\( f(x) = \begin{cases} 2 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases} \)

Domain: \( \mathbb{R} \) (set of numbers)
Range: \( \{0, 2\} \)

Some mapping

Random variable \( X \) is a probability model

Experimental procedure and observation

\( X \sim \text{Uniform} \) two
\[ A = \{x \in Y \mid x(s) = x\} \]

\[ P \{ x = x \} \equiv P[A] \]

\[ \forall x \in \{ x \mid x \neq y \} = f \]

\[ \{ x = y \} \cup \{ x \neq y \} = \phi \]

\[ \text{Domain} \]

\[ \text{Image} \]
A discrete random variable is said to be

discrete if its set of possible values is discrete.

\[ P(X = x) = \sum_{x \in \mathbb{N}} P(A) \]

Domain

\[ P(X = x) = \frac{X}{X(s)} \]

Range

\[ P(X = x) \]

A discrete random variable is characterized by its

\[ P(X = x) = \int_{x \in \mathbb{I}} P(A) \]

Set of possible values
Consider: posterior probability $p$, and success, $\text{success}_i$.

Each independent subexperiment gives two possibilities:

and independent subproblems.

Recall: consider independent subproblems.
\begin{align*}
& \text{Arrival} \quad \text{Arrival} \\
& \text{Count} \quad \text{Count} \\
& \text{Arrival times} \quad \text{Arrival times} \\
& \text{Number of arrivals} = \lambda t \\
& \text{Probability of exactly} k \text{ arrivals} \quad \text{Probability of exactly} k \text{ arrivals} \\
& \text{Binomial distribution} \quad \text{Binomial distribution} \\
& \text{Number of successes in} \ n \text{ trials} \\
& \text{Success (inclusive)} \\
& \text{Failure (exclusive)} \\
& \text{Geometric distribution} \quad \text{Geometric distribution} \\
& \text{Negative binomial distribution} \quad \text{Negative binomial distribution} \\
& \text{Poisson distribution} \quad \text{Poisson distribution} \\
& \text{Markov chain} \quad \text{Markov chain} \\
& \text{Transition probabilities} \quad \text{Transition probabilities} \\
\end{align*}
Also describes a complete probability model

Cumulative Distribution Function (CDF) (CDF)

mode of a discrete random variable

\[ F_X(x) = \begin{cases} 0 & x < 0 \\ \frac{1}{2} \quad 0 \leq x < 1 \\ 1 & x \geq 1 \end{cases} 
\]

\[ X = \sum \text{Count times}\]

\[ \text{Demand the average number of services}\]

\[ \text{on I until times}\]

\[ \text{A denote the average number of services}\]
\[ \left\{ x > x \right\} P \triangleq \left\{ x \in \mathbb{R} \text{ such that } P(x) \right\} = \bigcup_{P(x)} \]
(c) $F(x)$ is continuous from the right, but $F(x)$ is not necessarily continuous from the left.

$x \rightarrow x_0 \rightarrow x^\prime \rightarrow x^\prime \prime \rightarrow \ldots \rightarrow x_n \rightarrow \infty$

$x \rightarrow x_0 \rightarrow x^\prime \rightarrow x^\prime \prime \rightarrow \ldots \rightarrow x_n \rightarrow \infty$

$F(x) = \lim_{x \rightarrow x_n} F(x_n)$
The largest integer in the set that is less than 5 is 4.

The integer part of 4 is 4.

The largest integer not larger than 4 is 4.

The largest integer not larger than 4 is 4.
\( \lceil y \rceil \) is the smallest integer that is not smaller than \( y \).

A **statistic** is a single number derived from (numerical)

*The average value of a set of experiment outcomes is a statistic of the outcomes.*

Three averages of interest:

- **mean** (or expected value, or expectation)
- **median**
- **mode** (unimodal, multimodal)
Relative frequency interpretation

We can interpret \( P(X = x) = \frac{1}{N} \)

\[ m_n = \frac{1}{N} \sum_{x \in S} x \]

\( m_n \) = sample average

\( \frac{1}{N} \sum_{x \in S} x \) = sample average

Consider an experiment that produces a random

Perform in independent trials of this
\[ \{ x \in \mathbb{R} | x \geq 5 \} \subset \mathbb{Z} \]

\[ x = x \in \mathbb{Z} \]

\[ \text{If } x \in \mathbb{Z} \text{, then } x \geq 5 \]

\[ \lim_{x \to a} \frac{x-a}{x} = \frac{0}{0} \]
\[ \frac{2}{\gamma - 1} \frac{\bar{y}}{\bar{x}} = c = \frac{2}{\gamma - 1} \frac{\bar{y}}{\bar{x}} \]

\[ a_{\bar{y}} \frac{\bar{y}}{\bar{x}} = \frac{2}{\gamma - 1} \frac{\bar{y}}{\bar{x}} \]

\[ \frac{\bar{y}}{\bar{x}} (1 - \frac{\bar{y}}{\bar{x}}) = \frac{2}{\gamma - 1} \frac{\bar{y}}{\bar{x}} \]

\[ \frac{2}{\gamma - 1} \frac{\bar{y}}{\bar{x}} = c = \frac{2}{\gamma - 1} \frac{\bar{y}}{\bar{x}} \]
A = \{ x \in \mathbb{R} \mid f(x) \in S \}

