FROM AMATEUR MUSICIANSHIP TO COMPUTATIONAL PREDICTORS OF MEDIA CONSUMPTION EXPERIENCES

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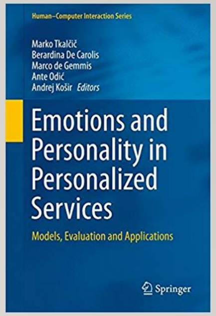
2 ABOUT ME

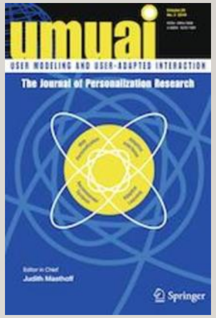
- Associate Professor of Computer Science at the University of Primorska in Koper, Slovenia
  - Assist. Prof. at Free University of Bolzano, Italy
  - Postdoc at JKU Linz, Austria
  - PhD at University of Ljubljana

- 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 https://www.springer.com/gp/book/9783319314112
- Editorial board member:
  - Springer User Modeling and User-adapted Interaction,
  - Frontiers in Computer Science
  - Frontiers in Psychology
- Program Chair at the ACM UMAP 2021 conference
- Active in the RecSys and UMAP communities





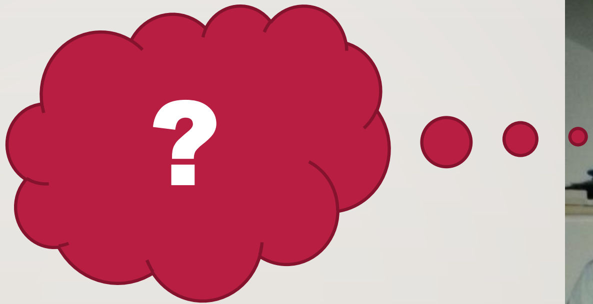
4 FROM AMATEUR MUSICIANSHIP...

5 FROM AMATEUR MUSICIANSHIP...

ME

?

6 FROM AMATEUR MUSICIANSHIP...



7 FROM AMATEUR MUSICIANSHIP…

?

Personality?
Education?
Nostalgia?
Cultural background?

ISSUE IN CONTEMPORARY USER MODELING

- Majority of user modelling for recommender system uses behavioural data
- Behaviour (implicit data) is only part of the knowledge about users in recommender systems
  - Cognitive models are important, too
- Two stories
  - Netflix
  - La vita e' bella

9 INSPIRATION

Behaviorism is Not Enough: Better Recommendations through Listening to Users

Michael D. Ekstrand[1,2] and Martijn C. Willemsen[3]

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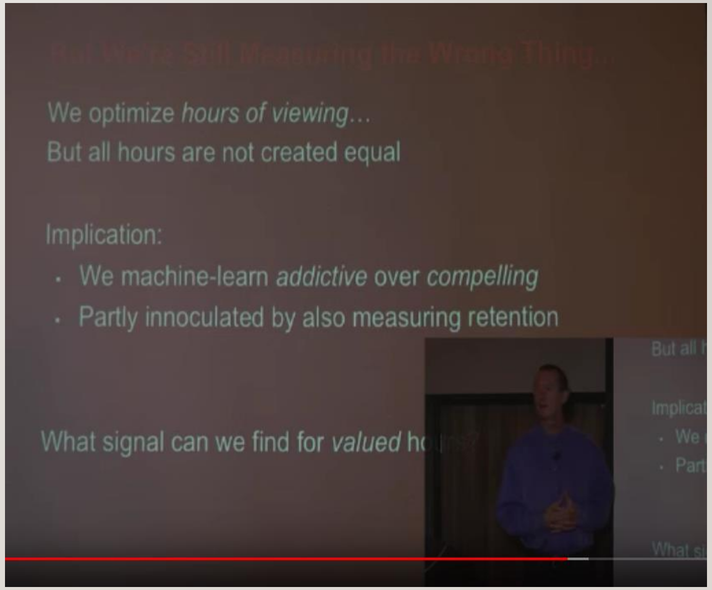
10 WHY DO WE CONSUME CONTENT? MOOD REGULATION

	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

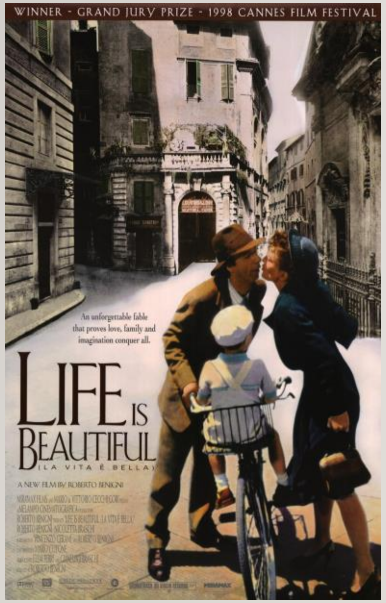
1-THE NETFLIX STORY

- 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

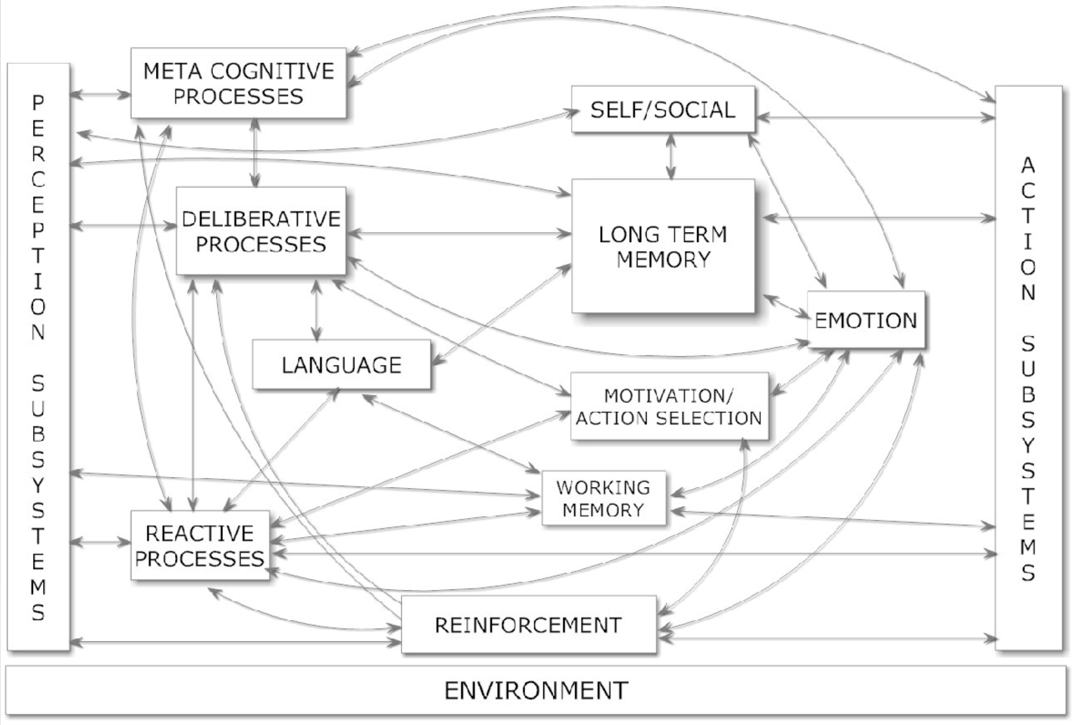
2-THE “LIFE IS BEAUTIFUL (1997)” STORY



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

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

13 EXISTING MODELS OF MIND, COGNITION, DECISION MAKING



Goertzel, Ben, Matt Iklé, and Jared Wigmore. "The architecture of human-like general intelligence." *Theoretical Foundations of Artificial General Intelligence*. Atlantis Press, Paris, 2012. 123-144.

