

LLMs and Cognitive Models in Recommender Systems

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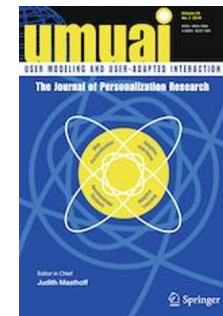
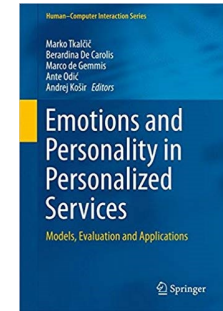
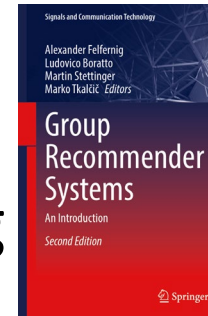
About me

- Associate Professor of Computer Science at the University of Primorska in Koper, Slovenia
 - Assist. Prof. at Free University of Bolzano, Italy
 - Postdoc at JKU Linz, Austria
 - PhD at University of Ljubljana
- I aim at improving **personalized services** (e.g. recommender systems) through the usage of **psychological models** in **personalization algorithms**. To achieve this, I use diverse research methodologies, including **data mining**, **machine learning**, and **user studies**.



About me

- Book co-editor, Emotions and Personality in Personalized Services, 2016
- Book co-editor, Group Recommender Systems, 2nd ed. 2024
- Editorial board member: Springer User Modeling and User-adapted Interaction,
- Program Chair at the ACM UMAP 2021 conference
- Active in the RecSys, UMAP and IUI communities

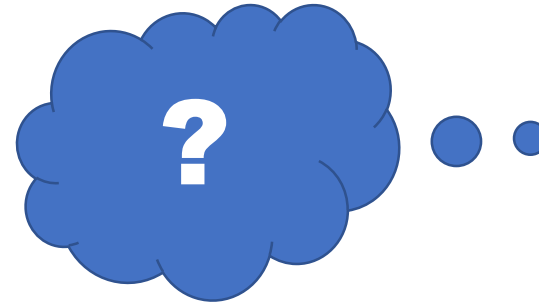


From amateur musicianship...

ME



From amateur musicianship...



From amateur musicianship...



From amateur musicianship...



