EmployeeRetention

February 20, 2019

1 Data Challenge 1: Employee Retention

1.1 Load Libraries

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

```
In [2]: #add path to my Dropbox
        #get path to my dropbox directory, assuming jq is install
        s = !jq -r ".personal.path" < ~/.dropbox/info.json
        print("path to dropbox: ", s)
        import sys
        sys.path.insert(0, s[0])
        from pytools import data_tools
```

```
path to dropbox:  ['/home/marcel/Dropbox']
```

1.2 Load The Data

```
In [3]: employee = pd.read_csv('data/employee_retention_data.csv')
        df = employee.copy()
```

1.3 Shape of Data

```
In [4]: print("Number of sample = {} and number of features = {}".format(df.shape[0], df.shape
```

```
Number of sample = 24702 and number of features = 7
```

1.4 Check Data Types

```
In [5]: df.dtypes
```

```
Out[5]: employee_id    float64
        company_id       int64
        dept            object
        seniority        int64
        salary         float64
        join_date       object
        quit_date       object
        dtype: object
```

Note:
- **Employee_Id** is currently type float but should be int - **join_date** and **quit_date** are currently objects, but should be datetime

1.5 Convert data types to appropriate types

```
In [6]: df.join_date = pd.to_datetime(df.join_date)
        df.quit_date = pd.to_datetime(df.quit_date)
        df.employee_id = df.employee_id.astype(int)
        df.company_id = df.company_id.astype('object')
        df.dtypes
```

```
Out[6]: employee_id             int64
        company_id             object
        dept                   object
        seniority               int64
        salary                float64
        join_date      datetime64[ns]
        quit_date      datetime64[ns]
        dtype: object
```

```
In [7]: df.head()
```

```
Out[7]:    employee_id company_id             dept  seniority    salary  join_date  \
        0        13021          7  customer_service         28   89000.0 2014-03-24
        1       825355          7         marketing         20  183000.0 2013-04-29
        2       927315          4         marketing         14  101000.0 2014-10-13
        3       662910          7  customer_service         20  115000.0 2012-05-14
        4       256971          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
```

1.6 Missing Values

```
In [8]: df.isnull().sum()
```

```
Out[8]: employee_id        0
        company_id         0
        dept               0
        seniority          0
        salary             0
        join_date          0
        quit_date      11192
        dtype: int64
```

1.7 Summary

```
In [9]: df.describe()
```

```
Out[9]:          employee_id     seniority          salary
        count   24702.000000  24702.000000   24702.000000
        mean   501604.403530     14.127803  138183.345478
        std    288909.026101      8.089520   76058.184573
        min        36.000000      1.000000   17000.000000
        25%    250133.750000      7.000000   79000.000000
        50%    500793.000000     14.000000  123000.000000
        75%    753137.250000     21.000000  187000.000000
        max    999969.000000     99.000000  408000.000000
```

We see there is an employee who has worked for 99 years (**seniority**). This does not seem right. Investigate further (there is another with seniority = 98)

```
In [10]: print(df.seniority.unique())
         df[(df.seniority == 98) | (df.seniority == 99)]
```

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

```
Out[10]:        employee_id  company_id        dept  seniority    salary  join_date  \
         24700        97289          10    engineer         98  266000.0 2011-12-13
         24701       604052           1   marketing         99  185000.0 2011-07-26

                quit_date
         24700 2015-01-09
         24701 2013-12-06
```

```
In [11]: #replace 98 and 99 with 29, the most reasonable highest value
         df.loc[24700, 'seniority'] = 29
         df.loc[24701, 'seniority'] = 29
```

1.8 Make sure there is only one entry per employee

```
In [12]: assert(len(df.employee_id.unique()) == df.shape[0])
```

Given that there is only one entry per employee, employee_id has no predictive value here. We can use it as index for the dataframe. This also means, we can't track employee salary in time, hence will not be able to know if an amployee quitted because their salary remained constant for a long time

1.9 Create a boolean column for quited

In [13]:
```
# quited = 0 if quit_date missing else 1
quit_mask = df.quit_date.isnull() == False
df['quited'] = quit_mask.apply(int)
df = df.set_index('employee_id', drop=True)
df.head(4)
```

Out[13]:
```
             company_id              dept  seniority    salary  join_date  \
employee_id
13021                 7  customer_service         28   89000.0 2014-03-24
825355                7         marketing         20  183000.0 2013-04-29
927315                4         marketing         14  101000.0 2014-10-13
662910                7  customer_service         20  115000.0 2012-05-14

              quit_date  quited
employee_id
13021        2015-10-30       1
825355       2014-04-04       1
927315              NaT       0
662910       2013-06-07       1
```

1.10 Print some general infos about dataframe

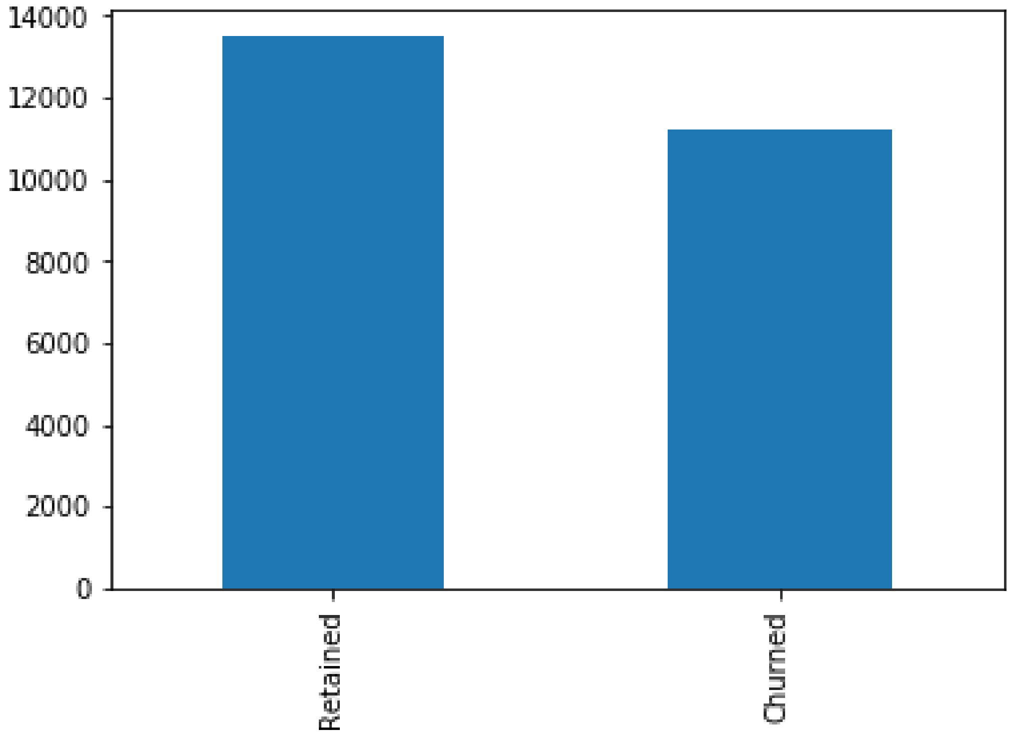
In [14]:
```
data_tools.print_infos(df)
```

```
Dataframe dimensions: (24702, 7)
                company_id    dept seniority   salary       join_date  \
column type         object  object     int64  float64  datetime64[ns]
Null values              0       0         0        0               0
Null values (%)          0       0         0        0               0
Number unique           12       6        29      367             995

                     quit_date quited
column type     datetime64[ns]  int64
Null values              11192      0
Null values (%)        45.3081      0
Number unique              664      2
```

