

Math Tools Lab

Summary Statistics and Probability Distributions

30 Oct 2020

Summary Statistics

- If you had to choose one number to explain your data, what number would you choose?
- Generally speaking you may want some point which is close to your cloud all of your data points
- What do we mean by close? How do we measure that?

$$\arg \min_c \left[\frac{1}{N} \sum_{n=1}^N |x_n - c|^p \right]^{1/p}$$

- Norms:

L_0

Mode

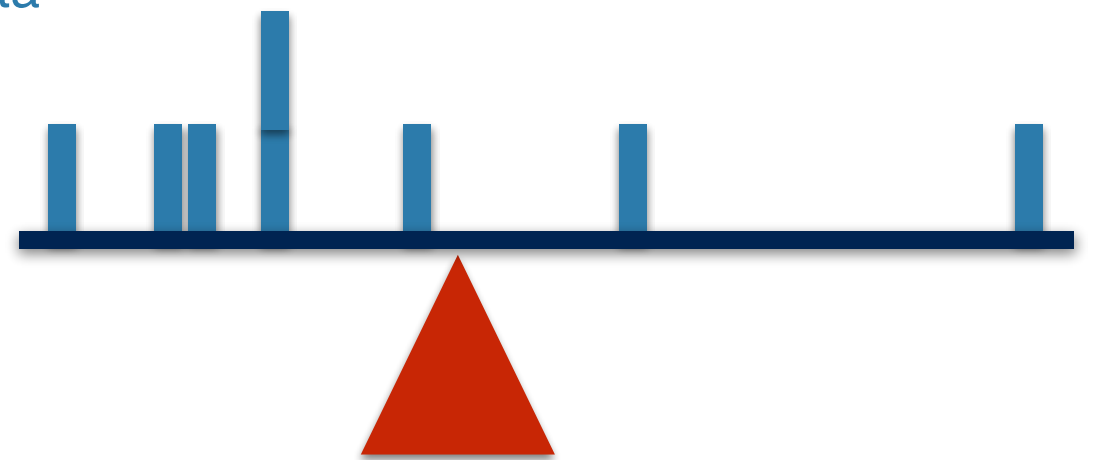
L_1

Median

L_2

Mean

Data

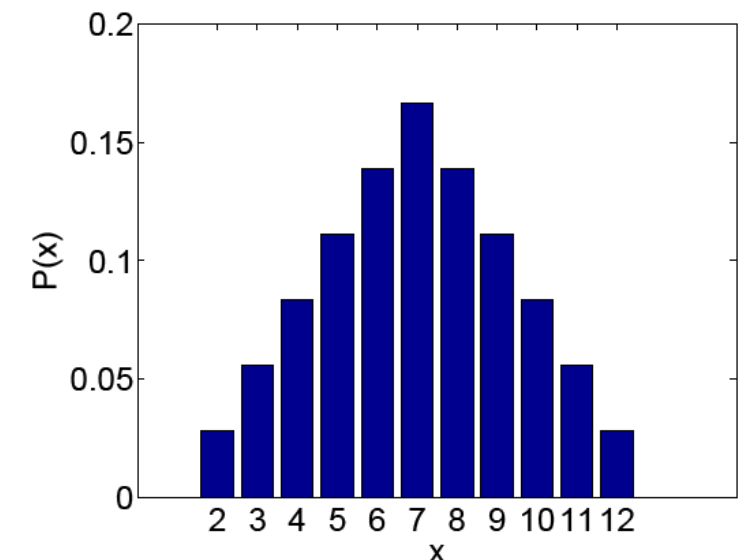


“Central tendency”

Exercises: Summary Stats

Discrete Probability Distributions: PMF

A discrete random variable is one that can equal a **finite number of values**. We can describe the distribution of a discrete r.v. using a **probability mass function (pmf)**, which must be non-negative for all inputs and sum to 1. A pmf describes the probability that a discrete r.v. X takes on a particular value, $P(X = x)$.



What is the pmf of (2)?

