

## Additivity rules:

For any events  $A, B$ :

$$\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) - \mathbb{P}(A \cap B)$$

## Conditional Probability

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

## Counting

$$\text{comb:} = \frac{n!}{(n-k)!} \quad \text{perm:} = \frac{n!}{k!(n-k)!} = \binom{n}{k}$$

$$\begin{aligned} \mathbb{P}(A \cap B | C) &= \mathbb{P}(A | C)\mathbb{P}(B | C) & \text{or} \\ \mathbb{P}(A | B \cap C) &= \mathbb{P}(A | C), \mathbb{P}(B \cap C) > 0 \end{aligned}$$

## Product Rule

- With events  $D_1$  to  $D_n$  where  $D_1 > D_2 > \dots > D_n$  ( $D_1$  largest,  $D_n$  smallest):

$$\mathbb{P}(D_n) = \mathbb{P}(D_1)\mathbb{P}(D_2 | D_1)\mathbb{P}(D_3 | D_2) \dots \mathbb{P}(D_n | D_{n-1}) \quad (\text{Product Rule 1})$$

- With events  $A_1$  to  $A_n$  with non-empty intersection, let  $D_k = A_1 \cap A_2 \cap \dots \cap A_k$ , then  $D_1 > D_2 > \dots > D_n$ :

$$\mathbb{P}(A_1 \cap \dots \cap A_n) = \mathbb{P}(A_1)\mathbb{P}(A_2 | A_1)\mathbb{P}(A_3 | A_1 \cap A_2) \dots \mathbb{P}(A_n | A_1 \cap \dots) \quad (\text{Product Rule 2})$$

## Total Probability Theorem in Bayes, & Independence

$$\mathbb{P}(A_k | B) = \frac{\mathbb{P}(B | A_k)\mathbb{P}(A_k)}{\mathbb{P}(B | A_1)\mathbb{P}(A_1) + \dots + \mathbb{P}(B | A_n)\mathbb{P}(A_n) \text{ or } \mathbb{P}(B)}$$

$$\begin{aligned} \mathbb{P}(A \cap B) &= \mathbb{P}(A)\mathbb{P}(B) & \text{or} \\ \mathbb{P}(A | B) &= \mathbb{P}(A), \mathbb{P}(B) > 0 \end{aligned}$$

## Covariance

$$\begin{aligned} \text{Cov}(X, Y) &= \mathbb{E}((X - \mathbb{E}(X))(Y - \mathbb{E}(Y))) \\ \rho &= \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \\ \text{Cov} = 0 &\Rightarrow \text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) \\ \text{indep} &\Rightarrow \text{Cov} = 0 \end{aligned}$$

## Pmfs

$$\begin{aligned} p_{X,Y}(x, y) &= \mathbb{P}(\{X = x\} \cap \{Y = y\}) \\ \mathbb{E}(Z) &= \sum_{x \in X} \sum_{y \in Y} g(x, y)p_{X,Y}(x, y) \\ p_{X|A}(x) &= \frac{\mathbb{P}(\{X = x\} \cap A)}{\mathbb{P}(A)} & p_{X|Y}(x | y) &= \frac{p_{X,Y}(x, y)}{p_Y(y)} \end{aligned}$$

## Discrete Random Variables

- Let  $p \in [0, 1]$ ; the **Bernoulli p pmf** be defined by:

$$p_X(k) = \begin{cases} p & \text{when } k = 1 \\ 1 - p & \text{when } k = 0 \end{cases}$$

$$\mathbb{E}(X) = p; \text{Var}(X) = p(1 - p)$$

$$p_X(k) = \binom{n}{k} p^k (1 - p)^{n-k} \quad 0 \leq k \leq n$$

- Poisson(X):

$$p_X(k) = e^{-\lambda} \frac{\lambda^k}{k!} \quad 0 \leq k \leq \infty (k \in \mathbb{N})$$

$$\mathbb{E}(X) = \lambda; \text{Var}(X) = \lambda$$

- Given positive integer  $n$ , some  $p \in [0, 1]$ , the **Binomial(n, p) pmf** is defined as:

## Expectation, Variance

$$\begin{aligned} \mathbb{E}(X) &= \sum_{x \in X} xp_X(x) \\ \mathbb{E}(Y) &= \sum_{x \in X} g(x)p_X(x) \\ \mathbb{E}(X | A) &= \int_{-\infty}^{\infty} xf_{X|A}(x)dx \\ \mathbb{E}(X | Y = y) &= \int_{-\infty}^{\infty} xf_{X|Y}(x | y)dx \forall y \\ \mathbb{E}(X) &= \mathbb{E}(\mathbb{E}(X | Y)) \end{aligned}$$

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}((X - \mathbb{E}(X))^2) \\ \text{Var}(X) &= \mathbb{E}(X^2) - (\mathbb{E}(X))^2 \\ \sigma_X &= \sqrt{\text{Var}(X)} \\ \text{Var}(X) &= \mathbb{E}(\text{Var}(X | Y)) + \text{Var}(\mathbb{E}(X | Y)) \\ \text{Var}(X) &= \mathbb{E}[(X - \mathbb{E}(X))^2] \\ \text{Var}(X) &= \int_{-\infty}^{\infty} (X - \mathbb{E})^2 f_X(x)dx \\ \text{Var}(X | Y) &= \mathbb{E}((X - \mathbb{E}(X | Y))^2 | Y) \end{aligned}$$

