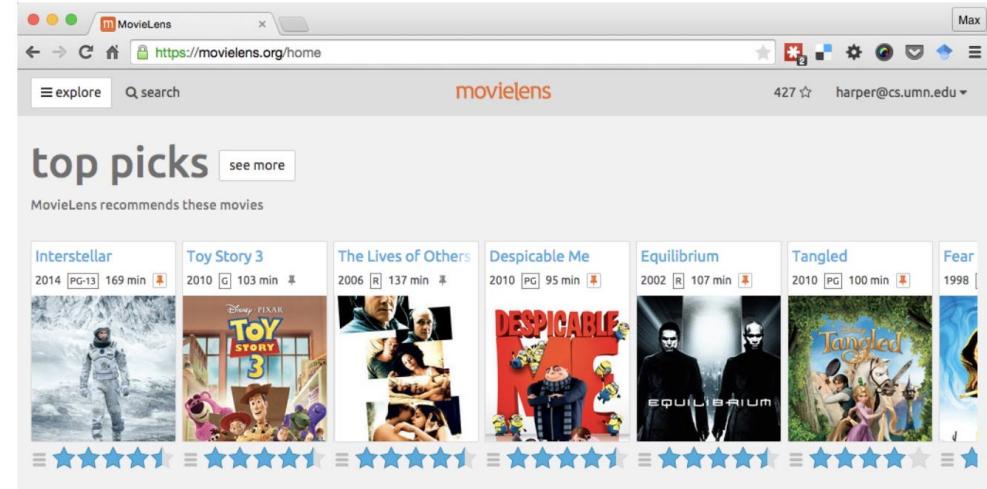
Query

Help user find out what they want

Figure out intents

(not highly personalized)

More focused?



Recommendation

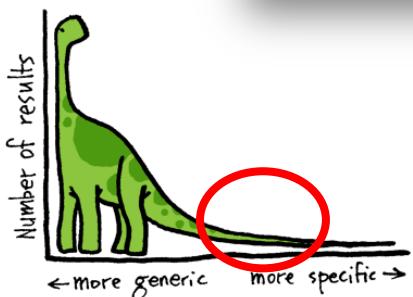
Previously rated items

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

Personalized

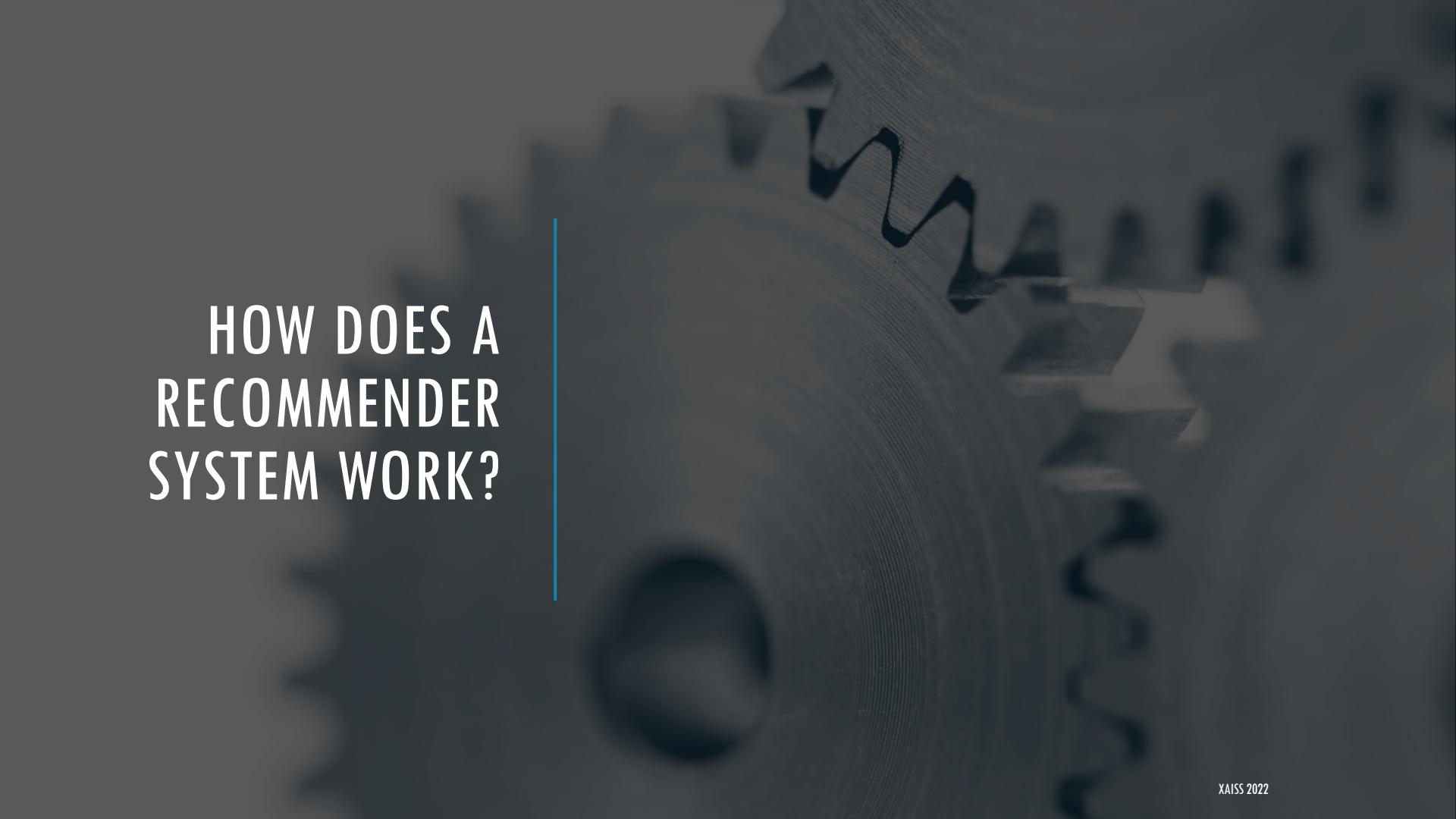
More exploratory?

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?

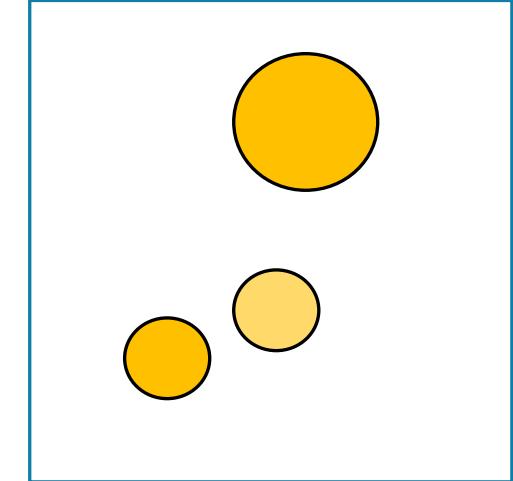
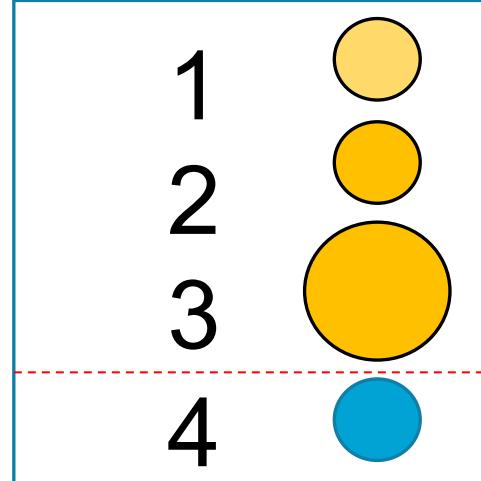
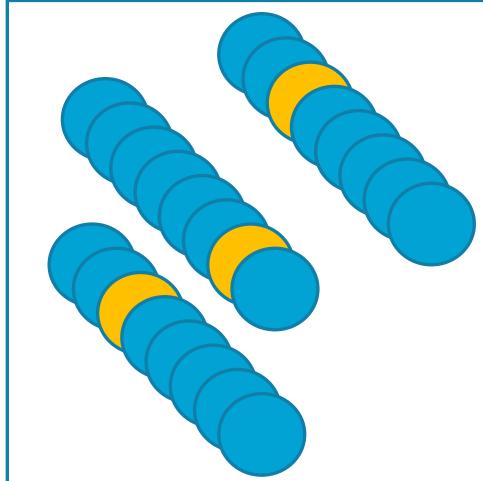
Systems that make personalized recommendations of goods, services, and people (Kautz)

User identifies one or more objects as being of interest

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

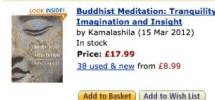
Ranking and filtering algorithm

- Ranks the options, filters out lower ranking options



amazon.co.uk

Recommended for you

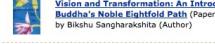


Add to Basket | Add to Wish List

Because you purchased...



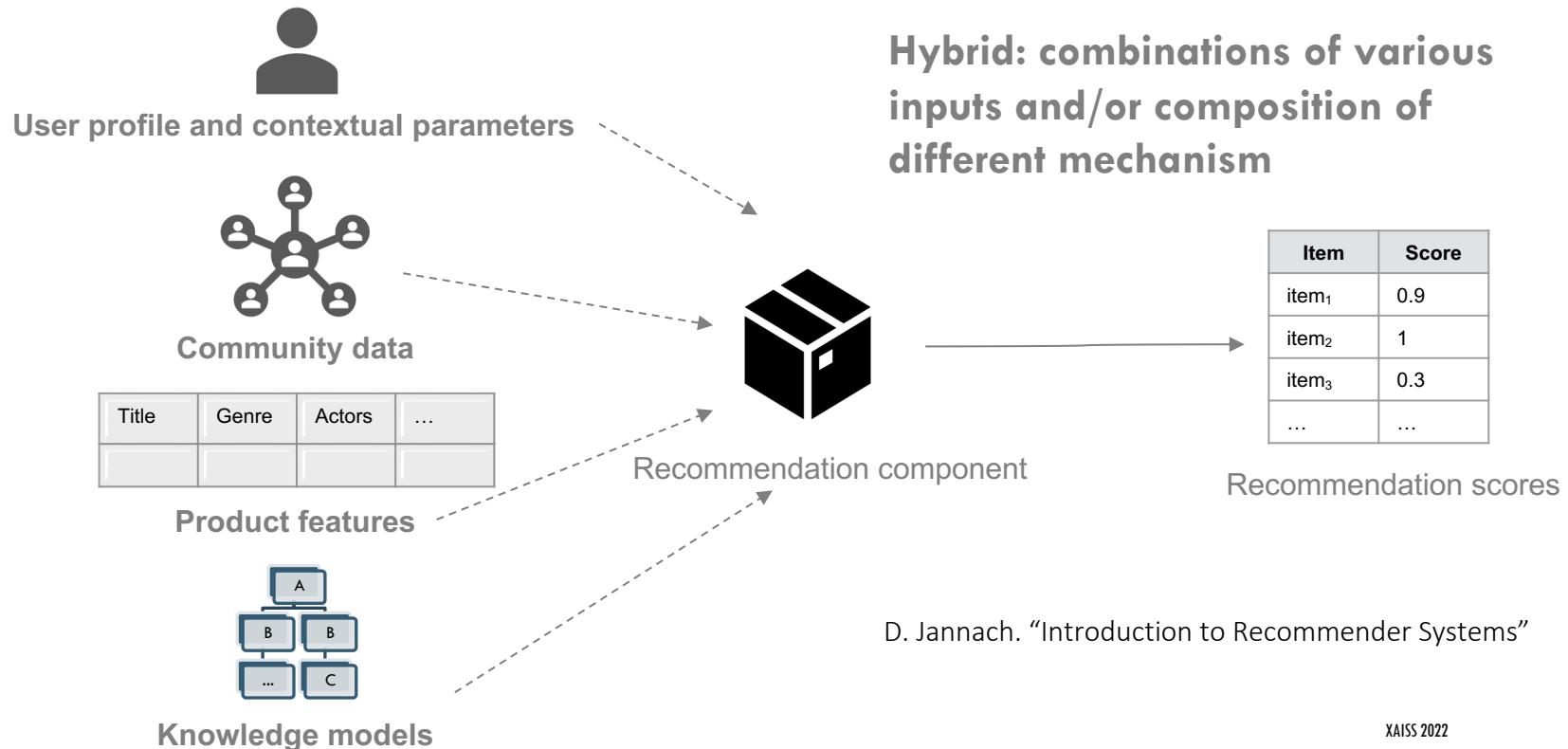
Don't use for recommendations



Don't use for recommendations

Help | Close window

What could be “similar”?



