



From toy models to tactics: What user simulation is good for

Christine Bauer

Univ.-Prof. Mag. DI Dr.

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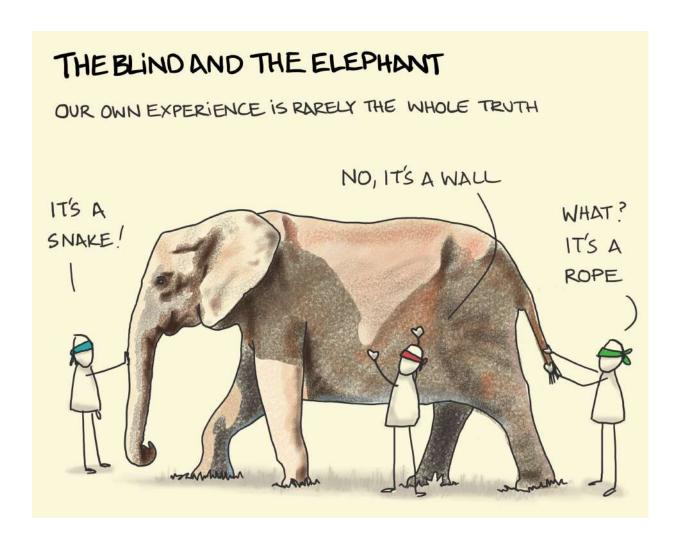
Professor of Interactive Intelligent Systems

EXDIGIT
Department of Artificial Intelligence and
Human Interfaces
Faculty of Digital and Analytical Sciences



Context

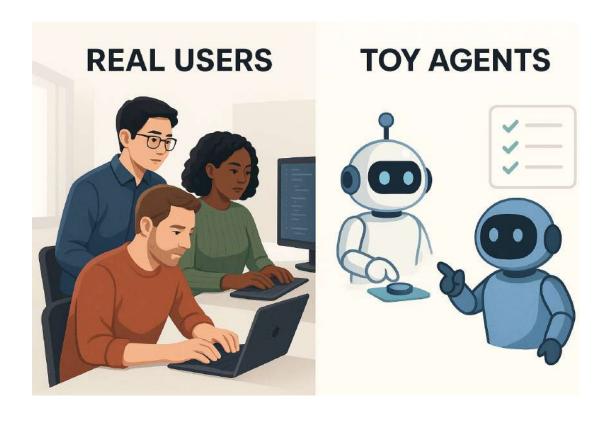
- Recommender systems
 - → I use recommender's terminology
- Interdisciplinary
 - → drawing from various disciplines
 - → also mixing terminology → I'm not perfect...
- Human-centered computing
 - → I care about humans: again and again—always!





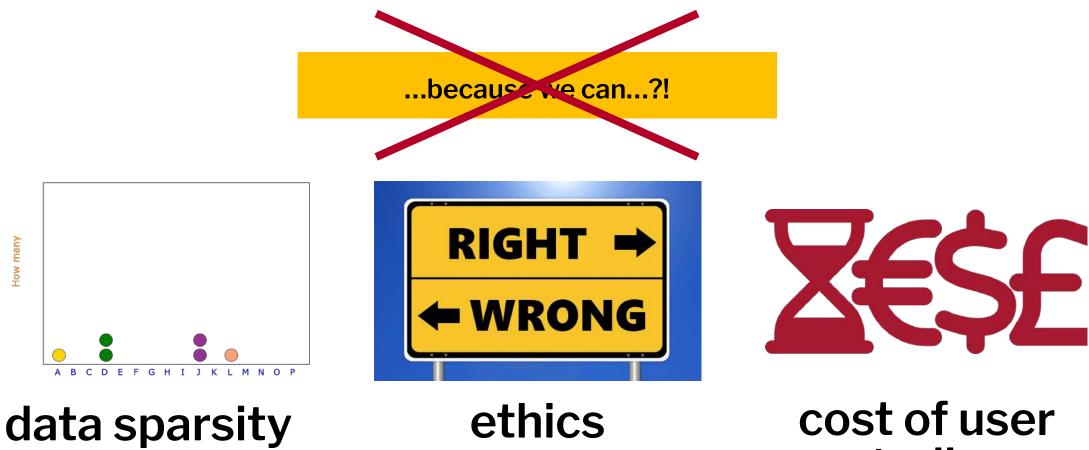
What can we learn from imagined users that real users cannot teach us?

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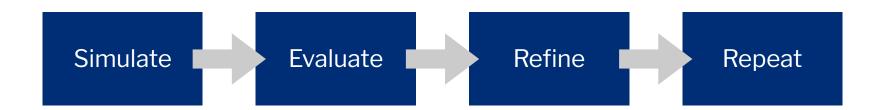
Motivation: Why user simulation?



studies



Simulation as design tool



Simulations help us design with foresight, not just afterthought.



