Regression Problem: Forest Fires dataset

In [1]:

```
import os, sys
import re
import pandas as pd
from scipy import stats
import numpy as np

import urllib.request
import json

import matplotlib.pyplot as plt
import seaborn as sns
# all the scikit-learn libraries

from sklearn.preprocessing import scale, LabelEncoder
import sklearn.linear_model as skl_lm
from sklearn.metrics import mean_squared_error, r2_score
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.preprocessing import label_binarize, PolynomialFeatures
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, roc_curve, auc, classification_report
from sklearn.preprocessing import scale, StandardScaler
from sklearn import model_selection
from sklearn.linear_model import LinearRegression, Ridge, RidgeCV, Lasso, LassoCV
from sklearn.decomposition import PCA
from sklearn.cross_decomposition import PLSRegression
from sklearn.model_selection import KFold, cross_val_score
from patsy import dmatrix

%matplotlib inline
plt.style.use('ggplot')
```

```
/Users/User/anaconda/lib/python3.5/site-packages/statsmodels/compat/pandas.p
y:56: FutureWarning: The pandas.core.datetools module is deprecated and will
be removed in a future version. Please use the pandas.tseries module instea
d.
  from pandas.core import datetools
```

LOAD THE DATASET :

We import urllib.request to load the dataset dynamically from the repository, instead of having to save it/ downloading it prior to running the notebook

In [2]:

```
url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/forest-fires/forestfi
```

In [3]:

```
raw_firedata = urllib.request.urlopen(url)
```

In [4]:

```
fire_dataset = raw_firedata.read().decode('utf-8')
with open('forestfires.csv', 'w+') as f:
    f.write(fire_dataset)
f.close()
```

Dataset Visualization

In [5]:

```
fire_df = pd.read_csv('forestfires.csv', na_values='?').dropna()
fire_df.head(7)
```

Out[5]:

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
0	7	5	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0
1	7	4	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0
2	7	4	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0
3	8	6	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0
4	8	6	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0
5	8	6	aug	sun	92.3	85.3	488.0	14.7	22.2	29	5.4	0.0	0.0
6	8	6	aug	mon	92.3	88.9	495.6	8.5	24.1	27	3.1	0.0	0.0

In [6]:

```
fire_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 517 entries, 0 to 516
Data columns (total 13 columns):
X        517 non-null int64
Y        517 non-null int64
month    517 non-null object
day      517 non-null object
FFMC     517 non-null float64
DMC      517 non-null float64
DC       517 non-null float64
ISI      517 non-null float64
temp     517 non-null float64
RH       517 non-null int64
wind     517 non-null float64
rain     517 non-null float64
area     517 non-null float64
dtypes: float64(8), int64(3), object(2)
memory usage: 56.5+ KB
```

In [7]:

```
fire_df.describe()
```

Out[7]:

