Lab 4. Classification and Regression

Intro to Machine Learning
Fall 2018, Innopolis University

Lecture recap

- What is cross-validation?
- Why is cross-validation important?
- What are its different variants?
- What is regularization?
- Why is it important?
- What are its different variants?
- Non-parametric classifier (KNN)
- Practice (Cross-validation + Regularization + Regression)

Questions about the lecture

Was the material already familiar to you?

What new things have you learned?

What was hard to understand?

Regularization

What is Regularization in Machine Learning?

Regularization

What does Regularization achieve?

Let's See Empirically Why Penalize the Magnitude?

Lets empirically see the impact of model complexity on the magnitude of coefficients. As an example, let's simulate a data and added some random noise using the following code to fit the regression model:

In [14]:
```
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 12, 10
```

In [15]:
```
#Define input array with angles from 60deg to 300deg converted to radians
x = np.array([i*np.pi/180 for i in range(60,300,4)])
np.random.seed(10)  #Setting seed for reproducability
y = np.sin(x) + np.random.normal(0,0.15,len(x))
data = pd.DataFrame(np.column_stack([x,y]),columns=['x','y'])
plt.plot(data['x'],data['y'],'.')
```

Let’s See Empirically Why Penalize the Magnitude?

Lets try to estimate the sine function using regression with powers of x from 1 to 15. Let's add a column for each power upto 15 in our dataframe. This can be accomplished using the following code:

In [27]:
```
for i in range(2,16):  #power of 1 is already there
    colname = 'x_%d'%i      #new var will be x_power
    data[colname] = data['x']**i
#print data.head()
data[:20]
```

Out[27]:

	x	y	x_2	x_3	x_4	x_5	x_6
0	1.047198	1.065763	1.096623	1.148381	1.202581	1.259340	1.318778
1	1.117011	1.006086	1.247713	1.393709	1.556788	1.738948	1.942424
2	1.186824	0.695374	1.408551	1.671702	1.984016	2.354677	2.794587
3	1.256637	0.949799	1.579137	1.984402	2.493673	3.133642	3.937850
4	1.326450	1.063496	1.759470	2.333850	3.095735	4.106339	5.446854
5	1.396263	0.876795	1.949551	2.722087	3.800751	5.306850	7.409760

Let's See Empirically Why Penalize the Magnitude?

First, let's define a generic function which takes in the required maximum power of x as an input and returns a list containing – *[model RSS, intercept, coef_x, coef_x2, … upto entered power]*.

In [28]:

```
#Import Linear Regression model from scikit-learn.
from sklearn.linear_model import LinearRegression
def linear_regression(data, power, models_to_plot):
    #initialize predictors:
    predictors=['x']
    if power>=2:
        predictors.extend(['x_%d'%i for i in range(2,power+1)])

    #Fit the model
    linreg = LinearRegression(normalize=True)
    linreg.fit(data[predictors],data['y'])
    y_pred = linreg.predict(data[predictors])

    #Check if a plot is to be made for the entered power
    if power in models_to_plot:
        plt.subplot(models_to_plot[power])
        plt.tight_layout()
        plt.plot(data['x'],y_pred)
        plt.plot(data['x'],data['y'],'.')
        plt.title('Plot for power: %d'%power)

    #Return the result in pre-defined format
    rss = sum((y_pred-data['y'])**2)
    ret = [rss]
    ret.extend([linreg.intercept_])
    ret.extend(linreg.coef_)
    return ret
```

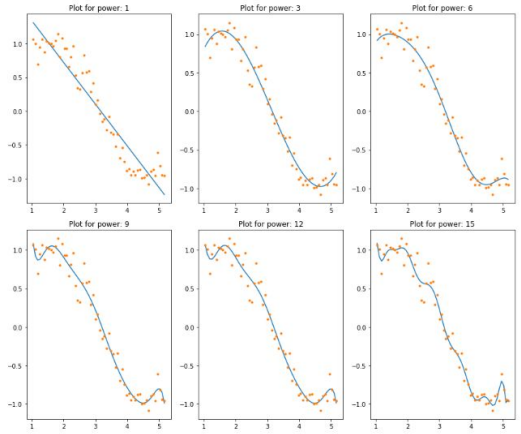
Let’s See Empirically Why Penalize the Magnitude?

