Psychological Aspects in Retrieval and Recommendation

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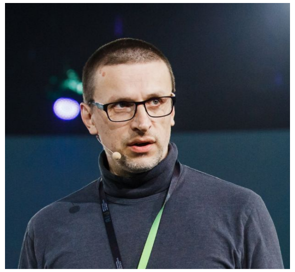

About Markus Schedl

JOHANNES KEPLER UNIVERSITÄT LINZ

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MULTIMEDIA MINING AND SEARCH GROUP

- Full Professor at Johannes Kepler University (JKU) Linz, Austria
- Head of *Multimedia Mining and Search* (MMS) group at Institute of Computational Perception
- Head of *Human-centered Artificial Intelligence* (HCAI) group at Linz Institute of Technology (LIT), AI Lab
- Lab: https://hcai.at | https://www.jku.at/en/institute-of-computational-perception
- Interests: recommender systems, user modeling, information retrieval, machine learning, natural language processing, multimedia, data analysis, AI fairness

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- PI AI for Society Lab at Institute of Human-Centred Computing (HCC)
- Lab page: https://socialcomplab.github.io/
- Interests: user modeling, recommender systems, information retrieval, natural language processing, computational social science, HCI, inclusive technologies

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About Marko Tkalcic

- Full Professor, HICUP Lab, University of Primorska, Slovenia.
- Lab page: https://hicup.famnit.upr.si/
- Interests: improving personalized services (e.g. recommender systems) through the usage of psychological models in personalization algorithms
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Introduction and Background

Motivation

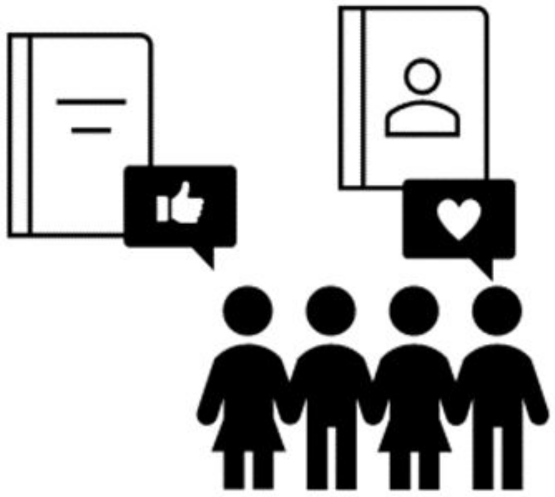
- *Information retrieval (IR)* and *recommender systems (RS)* affect many aspects of our daily lives, influencing which content we are exposed to on the web or social media platforms, which products we buy, or which music we listen to.
- *Psychological processes* play a critical role in shaping *users' interactions* with IR and RS technology.

→ Studying *human cognition*, *decision-making processes*, and psychological factors such as *personality* and *emotion* is vital to understand how users interact with the systems and to enable user-centric IR and RS.

→ Understanding whether these aspects are also present (to some extent) in the systems themselves (e.g., in training data, ranking models, or outputs), or even integrating them on purpose, can inform the development of *psychology-inspired systems*.

Motivation

- Recommendation and search/retrieval systems historically motivated by observations that humans base their decisions on recommendations from other people
- Early RS aimed to mimic that behavior and were based on findings from psychology
    - Emotion & attention
    - User satisfaction / mood
    - Decision making
    - …
- Now: vast amounts of behavioral data available (queries, interactions, logs, …)
- Combine data-driven approaches with psychological models to improve the search and recommendation process



Objectives

Overall: Providing an introduction to various psychological concepts and factors that are important in the ecosystem of search, retrieval, and recommendation, in particular: *cognitive architectures*, *cognitive effects and biases*, *personality and affect*

After attending this tutorial, you will:

- know the most important cognitive architectures and processes, and how they affect human decision making
- know how to create RS technology based on these cognitive models
- understand the most important cognitive effects and biases in humans, and how they manifest in IR and RS
- have some ideas about how to leverage negative and mitigate positive effects of cognitive biases in IR and RS contexts
- be able to model and acquire personality and mood according to psychological theories and results of empirical studies
- be aware of methods for integrating affective information into IR and RS

Tutorial Materials

https://github.com/aisocietylab/Psy-IR-RecSys-SIGIR25

Overview

Part I: Cognitive Architectures (~50 minutes)

We introduce cognitive architectures as computational frameworks that model human cognitive processes such as memory, learning, attention, and decision-making. We discuss how these architectures can be leveraged to improve IR and RS by making them more adaptive, interpretable, and user-centric.
Concrete subject matters include:

1) Fundamentals of human cognition
2) Introduction to cognitive architectures
3) Cognitive load and information overload
4) Major cognitive architectures in IR and RS
    a) ACT-R
    b) SOAR
    c) CLARION
    d) LIDA
5) Case studies of cognitive architectures
6) Pros and cons

Part II: Cognitive Effects and Biases (~50 minutes)

We discuss a mixture of well-studied and lesser-studied cognitive biases in the context of IR and RS, pertaining to both the system (training, model, and inference) and the user-system interactions.
Concrete subject matters include:

1) Rationality and decision heuristics
2) Role of cognitive biases in human decision making
3) Primacy/Recency effects and position bias
4) Bandwagon effect and popularity bias
5) Feature-positive effect
6) Cultural homophily
7) Conformity bias
8) Anchoring and decoy effect
9) Confirmation bias
10) Halo and horn effects
11) Strategies to mitigate and leverage cognitive biases in IR and RS

Part III: Personality and Affect (~50 minutes)

We introduce models of personality and affect and discuss how they can be used in IR and RS.
Concrete subject matters include:

1) States vs. traits: background
2) Emotion models
3) Usage of emotions in IR and RS
4) Emotion acquisition
5) Personality models
6) Usage of personality in IR and RS
7) Acquisition of personality
8) Eudaimonia and hedonia as traits and item characteristics
9) Other psychological constructs (needs...)

Part I: Cognitive Architectures

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Motivation

- Users frequently overwhelmed by sheer amount of search results and recommendations
- Current IR/RS often ignore users’ cognitive states and limitations

→ Need for systems that adapt to human memory, attention, and decision-making

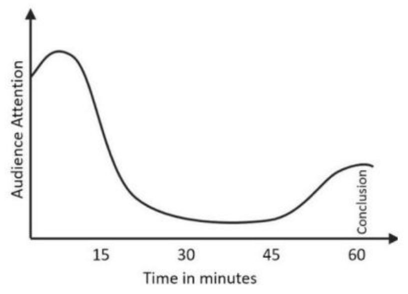
Fundamentals of Human Cognition

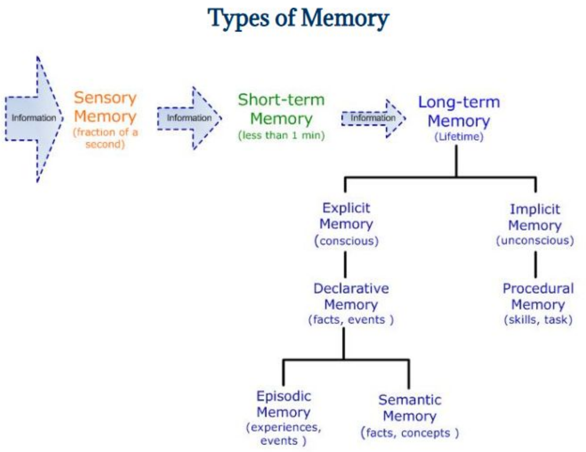
- Set of mental processes involved in acquiring, processing, storing and utilizing information (Neisser, 1967)
- Defines how humans interact with & make sense of world
- Includes perception, attention, memory, learning, reasoning, decision-making, problem-solving

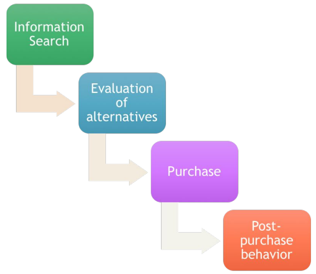
→ Core to how users interact with IR and RS, search, perceive results and make choices in IR/RS contexts.

Key Cognitive Processes

- Attention: defines what we focus on / what enters our memory
- Memory: enables to acquire, retain, and recall information one has experienced
- Decision-Making: bounded rationality, heuristics-based





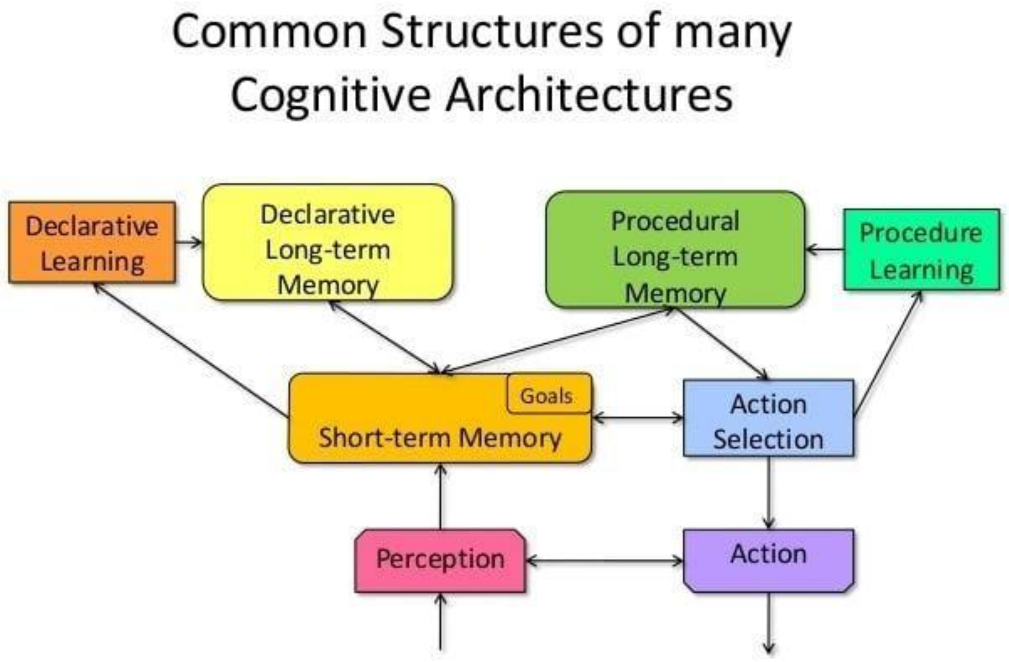


Mapping IR/RS Tasks to Cognitive Processes

IR/RS Task	Cognitive Process
Query (Re-)formulation	Working memory, attention
Ranking, Interface Design	Attention, perception
Session continuation or abandonment	Episodic memory, fatigue
Item selection	Decision-making, heuristics
Personalization (over time)	Long-term memory, learning

IR/RS tasks are grounded in cognitive processes - understanding these can help us design better systems!

Cognitive Architectures

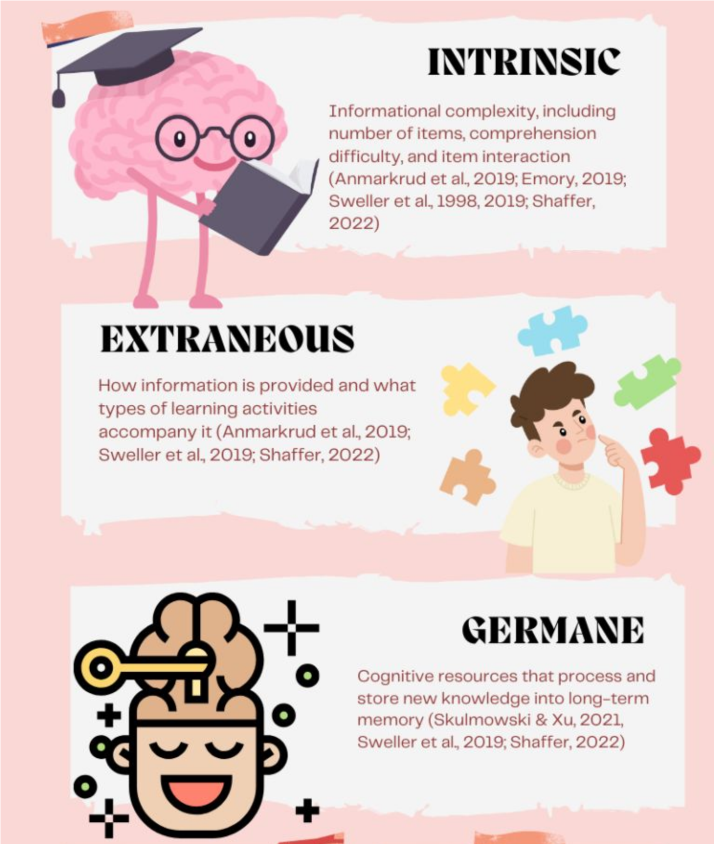


- Computational frameworks to simulate human cognition
- Help test and consolidate cognitive psychology findings
- Support both symbolic (rule-based) and subsymbolic (neural, statistical) processing
- Include components for perception, memory, attention, reasoning, and learning
- Tools for building intelligent agents
- Examples: ACT-R, Soar, CLARION, LIDA

Why Cognitive Architectures in IR/RS?

- Model users as bounded rational agents
- Capture critical aspects of cognition that matter in IR/RS
    - attention, memory, forgetting, habits
- Enable transparent user behavior modeling
- Inspired by psychological and neuroscientific theories
- Support development of adaptive and personalized agents
- Can be used to simulate, predict, and shape human-system interactions
- Alignment of models with user cognitive states
- Can give insights into users’ cognitive states during activities

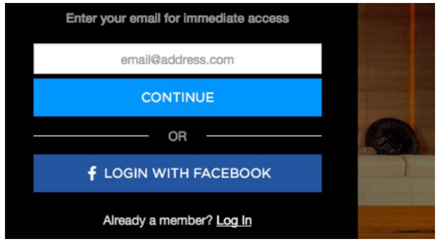
Cognitive Load

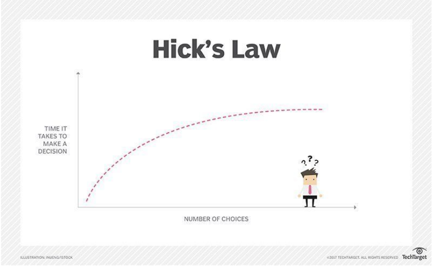


https://betsylewis.blog/2024/06/12/cognitive-load-theory

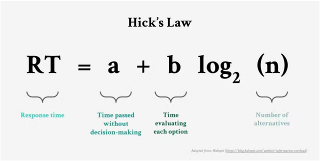
- Cognitive Load Theory (CLT) (Sweller, 1988):
  - Users have limited working memory
  - Performance depends on used capacity of working memory
- CLT defines three types of load:
  - Intrinsic: inherent difficulty of task
  - Extraneous: poor interface/irrelevant info
  - Germane load: effort needed to build useful insights (“schemas in memory”)

High Cognitive Load in IR/RS: Some Reasons



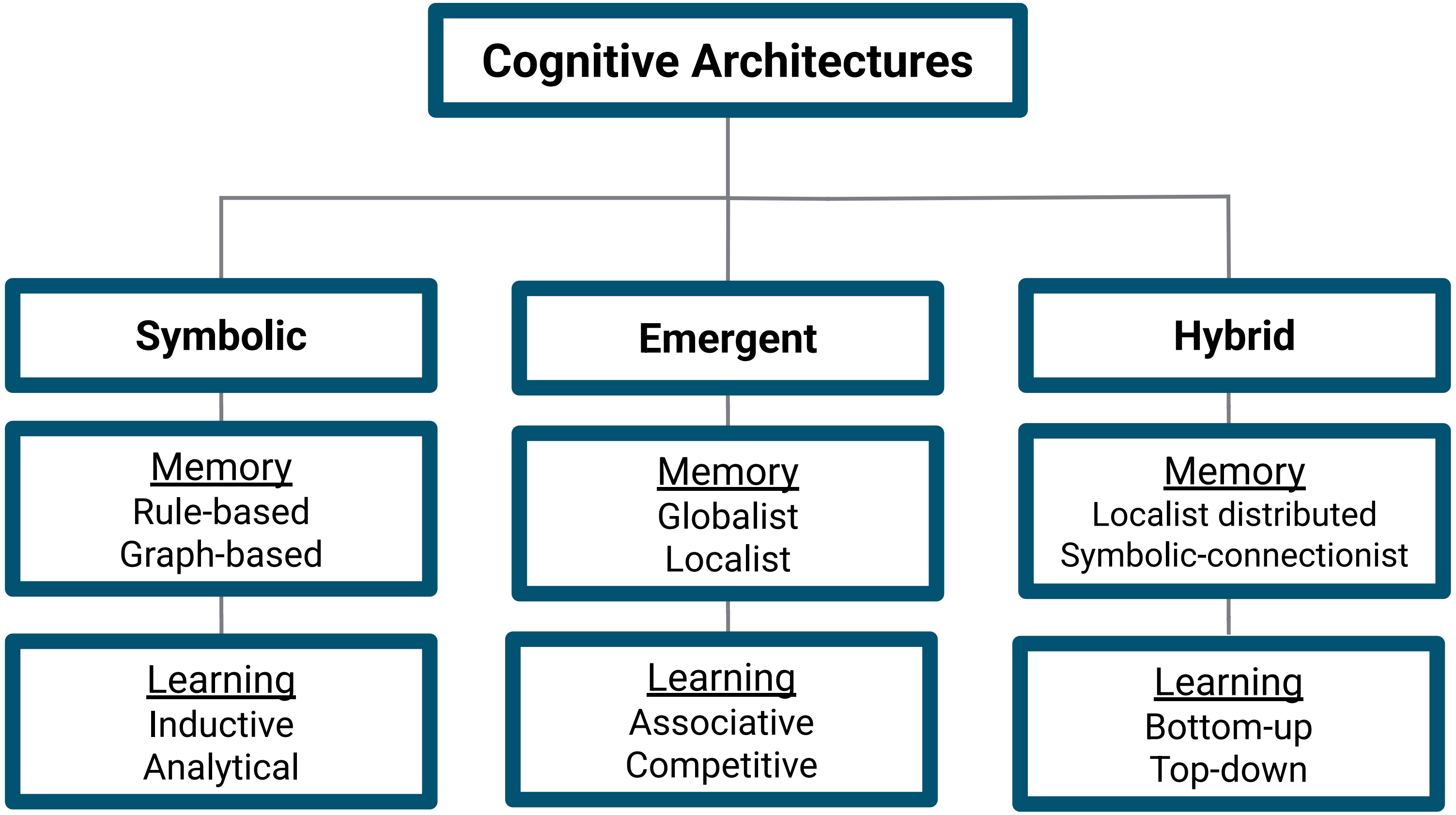


- Unclear actions
  - e.g. requiring registration before anything can be done without telling the user why you collect their data
- Unclear interfaces / Overstimulation
  - Ambiguous icons, user has a hard time figuring out how to complete an action
  - Cluttered, distracting interfaces
- Too many options: Hick's Law
  - The more options a user has, the more time they will take to make a decision



https://www.smashingmagazine.com/2016/09/reducing-cognitive-overload-for-a-better-user-experience/

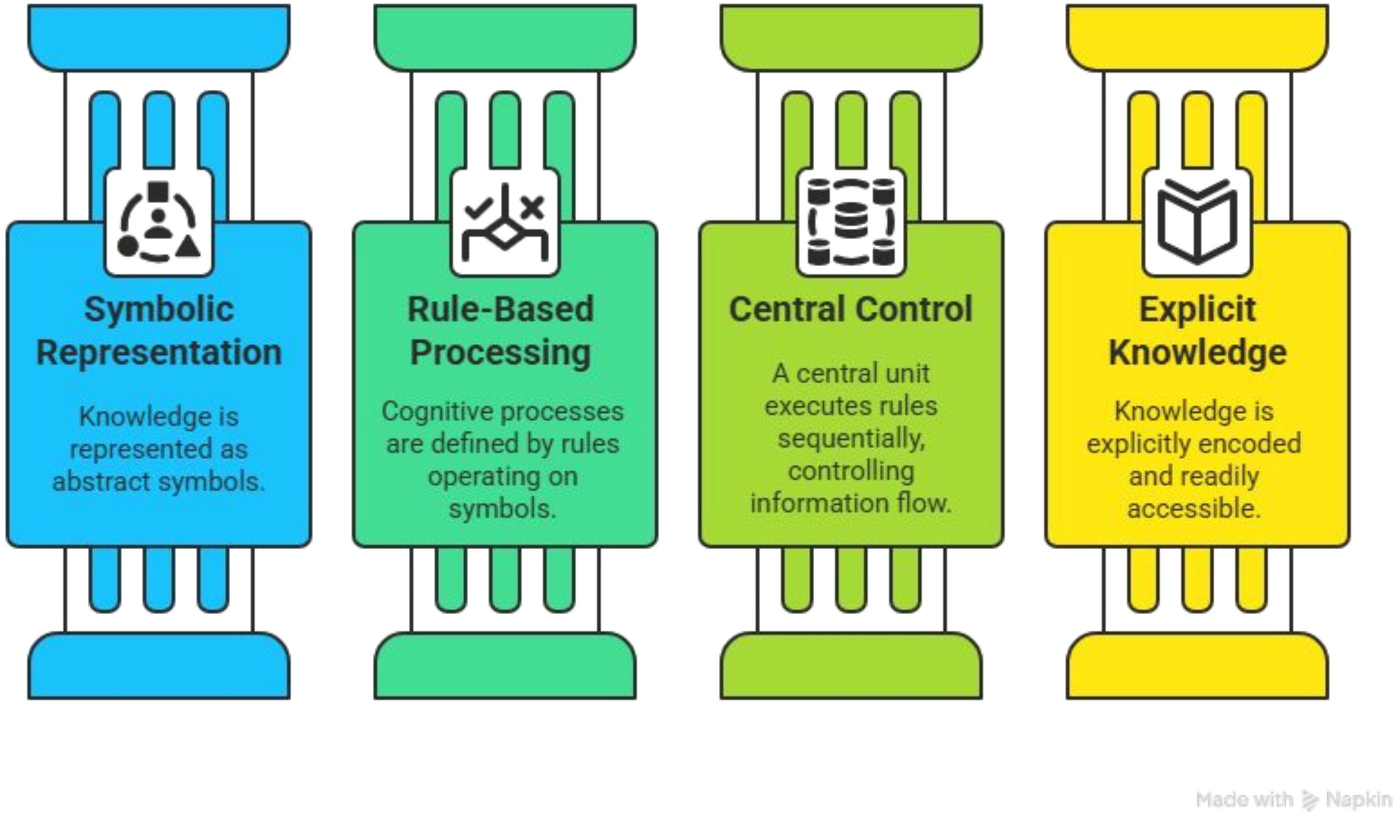
Taxonomy of Cognitive Architectures



Adapted from: https://www.semanticscholar.org/paper/Comparative-study-of-cognitive-architectures-Asselman-Souhaib/d45102427d2d6700b245047fbf2e91edd9b479fe

Symbolic Architectures

Symbols: abstract entities such as concepts, objects, relationships



Pros and Cons of Symbolic Architectures

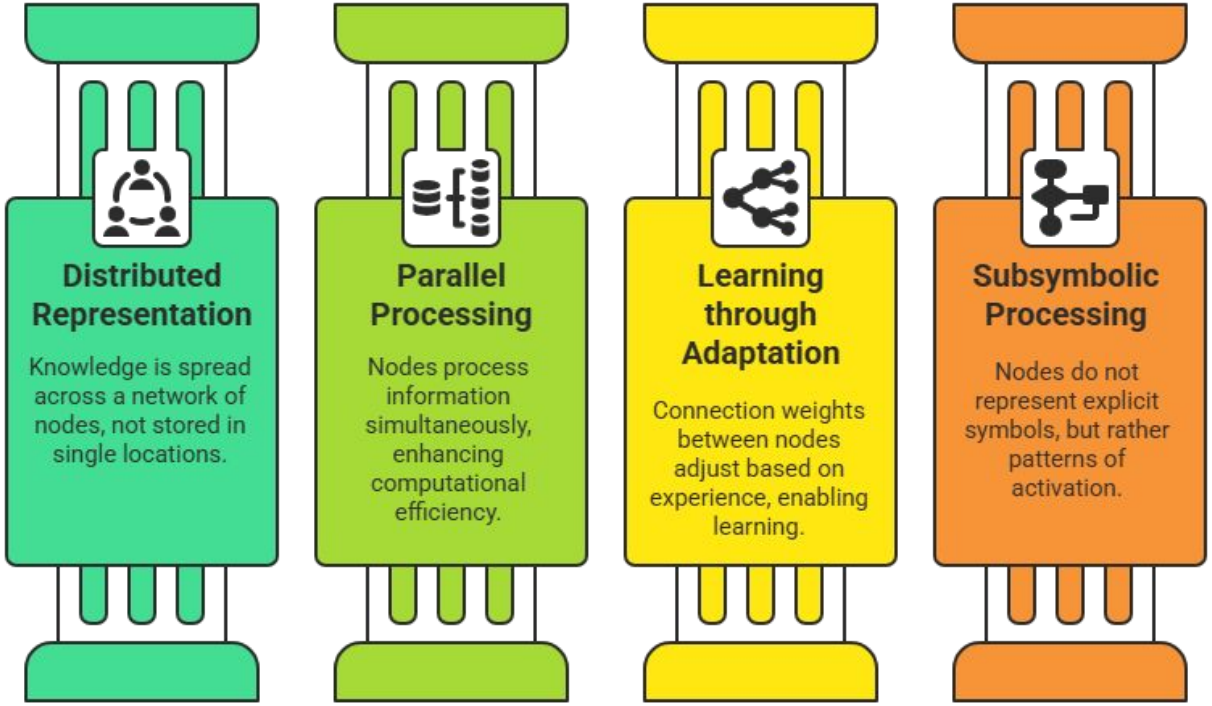
Pros:

- Explainability: rules and symbols are explicitly defined; reasoning process can be traced
- Good for problem-solving tasks requiring deductive inference
- Explicit Knowledge representation

Cons:

- Scalability
- Adaptation to dynamic environments can be challenging
- Explicitly defined rules and symbols - requires work to find the best ones

