Lab 7

October 17, 2021

1 Lab 7

In this lab we discuss two-way table, conditional and marginal proportions, relative risk, and odds ratio.

1.1 Two-way Table

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.graphics.mosaicplot import mosaic
```

[2]:
```
# Read .csv data
df = pd.read_csv("titanic.csv")
# The titanic.csv file contains data for 891 of the real Titanic passengers.
# Each row represents one person. The columns describe different attributes␣
↪about the person including
# whether they survived, their ID, their ticket-class, and their gender.
df.head(5)
```

[2]:
```
   PassengerID LivingStatus  TicketClass     Sex
0            1         Died            3    male
1            2     Survived            1  female
2            3     Survived            3  female
3            4     Survived            1  female
4            5         Died            3    male
```

pd.crosstab: https://pandas.pydata.org/docs/reference/api/pandas.crosstab.html

[3]:
```
# Two-way Table of LivingStatus vs. Sex
twoway_table = pd.crosstab(index = df["LivingStatus"], columns = df["Sex"])
twoway_table
```

[3]:
```
Sex           female  male
LivingStatus
Died              81   468
```

```
Survived          233    109
```

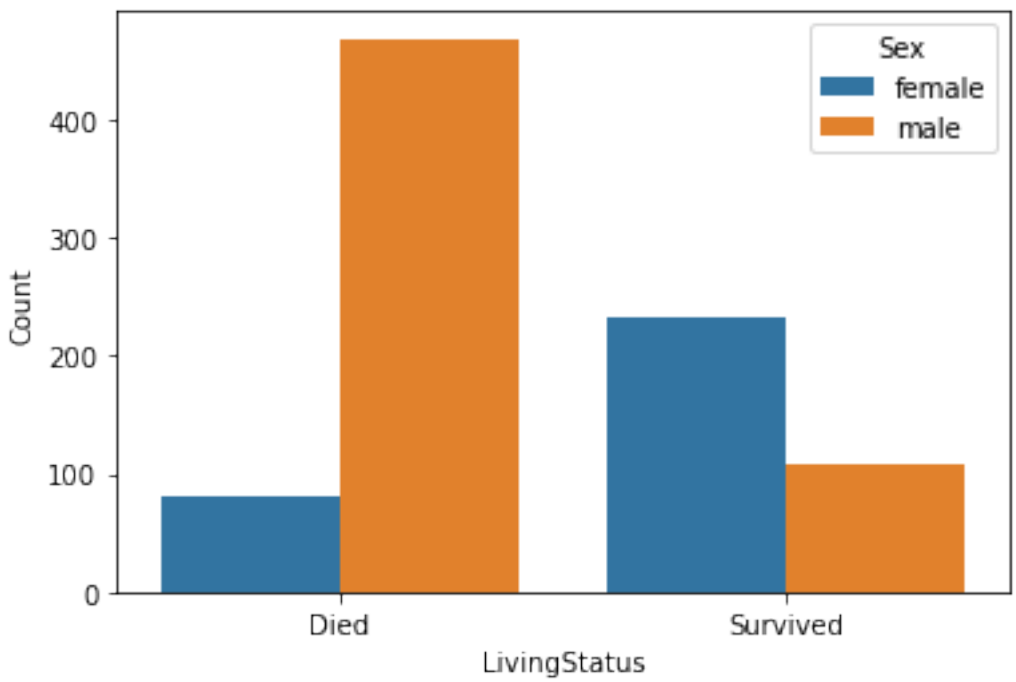
[4]:
```python
# We can also present the table in another way.
table_new = twoway_table.stack().reset_index().rename(columns = {0:'Count'})
table_new
```

[4]:

	LivingStatus	Sex	Count
0	Died	female	81
1	Died	male	468
2	Survived	female	233
3	Survived	male	109

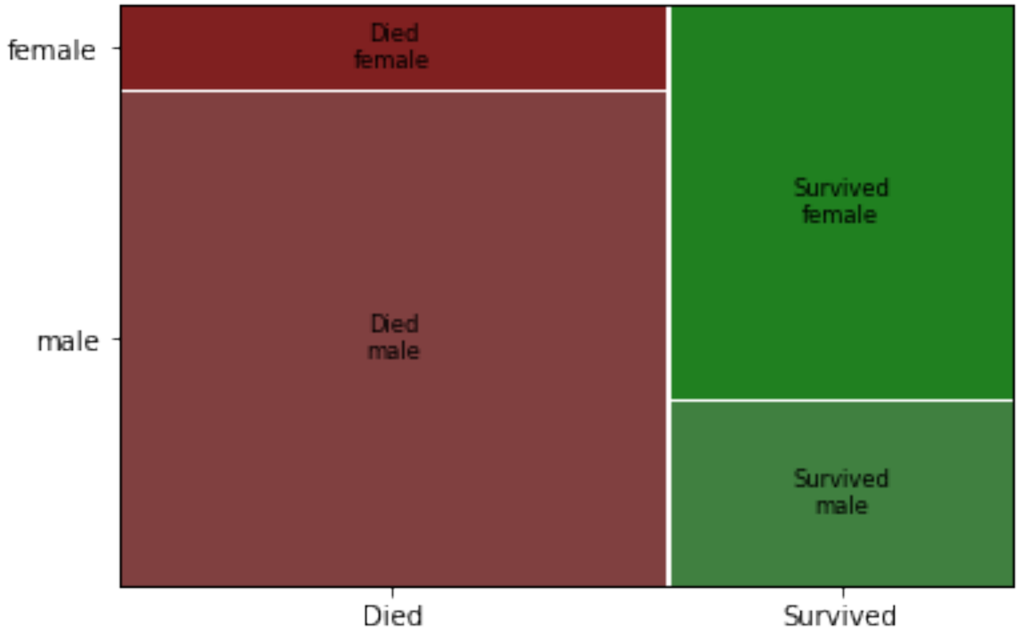
sns.barplot: https://seaborn.pydata.org/generated/seaborn.barplot.html

[5]:
```python
# Let's create a bidimensional barplot.
sns.barplot(x = "LivingStatus", hue = "Sex", y = "Count", data = table_new)
plt.show()
```

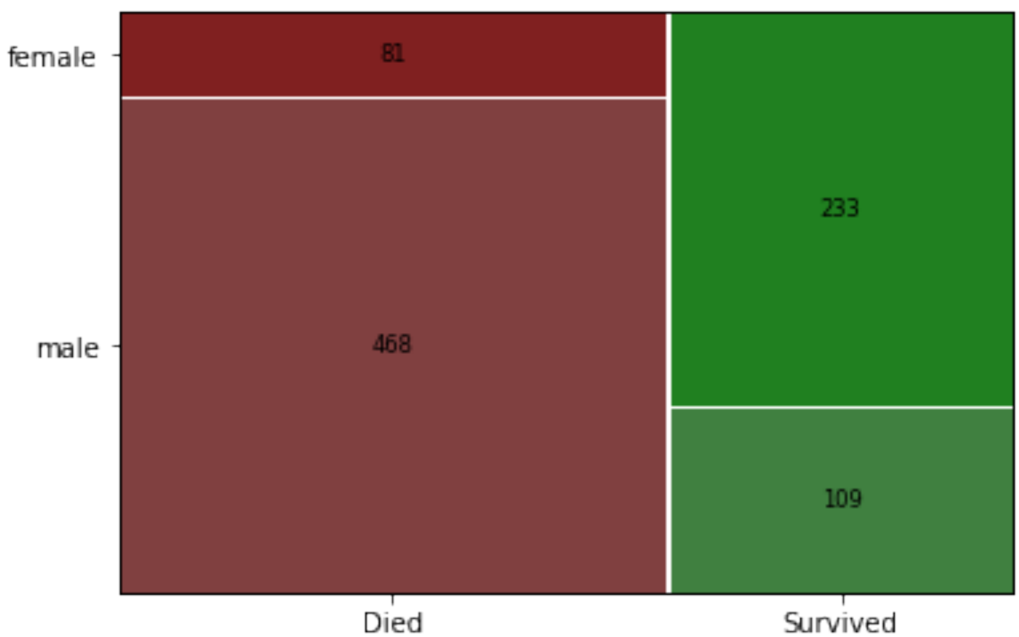


mosaicplot: https://www.statsmodels.org/stable/generated/statsmodels.graphics.mosaicplot.mosaic.html

[8]:
```python
# the mosaic plot is a graphical method for visualizing data from two␣
↪categorical variables.
