Basically I was given two data sources, one is sales and another repairs. Sales data was from January/2005 to February/2008 :

module_category	component_category	year/month	number_sale
M4	P10	2007/1	0
M4	P27	2005/5	1042
M1	P22	2005/9	1677

Repairs data was from February/2005 to December/2009, for example:

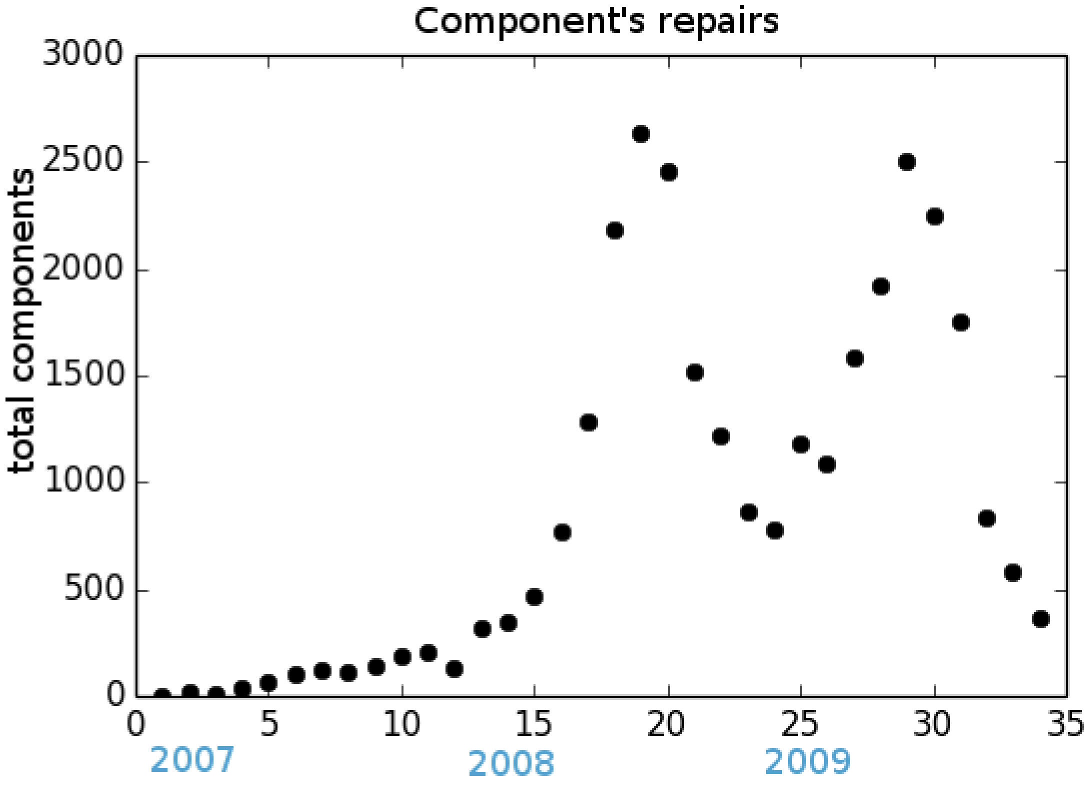
module_category	component_category	year/month(sale)	year/month(repair)	number_repair
M6	P16	2007/9	2009/4	1
M2	P30	2007/9	2009/8	1
M1	P12	2006/10	2008/2	2
M1	P30	2006/5	2007/7	1
M3	P06	2007/8	2007/12	1
M7	P19	2006/7	2007/6	1

And I was trying to predict the monthly repair amount for each module-component from January/2010 to July/2011 (for 19 months) . The prediction was evaluated using mean absolute error (MAE) which is the difference bertween the number of repairs I predicted vs real repairs data ASUS had, devided by total of prediction rows.

Just to explore the data using Python’s Pandas DataFrame, grouping by module,component and date,.

```
repair_data.groupby(['module_category','component_category','year/month(repair)'
],as_index=False).agg({'number_repair':np.sum})
```

Just one component’s graph of the total repairs 2005 to 2009 time series will look like this :



We can see that the number of repairs grows as more components are sold and also as the time passes, but falls off around two years mark as the first sold models reach that age. Not sure why the drop but my assumption was that the warranty expired. The number of repairs in the end of 2009 is zero or almost zero for most components and we need to predict what happens in the next 19 months. The easiest would be just take the last points and fit some linear regression or moving average, that would bring us above the baseline(which is predict that we have only zero repairs) but it would not be the best model.

