### Random variables

9.07

2/19/2004

### A few notes on the homework

- If you work together, tell us who you're working with.
  - You should still be generating your own homework solutions. Don't just copy from your partner. We want to see your own words.
- Turn in your MATLAB code (this helps us give you partial credit)
- Label your graphs
  - xlabel('text')
  - ylabel('text')
  - title('text')

### More homework notes

- Population vs. sample
  - The population to which the researcher wants to generalize can be considerably more broad than might be implied by the narrow sample.
    - High school students who take the SAT
    - High school students
    - Anyone who wants to succeed
    - Anyone

### More homework notes

#### • MATLAB:

- If nothing else, if you can't figure out something in MATLAB, find/email a TA, or track down one of the zillions of fine web tutorials.
- Some specifics...

#### **MATLAB**

- Hint: MATLAB works best if you can think of your problem as an operation on a matrix. Do this instead of "for" loops, when possible.
  - E.G. coinflip example w/o for loops
    x = rand(5,10000);
    coinflip = x>0.5;
    numheads = sum(coinflip); % num H in 5 flips

#### **MATLAB**

- randn(N) -> NxN matrix!
- $randn(1,N) \rightarrow 1xN matrix$
- sum(x) vs. sum(x,2)
- hist(data, 1:10) vs. hist(data, 10)
- plot(hist(data)) vs.[n,x]=hist(data); plot(x,n)

#### A few more comments

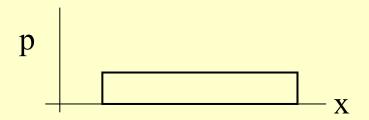
- Expected value can tell you whether or not you want to play game even once.
  - It tells you if the "game" is in your favor.
- In our example of testing positive for a disease, P(D) is the *prior* probability that you have the disease. What was the probability of you having the disease before you got tested? If you are from a risky population, P(D) may be higher than 0.001. Before you took the test you had a higher probability of having the disease, so after you test positive, your probability of having the disease, P(D|+) will be higher than 1/20.

### Random Variables

- Variables that take numerical values associated with events in an experiment
  - Either discrete or continuous
    - Integral (not sum) in equations below for continuous r.v.
  - Mean, μ, of a random variable is the sum of each possible value multiplied by its probability:  $\mu = \sum x_i P(x_i) \equiv E(x)$ 
    - Note relation to "expected value" from last time.
  - Variance is the average of squared deviations multiplied by the probability of each value
  - $\sigma^2 = \sum (x_i \mu)^2 P(x_i) \equiv E((x \mu)^2)$

# We've already talked about a few special cases

- Normal r.v.'s (with normal distributions)
- Uniform r.v.'s (with distributions like this:)



• Etc.

### Random variables

• Can be made out of functions of other random variables.

• 
$$X \text{ r.v., } Y \text{ r.v. } ->$$
 $Z=X+Y \text{ r.v.}$ 
 $Z=\operatorname{sqrt}(X)+5Y+2 \text{ r.v.}$ 

## Linear combinations of random variables

- We talked about this in lecture 2. Here's a review, with new E() notation.
- Assume:

- 
$$E(x) = \mu$$
  
-  $E(x-\mu)^2 = E(x^2-2\mu x + \mu^2) = \sigma^2$ 

• 
$$E(x+5) = E(x) + E(5) = E(x) + 5 = \mu + 5 = \mu$$

• 
$$E((x+5-\mu')^2) = E(x^2+2(5-\mu')x + (5-\mu')^2)$$
  
=  $E(x^2-2\mu x + \mu^2) = \sigma^2 = (\sigma')^2$ 

Adding a constant to x adds that constant to  $\mu$ , but leaves  $\sigma$  unchanged.

## Linear combinations of random variables

• 
$$E(2x) = 2E(x) = 2\mu = \mu$$

• 
$$E((2x-\mu')^2) = E(4x^2 - 8x\mu + 4\mu^2) = 4\sigma^2 = (\sigma')^2$$
  
 $\sigma' = 2\sigma$ 

Scaling x by a constant scales both  $\mu$  and  $\sigma$  by that constant. But...

### Multiplying by a negative constant

• 
$$E(-2x) = 2E(x) = -2\mu = \mu$$

• 
$$E((-2x-\mu')^2) = E(4x^2 + 2(2x)(-2\mu) + (-2\mu)^2)$$
  
=  $E(4x^2 - 8x\mu + 4\mu^2) = 4\sigma^2 = (\sigma')^2$   
 $\sigma' = 2\sigma$ 

Scaling by a negative number multiples the mean by that number, but multiplies the standard deviation by –(the number). (Standard deviation is always positive.)

# What happens to z-scores when you apply a transformation?

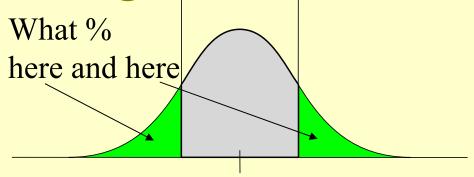
- Changes in scale or shift do not change "standard units," i.e. z-scores.
  - When you transform to z-scores, you're already subtracting off any mean, and dividing by any standard deviation. If you change the mean or standard deviation, by a shift or scaling, the new mean (std. dev.) just gets subtracted (divided out).

## Special case: Normal random variables

• Can use z-tables to figure out the area under part of a normal curve.