In [29]:
```
#Initialize a dataframe to store the results:
col = ['rss','intercept'] + ['coef_x_%d'%i for i in range(1,16)]
ind = ['model_pow_%d'%i for i in range(1,16)]
coef_matrix_simple = pd.DataFrame(index=ind, columns=col)

#Define the powers for which a plot is required:
models_to_plot = {1:231,3:232,6:233,9:234,12:235,15:236}

#Iterate through all powers and assimilate results
for i in range(1,16):
    coef_matrix_simple.iloc[i-1,0:i+2] = linear_regression(data, power=i, models_to_plot=models_to_plot)
```

Now, we can make all 15 models and compare the results.



Let’s See Empirically Why Penalize the Magnitude?

This clearly aligns with our initial understanding. As the model complexity increases, the models tends to fit even smaller deviations in the training data set. Though this leads to overfitting, lets keep this issue aside for some time and come to our main objective, i.e. the impact on the magnitude of coefficients. This can be analysed by looking at the data frame.

```
In [30]: pd.options.display.float_format = '{:,.2g}'.format
         coef_matrix_simple
```

Out[30]:

	rss	intercept	coef_x_1	coef_x_2	coef_x_3	coef_x_4	coef_x_5	coef_x_6	coef_x_7	coef_x_8	coef_x_9	coef_x_10	coef_x_11	coef_x_12
model_pow_1	3.3	2	-0.62	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
model_pow_2	3.3	1.9	-0.58	-0.006	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
model_pow_3	1.1	-1.1	3	-1.3	0.14	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
model_pow_4	1.1	-0.27	1.7	-0.53	-0.036	0.014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
model_pow_5	1	3	-5.1	4.7	-1.9	0.33	-0.021	NaN	NaN	NaN	NaN	NaN	NaN	NaN
model_pow_6	0.99	-2.8	9.5	-9.7	5.2	-1.6	0.23	-0.014	NaN	NaN	NaN	NaN	NaN	NaN
model_pow_7	0.93	19	-56	69	-45	17	-3.5	0.4	-0.019	NaN	NaN	NaN	NaN	NaN
model_pow_8	0.92	43	-1.4e+02	1.8e+02	-1.3e+02	58	-15	2.4	-0.21	0.0077	NaN	NaN	NaN	NaN
model_pow_9	0.87	1.7e+02	-6.1e+02	9.6e+02	-8.5e+02	4.6e+02	-1.6e+02	37	-5.2	0.42	-0.015	NaN	NaN	NaN
model_pow_10	0.87	1.4e+02	-4.9e+02	7.3e+02	-6e+02	2.9e+02	-87	15	-0.81	-0.14	0.026	-0.0013	NaN	NaN
model_pow_11	0.87	-75	5.1e+02	-1.3e+03	1.9e+03	-1.6e+03	9.1e+02	-3.5e+02	91	-16	1.8	-0.12	0.0034	NaN
model_pow_12	0.87	-3.4e+02	1.9e+03	-4.4e+03	6e+03	-5.2e+03	3.1e+03	-1.3e+03	3.8e+02	-80	12	-1.1	0.062	-0.0016

Let's See Empirically Why Penalize the Magnitude?

