



Statistical Methods in AI and ML

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A powerful and flexible set of tools for modeling
problems in AI/ML

Judea Pearl won the Turing award for his work on
Bayesian networks!
(among other achievements)

Exploit **locality** and structural features of a given model in order to gain insight about **global properties**

- What this course is:
 - Probabilistic graphical models
 - Topics:
 - representing data
 - exact and approximate statistical inference
 - model learning
 - variational methods in ML

- What you should be able to do at the end:
 - Design statistical models for applications in your domain of interest
 - Apply learning and inference algorithms to solve real problems (exactly or approximately)
 - Understand the complexity issues involved in the modeling decisions and algorithmic choices

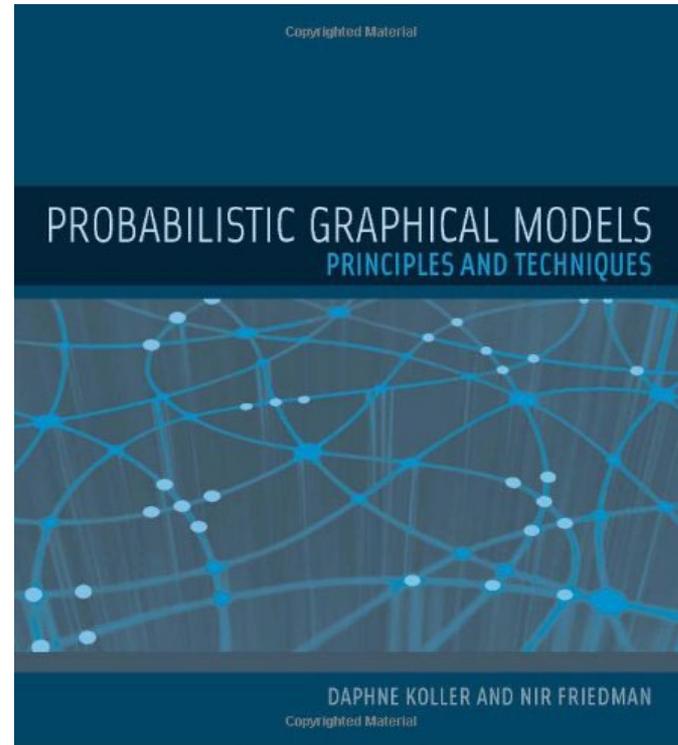
- CS 5343: Algorithm Analysis and Data Structures
- CS 3341: Probability and Statistics in Computer Science and Software Engineering
- Basically, comfort with probability and algorithms (machine learning is helpful, but not required)

Suggested Textbook



Readings will be posted
online before each
lecture

Check the course website
for additional resources
and papers



- In addition, some lecture notes, in book format, will be made available for the main topics
- The idea is to build a set of notes that aligns well with the presentation of course material
- Comments, suggestions, corrections are welcome/encouraged

- 4-6 problem sets (70%)
 - See collaboration policy on the web
- Final project (25%)
- Class/Piazza participation & extra credit (5%)

-subject to change-

Course Info.



- Instructor: Nicholas Ruoizzi
 - Office: ECSS 3.409
 - Office hours: W. 1pm-2pm, and by appointment
- TA: TBD
 - Office hours and location TBD
- Course website:
<http://www.utdallas.edu/~nrr150130/cs6347/2023sp/>

- Model the world (or at least the problem) as a collection of random variables related through some joint probability distribution
 - Compactly represent the distribution
 - Undirected graphical models
 - Directed graphical models
- Learn the distribution from observed data
 - Maximum likelihood, SVMs, etc.
- Make predictions (statistical inference)