User simulation in information access





Mimicking users in information retrieval research

- following Cranfield paradigm → mimic potential requests of users:
 - "removing actual users from the experiment but including a static user component: the ground truth"
 - simplifying assumption that a single set of judgments for a topic is representative of the user population
- mimicking user requests → essentially, this is user simulation

Cyril W. Cleverdon (1991). The significance of the Cranfield tests on index languages. Proceedings of the 14th Annual international ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '91). ACM, New York, NY, USA, 3–12. DOI: 10.1145/122860.122861

Ellen M. Voorhees (2002). The Philosophy of Information Retrieval Evaluation. In: Peters, C., Braschler, M., Gonzalo, J., Kluck, M. (eds) Evaluation of Cross-Language Information Retrieval Systems. CLEF 2001. Lecture Notes in Computer Science, vol 2406. Springer, Berlin, Heidelberg. DOI: 10.1007/3-540-45691-0_34



Mimicking users in recommender systems research

- assumptions:
 - historic behavior is representative for future behavior
 - taking the average of all users
- mimicking user behavior in "offline evaluation" → essentially, this is user simulation



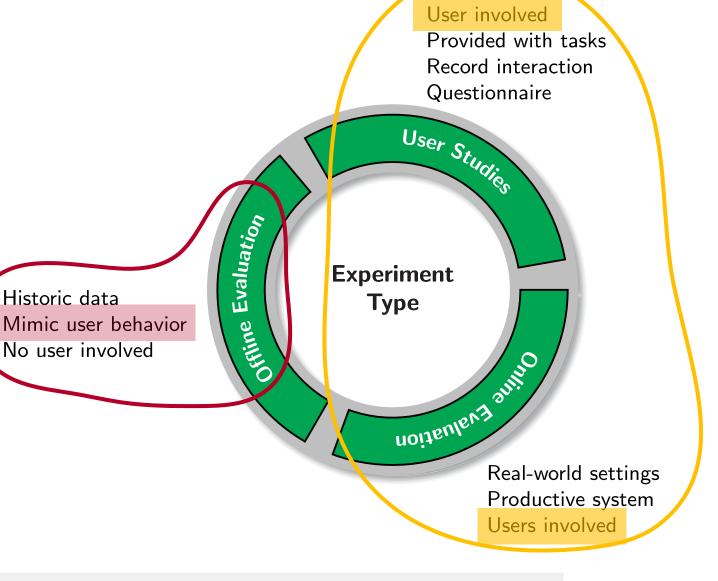


Is all what we do user simulation in the end?

No!



Experiment types in recommender systems research



Different (sub-)communities

- **→different terminology**
- Computational or algorithmic approaches
- User studies (in the lab or online)
- Field study/experiment (using real-world system)

Eva Zangerle & Christine Bauer (2022). Evaluating recommender systems: survey and framework. ACM Computing Surveys, 55(8), Art no. 170, pp 1-38. DOI: 10.1145/3556536

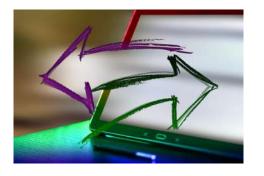


Basically: Addressing more than mere one-shot mimicking.

Longitudinal

e.g.,

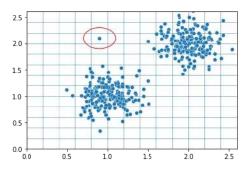
Dynamics



effects

1
0.75
0.5
0.25
April May June July

Special/rare cases or extremes

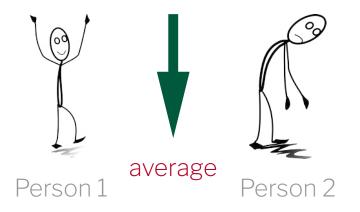




We consider the "typical", "average", ... user.

But who's that?

The "average" might *not* even exist.









Is it all wrong?

Well, it depends!



Accuracy/ realism VS. abstraction/ simplification



https://miro.medium.com/v2/resize:fit:1400/format:webp/1*ZCPI3n2DG5ksaWAAQ7X_gA.png



A model is per definition a simplification.

