2_Ridge_Regression

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1 Ridge Regression

1.1 Implementation and Cheat Sheet

This page documents the summary theory and implementation of ridge regression. In particular, it covers:

- Ridge regression
- k-fold cross validation to find best l2-penalty

```
[1]: import pandas as pd
  import os
  import numpy as np
  import re
  import csv
  from IPython.display import display, Math, Latex
  from sklearn import datasets, linear_model
  from sklearn.utils import shuffle
  import matplotlib.pyplot as plt
  %matplotlib inline

def load_csv_data(folder_name, file_name, dtype_dict=None):
      csv_path = os.path.join(folder_name, file_name+".csv")
      return pd.read_csv(csv_path, dtype=dtype_dict)
```

2 Loading data

```
[3]: df_train_ridge = load_csv_data("data", "kc_house_train_data", dtype_dict) df_test_ridge = load_csv_data("data", "kc_house_test_data", dtype_dict)
```

3 Ridge Regression

Regression model:

$$\mathbf{y} = \mathbf{X}\mathbf{w} + \epsilon,\tag{1}$$

where $\mathbf{y} \in \mathbb{R}^{N \times 1}, \mathbf{X} \in \mathbb{R}^{N \times p}, \mathbf{w} \in \mathbb{R}^{p \times 1}, \epsilon \in \mathbb{R}^{N \times 1}$

Total cost = measure of fit + measure of magnitude of coefficients = $RSS(\mathbf{w}) + \lambda ||\mathbf{w}||_2^2$

where $||\mathbf{w}||_2^2 = w_0^2 + w_1^2 + \dots + w_{p-1}^2$. Here, w_0 is the intercept, and there are p-1 actual features, giving a total of p features.

Here,

$$RSS(\mathbf{w}) = (\mathbf{y} - \widehat{\mathbf{y}})^{\mathrm{T}}(\mathbf{y} - \widehat{\mathbf{y}}) = (\mathbf{y} - \mathbf{X}\mathbf{w})^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\mathbf{w})$$
(2)

and

$$||\mathbf{w}||_2^2 = \mathbf{w}^{\mathrm{T}}\mathbf{w} \tag{3}$$

Therefore,

Total cost =
$$(\mathbf{y} - \mathbf{X}\mathbf{w})^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\mathbf{w}) + \lambda \mathbf{w}^{\mathrm{T}}\mathbf{w}$$
 (4)

Taking the gradient of the cost,

$$\nabla(RSS(\mathbf{w}) + \lambda ||\mathbf{w}||_2^2) = \nabla((\mathbf{y} - \mathbf{X}\mathbf{w})^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\mathbf{w}) + \lambda \mathbf{w}^{\mathrm{T}}\mathbf{w})$$
(5)

$$= -2\mathbf{X}^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\mathbf{w}) + \lambda(2\mathbf{w}) = -2\mathbf{X}^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\mathbf{w}) + 2\lambda \mathbb{I}\mathbf{w}$$
 (6)

The closed form solution can be found by setting the gradient to 0:

$$\nabla(\cot(\widehat{\mathbf{w}})) = \nabla(-2\mathbf{X}^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\widehat{\mathbf{w}}) + 2\lambda \mathbb{I}\widehat{\mathbf{w}}) = 0$$
(7)

$$\widehat{\mathbf{w}}^{\text{ridge}} = (\mathbf{X}^{\text{T}}\mathbf{X} + \lambda \mathbb{I})^{-1}\mathbf{X}^{\text{T}}\mathbf{y}$$
(8)

However, we do not want to penalize the intercept w_0 for being large. Therefore, use a modified

$$\mathbb{I}^{\text{mod}} = \begin{bmatrix} 0 & & & & \\ & 1 & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix}, \text{ with } \mathbb{I} \in \mathbb{R}^{p \times p}$$

