

Bios 6301: Assignment 3

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Due Tuesday, 27 September, 1:00 PM

50 points total.

Add your name as **author** to the file's metadata section.

Submit a single knitr file (named **homework3.rmd**) by email to tianyi.sun@vanderbilt.edu. Place your R code in between the appropriate chunks for each question. Check your output by using the Knit HTML button in RStudio.

$5^{n=\text{day}}$ points taken off for each day late.

Question 1

15 points

Write a simulation to calculate the power for the following study design. The study has two variables, treatment group and outcome. There are two treatment groups (0, 1) and they should be assigned randomly with equal probability. The outcome should be a random normal variable with a mean of 60 and standard deviation of 20. If a patient is in the treatment group, add 5 to the outcome. 5 is the true treatment effect. Create a linear model for the outcome by the treatment group, and extract the p-value (hint: see assignment1). Test if the p-value is less than or equal to the alpha level, which should be set to 0.05.

Repeat this procedure 1000 times. The power is calculated by finding the percentage of times the p-value is less than or equal to the alpha level. Use the `set.seed` command so that the professor can reproduce your results.

1. Find the power when the sample size is 100 patients. (10 points) power is $239/1000 \times 100 = 23.9\%$.

```
n.sim =1000

n <- 100
mean <- 60
sd <- 20
p_value = NULL
treatment.groups <-c(0,1)

set.seed(2)
for (j in 1:n.sim) {
  t.s <- sample(treatment.groups, n, replace=TRUE)
  outcome<- rnorm(n, mean, sd)
  for (i in 1:n) {
    if (t.s[i]==1){
      outcome[i]<- outcome[i] +5}
    else {outcome[i] <- outcome[i] }
  }
}
```

```
summary(coef(lm(outcome~t.s)))
p_value[j] = coef(summary(lm(outcome~t.s)))[2,4]
}
p_value <0.05
```

```
## [1] FALSE FALSE FALSE FALSE TRUE FALSE FALSE TRUE FALSE FALSE FALSE FALSE
## [13] FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
## [25] FALSE TRUE FALSE FALSE TRUE FALSE TRUE FALSE FALSE FALSE TRUE FALSE
## [37] FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE
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## [121] TRUE FALSE FALSE FALSE TRUE FALSE TRUE TRUE FALSE FALSE TRUE FALSE
## [133] FALSE FALSE TRUE FALSE FALSE FALSE TRUE TRUE FALSE TRUE FALSE TRUE
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## [157] TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE
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## [565] FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE
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## [577] FALSE FALSE TRUE TRUE FALSE TRUE TRUE TRUE FALSE FALSE FALSE TRUE
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## [613] FALSE FALSE TRUE FALSE TRUE FALSE TRUE TRUE FALSE FALSE FALSE TRUE
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## [961] FALSE FALSE FALSE TRUE TRUE FALSE FALSE TRUE TRUE FALSE FALSE FALSE
## [973] FALSE FALSE FALSE TRUE FALSE FALSE TRUE TRUE TRUE FALSE FALSE FALSE
## [985] FALSE TRUE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE
## [997] TRUE FALSE FALSE FALSE
```

```
sum(p_value < 0.05)
```

```
## [1] 239
```

1. Find the power when the sample size is 1000 patients. (5 points) power is $46/1000 \times 100 = 4.6\%$

```
n2.sim = 1000

n2 <- 1000
mean2 <- 60
sd2 <- 20
p_value2 = NULL
treatment.groups2 <- c(0,1)

set.seed(2)
for (j2 in 1:n2.sim) {
```

```

t.s2 <- sample(treatment.groups2, n2, replace=TRUE)
outcome2<- rnorm(n2, mean2, sd2)
for (i2 in 1:n2) {
  if (t.s2[i2]==1){
    outcome2[i2]<- outcome2[i2] +5}
  else {outcome2[i2] <- outcome2[i2] }
}
summary(coef(lm(outcome2~t.s2)))
p_value2[j2] = coef(summary(lm(outcome2~t.s2)))[2,4]
}
p_value2 <0.05

```

```

##      [1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
##     [13] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
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## [997] FALSE FALSE FALSE FALSE
```

```
sum(p_value2 <0.05)
```

```
## [1] 46
```

Question 2

14 points

Obtain a copy of the football-values lecture. Save the 2021/proj_wr21.csv file in your working directory. Read in the data set and remove the first two columns.

