The road from Explainability in Recommender Systems to Visual XAI

Denis Parra
PUC Chile & CENIA, iHealth, IMFD

IR seminar series, University Of Glasgow
October 17th 2022

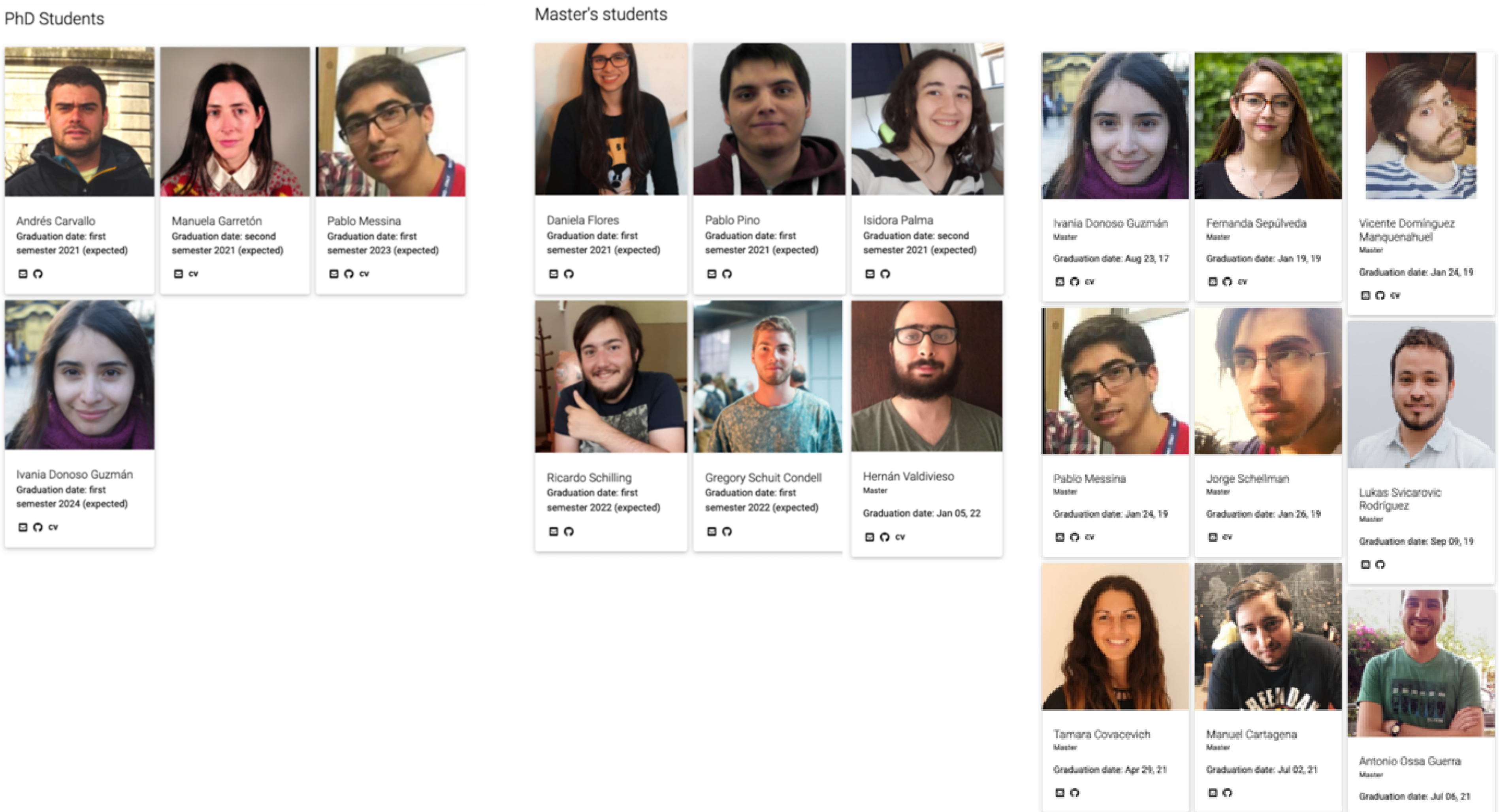
@denisparra

Presents …

Denis Parra

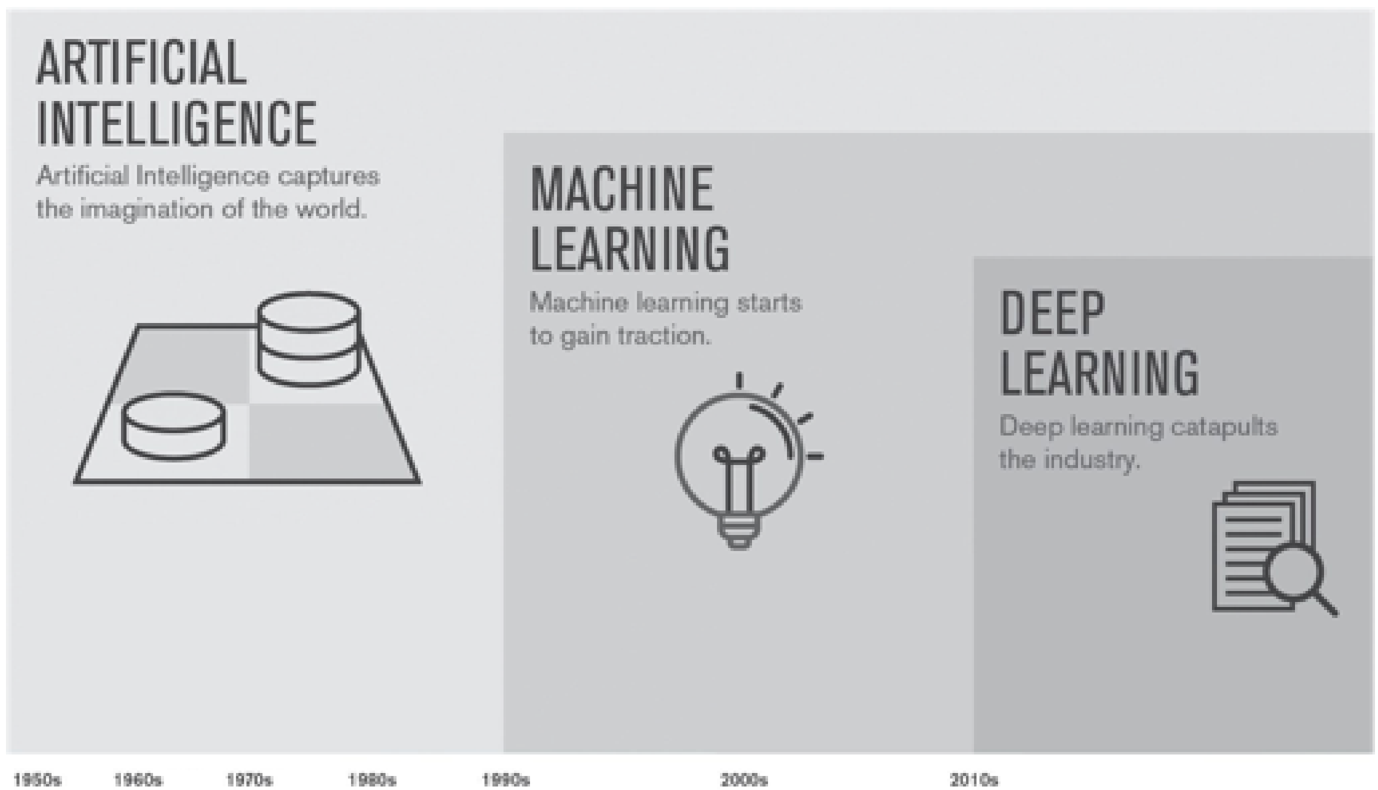
- Associate Professor, CS Department, PUC Chile
- Teaching: Recommender Systems, Information Visualization
- Research: HAIVis Lab ⊂ IA Lab
  - Machine learning applications (RecSys, Medical & Creative AI), intelligent user interfaces, information visualization
  - Supervising: 5 PhD, 5 Master, 2 Undergraduate students
- Principal Researcher at:
  - Chile's National Center on Artificial Intelligence (CENIA, 2021 -)
  - Millenium Institute for Healthcare Engineering (iHealth, 2021 -)
  - Millenium Institute Foundational Research on Data (IMFD, 2018 -)

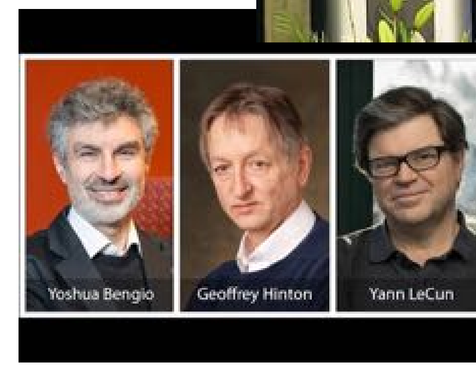
HAIVis UC: This research has been possible thanks to



We are living incredible days…

- Technology is showing results which resemble science fiction, specially in the area of Artificial Intelligence.





Self-Driving Cars

Mastering Go

Google AI algorithm masters ancient game of Go

Deep-learning software defeats human professional for first time.

Elizabeth Gibney

27 January 2016

PDF | Rights & Permissions

The computer that mastered Go

Nature Video

Text-to-Image Generation

https://github.com/CompVis/stable-diffusion/blob/main/assets/txt2img-preview.png

But there are some problems with AI

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016

ON A SPRING AFTERNOON IN 2014, Brisha Borden was running late to pick up her god-sister from school when she spotted an unlocked kid's blue Huffy bicycle and a silver Razor scooter. Borden and a friend grabbed the bike and scooter and tried to ride them down the street in the Fort Lauderdale suburb of Coral Springs.

Just as the 18-year-old girls were realizing they were too big for the tiny conveyances — which belonged to a 6-year-old boy — a woman came running after them saying, "That's my kid's stuff." Borden and her friend immediately dropped the bike and scooter and walked away.

- When the COMPAS system correctly predicts recidivism, it does it similarly to black and white,
- But, when it fails to predict correctly:

Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm

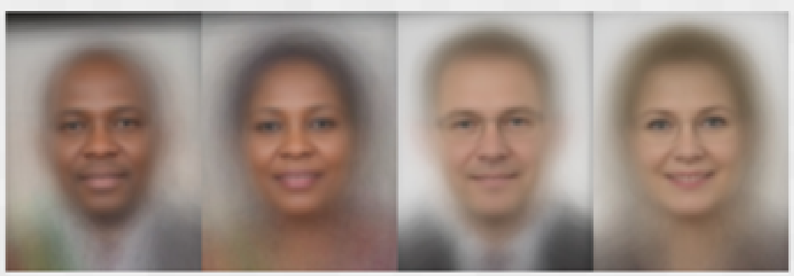
Other case: Gender Shades

- A Project by Joy Buolamwini, researcher at MIT Media Lab
- Examination of facial-analysis software shows error rate of 0.8 percent for light-skinned men, 34.7 percent for dark-skinned women.

When we analyze the results by intersectional subgroups - darker males, darker females, lighter males, lighter females - we see that all companies perform worst on darker females.

IBM and Microsoft perform best on lighter males. Face++ performs best on darker males.

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%



https://www.media.mit.edu/projects/gender-shades/overview/

http://gendershades.org/overview.html

https://news.mit.edu/2018/study-finds-gender-skin-type-bias-artificial-intelligence-systems-0212

XAI (2017)

- XAI is a term coined by David Gunning, program manager at DARPA

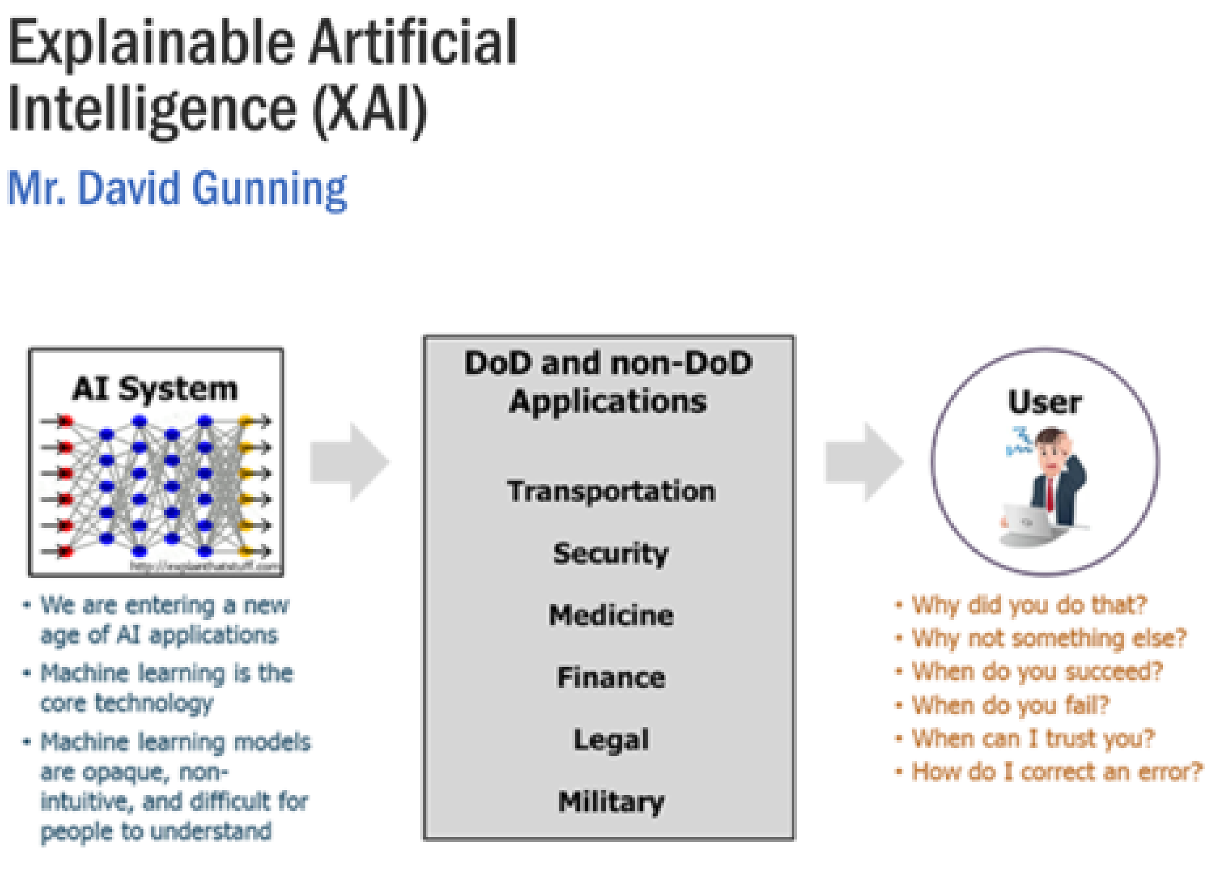
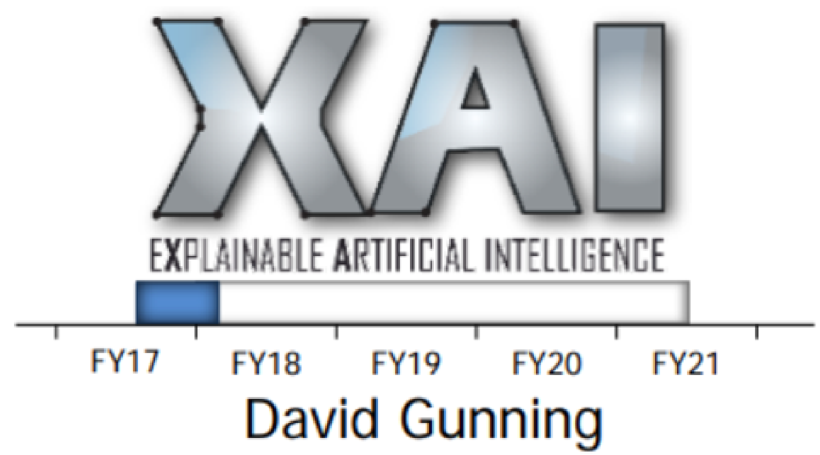


Figure 1. The Need for Explainable AI



What does XAI mean ?

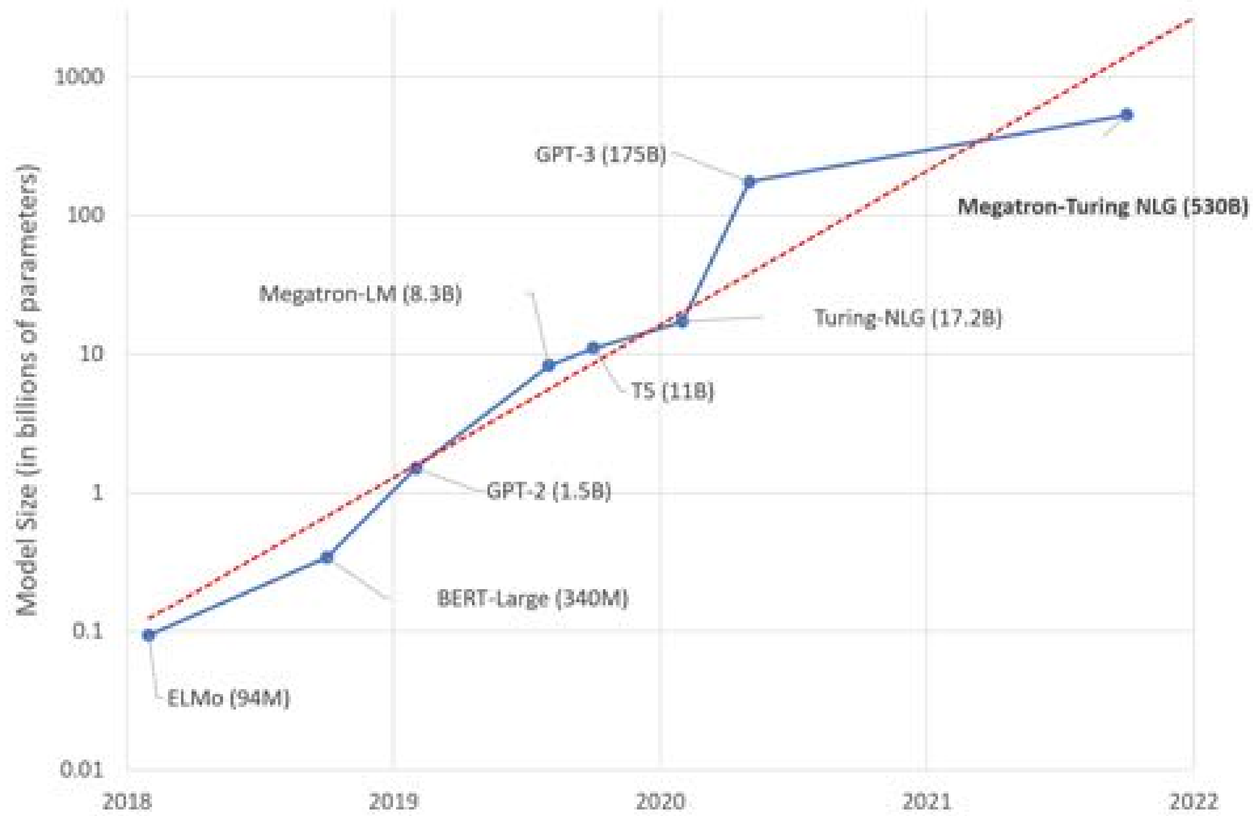
- In Gunning et al (2019), an X-AI system is defined by it ***Purpose***:
  - to make its behavior more intelligible to humans by providing explanations.

- Some general principles mentioned: The XAI system should be able to
  - explain its **capabilities** and **understandings**;
  - explain what it **has done**, what it is **doing now**, and what will **happen next**; and
  - **disclose** the **salient information** that it is acting on

Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI—Explainable artificial intelligence. *Science Robotics*, *4*(37), eaay7120.