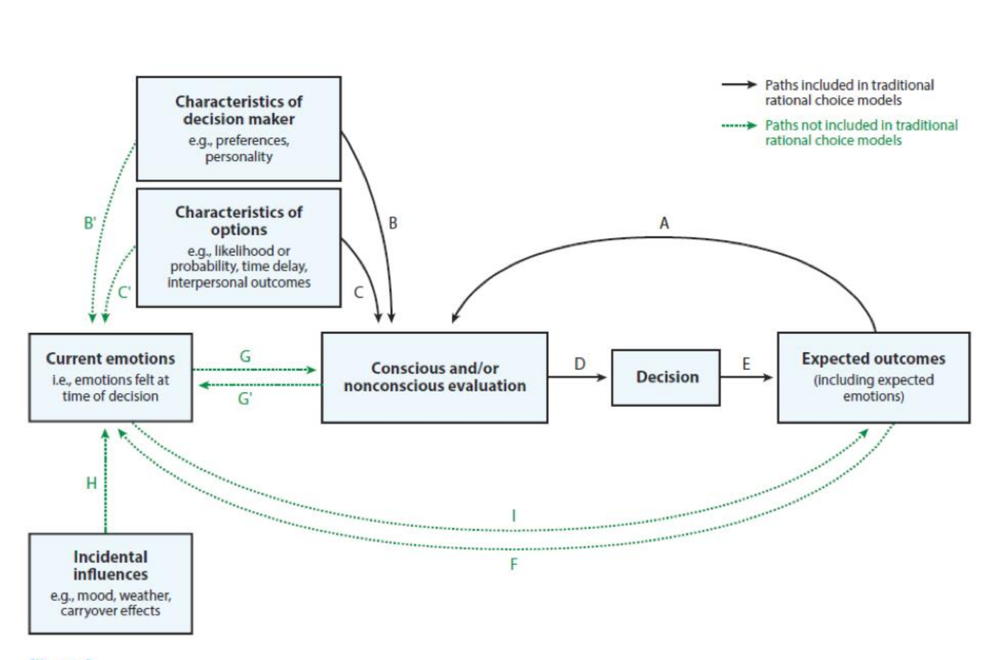
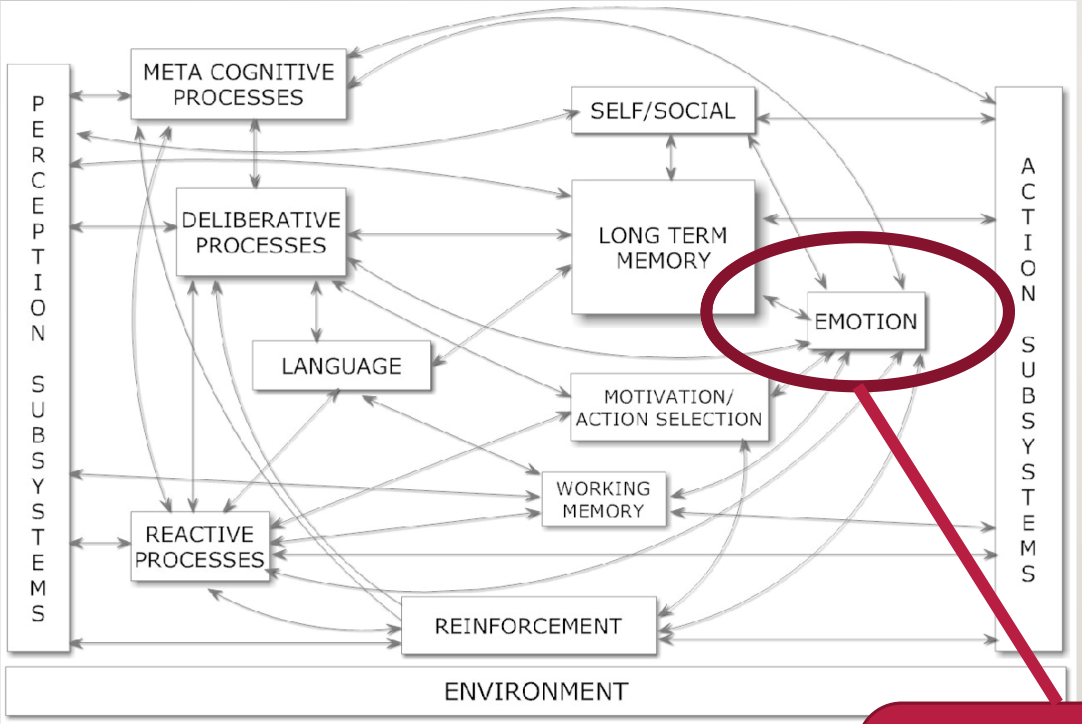
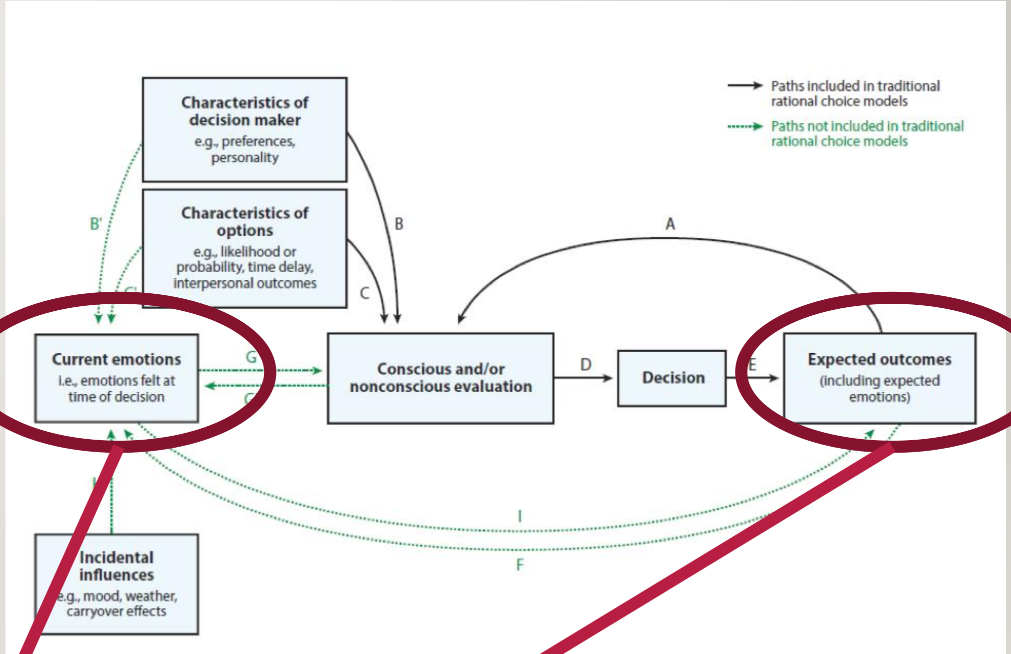


Figure 2
Toward a general model of affective influences on decision making: the emotion-imbued choice model.

Lerner, Jennifer S., et al. "Emotion and decision making." Annual review of psychology 66 (2015): 799-823.