## An example of using the table

- P(-0.75 < z < 0.75) = 0.5467
- P(z<-0.75 or z>0.75) = 1-0.5467 $\approx 0.45$
- That's our answer.

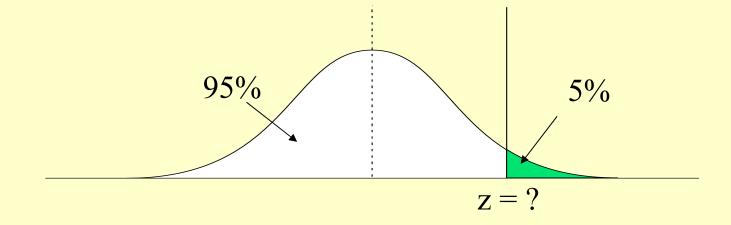


75 0 .75	
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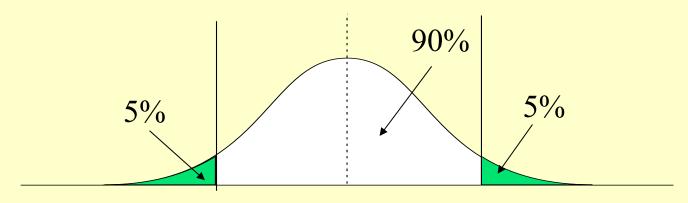
Z	Height	Area
•••	• • •	• • •
0.70	31.23	51.61
0.75	30.11	54.67
0.80	28.97	57.63
• • •	• • •	• • •

## Another way to use the z-tables

- Mean SAT score = 500, std. deviation = 100
- Assuming that the distribution of scores is normal, what is the score such that 95% of the scores are below that value?



# Using z-tables to find the 95 percentile point



• From the tables:

Z	Height	Area
1.65	10.23	90.11

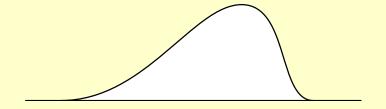
- $z=1.65 \rightarrow x=?$  Mean=500, s.d.=100
- 1.65 = (x-500)/100; x = 165+500 = 665

### Normal distributions

- A lot of data is normally distributed because of the central limit theorem from last time.
  - Data that are influenced by (i.e. the "sum" of) many small and unrelated random effects tend to be approximately normally distributed.
  - E.G. weight (I'm making up these numbers)
    - Overall average = 120 lbs for adult women
    - Women add about 1 lb/year after age 29
    - Illness subtracts an average of 5 lbs
    - Genetics can make you heavier or thinner
    - A given "sample" of weight is influenced by being an adult woman, age, health, genetics, ...

### Non-normal distributions

- For data that is approximately normally distributed, we can use the normal approximation to get useful information about percent of area under some fraction of the distribution.
- For non-normal data, what do we do?

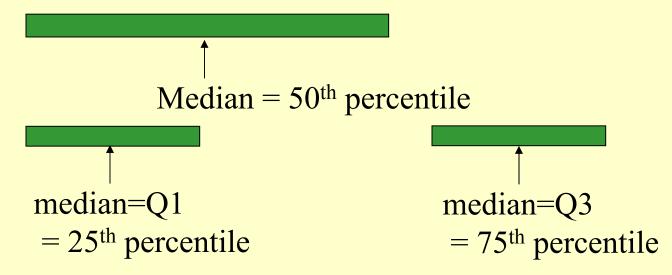


### Non-normal distributions

- E.G. income distributions tend to be very skewed
- Can use percentiles, much like in the last ztable example (except without the tables)
  - What's the 10<sup>th</sup> percentile point? The 25<sup>th</sup> percentile point?

## Percentiles & interquartile range

• Divide data into 4 groups, see how far about the extreme groups are.



• Q3-Q1 = IQR = 75<sup>th</sup> percentile -25<sup>th</sup> percentile

# What do you do for other percentiles?

- Median = point such that 50% of the data lies below that point
- Similarly, 10<sup>th</sup> percentile = point such that 10% of the data lies below that point.

# What do you do for other percentiles?

- If you have a theory for the distribution of the data, you can use that to find the nth percentile.
- Estimating it from the data, using MATLAB (to a first approximation)

```
(x = the data)
y = sort(x);
N = length(x);  % how many data points there are
TenthPerc = y(0.10*N);
```

• This isn't exactly right (remember, for instance, that median (1 2 4 6) is 3), but it's close enough for our purposes.

## How do you judge if a distribution is normal?

• So far we've been eyeballing it. (Does it look symmetric? Is it about the right shape?) Can we do better than this?

## Normal quantile Plots

- A useful way to judge whether or not a set of samples comes from a normal distribution.
- We'll still be eyeballing it, but with a more powerful visualization.

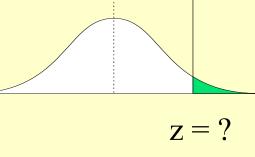
## Normal quantile plots

data

For each datum, what % of the data is below this value – what's its percentile?

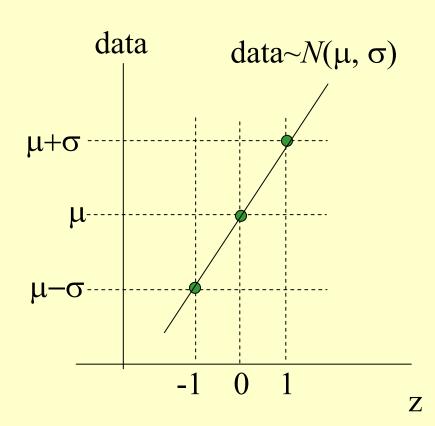
If this were a normal distribution, what z would correspond to that percentile?

Compare the actual data values to those predicted (from the percentiles) if it were a standard normal (z) distribution.



## Normal quantile plots

- If the data~N(0, 1), the points should fall on a 45 degree line through the origin.
- If the data $\sim N(\mu, 1)$ , the points should fall on a 45 degree line.
- If the data $\sim N(\mu, \sigma)$ , the points will fall on a line with slope  $\sigma$  (or  $1/\sigma$ , depending on how you plotted it).



## Normal Quantile Plots

#### • Basic idea:

- Order the samples from smallest to largest. Assume you have N samples. Renumber the ordered samples  $\{x_1, x_2, ..., x_N\}$ .
- Each sample  $x_i$  has a corresponding percentile  $k_i = (i-0.5)/N$ . About  $k_i\%$  of the data in the sample is <  $x_i$ .
- If the distribution is normal, we can look up  $k_i$  % in the z-tables, and get a corresponding value for  $z_i$ .
- Plot  $x_i$  vs.  $z_i$  (it doesn't matter which is on which axis)

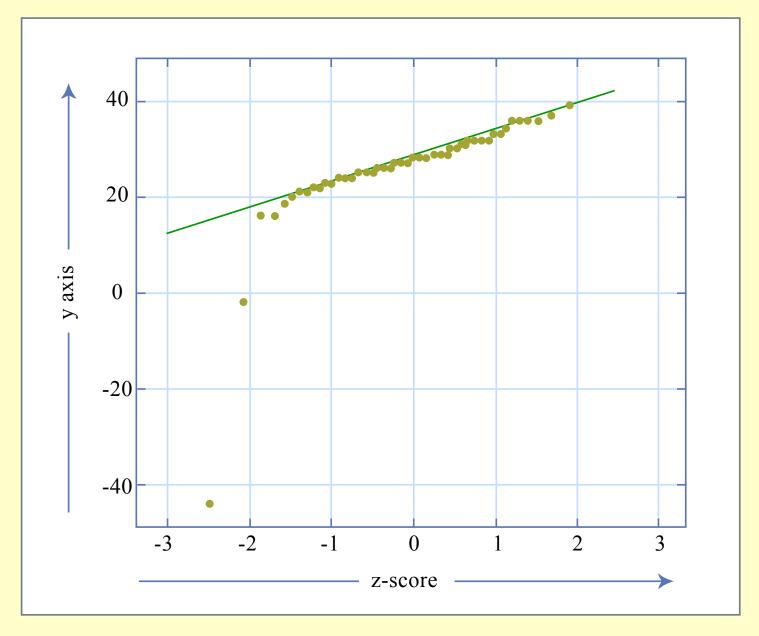


Figure by MIT OCW.

• Let's remove those outliers...

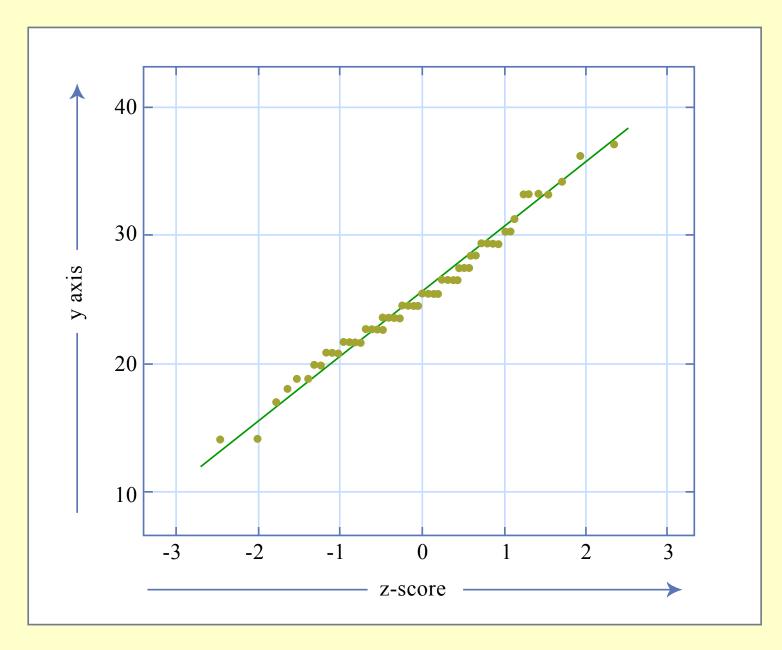


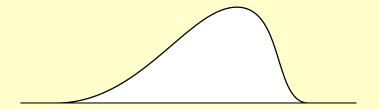
Figure by MIT OCW.

• The normal quantile plot allows us to see which points deviate strongly from a line. This helps us locate outliers.

