

# Machine Learning Foundations

## **Chapter 6: Probability**

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# Outline for Chapter 6 : Probability

**6.1 : Discrete Random Variables**

6.2 : Continuous Random Variables

6.3 : Maximum Likelihood and other advanced topics

# Outline for Chapter 6 : Probability

## **6.1 : Discrete Random Variables**

1. Probability space
2. Conditioning
3. Random variables
4. Expectation and Variance
5. Multiple Random Variables

## **6. Bernoulli, Binomial, Poisson and Geometric RVs**

## 6.2 : Continuous Random Variables

## 6.3 : Maximum Likelihood and other advanced topics

# Bernoulli distribution

$$f(1) = p$$

$$f(0) = 1-p$$

$$X \sim \text{Bernoulli}(p)$$

$$\begin{aligned} E[X] &= P(X=1) \\ &= p \end{aligned}$$

$$\begin{aligned} \text{Var}[X] &= EX^2 - (EX)^2 \\ &= p - p^2 \\ &= p(1-p) \end{aligned}$$

# Bernoulli distribution

# Binomial distribution

$$\text{Bin}(n, p)$$

$X_1, X_2, \dots, X_n$  are independent  
Bernoulli( $p$ ) RVs.

$$X = \sum_{i=1}^n X_i$$

$$X \sim \text{Bin}(n, p)$$

$$f_X(k) = P(X=k)$$

$$= \binom{n}{k} \cdot p^k (1-p)^{n-k}$$

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# Binomial distribution

$$\begin{aligned}\sum_{k=0}^n f(k) &= \sum_{k=0}^n \binom{n}{k} \cdot (p)^k (1-p)^{n-k} \\ &= (p + (1-p))^n \\ &= 1\end{aligned}$$

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$$\begin{aligned}EX &= ? \\ &= \sum_{i=1}^n EX_i = np\end{aligned}$$

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$$\begin{aligned}\text{Var}[X] &= \sum_{i=1}^n \text{Var}[X_i] = np(1-p) \\ &= npq\end{aligned}$$

# Poisson distribution

Bin  $(n, p)$   
     $\downarrow$      $\downarrow$   
Large   Small

$X \sim \text{Poisson}(\lambda)$

$$f_X(k) = P(X=k) \\ = e^{-\lambda} \frac{\lambda^k}{k!}$$

$$\sum_{k=0}^{\infty} f_X(k) = e^{-\lambda} \cdot \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} \\ = e^{-\lambda} \cdot e^{\lambda} = 1$$



# Poisson distribution

$X \sim \text{Poisson}(\lambda)$  takes value  $0, 1, \dots$

$$EX = \sum_{k=0}^{\infty} k \cdot f_X(k)$$

$$= \sum_{k=1}^{\infty} k \cdot e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

$$= e^{-\lambda} \cdot \sum_{k=1}^{\infty} \frac{\lambda^k}{(k-1)!}$$

$$= e^{-\lambda} \cdot \lambda \cdot \sum_{k=1}^{\infty} \frac{\lambda^{(k-1)}}{(k-1)!} = \lambda$$

# Geometric distribution

$X \sim \text{Geom}(p)$        $X$  takes values  $1, \dots$

$$\begin{aligned} f_X(k) &= P(X=k) \\ &= (1-p)^{k-1} p \end{aligned}$$

$$\begin{aligned} \sum_{k=1}^{\infty} (1-p)^{k-1} \cdot p &= p \cdot \sum_{k=1}^{\infty} (1-p)^{k-1} \\ &= p \cdot \frac{1}{1-(1-p)} = 1 \end{aligned}$$

# Geometric distribution

$$EX = \sum_{k=1}^{\infty} k \cdot (1-p)^{k-1} \cdot p$$

$$\sum_{k=1}^{\infty} (1-p)^k = \frac{1-p}{1-(1-p)} = \frac{1-p}{p}$$

$$\sum_{k=1}^{\infty} k (1-p)^{k-1} (-1) = \frac{p(-1) - (1-p)}{p^2}$$

$$\sum_{k=1}^{\infty} k (1-p)^{k-1} = \frac{p + (1-p)}{p^2} = \frac{1}{p^2}$$

$$EX = \frac{1}{p}$$