

run

February 20, 2019

1 Imports

```
In [1]: # Imports
import csv
import os
import pandas as pd
import copy
import matplotlib.pyplot as plt
import numpy as np

# sklearn
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing
from sklearn.model_selection import KFold
from sklearn.preprocessing import OneHotEncoder
```

2 Load data

```
In [2]: filename = os.path.join('data', 'employee_retention_data.csv')
# Load data to pandas
df = pd.read_csv(filename)
df.head(5)
```

```
Out[2]:
```

	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

3 Format Data & add additional columns

```
In [3]: # Convert to date times
df['join_date'] = pd.to_datetime(df['join_date'])
df['quit_date'] = pd.to_datetime(df['quit_date'])

In [4]: # Add column for still working
df['still_working'] = pd.isnull(df['quit_date'])

In [5]: # Add a column for quit date minus join date
df['duration'] = df['quit_date'] - df['join_date']

# Convert to days
df['duration'] = df['duration'].dt.days

In [6]: # Add "min" columns
# These columns assume the employee quits on the last day of the data set - 2015/12/13
# These will be used for later analysis

# Add quit_date_min
df['quit_date_min'] = df['quit_date']
df.loc[pd.isnull(df['quit_date']), ['quit_date_min']] = pd.to_datetime('2015/12/13')

In [7]: # Add duration_min
df['duration_min'] = df['quit_date_min'] - df['join_date']

# Convert to days
df['duration_min'] = df['duration_min'].dt.days

In [8]: # Get rid of this, since we no longer need
df = df.drop('quit_date_min', 1)

In [9]: # Add columns for join year
#df['joined2011']
df['j2011'] = df['join_date'] < pd.to_datetime('2012')
df['j2012'] = (df['join_date'] >= pd.to_datetime('2012')) & (df['join_date'] < pd.to_d
df['j2013'] = (df['join_date'] >= pd.to_datetime('2013')) & (df['join_date'] < pd.to_d
df['j2014'] = (df['join_date'] >= pd.to_datetime('2014')) & (df['join_date'] < pd.to_d
df['j2015'] = (df['join_date'] >= pd.to_datetime('2015')) & (df['join_date'] < pd.to_d

In [10]: df.head()
```

Out[10]:

	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	still_working	duration	duration_min	j2011	j2012	j2013	\
0	2015-10-30	False	585.0	585	False	False	False	
1	2014-04-04	False	340.0	340	False	False	True	
2	NaT	True	NaN	426	False	False	False	
3	2013-06-07	False	389.0	389	False	True	False	
4	2014-08-22	False	1040.0	1040	True	False	False	

	j2014	j2015
0	True	False
1	False	False
2	True	False
3	False	False
4	False	False

In []:

4 EDA - Exploratory Data Analysis

4.1 Basic data properties

```
In [11]: # Data types
print(df.dtypes)
```

```
employee_id      float64
company_id       int64
dept             object
seniority         int64
salary           float64
join_date        datetime64[ns]
quit_date        datetime64[ns]
still_working     bool
duration         float64
duration_min     int64
j2011            bool
j2012            bool
j2013            bool
j2014            bool
j2015            bool
dtype: object
```

```
In [12]: # Number of unique companies
print('Unique company ids')
print(df.company_id.unique())
print('Number of unqiue companies = {}'.format(str(len(df.company_id.unique()))))
```

```
Unique company ids
[ 7  4  2  9  1  6 10  5  3  8 11 12]
```

Number of unique companies = 12

```
In [13]: # Number of unique depts
print('Unique company ids')
print(df.dept.unique())
print('Number of unique depts = {}'.format(str(len(df.dept.unique()))))
```

Unique company ids

['customer_service' 'marketing' 'data_science' 'engineer' 'sales' 'design']

Number of unique depts = 6

```
In [14]: # Number of unique seniority
print('Unique company ids')
print(df.seniority.unique())
print('Number of unique seniorities = {}'.format(str(len(df.seniority.unique()))))
```

Unique company ids

[28 20 14 23 21 4 7 13 17 1 10 6 19 15 26 27 5 18 16 25 9 2 29 3
8 22 24 12 11 98 99]

Number of unique seniorities = 31

```
In [15]: # Sort seniorities
foo = df.seniority.unique()
foo.sort()
```

```
In [16]: print("Number of years experience when hired, sorted unique values: " + str(foo))
```

