bike sharing demand

June 28, 2016

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In [ ]: # Bike sharing demand , kaggle knowledge competetion
        # to be solved :
        # Prediction of bike rental count hourlybased on the environmental and seasonal settings.

        # Approach

        # Researching the problem
        # Initial exploration on the data,
        # Forming some hypothesis about the trends existing in the data,
        # Proving the hypothesis by looking at the data,
        # Training different regressor and comparing the results and score of each regressor
        # Writing an outlook on how to proceed.
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In [74]: import pandas as pd
         import numpy as np
         from sklearn.cross_validation import train_test_split
         from sklearn.tree import DecisionTreeRegressor
         from sklearn.metrics import mean_squared_error
         from sklearn.metrics import mean_absolute_error
         from sklearn import preprocessing
         from sklearn import linear_model, metrics
         from sklearn.ensemble import RandomForestRegressor
         from sklearn import svm
         import matplotlib
         import matplotlib.pyplot as plt
         matplotlib.style.use('ggplot')
         %pylab inline
```

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Populating the interactive namespace from numpy and matplotlib
```

```
In [75]: def linReg(X_train, X_test, y_train, y_test):

             regr = linear_model.LinearRegression()
             y_predict=regr.fit(X_train, y_train).predict(X_test)
             #crossArr= cross_validation.cross_val_score(regr, X, y, cv=5)
             #crossScore=np.mean(crossArr)
             acc= metrics.r2_score(y_test, y_predict)
             mse=mean_squared_error(y_test,y_predict)
             mae=mean_absolute_error(y_test,y_predict)
             print ('for Linear Regression  R^2 is %s,Mean Square error is:%s & mean absolute error is
             return y_predict,[acc,mse,mae]
```

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In [76]: def treeReg(X_train, X_test, y_train, y_test):
             #Training a Regression Tree model  Tried different depth, 10 seems to have a good score
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    # with 10 one gets a better score however the danger of overfitting is there.

    regr = DecisionTreeRegressor(max_depth=10)
    # fit the Training set to the regression tree model.
    regr.fit(X_train, y_train)
    # predicting values of y of the test set
    y_predict = regr.predict(X_test)

    acc= metrics.r2_score(y_test, y_predict)
    mse=mean_squared_error(y_test,y_predict)
    mae=mean_absolute_error(y_test,y_predict)

    print ('for Tree Regression R^2 is:%s ,Mean Square error is:%s & mean absolute error is :%
    return y_predict,[acc,mse,mae]
```

```
In [77]: def supportVectorReg(X_train, X_test, y_train, y_test):
             #Fit supporT vector regression
             clf = svm.SVR(C=100, cache_size=200, coef0=0.0, degree=2, epsilon=0.05, gamma='auto',
                 kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
             clf.fit(X_train, y_train)
             y_predict = clf.predict(X_test)
             acc= metrics.r2_score(y_test, y_predict)
             mse=mean_squared_error(y_test,y_predict)
             mae=mean_absolute_error(y_test,y_predict)

             print ('for Support Vector Regression R^2 is %s,Mean Square error is:%s & mean absolute er
             return y_predict,[acc,mse,mae]
```

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In [78]: def randomForestReg(X_train, X_test, y_train, y_test):
             clf=RandomForestRegressor()
             clf.fit(X_train, y_train)
             y_predict = clf.predict(X_test)
             acc= metrics.r2_score(y_test, y_predict)
             mse=mean_squared_error(y_test,y_predict)
             mae=mean_absolute_error(y_test,y_predict)

             print ('for Support Vector Regression R^2 is %s,Mean Square error is:%s & mean absolute er
             return y_predict,[acc,mse,mae]
```

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In [79]: # Reading the data into a pandas data frame
         df = pd.read_csv(r'hour.csv', header=0)
```

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In [84]: # Looking at a summary of the data

         df.describe()
```

Out[84]:

	instant	season	yr	mnth	hr \
count	17379.0000	17379.000000	17379.000000	17379.000000	17379.000000
mean	8690.0000	2.501640	0.502561	6.537775	11.546752
std	5017.0295	1.106918	0.500008	3.438776	6.914405
min	1.0000	1.000000	0.000000	1.000000	0.000000
25%	4345.5000	2.000000	0.000000	4.000000	6.000000
50%	8690.0000	3.000000	1.000000	7.000000	12.000000
75%	13034.5000	3.000000	1.000000	10.000000	18.000000
max	17379.0000	4.000000	1.000000	12.000000	23.000000

