Fairness, Accountability and Transparency (FAT) in Recommender Systems

Denis Parra
PUC Chile & IMFD

IIC3633
(basada en charla LARS / Fortaleza, Brasil, Oct. 2019)

We are living incredible days…

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

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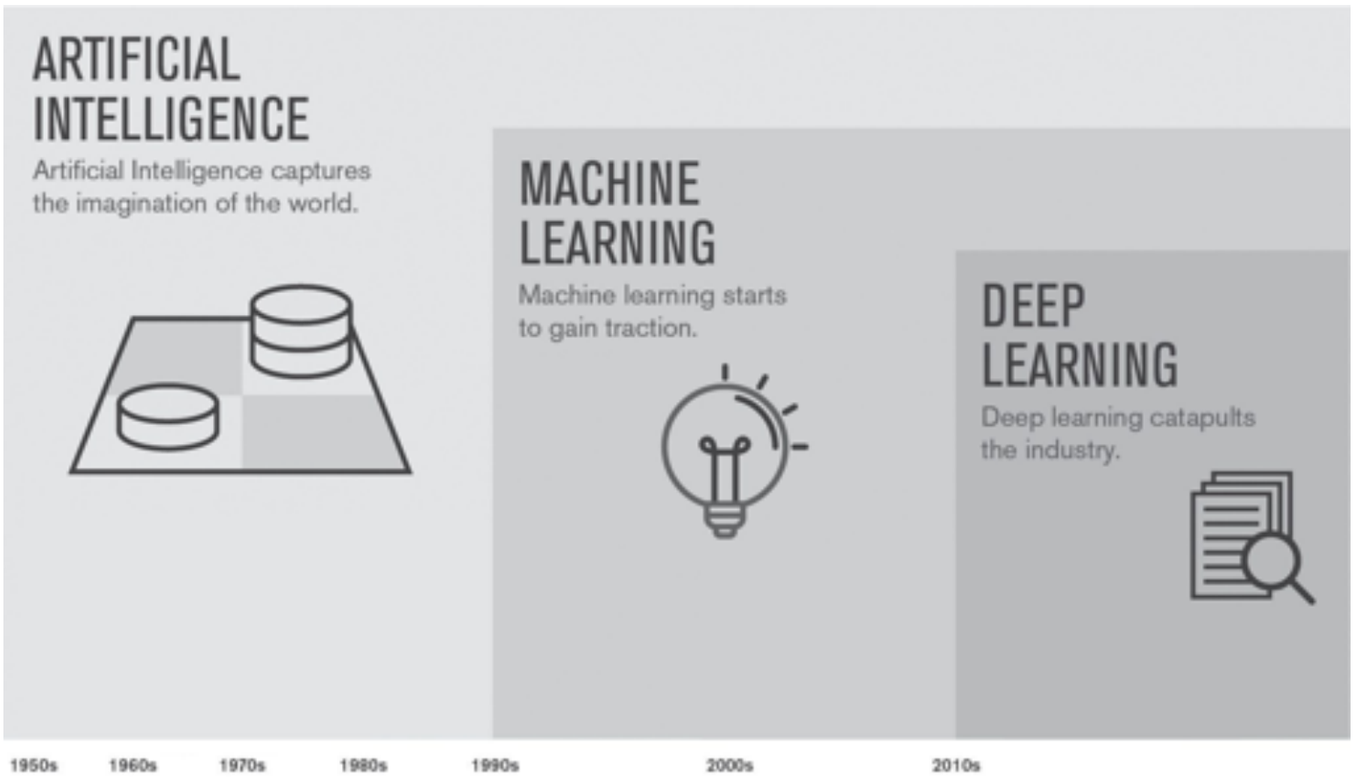


Natural Language Processing

- (2010-2011) IBM Watson beats humans in Jeopardy. << ... With all of its processing CPU power, Watson can scan two million pages of data in three seconds.>>

E. Nyberg, CMU professor

http://www.aaai.org/Magazine/Watson/watson.php

Self-Driving Cars

Mastering Go

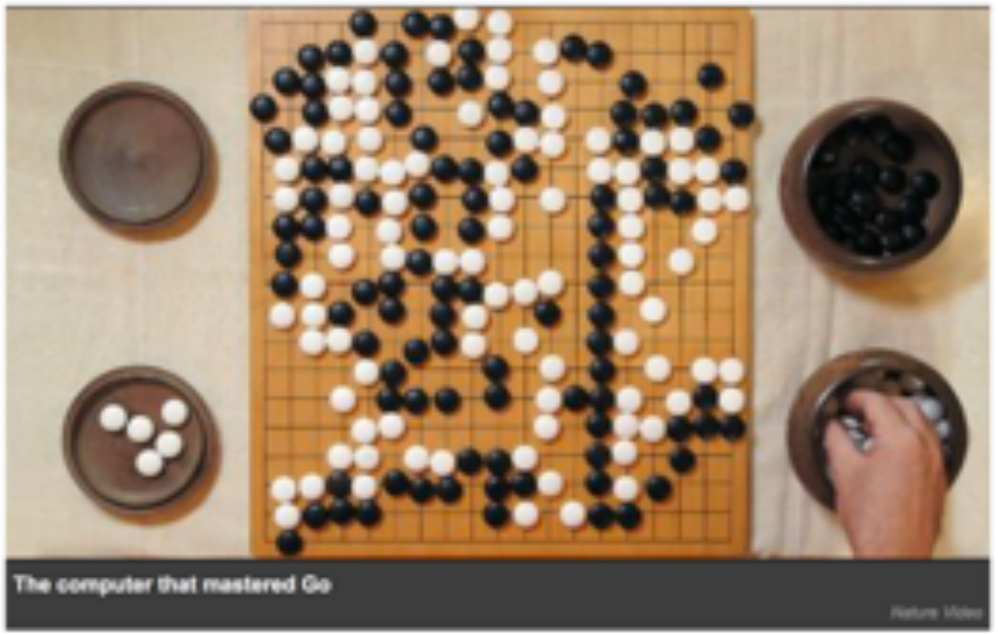
Google AI algorithm masters ancient game of Go

Deep-learning software defeats human professional for first time.

Elizabeth Gibney

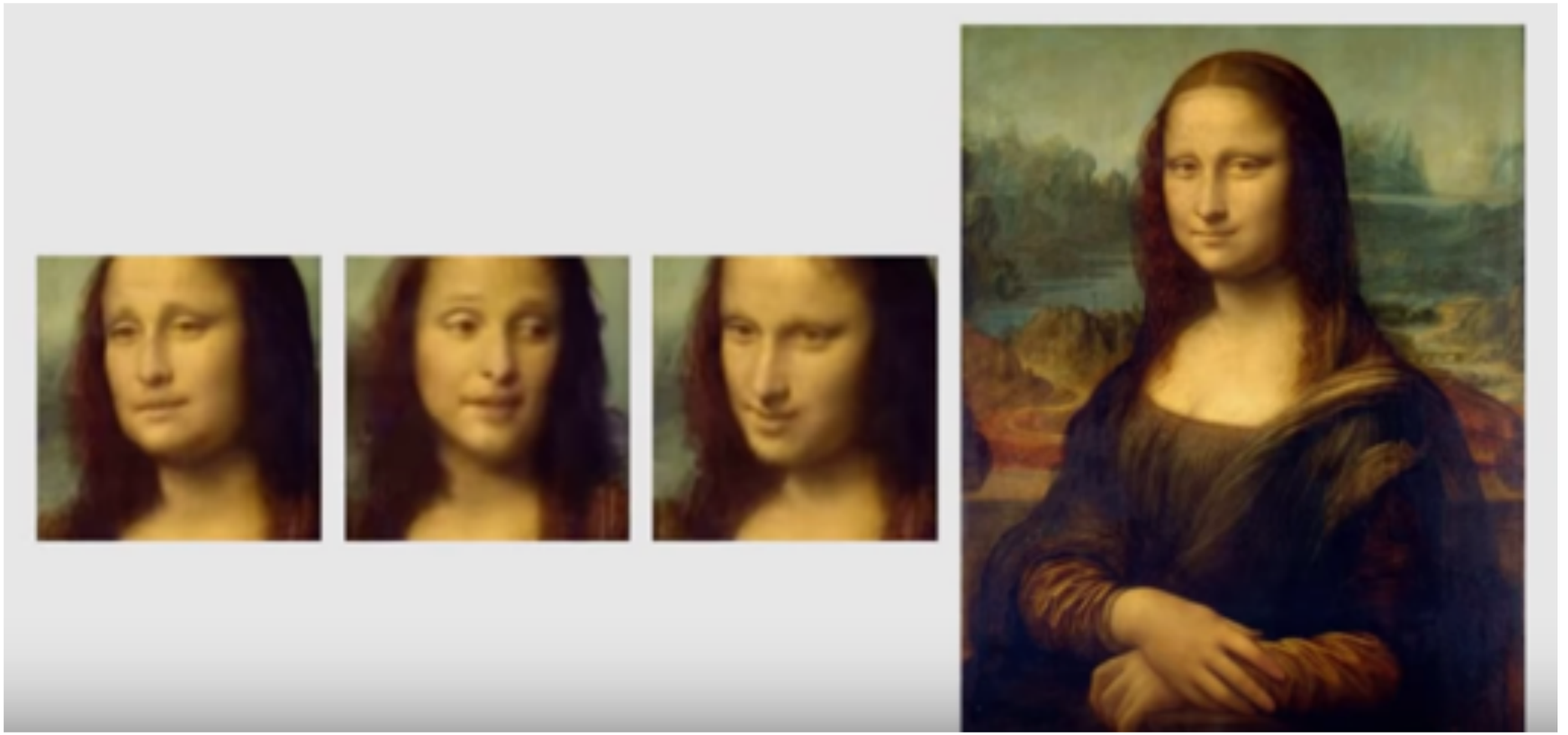
27 January 2016

PDF | Rights & Permissions



The computer that mastered Go

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

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.

- 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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- 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

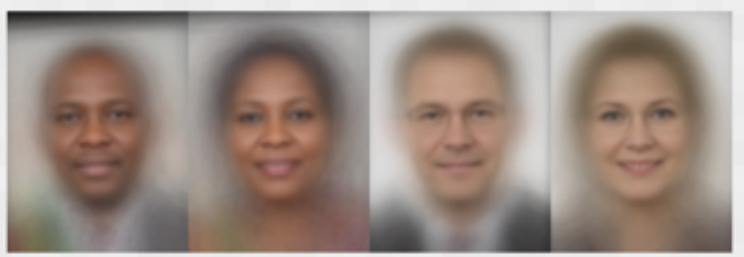
Other case: Gender Shades

- 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

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%



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

Some voices call for deeper discussion

We need to realize that the current public dialog on AI—which focuses on a narrow subset of industry and a narrow subset of academia—risks blinding us to the challenges and opportunities that are presented by the full scope of AI, IA and II.

Photo credit: Peg Skorpinski

Artificial Intelligence—The Revolution Hasn't Happened Yet

Thus, just as humans built buildings and bridges before there was civil engineering, humans are proceeding with the building of societal-scale, inference-and-decision-making systems that involve machines, humans and the environment.

Just as early buildings and bridges sometimes fell to the ground—in unforeseen ways and with tragic consequences—many of our early societal-scale inference-and-decision-making systems are already exposing serious conceptual flaws.

https://medium.com/@mijordan3/artificial-intelligence-the-revolution-hasnt-happened-yet-5e1d5812e1e7

Can Recommender Systems be affected?

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- Yes

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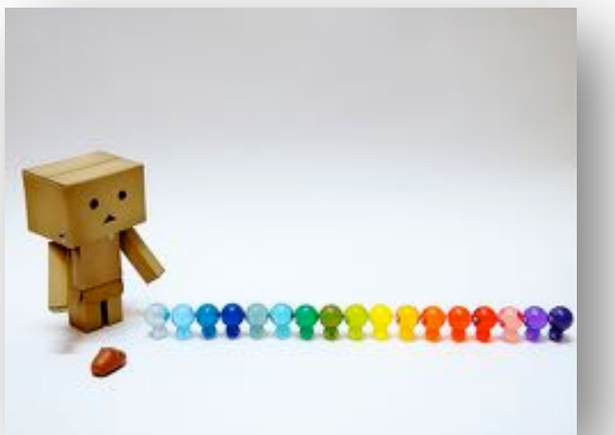
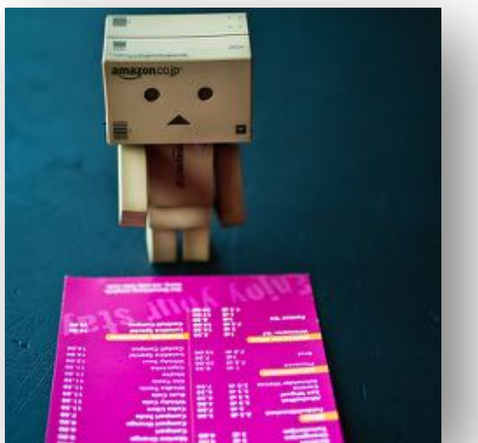
- Yes, RecSys are socio-technical systems !

- RecSys help people on filtering noise, identifying relevant items from a large information space. They are usually optimized on accuracy and ranking metrics, not on fairness.





Can Recommender Systems be affected?

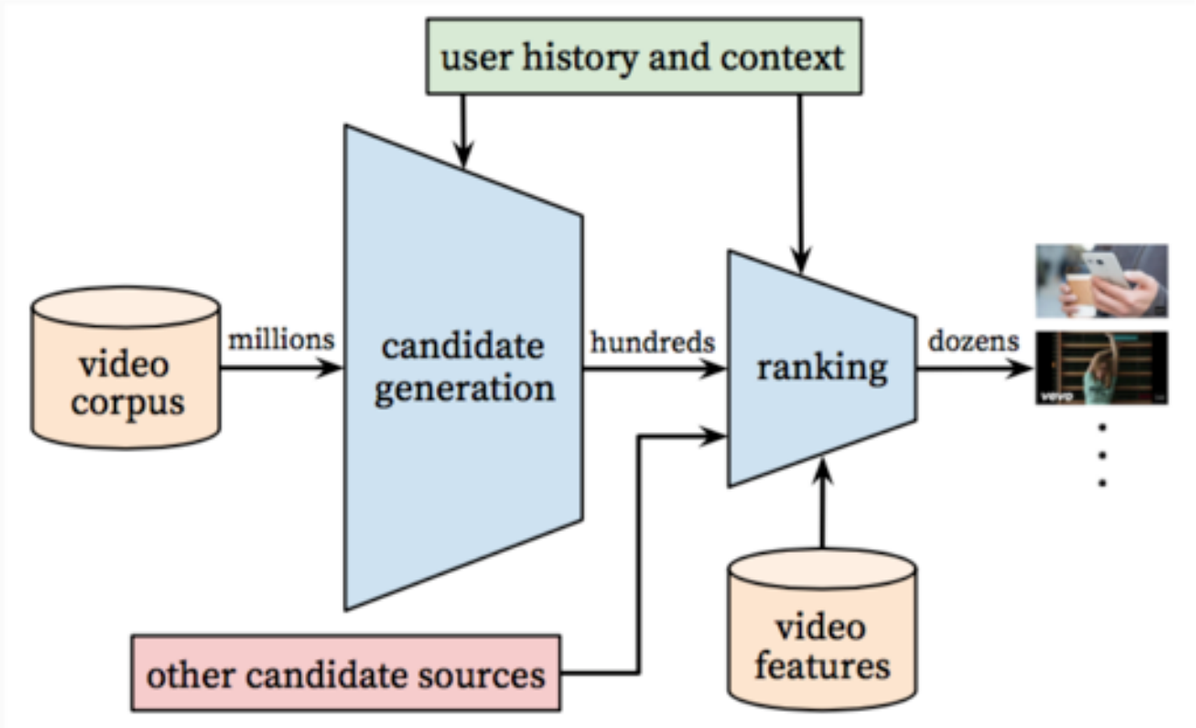
- Yes, RecSys are socio-technical systems !

- RecSys help people on filtering noise, identifying relevant items from a large information space. They are usually optimized on accuracy and ranking metrics, not fairness.

- The actual effects on user experience due to optimizing an accuracy/ranking metric are hard to predict.

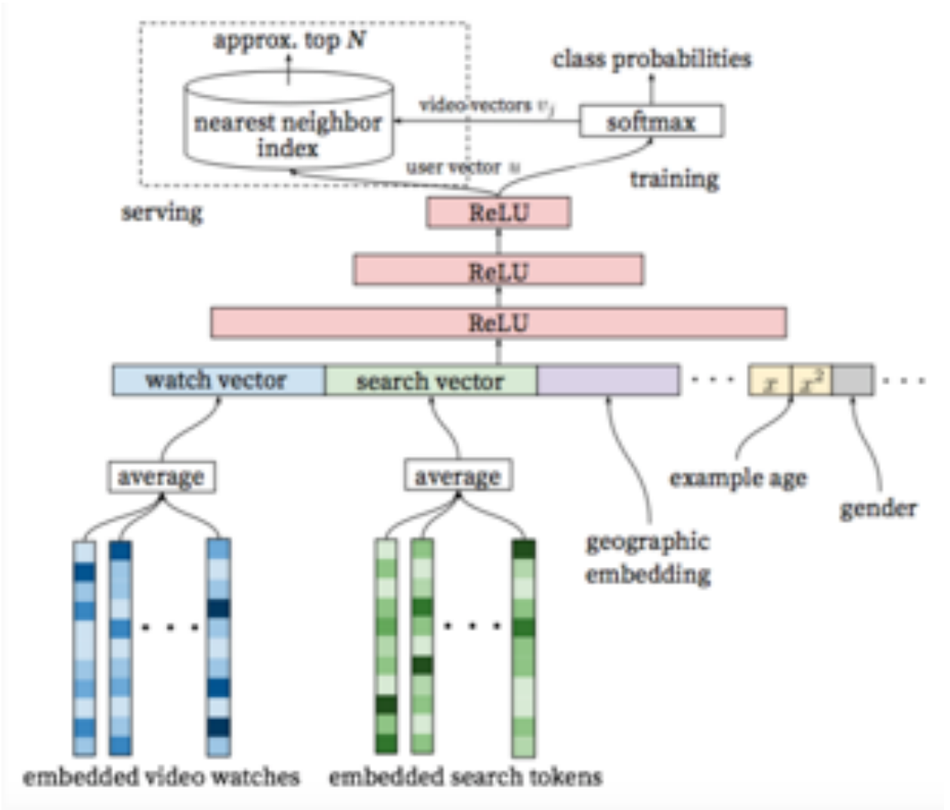
YouTube Deep Recommender System

- YouTube, ACM RecSys (2016)

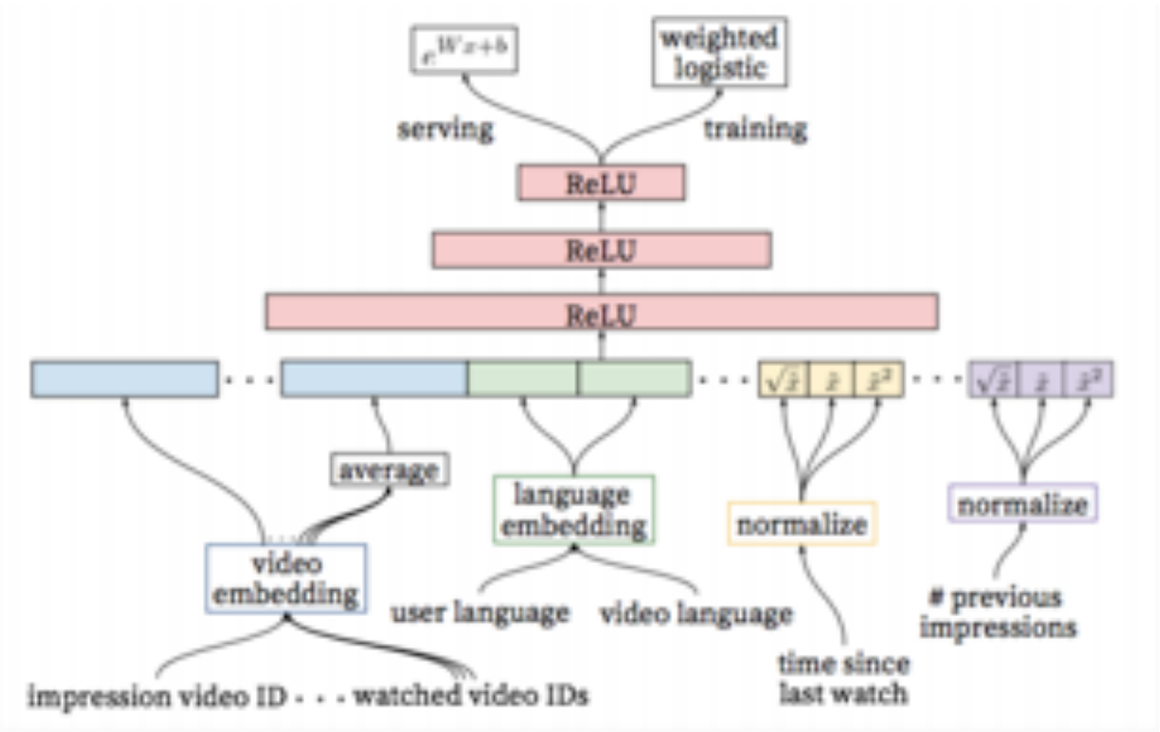


Covington, P., Adams, J., & Sargin, E. (2016, September). Deep neural networks for youtube recommendations. In *Proceedings of the 10th ACM conference on recommender systems* (pp. 191-198). ACM.

