Stephen_Filios_Employee_Retention

February 19, 2019

```
In [2]: import matplotlib.pyplot as plt
        import numpy as np
        import pandas as pd
        from rfpimp import *
        import seaborn as sns
        from sklearn.ensemble import RandomForestRegressor
        from sklearn.model_selection import train_test_split
        from sklearn import preprocessing
```

```
In [3]: df = pd.read_csv('employee_retention_data.csv')
```

```
In [4]: df.head()
```

```
Out[4]:    employee_id  company_id             dept  seniority    salary   join_date  \
        0      13021.0           7  customer_service         28   89000.0  2014-03-24
        1     825355.0           7        marketing          20  183000.0  2013-04-29
        2     927315.0           4        marketing          14  101000.0  2014-10-13
        3     662910.0           7  customer_service         20  115000.0  2012-05-14
        4     256971.0           2      data_science         23  276000.0  2011-10-17

            quit_date
        0  2015-10-30
        1  2014-04-04
        2         NaN
        3  2013-06-07
        4  2014-08-22
```

```
In [5]: df.describe()
```

```
Out[5]:          employee_id    company_id     seniority         salary
        count   24702.000000  24702.000000  24702.000000   24702.000000
        mean   501604.403530      3.426969     14.127803  138183.345478
        std    288909.026101      2.700011      8.089520   76058.184573
        min        36.000000      1.000000      1.000000   17000.000000
        25%    250133.750000      1.000000      7.000000   79000.000000
        50%    500793.000000      2.000000     14.000000  123000.000000
        75%    753137.250000      5.000000     21.000000  187000.000000
        max    999969.000000     12.000000     99.000000  408000.000000
```

```
In [6]: df.isnull().sum()

Out[6]: employee_id        0
        company_id         0
        dept               0
        seniority          0
        salary             0
        join_date          0
        quit_date      11192
        dtype: int64
```

From a preliminary look at the data, we can see that some descriptive stats about median/mean pay and seniority. We also see that there are 11,192 people who haven't quit yet. These people may be useful to look at later too!

I'll convert the join and quit dates as datetime values so that we can easily calculate how long they have been at the company. Prediction church is more than predicting **if** someone will leave. We also want to maximize how long they will stay.

```
In [7]: df['join_as_date'] = pd.to_datetime(df.join_date)

In [8]: df['quit_as_date'] = pd.to_datetime(df.quit_date)

In [9]: df.head()

Out[9]:    employee_id  company_id              dept  seniority    salary   join_date  \
        0      13021.0           7  customer_service         28   89000.0  2014-03-24
        1     825355.0           7         marketing         20  183000.0  2013-04-29
        2     927315.0           4         marketing         14  101000.0  2014-10-13
        3     662910.0           7  customer_service         20  115000.0  2012-05-14
        4     256971.0           2      data_science         23  276000.0  2011-10-17

            quit_date join_as_date quit_as_date
        0  2015-10-30   2014-03-24   2015-10-30
        1  2014-04-04   2013-04-29   2014-04-04
        2         NaN   2014-10-13          NaT
        3  2013-06-07   2012-05-14   2013-06-07
        4  2014-08-22   2011-10-17   2014-08-22
```

We can also give a time at the company to people who are missing a quit value. To do this, we will have a column that is a boolean of whether or not they have quit, and then impute the date of the survey to everyone else by filling na's.

```
In [10]: df['quit_bool'] = ~df.quit_as_date.isnull()

In [11]: a = pd.datetime(2015,12,13)

In [12]: df.quit_as_date.fillna(a, inplace=True)
```

I don't think we need the dates as numbers/strings anymore, so let's make a new dataframe without those.

```
In [13]: data = df[['employee_id','company_id','dept','seniority','salary','join_as_date','qui
```

And now we can calculate time at company

```
In [14]: data['time_at_company'] = data['quit_as_date']-data['join_as_date']
```

```
/home/lubuntu/anaconda3/envs/project/lib/python3.6/site-packages/ipykernel_launcher.py:1: Setti
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

```
In [15]: data.head()
```

```
Out[15]:    employee_id  company_id              dept  seniority    salary  \
         0      13021.0           7  customer_service         28   89000.0
         1     825355.0           7         marketing         20  183000.0
         2     927315.0           4         marketing         14  101000.0
         3     662910.0           7  customer_service         20  115000.0
         4     256971.0           2      data_science         23  276000.0

           join_as_date quit_as_date  quit_bool time_at_company
         0   2014-03-24   2015-10-30       True        585 days
         1   2013-04-29   2014-04-04       True        340 days
         2   2014-10-13   2015-12-13      False        426 days
         3   2012-05-14   2013-06-07       True        389 days
         4   2011-10-17   2014-08-22       True       1040 days
```

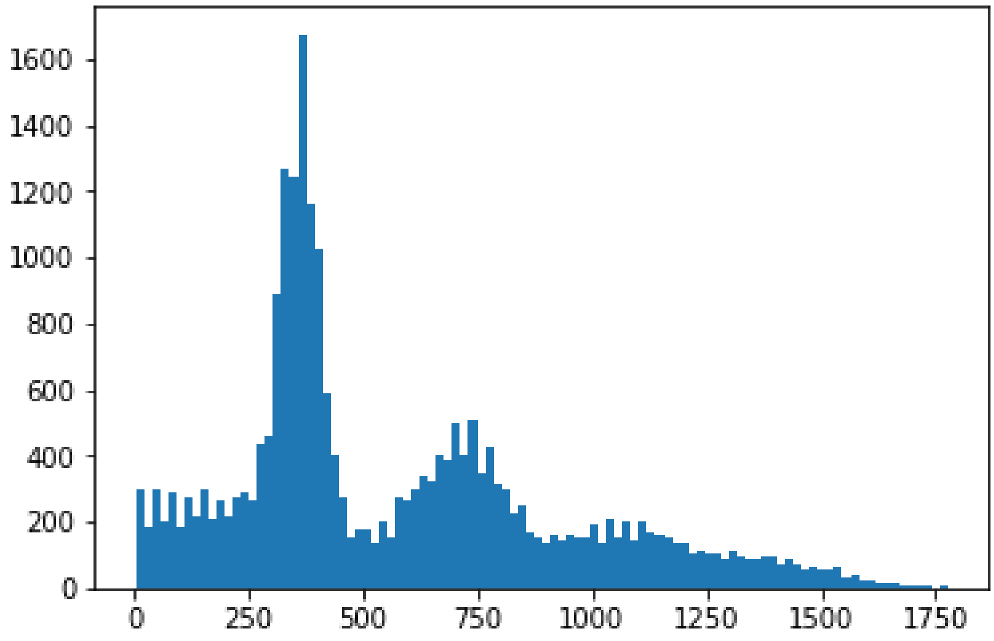
```
In [16]: data.describe()
```