Emergent (Connectionist) Architectures



Pros and Cons of Connectionist Architectures

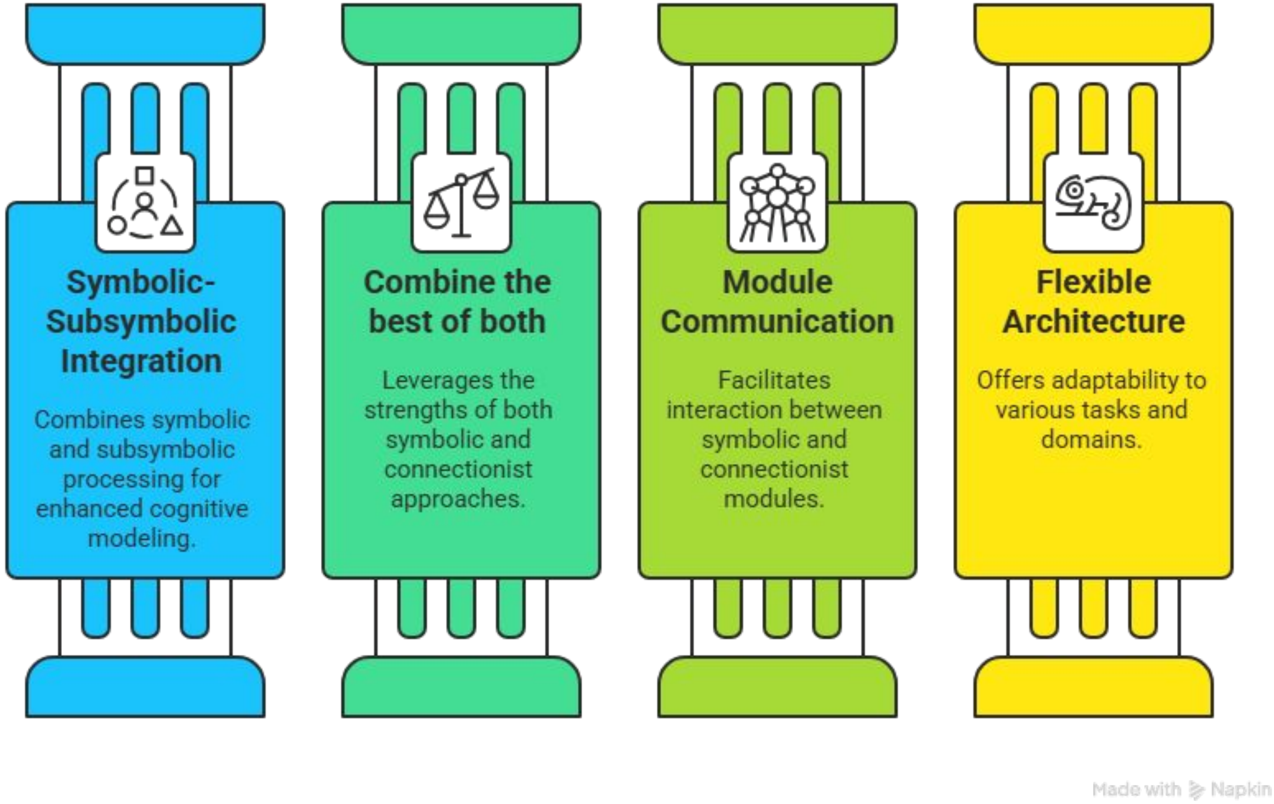
Pros:

- They can learn complex patterns and relationships from data
- Generalize well to new situations based on learned patterns
- No need to explicitly model symbols/rules

Cons:

- Explainability: difficult to explain
- Limited logical reasoning capabilities and symbolic manipulation
- Representing knowledge and relationships is challenging and requires a lot of data

Hybrid Architectures



Pros and Cons of Hybrid Architectures

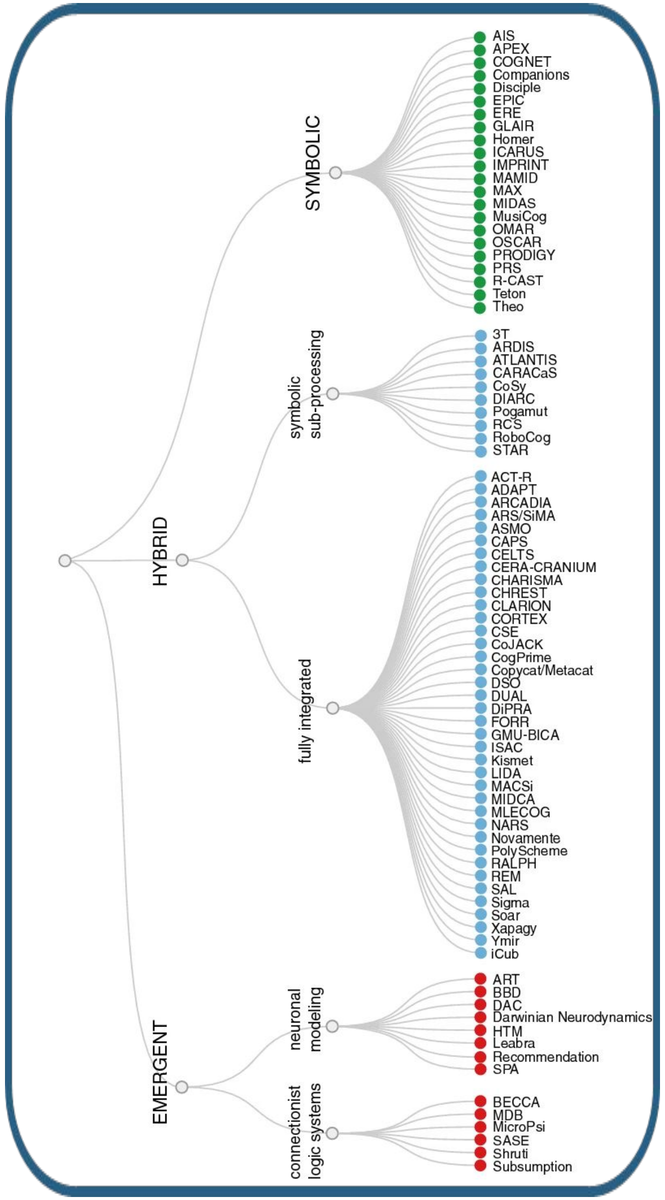
Pros:

- Better explainability but also good learning capabilities
- Can do both explicit knowledge representation and pattern recognition
- Can be adapted to dynamic environments and new tasks

Cons:

- Higher complexity due to combination of different learning paradigms
- Can be computationally expensive

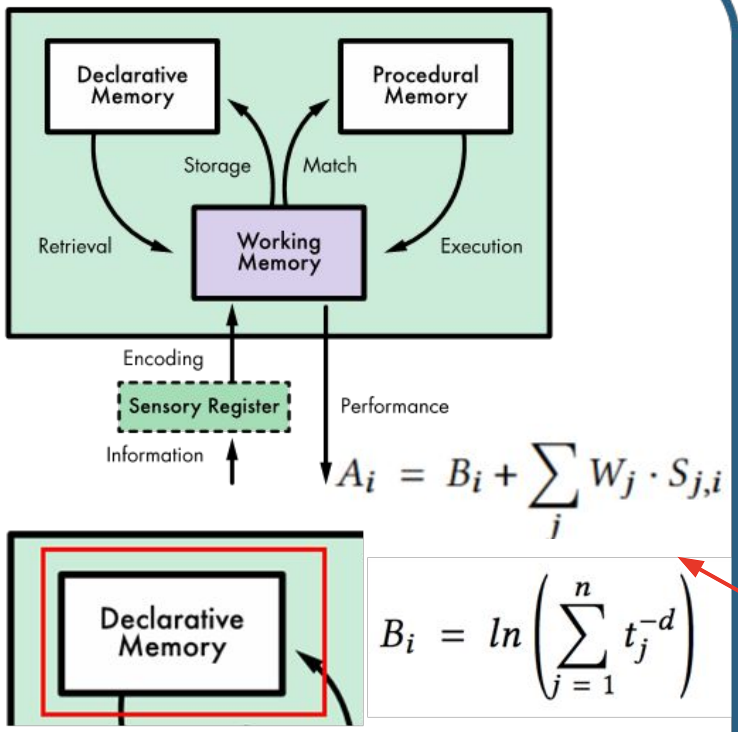
Major Cognitive Architectures



- Manifold cognitive architectures have been proposed to model human cognition
- Ranging from symbolic to subsymbolic to hybrid and emergent approaches
- Some are particularly suited for modeling user behavior in IR/Rs:
  - ACT-R
  - Soar
  - CLARION
  - LIDA

https://link.springer.com/article/10.1007/s10462-018-9646-y#Fig3

ACT-R: Adaptive Control of Thought - Rational



ACT-R model (Anderson 2004)

- Modular architecture: symbolic & subsymbolic components
- Core components:
  - Working memory
    - Composed of temporary buffers holding active chunks
    - Represents system’s current state and focus
  - Procedural memory
    - Contains production rules that drive cognition using “if-then” logic
    - Rules match buffer contents and trigger actions
  - Declarative memory
    - Knowledge stored as chunks (types and attributes)
    - Supports activation-based retrieval (influenced by recency and frequency of prior use)
    - Used for recalling facts, goals, past experiences

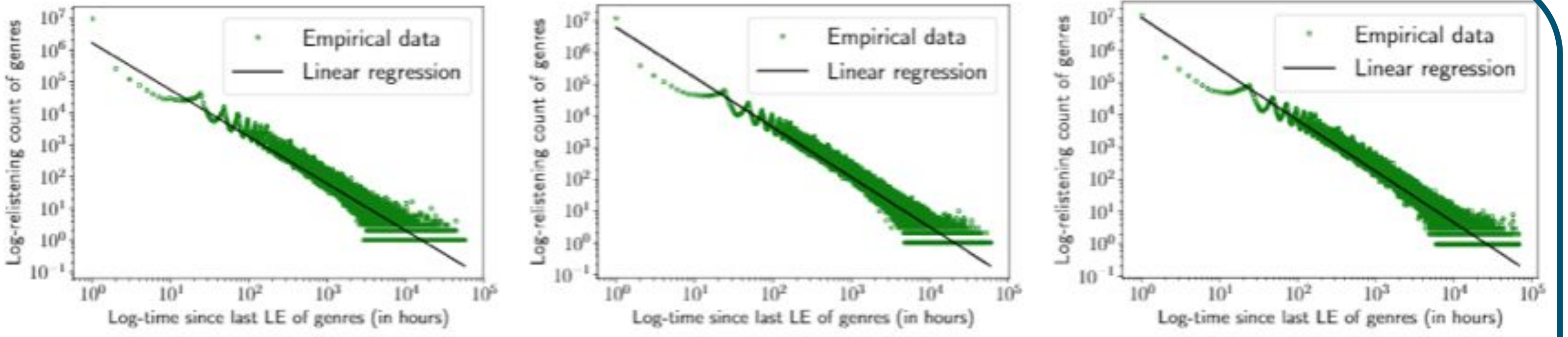
Example: Music Preferences and ACT-R

[Lex et al., 2020]

- Motivation: **Popularity bias** for consumers of low mainstream music
- Idea: Psychology-informed model of music consumption behavior
- Aim: **Predict music genre preferences for low, medium & high mainstream consumers**
- Approach
  - 1.1 billion listening events (LEs) from LFM-1b [Schedl, 2016]
    - Each LE contains a user identifier, artist, album, track name, and timestamp
    - Plus: mainstreaminess score:
      - Overlap between a user's personal listening history and the aggregated listening history of all Last.fm users in the dataset.
  - Created 3 equally sized groups based on mainstreaminess: low, medium, high mainstream

Temporal Dynamics of Music Consumption

- Re-listening count of genres over time plotted on log-log scale



(a) User group: LowMS
Linear regression: α = -1.480

(b) User group: MedMS
Linear regression: α = -1.574

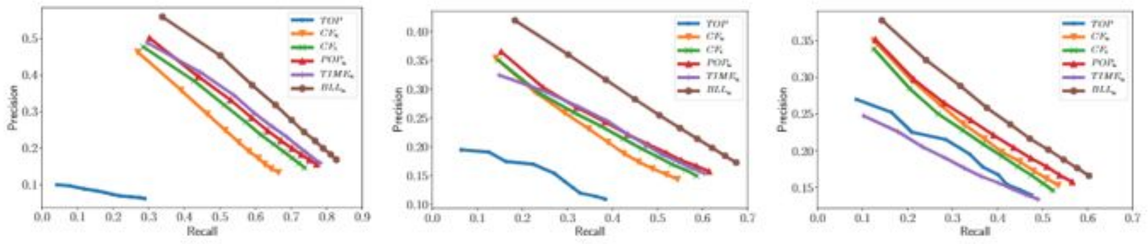
(c) User group: HighMS
Linear regression: α = -1.587

--> the shorter the time since the last listening event of a genre the higher its relistening count!

$$B_i = ln\left(\sum_{j=1}^{n} t_j^{-d}\right)$$

ACT-R for Genre Prediction

User group	Evaluation metric	TOP	CF_u	CF_i	POP_u	$TIME_u$	BLL_u
LowMS	F1@5	.108	.311	.341	.356	.368	.397***
	MRR@10	.101	.389	.425	.443	.445	.492***
	MAP@10	.112	.461	.505	.533	.550	.601***
	nDCG@10	.180	.541	.590	.618	.625	.679***
MedMS	F1@5	.196	.271	.284	.292	.293	.338***
	MRR@10	.146	.248	.264	.274	.272	.320***
	MAP@10	.187	.319	.336	.351	.365	.419***
	nDCG@10	.277	.419	.441	.460	.452	.523***
HighMS	F1@5	.247	.273	.266	.282	.228	.304***
	MRR@10	.188	.232	.229	.242	.201	.266***
	MAP@10	.246	.304	.298	.314	.267	.348***
	nDCG@10	.354	.413	.402	.429	.357	.462***



(a) User group: LowMS (b) User group: MedMS (c) User group: HighMS

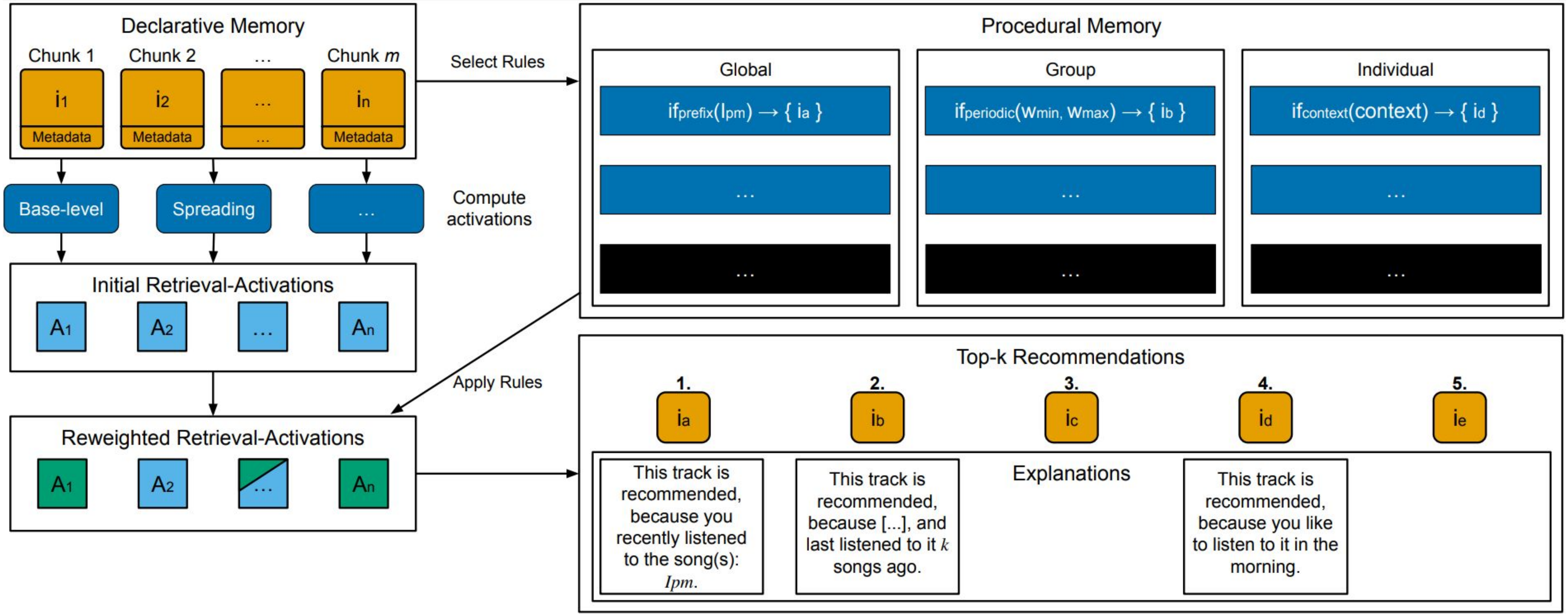
Approach:

1. Compute base-level activation of a genre for a user
2. Normalize using softmax function
3. Predict top-k genres with highest activation

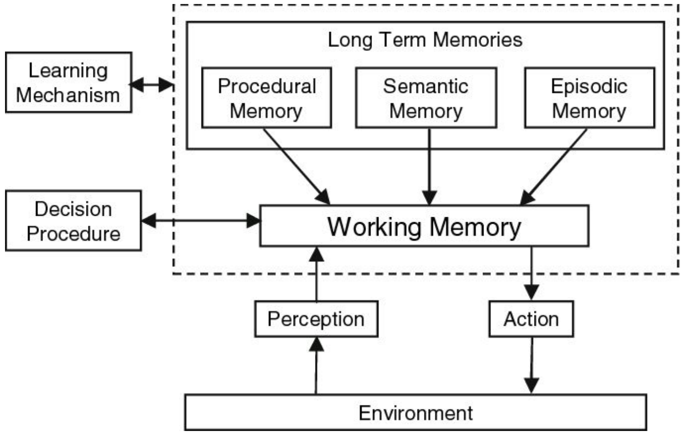
ACT-R-based BLL algorithm outperforms all baselines for different user groups

Combining Declarative and Procedural Memory of ACT-R for Personalization

[Innerebner et al., 2025]



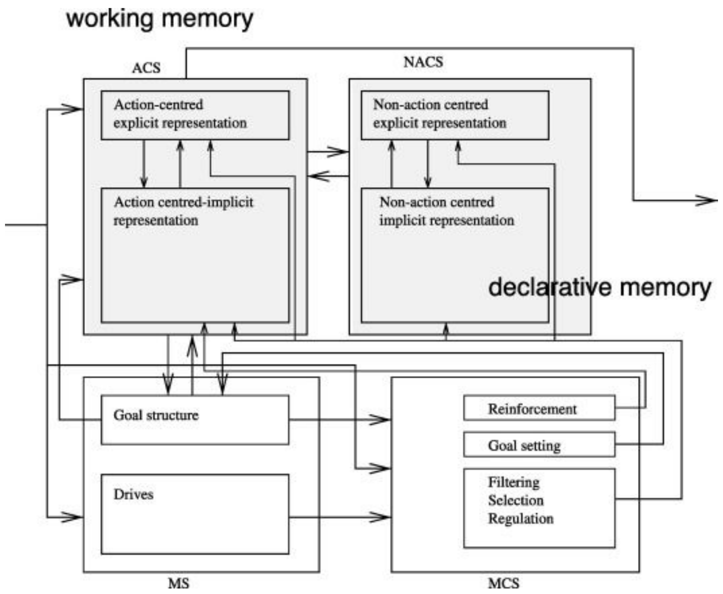
SOAR Architecture



https://link.springer.com/article/10.1007/s10462-009-9094-9

- Symbolic architecture
- Focus: goal-oriented behavior, learning, decision-making
- Core mechanisms:
  - Working memory holds current state of the task
  - Semantic memory stores structured general knowledge
  - Episodic memory stores specific experiences with context
  - Production rules match working memory & propose actions
  - Chunking generalizes problem-solving episodes into reusable rules
  - Impasse-driven subgoaling enables handling of uncertainty via dynamic subgoals
- Great at adapting to new problems via learning
  - E.g. dynamic, interactive environments

CLARION (Connectionist Learning with Adaptive Rule Induction Online) Architecture



- Hybrid cognitive architecture
- Based on dual-process theory
    - Implicit (subsymbolic): learned bottom-up via NNs
    - Explicit (symbolic): rule-based reasoning extracted from implicit knowledge
- Core components:
    - Action-centered Subsystem (ACS): procedural knowledge and skill learning
    - Non-action-centered Subsystem (NACS): include declarative, goal, and motivational knowledge
- Applications: human decision-making, models of skill acquisition, explainable behavior

LIDA (Learning IDA) Architecture (Franklin,

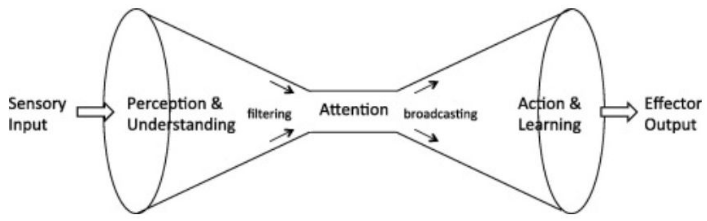


Figure 3: Schematic diagram of the cognitive cycle of the LIDA model

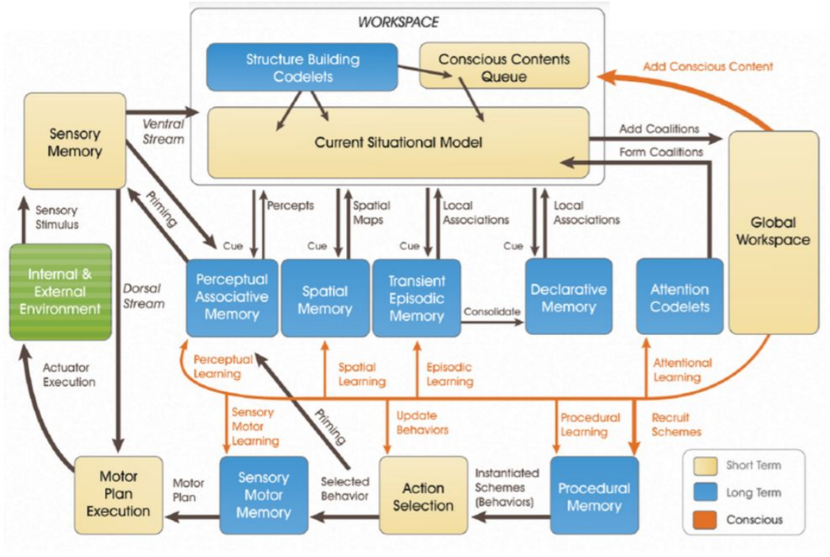
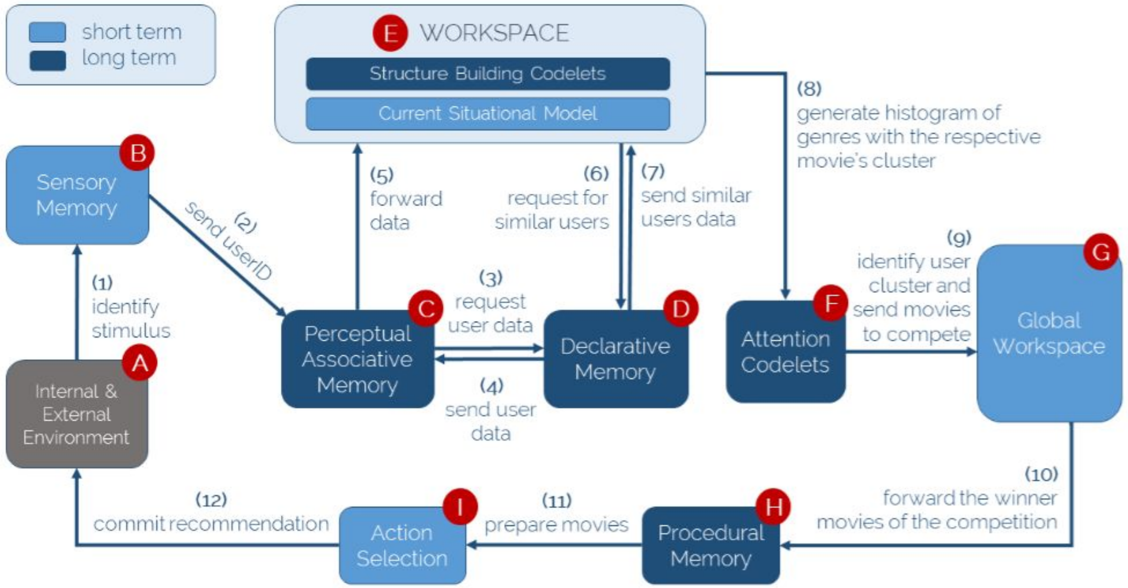


Figure 5: LIDA's cognitive cycle

- Basis: Global Workspace Theory (Baars, 1988)
- Fast, repeating cognitive cycles with modules for memory, attention, decision-making
- Core components:
  - Perceptual Associative Memory: processes sensory input
  - Global Workspace: sends content to all modules
  - Attention components
  - Declarative, episodic, procedural memory modules

Example: LIDA-based System used for movie recommendations (MIRA)

[Santos et al., 2019]



https://arxiv.org/abs/1902.09291

- Approach:
    a. Sensory memory detects the user (userID)
    b. Perceptual memory requests user history
    c. Declarative memory provides user history & ratings; plus, finds users with similar preferences
    d. Workspace creates a situational model of genres and patterns; clusters movies by genres
    e. Attention codelets identify top candidates for user
    f. Global Workspace selects best movies based on ratings
    g. Procedural memory creates movie list
    h. Action selection sends list of recommendations to user

Comparison of Discussed Architectures

Feature	ACT-R	SOAR	CLARION	LIDA
Type	Hybrid	Symbolic	Hybrid	Hybrid
Memory Types	Declarative, procedural, working (buffers)	Semantic, episodic, working	Implicit, explicit, motivational	Episodic, declarative, perceptual
Learning mechanism	Chunking,activation decay	Chunking, reinforcement	Reinforcement, rule induction	Episodic, perceptual, procedural
Cognitive focus	Memory, decision	Problem-solving, reasoning	Habits, motivation	Attention, learning, awareness
Strengths	Great predictor of user preferences	Goal decomposition into subgoals	Can capture implicit habits	Conscious processing model

Benefits & Challenges in Using Cognitive Architectures

- Benefits:
  - Typically, better interpretability - potential for explainability
  - Allow for user-centric modeling
  - Adaptive, cognitive plausible systems
-
- Challenges:
  - Scalability to large datasets and real-time systems
  - Integration with advanced deep learning models
  - Explainability vs. accuracy trade-offs
  - Learning curve for researchers (interdisciplinarity!)

