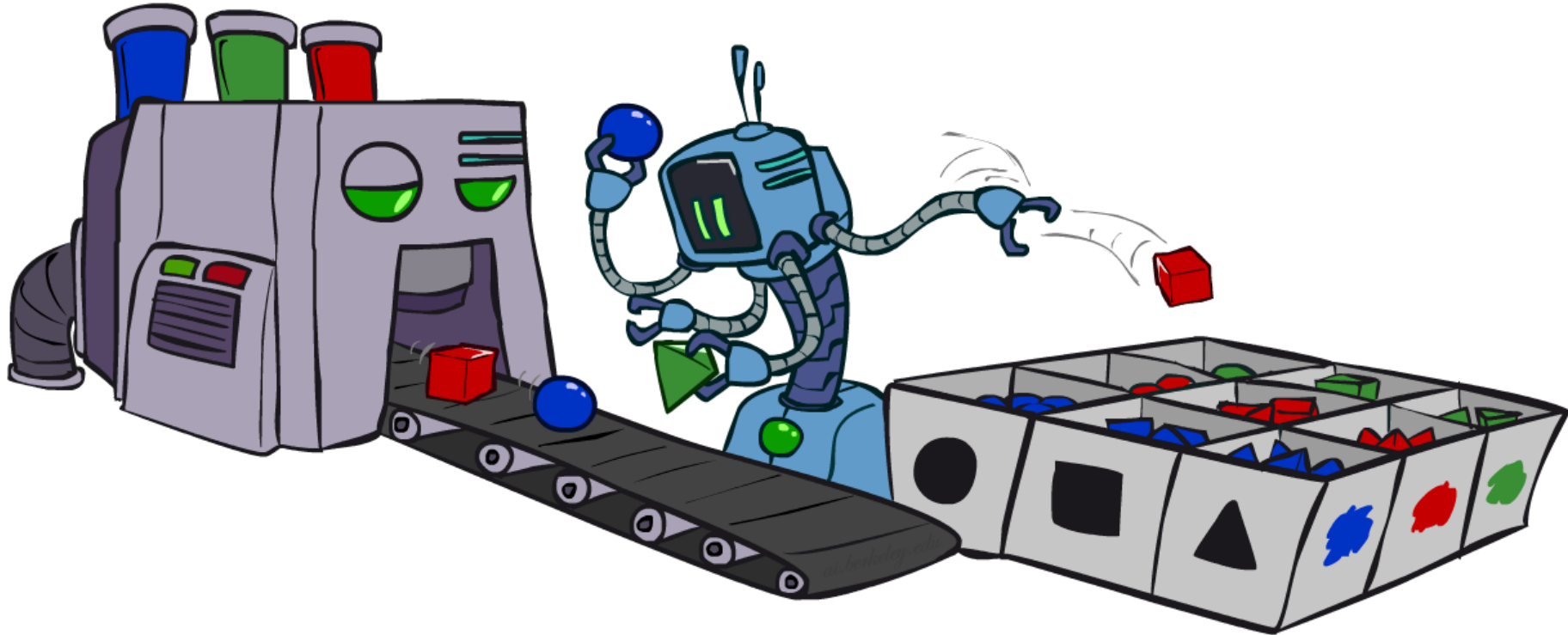


# Bayes' Nets: Sampling



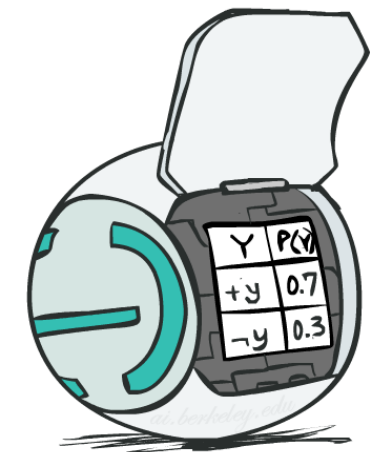
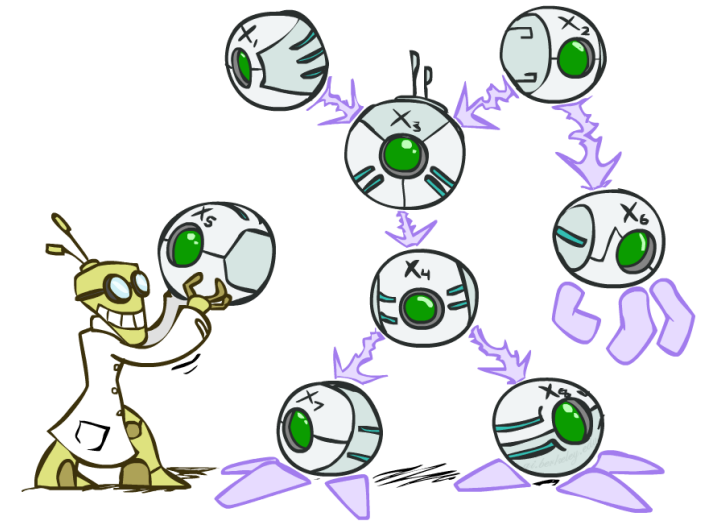
# Review: Bayes' Net Representation

- 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

$$P(X|a_1 \dots a_n)$$

- 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:

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^n P(x_i | \text{parents}(X_i))$$



# Review: Inference by Enumeration

- General case:

- Evidence variables:  $E_1 \dots E_k = e_1 \dots e_k$
  - Query\* variable:  $Q$
  - Hidden variables:  $H_1 \dots H_r$
- }  $X_1, X_2, \dots, X_n$   
All variables

- We want:

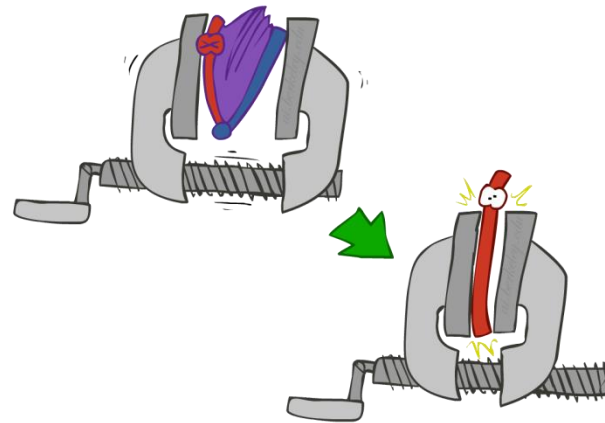
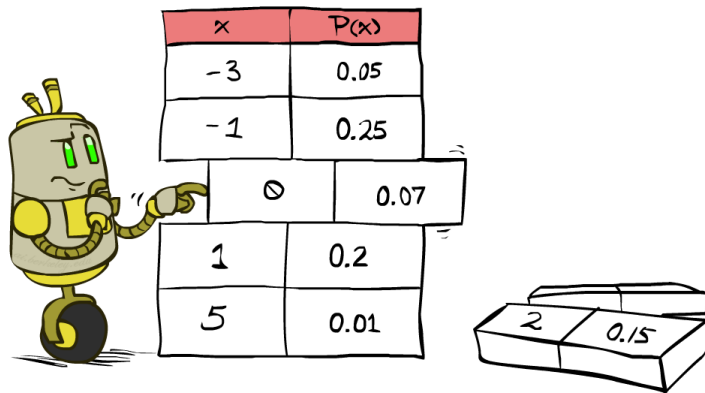
$$P(Q|e_1 \dots e_k)$$