1.11 Class Proportions

In [15]:
```
def plot_class_proportion(labels):
```

```
    ratio = labels.value_counts()
    ratio.index = ['Retained', 'Churned']
    ratio.plot(kind='bar')
    #plt.savefig('figures/class_proportions.png')
plot_class_proportion(df.quited)
```



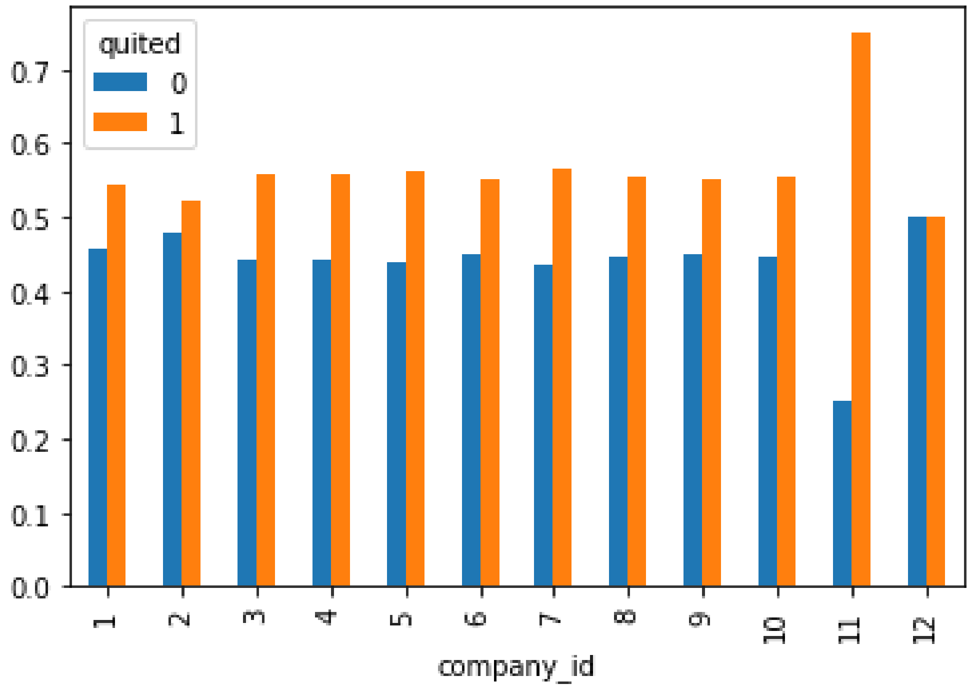
2 Data Exploration

```
In [16]: #helper function to perform ztest of proportions
         def ztest(df, column, group1, group2):
             """
             perform ztest for two groups.
             df    : the dataframe
             column: the column we are interested in
             group1: one of the categories in the column
             group2: another category
             """
             import statsmodels.api as sm

             #count the number of positive instance in group1
             p0 = len(df[(df[column] == group1) & (df.quited == 1)])
             #total number oof instances in group1
```

```
    n0 = len(df[(df[column] == group1)])

    p1 = len(df[(df[column] == group2) & (df.quited == 1)])
    n1 = len(df[(df[column] == group2)])

    z_score, p_value = sm.stats.proportions_ztest(count=[p0, p1], nobs=[n0, n1])
    return z_score, p_value

def proportion_ztest(df, column, alpha=0.05):
    """
    performs independent ztests on all pairs of groups
    """
    import statsmodels.api as sm

    options = list(df[column].unique())
    insignificant = []
    significant = []

    #find unique pairs
    pairs = []
    for i in range(0, len(options)):
        for j in range(i+1, len(options)):
            pairs.append((options[i], options[j]))

    for pair in pairs:
        z_score, p_value = ztest(df, column, pair[0], pair[1])
        if p_value < alpha: #reject H_0
            insignificant.append((pair, p_value))
        else:
            significant.append((pair, p_value))
    return insignificant, significant
```

2.0.1 Correlation between target and company_id

```
In [17]: #plt.rcParams.update({'font.size': 12})
         _ = pd.crosstab(df.company_id, df.quited, normalize=0).plot(kind='bar')
```



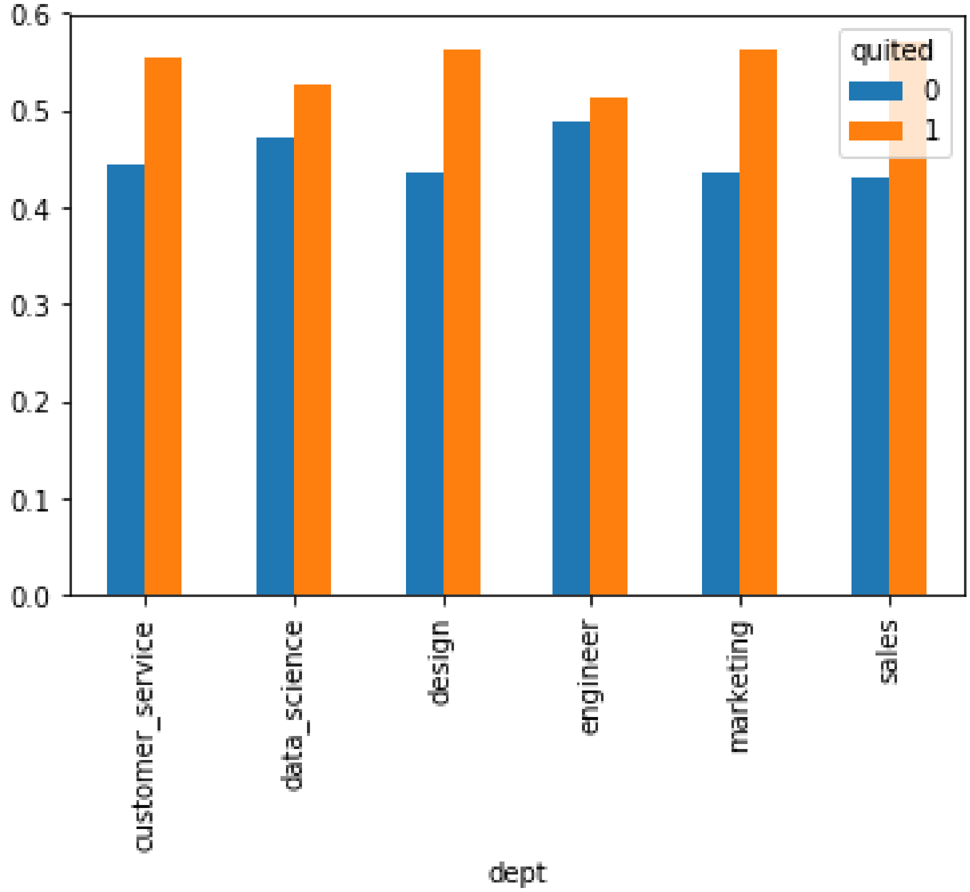

```
In [18]: insignificant, significant = proportion_ztest(df, 'company_id')
         insignificant
```

```
Out[18]: [((7, 2), 0.008147216455192572),
          ((4, 2), 0.006220849169380669),
          ((2, 1), 0.018908302229472415),
          ((2, 5), 0.007939968967133589),
          ((2, 3), 0.004847933191832574)]
```