```
Out[16]:          employee_id    company_id     seniority         salary  \
         count   24702.000000  24702.000000  24702.000000   24702.000000
         mean   501604.403530      3.426969     14.127803  138183.345478
         std    288909.026101      2.700011      8.089520   76058.184573
         min        36.000000      1.000000      1.000000   17000.000000
         25%    250133.750000      1.000000      7.000000   79000.000000
         50%    500793.000000      2.000000     14.000000  123000.000000
         75%    753137.250000      5.000000     21.000000  187000.000000
         max    999969.000000     12.000000     99.000000  408000.000000

                          time_at_company
         count                      24702
         mean    574 days 07:39:28.812241
         std     361 days 14:13:01.578145
         min              3 days 00:00:00
         25%            333 days 00:00:00
         50%            424 days 00:00:00
         75%            781 days 00:00:00
         max           1777 days 00:00:00
```

```
In [17]:  data['time_delta_int'] = data.time_at_company.astype('timedelta64[D]')
```

```
In [18]: plt.hist(data.time_delta_int, bins=100)
```

```
Out[18]: (array([2.950e+02, 1.870e+02, 2.950e+02, 2.010e+02, 2.860e+02, 1.840e+02,
                 2.700e+02, 2.130e+02, 2.960e+02, 2.070e+02, 2.690e+02, 2.130e+02,
                 2.770e+02, 2.920e+02, 2.690e+02, 4.360e+02, 4.620e+02, 8.870e+02,
                 1.267e+03, 1.241e+03, 1.673e+03, 1.164e+03, 1.024e+03, 5.890e+02,
                 4.010e+02, 2.700e+02, 1.500e+02, 1.790e+02, 1.790e+02, 1.340e+02,
                 1.980e+02, 1.510e+02, 2.700e+02, 2.610e+02, 2.990e+02, 3.400e+02,
                 3.180e+02, 4.010e+02, 3.850e+02, 5.010e+02, 3.990e+02, 5.110e+02,
                 3.420e+02, 4.300e+02, 3.110e+02, 2.940e+02, 2.230e+02, 2.480e+02,
                 1.710e+02, 1.530e+02, 1.390e+02, 1.630e+02, 1.460e+02, 1.560e+02,
                 1.540e+02, 1.480e+02, 1.910e+02, 1.380e+02, 2.090e+02, 1.540e+02,
                 1.970e+02, 1.430e+02, 2.020e+02, 1.690e+02, 1.610e+02, 1.530e+02,
                 1.380e+02, 1.370e+02, 1.060e+02, 1.140e+02, 1.010e+02, 1.020e+02,
                 8.600e+01, 1.120e+02, 9.400e+01, 8.500e+01, 8.500e+01, 9.800e+01,
                 9.200e+01, 7.000e+01, 8.500e+01, 7.300e+01, 5.800e+01, 6.300e+01,