Inference and Learning

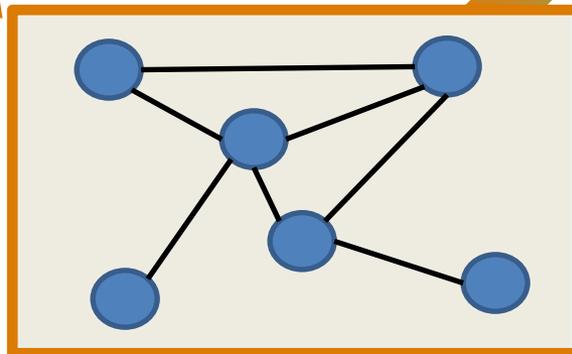


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Collect Data

$$Z(\theta) = \sum_x p(x; \theta)$$

Use the model to do inference / make predictions



“Learn” a model that represents the observed data

Inference and Learning

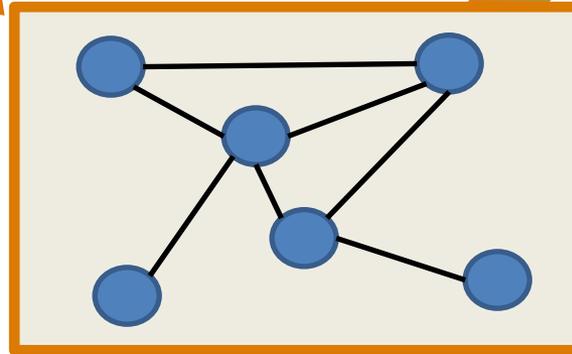


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**Data sets can
be large**

$$Z(\theta) = \sum_x p(x; \theta)$$

**Inference needs to
be fast**



**Data must be
compactly modeled**

Applications



- Computer vision
- Natural language processing
- Robotics
- Computational biology
- Computational neuroscience
- Text translation
- Text-to-speech
- Many more...

- A graphical model is a graph together with "local interactions"
- The graph and interactions model a global optimization or learning problem
- The study of graphical models is concerned with how to exploit local structure to solve these problems either exactly or approximately



Probability Review

- **Sample space** specifies the set of possible outcomes
 - For example, $\Omega = \{H, T\}$ would be the set of possible outcomes of a coin flip
- Each element $\omega \in \Omega$ is associated with a number $p(\omega) \in [0,1]$ called a **probability**

$$\sum_{\omega \in \Omega} p(\omega) = 1$$

- For example, a biased coin might have $p(H) = .6$ and $p(T) = .4$

- An **event** is a subset of the sample space
 - Let $\Omega = \{1, 2, 3, 4, 5, 6\}$ be the 6 possible outcomes of a dice roll
 - $A = \{1, 5, 6\} \subseteq \Omega$ would be the event that the dice roll comes up as a one, five, or six
- The probability of an event is just the sum of all of the outcomes that it contains
 - $p(A) = p(1) + p(5) + p(6)$

Independence

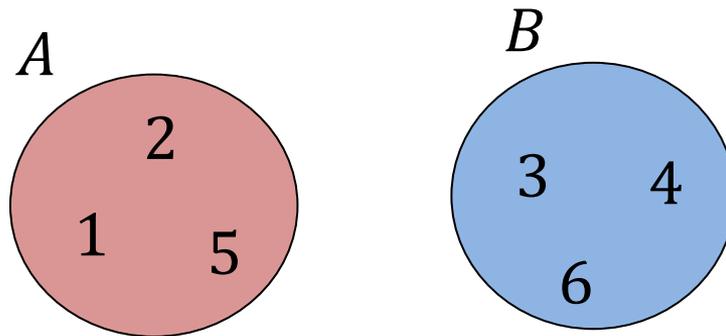


- Two events A and B are **independent** if

$$p(A \cap B) = p(A)p(B)$$

Let's suppose that we have a fair die: $p(1) = \dots = p(6) = 1/6$

If $A = \{1, 2, 5\}$ and $B = \{3, 4, 6\}$ are A and B independent?