*\* Works fine with multiple query variables, too*

- Step 1: Select the entries consistent with the evidence

- Step 2: Sum out H to get joint of Query and evidence

- Step 3: Normalize



$$\times \frac{1}{Z}$$

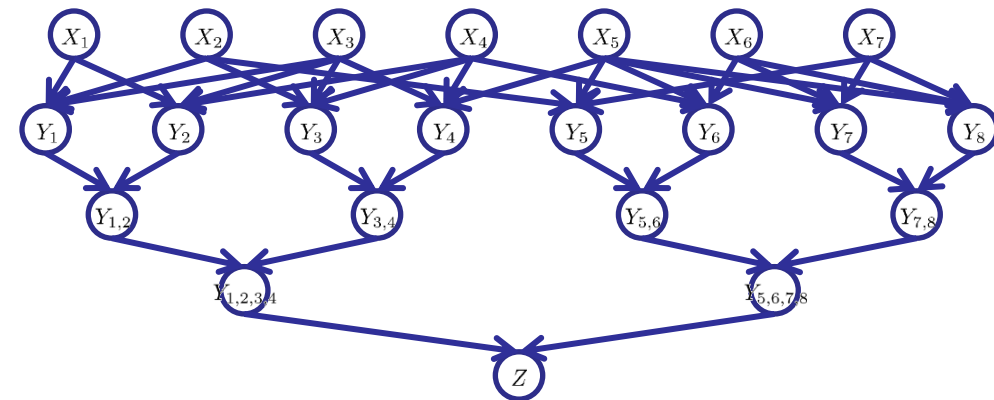
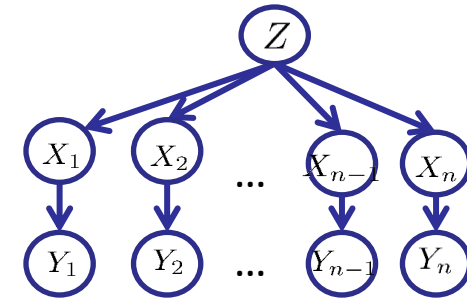
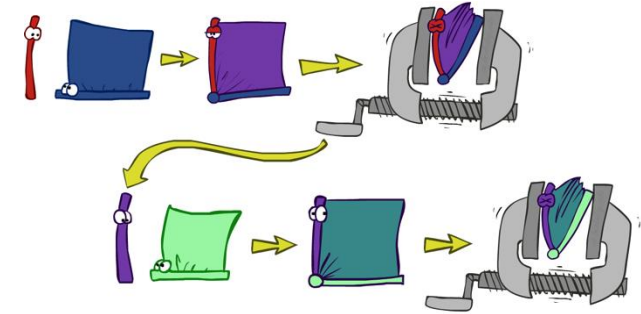
$$P(Q, e_1 \dots e_k) = \sum_{h_1 \dots h_r} \underbrace{P(Q, h_1 \dots h_r, e_1 \dots e_k)}_{X_1, X_2, \dots, X_n}$$

$$Z = \sum_q P(Q, e_1 \dots e_k)$$

$$P(Q|e_1 \dots e_k) = \frac{1}{Z} P(Q, e_1 \dots e_k)$$

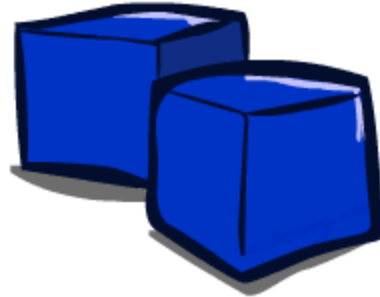
# Review: Variable Elimination

- 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



# Approximate Inference: Sampling

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# Sampling

- Sampling is a lot like repeated simulation

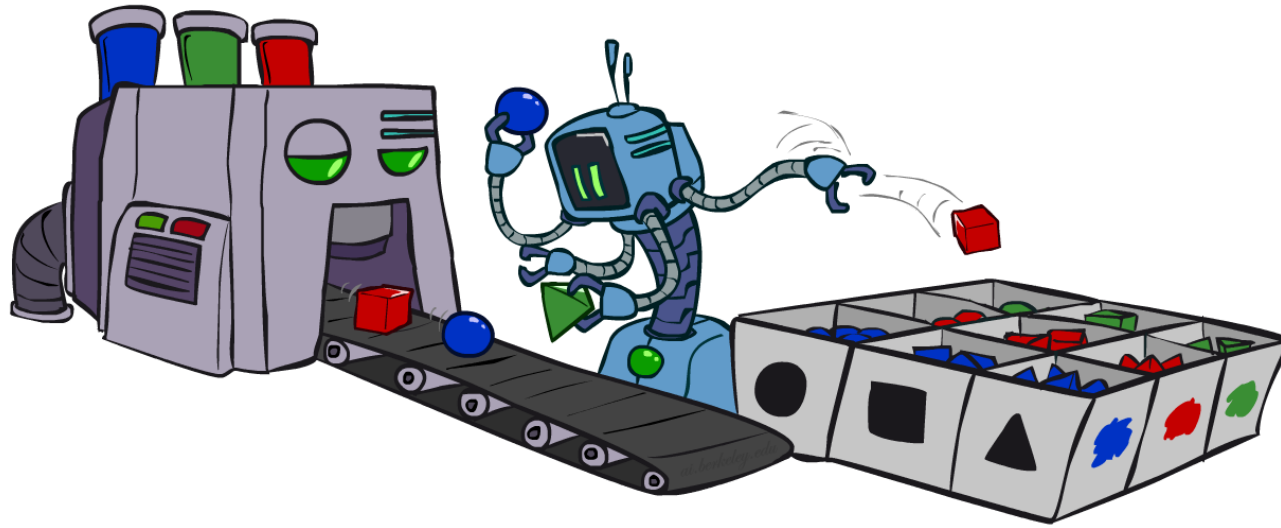
- Predicting the weather, basketball games, ...

- Basic idea

- Draw  $N$  samples from a sampling distribution  $S$
- Compute an approximate posterior probability
- Show this converges to the true probability  $P$

- Why sample?

