

This Week

Monday

- Modeling and Simulating Uncertainty;
Lab Exercise: RV Modeling and Simulation

Wednesday

- NO CLASS

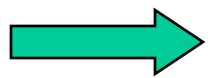
Topics

- **Characterizing Uncertainty**
- **Probability Functions in Excel**
- **Generating Random Variables in Excel**

A Problem Solving Framework

1. Define the Problem

2. Collect and Organize Data



3. Characterize Uncertainty and Data Relationships



4. Build an Evaluation Model

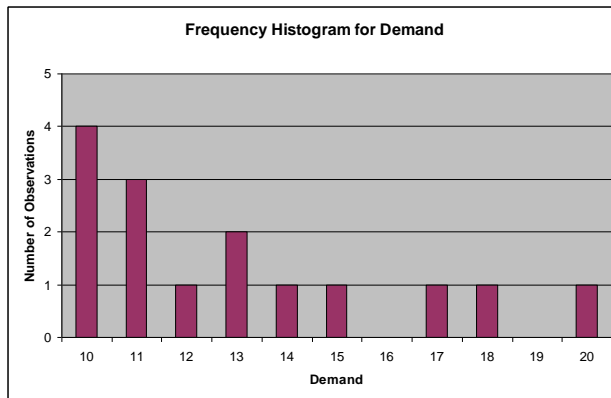
5. Formulate a Solution Approach

6. Evaluate Potential Solutions

7. Recommend a Course of Action

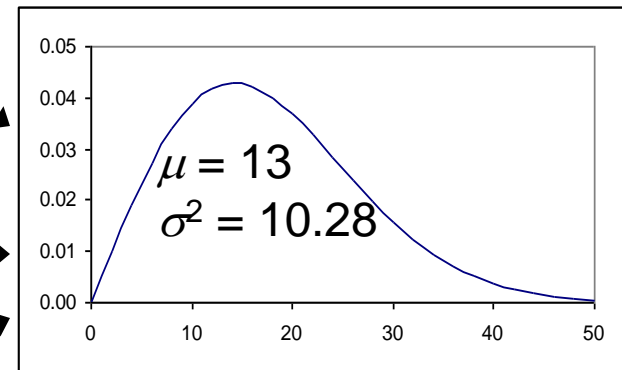
A Problem Solving Framework

3. *Characterize uncertainty for modeling purposes* by choosing specific probability functions or processes to represent sources of uncertainty within the context of the modeling framework:



