**Bayes’ Net Representation**

- A directed, acyclic graph, one node per random variable
- A conditional probability table (CPT) for each node
  - A collection of distributions over \(X\), one for each combination of parents’ values
  \[ P(X|\sigma_1 \ldots \sigma_n) \]
- Bayes’ nets implicitly encode joint distributions
  - As a product of local conditional distributions
  - To see what probability a BN gives to a full assignment, multiply all the relevant conditionals together:
  \[
P(x_1, x_2, \ldots, x_n) = \prod_{i=1}^{n} P(x_i|\text{parents}(X_i))
\]

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**Variable Elimination**

- Interleave joining and marginalizing
- \(d^k\) entries computed for a factor over \(k\) variables with domain sizes \(d\)
- Ordering of elimination of hidden variables can affect size of factors generated
- Worst case: running time exponential in the size of the Bayes’ net

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**Approximate Inference: Sampling**

- Sampling is a lot like repeated simulation
  - Predicting the weather, basketball games, ...
- Basic idea
  - Draw \(N\) samples from a sampling distribution \(S\)
  - Compute an approximate posterior probability
  - Show this converges to the true probability \(P\)

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**Sampling**

- Why sample?
  - Learning: get samples from a distribution you don’t know
  - Inference: getting a sample is faster than computing the right answer (e.g. with variable elimination)
- Sampling is from given distribution
  - Step 1: Get sample \(u\) from uniform distribution over \((0, 1)\)
    - E.g., random() in Python
  - 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
- Example
  - \(C\)
  - \(P(C)\)
  - \(0 \leq u < 0.6\), \(\rightarrow C = \text{red}\)
  - \(0.6 \leq u < 0.7\), \(\rightarrow C = \text{green}\)
  - \(0.7 \leq u < 1\), \(\rightarrow C = \text{blue}\)
  - If random() returns \(u = 0.38\), then our sample is \(C = \text{blue}\)
  - E.g., after sampling 8 times
Sampling in Bayes’ Nets

- Prior Sampling
- Rejection Sampling
- Likelihood Weighting
- Gibbs Sampling

Prior Sampling

- For \( i = 1, 2, ..., n \)
  - Sample \( x_i \) from \( P(X_i | \text{Parents}(X_i)) \)
  - Return \( \{x_1, x_2, ..., x_n\} \)

Example

- We’ll get a bunch of samples from the BN:
  - \( +c, +s, +r, +w \)
  - \( +c, +s, +r, -w \)
  - \( -c, +s, +r, +w \)
  - \( -c, -s, +r, +w \)

  - If we want to know \( P(W) \)
    - We have counts \(+w:4, -w:1\)
    - Normalize to get \( P(W) = \{+w:0.8, -w:0.2\} \)
    - This will get closer to the true distribution with more samples
    - Can estimate anything else, too
    - What about \( P(C | +w) \)? \( P(C | +r) \)? \( P(C | +r, +w) \)?
    - Fast: can use fewer samples if less time (what’s the drawback?)
Rejection Sampling

- Let’s say we want $P(C)$
  - No point keeping all samples around
  - Just tally counts of $C$ as we go

- Let’s say we want $P(C \mid +s)$
  - Same thing: tally outcomes, but ignore (reject) samples which don’t have $S=+s$
  - This is called rejection sampling
  - It is also consistent for conditional probabilities (i.e., correct in the limit)

Rejection Sampling

- Input: evidence instantiation
- For $i = 1, 2, \ldots, n$
  - Sample $x_i$ from $P(X_i \mid \text{Parents}(X_i))$
  - If $x_i$ not consistent with evidence
    - Reject: return – no sample is generated in this cycle
  - Return $(x_1, x_2, \ldots, x_n)$

Likelihood Weighting

- Problem with rejection sampling:
  - If evidence is unlikely, rejects lots of samples
  - Evidence not exploited as you sample
  - Consider $P(\text{Shape} \mid \text{blue})$

- Idea: fix evidence variables and sample the rest
- Problem: sample distribution not consistent!
- Solution: weight by probability of evidence given parents

Samples:
- $+c, +s, +r, +w$
- $-c, +s, +r,$
- $-w$
- $+c, -s, +r, +w$
- $-c, +s, +r,$
- $-w$
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- $-c, +s, -r,$
- $-w$
Likelihood Weighting

