

# Poisson Distribution

## What is the Poisson Distribution for?

To predict the # of events that may occur in an interval.

Suppose you run an Internet shopping mall.

How many people will visit my shopping mall website per hour, day, week, etc.?

How many of them will actually purchase items from my mall in a week?

How many of them will return their purchased items within a month?

How many of those purchased customers will post review within a month?

# Convenience of Poisson Distribution!

The only parameter of the Poisson distribution is the rate  $\lambda$ , the expected value of  $X$ .

The probability of observing  $k$  events in an interval is:

$$P(k \text{ events in interval}) = e^{-\lambda} \frac{\lambda^k}{k!}$$



where

- $\lambda$  is the average number of events per interval
- $e$  is the number 2.71828... (**Euler's number**) the base of the natural logarithms
- $k$  takes values 0, 1, 2, ...

Variance is also  $\lambda$ .

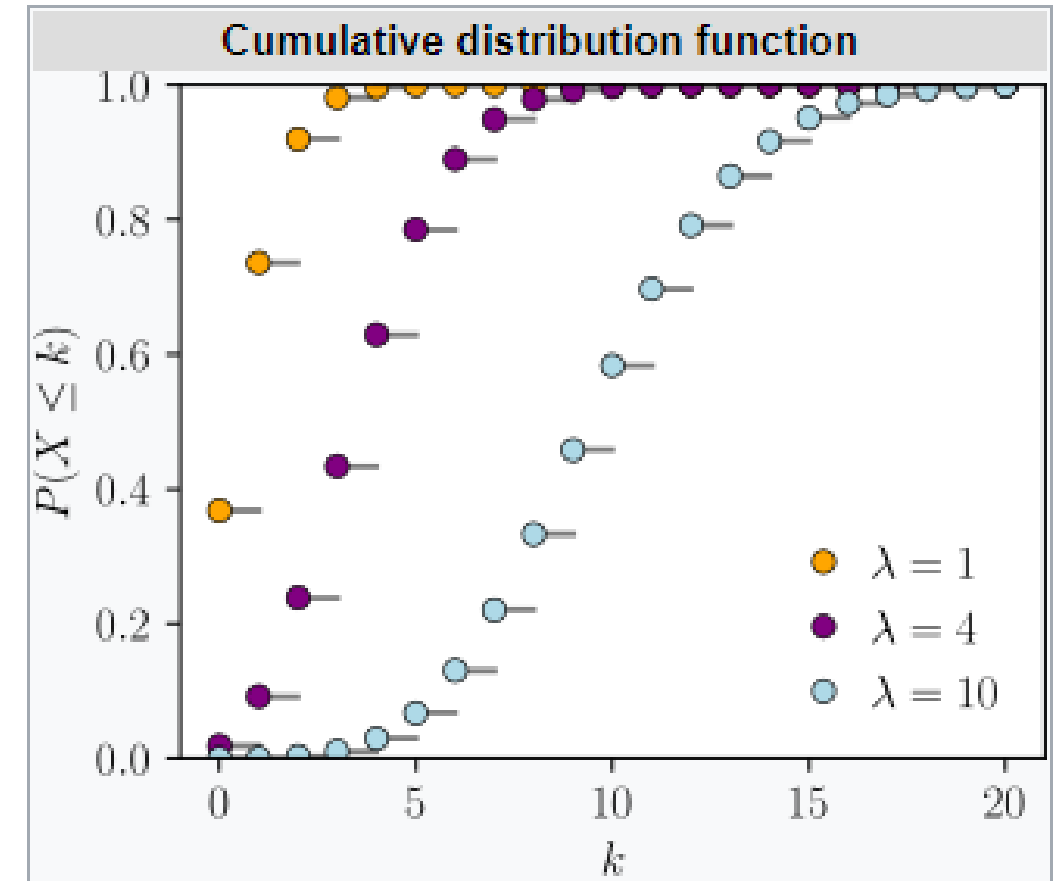
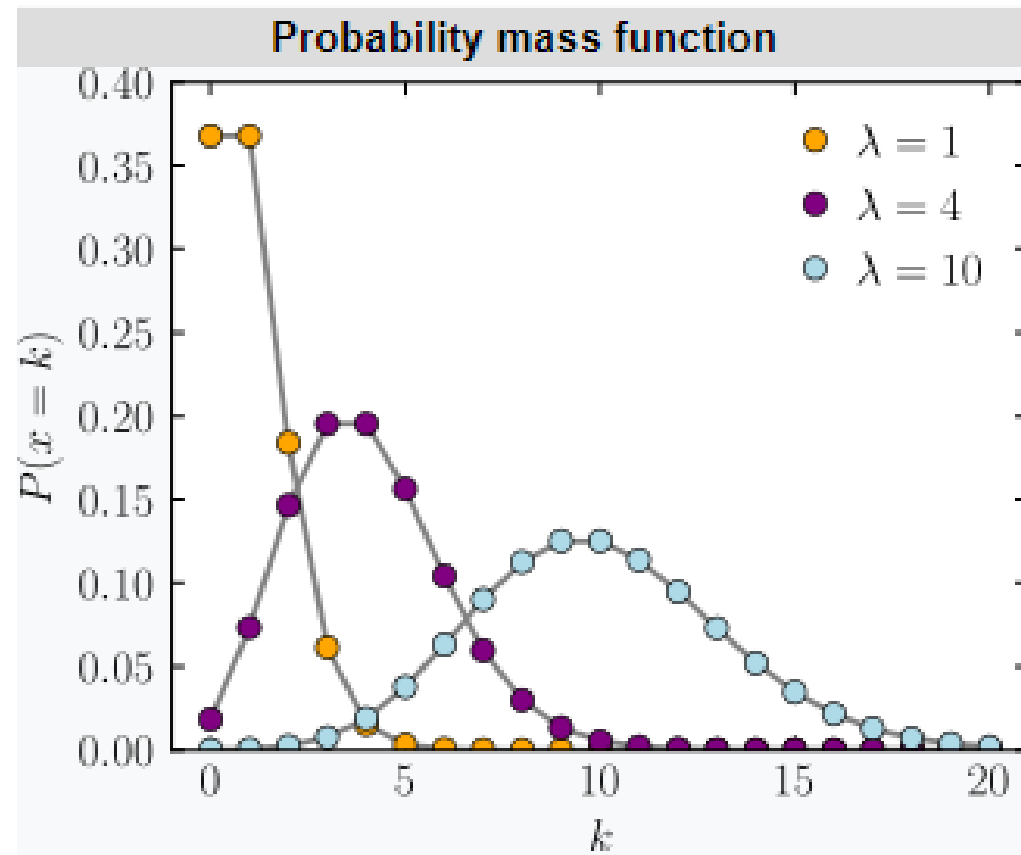
# Poisson distribution typically is to model rare events.