$$\bar{X} = 13, s^2 = 10.28$$

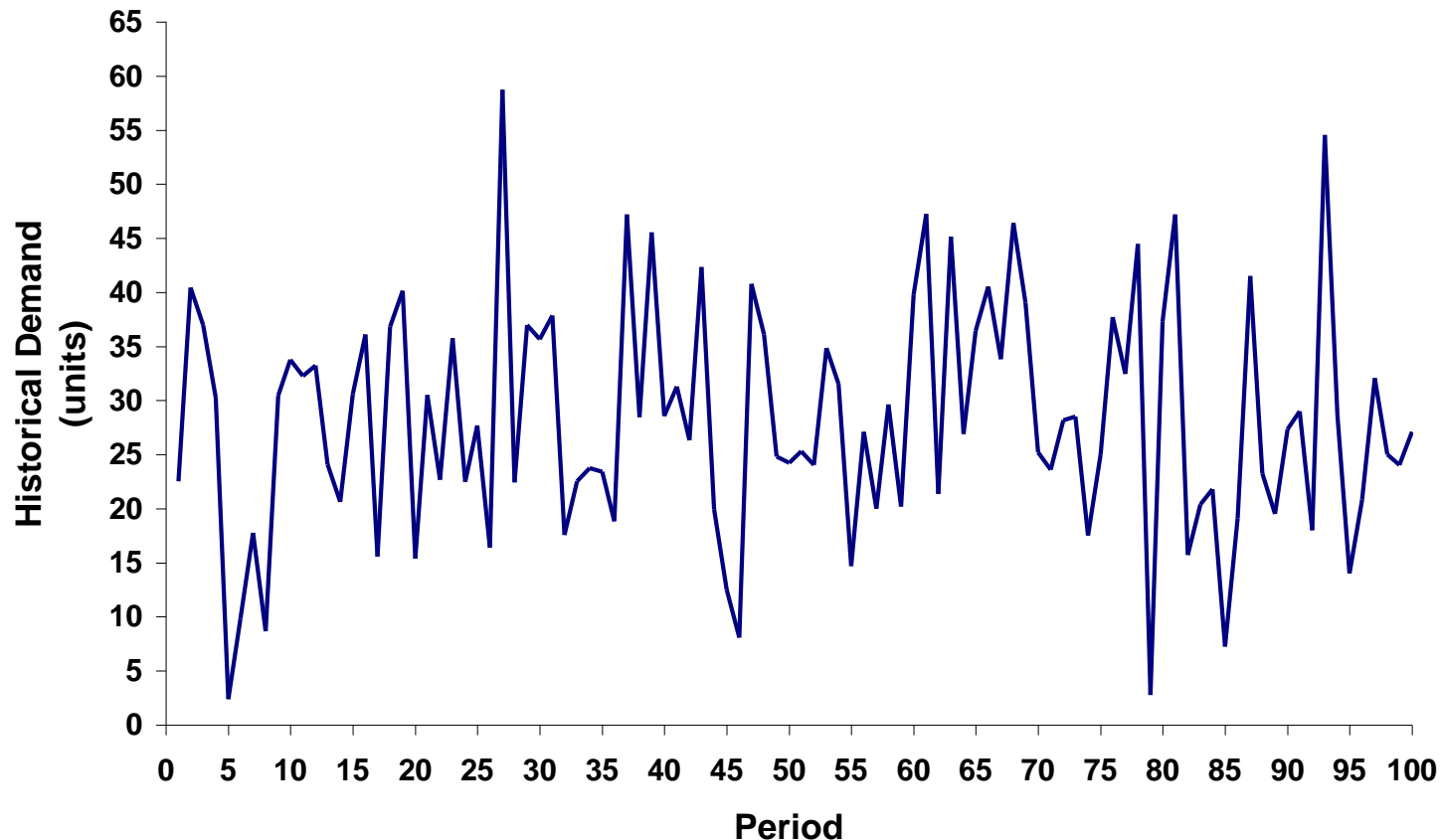
**Problem Definition
and Parameters**



Example: Demand Planning

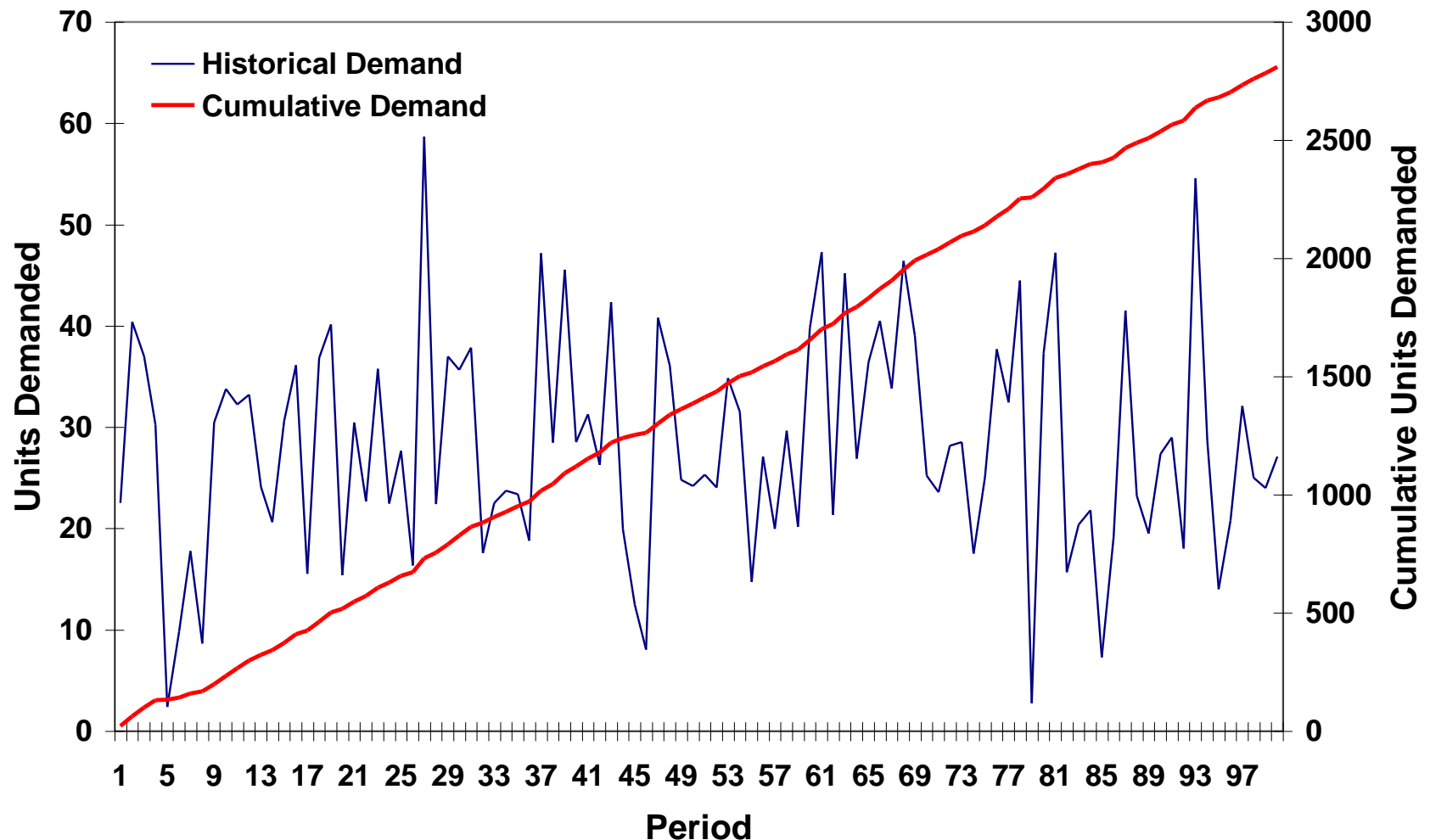
How can we characterize the uncertainty associated with future demand?