1. Show the correlation matrix of this data set. (4 points)

```
getwd()
```

```
## [1] "C:/Users/gibsondk/Dannielle-Gibson-BIOS6301"
```

```
proj_wr21<- data.frame(read.csv(file = "proj_wr21(original).csv"))
df<- proj_wr21[-c(1,2)]
df
```

##	rec_att	rec_yds	rec_tds	rush_att	rush_yds	rush_tds	fumbles	fpts
## 1	100.2	1436.2	12.3	12.9	82.4	0.8	0.7	229.2
## 2	122.5	1462.5	12.8	0.0	0.0	0.0	0.8	221.3
## 3	113.5	1474.5	9.3	2.4	15.6	0.1	1.2	202.4
## 4	99.3	1415.3	8.8	4.6	26.2	0.1	0.8	196.1
## 5	122.1	1467.7	7.6	0.9	4.4	0.0	1.5	190.2
## 6	86.6	1301.3	9.9	0.3	1.3	0.0	1.4	187.2
## 7	93.5	1392.3	7.9	0.4	1.5	0.0	0.8	185.2
## 8	84.5	1267.9	9.8	0.5	7.5	0.0	0.9	184.5
## 9	111.2	1208.6	7.9	3.0	16.3	0.1	1.0	168.4
## 10	76.1	1113.5	9.4	0.0	0.0	0.0	0.7	166.5
## 11	91.5	1235.7	6.5	1.8	12.1	0.1	0.7	162.9
## 12	98.3	1223.4	6.9	0.3	0.3	0.0	0.7	162.6
## 13	89.8	1187.7	7.2	2.6	11.7	0.0	0.7	161.9
## 14	79.6	1021.5	9.2	3.2	14.6	0.3	0.7	158.9
## 15	97.3	1080.4	6.0	17.0	106.5	0.9	0.8	158.4
## 16	84.6	1099.7	6.6	8.5	61.2	0.6	0.8	157.7
## 17	93.4	1063.1	8.4	1.0	2.7	0.0	0.7	155.6
## 18	77.8	1102.8	7.2	0.5	-0.5	0.0	0.7	152.3
## 19	82.3	1186.1	5.4	3.1	20.1	0.1	0.8	151.9
## 20	92.8	1066.6	7.1	3.9	23.7	0.1	0.7	150.9
## 21	82.1	1067.3	7.5	0.3	2.0	0.0	0.8	150.1
## 22	79.2	1058.3	6.4	2.3	12.4	0.0	0.8	144.0
## 23	71.1	994.3	6.5	5.6	50.6	0.3	0.7	143.7
## 24	73.1	926.3	6.5	14.6	82.4	0.7	0.7	142.8
## 25	69.9	1033.1	6.3	0.0	0.0	0.0	0.7	139.9
## 26	93.9	981.0	6.6	4.4	27.4	0.1	1.4	137.7
## 27	71.9	1041.7	5.8	1.5	8.2	0.0	1.2	137.7
## 28	69.6	892.1	6.8	8.3	44.3	0.6	0.9	136.6
## 29	70.0	992.9	6.3	1.7	9.4	0.0	0.7	136.6
## 30	75.3	1052.5	5.2	0.8	6.8	0.0	0.7	135.9
## 31	73.1	1030.8	5.5	0.0	0.0	0.0	0.8	134.5
## 32	70.4	898.6	4.7	13.5	99.3	0.7	0.8	130.8
## 33	80.3	991.3	5.2	2.5	12.3	0.1	0.8	130.6
## 34	89.3	901.9	6.7	0.0	0.0	0.0	0.9	128.6
## 35	70.6	941.6	5.9	0.3	3.3	0.0	0.6	128.4
## 36	64.1	941.7	5.9	0.0	0.0	0.0	0.6	128.3
## 37	84.0	932.0	5.5	2.1	15.7	0.0	0.8	126.5
## 38	56.7	925.1	5.7	0.3	0.5	0.0	0.6	125.8
## 39	75.0	825.8	4.9	19.7	108.7	0.5	0.7	124.5
## 40	68.7	876.4	6.3	0.3	0.0	0.0	0.6	124.3
## 41	61.2	824.6	7.0	1.5	8.0	0.0	0.6	124.1
## 42	62.3	735.2	4.8	24.6	128.5	1.1	0.7	120.4

