

Discrete Probability Functions

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Outline

- **Discrete RVs, PMFs, CDFs**
- **Discrete Expectations**
- **Discrete Moments**
- **Discrete Distributions**

Discrete Random Variables

A random variable is a function from a sample space S into the real numbers X .

Examples:

Experiment	Random Variable
Toss two die	X =sum of numbers
Toss a coin 25 times	X = # heads in 25 tosses
Apply different amounts of fertilizer to plants	X =yield/acre

Discrete Probability Mass Functions

Example: Toss a coin twice.

$$S = \{HH, HT, TH, TT\}$$

X = number of heads.

Sample space
outcomes

Real Numbers

$X(s)$ is a mapping from S to X .

$$s_1 = HH, s_2 = HT, s_3 = TH, s_4 = TT$$

$$X_1 = 2, X_2 = 1, X_3 = 1, X_4 = 0$$

$P(X)$ is a mapping from X to $[0, 1]$.

Real Numbers

Unit interval

s	HH	HT	TH	TT
$X(s)$	2	1	1	0

x	0	1	2
$P(X=x)$	1/4	1/2	1/4

Discrete Cumulative Distribution Functions

The *cdf* of a random variable X , $F_X(x)$, is

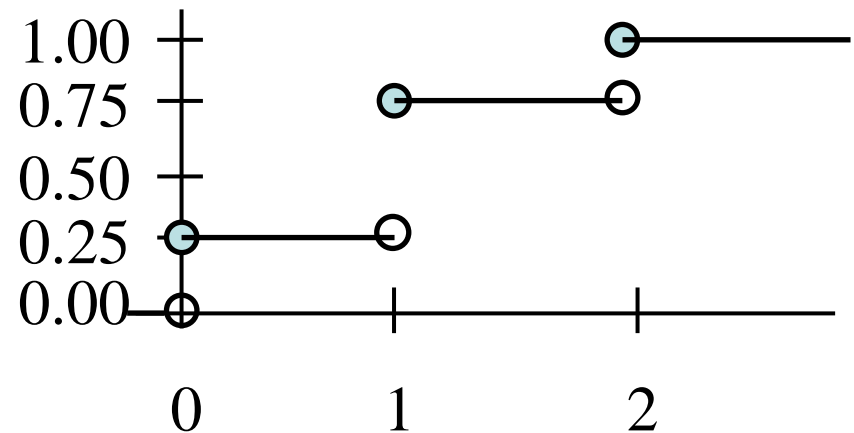
$$F_X(x) = P_X(X \leq x), \text{ for all } x.$$

$$F_X(x) = \sum_{X \leq x} P_X(X = x)$$

Example: Tossing a coin twice

x	0	1	2
$P(X=x)$	1/4	1/2	1/4

$$F_X(x) = \begin{cases} 0/4 & -\infty < x < 0 \\ 1/4 & 0 \leq x < 1 \\ 3/4 & 1 \leq x < 2 \\ 4/4 & 2 \leq x < \infty \end{cases}$$



Discrete RVs, PMFs, and CDFs

Assume that the discrete random variable (RV) takes on values

$$x_1, x_2, x_3 \dots$$

if the probability of each of value x_j is

$$P(X = x_j | \theta)$$

then, the probability mass function (PMF) is given by

$$f(x_j | \theta) = P(X = x_j | \theta) \text{ for } j = 1, 2, 3 \dots$$

where θ are any parameters that the PMF depends on.

Discrete RVs, PMFs, and CDFs

Further, the cumulative distribution function (CDF) is given by

$$F(x | \theta) = \sum_{x_j \leq x} f(x_j | \theta)$$

i.e. $F(x | \theta) = f(x_j | \theta) + \dots + f(x_k | \theta)$

where x_k (largest value) $\leq x$.

Additionally, any PMF must satisfy

1) $0 \leq f(x_j | \theta) \leq 1$

2) $\sum_{x_j} f(x_j | \theta) = 1$.