EXISTING MODELS OF MIND, COGNITION, DECISION MAKING





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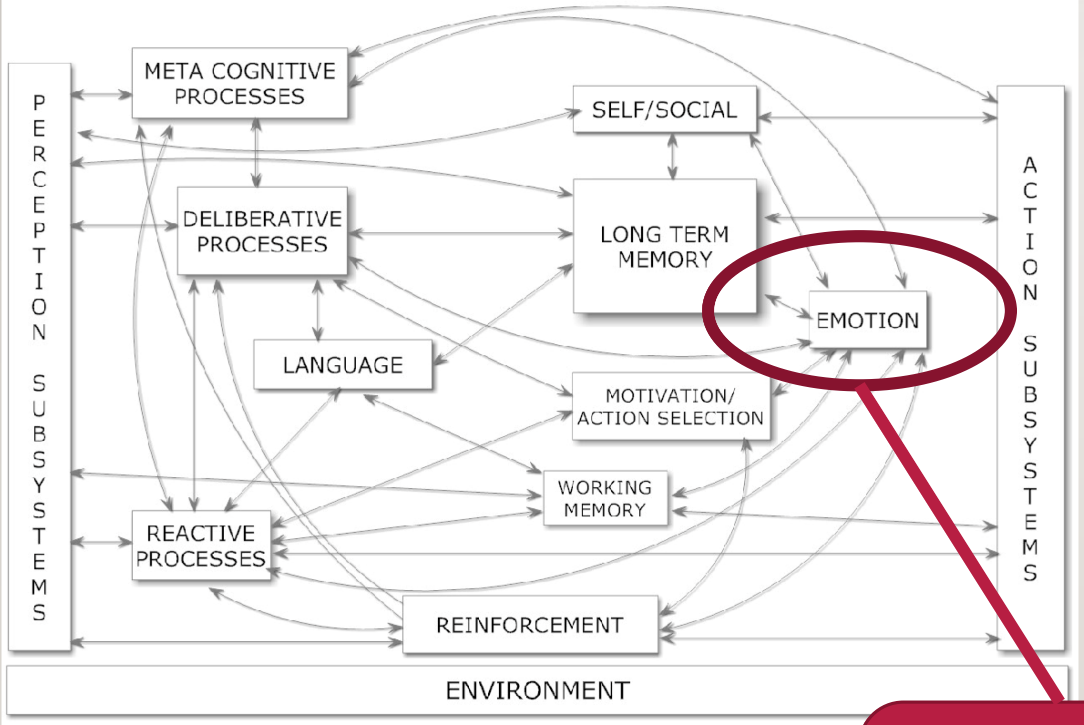
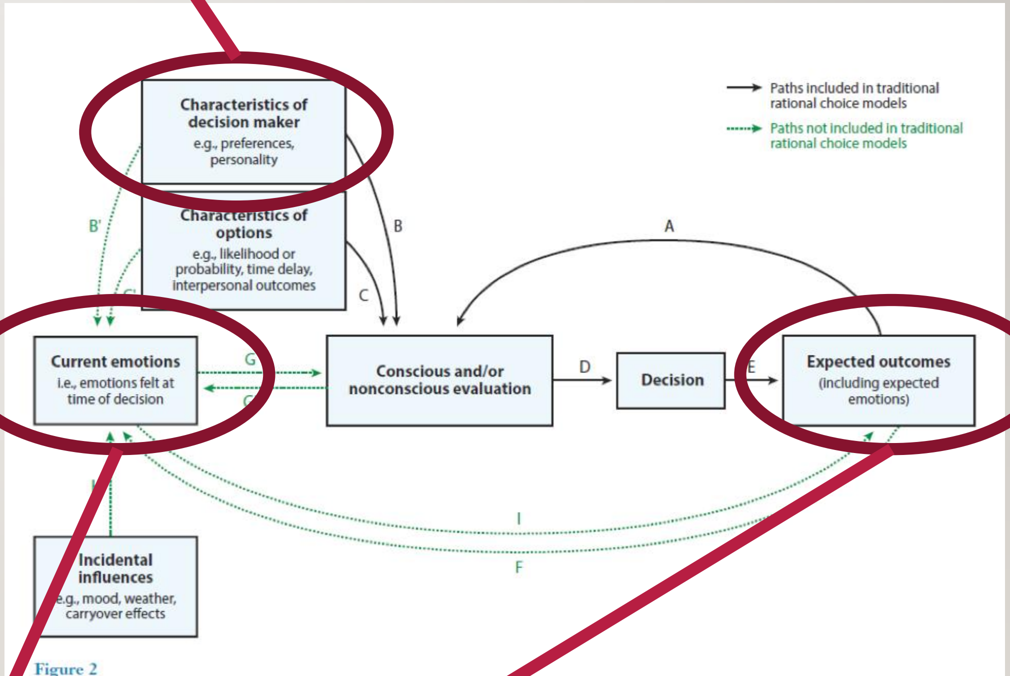
..., et al. "...motion and decision making." Annual review of ... 15): 799-823.

EMOTIONS

EXISTING MODELS OF [...]N, DECISION MAKING

PERSONALITY





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EMOTIONS

Goertzel, Ben, Matt Iklé, and Jared Wigmore. "The architecture of [...] intelligence." *Theoretical Foundations of Artificial General Intelligence*. A[...] Paris, 2012. 123-144.

[...], et al. "E[...]motion and decision making." Annual review of [...] [...]15): 799-823.

OUTLINE

- Personality and Emotions in RecSys
- Current: Positive Psychology in RecSys
- Conclusion

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- Current: Positive Psychology in RecSys
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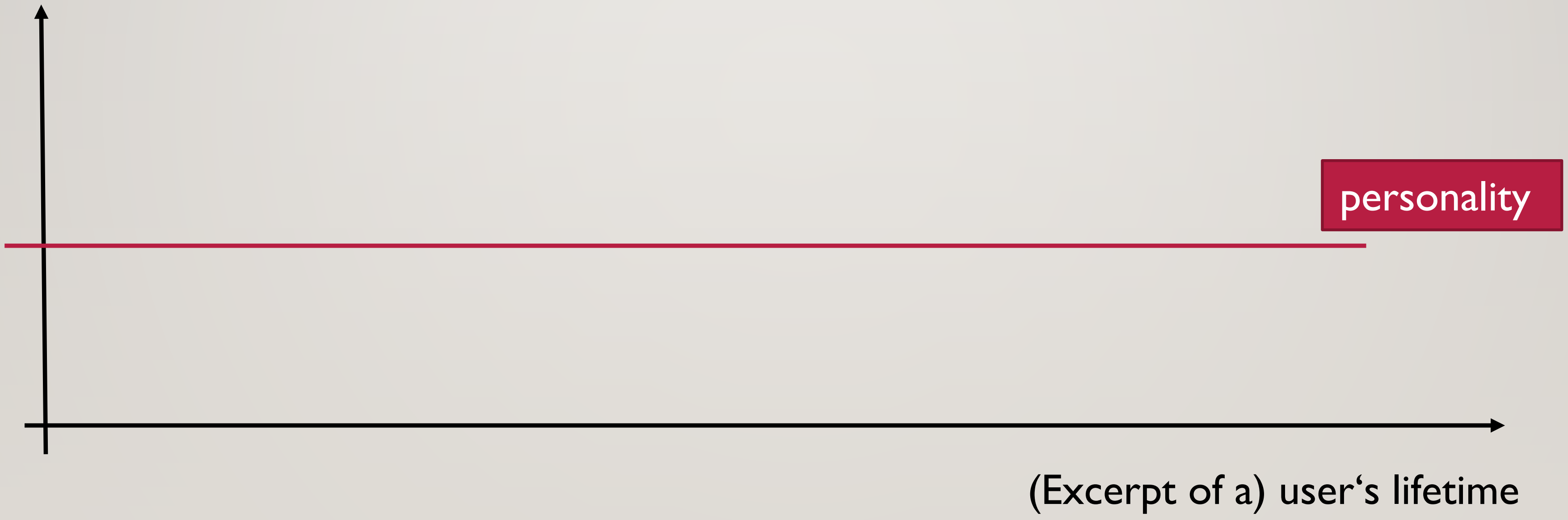
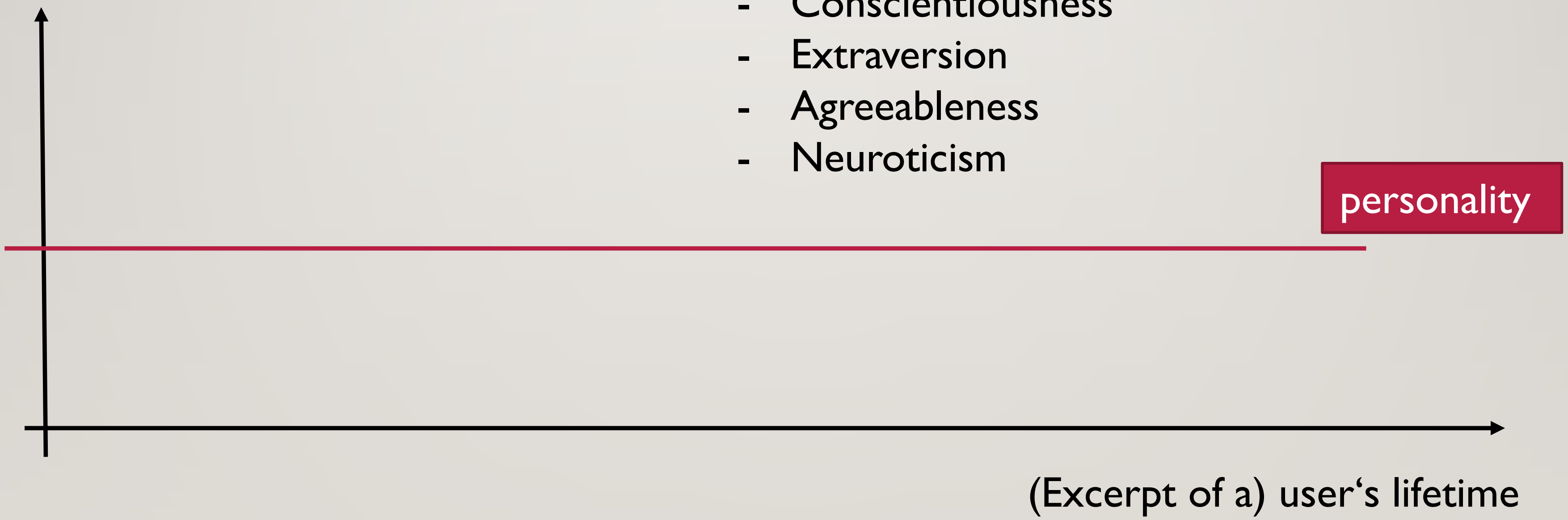
18 PERSONALITY AND EMOTIONS