Input: evidence instantiation
\[ w = 1.0 \]
\[ \text{for } i = 1, 2, \ldots, n \]
  - if \( X_i \) is an evidence variable
    - \( w = w \cdot P(x_i | \text{Parents}(X_i)) \)
  - else
    - Sample \( x_i \) from \( P(X_i | \text{Parents}(X_i)) \)
  - return \( \{x_1, x_2, \ldots, x_n\}, w \)

Likelihood Weighting

- Likelihood weighting is good
  - We have taken evidence into account as we generate the sample
  - E.g., here, \( W' \)’s value will get picked based on the evidence values of \( S, R \)
  - More of our samples will reflect the state of the world suggested by the evidence
- Likelihood weighting doesn’t solve all our problems
  - Evidence influences the choice of downstream variables, but not upstream ones (it’s not more likely to get a value matching the evidence)
  - We would like to consider evidence when we sample every variable (leads to Gibbs sampling)

Gibbs Sampling

Procedure:
- Keep track of a full instantiation \( x_1, x_2, \ldots, x_n \). Start with an arbitrary instantiation consistent with the evidence. Sample one variable at a time, conditioned 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 (i.e. conditioned on evidence).
- Rationale: both upstream and downstream variables condition on evidence.
- In contrast: likelihood weighting only conditions on upstream evidence, and hence weights obtained in likelihood weighting can sometimes be very small. Sum of weights over all samples is indicative of how many “effective” samples were obtained, so we want high weight.

Gibbs Sampling

Step 1: Fix evidence
- \( R = +r \)

Step 2: Initialize other variables
- Randomly

Steps 3: Repeat
- Choose a non-evidence variable \( X \)
- Resample \( X \) from \( P(X| \text{all other variables}) \)

Sample from \( P[S] + c, -w, +r) \) \nSample from \( P[C] + s, -w, +r) \) \nSample from \( P[W] + s, +c, +r) \)

Likelihood Weighting

- Sampling distribution if \( z \) sampled and \( e \) fixed evidence
\[ S_W(z, e) = \prod_{i=1}^{n} P(z_i | \text{Parents}(z_i)) \]
- Now, samples have weights
\[ w(x, e) = \prod_{i=1}^{n} P(e_i | \text{Parents}(e_i)) \]
- Together, weighted sampling distribution is consistent
\[ S_W(z, e) \cdot w(z, e) = \prod_{i=1}^{n} P(z_i | \text{Parents}(z_i)) \prod_{i=1}^{n} P(e_i | \text{Parents}(e_i)) = P(z, e) \]
Efficient Resampling of One Variable

- Sample from \( P(S | +c, +r, -w) \)
  \[
P(S | +c, +r, -w) = \frac{P(S | +c, +r, -w)}{P(S, +c, +r, -w)}
  = \sum P(S | +c, +r, -w)
  = \frac{P(S | +c)P(S | +r)P(-w | S, +r)}{\sum P(S | +c)P(S | +r)P(-w | S, +r)}
  = \frac{P(S | +c)P(S | +r)P(-w | S, +r)}{\sum P(S | +c)P(S | +r)P(-w | S, +r)}
  = \frac{P(S | +c)P(S | +r)P(-w | S, +r)}{\sum P(S | +c)P(-w | S, +r)}
  = \frac{P(S | +c)P(S | +r)P(-w | S, +r)}{\sum P(S | +c)P(-w | S, +r)}
\]

- Many things cancel out – only CPTs with \( S \) remain!
- More generally: only CPTs that have resampled variable need to be considered, and joined together

Bayes’ Net Sampling Summary

- Prior Sampling \( P(Q) \)
- Rejection Sampling \( P(Q | e) \)
- Likelihood Weighting \( P(Q | e) \)
- Gibbs Sampling \( P(Q | e) \)

Further Reading on Gibbs Sampling*

- Gibbs sampling produces sample from the query distribution \( P(Q | e) \)
  in limit of re-sampling infinitely often
- Gibbs sampling is a special case of more general methods called
  Markov chain Monte Carlo (MCMC) methods
    - Metropolis-Hastings is one of the more famous MCMC methods (in fact, Gibbs
      sampling is a special case of Metropolis-Hastings)
- You may read about Monte Carlo methods – they’re just sampling