INF -552 (Machine Learning for Data Informatics)
Homework1 – Report

1. MNIST Database One of the most famous applications of machine learning is classification of handwritten digits. A well known benchmark database that is extensively used in the literature is the MNIST, which contains a large number of handwritten digits, centered and normalized into fixed-size images (28 × 28 pixels).

   (a) Download the MNIST data from: http://yann.lecun.com/exdb/mnist/ or https://archive.ics.uci.edu/ml/databases/mnist/. You will see the following
   • database_train_images- A 60000 × 784 matrix. Each row is an image, of size 28 × 28, unrolled into a vector.
   • database_train_labels - A 60000 × 1 vector. Each row is the digit that corresponds to database_train_images.
   • database_test_images - A 10000 × 784 matrix with test images.
   • database_test_labels - A 10000 × 1 vector with corresponding digits.

   (b) Visualization of data from MNIST database Many machine learning problems come from real-life applications. If possible, it is important to visualize the data, in order to gain intuition, and learn what methods we want to apply. In our case, the data observations are 28×28 gray-scale images of digits.

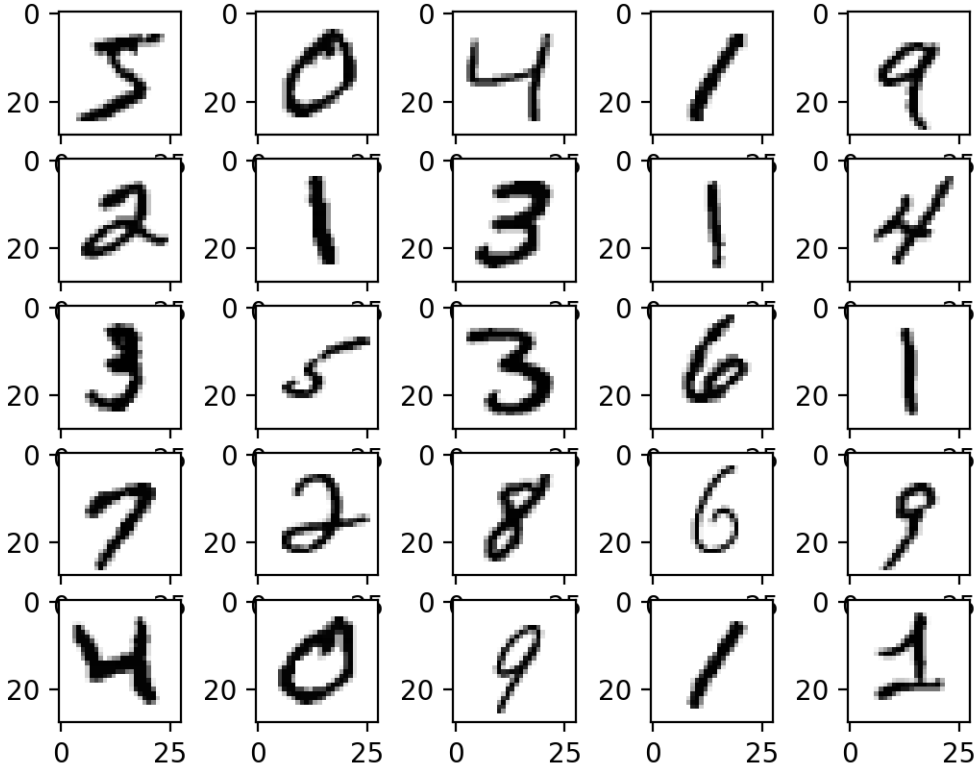
   i. Plot the first 25 images in the training set. Do all images of 9 look alike?

   Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np

x_train, t_train, x_test, t_test = mnist.load()
X = 255-x_train
plt.gray()
for i in range(25):
   plt.subplot(5, 5, i+1)
   plt.imshow((X[i]).reshape((28,28)))
plt.show()
```

Output:



Inference:

All images of 9 do not look alike. They tend to have variations owing to the nature of the dataset - which is handwritten.

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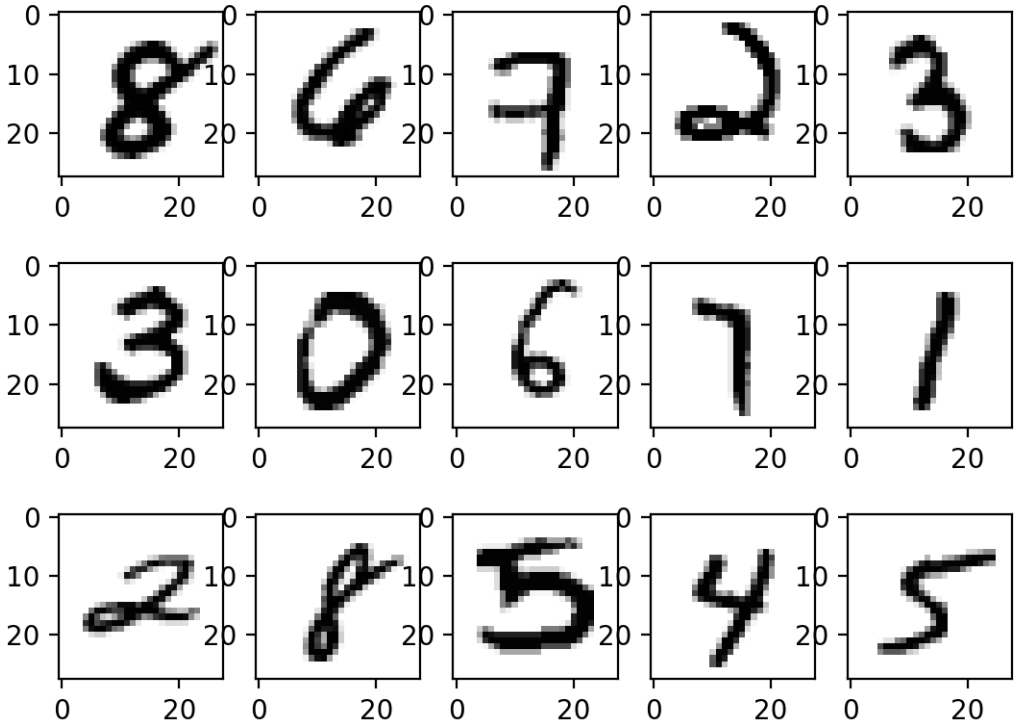
ii. Plot 15 randomly selected images from the test set without looking at the corresponding labels and try to guess them. Were all of your guesses correct?

Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from random import *
```

```
x_train, t_train, x_test, t_test = mnist.load()
X = 255-x_train
plt.gray()
i=0
while i<15:
    i=i+1
    plt.subplot(3,5,i)
    plt.imshow((X[randint(1,60000)]).reshape((28,28)))
plt.show()
```

Output:



Inference:

Yes, I am able to guess all the 15 numbers in the random images I plot.
It seems pretty clear that the numbers plotted are 8,6,7,2,3,3,0,6,7,1,2,8,5,4,5.

****

iii. Let us explore the data even more. Find 2 different digits that look alike. Find 3 samples of the same digit that do not look alike at all.

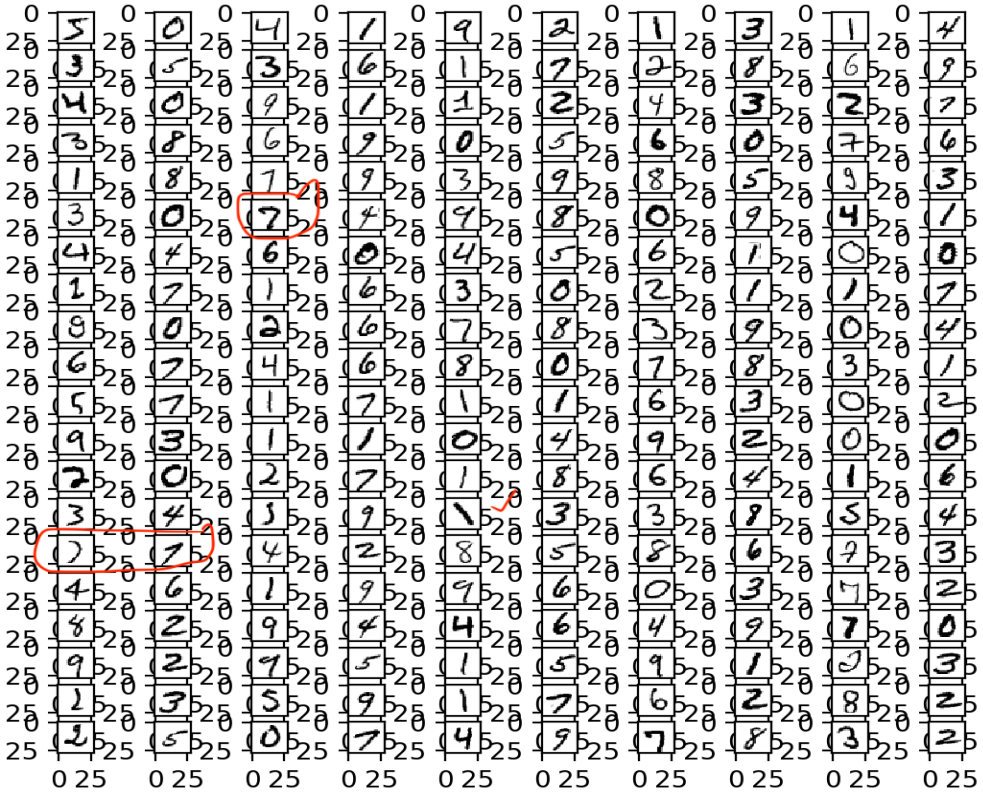
Code:

```
#2 different images that look alike
import mnist
import matplotlib.pyplot as plt
import numpy as np
from random import *

x_train, t_train, x_test, t_test = mnist.load()
X = 255-x_train
plt.gray()
for i in range(100):
   plt.subplot(10, 10, i+1)
   plt.imshow((X[i]).reshape((28,28)))
print((t_train[0:100]).reshape(10,10))
plt.show()
```

```
#same digit that do not look alike.
import mnist
import matplotlib.pyplot as plt
import numpy as np
from random import *

x_train, t_train, x_test, t_test = mnist.load()
X = 255-x_train
plt.gray()
for i in range(200):
   plt.subplot(20, 10, i+1)
   plt.imshow((X[i]).reshape((28,28)))
print((t_train[0:200]).reshape(20,10))
plt.show()
```

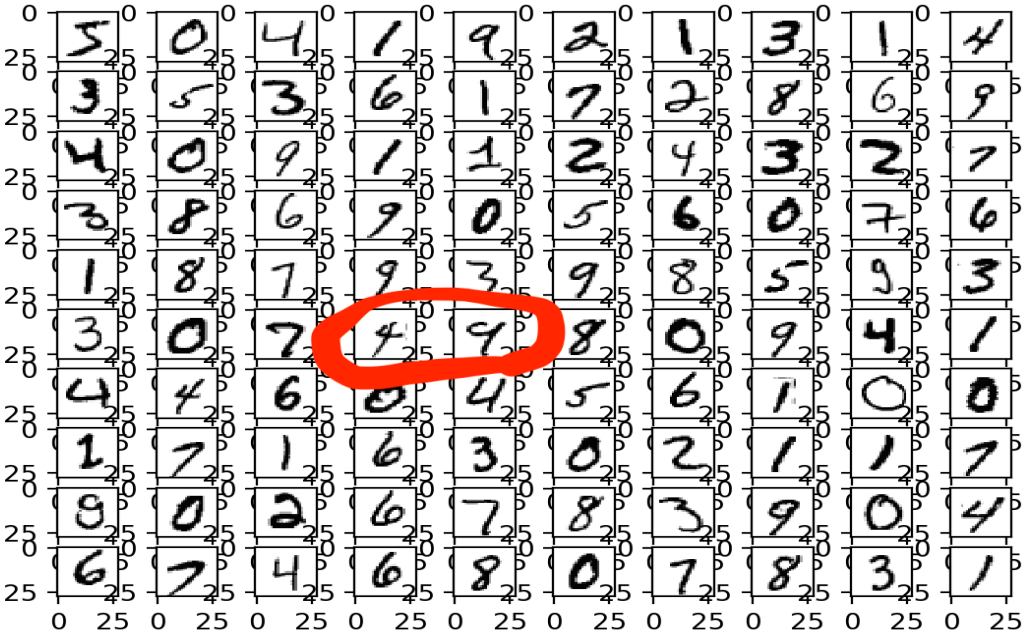
Output:

The three samples indicated are of the same number but do not look alike



:

Samples 64 and 65 look alike, but they are 4 and 9 respectively.



(c) Classification using KNN on MNIST database

i. What is the nearest neighbor of a train sample, assuming it is included in the training set?

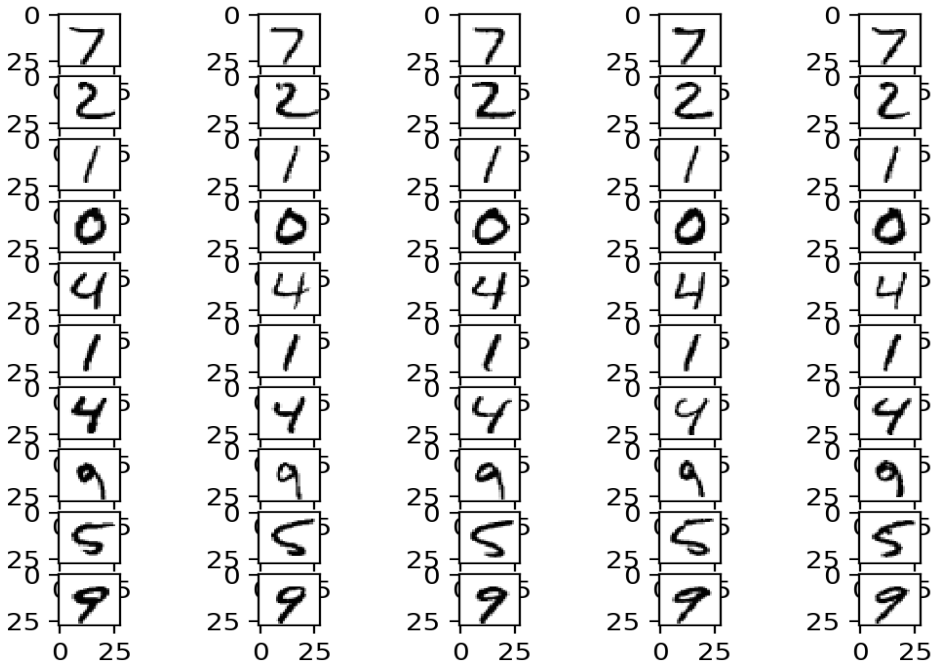
The nearest neighbor of a train sample assuming it is included in the training set is itself.

ii. Write code for k-nearest neighbors with Euclidean metric (or use a software package). Find 5 nearest neighbors for the first 10 test samples and plot them together.

Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from sklearn.neighbors import KNeighborsClassifier