\text{for } f(x) \text{ as shown.}

X \rightarrow \text{complexity statistics characterization}

\text{domain}

\text{range}

\text{domain}
\( f'(x) = g(x) \) for all \( x \in \mathbb{R} \) and \( h(x) \) is a constant function.

\[ h(x) = g(x) \]

1. \( \lim_{x \to a} f(x) = f(a) \)
2. \( \lim_{x \to a} g(x) = g(a) \)

\[ S \]

\[ X \]
\[ h = b \cdot \theta(x) \]

\[ f(x) \subseteq \mathbb{Z} \]

\[ \{ f(x) \mid \theta(x) = h \} \]

\[ \{ y \mid b \cdot \theta(s, x) \} = \{ y \mid (\theta(s, x), y) \} \]

\[ A = \{ y \mid f(y) = y \} \]

\[ \text{when } f = y \]
Given $x(t)$ and $y = g(x)$, the approach to finding $y(t)$ is as follows:

With the approach of finding $R(x)$, we have:

First, calculate $g(x)$ and then find $y(t)$ using the given function $y = g(x)$. The diagram illustrates the relationship between $x(t)$ and $y(t)$.
Law of Inverse Functions

Domain: \( x \in \mathbb{R} \)

\( x \rightarrow y \)

\( y \rightarrow x \)

\( f(x) = y \)

\( f^{-1}(y) = x \)
For any two linear operators $T_1$ and $T_2$, we have

$(T_1 + T_2)[x] = T_1[x] + T_2[x]$. 

This is a property of superposition (linearity). 

Let's consider the specific case:

$$\sum_{i=1}^{n} a_i x_i = \sum_{i=1}^{n} a_i \frac{\partial}{\partial x_i}$$

where $a_i$ are coefficients and $x_i$ are variables. 

An operator $T$ is said
$S[y]$, \[ S[y] = S[y] \]

Expectation is linear. \[ E[y] \rightarrow \overline{E} \rightarrow 0 \]

pf for theorem 2.12: \[ \overline{E} \rightarrow \overline{E} \rightarrow \overline{E} \rightarrow 2 \]

Let \( Y = g(x) = ax + b \). Then, from theorem 2.12:

\[
E[Y] = \sum_{x \in S_X} g(x) p_x(x) = \sum_{x \in S_X} (ax + b) p_x(x)
\]

\[
= a \sum_{x \in S_X} x p_x(x) + b \sum_{x \in S_X} p_x(x) \quad Q.E.D.
\]
\[ E_{[W]} = g(\mathbb{E}[R]) \]

Therefore, if

\[ g_{W} = g_{R} \]

then

\[ E_{[W]} \neq g_{W}(\mathbb{E}[R]) \]

so if \( W = g_{R}(R) \) when \( g_{R} \)
model of \( x \), and so does \( f(x) \).

\( F(x) \) correctly denotes the probability.
of x positive to m

\[ \forall \mathcal{X} \subseteq \mathbb{X} \text{ which descends the dispersion} \]

\[ P \times \in (m_1, M_1, M_1 + \epsilon) \]

\[ \mathbb{X} \overset{\epsilon}{\leftarrow} x \overset{\epsilon}{\rightarrow} M - \epsilon, M + \epsilon \]

For some x
\[ \text{Var}(X) = \mathbb{E}(X - \mu_X)^2 \]

\[ \text{Law of } \mu_X = \sum_{x \in S_X} (x - \mu_X)^2 \frac{\mathbb{P}_X(x)}{\mu_X} \]

Unconscious statistician:

\[ \mathbb{E}[X^2] \text{ is commonly called the mean square value of } X. \]
$\mathbb{E}[X^2] \geq \mu^2$ for any $\mu \geq 0$

$\mathbb{E}[X^2 - \mu^2] \geq 0$

For any $\mu \geq \mathbb{E}[X - \mu]^2 \geq 0$

Moment of $X$

Some text discussing the properties

$\mathbb{E}[X^n]$ for moments $\{\mathbb{E}[X^n] \mid n \geq 1, 2, \ldots \}$
If two events A and B are disjoint, then

\[ P(A \cup B) = P(A) + P(B) \]

where

\[ P(A \mid B) = \frac{P(A \cap B)}{P(B)} \]

