Deep Exponential Families: Biologically-Plausible Hierarchical Bayesian Inference?

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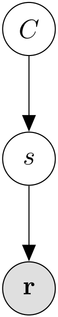
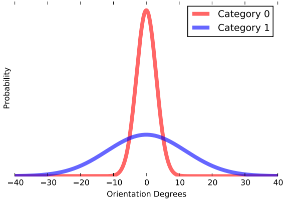
Background

- Humans and animals have been shown to perform near optimal hierarchical Bayesian inference in a wide variety of perceptual and cognitive tasks
  - But analytic computation of full posterior is often intractable and must be approximated
- What plausible neural algorithms could support this?



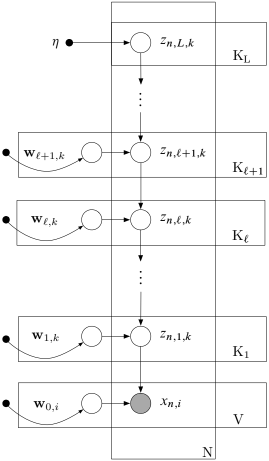


Previous Work

- One proposal: variational inference (Beck et al. 2012)
  - Assume a parametric form of distributions for approximation and then use coordinate ascent (EM) to minimize KL divergence to true posterior
  - The coordinate ascent method produces dynamic equations which could be implemented by neurons after a lot of training
- Requires analytic derivation of coordinate ascent equations
  - No understanding of learning process
- Often involves complex nonlinear operations

Approach

- Interpret a Deep Neural Net as a generative model (Ranganath et al. 2015)
- Each layer of neurons corresponds to a layer in the hierarchical distribution
- Model learns the weights (i.e. how layers are connected) through training
  - (In theory)

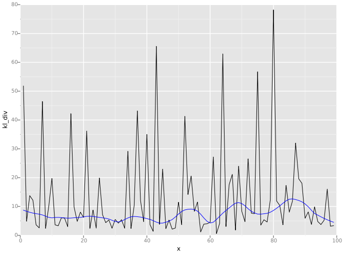


Why is this plausible?

- Requires that neurons sample from exponential family distributions
  - We already model neural noise as exponential family distributions!
- Other computations are just linear sums
- No need to specify tuning curves of input layer or how to integrate information from input layer
- Only uses information from neighboring layers
- Algorithm finds closest approximation with arbitrary exponential-family distributions
- Caveats
  - A lot of reliance on feedback connections
  - Need to be able to semiaccurately modulate mean/variance of synaptic weights/spikes
  - Need to be able to extract mean rate (i.e. integrate) over a number of spikes

Results

- ...None
- Seems to be very difficult to learn distributions
  - Perhaps due to variational assumption about weights
- Tried simplifying models and smarter learning rates (RMSProp)



Conclusions/Future Work

- Potentially interesting, more biologically plausible Bayesian inference AND learning
- Related to recent work on STDP as gradient descent in variational inference by Bengio et al. (2015)
- Future work
  - Compare to C code posted by authors this weekend
  - Try Bayesian filtering approach to gradient descent updates as in Houlsby and Blei (2014)