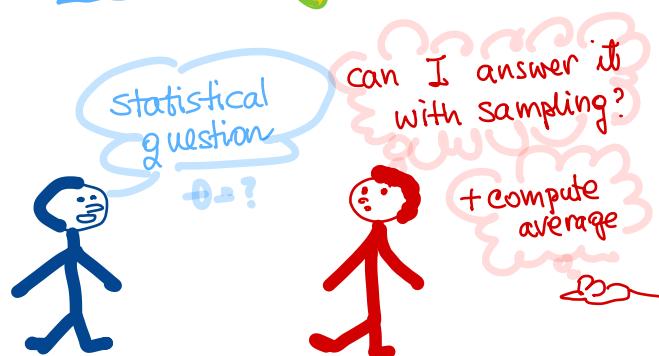


# Lecture 2

Resampling Inference =  
Embracing Randomness

- Web site
- HW ⚡  $\geq 50\%$
- Labs



# Lecture Notes 0 – Probability

Marina Meila  
[mmp@stat.washington.edu](mailto:mmp@stat.washington.edu)

Department of Statistics  
University of Washington

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Random Variables 

Expected Value 

Common Distributions 

Useful Theorems

Estimators and Estimation Theory

R.V. = distribution  $P$

$S$  = sample space

$x \in S$    
 discrete   
 continuous

$$S \subseteq (-\infty, \infty)$$

finite  $S = \{0, 1\}$  Bernoulli,  $S = \{1, 2, 3, \dots, n\}$  Categorical distribution  
countable  $S = \{0, 1, 2, \dots\}$

Ex: Geometric

$$P(x) \propto \lambda^x \quad \lambda \in (0, 1)$$

"proportional to"  $\uparrow$  parameter

$$P(x) = \frac{1}{Z_\lambda} \lambda^x$$

normalization constant

Ex: Poisson

$$P(x) = e^{-\lambda} \frac{\lambda^x}{x!}$$

$$= \frac{1}{e^\lambda} = \frac{1}{Z_\lambda}$$

• describe discrete  $P$

-  $P(x)$  for all  $x$  = PMF  
prob. Mass Function

• binomial  $(p, n)$  Family of distributions  
 $p \in (0, 1)$   $n \in \{0, 1, 2, \dots\}$

- CDF Cumulative Distrib. Function

$p, n$  fixed:  $S = \{0, 1, \dots, n\} \leftarrow$  finite for any  $n$

$X = \# \text{ successes in } n \text{ trials}$

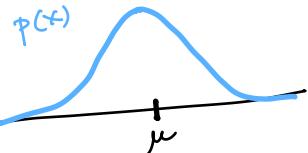
Continuous  $S$

$S = \text{interval} \subseteq (-\infty, \infty)$

Ex: Normal  $(\mu, \sigma^2)$  :  $S = (-\infty, \infty)$

Uniform  $(a, b)$  :  $S = [a, b]$

$$p(x) = \begin{cases} 0 & \text{if } x \notin [a, b] \\ \frac{1}{b-a} & \text{if } x \in [a, b] \end{cases}$$

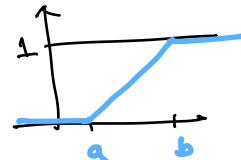
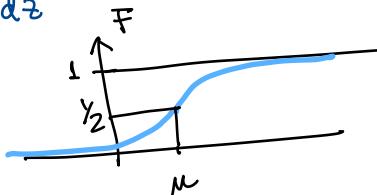


Describing  $P$  : PDF = density

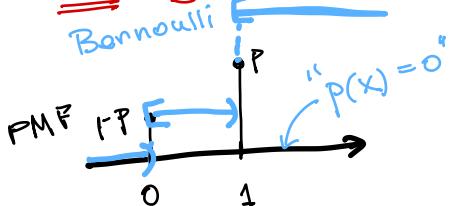
CDF

$$F(x) = P(-\infty, x] \equiv P[X \leq x]$$

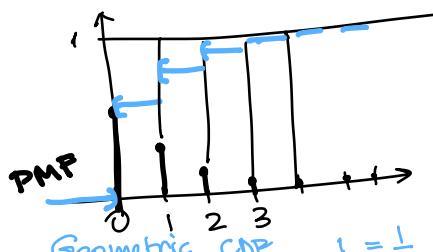
$$= \int_{-\infty}^x p(z) dz$$



- CDF Cumulative Distrib. Function



$$\text{CDF} : P[X \leq x]$$



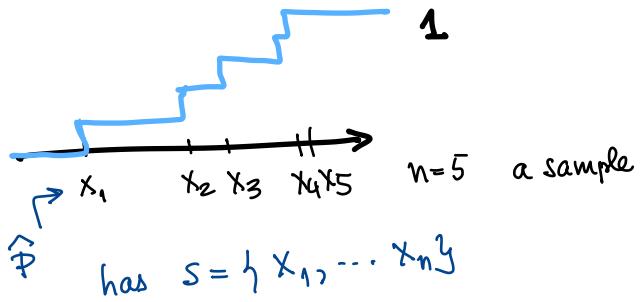
$$\text{Geometric CDF} \quad \lambda = \frac{1}{2}$$

