## Around Simpson's Paradox

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#### Introduction

The first study was carried in 1977, the second study in 1995.

#### Question 1

TODO pie chart

```
df = read.csv("Subject6_smoking.csv")
compute_mortality_rate <- function(smoker_arg,df_arg, title_arg){
    nb_alive= df_arg %>% filter(Status == "Alive" & Smoker== smoker_arg) %>% nrow()
    nb_dead= df_arg %>% filter(Status == "Dead" & Smoker== smoker_arg) %>% nrow()

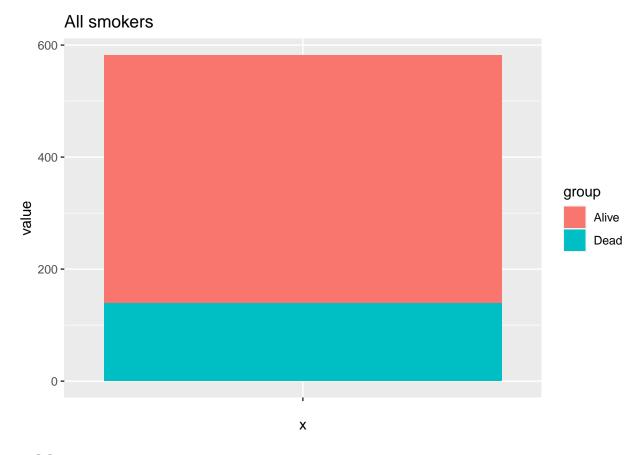
df <- data.frame(
    group = c("Alive", "Dead"),
    value = c(nb_alive,nb_dead)
)

bp<- ggplot(df, aes(x="", y=value, fill=group))+
    geom_bar(width = 1, stat = "identity") + ggtitle(title_arg)
    print(bp)

nb_dead / (nb_alive+nb_dead) # divide the number of dead by the total, the total being the addition of the state o
```

We declare a function so that we can' compute both rates (for smokers and non smokers), without repeating our code

```
compute_mortality_rate(smoker_arg = "Yes", df_arg =df,title_arg = "All smokers")
```

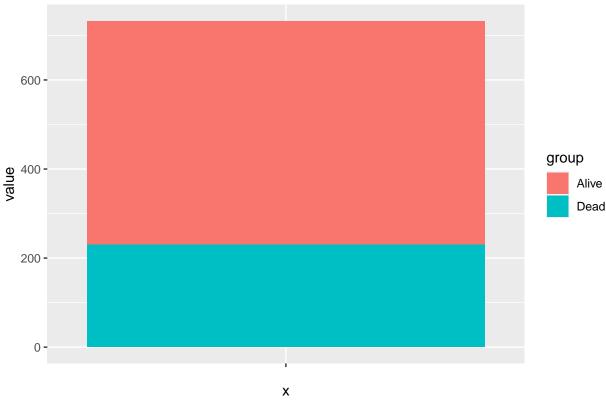


## [1] 0.2388316

The rate for the smoker group

compute\_mortality\_rate(smoker\_arg = "No", df\_arg =df, title\_arg = "All non smokers")

# All non smokers



## [1] 0.3142077

The rate for the non smoking group

The mortality rate is significantly higher for the group that is not smoking. In other words, in with this data, a woman who smoked in 1977 is less likely to have died in 1995 than a woman who did not smoke in 1977.

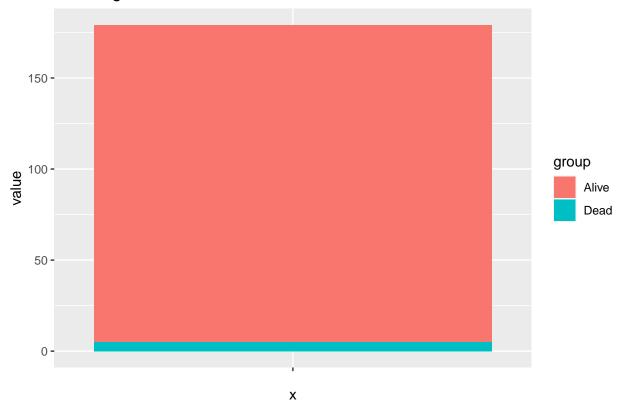
Of course, this is very surprising because it is now known that smoking cigarette increases the risk of death, trough various mechanisms, such as increased risk of cancer and cardiovascular disease. For more details, consult the relevant wikipedia article.

