Computer Science

# CSC380: Principles of Data Science

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Acknowledgement: Built on Jason Pacheco, Kwang-Sung Jun, Chicheng Zhang's slides

1

## Review

2

- What is probability?
- Axioms
- Event = set ⇒ use set theory!
- Set theory + axiom 3 is quite useful
- Draw diagrams
- Lots of jargons

- Make your own cheatsheet.

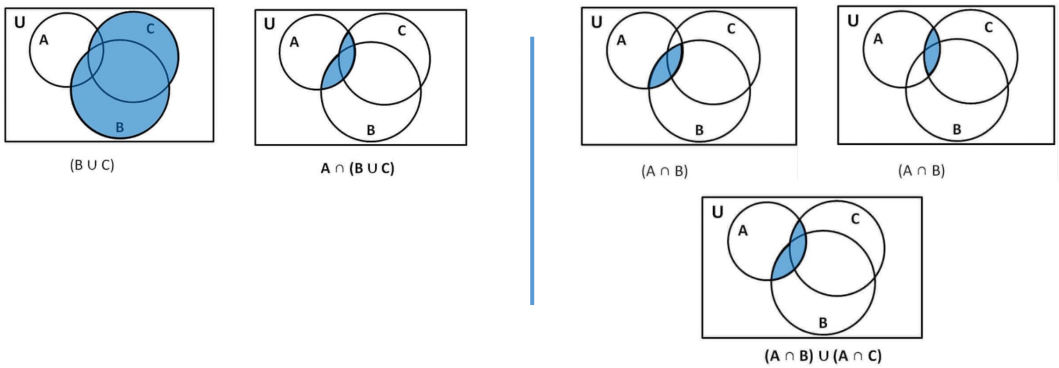
2

# Review

3

- $A \cap (B \cup C) = (A \cap \mathrm{B}) \cup (A \cap \mathrm{C})$

distributive law by Venn diagram

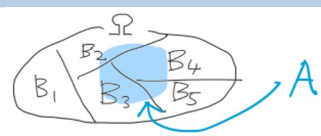



3

# Review

4

- $A \cap (B \cup C) = (A \cap \mathrm{B}) \cup (A \cap \mathrm{C})$
- $A = A \cap \Omega = A \cap (\cup_i B_i) = \cup_i (A \cap B_i)$
  $= \mathrm{A} \cap (B_1 \cup B_2 \cup B_3 \ldots \cup B_n)$
  $= (\mathrm{A} \cap B_1) \cup (\mathrm{A} \cap B_2) \cup (\mathrm{A} \cap B_3) \ldots \cup (\mathrm{A} \cap B_n)$




**Law of total probability**: Let $A$ be an event. For any events $\mathrm{B}_1, \mathrm{B}_2, \ldots$ that partitions $\Omega$, we have

$$P(A) = \sum_i P(A \cap B_i)$$

4

# Review

5

$$P(A) = \sum_i P(A \cap B_i)$$

$A$: the customer (100)
$B$: fill gas

- $B_1$: unleaded (30)
- $B_2$: mid grade (30)
- $B_3$: premium (40)



$\mathrm{P(A = student)}$
$= \mathrm{P(A = student, B = B_1) + P(A = student, B = B_2) + P(A = student, B = B_3)}$
$= \mathrm{P(A = student|B = B_1)P(B = B_1) + P(A = student|B = B_2)P(B = B_2) +}$
$\mathrm{P(A = student|B = B_3)}P\mathrm{(B = B_3)}$

5

# Overview

6

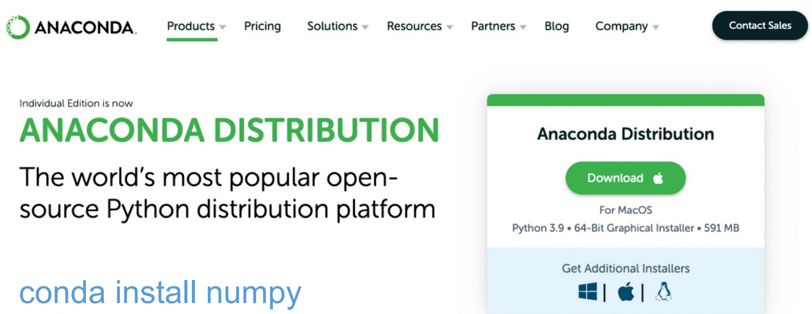
- Numpy package
- Conditional probability
- Independence

