

# Political Science 209 - Fall 2018

## Probability III

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8th November 2018

# Random Variables and Probability Distributions

- What is a random variable? We assigns a number to an event
  - coin flip: tail= 0; heads= 1
  - Senate election: Ted Cruz= 0; Beto O'Rourke= 1
  - Voting: vote = 1; not vote = 0

# Random Variables and Probability Distributions

- What is a random variable? We assigns a number to an event
  - coin flip: tail= 0; heads= 1
  - Senate election: Ted Cruz= 0; Beto O'Rourke= 1
  - Voting: vote = 1; not vote = 0

Probability distribution: Probability of an event that a random variable takes a certain value

# Random Variables and Probability Distributions

- $P(\text{coin} = 1)$ ;  $P(\text{coin} = 0)$
- $P(\text{election} = 1)$ ;  $P(\text{election} = 0)$

# Random Variables and Probability Distributions

- **Probability density function (PDF):**  $f(x)$  How likely does  $X$  take a particular value?
- **Probability mass function (PMF):** When  $X$  is discrete,  
 $f(x)=P(X =x)$

# Random Variables and Probability Distributions

- **Probability density function (PDF):**  $f(x)$  How likely does  $X$  take a particular value?
- **Probability mass function (PMF):** When  $X$  is discrete,  $f(x)=P(X =x)$
- **Cumulative distribution function (CDF):**  $F(x) = P(X \leq x)$ 
  - What is the probability that a random variable  $X$  takes a value equal to or less than  $x$ ?
  - Area under the density curve (either we use the sum  $\Sigma$  or integral  $\int$ )
  - Non-decreasing

# Random Variables and Probability Distributions: Binomial Distribution

- **PMF**: for  $x \in \{0, 1, \dots, n\}$ ,  
$$f(x) = P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$
- **PMF** function to tell us: what is the probability of  $x$  *successes* given  $n$  trials with  $P(x) = p$

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- **PMF** function to tell us: what is the probability of  $x$  *successes* given  $n$  trials with  $P(x) = p$

In R:

```
dbinom(x = 2, size = 4, prob = 0.1) ## prob of 2 successes :
```

```
[1] 0.0486
```



# Random Variables and Probability Distributions: Binomial Distribution

- CDF: for  $x \in \{0, 1, \dots, n\}$

$$F(x) = P(X \leq x) = \sum_{k=0}^x \binom{n}{k} p^k (1-p)^{n-k}$$

- CDF function to tell us: what is the probability of  $x$  or *fewer* successes given  $n$  trials with  $P(x) = p$

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- **CDF** function to tell us: what is the probability of  $x$  or *fewer* successes given  $n$  trials with  $P(x) = p$

In R:

```
pbinom(2, size = 4, prob = 0.1) ## prob of 2 or fewer successes
```

```
[1] 0.9963
```

CDF of  $F(x)$  is equal to the sum of the results from calculating the PMF for all values smaller and equal to  $x$

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In *R*:

```
pbinom(2, size = 4, prob = 0.1) ## CDF
```

```
sum(dbinom(c(0,1,2),4,0.1)) ## summing up the pdfs
```

```
[1] 0.9963
```

```
[1] 0.9963
```

# Random Variables and Probability Distributions: Binomial Distribution

- Example: flip a fair coin 3 times

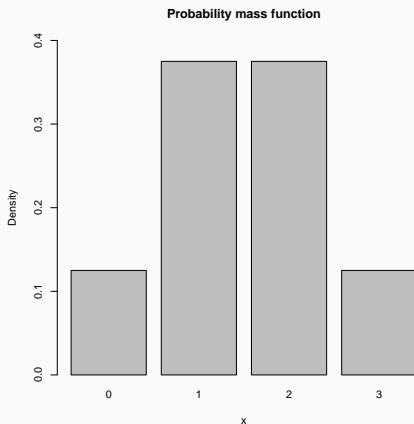
$$f(x) = P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$

$$f(x) = P(X = 1) = \binom{3}{1} 0.5^1 (0.5)^2 = 3 * 0.5 * 0.5^2 = 0.375$$

# Random Variables and Probability Distributions: Binomial Distribution

```
x <- 0:3  
barplot(dbinom(x, size = 3, prob = 0.5), ylim = c(0, 0.4), names.arg = x, xlab = "x",  
        ylab = "Density", main = "Probability mass function")
```

