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# 15: General Inference

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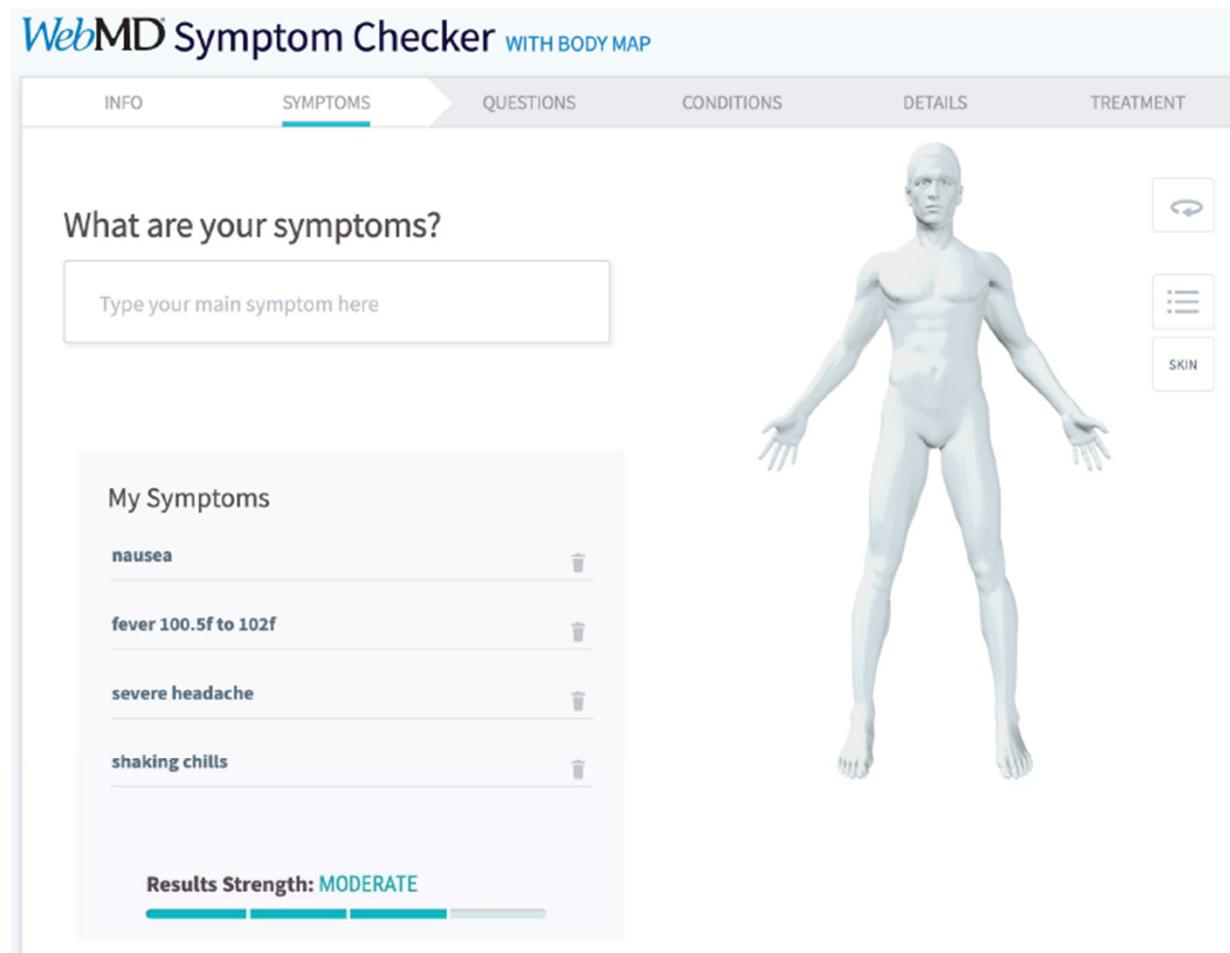
Jerry Cain  
February 12, 2024

[Lecture Discussion on Ed](#)



