In [5]:
```
# Group 9- EMPLOYEE ATTRITION: FINAL CODE

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# Jeffrey Younghoon Kim
```

In [6]:
```
import numpy as np
import pandas as pd
import math
import matplotlib.pylab as plt
import seaborn as sns
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.model_selection import GridSearchCV


%matplotlib inline
sns.set(style='ticks', palette='Set2')

import sys
sys.path.append("..")
!sudo pip install html2text
from ds_utils.features_pipeline_3 import pipeline_from_config

# URL
url = "https://raw.githubusercontent.com/ShimengC/test1/master/WA_Fn-UseC_-H
hr_df = pd.read_csv(url).dropna()
# list(hr_df)
```

```
The directory '/home/ubuntu/.cache/pip/http' or its parent directory is n
ot owned by the current user and the cache has been disabled. Please chec
k the permissions and owner of that directory. If executing pip with sud
o, you may want sudo's -H flag.
The directory '/home/ubuntu/.cache/pip' or its parent directory is not ow
ned by the current user and caching wheels has been disabled. check the p
ermissions and owner of that directory. If executing pip with sudo, you m
ay want sudo's -H flag.
Requirement already satisfied: html2text in /usr/local/lib/python3.5/dist
-packages (2018.1.9)
```

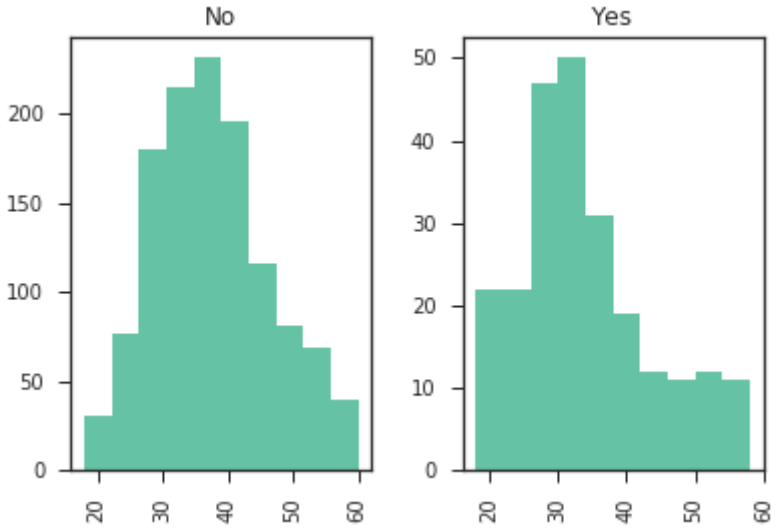
In [7]:
```
hr_df.head()
```

Out[7]:

eeNumber	...	RelationshipSatisfaction	StandardHours	StockOptionLevel	TotalWorkingYears	Training1
1	...	1	80	0	8	
2	...	4	80	1	10	
4	...	2	80	0	7	
5	...	3	80	0	8	
7	...	4	80	1	6	

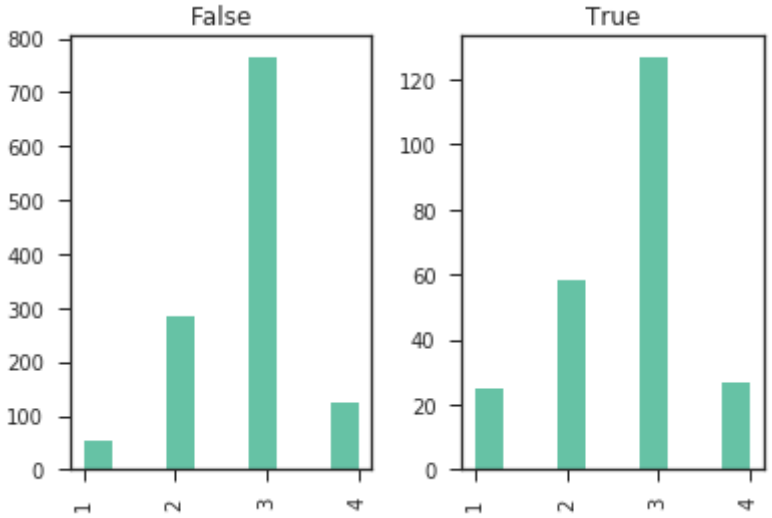
In [8]:
```
hr_df.Age.hist(by=hr_df["Attrition"])
```

Out[8]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7ffa2b8bbac8>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7ffa2b889d30>],
      dtype=object)
```



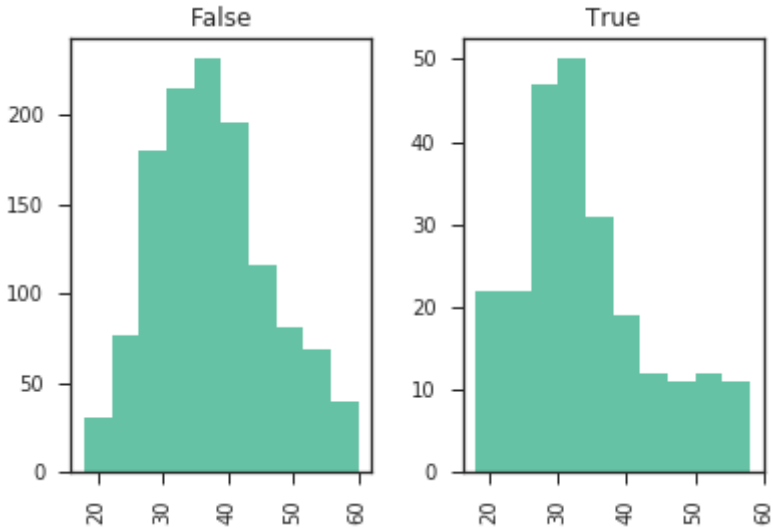
In [9]:
```
hr_df.WorkLifeBalance.hist(by=(hr_df["Attrition"]=="Yes"))
```

Out[9]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7ffa2b7f6c50>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7ffa2b811c18>],
      dtype=object)
```



In [10]:
```
hr_df.Age.hist(by=hr_df["Attrition"]=='Yes')
```

Out[10]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x7ffa297b2208>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x7ffa29768898>],
      dtype=object)
```



In [11]:
```
config = [
    {
        "field": "Attrition",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "Age",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "BusinessTravel",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "DailyRate",
        "transformers": [
            {"name": "standard_numeric"}
#             {
#                 "name": "quantile_numeric",
#                 "config": {"n_quantiles": 10}
#             }
        ]
    } ,
    {
        "field": "Department",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "DistanceFromHome",
        "transformers": [
            {"name": "range_numeric"}
        ]
    } ,
    {
        "field": "Education",
        "transformers": [
            {"name": "dummyizer"}
        ]
    } ,
    {
        "field": "EducationField",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "EmployeeCount",
        "transformers": [
```

```
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "EmployeeNumber",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "EnvironmentSatisfaction",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "Gender",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "HourlyRate",
        "transformers": [
            {"name": "standard_numeric"}
#             {
#                 "name": "quantile_numeric",
#                 "config": {"n_quantiles": 10}
#             }
        ]
    },
    {
        "field": "JobInvolvement",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "JobLevel",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "JobRole",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "JobSatisfaction",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "MaritalStatus",
```