Future Research Directions

- Neuro-symbolic IR and RS
- Hybrid models combining cognitive models + data-driven machine learning
- Real-time adaptation based on user cognitive signals
- Evaluation frameworks based on cognitive plausibility
- Potential for interpretable and adaptive IR/RS

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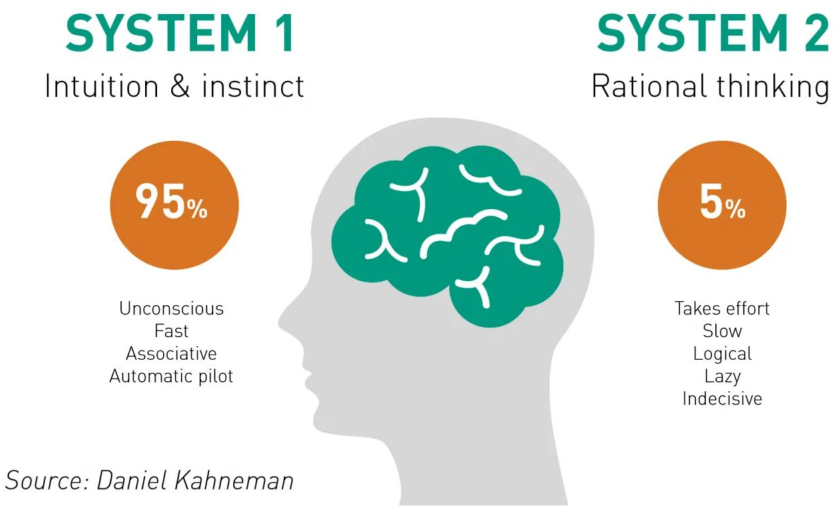
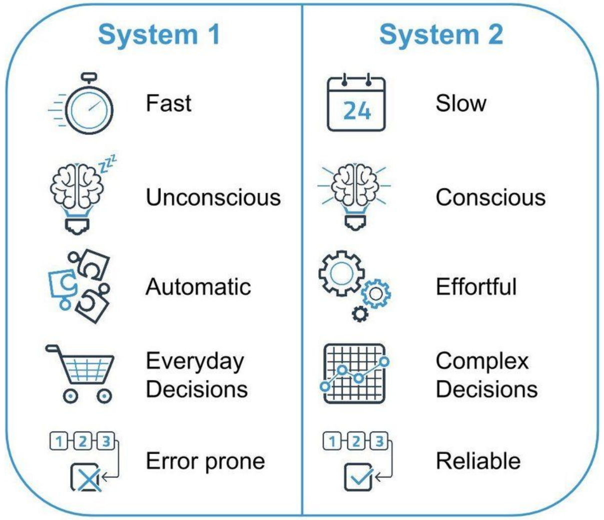
3) Usage of emotions in IR and RS
4) Emotion acquisition
5) Personality models
6) Usage of personality in IR and RS
7) Acquisition of personality
8) Eudaimonia and hedonia as traits and item characteristics
9) Other psychological constructs (needs...)

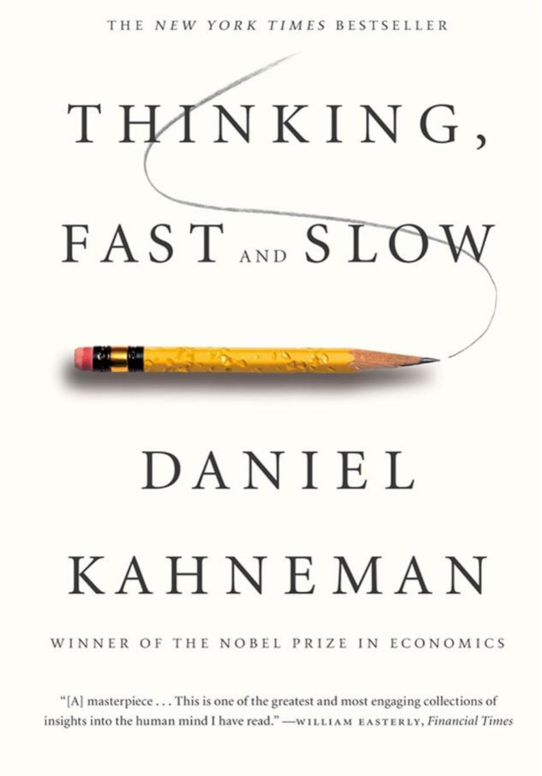
Human Decision Making

How Do We Make Decisions?





© *Daniel Vanderbyl*



Tversky, A., Kahneman, D. **Judgment Under Uncertainty: Heuristics and Biases: Biases in Judgments Reveal Some Heuristics of Thinking Under Uncertainty**, Science, 185(4157):1124-1131, 1974.

What Are Cognitive Biases?

- *Psychology:* systematic perceptual deviations of the individual from rationality pertaining to judgment or decision-making, which often happens unconsciously

- *Sociology:* collective prejudices of a society that favor one group's values, norms, and traditions over others

→ Results of "System 1" Thinking: Humans often rely on heuristics or mental shortcuts when making decisions

Rationality

Ideal standard *of decision-making and reasoning, based on logic, evidence, and objective analysis;* ***Benchmark*** *for how we should think and act; entails:*

- *Logical Reasoning:* Using deductive and inductive logic to draw conclusions from premises or evidence
- *Evidence-based Thinking***:** Basing decisions and conclusions on available facts, data, and verifiable information; not on intuition or heuristics
- *Objectivity:* Evaluating information without the influence of personal beliefs, desires, or emotions
- *Consistency:* Making decisions or drawing conclusions that are consistent with each other and with the available evidence, rather than being contradictory
- *Probability Assessment:* Accurately estimating the likelihood of different outcomes and making decisions based on the expected value of those probabilities
- *Optimal Outcomes:* Making choices that lead to the best possible outcome, given the available information and constraints, often defined by maximizing utility or achieving goals efficiently

Motivation to Study Cognitive Biases in IR/RS

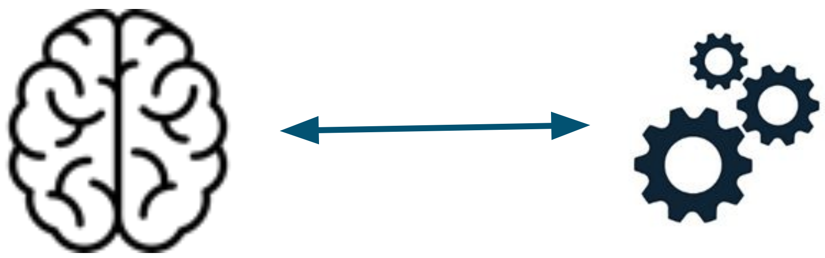
Human decisions are affected by

cognitive biases

Human decisions are supported (or even replaced) by

retrieval and recommendation algorithms/systems, chatbots (LLMs)

→ **CoBis and IR/RS should be considered together!**



Guiding Questions

- *Which* cognitive biases (CoBis) play a role in (human and machine) decision making?
- *In which parts* of the (algorithmic) decision-making/ranking pipeline in IR and RS can we observe CoBis, e.g., user-item interactions, side information, training data, ranking model, presentation of results?
- Can we *leverage* (positive) and *mitigate* (negative) cognitive biases in algorithmic decision-making/ranking and the human in the loop?

Ranking Systems and Cognitive Biases

- Information Retrieval (IR) / Search
  - User → Query → Algorithm/Model → Retrieved Documents → Presentation (UI)
  - Potentially, CoBis reflected in all(?) of the above

- Recommender Systems (RecSys, RSs)
  - Interactions → User Profile → Algorithm/Model → Recommended Items → Presentation (UI)
  - Potentially, CoBis reflected in all(?) of the above

- Large Language Models (LLMs)
  - Generative models / Decoders (e.g., ChatGPT, Gemini, Mistral) → CoBis in prompts and responses
  - Word embeddings / Encoders (e.g., BERT, RoBERTa, T5) → When used in ranking tasks (IR/RS), CoBis in retrieval/recommendation lists

Cognitive Biases: Examples

- Feature-Positive Effect
- IKEA Effect
- (Cultural) Homophily
- Conformity Bias
- Declinism
- Primacy/Recency Effects, Position Bias
- Bandwagon Effect, Popularity Bias
- Halo Effect
- Anchoring, Decoy Effect
- Confirmation Bias
- Authority Bias

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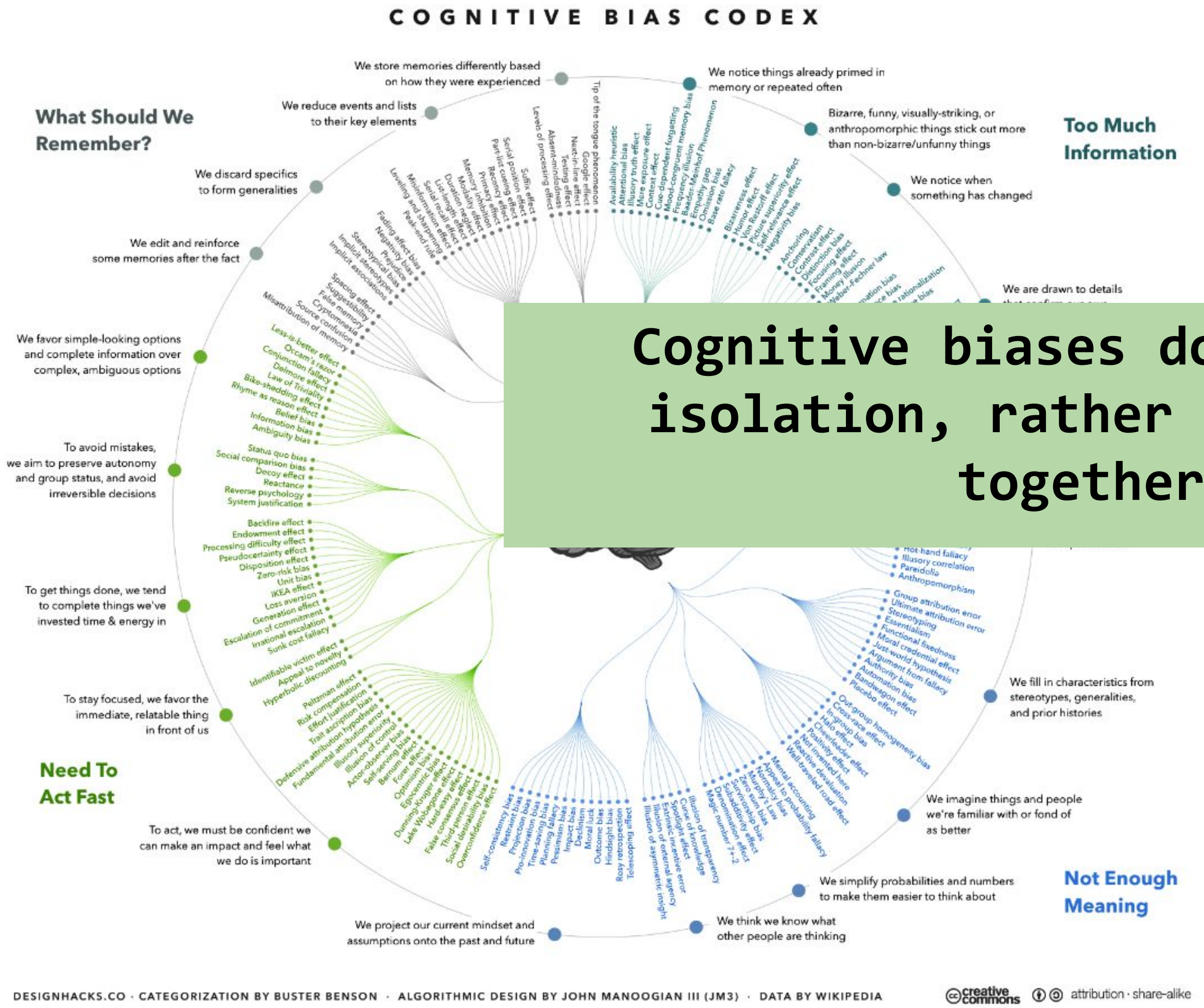
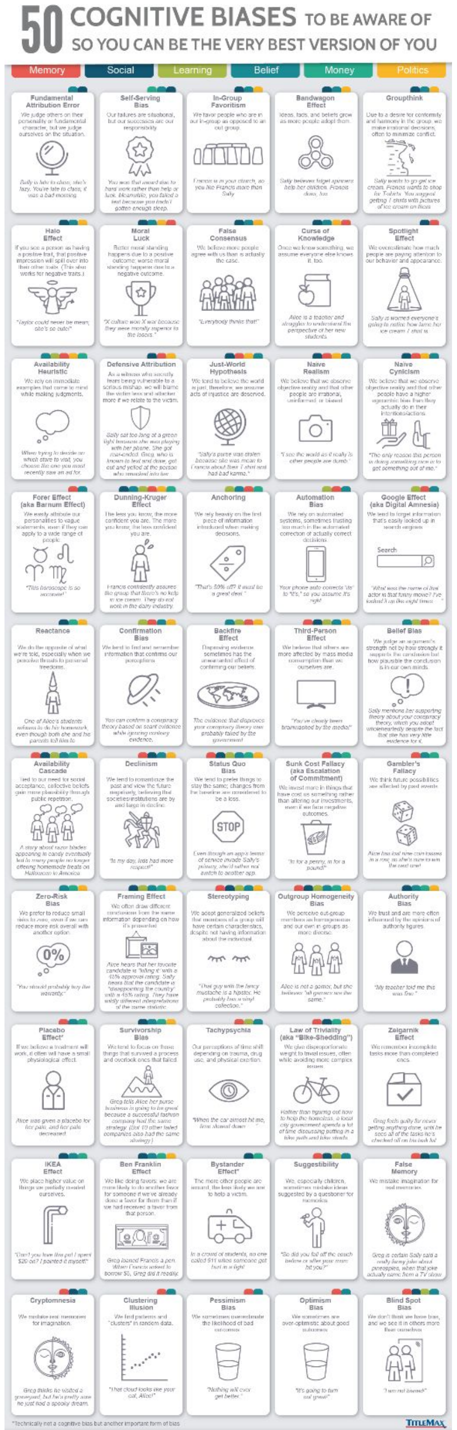


Cognitive biases don't work in isolation, rather are at play together!



https://commons.wikimedia.org/wiki/File:Cognitive_bias_codex_en.svg https://www.visualcapitalist.com/50-cognitive-biases-in-the-modern-world

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Feature-Positive Effect

Example:

- What do these lists have in common? 936, 193, 496, 829, 930, 559, 976, 139
- And these lists? 125, 922, 834, 998, 147, 980, 237, 710

Definition/Meaning:

- Humans are better at realizing (and put more emphasis on) the presence of a stimulus rather than its absence

Possible manifestations and uses in the context of IR/RS:

- Possible important role in *fairness/non-discrimination*: e.g., users of an LLM might not realize that an answer is biased, e.g., some cultural group, gender, etc. is ignored
- *Explainability* through counterfactuals: e.g., which (maybe better-suited) items would have been recommended to a user if they had different traits?
- Which aspects of the data did the system consider during training/inference? (And, more importantly, which ones did it *not* consider?)

[Allison et al., 1988] The Feature-positive Effect, Attitude Strength, and Degree of Perceived Consensus, Personality and Social Psychology Bulletin 14, 1988, 231–241

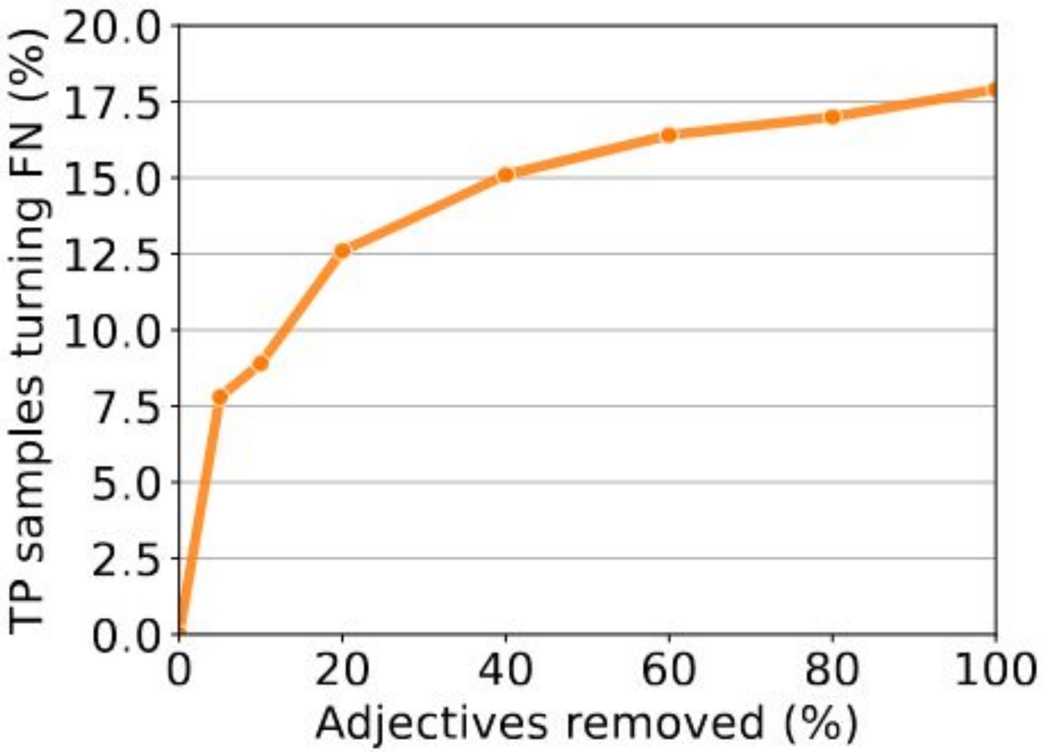
Feature-Positive Effect in Job/Candidate RecSys

- **Recruitment-related RS:** Training process may focus on what is present in job ads, overlooking what is missing
- Content-based/Text-based RecSys (matching CVs with job ads)
- Distil-RoBERTa cross-encoder model
- Employed GPT-4o to generate 2,100 CVs (350 CVs per job)
  - 6 job categories (dentist, nurse, photographer, software engineer, accountant, and teacher)
  - 1,358 samples of job advertisement from UK job board
- Trained with pairs of CV and job ad in a binary classification setup
  - For each positive sample we used 4 negative samples
  - 80% : 20% split
- Evaluate on 272 job ads and 336 unique applicants
  - Consider as positive prediction if job title in CV and job ad matches
  - 13,607 true positive (TP) and 1,625 false negative (FN) predictions

Schedl, M., Lesota, O., Masoudian, S. **The Importance of Cognitive Biases in the Recommendation Ecosystem: Evidence of Feature-Positive Effect, Ikea Effect, and Cultural Homophily**, Proceedings of the 11th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems (IntRS @ RecSys 2024), Bari, Italy, October 2024. https://ceur-ws.org/Vol-3815/paper10.pdf

Feature-Positive Effect: Experiment 1

- Simulate FPE in candidate recommendation: Adjust what content the RecSys “sees” and does not “see” during training
- **Method:** Removing *adjectives* (randomly) from job ads and analyze the changes in the decisions of the candidate RecSys
  - TP : if **p** *(job ad)* then **q** *(candidate)*
  - FN : if **p** then not **q**
- **Results:** The more adjectives removed the more positive samples became negative, even though they should objectively not change result (e.g., “a passionate dentist”)
- **Conclusion:** Presence (or absence) of adjectives plays significant role in decision making of model



Feature-Positive Effect: Experiment 2

- Can FN samples become TP by leveraging adjectives that are missing in them?
- **Method:**
  - Group job ads into low-recall and high-recall group
  - Create a set of unique *adjectives* A:
    - Present in high recall but missing in low recall group
    - A considered as **unique information missing in the FN samples** (responsible for low recall)
  - Randomly replace adjectives from FN samples with those from A and re-evaluate the model

Group	Adjectives
Low Recall	small, referral, sexual, steady, ...
High Recall	new, full, other, good, professional, ...
Unique set	technical, annual, innovative, complex, ...

- **Results:**
  - Average score of the CE ranking model for FN samples increased from 0.046 to 0.152
  - 52.0% improvement in FN (12.9% reclassified as TPs)
- **Conclusion:** Injecting random adjectives from high-recall group can have positive effect on decisions of candidate ranking system

Feature-Positive Effect: Experiment 2

- Can FN samples become TP by leveraging adjectives that are missing in them?
- **Method:**
  - Group job ads into low-recall and high-recall group

Group	Adjectives

Exploitation Potential: Increasing Transparency

For *recruiters*: direct feedback on how recommended applicants change when adjusting wording of job ad

For *applicants*: identify salient words in their CVs, investigate counterfactual recommendations (e.g., altering gender or work experience)

- **Conclusion:** Injecting random adjectives from high-recall group can have positive effect on decisions of candidate ranking system

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IKEA Effect

Example:
- *"The cookies I baked are much tastier than the ones I bought."*

Definition/Meaning:
- The more effort a person invested in something, the more they will value it
- Human desire to justify their efforts

Possible manifestations and uses in the context of IR/RS:
- Users of streaming platforms prefer listening to content collections they (helped) create *themselves* over collections created and shared by *others*
- Generative LLMs may give higher preference scores to content they created themselves than content provided by others

[Norton et al., 2012] The IKEA Effect: When Labor Leads to Love, Journal of Consumer Psychology 22, 2012, 453–460
[Marshet al., 2018] When and How Does Labour Lead to Love? The Ontogeny and Mechanisms of the IKEA Effect, Cognition 170, 2018, 245–253

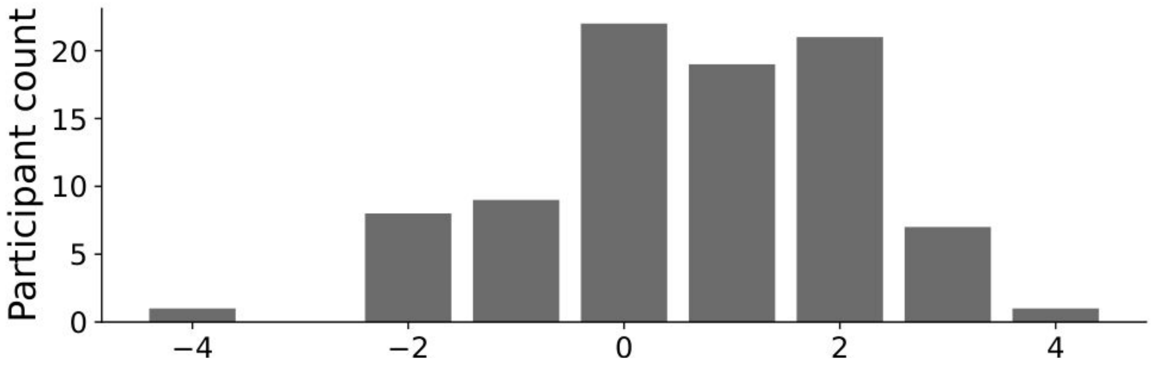
IKEA Effect in Music Playlist Generation

- **Method:**
  - User study on Prolific with 100 US users of music streaming services
  - Questionnaire with 5-point Likert scale: *Never (1) ... Very often (5)*
  - *S1: “I create or edit music collections.”*
  - *S2: “I play music collections (created by me or someone else).”*
  - *S3: “I play music collections I created or helped create myself.”*
  - *S4: “I play music collections created by someone else.”*

Schedl, M., Lesota, O., Masoudian, S. **The Importance of Cognitive Biases in the Recommendation Ecosystem: Evidence of Feature-Positive Effect, Ikea Effect, and Cultural Homophily**, Proceedings of the 11th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems (IntRS @ RecSys 2024), Bari, Italy, October 2024. https://ceur-ws.org/Vol-3815/paper10.pdf

IKEA Effect in Music Playlist Generation

- **Results:**
  - Users prefer listening to their own playlists over others': μ (*S3*-*S4*) = 0.65 (σ = 1.52)
  - Users who invest more time creating playlists (*S1*) tend to listen more often to their own playlists (*S3*) Spearman's ρ (*S1*, *S3*) = 0.75
  - Users who spend more time listening to playlists in general tend to listen to the playlists they contributed to more often Spearman's ρ (*S2*, *S3*) = 0.66; but not to playlists created by someone else!
- **Conclusion:** Users tend to interact more with playlists they invested effort in, which we interpret as a variant of the IKEA effect



Distribution of the *consumption frequency difference* between own and other playlists (responses to S3-S4). Positive values show preference towards own playlists.

S1: "I create or edit music collections."
S2: "I play music collections (created by me or someone else)."
S3: "I play music collections I created or helped create myself."
S4: "I play music collections created by someone else."

IKEA Effect in Music Playlist Generation

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  - Users prefer listening to their own playlists over others':
    μ (*S3*-*S4*) = 0.65 (σ = 1.52)

Exploitation Potential: Increasing User Experience

For instance, in sequential recommendation, items present in the user's playlists (the user put effort into picking and assigning them) can serve as *anchors* to retain user engagement within the current listening session. Using them for *explanations* could foster user trust in RecSys.