Neural Networks



Candidate Generation



Ranking

What does YouTube RecSys try to learn ?

- Artificial Intelligence systems still do not decide what to learn: a human tells them the task(s).

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- In the case of YouTube, tasks are: 1) predict the next video watched, and 2) predict the time the user spent watching the next coming video.

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- In the case of YouTube, tasks are: 1) predict the next video watch, and 2) predict the time the user spent watching the next coming

- The system is never told to distinguish good from bad content quality (fake news, violence, etc.)

What Does YouTube RecSys recommends the most?

- Guillaume Chaslot

- He worked developing the first recommender system of YouTube.

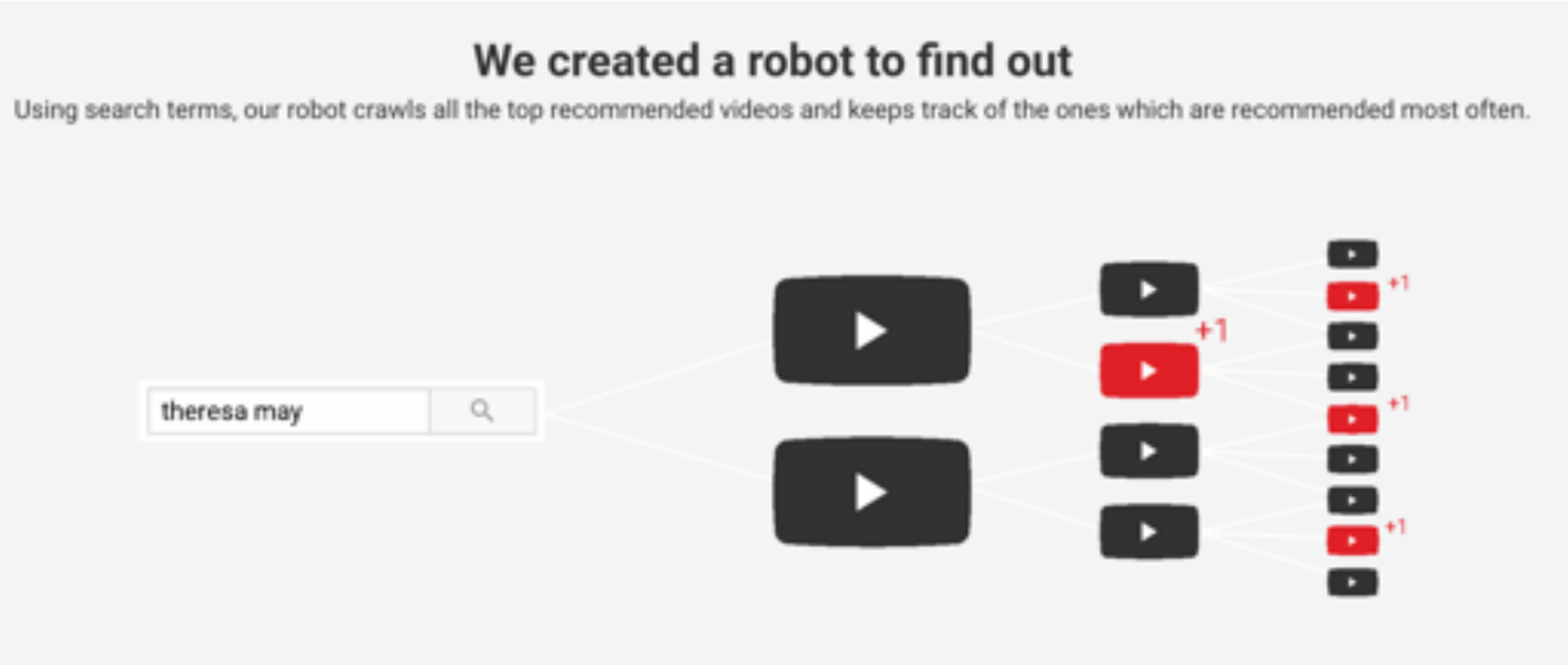
What Does YouTube RecSys recommends the most?

- Guillaume Chaslot

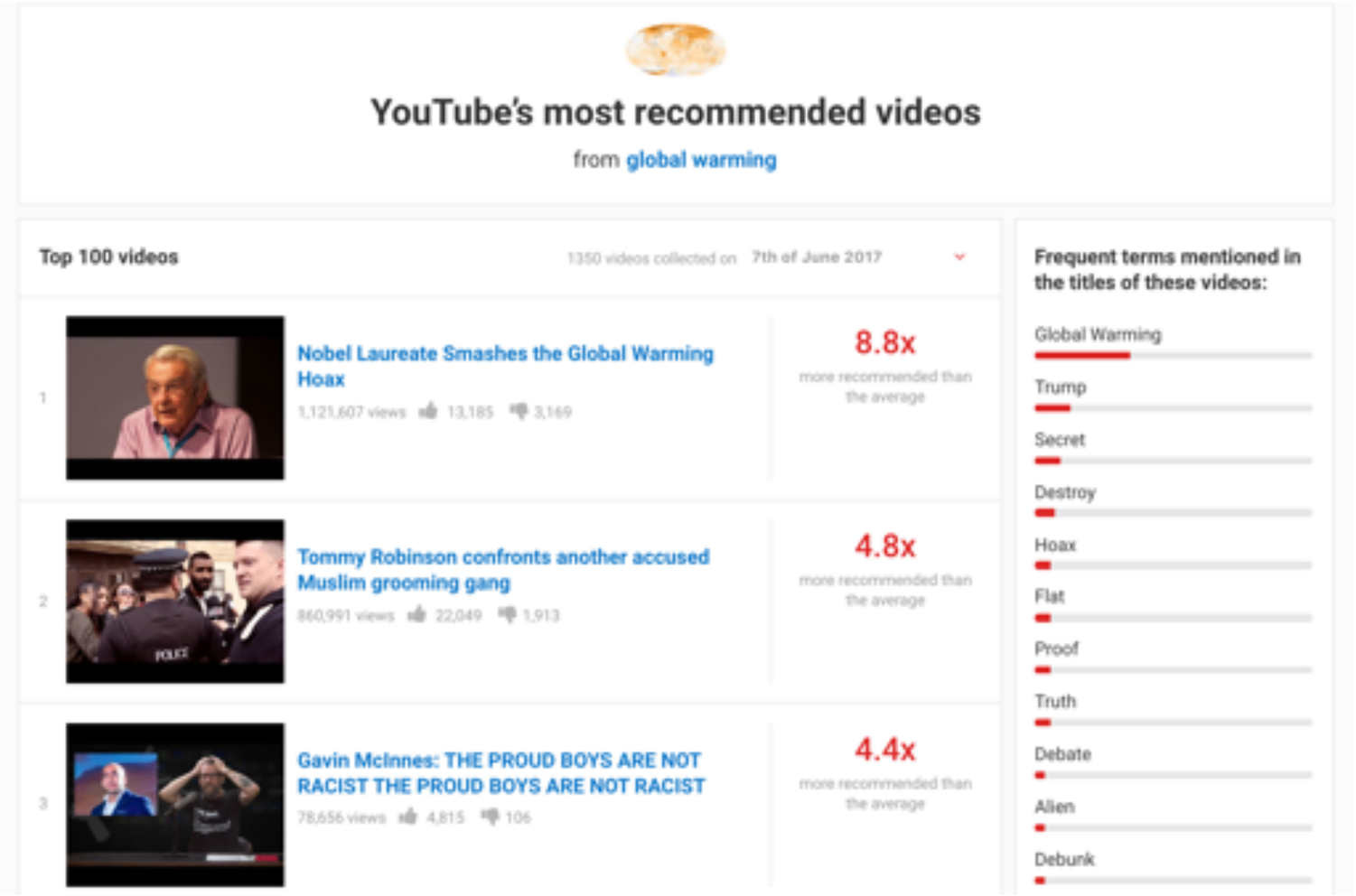
- After resigning from YouTube, he created a system to estimate what was being recommended

https://www.theguardian.com/technology/2018/feb/02/youtube-algorithm-election-clinton-trump-guillaume-chaslot

https://algotransparency.org



https://algotransparency.org



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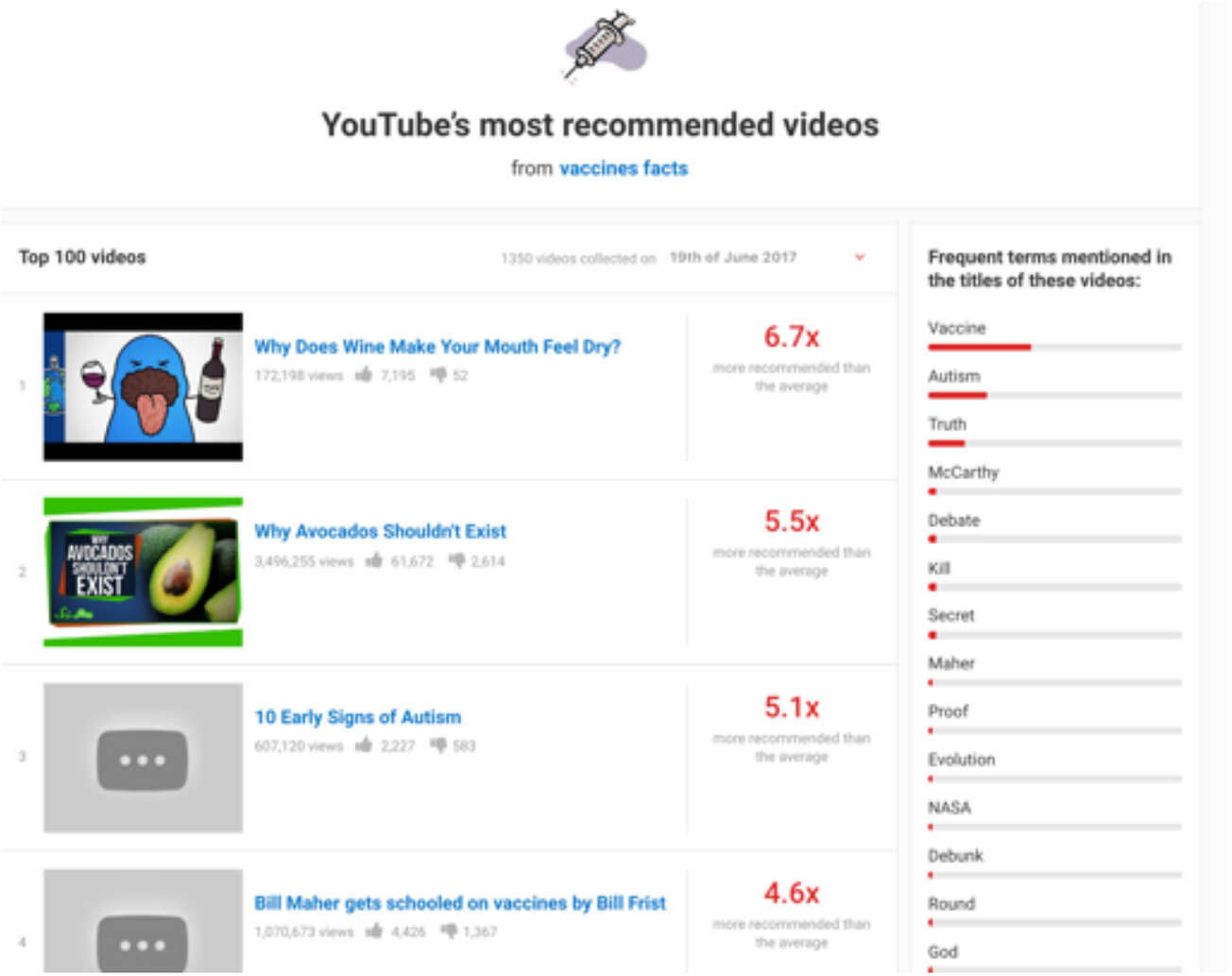


Do people consume YouTube Recommendations ?

Many Turn to YouTube for Children's Content, News, How-To Lessons

An analysis of videos suggested by the site's recommendation engine finds that users are directed toward progressively longer and more popular content

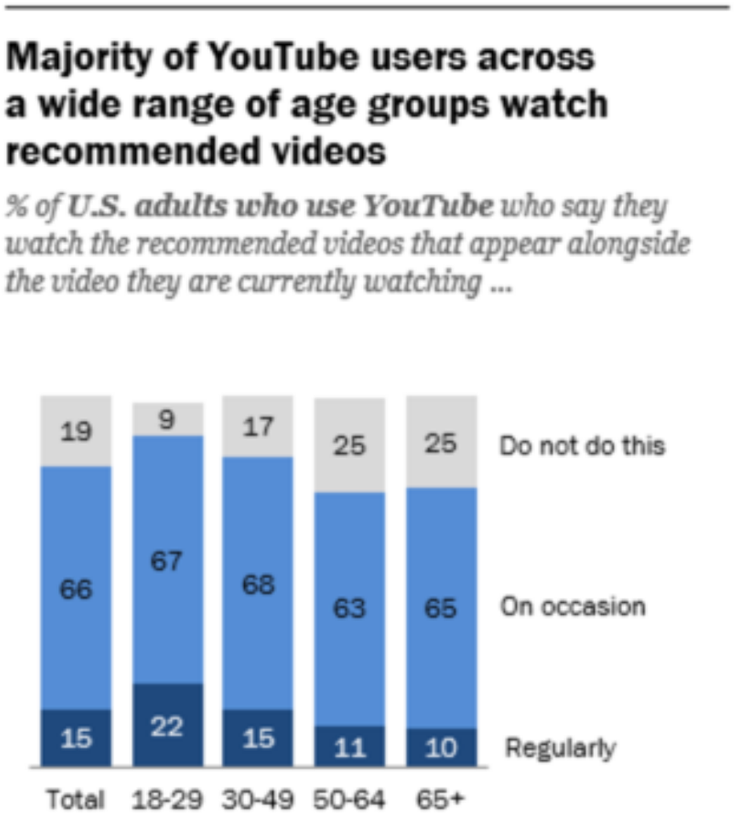
BY AARON SMITH, SKYE TOOR AND PATRICK VAN KESSEL

(MaaHoo Studio/Getty Images)

https://www.pewinternet.org/2018/11/07/many-turn-to-youtube-for-childrens-content-news-how-to-lessons

People do follow recommendations, indeed.

- Study by Pew Research Center



Methodology (Pew Research Internet)

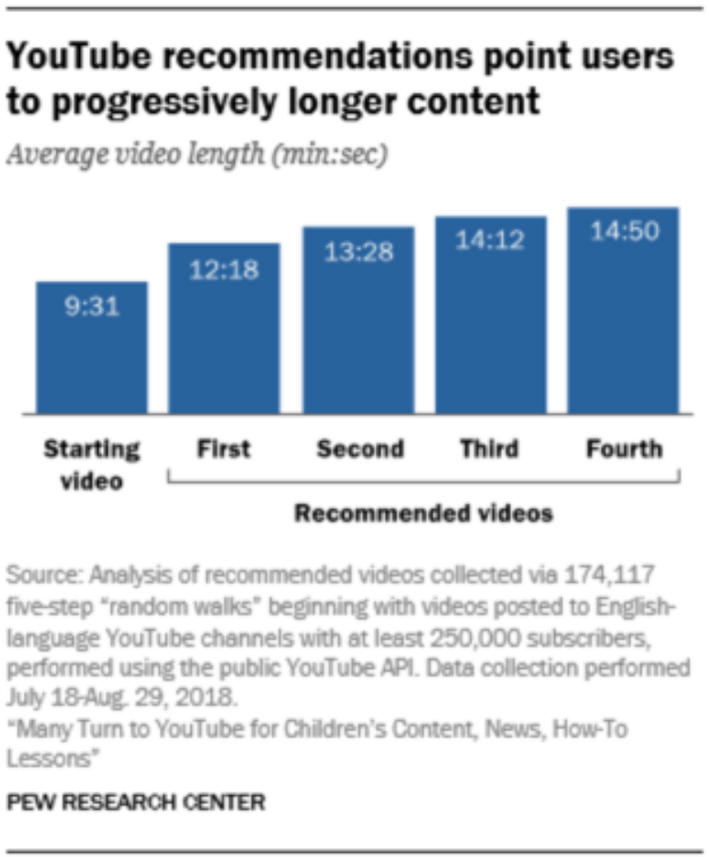
174,117 random walks resulted in

696,468 total encounters with

346,086 unique recommended videos

Are there trends in terms of Video length ?

- Data from Pew Research Center



Are there trends in terms of Video Popularity ?

- Data from Pew Research Center

New YouTube Recommender

- Presented in RecSys 2019, main change: multitask learning
- Still not addressing the issue of video quality / fake news

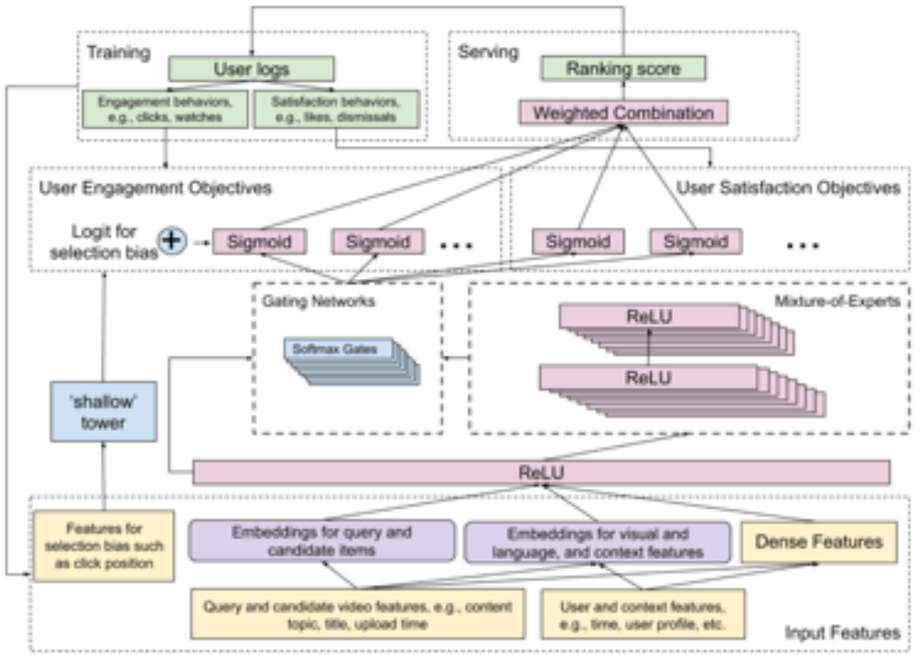


Figure 1: Model architecture of our proposed ranking system. It consumes user logs as training data, builds Multi-gate Mixture-of-Experts layers to predict two categories of user behaviors, i.e., engagement and satisfaction. It corrects ranking selection bias with a side-tower. On top, multiple predictions are combined into a final ranking score.

Should I care about this ?

- How can this affect my regular practice as professional developing or evaluating recommender systems ?

Law: What happened in May 25th, 2018 ?

- The EU General Data Protection Regulation (GDPR) becomes enforceable.

And why do we care in this room ?