Examples of discrete r.v.'s

- (1) X = fair die
- (2) X = sum of two rolled dice
- (3) X = maximum of two rolled dice
- (4) X = # of coin flips until the 1st heads
- (5) X = number of kids in a family

x	2	3	4	5	6	7	8	9	10	11	12
P(X=x)	1/36	2/36	3/36	4/36	5/36	6/36	5/36	4/36	3/36	2/36	1/36

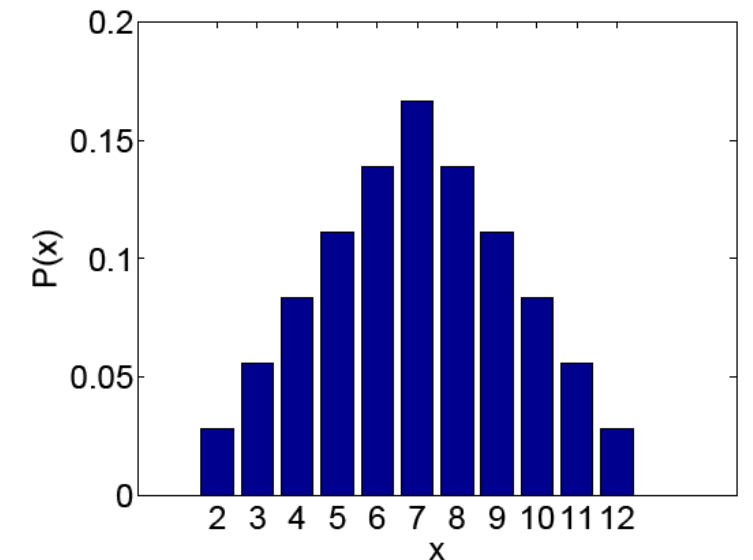
Now, what is the probability that the sum of two rolls is at least 5? What about no more than 8?

$$P(X \geq 5) = \frac{4}{36} + \frac{5}{36} + \frac{6}{36} + \frac{4}{36} + \frac{3}{36} + \frac{2}{36} + \frac{1}{36} = \frac{25}{36}$$

$$P(X \leq 8) = \frac{1}{36} + \frac{2}{36} + \frac{3}{36} + \frac{4}{36} + \frac{5}{36} + \frac{6}{36} + \frac{5}{36} = \frac{26}{36}$$

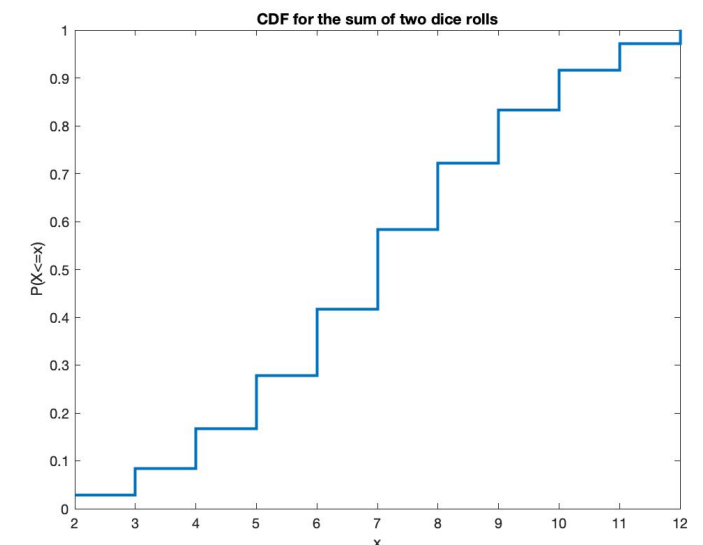
Discrete Probability Distributions: CDF

Another way to describe a r.v.'s distribution is with a **cumulative distribution function (cdf)**, which describes the probability that a discrete r.v. X is less than or equal to a particular value k , $P(X \leq k)$.



Back to our example: what is the cdf of the sum of two dice rolls?

x	2	3	4	5	6	7	8	9	10	11	12
$P(X=x)$	1/36	2/36	3/36	4/36	5/36	6/36	5/36	4/36	3/36	2/36	1/36
$P(X \leq x)$	1/36	3/36	6/36	10/36	15/36	21/36	26/36	30/36	33/36	35/36	36/36



We can use the cumulative distribution function to generate data/draw samples from a distribution (will go through in exercise)

Expected Value

The **expected value** of a r.v. X is a **weighted average** of all the **possible values** of X .

Discrete r.v.: $E(X)$ is a sum

$$\mathbb{E}(x) = \sum_{n=1}^N x_n p(x_n)$$

Linearity of expectation: If $Y = aX + b$, then $E(Y) = E(aX + b) = aE(X) + b$

Example 1: Suppose you roll a die, and are paid \$1 for odd rolls and \$2 for even rolls. What is the expected value for one roll?