```
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "MonthlyIncome",
        "transformers": [
            {"name": "standard_numeric"}
#             {
#                 "name": "quantile_numeric",
#                 "config": {"n_quantiles": 10}
#             }
        ]
    },
    {
        "field": "MonthlyRate",
        "transformers": [
            {"name": "standard_numeric"}
#             {
#                 "name": "quantile_numeric",
#                 "config": {"n_quantiles": 10}
#             }
        ]
    },
    {
        "field": "NumCompaniesWorked",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "Over18",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "OverTime",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "PercentSalaryHike",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "PerformanceRating",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "RelationshipSatisfaction",
        "transformers": [
```

```
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "StandardHours",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "StockOptionLevel",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "TotalWorkingYears",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "TrainingTimesLastYear",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "WorkLifeBalance",
        "transformers": [
            {"name": "dummyizer"}
        ]
    },
    {
        "field": "YearsAtCompany",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "YearsInCurrentRole",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "YearsSinceLastPromotion",
        "transformers": [
            {"name": "range_numeric"}
        ]
    },
    {
        "field": "YearsWithCurrManager",
        "transformers": [
            {"name": "range_numeric"}
        ]
    }
```

```
]

from sklearn.model_selection import train_test_split

# train_df, test_df, y_train, y_test = train_test_split(hr_df, hr_df["Attrit

pipeline = pipeline_from_config(config)
# X_train = pipeline.fit_transform(train_df)
# X_test = pipeline.transform(test_df)

# model = LogisticRegression()
# model.fit(X_train, y_train)

transformed = pipeline.fit_transform(hr_df)
```

```
/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: D
ataConversionWarning: Data with input dtype int64 was converted to float6
4 by MinMaxScaler.
  warnings.warn(msg, DataConversionWarning)
/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: D
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  warnings.warn(msg, DataConversionWarning)
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ataConversionWarning: Data with input dtype int64 was converted to float6
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4 by MinMaxScaler.
  warnings.warn(msg, DataConversionWarning)
/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: D
```

```
ataConversionWarning: Data with input dtype int64 was converted to float6
4 by MinMaxScaler.
  warnings.warn(msg, DataConversionWarning)
/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: D
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/usr/local/lib/python3.5/dist-packages/sklearn/utils/validation.py:475: D
ataConversionWarning: Data with input dtype int64 was converted to float6
4 by MinMaxScaler.
  warnings.warn(msg, DataConversionWarning)
```

In [12]:
```
np.size(transformed,1)
np.size(transformed,0)
transformed_df=pd.DataFrame(transformed)
transformed_df.head()
```

Out[12]:

	0	1	2	3	4	5	6	7	8	9	...	70	71	72	73	74	75
0	1.0	0.547619	0.0	0.0	1.0	0.742527	0.0	0.0	1.0	0.000000	...	0.200	0.0	1.0	0.0	0.0	0.0
1	0.0	0.738095	0.0	1.0	0.0	-1.297775	0.0	1.0	0.0	0.250000	...	0.250	0.5	0.0	0.0	1.0	0.0
2	1.0	0.452381	0.0	0.0	1.0	1.414363	0.0	1.0	0.0	0.035714	...	0.175	0.5	0.0	0.0	1.0	0.0
3	0.0	0.357143	0.0	1.0	0.0	1.461466	0.0	1.0	0.0	0.071429	...	0.200	0.5	0.0	0.0	1.0	0.0
4	0.0	0.214286	0.0	0.0	1.0	-0.524295	0.0	1.0	0.0	0.035714	...	0.150	0.5	0.0	0.0	1.0	0.0

5 rows × 80 columns

In [13]:
```
transformed_df.columns = [
 'Attrition',
 'Age',
 'BusinessTravel_None','BusinessTravel_Frequently', 'BusinessTravel_Rarely',
 'DailyRate',
 'Department_HR','Department_RnD','Department_Sales',
 'DistanceFromHome',
 'Education_BelowCollege','Education_College','Education_Bachelor','Educatio
 'EducationField_HR','EducationField_LS','EducationField_MKT','EducationFiel
 'EmployeeCount',
 'EmployeeNumber',
 'EnvironmentSatisfaction_L','EnvironmentSatisfaction_M','EnvironmentSatisfa
 'Gender',
 'HourlyRate',
 'JobInvolvement_L','JobInvolvement_M','JobInvolvement_H','JobInvolvement_VH
 'JobLevel_1','JobLevel_2','JobLevel_3','JobLevel_4','JobLevel_5',
 'JobRole_HCR','JobRole_HR','JobRole_LT','JobRole_M','JobRole_MD','JobRole_R
 'JobSatisfaction_L','JobSatisfaction_M','JobSatisfaction_H','JobSatisfactio
 'MaritalStatus_Divorced', 'MaritalStatus_Married', 'MaritalStatus_Single',
 'MonthlyIncome',
 'MonthlyRate',
 'NumCompaniesWorked',
 'Over18',
 'OverTime',
 'PercentSalaryHike',
 'PerformanceRating',
 'RelationshipSatisfaction_L','RelationshipSatisfaction_M','RelationshipSati
 'StandardHours',
 'StockOptionLevel_0','StockOptionLevel_1','StockOptionLevel_2','StockOption
 'TotalWorkingYears',
 'TrainingTimesLastYear',
 'WorkLifeBalance_Bad','WorkLifeBalance_Good','WorkLifeBalance_Better','Work
 'YearsAtCompany',
 'YearsInCurrentRole',
 'YearsSinceLastPromotion',
 'YearsWithCurrManager']
```

In [14]:
```
transformed_df.head()
```

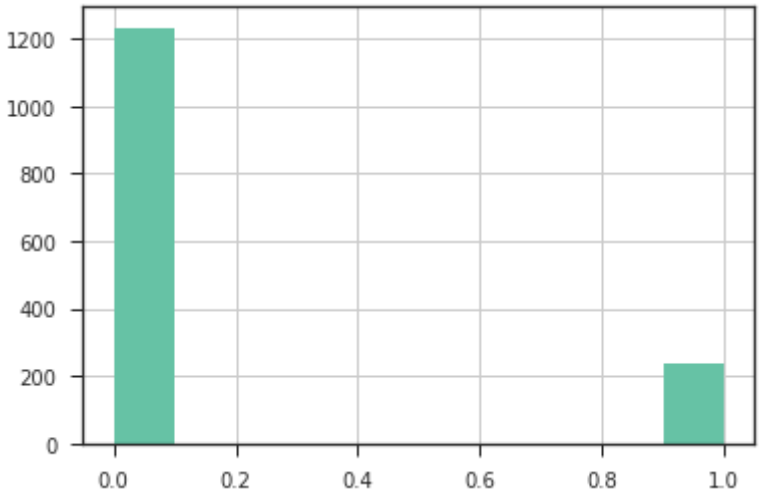
Out[14]:

	Attrition	Age	BusinessTravel_None	BusinessTravel_Frequently	BusinessTravel_Rarely	DailyR
0	1.0	0.547619	0.0	0.0	1.0	0.742
1	0.0	0.738095	0.0	1.0	0.0	-1.297
2	1.0	0.452381	0.0	0.0	1.0	1.414
3	0.0	0.357143	0.0	1.0	0.0	1.461
4	0.0	0.214286	0.0	0.0	1.0	-0.524

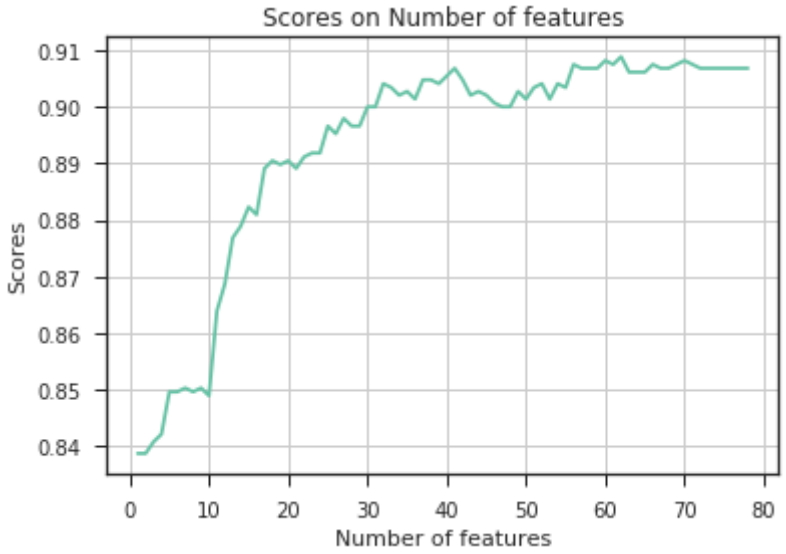
5 rows × 80 columns

In [15]:
```
transformed_df.Attrition.hist()
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffa29736080>
```



In [16]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression


# dataframe = read_csv(url)
array = transformed_df.values
array.view()
np.size(array,0)
X = array[:,1:80]
a = array[:,0:1]
Y = a.ravel()
np.size(Y)

model = LogisticRegression()

scores = []
num_features = []
score_max=0
num_features_max=0
for i in range (1,79):
    rfe = RFE(model, i)
    fit = rfe.fit(X, Y)
    s=fit.score(X, Y)
#     print ("%d %0.3f" %(i, s))
    scores.append(s)
    num_features.append(i)
    if(s>score_max):
        score_max=s
        num_features_max=i

plt.plot(num_features,scores)
plt.title("Scores on Number of features")
plt.xlabel("Number of features")
plt.ylabel("Scores")
plt.grid()
plt.show()

rfe = RFE(model, 32)
fit = rfe.fit(X, Y)
final_score=fit.score(X, Y)

# fit.support_
# fit.ranking_
names = list(transformed_df)[1:]

print ("Features sorted by their rank:")
print (num_features_max)
print (final_score)
print (sorted(zip(map(lambda x: round(x, 4), fit.ranking_), names)))
```

