

Warm-up as you walk in

Given these N=10 observations of the world:

What is the approximate value for $P(-c \mid -a, +b)$?

- A. 1/10
- B. 5/10
- C. 1/4
- D. 1/5
- E. I'm not sure

$-a, -b, +c$
 $+a, -b, +c$
 $-a, -b, +c$
 $-a, +b, +c$
 $+a, -b, +c$
 $-a, +b, -c$
 $-a, +b, +c$
 $-a, +b, +c$
 $+a, -b, +c$
 $-a, +b, +c$

Counts

+a	+b	+c	0
+a	+b	-c	0
+a	-b	+c	3
+a	-b	-c	0
-a	+b	+c	4
-a	+b	-c	1
-a	-b	+c	2
-a	-b	-c	0

Announcements

Assignments:

- HW10 and P5 out after midterm

Midterm:

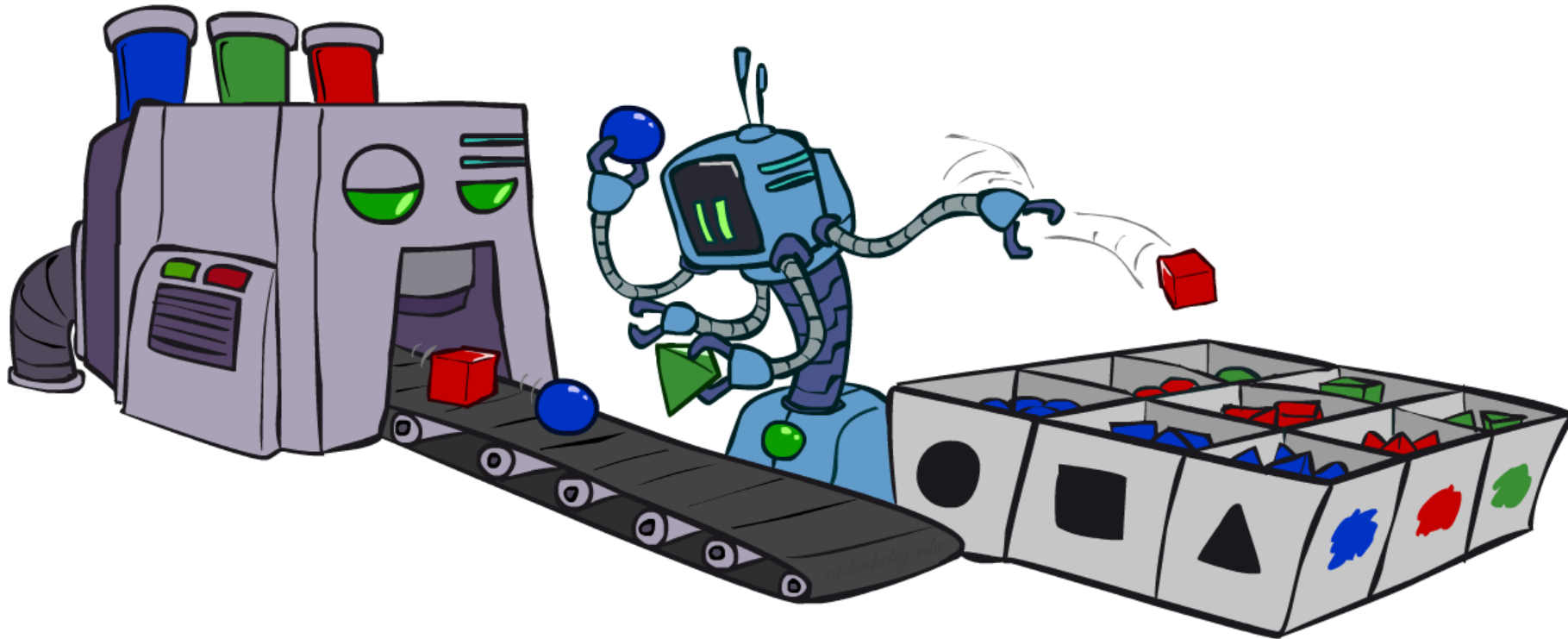
- Tue 11/12, in-class
 - See Piazza for details

Piazza:

- Lecture thread on piazza

AI: Representation and Problem Solving

Bayes Nets Sampling



Instructors: Pat Virtue & Fei Fang

Slide credits: CMU AI and <http://ai.berkeley.edu>

Review: Bayes Nets

Joint distributions $\rightarrow$ answer any query

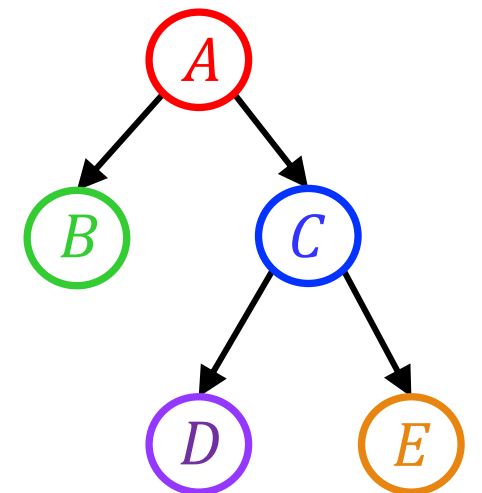
$$P(a \mid e) = \frac{1}{Z} P(a, e) = \frac{1}{Z} \sum_b \sum_c \sum_d P(a, b, c, d, e)$$

Break down joint using chain rule

$$P(A, B, C, D, E) = P(A) P(B|A) P(C|A, B) P(D|A, B, C) P(E|A, B, C, D)$$

With Bayes nets

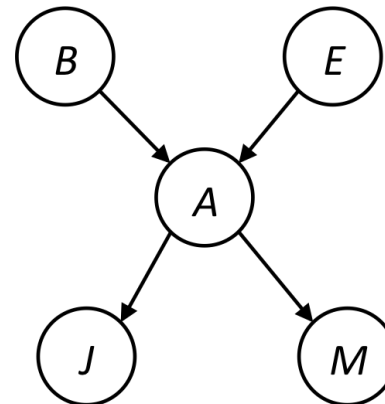
$$P(A, B, C, D, E) = P(A) P(B|A) P(C|A) P(D|C) P(E|C)$$



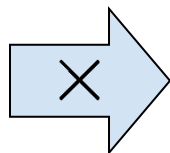
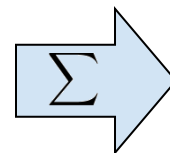
Example

Query $P(B \mid j, m)$

$P(B)$	$P(E)$	$P(A \mid B, E)$	$P(j \mid A)$	$P(m \mid A)$
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Choose A

 $P(A \mid B, E)$ $P(j \mid A)$ $P(m \mid A)$  $P(A, j, m \mid B, E)$  $P(j, m \mid B, E)$

$P(B)$	$P(E)$	$P(j, m \mid B, E)$
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Example

$P(B)$	$P(E)$	$P(j,m B,E)$
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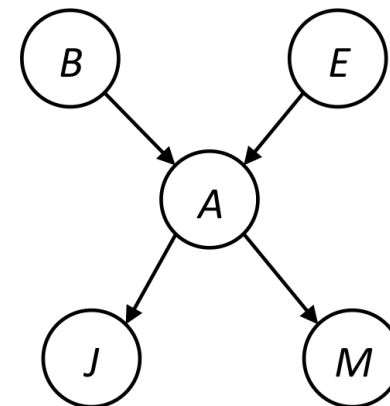
Choose E

$$\begin{array}{c} P(E) \\ P(j,m|B,E) \end{array} \xrightarrow{\times} P(E,j,m|B) \xrightarrow{\Sigma} P(j,m|B)$$

$P(B)$	$P(j,m B)$
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Finish with B

$$\begin{array}{c} P(B) \\ P(j,m|B) \end{array} \xrightarrow{\times} P(j,m,B) \xrightarrow{\text{Normalize}} P(B | j,m)$$



