

Correlations

For the Binomial distribution

$$\underline{X} = \sum_{i=1}^n B_i$$

B_i : Random variable following the Bernoulli dist.

Toss a coin N times

$B_i \rightarrow$ follows the same distribution

\hookrightarrow the same object

$$P(B_i=0) = P(B_i=1) = 1/2$$

true for every $i = 1, \dots, N$

Why don't we use the same variable?

\hookrightarrow we're repeating the experiment.

$$\underline{X}_i = \sum_{i=1}^N B = NB \begin{cases} 0 \\ N \end{cases}$$

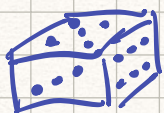
we're missing all the values in between

If each B_i is independent \rightarrow we can have $0 \leq X \leq N$

the outcome of a given experiment is completely independent from the outcome of the previous one

Random variables do NOT need to be independent.

Let's consider a dice



\underline{X} : one side of the dice

\underline{Y} : opposite side of \underline{X}

$\underline{X} + \underline{Y} = 7 \Rightarrow$ we know by construction

\underline{X} : 2 5 6 1 1 3 4
 \underline{Y} : 5 2 1 6 6 4 3
 $\underline{X+Y}$: 7 7 7 7 7 7 7 Not random anymore

Perfect correlation: we can infer the value of \underline{Y} by only measuring \underline{X} .

\underline{X} : 2 5 6 1 1 3 4
 $\underline{X+Y}$: 7 6 7 7 8 9 7 There's a degree a correlation, but it is not perfect

Correlations are not restricted to the sum of two (or more) random variables

↳ In general, we see correlations in the output of an operation

Joint probability distribution

\underline{X} : It follows a distribution $P(k) : \sum_k P(k) = 1$

\underline{Y} : It follows a distribution $P'(l) : \sum_l P'(l) = 1$

k are the possible values that \underline{X} can take

l are the possible values that \underline{Y} can take

We need a joint prob. dist.

$$P(\underline{X}=k, \underline{Y}=l)$$

Probability that $\underline{X}=k$ while $\underline{Y}=l$.

The normalization becomes

$$\sum_k \sum_l P(\underline{X}=k; \underline{Y}=l) = 1$$

$$\sum_{k,l} P(k,l) = 1$$

If the two random variables are independent

$$P(X=k, Y=l) = P(X=k) P'(Y=l)$$

Coin 1		Coin 2			
H	T	H	T	H, H	$\frac{1}{2} \cdot \frac{1}{2} = 1/4$
$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	H, T	$1/2 \cdot 1/2 = 1/4$
				T, H	$1/2 \cdot 1/2 = 1/4$
				T, T	$1/2 \cdot 1/2 = 1/4$

In general, we have that

$$P(X=k, Y=l) \neq P(X=k) P'(Y=l)$$

We have correlated random variables

There are correlations between the variables

Reduced probability distribution

$$\sum_l P(k, l) = P_X(k) \quad \text{Probability of } X=k \text{ independent of the value of } Y$$

$$\sum_k P(k, l) = P_Y(l) \quad \text{Probability of } Y=l \text{ independent of the value of } X.$$

Note that in general $P(k, l) \neq P_X(k) P_Y(l)$

This is a good approximation

"we're neglecting the correlations between X and Y "

Average is linear: Proof

$$\langle X + Y \rangle = \sum_{k, l} (k + l) P(k, l)$$

$$= \sum_{k, l} k P(k, l) + \sum_{k, l} l P(k, l)$$

$$\begin{aligned}
&= \sum_k k \sum_l P(k,l) + \sum_l l \sum_k P(k,l) \\
&= \sum_k k P_X(k) + \sum_l l P_Y(l) \\
&= \langle X \rangle + \langle Y \rangle
\end{aligned}$$

This also applies to the scaling of the random variable $\langle \alpha X + \beta Y \rangle$ $\alpha, \beta \in \mathbb{R}$.

$$\langle \alpha X + \beta Y \rangle = \alpha \langle X \rangle + \beta \langle Y \rangle$$

In contrast, we don't have $\langle XY \rangle = \langle X \rangle \langle Y \rangle$

This is not true in general.

$\langle XY \rangle = \langle X \rangle \langle Y \rangle$ only if X and Y are uncorrelated

Proof:

$$\begin{aligned}
\langle XY \rangle &= \sum_{k,l} k l P(k,l) \\
&= \sum_{k,l} k l P(k) P'(l) \\
&= \sum_k \sum_l k l P(k) P'(l) \\
&= \sum_k k P(k) \sum_l l P'(l) = \langle X \rangle \langle Y \rangle
\end{aligned}$$

If $P(k,l) \neq P(k) P'(l)$

$$\langle XY \rangle = \sum_{k,l} k l P(k,l) = \sum_k k \sum_l l P(k,l)$$

$$\langle Y \rangle_k = \sum_l l P(k,l) = \sum_k k \langle Y \rangle_k = \langle XY \rangle$$