The rate parameter  $\lambda$  modeling rare events can be any number -- it does not have to be a small number.

The Poisson Distribution is asymmetric — it is always skewed toward the right. Because it is inhibited by the zero occurrence barrier (there is no “minus” number of events) on the left and it is unlimited on the other side.

As  $\lambda$  becomes bigger, the graph looks more like a normal distribution.



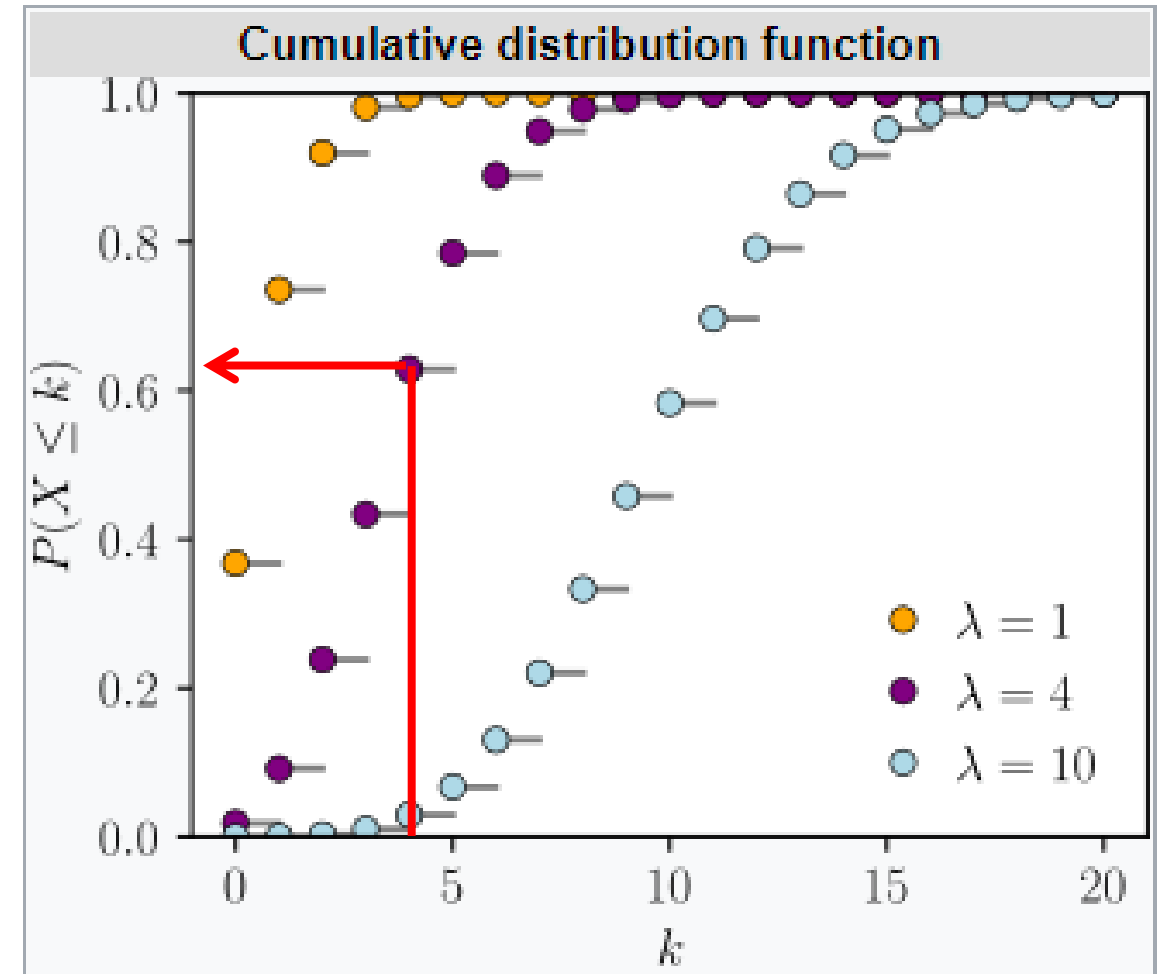
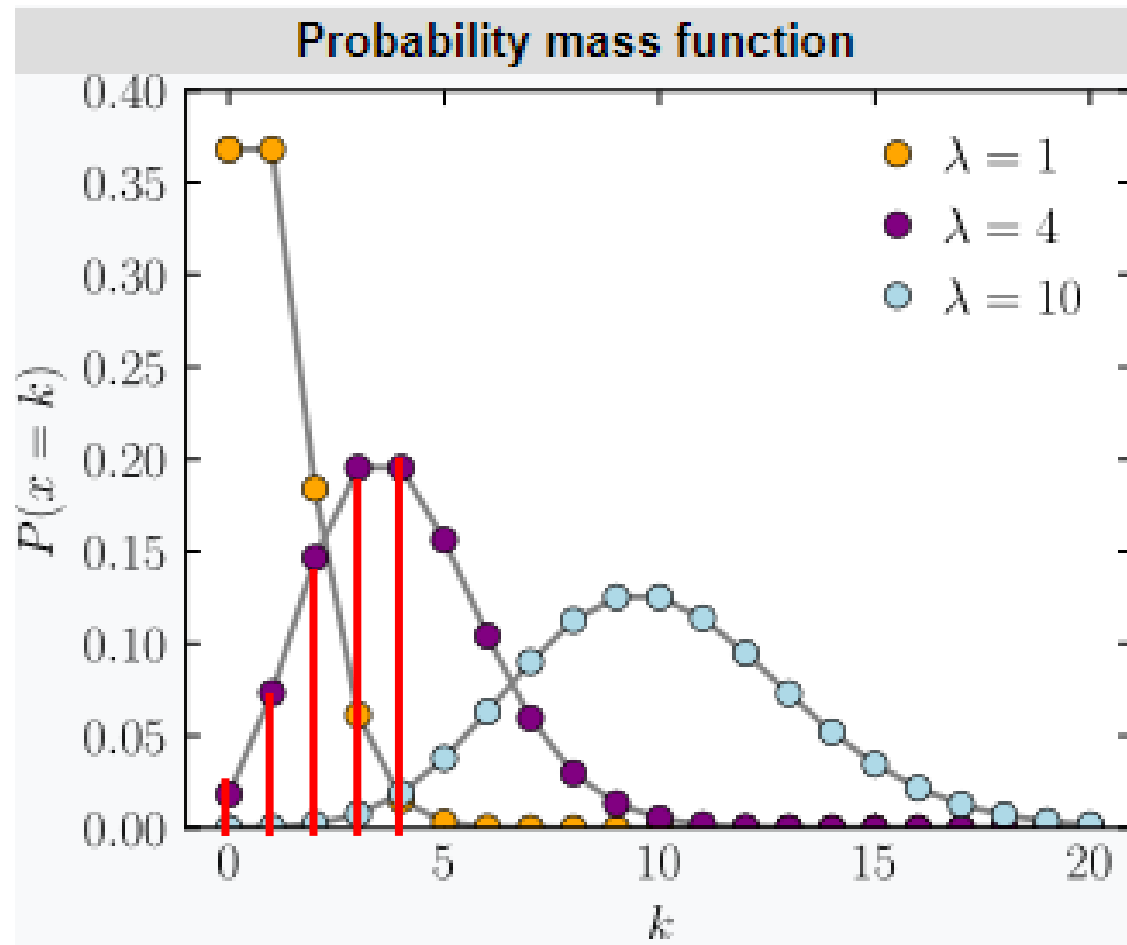
# Poisson distribution typically is to model rare events.



Let  $\lambda = 4$  be the number of houses a real estate agent Sue can sell per months.

Show value!

What would be the probability that Sue can indeed sell four houses next month?



Assume \$4,000 commission per house sold. What is the probability that Sue makes \$16,000 next months?

# Poisson Distribution

```
import numpy as np
from scipy.stats import poisson
import matplotlib.pyplot as plt
```

```
fig, ax = plt.subplots(1, 1)
```

```
mu = 4 # mean - lambda; variance is also lambda.
mean, var, skew, kurt = poisson.stats(mu, moments='mvsk')
x = np.arange(poisson.ppf(0.001, mu),
              poisson.ppf(0.999, mu))
```