- Visually, all companies have similar retention rates, except company 11
- Company 12 seems to have almost equal ratio of employee who quitted and those who are still present
- Maybe then **company_id** can be transformed into 3 categories instead of 12
  - one category for company 11
  - one category for company 12
  - one category for all the rest (since they all look similar in terms of relation to target)
- **ztest** suggests that only company 2 might have a significant difference from others in terms of churn proportion
- Maybe have only two categories, one for company 2 and one for others

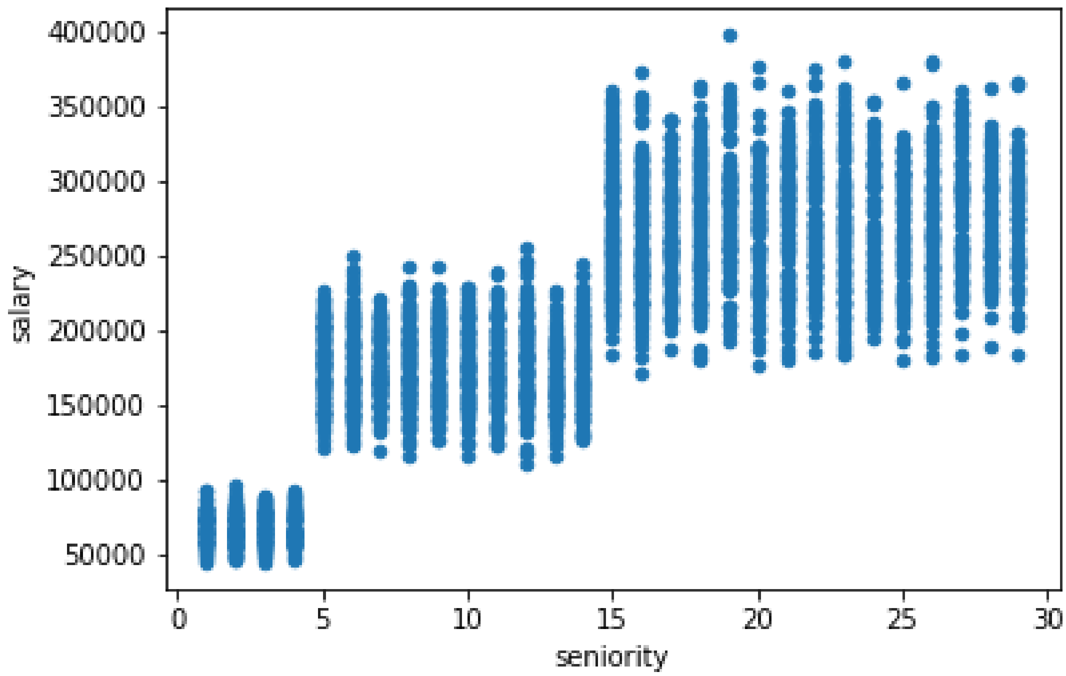
2.0.2 Correlation between target and department

```
In [19]: _ = pd.crosstab(df.dept, df.quited, normalize=0).plot(kind='bar')
```



2.1 Loking at Salary vs Seniority

```
In [20]: _ = df[df.dept=='data_science'].plot(x='seniority', y='salary', kind='scatter')
```



Note:
It appears that salary increase is incremental with 3 chuck
- 1-5 years fall in thesame seniority category - 5-15 years - 15 years and above

2.1.1 Perform ztest of proportion to see if the difference between departments is significant

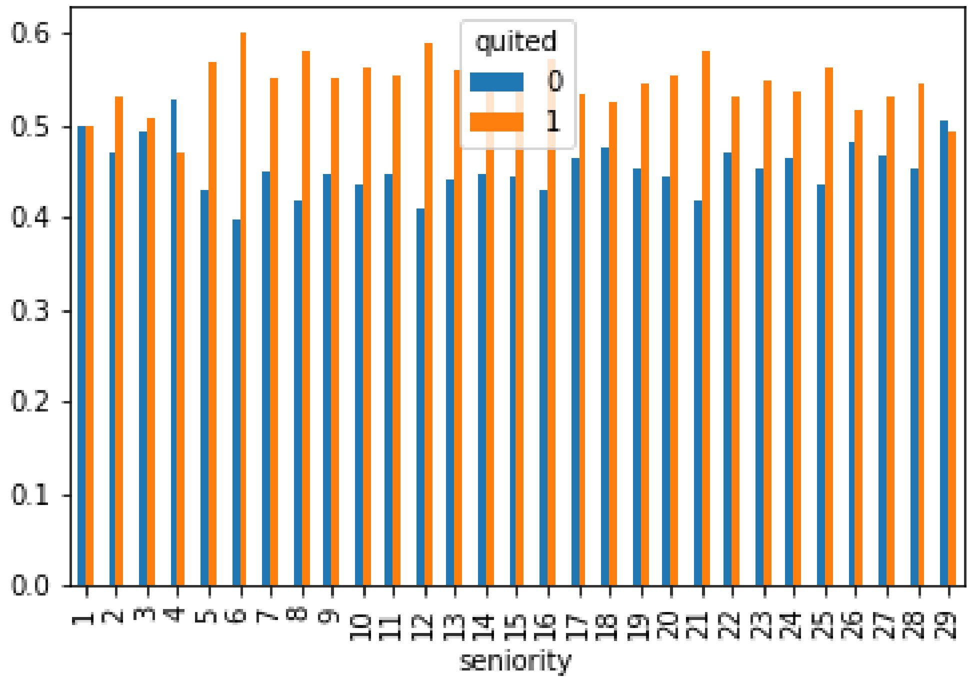
```
In [21]: insignificant, significant = proportion_ztest(df, 'dept')
         insignificant
```

```
Out[21]: [(('customer_service', 'data_science'), 0.006913411144791306),
          (('customer_service', 'engineer'), 1.8736125427555084e-06),
          (('marketing', 'data_science'), 0.004240992230664227),
          (('marketing', 'engineer'), 9.587221589710114e-06),
          (('data_science', 'sales'), 0.0004664658059825876),
          (('data_science', 'design'), 0.023082128137744837),
          (('engineer', 'sales'), 3.0459598924820376e-07),
          (('engineer', 'design'), 0.0007347384283784 15)]
```

