

# MT18242\_A4\_VM

November 8, 2019

## 1 DSc Assignment 4

### 1.1 Survival Analysis

```
[2]: # Data taken from http://sphweb.bumc.bu.edu/otlt/MPH-Modules/BS/BS704\_Survival/BS704\_Survival\_print.html
```

```
[3]: import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from random import sample
```

```
[4]: time = [0, 1, 2, 3, 5, 6, 9, 10, 11, 12, 13, 14, 17, 18, 19, 21, 23, 24]
nt = [20, 20, 19, 18, 17, 16, 15, 14, 13, 12, 11, 10, 9, 7, 6, 5, 4, 3]
dt = [0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0]

df = pd.DataFrame({'Time':time,
                   'Number at Risk':nt,
                   'Number of Deaths':dt})
```

```
[5]: df
```

```
[5]:
```

	Time	Number at Risk	Number of Deaths
0	0	20	0
1	1	20	1
2	2	19	0
3	3	18	1
4	5	17	1
5	6	16	0
6	9	15	0
7	10	14	0
8	11	13	0
9	12	12	0
10	13	11	0
11	14	10	1
12	17	9	1
13	18	7	0
14	19	6	0

15	21	5	0
16	23	4	1
17	24	3	0

$$S_{t-1} = S_t * ((N_{t+1} - D_{t+1}) / N_{t+1})$$

```
[6]: def survival(df):
      # see formula above
      surv = [1]
      for i in range(1,df.shape[0]):
          temp = surv[i-1] * ((df.iloc[i,1] - df.iloc[i,2])/ df.iloc[i,1])
          surv.append(temp)
      return surv
```

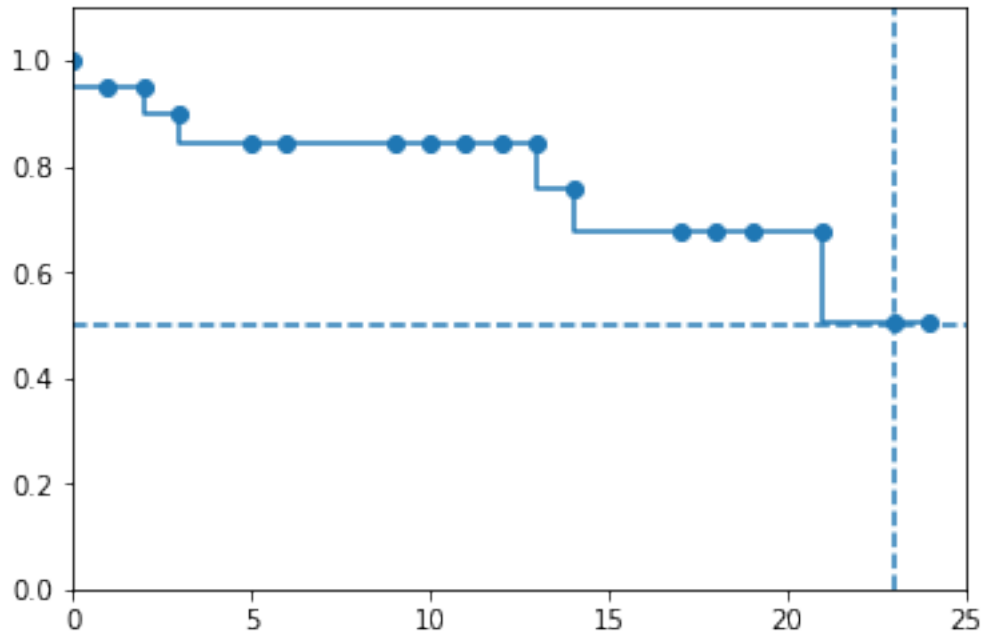
```
[7]: surv = survival(df)
```

```
[8]: surv
```

```
[8]: [1,
      0.95,
      0.95,
      0.8972222222222221,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.8444444444444443,
      0.7599999999999999,
      0.6755555555555555,
      0.6755555555555555,
      0.6755555555555555,
      0.6755555555555555,
      0.6755555555555555,
      0.5066666666666666,
      0.5066666666666666]
```

```
[9]: plt.step(df[['Time']], surv, linestyle = '-', marker = 'o')
      plt.ylim([0,1.1])
      plt.xlim([0,25])
      plt.axhline(0.5,linestyle = '--')
      plt.axvline(23, linestyle = '--')
```

```
[9]: <matplotlib.lines.Line2D at 0x1f6ba6a9cc0>
```



```
[10]: # The median survival time is 23 years
```