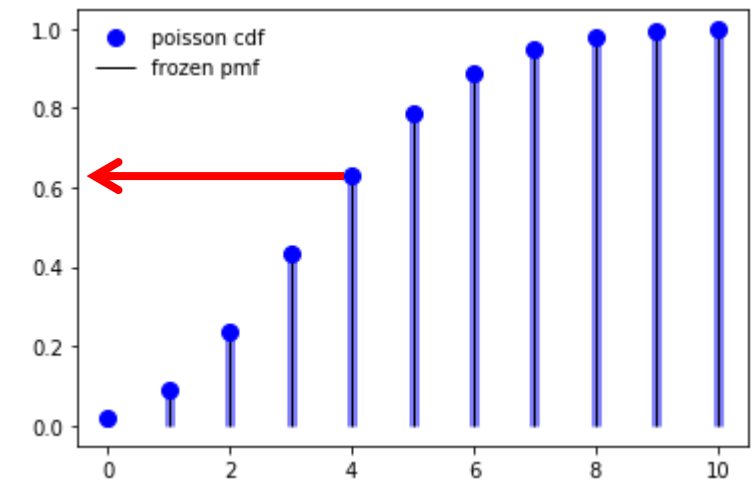
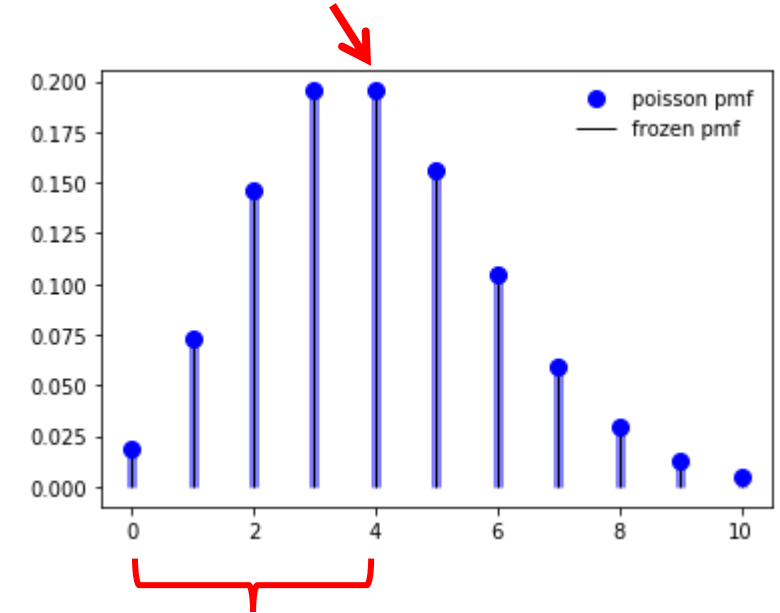
```
ax.plot(x, poisson.pmf(x, mu), 'bo', ms=8, label='poisson pmf')
ax.vlines(x, 0, poisson.pmf(x, mu), colors='b', lw=5, alpha=0.5)
rv = poisson(mu)
ax.vlines(x, 0, rv.pmf(x), colors='k', linestyle='-', lw=1,
          label='frozen pmf')
```

```
ax.legend(loc='best', frameon=False)
plt.show()
```

```
poisson.cdf(4, mu)
0.6288369351798734
```

If you change **pmf** to **cdf** →

```
poisson.pmf(4, mu)
0.19536681481316454
```



# Gamma ( $\Gamma$ ) Distribution

## Clarifying two different parameterization sets — $(k, \theta)$ or $(\alpha, \beta)$

For  $(k, \theta)$  parameterization:  $\theta$  is a reciprocal of the event rate  $\lambda$ , which is the mean wait time (the average time between event arrivals).

$$\theta = 1/\lambda$$

For  $(\alpha, \beta)$  parameterization: Substitute  $k$  (the # of events) with  $\alpha$  and  $\lambda$  (the rate of events) with  $\beta$ .  $\beta = \lambda$

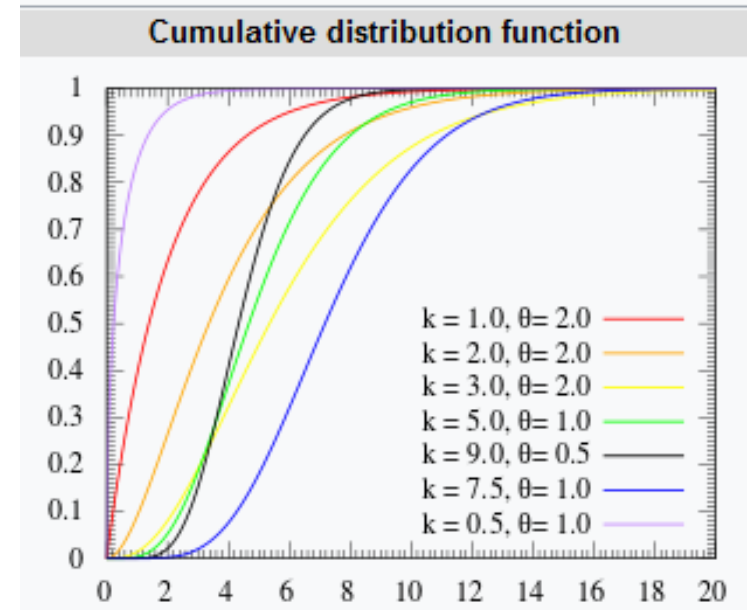
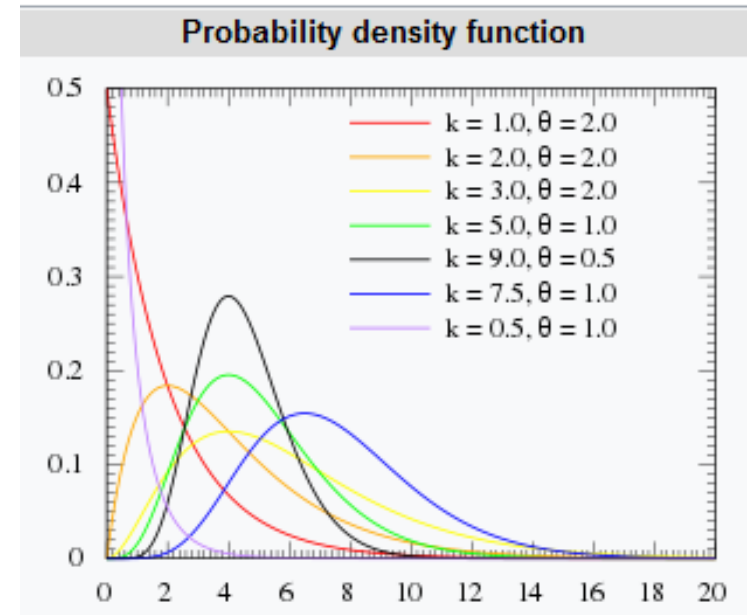
# Gamma ( $\Gamma$ ) Distribution



