Steph_Gervasi_Employee_Retention

February 20, 2019

In [2]:
```
# Import the basics for some inital EDA

import numpy as np
import pandas as pd
from scipy import stats
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0)
import seaborn as sns
```

In [3]:
```
# Some information I've been given about the data:

##### Columns I have:
## 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 
## quit_date: when the employee left her job (if she is still employed as of 2015/12/1
```

In [4]:
```
# Get the data
dc1 = pd.read_csv("employee_retention_data.csv")
```

In [5]:
```
# Check data dimensions
print("The data has {0} rows and {1} columns".format(dc1.shape[0], dc1.shape[1]))
```

```
The data has 24702 rows and 7 columns
```

In [6]:
```
# Take a quick look to see what the data look like
dc1.head()
```

Out[6]:
```
   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 [7]:
```
# Confirm column names
list(dc1.columns.values)
```

Out[7]:
```
['employee_id',
 'company_id',
 'dept',
 'seniority',
 'salary',
 'join_date',
 'quit_date']
```

In [8]:
```
# Get info about data types and missingness
dc1.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 [9]:
```
# Check percentage of missing values in the columns to decide whether to drop, impute,
miss = dc1.isnull().sum()/len(dc1)
print(type(miss))
miss = miss[miss > 0]
miss.sort_values(inplace = True)
miss
# I know that these data are missing because it means that the people still work there
```

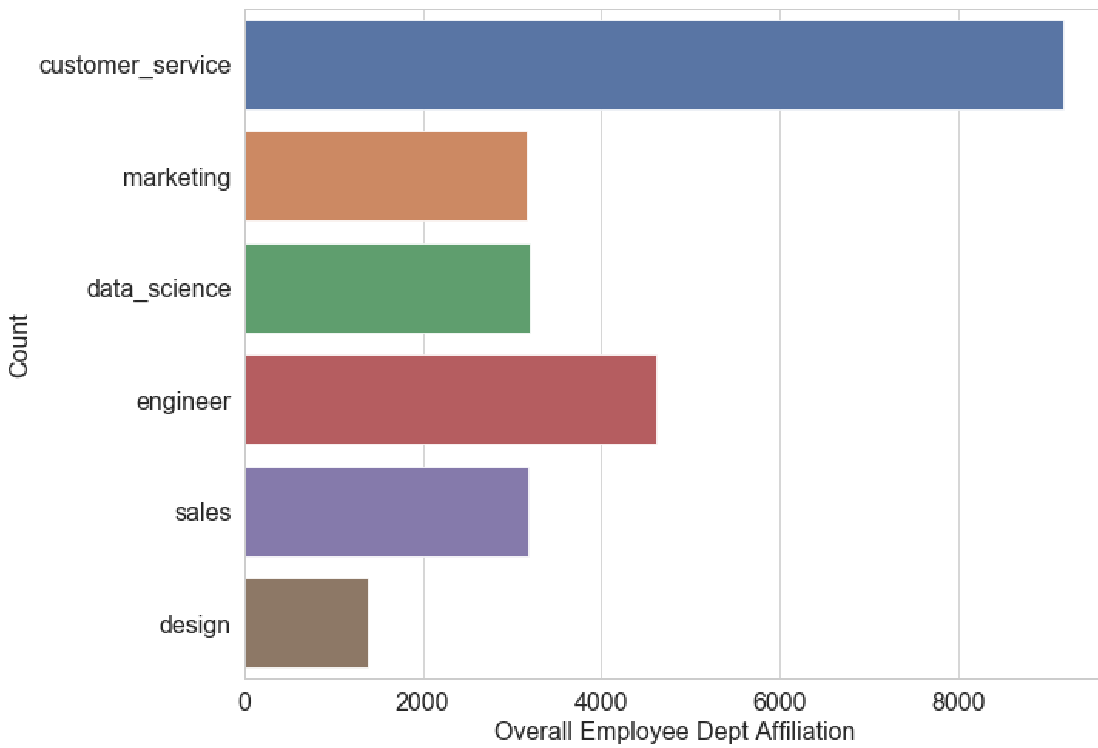
```
<class 'pandas.core.series.Series'>
```

Out[9]:
```
quit_date    0.453081
dtype: float64
```

In [10]:
```
# Now look at the other variables/columns in the dataset
# First look at dept variable
dc1['dept'].unique()
# there are 6
```

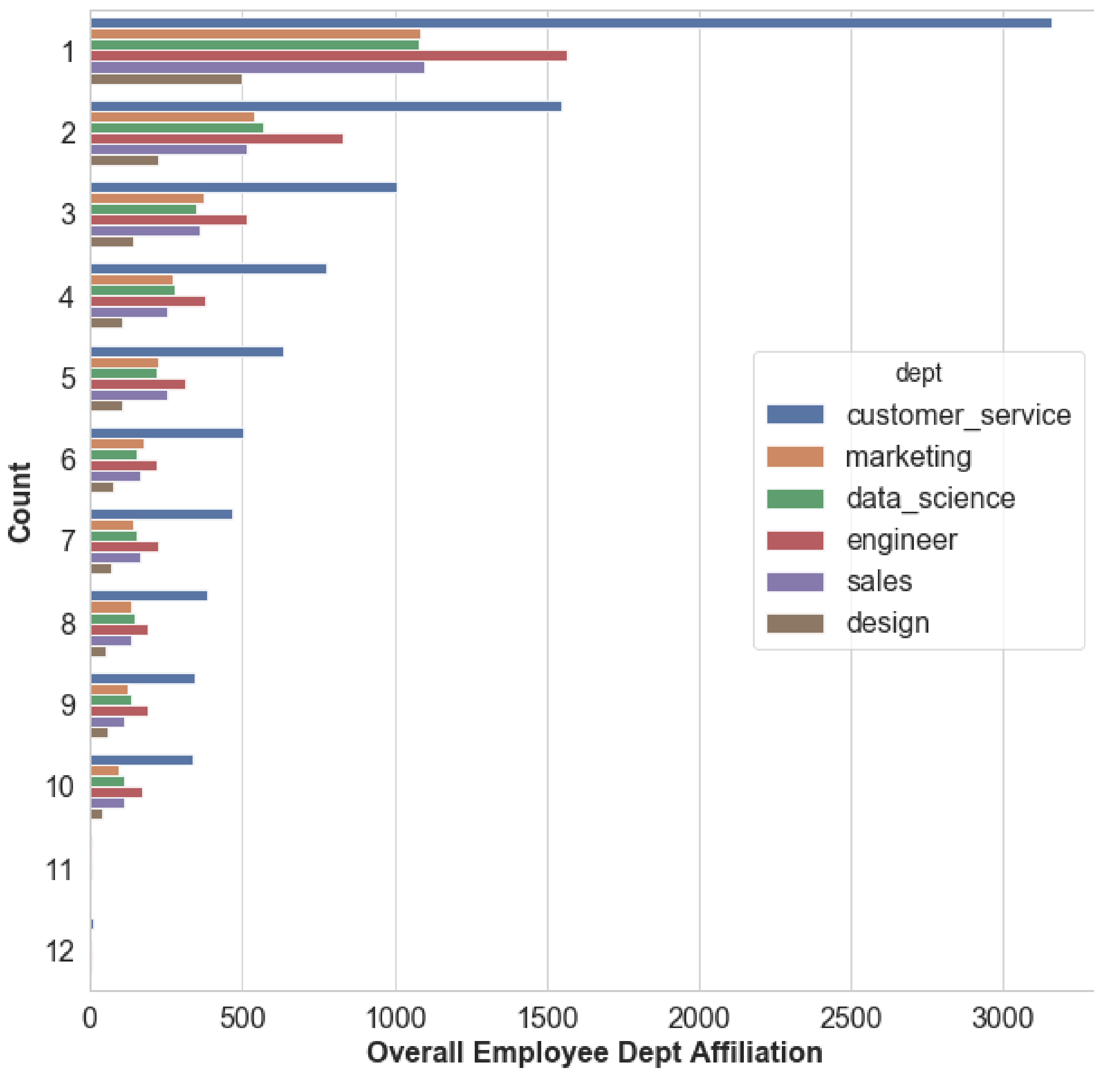
Out[10]:
```
array(['customer_service', 'marketing', 'data_science', 'engineer',
       'sales', 'design'], dtype=object)
```

In [11]:
```
# What is the break down/count of number of employees by department across all compan
sns.set(style="whitegrid", color_codes=True)
plt.rcParams['figure.figsize'] = (10.0, 8.0)
sns.set_context("paper", rc={"font.size":16,"axes.titlesize":16,"axes.labelsize":16,
ax = sns.countplot(y="dept", data=dc1)
ax.set(xlabel='Overall Employee Dept Affiliation', ylabel='Count')
plt.show()

# CONCLUDE:
# Greatest bulk of employees are coming from customer service category. May want to c
```



In [206]:
```
# What is the break down/count of number of employees by department shown for each c
sns.set(style="whitegrid", color_codes=True)
plt.rcParams['figure.figsize'] = (10.0, 10.0)
sns.set_context("paper", rc={"font.size":16,"axes.titlesize":16,"axes.labelsize":16,
```

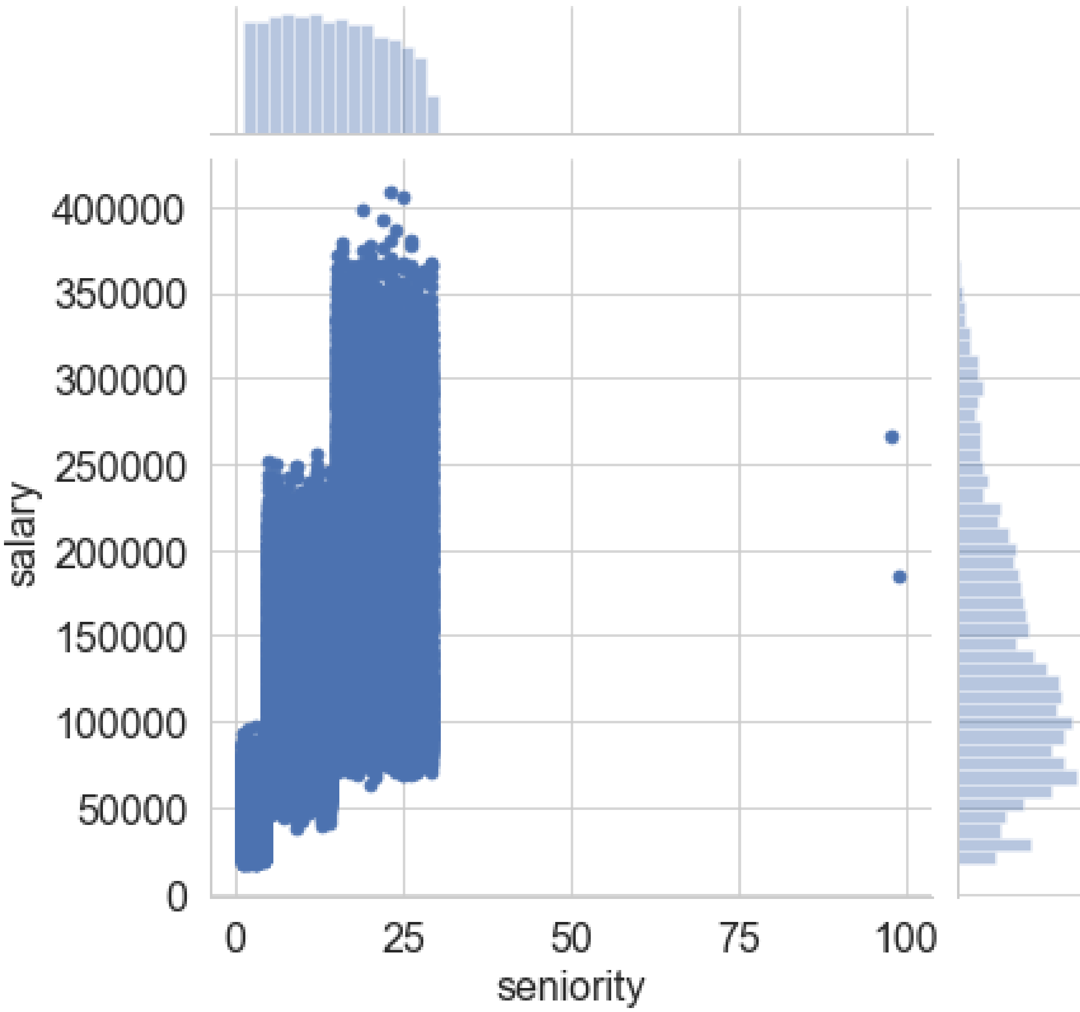
```
ax = sns.countplot(y="company_id", hue = "dept", data=dc1)
ax.set(xlabel='Overall Employee Dept Affiliation', ylabel='Count')
plt.show()

# CONCLUDE:
# Trend observed above seems to also be present in the within company context : most
# Company 11 and 12 are very different from the rest. May want to think about includ
```




```
In [13]: # Next look at the seniority variable:
         np.sort(dc1['seniority'].unique())
         # It is highly unlikely that someone has a seniority status of 98 or np.sort(dc1['sen

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

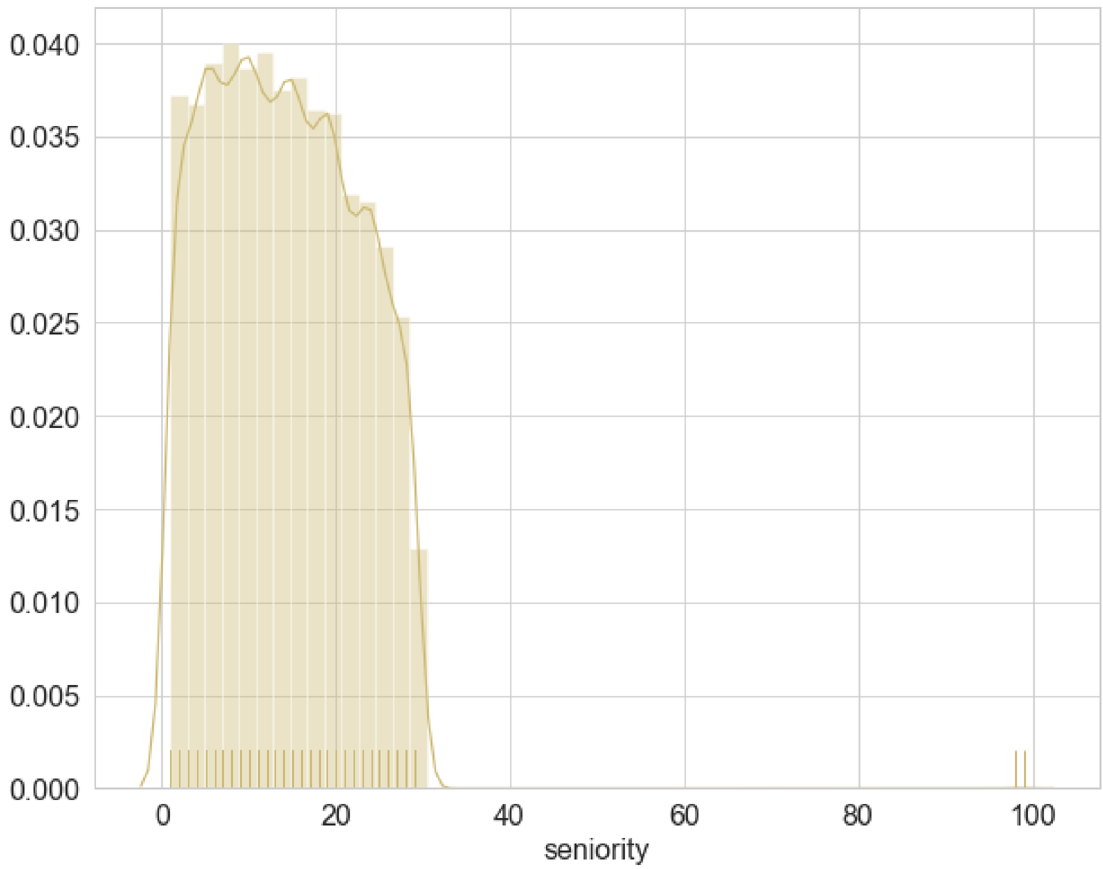
In [14]:
```
# Quickly, look at seniority and salary relationship (see both distribution/histogram
sns.jointplot(x="seniority", y="salary", data=dc1)

# CONCLUDE:
# Need to get rid of those outliers - don't have any information on how to correct th
```

Out[14]: <seaborn.axisgrid.JointGrid at 0x102bc1588>

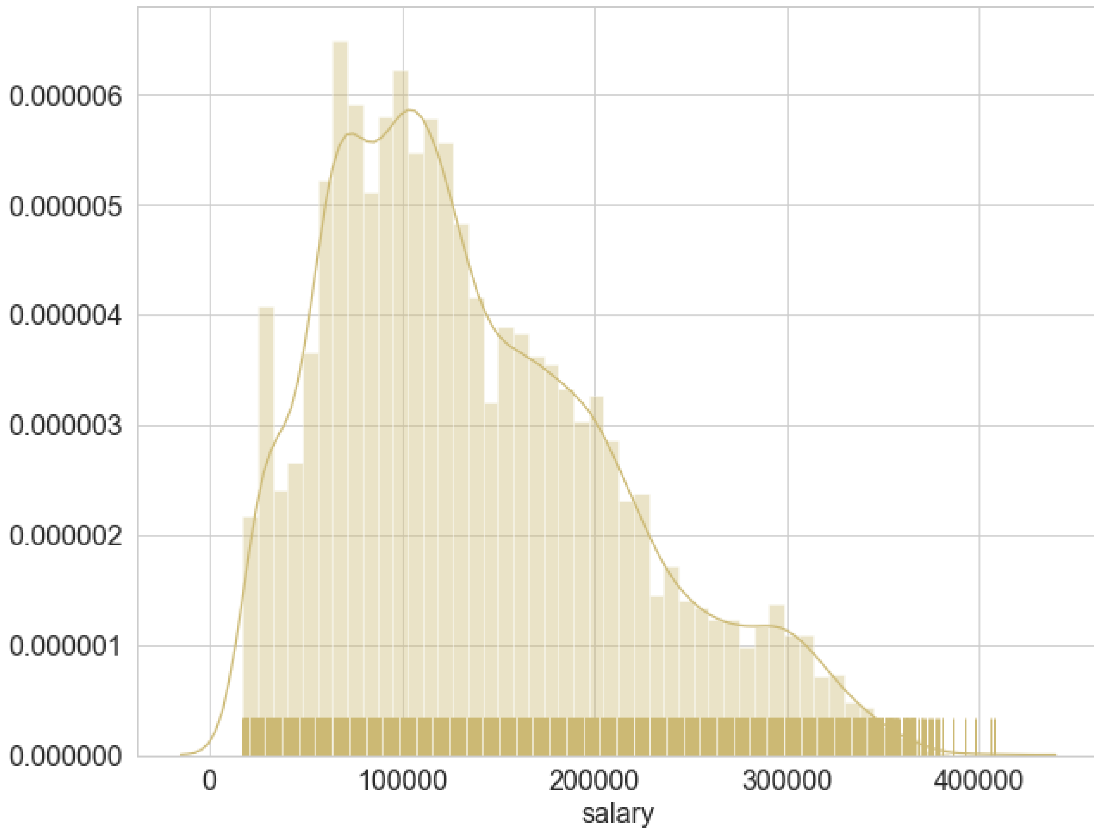


In [15]:
```
# plot distribution of seniority values - outliers evident here too
sns.distplot(dc1['seniority'], rug = True, color = 'y')
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1a09baed30>




```
In [16]: # deal with outliers in seniority column, here only 2, so will remove. Check shape be
         dc1.shape

Out[16]: (24702, 7)

In [17]: # Process of removing seniority outliers based on being above 3 st deviations of the 
         target = dc1['seniority']
         mean = target.mean()
         sd = target.std()
         reduced_dc1 = dc1[(target > mean - 3*sd) & (target < mean + 3*sd)]
         reduced_dc1.shape

         # this removed 2 outliers that were beyond 3 sd of the mean.

Out[17]: (24700, 7)

In [18]: # Now take a look at the variable, salary, by itself
         sns.distplot(reduced_dc1['salary'], rug = True, color = 'y')
         # looks like some outliers here, too, at the high end. These could interfere with pre

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1a15240b00>
```



