CS 273a - Introduction to Machine Learning (Winter '15)* Prof. Alex Ihler

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Homework 2^{†‡}

Problem 1: Linear Regression

(a) I loaded the data from data/curve80.data into the curve variable. Then the variable X stores the data and Y stores the regressed values. I then split the data into a 75-25 partition and store it in the individual variables. Shown in Listing 1.

Listing 1: Fetching the data/curve80.data and splitting it with a 75-25 partition.

```
1 % Fetching the dataset and separating it into X and Y.
2 curve=load('data/curve80.txt'); % load the text file
3 y = curve(:,end);
                              % target value is last column
4 X = curve(:,1);
                       % features are other columns
5 whos
7 % Part (a)
8 % Splitting the data into 75-25 split.
9 [Xtr, Xte, Ytr, Yte] = splitData(X,y, .75);
10
11 >> whos
    Name
                Size
                                Bytes Class
                                                 Attributes
12
13
    Χ
               80x1
                                  640 double
14
               20x1
                                  160
                                       double
15
    Xte
               60x1
                                  480
                                       double
16
    Xtr
    Yte
               20x1
                                  160
                                       double
17
    Ytr
               60x1
                                  480
                                       double
18
                                 1280
19
     curve
               80x2
                                       double
               80x1
                                  640 double
20
```

(b) After loading the data, we use the linearRegress class's predict () to get the prediction of the model. The code is given in Listing 2. The plot can be seen at Figure 1.

Listing 2: Getting a prediction for the model built on the Training data.

```
1 %% Part (b)
2 % Training the linear regression with Xtr as an input
3 lr = linearRegress( Xtr, Ytr );
4 xs = [0:.05:10]';
5 ys = predict(lr, xs);
6 ys1 = predict(lr, Xte);
7
8 % Plotting the training data and the predicted function in the same plot.
9 f=figure;
10 scatter(Xtr, Ytr, 'filled');
11 hold on;
12 plot(xs, ys);
13 hold off;
14 saveas(f,'lr.jpg','jpg');
15
16 % MSE for both Training and Test data
17 mse(lr, Xtr, Ytr)
```

^{*}Website: http://sli.ics.uci.edu/Classes/2015W-273a

[†]Questions available at http://sli.ics.uci.edu/Classes/2015W-273a?action=download&upname=HW2.pdf

[‡]All the figures and listing numbers are auto-refered.

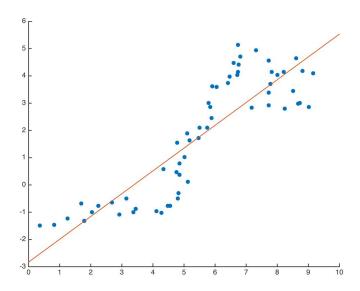


Figure 1: Training data and the learned function in Listing 2

```
18 % ans = 1.1277

19 mse(lr, Xte, Yte)

20 % ans = 2.2423
```

(c) The higher degree polynomials are created as per the Listing 3. The higher-degree polynomials are created by the fploy() function provided. Using the new dataset, we rescale it and train the linear regression model using linearRegress class.

Listing 3: Getting a prediction for the model built on the Training data.

```
1 f = figure;
2 i = 1;
3 \text{ errorsTr} = \text{zeros}(1, 6);
  errorsTe = zeros(1, 6);
5 d=[1,3,5,7,10,18];
6 for degree=[1,3,5,7,10,18];
7
       XtrP = fpoly(Xtr, degree, false); % create poly features up to given ...
           degree; no "1" feature.
       [XtrP, M, S] = rescale(XtrP); % it's often a good idea to scale the ...
9
           features
       lr = linearRegress( XtrP, Ytr ); % create and train model
10
11
       % XS vs YS plot.
12
       xs = [0:.05:10]';
13
       xsP = rescale( fpoly(xs, degree, false), M,S);
14
       ysP = predict( lr, xsP );
15
16
       % Scatter plot and the learned function on the data.
17
       subplot(2,3,i);
18
       title(strcat({'degree= '}, num2str(degree)))
19
20
       scatter(Xtr, Ytr, 'filled');
       ax = axis;
23
       hold on;
^{24}
       plot(xs, ysP);
       axis(ax);
25
^{26}
```