## 2 Logrank Test

```
[11]: # For the logrank test, we take two groups and compare their survival
# data is again taken from the above mentioned link
```

```
[12]: time = [8,12,14,21,26,27,28,33,41]
n1t = [10,8,7,5,4,3,2,1,0]
n2t = [10,10,10,10,8,8,8,7,5]
nt = [20,18,17,15,12,11,10,8,5]
o1t = [1,1,1,1,1,1,0,0,0]
o2t = [0,0,0,0,0,0,1,1,1]
ot = [1,1,1,1,1,1,1,1,1]

lr_df = pd.DataFrame({'Time':time,
                      'Number_atRisk_Grp1':n1t,
                      'Number_atRisk_Grp2':n2t,
                      'Total_Number_atRisk':nt,
                      'Number_ofEvents_Grp1':o1t,
                      'Number_ofEvents_Grp2':o2t,
                      'Total_Number_ofEvents':ot})
```

```
[13]: lr_df
```

```
[13]:
```

	Time	Number_atRisk_Grp1	Number_atRisk_Grp2	Total_Number_atRisk	\
0	8	10	10	20	
1	12	8	10	18	
2	14	7	10	17	
3	21	5	10	15	
4	26	4	8	12	
5	27	3	8	11	
6	28	2	8	10	
7	33	1	7	8	
8	41	0	5	5	

	Number_ofEvents_Grp1	Number_ofEvents_Grp2	Total_Number_ofEvents
0	1	0	1
1	1	0	1
2	1	0	1
3	1	0	1
4	1	0	1
5	1	0	1
6	0	1	1
7	0	1	1
8	0	1	1

$$E_{1t} = N_{1t} * (O_t / N_t)$$

```
[14]: e1t = []
e2t = []
for i in range(lr_df.shape[0]):
    e1t.append(n1t[i]*(ot[i]/nt[i]))
    e2t.append(n2t[i]*(ot[i]/nt[i]))
```

$$\chi^2 = \sum \frac{(\sum O_{jt} - \sum E_{jt})^2}{\sum E_{jt}}$$

```
[15]: def logrank(df, exp1, exp2):
    ojt = sum(df['Number_ofEvents_Grp1'].tolist())
    ojt2 = sum(df['Number_ofEvents_Grp2'].tolist())
    e1t = sum(exp1)
    e2t = sum(exp2)
    temp = [((ojt - e1t)**2)/(e1t), ((ojt2 - e2t)**2)/(e2t)]
    return sum(temp)
```

```
[16]: logrank(lr_df, e1t, e2t)
```

```
[16]: 6.148087536256202
```

We now need the critical value of the  $\chi^2$  distribution at  $\alpha = 0.05$ . Tabular  $\chi^2_{0.05} = 3.841$  Since the calculated value is higher than the tabular value, we reject the null hypothesis that there is no difference in the two groups.

```
[17]: new_df = pd.DataFrame({'Time':lr_df.iloc[:,0],
                             'At_risk':lr_df.iloc[:,2],
                             'Death':lr_df.iloc[:,5]})
```

```
[18]: survival(new_df)
```

```
[18]: [1, 1.0, 1.0, 1.0, 1.0, 1.0, 0.875, 0.75, 0.6000000000000001]
```