Number of years experience when hired, sorted unique values: [1 2 3 4 5 6 7 8 9 10 11
25 26 27 28 29 98 99]

```
In [17]: # For some reason, some people have 98 or 99 years experience? Look at these values...
```

```
# experience = 98 - one lucky engineer
df[df['seniority'] == 98]
```

```
Out[17]:
```

	employee_id	company_id	dept	seniority	salary	join_date	\
	24700	97289.0	10	engineer	98	266000.0	2011-12-13

	quit_date	still_working	duration	duration_min	j2011	j2012	j2013	\
	24700	2015-01-09	False	1123.0	1123	True	False	False

	j2014	j2015	
	24700	False	False

```
In [18]: # experience = 99
df[df['seniority'] == 99]
```

```
Out[18]:
```

	employee_id	company_id	dept	seniority	salary	join_date	\
24701	604052.0	1	marketing	99	185000.0	2011-07-26	

	quit_date	still_working	duration	duration_min	j2011	j2012	j2013	\
24701	2013-12-06	False	864.0	864	True	False	False	

	j2014	j2015
24701	False	False

```
In [19]: # Replace these values with more reasonable numbers
```

```
df = df.replace({'seniority': 98}, 40)
df = df.replace({'seniority': 99}, 40)
# Verify it works
df[24700:24704]
```

```
Out[19]:
```

	employee_id	company_id	dept	seniority	salary	join_date	\
24700	97289.0	10	engineer	40	266000.0	2011-12-13	
24701	604052.0	1	marketing	40	185000.0	2011-07-26	

	quit_date	still_working	duration	duration_min	j2011	j2012	j2013	\
24700	2015-01-09	False	1123.0	1123	True	False	False	
24701	2013-12-06	False	864.0	864	True	False	False	

	j2014	j2015
24700	False	False
24701	False	False

```
In [ ]:
```

4.2 Number of goods vs bads (nans vs non-nans)

```
In [20]: # Save dataframes containing only nans and only non-nans
```

```
df_good = df.dropna()
df_bad = df[pd.isnull(df['quit_date'])]
```

```
In [21]: df_good.head(5)
```

```
Out[21]:
```

	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	
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	

	quit_date	still_working	duration	duration_min	j2011	j2012	j2013	\
0	2015-10-30	False	585.0	585	False	False	False	
1	2014-04-04	False	340.0	340	False	False	True	
3	2013-06-07	False	389.0	389	False	True	False	

4	2014-08-22	False	1040.0	1040	True	False	False
5	2013-08-30	False	578.0	578	False	True	False

	j2014	j2015
0	True	False
1	False	False
3	False	False
4	False	False
5	False	False

In [22]: df_bad.head(5)

```
Out[22]:
```

	employee_id	company_id	dept	seniority	salary	join_date	\
2	927315.0	4	marketing	14	101000.0	2014-10-13	
6	88600.0	4	customer_service	21	107000.0	2013-10-21	
7	716309.0	2	customer_service	4	30000.0	2014-03-05	
9	504159.0	1	sales	7	104000.0	2012-06-12	
11	904158.0	2	marketing	17	230000.0	2015-05-11	

	quit_date	still_working	duration	duration_min	j2011	j2012	j2013	\
2	NaT	True	NaN	426	False	False	False	
6	NaT	True	NaN	783	False	False	True	
7	NaT	True	NaN	648	False	False	False	
9	NaT	True	NaN	1279	False	True	False	
11	NaT	True	NaN	216	False	False	False	

	j2014	j2015
2	True	False
6	False	False
7	True	False
9	False	False
11	False	True

In [23]: # Lengths

N = len(df)

Ngood = len(df_good)

Nbad2 = N-Ngood

Nbad = len(df_bad)

In [24]: print('N={}, Ngood={}, Nbad={}, Nbad2={}'.format(str(N), str(Ngood), str(Nbad), str(Nbad2)))

N=24702, Ngood=13510, Nbad=11192, Nbad2=11192

In []:

5 Plot Histograms

```
In [25]: # Copy before messing
df2 = df.copy();
```

```
In [ ]:
```

```
In [26]: df2.head()
```

```
Out[26]:
```