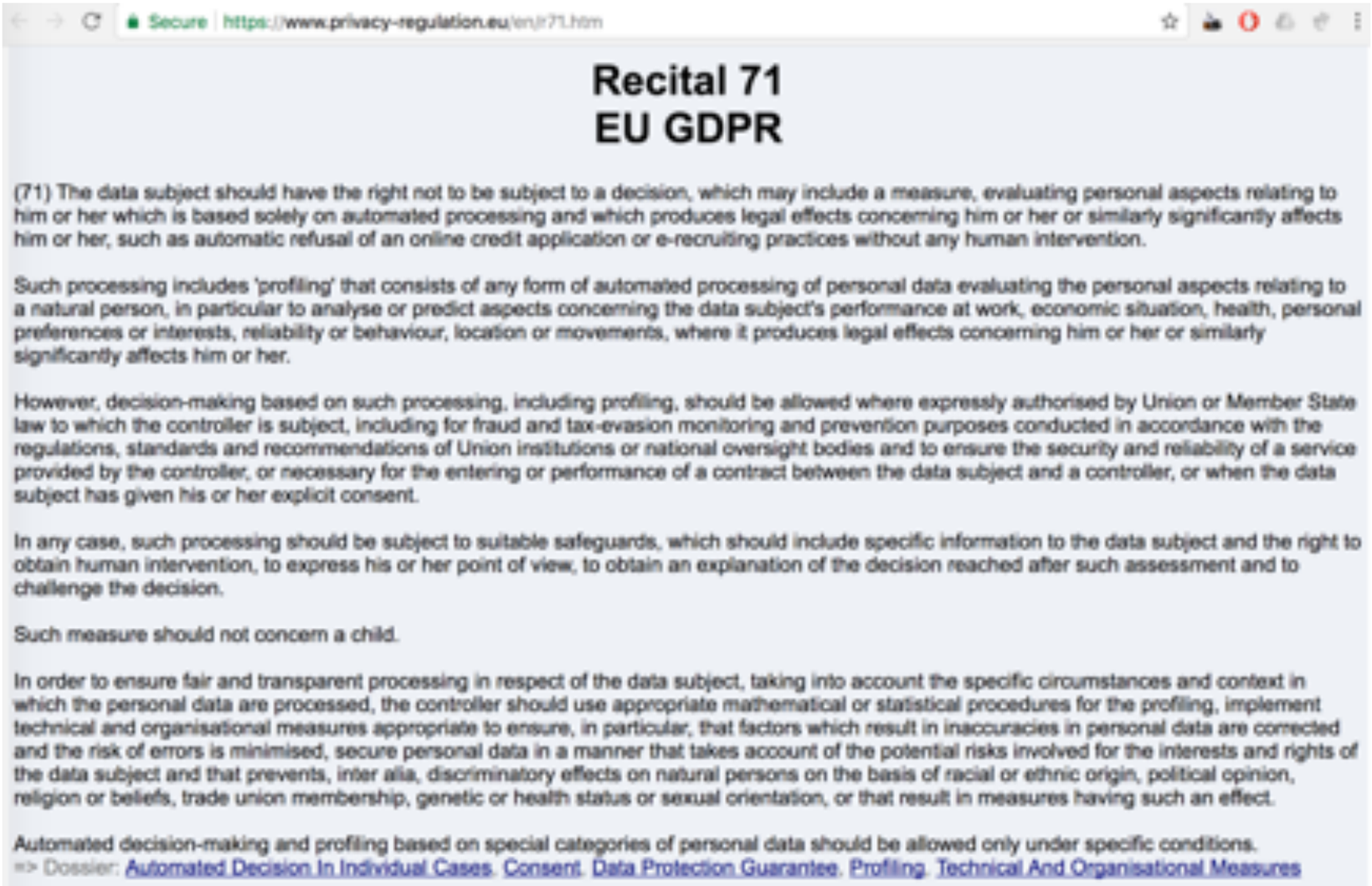
- The GDPR **not only applies to organisations located within the EU** but it will also apply to **organisations located outside of the EU** if they offer goods or services to, or monitor the behaviour of, EU data subjects.
- **It applies to all companies processing and holding the personal data** of data subjects residing in the European Union, regardless of the company's location.

Which is the effect on my current practice ?

Right to explanation

- Article 15 "**Right of access by the data subject**"
- Article 22 "**Automated individual decision-making, including profiling**"
- Recital 71 (linked to **art. 22**)

Recital 71



Secure | https://www.privacy-regulation.eu/en/r71.htm

Recital 71
EU GDPR

(71) The data subject should have the right not to be subject to a decision, which may include a measure, evaluating personal aspects relating to him or her which is based solely on automated processing and which produces legal effects concerning him or her or similarly significantly affects him or her, such as automatic refusal of an online credit application or e-recruiting practices without any human intervention.

Such processing includes 'profiling' that consists of any form of automated processing of personal data evaluating the personal aspects relating to a natural person, in particular to analyse or predict aspects concerning the data subject's performance at work, economic situation, health, personal preferences or interests, reliability or behaviour, location or movements, where it produces legal effects concerning him or her or similarly significantly affects him or her.

However, decision-making based on such processing, including profiling, should be allowed where expressly authorised by Union or Member State law to which the controller is subject, including for fraud and tax-evasion monitoring and prevention purposes conducted in accordance with the regulations, standards and recommendations of Union institutions or national oversight bodies and to ensure the security and reliability of a service provided by the controller, or necessary for the entering or performance of a contract between the data subject and a controller, or when the data subject has given his or her explicit consent.

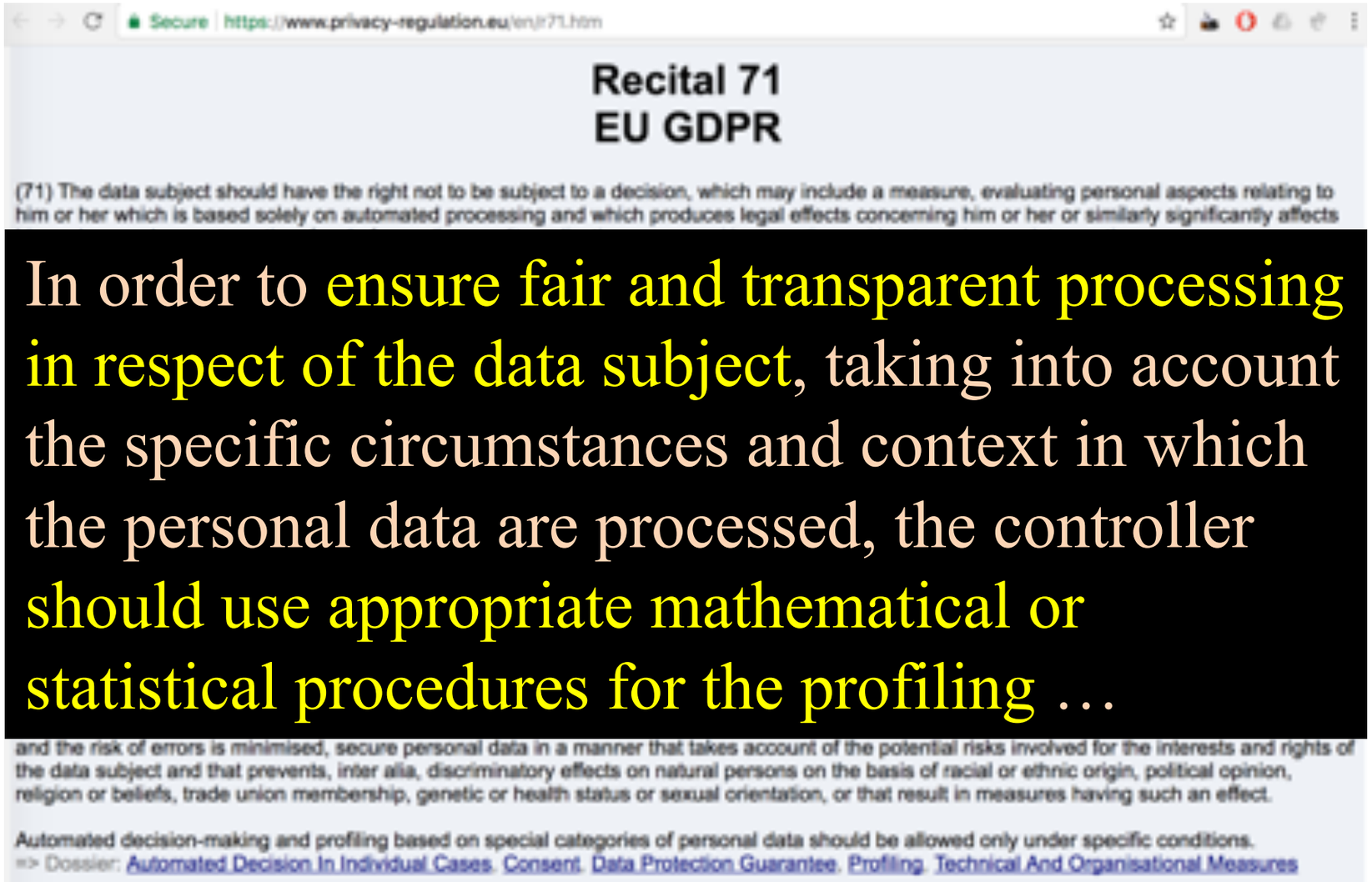
In any case, such processing should be subject to suitable safeguards, which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision.

Such measure should not concern a child.

In order to ensure fair and transparent processing in respect of the data subject, taking into account the specific circumstances and context in which the personal data are processed, the controller should use appropriate mathematical or statistical procedures for the profiling, implement technical and organisational measures appropriate to ensure, in particular, that factors which result in inaccuracies in personal data are corrected and the risk of errors is minimised, secure personal data in a manner that takes account of the potential risks involved for the interests and rights of the data subject and that prevents, inter alia, discriminatory effects on natural persons on the basis of racial or ethnic origin, political opinion, religion or beliefs, trade union membership, genetic or health status or sexual orientation, or that result in measures having such an effect.

Automated decision-making and profiling based on special categories of personal data should be allowed only under specific conditions.
=> Dossier: Automated Decision In Individual Cases, Consent, Data Protection Guarantee, Profiling, Technical And Organisational Measures

Recital 71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Human Interpretability in ML

- https://arxiv.org/abs/1606.08813

Other Initiatives

The first bill to examine 'algorithmic bias' in government agencies has just passed in New York City

BI Zoë Bernard
Business Insider December 19, 2017

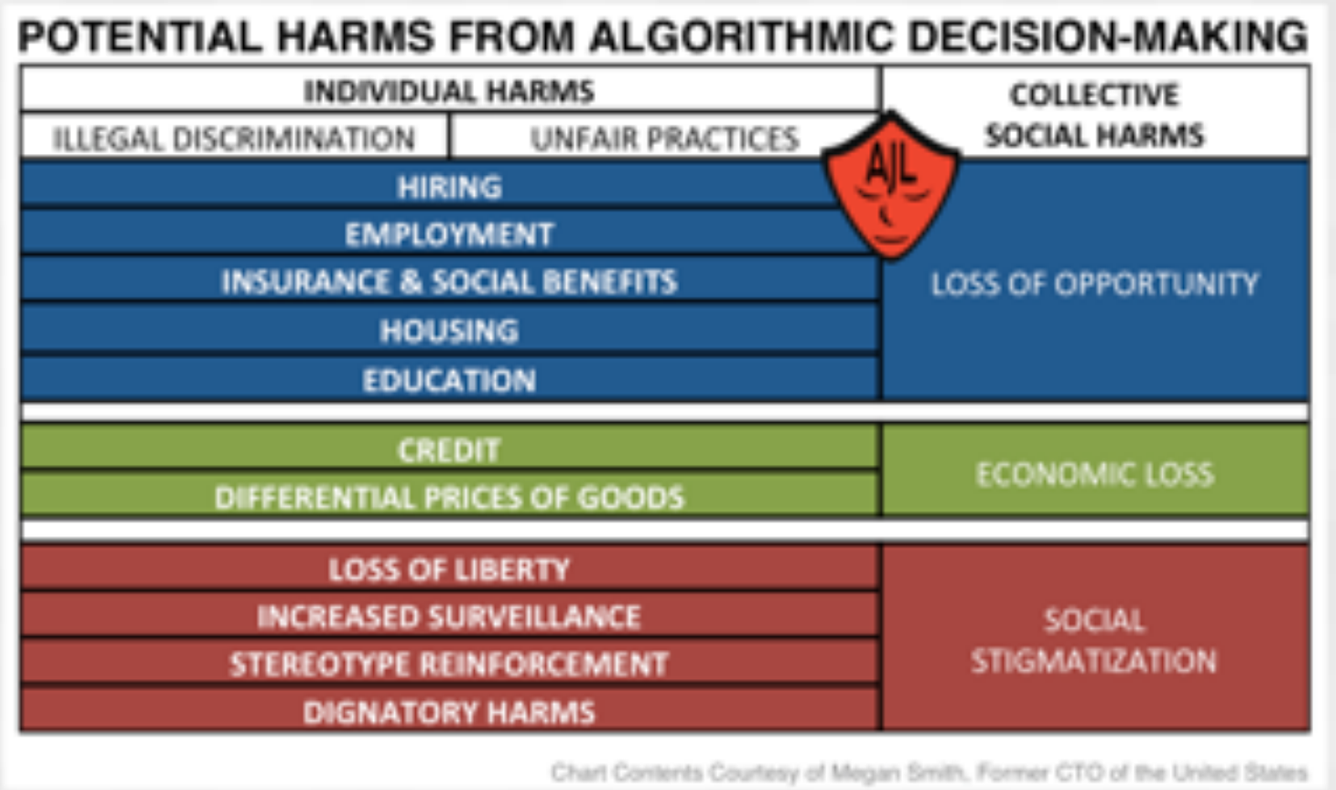
- New York City has passed the algorithmic accountability bill, which will assign a task force to examine the way that city government agencies use algorithms.
- Algorithmic bias is a critical issue in the justice system, which often relies on algorithmic risk assessments to inform criminal sentencing in federal court.
- The bill is the first of its kind to be passed in the nation, and will attempt to provide transparency in the way that the government uses algorithms.

This bill would require the creation of a task force that provides recommendations on how information on agency automated decision systems may be shared with the public and how agencies may address instances where people are harmed by agency automated decision systems.

Potential Harms on algorithmic Decision Making

Automated systems are not inherently neutral. They reflect the priorities, preferences, and prejudices - the coded gaze - of those who have the power to mold artificial intelligence.

We risk losing the gains made with the civil rights movement and women's movement under the false assumption of machine neutrality. We must demand increased transparency and accountability.



http://gendershades.org/overview.html

- How are researchers and practitioners addressing these issues ?

The FAT* Conference

- https://fatconference.org
- A computer science conference with a cross-disciplinary focus that brings together researchers and practitioners interested in fairness, accountability, and transparency in socio-technical systems.

The FATML group

- The FATML group suggests best practices:
- https://www.fatml.org/resources/principles-and-best-practices

Workshops & Tutorials

- Tutorial on Fairness & Discrimination in Retrieval & Recommendation: M. Ekstrand, F. Diaz, R. Burke (SIGIR & RecSys 2019) https://boi.st/FairIRTutorial
- Tutorial on ExplainAble Recommendation and Search: Y. Zhang, Q. Ai, J. Mao, X. Chen (SIGIR 2019)
- Tutorial on Fairness and Transparency in Ranking: Carlos Castillo (LA-Web 2019, DAB 2018)

How to Measure, Study and Prevent Bias in RecSys?

- Some definitions
- Explainability and transparency in RecSys
- Fairness in RecSys
- Open challenges
- Summary and conclusions

FAT definitions

- Fairness
- Accountability
- Transparency

FAT definitions

- **Fairness**: The property of being fair or equitable

  vs. **Bias**: inclination towards something; predisposition, partiality, prejudice, preference, predilection, discrimination.

- Accountability:

- Transparency

FAT definitions

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  vs. **Bias**: inclination towards something; predisposition, partiality, prejudice, preference, predilection, discrimination.

- According to Friedman and Nissembaum (1994) a computer system is biased "if it systematically and unfairly discriminate[s] against certain individuals or groups of individuals in favor of others."

Batya Friedman and Helen Nissenbaum. 1996. Bias in computer systems. ACM Transactions on Information Systems 14, 3 (1996), 330–347.

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  - "… a system discriminates unfairly if it denies an opportunity or a good or if it assigns an undesirable outcome to an individual or a group of individuals on grounds that are unreasonable or inappropriate."

Batya Friedman and Helen Nissenbaum. 1996. Bias in computer systems. ACM Transactions on Information Systems 14, 3 (1996), 330–347.

FAT Definitions

- Fairness

- **(Algorithmic) Accountability**: To be accountable means to be subject to giving an account or having the obligation to report, explain or justify something -> explainable AI (**XAI**).

- Transparency

FAT Definitions

- Fairness

- Accountability

- **(Algorithmic) Transparency:** is the principle that the factors that influence the decisions made by algorithms should be visible, or transparent, to the people who use, regulate, and are affected by systems that employ those algorithms.

Important Distinction

- Algorithmic accountability vs algorithmic transparency: Some people use it interchangeably, but a system can be accountable (provide explanations, justifications) without necessarily being transparent (completely opening the complexity of a black-box)
- From the DARPA XAI Program

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

Other relevant terms

- Interpretability, in the context of AI/ML:
  - "the degree to which a human can understand the cause of a decision" (T. Miller, et al. AI 2018)
  - "the degree to which a human can consistently predict the model's result" (B. Kim, et al. NIPS 2016)
  - "the ability to explain or to present in understandable terms to a human" (Doshi-Velez and Kim, 2017)

1. EXPLAINABILITY & TRANSPARENCY

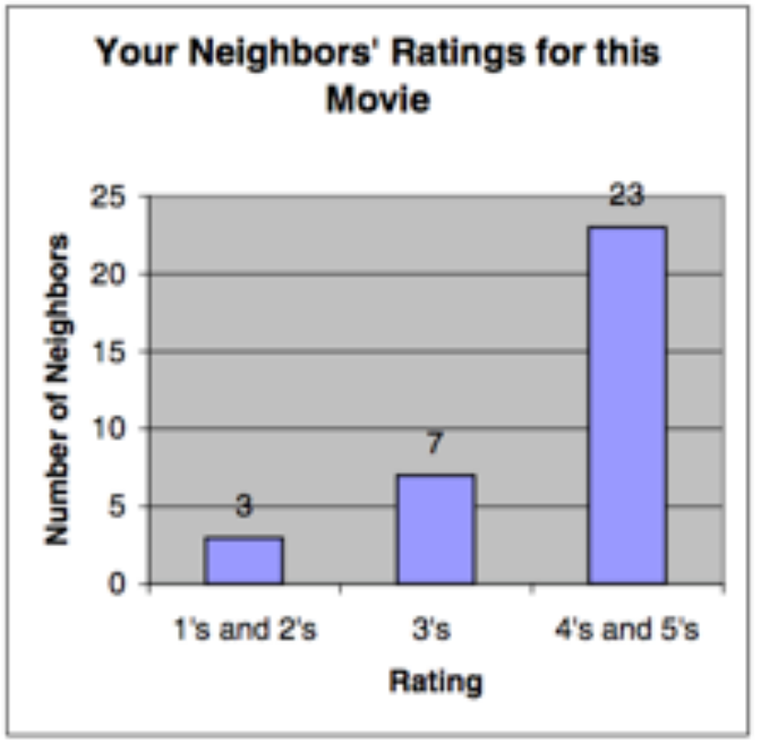
FAT in Recommender Systems

- 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.

FAT 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



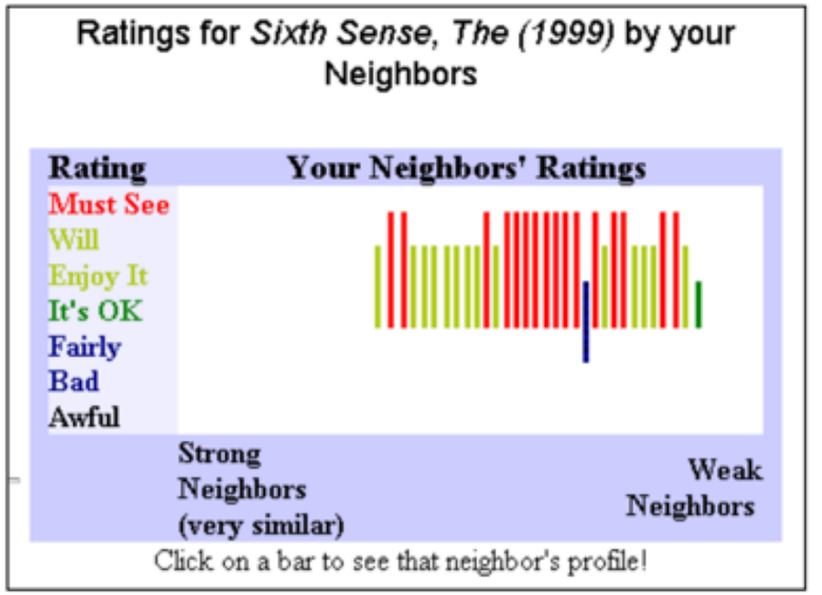
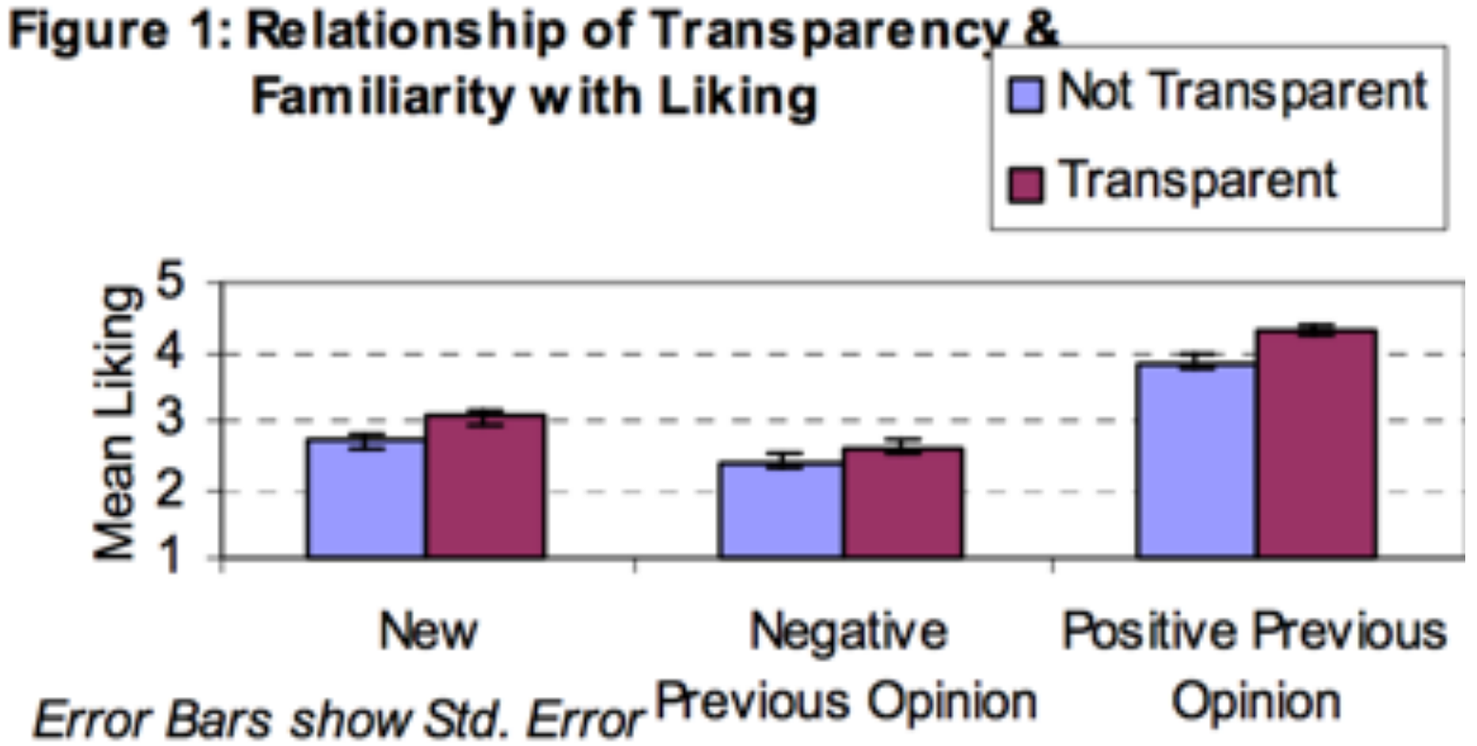


Figure 4. A screen explaining the recommendation for the movie "The Sixth Sense." Each bar represents a rating of a neighbor. Upwardly trending bars are positive ratings, while downward trending ones are negative. The x-axis represents similarity to the user.

