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A discrete r.v. has probability mass function (pmf)
 $p(x) := P(X=x)$ and the r.v. $X \sim p(x)$ where x is the "realized value" x, x

The cumulative distribution function (cdf) is
 $F(x) := P(X \leq x)$

and complementary cdf or "survival function" is
 $S(x) := P(X > x) = 1 - F(x)$

This rv has support given by $\text{Supp}[X] := \{x: p(x) > 0, x \in \mathbb{R}\}$

$|\text{Supp}[X]| \leq |\mathbb{N}|$ countably infinite at most

↑
 #elements in a set

Sets this size are called "discrete sets"

The support and pmf are related by the following identity:

$$\sum_{x \in \text{Supp}[X]} p(x) = 1$$

The most "fundamental" rv is the Bernoulli: (Brand name)

$X \sim \text{Bern}(p) := p^x(1-p)^{1-x}$ with support $\text{Supp}[X] = \{0, 1\}$

not in
 support

$$p(7) = p^7(1-p)^{-6}$$

Let's define the "indicator function"

$$\mathbb{1}_A := \begin{cases} 1 & \text{if } A \\ 0 & \text{if } A^c \end{cases} \Rightarrow X \sim \text{Bern}(p) := \underbrace{p^x(1-p)^{1-x}}_{p(x)} \underbrace{\mathbb{1}_{x \in \{0,1\}}}_{p^{\text{old}}(x)}$$

$$\Rightarrow \sum_{x \in \mathbb{R}} p(x) = 1$$

$$\text{What if } p=1? \quad X \sim \text{Bern}(1) = 1^x(1-x)^{1-x} \mathbb{1}_{x \in \{0,1\}} = \{1 \text{ w.p. } 1 = \mathbb{1}_{x=1}\}$$

$$X \sim \text{Deg}(1) = \{1 \text{ w.p. } 1 \quad X \sim \text{Deg}(c) := \mathbb{1}_{x=c}$$

↑
 with probability

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$$X \sim \text{Bern}(p) = \text{Deg}(p)$$

The convention in this class is that the parameter values (p is the parameter of the Bernoulli) that yield degenerate rv's are not part of the legal "parameter space".

$$p \in (0, 1)$$

If we have more than one rv X_1, X_2, \dots, X_n we can group them together in a column vector:

$$\vec{X} := [X_1, X_2, \dots, X_n]^T$$

and then define the "joint mass function" (jmf) as

$$p_{\vec{X}}(\vec{x}) = p_{(x_1, \dots, x_n)} \text{ valid for } \vec{x} \in \mathbb{R}^n \text{ and } \sum_{\vec{x} \in \mathbb{R}^n} p(\vec{x}) = 1$$

$$\text{if } X_1, X_2, \dots, X_n \text{ are independent, then } p_{\vec{X}}(\vec{x}) = p_{X_1}(x_1) \cdot p_{X_2}(x_2) \cdot \dots \cdot p_{X_n}(x_n)$$

$$= \prod_{i=1}^n p_{X_i}(x_i) \quad \text{"multiplication rule"}$$

if $X_1 \stackrel{d}{=} X_2 \stackrel{d}{=} \dots \stackrel{d}{=} X_n$ this denotes "equal in distribution" meaning their pdfs are the same. However, this offers no simplification of the jmf unless.

$$\forall x \quad p_{X_1}(x) = p_{X_2}(x) = \dots = p_{X_n}(x)$$

$$X_1, X_2, \dots, X_n \stackrel{\text{iid}}{\sim} \text{that means independent and identically distributed.}$$

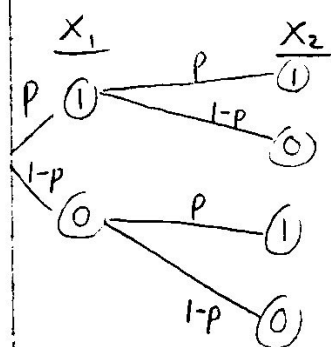
$$\Rightarrow p_{\vec{X}}(\vec{x}) = \prod_{i=1}^n p(x_i)$$

$$\text{let } X_1, X_2 \stackrel{\text{iid}}{\sim} \text{Bern}(p), \text{ let } T_2 = f(X_1, X_2) = X_1 + X_2 \stackrel{?}{\sim} P_T(?)$$

$$\text{Derived } P_T(t) = p_{X_1}(x) * p_{X_2}(x)$$

Convolution Operator

$$\text{Supp}[T_2] = \{0, 1, 2\}$$



$p_{X_1, X_2}(x_1, x_2)$

p^2
 $p(1-p)$
 $(1-p)p$
 $(1-p)^2$