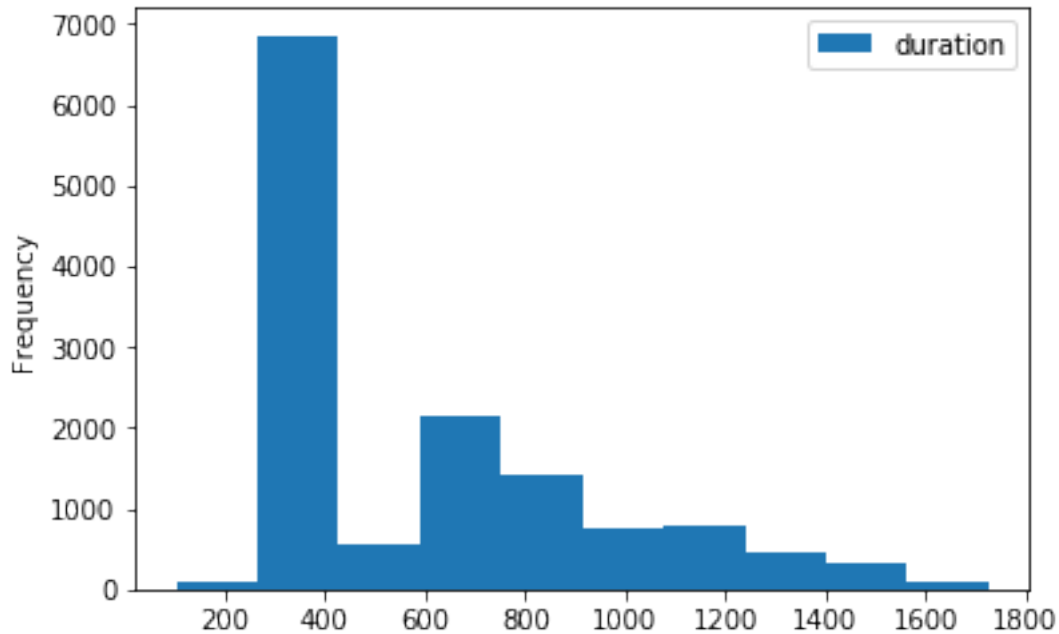
	employee_id	company_id	dept	seniority	salary	join_date	\
0	13021.0	7	customer_service	28	89000.0	2014-03-24	
1	825355.0	7	marketing	20	183000.0	2013-04-29	
2	927315.0	4	marketing	14	101000.0	2014-10-13	
3	662910.0	7	customer_service	20	115000.0	2012-05-14	
4	256971.0	2	data_science	23	276000.0	2011-10-17	

	quit_date	still_working	duration	duration_min	j2011	j2012	j2013	\
0	2015-10-30	False	585.0	585	False	False	False	
1	2014-04-04	False	340.0	340	False	False	True	
2	NaT	True	NaN	426	False	False	False	
3	2013-06-07	False	389.0	389	False	True	False	
4	2014-08-22	False	1040.0	1040	True	False	False	

	j2014	j2015
0	True	False
1	False	False
2	True	False
3	False	False
4	False	False

```
In [27]: # Plot durations of all still working
foo = df.loc[df['still_working'] == False, ['duration']]
plt.figure();
foo.plot.hist();
```