Using Gradient Descent:

init $t = 1, \mathbf{w}^{(1)} = 0$ or randomly or smartly while $||\nabla RSS(\mathbf{w}^{(t)})|| >$ threshold:

$$\mathbf{w}^{(t+1)} \le \mathbf{w}^{(t)} + 2\eta(\mathbf{X}^{\mathrm{T}}(\mathbf{y} - \mathbf{X}\mathbf{w}^{(t)}) - \lambda \mathbb{I}^{\mathrm{mod}}\mathbf{w})$$
(9)

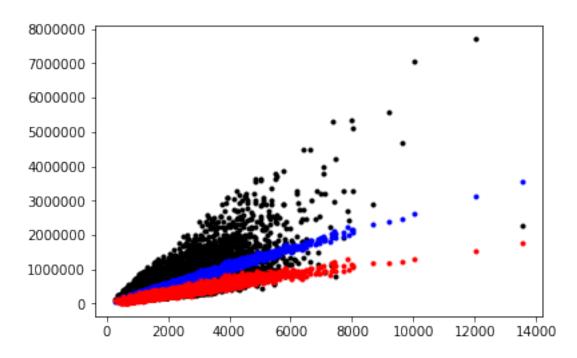
```
def dataframe_prepare(dataframe,features,target):
    dataframe["constant"]=1
    one_padded_features=["constant"]
    one_padded_features.extend(features)
    X = dataframe[one_padded_features].values
    Y = dataframe[target].values
    return X,Y
```

```
[7]: def predict_outcome(feature_matrix, weights):
          predictions = np.matmul(feature_matrix, weights)
          return(predictions)
 [8]: simple_features = ['sqft_living', 'sqft_living15']
      X_train,Y_train=dataframe_prepare(df_train_ridge,simple_features,['price'])
      X_test,Y_test=dataframe_prepare(df_test_ridge,simple_features,['price'])
      initial_weights = np.array([[-100000.], [0.], [0.]])
      step_size = 1e-12
      max_iterations= 10000
      multiple_weights_small_penalty = ridge_regression_gradient_descent(X_train,_u
      →Y_train, initial_weights=initial_weights,\
                                                  step_size=step_size, 12_penalty=1.
      →5e-5, max iterations=max iterations)
      print("The small-penalty weights from ridge gradient descent are: ")
      print(multiple_weights_small_penalty)
      weights_closed = ridge_regression_closed_form(X_train, Y_train, 12_penalty=1.
      -5e-5)
      print("The small-penalty weights from ridge closed form solution are: ")
      print(weights_closed)
     The small-penalty weights from ridge gradient descent are:
     [[-9.99999771e+04]
      [ 2.45183819e+02]
      [ 6.51587638e+01]]
     The small-penalty weights from ridge closed form solution are:
     [[-1.00262175e+05]
      [ 2.45188714e+02]
      [ 6.52715852e+01]]
     Verify with Scikit Learn
 [9]: 12_small_penalty = 1.5e-5
      model = linear_model.Ridge(alpha=12_small_penalty,max_iter=10000,tol=None,__
       →normalize=True)
      model.fit(X_train, Y_train)
 [9]: Ridge(alpha=1.5e-05, copy_X=True, fit_intercept=True, max_iter=10000,
         normalize=True, random_state=None, solver='auto', tol=None)
[10]: model.intercept
[10]: array([-100259.76546574])
[11]: model.coef_
```

```
[11]: array([[ 0. , 245.18141126, 65.27802084]])
     Explore 0-penalty and infinity-penalty effects
[12]: multiple_weights_0_penalty = ridge_regression_gradient_descent(X_train,__
       →Y_train, initial_weights=initial_weights,\
                                                  step_size=step_size, 12_penalty=0,_u
       →max_iterations=max_iterations)
      print("The 0-penalty weights from ridge gradient descent are: ")
      print(multiple_weights_0_penalty)
      weights_closed = ridge_regression_closed_form(X_train, Y_train,12_penalty=0)
      print("The 0-penalty weights from ridge closed form solution are: ")
      print(weights_closed)
      multiple_weights_high_penalty = ridge_regression_gradient_descent(X_train,_u
      →Y_train, initial_weights=initial_weights,\
                                                  step_size=step_size,_
      →12_penalty=1e11, max_iterations=max_iterations)
      print("The high-penalty weights from ridge gradient descent are: ")
      print(multiple_weights_high_penalty)
      weights_closed = ridge_regression_closed_form(X train, Y train, 12 penalty=1e11)
      print("The high-penalty weights from ridge closed form solution are: ")
      print(weights_closed)
     The O-penalty weights from ridge gradient descent are:
     [[-9.99999771e+04]
      [ 2.45183819e+02]
      [ 6.51587638e+01]]
     The O-penalty weights from ridge closed form solution are:
     [[-1.00262175e+05]
      [ 2.45188714e+02]
      [ 6.52715852e+01]]
     The high-penalty weights from ridge gradient descent are:
     [[-9.99169711e+04]
      [ 1.04826258e+02]
      [ 9.19077002e+01]]
     The high-penalty weights from ridge closed form solution are:
     [[4.25149484e+05]
      [3.47447641e+01]
      [2.11214072e+01]]
[13]: plt.plot(X_train[:,1],Y_train,'k.',
```

