

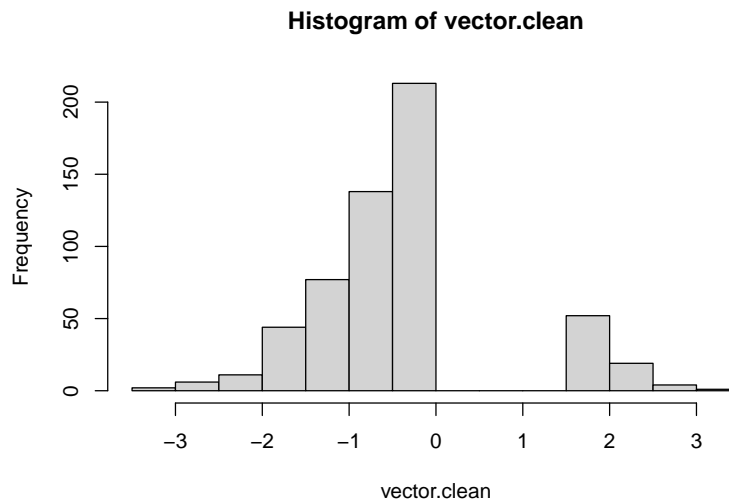
# SC306 Homework 3: R Intro Part 2

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## Question 1

```
vector.raw = rnorm(1000,mean = 0, sd = 1)
vector.clean = vector.raw[!(vector.raw >= 0 & vector.raw <= 1.5)]
hist(vector.clean)
```



## Question 2

```
vector.1_100 = abs(abs(-99:99)-100)
vector.1_100
```

```
## [1] 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
## [19] 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36
## [37] 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54
## [55] 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72
## [73] 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90
## [91] 91 92 93 94 95 96 97 98 99 100 99 98 97 96 95 94 93 92
## [109] 91 90 89 88 87 86 85 84 83 82 81 80 79 78 77 76 75 74
## [127] 73 72 71 70 69 68 67 66 65 64 63 62 61 60 59 58 57 56
## [145] 55 54 53 52 51 50 49 48 47 46 45 44 43 42 41 40 39 38
## [163] 37 36 35 34 33 32 31 30 29 28 27 26 25 24 23 22 21 20
## [181] 19 18 17 16 15 14 13 12 11 10 9 8 7 6 5 4 3 2
## [199] 1
```

### Question 3

```
library(knitr)

us_sorted <- USArrests[order(USArrests$Murder, decreasing = TRUE), ]

us_sorted
```

##	Murder	Assault	UrbanPop	Rape
## Georgia	17.4	211	60	25.8
## Mississippi	16.1	259	44	17.1
## Florida	15.4	335	80	31.9
## Louisiana	15.4	249	66	22.2
## South Carolina	14.4	279	48	22.5
## Alabama	13.2	236	58	21.2
## Tennessee	13.2	188	59	26.9
## North Carolina	13.0	337	45	16.1
## Texas	12.7	201	80	25.5
## Nevada	12.2	252	81	46.0
## Michigan	12.1	255	74	35.1
## New Mexico	11.4	285	70	32.1
## Maryland	11.3	300	67	27.8
## New York	11.1	254	86	26.1
## Illinois	10.4	249	83	24.0
## Alaska	10.0	263	48	44.5
## Kentucky	9.7	109	52	16.3
## California	9.0	276	91	40.6
## Missouri	9.0	178	70	28.2
## Arkansas	8.8	190	50	19.5
## Virginia	8.5	156	63	20.7
## Arizona	8.1	294	80	31.0
## Colorado	7.9	204	78	38.7
## New Jersey	7.4	159	89	18.8
## Ohio	7.3	120	75	21.4
## Indiana	7.2	113	65	21.0
## Wyoming	6.8	161	60	15.6
## Oklahoma	6.6	151	68	20.0
## Pennsylvania	6.3	106	72	14.9
## Kansas	6.0	115	66	18.0
## Montana	6.0	109	53	16.4
## Delaware	5.9	238	72	15.8
## West Virginia	5.7	81	39	9.3
## Hawaii	5.3	46	83	20.2
## Oregon	4.9	159	67	29.3
## Massachusetts	4.4	149	85	16.3
## Nebraska	4.3	102	62	16.5
## Washington	4.0	145	73	26.2
## South Dakota	3.8	86	45	12.8
## Rhode Island	3.4	174	87	8.3
## Connecticut	3.3	110	77	11.1
## Utah	3.2	120	80	22.9
## Minnesota	2.7	72	66	14.9
## Idaho	2.6	120	54	14.2
## Wisconsin	2.6	53	66	10.8
## Iowa	2.2	56	57	11.3
## Vermont	2.2	48	32	11.2
## Maine	2.1	83	51	7.8
## New Hampshire	2.1	57	56	9.5
## North Dakota	0.8	45	44	7.3