Variable Elimination order matters

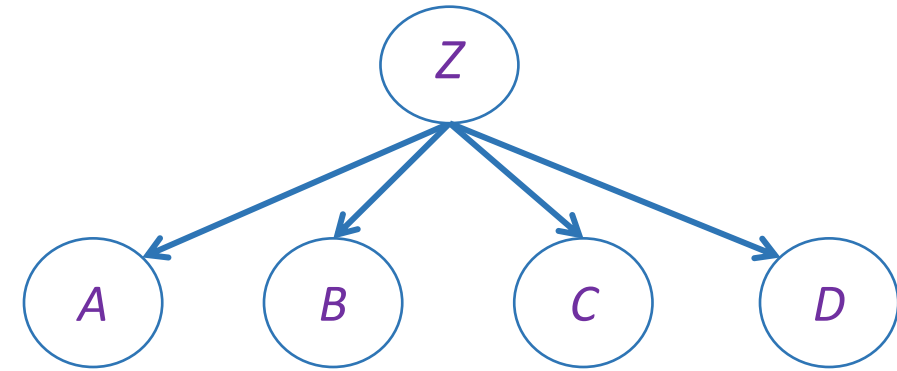
- Elimination order: C, B, A, Z

- $P(D) = \alpha \sum_{z,a,b,c} P(D|z) P(z) P(a|z) P(b|z) P(c|z)$
- $= \alpha \sum_z P(D|z) P(z) \sum_a P(a|z) \sum_b P(b|z) \sum_c P(c|z)$
- Largest factor has 2 variables (D,Z)

- Elimination order: Z, C, B, A

- $P(D) = \alpha \sum_{a,b,c,z} P(a|z) P(b|z) P(c|z) P(D|z) P(z)$
- $= \alpha \sum_a \sum_b \sum_c \sum_z P(a|z) P(b|z) P(c|z) P(D|z) P(z)$
- Largest factor has 4 variables (A,B,C,D)

- In general, with n leaves, factor of size 2^n



VE: Computational and Space Complexity

The computational and space complexity of variable elimination is determined by the largest factor (and it's space that kills you)

The elimination ordering can greatly affect the size of the largest factor.

- E.g., previous slide's example 2^n vs. 2

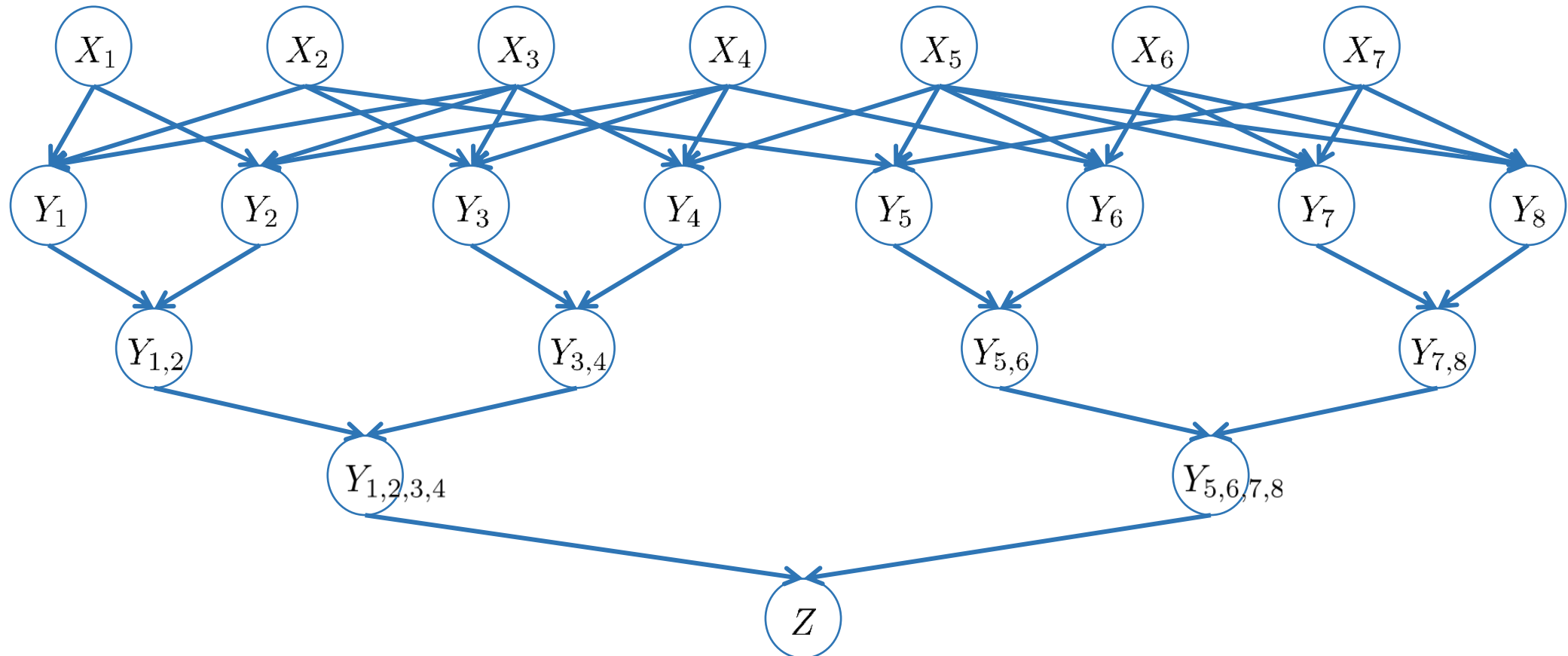
Does there always exist an ordering that only results in small factors?

- No!

VE: Computational and Space Complexity

Inference in Bayes' nets is NP-hard.

No known efficient probabilistic inference in general.



Bayes Nets

✓ Part I: Representation

✓ Part II: Exact inference

- ✓ ■ Enumeration (always exponential complexity)
- ✓ ■ Variable elimination (worst-case exponential complexity, often better)
- ✓ ■ Inference is NP-hard in general

Part III: Approximate Inference

Warm-up as you walk in

Given these N=10 observations of the world:

What is the approximate value for $P(-c \mid -a, +b)$?

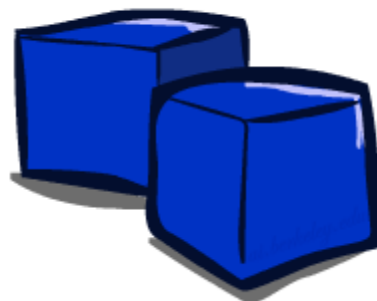
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+a	-b	-c	0
-a	+b	+c	4
-a	+b	-c	1
-a	-b	+c	2
-a	-b	-c	0

Approximate Inference: Sampling



Inference vs Sampling

Motivation for Approximate Inference

Sampling

Sampling 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 outcome associated with a sub-interval of $[0,1)$ with sub-interval size equal to probability of the outcome



Example

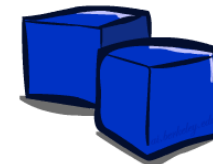
C	P(C)
red	0.6
green	0.1
blue	0.3

$$0 \leq u < 0.6, \rightarrow C = \text{red}$$

$$0.6 \leq u < 0.7, \rightarrow C = \text{green}$$

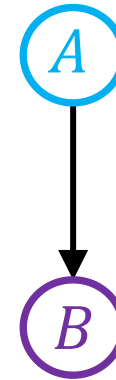
$$0.7 \leq u < 1, \rightarrow C = \text{blue}$$

- If `random()` returns $u = 0.83$, then our sample is $C = \text{blue}$
- E.g, after sampling 8 times:



Sampling

How would you sample from a conditional distribution?



