

## Sets and Bayes Rule

### Properties of Sets

$$P(A) = P(A|B)P(B) + P(A|\neg B)P(\neg B)$$

$$P(\neg A) = 1 - P(A)$$

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

$$\begin{aligned} P(A \cap B) &= P(A|B)P(B) \\ &= P(B|A)P(A) \end{aligned}$$

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

### Bayes Rule

$$\begin{aligned} P(A|B) &= \frac{P(B|A)P(A)}{P(B)} \\ &= \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|\neg A)P(\neg A)} \end{aligned}$$

## Measures of Spread

### Variance

$$\text{Var}(X) \equiv E[(X - E[X])^2]$$

- $\text{Var}(c) = 0$ , where  $c$  is a constant
- $\text{Var}(X) = E[X^2] - E[X]^2$
- $\text{Var}(aX) = a^2 \cdot \text{Var}(X)$ , where  $a$  is a constant
- $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$
- $\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y)$ , independent  $X, Y$

### Covariance

$$\text{Cov}(X, Y) \equiv E[(X - E[X])(Y - E[Y])]$$

- $\text{Cov}(X, X) = \text{Var}(X)$
- $\text{Cov}(X, c) = 0$ , where  $c$  is a constant
- $\text{Cov}(X, Y) = E[XY] - E[X]E[Y]$
- $\text{Cov}(X, Y) = 0$  for independent  $X, Y$
- $\text{Cov}(X, Y) = \text{Cov}(Y, X)$
- $\text{Cov}(aX, Y) = a \cdot \text{Cov}(X, Y)$
- $\text{Cov}(X, Y + Z) = \text{Cov}(X, Y) + \text{Cov}(X, Z)$

### Correlation

$$\text{Corr}(X, Y) \equiv \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$$

- $\text{Corr}(X, X) = 1$
- $\text{Corr}(X, Y) = \text{Corr}(Y, X)$
- $X, Y$  independent  $\implies \text{Corr}(X, Y) = 0$
- $-1 \leq \text{Corr}(X, Y) \leq 1$
- $\text{Corr}(aX, Y) = \text{sgn}(a) \text{Corr}(X, Y)$

## Joint, Marginal, Conditional

### Conditional Expectation

$$E[X|Y = y] = \sum_{\text{all } x} xP(X = x|Y = y)$$

$$E[X|Y = y] = \int_{\text{over } x} x f_{X|Y}(x, y) dx$$

$$f_Y(y) = \int_{\text{over } x} f(x, y) dx$$

- $E[E(Y|X)] = E[Y]$
- $E[X + Y|Z] = E[X|Z] + E[Y|Z]$
- $E[Y] = \sum_{\text{all } x} E[Y|X = x]P(X = x)$
- $E[g(X)Y|X] = g(X)E[Y|X]$
- $\text{Var}(X) = E[\text{Var}(X|Y)] + \text{Var}(E[X|Y])$

### Joint, Marginal, Conditional Probabilities

$$P(X = x, Y = y) = P(x, y)$$

$$P(X = x) = \sum_{\text{all } y} P(X = x, Y = y)$$

$$= \sum_{\text{all } y} P(X = x|Y = y)P(Y = y)$$

$$f(x, y) = \int_{\text{over } x} \int_{y(x)} f(x, y) dx dy = 1$$

$$f_X(x) = \int_{y(x)} f(x, y) dy$$

$$f_{X|Y}(x, y) = \frac{f(x, y)}{f_Y(y)}$$

## Moment Generating Functions

### Definitions and Properties

$$M_X(t) = E[e^{tX}] = \sum_{\text{all } x} e^{tx} p_X(x)$$

$$M_X(t) = E[e^{tX}] = \int_{\text{over } x} e^{tx} f_X(x) dx$$

$$M_{X+Y}(t) = M_X(t) \cdot M_Y(t)$$

$$\frac{d}{dt}[M_X(t)] = E[X], \quad \frac{d^2}{dt^2}[M_X(t)] = E[X^2]$$

### Common Distributions

$$\text{Binomial}(n, p) : (1 - p + pe^t)^n$$

$$\text{Geometric}(p) : \frac{pe^t}{1 - (1 - p)e^t} \text{ for } t < -\ln(1 - p)$$

$$\text{Poisson}(\lambda) : e^{\lambda(e^t - 1)}$$

$$\text{Gamma}(r, \lambda) : \left(1 - \frac{t}{\lambda}\right)^{-r}$$

$$\mathcal{N}(\mu, \sigma^2) : \exp\left(t\mu + \frac{1}{2}\sigma^2 t^2\right)$$