                 5.200e+01, 5.200e+01, 6.100e+01, 3.200e+01, 3.500e+01, 2.500e+01,
                 2.400e+01, 1.500e+01, 1.800e+01, 1.600e+01, 1.000e+01, 9.000e+00,
                 4.000e+00, 3.000e+00, 1.000e+00, 7.000e+00]),
          array([   3.  ,   20.74,   38.48,   56.22,   73.96,   91.7 ,  109.44,
                  127.18,  144.92,  162.66,  180.4 ,  198.14,  215.88,  233.62,
                  251.36,  269.1 ,  286.84,  304.58,  322.32,  340.06,  357.8 ,
                  375.54,  393.28,  411.02,  428.76,  446.5 ,  464.24,  481.98,
                  499.72,  517.46,  535.2 ,  552.94,  570.68,  588.42,  606.16,
                  623.9 ,  641.64,  659.38,  677.12,  694.86,  712.6 ,  730.34,
                  748.08,  765.82,  783.56,  801.3 ,  819.04,  836.78,  854.52,
                  872.26,  890.  ,  907.74,  925.48,  943.22,  960.96,  978.7 ,
                  996.44, 1014.18, 1031.92, 1049.66, 1067.4 , 1085.14, 1102.88,
                 1120.62, 1138.36, 1156.1 , 1173.84, 1191.58, 1209.32, 1227.06,
                 1244.8 , 1262.54, 1280.28, 1298.02, 1315.76, 1333.5 , 1351.24,
                 1368.98, 1386.72, 1404.46, 1422.2 , 1439.94, 1457.68, 1475.42,
                 1493.16, 1510.9 , 1528.64, 1546.38, 1564.12, 1581.86, 1599.6 ,
                 1617.34, 1635.08, 1652.82, 1670.56, 1688.3 , 1706.04, 1723.78,
                 1741.52, 1759.26, 1777.  ]),
          <a list of 100 Patch objects>)
```



0.0.1 Time at company in days.

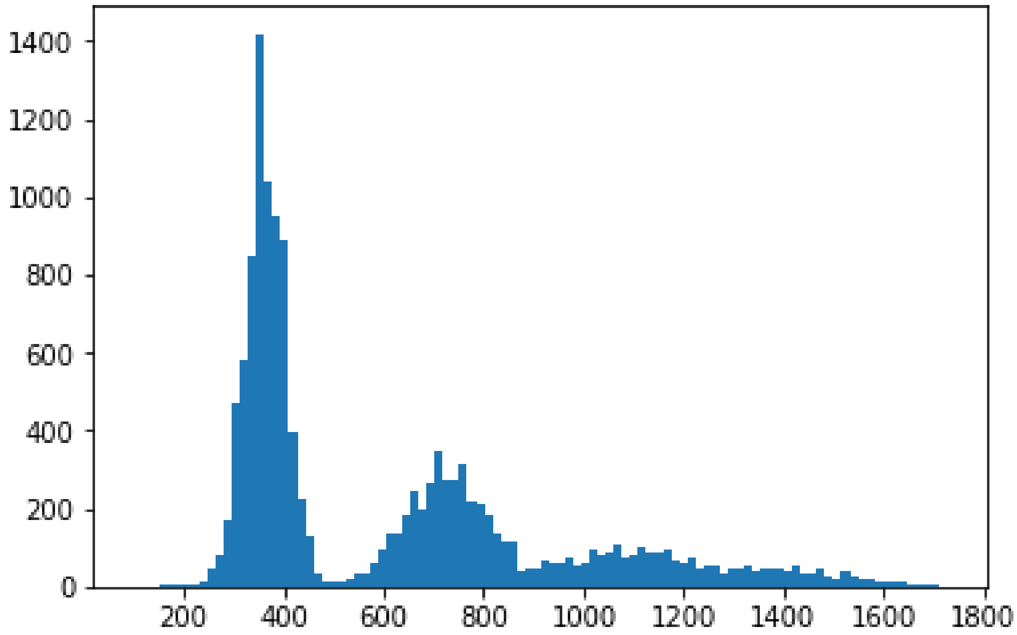
There's an interesting and logical distribution of how long people are staying- we see a huge peak of people who only stay at their job for one year, a second peak at two years, and then a tiny bump at three years. Things trail off from there.

What does this tell us!? First, that **the first year is important** - most people are leaving after just about one year. If we want to do something to improve retention, the first year looks like a good place to start. There's also another bump at just about two years, so the second year seems to be pretty important too.

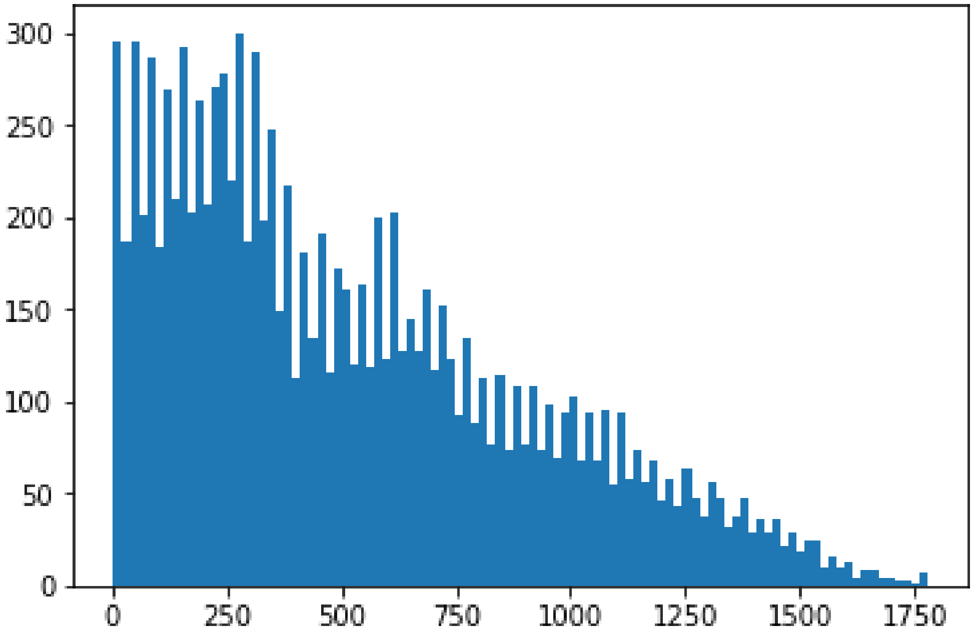
Let's make sure that this isn't just a bias in the data. The previous chart was all employee, but let's look at the time spent at company only for people who have quit, and then only for people who have not yet quit.

```
In [19]: plt.hist(data[data['quit_bool']==True].time_delta_int, bins=100)
```