Discrete Expectation

Given an arbitrary discrete probability mass $f(x_j|\theta)$, we want to compute quantitative population summaries of it such as

population mean, $\mu = \sum_{j=1}^{\infty} x_j f(x_j | \theta)$

population variance, $\sigma^2 = \sum_{j=1}^{\infty} (x_j - \mu)^2 f(x_j | \theta)$

population standard deviation, $\sigma = \sqrt{\sigma^2}$

Discrete Expectation

These population numerical summaries are found by expectation

$$E[g(X) | \theta] = \sum_{j=1}^{\infty} g(x_j) f(x_j | \theta) \quad .$$

The mean is

$$\mu = E(X | \theta)$$

and the variance is

$$\sigma^2 = E[(X - \mu)^2 | \theta] \quad .$$

Discrete Expectation

Linearity Property:

$$E\left[\sum_{j=1}^n g_j(X) \mid \theta\right] = \sum_{j=1}^n E[g_j(X) \mid \theta]$$

i.e. $E[g_1(X) + g_2(X) \mid \theta] = E[g_1(X) \mid \theta] + E[g_2(X) \mid \theta]$

$$\begin{aligned} E[g_1(X) + g_2(X) \mid \theta] &= \sum_{j=1}^{\infty} [g_1(x_j) + g_2(x_j)] f(x_j \mid \theta) \\ &= \sum_{j=1}^{\infty} [g_1(x_j) f(x_j \mid \theta) + g_2(x_j) f(x_j \mid \theta)] \\ &= \sum_{j=1}^{\infty} g_1(x_j) f(x_j \mid \theta) + \sum_{j=1}^{\infty} g_2(x_j) f(x_j \mid \theta) \end{aligned}$$

Discrete Expectation

Example:

x	0	1	2
$P(X=x)$	1/4	1/2	1/4

$$E[g(X) | \theta] = \sum_{j=1}^{\infty} g(x_j) f(x_j | \theta)$$

$$g(X) = X$$

$$\mu = (0)(1/4) + (1)(2/4) + (2)(1/4)$$

$$\mu = 1$$

Discrete Expectation

Example:

x	0	1	2
$P(X=x)$	1/4	1/2	1/4

$$E[g(X) | \theta] = \sum_{j=1}^{\infty} g(x_j) f(x_j | \theta)$$

$$g(X) = (X - \mu)^2$$

$$\sigma^2 = (0 - 1)^2 (1/4) + (1 - 1)^2 (2/4) + (2 - 1)^2 (1/4)$$

$$\sigma^2 = 1/2$$

Discrete Moments

For each integer n , the n th moment of X , μ'_n , is

$$\mu'_n = E(X^n | \theta) .$$

The n th central moment of X , μ_n , is

$$\mu_n = E[(X - \mu)^n | \theta]$$

where $\mu'_1 = E(X | \theta)$.

Discrete Distributions

Uniform:

A random variable x has a discrete uniform distribution, $x \sim \text{uniform}(N)$ if

$$P(X = x | N) = \frac{1}{N}$$

where, $N=1,2,\dots$, $x=1,2,\dots,N$.

i.e. flipping a coin, rolling a die.

Discrete Distributions

Uniform:

It can be shown that

$$\begin{aligned}\mu &= \sum_{j=1}^{\infty} x_j P(X = x_j) \\ &= \sum_{j=1}^N j \frac{1}{N} \\ &= \frac{N+1}{2}\end{aligned}$$

Note:

$$1 + 2 + 3 + \dots + N = \frac{N(N+1)}{2}$$

Discrete Distributions

Uniform:

that

$$\sigma^2 = \sum_{j=1}^{\infty} (x_j - \mu)^2 P(X = x_j)$$

$$= \sum_{j=1}^N \left(j - \frac{N+1}{2} \right)^2 \frac{1}{N}$$

$$= \frac{N^2 - 1}{12}$$

Note:

$$1 + 2^2 + 3^2 + \dots + N^2 = \frac{N(N+1)(2N+1)}{6}$$

Discrete Distributions

Uniform:

$$P(X = x | N) = \frac{1}{N} \quad \text{where, } N=1,2,\dots, x=1,2,\dots,N.$$

Uniform discrete random variates can be generated by either partitioning the unit interval into N bins, generating uniform $[0,1]$ numbers and for each random number convert to j if it is in the j^{th} bin or