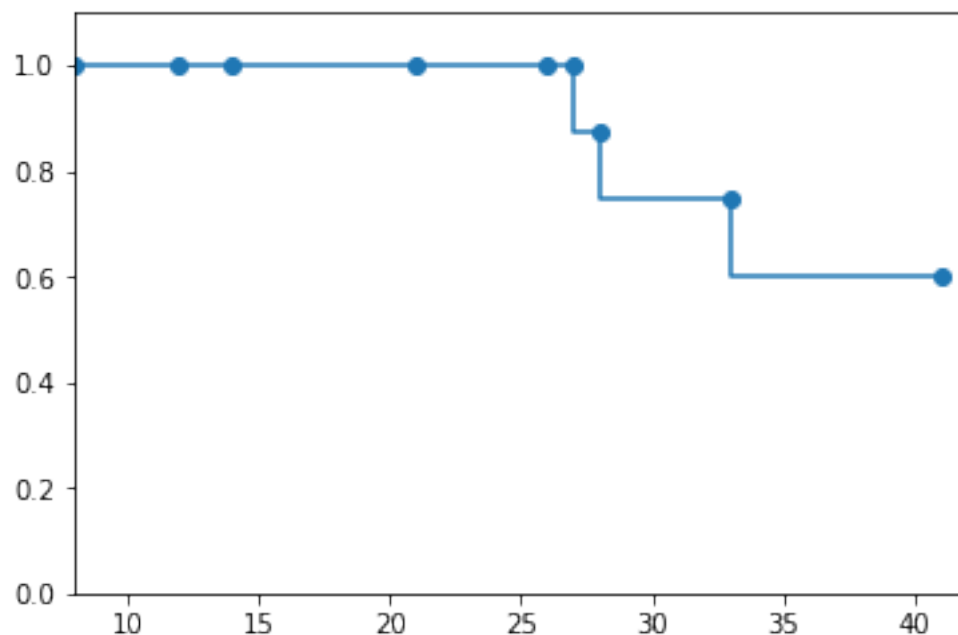
```
[19]: new_df
```

```
[19]:
```

	Time	At_risk	Death
0	8	10	0
1	12	10	0
2	14	10	0
3	21	10	0
4	26	8	0
5	27	8	0
6	28	8	1
7	33	7	1
8	41	5	1

```
[21]: plt.step(new_df.iloc[:,0], survival(new_df), linestyle = '--', marker = 'o')
plt.xlim([8,42])
plt.ylim([0,1.1])
```

```
[21]: (0, 1.1)
```



```
[22]: # We never reach the median value for this dataset, we may assume it as  
# the value at 0.6, that is 41 years.
```