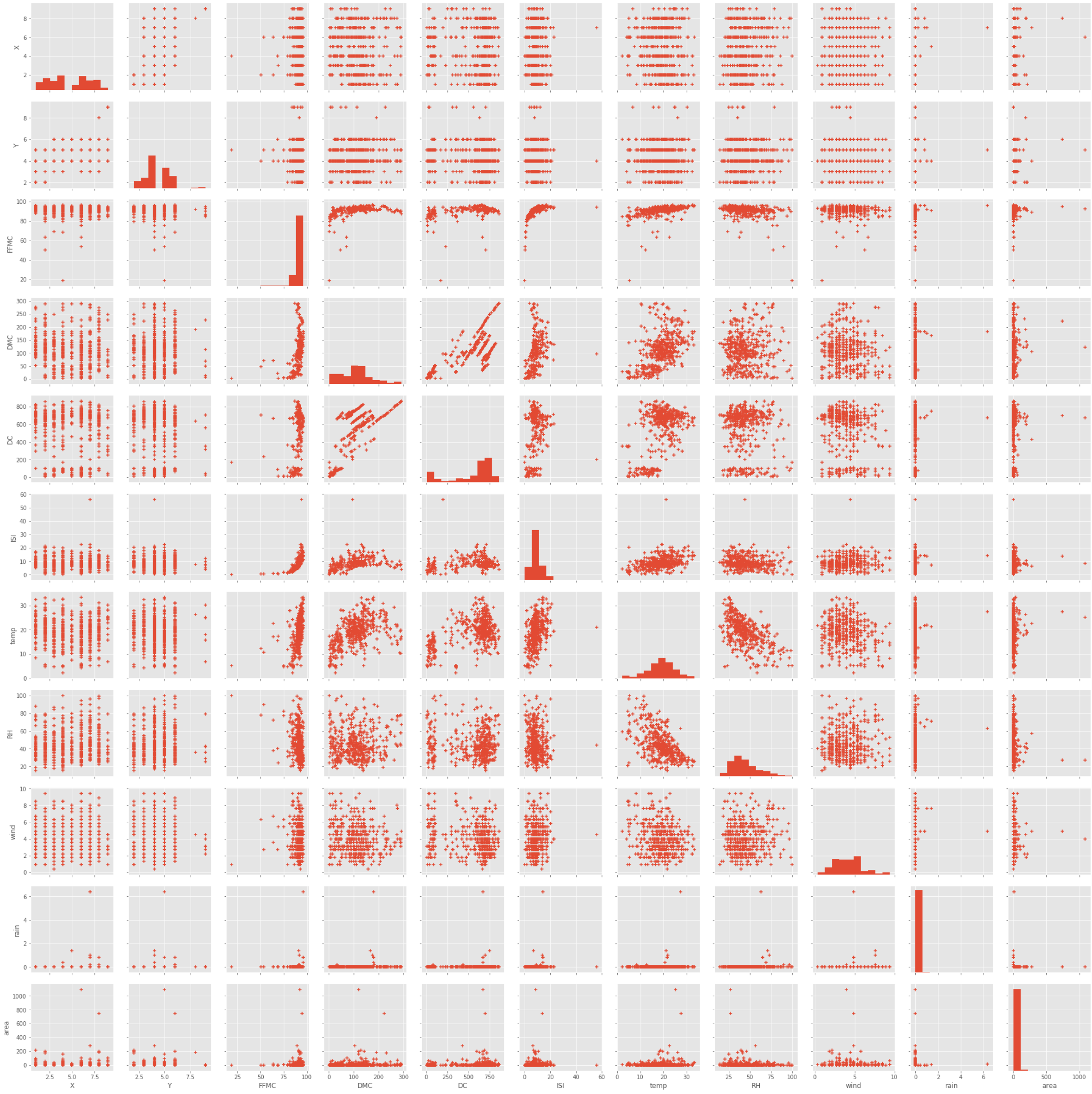
	X	Y	FFMC	DMC	DC	ISI	temp	
count	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	517.000000	51
mean	4.669246	4.299807	90.644681	110.872340	547.940039	9.021663	18.889168	4
std	2.313778	1.229900	5.520111	64.046482	248.066192	4.559477	5.806625	1
min	1.000000	2.000000	18.700000	1.100000	7.900000	0.000000	2.200000	1
25%	3.000000	4.000000	90.200000	68.600000	437.700000	6.500000	15.500000	3
50%	4.000000	4.000000	91.600000	108.300000	664.200000	8.400000	19.300000	4.
75%	7.000000	5.000000	92.900000	142.400000	713.900000	10.800000	22.800000	5
max	9.000000	9.000000	96.200000	291.300000	860.600000	56.100000	33.300000	10

In [8]:

```
sns.pairplot(fire_df, markers='+')
```

Out[8]:

<seaborn.axisgrid.PairGrid at 0x110937b00>



Dataset Cleaning

In [9]:

```
# converting categorical variables into numerical values
label = LabelEncoder()
fire_df.month = label.fit_transform(fire_df.month)
fire_df.day = label.fit_transform(fire_df.day)
```