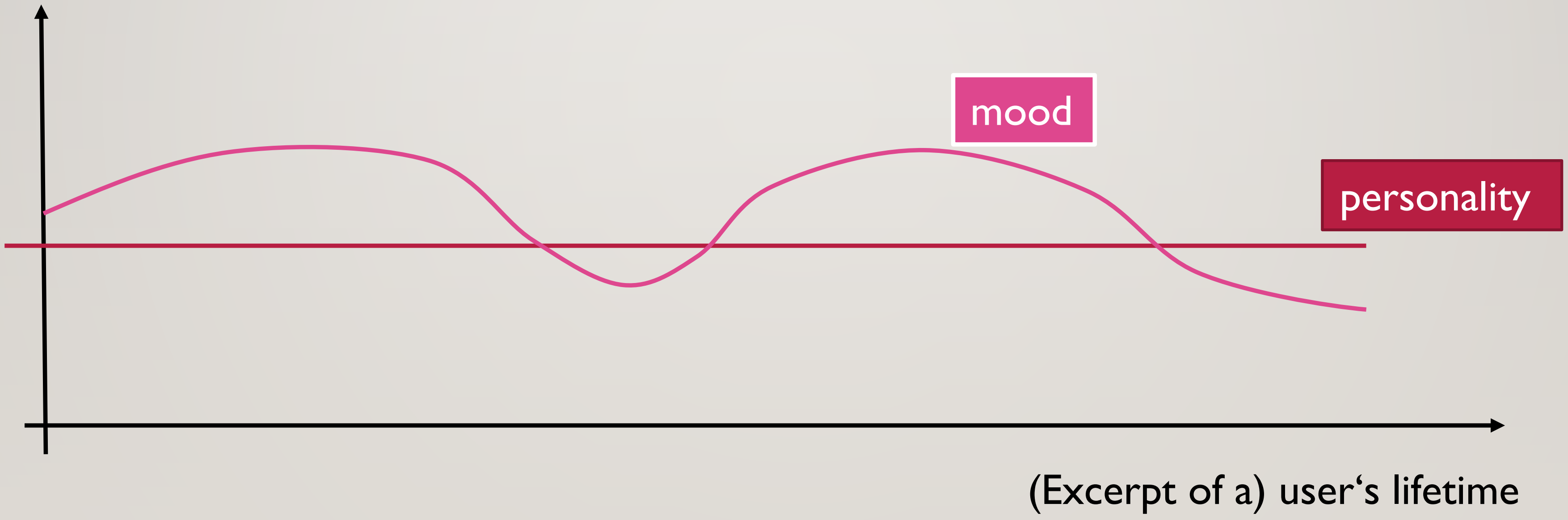


19 PERSONALITY AND EMOTIONS

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

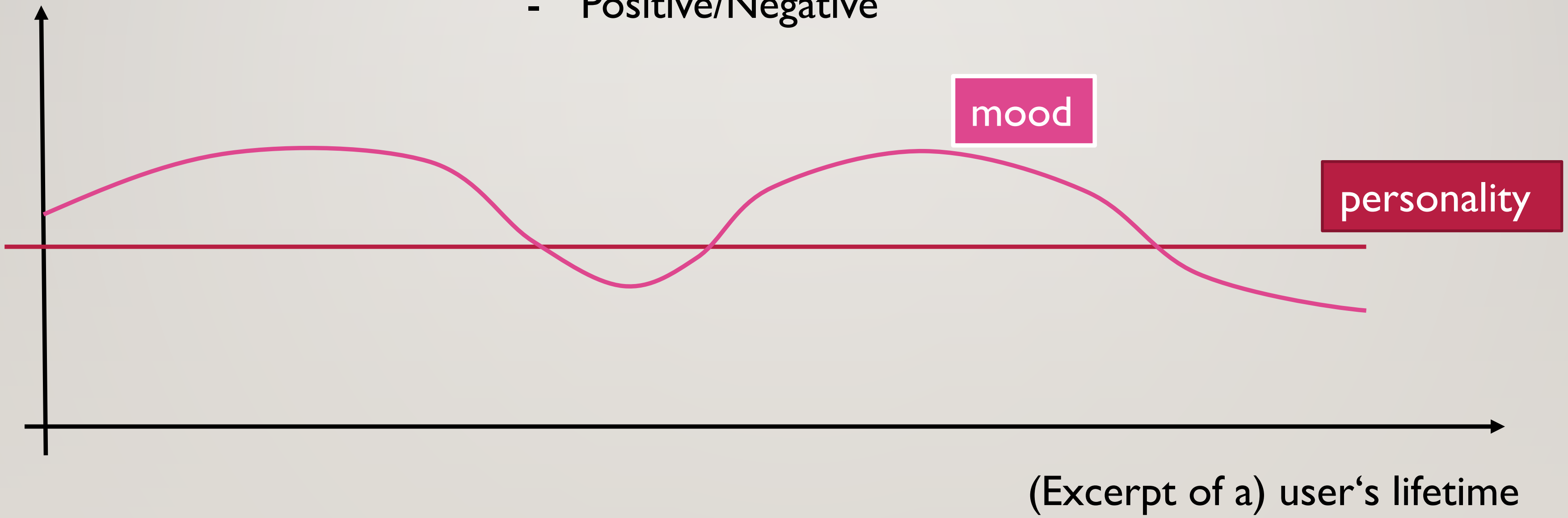


PERSONALITY AND EMOTIONS

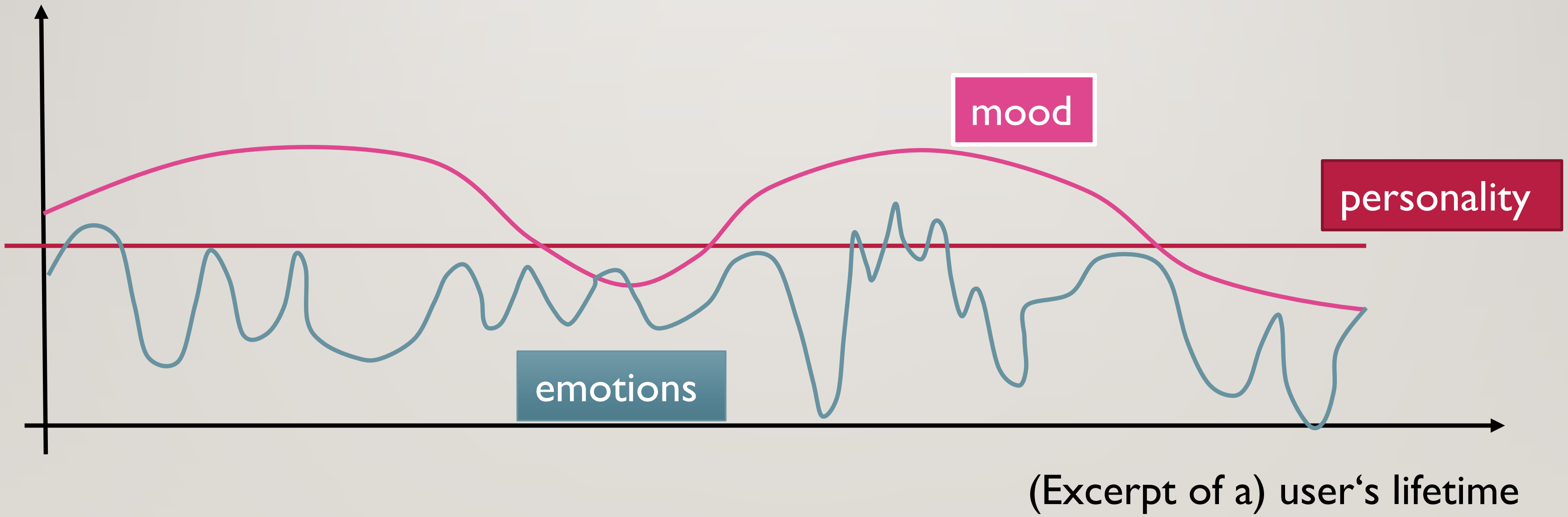


PERSONALITY AND EMOTIONS

- No particular trigger
- Positive/Negative

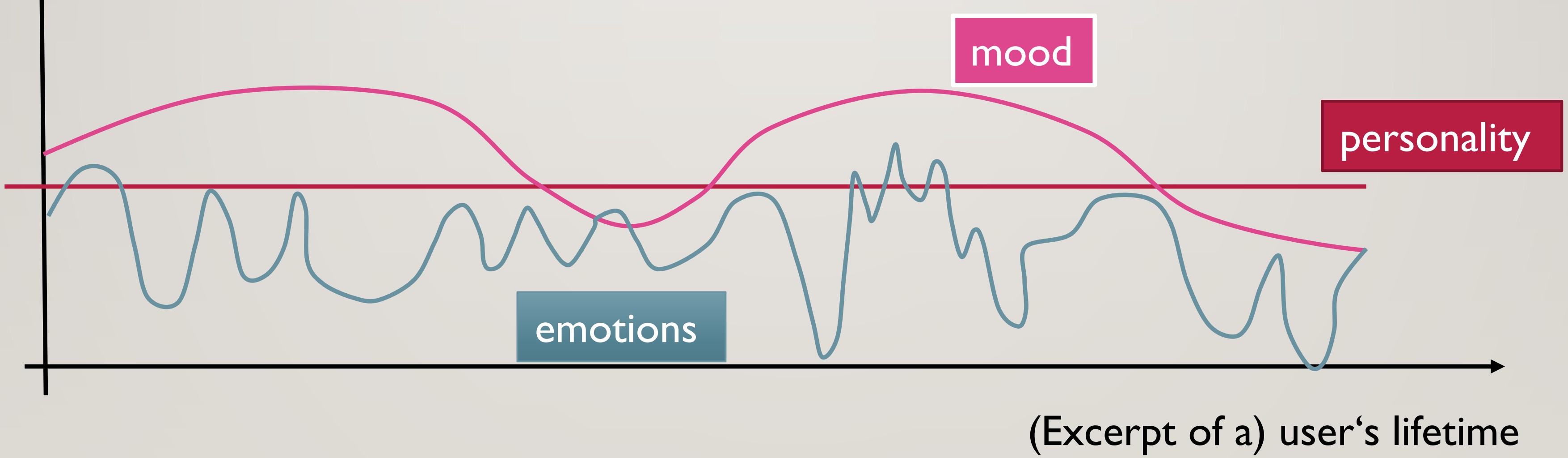


22 PERSONALITY AND EMOTIONS



23 PERSONALITY AND EMOTIONS

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

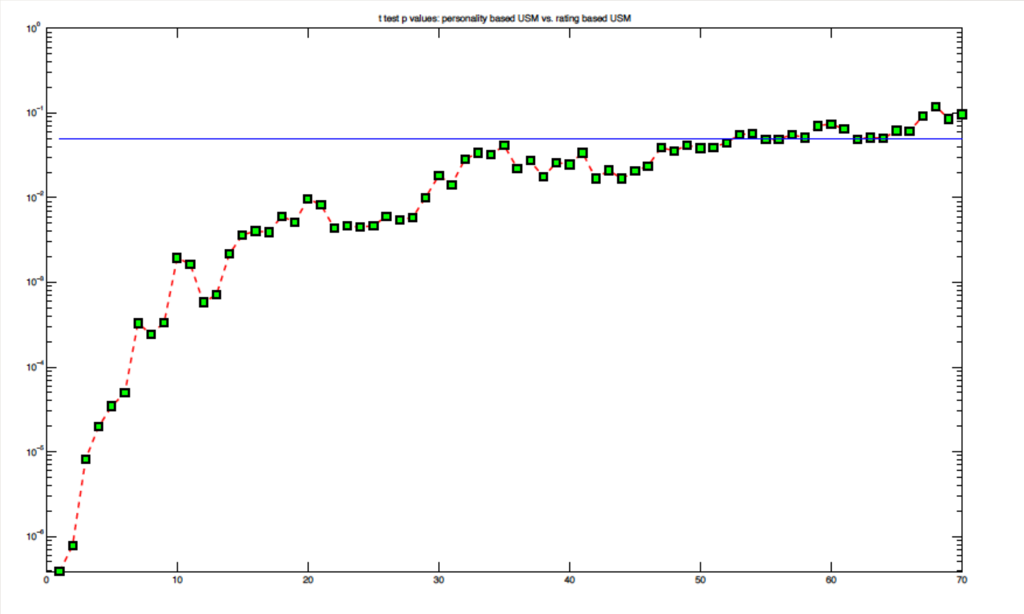


24 USAGE OF PERSONALITY AND EMOTIONS FOR BETTER RECOMMENDATIONS

- **Personality:**
  - **New-user problem (user similarity)**
  - **Preferences**
  - **Acquisition**
- Emotions:
  - Emotions as feedback
  - Acquisition

25 PERSONALITY AS USER SIMILARITY I

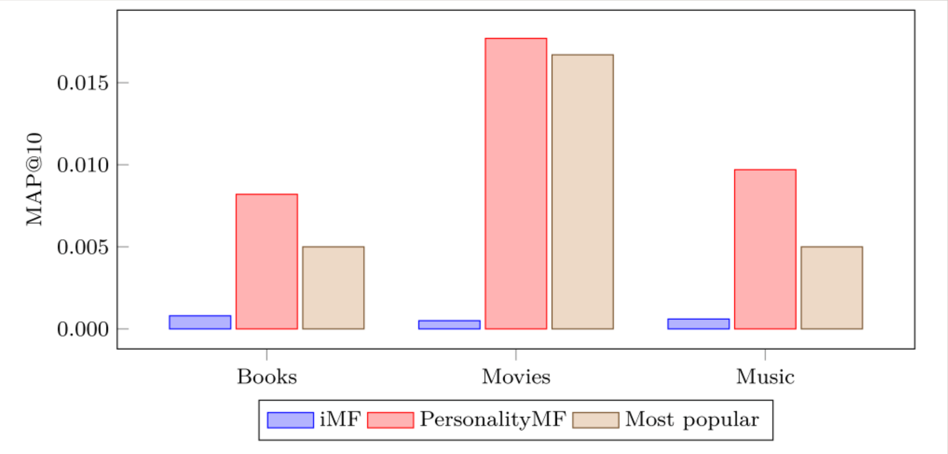
- New user problem
- N = 52, images = 70
- User similarities
  - Rating-based
  - Personality-based
- Rating-based catches the personality only after 40 ratings have been entered