Spearman's ρ (*S2*, *S3*) = 0.66

- **Conclusion:** Users tend to interact more with playlists they invested effort in, which we interpret as a variant of the IKEA effect

S1: "I create or edit music collections."
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Homophily (Social/Cultural)

Example:

- *"I use to hang out with my friends because they are liberals and love reggae music."*

Definition/Meaning:

- Humans tend to associate and form connections with others who have similar characteristics (e.g., age, culture, or religion) more often than with people who have different traits

Possible manifestations and uses in the context of IR/RS:

- Users with a specific trait (e.g., country, culture, or social group) may prefer content created by producers with the same trait (e.g., domestic vs. foreign music consumption)
- Generative LLMs may produce content that is biased towards traits of its users, esp. when included in the prompt
  Ex.: If queried for a particular group of people (e.g., researchers working on cognitive biases), the result of LLMs may be biased towards people with similar traits

[Mark, 2003] Culture and Competition: Homophily and Distancing Explanations for Cultural Niches, American Sociological Review 68, 2003, 319–345

Cultural Homophily in Music

Cultural homophily in music *consumption*, *recommendation*, and simulated *feedback loop*

- **Method:**
  - LFM-2b dataset (subsample: 2018-2019, 5-core-filtered)
  - ~100K songs, ~12K users, ~2.3M interactions
  - Artists' countries retrieved from MusicBrainz
  - MultVAE as base recommender
  - Feedback loop *simulation* with simple choice model (select one recommended item)

Schedl, M., Lesota, O., Masoudian, S. **The Importance of Cognitive Biases in the Recommendation Ecosystem: Evidence of Feature-Positive Effect, Ikea Effect, and Cultural Homophily**, Proceedings of the 11th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems (IntRS @ RecSys 2024), Bari, Italy, October 2024. https://ceur-ws.org/Vol-3815/paper10.pdf

Homophily in Music Consumption

	base	*Con*	*Con/base*
US	**0.397**	**0.626**	1.578
UK	0.155	0.266	1.713
DE	0.068	0.169	2.481
SE	0.045	0.159	3.519
CA	0.038	0.083	2.202
FR	0.028	0.091	3.232
AU	0.023	0.077	3.289
FI	0.023	0.170	**7.536**
BR	0.022	0.141	6.288
RU	0.019	0.073	3.870

Proportions of domestic music among all available tracks (*base*), among consumed tracks by users from the country (*Con*), and in relation (*Con*/*base*)

Ex.:

~40% of all tracks on a music streaming platform have been created by US artists

~63% of tracks consumed by US users have been created by US artists

→ Significant effect for all investigated countries, but particularly for *FI* and *BR*

Homophily in Music Recommendation

Cultural homophily in music consumption, recommendation, and simulated feedback loop

- **Results:**

	base	*Con*	*Con/base*	Rec_1	$Rec_1/base$	Rec_{20}	$Rec_{20}/base$
US	**0.397**	**0.626**	1.578	**0.629**	1.587	**0.595**	1.501
UK	0.155	0.266	1.713	0.227	1.458	0.232	1.495
DE	0.068	0.169	2.481	0.176	2.590	0.166	2.439
SE	0.045	0.159	3.519	0.102	2.266	0.088	1.948
CA	0.038	0.083	2.202	0.030	0.797	0.041	1.091
FR	0.028	0.091	3.232	0.039	1.377	0.041	1.447
AU	0.023	0.077	3.289	0.017	0.728	0.026	1.103
FI	0.023	0.170	**7.536**	0.166	7.325	0.132	5.820
BR	0.022	0.141	6.288	0.187	**8.347**	0.150	**6.714**
RU	0.019	0.073	3.870	0.081	4.262	0.066	3.515

Proportions of domestic music among all available tracks (*base*), among consumed tracks by users from the country (*Con*), and among recommender tracks (*Rec*) at iteration *1* and *20* of the simulation

Homophily in Music Consumption and Rec.

Cultural homophily in music consumption, recommendation, and simulated feedback loop

- **Conclusion:**
  - Users listen more frequently to music originating from their own country than a random choice would warrant
  - Effect strength varies strongly between countries (cf. US, UK vs. FI, BR)
  - RecSys and feedback loops can have some leveraging effect for cultural homophily (e.g. SE, FI)
  - In some cases (e.g. CA, AU), RecSys even introduces a “homophobic” behavior w.r.t. domestic recommendations

	base	*Con*	*Con/base*	Rec_1	$Rec_1/base$	Rec_{20}	$Rec_{20}/base$
US	**0.397**	**0.626**	1.578	**0.629**	1.587	**0.595**	1.501
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Homophily in Music Consumption and Rec.

Cultural homophily in music consumption, recommendation, and simulated feedback loop

- **Conclusion:**
  - Users listen more frequently to music originating from their own country than a random choice would warrant

Exploitation Potential: Diversification and Calibration

Formalized *homophily models* as additional indicator of user taste could be useful for: (1) diversification of recommendations, (2) calibration between user profiles and recommendations, in terms of country, etc.

UK	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DE	0.068	0.169	2.481	0.176	2.590	0.166	2.439
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Conformity Bias

Example:

- In a meeting: *I am quite sure all the others are wrong, but I won't raise my voice; don't want to cause the meeting to last forever; and the others may be right anyway (Why else would they all have an opposite opinion to mine?)*

Definition/Meaning:

- Tendency of individuals to align their beliefs, behaviors, and actions with those of a group, often disregarding their own independent judgment

Possible manifestations and uses in the context of IR/RS:

- Showing users (artificial or true) *averaged ratings* before asking them to provide their own ratings on an item changes their behavior towards the shown ones
- Users are more likely to click on an item if they see that *many other users* clicked on it

[Adomavicius et al., 2011] Recommender Systems, Consumer Preferences, and Anchoring Effects, Proceedings of the Workshop on Human Decision Making in Recommender Systems, 2011, pp. 35–42.
[Zheng et al., 2021] Disentangling User Interest and Conformity for Recommendation with Causal Embedding, Proceedings of The Web Conference, 2021, pp. 2980–2991.
[Ma et al., 2024] Temporal Conformity-aware Hawkes Graph Network for Recommendations, Proceedings of The Web Conference, 2024, pp. 3185–3194.

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Exploitation Potential: Influencing Rating/Consumption Behavior

- Showing them adjusted (or even fake) ratings could *trick users* into believing their preference towards an item is higher or lower than it actually is.

+ Confronting users with their change in rating behavior (given them as reference their typical rating for highly similar items) may also serve to *raise awareness* of the phenomenon.

- Users are more likely to click on an item if they see that *many other users* clicked on it

[Adomavicius et al., 2011] Recommender Systems, Consumer Preferences, and Anchoring Effects, Proceedings of the Workshop on Human Decision Making in Recommender Systems, 2011, pp. 35–42.
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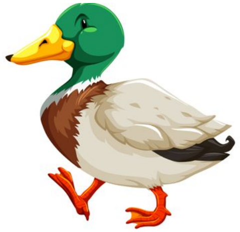

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Declinism

Example:

- *"Music used to be much better in the 90s."*
- *"The world was a much better place when I was a teenager than today!"*

Definition/Meaning:

- The perception that the world or society is declining, i.e., things get worse over time
- Partly the result of *rosy retrospection* — humans' tendency to remember the past as more positive as it actually was

Possible manifestations and uses in the context of IR/RS:

- Identifying trends, e.g., in sentiment (positive or negative) in lyrics, social media or news articles, tags, etc.; formalize them via statistical models
- Can these models be used to adjust outcomes, to counteract (or amplify) declinism?
- Is declinism reflected in interaction logs (used as training data) with news or music (spanning decades), extracted from item or user *side information*?

[Mitchell et al., 1997] Temporal Adjustments in the Evaluation of Events: The "Rosy View", Journal of Experimental Social Psychology 33, 421-448, 1997

Declinism in Music Lyrics

- **Method:**
  - 353,320 songs from LFM-2b
  - 5 genres (Pop, Rock, Rap, Country, R&B), 5 decades (1970-2020)
  - Lyrics from Genius.com
  - LIWC dictionary to describe emotions (positive/negative)
  - Linear regression on (positive/negative) emotions over all years
- **Results:**
  - Increase of negative emotions: Rap (*m=0.0217*), R&B *(m=0.0187)*
  - Decrease of positive emotions: R&B *(m=−0.048552)*, Country *(m=−0.0217)*
- **Conclusion:**
  - Clear overall trend towards more positive and less negative emotions in the past

Parada-Cabaleiro, E., Mayerl, M., Brandl, S., Skowron, M., Schedl, M., Lex, E., Zangerle, E. **Song Lyrics Have Become Simpler and More Repetitive over the Last Five Decades**, Nature Scientific Reports, 14, 5531, 2024. https://www.nature.com/articles/s41598-024-55742-x

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  - Lyrics from Genius.com
  - LIWC dictionary to describe emotions („positive emotions“)

Exploitation Potential: Adjust Level of Positiveness/Negativeness

Together with users’ interaction history, fine-granular information on declinism (e.g., for different content categories) could help create *personalized long-term declinism models*, used to tailor recommendations.

- **Conclusion:**
  - Clear overall trend towards more positive and less negative emotions in the past






Cognitive Biases

- Feature-Positive Effect
- IKEA Effect
- (Cultural) Homophily
- Conformity Bias
- Declinism
- **Primacy/Recency Effects, Position Bias**
- Bandwagon Effect, Popularity Bias
- Halo Effect
- Anchoring, Decoy Effect
- Confirmation Bias
- Authority Bias

Primacy/Recency Effects, Position Bias

Example:

- Which of the animals shown on the previous slides can you name?

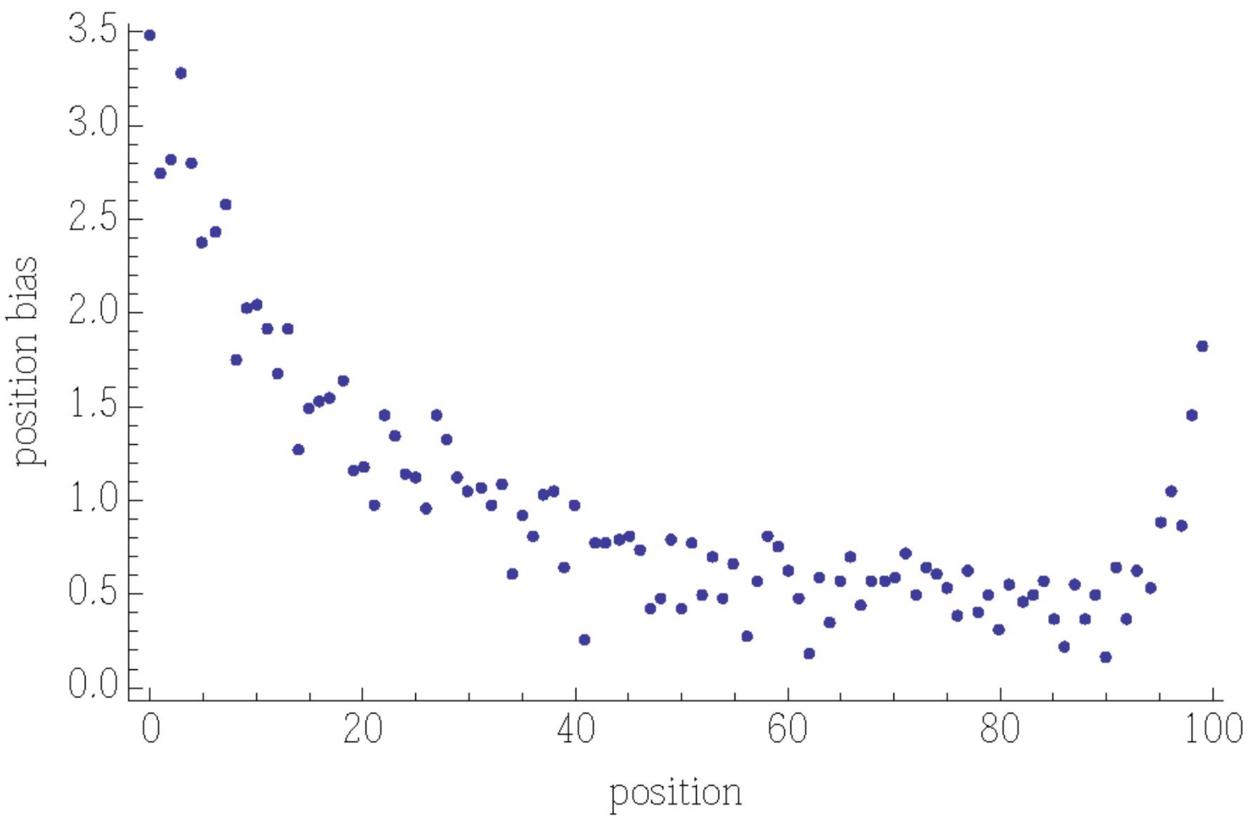
Definition/Meaning:

- Human tendency to easier recall first and last items from a sequence as opposed to the items from the middle of the sequence

Possible manifestations and uses in the context of IR/RS:

- Users are more likely to interact with items appearing at the beginning (primacy effect) and at the end (recency effect) of a list of recommendations or retrieved documents
- Negative effect in terms of expose for mid-ranked items
- To which extent does position bias depend on the algorithm, recommendation task, and presentation of results (UI)? (e.g., top-N recommendations vs. “endless” list)
- Can we counteract this effect by algorithmic in-processing or post-processing techniques (e.g. reranking)?

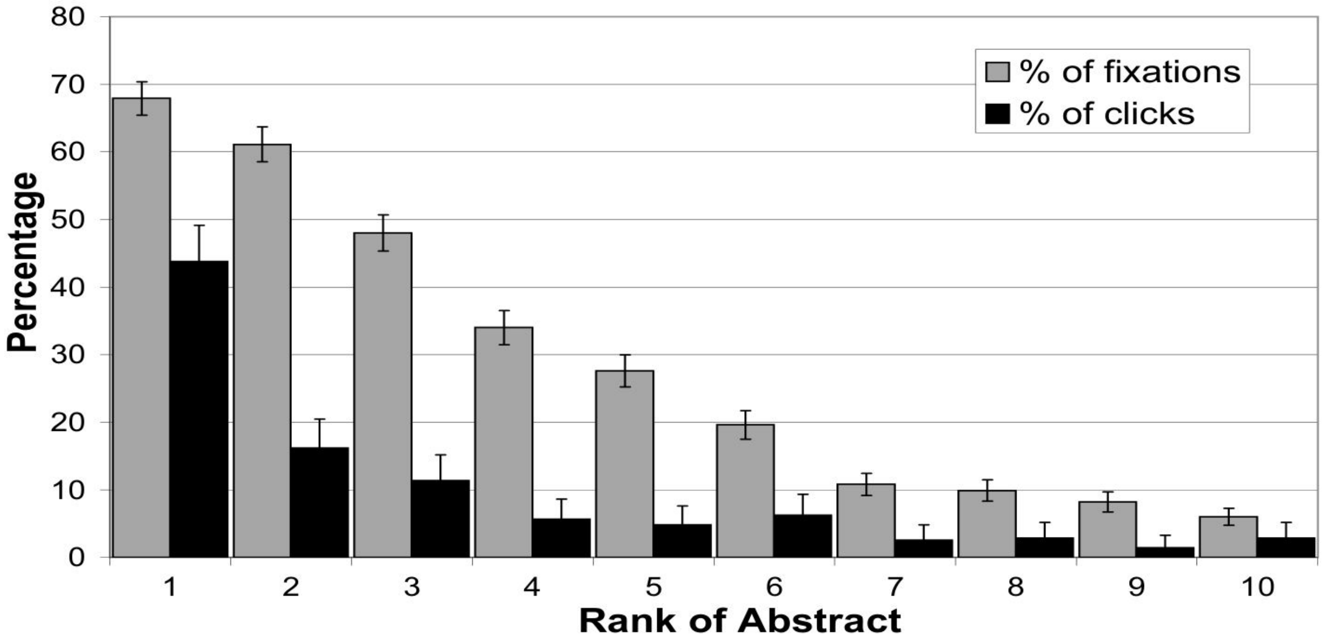
Primacy/Recency Effects in Story Recommendation



Relative increase or decrease in number of ratings (votes) for each position of an item (story) in the recommendation list, compared to the average number

Lerman, K. and Hogg, T. **Leveraging Position Bias to Improve Peer Recommendation**, PLoS ONE 9(6): e98914, 2014.
https://doi.org/10.1371/journal.pone.0098914

Primacy/Recency Effects in Web Search



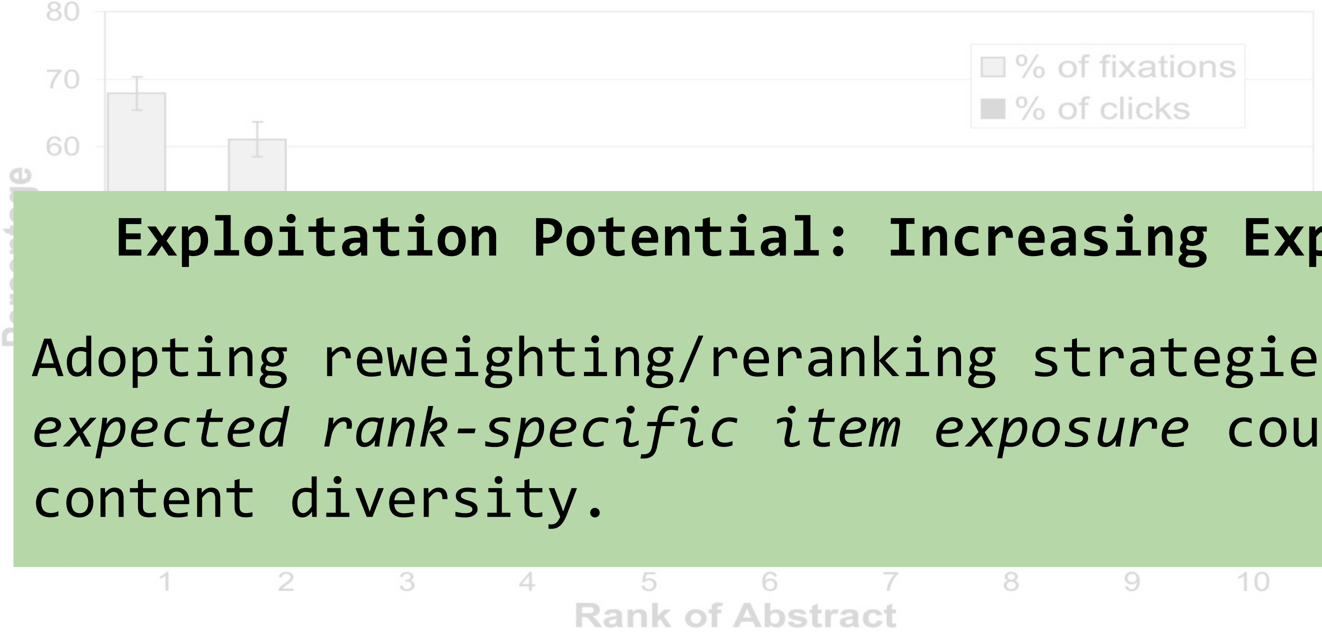
Percentage of times an abstract was viewed or clicked, depending on the rank of the retrieved document (using Google Search)

Trust Bias:
More clicks on links ranked highly by Google, even if those abstracts are less relevant than other abstracts the user viewed

Quality Bias:
Users' clicking decision is not only influenced by the relevance of the clicked link, but also by the overall quality of the other abstracts in the ranking

Joachims, T., Granka, L., Pan, B., Hembrooke, H., Gay, G. **Accurately Interpreting Clickthrough Data as Implicit Feedback**, Proceedings of SIGIR, pp. 154-161, 2005. https://doi.org/10.1145/1076034.1076063

Primacy/Recency Effects



Percentage of times an abstract was viewed or clicked, depending on the rank of the retrieved document (using Google Search)

Trust Bias:
More clicks on links ranked highly by Google, even if those abstracts are less relevant than

Exploitation Potential: Increasing Exposure of Underexposed Contents

Adopting reweighting/reranking strategies to *balance relevance and expected rank-specific item exposure* could increase creator fairness and content diversity.

Cognitive Biases

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- Halo Effect
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- Confirmation Bias
- Authority Bias

Bandwagon Effect, Popularity Bias

Example:

- *“I don’t really like this new fashion style, but it has become so popular that I can’t resist.”*
- *“Should I buy that stock? Many others bought it, so it must be great even if it's clearly overpriced.”*

Definition/Meaning:

- Human tendency of adopting certain behaviors or beliefs because many other people do the same (“hop on the bandwagon”)

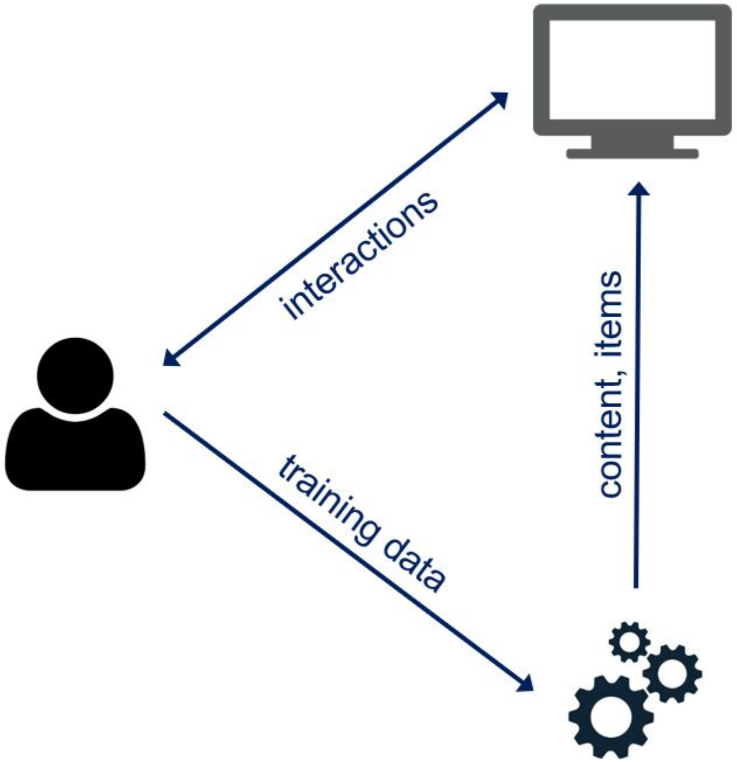
Possible manifestations and uses in the context of IR/RS:

- Overly many user-item interactions with popular items (in training data) may result in a popularity-biased ranking model, which in turn favors already popular content
- Due to their higher exposure to popular content during training, LLMs could pick up this bias and reproduce it at generation stage

[Kiss and Simonovits, 2014] Identifying the Bandwagon Effect in Two-round Elections, Public Choice 160, 327-344, 2014
[Shyam Sundar, S. et al., 2008] The Bandwagon Effect of Collaborative Filtering Technology, CHI Extended Abstracts, 3453-3458, 2008
[Knyazev and Oosterhuis, 2022] The Bandwagon Effect: Not Just Another Bias, Proceedings of ICTIR 2022: 243-253

Popularity Bias in Recommendation

Problem: Reinforcing already popular items/content, while limiting exposure of less popular ones (harmful for content creators and users)
→ Rich-get-richer effect / Matthew effect



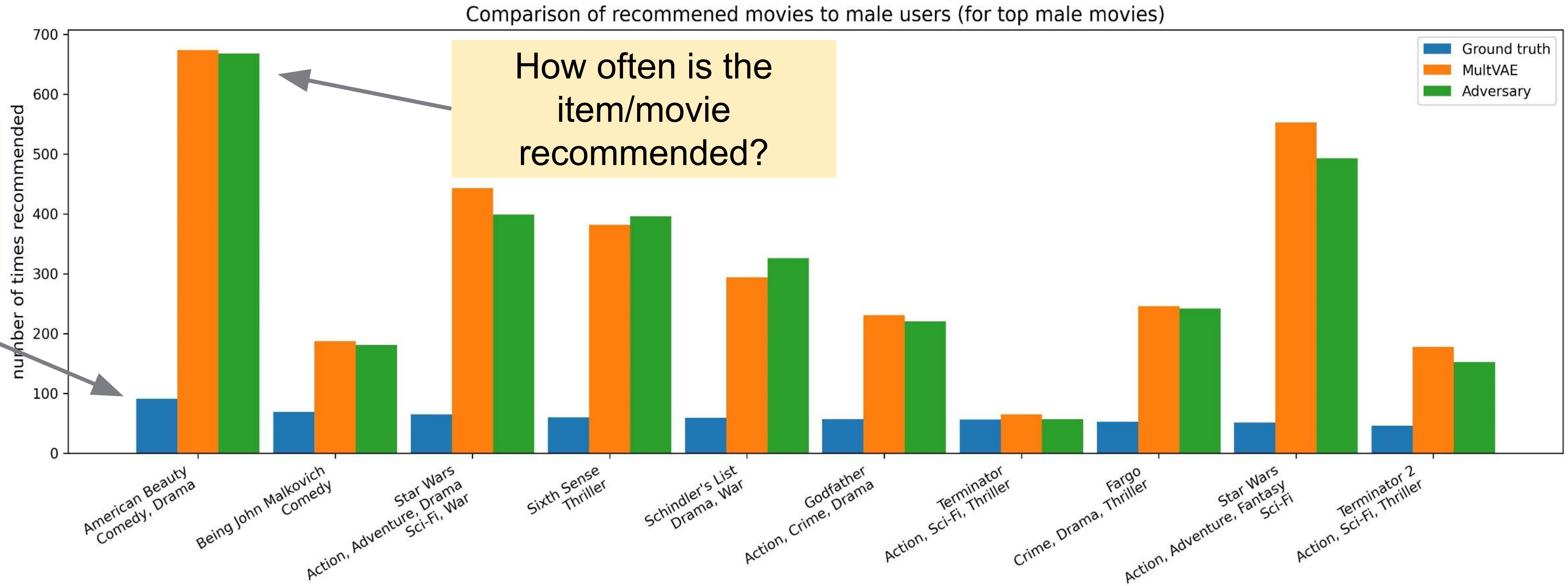
Di Noia, T., Tintarev, N., Fatourou, P., and Schedl, M. **Recommender Systems Under European AI Regulations**, Communications of the ACM, volume 65, issue 4, pp. 69-73, 2022. https://dl.acm.org/doi/10.1145/3512728

Popularity Bias: How to Measure It?