- Inference: getting a sample is faster than computing the right answer (e.g. with variable elimination)
- Learning: get samples from a distribution you don't know



# 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

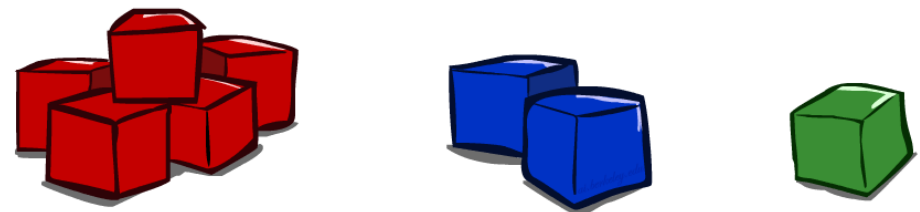
C	P(C)
red	0.6
green	0.1
blue	0.3

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

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

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

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



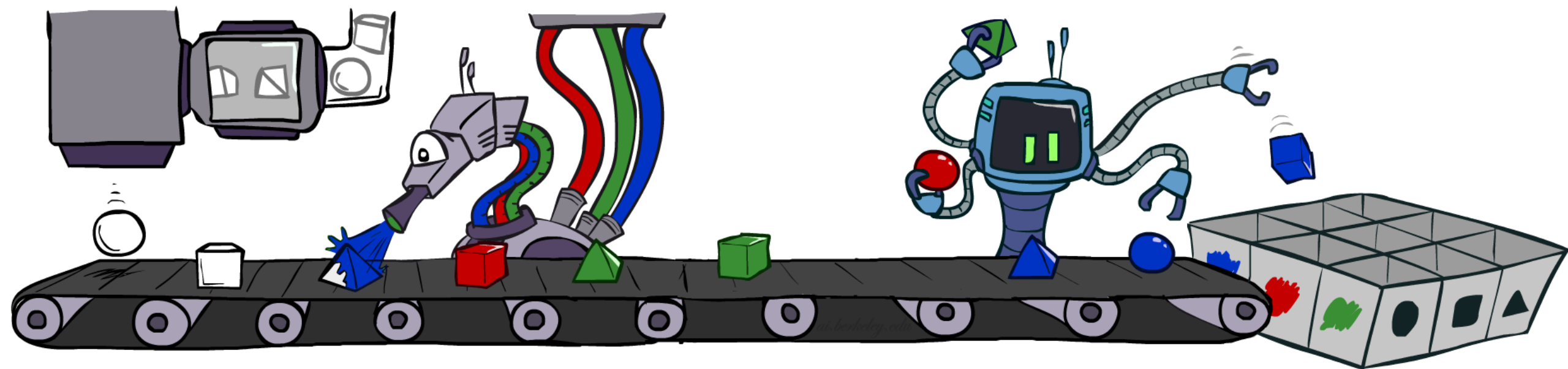
# Sampling in Bayes' Nets

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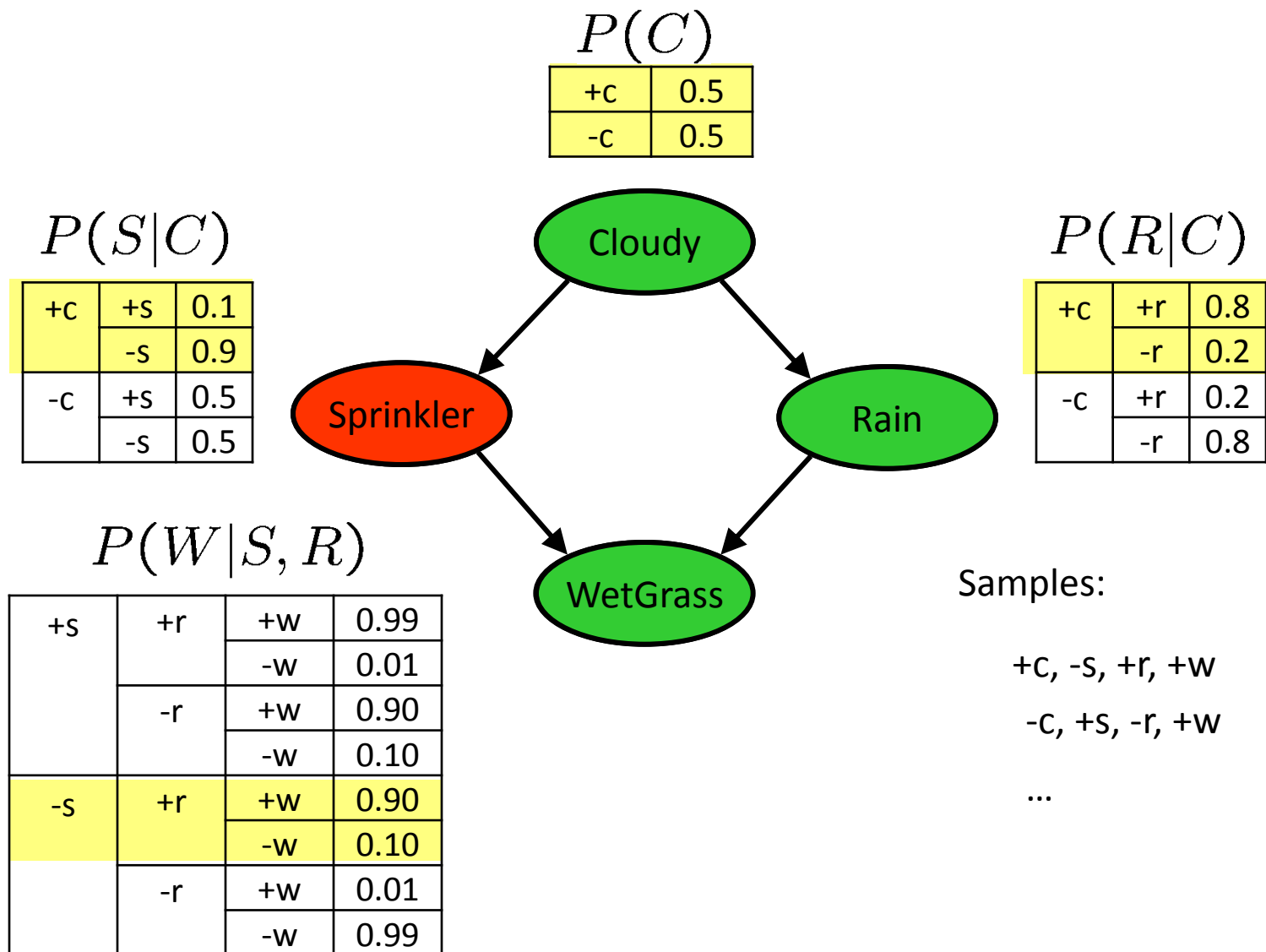
- Prior Sampling
- Rejection Sampling
- Likelihood Weighting
- Gibbs Sampling