$P(A)$

+a	1/2
-a	1/2

$P(B|A)$

+a	+b	1/10
	-b	9/10
-a	+b	1/2
	-b	1/2

Sampling in Bayes' Nets

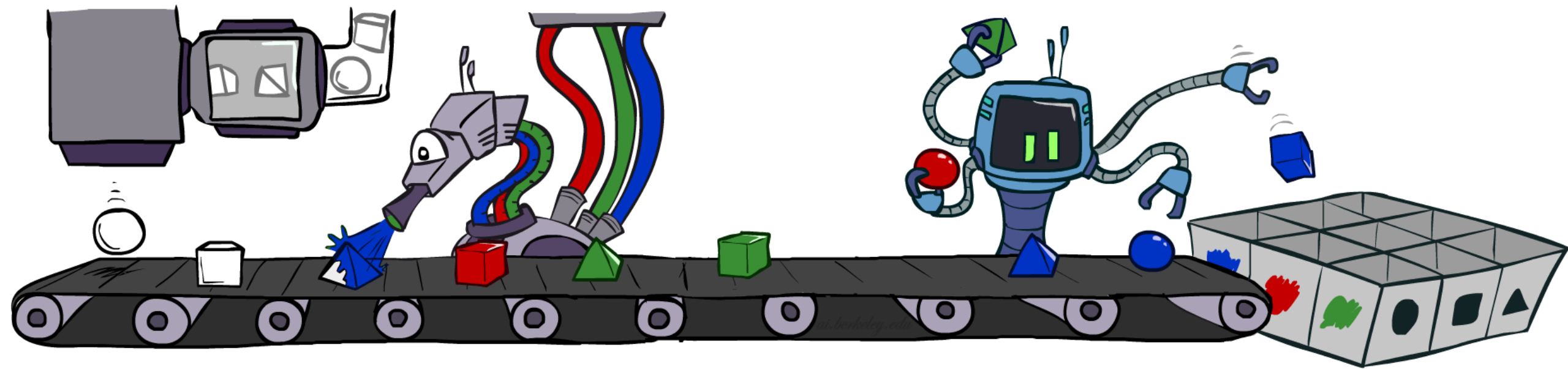
Prior Sampling

Rejection Sampling

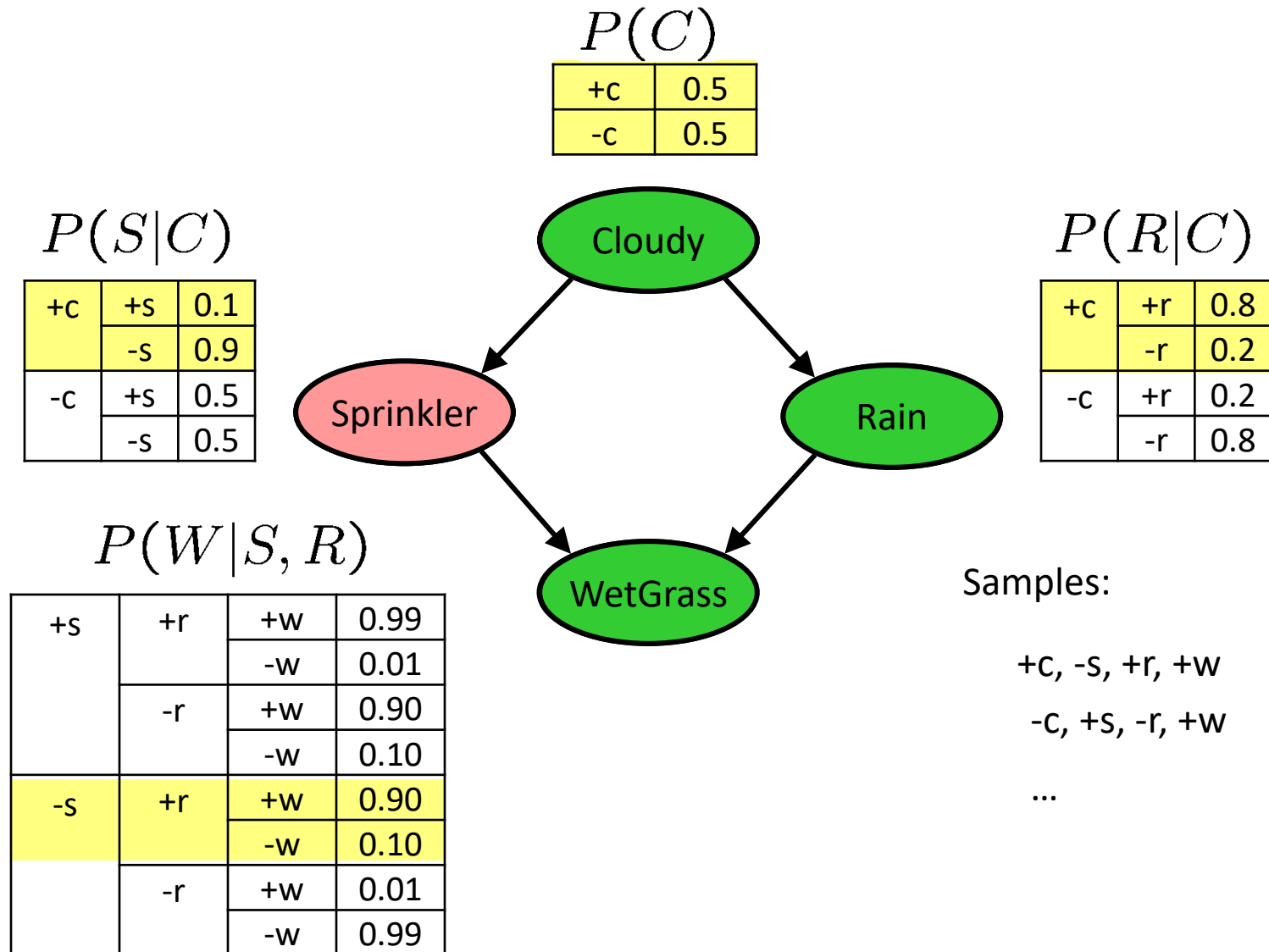
Likelihood Weighting

Gibbs Sampling

Prior Sampling



Prior Sampling

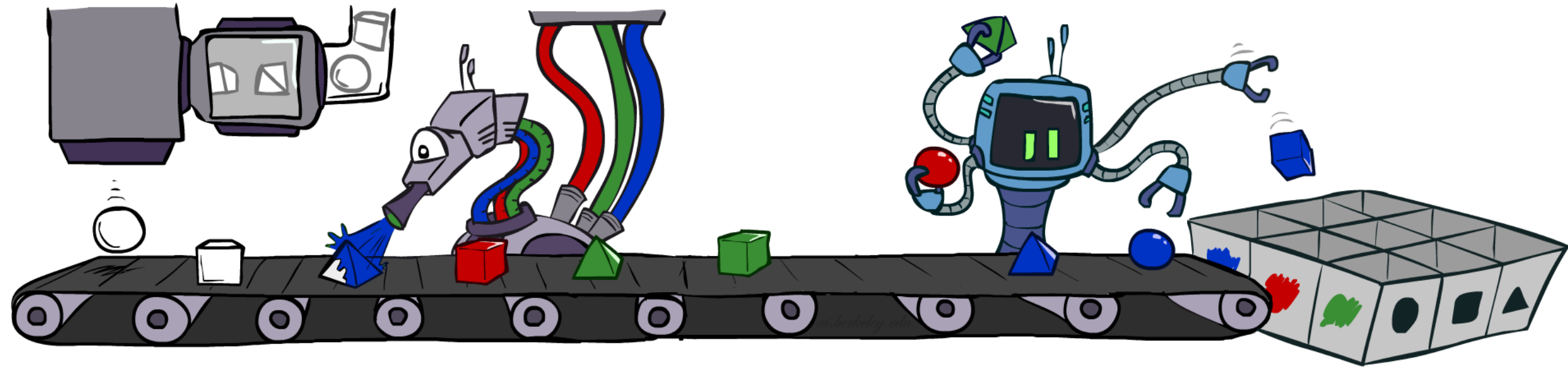


Prior Sampling

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

- Sample x_i from $P(X_i \mid \text{Parents}(X_i))$

Return $(x_1, x_2, \dots, x_n)$



Probability of a sample

Given this Bayes Net & CPT,
what is $P(+a, +b, +c)$?