$$F(x) = P[X \leq x]$$

$$\lambda^0 + \lambda^1 + \dots + \lambda^n + \dots = \frac{1}{1-\lambda}$$

$$P(X) = (1-\lambda)^X$$

$$\lambda = \frac{1}{2} \rightarrow = \frac{1}{2} \cdot \frac{1}{2^X}$$



**Multiple variables**  $x, y$   $P_{xy}$

$$\text{PDF (if \exists)} \quad P_{xy} = \frac{\partial^2 F(x,y)}{\partial x \partial y}$$

$$S = S_x \times S_y$$

$$\text{Data} = \{(x_1, y_1), \dots, (x_n, y_n)\}$$

$$\text{CDF} \quad F(x,y) = \underset{x,y}{P} [X \leq x, Y \leq y]$$

$$\text{Conditional density} \quad P_{y|x}(y|x) = \frac{P_{xy}(x,y)}{P_x(x)}$$

$$\text{Marginal density} \quad P_x(x) = \int_{-\infty}^{\infty} P_{xy}(x,y) dy$$

## Random Variables

$X \sim F$  or  $X \sim p$

For two random variables  $X, Y$ , their joint CDF is

$$P_{XY}(x, y) = F(x, y) = P(X \leq x, Y \leq y).$$

The corresponding joint PDF is

$$p(x, y) = \frac{\partial^2 F(x, y)}{\partial x \partial y}.$$

The *conditional PDF* of  $Y$  given  $X = x$  is

$$p(y|x) = \frac{p(x, y)}{p(x)},$$

where  $p(x) = \int_{-\infty}^{\infty} p(x, y) dy$

## Expected Value

$$\mathbb{E}(g(X)) = \int g(x)dF(x) = \begin{cases} \int_{-\infty}^{\infty} g(x)p(x)dx, & \text{if } X \text{ is continuous} \\ \sum_x g(x)p(x), & \text{if } X \text{ is discrete} \end{cases}.$$

- ▶  $\mathbb{E}(\sum_{j=1}^k c_j g_j(X)) = \sum_{j=1}^k c_j \cdot \mathbb{E}(g_j(X_i)).$
- ▶ Notation  $\mu = \mathbb{E}(X)$
- ▶  $\text{Var}(X) = \mathbb{E}((X - \mu)^2)$  is the variance of  $X$ .
- ▶ If  $X_1, \dots, X_n$  are independent, then

$$\mathbb{E}(X_1 \cdot X_2 \cdots X_n) = \mathbb{E}(X_1) \cdot \mathbb{E}(X_2) \cdots \mathbb{E}(X_n).$$

- ▶ If  $X_1, \dots, X_n$  are independent, then

$$\text{Var}\left(\sum_{i=1}^n a_i X_i\right) = \sum_{i=1}^n a_i^2 \cdot \text{Var}(X_i).$$

- ▶ Covariance

$$\text{Cov}(X, Y) = \mathbb{E}((X - \mu_x)(Y - \mu_y)) = \mathbb{E}(XY) - \mu_x \mu_y$$

- ▶ (Pearson's) correlation

$$\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_x \sigma_y}.$$

P distribution  $x \in S \subseteq (-\infty, \infty)$

$$E[X] = \mu_p = \begin{cases} \sum_{S \text{ discrete}} x P(x) \\ \int_{-\infty}^{\infty} x p(x) dx \end{cases}$$

S discrete

S continuous

### Properties

- $E[X]$  Linear

$$x, x' \in S$$

$$\Rightarrow E[z] = aE[x] + bE[x']$$

$$z = ax + bx'$$

NO MATTER  
If  $x, x'$   
dependent  
or NOT

$$P_{XY}(x,y) \\ CDF = P[X \leq x, Y \leq y] = \int_{-\infty}^x \int_{-\infty}^y p_{XY}(x,y) dx dy = F(x,y)$$