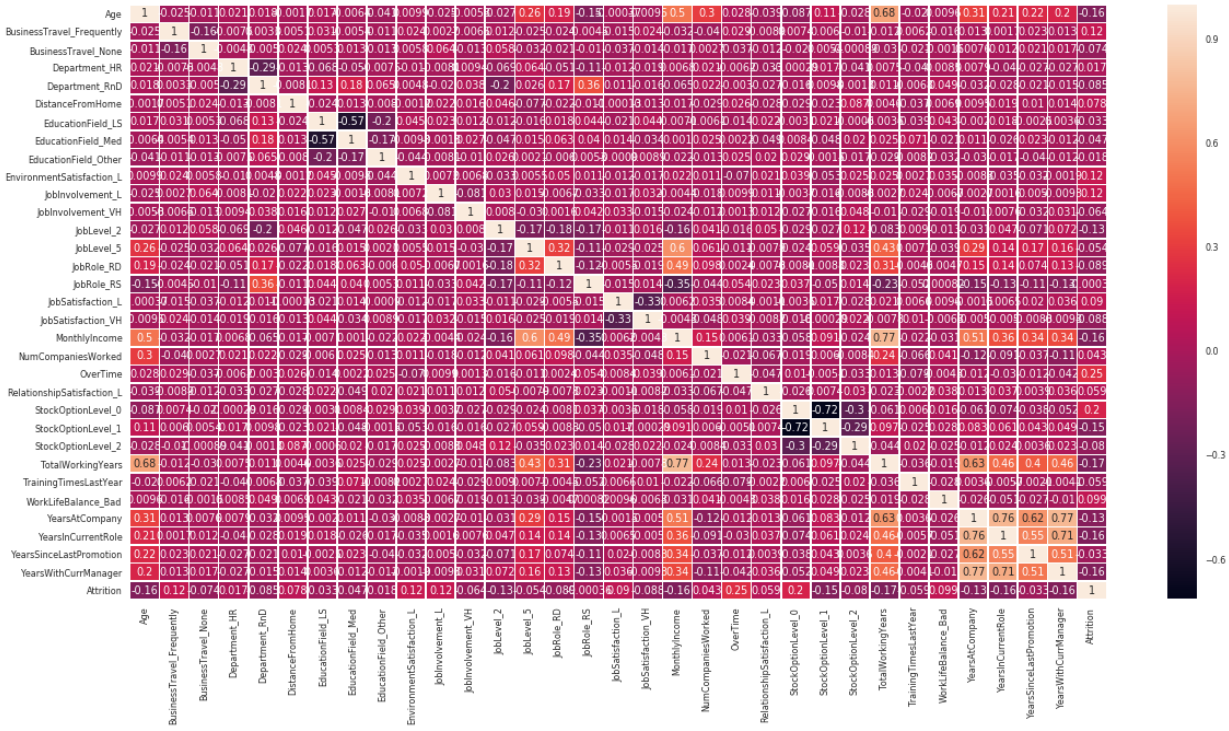



```
Features sorted by their rank:
62
0.9040816326530612
[(1, 'Age'), (1, 'BusinessTravel_Frequently'), (1, 'BusinessTravel_Non
e'), (1, 'Department_HR'), (1, 'Department_RnD'), (1, 'DistanceFromHom
e'), (1, 'EducationField_LS'), (1, 'EducationField_Med'), (1, 'EducationF
ield_Other'), (1, 'EnvironmentSatisfaction_L'), (1, 'JobInvolvement_L'),
(1, 'JobInvolvement_VH'), (1, 'JobLevel_2'), (1, 'JobLevel_5'), (1, 'JobR
ole_RD'), (1, 'JobRole_RS'), (1, 'JobSatisfaction_L'), (1, 'JobSatisfacti
on_VH'), (1, 'MonthlyIncome'), (1, 'NumCompaniesWorked'), (1, 'OverTim
e'), (1, 'RelationshipSatisfaction_L'), (1, 'StockOptionLevel_0'), (1, 'S
tockOptionLevel_1'), (1, 'StockOptionLevel_2'), (1, 'TotalWorkingYears'),
(1, 'TrainingTimesLastYear'), (1, 'WorkLifeBalance_Bad'), (1, 'YearsAtCom
pany'), (1, 'YearsInCurrentRole'), (1, 'YearsSinceLastPromotion'), (1, 'Y
earsWithCurrManager'), (2, 'WorkLifeBalance_Better'), (3, 'JobLevel_4'),
(4, 'JobRole_HCR'), (5, 'EducationField_Tech'), (6, 'JobInvolvement_H'),
(7, 'RelationshipSatisfaction_VH'), (8, 'RelationshipSatisfaction_M'),
(9, 'RelationshipSatisfaction_H'), (10, 'Gender'), (11, 'JobRole_SE'), (1
2, 'MaritalStatus_Divorced'), (13, 'MaritalStatus_Married'), (14, 'JobLev
el_1'), (15, 'EmployeeNumber'), (16, 'EducationField_HR'), (17, 'Environm
entSatisfaction_VH'), (18, 'EnvironmentSatisfaction_H'), (19, 'Environmen
tSatisfaction_M'), (20, 'PercentSalaryHike'), (21, 'JobRole_SR'), (22, 'J
obRole_LT'), (23, 'Education_BelowCollege'), (24, 'JobRole_M'), (25, 'Dai
lyRate'), (26, 'WorkLifeBalance_Best'), (27, 'WorkLifeBalance_Good'), (2
8, 'StockOptionLevel_3'), (29, 'BusinessTravel_Rarely'), (30, 'Department
_Sales'), (31, 'JobRole_HR'), (32, 'MaritalStatus_Single'), (33, 'JobRole
_MD'), (34, 'Education_Doc'), (35, 'JobSatisfaction_M'), (36, 'JobSatisfa
ction_H'), (37, 'JobLevel_3'), (38, 'JobInvolvement_M'), (39, 'MonthlyRat
e'), (40, 'HourlyRate'), (41, 'PerformanceRating'), (42, 'EducationField_
MKT'), (43, 'Education_College'), (44, 'Education_Master'), (45, 'Educati
on_Bachelor'), (46, 'Over18'), (47, 'StandardHours'), (48, 'EmployeeCoun
t')]
```

