

15: General Inference

Lisa Yan

May 8, 2020

Quick slide reference

3	General Inference: intro	15a_inference
15	Bayesian Networks	15b_bayes_nets
22	Inference (I): Math	15c_inference_math
29	Inference (II): Rejection sampling	LIVE
54	Inference (III): Gibbs sampling (extra)	(no video)

General Inference: Introduction

Inference

*Web*MD[®]

Inference

WebMD Symptom Checker BETA

INFO SYMPTOMS QUESTIONS CONDITIONS DETAILS TREATMENT

What is your main symptom?

Type your main symptom here

or Choose common symptoms

bloating cough diarrhea dizziness fatigue

fever headache muscle cramp nausea

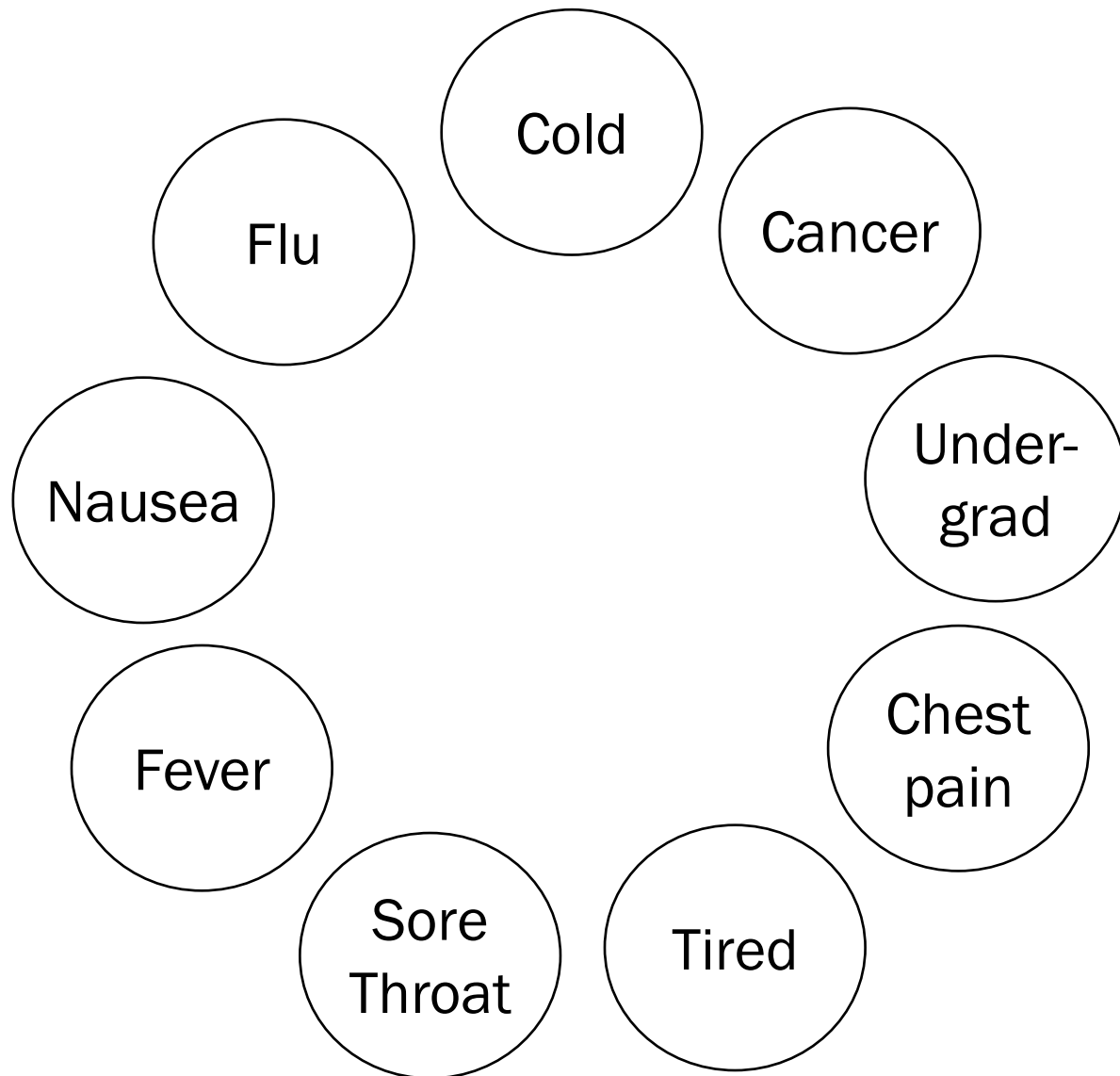
throat irritation

AGE 28 GENDER Female

No symptoms added

< Previous Continue >

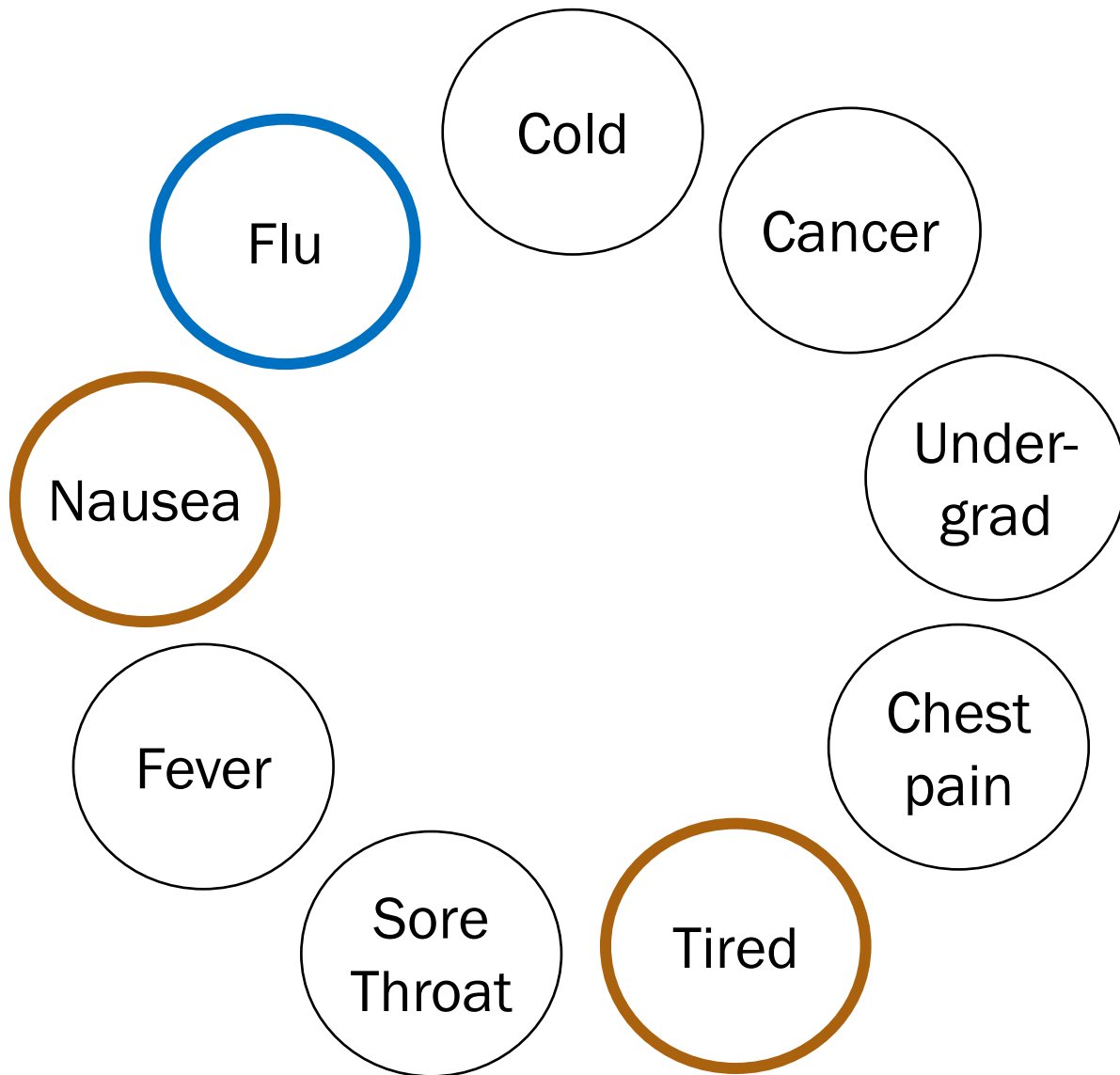
Inference



General **inference** question:

Given the values of some random variables, what is the conditional distribution of some other random variables?

Inference

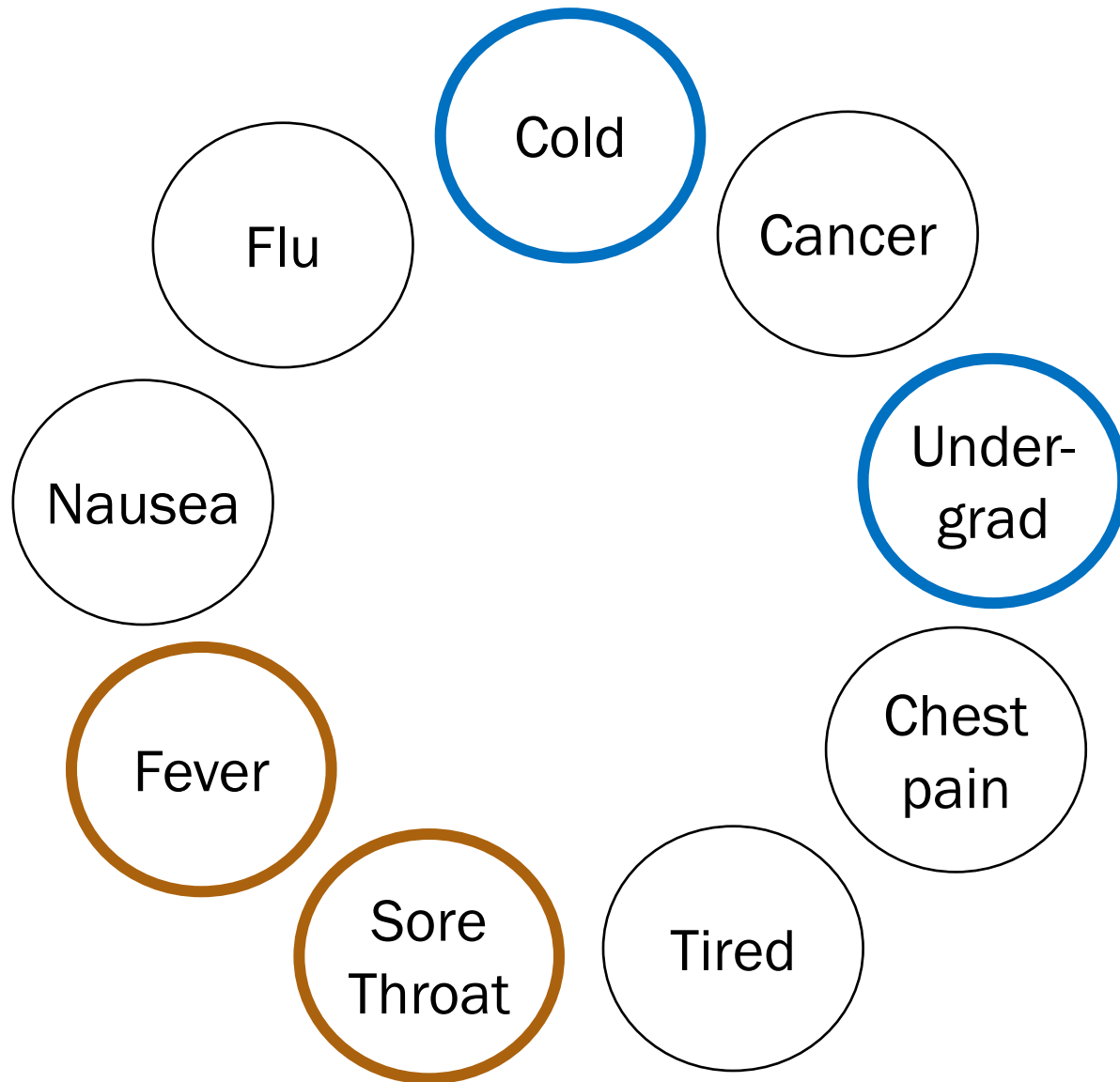


One inference question:

$$P(F = 1 | N = 1, T = 1)$$

$$= \frac{P(F = 1, N = 1, T = 1)}{P(N = 1, T = 1)}$$

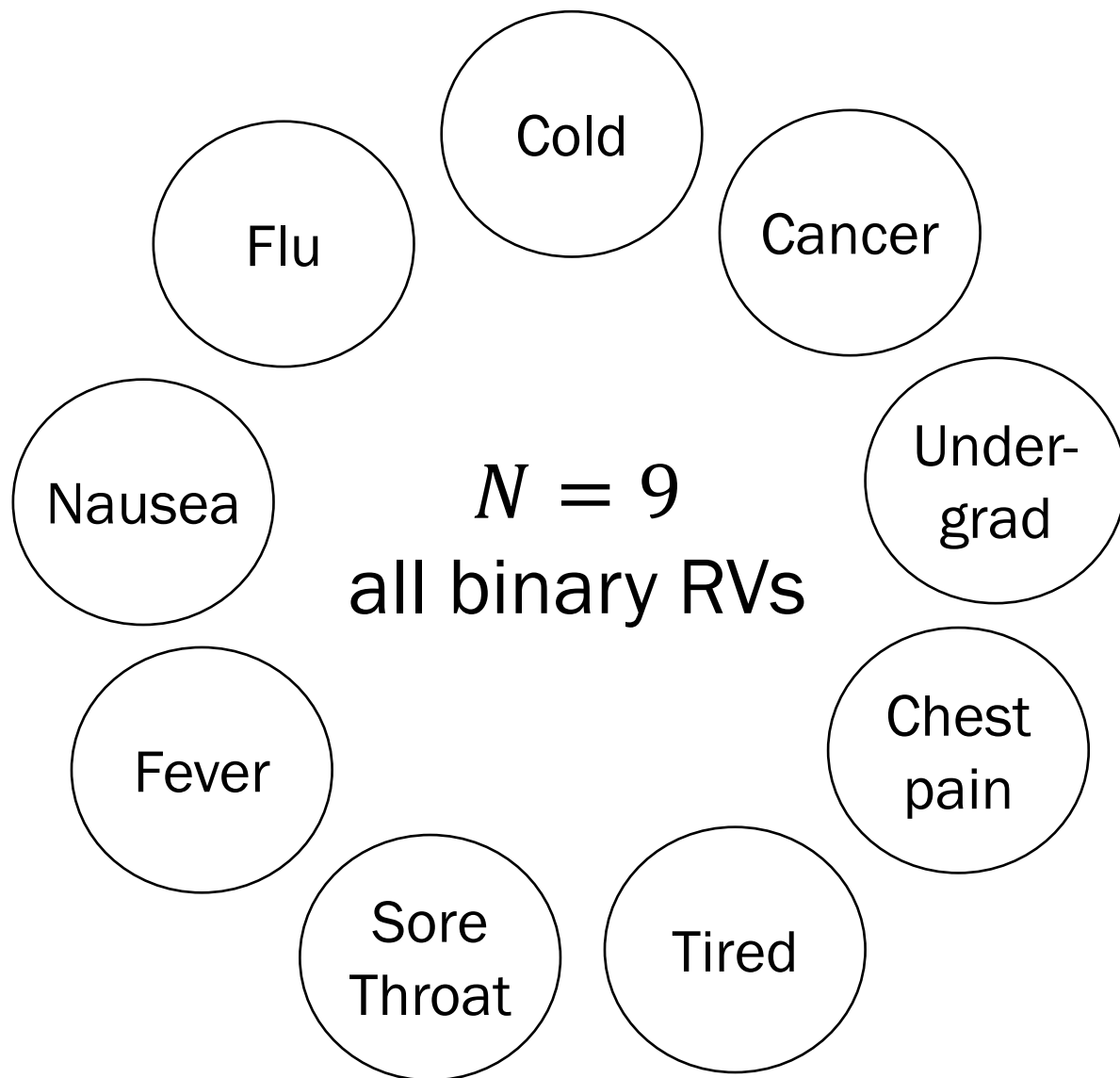
Inference



Another inference question:

$$P(C_o = 1, U = 1 | S = 0, F_e = 0) \\ = \frac{P(C_o = 1, U = 1, S = 0, F_e = 0)}{P(S = 0, F_e = 0)}$$

Inference



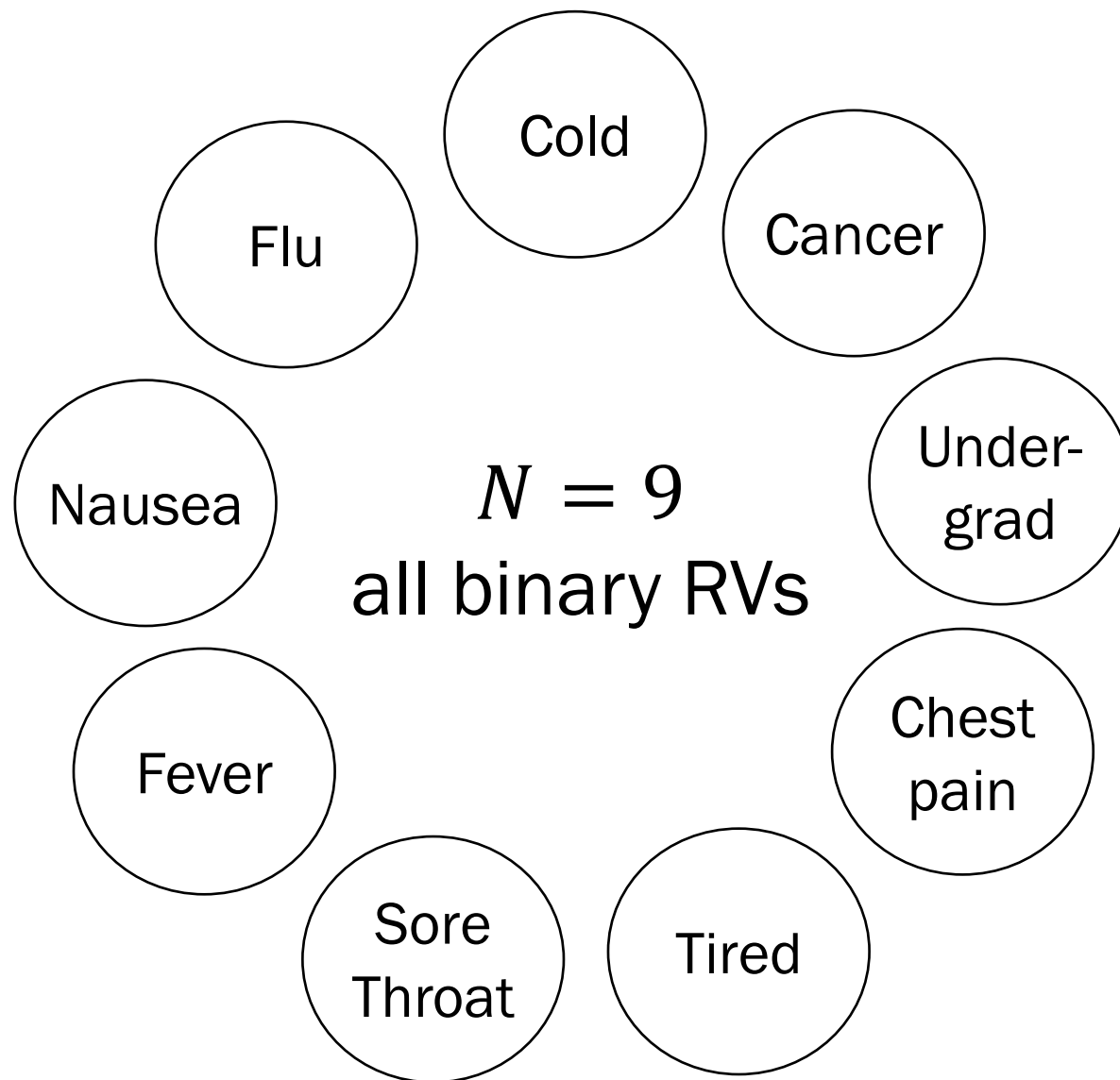
If we knew the **joint distribution**, we can answer all probabilistic inference questions.

What is the size of the joint probability table?

- A. 2^{N-1} entries
- B. N^2 entries
- C. 2^N entries
- D. None/other/don't know



Inference



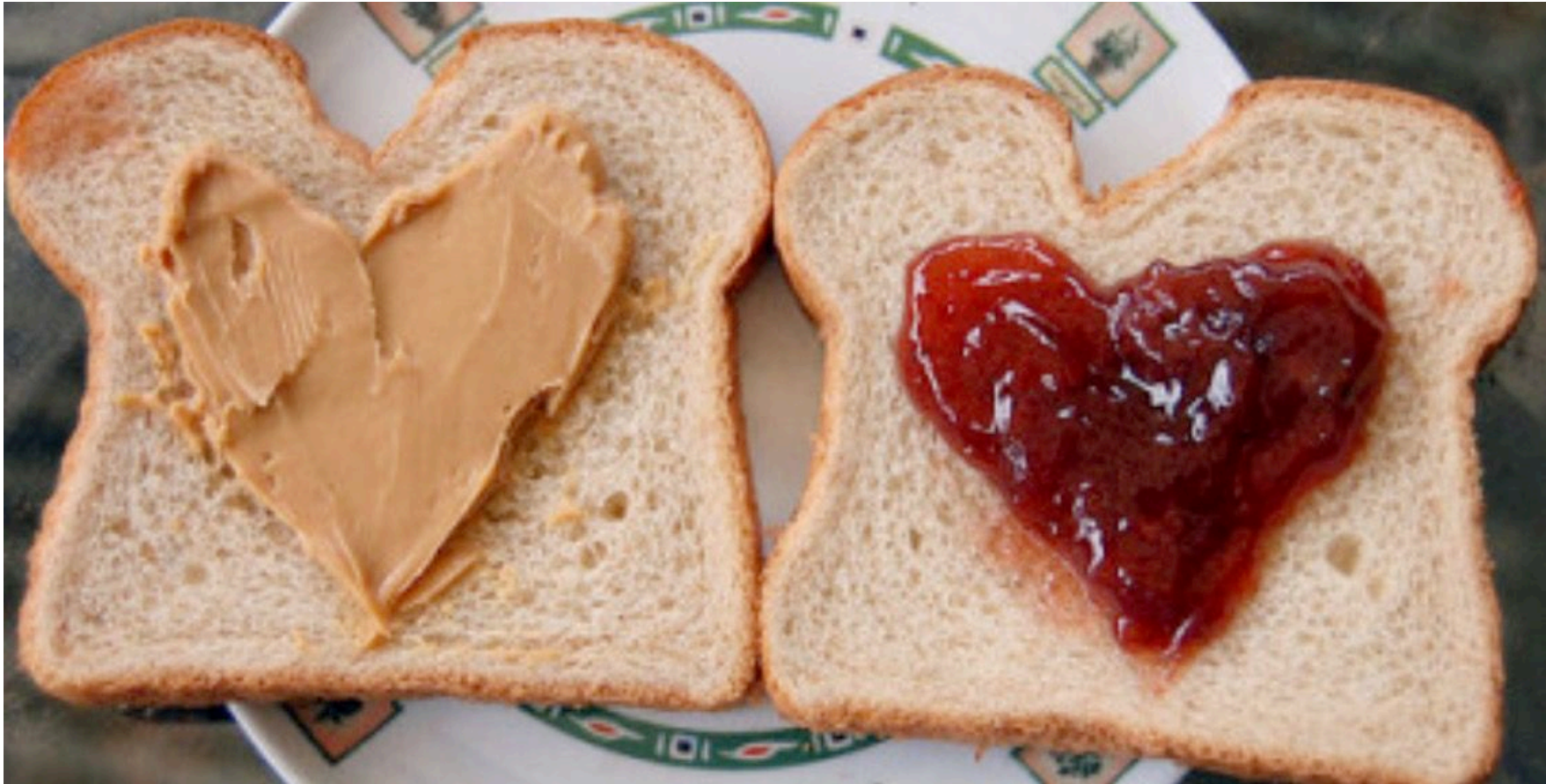
If we knew the **joint distribution**, we can answer all probabilistic inference questions.

What is the size of the joint probability table?

- A. 2^{N-1} entries
 - B. N^2 entries
 - C. 2^N entries
 - D. None/other/don't know
- $P(x_1 = -, x_2 = -, \dots, x_9 = -)$

Naively specifying a joint distribution is often intractable.

Conditionally Independent RVs



~~Conditional Probability~~
~~Conditional Distributions~~

~~Independence~~
~~Independent RVs~~

Conditionally Independent RVs

Recall that two events A and B are conditionally independent given E if:

$$P(AB|E) = P(A|E)P(B|E)$$

n discrete random variables X_1, X_2, \dots, X_n are called **conditionally independent given Y** if:

for all x_1, x_2, \dots, x_n, y :

$$P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n | Y = y) = \prod_{i=1}^n P(X_i = x_i | Y = y)$$

This implies the following (cool to remember for later):

$$\log P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n | Y = y) = \sum_{i=1}^n \log P(X_i = x_i | Y = y)$$

Recall independence of n events E_1, E_2, \dots, E_n :

for $r = 1, \dots, n$:

for every subset E_1, E_2, \dots, E_r :

$$P(E_1, E_2, \dots, E_r) = P(E_1)P(E_2) \cdots P(E_r)$$

We have independence of n **discrete random variables** X_1, X_2, \dots, X_n if for all x_1, x_2, \dots, x_n :

$$P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = \prod_{i=1}^n P(X_i = x_i)$$

Errata (edited May 3): Removed the independent RV requirement for all subsets of size $r = 1, \dots, n$. Do you see why this requirement is unnecessary?