Creating realistic user simulation models:

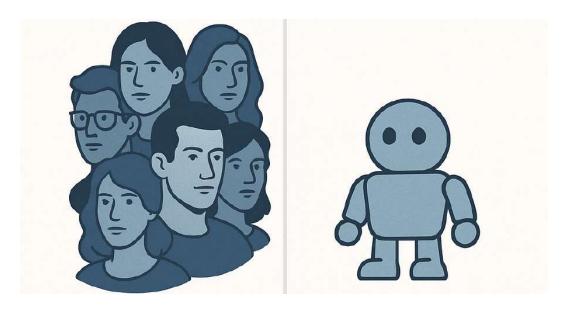
- is complex
- requires in-depth study to develop realistic assumptions
- may <u>not always</u> be necessary



Simulation ≠ faithful replication

We do not simulate to replicate reality.

We simulate to explore possibilities.



Realistic user model— Toy agents detail, complexity, accuracy abstraction, simplicity



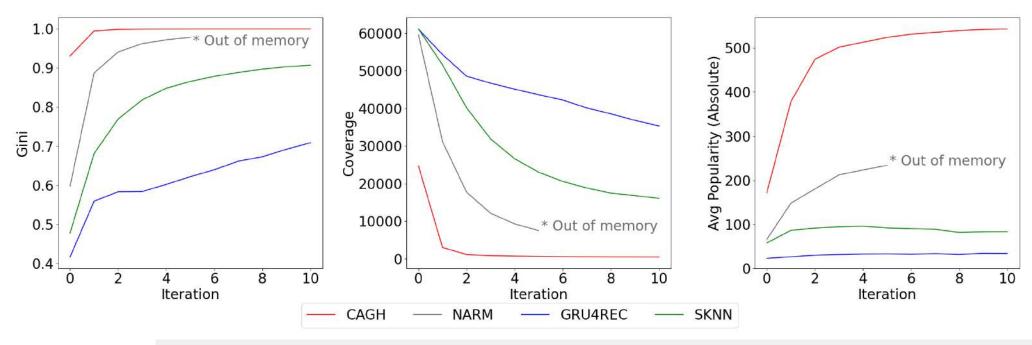
Longitudinal effects

- Simulating sessions, habits, or drift over time
- Generative science approach:
 - → modeling at the micro-level, insights on the macro-level
 - → simulate "what-if" scenarios (e.g., how changing one behavior rule affects the whole system)
 - → Discover non-obvious dynamics (e.g., tipping points, paradoxes)





Studying concentration, coverage, and popularity effects in session-based recommendation



Andres Ferraro, Dietmar Jannach, and Xavier Serra (2020). Exploring Longitudinal Effects of Session-based Recommendations. Proceedings of the 14th ACM Conference on Recommender Systems (RecSys '20). ACM, New York, NY, USA, 474–479. DOI: 10.1145/3383313.3412213



Comparing impact of (strongly) diverging behaviors

4 simple—possibly unrealistic—user choice models



Deterministic

User listens to all top N recommendations

Random

User listens to each item with probability 50%

Inspection-Abandon

User listens to each item with probability 50%,

after item: stop listening entirely with probability 30%

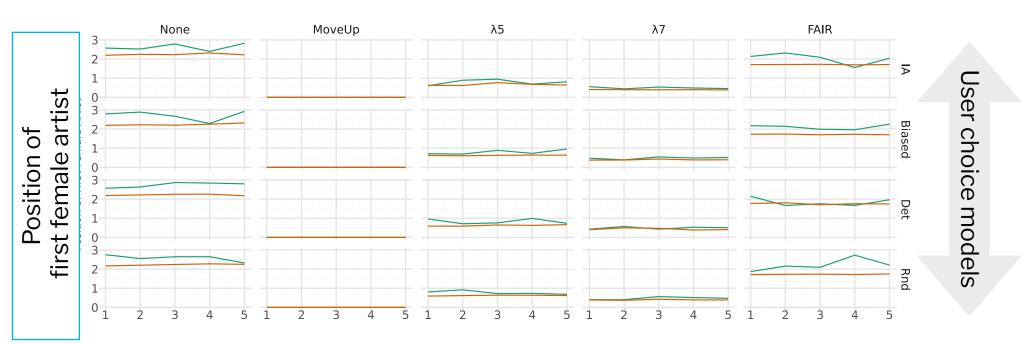
Biased

Like Inspection-Abandon, but users are 10% more likely to listen to male artists

Andrés Ferraro, Michael D. Ekstrand, & **Christine Bauer** (2024). It's not you, it's me: the impact of choice models and ranking strategies on gender imbalance in music recommendation. Proceedings of the 18th ACM Conference on Recommender Systems (RecSys 2024). Bari, Italy, 14-18 October, pp 884-889. DOI: 10.1145/3640457.3688163