In [17]:
```
predicted_array = sorted(zip(map(lambda x: round(x, 4), fit.ranking_), names

predictors=[]
for r in range (0,32):
    predictors.append(predicted_array[[r][0]][1])

# len(predictors)
predictors
```

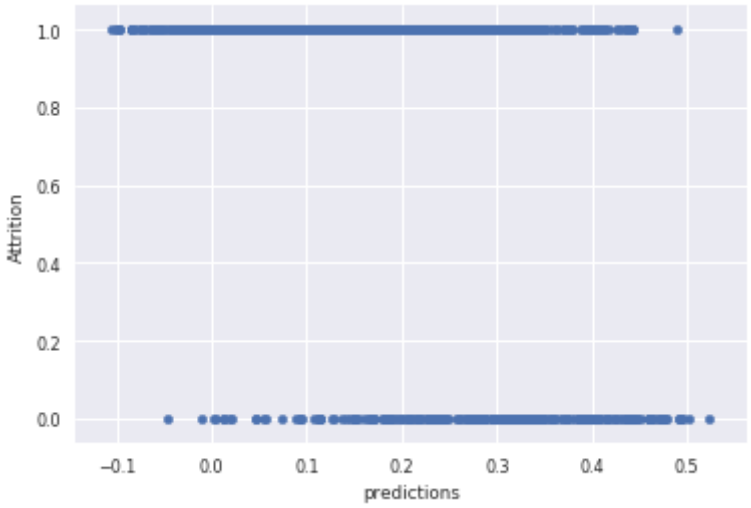
Out[17]:
```
['Age',
 'BusinessTravel_Frequently',
 'BusinessTravel_None',
 'Department_HR',
 'Department_RnD',
 'DistanceFromHome',
 'EducationField_LS',
 'EducationField_Med',
 'EducationField_Other',
 'EnvironmentSatisfaction_L',
 'JobInvolvement_L',
 'JobInvolvement_VH',
 'JobLevel_2',
 'JobLevel_5',
 'JobRole_RD',
 'JobRole_RS',
 'JobSatisfaction_L',
 'JobSatisfaction_VH',
 'MonthlyIncome',
 'NumCompaniesWorked',
 'OverTime',
 'RelationshipSatisfaction_L',
 'StockOptionLevel_0',
 'StockOptionLevel_1',
 'StockOptionLevel_2',
 'TotalWorkingYears',
 'TrainingTimesLastYear',
 'WorkLifeBalance_Bad',
 'YearsAtCompany',
 'YearsInCurrentRole',
 'YearsSinceLastPromotion',
 'YearsWithCurrManager']
```

In [18]:
```
new_list = []
new_list = predictors.copy()
new_list.append("Attrition")

pred_target_df=transformed_df[new_list]

sns.set(font_scale=.8)
plt.figure(figsize=(20,10))
sns.heatmap(pred_target_df.corr(),annot=True, linewidths=0.5)
plt.xticks(rotation=90)
plt.show()
```



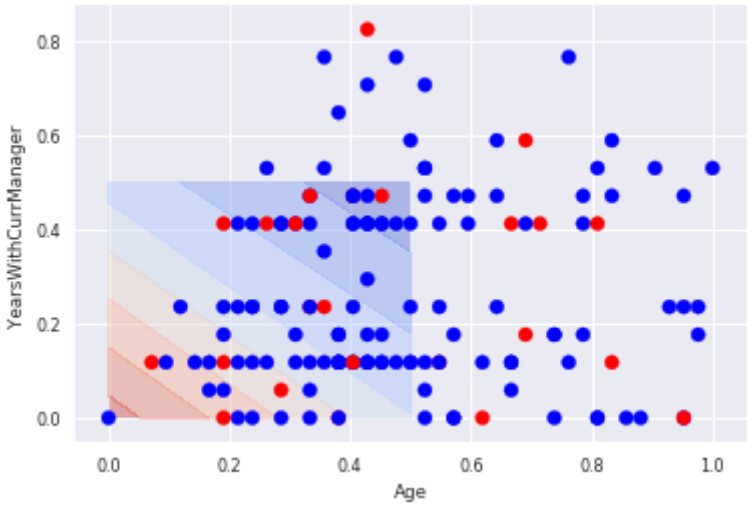
In [19]:
```
from sklearn import linear_model
from sklearn.model_selection import train_test_split

cleaned_df = transformed_df
target = "Attrition"

linear = linear_model.Lasso(alpha=0.01)
linear.fit(cleaned_df[predictors], cleaned_df[target])

pd.DataFrame([dict(zip(predictors, linear.coef_))])

X_train, X_test, y_train, y_test = train_test_split(cleaned_df[predictors],
                                                    cleaned_df[target],
                                                    test_size=0.25,
                                                    random_state=42)
linear.fit(X_train, y_train)
preds = linear.predict(cleaned_df[predictors])
predictions_df = cleaned_df.assign(predictions=preds)

pd.to_numeric(predictions_df['Attrition']).astype(float)
predictions_df['Attrition'] = predictions_df['Attrition'].factorize()[0]
predictions_df.plot(kind="scatter", x="predictions", y="Attrition")

# predictions_df
# cleaned_df[target]
# predictors
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffa296fccf8>



In [20]:
```
ls_utils.decision_surface import *
 search using C for logistic regression .C is the inverse of parameter regula
 = {
penalty':['l1','l2'],
':[0.001, 0.01, 0.1, 1.0, 5.0, 7.5,10.0,15.0, 20.0, 40.0, 100.0]