Note:

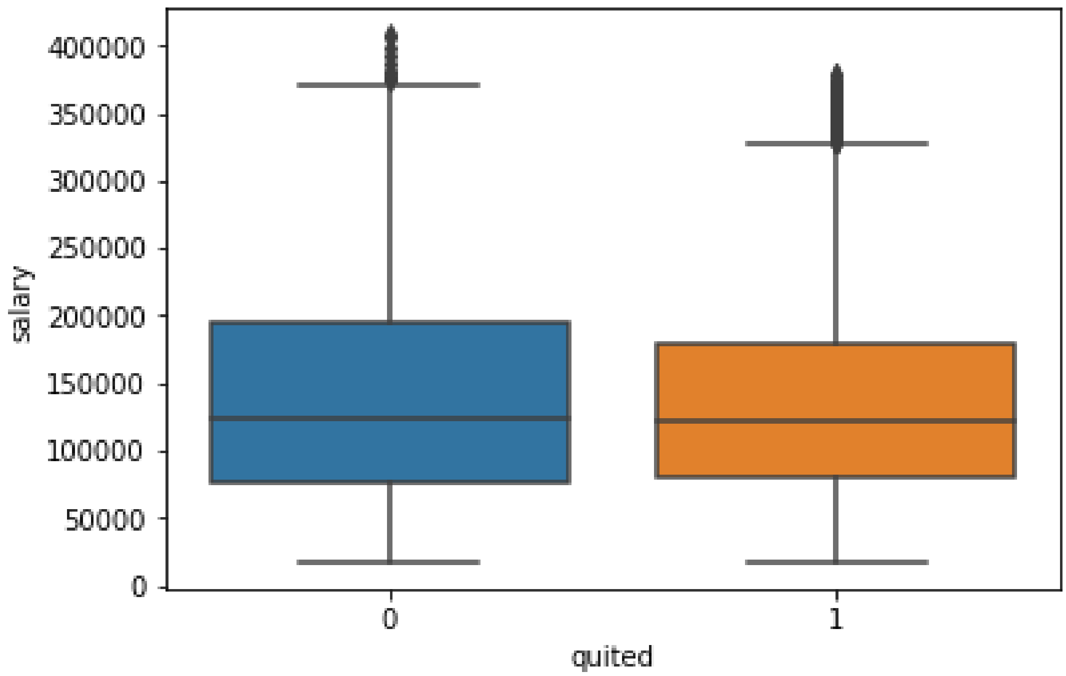
- The feature **dept** has 5 categories, but can be grouped into 2 main categories according to how the proportions of people who quitted varies between the categories
- **engineer** and **data_science** employee seem to fall in one category
- **customer_service**, **sales**, and **design** can be grouped into one category

In [22]:
```
_ = pd.crosstab(df.seniority, df.quited, normalize=0).plot(kind='bar')
```



In [23]:
```
#insignificant, significant = proportion_ztest(df, 'seniority')
#len(insignificant)
```

In [24]:
```
import seaborn as sns
_ = sns.boxplot(x='quited', y='salary', data=df)
```




```
In [25]: import statsmodels
         import scipy

         x1 = df[df.quited == 1]['salary']
         x2 = df[df.quited == 0]['salary']
         print("Test of Normality", scipy.stats.normaltest(x1))

         statsmodels.stats.weightstats.ztest(x1, x2)
```

```
Test of Normality NormaltestResult(statistic=957.1125738370777, pvalue=1.4643514148823831e-208
```

```
Out[25]: (-5.7498619463708875, 8.93163494288991e-09)
```

Note:
The test of normality shows that the samples from employees who churned and those who are still present do not follow a normal distribution, so the ztest for means is not even appropriate here.

3 Modeling

```
In [26]: from sklearn.preprocessing import LabelEncoder, OneHotEncoder
         from sklearn.linear_model import LogisticRegression, SGDClassifier, SGDRegressor
         from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
```

```
from sklearn.neural_network import MLPClassifier, MLPRegressor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVR, SVR, LinearSVC
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import accuracy_score, precision_recall_curve, confusion_matrix
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.pipeline import Pipeline, FeatureUnion
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Imputer, LabelEncoder
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.dummy import DummyClassifier

from mlencoders.weight_of_evidence_encoder import WeightOfEvidenceEncoder
from mlencoders.target_encoder import TargetEncoder
import warnings
warnings.filterwarnings("ignore")


def count_months(join_date, quit_date):
    """
    compute the number of months between join_date and quit_date
    input: join_date, quit_date - series
    return: list, number of months if employee quited
           assume 30 years for missing quit date (employee still around)
    """

    from dateutil.relativedelta import relativedelta
    delta = []
    for d1, d2 in zip(join_date, quit_date):
        if pd.isnull(d2):
            #employee still present, assume 30 * 12 months of service
            delta.append(30*12)
        else:
            #employee quited, caculate number of months
            time_dif = relativedelta(d2, d1)
            delta.append(time_dif.years*12+time_dif.months)

    return delta

class DataFrameSelector(BaseEstimator, TransformerMixin):

    def __init__(self, attribute_names):
        self.attribute_names = attribute_names
```

```python
    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X[self.attribute_names].values

class AttributeAdder(BaseEstimator, TransformerMixin):

    def __init__(self, attribute_names=None):
        self.attribute_names = attribute_names

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        group = ['tech_yes' if value in ['data_science', 'engineer'] else 'tech_no' fo
        company = ['company_id_2' if value == 2 else 'company_id_others' for value in
        X['technical'] = group
        X['company_2'] = company

        #date components
        X['join_year'] = X['join_date'].dt.year
        X['join_month'] = X['join_date'].dt.month
        X['join_day'] = X['join_date'].dt.day
        X['total_months'] = count_months(X['join_date'], X['quit_date'])

        stats = X.groupby('dept')['salary'].agg(['mean', 'max', 'min'])
        stats.columns = ['mean_salary_dept', 'max_salary_dept', 'min_salary_dept']

        # Merge with the clients dataframe
        X = X.merge(stats, left_on = 'dept', right_index=True, how = 'left')

        return X


class MultiColumnLabelEncoder:
    def __init__(self,columns = None):
        self.columns = columns # array of column names to encode

    def fit(self,X,y=None):
        return self # not relevant here

    def transform(self,X):
        '''
        Transforms columns of X specified in self.columns using
        LabelEncoder(). If no columns specified, transforms all
        columns in X.
        '''
```

```
        output = X.copy()
        if self.columns is not None:
            for col in self.columns:
                output[col] = LabelEncoder().fit_transform(output[col])
        else:
            for colname,col in output.iteritems():
                output[colname] = LabelEncoder().fit_transform(col)
        return output

    def fit_transform(self,X,y=None):
        return self.fit(X,y).transform(X)
```