AI growing complexity

- With the growing complexity of AI models, the need for understanding their inner-workings has increased



Simon, J. (2021) Large Language Models: A New Moore's Law?
https://huggingface.co/blog/large-language-models

One approach: Visual XAI

- With the growing complexity of AI models, the need for understanding their inner-workings has increased
- Information Visualization can play an important role to address this need:
  - [visxai.io – 5th VisXAI at IEEE Vis]

5th Workshop on Visualization for AI Explainability

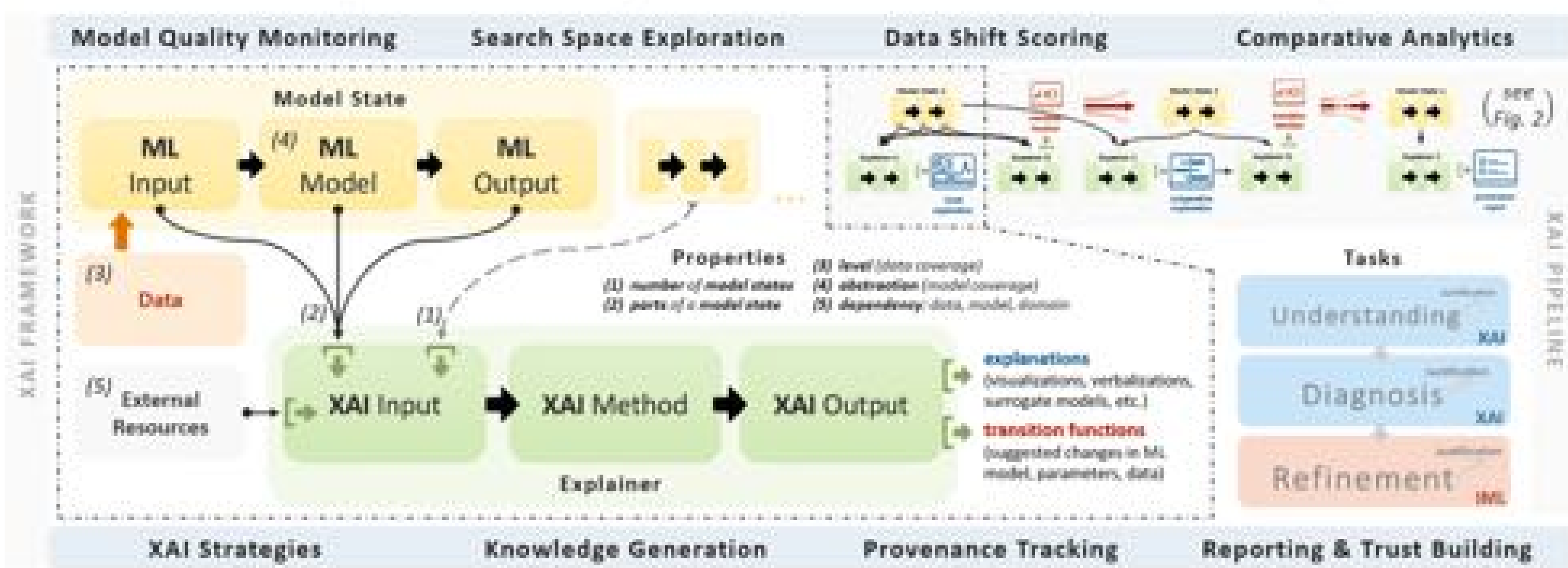
October 16th or 17th, 2022 at IEEE VIS in Oklahoma City, Oklahoma

The role of visualization in artificial intelligence (AI) gained significant attention in recent years. With the growing complexity of AI models, the critical need for understanding their inner-workings has increased. Visualization is potentially a powerful technique to fill such a critical need.

The goal of this workshop is to initiate a call for *"explainables"* / *"explorables"* that explain how AI techniques work using visualization. We believe the VIS community can leverage their expertise in creating visual narratives to bring new insight into the often obfuscated complexity of AI systems.

Visual XAI Frameworks

- Several approaches leveraging Visualization Systems have been introduced in the latest years, such as the **ExplAIner** framework proposed in 2019:

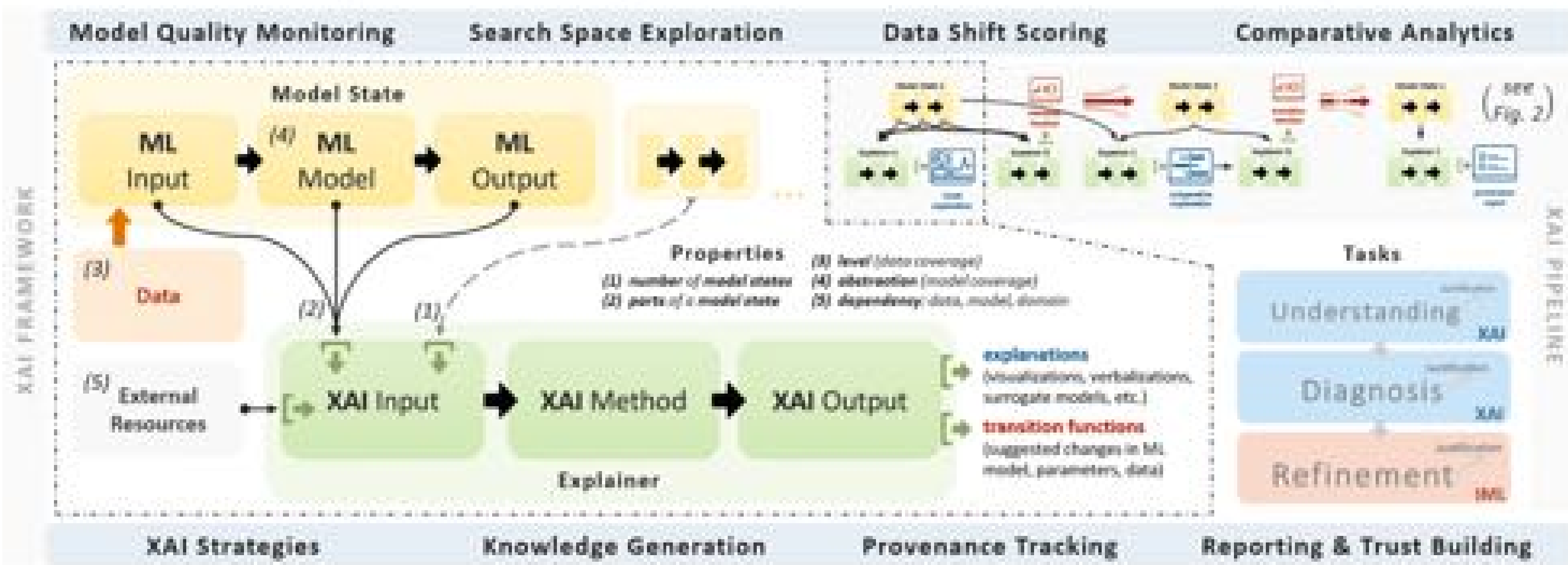


Spinner, T., et al (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE TVCG, 26(1), 1064-1074.

Visual XAI Frameworks

- Several approaches leveraging Visualization Systems have been introduced in the latest years, and even a framework was proposed in 2019: ExplAIner

ExplAIner tells you the steps towards creating a Visual XAI, but **Not** How to **design** and **analyze** a visualization for XAI



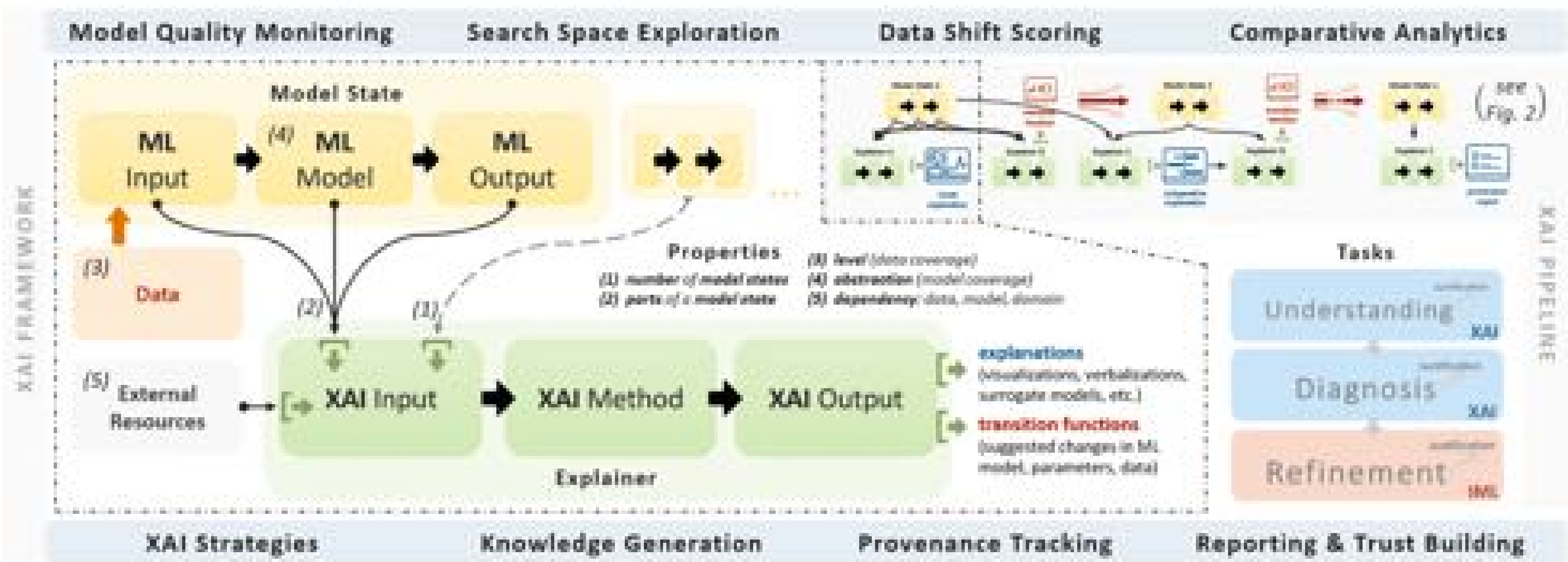
Spinner, T., et al (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE TVCG, 26(1), 1064-1074.

Visual XAI Frameworks

- Several approaches leveraging Visualization Systems have been introduced in the latest years, and even a framework was proposed in 2019: ExplAIner

ExplAIner tells you the steps towards creating a Visual XAI, but **Not** How to **design** and **analyze** a visualization for XAI

- Visual
- Interaction

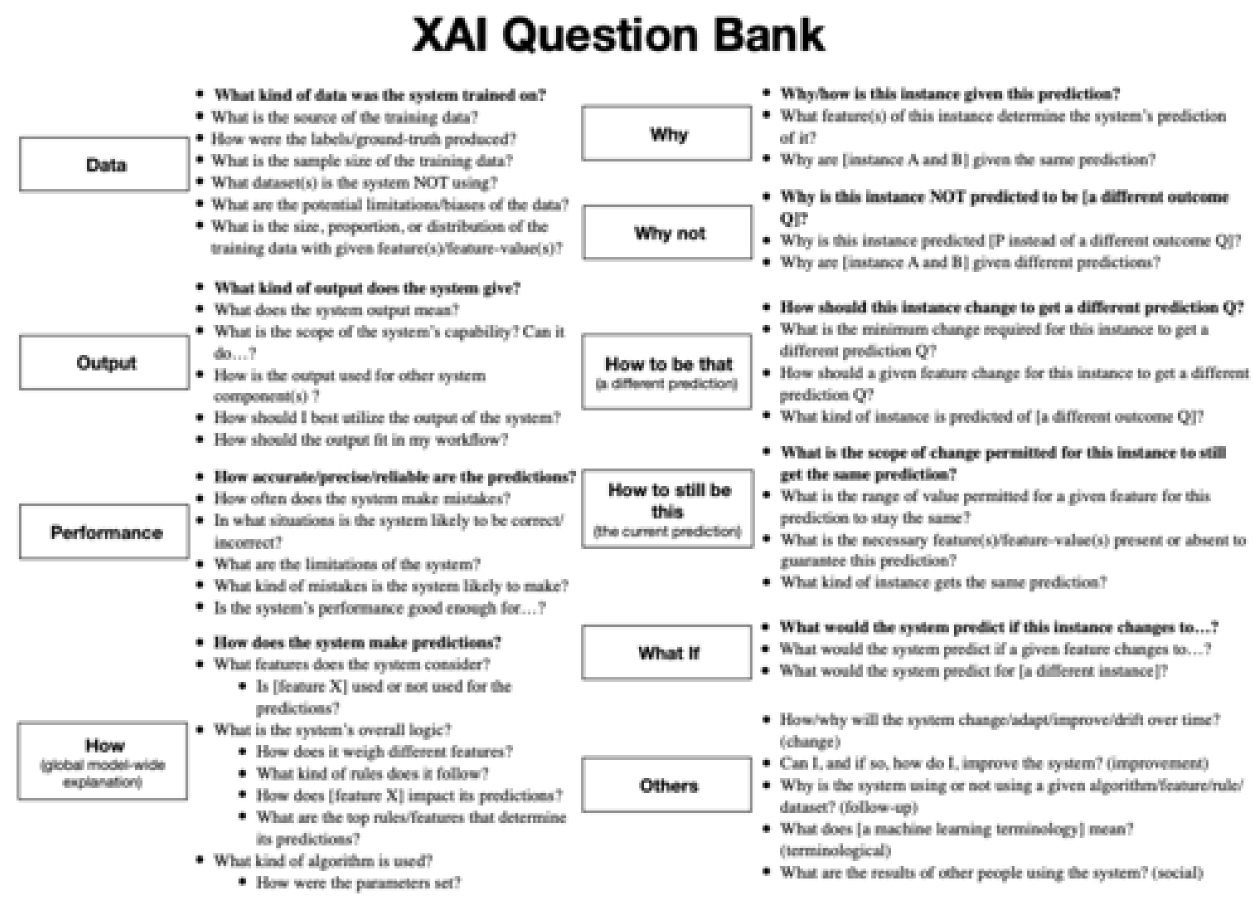


Spinner, T., et al (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE TVCG, 26(1), 1064-1074.

XAI question bank

- Liao, Gruen and Miller introduced a XAI question bank to guide the design process of XAI systems

- But they still do not provide clear guidelines for visual XAI applications



Liao, Q. V., Gruen, D., & Miller, S. (2020). Questioning the AI: informing design practices for explainable AI user experiences. CHI 2020.

XAI Challenges – Adaptation & Personalization

- An effective explanation will take the target user group of the system into account, **who might vary** in their **background knowledge** and **needs** for what should be explained.
  - How should we proceed under these circumstances ?

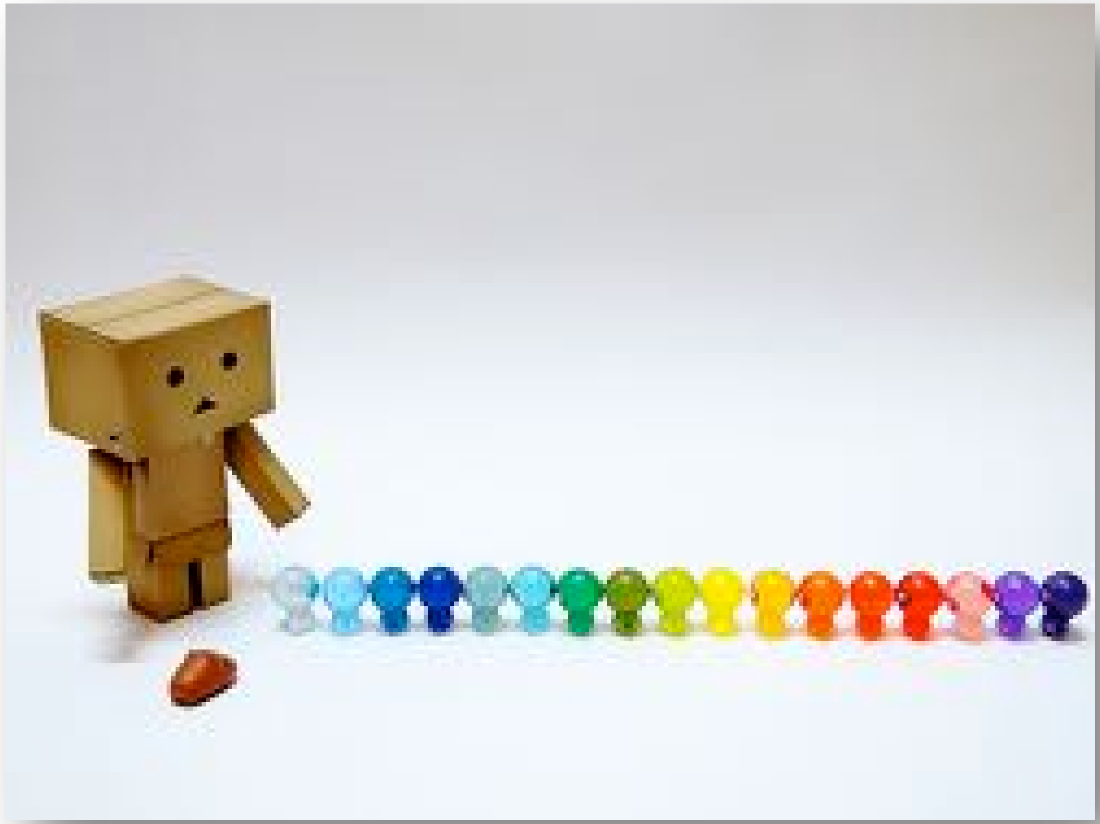
- Decision making for analysts, judges and operators: **Each user group may have a preferred explanation** type that is able to communicate information in the most effective way.

Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., & Yang, G. Z. (2019). XAI—Explainable artificial intelligence. *Science Robotics*, *4*(37), eaay7120.

The role of RecSys in XAI

Recommender Systems (RecSys) and XAI

- Recommender Systems are a type of systems/technology which strongly relies on AI algorithms
- Explainability and Transparency in Recommender Systems has been studied for at least 20 years
- What can we learn from such research for XAI ?



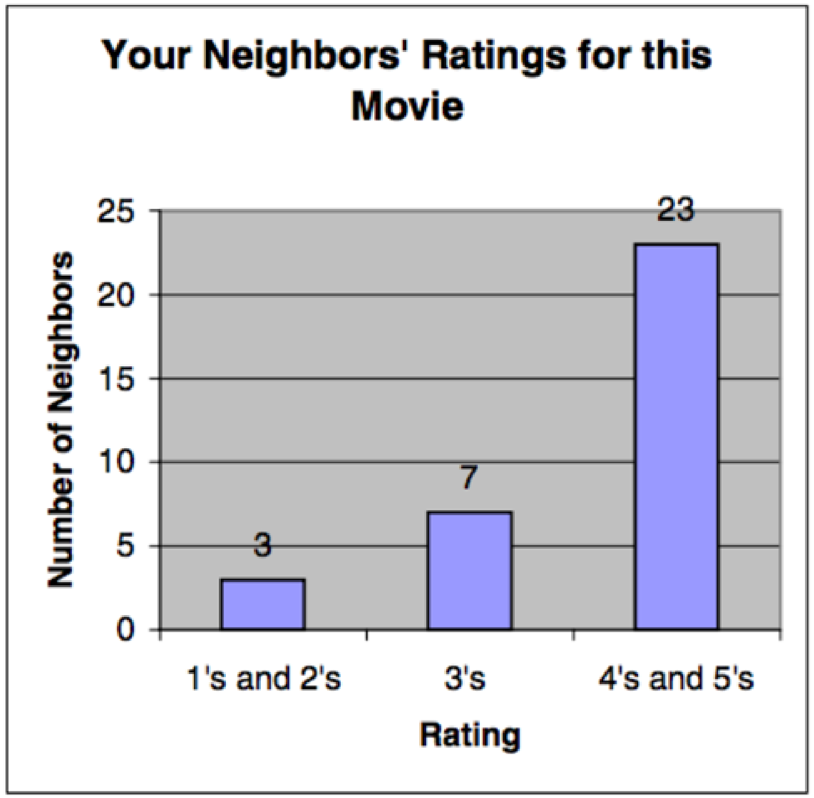
XAI in Recommender Systems: back to 2000s

- Herlocker, J. L., Konstan, J. A., & Riedl, J. (**2000**). ***Explaining collaborative filtering recommendations***. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work* (pp. 241-250). ACM.

- Sinha, R., & Swearingen, K. (**2002**). ***The role of transparency in recommender systems***. In *CHI'02 extended abstracts on Human factors in computing systems* (pp. 830-831). ACM.

XAI in Recommender Systems (movies)

- Herlocker, J. L., Konstan, J. A., & Riedl, J. (2000). Explaining collaborative filtering recommendations. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work* (pp. 241-250). ACM.