(Hint: independence of RVs implies independence of all events)

Bayesian Networks

Bayes Nets

A simpler WebMD

Flu

Under-
grad

Fever

Tired

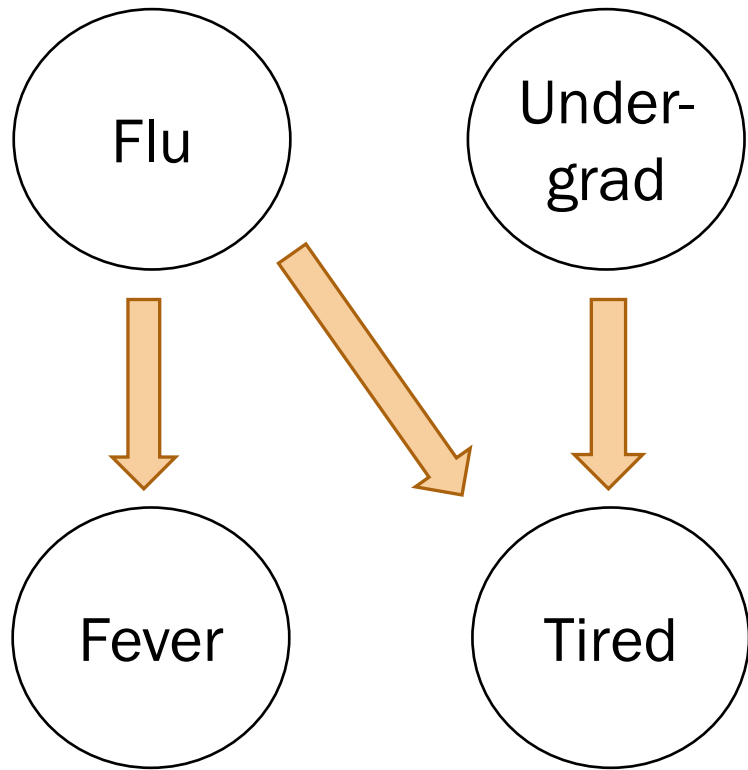
Great! Just specify $2^4 = 16$ joint probabilities...?

$$P(F_{lu} = a, F_{ev} = b, U = c, T = d)$$

What would a Stanford flu expert do?

Describe the joint distribution using causality!!!

Constructing a Bayesian Network

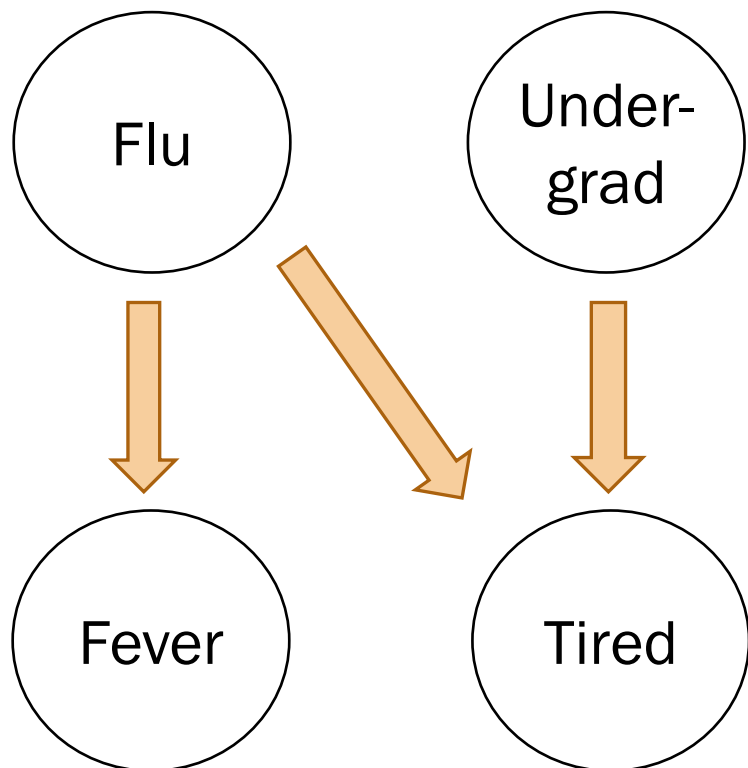


What would a Stanford flu expert do?

1. Describe the joint distribution using causality.

2. **Assume**
conditional
independence.

Constructing a Bayesian Network



In a Bayesian Network,
Each random variable is **conditionally independent** of its non-descendants, **given its parents**.

- Node: random variable
- Directed edge: conditional dependency

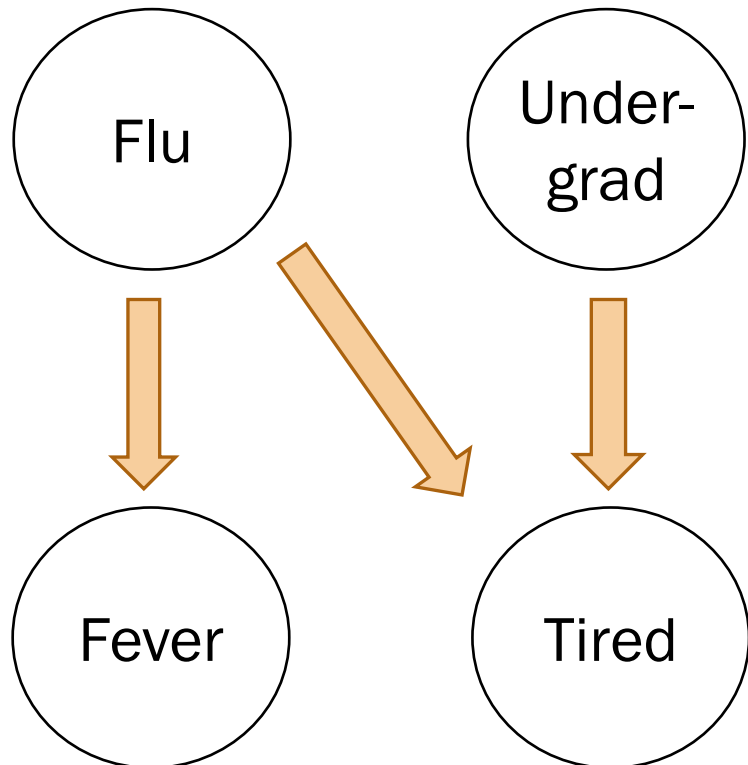
Examples:

- $P(F_{ev} = 1 | T \neq 0, F_{lu} = 1) = P(F_{ev} = 1 | F_{lu} = 1)$
- $P(F_{lu} = 1, U = 0) = P(F_{lu} = 1)P(U = 0)$

Constructing a Bayesian Network

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$

$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

What would a Stanford flu expert do?

1. Describe the joint distribution using causality.
2. Assume conditional independence.
3. Provide $P(\text{values}|\text{parents})$ for each random variable

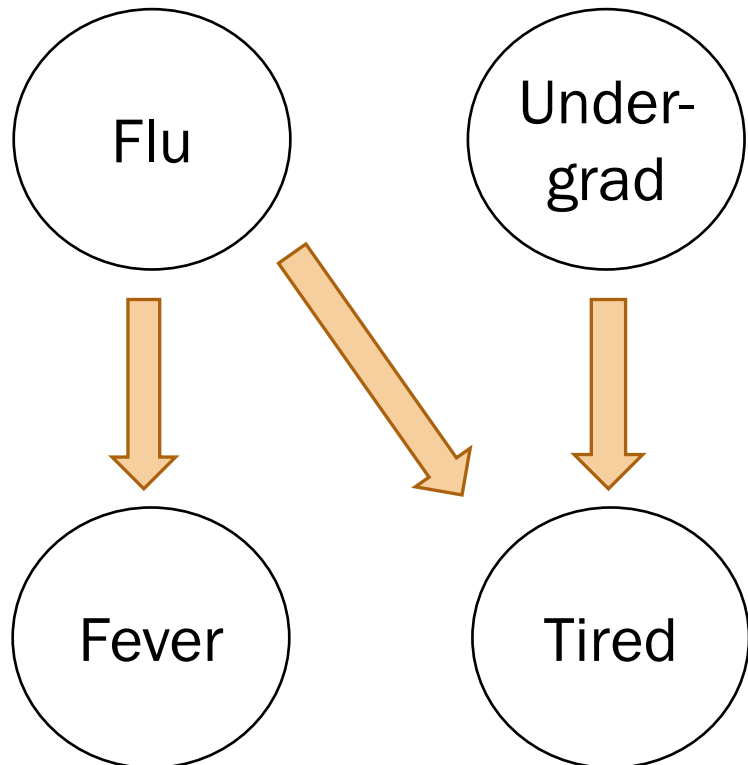
What conditional probabilities should our expert specify?



Constructing a Bayesian Network

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

What would a Stanford flu expert do?

1. Describe the joint distribution using causality.
2. Assume conditional independence.
3. Provide $P(\text{values}|\text{parents})$ for each random variable

What conditional probabilities should our expert specify?

$$P(T = 1 | F_{lu} = 0, U = 0)$$

$$P(T = 1 | F_{lu} = 0, U = 1)$$

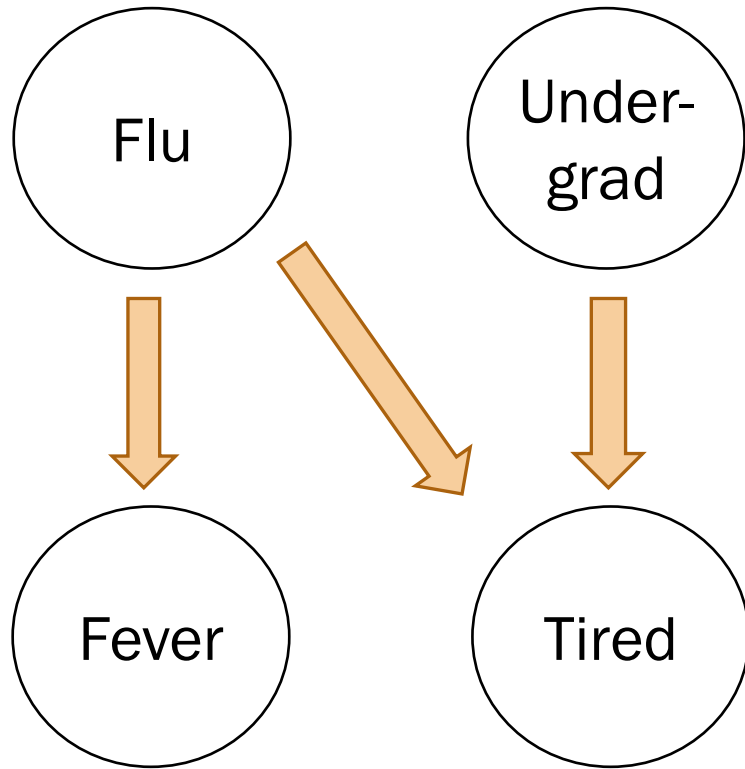
$$P(T = 1 | F_{lu} = 1, U = 0)$$

$$P(T = 1 | F_{lu} = 1, U = 1)$$

Using a Bayes Net

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

What would a CS109 student do?

1. Populate a Bayesian network by asking a Stanford flu expert or by using reasonable assumptions

2. Answer inference questions



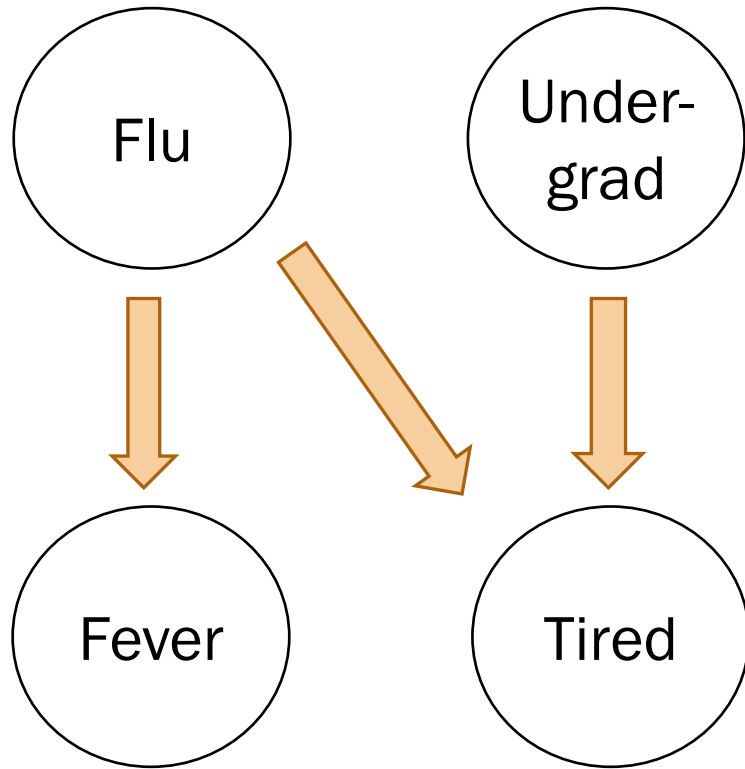
Our focus today

Inference (I): Math

Bayes Nets: Conditional independence

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



In a Bayesian Network,
Each random variable is **conditionally independent** of its non-descendants, **given its parents**.