In [10]:

```
fire_df.head()
```

Out[10]:

	X	Y	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area
0	7	5	7	0	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0
1	7	4	10	5	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0
2	7	4	10	2	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0
3	8	6	7	0	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0
4	8	6	7	3	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0

In [11]:

```
fire_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 517 entries, 0 to 516
Data columns (total 13 columns):
X        517 non-null int64
Y        517 non-null int64
month    517 non-null int64
day      517 non-null int64
FFMC     517 non-null float64
DMC      517 non-null float64
DC       517 non-null float64
ISI      517 non-null float64
temp     517 non-null float64
RH       517 non-null int64
wind     517 non-null float64
rain     517 non-null float64
area     517 non-null float64
dtypes: float64(8), int64(5)
memory usage: 76.5 KB
```

In [12]:

```
fireX = fire_df.drop(["area"], axis=1) # X = all columns excluding the response
print(fireX.shape)

fireY = fire_df.area # Y = response (area column)
print(fireY.shape)

# split the training and test data
X_train, X_test, y_train, y_test = train_test_split(fireX, fireY, test_size = 0.3, ran
```

```
(517, 12)
(517,)
```

Model I: Multiple Linear Regression

In [13]:

```
xcolumns = fireX.iloc[0:0, :]
print(xcolumns)
```

```
Empty DataFrame
Columns: [X, Y, month, day, FFMC, DMC, DC, ISI, temp, RH, wind, rain]
Index: []
```

In [14]:

```
smf_regr = 'area ~ '

xcols = ['X', 'Y', 'month', 'day', 'FFMC', 'DMC', 'DC', 'ISI', 'temp', 'RH', 'wind', '

for i in xcols[:-1]:
    # script to create multiple linear regression formula for statmodels
    smf_regr += '{} + '.format(i)
smf_regr += xcols[-1]

print(smf_regr)
```

```
area ~ X + Y + month + day + FFMC + DMC + DC + ISI + temp + RH + wind + rain
```

In [15]:

```
# statsmodels -- ordinary least squares without any interaction term
# try to fit the model to all the data
est = smf.ols(smf_regr, fire_df).fit()
est.summary().tables[1]
```

Out[15]:

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-11.5006	63.324	-0.182	0.856	-135.912	112.911
X	1.8812	1.450	1.298	0.195	-0.967	4.729
Y	0.5268	2.740	0.192	0.848	-4.856	5.910
month	0.9733	0.776	1.254	0.210	-0.551	2.498
day	0.4995	1.497	0.334	0.739	-2.442	3.441
FFMC	-0.1074	0.664	-0.162	0.872	-1.411	1.197
DMC	0.1098	0.072	1.524	0.128	-0.032	0.251
DC	-0.0146	0.019	-0.779	0.437	-0.052	0.022
ISI	-0.6108	0.779	-0.784	0.433	-2.141	0.920
temp	0.9801	0.802	1.222	0.222	-0.596	2.556
RH	-0.1849	0.240	-0.770	0.442	-0.657	0.287
wind	1.7823	1.680	1.061	0.289	-1.519	5.084
rain	-3.2517	9.699	-0.335	0.738	-22.306	15.803

In this model where we consider all the input features for regression, some of the features have positive coefficients while others have negative. The p-values are rather high for all the input features.

In [16]:

```
1 est.summary().tables[0]
```

Out[16]:

OLS Regression Results

Dep. Variable:	area	**R-squared:**	0.025
Model:	OLS	**Adj. R-squared:**	0.002
Method:	Least Squares	**F-statistic:**	1.065
Date:	Sat, 12 May 2018	**Prob (F-statistic):**	0.388
Time:	19:18:46	**Log-Likelihood:**	-2874.0
No. Observations:	517	**AIC:**	5774.
Df Residuals:	504	**BIC:**	5829.
Df Model:	12		
Covariance Type:	nonrobust		

A good model will have an F-statistic much greater than 1. The F-statistic for this model(when all the input features are considered) is low, i.e, close to 1. An R-squared statistic near 0 indicates that the regression did not explain much of the variability in the response; this might occur because the linear model is wrong, or the inherent error(variance) is high, or both.

