FROM IMPLICIT DATA TO COGNITIVE MODELS FOR RECOMMENDER SYSTEMS

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Athabasca University Talk, September 2022

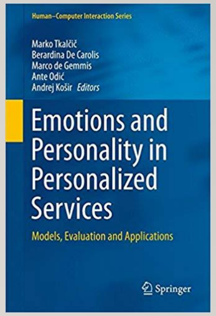
ABOUT ME

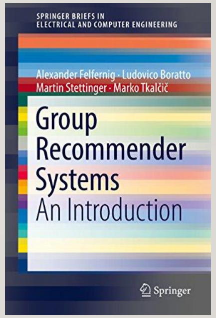
- Associate Professor of Computer Science at the University of Primorska in Koper, Slovenia
  - Assist. Prof. at Free University of Bolzano, Italy
  - Postdoc at JKU Linz, Austria
  - PhD at University of Ljubljana

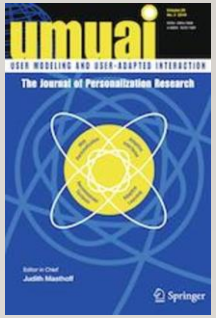
- I aim at improving **personalized services** (e.g. recommender systems) through the usage of **psychological models** in **personalization algorithms**. To achieve this, I use diverse research methodologies, including **data mining**, **machine learning**, and **user studies**.

ABOUT ME

- Book co-editor, Emotions and Personality in Personalized Services, 2016 https://www.springer.com/gp/book/9783319314112
- Book co-editor, Group Recommender Systems, 2018, https://www.springer.com/gp/book/9783319750668
- Editorial board member: Springer User Modeling and User-adapted Interaction, Human-Media Interaction in Frontiers in Computer Science/Psychology
- Program Chair at the ACM UMAP 2021 conference, IIR 2018 w Nicola
- Active in the RecSys and UMAP communities







HICUP LAB
“HUMANS INTERACTING WITH COMPUTERS”

- Running a lab with Matjaž Kljun and Klen Čopič Pucihar
- 4 profs
- 1 postdoc
- 5 PhD students
- Topics
    - Recommender Systems, User Modeling
    - HCI
    - VR

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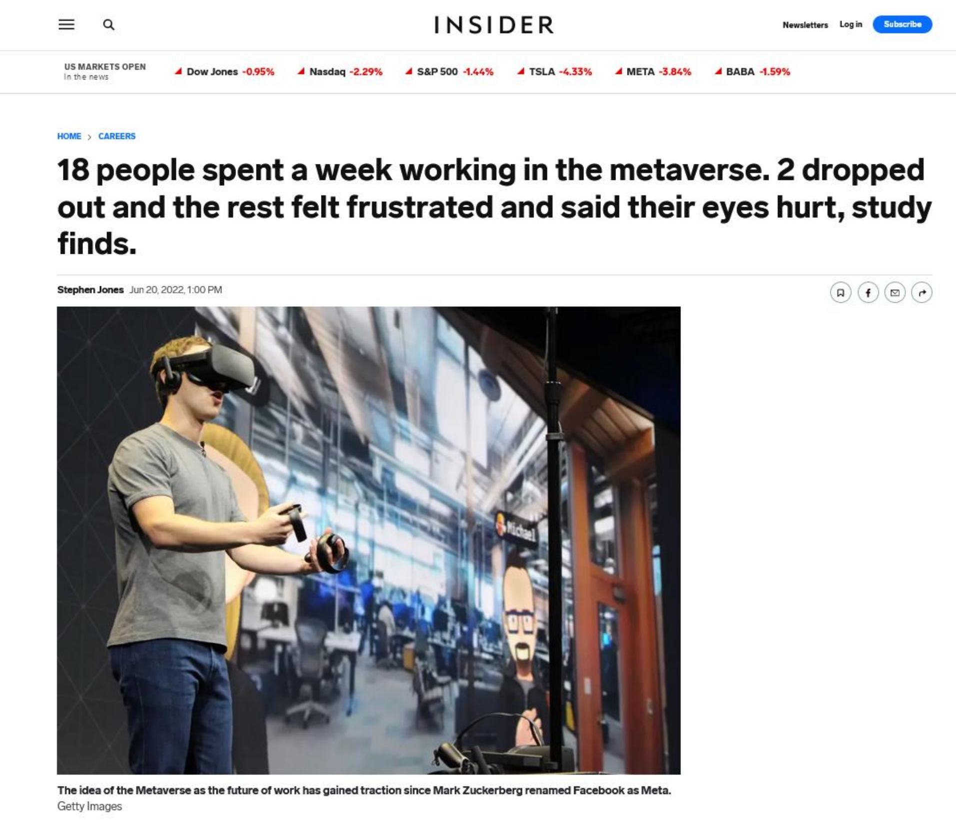


18 people spent a week working in the metaverse. 2 dropped out and the rest felt frustrated and said their eyes hurt, study finds.

Stephen Jones Jun 20, 2022, 1:00 PM

The idea of the Metaverse as the future of work has gained traction since Mark Zuckerberg renamed Facebook as Meta.
Getty Images

OUTLINE

- Motivation: Why Cognitive Modeling in Recommender Systems?
- Models of Personality and Emotions
- Usage of Personality and Emotions in Recommender Systems
- Work-in-progress: Eudaimonia and Hedonia
- Conclusion

GOAL OF THE TALK

- Behaviour (implicit data) is only part of the knowledge about users in recommender systems
  - Cognitive models are important, too
- Three stories
  - Netflix
  - Nature and Nurture
  - La vita e' bella

WHAT DO I MEAN BY BEHAVIOUR?

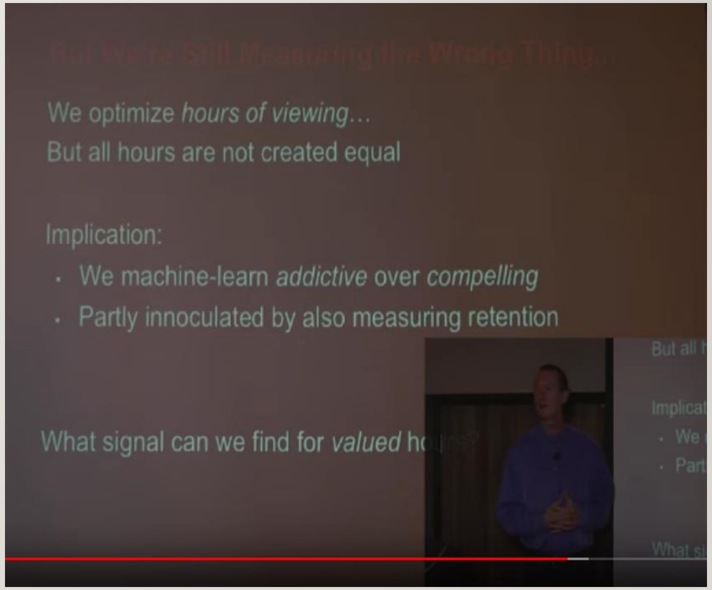
	Godfather	Inception	Hangover	Sophie's Choice
Peter	4	5	5	?
Paul	?	3	1	4
Mary	2	?	?	3
Joan	?	2	?	4

Behavioral/Implicit Data
->
Machine Learning

	Godfather	Inception	Hangover	Sophie's Choice
Peter	4	5	5	4
Paul	3	3	1	4
Mary	2	3	2	3
Joan	1	2	3	4

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?



But We're Still Measuring the Wrong Thing...

We optimize *hours of viewing*...
But all hours are not created equal

Implication:

- We machine-learn *addictive* over *compelling*
- Partly innoculated by also measuring retention

What signal can we find for *valued* ho

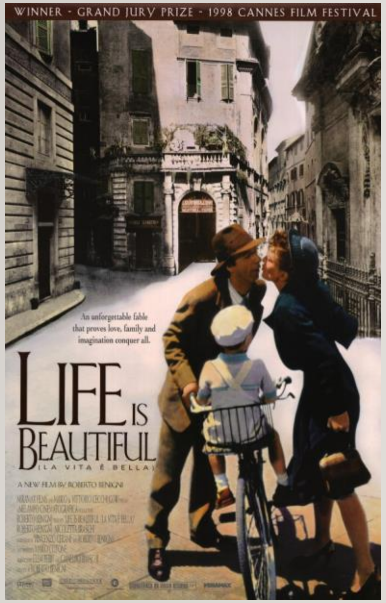
*https://youtu.be/lYcDR8z-rRY?t=4727

2-THE NATURE AND NURTURE STORY

- How much of the human mind is **built-in**, and how much of it is constructed by **experience**?
    - Skinner-Chomsky debate on language learning
        - Blank state: there's nothing underneath to understand (Locke, Skinner)
        - Language acquisition device: we need to understand the underlying mechanisms (Chomsky, Pinker)
- *To get computers to think like humans, we need a new A.I. paradigm, one that places **top down** and **bottom up** knowledge on equal footing. Bottom-up knowledge is the kind of raw information we get directly from our senses, like patterns of light falling on our retina. Top-down knowledge comprises cognitive models of the world and how it works.*

Marcus, Gary. "Innateness, alphazero, and artificial intelligence." arXiv preprint arXiv:1801.05667 (2018).
Marcus, Gary, Artificial Intelligence Is Stuck. Here's How to Move It Forward. New York Times, July 29, 2017

3-THE "LIFE IS BEAUTIFUL (1997)" STORY



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

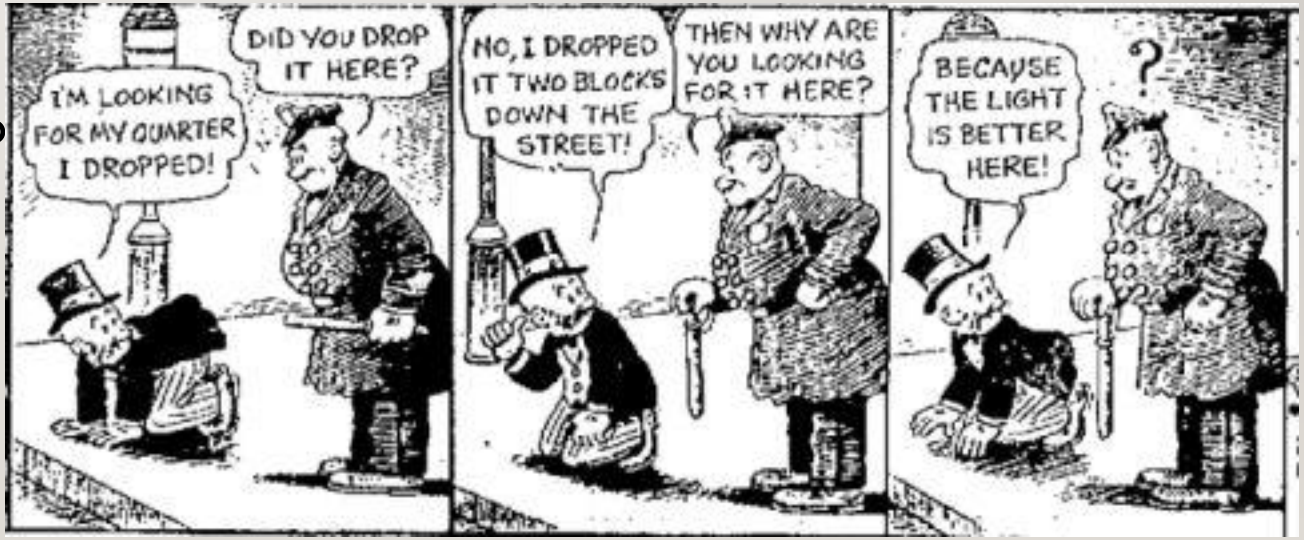
- What does thumbs up mean?
  - Liked the jokes?
  - Moved by the drama?

