RSA Approximations

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Abstract

RSA is expensive. We evaluate some approximations.

What is RSA even doing? Can we pull a principled approximation from a higher-level description?

1 Introduction

Only need to talk about **?** in the intro, other stuff isnt super relevant.

RSA applies at the sequence level, which makes inference in pragmatic speakers difficult. Can get around this with listeners, since the distractor utterances do not have to be that good. A couple approaches in recent literature: 1) Train an inference network to approximate the output of RSA (**?**). Compare to a sample and rerank from the literal speaker, not the amortized one. I guess that will be my contribution XD, plus a re-writing of their paper.

2 Related Work

Language drift papers, https://proceedings.neurips.cc/paper/2017/file/70222949cc0db89ab32c9969754d4758-Paper.pdf http://proceedings.mlr.press/v70/jaques17a/jaques17a.pdf but really this is just bayes rule + VI.

2) Incremental approximation using an autoregressive model (**?**), I think? Not totally sure what this is doing. Could analyze bias?

Defines RSA objective (**?**), also Yuan.

For listeners: 1) Learns with margin-based approximation of pseudolikelihood (**?**)? 2) Learns through approximate RSA procedure by subsampling utterances (**?**)

3 Problem Setup

4 Model

5 Inference

$$\begin{aligned}
&\max_\phi D_{\mathrm{KL}}\left[q_\phi(u) || p(u)\right] \\
&= \max_\phi \mathbb{E}_{q_\phi(u)}\left[\log q_\phi(u) - \log p(u)\right] \\
&= \max_\phi \mathbb{E}_{q_\phi(u)}\left[\log q_\phi(u) - \log \tilde{p}(u) + A\right] \\
&= \max_\phi \mathbb{E}_{q_\phi(u)}\left[\log q_\phi(u) - \log \tilde{p}(u)\right]
\end{aligned} \tag{1}$$

where the log partition function, A, can be dropped from the maximization since the expectation of a constant is a constant, and all conditioning has been dropped for brevity.

6 Experiments

6.1

6.2

6.3

7 Results

8 Discussion

References

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Appendix

A Blah