<b>Parameters</b>	<ul style="list-style-type: none"> <li>• <math>k &gt; 0</math> shape</li> <li>• <math>\theta &gt; 0</math> scale</li> </ul>	<ul style="list-style-type: none"> <li>• <math>\alpha &gt; 0</math> shape</li> <li>• <math>\beta &gt; 0</math> rate</li> </ul>
<b>Support</b>	$x \in (0, \infty)$	$x \in (0, \infty)$
<b>PDF</b>	$f(x) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-\frac{x}{\theta}}$	$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$
<b>CDF</b>	$F(x) = \frac{1}{\Gamma(k)} \gamma\left(k, \frac{x}{\theta}\right)$	$F(x) = \frac{1}{\Gamma(\alpha)} \gamma(\alpha, \beta x)$
<b>Mean</b>	$k\theta$	$\frac{\alpha}{\beta}$
<b>Median</b>	No simple closed form	No simple closed form
<b>Mode</b>	$(k - 1)\theta$ for $k \geq 1$	$\frac{\alpha - 1}{\beta}$ for $\alpha \geq 1$
<b>Variance</b>	$k\theta^2$	$\frac{\alpha}{\beta^2}$

$$\alpha = k$$

$$\beta = 1/\theta$$

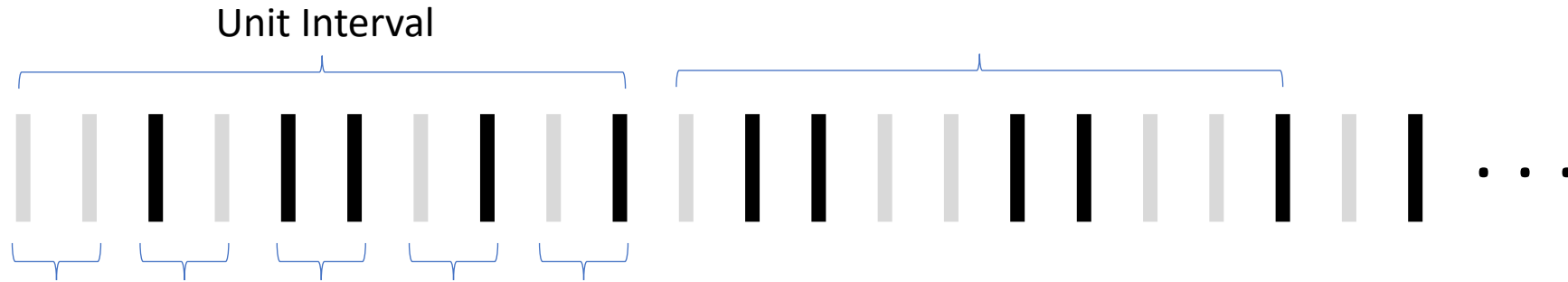


# # of event occurrences & Rate of event occurrence

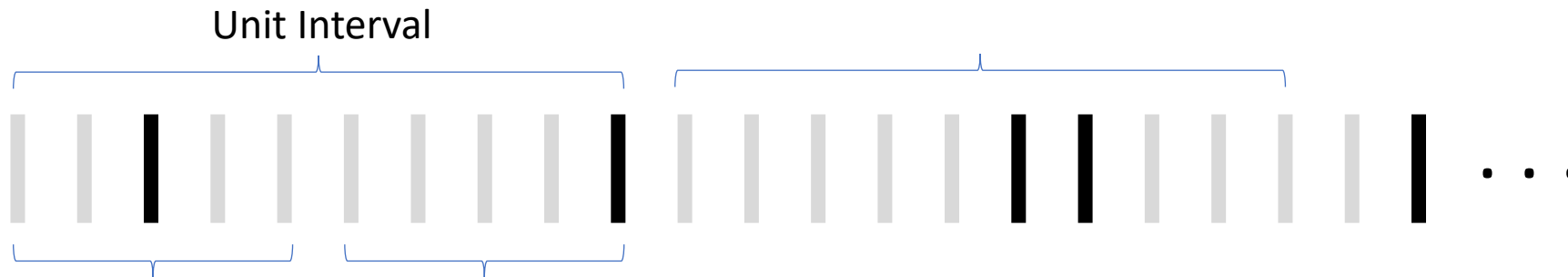


## What is this **Gamma ( $\Gamma$ ) Distribution** for?

To predict the wait time until future events, specifically until the “k-th” event occurs.