6

# Numpy Library

7

*Package containing many useful numerical functions…*




conda install numpy

If you use pip:
pip install numpy

*…we are interested in numpy.random at the moment*

7

# numpy.random

8

**numpy.random.randint**

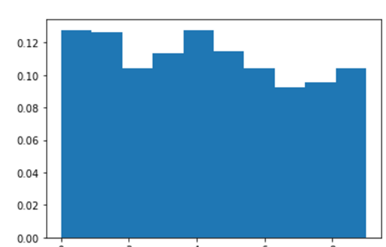
**numpy.random.randint**(*low, high=None, size=None, dtype='l'*)

Return random integers from *low* (inclusive) to *high* (exclusive).

Return random integers from the "discrete uniform" distribution of the specified dtype in the "half-open" interval [*low, high*). If *high* is None (the default), then results are from [0, *low*).

Sample a discrete uniform random variable,

```
import matplotlib.pyplot as plt
X = np.random.randint(0,10,1000)
count, bins, ignored = plt.hist(X, 10, density=True)
plt.show()
```




- **Caution** Interval is [low,high) and upper bound is **exclusive**
- `Size` argument accepts tuples for sampling ndarrays (multidimentional arrays)

8

# numpy.random

9

*Allows sampling from many common distributions*

Set (global) random seed as,

```
import numpy as np

seed = 12345
np.random.seed(seed)
```

- ☺ easier to debug (otherwise, you may have ‘stochastic’ bug)
- ☹ can be risky

E.g., buy into the result based on a particular seed, publish a report. … turns out, you get a widely different result if you use a different seed!

Recommendation: change the seed every now and then

9

# Conditional Probability

10

10

# Conditional Probability

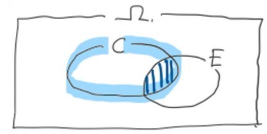
11

- Two fair dice example:
  - Suppose I roll two dice secretly and tell you that one of the dice is 2. C
  - **In this situation**, find the probability of two dice summing to 6. E

```
import numpy as np
for n in [10,100,1000,10_000,100_000, 1_000_000]:
    res_dice1 = np.random.randint(6,size=n) + 1
    res_dice2 = np.random.randint(6,size=n) + 1
    res = [(res_dice1[i], res_dice2[i]) for i in range(len(res_dice1))]

    conditioned = list(filter(lambda x: x[0] == 2 or x[1] == 2, res))
    n_eff = len(conditioned)

    cnt = len(list(filter(lambda x: x[0] + x[1] == 6, conditioned)))
    print("n=%9d, n_eff=%9d, result: %.4f " % (n, n_eff, cnt/n_eff))
```




compare:
without conditioning,
it was 0.138.

```
n=      10, n_eff=       4, result: 0.0000
n=     100, n_eff=      32, result: 0.2500
n=    1000, n_eff=     300, result: 0.1733
n=   10000, n_eff=    3002, result: 0.1742
n=  100000, n_eff=   30590, result: 0.1823
n= 1000000, n_eff=  305616, result: 0.1818
```

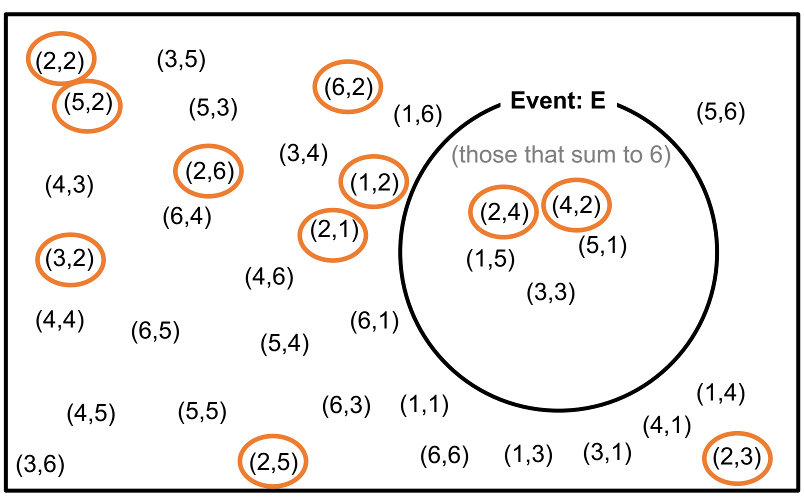
```
n=      10, n_eff=       3, result: 0.3333
n=     100, n_eff=      32, result: 0.0625
n=    1000, n_eff=     343, result: 0.2245
n=   10000, n_eff=    3062, result: 0.1897
n=  100000, n_eff=   30651, result: 0.1811
n= 1000000, n_eff=  305580, result: 0.1808
```