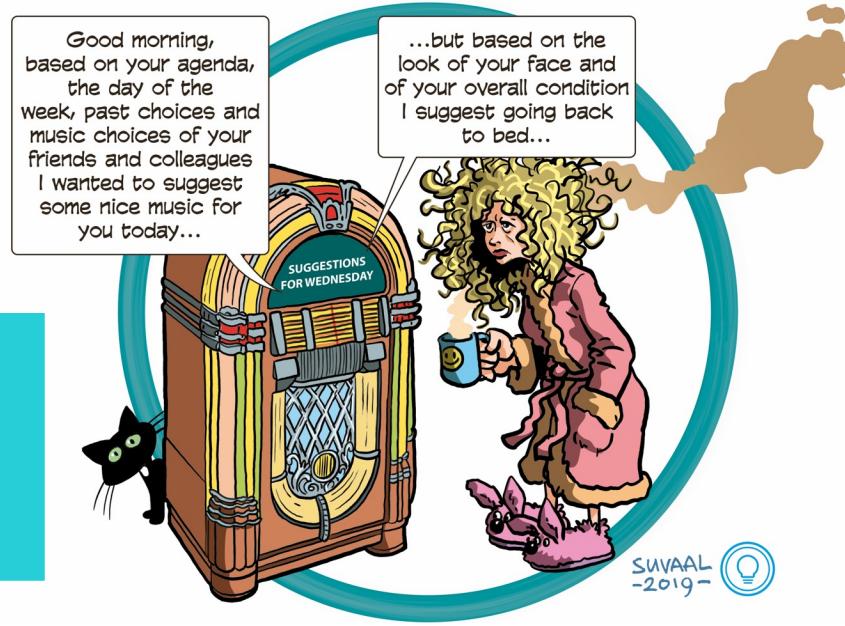
OVERVIEW

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)





A close-up photograph of a red and yellow toy robot arm. The robot's hand is holding a black smartphone, which displays a presentation slide with a yellow background and a dark overlay. The slide contains the text "EXPLANATIONS CAN SERVE DIFFERENT PURPOSES" in white capital letters, separated by a thin horizontal line.

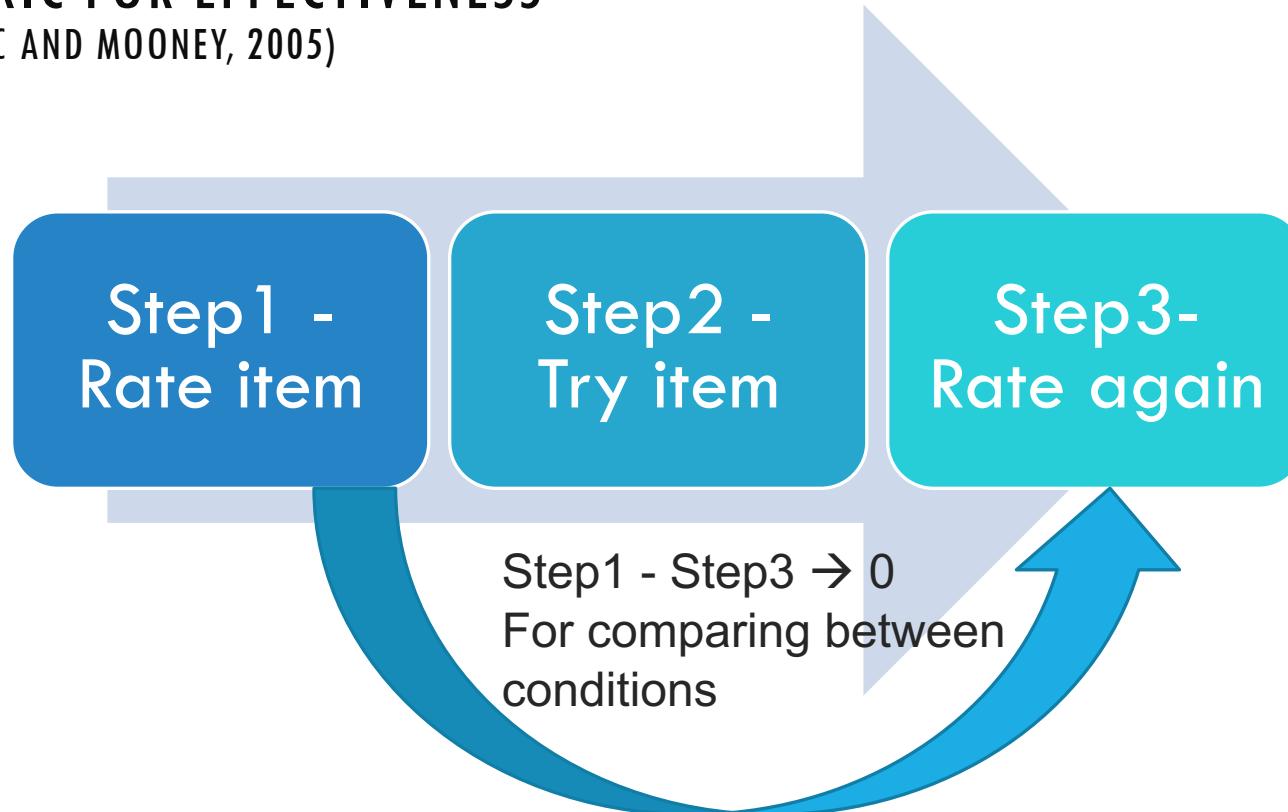
EXPLANATIONS CAN SERVE DIFFERENT PURPOSES

WHY EXPLAIN (RECSYS)

Purpose	Description
Transparency	How was this recommendation made?
Effectiveness	Why (not) this item?
Trust	Increase users' confidence in the system
Trade-offs?	
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

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

METRIC FOR EFFECTIVENESS (BILGIC AND MOONEY, 2005)



PHD: PERSONALIZED EXPLANATIONS

(TINTAREV & MASTHOFF, 🏆 AH 2008)

More ...

effective?

persuasive?

satisfying?

The screenshot shows a user interface for a movie recommendation system. At the top, the title "Johnny Mnemonic" is displayed in a large, bold, serif font. Below the title, a message states: "This movie is not one of the top 250 movies in the Internet Movie Database (IMDB)." To the left of this message is a small icon containing a question mark. At the bottom of the interface is a blue button with the text "I might know this movie, please skip to another one...".

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

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!

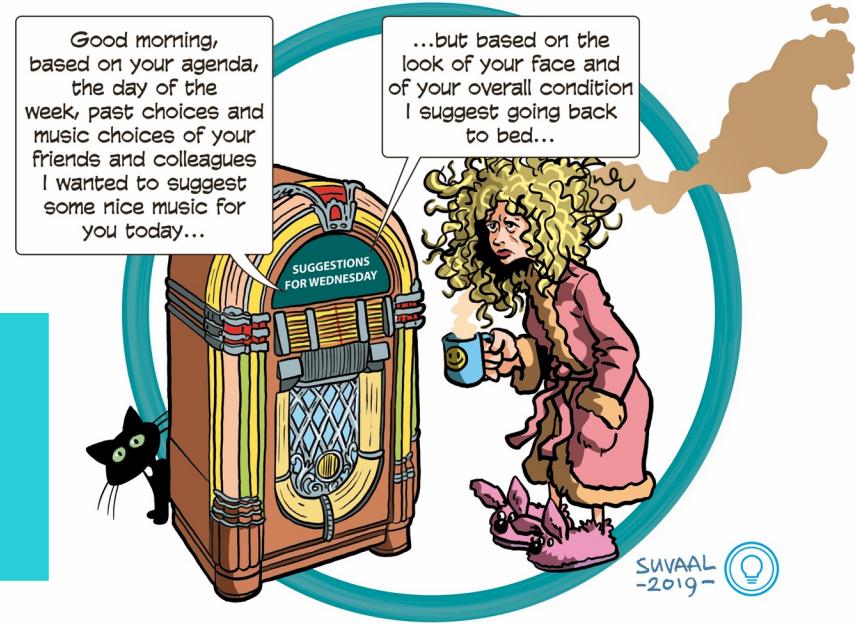
Change in opinion ok for baseline, but lots of cases where no opinion could be given.