It is clear evident that the **size of coefficients increase exponentially with increase in model complexity**. I hope this gives some intuition into why putting a constraint on the magnitude of coefficients can be a good idea to reduce model complexity.

	rss	intercept	coef_x_1	coef_x_2	coef_x_3	coef_x_4	coef_x_5	coef_x_6	coef_x_7	coef_x_8	coef_x_9	coef_x_10	coef_x_11	c
model_pow_1	3.3	2	-0.62	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
model_pow_2	3.3	1.9	-0.58	-0.006	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
model_pow_3	1.1	-1.1	3	-1.3	0.14	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
model_pow_4	1.1	-0.27	1.7	-0.53	-0.036	0.014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
model_pow_5	1	3	-5.1	4.7	-1.9	0.33	-0.021	NaN	NaN	NaN	NaN	NaN	NaN	N
model_pow_6	0.99	-2.8	9.5	-9.7	5.2	-1.6	0.23	-0.014	NaN	NaN	NaN	NaN	NaN	N
model_pow_7	0.93	19	-56	69	-45	17	-3.5	0.4	-0.019	NaN	NaN	NaN	NaN	N
model_pow_8	0.92	43	-1.4e+02	1.8e+02	-1.3e+02	58	-15	2.4	-0.21	0.0077	NaN	NaN	NaN	N
model_pow_9	0.87	1.7e+02	-6.1e+02	9.6e+02	-8.5e+02	4.6e+02	-1.6e+02	37	-5.2	0.42	-0.015	NaN	NaN	N
model_pow_10	0.87	1.4e+02	-4.9e+02	7.3e+02	-6e+02	2.9e+02	-87	15	-0.81	-0.14	0.026	-0.0013	NaN	N
model_pow_11	0.87	-75	5.1e+02	-1.3e+03	1.9e+03	-1.6e+03	9.1e+02	-3.5e+02	91	-16	1.8	-0.12	0.0034	N
model_pow_12	0.87	-3.4e+02	1.9e+03	-4.4e+03	6e+03	-5.2e+03	3.1e+03	-1.3e+03	3.8e+02	-80	12	-1.1	0.062	-(
model_pow_13	0.86	3.2e+03	-1.8e+04	4.5e+04	-6.7e+04	6.6e+04	-4.6e+04	2.3e+04	-8.5e+03	2.3e+03	-4.5e+02	62	-5.7	0
model_pow_14	0.79	2.4e+04	-1.4e+05	3.8e+05	-6.1e+05	6.6e+05	-5e+05	2.8e+05	-1.2e+05	3.7e+04	-8.5e+03	1.5e+03	-1.8e+02	1
model_pow_15	0.7	-3.6e+04	2.4e+05	-7.5e+05	1.4e+06	-1.7e+06	1.5e+06	-1e+06	5e+05	-1.9e+05	5.4e+04	-1.2e+04	1.9e+03	-:

Ridge Regression

This code takes ‘alpha’ as a parameter on initialization. Also, keep in mind that normalizing the inputs is generally a good idea in every type of regression and should be used in case of ridge regression as well.

In [31]:

```
##### Ridge Regression
from sklearn.linear_model import Ridge
def ridge_regression(data, predictors, alpha, models_to_plot={}):
    #Fit the model
    ridgereg = Ridge(alpha=alpha,normalize=True)
    ridgereg.fit(data[predictors],data['y'])
    y_pred = ridgereg.predict(data[predictors])

    #Check if a plot is to be made for the entered alpha
    if alpha in models_to_plot:
        plt.subplot(models_to_plot[alpha])
        plt.tight_layout()
        plt.plot(data['x'],y_pred)
        plt.plot(data['x'],data['y'],'.')
        plt.title('Plot for alpha: %.3g'%alpha)

    #Return the result in pre-defined format
    rss = sum((y_pred-data['y'])**2)
    ret = [rss]
    ret.extend([ridgereg.intercept_])
    ret.extend(ridgereg.coef_)
    return ret
```

Ridge Regression

Let's analyze the result of Ridge regression for 10 different values of α ranging from 1e-15 to 20. These values have been chosen so that we can easily analyze the trend with change in values of α. These would however differ from case to case.