In [17]:

```
1 print('Residual Sum of Squares =', est.mse_resid)
```

```
Residual Sum of Squares = 4045.97315219
```

Feature Selection: Backward Step-wise

Metric considered: F-statistic

In [18]:

```
# Backward selection for Advertising dataset -- a modification of the Forward Selectio

def backward_selected(data, response):
    """Linear model designed by backward selection.
    Parameters:
    -----------
    data : pandas dataframe (fire_df)
    response: string, name of response column in fire_df2 ("area")
    Returns:
    --------
    model: an "optimal" fitted statsmodels linear model
    with an intercept
    selected by backward selection
    evaluated by F-statistic
    """

    # in this algorithm, we start with all the values and begin to eliminate features p
    remaining = list(data.columns) # initializing the list 'remaining' with a set of th
    remaining.remove(response) # the output/response field is removed from the list of

    selected = [] # list initialized to progressively add best features

    # create the formula to calculate the OLS of all data first (to evaluate Rsquare-va
    formula = "{} ~ {} + 1".format(response, ' + '.join(remaining))

    total_score = smf.ols(formula, data).fit().fvalue
    print('F-statistic with all the features =', total_score, '\n')

    for candidate in remaining:
        backup = remaining[:] # keep the original list of predictors intact, and use a
        backup.remove(candidate) # test for Rsqr-value by removing each candidate

        formula = "{} ~ {} + 1".format(response, ' + '.join(backup))
        #print()
        #print(formula)

        score = smf.ols(formula, data).fit().fvalue # the rsquared_adj() method is spe
        print(score)
        if score > total_score:
            total_score = score # total score get assigned the new value of the highest
            remaining.remove(candidate) # only features responsible for this best fit a

    formula = "{} ~ {} + 1".format(response, ' + '.join(remaining))
    model = smf.ols(formula, data).fit() # model.formula
    return model

# call the function to perform feature selection on the forest fire dataset
b_model = backward_selected(fire_df, 'area') # data = dataset, response = output

print('\nFinal F-statistic for the model with selected features =', '{:3.10f}'.format(b
print('\nOriginal feature set: \n', smf_regr)
print('\nOptimized feature set: \n', b_model.model.formula)
```

```
F-statistic with all the features = 1.06472438483

1.00705467957
1.16036964164
1.266888283
```

```
1.13941624267
1.33941934275
1.36792604734
1.46467104637

Final F-statistic for the model with selected features = 1.4646710464

Original feature set:
 area ~ X + Y + month + day + FFMC + DMC + DC + ISI + temp + RH + wind + r
ain

Optimized feature set:
 area ~ X + month + FFMC + DMC + ISI + RH + rain + 1
```

In [19]:

```
est_rsqr = smf.ols(b_model.model.formula, fire_df).fit()
est_rsqr.summary().tables[0]
```

Out[19]:

OLS Regression Results

Dep. Variable:	area	**R-squared:**	0.020
Model:	OLS	**Adj. R-squared:**	0.006
Method:	Least Squares	**F-statistic:**	1.465
Date:	Sat, 12 May 2018	**Prob (F-statistic):**	0.177
Time:	19:18:46	**Log-Likelihood:**	-2875.3
No. Observations:	517	**AIC:**	5767.
Df Residuals:	509	**BIC:**	5801.
Df Model:	7		
Covariance Type:	nonrobust		

F-statistic of the final model is higher than the original model.