FAT 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.



FAT 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.

FAT 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.

XAI (2017)

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

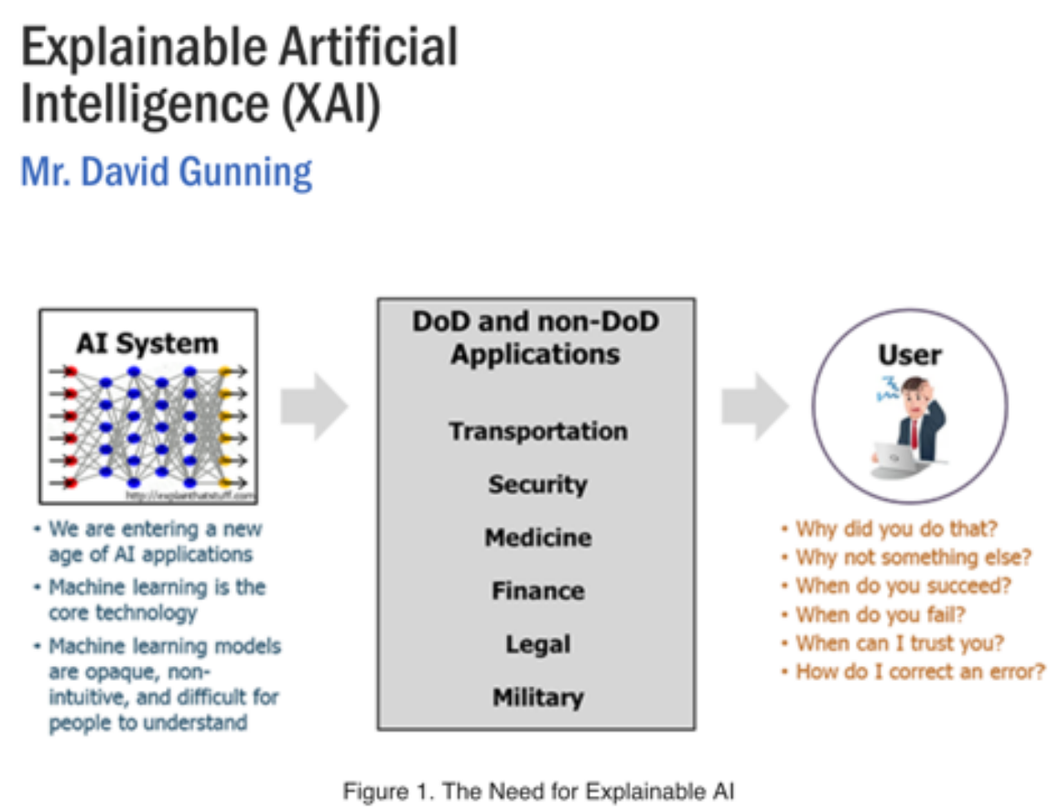


Figure 1. The Need for Explainable AI

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

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 !

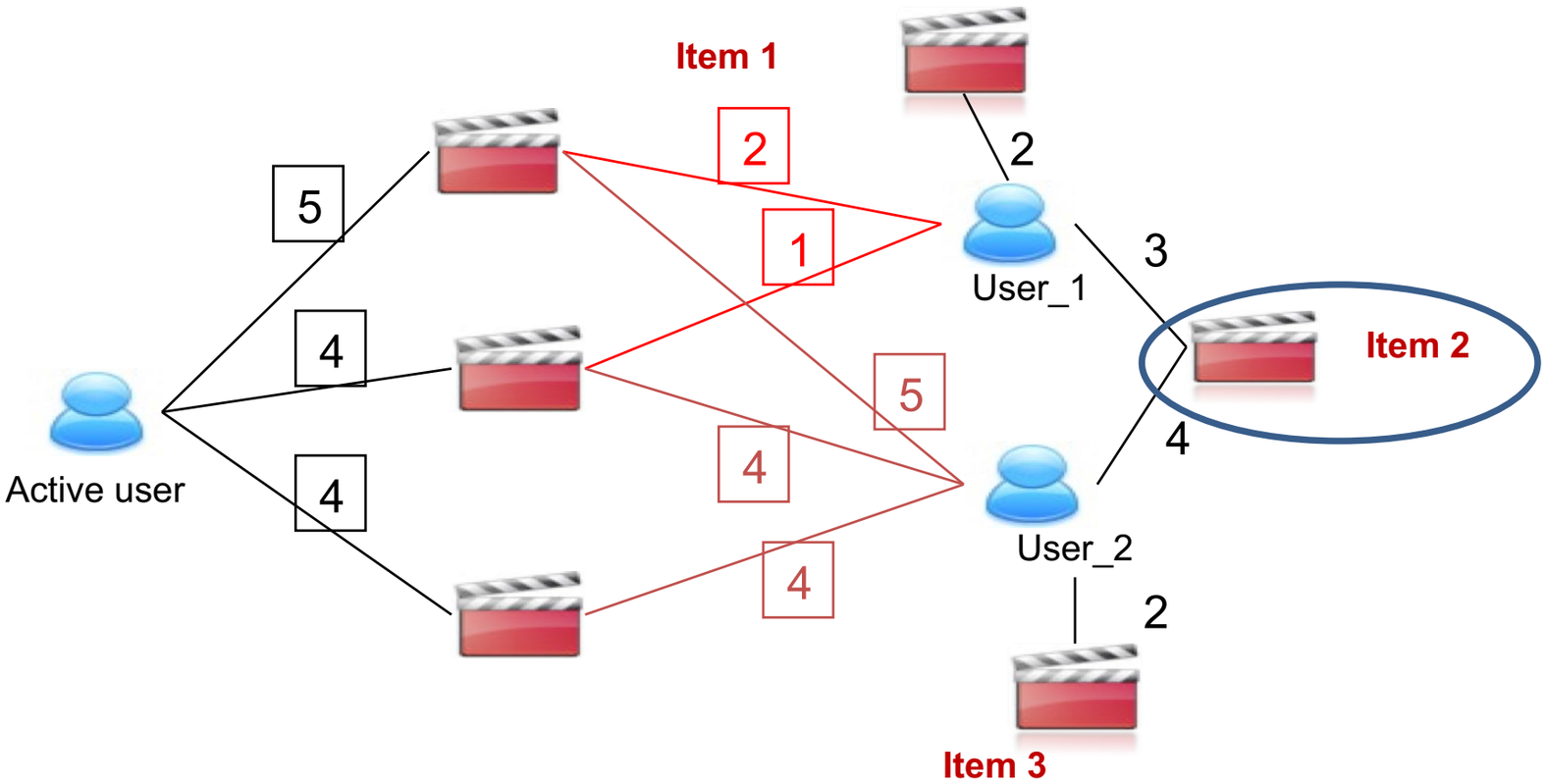
1st generation of RecSys

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

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

1st generation of RecSys

- User Based KNN



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

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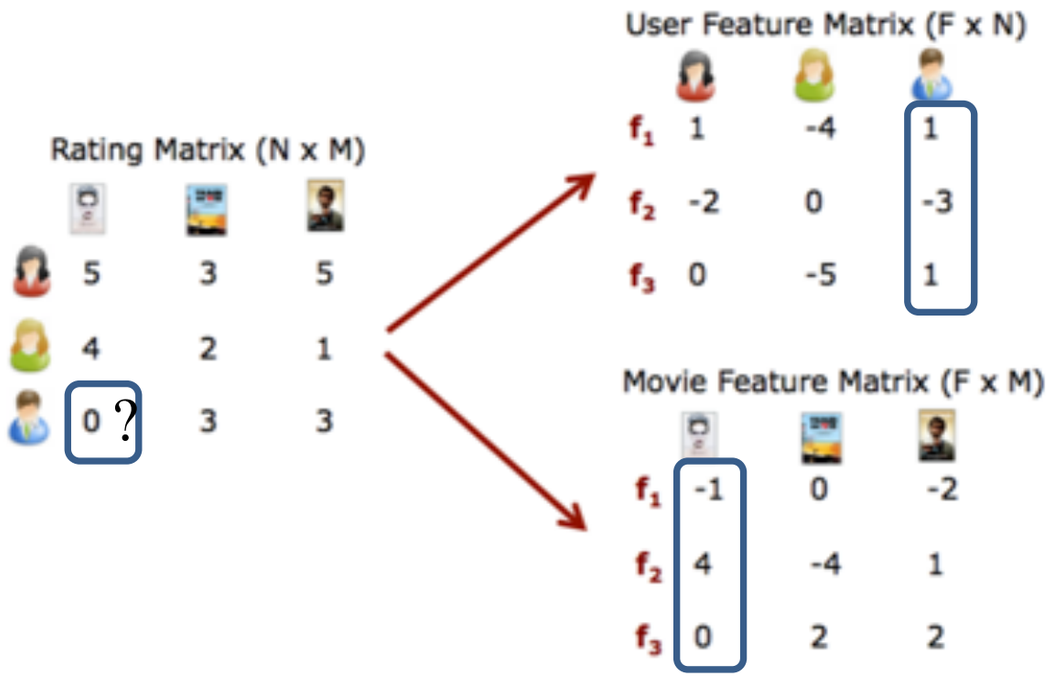
2nd generation of RecSys

- Matrix Factorization - latent factor models: difficult to explain



$$\min_{q*,p*} \sum_{(u,i)\in K} (r_{ui} - q_i^T \cdot p_u)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

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"

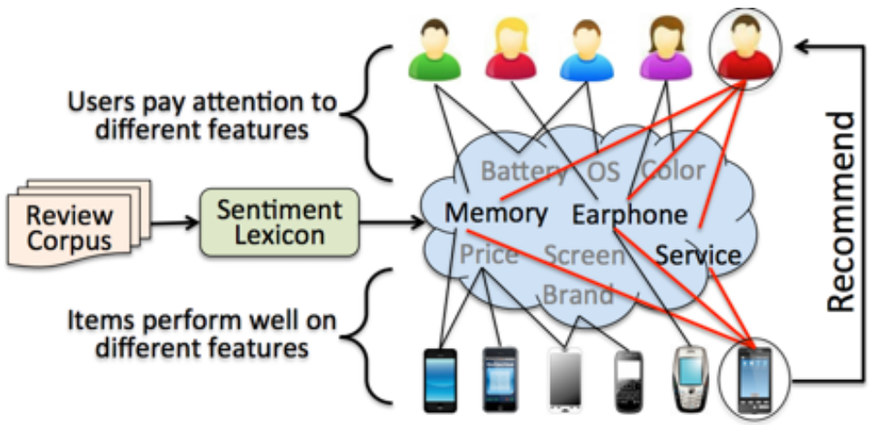


Figure 1: The product feature word and user opinion word pairs are extracted from user review corpus to construct the sentiment lexicon, and the feature word set further serves as the explicit feature space. An item would be recommended if it performs well on the features that a user cares.

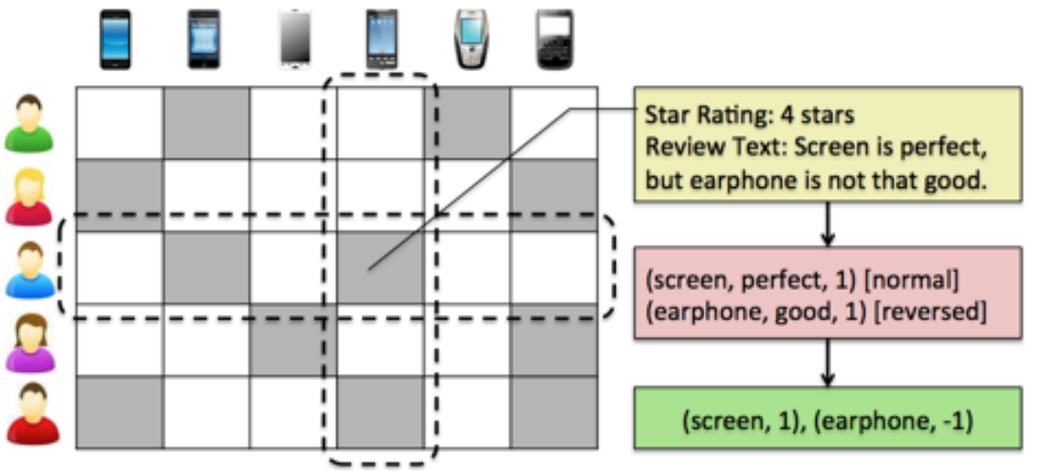


Figure 2: An example of user-item review matrix, where each shaded block is a review made by a user towards an item; the entries included in the review are extracted, and further transformed to feature scores while considering the negation words.

XAI for Recommender Systems

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

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- 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

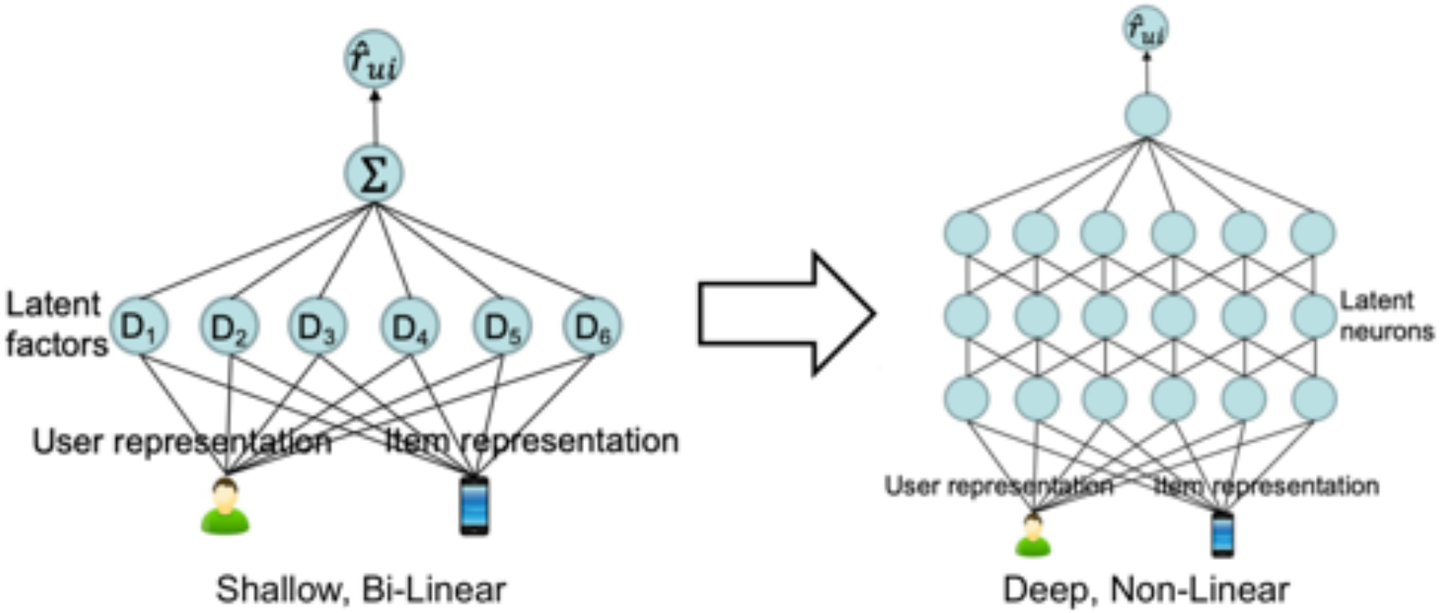


Image from Zhang et al. (2019) Tutorial on ExplainAble Recommendation and Search

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.)

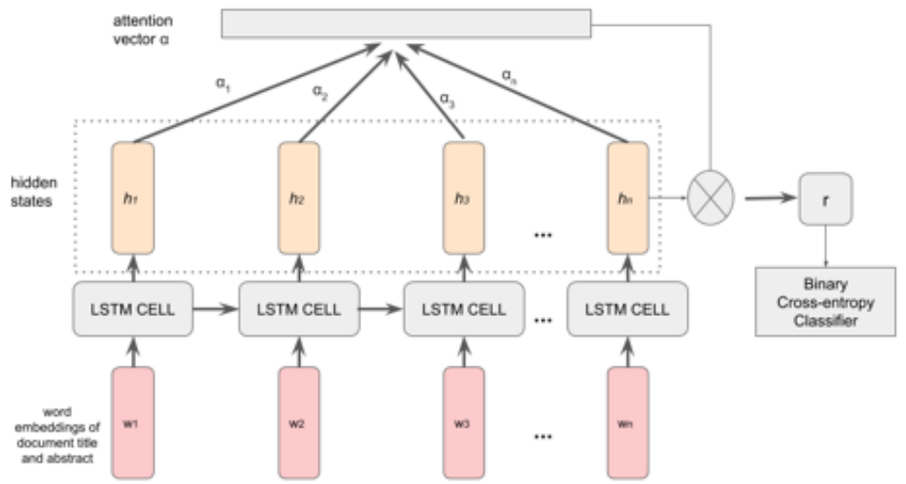
Neural Attention

- 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 attend to reasonable words ?



A meta analysis of birth origin effects on reproduction in diverse captive environments

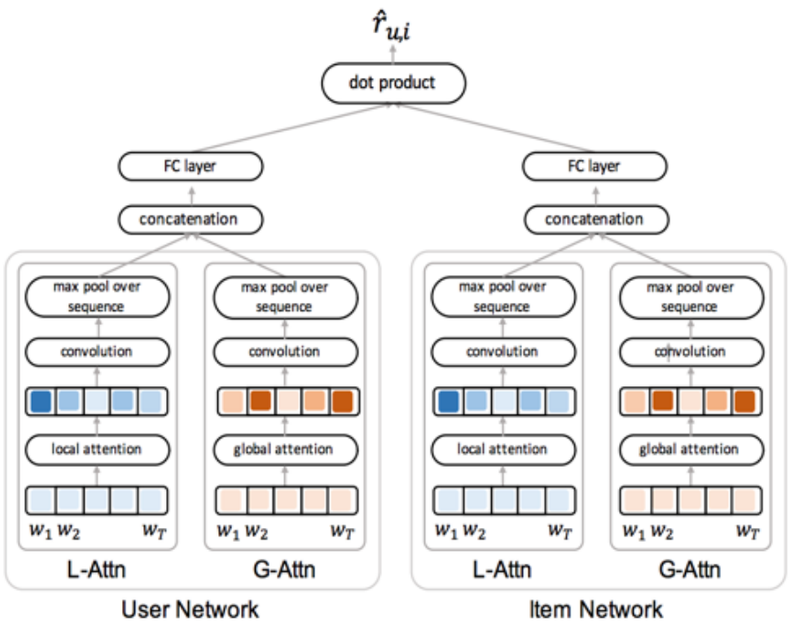
Prediction: Not Relevant (NR)

Ground truth: Not Relevant (NR)

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 decreased odds of reproductive success in captivity compared to their wild born counterparts the largest effects are seen in commercial aquaculture relative to conservation or laboratory settings and offspring survival and offspring quality were the most sensitive traits although somewhat weaker trend reproductive success in conservation and laboratory research breeding programs is also in negative direction for captive born animals our study provides the foundation for future investigation of non genetic and genetic drivers of change

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.