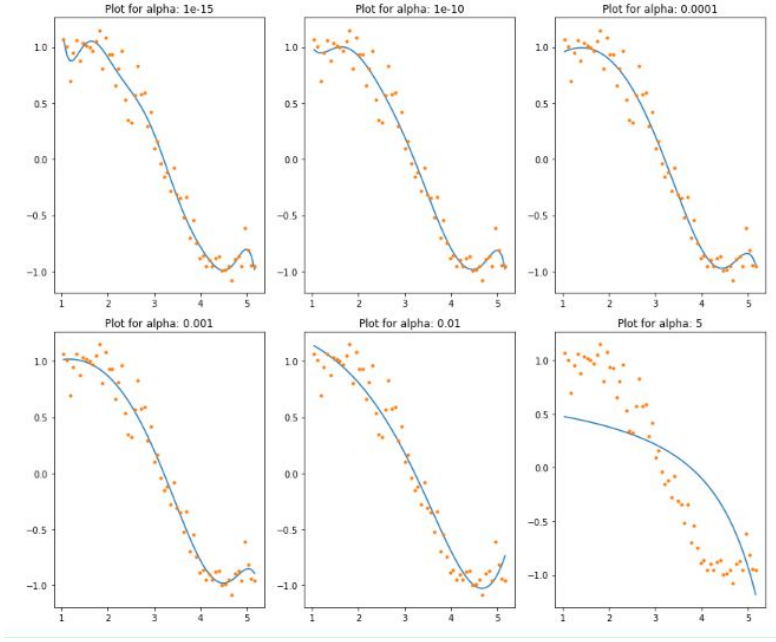
Note that each of these 10 models will contain all the 15 variables and only the value of alpha would differ. This is different from the simple linear regression case where each model had a subset of features.

In [32]:
```
#Initialize predictors to be set of 15 powers of x
predictors=['x']
predictors.extend(['x_%d'%i for i in range(2,16)])

#Set the different values of alpha to be tested
alpha_ridge = [1e-15, 1e-10, 1e-8, 1e-4, 1e-3,1e-2, 1, 5, 10, 20]

#Initialize the dataframe for storing coefficients.
col = ['rss','intercept'] + ['coef_x_%d'%i for i in range(1,16)]
ind = ['alpha_%.2g'%alpha_ridge[i] for i in range(0,10)]
coef_matrix_ridge = pd.DataFrame(index=ind, columns=col)

models_to_plot = {1e-15:231, 1e-10:232, 1e-4:233, 1e-3:234, 1e-2:235, 5:236}
for i in range(10):
    coef_matrix_ridge.iloc[i,] = ridge_regression(data, predictors, alpha_ridge[i], models_to_plot)
```



Ridge Regression

Here we can clearly observe that **as the value of alpha increases, the model complexity reduces**. Though higher values of alpha reduce overfitting, significantly high values can cause underfitting as well (eg. alpha = 5). Thus alpha should be chosen wisely. **A widely accept technique is cross-validation, i.e. the value of alpha is iterated over a range of values and the one giving higher cross-validation score is chosen.**

```
In [33]: #Set the display format to be scientific for ease of analysis
         pd.options.display.float_format = '{:,.2g}'.format
         coef_matrix_ridge
```

