Insight Datachallenge #1 Employee retention

Goal

Employee turnover is a very costly problem for companies. The cost of replacing an employee if often larger than 100K USD, taking into account the time spent to interview and find a replacement, placement fees, sign-on bonuses and the loss of productivity for several months. t is only natural then that data science has started being applied to this area. Understanding why and when employees are most likely to leave can lead to actions to improve employee retention as well as planning new hiring in advance. This application of DS is sometimes called people analytics or people data science (if you see a job title: people data scientist, this is your job). In this challenge, you have a data set with info about the employees and have to predict when employees are going to quit by understanding the main drivers of employee churn.

Challenge Description

We got employee data from a few companies. We have data about all employees who joined from 2011/01/24 to 2015/12/13. For each employee, we also know if they are still at the company as of 2015/12/13 or they have quit. Beside that, we have general info about the employee, such as avg salary during her tenure, dept, and yrs of experience. As said above, the goal is to predict employee retention and understand its main drivers

Hints:

What are the main factors that drive employee churn? Do they make sense? Explain your findings. What might you be able to do for the company to address employee Churn, what would be follow-up actions? If you could add to this data set just one variable that could help explain employee churn, what would that be? Your output should be in the form a a jupyter notebook and pdf output of a jupyter notebook in which you specify your results and how you got them.

Data

The table is: "employee_retention" - comprehensive information about employees.

Columns:

employee_id : id of the employee. Unique by employee per company
company_id : company id.
dept : employee dept
seniority : number of yrs of work experience when hired
salary: avg yearly salary of the employee during her tenure within the company
join_date: when the employee joined the company, it can only be between 2011/01/24 and 2015/12/13
quit_date: when the employee left her job (if she is still employed as of 2015/12/13, this field is NA)

Strategy:

- make sure data is clean (check the datatype for all columns)
- create the following new columns
  - still at company (yes/no)
  - length of employment
  - salary/years of experience
- do some EDA to find out more about the companies:
  - what is proportion of different roles for different companies
  - average retention rate
- run some sort of logistic regression model

In [1]:
```
### Load in some useful packages

%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from scipy import stats
import qgrid
import seaborn as sns; sns.set() # this is another plotting program

pd.show_versions()
```

```
INSTALLED VERSIONS
------------------
commit: None
python: 3.7.1.final.0
python-bits: 64
OS: Darwin
OS-release: 18.2.0
machine: x86_64
processor: i386
byteorder: little
LC_ALL: None
LANG: en_US.UTF-8
LOCALE: en_US.UTF-8

pandas: 0.23.4
pytest: None
pip: 18.1
setuptools: 40.6.3
Cython: None
numpy: 1.15.4
scipy: 1.1.0
pyarrow: None
xarray: None
IPython: 7.2.0
sphinx: None
patsy: 0.5.1
dateutil: 2.7.5
pytz: 2018.9
blosc: None
bottleneck: None
tables: None
numexpr: None
feather: None
matplotlib: 3.0.2
openpyxl: None
xlrd: None
xlwt: None
xlsxwriter: None
lxml: None
bs4: None
html5lib: None
sqlalchemy: None
pymysql: None
psycopg2: None
jinja2: 2.10
s3fs: None
fastparquet: None
pandas_gbq: None
pandas_datareader: None
```

In [2]:
```
## read in the data

raw_data = pd.read_csv('employee_retention_data.csv')
```

In [3]:
```
raw_data.shape
```
Out[3]:
```
(24702, 7)
```

In [4]:
```
## look at table

qgrid.show_grid(raw_data)
```

In [5]:
```
raw_data.dtypes
```
Out[5]:
```
employee_id    float64
company_id       int64
dept            object
seniority        int64
salary         float64
join_date       object
quit_date       object
dtype: object
```

In [6]:
```
## need to convert the Joindate into date
from datetime import datetime # this calls the datetime package

raw_data['join_date'] = pd.to_datetime(raw_data['join_date'])
raw_data['quit_date'] = pd.to_datetime(raw_data['quit_date'])
raw_data.dtypes
```
Out[6]:
```
employee_id           float64
company_id              int64
dept                   object
seniority               int64
salary                float64
join_date      datetime64[ns]
quit_date      datetime64[ns]
dtype: object
```

In [7]:
```
## create new column that indicates if employee has quit or not
## if the quit date is NaT then should be 0/False, if there is something
 then should be 1/True

raw_data['employed'] = raw_data['quit_date'].apply(lambda col: pd.isnull
(col))
raw_data.head()
```

Out[7]:

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

In [9]:
```
### replace the NaT with the current date 2015/12/13, so that we can cal
culate lenght of employment for all employees
from datetime import datetime, date

raw_data.quit_date = raw_data.quit_date.fillna(date(year = 2015, month =
 12, day = 13))
raw_data.head()
```

Out[9]:

	employee_id	company_id	dept	seniority	salary	join_date	quit_date	e
0	13021.0	7	customer_service	28	89000.0	2014-03-24	2015-10-30	F
1	825355.0	7	marketing	20	183000.0	2013-04-29	2014-04-04	F
2	927315.0	4	marketing	14	101000.0	2014-10-13	2015-12-13	T
3	662910.0	7	customer_service	20	115000.0	2012-05-14	2013-06-07	F
4	256971.0	2	data_science	23	276000.0	2011-10-17	2014-08-22	F

In [10]:
```
raw_data.dtypes
```

Out[10]:
```
employee_id               float64
company_id                  int64
dept                       object
seniority                   int64
salary                    float64
join_date          datetime64[ns]
quit_date          datetime64[ns]
employed                     bool
dtype: object
```

In [11]:
```
## make new column with lenght of employment

raw_data['length_employed'] = raw_data['quit_date'] - raw_data['join_dat
e']
raw_data.head()
```

Out[11]:

	employee_id	company_id	dept	seniority	salary	join_date	quit_date	e
0	13021.0	7	customer_service	28	89000.0	2014-03-24	2015-10-30	F
1	825355.0	7	marketing	20	183000.0	2013-04-29	2014-04-04	F
2	927315.0	4	marketing	14	101000.0	2014-10-13	2015-12-13	T
3	662910.0	7	customer_service	20	115000.0	2012-05-14	2013-06-07	F
4	256971.0	2	data_science	23	276000.0	2011-10-17	2014-08-22	F

In [12]:
```
raw_data.dtypes
```

Out[12]:
```
employee_id                  float64
company_id                     int64
dept                          object
seniority                      int64
salary                       float64
join_date             datetime64[ns]
quit_date             datetime64[ns]
employed                        bool
length_employed      timedelta64[ns]
dtype: object
```

In [13]:
```
# make new column with salary/seniority (years of experience)

raw_data['salary/seniority'] = raw_data['salary'] / raw_data['seniority'
]
raw_data.head()
```

Out[13]:

	employee_id	company_id	dept	seniority	salary	join_date	quit_date	e
0	13021.0	7	customer_service	28	89000.0	2014-03-24	2015-10-30	F
1	825355.0	7	marketing	20	183000.0	2013-04-29	2014-04-04	F
2	927315.0	4	marketing	14	101000.0	2014-10-13	2015-12-13	T
3	662910.0	7	customer_service	20	115000.0	2012-05-14	2013-06-07	F
4	256971.0	2	data_science	23	276000.0	2011-10-17	2014-08-22	F

some EDA

- look at distribution of the data
- look on a per company basis - what is average emplyoment
- look on a per role basis - was is average employment
- do I have any missing data and if yes how much

In [14]:
```
raw_data.isnull().sum()
```

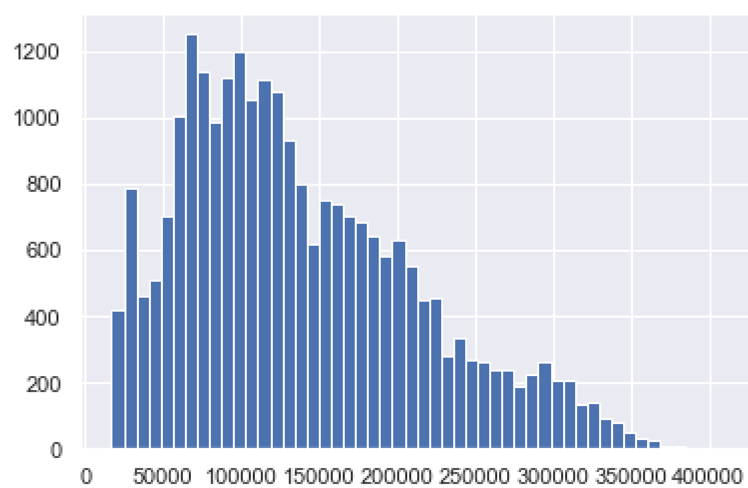
Out[14]:
```
employee_id         0
company_id          0
dept                0
seniority           0
salary              0
join_date           0
quit_date           0
employed            0
length_employed     0
salary/seniority    0
dtype: int64
```

In [15]:
```
raw_data['length_employed'].mean()
```

Out[15]:
```
Timedelta('574 days 07:39:28.812241')
```

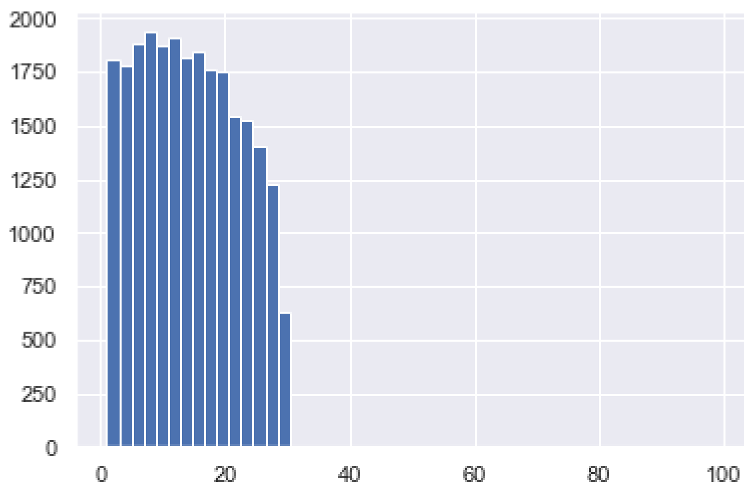
In [16]:
```
# look at distribution of data
plt.hist(raw_data['salary'], bins = 50)
```

Out[16]:
```
(array([4.180e+02, 7.870e+02, 4.640e+02, 5.120e+02, 7.050e+02, 1.008e+0
3,
        1.253e+03, 1.142e+03, 9.880e+02, 1.120e+03, 1.202e+03, 1.057e+0
3,
        1.118e+03, 1.077e+03, 9.340e+02, 8.020e+02, 6.190e+02, 7.530e+0
2,
        7.390e+02, 7.010e+02, 6.860e+02, 6.450e+02, 5.850e+02, 6.300e+0
2,
        5.520e+02, 4.470e+02, 4.580e+02, 2.810e+02, 3.320e+02, 2.700e+0
2,
        2.590e+02, 2.390e+02, 2.390e+02, 1.900e+02, 2.240e+02, 2.640e+0
2,
        2.100e+02, 2.100e+02, 1.370e+02, 1.420e+02, 9.200e+01, 8.300e+0
1,
        5.000e+01, 3.300e+01, 2.800e+01, 7.000e+00, 5.000e+00, 1.000e+0
0,
        2.000e+00, 2.000e+00]),
 array([ 17000.,  24820.,  32640.,  40460.,  48280.,  56100.,  63920.,
         71740.,  79560.,  87380.,  95200., 103020., 110840., 118660.,
        126480., 134300., 142120., 149940., 157760., 165580., 173400.,
        181220., 189040., 196860., 204680., 212500., 220320., 228140.,
        235960., 243780., 251600., 259420., 267240., 275060., 282880.,
        290700., 298520., 306340., 314160., 321980., 329800., 337620.,
        345440., 353260., 361080., 368900., 376720., 384540., 392360.,
        400180., 408000.]),
 <a list of 50 Patch objects>)
```



In [17]:
```
plt.hist(raw_data['seniority'], bins = 50)
```

Out[17]:
```
(array([1803., 1776., 1886., 1936., 1871., 1912., 1814., 1847., 1765.,
        1754., 1546., 1528., 1409., 1227.,  626.,    0.,    0.,    0.,
           0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,
           0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,
           0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,
           0.,    0.,    0.,    0.,    2.]),
 array([ 1.  ,  2.96,  4.92,  6.88,  8.84, 10.8 , 12.76, 14.72, 16.68,
        18.64, 20.6 , 22.56, 24.52, 26.48, 28.44, 30.4 , 32.36, 34.32,
        36.28, 38.24, 40.2 , 42.16, 44.12, 46.08, 48.04, 50.  , 51.96,
        53.92, 55.88, 57.84, 59.8 , 61.76, 63.72, 65.68, 67.64, 69.6 ,
        71.56, 73.52, 75.48, 77.44, 79.4 , 81.36, 83.32, 85.28, 87.24,
        89.2 , 91.16, 93.12, 95.08, 97.04, 99.  ]),
 <a list of 50 Patch objects>)
```



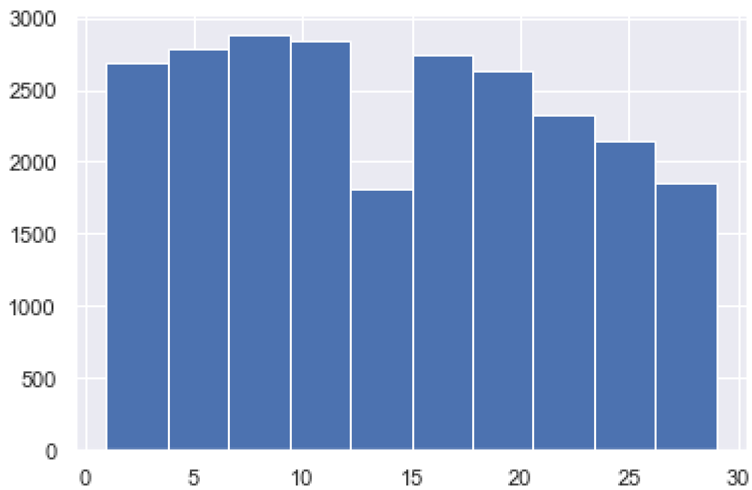
looks like there is two outliers in the years of experience, went up and checked in qgrid. There are two records where work experience is indicated with 98 and 99 years. Dropped these records.

is index 24700 and 24701

In [18]:
```
#dropped two outliers

data = raw_data.drop([24700, 24701], axis=0)
plt.hist(data['seniority'])
```

Out[18]:
```
(array([2684., 2781., 2880., 2839., 1814., 2740., 2626., 2331., 2152.,
         1853.]),
 array([ 1. ,  3.8,  6.6,  9.4, 12.2, 15. , 17.8, 20.6, 23.4, 26.2, 29.
]),
 <a list of 10 Patch objects>)
```



In [19]:
```
data.groupby('dept').mean()
```

Out[19]:

	employee_id	company_id	seniority	salary	employed	sal
dept						
customer_service	498143.365251	3.441721	14.171133	82245.424837	0.445098	76
data_science	500726.793103	3.440439	14.189028	206885.893417	0.472727	19
design	500995.411594	3.386957	14.197826	137460.869565	0.436232	12
engineer	502682.060711	3.428448	14.153946	205531.439722	0.488075	19
marketing	502645.858181	3.384397	13.966835	135582.438408	0.437145	12
sales	510257.236129	3.427175	13.979823	135912.358134	0.429067	12

In [20]:
```
data.groupby('company_id').mean()
```

Out[20]:

	employee_id	seniority	salary	employed	salary/seniority
company_id					
1	501761.214260	14.131998	152163.700648	0.455510	14244.829457
2	503864.736618	14.297489	155728.090952	0.477499	14196.348497
3	496656.524918	14.054565	122118.588578	0.443070	11410.891741
4	513380.616392	14.023763	122721.144520	0.440834	11552.797771
5	507257.065527	14.474644	123348.717949	0.439886	11162.462194
6	490152.278079	14.089853	119925.639040	0.448490	11097.503672
7	501416.076797	13.906046	121582.516340	0.434641	11605.597233
8	493358.904489	13.867240	122284.622732	0.446991	11508.691307
9	505596.132154	13.778356	123905.306972	0.449532	12004.257711
10	491290.082176	13.991898	121386.574074	0.445602	11704.733368
11	437283.312500	14.375000	109562.500000	0.250000	10130.014918
12	442431.541667	11.166667	73000.000000	0.500000	9024.816170

Run a logistic Regression model

- need to standardize/normalize variables to mean 0, variance 1
- need to make dummy variables from dep and from company_id
- drop: join_date, quit_date, employee_id
- outcome variable is employed - also needs to be dropped from feature table

In [21]:
```
# scale data to mean 0 and variance 1

from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

data['salary']= preprocessing.scale(data['salary'])
data['seniority']= preprocessing.scale(data['seniority'])
data['length_employed']= preprocessing.scale(data['length_employed'])
data['salary/seniority']= preprocessing.scale(data['salary/seniority'])
data.mean()
```

```
/anaconda3/envs/insight/lib/python3.7/site-packages/sklearn/utils/valid
ation.py:595: DataConversionWarning: Data with input dtype int64 was co
nverted to float64 by the scale function.
  warnings.warn(msg, DataConversionWarning)
/anaconda3/envs/insight/lib/python3.7/site-packages/sklearn/utils/valid
ation.py:595: DataConversionWarning: Data with input dtype timedelta64
[ns] was converted to float64 by the scale function.
  warnings.warn(msg, DataConversionWarning)
/anaconda3/envs/insight/lib/python3.7/site-packages/sklearn/preprocessi
ng/data.py:176: UserWarning: Numerical issues were encountered when cen
tering the data and might not be solved. Dataset may contain too large
values. You may need to prescale your features.
  warnings.warn("Numerical issues were encountered "
```

Out[21]:
```
employee_id         5.016166e+05
company_id          3.426802e+00
seniority          -4.955101e-17
salary              4.955101e-17
employed            4.531174e-01
length_employed     2.270788e-17
salary/seniority   -1.765569e-16
dtype: float64
```

In [22]:
```
# need to first make the company ID to a string
data['company_id'] = data['company_id'].apply(str)
data.dtypes
```

Out[22]:
```
employee_id                float64
company_id                  object
dept                        object
seniority                  float64
salary                     float64
join_date           datetime64[ns]
quit_date           datetime64[ns]
employed                      bool
length_employed            float64
salary/seniority           float64
dtype: object
```

In [23]:
```
# make dummy variables out of categorical features

data = pd.get_dummies(data, dummy_na=False, drop_first=True)
data.head()
```

Out[23]:

	employee_id	seniority	salary	join_date	quit_date	employed	length_employed	s
0	13021.0	1.723252	-0.646590	2014-03-24	2015-10-30	False	0.029634	-
1	825355.0	0.729954	0.589361	2013-04-29	2014-04-04	False	-0.647952	-
2	927315.0	-0.015020	-0.488809	2014-10-13	2015-12-13	True	-0.410105	-
3	662910.0	0.729954	-0.304731	2012-05-14	2013-06-07	False	-0.512435	-
4	256971.0	1.102441	1.812164	2011-10-17	2014-08-22	False	1.288006	-

5 rows × 24 columns

In [24]:
```
y = data['employed']
```

In [25]:
```
# drop the columns I don't need and make new dataframe used for analysis

X = data.drop([
 'employee_id',
 'join_date',
 'quit_date',
 'employed'], axis=1)
```

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

Out[26]:

	seniority	salary	length_employed	salary/seniority	company_id_10	company_id_
0	1.723252	-0.646590	0.029634	-0.997049	0	0
1	0.729954	0.589361	-0.647952	-0.383494	0	0
2	-0.015020	-0.488809	-0.410105	-0.582385	0	0
3	0.729954	-0.304731	-0.512435	-0.732838	0	0
4	1.102441	1.812164	1.288006	-0.090661	0	0

In [27]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 random_state=0)
logreg = LogisticRegression(penalty='l1')
logreg.fit(X_train, y_train)
```

```
/anaconda3/envs/insight/lib/python3.7/site-packages/sklearn/linear_mode
l/logistic.py:433: FutureWarning: Default solver will be changed to 'lb
fgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

Out[27]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=
True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l1', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [28]:
```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.f
ormat(logreg.score(X_test, y_test)))
```

```
Accuracy of logistic regression classifier on test set: 0.63
```

In [29]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[2312  394]
 [1456  778]]
```

In [30]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))

#precision is true postives/everything that is selected
#recall: out of all true positives how many are actually selected
```

```
              precision    recall  f1-score   support

       False       0.61      0.85      0.71      2706
        True       0.66      0.35      0.46      2234

   micro avg       0.63      0.63      0.63      4940
   macro avg       0.64      0.60      0.59      4940
weighted avg       0.64      0.63      0.60      4940
```

In [31]:
```
#figure out the coeffiences for each columnh
column = X.columns.tolist()

logreg.coef1_ = np.transpose(logreg.coef_)
logreg.coef1_ = logreg.coef1_.tolist()

coef = pd.DataFrame(logreg.coef1_, index=column)
qgrid.show_grid(coef)
#coef.shape
```

Conclusion:

What are the main factors that drive employee churn? Do they make sense? The main factor driving employee churn are years employed at the company (coeff -0.24). Some other less important factors of people retention is company ID (company 11 vs company 12, salary and type of role. of the Less importantly company ID is important. The fact that the lenght of employment at a company is a big contributer to people leaving makes sense.

What might you be able to do for the company to address employee Churn, what would be follow-up actions?
Give some incentives, benefits for people who have been employed for a certain number of years. For example more vacation days, special bonuses etc.

If you could add to this data set just one variable that could help explain employee churn, what would that be?
Since salary is a "retention factor" and length of employment is a "leaving factor" an interesting variable to include in this problem is the amount of salary growth over time.