')

X_train[:,1],predict_outcome(X_train, multiple_weights_0_penalty),'b.',
X_train[:,1],predict_outcome(X_train, multiple_weights_high_penalty),'r.



4 k-fold cross validation to find l2-penalty

```
[14]: def k_fold_cross_validation(k, 12_penalty, data,__
       →output, features=False, degree=False):
          N = len(data)
          RSS list=[]
          for i in range(k):
              #get the fold splits for the current iteration
              start = int(np.ceil((N*i)/k))
              end = int(np.ceil((N*(i+1))/k-1))
              training_data = data[0:start].append(data[end+1:N])
              validation_data = data[start:end+1]
              training_target = output[0:start].append(output[end+1:N])
              validation_target= output[start:end+1]
              #training on training split
              model = linear_model.Ridge(alpha=12_penalty, normalize=True)
              if (features):
                  model.fit(training_data[features], training_target)
```

```
else:
                 model.fit(training_data, training_target)
              #RSS on validation split
             validation_data.loc[:,'price']=validation_target
             if(degree):
                  features = ["power_"+str(i) for i in range(1,degree+1)]
       →X,Y=dataframe_prepare(dataframe=validation_data,features=features,target=['price'])
              weights = np.concatenate((np.array([model.intercept_]), model.
       →coef_),axis=0).reshape(-1,1) #merging intercept and coeffs
             RSS = compute RSS(X,Y,weights)
             RSS_list.append(RSS)
         return RSS_list,np.mean(RSS_list)
[15]: def compute_RSS(X,y,w):
         RSS = np.matmul(np.transpose(y-predict_outcome(X,w)),y-predict_outcome(X,w))
         return RSS
[16]: df_train_ridge_shuffled = shuffle(df_train_ridge)
      features = ['sqft_living', 'sqft_living15']
      mean_RSS_list=[]
      \#get\ best\ l2-penalty\ using\ 10-fold\ cross\ validation
      12 = np.logspace(-9, 9, num=26)
      for 12_penalty in 12:
         _ , mean_RSS = k_fold_cross_validation(k=10, l2_penalty=12_penalty,__
      →data=df_train_ridge_shuffled,
      →output=df_train_ridge_shuffled["price"],features=['sqft_living',__
      #print(mean RSS)
         mean_RSS_list.append(mean_RSS)
      val, idx = min((val, idx) for (idx, val) in enumerate(mean_RSS_list))
      print("Best 12-penalty based on lowest RSS:"+str(12[idx]))
      #training new model using best 12-penalty
      model = linear_model.Ridge(alpha=12[idx], normalize=True)
      model.fit(df_train_ridge_shuffled[features], df_train_ridge_shuffled["price"])
      print("Weights of final model: ")
      print(model.intercept_)
      print(model.coef_)
      #testing on test set
      X test, Y test=dataframe prepare(dataframe=df test ridge, features=features, target=['price'])
```

```
weights = np.concatenate((np.array([model.intercept_]), model.coef_),axis=0).
 \rightarrowreshape(-1,1)
test_RSS = compute_RSS(X_test,Y_test,weights)
print("Test set RSS with the best 12-penalty: "+str(test RSS))
/Users/raiyanabdulbaten/Dropbox/ROC/handson-ml/my_codes/env/lib/python3.6/site-
packages/pandas/core/indexing.py:537: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
/Users/raiyanabdulbaten/Dropbox/ROC/handson-ml/my_codes/env/lib/python3.6/site-
packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
Best 12-penalty based on lowest RSS:0.003019951720402013
Weights of final model:
-99770.3868120372
[243.73362872 66.54793933]
Test set RSS with the best 12-penalty: [[2.7020516e+14]]
```