```
Out[19]: (array([1.000e+00, 2.000e+00, 2.000e+00, 4.000e+00, 6.000e+00, 3.000e+00,
                 6.000e+00, 6.000e+00, 1.100e+01, 4.700e+01, 8.300e+01, 1.710e+02,
                 4.710e+02, 5.820e+02, 8.480e+02, 1.419e+03, 1.043e+03, 9.490e+02,
                 8.920e+02, 3.970e+02, 2.250e+02, 1.280e+02, 3.200e+01, 1.100e+01,
                 9.000e+00, 1.400e+01, 2.100e+01, 3.200e+01, 3.400e+01, 6.300e+01,
                 9.500e+01, 1.380e+02, 1.390e+02, 1.810e+02, 2.440e+02, 1.970e+02,
                 2.630e+02, 3.510e+02, 2.710e+02, 2.760e+02, 3.130e+02, 2.180e+02,
                 2.120e+02, 1.860e+02, 1.340e+02, 1.120e+02, 1.140e+02, 4.100e+01,
                 4.600e+01, 4.700e+01, 6.800e+01, 6.000e+01, 6.100e+01, 7.700e+01,
                 5.300e+01, 5.700e+01, 9.700e+01, 8.200e+01, 8.600e+01, 1.060e+02,
                 7.500e+01, 8.200e+01, 1.000e+02, 8.800e+01, 8.700e+01, 9.400e+01,
                 7.000e+01, 6.100e+01, 7.600e+01, 4.700e+01, 5.100e+01, 5.500e+01,
                 3.400e+01, 4.500e+01, 4.600e+01, 5.200e+01, 4.300e+01, 4.500e+01,
                 5.000e+01, 4.800e+01, 3.700e+01, 5.400e+01, 3.200e+01, 3.200e+01,
                 5.000e+01, 2.500e+01, 2.000e+01, 3.800e+01, 2.700e+01, 2.000e+01,
                 2.100e+01, 1.500e+01, 9.000e+00, 9.000e+00, 1.000e+01, 8.000e+00,
                 6.000e+00, 5.000e+00, 4.000e+00, 2.000e+00]),
          array([ 102.  ,  118.24,  134.48,  150.72,  166.96,  183.2 ,  199.44,
                  215.68,  231.92,  248.16,  264.4 ,  280.64,  296.88,  313.12,
                  329.36,  345.6 ,  361.84,  378.08,  394.32,  410.56,  426.8 ,
                  443.04,  459.28,  475.52,  491.76,  508.  ,  524.24,  540.48,
                  556.72,  572.96,  589.2 ,  605.44,  621.68,  637.92,  654.16,
                  670.4 ,  686.64,  702.88,  719.12,  735.36,  751.6 ,  767.84,
                  784.08,  800.32,  816.56,  832.8 ,  849.04,  865.28,  881.52,
                  897.76,  914.  ,  930.24,  946.48,  962.72,  978.96,  995.2 ,
                 1011.44, 1027.68, 1043.92, 1060.16, 1076.4 , 1092.64, 1108.88,
                 1125.12, 1141.36, 1157.6 , 1173.84, 1190.08, 1206.32, 1222.56,
                 1238.8 , 1255.04, 1271.28, 1287.52, 1303.76, 1320.  , 1336.24,
                 1352.48, 1368.72, 1384.96, 1401.2 , 1417.44, 1433.68, 1449.92,
                 1466.16, 1482.4 , 1498.64, 1514.88, 1531.12, 1547.36, 1563.6 ,
                 1579.84, 1596.08, 1612.32, 1628.56, 1644.8 , 1661.04, 1677.28,
                 1693.52, 1709.76, 1726.  ]),
          <a list of 100 Patch objects>)
```



```
In [20]: plt.hist(data[data['quit_bool']==False].time_delta_int, bins=100)