x_train, t_train, x_test, t_test = mnist.load()
plt.gray()
neigh = KNeighborsClassifier(n_neighbors=5,metric="euclidean")
X = 255-x_train
y = t_train
x_test = 255 - x_test
neigh.fit(X[:60000],y[:60000])
k_images = neigh.kneighbors(X=x_test[0:10], n_neighbors=5, return_distance=False)
print(k_images)
for i in range(10):
   for j in range(5):
      plt.subplot(10, 5, (i*5)+(j+1))
      plt.imshow((X[k_images[i][j],:]).reshape((28,28)))
plt.show()
```

Output:



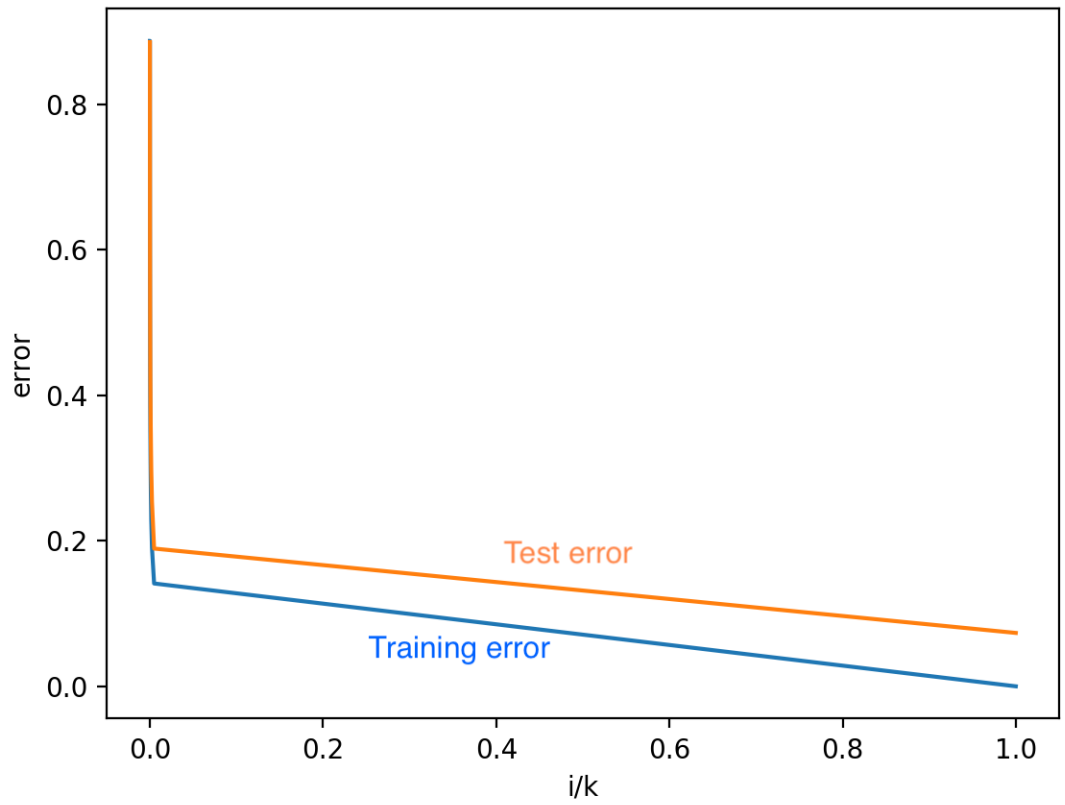
iii. Test all 10000 digits in the test database with k nearest neighbors. Take decisions by majority polling. Plot train and test errors in terms of 1/k for k ∈ {1, 201, 401, . . . , 10001}. You are welcome to use smaller increments of k. Which k ∗ is the most suitable k among those values?

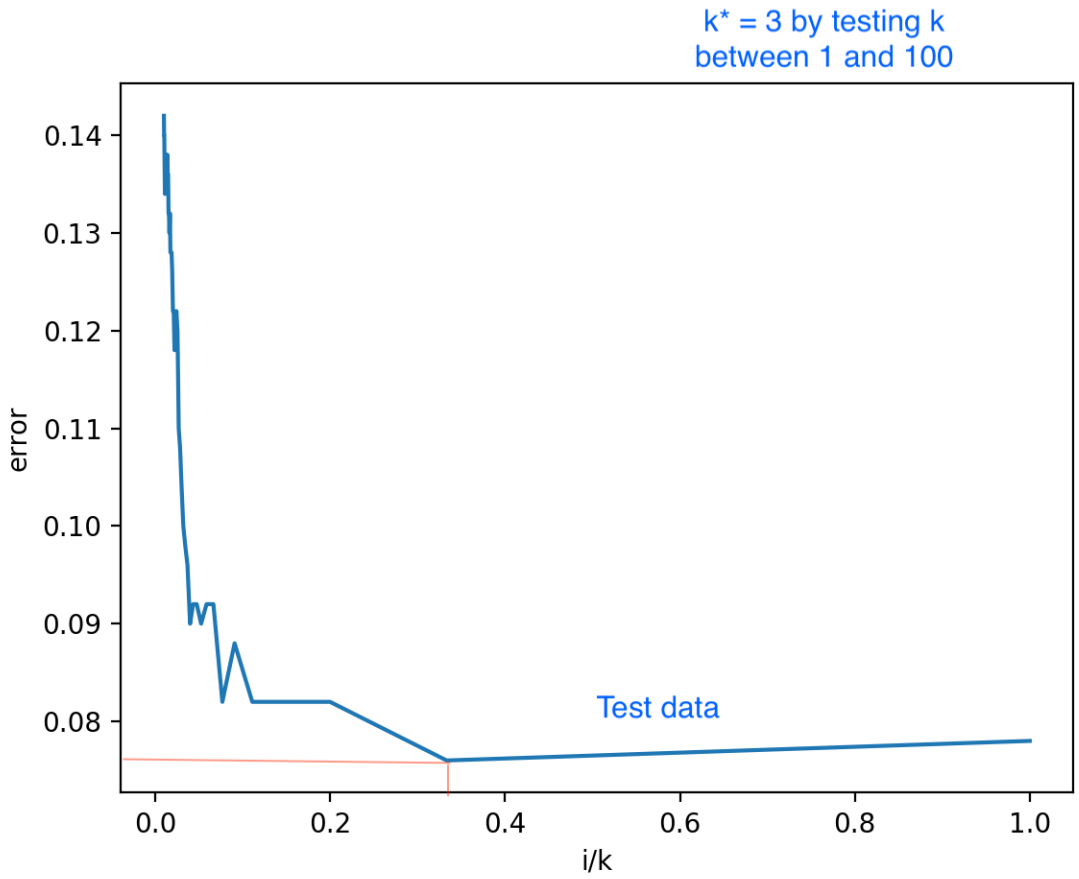
Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from sklearn.neighbors import KNeighborsClassifier

x_train, t_train, x_test, t_test = mnist.load()
X = x_train
y = t_train
neighbours = []
scores_training = []
scores_test = []
print(x_train.shape)
print(t_train.shape)
print(x_test.shape)
print(t_test.shape)
```

```
for k in range (1,10000,200):
    neighbours.append(1/k)
    neigh = KNeighborsClassifier(n_neighbors=k,n_jobs=4,algorithm=”ball_tree”)
    neigh.fit(X[:60000],y[:60000])
    scores1 = neigh.score(X[:10000],y[:10000])
    print (scores1)
    scores_training.append(1-scores1)
    scores2 = neigh.score(x_test[:10000],t_test[:10000])
    print(scores2)
    scores_test.append(1-scores2)
plt.plot(neighbours,scores_training,label="training error")
plt.plot(neighbours,scores_test,label="test error")
plt.xlabel('i/k')
plt.ylabel('error')
plt.show()
```

Output:





Inference:

Since the specified intervals of 200 did not seem to converge to a k* on the test set I decided to make smaller increments and locate k* within 100 which is depicted in 2nd plot. This evidently shows that k* can be concluded to be 3.

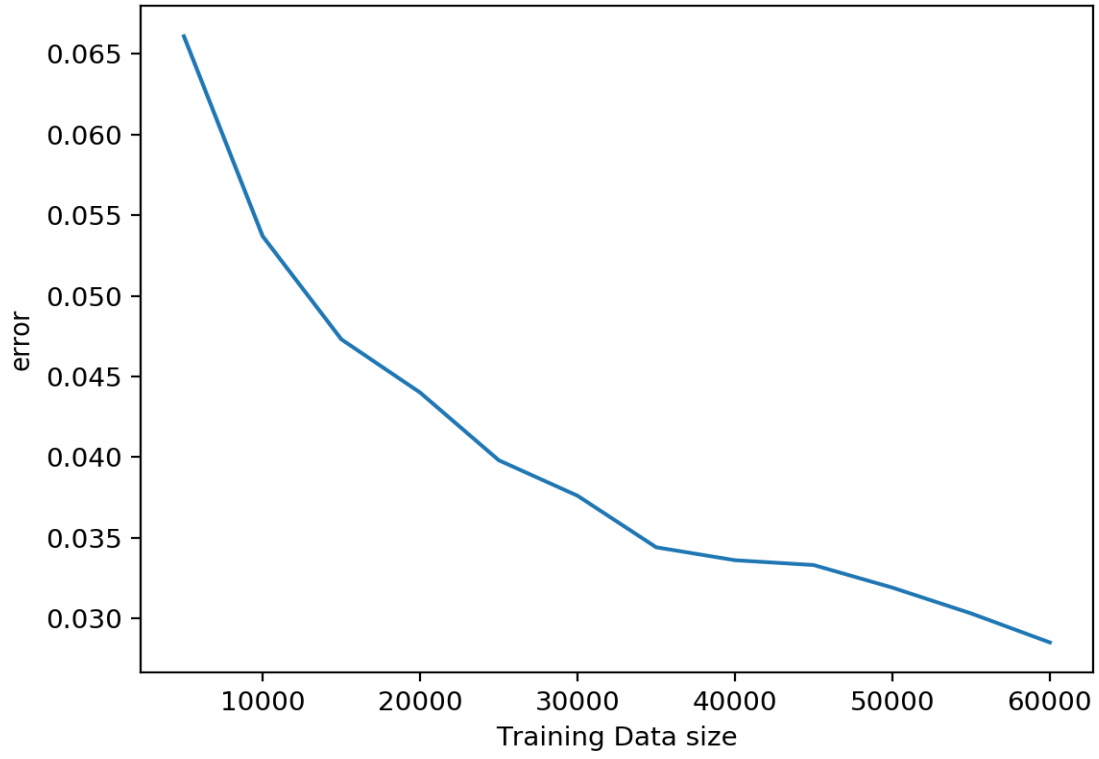
iv. Since the computation time depends on the size of the training set, one may only use a subset of the training set. Plot the best error rate, which is obtained by some value of k, against the size of training set, when the size of training set is N ∈ {5000, 10000, 15000, . . . , 55000, 60000}. (You are welcome to choose smaller increments of N).

Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from sklearn.neighbors import KNeighborsClassifier

x_train, t_train, x_test, t_test = mnist.load()
```

```
X = x_train
y = t_train
data_size = []
scores_training = []
scores_test = []
print(x_train.shape)
print(t_train.shape)
print(x_test.shape)
print(t_test.shape)
for k in range (5000,60001,5000):
    data_size.append(k)
    neigh = KNeighborsClassifier(n_neighbors=3,n_jobs=4)
    neigh.fit(X[:k],y[:k])
    scores2 = neigh.score(x_test[:10000],t_test[:10000])
    print(scores2)
    scores_test.append(1-scores2)
plt.plot(data_size,scores_test,label="test error")
plt.xlabel('Training Data size')
plt.ylabel('error')
plt.show()
```

Output:



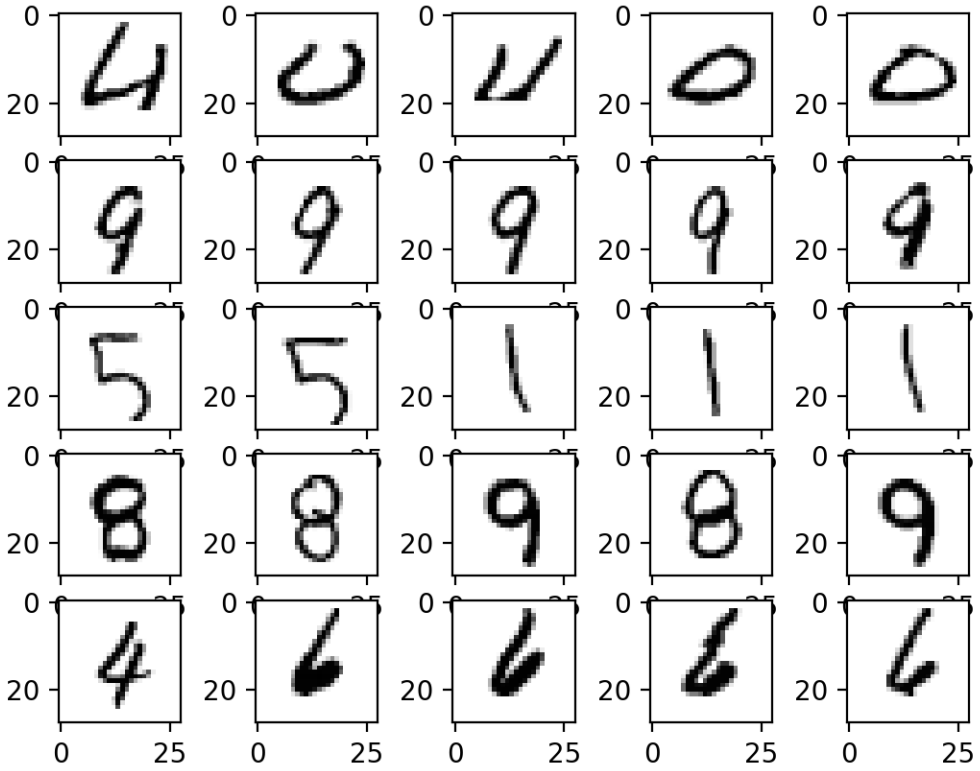
(d) Plot the k nearest neighbors of some of misclassified samples.

Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
np.set_printoptions(threshold=np.inf)
x_train, t_train, x_test, t_test = mnist.load()
X = x_train
y = t_train
data_size = []
scores_training = []
scores_test = []
print(x_train.shape)
print(t_train.shape)
print(x_test.shape)
print(t_test.shape)
neigh = KNeighborsClassifier(n_neighbors=5,n_jobs=4)
neigh.fit(X,y)
scores2 = neigh.predict(x_test[:10000])
print(scores2)
print(t_test)
bool_idx=[scores2 != t_test]
print(bool_idx)
print(x_test[bool_idx])
misclassified = x_test[bool_idx]
k_images = neigh.kneighbors(misclassified[0].reshape(1,-1), n_neighbors=5,
return_distance=False)
print(k_images)
for j in range(5):
    plt.subplot(1, 5,j+1)
    plt.imshow((X[k_images[0][j]]).reshape((28,28)))
plt.show()
```

Output:

Each row shows 5 nearest neighbours of a misclassified example generated using Boolean indexing of the test result with test labels.



(e) Replace the Euclidean metric with the following metrics and test them. Summarize the test errors (i.e., when k = k ∗) in a table.

i. Minkowski Distance:

A. which becomes Manhattan Distance with p = 1

B. with log10(p) ∈ {0.1, .2, .3, . . . , 1}

C. which becomes Chebyshev Distance with p → ∞

ii. Mahalanobis Distance

iii. Hausdroff Distance iv. (More Fun) with Hausdroff Distances 1, 2, 3 introduced in the paper Hausdorff Distance with k-Nearest Neighbors by Jun Wang and Ying Tan

Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
import math
from scipy.spatial.distance import directed_hausdorff
```

```
x_train, t_train, x_test, t_test = mnist.load()
X = x_train
y = t_train
neighbours = []
scores_training = []
scores_test = []
def hausdroffDistanceCalc(a,b):
   return max(directed_hausdorff((a).reshape(28,28),
(b).reshape(28,28))[0],directed_hausdorff((b).reshape(28,28), (a).reshape(28,28))[0])
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=1)
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Manahttan error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,1/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.1) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,2/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.2) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,3/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.3) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,4/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.4) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,5/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.5) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,6/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.6) error")
print(1-scores2)
```

```
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,7/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.7) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,8/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.8) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,9/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(0.9) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=math.pow(10,10/10))
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Minkowski p = log(1.0) error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="chebyshev")
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Chebyshev error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="mahalanobis",metric_params={'VI':
np.cov(X[:30000])},algorithm="brute")
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Mahalanobis error")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric=hausdroffDistanceCalc)
neigh.fit(X[:30000],y[:30000])
scores2 = neigh.score(x_test[:5000],t_test[:5000])
print("Hausdroff error")
print(1-scores2)
```

Output:

```
Manahttan error
0.066
Minkowski p = log(0.1) error
0.0612
Minkowski p = log(0.2) error
0.0572
Minkowski p = log(0.3) error
0.054
```

```
Minkowski p = log(0.4) error
0.051
Minkowski p = log(0.5) error
0.0488
Minkowski p = log(0.6) error
0.0472
Minkowski p = log(0.7) error
0.0474
Minkowski p = log(0.8) error
0.0454
Minkowski p = log(0.9) error
0.0452
Minkowski p = log(1.0) error
0.0456
Chebyshev error
0.2572
Mahalanobis error
0.42
Hausdroff error
0.2642
```

(f) Replace the majority polling decision with another reasonable method devised by yourself. Use it with Euclidean, Manhattan, and Chebyshev distances and report the best test errors.

Code:

```
import mnist
import matplotlib.pyplot as plt
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
import math
from scipy.spatial.distance import directed_hausdorff
np.set_printoptions(threshold=np.inf)
x_train, t_train, x_test, t_test = mnist.load()
X = x_train
y = t_train
neighbours = []
scores_training = []
scores_test = []
def customWeights(a):
    a = [8,4,2]
    return a
neigh = KNeighborsClassifier(n_neighbors=3,metric="euclidean",weights=customWeights)
neigh.fit(X[:60000],y[:60000])
scores2 = neigh.score(x_test[:10000],t_test[:10000])
print("Eucledian error -- " )
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="minkowski",p=1,weights =
customWeights)
```

```
neigh.fit(X[:60000],y[:60000])
scores2 = neigh.score(x_test[:10000],t_test[:10000])
print("Manhattan error --")
print(1-scores2)
neigh = KNeighborsClassifier(n_neighbors=3,metric="chebyshev")
neigh.fit(X[:60000],y[:60000])
scores2 = neigh.score(x_test[:10000],t_test[:10000])
print("Chebyshev error --")
print(1-scores2)
```

Output:

```
Eucledian error --
0.03090000000000004
Manhattan error --
0.036900000000000044
Chebyshev error --
0.1936
```

Note:
The alternative to majority polling used here is a user defined function that weighs the nearer neighbors higher than the farther ones instead of the majority polling approach used conventionally.

(g) What is the lowest error rate you achieved in this exercise?

Euclidean distance with majority polling replaced by weighted polling has recorded the lowest error rate of 0.0369.

2. **Forest Fire Data**

In this exercise, we investigate a difficult regression task, where the aim is to predict the burned area of forest fires in the northeast region of Portugal.
(a) Download the Forest Fire data from: https://archive.ics.uci.edu/ml/datasets/ Forest+Fires.

(b) Exploring the data:

i. How many rows are in this data set? How many columns? What do the rows and columns represent?

The data set consists of 517 rows and 13 columns.
Each row represents a training data .Hence we have 517 training samples.
Each column represents a feature/predictor except for the last column which is the dependent variable or output.

Description of the column variables as provided with the dataset.

1. X - x-axis spatial coordinate within the Montesinho park map: 1 to 9
2. Y - y-axis spatial coordinate within the Montesinho park map: 2 to 9
3. month - month of the year: 'jan' to 'dec'
4. day - day of the week: 'mon' to 'sun'
5. FFMC - FFMC index from the FWI system: 18.7 to 96.20
6. DMC - DMC index from the FWI system: 1.1 to 291.3
7. DC - DC index from the FWI system: 7.9 to 860.6
8. ISI - ISI index from the FWI system: 0.0 to 56.10
9. temp - temperature in Celsius degrees: 2.2 to 33.30
10. RH - relative humidity in %: 15.0 to 100
11. wind - wind speed in km/h: 0.40 to 9.40
12. rain - outside rain in mm/m2 : 0.0 to 6.4
13. area - the burned area of the forest (in ha): 0.00 to 1090.84

ii. Explain why the transformation Y1 = ln(1 + Y), where Y is the response variable is useful for this dataset. In the following, use Y1 as the new response variable.

The area data seems to be skewed towards the value 0. hence ln(1+Y) would reduce the skewness of the data and henceforth create a healthy distribution for regression analysis.

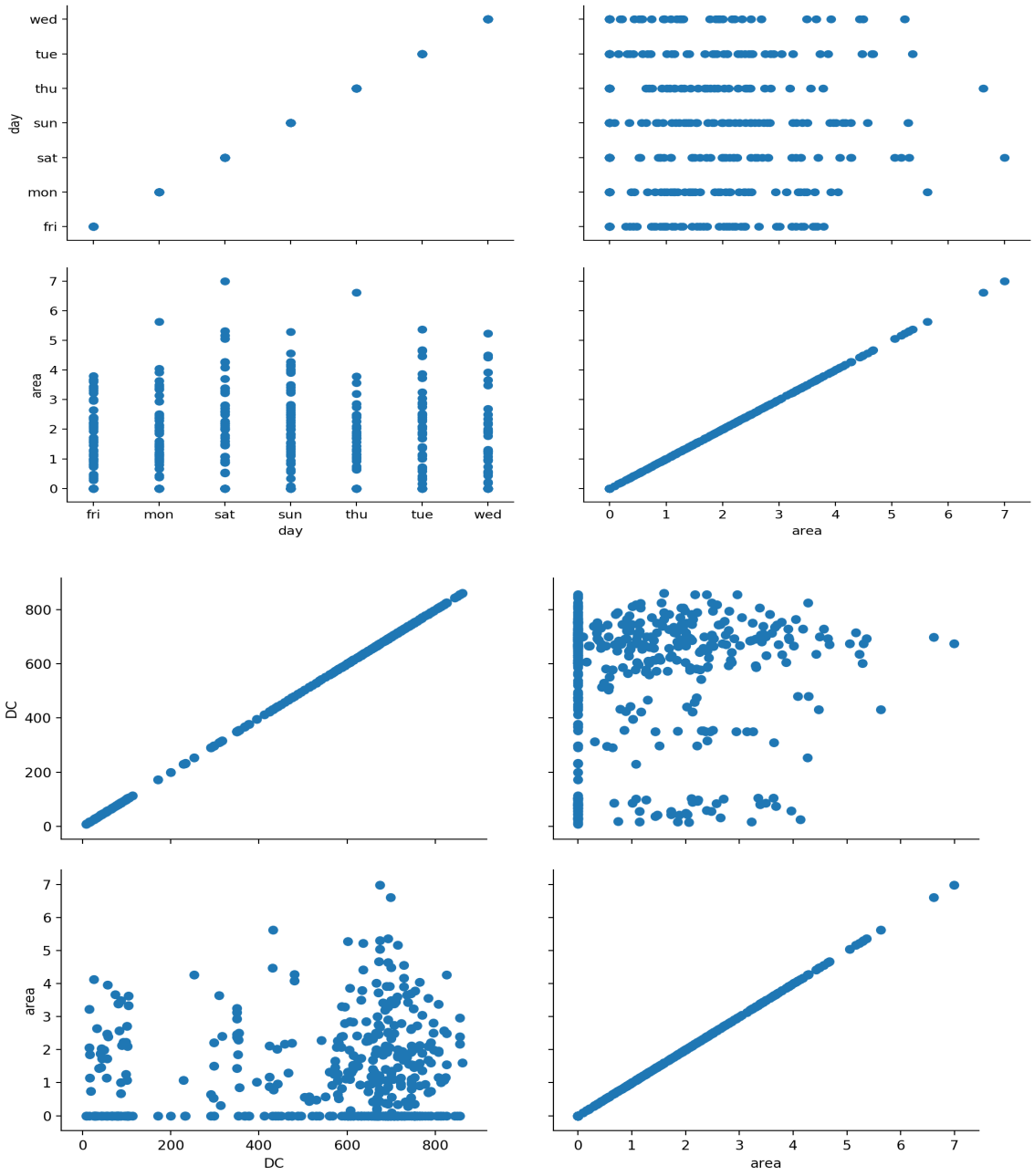
iii. Make pairwise scatterplots of the predictors (columns) in this data set with the dependent variable. Describe your findings.

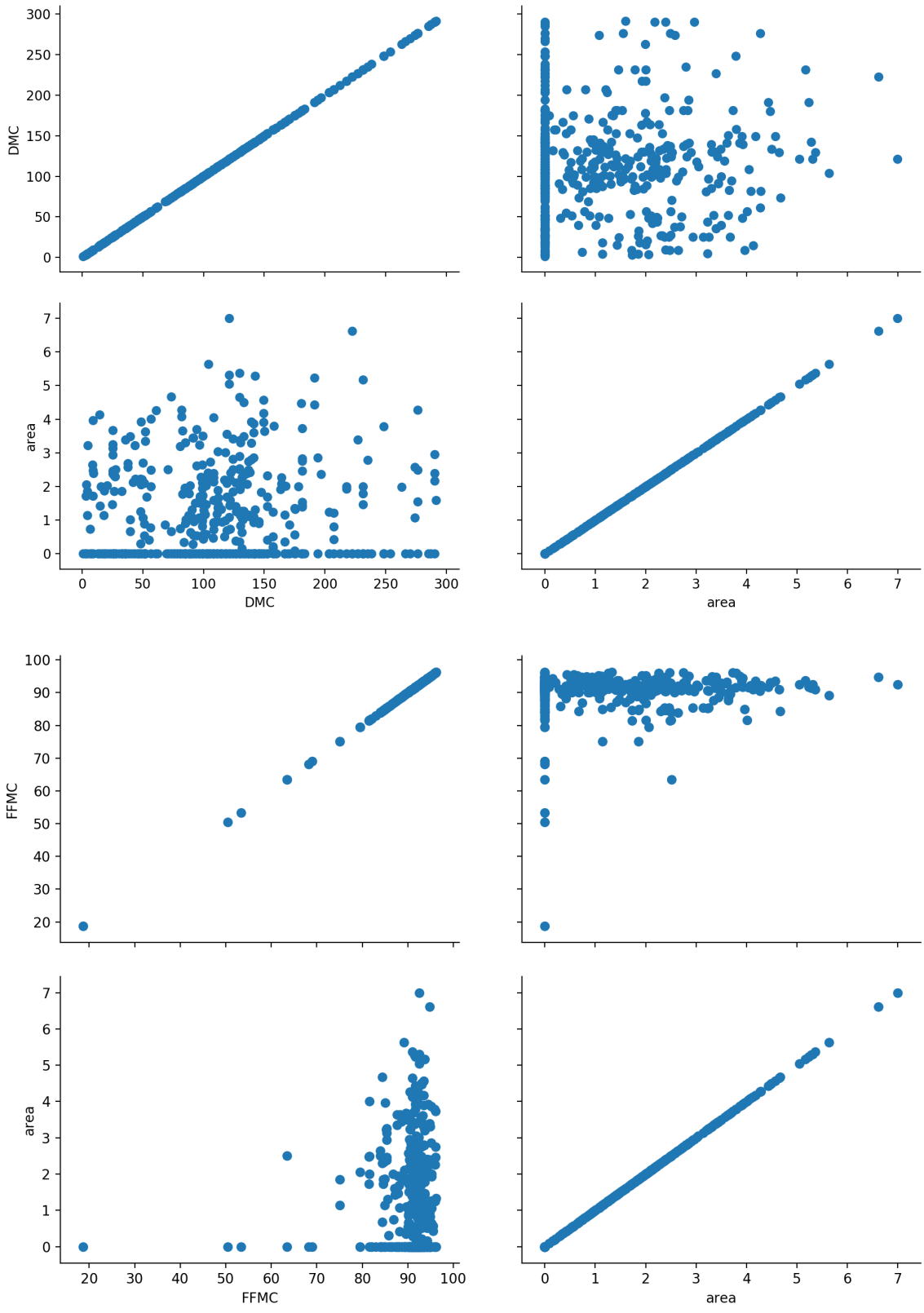
Code:

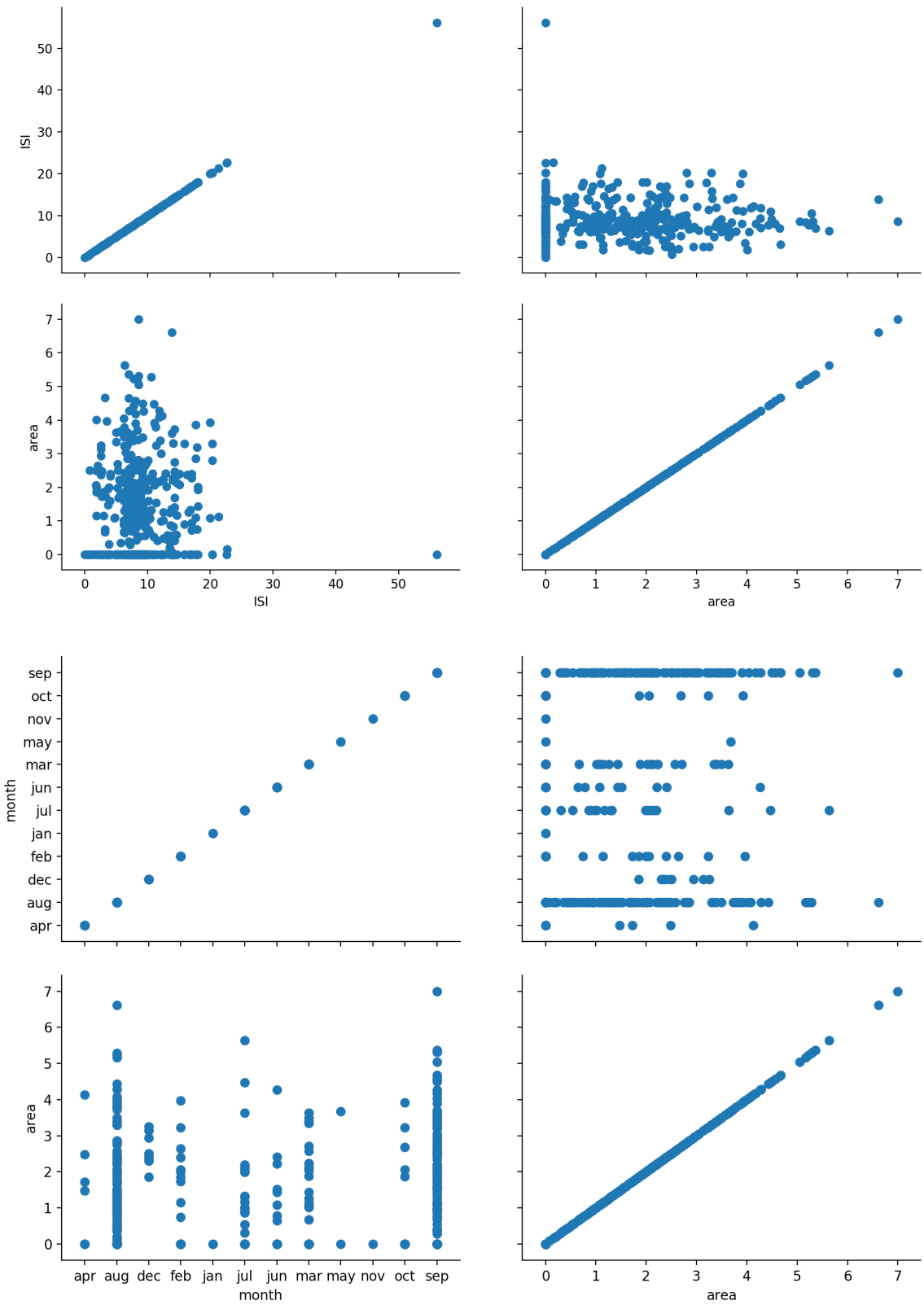
```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))
g = sns.PairGrid(ff_df, vars=["X", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["Y", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["month", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["day", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["FFMC", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["DMC", "area"],size=3)
```

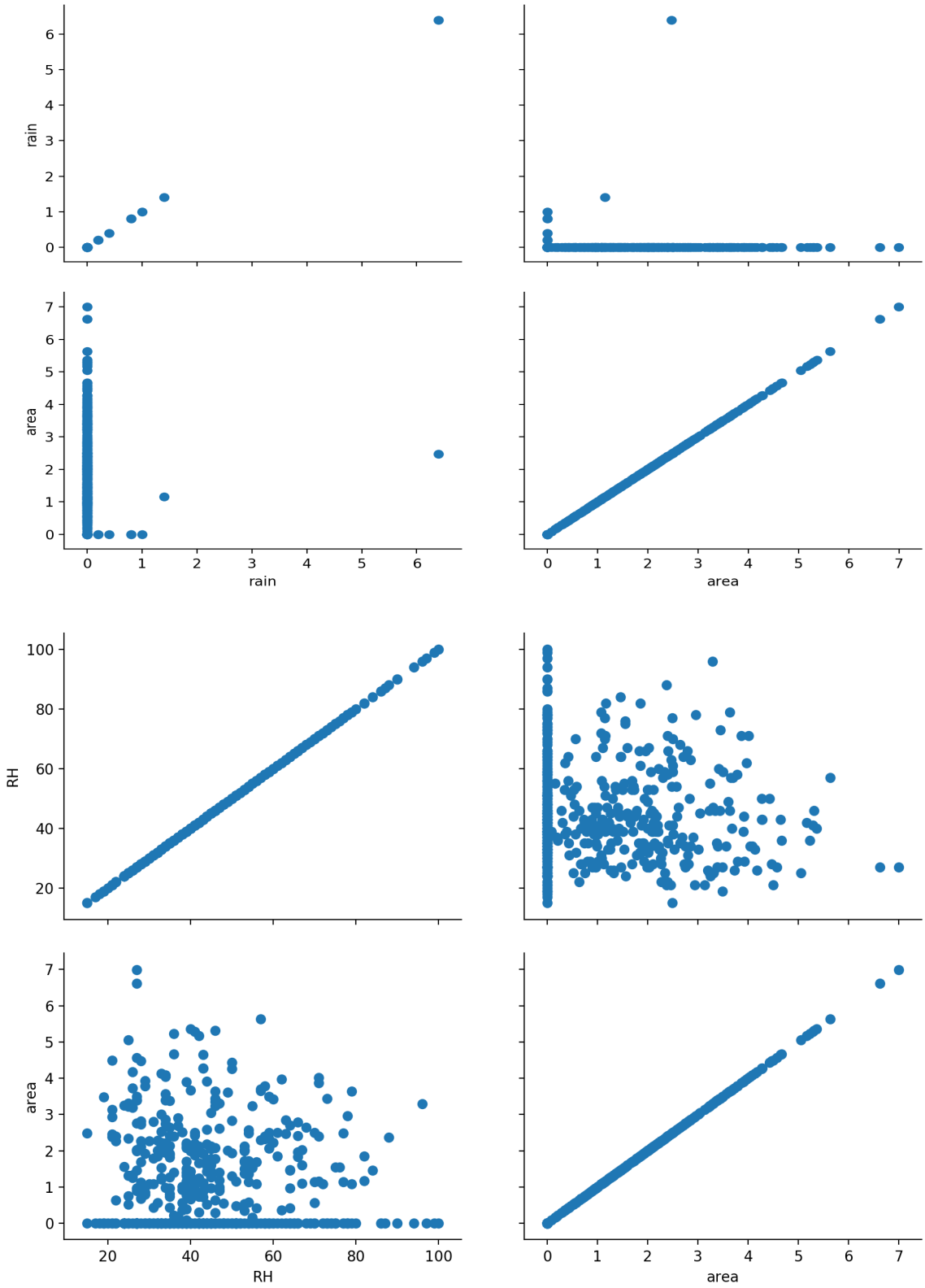
```
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["DC", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["ISI", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["temp", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["RH", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["wind", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
g = sns.PairGrid(ff_df, vars=["rain", "area"],size=3)
g = g.map(plt.scatter)
plt.show()
print(ff_df)
```

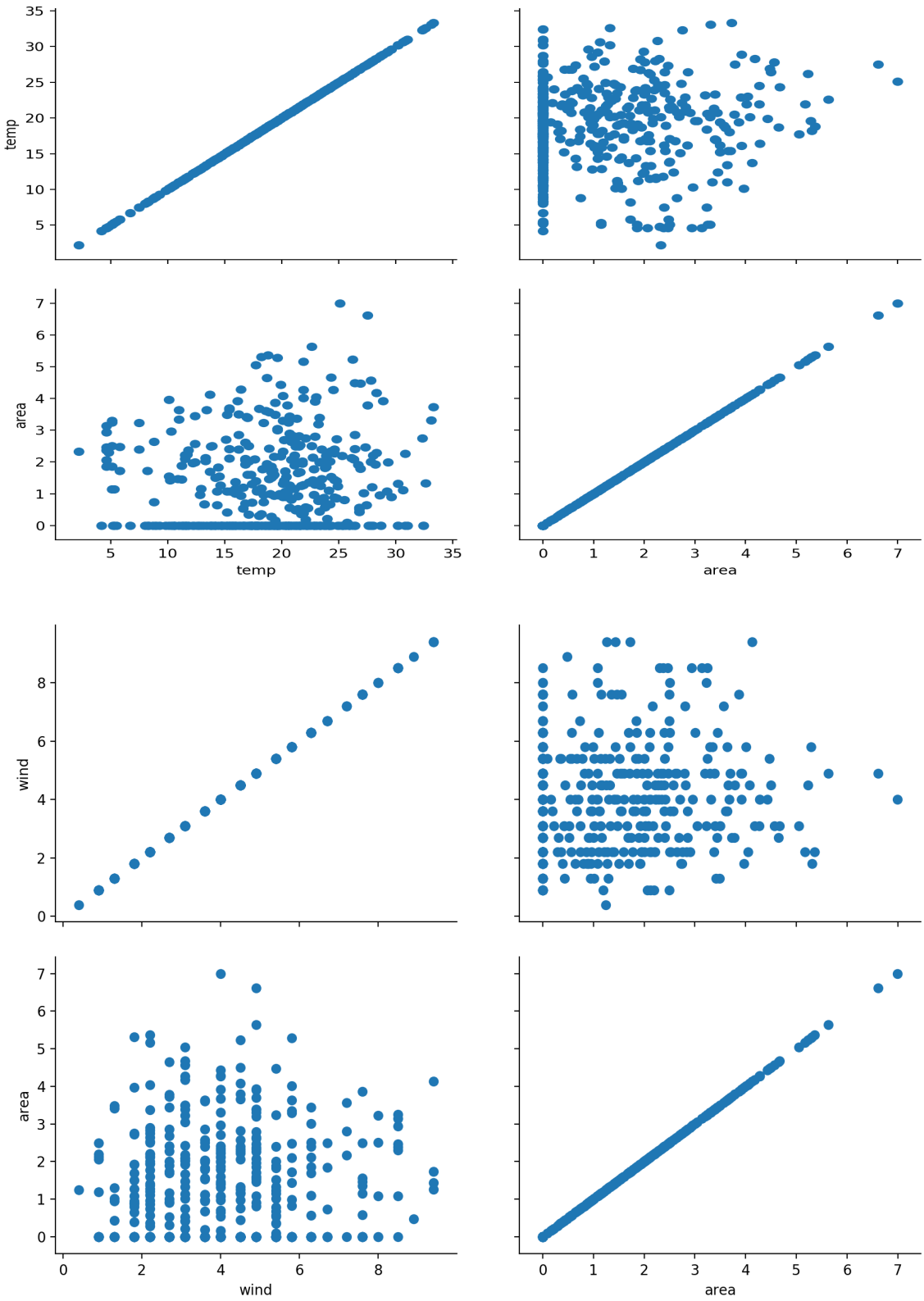
Output:

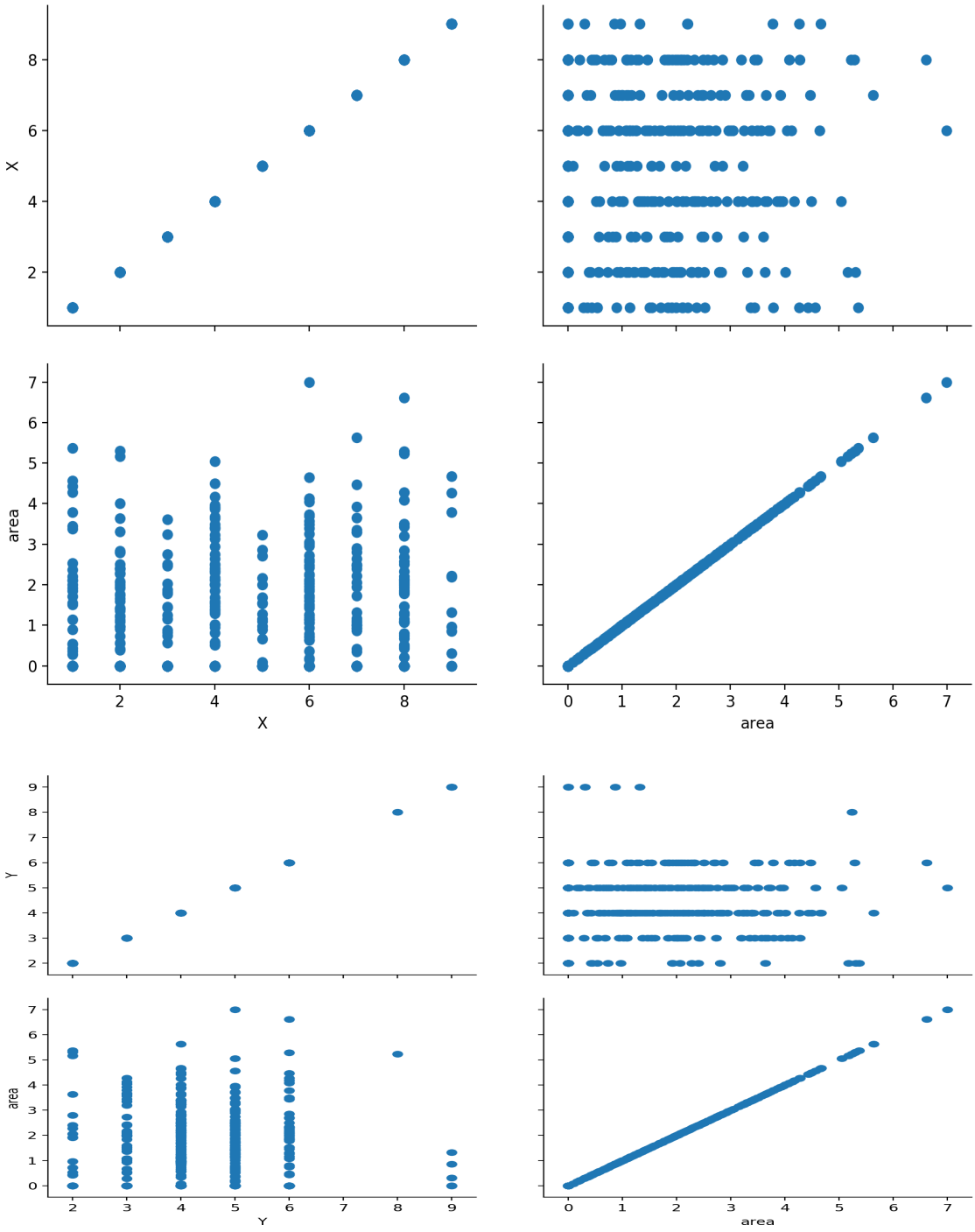

day
wed
tue
thu
sun
sat
mon
fri
area
0
1
2
3
4
5
6
7
fri
mon
sat
sun
thu
tue
wed
day
area
DC
0
200
400
600
800
DC


DMC
area
FFMC
area
DMC
area
FFMC
area


ISI
area
month
ISI
area
month
area
apr aug dec feb jan jul jun mar may nov oct sep


rain
area
RH
rain
area
RH
area


temp
area
wind
area
temp
area
wind
area



Inferences:

X and area :

Co-ordinates 3,5 and 9 look less prone to large forest fires. Other co-ordinates seem inconclusive.

Y and area:

Co-ordinates 7 and 8 have no data regarding forest fires and forest fires at co-ordinate 9 has not spread out to large areas.

Wind and area:
Very high and very low winds seem to have created only smaller forest fires , but wind levels between 2 and 6 have created a large forest fire.

Temp and area:
The relationship between temperature and area when there is a forest fire seems to be correlated to some extend. But since temperature alone is not a causal reason for forest fires the high temperature also records zero area which may have a negative effect on our regression model.

RH and area:
Low RH has always created large forest fires. Humidity seems to have a visible negative effect on forest fires.

Rain and area:
Rain has always been effective in suppressing forest fires to the extent that any rainy day can be for sure classified as a no forest fire or zero area.

Area and month:
August and September seem to have a lot of forest fires. Probably the climate is also hot(summer) and this has an effect on the areas covered. But again since the data points for no forest fire are also considered their overall effect on the mode might be inconclusive.

Area and ISI:
There is no visible correlation between ISI and area except for the fact that there are outliers in the data regarding ISI. Whether this is an important information or an outlier can be decided on statistical values in regressing these data.

Area and FFMC:
Again there is a heavy imbalance in data. This makes any possible correlation in this data impossible. But a high value of FFMC is always prone to large area.

Area and DMC:
No correlation visible in plot.

Area and DC:
There seems to be a lot of data for DC>600 and lesser data for DC<600. But there seems to be not much of correlation between area.

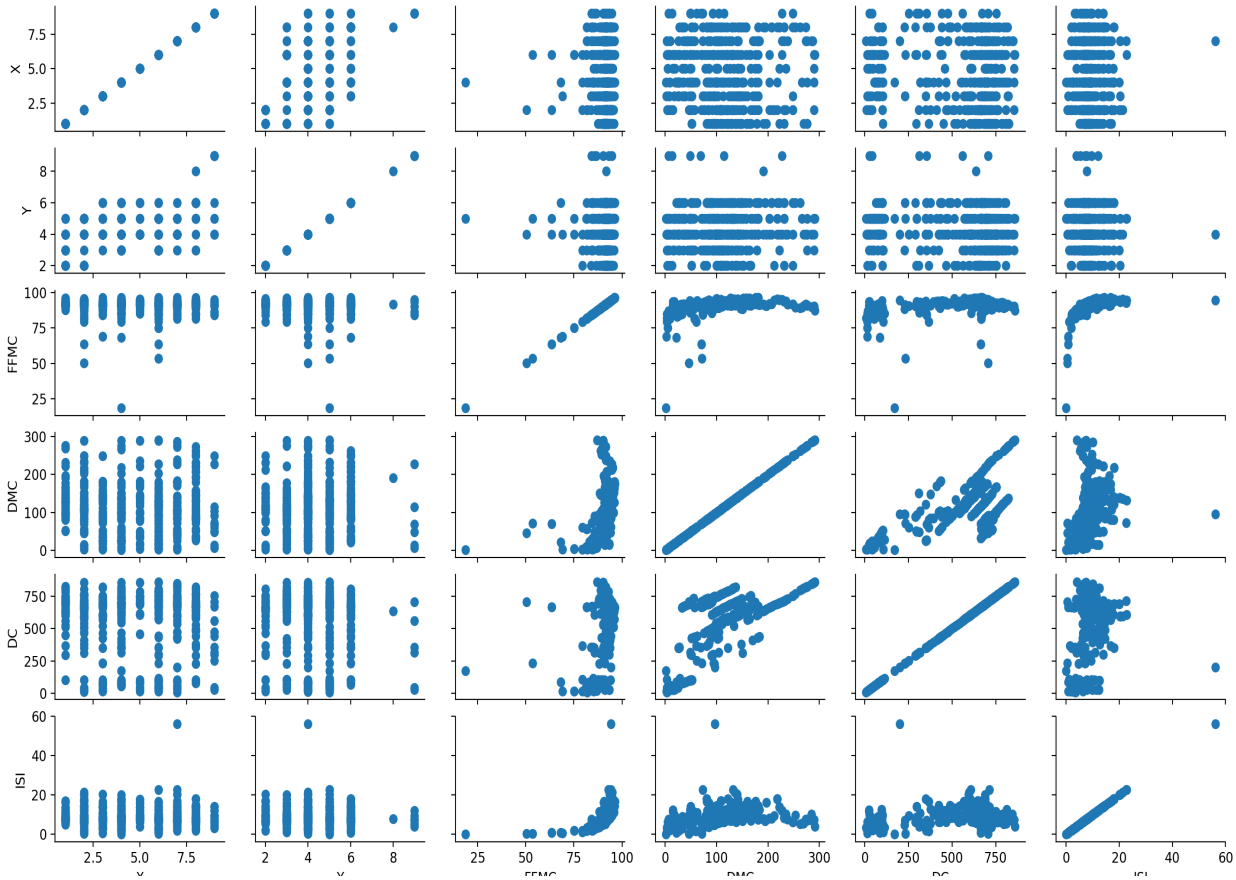
Area and day:
No correlation visible in plot.

iv. Make at least 16 pairwise scatterplots of predictors of your choice and describe your findings. You are welcome to make all possible scatter plots.

Code:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))
g = sns.PairGrid(ff_df.iloc[:,0:8])
g = g.map(plt.scatter)
plt.show()
print(ff_df)
```