In [20]:

```
print('Residual Sum of Squares =', est_rsqr.mse_resid)
```

```
Residual Sum of Squares = 4026.68033268
```

Model II : kNN

Original feature set: area ~ Y + day + DC + + temp + + wind +

Optimized feature set: area ~ X + month + FFMC + DMC + ISI + RH + rain + 1

In [21]:

```
fireX = fire_df.drop(["area"], axis=1) # X = all columns excluding the response
print(fireX.shape)

fireY = fire_df.area # Y = response (area column)
print(fireY.shape)

# split the training and test data
X_train, X_test, y_train, y_test = train_test_split(fireX, fireY, test_size = 0.3, ran
```

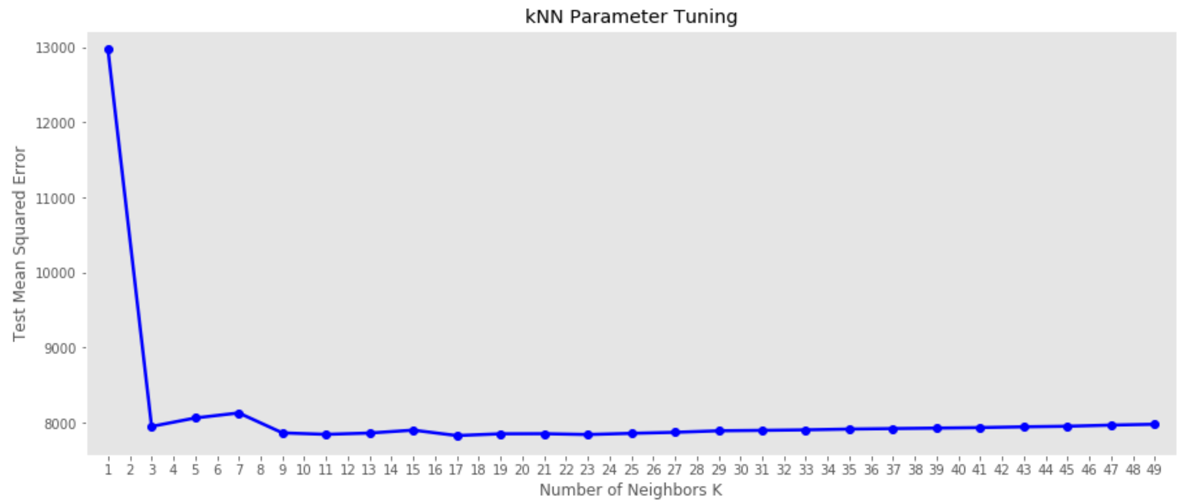
```
(517, 12)
(517,)
```

In [22]:

```
from sklearn.neighbors import KNeighborsRegressor

# Creating odd list of K for KNN
myList = list(range(1,50))

# Subsetting just the odd ones
neighbors = list(filter(lambda x: x % 2 != 0, myList))

# Empty list that will hold cv scores
MSE = []

#Find the best k
for k in neighbors:
    knn = KNeighborsRegressor(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_test_pred = knn.predict(X_test)
    scores = mean_squared_error(y_test, y_test_pred)
    MSE.append(scores)
```

In [23]:

```
# Plot misclassification error vs k
plt.figure(figsize=(15,6))
plt.plot(neighbors, MSE, 'b-o', linewidth =2.5)
plt.xlim(0, 50)
plt.xticks(range(1,50))
plt.xlabel('Number of Neighbors K')
plt.ylabel('Test Mean Squared Error')
plt.title('kNN Parameter Tuning')
plt.grid()
plt.show()

# # Determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print ("The optimal number of neighbors is %d" % optimal_k)
print("Best Test MSE = ", min(MSE))
```




```
The optimal number of neighbors is 17
Best Test MSE =  7826.06492685
```