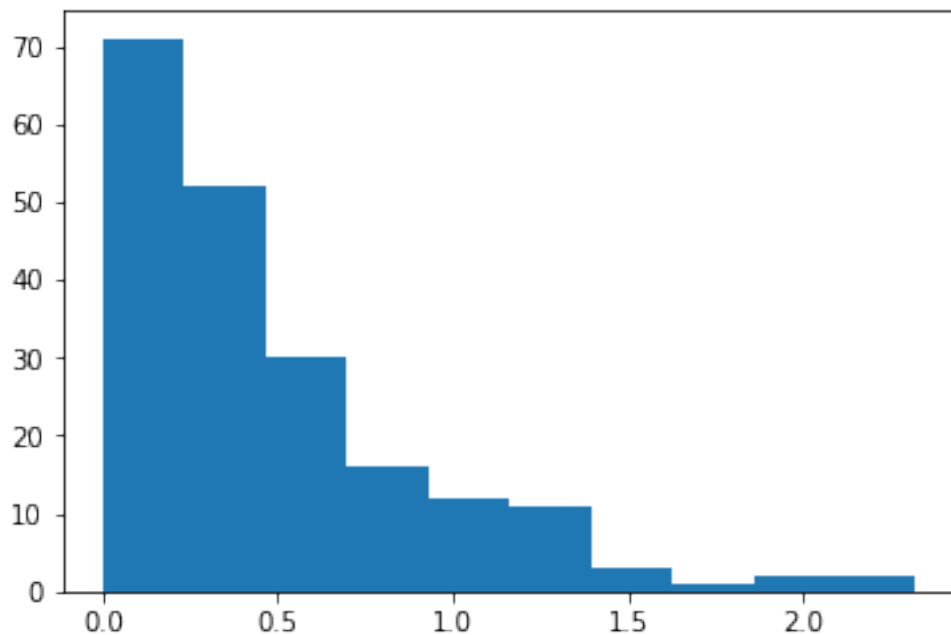
### 3 Ques 2

Simulating data from an exponential distribution  $f(x; \frac{1}{\beta}) = \frac{1}{\beta} \exp(-\frac{x}{\beta})$  Taken from numpy's page

```
[56]: # lambda = 2  
data1 = np.random.exponential(scale = 0.5, size = 200).tolist()  
# lambda = 4  
data2 = np.random.exponential(scale = 0.25, size = 200).tolist()
```

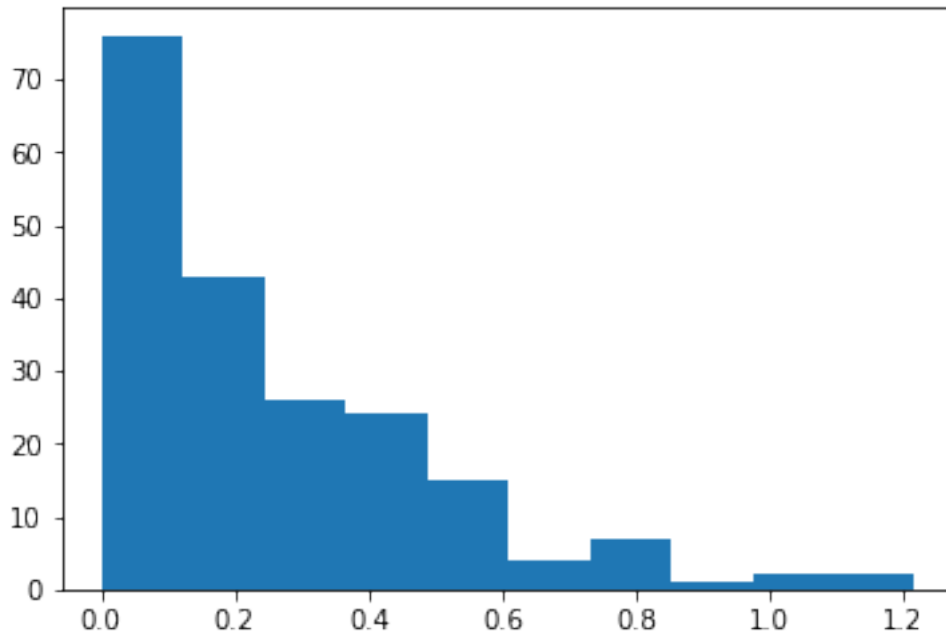
```
[57]: plt.hist(data1)
```

```
[57]: (array([71., 52., 30., 16., 12., 11., 3., 1., 2., 2.]),  
array([1.86068052e-03, 2.33623903e-01, 4.65387125e-01, 6.97150347e-01,  
9.28913569e-01, 1.16067679e+00, 1.39244001e+00, 1.62420324e+00,  
1.85596646e+00, 2.08772968e+00, 2.31949290e+00])),  
<a list of 10 Patch objects>)
```



```
[58]: plt.hist(data2)
```

```
[58]: (array([76., 43., 26., 24., 15., 4., 7., 1., 2., 2.]),
      array([0.00177864, 0.12328252, 0.24478639, 0.36629026, 0.48779413,
            0.609298 , 0.73080187, 0.85230574, 0.97380961, 1.09531348,
            1.21681735])),
      <a list of 10 Patch objects>)
```



```
[59]: # censoring with a probability of 10%
      censor1 = np.random.choice(2, size = 100, p = [0.9,0.1]).tolist()
      censor2 = np.random.choice(2, size = 100, p = [0.9, 0.1]).tolist()
```

```
[60]: int_data1 = [int(x*1000) for x in data1]
      int_data2 = [int(x*1000) for x in data2]
```

```
[61]: set1 = set(sorted(int_data1))
      set2 = set(sorted(int_data2))
```

```
[62]: sample1 = sorted(sample(list(set1), 100))
      sample2 = sorted(sample(list(set2), 100))
```

```
[63]: # deaths
      death1 = np.random.choice(2, size = 100, p = [0.3, 0.7]).tolist()
      death2 = np.random.choice(2, size = 100, p = [0.3, 0.7]).tolist()
```

```
[64]: mera_df = pd.DataFrame({'Time':sample1,
                             'Risk1':[100 for _ in range(100)],
```

```

        'Death1':death1,
        'Censor1':censor1})
mera_df2 = pd.DataFrame({'Time':sample2,
        'Risk2':[100 for _ in range(100)],
        'Death2':death2,
        'Censor2':censor2})