More variation between columns than rows

Algorithms have

Algorithms have more impact than user choice models

Andrés Ferraro, Michael D. Ekstrand, & **Christine Bauer** (2024). It's not you, it's me: the impact of choice models and ranking strategies on gender imbalance in music recommendation. Proceedings of the 18th ACM Conference on Recommender Systems (RecSys 2024). Bari, Italy, 14-18 October, pp 884-889. DOI: 10.1145/3640457.3688163

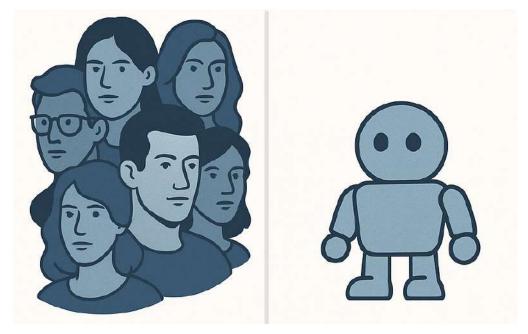


From toy models to tactical insights

Toy models

- → not the whole picture
- → no subtle details

Tactical insights on what the user simulation was specifically designed for.





Simulating extremes (e.g., to investigate implications)

Extremes can mean:

- Rare user behavior (e.g., a new user binge-clicking unrelated items)
- Unusual preference shifts (e.g., a user drastically changing interests overnight)
- Outlier content dynamics (e.g., one item going unexpectedly viral)
- Adversarial user behaviors (e.g., flooding clicks to boost an item)



...

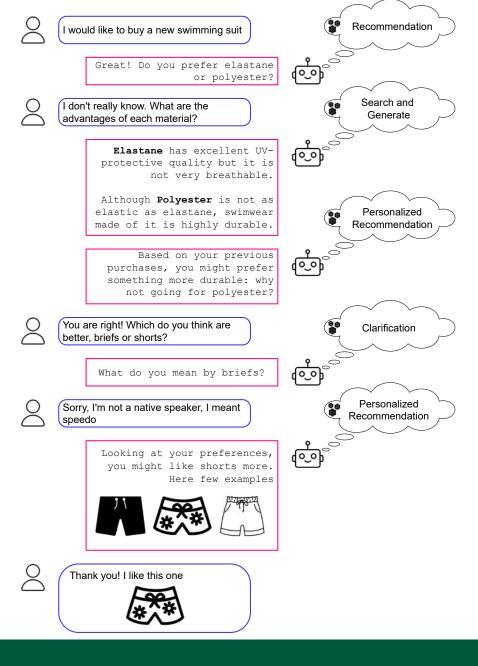


Dealing with complexity

e.g., CONversational Information ACcess agents (CONIAC)

- → Multi-turn interactions
- → Combination of retrieval, recommendation, clarification, explanations,...
- → Exploring "what ifs"

Christine Bauer, Li Chen, Nicola Ferro, Norbert Fuhr, et al. (2025). Conversational Agents: A Framework for Evaluation (CAFE) (Manifesto from Dagstuhl Perspectives Workshop 24352). DOI: 10.48550/arXiv.2506.11112





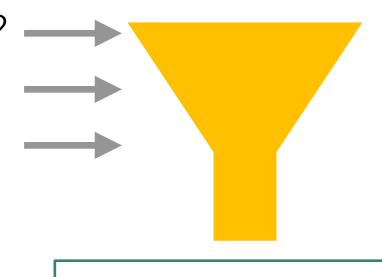
Abstraction: What we lose and gain

Aspect	Abstracted model	Realistic model
Speed		×
Fidelity	×	
Interpretability		×
Generalization		×



3 questions to ask

- What question are you trying to answer?
- What level of realism is necessary?
- How will you validate your insights?



design choice for user simulation

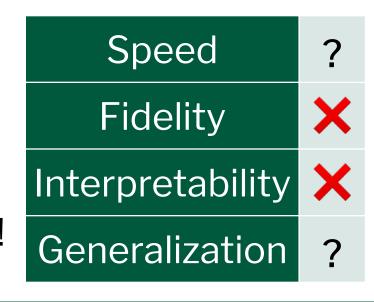


Simulation with LLMs: the good, the bad, and the ugly

LLM-based simulations can be useful → growing number of research papers!

Yet, critical challenges require attention:

- Neither representative of the general population nor based on a well-defined, controlled user model
- How biased are they? → We do not know!





Takeaways

- Simulation is about reasoning, not realism
- Simple agents can yield deep insights
- Thoughtful abstraction is a strength, not a flaw
- Don't you dare using "unthoughtful abstraction"!









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BEYOND 2025 @RecSys 2025

Submission deadline: Aug 7th, 2025 https://beyondrecsys.github.io

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