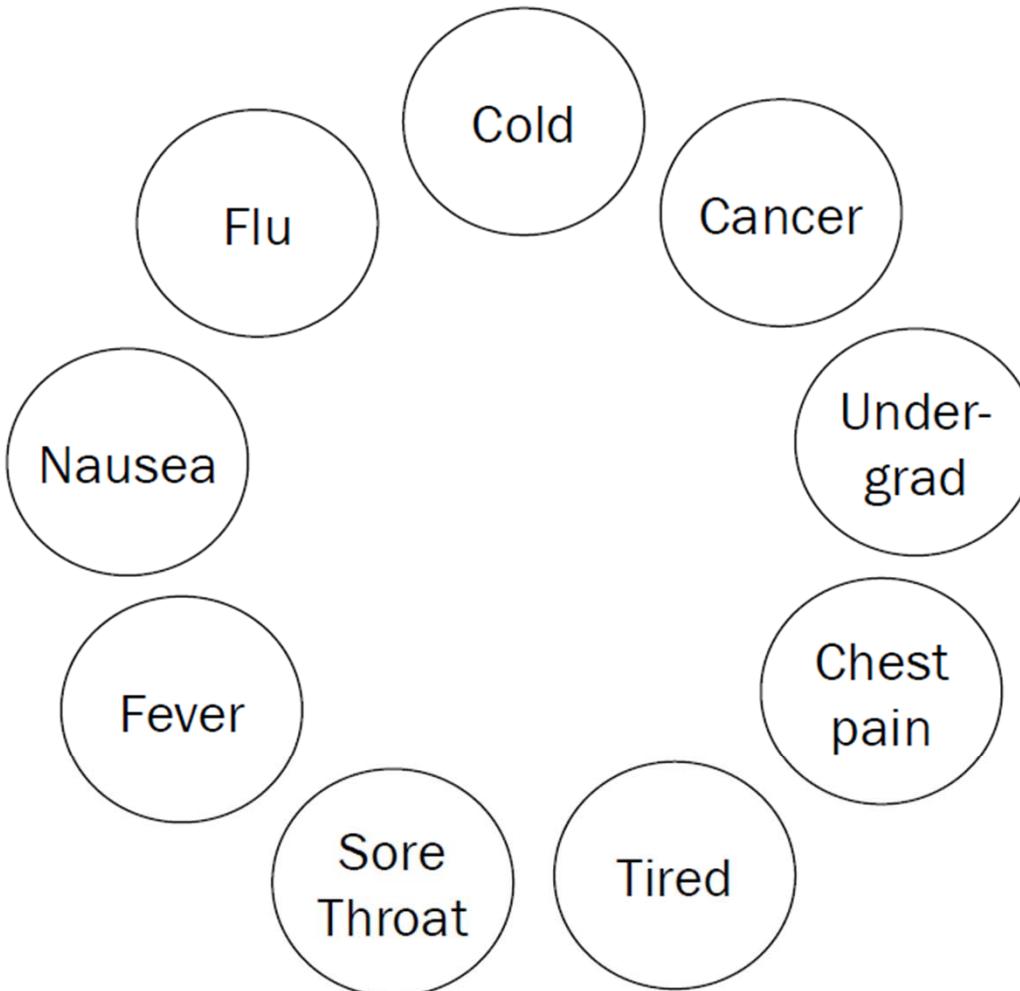
# General Inference: Introduction

# Inference



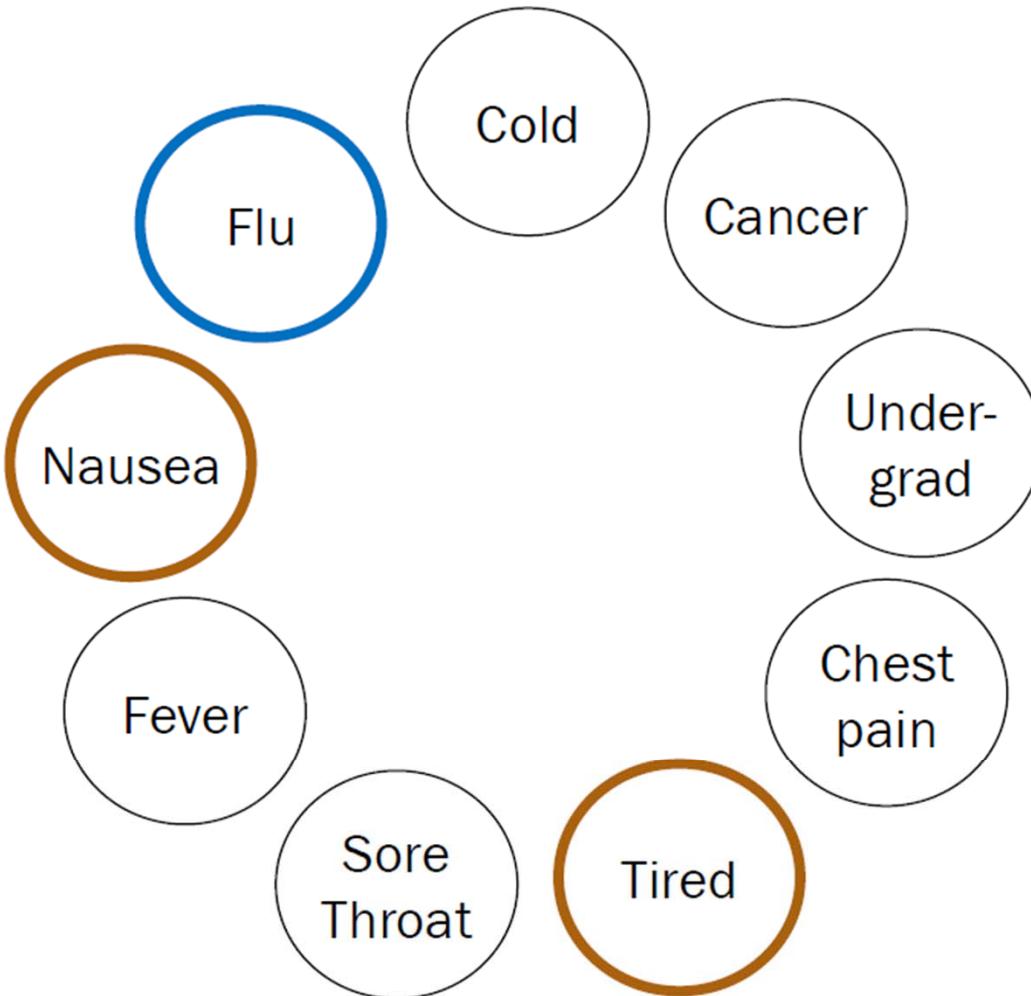
# Inference

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General inference question: ✗  
Given the values of some random variables, what is the conditional distribution of some other random variables?

# Inference

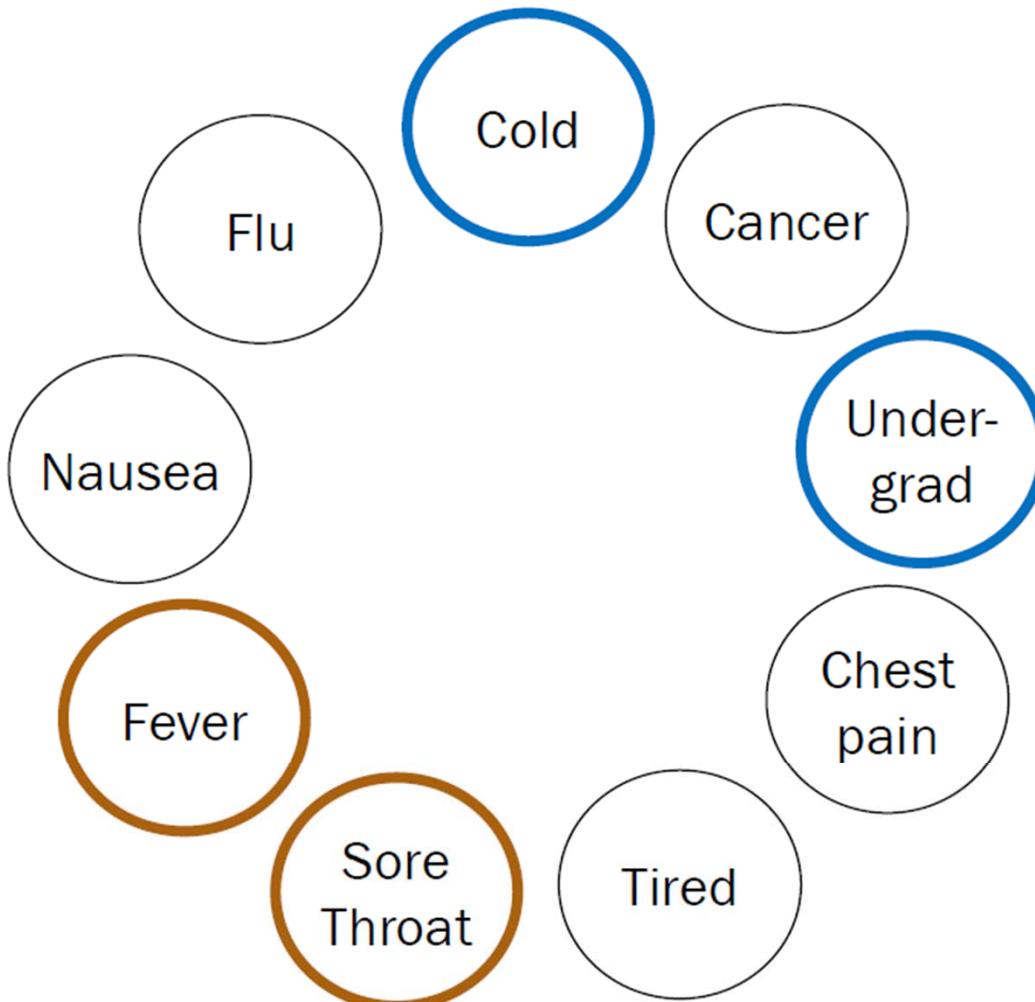


One inference question:

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

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

# Inference

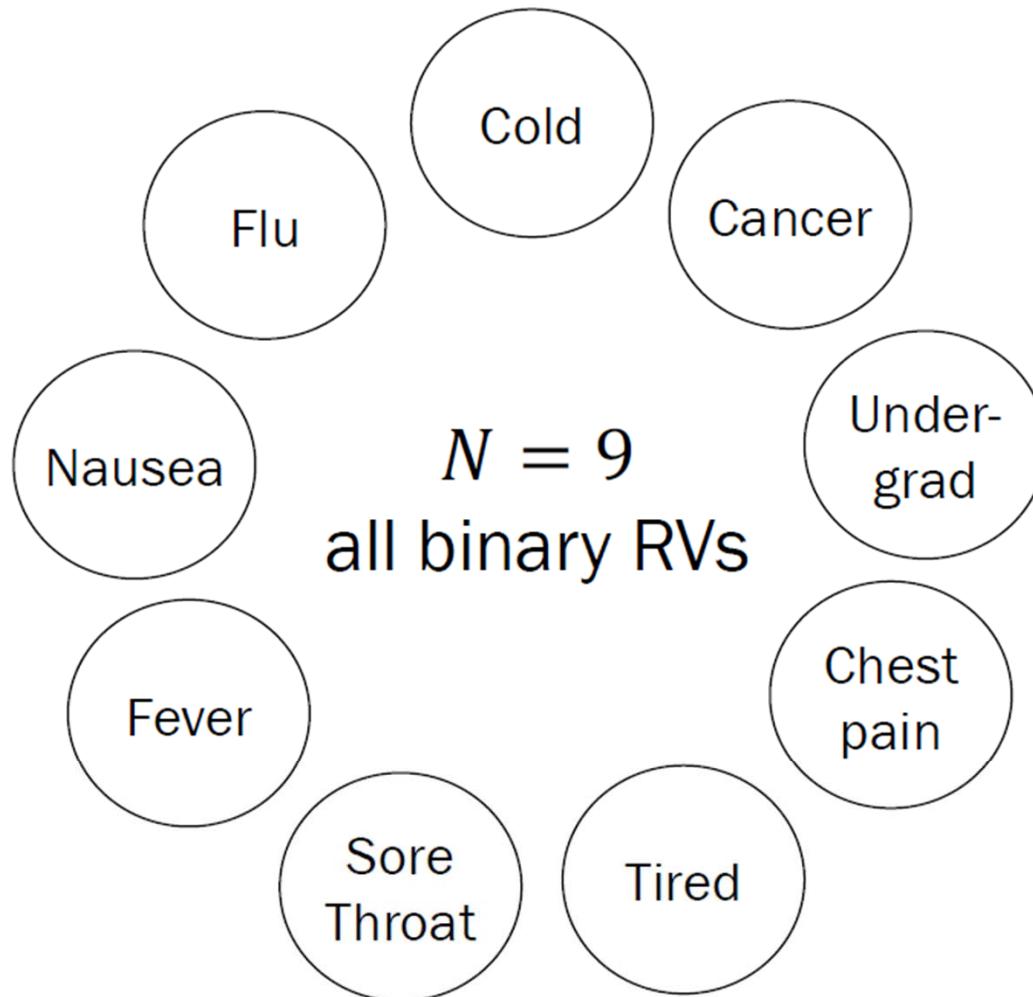


Another inference question:

$$P(C_o = 1, U = 1 | S = 0, F_e = 0)$$

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

# Inference



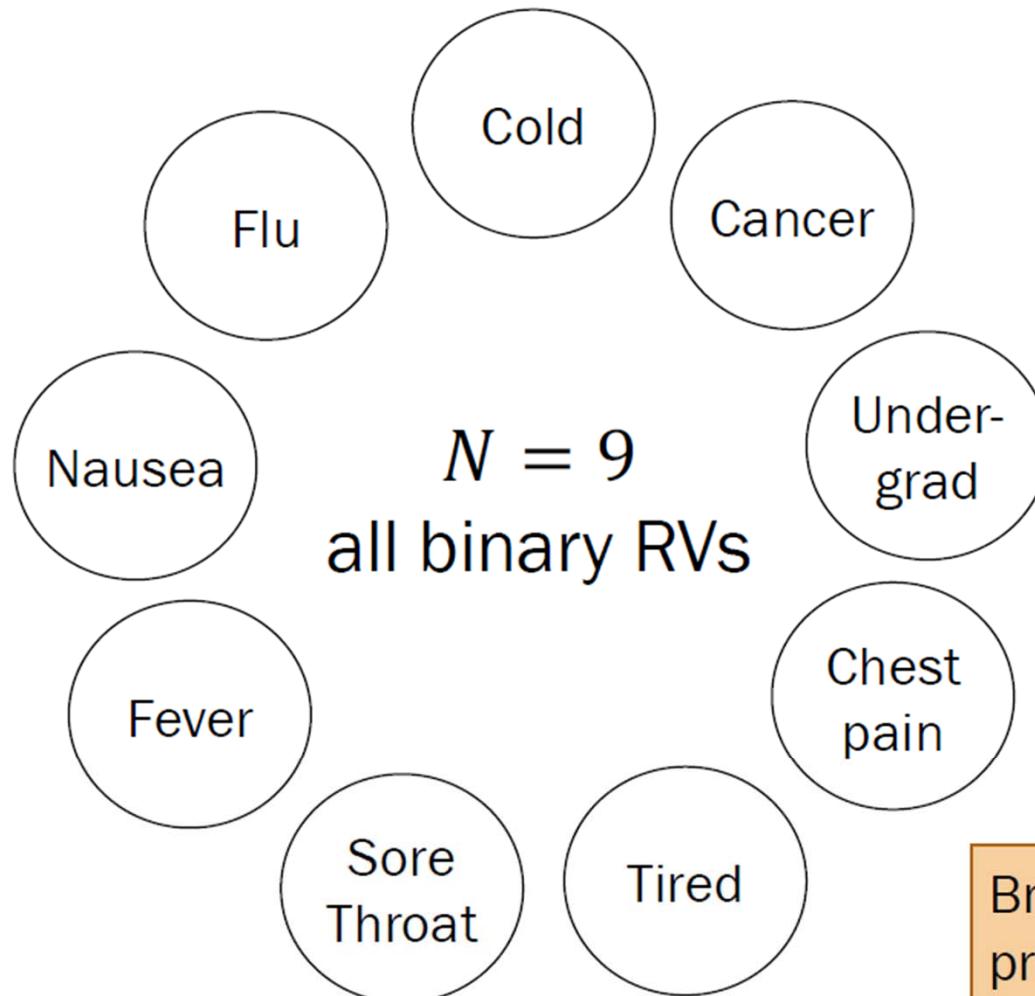
If we know the full joint distribution, we can answer all probabilistic inference questions.

What is the size of the joint probability table?

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



# Inference



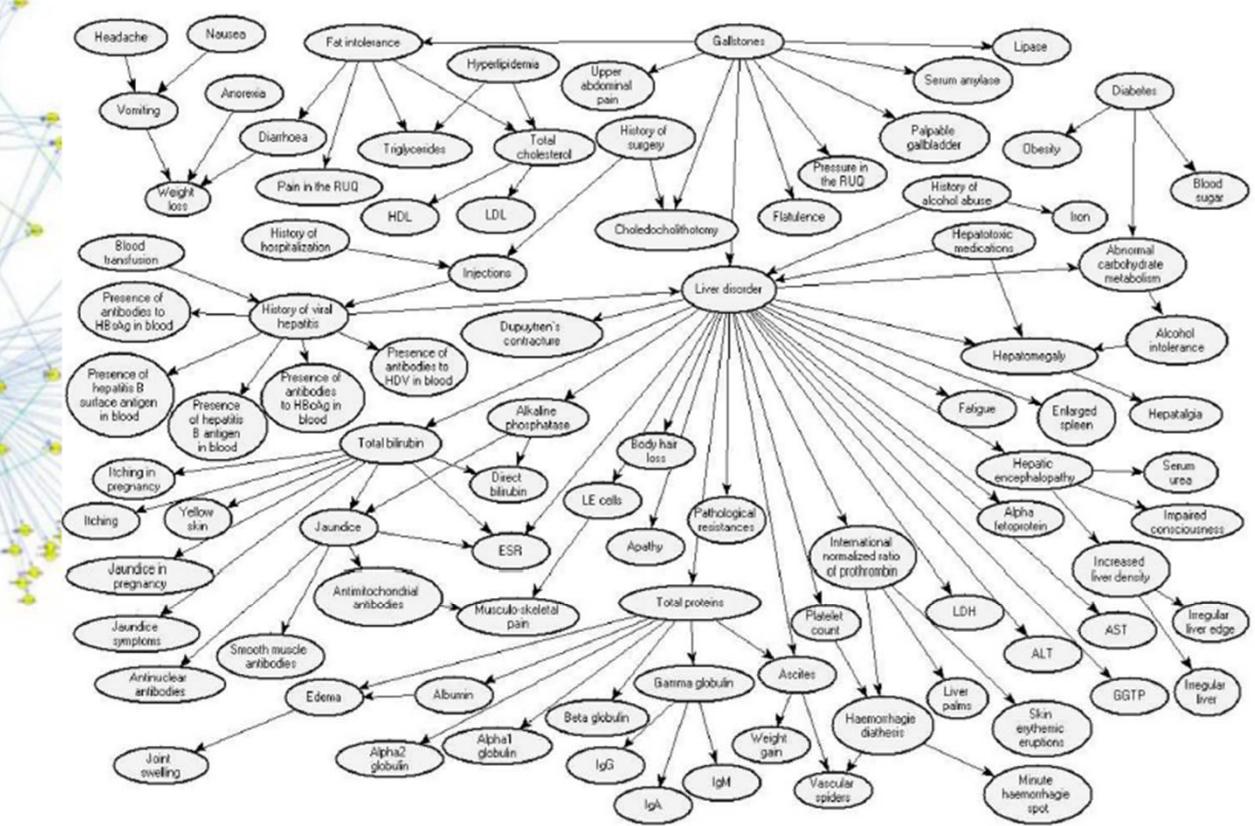
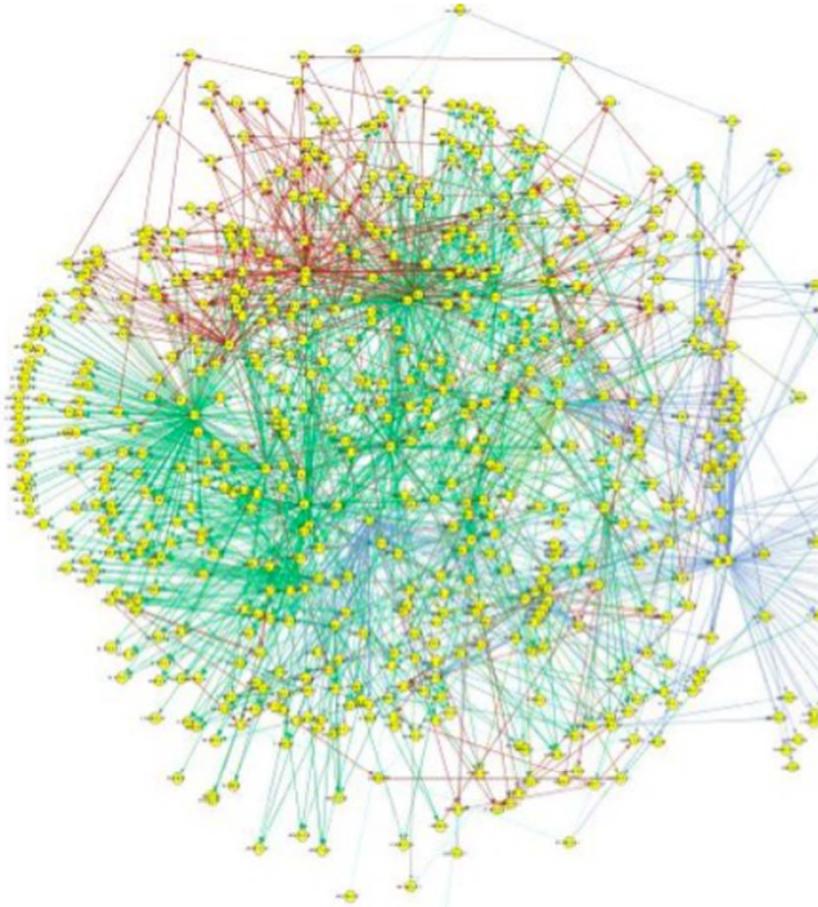
If we know the full joint distribution, we can answer all probabilistic inference questions.