_lr_model = GridSearchCV(LogisticRegression(), grid, scoring="roc_auc")
_lr_model.fit(X_train, y_train)

("Best ROC for logistic regression: %0.3f, using " % tuned_lr_model.best_sco
(tuned_lr_model.best_params_)
(tuned_lr_model.best_score_)

on_Surface(transformed_df[predictors], "Age", "YearsWithCurrManager", transf
```

```
Best ROC for logistic regression: 0.865, using
{'penalty': 'l2', 'C': 5.0}
0.8648788601600299
```



In [21]:
```
#Grid search for random forest
grid = {
    "n_estimators": list(range(1, 100, 5))
}

rf_tuned_model = GridSearchCV(RandomForestClassifier(), grid, scoring="roc_a
rf_tuned_model.fit(X_train, y_train)

print ("Best ROC for random forest: %0.3f, using: " % rf_tuned_model.best_sc
print (rf_tuned_model.best_params_)
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fits
Best ROC for random forest: 0.813, using:
{'n_estimators': 66}

[Parallel(n_jobs=1)]: Done  60 out of  60 | elapsed:    6.3s finished
```

In [22]:
```
#Grid search for decision tree
grid = {
    "min_samples_leaf": list(range(5, 100, 5))
}

#tuned model for decision tree
tuned_model = GridSearchCV(DecisionTreeClassifier(), grid, scoring="roc_auc"
tuned_model.fit(X_train, y_train)

print ("Best ROC for decision tree classifier: %0.3f, using: " % tuned_model
print (tuned_model.best_params_)
```

```
Best ROC for decision tree classifier: 0.753, using:
{'min_samples_leaf': 20}
```

In [23]:
```
import sklearn.model_selection as cv
from sklearn.metrics import accuracy_score

def evaluate_model_on_sample(df, model, predictor_cols, class_col, pct, scor
    kf = cv.StratifiedKFold(n_splits=2, shuffle=True, random_state=42)
    scores = []

    X = df[predictor_cols]
    y = df[class_col]

    for train_index, test_index in kf.split(X, y):

        sampled_indices = np.random.permutation(range(len(train_index)))[:in
        np_train = np.array(train_index)
        to_get = np_train[sampled_indices]

        model.fit(X.loc[to_get], y[to_get])
        scores.append(scoring(y[test_index], model.predict(X.loc[test_index]

    return np.mean(scores), np.std(scores)
```

In [24]:

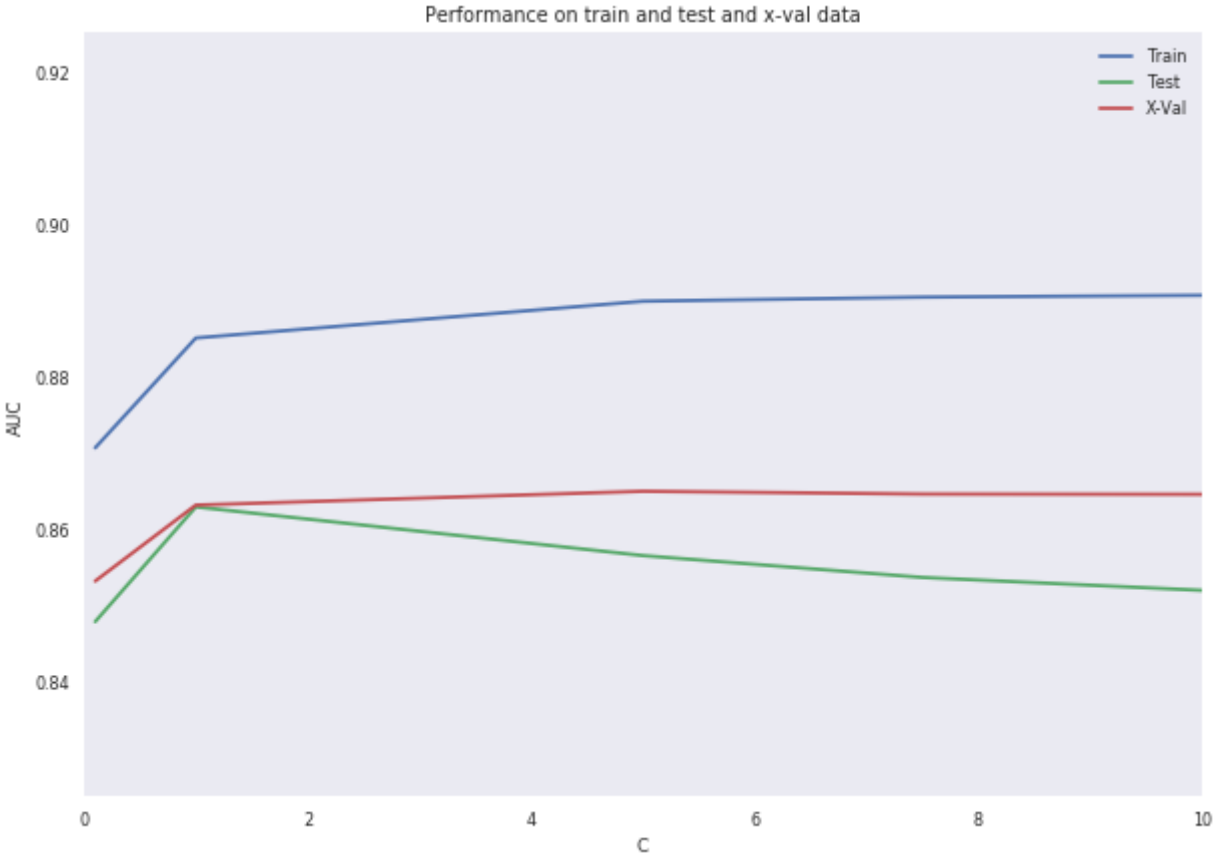
```
pcts = np.linspace(0.01,1,100).tolist()
dt_scores = [evaluate_model_on_sample(transformed_df,
                                      DecisionTreeClassifier(),
                                      predictors,
                                      "Attrition",
                                      pct)
             for pct in pcts]


lr_scores = [evaluate_model_on_sample(transformed_df,
                                       LogisticRegression(),
                                       predictors,
                                       "Attrition",
                                       pct)
             for pct in pcts]