Output:



Inference:
The scatter plots show correlation between features which can be exploited for interaction. The pairs that have a good correlation are DMC:DC , FFMC:ISI. These hint us that we have to check for interaction between features which can help us in improving our model.

v. What are the mean, the median, range, first and third quartiles, and interquartile ranges of each of the variables in the dataset? Summarize them in a table.

Code:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))
describe = ff_df.describe()
#print(describe.loc["mean"])
table = pd.DataFrame()
table["Mean"] = describe.loc["mean"]
table["Median"] = ff_df.median()
#table["Range"] = describe.loc["max"] + "-" + describe.loc["min"]
table["Range"] = describe.loc["max"] - describe.loc["min"]
table["FistQuartile"] = describe.loc["25%"]
table["ThirdQuartile"] = describe.loc["75%"]
table["Interquartile"] = describe.loc["75%"]-describe.loc["25%"]
print(final)
```

Output:

```
Ashvants-MacBook-Pro:2B ashvant$ python3 HW1Q2B5.py
              mean     median       range  fistQuartile  thirdQuartile  \
X         4.669246    4.00000     8.00000           3.0       7.000000
Y         4.299807    4.00000     7.00000           4.0       5.000000
FFMC     90.644681   91.60000    77.50000          90.2      92.900000
DMC     110.872340  108.30000   290.20000          68.6     142.400000
DC      547.940039  664.20000   852.70000         437.7     713.900000
ISI       9.021663    8.40000    56.10000           6.5      10.800000
temp     18.889168   19.30000    31.10000          15.5      22.800000
RH       44.288201   42.00000    85.00000          33.0      53.000000
wind      4.017602    4.00000     9.00000           2.7       4.900000
rain      0.021663    0.00000     6.40000           0.0       0.000000
area      1.111026    0.41871     6.99562           0.0       2.024193

       interquartile
X           4.000000
Y           1.000000
FFMC        2.700000
DMC        73.800000
DC        276.200000
ISI         4.300000
temp        7.300000
RH         20.000000
wind        2.200000
rain        0.000000
area        2.024193
Ashvants-MacBook-Pro:2B ashvant$
```

(c) For each predictor, fit a simple linear regression model to predict the response. Describe your results. In which of the models is there a statistically significant association between the predictor and the response? Create some plots to back up your assertions. Are there any outliers that you would like to remove from your data for each of these regression tasks?

Code:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
from statsmodels.formula.api import ols
from scipy import stats
import numpy as np
import seaborn as sns
ff_df = pd.read_csv("forestfires.csv")
#applying lambda transform
ff_df['area'] = ff_df['area'].apply(lambda x:math.log1p(x))

pvalues = []
rsquaredvalues = []
colnames=[]

##Linear regression for each variable
model = ols("area ~ X", ff_df).fit()
```

```
print(model.summary())
pvalues.append(model.pvalues["X"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ Y", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["Y"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ month", ff_df).fit()
print(model.summary())
rsquaredvalues.append(model.rsquared)
for key in list(model.pvalues)[1:]:
    pvalues.append(key)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ day", ff_df).fit()
print(model.summary())
rsquaredvalues.append(model.rsquared)
for key in list(model.pvalues)[1:]:
    pvalues.append(key)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ FFMC", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["FFMC"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ DMC", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["DMC"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ DC", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["DC"])
```

```
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ ISI", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["ISI"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ temp", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["temp"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ RH", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["RH"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ wind", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["wind"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ rain", ff_df).fit()
print(model.summary())
pvalues.append(model.pvalues["rain"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

print(pvalues)
print(colnames)


##Graphs on p-values
y_pos = range(len(colnames))
a = plt.bar(y_pos, pvalues, align='center', alpha=0.5)
```

```
plt.xticks(y_pos, colnames,rotation='vertical')
plt.ylabel('p-values')
plt.title('predictors')
plt.show()


colnames2 = []
for column in ff_df.columns[0:12]:
    colnames2.append(column)

y_pos = range(len(colnames2))
##Graph on r-squared values
plt.bar(y_pos, rsquaredvalues, align='center', alpha=0.5)
plt.xticks(y_pos, colnames2,rotation='vertical')
plt.ylabel('r-squared values')
plt.title('predictors')
plt.show()

#Removing outliers for non -categorical variables
a_df = ff_df.loc[:, ff_df.columns != 'month']
new_df = a_df.loc[:,a_df.columns != 'day' ]
new_df = new_df.loc[:,new_df.columns != 'area' ]
new_df = new_df.loc[:,new_df.columns != 'rain' ]
low = .03
high = .97
quant_df = new_df.quantile([low, high])
new_df = new_df.apply(lambda x: x[(x>=quant_df.loc[low,x.name]) &
                                  (x <= quant_df.loc[high,x.name])], axis=0)
new_df = pd.concat([ff_df.loc[:,'month'], new_df], axis=1)
new_df = pd.concat([ff_df.loc[:,'day'], new_df], axis=1)
new_df = pd.concat([ff_df.loc[:,'area'], new_df], axis=1)
new_df = pd.concat([ff_df.loc[:,'rain'], new_df], axis=1)
new_df.dropna(inplace=True)
print(new_df)

#Boxplots to show to what extent outliers are removed
colnames = []
for column in ff_df.columns[0:2]:
    colnames.append(column)
for column in ff_df.columns[4:12]:
    colnames.append(column)
fig, ax = plt.subplots(nrows=2, ncols = 10, squeeze=True)
j=0
for row in ax:
    i=0
    for col in row:
```

```
        if j==0:
            col.boxplot(ff_df[colnames[i]].values)
        if j==1:
            col.boxplot(new_df[colnames[i]].values)
        i=i+1
    j=j+1
plt.show()

#Converting rain to a categorical tackle data imbalance after removing outliers in other features -
0 dominates.

rainlist = np.array(new_df["rain"])
new_rainlist = []
for i in rainlist:
    if i==0:
        new_rainlist.append("No_rain")
    else:
        new_rainlist.append("Yes_rain")
new_df["rain"] = new_rainlist
print(new_df)

#Again running linear regression for data without outliers.

pvalues = []
rsquaredvalues = []
colnames=[]

##Linear regression for each variable
model = ols("area ~ X", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["X"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ Y", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["Y"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ month", new_df).fit()
print(model.summary())
rsquaredvalues.append(model.rsquared)
```

```
for key in list(model.pvalues)[1:]:
    pvalues.append(key)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ day", new_df).fit()
print(model.summary())
rsquaredvalues.append(model.rsquared)
for key in list(model.pvalues)[1:]:
    pvalues.append(key)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ FFMC", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["FFMC"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ DMC", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["DMC"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ DC", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["DC"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ ISI", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["ISI"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ temp", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["temp"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
```

```
    colnames.append(key)

model = ols("area ~ RH", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["RH"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ wind", new_df).fit()
print(model.summary())
pvalues.append(model.pvalues["wind"])
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

model = ols("area ~ rain", new_df).fit()
print(model.summary())
for key in list(model.pvalues)[1:]:
    pvalues.append(key)
rsquaredvalues.append(model.rsquared)
for key in model.pvalues.keys()[1:]:
    colnames.append(key)

print(pvalues)
print(colnames)


##Graphs on p-values
y_pos = range(len(colnames))
a = plt.bar(y_pos, pvalues, align='center', alpha=0.5)
plt.xticks(y_pos, colnames,rotation='vertical')
plt.ylabel('p-values')
plt.title('predictors')
plt.show()


colnames2 = []
for column in ff_df.columns[0:12]:
    colnames2.append(column)

y_pos = range(len(colnames2))
##Graph on r-squared values
plt.bar(y_pos, rsquaredvalues, align='center', alpha=0.5)
plt.xticks(y_pos, colnames2,rotation='vertical')
plt.ylabel('r-squared values')
```

```
plt.title('predictors')
plt.show()
```

Output and Inferences:

X vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                  0.002
Method:                 Least Squares   F-statistic:                     1.987
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.159
Time:                        08:10:50   Log-Likelihood:                -905.47
No. Observations:                 517   AIC:                             1815.
Df Residuals:                     515   BIC:                             1823.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9361      0.138      6.759      0.000       0.664       1.208
X              0.0375      0.027      1.410      0.159      -0.015       0.090
==============================================================================
Omnibus:                       93.301   Durbin-Watson:                   0.939
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              141.843
Skew:                           1.204   Prob(JB):                     1.58e-31
Kurtosis:                       3.887   Cond. No.                         12.1
==============================================================================
```

Normally p-value of 0.159 is not a strong a conclusion against the null hypothesis. But in this scenario relative p-values suggest that X is one if the factors that to an extent correlates with area.

Y vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.7780
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.378
Time:                        08:10:50   Log-Likelihood:                -906.08
No. Observations:                 517   AIC:                             1816.
Df Residuals:                     515   BIC:                             1825.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9211      0.224      4.114      0.000       0.481       1.361
Y              0.0442      0.050      0.882      0.378      -0.054       0.143
==============================================================================
Omnibus:                       94.666   Durbin-Watson:                   0.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              144.912
Skew:                           1.213   Prob(JB):                     3.41e-32
Kurtosis:                       3.915   Cond. No.                         17.0
==============================================================================
```

The p and t statistics suggest that null hypothesis cannot be ruled out for Y co-ordinates.