	rss	intercept	coef_x_1	coef_x_2	coef_x_3	coef_x_4	coef_x_5	coef_x_6	coef_x_7	coef_x_8	coef_x_9	coef_x_10	coef_x_11	coe
alpha_1e-15	0.87	95	-3e+02	3.8e+02	-2.4e+02	66	0.96	-4.8	0.64	0.15	-0.026	-0.0054	0.00086	0.0
alpha_1e-10	0.92	11	-29	31	-15	2.9	0.17	-0.091	-0.011	0.002	0.00064	2.4e-05	-2e-05	-4.2
alpha_1e-08	0.95	1.3	-1.5	1.7	-0.68	0.039	0.016	0.00016	-0.00036	-5.4e-05	-2.9e-07	1.1e-06	1.9e-07	2e-
alpha_0.0001	0.96	0.56	0.55	-0.13	-0.026	-0.0028	-0.00011	4.1e-05	1.5e-05	3.7e-06	7.4e-07	1.3e-07	1.9e-08	1.9
alpha_0.001	1	0.82	0.31	-0.087	-0.02	-0.0028	-0.00022	1.8e-05	1.2e-05	3.4e-06	7.3e-07	1.3e-07	1.9e-08	1.7
alpha_0.01	1.4	1.3	-0.088	-0.052	-0.01	-0.0014	-0.00013	7.2e-07	4.1e-06	1.3e-06	3e-07	5.6e-08	9e-09	1.1
alpha_1	5.6	0.97	-0.14	-0.019	-0.003	-0.00047	-7e-05	-9.9e-06	-1.3e-06	-1.4e-07	-9.3e-09	1.3e-09	7.8e-10	2.4
alpha_5	14	0.55	-0.059	-0.0085	-0.0014	-0.00024	-4.1e-05	-6.9e-06	-1.1e-06	-1.9e-07	-3.1e-08	-5.1e-09	-8.2e-10	-1.3
alpha_10	18	0.4	-0.037	-0.0055	-0.00095	-0.00017	-3e-05	-5.2e-06	-9.2e-07	-1.6e-07	-2.9e-08	-5.1e-09	-9.1e-10	-1.6
alpha_20	23	0.28	-0.022	-0.0034	-0.0006	-0.00011	-2e-05	-3.6e-06	-6.6e-07	-1.2e-07	-2.2e-08	-4e-09	-7.5e-10	-1.4

Ridge Regression

This straight away gives us the following inferences:

1. The RSS increases with increase in alpha, this model complexity reduces
2. An alpha as small as 1e-15 gives us significant reduction in magnitude of coefficients. How? Compare the coefficients in the first row of this table to the last row of simple linear regression table.
3. High alpha values can lead to significant underfitting. Note the rapid increase in RSS for values of alpha greater than 1
4. Though the coefficients are **very very small**, they are **NOT zero**.

The first 3 are very intuitive. But #4 is also a crucial observation.

Lasso Regression

Notice the additional parameter defined in Lasso function is '*max_iter*'. This is the maximum number of iterations for which we want the model to run if it doesn't converge before. This exists for Ridge as as well but setting this to a higher than default value was required in this case.

In [35]:

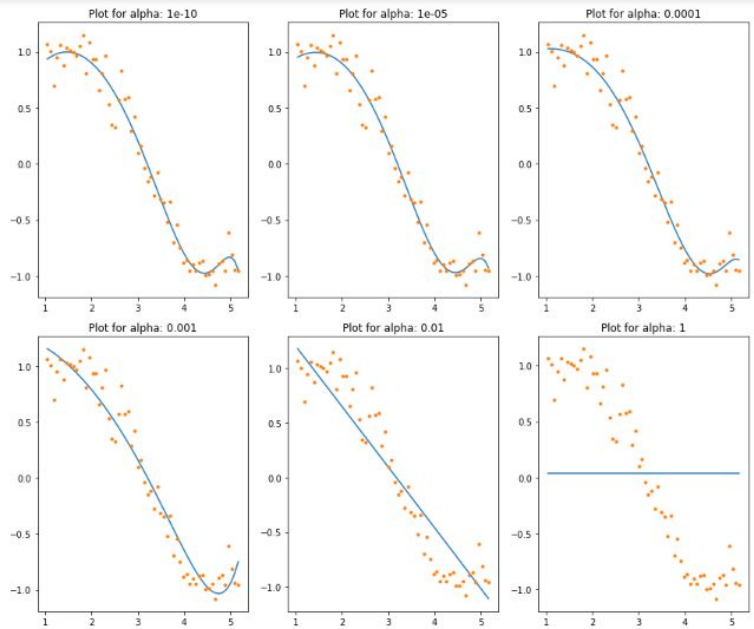
```
###### Lasso Regression
from sklearn.linear_model import Lasso
def lasso_regression(data, predictors, alpha, models_to_plot={}):
    #Fit the model
    lassoreg = Lasso(alpha=alpha,normalize=True, max_iter=1e5)
    lassoreg.fit(data[predictors],data['y'])
    y_pred = lassoreg.predict(data[predictors])

    #Check if a plot is to be made for the entered alpha
    if alpha in models_to_plot:
        plt.subplot(models_to_plot[alpha])
        plt.tight_layout()
        plt.plot(data['x'],y_pred)
        plt.plot(data['x'],data['y'],'.')
        plt.title('Plot for alpha: %.3g'%alpha)

    #Return the result in pre-defined format
    rss = sum((y_pred-data['y'])**2)
    ret = [rss]
    ret.extend([lassoreg.intercept_])
    ret.extend(lassoreg.coef_)
    return ret
```