- Node: random variable
- Directed edge: conditional dependency

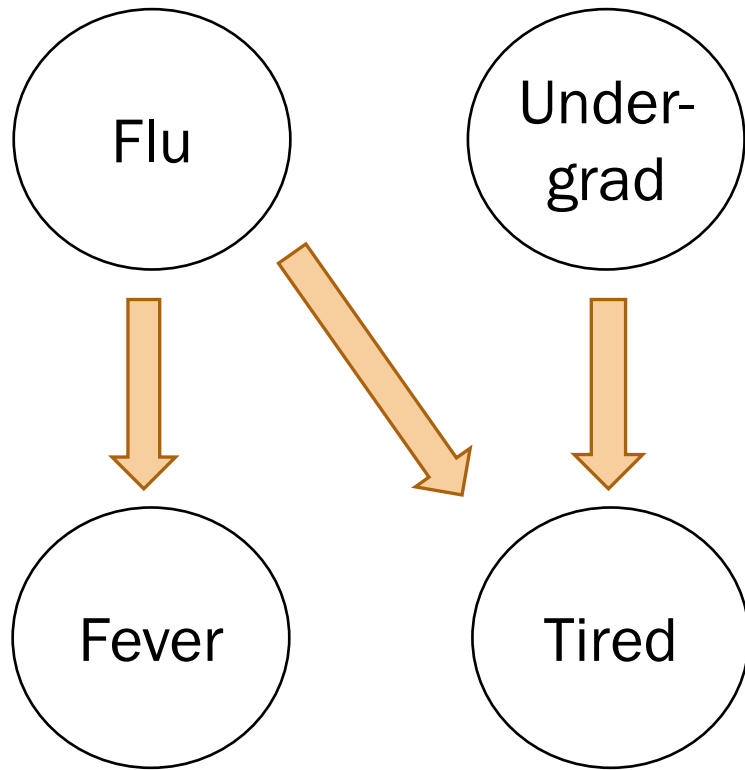
$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

1. $P(F_{lu} = 0, U = 1, F_{ev} = 0, T = 1)$?

Compute joint probabilities using chain rule.

$$= P(F_{lu} = 0) P(U = 1 | F_{lu} = 0) P(F_{ev} = 0 | F_{lu} = 0, U = 1) \\ \cdot P(T = 1 | F_{lu} = 0, U = 1, F_{ev} = 0)$$

$$= P(F_{lu} = 0) P(U = 1) P(F_{ev} = 0 | F_{lu} = 0) \\ \cdot P(T = 1 | F_{lu} = 0, U = 1)$$

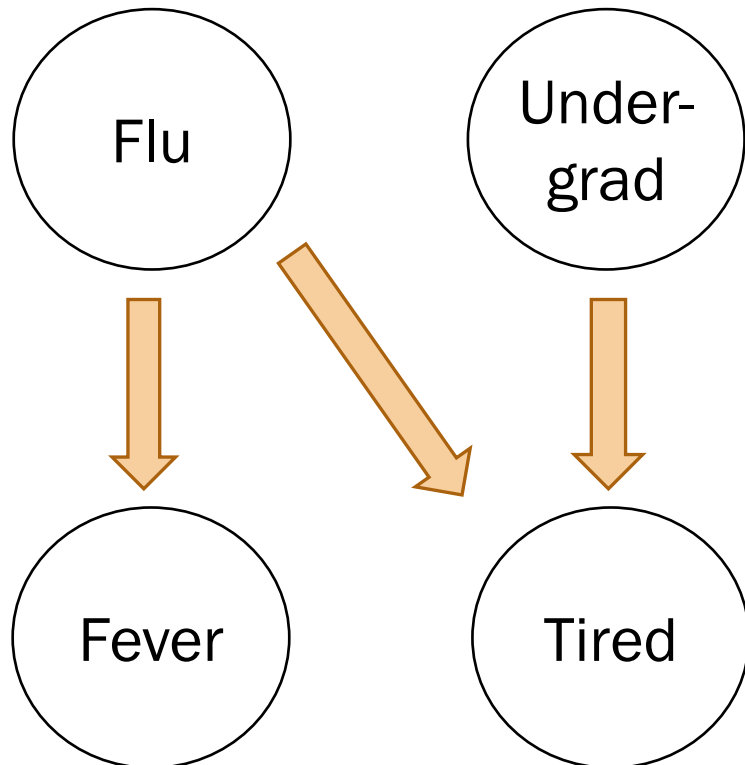
$$= 0.9 (0.8) 0.95 (0.8)$$

$$= 0.5472$$

Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1|F_{lu} = 1) = 0.9$$

$$P(F_{ev} = 1|F_{lu} = 0) = 0.05$$

$$P(T = 1|F_{lu} = 0, U = 0) = 0.1$$

$$P(T = 1|F_{lu} = 0, U = 1) = 0.8$$

$$P(T = 1|F_{lu} = 1, U = 0) = 0.9$$

$$P(T = 1|F_{lu} = 1, U = 1) = 1.0$$

2. $P(F_{lu} = 1|F_{ev} = 0, U = 0, T = 1)$?

1. Compute joint probabilities

$$P(F_{lu} = 1, F_{ev} = 0, U = 0, T = 1)$$

$$P(F_{lu} = 0, F_{ev} = 0, U = 0, T = 1)$$

given

2. Definition of conditional probability

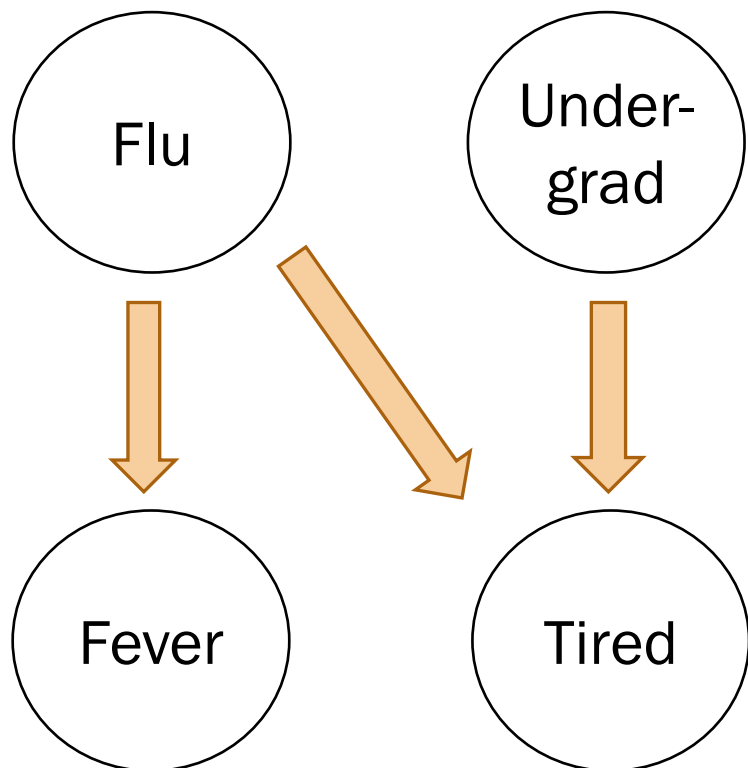
$$\frac{P(F_{lu} = 1, F_{ev} = 0, U = 0, T = 1)}{\sum_x P(F_{lu} = x, F_{ev} = 0, U = 0, T = 1)}$$

$$= 0.095$$

Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



3. $P(F_{lu} = 1 | U = 1, T = 1)$?

$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

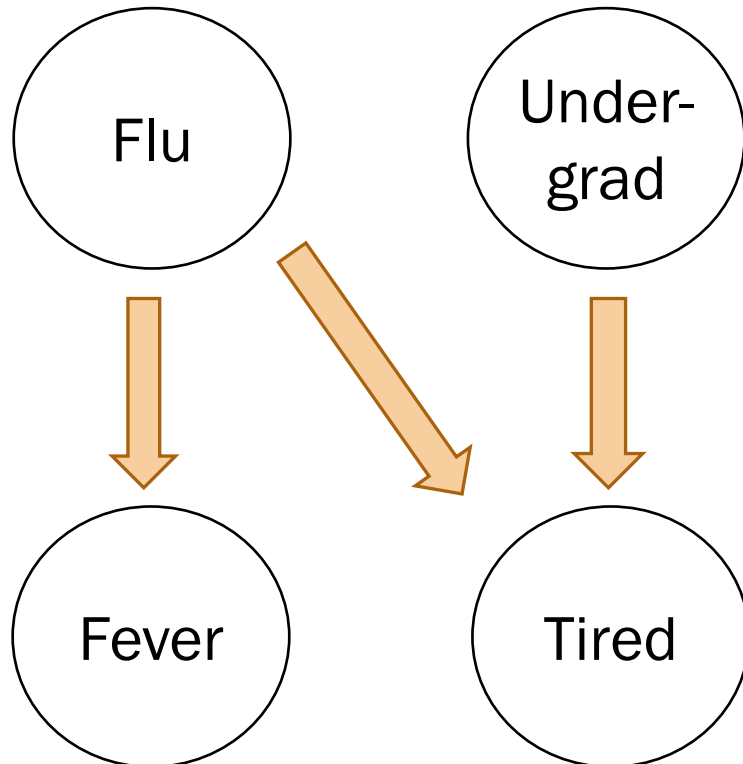
$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$



Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1|F_{lu} = 1) = 0.9$$

$$P(F_{ev} = 1|F_{lu} = 0) = 0.05$$

$$P(T = 1|F_{lu} = 0, U = 0) = 0.1$$

$$P(T = 1|F_{lu} = 0, U = 1) = 0.8$$

$$P(T = 1|F_{lu} = 1, U = 0) = 0.9$$

$$P(T = 1|F_{lu} = 1, U = 1) = 1.0$$

3. $P(F_{lu} = 1|U = 1, T = 1)$?

1. Compute joint probabilities

$$P(F_{lu} = 1, U = 1, F_{ev} = 1, T = 1)$$

...

$$P(F_{lu} = 0, U = 1, F_{ev} = 0, T = 1)$$

2. Definition of conditional probability

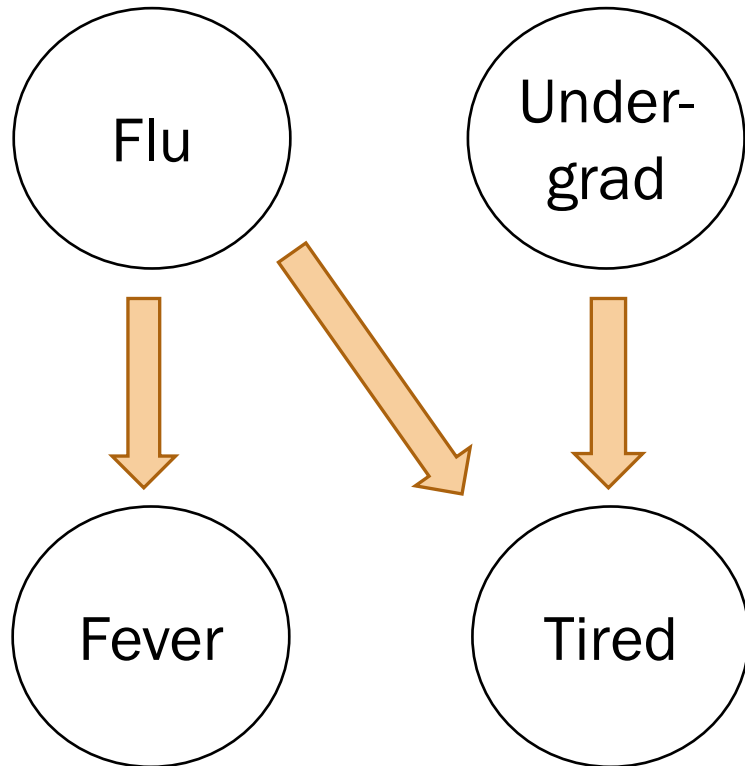
$$\frac{\sum_y P(F_{lu} = 1, U = 1, F_{ev} = y, T = 1)}{\sum_x \sum_y P(F_{lu} = x, U = 1, F_{ev} = y, T = 1)}$$

$$= 0.122$$

Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Solving inference questions precisely is possible, but sometimes tedious.