$\lambda = 5 \rightarrow$  reciprocal  $\theta = 1/5 = 0.2$  (every 0.2 interval the event occurs).



$\lambda = 2 \rightarrow$  reciprocal  $\theta = 1/2 = 0.5$  (every 0.5 interval the event occurs).



# Time for k-th event to occur

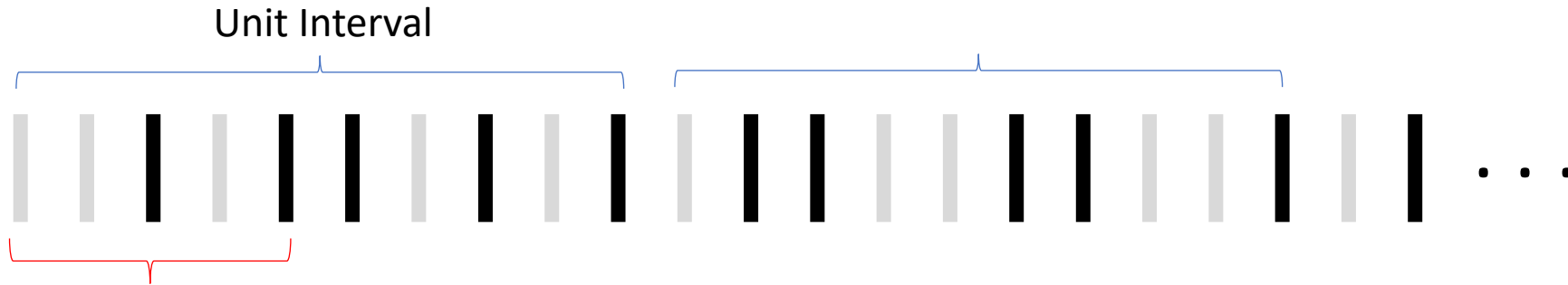


To predict the wait time until future events, specifically until the “k-th” event occurs.

Assume Sue and John are two real estate agents. Sue is selling houses faster than John. Assume 10 showings per month in each case with “**Sell**” and “**No-sell**”.

Sue

$\lambda = 5$ , or  
 $1/\lambda = 0.2$



$k = 1 \rightarrow$  After 3 trials.

$k = 2 \rightarrow$  After 5 trials.

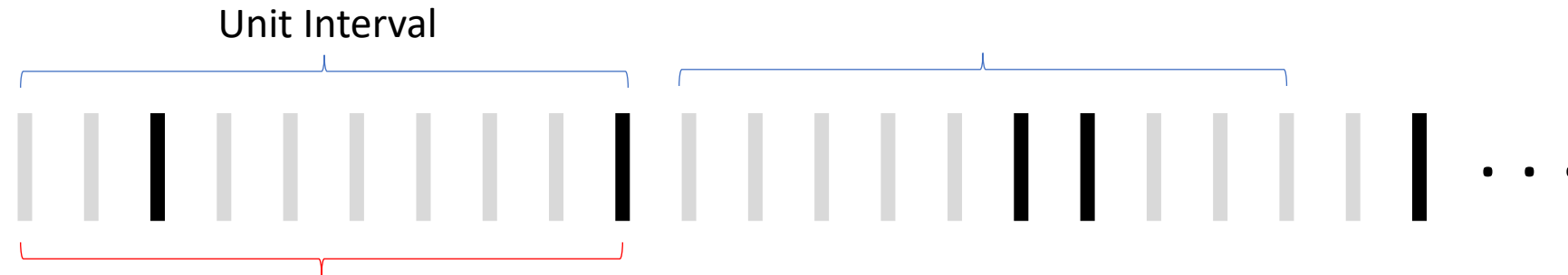
$k = 1 \rightarrow$  After ? trials.

$k = 2 \rightarrow$  After ? trials.

On average, how many trials for Sue to sell 2 houses? Translate that trials into portion of unit time?

John

$\lambda = 2$ , or  
 $1/\lambda = 0.5$



$k = 1 \rightarrow$  After 3 trials.

$k = 2 \rightarrow$  After 10 trials.

$k = 1 \rightarrow$  After ? trials.

$k = 2 \rightarrow$  After ? trials.

On average, how many trials for Sue to sell 2 houses? Translate that trials into portion of unit time?