What is the size of the joint probability table? why  $2^N$ ? V

- A.  $2^{N-1}$  entries  $P(X_1=_-, X_2=_-, \dots, X_N=_-)$
  - B.  $N^N$  entries
  - C.  $2^N$  entries
  - D. None/other/don't know
- = some value, but each underscore can be filled in in one of two ways.*

Brute-force computation of a full joint probability mass function is often intractable. 다루기 힘들

N can be large...



# Conditionally Independent RVs

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

$$\underline{P(AB|E)} = \underline{P(A|E)} \underline{P(B|E)}$$

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

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

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

when  $n=2 \quad P(x_1=x_1, x_2=x_2 | Y=y) = P(x_1=x_1 | Y=y) \cdot P(x_2=x_2 | Y=y)$

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

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

*useful when  $N$  is large  
and probabilities are so small  
that numerical stability  
is at risk!*



# Bayesian Networks

# A simpler WebMD

Flu

Under-  
grad

Fever

Tired

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

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

*each take on either 0 or 1 independently  
of each other*

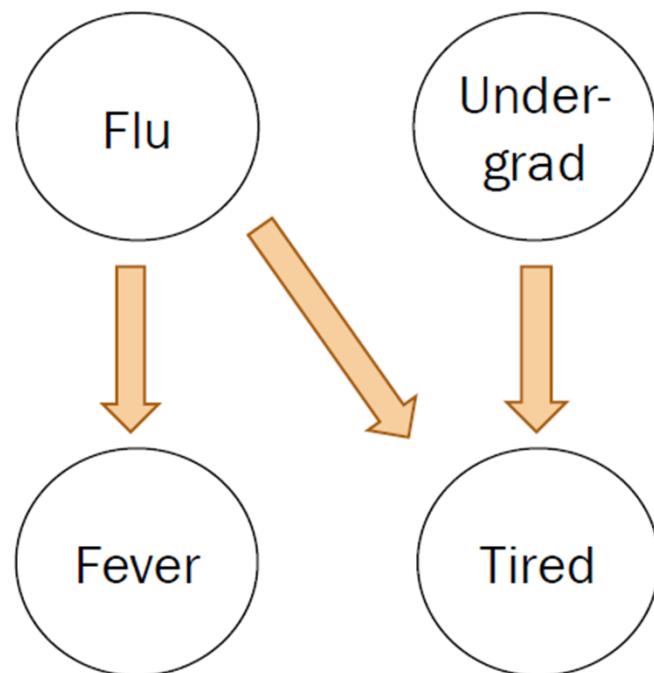
*$\downarrow$*   
 *$2^4$  possibilities*

What would an infectious diseases (ID) expert do?

인과관계

Describe the joint distribution using **causality!**

# Constructing a Bayesian Network



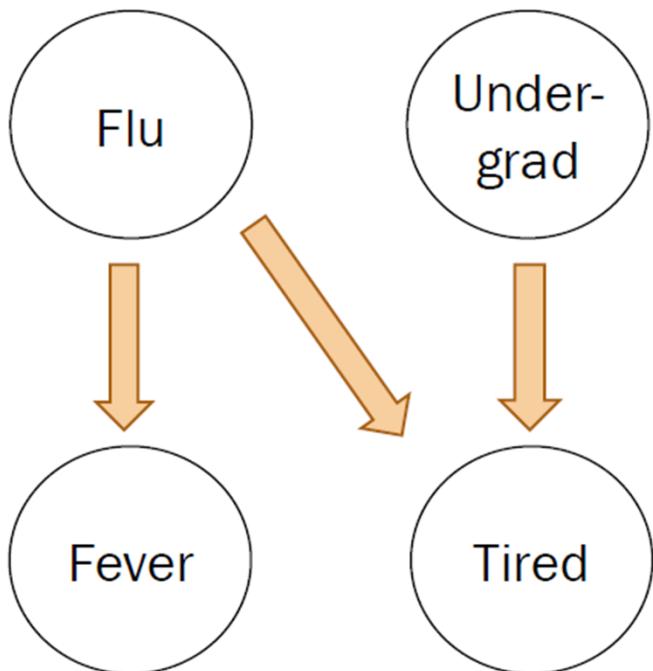
What would an ID expert do?

1. Describe the joint distribution using causality.

2. **Assume conditional independence.**

# Constructing a Bayesian Network

*must be a  
directed, acyclic  
graph*



In a Bayesian Network,

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

fancy speak that says two variables are conditionally  
independent of each other if  
there's no path between  
them

- Node: random variable
- Directed edge: conditional dependency

in practice, a causal  
dependency as well

Examples:

*doesn't inform Fev*

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

$$\textcircled{2} \quad P(F_{lu} = 1, U = 0) = P(F_{lu} = 1)P(U = 0)$$

*no conditional dependencies*

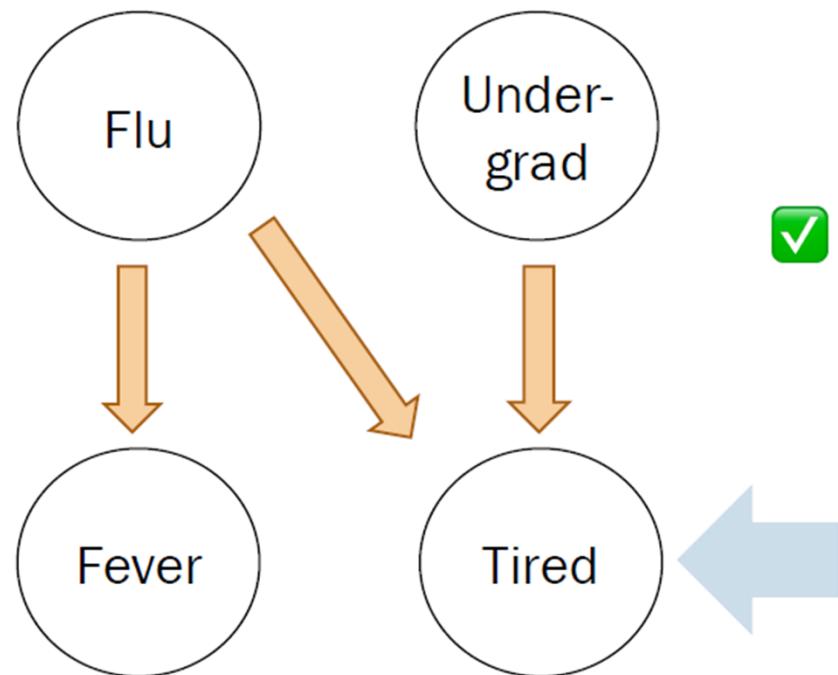
*expressed in the network, so independent*

Stanford University

# Constructing a Bayesian Network

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

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



What would an ID 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?

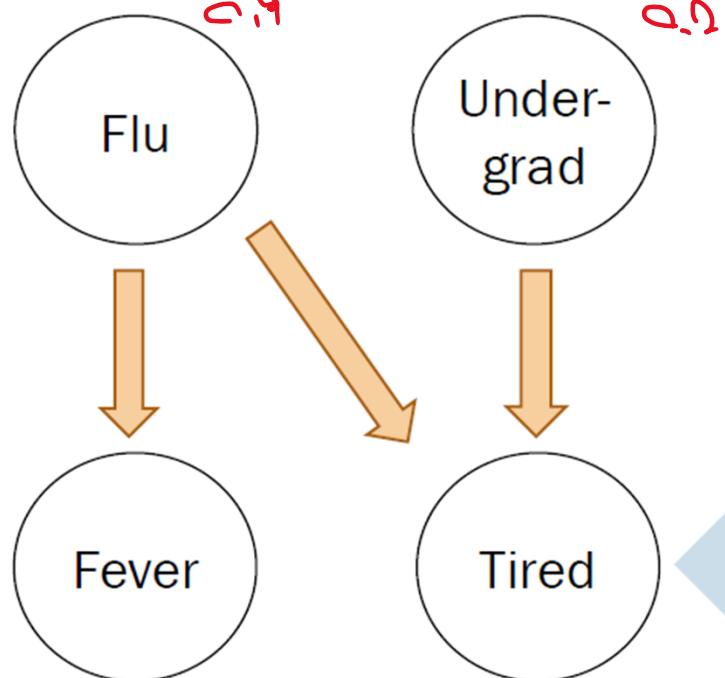
$$P(F_{ev} = 1|F_{lu} = 1) = 0.9$$

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



# Constructing a Bayesian Network

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



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

What would an ID 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?