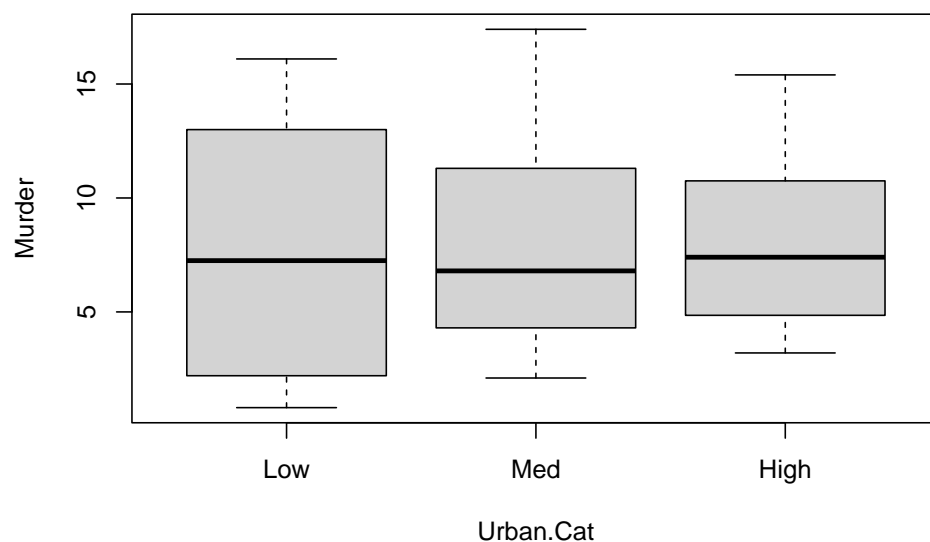
## Question 4

```
USArrests$Urban.Cat = cut(USArrests$UrbanPop,3, labels = c("Low", "Med", "High"))
USArrests
```