Out[20]: (array([295., 187., 295., 201., 286., 183., 269., 210., 292., 203., 264.,
                 207., 271., 278., 220., 300., 187., 289., 198., 248., 149., 217.,
       113., 181., 135., 191., 116., 172., 160., 120., 163., 119., 199.,
       123., 202., 127., 144., 127., 160., 117., 152., 123.,  93., 135.,
        88., 113.,  76., 114.,  74., 108.,  76., 108.,  73.,  98.,  69.,
        94., 103.,  68.,  94.,  68.,  95.,  55.,  94.,  57.,  74.,  56.,
        68.,  46.,  57.,  43.,  63.,  47.,  37.,  56.,  48.,  32.,  38.,
        47.,  28.,  36.,  28.,  36.,  21.,  29.,  18.,  24.,  24.,  10.,
        16.,  10.,  13.,   4.,   8.,   8.,   4.,   4.,   3.,   2.,   1.,
         7.]),
array([   3.  ,   20.74,   38.48,   56.22,   73.96,   91.7 ,  109.44,
        127.18,  144.92,  162.66,  180.4 ,  198.14,  215.88,  233.62,
        251.36,  269.1 ,  286.84,  304.58,  322.32,  340.06,  357.8 ,
        375.54,  393.28,  411.02,  428.76,  446.5 ,  464.24,  481.98,
        499.72,  517.46,  535.2 ,  552.94,  570.68,  588.42,  606.16,
        623.9 ,  641.64,  659.38,  677.12,  694.86,  712.6 ,  730.34,
        748.08,  765.82,  783.56,  801.3 ,  819.04,  836.78,  854.52,
        872.26,  890.  ,  907.74,  925.48,  943.22,  960.96,  978.7 ,
        996.44, 1014.18, 1031.92, 1049.66, 1067.4 , 1085.14, 1102.88,
       1120.62, 1138.36, 1156.1 , 1173.84, 1191.58, 1209.32, 1227.06,
       1244.8 , 1262.54, 1280.28, 1298.02, 1315.76, 1333.5 , 1351.24,
       1368.98, 1386.72, 1404.46, 1422.2 , 1439.94, 1457.68, 1475.42,
       1493.16, 1510.9 , 1528.64, 1546.38, 1564.12, 1581.86, 1599.6 ,
       1617.34, 1635.08, 1652.82, 1670.56, 1688.3 , 1706.04, 1723.78,
       1741.52, 1759.26, 1777.  ]),
<a list of 100 Patch objects>)
```



So, it looks like people who quit are indeed quitting at very distinct times (around 1 or two years). People who are still employed have been at their jobs at pretty evenly distributed times until about a year, and then there's a step down. Then another step down around two years. This is another strong indicators that people tend to quit after getting a certain amount of experience/time at a company.

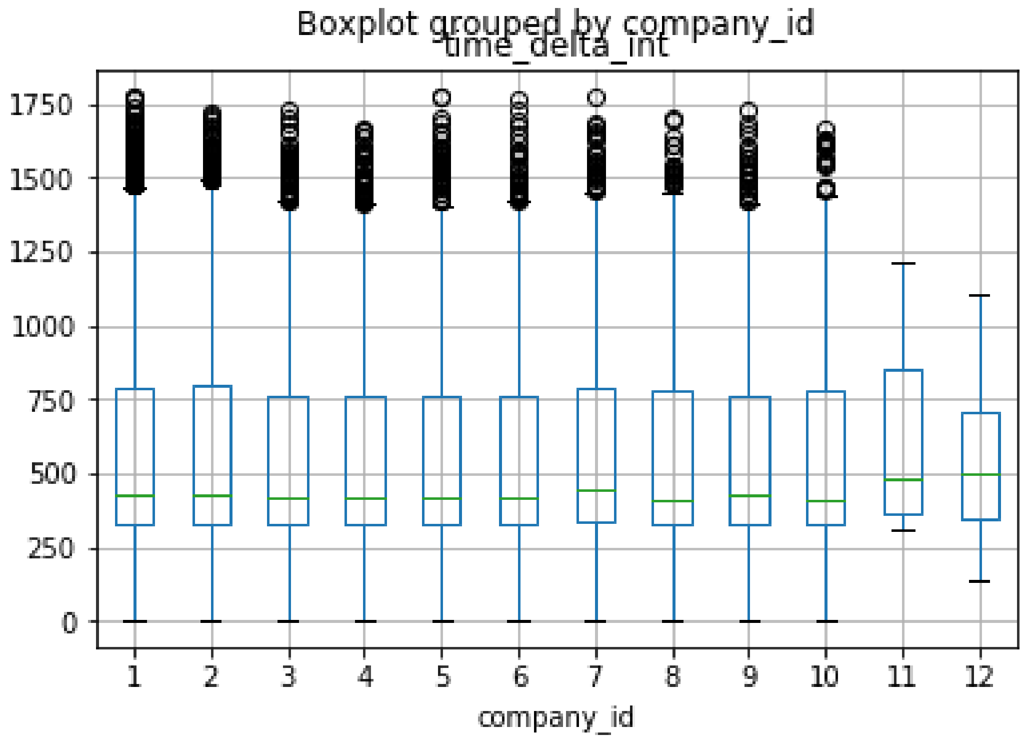
There are lots of things that could be going on here that we can't yet test. Are these people getting a yearly performance review and not doing well? Maybe people have decided to leave long before the year ends, but stay there until they feel like an acceptable amount of time has passed that it won't reflect negatively on them. Lots of places where some more data would be useful.

0.0.2 Do we see the same time spent at a company for all companies and across all departments?

It could be that some companies are better than others at retaining employees. Let's look at how long people stay at each company.

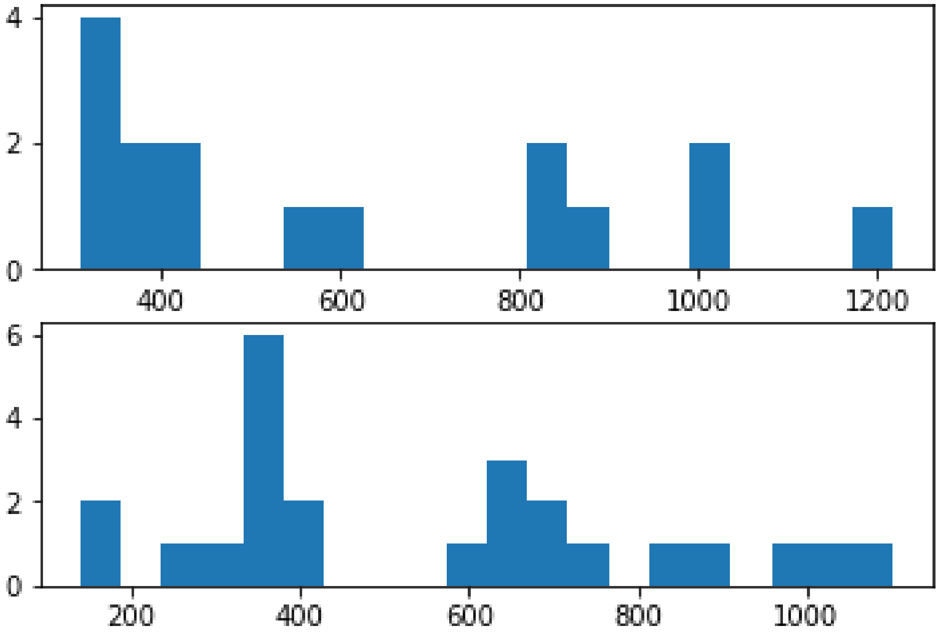
```
In [21]: data.boxplot(column='time_delta_int', by='company_id')
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x7f48f7c1cd30>
```



It looks like companies 11 and 12 might have something interesting going on. Their median time of employment is higher, and they have much shorter tails of people leaving quickly. One possible recommendation is to look into the practices of these companies and determine what they are doing differently.

```
In [22]: #do the normal distributions for 11 and 12 hold true?
         subset = data[data['company_id']==11]
         plt.subplot(2,1,1)
         plt.hist(subset.time_delta_int, bins =20)

         subset = data[data['company_id']==12]
         plt.subplot(2,1,2)
         plt.hist(subset.time_delta_int, bins = 20)

         plt.show()
```



From the above, it looks like the two companies that had higher median time at company are small companies. It may be that company size is an important feature. Let's check company size for each company

```
In [23]: data.company_id.value_counts()

Out[23]: 1      8486
         2      4222
         3      2749
         4      2062
         5      1755
         6      1291
         7      1224
         8      1047
         9       961
         10      865
```

```
12      24
11      16
Name: company_id, dtype: int64
```

Indeed, we can confirm that companies 11 and 12 are much smaller than all the other companies. So either there is something about being a small company that allows you to retain people for slightly longer, or they simply don't have enough samples. This is hard to distinguish, because we can't hold factors constant and only vary the number of employees. Company culture and experience change with size in real life.

