Winter 2019 Math 106
Topics in Applied Mathematics
Data-driven Uncertainty Quantification

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Lecture 7: Monte Carlo

7.1 Monte Carlo Integration

For a function $f(x)$ which is integrable over $[0,1]^d$, we want to calculate the mean value of f

$$I[f] = \int_{[0,1]^d} f(x)dx = \overline{f}.$$

Setting: We assume that we know how to evaluate $f(x)$ but there is not simple formula for the antiderivative of $f(x)$.

- If we use a grid-based methods, the **convergence rate** is $\mathcal{O}(n^{-k/d})$ where k is the order of the grid-based method.
- The Monte Carlo integration draws a sample $\{x_i\}$ from the inform distribution on $[0,1]^d$ and estimate the integral

$$I[f] \approx \hat{I}_n[f] = \frac{1}{n}\sum_i f(x_i).$$

- The convergence rate of the Monte Carlo integration is $\mathcal{O}(n^{-1/2})$.

7.1 Monte Carlo Integration

- The probabilistic interpretation of $I[f]$ is that $I[f]$ is an expected value of $f(x)$ where x has the uniform density in $[0,1]^d$

$$I[f] = E[f] = \int_{[0,1]^d} f(x)dx$$

- From the law of large numbers,

$$\hat{I}_n[f] \to I[f].$$

- Also, $\hat{I}_n[f]$ is unbiased

$$E[\hat{I}_n[f]] = I[f].$$

7.1 Monte Carlo Integration

- Let $e_n[f]$ be the error of the Monte Carlo estimator

$$e_n[f] = I_n[f] - I[f].$$

- From the Central limit theorem, for n large, we have

$$e_n[f] \approx \sigma n^{-1/2} \nu$$

in which ν is a standard normal random variable and the constant σ^2 is the variance of f, that is,

$$\sigma^2 = \left(\int (f - I[f])^2 \right)^{1/2}.$$

7.1 Monte Carlo Integration

Now we are interested in

$$I[fp] = \int_{[0,1]^d} f(x)p(x)dx$$

where $p(x) \geq 0$, $\int_{[0,1]^d} p(x)dx = 1$.
There are two approaches for this problem

1. Draw a sample $\{x_i\}$ of size n from the uniform density of $[0,1]^d$ and

$$I[fp] \approx \frac{1}{n} \sum_i f(x_i)p(x_i).$$

2. Or draw a sample $\{x_i\}$ of size n from the density $p(x)$ and

$$I[fp] = I_p[f] \approx \frac{1}{n} \sum_i f(x_i).$$

7.1 Monte Carlo Integration

How do you decide which method to use?

7.1 Monte Carlo Integration

How do you decide which method to use?
Check the variances

$$\sigma_1^2 = \int (fp - I[fp])^2 dx$$

and

$$\sigma_2^2 = \int (f - I_p[f])^2 p dx.$$

Choose the method with a smaller variance.

7.2 Sampling Methods

Now we are concerned with a sampling method to generate a sample from a given density $p(x)$.

- Transformation method
- Acceptance-rejection method

7.2.1 Transformation method

Let Y be a uniform random variable and look for a transformation $X = f(Y)$ such that the density of X is $p(x)$.

Example. Cauchy distribution $p(x) = \frac{1}{\pi(1+x^2)}$.

Example. Gaussian distribution $p(x; 0, 1) = \frac{1}{\sqrt{2\pi}} e^{-(x)^2/2}$

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$$P_X(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-t^2/2} dt$$

$$= \frac{1}{2} + \frac{1}{2} erf(x/\sqrt{2})$$

where $erf(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2} dt$, the error function.

$$y = P_Y(y) = P_X(x) = \frac{1}{2} + \frac{1}{2} erf(x/\sqrt{2})$$

$$x = \sqrt{2} erf^{-1}(2y-1).$$

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Another method: Box-Muller method.