Yelp (user), L-Attn-only model: local attention

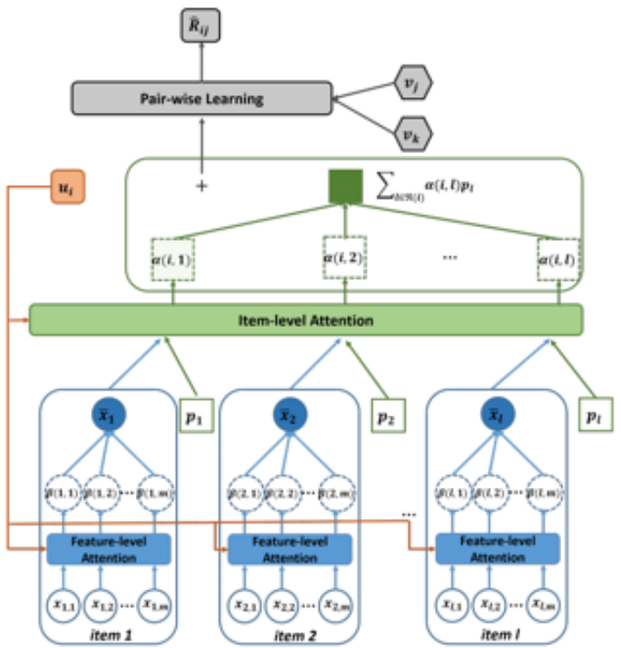
They carry some rare things that you can't find anywhere else. The staff is pretty damn cool too best in Arizona . I prefer ma-and-pa. They treat you the best and they value your business extreme . They are good people great atmosphere and music. I definitely believe that Lux has the best coffee I've ever had at this point. Screw all my previous reviews. This place has coffee down , they make damn good toast too .

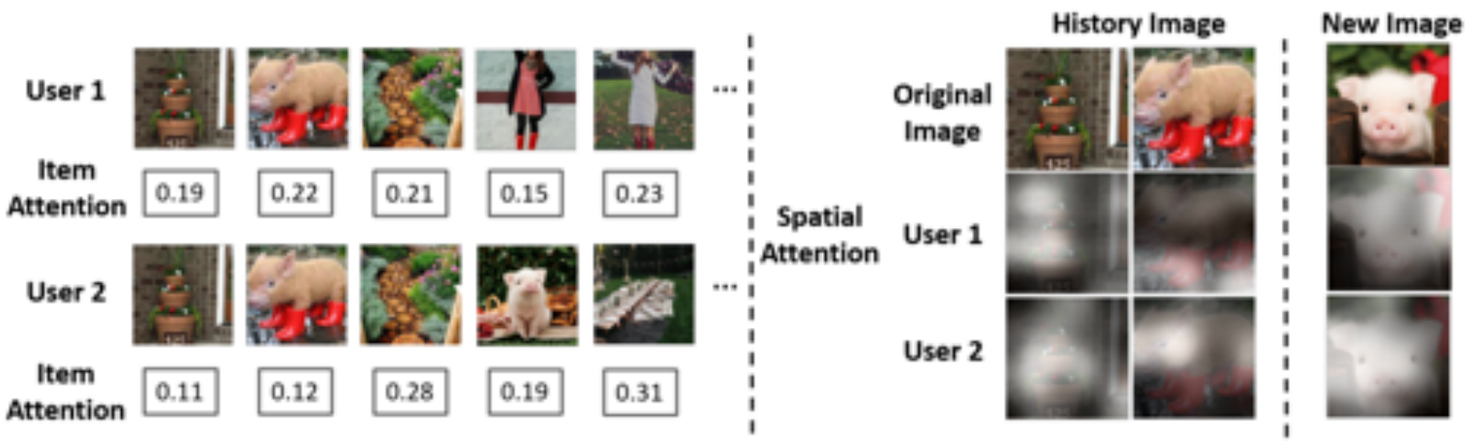
Yelp (user), G-Attn-only model: global attention

They carry some rare things that you can't find anywhere else . The staff is pretty damn cool too best in Arizona. I prefer ma- and - pa. They treat you the best and they value your business extreme. They are good people great atmosphere and music. I definitely believe that Lux has the best coffee I've ever had at this point. Screw all my previous reviews. This place has coffee down, they make damn good toast too.

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

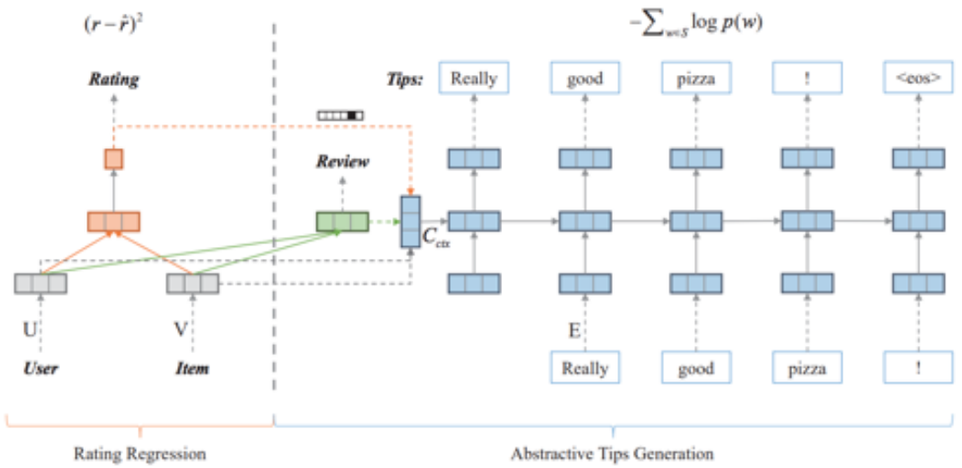


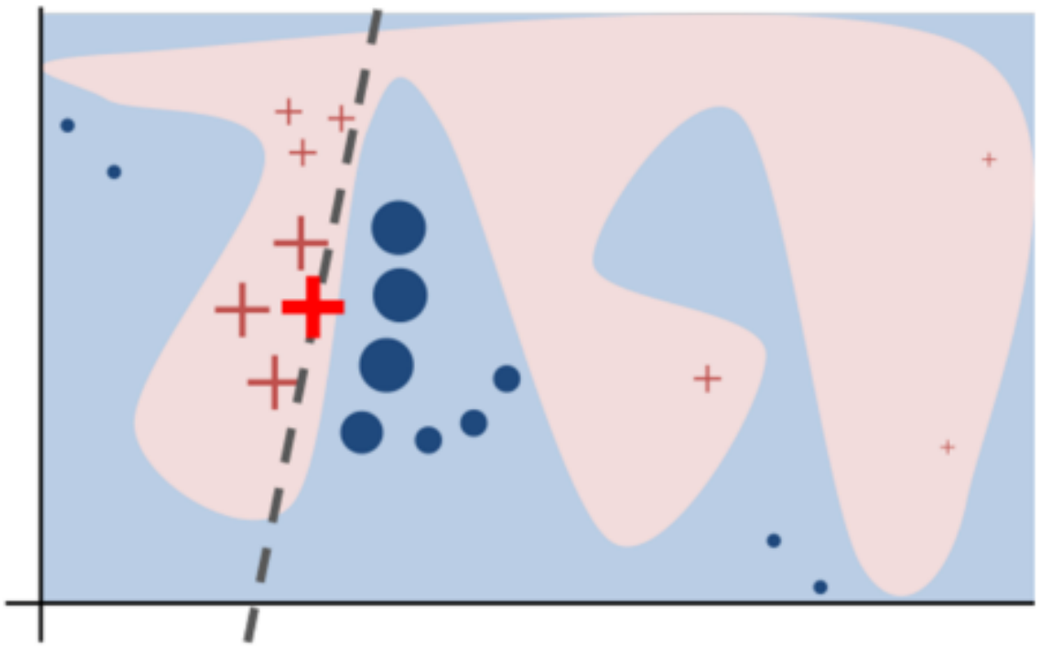
Figure 2: Our proposed framework NRT for rating regression and abstractive tips generation.

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.

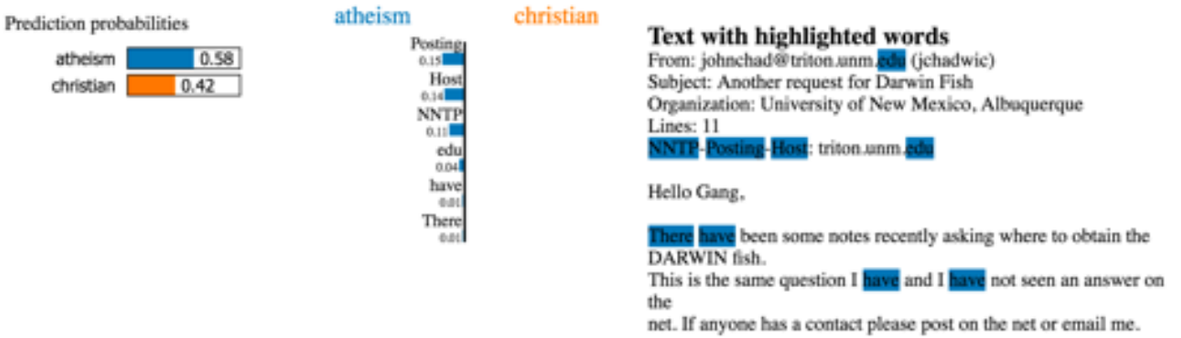
Rating	Tips
4.64	***This is a great product for a great price.***
5	Great product at a great price.
4.87	***I purchased this as a replacement and it is a perfect fit and the sound is excellent.***
5	Amazing sound.
4.69	***I have been using these for a couple of months.***
4	Plenty of wire gets signals 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

- LIME: Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should i trust you?: Explaining the predictions of any classifier. KDD 2016.

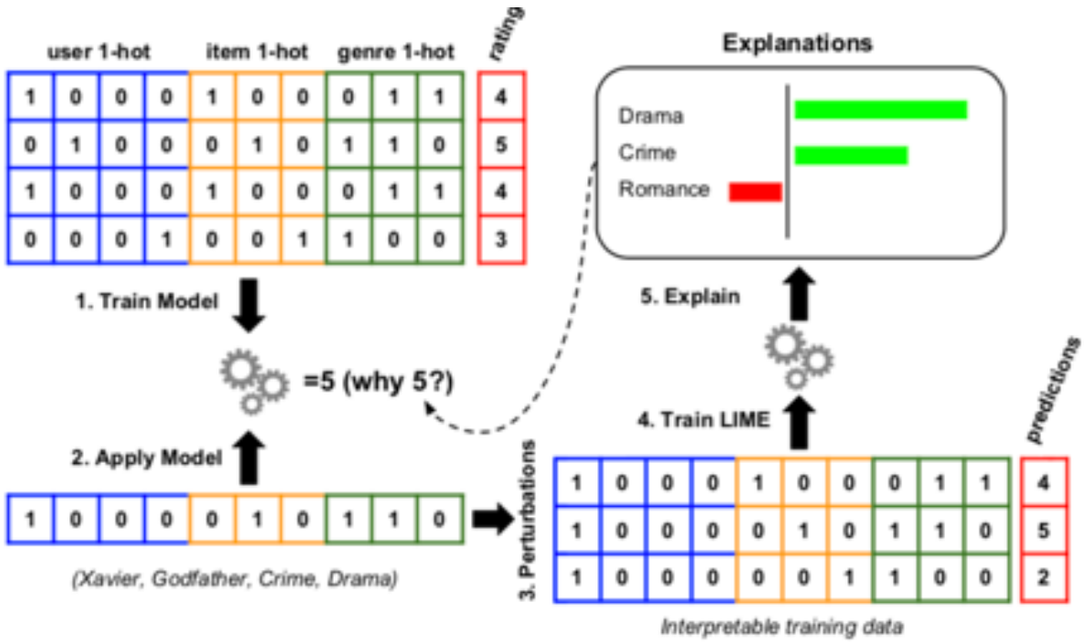


$$\xi(x) = \underset{g \in G}{\operatorname{argmin}} \ \mathcal{L}(f, g, \pi_x) + \Omega(g)$$



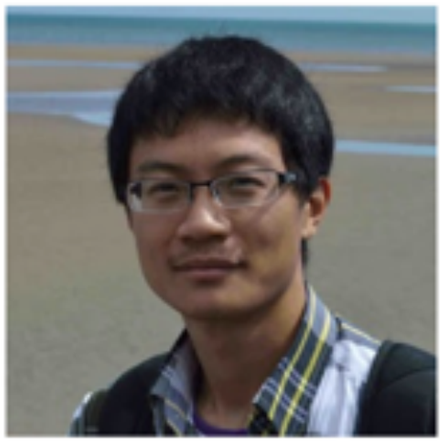
Adapting current XAI approaches to RecSys

- 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/



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Qingyao Ai

Assistant Professor

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Accountability: the Role of Interactive Visualization

- 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)

Open Challenges

- Recent advance in NLP models, neural attention architectures (the transformer), and generative models provide a big potential for this area. Notice that interpretable != transparent.

- Visualization has not been deeply explored for supporting transparency and explainability in recommender systems, and it is and open field for further research.

- For a glimpse of what can be done combining the aforementioned points, check https://distill.pub as well as https://visxai.io

SoCVis
PUC SOCIAL COMPUTING & VISUALIZATION GROUP

Millennium Institute
Foundational
Research on Data

The Effect of Explanations and Algorithmic Accuracy on Visual Recommender Systems of Artistic Images

Vicente Domínguez

Pablo Messina

Ivania Donoso-Guzmán

Denis Parra

Pontificia Universidad Católica de Chile (PUC Chile)

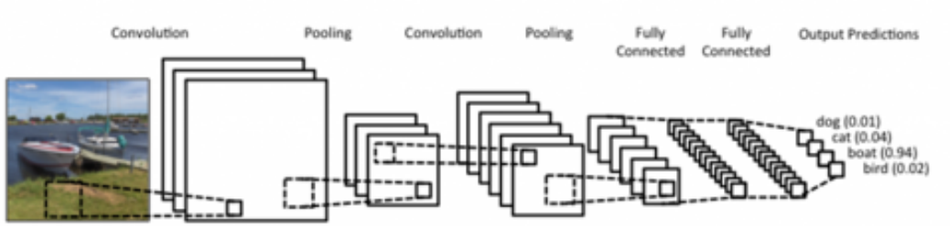
Open Questions

- We learned that visual features from DNNs perform better than attractiveness visual features.

Average brightness
Saturation
Sharpness
Entropy
RGB-contrast
Colorfulness
Naturalness

<

Predictive Accuracy



Attractiveness visual features

Deep Learning visual features

Open Questions from Content-Based RecSys

- We learned that visual features from DNNs perform better than attractiveness visual features, ***but they are harder to explain***.

Average brightness
Saturation
Sharpness
Entropy
RGB-contrast
Colorfulness
Naturalness

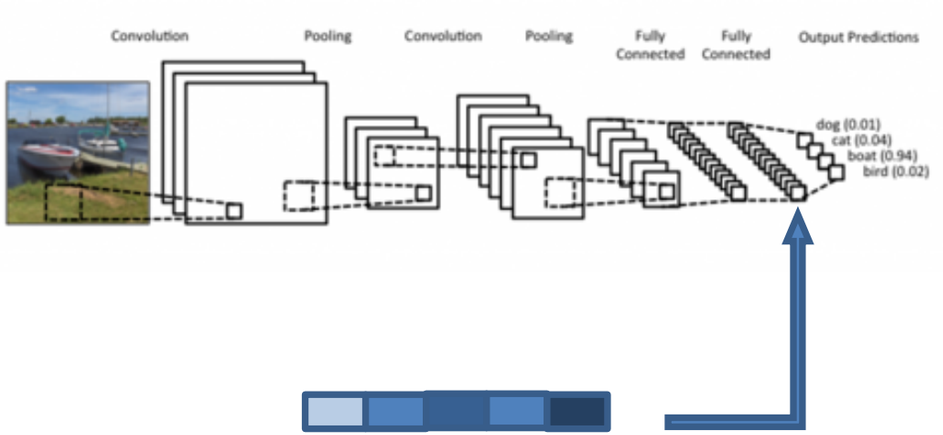
Attractiveness visual features

<

Predictive Accuracy

>

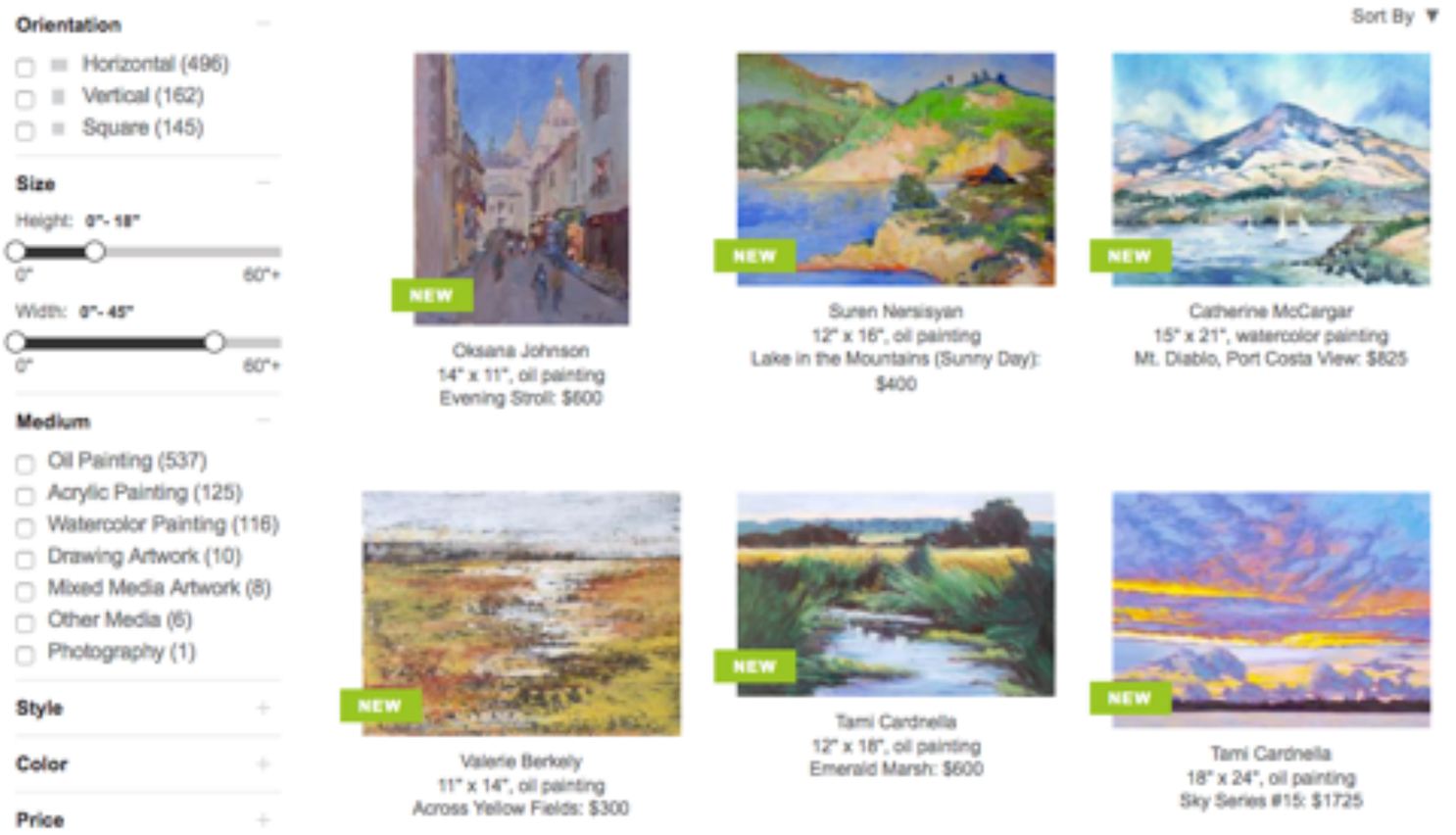
Explainability



Deep Learning visual features

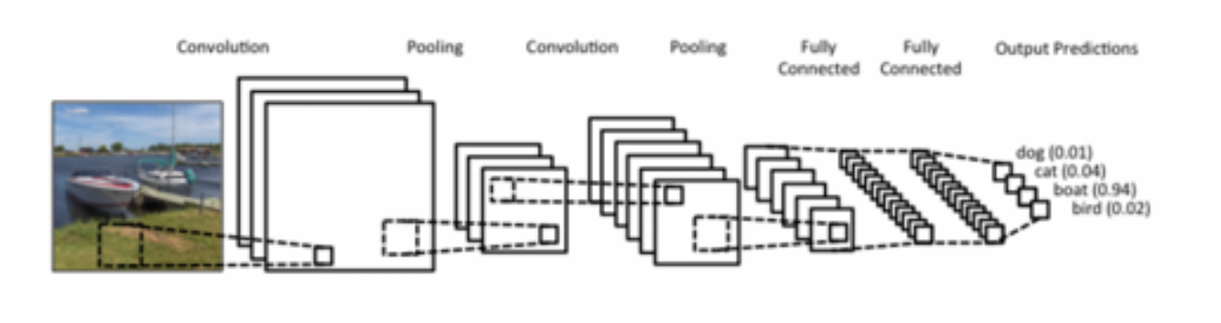
Data: UGallery

- Online Artwork Store, based on CA, USA.
- Mostly sales one-of-a-kind physical artwork.