**Personality?
Education?
Nostalgia?
Cultural background?**



...to user modeling and recommender systems



...to user modelling and recommender systems



USER MODEL

Personality

Emotions

Need for Cognition

Need for Eudaimonia

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USER MODEL

Personality

Emotions

Need for Cognition

Need for Eudaimonia

ITEM MODEL

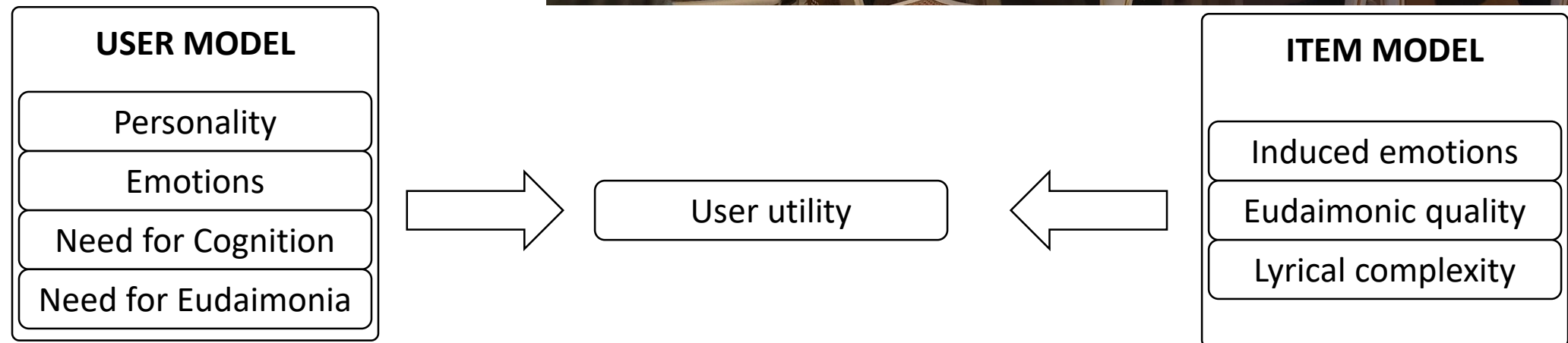
Induced emotions

Eudaimonic quality

Lyrical complexity

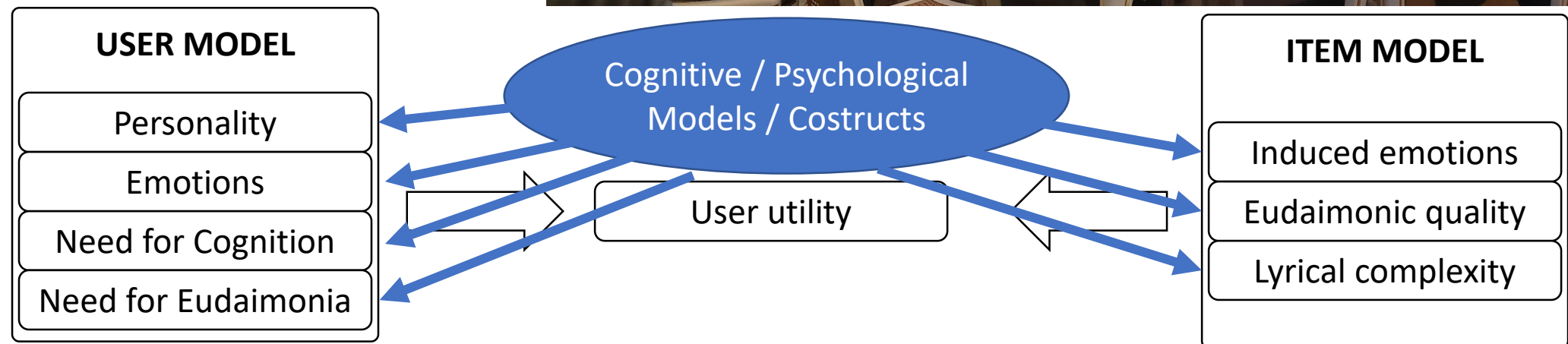
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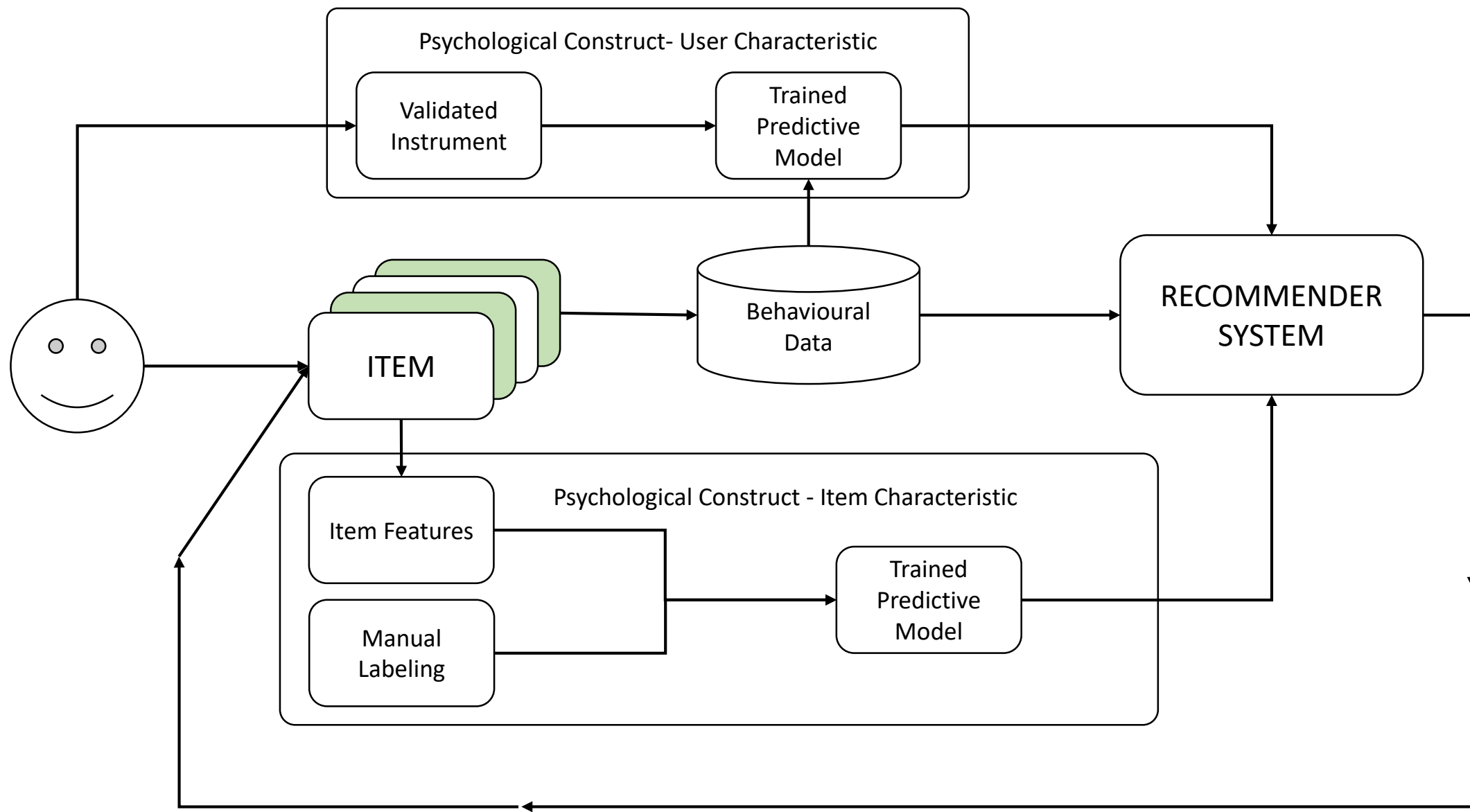