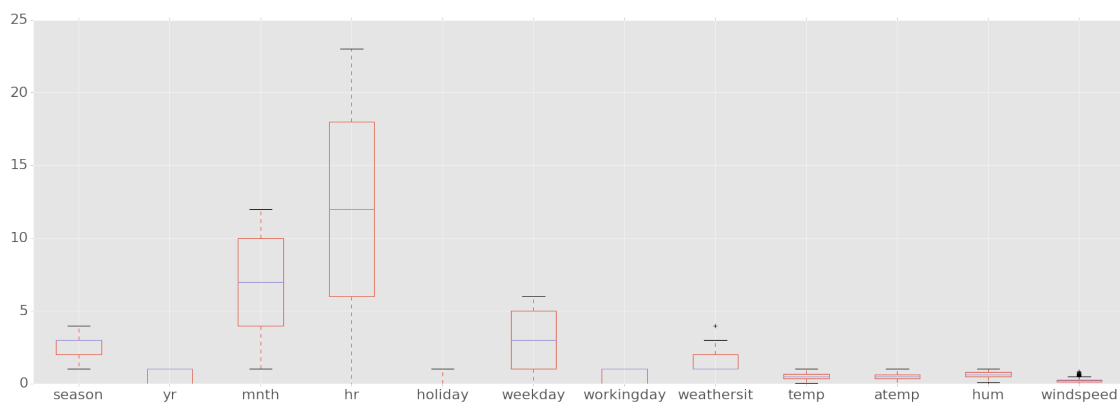
```
            holiday       weekday    workingday    weathersit          temp  \
count  17379.000000  17379.000000  17379.000000  17379.000000  17379.000000
mean       0.028770      3.003683      0.682721      1.425283      0.496987
std        0.167165      2.005771      0.465431      0.639357      0.192556
min        0.000000      0.000000      0.000000      1.000000      0.020000
25%        0.000000      1.000000      0.000000      1.000000      0.340000
50%        0.000000      3.000000      1.000000      1.000000      0.500000
75%        0.000000      5.000000      1.000000      2.000000      0.660000
max        1.000000      6.000000      1.000000      4.000000      1.000000

              atemp           hum     windspeed        casual    registered  \
count  17379.000000  17379.000000  17379.000000  17379.000000  17379.000000
mean       0.475775      0.627229      0.190098     35.676218    153.786869
std        0.171850      0.192930      0.122340     49.305030    151.357286
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.333300      0.480000      0.104500      4.000000     34.000000
50%        0.484800      0.630000      0.194000     17.000000    115.000000
75%        0.621200      0.780000      0.253700     48.000000    220.000000
max        1.000000      1.000000      0.850700    367.000000    886.000000

                cnt
count  17379.000000
mean     189.463088
std      181.387599
min        1.000000
25%       40.000000
50%      142.000000
75%      281.000000
max      977.000000
```

In [82]:
```
# looking at the box plot of the features (Gives you the five-number-summary.)
df.iloc[:,1:14].plot.box()

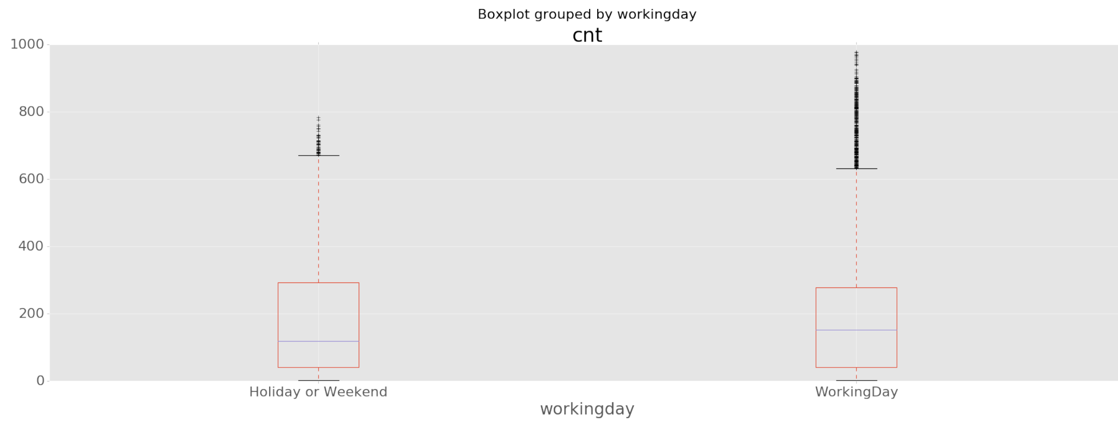
#Making the inline plot bigger
matplotlib.rcParams['figure.figsize'] = (30.0, 10.0)
#Making the font size of the plot bigger
matplotlib.rcParams.update({'font.size': 22})
```