# Simple mosaic plot, without counts or percentages
mosaic(df, ['LivingStatus', 'Sex'])
plt.show()
```



[9]:
```
# Bonus! Adding the counts to the mosaic plot
labelizer = lambda k:{('Died', 'female'):81, ('Died', 'male'):468,
                      ('Survived', 'female'):233, ('Survived', 'male'):109}[k]
mosaic(df, ['LivingStatus', 'Sex'], labelizer = labelizer)
plt.show()
```



1.2 Marginal and Conditional Proportions

[10]:
```python
# Table of LivingStatus vs. TicketClass
# Getting the marginal counts (totals for each row and column)
pd.crosstab(index = df["LivingStatus"], columns = df["TicketClass"], margins =␣
↪True)
```

[10]:
```
TicketClass     1    2    3  All
LivingStatus
Died           80   97  372  549
Survived      136   87  119  342
All           216  184  491  891
```

[8]:
```python
# Getting the proportion of counts along each column,
# i.e. the survival proportions conditional on ticket-class (dividing by the␣
↪column totals)
pd.crosstab(index = df["LivingStatus"], columns = df["TicketClass"], normalize␣
↪= 'columns')
```

[8]:
```
TicketClass         1         2         3
LivingStatus
Died          0.37037  0.527174  0.757637
Survived      0.62963  0.472826  0.242363
```

[11]:
```python
# Getting the proportion of counts along each row (dividing by the row totals)
# i.e. the class proportions conditional on living status
pd.crosstab(index = df["LivingStatus"], columns = df["TicketClass"], normalize␣
↪= 'index')
```

[11]:
```
TicketClass          1         2         3
LivingStatus
Died          0.145719  0.176685  0.677596
Survived      0.397661  0.254386  0.347953
```

[14]:
```python
# Getting the total proportion of counts in each cell (dividing the table by␣
↪the grand total)
# and the marginal proportions
pd.crosstab(index = df["LivingStatus"], columns = df["TicketClass"], normalize␣
↪= 'all', margins=True)
```

[14]:
```
TicketClass          1         2         3       All
LivingStatus
Died          0.089787  0.108866  0.417508  0.616162
Survived      0.152637  0.097643  0.133558  0.383838
All           0.242424  0.206510  0.551066  1.000000
```