# Prior Sampling

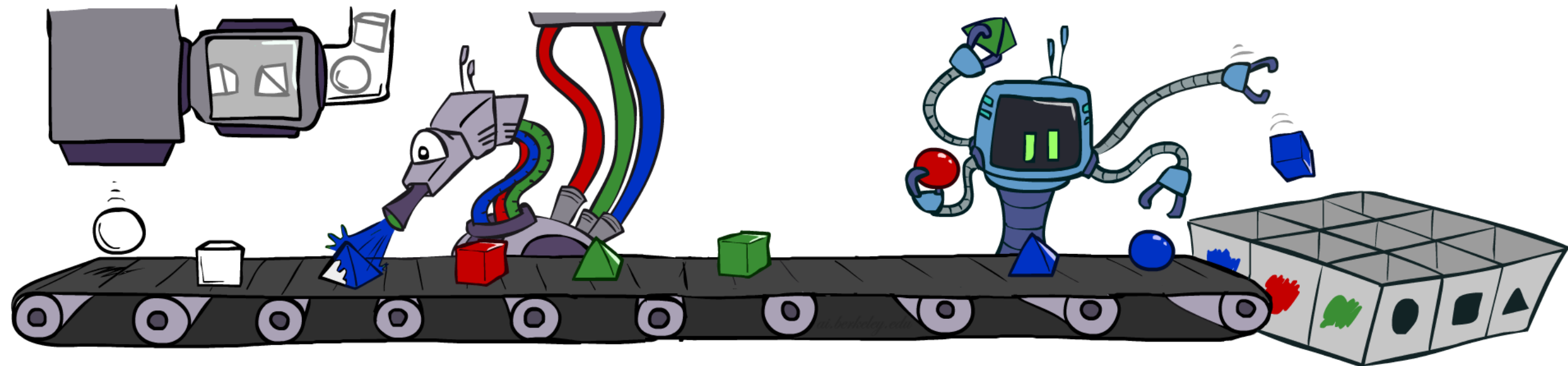


# Prior Sampling



# Prior Sampling

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



# 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 
$$\begin{aligned} \lim_{N \rightarrow \infty} \hat{P}(x_1, \dots, x_n) &= \lim_{N \rightarrow \infty} N_{PS}(x_1, \dots, x_n) / N \\ &= S_{PS}(x_1, \dots, x_n) \\ &= P(x_1 \dots x_n) \end{aligned}$$
- I.e., the sampling procedure is **consistent**

# Example

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

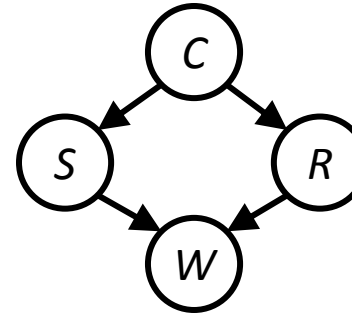
+c, -s, +r, +w

+c, +s, +r, +w

-c, +s, +r, -w

+c, -s, +r, +w

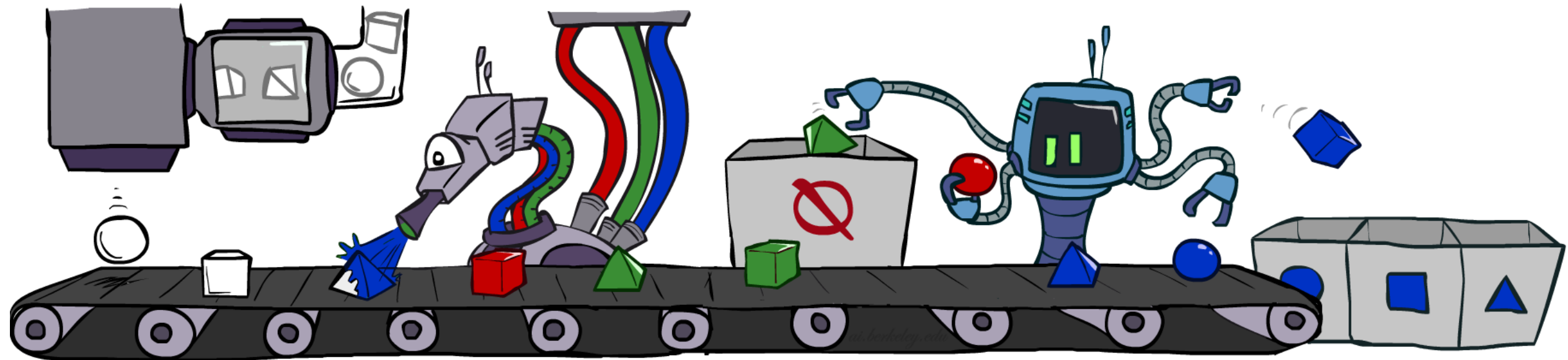
-c, -s, -r, +w



- If we want to know  $P(W)$

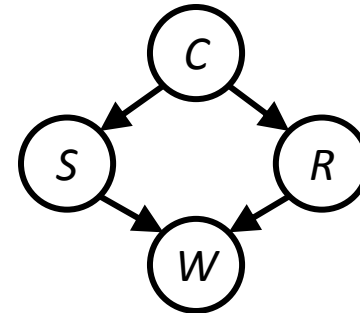
- We have counts  $\langle +w:4, -w:1 \rangle$
- Normalize to get  $P(W) = \langle +w:0.8, -w:0.2 \rangle$
- This will get closer to the true distribution with more samples
- Can estimate anything else, too
- What about  $P(C \mid +w)$ ?  $P(C \mid +r, +w)$ ?  $P(C \mid -r, -w)$ ?
- Fast: can use fewer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

# Rejection Sampling



# Rejection Sampling

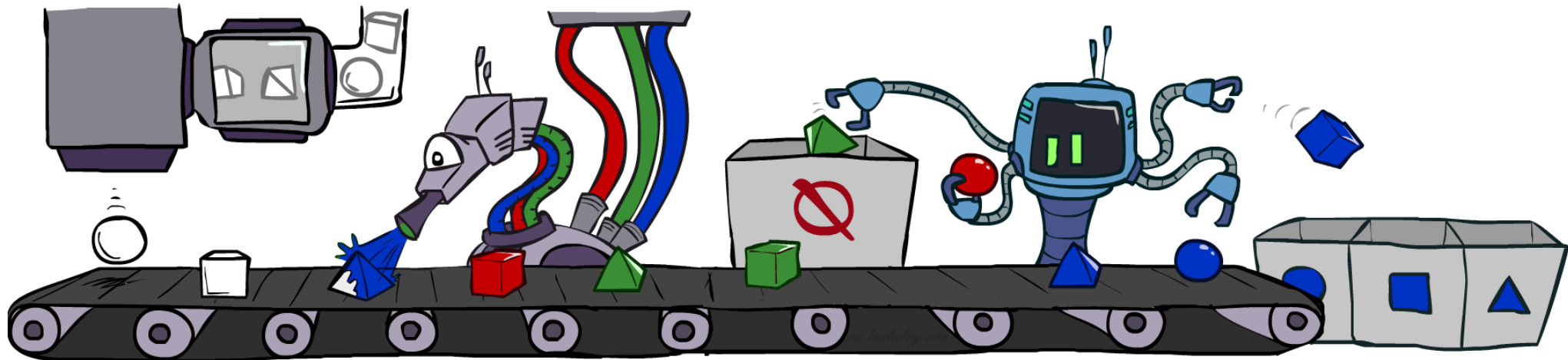
- Let's say we want  $P(C)$ 
  - No point keeping all samples around
  - Just tally counts of  $C$  as we go
- Let's say we want  $P(C | +s)$ 
  - Same thing: tally  $C$  outcomes, but ignore (reject) samples which don't have  $S=+s$
  - This is called rejection sampling
  - It is also consistent for 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

