

# Probabilistic ML

$x$        $y$

$P(x, y)$



benign

malignant



Tumor: color, size  
          ↙      ↘      ↙      ↘  
dark red   pink   large   small

$P(\text{color} = \text{dark red}, \text{size} = \text{large}, \text{class} = \text{benign})$   
 $P$

---

What is the class?

given (dark red, large)

$P(\text{class} = \text{benign} \mid \text{color} = \text{dark red}, \text{size} = \text{large})$

---

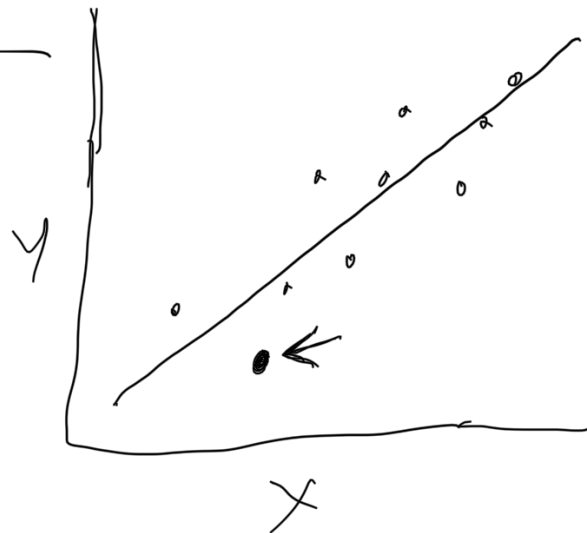
---

## random variables

$X \rightarrow$  take any value in a domain

---

Monday March 29



$(X, Y)$

$(Y | X)$

$(X | Y)$

---

$X = 1$	if face is <u>heads</u>
$X = 0$	if face is <u>tails</u>

---

Distribution Distribution

# Probability distribution

Discrete  $\rightarrow$  pmf  
probability mass function.

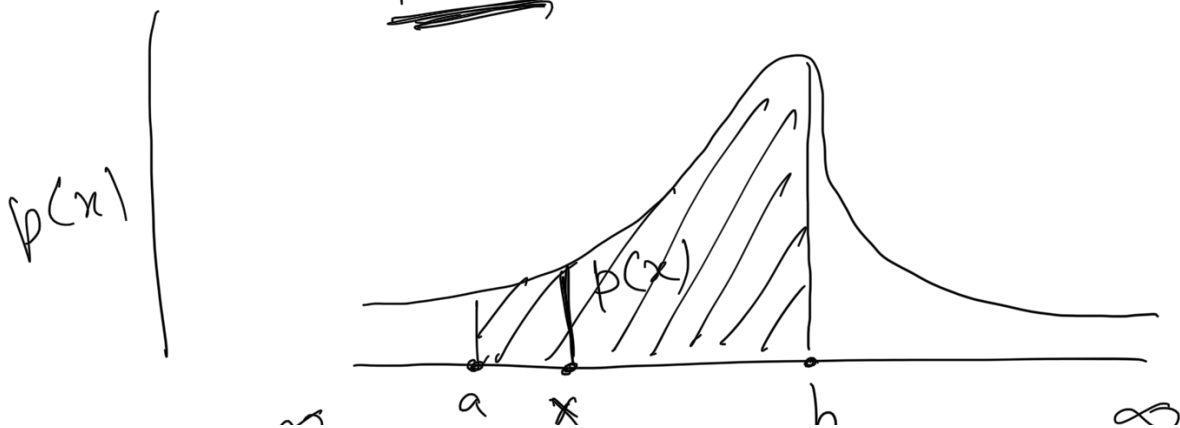
Continuous  $X \in (-\infty, \infty)$   
 $X \in (0, \infty)$   
 $X \in (0, 1)$