Independence

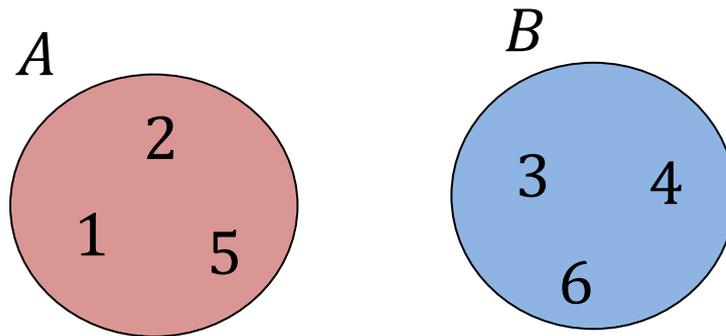


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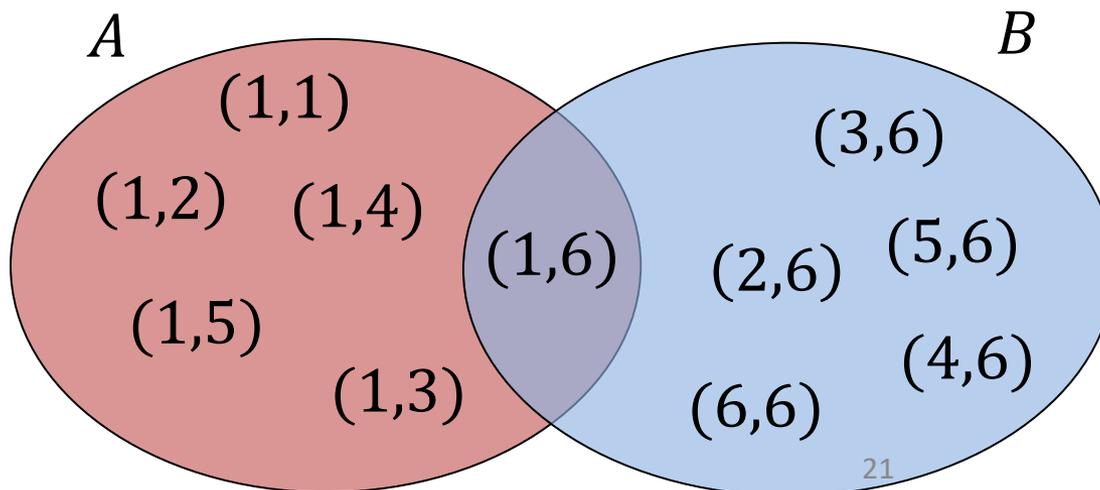
No!

$$p(A \cap B) = 0 \neq \frac{1}{4}$$

Independence



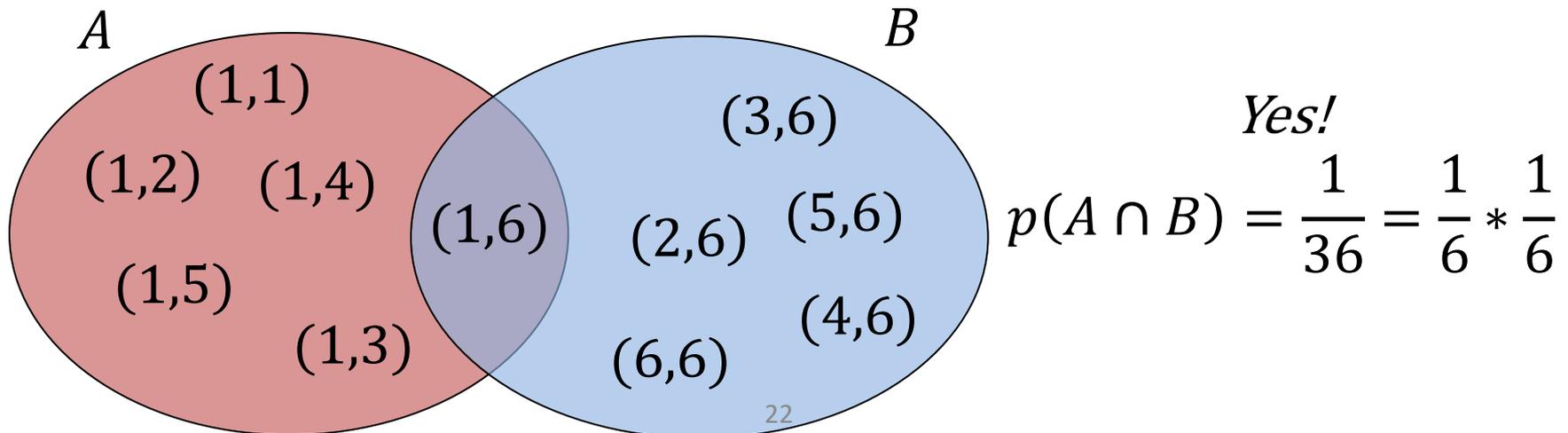
- Now, suppose that $\Omega = \{(1,1), (1,2), \dots, (6,6)\}$ is the set of all possible rolls of two **unbiased** dice
- Let $A = \{(1,1), (1,2), (1,3), \dots, (1,6)\}$ be the event that the first die is a one and let $B = \{(1,6), (2,6), \dots, (6,6)\}$ be the event that the second die is a six
- Are A and B independent?