In [22]:
```
# Hypothesis : On average more bikes are rented out on work days ( s)
#fig, axs = plt.subplots(1,2 ,sharex=True, sharey=True)

#df[df['workingday']>0].cnt.plot(ax=axs[0],kind='box',title='Working Day',fontsize=22)
#df[df['workingday']==0].cnt.plot(ax=axs[1],kind='box',title='Holiday or weekend',fontsize=22)
ax=df.boxplot(column=u'cnt', by=u'workingday')
ax.set_xticklabels(['Holiday or Weekend','WorkingDay'])
```

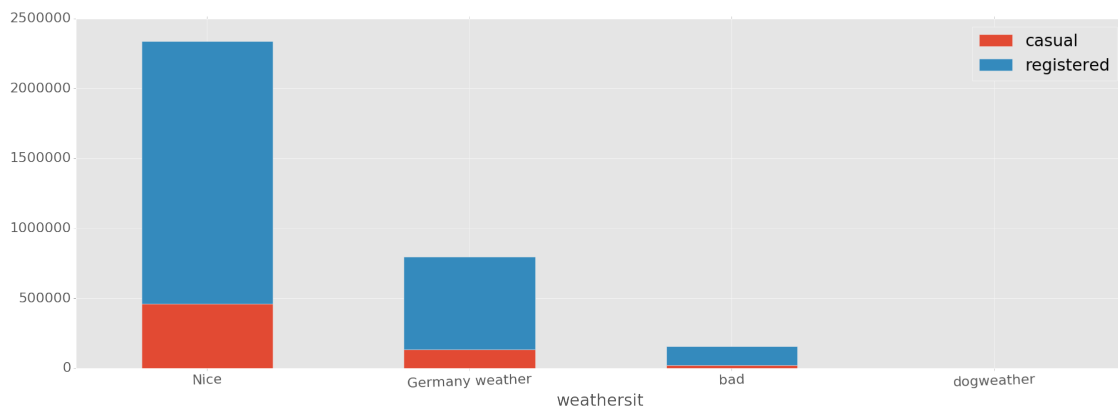
Out[22]:
```
[<matplotlib.text.Text at 0xb558370>, <matplotlib.text.Text at 0x130697f0>]
```



In [16]:
```
#hypothesis : if it is cold , less  bikes are rented
# subhypthesis Registered user take more bikes than the casual user

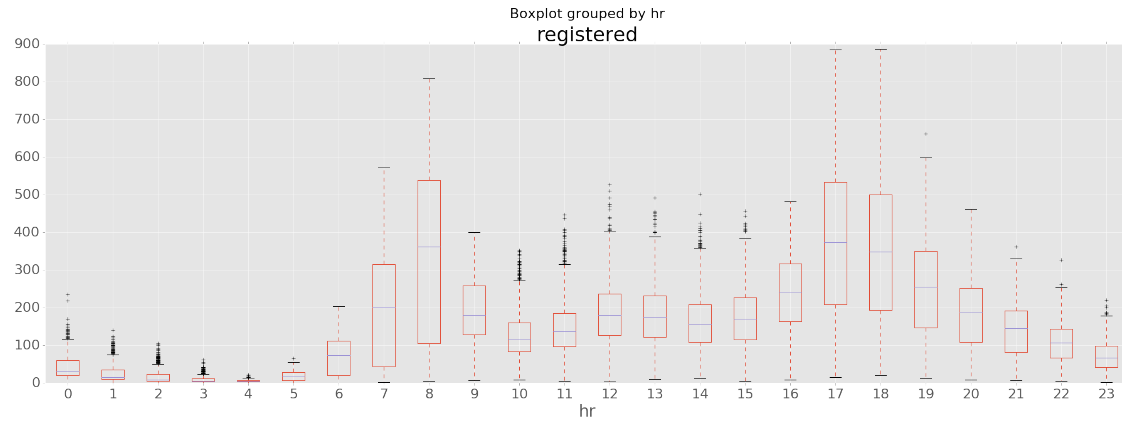
# Groupby the weathersit and sum the casual and registered user.
ax=df.groupby('weathersit')['casual','registered'].sum().plot(kind='bar',rot=2,stacked=True)
ax.set_xticklabels(['Nice','Germany weather','bad','dogweather'])
```