##		Murder	Assault	UrbanPop	Rape	Urban.Cat
##	Alabama	13.2	236	58	21.2	Med
##	Alaska	10.0	263	48	44.5	Low
##	Arizona	8.1	294	80	31.0	High
##	Arkansas	8.8	190	50	19.5	Low
##	California	9.0	276	91	40.6	High
##	Colorado	7.9	204	78	38.7	High
##	Connecticut	3.3	110	77	11.1	High
##	Delaware	5.9	238	72	15.8	High
##	Florida	15.4	335	80	31.9	High
##	Georgia	17.4	211	60	25.8	Med
##	Hawaii	5.3	46	83	20.2	High
##	Idaho	2.6	120	54	14.2	Med
##	Illinois	10.4	249	83	24.0	High
##	Indiana	7.2	113	65	21.0	Med
##	Iowa	2.2	56	57	11.3	Med
##	Kansas	6.0	115	66	18.0	Med
##	Kentucky	9.7	109	52	16.3	Med
##	Louisiana	15.4	249	66	22.2	Med
##	Maine	2.1	83	51	7.8	Low
##	Maryland	11.3	300	67	27.8	Med
##	Massachusetts	4.4	149	85	16.3	High
##	Michigan	12.1	255	74	35.1	High
##	Minnesota	2.7	72	66	14.9	Med
##	Mississippi	16.1	259	44	17.1	Low
##	Missouri	9.0	178	70	28.2	Med
##	Montana	6.0	109	53	16.4	Med
##	Nebraska	4.3	102	62	16.5	Med
##	Nevada	12.2	252	81	46.0	High
##	New Hampshire	2.1	57	56	9.5	Med
##	New Jersey	7.4	159	89	18.8	High
##	New Mexico	11.4	285	70	32.1	Med
##	New York	11.1	254	86	26.1	High
##	North Carolina	13.0	337	45	16.1	Low
##	North Dakota	0.8	45	44	7.3	Low
##	Ohio	7.3	120	75	21.4	High
##	Oklahoma	6.6	151	68	20.0	Med
##	Oregon	4.9	159	67	29.3	Med
##	Pennsylvania	6.3	106	72	14.9	High
##	Rhode Island	3.4	174	87	8.3	High
##	South Carolina	14.4	279	48	22.5	Low
##	South Dakota	3.8	86	45	12.8	Low
##	Tennessee	13.2	188	59	26.9	Med
##	Texas	12.7	201	80	25.5	High
##	Utah	3.2	120	80	22.9	High
##	Vermont	2.2	48	32	11.2	Low
##	Virginia	8.5	156	63	20.7	Med
##	Washington	4.0	145	73	26.2	High
##	West Virginia	5.7	81	39	9.3	Low
##	Wisconsin	2.6	53	66	10.8	Med
##	Wyoming	6.8	161	60	15.6	Med

## Question 5

```
boxplot(Murder ~ Urban.Cat, data = USArrests)
```



Percent urban, as defined by the three categories in `Urban.Cat` does not appear to have a meaningful association with the murder rate in any given city.

```
cor(USArrests$UrbanPop, USArrests$Murder)
```

```
## [1] 0.06957262
```

```
summary(lm(Murder ~ UrbanPop, data = USArrests))
```

```
##
## Call:
## lm(formula = Murder ~ UrbanPop, data = USArrests)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.537  -3.736  -0.779   3.332   9.728
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.41594    2.90669   2.207  0.0321 *
## UrbanPop      0.02093    0.04333   0.483  0.6312
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.39 on 48 degrees of freedom
## Multiple R-squared:  0.00484,    Adjusted R-squared: -0.01589
## F-statistic: 0.2335 on 1 and 48 DF,  p-value: 0.6312
```

These data show the “urbanness” of a city is effectively unrelated to its murder rate.