If \( P(B) \neq 0 \), then

\[ P(A \mid B) = \frac{0}{P(B)} = 0 \]

That means, the conditional probability of event A given event B occurs, will be 0. Conversely, if \( P(B) = 0 \), the conditional probability of event A given event B also occurs, it is undefined.
\[
\frac{P[B]}{P[X_{1\leq B}(\cdot), Y_{1\leq B}(\cdot)]} \approx \frac{P[X=x | B]}{P[X=x | B]} = P[X=x | B] = P[X=x | B]
\]
\[ P(X \leq x | \mathcal{B}) = \begin{cases} \frac{P(x \leq x | \mathcal{B})}{P(X \leq x | \mathcal{B})} \\ x \in \mathcal{B} \end{cases} \]

\[ \text{If } x \in \mathcal{B}, \]

\[ P(X = x | \mathcal{B}) = \begin{cases} \frac{P(x = x | \mathcal{B})}{P(X = x | \mathcal{B})} \\ x \in \mathcal{B} \end{cases} \]
\[ \mathbb{E} \{ \mathbf{x} + 6 \mid \mathbf{z} \} = \mathbf{z} - \mathbf{E} \{ x \mid \mathbf{z} \} + 6. \]

\[ \mathbb{E} \{ x \mid \mathbf{z} \} = \sum_{x \in \mathbb{X}} x \cdot \Pr \{ x \mid \mathbf{z} \}. \]
Grade (letter) → Grade (number)
The event of outcomes \( \Omega \) is defined as \( \Omega = \{ \mathbf{x} \in \mathbb{R}^n \mid f(x) \geq t \} \).
\[ P(A \mid X = x) = \frac{P(X = x) \cdot P(A)}{P(X = x)} \]

Defining event \( A = \{ X = x \} \)

\[ P(A) = \int_{x \in S} P(A \mid X = x) \cdot f_X(x) \, dx \]

\[ \int_{x \in S} P(A \mid X = x) \cdot f_X(x) \, dx = 1 \]

Ax1) \[ P(\emptyset) = 0 \]

Ax2) \[ P(S) = 1 \]

Ax3) \[ \text{If } A \subseteq B \text{ then } P(A) \leq P(B) \]

P(A) \[ \geq \int_{x \in A} f_X(x) \, dx \]

For any \( x \)

\[ P(A) = \int_{x \in A} f_X(x) \, dx \]

Ax4) \[ X \text{ is a rv} \]

\[ P(A) = \int_{x \in A} f_X(x) \, dx \]

Ax5) \[ \text{If } A \text{ and } B \text{ are disjoint, then } P(A \cup B) = P(A) + P(B) \]

\[ P(A) = \int_{x \in A} f_X(x) \, dx \]

Ax6) \[ P(A \cap B) = P(A) \cdot P(B) \]

\[ \int_{x \in A} f_X(x) \, dx \cdot \int_{x \in B} f_X(x) \, dx = \int_{x \in A \cap B} f_X(x) \, dx \]
\[ \text{Let } A \ni \exists x \ni A(x) \land \neg A(x) \]

\[ \{ x \mid x \in \exists \} = \emptyset \]
\[ x \in A \iff \exists y \in B (x) \]

Then,

\[ x \in A \iff \exists y \in B (x) \]

Axiom 3

\[ x \in A \iff \exists y \in B (x) \]

\[ \exists x \in A \iff \exists y \in B (x) \]

\[ \exists x \in A \iff \exists y \in B (x) \]

\[ \exists x \in A \iff \exists y \in B (x) \]

For any \( B \subseteq \mathcal{P}(X) \), the predicate

\[ x \in A \iff \exists y \in B (x) \]
A statistic is a single number calculated from a probability distribution or a sample of data. It is used to analyze data and make inferences about a population. Common examples include mean, median, and standard deviation.

The probability distribution of a statistic is often used to determine the likelihood of certain outcomes. For example, the normal distribution is a common probability distribution used in statistics.

In the case of a single random variable, the probability mass function (PMF) describes the probability of each possible value. The cumulative distribution function (CDF) gives the probability that the random variable is less than or equal to a given value.

The sampling distribution of a statistic is the distribution of the statistic when the sample is drawn repeatedly from the same population. This distribution is often used to determine the standard error of the statistic, which is a measure of the variability of the statistic.
\[ \Sigma = \Sigma [x^2 - \frac{1}{n}] = \Sigma [x^2 - 2mx + m^2 + \frac{m^2}{n}] = \Sigma [x - mx]^2 = \Sigma [(x - mx) + m^2] \]

Since \( \Sigma [x - mx] \neq 0 \) in general,