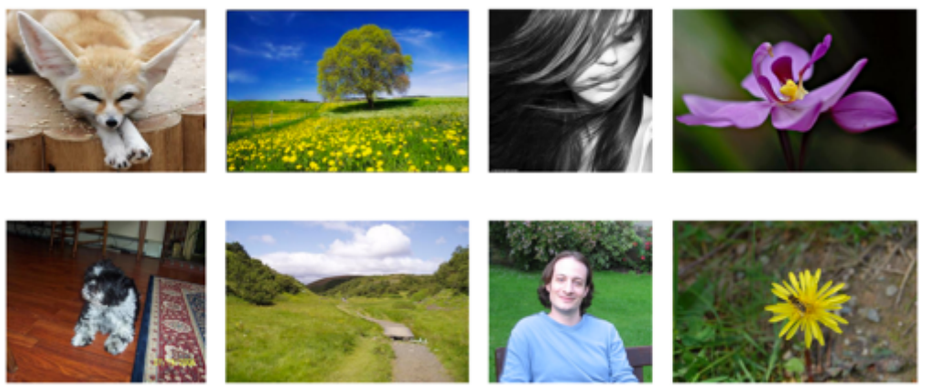


CB RecSys algorithm: Visual Features

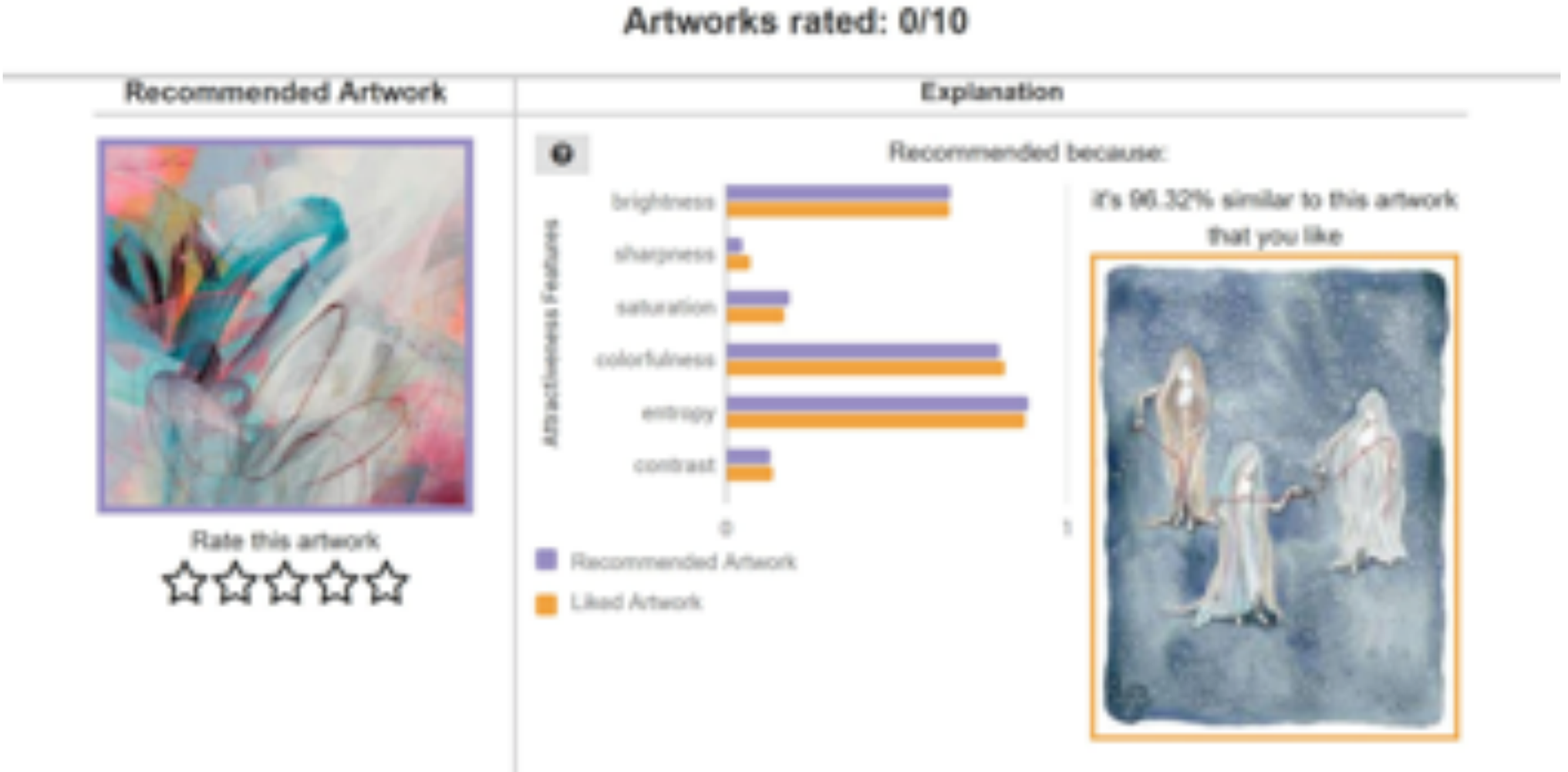
- (DNN) Deep Neural Networks



- (AVF) Attractiveness-based



White-box Explanation (AVF)

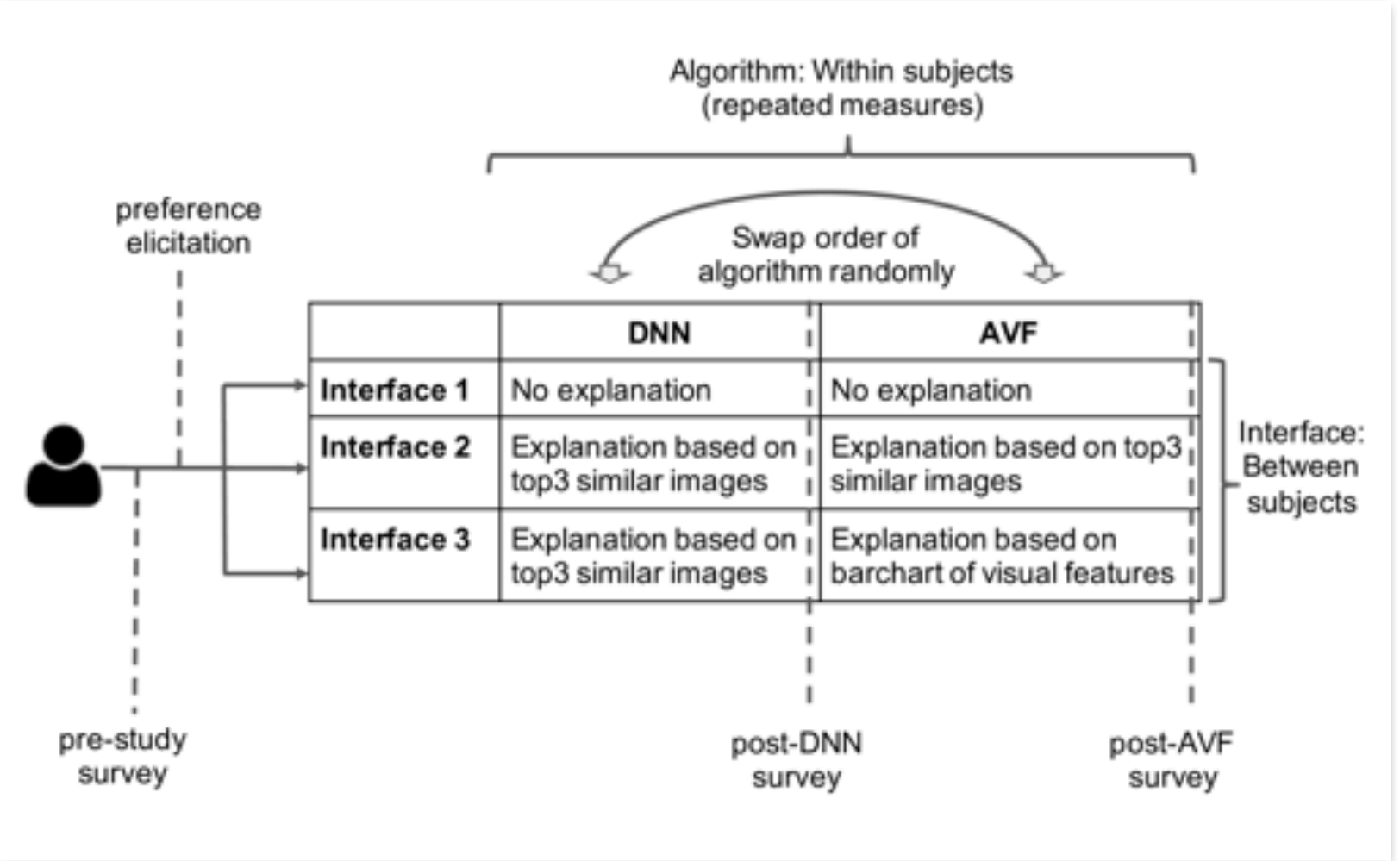


Black-box explanation

Artworks rated: 2/10

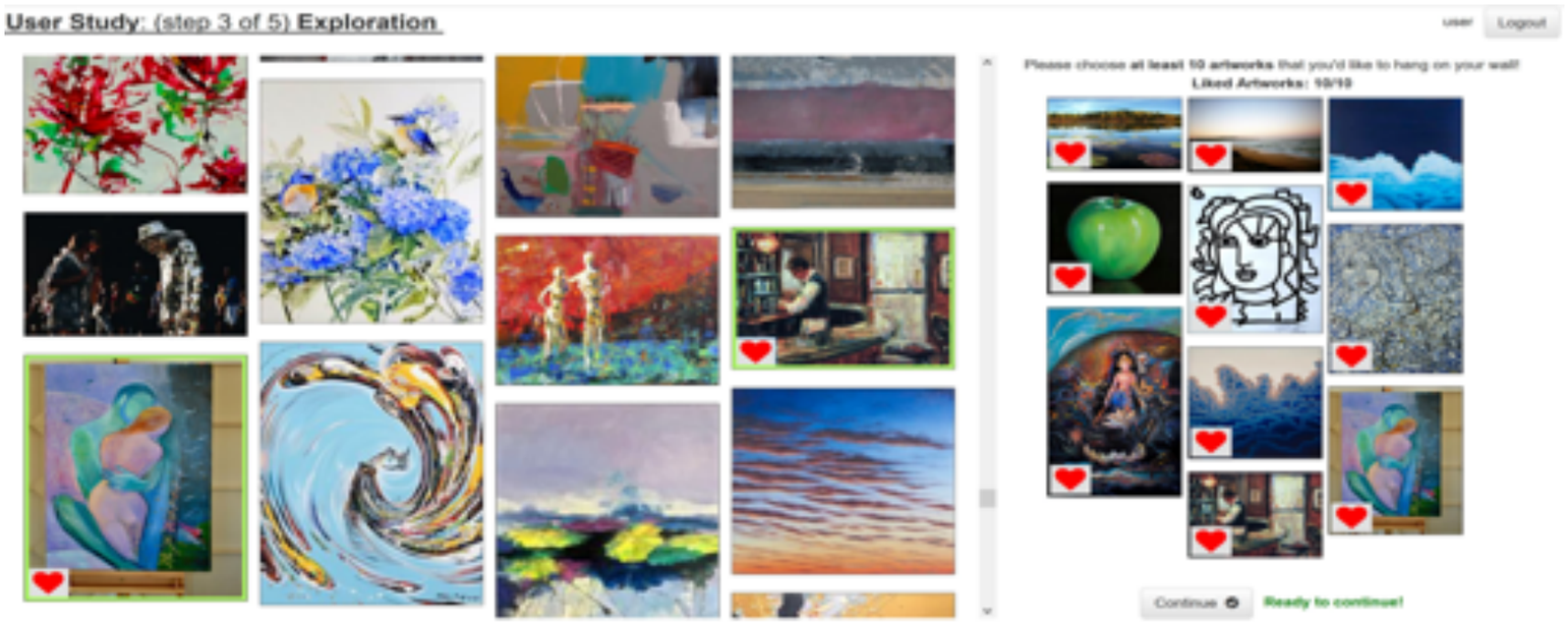
Recommended Artwork	Explanation
 Successfully rated! ★★★★★	Recommended because: it's 81.96% similar to this artwork that you like  it's 70.10% similar to this artwork that you like  it's 68.52% similar to this artwork that you like  With an average of 73.53%

Study Procedure

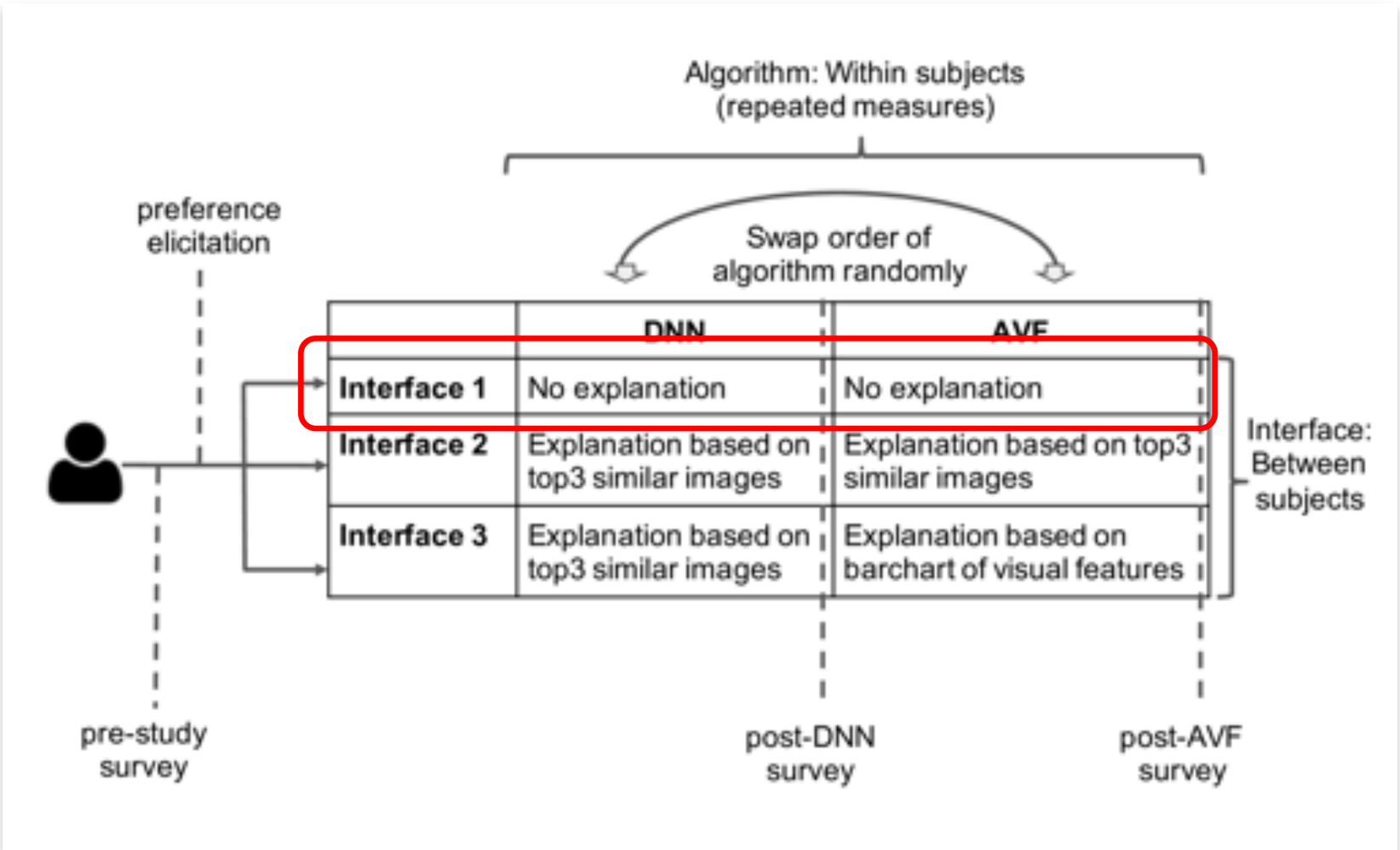


Preference Elicitation

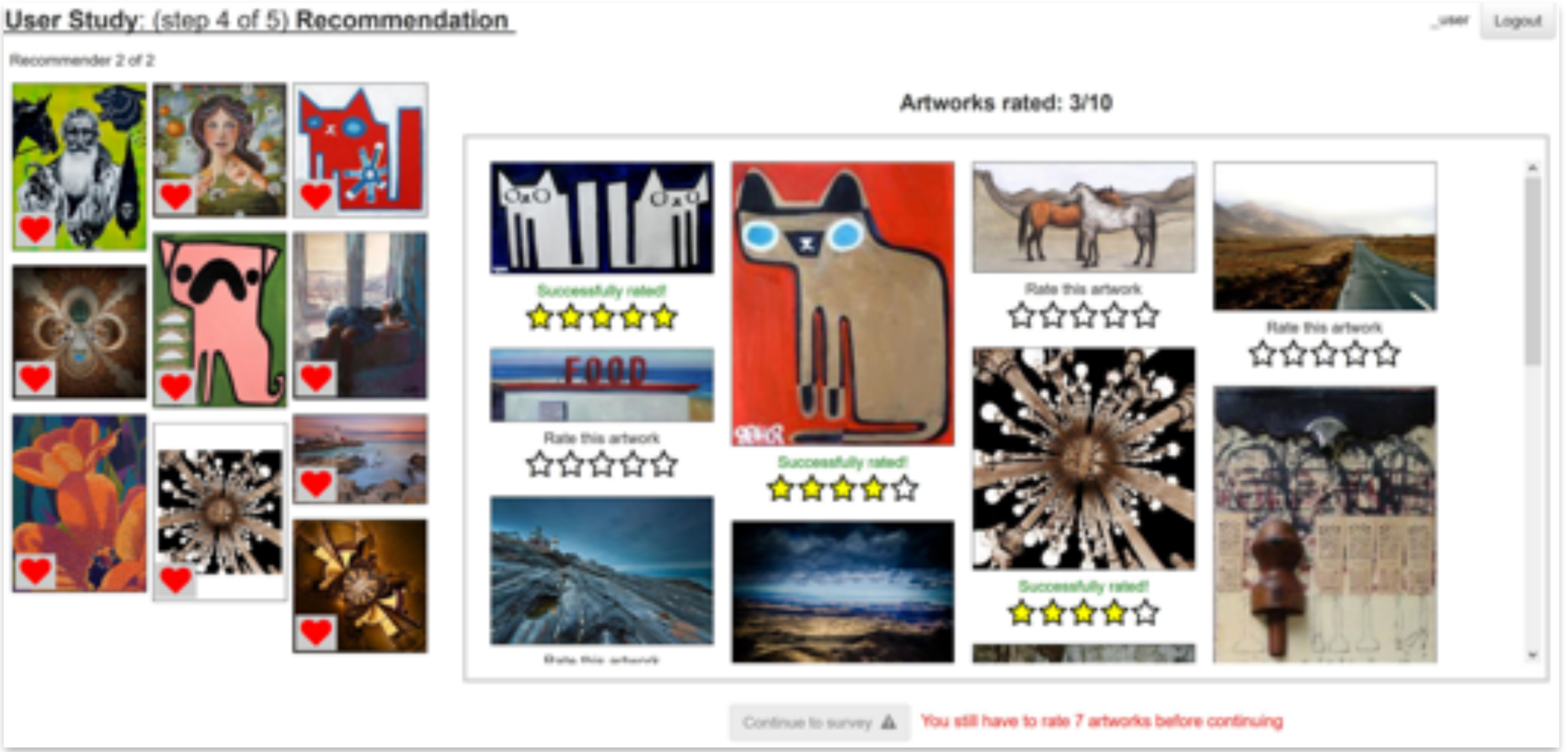
- We collect user preferences from a Pinterest-like interface



