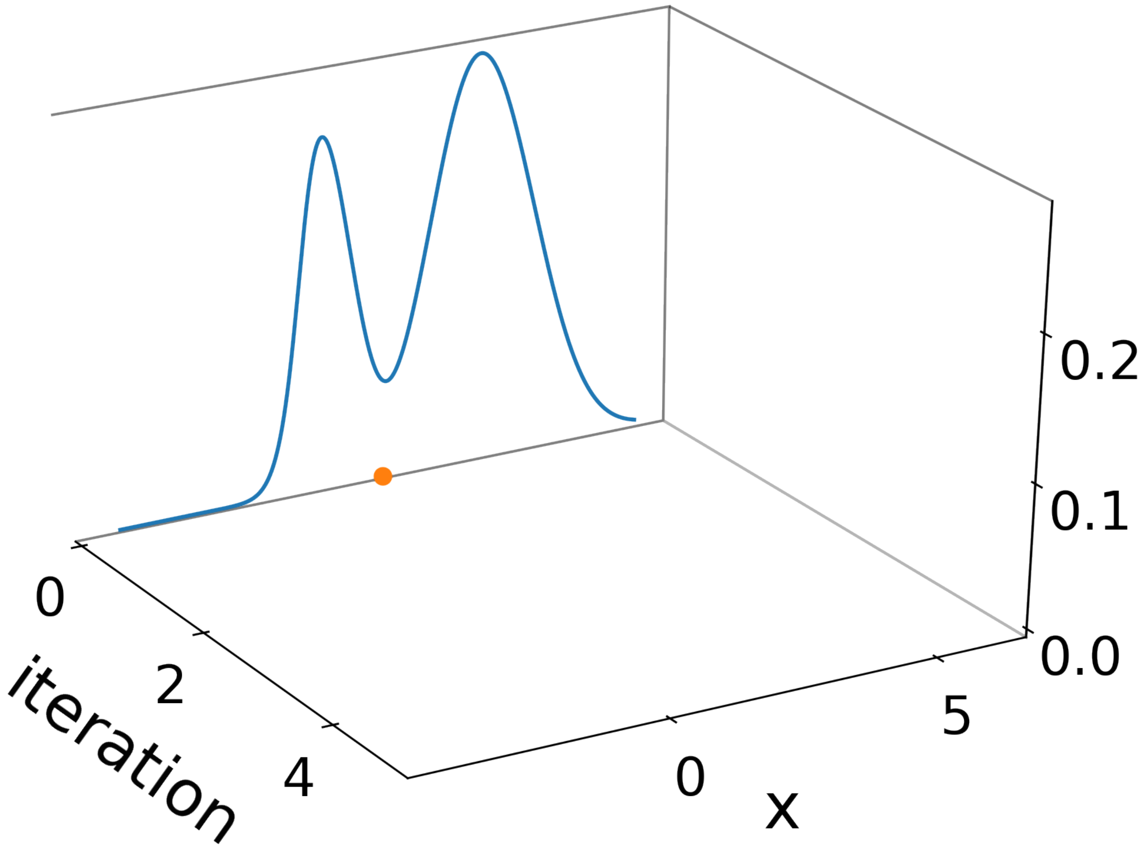
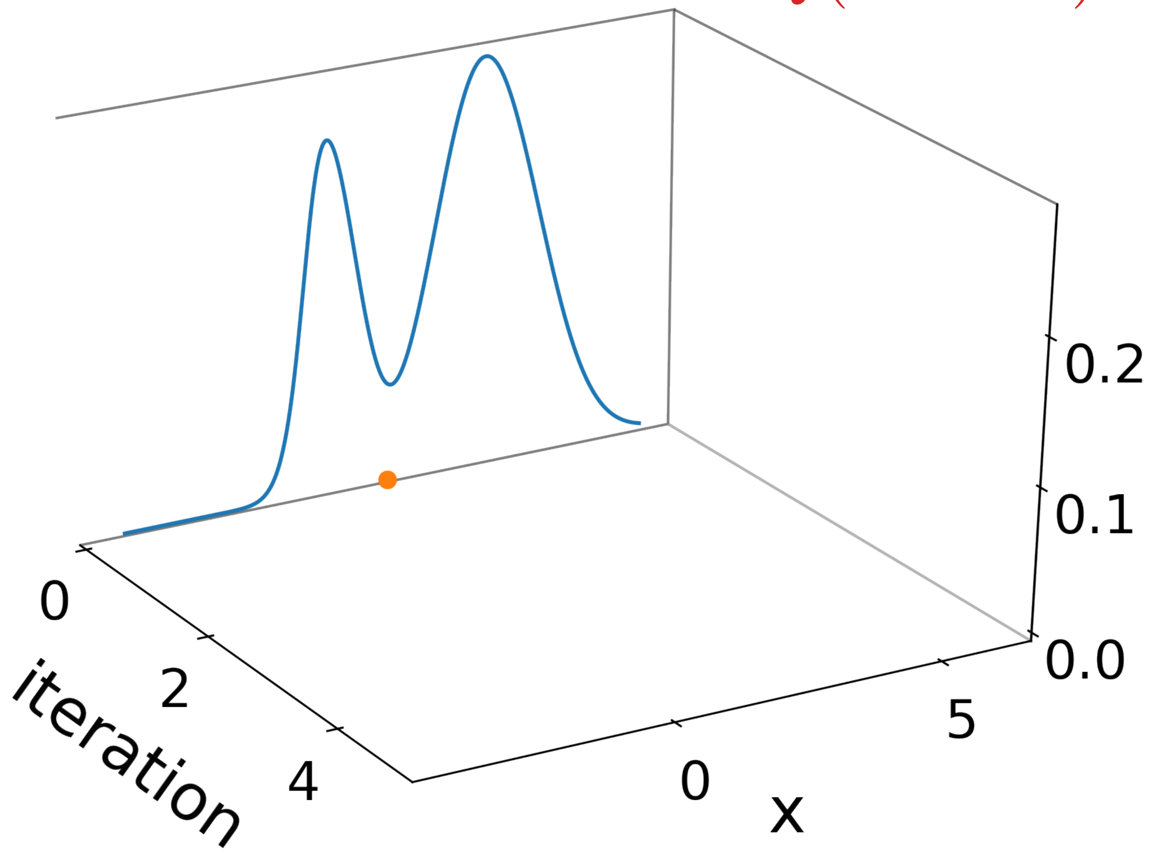
Demo