4.1 Revisiting the polynomial regression problem with k-fold CV

Please refer to the polynomial regression code in the file 'Linear Regression Basics'. Here a maximum polynomial degree of 15 is used (which performed horribly without regularization). Using l2-penalty, the performance is improved.

```
[17]: train_valid_shuffled = □ □ □ □ □ □ load_csv_data("data", "wk3_kc_house_train_valid_shuffled", dtype_dict)

test = load_csv_data("data", "wk3_kc_house_test_data", dtype_dict)
```

```
[18]: def polynomial_dataframe(feature, degree):
    poly_dataframe = pd.DataFrame()
    poly_dataframe["power_1"] = feature
    if degree > 1:
        for power in range(2, degree+1):
            name = 'power_' + str(power)
            poly_dataframe[name] = feature.apply(lambda x: x**power)
        return poly_dataframe
```

```
[19]: degree=15
      poly15_data = polynomial_dataframe(train_valid_shuffled['sqft_living'], degree)
      mean_RSS_list=[]
      #qet best 12-penalty using 10-fold cross validation
      12 = np.logspace(-9, 9, num=26)
      for 12_penalty in 12:
          _ , mean_RSS = k_fold_cross_validation(k=10, 12_penalty=12_penalty,_

data=poly15_data,

⊔
       →output=train_valid_shuffled["price"],features=False,degree=degree)
          #print(mean_RSS)
          mean_RSS_list.append(mean_RSS)
      val, idx = min((val, idx) for (idx, val) in enumerate(mean RSS_list))
      print("Best 12-penalty based on lowest RSS:"+str(12[idx]))
      #training new model using best 12-penalty
      model = linear_model.Ridge(alpha=12[idx], normalize=True)
      model.fit(poly15_data, train_valid_shuffled["price"])
      #testing on test set
      poly15_test = polynomial_dataframe(test['sqft_living'], degree)
      poly15_test['price']=test['price']
      features = ["power_"+str(i) for i in range(1,degree+1)]
      X_test,Y_test=dataframe_prepare(dataframe=poly15_test,features=features,target=['price'])
      weights = np.concatenate((np.array([model.intercept_]), model.coef_),axis=0).
      \rightarrowreshape(-1,1)
      test_RSS = compute_RSS(X_test,Y_test,weights)
      print("Test set RSS with the best 12-penalty: "+str(test_RSS))
     /Users/raiyanabdulbaten/Dropbox/ROC/handson-ml/my_codes/env/lib/python3.6/site-
     packages/pandas/core/indexing.py:357: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: http://pandas.pydata.org/pandas-
     docs/stable/indexing.html#indexing-view-versus-copy
       self.obj[key] = _infer_fill_value(value)
     /Users/raiyanabdulbaten/Dropbox/ROC/handson-ml/my_codes/env/lib/python3.6/site-
     packages/pandas/core/indexing.py:621: SettingWithCopyWarning:
     A value is trying to be set on a copy of a slice from a DataFrame.
     Try using .loc[row_indexer,col_indexer] = value instead
     See the caveats in the documentation: http://pandas.pydata.org/pandas-
     docs/stable/indexing.html#indexing-view-versus-copy
       self.obj[item_labels[indexer[info_axis]]] = value
     /Users/raiyanabdulbaten/Dropbox/ROC/handson-ml/my_codes/env/lib/python3.6/site-
```

packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy

Best 12-penalty based on lowest RSS:0.08317637711026708
Test set RSS with the best 12-penalty: [[1.37392658e+14]]