Demand Time Series



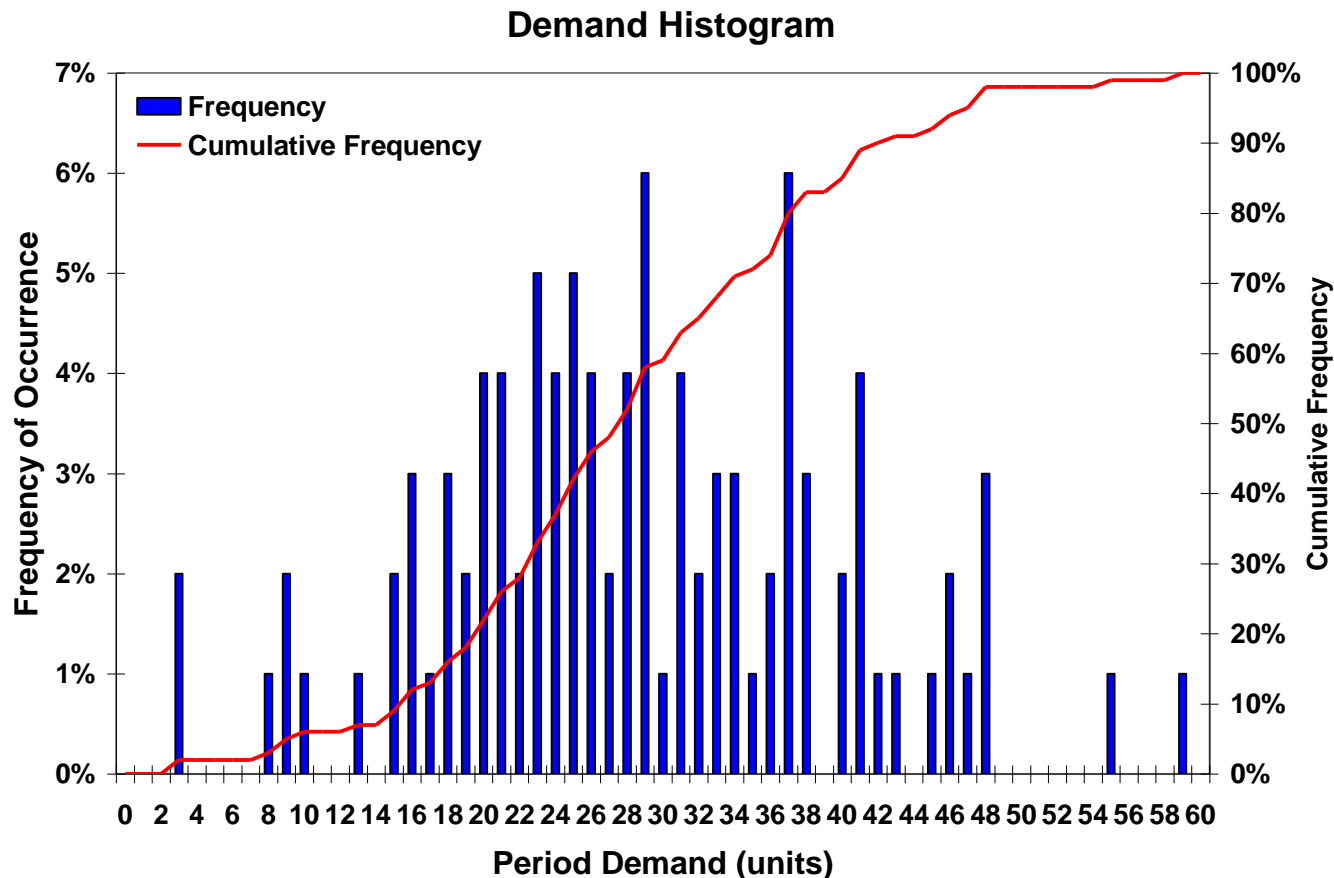
Cumulative View of Historical Demand

Demand Time Series



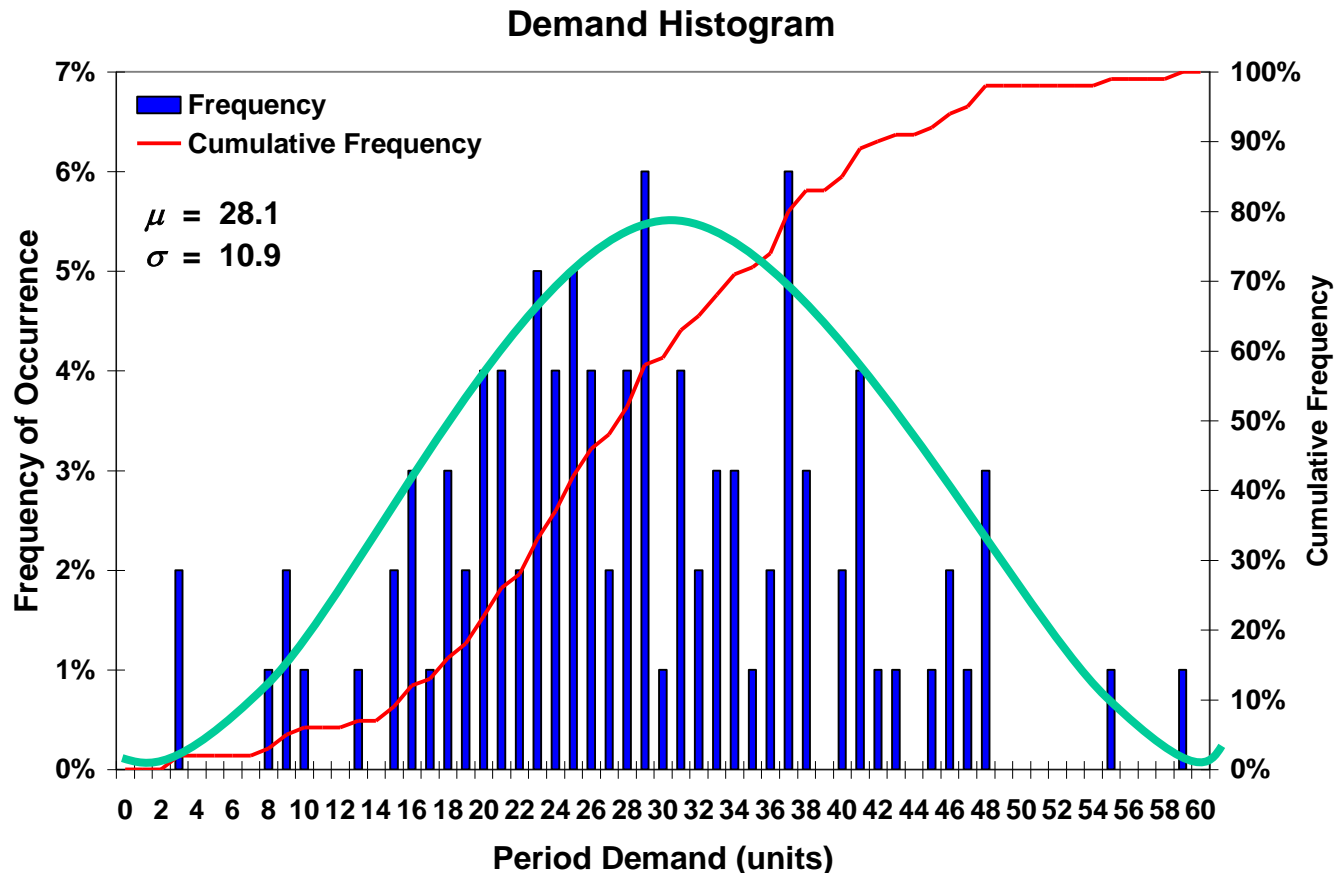
Characterizing Demand Uncertainty

One option: Using some number of past periods, construct a *frequency histogram* and use these frequencies to represent the probability function for future demand.