# Random Variables and Probability Distributions: Binomial Distribution

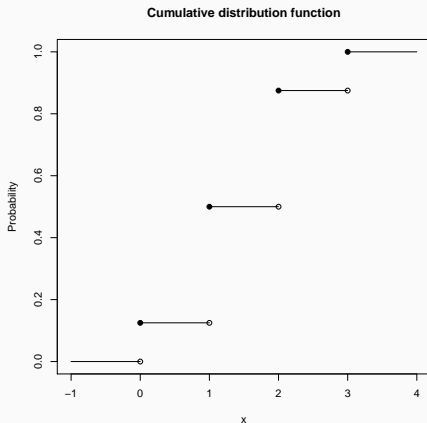


# Random Variables and Probability Distributions: Binomial Distribution

```
x <- -1:4
pb <- pbinom(x, size = 3, prob = 0.5)
plot(x[1:2], rep(pb[1], 2), ylim = c(0, 1), type = "s", xlim = c(-1, 4), xlab = "x",
     ylab = "Probability", main = "Cumulative distribution function")
for (i in 2:(length(x)-1)) {
  lines(x[i:(i+1)], rep(pb[i], 2))
}
points(x[2:(length(x)-1)], pb[2:(length(x)-1)], pch = 19)
points(x[2:(length(x)-1)], pb[1:(length(x)-2)])
```

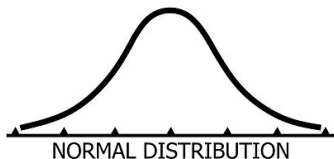


# Random Variables and Probability Distributions: Binomial Distribution



# Random Variables and Probability Distributions: Normal Distribution

## Normal distribution



# Random Variables and Probability Distributions: Normal Distribution

Normal distribution also called Gaussian distribution



# Normal distribution

- Takes on values from  $-\infty$  to  $\infty$
- Defined by two things:  $\mu$  and  $\sigma^2$ 
  - Mean and Variance (standard deviation squared)
- Mean defines the location of the distribution
- Variance defines the spread

# Random Variables and Probability Distributions: Normal Distribution

Normal distribution with mean  $\mu$  and standard deviation  $\sigma$

- PDF:  $f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$

# Random Variables and Probability Distributions: Normal Distribution

Normal distribution with mean  $\mu$  and standard deviation  $\sigma$

- PDF:  $f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$

In R:

```
dnorm(2, mean = 2, sd = 2) ## probability of x =2 with normal
```

```
[1] 0.1994711
```

# Random Variables and Probability Distributions: Normal Distribution

- CDF (no simple formula. use to compute it):

$$F(x) = P(X \leq x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(t-\mu)^2}{2\sigma^2}\right) dt$$

- What will be  $F(x=2)$  for  $N(2,4)$ ?

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In R:

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pnorm(2, mean = 2, sd = 2) ## probability of x =2 with normal
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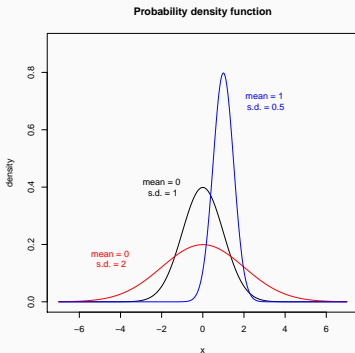
```
[1] 0.5
```



# Normal distribution

- Normal distribution is symmetric around the mean
- Mean = Median

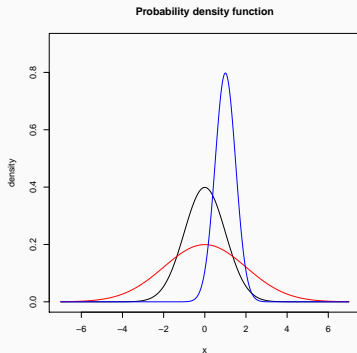
# Random Variables and Probability Distributions: Normal Distribution



# Random Variables and Probability Distributions: Normal Distribution in R

```
x <- seq(from = -7, to = 7, by = 0.01)
plot(x, dnorm(x), xlab = "x", ylab = "density", type = "l",
     main = "Probability density function", ylim = c(0, 0.9))
lines(x, dnorm(x, sd = 2), col = "red", lwd = lwd)
lines(x, dnorm(x, mean = 1, sd = 0.5), col = "blue", lwd = lwd)
```

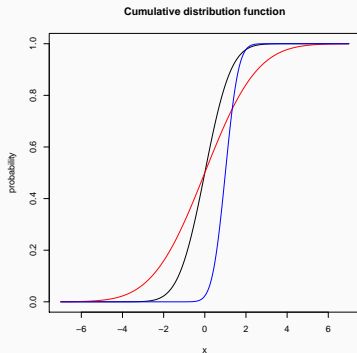
# Random Variables and Probability Distributions: Normal Distribution in R



# Random Variables and Probability Distributions: Normal Distribution in R

```
plot(x, pnorm(x), xlab = "x", ylab = "probability", type = "l",  
     main = "Cumulative distribution function", lwd = lwd)  
lines(x, pnorm(x, sd = 2), col = "red", lwd = lwd)  
lines(x, pnorm(x, mean = 1, sd = 0.5), col = "blue", lwd = lwd)
```