$$P(X = x)$$

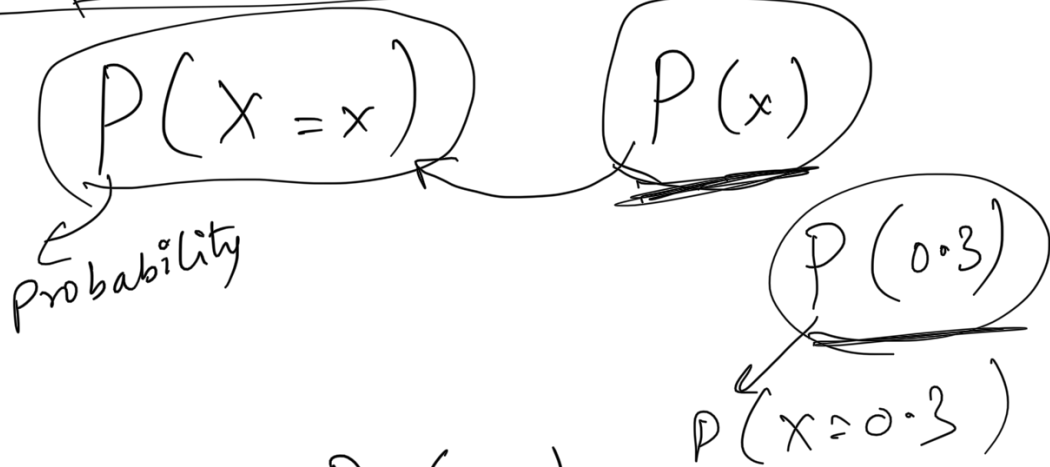
$$P(X = 0.25)?$$

$\rightarrow \approx 0$

probability density function  $p(x)$   $p(x)$

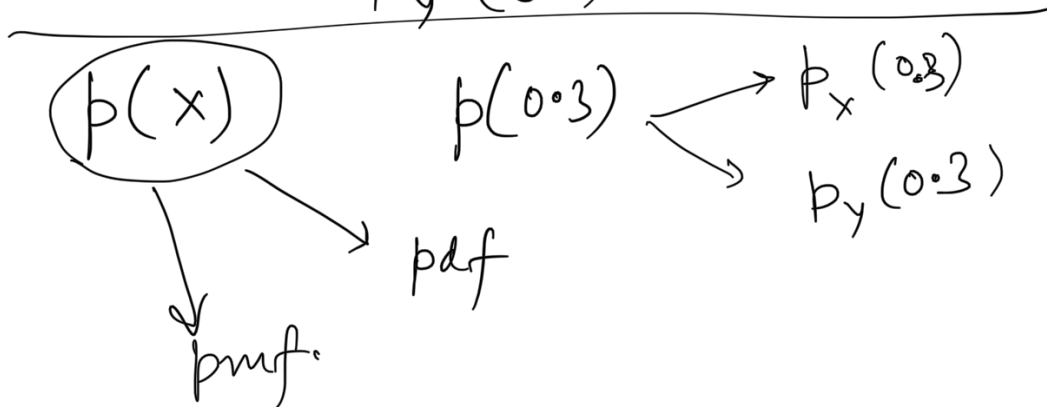


$$\int_{-\infty}^{\infty} p(x) dx = 1$$



$$P_x(0.3)$$

$$P_y(0.3)$$



$$X = \begin{cases} 1 & \text{if } q. = \text{heads} \\ 0 & \text{if } q. = \text{fail} \end{cases}$$

$Y = \begin{cases} 1 & \text{if } p = \text{heads} \\ 0 & \text{if } p = \text{tails} \end{cases}$

$X, Y$

$P(X=1, Y=1)$   
 $P(X=1, Y=0)$

$X=1 \mid Y=1$

Bayes Rule

$$P(X=x \mid Y=y) = \frac{P(Y=y \mid X=x)P(X=x)}{\sum_{x' \in \mathcal{X}} P(X=x')P(Y=y \mid X=x')}$$

What we really want:

$$P(Y=1 \mid X=1)$$

→ Probability that I have cancer,  
given that I have tested +ve.