In [19]:
```
## Here applying the same process/criteria for outlier removal in the salary column a
target2 = reduced_dc1['salary']
mean2 = target2.mean()
sd2 = target2.std()
reduced2_dc1 = reduced_dc1[(target2 > mean2 - 3*sd2) & (target2 < mean2 + 3*sd2)]
reduced2_dc1.shape
# As a result, this removed 22 additional data points.
```

Out[19]: (24678, 7)

In [20]:
```
# give the new dataframe a more intuitive name after outlier removal from the seniori
dc1_NEW = reduced2_dc1
```

In [21]:
```
# Our reduced dataframe:
dc1_NEW.head()
```

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	
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 [22]: # Now, look at company_id variable
         dc1_NEW['company_id'].nunique()
         # size of companies clearly varies 11 and 12 are smaller than the rest - this could b
```

```
Out[22]: 12
```

```
In [23]: # Now, check the employee_id variable (make sure no duplicate IDs; # rows shoudl = #
         dc1_NEW['employee_id'].nunique()
```

```
Out[23]: 24678
```

```
In [ ]: # The next steps will be to join and quit dates: first take a look and then convert th
```

```
In [236]: # First do a quick visual scan to make sure they're all in the same format (although
          #dc1_NEW['join_date'].value_counts(dropna = False)
```

```
In [237]: #dc1_NEW['quit_date'].value_counts(dropna = False)
```

```
In [26]: # get all dates in standard format before calculating difference in time to get tenur
         import datetime
         dc1_NEW['join_date'] = pd.to_datetime(dc1_NEW['join_date'])
         dc1_NEW['quit_date'] = pd.to_datetime(dc1_NEW['quit_date'])
         dc1_NEW.head()
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  This is separate from the ipykernel package so we can avoid doing imports until
```

```
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
0 2015-10-30
1 2014-04-04
2        NaT
3 2013-06-07
4 2014-08-22
```

In [27]:
```python
# Check updated format of date columns
dc1_NEW.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24678 entries, 0 to 24699
Data columns (total 7 columns):
employee_id    24678 non-null float64
company_id     24678 non-null int64
dept           24678 non-null object
seniority      24678 non-null int64
salary         24678 non-null float64
join_date      24678 non-null datetime64[ns]
quit_date      13501 non-null datetime64[ns]
dtypes: datetime64[ns](2), float64(2), int64(2), object(1)
memory usage: 1.5+ MB
```

In [29]:
```python
# Calcualte a new column for total tenure, which is the time someone has worked at th
dc1_NEW['total_tenure'] = dc1_NEW['quit_date'] - dc1_NEW['join_date']
dc1_NEW.head()
# string and number are the output of this new column
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

Out[29]:
```
   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 total_tenure
0 2015-10-30     585 days
1 2014-04-04     340 days
2        NaT          NaT
3 2013-06-07     389 days
4 2014-08-22    1040 days
```

In [30]:
```python
# Convert the variable total_tenure that was just created so that it only includes th
dc1_NEW['days_employeed'] = (dc1_NEW['quit_date'] - dc1_NEW['join_date']).dt.days
dc1_NEW.head()
# just number of days and NaNs in this new column, days_employeed
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
```

Out[30]:
```
   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 total_tenure  days_employeed
0 2015-10-30     585 days           585.0
1 2014-04-04     340 days           340.0
2        NaT          NaT             NaN
3 2013-06-07     389 days           389.0
4 2014-08-22    1040 days          1040.0
```

In [32]:
```python
# Change the NAs in the new days_employeed column to something meaningful, because th
dc1_NEW['days_employeed'].fillna('currently_employeed', inplace = True)
dc1_NEW.head()
```

```
/anaconda3/lib/python3.6/site-packages/pandas/core/generic.py:5434: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  self._update_inplace(new_data)
```

Out[32]:
```
   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 total_tenure       days_employeed
0 2015-10-30     585 days                  585
1 2014-04-04     340 days                  340
2        NaT          NaT  currently_employeed
3 2013-06-07     389 days                  389
4 2014-08-22    1040 days                 1040
```

In [33]:
```
# Also create new columns for start year and month since this could potentially tell
dc1_NEW['start_year'] = (dc1_NEW['join_date'].dt.year)
dc1_NEW['start_month'] = (dc1_NEW['join_date'].dt.month)
dc1_NEW.head()
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  This is separate from the ipykernel package so we can avoid doing imports until
```

Out[33]:
```
   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 total_tenure       days_employeed  start_year  start_month
0 2015-10-30     585 days                  585        2014            3
1 2014-04-04     340 days                  340        2013            4
2        NaT          NaT  currently_employeed        2014           10
3 2013-06-07     389 days                  389        2012            5
4 2014-08-22    1040 days                 1040        2011           10
```

In [ ]:
```
# May also want to take the continuous column/feature called days_employeed and turn i
```

In [34]:
```
# First, duplicate the column and call it days_employed_cont
dc1_NEW['days_employeed_cont']=dc1_NEW['days_employeed']

# Now, turn the string 'curr_employeed' into a high number 1800 is 5 years so use 185
```

```
dc1_NEW['days_employeed_cont'] = dc1_NEW['days_employeed_cont'].replace('currently_emp
dc1_NEW.head()
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html

/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """
```

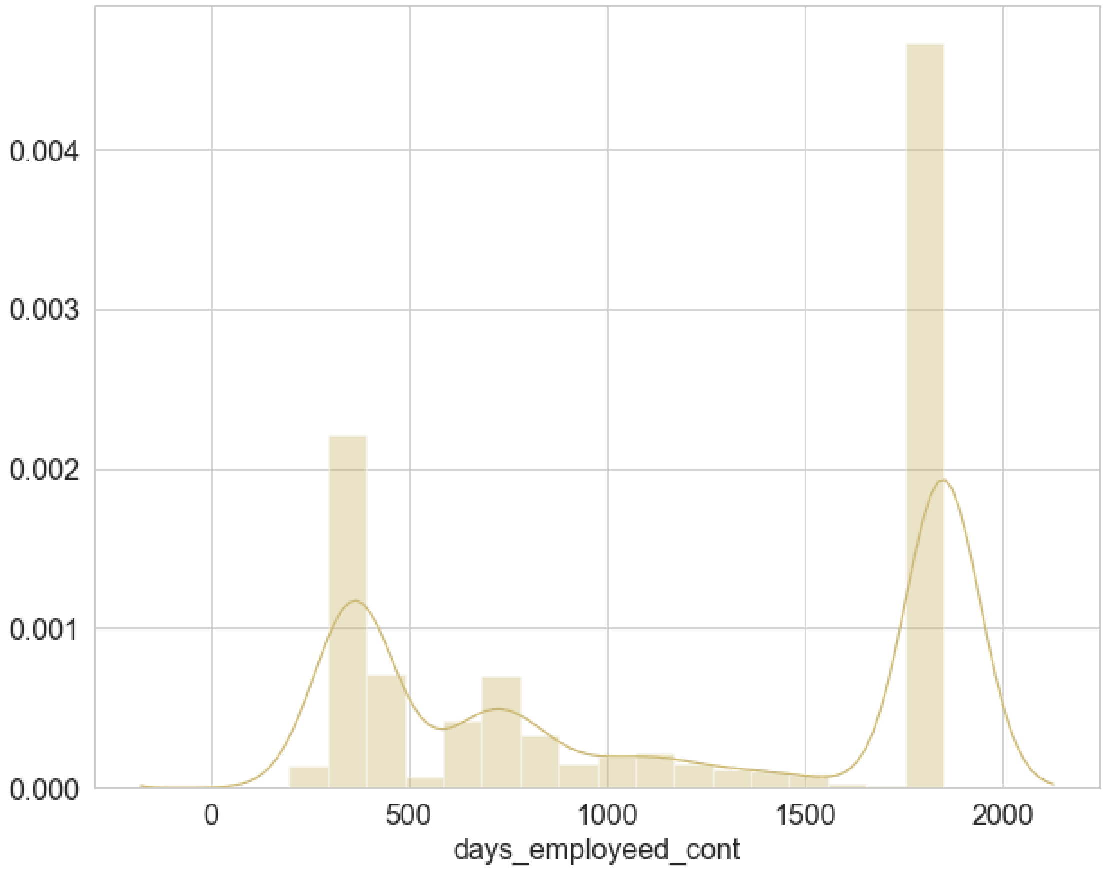
Out[34]:

```
   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 total_tenure       days_employeed  start_year  start_month  \
0 2015-10-30     585 days                  585        2014            3
1 2014-04-04     340 days                  340        2013            4
2        NaT          NaT  currently_employeed        2014           10
3 2013-06-07     389 days                  389        2012            5
4 2014-08-22    1040 days                 1040        2011           10

   days_employeed_cont
0                585.0
1                340.0
2               1850.0
3                389.0
4               1040.0
```

In [36]:

```
# Now, the column days_employeed_cont is all numeric values, and we can inspect furth
sns.distplot(dc1_NEW['days_employeed_cont'], kde=True, rug=False, norm_hist= False, co
# looks like at least 4 major natural breakpoints where people worked for 1 year, ~ 2
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1a18b68c50>




```
In [37]: # After first trying to use the quartile method, it seems like it might be best to ma
         bins = [0, 360, 720, 1080, 1440, 1850]
         names = ['<1yr', '1-2yr', '2-3yr', '3-4yr', '4+yrs']

         # a new column called tenure_category is the binned times/durations that people were
         dc1_NEW['tenure_category'] = pd.cut(dc1_NEW['days_employeed_cont'], bins, labels=names
         dc1_NEW.head(20)

         #print(dc1_NEW.dtypes)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """
```

```
Out[37]:     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
10      892155.0             6  customer_service         13   72000.0 2012-11-12
11      904158.0             2         marketing         17  230000.0 2015-05-11
12      939058.0             1         marketing          1   48000.0 2012-12-10
13      163427.0            10         marketing         23  154000.0 2012-06-18
14      461248.0             2             sales         20  201000.0 2013-09-16
15      265226.0             1      data_science          4   80000.0 2014-05-27
16      932790.0             7         marketing         10   88000.0 2011-11-30
17       69693.0             7  customer_service          6   54000.0 2014-03-31
18      721600.0             2         marketing         20  193000.0 2014-12-29
19      982668.0             1  customer_service         14   76000.0 2015-07-27

    quit_date total_tenure       days_employeed  start_year  start_month  \
0  2015-10-30     585 days                  585        2014            3
1  2014-04-04     340 days                  340        2013            4
2         NaT          NaT  currently_employeed        2014           10
3  2013-06-07     389 days                  389        2012            5
4  2014-08-22    1040 days                 1040        2011           10
5  2013-08-30     578 days                  578        2012            1
6         NaT          NaT  currently_employeed        2013           10
7         NaT          NaT  currently_employeed        2014            3
8  2015-10-23    1047 days                 1047        2012           12
9         NaT          NaT  currently_employeed        2012            6
10 2015-02-27     837 days                  837        2012           11
11        NaT          NaT  currently_employeed        2015            5
12 2013-11-15     340 days                  340        2012           12
13 2015-09-25    1194 days                 1194        2012            6
14 2014-08-22     340 days                  340        2013            9
15 2015-07-10     409 days                  409        2014            5
16 2013-11-22     723 days                  723        2011           11
17        NaT          NaT  currently_employeed        2014            3
18        NaT          NaT  currently_employeed        2014           12
19        NaT          NaT  currently_employeed        2015            7

    days_employeed_cont tenure_category
0                 585.0           1-2yr
1                 340.0            <1yr
2                1850.0           4+yrs
3                 389.0           1-2yr
4                1040.0           2-3yr
```

```
5                578.0          1-2yr
6               1850.0          4+yrs
7               1850.0          4+yrs
8               1047.0          2-3yr
9               1850.0          4+yrs
10               837.0          2-3yr
11              1850.0          4+yrs
12               340.0           <1yr
13              1194.0          3-4yr
14               340.0           <1yr
15               409.0          1-2yr
16               723.0          2-3yr
17              1850.0          4+yrs
18              1850.0          4+yrs
19              1850.0          4+yrs
```

```
In [42]: #Also, consider creating a lower resolution, binary column that tellus us just whethe
         dc1_NEW['still_employeed'] = np.where(pd.isnull(dc1_NEW['quit_date']), '1', '0')
         dc1_NEW.head(10)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

```
Out[42]:    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 total_tenure       days_employeed  start_year  start_month  \
         0 2015-10-30     585 days                  585        2014            3
         1 2014-04-04     340 days                  340        2013            4
         2        NaT          NaT  currently_employeed        2014           10
         3 2013-06-07     389 days                  389        2012            5
         4 2014-08-22    1040 days                 1040        2011           10
         5 2013-08-30     578 days                  578        2012            1
         6        NaT          NaT  currently_employeed        2013           10
```

```
7        NaT          NaT  currently_employeed       2014            3
8 2015-10-23    1047 days                 1047       2012           12
9        NaT          NaT  currently_employeed       2012            6

   days_employeed_cont tenure_category still_employeed
0                585.0           1-2yr               0
1                340.0            <1yr               0
2               1850.0           4+yrs               1
3                389.0           1-2yr               0
4               1040.0           2-3yr               0
5                578.0           1-2yr               0
6               1850.0           4+yrs               1
7               1850.0           4+yrs               1
8               1047.0           2-3yr               0
9               1850.0           4+yrs               1
```

In [40]:
```
#Look at counts of two created groups for still employeed or not to see if they are b
dc1_NEW['still_employeed'].value_counts(dropna = False)
```

Out[40]:
```
0    13501
1    11177
Name: still_employeed, dtype: int64
```

In [41]:
```
# Sanity check
dc1_NEW.isnull().sum(axis = 0)
```

Out[41]:
```
employee_id               0
company_id                0
dept                      0
seniority                 0
salary                    0
join_date                 0
quit_date             11177
total_tenure          11177
days_employeed            0
start_year                0
start_month               0
days_employeed_cont       0
tenure_category           0
still_employeed           0
dtype: int64
```

In [44]:
```
# I also want to create a salary ranking column in case this is a better predictor th
dc1_NEW['salary_rank']=pd.qcut(dc1_NEW['salary'],4,labels=['low','med','high','very_hi
dc1_NEW.head(20)
```

```
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

Out[44]:

```
    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
10     892155.0           6  customer_service         13   72000.0 2012-11-12
11     904158.0           2         marketing         17  230000.0 2015-05-11
12     939058.0           1         marketing          1   48000.0 2012-12-10
13     163427.0          10         marketing         23  154000.0 2012-06-18
14     461248.0           2             sales         20  201000.0 2013-09-16
15     265226.0           1      data_science          4   80000.0 2014-05-27
16     932790.0           7         marketing         10   88000.0 2011-11-30
17      69693.0           7  customer_service          6   54000.0 2014-03-31
18     721600.0           2         marketing         20  193000.0 2014-12-29
19     982668.0           1  customer_service         14   76000.0 2015-07-27

    quit_date total_tenure       days_employeed  start_year  start_month  \
0  2015-10-30     585 days                  585        2014            3
1  2014-04-04     340 days                  340        2013            4
2         NaT          NaT  currently_employeed        2014           10
3  2013-06-07     389 days                  389        2012            5
4  2014-08-22    1040 days                 1040        2011           10
5  2013-08-30     578 days                  578        2012            1
6         NaT          NaT  currently_employeed        2013           10
7         NaT          NaT  currently_employeed        2014            3
8  2015-10-23    1047 days                 1047        2012           12
9         NaT          NaT  currently_employeed        2012            6
10 2015-02-27     837 days                  837        2012           11
11        NaT          NaT  currently_employeed        2015            5
12 2013-11-15     340 days                  340        2012           12
13 2015-09-25    1194 days                 1194        2012            6
14 2014-08-22     340 days                  340        2013            9
15 2015-07-10     409 days                  409        2014            5
16 2013-11-22     723 days                  723        2011           11
17        NaT          NaT  currently_employeed        2014            3
18        NaT          NaT  currently_employeed        2014           12
19        NaT          NaT  currently_employeed        2015            7
```

	days_employeed_cont	tenure_category	still_employeed	salary_rank
0	585.0	1-2yr	0	med
1	340.0	<1yr	0	high
2	1850.0	4+yrs	1	med
3	389.0	1-2yr	0	med
4	1040.0	2-3yr	0	very_high
5	578.0	1-2yr	0	high
6	1850.0	4+yrs	1	med
7	1850.0	4+yrs	1	low
8	1047.0	2-3yr	0	high
9	1850.0	4+yrs	1	med
10	837.0	2-3yr	0	low
11	1850.0	4+yrs	1	very_high
12	340.0	<1yr	0	low
13	1194.0	3-4yr	0	high
14	340.0	<1yr	0	very_high
15	409.0	1-2yr	0	med
16	723.0	2-3yr	0	med
17	1850.0	4+yrs	1	low
18	1850.0	4+yrs	1	very_high
19	1850.0	4+yrs	1	low

In [70]:
```
# Similarly, I may want to just compare size of companies - could be important to tak
total_employees_count = dc1_NEW.groupby(['company_id']).size().reset_index(name='total
total_employees_count.head(12)
```

Out[70]:

	company_id	total_number_of_employees
0	1	8472
1	2	4213
2	3	2749
3	4	2062
4	5	1755
5	6	1291
6	7	1224
7	8	1047
8	9	961
9	10	864
10	11	16
11	12	24

In [72]:
```
total_employees_by_dept = dc1_NEW.groupby(['company_id', 'dept']).size().reset_index(n
total_employees_by_dept.tail(20) # check tail for those small companies - 11 and 12.
```

Out[72]:

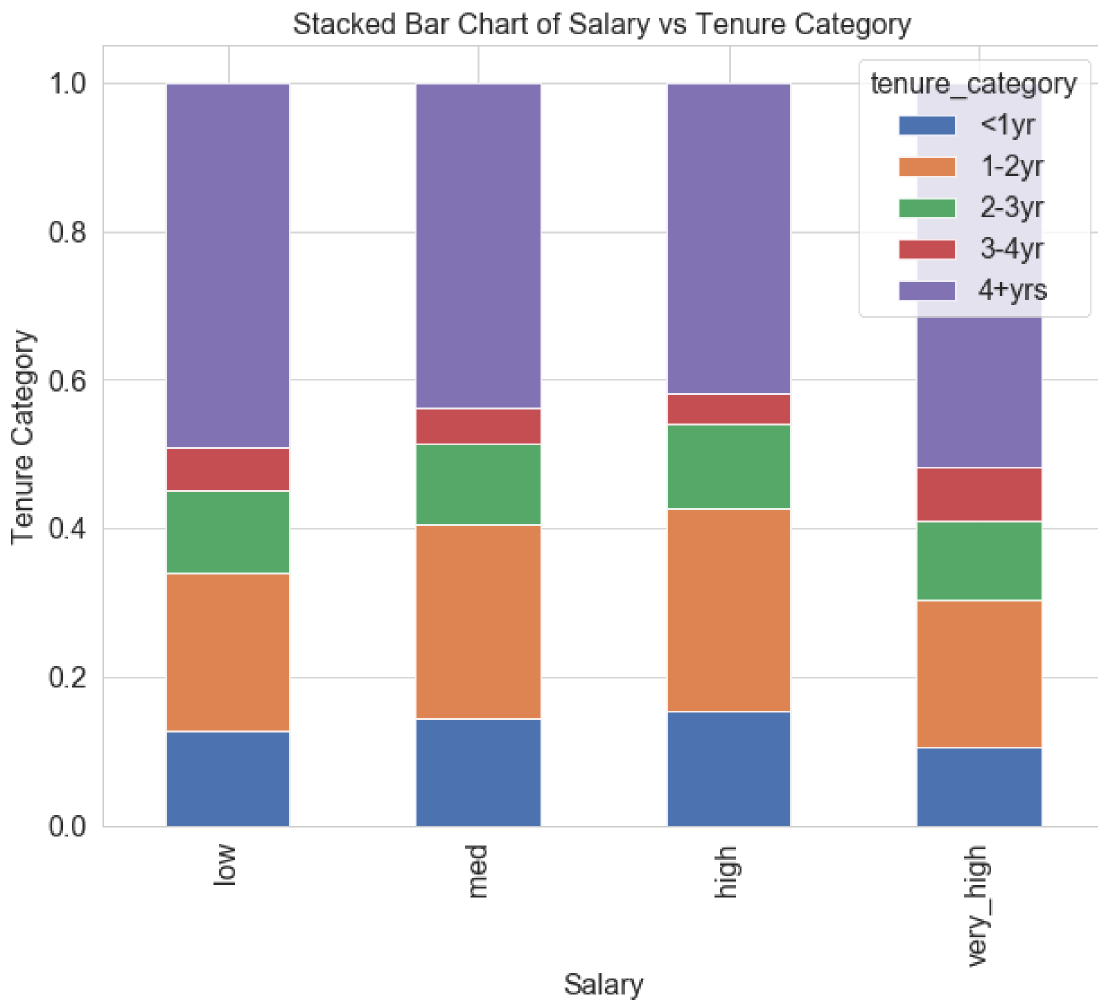
	company_id	dept	number_of_employees_by_dept
50	9	design	60
51	9	engineer	188
52	9	marketing	124
53	9	sales	113

```
54          10  customer_service                            336
55          10      data_science                            109
56          10            design                             41
57          10          engineer                            171
58          10         marketing                             96
59          10             sales                            111
60          11  customer_service                              6
61          11      data_science                              2
62          11          engineer                              6
63          11         marketing                              2
64          12  customer_service                             12
65          12      data_science                              4
66          12            design                              1
67          12          engineer                              4
68          12         marketing                              1
69          12             sales                              2
```

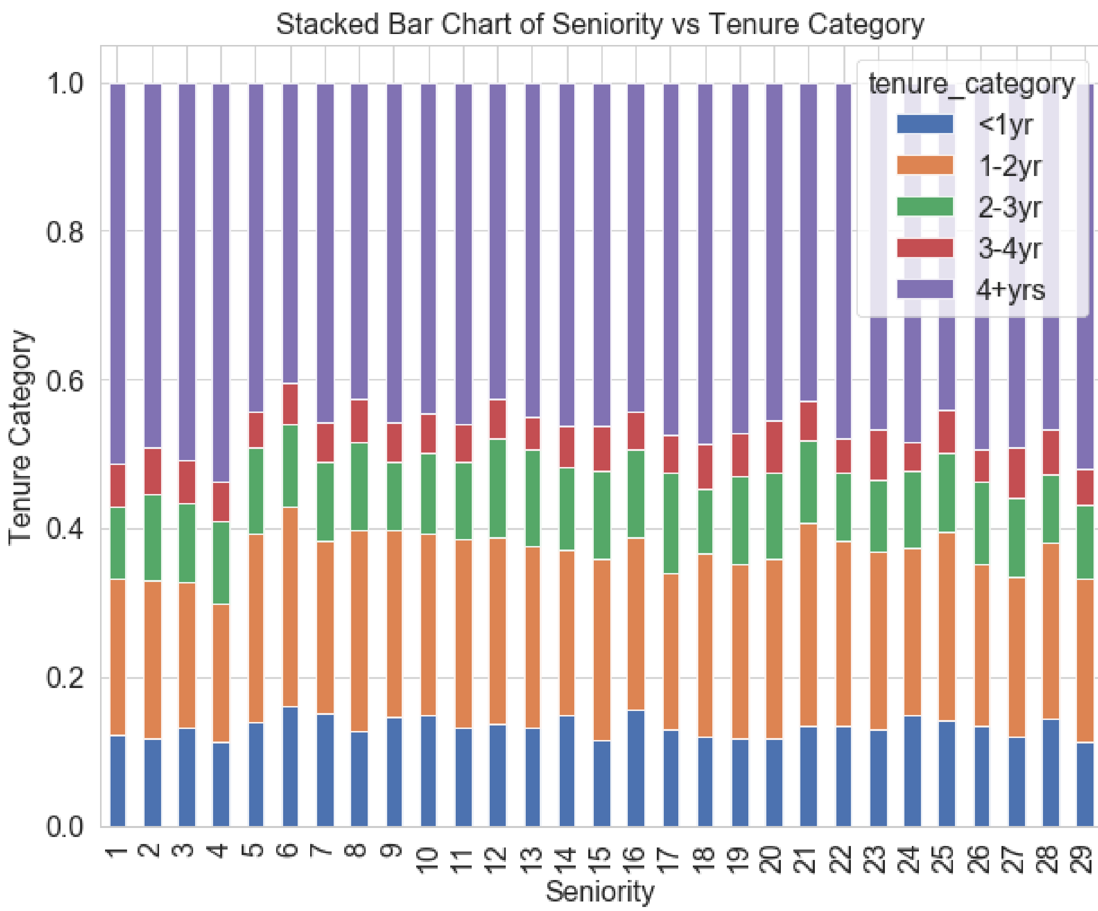
In [ ]:
```
########## A few quick visuals to look at how some of the features are potentially rel
```

In [45]:
```
# Salary and tenure category:
table=pd.crosstab(dc1_NEW.salary_rank, dc1_NEW.tenure_category)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Salary vs Tenure Category')
plt.xlabel('Salary')
plt.ylabel('Tenure Category')

# CONCLUDE:
# Really, not stand-out trends. But, it is surprising that the very high salary group
```

Out[45]:
```
Text(0, 0.5, 'Tenure Category')
```

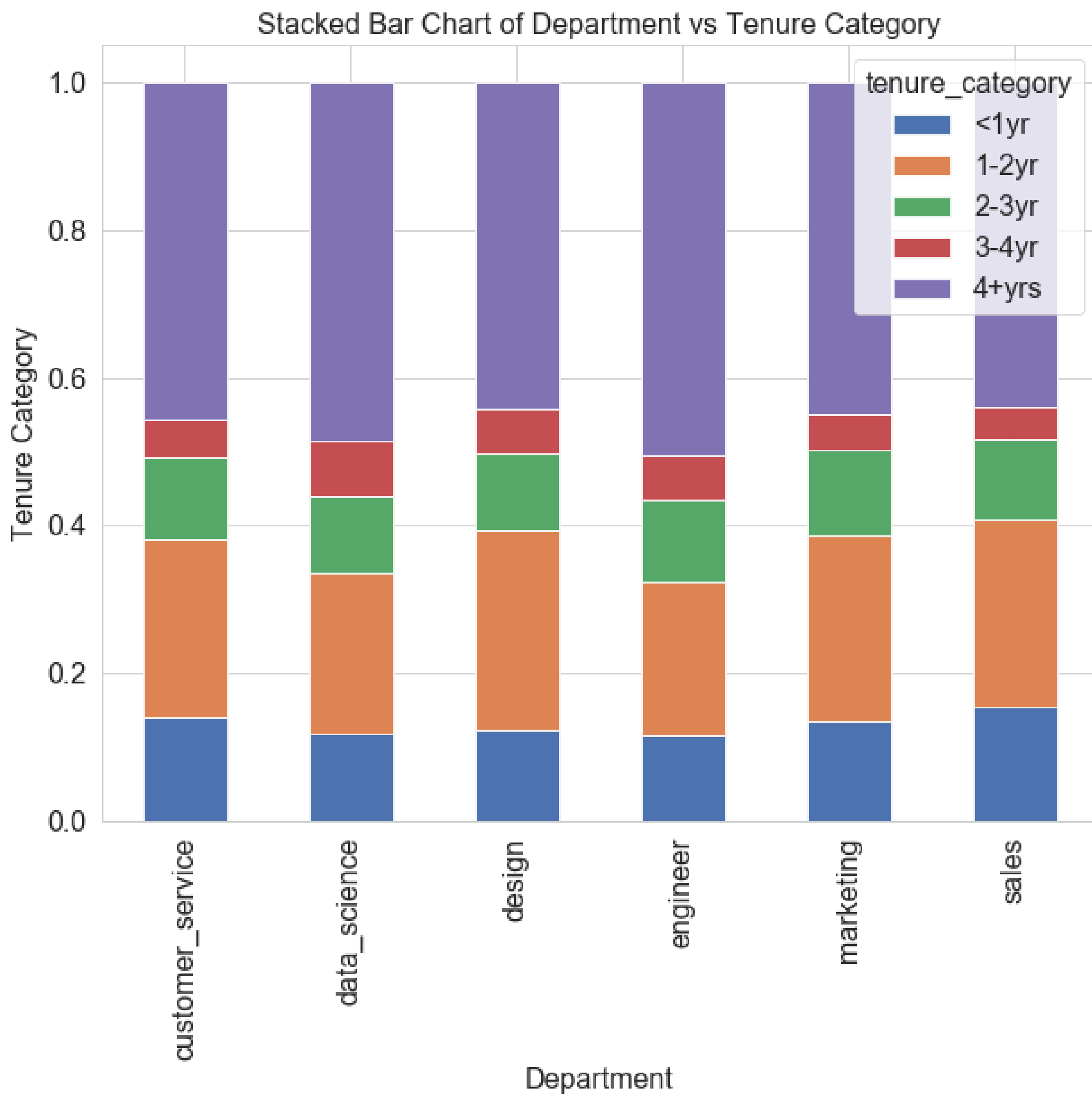



```
In [46]: # Seniority and tenure category:
         table=pd.crosstab(dc1_NEW.seniority, dc1_NEW.tenure_category)
         table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
         plt.title('Stacked Bar Chart of Seniority vs Tenure Category')
         plt.xlabel('Seniority')
         plt.ylabel('Tenure Category')

         # CONCLUDE:
         # No major stand-out trends.

Out[46]: Text(0, 0.5, 'Tenure Category')
```



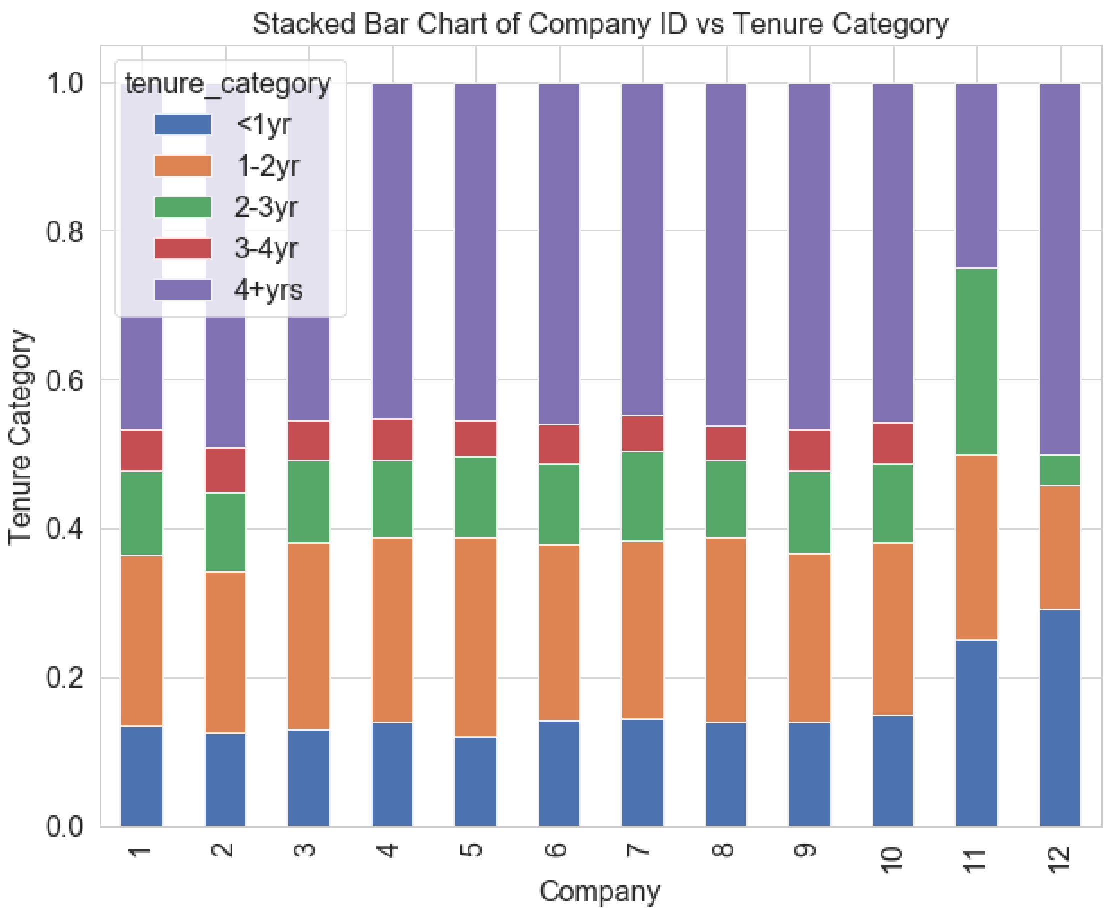
In [47]:
```
# Department and tenure category:
table=pd.crosstab(dc1_NEW.dept, dc1_NEW.tenure_category)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Department vs Tenure Category')
plt.xlabel('Department')
plt.ylabel('Tenure Category')

# CONCLUDE:
# No real trends here either.
```

Out[47]:
```
Text(0, 0.5, 'Tenure Category')
```



In [48]:
```
# Company ID and tenure category:
table=pd.crosstab(dc1_NEW.company_id, dc1_NEW.tenure_category)
table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=True)
plt.title('Stacked Bar Chart of Company ID vs Tenure Category')
plt.xlabel('Company')
plt.ylabel('Tenure Category')

# CONCLUDE:
# company 11 and 12 really appear different than the others.
# previously looked at sum of number of employees - counts - need to include this her
```

Out[48]:
```
Text(0, 0.5, 'Tenure Category')
```

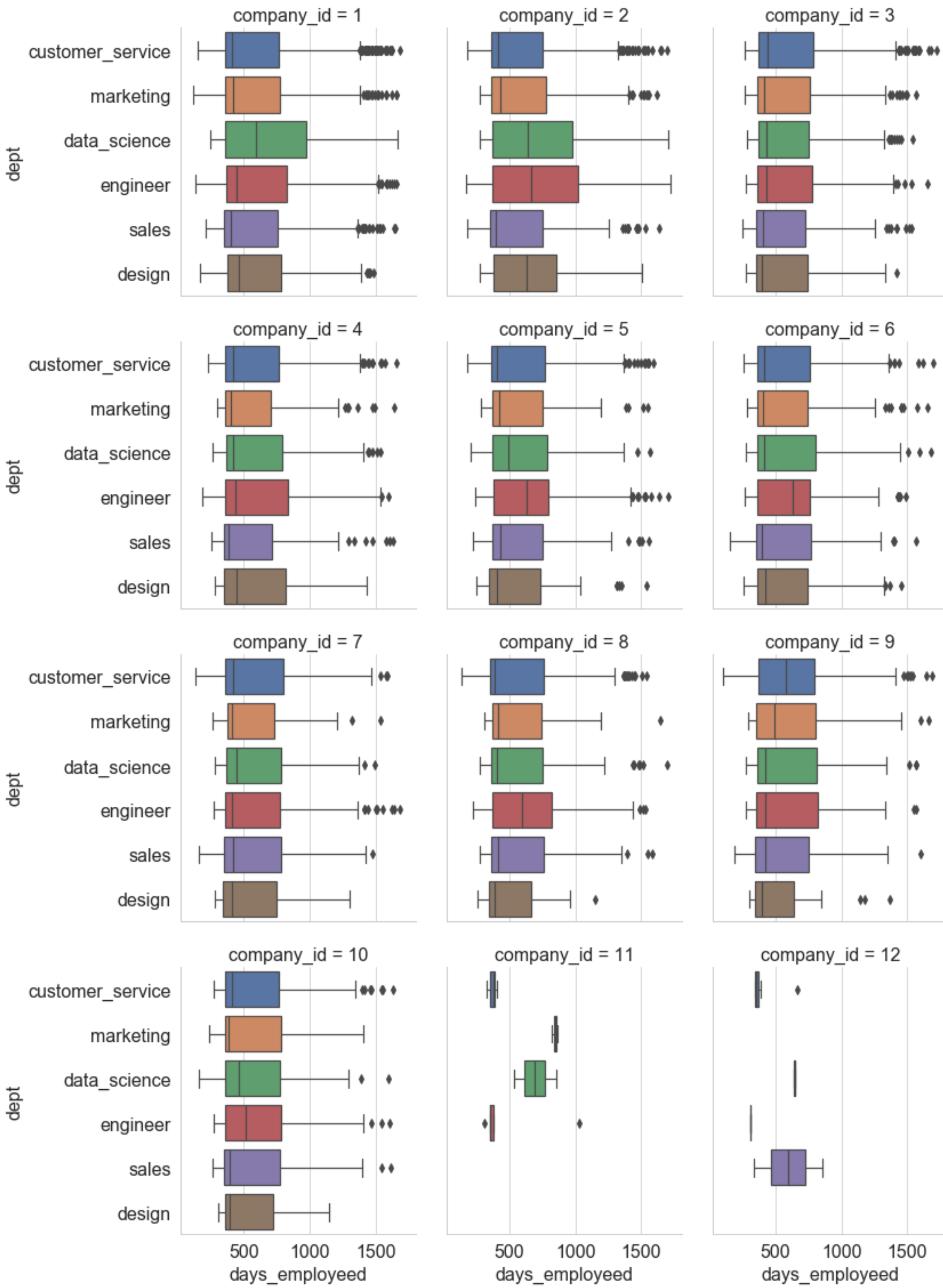



```
In [51]: # Just to get some real counts for eyeball comparison of employment (y/n) across depa
         counts = dc1_NEW.groupby(['still_employeed'])['dept'].value_counts().values
         counts
         # what is returned is whether someone is still employeed : 0 or 1 in that order for e
         # customer service: 5094 not employeed; 2355 employeed... and so on.