Out[16]:
```
[<matplotlib.text.Text at 0xb6a10f0>,
 <matplotlib.text.Text at 0x10ea410>,
 <matplotlib.text.Text at 0x111c6f0>,
 <matplotlib.text.Text at 0x111ccd0>]
```



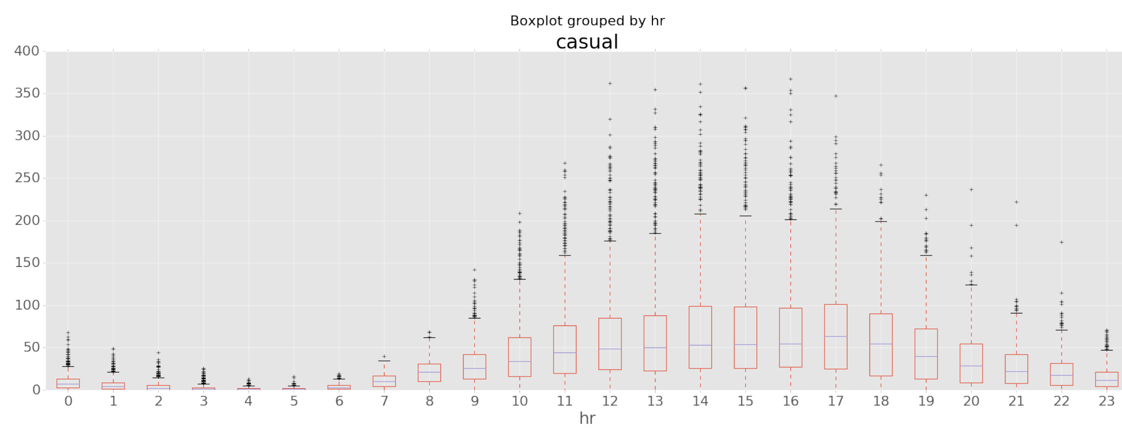
In [18]:
```
#Hypothesis : The registered users tend to go to work and come back with the bike
#in other word , the registered user tend to rent the bike mostly between 7-9 and 17-19
df.boxplot(column=u'registered', by=u'hr')
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1351bff0>



In [19]:
```
# as for casual users they have a different trend
df.boxplot(column=u'casual', by=u'hr')
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x12684df0>



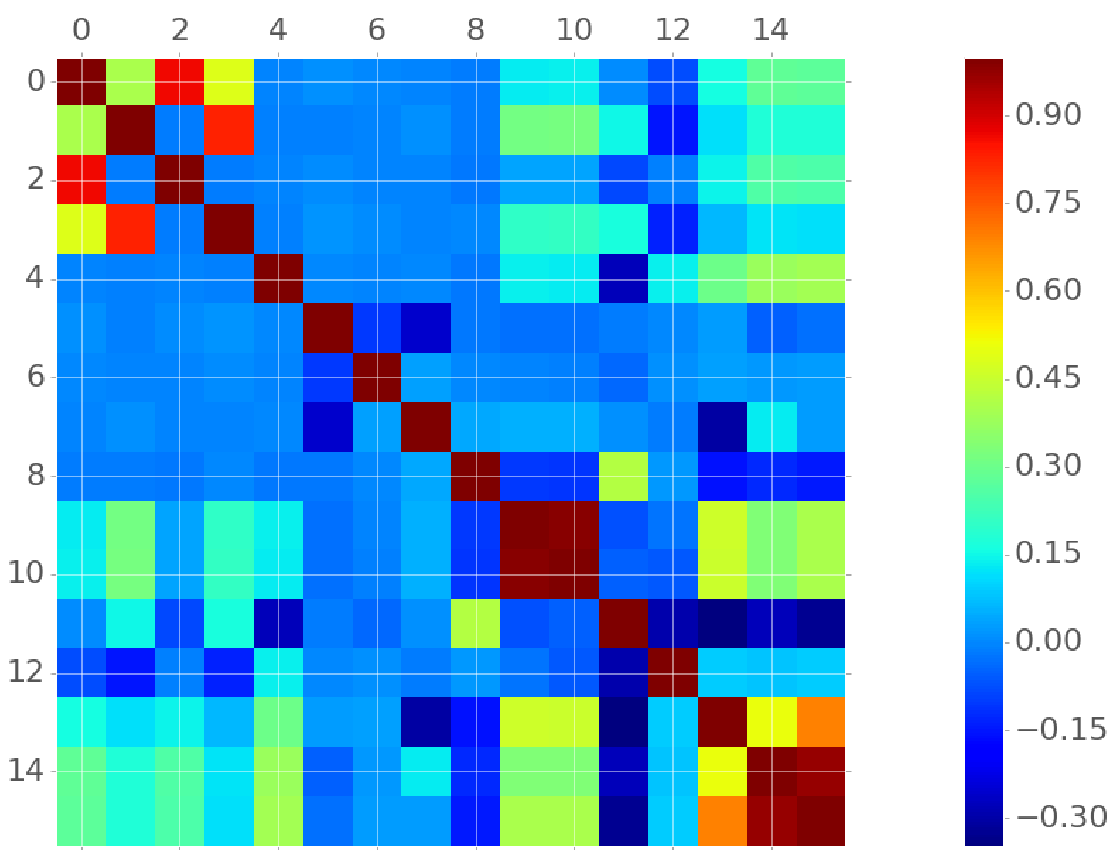
In [23]:
```
# we have an increse in number of rented bikes in year 2012.
ax=df.boxplot(column=u'cnt', by=u'yr')
ax.set_xticklabels(['2011','2012'])
```