If you were given data on how much you money you made on each roll, you could get the sample mean of the money made on one roll

x	1	2	3	4	5	6
P(X=x)	1/6	1/6	1/6	1/6	1/6	1/6
Amount (\$)	1	2	1	2	1	2

$$E(X) = 1\left(\frac{1}{6}\right) + 2\left(\frac{1}{6}\right) + 1\left(\frac{1}{6}\right) + 2\left(\frac{1}{6}\right) + 1\left(\frac{1}{6}\right) + 2\left(\frac{1}{6}\right) = \frac{9}{6} = 1.5$$

$$\frac{1}{N} \sum_{n=1}^N x_n = \frac{1}{N} \vec{1}^T \vec{x}$$

Variance and Standard Deviation

For any r.v., we want to summarize its central tendency but also its spread. The variance of a r.v. X is given by finding the **average squared deviation** of X from its mean, $E(X)$.

$$Var(X) = \sigma_X^2 = E[(X - E(X))^2] = E(X^2) - [E(X)]^2 \quad s_X^2 = \frac{1}{N} \sum_{n=1}^N x_n^2 - \bar{x}^2 = \frac{1}{N} \|\vec{x}\|^2 - \bar{x}^2$$

Since variance averages **squared deviations**, its units are the square of the units of the original r.v. So we define **standard deviation**.

$$\sigma_X = \sqrt{Var(X)}$$

$$s_X = \sqrt{\frac{1}{N} \|\vec{x}\|^2 - \bar{x}^2}$$

Example: Let X = the number of bases a baseball player earns per at-bat. Given the probability function below, find the expected value, variance, and standard deviation of X .

$$E(X) = 0(0.65) + 1(0.25) + 2(0.06) + 3(0.01) + 4(0.03) = 0.52$$

$$E(X^2) = \sum_{k=0}^4 k^2 P(X = k) = 1.06$$

$$Var(X) = E(X^2) - E(X)^2 = 1.06 - 0.52^2 = 0.7896$$

$$sd(X) = \sqrt{Var(X)} = 0.8886$$

k	0	1	2	3	4
P(X=k)	0.65	0.25	0.06	0.01	0.03

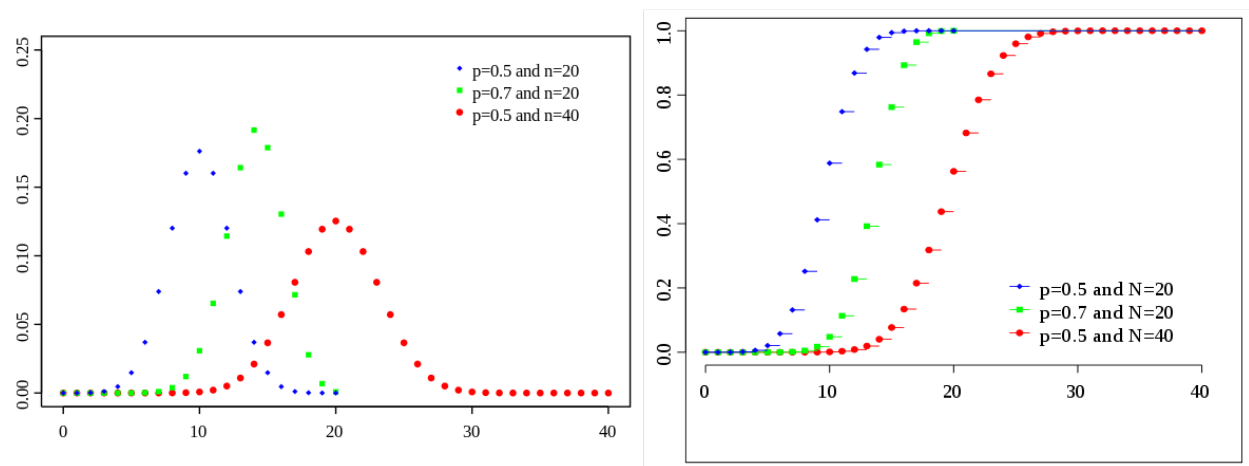
Discrete Probability Distributions: Examples

Binomial Distribution

The distribution for the number of successes in a sequence of n independent experiments, each with 2 possible outcomes where p is the probability of success. Example: flipping a coin.

