Bayesian Brain meets Bayesian Recommender
Towards Systems with Empathy for the Human Nature

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ABSTRACT
In this paper we consider the modern theory of the Bayesian brain from cognitive neurosciences in the light of recommender systems and expose potentials for our community. In particular, we elaborate on noisy user feedback and the thus resulting multicomponent user models, which have indeed a biological origin. In real user experiments we observe the impact of both factors directly in a repeated rating task along with recommendation. As a consequence, this contribution supports the plausibility of contemporary theories of mind in the context of recommender systems and can be understood as a solicitation to integrate ideas of cognitive neurosciences into our systems in order to further improve the prediction of human behaviour.

KEYWORDS
Bayesian Brain, Neural Coding, Human Uncertainty, Noise, User Models

1 INTRODUCTION
In our community of recommender systems, there are continual efforts to make predictions more precise and systems more efficient and user-friendly. In doing so, the classic approach is to model the relationship between a user and items in terms of optimising a target function in order to predict future user decisions based on training data. However, there are two major problems that are caused by human nature. First of all, many studies prove that users are not entirely certain about a decision so that a given rating may fluctuate when the rating task is repeated (noisy user feedback) [1, 2, 8, 10]. Second, optimising a target function might not sufficiently account for dynamic changes in behaviour (need for multicomponent user models) which again can be proven in systematic user experiments [13]. The theories of cognitive neurosciences know these phenomena and describe these aspects of human cognition by means of probabilistic models. For example, the origin of volatile decision-making and noisy user feedback is due to the irregular transmission of informations through the synaptic cleft. A Bayesian formulation of this effect leads directly to multicomponent models as an explicit consequence of user noise. Both of these factors, noisy user feedback and multicomponent models, have recently been proven...

Bayesian Learning Basics
From the perspective of cognitive neuroscience, it all starts with the brain observing sensory input $Y$ (visual, auditory, etc.) and making an estimate of the state of the world $X$ [3]. To continuously improve this estimation - or subjective beliefs to be more precisely - the brain has to learn by comparing reality against predictions based on these beliefs [5]. This makes the human brain a highly sophisticated recommender system itself. The Bayes Theorem provides the basis for the processing of beliefs along with real world evidence. Those confirmed or modified beliefs are thereby brought to ever new situations. Mathematically spoken, the posterior serves as indication for possible deficiencies within the field of recommender research in case of omission.

2 THEORY AND EXPERIMENTS
The Bayesian brain theory is a composition of Bayesian inference and theoretical neurology. We will first demonstrate similarity to Bayesian recommender systems and then discuss the modelling of noisy data as well as multicomponent user models.

Figure 1: Hierarchical message passing through cortex layers.

to have a significant impact on prediction quality in recommender systems [1, 9, 12]. Therefore, this contributions seeks the benefits of implementing neuroscientific models and will give experimental indication for possible deficiencies within the field of recommender research in case of omission.
When it comes to a repeated product rating where the participant trolling experiment, the process of decision making is restarted. However, same signals never result into emitting the same amount of transmitters (neural noise) [4–6, 15]. This noise may raise too weak (or sufficient) signals above (or below) a certain threshold, causing a neuron to inhibit (or to fire) [3]. In fact, for the firing of a neuron, we can only specify a probability [3, 7]. In a recommender’s language, biological irregularity implies that every time a decision-making is repeated, other prior probabilities might be used and thus the resulting belief is never quite the same as before. In a systematic experiment, real users repeatedly rated theatrical trailers on a 5-star scale. It turns out that only 35% of all users show constant rating behaviour, whereas about 50% use two different answer categories and 15% of all users make use of three or more categories. Figure 2 is a characteristic example for these results. This sows that individuals are not able to perfectly reproduce their decision-making. These fluctuations can be explained by the theory of neural noise, and have a direct effect on recommender systems. Assumption the model based prediction to be π = 3, a user rating r = 4 cannot be seen as a deviation according to Figure 2. Furthermore, by gathering information about temporary belief posteriors [14], it can be proven that all user responses (aggregated for each item) hold the same expectation. This is an indication for a common source of noise with constant magnitude, i.e. the manifestation of neural noise.