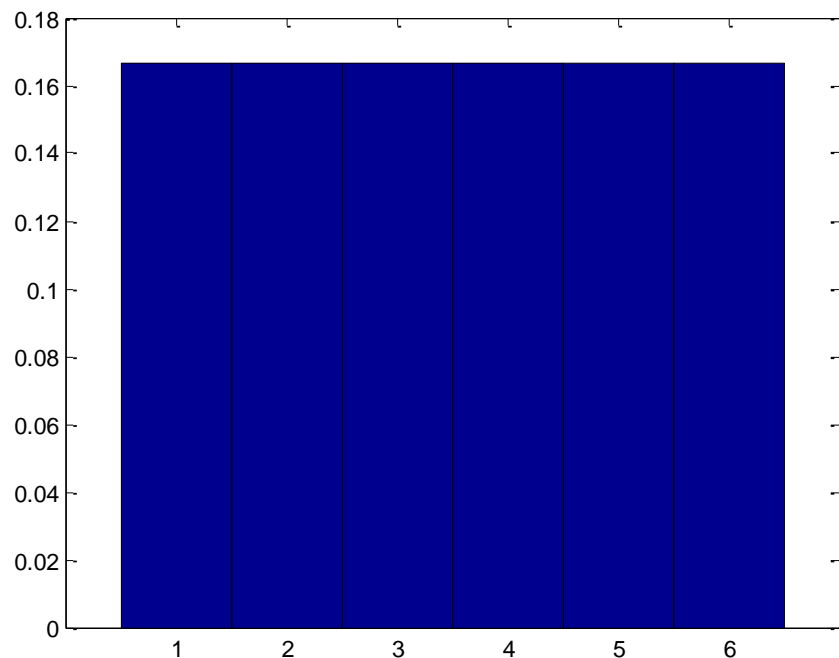
$N=6;$

$x=\text{unidrnd}(N)$

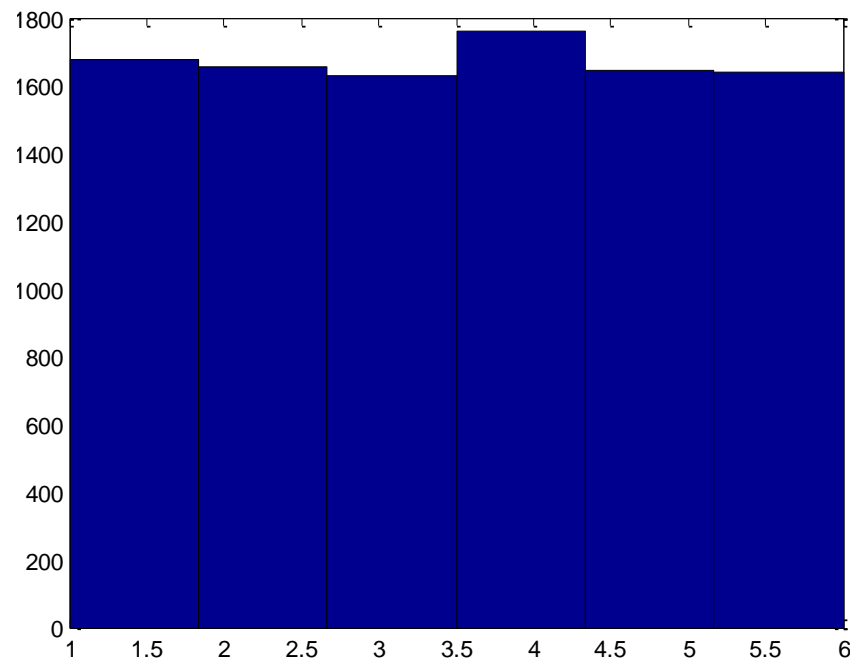
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Discrete Distributions