Lasso Regression

Let's check the output for 10 different values of alpha:



In [36]:
```
#Initialize predictors to all 15 powers of x
predictors=['x']
predictors.extend(['x_%d'%i for i in range(2,16)])

#Define the alpha values to test
alpha_lasso = [1e-15, 1e-10, 1e-8, 1e-5,1e-4, 1e-3,1e-2, 1, 5, 10]

#Initialize the dataframe to store coefficients
col = ['rss','intercept'] + ['coef_x_%d'%i for i in range(1,16)]
ind = ['alpha_%.2g'%alpha_lasso[i] for i in range(0,10)]
coef_matrix_lasso = pd.DataFrame(index=ind, columns=col)

#Define the models to plot
models_to_plot = {1e-10:231, 1e-5:232,1e-4:233, 1e-3:234, 1e-2:235, 1:236}

#Iterate over the 10 alpha values:
for i in range(10):
    coef_matrix_lasso.iloc[i,] = lasso_regression(data, predictors, alpha_lasso[i], models_to_plot)
```

Key Difference

- **Ridge:** It includes all (or none) of the features in the model. Thus, the major advantage of ridge regression is coefficient shrinkage and reducing model complexity.

- **Lasso:** Along with shrinking coefficients, lasso performs feature selection as well. As we observed earlier, some of the coefficients become exactly zero, which is equivalent to the particular feature being excluded from the model.

In Machine Learning, ridge and lasso regression provide very good alternatives as they give much **better output**, require **fewer tuning parameters** and can be **automated** to a large extend.

Use Cases

- **Ridge:** It is majorly used to *prevent overfitting*. Since it includes all the features, it is not very useful in case of exorbitantly high #features, say in millions, as it will pose computational challenges.

- **Lasso:** Since it provides *sparse solutions*, it is generally the model of choice (or some variant of this concept) for modelling cases where the #features are in millions or more. In such a case, getting a sparse solution is of great computational advantage as the features with zero coefficients can simply be ignored.

It's not hard to see why the stepwise selection techniques become practically very cumbersome to implement in high dimensionality cases. Thus, lasso provides a significant advantage.

Presence of Highly Correlated Features

- **Ridge:** It generally works well even in presence of highly correlated features as it will include all of them in the model but the coefficients will be distributed among them depending on the correlation.

- **Lasso:** It arbitrarily selects any one feature among the highly correlated ones and reduced the coefficients of the rest to zero. Also, the chosen variable changes randomly with change in model parameters. This generally doesn’t work that well as compared to ridge regression.

Ridge and Lasso using Cross-Validation

- **Lets see the behavior of Ridge models in cross-validation on another dataset, i.e. for different values of alpha as similar we observe in previous examples. You are required to use the same values for Lasso implementation.**

Ridge in Cross-Validation

Download the “Hitters.csv” from https://vincentarelbundock.github.io/Rdatasets/datasets.html

```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import scale
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge, RidgeCV, Lasso, LassoCV
from sklearn.metrics import mean_squared_error
```

```
df = pd.read_csv('Hitters.csv').dropna().drop('Player', axis = 1)
##df.info()
dummies = pd.get_dummies(df[['League', 'Division', 'NewLeague']])
```

```
y = df.Salary
# Drop the column with the independent variable (Salary), and columns for which we created dummy variables
X_ = df.drop(['Salary', 'League', 'Division', 'NewLeague'], axis = 1).astype('float64')
# Define the feature set X.
X = pd.concat([X_, dummies[['League_N', 'Division_W', 'NewLeague_N']]], axis = 1)
##X.info()
```