## 43	73.6	885.3	5.0	1.9	9.7	0.3	0.8	120.1
## 44	63.7	895.8	5.1	1.0	6.2	0.0	1.2	118.3
## 45	66.6	849.1	5.3	0.0	0.0	0.0	0.6	115.6
## 46	65.5	833.0	5.5	0.0	0.0	0.0	0.7	115.0
## 47	71.8	857.0	4.9	0.3	-0.8	0.0	0.7	113.5
## 48	63.2	824.7	4.5	3.4	22.7	0.0	0.7	110.8
## 49	68.2	887.1	3.9	0.0	0.0	0.0	0.8	110.5
## 50	52.1	796.1	4.4	10.4	58.3	0.1	1.7	109.2
## 51	52.4	732.1	5.5	6.4	43.8	0.1	1.7	108.0
## 52	63.5	711.5	6.0	2.0	11.4	0.0	0.6	106.9
## 53	65.5	778.0	4.5	2.7	15.5	0.0	0.7	105.1
## 54	56.0	802.5	4.3	0.0	0.0	0.0	0.7	104.7
## 55	51.8	788.9	4.1	1.4	8.7	0.0	0.0	104.6
## 56	57.1	764.6	4.7	1.5	8.6	0.0	1.2	103.2
## 57	56.1	743.0	5.0	0.0	0.0	0.0	0.6	102.9
## 58	57.1	696.3	5.0	1.1	6.7	0.1	0.6	99.1
## 59	64.0	737.8	4.4	0.0	0.0	0.0	0.6	99.1
## 60	54.5	730.9	4.1	3.1	17.5	0.1	0.7	98.3
## 61	50.6	714.5	4.5	0.3	1.3	0.0	0.7	97.2
## 62	66.3	720.9	4.1	1.3	6.1	0.0	0.6	95.9
## 63	59.5	719.1	3.7	0.7	4.2	0.0	0.4	93.9
## 64	42.7	629.5	5.0	0.3	0.0	0.0	0.1	92.8
## 65	56.1	714.2	3.5	0.7	3.6	0.0	0.5	91.9
## 66	42.1	596.1	5.1	0.3	0.5	0.0	0.1	89.8
## 67	49.5	684.3	3.8	0.5	2.0	0.0	1.0	89.3
## 68	49.8	643.3	4.1	0.0	0.0	0.0	0.4	88.4
## 69	62.1	636.4	3.5	3.3	26.0	0.3	0.6	87.7
## 70	51.7	633.6	4.2	0.0	0.0	0.0	0.7	86.9
## 71	50.6	612.6	4.3	1.5	7.6	0.0	0.7	86.6
## 72	54.1	663.7	3.6	1.1	6.1	0.0	1.2	86.3
## 73	48.6	632.4	3.5	0.5	2.8	0.0	1.2	82.4
## 74	54.0	605.4	3.7	0.3	3.3	0.0	0.7	81.5
## 75	45.1	545.3	3.8	3.9	26.9	0.0	0.6	79.4
## 76	46.1	559.2	3.3	4.8	30.1	0.2	0.4	78.9
## 77	35.5	561.0	3.6	2.8	17.1	0.1	0.6	78.8
## 78	41.1	543.0	4.1	0.8	4.8	0.0	0.6	78.0
## 79	40.8	551.3	3.7	1.3	9.7	0.0	0.6	76.9
## 80	42.4	558.9	3.4	0.0	0.0	0.0	0.3	75.7
## 81	42.5	566.1	3.3	0.0	0.0	0.0	0.3	75.6
## 82	41.2	556.5	3.5	0.8	2.6	0.0	0.6	75.5
## 83	46.1	545.8	2.8	2.2	10.3	0.1	0.8	71.5
## 84	40.3	487.2	3.4	1.4	5.8	0.0	0.1	69.8
## 85	43.4	519.6	3.1	0.0	0.0	0.0	0.6	69.2
## 86	37.5	525.1	2.7	0.0	0.0	0.0	0.7	67.4
## 87	43.0	522.8	2.6	0.0	0.0	0.0	0.3	67.2
## 88	37.6	462.0	3.5	0.8	7.5	0.0	0.6	66.9
## 89	36.1	469.4	3.1	0.8	4.5	0.0	0.6	64.9
## 90	25.7	438.1	3.3	2.5	14.8	0.0	0.6	64.4
## 91	33.3	451.7	2.9	0.0	0.0	0.0	0.6	61.4
## 92	30.7	415.3	3.3	0.3	2.0	0.0	0.1	61.4
## 93	35.7	460.9	2.7	0.0	0.0	0.0	0.5	61.1
## 94	35.3	423.3	3.3	0.0	0.0	0.0	0.6	60.9
## 95	16.0	188.0	1.0	54.0	225.0	2.0	0.0	59.3
## 96	32.6	391.7	2.4	8.9	43.9	0.2	0.6	57.9