```
In [24]: #since company size could be a useful feature, we will add it here to our dataframe
         data['company_size']=0

         for x, y in enumerate(data.company_id.value_counts()):
             data.loc[data['company_id']==x+1, 'company_size']= y
```

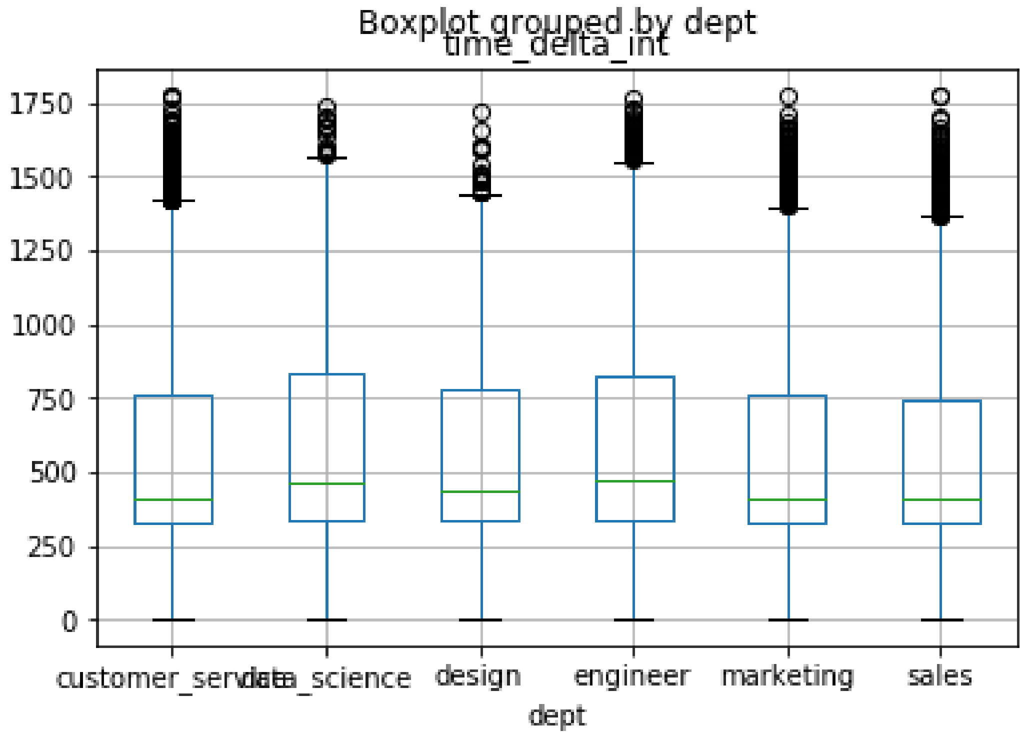
```
In [25]: data.head()
```

```
Out[25]:    employee_id  company_id             dept  seniority    salary  \
         0      13021.0           7  customer_service         28   89000.0
         1     825355.0           7         marketing         20  183000.0
         2     927315.0           4         marketing         14  101000.0
         3     662910.0           7  customer_service         20  115000.0
         4     256971.0           2      data_science         23  276000.0

           join_as_date quit_as_date  quit_bool time_at_company  time_delta_int  \
         0   2014-03-24   2015-10-30       True        585 days           585.0
         1   2013-04-29   2014-04-04       True        340 days           340.0
         2   2014-10-13   2015-12-13      False        426 days           426.0
         3   2012-05-14   2013-06-07       True        389 days           389.0
         4   2011-10-17   2014-08-22       True       1040 days          1040.0

            company_size
         0          1224
         1          1224
         2          2062
         3          1224
         4          4222
```

Now let's check by department how long people are staying

```
In [26]: data.boxplot(column='time_delta_int', by='dept')
```

```
Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7f48f79a39e8>
```



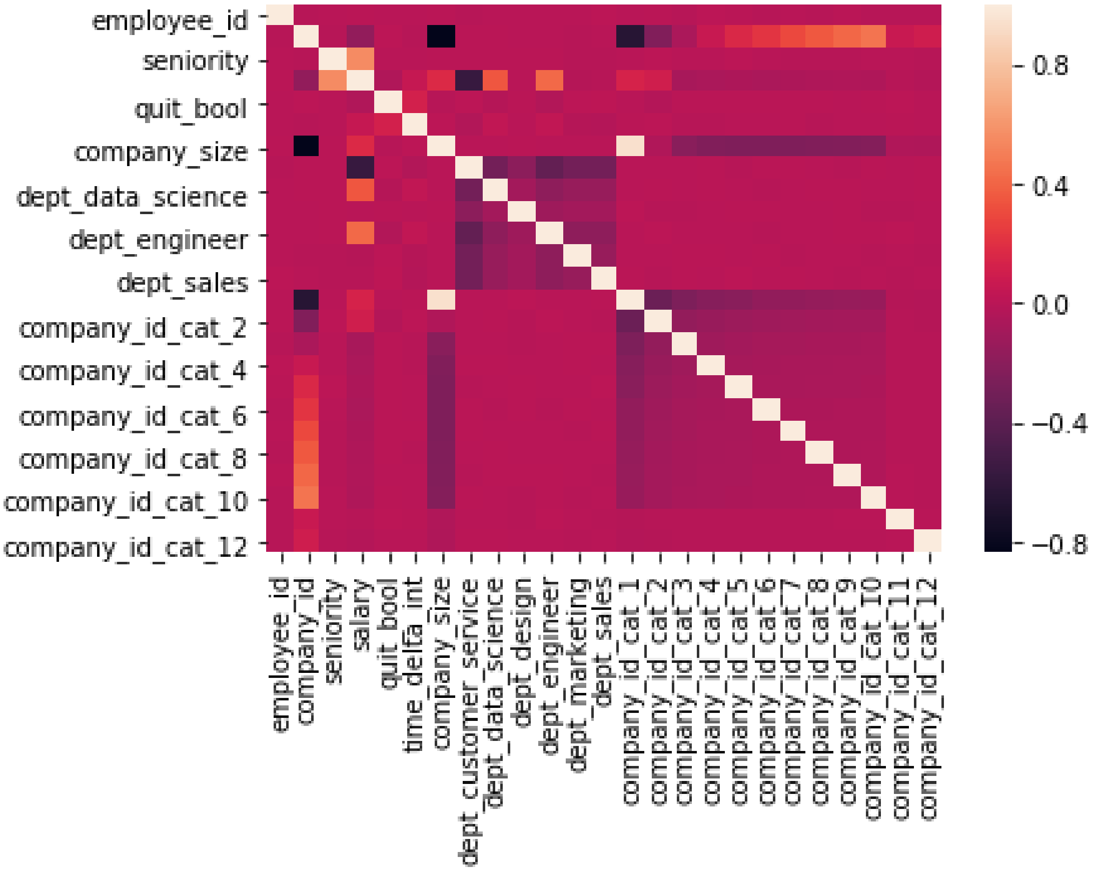
Engineers and data scientists tend to stay slightly longer than other departments.

We've looked at a few specific hypotheses so far, but let's see if we can pull any correlations out of the data. We need to convert some of the categorical variables to values in order to get correlations. This can be done through one-hot encoding or by changing the categories into a number. Because we aren't dealing with high-cardinality for most of these, we will one-hot encode them.

0.0.3 Look at all other correlations

We can check to see if there are any other correlations with the length of time someone stays at the company, since that's what we want to maximize. To do this, we'll make one-hot columns for each department and company (because these are categorical data), and make a correlation table. Then, we will look at the correlation between each variable and time at company

