Class project: Amortized RSA

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Abstract

The RSA inference procedure is expensive, as exact inference requires considering all possible utterances. White et al. (2020) amortize the cost of inference with a language model. We build upon their work, drawing connections to language drift () and energy networks (Belanger and McCallum, 2016).

1 Introduction

RSA is an inference procedure based on Gricean maxims for generating and understanding language in a collaborative setting. RSA has had empirical success in small domains, in particular simple reference games with very limited vocabularies.RSA is potentially useful beyond these domains as a heuristic for utility maximization. Extensions of RSA to nontrivial vocabularies requires approximations: incremental RSA (), reranking (), and variational inference (White et al., 2020).

more on the recursive reasoning inspiration? not sure what the right word is

examples of phenomena?

We focus on amortization for approximate inference, which has had empirical success in applications such as VAEs, RL . We highlight two broad classes of errors in text generation, and examine their effects on the COLORS dataset ().

policy parameterization is amortization

- Model error (listener/likelihood, prior)
- Search error (amortization, objective)

While each of these may manifest in various ways, we examine two manifestations of each.

expand

2 Related Work

Cho's paper on training a greedy decoder (Gu et al., 2017). Amortized VI, SVI. Sequence KD. Descent-based methods for RL, policy grad.

Language drift papers? https://proceedings.neurips.cc/paper/2017/file/70222949cc0db89ab Paper.pdf http://proceedings.mlr.press/v70/jaques17a/jaques17a.pdf but really the approach here is just bayes rule + VI.

Incremental RSA (Cohn-Gordon et al., 2018)

right paper?

Defines RSA objective (Zaslavsky et al., 2020), also Yuan.

For listeners: 1) Learns with margin-based approximation of pseudolikelihood (Gulordava et al., 2020)? 2) Learns through approximate RSA procedure by subsampling utterances (McDowell and Goodman, 2019)

3 Problem Setup

The SHAPESWORLD dataset consists of games where two players, a speaker and a listener, collaborate to identify a target object out of a given set. Given a set of three objects, $o = \{o_1, o_2, o_3\}$, the goal of the speaker is to accurately describe the object at index $t \in [3]$, to the listener through a single utterance $u = \langle u_1, \ldots, u_L \rangle$ consisting of words u_l. The speaker is a distribution over utterances $p(u \mid t, o)$, while the listener is a distribution over targets $p(t \mid u, o)$.

4 Noisy Channel

Noisy channel in the spirit of RSA RSA hypothesizes that agents reason about partners recursively repeatedly.

5 Method

Noisy channel decoding. Interested in optimizing the following objective:

$$\underset{u}{\operatorname{argmax}}\, p(u \mid t, o), \tag{1}$$

where the posterior is given by

$$p(u \mid t, o) = \frac{p(t \mid u, o)p(u \mid o)}{p(t \mid o)}. \tag{2}$$

Normally inference is difficult because the denominator is intractable. In this case the denominator is a constant since the referent is uniformly chosen from the context. The issue here is that the likelihood term, $p(t \mid u, o)$ does not decompose over the sequence u, i.e. it only operates over full sequences, preventing efficient inference which requires the scoring of prefixes.

Rather than decoding by enumerating all possible sequence for each context, White et al. (2020) propose to amortize the cost of inference. Basically doing backups through SGD. This is accomplished by, rather than independently optimizing

Variational objective Non-decomposable Bayes' rule, introduce variational objective:

$$\begin{aligned} &\min_\phi \mathcal{L}(\phi) \\ &= \min_\phi D_{\mathrm{KL}}\left[q_\phi(u \mid t) \mid\mid p(u \mid t)\right] \\ &= \min_\phi \mathbb{E}_{q_\phi(u)}\left[\log q_\phi(u \mid t) - \log p(u \mid t)\right] \\ &= \min_\phi \mathbb{E}_{q_\phi(u)}\left[\log q_\phi(u \mid t) - \log p(t \mid u)p(u)\right], \end{aligned} \tag{3}$$

where conditioning on the full context o has been dropped for brevity, and the denominator $p(t \mid o)$ from the posterior is constant wrt ϕ and can be safely ignored. Importantly, we ensure that $q_\phi(u)$ decomposes and thus admits a tractable search procedure.

Comparison to imitation learning Objective is reverse KL. Do not have to model full conditional distribution, just what is both informative and fluent. Similar to mode-dropping in GANs, which allows the model to better utilize its limited capacity.

6 Experiments

We analyze the performance of the amortized speaker from two lenses: model error and search error. Model error pertains to issues with the generative model, which is given in Equation **??**. The model informs the variational objective during inference. The search error encompasses the search procedure itself, which includes the training of the amortized speaker and subsequent generation using the amortized speaker.

6.1 Model Error

The objective consists of two terms: the likelihood of the target given an utterance $p(t \mid u, c)$ and the utterance prior $p(u \mid c)$.

Prior Ideally the utterance prior would be close to the human distribution over utterances, otherwise optimizing the objective would lead to non-humanlike utterances. We experiment with a couple formulations, the uniform given length prior (White et al., 2020) and a more informative language model prior.

Likelihood We also evaluate the listener's accuracy on validation data, as well as sensitivity low-probability words.

6.2 Search Error

intro

Amortization error We examine whether the

7 Results

8 Discussion

References

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Appendix

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