NEED TO UNDERSTAND THE USER

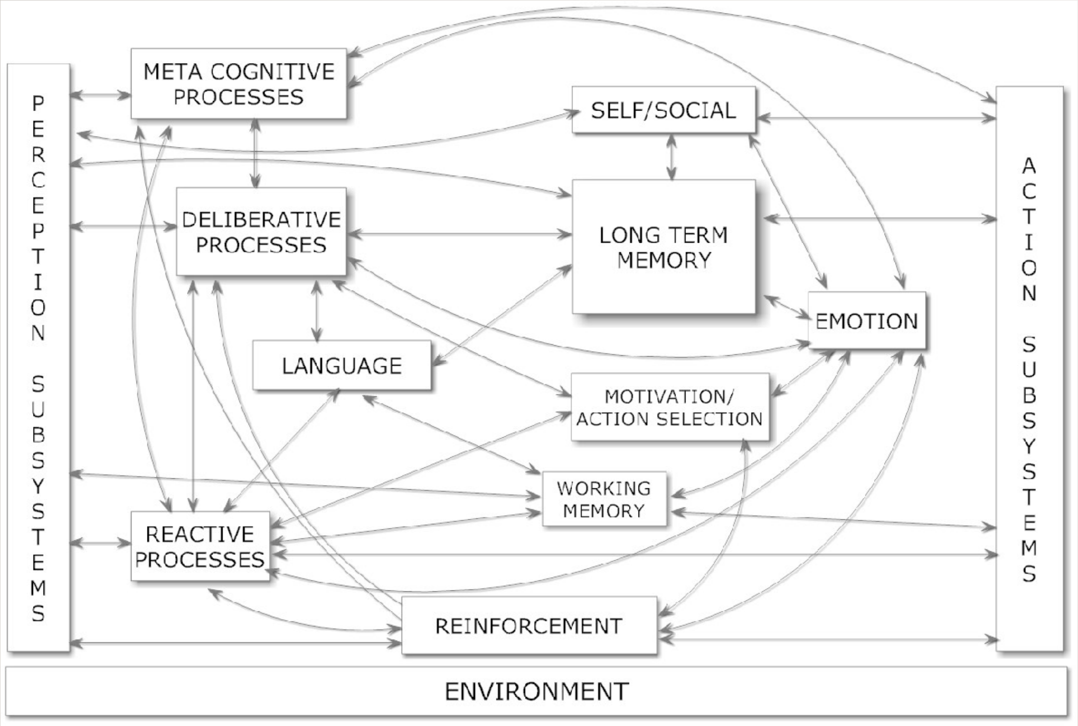
- Observing purely behavioral data might lead to inaccurate/incomplete conclusions
- Hence, we need to understand which cognitive processes are driving the behaviour
- Cognitive modelling aims at predicting cognitive models parameters from behavioural data
- These models can be then used in recommender systems

NEED TO UNDERSTAND THE USER

- Observing purely behavioral data might lead to wrong conclusions
- Hence, we need to understand which cognitive processes are driving the behaviour
- Cognitive modelling aims at predicting cognitive models parameters from behavioural data
- These models can be then used in reco
- It is hard, data not readily available



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.

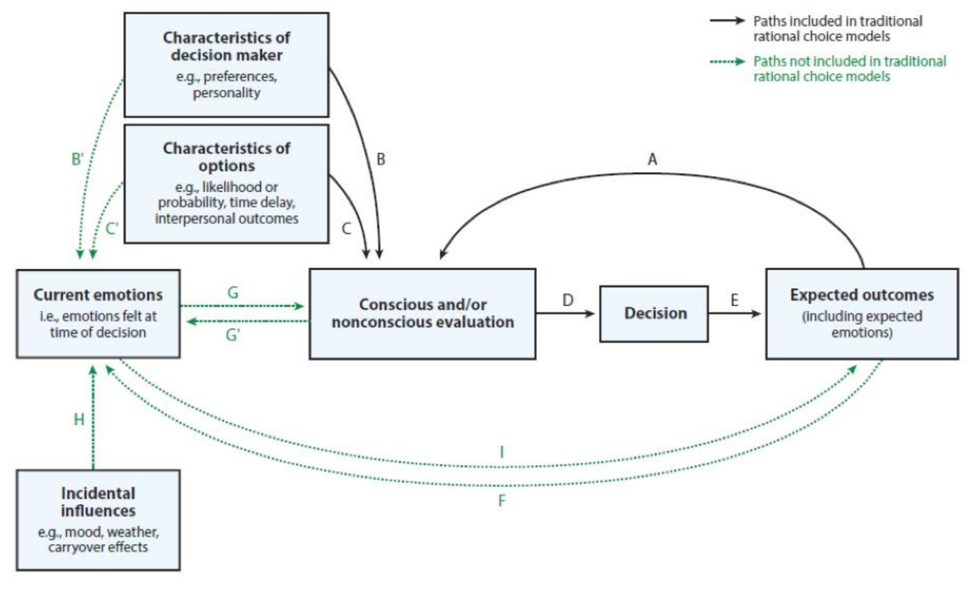
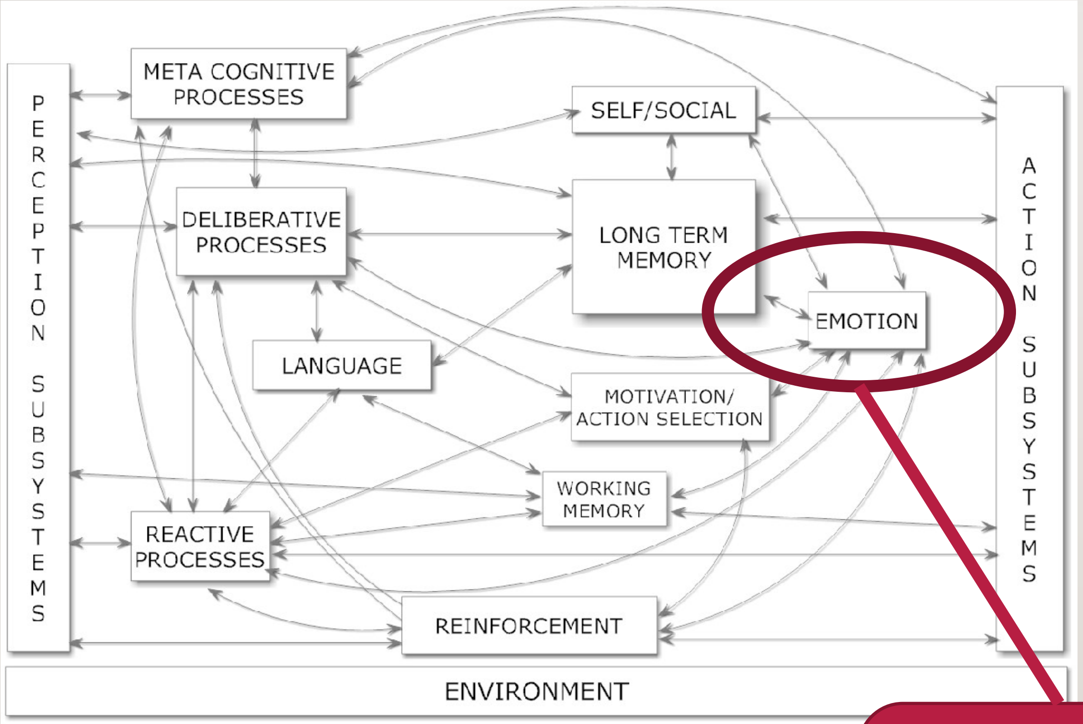
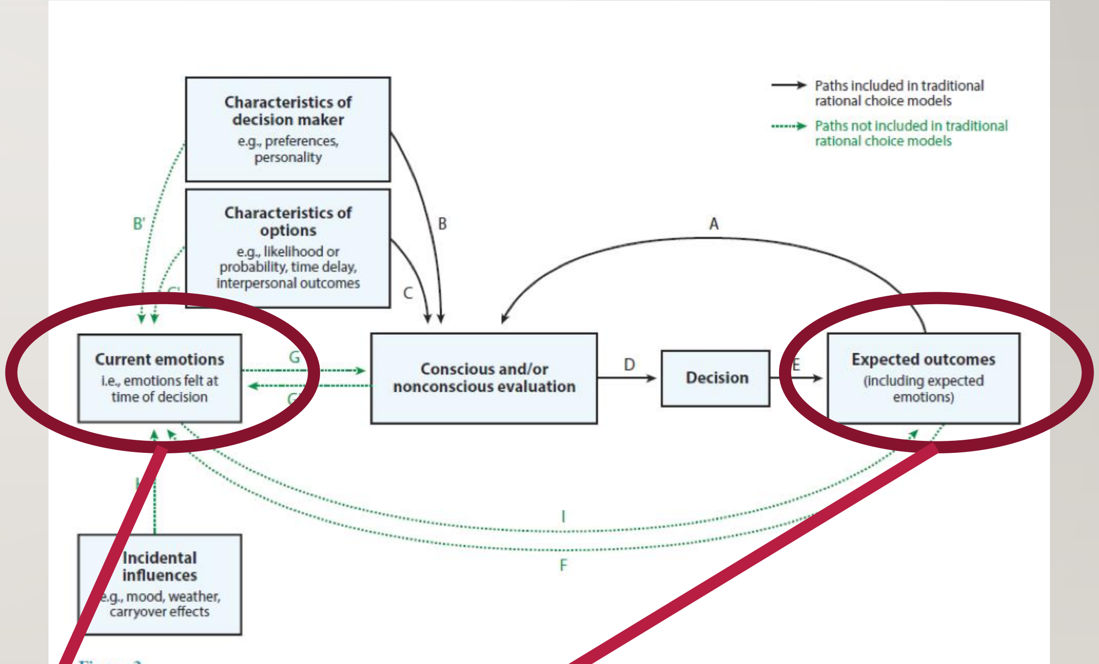


Figure 2
Toward a general model of affective influences on decision making: the emotion-imbued choice model.

