data challenge 1

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In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
data = pd.read_csv('employee_retention_data.csv')
print(data.shape)
data.head()
```

```
(24702, 7)
```

Out[2]:

	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 [3]:
```
data.dtypes
```

Out[3]:
```
employee_id    float64
company_id       int64
dept            object
seniority        int64
salary         float64
join_date       object
quit_date       object
dtype: object
```

```
In [4]: #not an imbalanced dataset
        data['quit_date'].isna().sum()

Out[4]: 11192

In [5]: #check nans, no rows need to be eliminated
        data.isna().sum()

Out[5]: employee_id        0
        company_id         0
        dept               0
        seniority          0
        salary             0
        join_date          0
        quit_date      11192
        dtype: int64

In [6]: #convert the dates to the appropriate types
        data['join_date']=data['join_date'].astype('M')
        data['quit_date']=data['quit_date'].astype('M')
        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]: #check that nans were maintained
        data['quit_date'].isna().sum()

Out[7]: 11192

In [8]: #add a quit column
        data['quit']=data['quit_date'].notna()

In [9]: #calculate months at company
        def monthsAtCompany(start,end):
            if type(end) == type(pd.NaT):#very tricky comparison to make
                period=(pd.to_datetime('2015-12-13', format='%Y-%m-%d')
                        -start)/np.timedelta64(1, 'M')
            else:
                period=(end-start)/np.timedelta64(1, 'M')
            return period

        #np.vectorize(monthsAtCompany)(data['join_date'], data['quit_date'])
```

In [10]:
```
#check that calculation works
monthsAtCompany(data['join_date'][2], data['quit_date'][2])
```

Out[10]:
```
13.996180619725251
```

In [11]:
```
#define tenure duration column
for i in range(len(data)):
    data.loc[i,'tenure']=monthsAtCompany(data['join_date'][i], data['quit_date'][i])
```

In [12]:
```
#check if tenure seems correct
data.head()
```

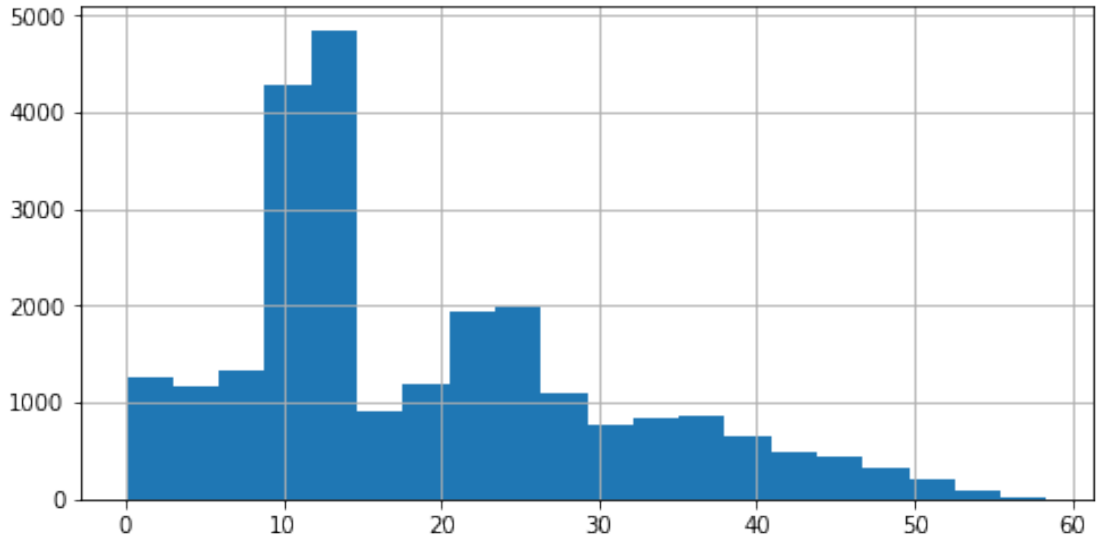
Out[12]:

	employee_id	company_id	dept	seniority	salary	join_date	quit_date	quit	tenure
0	13021.0	7	customer_service	28	89000.0	2014-03-24	2015-10-30	True	19.220107
1	825355.0	7	marketing	20	183000.0	2013-04-29	2014-04-04	True	11.170661
2	927315.0	4	marketing	14	101000.0	2014-10-13	NaT	False	13.996181
3	662910.0	7	customer_service	20	115000.0	2012-05-14	2013-06-07	True	12.780550
4	256971.0	2	data_science	23	276000.0	2011-10-17	2014-08-22	True	34.169079

In [13]:
```
print(data['tenure'].describe())
data['tenure'].hist(bins=20,figsize=(8, 4))
```

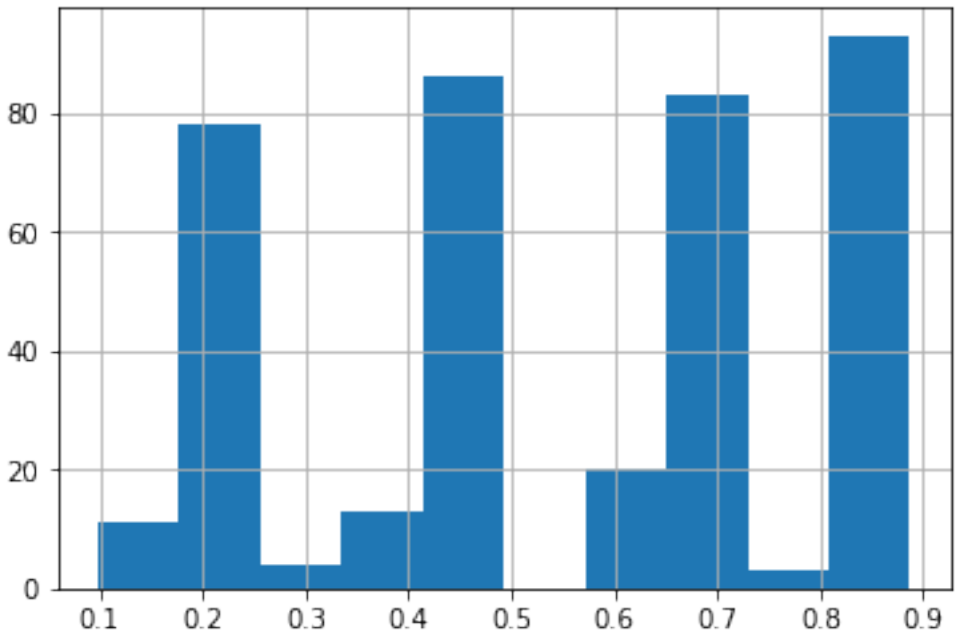
```
count    24702.000000
mean        18.869187
std         11.880076
min          0.098565
25%         10.940676
50%         13.930471
75%         25.659664
max         58.383129
Name: tenure, dtype: float64
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0f9fffa20>
```



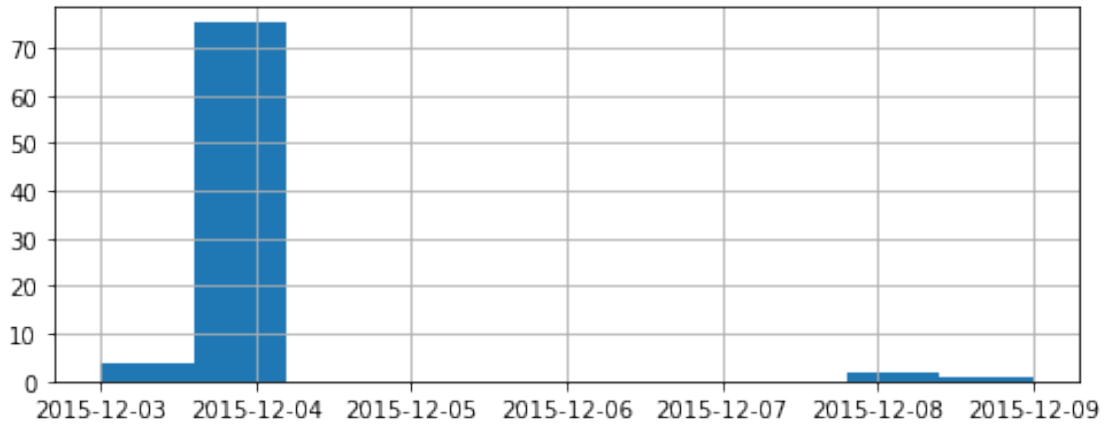
In [14]:
```
#people in the region below a month at the company
data[data['tenure']<1]['tenure'].hist()
```

Out[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd0f6daebe0>
```



In [15]:
```
#people in the region near december 2015
data[data['quit_date']>pd.to_datetime('2015-12-01', format='%Y-%m-%d')
    ]['quit_date'].hist(figsize=(8, 3))
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd0f6d33978>
```



- what's tricky about this problem is that we're being asked to predict when an employer is going to quit.
- This seems like a regression problem, but in fact mixes two predictions, whether an employee is going to quit (classification problem) and when (regression)
- might be simpler to **first attempt a binary classification** on retention and then try to predict the tenure length
- afterwards a regressor can be trained, but only by using data on employees that quit. I'm not sure how to then combine both predictions.
- **Note:** the relevant dates (join, quit) are in the period between 2011 and 2015 which I think does not overlap with any major economical downturn which could be very important for the analysis (indeed, I confirmed this suspicion below). Also, from the description of the problem **I assume that employees that left, did so by quitting and from being fired**.

```
In [16]: #sanity checks:
         print(data['seniority'].describe())
         data['seniority'].value_counts().sort_index(ascending=False)

count    24702.000000
mean        14.127803
std          8.089520
min          1.000000
25%          7.000000
50%         14.000000
75%         21.000000
max         99.000000
Name: seniority, dtype: float64


Out[16]: 99       1
         98       1
```

```
29     626
28     585
27     642
26     694
25     715
24     743
23     785
22     764
21     782
20     844
19     910
18     872
17     893
16     936
15     911
14     920
13     894
12     988
11     924
10     927
9      944
8     1008
7      928
6      950
5      936
4      895
3      881
2      942
1      861
Name: seniority, dtype: int64
```

```
In [17]: #two values are incorrect, so erase them:
         data[data['seniority']> 30]
```

```
Out[17]:        employee_id  company_id       dept  seniority    salary  join_date  \
         24700      97289.0          10   engineer         98  266000.0 2011-12-13
         24701     604052.0           1  marketing         99  185000.0 2011-07-26

                quit_date  quit     tenure
         24700 2015-01-09  True  36.896035
         24701 2013-12-06  True  28.386620
```

```
In [18]: data.drop([24700,24701],inplace=True)
         data.shape
```

```
Out[18]: (24700, 9)
```

```
In [19]: def convert4prediction(series,inverse=False):
             '''
```

```
        converts a datetime64 pandas data type to a numerical value, by
        using unix time (number of nanoseconds since 1970-01-01) as a
        reference point:
        https://stackoverflow.com/questions/50979873/linear-fit-to-pandas-datetime64-values
        The function returns the number of years passed since 2011-01-01
        (date from problem statement).
        Function can apply the inverse function too by seeting the second
        parameter to True.
        '''
        if inverse:
            return pd.to_datetime((series+41)*(1e9 *60*60*24*365))
        else:
            return pd.to_numeric(series)/(1e9 *60*60*24*365) -41
```

In [20]:
```
#remove employee_id from variables
variables=data.columns.tolist()
print(variables)
del variables[0]
variables
```

```
['employee_id', 'company_id', 'dept', 'seniority', 'salary', 'join_date', 'quit_date', 'quit', '
```

Out[20]:
```
['company_id',
 'dept',
 'seniority',
 'salary',
 'join_date',
 'quit_date',
 'quit',
 'tenure']
```

In [21]:
```
#copy data to new dataframe and convert timestamp colums to numerical
df=data[variables].copy()
df['join_date']=convert4prediction(data['join_date'])
#nan positions preserved because of matching index:
df['quit_date']=convert4prediction(data[data['quit']]['quit_date'])
df.head()
```

Out[21]:

	company_id	dept	seniority	salary	join_date	quit_date	quit	tenure
0	7	customer_service	28	89000.0	3.254795	4.857534	True	19.220107
1	7	marketing	20	183000.0	2.353425	3.284932	True	11.170661
2	4	marketing	14	101000.0	3.810959	NaN		
3	7	customer_service	20	115000.0	1.394521	2.460274		
4	2	data_science	23	276000.0	0.819178	3.668493		

```
2  False  13.996181
3   True  12.780550
4   True  34.169079
```

```
In [22]: #encode categoricals
         df['dept'].value_counts()
```

```
Out[22]: customer_service    9180
         engineer            4612
         data_science        3190
         sales               3172
         marketing           3166
         design              1380
         Name: dept, dtype: int64
```

```
In [29]: data['company_id'].value_counts()
```

```
Out[29]: 1     8485
         2     4222
         3     2749
         4     2062
         5     1755
         6     1291
         7     1224
         8     1047
         9      961
         10     864
         12      24
         11      16
         Name: company_id, dtype: int64
```

```
In [23]: df = pd.get_dummies(df, columns=['dept'])
         df = pd.get_dummies(df, columns=['company_id'])
         df['quit']=df['quit'].map({True:1,False:0})
         df.head()
```

```
Out[23]:    seniority    salary  join_date  quit_date  quit     tenure  \
         0         28   89000.0   3.254795   4.857534     1  19.220107
         1         20  183000.0   2.353425   3.284932     1  11.170661
         2         14  101000.0   3.810959        NaN     0  13.996181
         3         20  115000.0   1.394521   2.460274     1  12.780550
         4         23  276000.0   0.819178   3.668493     1  34.169079

            dept_customer_service  dept_data_science  dept_design  dept_engineer  \
         0                      1                  0            0              0
         1                      0                  0            0              0
         2                      0                  0            0              0
         3                      1                  0            0              0
         4                      0                  1            0              0
```

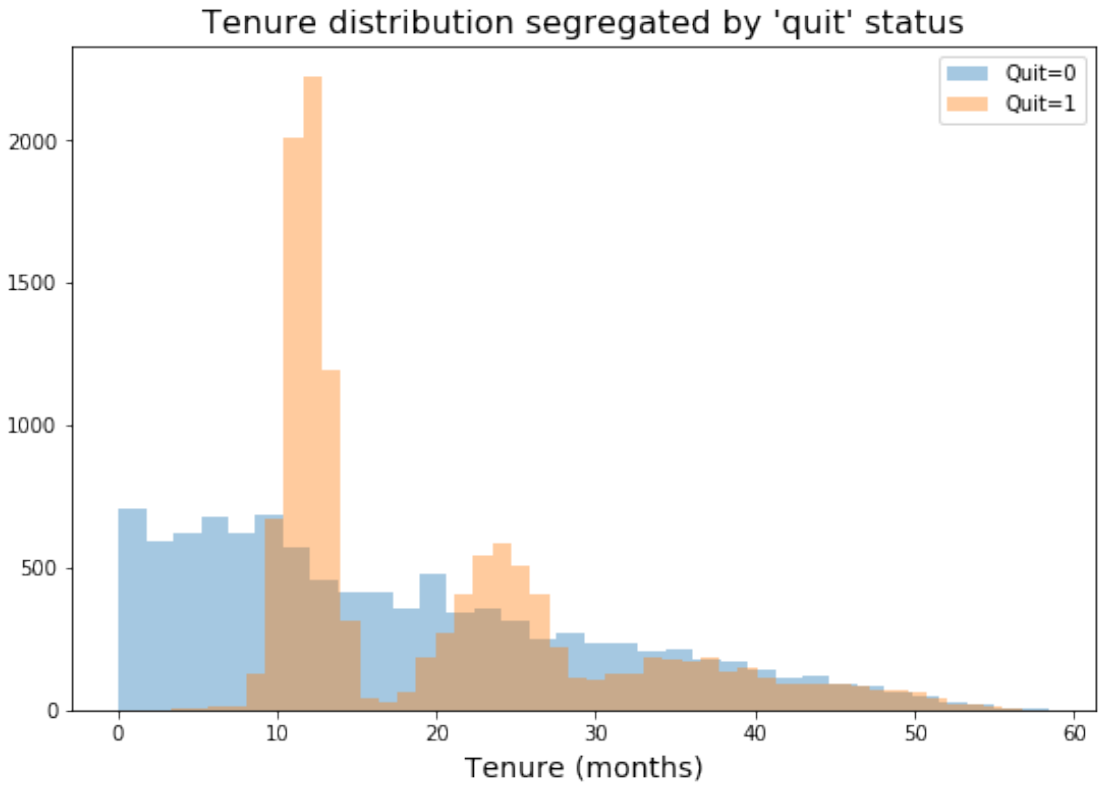
```
        ...        company_id_3  company_id_4  company_id_5  company_id_6  \
0       ...                   0             0             0             0
1       ...                   0             0             0             0
2       ...                   0             1             0             0
3       ...                   0             0             0             0
4       ...                   0             0             0             0

   company_id_7  company_id_8  company_id_9  company_id_10  company_id_11  \
0             1             0             0              0              0
1             1             0             0              0              0
2             0             0             0              0              0
3             1             0             0              0              0
4             0             0             0              0              0

   company_id_12
0              0
1              0
2              0
3              0
4              0

[5 rows x 24 columns]
```

In [24]:
```
#separate into train, cv, test:
from sklearn import model_selection #for StratifiedKFold, cross_val_score
from sklearn.linear_model import LogisticRegression
```

In [25]:
```
seed=106637
train,test = model_selection.train_test_split(df,test_size=0.1,
                                              random_state=seed,stratify=df['quit'])
```

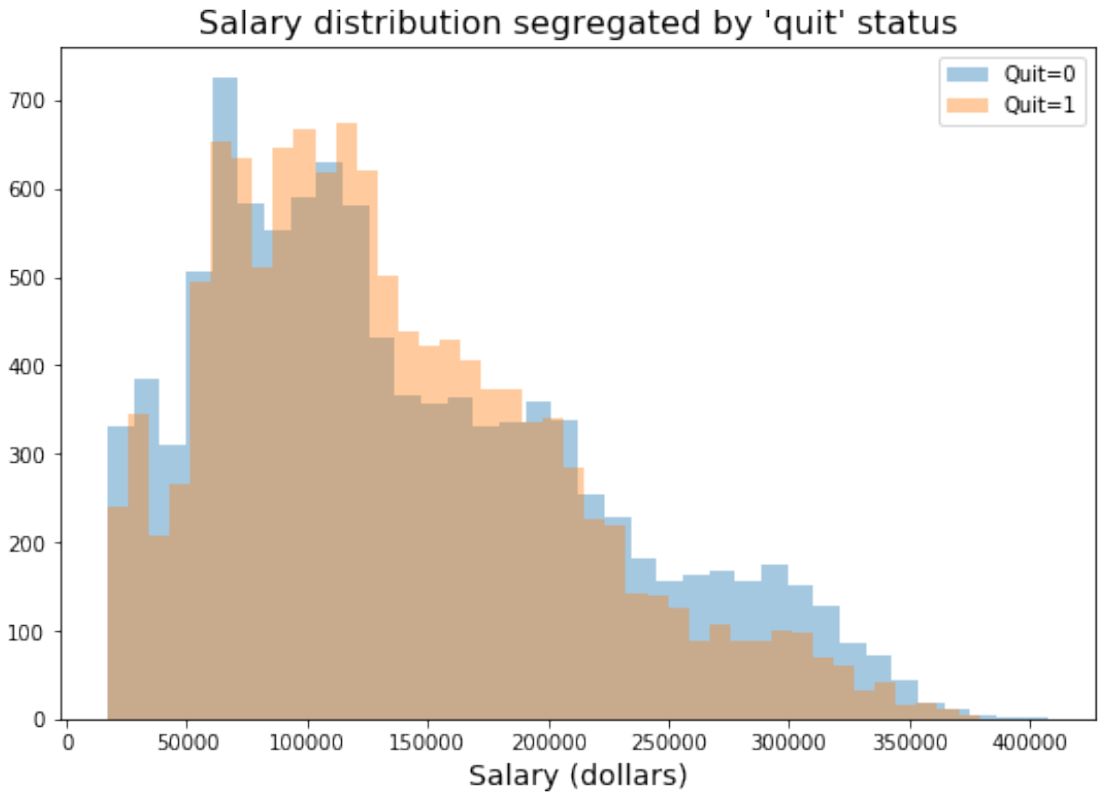
In [26]:
```
#some EDA
def distributionPlot(df,col,units,grouping='quit'):
    '''conveniently making EDA plots'''
    plt.figure(figsize=(9,6))
    sns.distplot(df.groupby(grouping)[col].get_group(0),kde=False,rug=False, label=grou
    sns.distplot(df.groupby(grouping)[col].get_group(1),kde=False,rug=False, label=grou
    plt.xlabel(col.capitalize()+units, fontsize=14)
    plt.title(col.capitalize()+' distribution segregated by \''+grouping+'\' status', f
    plt.legend();

distributionPlot(train,'tenure',' (months)')
```

```
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



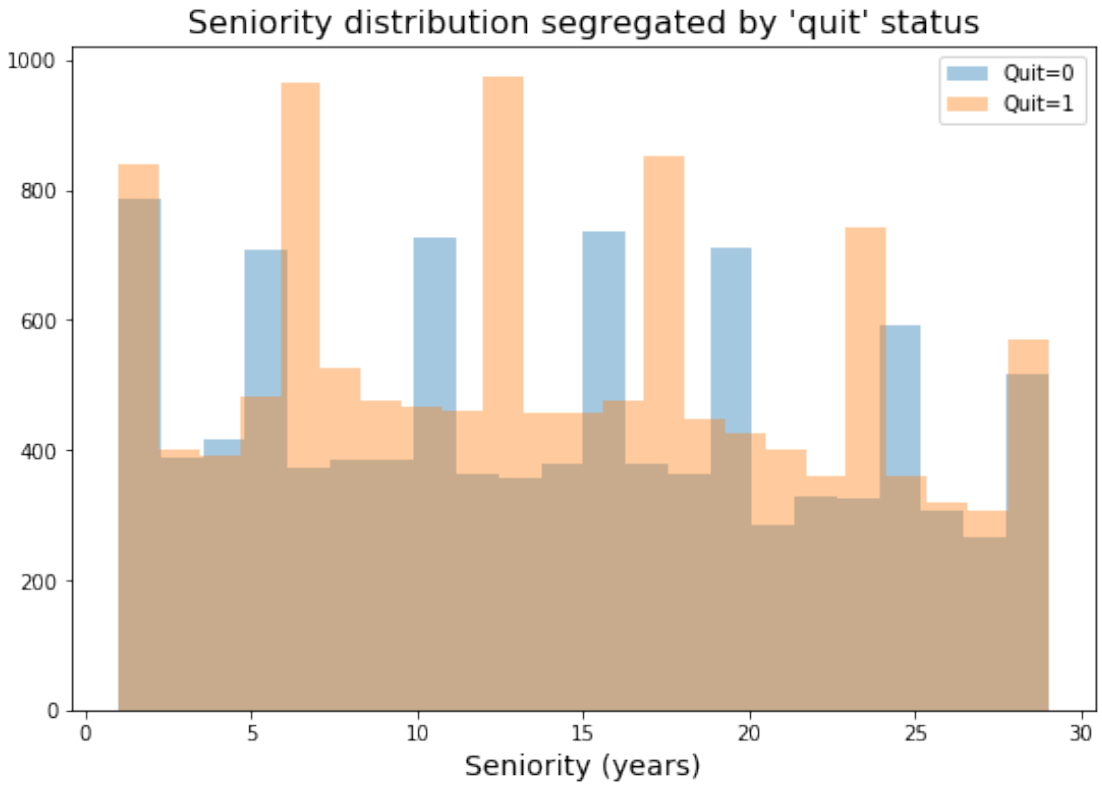

```
In [27]: distributionPlot(train,'salary',' (dollars)')
```

```
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



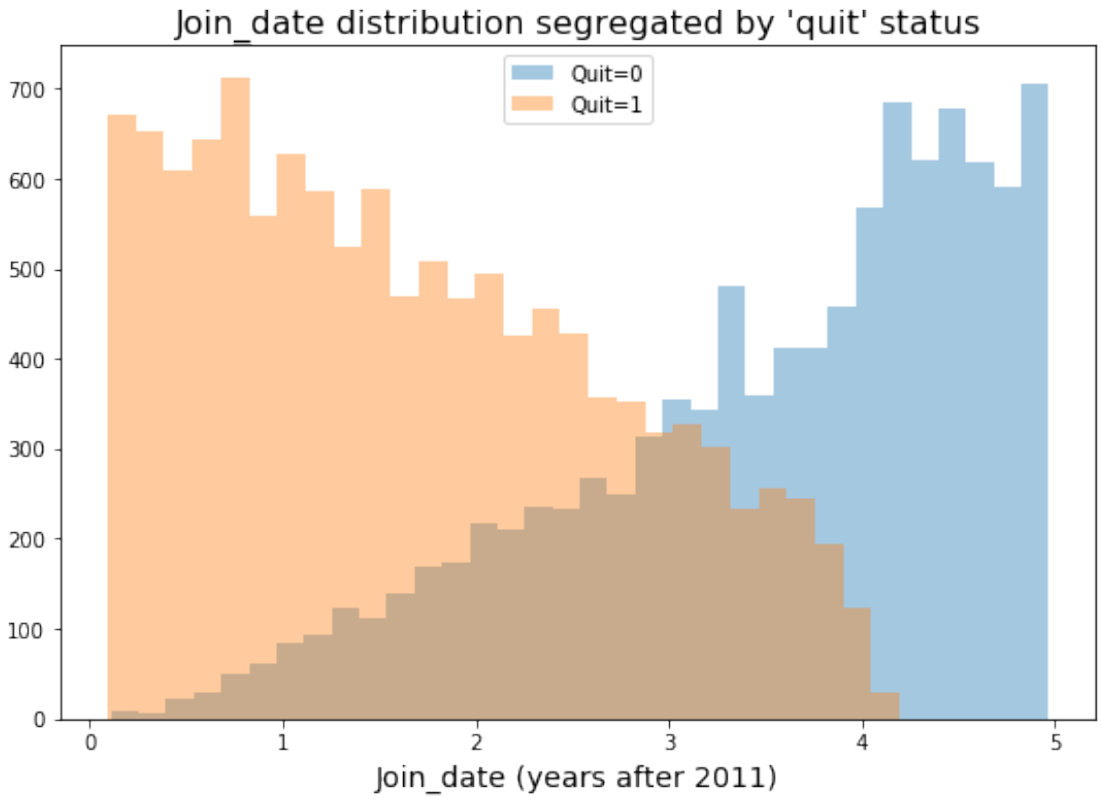

```
In [28]: distributionPlot(train,'seniority',' (years)')
```

```
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```



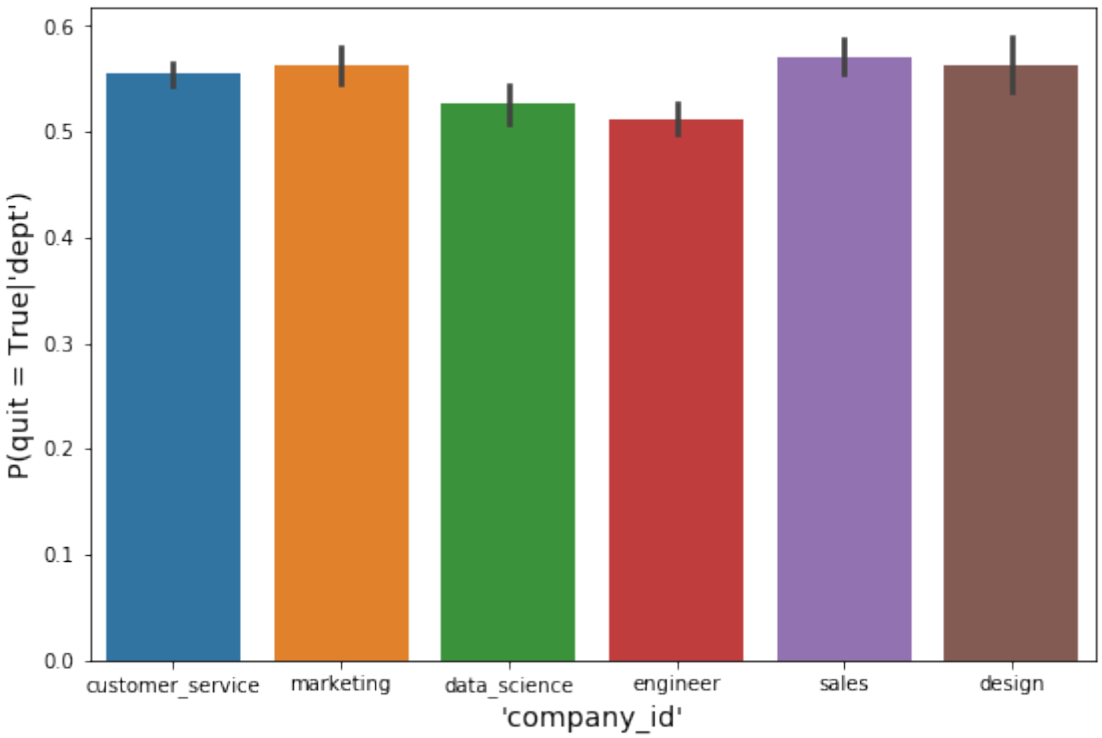

```
In [42]: distributionPlot(train,'join_date',' (years after 2011)')
         #this is a nice plot :)
```

```
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/home/perro/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: Th
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

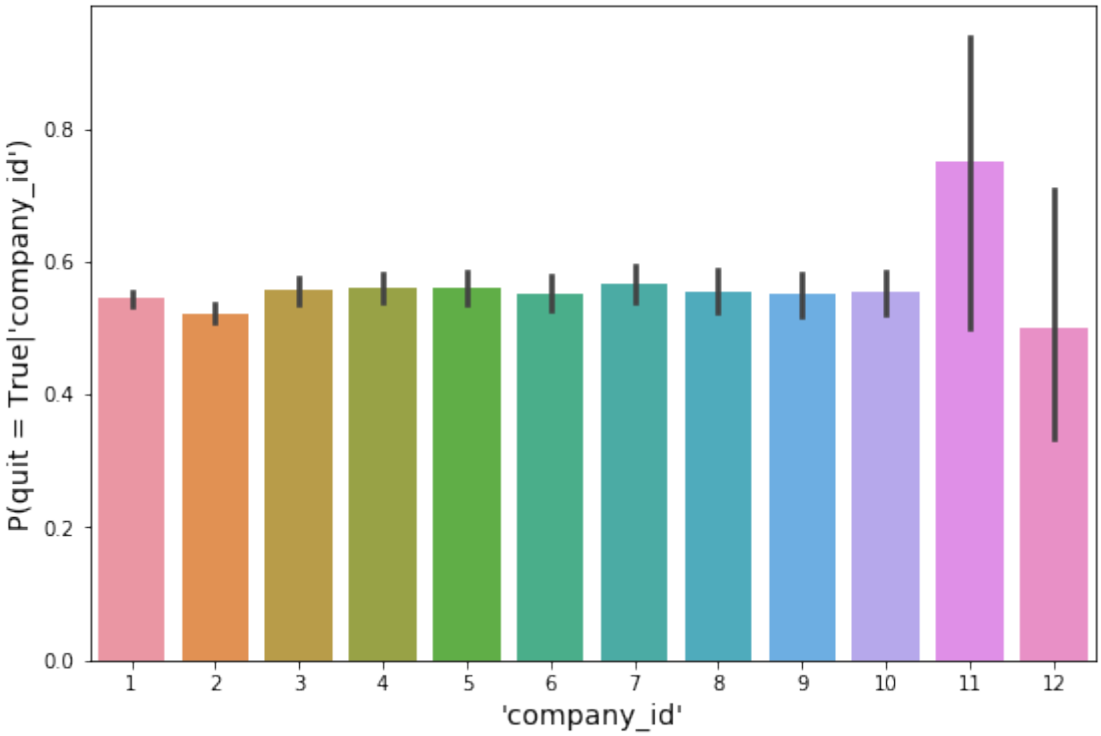


- data distributions segregated by quitting status show that `salary` and `seniority` do not seem to play an obviously important role
- however it seems that `join_date` **is important** for predicting wheter an employee quits or not. Seems that the closest to the 'great recession' the employee joined the company, the longer the he or she stayed at the company. As the economy improved employees were more secure that they will be able to find jobs elsewhere
- department and company variables might show good predictive power
- I will use the original data to show these two variables (`dept` and `company_id`)

```
In [41]: plt.figure(figsize=(9,6))
         sns.barplot(x='dept',y='quit',data=data)
         plt.xlabel('\'company_id\'', fontsize=14)
         plt.ylabel('P(quit = True|\'dept\')', fontsize=14);
         #there seems to be some statistically significant differences between departments (i.e
```




```
In [40]: plt.figure(figsize=(9,6))
         sns.barplot(x='company_id',y='quit',data=data)
         plt.xlabel('\'company_id\'', fontsize=14)
         plt.ylabel('P(quit = True|\'company_id\')', fontsize=14);
         #the confidence bar sizes are obvious given the sizes of companies 11 and 12
         #seems that company 2 has a bit of difference with respect to other companies
```



0.0.1 Let's build a predictive model...

(logistic regression has already been loaded)

```
In [47]: target='quit'
         features = df.columns.tolist()
         features

Out[47]: ['seniority',
          'salary',
          'join_date',
          'quit_date',
          'quit',
          'tenure',
          'dept_customer_service',
          'dept_data_science',
          'dept_design',
          'dept_engineer',
          'dept_marketing',
          'dept_sales',
          'company_id_1',
          'company_id_2',
          'company_id_3',
```

```
 'company_id_4',
 'company_id_5',
 'company_id_6',
 'company_id_7',
 'company_id_8',
 'company_id_9',
 'company_id_10',
 'company_id_11',
 'company_id_12']
```

```
In [48]: features.remove('quit') #the target
         features.remove('quit_date')#will keep tenure which is obtained from join_date and quit
         features
```

```
Out[48]: ['seniority',
          'salary',
          'join_date',
          'tenure',
          'dept_customer_service',
          'dept_data_science',
          'dept_design',
          'dept_engineer',
          'dept_marketing',
          'dept_sales',
          'company_id_1',
          'company_id_2',
          'company_id_3',
          'company_id_4',
          'company_id_5',
          'company_id_6',
          'company_id_7',
          'company_id_8',
          'company_id_9',
          'company_id_10',
          'company_id_11',
          'company_id_12']
```

```
In [49]: model1=LogisticRegression()
```

scaling the data...

```
In [50]: from sklearn.preprocessing import MinMaxScaler
         scaler = MinMaxScaler()
         X_train = scaler.fit_transform(train[features])
         X_test = scaler.transform(test[features])
```

```
In [51]: model1.fit(X_train, train['quit'])
         print('Accuracy of Logistic regression classifier on training set: {:.2f}'
               .format(model1.score(X_train, train['quit'])))
```

```
        print('Accuracy of Logistic regression classifier on test set: {:.2f}'
             .format(model1.score(X_test, test['quit'])))
        #maybe overfitting?
```

```
Accuracy of Logistic regression classifier on training set: 0.95
Accuracy of Logistic regression classifier on test set: 0.94
```

- indeed `join_date` **is the most important feature**. Note that salary is the least important one!!

```
In [55]: feat_importance = pd.DataFrame(data={'feature': features, 'coefficient': model1.coef_[0
         feat_importance
```

Out[55]:

	feature	coefficient
0	seniority	0.055041
1	salary	0.006682
2	join_date	-28.932032
3	tenure	-26.271436
4	dept_customer_service	3.481349
5	dept_data_science	3.420261
6	dept_design	3.475565
7	dept_engineer	3.307320
8	dept_marketing	3.535647
9	dept_sales	3.521635
10	company_id_1	1.923724
11	company_id_2	1.827702
12	company_id_3	2.021130
13	company_id_4	2.037103
14	company_id_5	2.003422
15	company_id_6	1.902295
16	company_id_7	1.898818
17	company_id_8	1.972261
18	company_id_9	1.995502
19	company_id_10	1.956661
20	company_id_11	0.686219
21	company_id_12	0.516941

0.0.2 Predicting tenure:

```
In [62]: reduced=df[df['quit']==1]
         reduced.head()
```

Out[62]:

	seniority	salary	join_date	quit_date	quit	tenure	\
0	28	89000.0	3.254795	4.857534	1	19.220107	
1	20	183000.0	2.353425	3.284932	1	11.170661	
3	20	115000.0	1.394521	2.460274	1	12.780550	
4	23	276000.0	0.819178	3.668493	1	34.169079	
5	14	165000.0	1.106849	2.690411	1	18.990123	

```
   dept_customer_service  dept_data_science  dept_design  dept_engineer  \
0                      1                  0            0              0
1                      0                  0            0              0
3                      1                  0            0              0
4                      0                  1            0              0
5                      0                  1            0              0

       ...        company_id_3  company_id_4  company_id_5  company_id_6  \
0      ...                   0             0             0             0
1      ...                   0             0             0             0
3      ...                   0             0             0             0
4      ...                   0             0             0             0
5      ...                   0             1             0             0

   company_id_7  company_id_8  company_id_9  company_id_10  company_id_11  \
0             1             0             0              0              0
1             1             0             0              0              0
3             1             0             0              0              0
4             0             0             0              0              0
5             0             0             0              0              0

   company_id_12
0              0
1              0
3              0
4              0
5              0

[5 rows x 24 columns]
```

In [59]:
```
Rtrain,Rtest = model_selection.train_test_split(reduced,test_size=0.1,random_state=seed
```

In [60]:
```
from sklearn.linear_model import LinearRegression
model2= LinearRegression()
```

In [72]:
```
Rtarget='quit_date'
Rfeatures = reduced.columns.tolist()
Rfeatures
```

Out[72]:
```
['seniority',
 'salary',
 'join_date',
 'quit_date',
 'quit',
 'tenure',
 'dept_customer_service',
 'dept_data_science',
 'dept_design',
```

```
 'dept_engineer',
 'dept_marketing',
 'dept_sales',
 'company_id_1',
 'company_id_2',
 'company_id_3',
 'company_id_4',
 'company_id_5',
 'company_id_6',
 'company_id_7',
 'company_id_8',
 'company_id_9',
 'company_id_10',
 'company_id_11',
 'company_id_12']
```

In [73]:
```
Rfeatures.remove(Rtarget) #the target
Rfeatures.remove('quit')
Rfeatures.remove('tenure')
Rfeatures
```

Out[73]:
```
['seniority',
 'salary',
 'join_date',
 'dept_customer_service',
 'dept_data_science',
 'dept_design',
 'dept_engineer',
 'dept_marketing',
 'dept_sales',
 'company_id_1',
 'company_id_2',
 'company_id_3',
 'company_id_4',
 'company_id_5',
 'company_id_6',
 'company_id_7',
 'company_id_8',
 'company_id_9',
 'company_id_10',
 'company_id_11',
 'company_id_12']
```

In [74]:
```
R_train = scaler.fit_transform(Rtrain[Rfeatures])
R_test = scaler.transform(Rtest[Rfeatures])
```

In [75]:
```
model2.fit(R_train, Rtrain[Rtarget])
print('R^2 of Linear regression on training set: {:.2f}'
      .format(model2.score(R_train, Rtrain[Rtarget])))
```

```
        print('R^2 of Linear regression on test set: {:.2f}'
             .format(model2.score(R_test, Rtest[Rtarget])))
        #very hard to estimate quit_date
```

```
R^2 of Linear regression on training set: 0.42
R^2 of Linear regression on test set: 0.40
```

```
In [78]: Rfeat_importance = pd.DataFrame(data={'feature': Rfeatures, 'coefficient': model2.coef_
         Rfeat_importance
```

Out[78]:

	feature	coefficient
0	seniority	-2.380067e-01
1	salary	5.859169e-01
2	join_date	2.647304e+00
3	dept_customer_service	8.413237e+12
4	dept_data_science	8.413237e+12
5	dept_design	8.413237e+12
6	dept_engineer	8.413237e+12
7	dept_marketing	8.413237e+12
8	dept_sales	8.413237e+12
9	company_id_1	-1.793222e+13
10	company_id_2	-1.793222e+13
11	company_id_3	-1.793222e+13
12	company_id_4	-1.793222e+13
13	company_id_5	-1.793222e+13
14	company_id_6	-1.793222e+13
15	company_id_7	-1.793222e+13
16	company_id_8	-1.793222e+13
17	company_id_9	-1.793222e+13
18	company_id_10	-1.793222e+13
19	company_id_11	-1.793222e+13
20	company_id_12	-1.793222e+13