4 Feature Engineering

Engineer new features: - **technical :** whether the employee is from a technical department or not - **company_2 :** whether the company has company_id = 2 - **join_year**, **join_month**, **join_day** - **mean_salary_dept:** the average salary per department - **max_salary_dept:** the maximum salary per department - **min_salary_dept:** the minimum salary per department - **total_month** this is a target variable to predict

In [27]:
```
adder = AttributeAdder()
df = adder.fit_transform(df); df[df.columns[7:]].head()
```

Out[27]:
```
               technical          company_2  join_year  join_month  join_day  \
employee_id
13021            tech_no  company_id_others       2014           3        24
825355           tech_no  company_id_others       2013           4        29
927315           tech_no  company_id_others       2014          10        13
662910           tech_no  company_id_others       2012           5        14
256971          tech_yes       company_id_2       2011          10        17

             total_months  mean_salary_dept  max_salary_dept  min_salary_dept
employee_id
13021                  19      82245.424837         166000.0          17000.0
825355                 11     135598.042311         262000.0          30000.0
927315                360     135598.042311         262000.0          30000.0
662910                 12      82245.424837         166000.0          17000.0
256971                 34     206885.893417         398000.0          44000.0
```

5 Create Pipelines

In [28]:
```
targets = ['total_months', 'quited']
num_attribs, cat_attribs, date_attribs = data_tools.getColumnDataTypes(df.drop(target
#num_attribs = ['join_year', 'salary', 'join_day', 'seniority', 'join_month']
#cat_attribs = ['company_id', 'dept']
def make_numeric_pipeline(attribs):
    num_pipeline = Pipeline([
```

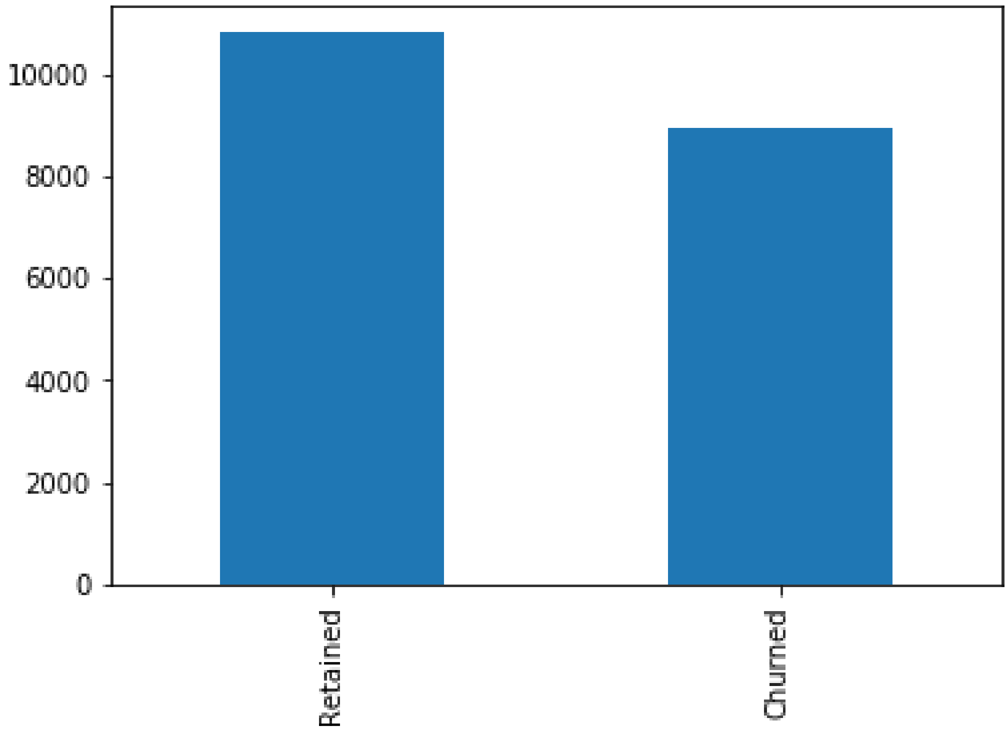
```
            ('selector', DataFrameSelector(num_attribs)),
            ('scaler', StandardScaler()),
        ])
        return num_pipeline

    def make_categoric_pipeline(attribs):
        cat_pipeline = Pipeline([
            ('selector', DataFrameSelector(attribs)),
            ('encoder', OneHotEncoder(sparse=False)),
            #('encoder', TargetEncoder()),
        ])
        return cat_pipeline


    def make_pipeline(num_attribs, cat_attribs):

        num_pipeline = make_numeric_pipeline(num_attribs)
        cat_pipeline = make_categoric_pipeline(cat_attribs)

        full_pipeline = FeatureUnion(
            transformer_list=[
                ('num_pipeline', num_pipeline),
                ('cat_pipeline', cat_pipeline),
            ])
        return full_pipeline, num_pipeline, cat_pipeline

    full_pipeline, num_pipeline, cat_pipeline = make_pipeline(num_attribs, cat_attribs)

    print("Numeric attributes:\n", num_attribs)
    print("\nCategorical attributes:\n", cat_attribs)
```

```
Numeric attributes:
 ['seniority', 'salary', 'join_year', 'join_month', 'join_day', 'mean_salary_dept', 'max_salary

Categorical attributes:
 ['company_id', 'dept', 'technical', 'company_2']
```

