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# From Transparency and Users' Control in Recommender System Interfaces to Guidelines for Visual XAI

Denis Parra

PUC Chile & CENIA, iHealth, IMFD

APEX-UI Workshop co-located at ACM IUI  
Virtually hosted by U. Of Helsinki, Finland

March 21st, 2022



@denisparra

# Presents ...

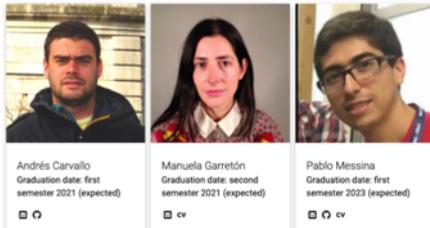


**Denis Parra**

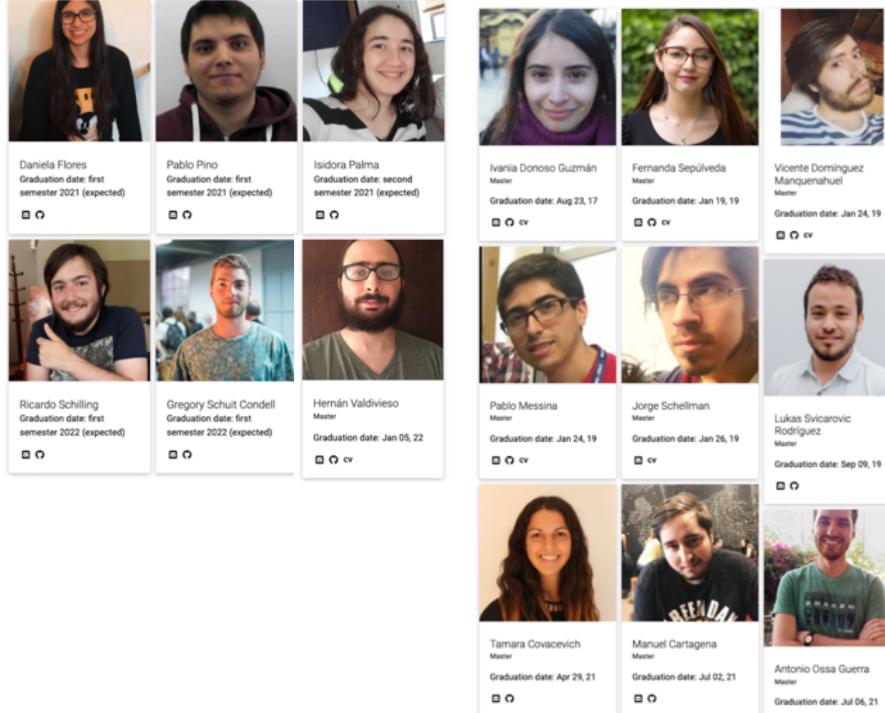
- Associate Professor, CS Department, PUC Chile
- Teaching: Recommender Systems, Information Visualization
- Research: HAiVis Lab c IA Lab
  - Machine learning applications (RecSys, Medical & Creative AI), intelligent user interfaces, information visualization
  - Students: 5 PhD, 5 Master, 1 Undergraduate
- Principal Researcher at:
  - Chile's National Center on Artificial Intelligence (CENIA, 2021 - )
  - Millennium Institute in Healthcare Engineering (iHealth, 2021 - )
  - Millennium Institute Foundational Research on Data (IMFD, 2018 - )

# HAIVis UC: This research has been possible thanks to

PhD Students

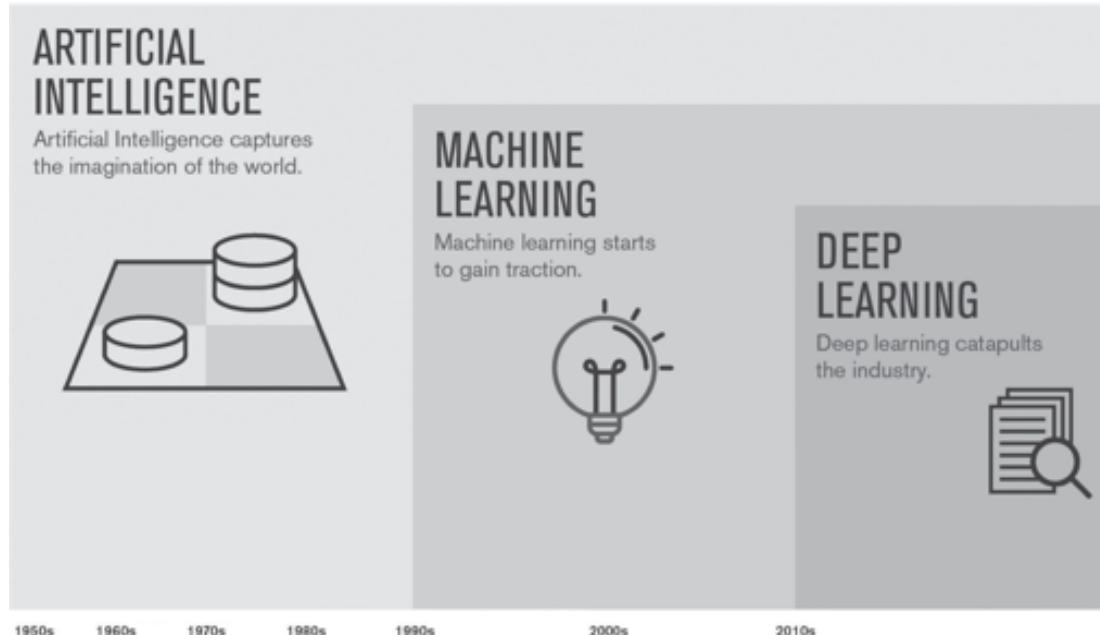


Master's students



# 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



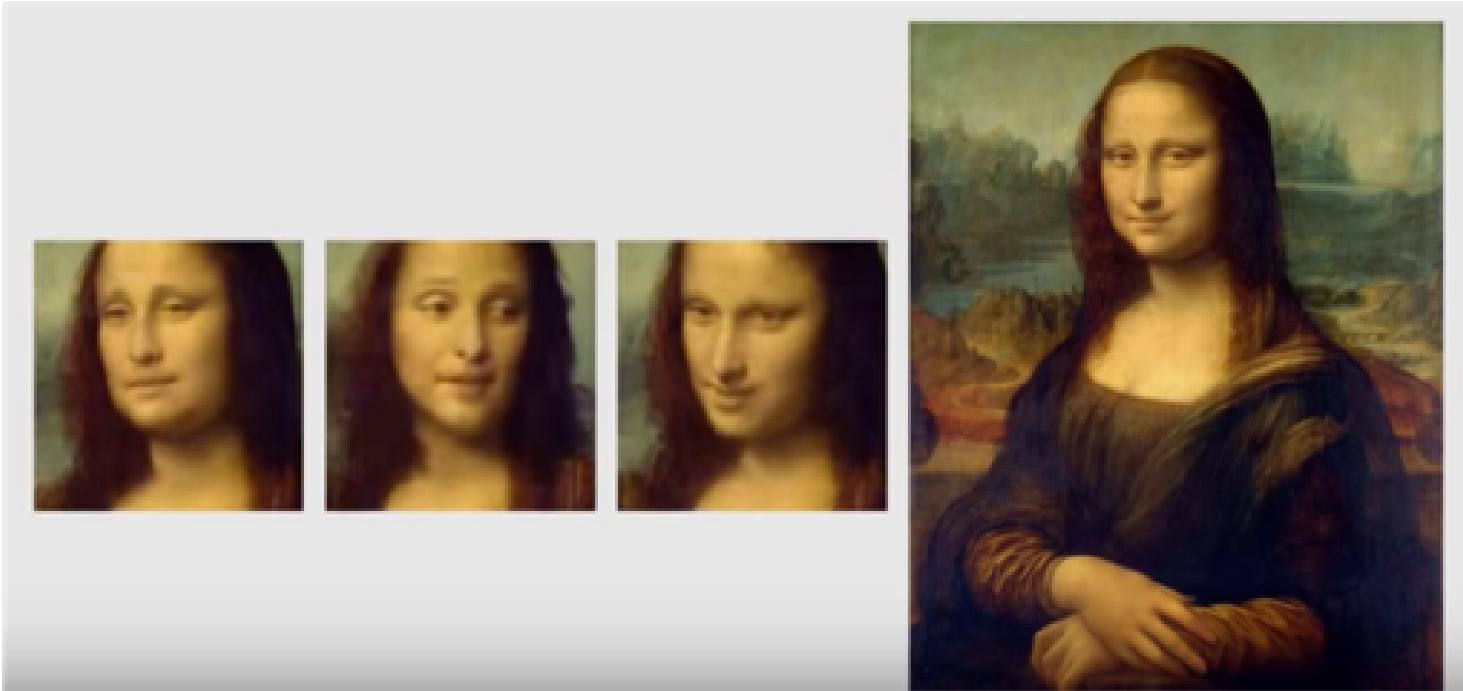
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The computer that mastered Go

Nature Video

# Zero Shot Learning: Picture to Movie



Zakharov, E., Shysheya, A., Burkov, E., & Lempitsky, V. (2019). Few-Shot Adversarial Learning of Realistic Neural Talking Head Models. *arXiv preprint arXiv:1905.08233*.

# But there are some problems



## 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

**O**N 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.

- The COMPAS system is used in the USA to predict recidivism

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<https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>

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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.)

