John_Kattirtzi_EmployeeRetention

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In [1]:
```
import pandas as pd
import numpy as np

df = pd.read_csv('employee_retention_data.csv')


df.head()
```

Out[1]:

	employee_id	company_id	dept	seniority	salary	join_date	quit_date
0	13021.0	7	customer_service	28	89000.0	2014-03-24	2015-10-30
1	825355.0	7	marketing	20	183000.0	2013-04-29	2014-04-04
2	927315.0	4	marketing	14	101000.0	2014-10-13	NaN
3	662910.0	7	customer_service	20	115000.0	2012-05-14	2013-06-07
4	256971.0	2	data_science	23	276000.0	2011-10-17	2014-08-22

In [2]:
```
#Create a column that has value 0 or 1 if they stayed or not
#This will be the y that we will predict

df['left']= np.where(df['quit_date'].isnull(), 0, 1)
```

In [ ]:
```
#Lets look at the date range
```

In [3]:
```
df['quit_date']=pd.to_datetime(df['quit_date'])
```

In [4]:
```
df['join_date']=pd.to_datetime(df['join_date'])
```

In [5]:
```
df['quit_date'].max()
```

Out[5]:
```
Timestamp('2015-12-09 00:00:00')
```

In [6]:
```
df['quit_date'].min()
```

```
Out[6]: Timestamp('2011-10-13 00:00:00')

In [7]: df['join_date'].max()

Out[7]: Timestamp('2015-12-10 00:00:00')

In [9]: max_day=df['join_date'].max()+pd.DateOffset(days=1)

In [10]: max_day

Out[10]: Timestamp('2015-12-11 00:00:00')

In [11]: #set time at company from max date for those who continue to work there
         df['time_at_company']=df['quit_date']
         df['time_at_company'].fillna(max_day,inplace=True)
         df['time_at_company']-=df['join_date']

In [12]: df.head()

Out[12]:    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  left time_at_company
         0 2015-10-30     1        585 days
         1 2014-04-04     1        340 days
         2        NaT     0        424 days
         3 2013-06-07     1        389 days
         4 2014-08-22     1       1040 days

In [13]: df['time_at_company']=pd.to_timedelta(df['time_at_company'])
         df['time_at_company']=df['time_at_company'].dt.days

In [14]: #salary and seniority are related and senior people who aren't paid much more likely to
         df['pay_per_seniority']=df['salary']/df['seniority']

In [15]: #set up a scaled salary by department - not to compare salary of DS with CS, standardiz

         df['salary_by_dept']=df.groupby(['dept'])['salary'].transform(lambda x: (x - x.mean())

In [16]: #maybe look at current seniority- combine time at company with time before
         df['current_seniority']=df['seniority']+(df['time_at_company']/365.0)

In [17]: #try salary per combined seniority
         df['pay_by_csenior']=df['salary']/df['current_seniority']

In [18]: #try looking at standardized salary taking into account department and seniority

         df['csenior_salary_by_dept']=df.groupby(['dept'])['pay_by_csenior'].transform(lambda x:
```

In [19]:
```
#look at correlations? is this reasonable for logistic regression??
dfcorr = df.corr(method='spearman')['left']
dfcorr = pd.DataFrame(dfcorr)
dfcorr.columns = ["Correlation"]
dfcorr2 = dfcorr.sort_values(by=['Correlation'], ascending=False)
print(dfcorr2)
```

```
                        Correlation
left                       1.000000
time_at_company            0.172171
current_seniority          0.015000
company_id                 0.012738
employee_id                0.001665
seniority                  0.001016
salary_by_dept            -0.003803
salary                    -0.014690
pay_per_seniority         -0.026863
csenior_salary_by_dept    -0.027666
pay_by_csenior            -0.043400
```

