ENM 360: Introduction to Data-driven Modeling

Lecture #25:Variational inference



Bayesian inference

$$p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta|)p(\theta)}{p(\mathcal{D})} = \frac{p(\mathcal{D}|\theta|)p(\theta)}{\int p(\mathcal{D}|\theta|)p(\theta)d\theta}$$

MCMC: cleverly construct a Markov Chain whose stationary distribution approximates $p(\theta|\mathcal{D})$

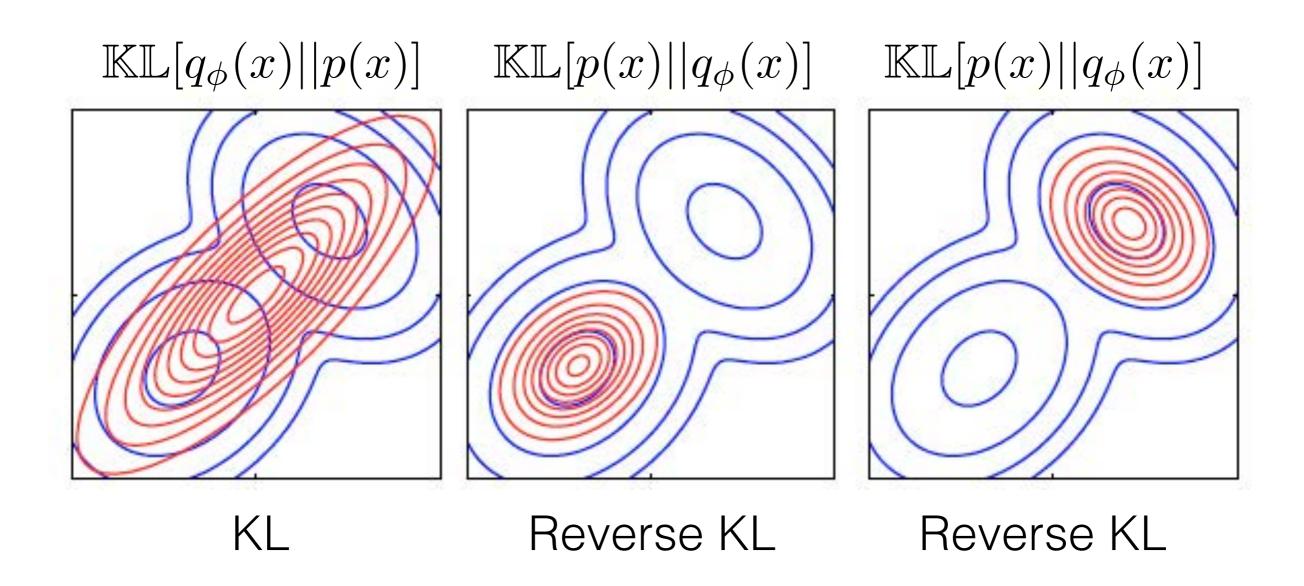
- It's asymptotically exact, meaning that if we run the chain long enough, we should get samples from the posterior distribution
- Tuning MCMC can be tricky
- In practice requires thousands of samples, and each draw involves multiple (likely tens, perhaps hundreds) of evaluations of the un-normalised log posterior.
- This is fine for many models, but sometimes it just takes too long.
- It is hard to scale to large data-sets and models with many parameters and singular posteriors (e.g. deep learning).

Variational inference

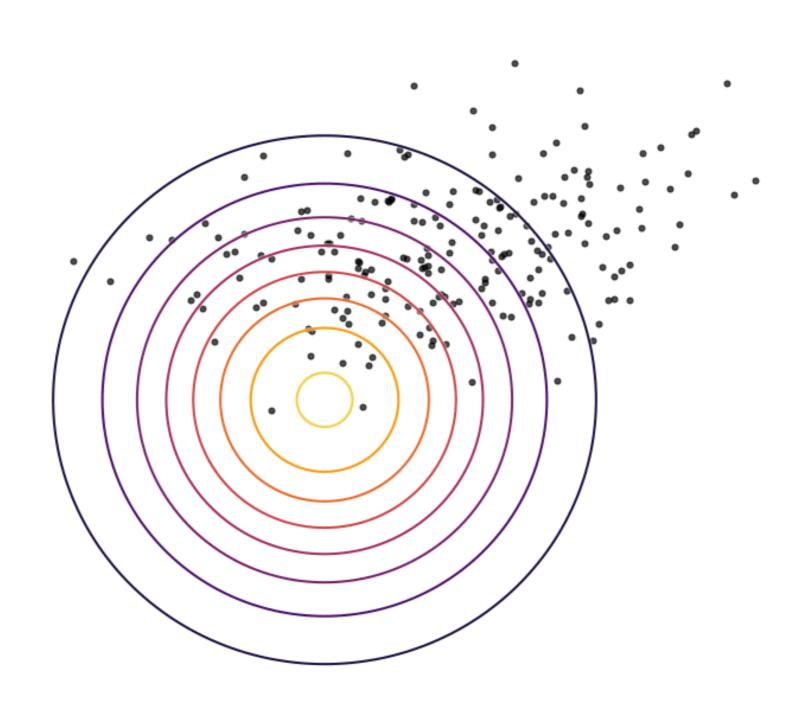
$$p(\theta|\mathcal{D}) = \frac{p(\mathcal{D}|\theta|)p(\theta)}{p(\mathcal{D})} = \frac{p(\mathcal{D}|\theta|)p(\theta)}{\int p(\mathcal{D}|\theta|)p(\theta)d\theta}$$

- Variational inference is another way to do Bayesian inference.
- The idea is that we'll approximate the posterior distribution with a family of distributions that is easy to work with.
- It will provide us with a set of tools for transforming the sampling problem (integration) to an optimization problem, that can be scaled to large models (i.e. with many parameters) and large data-sets.
- It also tends to favor approximations that underestimate the variance, and it usually will result in approximate distributions that get the means right but underestimate the variance.

Variational inference



Variational inference



Probabilistic programming

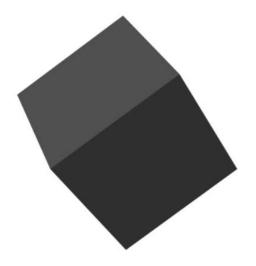




http://mc-stan.org/

https://github.com/pymc-devs/pymc3

Edward



http://edwardlib.org/



https://github.com/uber/pyro