our belief dynamics model is best fit to averages over LLM behavior rather than its raw data. This is reminiscent of work in cognitive science showing that individual human behaviors may be suboptimal due to resource constraints, but in aggregate, populations of people (Davis-Stober et al., 2014) - or even repeated sampling from an individual person (Vul and Pashler, 2008) - can behave optimally.

We see there being a number of exciting directions for future follow-up work. The findings in our work may have practical implications for model control, to help practitioners understand how to best combine behavioral methods like ICL with mechanistic interventions for the purpose of controlling language models. The phase boundaries we find across ICL and steering could also have important consequences for AI safety, since language model behavior might suddenly and dramatically change after some threshold of context or steering is passed. Predicting these transition points, as we have done in this work, may prove to be an essential tool for safe and effective control of language models. One limitation of this work is that we only consider binary concepts and use only one method for constructing steering vectors (CAA). Future work may explore how our theory and model generalize to non-binary concept spaces, where there may be more than one direction for belief to vary across. Another compelling direction for future work is to explore how belief is updated with alternative steering vector methods such as SAEs (Templeton et al., 2024). In order to better understand the intersection of ICL and activation steering, another experiment we performed was to compute steering vectors over multiple shots (see App. D). We found that, counter-intuitively, after vectors were normalized to equal magnitude, steering vectors computed over multiple shots had an even weaker effect than steering with vectors computed over a single query. Further work is required to explain this effect. Finally, we also hope to explore in future work how activation steering and ICL interact with larger and more capable LLMs. Overall, by revealing a common Bayesian mechanism linking prompting and activation steering, our work re-frames how we understand belief and representation in LLMs, opening a rich space for theoretical exploration and principled model control in future work.

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