Probabilistic Graphical Models

Introduction

Logistics

Textbooks:

- Christopher Bishop, Pattern Recognition and Machine Learning
- Kevin Murphy, Machine Learning: A probabilistic Perspective
- Daphne Koller and Nir Friedman, Probabilistic Graphical Models
- Class website: <u>https://polyhedron.math.uoc.gr/2223/moodle/course/view.php?id=18</u>
- Grading:
- 2 homework assignments: 20% of grade
 - Theory exercises, Implementation exercises
- Project: 40% of grade
 - □ Pick a paper (not introductory) from *M.I. Jordan (editor), Learning in Graphical Models*
 - Present it in class.
 - Implement the method
 - Apply it on a real or simulated data set.
 - March 6th :Deadline for project proposal

What Are Graphical Models?



Model

 M_G

Data

 $\left\{x_{1}^{(i)}, \dots, x_{n}^{i}\right\}_{i=1}^{N}$

Slides by Eric Xing @ CMU, 2005-2020

Reasoning under uncertainty!



Planning

The Fundamental Questions

Representation

- How to capture/model uncertainties in possible worlds?
- How to encode our domain knowledge/assumptions/constraints?

Inference

How do I answer questions/queries according to my model and/or based given data?

e.g.: $P(X_i | D)$

- Learning
 - What model is "right" for my data?

```
e.g.: M = \underset{M \in M}{\operatorname{arg\,max}} F(D;M)
```

Representing multivariate distributions

• Representation: what is the joint probability dist. on multiple variables?

P(A, B, C, D, E, F, G, H)

- How many state configurations in total ? --- 2⁸
- Are they all needed to be represented?
- Do we get any scientific/medical insight?
- Learning: where do we get all this probabilities?
 - Maximal-likelihood estimation? but how many data do we need?
 - Are there other est. principles?
 - Where do we put domain knowledge in terms of plausible relationships between variables, and plausible values of the probabilities?
- Inference: If not all variables are observable/observed, how to compute the conditional distribution of latent variables given evidence?
 - Computing P(H|A) would require summing over all 2^6 configurations of the unobserved variables

A		8
C	D	Ē
	F	
G	H	

- --- Multivariate Distribution in High-D Space
 - A possible world for cellular signal transduction:



GM: Structure Simplifies Representation

Dependencies among variables



Probabilistic Graphical Models

□ If X_i 's are conditionally independent (as described by a PGM), the joint can be factored to a product of simpler terms, e.g.,



P(A, B, C, D, E, F, G, H) = P(A) P(B) P(C|A) P(D|B) P(E|B)P(F|C, D) P(G|F) P(H|E, F)

□ Why we may favor a PGM?

□ Incorporation of domain knowledge and causal (logical) structures

1+1+2+2+2+4+2+4=18, a 16-fold reduction from 2⁸ in representation cost !

GMs are your old friends

Density estimation

Parametric and nonparametric methods

Regression

Linear, conditional mixture, nonparametric

Classification

Generative and discriminative approach Clustering







Probabilistic Graphical Models

Probability recap

- ➢ Reading: Murphy, Secs. 2.1 and 2.2.
- Lots of slides from: Eli Upfal, Jason Panjeho.

Suppose we roll <u>two fair dice</u>...

- > What are the possible outcomes?
- > What is the *probability* of rolling **even** numbers?
- > What is the *probability* of rolling **odd** numbers?
- If one die rolls 1, then what is the probability of the second die also rolling 1?
- How to mathematically formulate outcomes and their probabilities?

...this is an experiment or random process.

Formulate as probability space having 3 components





A sample space Ω : set of all possible outcomes of the experiment.

Dice Example: All combinations of dice rolls,

 $\Omega = \{(1,1), (1,2), \dots, (6,5), (6,6)\}$



An event space F: Family of sets representing <u>allowable events</u>, where each set in F is a subset of the sample space Ω.

Dice Example: Event that we roll even numbers,

$$E = \{(2,2), (2,4), \dots, (6,4), (6,6)\} \in \mathcal{F}$$

A probability function $P : \mathcal{F} \to \mathbf{R}$ satisfying:

- 1. For any event $E, 0 \le P(E) \le 1$
- **2.** $P(\Omega) = 1$ and $P(\emptyset) = 0$
- 3. For any *finite* or *countably infinite* sequence of <u>pairwise mutually disjoint events</u> E_1, E_2, E_3, \ldots

$$P\Big(\bigcup_{i\geq 1} E_i\Big) = \sum_{i\geq 1} P(E_i)$$



(Fair) Dice Example: Probability that we roll <u>even numbers</u>, $P((2,2) \cup (2,4) \cup \ldots \cup (6,6)) = P((2,2)) + P((2,4)) + \ldots + P((6,6))$

9 Possible outcomes, each with equal probability of occurring

$$=\frac{1}{36}+\frac{1}{36}+\ldots+\frac{1}{36}=\frac{9}{36}$$

Some rules regarding set of event space \mathcal{F} ...

- $\succ \mathcal{F}$ must include \emptyset and Ω
- > \mathcal{F} is **closed** under countable unions, countable intersections and complement: if $E_1, E_2 \in \mathcal{F}$ then:
 - $E_1 \cup E_2 \in \mathcal{F}$
 - $E_1 \cap E_2 \in \mathcal{F}$
 - $\overline{E_1} = \Omega E_1 \in \mathcal{F}$

Two dice example: If $E_1, E_2 \in \mathcal{F}$ where,

 $E_1: \textit{First} \text{ die equals 1} \qquad E_2: \textit{Second} \text{ die equals 1} \\ E_1 = \{(1,1), (1,2), \dots, (1,6)\} \qquad E_2 = \{(1,1), (2,1), \dots, (6,1)\}$

Then we must include the following events...