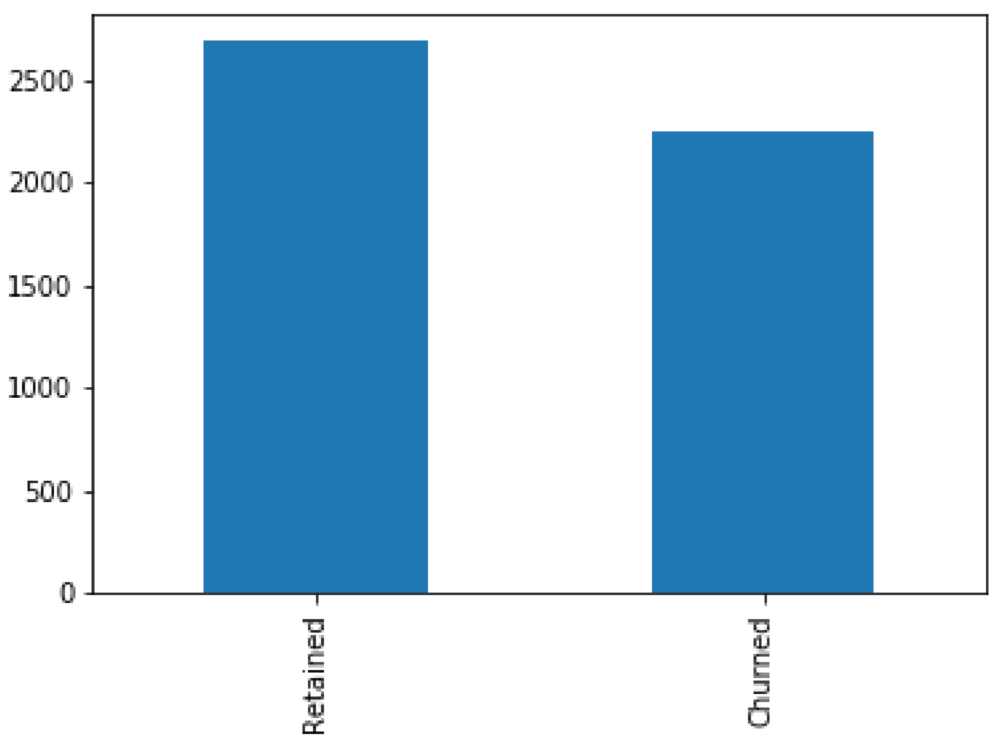
In [29]:
```
#encoder = MultiColumnLabelEncoder(columns = ['dept'])
y = df.quited
X = df[num_attribs+cat_attribs]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
X_train_encoded = full_pipeline.fit_transform(X_train, y_train)
X_test_encoded = full_pipeline.transform(X_test)
```

In [30]:
```
plot_class_proportion(y_train)
sum(y_train)/len(y_train)
```

Out[30]: 0.5474419310763625




```
In [31]: plot_class_proportion(y_test)
```



In [32]:
```
#https://github.com/scikit-learn/scikit-learn/issues/10786
from sklearn.utils import check_X_y

model = DummyClassifier(random_state = 0, strategy='most_frequent')
X_converted, y_converted = \
                 check_X_y(X=X_train_encoded, y=y_train)
model.fit(X=X_converted, y=y_converted)

y_pred = model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy on test set:", accuracy)
```

```
Accuracy on test set: 0.5448289819874519
```

5.1 Use Random Forest to Select Subset of Important Features

In [33]:
```
model = RandomForestClassifier(random_state = 0,
                               max_features = 'auto',
                               max_depth = 11,
                               min_samples_split= 6,
                               n_estimators = 100,
                              )


model.fit(X_train_encoded, y_train)

predictions = model.predict(X_test_encoded)
pred_train = model.predict(X_train_encoded)
accuracy_train = accuracy_score(y_train, pred_train)
accuracy_test = accuracy_score(y_test, predictions)
print("Accuracy Score Train = ", accuracy_train)
print("Accuracy Score Test = ", accuracy_test)
```

```
Accuracy Score Train =  0.8162542381458429
Accuracy Score Test =  0.8002428658166363
```

In [34]:
```
cat_encoder = cat_pipeline.named_steps['encoder']

cat_cols = []
#get feature names
for i in range(len(cat_encoder.categories_)):
    cat_cols += list(cat_encoder.categories_[i])

attributes = num_attribs + cat_cols
```

```
importance = model.feature_importances_
sorted(zip(importance, attributes), reverse=True)
```

Out [34]:
```
[(0.7716480966306136, 'join_year'),
 (0.06067520024081901, 'salary'),
 (0.04169078623991721, 'join_day'),
 (0.038951856855991736, 'seniority'),
 (0.03818807844766044, 'join_month'),
 (0.004284021002916861, 'max_salary_dept'),
 (0.004211068192215684, 'mean_salary_dept'),
 (0.0032673897445408416, 1),
 (0.0032567114344587405, 'min_salary_dept'),
 (0.0028364438676070063, 3),
 (0.002700462994969473, 5),
 (0.0025153628948011964, 8),
 (0.0025073847568369266, 4),
 (0.002382772123187257, 9),
 (0.0023277156274095 9, 6),
 (0.0020268442121725975, 2),
 (0.002008411132209193, 10),
 (0.0020015006784852418, 7),
 (0.0018265837614271593, 'company_id_others'),
 (0.001695154488216629, 'company_id_2'),
 (0.0012953108317096643, 'marketing'),
 (0.001282831161356929, 'engineer'),
 (0.0012283259609048767, 'sales'),
 (0.0010960170751523571, 'design'),
 (0.0010221731439846564, 'tech_yes'),
 (0.0008853800736976744, 'customer_service'),
 (0.0008586292635060603, 'data_science'),
 (0.0007827737826581095, 'tech_no'),
 (0.0003299847706724393, 11),
 (0.00021672860990043914, 12)]
```

Note:
It looks like the most relevant features are - **join_year** - **salary** - **join_day** - **seniority** - **join_month**
We can ignore the other features for the rest of the analysis

5.2 How Does Logistic Regression Perform?

In [35]:
```
num_attribs = ['join_year', 'salary', 'join_day', 'seniority', 'join_month']
cat_attribs = ['dept']
full_pipeline, num_pipeline, cat_pipeline = make_pipeline(num_attribs, cat_attribs)

y = df.quited
X = df[num_attribs+cat_attribs]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=
```

```
X_train_encoded = full_pipeline.fit_transform(X_train, y_train)
X_test_encoded = full_pipeline.transform(X_test)


model = LogisticRegression()
model.fit(X_train_encoded, y_train)

predictions = model.predict(X_test_encoded)
pred_train = model.predict(X_train_encoded)
accuracy_train = accuracy_score(y_train, pred_train)
accuracy_test = accuracy_score(y_test, predictions)
print("Accuracy Score Train = ", accuracy_train)
print("Accuracy Score Test = ", accuracy_test)
```

```
Accuracy Score Train =  0.7921157836141896
Accuracy Score Test =  0.7980165958308035
```

5.3 How About Support Vector Classifier?

In [36]:
```
model = LinearSVC(C=0.1)
model = SVC(kernel='rbf', gamma=0.1, C=0.5)
model.fit(X_train_encoded, y_train)

predictions = model.predict(X_test_encoded)
pred_train = model.predict(X_train_encoded)
accuracy_train = accuracy_score(y_train, pred_train)
accuracy_test = accuracy_score(y_test, predictions)
print("Accuracy Score Train = ", accuracy_train)
print("Accuracy Score Test = ", accuracy_test)
```

```
Accuracy Score Train =  0.7952532766560396
Accuracy Score Test =  0.7972070431086824
```