rf_scores = [evaluate_model_on_sample(transformed_df,
                                       RandomForestClassifier(),
                                       predictors,
                                       "Attrition",
                                       pct)
             for pct in pcts]
```

In [60]:
```
raw_dt_score = np.array([s[0] for s in dt_scores])
std_dt_score = np.array([s[1] for s in dt_scores])

raw_lr_score = np.array([s[0] for s in lr_scores])
std_lr_score = np.array([s[1] for s in lr_scores])

raw_rf_score = np.array([s[0] for s in rf_scores])
std_rf_score = np.array([s[1] for s in rf_scores])


plt.plot(pcts, raw_dt_score, label="Decision Tree")
plt.plot(pcts, raw_lr_score, label="Logistic Regression")
plt.plot(pcts, raw_rf_score, label="Random Forest")

plt.xlabel("Percent of data")
plt.ylabel("ROC-AUC")
plt.legend()
plt.show()
```

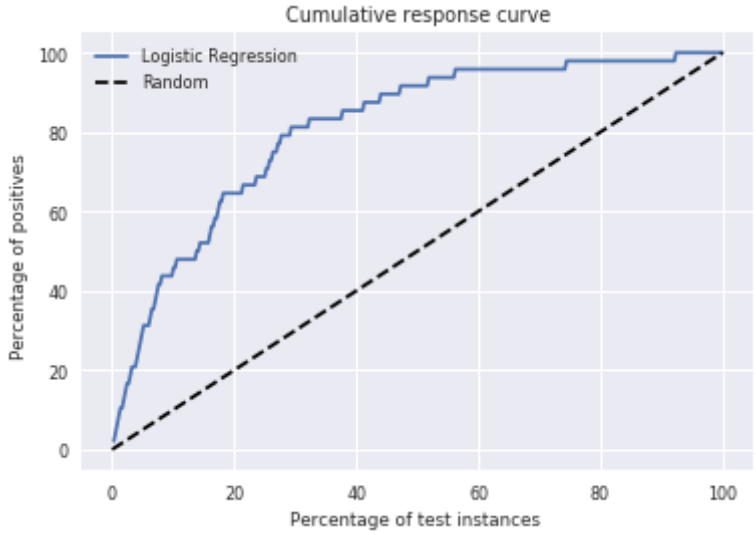
In [26]:
```
# Cross Validation

from sklearn import model_selection
from sklearn.model_selection import cross_val_score
kfold = model_selection.KFold(n_splits=10, random_state=7)
modelCV = LogisticRegression()
scoring = 'roc_auc'
results = model_selection.cross_val_score(modelCV, X_train, y_train, cv=kfol
print("10-fold cross validation average accuracy: %.3f" % (results.mean()))
```

```
10-fold cross validation average accuracy: 0.856
```

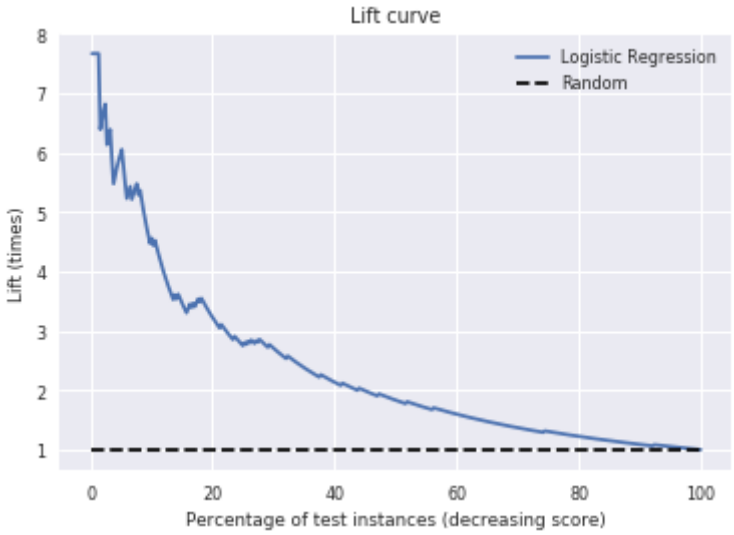
In [61]:
```
#Fitting Curve

aucs_train = []
aucs_test = []
aucs_xval = []
# maxdepth = 30
C_val = [0.1, 1.0, 5.0, 7.5,10.0,15.0, 20.0, 25.0]

plt.figure(figsize=[10,7])

for c in C_val:
    model = LogisticRegression(C=c, penalty='l2')
    model.fit(X_train, y_train)

    aucs_train.append(roc_auc_score(y_train, model.predict_proba(X_train)[:,
    aucs_test.append(roc_auc_score(y_test, model.predict_proba(X_test)[:,1])

    scores = cross_val_score(model, X_train, y_train, scoring="roc_auc")
    aucs_xval.append(scores.mean())

plt.plot( C_val,aucs_train,label="Train")
plt.plot( C_val,aucs_test,label="Test")
plt.plot( C_val,aucs_xval,label="X-Val")
plt.title("Performance on train and test and x-val data")
plt.grid()
plt.xlabel("C")
plt.ylabel("AUC")
plt.ylim([0.825, 0.925])
plt.xlim([0,10])
plt.legend()
plt.show()
```


Performance on train and test and x-val data
Train
Test
X-Val
AUC
0.92
0.90
0.88
0.86
0.84
0
2
4
6
8
10
C

In [62]:
```
# Cumalative response curve

model = LogisticRegression(C=5.0,penalty='l2')
model.fit(X_train, y_train)


Y_test_predicted = model.predict(X_test)
Y_test_probability = model.predict_proba(X_test)[:, 1]


order = np.argsort(Y_test_probability)[::-1]
Y_test_predicted_sorted = Y_test_predicted[order]
Y_test_sorted = np.array(y_test)[order]

total_test_positives = y_test.sum()

y_cumulative = Y_test_sorted.cumsum()*100/float(total_test_positives)
x_cumulative = np.linspace(1, len(y_cumulative), len(y_cumulative))*100/len(



plt.plot(x_cumulative, y_cumulative, label="Logistic Regression")
plt.plot([0,100], [0,100], 'k--', label="Random")
plt.xlabel("Percentage of test instances ")
plt.ylabel("Percentage of positives ")
plt.title("Cumulative response curve")
plt.legend()
plt.show()
```



In [63]:
```
# Lift curve

y_lift = y_cumulative/x_cumulative

plt.plot(x_cumulative, y_lift, label="Logistic Regression")
plt.plot([0,100], [1,1], 'k--', label="Random")
plt.xlabel("Percentage of test instances (decreasing score)")
plt.ylabel("Lift (times)")
plt.title("Lift curve")
plt.legend()
plt.show()
```



In [64]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(C=5.0, penalty='l2')
model.fit(X_train, y_train)
predValues = model.predict(X_test)

# "pretty print" the confusion matrix
from sklearn import metrics

conf_matrix = metrics.confusion_matrix(y_test, predValues, labels=[1, 0]).T
confusion_matrix_one = pd.DataFrame(conf_matrix, columns=['p', 'n'], index=[

confusion_matrix_one
```