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

```
ridge = Ridge(normalize = True)
coefs = []
for a in alphas:
    ridge.set_params(alpha = a)
    ridge.fit(X, y)
    coefs.append(ridge.coef_)
np.shape(coefs)
```

```
# Split data into training and test sets
X_train, X_test , y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=1)
```

```
ridgecv = RidgeCV(alphas = alphas, scoring = 'neg_mean_squared_error', normalize = True)
ridgecv.fit(X_train, y_train)
ridgecv.alpha_
```

```
0.57487849769886779
```

```
ridge4 = Ridge(alpha = ridgecv.alpha_, normalize = True)
ridge4.fit(X_train, y_train)
mean_squared_error(y_test, ridge4.predict(X_test))
```

```
99825.648962927298
```

```
ridge4.fit(X, y)
pd.Series(ridge4.coef_, index = X.columns)
```

Lesso in Cross-Validation -- First four modules will remain the same

```
lasso = Lasso(max_iter = 10000, normalize = True)
coefs = []

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

ax = plt.gca()
ax.plot(alphas*2, coefs)
ax.set_xscale('log')
plt.axis('tight')
plt.xlabel('alpha')
plt.ylabel('weights')
```

```
lassocv = LassoCV(alphas = None, cv = 10, max_iter = 100000, normalize = True)
lassocv.fit(X_train, y_train)

lasso.set_params(alpha=lassocv.alpha_)
lasso.fit(X_train, y_train)
mean_squared_error(y_test, lasso.predict(X_test))
```

```
104960.65853895503
```

```
# Some of the coefficients are now reduced to exactly zero.
pd.Series(lasso.coef_, index=X.columns)
```

Regression in Polynomial

```
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.preprocessing import PolynomialFeatures


X_train, X_test, y_train, y_test = train_test_split(X_F1, y_F1,
                                                    random_state = 0)
linreg = LinearRegression().fit(X_train, y_train)

print('linear model coeff (w): {}'
     .format(linreg.coef_))
print('linear model intercept (b): {:.3f}'
     .format(linreg.intercept_))
print('R-squared score (training): {:.3f}'
     .format(linreg.score(X_train, y_train)))
print('R-squared score (test): {:.3f}'
     .format(linreg.score(X_test, y_test)))

print('\nNow we transform the original input data to add\n\
polynomial features up to degree 2 (quadratic)\n')
poly = PolynomialFeatures(degree=2)
X_F1_poly = poly.fit_transform(X_F1)

X_train, X_test, y_train, y_test = train_test_split(X_F1_poly, y_F1,
                                                    random_state = 0)
```

```
linreg = Ridge().fit(X_train, y_train)

print('(poly deg 2 + ridge) linear model coeff (w):\n{}'
     .format(linreg.coef_))
print('(poly deg 2 + ridge) linear model intercept (b): {:.3f}'
     .format(linreg.intercept_))
print('(poly deg 2 + ridge) R-squared score (training): {:.3f}'
     .format(linreg.score(X_train, y_train)))
print('(poly deg 2 + ridge) R-squared score (test): {:.3f}'
     .format(linreg.score(X_test, y_test)))
```

KNN Classification -- Sklearn

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
# Assign colum names to the dataset
names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'Class']
# Read dataset to pandas dataframe
dataset = pd.read_csv(url, names=names)
dataset.head()
```

	sepal-length	sepal-width	petal-length	petal-width	Class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 4].values
```

```
## Train Test Split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
```

KNN Classification - With Static Value of k

```
## Feature Scalling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

```
## Build The Model
from sklearn.neighbors import KNeighborsClassifier
#classifier = KNeighborsClassifier(n_neighbors=5)
classifier = KNeighborsClassifier(algorithm='auto',
                     leaf_size=30,
                     metric='minkowski',
                     metric_params=None,
                     n_jobs=1,
                     n_neighbors=5,
                     p=2,
                     weights='uniform')
classifier.fit(X_train, y_train)
```