```

$$N_{t+1} = N_t - D_t - C_t$$

```

[65]: for i in range(1,mera_df.shape[0]):
        mera_df.iloc[i,1] = mera_df.iloc[i-1,1] - mera_df.iloc[i-1,2] - mera_df.
        ↪iloc[i-1,3]
    for i in range(1,mera_df2.shape[0]):
        mera_df2.iloc[i,1] = mera_df2.iloc[i-1,1] - mera_df2.iloc[i-1,2] - mera_df2.
        ↪iloc[i-1,3]

```

```

[66]: mera_df.iloc[99,3] = mera_df.iloc[99,1]
        mera_df2.iloc[99,3] = mera_df2.iloc[99,1]

```

```

[70]: surv1 = survival(mera_df)
        surv2 = survival(mera_df2)

```

```

[71]: plt.step(mera_df.iloc[:,0], surv1, linestyle = '-', marker = '|')
        plt.step(mera_df2.iloc[:,0], surv2, linestyle = '-', marker = '|', color =
        ↪'red')
        plt.axhline(0.5, linestyle = '--', color = 'black')
        plt.ylim([0,1.1])
        plt.xlim([0, 2681])

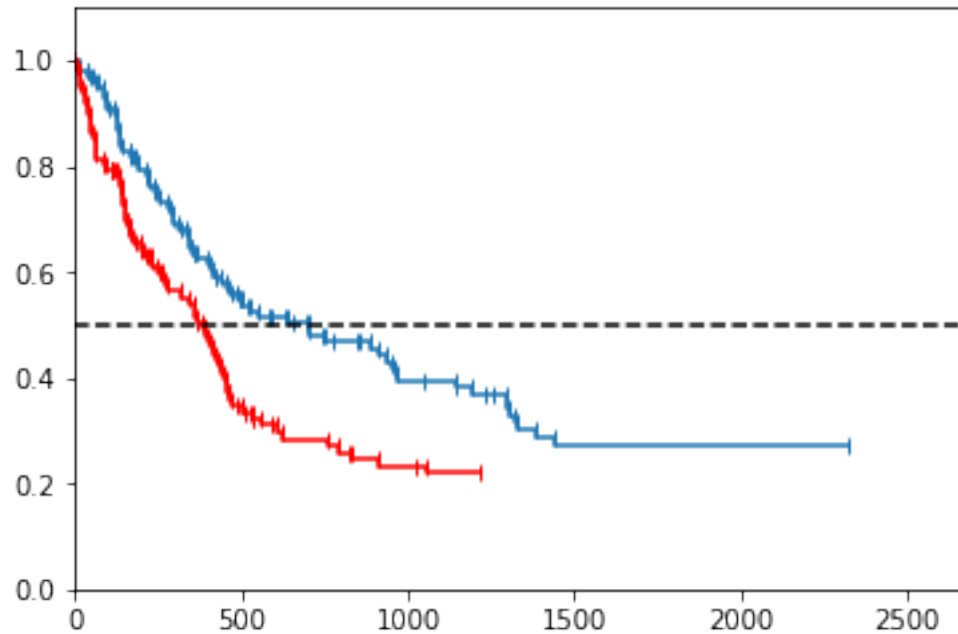
```

```

[71]: (0, 2681)