```
[18]: #help(pd.crosstab)
```

1.3 Relative Risk and Odds Ratio

```
[37]: # The following 2x2 table illustrates the number of cancer cases versus␣
      ↪non-cancer cases for smokers and non-smokers.
      df_new = pd.DataFrame({'Cancer-Yes':[30, 10], 'Cancer-No':[70, 90]}, index =␣
      ↪['Smoker', 'Non-Smoker'])
      df_new
```

[37]:

	Cancer-Yes	Cancer-No
Smoker	30	70
Non-Smoker	10	90

```
[38]: # let us calculate the proportions of developing cancer conditional on smoking␣
      ↪status
      p_smoker = 30/100
      p_nonsmoker = 10/100
```

```
[39]: # the relative risk of developing cancer in the smoker group compared to␣
      ↪non-smokers is:
      RR = p_smoker/p_nonsmoker
      print(RR)
      round(RR,2)
```

```
2.9999999999999996
```

```
[39]: 3.0
```

sm.stats.Table2x2: https://www.statsmodels.org/stable/generated/statsmodels.stats.contingency_tables.Table

```
[40]: # Alternative way to find the relative risk
      array = np.array([[30, 70], [10, 90]])
      relative_risk = sm.stats.Table2x2(array).riskratio
      print('Relative Risk =',round(relative_risk,2))
```

```
Relative Risk = 3.0
```

```
[41]: # Now we can also find the odds ratio (OR) of developing cancer in the smoker␣
      ↪group compared to non-smokers:
      odds_smoker = 30/70
      odds_nonsmoker = 10/90
      OR = odds_smoker/odds_nonsmoker
      print('The odds ratio is', round(OR,2))
```

```
The odds ratio is 3.86
```

[42]:

```
# Alternative way to find the odds ratio
odds_ratio = sm.stats.Table2x2(array).oddsratio
print('Odds Ratio =', odds_ratio.round(2))
```

```
Odds Ratio = 3.86
```

[ ]:

```

```