My most most successful model was built using a simple survival analysis (using Python's Lifelines package) blended with linear regression for the tail of the 19 months to forecast

I took the time from sale of component to repair as time to death/event and the rest of the components were right censored(never had death event). Didn't matter when the component was sold because it was all relative. I got let's say couple of thousands deaths with 1 to ~ 45 months from been sold to the repaired/death event and ~500k of right censored items and then estimated the hazard rates using Nelson-Aalen estimator from Lifelines library. data would look like this, an array of deaths :

```
data_events[0:100]
array([ 70.,   1.,   1.,   1.,   1.,   1.,   1.,   1.,   2.,   2.,   2.,
    2.,   2.,   2.,   2.,   2.,   2.,   2.,   2.,   2.,   2.,   2.,
    2.,   2.,   2.,   2.,   2.,   2.,   2.,   2.,   3.,   3.,   3.,
    3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,
    3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,
    3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,   3.,
    3.,   3.,   3.,   3.,   3.,  12.,  12.,  12.,  12.,  12.,  12.,
   12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,
   12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,  12.,
   12.])
```

the first cell for example has a value of 70 it is a component that never was repaired but right censored, it can be any arbitrary high number. other cells with values like 1 or 12 or 3 is after how many months the component was repaired. If it was sold in September/2008 and repaired in September/2009 it means 12 months later death event occured. So I would have arrays of size around 500k mostly with a value of 70 (component that never repaired). Fitting the data:

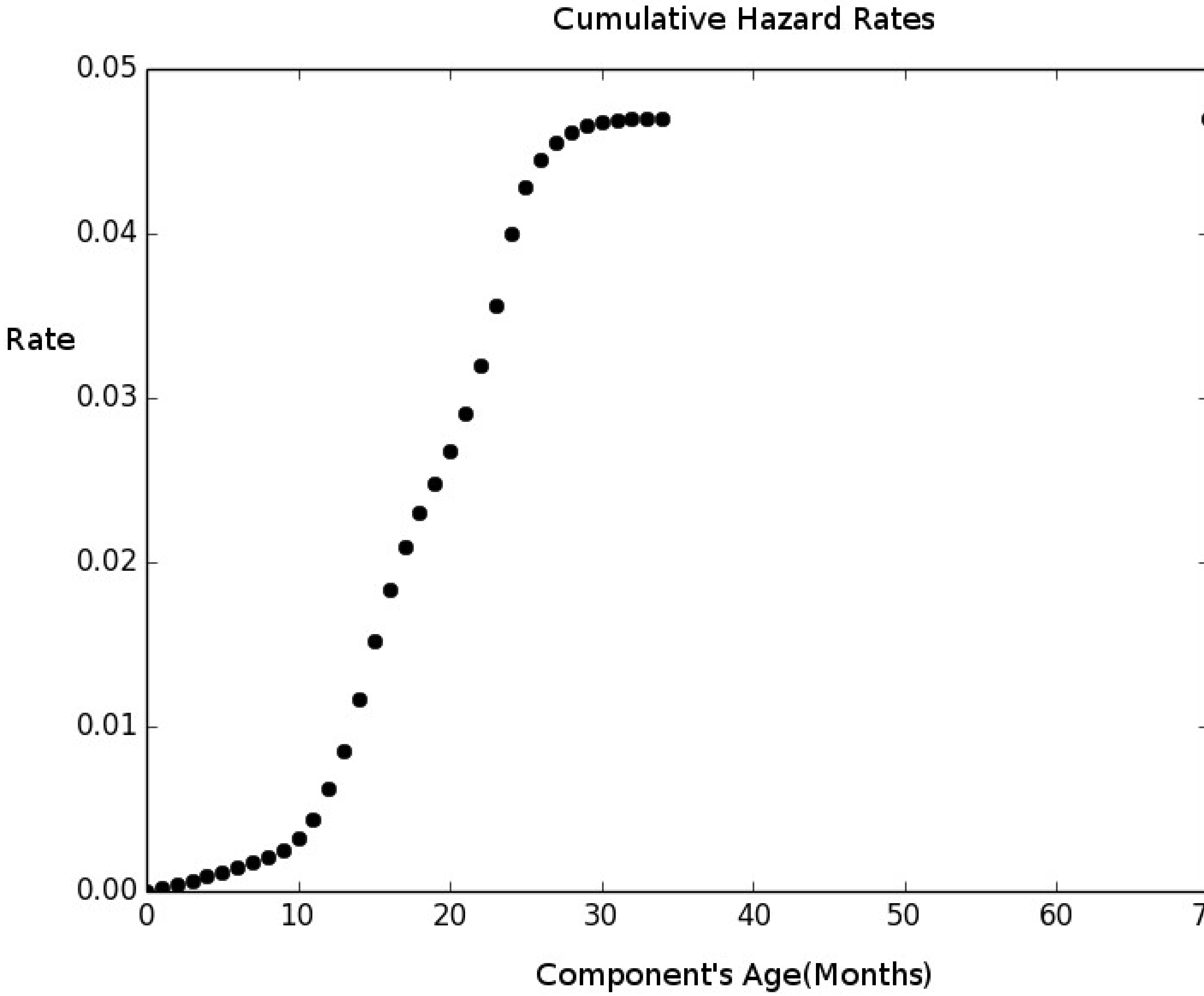
naf = NelsonAalenFitter() naf.fit(data_events, event_observed=C)