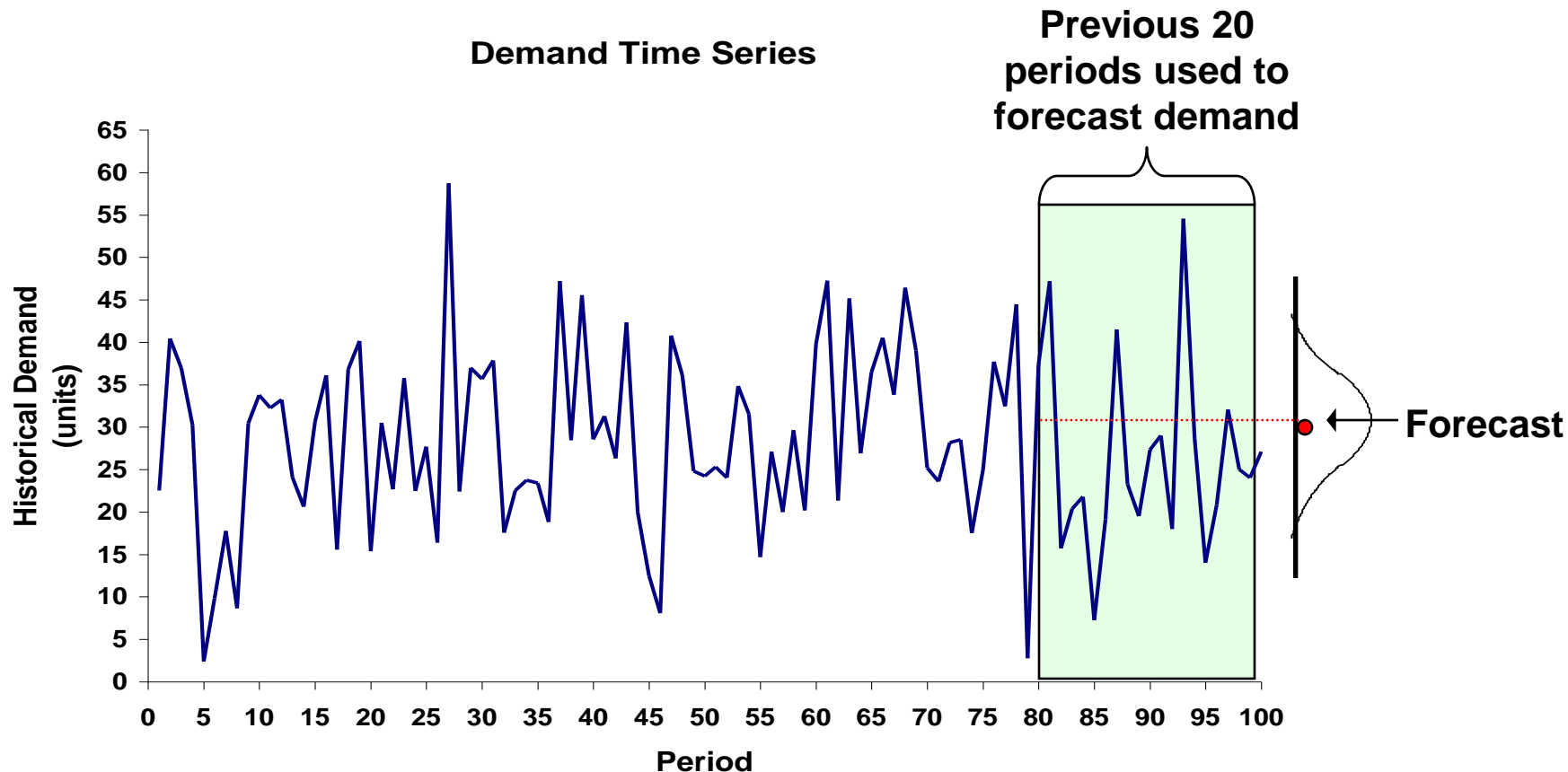
Characterizing Demand Uncertainty

Another option: Use a *well-defined probability function* whose shape resembles the frequency histogram (e.g. Normal) to represent future demand uncertainty.



Characterizing Demand Uncertainty

A third option: Use a *well-defined function* of past periods' demand to predict future demand and a *well-defined probability function* to represent the *forecast errors*.



Bottom Line on Modeling Uncertainty

- If the chosen model/function *closely resembles* the true likelihoods, then we can:
 - *Accurately assess the risk* of different events.
 - State that our conclusions and decisions are valid with a *high level of confidence*.
- If the chosen model/function *does not resemble* the true likelihoods, then:
 - Our analyses and assessment of risk may be *inaccurate*.
 - Our conclusions/decisions may be *wrong*.

Commonly Used Families of Probability Functions

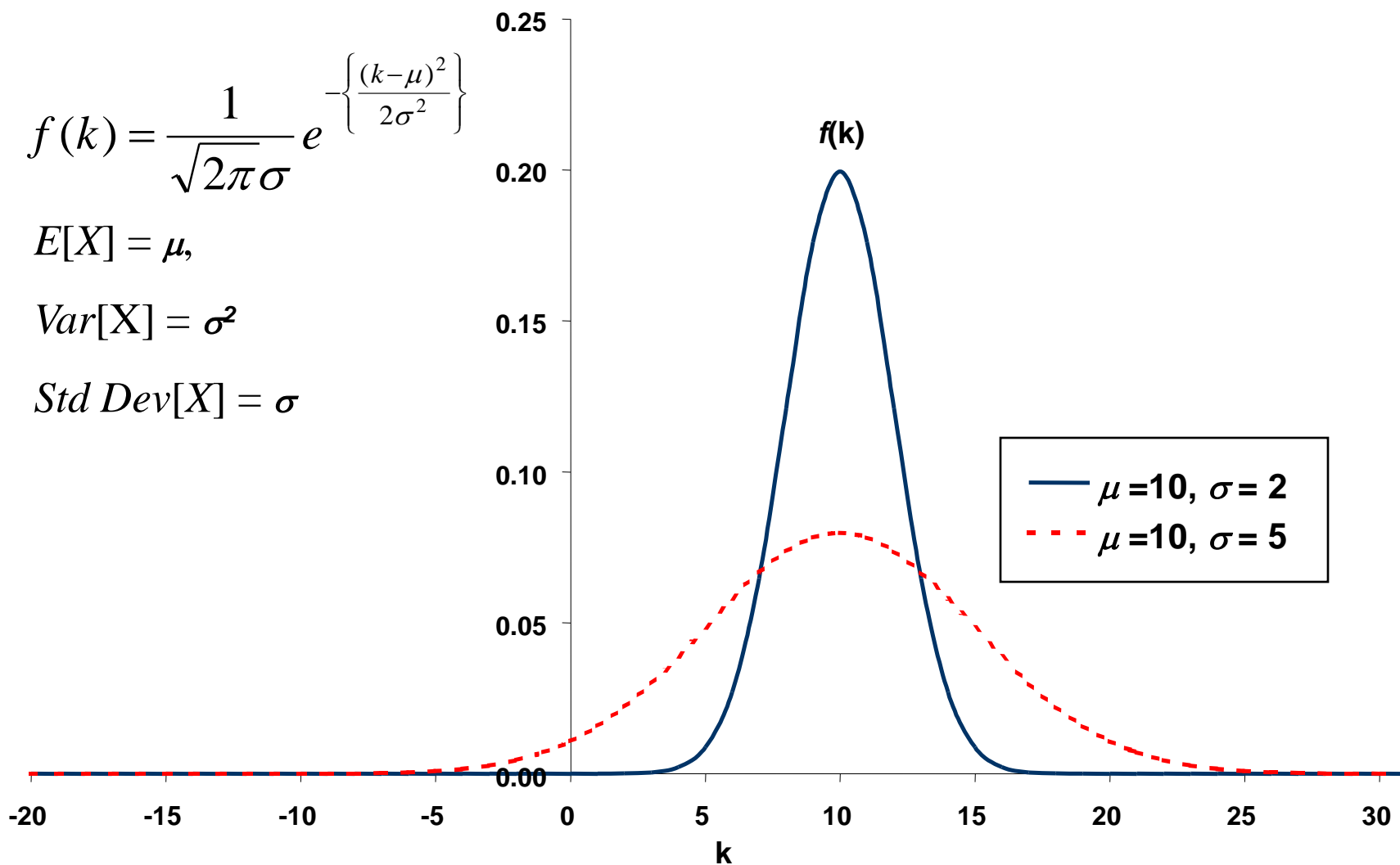
Family	Type	Range	Parameters
Normal	Continuous	$(-\infty, +\infty)$	2 (μ and σ)
Binomial	Discrete	$[0, 1, \dots, n]$	2 (n and p)
Poisson	Discrete	$[0, 1, \dots, +\infty)$	1 (λ)
Exponential	Continuous	$(0, +\infty)$	1 (λ)