## Non-linear plots

Concave-up (with the axes as shown here)
 means positive skew

Concave-down means negative skew



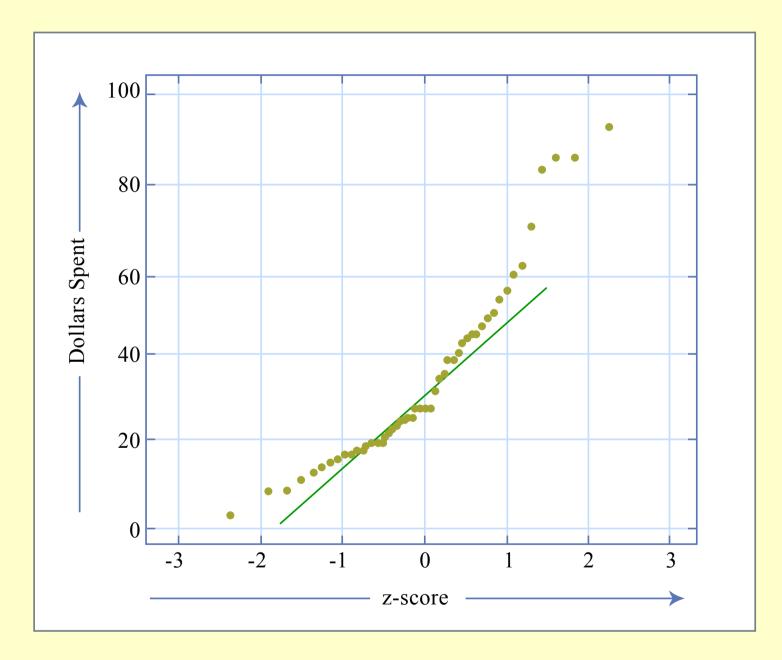


Figure by MIT OCW.

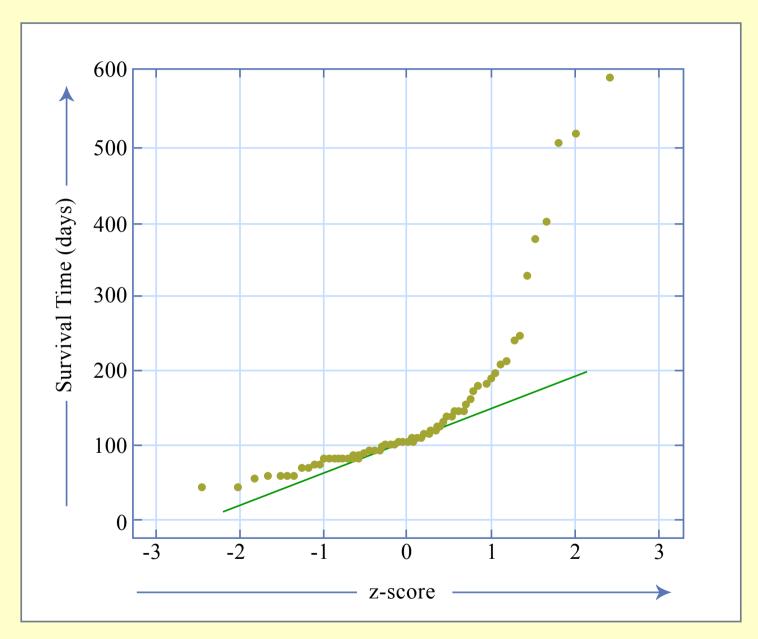


Figure by MIT OCW.

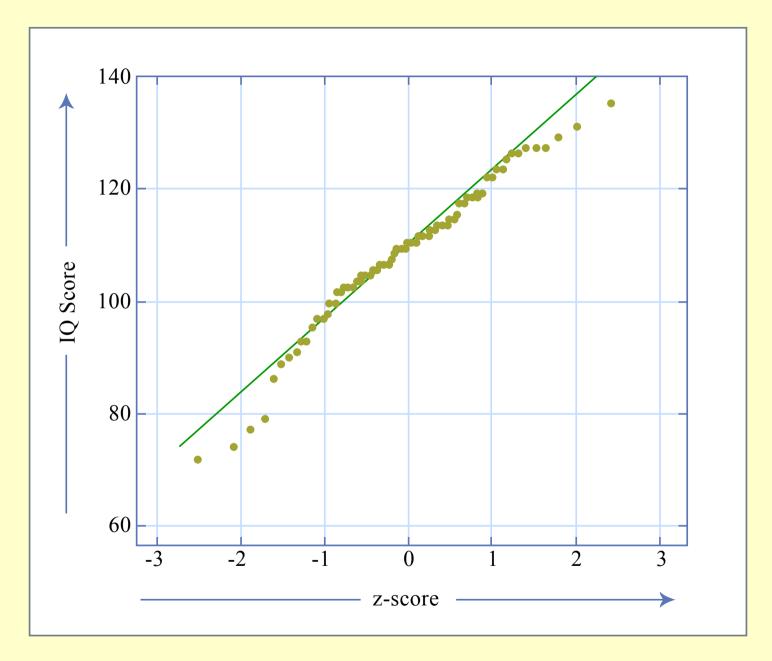


Figure by MIT OCW.

#### Granularity

- When the r.v. can only take on certain values,
   the normal quantile plot looks like funny stair
   steps
- E.G. binomial distributions we'll get there in a sec.