Independence



- Now, suppose that $\Omega = \{(1,1), (1,2), \dots, (6,6)\}$ is the set of all possible rolls of two **unbiased** dice
- Let $A = \{(1,1), (1,2), (1,3), \dots, (1,6)\}$ be the event that the first die is a one and let $B = \{(1,6), (2,6), \dots, (6,6)\}$ be the event that the second die is a six
- Are A and B independent?



- The **conditional probability** of an event A given an event B with $p(B) > 0$ is defined to be

$$p(A|B) = \frac{p(A \cap B)}{P(B)}$$

- This is the probability of the event $A \cap B$ over the sample space $\Omega' = B$
- Some properties:
 - $\sum_{\omega \in B} p(\omega|B) = 1$
 - If A and B are independent, then $p(A|B) = p(A)$

Simple Example



Cheated	Grade	Probability
Yes	A	.15
Yes	F	.05
No	A	.5
No	F	.3

Simple Example



Cheated	Grade	Probability
Yes	A	.15
Yes	F	.05
No	A	.5
No	F	.3

$$p(\text{Cheated} = \text{Yes} \mid \text{Grade} = \text{F}) = ?$$

Simple Example



Cheated	Grade	Probability
Yes	A	.15
Yes	F	.05
No	A	.5
No	F	.3

$$p(\text{Cheated} = \text{Yes} | \text{Grade} = \text{F}) = \frac{.05}{.35} \approx .14$$

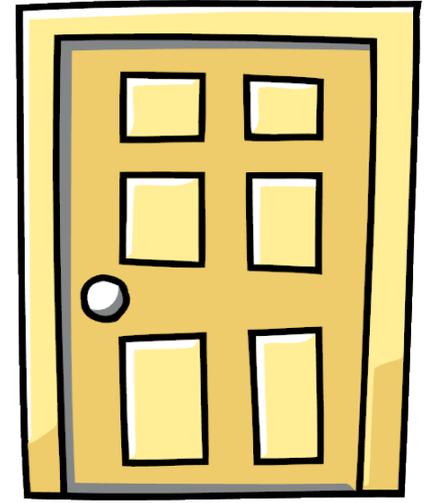
The Monty Hall Problem



1



2



3

$$p(A \cap B) = p(A)p(B|A)$$

$$\begin{aligned} p(A \cap B \cap C) &= p(A \cap B)p(C|A \cap B) \\ &= p(A)p(B|A)p(C|A \cap B) \end{aligned}$$

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$$p\left(\bigcap_{i=1}^n A_i\right) = p(A_1)p(A_2|A_1) \dots p(A_n|A_1 \cap \dots \cap A_{n-1})$$