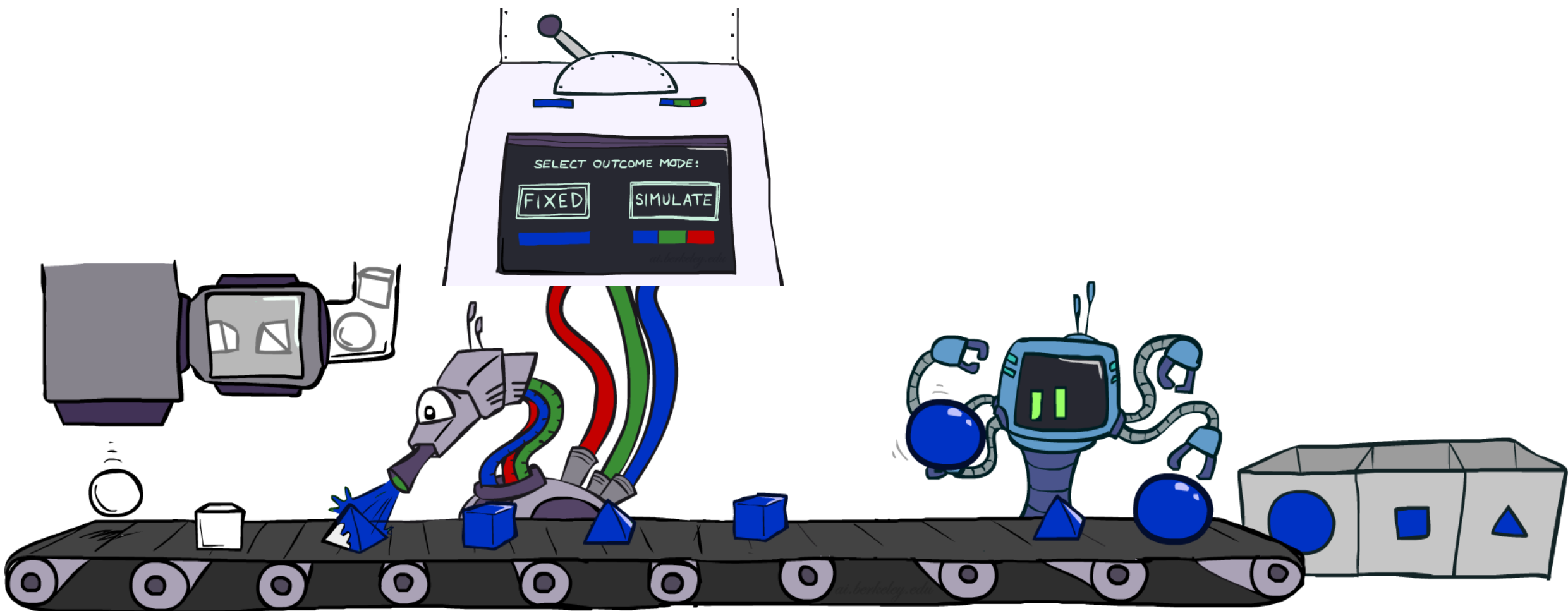
# Rejection Sampling

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



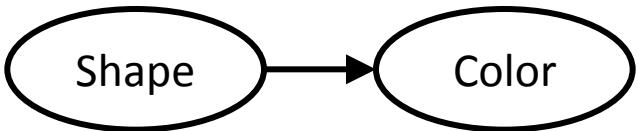


# Likelihood Weighting

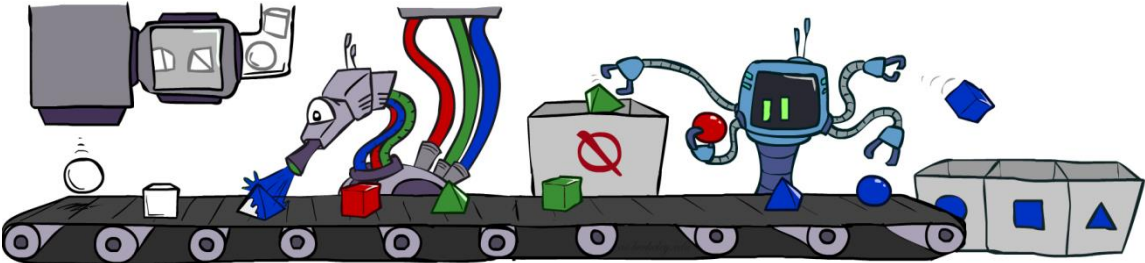


# Likelihood Weighting

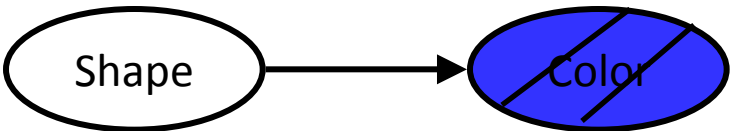
- Problem with rejection sampling:
  - If evidence is unlikely, rejects lots of samples
  - Evidence not exploited as you sample
  - Consider  $P(\text{Shape} | \text{blue})$



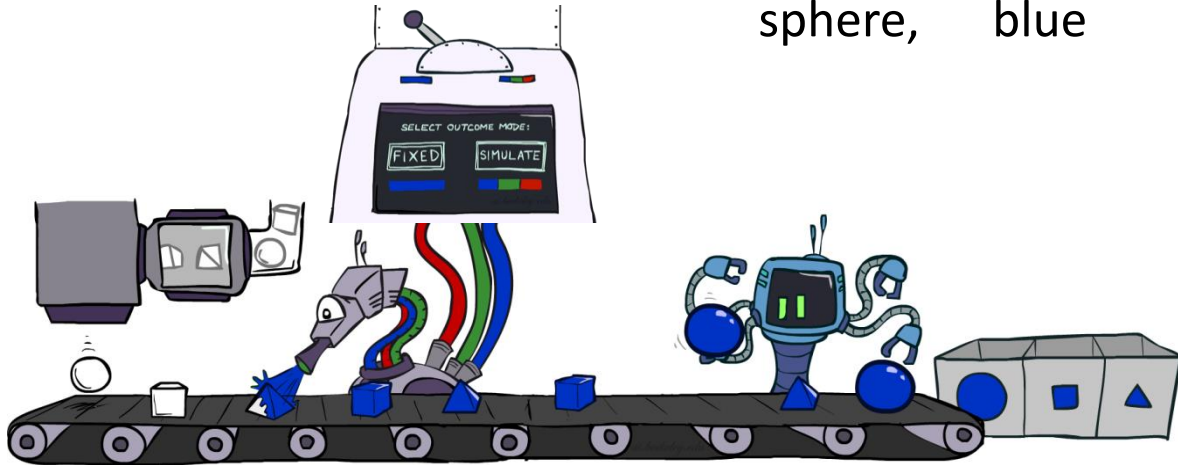
~~pyramid, green~~  
~~pyramid, red~~  
 sphere, blue  
 cube, red  
~~sphere, green~~