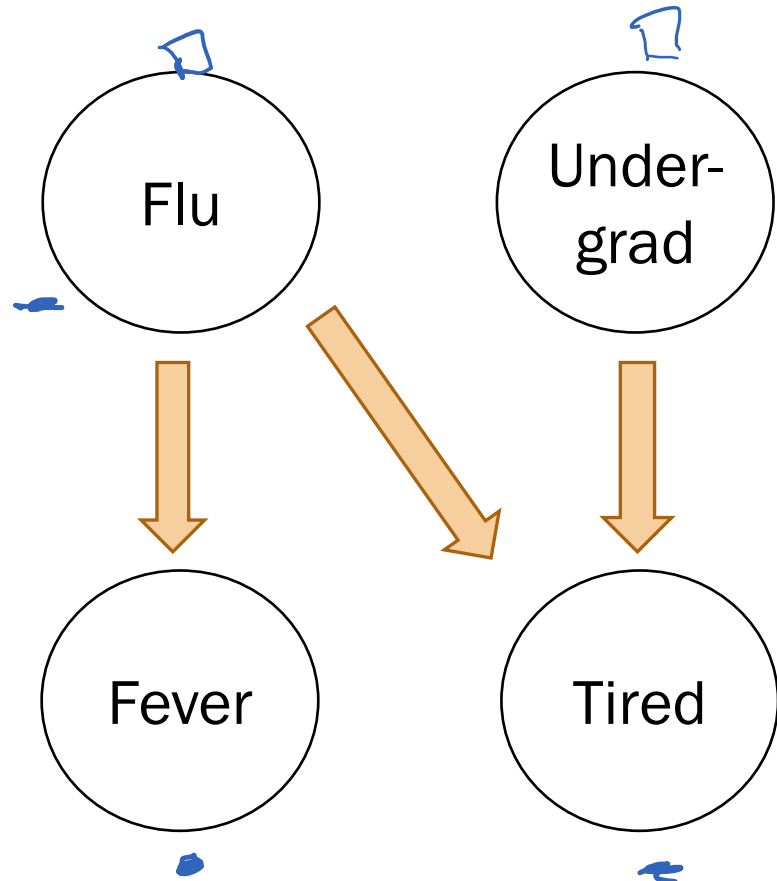
Can we use sampling to do approximate inference?

Yes.

15: General Inference (live)

Lisa Yan

May 8, 2020



In a Bayesian Network,
Each random variable is **conditionally independent** of its non-descendants, **given its parents**.

- Node: random variable
- Directed edge: conditional dependency *causality*

Examples:

- $P(F_{ev} = 1 | T = 0, F_{lu} = 1) = P(F_{ev} = 1 | F_{lu} = 1)$
- $P(F_{lu} = 1, U = 0) = P(F_{lu} = 1)P(U = 0)$

Breakout Rooms

Check out the question on the next slide (Slide 31). Post any clarifications here!

<https://us.edstem.org/courses/109/discussion/59206>

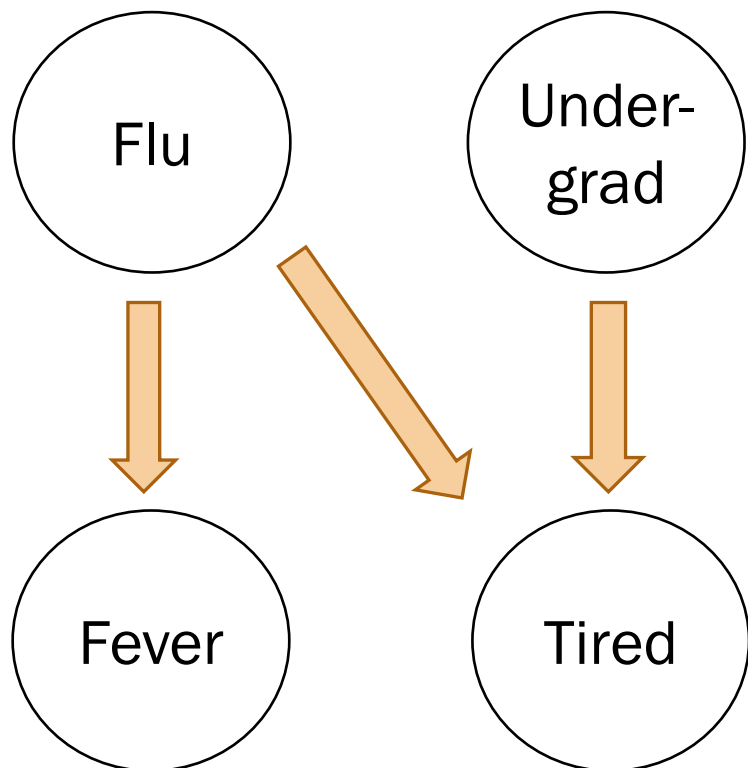
Breakout rooms: 4 min. Introduce yourself!



Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{lu} = 1 | F_{ev} = 1, U = 1, T = 1)?$$

Handwritten notes:

$$0.9 + 0.05 = 1 ?$$
$$1 = P(F_{ev} = 1 | F_{lu} = 1) + P(F_{ev} = 0 | F_{lu} = 1)$$

0.9 0.1

$$1 = P(F_{ev} = 1 | F_{lu} = 0) + P(F_{ev} = 0 | F_{lu} = 0)$$

0.05 0.95

$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

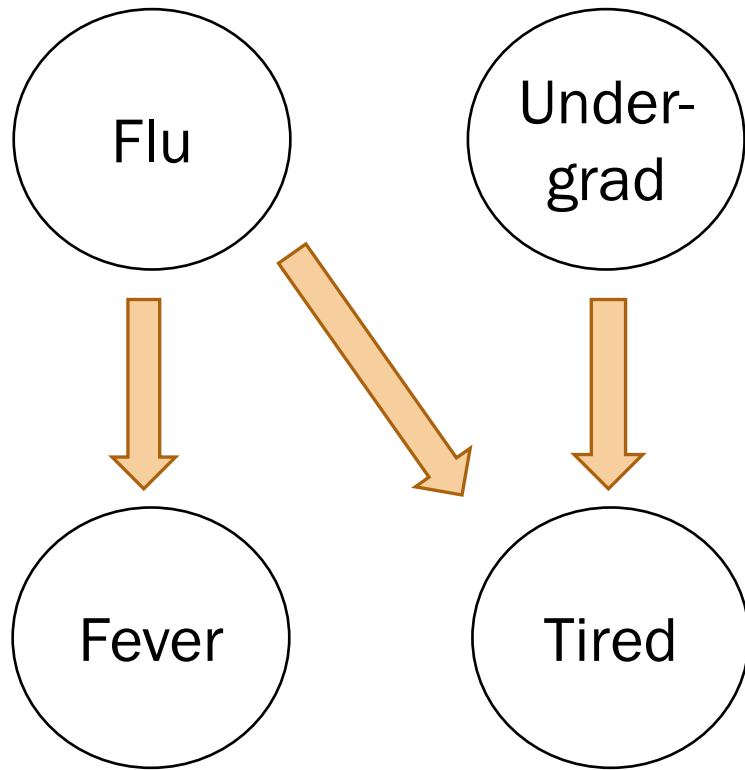
$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$



Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{lu} = 1 | F_{ev} = 1, U = 1, T = 1)?$$

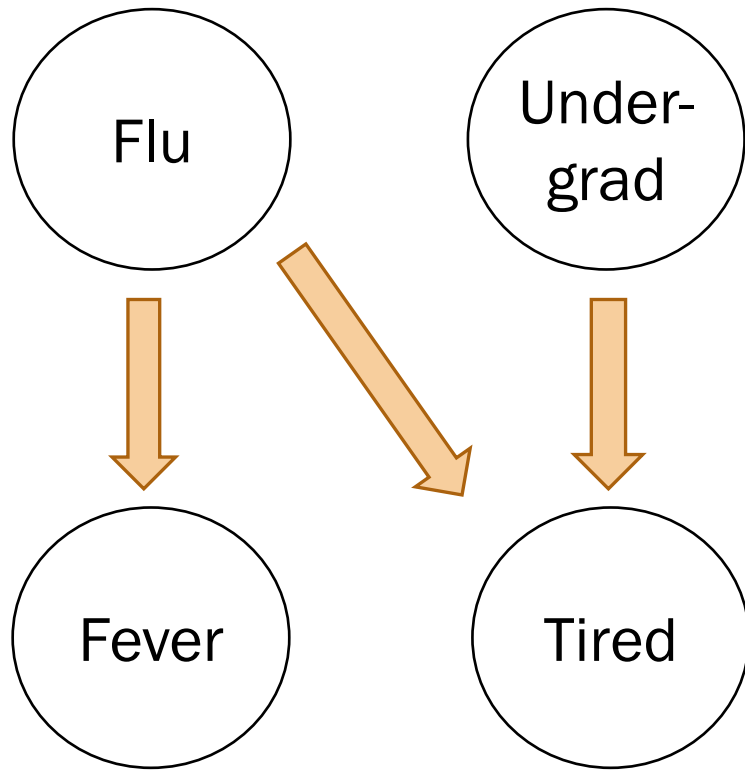
$$\begin{aligned}
 &= \frac{P(F_{lu}=1, F_{ev}=1, U=1, T=1)}{P(F_{ev}=1, U=1, T=1)} \\
 &= \frac{0.1 \cdot 0.8 \cdot 0.9 \cdot 1.0}{0.1 \cdot 0.8 \cdot 0.9 \cdot 1.0 + 0.9 \cdot 0.8 \cdot 0.05 \cdot 0.8} \\
 &\approx 0.714
 \end{aligned}$$

$$\begin{aligned}
 P(F_{ev} = 1 | F_{lu} = 1) &= 0.9 \\
 P(F_{ev} = 1 | F_{lu} = 0) &= 0.05
 \end{aligned}$$

$$\begin{aligned}
 P(T = 1 | F_{lu} = 0, U = 0) &= 0.1 \\
 P(T = 1 | F_{lu} = 0, U = 1) &= 0.8 \\
 P(T = 1 | F_{lu} = 1, U = 0) &= 0.9 \\
 P(T = 1 | F_{lu} = 1, U = 1) &= 1.0
 \end{aligned}$$

Inference via math

$$P(F_{lu} = 1) = 0.1 \quad \leftarrow \quad P(U = 1) = 0.8 \quad \leftarrow$$



$$P(F_{lu} = 1 | F_{ev} = 1, U = 1, T = 1)?$$

numerator $P(F_{lu} = 1, F_{ev} = 1, U = 1, T = 1)$

$$= P(F_{lu} = 1) P(U = 1 | F_{lu} = 1)$$

$$\cdot P(F_{ev} = 1 | F_{lu} = 1, U = 1)$$

$$\cdot P(T = 1 | F_{lu} = 1, U = 1, F_{ev} = 1)$$

$$0.1 (0.9) (0.8) \underline{1}$$

$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9 \quad \leftarrow$$

$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$

$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$

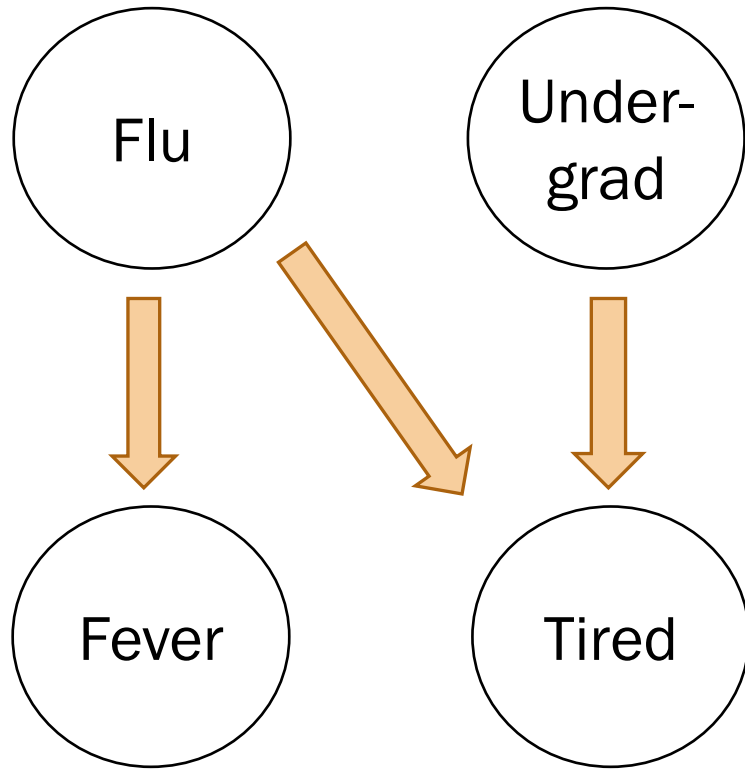
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$