## Pdf, Cdf Def

$$\begin{aligned}\mathbb{P}(a \leq X \leq b) &= \int_a^b f_X(x) dx & F_X(x) &= \int_{-\infty}^x f_X(t) dt \text{ cont } \\ \mathbb{P}(\{X \in V\}) &= \int_V f_X(x) dx & f_X(x) &= \frac{d}{dx} F_X(x) \\ p_X(x_k) &= F_X(x_k) - F_X(x_{k-1}) & F_X(x) &= \mathbb{P}(\{X \leq x\}) \text{ discr } \\ & & F_X(x) &= \sum_{\{x_k | x_k \leq x\}} p_X(x_k)\end{aligned}$$

## Mean and Variance: Continuous

$$\begin{aligned}\mathbb{E}(X) &= \int_{-\infty}^{+\infty} x f_X(x) dx \\ \text{Var}(X) &= \mathbb{E}[(X - \mathbb{E}[X])^2]\end{aligned}$$

## Conditional Prob Def

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

## Types of continuous rvs

- **X uniform on [a,b]:**

$$\begin{aligned}f_X(x) &= \begin{cases} \frac{1}{b-a} & \text{when } x \in [a, b] \\ 0 & \text{else} \end{cases} \\ F_X(x) &= \begin{cases} 0 & \text{when } x < a \\ \frac{x-a}{b-a} & \text{when } a \leq x \leq b \\ 1 & \text{when } x > b \end{cases} \\ \mathbb{E}[X] &= \frac{b+a}{2} & \text{Var}(X) &= \frac{(b-a)^2}{12}\end{aligned}$$

- **standard normal:**

$$\begin{aligned}f_X(x) &= \frac{1}{\sqrt{2\pi}} e^{-x^2/2} & \therefore \mathbb{E}(X) &= 0, \text{ Var} = 1 \\ \Phi(x) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt \\ \mathbb{P}(\{X > x\}) &= \mathbb{P}(\{\sigma + Y + M > x\}) = \mathbb{P}\left(Y > \frac{x-M}{\sigma}\right)\end{aligned}$$

## Joint Pdf

$$\begin{aligned}\mathbb{P}(\{(X, Y) \in V\}) &= \iint_V f_{X,Y}(x, y) dx dy & f_X(x) &= \int_{-\infty}^{+\infty} f_{X,Y}(x, y) dy \\ \mathbb{E}[g(X, Y)] &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} g(X, Y) f_{X,Y}(x, y) dx dy & f_Y(y) &= \int_{-\infty}^{+\infty} f_{X,Y}(x, y) dx \\ F_{X,Y}(x, y) &= \mathbb{P}(X \leq x, Y \leq y) & f_{X,Y}(x, y) &= \frac{\delta F_{X,Y}}{\delta x \delta y}(x, y)\end{aligned}$$

## Independence: Continuous

- $f_{X,Y}(x, y) = f_X(x) f_Y(y) \quad \forall x, y$
- $\mathbb{E}(XY) = \mathbb{E}(X) \mathbb{E}(Y)$
- $\mathbb{E}(g(X)h(Y)) = \mathbb{E}(g(X)) \mathbb{E}(h(Y))$
- $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$

## Conditioning on Event

$$\begin{aligned}\mathbb{P}(\{X \in V\} | A) &= \int_V f_{X|A}(x) dx \\ f_{X|A}(x) &= \begin{cases} \frac{f_X(x)}{\mathbb{P}(\{X \in W\})} & \text{when } X \in W \\ 0 & \text{otherwise} \end{cases} \\ \mathbb{E}(X | A) &= \int_{-\infty}^{+\infty} x f_{X|A}(x) dx \\ \mathbb{E}(X | A) &= \sum_{x \in X} x p_{X|A}(x)\end{aligned}$$

## Conditioning on rv

$$\begin{aligned}f_{X|Y}(x | y) &= \frac{f_{X,Y}(x, y)}{f_Y(y)} \\ f_X(x) &= \int_{-\infty}^{+\infty} f_Y(y) f_{X|Y}(x | y) dy \\ \mathbb{E}[X | Y = y] &= \int_{-\infty}^{+\infty} x f_{X|Y}(x | y) dx\end{aligned}$$

## Ineqs, Moment Functions, Limit Theorems

$$\begin{aligned}\mathbb{P}(\{|X - \mu| \geq c\}) &\leq \frac{\text{Var}(X)}{c^2} & M_X(s) &= \mathbb{E}(e^{sX}) & S_n &= X_1 + \dots + X_n \text{ iid} & \mathbb{E}(S_n) &= n\mu & \text{Var}(S_n) &= n\sigma^2 \\ \mathbb{P}(\{X \geq c\}) &\leq \frac{\mathbb{E}(X)}{c} & M_{\alpha Y + \beta} &= e^{\beta s} M_Y(\alpha s) & M_n &= \frac{1}{n} S_n & \mathbb{E}(M_n) &= \mu & \text{Var}(M_n) &= \frac{2}{n} \\ & & & & Z_n &= \frac{X_1 + \dots + X_n - n\mu}{\sqrt{n}\sigma} & \mathbb{E}(Z_n) &= 0 & \text{Var}(Z_n) &= 1\end{aligned}$$