C is the index of right censored components in the array (the ones with 70)

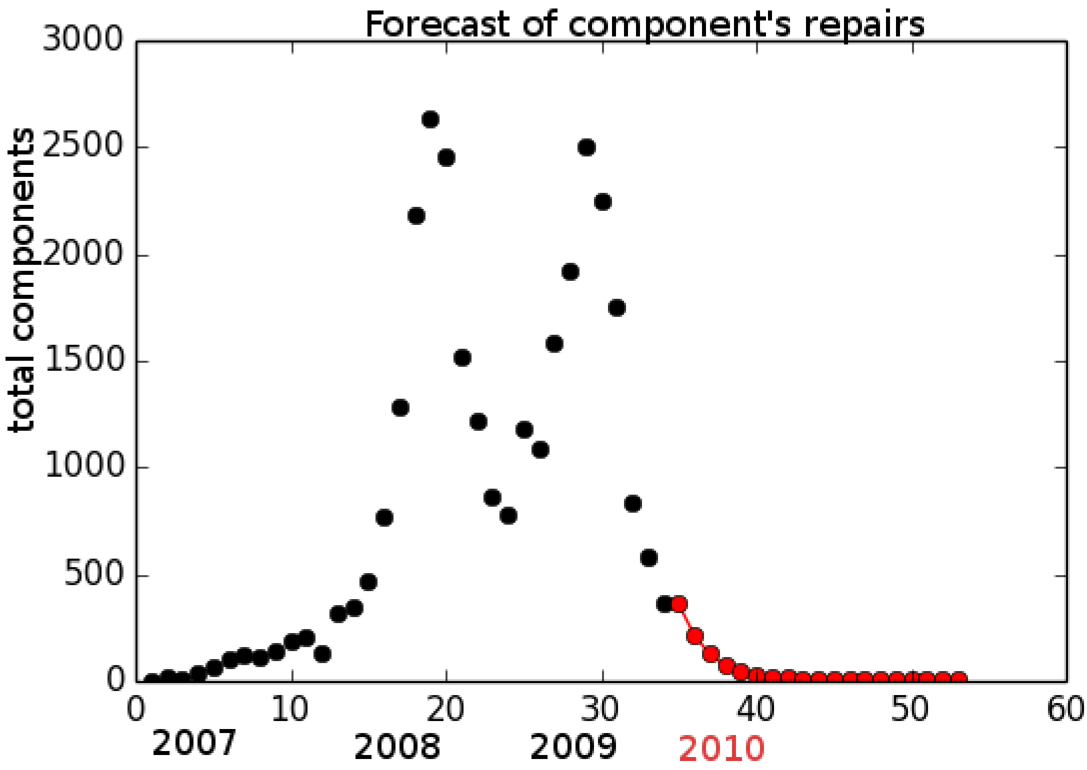
What I get is the cumulative hazard rate, which is an integration of survival function

```
naf.cumulative_hazard_

  timeline   NA-estimate
  0            0.000000
  1            0.000071
  2            0.000339
  3            0.000785
  4            0.001369
  5            0.001962
  ...
  ...
```



What is important in this graph is the rate of change, in the beginning the slope is quite high that is basically gives high hazard rate at any moment(more repairs) and then after two years it would stabilize and have almost a zero slope which is equivalent to no or very little repairs/death events. let's say 10000 components were sold on Nov/2009 I need to know how many of them will be repaired in Feb/2010 which is 3 months after the sale. From the cumulative hazard I can see that at 3 months the cumulative hazard is 0.000785 and at 2 months 0.000339 , the slope will be 0.000785-0.000339=.000446 . Taking the population multiplied by instantenious hazard 10000*0.000446 = 4.46 . On Feb/2010 4 components will be returned for repairs. Based on the data, usually from 0 to 45 months it gave a nice prediction but for components that were sold earlier and I had to extrapolate how many will be repaired after 4-5 years I used a modified linear regression based only on the last couple of points and I would slowly decay the hazard value from this regression.
I would also manually add extra weight for summer months, because it looked like in summer months the components failed more.



The red dots are the forecasted repairs.