Model III: Lasso Regression

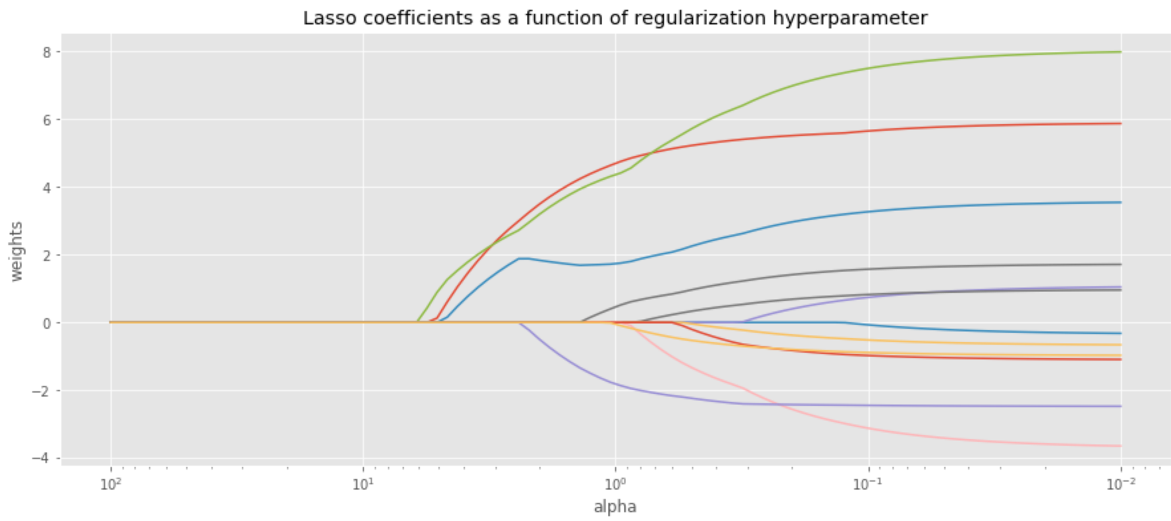
In [24]:

```
fireX = fire_df.drop(["area"], axis=1) # X = all columns excluding the response
print(fireX.shape)

fireY = fire_df.area # Y = response (area column)
print(fireY.shape)

# Feature Scaling
scaler = StandardScaler()
fireX_scaled = scaler.fit_transform(fireX)

# split the training and test data
X_train, X_test, y_train, y_test = train_test_split(fireX_scaled, fireY, test_size = 0
```

```
(517, 12)
(517,)
```

In [25]:

```
alphas = 10**np.linspace(2,-2,100)*0.5

lasso = Lasso()
coefs = []

for a in alphas*2:
    lasso.set_params(alpha=a)
    lasso.fit(X_train, y_train)
    coefs.append(lasso.coef_)

ax = plt.gca()
# labels = ['X' ,'Y' ,'month','day ','FFMC' ,'DMC' ,'DC','ISI' ,'temp','RH','wind', 'r
ax.plot(alphas*2, coefs)
ax.set_xscale('log')
ax.set_xlim(ax.get_xlim()[::-1])  # reverse axis
plt.axis('tight')
plt.xlabel('alpha')
plt.ylabel('weights')
# plt.legend()
plt.title('Lasso coefficients as a function of regularization hyperparameter')
plt.gcf().set_size_inches(15,6)
```



In [26]:

```
lassocv = LassoCV(alphas=None, cv=10)
lassocv.fit(X_train, y_train)
```

Out[26]:

```
LassoCV(alphas=None, copy_X=True, cv=10, eps=0.001, fit_intercept=True,
    max_iter=1000, n_alphas=100, n_jobs=1, normalize=False, positive=False,
    precompute='auto', random_state=None, selection='cyclic', tol=0.0001,
    verbose=False)
```

In [27]:

```
print('Best alpha (Lasso) =',lassocv.alpha_)
print('Test MSE =',mean_squared_error(y_test, lassocv.predict(X_test)))
```

```
Best alpha (Lasso) = 1.71868752562
Test MSE = 7936.52990235
```

In [28]:

```
# Best Lasso Coefficients
pd.Series(lassocv.coef_, index=fireX.columns)
```