Out[23]: [<matplotlib.text.Text at 0x130223b0>, <matplotlib.text.Text at 0x1304c8d0>]

In [83]:
```
#  the highly correlated features can be dropped out
#with correlation matrix one can see the correlation of the data points
# The Heatmap shows a high correalation between atemp, and temp ( therefore atemp can be remov
#there is negative corelation between

fig= plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(df.corr())
fig.colorbar(cax)
```

Out[83]: <matplotlib.colorbar.Colorbar at 0x1b99dcd0>



```
In [42]: #Dummifying the categorical features Weathersit and season and writing to a new dataframe

         df1 = df.join(pd.get_dummies(df.weathersit, prefix='weathersit'))
         df1= df1.join(pd.get_dummies(df1.season, prefix='season'))

         #choosing the features of interest , the causual and registered are removed,


         keys=['yr', 'mnth', 'hr', 'holiday', 'weekday', 'workingday', 'temp',
                'hum', 'windspeed', 'weathersit_1',
                'weathersit_2', 'weathersit_3', 'weathersit_4', 'season_1', 'season_2',
                'season_3', 'season_4']

         #Scaling of the data
         df1_scaled = preprocessing.scale(df1[keys])

In [43]: #splitting the data into training and test set, 10% of the data is used for testing
         X_train, X_test, y_train, y_test = cross_validation.train_test_split(df1_scaled, df1.cnt,
                                                                              test_size=0.1, random_stat

In [72]: y_predict_linReg,score_linReg=linReg(X_train, X_test, y_train, y_test)

for Linear Regression  R^2 is 0.393360195068,Mean Square error is:19615.9700528 & mean absouloute error

In [71]: y_predict_svm,score_svm=supportVectorReg(X_train, X_test, y_train, y_test)

for Support Vector Regression R^2 is 0.547938708012,Mean Square error is:14617.6045383 & mean absoulout

In [70]: y_predict_tree,score_tree=treeReg(X_train, X_test, y_train, y_test)

for Tree Regression R^2 is:0.898667890435 ,Mean Square error is:3276.61919058 & mean absouloute error i

In [62]: y_predict_randomForest,score_randomForest=randomForestReg(X_train, X_test, y_train, y_test)

for Support Vector Regression R^2 is 0.941140412933,Mean Square error is:1903.25113493 & mean absoulout

In [ ]: #Outlook
        # #
        # There are still much more to do :
        # Tweaking model parameter to get a better score
        # The random forest works better than the other methods , however in order to make a better pre
        # features of the random forest, for example playing with the number of trees.

        # Feature engineering
        # The next step would be also to try different scaling approach , and also to create extra feat
        # weekend (from the weekday ) .

        # Avoiding over fitting
        # By using ensemble models or adding the regularization parameter to linear regression or
        # by cross validating, one can stop the over fitting from happening.

        # Timing
        # which algorithm works faster (find a trade off between time and accuracy)

        # Nasim Khadem
        #for more info please email me at nasim.khadem@rwth-aachen.de
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