Tkalčič, M., Kunaver, M., Košir, A., and Tasič, J. (2011). Addressing the new user problem with a personality based user similarity measure. In UMMS 2011 proceedings

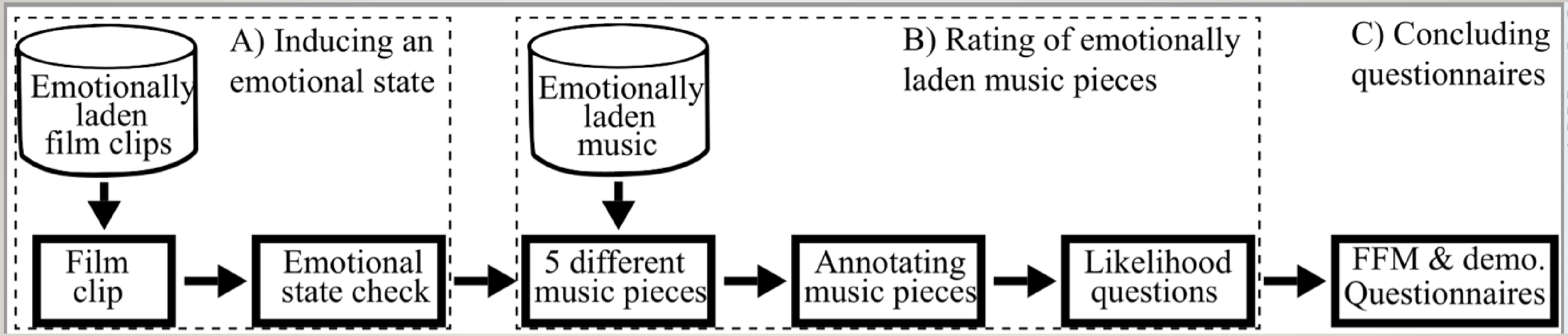
26 PERSONALITY AS USER SIMILARITY II - IN MATRIX FACTORIZATION

- In (Elahi et al., 2013) Injection of personality factors in MF as additional features
  - $r_{ui} = q_i(p_u + \sum_{a \in A(u)} y_a)$
  - personality u = (2.3,4.0,3.6,5.0,1.2) maps to A(u) = {ope2, con4, ext4, agr5,neu1}.



Elahi, M., Braunhofer, M., Ricci, F., and Tkalčič, M. (2013). Personality-based active learning for collaborative filtering recommender systems. In M. Baldoni, C. Baroglio, G. Boella, and O. Micalizio (Eds.), AI*IA 2013: Advances in Artificial Intelligence (pp. 360–371).

27 PERSONALITY FOR MOOD REGULATION



- High on openness, extraversion, and agreeableness more inclined to listen to happy music when they are feeling sad.
- High on neuroticism listen to more sad songs when feeling

B. Ferwerda, M. Schedl, and M. Tkalcic, "Personality & Emotional States : Understanding Users ' Music Listening Needs," in *UMAP 2015 Extended Proceedings*, 2015.

