ENM 531: Data-driven Modeling and Probabilistic Scientific Computing

Lecture #9: Variational inference

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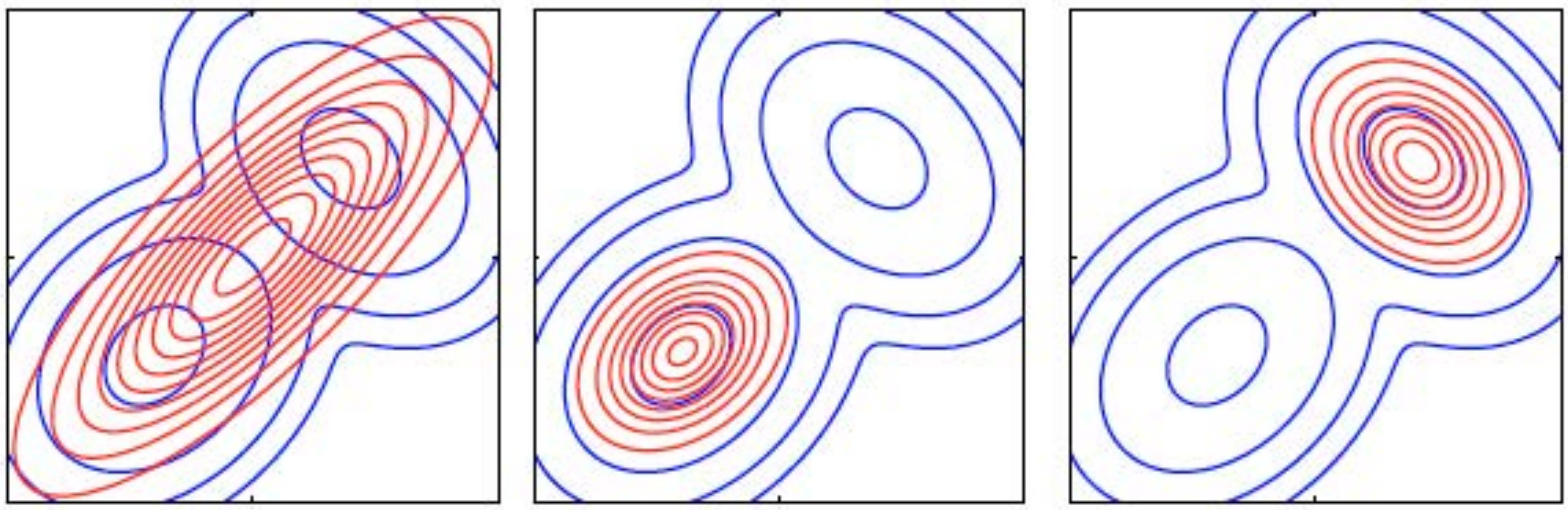
Variational inference

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

- Variational inference provides a computational framework for approximate 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.

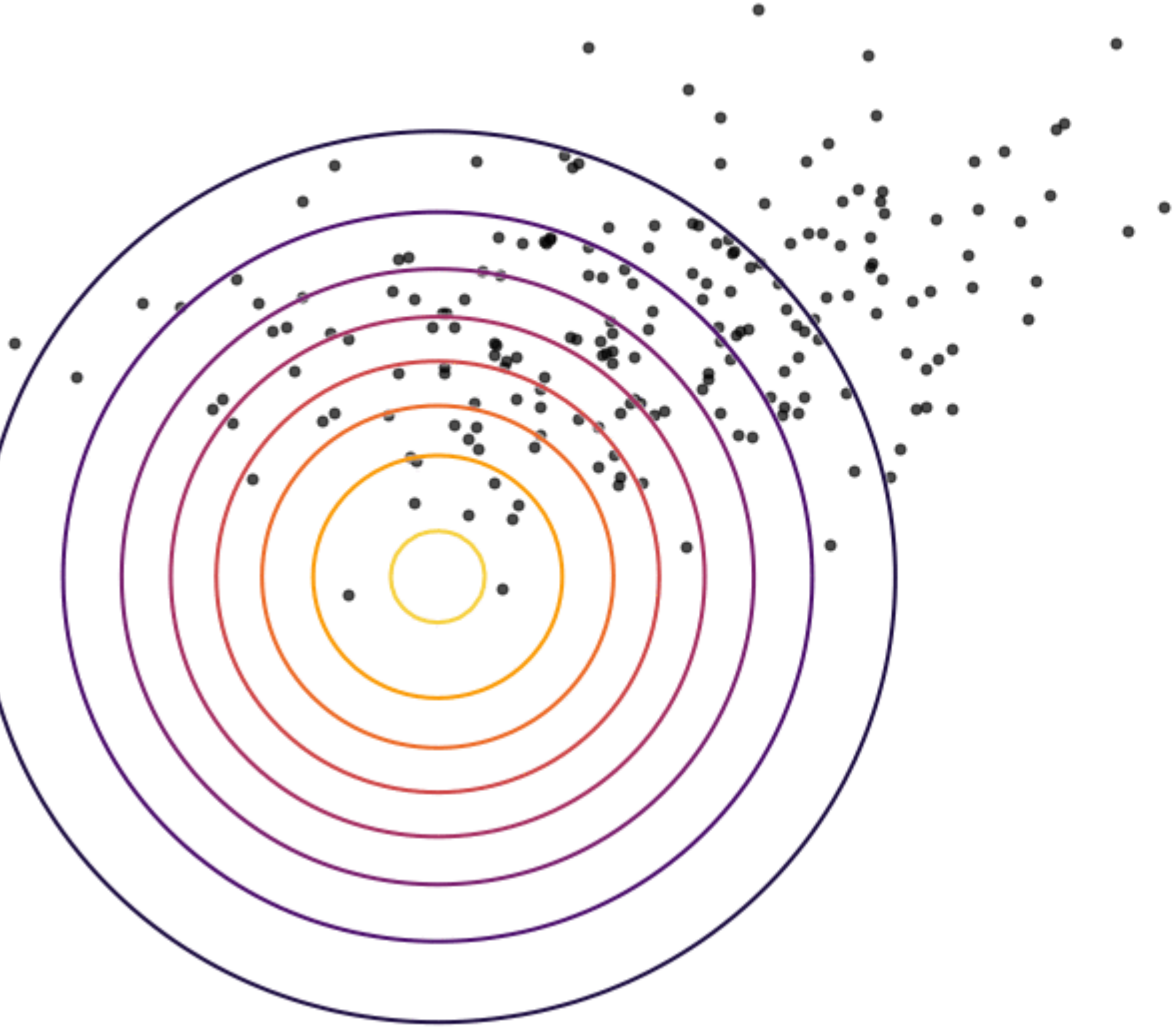
Variational inference

$\mathbb{KL}[q_\phi(x)||p(x)]$ $\mathbb{KL}[p(x)||q_\phi(x)]$ $\mathbb{KL}[p(x)||q_\phi(x)]$



KL Reverse KL Reverse KL

Variational inference



Probabilistic programming

Stan

http://mc-stan.org/

PyMC3

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

Edward

http://edwardlib.org/

https://github.com/uber/pyro