Uniform: $P(X = x) = \frac{1}{6}$



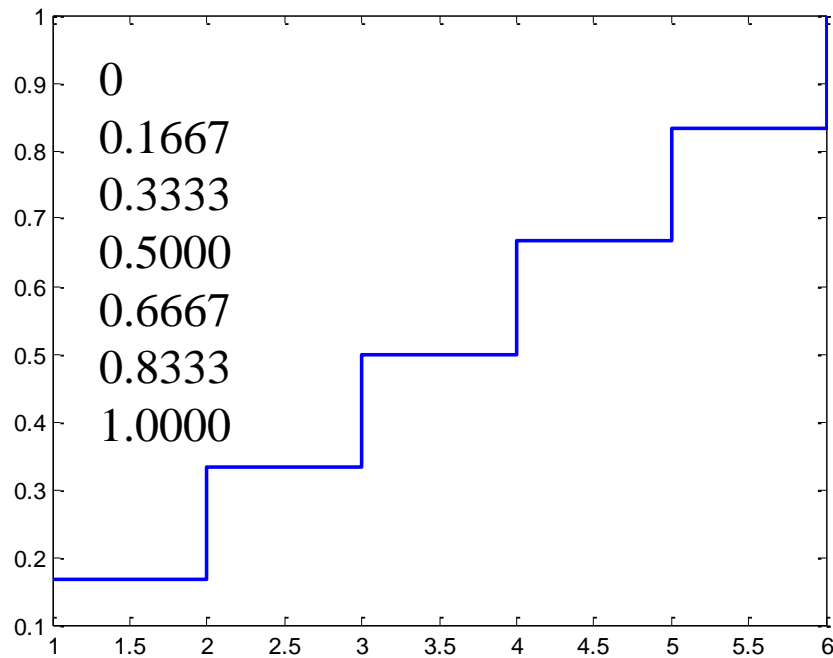
```
N=6;  
xpop=(1:N);  
ypop = unidpdf(x,N);  
bar(xpop,ypop,1)
```



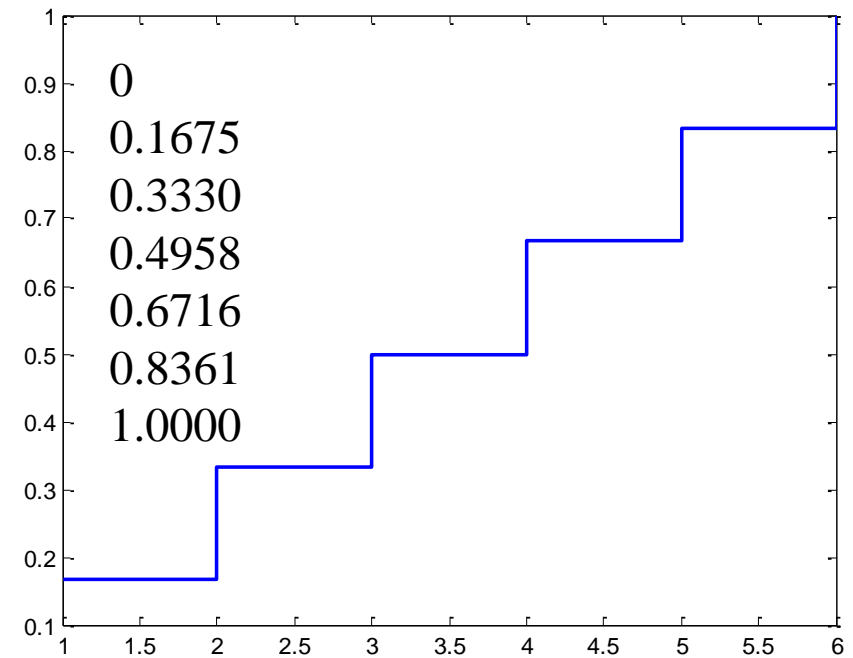
```
N=6;, num=10000;  
xsamp=unidrnd(N,num,1);  
hist(xsamp,N)
```

Discrete Distributions

Uniform: $P(X = x) = \frac{1}{6}$



```
ducdf =unidcdf(x,6)
stairs(x, ducdf,'LineWidth',2)
```



```
[F,x]=ecdf(xsamp);
stairs(x,F,'LineWidth',2)
```

Discrete Distributions

Uniform: $P(X = x) = \frac{1}{6}$

unidstat(N)		True	Simulated
mean(xsamp)	μ	3.5	3.4960
var(xsamp)	σ^2	2.9167	2.8987

Discrete Distributions

Bernoulli:

A random variable x has a discrete Bernoulli distribution, $x \sim \text{Bernoulli}(p)$ if

$$P(X = x | p) = p^x (1 - p)^{1-x}$$

where, $0 \leq p \leq 1$, $x = 0, 1$.

x = the number of successes out of 1 trial.

p = the probability of success on the trial.