### Question 2

We will use the recommended age grouping.

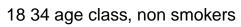
```
class1834 = df %>% filter(Age >= 18 & Age < 34)
class3454 = df %>% filter(Age >= 34 & Age < 54)
class5464 = df %>% filter(Age >= 54 & Age < 64)
class64 = df %>% filter(Age >= 64)
compute_mortality_rate(smoker_arg = "Yes", df_arg = class1834,title_arg = "18 34 age class, smokers")
```

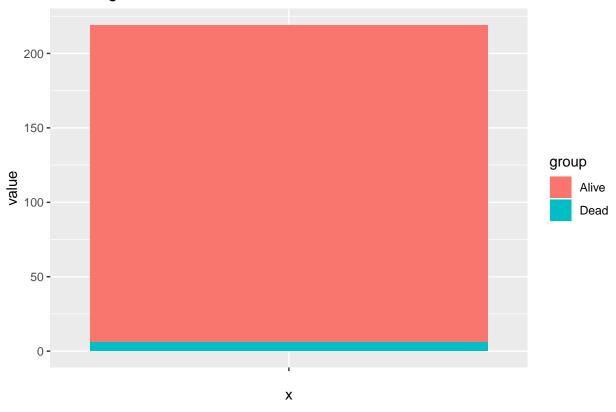
18 34 age class, smokers



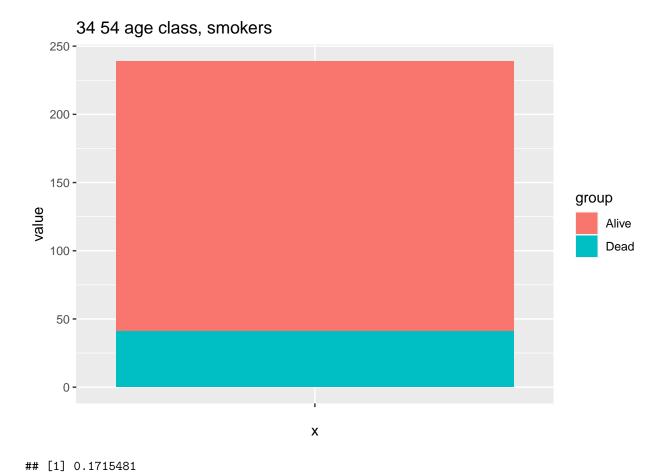
## [1] 0.02793296

compute\_mortality\_rate(smoker\_arg = "No", df\_arg = class1834,title\_arg = "18 34 age class, non smokers"



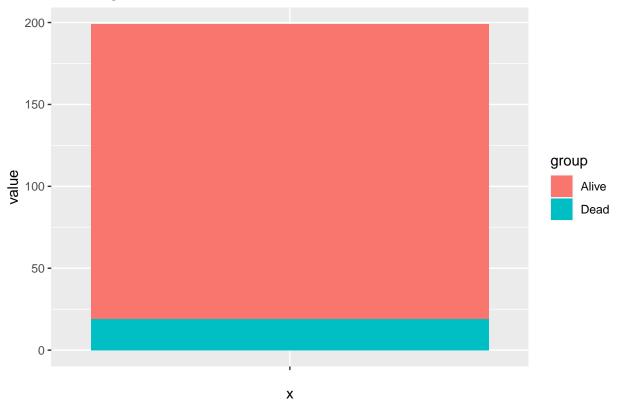


## [1] 0.02739726
compute\_mortality\_rate(smoker\_arg = "Yes", df\_arg = class3454,title\_arg = "34 54 age class, smokers")

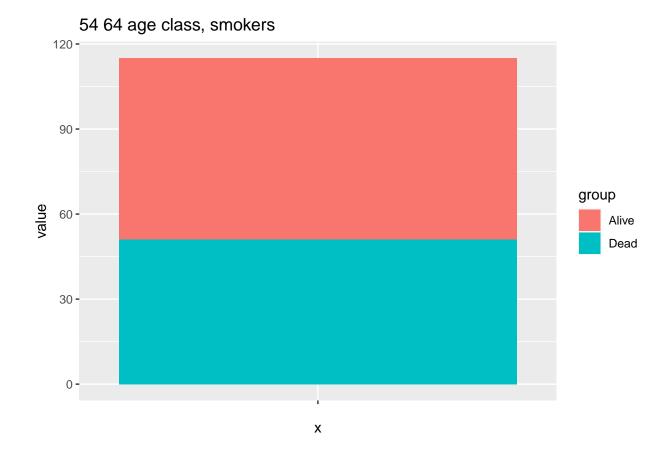


compute\_mortality\_rate(smoker\_arg = "No", df\_arg = class3454,title\_arg = "34 54 age class, non smokers"