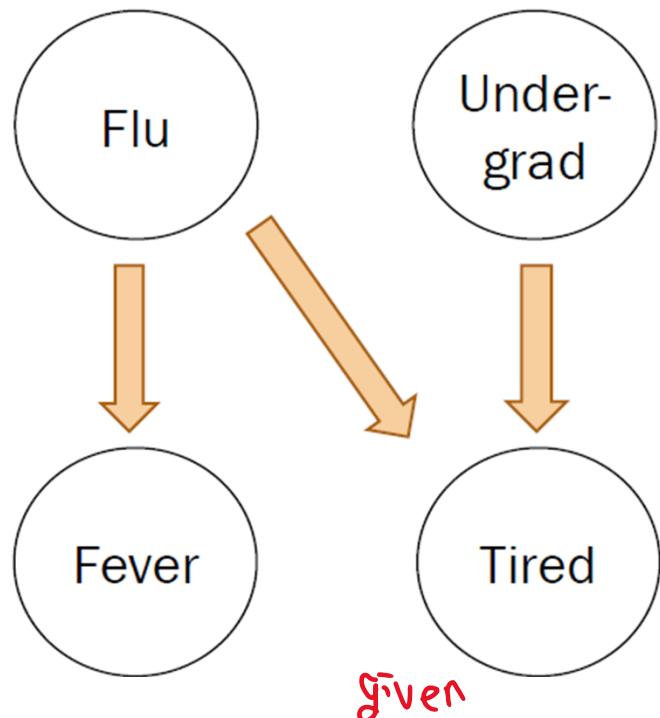
$$\begin{aligned} P(T = 1|F_{lu} = 0, U = 0) \\ P(T = 1|F_{lu} = 0, U = 1) \\ P(T = 1|F_{lu} = 1, U = 0) \\ P(T = 1|F_{lu} = 1, U = 1) \end{aligned}$$

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

# 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 an infectious diseases expert or by using reasonable assumptions

2. Answer inference questions

Our focus  
today

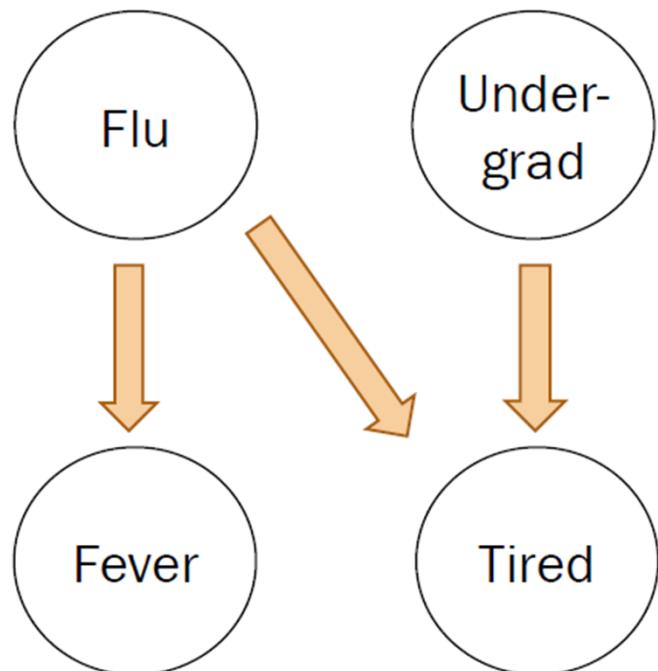
# Inference: Math

# Inference via math

Chap 4. Chain Rule (aka Product rule)  
 $P(EF) = P(F) P(E|F)$

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

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



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

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

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

Compute joint probabilities using chain rule.

$$F_{lu} \rightarrow P(F_{lu} = 0)$$

$$U \rightarrow P(U = 1)$$

$$F_{ev} \rightarrow P(F_{ev} = 0 | F_{lu} = 0)$$

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

$$= 0.9$$

$$= 0.8$$

$$= 0.95$$

$$= 0.8$$

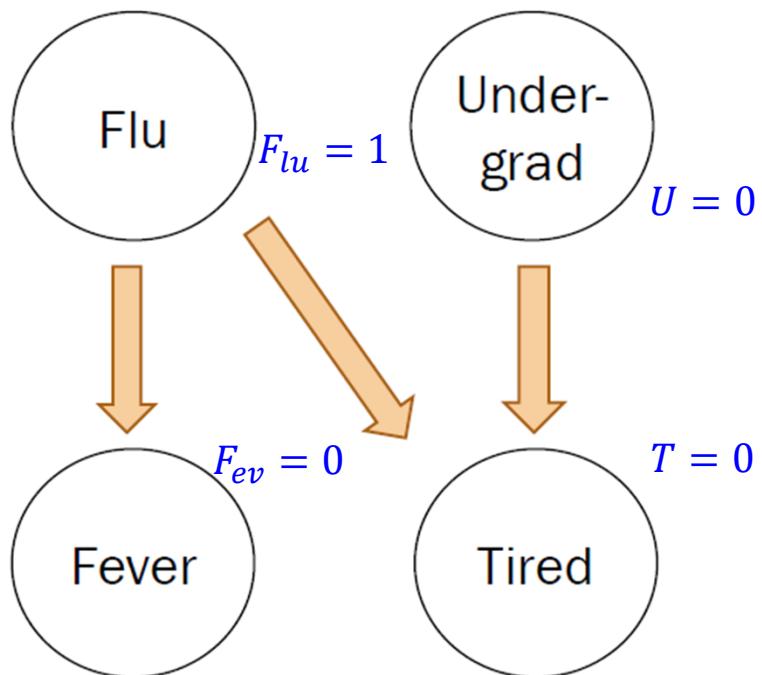
$$\underline{\underline{0.5472}}$$

all four variables contribute to joint probability value, but how some contribute is influenced by what they are conditioned on.

# 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<sub>lu</sub> = 1 | F<sub>ev</sub> = 0, U = 0, T = 1)?~~

1. Compute joint probabilities

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

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

2. Definition of conditional probability

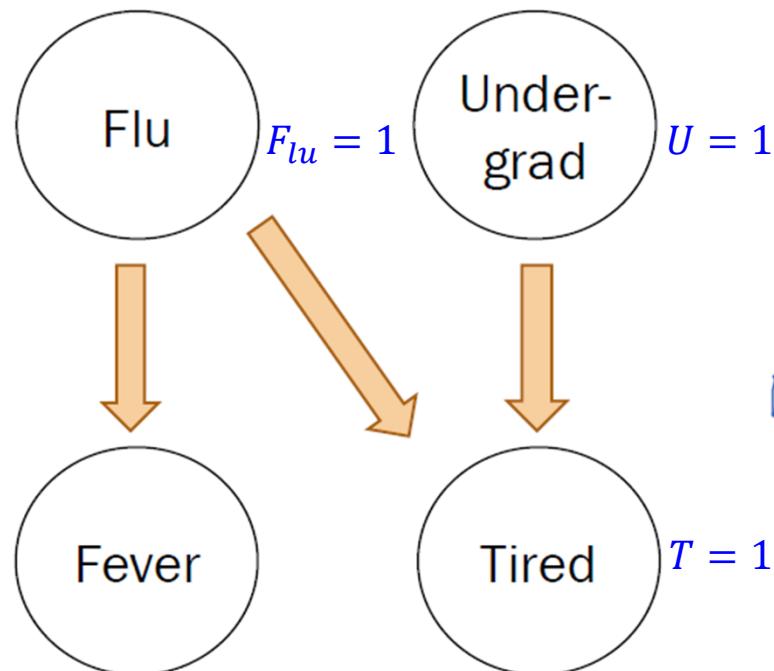
$$\frac{P(F_{lu} = 1, F_{ev} = 0, U = 0, T = 1)}{\sum_x P(F_{lu} = x, F_{ev} = 0, U = 0, T = 1)}$$

denominator results from application  
of law of total probability  
with one unknown  
 $= 0.095$