Discrete Distributions

Bernoulli:

It can be shown that

$$\begin{aligned}\mu &= \sum_{j=1}^{\infty} x_j P(X = x_j) \\ &= (0)(1-p) + (1)p \\ &= p\end{aligned}$$

Discrete Distributions

Bernoulli:

that

$$\begin{aligned}\sigma^2 &= \sum_{j=1}^{\infty} (x_j - \mu)^2 P(X = x_j) \\ &= (0 - p)^2 (1 - p) + (1 - p)^2 p \\ &= p(1 - p)\end{aligned}$$

Discrete Distributions

Bernoulli:

$$P(X = x | p) = p^x (1 - p)^{1-x} \quad \text{where, } 0 \leq p \leq 1, \quad x = 0, 1 .$$

Bernoulli discrete random variates can be generated by either partitioning the unit interval into 2 bins, generating uniform $[0, 1]$ numbers and for each random number convert to $j-1$ if it is in the j^{th} bin or

```
p=1/2; n=1;  
x=binornd(1,p)  
1
```


Discrete Distributions

Bernoulli:

$$P(X = x | p) = p^x (1 - p)^{1-x}$$

`n=1; p=1/2; num=10^4;`

`x=binornd (n,p,num,1);`

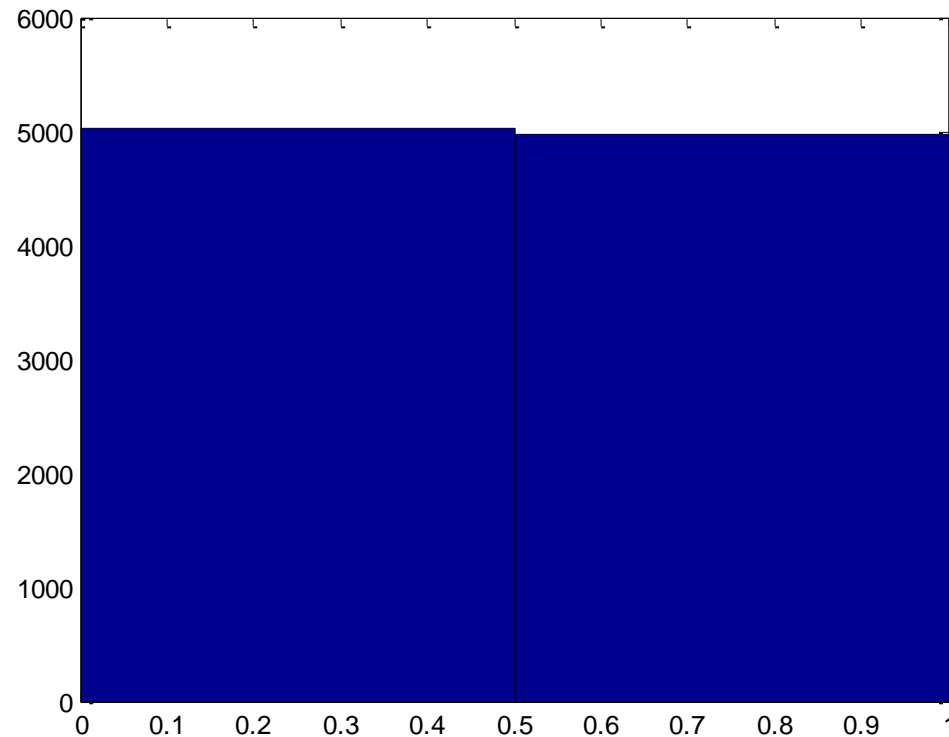
`mean(x)`

`var(x)`

`hist(x,2)`

	True	Simulated
μ	0.5	0.4971
σ^2	0.25	0.2500

Can also find and plot ECDF.