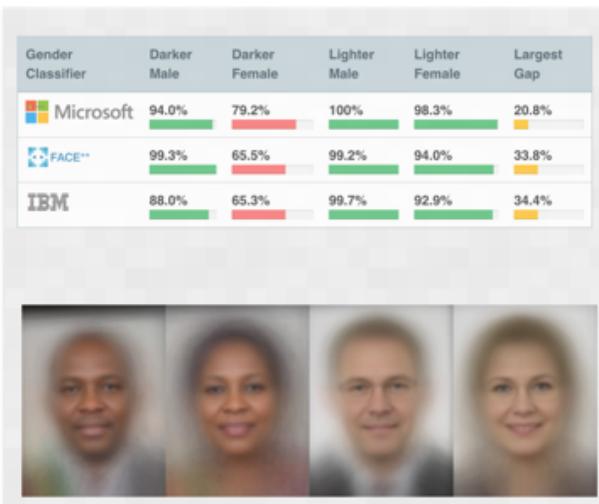
<https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm>

# 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.



<http://gendershades.org/overview.html>

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

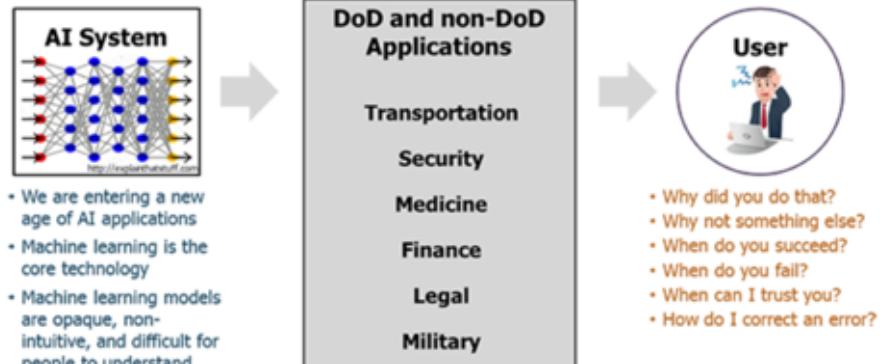
<https://news.mit.edu/2018/study-finds-gender-skin-type-bias-artificial-intelligence-systems-0212>



# XAI (2017)

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

**Explainable Artificial Intelligence (XAI)**  
Mr. David Gunning



Mr. David Gunning  
Information Innovation Office (I2O)  
Program Manager

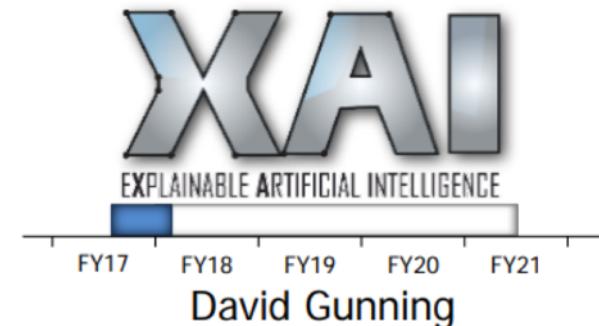


Figure 1. The Need for Explainable AI

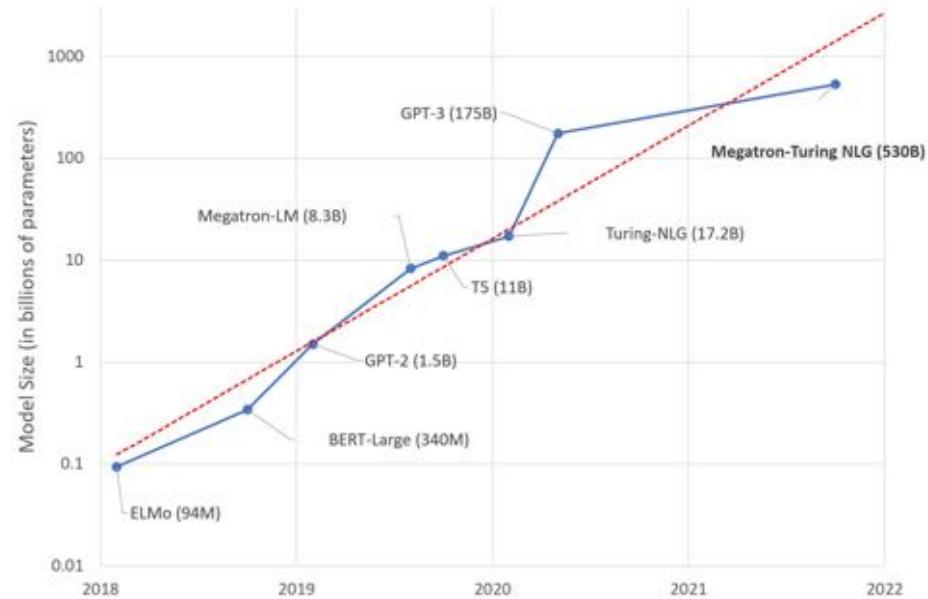
# What does XAI mean ?

- In Gunning et al (2019), an X-AI system is defined by its *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.

# Visual XAI

- 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>

# 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 – 5<sup>th</sup> VisXAI at IEEE Vis]

## 5<sup>th</sup> Workshop on Visualization for AI Explainability

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



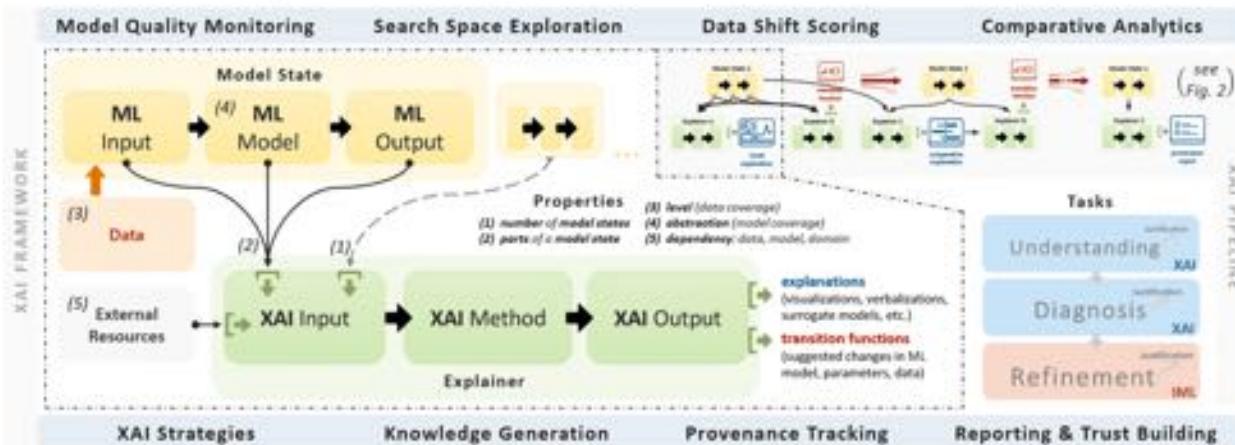
The role of visualization in artificial intelligence (AI) gained significant attention in recent years. With the growing complexity of AI models, the critical need for understanding their inner-workings has increased. Visualization is potentially a powerful technique to fill such a critical need.

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, and even a framework was proposed in 2019:  
ExplAIner

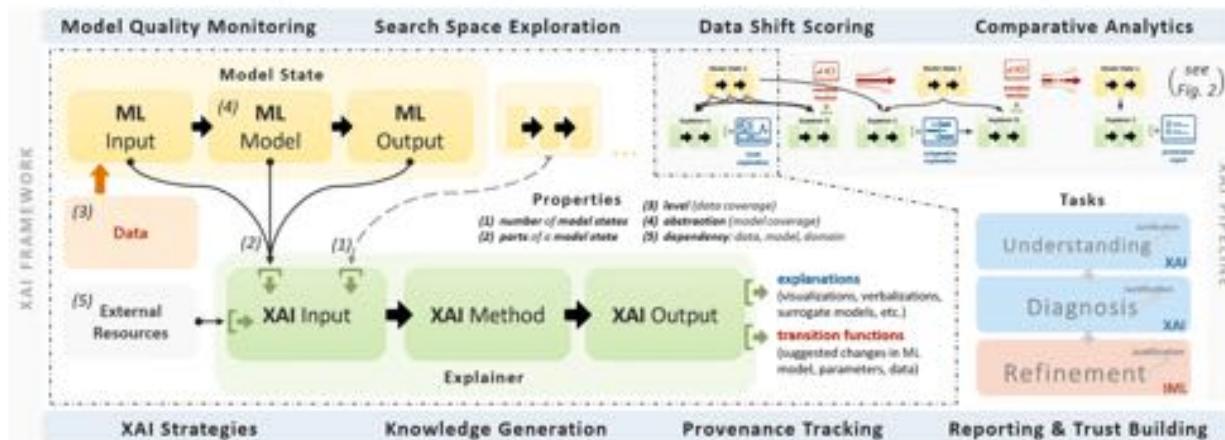


Spinner, T., et al (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE TVCG, 26(1), 1064-1074.