# Inference via math

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

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



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

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

Lisa Yan, Chris Piech, Mehran Sahami, and Jerry Cain, CS109, Winter 2023

3.  ~~$P(F_{lu} = 1 | U = 1, T = 1)$~~  *conditional probability that ignores Fev*

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

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

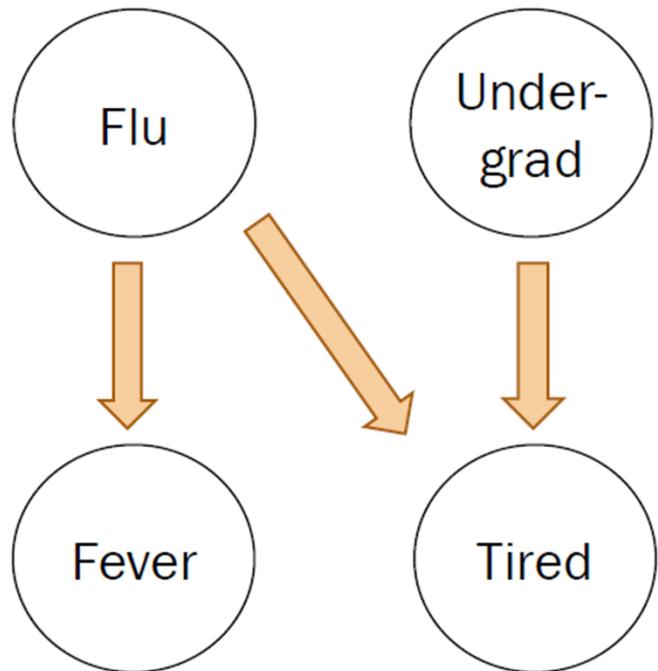
there  
are four  
such  
probabilities  
here

$$= 0.122$$

# Inference via math

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

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



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

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

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Solving inference questions precisely is possible, but sometimes tedious.

Can we use sampling to do approximate inference?



# Rejection Sampling

정확한 확률밀도 함수를 알기 힘들거나 확률밀도 함수가 주어졌을 때, 해당 함수로부터 sample을 추출하기 어려운 경우 sampling 하는 기본적인 방법

[Rejection sampling - Wikipedia](#)

[https://en.wikipedia.org/wiki/Rejection\\_sampling](https://en.wikipedia.org/wiki/Rejection_sampling)

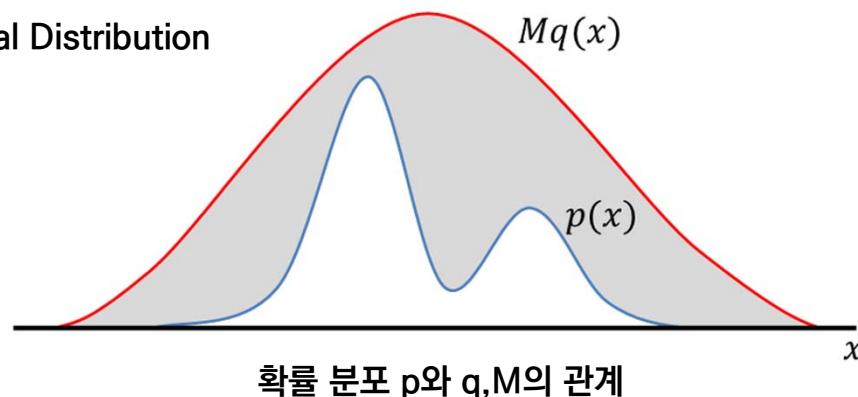
<https://untitledtblog.tistory.com/134>

<https://untitledtblog.tistory.com/134>

### Rejection sampling의 기본적인 동작

- 쉽게 샘플을 생성할 수 있는  $q$ 에서 샘플들을 생성한 뒤에 이 샘플들의 분포가  $p$ 를 따르도록 수정하는 것
- 이를 통해 실제로는  $q$ 에서 샘플이 생성되었지만, 그 결과는  $p$ 에서 생성된 것처럼 만드는 것이다. 이때 쉽게 샘플을 생성할 수 있도록 임의로 설정한  $q$ 를 제안 분포 (proposal distribution)이라고 한다.
- 제안 분포는 uniform distribution, normal distribution 등이 이용될 수 있으며, 가능하면  $p$ 와 비슷한 형태의 확률 분포를 사용하는 것이 좋다.

1) Proposal Distribution



확률 분포  $p$ 와  $q, M$ 의 관계

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### Algorithm 1: Rejection sampling

---

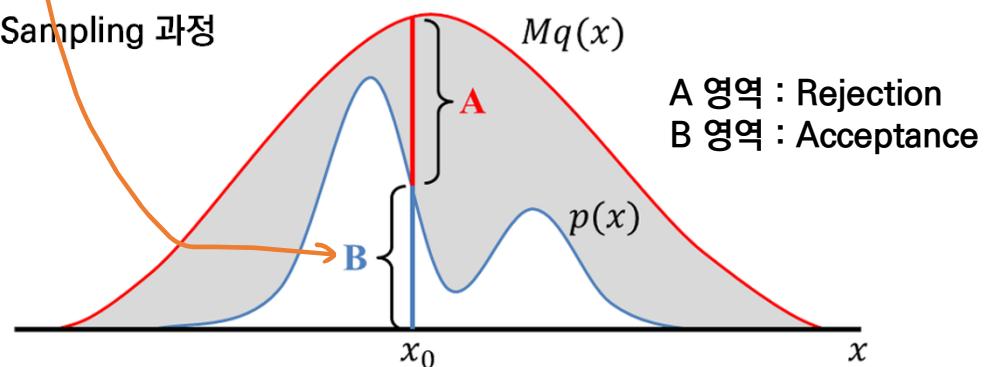
**Input** : the number of samples  $N$ ,  
target distribution  $p$ ,  
proposal distribution  $q$ ,  
a given constant  $M$

**Output** : samples  $X = \{x_1, x_2, \dots, x_N\}$

```
1  $X = \{\}$ 
2 while  $n < N$  do
3    $x_0 \sim q(x)$ 
4    $u \sim U(0, 1)$ 
5   if  $u < \frac{p(x_0)}{Mq(x_0)}$  then
6      $X \leftarrow X \cup \{x_0\}$ 
7    $n \leftarrow n + 1$ 
8 end
9 end
```

---

2) Sampling 과정



확률 분포  $q$ 로 부터 샘플 생성 및 Rejection /  
Acceptance 반복 수용

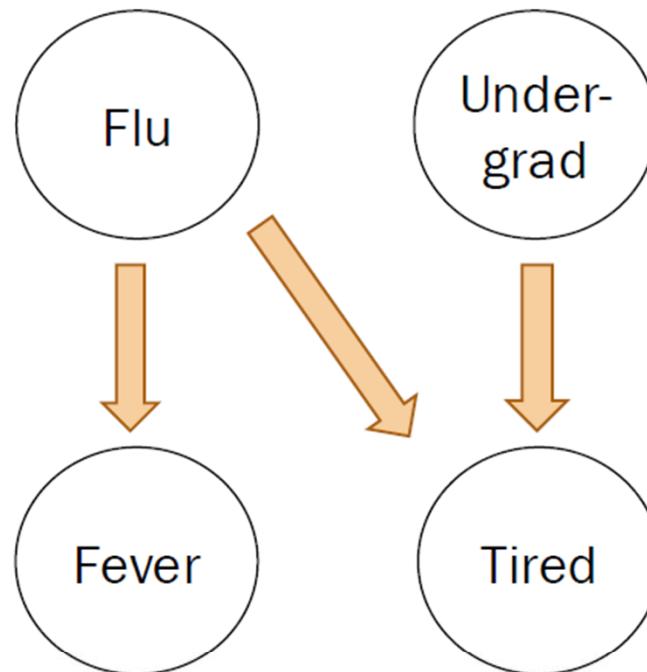
제안 분포를 설정한 다음에는 상수  $M$ 을 모든  $x$ 에 대해  
 $p(x) \leq Mq(x)$ 이 되도록 설정한다.

# Rejection sampling algorithm

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

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

Step 0:  
Require a fully specified  
Bayesian Network



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

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

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

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

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

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

# Rejection sampling algorithm

this is the  
observation or  
the given information

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)
```

[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)
```

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

# Rejection sampling algorithm

Inference  
question:

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

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

Why would this definition of approximate probability make sense?