## Question 6

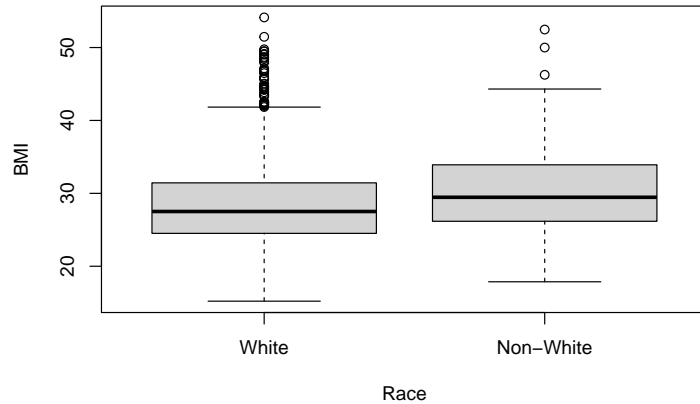
```
hersdata <- read.csv("C:/Users/Othar Zaldastani/Downloads/hersdata.csv")
head(hersdata)
```

```
##           HT age           raceth nonwhite smoking drinkany exercise
## 1      placebo 70 African American      yes      no      no      no
## 2      placebo 62 African American      yes      no      no      no
## 3 hormone therapy 69           White      no      no      no      no
## 4      placebo 64           White      no      yes      yes      no
## 5      placebo 65           White      no      no      no      no
## 6 hormone therapy 68 African American      yes      no      yes      no
##           physact globrat poorfair medcond htnmeds statins diabetes
## 1      much more active      good      no      0      yes      yes      no
## 2      much less active      good      no      1      yes      no      no
## 3      about as active      good      no      0      yes      no      yes
## 4      much less active      good      no      1      yes      no      no
## 5 somewhat less active      good      no      0      no      no      no
## 6      about as active      good      no      0      no      no      no
## dmpills insulin weight      BMI waist      WHR glucose weight1      BMI1 waist1      WHR1
## 1      no      no      73.8 23.69 96.0 0.932      84      73.6 23.63 93.0 0.912
## 2      no      no      70.9 28.62 93.0 0.964      111     73.4 28.89 95.0 0.964
## 3      no      no      102.0 42.51 110.2 0.782      114     96.1 40.73 103.0 0.774
## 4      no      no      64.4 24.39 87.0 0.877      94      58.6 22.52 77.0 0.802
## 5      no      no      57.9 21.90 77.0 0.794      101     58.9 22.28 76.5 0.757
## 6      no      no      60.9 29.05 96.0 1.000      116     57.7 27.52 86.0 0.910
## glucose1 tchol      LDL HDL      TG tchol1      LDL1 HDL1 TG1 SBP DBP age10
## 1      94      189 122.4 52 73      201 137.6 48 77 138 78 7.0
## 2      78      307 241.6 44 107     216 150.6 48 87 118 70 6.2
## 3      98      254 166.2 57 154     254 156.0 66 160 134 78 6.9
## 4      93      204 116.2 56 159     207 122.6 57 137 152 72 6.4
## 5      92      214 150.6 42 107     235 172.2 35 139 175 95 6.5
## 6      115     212 137.8 52 111     202 126.6 53 112 174 98 6.8
```

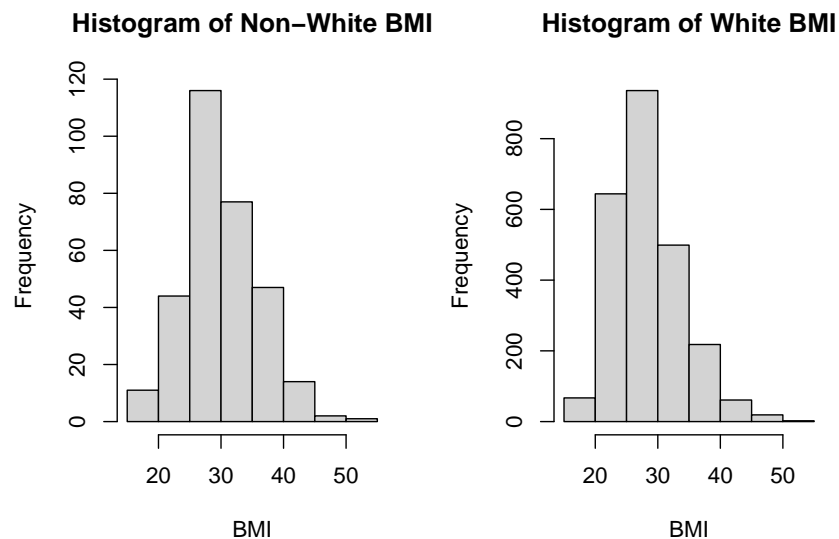
```
names(hersdata)
```

```
## [1] "HT"      "age"      "raceth"    "nonwhite" "smoking"  "drinkany"
## [7] "exercise" "physact"  "globrat"   "poorfair" "medcond"  "htnmeds"
## [13] "statins"  "diabetes" "dmpills"   "insulin"  "weight"   "BMI"
## [19] "waist"    "WHR"      "glucose"   "weight1"  "BMI1"     "waist1"
## [25] "WHR1"     "glucose1" "tchol"     "LDL"      "HDL"      "TG"
## [31] "tchol1"   "LDL1"     "HDL1"     "TG1"      "SBP"      "DBP"
## [37] "age10"
```

```
boxplot(BMI ~ nonwhite, data = hersdata, xlab = "Race", names = c("White", "Non-White"))
```



```
par(mfrow = c(1,2))
hist(hersdata$BMI[hersdata$nonwhite == "yes"], main = "Histogram of Non-White BMI", xlab = "BMI")
hist(hersdata$BMI[hersdata$nonwhite == "no"], main = "Histogram of White BMI", xlab = "BMI")
```



```
hersdata$LnBMI = log(hersdata$BMI)
t.test(LnBMI ~ nonwhite, hersdata)
```

```
##
## Welch Two Sample t-test
##
## data: LnBMI by nonwhite
## t = -5.0211, df = 386.75, p-value = 7.857e-07
## alternative hypothesis: true difference in means between group no and group yes is not equal to 0
## 95 percent confidence interval:
```

```
## -0.08135354 -0.03556994
## sample estimates:
## mean in group no mean in group yes
##          3.328232          3.386694
```