<Figure size 432x288 with 0 Axes>



```
In [28]: # Joined in 2011
foo = df.loc[(df['still_working'] == False) & (df['j2011']), ['duration']]
plt.figure();
foo.plot.hist();
plt.title('Joined 2011');

# Joined in 2012
foo = df.loc[(df['still_working'] == False) & (df['j2012']), ['duration']]
plt.figure();
foo.plot.hist();
plt.title('Joined 2012');

# Joined in 2013
foo = df.loc[(df['still_working'] == False) & (df['j2013']), ['duration']]
plt.figure();
foo.plot.hist();
plt.title('Joined 2013');

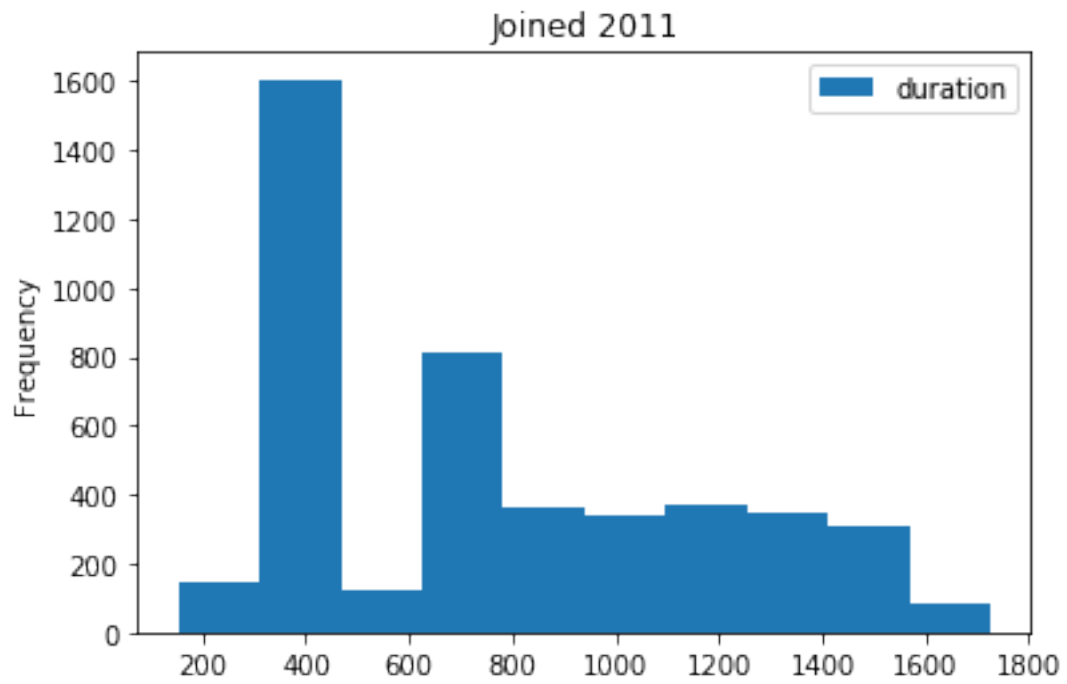
# Joined in 2014
foo = df.loc[(df['still_working'] == False) & (df['j2014']), ['duration']]
plt.figure();
foo.plot.hist();
plt.title('Joined 2014');

# Joined in 2015
foo = df.loc[(df['still_working'] == False) & (df['j2015']), ['duration']]
```

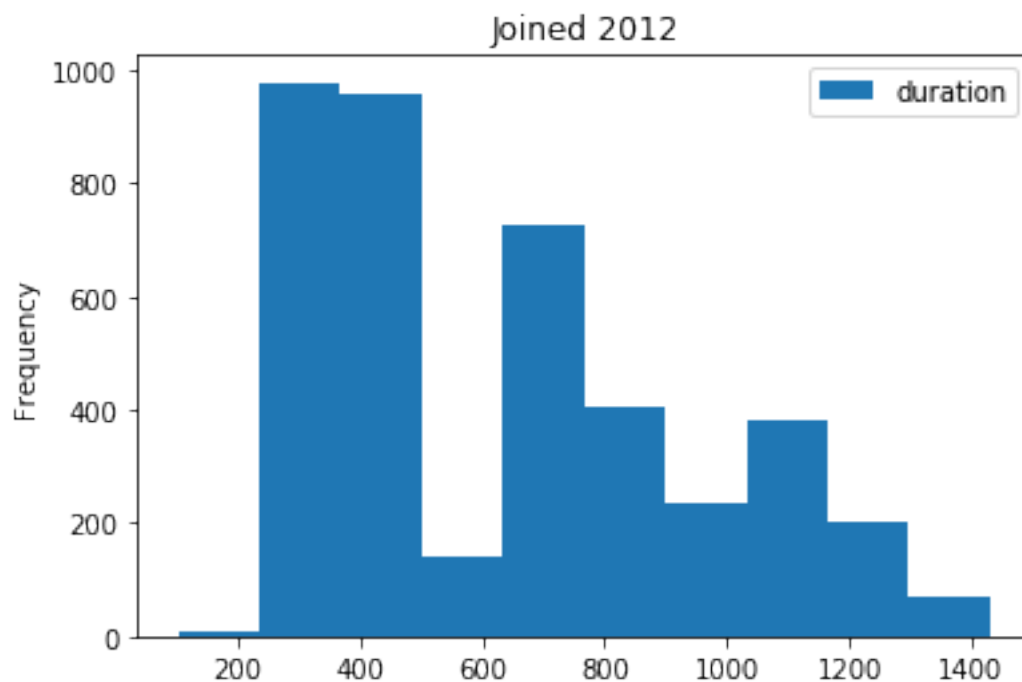


```
plt.figure();  
foo.plot.hist();  
plt.title('Joined 2015');
```

