# EECS 126: Probability & Random Processes Fall 2021

Elementary Probability
Shyam Parekh

# Course Organization

https://inst.eecs.berkeley.edu/~ee126/fa21/

#### Definition

Fig. A.1



- Probability = # of favorable outcomes/# of possible outcomes
- Experiment outcome and random variables
- Probability is additive:  $P(A_1 \cup A_2) = P(A_1) + P(A_2) P(A_1 \cap A_2)$

#### **Conditional Probability**





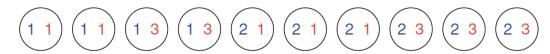
- $P[C|D] = P(C \cap D)/P(D)$
- Maximum A Posteriori (MAP) estimate of B given  $\{R = r\} = \underset{b}{argmax} P[B = b | R = r]$ 
  - Which value of B most likely given R = r?
- Maximum Likelihood Estimate (MLE) of B given  $\{R = r\} = \underset{b}{argmax} P[R = r|B = b]$ 
  - Which value B makes R = r most likely?
- MAP vs MLE for Ebola vs Flu

# **Examples of Common Confusion**

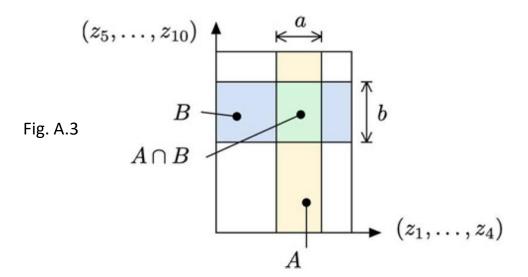
- Definition of the experiment and its outcomes
  - Bill has two children and one of them is named Isabelle. What's the probability Bill has two daughters?
  - Bill has two children and the younger one is named Isabelle. What's probability Bill has two daughters?
- Regression to the mean

#### Independence

Fig. A.2

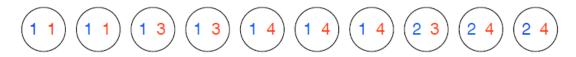


- B and R are independent: For  $\forall r, b, \ P[B=b|R=r] = P(B=b)$ , or P[R=r|B=b] = P(R=r), or P(B=b,R=r) = P(B=b)P(R=r)
- 10 flips of a fair coin: X = # of heads in first 4 flips, Y = # of heads in the last 6 flips. Show X and Y are independent.



#### Expectation

Fig. A.1



- E(B), E(R)
- $E(X) = \sum_{m=1}^{M} x_m P(X = x_m) = \sum_{m=1}^{M} x_m p_m$
- E(a) = a
- $E(X) = \sum_{n=1}^{N} X(n) \frac{1}{N} = \sum_{m=1}^{M} (p_m N) x_m \frac{1}{N}$
- Expectation is linear:

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$$E(X + Y) = E(X) + E(Y), E(5 + 3X^2 + 5Y^3) = 5 + 3E(X^2) + 5E(Y^3)$$

- Expectation is monotone:  $X \le Y \Rightarrow E(X) \le E(Y)$ .
- X and Y are independent  $\Rightarrow$  E(XY) = E(X)E(Y).

- 
$$E(XY) = \sum_i \sum_j x_i y_j P(X = x_i, Y = y_j) = (\sum_i x_i P(X = x_i))(\sum_j y_j P(Y = y_j))$$

- In the example,  $E(BR) \neq E(B)E(R)$  → B and R are not independent.
- $E(XY) = E(X)E(Y) \Rightarrow X$  and Y are independent.

#### Variance

- $var(X) = E((X E(X))^2)$
- $var(X) \ge 0$
- $var(X) = E(X^2) [E(X)]^2$
- For a constant a,  $var(aX) = a^2 var(X)$
- X and Y are independent  $\Rightarrow var(X + Y) = var(X) + var(Y)$
- Standard Deviation = Square Root of Variance
  - $\sqrt{var(X)} = \sigma_X$

# Inequalities

- Markov's Inequality: RV  $X \ge 0$ . Then,  $P(X \ge a) \le \frac{E(X)}{a}$ , a > 0.
- Chebyshev's Inequality:  $P(|X E(X)| \ge \epsilon) \le \frac{var(X)}{\epsilon^2}$ ,  $\epsilon > 0$ .

# Weak Law of Large Numbers

• Assume  $X_1, X_2, X_3, \dots$  are independent RVs with the same expected value  $\mu$  and the same variance  $\sigma^2$ , and define  $Y = (X_1 + X_2 + \dots + X_n)/n$ .

- 
$$P(|Y - \mu| \ge \epsilon) \le \frac{\sigma^2}{n\epsilon^2} \to 0 \text{ as } n \to \infty$$

#### Covariance and Linear Regression

- cov(X,Y) = E(XY) E(X)E(Y) = E((X E(X))(Y E(Y)))
- X and Y are independent  $\Rightarrow cov(X, Y) = 0$ .
  - X and Y are uncorrelated RVs if cov(X, Y) = 0.
  - X and Y are uncorrelated RVs ⇒ X and Y are independent RVs.
- Observe X and want to estimate Y by  $\hat{Y}$ .
  - Restrict  $\hat{Y}$  to linear functions of X such that  $E((Y \hat{Y})^2)$  is minimized.
  - Linear Least Squares Estimate (LLSE):  $\hat{Y} = E(Y) + \frac{cov(X,Y)}{var(X)}(X E(X))$
  - Linear Regression of Y against X: Same as the LLSE assuming the observed (X, Y)
    pairs are from equally likely samples

# Need for a Sophisticated Framework

- Extend to RVs that can assume infinite or even uncountably many possible values.
- Classical Probability Theory due to Kolmogorov.
  - Relies on Axiom of Choice.
  - $A_1 \subset A_2 \subset A_3 \dots, A = \bigcup_n A_n \Rightarrow P(A) = \lim_n P(A_n).$
  - SLLN