Out[51]: array([5094, 2355, 1811, 1782, 1681,  778, 4086, 2245, 1499, 1384, 1361,
                 602])

In [238]: # Now, let's quickly take a look JUST at the people who quit:

          past_employees_df = dc1_NEW[dc1_NEW.still_employeed == '0']
          #past_employees_df.head(20)

          # also check the opposite
          #current_employees_df = dc1_NEW[dc1_NEW.still_employeed == '1']
          #current_employees_df.head(20)

In [62]: # Change data types for next step visualizations
         past_employees_df["company_id"] = past_employees_df["company_id"].astype(int)
```

```
past_employees_df["days_employeed"] = past_employees_df["days_employeed"].astype(int)
past_employees_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13501 entries, 0 to 24699
Data columns (total 15 columns):
employee_id           13501 non-null float64
company_id            13501 non-null int64
dept                  13501 non-null object
seniority             13501 non-null int64
salary                13501 non-null float64
join_date             13501 non-null datetime64[ns]
quit_date             13501 non-null datetime64[ns]
total_tenure          13501 non-null timedelta64[ns]
days_employeed        13501 non-null int64
start_year            13501 non-null int64
start_month           13501 non-null int64
days_employeed_cont   13501 non-null float64
tenure_category       13501 non-null category
still_employeed       13501 non-null object
salary_rank           13501 non-null category
dtypes: category(2), datetime64[ns](2), float64(3), int64(5), object(2), timedelta64[ns](1)
memory usage: 2.1+ MB


/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
  """Entry point for launching an IPython kernel.
/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```

```
In [63]: # Let's visualize days employeed by department and company for this past employees da
         g = sns.catplot(x="days_employeed", y="dept", col="company_id", data=past_employees_d

         # CONCLUDE:
         # For the people who *have* quit, iut doesn't look like there's a huge departmental d
         # Company 11 and 12 are really different than the rest b/c of the dept that they have
```

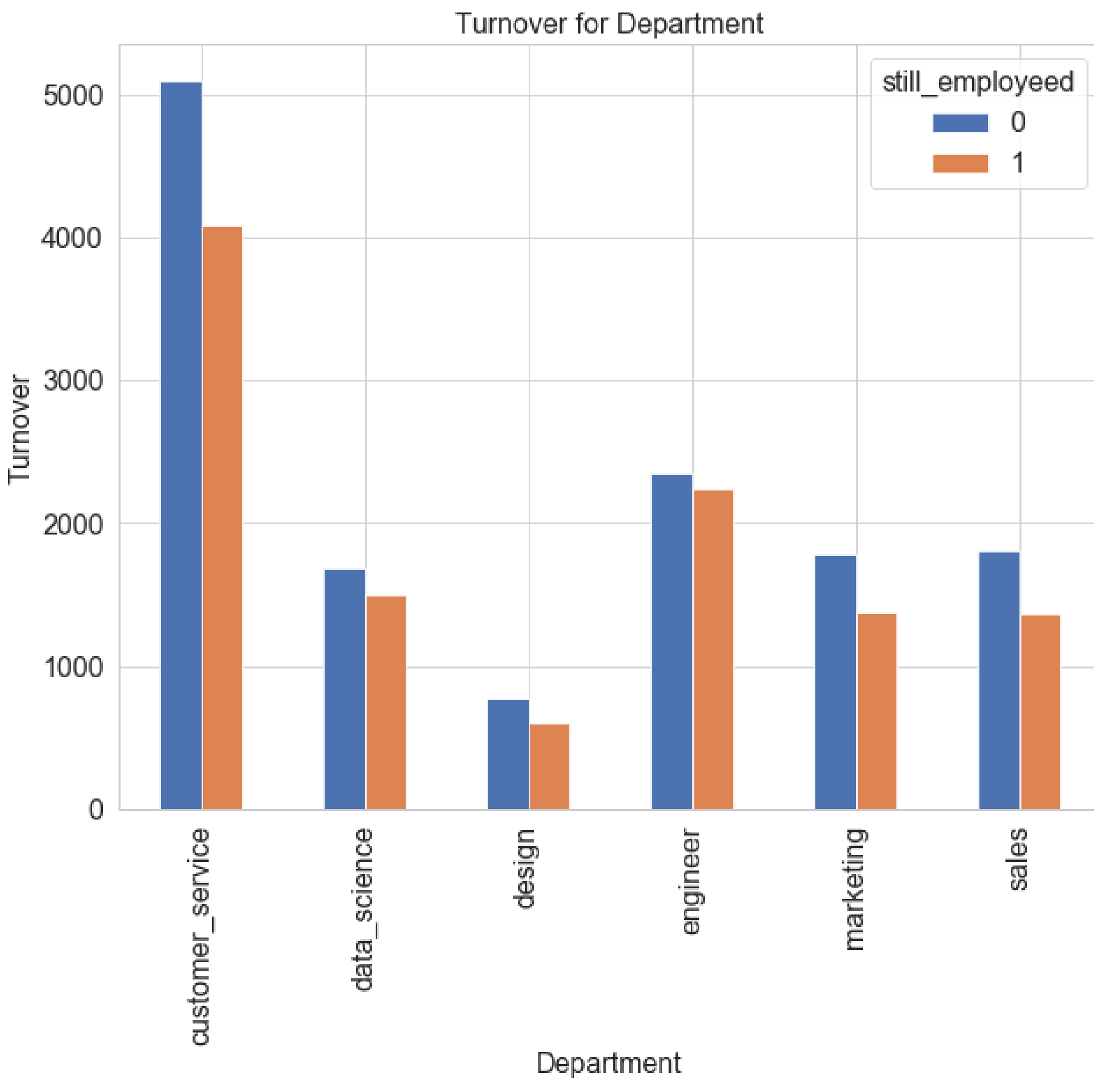


In [49]: # Swithcing back to large/whole dataset, visualize relationship between dept and bina

```
pd.crosstab(dc1_NEW.dept,dc1_NEW.still_employeed).plot(kind='bar')
```

```
plt.title('Turnover for Department')
plt.xlabel('Department')
plt.ylabel('Turnover')

# CONCLUDE:
# Maybe, the gap between those who have left (0) and those who have stayed (1) at the
```

Out[49]: Text(0, 0.5, 'Turnover')



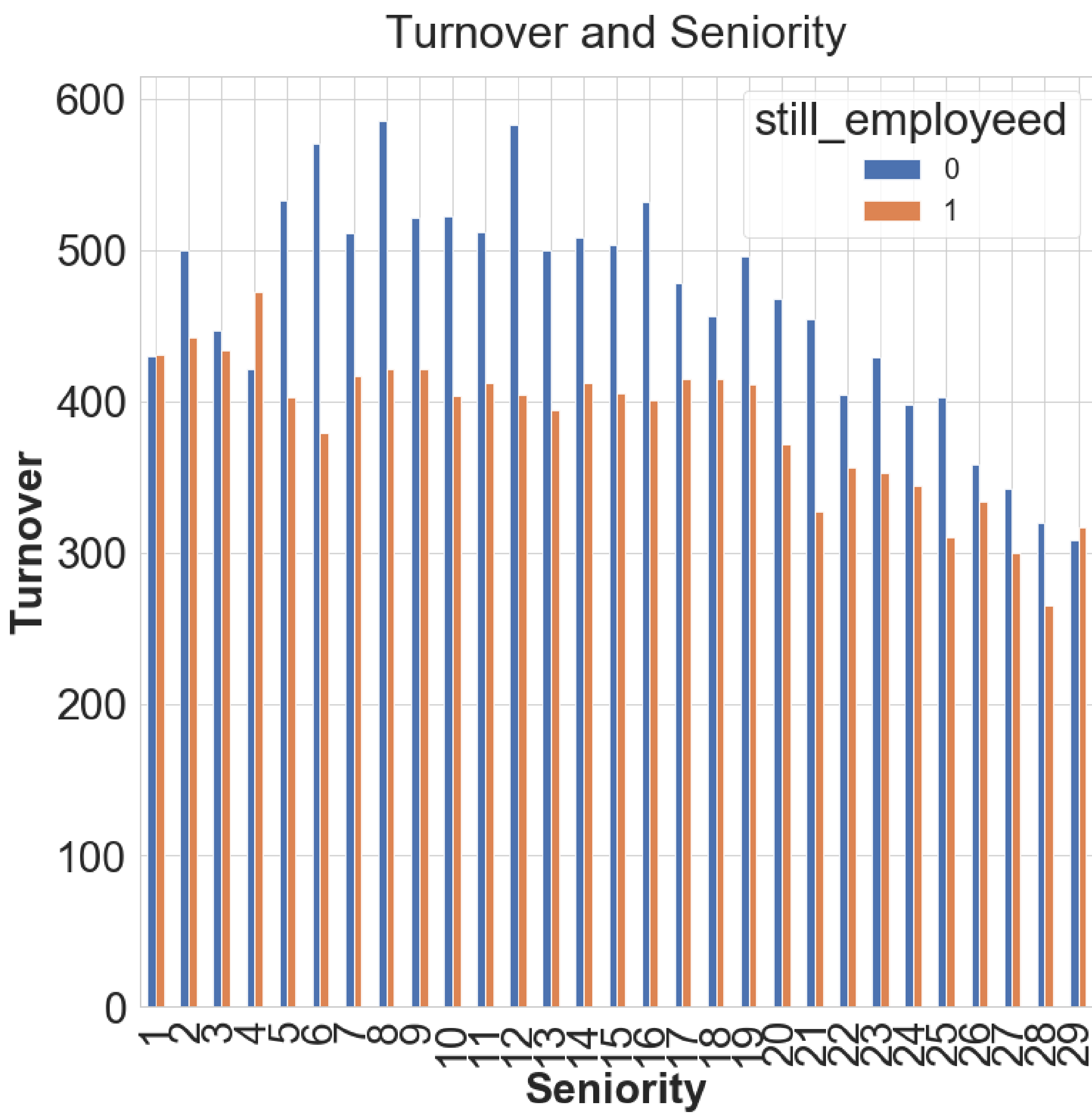
In [50]:
```
# Salary and turnover classification (still employeed or not)
pd.crosstab(dc1_NEW.salary_rank,dc1_NEW.still_employeed).plot(kind='bar')
plt.title('Turnover and Salary')
plt.xlabel('Salary')
plt.ylabel('Turnover')
```

```
# CONCLUDE:
# Maybe, the gap between those who quit and those who are still working is larger for
```

Out[50]: Text(0, 0.5, 'Turnover')


```
In [235]: # Seniority and turnover classification (still employeed or not)
          plt.rcParams['figure.figsize'] = (12.0, 12.0)
          pd.crosstab(dc1_NEW.seniority,dc1_NEW.still_employeed).plot(kind='bar')
          plt.title('Turnover and Seniority')
          plt.xlabel('Seniority')
          plt.ylabel('Turnover')

          # CONCLUDE:
          # Not a super striking pattern, but maybe for mid-range seniority levels 5-20 years,
          # Only instance where more people stayed than left is 4 years experience.
```

Out[235]: Text(0, 0.5, 'Turnover')




```
In [65]: # OK! Now we've looked at the data and are ready to get started with analyses with ei
         # A categorical Y/outcome could be the multiple tenure categories or the binary tenur
         dc1_NEW.head(20)
```

Out[65]:

	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
10     892155.0            6  customer_service         13   72000.0 2012-11-12
11     904158.0            2         marketing         17  230000.0 2015-05-11
12     939058.0            1         marketing          1   48000.0 2012-12-10
13     163427.0           10         marketing         23  154000.0 2012-06-18
14     461248.0            2             sales         20  201000.0 2013-09-16
15     265226.0            1      data_science          4   80000.0 2014-05-27
16     932790.0            7         marketing         10   88000.0 2011-11-30
17      69693.0            7  customer_service          6   54000.0 2014-03-31
18     721600.0            2         marketing         20  193000.0 2014-12-29
19     982668.0            1  customer_service         14   76000.0 2015-07-27

    quit_date total_tenure       days_employeed  start_year  start_month  \
0  2015-10-30     585 days                  585        2014            3
1  2014-04-04     340 days                  340        2013            4
2         NaT          NaT  currently_employeed        2014           10
3  2013-06-07     389 days                  389        2012            5
4  2014-08-22    1040 days                 1040        2011           10
5  2013-08-30     578 days                  578        2012            1
6         NaT          NaT  currently_employeed        2013           10
7         NaT          NaT  currently_employeed        2014            3
8  2015-10-23    1047 days                 1047        2012           12
9         NaT          NaT  currently_employeed        2012            6
10 2015-02-27     837 days                  837        2012           11
11        NaT          NaT  currently_employeed        2015            5
12 2013-11-15     340 days                  340        2012           12
13 2015-09-25    1194 days                 1194        2012            6
14 2014-08-22     340 days                  340        2013            9
15 2015-07-10     409 days                  409        2014            5
16 2013-11-22     723 days                  723        2011           11
17        NaT          NaT  currently_employeed        2014            3
18        NaT          NaT  currently_employeed        2014           12
19        NaT          NaT  currently_employeed        2015            7

    days_employeed_cont tenure_category still_employeed salary_rank
0                 585.0           1-2yr               0         med
1                 340.0            <1yr               0        high
2                1850.0           4+yrs               1         med
3                 389.0           1-2yr               0         med
4                1040.0           2-3yr               0   very_high
5                 578.0           1-2yr               0        high
6                1850.0           4+yrs               1         med
7                1850.0           4+yrs               1         low
8                1047.0           2-3yr               0        high
9                1850.0           4+yrs               1         med
10                837.0           2-3yr               0         low
11               1850.0           4+yrs               1   very_high
```

```
12           340.0        <1yr            0         low
13          1194.0       3-4yr            0        high
14           340.0        <1yr            0   very_high
15           409.0       1-2yr            0         med
16           723.0       2-3yr            0         med
17          1850.0       4+yrs            1         low
18          1850.0       4+yrs            1   very_high
19          1850.0       4+yrs            1         low
```

In [73]:
```python
# I have a dataframe called 'dc1_NEW' that includes all 12 companies.