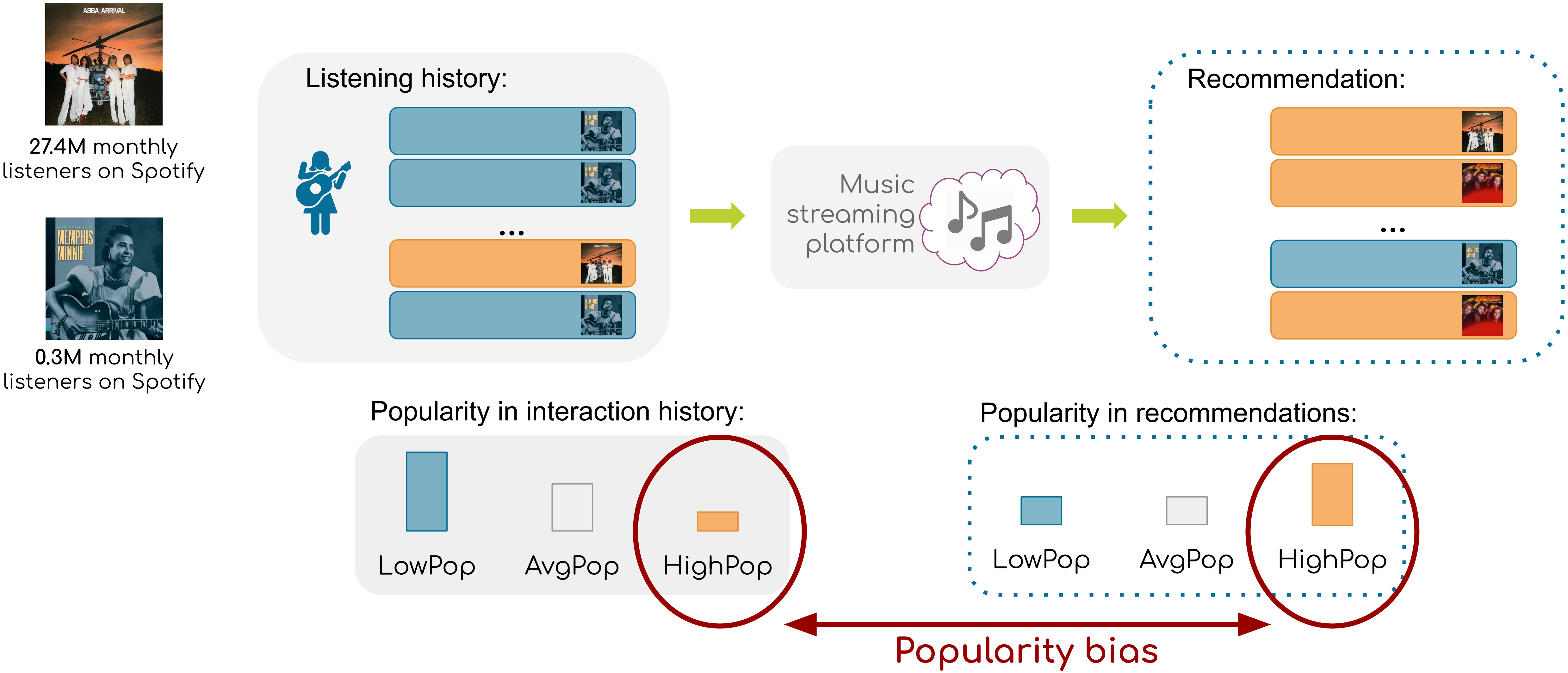
Ad-hoc variant: Difference between an item's recommendation frequency and consumption frequency in user profiles

Shortcoming: Does not reflect how users perceive popularity bias! [Lesota et al., SIGIR 2023]; [Ferwerda et al., CHIIR 2023]; Does not consider the *user's individual preference* for popular content.

How often is the item/movie consumed?



Popularity Bias in Music Recommendation



Measuring Popularity Bias

Assumption: Users prefer "calibrated" recommendations, i.e., the RS should mimic the interaction distribution w.r.t. an attribute (popularity in our case): $pop(H_{u_i}) \sim pop(R_{u_i})$.

pop	some measure of popularity (e.g., total number of interactions with items, number of interacting users)
H_{u_i}	historical interaction list of user u_i's over items
R_{u_i}	recommendation list created for user u_i (top recommendations at fixed cut-off)

Delta metrics: *statistical moments* of popularity differences between items in H_{u_i} and R_{u_i}

Distribution-based metrics: difference between popularity distributions (e.g., KL divergence or Kendall's τ)

Lesota, O., Melchiorre, A., Rekabsaz, N., Brandl, S., Kowald, D., Lex, E., and Schedl, M. **Analyzing Item Popularity Bias of Music Recommender Systems: Are Different Genders Equally Affected?**, Proceedings of the 15th ACM Conference on Recommender Systems (RecSys 2021), Amsterdam, the Netherlands, October-November 2021. https://dl.acm.org/doi/10.1145/3460231.3478843

Measuring Popularity Bias: Delta Metrics

$$\%\Delta\xi(u_i) = \frac{\xi\left(R_{u_i}\right) - \xi\left(H_{u_i}\right)}{\xi\left(H_{u_i}\right)} \cdot 100$$

$\%\Delta\xi$ relative popularity difference between items in H_{u_i} and R_{u_i} in terms of statistical measure ξ (e.g., mean, median, variance, skew)

Aggregate over all users (bias of the RS): $\%\Delta\xi = \ Median\left(\%\Delta\xi(u_i)\right)$

→ Positive $\%\Delta Mean$ and $\%\Delta Median$ indicate that more popular items are recommended to user u_i than warranted given his or her consumption history ("miscalibration").

→ Positive $\%\Delta Variance$ indicate that recommendation list is more diverse w.r.t. covering differently popular items than user u_i's consumption history.

Lesota, O., Melchiorre, A., Rekabsaz, N., Brandl, S., Kowald, D., Lex, E., and Schedl, M. **Analyzing Item Popularity Bias of Music Recommender Systems: Are Different Genders Equally Affected?**, Proceedings of the 15th ACM Conference on Recommender Systems (RecSys 2021), Amsterdam, the Netherlands, October-November 2021. https://dl.acm.org/doi/10.1145/3460231.3478843

Popularity Bias: Results on LFM-2b

Alg.	Users	%ΔMean	%ΔMedian	%ΔVar.	%ΔSkew	%ΔKurtosis	KL	Kendall's τ	NDCG@10
RAND	*All*	−91.8	−87.2	−99.5	11.5	15.3	3.904	0.165	0.000
	ΔFemale	−1.8	−3.5	−0.2	+0.0	−3.5	+0.976	−0.189	−0.000
	ΔMale	+0.5	+1.1	+0.1	−0.0	+1.3	−0.281	+0.053	+0.000
POP	*All*	432.5	975.2	487.0	−58.0	−87.0	6.023	0.057	0.045
	ΔFemale	+11.0	+282.1	−172.2	−2.1	−1.9	+1.626	−0.033	+0.003
	ΔMale	−2.8	−115.8	+55.9	+0.5	+0.5	−0.380	+0.016	−0.001
ALS	*All*	121.8	316.6	72.6	−25.2	−43.9	4.368	0.046	0.184
	ΔFemale	+9.9	+27.4	−7.1	−3.2	−5.4	+0.467	+0.110	−0.017
	ΔMale	−2.7	−6.6	+1.6	+0.8	+1.5	−0.121	−0.023	+0.005
BPR	*All*	−49.0	−3.7	−87.4	−14.8	−29.4	1.202	0.268	0.129
	ΔFemale	+5.2	+7.7	+2.1	−1.4	−3.9	+0.476	−0.043	−0.011
	ΔMale	−1.1	−1.9	−0.6	+0.4	+1.1	−0.110	+0.010	+0.003
ItemKNN	*All*	9.6	4.6	5.7	−14.3	−29.0	0.175	0.423	0.301
	ΔFemale	+2.0	+5.8	−2.6	−2.1	−3.2	+0.128	−0.037	−0.042
	ΔMale	−0.5	−1.3	+0.9	+0.8	+0.9	−0.020	+0.008	+0.012
SLIM	*All*	49.8	99.8	56.0	−12.5	−26.0	0.424	0.189	0.365
	ΔFemale	−6.4	−13.1	−17.4	−1.7	−4.6	+0.217	+0.052	−0.048
	ΔMale	+1.9	+3.9	+5.6	+0.6	+1.1	−0.029	−0.012	+0.014
VAE	*All*	303.9	736.3	351.0	−45.2	−70.1	4.823	−0.028	0.191
	ΔFemale	+10.1	+56.4	−69.3	−6.2	−6.6	+0.633	+0.146	−0.020
	ΔMale	−2.3	−20.4	+17.3	+1.8	+2.1	−0.161	−0.042	+0.006

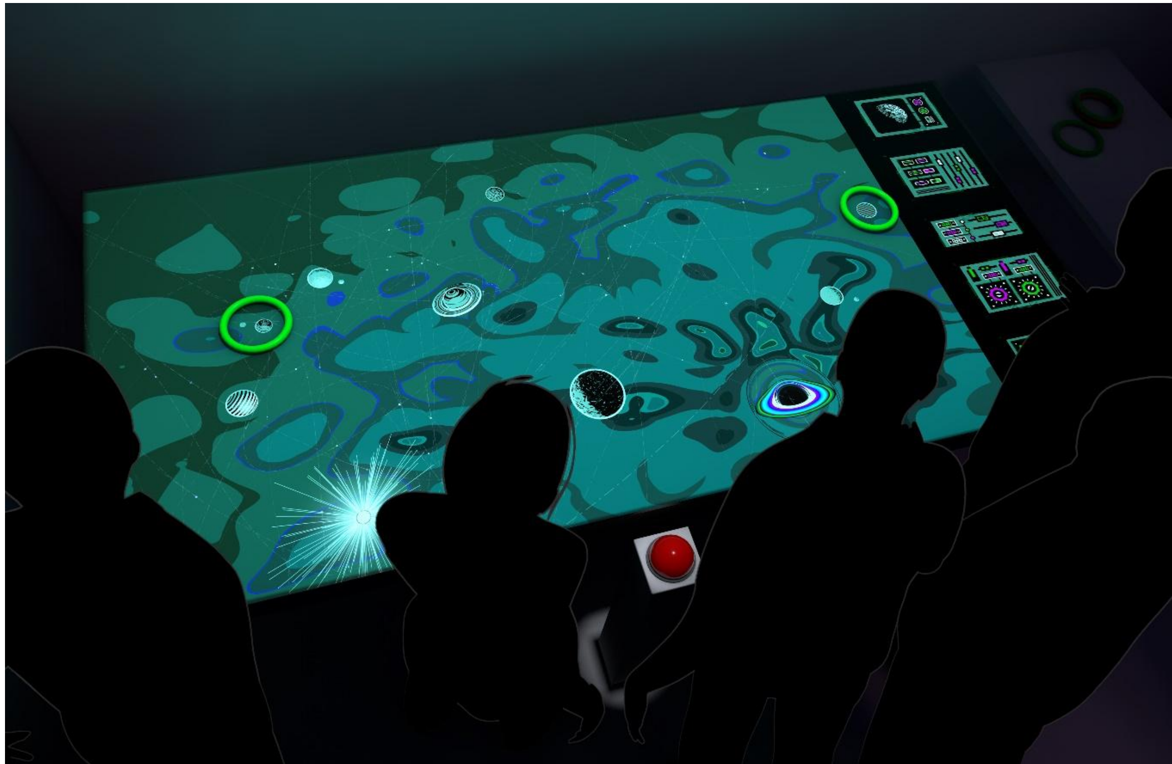
- Most RS algorithms are prone to **popularity bias** (%ΔMean)
- Some algorithms are affected more than others
- Most RSs create a higher popularity bias for female than male users, pointing to **demographic bias** (+/- values are relative to values in row *All*)

Lesota, O., Melchiorre, A., Rekabsaz, N., Brandl, S., Kowald, D., Lex, E., and Schedl, M. **Analyzing Item Popularity Bias of Music Recommender Systems: Are Different Genders Equally Affected?**, Proceedings of the 15th ACM Conference on Recommender Systems (RecSys 2021), Amsterdam, the Netherlands, October-November 2021. https://dl.acm.org/doi/10.1145/3460231.3478843

https://ars.electronica.art/planetb/en/black-holes-of-popularity

Black Holes of Popularity

- Artistic/scientific project presented at Ars Electronica Festival of Media Arts 2022
- Raising awareness of artist popularity bias in music recommendation
- Exploration of music via genre, using metaphor of a universe
- Cosmic bodies represent songs with varying levels of popularity (planets, stars, black holes)
- User interacts by means of a lifebuoy with planets and stars, selecting which ones to save from being eaten by the black hole
- Influence of user's song saving activities is computed by in/decrease of fairness score, shown to the user
- Explanatory video: https://bit.ly/3VBAbqT

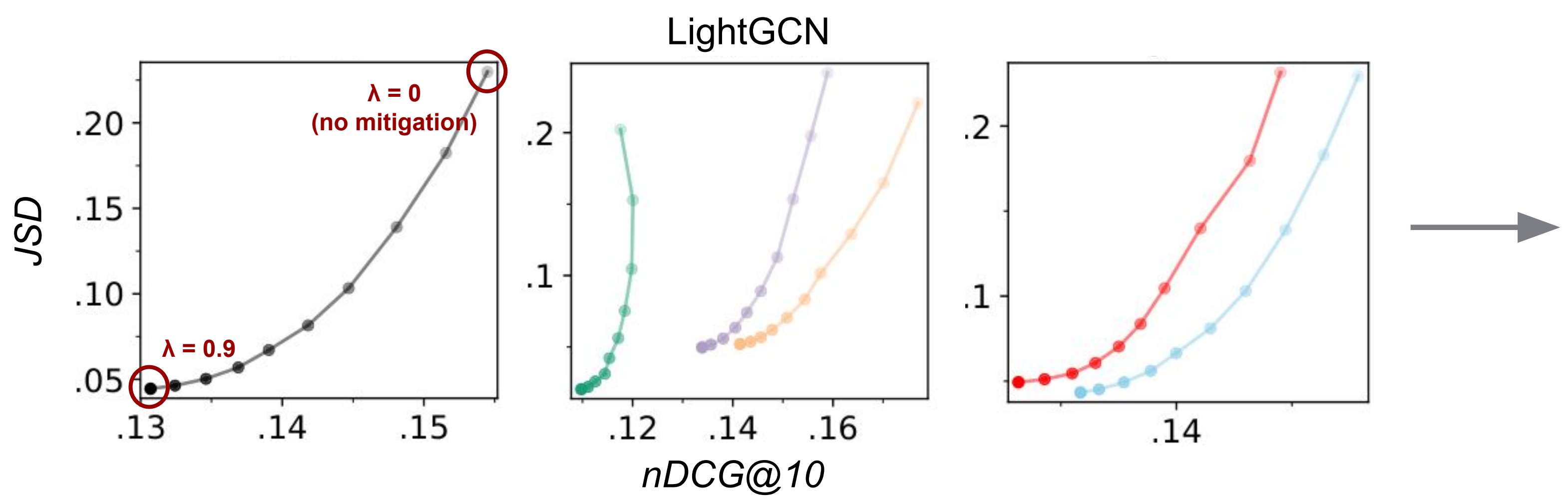


Mitigating Popularity Bias (Post-processing)

Idea: Reduce difference in popularity distribution of items in user u_i's historical interactions H_{u_i} and recommendation list R_{u_i}

Method: Create a personalized popularity-aware recommendation list $R^*_{u_i}$ by optimizing

$R^*_{u_i} = \arg\max_{L_{u_i}} \, (1-\lambda)\cdot Rel(L_{u_i}) - \lambda \cdot JSD\left(H_{u_i}, L_{u_i}\right),\; L_{u_i} \subset R_{u_i},\; \lambda$ strength of bias mitigation



- Trade-off between popularity bias (JSD) and recommendation accuracy (NDCG@10) is different for users preferring **HighPop**, **LowPop**, or **AvgPop** content; as well as for **male** and **female** users
- λ can be adjusted depending on the user group to optimize trade-off

Lesota, O., Melchiorre, A., Rekabsaz, N., Brandl, S., Kowald, D., Lex, E., and Schedl, M. **Analyzing Item Popularity Bias of Music Recommender Systems: Are Different Genders Equally Affected?**, Proceedings of the 15th ACM Conference on Recommender Systems (RecSys 2021), Amsterdam, the Netherlands, October-November 2021. https://dl.acm.org/doi/10.1145/3460231.3478843

Cognitive Biases

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- Bandwagon Effect, Popularity Bias
- **Halo Effect**
- Anchoring, Decoy Effect
- Confirmation Bias
- Authority Bias

Halo and Horn Effects

Example:

- *"This student is so articulate, he will surely deliver excellent performance at the exam."*
- *"This new singer is so beautiful, for sure she also has a gorgeous voice."*
- *"Look how badly dressed he came to the job interview. I am sure he is lazy, too."*

Definition/Meaning:

- An individual's perception of a single attribute (positive or negative) influences their opinion on other unrelated attributes.

Possible manifestations and uses in the context of IR/RS:

- Ratings of users may be influenced by their first impression of an unknown item (esp. in the presence of visual stimuli; e.g., photos of artists, actors, potential dating partners)
- Visual appeal of the presentation of (some) search results can influence clicking/consumption behavior.

[Dion, Berscheid, Walster, 1972] What is Beautiful is Good, Journal of Personality and Social Psychology, 24(3), 285.
[Nisbett and Wilson, 1977] The Halo Effect: Evidence for Unconscious Alteration of Judgments, Journal of Personality and Social Psychology, 35(4), 250–256.

Halo Effect in the Music Domain

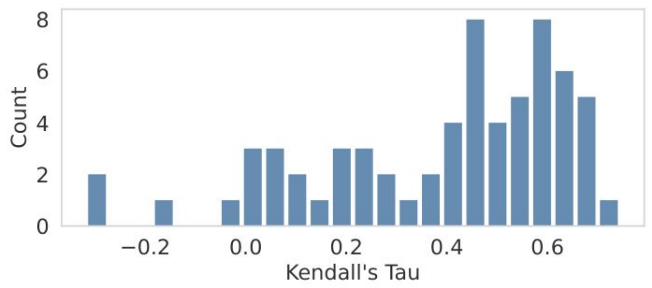
- Is there evidence for a halo effect when songs are accompanied by album covers?
- **Method:**
  - 100 US-based participants recruited via Prolific
  - Study 1: Each participant rated 40 tracks (audio) and 40 album covers (image), randomly selected from subset of Music4All dataset, individually; Likert-7 scale and whether they recognize song/artist/album
  - Study 2: For each participant, only using unknown tracks and albums, top-ranked songs are paired with bottom-ranked albums (and vice versa); Participants rated songs again on Likert-7 scale.
  - Compute Kendall's τ on each participant's track ratings in study 1 (no album cover present) vs. study 2 (album cover with contradicting appeal present)
  - Compute difference in song ratings between study 2 and 1 as function of album cover ratings from study 1

Lesota, O., Hausberger, A., Pshenychna, I., Shvydanenko, O., Yehorova, O., Schedl, M. **Investigating Music Track Liking in the Halo of Album Covers**, Proceedings of the 26th International Society for Music Information Retrieval Conference (ISMIR 2025), Daejeon, Korea, September 2025.

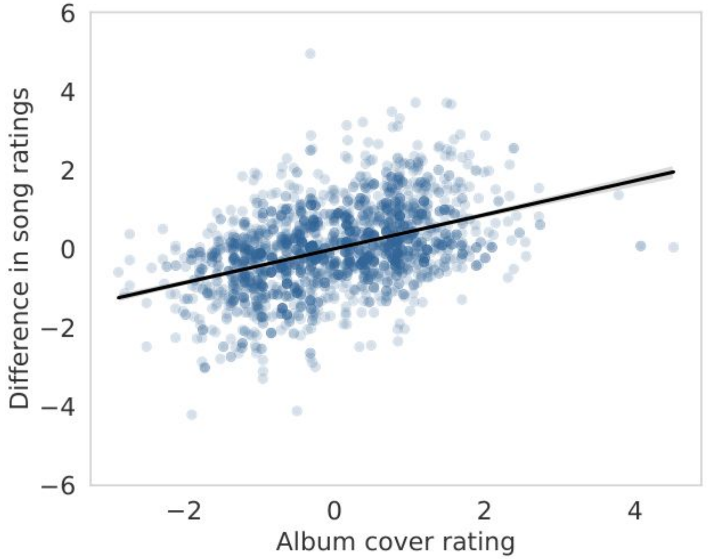
Halo Effect in the Music Domain

- **Results:**
  - Kendall's τ:
    Mean=0.39, SD=0.25, Min.=−0.32, Max.=0.74
  - Spearman's rank correlation between album cover rating and difference in song ratings: 0.4

- **Conclusion:**
  - Notable change in track liking, introduced by showing album covers during playback
  - Presence of halo/horn effects evidenced by significant positive correlation between album cover appeal and difference in track liking



Distribution of Kendall's τ over participants.



Difference in std. song ratings (study 2 - study 1) related to standardized album cover ratings (study 1)

Cognitive Biases: Examples

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- Authority Bias

Conclusions and Open Challenges

- Strong evidence of various cognitive biases in retrieval and recommendation processes
- Most studies face several limitations (e.g., only single or few domains, standard top-N recommendation scenario, ignoring confounding factors)

- How to (mathematically) *formalize* accurate models of cognitive biases?
- Which CoBis are *intertwined* and how does their entanglement manifest?
- Which CoBis are important for different *stakeholders*?
- What role does the *user interface* play?
- How do CoBis manifest in *other retrieval and recommendation tasks and domains*, e.g., sequential recommendation; video, travel, people?

We advocate for a holistic discussion of *both negative and positive effects of cognitive biases*, and for new approaches to algorithmic decision making that mitigate the former while leveraging the latter.

Part III: Personality and Affect

Overview

Part I: Cognitive Architectures
(~50 minutes)

We introduce cognitive architectures as computational frameworks that model human cognitive processes such as memory, learning, attention, and decision-making. We discuss how these architectures can be leveraged to improve IR and RS by making them more adaptive, interpretable, and user-centric.
Concrete subject matters include:

1) Fundamentals of human cognition
2) Introduction to cognitive architectures
3) Cognitive load and information overload
4) Major cognitive architectures in IR and RS
5) ACT-R
6) SOAR
7) CLARION
8) LIDA
9) Case studies of cognitive architectures
10) Pros and cons

Part II: Cognitive Effects and Biases
(~50 minutes)

We discuss a mixture of well-studied and lesser-studied cognitive biases in the context of IR and RS, pertaining to both the system (training, model, and inference) and the user-system interactions.
Concrete subject matters include:

1) Rationality and decision heuristics
2) Role of cognitive biases in human decision making
3) Primacy/Recency effects and position bias
4) Bandwagon effect and popularity bias
5) Feature-positive effect
6) Cultural homophily
7) Conformity bias
8) Anchoring and decoy effect
9) Confirmation bias
10) Halo and horn effects
11) Strategies to mitigate and leverage cognitive biases in IR and RS

Part III: Personality and Affect
(~50 minutes)

We introduce models of personality and affect and discuss how they can be used in IR and RS.
Concrete subject matters include:

1) States vs. traits: background
2) Emotion models
3) Usage of emotions in IR and RS
4) Emotion acquisition
5) Personality models
6) Usage of personality in IR and RS
7) Acquisition of personality
8) Eudaimonia and hedonia as traits and item characteristics
9) Other psychological constructs (needs...)