# Random Variables and Probability Distributions: Normal Distribution in R



# Random Variables and Probability Distributions: Normal Distribution

Let  $X \sim N(\mu, \sigma^2)$ , and  $c$  be some constant

- Adding/subtracting to/from a random variable that is normally distributed also results in a variable with a normal distribution:  
 $Z = X + c$  then  $Z \sim N(\mu + c, \sigma^2)$

# Random Variables and Probability Distributions: Normal Distribution

Let  $X \sim N(\mu, \sigma^2)$ , and  $c$  be some constant

- Adding/subtracting to/from a random variable that is normally distributed also results in a variable with a normal distribution:  
 $Z = X + c$  then  $Z \sim N(\mu + c, \sigma^2)$
- Multiplying or dividing a random variable that is normally distributed also results in a variable with a normal distribution:  
 $Z = X \times c$  then  $Z \sim N(\mu \times c, (\sigma \times c)^2)$
- Z-score of a random variable that is normally distributed has mean 0 and  $\text{sd} = 1$



# Random Variables and Probability Distributions: Normal Distribution

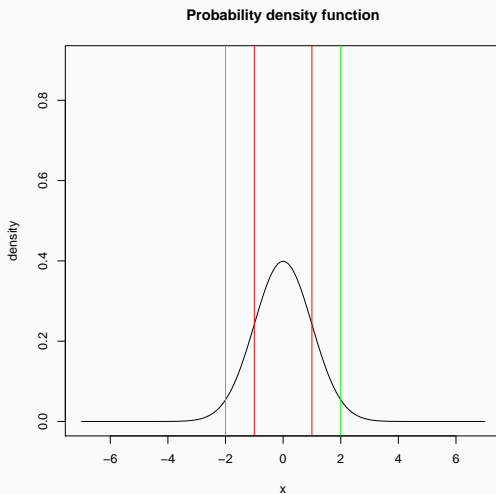
Curve of the standard normal distribution:

- Symmetric around 0
- Total area under the curve is 100%
- Area between -1 and 1 is ~68%
- Area between -2 and 2 is ~95%
- Area between -3 and 3 is ~99.7%

# Random Variables and Probability Distributions: Normal Distribution

```
x <- seq(from = -7, to = 7, by = 0.01)
lwd <- 1.5
plot(x, dnorm(x), xlab = "x", ylab = "density", type = "l",
     main = "Probability density function", ylim = c(0, 0.9))
abline(v= -1, col = "red")
abline(v= 1, col = "red")
abline(v= -2, col = "green")
abline(v= 2, col = "green")
```

# Random Variables and Probability Distributions: Normal Distribution



# Random Variables and Probability Distributions: Normal Distribution

Curve of the **any** normal distribution:

- Symmetric around 0
- Total area under the curve is 100%
- Area between  $-1SD$  and  $+1SD$  is  $\sim 68\%$
- Area between  $-2SD$  and  $+2SD$  is  $\sim 95\%$
- Area between  $-3SD$  and  $+3SD$  is  $\sim 99.7\%$

## *Expectations, Means, and Variances*

For probability distributions, means should not be confused with *sample means*

Expectations or means of a random variable have specific meanings for its the probability distribution

A sample mean varies from sample to sample

Mean of a probability distribution is a theoretical construct and constant

# Means and Expectation

A sample mean varies from sample to sample

Mean of a probability distribution is a theoretical construct and constant

Example: Age of undergraduate body at A&M

# Means and Expectation

The expectation of a random variable is equal to the sum of all possibilities *weighted* by the probabilities



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Example: expectation of rolling one die

$$\mathbb{E}(X) = \frac{1}{6} \times 1 + \frac{1}{6} \times 2 + \frac{1}{6} \times 3 + \frac{1}{6} \times 4 + \frac{1}{6} \times 5 + \frac{1}{6} \times 6 = 3.5$$

The expectation of a random variable is equal to the sum of all possibilities *weighted* by the probabilities

$$\mathbb{E}(X) = \begin{cases} \sum_x x f(x) & \text{if } X \text{ is discrete} \\ \int x f(x) dx & \text{if } X \text{ is continuous} \end{cases}$$

# Means and Expectation

Remember the lottery!

Expected value:  $\text{winnings} \times p(\text{winning}) + 0 \times p(\text{not winning})$

What is  $\mathbb{E}(X)$  for the number of heads in 100 coin flips?

What is  $\mathbb{E}(X)$  for the number of heads in 100 coin flips?

$$\mathbb{E}(X) = 0.5 \times 1 + 0.5 \times 1 + \dots + 0.5 \times 1 = 0.5 * 100 = 50$$

- Variance is standard deviation squared
- Variance in a probability distribution indicates how much uncertainty exists
- Similar **but not the same** as sample standard deviation

Population variance:

$$\mathbb{V}(X) = \mathbb{E}[\{X - \mathbb{E}(X)\}^2] = \mathbb{E}(X^2) - \{\mathbb{E}(X)\}^2$$