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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EMOTIONS

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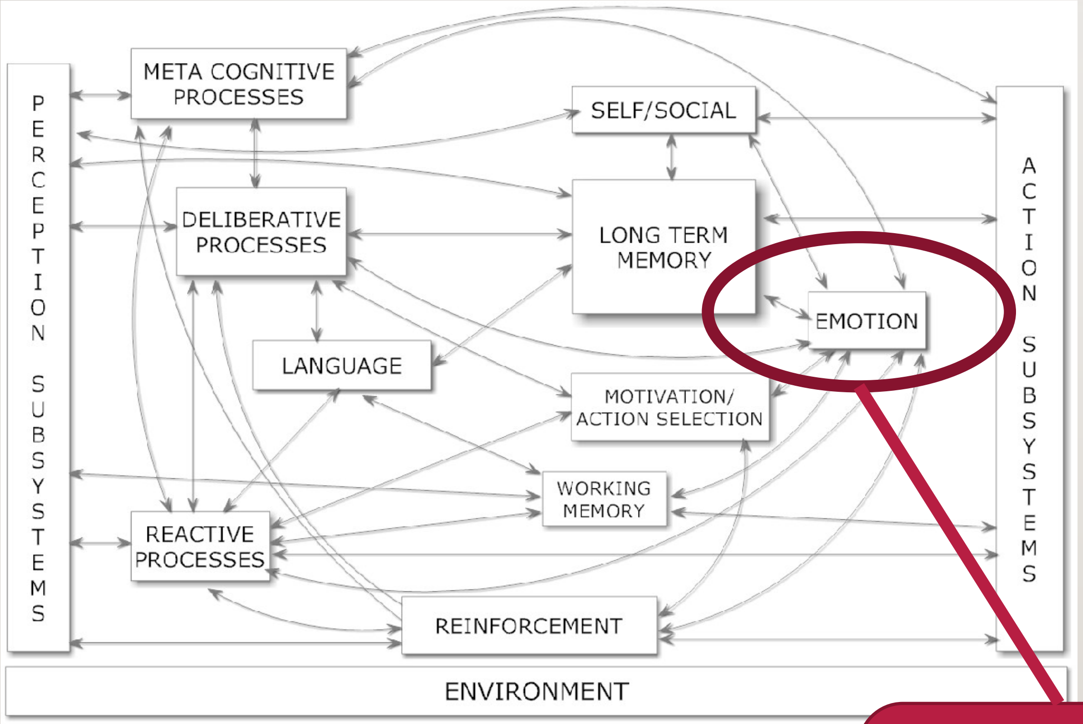
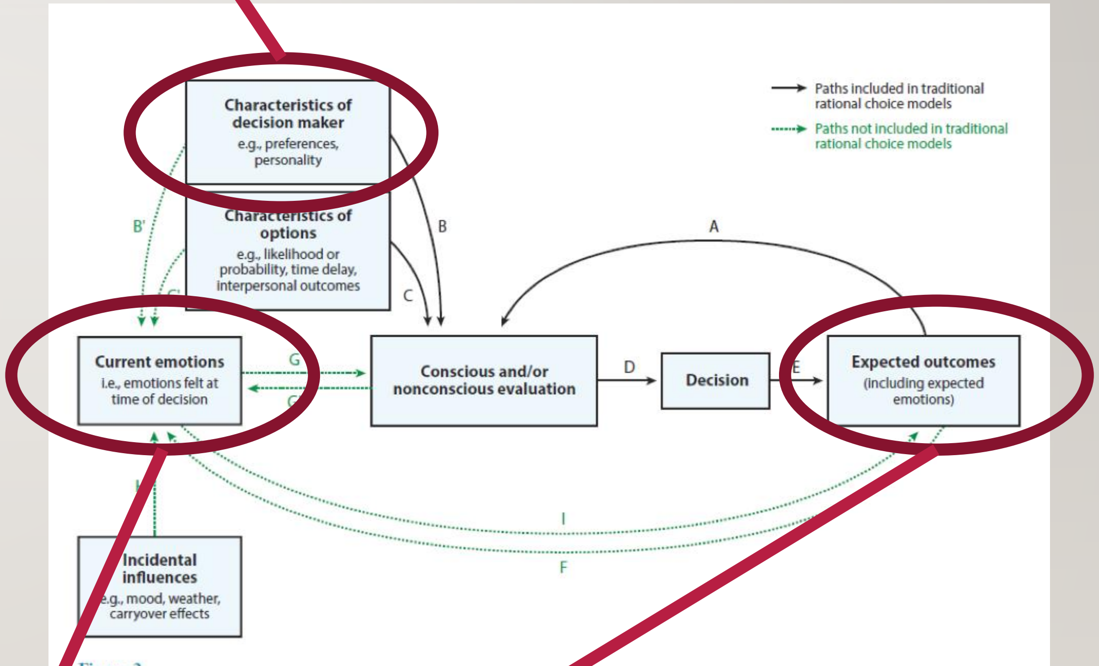
, et al. "Emotion and decision making." Annual review of 015): 799-823.

EXISTING MODELS OF N, DECISION MAKING

PERSONALITY





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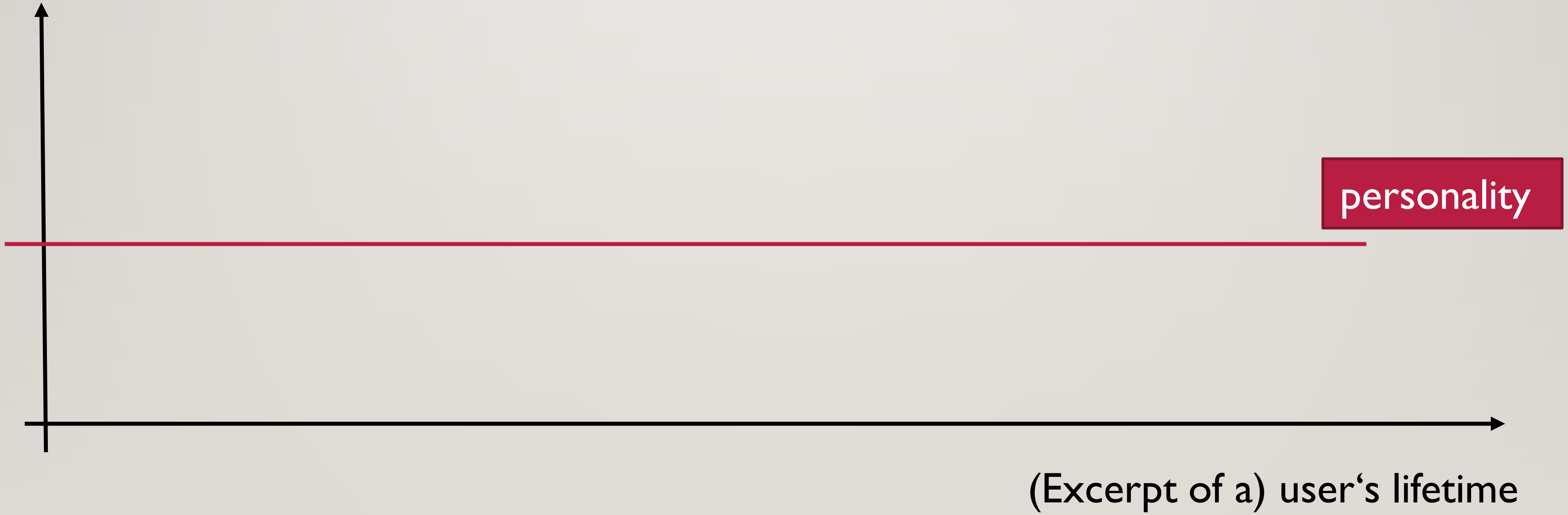
, et al. "Emotion and decision making." Annual review of 015). 799-823.