Month Vs Area

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.037
Model:                            OLS   Adj. R-squared:                  0.016
Method:                 Least Squares   F-statistic:                     1.765
Date:                Wed, 31 Jan 2018   Prob (F-statistic):             0.0572
Time:                        08:10:50   Log-Likelihood:                -896.72
No. Observations:                 517   AIC:                             1817.
Df Residuals:                     505   BIC:                             1868.
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.0892      0.462      2.356      0.019       0.181       1.998
month[T.aug]  -0.0440      0.474     -0.093      0.926      -0.974       0.886
month[T.dec]   1.4824      0.654      2.267      0.024       0.198       2.767
month[T.feb]  -0.0014      0.557     -0.002      0.998      -1.095       1.093
month[T.jan]  -1.0892      1.084     -1.004      0.316      -3.220       1.041
month[T.jul]  -0.0056      0.523     -0.011      0.991      -1.034       1.023
month[T.jun]  -0.2461      0.572     -0.430      0.667      -1.370       0.877
month[T.mar]  -0.3167      0.499     -0.634      0.526      -1.298       0.665
month[T.may]   0.7487      1.084      0.690      0.490      -1.382       2.879
month[T.nov]  -1.0892      1.462     -0.745      0.457      -3.962       1.784
month[T.oct]  -0.1722      0.585     -0.294      0.769      -1.321       0.977
month[T.sep]   0.1853      0.474      0.391      0.696      -0.747       1.117
==============================================================================
Omnibus:                      101.243   Durbin-Watson:                   0.935
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              160.967
Skew:                           1.250   Prob(JB):                     1.11e-35
Kurtosis:                       4.107   Cond. No.                         32.8
==============================================================================
```

The one hot encoded month variables do not seem to have a correlation with area according to the suggested p-values.

Day vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                 -0.008
Method:                 Least Squares   F-statistic:                    0.3568
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.906
Time:                        08:10:50   Log-Likelihood:                -905.39
No. Observations:                 517   AIC:                             1825.
Df Residuals:                     510   BIC:                             1855.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9698      0.152      6.370      0.000       0.671       1.269
day[T.mon]     0.1202      0.223      0.539      0.590      -0.318       0.559
day[T.sat]     0.2566      0.216      1.188      0.235      -0.168       0.681
day[T.sun]     0.1543      0.210      0.736      0.462      -0.257       0.566
day[T.thu]     0.0565      0.236      0.240      0.811      -0.406       0.519
day[T.tue]     0.2609      0.232      1.123      0.262      -0.195       0.717
day[T.wed]     0.1439      0.244      0.589      0.556      -0.336       0.624
==============================================================================
```

```
Omnibus:                       91.365   Durbin-Watson:                   0.926
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              137.596
Skew:                           1.189   Prob(JB):                     1.32e-30
Kurtosis:                       3.854   Cond. No.                         7.43
==============================================================================
```

Even the p-values of days suggest nothing positive towards elimination of null hypothesis. The r-squared values also do not suggest any statistical significance.

FFMC Vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     1.130
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.288
Time:                        08:10:50   Log-Likelihood:                -905.90
No. Observations:                 517   AIC:                             1816.
Df Residuals:                     515   BIC:                             1824.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0364      1.013      0.036      0.971      -1.953       2.026
FFMC           0.0119      0.011      1.063      0.288      -0.010       0.034
==============================================================================
Omnibus:                       93.878   Durbin-Watson:                   0.927
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              143.139
Skew:                           1.208   Prob(JB):                     8.28e-32
Kurtosis:                       3.900   Cond. No.                     1.50e+03
==============================================================================
```

Again, the p-values and t-statistic do not give an assertion to eliminate the null hypothesis.
R squared value is also too low to create a statistical significance. Neither the coefficient value is high to create an impact.

DMC Vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                  0.003
Method:                 Least Squares   F-statistic:                     2.333
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.127
Time:                        08:10:50   Log-Likelihood:                -905.30
No. Observations:                 517   AIC:                             1815.
Df Residuals:                     515   BIC:                             1823.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9485      0.123      7.718      0.000       0.707       1.190
DMC            0.0015      0.001      1.527      0.127      -0.000       0.003
==============================================================================
```

```
Omnibus:                       92.181   Durbin-Watson:                   0.923
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              139.319
Skew:                           1.197   Prob(JB):                     5.59e-31
Kurtosis:                       3.855   Cond. No.                         256.
==============================================================================
```

Though the p-value suggests a high probability of the result to be close to the population mean , relatively , it gives an evidence of correlation when compared to other variables. Neither the coefficient value is high to create an impact.

DC vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                  0.002
Method:                 Least Squares   F-statistic:                     2.278
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.132
Time:                        08:10:50   Log-Likelihood:                -905.33
No. Observations:                 517   AIC:                             1815.
Df Residuals:                     515   BIC:                             1823.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9060      0.149      6.078      0.000       0.613       1.199
DC             0.0004      0.000      1.509      0.132      -0.000       0.001
==============================================================================
Omnibus:                       93.787   Durbin-Watson:                   0.921
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              142.918
Skew:                           1.208   Prob(JB):                     9.24e-32
Kurtosis:                       3.895   Cond. No.                     1.46e+03
==============================================================================
```

This case is similar to DMC

ISI vs Area:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.000
Model:                            OLS   Adj. R-squared:                 -0.002
Method:                 Least Squares   F-statistic:                    0.05514
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.814
Time:                        08:10:50   Log-Likelihood:                -906.44
No. Observations:                 517   AIC:                             1817.
Df Residuals:                     515   BIC:                             1825.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.1397      0.137      8.344      0.000       0.871       1.408
ISI           -0.0032      0.014     -0.235      0.814      -0.030       0.023
==============================================================================
Omnibus:                       94.904   Durbin-Watson:                   0.925
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              145.494
Skew:                           1.214   Prob(JB):                     2.55e-32
Kurtosis:                       3.927   Cond. No.                         22.6
==============================================================================
```

The p-value and coefficient suggests that null hypothesis is very much possible for ISI.

Temp vs Area:

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.478
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.225
Time:                        08:10:50   Log-Likelihood:                -905.73
No. Observations:                 517   AIC:                             1815.
Df Residuals:                     515   BIC:                             1824.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.8677      0.209      4.144      0.000       0.456       1.279
temp           0.0129      0.011      1.216      0.225      -0.008       0.034
==============================================================================
Omnibus:                       91.757   Durbin-Watson:                   0.923
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              138.327
Skew:                           1.197   Prob(JB):                     9.18e-31
Kurtosis:                       3.831   Cond. No.                         67.5
==============================================================================
```

The co-efficient and p-values do not suggest any vital statistical relationship.

RH Vs Area

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.487
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.223
Time:                        08:10:50   Log-Likelihood:                -905.72
No. Observations:                 517   AIC:                             1815.
Df Residuals:                     515   BIC:                             1824.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.3147      0.178      7.387      0.000       0.965       1.664
RH            -0.0046      0.004     -1.220      0.223      -0.012       0.003
==============================================================================
Omnibus:                       92.444   Durbin-Watson:                   0.927
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              139.921
Skew:                           1.199   Prob(JB):                     4.14e-31
Kurtosis:                       3.866   Cond. No.                          137.
==============================================================================
```

No statistical significance .. very insignificant co-efficient value and high p-value. Null hypothesis cannot be eliminated.

Wind vs Area

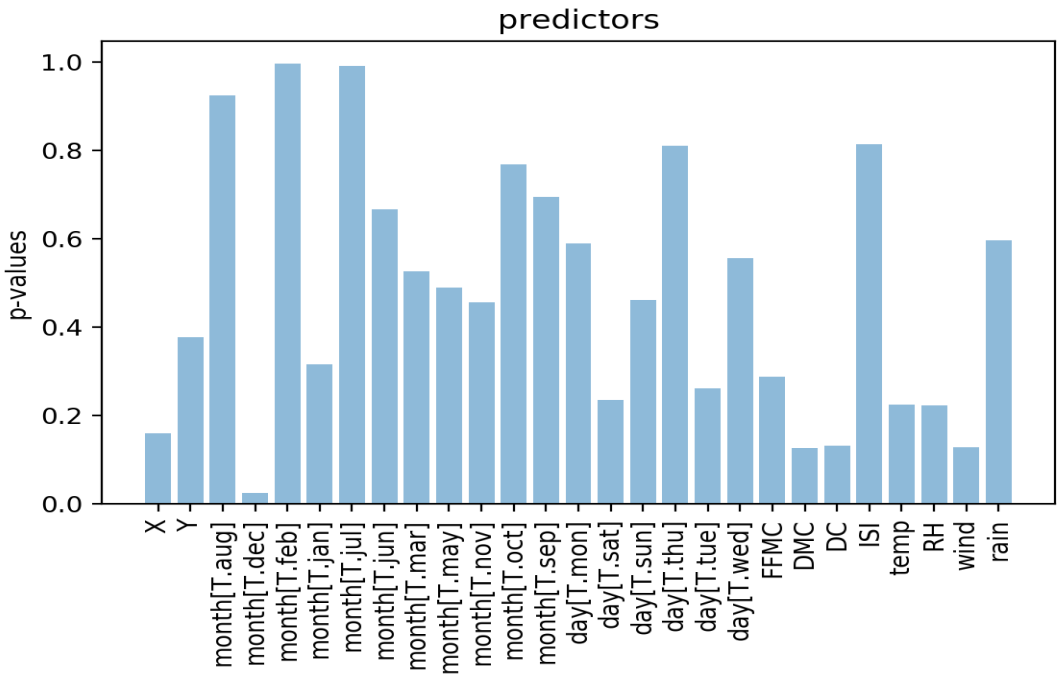
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                  0.003
Method:                 Least Squares   F-statistic:                     2.320
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.128
Time:                        08:10:50   Log-Likelihood:                -905.31
No. Observations:                 517   AIC:                             1815.
Df Residuals:                     515   BIC:                             1823.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9010      0.151      5.969      0.000       0.604       1.198
wind           0.0523      0.034      1.523      0.128      -0.015       0.120
==============================================================================
Omnibus:                       95.685   Durbin-Watson:                   0.926
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              147.420
Skew:                           1.216   Prob(JB):                     9.73e-33
Kurtosis:                       3.962   Cond. No.                         11.3
==============================================================================
```

Relatively better co-efficient and p-value. Can be further investigated for interaction and polynomial regression.

Rain Vs Area:

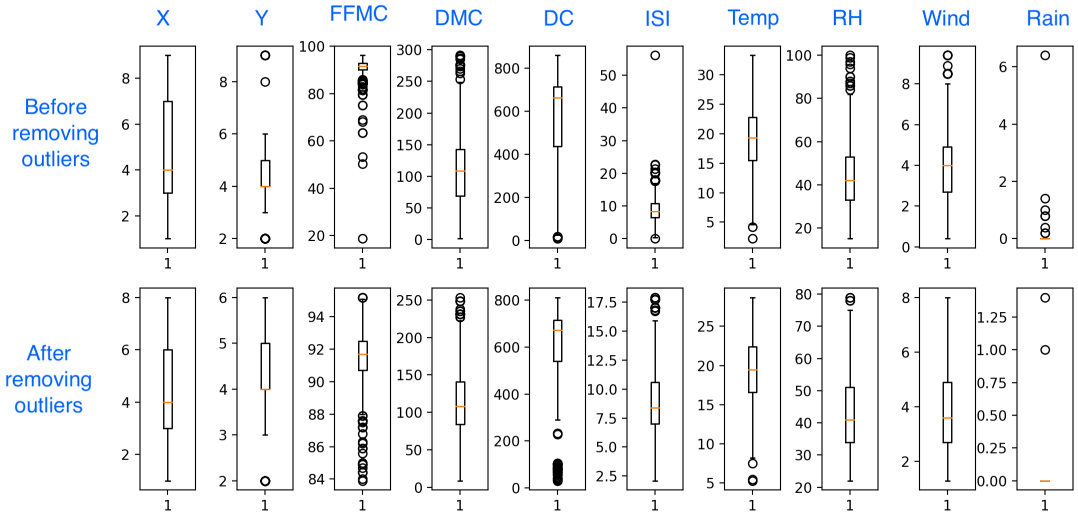
```
                            OLS Regression Results

==============================================================================
Dep. Variable:                   area   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.2800
Date:                Wed, 31 Jan 2018   Prob (F-statistic):              0.597
Time:                        08:10:50   Log-Likelihood:                -906.33
No. Observations:                 517   AIC:                             1817.
Df Residuals:                     515   BIC:                             1825.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.1086      0.062     17.965      0.000       0.987       1.230
rain           0.1101      0.208      0.529      0.597      -0.299       0.519
==============================================================================
Omnibus:                       95.434   Durbin-Watson:                   0.927
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              146.699
Skew:                           1.218   Prob(JB):                     1.40e-32
Kurtosis:                       3.937   Cond. No.                         3.38
==============================================================================
```

Though co-efficients are relatively high . High p-value suggests a null hypothesis may be present. Hence, no statistical conclusion can be made.



The above plot shows the p-values for various predictors and it is very much conclusive that none of the variables have a strong statistical significance, that is, null hypothesis cannot be eliminated.

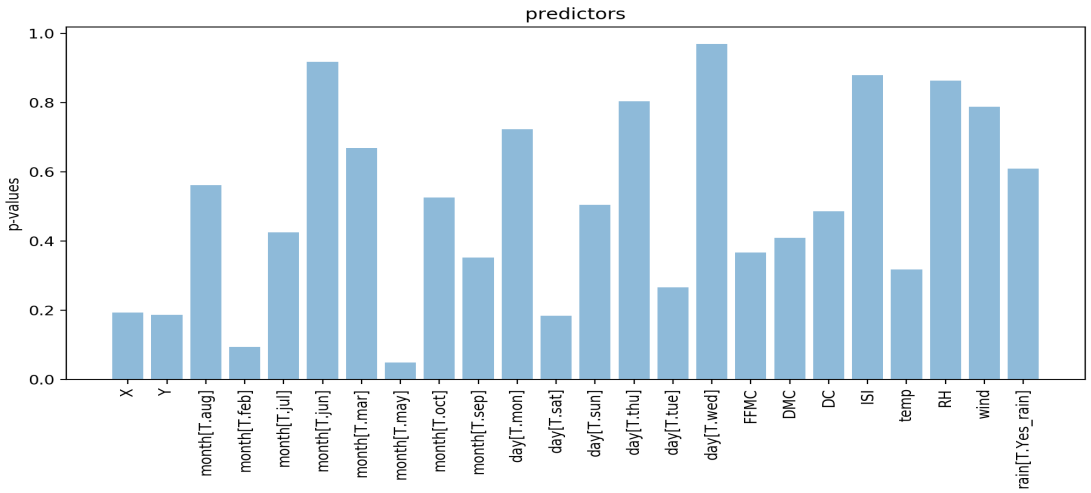
To estimate the outliers, we make a box plot before and after the outliers are removed for each variable:



The above plots show the removal of outliers. There are few outliers still present , but it is important to note that the range of the box plots differ in the two cases meaning these are newly formed outliers.

But removing outliers do not necessarily have to have positive effect on out model. Sometimes outliers carry important information.

Hence we run a linear regression again on the data after removing outliers and plot the p-values to see if there are any positive effects.



It is evident that removing outliers did not have a very positive effect on the p-values of each of the predictors.

(d) Fit a multiple regression model to predict the response using all of the predictors. Describe your results. For which predictors can we reject the null hypothesis H0: βj = 0?

Code:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))

model = ols("area ~ X+Y+month+day+FFMC+DMC+DC+ISI+temp+RH+wind+rain",
ff_df).fit()
```

```
print(model.summary())

pvalues = []
keys = []
intercept=[]

for key in model.pvalues.keys()[1:]:
    intercept.append(model.params[key])
    keys.append(key)
    pvalues.append(model.pvalues[key])

y_pos = range(len(keys))
a = plt.bar(y_pos, intercept, align='center', alpha=0.5)
plt.xticks(y_pos, keys,rotation='vertical')
plt.ylabel('intercept values')
plt.title('predictors')
plt.show()

y_pos = range(len(keys))
a = plt.bar(y_pos, pvalues, align='center', alpha=0.5)
plt.xticks(y_pos, keys,rotation='vertical')
plt.ylabel('p-values')
plt.title('predictors')
plt.show()
```