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

Mean = np ; variance = $np(1 - p)$

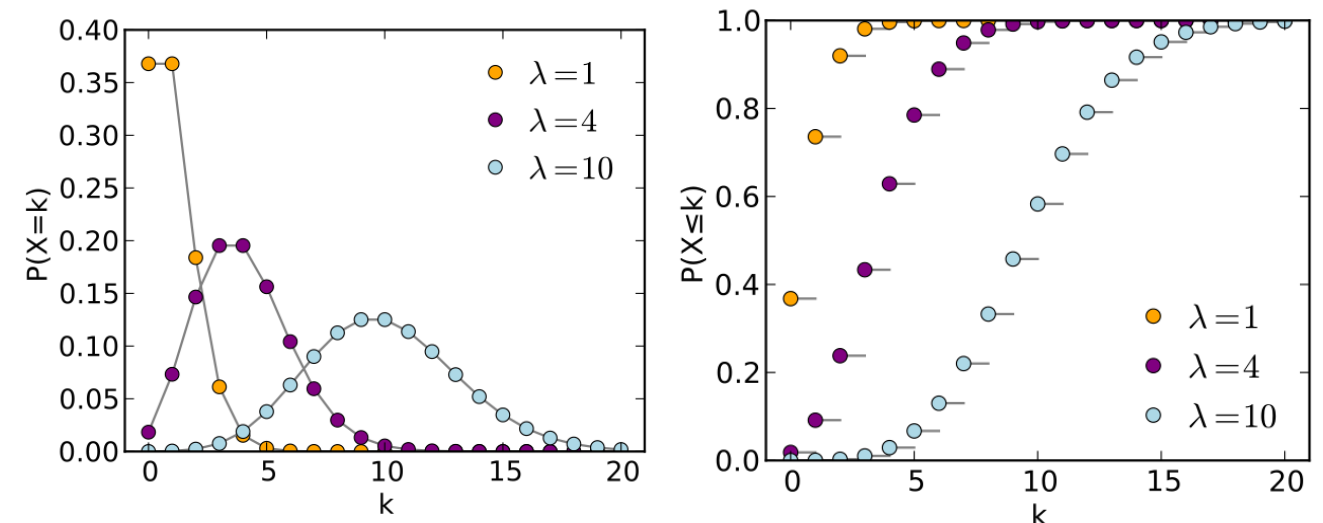


Poisson Distribution

The distribution that expresses the probability that a given number of events will occur in a fixed interval of time λ . The event must occur with a constant rate and independently of the last event. Example: neural spike counts.

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

Mean = λ ; variance = λ



Exercises: Probability Distributions

Covariance and the covariance matrix

Covariance measures the **joint variability of two r.v.'s**. If both X and Y tend to be "big" at the same time, then $Cov(X, Y) > 0$. If one tends to be "big" when the other is "small", then $Cov(X, Y) < 0$.

$$\begin{aligned} Cov(X, Y) &= Cov(Y, X) \\ &= E(XY) - E(X)E(Y) \end{aligned}$$

$$Cov(X, X) = Var(X)$$

The covariance matrix is a matrix whose element in the i, j position represents **the covariance between the i^{th} and j^{th} elements** of a random vector (a r.v. with multiple dimensions). This generalizes the notion of covariance to multiple dimensions. For example, the variation of a collection of two-dimensional points cannot be fully characterized by a single number or just the variances in the x and y directions: a 2×2 matrix is needed.

eg. We have random variables X and Y , then the covariance matrix is

To get the sample covariance matrix

from data $\vec{d}_n = \begin{bmatrix} x_1 & x_2 & \dots & x_n \\ y_1 & y_2 & \dots & y_n \end{bmatrix}$