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



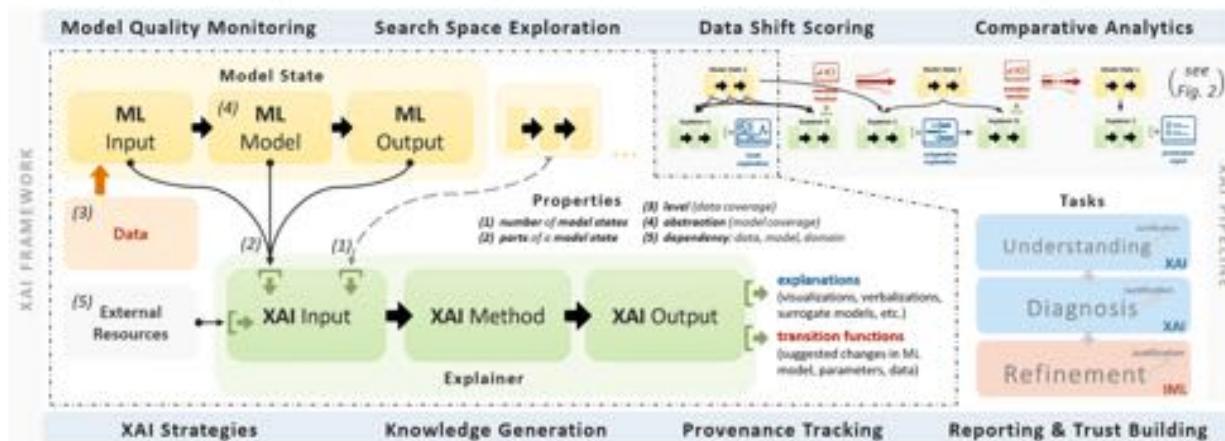
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- Visual
- Interaction

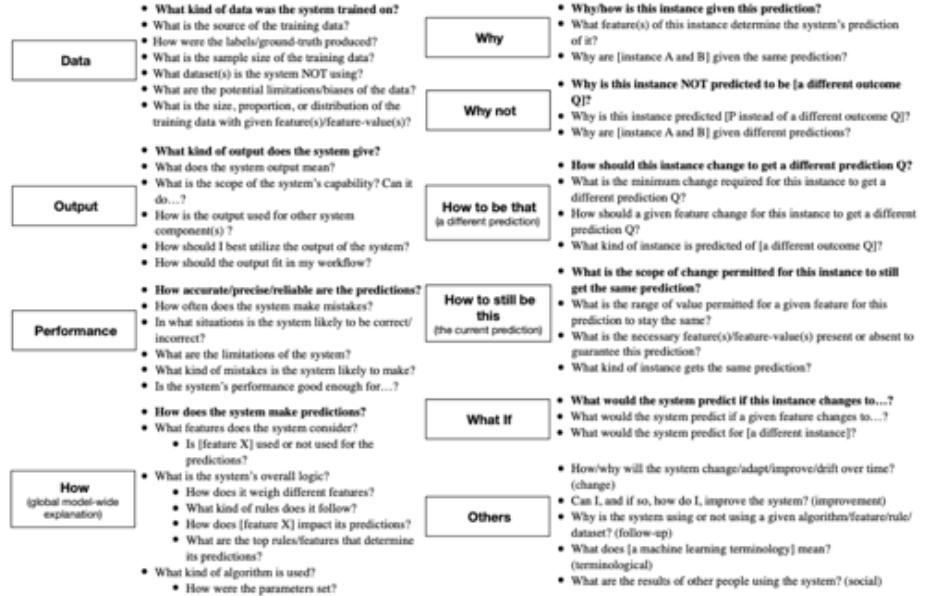


Spinner, T., et al (2019). explAIner: A visual analytics framework for interactive and explainable machine learning. IEEE TVCG, 26(1), 1064-1074.

# XAI question bank

- Vera 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

## XAI Question Bank



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.

# 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 ?



Picture licensed under CC

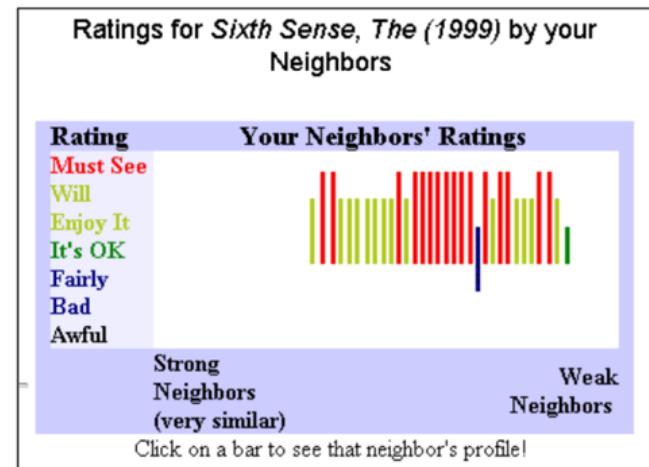
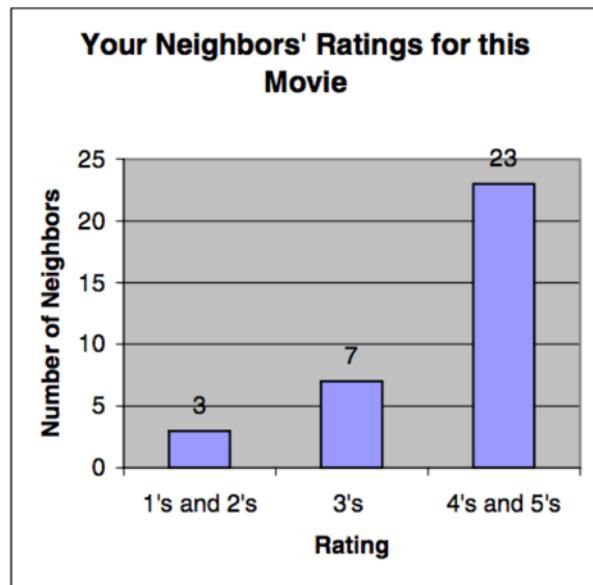
<http://www.flickr.com/photos/meaganmakes/6769496875/sizes/m/>

# 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.

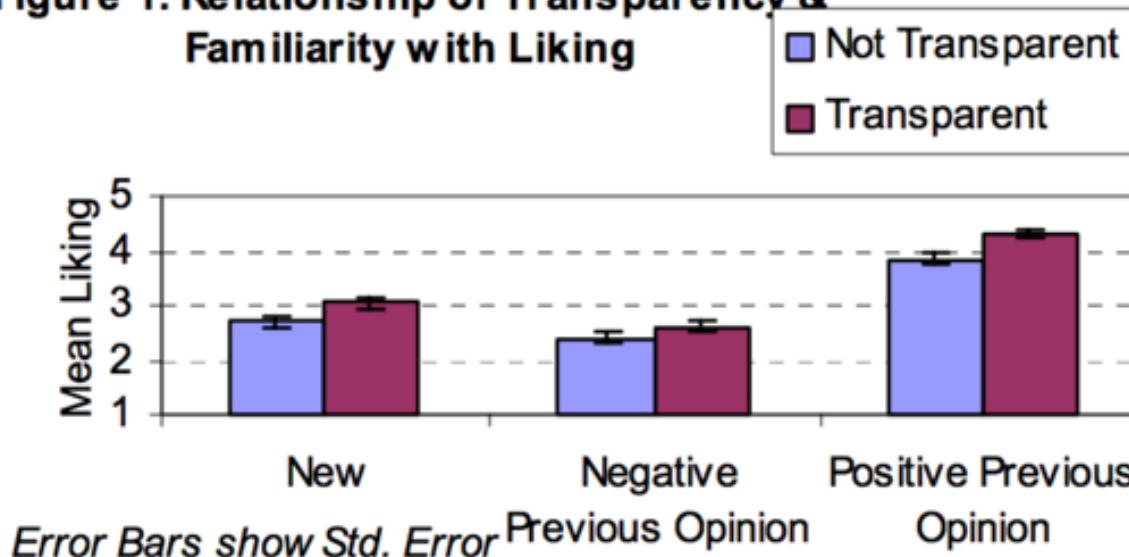


**Figure 4.** A screen explaining the recommendation for the movie “The Sixth Sense.” Each bar represents a rating of a neighbor. Upwardly trending bars are positive ratings, while downward trending ones are negative. The x-axis represents similarity to the user.

# 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.

**Figure 1: Relationship of Transparency & Familiarity with Liking**



# 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

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2007



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 ?

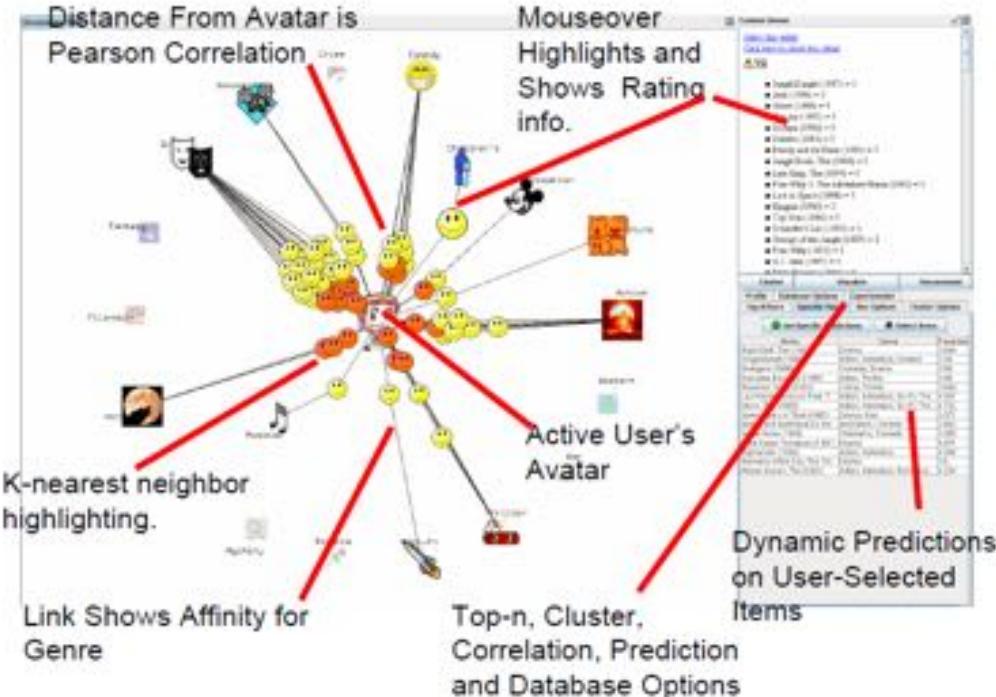
- There were actually many works related to explainability, transparency, trust and user controllability in RecSys.
- In the coming slides, I will focus on research related **Visual User Interfaces** for recommendation Systems and how they contributed early to XAI and Visual XAI.