Discrete Distributions

Binomial:

For the Bernoulli distribution, $P(X = x | p) = p^x (1 - p)^{1-x}$.

Let $X_1 \sim \text{Bernoulli}(p)$ and $X_2 \sim \text{Bernoulli}(p)$,

Define $X = X_1 + X_2$. i.e. $X = \text{total number of successes}$

The distribution of X is binomial(2, p).

This can be repeated to get binomial(n , p).

Discrete Distributions

Binomial:

A random variable x has a discrete binomial distribution, $x \sim \text{binomial}(n, p)$ if

$$P(X = x | n, p) = \frac{n!}{\underbrace{x!(n-x)!}_{n(x \text{ successes})}} \underbrace{p^x (1-p)^{n-x}}_{P(x \text{ successes and } n-x \text{ failures})}$$

where, $0 \leq p \leq 1$, $n = 1, 2, 3, \dots$, $x = 0, 1, \dots, n$.

n = number of trials or times we repeat the experiment.

x = the number of successes out of n trials.

p = the probability of success on an individual trial.

Discrete Distributions

Binomial:

It can be shown that

$$\begin{aligned}\mu &= \sum_{j=1}^{\infty} x_j P(X = x_j) \\ &= \sum_{x=0}^n x \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x} \\ &= np\end{aligned}$$

Discrete Distributions

Binomial:

that

$$\begin{aligned}\sigma^2 &= \sum_{j=1}^{\infty} (x_j - \mu)^2 P(X = x_j) \\ &= \sum_{x=0}^n (x - np)^2 \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x} \\ &= np(1-p)\end{aligned}$$

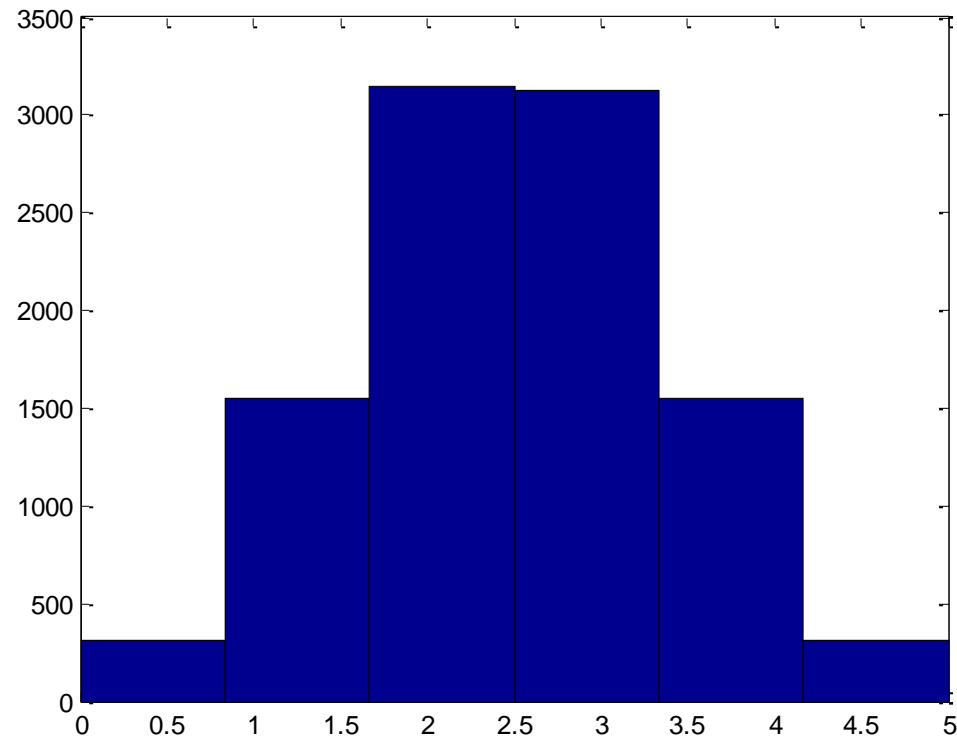
Discrete Distributions

Binomial:
$$P(X = x | n, p) = \frac{n!}{x!(n-x)!} p^x (1-p)^{n-x}$$

```
n=5; p=1/2; num=10^4;
x=binornd (n,p,num,1);
mean(x)
var(x)
hist(x,6)
```

	True	Simulated
μ	2.5	2.4982
σ^2	1.25	1.2455

Can also find and plot ECDF.