Notation: $X \sim N(\mu=10, \sigma=2)$

This means that the random variable X has a normal distribution with the specified parameters.

Other Examples: $X \sim \text{Bin}(n=20, p=.05)$, $X \sim \text{Po}(\lambda=10)$, $X \sim \text{Exp}(\lambda=0.2)$

The Normal Distribution

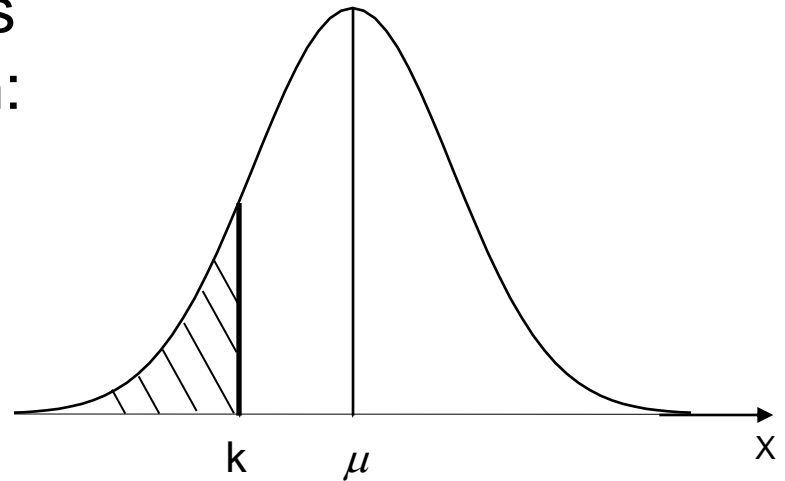


Normal Distribution in Excel

Excel has the following functions related to the normal distribution:

$$X \sim N(\mu, \sigma)$$

- **=NORM.DIST(k,μ,σ,TRUE)**
returns $P(X \leq k)$. (If last parameter is **FALSE**, then $f(k)$ is returned.)
- **=NORM.INV(percentile,μ,σ)**
returns the value k such that $P(X \leq k) = \text{percentile}$.
- **=NORM.S.DIST(k)** and **=NORM.S.INV(percentile)**
return analogous values for $Z \sim N(0, 1)$.
- **=STANDARDIZE(x,μ,σ)**
returns the standardized value $z = (x - \mu)/\sigma$.



A Decision Problem

- A management consulting firm has interviewed several candidates for entry-level positions and would like to make job offers to some of them. For logistical reasons, all job offers must be issued at the same time.
- Ideally, the firm would like to hire between 5 and 7 new people.
- Past experience has shown that on average, 80% of job offers are accepted (20% are rejected).

How many offers should the firm make to have the highest likelihood of meeting their hiring target?

The Binomial Distribution

$$f(k) = \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$

$$E[X] = np$$

$$\text{Var}[X] = np(1-p)$$

$$\text{StdDev}[X] = \sqrt{np(1-p)}$$

Used to model the total **number of successes** that occur in ***n*** trials where each trial has the same success probability ***p***.

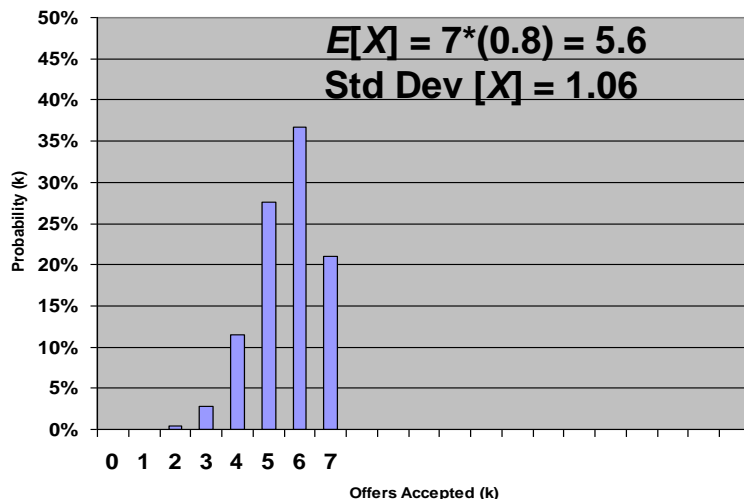
Number of Offers (*n*):

7

Probability of Acceptance (*p*):

80%

Probability Distribution of Offers Accepted



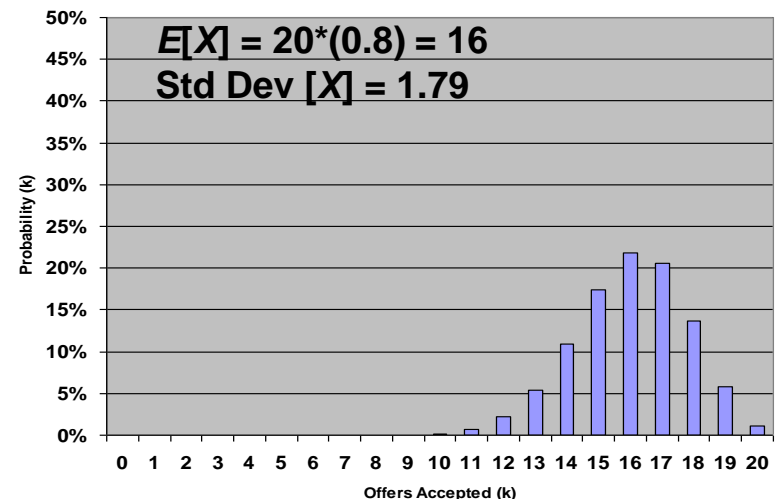
Number of Offers (*n*):