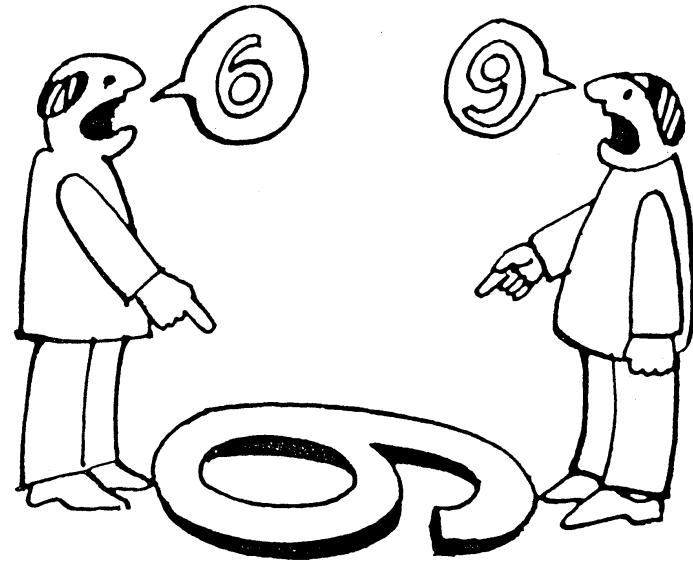
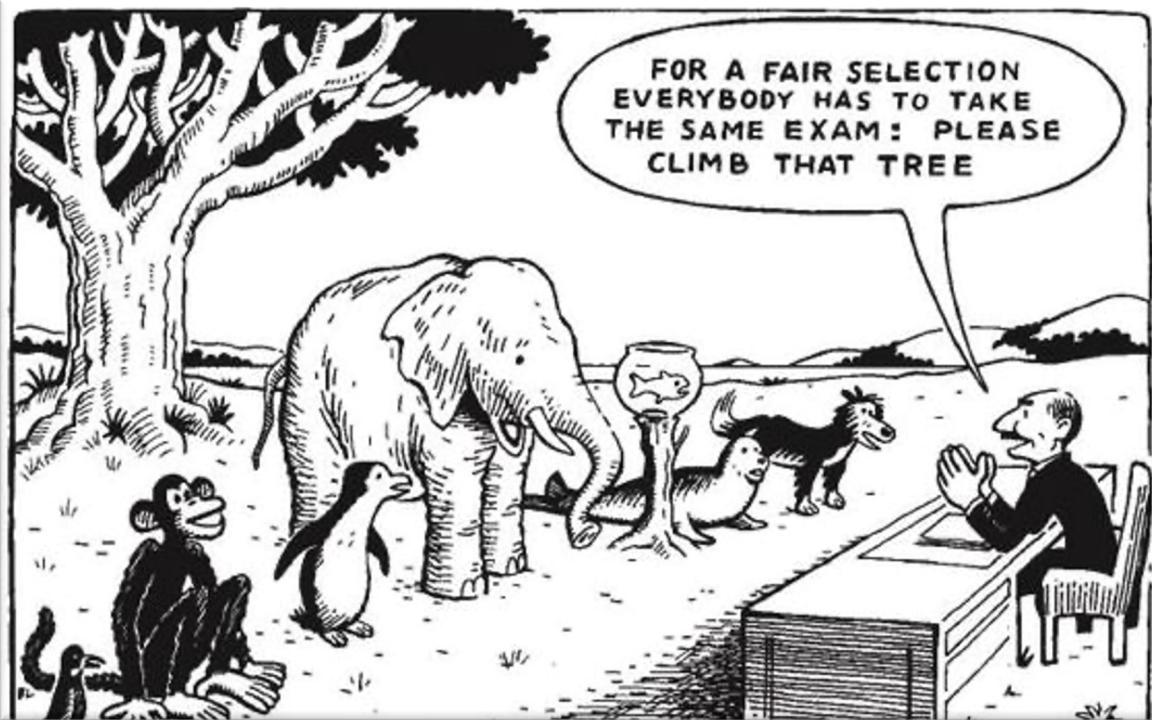
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DIFFERENT PEOPLE NEED
DIFFERENT EXPLANATIONS |

INTELLIGENT USER INTERFACES

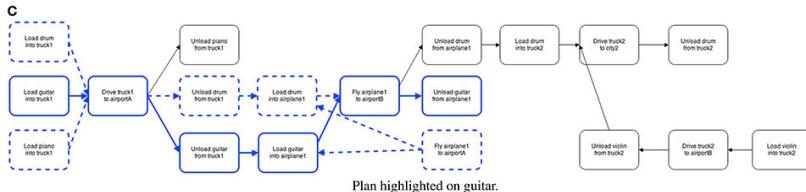
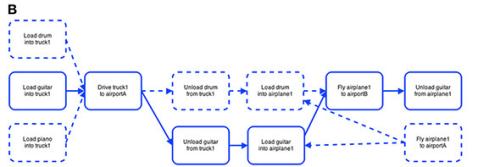
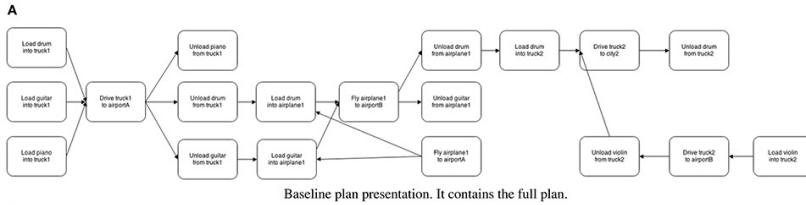
User interface – what the system shows of its internal state to a user, and allows the user to modify it to something resembling their internal model. NB: Includes chatbots!

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

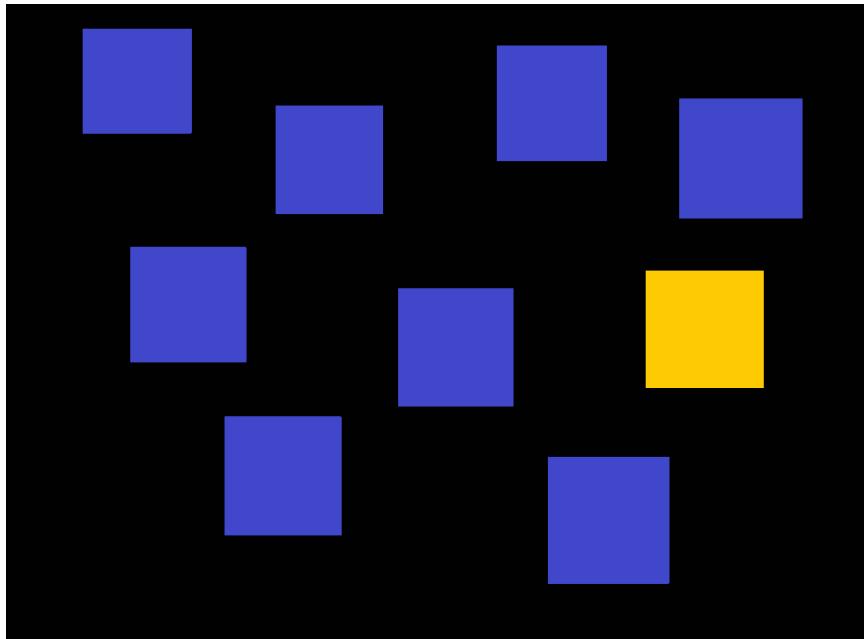
Example 1: 4th year student versus 1st year student

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?

Welcome Nava Tintarev [Log Out](#)

Your task is to: find a good playlist of rhythmic music for a dance party to celebrate my birthday.

I am happy with the playlist now

Recommendations source

The top artists you have

- David Gray
- Kundalini: Yoga, Meditation...
- Amos Lee
- Linkin Park
- Daniel Champagne

The top tracks you have

- Inner Focus
- On The Wing
- Serenity
- Gravity
- Fragilidad

The top genres you have

- acoustic
- african
- afrobeat
- alt-rock
- alternative
- ambient

Recommendations Processor

Weight of selected artists: 50

- Amos Lee
- David Gray
- Daniel Champagne

Weight of selected tracks: 88

- On The Wing
- Gravity

Weight of selected genres: 50

- acoustic
- ambient

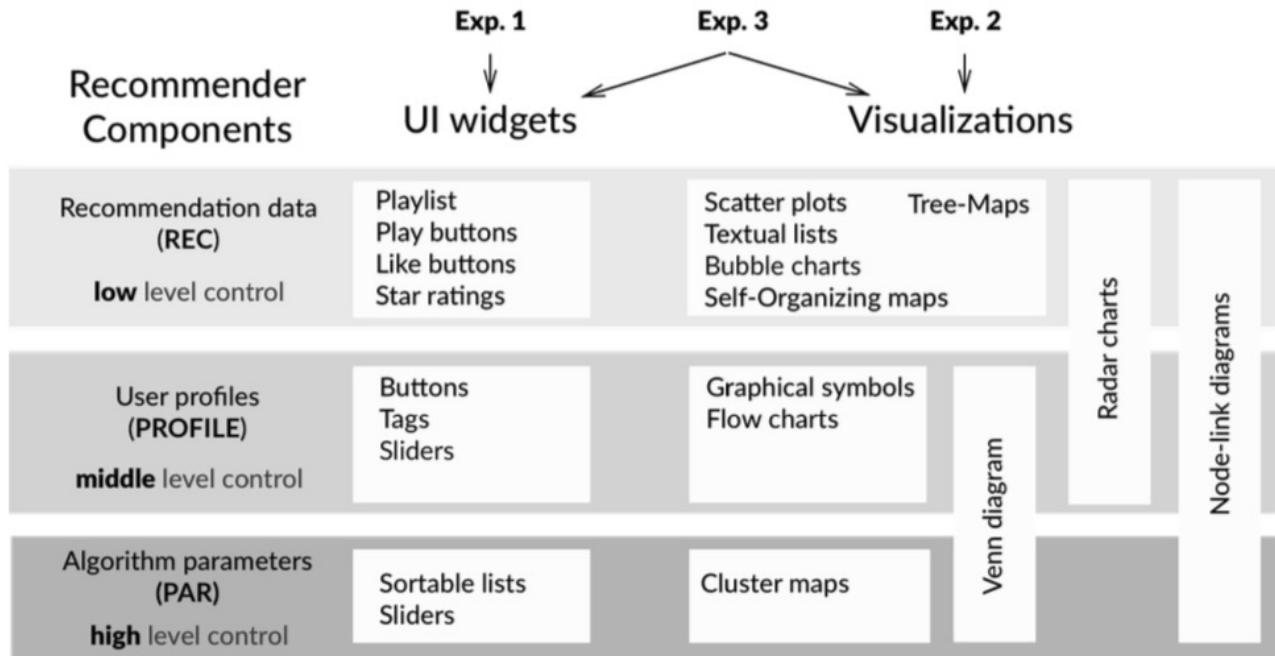
A playlist containing ambient

Rank	Song	Artist	Length
1	"we circle through the n...	Max Richter	9:54
2	Moments	Deep Watch	3:35
3	Peripherescence	Glowworm	3:58
4	Now Is the Time To Lea...	August Wilhelmsson	2:08
5	Our Secret Universe	Alan Ellis	2:22
6	Comet	Christopher Willits	6:13
7	Suaimhneas	Ceilidh	3:31
8	At Last	Martin Landau	2:48
9	Limbo	They Dream By Day	2:13

Recommendations

The top 20 songs

Rank	Song	Artist	Length
1	Free	Donavon Frankenreiter	0:32
2	Hey Ya - solo version	Obadiah Parker	0:00
3	While My Guitar Gently ...	Regina Spektor	0:00
4	It Only Takes a Taste	Drew Gehling, Jessie Mu...	0:00
5	Night Train	Amos Lee	0:00
6	Thought Of You	Justin Bieber	0:00
7	When The Tequila Runs O...	Dawes	0:00



PERSONAL CHARACTERISTICS EXAMPLE 1

YUCHENG JIN ET AL, INTRS WORKSHOP@RECSYS'17



Yucheng Jin

Welcome Nava Tintarev Log Out I am happy with the playlist now

Your task is to: find a good playlist of rhythmic music for a dance party to celebrate my birthday.

