

# ETC5242 Class 2 Probability & MLE

授课老师: Joe



- Week 6
  - Probability
  - Maximum likelihood estimate (MLE)
  - Bootstrapping for model parameters



There are three fundamental rules of probability.

- If Pr(A) is the probability associated with event A, then  $0 \le Pr(A) \le 1$
- The total probability of all outcomes in the sample space is 1
- If  $A_1, A_2, ...$  is a sequence of **mutually exclusive** events, then

$$\Pr(A_1 \cup A_2 \cup \ldots) = \Pr(A_1) + \Pr(A_2) + \ldots$$

Mutually exclusive events are sometimes referred to as disjoint events.

These are events that cannot happen simultaneously (their intersection is empty)

- From the third axiom, if events  $A_1$  and  $A_2$  are **mutually exclusive**
- Then  $Pr(A_1 \text{ or } A_2) = Pr(A_1) + Pr(A_2)$

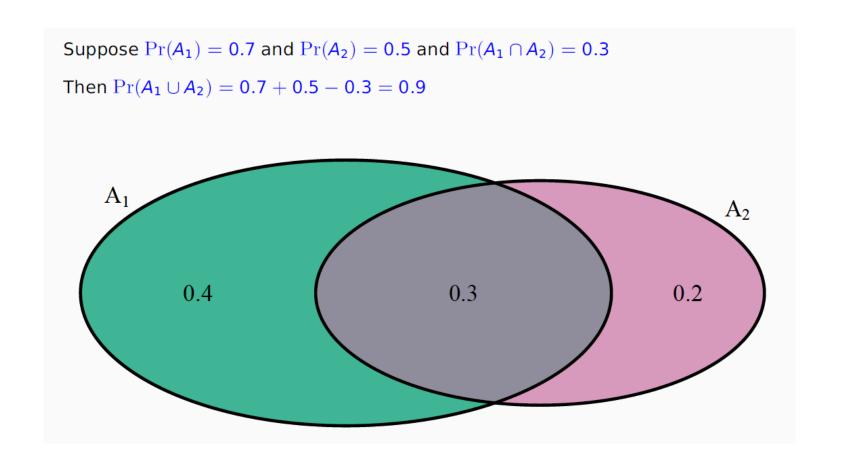
#### Non-disjoint events

- Outcomes that overlap are called non-disjoint events
  - We need a more general rule for working out their probabilities

#### **Example: Consider events** (X > 2) and (X < 4)

- These are NOT disjoint!
- No "double counting" of probability allowed!!
- Need to take out the "double counted" (overlap) part:

$$\Pr(X > 2 \cup X < 4) = \Pr(X > 2) + \Pr(X < 4) - \Pr(X > 2 \cap X < 4)$$



#### Example

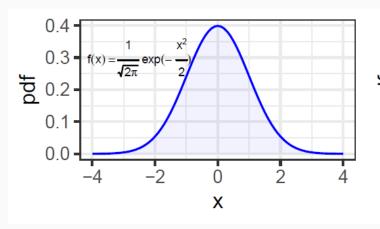
X = x	$\Pr(X = x)$
X = 1	1/2
X = 2	1/8
<i>X</i> = 3	1/4
X = 4	1/8

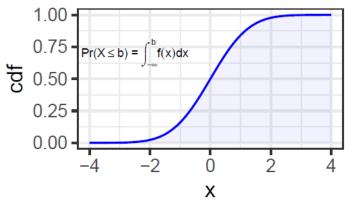
Find probabilities for given events:

- 1 Pr(X = 2)
- $\Pr(X \leq 2)$
- $\Pr(X \text{ is even})$
- 4  $\Pr(X < 4)$
- 5  $Pr(X > 2 \text{ and } X < 3) = Pr(X > 2 \cap X < 3)$
- 6  $Pr(X > 2 \text{ or } X < 3) = Pr(X > 2 \cup X < 3)$

#### **Example: Continuous random variable over an infinite sample space**

If  $X \sim N(0,1)$ 





#### Find

- $\mathbf{1} \quad \Pr(X = \mathbf{1})$
- 2 Pr(X < 1)
- $\Pr(X \text{ is even})$
- 4  $\Pr(X < -\frac{1}{2})$
- 5  $Pr(X > 2 \text{ and } X < 3) = Pr(X > 2 \cap X < 3)$
- 6  $\Pr(X > 2 \text{ or } X < 3) = \Pr(X > 2 \cup X < 3)$

**Two** processes are **independent** if knowing the outcome of one provides no useful information about the outcome of the other

