

Bayes' Nets: Sampling

⇒ Why Sample?

- Learning: Get samples from a distribution you don't know.
- Inference: Getting a sample is faster than computing the right answer.

* Sampling from given distribution

* Step 1: Get sample u from uniform distribution over $[0, 1]$

* Step 2: Convert this sample u into an outcome for the given distribution by having each target outcome associated with a sub-interval of $[0, 1]$ with sub-interval size equal to probability of the outcome.

* Sampling in Bayes' Nets

- ① Prior Sampling
- ② Rejection Sampling
- ③ Likelihood Weighting
- ④ Gibbs Sampling

* Perion Sampling

- For $i=1, 2, \dots, n$
 - Sample x_i from $P(x_i | \text{Parnts}(x_i))$
- Return (x_1, x_2, \dots, x_n)

\Rightarrow This process generates samples with probability:

$$S_{ps}(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | \text{Parnts}(x_i)) = P(x_1, \dots, x_n)$$

\Rightarrow Let the number of samples of an event be $N_{ps}(x_1, \dots, x_n)$

$$\begin{aligned} \Rightarrow \lim_{N \rightarrow \infty} \tilde{P}(x_1, \dots, x_n) &= \lim_{N \rightarrow \infty} N_{ps}(x_1, \dots, x_n) / N \\ &= S_{ps}(x_1, \dots, x_n) \\ &= P(x_1, \dots, x_n) \end{aligned}$$

\Rightarrow I.e., the sampling procedure is consistent.

* Rejection Sampling

Input: evidence instantiation

For $i=1, 2, \dots, n$

- Sample x_i from $P(x_i | \text{Parnts}(x_i))$
- If x_i not consistent with evidence
 - Reject: return - no sample is generated in this cycle

Return (x_1, x_2, \dots, x_n)

* Likelihood Weighting

⇒ Problem with rejection sampling:

- ↳ If evidence is unlikely, rejects lots of samples.
- ↳ Evidence not exploited as you sample

Idea: Fix evidence variables and sample the rest.

↳ Problem: Sample distribution not consistent.

↳ Solution: Weight by probability of evidence given Params.

- Input: evidence instantiation
- $W = 1.0$
- for $i = 1, 2, \dots, n$
 - If x_i is an evidence variable
 - ↳ $x_i = \text{Observation } x_i \text{ for } X_i$
 - ↳ Set $W = W * P(x_i | \text{Params}(x_i))$
 - else
 - ↳ Sample x_i from $P(X_i | \text{Params}(X_i))$
- return $(x_1, x_2, \dots, x_n), W$

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⇒ Sampling distribution if z sampled and e fixed evidence

$$S_{ws}(z, e) = \prod_{i=1}^l P(z_i | \text{Parents}(z_i))$$

⇒ Now, samples have weights

$$\omega(z, e) = \prod_{i=1}^m P(e_i | \text{Parents}(e_i))$$

⇒ Together, weighted sampling distribution is consistent

$$\begin{aligned} S_{ws}(z, e) \cdot \omega(z, e) &= \prod_{i=1}^l P(z_i | \text{Parents}(z_i)) \prod_{i=1}^m P(e_i | \text{Parents}(e_i)) \\ &= P(z, e) \end{aligned}$$

⇒ Likelihood weighting doesn't solve all our problems:

- Evidence influences the choice of downstream variables, but not upstream ones
- We would like to consider evidence when we sample every variable (leads to Gibbs sampling)

* Gibbs Sampling

• Procedure

- Keep track of a full instantiation X_1, X_2, \dots, X_n .
- Start with an arbitrary instantiation consistent with the evidence.
- Sample one variable at a time, conditional on all the rest, but keep evidence fixed.
- Keep repeating this for a long time.

• Property

- In the limit of repeating this infinitely many times the resulting samples come from the correct distribution.

• Rationale

- Both upstream & downstream variable conditional on evidence.

⇒ Gibbs sampling is a special case of more general methods called Markov chain Monte Carlo (MCMC) methods.