```
In [27]: data['company_id_cat'] = data.company_id.astype('category')

In [28]: one_hots = pd.get_dummies(data)

In [29]: corr = one_hots.corr()

In [30]: sns.heatmap(corr)

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x7f48f78a9550>
```



```
In [31]: corr.time_delta_int.sort_values()
```

```
Out[31]: dept_customer_service   -0.027163
         dept_sales              -0.022616
         dept_marketing          -0.015712
         company_id              -0.009987
         company_id_cat_3        -0.009677
         company_id_cat_4        -0.009132
         company_id_cat_8        -0.006141
         company_id_cat_6        -0.004732
         company_id_cat_5        -0.003184
         company_id_cat_9        -0.002905
         company_id_cat_10       -0.002120
         company_id_cat_12       -0.001961
         employee_id             -0.001777
         dept_design             -0.000697
         seniority                0.000742
         company_id_cat_11        0.002930
         company_id_cat_7         0.005358
```

```
company_id_cat_1        0.007593
company_size            0.011070
company_id_cat_2        0.012875
dept_data_science       0.034372
dept_engineer           0.037408
salary                  0.053914
quit_bool               0.119012
time_delta_int          1.000000
Name: time_delta_int, dtype: float64
```

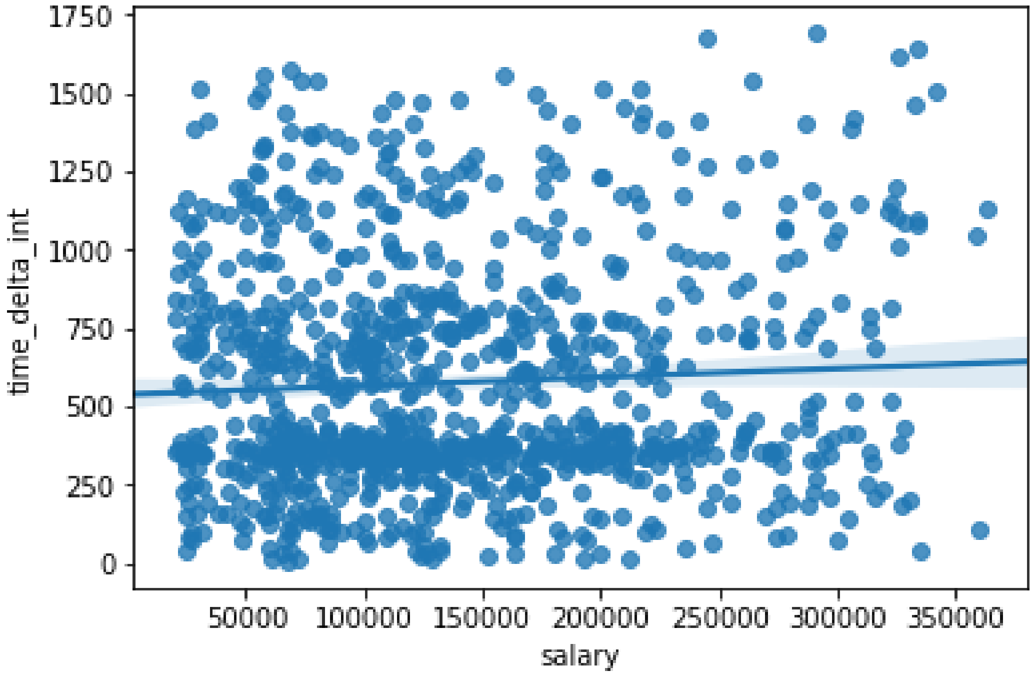
If we look at a list of all of the factors correlated with "time at company": the most strongly correlated factors tend to be salary and being an whether or not that person is an engineer/data scientist.

The most strongly correlated factor (whether or not they have quit) simply indicates that the longer someone has spent at a company, the more likely they are to have quit. No surprises there.

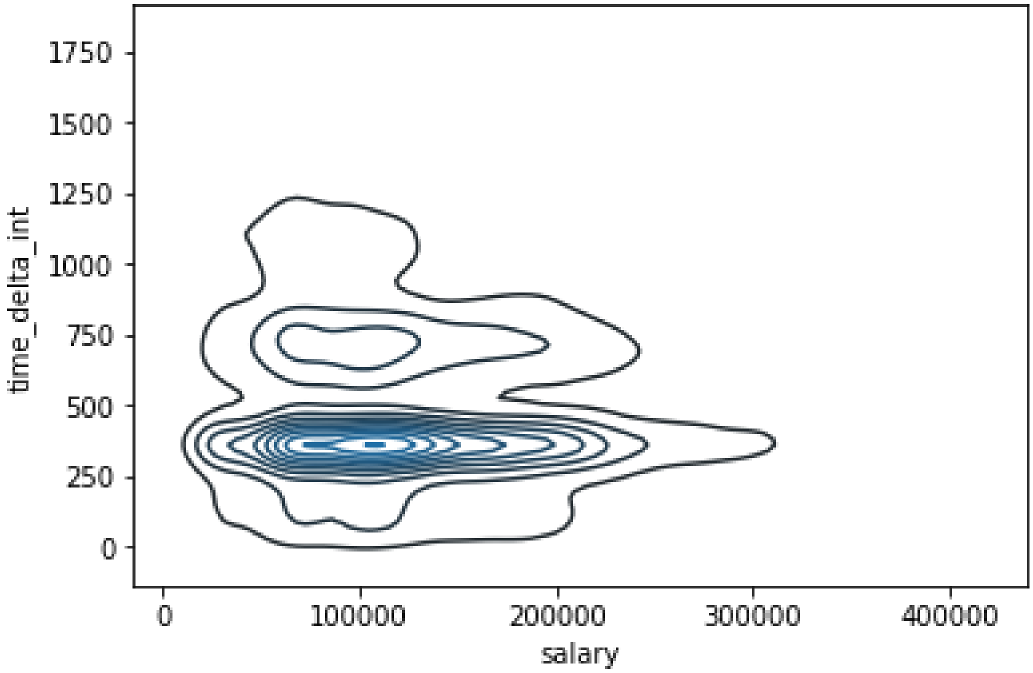
Another interesting factor is strong negative correlation of being in sales and customer service and time at company. This tells us that people who are in these departments turn over more quickly.

0.0.4 Let's look at salary and time at company