Discrete Distributions

Poisson:

A random variable x has a discrete Poisson distribution, $x \sim \text{Poisson}(\lambda)$ if

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

where, $\lambda > 0$, $x = 0, 1, \dots$.

λ is called the intensity parameter

Discrete Distributions

Poisson:

It can be shown that

$$\begin{aligned}\mu &= \sum_{j=1}^{\infty} x_j P(X = x_j) \\ &= \sum_{x=0}^{\infty} x \frac{\lambda^x e^{-\lambda}}{x!} \\ &= \lambda\end{aligned}$$

Discrete Distributions

Poisson:

that

$$\begin{aligned}\sigma^2 &= \sum_{j=1}^{\infty} (x_j - \mu)^2 P(X = x_j) \\ &= \sum_{x=0}^{\infty} (x - \lambda)^2 \frac{\lambda^x e^{-\lambda}}{x!} \\ &= \lambda\end{aligned}$$

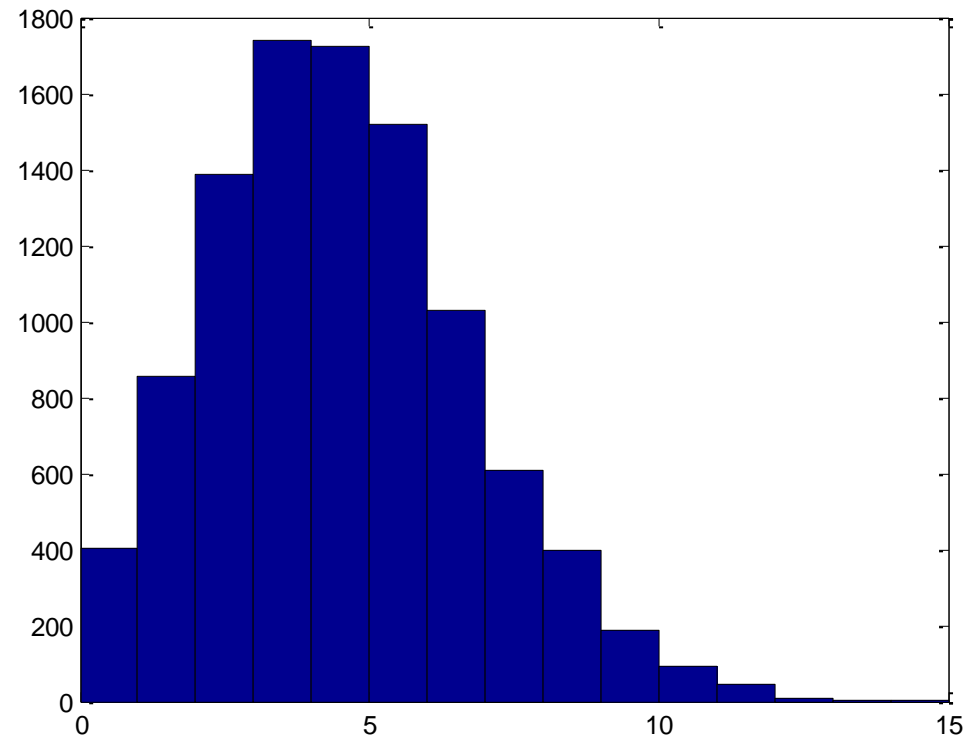
Discrete Distributions

Poisson:
$$P(X = x | \lambda) = \frac{\lambda^x e^{-\lambda}}{x!}$$

```
lam=5;num=10^4;
x=poissrnd(lam,num,1);
mean(x)
var(x)
hist(x,15)
```

	True	Simulated
μ	5	5.0181
σ^2	5	5.1069

Can also find and plot ECDF.