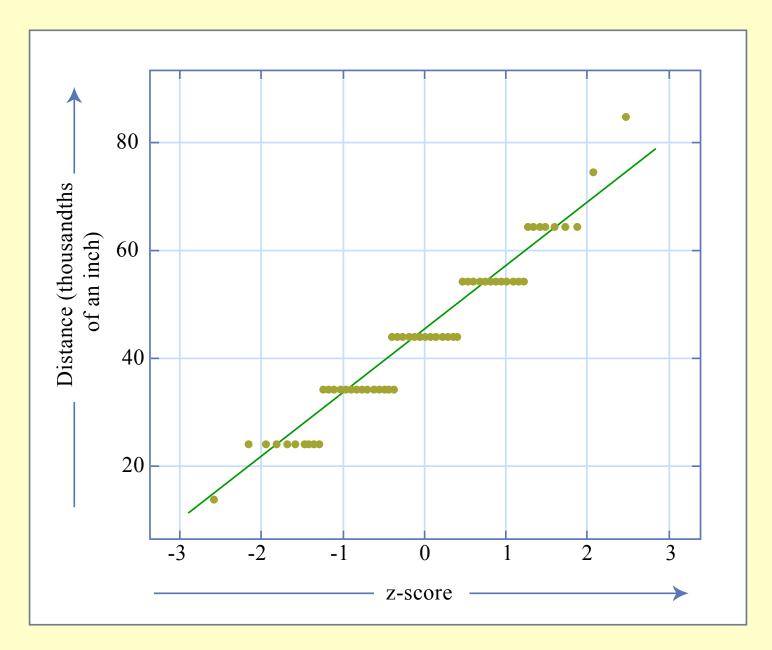


Figure by MIT OCW.

#### Normal quantile plots in MATLAB

- qqplot(x) generates a normal quantile plot for the samples in vector x
- You should have access to this command on the MIT server computers.

#### The binomial distribution

- An important special case of a probability distribution.
- One of the most frequently encountered distributions in statistics
- Two possible outcomes on each trial, e.g. {H, T}
- One outcome is designated a "success", the other a "failure"
- The binomial distribution is the distribution of the number of successes on N trials.
- E.G. the distribution of the number of heads, when you flip the coin 10 times.

### Example

- Flip a fair coin 6 times.
- What is P(4H, 2T)?
- Well, first, note that  $P(TTHHHHH) = P(THHHHHT) = ... = (0.5)^4 (1-0.5)^2 = (0.5)^6$ 
  - All events with 4H have the same probability
  - How many such events are there?
- P(4H, 2T) =(# events of this type) x  $(0.5)^4 (1-0.5)^2$

## How many events of this type are there? The binomial coefficient

• Equals number of possible combinations of N draws such that you have k successes.

$$\equiv \binom{N}{k} = \frac{N!}{k!(N-k)!}$$

- N! = N factorial = N(N-1)(N-2)...(1) = factorial(N) in MATLAB
- 0! = 1

#### Intuition for the binomial coefficient

- N! = number of possible ways to arrange 6 unique items (a,b,c,d,e,f)
  - 6 in 1<sup>st</sup> slot, 5 remain for 2<sup>nd</sup> slot, etc.
- But, they aren't unique. k are the same (successes), and the remaining (N-k) are the same (failures).
- k! and (N-k)! are the # of "duplicates" you get from having k and N-k items be the same.
- The result is the number of combinations with k successes.

#### Binomial coefficient

- Number of ways of getting k heads in N tosses
- Number of ways of drawing 2 R balls out of 5 draws, with p(R) = 0.1
- Number of ways of picking 2 people out of a group of 5 (less obvious)
  - Associate an indicator function with each person = 1 if picked, 0 if not
  - p(p1 = 1) is like p(toss 1 = H)

#### The Binomial distribution

- Probability of k successes in N tries
- Repeatable sampling of a binomial variable (e.g., tossing a coin), where you decide the number of samples in advance
  - (versus: I keep drawing a ball until I get 2 reds, then I quit. What was my probability of getting 2R and 3G?)
- Three critical properties
  - Result of each trial may be either a failure or a success
  - Probability of success is the same for each trial
  - The trials are independent

### Back to tossing coins...

- The coin-toss experiment is an example of a binomial process
- Let's arbitrarily designate "heads" as a success
- p(heads) = 0.5
- What is the probability of obtaining 4 heads in 6 tosses?

### Example

• P(4 H in 6 tosses) =

$$\binom{N}{k} p^k (1-p)^{N-k}$$

$$= \binom{6}{4} (0.5)^4 (0.5)^2$$

$$= \frac{6 \cdot 5 \cdot 4 \cdot 3 \cdot 2 \cdot 1}{4 \cdot 3 \cdot 2 \cdot 1 \cdot 2 \cdot 1} \times \frac{1}{64} = \frac{15}{64}$$

## Kangaroo example from book

- 10 pairs of kangaroos
- Half of them get vitamins
- 10 races (vitamin vs. no vitamin)
- 7 out of 10 races, the kangaroo taking vitamins wins
- Do the vitamins help, or is this just happening by chance?

#### How do we decide?

- What we want to do is to set a criterion # of wins, and decide that the vitamins had an effect if we see a # of wins equal to or greater than the criterion.
- How do we set the criterion?
- Well, what if we had set the criterion right at 7 wins? What would be our probability of saying there was an effect of the vitamins, when really the results were just due to chance?

#### Roo races

- If we set the criterion at 7 wins, and there were no effect of vitamins, what is the probability of us thinking there were an effect?
- Probability of the vitamin roo winning, if vitamins don't matter, = p = 0.5
- What is the probability, in this case, of 7 wins, or 8, or 9, or 10?