```





```
[39]: #surv1.index( 0.505895437823829)
```

```
[40]: #surv2.index( 0.5098612291287132)
```

```
[41]: mera_df.iloc[92,:]
```

```
[41]: Time      1259
Risk1         28
Death1         1
Censor1         0
Name: 92, dtype: int64
```

```
[42]: mera_df2.iloc[70,:]
```

```
[42]: Time      355
Risk2         44
Death2         0
Censor2         0
Name: 70, dtype: int64
```

```
[43]: # For choice of stochastic parameters -
# The median survival for group 1 is 1287 units
# The median survival for group 2 is 286 units.
```

```
[44]: # Logrank test
```

```
[45]: mera_df.iloc[1:5,:]
```

```
[45]:   Time  Risk1  Death1  Censor1
1    12     99       0         0
2    18     99       1         0
3    31     98       1         0
4    32     97       1         0
```

```
[46]: mera_df2.iloc[1:5,:]
```

```
[46]:   Time  Risk2  Death2  Censor2
1     3     99       0         0
2     4     99       1         1
3     9     97       1         0
4    11     96       1         0
```

```
[47]: e1t = []
      e2t = []
      for i in range(lr_df.shape[0]):
          e1t.append(n1t[i]*(ot[i]/nt[i]))
          e2t.append(n2t[i]*(ot[i]/nt[i]))

      def logrank(df, exp1, exp2):
          ojt = sum(df['Number_ofEvents_Grp1'].tolist())
          ojt2 = sum(df['Number_ofEvents_Grp2'].tolist())
          e1t = sum(exp1)
          e2t = sum(exp2)
          temp = [((ojt - e1t)**2)/(e1t), ((ojt2 - e2t)**2)/(e2t)]
          return sum(temp)

      logrank(lr_df, e1t, e2t)
```

```
[47]: 6.148087536256202
```

```
[51]: e1t = []
      e2t = []
      for i in range(mera_df.shape[0]):
          e1t.append(mera_df.iloc[i,1] * ((mera_df.iloc[i,2]+mera_df2.iloc[i,2])/
          ↪(mera_df.iloc[i,1]+mera_df2.iloc[i,1])))
          e2t.append(mera_df2.iloc[i,1] * ((mera_df.iloc[i,2]+mera_df2.iloc[i,2])/
          ↪(mera_df.iloc[i,1]+mera_df2.iloc[i,1])))
```

```
[52]: def logrank2(mera_df, mera_df2, exp1, exp2):
      ojt = sum(mera_df['Death1'].tolist() + mera_df['Censor1'].tolist())
      ojt2 = sum(mera_df2['Death2'].tolist() + mera_df2['Censor2'].tolist())
      e1t = sum(exp1)
      e2t = sum(exp2)
```

```
temp = [((ojt - e1t)**2)/(e1t),((ojt2 - e2t)**2)/(e2t)]  
return sum(temp)
```

```
[53]: logrank2(mera_df, mera_df2, e1t, e2t)
```

```
[53]: 24.375952598006688
```

We now need the critical value of the  $\chi^2$  distribution at  $\alpha = 0.05$ . Tabular  $\chi^2_{0.05} = 3.841$  Since the calculated value is higher than the tabular value, We reject the null hypothesis that there is no difference in the two groups.