PERSONALITY PREDICTION

- Questionnaires
  - BFI: 44 questions
  - TIPI: 10 questions
  - NEO-IPIP: 300 questions

29 PERSONALITY PREDICTION

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

ML model

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

PERSONALITY PREDICTION

- From Instagram

	O	C	E	A	N
Red	-0.06	0.02	**-0.17^**	-0.05	0.03
Green	**0.17^**	0.14	**0.23^^**	0.03	-0.12
Blue	-0.01	0	**0.17^**	0.02	-0.01
Yellow	0.01	0.04	0.01	0.14	-0.07
Orange	-0.03	-0.07	**-0.16^**	-0.02	0.06
Violet	0	-0.06	-0.09	-0.07	0.06
Bright.mean	**-0.25***	-0.1	**-0.19^**	-0.07	**0.22^**
Bright.var.	0.06	0	0	-0.07	0.05
Bright.low	**0.28****	0.09	**0.16^**	-0.05	**-0.16^**
Bright.mid	-0.09	0.06	0.04	**0.15^**	-0.06
Bright.high	**-0.2^**	-0.12	**-0.18^**	-0.08	**0.21^**
Sat.mean	**0.16^**	0.06	0.03	-0.04	0
Sat.var.	**0.2^^**	**0.16^**	**0.19^^**	0.1	-0.05
Sat.low	-0.08	-0.02	0.02	0.07	0.01
Sat.mid	0.08	-0.09	0.02	0.07	0.01
Sat.high	0.13	0.1	0.04	-0.01	0.01
Warm	**-0.05^^**	-0.04	-0.2	0	0.03
Cold	**0.05^^**	0.04	0.2	0	-0.03
Pleasure	**-0.19^^**	-0.08	**-0.18^**	-0.09	**0.22^^**
Arousal	**0.23***	0.09	0.1	0	-0.08
Dominance	**0.28****	0.11	**0.17^**	0.05	**-0.18^^**
# of faces	**-0.16^**	0.03	0.11	-0.11	-0.03
# of people	**-0.22^^**	-0.05	-0.07	-0.01	0.07

Note. ^p<0.1, ^^p<.05, *p<.01, **p<.001.

Ferwerda, Bruce, Markus Schedl, and Marko Tkalčič. 'Using Instagram Picture Features to Predict Users' Personality'. In *MultiMedia Modeling*, edited by Qi Tian, Nicu Sebe, Guo-Jun Qi, Benoit Huet, Richang Hong, and Xueliang Liu, 9516:850–61. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2016. https://doi.org/10.1007/978-3-319-27671-7_71.

PERSONALITY PREDICTION

- From Instagram and Twitter

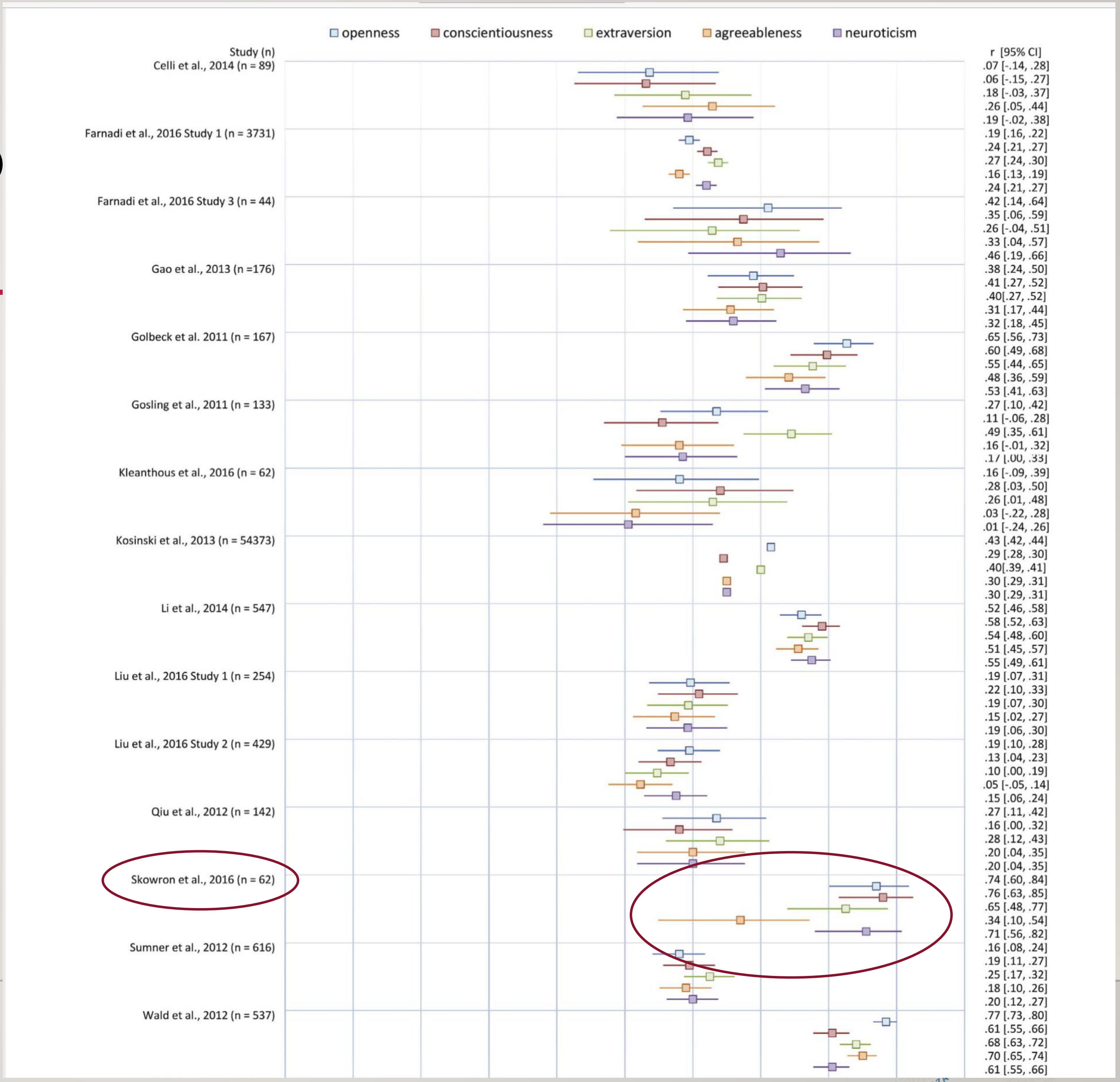
	RMSE		MAE		PCC	
	T [7]	$\mathbf{T}_{\mathrm{lm}}\mathbf{I}_{\mathrm{li}}$	**T** [2]	$\mathbf{T}_{\mathrm{lm}}\mathbf{I}_{\mathrm{li}}$	**FB** [4]	$\mathbf{T}_{\mathrm{lm}}\mathbf{I}_{\mathrm{li}}$
O	0.69	**0.51**	0.12	**0.11**	0.43	**0.74**
C	0.76	**0.67**	0.14	**0.11**	0.29	**0.76**
E	0.88	**0.71**	**0.16**	0.17	0.40	**0.65**
A	0.79	**0.50**	0.12	0.12	0.30	**0.34**
N	0.85	**0.73**	0.19	**0.16**	0.30	**0.71**
AVG	0.79	**0.73**	0.15	**0.13**	0.30	**0.64**

Table 2: Personality traits regression accuracy of $\mathbf{T}_{\mathrm{lm}}\mathbf{I}_{\mathrm{li}}$ along the state-of-the-art systems inferred from different SNSs: (T)witter, (I)nstagram, FB - Facebook, in terms of RMSE, MAE - Mean Absolute Error, PCC - Pearson Correlation Coefficient.

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.