#### **Multiplication Rule for independent processes**

- If A and B are simple events from two **different** and **independent** processes
  - two compound processes but "simple" relationship between them due to assumed independence
- Then the event that **both** A and B occur corresponds to an **intersection** 
  - the joint probability can calculated as the product of the individual probabilities:

$$Pr(A \text{ and } B) = Pr(A) \times Pr(B)$$

- Similarly, if there are k simple events  $A_1, A_2, ..., A_k$  from k independent processes
  - Then the probability that all events will occur is given by

$$\Pr(A_1) \times \Pr(A_2) \times \cdots \times \Pr(A_k)$$

#### **Example: Two independent coin tosses**

For i = 1 and i = 2

$$X_i = x$$
  $\Pr(X_i = x)$ 
 $X$  Head 0.5
 $Tail$  0.5

- If two fair coin tosses are **independent**, then any **joint probability** about **each outcome** will be the **product of the two marginal probabilities** about each outcome.
- What is the probability of a "Head" on the **first** toss and a "Tail" on the **second** toss?

$$\Pr(X_1 = \text{Head and } X_2 = \text{Tail})$$

$$= \Pr(X_1 = \text{Head}) \times \Pr(X_2 = \text{Tail})$$

$$= (0.5) \times (0.5)$$

$$= 0.25$$

#### **Example: Left-handedness**

- About 9% of people in the population are left-handed
- Suppose 2 people are selected at random from the Australian population
  - (Assume population is so large that the outcomes for the two selected are independent)
- What is the probability that both people selected are left-handed? (0.09)(0.09) = 0.0081
- 8 What is the probability that both people selected are right-handed?
- $(1 0.09)(1 0.09) = (0.91)^2 = 0.8281$
- What is the probability that one person selected is left-handed, and the other is right-handed?
- Note probabilities of all events must sum to one
- 1 (0.0081 + 0.8281) = 0.1638



#### Example: Travel survey data

- Random sample survey of 100 people with particular credit card
- Are you planning to travel abroad next year?
- Take these as proportional to "true probabilities"

			Age group		
		25 or less	26-40	41 or more	Total
Response	Yes	2	12	15	29
	Undecided	5	10	16	31
	No	10	15	15	40
	Total	17	37	46	100

- $\Pr(\mathsf{Card} \; \mathsf{holder} \; \mathsf{intends} \; \mathsf{to} \; \mathsf{travel} \; \mathsf{over} \; \mathsf{next} \; \mathsf{12} \; \mathsf{months})?$
- $\Pr(\text{Card holder intends to travel over next 12 months OR is undecided})?$
- $\Pr(\text{Card holder intends to travel over next 12 months AND is 25 years old or less})?$



- Joint probability
  - probability of outcomes for two or more variables or processes
- Marginal probability
  - probability of outcomes for a single variable or process
- Conditional probability
  - probability of outcomes for a single variable or process given information about a second variable or process



#### **Example: Travel survey data (revisited)**

Probability for all possible pairs

Age group AND Response combination	Prob
Yes response AND (25 or less)	0.02
Yes response AND (26-40)	0.12
Yes response AND (41 or more)	0.15
Undecided response AND (25 or less)	0.05
Undecided response AND (26-40)	0.10
Undecided response AND (41 or more)	0.16
No response AND (25 or less)	0.10
No response AND (26-40)	0.15
No response AND (41 or more)	0.15
	1.0



The conditional probability for a single **outcome of interest** *A*, given **conditioned on an event** *B*, is defined as

$$\Pr(A \mid B) = \frac{\Pr(A \text{ and } B)}{\Pr(B)}$$

#### **General Multiplication Rule**

■ If A and B represent two outcomes or events, then

$$Pr(A \text{ and } B) = Pr(A \mid B) \times Pr(B)$$

- Here *A* is the outcome of interest, and *B* is the event being conditioned upon
- Alternatively,

$$Pr(A \text{ and } B) = Pr(B \mid A) \times Pr(A)$$

#### Expected value & variance of discrete random variable

■ If X takes outcomes  $x_1, \ldots, x_k$  with probabilities  $\Pr(X = x_1), \ldots, \Pr(X = x_k)$ , respectively, then the **expected value** of X is

$$E[X] = x_1 \Pr(X = x_1) + \dots + x_k \Pr(X = x_k) = \sum_{i=1}^k x_i \Pr(X = x_i)$$

$$Var(X) = (x_1 - \mu)^2 \Pr(X = x_1) + \dots + (x_k - \mu)^2 \Pr(X = x_k) = \sum_{i=1}^k (x_i - \mu)^2 \Pr(X = x_i)$$