20

Probability of Acceptance (*p*):

80%

Probability Distribution of Offers Accepted

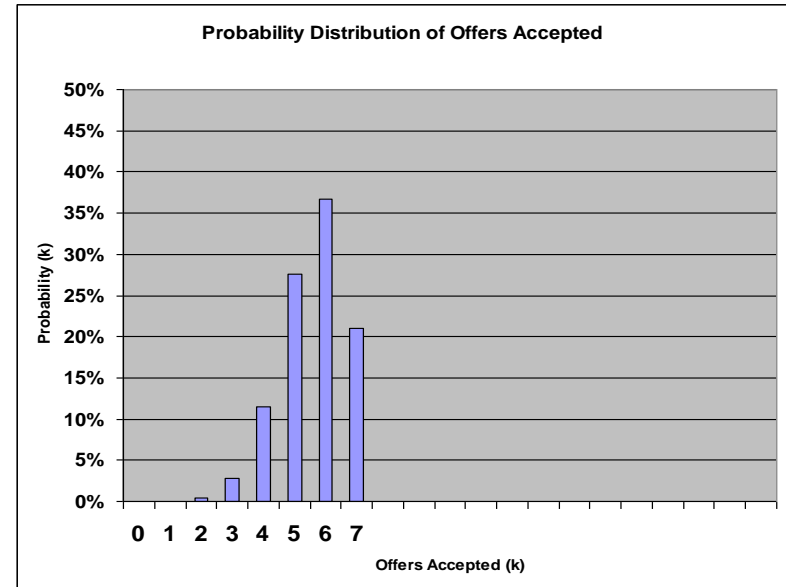


Binomial Distribution in Excel

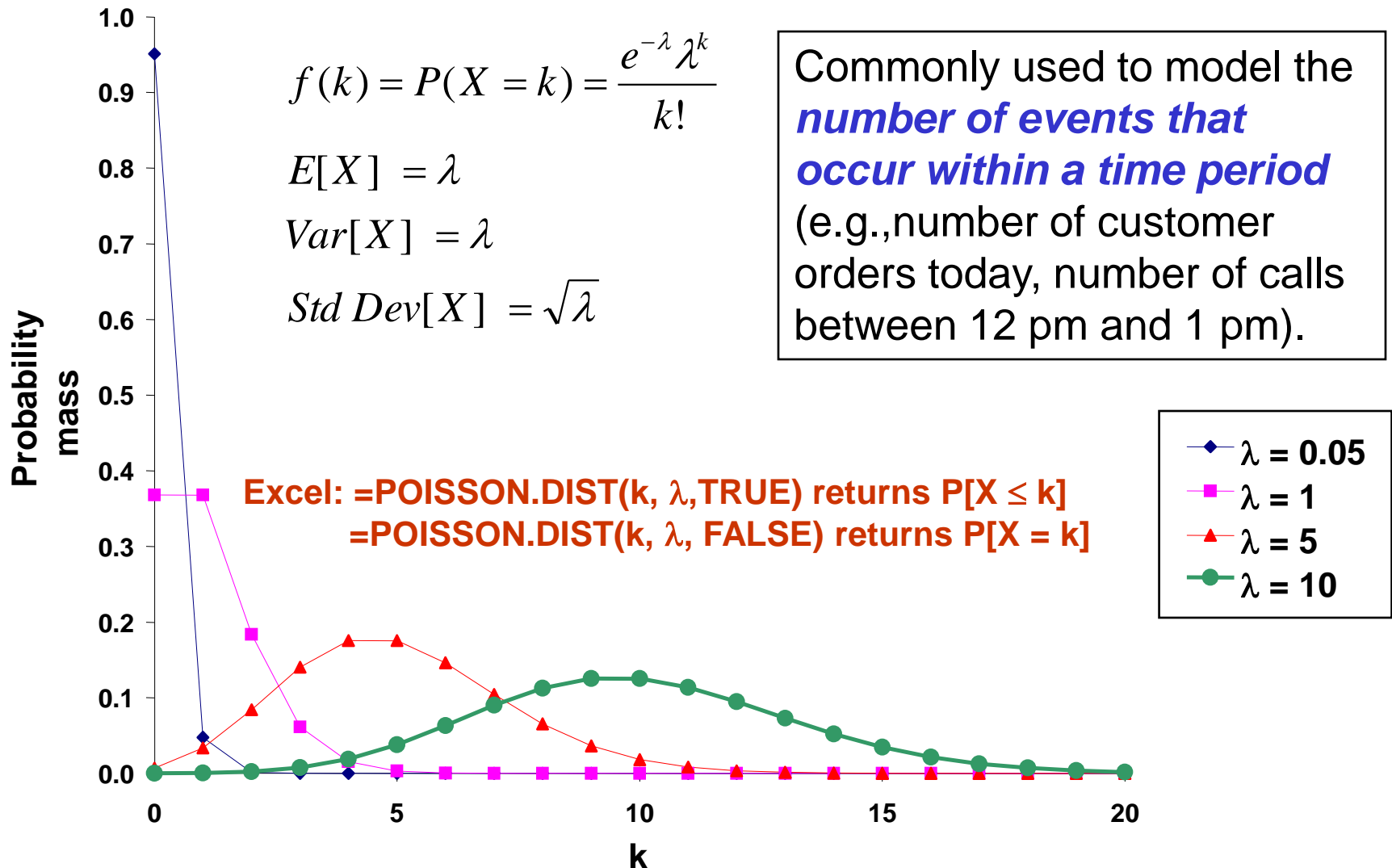
Excel has the following functions related to the binomial distribution:

$$X \sim \text{Bin}(n, p)$$

- **=BINOM.DIST(k,n,p,TRUE)**
returns $P(X \leq k)$. (If last parameter is FALSE, then $f(k) = P(X = k)$ is returned.)
- **=BINOM.INV(n,p,cutoff_prob)**
returns the smallest value k such that $P(X \leq k) \geq \text{cutoff_prob}$. This is similar to finding a value that corresponds to a particular percentile, except we are dealing with discrete values.