Demo

$$Q(x \to x') = \mathcal{N}(x, 1)$$



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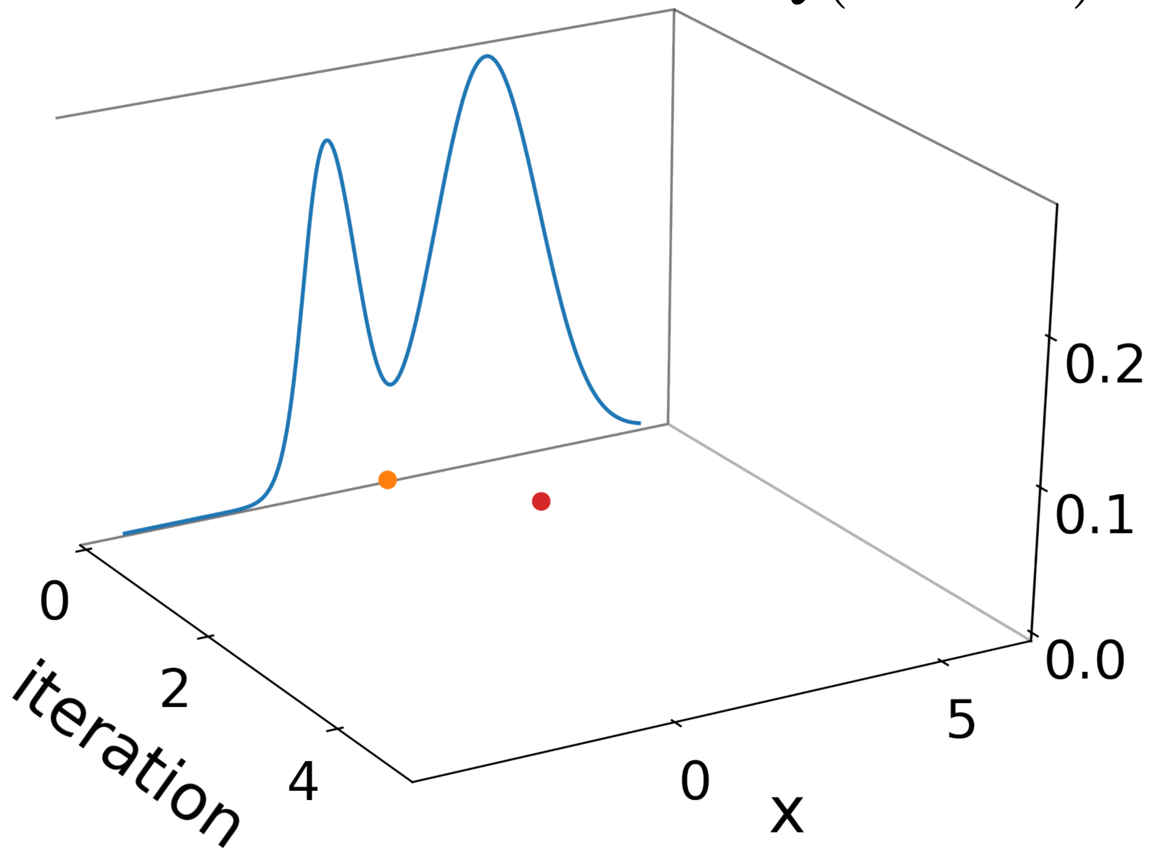

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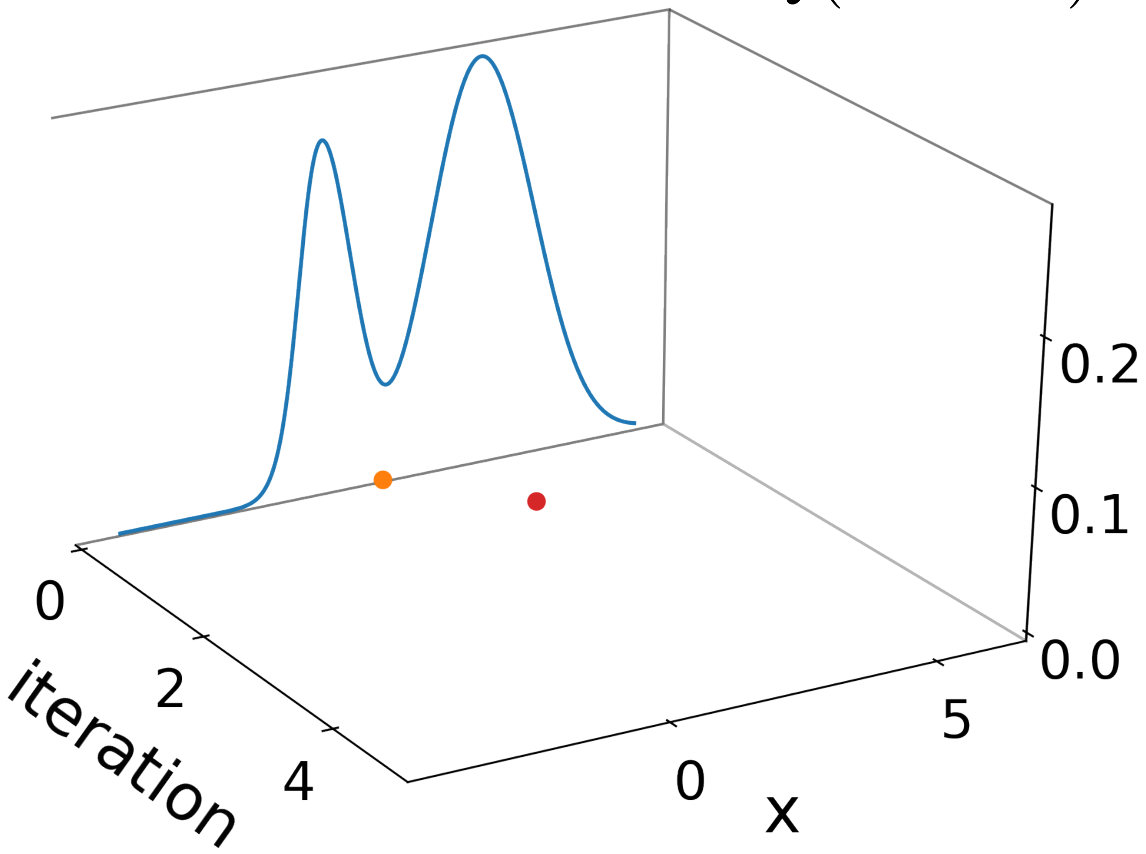

$$A(x \to x') = \min\left(1, \frac{\pi(x')Q(x' \to x)}{\pi(x)Q(x \to x')}\right)$$

Demo

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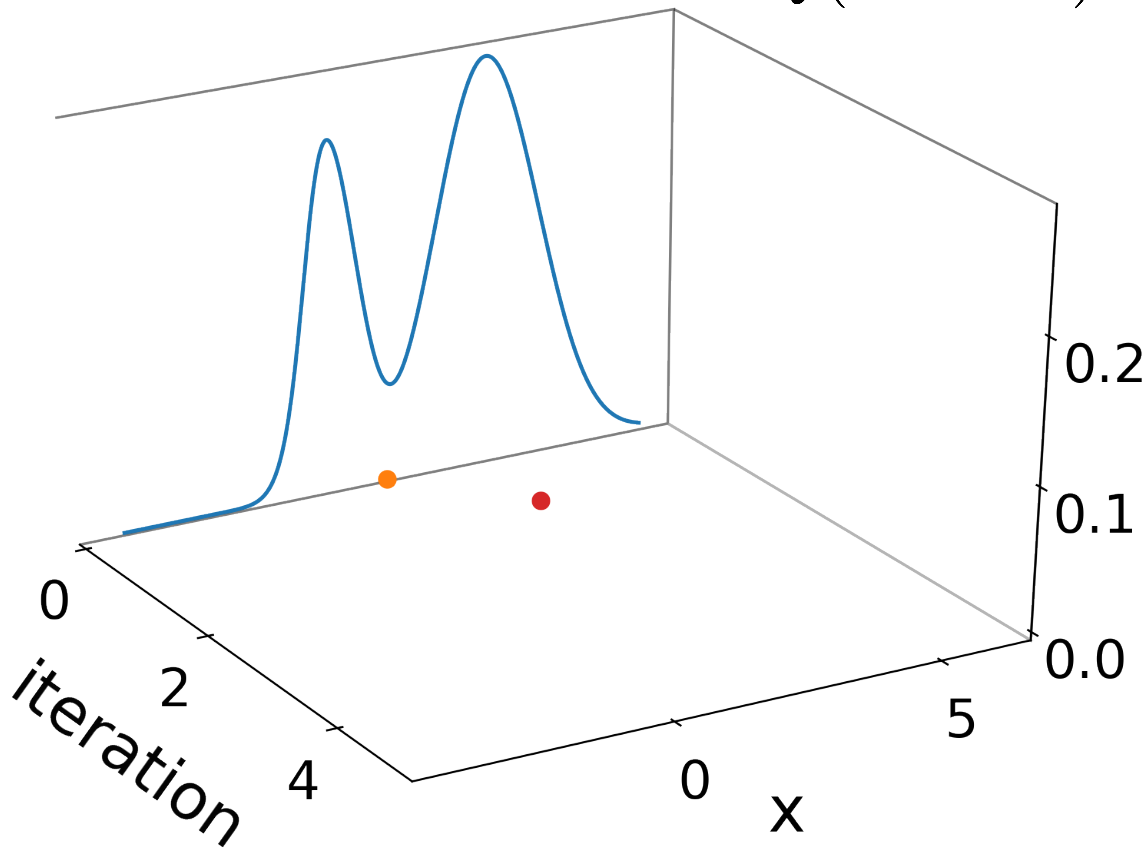