```
In [42]: # plt.scatter(data.salary, data.time_delta_int)
         plot = one_hots.sample(1000)
         ax = sns.regplot(x="salary", y="time_delta_int", data=plot)
```



```
In [43]: sns.kdeplot(one_hots.salary, one_hots.time_delta_int)

/home/lubuntu/anaconda3/envs/project/lib/python3.6/site-packages/scipy/stats/stats.py:1713: Fu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval


Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7f48f5e3c518>
```



Above, we see a chart that displays the density plot of salary vs time at company. Despite increasing salaries, we don't see a strong increase in the number of days that someone stays at the company.

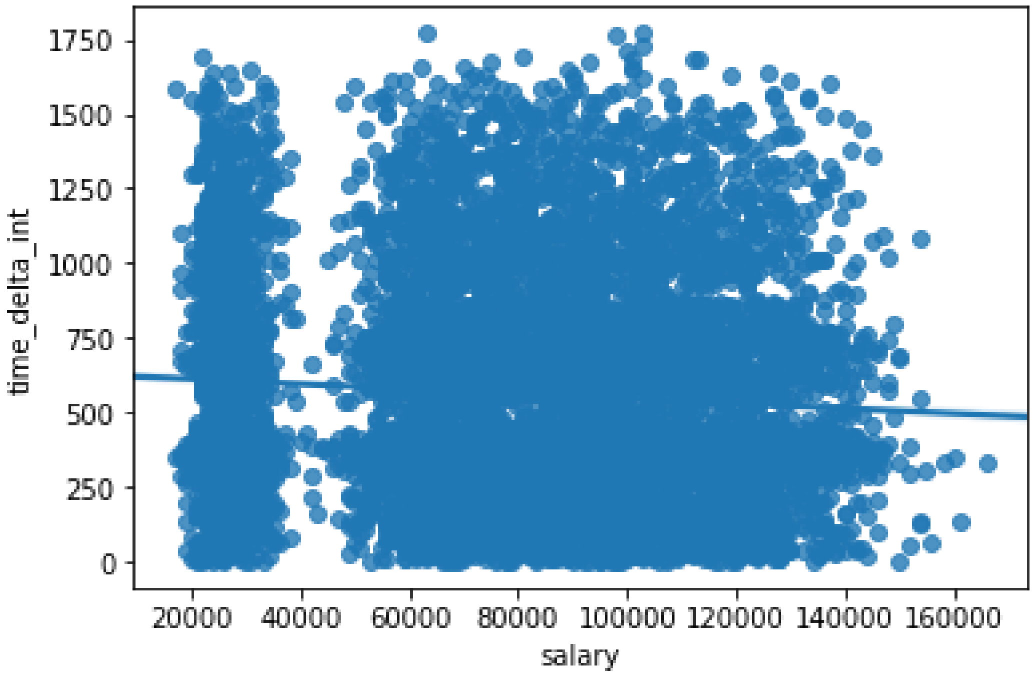
We know that there is a positive relationship, as plotted above, but it doesn't look very strong.

There also still exists the pattern where lots of people are leaving at around a year, and then another group at around two years. The horizontal blob means that people are only staying this long along lots of different salaries.

0.0.5 One more look at Salary

So far, we have seen that salary is associated with a slight increase in time at company, and that customer service jobs have the highest turnover. Let's look specifically to see if increasing salary in customer service jobs is associated with a longer time at the company

```
In [44]: x = data[data['dept']=='customer_service']
         ax = sns.regplot(x="salary", y="time_delta_int", data=x)

/home/lubuntu/anaconda3/envs/project/lib/python3.6/site-packages/scipy/stats/stats.py:1713: Fu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Hot dang! There's actually a slight negative correlation between salary and time spent at company in customer service jobs. This means that our intuition to try to pay them more is **wrong**

1 Conclusions:

1. People leave cyclically. Most people leave after a year, and then another group after two.
2. Salary and type of position are the main drivers **within the data that we have**, but they are not highly predictive. Getting paid more and being an Engineer/Data scientist are correlated with staying longer. Being in customer service is correlated with staying for **less** time.

2 Recommended Actions:

1. Make people really enjoy their first year of work. Better to make the first two years great.
2. Help make life better for customer service workers, but don't do that by paying them more. Survey them to see what would make their life at work better.

3 Helpful Data for the Future:

It would be wonderful to know the performance review for each employee. I hypothesize that people who are succeeding in performance reviews are more likely to stay at their current company.