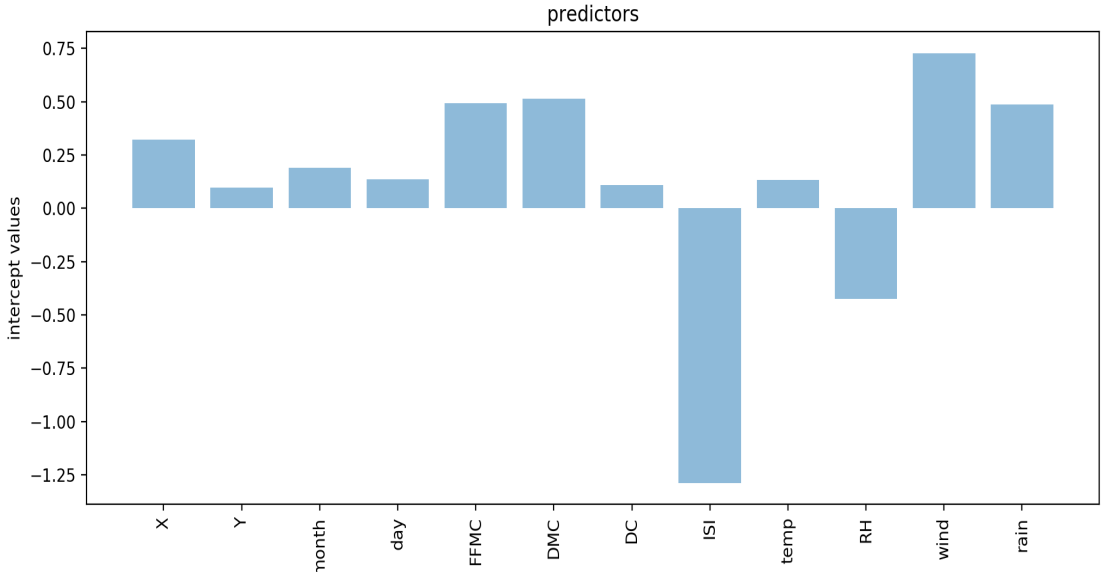
Output:

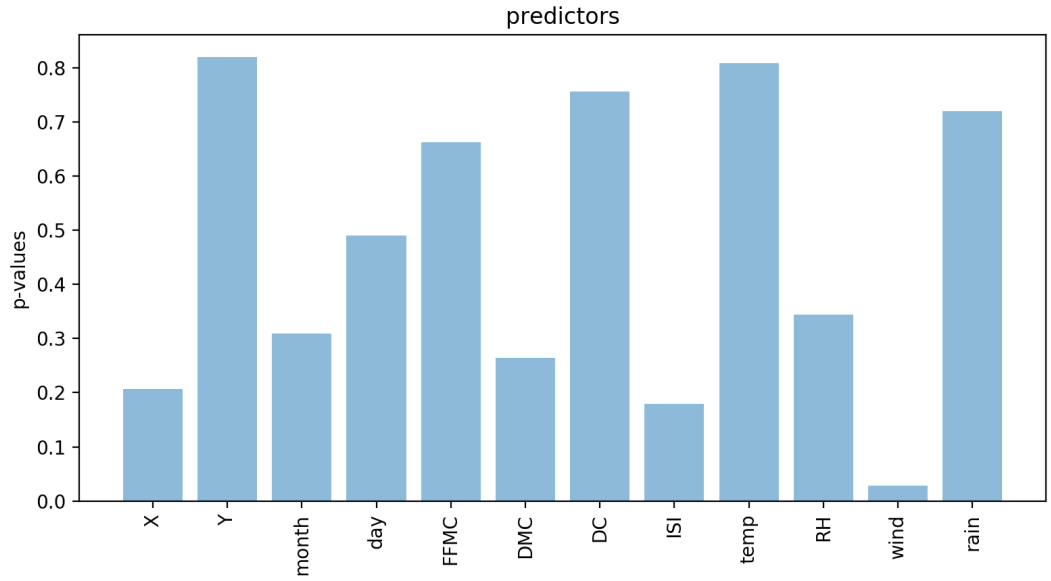
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.028
Model:                            OLS   Adj. R-squared:                  0.005
Method:                 Least Squares   F-statistic:                     1.207
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.275
Time:                        02:18:38   Log-Likelihood:                -899.15
No. Observations:                 517   AIC:                             1824.
Df Residuals:                     504   BIC:                             1880.
Df Model:                          12
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.0388      1.071      0.036      0.971      -2.065       2.142
X              0.3213      0.254      1.263      0.207      -0.178       0.821
Y              0.0957      0.421      0.227      0.820      -0.731       0.922
month          0.1905      0.187      1.018      0.309      -0.177       0.558
day            0.1361      0.197      0.691      0.490      -0.251       0.523
FFMC           0.4920      1.128      0.436      0.663      -1.724       2.708
DMC            0.5131      0.459      1.119      0.264      -0.388       1.414
DC             0.1089      0.351      0.310      0.757      -0.581       0.799
ISI           -1.2887      0.959     -1.344      0.179      -3.172       0.595
temp           0.1323      0.547      0.242      0.809      -0.943       1.207
RH            -0.4245      0.448     -0.948      0.344      -1.305       0.456
wind           0.7279      0.332      2.194      0.029       0.076       1.380
rain           0.4870      1.361      0.358      0.721      -2.188       3.162
```

Omnibus:	84.922	Durbin-Watson:	0.941
Prob(Omnibus):	0.000	Jarque-Bera (JB):	123.977
Skew:	1.142	Prob(JB):	1.20e-27
Kurtosis:	3.731	Cond. No.	52.1

The summary of a multiple linear regression on all variables.

Below are the plots of the co-efficients and p-values of the variable.





A multiple Linear Regression requires that all features are considered. Hence it is important that we normalize the variables to avoid possible bias towards a value that has higher magnitude. I have also label encoded the categorical variables for better interpretation.

The null hypothesis can be eliminated for the feature wind. Other p-values are higher than 0.1. Hence null hypothesis cannot be eliminated for other variables. Wind also has a high co-efficient supporting the claim that wind has a considerable effect on the area of forest fires.

Note: For this and the following questions the variables are normalized and categorical variables are label encoded for better interpretability.

(e) How do your results from 2c compare to your results from 2d? Create a plot displaying the univariate regression coefficients from 2c on the x-axis, and the multiple regression coefficients from 2d on the y-axis. That is, each predictor is displayed as a single point in the plot. Its coefficient in a simple linear regression model is shown on the x-axis, and its coefficient estimate in the multiple linear regression model is shown on the y-axis.

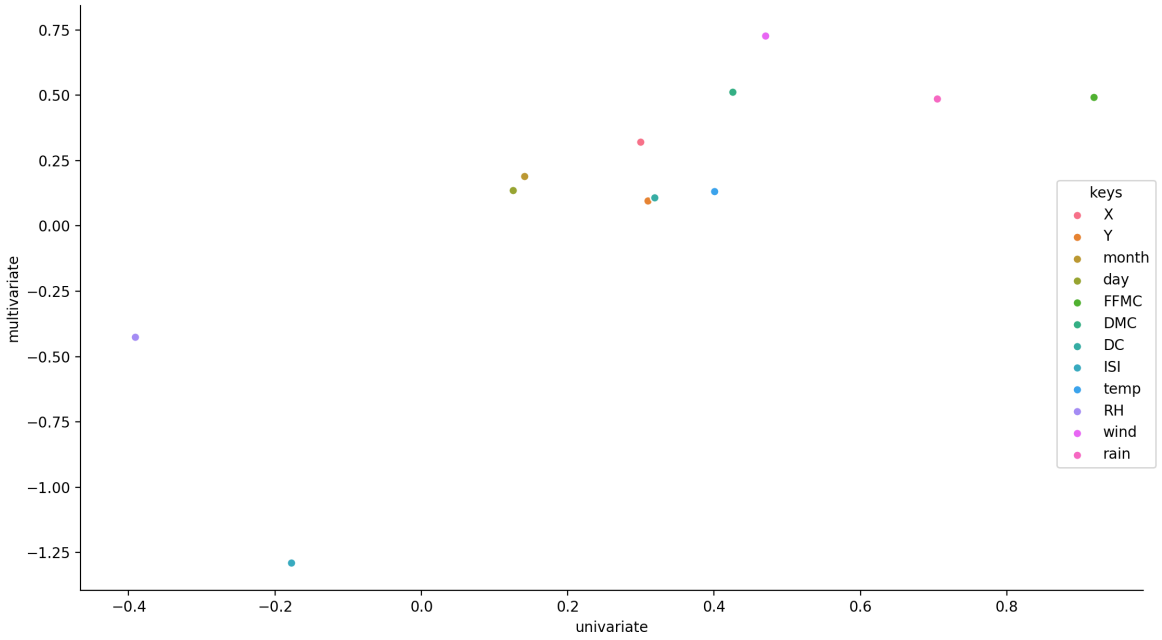
Code:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn import preprocessing

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))



le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])

normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]

model = ols("area ~ X+Y+month+day+FFMC+DMC+DC+ISI+temp+RH+wind+rain",
normalized_df).fit()
#print(list(model.params)[1:])

multiple = dict()
```

```
for key in model.params.keys()[1:]:
    multiple[key] = model.params[key]
#print(multiple)

single=dict()
model = ols("area ~ X", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ Y", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ month", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ day", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ FFMC", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ DMC", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ DC", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ ISI", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ temp", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ RH", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ wind", normalized_df).fit()
```

```
for key in model.params.keys()[1:]:
    single[key] = model.params[key]

model = ols("area ~ rain", normalized_df).fit()
for key in model.params.keys()[1:]:
    single[key] = model.params[key]
#print(single)

singleList = []
multipleList = []
keyList = []
for key in single.keys():
    singleList.append(single[key])
    multipleList.append(multiple[key])
    keyList.append(key)

df = pd.DataFrame()
df["univariate"] = singleList
df["multivariate"] = multipleList
df["keys"] = keyList
print(df)
sns.pairplot(x_vars=["univariate"], y_vars=["multivariate"], data=df, hue="keys", size=5)
plt.show()
```

Output:



Comparing the Rsquared values of individual regression and multiple regression, there has been a considerable increase as the features together have improved the model. Hence, we continue with using multiple regression and improve the model with interaction and polynomial regression.

The co-efficient values have visible broadened outwards from 0 and hence created a greater impact in multiple regression. But still most features have not shown any correlation and hence it is important to try out polynomial regression of variables.

(f) Is there evidence of nonlinear association between any of the predictors and the response? To answer this question, for each predictor X, fit a model of the form Y1 = β0 + β1X + β2X 2 + β3X 3 +

CODE:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn import preprocessing


ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))


le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])

normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]

pvalues=[]
keys=[]
intercept = []
for column in list(ff_df.columns[:-1]):

print("**********************************"+column.upper()+"**********************
******************")
```

```
    model = ols("area ~ "+column+"+ I("+column+"** 2.0)+ I("+column+"**3.0)",
normalized_df).fit()
    print(model.summary())
    for key in model.pvalues.keys()[1:]:
        intercept.append(model.params[key])
        pvalues.append(model.pvalues[key])
        keys.append(column+"-"+key)
##Graphs on p-values
y_pos = range(len(keys))
a = plt.bar(y_pos, pvalues, align='center', alpha=0.5)
plt.xticks(y_pos, keys,rotation='vertical')
plt.ylabel('p-values')
plt.title('predictors')
plt.show()

##Graphs on intercept values
y_pos = range(len(keys))
a = plt.bar(y_pos, intercept, align='center', alpha=0.5)
plt.xticks(y_pos, keys,rotation='vertical')
plt.ylabel('intercept')
plt.title('predictors')
plt.show()
```

Output:

```
**********************************X*****************************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.007
Model:                            OLS   Adj. R-squared:                  0.002
Method:                 Least Squares   F-statistic:                     1.281
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.280
Time:                        02:41:57   Log-Likelihood:                -904.54
No. Observations:                 517   AIC:                             1817.
Df Residuals:                     513   BIC:                             1834.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.1370      0.183      6.226      0.000       0.778       1.496
X             -1.0317      1.686     -0.612      0.541      -4.344       2.280
I(X ** 2.0)    1.9757      4.211      0.469      0.639      -6.297      10.248
I(X ** 3.0)   -0.6284      2.932     -0.214      0.830      -6.388       5.131
==============================================================================
Omnibus:                       91.338   Durbin-Watson:                   0.948
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              137.489
Skew:                           1.191   Prob(JB):                     1.40e-30
Kurtosis:                       3.842   Cond. No.                         103.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************Y*****************************************
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:                   area   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                 -0.002
Method:                 Least Squares   F-statistic:                    0.6123
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.607
Time:                        02:41:57   Log-Likelihood:                -905.54
No. Observations:                 517   AIC:                             1819.
Df Residuals:                     513   BIC:                             1836.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.9271      0.199      4.664      0.000       0.537       1.318
Y              0.6619      1.779      0.372      0.710      -2.834       4.158
I(Y ** 2.0)    0.2585      4.789      0.054      0.957      -9.150       9.667
I(Y ** 3.0)   -1.0194      3.497     -0.292      0.771      -7.889       5.850
==============================================================================
Omnibus:                       96.141   Durbin-Watson:                   0.938
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              148.391
Skew:                           1.221   Prob(JB):                     5.99e-33
Kurtosis:                       3.961   Cond. No.                         106.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************MONTH***********************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.013
Model:                            OLS   Adj. R-squared:                  0.008
Method:                 Least Squares   F-statistic:                     2.334
Date:                Sat, 03 Feb 2018   Prob (F-statistic):             0.0732
Time:                        02:41:57   Log-Likelihood:                -902.96
No. Observations:                 517   AIC:                             1814.
Df Residuals:                     513   BIC:                             1831.
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept        0.7981      0.262      3.045      0.002       0.283       1.313
month            4.3443      3.129      1.388      0.166      -1.803      10.491
I(month ** 2.0) -12.1021      7.317     -1.654      0.099     -26.476       2.272
I(month ** 3.0)   8.2340      4.494      1.832      0.068      -0.596      17.064
==============================================================================
Omnibus:                       93.415   Durbin-Watson:                   0.926
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              142.233
Skew:                           1.201   Prob(JB):                     1.30e-31
Kurtosis:                       3.912   Cond. No.                         203.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************DAY***********************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.004
Method:                 Least Squares   F-statistic:                    0.3696
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.775
Time:                        02:41:57   Log-Likelihood:                -905.91
No. Observations:                 517   AIC:                             1820.
Df Residuals:                     513   BIC:                             1837.
Df Model:                           3
```

```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept         0.9710      0.147      6.603      0.000       0.682       1.260
day               1.2083      1.444      0.837      0.403      -1.630       4.046
I(day ** 2.0)    -2.3576      3.685     -0.640      0.523      -9.598       4.882
I(day ** 3.0)     1.3364      2.479      0.539      0.590      -3.534       6.207
==============================================================================
Omnibus:                       92.733   Durbin-Watson:                   0.930
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              140.572
Skew:                           1.200   Prob(JB):                     2.99e-31
Kurtosis:                       3.874   Cond. No.                         90.5
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************FFMC*********************************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                 -0.003
Method:                 Least Squares   F-statistic:                    0.4899
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.689
Time:                        02:41:57   Log-Likelihood:                -905.73
No. Observations:                 517   AIC:                             1819.
Df Residuals:                     513   BIC:                             1836.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept        -0.1225      1.394     -0.088      0.930      -2.862       2.617
FFMC              0.3245      8.822      0.037      0.971     -17.006      17.656
I(FFMC ** 2.0)    3.5876     17.104      0.210      0.834     -30.015      37.191
I(FFMC ** 3.0)   -2.6827      9.420     -0.285      0.776     -21.190      15.825
==============================================================================
Omnibus:                       94.270   Durbin-Watson:                   0.925
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              144.077
Skew:                           1.209   Prob(JB):                     5.18e-32
Kurtosis:                       3.917   Cond. No.                         627.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************DMC**********************************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.8103
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.489
Time:                        02:41:57   Log-Likelihood:                -905.25
No. Observations:                 517   AIC:                             1818.
Df Residuals:                     513   BIC:                             1835.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept         0.9465      0.232      4.085      0.000       0.491       1.402
DMC               0.2450      2.129      0.115      0.908      -3.937       4.427
I(DMC ** 2.0)     0.8333      5.446      0.153      0.878      -9.866      11.532
I(DMC ** 3.0)    -0.7630      3.824     -0.200      0.842      -8.275       6.749
==============================================================================
```