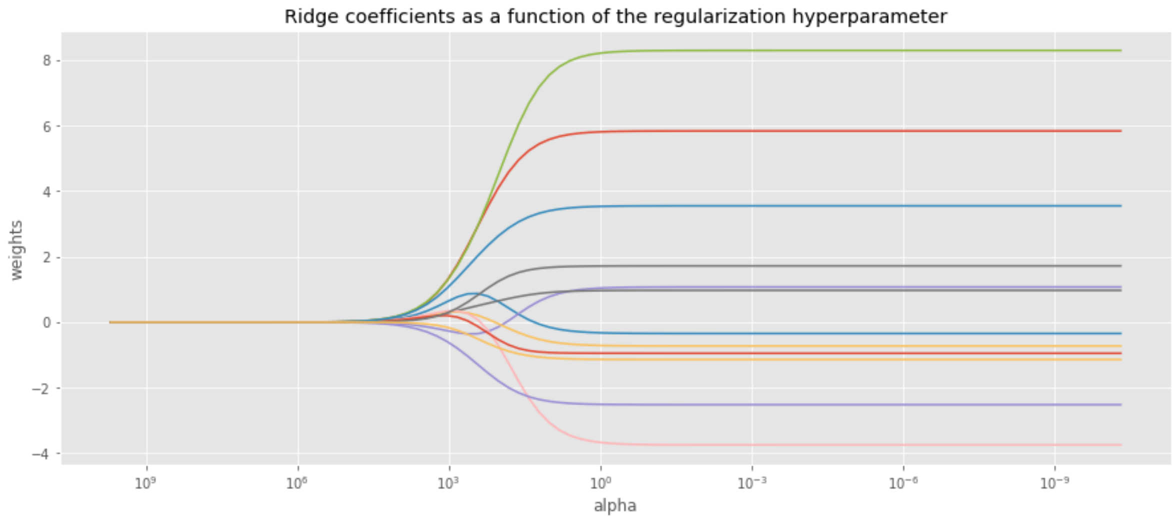
Out[28]:

```
X         3.837107
Y         0.000000
month    -0.000000
day       0.000000
FFMC      0.000000
DMC       3.536034
DC       -0.000000
ISI       0.000000
temp      1.767039
RH       -0.885794
wind      0.000000
rain     -0.000000
dtype: float64
```

Model IV: Ridge Regression

In [29]:

```
alphas = 10**np.linspace(10,-10,100)*0.5

ridge = Ridge()
coefs = []

for a in alphas:
    ridge.set_params(alpha=a)
    ridge.fit(scale(X_train), y_train)
    coefs.append(ridge.coef_)

ax = plt.gca()
ax.plot(alphas, coefs)
ax.set_xscale('log')
ax.set_xlim(ax.get_xlim()[::-1])  # reverse axis
plt.axis('tight')
plt.xlabel('alpha')
plt.ylabel('weights')
plt.title('Ridge coefficients as a function of the regularization hyperparameter');
plt.gcf().set_size_inches(15,6)
```



In [30]:

```
ridgecv = RidgeCV(alphas=alphas, cv=10)
ridgecv.fit(scale(X_train), y_train)
```

Out[30]:

```
RidgeCV(alphas=array([  5.00000e+09,   3.14015e+09, ...,   7.96141e-11,   5.
00000e-11]),
    cv=10, fit_intercept=True, gcv_mode=None, normalize=False,
    scoring=None, store_cv_values=False)
```

In [31]:

```
ridgecv.alpha_
```

Out[31]:

```
1715.2346431574597
```

In [32]:

```
print('Test MSE =',mean_squared_error(y_test, ridgecv.predict(X_test)))
```

```
Test MSE = 7945.21888668
```

In [33]:

```
#Best Ridge Coefficients
pd.Series(ridge.coef_, index=fireX.columns)
```

Out[33]:

```
X        5.835932
Y       -0.344120
month    1.075099
day      0.971851
FFMC    -0.725321
DMC      8.293224
DC      -3.744169
ISI     -0.947774
temp     3.550765
RH      -2.517020
wind     1.718755
rain    -1.138975
dtype: float64
```