## 97	31.6	449.8	2.0	0.3	0.8	0.0	0.1	57.2
## 98	27.4	419.3	2.3	2.5	10.6	0.1	0.1	56.9
## 99	22.8	369.9	2.6	2.5	15.0	0.0	0.0	54.3
## 100	26.5	395.9	2.6	0.0	0.0	0.0	0.6	53.8
## 101	32.7	373.2	2.6	1.1	5.5	0.0	0.0	53.5
## 102	27.4	381.3	2.4	0.5	3.0	0.0	0.6	51.5
## 103	28.5	375.1	2.5	0.0	0.0	0.0	0.6	51.2
## 104	26.8	392.2	2.0	0.3	1.4	0.0	0.1	50.9
## 105	29.4	351.5	1.9	6.5	39.7	0.2	0.3	50.9
## 106	28.3	379.0	2.1	0.0	0.0	0.0	0.0	50.7
## 107	35.6	371.9	2.2	1.3	5.7	0.0	0.5	49.7
## 108	35.2	411.0	2.1	1.0	5.5	0.5	4.0	49.5
## 109	27.3	371.5	2.1	0.0	0.0	0.0	0.2	49.5
## 110	29.3	372.1	2.0	0.0	0.0	0.0	0.2	49.2
## 111	23.6	303.2	2.9	0.0	0.0	0.0	0.6	46.3
## 112	26.5	350.3	1.8	0.0	0.0	0.0	0.2	45.7
## 113	27.0	304.7	1.6	7.3	47.9	0.1	0.2	45.2
## 114	23.7	311.8	2.2	0.0	0.0	0.0	0.2	44.1
## 115	24.1	427.0	1.4	1.5	0.0	0.0	4.0	43.2
## 116	29.5	339.7	1.7	0.3	2.0	0.0	0.6	43.1
## 117	30.3	331.0	1.6	0.0	0.0	0.0	0.1	42.4
## 118	24.2	328.6	1.4	0.0	0.0	0.0	0.2	41.1
## 119	22.6	290.2	2.0	0.0	0.0	0.0	0.2	40.8
## 120	17.0	244.6	1.8	1.4	7.7	0.1	0.1	36.5
## 121	21.4	270.4	1.5	0.0	0.0	0.0	0.1	35.8
## 122	18.9	200.3	1.9	5.7	28.6	0.2	0.1	35.5
## 123	18.3	275.6	1.5	1.0	4.0	0.0	1.0	35.0
## 124	19.2	249.1	1.2	0.0	0.0	0.0	0.1	31.9
## 125	19.6	231.1	1.5	0.0	0.0	0.0	0.0	31.8
## 126	18.0	221.4	1.3	2.0	12.4	0.1	0.1	31.5
## 127	19.8	233.0	1.2	0.0	0.0	0.0	0.1	30.4
## 128	20.2	233.1	1.2	0.0	0.0	0.0	0.2	30.3
## 129	16.2	196.4	1.4	0.9	5.2	0.0	0.1	28.8
## 130	15.2	190.4	1.5	0.0	0.0	0.0	0.1	27.8
## 131	17.2	190.2	1.3	1.7	11.7	0.0	0.1	27.6
## 132	15.7	207.4	1.1	0.0	0.0	0.0	0.1	27.0
## 133	15.4	189.9	1.1	0.0	0.0	0.0	0.0	25.6
## 134	13.4	154.7	0.8	6.2	33.9	0.2	0.1	24.7
## 135	13.2	138.0	0.9	8.5	39.1	0.1	0.1	23.2
## 136	14.5	155.5	1.2	0.7	3.6	0.0	0.1	23.2
## 137	10.6	120.7	0.9	2.5	14.9	0.1	0.1	19.3
## 138	10.2	133.3	0.9	0.0	0.0	0.0	0.1	18.6
## 139	15.0	146.7	0.7	0.0	0.0	0.0	0.1	18.5
## 140	10.1	108.6	0.6	4.6	26.1	0.1	0.1	17.7
## 141	12.4	145.1	0.5	0.0	0.0	0.0	0.1	17.4
## 142	11.3	113.1	0.7	3.0	19.2	0.1	0.2	17.3
## 143	11.0	136.6	0.6	0.0	0.0	0.0	0.1	17.2
## 144	9.1	123.4	0.7	0.8	4.9	0.0	0.1	17.1
## 145	11.2	131.1	0.7	0.0	0.0	0.0	0.1	17.0
## 146	9.7	126.7	0.7	0.0	0.0	0.0	0.1	16.6
## 147	8.7	110.2	0.8	0.0	0.0	0.0	0.1	15.8
## 148	9.0	104.2	0.8	1.3	6.7	0.0	0.0	15.6
## 149	9.2	114.8	0.6	0.0	0.0	0.0	0.0	15.2
## 150	8.9	109.1	0.7	0.0	0.0	0.0	0.0	14.8