# The Role of Interactive Visualization in RecSys XAI

- PeerChooser (O'Donovan et al, 2008)
- SmallWorlds (Gretarsson 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

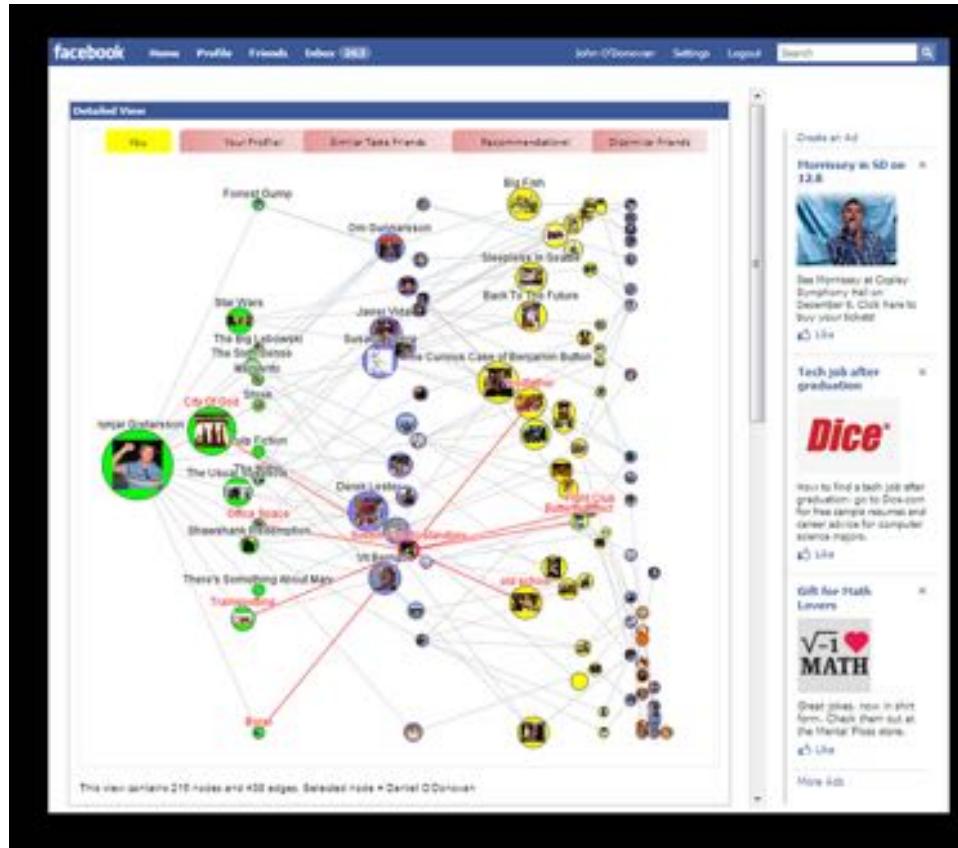
- PeerChooser  
(CHI 2008)
- John O'Donovan,  
Barry Smyth,  
Brynjar  
Gretarsson,  
Svetlin  
Bostandjiev,  
Tobias Hollerer



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



# 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

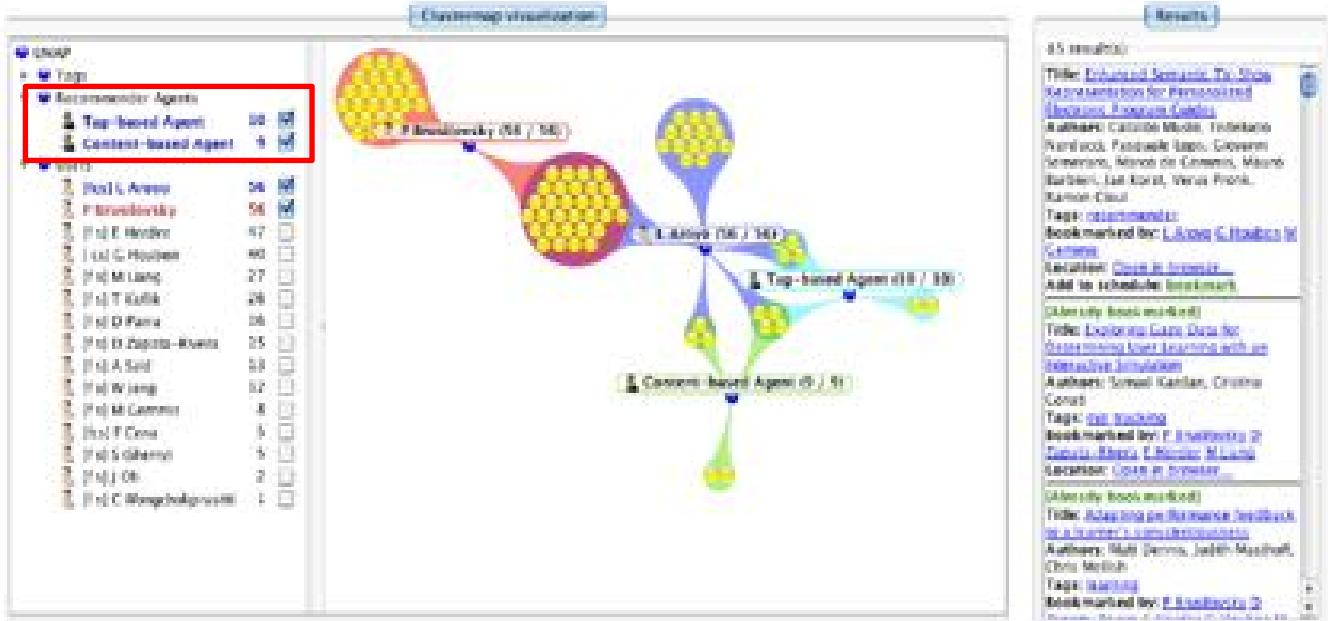
- TasteWeights: a visual interactive hybrid recommender system (RecSys 2012)
- Bostandjiev, S., O'Donovan, J., & Höllerer, T.



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 (IUI 2013)
  - Verbert, K., Parra, D., Brusilovsky, P., & Duval, E.



