In [1]:
```
#Importing packages
import pandas as pd
import numpy as np
import seaborn as sns
import datetime as dt
import matplotlib.pyplot as plt
```

In [2]:
```
#Importing ML packages
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import accuracy_score, classification_report
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
```

In [3]:
```
#Loading the data into a dataframe
df=pd.read_csv("employee_retention_data.csv")
df.head()
```

Out[3]:

	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 [4]:
```
#Describing the data
df.describe()
```

Out[4]:

	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 [8]:
```
#Determining if there are any missing values; probably are for the quit
 date
df.isnull().any()
```

Out[8]:
```
employee_id    False
company_id     False
dept           False
seniority      False
salary         False
join_date      False
quit_date       True
dtype: bool
```

In [9]:
```
#Determining the type of data in each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24702 entries, 0 to 24701
Data columns (total 7 columns):
employee_id    24702 non-null float64
company_id     24702 non-null int64
dept           24702 non-null object
seniority      24702 non-null int64
salary         24702 non-null float64
join_date      24702 non-null object
quit_date      13510 non-null object
dtypes: float64(2), int64(2), object(3)
memory usage: 1.3+ MB
```

In [10]:
```
#Casting categorical data into numerical data
df.describe(include=['O'])
```

Out[10]:

	dept	join_date	quit_date
count	24702	24702	13510
unique	6	995	664
top	customer_service	2012-01-03	2015-05-08
freq	9180	105	111

In [11]:
```
df['dept'].unique()
```

Out[11]:
```
array(['customer_service', 'marketing', 'data_science', 'engineer',
       'sales', 'design'], dtype=object)
```

In [12]:
```
#Mapping departments to numbers
df['dept']=df['dept'].map({'customer_service':0 ,'marketing':1, 'data_sc
ience':2, 'engineer':3, 'sales':4, 'design':5}).astype(int)
df.head()
```

Out[12]:

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

In [13]:
```
#Creating a new "quit" column where 0 is not quit, and 1 is quit
df.insert(len(df.columns),'quit', 1)
df.head()
```

Out[13]:

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

In [14]:
```
df.loc[(pd.isnull(df.quit_date)), 'quit']=0
df.describe()
```

Out[14]:

	employee_id	company_id	dept	seniority	salary	quit
count	24702.000000	24702.000000	24702.000000	24702.000000	24702.000000	24702.000000
mean	501604.403530	3.426969	1.739697	14.127803	138183.345478	0.546919
std	288909.026101	2.700011	1.658392	8.089520	76058.184573	0.497804
min	36.000000	1.000000	0.000000	1.000000	17000.000000	0.000000
25%	250133.750000	1.000000	0.000000	7.000000	79000.000000	0.000000
50%	500793.000000	2.000000	2.000000	14.000000	123000.000000	1.000000
75%	753137.250000	5.000000	3.000000	21.000000	187000.000000	1.000000
max	999969.000000	12.000000	5.000000	99.000000	408000.000000	1.000000

In [15]:
```
#Creating a new column showing how long the person was at the company
df.insert(len(df.columns),'work_length', 1)
```

In [16]:
```
#Making the join and quit dates as datetime structures
df['join_date'] = pd.to_datetime(df['join_date'], format='%Y-%M-%d')
df['quit_date'] = pd.to_datetime(df['quit_date'], format='%Y-%M-%d')
```

In [17]:
```
df['work_length'] = (df['quit_date'] - df['join_date'])
```

In [18]:
```
last_day = pd.to_datetime('2015-12-13')
df.loc[(pd.isnull(df.work_length)), 'work_length']=(last_day-df['join_da
te'])
df = df.drop(['join_date','quit_date','employee_id'], axis=1)
```

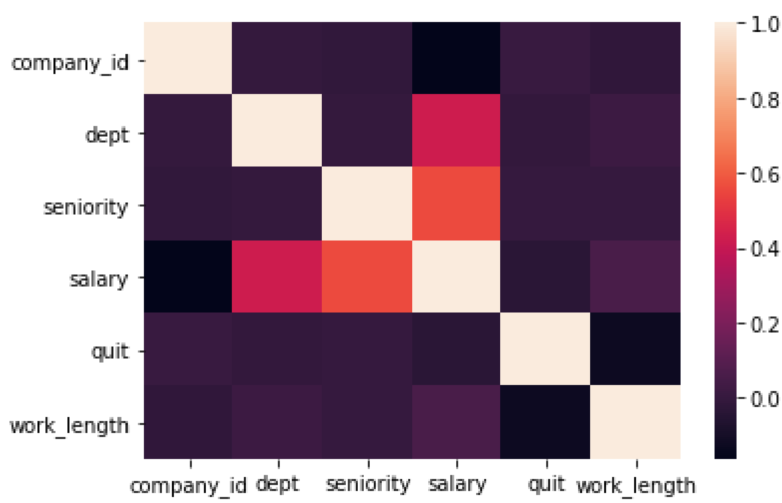
In [19]:
```
df['work_length']=df['work_length'].dt.days
```

Before I begin looking at the factors in this data set that drive employee churn, several factors that drive employee churn in general include: salary, type of company, number of hours spent at work, number of projects, high stress, etc.