Algorithm: Multiply likelihood of
each node given parents:

- $w = 1.0$
- for $i=1, 2, \dots, n$
 - Set $w = w * P(x_i \mid \text{Parents}(X_i))$
- return w



$P(A)$

+a	1/2
-a	1/2

$P(B|A)$

+a	+b	1/10
	-b	9/10
-a	+b	1/2
	-b	1/2

$P(C|B)$

+b	+c	4/5
	-c	1/5
-b	+c	1
	-c	0

Prior Sampling

This process generates samples with probability:

$$S_{PS}(x_1 \dots x_n) = \prod_{i=1}^n P(x_i | \text{Parents}(X_i)) = P(x_1 \dots x_n)$$

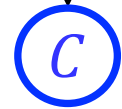
...i.e. the BN's joint probability

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

Then

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

Prior Sampling



$P(A)$

+a	1/2
-a	1/2

$P(B|A)$

+a	+b	1/10
	-b	9/10
-a	+b	1/2
	-b	1/2

$P(C|B)$

+b	+c	4/5
	-c	1/5
-b	+c	1
	-c	0

Example

We'll get a bunch of samples from the BN:

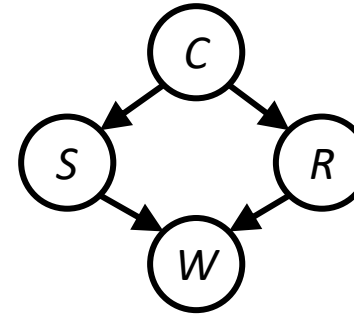
+c, -s, +r, +w

+c, +s, +r, +w

-c, +s, +r, -w

+c, -s, +r, +w

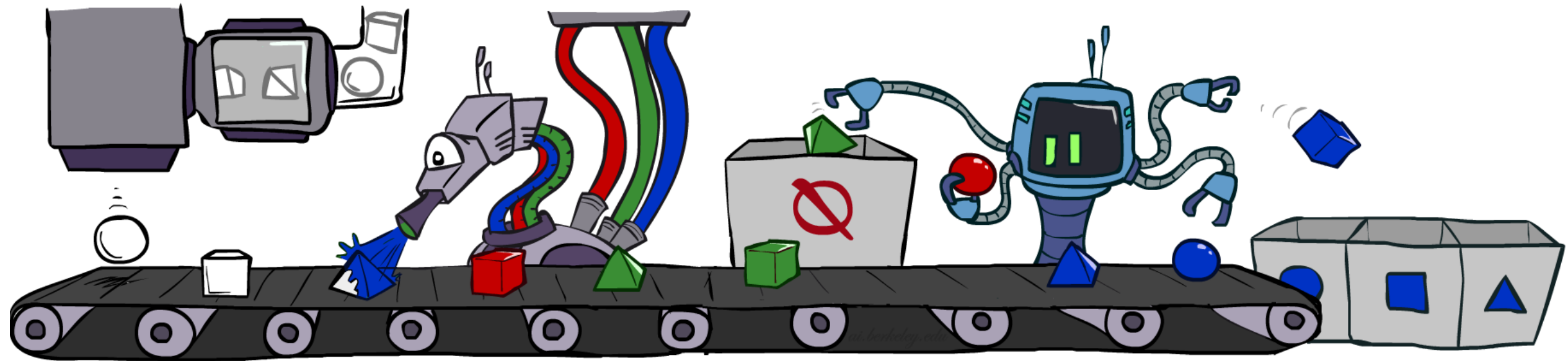
-c, -s, -r, +w



If we want to know $P(W)$

- We have counts $\langle +w:4, -w:1 \rangle$
- Normalize to get $P(W) = \langle +w:0.8, -w:0.2 \rangle$
- This will get closer to the true distribution with more samples
- Can estimate anything else, too
- What about $P(C \mid +w)$? $P(C \mid +r, +w)$? $P(C \mid -r, -w)$?
- Fast: can use fewer samples if less time (what's the drawback?)

Rejection Sampling



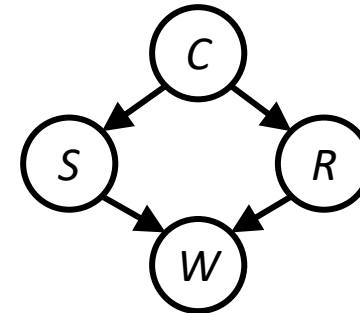
Rejection Sampling

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 C 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)



+c, -s, +r, +w
+c, +s, +r, +w
-c, +s, +r, -w
+c, -s, +r, +w
-c, -s, -r, +w

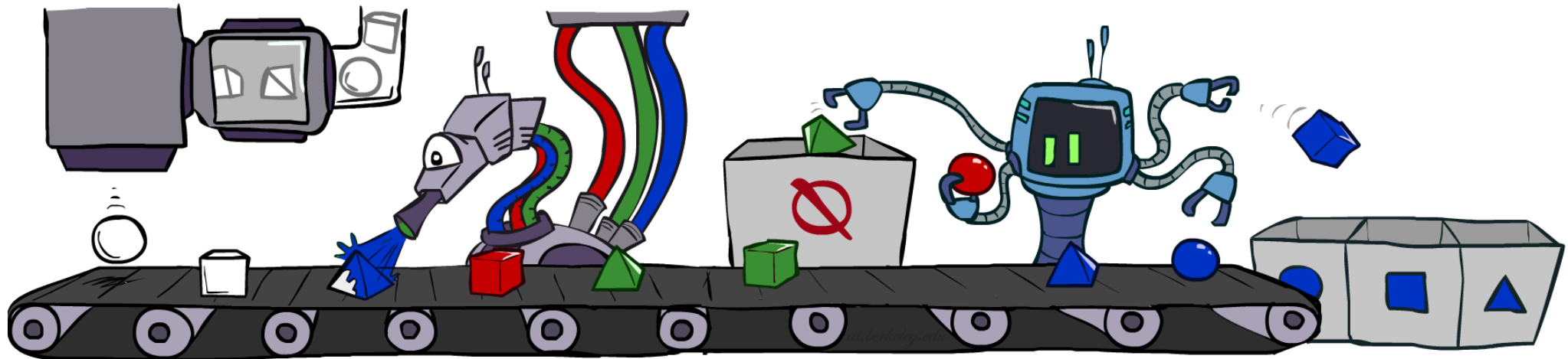
Rejection Sampling

IN: evidence instantiation

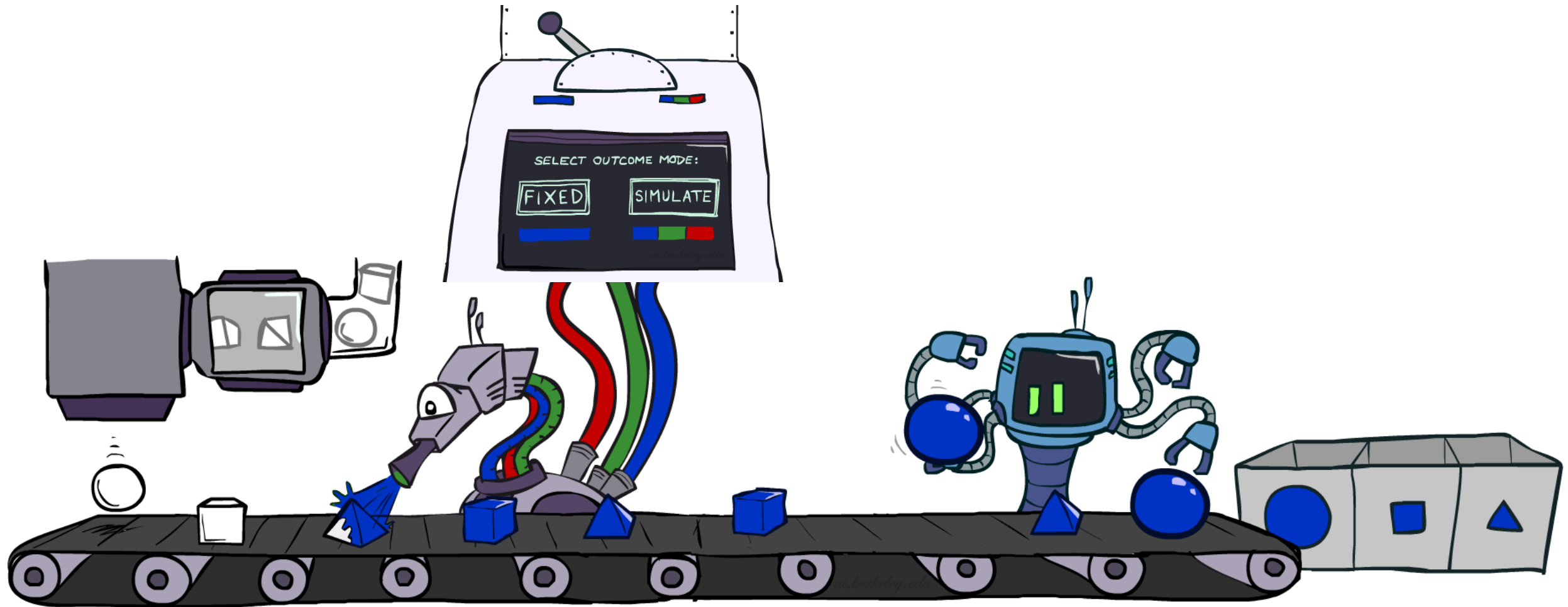
For $i=1, 2, \dots, n$

- Sample x_i from $P(X_i \mid \text{Parents}(X_i))$
- If x_i not consistent with evidence
 - Reject: Return, and no sample is generated in this cycle