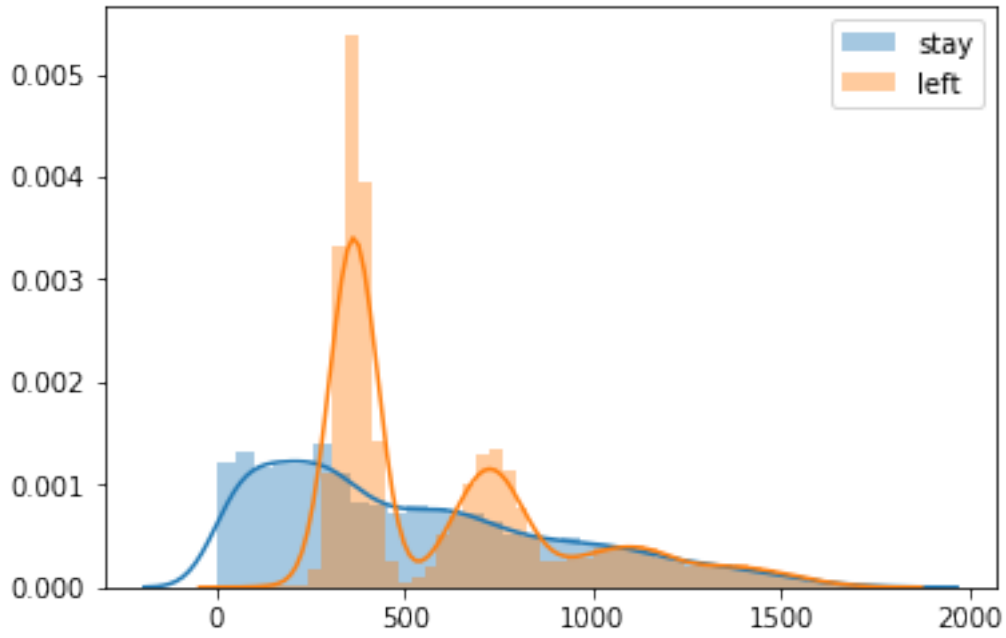
In [ ]:
```
#oh no nothing is correlated...
```

In [21]:
```
#lets look at distributions of those who stayed vs who left
df1=df.loc[df['left'] == 1]
df0=df.loc[df['left'] == 0]
```