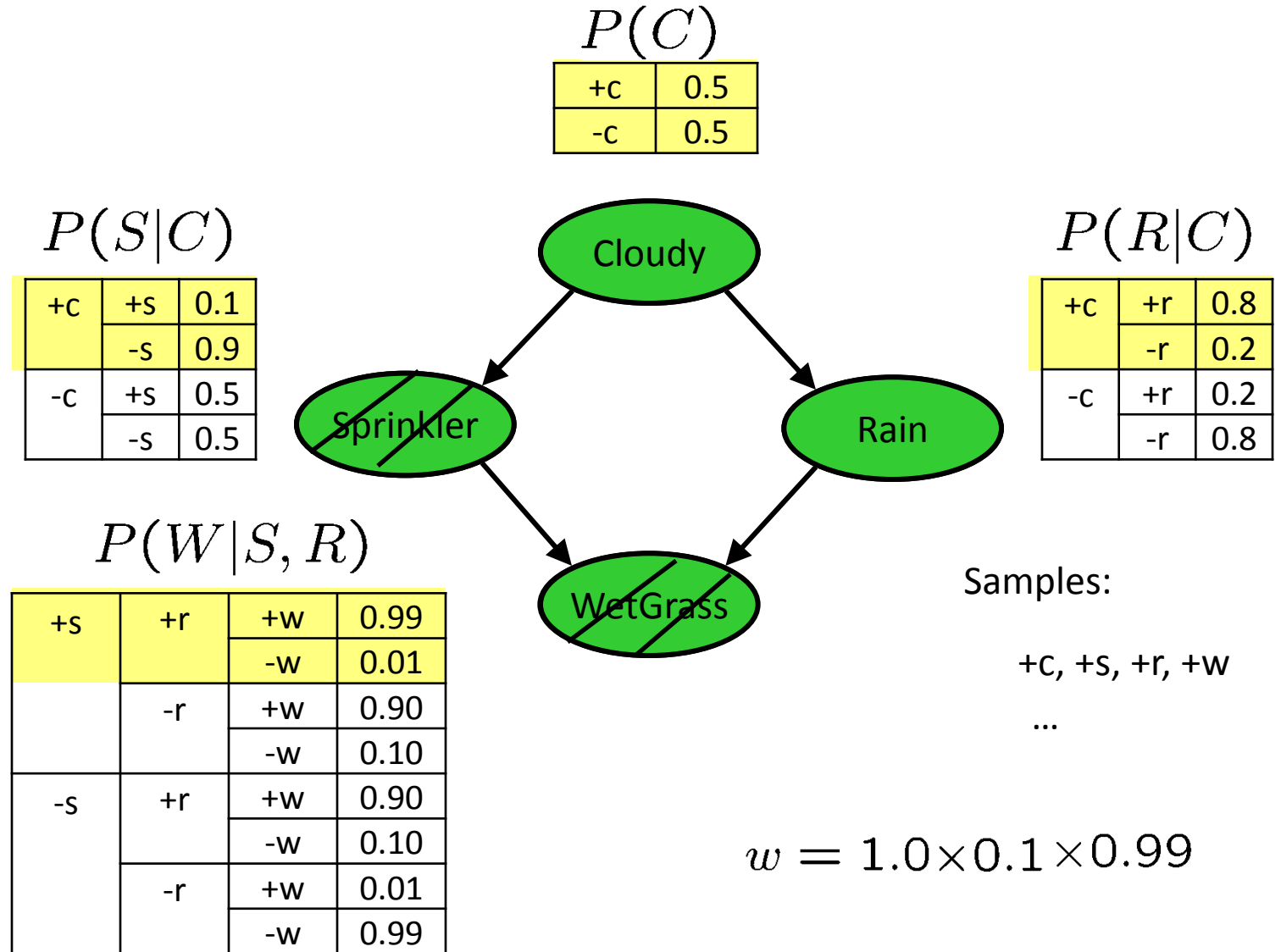
- Idea: fix evidence variables and sample the rest
  - Problem: sample distribution not consistent!
  - Solution: weight by probability of evidence given parents



pyramid, blue  
 pyramid, blue  
 sphere, blue  
 cube, blue  
 sphere, blue

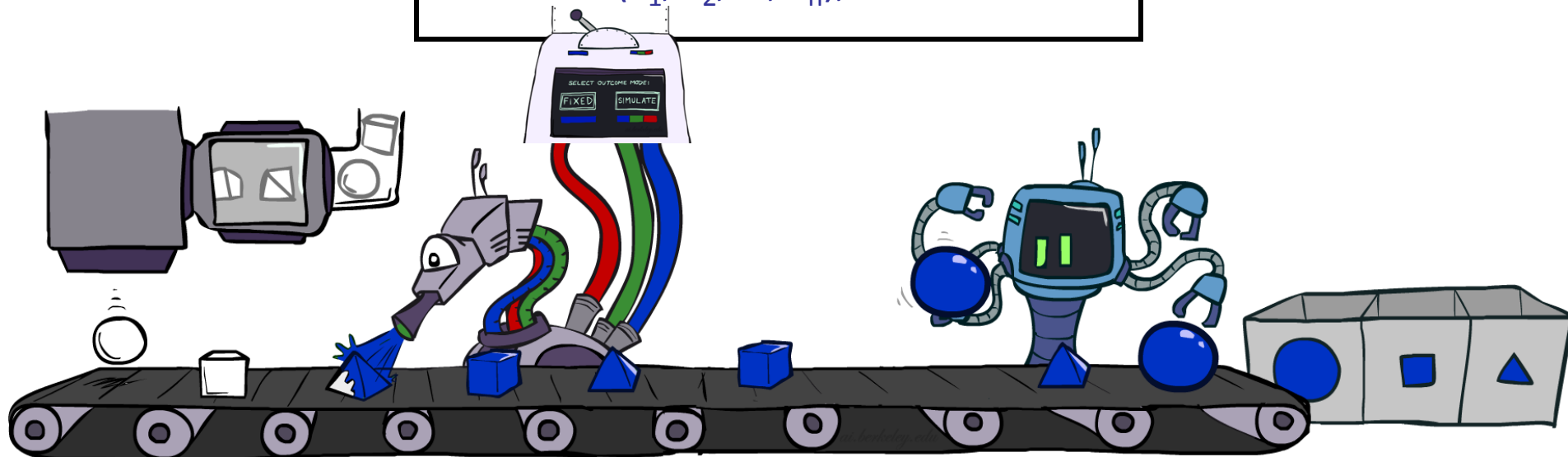


# Likelihood Weighting



# 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  $w = w * P(x_i | \text{Parents}(X_i))$
  - else
    - Sample  $x_i$  from  $P(X_i | \text{Parents}(X_i))$
- return  $(x_1, x_2, \dots, x_n), w$