Out[64]:

	p	n
Y	21	11
N	27	309

In [33]:
```
conf_matrix_probs = conf_matrix/float(conf_matrix.sum())
confusion_matrix_one_probs = pd.DataFrame(conf_matrix_probs, columns=['p', '

confusion_matrix_one_probs
```

Out[33]:

	p	n
Y	0.057065	0.029891
N	0.073370	0.839674

In [35]:
```
precision = metrics.precision_score(y_test, predValues)
recall = metrics.recall_score(y_test, predValues)

print ("precision: %0.3f, recall: %0.3f" % (precision, recall))
```

```
precision: 0.656, recall: 0.438
```

In [49]:
```
from sklearn.cluster import KMeans

# non_confounding=pred_target_df[
km = KMeans(n_clusters=2, init='k-means++', n_init=10)
```

In [50]:
```
km.fit(pred_target_df)
cluster = km.fit_predict(pred_target_df)
# len(cluster)
# cluster
pred_target_df["Clusters"]=cluster
pred_target_df.head()

# km.fit(transformed_df)
# cluster = km.fit_predict(transformed_df)
# # len(cluster)
# # cluster
# transformed_df["Clusters"]=cluster
# transformed_df.head()
```

```
/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:5: SettingWi
thCopyWarning:
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-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  """
```

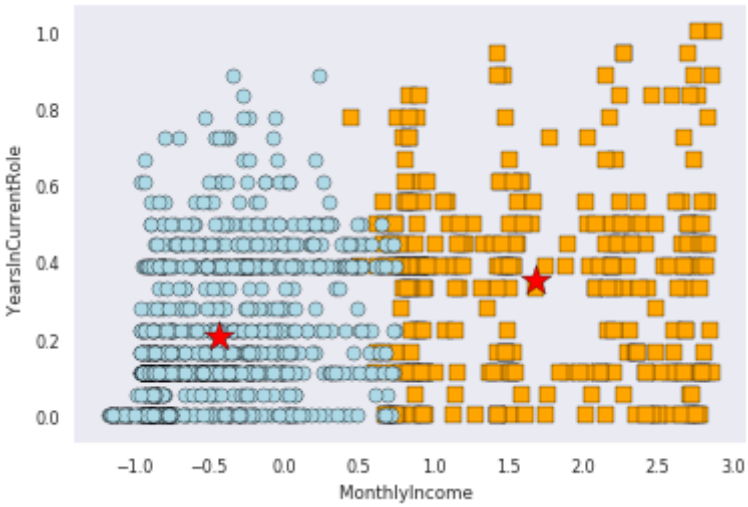
Out[50]:

	Age	BusinessTravel_Frequently	BusinessTravel_None	Department_HR	Department_RnD	Dist
0	0.547619	0.0	0.0	0.0	0.0	
1	0.738095	1.0	0.0	0.0	1.0	
2	0.452381	0.0	0.0	0.0	1.0	
3	0.357143	1.0	0.0	0.0	1.0	
4	0.214286	0.0	0.0	0.0	1.0	

5 rows × 34 columns

In [57]:
```
Cluster0=pred_target_df[pred_target_df['Clusters'] == 0]
left_Cluster0=Cluster0[Cluster0['Attrition'] == 1]
stayed_Cluster0=Cluster0[Cluster0['Attrition'] == 0]

Cluster1=pred_target_df[pred_target_df['Clusters'] == 1]
left_Cluster1=Cluster1[Cluster1['Attrition'] == 1]
stayed_Cluster1=Cluster1[Cluster1['Attrition'] == 0]

# Cluster2=pred_target_df[pred_target_df['Clusters'] == 2]
# left_Cluster2=Cluster2[Cluster2['Attrition'] == 1]
# stayed_Cluster2=Cluster2[Cluster2['Attrition'] == 0]

# len(Cluster0['Attrition'])
# len(Cluster1)
# len(pred_target_df["Clusters"] == 1)
# left_df=transformed_df[transformed_df['Attrition'] == 1]
# stayed_df=transformed_df[transformed_df['Attrition'] == 0]

# len(left_df)
# len(stayed_df)
```

In [58]:
```
# attrition=pred_target_df['Attrition']

plt.scatter(Cluster0['MonthlyIncome'],
            Cluster0["YearsInCurrentRole"],
             s=50, c='orange',
             marker='s', edgecolor='black',
             label='cluster 1')
plt.scatter(Cluster1['MonthlyIncome'],
             Cluster1["YearsInCurrentRole"],
             s=50, c='lightblue',
             marker='o', edgecolor='black',
             label='cluster 2')
# plt.scatter(pred_target_df[cluster == 2],
#               pred_target_df[cluster == 2],
#               s=50, c='red',
#               marker='o', edgecolor='black',
#               label='cluster 3')
plt.scatter(km.cluster_centers_[:, 18],
             km.cluster_centers_[:, 29],
             s=250, marker='*',
             c='red', edgecolor='black',
             label='centroids')
# plt.legend(scatterpoints=1)
plt.xlabel("MonthlyIncome ")
plt.ylabel("YearsInCurrentRole ")
plt.grid()
plt.show()

# list(Cluster1)
# Cluster1.head()
```



In [86]:
```
# %matplotlib inline
# columns=list(Cluster0)
# len(columns)

# rows=len(columns)-3
# cols=len(columns)-4
# ct=0
# # plt.figure(figsize=[15,7*rows])
# for i in range(len(columns) - 3):
#     for j in range(i+1, len(columns)):
#         coli = Cluster0.columns[i]
#         colj = Cluster0.columns[j]
# #         plt.subplot(rows, cols, ct)
#         plt.scatter(Cluster0['MonthlyIncome'],
#                     Cluster0["YearsInCurrentRole"],
#                      s=50, c='orange',
#                      marker='s', edgecolor='black',
#                      label='cluster 1')
#         plt.scatter(Cluster1['MonthlyIncome'],
#                      Cluster1["YearsInCurrentRole"],
#                      s=50, c='lightblue',
#                      marker='o', edgecolor='black',
#                      label='cluster 2')
# # # plt.scatter(pred_target_df[cluster == 2],
# # #              pred_target_df[cluster == 2],
# # #              s=50, c='red',
# # #              marker='o', edgecolor='black',
# # #              label='cluster 3')
#         plt.scatter(km.cluster_centers_[:, 18],
#                      km.cluster_centers_[:, 29],
#                      s=250, marker='*',
#                      c='red', edgecolor='black',
#                      label='centroids')
#         # plt.legend(scatterpoints=1)
#         plt.xlabel(coli)
#         plt.ylabel(colj)
#         plt.grid()
#         plt.show()
```

In [53]:
```
import pandas as pd
from scipy import stats
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

# final_df=transformed_df[predictors]
cluster0_mean_df=Cluster0.groupby("Attrition").mean()
# .std()

diff_abs=abs(cluster0_mean_df.iloc[0]-cluster0_mean_df.iloc[1])/cluster0_mea

diff=pd.DataFrame(diff_abs)
diff_sort=diff.sort_values(0,ascending=False)
diff_sort
# 2.146464579505202
```