$$A(x \to x') = \min\left(1, \frac{\pi(x')Q(x' \to x)}{\pi(x)Q(x \to x')}\right) = \min\left(1, \frac{\pi(x')}{\pi(x)}\right)$$

Demo

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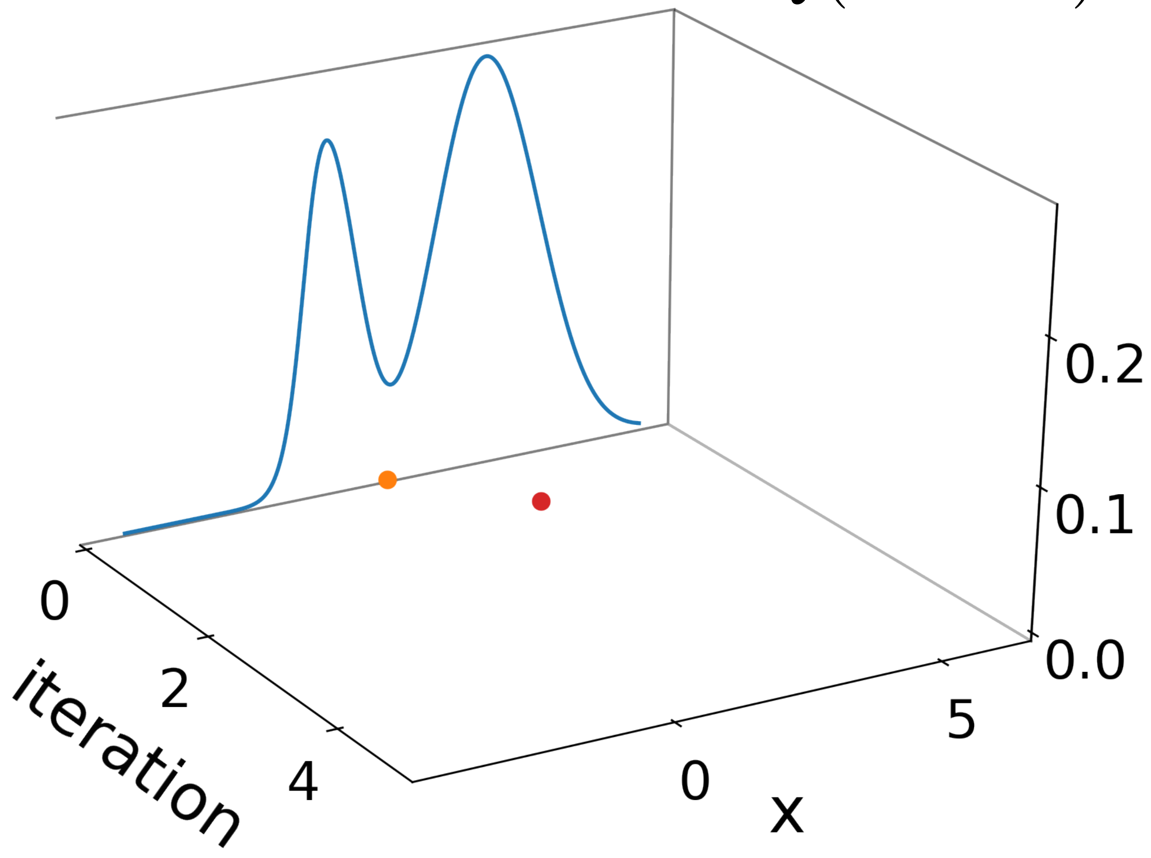

$$A(x \to x') = \min\left(1, \frac{0.27}{0.07}\right) = \min(1, 3.87)$$

Demo

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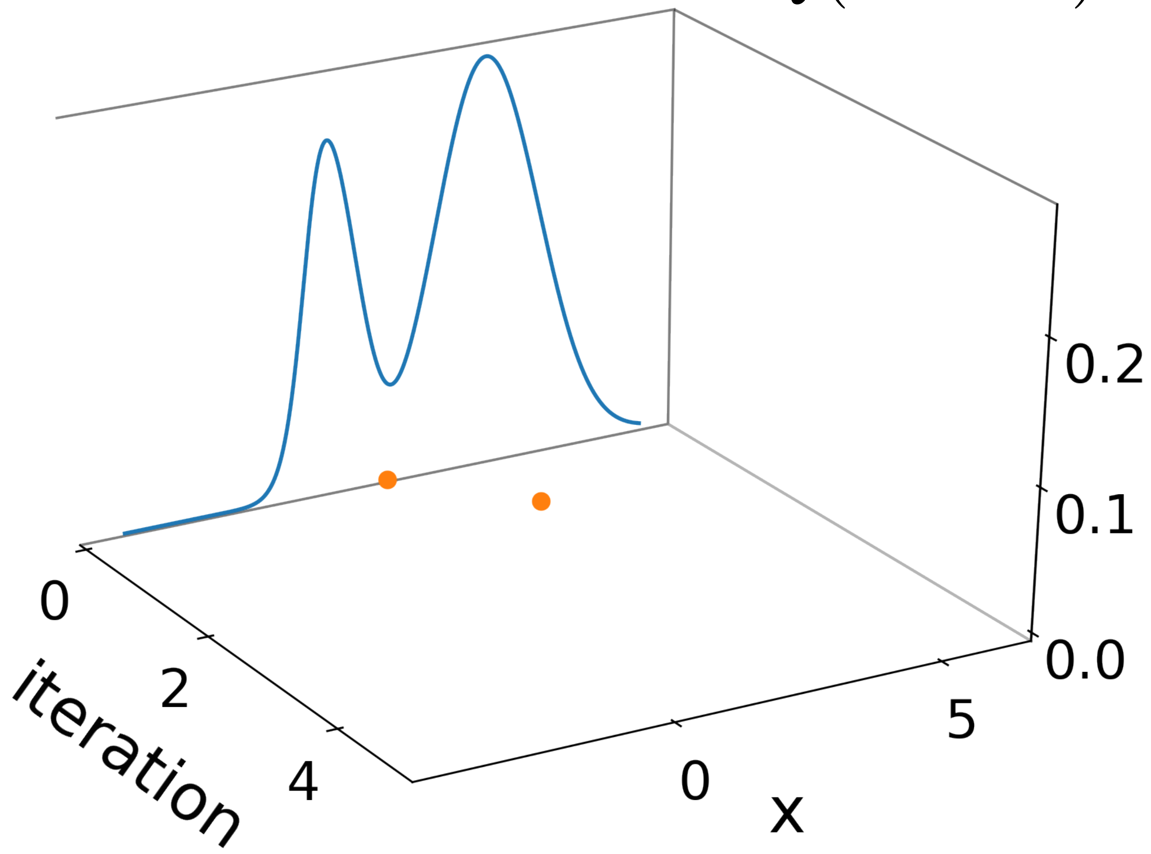