The Poisson Distribution



The Exponential Distribution

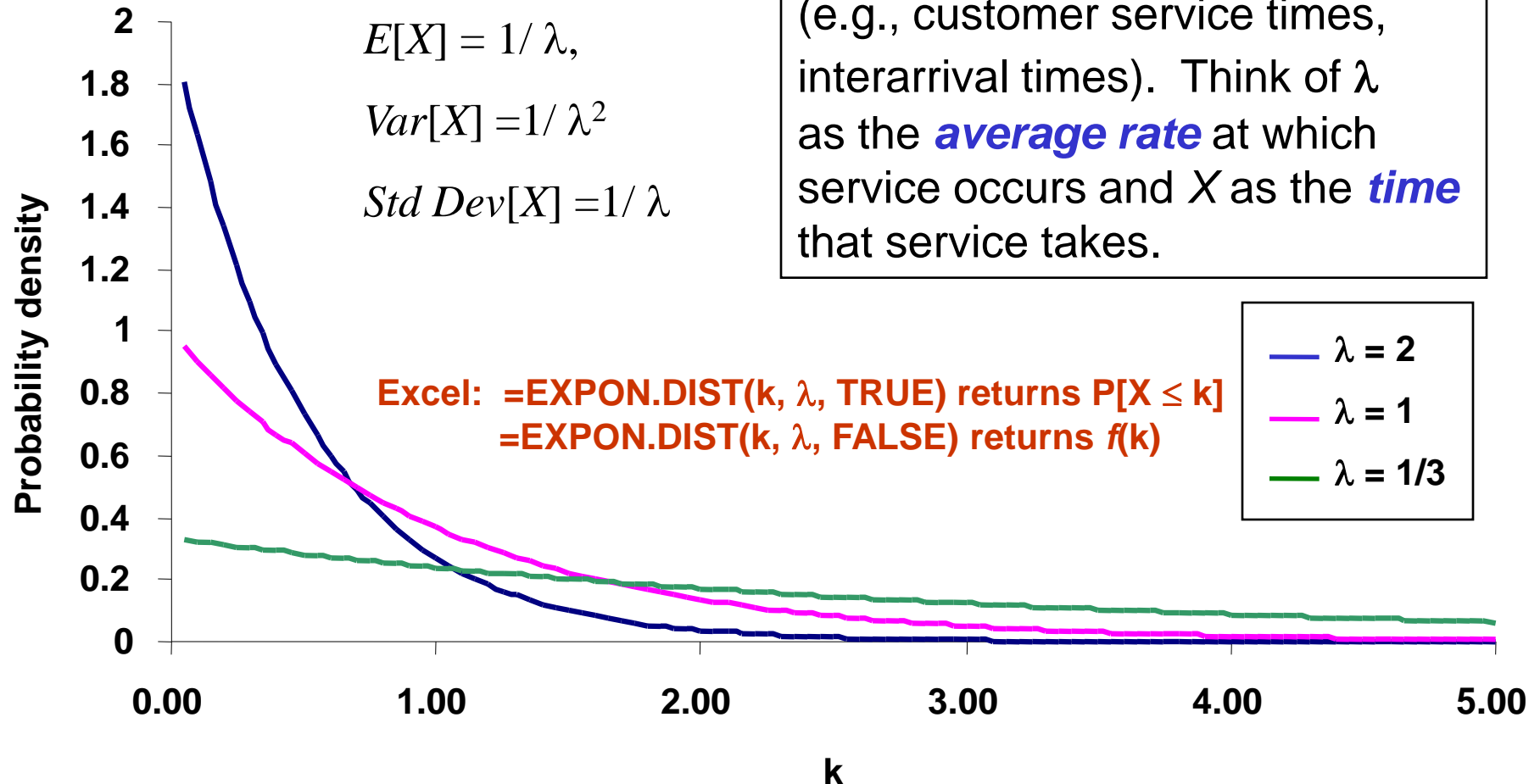
$$f(k) = \lambda e^{-k\lambda}$$

$$E[X] = 1/\lambda,$$

$$\text{Var}[X] = 1/\lambda^2$$

$$\text{Std Dev}[X] = 1/\lambda$$

Commonly used to model **times** (e.g., customer service times, interarrival times). Think of λ as the **average rate** at which service occurs and X as the **time** that service takes.



Other Distributions in Excel

- In addition, Excel has numerous other built-in probability functions. Here are some of the more commonly used:
 - **BETA.DIST** (Beta)
 - **CHISQ.DIST** (Chi-Squared)
 - **F.DIST** (F)
 - **GAMMA.DIST** (Gamma)
 - **HYPGEOM.DIST** (Hypergeometric)
 - **LOGNORM.DIST** (Lognormal)
 - **NEGBINOM.DIST** (Negative Binomial)
 - **T.DIST** (Student's t)
 - **WEIBULL.DIST** (Weibull)

Generating Random Variables

To generate a random variable X with cdf F :

- **Inversion Method**

- Generates a standard uniform random variable U over $[0,1]$ and returns $X = F^{-1}(U)$. *We will focus on this method.*

- **Acceptance-Rejection Method**

- Good for positive, bounded random variables.
- Uses two uniform random variables U_1 and U_2 to generate a point (x,y) in a specially-sized 2D-box, where part of the box is designated “acceptable” and the rest is not.
- Returns $X = x$ if (x,y) falls in the “acceptable” region, else tries again.

- **Convolution Method**

- Good for random variables $X = Y_1 + \dots + Y_n$ that are the sums of (not too many) other independent random variables.
- Generates the independent pieces (using one of the other methods), then adds them together.

Inversion Method in Excel

- **Excel:** **=RAND()** generates a standard uniform random variable U over $[0,1]$.
- In Excel, can generate $X = F^{-1}(U)$ by computing $F^{-1}(\cdot)$ explicitly or by using one of many built-in functions:
 - **NORM.INV**, **NORM.S.INV** (Inverse of Normal, Standard Normal)
 - **BINOM.INV** (Inverse of Binomial)
 - **BETA.INV** (Inverse of Beta)
 - **CHISQ.INV** (Inverse of Chi-Squared)
 - **F.INV** (Inverse of F)
 - **GAMMA.INV** (Inverse of Gamma)
 - **LOGNORM.INV** (Inverse of Lognormal)
 - **T.INV** (Inverse of Student's t)
- Examples:
 - If $X \sim N(\mu=10, \sigma=2)$, then generate X with: **=NORM.INV(RAND(),10,2)**
 - If $X \sim \text{Exp}(\lambda=0.2)$, then generate X explicitly with: **=-LN(1 - RAND())/0.2**

Discrete Random Variable Example

- Consider an experiment that is the roll of two fair dice.