Return $(x_1, x_2, \dots, x_n)$



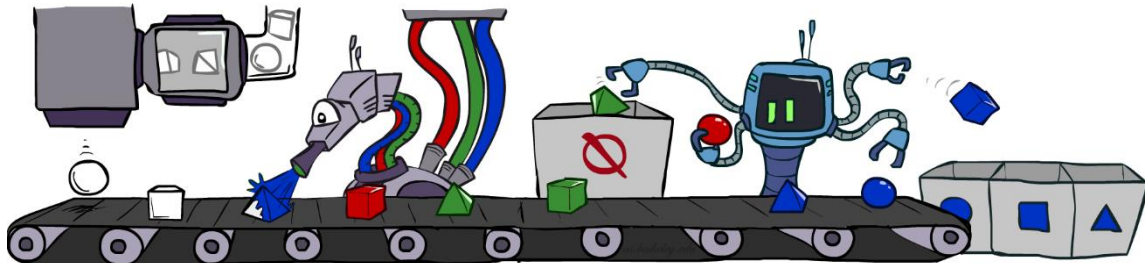
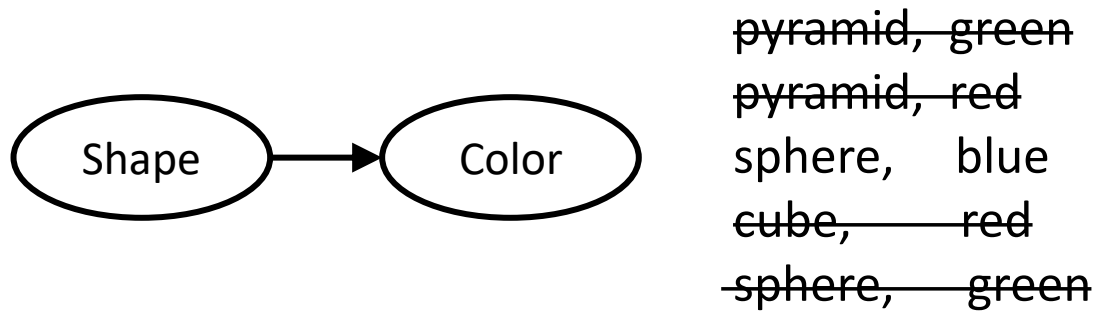
Likelihood Weighting



Likelihood Weighting

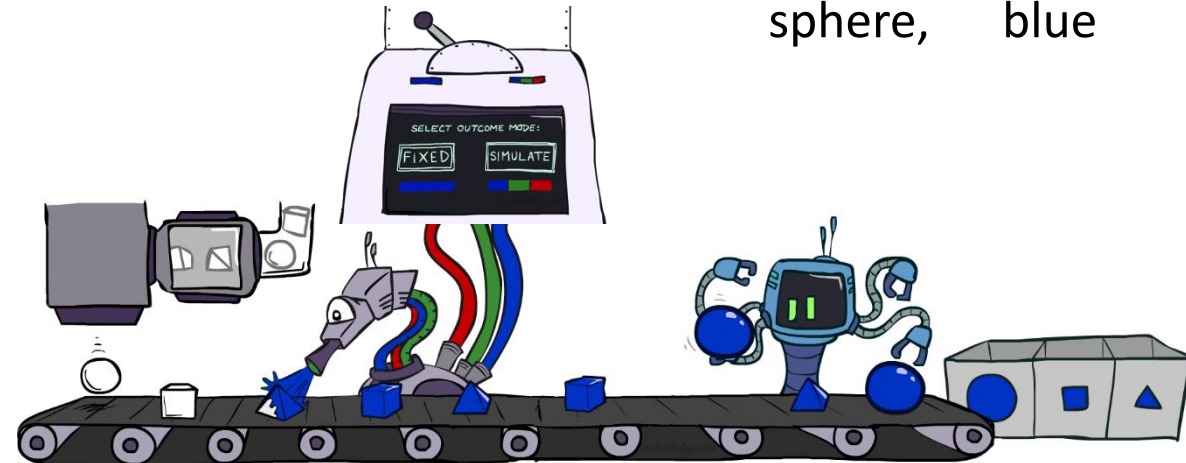
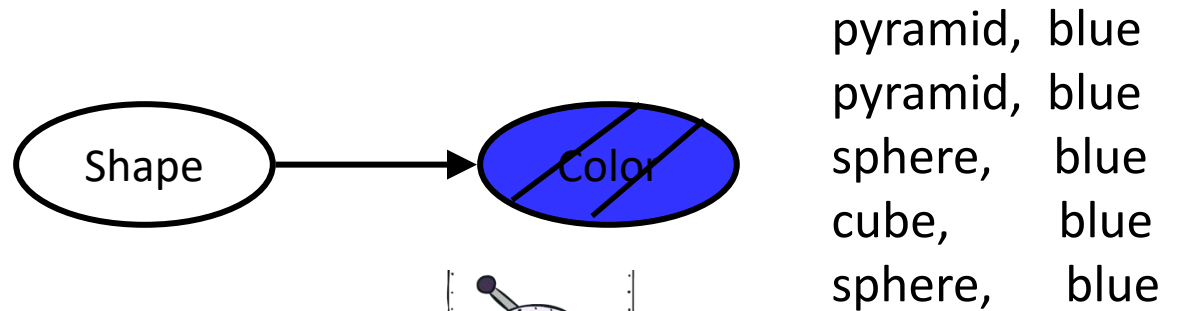
Problem with rejection sampling:

- If evidence is unlikely, rejects lots of samples
- Evidence not exploited as you sample
- Consider $P(\text{Shape} | \text{blue})$