I ran a t-test with a null hypothesis of no BMI difference between `white` and `nonwhite` women and an alternative hypothesis of a difference in average BMI existing between the two groups. The test gave us a t-score of -5.02, for a p-value of  $\ll 0.01$  in favor of rejecting the null hypothesis. The data show a clear association between BMI and `white/nonwhite` status.

## Question 7

```
# Confidence interval function
ci.prop.conf = function(x,n,c) {
  p_hat = x/n
  se = sqrt(p_hat * (1-p_hat) / n)

  alpha = 1 - c
  z = qnorm(1-alpha/2)

  lower = p_hat - z * se
  upper = p_hat + z * se
  return(list(
    proportion = p_hat,
    confidence.interval = c,
    lower = lower,
    upper = upper
  ))}
ci.prop.conf(46, 200, .95)
```

```
## $proportion
## [1] 0.23
##
## $confidence.interval
## [1] 0.95
##
## $lower
## [1] 0.1716767
##
## $upper
## [1] 0.2883233
```

$\hat{p} = 0.23$ , and the 95% confidence interval is  $[0.192 : 0.268]$ .

## Question 8

### Part A Completed Table

Occupation	# With Latex Allergy	Total # in Group	Frequency per 1,000 people
Health Care Workers	13	58	224.1
Non-Health Care Workers	25	1093	22.9
Painters	2	32	62.5
Hairdressers	3	59	50.8
Food Handlers	7	41	170.7
Cleaners	3	78	38.5

**Part B** The name of the measurement of disease calculated above is prevalence. Here it is represented as  $\frac{\text{Number with Latex Allergy}}{\text{Total in Group}} \times 1000$ .

**Part C** To determine cumulative incidence, the previous positive results are excluded from the at-risk population. Baseline positives number 164 and the at-risk population is then  $2030 - 164 = 1866$ . The total number of new cases is 47, making the cumulative incidence  $\frac{47}{1866} = 0.0252$ .

**Part D** Person time can be calculated by taking the sum of the products of participants and the number of monthly visits they completed.  $(1532 \cdot 24) + (17 \cdot 22) + (19 \cdot 19) + (41 \cdot 16) + (232 \cdot 12) + (25 \cdot 7) = 41,118$  person months, or 3426.5 person-

**Part E** Incidence density is the number of new cases divided by the person-time.

With 47 new cases and 41,118 person-months, the incidence density is equal to  $\frac{47}{41118} \times 1000 \approx 1.14$  cases per 1000 person-months.

**Part F** This is an example of a proportion because it is calculated by dividing the number of cases by the number of workers. It could also be described as point prevalence because it describes the prevalence of workers with the Latex allergy at a specific point in time (the first week in June). No person-time means it's not incidence density, no follow-up eliminates incidence proportion, and it is not period prevalence because it is a measure at one point in time.