PERSONALITY PRED

- From Instagram and Twitter



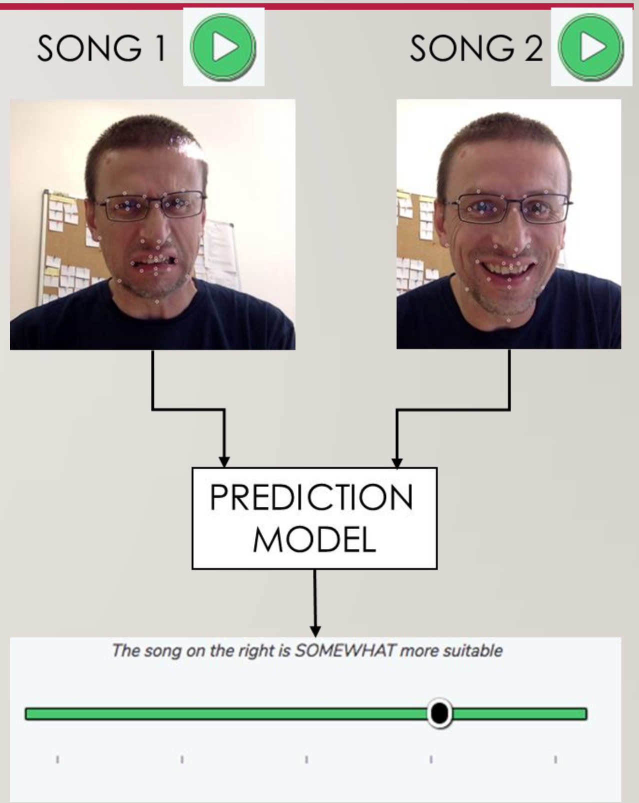
Azucar, Danny, Davide Marengo, and Michele Settanni. 'Predicting the Big 5 Personality Traits from Digital Footprints on Social Media: A Meta-Analysis'. *Personality and Individual Differences* 124 (April 2018): 150–59. https://doi.org/10.1016/j.paid.2017.12.018.

USAGE OF PERSONALITY AND EMOTIONS FOR BETTER RECOMMENDATIONS

- Personality:
    - New-user problem (user similarity)
    - Preferences
    - Acquisition
- **Emotions:**
    - **Emotions as feedback**
    - **Acquisition**

EMOTIONS AS FEEDBACK

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

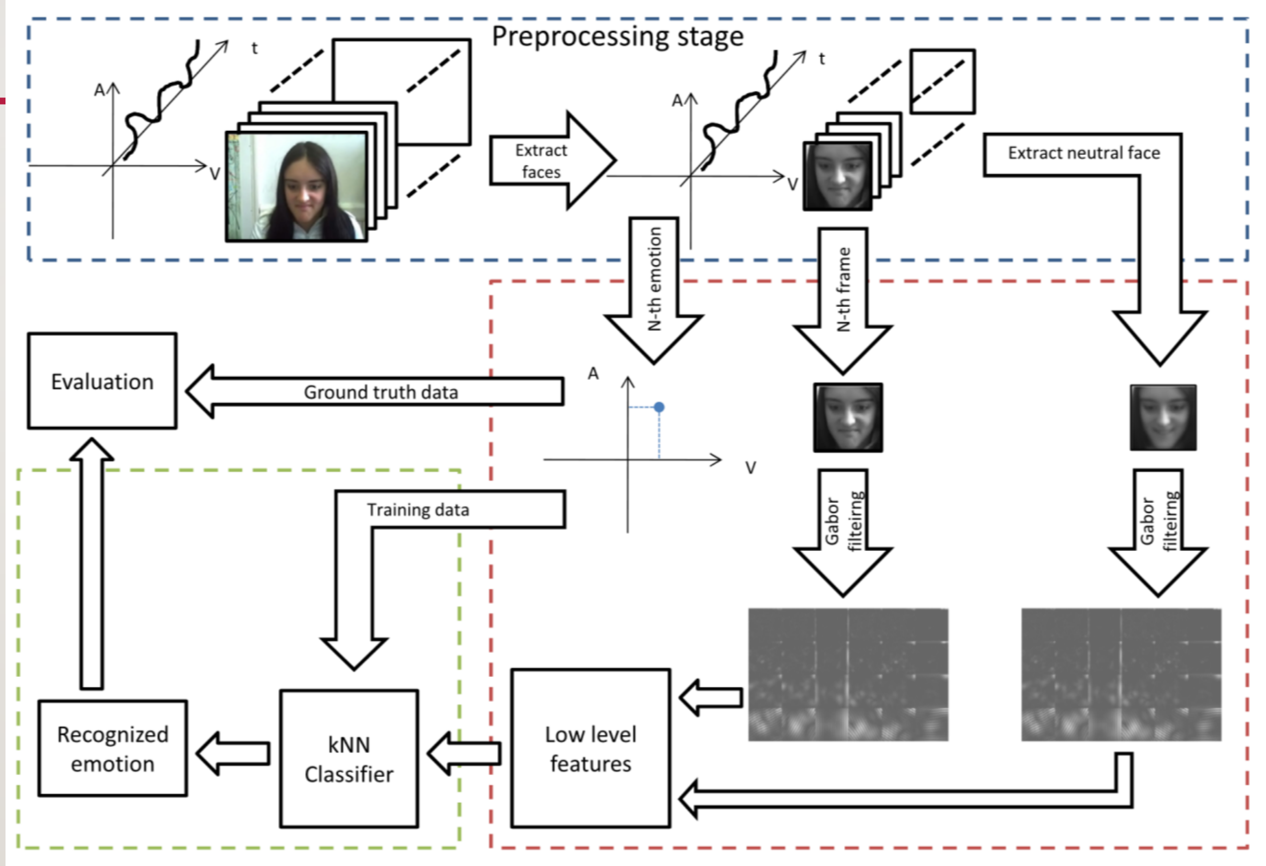


Tkalčič, M., Maleki, N., Pesek, M., Elahi, M., Ricci, F., & Marolt, M. (2019). Prediction of music pairwise preferences from facial expressions. *Proceedings of the 24th International Conference on Intelligent User Interfaces - IUI '19*, 150–159. https://doi.org/10.1145/3301275.3302266

EMOTION PREDICTION

- Questionnaires
- Multimodal prediction:
  - Modalities: Audio, language, visual, physiology

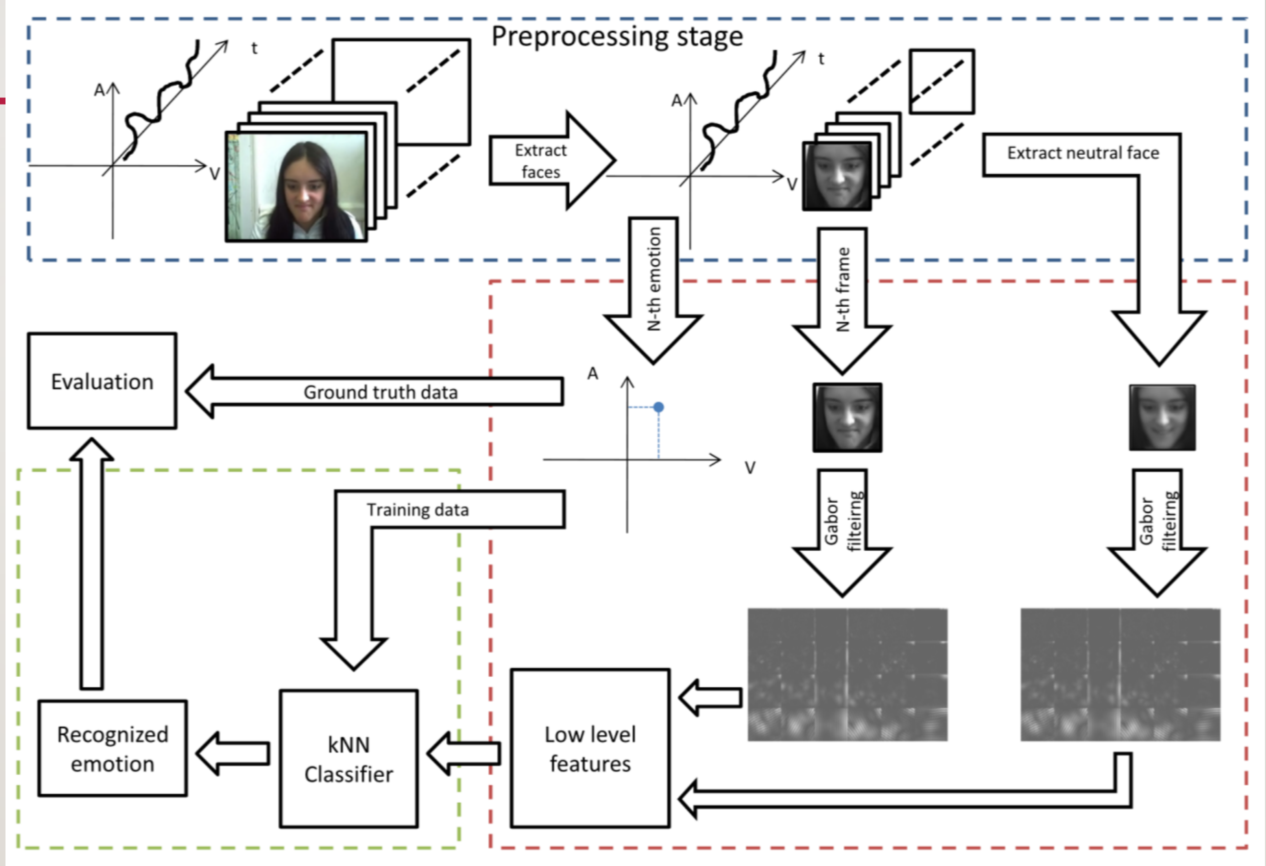
EMOTION PREDICTION VALIDATION



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.