$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0 \quad \leftarrow$$

Inference via math

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

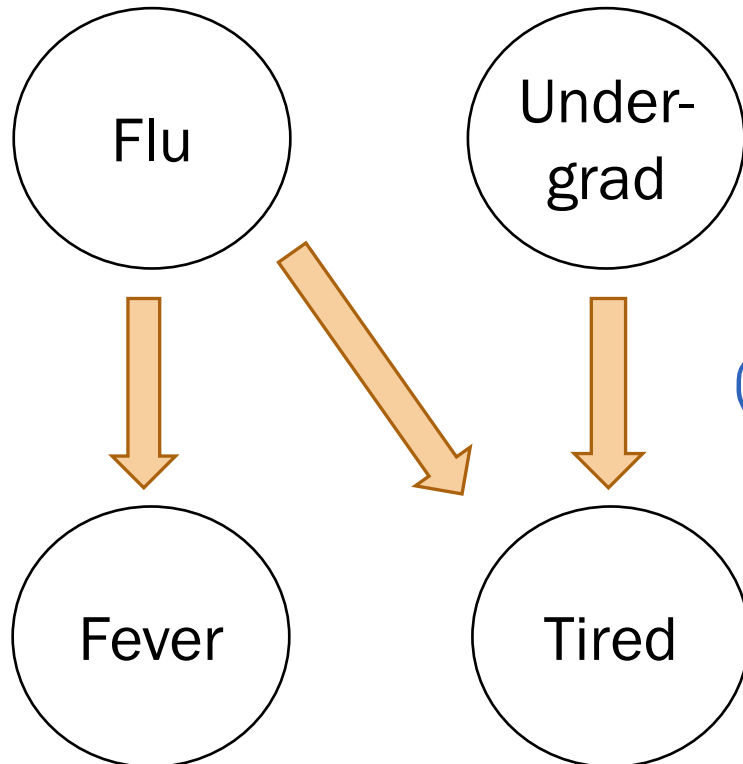
Solving inference questions precisely is possible, but sometimes tedious.

Can we use sampling to do approximate inference?

Yes.

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



(3) What is $P(F_{lu} = 1 | U = 1, T = 1)$?

$$= 0.122$$

(from pre-lecture video)

$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

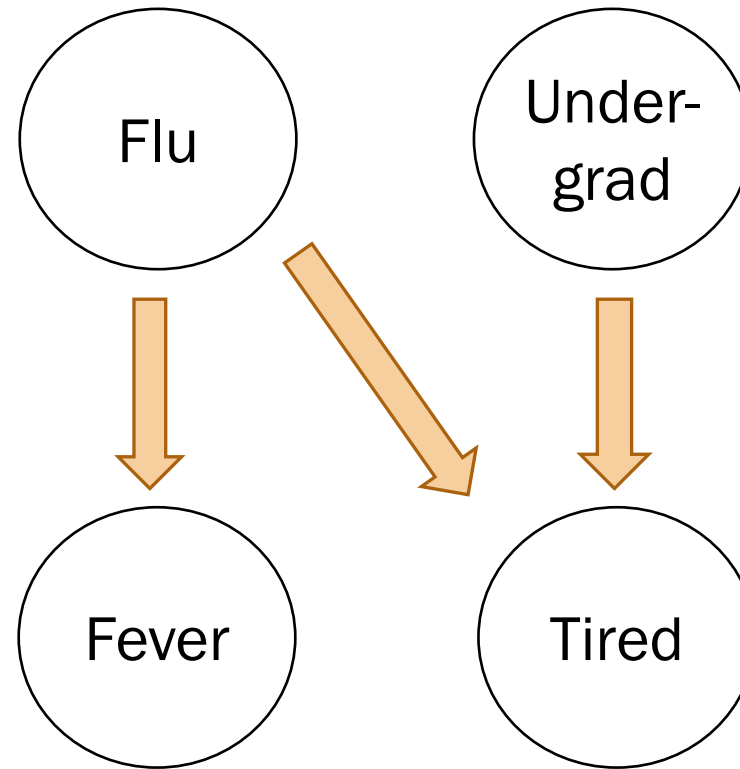
$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Rejection sampling algorithm

Step 0:
Have a fully specified
Bayesian Network

$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation = ...  
        # number of samples with (U = 1, T = 1)  
    samples_event = ...  
        # number of samples with (Flu = 1, U = 1, T = 1)  
    return len(samples_event) / len(samples_observation)
```

[flu, und, fev, tir]

```
Sampling...  
[0, 1, 0, 1]  
[0, 1, 0, 1]  
[0, 1, 0, 1]  
[0, 0, 0, 0]  
[0, 1, 0, 1]  
[0, 1, 1, 1]  
[0, 1, 0, 0]  
[1, 1, 1, 1]  
[0, 0, 1, 1]  
...  
[0, 1, 0, 1]  
Finished sampling
```

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation = ...  
        # number of samples with  $(U = 1, T = 1)$   
    samples_event = ...  
        # number of samples with  $(F_{lu} = 1, U = 1, T = 1)$   
return len(samples_event) / len(samples_observation)
```

$$\text{Approximate Probability} = \frac{\# \text{ samples with } (F_{lu} = 1, U = 1, T = 1)}{\# \text{ samples with } (U = 1, T = 1)}$$

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

$$\text{Approximate Probability} = \frac{\# \text{ samples with } (F_{lu} = 1, U = 1, T = 1)}{\# \text{ samples with } (U = 1, T = 1)}$$

Why would this definition of approximate probability make sense?



Think

Slide 41 has a question to go over by yourself.

Post any clarifications here!

<https://us.edstem.org/courses/109/discussion/59206>

Think by yourself: 2 min



Why would this approximate probability make sense?

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

$$\text{Approximate Probability} = \frac{\# \text{ samples with } (F_{lu} = 1, U = 1, T = 1)}{\# \text{ samples with } (U = 1, T = 1)}$$

Recall our definition of probability as a frequency: $P(E) = \lim_{n \rightarrow \infty} \frac{n(E)}{n}$ $n = \#$ of total trials
 $n(E) = \#$ trials where E occurs



Why would this approximate probability make sense?

Inference question:

What is $P(F_{lu} = 1 | U = 1, T = 1)$?

$$= \frac{P(F_{lu} = 1, U = 1, T = 1)}{P(U = 1, T = 1)} = \frac{\frac{n(F_{lu} = 1, U = 1, T = 1)}{n \text{ of samples}}}{\frac{n(U = 1, T = 1)}{n \text{ of samples}}}$$

Approximate Probability =

$$\frac{\# \text{ samples with } (F_{lu} = 1, U = 1, T = 1)}{\# \text{ samples with } (U = 1, T = 1)}$$

Recall our definition of probability as a frequency:

$$P(E) = \lim_{n \rightarrow \infty} \frac{n(E)}{n}$$

n = # of total trials

$n(E)$ = # trials where E occurs

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation = ...  
        # number of samples with (U = 1, T = 1)  
    samples_event = ...  
        # number of samples with (Flu = 1, U = 1, T = 1)  
    return len(samples_event) / len(samples_observation)
```

[flu, und, fev, tir]

```
Sampling...  
[0, 1, 0, 1]  
[0, 1, 0, 1]  
[0, 1, 0, 1]  
[0, 0, 0, 0]  
[0, 1, 0, 1]  
[0, 1, 1, 1]  
[0, 1, 0, 0]  
[1, 1, 1, 1]  
[0, 0, 1, 1]  
...  
[0, 1, 0, 1]  
Finished sampling
```

Rejection sampling algorithm

```
N_SAMPLES = 100000
# Method: Sample a ton
# -----
# create N_SAMPLES with likelihood proportional
# to the joint distribution
def sample_a_ton():
    samples = []
    for i in range(N_SAMPLES):
        sample = make_sample() # a particle
        samples.append(sample)
    return samples
```

How do we make a sample
 $(F_{lu} = a, U = b, F_{ev} = c, T = d)$
according to the
joint probability?

Create a sample using the Bayesian Network!!

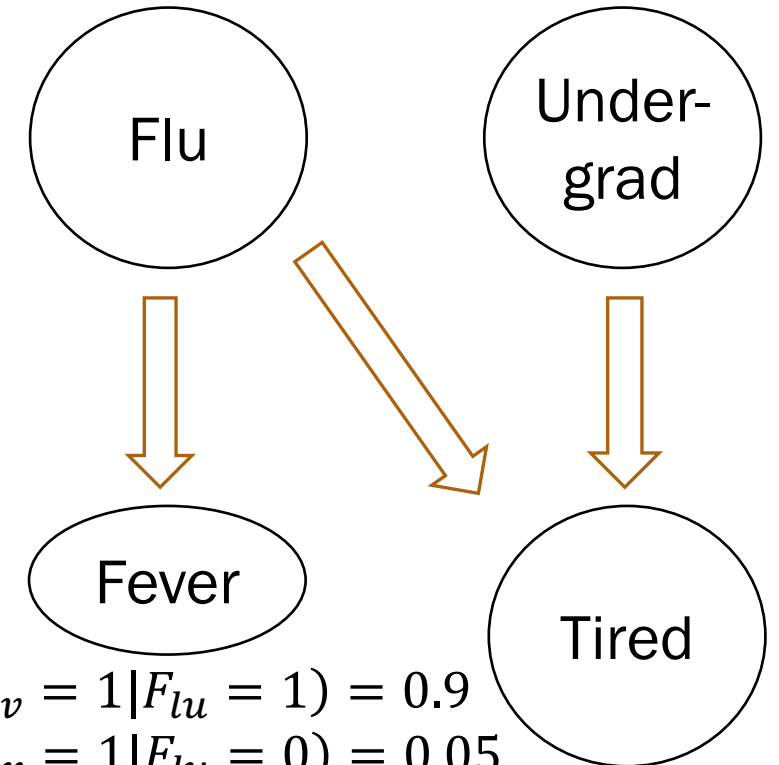
Rejection sampling algorithm

```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # choose fever based on flu
    if flu == 1: fev = bernoulli(0.9)
    else: fev = bernoulli(0.05)

    # choose tired based on (undergrad and flu)
    #
    # TODO: fill in
    #
    # a sample from the joint has an
    # assignment to *all* random variables
    return [flu, und, fev, tir]
```

$$P(F_{lu} = 1) = 0.1 \quad P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

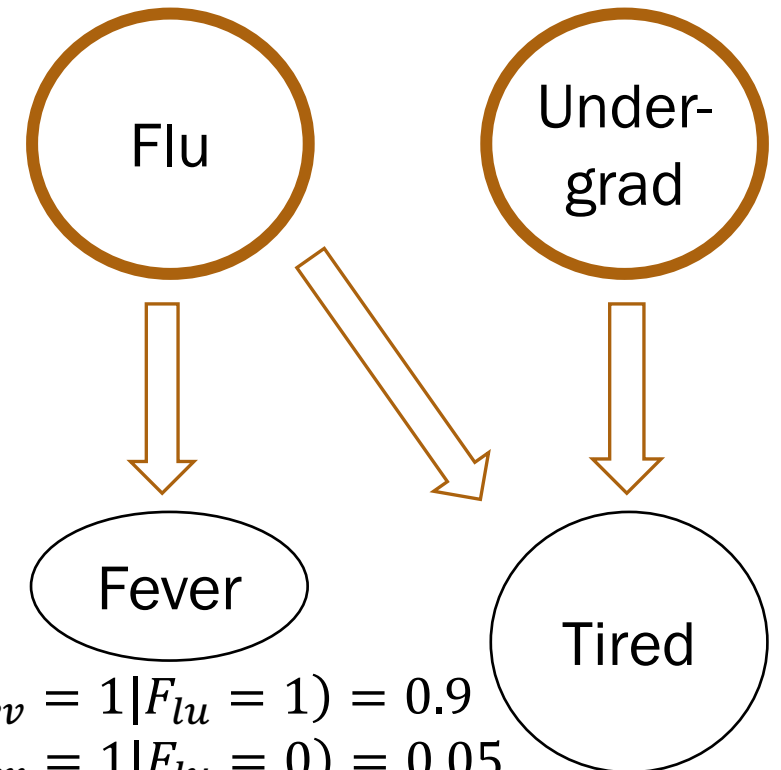
Rejection sampling algorithm

```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # choose fever based on flu
    if flu == 1: fev = bernoulli(0.9)
    else: fev = bernoulli(0.05)