Recommendations source

The top artists you have +

David Gray Kundalini: Yoga, Meditation...
Amos Lee India Sub Daniel Chemlaune

Recommendations Processor

Weight of selected artists: 50

A playlist containing ambient

Ambient Chill "we circle through t... Max Richter

Recommendations

The top 20 songs

Free Donavon Frankenreiter

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

acoustic afrobeat alt-rock alternative
ambient

acoustic ambient

8 At Last Martin Landh 2:48
9 Limbo They Dream By Day 2:13

Thought Of You Justin Bieber 0:00

When The Tequila Runs O... Dawes 0:00



Katrien Verbert

EXAMPLE 2. CONTROL + SIMBUB

Your task is to: find a good playlist which contains faster and louder music for a sleepless night. ⚡

Recommendations source

The top artists you have

- Owl City
- Imagine Dragons
- Armin van Buuren
- Capital Cities
- Calvin Harris

The top tracks you have

- Youtopia
- Youtopia - Michael Woo...
- Safe And Sound
- Get Lucky (feat. Pharrell...)
- Radioactive

The top genres you have ↗

- acoustic
- afrobeat
- alt-rock
- alternative
- ambient

Recommendations Processor

Weight of selected artists: 50

Owl City

A playlist containing acoustic

Acoustic Covers Spotify

1 Stay... 2:54 Ang...

2 Can... 3:18 Ed S...

3 Ho... 2:53 Gar...

4 Blan... 5:03 Ima...

5 Stol... 3:55 Twin...

6 Sen... 3:45 I'm ...

7 I'm ... 3:15 Dua ...

Weight of selected tracks: 50

Youtopia

Weight of selected genres: 50

acoustic

Recommendations

Popularity

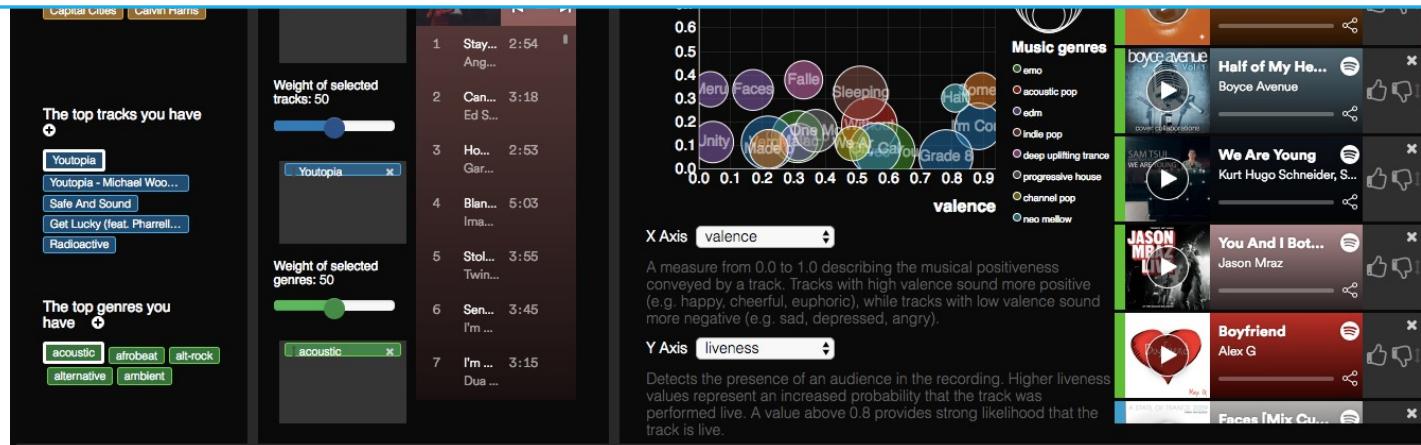
Music genres

- chamber pop
- metropolis
- alternative pop rock
- canadian punk
- big room
- progressive house
- disco house
- emo
- edm
- dance pop
- neo mellow
- canadian pop
- folk-pop
- acoustic pop

- Frozen Gro... Ilan Bluestone
- Heartless Kris Allen
- Babel Mumford & Sons
- Out Of To... Justin Bieber
- Hear Me N... Boyce Avenue
- Hey, Soul S... Train
- Siren IAN...

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	Experiment 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)

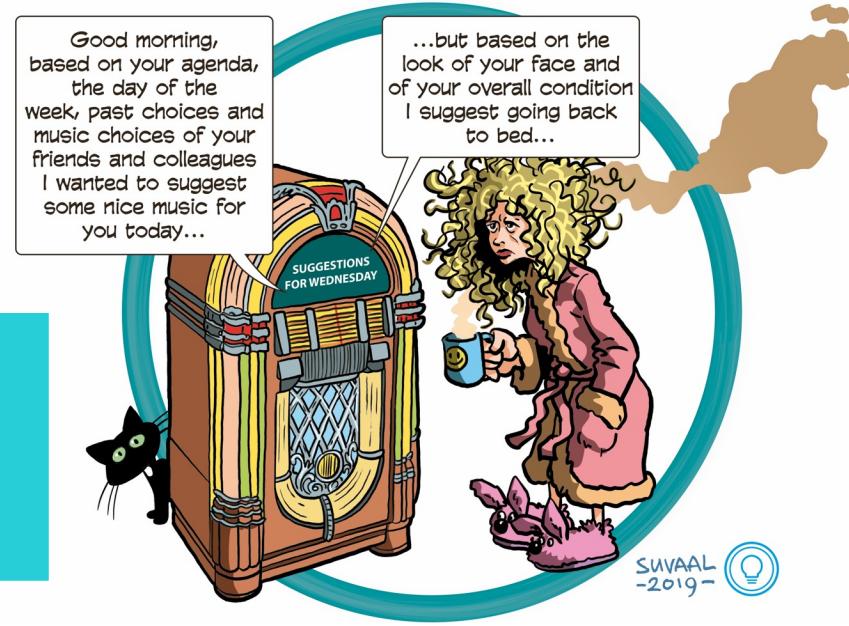
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There is a benefit in interactive explanations (especially for complex domains)



QUESTIONS?



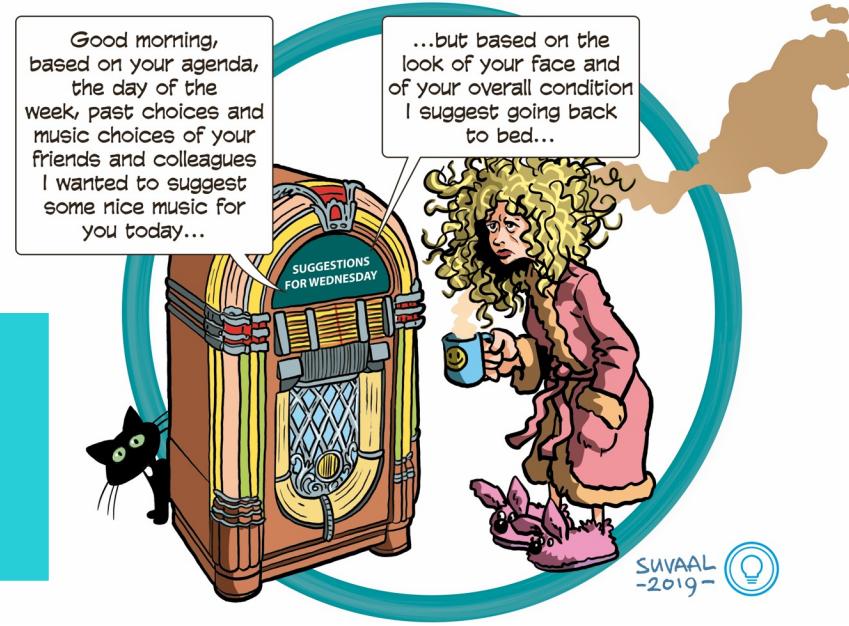
TAKE HOME PREVIEW

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)



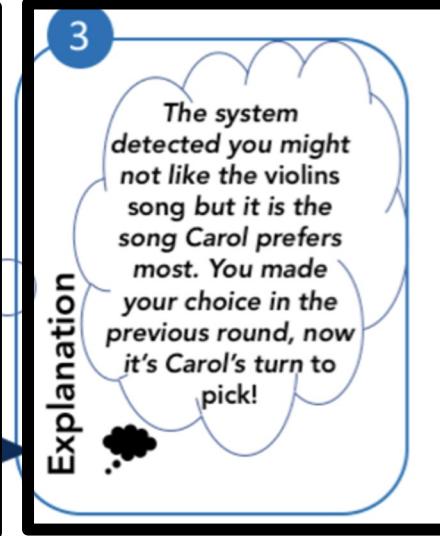
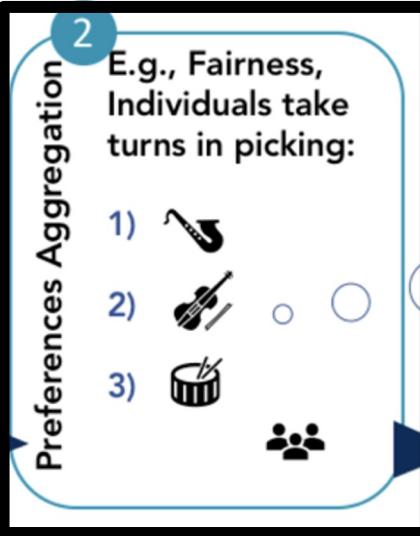
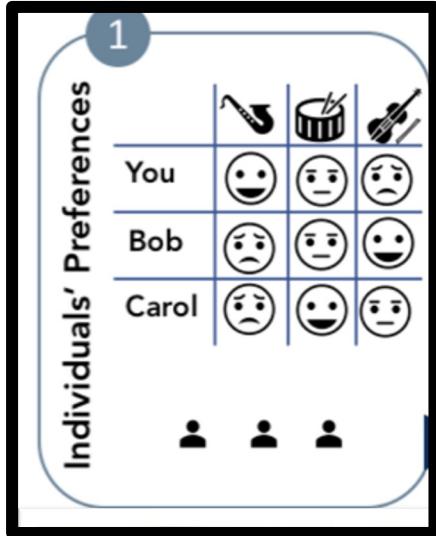


DIFFERENT SITUATIONS CALL FOR
DIFFERENT EXPLANATIONS

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

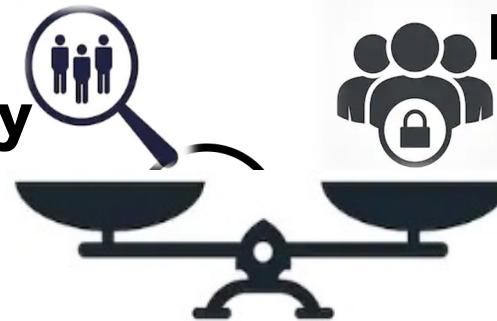
(NAJAFIAN ET AL, UMAP'21)

Group Composition



Perceived Transparency

Personality



Perceived Privacy



Relationship Type



Recommendation Outcome



Name



Rating

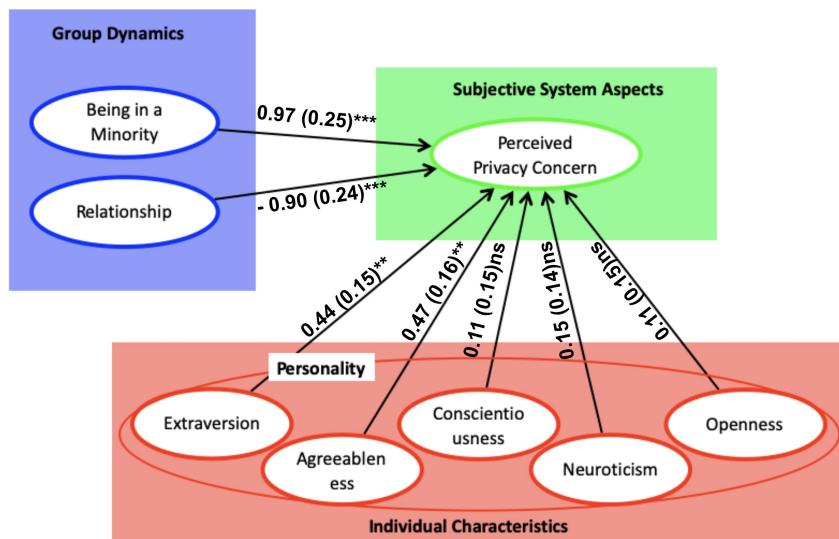


Personality



Song X is playing!