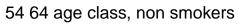
34 54 age class, non smokers

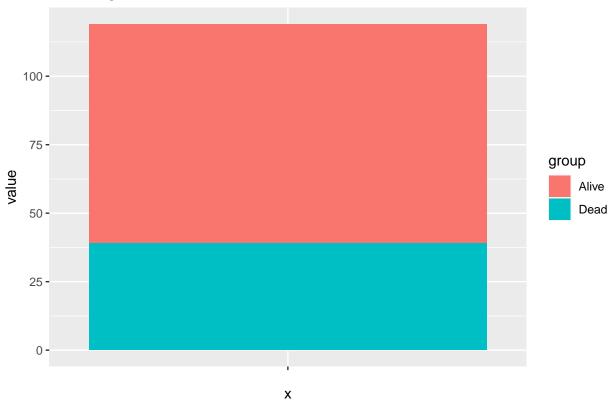


## [1] 0.09547739
compute\_mortality\_rate(smoker\_arg = "Yes", df\_arg = class5464,title\_arg = "54 64 age class, smokers")

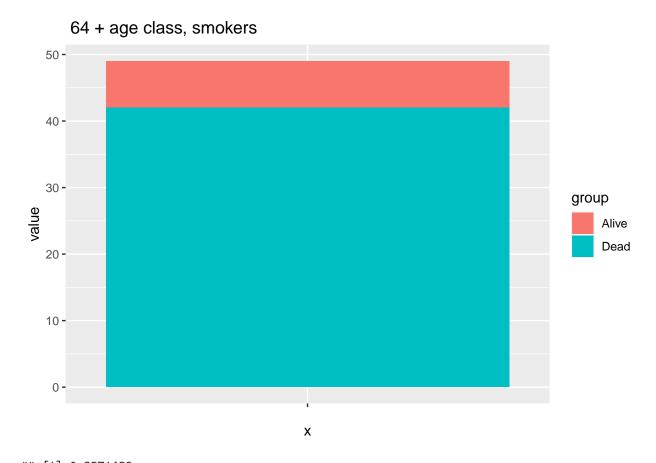


## [1] 0.4434783
compute\_mortality\_rate(smoker\_arg = "No", df\_arg = class5464,title\_arg = "54 64 age class, non smokers"

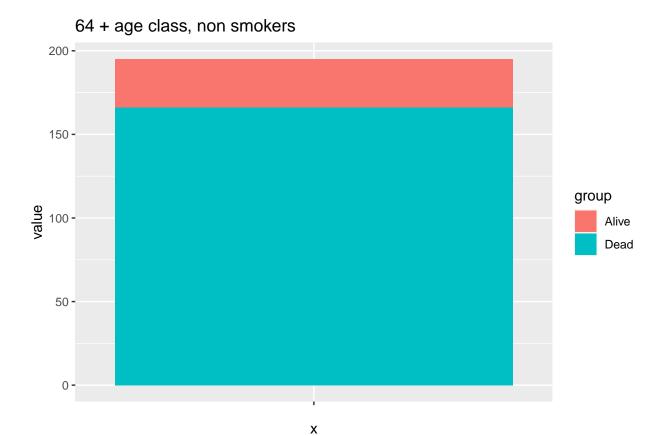




## [1] 0.3277311
compute\_mortality\_rate(smoker\_arg = "Yes", df\_arg = class64,title\_arg = " 64 + age class, smokers")



## [1] 0.8571429
compute\_mortality\_rate(smoker\_arg = "No", df\_arg = class64,title\_arg = "64 + age class, non smokers")



## [1] 0.8512821

This is very surprising, because, as we saw in question 1, the mortality rate was higher for  $non\ smoker$ . But now, after organizing the data in age classes, for every single class, the mortality is higher for the smoker group. relevant youtube video # Conclusion