    # choose tired based on (undergrad and flu)
    #
    # TODO: fill in
    #
    # a sample from the joint has an
    # assignment to *all* random variables
    return [flu, und, fev, tir]
```

$$P(F_{lu} = 1) = 0.1 \quad P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

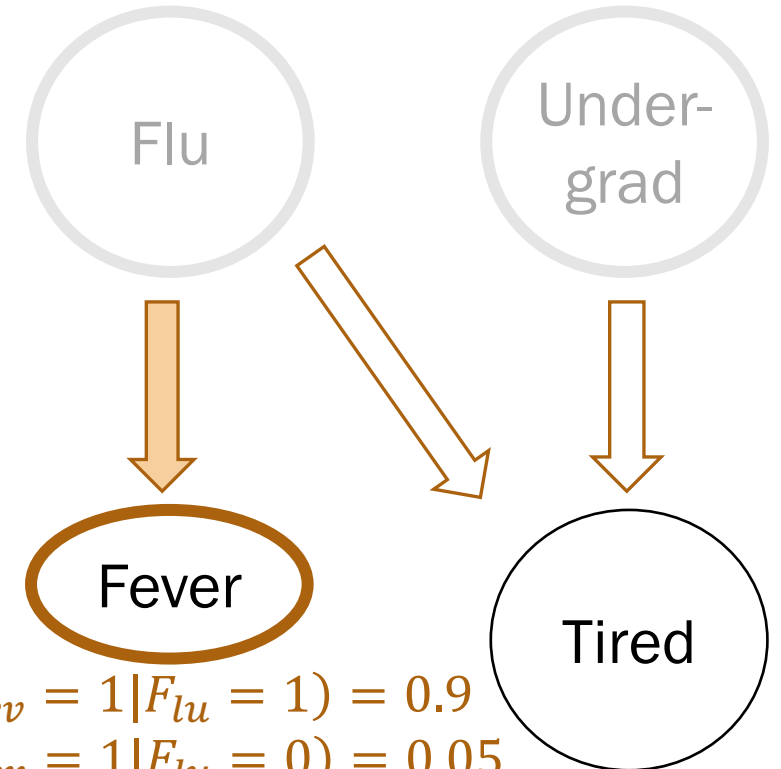
Rejection sampling algorithm

```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # choose fever based on flu
    if flu == 1: fev = bernoulli(0.9)
    else: fev = bernoulli(0.05)

    # choose tired based on (undergrad and flu)
    #
    # TODO: fill in
    #
    # a sample from the joint has an
    # assignment to *all* random variables
    return [flu, und, fev, tir]
```

$$P(F_{lu} = 1) = 0.1 \quad P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$

$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$

$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$

$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$

$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

$$\sum_{i=90}^{99} i$$

Interlude for jokes/announcements

Announcements

Quiz #1

Solutions: after class
Grades: after class
Regrades: by next Friday

Mid-quarter feedback form

Open until: [link](#) next Friday

Problem Set 4

Out: later today
Due: Monday 5/18 10am
Covers: Up to and including today

Giant sheet of all equations covered so far?

Announcements: CS109 contest



Do something cool and creative
with probability

Replaces one “passing” work requirement]

Optional Proposal: *Week 7* Sat. 5/23 11:59pm]

Due: *Week 10* Monday 6/8, 11:59pm

Winner, 2 Finalists \$

https://web.stanford.edu/class/cs109/psets/cs109_contest.pdf

Interesting probability news

<http://www.intuitor.com/statistics/TwentyQs.html>

[CS109 Current Events Spreadsheet](#)

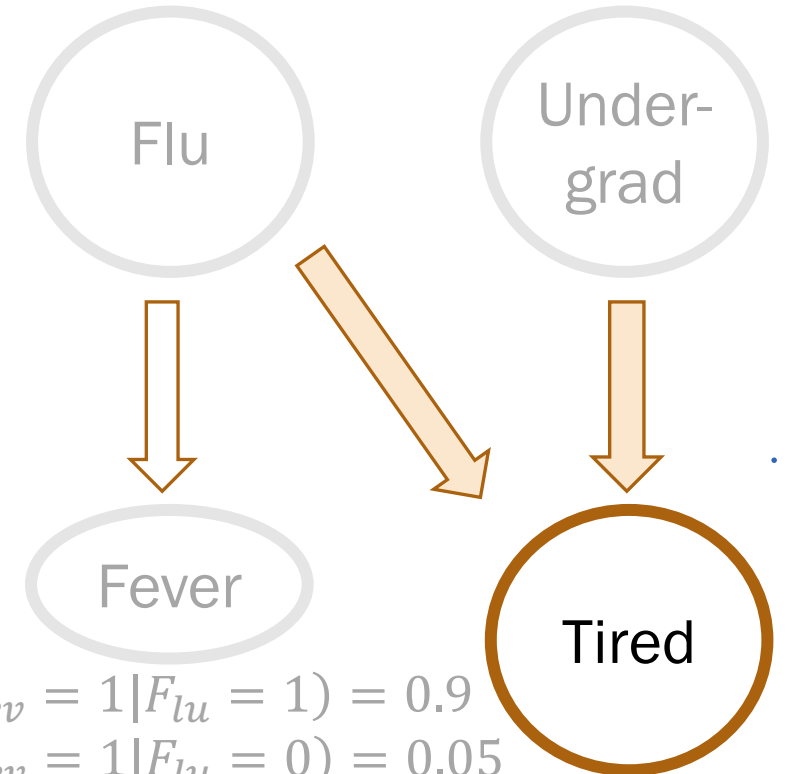
Rejection sampling algorithm

```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # choose fever based on flu
    if flu == 1: fev = bernoulli(0.9)
    else: fev = bernoulli(0.05)

    # choose tired based on (undergrad and flu)
    #
    # TODO: fill in 🤔
    #
    #
    # a sample from the joint has an
    # assignment to *all* random variables
    return [flu, und, fev, tir]
```

$$P(F_{lu} = 1) = 0.1 \quad P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Rejection sampling algorithm

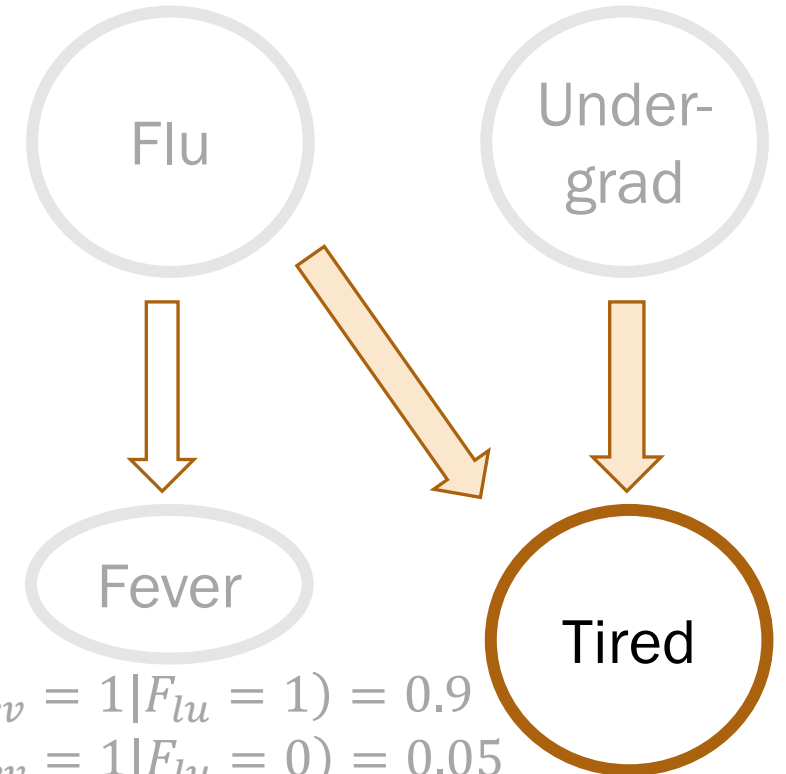
```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # choose fever based on flu
    if flu == 1: fev = bernoulli(0.9)
    else: fev = bernoulli(0.05)

    # choose tired based on (undergrad and flu)
    if flu == 0 and und == 0: tir = bernoulli(0.1)
    elif flu == 0 and und == 1: tir = bernoulli(0.8)
    elif flu == 1 and und == 0: tir = bernoulli(0.9)
    else: tir = bernoulli(1.0)

    # a sample from the joint has an
    # assignment to *all* random variables
    return [flu, und, fev, tir]
```

$$P(F_{lu} = 1) = 0.1 \quad P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$

$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$\rightarrow P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$

$$\rightarrow P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$

$$\rightarrow P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$

$$\rightarrow P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Rejection sampling algorithm

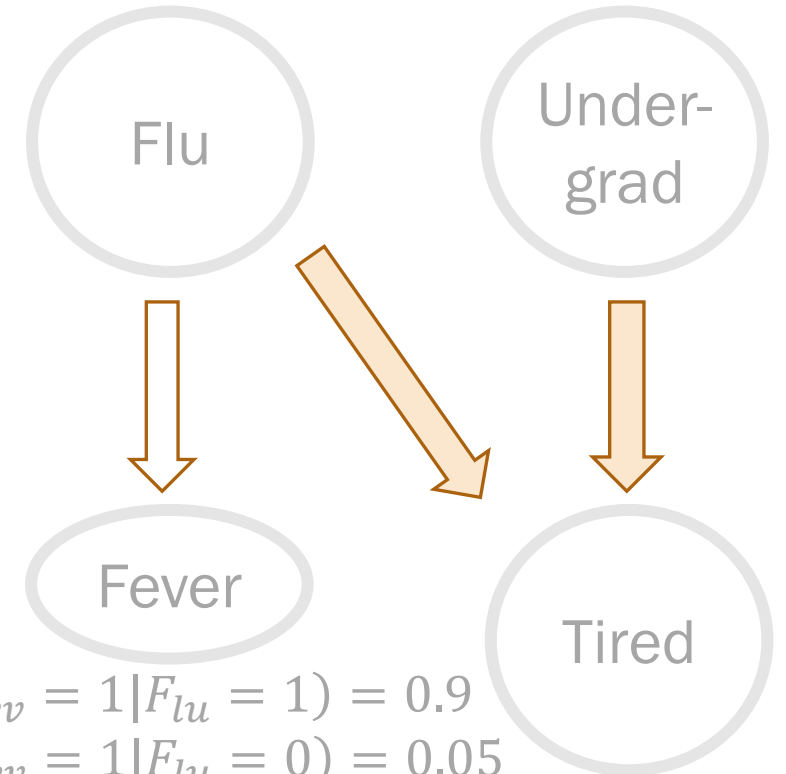
```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # choose fever based on flu
    if flu == 1: fev = bernoulli(0.9)
    else: fev = bernoulli(0.05)

    # choose tired based on (undergrad and flu)
    if flu == 0 and und == 0: tir = bernoulli(0.1)
    elif flu == 0 and und == 1: tir = bernoulli(0.8)
    elif flu == 1 and und == 0: tir = bernoulli(0.9)
    else: tir = bernoulli(1.0)

    # a sample from the joint has an
    # assignment to *all* random variables
    return [flu, und, fev, tir]
```

$$P(F_{lu} = 1) = 0.1 \quad P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$
$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$
$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$
$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$
$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation = ...  
    # number of samples with (U = 1, T = 1)  
    samples_event = ...  
    # number of samples with (Flu = 1, U = 1, T = 1)  
    return len(samples_event) / len(samples_observation)
```

[flu, und, fev, tir]

```
Sampling...  
[0, 1, 0, 1]  
[0, 1, 0, 1]  
[0, 1, 0, 1]  
[0, 0, 0, 0]  
[0, 1, 0, 1]  
[0, 1, 1, 1]  
[0, 1, 0, 0]  
[1, 1, 1, 1]  
[0, 0, 1, 1]  
...  
[0, 1, 0, 1]  
Finished sampling
```


Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation = ...  
        # number of samples with  $(U = 1, T = 1)$   
    samples_event =  
        # number of samples with  $(F_{lu} = 1, U = 1, T = 1)$   
    return len(samples_event)/len(samples_observation)
```

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation =  
        reject_inconsistent(samples, observation)  
    samples_event =  
        # number of samples with  $(F_{lu} = 1, U = 1, T = 1)$   
    return len(samples_event) / len(samples_observation)
```

Keep only samples that are consistent
with the observation $(U = 1, T = 1)$.