## 151	9.6	107.1	0.6	0.0	0.0	0.0	0.0	14.4
## 152	8.6	105.9	0.6	0.0	0.0	0.0	0.1	14.3
## 153	5.6	70.7	0.4	4.7	28.9	0.2	0.1	13.5
## 154	8.0	99.9	0.6	0.0	0.0	0.0	0.1	13.5
## 155	8.2	100.6	0.5	0.0	0.0	0.0	0.1	13.2
## 156	7.5	93.7	0.6	0.0	0.0	0.0	0.1	12.7
## 157	6.9	90.6	0.6	0.0	0.0	0.0	0.0	12.5
## 158	7.1	86.7	0.6	0.0	0.0	0.0	0.0	12.0
## 159	6.3	85.8	0.5	0.7	3.7	0.0	0.0	11.9
## 160	7.2	90.5	0.5	0.0	0.0	0.0	0.0	11.7
## 161	7.7	85.4	0.5	0.0	0.0	0.0	0.0	11.5
## 162	7.3	91.1	0.4	0.0	0.0	0.0	0.0	11.5
## 163	7.3	75.2	0.5	0.0	0.0	0.0	0.0	10.4
## 164	6.0	75.2	0.4	0.0	0.0	0.0	0.0	10.0
## 165	5.4	71.7	0.4	0.0	0.0	0.0	0.0	9.7
## 166	4.3	56.8	0.5	0.7	3.9	0.0	0.1	9.1
## 167	4.5	50.5	0.3	2.4	13.6	0.1	0.0	8.6
## 168	4.5	48.8	0.3	2.5	14.3	0.1	0.0	8.4
## 169	4.6	58.2	0.4	0.0	0.0	0.0	0.0	7.9
## 170	5.1	62.6	0.3	0.0	0.0	0.0	0.0	7.9
## 171	4.0	58.1	0.3	0.0	0.0	0.0	0.0	7.8
## 172	4.2	57.2	0.3	0.0	0.0	0.0	0.0	7.8
## 173	5.3	56.2	0.3	0.0	0.0	0.0	0.0	7.5
## 174	4.1	52.2	0.4	0.0	0.0	0.0	0.0	7.5
## 175	3.7	46.3	0.2	1.7	9.0	0.1	0.0	7.3
## 176	4.4	52.5	0.3	0.0	0.0	0.0	0.1	6.8
## 177	4.2	47.9	0.3	0.0	0.0	0.0	0.0	6.6
## 178	3.5	45.6	0.3	0.0	0.0	0.0	0.0	6.6
## 179	3.7	46.6	0.3	0.0	0.0	0.0	0.0	6.5
## 180	4.1	46.9	0.3	0.0	0.0	0.0	0.0	6.3
## 181	3.9	38.0	0.3	0.0	0.0	0.0	0.0	5.7
## 182	3.9	39.7	0.2	0.0	0.0	0.0	0.0	5.4
## 183	2.9	37.4	0.2	0.0	0.0	0.0	0.0	5.0
## 184	2.5	32.9	0.2	0.0	0.0	0.0	0.0	4.7
## 185	2.4	30.5	0.3	0.0	0.0	0.0	0.0	4.6
## 186	2.4	28.1	0.1	1.0	5.8	0.0	0.0	4.3
## 187	2.3	29.5	0.2	0.0	0.0	0.0	0.0	3.9
## 188	2.3	27.0	0.1	0.0	0.0	0.0	0.0	3.5
## 189	2.1	24.1	0.2	0.0	0.0	0.0	0.0	3.4
## 190	2.0	25.2	0.2	0.0	0.0	0.0	0.0	3.4
## 191	2.0	22.5	0.2	0.0	0.0	0.0	0.0	3.3
## 192	1.9	24.5	0.1	0.0	0.0	0.0	0.0	3.2
## 193	1.8	22.9	0.1	0.0	0.0	0.0	0.0	3.1
## 194	1.6	16.7	0.2	0.0	0.0	0.0	0.0	2.8
## 195	1.5	19.3	0.1	0.0	0.0	0.0	0.0	2.7
## 196	1.7	21.4	0.1	0.0	0.0	0.0	0.0	2.7
## 197	1.3	17.1	0.2	0.0	0.0	0.0	0.0	2.7
## 198	1.2	17.3	0.2	0.0	0.0	0.0	0.0	2.7
## 199	1.5	19.0	0.1	0.0	0.0	0.0	0.0	2.4
## 200	0.9	9.1	0.0	1.8	9.4	0.1	0.0	2.3
## 201	1.5	17.6	0.1	0.0	0.0	0.0	0.0	2.1
## 202	1.1	12.1	0.0	1.2	6.4	0.0	0.0	1.9
## 203	1.2	15.2	0.1	0.0	0.0	0.0	0.0	1.8
## 204	1.6	15.0	0.1	0.0	0.0	0.0	0.0	1.8

```
## 205      0.8      9.4      0.0      0.9      4.8      0.0      0.0      1.4
## 206      0.9      9.5      0.0      0.9      4.3      0.0      0.0      1.4
## 207      0.7      8.1      0.0      0.9      4.7      0.0      0.0      1.3
## 208      0.8     10.6      0.0      0.0      0.0      0.0      0.0      1.1
## 209      0.9     10.1      0.0      0.0      0.0      0.0      0.0      1.0
## 210      0.7      9.8      0.0      0.0      0.0      0.0      0.0      1.0
## 211      0.9      9.7      0.0      0.0      0.0      0.0      0.0      1.0
## 212      0.9      9.6      0.0      0.0      0.0      0.0      0.0      1.0
## 213      0.8      9.5      0.0      0.0      0.0      0.0      0.0      1.0
## 214      0.9      9.5      0.0      0.0      0.0      0.0      0.0      1.0
## 215      0.7      9.4      0.0      0.0      0.0      0.0      0.0      0.9
## 216      0.9      9.4      