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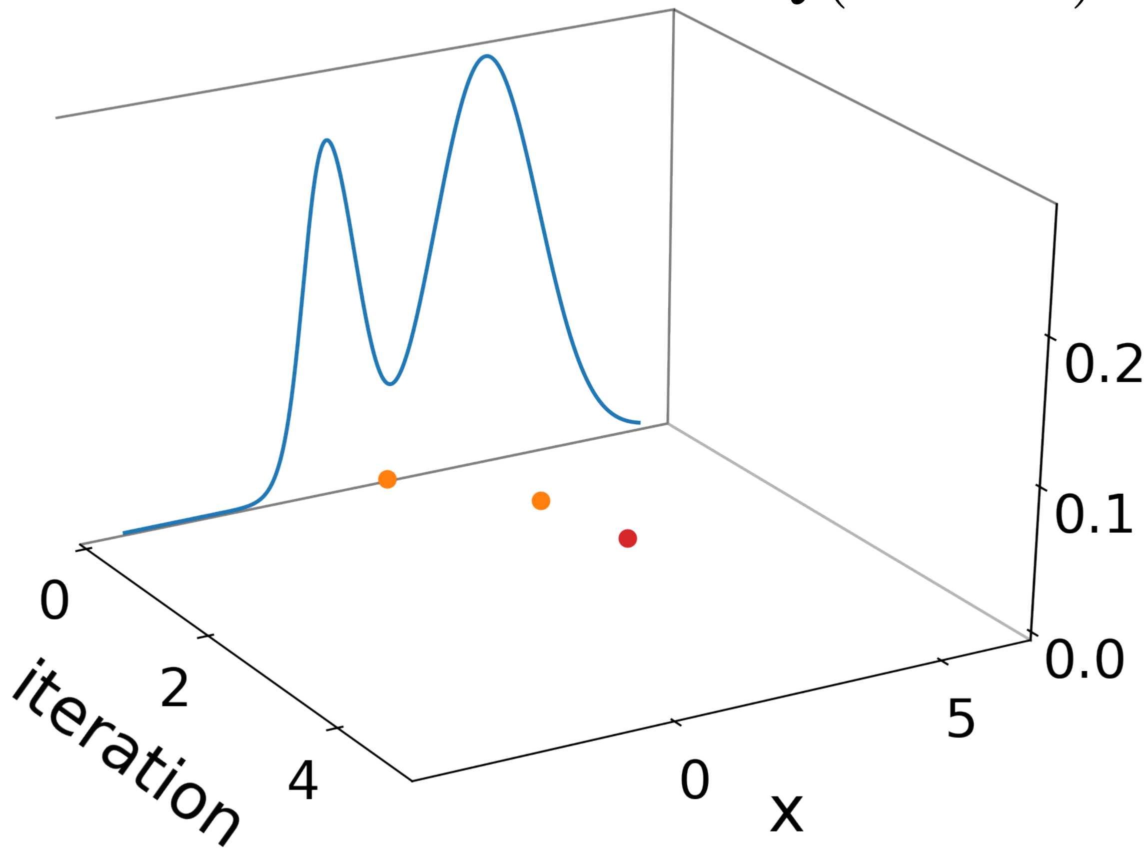

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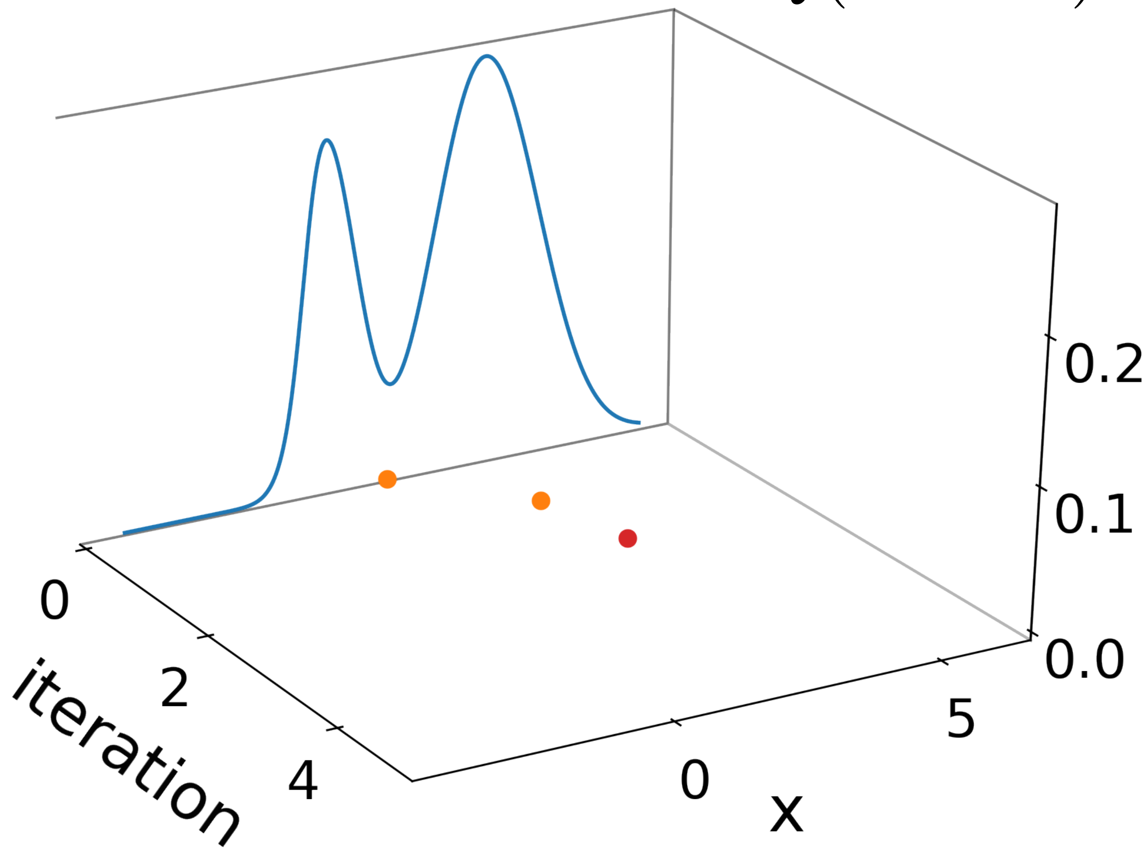