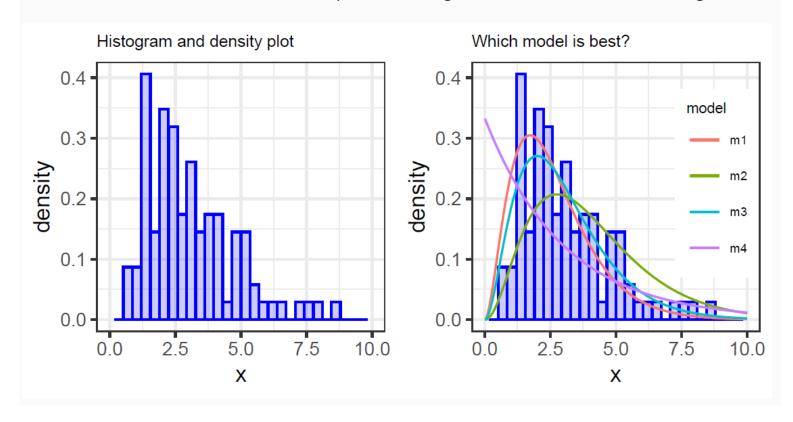
Expected value and variance of continuous random variable

$$E[X] = \mu = \int_{-\infty}^{\infty} x \, f(x) dx$$

$$Var(X) = E[(x - \mu)^{2}] = \int_{-\infty}^{\infty} (x - \mu)^{2} f(x) dx$$



- Which distributions might fit this data?
  - ► A normal distribution? An exponential? A gamma distribution? Something else?





- Assuming the data are a random sample, we need to **choose a model**  $F_X(x \mid \theta)$ 
  - We fit models using the sample and well-established distributional families
- $\blacksquare$  Once we choose a model, we'll need to **estimate** the parameter  $\theta$ 
  - use the maximum likelihood estimation (MLE) method
- A fitted model will imply an estimate of the population mean
  - and other features

#### **Likelihood Function**

If  $x_1, x_2, ..., x_n \overset{i.i.d.}{\sim} F_X(x \mid \theta)$ , then the likelihood function is

$$\mathcal{L}_n(\theta) = \prod_{i=1}^n f_X(x_i \mid \theta)$$

And the **MLE** for  $\theta$  is

$$\hat{\theta}_{MLE} = \arg \max_{\theta \in \Theta} \mathcal{L}_n(\theta)$$

#### **Gaussian density function (normal distribution)**

$$P(x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

Likelihood(Probability) of observing the three data points, 9, 9.5 and 11 given a particular gaussian density function, But we don't know the two parameters yet

We want to maximise this joint probability

$$\begin{split} P(9,9.5,11;\mu,\sigma) &= \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(9-\mu)^2}{2\sigma^2}\right) \times \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(9.5-\mu)^2}{2\sigma^2}\right) \\ &\quad \times \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(11-\mu)^2}{2\sigma^2}\right) \end{split}$$

#### **Optimising the likelihood function**

It is often easier to maximise the log-likelihood function

$$\ell_n(\theta) = \ln \mathcal{L}_n(\theta) = \left[\sum_{i=1}^n \ln f_X(x_i|\theta)\right]$$

- The **same**  $\hat{\theta}_{MLE}$  maximises  $\mathcal{L}_n(\theta)$  and  $\ell_n(\theta)$
- In simple cases we can solve for  $\hat{\theta}_{MLE}$  through differentiation
  - set first derivative of  $\ell_n(\theta)$  equal to zero and solve
  - then check the second derivative of  $\ell_n(\theta)$  is negative at  $\hat{\theta}_{MLE}$
- More generally MLE is found using numerical optimisation on a computer



### Very handy in R

```
fit <- fitdistr(x, "gamma")
fit

    shape    rate
    3.4697    1.1235
    (0.4690) (0.1634)</pre>
```

#### Bootstrapping for confidence interval of model parameters

- Generate a Bootstrap sample of B potential  $\hat{ heta}$  values
  - For each b in 1 : B
    - resample *n* draws from the observed data values, with replacement
    - label these values as  $\{x_1^{[b]}, x_2^{[b]}, \dots, x_n^{[b]}\}$
    - compute the MLE  $\hat{\theta}^{[b]}$  by maximising  $\mathcal{L}_n^{[b]}(\theta)$ , constructed from the bootstrap sample
  - Bootstrap sample:  $\{\hat{\theta}^{[1]}, \hat{\theta}^{[2]}, \dots, \hat{\theta}^{[B]}\}$
- Use the empirical distribution from this Bootstrap sample to approximate the sampling distribution of  $\hat{\theta}_{\textit{MLE}}$
- Construct an approximate 95% confidence interval by selecting interval from 2. with (empirical) probability (at least) 95%
- (lower) 2.5% quantile to 97.5% quantile