Out[53]:

	0
JobInvolvement_L	3.274691
JobRole_RS	1.000000
EducationField_Other	1.000000
EnvironmentSatisfaction_L	0.832011
OverTime	0.754873
JobRole_RD	0.736942
StockOptionLevel_0	0.619883
Department_HR	0.578348
StockOptionLevel_2	0.533670
JobSatisfaction_L	0.519890
WorkLifeBalance_Bad	0.465608
Department_RnD	0.412230
YearsSinceLastPromotion	0.384255
StockOptionLevel_1	0.371882
BusinessTravel_Frequently	0.338164
RelationshipSatisfaction_L	0.249322
NumCompaniesWorked	0.245216
BusinessTravel_None	0.240055
MonthlyIncome	0.235426
DistanceFromHome	0.214974
YearsAtCompany	0.208386
JobLevel_5	0.198495

	0
TrainingTimesLastYear	0.156951
JobInvolvement_VH	0.107890
JobSatisfaction_VH	0.086275
EducationField_LS	0.075742
EducationField_Med	0.048110
YearsInCurrentRole	0.048051
Age	0.008973
YearsWithCurrManager	0.005386
TotalWorkingYears	0.005061
JobLevel_2	NaN
Clusters	NaN

In [83]:
```
# !sudo pip install causalinference
# list(transformed_df)
```

In [85]:
```
from causalinference import CausalModel

causal_model = CausalModel(
    X=transformed_df[['JobInvolvement_L','WorkLifeBalance_Bad',
                      'EnvironmentSatisfaction_L',
                      'BusinessTravel_Frequently',
                      'StockOptionLevel_0',
                      'StockOptionLevel_2',
                      'BusinessTravel_None',
                      'JobSatisfaction_L']].values,
    D=transformed_df.OverTime.values,
    Y=transformed_df.Attrition.values
)
causal_model.est_propensity()
causal_model.trim_s()
causal_model.stratify_s()
causal_model.est_via_ols()
causal_model.est_via_matching(bias_adj=True)
causal_model.est_via_weighting()

print(causal_model.summary_stats)
print(causal_model.estimates)
print(causal_model.propensity)

print(causal_model.strata)
```

```
/usr/local/lib/python3.5/dist-packages/causalinference/core/summary.py:11
0: RuntimeWarning: invalid value encountered in true_divide
  return (mean_t-mean_c) / np.sqrt((sd_c**2+sd_t**2)/2)
/usr/local/lib/python3.5/dist-packages/causalinference/estimators/ols.py:
21: FutureWarning: `rcond` parameter will change to the default of machin
e precision times ``max(M, N)`` where M and N are the input matrix dimens
ions.
To use the future default and silence this warning we advise to pass `rco
nd=None`, to keep using the old, explicitly pass `rcond=-1`.
  olscoef = np.linalg.lstsq(Z, Y)[0]


Summary Statistics

                     Controls (N_c=1054)         Treated (N_t=416)

       Variable         Mean         S.d.         Mean         S.d.     R
aw-diff
------------------------------------------------------------------------
-------
             Y        0.104        0.306        0.305        0.461
  0.201

                     Controls (N_c=1054)         Treated (N_t=416)

       Variable         Mean         S.d.         Mean         S.d.     N
or-diff
------------------------------------------------------------------------
-------
            X0        0.055        0.228        0.060        0.238
  0.022
```

```
            X1        0.055        0.228        0.053        0.224
-0.009
            X2        0.211        0.408        0.149        0.357
-0.161
            X3        0.181        0.385        0.207        0.405
  0.065
            X4        0.426        0.495        0.438        0.497
  0.023
            X5        0.114        0.318        0.091        0.288
-0.074
            X6        0.109        0.312        0.084        0.278
-0.085
            X7        0.194        0.396        0.202        0.402
  0.019
```

Treatment Effect Estimates: Weighting

```
                     Est.       S.e.          z      P>|z|      [95% Con
f. int.]
------------------------------------------------------------------------
-------
           ATE      0.203      0.023      8.802      0.000      0.158
  0.248
```

Treatment Effect Estimates: Matching

```
                     Est.       S.e.          z      P>|z|      [95% Con
f. int.]
------------------------------------------------------------------------
-------
           ATE      0.218      0.026      8.437      0.000      0.168
  0.269
           ATC      0.225      0.027      8.310      0.000      0.172
  0.278
           ATT      0.201      0.025      8.007      0.000      0.152
  0.250
```

Treatment Effect Estimates: OLS

```
                     Est.       S.e.          z      P>|z|      [95% Con
f. int.]
------------------------------------------------------------------------
-------
           ATE      0.202      0.023      8.814      0.000      0.157
  0.247
           ATC      0.203      0.023      8.770      0.000      0.157
  0.248
           ATT      0.201      0.023      8.767      0.000      0.156
  0.246
```

Estimated Parameters of Propensity Score

```
                    Coef.       S.e.          z      P>|z|      [95% Con
f. int.]
------------------------------------------------------------------------
```

```
-------
     Intercept     -0.854      0.102     -8.328      0.000     -1.054
-0.653
            X0      0.118      0.248      0.476      0.634     -0.369
  0.605
            X1     -0.022      0.259     -0.085      0.933     -0.529
  0.485
            X2     -0.421      0.158     -2.671      0.008     -0.730
-0.112
            X3      0.142      0.148      0.961      0.336     -0.147
  0.431
            X4      0.016      0.123      0.130      0.896     -0.224
  0.256
            X5     -0.224      0.205     -1.089      0.276     -0.626
  0.179
            X6     -0.259      0.206     -1.259      0.208     -0.664
  0.145
            X7      0.034      0.146      0.236      0.813     -0.251
  0.320


Stratification Summary

              Propensity Score         Sample Size     Ave. Propensity
Outcome
   Stratum      Min.      Max.  Controls   Treated  Controls   Treated  R
aw-diff
-----------------------------------------------------------------------
-------
         1     0.147     0.254       353        99     0.228     0.231
  0.232
         2     0.257     0.299       239       121     0.294     0.294
  0.098
         3     0.301     0.367       462       196     0.314     0.315
  0.258


/usr/local/lib/python3.5/dist-packages/causalinference/estimators/matchin
g.py:100: FutureWarning: `rcond` parameter will change to the default of
machine precision times ``max(M, N)`` where M and N are the input matrix
dimensions.
To use the future default and silence this warning we advise to pass `rco
nd=None`, to keep using the old, explicitly pass `rcond=-1`.
  return np.linalg.lstsq(X, Y)[0][1:]  # don't need intercept coef
/usr/local/lib/python3.5/dist-packages/causalinference/estimators/weighti
ng.py:23: FutureWarning: `rcond` parameter will change to the default of
machine precision times ``max(M, N)`` where M and N are the input matrix
dimensions.
To use the future default and silence this warning we advise to pass `rco
nd=None`, to keep using the old, explicitly pass `rcond=-1`.
  wlscoef = np.linalg.lstsq(Z_w, Y_w)[0]
```

In [ ]:

Type *Markdown* and LaTeX: α^2