*this is the frequentist's definition of probability!*

# Why would this approximate probability make sense?

Inference question:

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

Why would this definition of approximate probability make sense?

$$\begin{aligned} P(F_{lu} = 1 | U = 1, T = 1) &= \frac{P(F_{lu} = 1, V = 1, T = 1)}{P(V = 1, T = 1)} \\ &= \frac{n(F_{lu} = 1, V = 1, T = 1)}{n(V = 1, T = 1)} \\ &= \frac{\text{num samples}}{\text{num samples}} \end{aligned}$$

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

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

(1) samples=sample\_a\_ton()

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)
```

[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

(1) samples=sample\_a\_ton()

```
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

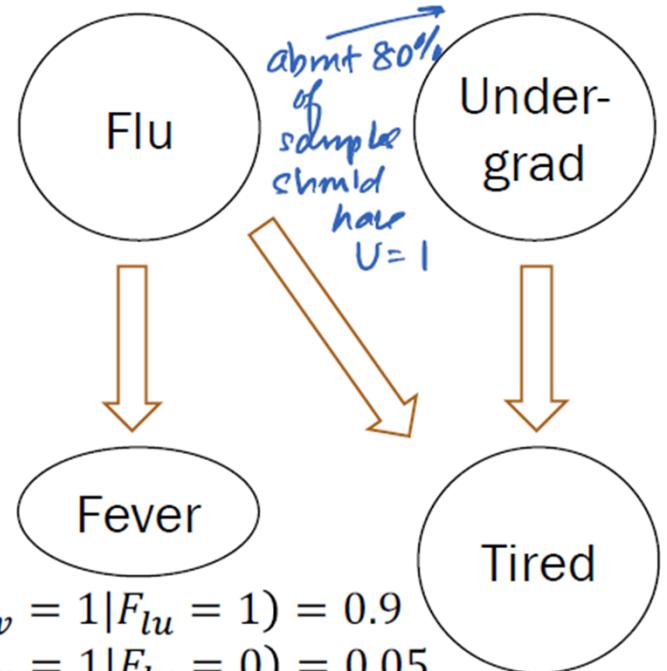
```
# Method: Make Sample
# -----
# create a single sample from the joint distribution
# based on the medical "WebMD" Bayesian Network
def make_sample():
    # prior on causal factors
    flu = bernoulli(0.1)
    und = bernoulli(0.8)

    # 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]
```

this suggests that about  
10% of samples should  
have  $F_{lu} = 0.1$

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



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

# Rejection sampling algorithm

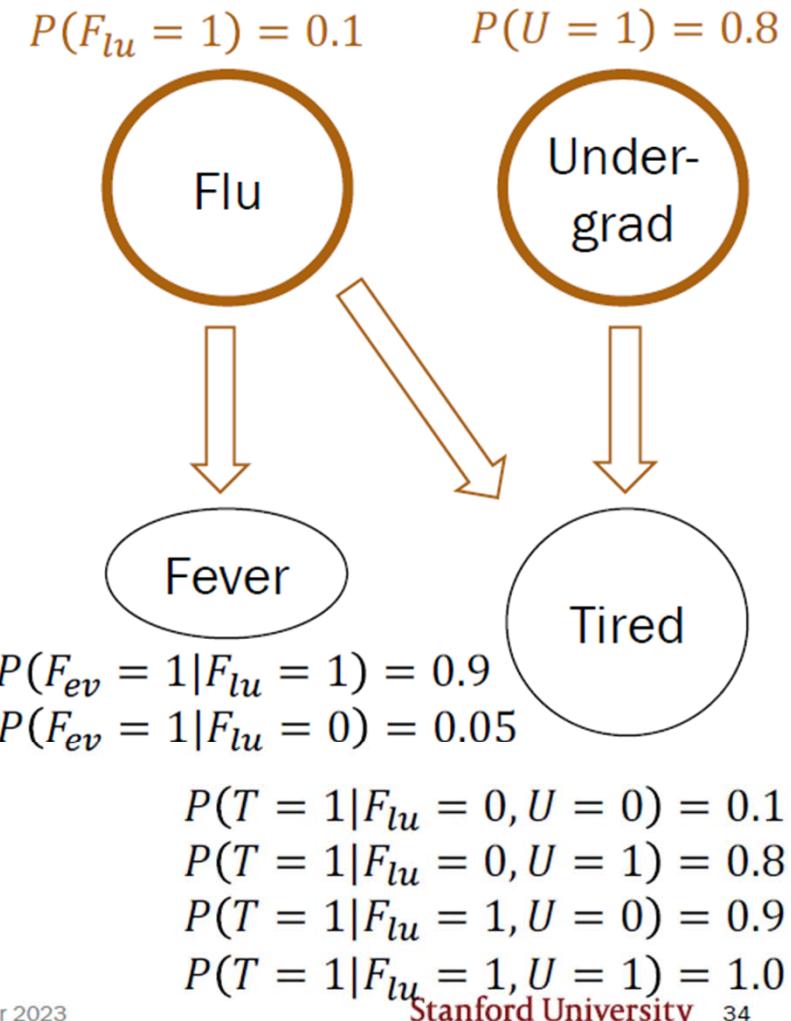
(1) samples=sample\_a\_ton()

```
# 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]
```



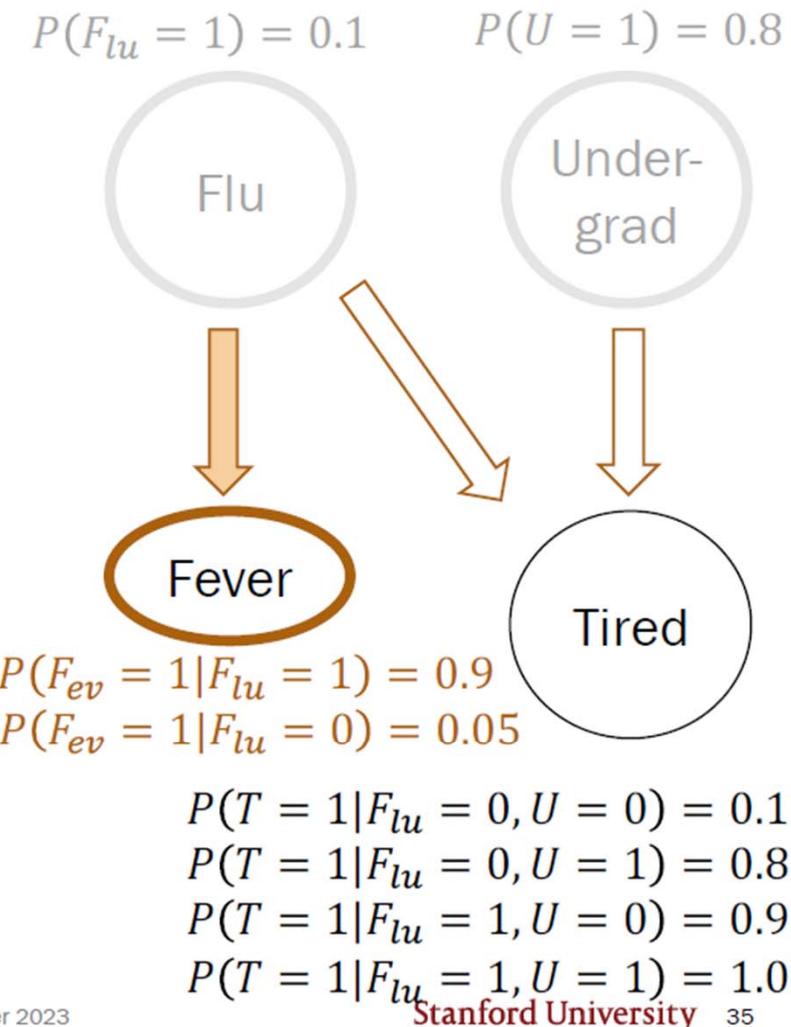
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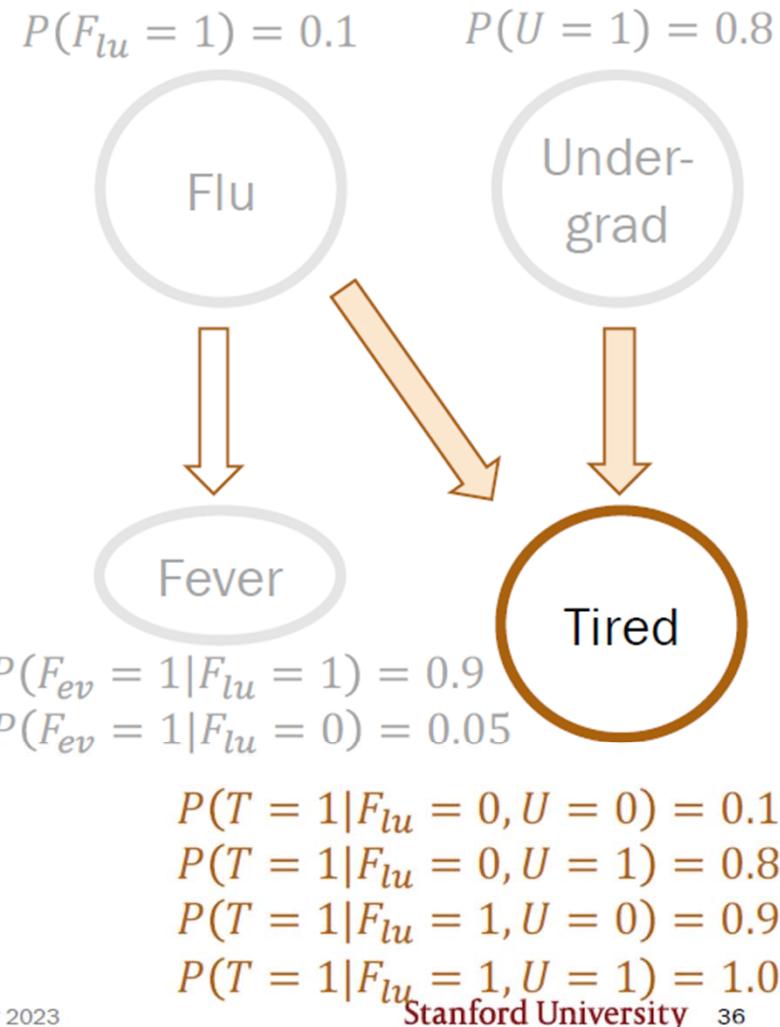
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# Rejection sampling algorithm