#### Roo races

- P(7 wins out of 10) + P(8 wins out of 10) +
   P(9 wins out of 10) + P(10 wins out of 10)
- Use the binomial formula, from before.
- $\approx 17\%$  (see problem 6, p. 258, answer on p. A-71)

#### Roo races

- Remember, this is the probability of us thinking there were an effect, when there actually wasn't, if we set the criterion at 7 wins.
- 17% is a pretty big probability of error. (In statistics we like numbers more like 5%, 1%, or 0.1%.)
- We probably wouldn't want to set the criterion at 7 wins. Maybe 8 or 9 would be better.
- We decide that the vitamins probably have no effect.

- We'll see LOTS more problems like the kangaroo problem in this class.
- And this whole business of setting a criterion will become more familiar and intuitive.
- For now, back to binomial random variables.

## Mean and variance of a binomial random variable

• The mean number of successes in a binomial experiment is given by:

$$-\mu = np$$

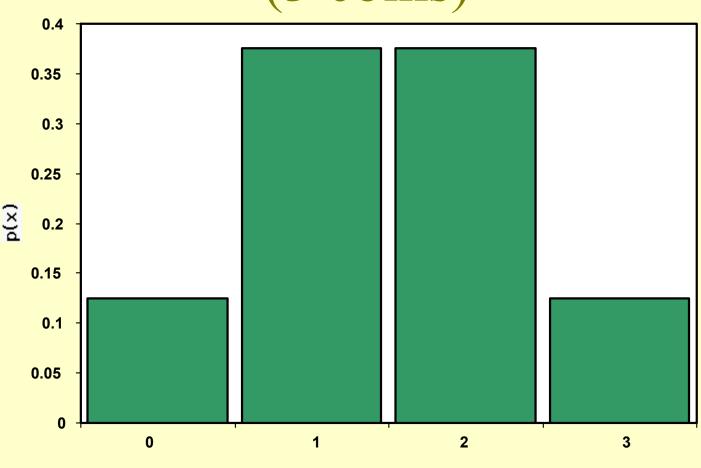
- n is the number of trials, p is the probability of success
- The variance is given by

$$-\sigma^2 = npq$$

$$- q = 1-p$$

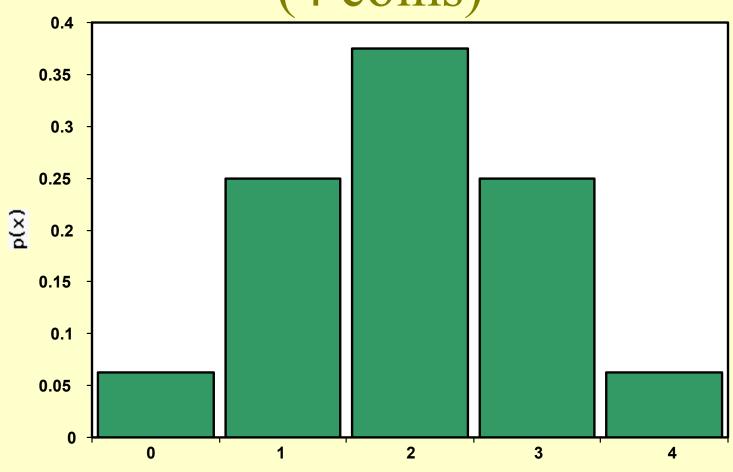
# What happens to the binomial distribution as you toss the coin more times?