$$A(x \to x') = \min\left(1, \frac{0.28}{0.27}\right) = \min(1, 1.01)$$

Demo

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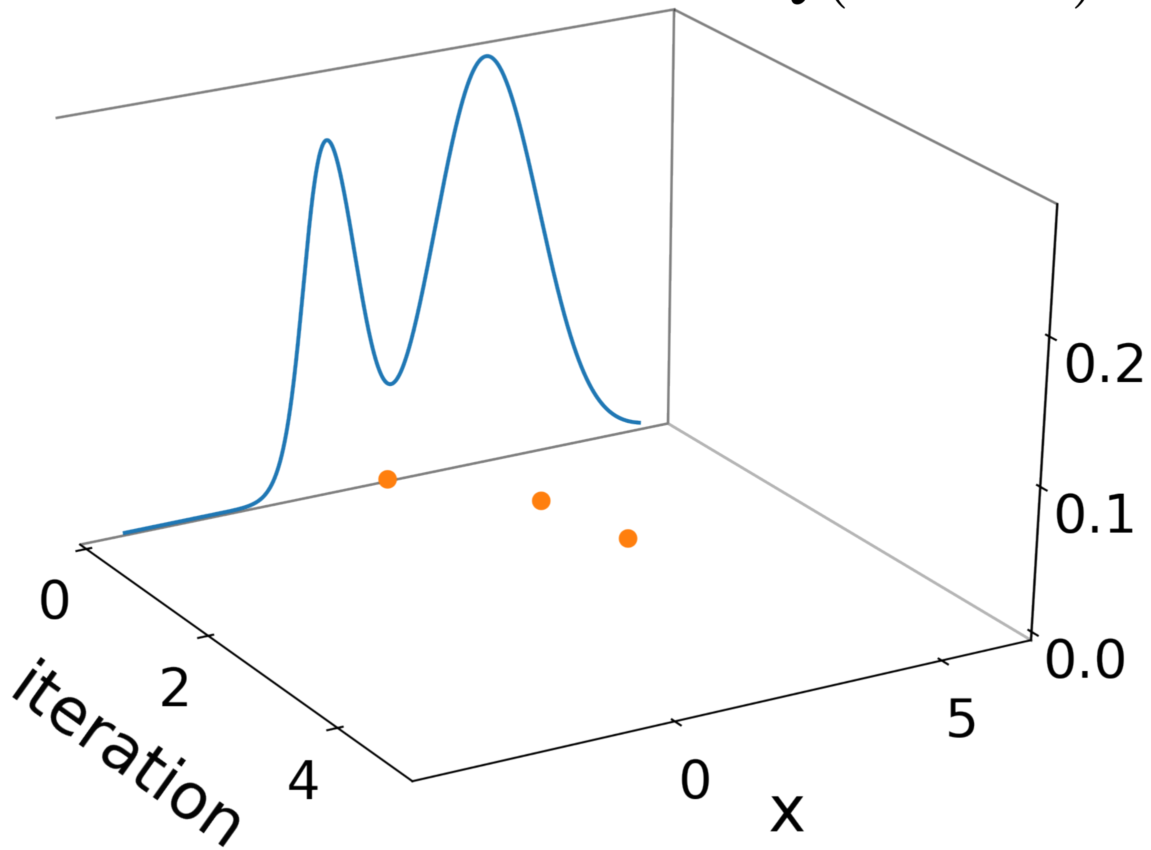

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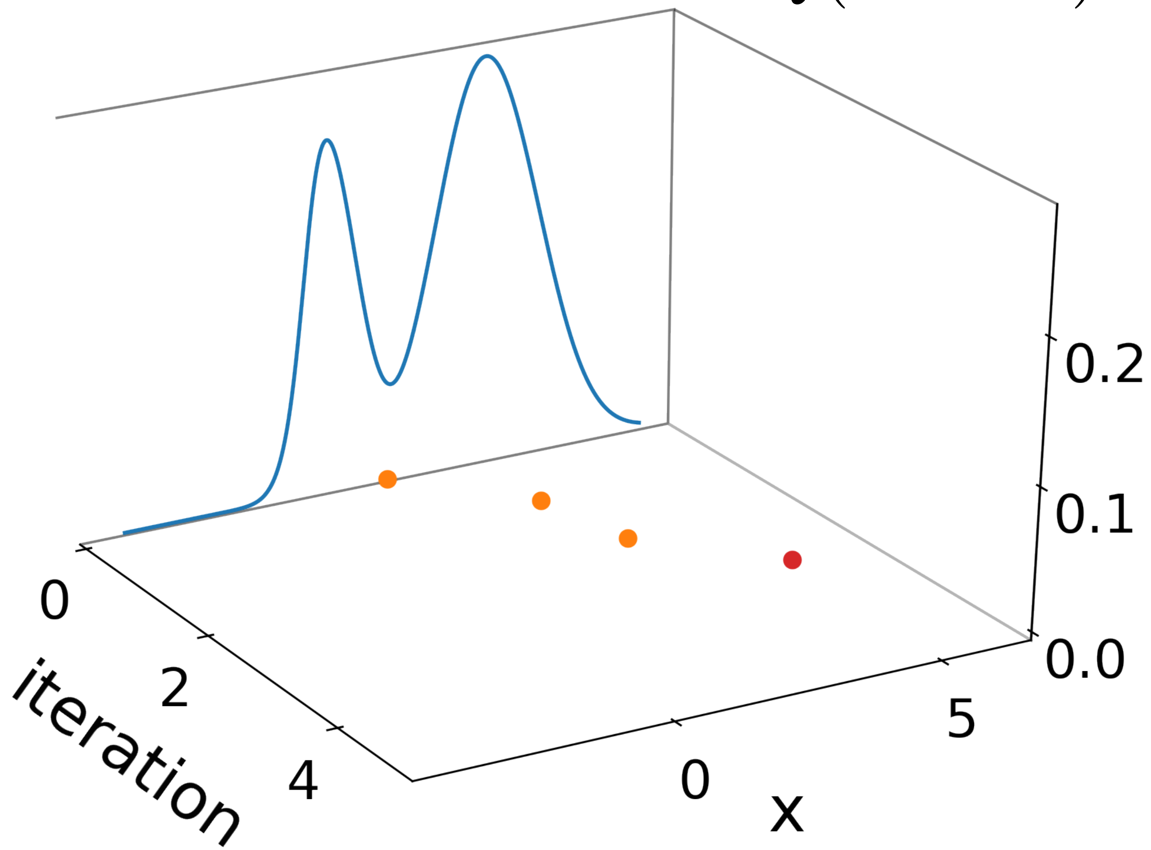

$$A(x \to x') = \min\left(1, \frac{0.04}{0.28}\right) = \min(1, 0.13)$$

Demo

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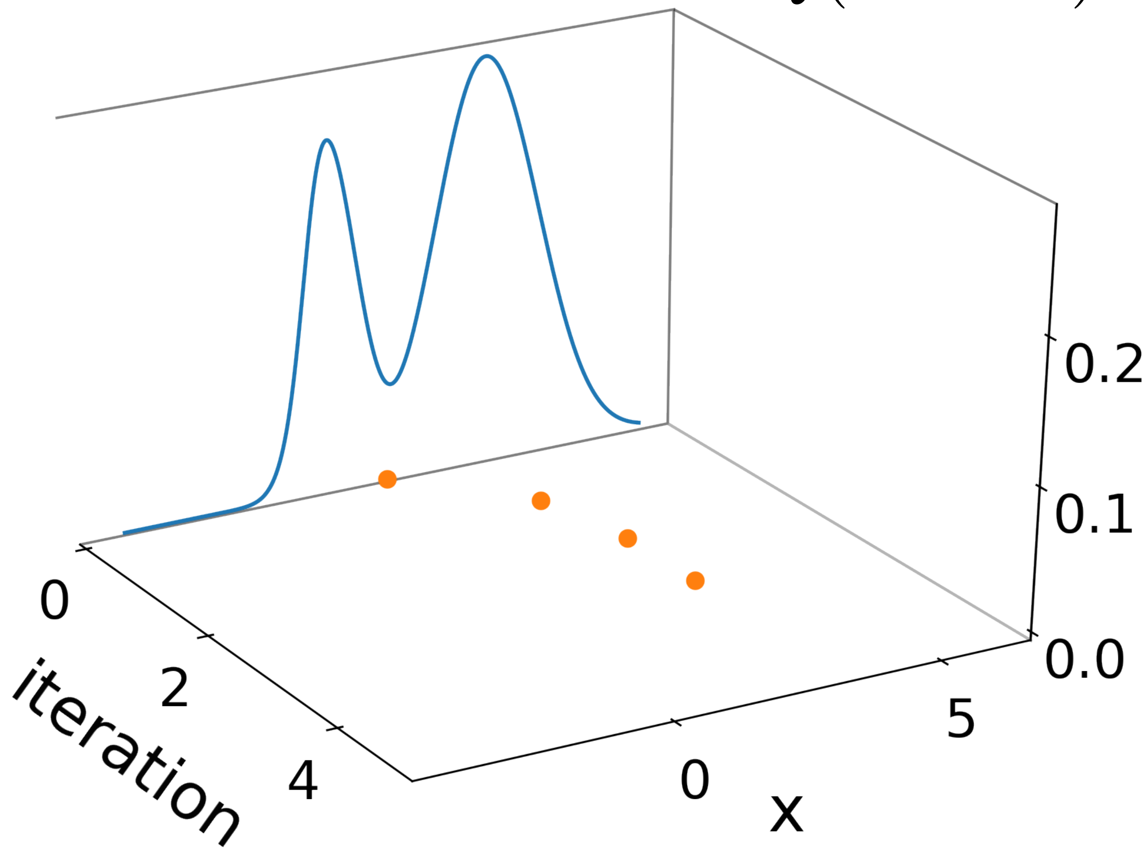