**Figure 2: TalkExplorer**

# SetFusion

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

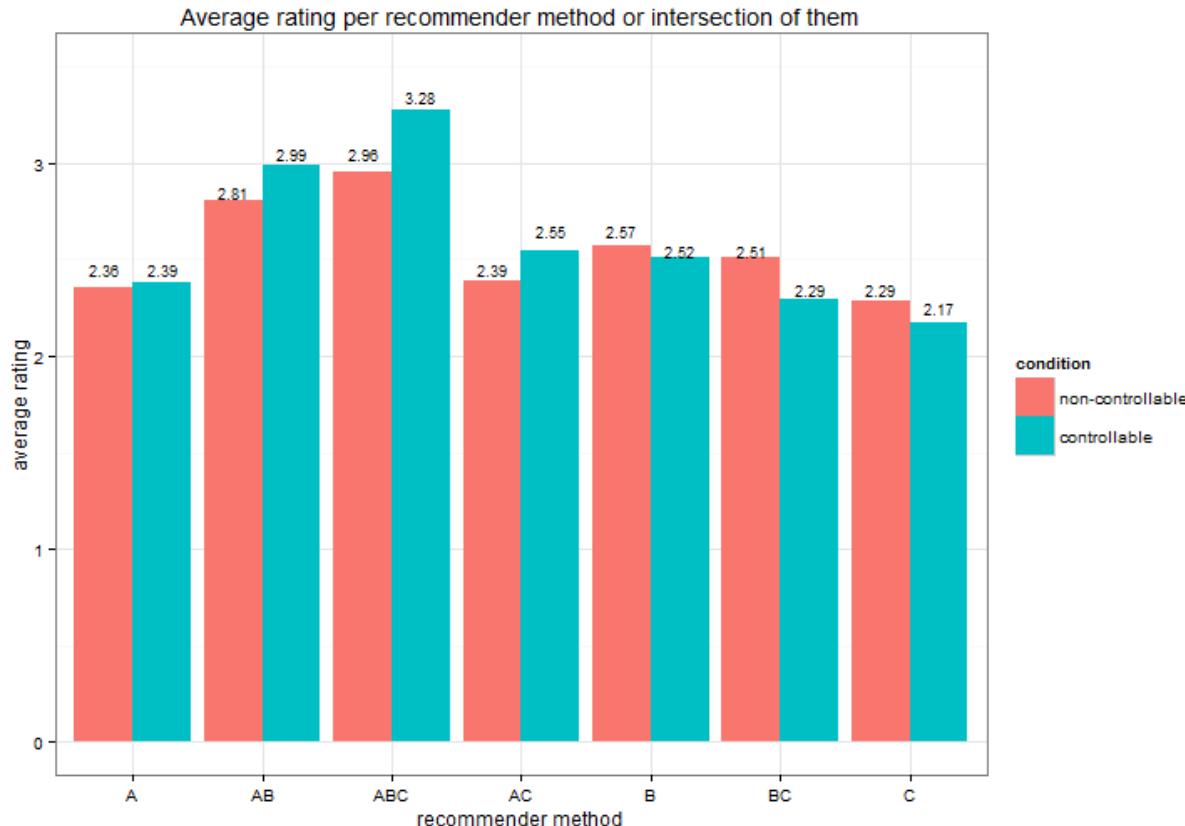


## SetFusion: A Controllable Hybrid Recommender

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

IUI 2014, Haifa, Israel

# SetFusion: User Control vs. non Control



# Effect of Gender on Color Preference

## Infographic Aesthetics: Designing for the First Impression

**Lane Harrison**  
Tufts University  
[lane@cs.tufts.edu](mailto:lane@cs.tufts.edu)

**Katharina Reinecke**  
University of Michigan  
[reinecke@umich.edu](mailto:reinecke@umich.edu)

**Remco Chang**  
Tufts University  
[remco@cs.tufts.edu](mailto:remco@cs.tufts.edu)

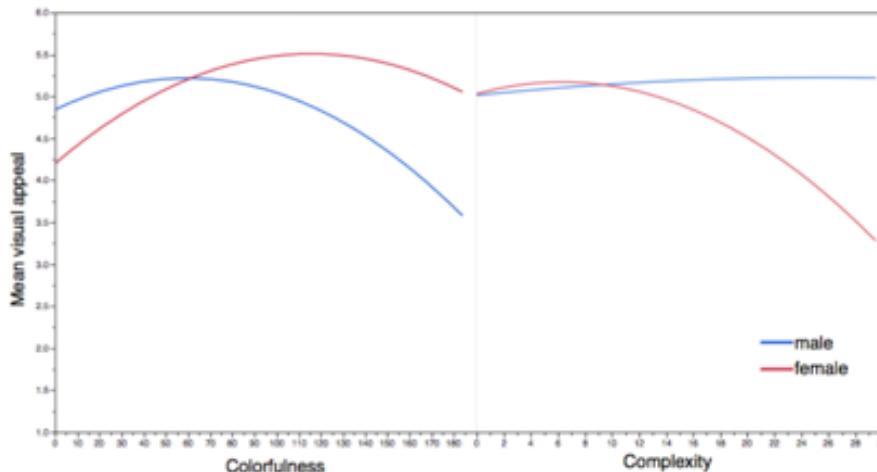
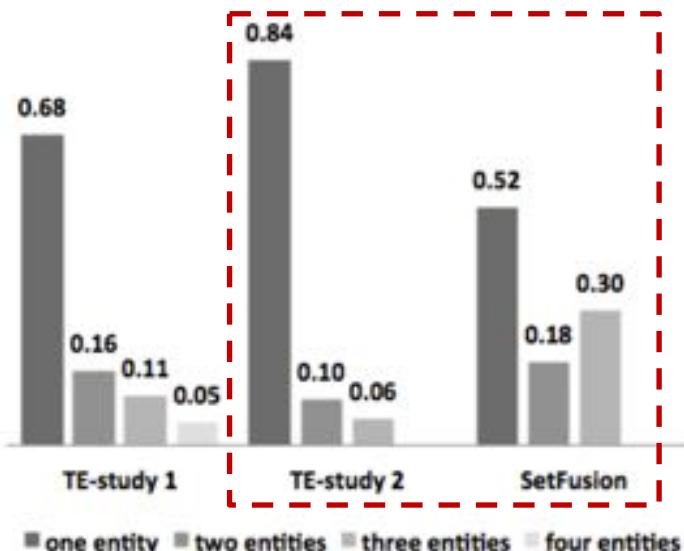


Figure 2: Average visual appeal ratings for different levels of colorfulness and complexity for females and males.

# TalkExplorer vs. SetFusion

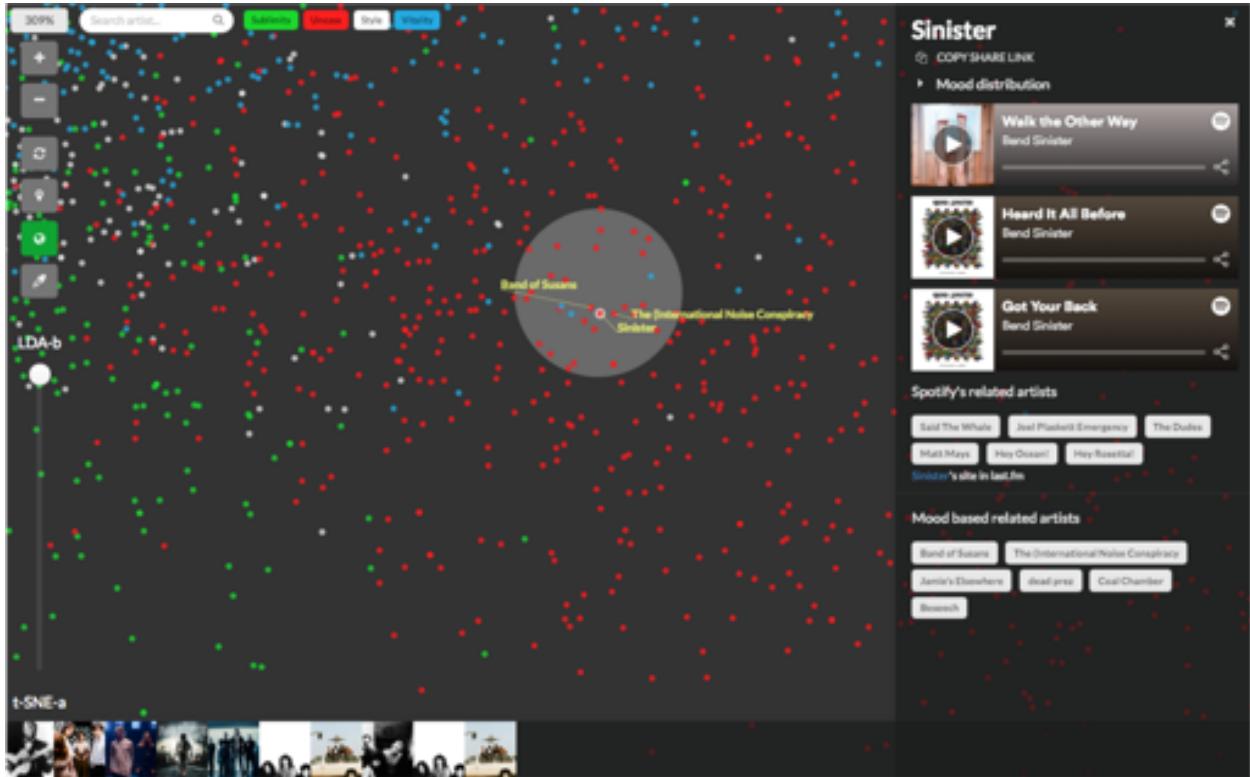
- How can we promote people's interaction?



- In TalkExplorer, 84% of the explorations over intersections were performed over clusters connecting to 1 entity
- .
- In SetFusion, was only 52%, compared to 48% (18% + 30%) of multiple intersections.

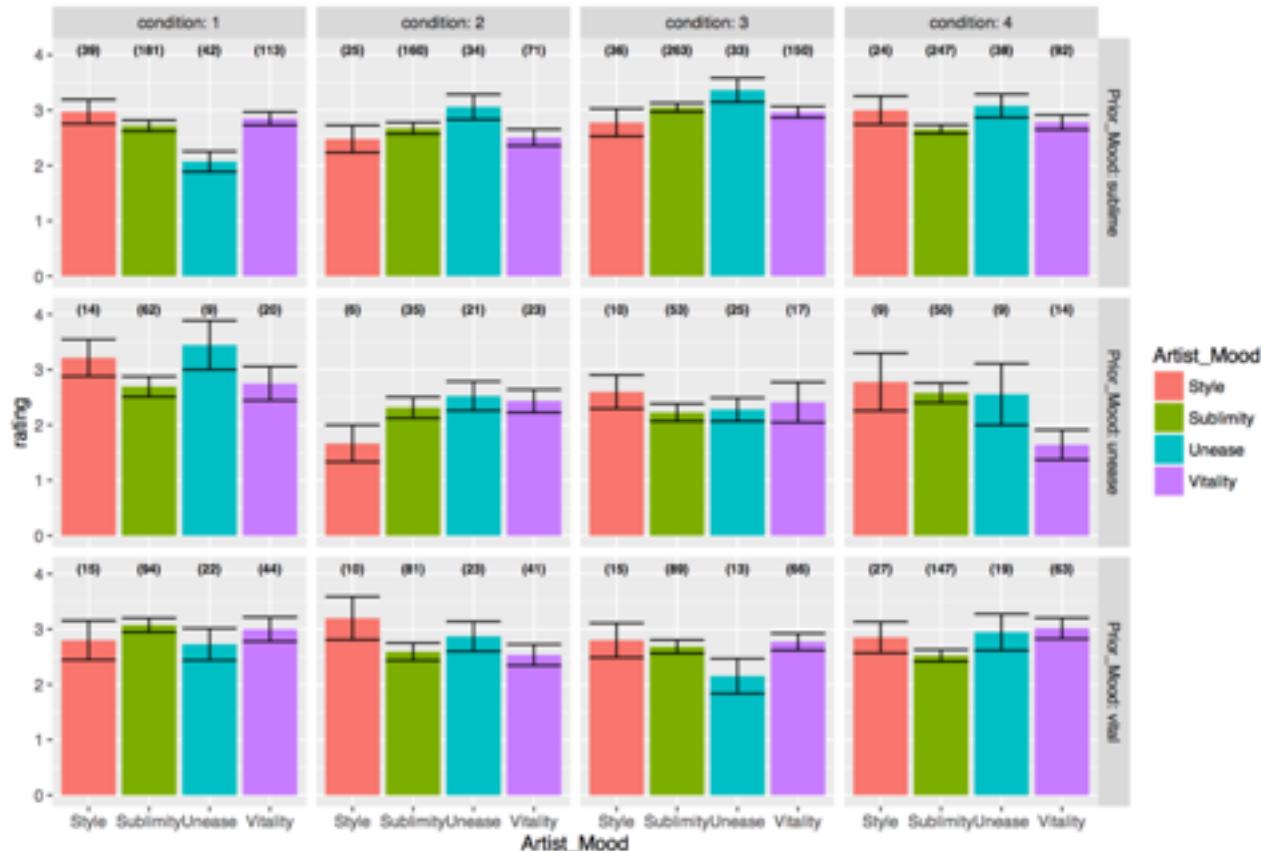
# Moodplay

- Moodplay:  
Interactive Mood-based Music Discovery and Recommendation.  
(UMAP 2016)
- Ivana Andjelkovic,  
Denis Parra, and John O'Donovan.