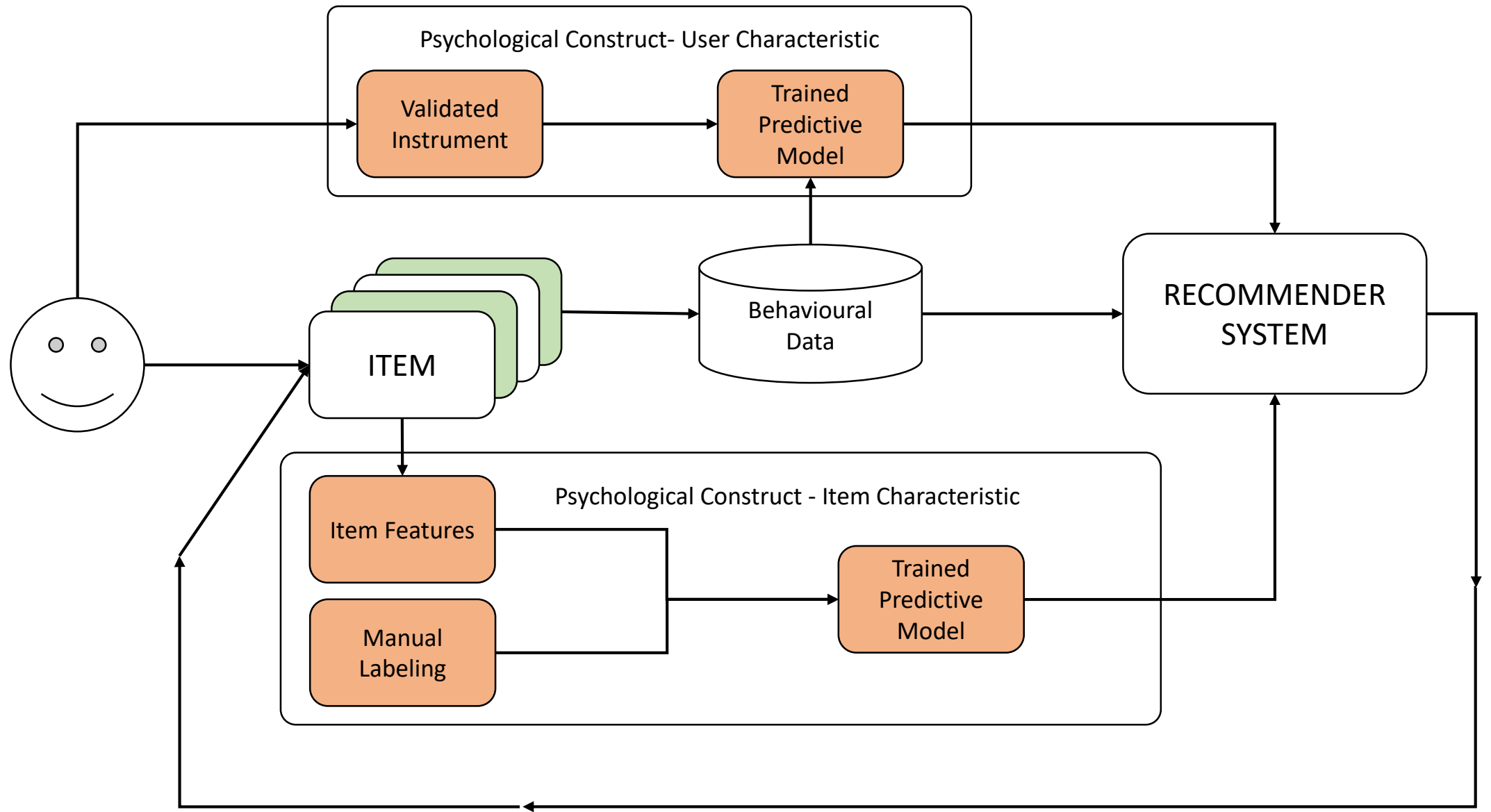
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Labeling Music Example