7.2.2 Acceptance-rejection method

For a given density $p(x)$, suppose that we know a function $q(x)$ satisfying

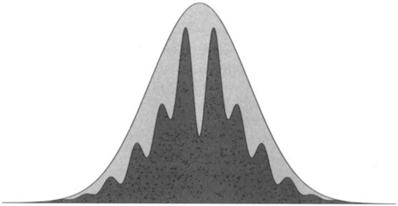
$$q(x) \geq p(x),$$

and that we have a way to sample from the density

$$\tilde{q}(x) = q(x)/I[q].$$

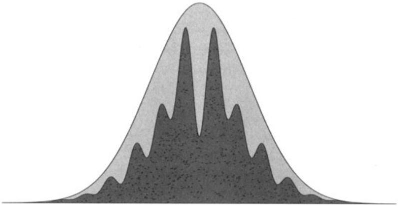
- Pick two random variables, x' and y, in which x' is a trial variable chosen according to $\tilde{q}(x')$, and y is a decision variable chosen according to the uniform density on $0 < y < 1$.
- Accept if $0 < y < p(x')/q(x')$
- Reject if $p(x')/q(x') < y < 1$.

7.2.2 Acceptance-rejection method



* black: density of interest, $p(x)$, * gray: Gaussian, $q(x)$

7.2.2 Acceptance-rejection method



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Idea of Proof.

$$p(x) = \frac{p(x)}{q(x)}\tilde{q}(x)I[q]$$

$$= \int_0^1 I(\frac{p(x)}{q(x)} > y)dy\tilde{q}(x)I[q]$$

where $I(\frac{p(x)}{q(x)} > y) = 1$ if $\frac{p(x)}{q(x)} > y$ and 0 otherwise. So,

$$\int f(x)p(x)dx = \int\int_0^1 f(x)I(\frac{p(x)}{q(x)} > y)dy\tilde{q}(x)I[q]dx$$

7.3 Accuracy and Improvements

In Monte Carlo integration $I[fp] = \int fp dx$, the error e and the number n of samples are related by

$$e = \mathcal{O}(\sigma n^{-1/2}),$$

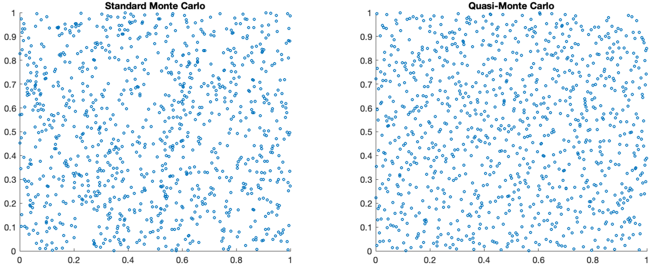
$$n = \mathcal{O}((\sigma/e)^2).$$

where σ is the variance of f (or fp).
There are two approaches to improve the accuracy

- Increase the convergence rate
- or decrease the variance, i.e., variance reduction.

7.3.1 Quasi-Monte Carlo

- A deterministic sequence, not random
- Maintains uniformity
- Convergence rate $\mathcal{O}((\ln n)^d n^{-1})$.



Standard Monte Carlo (left) and Quasi-Monte Carlo (right) samples of the same size 1000.

7.3.2 Variance Reduction

Method: Antithetic variates For a sample value x where m is a mean of $p(x)$, also use the value $x' = m - (x - m)$.
That is, if $\{x_i\}$ is a sample of size n,

$$I[fp] = I_p[f] \approx \frac{1}{2n} \sum_i^n (f(x_i) + f(m - (x_i - m)).$$

Motivation. If the standard deviation of $p(x)$, say std_p, is small,

$$f(x) = f(m) + f'(m) std_p \tilde{x} + \mathcal{O}(std_p^2)$$

where $x = std_p \tilde{x}$.