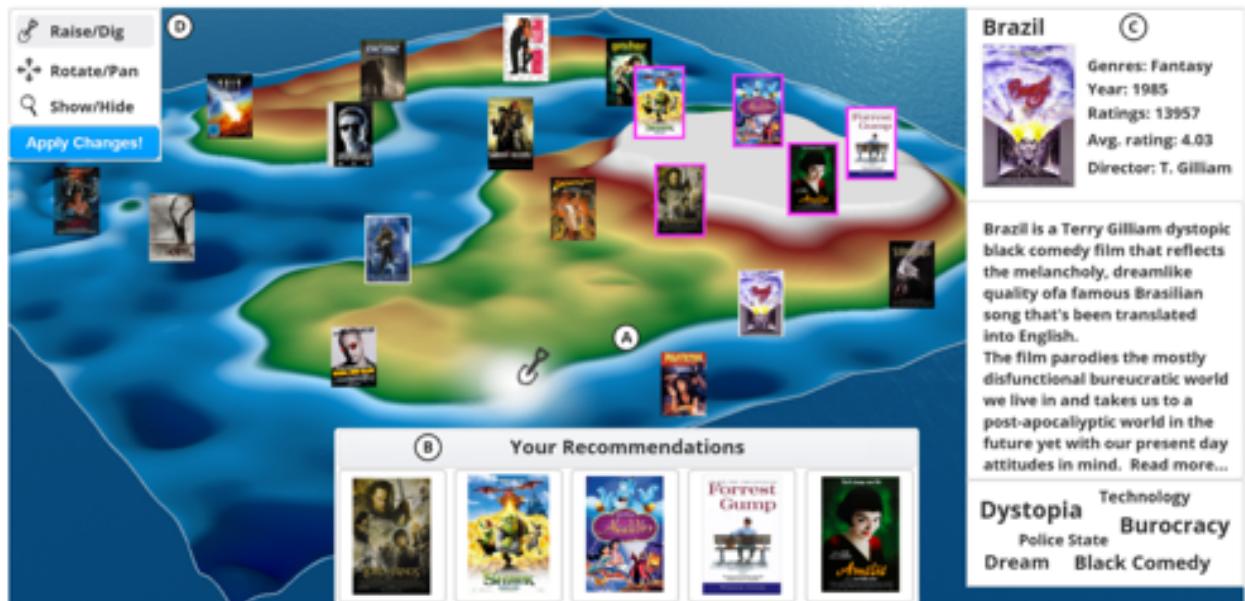
<http://moodplay.pythonanywhere.com/>

# Users' Prior Mood vs Artist Mood



# 3D Landscape

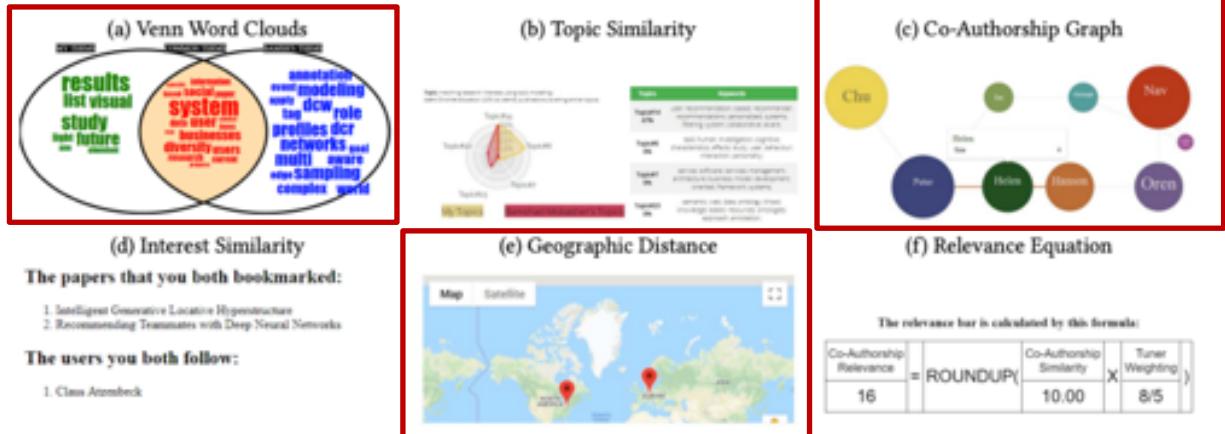
- A 3D item space visualization for presenting and manipulating user preferences in collaborative filtering (IUI 2017)
- Kunkel, J., Loepp, B., & Ziegler, J.



# Tuner+

- Explaining recommendations in an interactive hybrid social recommender (IUI 2019)
- Tsai, C. H., & Brusilovsky, P.

Profile	Relevance *	C Name	D Follow	Connect	Affiliation	Position
A	10 8 6 10	Bart	Following X	Waiting confirmation	University	Professor
B	5 10 6 6	Lulu	Follow	Add as connection	University	Student



# To Explain or Not

- To explain or not to explain: the effects of personal characteristics when explaining music recommendations (IUI 2019)



- Millecamp, M., Htun, N. N., Conati, C., & Verbert, K.

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

# What have we learned from this research?

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

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# What have we learned from this research?

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- We should let users choose whether see explanations or not
- Explanations should present different levels of details

# If time allows ... Levels of details



- A physicist, an engineer and a psychologist are called in as consultants to a dairy farm whose production has been below par.
  - **Engineer:** *Efficiency could be improved if the cows were more closely packed, with a net allotment of 275 cubic feet per cow*

# If time allows ...

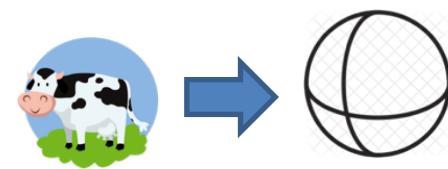


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  - **Psychologist:** *The inside of the barn should be painted green. This is a more mellow color than brown and should help induce greater milk flow.*

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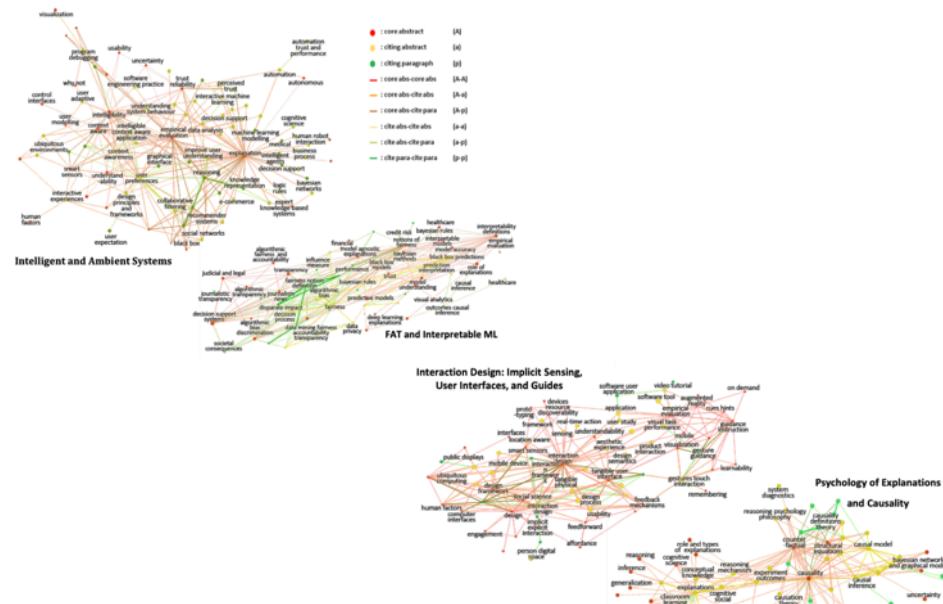
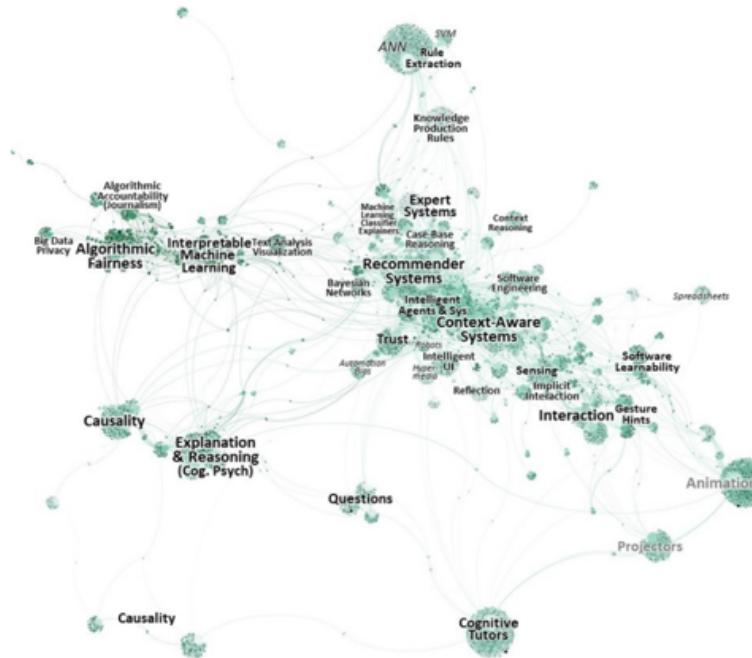


- A physicist, an engineer and a psychologist are called in as consultants to a dairy farm whose production has been below par.
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  - Psychologist: *The inside of the barn should be painted green. This is a more mellow color than brown and should help induce greater milk flow.*
  - **Physicist:** "Assume the cow is a sphere...."