# But, because company 11 and 12 seem to be very different from the rest, I may want

reduced_companies_df = dc1_NEW[dc1_NEW.company_id <= 10]
reduced_companies_df.head(20)
#reduced_companies_df['company_id'].unique() # double check that this did what I aske
```

Out[73]:
```
    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
10     892155.0           6  customer_service         13   72000.0 2012-11-12
11     904158.0           2         marketing         17  230000.0 2015-05-11
12     939058.0           1         marketing          1   48000.0 2012-12-10
13     163427.0          10         marketing         23  154000.0 2012-06-18
14     461248.0           2             sales         20  201000.0 2013-09-16
15     265226.0           1      data_science          4   80000.0 2014-05-27
16     932790.0           7         marketing         10   88000.0 2011-11-30
17      69693.0           7  customer_service          6   54000.0 2014-03-31
18     721600.0           2         marketing         20  193000.0 2014-12-29
19     982668.0           1  customer_service         14   76000.0 2015-07-27

    quit_date total_tenure      days_employeed  start_year  start_month  \
0  2015-10-30     585 days                 585        2014            3
1  2014-04-04     340 days                 340        2013            4
2         NaT          NaT  currently_employeed        2014           10
3  2013-06-07     389 days                 389        2012            5
4  2014-08-22    1040 days                1040        2011           10
5  2013-08-30     578 days                 578        2012            1
6         NaT          NaT  currently_employeed        2013           10
7         NaT          NaT  currently_employeed        2014            3
```

```
8  2015-10-23    1047 days                 1047        2012           12
9         NaT          NaT  currently_employeed        2012            6
10 2015-02-27     837 days                  837        2012           11
11        NaT          NaT  currently_employeed        2015            5
12 2013-11-15     340 days                  340        2012           12
13 2015-09-25    1194 days                 1194        2012            6
14 2014-08-22     340 days                  340        2013            9
15 2015-07-10     409 days                  409        2014            5
16 2013-11-22     723 days                  723        2011           11
17        NaT          NaT  currently_employeed        2014            3
18        NaT          NaT  currently_employeed        2014           12
19        NaT          NaT  currently_employeed        2015            7

    days_employeed_cont tenure_category still_employeed salary_rank
0                 585.0           1-2yr               0         med
1                 340.0            <1yr               0        high
2                1850.0           4+yrs               1         med
3                 389.0           1-2yr               0         med
4                1040.0           2-3yr               0   very_high
5                 578.0           1-2yr               0        high
6                1850.0           4+yrs               1         med
7                1850.0           4+yrs               1         low
8                1047.0           2-3yr               0        high
9                1850.0           4+yrs               1         med
10                837.0           2-3yr               0         low
11               1850.0           4+yrs               1   very_high
12                340.0            <1yr               0         low
13               1194.0           3-4yr               0        high
14                340.0            <1yr               0   very_high
15                409.0           1-2yr               0         med
16                723.0           2-3yr               0         med
17               1850.0           4+yrs               1         low
18               1850.0           4+yrs               1   very_high
19               1850.0           4+yrs               1         low
```

In [ ]:
```
# Now I also have a dataframe called 'reduced_companies_df' that includes just compani
```

In [ ]:
```
########## MODELING PORTION OF NB STARTS HERE ########## --->
```

In [97]:
```
# I will first define the X array and the Y/target variable in two sets from the redu
# 'Can I determine whether someone stays at a company for less than a year, 1-2 years

y = reduced_companies_df[['tenure_category']]

# I decided not to include company ID as a predictor here since I presumably want to
# will use continuous values of salary here, first instead of the categorical salary

X = reduced_companies_df[['dept','seniority', 'salary', 'start_year', 'start_month']]
```

In [98]:
```
# Check new X df
X.head()
#X.shape
```

Out[98]:

	dept	seniority	salary	start_year	start_month
0	customer_service	28	89000.0	2014	3
1	marketing	20	183000.0	2013	4
2	marketing	14	101000.0	2014	10
3	customer_service	20	115000.0	2012	5
4	data_science	23	276000.0	2011	10

In [99]:
```
# Check new y dataframe
y.head()
y.shape
```

Out[99]: (24638, 1)

In [100]:
```
# Get dummy variables for categorical features; use drop_first to get rid of the ext
X = pd.concat([X,pd.get_dummies(X['dept'], prefix='dept', drop_first=True)],axis=1)
X.head()

# drop old dept column since it is no longer informative.
X = X.drop(['dept'], axis=1)
X.head()
```

Out[100]:

	seniority	salary	start_year	start_month	dept_data_science	\
0	28	89000.0	2014	3	0	
1	20	183000.0	2013	4	0	
2	14	101000.0	2014	10	0	
3	20	115000.0	2012	5	0	
4	23	276000.0	2011	10	1	

	dept_design	dept_engineer	dept_marketing	dept_sales
0	0	0	0	0
1	0	0	1	0
2	0	0	1	0
3	0	0	0	0
4	0	0	0	0

In [101]:
```
#check new X dataframe
X.shape
```

Out[101]: (24638, 9)

In [102]:
```
# Import modules and libraries for modeling

from sklearn.model_selection import train_test_split # to create the split in traini
from sklearn.model_selection import RandomizedSearchCV # test a bunch of parameter v
from sklearn.model_selection import GridSearchCV # hone in on exact parameter values
```

```
from sklearn.model_selection import cross_val_score # to get performance in the 5 (o
from sklearn import metrics # to be able to use recall and any other metric for mode
from sklearn.metrics import classification_report # nice format to show all model pe
from sklearn.metrics import confusion_matrix # classic TP/FP assessment
from sklearn.metrics import roc_curve # another metric of performance for comparing 
```

In [103]:
```
# create training and test data sets based on X and y defined above. Will set test s

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

In [104]:
```
# take a look at the new X_train, X_test, y_train, and y_test
X_train.head()
X_train.shape
```

Out[104]: (19710, 9)

In [105]:
```
X_test.shape
```

Out[105]: (4928, 9)

In [106]:
```
y_train.shape
```

Out[106]: (19710, 1)

In [107]:
```
y_test.shape
y_test.head()
```

Out[107]:

	tenure_category
4396	<1yr
20473	2-3yr
9680	4+yrs
21359	4+yrs
15854	4+yrs

In [108]:
```
# Check for class imbalance, which could affect model performance metrics like accur
y_train.tenure_category.value_counts()
```

Out[108]:
```
4+yrs    9181
1-2yr    4654
<1yr     2625
2-3yr    2170
3-4yr    1080
Name: tenure_category, dtype: int64
```

In [109]:
```
y_test.tenure_category.value_counts()
```

Out[109]:
```
4+yrs    2296
1-2yr    1163
<1yr      656
2-3yr     543
3-4yr     270
Name: tenure_category, dtype: int64
```

In [110]:
```
# Determine that there is a pretty big class imbalance: i will use smote to balance

import imblearn as imblearn # for SMOTE applied to training set only
from imblearn.over_sampling import SMOTE # for SMOTE applied to training set only
from collections import Counter # to easily check old and new class sizes

sm = SMOTE(random_state=11)
X_res_train, y_res_train = sm.fit_resample(X_train, y_train)
print('Resampled dataset shape %s' % Counter(y_res_train))
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataConversionWarning:
  y = column_or_1d(y, warn=True)


Resampled dataset shape Counter({'1-2yr': 9181, '4+yrs': 9181, '<1yr': 9181, '2-3yr': 9181, '3
```

In [114]:
```
# Check new df
y_res_train.shape
#y_res_train
```

Out[114]: (45905,)

In [116]:
```
# Check new df
X_res_train.shape
#X_res_train
```

Out[116]: (45905, 9)

In [ ]:
```
# Great! Now I'm ready to run some classifier models. Can't use logistic regression wi
# I won't do any recursive feature selection to begin because there's already such a r
# Start by defining some randomized search parameters for hyperparameter tuning follow
```

In [144]:
```
# parameters that CAN be set in RF classifier; set up random space over which to sea

# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 10, stop = 100, num = 5)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt', 2, 4, 8]
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(2, 10, 2)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [10, 50]
# Minimum number of samples required at each leaf node
min_samples_leaf = [5, 10, 25]
# Method of selecting samples for training each tree
#bootstrap = [True]
```

```
In [145]: # Create the random grid
          random_grid = {'n_estimators': n_estimators,
                         'max_features': max_features,
                         'max_depth': max_depth,
                         'min_samples_split': min_samples_split,
                         'min_samples_leaf': min_samples_leaf,
                         'bootstrap': bootstrap}

          print(random_grid)

{'n_estimators': [10, 32, 55, 77, 100], 'max_features': ['auto', 'sqrt', 2, 4, 8], 'max_depth'
```

```
In [146]: from sklearn.ensemble import RandomForestClassifier

          # Use the random grid to search for best hyperparameters
          # First create the base model to tune
          RF = RandomForestClassifier()
          #RF.fit(X_res_train, y_res_train)
          #y_pred=RF.predict(X_test)
          #print(classification_report(y_test, y_pred))


          # Random search of parameters, using 5 fold cross validation, on the training set; I
          RF_random = RandomizedSearchCV(estimator = RF, param_distributions = random_grid, n_
```

```
In [147]: # Fit the random search model to the SMOTE adjusted training data set
          RF_random.fit(X_res_train, y_res_train)

Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   42.3s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  3.8min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  7.2min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  9.8min finished


Out[147]: RandomizedSearchCV(cv=5, error_score='raise-deprecating',
                    estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criter
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False),
                    fit_params=None, iid='warn', n_iter=100, n_jobs=-1,
                    param_distributions={'n_estimators': [10, 32, 55, 77, 100], 'max_features'
```

```
                    pre_dispatch='2*n_jobs', random_state=42, refit=True,
                    return_train_score='warn', scoring='accuracy', verbose=2)
```

In [148]:
```
# Get the best parameters from the randomized search
RF_random.best_params_
```

Out[148]:
```
{'n_estimators': 100,
 'min_samples_split': 10,
 'min_samples_leaf': 5,
 'max_features': 8,
 'max_depth': None,
 'bootstrap': True}
```

In [149]:
```
# Run cross validation using the best parameters and then average them to get an ide
CV_scores = cross_val_score(RF_random, X_res_train, y_res_train, cv=5, scoring = 'ac
print(CV_scores)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   40.9s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  2.5min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  5.2min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  7.0min finished


Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   30.1s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  4.7min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  6.8min finished


Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   29.0s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  4.5min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  6.1min finished


Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   27.7s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  4.3min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  5.9min finished
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   27.5s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed:  4.3min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  5.9min finished
```

```
[0.43048449 0.60141612 0.64858388 0.61448802 0.61023965]
```

In [150]:
```
print("Accuracy of A RF classifier in Cross Validation: %0.2f (+/- %0.2f)" % (CV_sco
```

```
Accuracy of A RF classifier in Cross Validation: 0.58 (+/- 0.15)
```

In [151]:
```
print(classification_report(y_test, y_pred))
# Not very good performance but notice that the model has an easier time classifying
# Maybe it would be easier to lump everyone who has quit (groups <1year up to 3-4yea
```

```
              precision    recall  f1-score   support

       1-2yr       0.33      0.37      0.35      1163
       2-3yr       0.20      0.20      0.20       543
       3-4yr       0.20      0.24      0.22       270
       4+yrs       0.71      0.70      0.70      2296
        <1yr       0.18      0.12      0.14       656

   micro avg       0.46      0.46      0.46      4928
   macro avg       0.32      0.33      0.32      4928
weighted avg       0.46      0.46      0.46      4928
```

In [152]:
```
# Showign the breakdown of classification with this RF model.
confusion_matrix(y_test, y_pred)
```

Out[152]:
```
array([[ 432,  168,  106,  315,  142],
       [ 222,  111,   60,   97,   53],
       [  96,   62,   65,   21,   26],
       [ 364,  125,   53, 1604,  150],
       [ 207,   89,   48,  233,   79]])
```

```
In [153]: print('Accuracy of A RF classifier on Test Set:', metrics.accuracy_score(y_test,y_pre
```

```
Accuracy of A RF classifier on Test Set: 0.4648944805194805
```

```
In [162]: # Re-run the model with parameters that I found above in randomized search:

          # {'n_estimators': 100,
           #'min_samples_split': 10,
           #'min_samples_leaf': 5,
           #'max_features': 8,
           #'max_depth': None,
           #'bootstrap': True}

          RF_test = RandomForestClassifier(n_estimators=100, min_samples_split=10, min_samples_
          #RF_test = RandomForestClassifier()
          RF_test.fit(X_res_train, y_res_train)
          y_pred=RF_test.predict(X_test)
          print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

       1-2yr       0.33      0.37      0.35      1163
       2-3yr       0.20      0.20      0.20       543
       3-4yr       0.21      0.32      0.25       270
       4+yrs       0.72      0.74      0.73      2296
        <1yr       0.18      0.08      0.11       656

   micro avg       0.48      0.48      0.48      4928
   macro avg       0.33      0.34      0.33      4928
weighted avg       0.47      0.48      0.47      4928
```

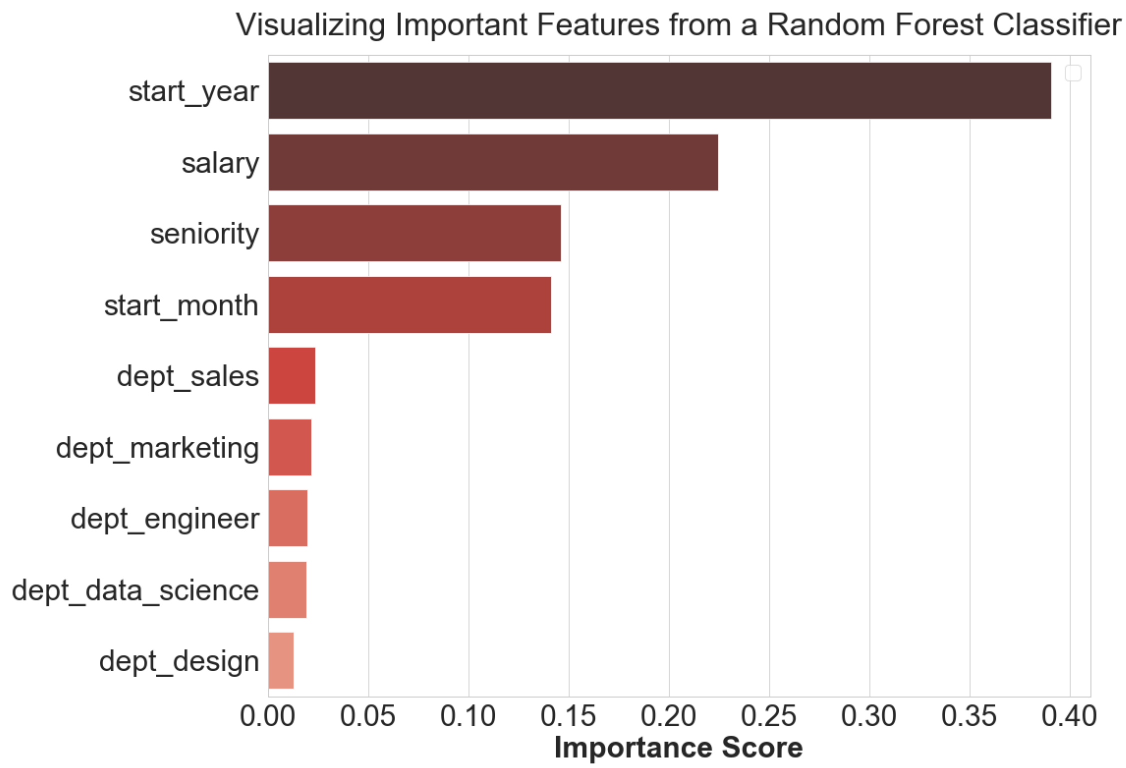
```
In [163]: # For this poorly performing model we can get an idea of which features might matter
          names = X.columns
          feature_imp = pd.Series(RF_test.feature_importances_,index=names).sort_values(ascendi
          feature_imp
```

```
Out[163]: start_year           0.390510
          salary               0.224351
          seniority            0.146317
          start_month          0.141169
          dept_sales           0.023781
          dept_marketing       0.021610
          dept_engineer        0.019929
          dept_data_science    0.019435
          dept_design          0.012898
          dtype: float64
```

In [164]:
```
# Plot feature imporance values from the RF classfier.

from matplotlib import rcParams

names = X.columns

feature_imp = pd.Series(RF_test.feature_importances_,index=names).sort_values(ascendi
feature_imp

plt.rcParams['figure.figsize'] = (15, 12)
plt.rcParams['axes.labelweight'] = 'bold'
#plt.rcParams["axes.labelsize"] = 30
rcParams['axes.titlepad'] = 20
sns.set(style='whitegrid')
sns.set_context("paper", rc={"font.size":32,"axes.titlesize":32,"axes.labelsize":30,

sns.barplot(x=feature_imp, y=feature_imp.index, palette='Reds_d')
# Add labels to your graph
plt.xlabel('Importance Score')
#plt.ylabel('Features')
plt.title("Visualizing Important Features from a Random Forest Classifier")
plt.legend()
```

```
No handles with labels found to put in legend.
```

Out[164]: <matplotlib.legend.Legend at 0x1a1dcc04e0>



In [ ]:
```
# Summary: the RF model does not do particularly well at predicting employee tenure wi
# Maybe, it would be better to predict based on the binary - quit or stayed (e.g. are y
# this means we could use an outcome variable like 'still_employeed' and apply logisti
# another alternative route would be to use days employeed as a continous outcome (e.g
```

In [165]:
```
# A quick reminder about the df: I will again use the reduced set of 10 companies fo

reduced_companies_df.head(20)
```

Out[165]:

	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	
10	892155.0	6	customer_service	13	72000.0	2012-11-12	
11	904158.0	2	marketing	17	230000.0	2015-05-11	
12	939058.0	1	marketing	1	48000.0	2012-12-10	
13	163427.0	10	marketing	23	154000.0	2012-06-18	
14	461248.0	2	sales	20	201000.0	2013-09-16	
15	265226.0	1	data_science	4	80000.0	2014-05-27	
16	932790.0	7	marketing	10	88000.0	2011-11-30	
17	69693.0	7	customer_service	6	54000.0	2014-03-31	
18	721600.0	2	marketing	20	193000.0	2014-12-29	
19	982668.0	1	customer_service	14	76000.0	2015-07-27	

	quit_date	total_tenure	days_employeed	start_year	start_month	\
0	2015-10-30	585 days	585	2014	3	
1	2014-04-04	340 days	340	2013	4	
2	NaT	NaT	currently_employeed	2014	10	
3	2013-06-07	389 days	389	2012	5	
4	2014-08-22	1040 days	1040	2011	10	
5	2013-08-30	578 days	578	2012	1	
6	NaT	NaT	currently_employeed	2013	10	
7	NaT	NaT	currently_employeed	2014	3	
8	2015-10-23	1047 days	1047	2012	12	
9	NaT	NaT	currently_employeed	2012	6	
10	2015-02-27	837 days	837	2012	11	
11	NaT	NaT	currently_employeed	2015	5	
12	2013-11-15	340 days	340	2012	12	

```
13 2015-09-25    1194 days                1194        2012             6
14 2014-08-22     340 days                 340        2013             9
15 2015-07-10     409 days                 409        2014             5
16 2013-11-22     723 days                 723        2011            11
17        NaT          NaT  currently_employeed        2014             3
18        NaT          NaT  currently_employeed        2014            12
19        NaT          NaT  currently_employeed        2015             7

    days_employeed_cont tenure_category still_employeed salary_rank
0                 585.0           1-2yr               0         med
1                 340.0            <1yr               0        high
2                1850.0           4+yrs               1         med
3                 389.0           1-2yr               0         med
4                1040.0           2-3yr               0   very_high
5                 578.0           1-2yr               0        high
6                1850.0           4+yrs               1         med
7                1850.0           4+yrs               1         low
8                1047.0           2-3yr               0        high
9                1850.0           4+yrs               1         med
10                837.0           2-3yr               0         low
11               1850.0           4+yrs               1   very_high
12                340.0            <1yr               0         low
13               1194.0           3-4yr               0        high
14                340.0            <1yr               0   very_high
15                409.0           1-2yr               0         med
16                723.0           2-3yr               0         med
17               1850.0           4+yrs               1         low
18               1850.0           4+yrs               1   very_high
19               1850.0           4+yrs               1         low
```

In [166]:
```python
# Here the outcome/predicted variable will be binary, still employeed or not.
y = reduced_companies_df[['still_employeed']]

# I decided not to include company ID as a predictor here since I presumably want to
# will use continuous values of salary here, first instead of the categorical salary

X = reduced_companies_df[['dept','seniority', 'salary', 'start_year', 'start_month']]
```

In [167]:
```python
y.head()
```

Out[167]:
```
  still_employeed
0               0
1               0
2               1
3               0
4               0
```

In [168]:
```python
y.shape
```

Out[168]: (24638, 1)