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):
```

```
    samples = sample_a_ton()
```

```
    samples_observation =  
        reject_inconsistent(samples, observation)
```

```
    samples
```

```
    # Method: Reject Inconsistent  
    # -----  
    # Rejects all samples that do not align with the outcome.  
    # Returns a list of consistent samples.  
    return def reject_inconsistent(samples, outcome):  
        consistent_samples = []  
        for sample in samples: 100,000 ↙ (U = 1, T = 1)  
            if check_consistent(sample, outcome):  
                consistent_samples.append(sample) ←  
        return consistent_samples
```

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

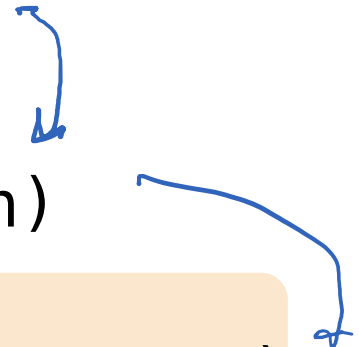
```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation =  
        reject_inconsistent(samples, observation)  $(u=1, T=1)$   
    samples_event =  
        reject_inconsistent(samples_observation, event)  $(F_{lu}=1, u=1, T=1)$   
    return len(samples_event) / len(samples_observation)
```

Conditional event = samples with $(F_{lu} = 1, U = 1, T = 1)$.

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation =  
        reject_inconsistent(samples, observation)  
    samples_event =  
        reject_inconsistent(samples_observation, event)
```



```
def reject_inconsistent(samples, outcome):  
    (Flu = x, U = 1, Fev = y, T = 1) (Flu = 1) = 1).
```

Condition

$(F_{lu} = x, U = 1, F_{ev} = y, T = 1)$ $(F_{lu} = 1)$ $= 1$.

```
return consistent_samples
```

Rejection sampling algorithm

Inference question: What is $P(F_{lu} = 1 | U = 1, T = 1)$?

```
def rejection_sampling(event, observation):  
    samples = sample_a_ton()  
    samples_observation =  
        reject_inconsistent(samples, observation)  
    samples_event =  
        reject_inconsistent(samples_observation, event)  
return len(samples_event)/len(samples_observation)
```

$$\text{Approximate Probability} = \frac{\# \text{ samples with } (F_{lu} = 1, U = 1, T = 1)}{\# \text{ samples with } (U = 1, T = 1)}$$

To the code!



Rejection sampling

If you can sample enough from the joint distribution, you can answer any probability inference question.

With enough samples, you can correctly compute:

- Probability estimates
- Conditional probability estimates
- Expectation estimates

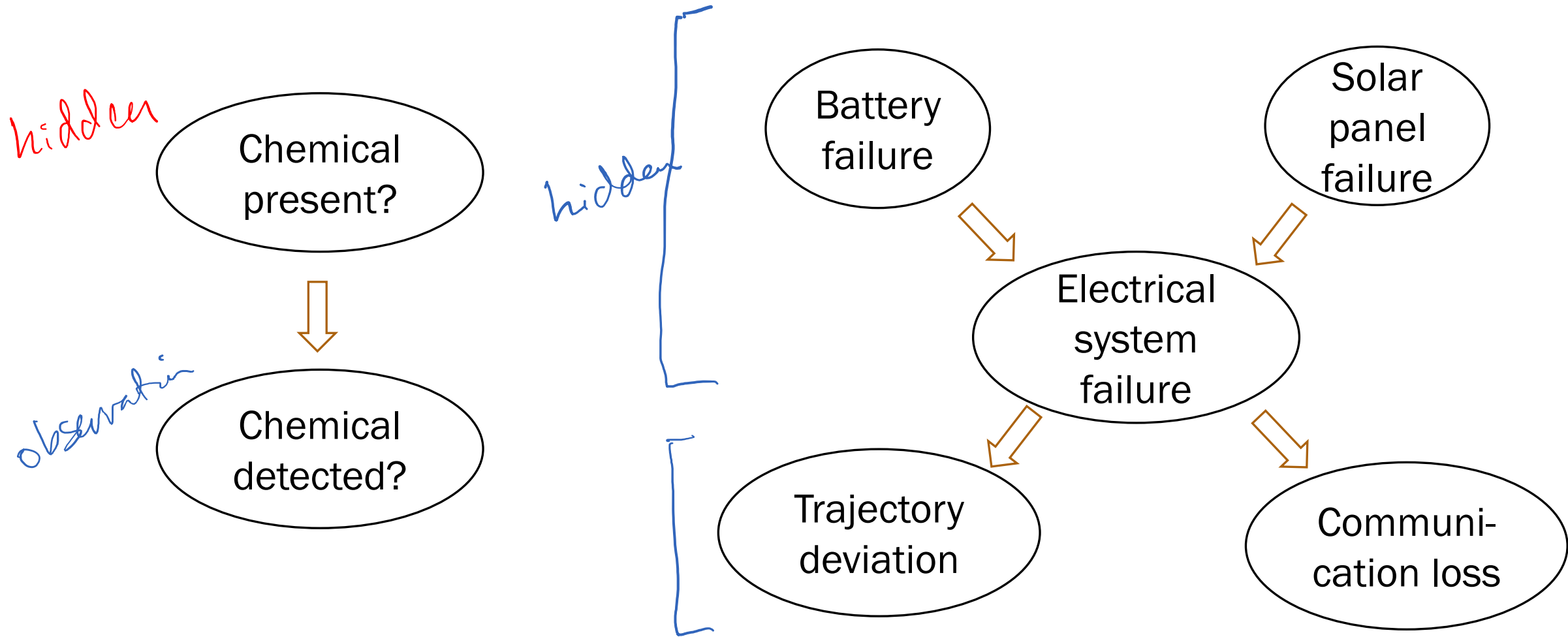
Because your samples are a representation of the joint distribution!

[flu, und, fev, tir]

```
Sampling...
[0, 1, 0, 1]
[0, 1, 0, 1]
[0, 1, 0, 1]
[0, 0, 0, 0]
[0, 1, 0, 1]
[0, 1, 1, 1]
[0, 1, 0, 0]
[1, 1, 1, 1]
[0, 0, 1, 1]
...
[0, 1, 0, 1]
Finished sampling
```

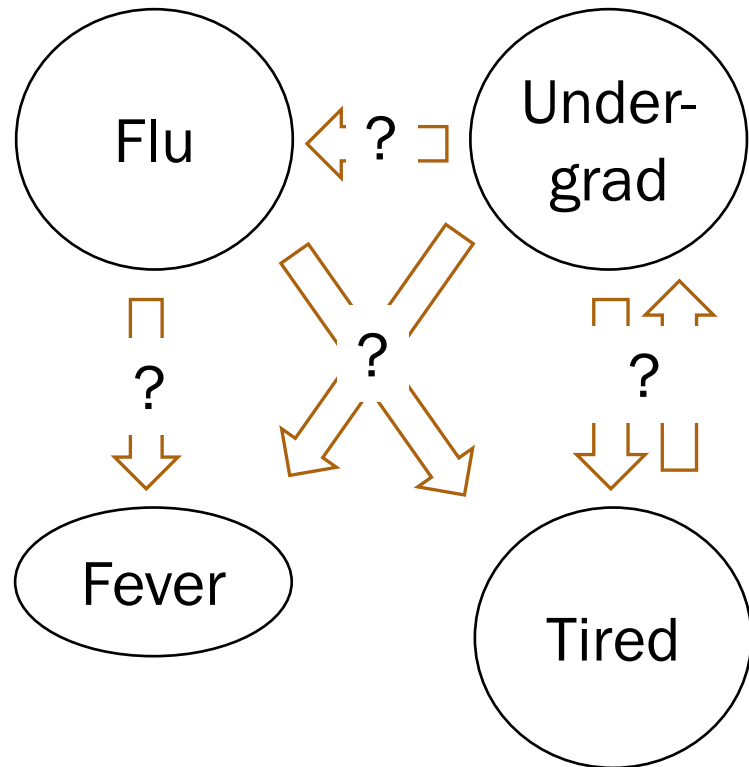
$$P(\text{has flu} \mid \text{undergrad and is tired}) = 0.122$$

Other applications



Take CS238/AA228: Decision Making under Uncertainty!

Challenge with Bayesian Networks



What if we don't know the structure?

Take CS228: Probabilistic Graphical Models!

Disadvantages of rejection sampling

$$P(F_{lu} = 1 | F_{ev} = 1)?$$

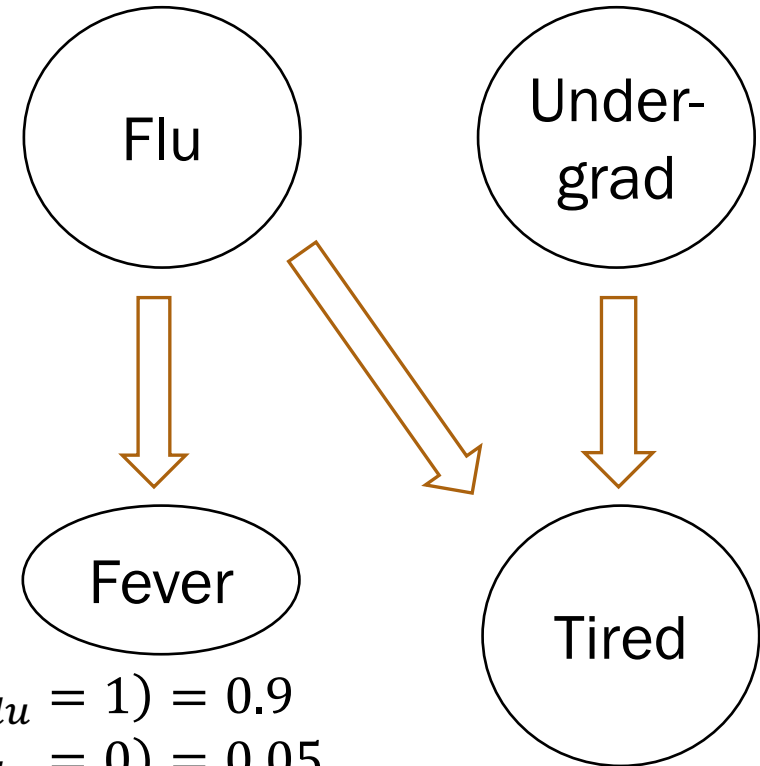
What if we never encounter some samples?

[flu=0, und, fev=1, tir]



$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$P(F_{ev} = 1 | F_{lu} = 1) = 0.9$$

$$P(F_{ev} = 1 | F_{lu} = 0) = 0.05$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$

$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$

$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$

$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Disadvantages of rejection sampling

$$P(F_{lu} = 1 | F_{ev} = \underline{99.4})?$$

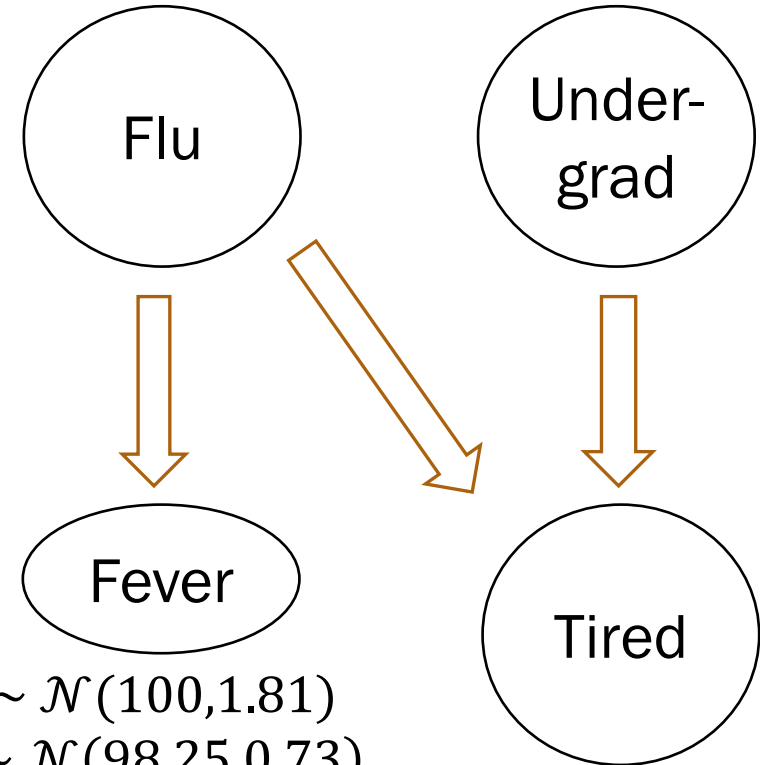
What if we never encounter some samples?

What if random variables are continuous?



$$P(F_{lu} = 1) = 0.1$$

$$P(U = 1) = 0.8$$



$$F_{ev} | F_{lu} = 1 \sim \mathcal{N}(100, 1.81)$$

$$F_{ev} | F_{lu} = 0 \sim \mathcal{N}(98.25, 0.73)$$

$$P(T = 1 | F_{lu} = 0, U = 0) = 0.1$$

$$P(T = 1 | F_{lu} = 0, U = 1) = 0.8$$

$$P(T = 1 | F_{lu} = 1, U = 0) = 0.9$$

$$P(T = 1 | F_{lu} = 1, U = 1) = 1.0$$

Gibbs sampling (extra)

Gibbs Sampling (not covered)

Basic idea:

- Fix all observed events
- Incrementally sample a new value for each random variable
- Difficulty: More coding for computing different posterior probabilities

Learn in extra slides/[extra notebook!](#)

(or by taking CS228/CS238)