EMOTIONS

PERSONALITY AND EMOTIONS



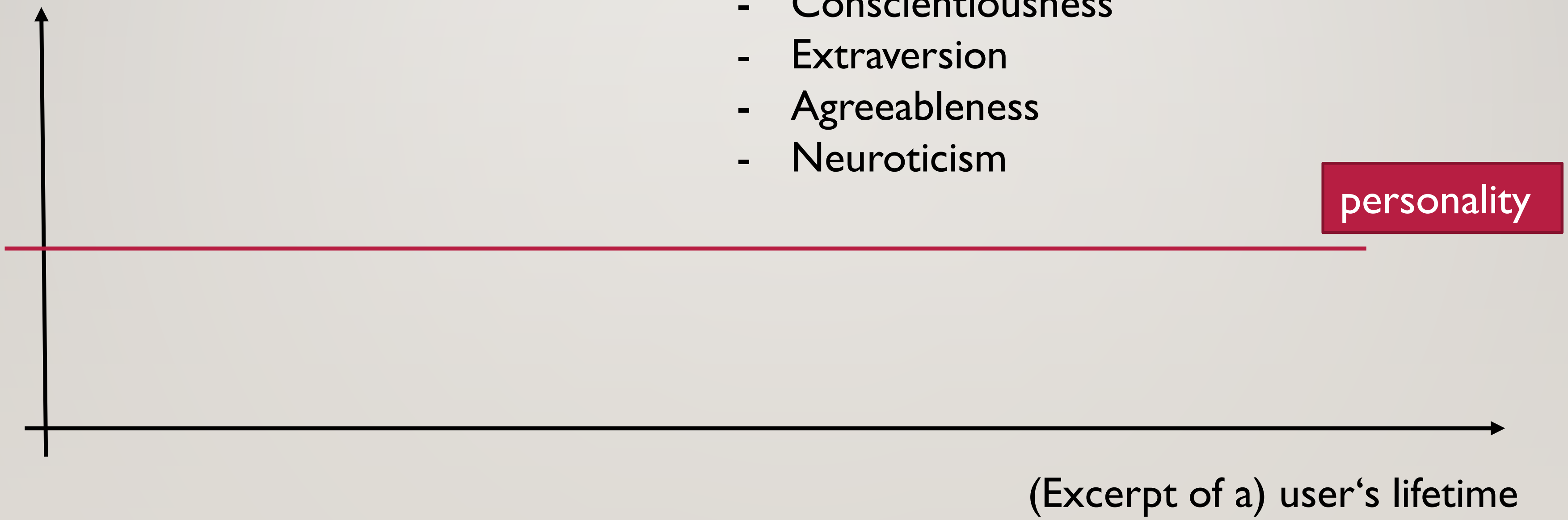
personality

(Excerpt of a) user‘s lifetime

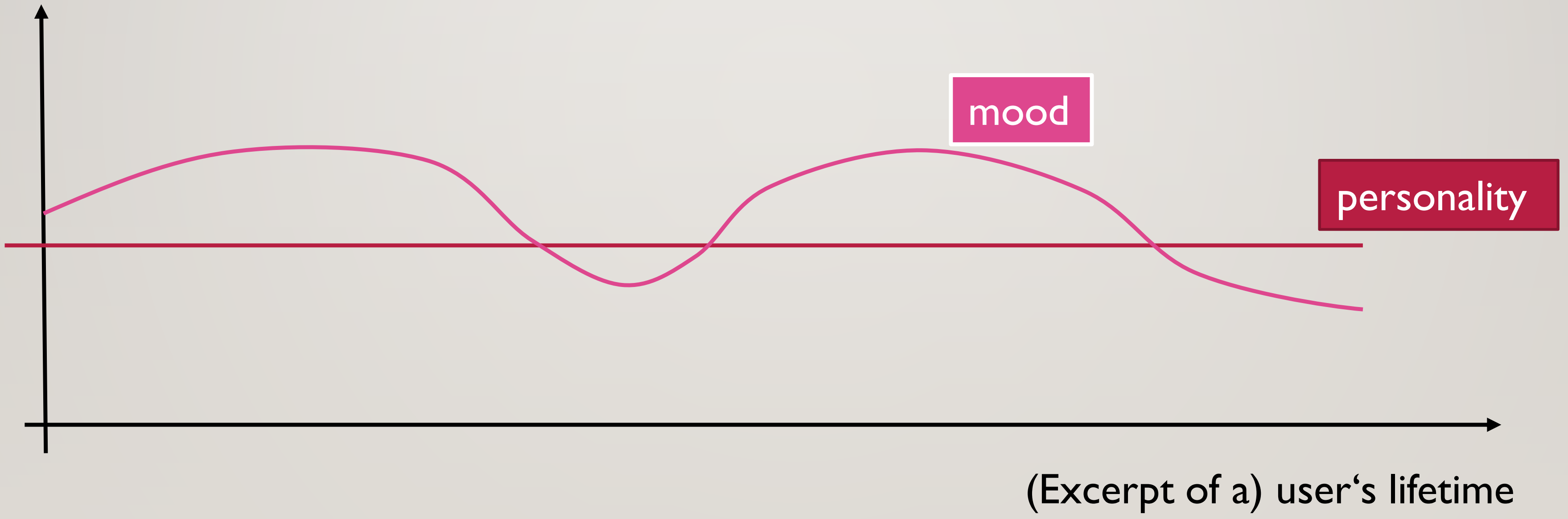
PERSONALITY AND EMOTIONS

Five Factor Model:

- Openness to new experiences
- Conscientiousness
- Extraversion
- Agreeableness
- Neuroticism



PERSONALITY AND EMOTIONS

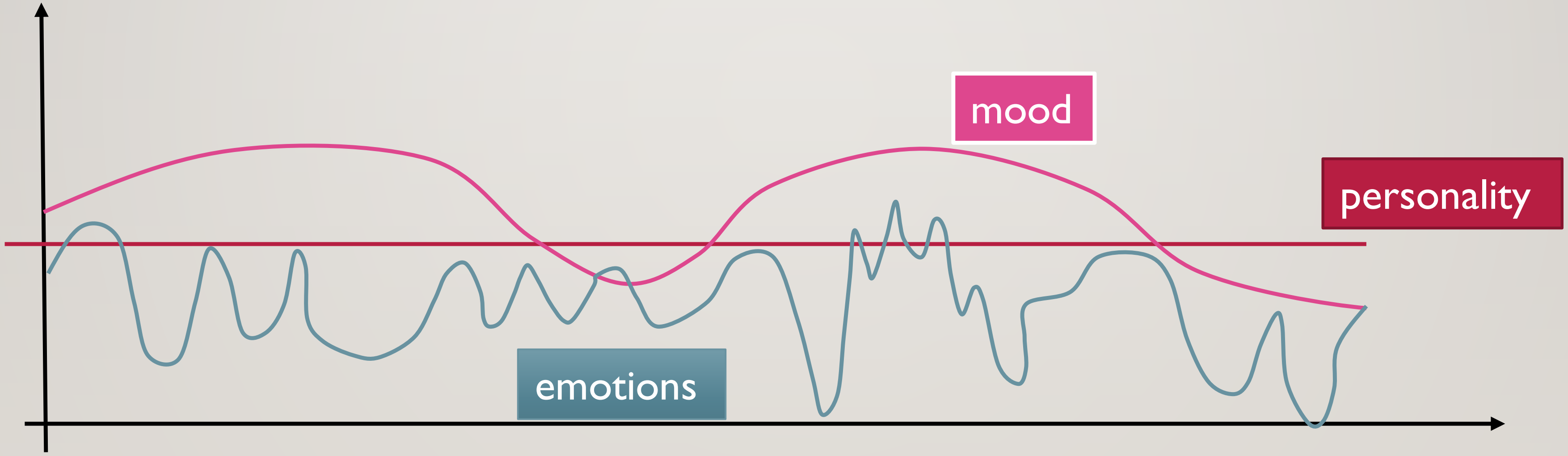


PERSONALITY AND EMOTIONS

- No particular trigger
- Positive/Negative

(Excerpt of a) user‘s lifetime

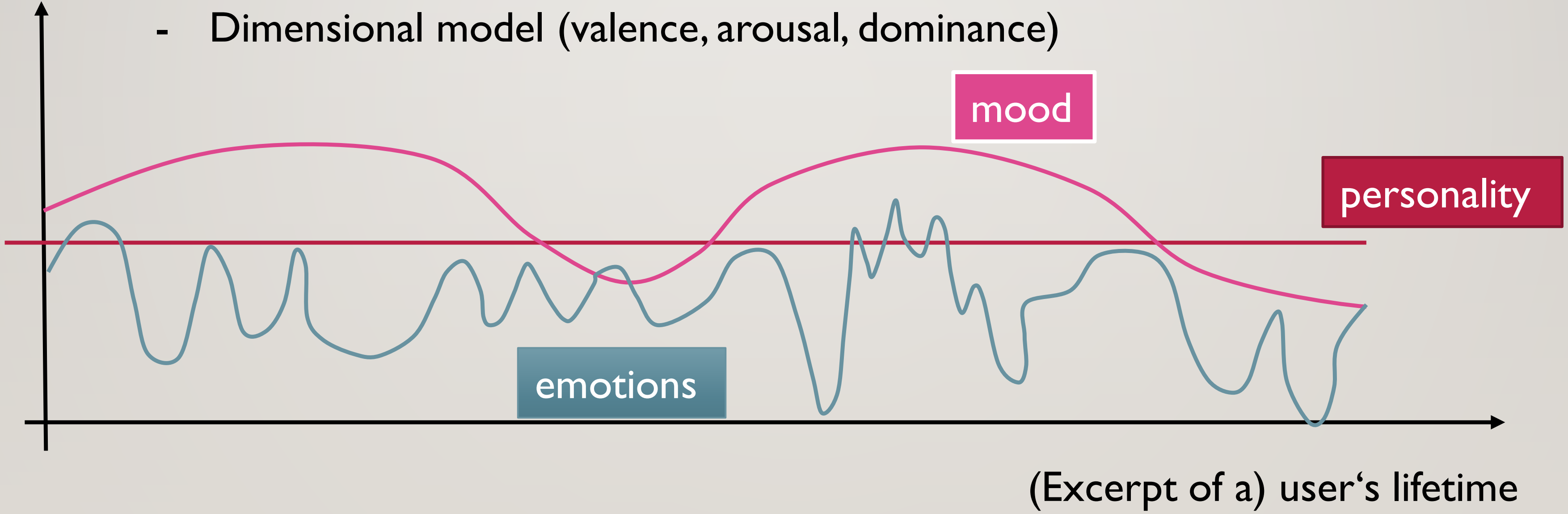
PERSONALITY AND EMOTIONS



(Excerpt of a) user‘s lifetime

PERSONALITY AND EMOTIONS

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



EMOTION VS. MOOD VS. SENTIMENT

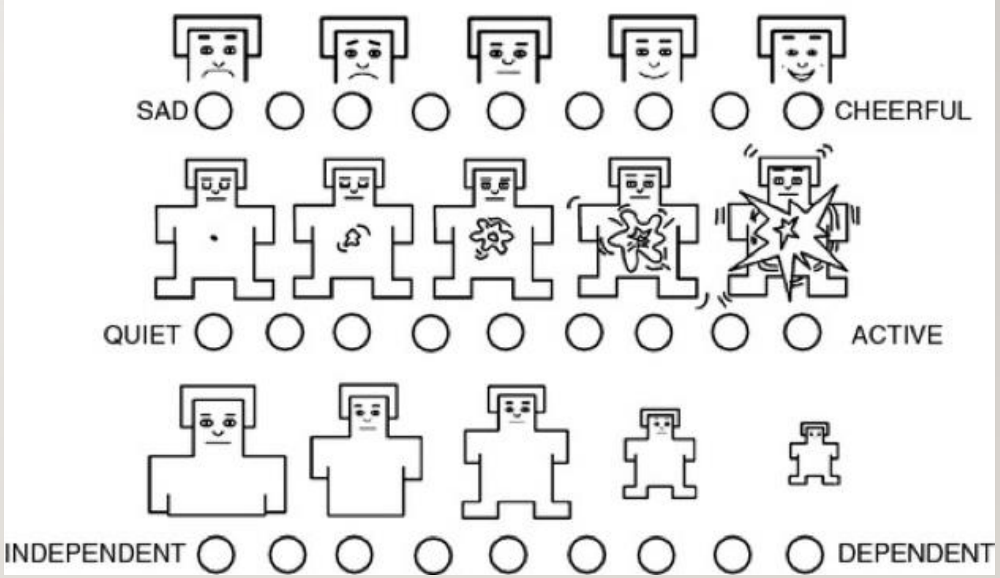
- Let's clear some terminology
    - Affect : umbrella term for describing the topics of emotion, feelings, and moods
    - Emotion:
        - brief in duration
        - consist of a coordinated set of responses (verbal, physiological, behavioral, and neural mechanisms)
        - triggered
    - Mood: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

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

- 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.