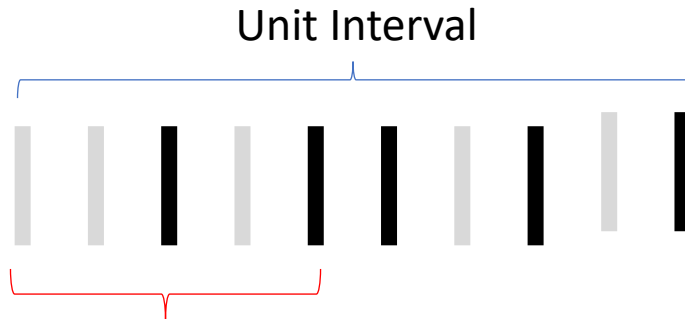
# Time for k-th event to occur



How long should Sue and John wait, respectively, to sell their respective two houses?

Sue

$\lambda = 5$ , or  
 $1/\lambda = 0.2$

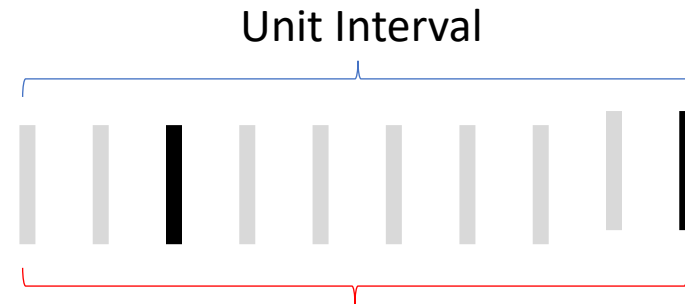


$k = 1 \rightarrow$  After 3 trials.

$k = 2 \rightarrow$  After 5 trials.

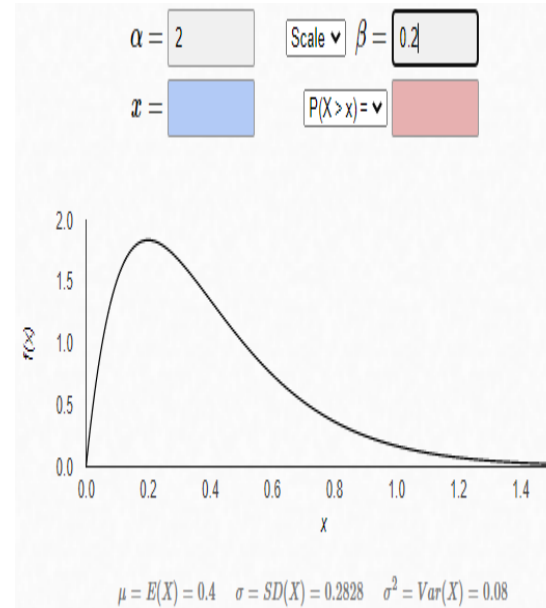
John

$\lambda = 2$ , or  
 $1/\lambda = 0.5$

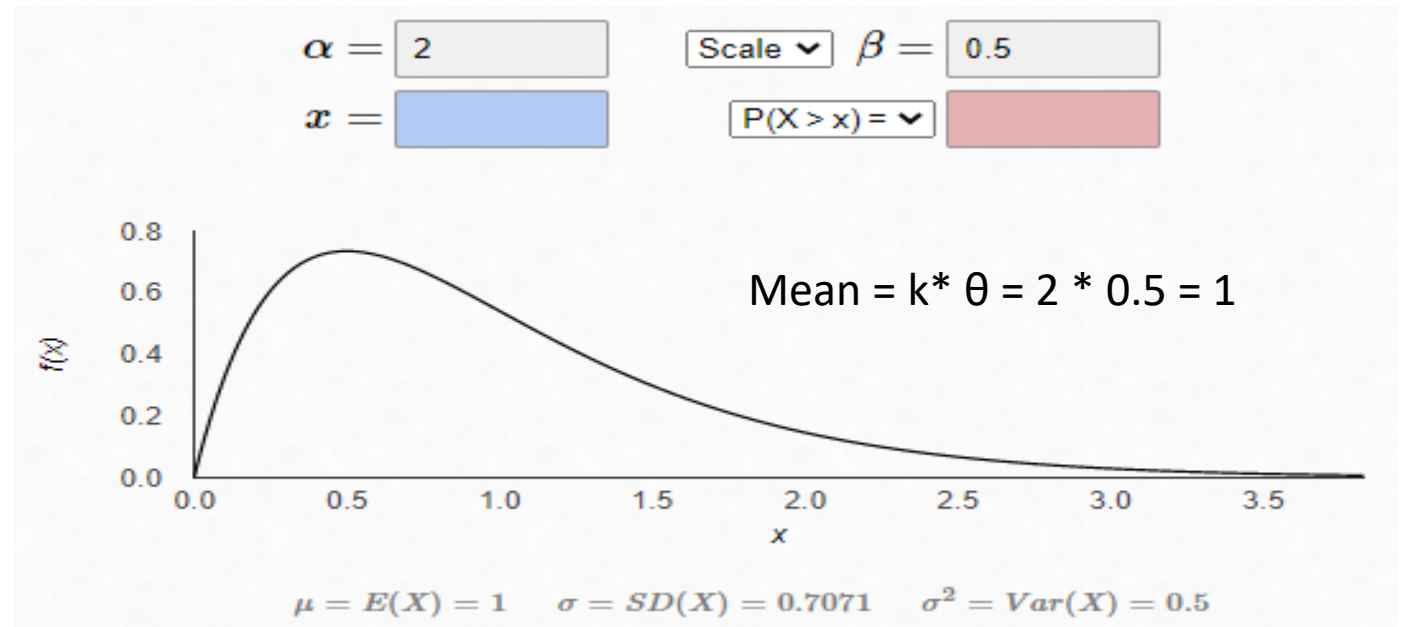


$k = 1 \rightarrow$  After 3 trials.