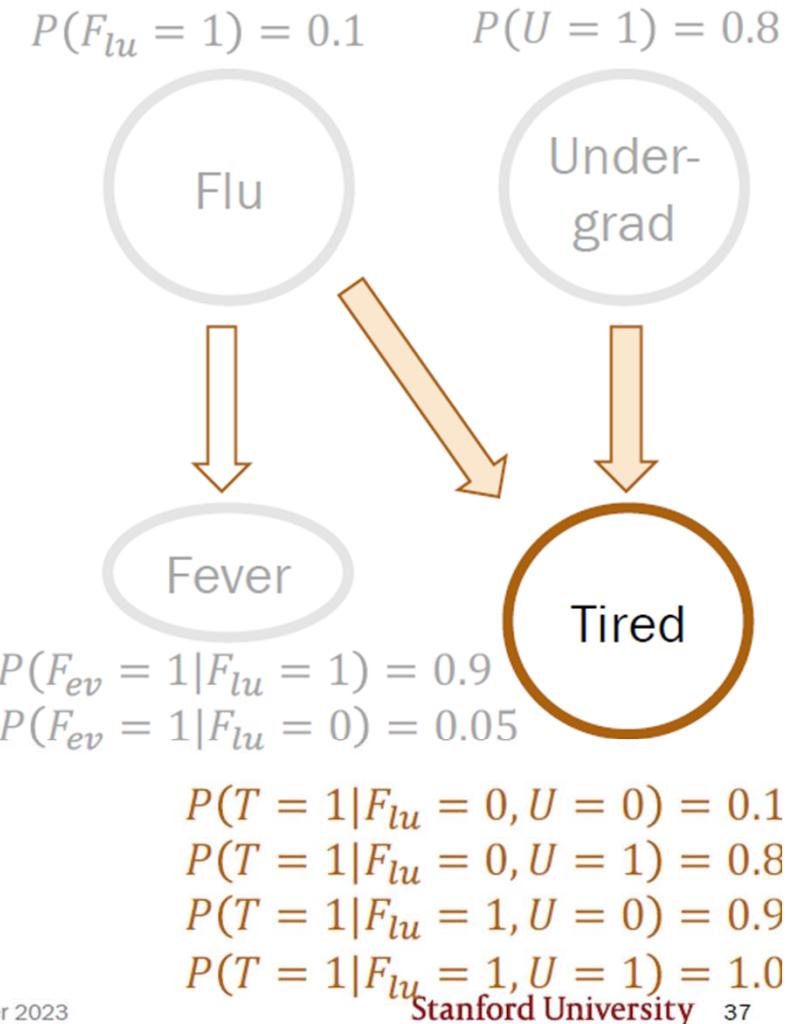
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    else:         fev = bernoulli(0.05)

    # 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]
```



# Rejection sampling algorithm

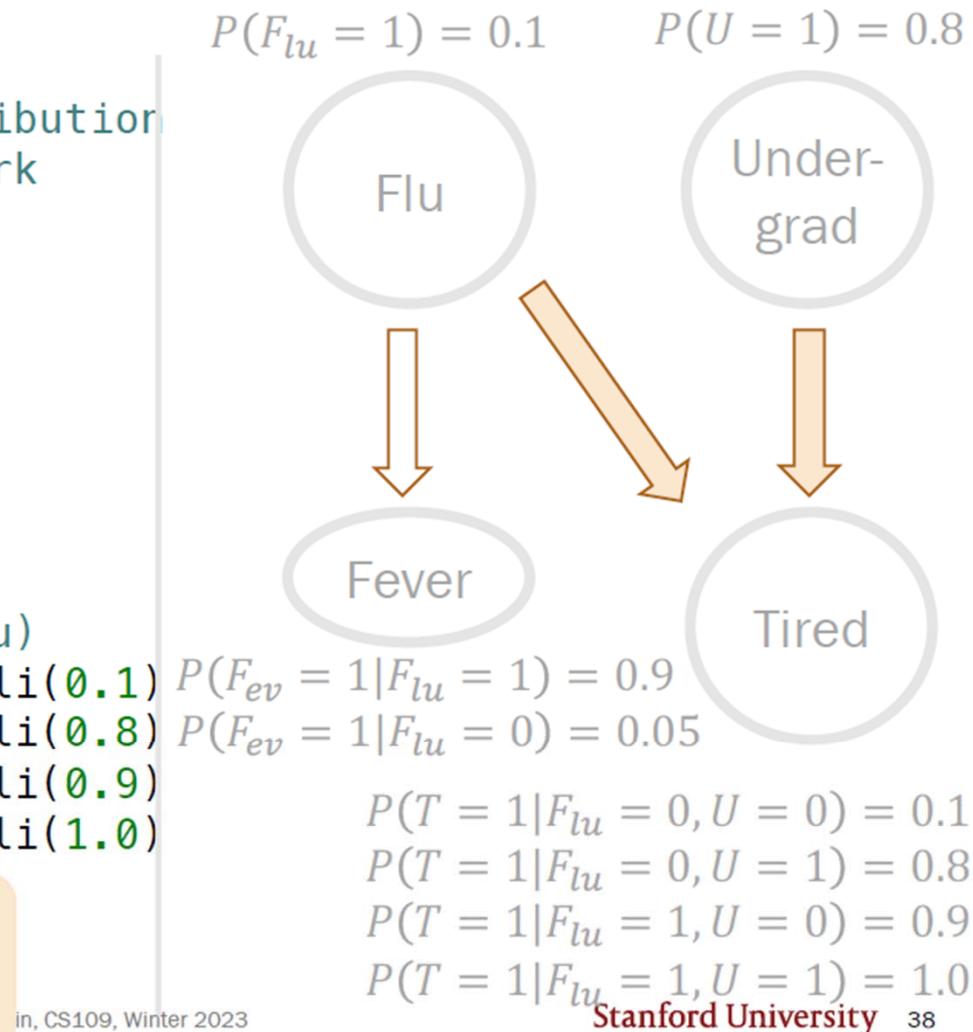
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    elif flu == 0 and und == 1: tir = bernoulli(0.8)
    elif flu == 1 and und == 0: tir = bernoulli(0.9)
    else: tir = bernoulli(1.0)

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



# Rejection sampling algorithm

(2) samples\_observation

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)
```

build a new set of samples that retains just those samples consistent with the supplied 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.
    def reject_inconsistent(samples, outcome):
        consistent_samples = []
        for sample in samples:
            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)
    samples_event =
        reject_inconsistent(samples_observation, event)
    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)
    return 1
```

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

```
def reject_inconsistent(samples, outcome):
    consistent_samples = [sample for sample in samples if sample[outcome]]
```

# 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)
```

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

# 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
- but approximately, even if the approximation is incredibly good*

Why? Because your samples represent the joint distribution incredibly well!

[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

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