Bayesian Neural Networks

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Bayesian Methods course

May 25, 2017

Project goal

Aim

Estimate posterior distribution of the model parameters from data

Problem

Monte Carlo sampling is very slow for high-dimensional data

Probabilistic Programming

- Uncertainty in predictions
- Uncertainty in representations
- Regularizations with priors
- Transfer learning
- Hiearchical Neural Networks

Related work

1. Salvatier J, Wiecki T. V., Fonnesbeck C. Probabilistic programming in Python using PyMC3. // *PeerJ Computer Science*. 2016.
2. Blundell C. et al. Weight Uncertainty in Neural Network // *Proceedings of The 32nd International Conference on Machine Learning*. 2015.
3. Kucukelbir A. et al. Automatic Differentiation Variational Inference // *arXiv preprint arXiv:1603.00788*. – 2017.

Problem Statement

Bayes Theorem

$$p(\theta|X) = \frac{p(X|\theta)p(\theta)}{p(X)}$$

Frequentist approach

$$\theta^* = \arg\max_{\theta} p(\theta|X) = \arg\max_{\theta} p(X|\theta) + p(\theta)$$

Monte Carlo approach

- Metropolis Hasting
- Gibbs sampling
- No-U-Turn Sampling (NUTS)

Variational Inference

$$\ln p(X) = \mathrm{KL}(q||p) + \mathrm{ELBO}(q)$$

$$\mathrm{KL}(q||p) = \int q(\theta) \ln \frac{q(\theta)}{p(\theta|X)} d\theta; \quad \mathrm{ELBO}(q) = \int q(\theta) \ln \frac{p(X,\theta)}{q(\theta)} d\theta$$

Problem

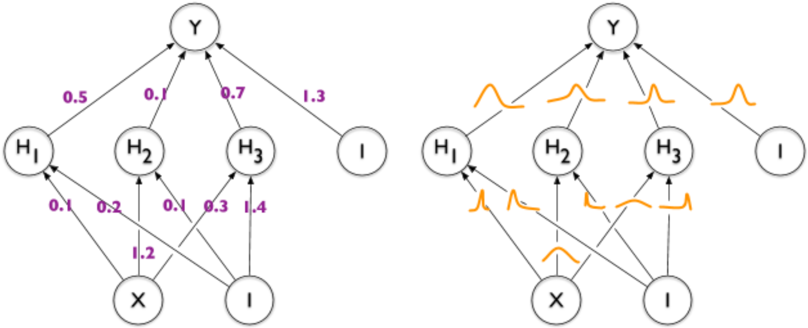
minimization of $\mathrm{KL}(q||p) \Leftrightarrow$ maximization of $\mathrm{ELBO}(q)$

ADVI

- Transformation of constrained variables
- $q(\theta)$ comes from parametric family (usually $\mathcal{N}(\mu, \mathrm{diag}(\sigma^2))$)
- Stochastic optimization
- Integral differentiation $\Rightarrow$ reparametrization trick

Neural Networks

- **Neural networks** predict values of parameters by fitting complex model on the huge dataset
- **Bayesian Neural Networks** predict the parameters distributions



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