USAGE OF PERSONALITY AND EMOTIONS FOR BETTER RECOMMENDATIONS

- Assume Personality and Emotions can be measured
- Personality:
  - New-user problem (user similarity)
  - Diversity
  - Acquisition
- Emotions:
  - Emotions as context
  - Modeling the target emotion
  - Emotions as feedback
  - Group setting: emotional contagion
  - Acquisition

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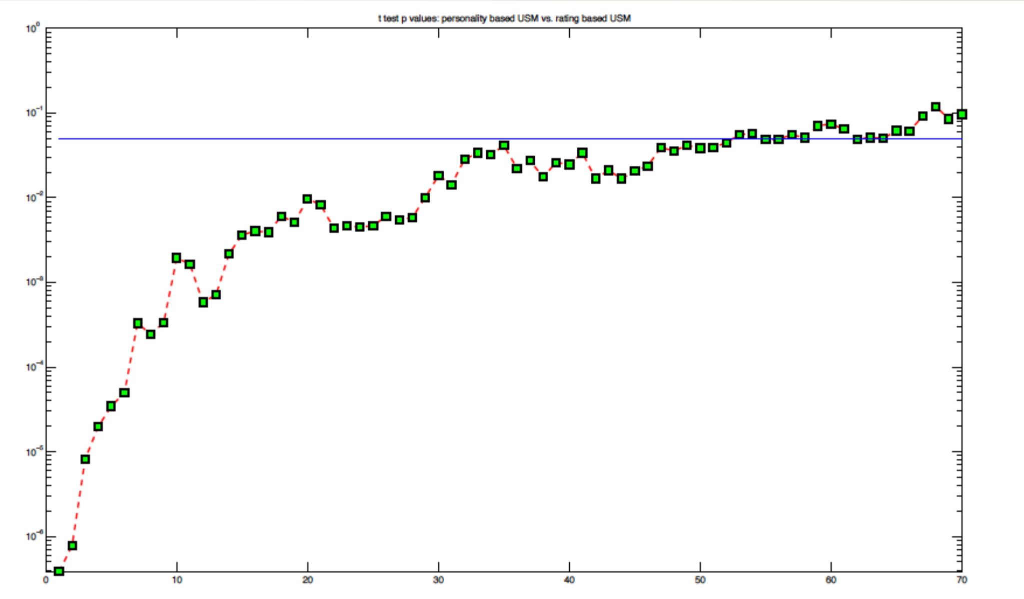
PERSONALITY AS USER SIMILARITY - I

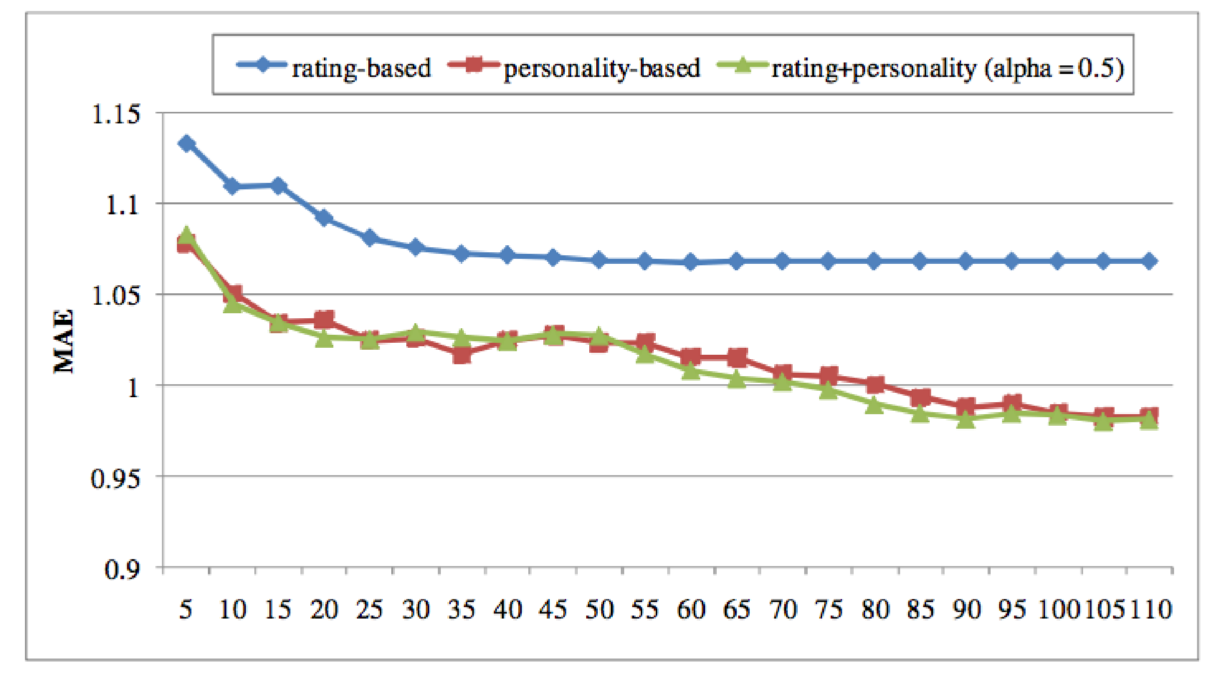
- New user problem
- N = 52, images = 70
- User similarities
  - Rating-based
  - Personality-based
- Rating-based catches the personality only after 40 ratings have been entered



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

PERSONALITY AS USER SIMILARITY - II

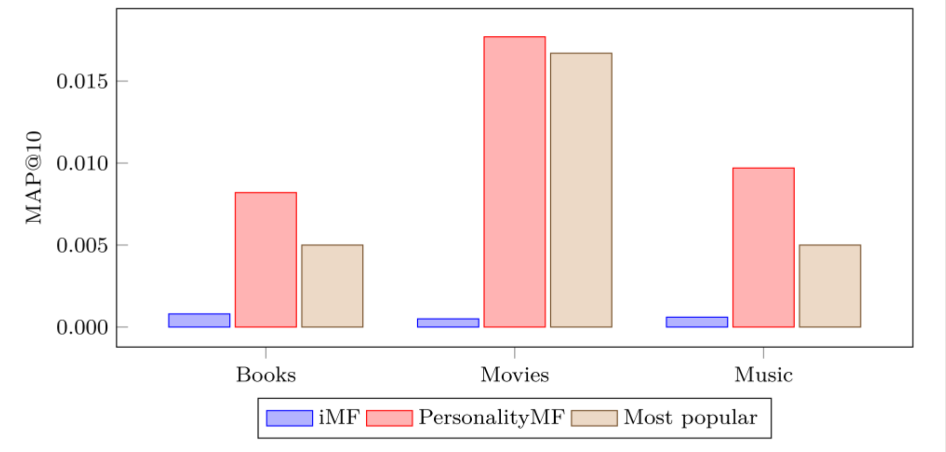
- N=111, 646 songs
- User similarities (Pearson CC)
  - Rating-based
  - Personality-based



Hu, R., and Pu, P. (2010). Using Personality Information in Collaborative Filtering for New Users. In Proceedings of the 2nd ACM RecSys'10 Workshop on Recommender Systems and the Social Web (pp. 17–24).

PERSONALITY AS USER SIMILARITY III - IN MATRIX FACTORIZATION

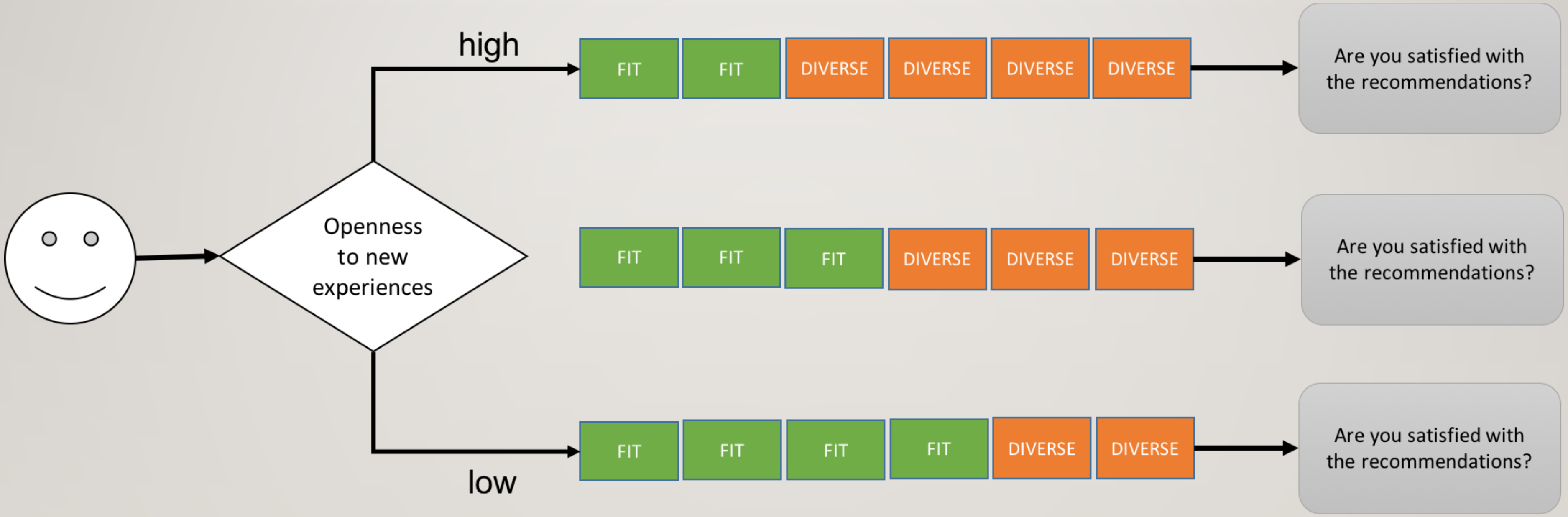
- In (Elahi et al., 2013) and (Fernández-Tobías, 2016)
- Injection of personality factors in MF as additional features
  - $r_{ui} = q_i(p_u + \sum_{a\in A(u)} y_a)$
  - personality u = (2.3,4.0,3.6,5.0,1.2) maps to A(u) = {ope2, con4, ext4, agr5,neu1}.



