Bayesian Semisupervised Learning with Deep Generative Models

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Objectives

The project is concerned with developing a deep generative model (DGM) for semi-supervised and active learning. The main objectives are:

- Develop a DGM with a discriminative component
- Accommodate semi-supervised learning
- Extend to Bayesian training and active learning

Variational Inference in Deep Models

Variational inference has enabled efficient training of large scale generative models. An example is the Variational autoencoder (VAE) (depicted for semi-supervised learning).

A parameterized approximate posterior \( q(z|x) \) is introduced, and the ELBO is maximized. In the case of a VAE, we have:

\[
\mathcal{L}_{\text{vae}} = \mathbb{E}_{q(z)} \left[ \log p_{\theta}(x|z) \right] - D_{KL} \left( q(z|x) \parallel p_{\theta}(z) \right)
\]

\[
\approx \frac{1}{T} \sum_{t=1}^{T} \log p_{\theta}(x|z^{(t)}) - \log q(z^{(t)}|x) + \log p_{\theta}(z^{(t)})
\]

where we have introduced the factorized approximation:

\[
q_{\phi}(z, y|x) = q_{\phi}(z|x) q_{\phi}(y|x)
\]

We can extend the model to Bayesian training. The ELBO becomes:

\[
\mathcal{L}^B(\theta, \phi, x, y) = \mathbb{E}_{q_{\phi}} \left[ \log p_{\theta}(x, y|z, w) \right] - D_{KL} \left( q_{\phi}(z|x, y) \parallel p(z) \right) - D_{KL} \left( q_{\phi}(w) \parallel p(w) \right)
\]

We can use the reparameterization trick for sampling \( w \sim q(w) \), and optimize as previously. Accounting for model uncertainty opens the door to active learning.

Future Work

The model has been implemented and experimented with in limited settings. Future goals are:

- Improve performance in the semi-supervised setting
- Stabilize Bayesian training
- Experiment with benchmark datasets
- Implement and explore active learning schemes

References