



Variational Bayesian Methods (in Neuroscience)

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Deisseroth (Tyler & Aaron) and Druckmann (Tyler) Labs



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2019-07-10

└ Roadmap

Introduction: Why care about the distribution of data?

Problem: Analyzing high dimensional data is hard

Background: Monte Carlo and variational methods

Example: variational autoencoder

Discussion: Neuroscience applications

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Background: Monte Carlo and variational methods



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Background: Monte Carlo and variational methods

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Introduction: Why care about the distribution of data?

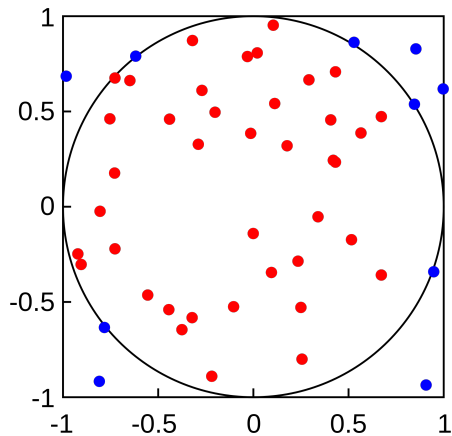
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Approximating the area of a circle with Monte Carlo



40/50 samples in circle gives area of $4 * 0.8 = 3.2 \approx \pi$. $\sim 2\%$ error

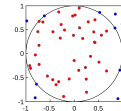
CCO 1.0, wikimedia, MonteCarloIntegrationCircle.svg

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Background: Monte Carlo and variational methods

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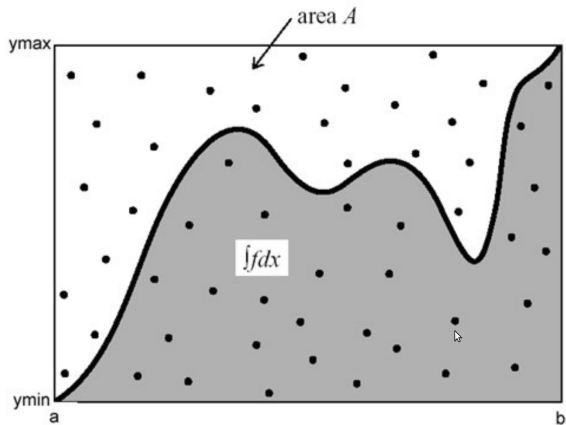
└ Approximating the area of a circle with Monte Carlo



40/50 samples in circle gives area of $4 * 0.8 = 3.2 \approx \pi$. $\sim 2\%$ error

CCO 1.0, wikimedia, MonteCarloIntegrationCircle.svg

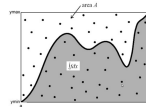
Useful for analytically intractable integrals



Robert Lin - Monte Carlo Integration

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- Background: Monte Carlo and variational methods
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 - Useful for analytically intractable integrals



Robert Lin - Monte Carlo Integration

Extension to unit hypercube



We can approximate a high-dimensional integral using a Monte Carlo approximation:

$$\int_0^1 \cdots \int_0^1 g(x_1, \dots, x_n) dx_1, \dots, dx_n \approx \frac{1}{N} \sum_{j=1}^N g(\bar{x}_j)$$

where $\bar{x}_1, \dots, \bar{x}_N \sim \mathcal{U}(0, 1)$ is the i^{th} random sample

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Background: Monte Carlo and variational methods

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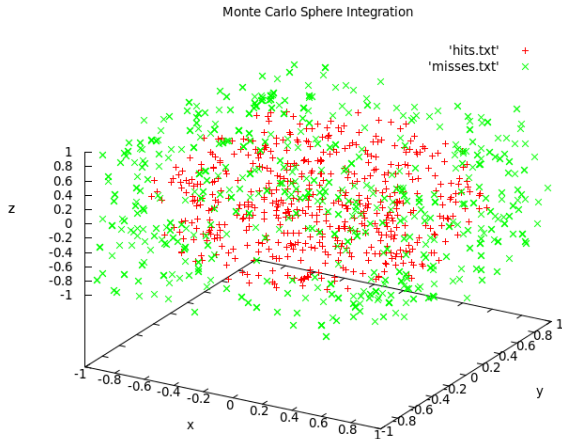
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Performance scales poorly with number of dimensions

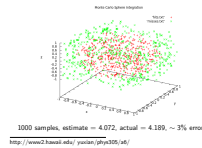


1000 samples, estimate = 4.072, actual = 4.189, $\sim 3\%$ error

<http://www2.hawaii.edu/~yuxian/phys305/a6/>

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Summary



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Example: variational autoencoder
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- Discussion: Neuroscience applications
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 - └ (backup slide) LFADS

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