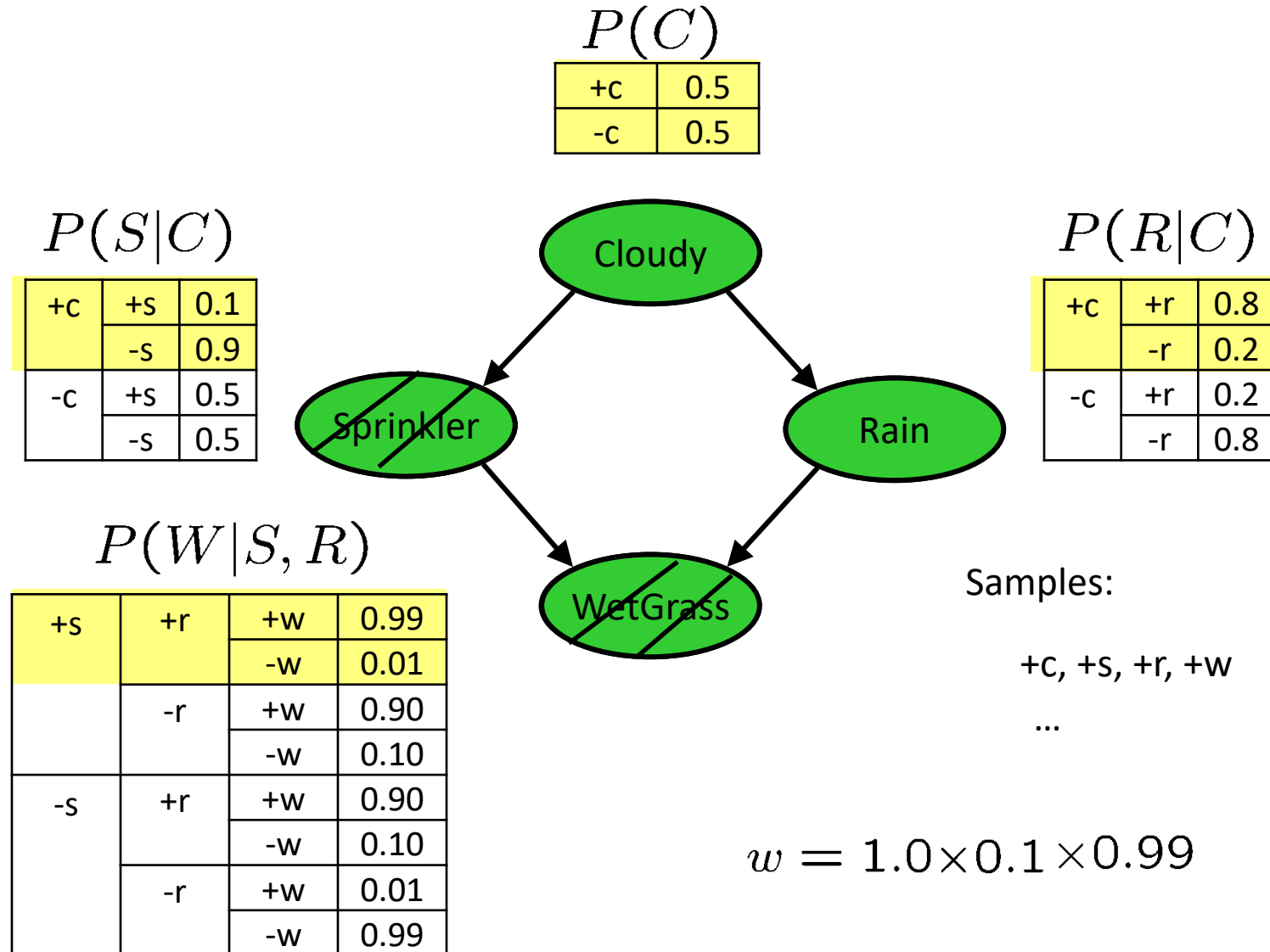


▪ Idea: fix evidence variables and sample the rest

- Problem: sample distribution not consistent!
- Solution: weight by probability of evidence given parents



Likelihood Weighting



Likelihood Weighting

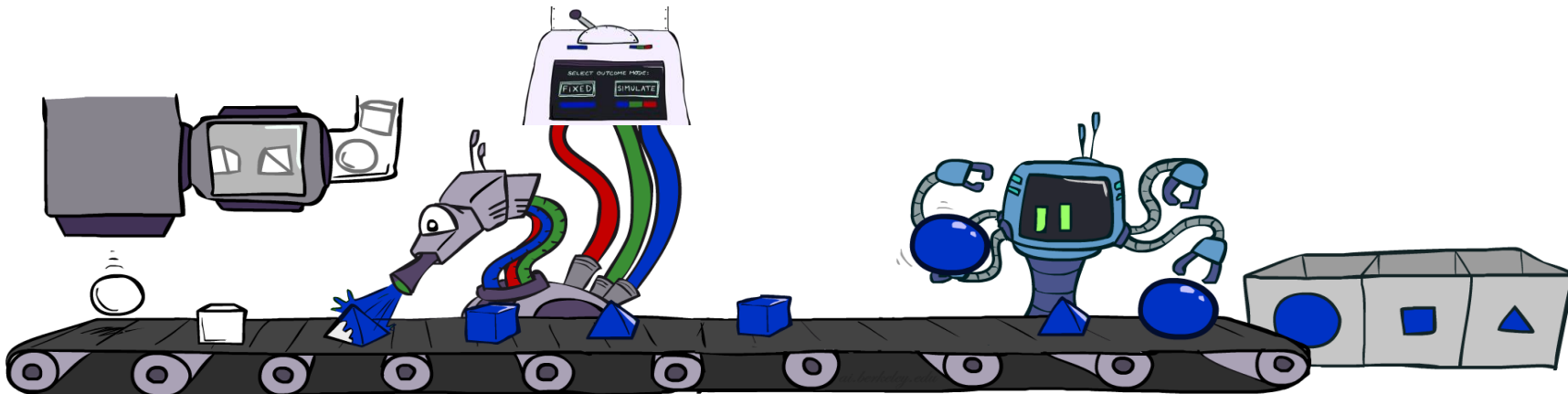
IN: evidence instantiation

$w = 1.0$

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

- if X_i is an evidence variable
 - $X_i = \text{observation } x_i \text{ for } X_i$
 - Set $w = w * P(x_i \mid \text{Parents}(X_i))$
- else
 - Sample x_i from $P(X_i \mid \text{Parents}(X_i))$

return $(x_1, x_2, \dots, x_n), w$



Likelihood Weighting

No evidence:
Prior Sampling

Input: no evidence

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

- Sample x_i from $P(X_i \mid \text{Parents}(X_i))$

return $(x_1, x_2, \dots, x_n)$

Some evidence:
Likelihood Weighted Sampling

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 $w = w * P(x_i \mid \text{Parents}(X_i))$

else

- Sample x_i from $P(X_i \mid \text{Parents}(X_i))$

return $(x_1, x_2, \dots, x_n), w$

All evidence:
Likelihood Weighted

Input: evidence instantiation

$w = 1.0$

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

- Set $w = w * P(x_i \mid \text{Parents}(X_i))$

return w

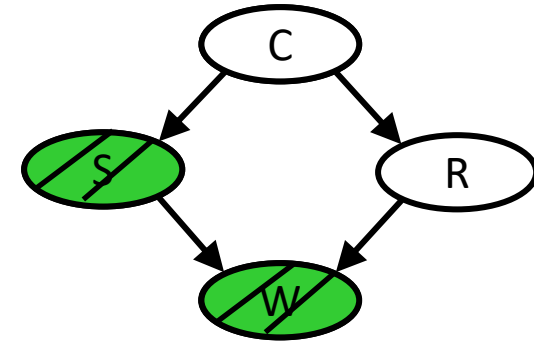
Likelihood Weighting

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

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



Together, weighted sampling distribution is consistent

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

Likelihood Weighting



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+a	1/2
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Likelihood Weighting

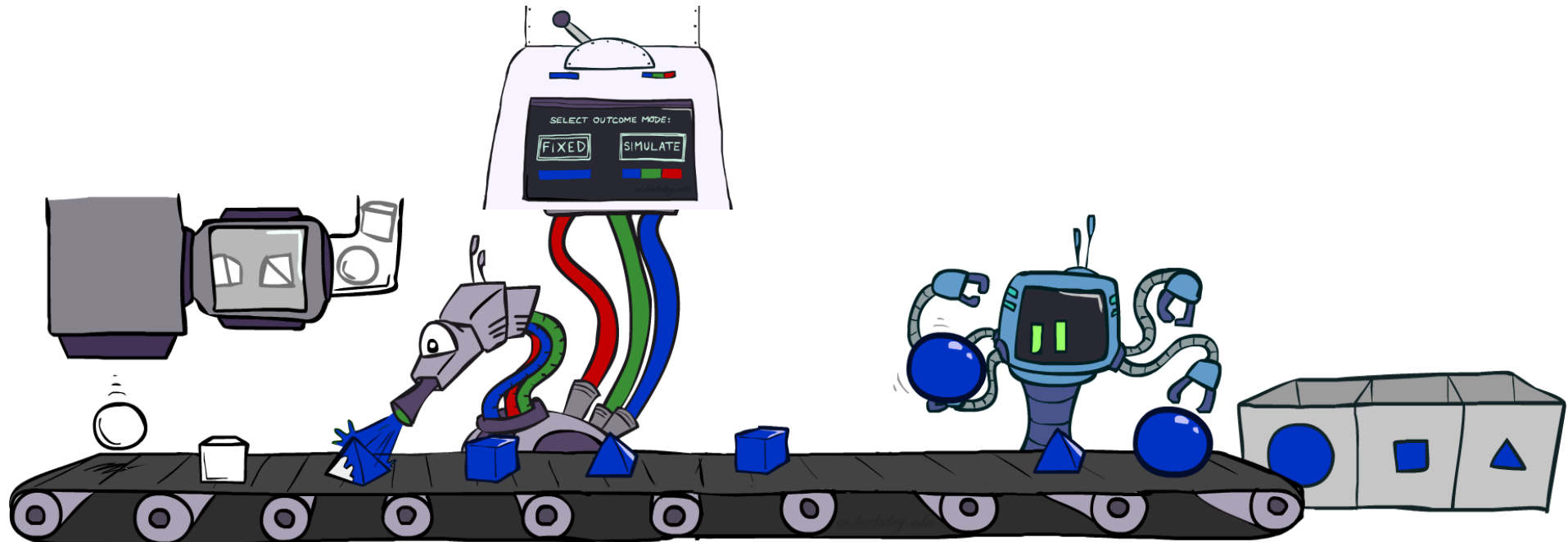
Likelihood weighting is good

- 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 (C isn't more likely to get a value matching the evidence)