Lawrence M. Krauss, Fear of Physics: A Guide for the Perplexed

## **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 there is no framework yet for designing Visual XAI

# Work in Progress: VD4XAI

## XAI Space

Threat: Wrong problem

Validate: Observe and interview end user

(NEW) Threat: Wrong explanation type

Validate: Justify explanation with literature or example and interview end user

(NEW) Threat: Wrong XAI method

Validate: Justify method with literature or example and interview end users

(NEW) Threat: Wrong visual justification

Validation: Analyze data availability

Nested model Tamara Munzer (3 last steps)

Validate: Test on target users, include anecdotal evidence of visual explanation utility about model response

Validate: Field study, document human usage of deployed system

Validate: Observe adoption rates

## Design Space

Nested model Tamara Munzer (3 last steps)

Threat: Wrong task/data abstraction

Threat: Ineffective encoding/interaction idiom

Validate: Justify encoding/interaction design

Threat: Slow algorithm

Validate: Analyze computational complexity

Implement system

Validate: Measure system time/memory

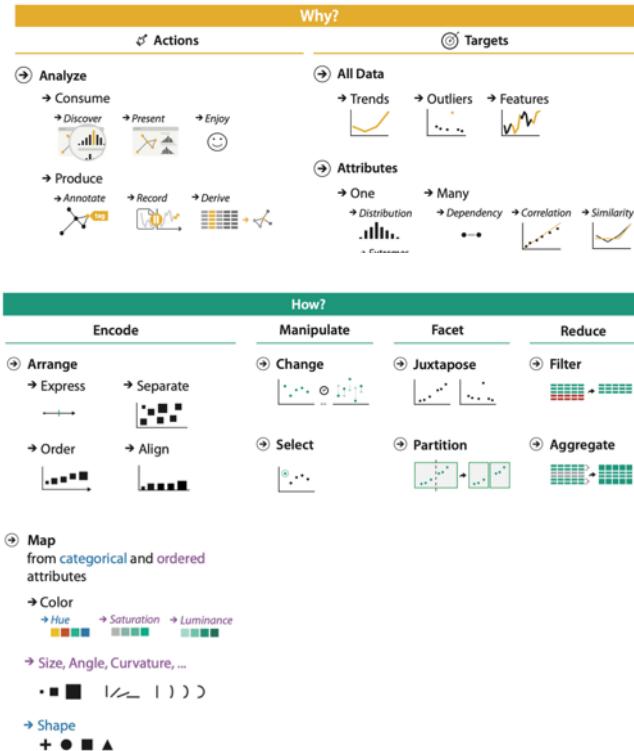
Validate: Qualitative/quantitative result analysis. Test on any users, informal usability study

Validate: Lab study, measure human time/errors for task.

H Valdivieso, D Parra, I Donoso, T Schreck, C Wang and K Verbert.

**VD4XAI: Connecting the Visualization Design Space with the Explainable AI Task Space.** Work in progress

# Munzner VAD model



## Design Space

### Nested model Tamara Munzer (3 last steps)

**Threat:** Wrong task/data abstraction

**Threat:** Ineffective encoding/interaction idiom

**Validate:** Justify encoding/interaction design

**Threat:** Slow algorithm

**Validate:** Analyze computational complexity

Implement system

**Validate:** Measure system time/memory

**Validate:** Qualitative/quantitative result image analysis Test on any users, informal usability study

**Validate:** Lab study, measure human time/errors for task

# Analyze LIME



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Text with highlighted words

From: USTS012@ubdpo.dpo.ub.edu

Subject: Should teenagers pick a church parents don't attend?

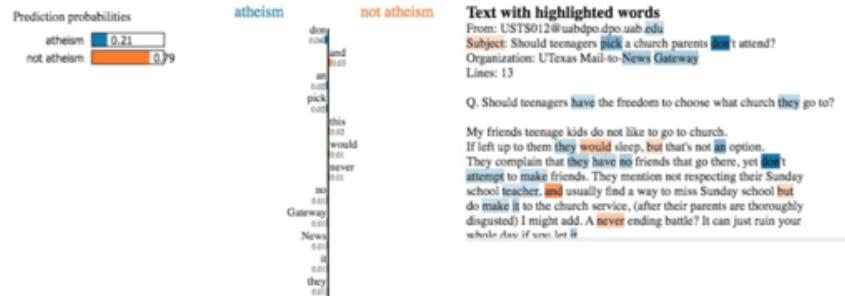
Organization: UTexas Mail-to-News Gateway

Lines: 13

Q. Should teenagers have the freedom to choose what church they go to?

My friends teenage kids do not like to go to church.  
If left up to them they would sleep, but that's not an option.  
They complain that they have no friends that go there, yet don't attempt to make friends. They mention not respecting their Sunday school teacher, and usually find a way to miss Sunday school but do make it to the church service, (after their parents are thoroughly disgusted) I might add. A never ending battle? It can just ruin your whole day if you let it.

# Analyze LIME: Marks, channels and Interaction



## Additional Mark - Circle Area (B)

Title: a meta analysis of birth origin effects on reproduction in diverse captive environments

Abstract: successfully establishing captive breeding programs is priority across diverse industries to address food security demand for ethical laboratory research animals and prevent extinction differences in reproductive success due to birth origin may threaten the long term sustainability of captive breeding our meta analysis examining effect sizes from species of invertebrates fish birds and mammals shows that overall captive born animals have

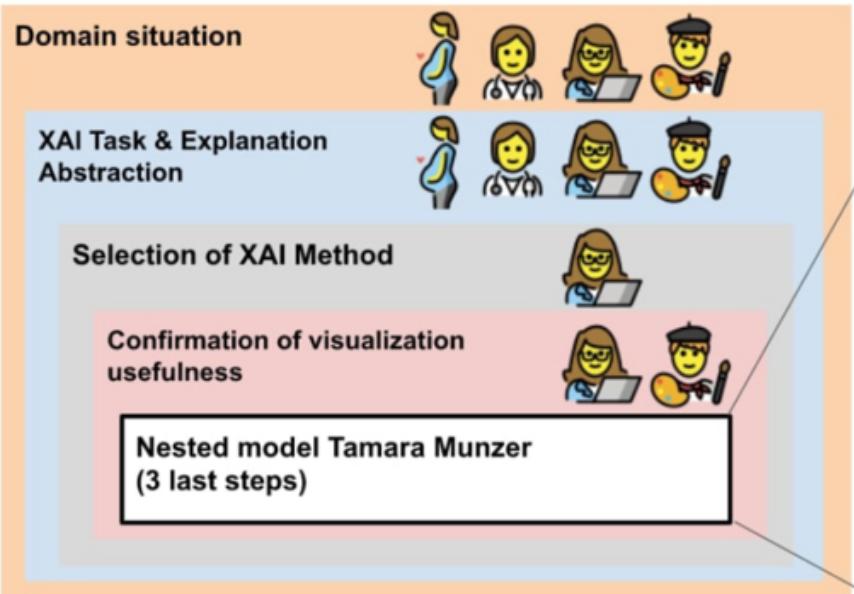
## Additional Mark - Bars Length (A)

Title: a meta analysis of birth origin effects on reproduction in diverse captive environments

Abstract: successfully establishing captive breeding programs is priority across diverse industries to address food security demand for ethical laboratory research animals and prevent extinction differences in reproductive success due to birth origin may threaten the long term sustainability of captive breeding our meta analysis examining effect sizes from species of invertebrates fish birds and mammals shows that overall captive born animals have

# XAI Space

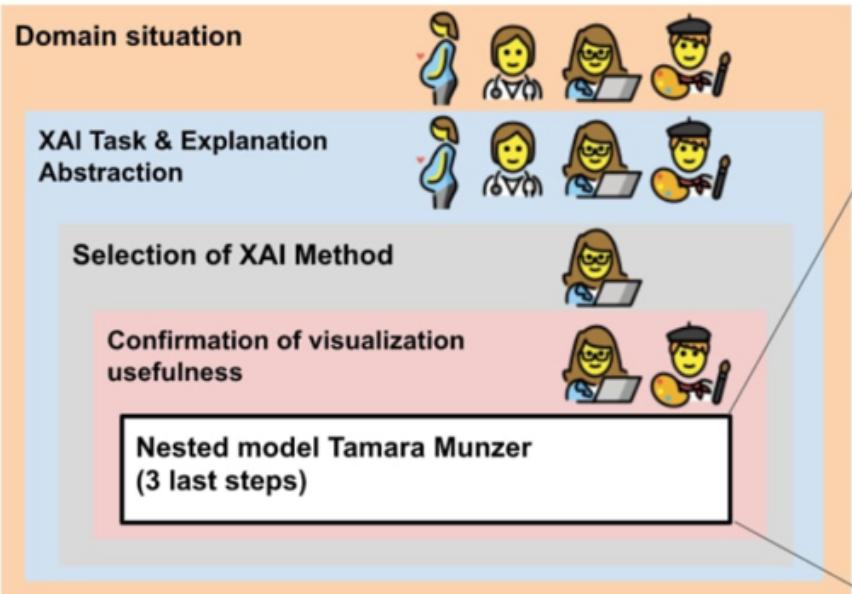
## XAI Space



- Data type: tabular, text, image, graph, etc.
- **XAI tasks** (Gunning et al., 2019):
  - Understand why does the given AI/ML model give its prediction,
  - Understand when does the AI/ML model fail,
  - Understand when does the AI/ML model succeed,
  - Understand why the AI/ML model does not predict something else