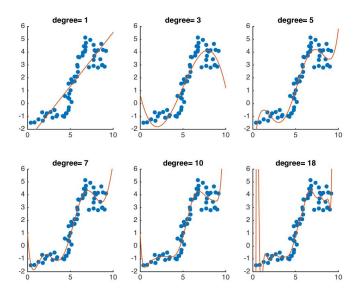


Figure 2: Plots for different degree polynomials and the learned functions

```
% For getting the right degree to get the best learning function.
       XteP = rescale(fpoly(Xte,degree,false), M,S);
       YteP = predict(lr, XteP);
29
30
       % MSE for both Training and Test data
31
       errorsTr(1, i) = mse(lr, XtrP, Ytr)
32
       errorsTe(1, i) = mse(lr, XteP, Yte)
33
       i = i + 1;
34
         now, apply the same polynomial expansion & scaling transformation ...
35
           to Xtest:
36
37
   end:
   hold off;
```

The trained functions and the scatter for various degree values can be seen in the visual representation seen in Figure 2. To get to a better approximation of the right degree, we learned the performance of the learner with the test data and plotted it, as can be seen in Figure 3. From this observation, I can see that for $\mathbf{degree} = \mathbf{10}$, the test error was the least.

Problem 2: Cross Validation

For each degree, I use cross validation within the loop iterating on all the degrees. Before I apply the cross-validation on this data and change its degree as well as rescale it, as seen in Listing 4. After that, I save the errors into an array and use that to plot, which can be seen in 4(a). From this plot, it can be seen that for **degree** = 5, the error is minimum. When we compare it with the error on the actual test data, the difference shows up. The actual test data fits better for degree = 10, whereas cross validated data fits better with degree = 5. This plot shows that error for cross-validated model follows similar pattern to a test data, thus we can build models on data which would generalize better, without the knowledge of the actual test data.

Listing 4: Training linear regression with cross-validation.

```
1 i = 1;
2 nFolds = 5;
```

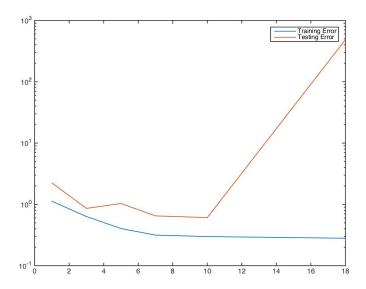
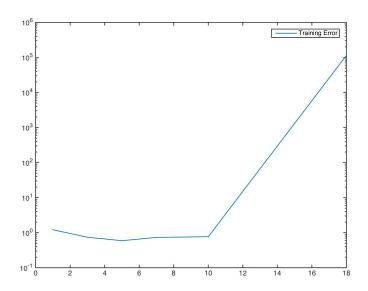
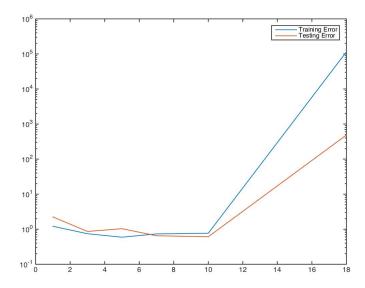


Figure 3: Train and Test Errors.

```
3 d=[1,3,5,7,10,18];
4 for degree=[1,3,5,7,10,18];
       % Degrees and scaling of the data
       XtrP = fpoly(Xtr, degree, false); % create poly features up to given ...
           degree; no "1" feature.
       [XtrP, M, S] = rescale(XtrP); % it's often a good idea to scale the features
       for iFold = 1:nFolds;
           [Xti, Xvi, Yti, Yvi] = crossValidate(XtrP, Ytr, nFolds, iFold);
           % take ith data block as v learner = linearRegress(...
10
           lr = linearRegress( Xti, Yti ); % create and train model
11
           % TODO: train on Xti, Yti , the data for this fold J(iFold) = \dots
12
13
           % TODO: now compute the MSE on Xvi, Yvi and save it
14
15
           J(iFold) = mse(lr, Xvi, Yvi);
16
       end;
       \$ the overall estimated validation performance is the average of the \dots
17
          performance on ea
       errors(i) = mean(J);
18
       i = i + 1;
19
20 end;
```



(a) Training Errors for various degrees when the data is cross-validated



(b) Train Errors on Cross-validated error as well as the Error on the Actual Test data

Figure 4: Running Various Experiments. The three bars are for Brute Force, I-Consistency and I-Consistency with MRV search. All the times given are in Seconds