

Lecture 4.2,
MATH-57091 Probability and Statistics for High-School
Teachers.

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A nice property: Consider a random variable X and constants a, b then

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When X and Y are discrete random variables the above condition of independence reduces to

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Indeed assume $p_{X,Y}(x,y) = p_X(x)p_Y(y)$, then

$$\begin{aligned} P(X \leq a, Y \leq b) &= \sum_{x \leq a} \sum_{y \leq b} p_{X,Y}(x,y) \\ &= \sum_{x \leq a} \sum_{y \leq b} p_X(x)p_Y(y) \\ &= \sum_{x \leq a} p_X(x) \sum_{y \leq b} p_Y(y) \\ &= P(X \leq a)P(Y \leq b). \end{aligned}$$

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$$\begin{aligned}\text{Var}(X + Y) &= \mathbb{E}([X + Y] - \mathbb{E}[X + Y])^2 = \mathbb{E}(X + Y - \mathbb{E}X - \mathbb{E}Y)^2 \\ &= \mathbb{E} \left[X^2 + Y^2 + (\mathbb{E}X)^2 + (\mathbb{E}Y)^2 + 2XY - 2X\mathbb{E}X - 2X\mathbb{E}Y - 2Y\mathbb{E}X - 2Y\mathbb{E}Y + 2\mathbb{E}X\mathbb{E}Y \right]\end{aligned}$$

If X and Y are independent discrete random variables, then

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Now we may use that X and Y are independent to get $\mathbb{E}(XY) = \mathbb{E}X\mathbb{E}Y$ and thus

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The Binomial Random Variable

Suppose that n independent trial, each of which results in a "success" with probability p and "failure" with probability $1 - p$ are to be performed. If X represents the number of successes that occur in the n trials, then X is said to be a **Binomial Random Variable** with parameters (n, p) . We note that

$$p_X(i) = P(X = i) = \binom{n}{i} p^i (1 - p)^{n-i}, \text{ for } i = 0, 1, \dots, n,$$

where $\binom{n}{i} = \frac{n!}{(n-i)!i!}$.

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Solution: We represent our Binomial random variable X as

$$X = X_1 + X_2 + \dots + X_n,$$

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$$Var(X) = Var(X_1) + Var(X_2) + \dots + Var(X_n) = n(p - p^2).$$