Song X is recommended to the group since it achieves the highest total rating. This decision does not support the preferences of Ana who did not rate this song highly. However, it supports the preferences of Bob and Carol who rated this song highly. Besides, we have detected that Bob and Carol really want to listen to this song and won't be talked out of it easily.

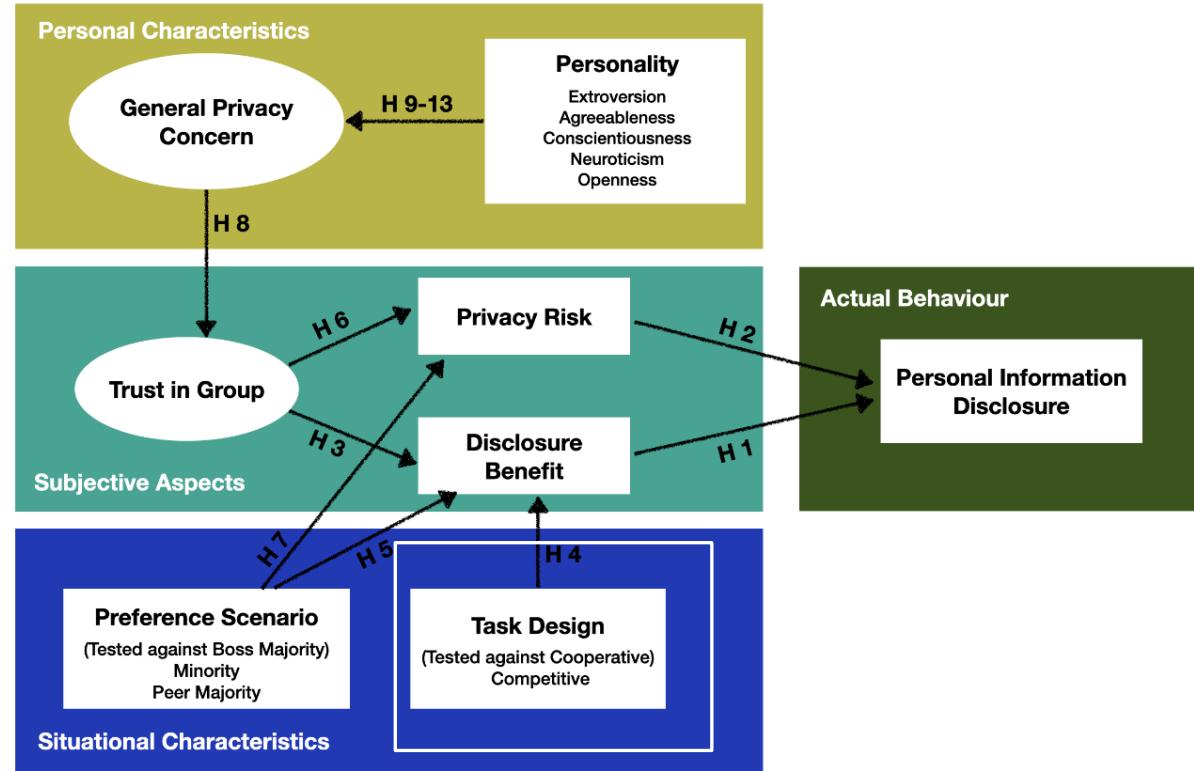


The "Bulldog coffeeshop" (cannabis store) has been recommended to your group since Carol will love it! The coffee-shop isn't the primary preference of Bob and John, but they are okay with it. Their preferences will be taken into account in the next recommendations.

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

Modeling individual satisfaction in a group context



Personality



Tie Strength

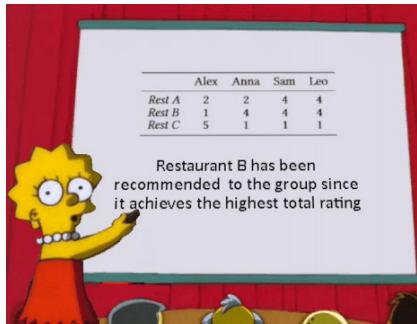


Group Context



Francesco Barile,
Assistant Professor,
Explainable
Recommender Systems

Social choice-based explanations for Group Recommendations

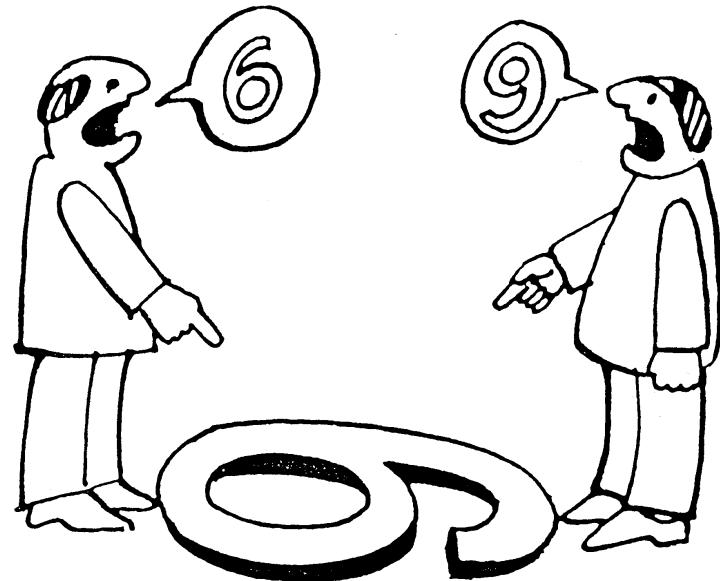


Effectiveness of social choice-based explanations
in terms of fairness, consensus, and satisfaction

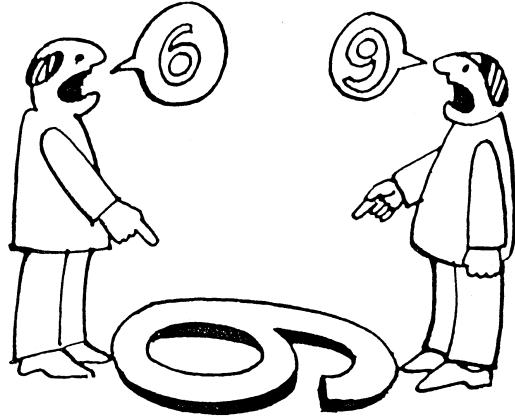
Complexity of rating scenario? Benefit of explanations?

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

ADAPTING TO CONTEXT: VIEWPOINT DIVERSITY

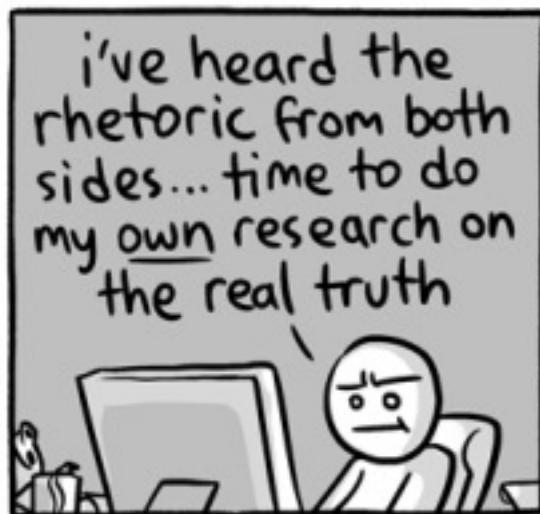


ADAPTING TO CONTEXT: VIEWPOINT DIVERSITY



- 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?



CHAINSAWSUIT.COM

MEASURING VIEWPOINT DIVERSITY FOR WEB SEARCH ON DEBATED TOPICS

The screenshot shows a Google search results page for the query "should I be vegan?". The results are presented in a grid format:

- Result 1:** "Be Healthier and Happier" (highlighted with a blue box).
 - Text: "Being vegan is great for your health... Vegans get all the nutrients they need to be healthy, such as plant protein, fiber, and minerals, without all the nasty stuff in meat that may slow you down and make you sick, such as cholesterol and saturated animal fat." (4 nov. 2019)
 - Image: A photo of a basket filled with various fruits and vegetables.
 - Text: "Why Going Vegan Should Be Your New Year's Resolution - Peta" (<https://www.peta.org/living/food/top-10-reasons-go-vegan-new-year>)
- Result 2:** "Mensen vragen ook"
 - Text: "Is it healthier to be vegan?"
 - Text: "What happens when you go vegan?"
 - Text: "What do I need to be vegan?"
 - Text: "Does being vegan make a difference?"
- Result 3:** "Why Going Vegan Should Be Your New Year's Resolution - Peta" (highlighted with a blue box).
 - Text: "https://www.peta.org/living/food/top-10-reasons... - Vertaal deze pagina" (4 nov. 2019 - Be Healthier and Happier Being vegan is great for your health... Vegans get all the nutrients that they need to be healthy, such as plant protein, fiber, and minerals, without all the nasty stuff in meat that may slow you down and make you sick, such as cholesterol and saturated animal fat.)
- Result 4:** "The 14 things you need to know before you go vegan | Life ..."
 - Text: "https://www.theguardian.com/lifeandstyle/jun/19/the... - Vertaal deze pagina" (19 jun. 2019 - The environmental, health and ethical benefits of veganism are beyond doubt. But what if... But vegans, in principle, should be really cheap.)
- Result 5:** "Why go vegan? | The Vegan Society"
 - Text: "https://www.vegansociety.com/go-vegan/why-go-vegan - Vertaal deze pagina" (Explore why veganism is kinder to animals, to people and to our planet's future.)
- Result 6:** "Six reasons to go vegan, according to science - The Telegraph"
 - Text: "https://www.telegraph.co.uk/.../Body - Vertaal deze pagina" (1 nov. 2019 - Today marks World Vegan Day, and the start of World Vegan Month. ... should put paid to anyone with the phrase "but what about protein?")
- Result 7:** "10 Reasons You Shouldn't Go Vegan | LIVEKINDLY"
 - Text: "https://www.livekindly.co/10-reasons-go-vegan - Vertaal deze pagina" (21 mrt. 2019 - There are many reasons why not to go vegan; here's the top ten, to help you realize why you should not embrace the benefits of a healthy...)
- Result 8:** "Why we shouldn't all be vegan - The Conversation"
 - Text: "theconversation.com/why-we-shouldnt-all-be-vegan... - Vertaal deze pagina" (16 jan. 2019 - It's a similar story in the UK, where the number of vegans has... Of course, there is much that can and should be done to improve the way...)

Annotations on the right side of the results:

- "Yes!" next to the first result.
- "Yes!" next to the second result.
- "Yes!" next to the third result.
- "Yes!" next to the fourth result.
- "Yes!" next to the fifth result.
- "Yes!" next to the sixth result.
- "Yes!" next to the seventh result.
- "No!" next to the eighth result.
- "No!" next to the ninth result.