$$A(x \to x') = \min\left(1, \frac{0.04}{0.28}\right) = \min(1, 0.13)$$

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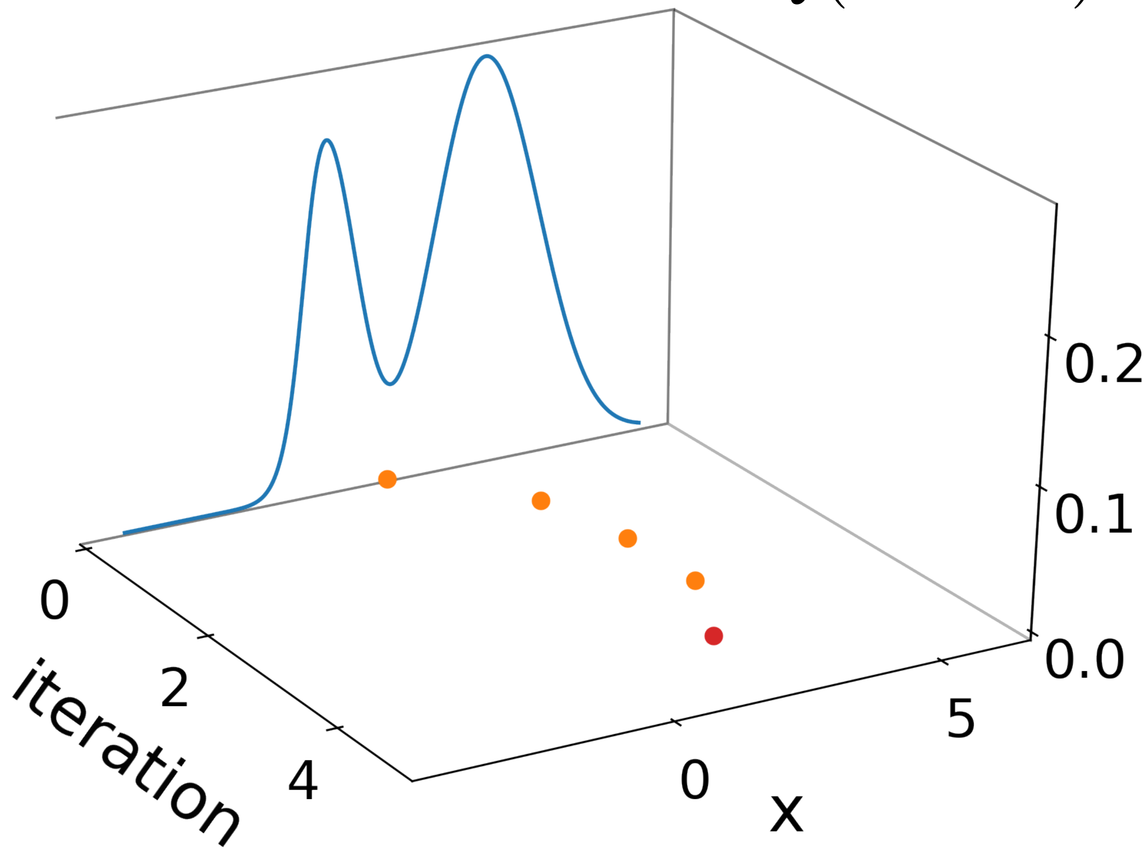
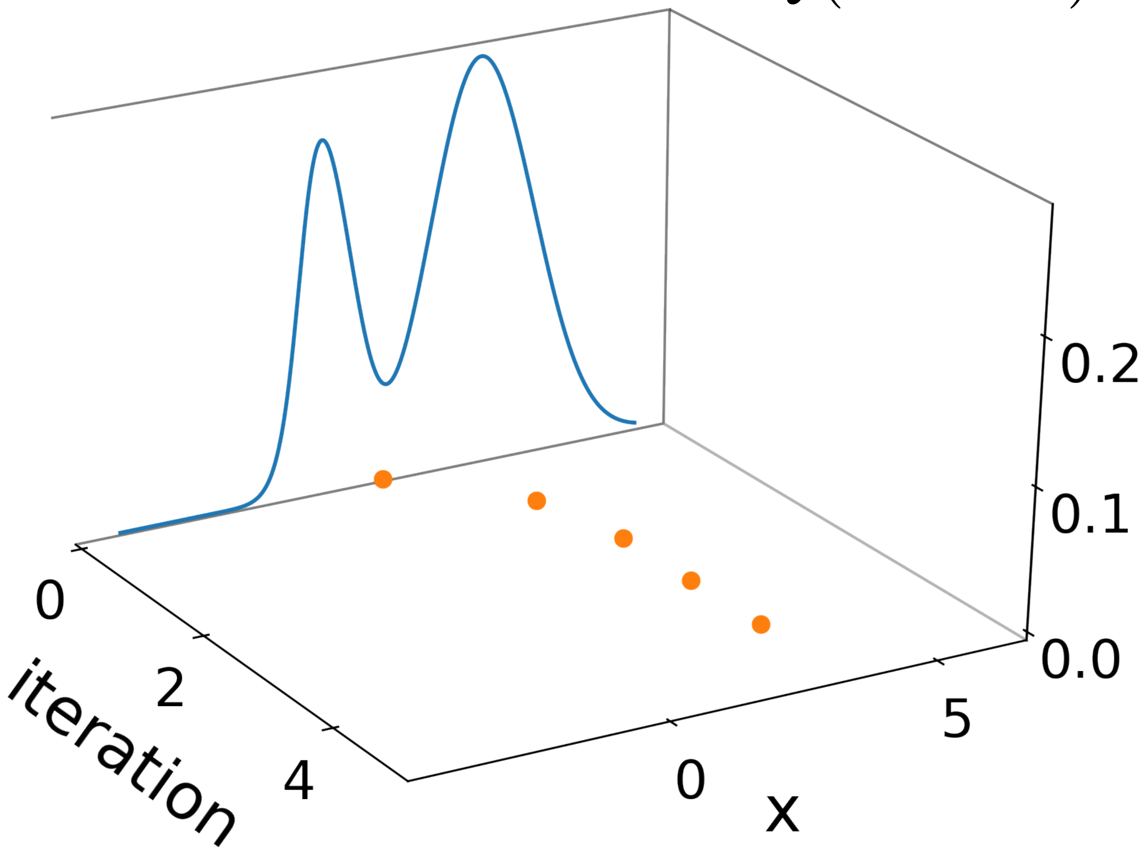