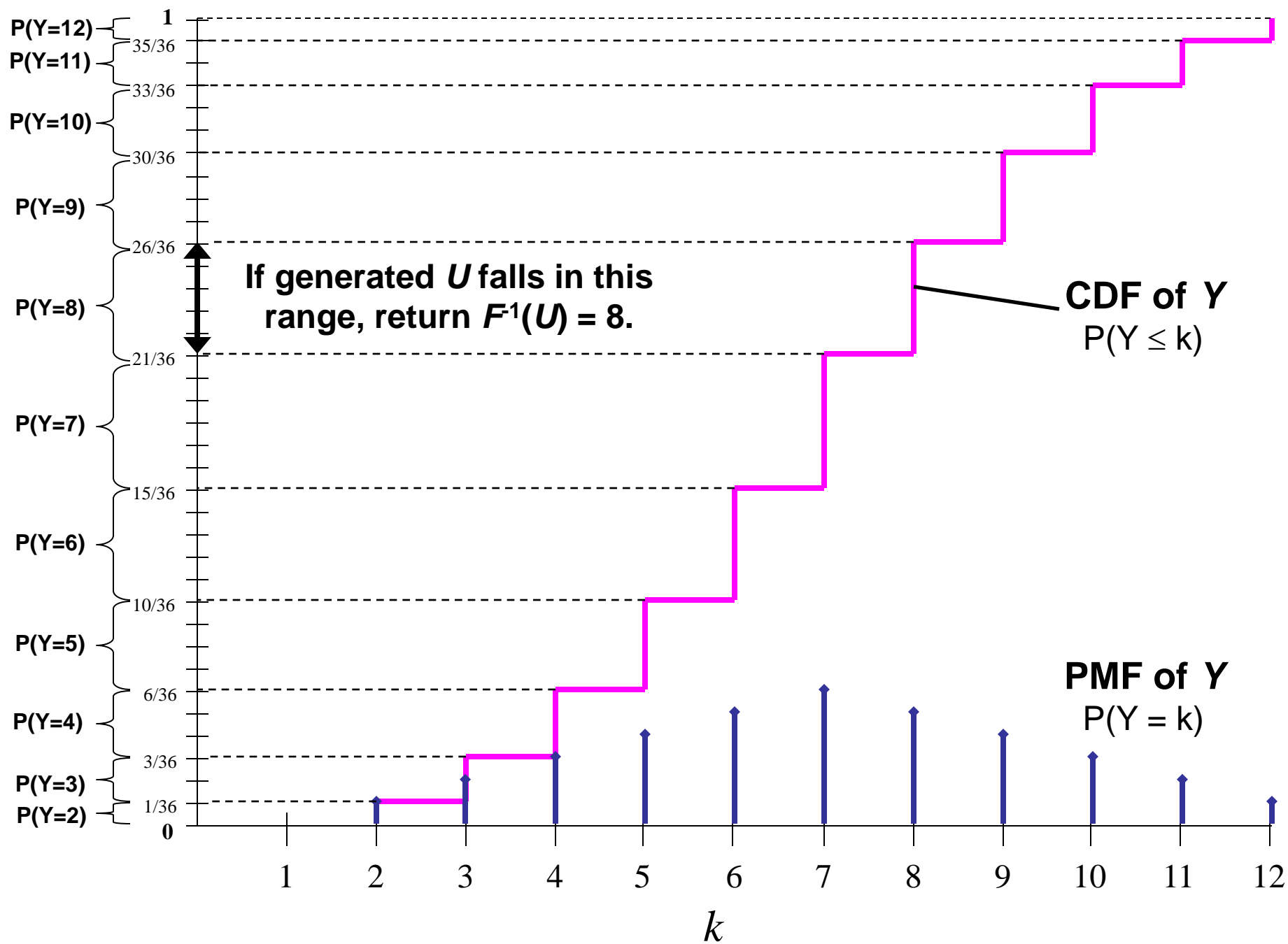
	$\Omega = \{(1,1), (1,2), (1,3), (1,4), (1,5), (1,6),$
Sum is 2	$(2,1), (2,2), (2,3), (2,4), (2,5), (2,6),$
Sum is 3	$(3,1), (3,2), (3,3), (3,4), (3,5), (3,6),$
Sum is 4	$(4,1), (4,2), (4,3), (4,4), (4,5), (4,6),$
Sum is 5	$(5,1), (5,2), (5,3), (5,4), (5,5), (5,6),$
Sum is 6	$(6,1), (6,2), (6,3), (6,4), (6,5), (6,6)\}$
Sum is 7	
	Sum is 8 Sum is 9 Sum is 10 Sum is 11 Sum is 12

- Define the random variable Y to be the sum of the numbers rolled.

Example (cont'd)

PMF and CDF of Y (assuming iid fair dice):

k	$P(Y = k)$	$P(Y \leq k)$
2	1/36	1/36
3	2/36	3/36
4	3/36	6/36
5	4/36	10/36
6	5/36	15/36
7	6/36	21/36
8	5/36	26/36
9	4/36	30/36
10	3/36	33/36
11	2/36	35/36
12	1/36	1



Sample Statistics vs. Distribution Parameters

If \mathbf{X} and \mathbf{Y} are
vectors of sample data:

$$\bar{X} = \sum_{i=1}^n X_i / n$$

$$s_{\mathbf{X}}^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$$

$$\text{cov}(\mathbf{X}, \mathbf{Y}) = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})$$

$$\text{corr}(\mathbf{X}, \mathbf{Y}) = \frac{\text{cov}(\mathbf{X}, \mathbf{Y})}{s_{\mathbf{X}} s_{\mathbf{Y}}}$$

If X and Y are
discrete random variables:

$$E[X] = \sum_{k=-\infty}^{\infty} k \cdot P(X = k)$$

Excel: =SUMPRODUCT(values,probs)

$$\sigma_X^2 = \sum_{k=-\infty}^{\infty} (k - E[X])^2 P(X = k)$$

$$\text{cov}(X, Y) = \sum_{\substack{\text{all pairs} \\ (x_i, y_i)}} (x_i - E[X])(y_i - E[Y]) f_{X,Y}(x_i, y_i)$$

$$\text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$