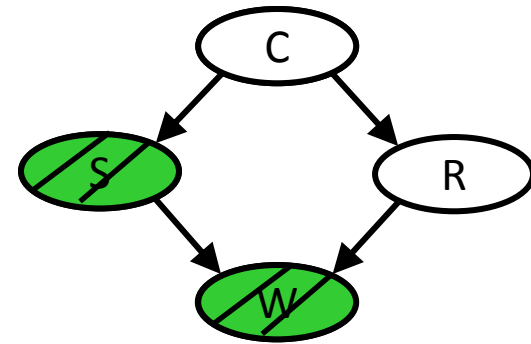
# Likelihood Weighting

- 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

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

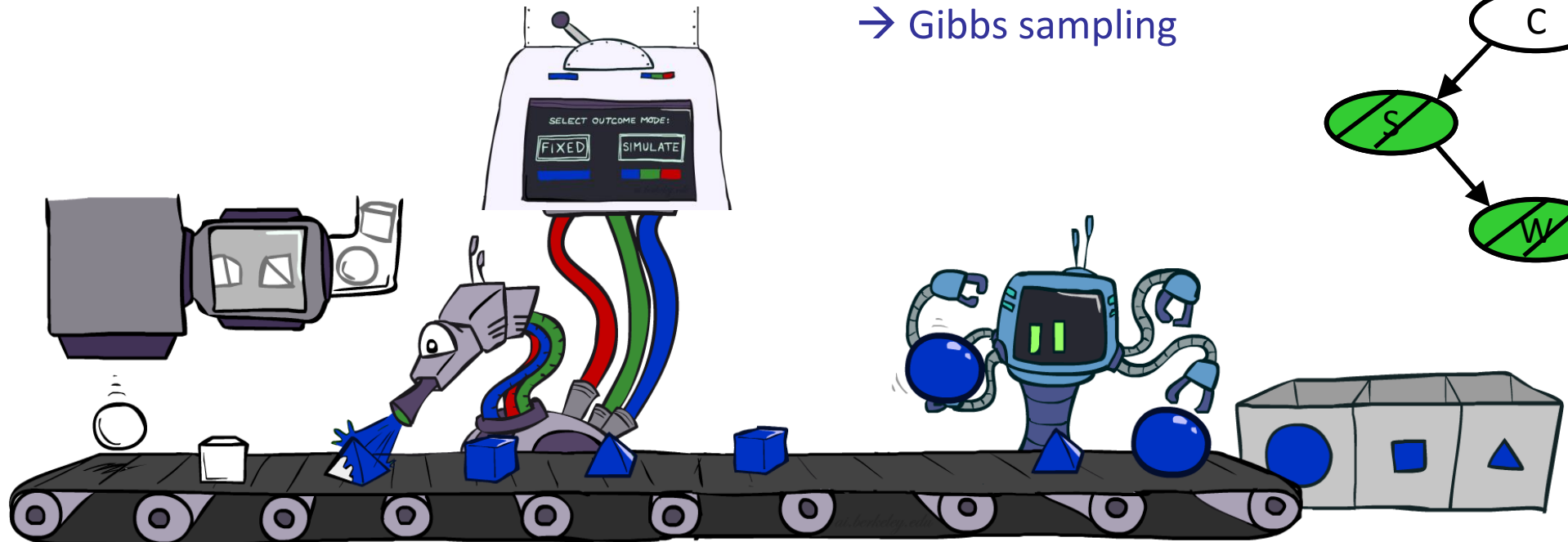


- Together, weighted sampling distribution is consistent

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

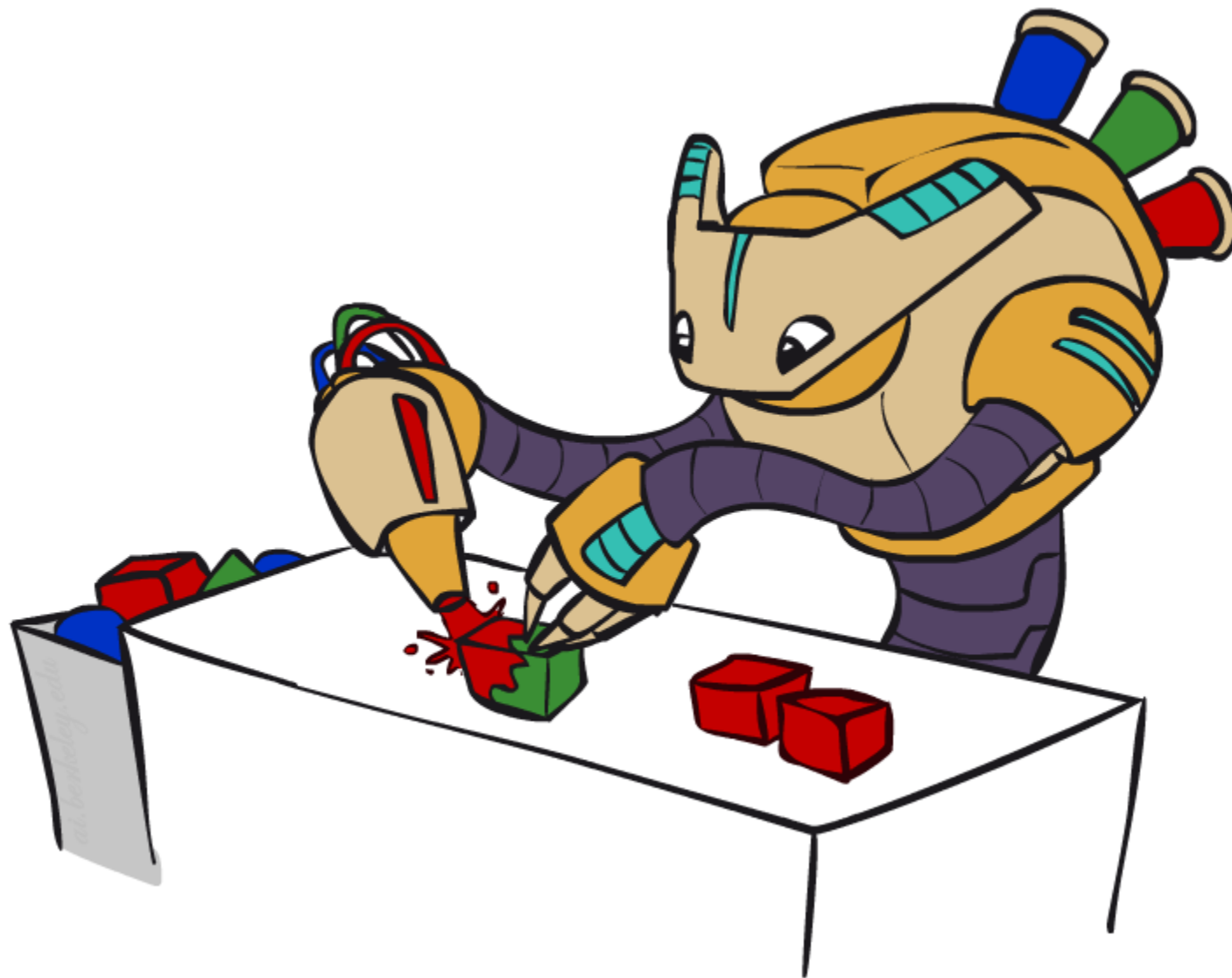
# Likelihood Weighting

- 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
  - Gibbs sampling



# Gibbs Sampling

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# Gibbs Sampling

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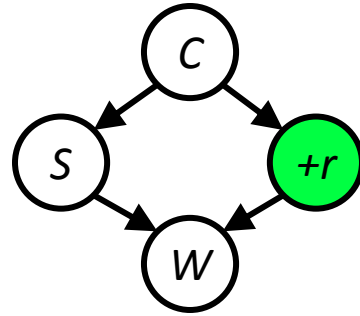
- *Procedure:* keep track of a full instantiation  $x_1, x_2, \dots, x_n$ . Start with an arbitrary instantiation consistent with the evidence. Sample one variable at a time, conditioned on all the rest, but keep evidence fixed. Keep repeating this for a long time.
- *Property:* in the limit of repeating this infinitely many times the resulting 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: $P(S | +r)$