In [169]:
```
X.head()
```

Out[169]:
```
                 dept  seniority    salary  start_year  start_month
0    customer_service         28   89000.0        2014            3
1           marketing         20  183000.0        2013            4
2           marketing         14  101000.0        2014           10
3    customer_service         20  115000.0        2012            5
4        data_science         23  276000.0        2011           10
```

In [170]:
```
# get dummy variables; use drop_first to get rid of the extra column when creating d
X = pd.concat([X,pd.get_dummies(X['dept'], prefix='dept', drop_first=True)],axis=1)
X.head()

# drop old dept column since it is no longer informative.
X = X.drop(['dept'], axis=1)
X.head()
```

Out[170]:
```
   seniority    salary  start_year  start_month  dept_data_science  \
0         28   89000.0        2014            3                  0
1         20  183000.0        2013            4                  0
2         14  101000.0        2014           10                  0
3         20  115000.0        2012            5                  0
4         23  276000.0        2011           10                  1

   dept_design  dept_engineer  dept_marketing  dept_sales
0            0              0               0           0
1            0              0               1           0
2            0              0               1           0
3            0              0               0           0
4            0              0               0           0
```

In [171]:
```
# create training and test data sets based on X and y defined above. Will set test s
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

In [173]:
```
# check for class imbalance
y_train.still_employeed.value_counts()
```

Out[173]:
```
0    10781
1     8929
Name: still_employeed, dtype: int64
```

In [175]:
```
# Class imbalance is not too bad here, but I will apply SMOTE anyway, to give us the
sm = SMOTE(random_state=11)
X_res_train, y_res_train = sm.fit_resample(X_train, y_train.values.ravel())
print('Resampled dataset shape %s' % Counter(y_res_train))
```

```
Resampled dataset shape Counter({'1': 10781, '0': 10781})
```

```
In [176]: # Now we are ready now to try logistic regression and then RF with this binary outco

          RF = RandomForestClassifier()
          RF.fit(X_res_train, y_res_train)
          y_pred=RF.predict(X_test)
          print(classification_report(y_test, y_pred))

          # Not too bad! no parameter tuning at this point and already doing better than the p
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The defau
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)


              precision    recall  f1-score   support

           0       0.75      0.81      0.78      2696
           1       0.75      0.67      0.71      2232

   micro avg       0.75      0.75      0.75      4928
   macro avg       0.75      0.74      0.75      4928
weighted avg       0.75      0.75      0.75      4928
```

```
In [177]: confusion_matrix(y_test, y_pred)

Out[177]: array([[2194,  502],
                 [ 726, 1506]])
```

```
In [179]: print('Overall accuracy of a binary RF classifier on the Test Set:', metrics.accuracy
```

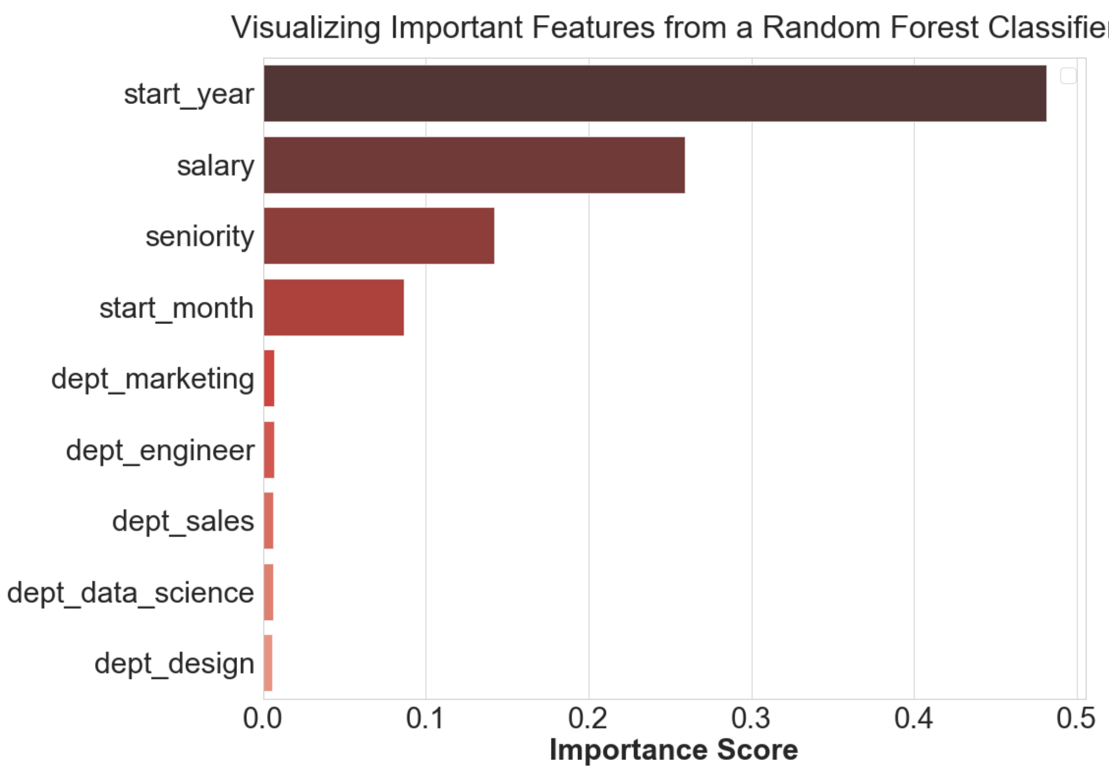
```
Overall accuracy of a binary RF classifier on the Test Set: 0.7508116883116883
```

```
In [180]: names = X.columns
          feature_imp = pd.Series(RF.feature_importances_,index=names).sort_values(ascending=Fa
          feature_imp

Out[180]: start_year          0.481252
          salary              0.259028
          seniority           0.141801
          start_month         0.086294
          dept_marketing      0.007004
          dept_engineer       0.006501
          dept_sales          0.006479
          dept_data_science   0.006001
          dept_design         0.005639
          dtype: float64
```

```
In [181]: names = X.columns

          feature_imp = pd.Series(RF.feature_importances_,index=names).sort_values(ascending=Fa
          feature_imp

          plt.rcParams['figure.figsize'] = (15, 12)
          plt.rcParams['axes.labelweight'] = 'bold'
          #plt.rcParams["axes.labelsize"] = 30
          rcParams['axes.titlepad'] = 20
          sns.set(style='whitegrid')
          sns.set_context("paper", rc={"font.size":32,"axes.titlesize":32,"axes.labelsize":30,

          sns.barplot(x=feature_imp, y=feature_imp.index, palette='Reds_d')
          # Add labels to your graph
          plt.xlabel('Importance Score')
          #plt.ylabel('Features')
          plt.title("Visualizing Important Features from a Random Forest Classifier")
          plt.legend()
```

```
No handles with labels found to put in legend.
```

```
Out[181]: <matplotlib.legend.Legend at 0x1a200bdd30>
```



```
In [195]: # Summary up to here: I could now tune the hyperparameters of this RF before moving 

          from sklearn.linear_model import LogisticRegression

          logreg = LogisticRegression()
          #logreg.fit(X_res_train, y_res_train)
          #y_pred = logreg.predict(X_test)
          #logreg.score(X_test,y_test)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
```

```
Out[195]: 0.5355113636363636
```

```
In [186]: c_space = np.logspace(-5, 8, 15)
          param_grid = {'C': c_space, 'penalty': ['l1', 'l2']}
```

```
In [187]: # Instantiate the GridSearchCV object: logreg_cv
          logreg_cv = GridSearchCV(logreg, param_grid, cv=5, scoring = 'accuracy')
```

```
In [188]: logreg_cv.fit(X_res_train, y_res_train)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
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  FutureWarning)
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  "the number of iterations.", ConvergenceWarning)
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/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
```

```
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  FutureWarning)
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  FutureWarning)
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  FutureWarning)
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  FutureWarning)
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  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: Def
  FutureWarning)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/svm/base.py:931: ConvergenceWarning: Liblinear 
  "the number of iterations.", ConvergenceWarning)
```

```
Out[188]: GridSearchCV(cv=5, error_score='raise-deprecating',
                 estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interc
                    intercept_scaling=1, max_iter=100, multi_class='warn',
                    n_jobs=None, penalty='l2', random_state=None, solver='warn',
                    tol=0.0001, verbose=0, warm_start=False),
                 fit_params=None, iid='warn', n_jobs=None,
                 param_grid={'C': array([1.00000e-05, 8.48343e-05, 7.19686e-04, 6.10540e-03, 5
                 4.39397e-01, 3.72759e+00, 3.16228e+01, 2.68270e+02, 2.27585e+03,
                 1.93070e+04, 1.63789e+05, 1.38950e+06, 1.17877e+07, 1.00000e+08]), 'penalty':
                 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                 scoring='accuracy', verbose=0)
```

```
In [189]: logreg_cv.best_params_
```

```
Out[189]: {'C': 268.2695795279727, 'penalty': 'l1'}
```

```
In [190]: CV_scores = cross_val_score(logreg, X_res_train, y_res_train, cv=5, scoring = 'accura
          print(CV_scores)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
```

```
[0.5336115  0.5403525  0.52017625 0.50834879 0.53200371]
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWarning: De
  FutureWarning)
```

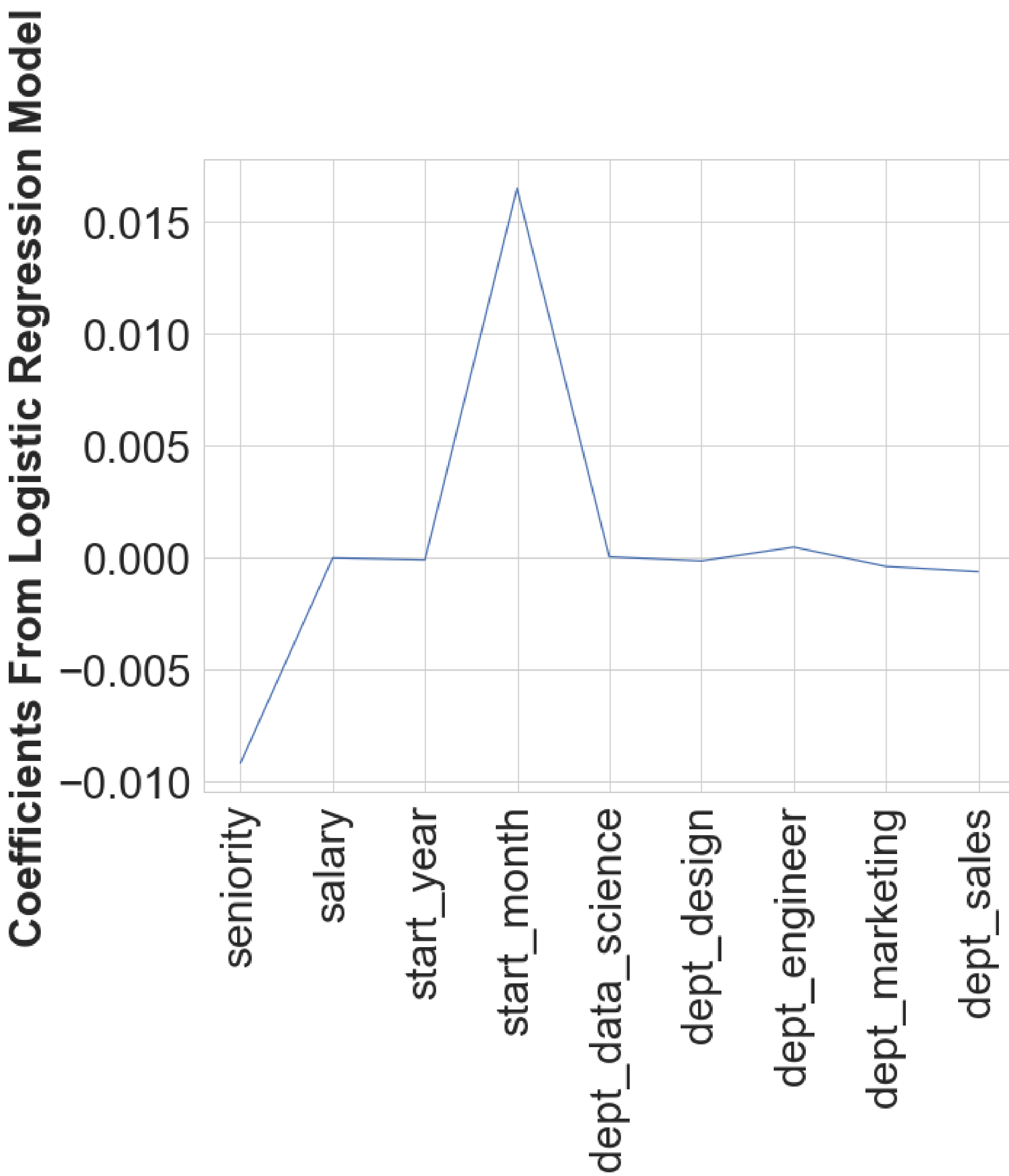
```
In [191]: print("Accuracy of A logistic regression classifier in Cross Validation: %0.2f (+/- %
```

```
Accuracy of A logistic regression classifier in Cross Validation: 0.53 (+/- 0.02)
```

```
In [192]: print('Accuracy of A logistic regression classifier on the Test Set:', metrics.accura
```

```
Accuracy of A logistic regression classifier on the Test Set: 0.5355113636363636
```

```
In [196]: coef = logreg.coef_[0]
          names = X.columns
          plt.rcParams['figure.figsize'] = (10.0, 8.0)
          _ = plt.plot(range(len(names)), coef)
          _ = plt.xticks(range(len(names)),names, rotation = 90)
          _ =plt.ylabel('Coefficients From Logistic Regression Model')
          plt.show()

          # start year and start month is important in both the RF and logreg models. There's
```



```
In [ ]: # So it appears that the logistic regression model performs less well than the random 
        # I will now go back to the RF classifier and look a little bit deeper at what the fea

In [198]: # Go back to the binary random forest classifier and do some hyperparameter tuning.

          RF = RandomForestClassifier()

In [201]: # parameters that CAN be set in RF classifier:

          # Number of trees in random forest
          n_estimators = [int(x) for x in np.linspace(start = 10, stop = 1000, num = 6)]
          # Number of features to consider at every split
          max_features = ['auto', 'sqrt', 2, 4, 8]
          # Maximum number of levels in tree
          max_depth = [int(x) for x in np.linspace(2, 10, 2)]
          max_depth.append(None)
          # Minimum number of samples required to split a node
          min_samples_split = [10, 50]
          # Minimum number of samples required at each leaf node
          min_samples_leaf = [5, 10, 25]
          # Method of selecting samples for training each tree
          #bootstrap = [True]

In [202]: # Create the random grid
          random_grid = {'n_estimators': n_estimators,
                         'max_features': max_features,
                         'max_depth': max_depth,
                         'min_samples_split': min_samples_split,
                         'min_samples_leaf': min_samples_leaf,
                         'bootstrap': bootstrap}

          print(random_grid)

{'n_estimators': [10, 208, 406, 604, 802, 1000], 'max_features': ['auto', 'sqrt', 2, 4, 8], 'ma

In [203]: # Random search of parameters, using 5 fold cross validation, on the training set
          RF_random = RandomizedSearchCV(estimator = RF, param_distributions = random_grid, n_
          # Fit the random search model to the SMOTE adjusted training data set
          RF_random.fit(X_res_train, y_res_train)

Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  2.1min
```

```
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  8.1min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 16.4min
/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/process_executo
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 22.8min finished
```

Out[203]:
```
RandomizedSearchCV(cv=5, error_score='raise-deprecating',
          estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criter
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False),
          fit_params=None, iid='warn', n_iter=100, n_jobs=-1,
          param_distributions={'n_estimators': [10, 208, 406, 604, 802, 1000], 'max_
          pre_dispatch='2*n_jobs', random_state=42, refit=True,
          return_train_score='warn', scoring='accuracy', verbose=2)
```

In [204]:
```
RF_random.best_params_
```

Out[204]:
```
{'n_estimators': 1000,
 'min_samples_split': 10,
 'min_samples_leaf': 5,
 'max_features': 'auto',
 'max_depth': 10,
 'bootstrap': True}
```

In [205]:
```
CV_scores = cross_val_score(RF_random, X_res_train, y_res_train, cv=5, scoring = 'ac
print(CV_scores)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  6.5min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 12.9min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 17.7min finished
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.5min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  6.7min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 13.0min
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/process_executo
  "timeout or by a memory leak.", UserWarning
/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/process_executo
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 18.0min finished


Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.4min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  7.2min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 13.0min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 17.4min finished


Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  6.7min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 13.1min
/anaconda3/lib/python3.6/site-packages/sklearn/externals/joblib/externals/loky/process_executo
  "timeout or by a memory leak.", UserWarning
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 17.4min finished


Fitting 5 folds for each of 100 candidates, totalling 500 fits


[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  6.2min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 11.7min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 17.5min finished


[0.78789986 0.80612245 0.78501855 0.79754174 0.81864564]
```

```
In [208]: print("Average accuracy of a tuned classifier in 5-fold cross validation on the trai
```

```
Average accuracy of a tuned classifier in 5-fold cross validation on the training data set : 0
```

```
In [209]: print('Accuracy of A logistic regression classifier on the held out test data set:',
```

```
Accuracy of A logistic regression classifier on the held out test data set: 0.7508116883116883
```

In [ ]: # The hyperparameter tuning applied to this RF classifier on a binary outcome (quit vs

In [210]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.75      0.82      0.78      2696
           1       0.75      0.67      0.71      2232

   micro avg       0.75      0.75      0.75      4928
   macro avg       0.75      0.74      0.75      4928
weighted avg       0.75      0.75      0.75      4928
```

In [213]:
```
# here is a list of the best parameters for the model:
#{'n_estimators': 1000,
 #'min_samples_split': 10,
 #'min_samples_leaf': 5,
 #'max_features': 'auto',
 #'max_depth': 10,
 #'bootstrap': True}

# fit a model with the parameters that were found so that I can get the feature impo
RF_test = RandomForestClassifier(n_estimators=1000, min_samples_split=10, min_samples
RF_test.fit(X_res_train, y_res_train)
y_pred=RF_test.predict(X_test)
print(classification_report(y_test, y_pred))

# so somehow with this random state the performance was just slightly better than be
```

```
              precision    recall  f1-score   support

           0       0.79      0.84      0.81      2696
           1       0.79      0.72      0.75      2232

   micro avg       0.79      0.79      0.79      4928
   macro avg       0.79      0.78      0.78      4928
weighted avg       0.79      0.79      0.79      4928
```