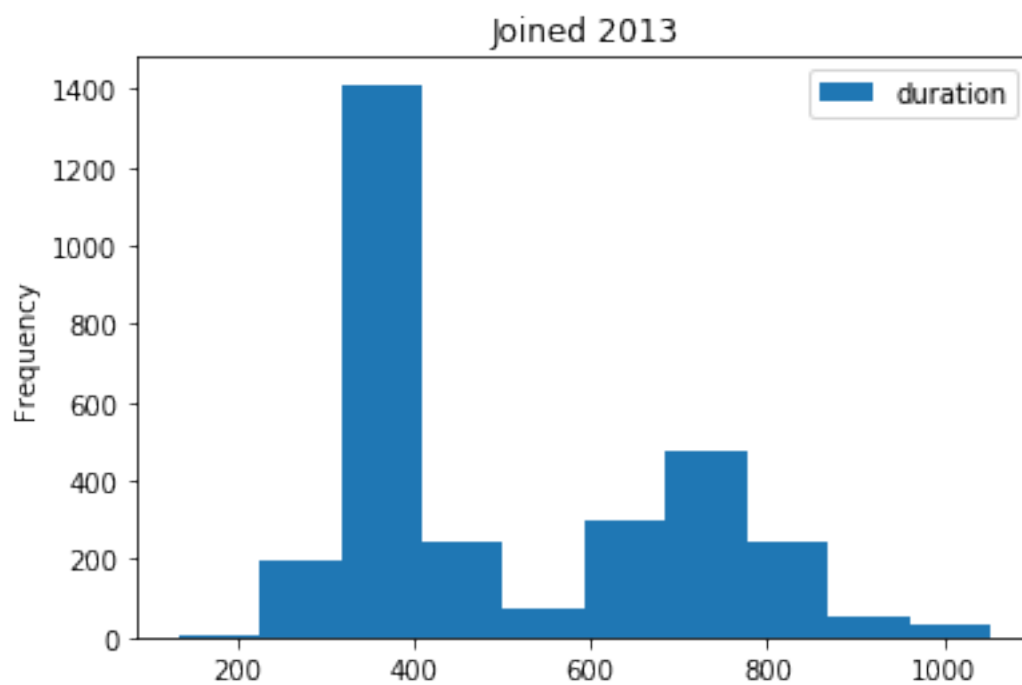
<Figure size 432x288 with 0 Axes>



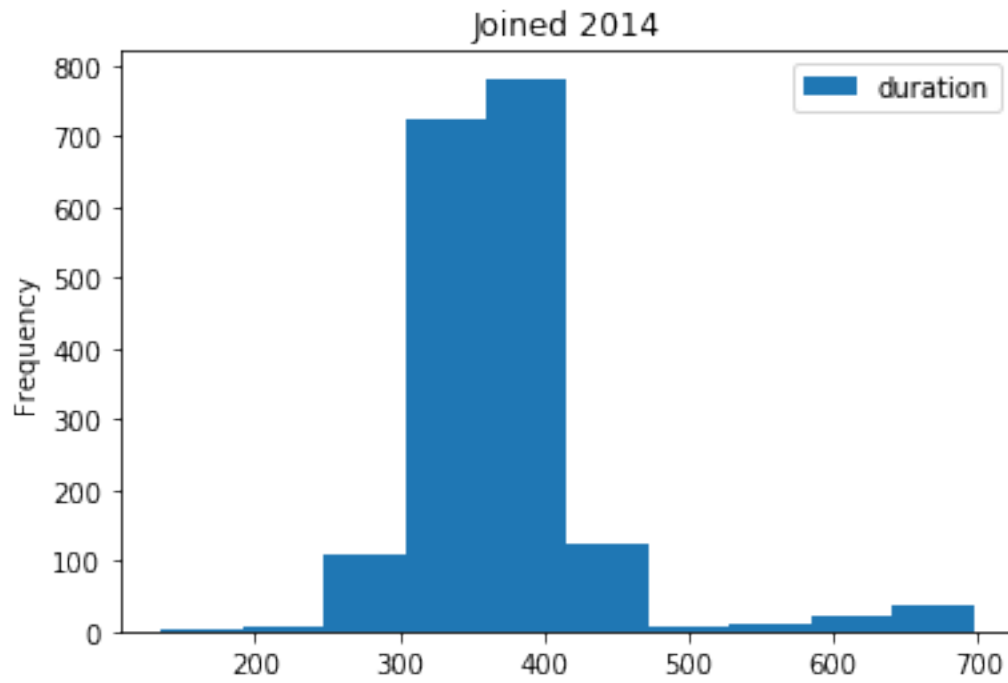
<Figure size 432x288 with 0 Axes>



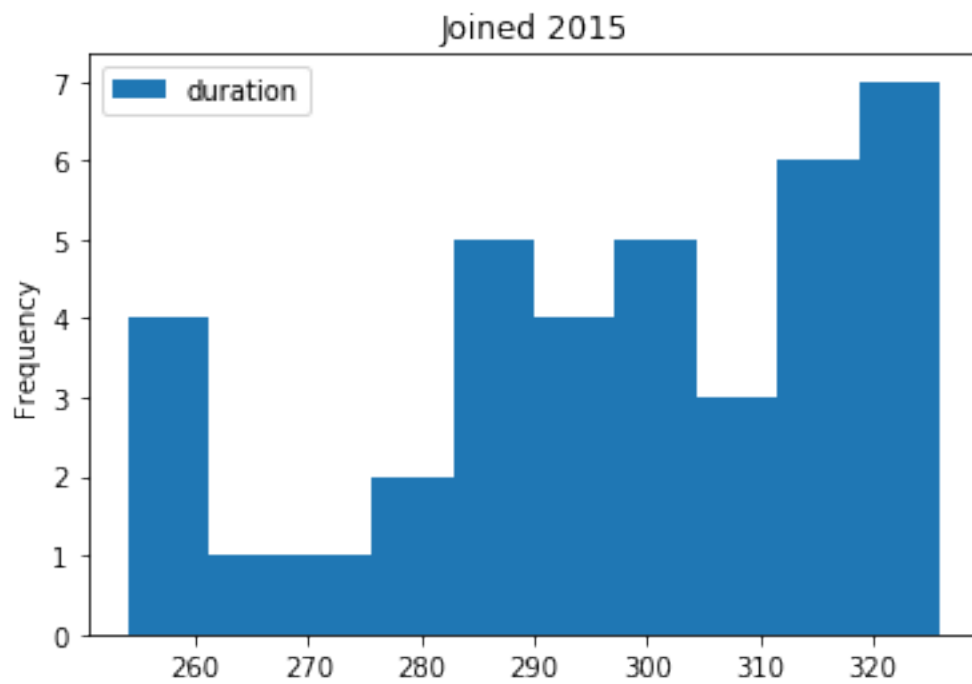
<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



```
In [29]: # Appears that one group tends to quit after around 300-400 days; some stragglers (lo
        # The data for employees that join in 2015 is highly biased.
```

```
In [ ]:
```

6 Fit Model A

```
In [30]: # Generate X variable
        # Drop columns we don't want to include as regressors
        foo = df_good
        foo = foo.drop(['employee_id'],1)
        foo = foo.drop(['company_id'],1)
        foo = foo.drop(['join_date'],1)
        foo = foo.drop(['quit_date'],1)
        foo = foo.drop(['still_working'],1)
        foo = foo.drop(['duration'],1)
        foo = foo.drop(['duration_min'],1)
        X = foo

        # Genreate Y variable
        y = pd.DataFrame(df_good['duration_min'])
```

```
In [31]: X.head()
```

```
Out[31]:
```

	dept	seniority	salary	j2011	j2012	j2013	j2014	j2015
0	customer_service	28	89000.0	False	False	False	True	False
1	marketing	20	183000.0	False	False	True	False	False
3	customer_service	20	115000.0	False	True	False	False	False
4	data_science	23	276000.0	True	False	False	False	False
5	data_science	14	165000.0	False	True	False	False	False

```
In [32]: y.head()
```

```
Out[32]:
```

	duration_min
0	585
1	340
3	389
4	1040
5	578

```
In [33]: model = LinearRegression()
        # model.fit(X,y)
```

For the next steps, I would convert the dept info to use one hot encoding and run the model.

7 Fit Model B

Now that Model A is working (the model trained on just the “good” data - e.g., the data associated with employees who have already quit), I will then train a second model, model B. For this model, I will populate the nan values of the duration column using the following algorithm.

- 1) For each nan value, use model A to predict the duration
- 2) If the predicted duration is longer than 2015/12/13 - join_date (e.g. their time worked up until 2015/12/13), I will substitute the nan with the predicted value. If the predicted duration is shorter, I will then use the value 2015/12/13 - join_date. This will partially correct for bias in the model associated with dropping these data points in model A.