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).

Fernández-Tobías, I., Braunhofer, M., Elahi, M., Ricci, F., and Cantador, I. (2016). Alleviating the new user problem in collaborative filtering by exploiting personality information. UMUAI, 26(2), 1–35. https://doi.org/10.1007/s11257-016-9172-z

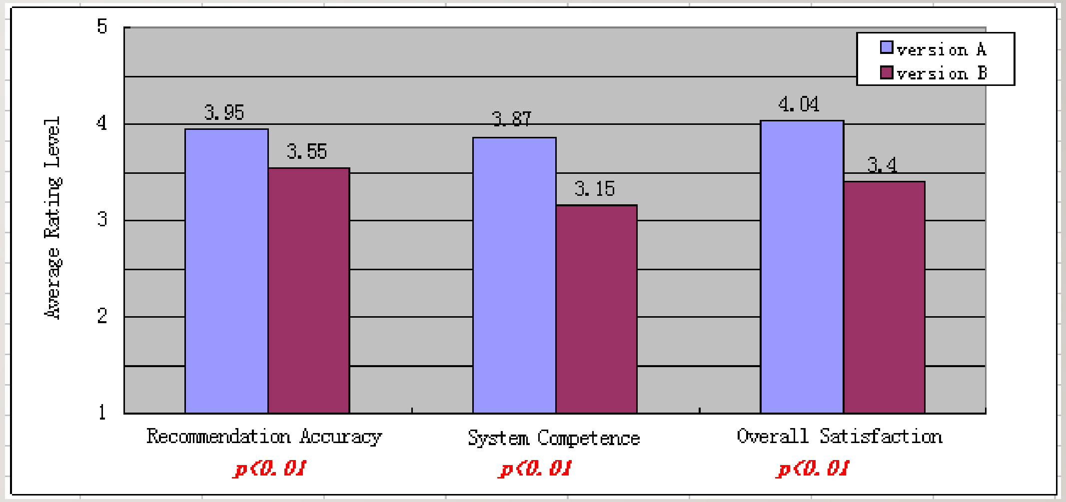
32 PERSONALITY AND DIVERSITY



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/10.1145/2468356.2468505

PERSONALITY AND DIVERSITY

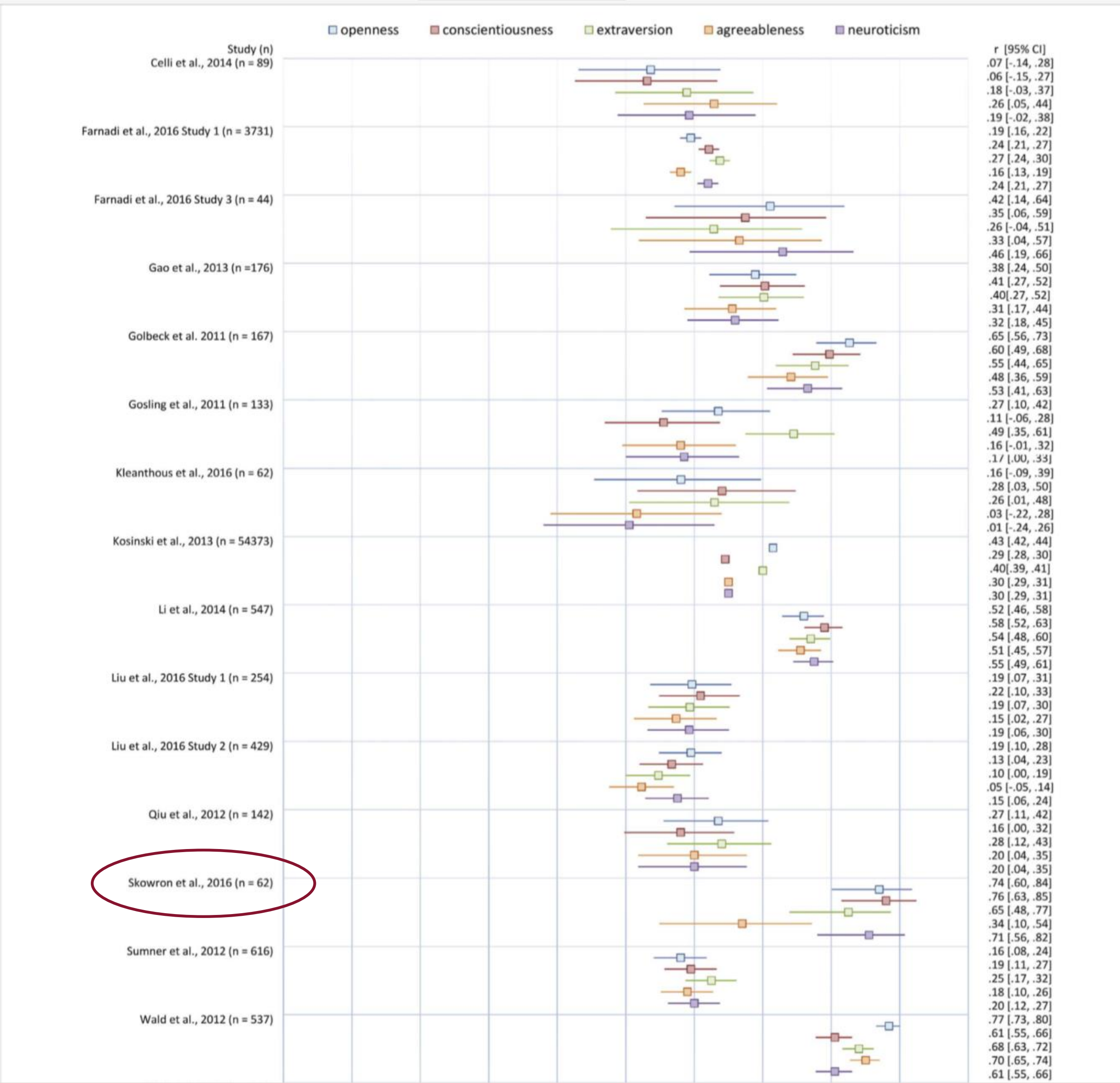
- Within subject N=52, movies
- Diversity per: genre, director, country, release time, actor
- Rules from the previous study
  - High Level of Openness is linked to high need for diversity w.r.t. actor/actress
  - Low Level of Conscientiousness is correlated with high need for the overall diversity



Wu, W., Chen, L., and He, L. (2013). Using personality to adjust diversity in recommender systems. Proceedings of the 24th ACM Conference on Hypertext and Social Media - HT '13, (May), 225–229.

PERSONALITY ACQUISITION

- Questionnaires
  - BFI: 44 questions
  - TIPI: 10 questions
  - NEO-IPIP: 300 questions
- Research on unobtrusive personality detection from digital traces
  - Twitter, Instagram, Facebook, eye gaze
- Off-the shelf solutions: inference from social media:
  - Cambridge University Psychometric Center: https://applymagicsauce.com/demo
  - IBM Watson Personality Insights: https://cloud.ibm.com/apidocs/personality-insights

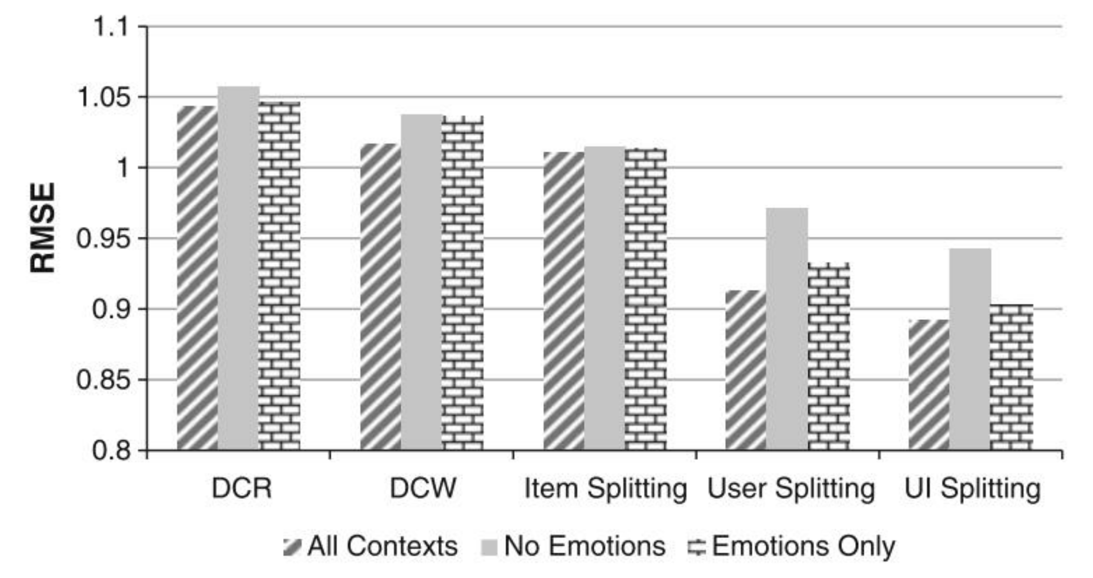

openness
conscientiousness
extraversion
agreeableness
neuroticism
Study (n)
r [95% CI]
Celli et al., 2014 (n = 89)
.07 [-.14, .28]
.06 [-.15, .27]
.18 [-.03, .37]
.26 [.05, .44]
.19 [-.02, .38]
Farnadi et al., 2016 Study 1 (n = 3731)
.19 [.16, .22]
.24 [.21, .27]
.27 [.24, .30]
.16 [.13, .19]
.24 [.21, .27]
Farnadi et al., 2016 Study 3 (n = 44)
.42 [.14, .64]
.35 [.06, .59]
.26 [-.04, .51]
.33 [.04, .57]
.46 [.19, .66]
Gao et al., 2013 (n =176)
.38 [.24, .50]
.41 [.27, .52]
.40[.27, .52]
.31 [.17, .44]
.32 [.18, .45]
Golbeck et al. 2011 (n = 167)
.65 [.56, .73]
.60 [.49, .68]
.55 [.44, .65]
.48 [.36, .59]
.53 [.41, .63]
Gosling et al., 2011 (n = 133)
.27 [.10, .42]
.11 [-.06, .28]
.49 [.35, .61]
.16 [-.01, .32]
.17 [.00, .33]
Kleanthous et al., 2016 (n = 62)
.16 [-.09, .39]
.28 [.03, .50]
.26 [.01, .48]
.03 [-.22, .28]
.01 [-.24, .26]
Kosinski et al., 2013 (n = 54373)
.43 [.42, .44]
.29 [.28, .30]
.40[.39, .41]
.30 [.29, .31]
.30 [.29, .31]
Li et al., 2014 (n = 547)
.52 [.46, .58]
.58 [.52, .63]
.54 [.48, .60]
.51 [.45, .57]
.55 [.49, .61]
Liu et al., 2016 Study 1 (n = 254)
.19 [.07, .31]
.22 [.10, .33]
.19 [.07, .30]
.15 [.02, .27]
.19 [.06, .30]
Liu et al., 2016 Study 2 (n = 429)
.19 [.10, .28]
.13 [.04, .23]
.10 [.00, .19]
.05 [-.05, .14]
.15 [.06, .24]
Qiu et al., 2012 (n = 142)
.27 [.11, .42]
.16 [.00, .32]
.28 [.12, .43]
.20 [.04, .35]
.20 [.04, .35]
Skowron et al., 2016 (n = 62)
.74 [.60, .84]
.76 [.63, .85]
.65 [.48, .77]
.34 [.10, .54]
.71 [.56, .82]
Sumner et al., 2012 (n = 616)
.16 [.08, .24]
.19 [.11, .27]
.25 [.17, .32]
.18 [.10, .26]
.20 [.12, .27]
Wald et al., 2012 (n = 537)
.77 [.73, .80]
.61 [.55, .66]
.68 [.63, .72]
.70 [.65, .74]
.61 [.55, .66]