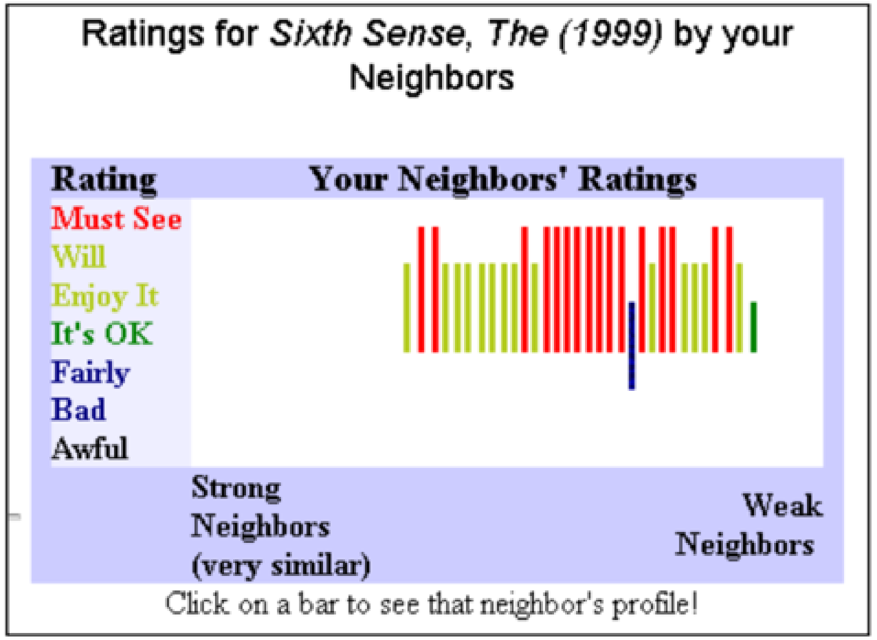
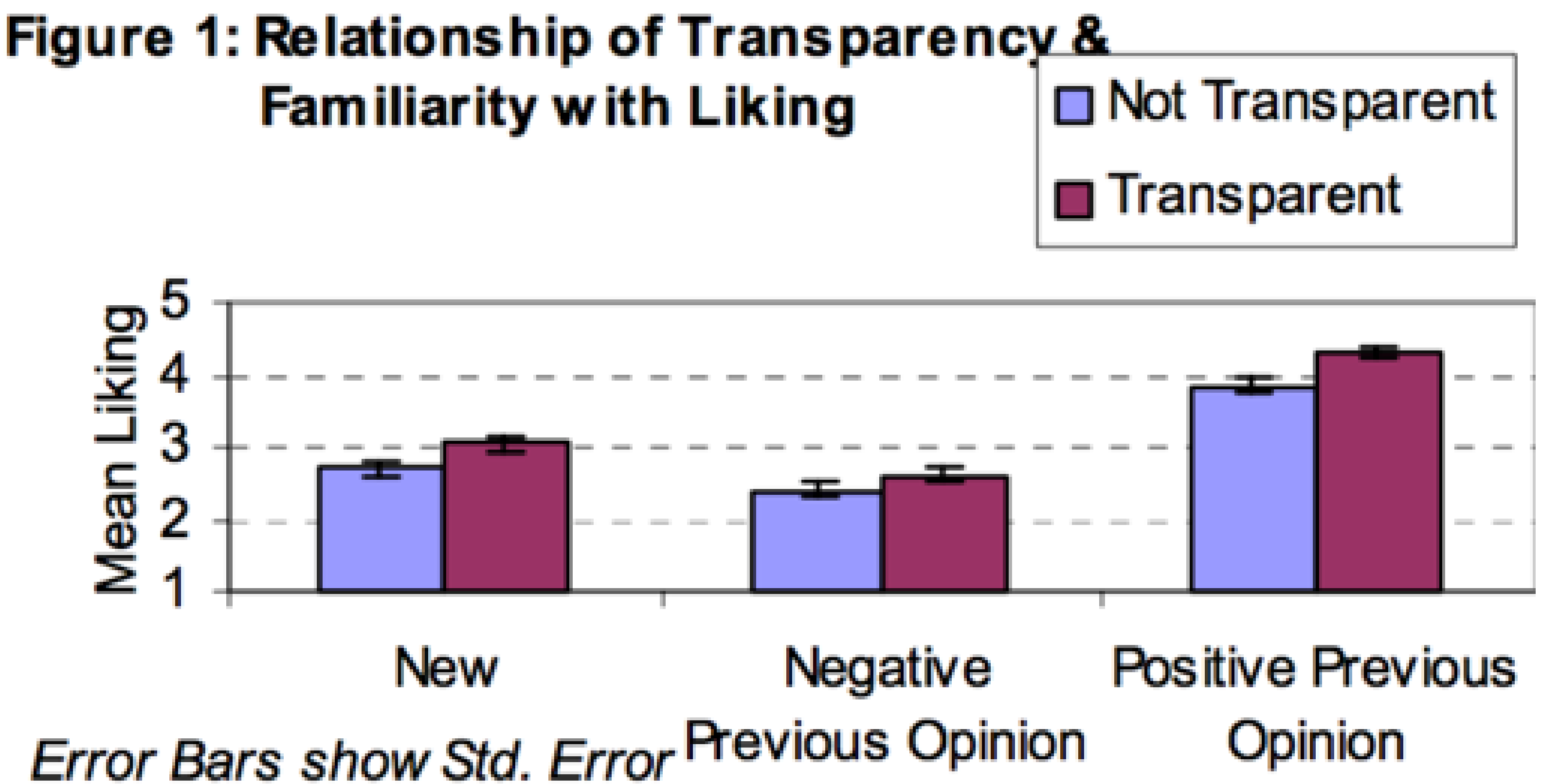


Figure 4. A screen explaining the recommendation for the movie "The Sixth Sense." Each bar represents a rating of a neighbor. Upwardly trending bars are positive ratings, while downward trending ones are negative. The x-axis represents similarity to the user.

XAI in Recommender Systems (music)

- Sinha, R., & Swearingen, K. (2002). The role of transparency in recommender systems. In *CHI'02 extended abstracts on Human factors in computing systems* (pp. 830-831). ACM.



XAI in Recommender Systems II

- Tintarev, N., & Masthoff, J. (2007). A survey of **explanations in recommender systems**. In *2007 IEEE 23rd international conference on data engineering workshop* (pp. 801-810). IEEE.
- Tintarev, N., & Masthoff, J. (2012). Evaluating the **effectiveness of explanations** for recommender systems. *User Modeling and User-Adapted Interaction, 22*(4-5), 399-439.
- Tintarev, N., & Masthoff, J. (2015). **Explaining recommendations: Design and evaluation**. In *Recommender systems handbook* (pp. 353-382). Springer, Boston, MA.

RecSys: Explanatory Goals and Definitions

Aim	Definition
Transparency (Tra.)	Explain how the system works
Scrutability (Scr.)	Allow users to tell the system it is wrong
Trust	Increase users' confidence in the system
Effectiveness (Efk.)	Help users make good decisions
Persuasiveness (Pers.)	Convince users to try or buy
Efficiency (Efc.)	Help users make decisions faster
Satisfaction (Sat.)	Increase the ease of usability or enjoyment

Tintarev, N., & Masthoff, J. (2007). A survey of explanations in recommender systems. In *2007 IEEE 23rd international conference on data engineering workshop* (pp. 801-810). IEEE.

RecSys: Explanatory Goals and Definitions

2007

Aim	Definition
Transparency (Tra.)	Explain how the system works
Scrutability (Scr.)	Allow users to tell the system it is wrong
Trust	Increase users' confidence in the system
Effectiveness (Efk.)	Help users make good decisions
Persuasiveness (Pers.)	Convince users to try or buy
Efficiency (Efc.)	Help users make decisions faster
Satisfaction (Sat.)	Increase the ease of usability or enjoyment

2017

User with a Task

- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?

User with a Task

- I understand why
- I understand why not
- I know when you'll succeed
- I know when you'll fail
- I know when to trust you
- I know why you erred

Tintarev, N., & Masthoff, J. (2007). A survey of explanations in recommender systems. In *2007 IEEE 23rd international conference on data engineering workshop* (pp. 801-810). IEEE.

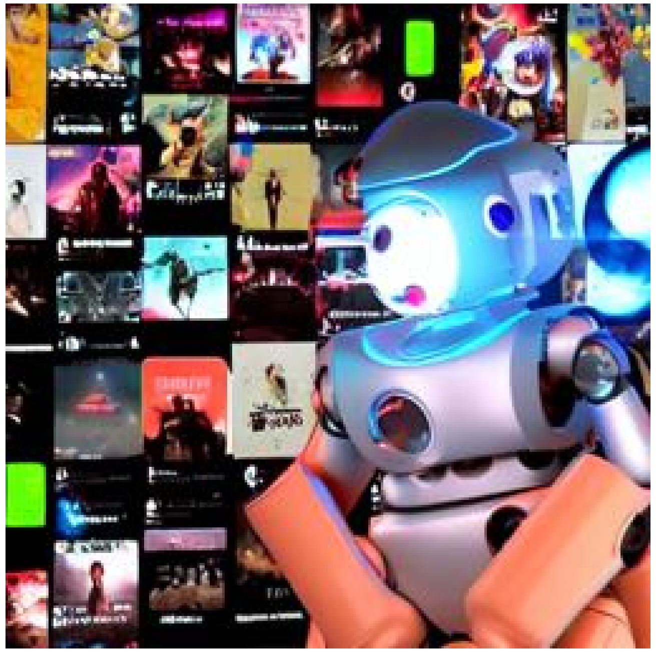
Did we do nothing between 2007-17 ?

- There were actually many works related to explainability, transparency, trust and user controllability in RecSys.

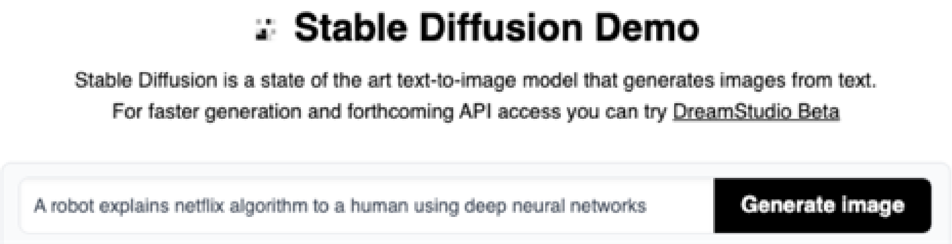
- In the coming slides, I will focus on research related **Visual User Interfaces** for recommendation Systems and how they contributed early to XAI and Visual XAI.

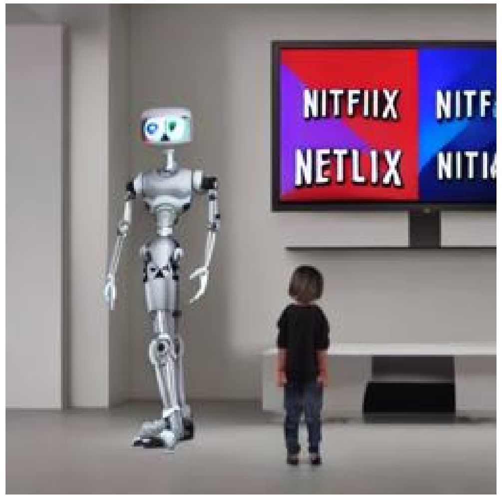
Let’s take a trip

- … through the history of explainability approaches **with** and **without** visualizations in RecSys



- (images generated with S.D.)





Non-visual approaches for XAI in RecSys

- A brief non-exhaustive list:

Zhang, Y., Lai, G., Zhang, M., Zhang, Y., Liu, Y., & Ma, S. (2014). **Explicit factor models for explainable recommendation based on phrase-level sentiment analysis**. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval* (pp. 83-92). ACM.

Seo, S., Huang, J., Yang, H., & Liu, Y. (2017). **Interpretable convolutional neural networks with dual local and global attention for review rating prediction**. RecSys 2017.

Chen, J., Zhang, H., He, X., Nie, L., Liu, W., & Chua, T. S. (2017). **Attentive collaborative filtering: Multimedia recommendation with item-and component-level attention**. SIGIR 2017.

Adapting LIME to recommendation: Nóbrega, C., & Marinho, L. (2019). **Towards explaining recommendations through local surrogate models**. ACM/SIGAPP Symposium on Applied Computing.

More information at this Tutorial web page: https://sites.google.com/view/ears-tutorial/

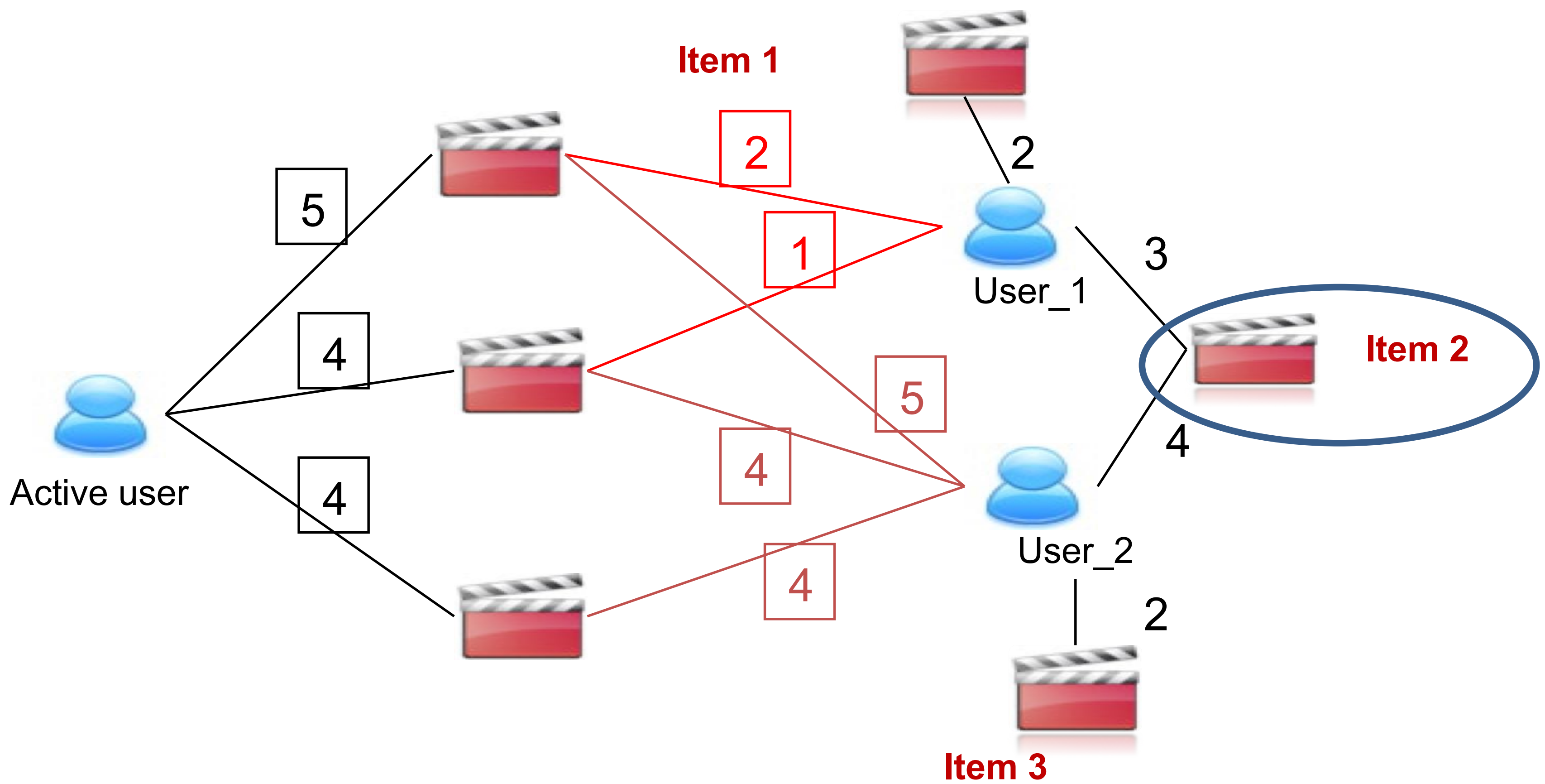
1st generation of RecSys

- Algorithms were simple and intuitive (User-based KNN, Item-Based KNN, Content-based, Case-based)

- Providing explanations for items recommended would not require a big engineering effort

1st generation of RecSys

- User Based KNN (collaborative filtering)



Explanation: Users who have similar ratings with you highly rated this item

1st generation of RecSys

- Content Based

Explanation: This items has similar content (features: description, actors, director, genre) to what you have liked in the past

XAI for Recommender Systems

- First generation of approaches for Recommender Systems were easily to explain: User and Item based CF, Content-based, Rule-based

- The Second generation of RecSys, based on Matrix Factorization made the process more difficult: latent user and item representation

- The Third generation based on Deep Learning makes accountability and transparency even more difficult !

2nd generation of RecSys

- Alternatives: try to assign explicit meaning to latent factor models:
  - Zhang, Y., Lai, G., Zhang, M., Zhang, Y., Liu, Y., & Ma, S. (2014). **Explicit factor models for explainable recommendation based on phrase-level sentiment analysis**. In *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval* (pp. 83-92). ACM.
  - Chen, X., Qin, Z., Zhang, Y., & Xu, T. (2016). **Learning to rank features for recommendation over multiple categories**. In *Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval* (pp. 305-314). ACM.
  - Wang, N., Wang, H., Jia, Y., & Yin, Y. (2018). **Explainable recommendation via multi-task learning in opinionated text data**. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* (pp. 165-174). ACM.

2nd generation of RecSys

- Zhang et al (2014) "Explicit factor models for explainable recommendation based on phrase-level sentiment analysis"

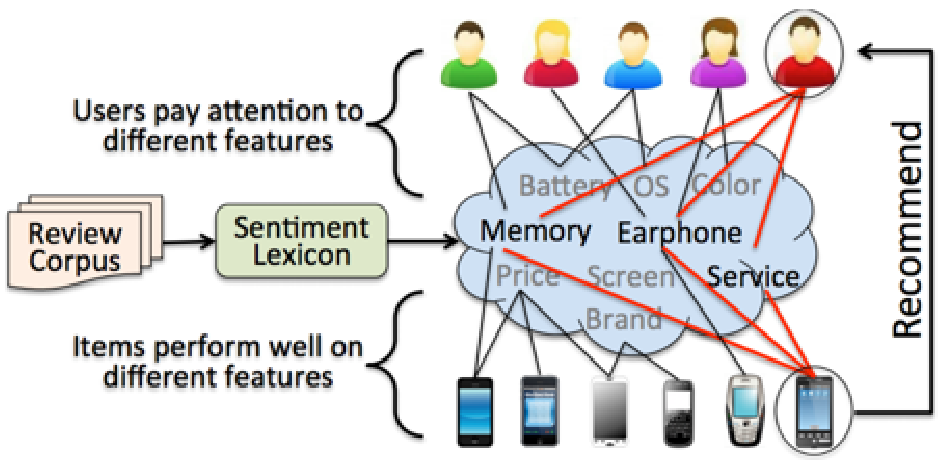


Figure 1: The product feature word and user opinion word pairs are extracted from user review corpus to construct the sentiment lexicon, and the feature word set further serves as the explicit feature space. An item would be recommended if it performs well on the features that a user cares.

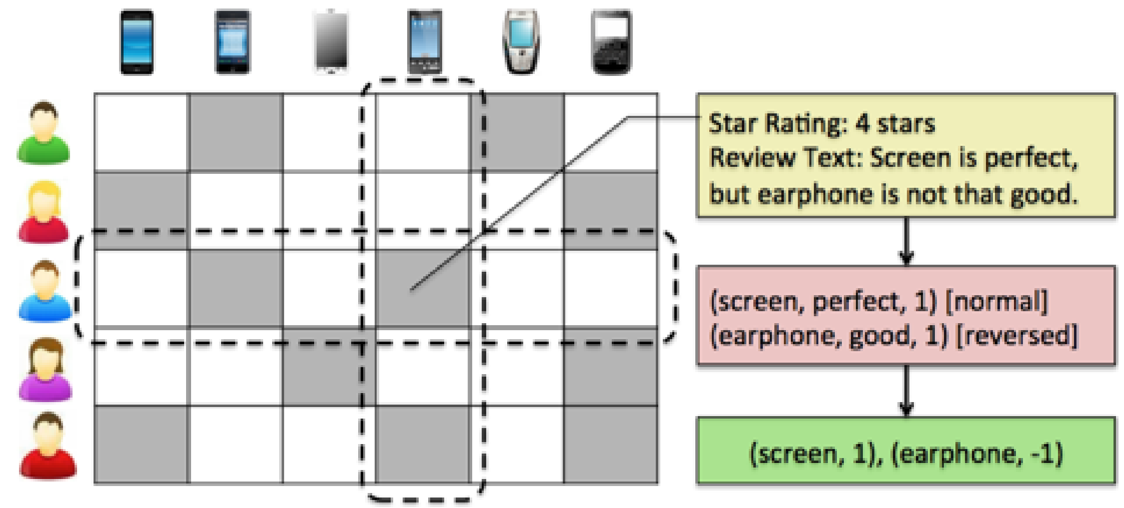


Figure 2: An example of user-item review matrix, where each shaded block is a review made by a user towards an item; the entries included in the review are extracted, and further transformed to feature scores while considering the negation words.