37 EMOTION PREDICTION VALIDATION

- Off-the shelf DL-based predictive models (Affectiva...)



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- **Current: Positive Psychology in RecSys**
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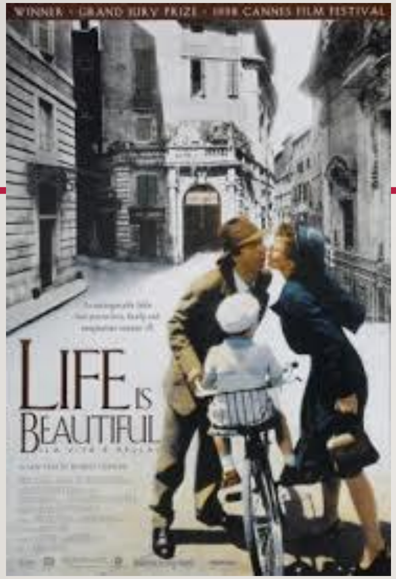
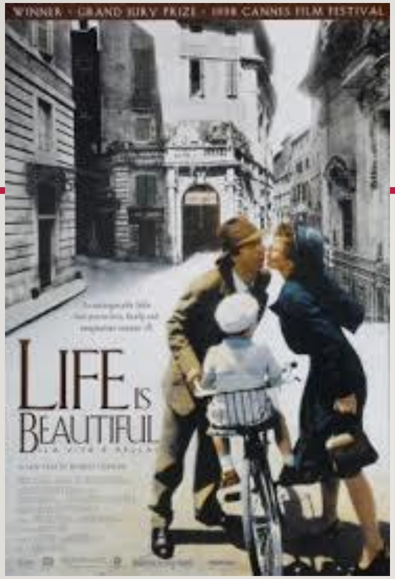
HEDONIA/EUDAIMONIA



HEDONIC	✓	✓	✗
EUDAIMONIC	✓	✗	✓

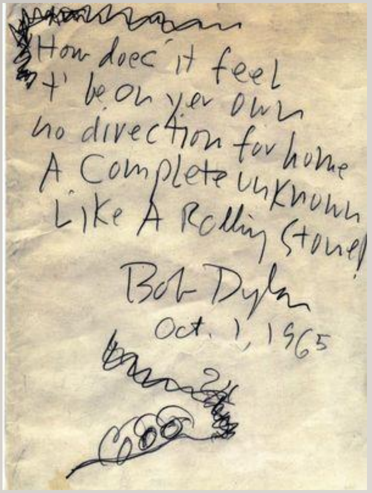
HEDONIA/EUDAIMONIA



HEDONIC	✔	✔	✘
EUDAIMONIC	✔	✘	✔

PETER	👎	👍	👎
PAUL	👎	👎	👍
MARY	👍	👎	👍
JOAN	👍	👍	👎

41 CURRENT RESEARCH



- Challenges:
  - Unobtrusive acquisition of item characteristics
    - **Music: Lyrics (Hrustanović, S., Kavšek, B., & Tkalčič, M. (2021). Recognition of Eudaimonic and Hedonic Qualities from Song Lyrics. *Proceedings of the 6th Human-Computer Interaction Slovenia Conference*, 9.)**
    - Movies: Subtitles (Motamedi, E., & Tkalcic, M. (2021). Prediction of Eudaimonic and Hedonic Movie Characteristics From Subtitles. *Proceedings of the 6th Human-Computer Interaction Slovenia Conference*, 8.)
    - Movies: Multi-modal (Motamedi, Kholg, Saghari, Elahi, Barile, Tkalčič)) Predicting Movies' Eudaimonic and Hedonic Scores: A Machine Learning Approach Using Metadata, Audio and Visual Features (IPM, under review)
  - Unobtrusive acquisition of user characteristics
    - Movies: From rating behavior (Motamedi, Elham, Francesco Barile, and Marko Tkalčič. 'Prediction of Eudaimonic and Hedonic Orientation of Movie Watchers'. Applied Sciences 12, no. 19 (22 September 2022): 9500. https://doi.org/10.3390/app12199500.)
    - Music: TBD
  - Efficient prediction of the user experience:
    - Music: Motamedi, E., Tkalcic, M., & Szlávik, Z. (2023). Eudaimonic and Hedonic Qualities as Predictors of Music Videos' Relevance to Users: A Human-Centric Study. Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization, 44–49. https://doi.org/10.1145/3563359.3597415

CURRENT RESEARCH

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    - **Movies: Multi-modal (Motamedi, Kholg, Saghari, Elahi, Barile, Tkalčič)) Predicting Movies' Eudaimonic and Hedonic Scores: A Machine Learning Approach Using Metadata, Audio and Visual Features (IPM, under review)**
  - Unobtrusive acquisition of user characteristics
    - Movies: From rating behavior (Motamedi, Elham, Francesco Barile, and Marko Tkalčič. 'Prediction of Eudaimonic and Hedonic Orientation of Movie Watchers'. Applied Sciences 12, no. 19 (22 September 2022): 9500. https://doi.org/10.3390/app12199500.)
    - Music: TBD
  - Efficient prediction of the user experience:
    - Music: Motamedi, E., Tkalcic, M., & Szlávik, Z. (2023). Eudaimonic and Hedonic Qualities as Predictors of Music Videos' Relevance to Users: A Human-Centric Study. Adjunct Proceedings of the 31st ACM Conference on User Modeling, Adaptation and Personalization, 44–49. https://doi.org/10.1145/3563359.3597415

CURRENT RESEARCH

- Challenges:
  - Unobtrusive acquisition of item characteristics
    - Music: Lyrics (Hrustanović, S., Kavšek, B., & Tkalčič, M. (2021). Recognition of Eudaimonic and Hedonic Qualities from Song Lyrics. *Proceedings of the 6th Human-Computer Interaction Slovenia Conference*, 9.)
    - Movies: Subtitles (Motamedi, E., & Tkalcic, M. (2021). Prediction of Eudaimonic and Hedonic Movie Characteristics From Subtitles. *Proceedings of the 6th Human-Computer Interaction Slovenia Conference*, 8.)
    - Movies: Multi-modal (Motamedi, Kholg, Saghari, Elahi, Barile, Tkalčič)) Predicting Movies' Eudaimonic and Hedonic Scores: A Machine Learning Approach Using Metadata, Audio and Visual Features (IPM, under review)
  - Unobtrusive acquisition of user characteristics
    - Movies: From rating behavior (Motamedi, Elham, Francesco Barile, and Marko Tkalčič. 'Prediction of Eudaimonic and Hedonic Orientation of Movie Watchers'. Applied Sciences 12, no. 19 (22 September 2022): 9500. https://doi.org/10.3390/app12199500.)
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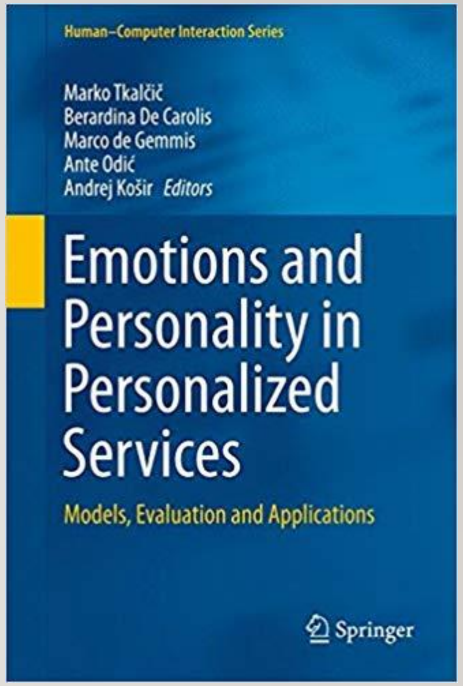
OUTLINE

- Personality and Emotions in RecSys
- Current: Positive Psychology in RecSys
- **Conclusion**

45 CONCLUSION

- Purely behavioral data might lead to inaccurate conclusions
- We need to understand which cognitive processes are driving the behaviour
- Cognitive models improve (certain aspects of) RecSys
- Rich knowledge from psychology can be transferred for explanations
- Lots of work done, still many challenges



THANK YOU

HAPPY TO TAKE QUESTIONS