We would like to consider evidence when we sample every variable



Likelihood Weighting

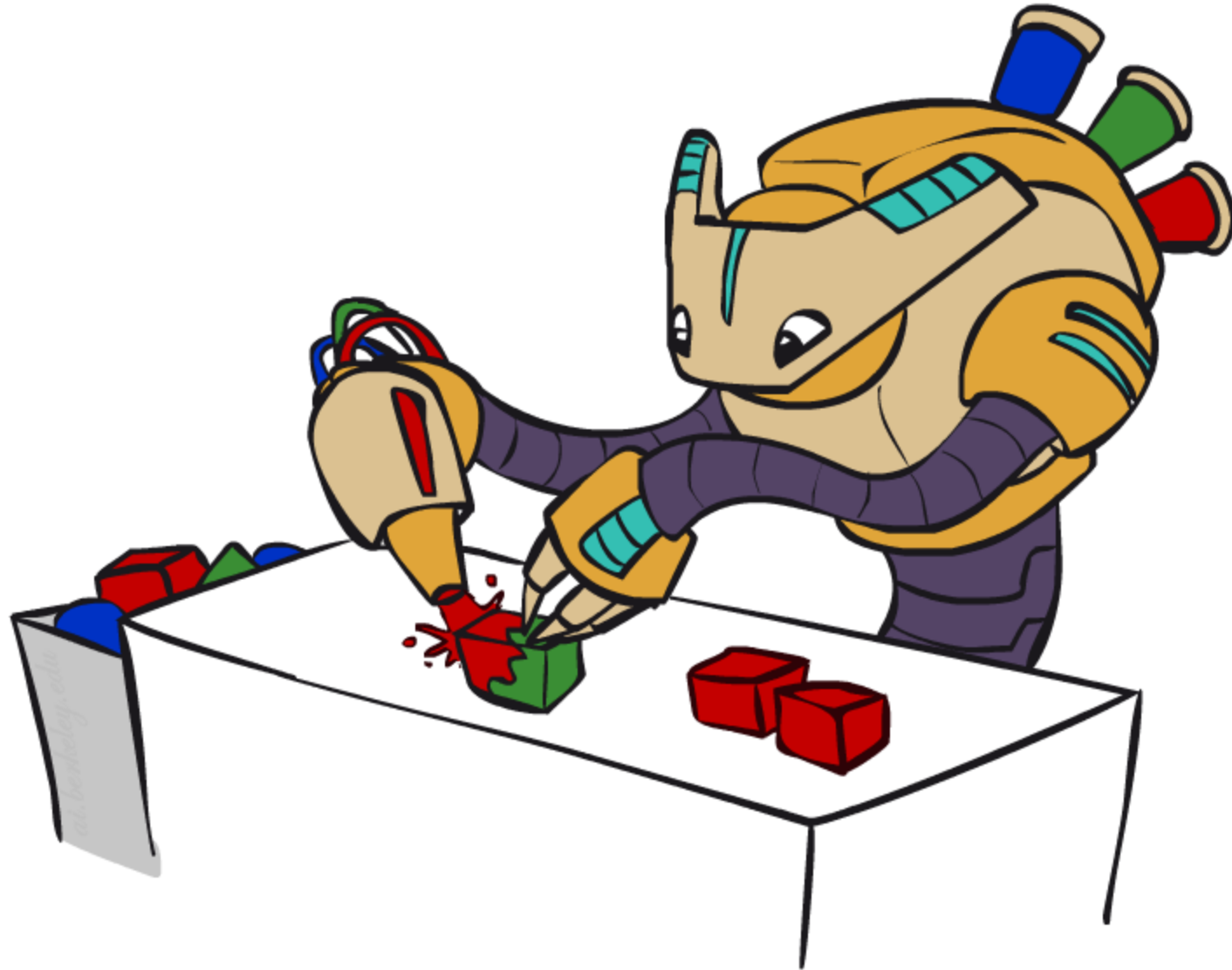
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We would like to consider evidence when we sample every variable

→ Gibbs sampling

Gibbs Sampling



Gibbs Sampling

Procedure: keep track of a full instantiation $x_1, x_2, \dots, x_n$.

1. Start with an arbitrary instantiation consistent with the evidence.
2. Sample one variable at a time, conditioned on all the rest, but keep evidence fixed.
3. Keep repeating this for a long time.

Property: in the limit of repeating this infinitely many times the resulting sample is coming from the correct distribution

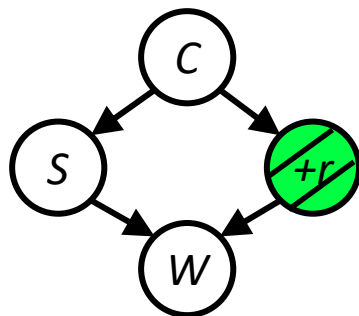
Rationale: both upstream and downstream variables condition on evidence.

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 want high weight.

Gibbs Sampling Example: $P(S \mid +r)$

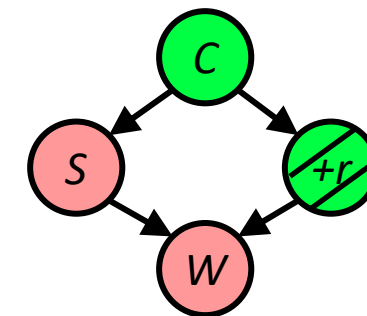
Step 1: Fix evidence

- $R = +r$



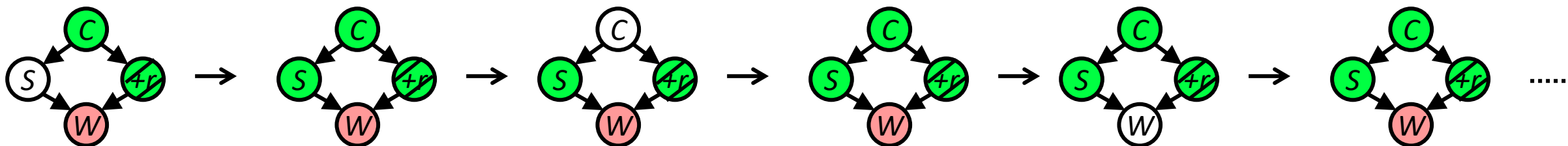
Step 2: Initialize other variables

- Randomly



Steps 3: Repeat

- Choose a non-evidence variable X
- Resample X from $P(X \mid \text{all other variables})$



Sample from $P(S \mid +c, -w, +r)$

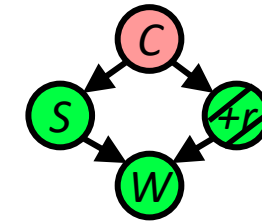
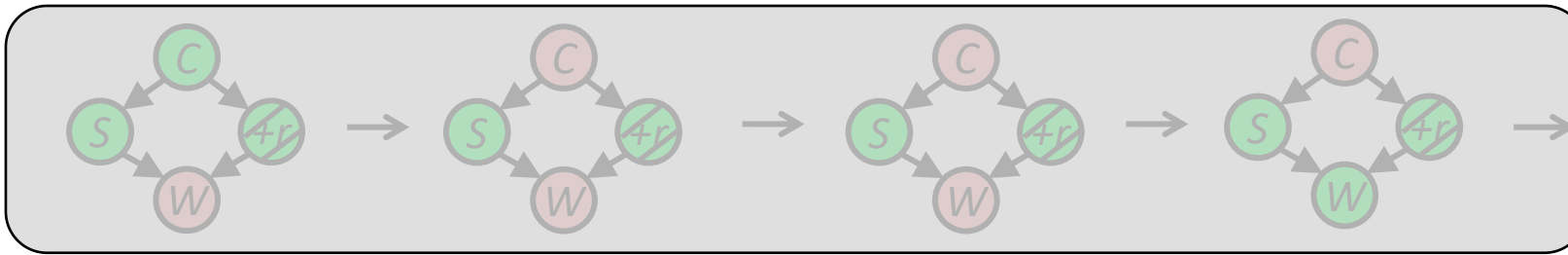
Sample from $P(C \mid +s, -w, +r)$