$$A(x \to x') = \min\left(1, \frac{0.20}{0.28}\right) = \min(1, 0.73)$$

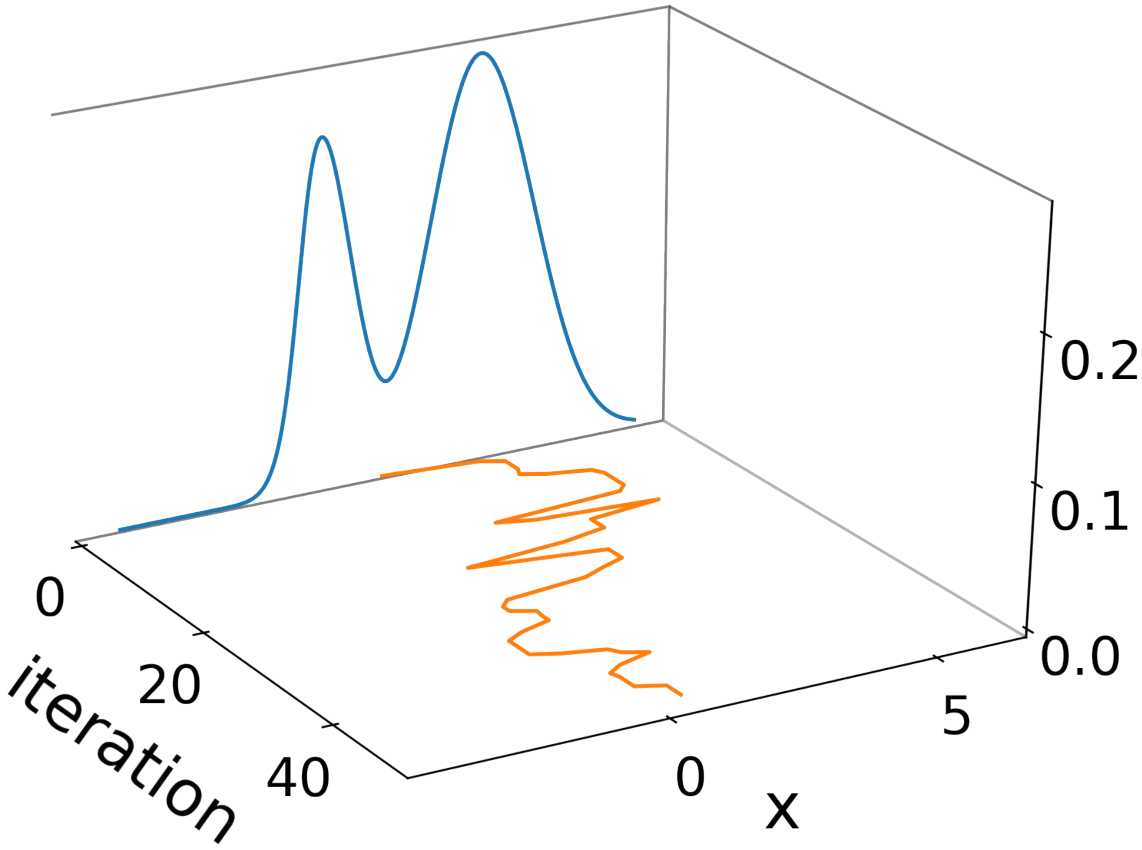
Demo

$$Q(x \to x') = \mathcal{N}(x, 1)$$



$$A(x \to x') = \min\left(1, \frac{0.20}{0.28}\right) = \min(1, 0.73)$$

Demo



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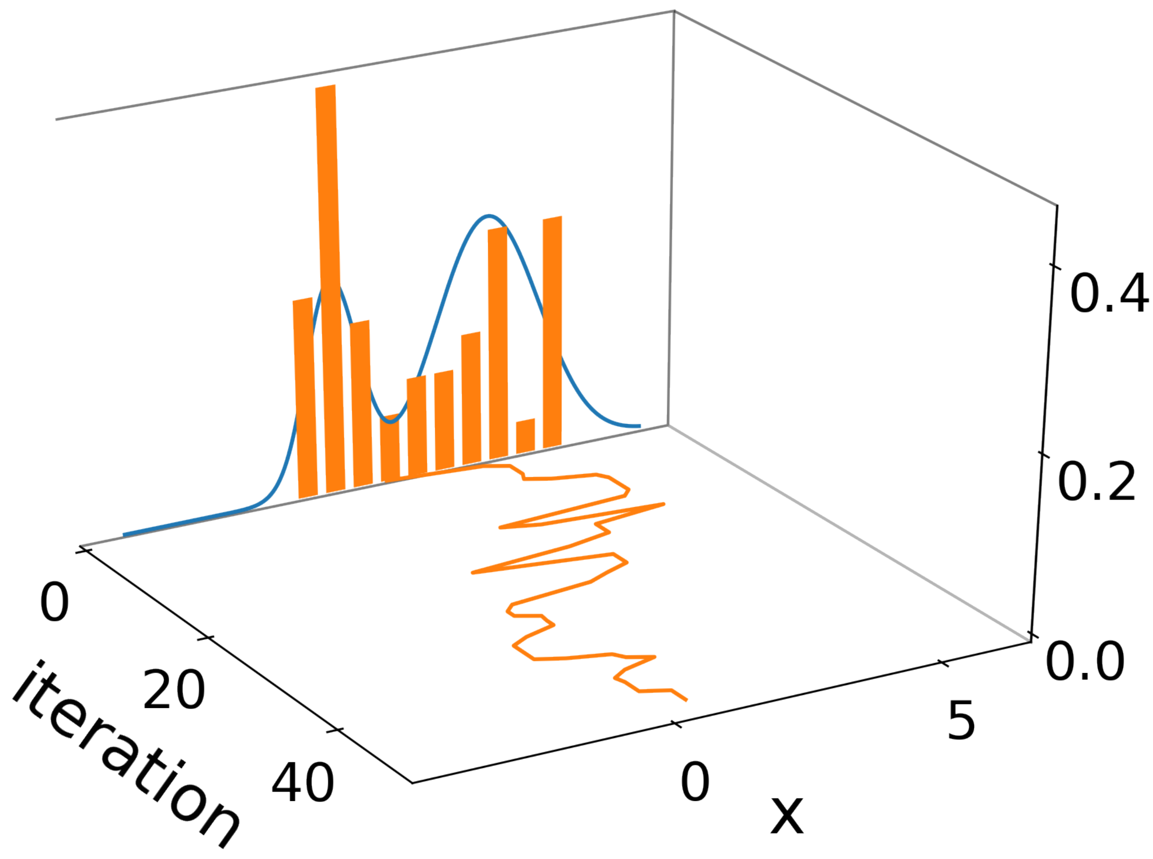