5.4 Compare a few Classifiers

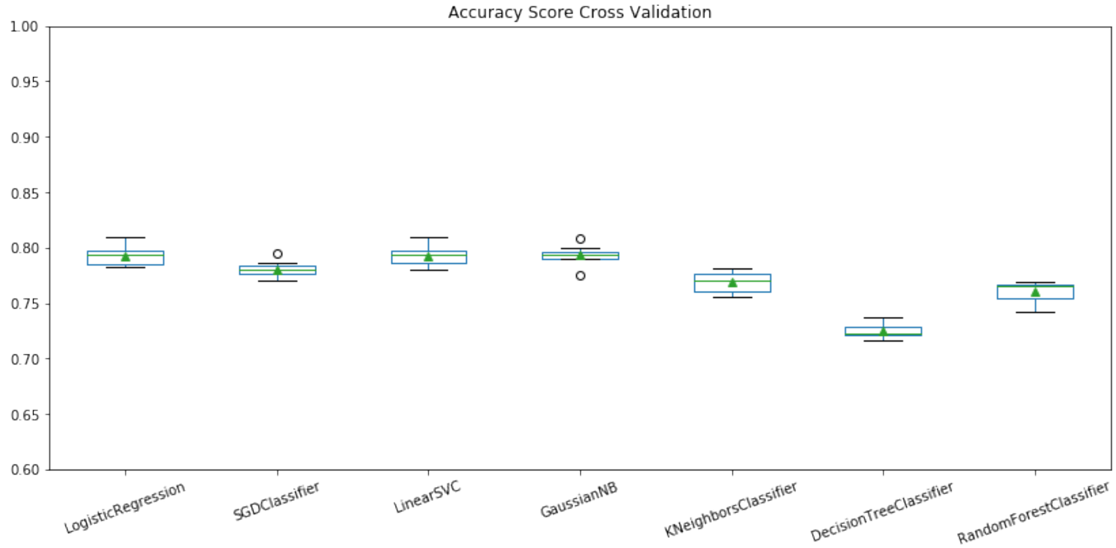
In [37]:
```
def get_cross_validation_scores(X, y, classifiers):
    """
    create a boxplot of cross validation scores to
    visualize how different classifiers perform with
    default parameters. Assumes all classifiers have been imported

    args:
        X -> numpy array, data to fit
        y -> class labels
        classifiers -> list of classifiers names (as strings)
```

```
    """

    cv_scores = {}
    train_scores = {}
    for name in classifiers:

        model = classifiers[name]
        model.fit(X, y)

        y_pred = model.predict(X)

        #calculate accuracy score for the cross validation set
        train_scores[name] = accuracy_score(y_pred, y)

        #cross validation
        cv_scores[name] = cross_val_score(model, X, y, cv=10)

    return train_scores, cv_scores
```

In [38]:
```
classifiers = {'LogisticRegression': LogisticRegression(),
               'SGDClassifier': SGDClassifier() ,
               'LinearSVC': LinearSVC(),
               'GaussianNB': GaussianNB(),
               'KNeighborsClassifier': KNeighborsClassifier() ,
               'DecisionTreeClassifier': DecisionTreeClassifier() ,
               'RandomForestClassifier': RandomForestClassifier()
              }

X_cv, y_cv = full_pipeline.fit_transform(df), y.values
train_scores, cv_scores = get_cross_validation_scores(X_cv, y_cv, classifiers=classif
```

In [39]:
```
def plot_model_cv_scores(cv_scores):

    scores = pd.DataFrame(cv_scores)
    fig = plt.figure(figsize=(14,6))
    ax1 = fig.add_subplot(111)
    ax1.set_ylim([0.6,1.0])
    _ = scores.plot(kind='box', showmeans=True, rot=20, ax=ax1, title='Accuracy Score
    #plt.savefig('figures/classifiers.png', dpi=200, bbox_inches='tight', pad_inches=
```

In [40]:
```
plot_model_cv_scores(cv_scores)
```



In [41]:
```
pd.DataFrame(cv_scores).mean()
```

Out[41]:
```
LogisticRegression        0.792891
SGDClassifier             0.780220
LinearSVC                 0.792486
GaussianNB                0.793418
KNeighborsClassifier      0.769249
DecisionTreeClassifier    0.724921
RandomForestClassifier    0.760344
dtype: float64
```

5.5 Use GridSearch to find best parameters

In [42]:
```
"""
estimator = RandomForestClassifier(random_state = 0,
                                   max_features = 'auto',
                                   max_depth = 11,
                                   min_samples_split= 6,
                                   n_estimators = 50,
                                  )
param_grid = {
    'max_depth': [7, 10, 15, 20],
    'max_features': ['auto', 'sqrt'],
    'min_samples_split': [2, 4, 6, 10],
    'n_estimators': [10, 50, 100, 150, 300]
}

CV_rfc = GridSearchCV(estimator=estimator, param_grid=param_grid, cv= 5)
CV_rfc.fit(X_train_encoded, y_train)
```

```
print(CV_rfc.best_params_)
"""
#results: {'max_depth': 7, 'max_features': 'auto', 'min_samples_split': 4, 'n_estimat
print()
```

5.6 Summary for Classification

- Two promising models:
  - Logistic Regression achieves accurary of 80% on test set
  - Support Vector Machine achieves accurary of 80% on test set
  - Random Forest with tuned parameters achieves accuracy of 80% on test set

6 Predict When Employee will Quit

In [43]:
```
from sklearn.linear_model import LogisticRegression, SGDClassifier, SGDRegressor
from sklearn.neural_network import MLPClassifier, MLPRegressor
from sklearn.svm import SVC, LinearSVR, SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error

from mlencoders.weight_of_evidence_encoder import WeightOfEvidenceEncoder
from mlencoders.target_encoder import TargetEncoder
```

In [44]:
```
df.head()
```

Out[44]:
```
             company_id              dept  seniority    salary  join_date  \
employee_id
13021                 7  customer_service         28   89000.0 2014-03-24
825355                7         marketing         20  183000.0 2013-04-29
927315                4         marketing         14  101000.0 2014-10-13
662910                7  customer_service         20  115000.0 2012-05-14
256971                2      data_science         23  276000.0 2011-10-17

              quit_date  quited technical         company_2  join_year  \
employee_id
13021        2015-10-30       1   tech_no  company_id_others       2014
825355       2014-04-04       1   tech_no  company_id_others       2013
927315              NaT       0   tech_no  company_id_others       2014
662910       2013-06-07       1   tech_no  company_id_others       2012
256971       2014-08-22       1  tech_yes       company_id_2       2011

             join_month  join_day  total_months  mean_salary_dept  \
```

```
employee_id
13021                  3        24            19      82245.424837
825355                 4        29            11     135598.042311
927315                10        13           360     135598.042311
662910                 5        14            12      82245.424837
256971                10        17            34     206885.893417

             max_salary_dept  min_salary_dept
employee_id
13021               166000.0          17000.0
825355              262000.0          30000.0
927315              262000.0          30000.0
662910              166000.0          17000.0
256971              398000.0          44000.0
```

