Lecture 27: Physicsinformed deep neural networks

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Sequential Monte Carlo

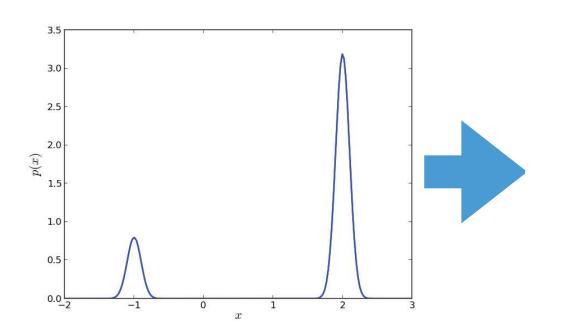


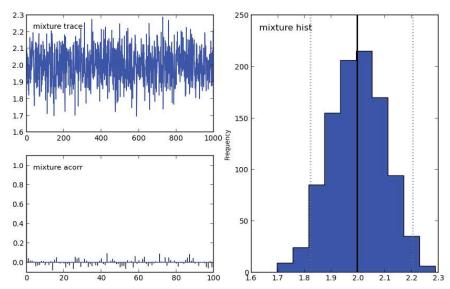
Limitations of MCMC

- Slow convergence.
- Trouble with multiple modes.
- Hard to calculate the normalization constant.



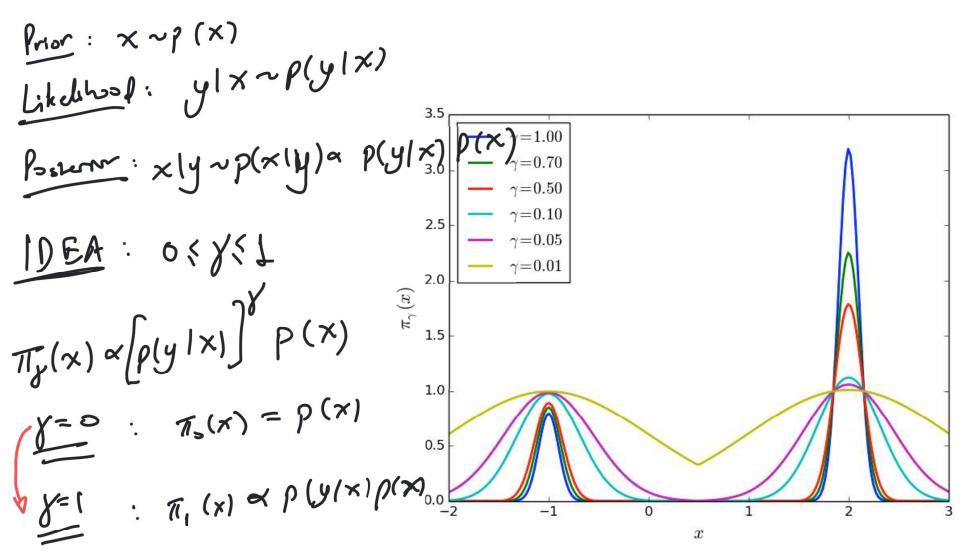
Example: Probability with two modes







Bridging densities





Sequential particle

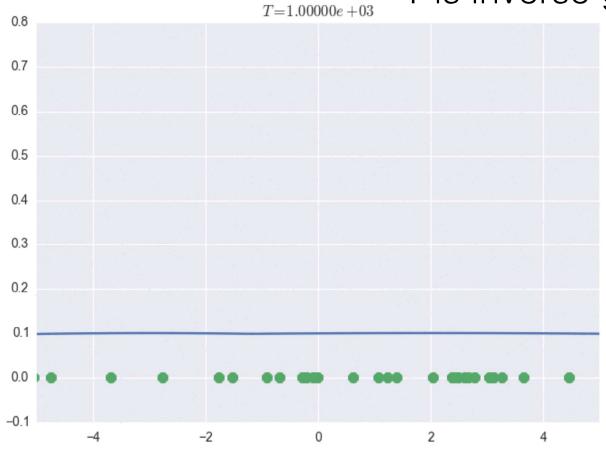
approximations

$$N = \# \text{ of power cles } (s = nples)$$
 $Y = 0 : X_0^{(i)} \sim p(X), v_0^{(i)} = \frac{1}{N}, \begin{cases} (X_1^{(i)} \vee v_0^{(i)}) \end{cases}_{i=1}^{N}$
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 $Y = 0 : X_0^{(i)} \sim p(X), v_0^{(i)} \sim p(X), v_0^$

Bilionis, I., et al. (2015). "Crop physiology calibration in the CLM." Geoscientific Model <u>Development</u> 8(4): 1071-1083.

Example

T is inverse gamma





Estimating the normalization constant

$$P(x|y) = \frac{p(y|x)p(x)}{2}$$

$$P(x|y) = \int p(y|x)p(x)dx$$

$$P(x) = \int p(y|x)p(x)$$

$$P(x) = \int p(x)p(x)$$

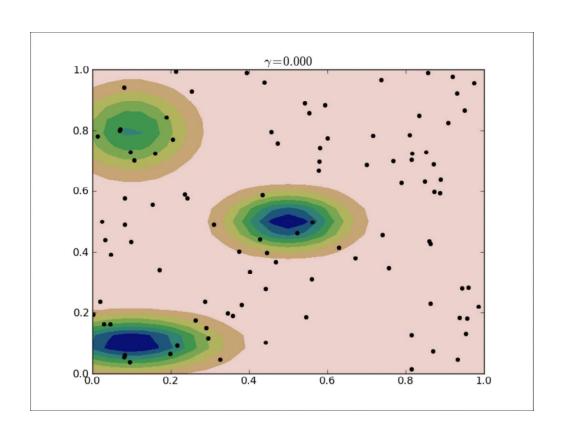
$$P(x) = \int p(x)$$

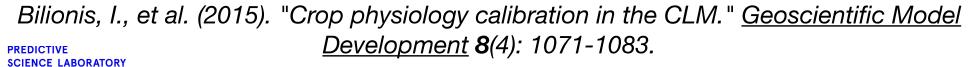
$$P(x)$$



Resampling

- Some particle weights become too small.
- Every once in a while we can through them away and redistribute the weights.
- This is resampling.

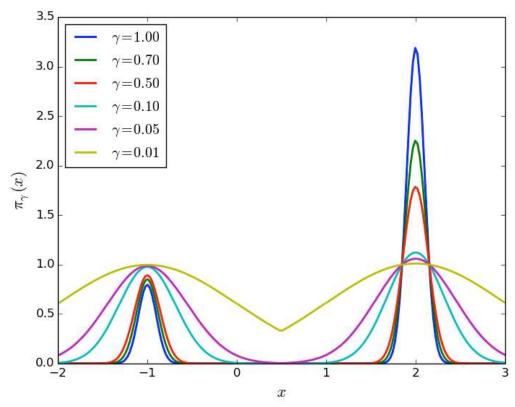


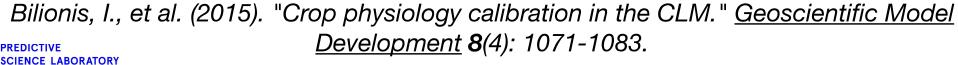


How fast should you change

 γ ?

- You can just pick a fixed schedule.
- Or you can adaptively pick it.





The complete SMC algorithm

- Build initial particle approximation (sample the prior).
- Find the next gamma.
- Resample if needed.
- Sample particle positions at new gamma starting from the old particles.