In [22]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.distplot((df0[['time_at_company']]), label='stay')
sns.distplot((df1[['time_at_company']]), label='left')
plt.legend()
```

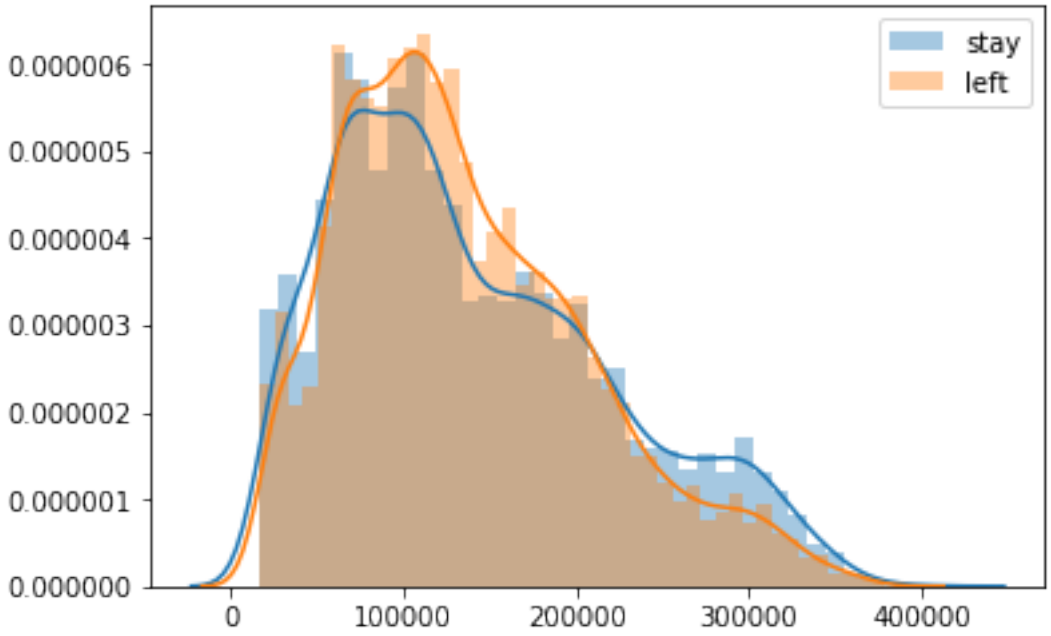
Out[22]:
```
<matplotlib.legend.Legend at 0x1a2207dc50>
```



In [ ]: *#observation- those who left tend to have 2 narrow distributions in their stay at the co*

In [23]:
```
sns.distplot(df0[['salary']], label="stay")
sns.distplot(df1[['salary']], label="left")
plt.legend()
```

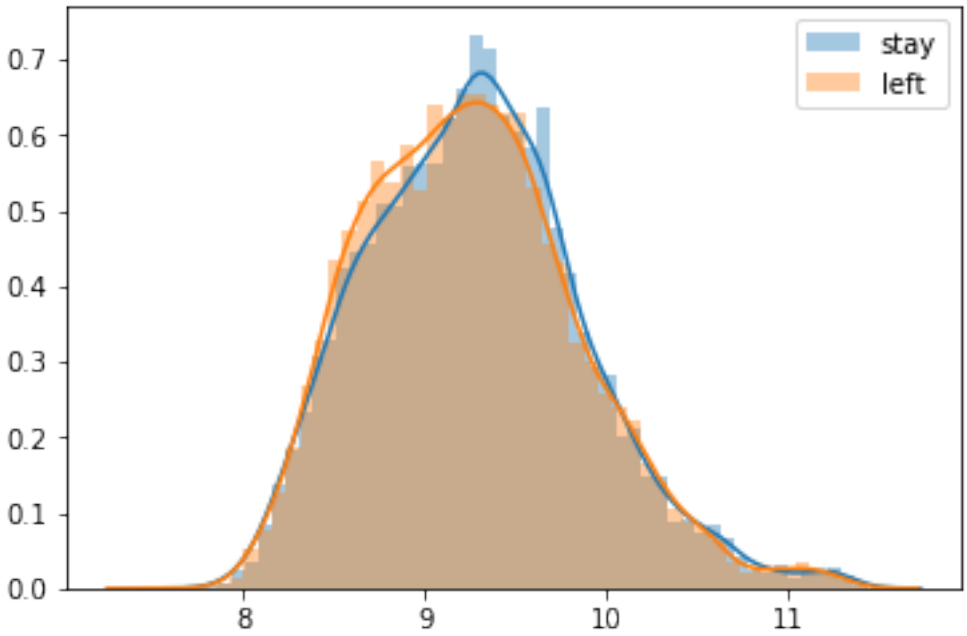
Out[23]: <matplotlib.legend.Legend at 0x1a21ee2908>



In [ ]:
```
#observation-
#P(200,000) > for those who left
#P(300,000) < if left the company
```

In [25]:
```
sns.distplot(np.log(df0[['pay_per_seniority']]), label='stay')
sns.distplot(np.log(df1[['pay_per_seniority']]), label='left')
plt.legend()
```

Out[25]: <matplotlib.legend.Legend at 0x11ed450b8>



In [ ]:
```
#pay per seniority seems similar
```

In [26]:
```
df1.head()
```

Out[26]:

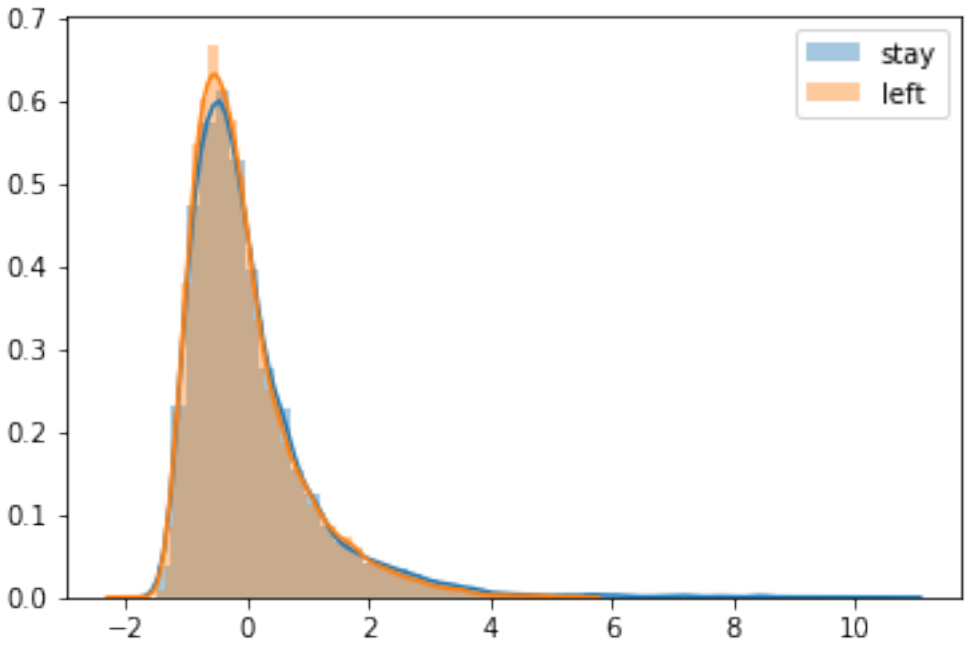
	employee_id	company_id	dept	seniority	salary	join_date	quit_date	left	time_at_company	pay_per_seniority	salary_by_dept
0	13021.0	7	customer_service	28	89000.0	2014-03-24	2015-10-30	1	585	3178.571429	0.213889
1	825355.0	7	marketing	20	183000.0	2013-04-29					
3	662910.0	7	customer_service	20	115000.0	2012-05-14					
4	256971.0	2	data_science	23	276000.0	2011-10-17					
5	509529.0	4	data_science	14	165000.0	2012-01-30					