USAGE OF PERSONALITY AND EMOTIONS FOR BETTER RECOMMENDATIONS

- Assume Personality and Emotions can be measured
- Personality:
  - Content recommendations (rule-based)
  - New-user problem (user similarity)
  - Diversity
  - Acquisition
- **Emotions:**
  - **Emotions as context**
  - **Modeling the target emotion**
  - **Emotions as feedback**
  - **Group setting: emotional contagion**
  - **Acquisition**

EMOTIONS AS CONTEXT

- Movie consumption dataset with several contextual variables
    - Time, part-of-day, season, location, weather, social, end emotion, dominant emotion, mood and others
- Various contextualization techniques



Yong Zheng, Bamshad Mobasher, Robin D. Burke: The Role of Emotions in Context-aware Recommendation. Decisions@RecSys 2013: 21-28

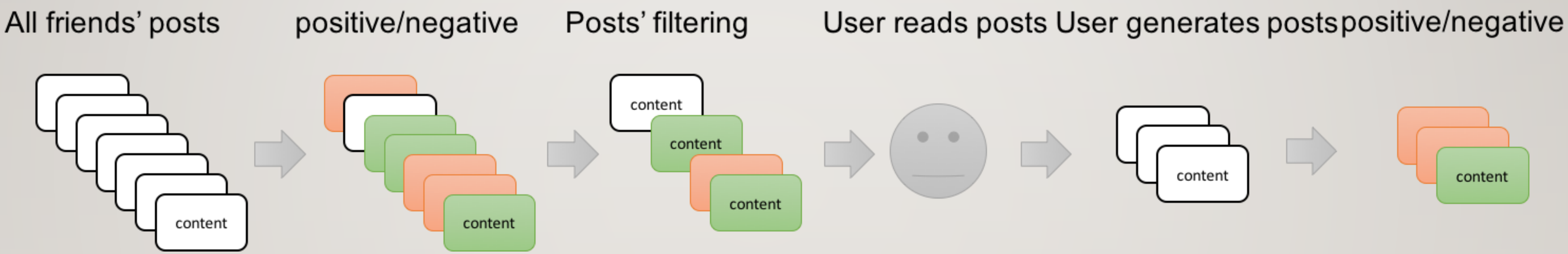
Zheng, Y., Mobasher, B., and Burke, R. (2016). Emotions in Context-Aware Recommender Systems (pp. 311–326). In M. Tkalčič, B. De Carolis, M. de Gemmis, A. Odić, and A. Košir (Eds.), Emotions and Personality in Personalized Services: Models, Evaluation and Applications

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

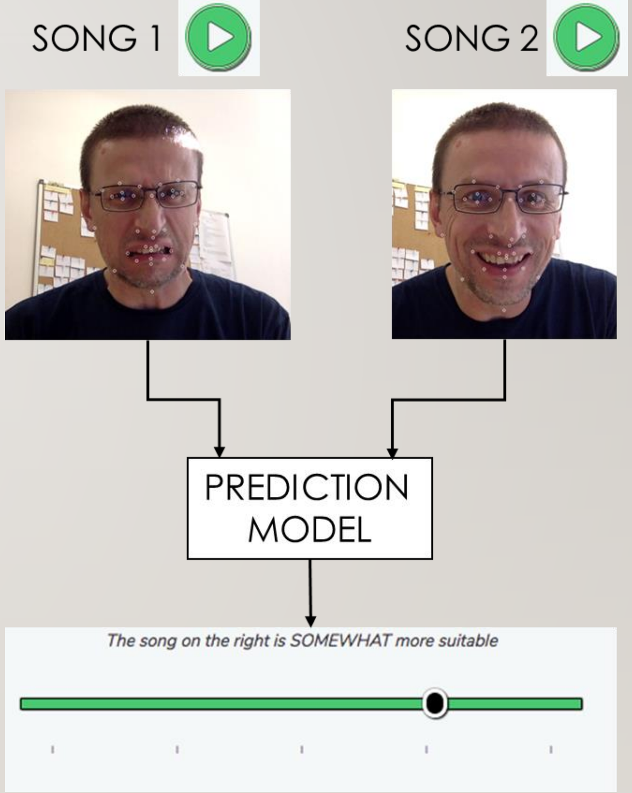
EMOTIONAL CONTAGION



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 AS FEEDBACK

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



SONG 1

SONG 2

PREDICTION MODEL

The song on the right is SOMEWHAT more suitable

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 ACQUISITION

- Questionnaires
- Multimodal detection:
  - Modalities: Audio, language, visual, physiology
  - Off-the-shelf solutions: Noldus, Affectiva, Microsoft Cloud, Amazon Cloud

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LATEST RESEARCH

- Matrix Factorization:
  - $r(u,i) = (p_1, p_2, \ldots)(q_1, q_2, \ldots)$
  - what do p_i, q_i, mean?

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  - $r(u,i) = (e_u, h_u)(e_i, h_i)$
    - Eudaimonia
    - Hedonia

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  - $r(u,i) = (e_u, h_u)(e_i, h_i)$
    - Eudaimonia
    - Hedonia
- Required features:
  - e_u : user propensity for eudaimonia
  - h_u : user propensity for hedonia
  - e_i : eudaimonic quality of item
  - h_i : hedonic quality of item

HEDONIA/EUDAIMONIA

HEDONIC	✓	✓	✗
EUDAIMONIC	✓	✗	✓

HEDONIA/EUDAIMONIA

HEDONIC	✓	✓	✗
EUDAIMONIC	✓	✗	✓

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

LATEST 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.)
  - Unobtrusive acquisition of user characteristics (work in progress)
    - From rating behavior. (Tkalčič, Motamedi, Puc, Mars Bitenc, 2022) Prediction of Hedonic and Eudaimonic Characteristics from User Interactions. *Adjunct Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '22 Adjunct), July 4--7, 2022, Barcelona, Spain*

UNOBTRUSIVE ACQUISITION OF EH IN MOVIES

- 177 users, 30 movies
  - Ratings
  - Hedonic/eudaimonic movie labels
  - Subtitles
- NLP
- TF-IDF, Fasttext for features
- Nested x-fold validation (10,3)
- RMSE (scale 1-10):
  - Eudaimonia: 1.26 (avg baseline) ->1.06 (Random Forest)
  - Hedonia: 1.34 -> 1.13

UNOBTRUSIVE ACQUISITION OF EH IN SONGS

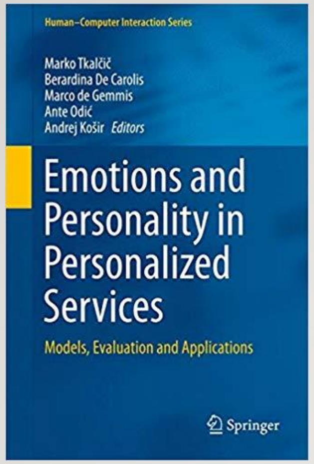
- 1991 users, 100 songs
    - Hedonic/eudaimonic labels
    - Lyrics
- NLP
- TF_IDF
- Nested x-fold validation (5,5)
- Binary prediction accuracy: just slight improvements (0.54/0.55) over majority baseline (0.5)

DATA COLLECTION

- https://hicupexperiments.famnit.upr.si/
- Goal: 1000 users, 1000movies, 10k ratings
- Stuck at 600+

CONCLUSION

- Purely behavioral data might lead to inaccurate conclusions
- We need to understand which cognitive processes are driving the behaviour



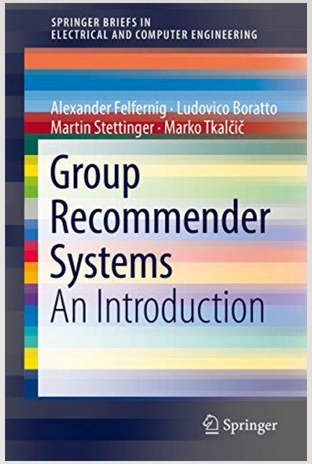
Human–Computer Interaction Series

Marko Tkalčič
Berardina De Carolis
Marco de Gemmis
Ante Odić
Andrej Košir *Editors*

Emotions and Personality in Personalized Services

Models, Evaluation and Applications

Springer



SPRINGER BRIEFS IN
ELECTRICAL AND COMPUTER ENGINEERING

Alexander Felfernig · Ludovico Boratto
Martin Stettinger · Marko Tkalčič

Group Recommender Systems
An Introduction

Springer

THANK YOU

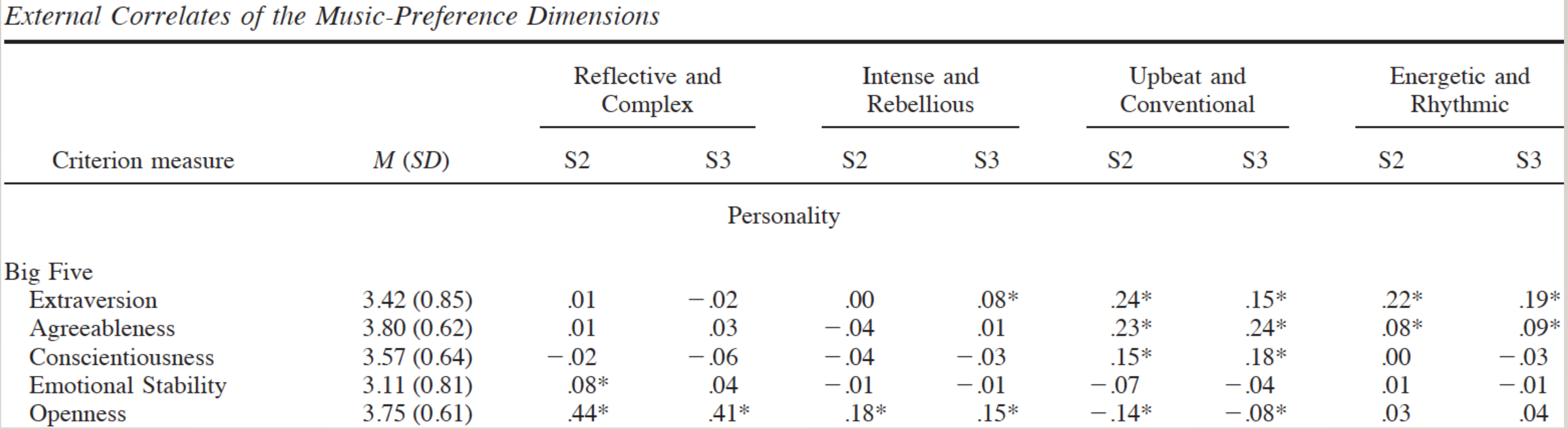
HAPPY TO TAKE QUESTIONS

HANDS-ON

- Web demo for emotion acquisition: https://osebje.famnit.upr.si/~marko.tkalcic/durham_lecture/
- Additional slide deck for building the interface available

PERSONALITY AND PREFERENCES

- Personality traits (extraverted/introverted, open/conservative etc.) are linked to music genre preferences (Rentfrow et al, 2003)



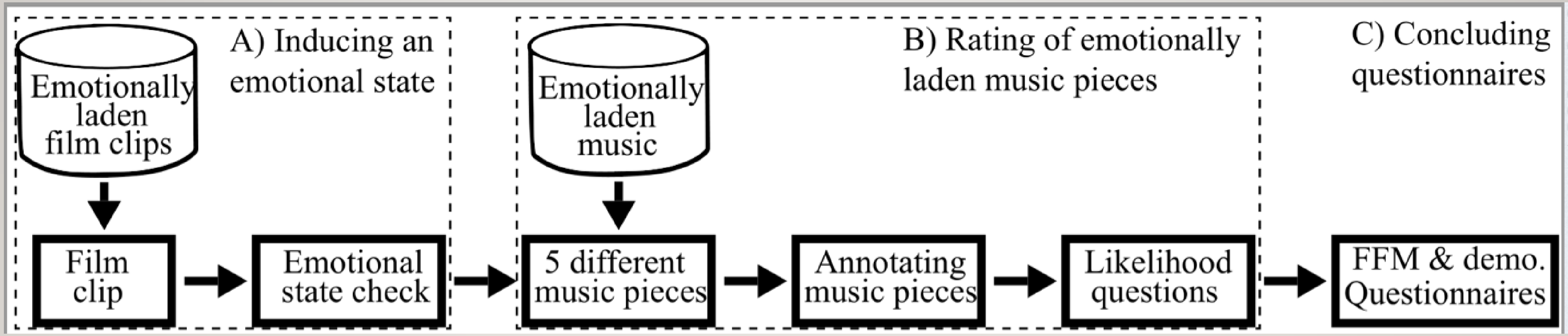
External Correlates of the Music-Preference Dimensions

		Reflective and Complex		Intense and Rebellious		Upbeat and Conventional		Energetic and Rhythmic	
Criterion measure	*M* (*SD*)	S2	S3	S2	S3	S2	S3	S2	S3
				Personality					
Big Five									
Extraversion	3.42 (0.85)	.01	−.02	.00	.08*	.24*	.15*	.22*	.19*
Agreeableness	3.80 (0.62)	.01	.03	−.04	.01	.23*	.24*	.08*	.09*
Conscientiousness	3.57 (0.64)	−.02	−.06	−.04	−.03	.15*	.18*	.00	−.03
Emotional Stability	3.11 (0.81)	.08*	.04	−.01	−.01	−.07	−.04	.01	−.01
Openness	3.75 (0.61)	.44*	.41*	.18*	.15*	−.14*	−.08*	.03	.04

Rentfrow, P. J., and Gosling, S. D. (2003). The do re mi's of everyday life: The structure and personality correlates of music preferences. Journal of Personality and Social Psychology, 84(6), 1236–1256.

Tkalčič, M., Ferwerda, B., Hauger, D., and Schedl, M. (2015). Personality Correlates for Digital Concert Program Notes. In UMAP 2015, Lecture Notes On Computer Science 9146 (Vol. 9146, pp. 364–369).

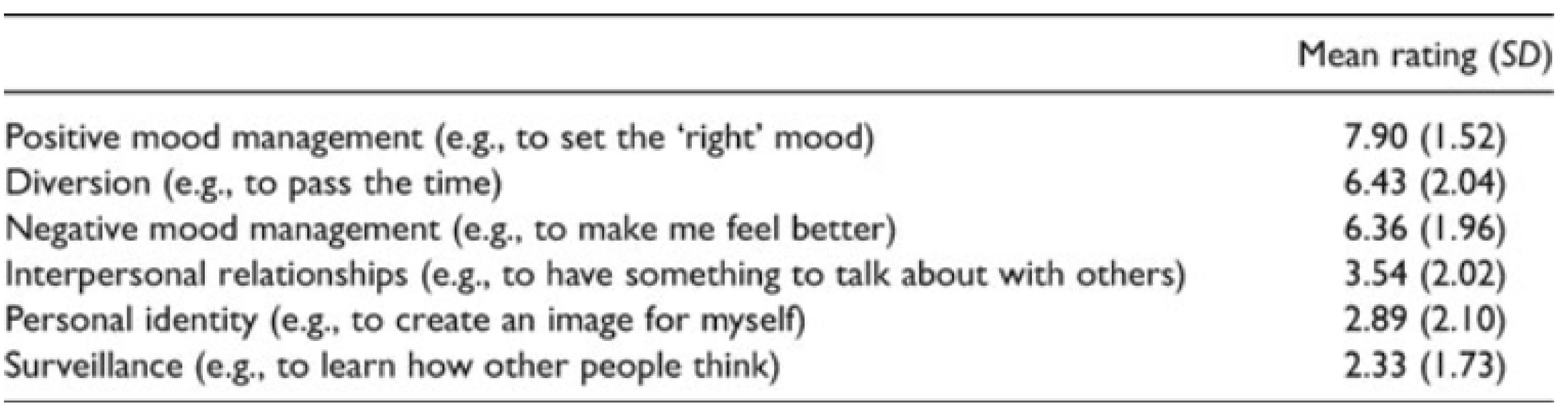
PERSONALITY FOR MOOD REGULATION



- 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.

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

HOWEVER, IT CAN GET COMPLICATED

- Why do we like drama, sad films?
- . . . under some circumstances, individuals may choose to view entertainment for reasons that may not be best described as driven by hedonic motivations but rather as driven by eudaimonic motivations: greater insight, self reflection, or contemplations of poignancy or meaningfulness (e.g., what makes life valuable).
- The Hangover
  - hedonic quality (comedy)
  - no eudaimonic quality
- La vita e' bella
  - hedonic quality (comedy)
  - eudaimonic quality

TIPI

TIPI: I see myself as (1-7 . . . agree/disagree):

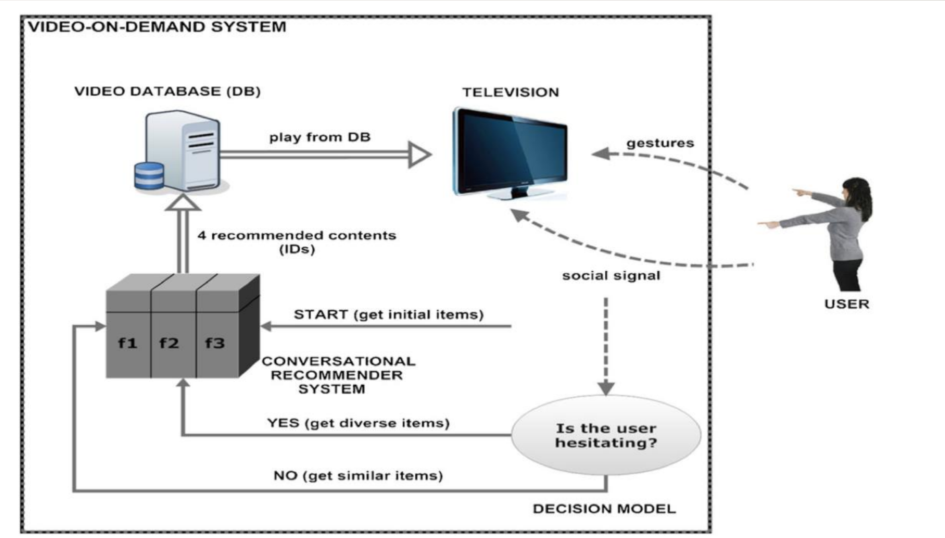
1. Extraverted, enthusiastic.
2. Critical, quarrelsome.
3. Dependable, self-disciplined.
4. Anxious, easily upset.
5. Open to new experiences, complex.
6. Reserved, quiet.
7. Sympathetic, warm.
8. Disorganized, careless.
9. Calm, emotionally stable.
10. Conventional, uncreative.

- b1 = q1 + (8 − q6) = Extraversion
- b2 = q2 + (8 − q7) = Agreeableness
- b3 = q3 + (8 − q8) = Conscientiousness
- b4 = q4 + (8 − q9) = Emotional Stability
- b5 = q5 + (8 − q10) = Openness to Experiences

Gosling, S. D., Rentfrow, P. J., and Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. Journal of Research in Personality, 37(6), 504–528. doi:10.1016/S0092-6566(03)00046-1

EMOTIONS AS FEEDBACK - I

- Video-on-demand scenario
- Usage of hesitation as feedback
- 4 recommendations, 1 selection
    - control group: recommend similar
    - hesitation group: recommend similar/diverse
- Quality of experience (QoE) is improved when hesitation is taken into account



Vodlan, T., Tkalčič, M., and Košir, A. (2015). The impact of hesitation, a social signal, on a user's quality of experience in multimedia content retrieval. Multimedia Tools and Applications. doi:10.1007/s11042-014-1933-2