- Experts annotations
 - 200 pop songs
 - Manual labels (trained musicians):
 - rhythm complexity
 - harmonic complexity
 - melodic complexity
 - lyrics complexity
 - lyrics depth
 - lyrics understandability

Labeling Music

Rate the rhythm complexity on a scale from 1 (lowest rhythm complexity) to 5 (highest rhythm complexity) for the following songs.

On a scale from 1 to 5, how would you rate the rhythm complexity of the songs below. Give score 1 to songs with the most simple rhythm complexity and 5 to the songs with the highest rhythm complexity. **A song with a highly complex rhythm has, for example, lots of syncopation, rhythmic variations, potentially polyrhythms, or odd time signatures.**

Inter-rater agreement		vs experts	vs experts	simple vs complex
Krippendorff alpha		-0,34	-0,20	0,37
Pearson Correlation		0,12	0,17	0,73
Song:	Experts Mean	ChatGPT Simple prompt	ChatGPT Complex Prompt	
10cc: I'm Not In Love	2,75	4	3	
A-Ha: Take On Me	1,67	3	2	
Abba: Dancing Queen	2,80	3	2	
Abba: The Winner Takes It All	2,33	2	2	
Ace Of Base: Don't Turn Around	1,75	2	2	
Amy Winehouse: Rehab	3,60	3	3	
Andy Gibb: Shadow dancing	3,50	3	2	
Aqua: Barbie girl	1,00	2	1	

Labeling Music - Harmonic Complexity

Pearson		0,44
	experts mean	ChatGPT simple
Song		
10cc: I'm Not In Love	3,75	5
A-Ha: Take On Me	2	3
Abba: Dancing Queen	4,2	3
Abba: The Winner Takes It All	3	5
Ace Of Base: Don't Turn Around	2,25	2
Amy Winehouse: Rehab	3,2	3
Andy Gibb: Shadow dancing	3,25	3
Aqua: Barbie girl	1	1
Audrey Hepburn: Moon River	2	4
Avril Lavigne: Complicated	2,6	2
Backstreet Boys: Everybody (Backstreet's Back)	2,333333333	2
Backstreet Boys: I Want It That Way	3	3
Barbra Streisand Neil Diamond: You Don't Bring Me Flowers	3,25	4
Barbra Streisand: My Heart Belongs To Me	4	4
Barbra Streisand: The Way We Were	3	4
Barry Manilow: Looks Like We Made It	3	3
Beach Boys: God Only Knows	3	5
Beatles: Hey Jude	2,5	3

IAPS Dataset: induced emotions

desc	IAPS ID	valmn	valsd	aromn	arosd	dom1mn	dom1sd	set
Cat	1000	4,76	2,80	6,30	2,31	4,31	2,72	12
Cat	1067	4,86	2,18	6,12	2,49	4,28	2,98	12
dog	1098	5,22	2,69	6,45	2,86	5,12	3,25	1
Dog	1167	4,80	2,92	6,93	3,12	4,27	2,63	1
Orange	1278	3,88	2,80	6,89	1,81	3,64	2,30	6
Apple	1298	4,09	1,82	5,98	2,51	3,98	2,35	12
Man	1378	3,68	2,61	7,02	2,84	3,57	2,97	11
Injury	1388	4,44	3,20	6,97	3,02	4,65	2,21	1

Lang, P. J., Bradley, M. M., Cuthbert, B. N., & Center for the Study of Emotion and Attention. (2020). International Affective Picture System [Dataset].
<https://doi.org/10.1037/t66667-000>

IAPS Dataset: induced emotions



What is the **valence** of this image?