Operation	Value	Interpretation
$E_1 \cup E_2$	$\{(1,1),(1,2),\ldots,(1,6),(2,1),\ldots,(6,1)\}$	Any die rolls 1
$E_1 \cap E_2$	$\{(1,1)\}$	Both dice roll 1
$E_1 - E_2$	$\{(1,2),(1,3),(1,4),(1,5),(1,6)\}$	First die rolls 1 only
$\overline{E_1 \cup E_2}$	$\{(2,2),(2,3),\ldots,(2,6),(3,2),\ldots,(6,6)\}$	No die rolls 1

Can interpret these operations as a Venn diagram...



Lemma: For <u>any</u> two events E_1 and E_2 ,

$$P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)$$

Graphical Proof:



Subtract from both sides

Lemma: For <u>any</u> two events E_1 and E_2 ,

 $P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)$

Proof:

 $P(E_1) = P(E_1 \setminus (E_1 \cap E_2)) + P(E_1 \cap E_2)$ $P(E_2) = P(E_2 \setminus (E_1 \cap E_2)) + P(E_1 \cap E_2)$

 $P(E_1 \cup E_2) = P(E_1 \setminus (E_1 \cap E_2)) + P(E_2 \setminus (E_1 \cap E_2)) + P(E_1 \cap E_2)$

Law of Total Probability

$P(A) = P(A \cap B) + P(A \cap B^c)$



Independence

Definition Two events A and B are independent if

$$P(A \cap B) = P(A)P(B).$$

We denote this as

$A \perp B$

Example

You roll a die. Consider the following two events

- A : "The outcome is an even number"
- B : "The outcome is one of the numbers {1, 2, 3, 4}"
- C: "The outcome is one of the numbers {1, 2, 3}"

```
Find P(A), P(B), and P(A \cap B)
```

Are A and B independent?

```
Find P(A), P(C), and P(A \cap C)
```

Are A and C independent?

Conditional Probability

One way to interpret the independence of events is as follows:

- Consider again the following two events:
 - A : "The outcome is an even number"
 - B : "The outcome is one of the numbers {1, 2, 3, 4}"
- You want to bet on event A. How much are you willing to bet?
- I roll the die and tell you that event B has happened (hence, the outcome is one of {1, 2, 3, 4}.
- How much are you willing to bet now?
- We just described the conditional probability

P(A = True | B = true)

Conditional Probability

Conditional Probability:

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

Law of Total Probability

$$P(A) = P(A \cap B) + P(A \cap B^c)$$

 $P(A) = P(A|B)P(B) + P(A|B^{c})P(B^{c})$



Bayes Rule

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

Very often, people confuse P(A|B) and P(B|A). These can be VERY different.

Think about it:

You read in the paper: "Half of the people hospitalized with covid-19 are fully vaccinated". Do you think that getting the vaccine lowers your chances of getting hospitalized?

Example

A box contains two coins: a regular coin and one fake two-headed coin (P(H) = 1). I choose a coin at random and toss it twice. Define the following events.

•A = First coin toss results in an H. •B = Second coin toss results in an H. •C= Coin 1 (regular) has been selected. Find $P(A|C), P(B|C), P(A \cap B|C), P(A), P(B), and P(A \cap B)$

Are A and B independent? Are A and B independent given C?

Bayes Rule

- Vacc: True if vaccinated, false otherwise
- Hosp: True if hospitalized, false otherwise.
- P(Hosp|Vacc) = 0.01
- $P(Hosp|Vacc^{c}) = 0.2$
- Consider these different possibilities: P(Vacc) = 0.5, 0.99

Let's use Bayes rule to compute *P*(*Vacc*|*Hosp*) for both cases.

Definition

Two events A and B are independent given an event C if

$$P(A \cap B|C) = P(A|C)P(B|C).$$

We denote this as

$A \perp B | C$

Random Variables

Suppose we are interested in a distribution over the <u>sum of dice</u>...

Option 1 Let E_i be event that the sum equals *i*

Two dice example:



 $E_2 = \{(1,1)\}$ $E_3 = \{(1,2), (2,1)\}$ $E_4 = \{(1,3), (2,2), (3,1)\}$

 $E_5 = \{(1,4), (2,3), (3,2), (4,1)\}$ $E_6 = \{(1,5), (2,4), (3,3), (4,2), (5,1)\}$

Enumerate all possible means of obtaining desired sum. Gets cumbersome for N>2 dice...

Random Variables

Suppose we are interested in a distribution over the <u>sum of dice</u>...

Option 2 Use a function of sample space...

Definition A random variable $X(\omega)$ for $\omega \in \Omega$ is a <u>real-valued function</u> $X : \Omega \to \mathbb{R}$. A discrete random variable takes on only a finite or countably infinite number of values.

For *discrete* RVs X = x is an **event** with **probability mass function**:

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

Random Variables

Some notes on random variables (RVs)...

- \succ We denote the RV by capital X and its realization by lowercase x
- > Generally use shorthand X instead of $X(\omega)$
- > Other common shorthand: p(x) = p(X = x)
- > Any function f(X) of an RV is also an RV, e.g. $Y(\omega) = f(X(\omega))$
- > More shorthand: the joint distribution of RVs $p(X, Y) = p(X \cap Y)$
- ➢We will use "distribution" loosely to refer to distributions, PMFs, probability density and cumulative distribution functions (defined later)