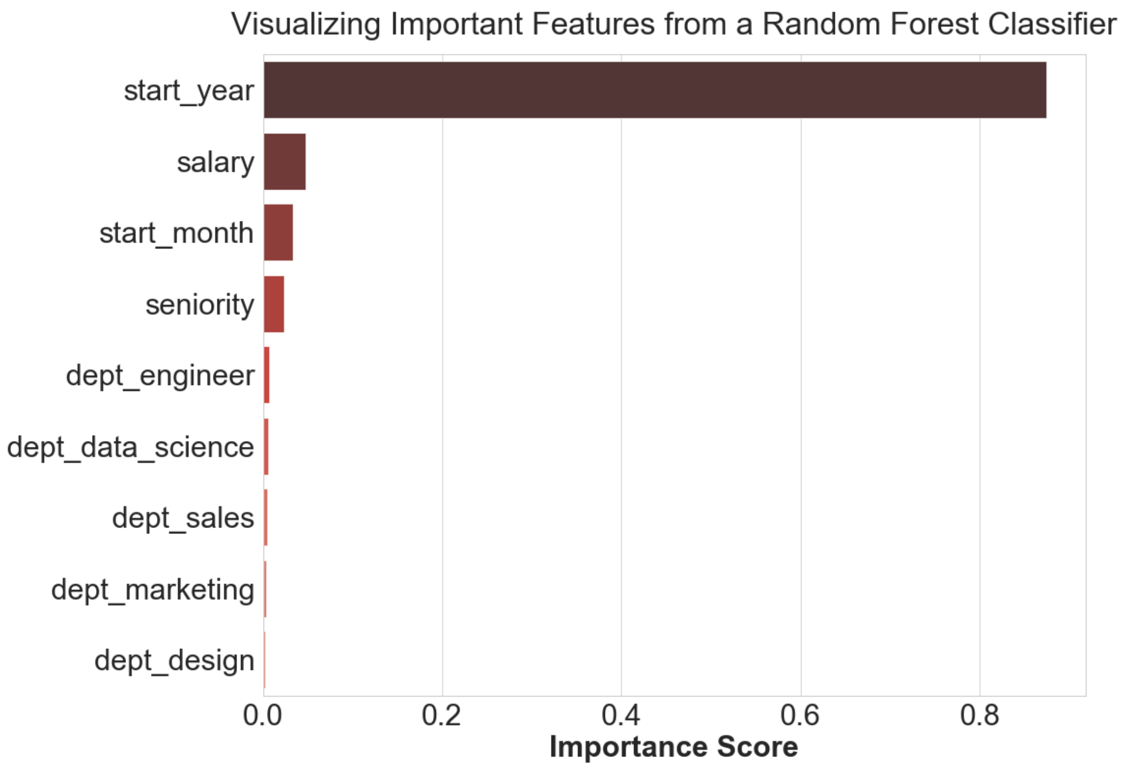
In [214]:
```
# Get final model feature imporance values and then plot
names = X.columns
feature_imp = pd.Series(RF_test.feature_importances_,index=names).sort_values(ascendi
feature_imp
```

Out[214]:
```
start_year           0.874300
salary               0.047493
```

```
start_month          0.032968
seniority            0.022776
dept_engineer        0.006700
dept_data_science    0.005563
dept_sales           0.004785
dept_marketing       0.003260
dept_design          0.002155
dtype: float64
```

In [215]:
```python
names = X.columns

feature_imp = pd.Series(RF_test.feature_importances_,index=names).sort_values(ascendi
feature_imp

plt.rcParams['figure.figsize'] = (15, 12)
plt.rcParams['axes.labelweight'] = 'bold'
#plt.rcParams["axes.labelsize"] = 30
rcParams['axes.titlepad'] = 20
sns.set(style='whitegrid')
sns.set_context("paper", rc={"font.size":32,"axes.titlesize":32,"axes.labelsize":30,

sns.barplot(x=feature_imp, y=feature_imp.index, palette='Reds_d')
# Add labels to your graph
plt.xlabel('Importance Score')
#plt.ylabel('Features')
plt.title("Visualizing Important Features from a Random Forest Classifier")
```

Out[215]:
```
Text(0.5, 1.0, 'Visualizing Important Features from a Random Forest Classifier')
```



In [ ]:
```
# OVERALL SUMMARY AND RESPONSES TO GOAL AND HINT QUESTIONS:
# A random forest classifier was used to predict whether an employee is still working

##############################################################

#### Caveats:
# I have tried includeing and excluding company ID in my predictive models. It did not
# I also did not include number of days as a covariate or run a regression model with
# In most of my analyses here, I used start year to potentiall explain stochasticity a

##############################################################

#### The goal was to predict employee retention and understand its main drivers.
# According to the RF model the main drivers of whether an employee was retained or no
# In terms of salary: Employees at medium and high salary levels (compared to low and
# In terms of seniority: Again, employees within the mid-range seniority category (mor
# In terms of start month: Only real anomoly is November; people whose hire date falls

# If you look at the further exploratory analysis below, you can see that really, year

##############################################################

#### Further questions:
```

```
## What are the main factors that drive employee churn? Do they make sense?
# We really need more information, but it seems like incentives for mid-range salary a

## What might you be able to do for the company to address employee Churn, what would
# Ask for more information about employees themselves. We do not have data from very f

## If you could add to this data set just one variable that could help explain employe
# I would want some information about rate of change in salary as well as some informa
```

In [ ]:
```
########## FURTHER INVESTIGATION BELOW (EXTRA) ########## -->
```

In [229]:
```
#dc1_NEW.head(20)
```

In [218]:
```
# Further exploration:
# RF model with company included and all 12 companies.
# Here the outcome/predicted variable will be binary, still employeed or not.
y = dc1_NEW[['still_employeed']]

# Here I use the full company set (1-12) company ID.
X = dc1_NEW[['company_id','dept','seniority', 'salary', 'start_year', 'start_month']]
```

In [219]:
```
# Get dummy variables for categorical features; use drop_first to get rid of the ext
X = pd.concat([X,pd.get_dummies(X['dept'], prefix='dept', drop_first=True)],axis=1)
X = pd.concat([X,pd.get_dummies(X['company_id'], prefix='company', drop_first=True)]

# drop old dept column since it is no longer informative.
X = X.drop(['dept'], axis=1)
X = X.drop(['company_id'], axis=1)
X.head()
```

Out[219]:

	seniority	salary	start_year	start_month	dept_data_science
0	28	89000.0	2014	3	0
1	20	183000.0	2013	4	0
2	14	101000.0	2014	10	0
3	20	115000.0	2012	5	0
4	23	276000.0	2011	10	1

	dept_design	dept_engineer	dept_marketing	dept_sales	company_2
0	0	0	0	0	0
1	0	0	1	0	0
2	0	0	1	0	0
3	0	0	0	0	0
4	0	0	0	0	1

	company_3	company_4	company_5	company_6	company_7	company_8
0	0	0	0	0	1	0
1	0	0	0	0	1	0
2	0	1	0	0	0	0

```
3          0          0          0          0          1          0
4          0          0          0          0          0          0

   company_9  company_10  company_11  company_12
0          0           0           0           0
1          0           0           0           0
2          0           0           0           0
3          0           0           0           0
4          0           0           0           0
```

In [220]:
```
# create training and test data sets based on X and y defined above. Will set test s
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

In [221]:
```
# check for class imbalance
y_train.still_employeed.value_counts()
```

Out[221]:
```
0    10801
1     8941
Name: still_employeed, dtype: int64
```

In [222]:
```
sm = SMOTE(random_state=11)
X_res_train, y_res_train = sm.fit_resample(X_train, y_train)
print('Resampled dataset shape %s' % Counter(y_res_train))
```

```
Resampled dataset shape Counter({'0': 10801, '1': 10801})


/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataConversionWarning:
  y = column_or_1d(y, warn=True)
```

In [225]:
```
# just try an out-of-the box RF here to see how it performs compared to previous mod

RF = RandomForestClassifier()
RF.fit(X_res_train, y_res_train)
y_pred=RF.predict(X_test)
print(classification_report(y_test, y_pred))
# performance is about equal - maybe a little bit better, but lots more features sin
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The defa
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)


              precision    recall  f1-score   support

           0       0.76      0.84      0.80      2700
           1       0.78      0.68      0.72      2236

   micro avg       0.76      0.76      0.76      4936
```

```
   macro avg       0.77      0.76      0.76      4936
weighted avg       0.77      0.76      0.76      4936
```

In [226]:
```
print('Overall accuracy of a binary RF classifier on the Test Set:', metrics.accurac
```

```
Overall accuracy of a binary RF classifier on the Test Set: 0.7647893030794165
```

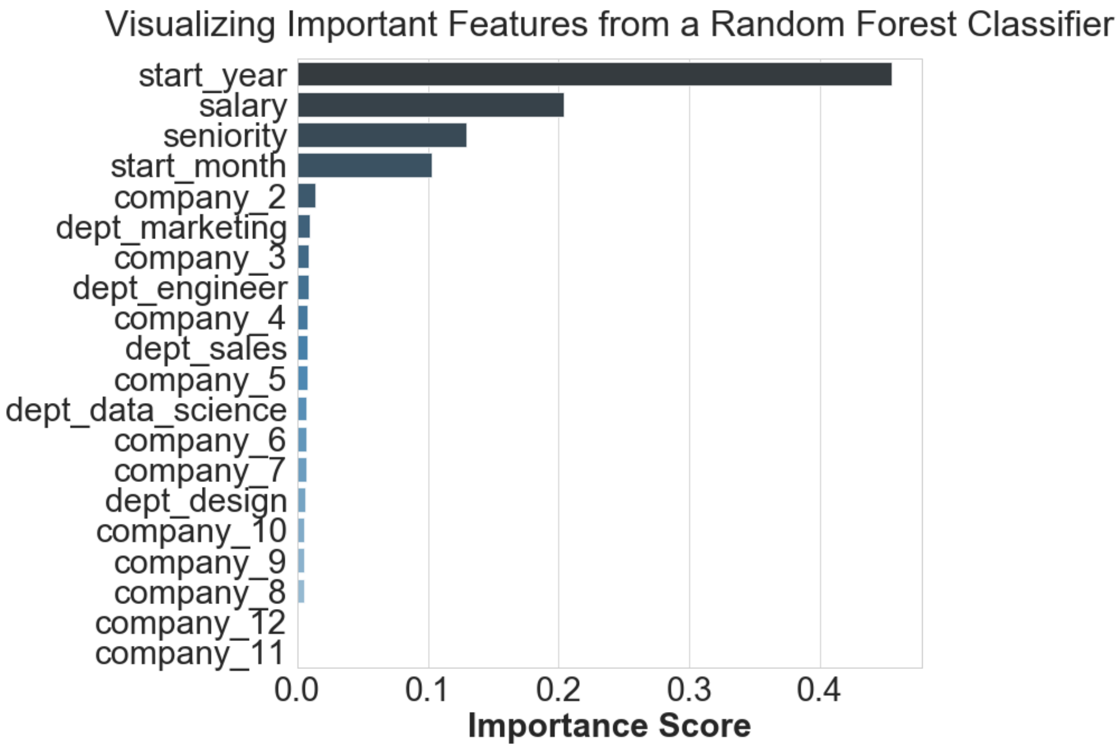
In [227]:
```
# Get feature imporance values and then plot
names = X.columns
feature_imp = pd.Series(RF.feature_importances_,index=names).sort_values(ascending=Fa
feature_imp
```

Out[227]:
```
start_year          0.454974
salary              0.204059
seniority           0.129628
start_month         0.102820
company_2           0.013910
dept_marketing      0.009270
company_3           0.009185
dept_engineer       0.008783
company_4           0.007978
dept_sales          0.007902
company_5           0.007783
dept_data_science   0.007013
company_6           0.006659
company_7           0.006651
dept_design         0.005853
company_10          0.005708
company_9           0.005627
company_8           0.005559
company_12          0.000321
company_11          0.000315
dtype: float64
```

In [231]:
```
names = X.columns

feature_imp = pd.Series(RF.feature_importances_,index=names).sort_values(ascending=Fa
feature_imp

plt.rcParams['figure.figsize'] = (10, 10)
plt.rcParams['axes.labelweight'] = 'bold'
rcParams['axes.titlepad'] = 20
sns.set(style='whitegrid')
sns.set_context("paper", rc={"font.size":32,"axes.titlesize":32,"axes.labelsize":30,

sns.barplot(x=feature_imp, y=feature_imp.index, palette='Blues_d')
```

```
# Add labels to your graph
plt.xlabel('Importance Score')
#plt.ylabel('Features')
plt.title("Visualizing Important Features from a Random Forest Classifier")
```

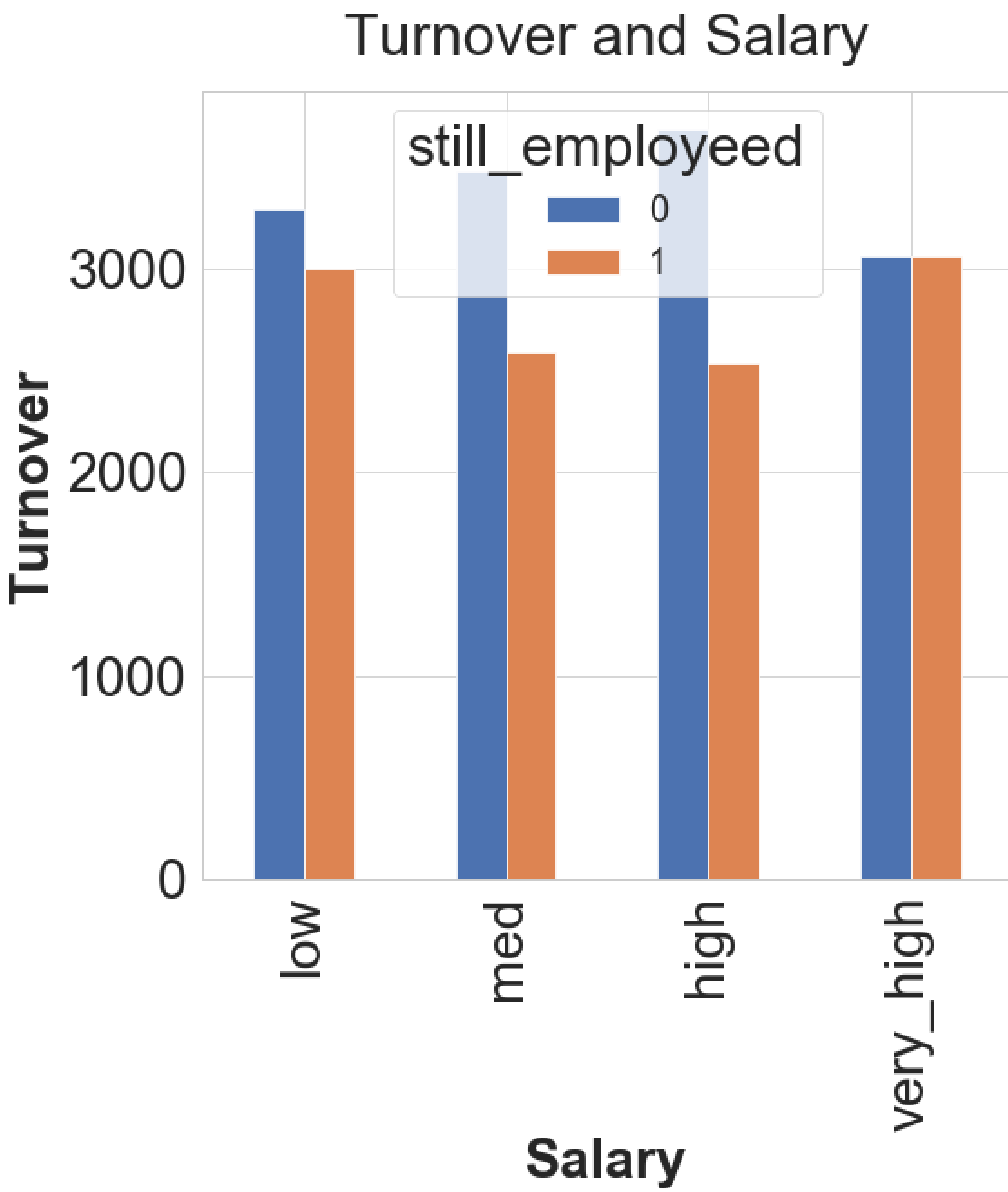
Out[231]: Text(0.5, 1.0, 'Visualizing Important Features from a Random Forest Classifier')



In [ ]:
```
# Overall, same features are important -- start year appears to be really driving tren
# Salary and seniority appear to be the next most important. Let's look closer since t
# If I had more time I could look at partial dependence plots to isolate effect of fea
```

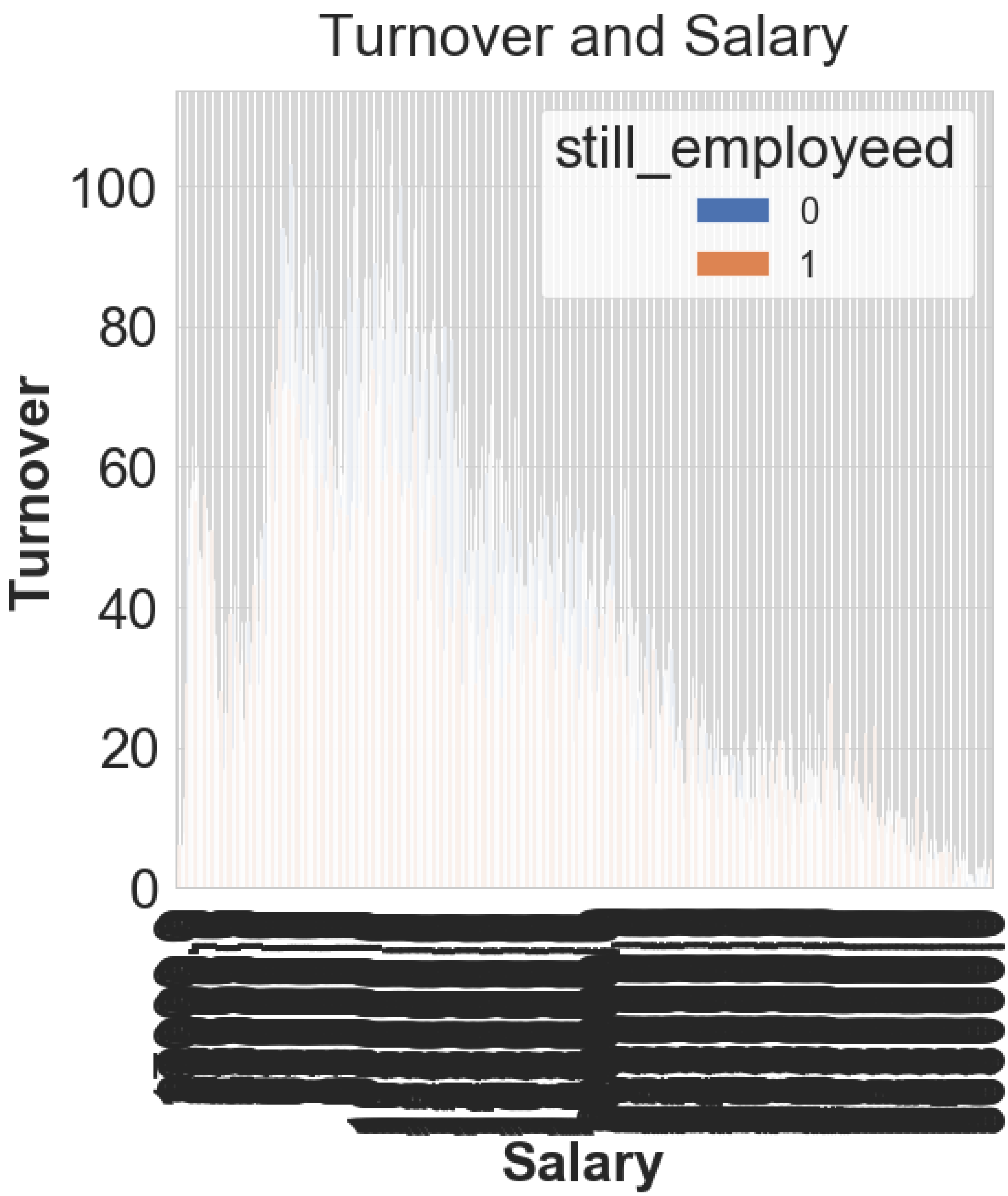
In [241]:
```
# Reminder: we saw this fig before -- maybe there is something here (salary has been
# Peraps at the highest salary level, it's true that equal numbers of people are sta
# At medium and high salary levels, more peopole are leaving than going. Maybe they
# The gap between those who quit and those who are still working is larger for peopl