## Probability Histogram (3 coins)



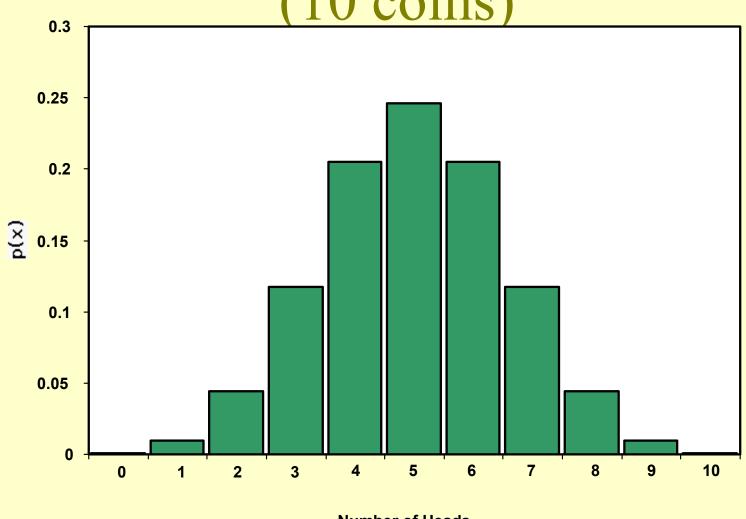
**Number of Heads** 

## Probability Histogram (4 coins)



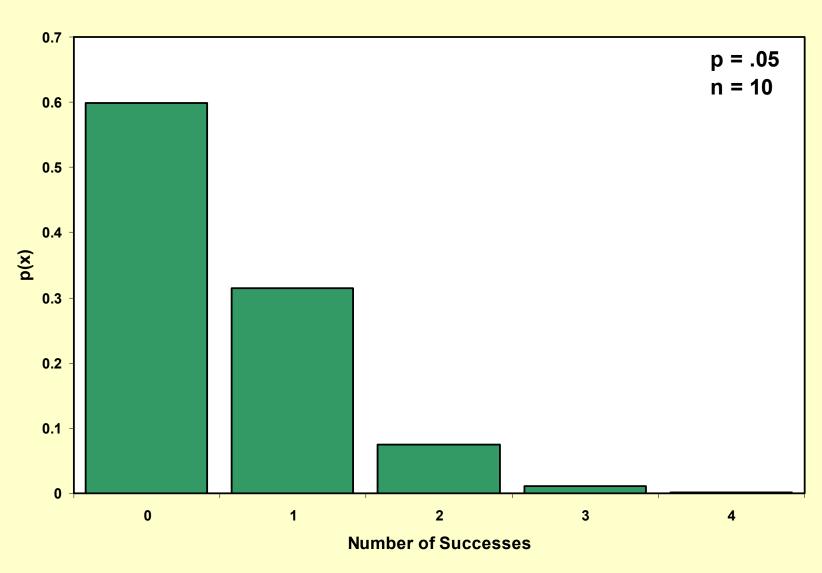
**Number of Heads** 

## Probability Histogram (10 coins)

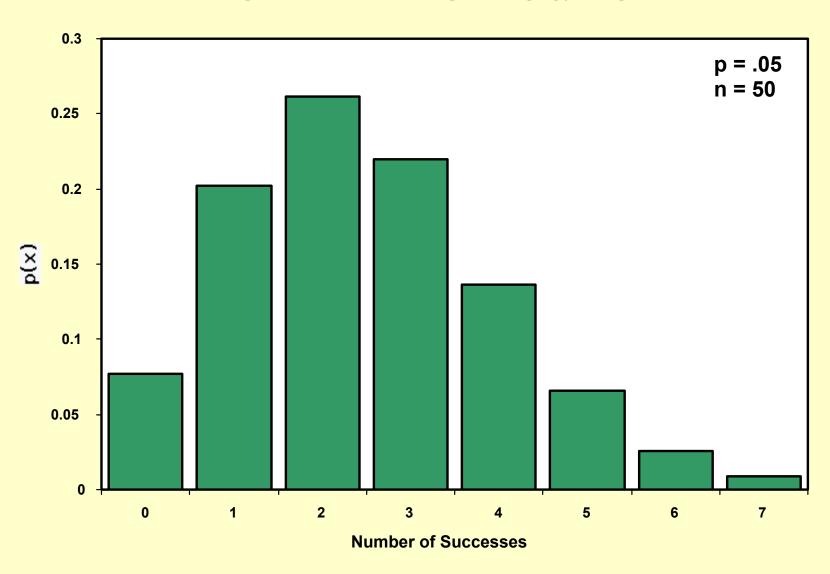


**Number of Heads** 

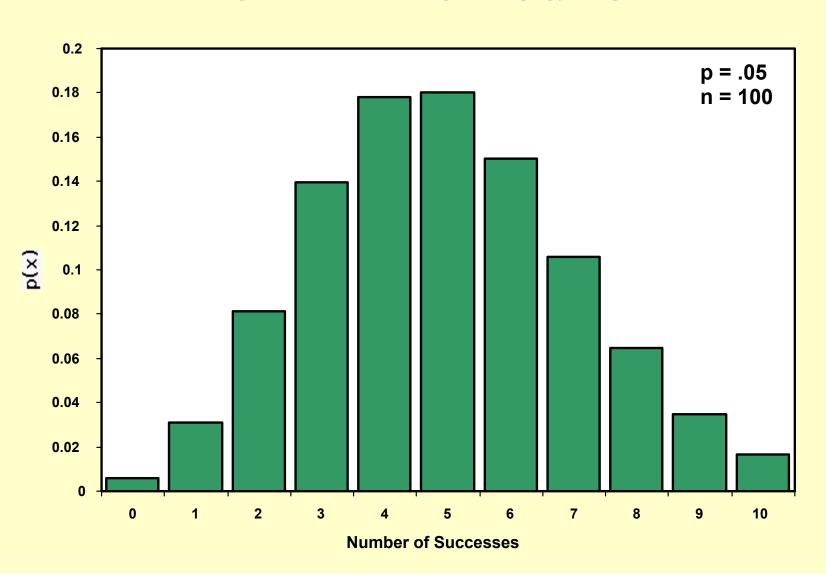
#### **Binomial Distribution**



#### **Binomial Distribution**



#### **Binomial Distribution**



#### The central limit theorem, again

- As the number of tosses goes up, the binomial distribution approximates a normal distribution.
- The total number of heads on 100 coin tosses = number on 5 tosses + number on next 5 tosses +
- Thus, a binomial process can be thought of as the sum of a bunch of independent processes, the central limit theorem applies, and the distribution approaches normal, for a large number of "coin tosses" = trials.

### The normal approximation

• This means we can use z-tables to answer questions about binomial distributions!

## Normal Approximation

• When is it OK to use the normal approximation?

- Use when n is large and p isn't too far from 0.5
  - The further p is from .5, the larger n you need
  - Rule of thumb: use when np≥10 and nq≥10

### Normal Approximation

• For any value of p, the binomial distribution of n trials with probability p is approximated by the normal curve with

```
-\mu = np and
```

$$-\sigma = \operatorname{sqrt}(\operatorname{npq})$$

• Where 
$$q = (1-p)$$

• Let's try it for 25 coin flips...

## 25 coin flips

• What is the probability that the number of heads is  $\leq 14$ ?