Conditional Independence



- Two events A and B are independent if learning something about B tells you nothing about A (and vice versa)
- Two events A and B are **conditionally independent** given C if

$$p(A \cap B|C) = p(A|C)p(B|C)$$

- This is equivalent to

$$p(A|B \cap C) = p(A|C)$$

- That is, given C , information about B tells you nothing about A (and vice versa)

Conditional Independence



- Let $\Omega = \{(H, H), (H, T), (T, H), (T, T)\}$ be the outcomes resulting from tossing two different fair coins
- Let A be the event that the first coin is heads
- Let B be the event that the second coin is heads
- Let C be the event that both coins are heads or both are tails
- A and B are independent, but A and B are not independent given C

- A discrete **random variable**, X , is a function from the state space Ω into a discrete space D

- For each $x \in D$,

$$p(X = x) \equiv p(\{\omega \in \Omega : X(\omega) = x\})$$

is the probability that X takes the **value** x

- $p(X)$ defines a probability distribution
 - $\sum_{x \in D} p(X = x) = 1$
- Random variables partition the state space into disjoint events

Example: Pair of Dice



- Let Ω be the set of all possible outcomes of rolling a pair of dice
- Let p be the uniform probability distribution over all possible outcomes in Ω
- Let $X(\omega)$ be equal to the sum of the value showing on the pair of dice in the outcome ω
 - $p(X = 2) = ?$
 - $p(X = 8) = ?$

Example: Pair of Dice



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- Let p be the uniform probability distribution over all possible outcomes in Ω
- Let $X(\omega)$ be equal to the sum of the value showing on the pair of dice in the outcome ω
 - $p(X = 2) = \frac{1}{36}$
 - $p(X = 8) = ?$

Example: Pair of Dice



- Let Ω be the set of all possible outcomes of rolling a pair of dice
- Let p be the uniform probability distribution over all possible outcomes in Ω
- Let $X(\omega)$ be equal to the sum of the value showing on the pair of dice in the outcome ω
 - $p(X = 2) = \frac{1}{36}$
 - $p(X = 8) = \frac{5}{36}$

- We can have vectors of random variables as well

$$X(\omega) = [X_1(\omega), \dots, X_n(\omega)]$$

- The **joint distribution** is $p(X_1 = x_1, \dots, X_n = x_n)$ is

$$p(X_1 = x_1 \cap \dots \cap X_n = x_n)$$

typically written as

$$p(x_1, \dots, x_n)$$

- Because $X_i = x_i$ is an event, all of the same rules - independence, conditioning, chain rule, etc. - still apply

- Two random variables X_1 and X_2 are independent if

$$p(X_1 = x_1, X_2 = x_2) = p(X_1 = x_1)p(X_2 = x_2)$$

for all values of x_1 and x_2

- Similar definition for conditional independence
- The conditional distribution of X_1 given $X_2 = x_2$ is

$$p(X_1 | X_2 = x_2) = \frac{p(X_1, X_2 = x_2)}{p(X_2 = x_2)}$$

this means that this relationship holds for all choices of x_1

Expected Value



- The **expected value** of a real-valued random variable is the weighted sum of its outcomes

$$E[X] = \sum_{x \in D} p(X = d) \cdot d$$

- Expected value is linear

$$E[X + Y] = E[X] + E[Y]$$

Expected Value: Lotteries



- Powerball Lottery currently has a grand prize of \$473 million
- Odds of winning the grand prize are $1/292,201,338$
- Tickets cost \$2 each
- Expected value of the game

$$= \left(\frac{292,201,337}{292,201,338} \right) (-2) + \left(\frac{1}{292,201,338} \right) \cdot (473,000,000 - 2)$$

$$\approx \$ - .38$$

- The **variance** of a random variable measures its squared deviation from its mean

$$\mathit{var}(X) = E[(X - E[X])^2]$$

- Estimates the square of the expected amount by which a random variable deviates from its expected value