

SVD: $A = U \Sigma V^T$

rectangular (pointing to U)
orthogonal (pointing to U and V^T)

Thm: QS factorization (a.k.a. polar decomposition)

any $n \times n$ matrix A can be written as $A = QS$

Proof: $A = U \Sigma V^T = U \underbrace{V^T V}_I \Sigma V^T =$

$= (UV^T) \cdot (V \Sigma V^T)$

why is $Q = UV^T$ orthogonal?

S is positive semi-def, b/c its eigenvalues, i.e. the diagonal entries of Σ , are ≥ 0

orthogonal (pointing to UV^T)
symmetric positive semi-def. (pointing to $V \Sigma V^T$)

$Q^T Q = (UV^T)^T UV^T = V^{TT} \underbrace{U^T U}_I V^T = V \cdot V^T = I$

Types of factorizations of matrices:

$A = LU$

$A = LDU$

$A = QR$

$A = VDV^{-1}$

$A = U \Sigma V^T$

$A = QS$

$n=1; a = g \cdot \Delta$

orthogonal means $g^2 = 1 \Rightarrow g = \pm 1$
pos semi-def means $\Delta \geq 0$

4 classes on probability \rightsquigarrow likelihood of unknown events
1 class on statistics \rightsquigarrow analysis of known events

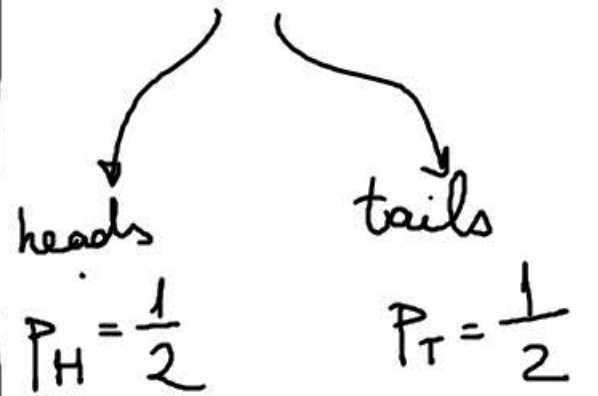
- experiment with n different outcomes, which happen with probabilities p_1, \dots, p_n (discrete probabilities)
- assume that each outcome comes with a real number value x_1, \dots, x_n
(e.g. an amount of money you win if the outcome is p_1, \dots, p_n respective)

CONSTRAINTS:

$$p_1, \dots, p_n > 0$$

$$p_1 + \dots + p_n = 1$$

example:
coin toss has 2 outcomes



Def: (mean = expected value)

is the weighted sum of values of outcomes

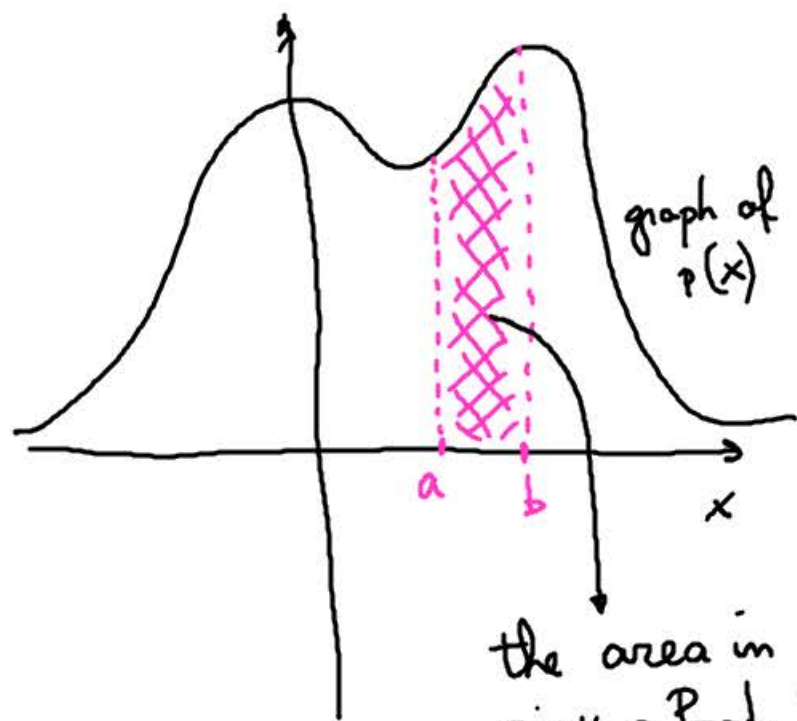
$$\mu = p_1 x_1 + \dots + p_n x_n$$

Def: (variance)