Sample from $P(W \mid +s, +c, +r)$

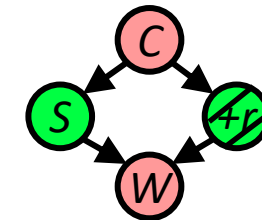
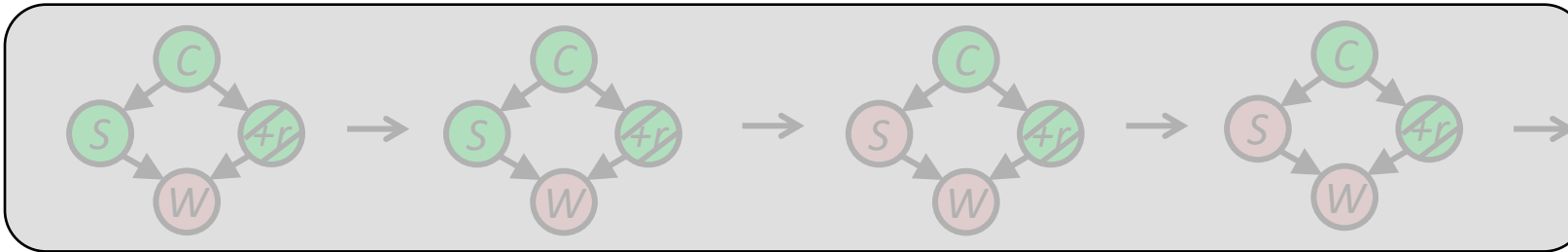
Gibbs Sampling Example: $P(S \mid +r)$

Keep only the last sample from each iteration:

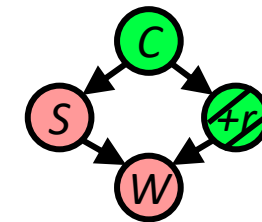
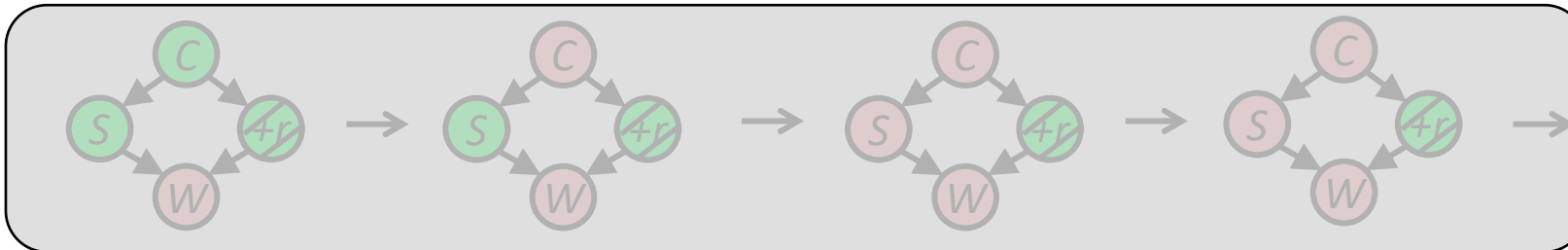
1.



2.



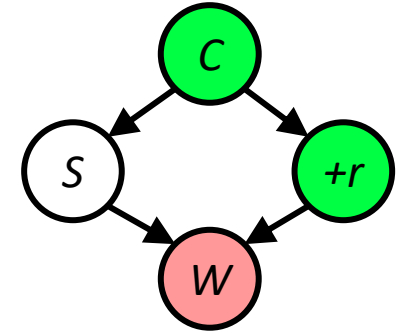
3.



Efficient Resampling of One Variable

Sample from $P(S \mid +c, +r, -w)$

$$\begin{aligned} P(S \mid +c, +r, -w) &= \frac{P(S, +c, +r, -w)}{P(+c, +r, -w)} \\ &= \frac{P(S, +c, +r, -w)}{\sum_s P(s, +c, +r, -w)} \\ &= \frac{P(+c)P(S \mid +c)P(+r \mid +c)P(-w \mid S, +r)}{\sum_s P(+c)P(s \mid +c)P(+r \mid +c)P(-w \mid s, +r)} \\ &= \frac{P(+c)P(S \mid +c)P(+r \mid +c)P(-w \mid S, +r)}{P(+c)P(+r \mid +c) \sum_s P(s \mid +c)P(-w \mid s, +r)} \\ &= \frac{P(S \mid +c)P(-w \mid S, +r)}{\sum_s P(s \mid +c)P(-w \mid s, +r)} \end{aligned}$$



Many things cancel out – only CPTs with S remain!

More generally: only CPTs that have resampled variable need to be considered, and joined together

Further Reading on Gibbs Sampling

Gibbs sampling produces sample from the query distribution $P(Q | e)$ in limit of re-sampling infinitely often

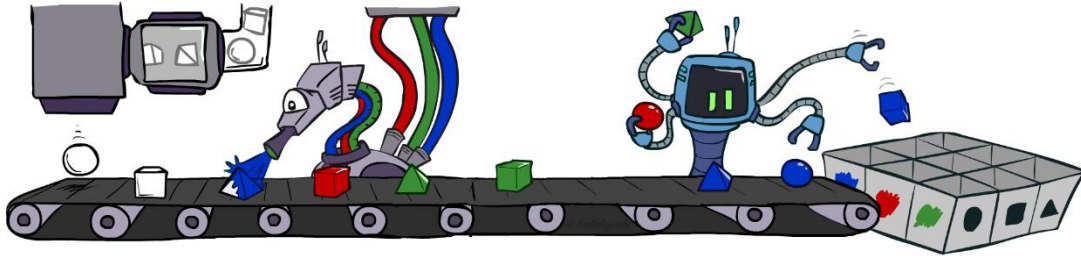
Gibbs sampling is a special case of more general methods called Markov chain Monte Carlo (MCMC) methods

- Metropolis-Hastings is one of the more famous MCMC methods (in fact, Gibbs sampling is a special case of Metropolis-Hastings)

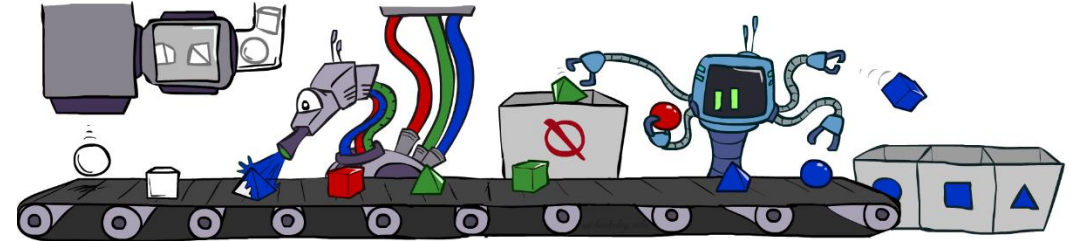
You may read about Monte Carlo methods – they're just sampling

Bayes' Net Sampling Summary

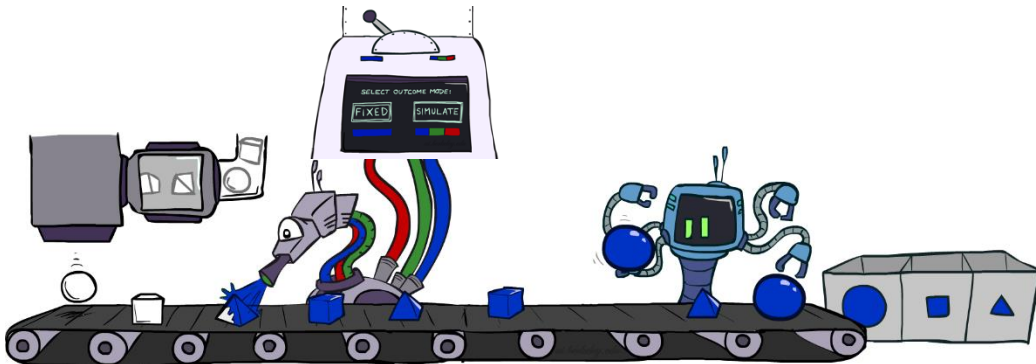
Prior Sampling $P(Q, E)$



Rejection Sampling $P(Q | e)$



Likelihood Weighting $P(Q, e)$



Gibbs Sampling $P(Q | e)$

