Lecture 03 - Gibbs sampling

- · Metropolis-Hastings is good, but a bit slow.
- · Would be nice to have a way of always accepting the next step => faster mixing.

If you know the conditionals of your function, you can use Gibbs sampling to achive this.

=) need to know $p(x, | x_2 = x_2^{(i)})$ and $p(x_2 | x_1 = x_1^{(i)})$

We will show leter that Gibbs sampling gives us indeed samples from our target distribution, but first:

How does Gibbs sampling work?

- · choose a random initialization [x(0), x(0)] ~ Uniform
- Sample: $X_{i}^{(i+1)}$ from $p(x_{1} | x_{2} = X_{2}^{(i)})$ $X_{2}^{(i+1)}$ from $p(x_{2} | x_{1} = X_{1}^{(i+1)})$

Let's look at an example:

This looks fairly complicated, but the conditionals are actually rather simple:

$$f(x,y) = x^{2} \cdot exp[-xy^{2} - 4x] \cdot exp[-y^{2} + 2y]$$

$$= x^{2} \cdot exp[-x(y^{2} + 4)] \cdot g(y)$$

$$= g(y) \cdot Gamma(3, y^{2} + 4)$$

=> f(X14) can be sampled from a Gamma distribution

Now the other way around:

$$f(x,y) = x^2 \exp[-y^2(1+x) + 2y] \cdot \exp[-4x]$$

= $e \times p[-y^2(1+x) + 2y] \cdot g(x)$

Completing the square:

$$= \exp\left[-\frac{1}{x+1}\right] \cdot \exp\left[\frac{1}{x+1}\right] \cdot \exp\left[\frac{1}{x+1}\right] \cdot S(x)$$

$$= \exp\left[\left(-\frac{1}{x+1} + \frac{2y}{x+1} - \frac{1}{(x+1)^{2}}\right) \cdot (x+1)\right] \cdot g'(x)$$

$$= \exp\left[-\left(y - \frac{1}{x+1}\right)^{2} \cdot (x+1)\right] \cdot g'(x)$$

=) f(Y|X) can be sampled from a normal distribution $\mathcal{N}\left(\frac{1}{x+1}, \frac{1}{\sqrt{x+1}}\right)$

PYTHON EXAMPLE