Discrete Distributions

Geometric:

A random variable x has a discrete geometric distribution, $x \sim \text{geometric}(p)$ if

$$P(X = x | p) = p(1 - p)^{x-1}$$

where, $0 \leq p \leq 1$, $x = 1, 2, \dots$.

x = the trial at which first successes occurs.

p = the probability of success on the trial.

Discrete Distributions

Geometric:

It can be shown that

$$\begin{aligned}\mu &= \sum_{j=1}^{\infty} x_j P(X = x_j) \\ &= \sum_{x=1}^{\infty} xp(1-p)^{x-1} \\ &= \frac{1}{p}\end{aligned}$$

$$q = (1 - p)$$

Discrete Distributions

Geometric:

that

$$\begin{aligned}\sigma^2 &= \sum_{j=1}^{\infty} (x_j - \mu)^2 P(X = x_j) \\ &= \sum_{x=1}^{\infty} \left(x - \frac{1}{p}\right)^2 p(1-p)^{x-1} \\ &= \frac{q}{p^2}\end{aligned}$$

$$q = (1 - p)$$

Discrete Distributions

Geometric:

$$P(X = x | p) = p(1 - p)^{x-1}$$

`p=1/2; num=10^4;`

`x= geornd(p,num,1)+1;`

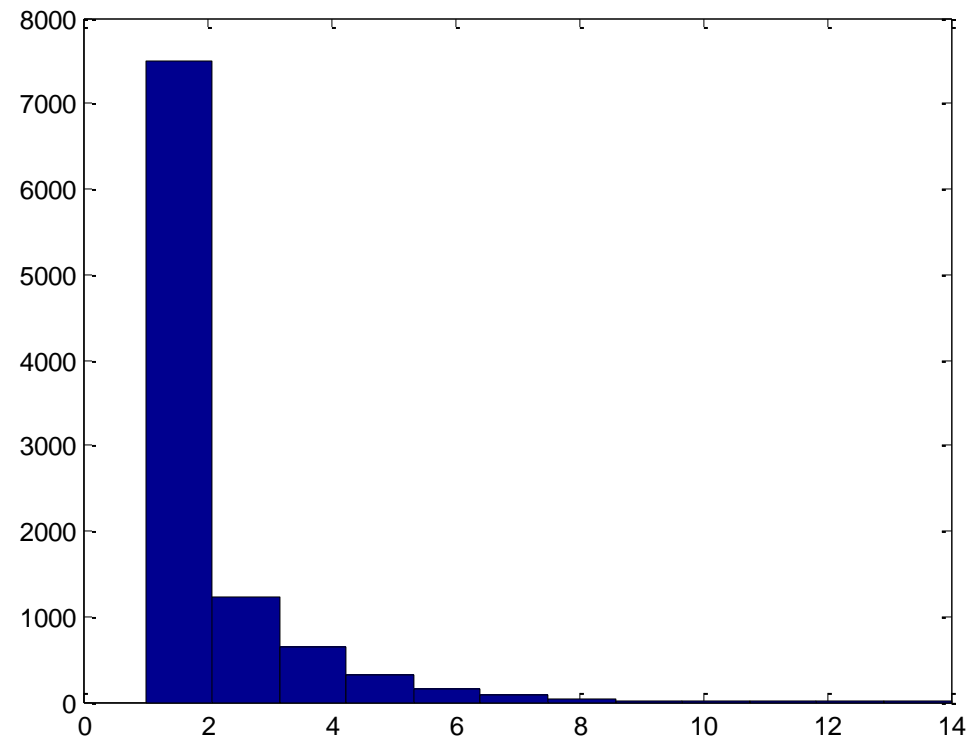
`mean(x)`

`var(x)`

`hist(x,12)`

	True	Simulated
μ	2	1.9994
σ^2	2	2.0358

Can also find and plot ECDF.



Homework 2:

- 1) Generate 10^6 observations from the discrete uniform, Bernoulli, binomial, Poisson, and geometric distributions. Use the parameter values I used.

Make a histogram. Compute sample mean and variance. Compare to what true values are.

Compute an empirical CDF and find 50th percentile.

Compute and plot an incremental sample mean and variance. When do you think you get convergence?