

Monte Carlo (MC) and Importance Sampling (IS)

Sensor fusion & nonlinear filtering

Lars Hammarstrand

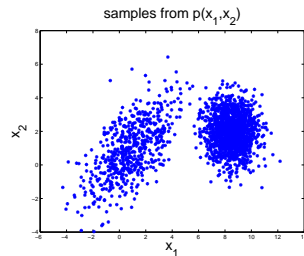
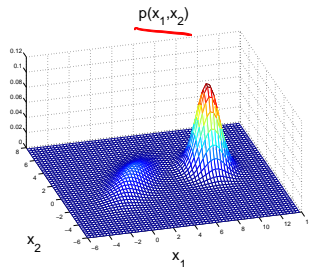
Monte Carlo approximations

Two perspectives on Monte Carlo approximation

Given independent samples $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(N)} \sim p(\mathbf{x})$ we can approximate

$$\mathbb{E}[\mathbf{g}(\mathbf{x})] \approx \frac{1}{N} \sum_{i=1}^N \mathbf{g}(\mathbf{x}^{(i)}) \quad (1)$$

$$p(\mathbf{x}) \approx \frac{1}{N} \sum_{i=1}^N \delta(\mathbf{x} - \mathbf{x}^{(i)}) \quad (2)$$



Remarks on Monte Carlo approximations:

- non-parametric approximation to $p(\mathbf{x})$.
- approximate all kinds of densities, $p(\mathbf{x})$. *Very flexible!*
- does not suffer from the curse of dimensionality, e.g., $\hat{\mu}$

$$\text{Cov}(\hat{\mu}) = \text{Cov} \left(\underbrace{\frac{1}{N} \sum_{i=1}^N \mathbf{x}^{(i)}}_{\hat{\mu}} \right) = \frac{1}{N} \text{Cov}(\underline{\mathbf{x}})$$

independently on $\dim(\mathbf{x})$!

- *Weakness:* it is often difficult to generate samples from $p(\mathbf{x})$.

Importance sampling

What can we do when it is difficult to sample from $p(\mathbf{x})$?

Importance sampling

- Generate samples, $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(N)}$, from a proposal density $q(\mathbf{x})$:

$$\mathbb{E}_{\underline{p(\mathbf{x})}}[\underline{\mathbf{g}(\mathbf{x})}] = \int \underbrace{\mathbf{g}(\mathbf{x}) \cdot \frac{p(\mathbf{x})}{q(\mathbf{x})}}_{\tilde{\mathbf{g}}(\mathbf{x})} d\mathbf{x} \approx \frac{1}{N} \sum_{i=1}^N \mathbf{g}(\mathbf{x}^{(i)}) \frac{p(\mathbf{x}^{(i)})}{q(\mathbf{x}^{(i)})}$$

$$\propto \sum_{i=1}^N \underbrace{\frac{p(\mathbf{x}^{(i)})}{q(\mathbf{x}^{(i)})}}_{\tilde{w}(i)} \cdot \mathbf{g}(\mathbf{x}^{(i)})$$

Importance sampling approximation to $p(\mathbf{x})$

- Generate samples, $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(N)}$, from $q(\mathbf{x})$ and set

$$\underline{p(\mathbf{x})} \approx \sum_{i=1}^N \underline{w^{(i)}} \underline{\delta(\mathbf{x} - \mathbf{x}^{(i)})}$$

where

$$\underline{w^{(i)}} = \frac{\tilde{w}^{(i)}}{\sum_{n=1}^N \tilde{w}^{(n)}} \quad \text{and} \quad \tilde{w}^{(i)} = \frac{p(\mathbf{x}^{(i)})}{q(\mathbf{x}^{(i)})}.$$

- Importance sampling is a flexible and powerful tool.
- It can perform very well as long as:
 1. it is easy to sample from $q(\mathbf{x})$,
 2. the support of $q(\mathbf{x})$ contains the support of $p(\mathbf{x})$,
 3. $q(\mathbf{x})$ is “similar” to $p(\mathbf{x})$.

Example – Importance sampling

- Approximate $p(x)$ using N independent samples from $q(x) = \mathcal{N}(x; 4, 1.5^2)$.