In [45]:
```
def log_transform(df, cols):
    for col in cols:
        df[col] = np.log(df[col])
    return df

num_attribs = ['join_year',
               'salary',
               'join_day',
               'seniority',
               'join_month',
               'mean_salary_dept',
               'max_salary_dept',
               'min_salary_dept'
              ]

cat_attribs = ['dept', 'company_id']
full_pipeline, num_pipeline, cat_pipeline = make_pipeline(num_attribs, cat_attribs)

df_quited = df[df.quited == 1]
df_quited = log_transform(df_quited, num_attribs)
y = df_quited.total_months
X = df_quited[num_attribs+cat_attribs]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=
X_train_encoded = full_pipeline.fit_transform(X_train, y_train)
X_test_encoded = full_pipeline.transform(X_test)


model = RandomForestRegressor(random_state=11,
                              max_depth = 11,
                              n_estimators=100)
#model = LinearSVR(C=100)
model.fit(X_train_encoded, y_train)
```

```
predictions = model.predict(X_test_encoded)
pred_train = model.predict(X_train_encoded)
baseline_preds = np.array([np.mean(y_test) for value in y_test])
```

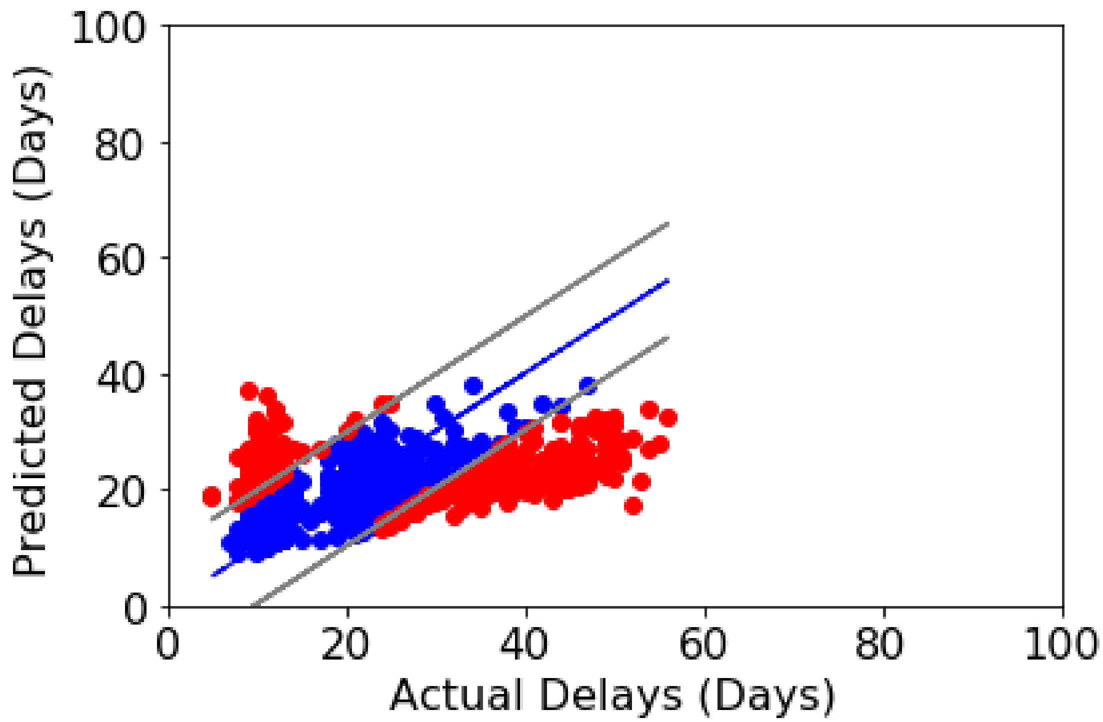
```
In [46]: train_rmse = np.sqrt(mean_squared_error(y_train, pred_train))
         base_rmse = np.sqrt(mean_squared_error(y_test, baseline_preds))
         test_rmse = np.sqrt(mean_squared_error(y_test, predictions))
         print('\nMean Square Errors:')
         print('-----------------------')
         print('Mean Square Error Train: ', round(train_rmse, 2))
         print('Mean Square Error Baseline: ', round(base_rmse, 2))
         print('Mean Square Error Test: ', round(test_rmse, 2))
         print('Percent Improvement from Baseline:', 100*(base_rmse-test_rmse)/base_rmse)
         print('Sample Std:', np.std(y_train))
```

```
Mean Square Errors:
-----------------------
Mean Square Error Train:  8.09
Mean Square Error Baseline:  10.97
Mean Square Error Test:  9.8
Percent Improvement from Baseline: 10.597580629121863
Sample Std: 10.783523266427673
```

```
In [47]: import matplotlib.pyplot as plt
         plt.rcParams.update({'font.size': 16})
         dyfit = test_rmse

         plt.xlim(0, 100);
         plt.ylim(0, 100);
         plt.xlabel('Actual Delays (Days)')
         plt.ylabel('Predicted Delays (Days)')


         y_low = y_test - test_rmse
         y_high= y_test + test_rmse

         bool_mask = (predictions < y_high) & (predictions > y_low)
         y_in = predictions[bool_mask]
         y_out = predictions[~bool_mask]

         plt.plot(y_test[bool_mask], y_in, 'o', color='blue')
         plt.plot(y_test[~bool_mask], y_out, 'o', color='red')
         plt.plot(y_test, y_test, '--', color='blue')
         plt.plot(y_test, y_test - dyfit, '-', color='gray')
         plt.plot(y_test, y_test + dyfit, '-', color='gray')
```

```
#plt.savefig('figures/delay_days_predictions.png', dpi=200, bbox_inches='tight', pad_
#plt.fill_between(y_test, y_test - dyfit, y_test + dyfit, color='gray', alpha=0.6)
```

Out[47]: [<matplotlib.lines.Line2D at 0x7f9a6d3105c0>]



7 Conclusion

- Features that are important in predicting which employee will quit are
  - **The year when the employee joined**
  - **The employee salary**
  - **The day when the employee joined** (not very important without the year, can even be ignored.)
  - **The seniority level, i.e. the number of years of service**
  - **The month when the employee joined** (not very important without the year, can even be ignored)

I believe features such as the year when the employee started working as well as the salary make sense. These are all non-academic jobs, and I think people will likely quit their job early in their careers, either because they realize that the first job was not the job they wanted or because they feel like they have gained some experience and would like better opportunities. Also, if salary has been stagnant, people will likely quit.

If I could add one feature, I would add I would add the age of the employee because this will determine if the employee is early in their career or a senior.