Facial expressions like a smile are typically associated with positive emotions, which contribute to a **high valence**.

What emotions would the image above induce in viewers? Please elaborate using the (i) **Ekman** space of emotions and the (ii) **valence-arousal-dominance** model

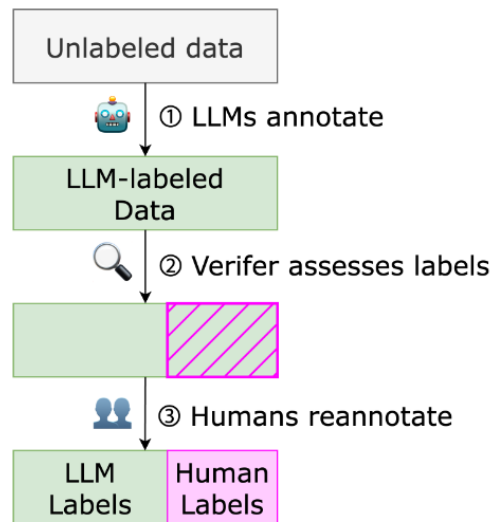
In summary, viewers are likely to experience a positive emotional reaction when viewing this image. Specifically:

- In Ekman's framework, **happiness** would be the predominant emotion felt.
- In the VAD model, viewers would likely experience **high valence**, **moderate arousal**, and **moderate dominance**, resulting in a feeling of calm, pleasant joy or contentment.

These dimensions collectively point to a positive, gentle emotional response triggered by the subject's warm and genuine smile.

LLM Labeling

- LLM assisted labeling



natural language inference, stance detection, and hate speech detection

Wang, X., Kim, H., Rahman, S., Mitra, K., & Miao, Z. (2024). Human-LLM Collaborative Annotation Through Effective Verification of LLM Labels. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–21. <https://doi.org/10.1145/3613904.3641960>

- Automatic labeling

- many studies
- diverse datasets
- (moderately) positive results

Li, J. (2024). *A Comparative Study on Annotation Quality of Crowdsourcing and LLM via Label Aggregation* (arXiv:2401.09760). arXiv. <http://arxiv.org/abs/2401.09760>

Cegin, J., Simko, J., & Brusilovsky, P. (2023). *ChatGPT to Replace Crowdsourcing of Paraphrases for Intent Classification: Higher Diversity and Comparable Model Robustness* (arXiv:2305.12947). arXiv. <http://arxiv.org/abs/2305.12947>

Tan, Z., Li, D., Wang, S., Beigi, A., Jiang, B., Bhattacharjee, A., Karami, M., Li, J., Cheng, L., & Liu, H. (2024). *Large Language Models for Data Annotation: A Survey* (arXiv:2402.13446). arXiv. <http://arxiv.org/abs/2402.13446>

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Simulating Users

Assume you get recommended a set of songs by a music platform. Assume that, personality-wise, you are **introverted, conscientious, open to new experiences and a bit neurotic**. Assume you have a **limited music knowledge**, you can play some chords on the guitar. Assume you were born and raised in **Italy**. Assume you have an **MSc degree in computer science**. How would you rank, from most preferred to least preferred, the following songs. Also explain why.

1. Bob Dylan: Tangled up in Blue

Why: As an open-minded and somewhat introverted person, Dylan's storytelling, introspective lyrics, and acoustic guitar-driven sound could deeply resonate. This song is poetic and introspective, appealing to someone who enjoys depth and complexity in music. Also, as someone who plays guitar, the chords in this song could be a source of inspiration.

2. Beatles: Yesterday

Why: "Yesterday" is a melancholic and introspective ballad that matches the introverted and slightly neurotic personality. The emotional depth and simplicity of the song could resonate well, especially with the reflective mood it often induces.

3. Bob Dylan: Like a Rolling Stone

Why: The mix of Dylan's rebellious energy, the intellectual nature of the lyrics, and its place in music history would appeal to someone open to new experiences. The song's challenging themes might engage someone with an inquisitive mind (MSc in Computer Science).

Open issues

- Trust
 - Understanding of the constructs by the LLM
 - Reliability (reproducibility)
- Technicalities:
 - Model choice
 - Configuration (e.g. temperature/randomness parameter)
 - Prompt engineering
- Generalization of such results?
- Majority Voting vs. Perspectivist Approach (subjective features)

THANK YOU* :-)

*and thanks to ChatGPT for the support in preparing these slides