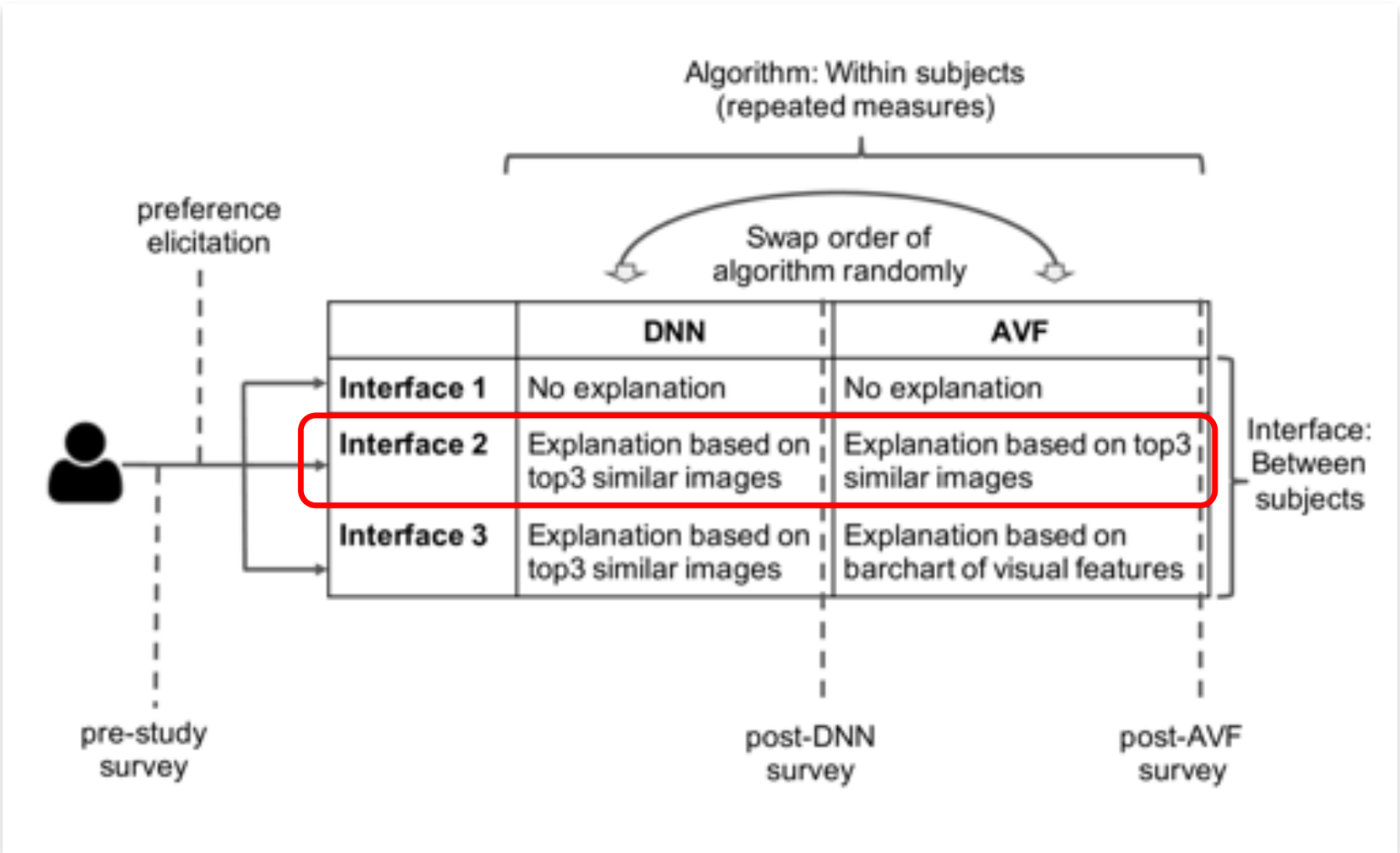
Study Procedure



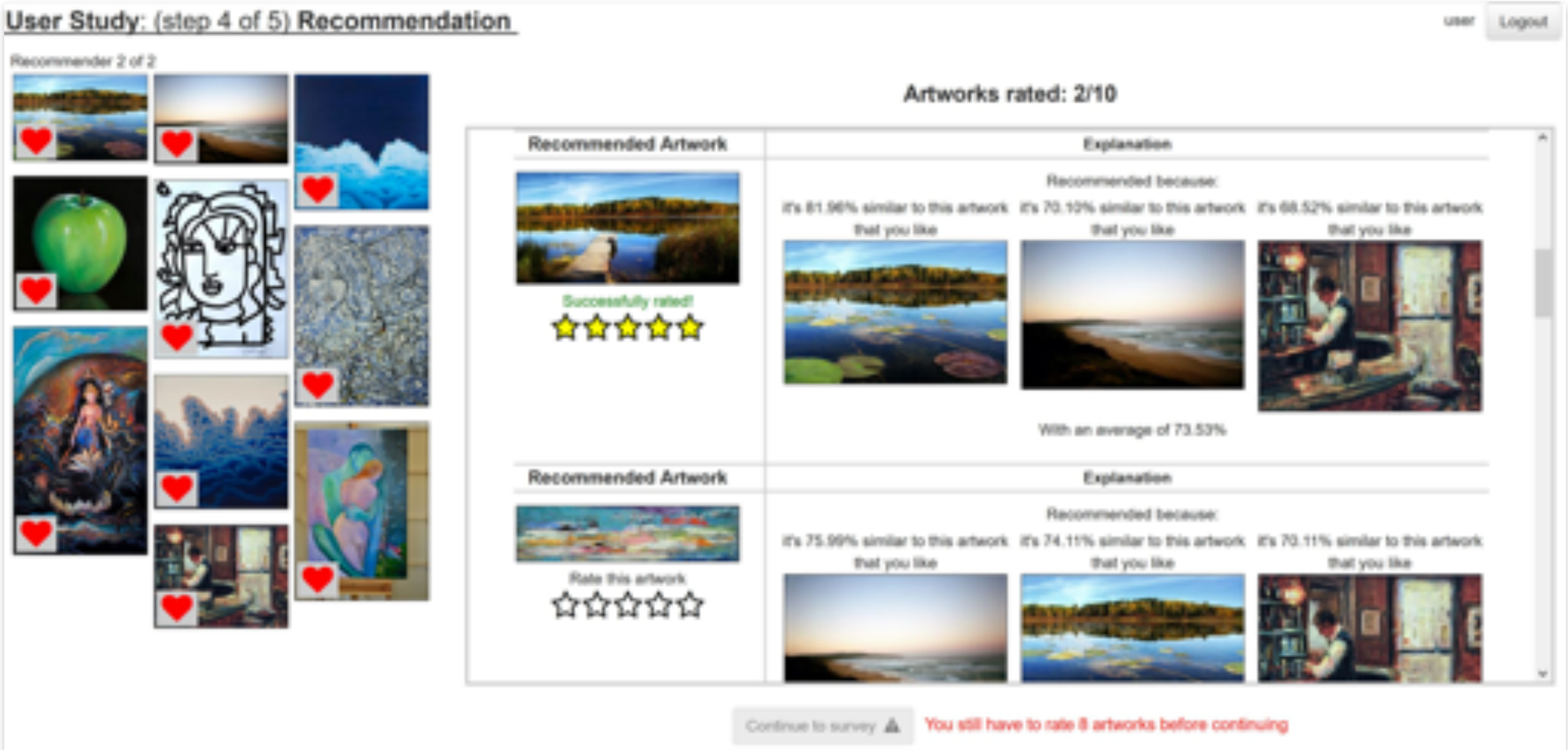
Interface 1: no explanation



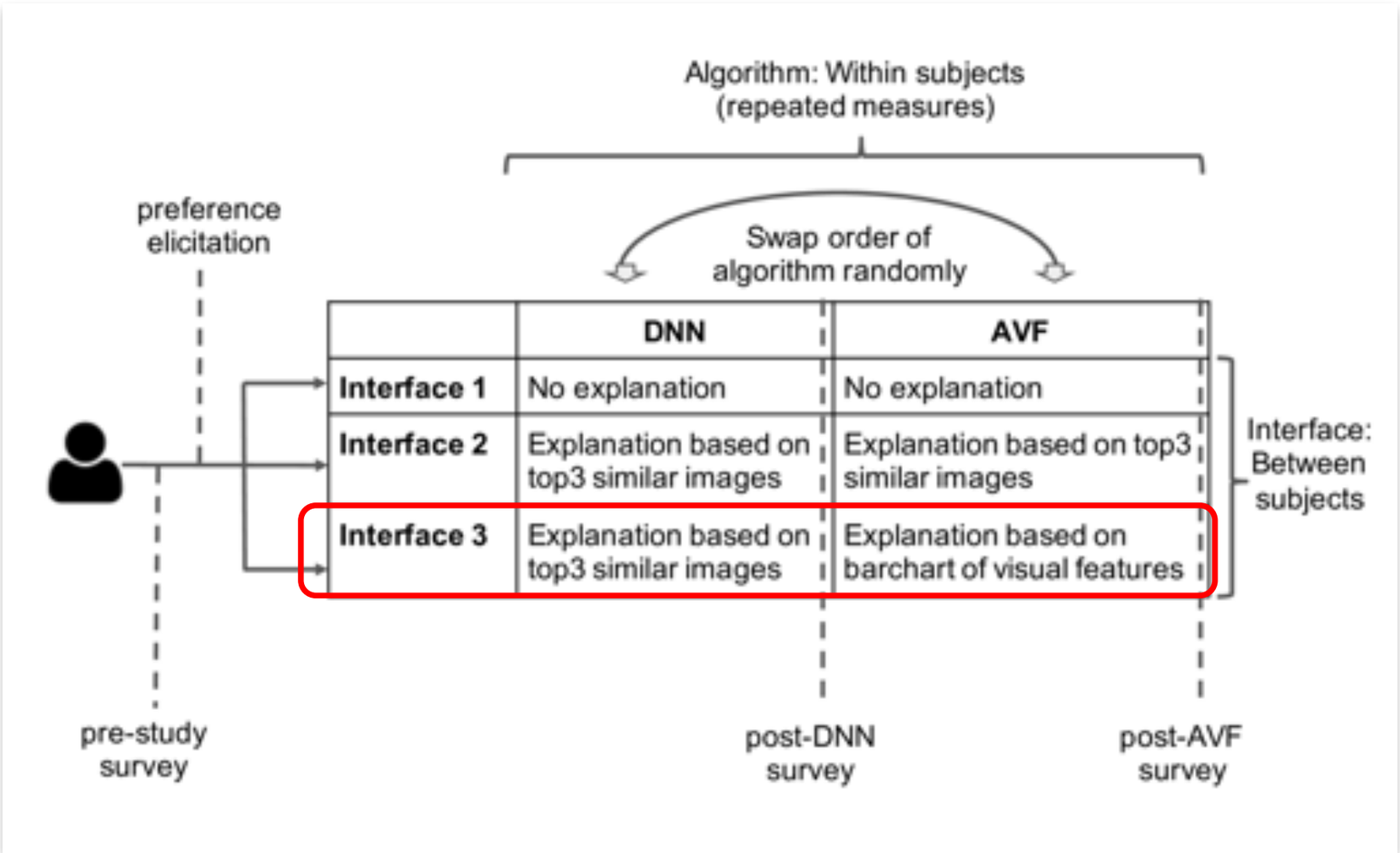
Study Procedure



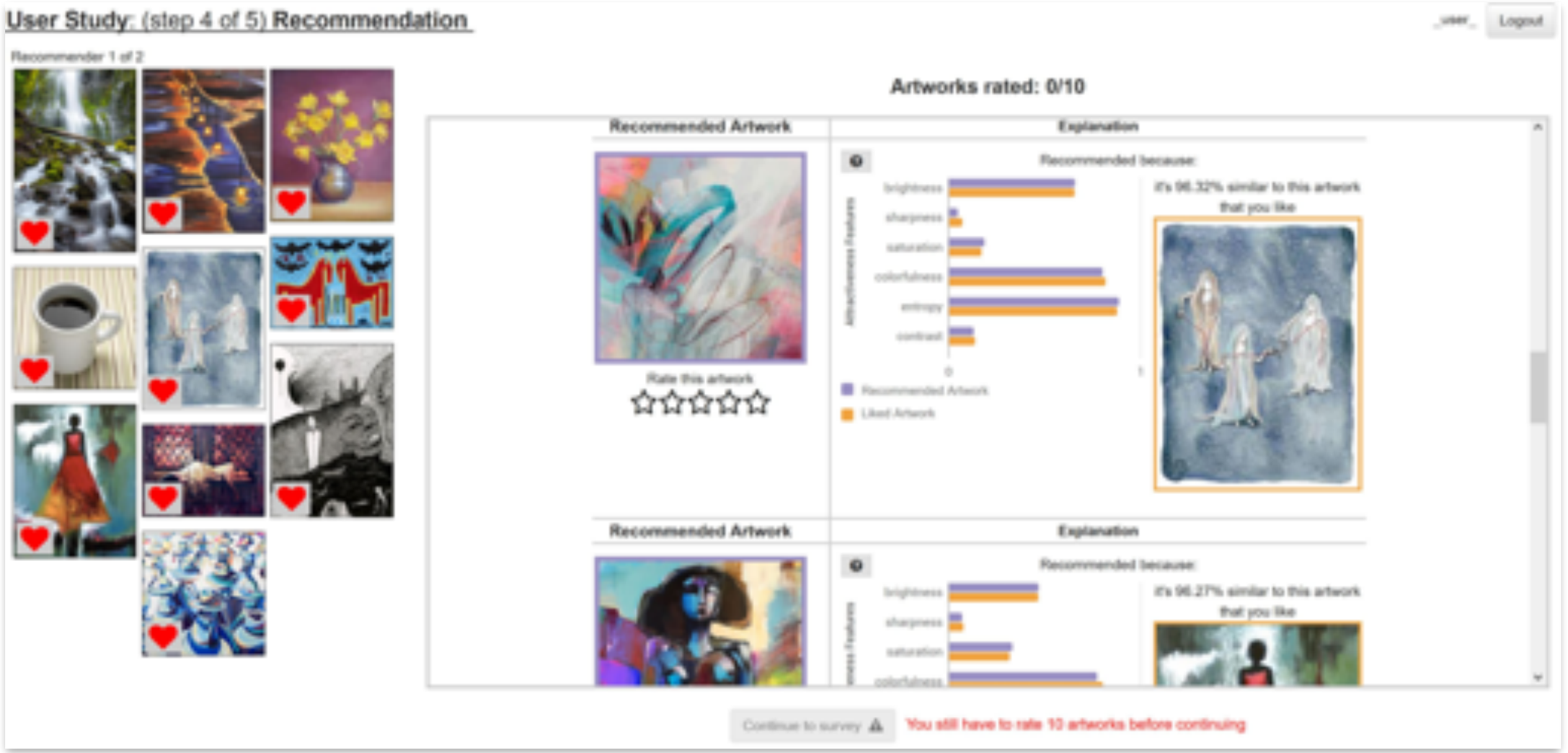
Int. 2: explainable, no transparency



Study Procedure



Interface 3: explainable & transparent



Evaluation & Results

Study on Amazon Mechanical Turk:

- 121 valid users completed correctly the study.
- Task took them around 10 minutes to complete.
- ~56% female, 44% male.
- 80% attended to 1 or more art classes at high school level or above.
- 80% visited museums or art galleries at least once a year.

Results

Condition	Evaluation Dimensions													
	Explainable		Relevance		Diverse		Interface Satisfaction		Use Again		Trust		Average Rating	
	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF
Interface 1 (No Explanations)	66.2*	51.4	69.0*	53.6	46.1	69.4*	69.9	62.1	65.8	59.7	69.3	63.7	3.55*	3.23
Interface 2 (DNN & AVF: Top-3 similar images)	83.5*†[1]	74.0†[1]	80.0*	61.7	58.8	69.9*	76.6*	61.7	76.1*	65.9	75.9*	62.7	3.67*	3.00
Interface 3 (DNN: Top-3 similar, AVF: feature bar chart)	84.2*†[1]	70.4†[1]	82.3*†[1]	56.2	65.3†[1]	71.2	69.9*	63.3	78.2*	58.7	77.7*	55.4	3.90*	2.99

Interface 1: UI without explanation
Interface 2: UI with example-based explanation
Interface 3: UI with transparent explanation (AVF)

Results

Condition	Evaluation Dimensions													
	Explainable		Relevance		Diverse		Interface Satisfaction		Use Again		Trust		Average Rating	
	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF
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7 dimensions evaluated, for DNN and AVF (scale 1-100):

Perception of:

- Explainability
- Relevance
- Diversity
- Satisfaction w/UI
- Intention of use
- Trust on RecSys
- Avg. Rating

Results

- Result : Explainable interfaces increase perception of explainability.

	Evaluation Dimensions													
	Explainable		Relevance		Diverse		Interface Satisfaction		Use Again		Trust		Average Rating	
Condition	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF
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- **Result expected**: people perceive the system as more explainable using the explainable interfaces than non explainable.

Evaluation & Results

- Result 2: Perception of relevance changes just by adding explanations -> User Interface really matters!!

	Evaluation Dimensions													
	Explainable		Relevance		Diverse		Interface Satisfaction		Use Again		Trust		Average Rating	
Condition	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF
Interface 1 (No Explanations)	66.2*	51.4	69.0*	53.6	46.1	69.4*	69.9	62.1	65.8	59.7	69.3	63.7	3.55*	3.23
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- Algorithm is the same (DNN), but by adding explanations people perceive recommendations as more relevant,
- Result is significant only with DNN.

Evaluation & Results

- Result 3: No difference in Trust between DNN and AVF in I1 (without explanations)

	Evaluation Dimensions													
	Explainable		Relevance		Diverse		Interface Satisfaction		Use Again		Trust		Average Rating	
Condition	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF	DNN	AVF
Interface 1 (No Explanations)	66.2*	51.4	69.0*	53.6	46.1	69.4*	69.9	62.1	65.8	59.7	69.3	63.7	3.55*	3.23
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- The difference in Trust between DNN and AVF becomes significant only when using explainable interfaces.

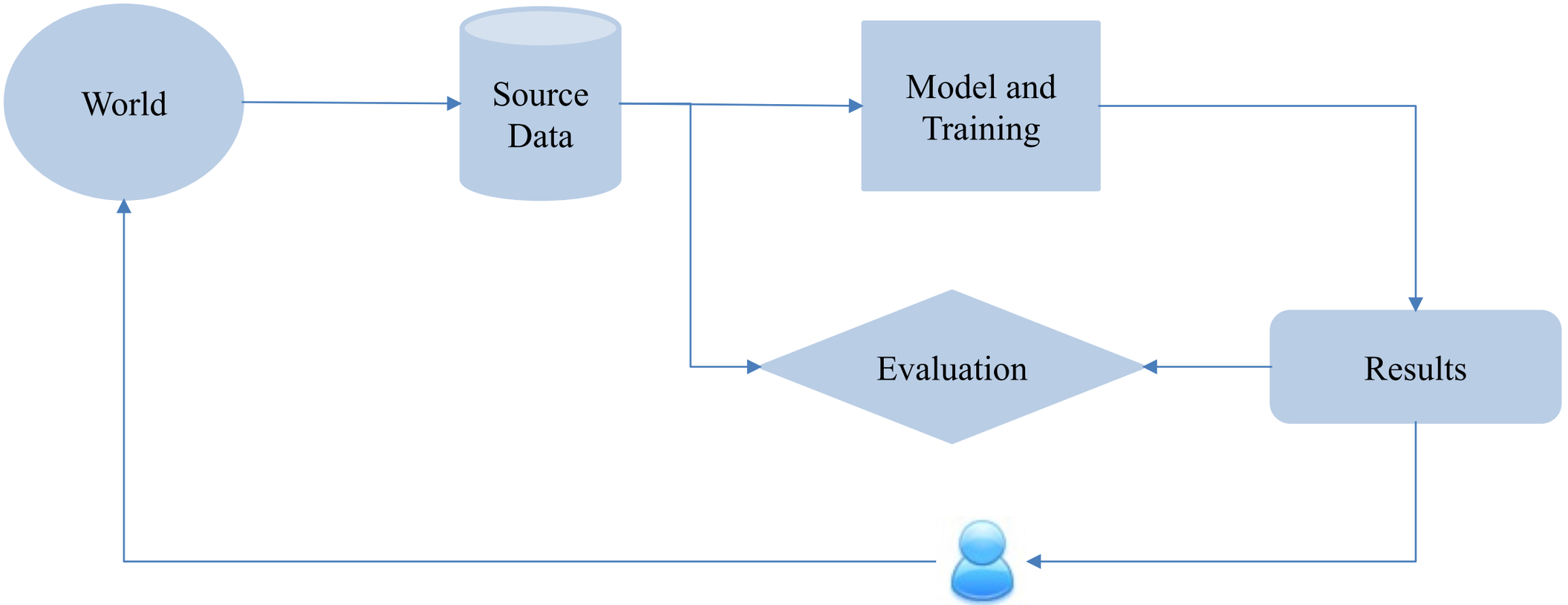
Take-away

- From the tutorial on XAI for IR and RecSys by Zhang, Ai, Mao, Chen:

- What is interpretability in the context of ML/AI?
  - "the degree to which a human can understand the cause of a decision" (T. Miller, et al. AI 2018)
  - "the degree to which a human can consistently predict the model's result" (B. Kim, et al. NIPS 2016)
  - "the ability to explain or to present in understandable terms to a human" (Doshi-Velez and Kim, 2017)

2. FAIRNESS IN RECSYS

Where does Unfairness come from ?



From tutorial by Diaz, Ekstrand & Burke (SIGIR and RecSys 2019): https://fair-ia.ekstrandom.net/sigir2019

World & Data Bias

Figure 5: Words most associated with women (left) and men (right), estimated with *Pointwise Mutual Information*. Font size is inversely proportional to PMI rank. Color encodes frequency (the darker, the more frequent).

Wagner, C., Graells-Garrido, E., Garcia, D., & Menczer, F. (2016). Women through the glass ceiling: gender asymmetries in Wikipedia. *EPJ Data Science*, *5*(1), 5.