States vs. traits

States:

- Enduring characteristics of a person
- Stable across time and situations
- Example: introversion, openness

Traits:

- Temporary psychological conditions
- Can vary from moment to moment
- Example: being nervous before a talk, feeling motivated after coffee

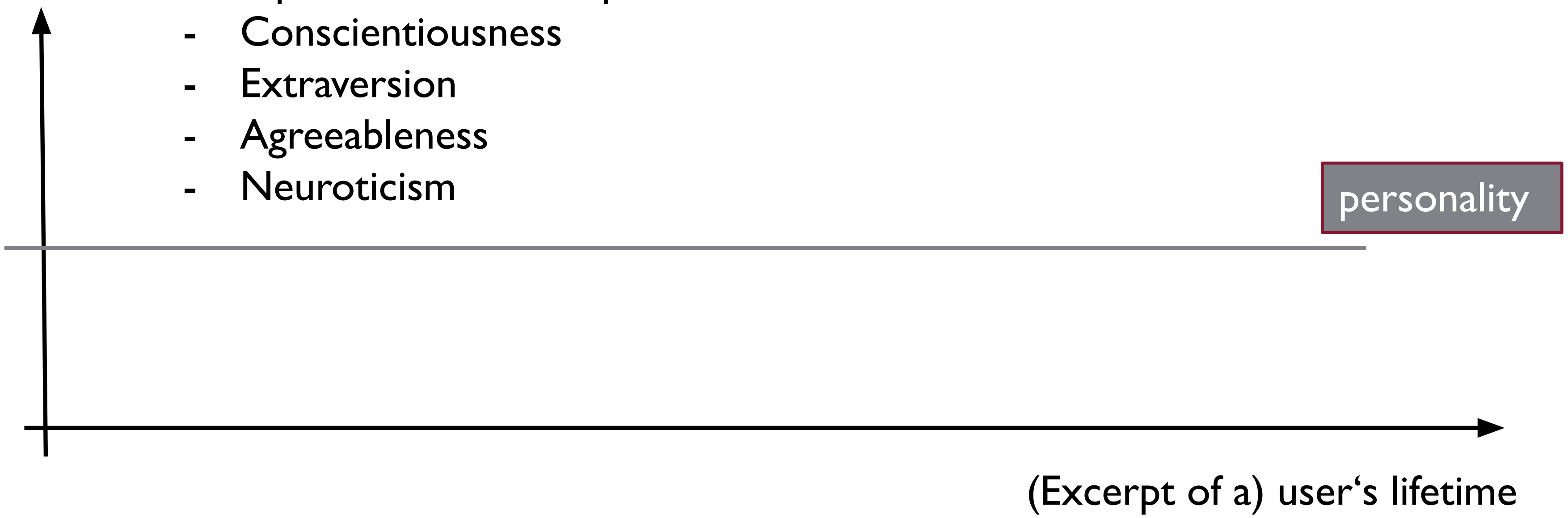
States vs. traits

	Traits	States
Stability	Long-term, consistent	Short-term, flluctuating
Measurement	Personality tests (e.g., Big Five)	Experience sampling, mood logs
Cause	Biological, developmental	Situational, contextual
Impact	Predicts overall behavior patterns	Influences moment-to-moment behavior

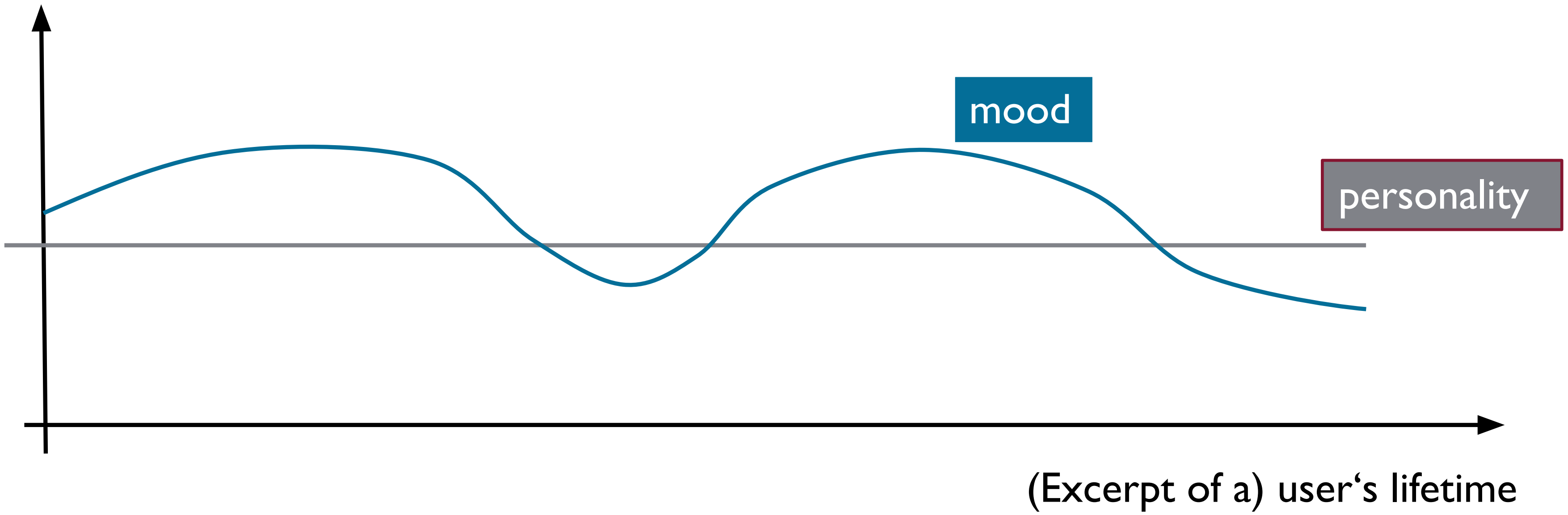
PERSONALITY AND EMOTIONS

PERSONALITY AND EMOTIONS

- Five Factor Model:
- Openness to new experiences
- Conscientiousness
- Extraversion
- Agreeableness
- Neuroticism

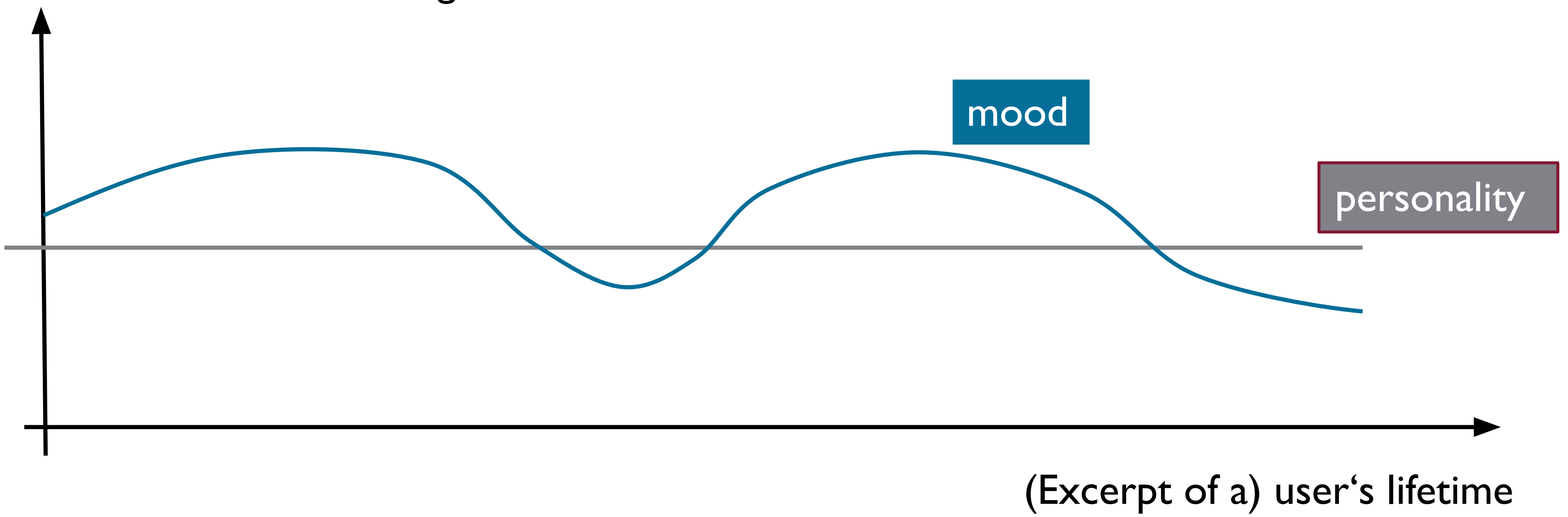


PERSONALITY AND EMOTIONS

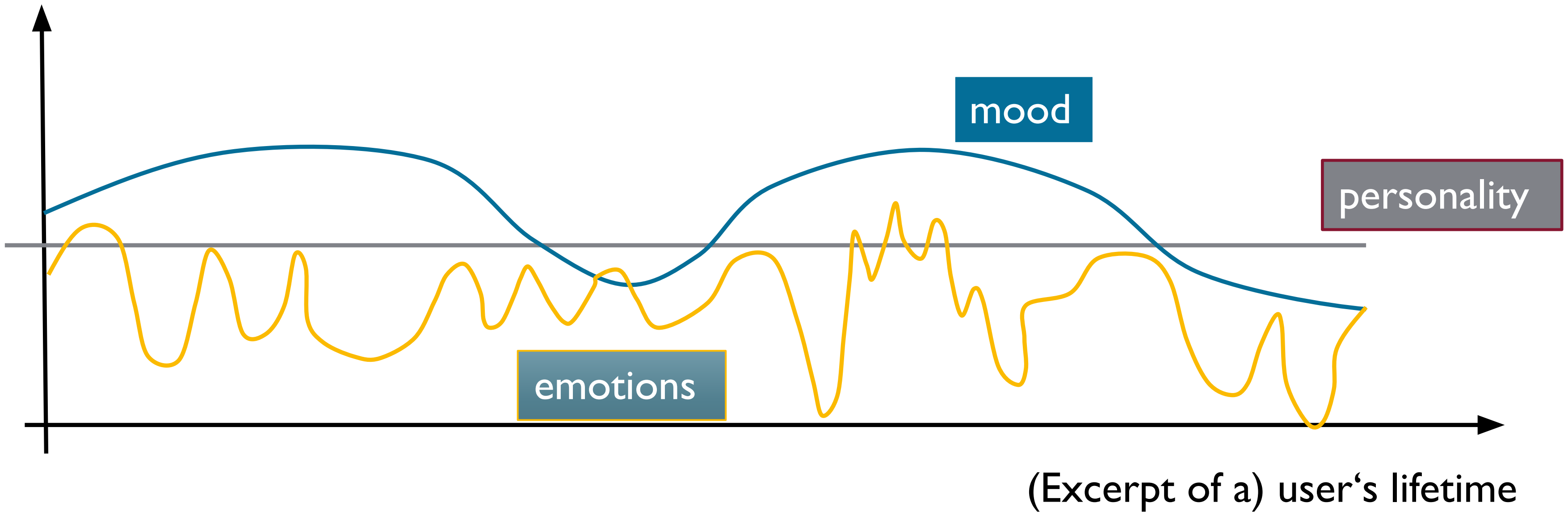


PERSONALITY AND EMOTIONS

- No particular trigger
- Positive/Negative

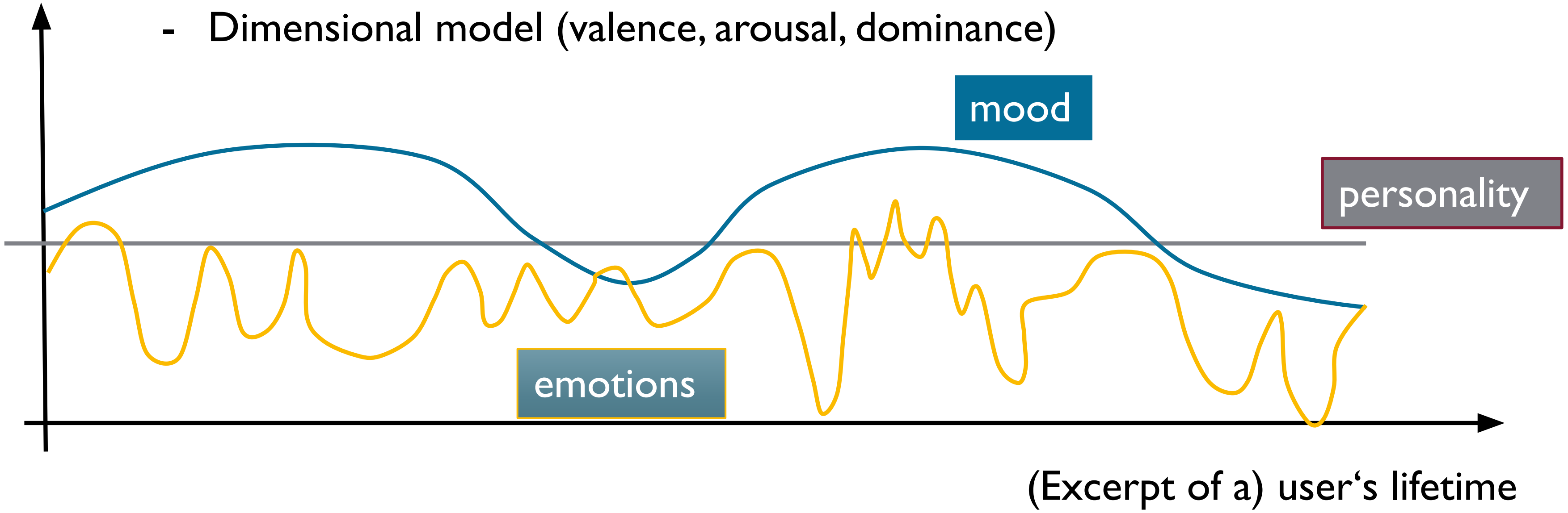


PERSONALITY AND EMOTIONS



PERSONALITY AND EMOTIONS

- Triggered
- Discrete emotions (anger, disgust, fear, happiness, sadness, surprise)
- Dimensional model (valence, arousal, dominance)



Emotions

Emotions vs mood vs sentiment

Let's clear some terminology

- Affect: umbrella term for describing the topics of emotion, feelings, and moods
- Emotion:
  - brief in duration
  - consist of a coordinated set of responses (verbal, physiological, behavioral, and neural mechanisms)
  - triggered
- Mood:
  - last longer
  - less intense than emotions
  - no trigger
- Sentiment
  - towards an object
  - positive/negative

Models of Emotions

- Emotions are complex human experiences
- Evolution-based
- Several definitions, we take simple models, easy to incorporate in computers:
    - Basic emotions
    - Dimensional model

Basic Emotions

- Discrete classes model
- Different sets
- Darwin: Expression of emotions in man and animal

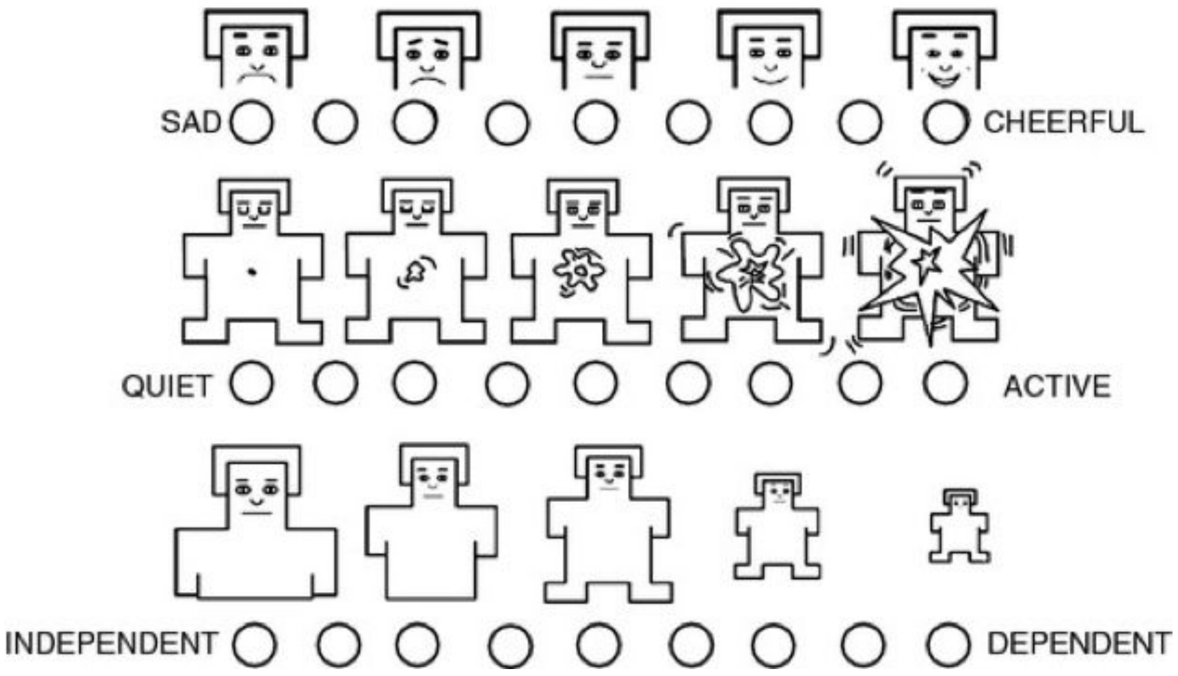
- Ekman definition (6 + neutral):
  - Happiness
  - Anger
  - Fear
  - Sadness
  - Disgust
  - Surprise

Dimensional model of Emotions

Three continuous dimensions

- Valence/Pleasure (positive-negative)
- Arousal (high-low)
- Dominance (high-low)

Each emotion is a point in the VAD space



Bradley, M. M., and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. Journal of Behavior Therapy and Experimental Psychiatry, 25(1), 49–59.

Choices are (also) driven by emotions

Why we choose to consume some kind of content?

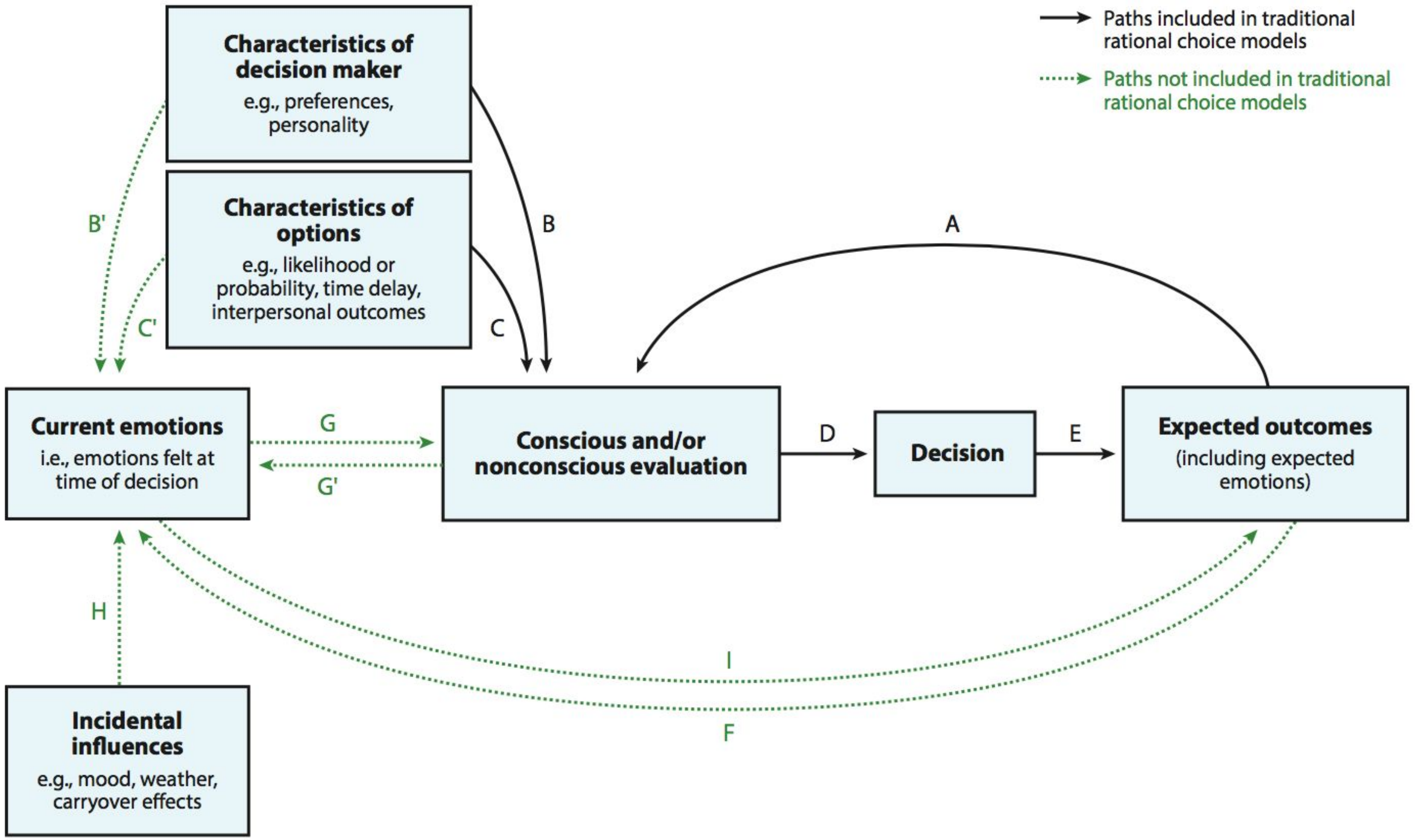
One of the main reasons why people consume music (Lonsdale, 2011) and films (Oliver, 2008) is **emotion regulation.**

	Mean rating (*SD*)
Positive mood management (e.g., to set the 'right' mood)	7.90 (1.52)
Diversion (e.g., to pass the time)	6.43 (2.04)
Negative mood management (e.g., to make me feel better)	6.36 (1.96)
Interpersonal relationships (e.g., to have something to talk about with others)	3.54 (2.02)
Personal identity (e.g., to create an image for myself)	2.89 (2.10)
Surveillance (e.g., to learn how other people think)	2.33 (1.73)

Lonsdale, A. J., and North, A. C. (2011). Why do we listen to music? A uses and gratifications analysis. British Journal of Psychology (London, England : 1953), 102(1), 108–34. https://doi.org/10.1348/000712610X506831

Oliver, M. B. (2008). Tender affective states as predictors of entertainment preference. Journal of Communication, 58(1), 40–61. https://doi.org/10.1111/j.1460-2466.2007.00373.x

Choices are (also) driven by emotions



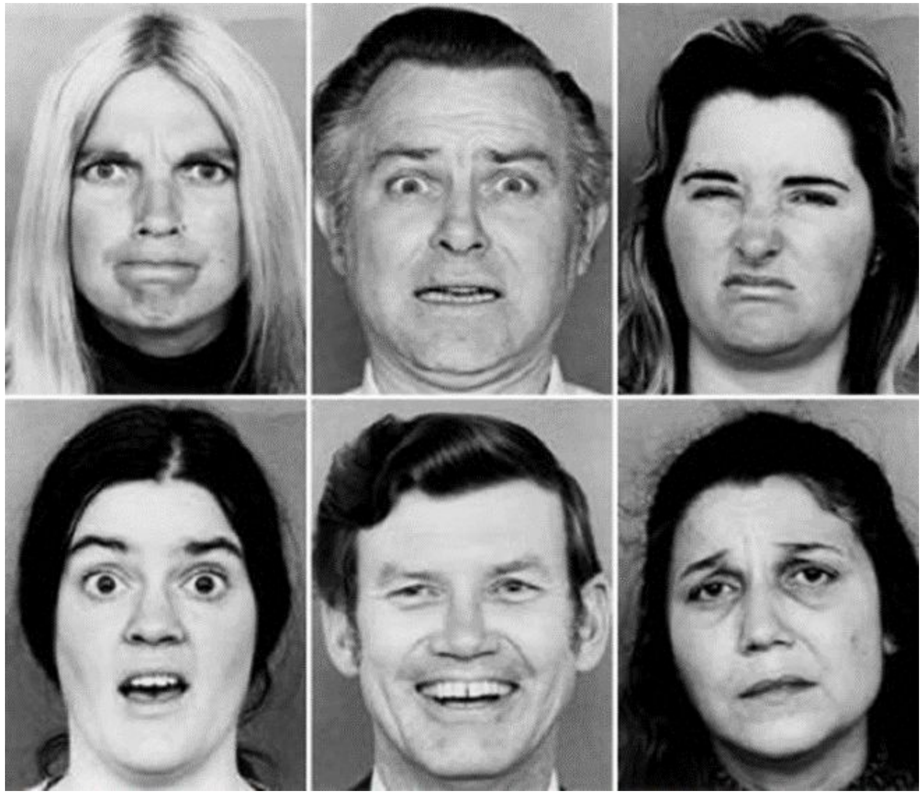
Lerner, J. S., Li, Y., Valdesolo, P., and Kassam, K. S. (2015). Emotion and Decision Making. Annual Review of Psychology, 66(1), 799–823.

Intentions of content creators

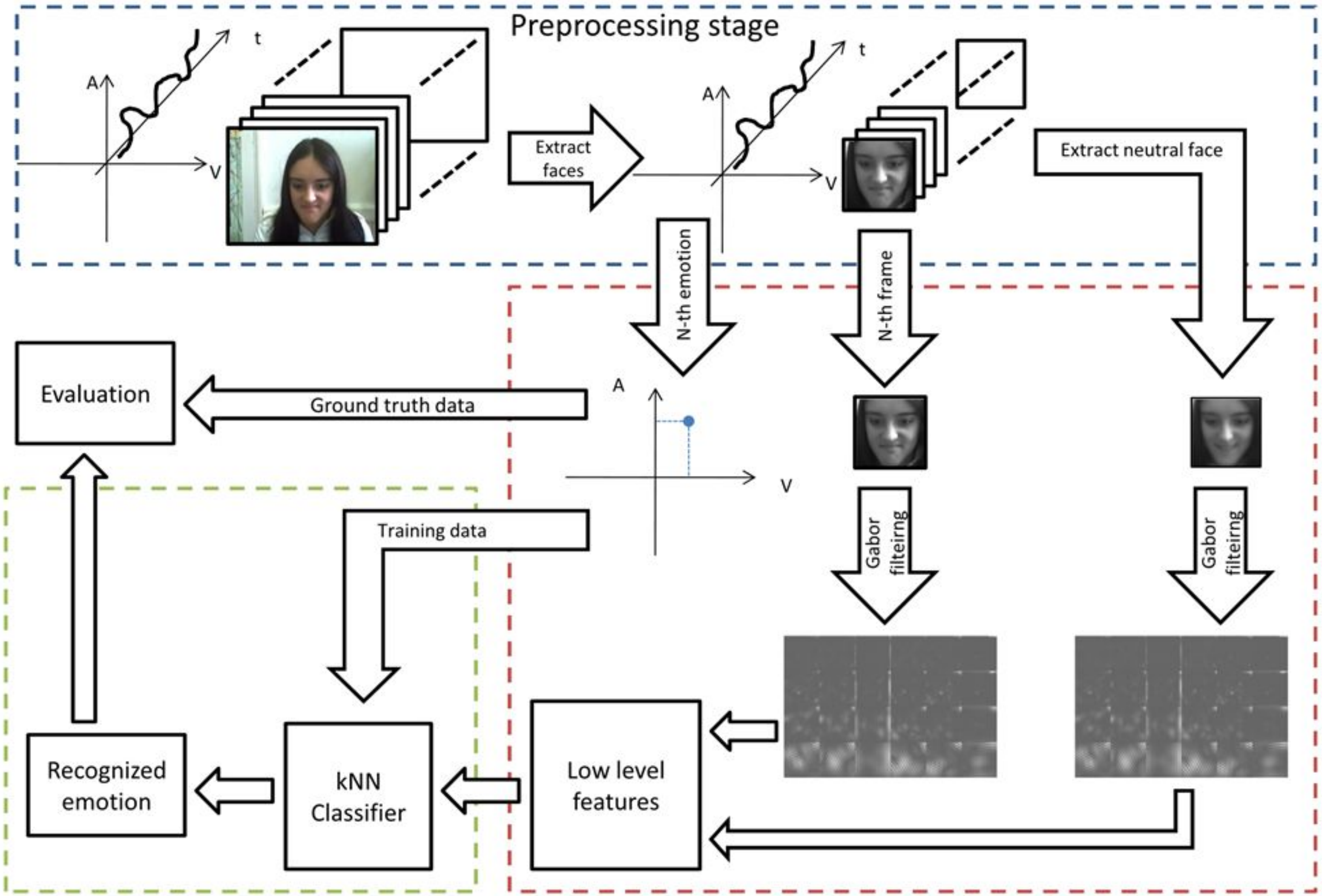
- “A film is - or should be - more like music than like fiction. It should be a **progression of moods and feelings**. The theme, what's behind the emotion, the meaning, all that comes later.” -- Stanley Kubrick
- “If my films make one more person **miserable**, I'll feel I have done my job.” -- Woody Allen
- “Through careful manipulation and good storytelling, you can get everybody to clap at the same time, to **laugh** at the same time, and to be **afraid** at the same time.” -- Steven Spielberg

How to measure emotions

- Questionnaires
- Multimodal prediction (affective computing):
  - Modalities: Audio, language, visual, physiology



Emotion Prediction from face video



Tkalčič, Marko, Ante Odić, and Andrej Košir. 'The Impact of Weak Ground Truth and Facial Expressiveness on Affect Detection Accuracy from Time-Continuous Videos of Facial Expressions'. Information Sciences 249 (November 2013): 13–23. https://doi.org/10.1016/j.ins.2013.06.006.