11

# Random Events and Probability

12

*What is the probability of having two numbers sum to 6 given one of dice is 2?*




Each outcome is equally likely.
by the **independence**
(will learn this concept later)
=> 1/36

\# sum to 6:
=> 5

\# one of dice is 2:
=> 11

\# sum to 6 and one of dice is 2:
=> 2

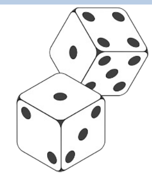
answer:
2/11 = 0.181818….

12

## Conditional Probability



Two fair dice example

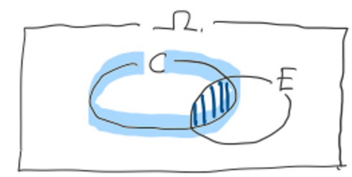


- Find the probability of one of the dice is 2 (event $C$) and two dice summing to 6 ( $E$ )

$$P(E \cap C)$$

- I secretly tell you one of the dice is 2, find the probability of two dice summing to 6.

$$\frac{P(E \cap C)}{P(C)}$$





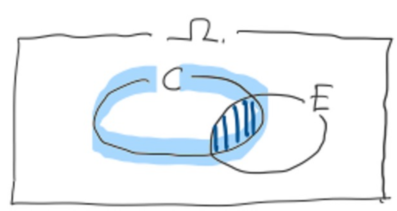

## Conditional Probability



- Two fair dice example:
  - Suppose I roll two dice and secretly tell you that one of the dice is 2. $C$
  - **<u>In this situation</u>**, find the probability of two dice summing to 6. $E$
- Turns out, such a probability can be computed by $\frac{P(E \cap C)}{P(C)}$
- It's like "zooming in" to the condition.
- This happens a lot in practice, so let's give it a notation:

$$P(E|C) := \frac{P(E \cap C)}{P(C)}$$

Say: probability of "$E$ given $C$", "$E$ conditioned on $C$"




"it's the ratio"

## Conditional Probability

15

Q: Conditional probability P(A|B) could be undefined. When?

- A: The denominator can be 0 already. In this case, numerator is also 0!

Note $P(A|B) \neq P(B|A)$ in general!

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

E.g., throw a fair die. X := outcome. A = {X=4}, B = {X is even}
**Question**: P(A | B) = P(B | A) ?

- $\mathrm{P(A)} = 1/6$
- $\mathrm{P(B)} = 1/2$
- $\mathrm{P\,(A \cap B)} = 1/6$
- Therefore, $\mathrm{P(A|B)} = 1/3$, $\mathrm{P(B|A)} = 1$

15

## Conditional Probability

16

**Chain rule**

- $P(A \cap B) = P(A|B)P(B)$ ←just a rearrangement of definition: $P(A|B) \coloneqq \frac{P(A \cap B)}{P(B)}$

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

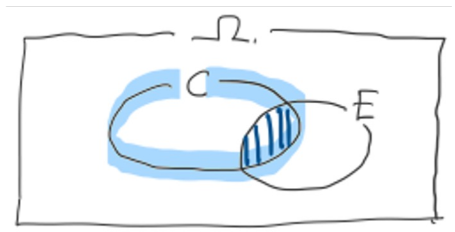
- $P(E_1 \cap E_2 \cap \cdots \cap E_n) = P(E_1) \prod_{i=2}^{n} P(E_i | \cap_{j=1}^{i-1} E_j)$ valid for any ordering!

16

## Conditional Probability

17

- $P(E \cap C) = P(E|C)P(C) = P(C|E)P(E)$




"it's the ratio"

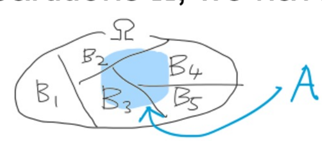
17

## Conditional Probability

18

Recall: let $A$ be an event. For events $\mathrm{B}_1, \mathrm{B}_2, \ldots$ that partitions $\Omega$, we have

$$P(A) = \sum_i P(A \cap B_i)$$




$A = A \cap \Omega = A \cap (\cup_i B_i) = \cup_i (A \cap B_i)$

Check axiom 3 & distributive law!