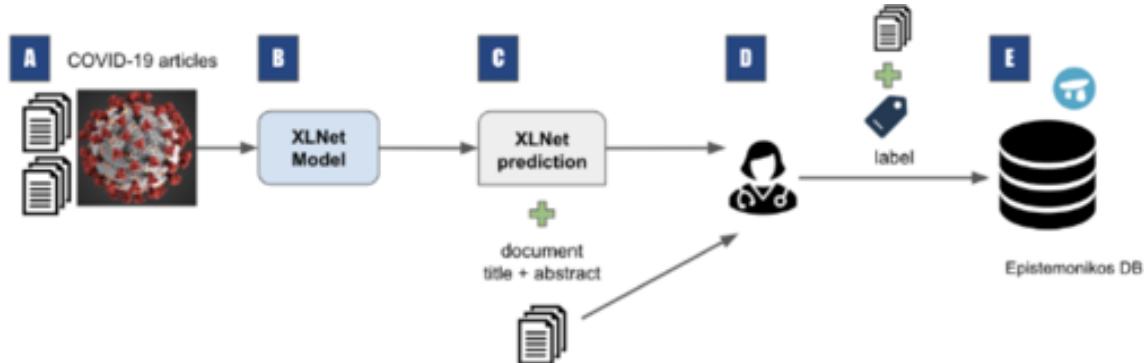
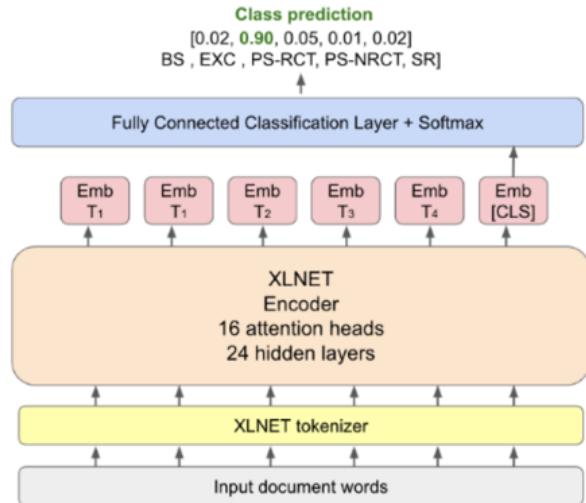
# XAI Space

## XAI Space



- **XAI Strategy:**
  - Feature importance,
  - Analogies (similar to),
  - Counterfactuals,
  - Rules
- **XAI method:**
  - Post-hoc: LIME, SHAP, etc.
  - Method-wise: DT, LR
  - Others
- AI model (neural network, SVM, DT, etc.)

# Recent study: Biomedical Document Classification



# Recent study: Biomedical Document Classification

The screenshot shows a web-based application interface for document classification. At the top, the URL is https://app.iloveevidence.com/screenings/80ca4723e689d3e0f4999c04. Below the URL, there's a header with COVID-19 News, Druud Syntheses (paper), Screening (highlighted in green), and Statistics.

**(A)** Predicted Label Confidence: Broad Synthesis (99.2% out of 100%)

**(B)** Show tutorial

**(C)** Scoping review of propelling aids for manual wheelchairs.  
Manual wheelchair (MWC) users face a variety of obstacles limiting their participation. Different MWC models and new add-on components intended to improve propulsion may impact users' function and participation, although there is a lack of research on this topic. The aims of this study were to 1) identify MWC propelling aids (PA) that are reported in the literature; 2) classify the outcomes used to evaluate the influence of PA according to the International Classification of Functioning, Disability and Health (ICF); and 3) summarize evidence for the influence of PA. A scoping review was conducted in 2017 using PubMed, Medline, Embase, CINAHL, Compendex, IEEE Xplore, RESNA, and ISS proceedings, Google, and Google Scholar. The content of each manuscript was assessed by two independent reviewers. A total of 28 PA (29 human-powered, 9 power-assisted) were identified from 163 manuscripts. The three most cited ICF subdomains were "Activity & Participation" ( $n = 125$ ), "Body Function" ( $n = 100$ ), and "Personal Factors" ( $n = 55$ ). The findings suggest an overall positive influence of PA on various ICF domain/subdomains, but initial findings should be interpreted with caution. Confirmation of the effect and safety of PA requires higher levels of evidence.

**(D)** Is this document a: Broad synthesis  
Yes      No

Select your expected label and click the button Next:  
Excluded      Randomized Trial      Non-randomized Studies      Systematic Review

**(E)** How much do you agree with the following two statements  
To choose the document category, it was useful:  
Predicted Label Confidence: Neutral  
Fully Agree      Fully Disagree  
The highlighted words in abstract: Neutral  
Fully Agree      Fully Disagree

**(F)** Epistemonikos User Study  
Phase 1 of 2: Fixed Visualizations  
Total progress: 3/100  
Background Color  
Link to challenge  
3/20

# Designs to test: marks and channels

## (A) Control group (plain text)

### CONCLUSION:

The CYP2B6 rs20046 variant T/T favors lower incidence of hot flashes/swelling under abiraterone + ADT treatment, suggesting endocrine-mediated effects. Based on findings from others, this SNP may potentially enhance treatment adherence and treatment efficacy. We plan to evaluate the clinical impact of this polymorphism during time, pending sufficient median follow up.

## (C) Word luminance

The study is designed as a Phase II, multi-center trial of tandem autologous transplant versus the strategy of autologous followed by Human Leukocyte Antigen (HLA)-matched sibling non-myeloablative allogeneic transplant. Study subjects will be biologically assigned to the experimental arm depending on the availability of an HLA-matched sibling. There is a limited concurrent phase II trial of observation versus maintenance therapy following the second autologous transplant for patients on the tandem autologous transplant arm.

## (B) Background color saturation

A randomized phase II trial of personalized peptide vaccine plus low dose estramustine phosphate (EMP) versus standard dose EMP in patients with castration resistant prostate cancer.

Personalized peptide vaccination (PPV) combined with [therotherapy] could be a novel approach for many cancer patients. In this randomized study, we evaluated the anti-tumor effect and safety of PPV plus low-dose estramustine phosphate (EMP) as

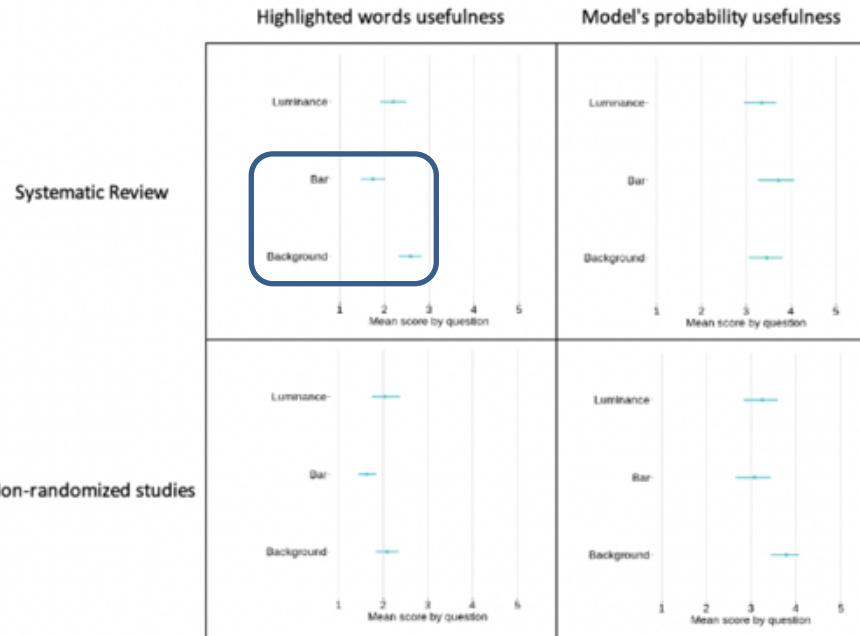
## (D) Bar length

### CONCLUSION:

Both methods LA and [BNA] provided excellent pain relief and lower morphine consumption following TKA. LA is a surgeon-controlled analgesic technique, which can be used to enhance patients' satisfaction and reduce the pain in the very early postoperative period by surgeon [independents].

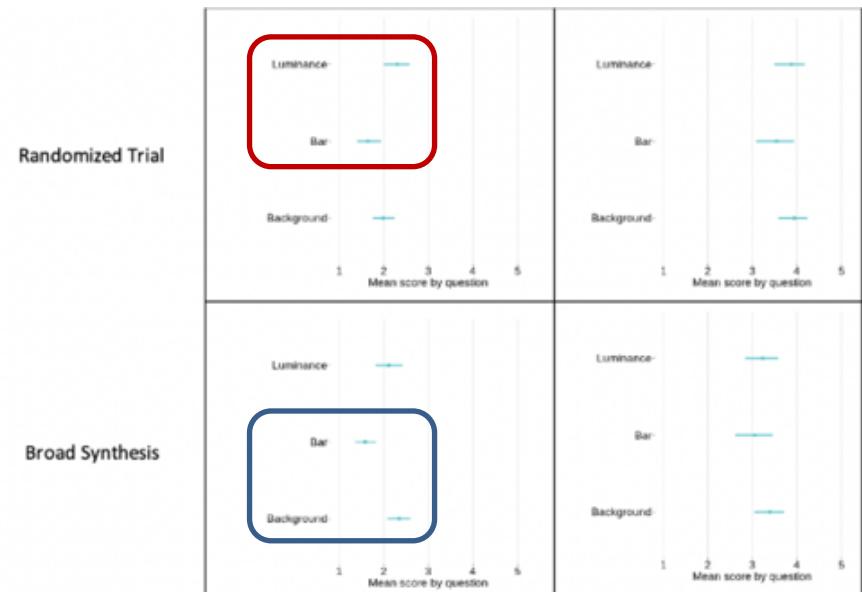
# Recent study: Document Classification

\* Perception of usefulness of visual XAI encoding for attention-based explanations vary depending on document type



Systematic Review

Non-randomized studies



Randomized Trial

Broad Synthesis

# 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

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**THANKS!**

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