Off-the-shelf solutions

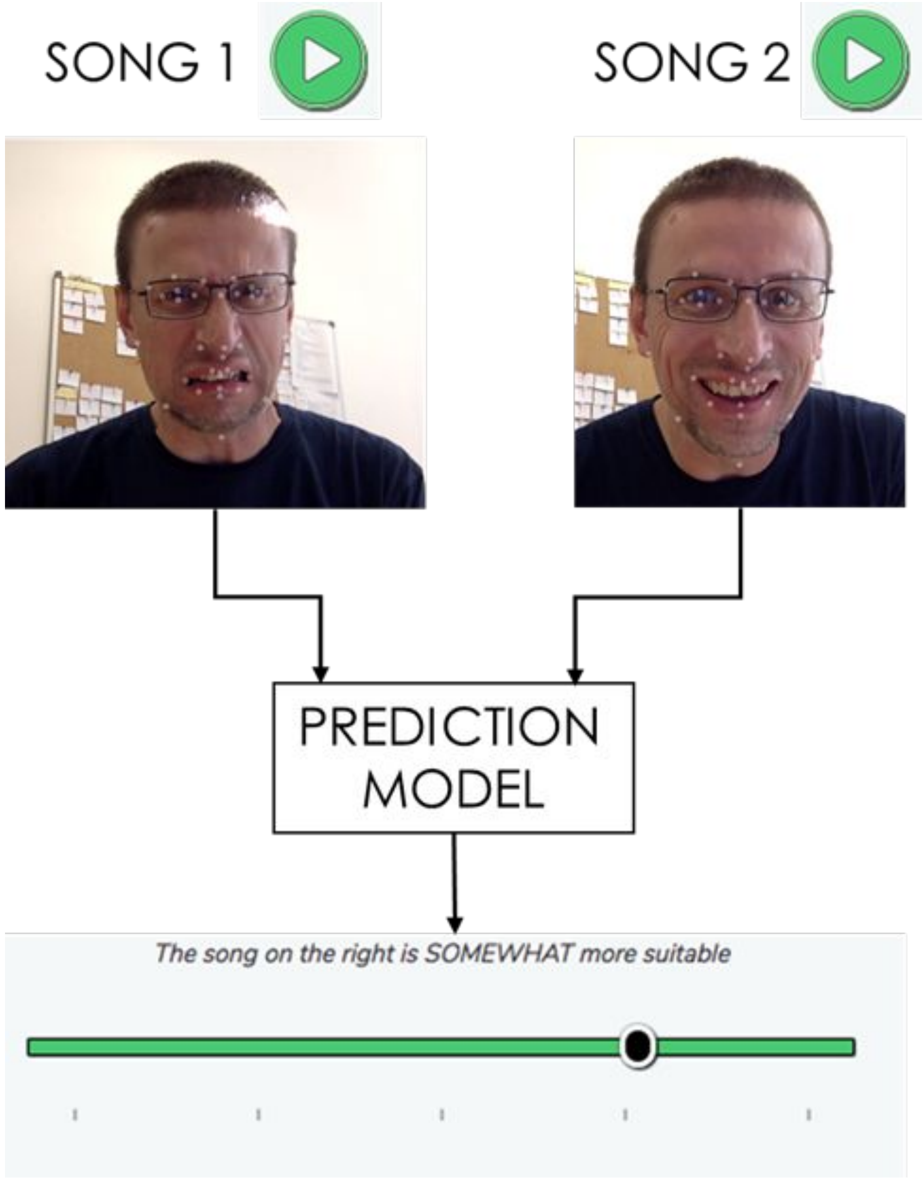
https://osebje.famnit.upr.si/~marko.tkalcic/durham_lecture/demo.html

Emotions in Recommender Systems

- Educational field
  - match task/lesson difficulty to stress
- Emotions as context
  - recommendations based on current emotions
- Emotion as feedback
- Group settings: emotional contagion

Emotions as feedback

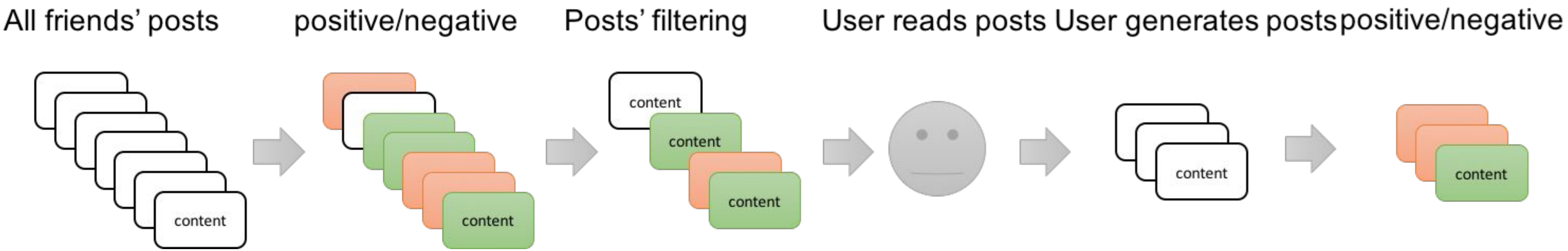
- Pairwise music preferences
- Differences in emotions predict the preferences
    - Contempt
    - Valence
    - Joy
    - Sadness



Tkalčič, M., Maleki, N., Pesek, M., Elahi, M., Ricci, F., & Marolt, M. (2019). Prediction of music pairwise preferences from facial expressions. Proceedings of the 24th International Conference on Intelligent User Interfaces - IUI ’19, 150–159. https://doi.org/10.1145/3301275.3302266

Emotional contagion

- RQ: does emotional contagion occur outside of in-person interactions?
  - Facebook users (N = 689,003)
  - 2 experiments:
    - exposure to friends' positive emotional content was reduced
      - group (only emotional content omitted)
      - control group (any content omitted)
    - exposure to friends' negative emotional content was reduced
      - group (only emotional content omitted)
      - control group (any content omitted)



Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. Proceedings of the National Academy of Sciences of the United States of America, 111(29), 8788–8790. https://doi.org/10.1073/pnas.1320040111

Emotions in Recommender Systems References

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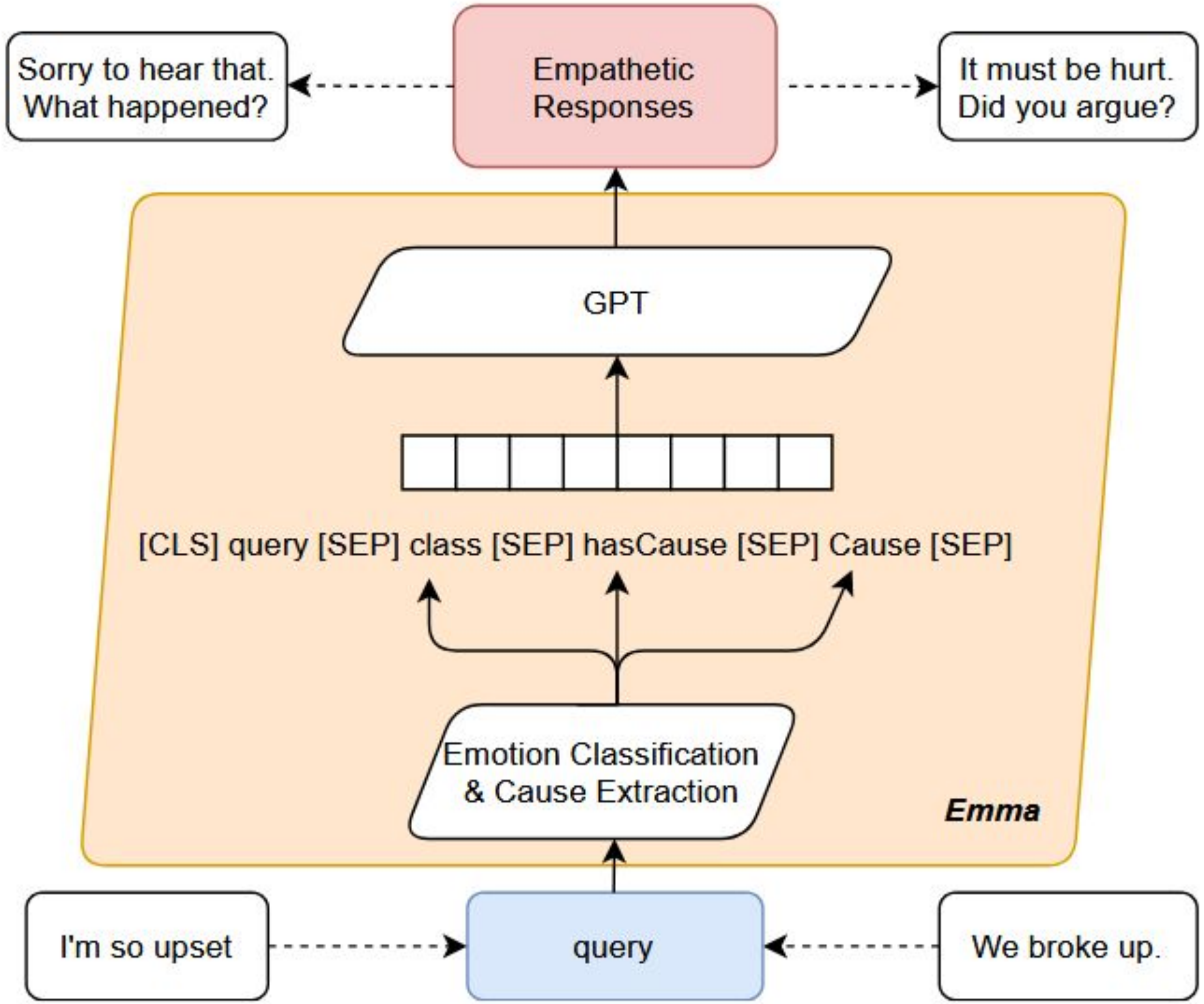
- Yong Zheng, Bamshad Mobasher, Robin D. Burke: The Role of Emotions in Context-aware Recommendation. Decisions@RecSys 2013: 21-28
- Zheng, Y., Mobasher, B., and Burke, R. (2016). Emotions in Context-Aware Recommender Systems (pp. 311–326). In M. Tkalčič, B. De Carolis, M. de Gemmis, A. Odić, and A. Košir (Eds.), Emotions and Personality in Personalized Services: Models, Evaluation and Applications

Emotions in information retrieval

- HOW to respond, not WHAT:
  - **It reframes the IR problem towards emotional relevance, not just topical relevance.**
  - Yanran Li, Ke Li, Hongke Ning, Xiaoqiang Xia, Yalong Guo, Che Wei, Jianwei Cui, and Bin Wang. 2021. Towards an Online Empathetic Chatbot with Emotio Causes. (SIGIR '21). https://doi.org/10.1145/3404835.463042



Personality

Personality models

What is personality?

Personality accounts for individual differences (= explains the variance in users) in our enduring emotional, interpersonal, experiential, attitudinal, and motivational styles

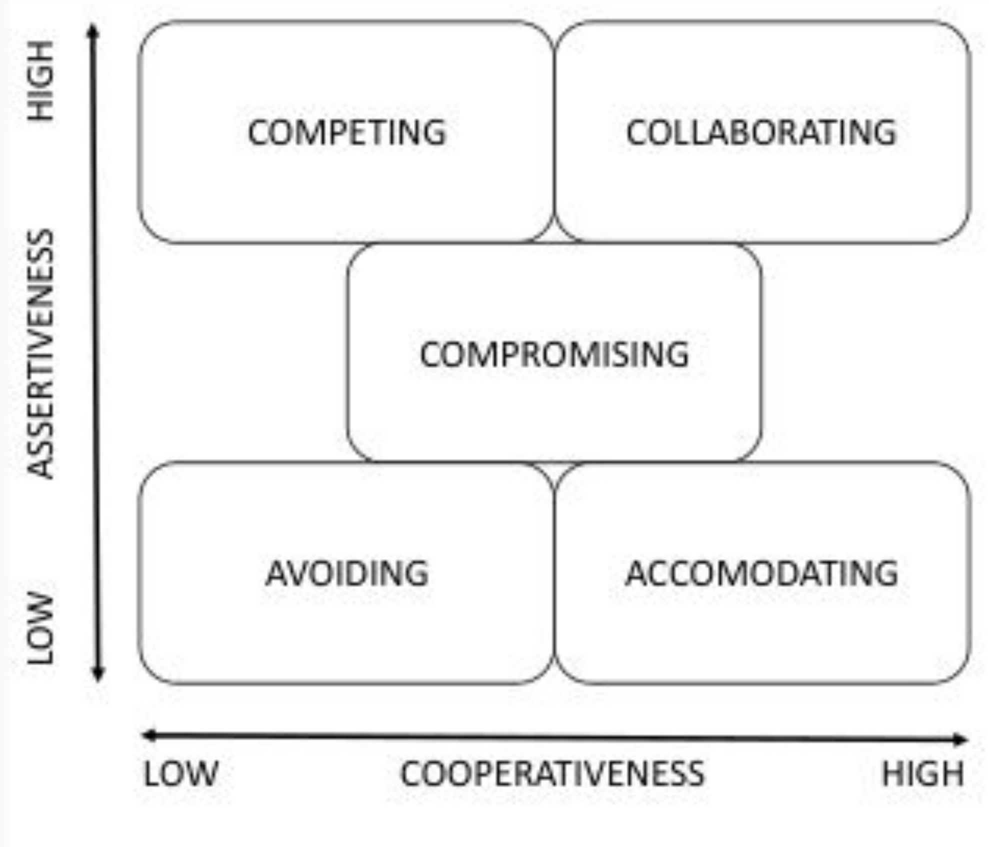
The Five Factor Model (Big 5);

- Extraversion
- Agreeableness
- Conscientousness
- Neuroticism (inverse = Emotional Stability)
- Openness (to new experiences)

McCrae, R. R., and John, O. P. (1992). An Introduction to the Five-Factor Model and its Applications. Journal of Personality, 60(2), p175-215.

Thomas-Kilmann Conflict Mode

Developed to measure the conflict resolution styles in groups



Thomas, K. L., and Kilman, R. H. (n.d.). Thomas-Kilman Conflict Mode Instrument.

How to measure personality?

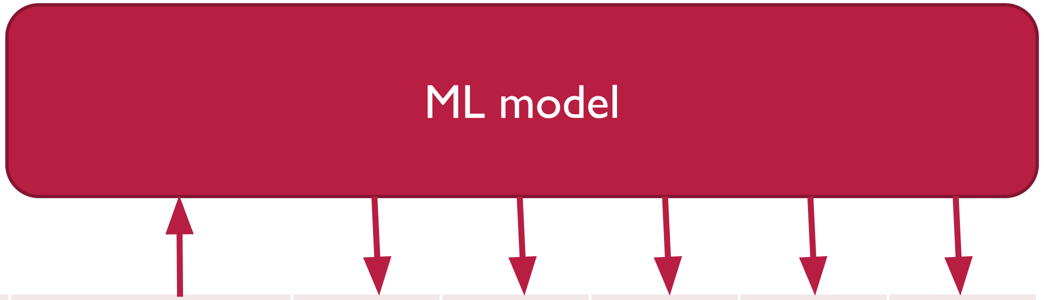
- Questionnaires
    - lengthy, time consuming, intrusive
    - NEO-PI-R: 240 items
    - IPIP-50
    - BFI: 44 items
    - TIPI: 10 items
- Inference from digital traces
    - pretrained models
    - ethical issues

Inference from digital traces

- Digital traces:
  - instagram
  - twitter
  - eye tracking data
  - brainwaves
  - physiological sensors
- Off-the shelf solutions
  - https://applymagicsauce.com/demo

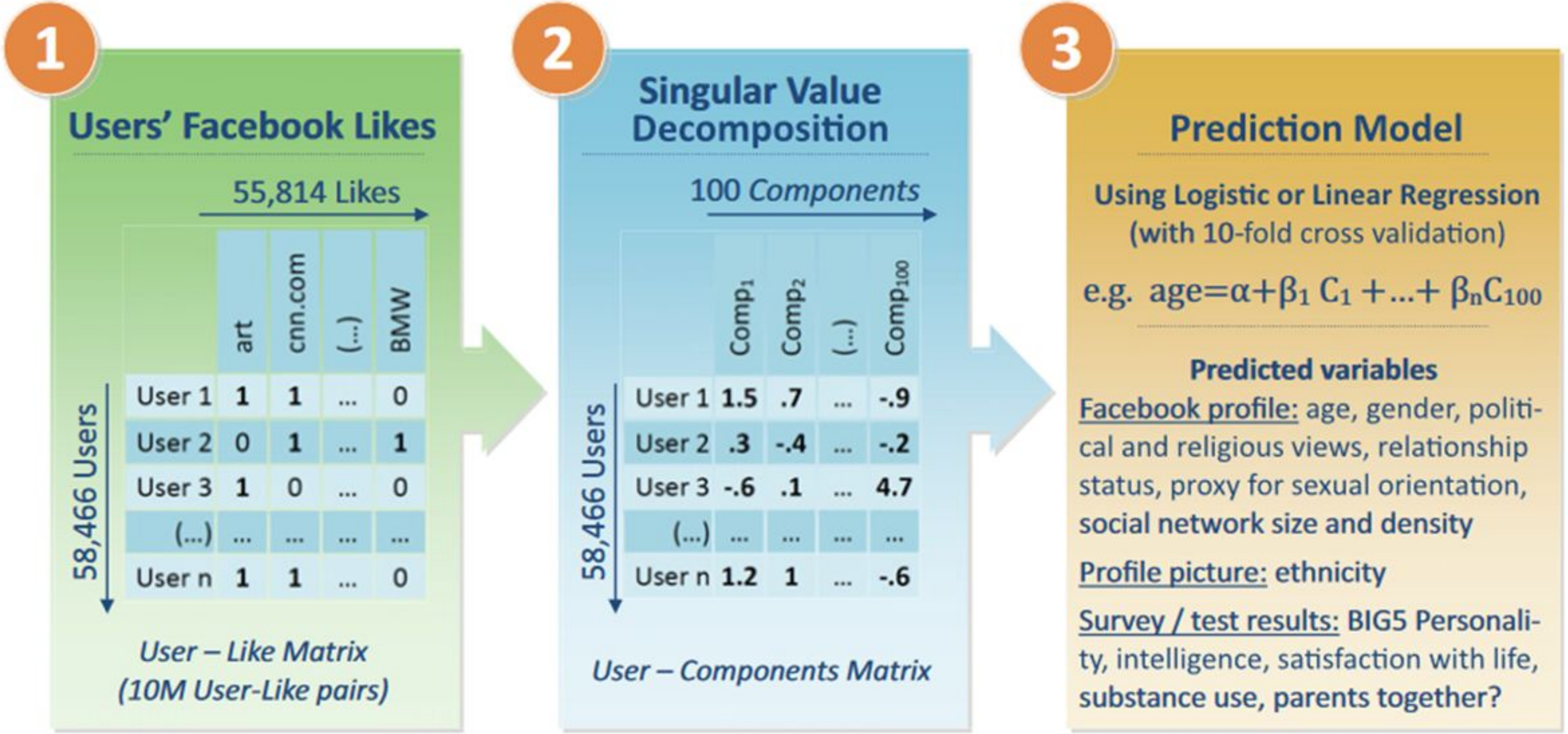
Inference from digital traces

- Questionnaires
  - BFI: 44 questions
  - TIPI: 10 questions
  - NEO-IPIP: 300 questions
- Unobtrusive prediction:
  - Self-reported Personality
  - User Social Media Digital Traces
    - Instagram
    - Twitter



user	digital traces	O	C	E	A	N
1	(f1....fM)	0,78	1,28	2,06	0,50	1,04
2	(f1....fM)	0,12	8,33	8,45	8,21	69,43
3	(f1....fM)	0,23	4,35	4,58	4,12	18,85
...		...	...	...	...	...
N	(f1....fM)	0,45	2,22	2,67	1,77	4,74

From Facebook



Kosinski, Michal, David Stillwell, and Thore Graepel. "Private Traits and Attributes Are Predictable from Digital Records of Human Behavior." *Proceedings of the National Academy of Sciences* 110, no. 15 (April 9, 2013): 5802–5. https://doi.org/10.1073/pnas.1218772110.

Skowron, Marcin, Marko Tkalčič, Bruce Ferwerda, and Markus Schedl. ‘Fusing Social Media Cues: Personality Prediction from Twitter and Instagram’. In Proceedings of the 25th International Conference Companion on World Wide Web - WWW ’16 Companion, 2016. https://doi.org/10.1145/2872518.2889368.

Azucar, Danny, Davide Marengo, and Michele Settanni. ‘Predicting the Big 5 Personality Traits from Digital Footprints on Social Media: A Meta-Analysis’. *Personality and Individual Differences* 124 (April 2018):150–59. https://doi.org/10.1016/j.paid.2017.12.018.

Inference from Digital Traces - References

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- R. V. Sharan, S. Berkovsky, R. Taib, I. Koprinska and J. Li, "Detecting Personality Traits Using Inter-Hemispheric Asynchrony of the Brainwaves," doi: 10.1109/EMBC44109.2020.9176108.
- Ronnie Taib, Shlomo Berkovsky, Irena Koprinska, Eileen Wang, Yucheng Zeng, and Jingjie Li. 2020. Personality Sensing: Detection of Personality Traits Using Physiological Responses to Image and Video Stimuli. https://doi.org/10.1145/3357459
- Skowron, M., Tkalčič, M., Ferwerda, B., & Schedl, M. (2016). Fusing Social Media Cues: Personality Prediction from Twitter and Instagram. https://doi.org/10.1145/2872518.2889368
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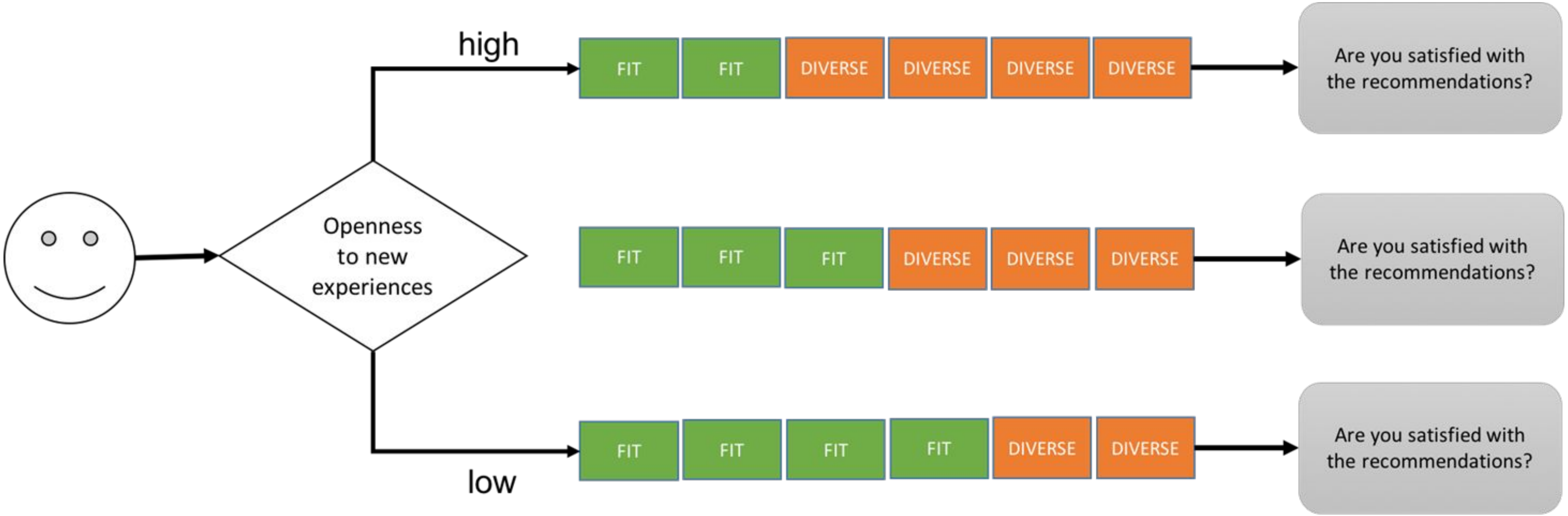
Personality in Recommender Systems

- Cold-start problem:
  - user-user similarity based on personality
- Diversity
  - Personality-based diversity adaptation
- Cross-domain recommendations
  - personality-based profiles in different domains
- Group recommender systems
  - Combining assertiveness and cooperativeness into the aggregation function
- Social media
  - followee recommendations

Personality and Diversity



Chen, L., Wu, W., and He, L. (2013). How personality influences users' needs for recommendation diversity? CHI ' 13 Extended Abstracts on Human Factors in Computing Systems on - CHI EA '13, 829. https://doi.org/10.1145/2468356.246850

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- M. Tkalcic, M. Kunaver, J. Tasic, A. Košir, Personality based user similarity measure for a collaborative recommender system, in 5th Workshop on Emotion in Human-Computer Interaction-Real World Challenges (2009), p. 30
- I. Fernández-Tobías, M. Braunhofer, M. Elahi, F. Ricci, I. Cantador, Alleviating the new userproblem in collaborative filtering by exploiting personality information. https://doi.org/10.1007/s11257-016-9172-z.
- W. Wu, L. Chen, Y. Zhao, Personalizing recommendation diversity based on user personality. https://doi.org/10.1007/s11257-018-9205-x.
- N. Tintarev, M. Dennis, J. Masthoff, Adapting recommendation diversity to openness to experience: a study of human behaviour, https://doi.org/10.1007/978-3-642-38844-6_16
- L. Quijano-Sanchez, J.A. Recio-Garcia, B. Diaz-Agudo, Personality and social trust in group recommendations, https://doi.org/10.1109/ICTAI.2010.92
- Tommasel, A., Corbellini, A., Godoy, D., & Schiaffino, S. (2016). Personality-aware followee recommendation algorithms: An empirical analysis. https://doi.org/10.1016/j.engappai.2016.01.016

Personality in Information Retrieval

- Few studies
  - mainly the personality of the system not the user
    - Yuta Imasaka and Hideo Joho. 2024. Effect of LLM's Personality Traits on Query Generation. (SIGIR-AP 2024). https://doi.org/10.1145/3673791.3698433
    - **IR as a multi-agent ecosystem, where "personality" is effectively the behavior profile of the query agent, controlled through LLM variants or prompting.**
- Lots of opportunities

Positive Psychology

E/H in Media Consumption

- Oliver & Raney (2011):
  - motivation for entertainment selection:
    - eudaimonic (truth-seeking)
    - hedonic (pleasure-seeking)

I like movies that challenge my way of seeing the world.
I like movies that make me more reflective.
I like movies that focus on meaningful human conditions.
My favorite kinds of movies are ones that make me think.
I am very moved by movies that are about people's search for greater understanding in life.
I like movies that have profound meanings or messages to convey.