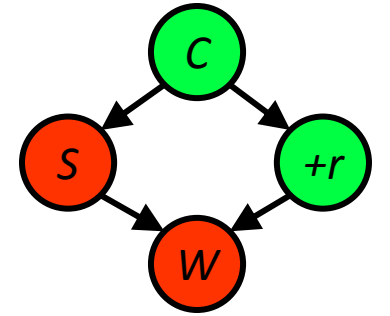
- Step 1: Fix evidence

- $R = +r$



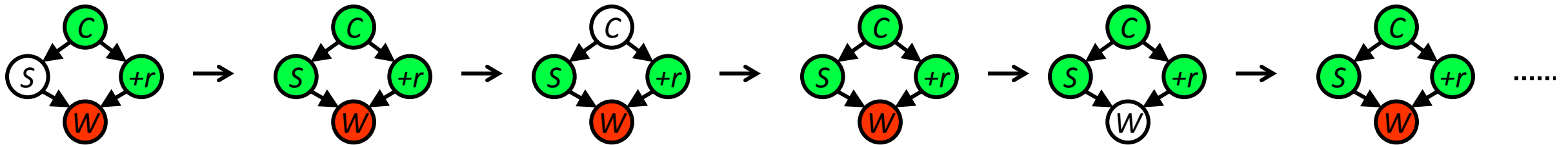
- Step 2: Initialize other variables

- Randomly



- Steps 3: Repeat

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



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

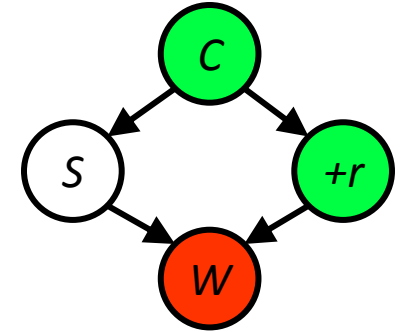
Sample from  $P(C | +s, -w, +r)$

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

# Efficient Resampling of One Variable

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

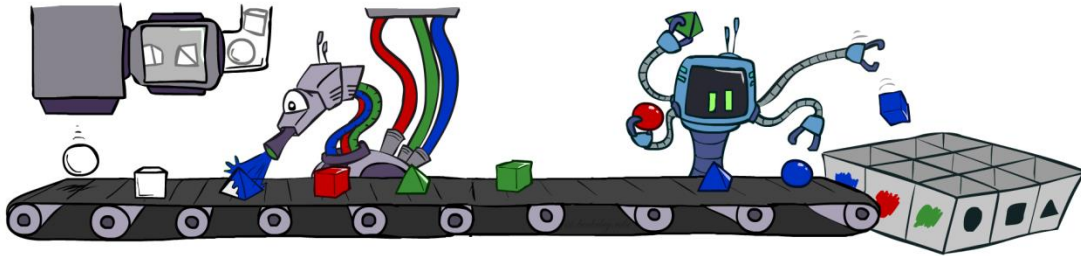
$$\begin{aligned} P(S \mid +c, +r, -w) &= \frac{P(S, +c, +r, -w)}{P(+c, +r, -w)} \\ &= \frac{P(S, +c, +r, -w)}{\sum_s P(s, +c, +r, -w)} \\ &= \frac{P(+c)P(S \mid +c)P(+r \mid +c)P(-w \mid S, +r)}{\sum_s P(+c)P(s \mid +c)P(+r \mid +c)P(-w \mid s, +r)} \\ &= \frac{P(+c)P(S \mid +c)P(+r \mid +c)P(-w \mid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



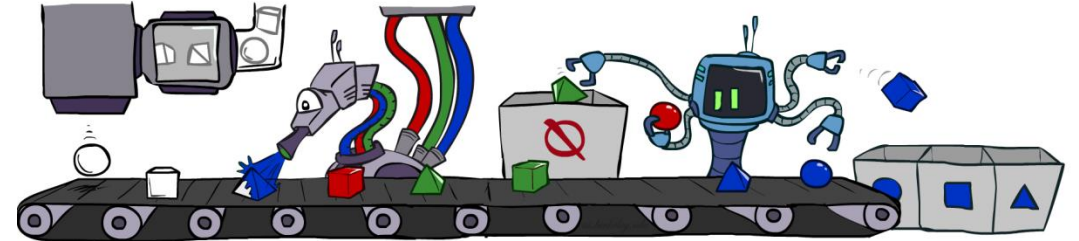
- Many things cancel out – only CPTs with S remain!
- More generally: only CPTs that have resampled variable need to be considered, and joined together

# Bayes' Net Sampling Summary

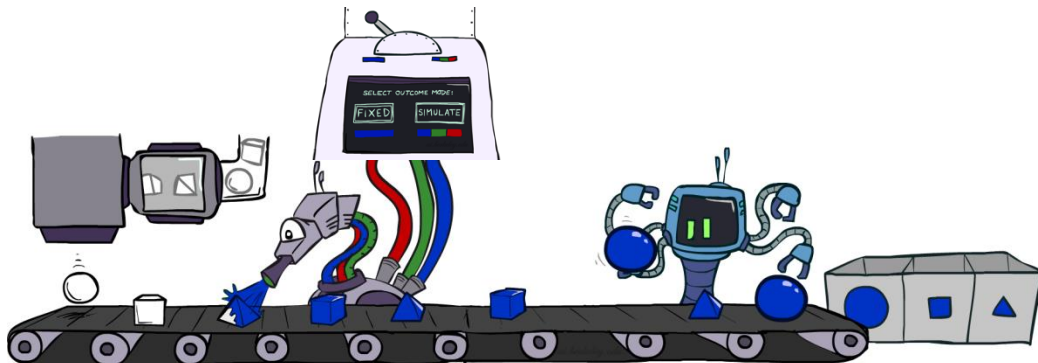
- Prior Sampling  $P$



- Rejection Sampling  $P(Q | e)$



- Likelihood Weighting  $P(Q | e)$



- Gibbs Sampling  $P(Q | e)$