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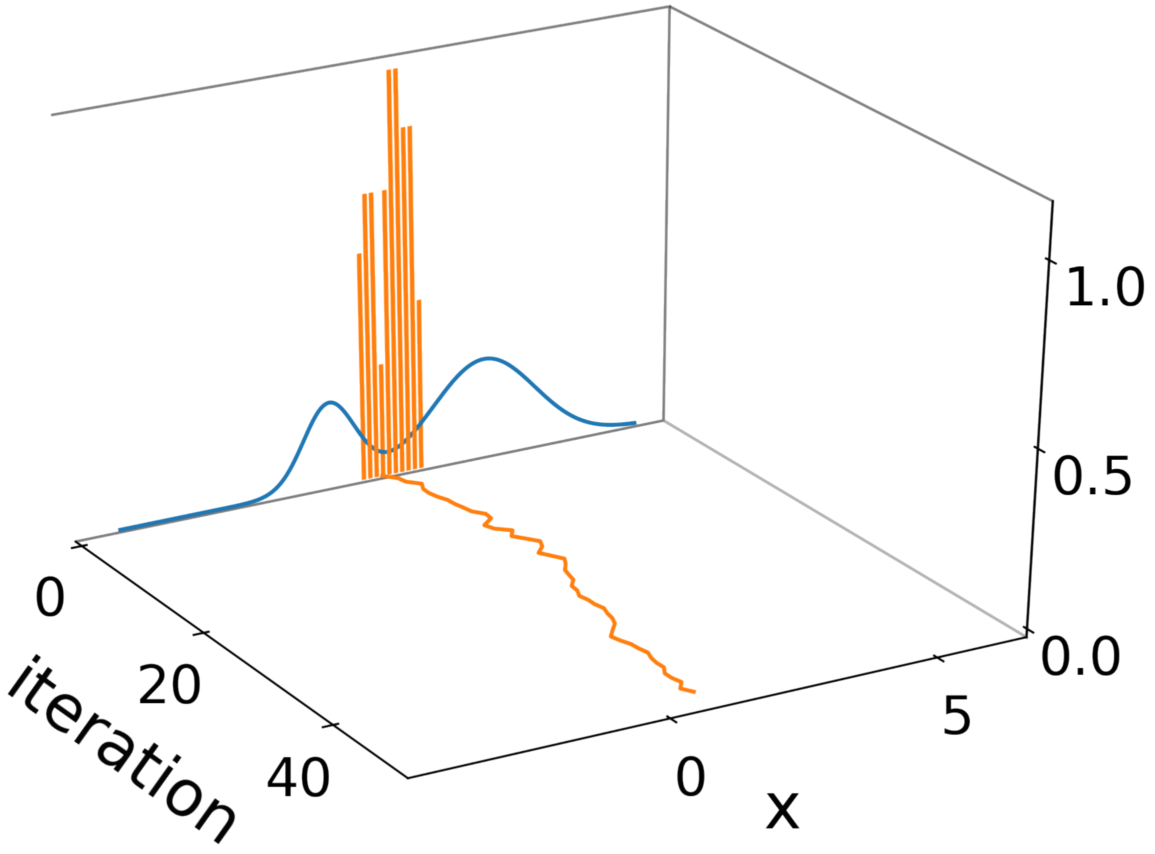
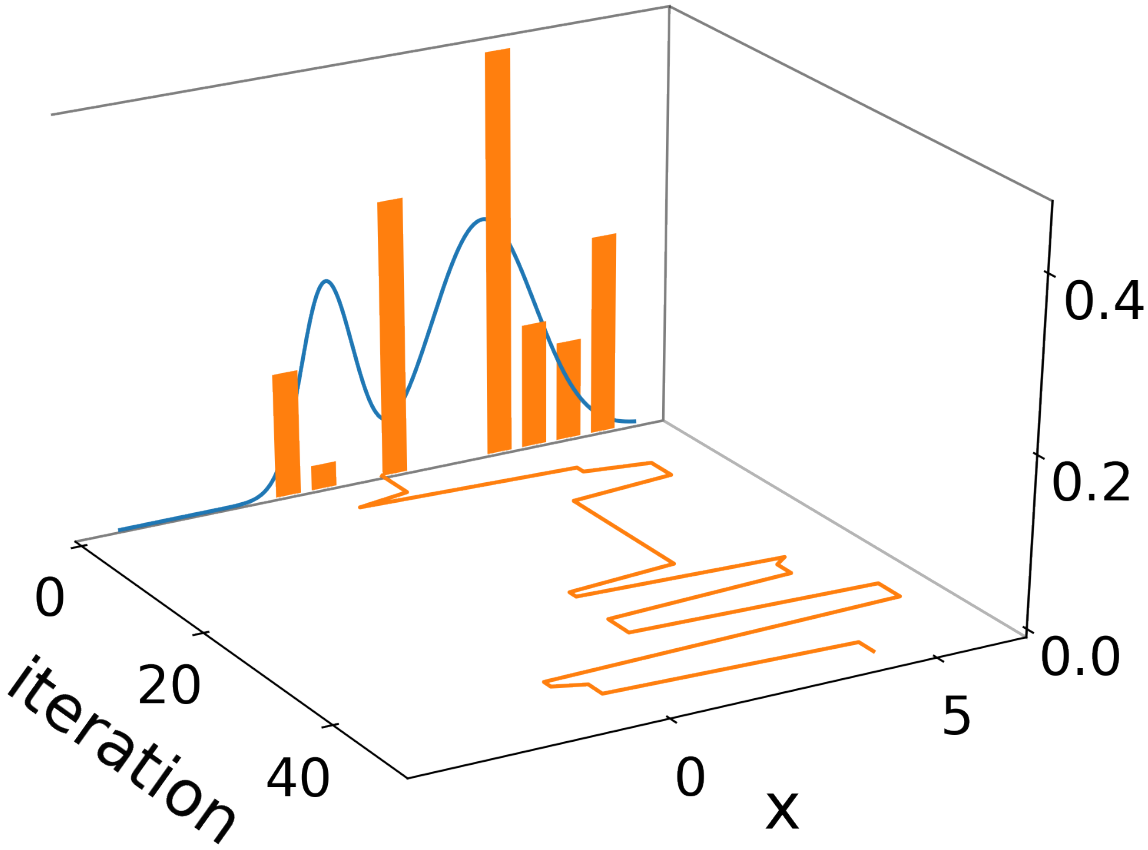


$$Q(x \to x') = \mathcal{N}(x, 0.1^2)$$

Demo



$$Q(x \to x') = \mathcal{N}(x, 10^2)$$

Metropolis Hastings as correction scheme

Metropolis Hastings as correction scheme

Recall Gibbs sampling

Metropolis Hastings as correction scheme

Recall Gibbs sampling

$$x_1^{k+1} \sim p(x_1 \mid x_2 = x_2^k, x_3 = x_3^k)$$

$$x_2^{k+1} \sim p(x_2 \mid x_1 = x_1^{k+1}, x_3 = x_3^k)$$

$$x_3^{k+1} \sim p(x_3 \mid x_1 = x_1^{k+1}, x_2 = x_2^{k+1})$$

Metropolis Hastings as correction scheme

Recall Gibbs sampling

Lets make it parallel

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$$x_3^{k+1} \sim p(x_3 \mid x_1 = x_1^{k+1}, x_2 = x_2^{k+1})$$

Metropolis Hastings as correction scheme

Recall Gibbs sampling

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Metropolis Hastings as correction scheme

Recall Gibbs sampling

Lets make it parallel

It's wrong now, but can correct with Metropolis Hastings!

$$x_1^{k+1} \sim p(x_1 \mid x_2 = x_2^k, x_3 = x_3^k)$$

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Summary

Rejection sampling applied to Markov Chains

Pros:

- You can choose among family of Markov Chains

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- Works for unnormalized densities
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- Samples are still correlated
- Have to choose among family of Markov Chains ☺