0.0      0.0      0.0      0.0      0.0      0.9
## 217      0.9      9.3      0.0      0.0      0.0      0.0      0.0      0.9
## 218      0.9      9.2      0.0      0.0      0.0      0.0      0.0      0.9
## 219      0.8      9.2      0.0      0.0      0.0      0.0      0.0      0.9
## 220      0.8      9.2      0.0      0.0      0.0      0.0      0.0      0.9
## 221      0.7      9.1      0.0      0.0      0.0      0.0      0.0      0.9
## 222      0.9      9.0      0.0      0.0      0.0      0.0      0.0      0.9
## 223      0.8      9.0      0.0      0.0      0.0      0.0      0.0      0.9
## 224      0.8      9.0      0.0      0.0      0.0      0.0      0.0      0.9
## 225      0.7      8.8      0.0      0.0      0.0      0.0      0.0      0.9
## 226      0.7      8.7      0.0      0.0      0.0      0.0      0.0      0.9
## 227      0.7      8.6      0.0      0.0      0.0      0.0      0.0      0.9
## 228      0.7      8.5      0.0      0.0      0.0      0.0      0.0      0.9
## 229      0.8      8.4      0.0      0.0      0.0      0.0      0.0      0.8
## 230      0.7      8.4      0.0      0.0      0.0      0.0      0.0      0.8
## 231      0.7      8.3      0.0      0.0      0.0      0.0      0.0      0.8
## 232      0.7      8.3      0.0      0.0      0.0      0.0      0.0      0.8
## 233      0.7      8.3      0.0      0.0      0.0      0.0      0.0      0.8
## 234      0.7      8.0      0.0      0.0      0.0      0.0      0.0      0.8
## 235      0.8      8.0      0.0      0.0      0.0      0.0      0.0      0.8
## 236      0.7      8.0      0.0      0.0      0.0      0.0      0.0      0.8
## 237      0.7      8.0      0.0      0.0      0.0      0.0      0.0      0.8
## 238      0.7      8.0      0.0      0.0      0.0      0.0      0.0      0.8
## 239      0.7      7.7      0.0      0.0      0.0      0.0      0.0      0.8
## 240      0.7      7.6      0.0      0.0      0.0      0.0      0.0      0.8
## 241      0.7      7.6      0.0      0.0      0.0      0.0      0.0      0.8
## 242      0.8      7.1      0.0      0.0      0.0      0.0      0.0      0.7
```

```
cor(df, method= c("pearson"))
```

```
##          rec_att  rec_yds  rec_tds  rush_att  rush_yds  rush_tds  fumbles
## rec_att  1.0000000 0.9889836 0.9620513 0.2242480 0.2810831 0.2312038 0.6423627
## rec_yds  0.9889836 1.0000000 0.9720400 0.2062038 0.2614786 0.2115013 0.6487247
## rec_tds  0.9620513 0.9720400 1.0000000 0.2004448 0.2540571 0.2151580 0.6021914
## rush_att 0.2242480 0.2062038 0.2004448 1.0000000 0.9779751 0.9308512 0.1446322
## rush_yds 0.2810831 0.2614786 0.2540571 0.9779751 1.0000000 0.9298581 0.1761579
## rush_tds 0.2312038 0.2115013 0.2151580 0.9308512 0.9298581 1.0000000 0.1809564
## fumbles  0.6423627 0.6487247 0.6021914 0.1446322 0.1761579 0.1809564 1.0000000
## fpts      0.9863078 0.9957911 0.9842850 0.2610623 0.3162080 0.2677821 0.6288445
##          fpts
## rec_att  0.9863078
## rec_yds  0.9957911
## rec_tds  0.9842850
```

```
## rush_att 0.2610623
## rush_yds 0.3162080
## rush_tds 0.2677821
## fumbles 0.6288445
## fpts 1.0000000
```