XAI for Recommender Systems

- First generation of approaches for Recommender Systems were easily to explain: User and Item based CF, Content-based, Rule-based

- The Second generation of RecSys, based on Matrix Factorization made the process more difficult: latent user and item representation

- The Third generation based on Deep Learning makes accountability and transparency even more difficult !

3rd Generation of RecSys

- In Matrix factorization we had one level of interactions, with deep learning we can have many! Making explanations more complex

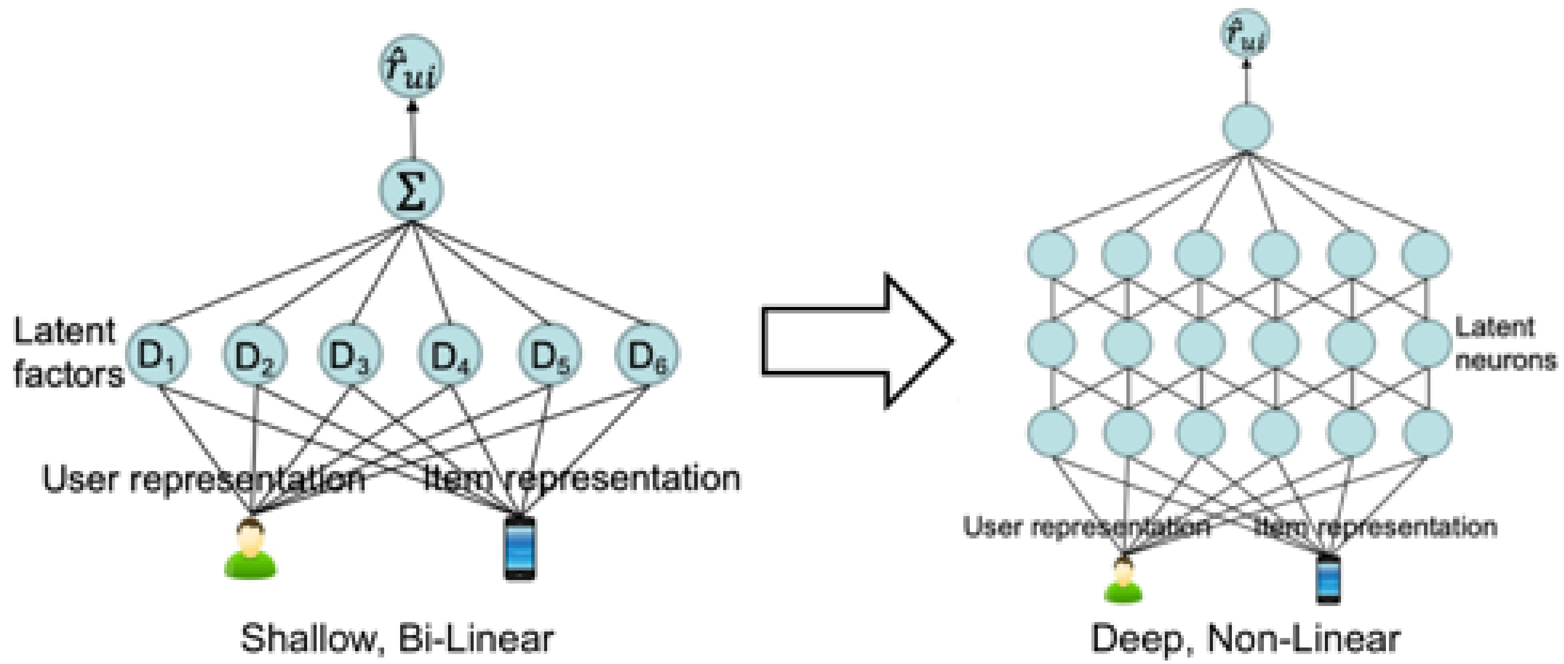


Image from Zhang et al. (2019) Tutorial on ExplainAble Recommendation and Search

3rd Generation of RecSys

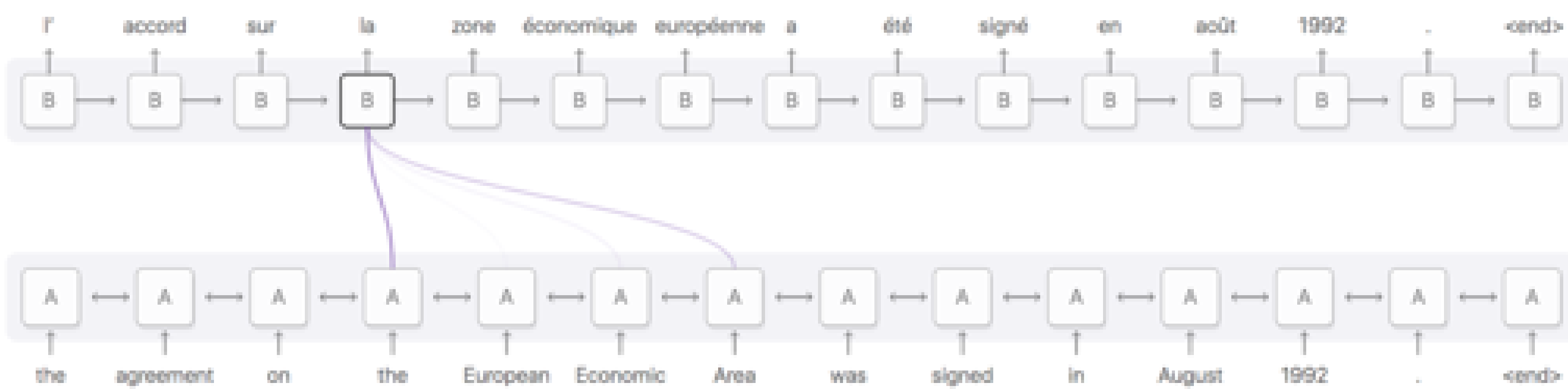
- Alternatives: use attention mechanism within the neural architecture (over text or images)

- Generate explanations directly (Natural Language Generation)

- Use a model agnostic approach: generate explanations after recommendation (LIME, SHAP, etc.)

Neural Attention

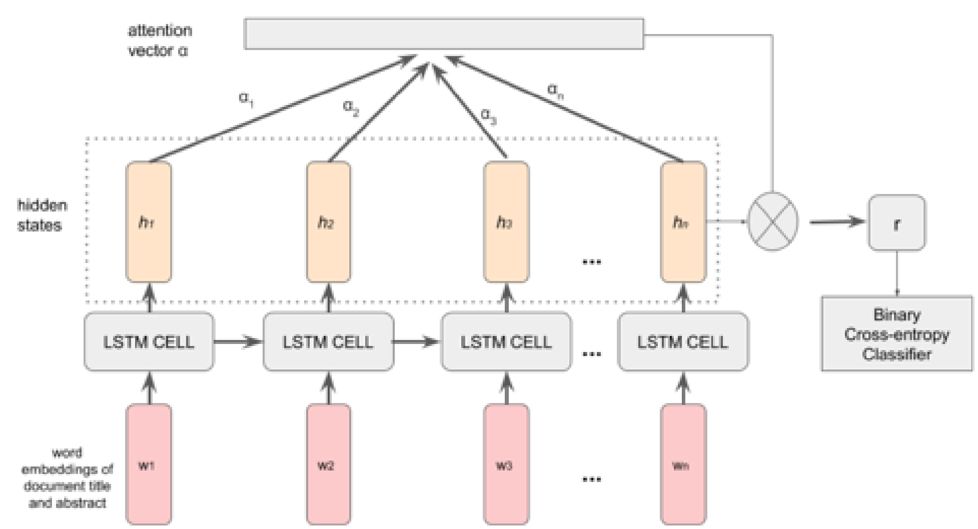
- Attention in neural networks is a mechanism which allows the model to focus selectively during the learning process.
- Eventually, we can observe where the network was attending to in order to make a prediction.



Olah, C., & Carter, S. (2016). Attention and augmented recurrent neural networks. Distill, 1(9), e1. http://doi.org/10.23915/distill.00001

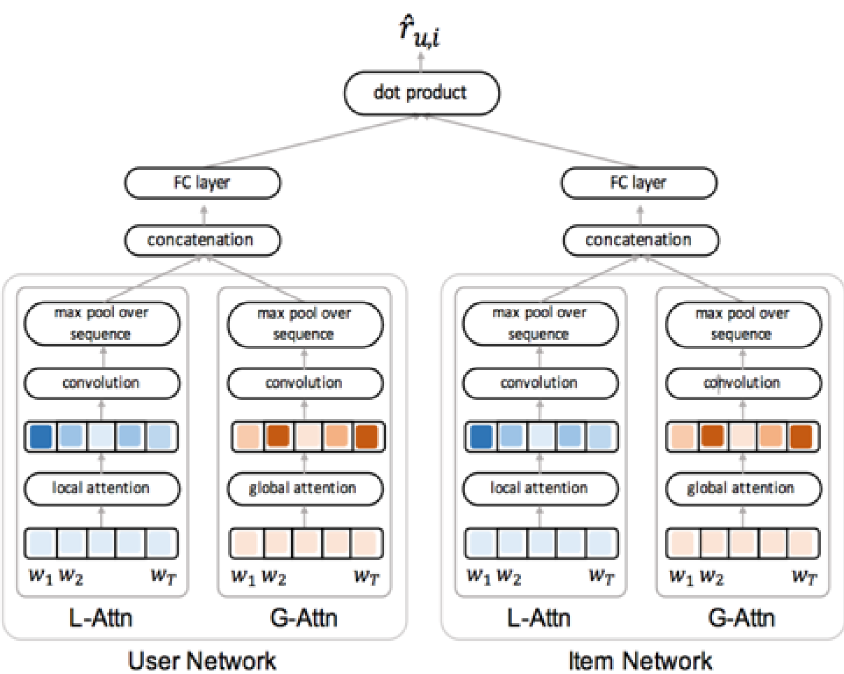
Neural Attention

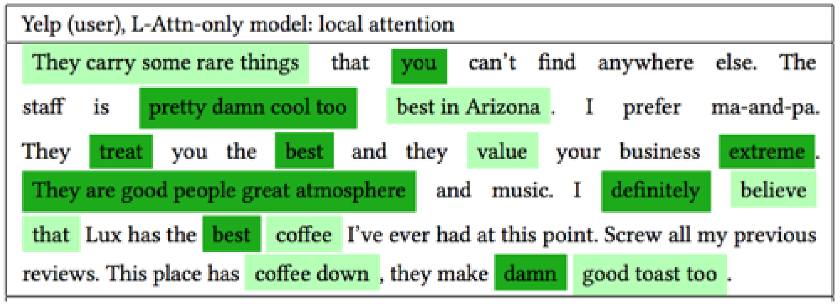
- Example of document classification: Does the model attends to reasonable words ?

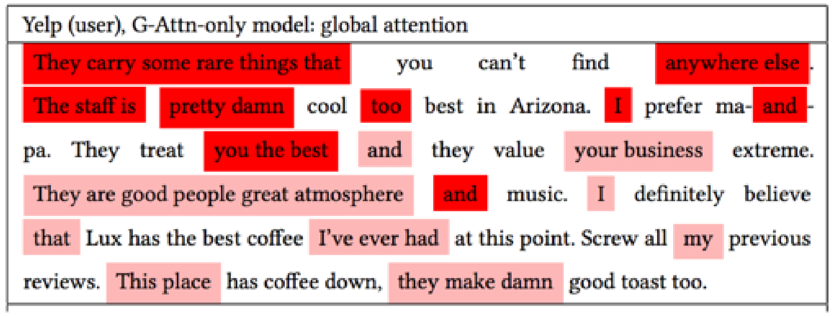


3rd Generation of RecSys

- Seo, S., Huang, J., Yang, H., & Liu, Y. (2017). **Interpretable convolutional neural networks with dual local and global attention for review rating prediction**. RecSys 2017.

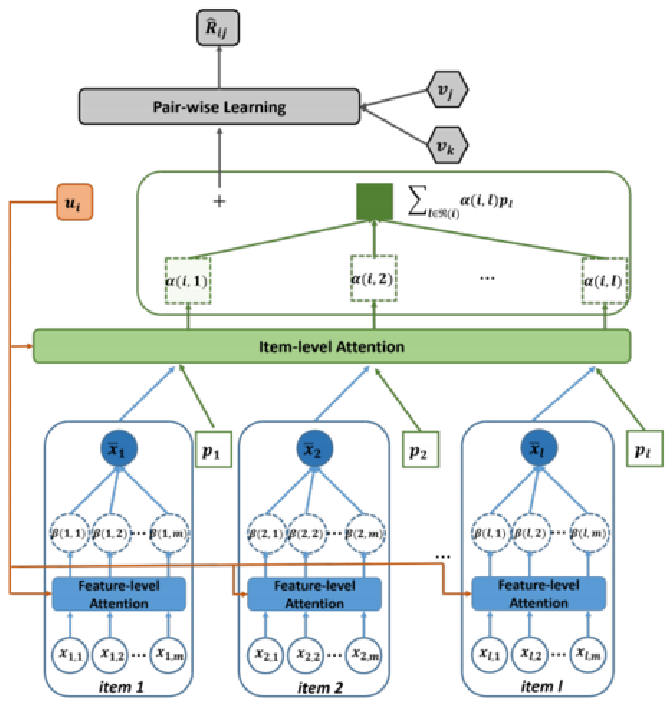


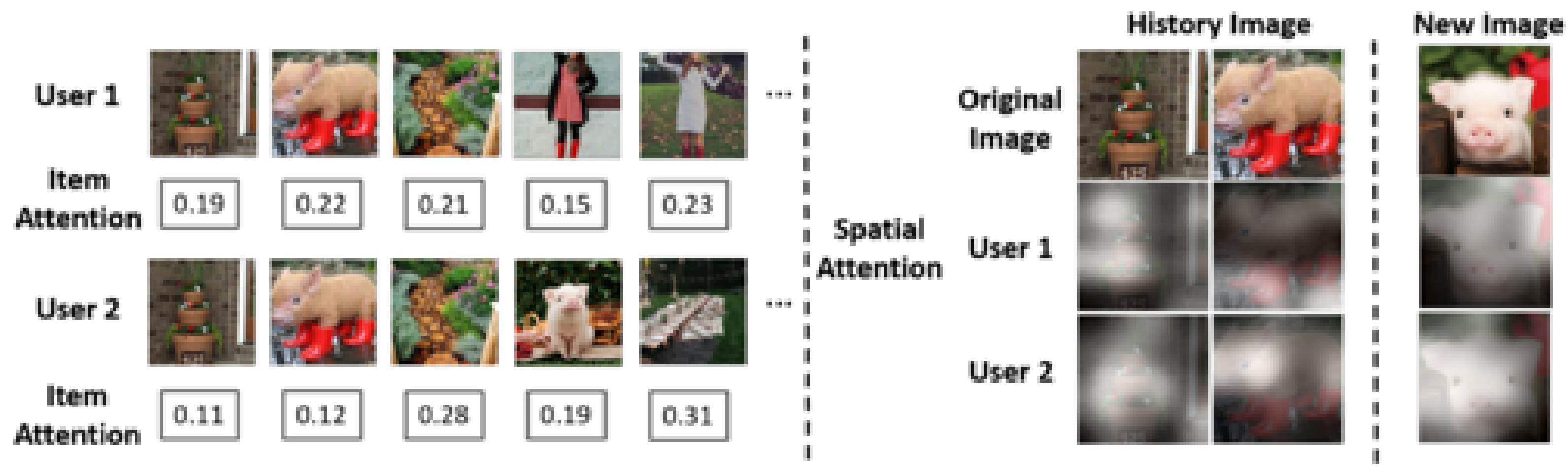




3rd Generation of RecSys

- Chen, J., Zhang, H., He, X., Nie, L., Liu, W., & Chua, T. S. (2017). Attentive collaborative filtering: Multimedia recommendation with item-and component-level attention. SIGIR 2017.





3rd Generation of RecSys

- Li, P., Wang, Z., Ren, Z., Bing, L., & Lam, W. (2017,). Neural rating regression with abstractive tips generation for recommendation. SIGIR 2017

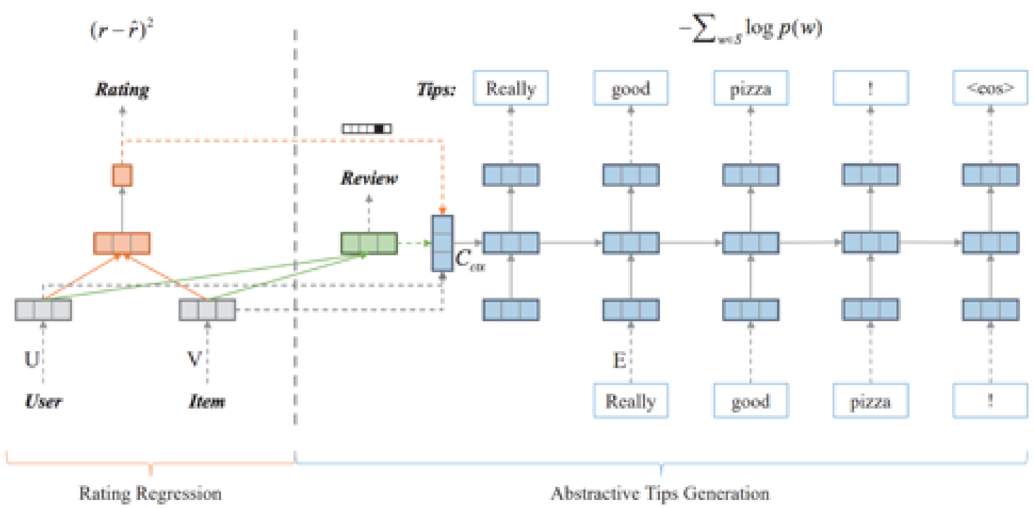


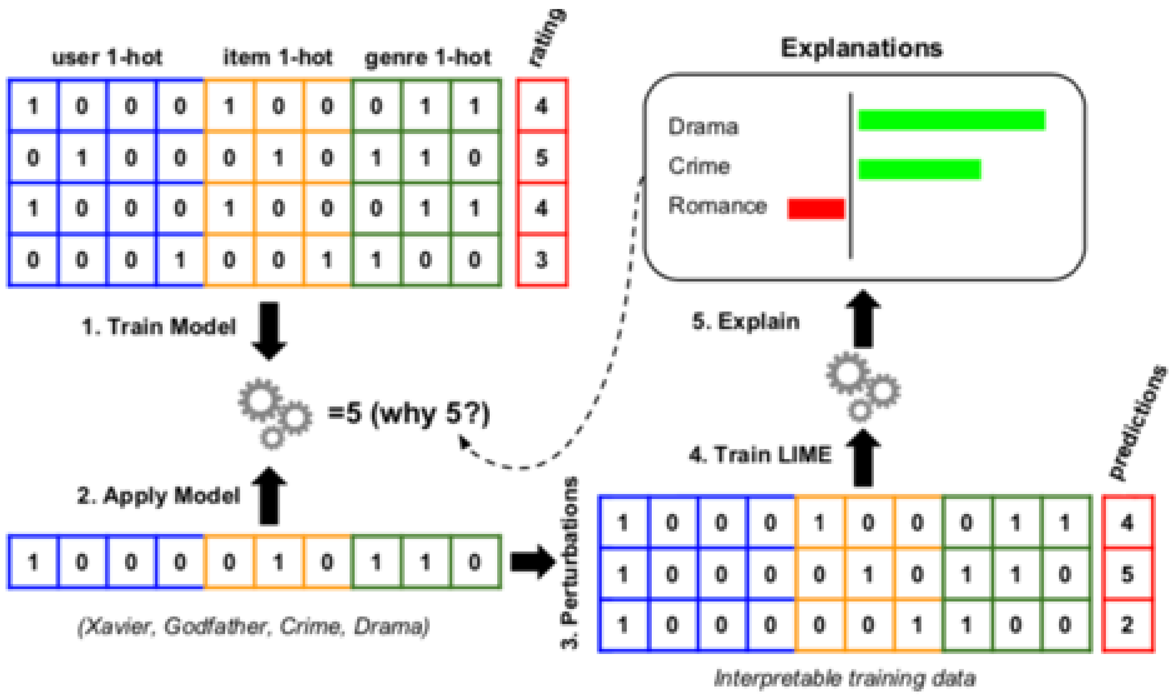
Figure 2: Our proposed framework NRT for rating regression and abstractive tips generation.

