data_challenge_1

February 21, 2019

1 Employee Retention

1.1 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.

1.2 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

1.3 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.

1.4 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)

1.5 Additional variable

- Internal mobility: did the patient get a promotion?
- satisfaction: reported at annual / bi-annual evaluation

2 Loading and preparing the data

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

        sns.set(style="ticks", color_codes=True)
```

```
In [42]: # Load the data and first look at it
         df = pd.read_csv('employee_retention_data.csv')
         display(df.head(10))
         display(df.describe())
```

```
   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
5     509529.0           4      data_science         14  165000.0  2012-01-30
6      88600.0           4  customer_service         21  107000.0  2013-10-21
7     716309.0           2  customer_service          4   30000.0  2014-03-05
8     172999.0           9          engineer          7  160000.0  2012-12-10
9     504159.0           1             sales          7  104000.0  2012-06-12

    quit_date
0  2015-10-30
1  2014-04-04
2         NaN
3  2013-06-07
4  2014-08-22
5  2013-08-30
6         NaN
7         NaN
8  2015-10-23
9         NaN
```

	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 [43]:
```
# Generating a new binary outcome variable,
df['quit'] = 0
df.loc[~df['quit_date'].isnull(), 'quit'] = 1
# Filling the NaNs in quit_date with the end time of the study
df['quit_date'].fillna('2015-12-13', inplace=True)
# Adding a new retention variable
df['retention'] = (pd.to_datetime(df['quit_date']) - pd.to_datetime(df['join_date']))
df['start_month'] = pd.to_datetime(df['join_date']).dt.month
# Dropping seniority of 99 years
df = df[df.seniority < 98]
df.head(10)
```

Out[43]:

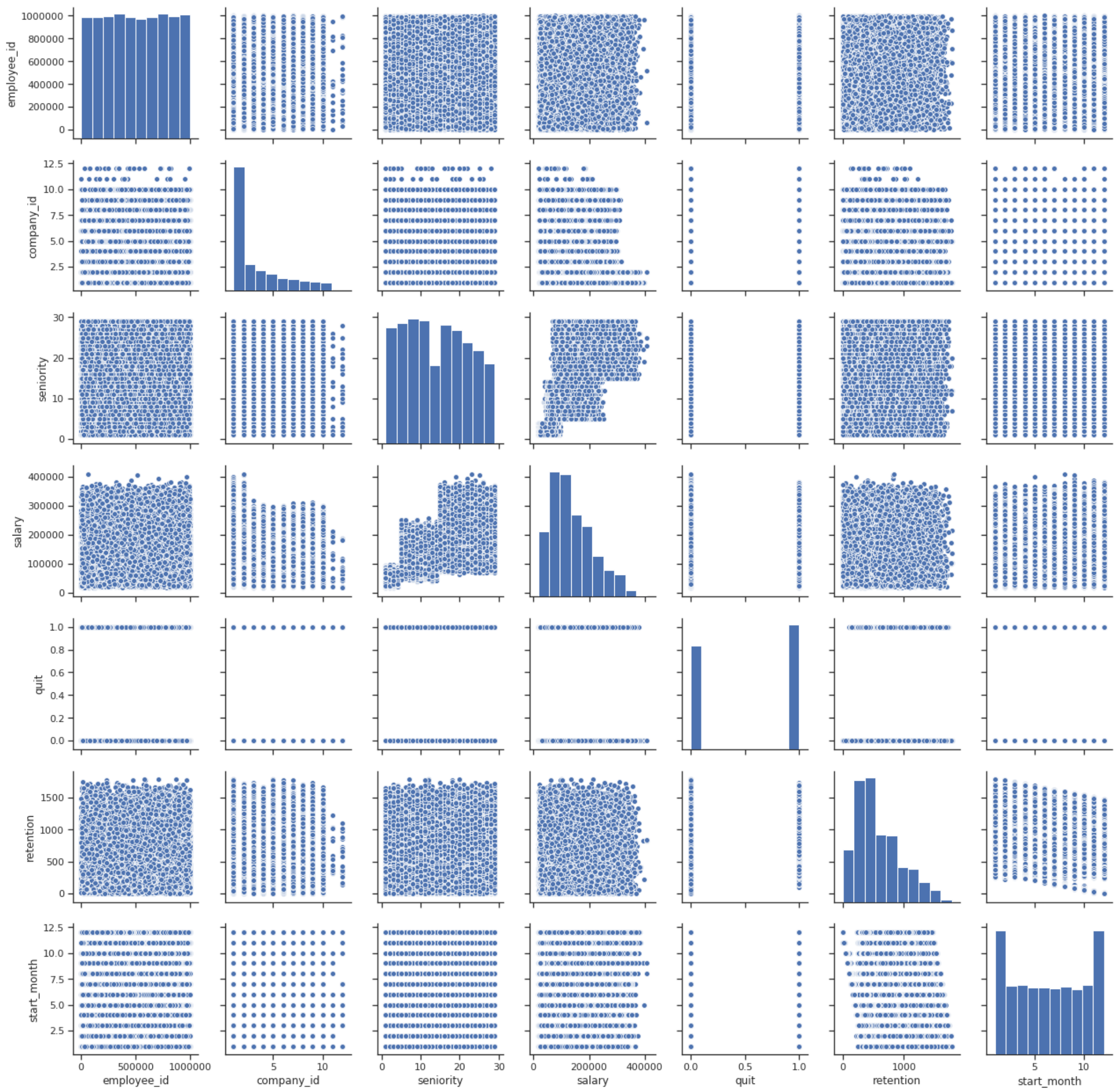
	employee_id	company_id	dept	seniority	salary	join_date	\
0	13021.0	7	customer_service	28	89000.0	2014-03-24	
1	825355.0	7	marketing	20	183000.0	2013-04-29	
2	927315.0	4	marketing	14	101000.0	2014-10-13	
3	662910.0	7	customer_service	20	115000.0	2012-05-14	
4	256971.0	2	data_science	23	276000.0	2011-10-17	
5	509529.0	4	data_science	14	165000.0	2012-01-30	
6	88600.0	4	customer_service	21	107000.0	2013-10-21	
7	716309.0	2	customer_service	4	30000.0	2014-03-05	
8	172999.0	9	engineer	7	160000.0	2012-12-10	
9	504159.0	1	sales	7	104000.0	2012-06-12	

	quit_date	quit	retention	start_month
0	2015-10-30	1	585	3
1	2014-04-04	1	340	4
2	2015-12-13	0	426	10
3	2013-06-07	1	389	5
4	2014-08-22	1	1040	10
5	2013-08-30	1	578	1
6	2015-12-13	0	783	10
7	2015-12-13	0	648	3
8	2015-10-23	1	1047	12
9	2015-12-13	0	1279	6

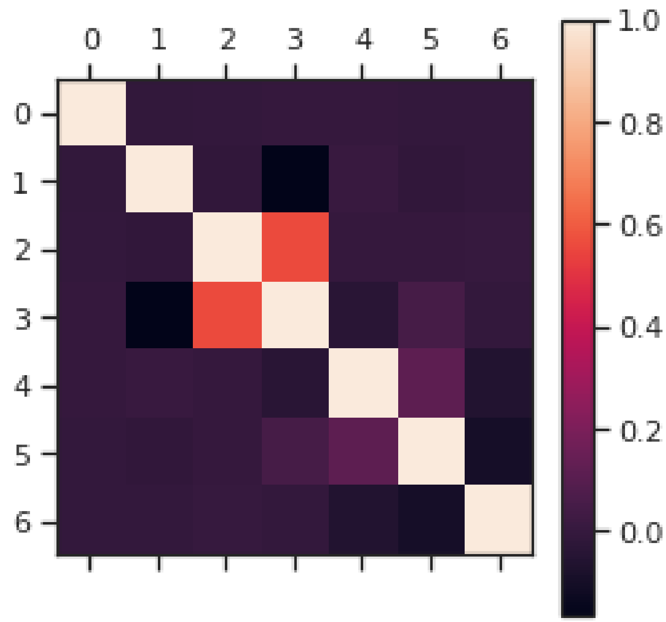
3 First look at the data

There are no very strong notable association in the data. Seniority seems to be correlated with salary. Interestingly, there could a trend between the month of hire and the duration of employment. Looking at the retention more carefully, I can see that there are prefered time when people quit: around year 1, then around year 2, ... This seems to be true across companies

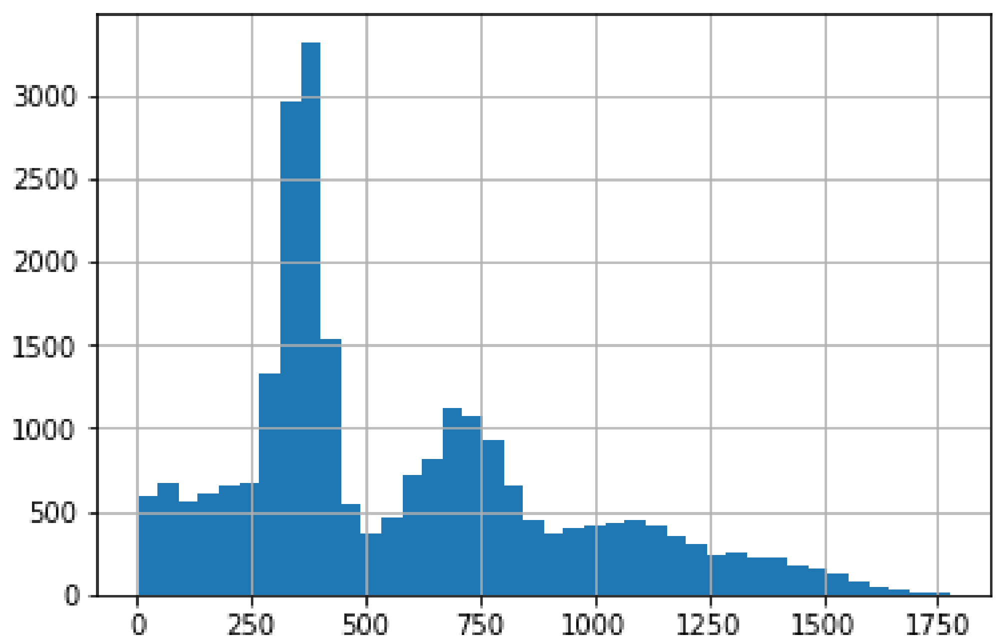
In [44]:
```
# Visualization of the relationship between variables (scatter)
g = sns.pairplot(df)
```

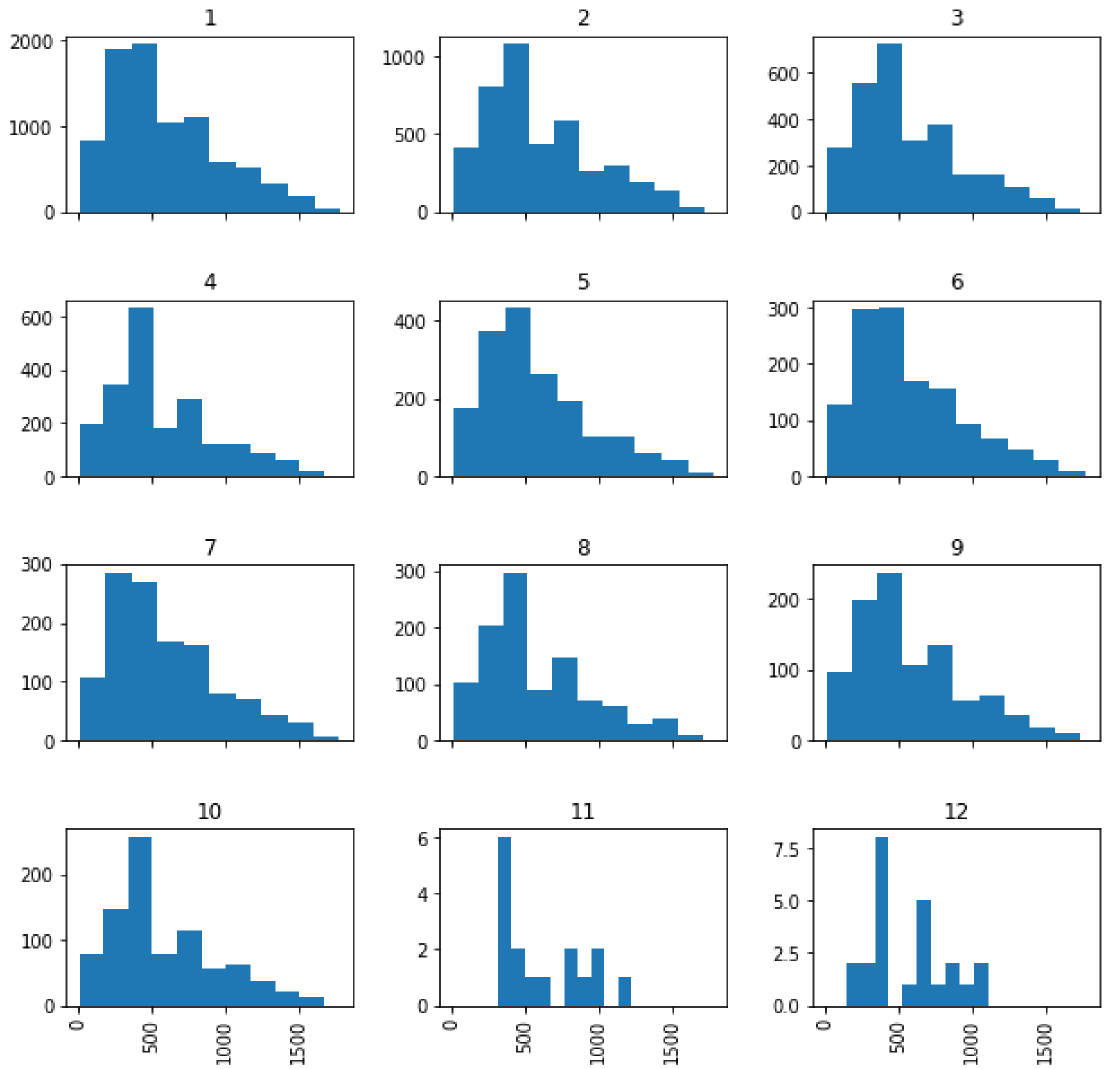


In [48]:
```
# Visualization of the relationship between variables (correlation)
plt.matshow(df.corr());
plt.colorbar();
```




```
In [6]: # Looking at retention overall and by company
        df['retention'].hist(bins=40);
        df.hist(column='retention', by='company_id', figsize=(10,10), sharex=True);
```





4 Looking at the company level

There is a wide range in terms of nb of employees between those company (16 to 8486 employees). There doesn't seems to be any strong association between variables at the company level, except possibly between seniority and retention.

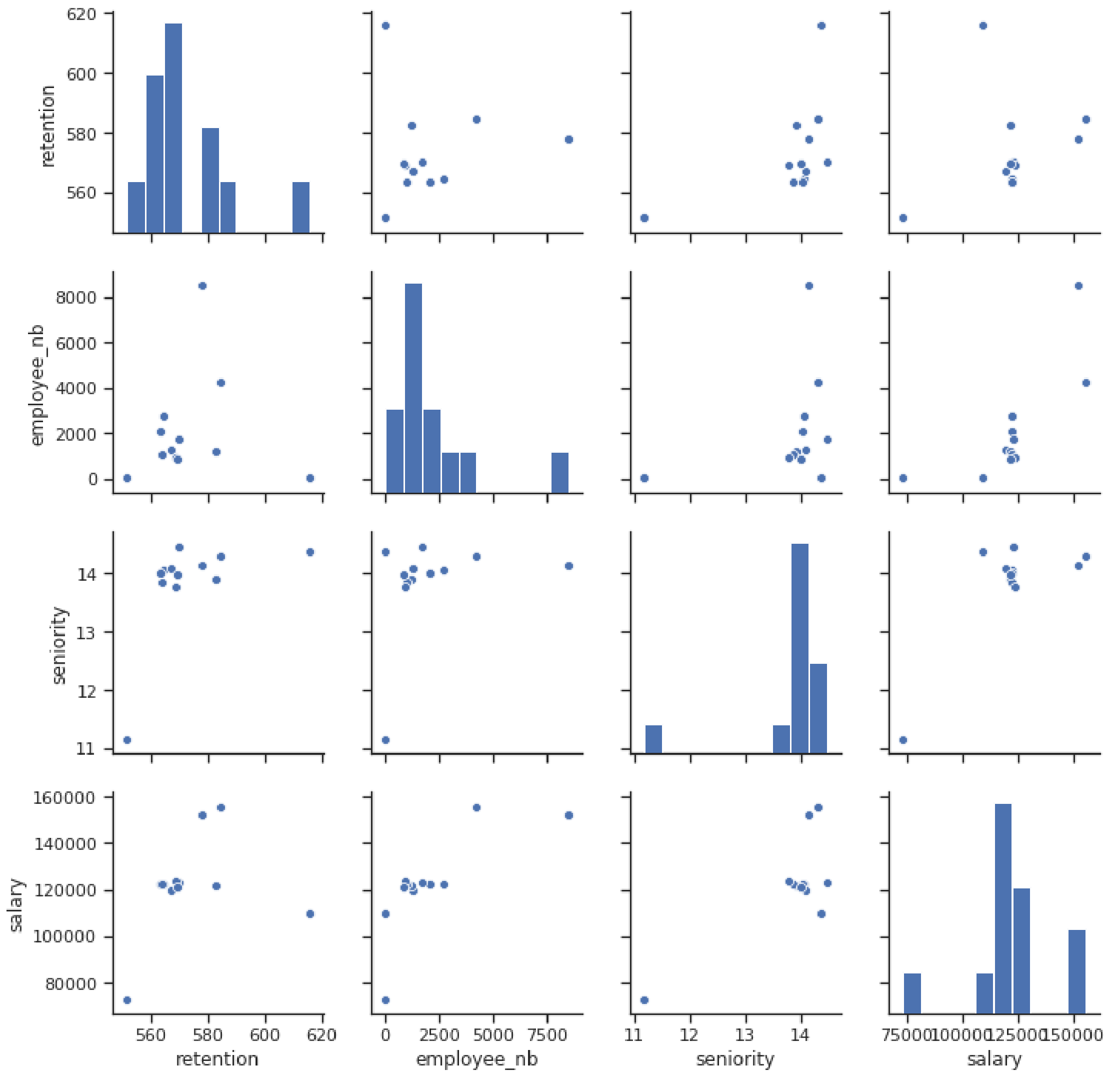
```
In [56]: # Building some company level averages
         df_company = pd.DataFrame({
             'retention': df.groupby('company_id')['retention'].mean(),
             'employee_nb': df.groupby('company_id')['employee_id'].count(),
             'seniority': df.groupby('company_id')['seniority'].mean(),
             'salary': df.groupby('company_id')['salary'].mean(),
         })
         df_company
```

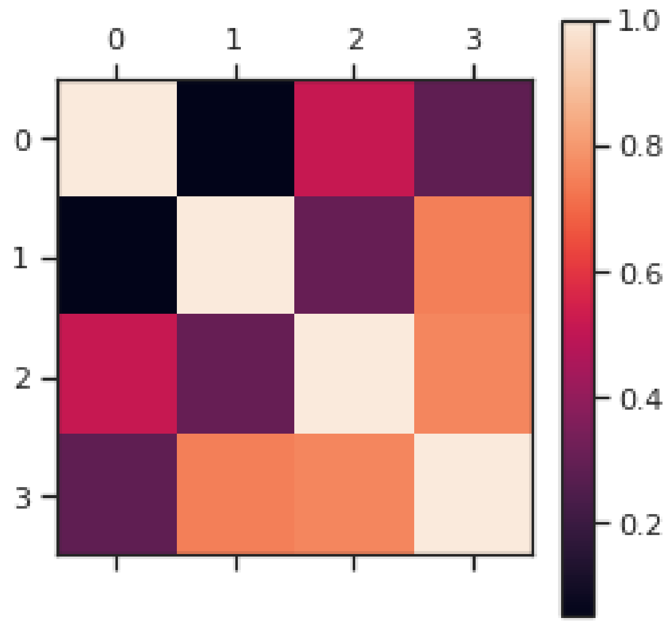
Out[56]:

company_id	retention	employee_nb	seniority	salary
1	578.080613	8485	14.131998	152163.700648
2	584.572241	4222	14.297489	155728.090952
3	564.431430	2749	14.054565	122118.588578
4	563.377789	2062	14.023763	122721.144520
5	570.156125	1755	14.474644	123348.717949
6	567.033308	1291	14.089853	119925.639040
7	582.803922	1224	13.906046	121582.516340
8	563.765043	1047	13.867240	122284.622732
9	569.098855	961	13.778356	123905.306972
10	569.656250	864	13.991898	121386.574074
11	615.937500	16	14.375000	109562.500000
12	551.583333	24	11.166667	73000.000000

In [57]:

```
# Visualization of the relationship between variables
g = sns.pairplot(df_company)
plt.matshow(df_company.corr());
plt.colorbar();
```


retention
employee_nb
seniority
salary
620
600
580
560
8000
6000
4000
2000
0
14
13
12
11
160000
140000
120000
100000
80000
560
580
600
620
0
2500
5000
7500
11
12
13
14
75000
100000
125000
150000



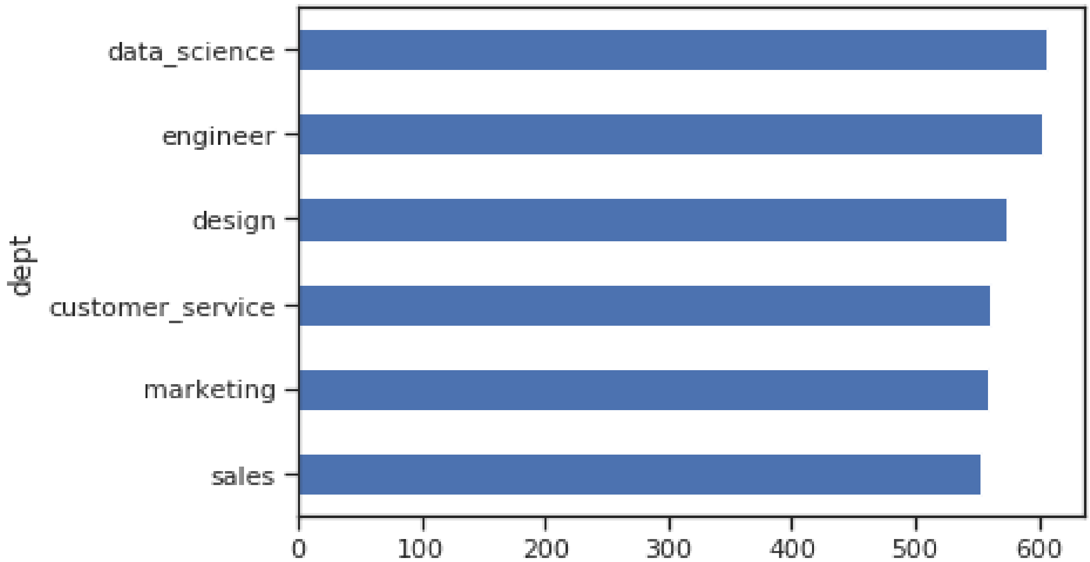
5 Looking at the dept level

Some departments have higher turnaround (e.g., sales).

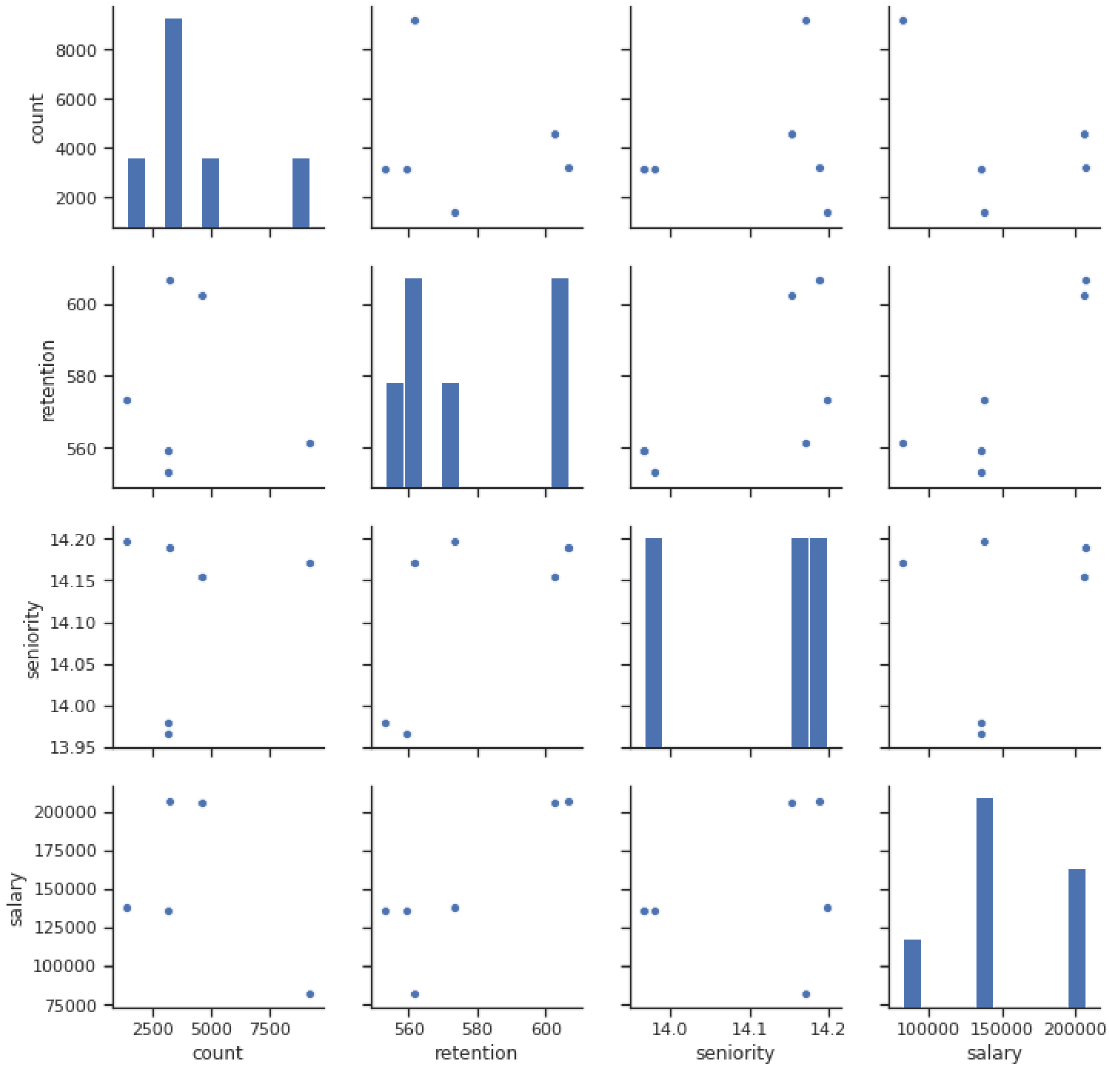
In [94]:
```
# Building some dpt level averages
df_dept = pd.DataFrame({
    'count': df.groupby('dept')['retention'].count(),
    'retention': df.groupby('dept')['retention'].mean(),
    'seniority': df.groupby('dept')['seniority'].mean(),
    'salary': df.groupby('dept')['salary'].mean(),
})
df_dept['retention'].sort_values().plot.barh()
g = sns.pairplot(df_dept)
plt.matshow(df_dept.corr());
plt.colorbar();
df_dept
```

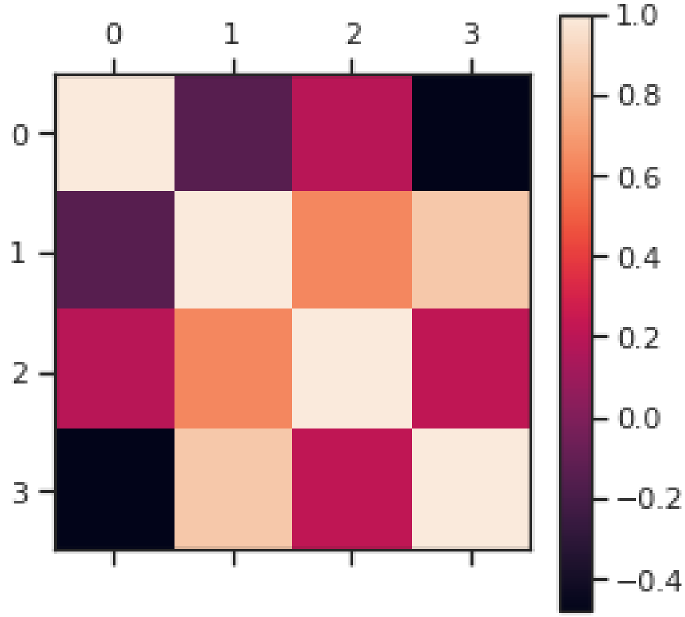
Out[94]:

dept	count	retention	seniority	salary
customer_service	9180	561.547821	14.171133	82245.424837
data_science	3190	606.593417	14.189028	206885.893417
design	1380	573.282609	14.197826	137460.869565
engineer	4612	602.433218	14.153946	205531.439722
marketing	3166	559.408402	13.966835	135582.438408
sales	3172	553.014502	13.979823	135912.358134



dept
data_science
engineer
design
customer_service
marketing
sales
0
100
200
300
400
500
600


count
retention
seniority
salary
8000
6000
4000
2000
600
580
560
14.20
14.15
14.10
14.05
14.00
13.95
200000
175000
150000
125000
100000
75000
2500
5000
7500
14.0
14.1
14.2



6 Building a regression model to predict employees leaving the company

Both the linear regression and the random forest achieve low accuracy on the training data, which limits the validity of the interpretation. However, a few interesting points: - for both methods, it seems that salary, seniority and start month play an important role - the lin reg that employees in company 11 and 12 quit earlier and that sales leave earlier

```
In [86]: from sklearn.linear_model import LinearRegression
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.metrics import r2_score
         from sklearn.preprocessing import MinMaxScaler, PolynomialFeatures

         df_reg = df[df.quit == 1]
         y = df_reg['retention'].values
         X = pd.get_dummies(df_reg[['company_id', 'dept', 'seniority', 'salary', 'start_month']
                            columns=['company_id', 'dept'], prefix='d')
         cols = X.columns
         X = X.values
         X = MinMaxScaler().fit_transform(X)

         reg = LinearRegression().fit(X, y)
         print(reg.score(X, y))

         from sklearn.model_selection import cross_val_score,cross_validate
```

```
scores = cross_validate(reg, X, y, cv=5)
print(scores)

pd.DataFrame({
    'name': cols,
    'importance': reg.coef_
}).sort_values(by='importance')
```

```
0.015220687997487992
{'fit_time': array([0.00546598, 0.00689745, 0.00783563, 0.00698972, 0.00570941]), 'score_time'
```

Out[86]:

	name	importance
14	d_12	-106.670319
0	seniority	-99.699541
2	start_month	-60.779078
13	d_11	-46.055175
20	d_sales	-23.817364
19	d_marketing	-4.087631
17	d_design	-3.700959
18	d_engineer	-3.303515
16	d_data_science	-2.331220
10	d_8	2.393509
3	d_1	5.507141
6	d_4	7.399863
8	d_6	15.001660
4	d_2	16.641007
5	d_3	18.578851
7	d_5	19.079630
9	d_7	19.216589
12	d_10	20.078396
11	d_9	28.828847
15	d_customer_service	37.240688
1	salary	262.986566

In [87]:

```
reg = RandomForestRegressor().fit(X, y)
print(reg.score(X, y))

from sklearn.model_selection import cross_val_score,cross_validate
scores = cross_validate(reg, X, y, cv=5)
print(scores)

pd.DataFrame({
    'name': cols,
    'importance': reg.feature_importances_
}).sort_values(by='importance')
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The defa
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
0.7737298743492773
{'fit_time': array([0.29985523, 0.2752378 , 0.30398917, 0.29813528, 0.28671575]), 'score_time'
```

Out[87]:

	name	importance
13	d_11	0.000299
14	d_12	0.000322
15	d_customer_service	0.005783
17	d_design	0.009649
12	d_10	0.012408
10	d_8	0.013267
9	d_7	0.013598
16	d_data_science	0.013781
11	d_9	0.013877
18	d_engineer	0.013966
8	d_6	0.014360
20	d_sales	0.014745
19	d_marketing	0.015035
7	d_5	0.017654
6	d_4	0.018244
5	d_3	0.021148
4	d_2	0.024936
3	d_1	0.027316
2	start_month	0.170865
0	seniority	0.220677
1	salary	0.358068

7 Training a classifier to find employees that quit

The RF gets a better accuracy (0.81), and uses mostly retention, salary, start month and seniority to make a decision. The logistic regression has consistent results except for seniority that has a low coefficient. There might be an imbalance in the distribution of dept, which could affect how those are influencing the classifier, but the current results indicate that employee get unhappy faster in marketing, customer service and sales compared to the other dept.

In [89]:

```
# Selecting the features and creating the dummy variables for the categorical ones
df2 = pd.get_dummies(df, columns=['dept', 'company_id'], prefix='d')
df2 = df2.drop(['employee_id', 'join_date', 'quit_date'], axis=1)
plt.matshow(df2.corr())
df2.head(10)
```

Out[89]:

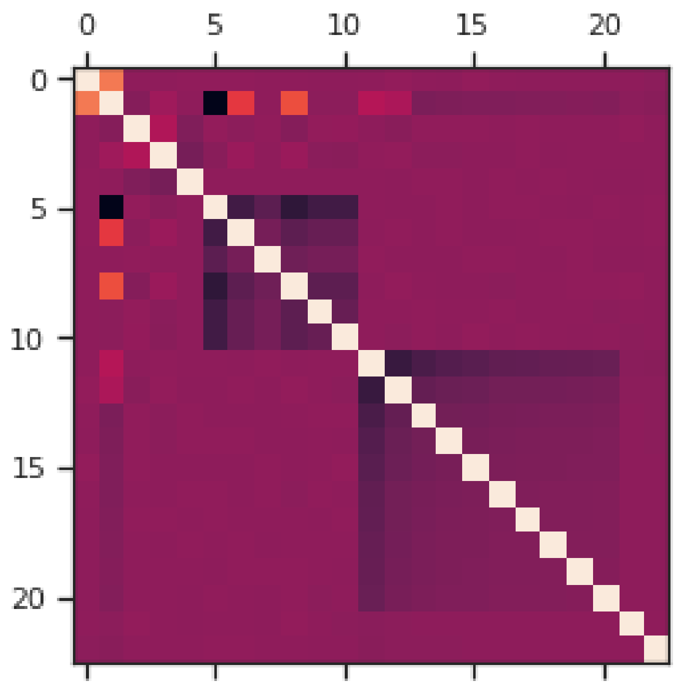
	seniority	salary	quit	retention	start_month	d_customer_service	\
0	28	89000.0	1	585	3	1	
1	20	183000.0	1	340	4	0	
2	14	101000.0	0	426	10	0	
3	20	115000.0	1	389	5	1	
4	23	276000.0	1	1040	10	0	
5	14	165000.0	1	578	1	0	

```
6          21  107000.0     0        783            10                   1
7           4   30000.0     0        648             3                   1
8           7  160000.0     1       1047            12                   0
9           7  104000.0     0       1279             6                   0

   d_data_science  d_design  d_engineer  d_marketing  ...  d_3  d_4  d_5  d_6  \
0               0         0           0            0  ...    0    0    0    0
1               0         0           0            1  ...    0    0    0    0
2               0         0           0            1  ...    0    1    0    0
3               0         0           0            0  ...    0    0    0    0
4               1         0           0            0  ...    0    0    0    0
5               1         0           0            0  ...    0    1    0    0
6               0         0           0            0  ...    0    1    0    0
7               0         0           0            0  ...    0    0    0    0
8               0         0           1            0  ...    0    0    0    0
9               0         0           0            0  ...    0    0    0    0

   d_7  d_8  d_9  d_10  d_11  d_12
0    1    0    0     0     0     0
1    1    0    0     0     0     0
2    0    0    0     0     0     0
3    1    0    0     0     0     0
4    0    0    0     0     0     0
5    0    0    0     0     0     0
6    0    0    0     0     0     0
7    0    0    0     0     0     0
8    0    0    1     0     0     0
9    0    0    0     0     0     0

[10 rows x 23 columns]
```

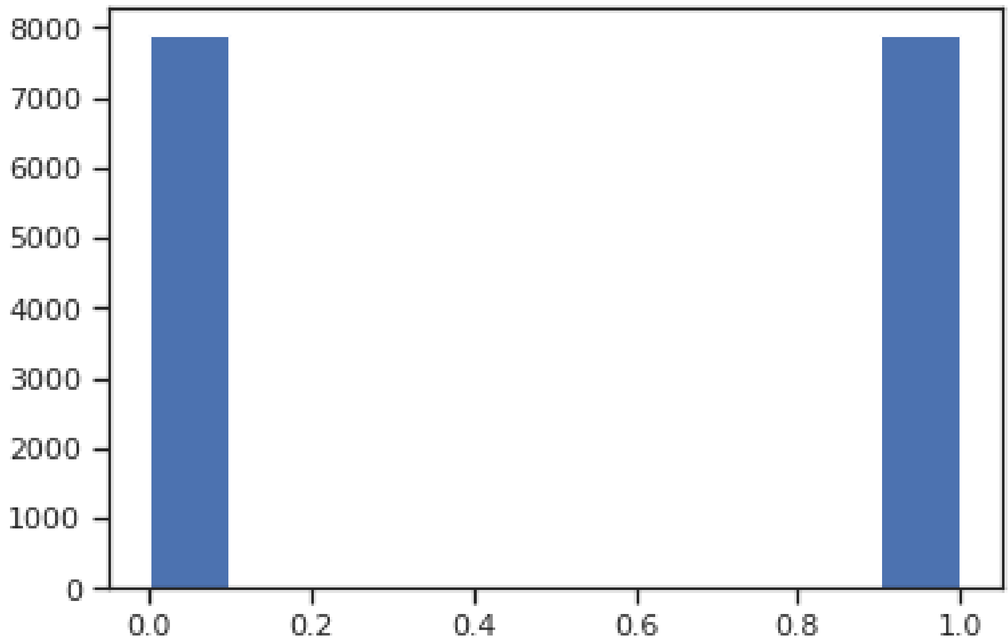


In [98]:
```
# Creating the train/test sets and balancing the classes
from sklearn.model_selection import train_test_split

Xb = df2.drop('quit', axis=1).values
Xb = MinMaxScaler().fit_transform(Xb)
col_names = df2.drop('quit', axis=1).columns
yb = df2['quit'].values
X_train, X_test, y_train, y_test = train_test_split(Xb, yb, test_size=0.3, random_sta

sel = y_train == 1
X0 = X_train[sel]
y0 = y_train[sel]
sub = np.random.choice(range(len(y0)), size=sum(~sel), replace=False)
X_train = np.concatenate([X_train[~sel,:], X0[sub,:]])
y_train = np.concatenate([y_train[~sel], y0[sub]])

plt.hist(y_train);
```




```
In [96]: # running a random classifier
         from sklearn.dummy import DummyClassifier
         dummy = DummyClassifier(strategy='most_frequent')
         dummy.fit(X_train, y_train)
         print(dummy.score(X_test, y_test))
```

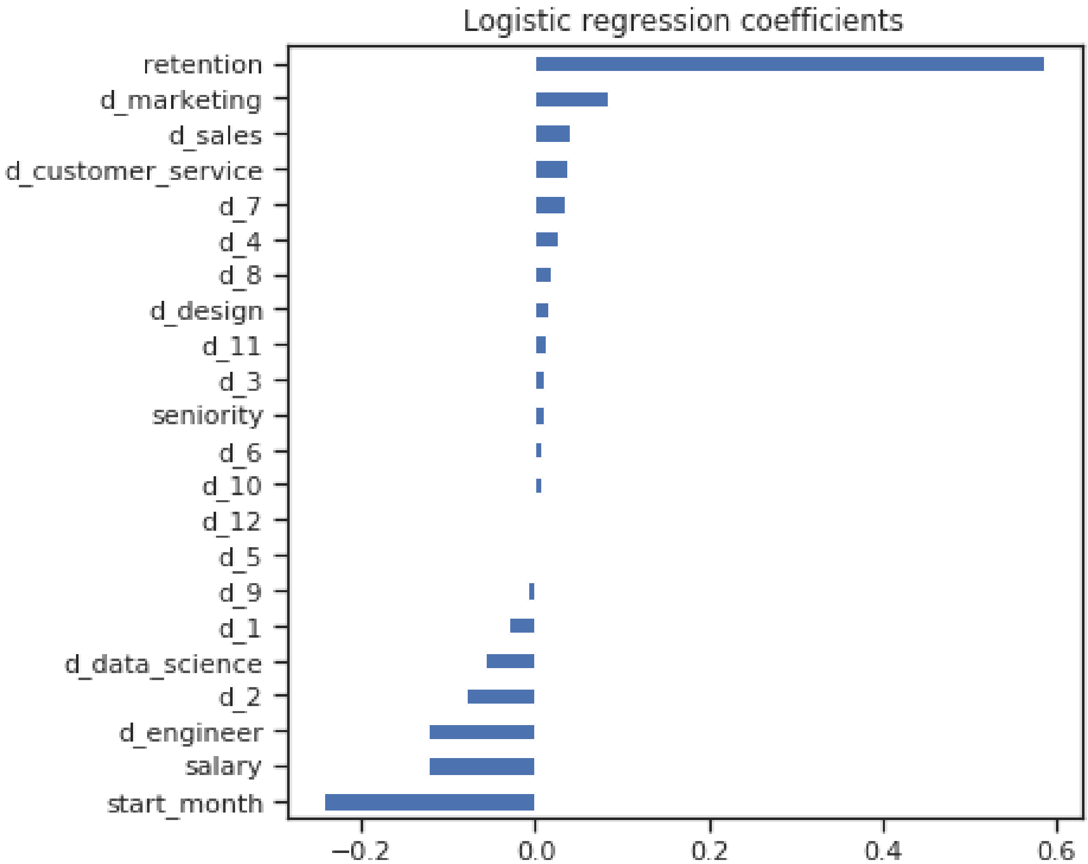
```
0.4456140350877193
```

```
In [99]: # Running a logistic regression classifier
         from sklearn.linear_model import LogisticRegressionCV

         clf = LogisticRegressionCV(cv=5, max_iter=300, solver='liblinear')
         clf.fit(X_train, y_train)
         print(clf.score(X_test, y_test))

         df3 = pd.DataFrame({'importance': clf.coef_[0]}, index=col_names)
         df3.sort_values(by='importance').plot.barh(legend=False, figsize=(6,6), title='Logist
```

```
0.5472334682860999
```

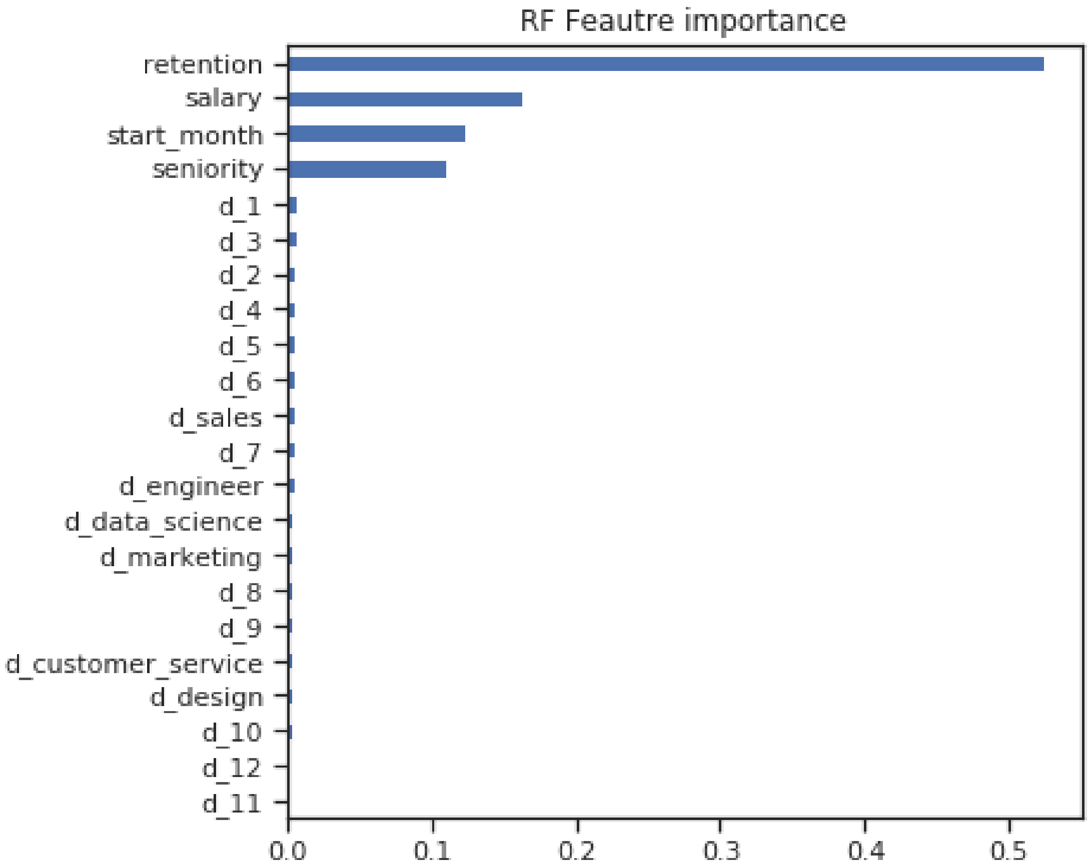


In [100]:
```
# Random forest
from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(n_estimators=200)
clf.fit(X_train, y_train)
print(clf.score(X_test, y_test))

df3 = pd.DataFrame({'importance': clf.feature_importances_}, index=col_names)
df3.sort_values(by='importance').plot.barh(legend=False, figsize=(6,6), title='RF Fea
```

```
0.8082321187584346
```



8 Overall conclusion

Based on my investigation of the regression and the classification, here are some possible conclusions: - a higher salary seems to keep employees happy - senior employees might leave the company earlier - the month of hire seems to have an influence - retention is predictive of who is quitting, meaning that the longer employees stay the more likely to leave, so it is wise to plan for it - client facing dept seem to have more difficulties to keep employees happy.