**Modelling User Preferences**

When it comes to a repeated product rating where the participant does not remember his previous response, as induced in our controlled experiment, the process of decision making is restarted. Accordingly, the participant receives a new and slightly different belief distribution for each rating trial. This has been mathematically explained in [6] and implies the need for multicomponent user models, which have recently been addressed in recommender systems research [9, 13]. Figure 3 shows the RMSEs of three different systems utilised in our experiment, based on one-component models along with the scores each system has achieved in each trial. It is apparent that some draws (scores) can not be drawn from the corresponding distribution. This indicates that users had changed their rating behaviour and sampled from different distributions for different trials. It can be proven via hypothesis testing that rating behaviour of trial 1 and 5 significantly deviates from trials 2 to 4. This can be explained by memory effects: In trial 1, decision-making was initialised for the first time. After the trial 2, participants got aware that the experiment was about repetition and so started to remember their ratings. Therefore, belief distributions remained more or less the same. After the trial 4 plus constant addition of new distractors, short-time memory was not able to keep all previous information and further decision-making produced different belief distributions again. These findings within simple recommendation scenarios can be entirely described by the Bayesian brain theory and may help systems to learn human behaviour more naturally.

**REFERENCES**

[1] Amatriain and others. 2009. I Like It… I Like It Not: Evaluating User Ratings Noise in Recommender Systems. UMAP Conference (2009).

[2] Xavier Amatriain and Josep Pujol. 2009. Rate It Again: Increasing Recommendation Accuracy by User Re-rating. In RecSys Conference. ACM.

[3] Kenji Doya. 2007. Bayesian Brain: Probabilistic Approaches. MIT Press.

[4] A Aldo Faisal, Luc PJ Selen, and Daniel M Wolpert. 2008. Noise in the nervous system. Nature reviews neuroscience 9, 4 (2008), 292–303.

[5] Karl Friston. 2010. The free-energy principle: a unified brain theory? Nature Reviews Neuroscience 11, 2 (2010), 127–138.

[6] Karl Friston. 2013. The anatomy of choice: active inference and agency. (2013).
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[7] Wulfram Gerstner. 2000. Population dynamics of spiking neurons: fast transients, asynchronous states, and locking. *Neural computation* 12, 1 (2000), 43–89.
[8] Will Hill. 1995. Recommending and Evaluating Choices. In *SIGCHI Conference*.
[9] Maria Iannario. 2014. Modelling Uncertainty and Overdispersion in Ordinal Data. *Communications in Statistics - Theory and Methods* 43 (2014), 771–786. Issue 14.
[10] Kevin Jasberg and Sergej Sizov. 2017. Probabilistic Perspectives on Collecting Human Uncertainty in Predictive Data Mining. *UMAP Conference* (2017).
[11] Miroslav Kubat. 2016. *An Introduction to Machine Learning*. Springer.
[12] Alan Said, Brijnesh Jain, Sascha Narr, and Till Plumbaum. 2012. Users and Noise: The Magic Barrier of Recommender Systems. In *User Modeling, Adaptation, and Personalization*. Vol. 7379. Springer Berlin / Heidelberg, 237–248.
[13] Sergej Sizov. 2017. Mining Ordinal Data Under Human Response Uncertainty. *Proceedings of Web Intelligence* 17 (2017).
[14] Lisa Stinken. 2016. Mit Schätzaufgaben zu einem adäquaten Verständnis von Messungsnauigkeiten. *PhyDid B-Didaktik der Physik* (2016).
[15] John A White, Jay T Rubinstein, and Alan R Kay. 2000. Channel noise in neurons. *Trends in neurosciences* 23, 3 (2000), 131–137.