$P(E \cap C)$
$= P(E|C)P(C)$
$= P(C|E)P(E)$

**<u>Law of total probability</u>**: If $A \in \mathcal{F}$ and $\{B_i \in \mathcal{F}\}_i$ partitions $\Omega$, then

$$P(A) = \sum_i P(A, B_i) = \sum_i P(B_i)P(A|B_i)$$

$$= \sum_i P(A)P(B_i|A)$$

(by definition)

Shortcut:
P(A,B) := P(A ∩ B)

18

# Review

19

- $P(A) = \sum_i P(A, B_i) = \sum_i P(B_i)P(A|B_i)$

  $\mathrm{P(A = student)}$
  $= \mathrm{P(A = student|B = B_1)P(B = B_1) + P(A = student|B = B_2)P(B = B_2) + P(A = student|B = B_3)}P(\mathrm{B = B_3})$

  $\mathrm{P(A = student)}$
  $= 10/30 \times 30/100 + 15/30 \times 30/100 + 5/40 \times 40/100$

- $\sum_i P(B_i|A) = 1$

  $\mathrm{P(B_1|A = student) + P(B_2|A = student) + P(B_3|A = student)}$
  $= \frac{10}{10+15+5} + \frac{15}{10+15+5} + \frac{5}{10+15+5} = 1$


30, 10 | 30, 15 | 40, 5

19

# Conditional Probability

20

The Public Health Department gives us the following information:

- A test for the disease yields a positive result (+) 90% of the time when the disease is present (Y)

  P(+ | Y) = 0.9

- A test for the disease yields a positive result 1% of the time when the disease is not present (N)

  P(+ | N) = 0.01

- One person in 1,000 has the disease.

  P(Y) = 0.001

**Q**: What is the probability that a person with positive test has the disease? P(Y | +)?

Pick a person uniformly at random from the population. Apply the test. When test=+, what is the probability of this person having the disease (Y) ?

20

## Conditional Probability

21

What we know:

Positive result — Patient positive

P(+ | Y) = 0.9 ⇒ P(- | Y) = 0.1

P(+ | N) = 0.01 ⇒ P(- | N) = 0.99

P(Y) = 0.001 ⇒ P(N) = 0.999

Question: P(Y | +)

$$= \frac{P(Y,+)}{P(+)}$$

$$P(+) = P(+,Y) + P(+,N)$$

$$P(+,Y) = P(+|\,Y)P(Y)$$

$$P(+,N) = P(+|\,N)P(N)$$

Law of total probability

$$P(A) = \sum_i P(A,B_i) = \sum_i P(B_i)P(A|B_i)$$

The answer is 0.0826…

21

## Terminology

22

When we have two events A and B…

- Conditional probability: $P(A|B), P(A^c|B), P(B|A)$ etc.
- Joint probability: $P(A,B)$ or $P(A^c,B)$ or …
- Marginal probability: $P(A)$ or $P(A^c)$

22

# Conditional Probability

23

Tip: Make a table of **joint probabilities**

P(+ | Y) = 0.9
P(+ | N) = 0.01
P(Y) = 0.001

Each cell is P(column event ∩ row event) = P(T=t ∩ D=d) = P(T= t | D= d) P(D=d)

| | Test = + | Test = - | |
|---|---|---|---|
| Disease=Y | | | 0.001 |
| Disease=N | | | 0.999 |
| | 0.01089 | 0.98911 | |

$P(test = +)$

Workflow:

- make a table, then fill in the cells.
- write down the target P(A|B) all in terms of joint probabilities and marginal probabilities.

23

# Conditional Probability

24

We can directly calculate:

$$P(Y|+) = \frac{P(Y,+)}{P(+)} = \frac{P(+|Y)P(Y)}{P(+)}$$

**Bayes rule**

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

proof: definition and definition!

⟹ particularly useful in practice: infer P(A|B) given P(B|A)!

P(A): **prior** probability e.g., A='dice sum to 6', B='one of the die is 2'
P(A|B): **posterior** probability e.g., A='disease=Y', B='test=+'

24