In [20]:
```
#Correlation Matrix
corr=df.corr()
corr=(corr)
sns.heatmap(corr, xticklabels=corr.columns.values, yticklabels=corr.colu
mns.values)
corr
```

Out[20]:

	company_id	dept	seniority	salary	quit	work_length
company_id	1.000000	-0.002573	-0.010026	-0.163892	0.013242	-0.014386
dept	-0.002573	1.000000	-0.002460	0.426412	-0.006684	0.020013
seniority	-0.010026	-0.002460	1.000000	0.559465	0.000496	0.002969
salary	-0.163892	0.426412	0.559465	1.000000	-0.036561	0.060455
quit	0.013242	-0.006684	0.000496	-0.036561	1.000000	-0.125430
work_length	-0.014386	0.020013	0.002969	0.060455	-0.125430	1.000000



In [21]:
```
#Salary
df[['quit', 'salary']].groupby(['quit'], as_index=False).mean().sort_values(by='salary', ascending=False)
```

Out[21]:

	quit	salary
0	0	141238.473910
1	1	135652.405625

With a higher salary, employees are more likely to stay. Thus, salary is a factor in employee churn.

In [22]:
```
#Seniority
df[['quit', 'seniority']].groupby(['quit'], as_index=False).mean().sort_values(by='seniority', ascending=False)
```

Out[22]:

	quit	seniority
1	1	14.131458
0	0	14.123392

Surprisingly, there is not much difference in employee attrition based on seniority.

In [23]:
```
#Work length
df[['quit', 'work_length']].groupby(['quit'], as_index=False).mean().sort_values(by='work_length', ascending=False)
```

Out[23]:

	quit	work_length
0	0	698.730879
1	1	606.316432

There is not much difference in employee attrition based on work length. However, there is a slight increase in the length of time worked by the employees who stay in their place of work.

In [24]:
```
#Quitting probability based on department type
df[['quit', 'dept']].groupby(['dept'], as_index=False).mean().sort_value
s(by='quit', ascending=False)
```

Out[24]:

	dept	quit
4	4	0.570933
5	5	0.563768
1	1	0.562993
0	0	0.554902
2	2	0.527273
3	3	0.512031

There is not much difference in employees staying depending upon the department. This was sorted by department since sorting by quitting would not provide much information.

In [25]:
```
#Company type
df[['quit', 'company_id']].groupby(['company_id'], as_index=False).mean
().sort_values(by='quit', ascending=False)
```

Out[25]:

	company_id	quit
10	11	0.750000
6	7	0.565359
4	5	0.560114
3	4	0.559166
2	3	0.556930
9	10	0.554913
7	8	0.553009
5	6	0.551510
8	9	0.550468
0	1	0.544544
1	2	0.522501
11	12	0.500000

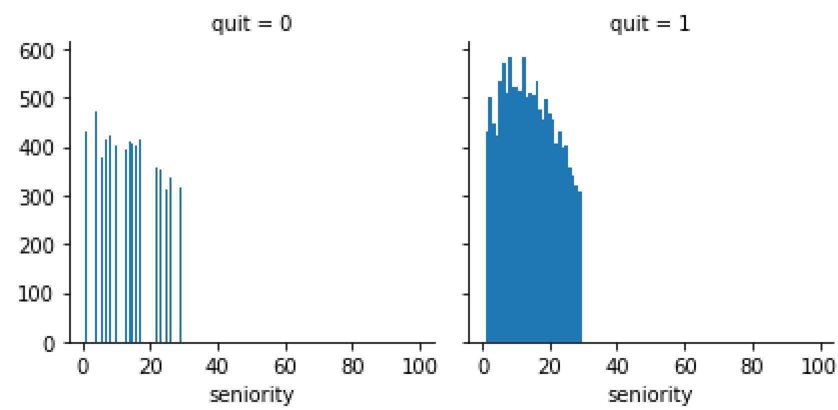
Employees really do not like to work at company 11, so company is a factor. Otherwise, there is not much difference in employee attrition baased on company.