```
Omnibus:                       91.691   Durbin-Watson:                   0.925
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              138.224
Skew:                           1.195   Prob(JB):                     9.66e-31
Kurtosis:                       3.841   Cond. No.                         124.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************DC**********************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.007
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.126
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.338
Time:                        02:41:57   Log-Likelihood:                -904.77
No. Observations:                 517   AIC:                             1818.
Df Residuals:                     513   BIC:                             1835.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.7122      0.243      2.934      0.003       0.235       1.189
DC             3.1777      2.733      1.163      0.245      -2.191       8.546
I(DC ** 2.0)  -6.5128      6.376     -1.021      0.308     -19.039       6.014
I(DC ** 3.0)   3.9958      4.114      0.971      0.332      -4.087      12.078
==============================================================================
Omnibus:                       95.146   Durbin-Watson:                   0.920
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              146.063
Skew:                           1.215   Prob(JB):                     1.92e-32
Kurtosis:                       3.934   Cond. No.                         179.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************ISI**********************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.005
Method:                 Least Squares   F-statistic:                    0.2203
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.882
Time:                        02:41:57   Log-Likelihood:                -906.14
No. Observations:                 517   AIC:                             1820.
Df Residuals:                     513   BIC:                             1837.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.0489      0.294      3.566      0.000       0.471       1.627
ISI            0.7250      3.885      0.187      0.852      -6.907       8.357
I(ISI ** 2.0) -1.6549     13.803     -0.120      0.905     -28.772      25.462
I(ISI ** 3.0) -0.0920     10.576     -0.009      0.993     -20.870      20.686
==============================================================================
Omnibus:                       94.468   Durbin-Watson:                   0.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              144.490
Skew:                           1.211   Prob(JB):                     4.21e-32
Kurtosis:                       3.916   Cond. No.                         292.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************TEMP**********************************
```

OLS Regression Results

Dep. Variable:	area	R-squared:	0.024
Model:	OLS	Adj. R-squared:	0.019
Method:	Least Squares	F-statistic:	4.278
Date:	Sat, 03 Feb 2018	Prob (F-statistic):	0.00536
Time:	02:41:57	Log-Likelihood:	-900.08
No. Observations:	517	AIC:	1808.
Df Residuals:	513	BIC:	1825.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.2780	0.487	4.677	0.000	1.321	3.235
temp	-8.4590	3.455	-2.448	0.015	-15.248	-1.670
I(temp ** 2.0)	15.4644	7.428	2.082	0.038	0.871	30.058
I(temp ** 3.0)	-7.7685	4.814	-1.614	0.107	-17.227	1.690

Omnibus:	94.948	Durbin-Watson:	0.955
Prob(Omnibus):	0.000	Jarque-Bera (JB):	145.652
Skew:	1.213	Prob(JB):	2.36e-32
Kurtosis:	3.936	Cond. No.	188.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

**********RH**********

OLS Regression Results

Dep. Variable:	area	R-squared:	0.005
Model:	OLS	Adj. R-squared:	-0.001
Method:	Least Squares	F-statistic:	0.7968
Date:	Sat, 03 Feb 2018	Prob (F-statistic):	0.496
Time:	02:41:57	Log-Likelihood:	-905.27
No. Observations:	517	AIC:	1819.
Df Residuals:	513	BIC:	1836.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.3699	0.335	4.090	0.000	0.712	2.028
RH	-1.9878	2.812	-0.707	0.480	-7.512	3.536
I(RH ** 2.0)	4.9270	6.831	0.721	0.471	-8.493	18.347
I(RH ** 3.0)	-4.0014	4.846	-0.826	0.409	-13.523	5.520

Omnibus:	93.062	Durbin-Watson:	0.933
Prob(Omnibus):	0.000	Jarque-Bera (JB):	141.360
Skew:	1.201	Prob(JB):	2.01e-31
Kurtosis:	3.891	Cond. No.	154.

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

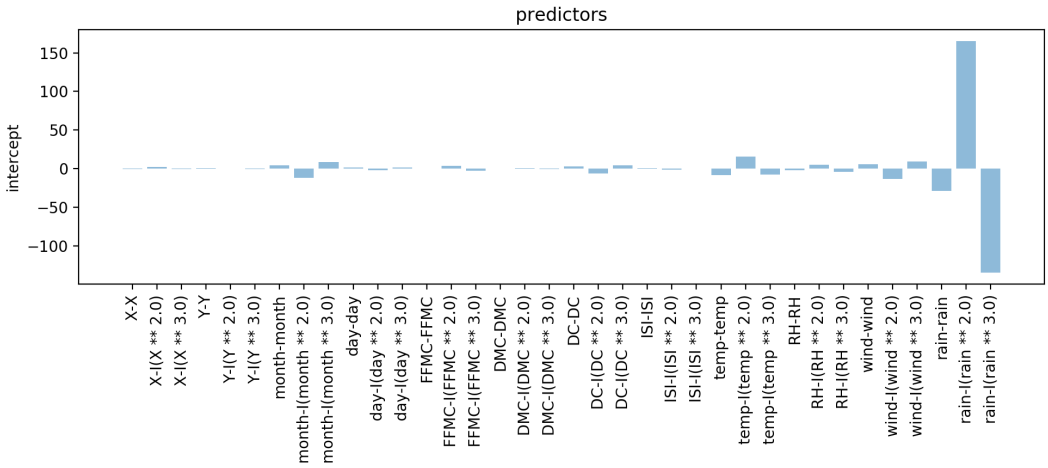
**********WIND**********

OLS Regression Results

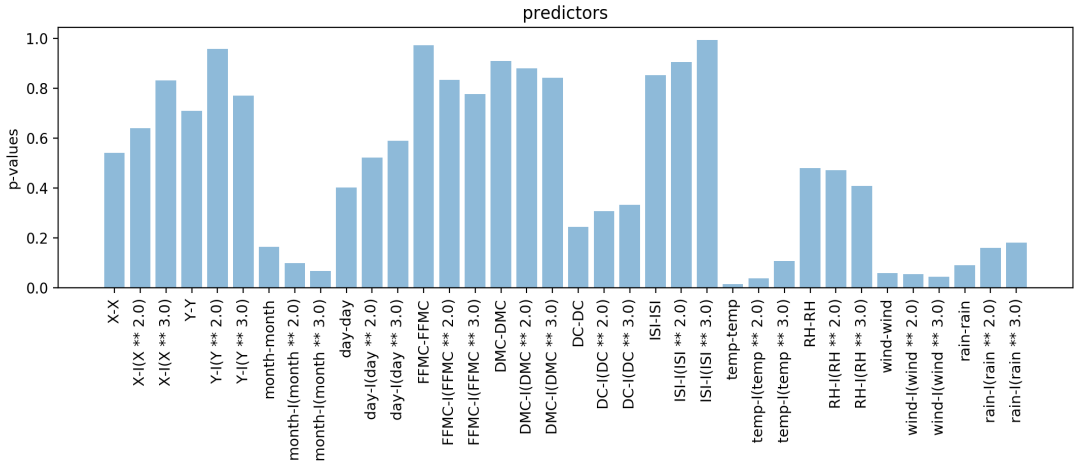
Dep. Variable:	area	R-squared:	0.012
Model:	OLS	Adj. R-squared:	0.007
Method:	Least Squares	F-statistic:	2.157
Date:	Sat, 03 Feb 2018	Prob (F-statistic):	0.0921
Time:	02:41:57	Log-Likelihood:	-903.23
No. Observations:	517	AIC:	1814.
Df Residuals:	513	BIC:	1831.

```
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.3865      0.386      1.001      0.317      -0.372       1.145
wind           5.7169      3.023      1.891      0.059      -0.222      11.656
I(wind ** 2.0)  -13.2356      6.908     -1.916      0.056     -26.807       0.336
I(wind ** 3.0)     9.2944      4.635      2.005      0.045       0.188      18.401
==============================================================================
Omnibus:                       96.599   Durbin-Watson:                   0.933
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              149.584
Skew:                           1.222   Prob(JB):                     3.30e-33
Kurtosis:                       3.986   Cond. No.                         159.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
**********************************RAIN*****************************************
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.009
Model:                            OLS   Adj. R-squared:                  0.003
Method:                 Least Squares   F-statistic:                     1.527
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.206
Time:                        02:41:57   Log-Likelihood:                -904.17
No. Observations:                 517   AIC:                             1816.
Df Residuals:                     513   BIC:                             1833.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      1.1205      0.062     18.116      0.000       0.999       1.242
rain         -29.0896     17.230     -1.688      0.092     -62.940       4.761
I(rain ** 2.0)   164.9341    117.278      1.406      0.160     -65.470     395.339
I(rain ** 3.0)  -134.4958    100.729     -1.335      0.182    -332.388      63.397
==============================================================================
Omnibus:                       95.367   Durbin-Watson:                   0.929
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              146.689
Skew:                           1.214   Prob(JB):                     1.40e-32
Kurtosis:                       3.955   Cond. No.                     2.53e+03
==============================================================================
```

Plots of coefficients of in polynomial regression:



Plot of p-values in polynomial regression:
The p-values of temperature, wind and rain have evidently improved in the model. Hence these can be used in the prediction process to better fit the data.



(g) Is there evidence of association of interactions of predictors with the response? To answer this question, run a full linear regression model with all pairwise interaction terms and state whether any interaction terms are statistically significant.

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn.feature_selection import RFE
from sklearn import preprocessing

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))
intercept1=[]
```

```
pvalues1 =[]
keys1=[]
intercept2=[]
pvalues2 =[]
keys2=[]
intercept3=[]
pvalues3 =[]
keys3=[]

le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])

normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]

model = ols("area ~
X+Y+month+day+FFMC+DMC+DC+ISI+temp+RH+wind+rain+X:Y+X:month+X:day+X:FF
MC+X:DMC+X:DC+X:ISI+X:temp+X:RH+X:wind+X:rain+Y:month+Y:day+Y:FFMC+Y:DM
C+Y:DC+Y:ISI+Y:temp+Y:RH+Y:wind+Y:rain+month:day+month:FFMC+month:DMC+mont
h:DC+month:ISI+month:temp+month:RH+month:wind+month:rain+day:FFMC+day:DMC+day
:DC+day:ISI+day:temp+day:RH+day:wind+day:rain+FFMC:DMC+FFMC:DC+FFMC:ISI+FF
MC:temp+FFMC:RH+FFMC:wind+FFMC:rain+DMC:DC+DMC:ISI+DMC:temp+DMC:RH+
DMC:wind+DMC:rain+DC:ISI+DC:temp+DC:RH+DC:wind+DC:rain+ISI:temp+ISI:RH+ISI:w
ind+ISI:rain+temp:RH+temp:wind+temp:rain+RH:wind+RH:rain+wind:rain",
normalized_df).fit()
print(model.summary())

for key in model.pvalues.keys()[1:40]:
    intercept1.append(model.params[key])
    pvalues1.append(model.pvalues[key])
    keys1.append(key)
for key in model.pvalues.keys()[40: ]:
    intercept2.append(model.params[key])
    pvalues2.append(model.pvalues[key])
    keys2.append(key)


##Graphs on p-values
y_pos = range(len(keys1))
a = plt.bar(y_pos, pvalues1,align='center', alpha=0.5)
plt.xticks(y_pos, keys1,size=8,rotation=90)
plt.ylabel('p-values')
```

```
plt.title('predictors')
plt.show()

##Graphs on p-values
y_pos = range(len(keys2))
a = plt.bar(y_pos, pvalues2, align='center', alpha=0.5)
plt.xticks(y_pos, keys2,rotation='vertical')
plt.ylabel('p-values')
plt.title('predictors')
plt.show()
```

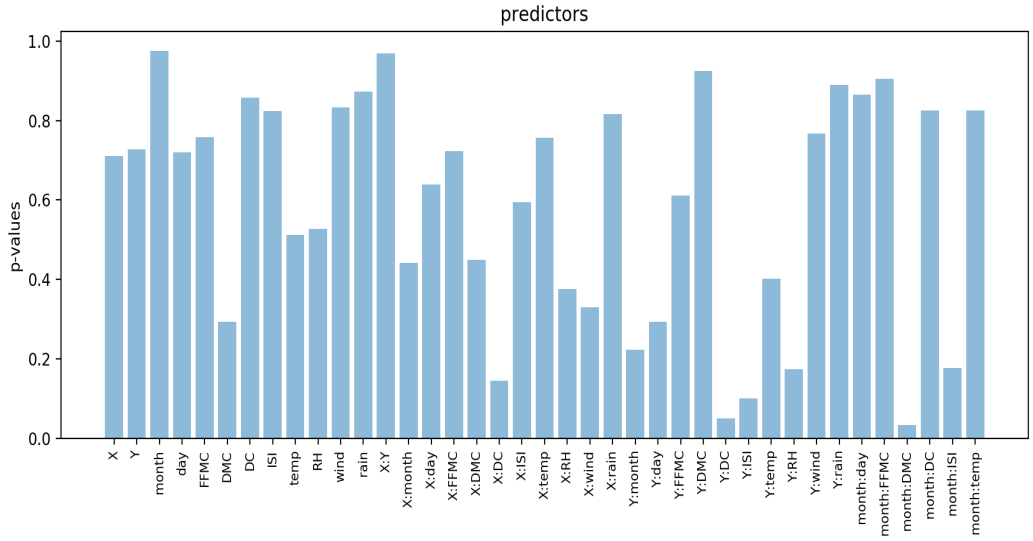
Output:

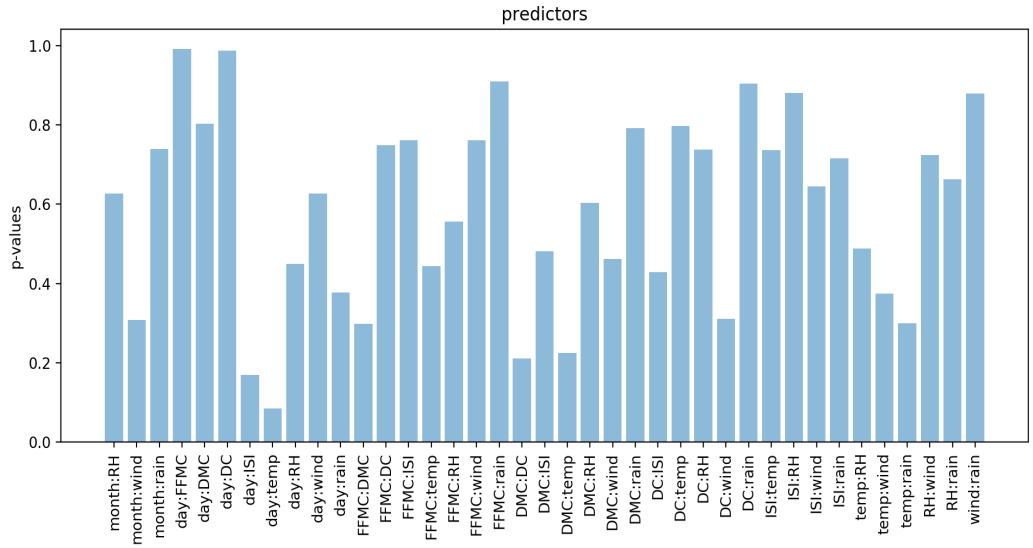
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   area   R-squared:                       0.149
Model:                            OLS   Adj. R-squared:                  0.007
Method:                 Least Squares   F-statistic:                     1.047
Date:                Sat, 03 Feb 2018   Prob (F-statistic):              0.382
Time:                        02:49:22   Log-Likelihood:                -864.73
No. Observations:                 517   AIC:                             1879.
Df Residuals:                     442   BIC:                             2198.
Df Model:                          74
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -4.0223     16.146     -0.249      0.803     -35.754      27.709
X             -2.9855      8.066     -0.370      0.711     -18.837      12.866
Y             -5.2388     15.051     -0.348      0.728     -34.820      24.342
month          0.1734      5.559      0.031      0.975     -10.752      11.098
day           -2.4088      6.710     -0.359      0.720     -15.596      10.778
FFMC           5.9496     19.270      0.309      0.758     -31.923      43.822
DMC          -18.3697     17.443     -1.053      0.293     -52.650      15.911
DC             1.5944      8.839      0.180      0.857     -15.776      18.965
ISI           -7.4387     33.377     -0.223      0.824     -73.036      58.158
temp          14.3643     21.867      0.657      0.512     -28.612      57.341
RH             7.7378     12.250      0.632      0.528     -16.337      31.812
wind          -1.5079      7.180     -0.210      0.834     -15.620      12.604
rain          -8.0701     50.308     -0.160      0.873    -106.943      90.803
X:Y           -0.0447      1.166     -0.038      0.969      -2.337       2.248
X:month        0.6638      0.861      0.771      0.441      -1.029       2.356
X:day          0.4210      0.897      0.470      0.639      -1.341       2.183
X:FFMC         3.1701      8.954      0.354      0.723     -14.428      20.768
X:DMC         -1.5075      1.992     -0.757      0.450      -5.422       2.407
X:DC          -2.3900      1.636     -1.461      0.145      -5.606       0.826
X:ISI          2.7787      5.211      0.533      0.594      -7.463      13.020
X:temp         0.7656      2.468      0.310      0.757      -4.086       5.617
X:RH           1.9443      2.193      0.886      0.376      -2.367       6.255
X:wind         1.5352      1.573      0.976      0.330      -1.556       4.626
X:rain        26.4613    113.998      0.232      0.817    -197.584     250.507
Y:month       -1.7599      1.445     -1.218      0.224      -4.599       1.079
Y:day          1.5345      1.461      1.051      0.294      -1.336       4.405
Y:FFMC         8.9531     17.641      0.508      0.612     -25.718      43.624
Y:DMC         -0.3463      3.649     -0.095      0.924      -7.518       6.825
Y:DC           5.1893      2.646      1.961      0.051      -0.011      10.390
Y:ISI        -15.0691      9.165     -1.644      0.101     -33.082       2.944
Y:temp        -3.6514      4.357     -0.838      0.402     -12.215       4.912
```

Y:RH	-5.3939	3.959	-1.362	0.174	-13.175	2.387
Y:wind	0.8061	2.715	0.297	0.767	-4.529	6.141
Y:rain	-27.0072	193.547	-0.140	0.889	-407.394	353.380
month:day	0.1146	0.672	0.171	0.865	-1.205	1.434
month:FFMC	0.7367	6.165	0.119	0.905	-11.380	12.853
month:DMC	3.1904	1.493	2.137	0.033	0.256	6.125
month:DC	-0.3388	1.529	-0.222	0.825	-3.344	2.666
month:ISI	-5.5707	4.121	-1.352	0.177	-13.671	2.529
month:temp	0.4299	1.942	0.221	0.825	-3.387	4.247
month:RH	-0.8157	1.678	-0.486	0.627	-4.114	2.483
month:wind	-1.1163	1.093	-1.021	0.308	-3.264	1.032
month:rain	74.4953	223.512	0.333	0.739	-364.783	513.773
day:FFMC	0.0850	7.517	0.011	0.991	-14.689	14.859
day:DMC	0.4003	1.599	0.250	0.802	-2.741	3.542
day:DC	-0.0204	1.269	-0.016	0.987	-2.514	2.473
day:ISI	-6.3243	4.594	-1.377	0.169	-15.354	2.705
day:temp	3.5995	2.083	1.728	0.085	-0.494	7.693
day:RH	1.3418	1.774	0.756	0.450	-2.144	4.828
day:wind	0.6003	1.234	0.486	0.627	-1.826	3.026
day:rain	-28.3175	32.008	-0.885	0.377	-91.224	34.589
FFMC:DMC	19.2444	18.485	1.041	0.298	-17.085	55.573
FFMC:DC	-2.9225	9.117	-0.321	0.749	-20.841	14.996
FFMC:ISI	10.8079	35.538	0.304	0.761	-59.037	80.653
FFMC:temp	-19.5141	25.491	-0.766	0.444	-69.613	30.585
FFMC:RH	-8.4149	14.273	-0.590	0.556	-36.466	19.636
FFMC:wind	2.4433	8.027	0.304	0.761	-13.332	18.219
FFMC:rain	-7.4241	64.750	-0.115	0.909	-134.681	119.833
DMC:DC	-2.9297	2.340	-1.252	0.211	-7.529	1.669
DMC:ISI	-7.6520	10.863	-0.704	0.482	-29.001	13.697
DMC:temp	6.6374	5.460	1.216	0.225	-4.094	17.369
DMC:RH	2.3283	4.484	0.519	0.604	-6.484	11.140
DMC:wind	-2.1906	2.975	-0.736	0.462	-8.037	3.656
DMC:rain	46.9047	177.134	0.265	0.791	-301.226	395.035
DC:ISI	4.2557	5.369	0.793	0.428	-6.297	14.808
DC:temp	0.8772	3.414	0.257	0.797	-5.833	7.587
DC:RH	-0.9058	2.697	-0.336	0.737	-6.205	4.394
DC:wind	2.0537	2.022	1.016	0.310	-1.920	6.027
DC:rain	-5.3174	43.789	-0.121	0.903	-91.377	80.742
ISI:temp	4.7383	14.031	0.338	0.736	-22.838	32.315
ISI:RH	1.5195	10.088	0.151	0.880	-18.307	21.346
ISI:wind	3.2351	7.022	0.461	0.645	-10.566	17.037
ISI:rain	-78.3362	214.507	-0.365	0.715	-499.916	343.244
temp:RH	1.7306	2.491	0.695	0.488	-3.165	6.626
temp:wind	-2.8258	3.182	-0.888	0.375	-9.080	3.429
temp:rain	82.0916	79.073	1.038	0.300	-73.314	237.497
RH:wind	-0.8790	2.483	-0.354	0.724	-5.760	4.002
RH:rain	-71.8417	164.595	-0.436	0.663	-395.328	251.644
wind:rain	-13.3816	87.837	-0.152	0.879	-186.013	159.249

Omnibus:	85.137	Durbin-Watson:	1.119
Prob(Omnibus):	0.000	Jarque-Bera (JB):	127.659
Skew:	1.086	Prob(JB):	1.90e-28
Kurtosis:	4.098	Cond. No.	1.10e+16

Plots:





In the plots we can see that few interaction terms seem to have good correlation with data. These terms can be considered for stepwise selection to output a good model that has statistical significance.

We can improve our model by considering the significant interaction terms, non-linear terms and linear terms to create a model that would come up with the least error rate.

Significant interaction terms: day:ISI , day:temp, x:DC,Y:DC,Y:ISI,month:DMC.

The Rsquared value has also improved drastically from 0.028 for multiple linear regression to 0.149 which visibly explains the error much better than linear regression. Hence interaction terms will be vital in our model building.

(h) Can you improve your model using possible interaction terms or nonlinear associations and between the predictors and response? Train the model on a randomly selected 70% subset of the data and test it on the remaining points and report your train and test results

Note:
In the following code I perform a stepwise selection of features by running a full linear regression on all possible terms and removing the term with the highest p-value.

The process stops when the R-squared value stops improving to give the most relevant subset of features.

After getting hold of the best subset of features a linear regression is performed to predict the area of the 30% data separated from the dataset for testing.

Finally the mean-squared error is calculated.

Code:

```
import pandas as pd
import math
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
import itertools
from sklearn.metrics import mean_squared_error
import numpy as np
from sklearn import preprocessing

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))
formulaList =
["X","Y","month","day","FFMC","DMC","DC","ISI","temp","RH","wind","rain","X:Y","X:FFMC","X
:DMC","X:DC","X:ISI","X:temp","X:RH","X:wind","X:rain","Y:FFMC","Y:DMC","Y:DC","Y:ISI","Y:te
mp","Y:RH","Y:wind","Y:rain","FFMC:DMC","FFMC:DC","FFMC:ISI","FFMC:temp","FFMC:RH","F
FMC:wind","FFMC:rain","DMC:DC","DMC:ISI","DMC:temp","DMC:RH","DMC:wind","DMC:rain",
"DC:ISI","DC:temp","DC:RH","DC:wind","DC:rain","ISI:temp","ISI:RH","ISI:wind","ISI:rain","temp
:RH","temp:wind","temp:rain","RH:wind","RH:rain","wind:rain","month:day","month:FFMC","
month:DMC","month:DC","month:ISI","month:temp","month:wind","month:rain","month:RH",
"day:FFMC","day:DMC","day:DC","day:ISI","day:temp","day:RH","day:wind","day:rain"]
```

```
le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])

normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]

for column in list(normalized_df.columns[:-1]):
      formulaList.append("I("+column+" ** 2.0)")
      formulaList.append("I("+column+" ** 3.0)")
#print(formulaList)
bestFormula = None
bestRsquared = 100
train, test = train_test_split(normalized_df, test_size=0.3)
while (len(formulaList)>2
"0):
   formula_now = ""
   for formula in formulaList:
      formula_now+="+"+formula
   model = ols("area ~"+formula_now, train).fit()
   op  = model.predict(test)
   test["predictedArea"] = op
   rms = np.sqrt(mean_squared_error(test["area"], test["predictedArea"]))
   pvalues = pd.DataFrame()
   pvalues = model.pvalues[1:].sort_values(ascending=False)
#    print(model.pvalues[1:].sort_values(ascending=False))
#    print(pvalues.keys()[0])
   formulaList.remove(pvalues.keys()[0])
   if(bestRsquared > rms):
      bestFormula = formula_now
      bestRsquared = rms
print(bestFormula)
print(bestRsquared)

model = ols("area ~"+bestFormula, train).fit()
print(model.summary())
op  = model.predict(test)
#print(op)
test["predictedArea"] = op
print(test)
```

```
rms = np.sqrt(mean_squared_error(test["area"], test["predictedArea"]))
print(rms)
```

Output:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    area   R-squared:                       0.158
Model:                            OLS   Adj. R-squared:                  0.106
Method:                 Least Squares   F-statistic:                     3.032
Date:                Sat, 03 Feb 2018   Prob (F-statistic):           1.30e-05
Time:                        02:56:44   Log-Likelihood:                -609.56
No. Observations:                 361   AIC:                             1263.
Df Residuals:                     339   BIC:                             1349.
Df Model:                          21
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
Intercept        -6.5507      4.164     -1.573      0.117     -14.742       1.640
DC               -1.2344      0.595     -2.074      0.039      -2.405      -0.064
ISI             -75.8325     39.497     -1.920      0.056    -153.523       1.858
RH                5.8985      4.483      1.316      0.189      -2.920      14.717
X:DMC            -2.3666      0.889     -2.663      0.008      -4.115      -0.618
X:wind            1.8648      0.717      2.599      0.010       0.454       3.276
FFMC:ISI         80.0580     40.412      1.981      0.048       0.569     159.547
FFMC:temp       -11.9665      3.600     -3.324      0.001     -19.048      -4.885
FFMC:RH         -11.3437      5.615     -2.020      0.044     -22.388      -0.300
DMC:temp          4.0467      1.213      3.336      0.001       1.661       6.433
ISI:RH            7.5050      6.242      1.202      0.230      -4.772      19.782
temp:RH           7.4038      2.805      2.639      0.009       1.886      12.922
month:DC          2.3244      0.639      3.635      0.000       1.067       3.582
month:ISI        -6.7099      2.827     -2.373      0.018     -12.271      -1.149
day:DC            0.5750      0.348      1.651      0.100      -0.110       1.260
day:rain        -26.6163     12.360     -2.153      0.032     -50.929      -2.304
I(X ** 3.0)       1.1408      0.541      2.109      0.036       0.077       2.205
I(Y ** 3.0)      -0.9207      0.654     -1.407      0.160      -2.208       0.367
I(FFMC ** 2.0)   34.5538     17.887      1.932      0.054      -0.630      69.738
I(FFMC ** 3.0)  -23.7935     14.143     -1.682      0.093     -51.614       4.026
I(temp ** 2.0)    7.1288      2.604      2.738      0.007       2.008      12.250
I(rain ** 2.0)   21.4845     10.275      2.091      0.037       1.274      41.695
==============================================================================
Omnibus:                       68.610   Durbin-Watson:                   1.624
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              109.291
Skew:                           1.143   Prob(JB):                     1.85e-24
Kurtosis:                       4.429   Cond. No.                     1.64e+03
==============================================================================
```

	area	predictedArea
487	2.856470	0.971857
180	1.845300	1.123156
53	0.000000	0.959808
406	1.599388	1.162061
156	0.959350	1.581326
151	0.858662	0.637886
204	2.707383	0.314267
40	0.000000	0.843878
214	3.389799	0.545852
77	0.000000	0.664550
248	0.000000	1.266927
131	0.000000	0.140286

```
306  0.343590       1.351954
237  5.365415       0.704589
348  0.000000       0.921876
89   0.000000       0.756112
55   0.000000       1.051854
165  1.144223       1.332324
277  2.462150       2.794532
59   0.000000       0.538765
444  2.394252       2.103993
377  5.168380       1.035754
106  0.000000       0.035043
58   0.000000       0.497600
353  1.000632       1.059121
107  0.000000       1.137977
143  0.536493       0.529147
161  1.064711       1.266747
11   0.000000       0.598062
221  3.607669       0.961693
..        ...            ...
264  2.020222       1.018894
299  0.000000      -0.418371
447  0.000000       1.407879
441  0.802002       1.307570
63   0.000000       0.571280
169  1.266948       1.235724
108  0.000000       1.149699
105  0.000000       0.671062
216  3.417071       0.673884
80   0.000000       0.911406
342  0.000000       0.754115
230  4.494127       1.272081
271  2.329227       1.144417
47   0.000000       0.691336
403  0.000000       1.480709
197  2.489894       1.083204
300  0.000000       0.878359
440  0.000000       1.046168
269  1.686399       0.797218
65   0.000000       0.638433
357  0.000000       0.880573
135  0.000000       0.685792
485  1.121678       0.985141
303  0.000000       0.391080
66   0.000000       0.839689
258  0.000000       0.873838
111  0.000000       0.020661
316  0.000000       1.584256
469  4.129229       2.278745
378  0.000000       1.611279

[156 rows x 14 columns]

Mean – Squared error : 1.3252481839
```

The mean squared error achieved in this regression task is 1.325.

(i) KNN Regression: Note that for this problem, we have a mixture of categorical and quantitative predictors. There is not a unique way to define a distance metric in such a situation. Describe your findings and heuristics. Can your metric be specific to this problem? Use a reasonable distance metric to answer the following questions:

Categorical data cannot be classified using Euclidean distance. We have an approach called hamming distance used in classification algorithms to calculate distances between categorical data.

Our categorical data here have an implied ordering which can be positively used to predict area depending on which month or day they fall in. Similarly, co-ordinates also have an implied order and the order can be used positively in a KNN problem.

Another important factor to be considered is normalization of variables. Since we go about calculating feature distances between various training samples it is important that all features are normalized by their range hence, no variable dominates the other variables because of its range.

i. **Use the first 4 predictors to perform k-nearest neighbor regression for this dataset. Find the value of k that gives you the best fit. Plot the train and test errors in terms of 1/k.**

Code:

```
import pandas as pd
import math
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
import itertools
from sklearn.metrics import mean_squared_error
import numpy as np
from sklearn.neighbors import KNeighborsRegressor

def hammingDistance(a,b):
    return abs(np.sum(a-b))

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))

le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])


normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]
```

```
print(normalized_df)

train, test = train_test_split(ff_df, test_size=0.1)

scores_training = []
scores_test = []
neighbours = []
for k in range (1,100,2):
    neighbours.append(1/k)
    print(k)
    neigh = KNeighborsRegressor(n_neighbors=k,metric=hammingDistance)
    neigh.fit(train.iloc[:,:4], train["area"])
    result = neigh.predict(train.iloc[:,:4])
    train["predictedArea"] = result
    rms = np.sqrt(mean_squared_error(train["area"], train["predictedArea"]))
    scores_training.append(rms)
    print(rms)
    result = neigh.predict(test.iloc[:,:4])
    test["predictedArea"] = result
    rms = np.sqrt(mean_squared_error(test["area"], test["predictedArea"]))
    scores_test.append(rms)
    print(rms)

plt.plot(neighbours,scores_training,label="training mean squared error")
plt.plot(neighbours,scores_test,label="test mean squared error")
plt.xlabel('i/k')
plt.ylabel('mean squared error')
plt.show()
```

Output:

On analyzing the test and training errors, k* is can be concluded to be around 83.

ii. Use the last 4 predictors to perform k-nearest neighbor regression for this dataset. Find the value of k that gives you the best fit. Plot the train and test errors in terms of 1/k.

Code:

```
import pandas as pd
import math
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
import itertools
from sklearn.metrics import mean_squared_error
import numpy as np
from sklearn.neighbors import KNeighborsRegressor


ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))

le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])


normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]
print(normalized_df)

train, test = train_test_split(normalized_df, test_size=0.1)

scores_training = []
scores_test = []
neighbours = []
```

```
for k in range (1,100,2):
    neigh = KNeighborsRegressor(n_neighbors=k)
    neighbours.append(1/k)
    print(k)
    neigh.fit(train.iloc[:,8:12], train["area"])
    result = neigh.predict(train.iloc[:,8:12])
    train["predictedArea"] = result
    rms = np.sqrt(mean_squared_error(train["area"], train["predictedArea"]))
    scores_training.append(rms)
    print(rms)
    result = neigh.predict(test.iloc[:,8:12])
    test["predictedArea"] = result
    rms = np.sqrt(mean_squared_error(test["area"], test["predictedArea"]))
    scores_test.append(rms)
    print(rms)
plt.plot(neighbours,scores_training,label="training mean squared error")
plt.plot(neighbours,scores_test,label="test mean squared error")
plt.xlabel('i/k')
plt.ylabel('mean squared error')
plt.show()
```

Output:

From the observed values of test and training error the k* is around 45 for the last 4 predictors also.

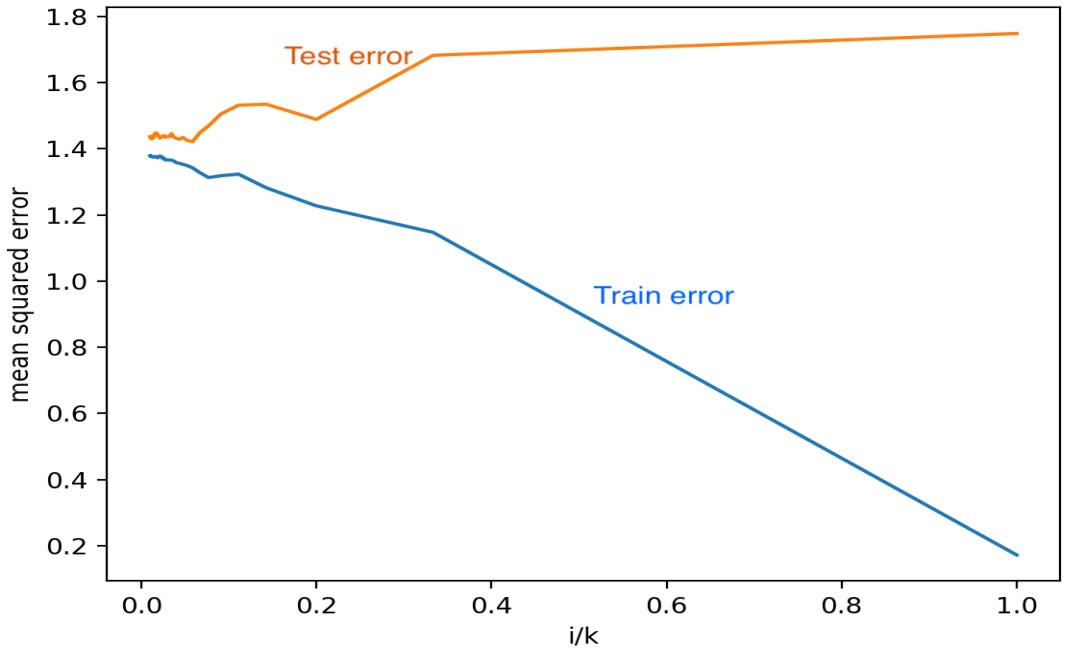
iii. Use predictors 1,2, 9, 10, 11 to perform k-nearest neighbor regression for this dataset. Find the value of k that gives you the best fit. Plot the train and test errors in terms of 1/k.

Code:

```
import pandas as pd
import math
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
import itertools
from sklearn.metrics import mean_squared_error
import numpy as np
from sklearn.neighbors import KNeighborsRegressor

def hammingDistance(a,b):
   return abs(np.sum(a-b))

ff_df = pd.read_csv("forestfires.csv")
ff_df['area']=ff_df['area'].apply(lambda x:math.log1p(x))

le = preprocessing.LabelEncoder()
le.fit(ff_df["month"])
ff_df["month"]=le.transform(ff_df["month"])
le.fit(ff_df["day"])
ff_df["day"]=le.transform(ff_df["day"])


normalized_df=(ff_df.iloc[:,:12]-ff_df.iloc[:,:12].min())/(ff_df.iloc[:,:12].max()-
ff_df.iloc[:,:12].min())
normalized_df["area"] = ff_df["area"]
#print(normalized_df)
final_df = pd.DataFrame()

final_df=pd.concat([normalized_df.iloc[:,0:2], normalized_df.iloc[:,8:11]], axis=1)
final_df["area"]=ff_df["area"]
print(final_df)
train, test = train_test_split(final_df, test_size=0.1)

scores_training = []
scores_test = []
neighbours = []
```

```
for k in range (1,100,2):
    neighbours.append(1/k)
    print(k)
    neigh = KNeighborsRegressor(n_neighbors=k)
    neigh.fit(train.iloc[:,0:5], train["area"])
    result = neigadsf.predict(train.iloc[:,0:5])
    train["predictedArea"] = result
    rms = np.sqrt(mean_squared_error(train["area"], train["predictedArea"]))
    scores_training.append(rms)
    print(rms)
    result = neigh.predict(test.iloc[:,0:5])
    test["predictedArea"] = result
    rms = np.sqrt(mean_squared_error(test["area"], test["predictedArea"]))
    print(rms)
    scores_test.append(rms)
plt.plot(neighbours,scores_training,label="training mean squared error")
plt.plot(neighbours,scores_test,label="test mean squared error")
plt.xlabel('i/k')
plt.ylabel('mean squared error')
plt.show()
```

Output:



k* = 47 (from the test error results)

(j) Compare the results of KNN Regression with linear regression and provide your analysis.

The mean squared error in Linear regression: 1.3252481839

The mean squared error in knn regression:

First 4 predictors: 1.66
Last 4 predictors: 1.52
Predictors 1,2,9, and 10: 1.433

Hence comparative analysis shows better performance of linear regression with stepwise selection performing better over knn regression of selected predictors.