```
## Pridiction
y_pred = classifier.predict(X_test)
```

```
## Evaluate the Classifier
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

KNN Classification - Cross validation

```
## Comparing the Error for Different values of K.
error = []
# Calculating error for K values between 1 and 40
for i in range(1, 40):
    ##knn = KNeighborsClassifier(n_neighbors=i)
    knn = KNeighborsClassifier(algorithm='auto',
                       leaf_size=30,
                       metric='minkowski',
                       metric_params=None,
                       n_jobs=1,
                       n_neighbors=i,
                       p=2,
                       weights='uniform')
    knn.fit(X_train, y_train)
    pred_i = knn.predict(X_test)
    error.append(np.mean(pred_i != y_test))
```

```
## Plot the Error
plt.figure(figsize=(12, 6))
plt.plot(range(1, 40), error, color='red', linestyle='dashed', marker='o',
         markerfacecolor='blue', markersize=10)
plt.title('Error Rate K Value')
plt.xlabel('K Value')
plt.ylabel('Mean Error')
```

KNN Classification -- Without Sklearn

```
import csv
import random
import math
import operator

def loadDataset(filename, split, trainingSet=[] , testSet=[]):
    with open(filename, 'rb') as csvfile:
        lines = csv.reader(csvfile)
        dataset = list(lines)
        for x in range(len(dataset)-1):
            for y in range(4):
                dataset[x][y] = float(dataset[x][y])
            if random.random() < split:
                trainingSet.append(dataset[x])
            else:
                testSet.append(dataset[x])


def euclideanDistance(instance1, instance2, length):
    distance = 0
    for x in range(length):
        distance += pow((instance1[x] - instance2[x]), 2)
    return math.sqrt(distance)

def getNeighbors(trainingSet, testInstance, k):
    distances = []
    length = len(testInstance)-1
    for x in range(len(trainingSet)):
        dist = euclideanDistance(testInstance, trainingSet[x], length)
        distances.append((trainingSet[x], dist))
    distances.sort(key=operator.itemgetter(1))
    neighbors = []
    for x in range(k):
        neighbors.append(distances[x][0])
    return neighbors

def getResponse(neighbors):
    classVotes = {}
    for x in range(len(neighbors)):
        response = neighbors[x][-1]
        if response in classVotes:
            classVotes[response] += 1
        else:
            classVotes[response] = 1
    sortedVotes = sorted(classVotes.iteritems(), key=operator.itemgetter(1), rever
    return sortedVotes[0][0]
```

```
def getAccuracy(testSet, predictions):
    correct = 0
    for x in range(len(testSet)):
        if testSet[x][-1] == predictions[x]:
            correct += 1
    return (correct/float(len(testSet))) * 100.0
```

```
def main():
    # prepare data
    trainingSet=[]
    testSet=[]
    split = 0.67
    loadDataset('iris.data', split, trainingSet, testSet)
    print 'Train set: ' + repr(len(trainingSet))
    print 'Test set: ' + repr(len(testSet))
    # generate predictions
    predictions=[]
    k = 3
    for x in range(len(testSet)):
        neighbors = getNeighbors(trainingSet, testSet[x], k)
        result = getResponse(neighbors)
        predictions.append(result)
        print('> predicted=' + repr(result) + ', actual=' + repr(testSet[x][-1]))
    accuracy = getAccuracy(testSet, predictions)
    print('Accuracy: ' + repr(accuracy) + '%')
```

Homework

- Download the wine quality data set, which has been widely utilize for Classification and Regression Problems. This dataset is related to red and white variants of the Portuguese "Vinho Verde" wine (More Details: [Web Link]).

- First use KNN to classify the data, and for that use cross validation to choose the best value for k as well as check the different distance function. Plot the Results for each distance function using cross validation to choose the best value for k.

- Use the same dataset for Ridge and Lasso regression models with cross validation and round the results from the these models to the nearest integer to form the classification.

- Using the best values for k (nearest neighbor) and alpha (Ridge and Lasso regression), compare and contrast the results of these techniques.