1. Generate a data set with 30 rows that has a similar correlation structure. Repeat the procedure 1,000 times and return the mean correlation matrix. (10 points)

```
library(MASS)
rho<- cor(df)
vcov<- var(df)
means<- colMeans(df)

df.sim <- mvrnorm(20, mu = means, Sigma = vcov)
df.sim = as.data.frame(df.sim)

(rho.sim<- cor(df.sim))
```

```
##          rec_att    rec_yds    rec_tds    rush_att    rush_yds
## rec_att  1.00000000  0.992489481  0.97896713 -0.043684584  0.016840089
## rec_yds  0.99248948  1.000000000  0.97874980 -0.052980964  0.007534164
## rec_tds  0.97896713  0.978749804  1.00000000 -0.062834766 -0.006750880
## rush_att -0.04368458 -0.052980964 -0.06283477  1.000000000  0.984445400
## rush_yds  0.01684009  0.007534164 -0.00675088  0.984445400  1.000000000
## rush_tds -0.11465390 -0.126411818 -0.11797805  0.927982073  0.921362860
## fumbles  0.52346889  0.544682123  0.49390683 -0.141140735 -0.067348051
## fpts     0.99190752  0.996348694  0.98753692  0.002749317  0.062123836
##          rush_tds    fumbles    fpts
## rec_att -0.11465390  0.52346889  0.991907519
## rec_yds -0.12641182  0.54468212  0.996348694
## rec_tds -0.11797805  0.49390683  0.987536916
## rush_att  0.92798207 -0.14114074  0.002749317
## rush_yds  0.92136286 -0.06734805  0.062123836
## rush_tds  1.00000000 -0.13901227 -0.067538742
## fumbles -0.13901227  1.00000000  0.516869426
## fpts     -0.06753874  0.51686943  1.000000000
```

```
rho
```

```
##          rec_att    rec_yds    rec_tds    rush_att    rush_yds    rush_tds    fumbles
## rec_att  1.0000000  0.9889836  0.9620513  0.2242480  0.2810831  0.2312038  0.6423627
## rec_yds  0.9889836  1.0000000  0.9720400  0.2062038  0.2614786  0.2115013  0.6487247
## rec_tds  0.9620513  0.9720400  1.0000000  0.2004448  0.2540571  0.2151580  0.6021914
## rush_att 0.2242480  0.2062038  0.2004448  1.0000000  0.9779751  0.9308512  0.1446322
## rush_yds 0.2810831  0.2614786  0.2540571  0.9779751  1.0000000  0.9298581  0.1761579
## rush_tds 0.2312038  0.2115013  0.2151580  0.9308512  0.9298581  1.0000000  0.1809564
## fumbles  0.6423627  0.6487247  0.6021914  0.1446322  0.1761579  0.1809564  1.0000000
## fpts     0.9863078  0.9957911  0.9842850  0.2610623  0.3162080  0.2677821  0.6288445
##          fpts
## rec_att  0.9863078
## rec_yds  0.9957911
## rec_tds  0.9842850
```

```
## rush_att 0.2610623
## rush_yds 0.3162080
## rush_tds 0.2677821
## fumbles 0.6288445
## fpts 1.0000000
```

```
keep.1=0
loops=10000

for (i in 1:loops) {
  df.sim = mvrnorm(20, mu = means, Sigma = vcov)
  keep.1=keep.1+cor(df.sim)/loops }
keep.1-rho
```

```
##          rec_att      rec_yds      rec_tds      rush_att      rush_yds
## rec_att -9.381385e-14 -6.187748e-04 -2.146039e-03 -8.784522e-03 -9.652938e-03
## rec_yds -6.187748e-04 -9.381385e-14 -1.672419e-03 -8.013501e-03 -8.880588e-03
## rec_tds -2.146039e-03 -1.672419e-03 -9.381385e-14 -8.312121e-03 -9.249453e-03
## rush_att -8.784522e-03 -8.013501e-03 -8.312121e-03 -9.381385e-14 -1.193939e-03
## rush_yds -9.652938e-03 -8.880588e-03 -9.249453e-03 -1.193939e-03 -9.381385e-14
## rush_tds -7.278976e-03 -6.544112e-03 -7.086723e-03 -3.330494e-03 -3.082884e-03
## fumbles -8.857264e-03 -9.514761e-03 -9.926437e-03 -6.127319e-03 -6.425819e-03
## fpts -8.017956e-04 -2.498811e-04 -9.746911e-04 -9.264005e-03 -1.003897e-02
##          rush_tds      fumbles      fpts
## rec_att -7.278976e-03 -8.857264e-03 -8.017956e-04
## rec_yds -6.544112e-03 -9.514761e-03 -2.498811e-04
## rec_tds -7.086723e-03 -9.926437e-03 -9.746911e-04
## rush_att -3.330494e-03 -6.127319e-03 -9.264005e-03
## rush_yds -3.082884e-03 -6.425819e-03 -1.003897e-02
## rush_tds -9.381385e-14 -6.421741e-03 -7.817458e-03
## fumbles -6.421741e-03 -9.381385e-14 -9.744527e-03
## fpts -7.817458e-03 -9.744527e-03 -9.381385e-14
```