In [26]:
```
#Determining how many people worked for each company (sample size)
for i in range(12):
    i+=1
    print (i, (df['company_id']==i).sum())
```

```
1 8486
2 4222
3 2749
4 2062
5 1755
6 1291
7 1224
8 1047
9 961
10 865
11 16
12 24
```

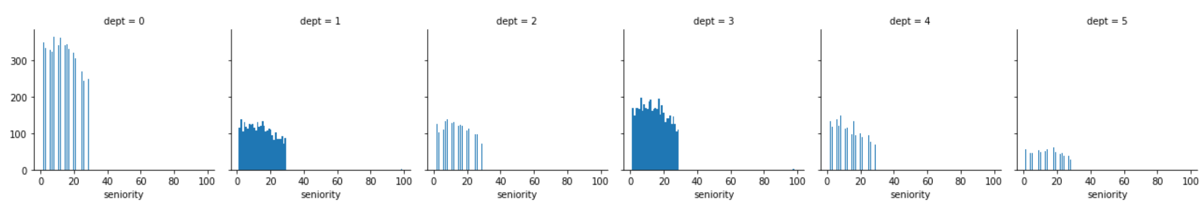
In [27]:
```
g=sns.FacetGrid(df, col='quit')
g.map(plt.hist, 'seniority', bins=100)
```

Out[27]: <seaborn.axisgrid.FacetGrid at 0x1a20c3f470>



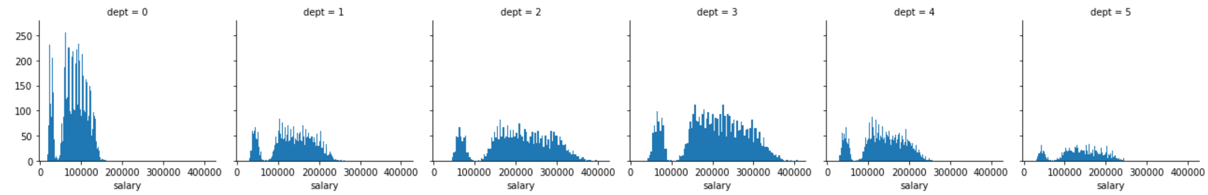
In [28]:
```
g=sns.FacetGrid(df, col='dept')
g.map(plt.hist, 'seniority', bins=100)
```

Out[28]: <seaborn.axisgrid.FacetGrid at 0x1a20db2c18>



```
In [29]: g=sns.FacetGrid(df, col='dept')
         g.map(plt.hist, 'salary', bins=100)
```

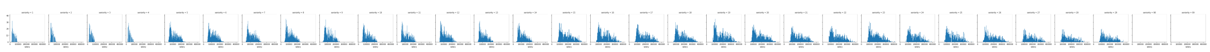
```
Out[29]: <seaborn.axisgrid.FacetGrid at 0x1a216c68d0>
```



Departments are correlated with salary- those with the salaries in the higher ranges are the departments with slightly higher employee attrition.

```
In [30]: g=sns.FacetGrid(df, col='seniority')
         g.map(plt.hist, 'salary', bins=100)
```

```
Out[30]: <seaborn.axisgrid.FacetGrid at 0x1a21f21080>
```



Salary distribution widens as seniority increases, which makes sense.

```
In [31]: #Splitting data into train and test for models
         nHead=int(len(df)*0.8)
         nTail=int(len(df)*0.2)
         X_train=df.drop("quit", axis=1).head(nHead)
         X_test=df.drop("quit", axis=1).tail(nTail)
         Y_train=df["quit"].head(nHead)
         Y_test=df["quit"].tail(nTail)
```

```
In [32]: #Logistic Regression
         logreg = LogisticRegression()
         logreg.fit(X_train, Y_train);
         accuracy_score(Y_test, logreg.predict(X_test))
```

```
/Users/kendallhoover/miniconda3/envs/challenges_env/lib/python3.7/site-
packages/sklearn/linear_model/logistic.py:433: FutureWarning: Default s
olver will be changed to 'lbfgs' in 0.22. Specify a solver to silence t
his warning.
  FutureWarning)
```

```
Out[32]: 0.5591093117408907
```

In [33]:
```
print(classification_report(Y_test, logreg.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.50      0.31      0.39      2190
           1       0.58      0.75      0.66      2750

   micro avg       0.56      0.56      0.56      4940
   macro avg       0.54      0.53      0.52      4940
weighted avg       0.55      0.56      0.54      4940
```

In [34]:
```
#K-Nearest Neighbor
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, Y_train)
acc_knn = knn.score(X_test, Y_test)
acc_knn
```

Out[34]:
```
0.8827935222672065
```

In [35]:
```
#Decision Tree
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
acc_decision_tree = decision_tree.score(X_test, Y_test)
acc_decision_tree
```

Out[35]:
```
0.9451417004048583
```

One potential variable to include would be the number of hours worked, trying to get at the work-life balance. I belive this would give more insight into whether employees would leave and quit the company.

In [ ]:
```
```