Table 10: Examples of the predicted ratings and the generated tips. The first line of each group shows the generated rating and tips. The second line shows the ground truth.

Rating	Tips
4.64	***This is a great product for a great price.***
5	Great product at a great price.
4.87	***I purchased this as a replacement and it is a perfect fit and the sound is excellent.***
5	Amazing sound.
4.69	***I have been using these for a couple of months.***
4	Plenty of wire gets signals and power to my amp just fine quality wise.
4.87	***One of my favorite movies.***
5	This is a movie that is not to be missed.
4.07	***Why do people hate this film.***
4	Universal why didnt your company release this edition in 1999.

Adapting current XAI approaches to RecSys

- Adapting LIME to recommendation: Nóbrega, C., & Marinho, L. (2019). Towards explaining recommendations through local surrogate models. ACM/SIGAPP Symposium on Applied Computing.



This survey is not exhaustive

- I strongly recommend visiting

https://sites.google.com/view/ears-tutorial/

Yongfeng Zhang

Assistant Professor

Rutgers University, New Brunswick, NJ, USA

Jiaxin Mao

Postdoc

Tsinghua University, Beijing, China

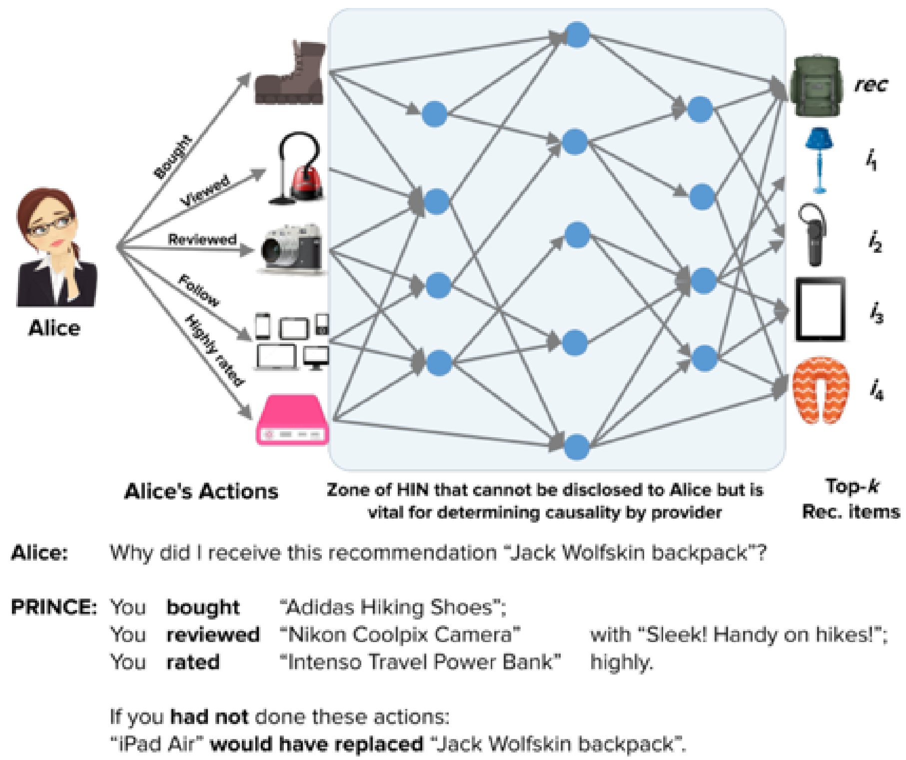
Qingyao Ai

Assistant Professor

University of Utah, Salt Lake City, UT, USA

PRINCE – graph based and counterfactuals

- Ghazimatin, A., Balalau, O., Saha Roy, R., & Weikum, G. (2020). PRINCE: Provider-side Interpretability with Counterfactual Explanations in Recommender Systems. WSDM 2020.



Araujo et al. – Attention on MOBA RecSys

- Villa, A., Araujo, V., Cattan, F. and Parra, D. "Interpretable Contextual Team-aware Item Recommendation: Application in Multiplayer Online Battle Arena Games." RecSys 2020.

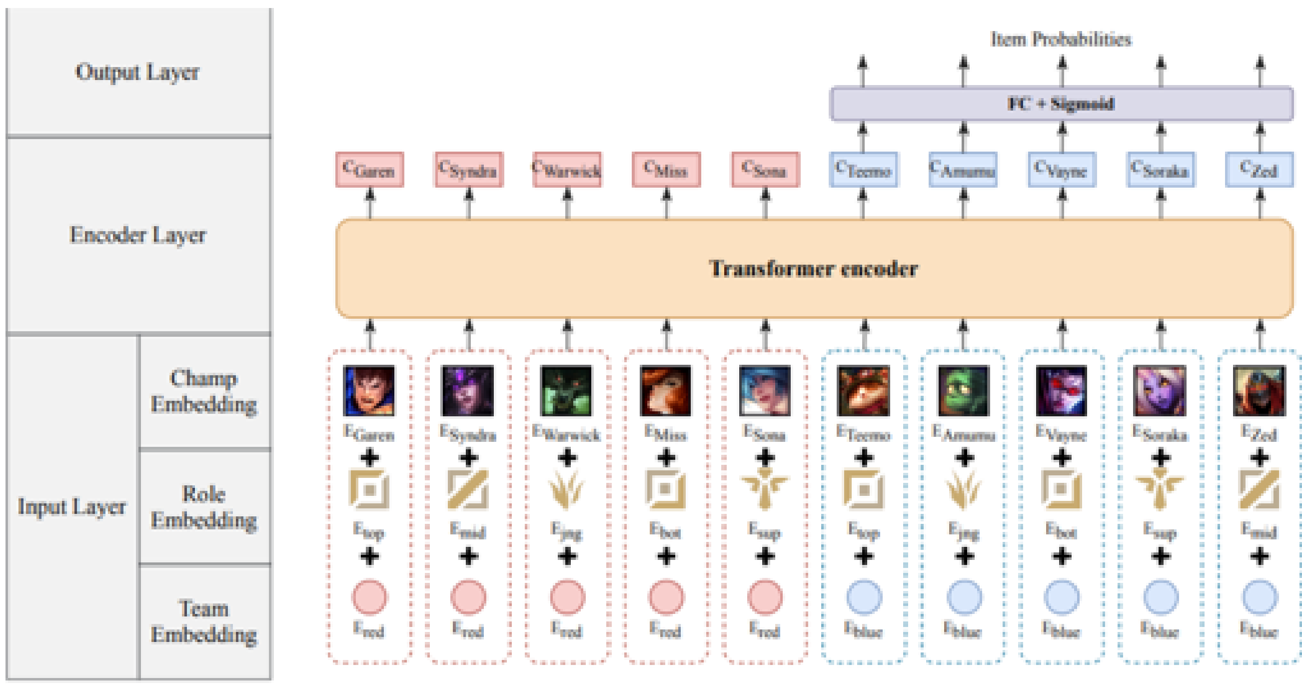


Fig. 2. Network architecture of TTIR.

Similarity-based explanations

- Marinho, L. B., da Costa, J. B. G., Parra, D., & Santos, R. L. (2022). Similarity-Based Explanations meet Matrix Factorization via Structure-Preserving Embedding. IUI 2022.

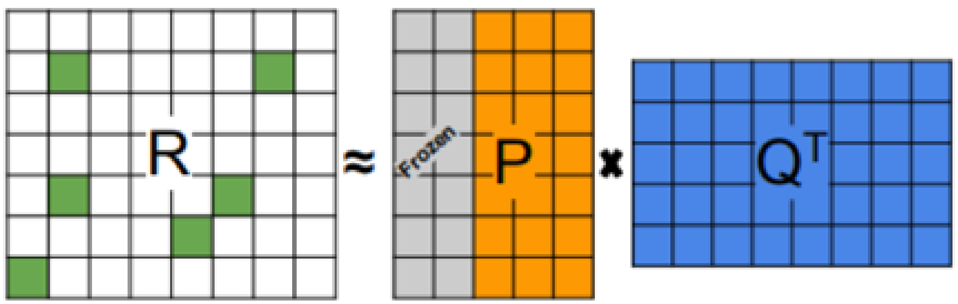
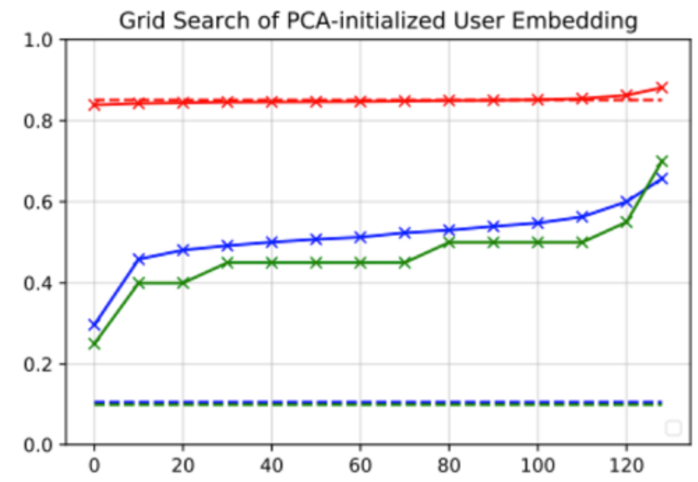


Figure 1: MF with the first two dimensions of P = *PCA*(R, *d*) frozen. By freezing the first factors of P, i.e., the factors that carry most of the data structure, we enable similarity-based explanations based on users that share similar preferences in the input data.



(c) Movielens 1M PCA-User

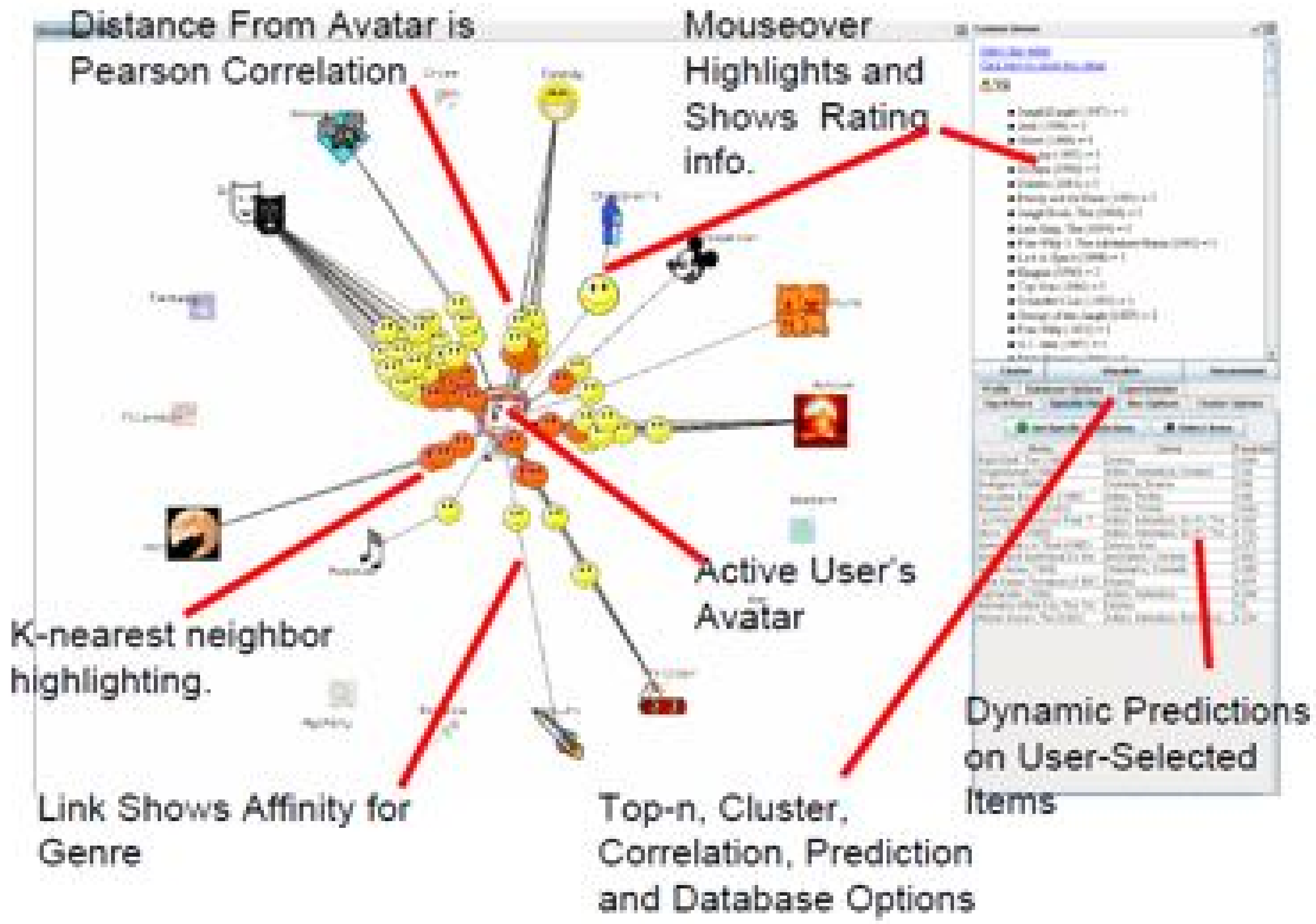
Figure 3: Grid search for the best trade-off between explainability and RMSE. Horizontal dashed lines denote: RMSE (red), Mantel (blue), and neighborhood overlap (green) w.r.t. biased MF.

The Role of Interactive Visualization in RecSys XAI

- PeerChooser (O'Donovan et al, 2008)
- SmallWorlds (Gretarsson et al, 2010)
- To each his own (Knijnenburg et al, 2010)
- TasteWeights (Bostandjev et al. 2012, Knijnenburg et al. 2012)
- TalkExplorer/Aduna (Verbert et al. 2013)
- SetFusion (Parra et al., 2014)
- Moodplay (Andjelkovic et al., 2016)
- 3D Inspector (Loepp et al, 2017)
- Tuner+ (Tsai et al, 2019)
- Explain or Not (Millecamp et al, 2019)

Peerchooser

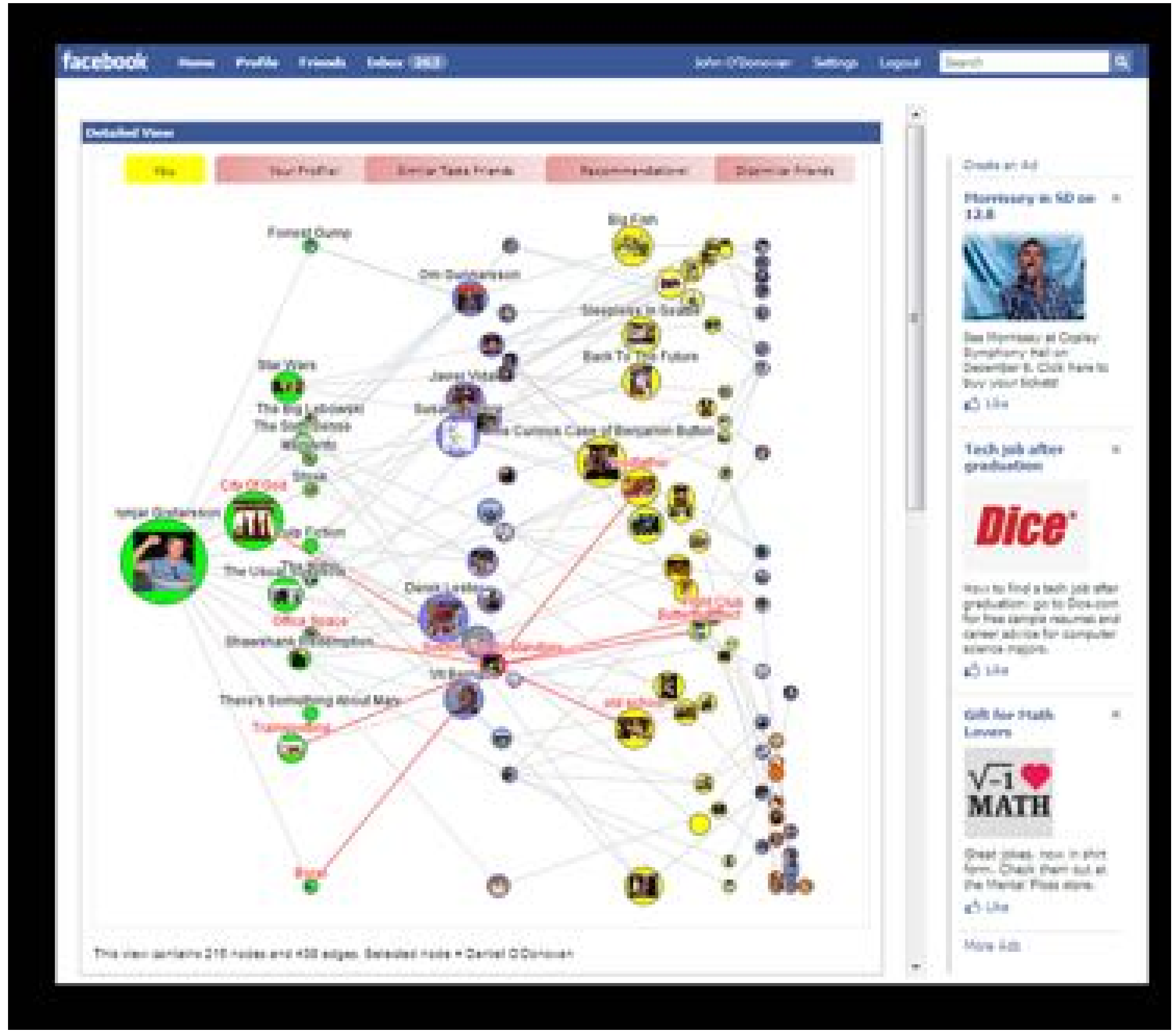
- PeerChooser (CHI 2008)
- John O'Donovan, Barry Smyth, Brynjar Gretarsson, Svetlin Bostandjiev, Tobias Hollerer



2: Annotated Screenshot of PeerChooser's Interactive Interface.