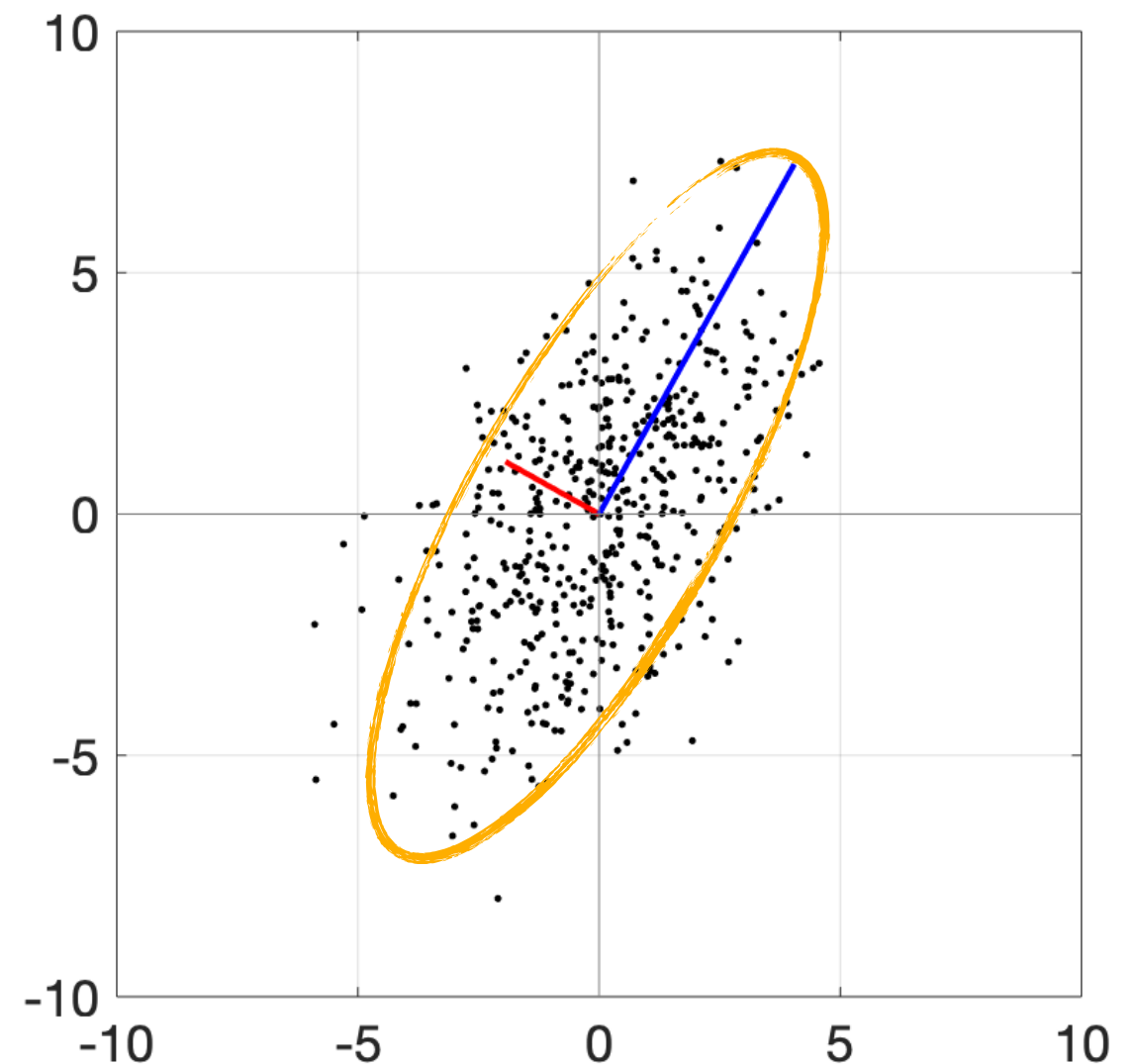
$$\begin{aligned} \begin{bmatrix} Cov(X, X) & Cov(X, Y) \\ Cov(Y, X) & Cov(Y, Y) \end{bmatrix} &= \begin{bmatrix} Var(X) & Cov(X, Y) \\ Cov(Y, X) & Var(Y) \end{bmatrix} &= \frac{1}{N} \begin{bmatrix} ||\vec{x}||^2 & \vec{x}^T \vec{y} \\ \vec{y}^T \vec{x} & ||\vec{y}||^2 \end{bmatrix} - \begin{bmatrix} \bar{x}^2 & \bar{x}\bar{y} \\ \bar{y}\bar{x} & \bar{y}^2 \end{bmatrix} = \begin{bmatrix} s_x^2 & s_{xy} \\ s_{xy} & s_y^2 \end{bmatrix} \\ &= \frac{1}{N} (\vec{d}_n - \bar{d})(\vec{d}_n - \bar{d})' \end{aligned}$$

Covariance and the covariance matrix

How can we use the covariance matrix?

Recall when we used it during the PCA Lab: we wanted to find the directions that captured the most spread in the data

One of the ways we did this was by getting the eigenvalue decomposition of $C = X'X$ which we now know is the covariance matrix.



With this in mind you'll go through two exercises which help us understand how a linear transformation of the data affects the covariance matrix (and the data), as well as how to get rid of covariances in the data (PCA whitening)

Exercises: Covariance Matrix & Transformations