# Salary and turnover classification (still employeed or not)
plt.rcParams['figure.figsize'] = (8, 8)
pd.crosstab(dc1_NEW.salary_rank,dc1_NEW.still_employeed).plot(kind='bar')
plt.title('Turnover and Salary')
plt.xlabel('Salary')
plt.ylabel('Turnover')
```

Out[241]: Text(0, 0.5, 'Turnover')



In [267]:
```
# Salary and turnover classification (still employeed or not)
plt.rcParams['figure.figsize'] = (8, 8)
pd.crosstab(dc1_NEW.salary,dc1_NEW.still_employeed).plot(kind='bar')
plt.title('Turnover and Salary')
plt.xlabel('Salary')
plt.ylabel('Turnover')
```

```
Out[267]: Text(0, 0.5, 'Turnover')
```

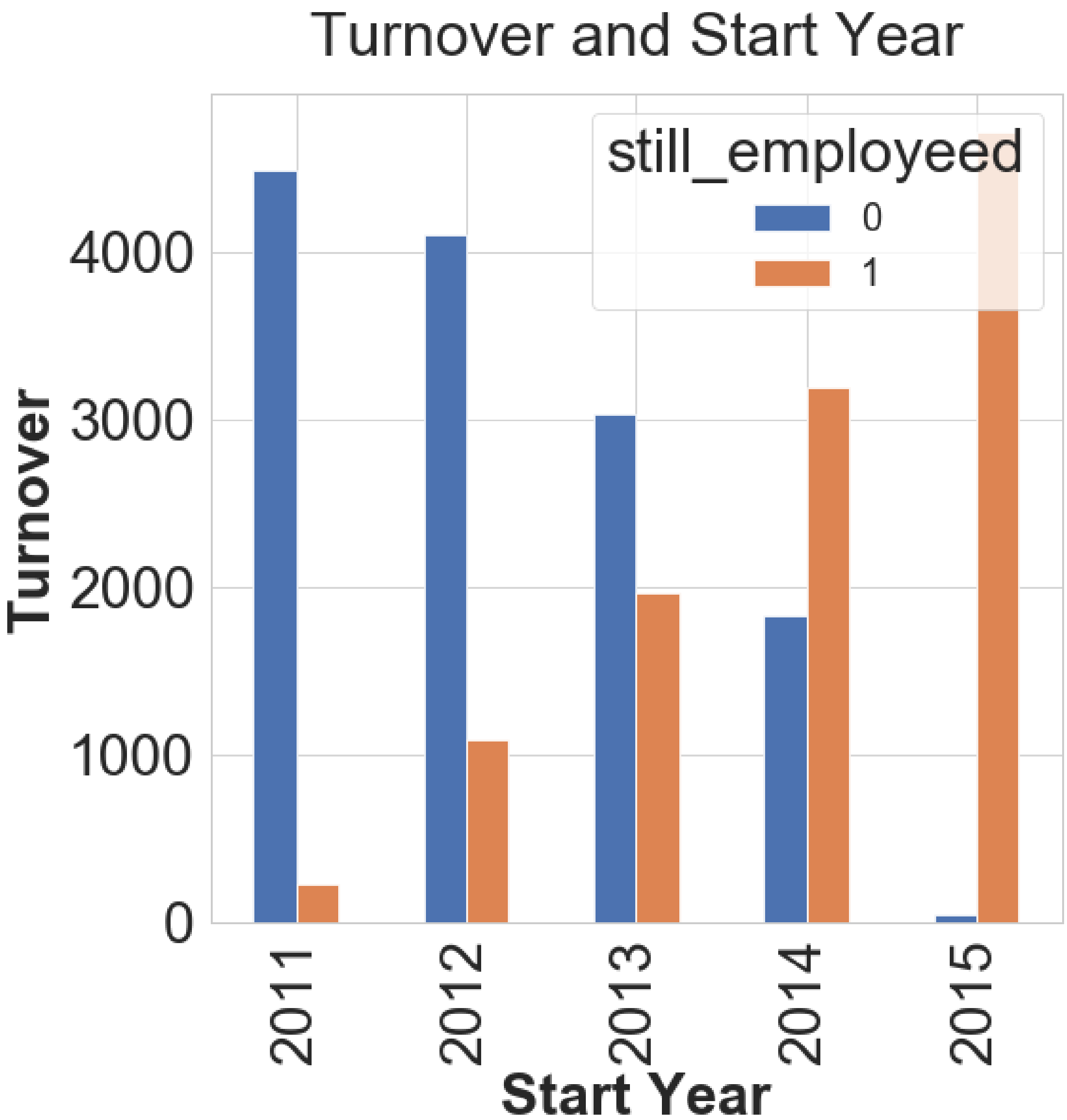



```
In [ ]: # Here are a couple of new visualizations for start year and month, with these effects
```

```
In [242]: pd.crosstab(dc1_NEW.start_year,dc1_NEW.still_employeed).plot(kind='bar')
          plt.title('Turnover and Start Year')
          plt.xlabel('Start Year')
          plt.ylabel('Turnover')
```

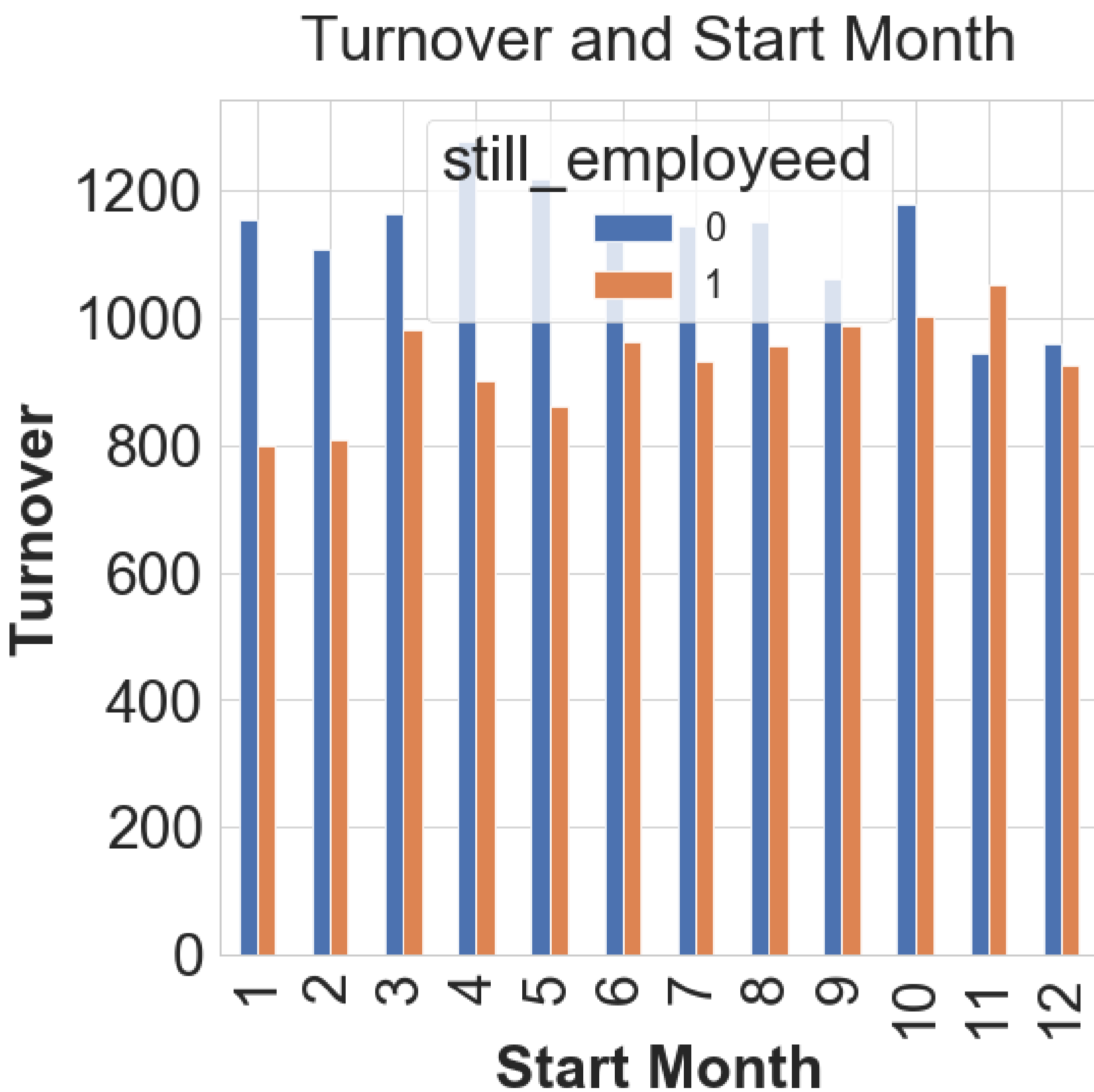
```
# CONCLUDE:
# Including start year is sort of like an artifact. More people are likely to have q
# Perhaps this should really be removed from the model, because it's giving the 'wro
```

Out[242]: Text(0, 0.5, 'Turnover')



In [243]:
```
pd.crosstab(dc1_NEW.start_month,dc1_NEW.still_employeed).plot(kind='bar')
plt.title('Turnover and Start Month')
plt.xlabel('Start Month')
plt.ylabel('Turnover')

# CONCLUDE
# The only month where number of people who have stayed vs. left is higher is Novemb
```

Out[243]: Text(0, 0.5, 'Turnover')



In [244]:
```
# One last thing... what happens when start year is removed from the final model abo

y = dc1_NEW[['still_employeed']]

# Here I use the full company set (1-12) company ID.
X = dc1_NEW[['company_id','dept','seniority', 'salary', 'start_month']]
```

In [245]:
```
# Get dummy variables for categorical features; use drop_first to get rid of the ext
X = pd.concat([X,pd.get_dummies(X['dept'], prefix='dept', drop_first=True)],axis=1)
X = pd.concat([X,pd.get_dummies(X['company_id'], prefix='company', drop_first=True)]

# drop old dept column since it is no longer informative.
```

```
X = X.drop(['dept'], axis=1)
X = X.drop(['company_id'], axis=1)
X.head()
```

Out[245]:

```
   seniority    salary  start_month  dept_data_science  dept_design  \
0         28   89000.0            3                  0            0
1         20  183000.0            4                  0            0
2         14  101000.0           10                  0            0
3         20  115000.0            5                  0            0
4         23  276000.0           10                  1            0

   dept_engineer  dept_marketing  dept_sales  company_2  company_3  company_4  \
0              0               0           0          0          0          0
1              0               1           0          0          0          0
2              0               1           0          0          0          1
3              0               0           0          0          0          0
4              0               0           0          1          0          0

   company_5  company_6  company_7  company_8  company_9  company_10  \
0          0          0          1          0          0           0
1          0          0          1          0          0           0
2          0          0          0          0          0           0
3          0          0          1          0          0           0
4          0          0          0          0          0           0

   company_11  company_12
0           0           0
1           0           0
2           0           0
3           0           0
4           0           0
```

In [247]:

```
# create training and test data sets based on X and y defined above. Will set test s
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_sta
```

In [248]:

```
# check for class imbalance
y_train.still_employeed.value_counts()
```

Out[248]:

```
0    10801
1     8941
Name: still_employeed, dtype: int64
```

In [249]:

```
sm = SMOTE(random_state=11)
X_res_train, y_res_train = sm.fit_resample(X_train, y_train)
print('Resampled dataset shape %s' % Counter(y_res_train))
```

```
Resampled dataset shape Counter({'0': 10801, '1': 10801})
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/utils/validation.py:761: DataConversionWarning:
  y = column_or_1d(y, warn=True)
```

```
In [250]: # just try an out-of-the box RF here to see how it performs compared to previous mod

          RF = RandomForestClassifier()
          RF.fit(X_res_train, y_res_train)
          y_pred=RF.predict(X_test)
          print(classification_report(y_test, y_pred))
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The defau
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
              precision    recall  f1-score   support

           0       0.56      0.64      0.60      2700
           1       0.47      0.38      0.42      2236

   micro avg       0.53      0.53      0.53      4936
   macro avg       0.51      0.51      0.51      4936
weighted avg       0.52      0.53      0.52      4936
```

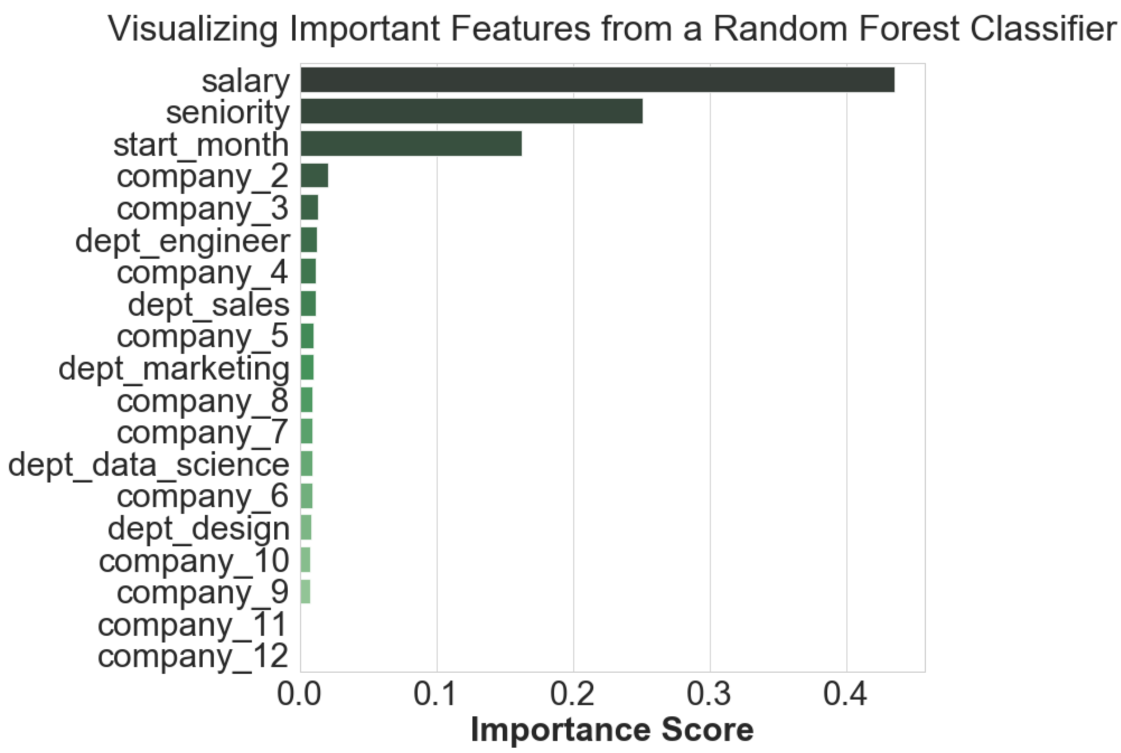
```
In [251]: print('Overall accuracy of a binary RF classifier on the Test Set:', metrics.accuracy

Overall accuracy of a binary RF classifier on the Test Set: 0.5251215559157212
```

```
In [252]: # Get feature imporance values and then plot
          names = X.columns
          feature_imp = pd.Series(RF.feature_importances_,index=names).sort_values(ascending=Fa
          feature_imp

Out[252]: salary                0.435520
          seniority             0.250622
          start_month           0.162833
          company_2             0.020925
          company_3             0.013500
          dept_engineer         0.012430
          company_4             0.011655
          dept_sales            0.011543
          company_5             0.010378
          dept_marketing        0.009656
          company_8             0.009457
          company_7             0.009100
          dept_data_science     0.009088
```

```
company_6          0.008901
dept_design        0.008119
company_10         0.007977
company_9          0.007313
company_11         0.000523
company_12         0.000462
dtype: float64
```

In [253]:
```
names = X.columns

feature_imp = pd.Series(RF.feature_importances_,index=names).sort_values(ascending=Fa
feature_imp

plt.rcParams['figure.figsize'] = (10, 10)
plt.rcParams['axes.labelweight'] = 'bold'
rcParams['axes.titlepad'] = 20
sns.set(style='whitegrid')
sns.set_context("paper", rc={"font.size":32,"axes.titlesize":32,"axes.labelsize":30,

sns.barplot(x=feature_imp, y=feature_imp.index, palette='Greens_d')
# Add labels to your graph
plt.xlabel('Importance Score')
#plt.ylabel('Features')
plt.title("Visualizing Important Features from a Random Forest Classifier")
```

Out[253]:
```
Text(0.5, 1.0, 'Visualizing Important Features from a Random Forest Classifier')
```



In [283]:
```
#Just for fun
sns.boxplot(x="still_employeed", y="salary", hue = 'seniority', data=dc1_NEW)
# Put the legend out of the figure
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[283]: <matplotlib.legend.Legend at 0x1a2c662da0>