$k = 2 \rightarrow$  After 10 trials.



Mean =  $k * \theta = 2 * 0.2 = 0.4$



Mean =  $k * \theta = 2 * 0.5 = 1$

```
import numpy as np
from scipy.stats import gamma
import matplotlib.pyplot as plt
```

```
def plot_gamma_lambda():
```

```
    """
```

```
    k : the number of events waiting to occur.
```

```
    λ : the rate of events happening following Poisson D.
```

```
    """
```

```
    a = 2 # k = 2
```

```
    x = np.linspace(0, 50, 1000)
```

```
    lambda_ = 2
```

```
    mean, var, skew, kurt = gamma.stats(a, scale=1/lambda_, moments='mvsk')
```

```
    y1 = gamma.pdf(x, a, scale=1/lambda_)
```

```
    lambda_ = 5
```

```
    mean, var, skew, kurt = gamma.stats(a, scale=1/lambda_, moments='mvsk')
```

```
    y2 = gamma.pdf(x, a, scale=1/lambda_)
```

```
        plt.title("PDF of Gamma Distribution (k = 2)")
```

```
    plt.xlabel("T")
```

```
    plt.ylabel("Probability Density")
```

```
    plt.plot(x, y1, label="λ = 2", color='black')
```

```
    plt.plot(x, y2, label="λ = 5", color='burlywood')
```

```
    plt.legend(bbox_to_anchor=(1, 1), loc='upper right', borderaxespad=1, fontsize=12)
```

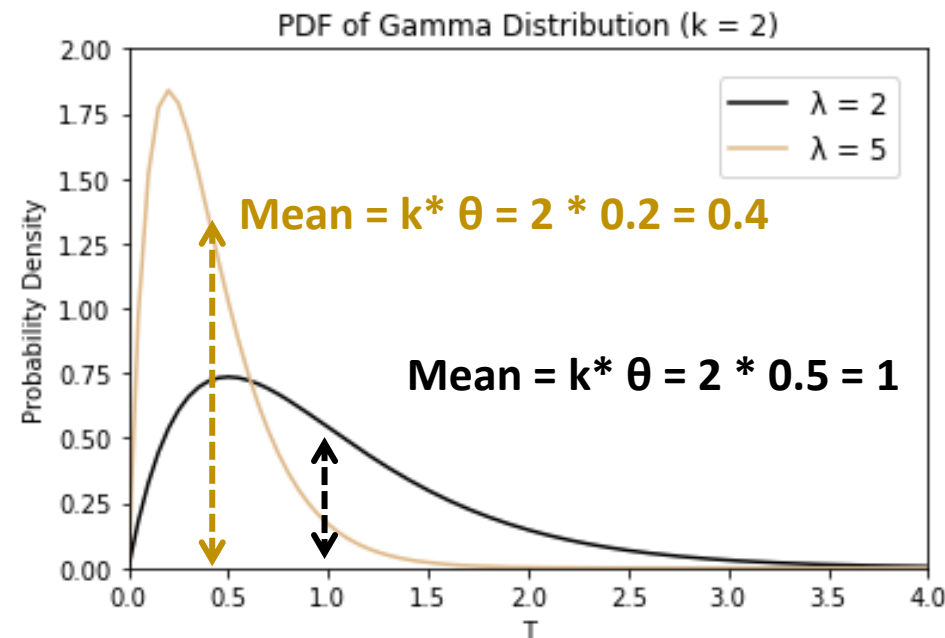
```
    plt.ylim([0, 2.0])
```

```
    plt.xlim([0, 4.0])
```

```
plot_gamma_lambda()
```

**Sue:**

**Wait 0.4 month.**



**John:**

**Wait 1 month.**

# Gamma ( $\Gamma$ ) Distribution

Gamma distribution is a distribution that arises naturally in processes for which **the waiting times between events are relevant**. It can be thought of as **“a waiting time”** between Poisson distributed events.

**Example** Suppose you are fishing and you expect to get a fish once every 1/2 hour. Compute the probability that you will have to **wait between 2 to 4 hours** before you catch **4 fish**. **Two fishes per hour!**

One fish every 1/2 hour  $\rightarrow \theta = 1 / 0.5 = 2$  fish every hour on average.

Using  $\theta = 2$  and  $k = 4$ , we can compute this as follows:

$$P(2 \leq X \leq 4) = \sum_{x=2}^4 \frac{x^{4-1} e^{-x/2}}{\Gamma(4) 2^4} = 0.12388$$

PDF	$f(x) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} e^{-\frac{x}{\theta}}$	$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$
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$$P(X > 2) = 0.98101$$

$$P(X > 4) = 0.85712$$

$$P(4 > X > 2) = 0.98101 - 0.85712 = 0.12389$$