$$\Sigma = p_1 (x_1 - \mu)^2 + \dots + p_n (x_n - \mu)^2$$

$\sigma = \sqrt{\Sigma}$ is the standard deviation

Continuous probability : any real number can be the value of our experiment, and the probability that this happens is governed by a



the area in pink = Prob that outcome lands between a and b

probability distribution

$$p(x): \mathbb{R} \rightarrow \boxed{\mathbb{R}_{\geq 0}}$$

(intuitively but incorrectly, $p(x)$ = the probability that the outcome is x)

for any interval $[a, b]$, the probability that the outcome lands between a and b is

$$\underbrace{\int_a^b p(x) dx}_{\text{Prob}(x \in [a, b])}$$

CONSTRAINT:

$$1 = \text{Prob}(X \in (-\infty, \infty)) = \int_{-\infty}^{\infty} p(x) dx$$

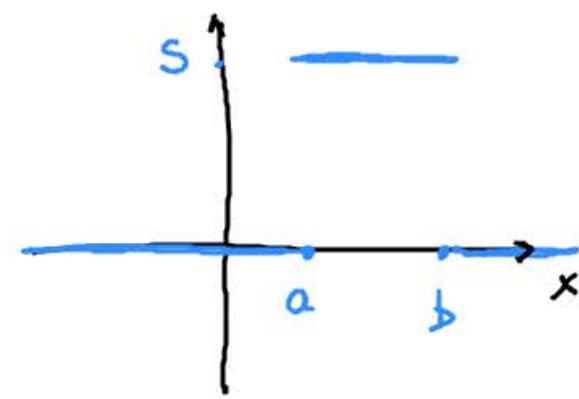
MEAN

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

VARIANCE

$$\Sigma = \int_{-\infty}^{\infty} p(x) (x - \mu)^2 dx$$

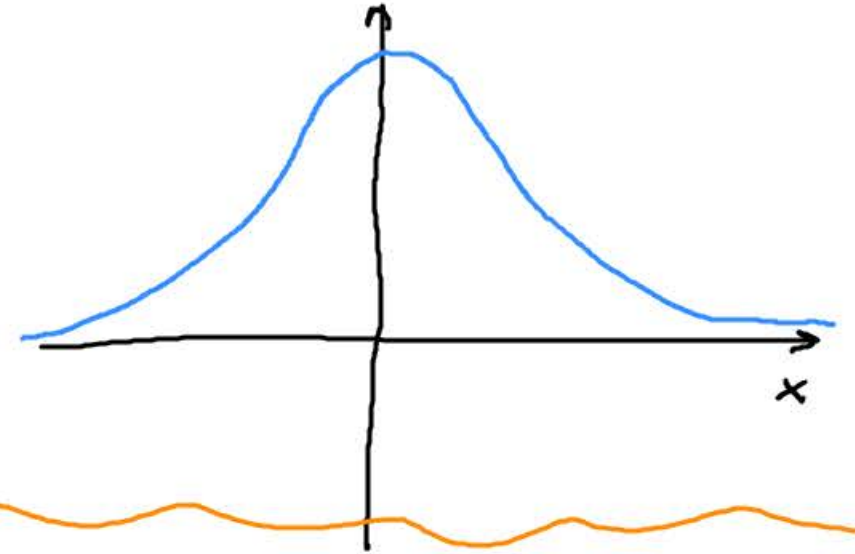
Examples: $p(x) = \begin{cases} s & \text{if } x \in [a, b] \\ 0 & \text{if } x \notin [a, b] \end{cases}$



$$1 = \int_{-\infty}^{\infty} p(x) dx = \int_a^b s \cdot dx = s(b-a) \implies s = \frac{1}{b-a}$$

Normal (Gaussian) distribution:

$$p(x) = \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}}$$



$$\mu = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} x dx = 0$$

$$\Sigma = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} x^2 dx = 1$$

$$\int_{-\infty}^{\infty} e^{-\frac{x^2}{2}} dx = \sqrt{2\pi}$$

if $p(x) = \frac{e^{-\frac{(x-\mu)^2}{2\Sigma}}}{\sqrt{2\pi\Sigma}}$ then the mean will be μ
the variance will be Σ