

Information Sheet: *Scalable Bayesian Preference Learning for Crowds*, Edwin Simpson and Iryna Gurevych.

Main Claims

1. A novel probabilistic model, crowdGPPL, for jointly inferring the preferences of individual users in a crowd as well as the consensus ratings of the crowd. It is the first fully-Bayesian joint model of consensus and personal preferences that we are aware of.
2. A scalable approximate inference method for crowdGPPL using **stochastic variational inference (SVI)**, enabling its application to very large datasets, since unlike rival methods, the time and memory complexity are independent of dataset size. This is the first use of SVI for Bayesian matrix factorisation with priors over all latent factors. SVI was previously applied to Gaussian process preference learning with a single user, but details of the method were not provided. Here, we provide the first derivation for single-user GPPL as well as our new model, crowdGPPL.
3. Modelling individual preferences helps to infer the consensus for subjective tasks, as users have different biases and their disagreements are not simply random labelling errors. This is important when crowdsourcing preference annotations, for example, to obtain training data for NLP models, so it is important to remove annotator bias from the training data.
4. Modelling the crowd's consensus also helps predict the preferences of users with little data. This allows us to make better recommendations or better predict rankings for new users. Beside recommender systems, this is important for NLP systems that adapt to users, e.g. to provide relevant summaries to a particular person from a small amount of user feedback.
5. A Bayesian approach that combines Gaussian processes with matrix factorisation can handle uncertainty due to noise in the training data, small datasets, or new users.

Evidence to support the main claims

1. The paper reviews related work to show the novelty of crowdGPPL.
2. We provide derivations of our SVI method that show how it limits time and memory complexity. Empirical results on a standard preference learning dataset show that performance is slightly better than previous methods, despite our scalable approximation. The results also show that the runtimes of our proposed method scale well as the dataset size increases, with minimal increases in total wall-clock time.
3. We present empirical results on synthetic and real-world data (an NLP task with > 1000 users), which show that modelling personal preferences improves consensus prediction over the previous state of the art.
4. We test crowdGPPL on two real-world datasets (one NLP dataset, one standard preference learning dataset) + synthetic data, which show that predictions of personal preferences benefit from modelling the consensus.
5. We show better results for recommendation than a baseline that is not fully Bayesian (GPVU). The results also show that user preferences are sufficiently different to benefit from personalised predictions provided through the matrix factorisation component of our model, including on the crowdsourced NLP task with noisy, sparse data. The results illustrate that the Bayesian approach uses only the number of components supported by the data, even if more components are specified.

Related Papers

Houlsby N, Huszar F, Ghahramani Z, Hernández-Lobato JM (2012). Collaborative Gaussian processes for preference learning. In: *Advances in Neural Information Processing Systems*, pp 2096–2104.

This paper proposes a similar model to ours, but without the ability to predict consensus preference functions from crowds. They also propose a different inference approach as their work predates the stochastic variational inference technique that we apply here.

Hensman J, Matthews AGdG, Ghahramani Z (2015). Scalable Variational Gaussian Process Classification. In: *Proceedings of the Eighteenth International Conference on Artificial Intelligence and Statistics*, pp 351–360.

This work derives a stochastic variational inference (SVI) method for GP classification. The technique is similar and it is the closest work on SVI to our method that we are aware of. However, our work applies SVI to pairwise preference learning rather than classification, and derives an iterative variational Bayes method rather than using gradient-based optimisation.

Khan ME, Ko YJ, Seeger M (2014). Scalable collaborative bayesian preference learning. In: *Proceedings of the 17th International Conference on Artificial Intelligence and Statistics*, vol 33, pp 475–483.

Another model that tries to solve a similar problem, namely scalable preference learning with multiple users. The proposed method makes use of GPs but uses a separate GP to model each user, rather than placing GPs over the latent factors. As a result, their model is not suitable for very large numbers of users, nor can it take advantage of GPs for predicting utilities for new items or users.

Previously published papers

Simpson, E. D., & Gurevych, I. (2018). Finding Convincing Arguments Using Scalable Bayesian Preference Learning. *Transactions of the Association for Computational Linguistics*, 6, 357-371.

This previous paper applied SVI to Gaussian process preference learning (GPPL) for a single user. Therefore, it focuses on a different model, GPPL, whereas the current paper proposes a new model, crowdGPPL. The previous work therefore does not use matrix factorisation to model different users. Our previous work also did not present the necessary equations for implementing SVI, which the new paper provides. These are necessary to derive SVI for the more complex crowdGPPL model. The previous work includes experiments on the *UKPConvArgSample* dataset, which we also use in the new work. In the new paper, we compare a new set of rival methods for consensus prediction and introduce a new task of predicting personal preferences.

Suggested Reviewers

This is a resubmission -- our original suggestions were:

- Eyke Hüllermeier -- expertise in preference learning methods.
- Steven Reece -- expertise in Bayesian methods, variational inference and Gaussian processes.
- Stephen J. Roberts -- Bayesian methods, variational inference, Gaussian processes.
- Edwin V. Bonilla -- Bayesian methods, variational inference, Gaussian processes, past work on preference learning.