Question 3

21 points

Here's some code:

```
nDist <- function(n = 100) {
  df <- 10
  prob <- 1/3
  shape <- 1
  size <- 16
  list(
    beta = rbeta(n, shape1 = 5, shape2 = 45),
    binomial = rbinom(n, size, prob),
    chisquared = rchisq(n, df),
    exponential = rexp(n),
    f = rf(n, df1 = 11, df2 = 17),
    gamma = rgamma(n, shape),
    geometric = rgeom(n, prob),
    hypergeometric = rhyper(n, m = 50, n = 100, k = 8),
```

```

    lognormal = rlnorm(n),
    negbinomial = rnbinom(n, size, prob),
    normal = rnorm(n),
    poisson = rpois(n, lambda = 25),
    t = rt(n, df),
    uniform = runif(n),
    weibull = rweibull(n, shape)
  )
}

```

1. What does this do? (3 points)

```
round(sapply(nDist(500), mean), 2)
```

```
##          beta      binomial    chisquared    exponential          f
##         0.10         5.44         9.92         1.06         1.18
##        gamma    geometric hypergeometric    lognormal    negbinomial
##         0.92         2.01         2.67         1.81         32.39
##        normal      poisson          t          uniform      weibull
##         0.01         24.79        -0.06         0.50         1.03
```

Sapply is simplifying the output by converting the list of functions into a vector. The mean of

2. What about this? (3 points)

```
sort(apply(replicate(20, round(sapply(nDist(10000), mean), 2)), 1, sd))
```

```
##          beta      uniform          f    exponential      gamma
## 0.000000000 0.003663475 0.006958524 0.009665457 0.009679060
##      normal      weibull hypergeometric          t      binomial
## 0.009986833 0.012096106 0.012311740 0.012396944 0.013869694
##   lognormal    geometric    chisquared    poisson    negbinomial
## 0.020749128 0.021588252 0.053555186 0.065652594 0.116821952
```

‘

Sapply is simplifying the output by converting the list of functions into a vector. The mean of

In the output above, a small value would indicate that $N=10,000$ would provide a sufficient sample size as to estimate the mean of the distribution. Let's say that a value *less than 0.02* is “close enough”.

3. For each distribution, estimate the sample size required to simulate the distribution's mean. (15 points)

```

nDist <- function(n = 100) {
  df <- 10
  prob <- 1/3
  shape <- 1
  size <- 16
  list(
    beta = rbeta(n, shape1 = 5, shape2 = 45),
    binomial = rbinom(n, size, prob),
    chisquared = rchisq(n, df),
    exponential = rexp(n),

```

```

    f = rf(n, df1 = 11, df2 = 17),
    gamma = rgamma(n, shape),
    geometric = rgeom(n, prob),
    hypergeometric = rhyper(n, m = 50, n = 100, k = 8),
    lognormal = rlnorm(n),
    negbinomial = rnbinom(n, size, prob),
    normal = rnorm(n),
    poisson = rpois(n, lambda = 25),
    t = rt(n, df),
    uniform = runif(n),
    weibull = rweibull(n, shape)
  )
}
round(sapply(nDist(500), mean), 2)

```

```

##      beta      binomial    chisquared    exponential      f
##      0.10        5.27       10.07        1.00        1.13
##      gamma    geometric hypergeometric    lognormal    negbinomial
##      0.94        1.94        2.65        1.76        32.14
##      normal      poisson          t        uniform      weibull
##     -0.01       25.25        0.04        0.50        0.99

```

Don't worry about being exact. It should already be clear that $N < 10,000$ for many of the distributions. You don't have to show your work. Put your answer to the right of the vertical bars (|) below.

distribution	N
beta	?
binomial	?
chisquared	?
exponential	?
f	?
gamma	?
geometric	?
hypergeometric	?
lognormal	?
negbinomial	?
normal	?
poisson	?
t	?
uniform	?
weibull	?