• We can calculate from the binomial formula that  $p(x \le 14)$  is .7878 exactly

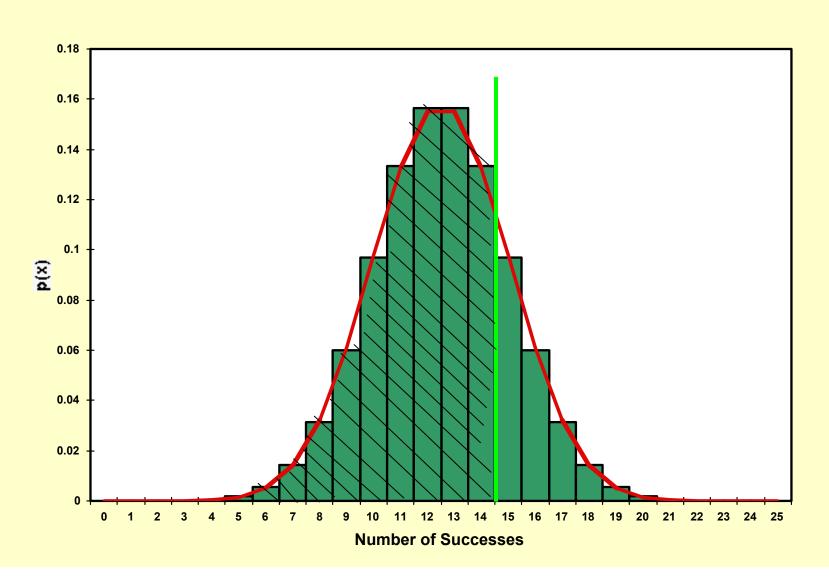
## Normal Approximation

Using the normal approximation with

$$\mu = np = (25)(5) = 12.5$$
 and  $\sigma = sqrt(npq) = sqrt((25)(.5)(.5)) = 2.5$  we get

- $p(x \le 14) = p(z \le (14-12.5)/2.5)$ =  $p(z \le .6) = .7257$
- .7878 vs. .7257 -- not great!!
- Need a better approximation...

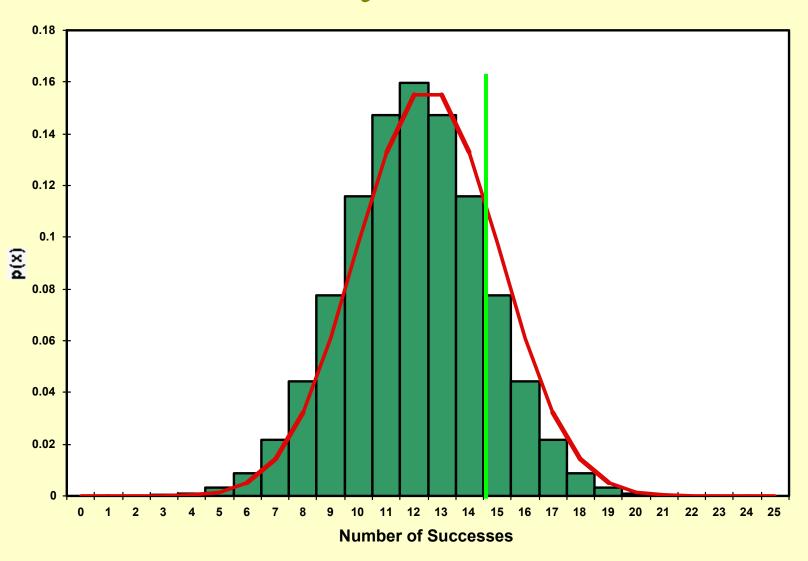
## Normal Approximation of Binomial Distribution



### Continuity Correction

- Notice that the bars are centered on the numbers
- This means that  $p(x \le 14)$  is actually the area under the bars less than x=14.5
- We need to account for the extra 0.5
- $P(x \le 14.5) = p(z \le .8) = .7881$  -- a much better approximation!

## **Continuity Correction**



## # of times you do an experiment, vs. # of trials in that experiment

#### • In MATLAB:

```
x = rand(5,10000);

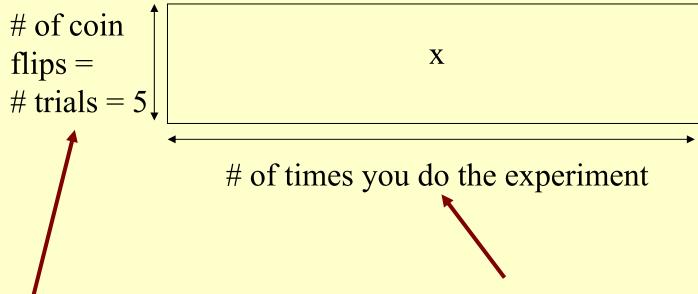
coinflip = x>0.5; % 1 = heads

y = sum(x); % number of heads
```

```
# of coin flips = X

# trials = 5

# of times you do the experiment
```



Increase this, and central limit thm. will start to apply – distribution will look more normal.

Increase this, and the empirical distribution will approach the theoretical distribution (and get less variable).

### Binomial distribution and percent

- Can also use binomial distribution for percent "success", by dividing by the number of samples (trials)
- Mean = np/n = p
- Std. deviation = sqrt(npq)/n = sqrt(pq/n)
- We'll use this a lot in class, as we often have a situation like that for elections: 45% favor Kerry, 39% favor Edwards are these different by chance, or is there a real effect there?