$$P(Y=1 | X=1) = P(Y=1) P(X=1 | Y=1)$$

$$+ P(Y=0) P(X=1 | Y=0)$$

$0.004$        $0.8$        $0.8$

$1 - P(Y=1) = 0.996$

$P(X=1 | Y=0)$  is different from  $P(X=1 | Y=1)$

and  $P(X=1 | Y=0) \neq 1 - P(X=1 | Y=1)$

Assume:  $P(X=1 | Y=0) = \underline{0.1}$

$$P(Y=1 | X=1) = \frac{0.004 * 0.8}{0.996 * 0.1 + 0.004 * 0.8}$$

$$= \underline{0.031} \ll \underline{0.8}$$

Wed 03/31

X  
n=5, 17

$$\frac{\prod_{x=1}^5 p(x)}{\sum_x p(x) P(X=x)}$$

$0.5$      $0.25$      $0.25$

$$E[g(X)] = \sum_{x \in X} x \cdot p(x)$$

Ex:

$$\text{dom}(X) = \{1, 2, 3\}$$

$$g(x) = \begin{cases} 7 & \text{if } x=1 \\ 3 & \text{if } x=2 \\ -1 & \text{if } x=3 \end{cases}$$

---

$$E[g(X)] = g(1)P(X=1) + g(2)P(X=2) + g(3)P(X=3)$$

$$= 7 \times 0.5 + 3 \times 0.25 + (-1) \times 0.25$$

---

If  $\bar{X}$  - continuous

$$E[g(X)] = \int a(x)h(x)dx$$

$$\frac{\mathbb{E}[c]}{\int_x y(x) f(x) dx}$$

---

$$\begin{aligned}\mathbb{E}[c] &= \sum_{x \in \mathcal{X}} c P(X=x) \\ &= c \sum_{x \in \mathcal{X}} P(X=x) \\ &= c\end{aligned}$$

---

Expectation of a random variable:

$$\mathbb{E}[x] = \sum_{x \in \mathcal{X}} x P(X=x)$$

$$\mathbb{E}[x] = \int x p(x) dx$$

$$\text{Mean of } x (\mu) = \mathbb{E}[x]$$

---

$$\text{var}[x] = \mathbb{E}[(x - \mathbb{E}[x])^2]$$

$$= \mathbb{E}[x^2 + (\mathbb{E}[x])^2 - 2x \mathbb{E}[x]]$$



$$= E[X^2] + \underbrace{(E[X])^2} - \underline{\underline{2E[X]E[X]}}$$

$$= E[X^2] - (E[X])^2$$


---

Binomial:

$X \equiv$  # of heads observed when a coin is tossed  ~~$n$~~  times with a success probability of  $\theta$ .  
 (0  $\leq$   $\theta$   $\leq$  1)  
 heads

$$P(X = k) = \binom{n}{k} \theta^k (1 - \theta)^{n-k}$$


---

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


---

Bernoulli  $X$   $\text{dom}(X) = \{0, 1\}$   
 $\theta$

---

If  $X$  is Binomial:

$$E[X] = \sum_{x=0}^n x \binom{n}{x} \theta^x (1 - \theta)^{n-x}$$


---

---

$$= n \theta$$

$$\text{if } n=20, \theta=0.3$$

$$\underline{E[X] = 6}$$

---

Poisson

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

Cumulative Distribution fn

$$F(a) = P[0 < X \leq a]$$

$$= \int_0^a p(x) dx$$

---

Gaussian

X is continuous

domain  $-\infty \leq X \leq \infty$   
, , ,  $(-\infty, \infty)$

den(x) = ( ~ , ~ )

## Central Limit Theorem

$$p(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left[ -\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2} \right]$$

## Multi-variate Gaussian

$$\underline{\mu} = \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix} \quad \Sigma = \begin{bmatrix} & & \\ & & \\ & & \end{bmatrix}$$

$D \times 1$                        $D \times D$

$$\underline{pdf}(x) = \mathcal{N}(x | \mu, \Sigma)$$

$$= \frac{1}{(2\pi)^{D/2} |\Sigma|^{D/2}} \exp \left[ -\frac{1}{2} \begin{matrix} (x-\mu)^T & \Sigma^{-1} & (x-\mu) \\ \downarrow & & \downarrow \\ 1 \times D & D \times D & 1 \times D \end{matrix} \right]$$