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

Our work (see website for papers)

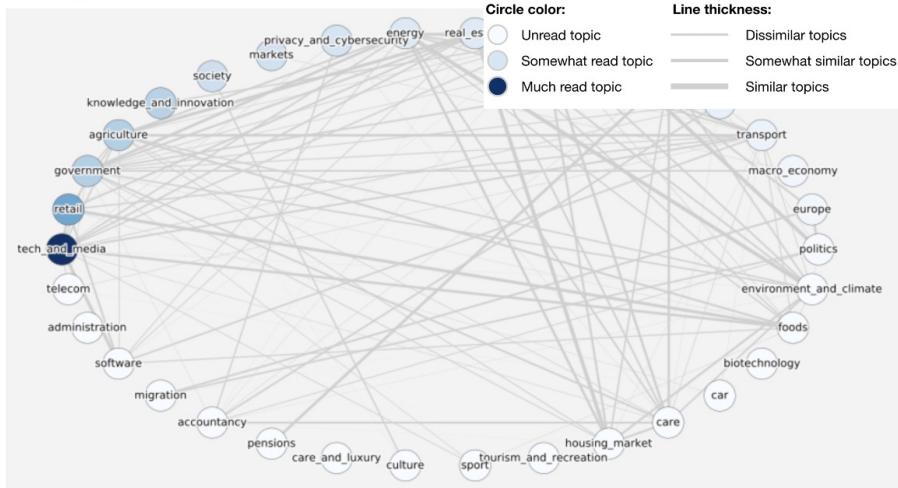
- Comprehensive viewpoint labels (SENTIRE 2020, HCOMP 2021, CHIIR 2022)
- Understanding algorithmic biases (BIAS 2020)
- Understanding cognitive biases of users (SIGIR 2021)

Tim Draws, PhD

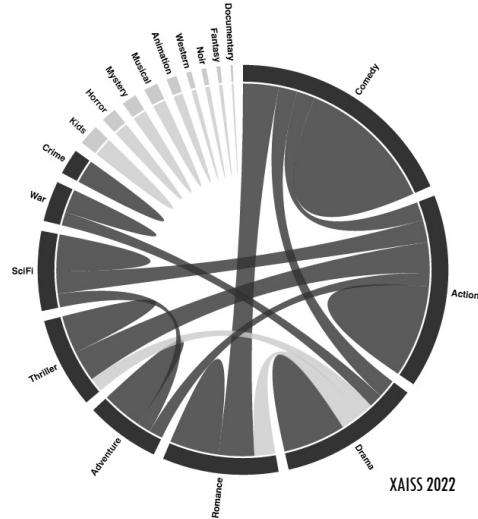


EXPLANATION INTERFACES FOR BIAS MITIGATION?

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



Tintarev et al. ACM Symposium On
Applied Computing, 2018





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

Caution!

This search result might reinforce your opinion, select another search result if you want to minimize the risk of confirmation bias

[\(I'm aware of the risk of confirmation bias, show item\)](#)

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).

Summary

Most people agree that it is valuable to look at different perspectives. You can do so by looking at the summary of the supporting and opposing arguments made in the contributions to the debate below:

Arguments in Favor

School uniform is harming the student's self expression

School uniforms are expensive

Arguments Against

School uniforms create a sense of equality/unity

School uniforms saves costs

[Show more](#)

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



UNIVERSITY
OF TWENTE.



Project,
Secondment
project partners

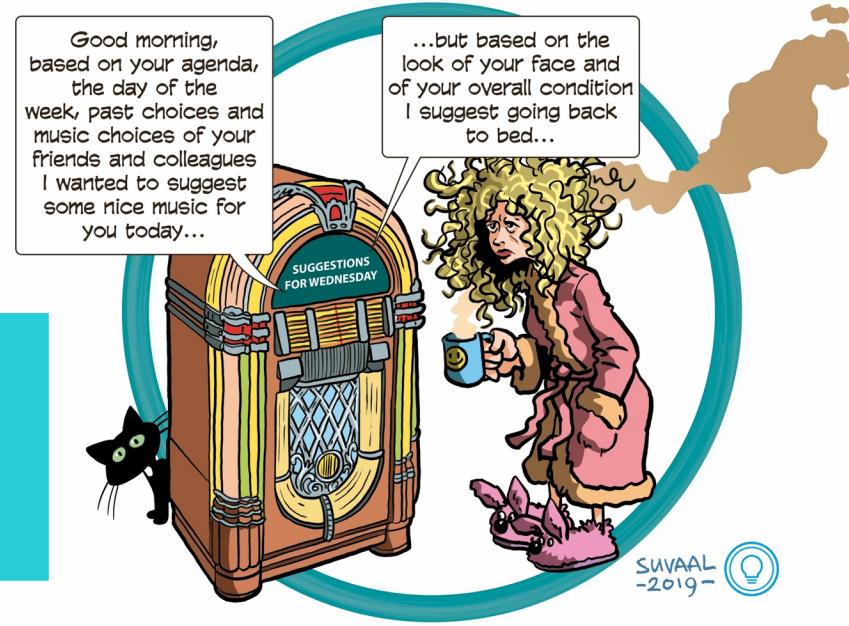
TAKE HOME PREVIEW

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

“Your Friends”
(People you follow)

ScreenName DIS2016 Go!

Find out what the #topics and people your friends are interested in but you don't see

HopTopics

I Follow... My Hashtags

- Larry Fisher @ACMLarry
- SIGCHI Finland @SigchiFinland
- ACM US Public Policy @USACM
- Emma Nicol @emmanicolworks
- ACM SIGGRAPH @siggraph
- ACM CHI PLAY @acmchiplay
- chi+med @chi_med

#London #CHI2016 #Jobs #SmartKitchen #Iran #DX #myfirstTweet

They Follow... Their Hashtags

- David Lally @davidmlally
- Re/code @Recode
- Manuel Alducin @malduclin
- Dimensional Imaging @di4dcom
- GIGAMacro @giga_macro
- Bonjour SIGGRAPH @bonjournsiggraph
- Epic Games @EpicGames

#VR #CES2016 #Oscar #VFX #AR #Paris #12hrLater

0/3 users selected. Dashboard On I'm Done!

“Your Friends’ Friends”
(People your friends follow)

384 Tweets recommended for @DIS2016

Sony Imageworks @imageworksvfx
Congratulations to the entire Hotel Transylvania 2 team on their VES Award nomination for Outstanding Visual Effects in an Animated Feature!

filter buttons

tweets from your friend only

RESET

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



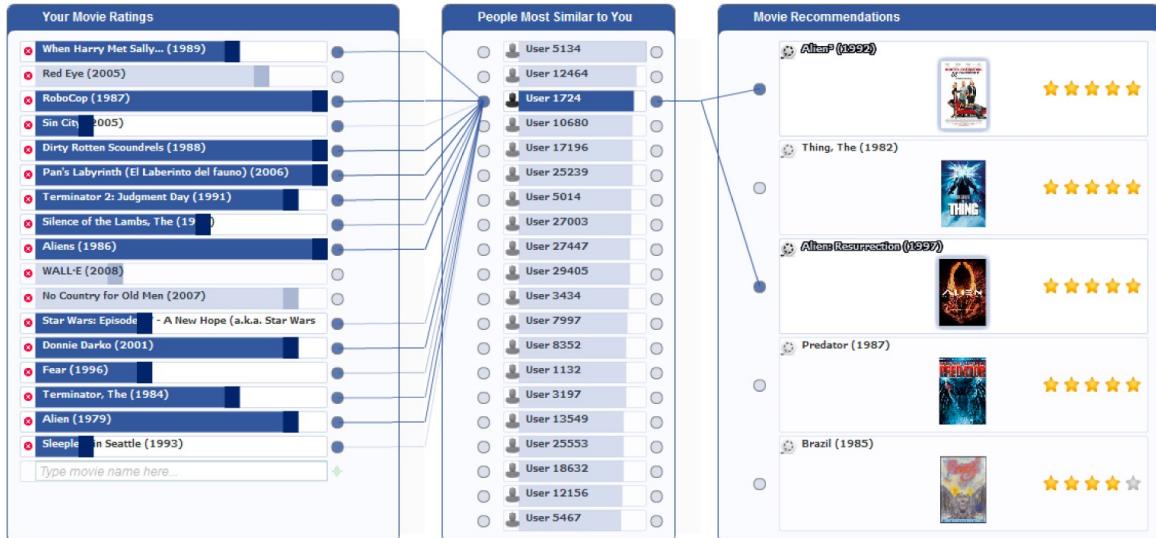
MOVIE RECOMMENDATIONS

SCAFFER ET AL, 2015

Left to right:

- 1) user's profile items
- 2) top-k similar users;
- 3) top-n recommendations.

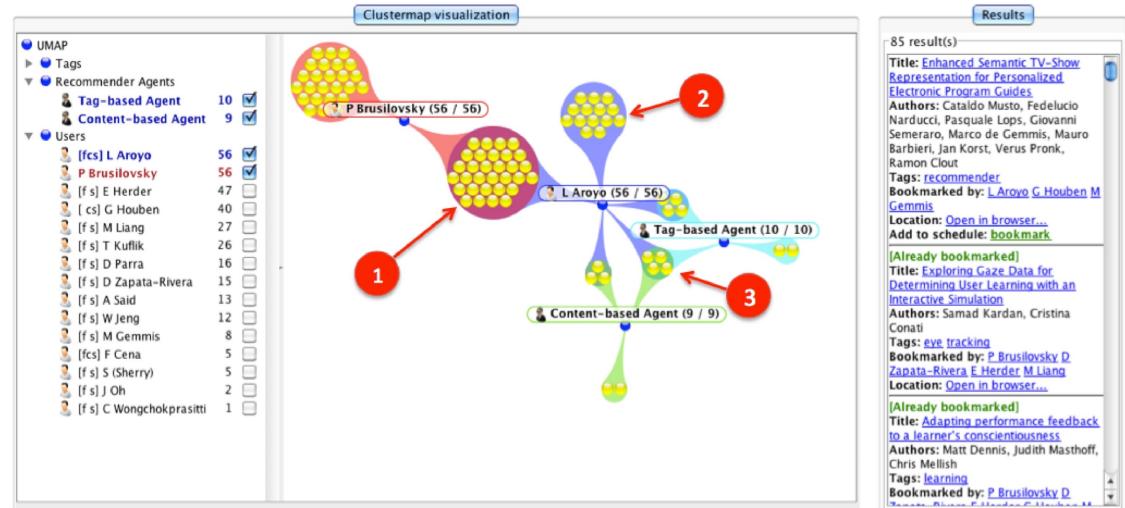
Adds, deletes, or re-rates produce updated recommendations



ACADEMIC TALKS

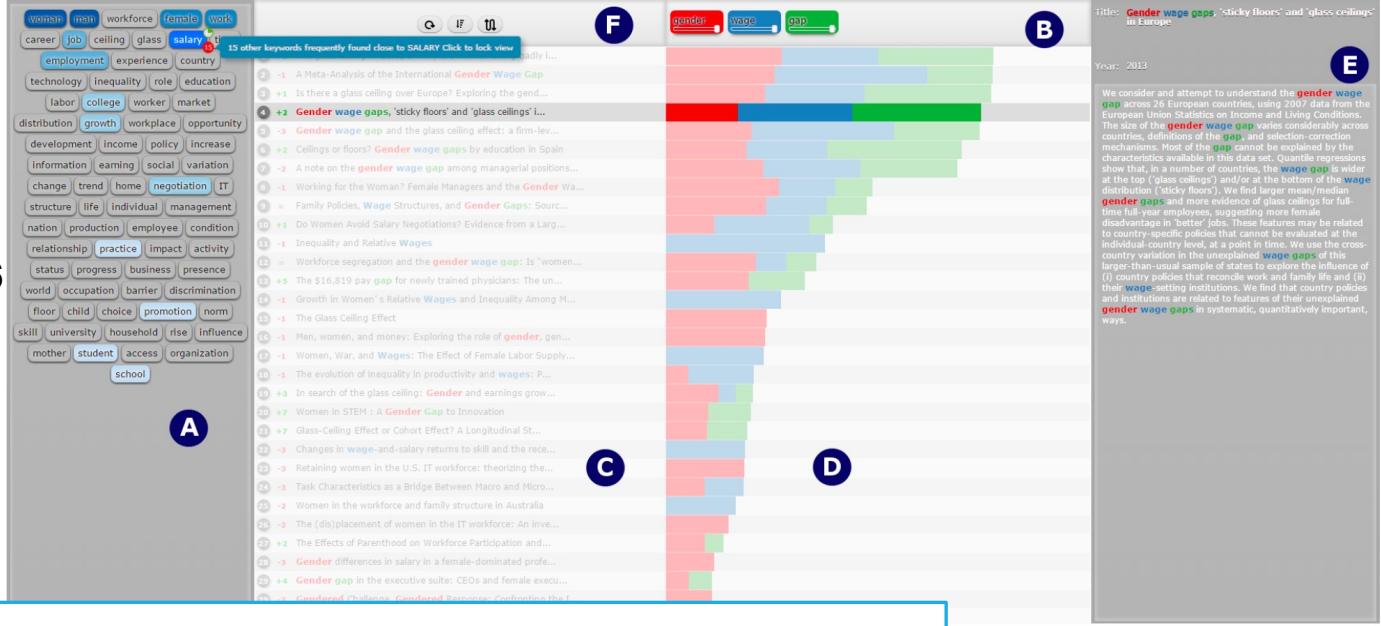
VERBERT ET AL. 2013

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

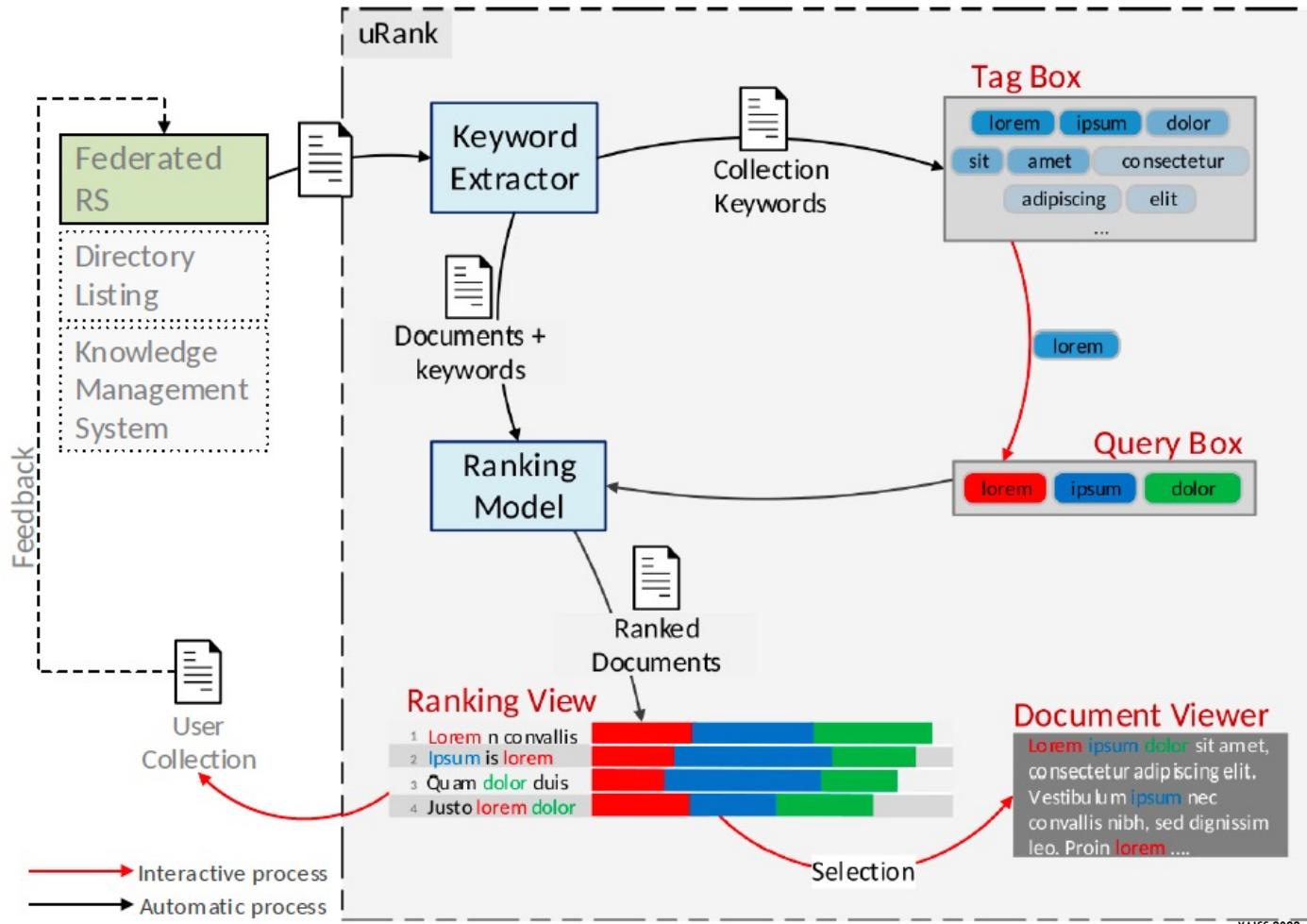


ARTICLES URANK

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



SETFUSION

PARRA & BRUSILOVSKY, 2015

Which items
or people

Look at the
intersections

The figure displays the SETFUSION interface. At the top left, a panel (a) titled "Tune weights of the recommender method" shows three sliders: "Most bookmarked papers" (0.4), "Similar to your favorite articles" (0.8), and "Frequently cited authors in ACM DL" (0.4). Below this is a button "Update Recommendation List →". A note at the bottom says "* Hover over circles to surface articles". At the bottom left, a panel (b) shows a Venn diagram with three overlapping circles: "Similar to your favorite articles" (yellow), "Most bookmarked papers" (blue), and "Articles in top 30" (green). A legend indicates: "Similar to your favorite articles" (yellow dots), "Most bookmarked papers" (blue dots), "Articles in top 30" (green dots), and "Articles not in top 30" (grey dots). A callout box labeled "2. Can't see the forest for the trees? A citation recommendation system" points to the blue circle. On the right, a large panel (c) lists 16 research papers, each with a small thumbnail, author(s), and a "[see abstract]" link. The papers are color-coded by category: yellow for "Similar to your favorite articles", blue for "Most bookmarked papers", green for "Articles in top 30", and grey for "Articles not in top 30".

2. Can't see the forest for the trees? A citation recommendation system
by C. Lee Giles, Cornelia Caragea, Adrian Silvescu, Prasenjit Mitra
[see abstract]

3. When thumbnails are and are not enough: Factors behind users
by Dan Albertson
[see abstract]

7. Gendered Artifacts and User Agency
by Andrea R. Marshall, Jennifer A. Rode
[see abstract]

8. Two Paths to Motivation through Game Design Elements: Reward-Based Gamification and Meaningful Gamification
by Scott Nicholson
[see abstract]

9. Automatic Identifying Search Tactic in Individual Information Seeking: A Hidden Markov Model Approach
by Zhen Yue, Shuguang Han, Daqing He
[see abstract]

11. Old Maps and Open Data Networks
by Werner Robitzka, Carl Lagoze, Bernhard Haslhofer, Keith Newman, Amanda Stefanik
[see abstract]

14. Effects of User Identity Information On Key Answer Outcomes in Social Q&A
by Erik Choi, Craig Scott, Chirag Shah
[see abstract]

15. Ebooks and cross generational perceived privacy issues
by Jennifer Sue Thiele, Renee Kapusniak
[see abstract]

16. Toward a mesoscopic analysis of the temporal evolution of scientific collaboration networks

Contribution
to results
(color-coded)

INTERSECTION EXPLORER CARDOSO ET AL. 2018

Resulting recs.

Choice of
algorithm,
user, content-
features

The figure consists of three panels illustrating the Intersection Explorer interface:

- Set Selection View (Left, Blue Border):** A sidebar for selecting search parameters.
 - Select from...**: A search bar.
 - Agents (number of papers)**:
 - top-10 agent (10)
 - tag-based agent (10)
 - bookmark-based agent (10)
 - bibliography agent (10)
 - ext. bookmarks agent (10)
 - Users (common bookmarks/total bookmarks)**:
 - Current User (18/18)
 - User₁ (10/43)
 - User₂ (9/43)
 - User₃ (9/37)
 - ...
 - User_n
 - Tags (number of related papers)**:
 - Tag₁ (10)
 - Tag₂ (1)
 - Tag₃ (1)
 - Tag₄ (2)
 - ...
 - Tag_n (2)
- Set Exploration View (Middle, Green Border):** A visualization showing the intersection of selected sets.
 - Papers recommended by the agent, bookmarked by the user, or tagged with the tag.**
 - Papers not recommended by the agent, bookmarked by the user, or tagged with the tag.**
 - Papers bookmarked by you.**
 - Sort rows by**: number of papers, Ascending, Descending.
 - Number of papers**: A histogram showing the distribution of paper counts across the selected sets.
 - Number of papers**: A bar chart showing the count of papers for each set category.
- Intersection Exploration View (Right, Blue Border):** A table of resulting recommendations.

Title	Authors	Bookmark
A Framework of Health Information Retrieval for Aging Population	Mingkun Gao	Bookmark this paper!
Adapting at Run-time: Exploring the Design Space of Personalized Fitness Coaches	Hanna Schneider	Bookmark this paper!
Towards Fine-Grained Adaptation of Exploration/Exploitation in Information Retrieval	Alan Medlar, Joel Pykkö, Dorota Giowacka	Bookmark this paper!
Personalizing Online Educational Tools	Michael J Lee, Bruce Fennerda	Bookmark this paper!
Visual Exploration and Analysis of Recommender Histories	Peter Hasitschka, Vedran Sabol	Bookmark this paper!

Which of the factors are used in the selection

HOPTOPICS

KANG ET AL 2016

Person to person (CF)
Also content-based

The screenshot displays the HopTopics application interface. At the top, there's a navigation bar with 'ScreenName' (set to 'DIS2016'), 'Get', and three filter buttons: 'One hop selected', 'Dashboard On', and 'I'm Done!'. Below the navigation is the main content area, which is divided into two main sections: 'I Follow...' and 'They Follow...'. Each section has a header and a list of users and their interests. A green dashed box highlights the 'They Follow...' section. To the right, a callout box points to the 'Your Friends' Friends' (People your friends follow) section. Another callout box indicates that the dashboard can be hidden for readability. At the bottom, there's a list of tweets with user profiles, a 'Source of tweet' section, and a 'filter buttons' section. The 'filter buttons' section includes options for 'tweets from your friend only', 'tweets from your friends' friend only', and a 'RESET' button. A callout box also points to the 'Star icons. Saved tweets have yellow star' feature.

"Your Friends"
(People you follow)

"Your Friends' Friends"
(People your friends follow)

dashboard can be hidden for readability

Two "hops"

filter buttons

tweets from your friend only

tweets from your friends' friend only

reset filtering

Star icons.
Saved tweets have yellow star



Byungkyu (Jay) Kang

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, regardless of actual recommendation accuracy.

Sweet spot for cognitive load

User profile (PRO)

User Profile

The top artists you have +

- Owl City
- Imagine Dragons
- Armin van Buuren
- Capital Cities
- Calvin Harris

The top tracks you have +

- Youtopia
- Youtopia - Micha...
- Safe And Sound
- Get Lucky (feat. P...
- Radioactive

The top genres you have +

- acoustic
- afrobeat
- alt-rock
- alternative
- ambient

a)

Algorithm parameters (PAR)

Algorithm Parameters

Weight of selected artists: 50

Owl City

Popularity: ★★★★☆

Genres: pop, pop punk, pop rock

#followers: 1475813

Weight of selected tracks: 50

Youtopia

Weight of selected genres: 50

acoustic

removing and sorting

grayed out slider

b)

Recommendations (REC)

Recommendations

The top 20 songs (If you have a problem to play the music by "play" button, you can try to click Spotify icon.)

Song	Artist	Spotify Icon	Like	Dislike	More
Under My Skin - Original Mix	Ilan Bluestone, Jerome Isma-Ae				
Grade 8	Ed Sheeran				
Only Girl (In the World)	Boyce Avenue				
Thank You	Dido				
Somebody To Love	Justin Bieber				
Telescope	Nashville Cast				
Find a Way - Listenbee Radio...	Ferry Corsten				
Freefalling - Cold Blue Mix	Dennis Shepard				
Let Go - Going Deeper Remix					

c)

Jin et al. 2016



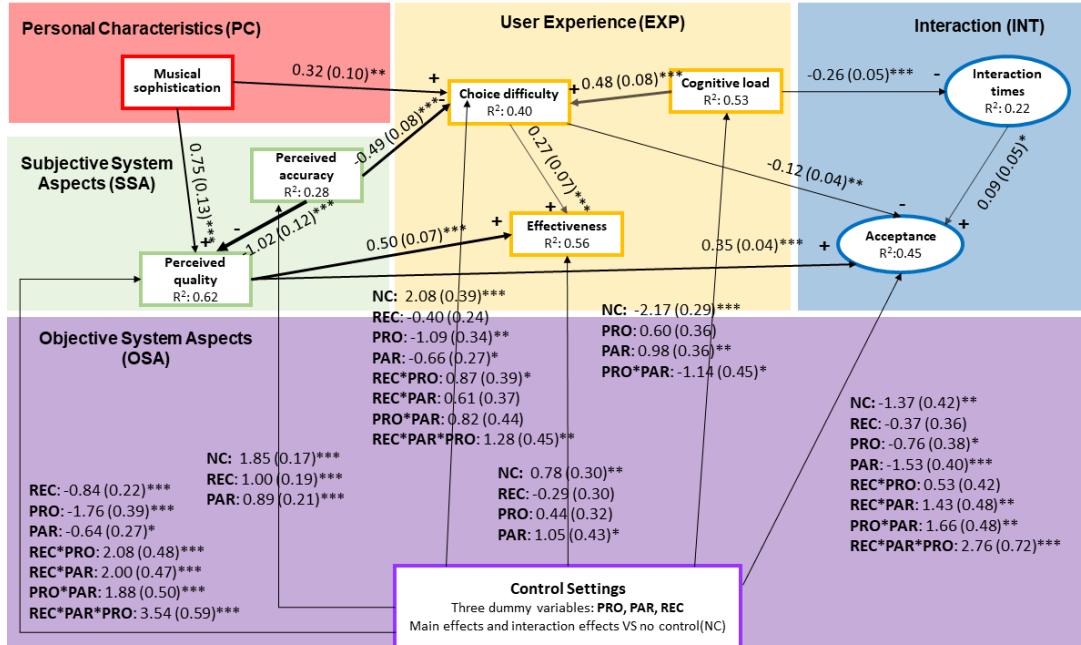
Between-subjects

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.



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

The fit of our SEM model

$$\chi^2(2, 98) = 257.410$$

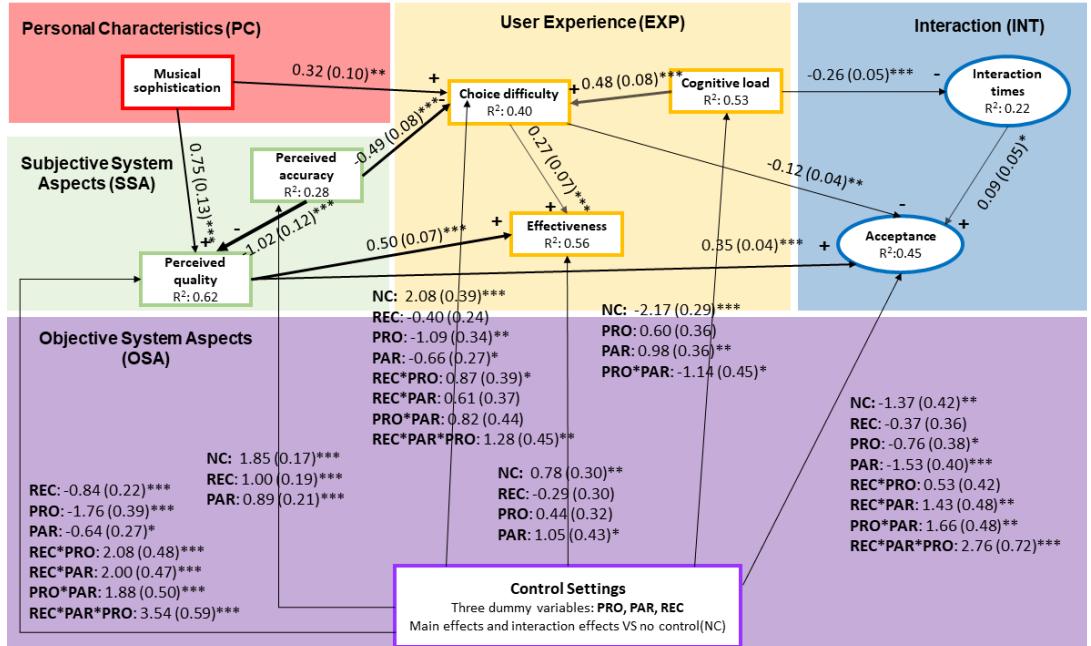
$p < .001$

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.



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

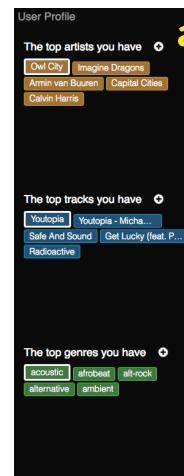
Main effects: REC has lowest cognitive load and highest acceptance

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

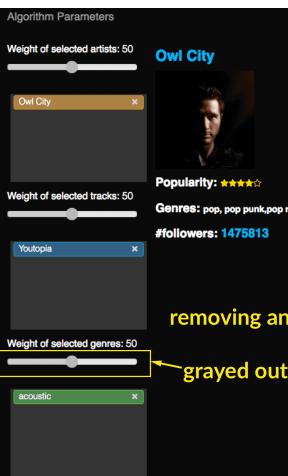
Three-way interaction: it increases acceptance, and does not lead to higher cognitive load. Increase interaction times and accuracy

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

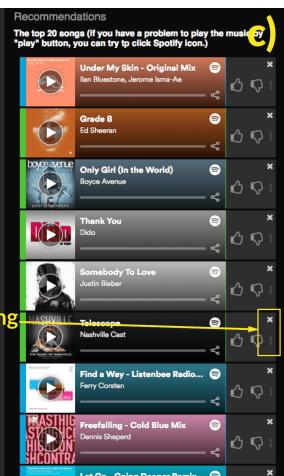
User profile
(PRO)



Algorithm parameters (PAR)



Recommendations (REC)



removing and sorting

grayed out slider

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**, incivility, 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.

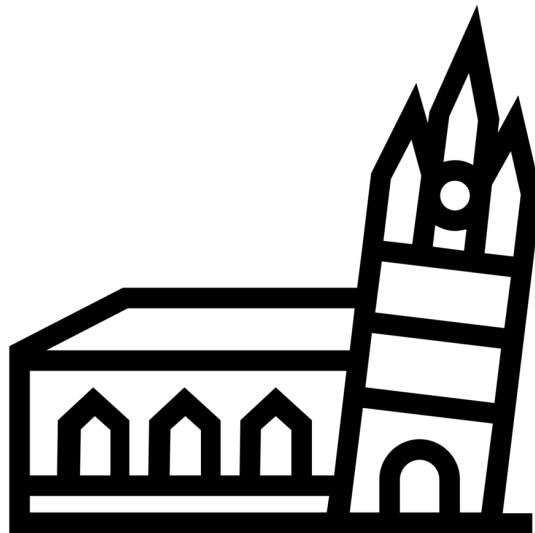
- TAIM – Trustworthy AI in Media (RTL/UvA)
- TROIKA - Trustworthy Collaborative Knowledge Accelerator (BIOMAXX/TUD)
- Notification around November 2022

ERC Consolidator grant under review

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

QUESTIONS?

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



XAISS 2022

Delft

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Representation

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

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.



Rishav Hada
Research Assistant
Maastricht University
r.hada@maastrichtuniversity.nl



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

The figure displays three screenshots of the Social Search Browser application, illustrating its user interface and functionality.

Screenshot 1 (Left): Shows the search interface with three dropdown filters: "time" (any time), "friendship" (everyones queries), and "similarity" (all queries). Below the filters is an "interactive map" of a city area, specifically Cork, Ireland, with various locations marked and zoom controls. A green callout box highlights the map area with the label "location of the user".

Screenshot 2 (Middle): Shows the search results for the query "anyone know whe..". The results include:

- A message from "Tung Sing": "anyone know where to get a nice chineese? issued 7 days ago".
- A section titled "Local Search Results" listing "Clarion Hotel" and "Irhs Dancing", each with a "+ button" to add them to the user's list.
- A section titled "Events" listing "Irhs Dancing".

An arrow labeled "additional information" points from the "Local Search Results" section to the "Events" section. Another arrow labeled "filters" points from the top of the screenshot to the filter dropdowns in Screenshot 1.

Screenshot 3 (Right): Shows the detailed view of the message from "Tung Sing". The message text is: "there is a good Vietnamese restaurant in this Street, but I don't recall its name." Below the message is a checkbox labeled "include location". Below the checkbox is a map showing the location of the restaurant, with a green dot indicating the user's current position. An arrow labeled "location of the answer" points from the map to the map area in Screenshot 1.

Annotations:

- location of the user:** Points to the map in Screenshot 1.
- filters:** Points to the filter dropdowns in Screenshot 1.
- interactive map:** Points to the map in Screenshot 1.
- additional information:** Points from the "Local Search Results" section in Screenshot 2 to the "Events" section in Screenshot 2.
- answer text:** Points to the message text in Screenshot 3.
- location of the answer:** Points to the map in Screenshot 3.