7.3.2 Variance Reduction

Method: Control variates If there is a function $g(x)$ such that g is similar to f and $I_p[g] = \int g(x)p9x)dx$ is known,

$$\int f(x)p(x)dx = \int (f(x) - g(x))p(x)dx + \int g(x)p(x)dx.$$

That is, the control variates is effective if the variance of $(f - g)$ is smaller than the variance of $f(x)$.
One may try the following idea to reduce the variance further.
Introduce a multiplier λ

$$\int f(x)p(x)dx = \int (f(x) - \lambda g(x))p(x)dx + \lambda \int g(x)p(x)dx.$$

Use λ minimizing the variance of $f - \lambda g$.

7.3.2 Variance Reduction

Method: Matching moments method Let m_1 and m_2 be the first and the second moments of $p(x)$. Also let α_1 and α_2 are the first and the second sample moments of a sample $\{x_i\}$.
Then, instead of $\{x_i\}$, use the following transformed sample $\{y_i\}$ that preserves the correct moments up to the second order

$$y_i = (x_i - \alpha_1)c + m_1$$

where $c = \sqrt{\frac{m_2 - m_1^2}{\alpha_2 - \alpha_1^2}}$.
Exercise. Show that the first two sample moments of $\{y_i\}$ are equal to the true moments m_1 and m_2.

7.3.2 Variance Reduction

Method: Stratification For simplicity, let us consider an interval $\Omega = [0, 1]$ and a problem of

$$\int_{[0,1]} f(x)dx.$$

For a fixed $m > 0$, divide $[0, 1]$ into M equal subintervals $\Omega_k = [\frac{k-1}{M}, \frac{k}{m}]$.
Also for simplicity, assume that the sample size n is a multiple of m. Then, for each $k \le m$, sample n/m points $\{x_i^k\}$ uniformly distributed in Ω_k.

$$\int_{[0,1]} f(x)dx \approx \frac{1}{n} \sum_k^m \sum_i^{n/m} f(x_i^k).$$

Then the error e is

$$e \approx n^{-1/2} \sigma_s$$

where $\sigma_s^2 = \sum_k^m \int_{\Omega_k} (f(x) - \overline{f}_k)^2 dx$ and $\overline{f}_k = \int_{\Omega_k} f(x)dx$.

7.3.2 Variance Reduction

Method: Stratification

Claim. The variance σ_s^2 is smaller than the variance without stratification $\sigma^2 = \int_{[0,1]} (f - \overline{f})^2 dx$ where $\overline{f} = \int_{[0,1]} f(x) dx$.

7.3.2 Variance Reduction

Method: Stratification

Claim. The variance σ_s^2 is smaller than the variance without stratification $\sigma^2 = \int_{[0,1]}(f - \overline{f})^2 dx$ where $\overline{f} = \int_{[0,1]} f(x)dx$.

Idea of proof. The minimizer c of $\int_{\Omega_k}(f(x) - c)^2 dx$ is $\overline{f}_k = \int_{\Omega_k} f(x)dx$.

7.4 Example

We want to calculate

$$p = \int_2^\infty \frac{1}{\pi(1+x^2)} dx = 0.15$$

- Estimator 1: $\hat{p}_1 = \frac{1}{n}\sum_i^n I(X_i > 2)$ where $\{X_i\}$ is from Cauchy
- Estimator 2:
  $\hat{p}_2 = \frac{1}{2n}\sum_i^n I(|X_i| > 2)$ where $\{X_i\}$ is from Cauchy
- Estimator 3: $\hat{p}_3 = \frac{1}{2} - \frac{1}{n}\sum_i^n \frac{1}{\pi(1+X_i)^2}$ where $\{X_i\}$ is from Uniform[0,2].
- Estimator 4: $\hat{p}_4 = \frac{1}{n}\sum_i^n \frac{X_i^{-2}}{\pi(1+X_i^{-2})}$ where $\{X_i\}$ is from Uniform[0,1/2].

Homework

1. Calculate the variances of estimator 1,2,3 and 4 in the previous slide (show your work).