It's important to me that I have fun when watching a movie.
Movies that make me laugh are among my favorites.
I find that even simple movies can be enjoyable as long as they are fun.
I like movies that may be considered "silly" or "shallow" if they can make me laugh and have a good time.
For me, the best movies are ones that are entertaining.
My favorite kinds of movies are happy and positive.

Oliver, M. B., & Raney, A. A. (2011). Entertainment as Pleasurable and Meaningful: Identifying Hedonic and Eudaimonic Motivations for Entertainment Consumption. *Journal of Communication*, *61*(5), 984–1004. https://doi.org/10.1111/j.1460-2466.2011.01585.x

Why People Choose Specific Content?

- Factor analysis:
  - Rewarding feelings:
    - fun
    - thrill
    - empathic sadness
  - Individuals' social and cognitive needs:
    - contemplative emotional experiences,
    - emotional engagement with characters,
    - social sharing of emotions
    - vicarious release of emotions.

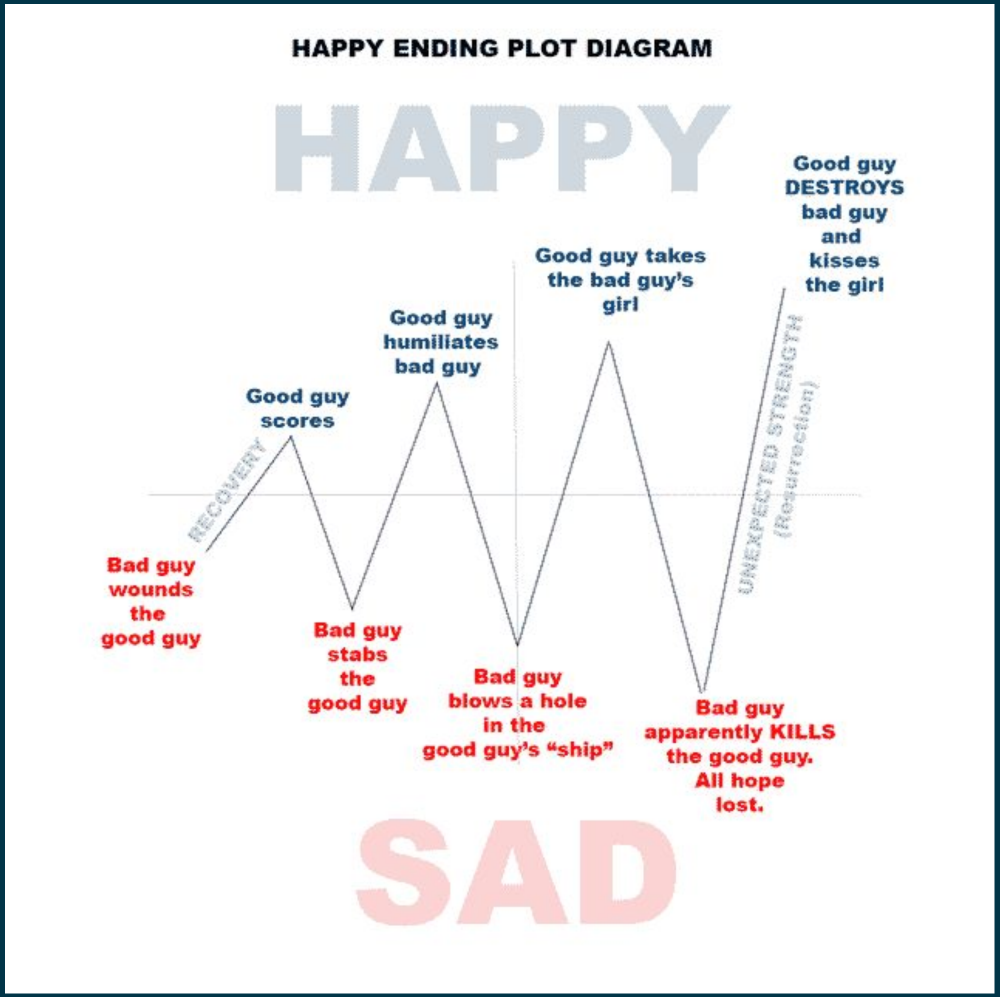
Bartsch, A. (2012). Emotional Gratification in Entertainment Experience. Why Viewers of Movies and Television Series Find it Rewarding to Experience Emotions. *Media Psychology*, *15*(3), 267–302. https://doi.org/10.1080/15213269.2012.693811

UM/RS + Positive Psychology

- UM/RS
    - What is Netflix recommending?
    - Movies/TV shows
        - I want to watch a funny movie tonight?
    - Funny is all you want?

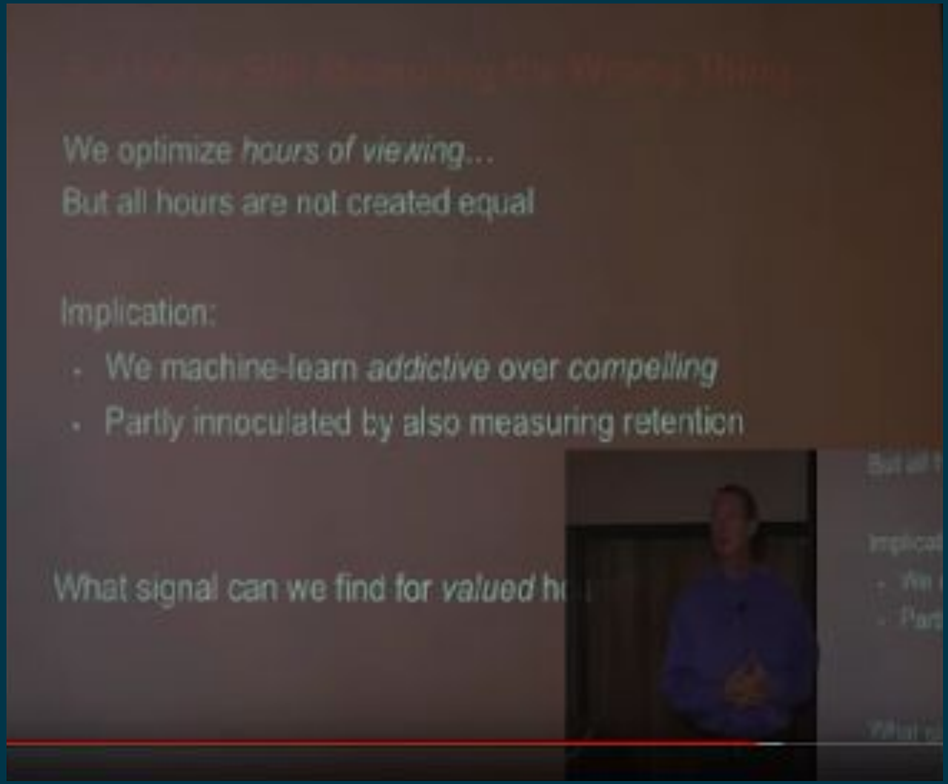
UM/RS + Positive Psychology

- UM/RS
    - What is Netflix recommending?
    - Movies/TV shows
        - I want to watch a funny movie tonight?
    - Funny is all you want?



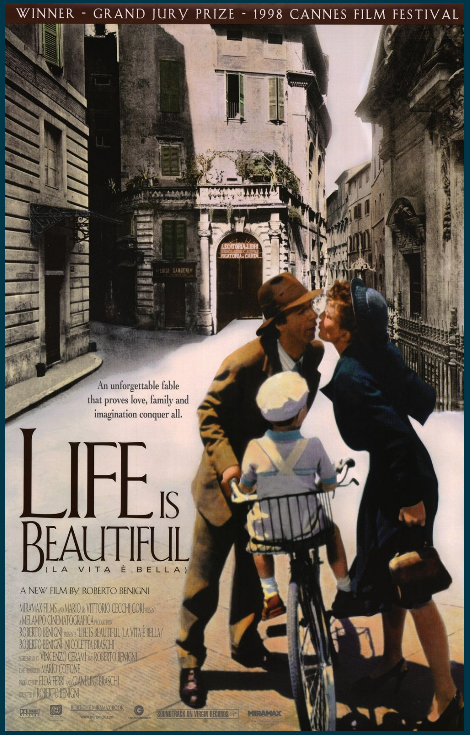
1-The Netflix Story

- Neil Hunt (Netflix), Keynote at RecSys 2014 : Quantifying the Value of Better Recommendations*:
    - We optimize for hours of viewing...
    - ...but all hours are not equal
        - Addiction
        - Compelling
    - We might be optimizing for addiction over compelling
    - How to qualify the viewing hours?



https://youtu.be/lYcDR8z-rRY?t=4727

2-The “Life is Beautiful (1997)” STORY



- Funny (hedonic quality)
- Tragic (eudaimonic quality)

- What does thumbs up mean?
  - Liked the jokes?
  - Moved by the drama?

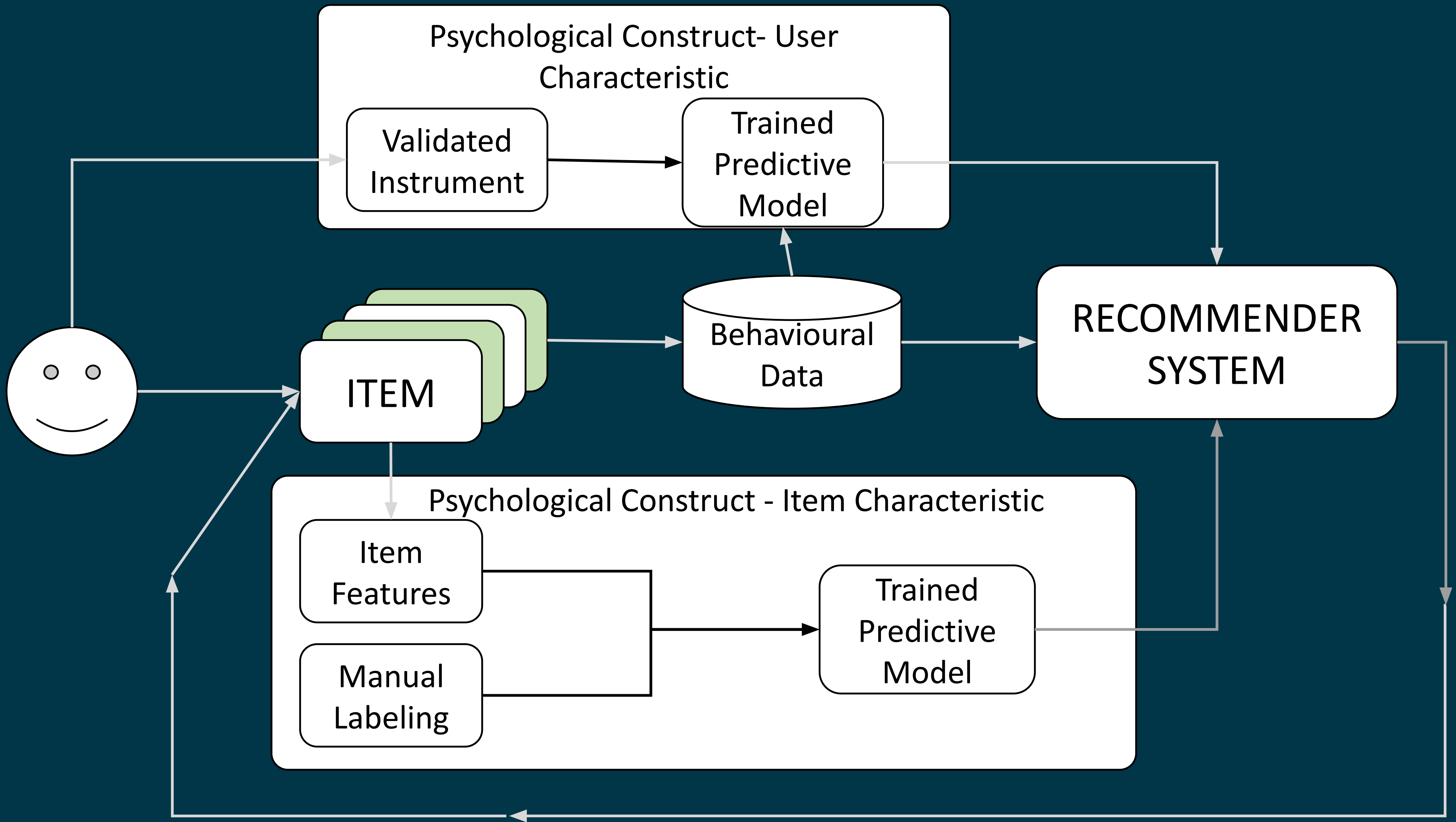
H/E IN MOVIES

HEDONIC	✓	✓	✗
EUDAIMONIC	✓	✗	✓

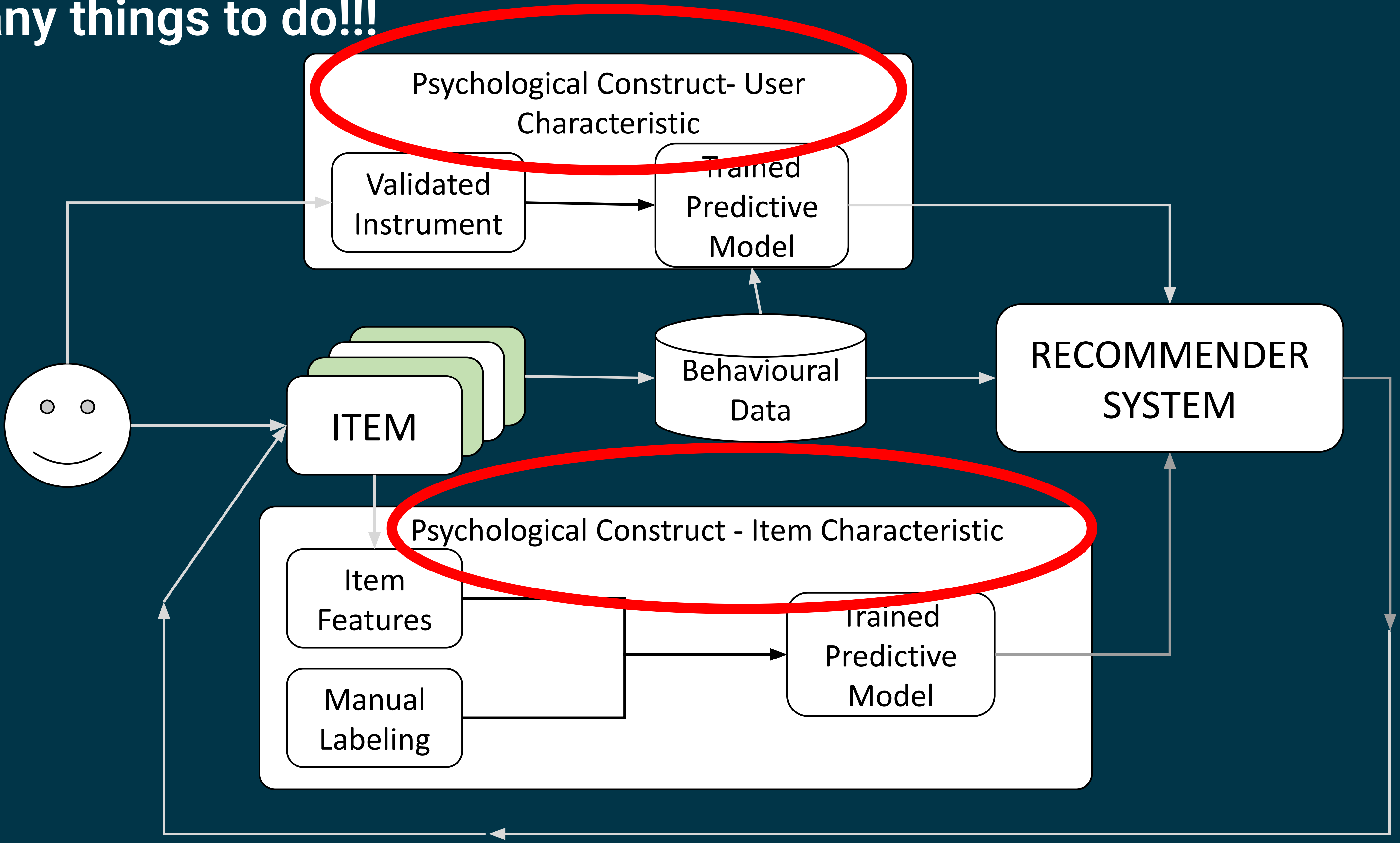
H/E IN MOVIES

HEDONIC	✓	✓	✗
EUDAIMONIC	✓	✗	✓
PETER	👎	👍	👎
PAUL	👎	👎	👍
MARY	👍	👎	👍
JOAN	👍	👍	👎

So many things to do!!!



So many things to do!!!



So many things to do!!!

Psychological Construct- User Characteristic

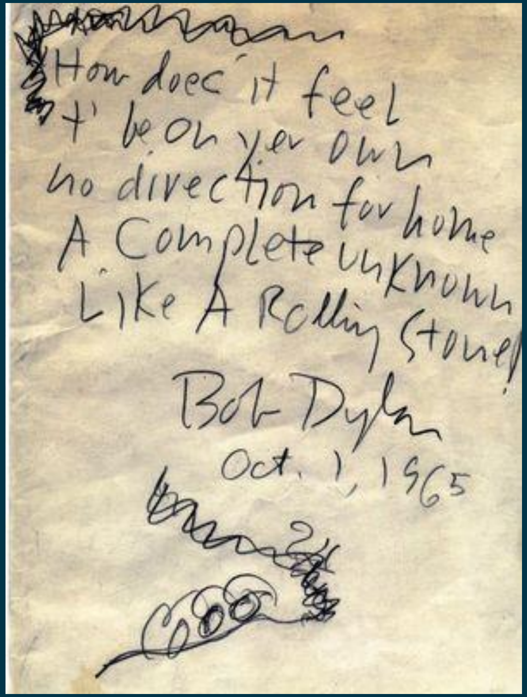
E: propensity of the user for Eudaimonic experiences
H: propensity of the user for hedonic experiences

E: capacity of the content to induce Eudaimonic experience
H: capacity of the content to induce HEdonic experience

Psychological Construct - Item Characteristic

EH Song Characteristics from Music

- Manual labeling:
  - 1991 participants
  - 130 songs
- Many classifiers, TF-IDF
- Eudaimonia classification (accuracy)
  - Majority baseline: 0.423
  - Best classifier: 0.538
- Hedonia classification:
  - Majority baseline: 0.408
  - Best classifier: 0.546



Hrustanović, S., Kavšek, B., & Tkalčič, M. (2021). Recognition of Eudaimonic and Hedonic Qualities from Song Lyrics. *Human-Computer Interaction Slovenia 2021, November 11, 2021, Koper, Slovenia*

EH Movie Characteristics from Subtitles

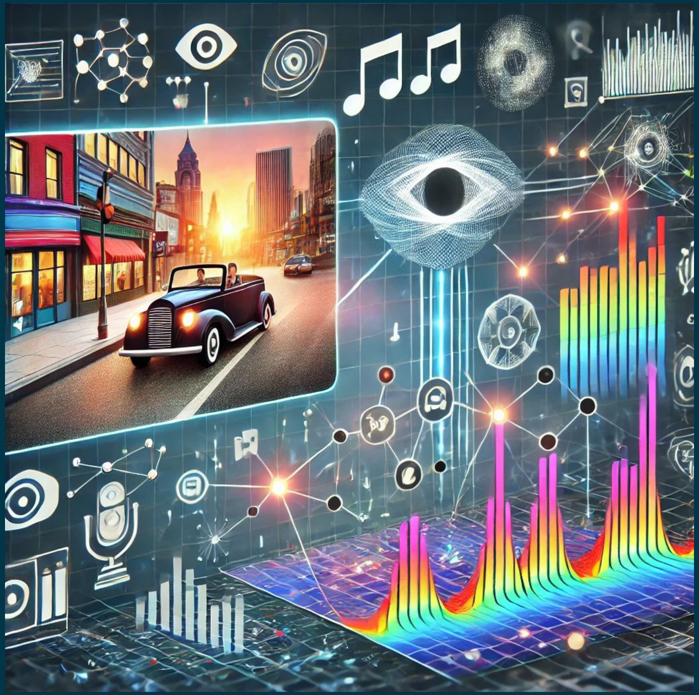
- Annotations
  - 177 users
  - 30 movies
  - 1-5 scale
- Several models, features: TFIDF, fasttext embeddings
- Eudaimonia RMSE: 1.06 (1.26 average baseline)
- Hedonia RMSE: 1.13 (1.34 average baseline)
- Just preliminary, too small a dataset

Motamedi, E., & Tkalčič, M. (2021). Prediction of Eudaimonic and Hedonic Movie Characteristics From Subtitles. *Human-Computer Interaction Slovenia 2021, November 11, 2021, Koper, Slovenia*, 8. https://ceur-ws.org/Vol-3054/paper6.pdf

EH Movie Characteristics from metadata, audio, video features

- Annotations
  - 370 users
  - 709 movies
  - 1-5 scale
- Several models
- Features:
  - metadata
  - audio features
  - video features
- Eudaimonia accuracy: 0.68
- Hedonia accuracy: 0.64

DATA ACQUISITION!!!



Motamedi, E., Kholgh, D. K., Saghari, S., Elahi, M., Barile, F., & Tkalcic, M. (2024). Predicting movies' eudaimonic and hedonic scores: A machine learning approach using metadata, audio and visual features. *Information Processing & Management*, *61*(2), 103610. https://doi.org/10.1016/j.ipm.2023.103610

EH User Characteristics

- Annotations
  - 350 users
  - 703 movies
  - 1-5 scale
- Features:
  - personality
  - genre preferences
  - film sophistication
- Eudaimonia MAE: 0.48 (0.85 average baseline)
- Hedonia MAE: 0.86 (0.97 average baseline)

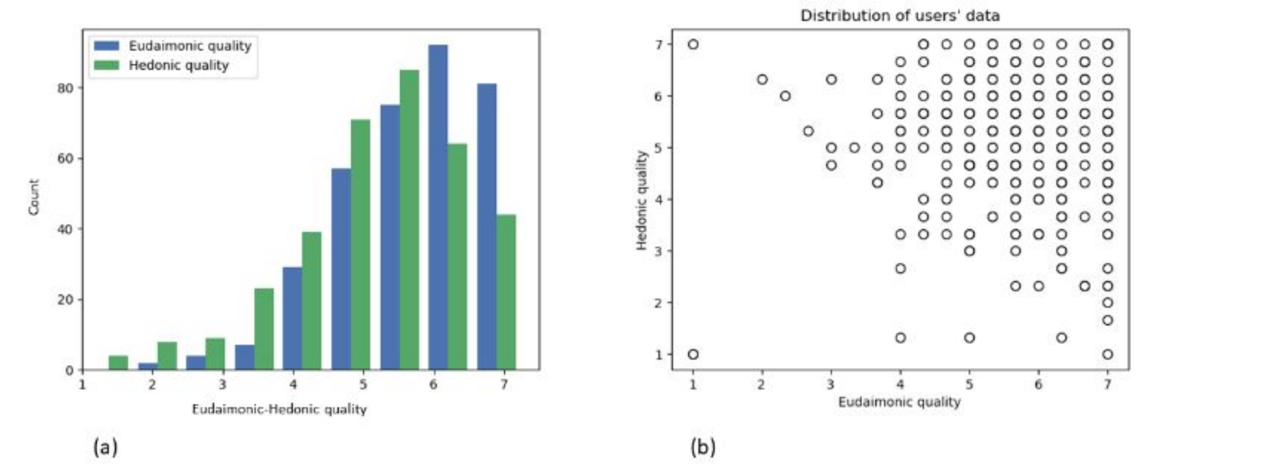


Figure 3. The distribution of users: (**a**) histogram of hedonic (blue) and eudaimonic (green) values and (**b**) eudaimonic vs. hedonic quality.

Motamedi, E., Barile, F., & Tkalčič, M. (2022). Prediction of Eudaimonic and Hedonic Orientation of Movie Watchers. *Applied Sciences (Switzerland)*, *12*(19). Scopus. https://doi.org/10.3390/app12199500

Conclusion on Positive Psychology

- Machine learning: digital traces can be used for predicting user and content EH characteristics
- Major challenges:
  - EH labeling
  - Context dependency

Open Challenges

Open Challenges: Part I

- Some cognitive architectures involve symbolic components and rule-based systems, which can be resource-intensive.

- Most cognitive architectures were designed before deep learning was the dominant approach, resulting in limited integration with DL-based models.

- Limited empirical validation of some cognitive architectures.

- Some cognitive models may oversimplify human decision making.

Open Challenges: Part II

- Understanding how human- and machine-related cognitive biases interact with and impact each other is still unclear.

- Understanding where, how, and how strong cognitive biases manifest in different parts of IR/RS (input, model, output), across domains, datasets, and algorithms.

- Mitigating negative and leveraging positive effects of cognitive effects and biases in retrieval, recommendation, and generative systems.

Open Challenges: Part III

- Open issues pertaining to data acquisition (technical, legal, and ethical aspects), in particular regarding sensitive user traits.

- Improving the communication between the relevant research communities, including computer science, artificial intelligence, psychology, and sociology, in order to foster interdisciplinarity.

Thank You!

Sponsors / Funding:

FWF Austrian Science Fund

CLUSTER OF EXCELLENCE

BILAI
Bilateral
Artificial
Intelligence

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Especially the bias/fairness part strongly relates to cognitive (and other) biases and their relation to fairness of IR and RSs

https://link.springer.com/book/10.1007/978-3-031-69978-8