Consumer vs. Producer Bias

- The figure, from Ekstrand, Diaz, Burke (2019) show different stakeholders on Information Access Systems

From tutorial by Diaz, Ekstrand & Burke (SIGIR and RecSys 2019): https://fair-ia.ekstrandom.net/sigir2019

Consumer Bias in RecSys

All The Cool Kids, How Do They Fit In? Popularity and Demographic Biases in Recommender Evaluation and Effectiveness*†

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Jennifer D. Ekstrand JENNIFEREKSTRAND@U.BOISESTATE.EDU
Oghenemaro Anuyah OGHENEMAROANUYAH@U.BOISESTATE.EDU
David McNeill DAVIDMCNEILL@U.BOISESTATE.EDU
Maria Soledad Pera SOLEPERA@BOISESTATE.EDU
People and Information Research Team, Dept. of Computer Science, Boise State University

Biases in RecSys

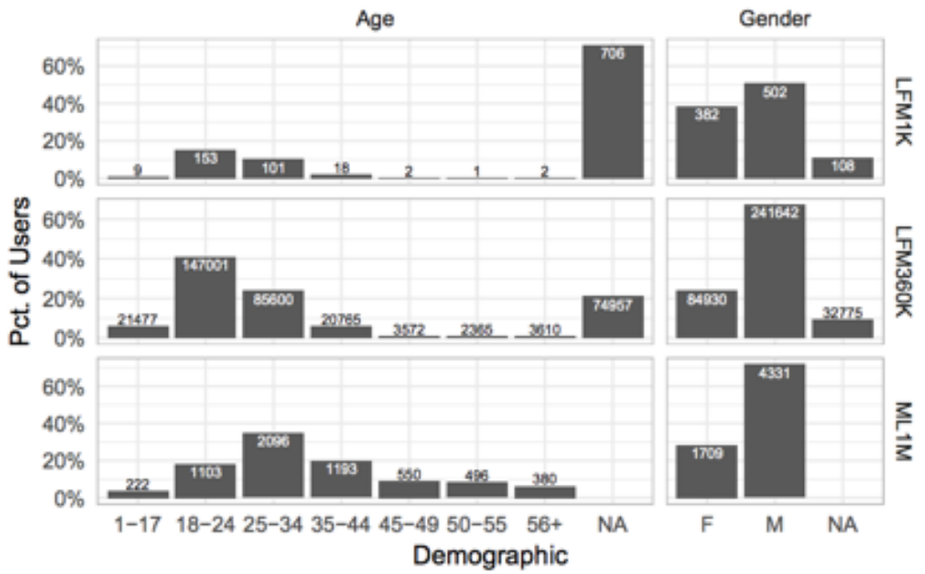


Figure 1: User distribution by demographic group. Numbers in bars are the number of users in that bin.

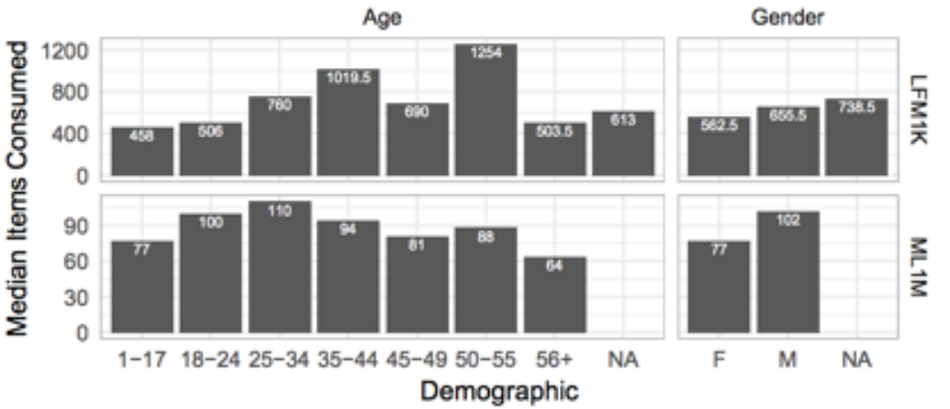
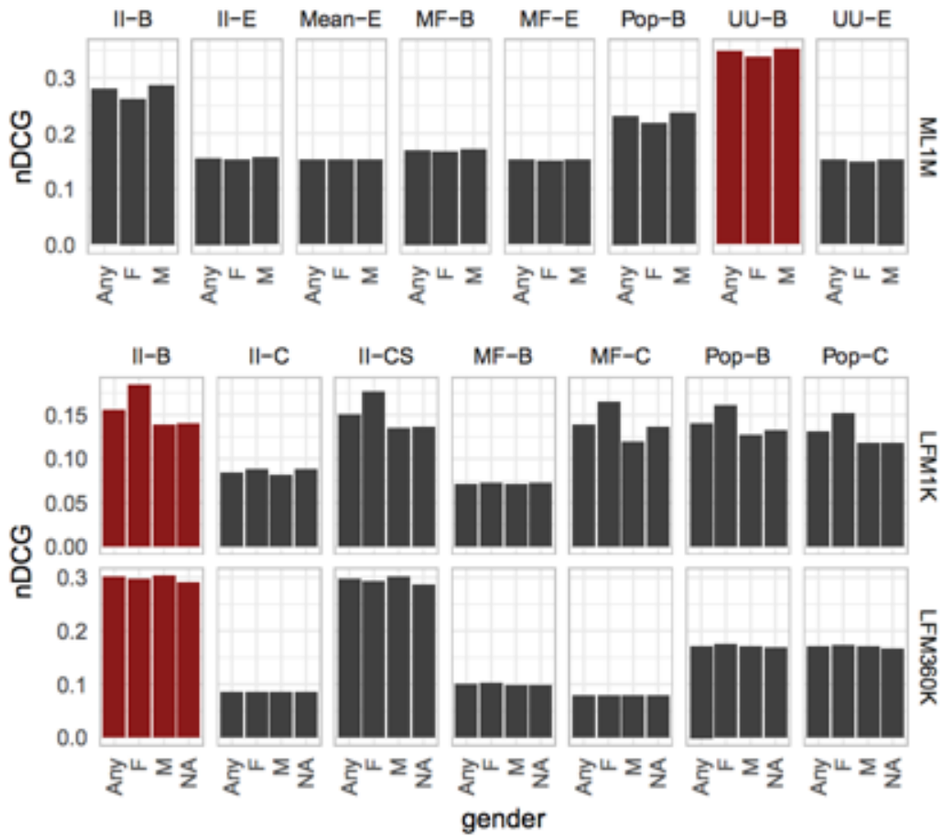


Figure 2: Median items consumed by users in each demographic group. We omit LFM360K since it only contains each user's top 50 artists.

Biases in RecSys



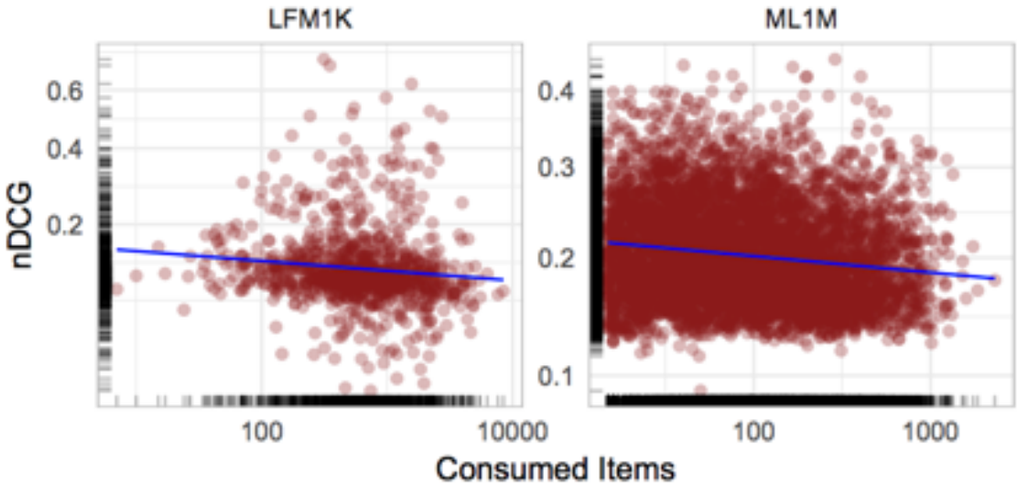
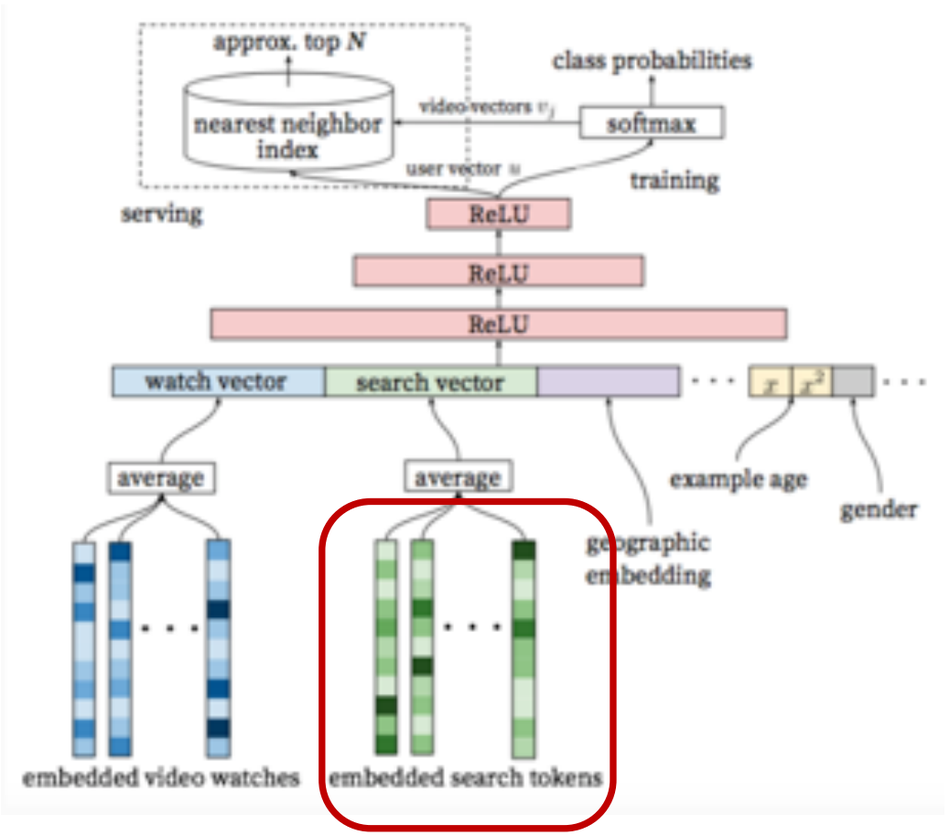
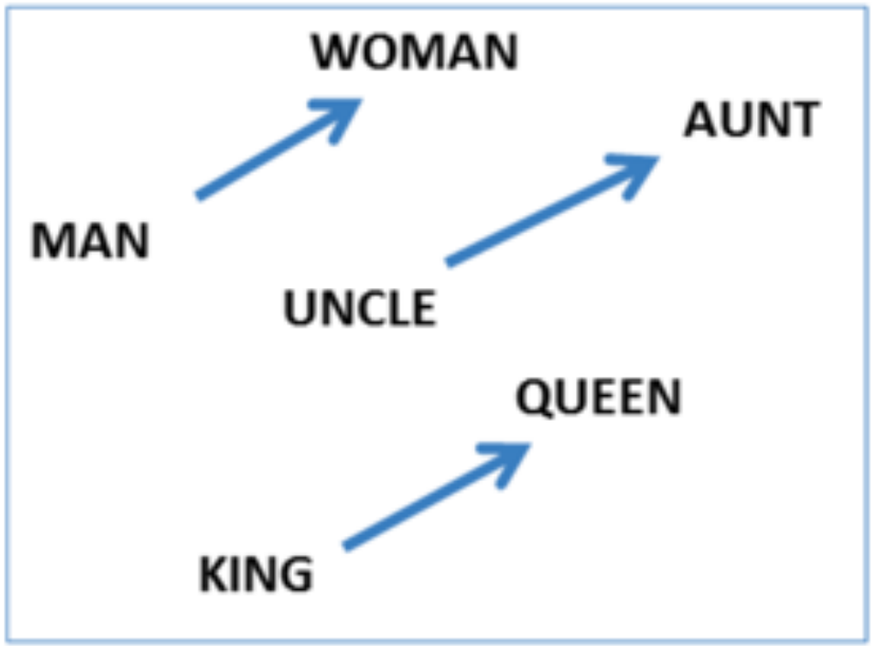


Figure 5: Models predicting nDCG with profile size.

Language models (word2vec, Glove, etc.)





https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

Bias in Language Models

- In addition to their ability to learn word meaning from text, embeddings, alas, also **reproduce the implicit biases and stereotypes** that were latent in the text.
- Bolukbasi et al. (2016) found that the closest occupation to ‘man’ - ‘computer programmer’ + ‘woman’ in word2vec embeddings trained on news text is ‘homemaker’

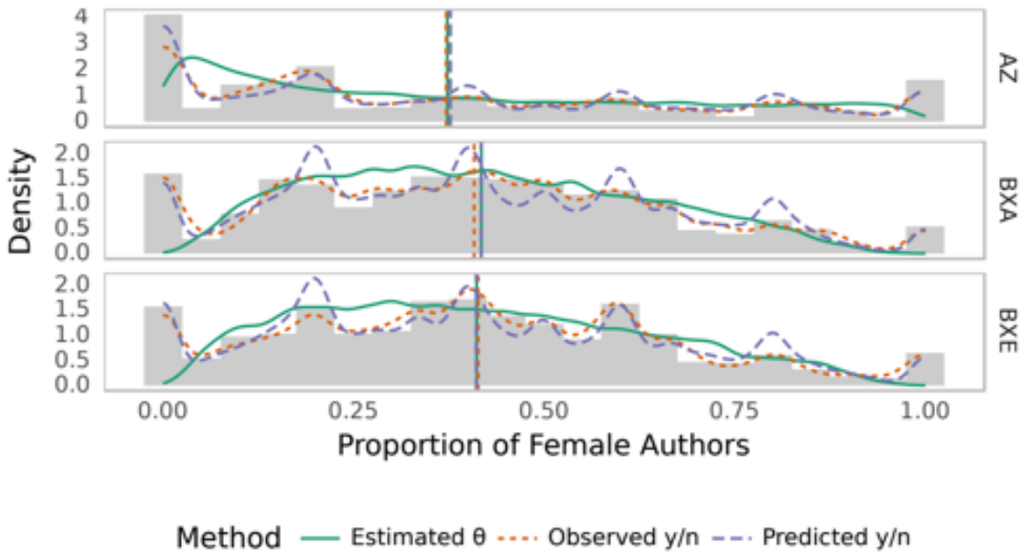
- https://web.stanford.edu/~jurafsky/slp3/6.pdf

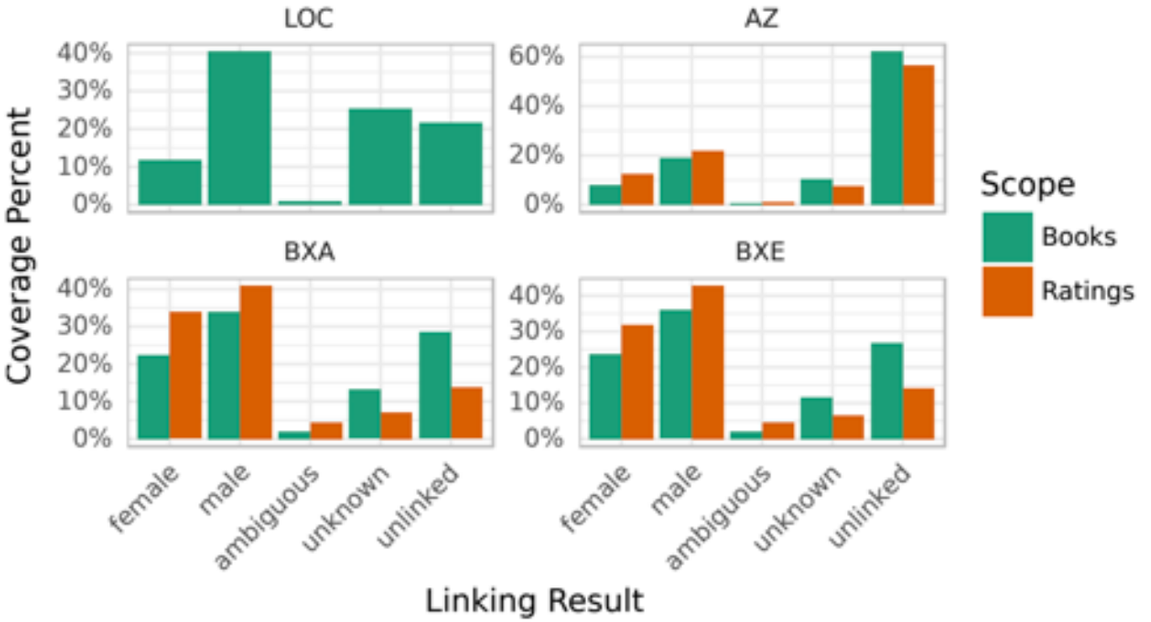
Debiasing in Language Models

- Recent research focuses on ways to try to remove these kinds of biases
- By developing a transformation of the embedding space that removes gender stereotypes but preserves definitional gender (Bolukbasi et al. 2016, Zhao et al. 2017) or changing the training procedure (Zhao et al., 2018).
- However, although these sorts of debiasing may reduce bias in embeddings, they do not eliminate it (Gonen and Goldberg, 2019), and this remains an open problem

Producer Bias

- Ekstrand, M. D., Tian, M., Kazi, M. R. I., Mehrpouyan, H., & Kluver, D. (2018). Exploring author gender in book rating and recommendation. ACM RecSys 2018.





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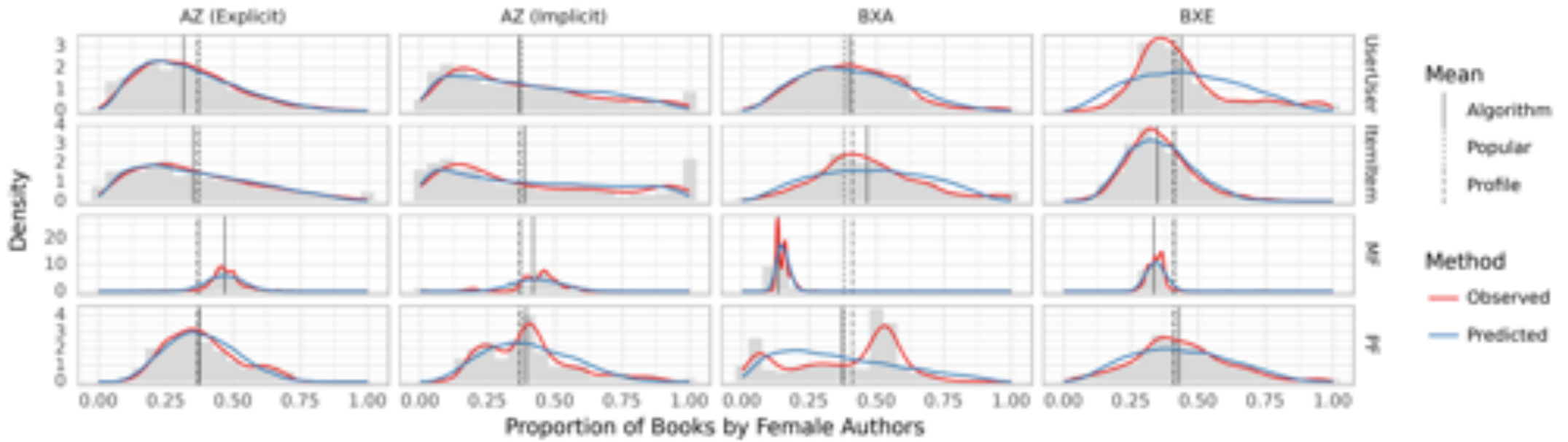

Filter Bubble

- The term filter bubble was popularized by Eli Pariser in his book “The filter bubble: What the Internet is hiding from you”.
- It refers to echo chambers and feedback loops: people gets stacked into a bubble without much option to escape and consume more diverse content.

- Chaney, A. J., Stewart, B. M., & Engelhardt, B. E. (2018). How algorithmic confounding in recommendation systems increases homogeneity and decreases utility. ACM RecSys.

Fairness methods in Ranking

- From Tutorial on Algorithmic Bias in Rankings (Carlos Castillo, 2(

1. Rank protected and unprotected separately

2. For each position:
   - Pick protected with probability *p*
   - Pick nonprotected with probability *1-p*

Continue until exhausting both lists

rank	gender
1	M
2	M
3	M
4	M
5	M
6	F
7	F
8	F
9	F
10	F

p=0

rank	gender
1	M
2	M
3	F
4	M
5	M
6	F
7	M
8	F
9	F
10	F

p=0.3

rank	gender
1	M
2	F
3	M
4	F
5	M
6	F
7	M
8	F
9	M
10	F

p=0.5

Yang, K., & Stoyanovich, J. (2017, June). Measuring fairness in ranked outputs. In *Proceedings of the 29th International Conference on Scientific and Statistical Database Management* (p. 22). ACM.

Recent articles (RecSys 2020)

- Tobias Schnabel and Paul N. Bennett. 2020. *Debiasing Item-to-Item Recommendations With Small Annotated Datasets*.
- Mesut Kaya, Derek Bridge, and Nava Tintarev. 2020. *Ensuring Fairness in Group Recommendations by Rank-Sensitive Balancing of Relevance*.
- Jin Huang, Harrie Oosterhuis, Maarten de Rijke, and Herke van Hoof. 2020. *Keeping Dataset Biases out of the Simulation: A Debiased Simulator for Reinforcement Learning based Recommender Systems*.

- FAccTRec workshop: https://facctrec.github.io/facctrec2020/program/

Open Challenges for Fairness in RecSys

- DATA: Most datasets do not have information to investigate these issues, identifying biases is an open area of research.

- There is no one-size-fits-all solution for fairness: What accurately represents the world? What accurately represents the world as it could or should be?

- We should consider both consumer and producer forms of bias: recommending most popular might be easy to implement and effective, but we are not promoting new producers.

Summary

- In this talk, I have presented, motivated, and defined several aspects of FAT, with a focus on the context of RecSys.

- I have also surveyed several works and areas of research related to FAT and XAI. There are many open research questions to address, and decisions to make in order to progress making RecSys useful but also fair.

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THANKS!