```
1 2014-04-04      1              340        9150.000000         0.904985
3 2013-06-07      1              389        5750.000000         1.037199
4 2014-08-22      1             1040       12000.000000         0.878623
5 2013-08-30      1              578       11785.714286        -0.532481
```

```
   current_seniority  pay_by_csenior  csenior_salary_by_dept
0          29.602740     3006.478482               -1.221037
1          20.931507     8742.801047               -0.338277
3          21.065753     5459.097412               -0.240867
4          25.849315    10677.265501               -0.723105
5          15.583562    10588.080169               -0.737496
```

In [28]:
```
sns.distplot((df0[['csenior_salary_by_dept']]), label='stay')
sns.distplot((df1[['csenior_salary_by_dept']]), label='left')
plt.legend()
```

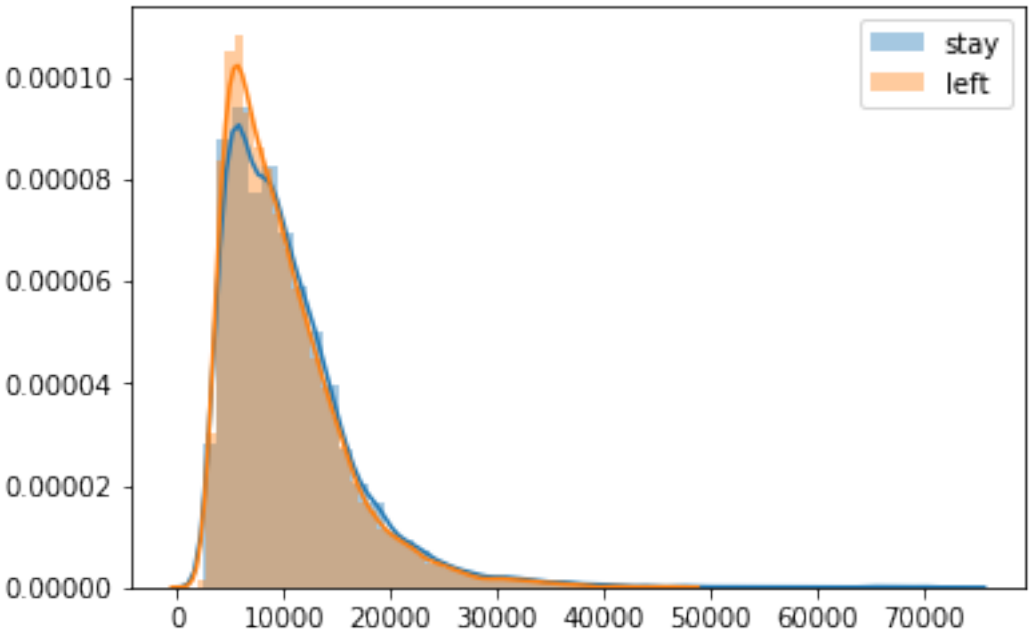
Out[28]: <matplotlib.legend.Legend at 0x1a228cb668>



In [ ]:
```
#csenior seems very similar
```

In [29]:
```
sns.distplot((df0[['pay_by_csenior']]), label='stay')
sns.distplot((df1[['pay_by_csenior']]), label='left')
plt.legend()
```

Out[29]: <matplotlib.legend.Legend at 0x1a228cb9e8>



In [ ]: *#variables are correlated, haven't been able to engineer one single feature*
#that stands out

In [ ]: *#next i would do logistic regression but I've run out of time to do it now*

In [ ]:

In [ ]:

In [ ]: