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1 Data Challenge 1: Employee Retention

1.1 Goal:

Employee turnover is a very costly problem for companies. The cost of replacing an employee is 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.

2 Preprocessing and feature engineering

First we import a few libraries that we use later

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.model_selection import GridSearchCV


        from sklearn.metrics import classification_report
        from sklearn.metrics import confusion_matrix
```

We then load the data and inspect its columns and entries

```
In [2]: df=pd.read_csv("employee_retention_data.csv")

In [3]: df.head()

Out[3]:    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 [4]: # Number of people who have quit
        df["quit_date"].isnull().sum()

Out[4]: 11192
```

Here we create a new column indicating whether the employee has quit or not. We also create a new column for employment duration of the employee in days.

```
In [5]: # creating a column indicating whether the employee has quit (1) or not (0)

        df["quit"]=~df["quit_date"].isnull()
        df["quit"]=df["quit"].astype(int)

In [6]: # a function to calculate the duration of employment in days
        def emp_dur(join_date, quit_date, quit):
```

```
    if quit==0:
        quit_date="2015-12-13"
    years=list(map(int, quit_date.split("-")))[0]-list(map(int, join_date.split("-")))[0
    months=list(map(int, quit_date.split("-")))[1]-list(map(int, join_date.split("-")))[
    days=list(map(int, quit_date.split("-")))[2]-list(map(int, join_date.split("-")))[2]

    return years*365+months*30+days
```

In [7]:
```
#  creating the new column for employment duration in days

df["employment_duration"]=df.apply(lambda x: emp_dur(x['join_date'], x['quit_date'], x['
df.head()
```

Out[7]:

	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	quit	employment_duration
0	2015-10-30	1	581
1	2014-04-04	1	340
2	NaN	0	425
3	2013-06-07	1	388
4	2014-08-22	1	1040

Here, we remove two outliers in seniority who had 99 years of experience!

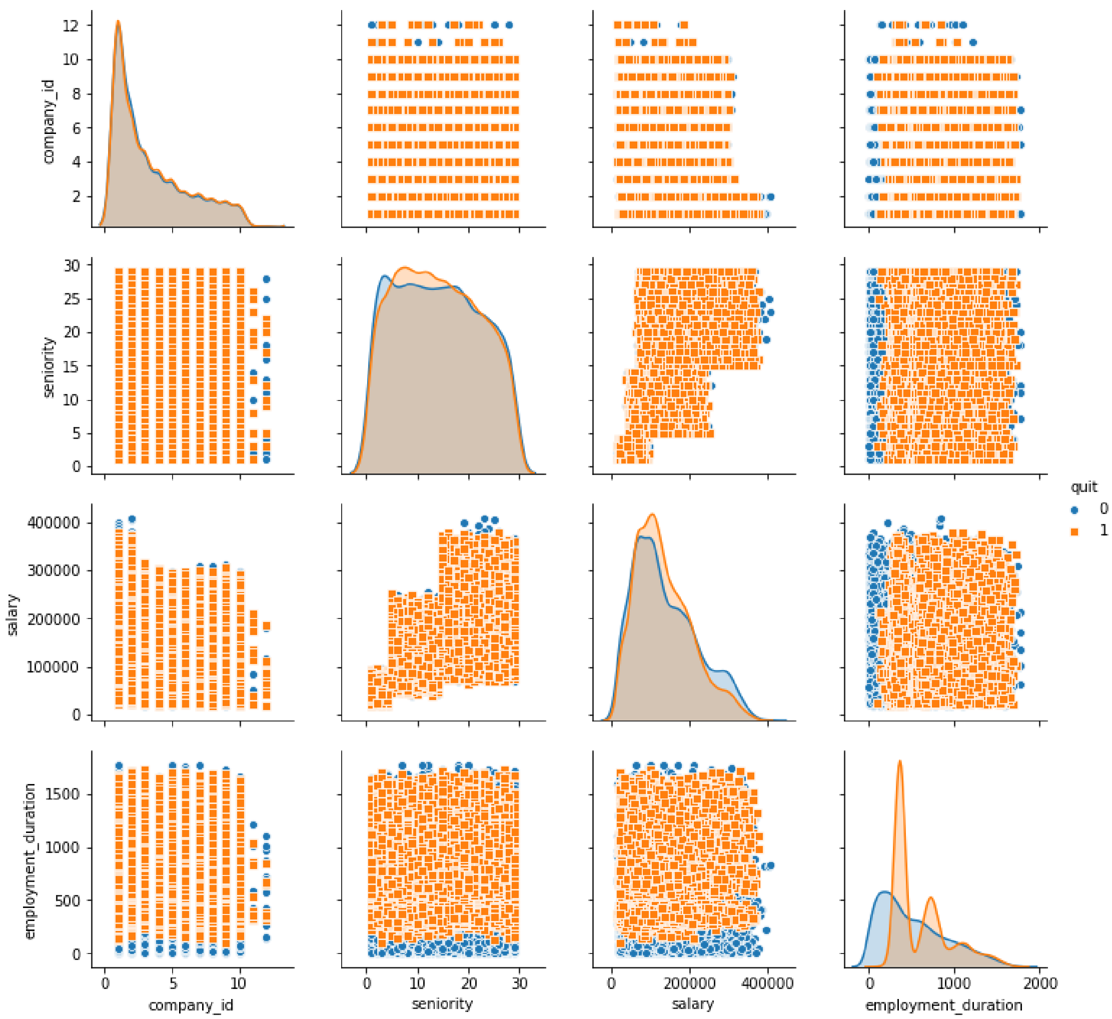
In [8]:
```
# There are two outliers in seniority with 99 years of experience (probably wrong data).
# df[df["seniority"]>29].index
df.drop(axis=0, index=df[df["seniority"]>29].index, inplace=True)
```

Here, we do a paitplot for numerical features of our dataset and distinguish them by whether the employee has quit or not

In [9]:
```
# pairplot of numerical features i.e. ['company_id','seniority','salary','employment_dur
sns.pairplot(df,vars=['company_id','seniority','salary','employment_duration'], hue="qui
```

```
C:\Users\hhash\Anaconda3\envs\Insight\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[9]: <seaborn.axisgrid.PairGrid at 0x25dd3ed5e10>

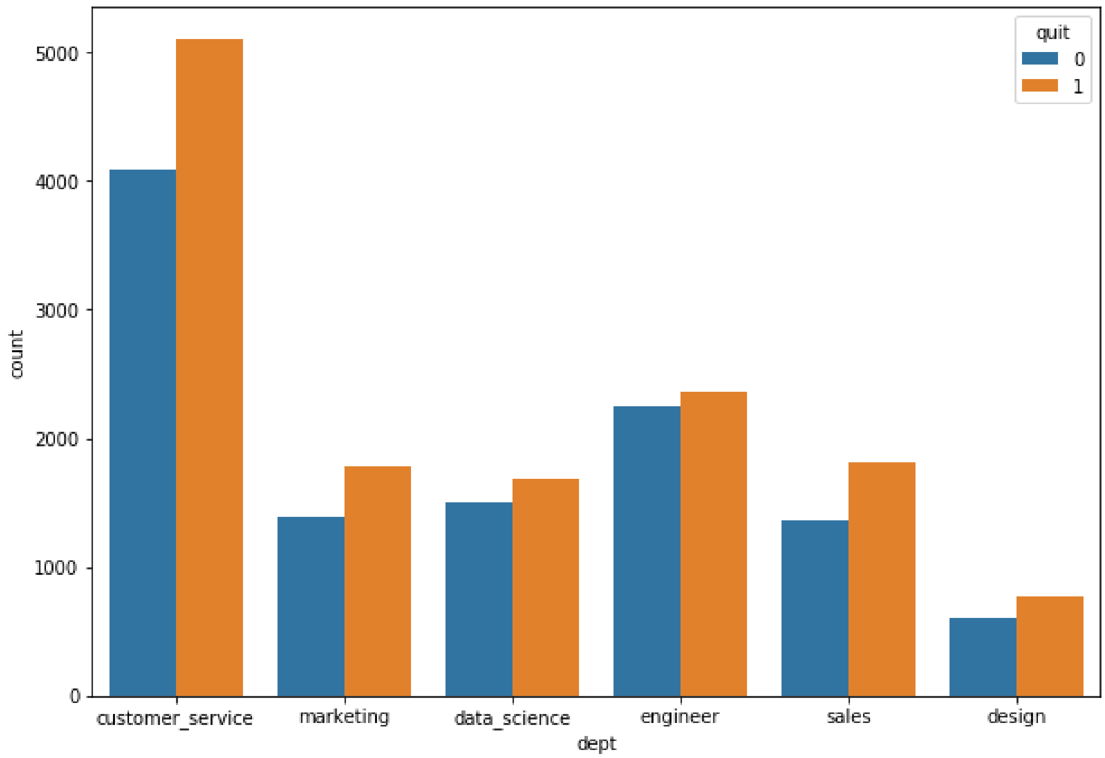


We also check the number of employees who are still with the companies or who have quit, over all departments.

```
In [10]: # comparison of churn rate in different departments

         plt.figure(figsize=(10,7))
         sns.countplot(data=df, x="dept", hue="quit")
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x25dd5c5fc50>
```



We also create a new feature as the joining month for each employee to capture any seasonality

```
In [11]: # capturing seasonality if any, by creating a new column for joining month for each emp

         df["join_month"]=df["join_date"].map(lambda x: x.split("-")[1])
         # df["quit_month"]=df["quit_date"].map(lambda x: list(map(int, x.split("-")))[1])
```

Here we create dummy variables for categorical features. This is needed for our classification models later on.

```
In [12]: #  creating the dummy variables for categorical features: company ID, department, and j

         df["company_id_cat"]=df["company_id"].astype(str)
         df_cat = pd.get_dummies(df[["company_id_cat","dept","join_month"]],drop_first = True)

In [13]: df.head()

Out[13]:    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  quit  employment_duration join_month company_id_cat
0  2015-10-30     1                  581         03              7
1  2014-04-04     1                  340         04              7
2         NaN     0                  425         10              4
3  2013-06-07     1                  388         05              7
4  2014-08-22     1                 1040         10              2
```

In [14]:
```
df_cat.columns
```

Out[14]:
```
Index(['company_id_cat_10', 'company_id_cat_11', 'company_id_cat_12',
       'company_id_cat_2', 'company_id_cat_3', 'company_id_cat_4',
       'company_id_cat_5', 'company_id_cat_6', 'company_id_cat_7',
       'company_id_cat_8', 'company_id_cat_9', 'dept_data_science',
       'dept_design', 'dept_engineer', 'dept_marketing', 'dept_sales',
       'join_month_02', 'join_month_03', 'join_month_04', 'join_month_05',
       'join_month_06', 'join_month_07', 'join_month_08', 'join_month_09',
       'join_month_10', 'join_month_11', 'join_month_12'],
      dtype='object')
```

In [15]:
```
# df_cat.columns
X=pd.concat([df[['seniority','salary','employment_duration']], df_cat], axis=1)
y=df['quit']
```

2.1 Modeling and validation: Classification

- Below we train two different models namely, logistic regression and random forest for classification
- for both models, we split the data into train and split with ratio of 30:70

2.1.1 Performance

- The trained logistic regression and random forest models below, have F-scores of 0.73 and 0.84 for predicting who quits
- Based on logistic regression, the top three informative features are: employment duration, seniority, department type
- Based on random forest, the top three informative features are: employment duration, salary, seniority

2.1.2 Conclusion

In general the available features are very limited and not very informative. Features on incentives such as bonuses and vacation days could be helpful. But given that salary and employment duration are already two driving factors, I would choose salary growth rate if I wanted to add another feature.

In [16]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1
lr=LogisticRegression()
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)
```

```
        print(classification_report(y_test, y_pred))
        print(confusion_matrix(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.72      0.31      0.44      3343
           1       0.61      0.90      0.73      4067

   micro avg       0.63      0.63      0.63      7410
   macro avg       0.67      0.61      0.58      7410
weighted avg       0.66      0.63      0.60      7410

[[1046 2297]
 [ 408 3659]]


C:\Users\hhash\Anaconda3\envs\Insight\lib\site-packages\sklearn\linear_model\logistic.py:433: Fu
  FutureWarning)
```

```
In [17]: lr_feature_importance =pd.DataFrame(lr.coef_[0], index = X_train.columns,
                                                    columns=['importance']).sort_values('importance',as
         lr_feature_importance.head(5)
```

Out[17]:

	importance
employment_duration	0.000643
seniority	0.000557
dept_sales	0.000027
join_month_04	0.000026
join_month_05	0.000024

```
In [18]: rf=RandomForestClassifier(max_depth = 30, random_state = 42)
         rf.fit(X_train, y_train)
         y_pred_rf=rf.predict(X_test)
         print(classification_report(y_test, y_pred_rf))
         print(confusion_matrix(y_test, y_pred_rf))
```

```
C:\Users\hhash\Anaconda3\envs\Insight\lib\site-packages\sklearn\ensemble\forest.py:246: FutureWa
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)


              precision    recall  f1-score   support

           0       0.79      0.82      0.81      3343
           1       0.85      0.83      0.84      4067

   micro avg       0.82      0.82      0.82      7410
   macro avg       0.82      0.82      0.82      7410
weighted avg       0.82      0.82      0.82      7410
```

```
[[2727  616]
 [ 705 3362]]
```

In [19]:
```
rf_feature_importance = pd.DataFrame(rf.feature_importances_, index = X_train.columns,
                                     columns=['importance']).sort_values('importance',asc
```

In [20]:
```
rf_feature_importance.head(5)
```

Out[20]:

	importance
employment_duration	0.551812
salary	0.149806
seniority	0.106883
join_month_03	0.011425
join_month_10	0.010779