Smallworlds

- SmallWorlds: Visualizing Social Recommendations (IEEE-TVCG 2010)
- Brynjar Gretarsson, John O'Donovan , Svetlin Bostandjiev, Christopher Hall, Tobias Höllerer
- User study with 17 users



Each to his own

- Each to his own: how different users call for different interaction methods in recommender systems (RecSys 2010)
- Knijnenburg, B. P., Reijmer, N. J., & Willemsen, M. C.
- UX with Interface details depends on previous user knowledge of the topic

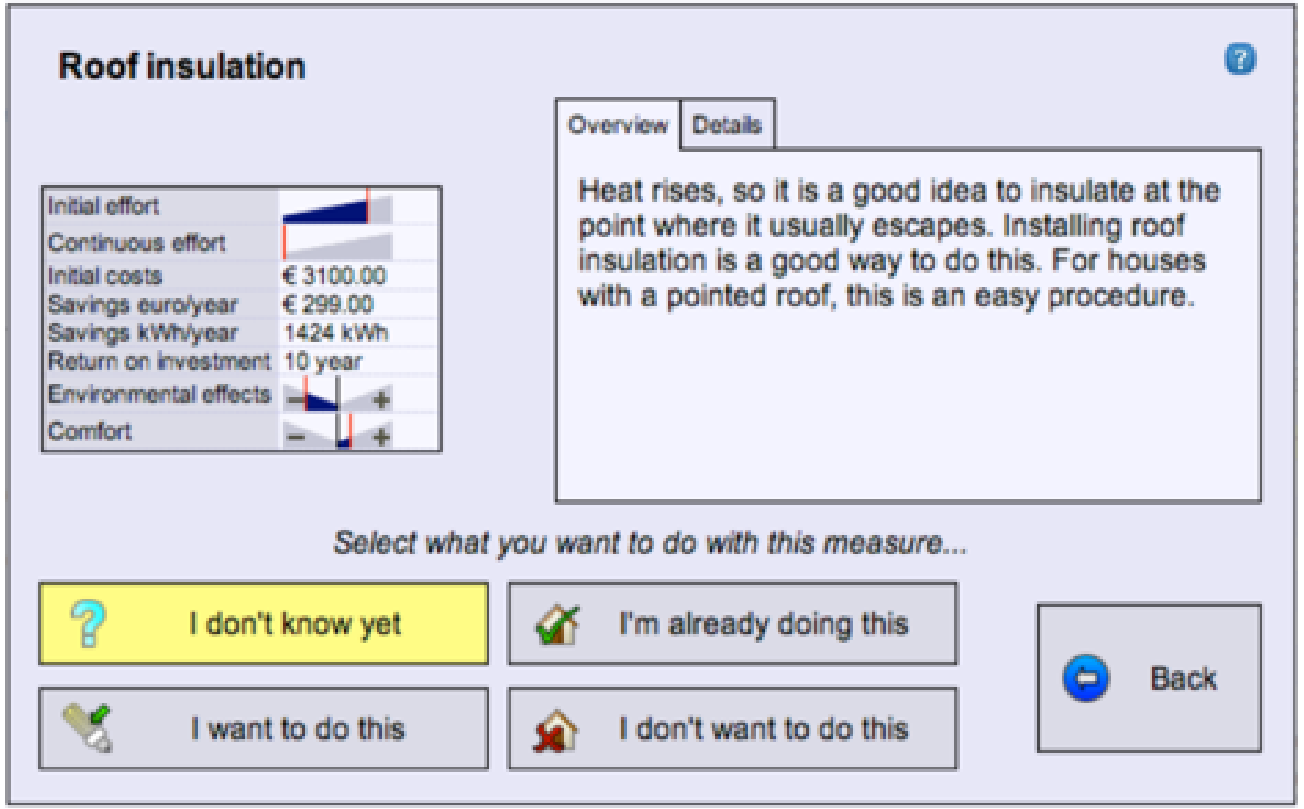
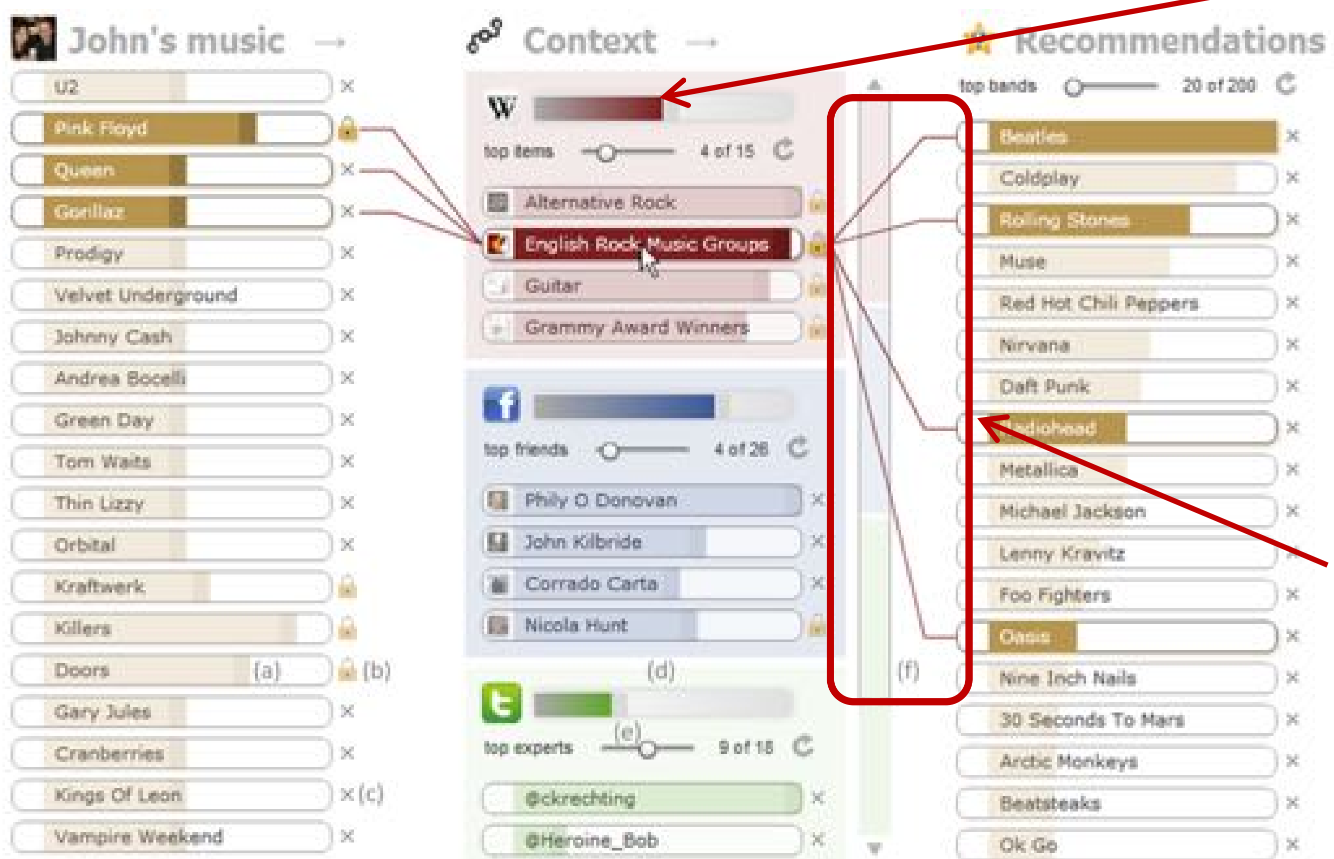


Figure 2. Screen shown to users when they click on an item

TasteWeights

- TasteWeights: a visual interactive hybrid recommender system (RecSys 2012)
- Bostandjiev, S., O'Donovan, J., & Höllerer, T.



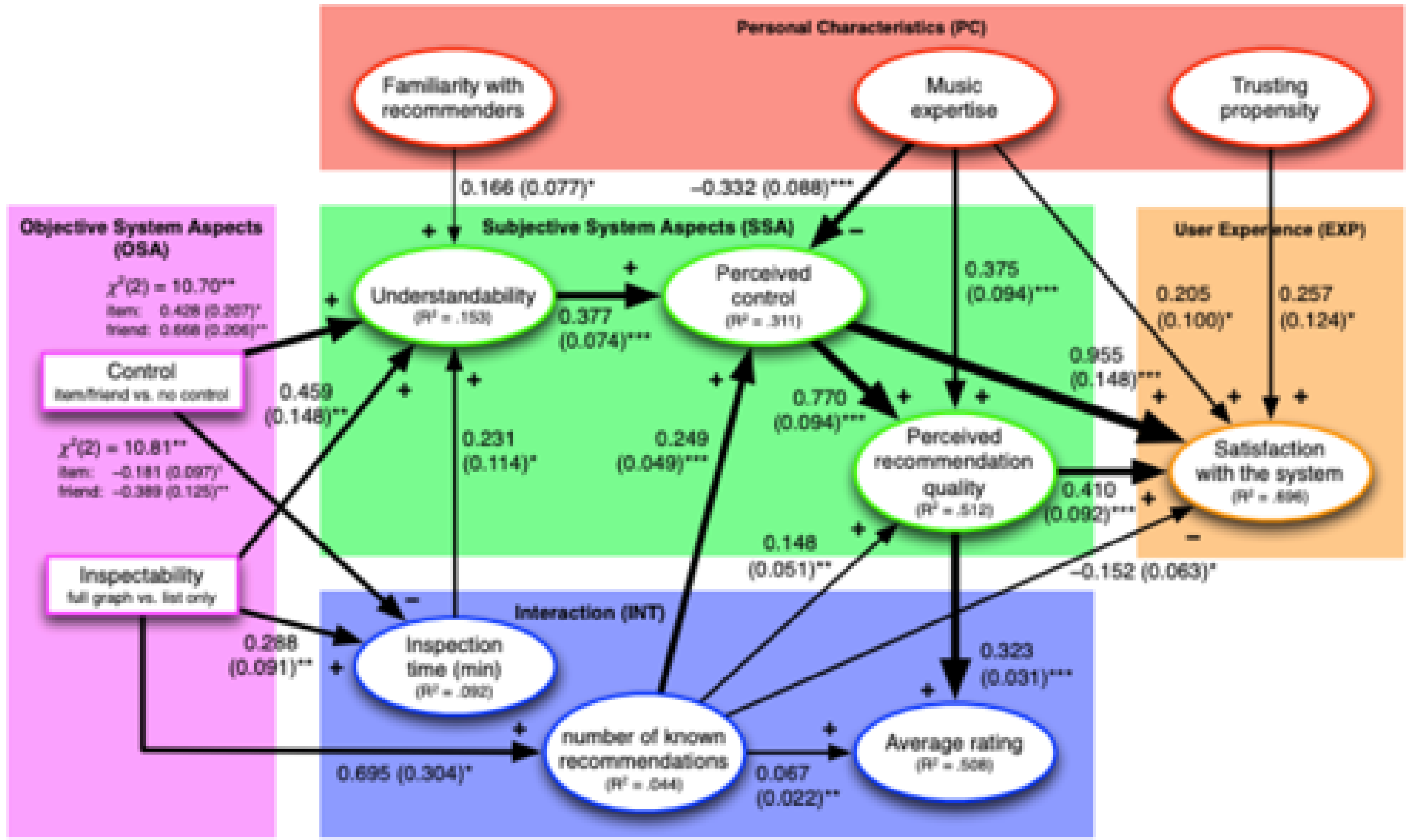
Controllability: Sliders that let users control the importance of preferences and contexts

Inspectability: lines that connect recommended items with contexts and user preferences

Also : Knijnenburg, B. P., Bostandjiev, S., O'Donovan, J., & Kobsa, A. (2012). Inspectability and control in social recommenders. In Proceedings of ACM RecSys.

TasteWeights II

- TasteWeights: a visual interactive hybrid recommender system (RecSys 2012)
- Bostandjiev, S., O'Donovan, J., & Höllerer, T.



Also : Knijnenburg, B. P., Bostandjiev, S., O'Donovan, J., & Kobsa, A. (2012). Inspectability and control in social recommenders. In Proceedings of ACM RecSys.

TalkExplorer

- Visualizing recommendations to support exploration, transparency and controllability
- Verbert, K., Parra, D., Brusilovsky, P., & Duval, E. (IUI 2013)

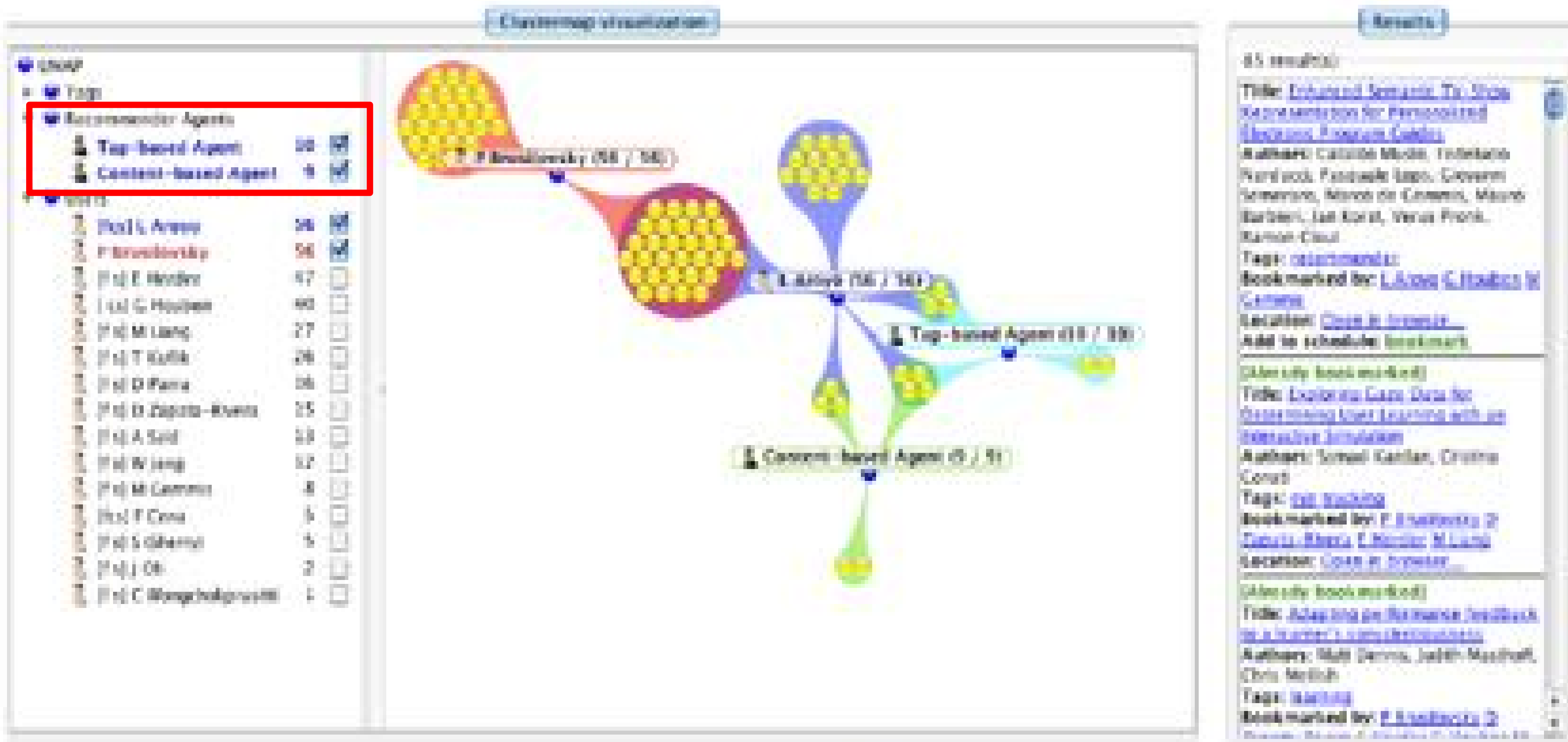
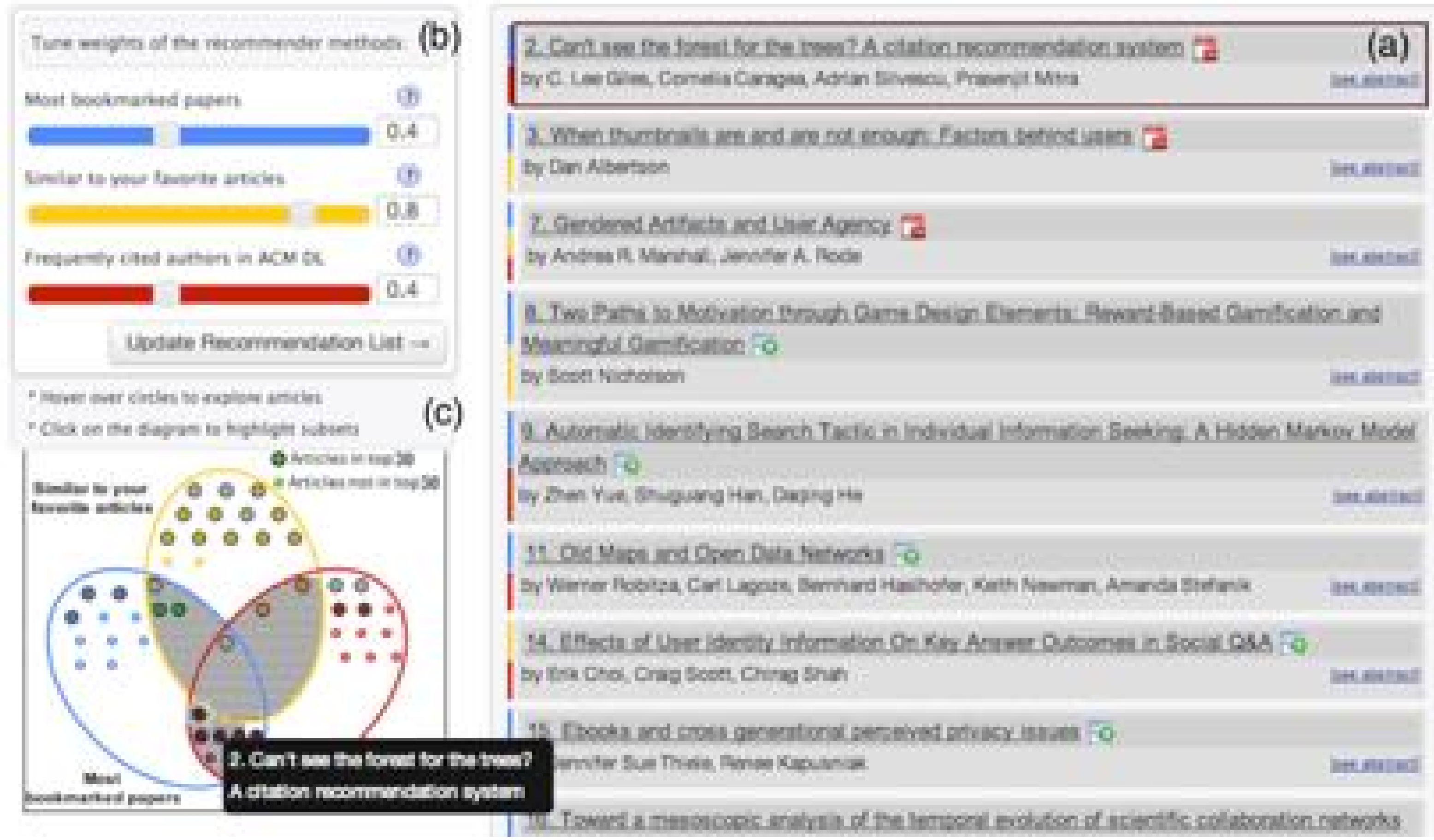


Figure 2: TalkExplorer

SetFusion

- See what you want to see: visual user-driven approach for hybrid recommendation
- Denis Parra, Peter Brusilovsky, and Christoph Trattner (IUI 2014)



SetFusion: A Controllable Hybrid Recommender

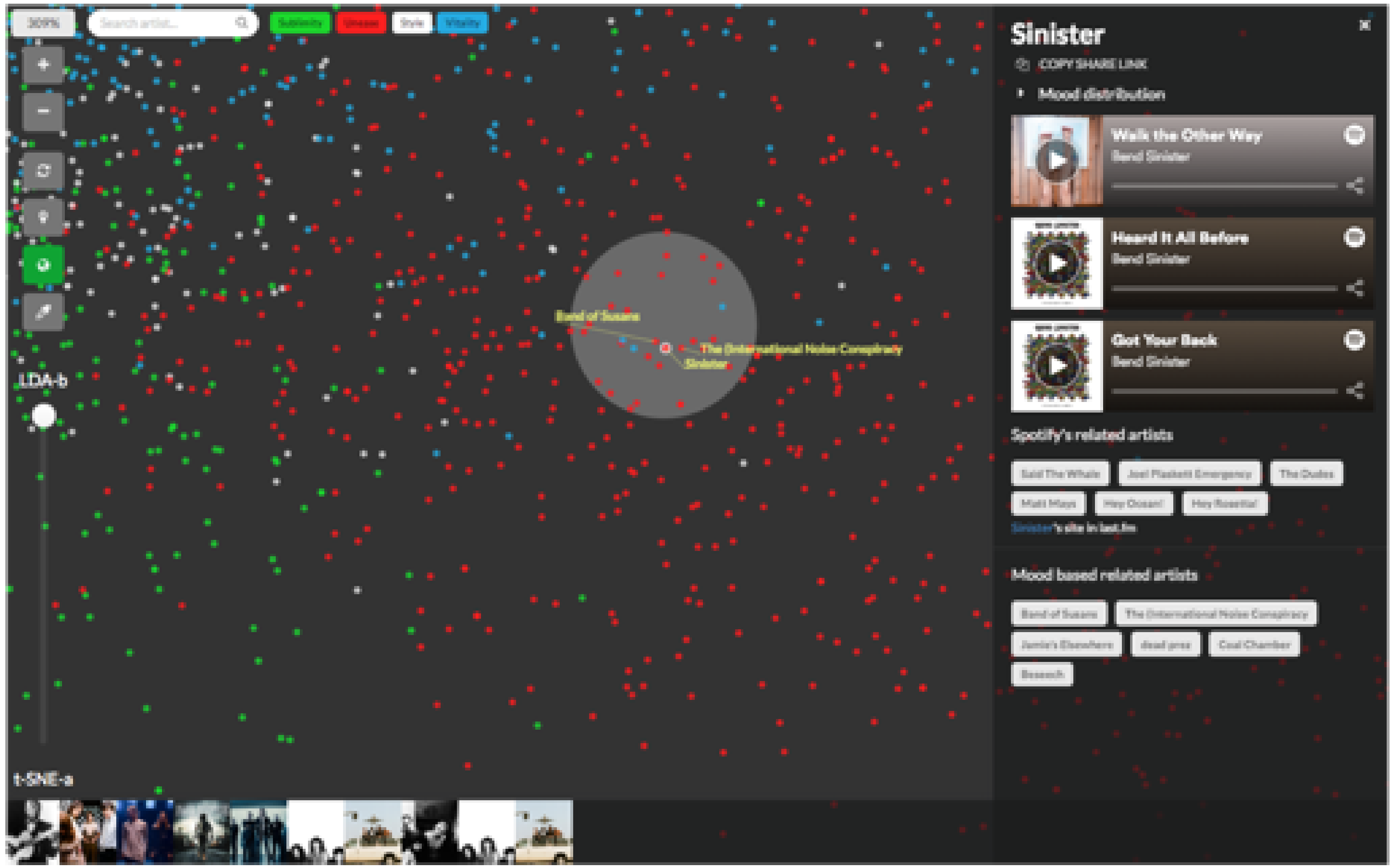
Parra, D., Brusilovsky, P., Trattner, C.

IUI 2014, Haifa, Israel

Moodplay

- Moodplay: Interactive Mood-based Music Discovery and Recommendation.

- Ivana Andjelkovic, Denis Parra, and John O'Donovan. (UMAP 2016; IJHCS 2019)



http://moodplay.pythonanywhere.com/

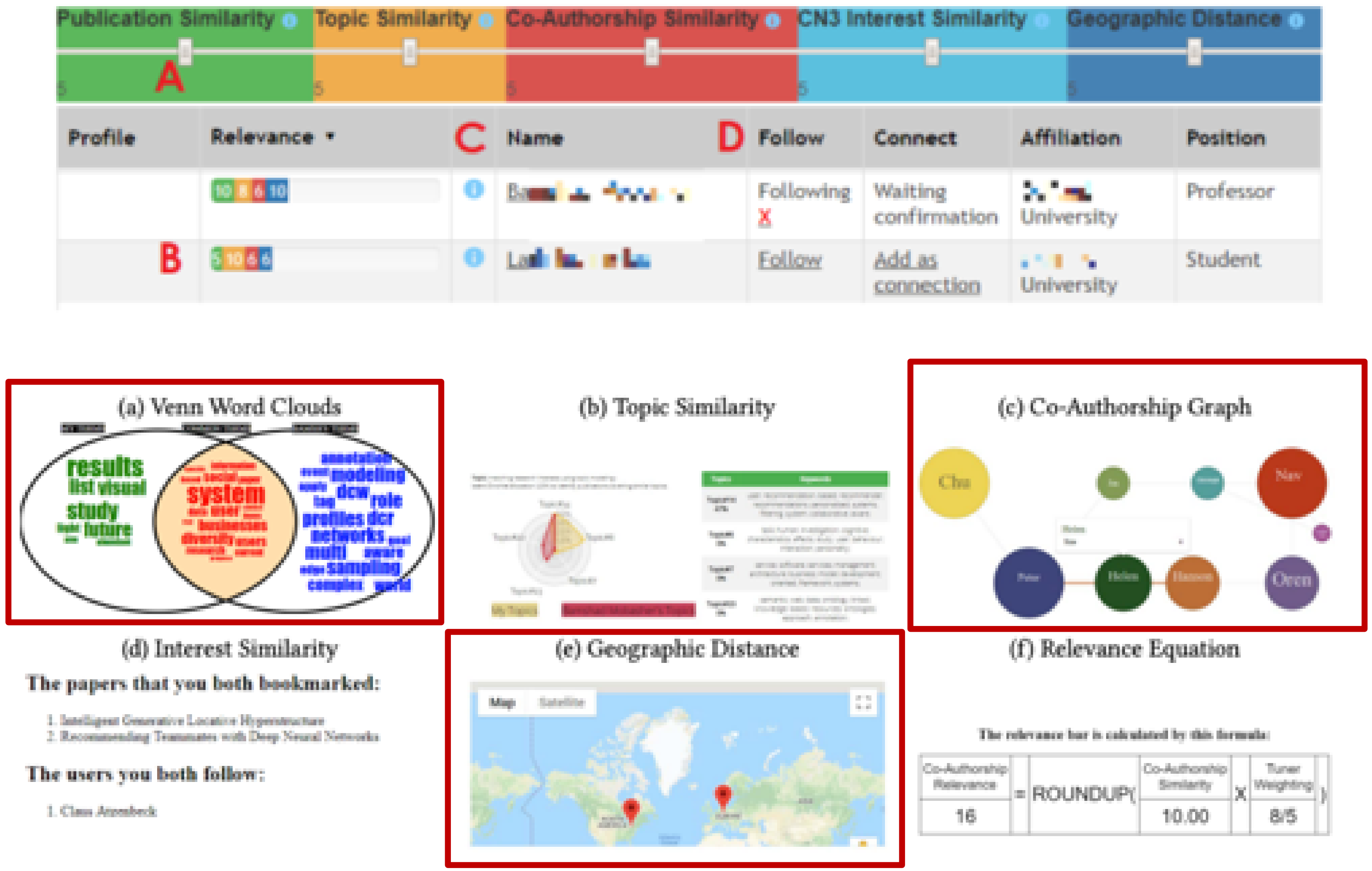
3D Landscape

- A 3D item space visualization for presenting and manipulating user preferences in collaborative filtering
- Kunkel, J., Loepp, B., & Ziegler, J. (IUI 2017)

Tuner+

- Explaining recommendations in an interactive hybrid social recommender

- Tsai, C. H., & Brusilovsky, P. (IUI 2019)



To Explain or Not

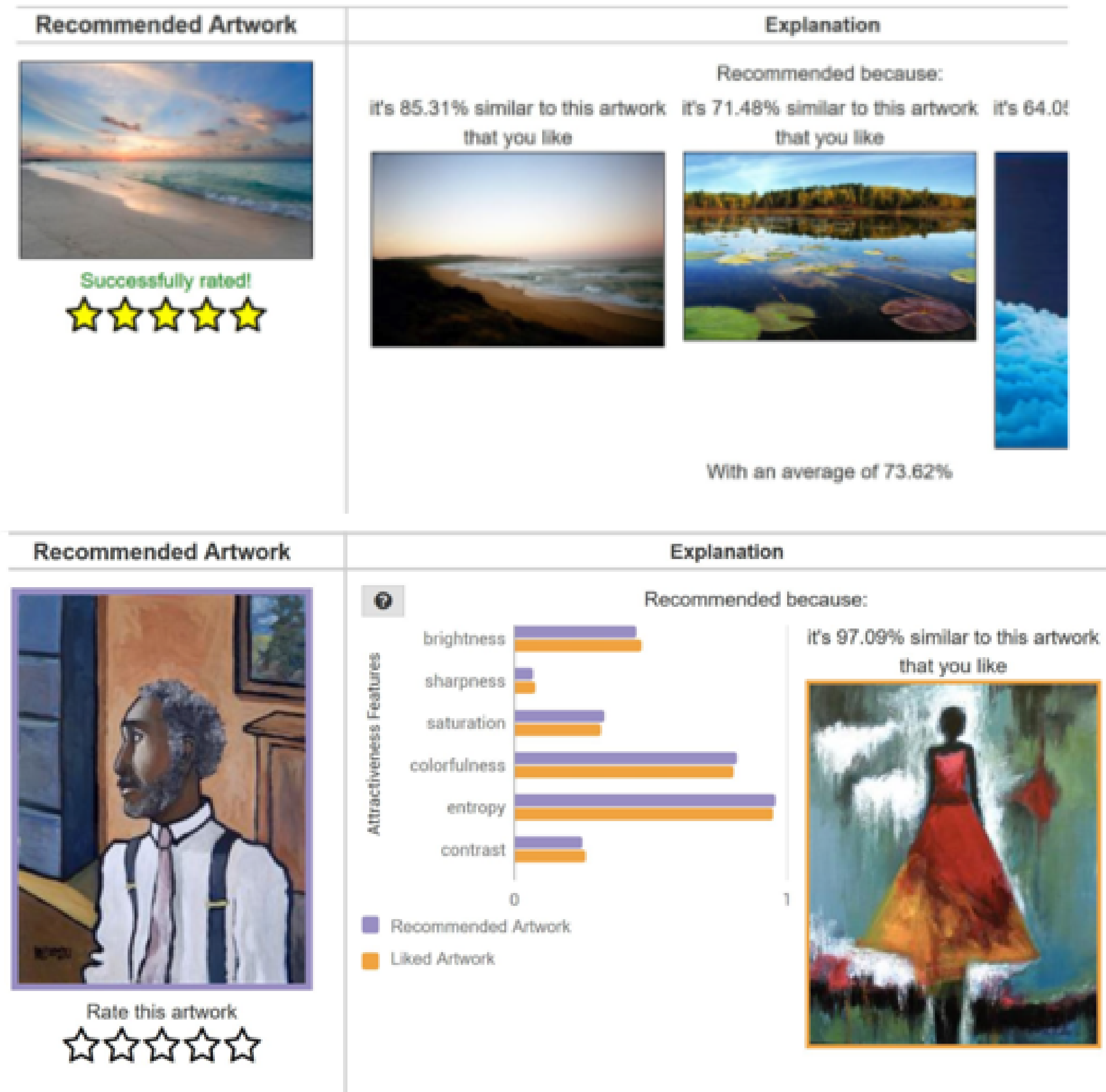
- To explain or not to explain: the effects of personal characteristics when explaining music recommendations

- Millecamp, M., Htun, N. N., Conati, C., & Verbert, K. (IUI 2019)

* Locus of control, need for cognition, musical sophistication, visual literacy.

“Explanations” only work with an accurate RecSys

- The Effect of Explanations and Algorithmic Accuracy on Visual Recommender Systems of Artistic Images (IUI2019)
- Dominguez et al.



RecSys 2021- TTIR LoL item RecSys

- Interpretable Contextual Team-aware Item Recommendation: Application in Multiplayer Online Battle Arena Games (RecSys2020)
- Villa, Araujo, Cattan, Parra
- Explanation Usefulness: mostly for newer players

Question	Global M±SD (N=16)	Subjects by year of first play 2009-11 (N=5)	2012-14 (N=5)	2015-2017 (N=6)
Q1. How good were the recommendations for the *Blue team* ?	7.98±1.22	7.7±1.24	7.7±1.16	8.46±1.3
Q2. Is it understandable the influence of every team member upon each champion being recommended ?	7.44±1.72	7.4±1.55	7.1±0.8	7.75±2.49
Q3. Is it useful the information provided by the visualization in order to understand the item recommendations made ?	6.9±2.15	6.7±1.98	6.6±1.65	7.33±2.87

What have we learned from this research?

What have we learned from this research?

- **Perception of control** is key, but how much depends on knowledge/literacy level of the users on the domain

What have we learned from this research?

- **Perception of control** is key, but how much depends on knowledge/literacy level of the users on the domain

- We should let users choose whether seeing explanations or not

What have we learned from this research?

- **Perception of control** is key, but how much depends on knowledge/literacy level of the users on the domain

- We should let users choose whether seeing explanations or not

- Explanations should present different levels of details, we should give users' control to explore them

Overview first, details on demand

– Schneiderman mantra

What have we learned from this research? II

- People **might prefer a less transparent recommender** if they are able to predict what the system is going to suggest

What have we learned from this research? II

- People **<u>might prefer a less transparent recommender</u>** if they are able to predict what the system is going to suggest

- The **explanation** must provide something **beyond the obvious** (we need further research on this)

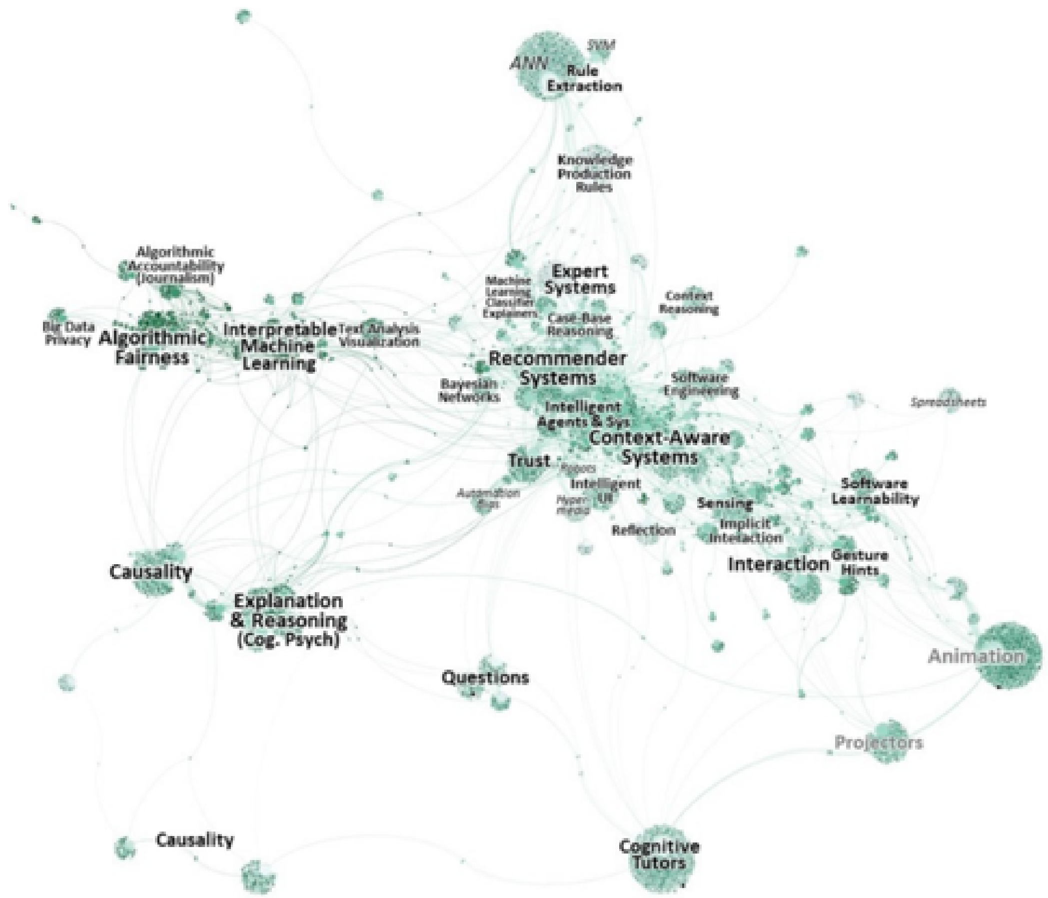
What have we learned from this research? II

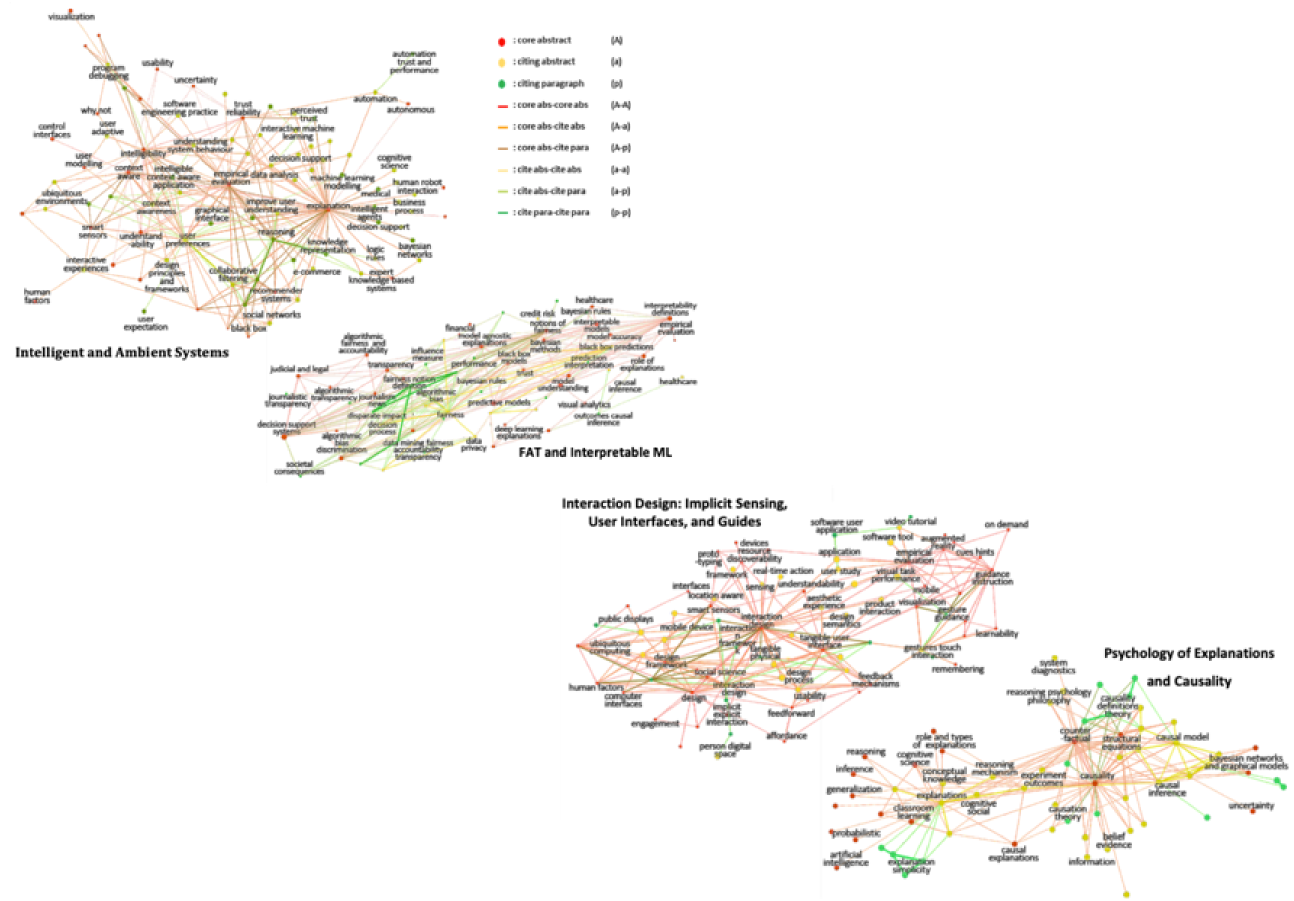
- People **might prefer a less transparent recommender** if they are able to predict what the system is going to suggest

- The **explanation** must provide something **beyond the obvious**! (we need further research on this)

- The **right visual encoding** can promote curiosity and exploratory behavior

Need for further interaction between AI/HCI communities



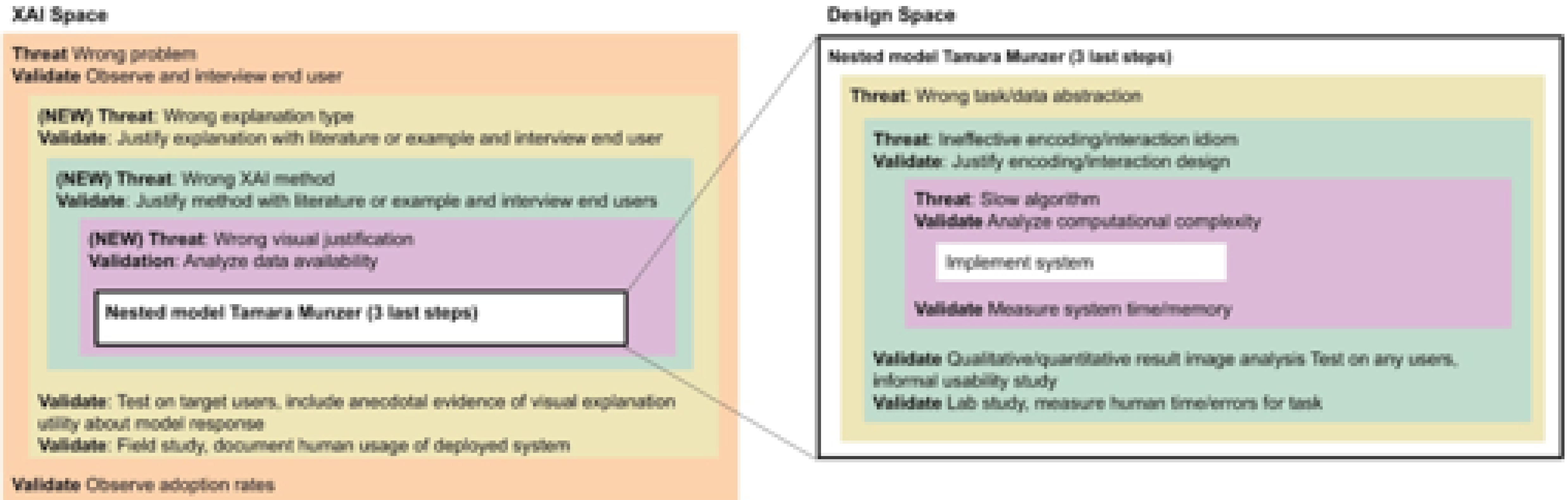


Abdul, A., Vermeulen, J., Wang, D., Lim, B. Y., & Kankanhalli, M. (2018). **Trends and trajectories for explainable, accountable and intelligible systems: An hci research agenda**. CHI 2018.

Back to Visual XAI

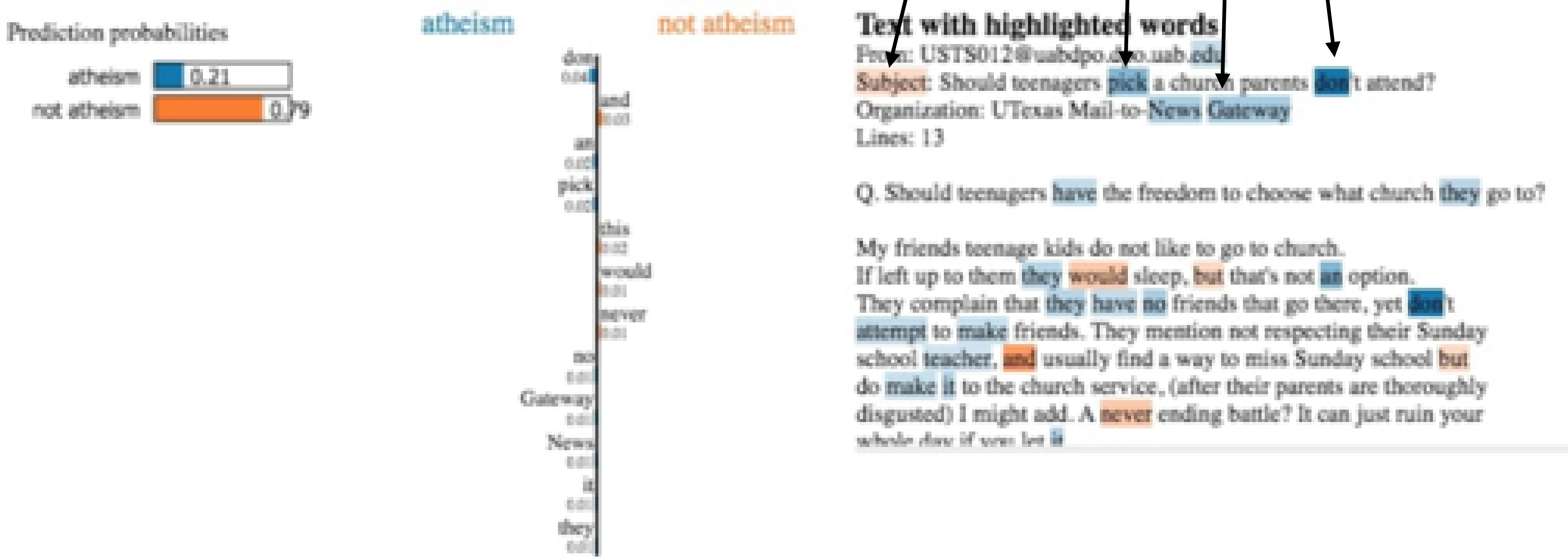
- How do we **analyze** and **design** visualizations for XAI?
- There are frameworks and guidelines for designing visualizations (e.g. Munzer VAD framework)
- … but the there is no framework yet for designing Visual XAI

Work in Progress: VD4XAI

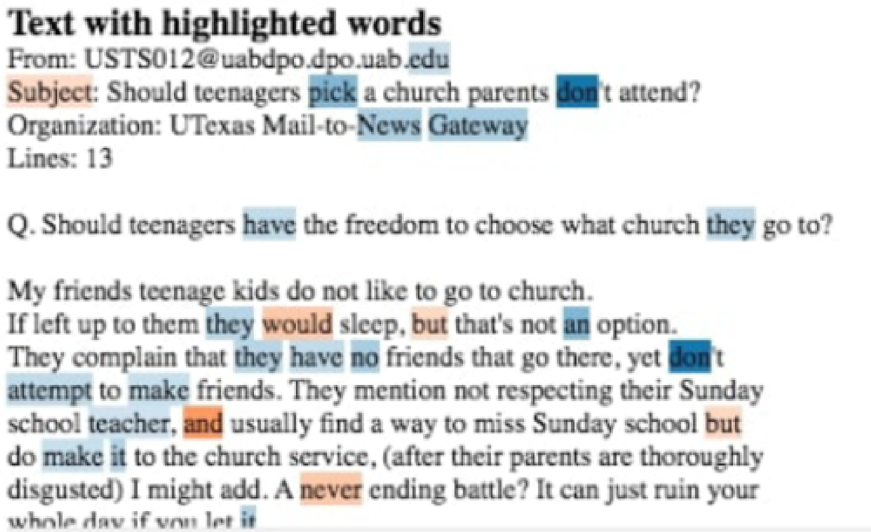


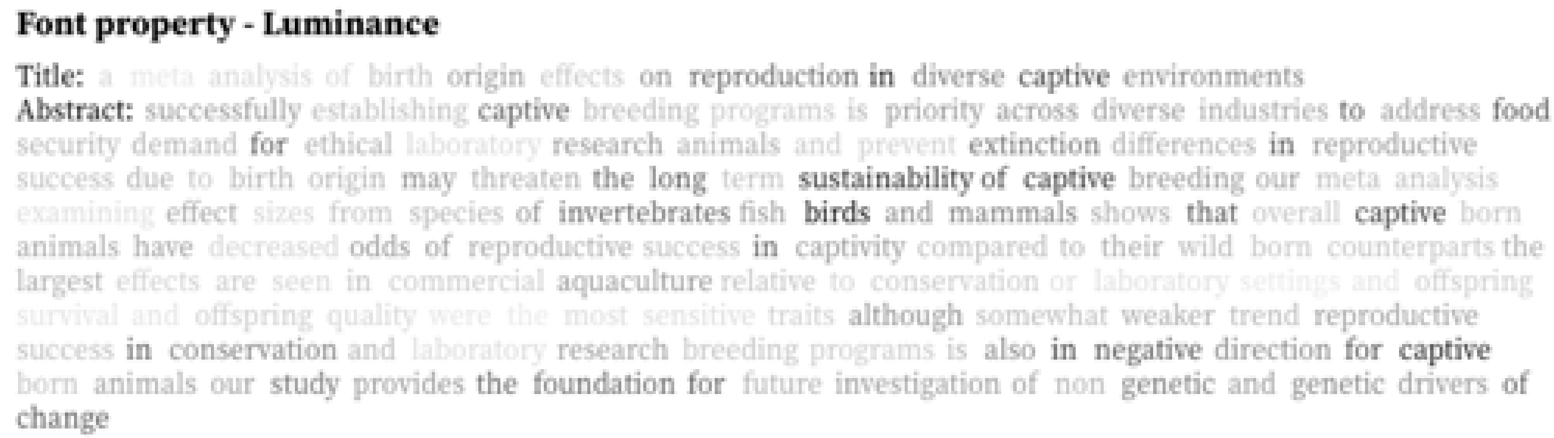
H Valdivieso, D Parra, I Donoso, K Verbert, et al.
VD4XAI: Connecting the Visualization Design Space with the Explainable AI Task Space. Work in progress

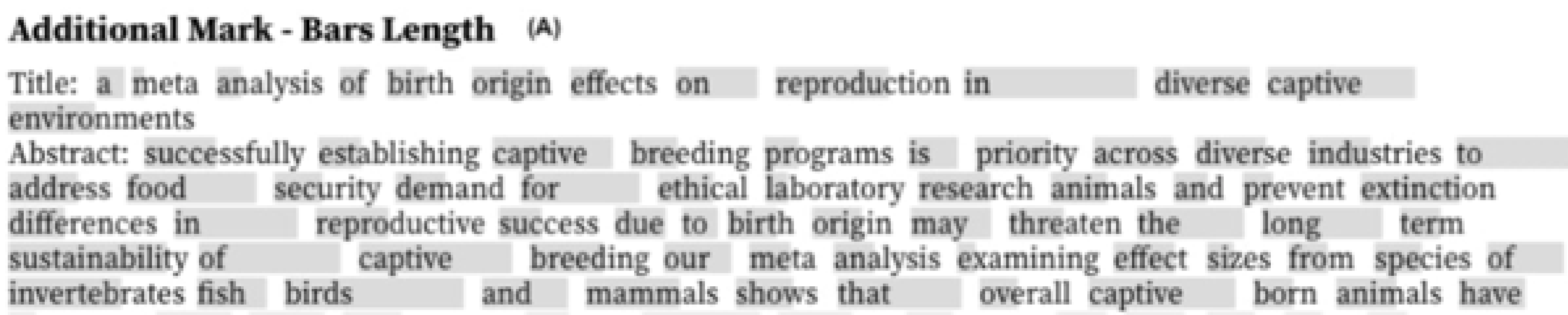
Analyze LIME: why colored background ?



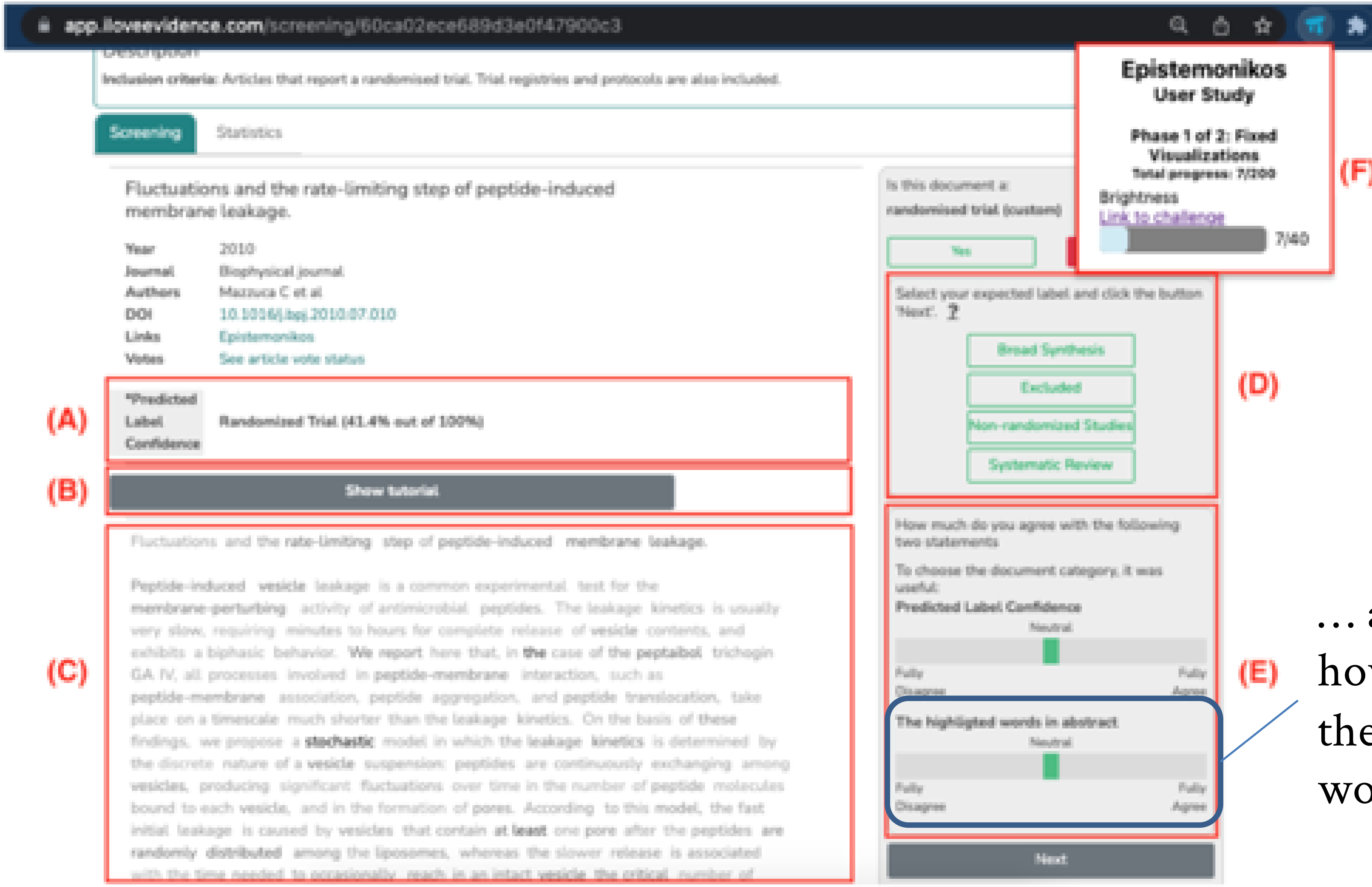
Analyze LIME: Marks, channels and Interaction





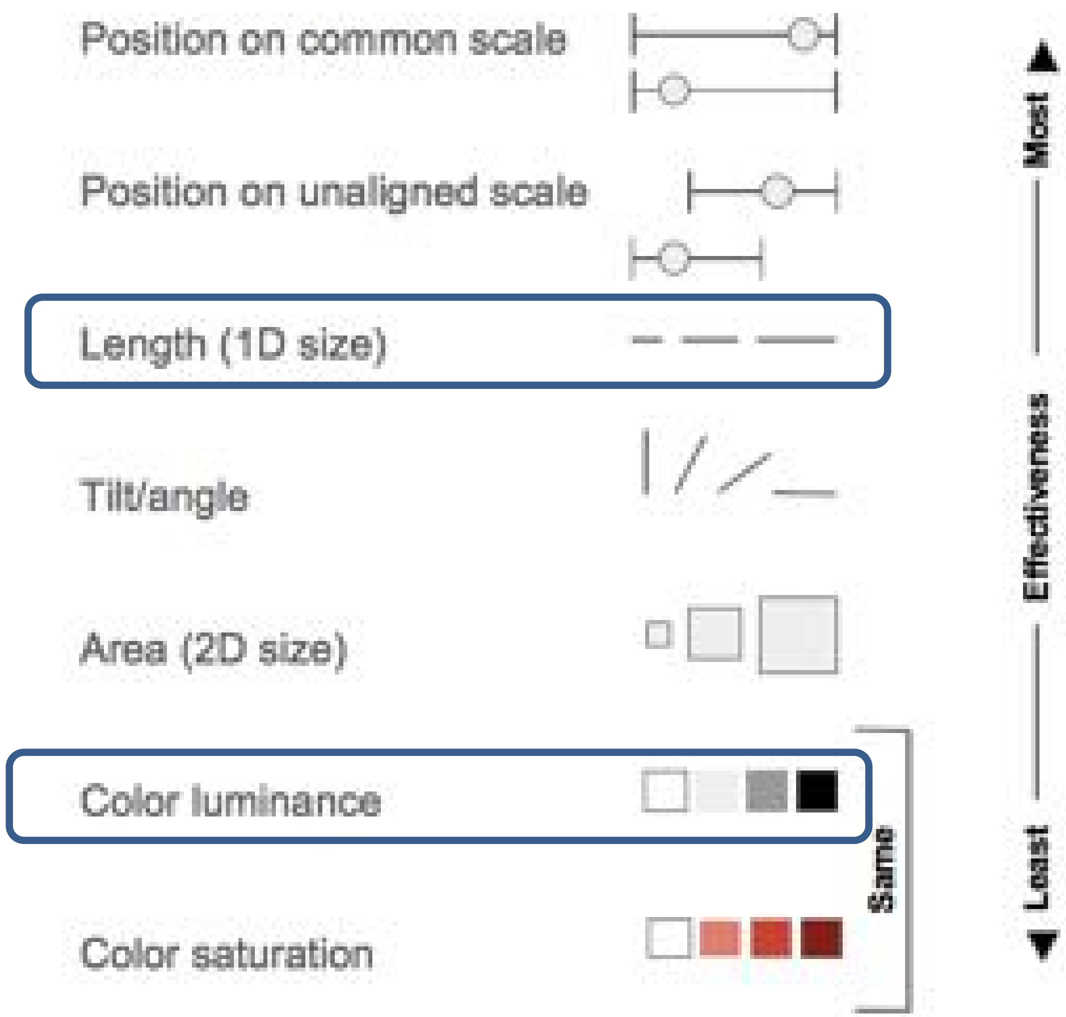


Recent study: Biomedical Document Classification



… and tell us how useful were the highlighted words

Designs: marks and channels (effectiveness principle)



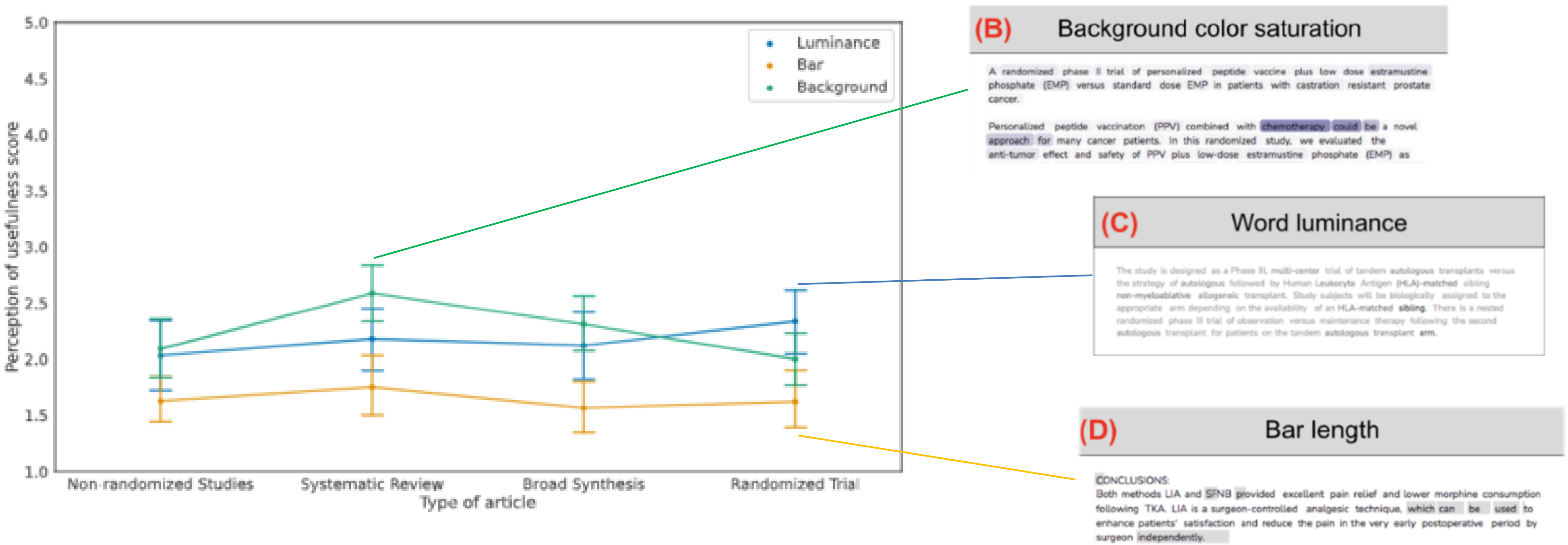
Do people prefer

more effective channels

for neural attention-based explanations?

Recent study: Document Classification

* In this task, **a more visually effective channel is not the most useful**
* Perception of usefulness **depends on document type**



Conclusion

- XAI and Visual XAI are active topics of critical research in AI
- Despite XAI being coined around 2017, the RecSys-IUI community has been researching explainability and transparency since early 2000s, and there are important lessons to contribute to XAI
- There's still a need to connect different disciplines and areas to address challenges in XAI and Visual XAI

dparra@ing.puc.cl

THANKS!