Rugularized Logistic Regression Application

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Rugularized Logistic Regression Application On Real Data

1. Dataset

The file `wine.csv` contains the information related to red wine, various factors affecting the quality.

For a given wine, we would like to predict whether it is of good or bad quality. So the task we have to perform is a classification and knowing that in this case, the label consists of only two different classes, thus it is a binary classification.

```
clear
X = readtable('wine.csv'); % Load comma separated data
```

```
Warning: Column headers from the file were modified to make them valid MATLAB identifiers
before creating variable names for the table. The original column headers are saved in the
VariableDescriptions property.
Set 'VariableNamingRule' to 'preserve' to use the original column headers as table variable names.
```

```
summary(X) % Summary of data
```

```
Variables:

    fixedAcidity: 1599×1 double

        Properties:
            Description:  fixed acidity
        Values:

            Min          4.6
            Median       7.9
            Max         15.9

    volatileAcidity: 1599×1 double

        Properties:
```

```
        Description:  volatile acidity
    Values:

        Min         0.12
        Median      0.52
        Max         1.58

citricAcid: 1599×1 double

    Properties:
        Description:  citric acid
    Values:

        Min            0
        Median      0.26
        Max            1

residualSugar: 1599×1 double

    Properties:
        Description:  residual sugar
    Values:

        Min          0.9
        Median       2.2
        Max         15.5

chlorides: 1599×1 double

    Properties:
        Description:  chlorides
    Values:

        Min        0.012
        Median     0.079
        Max        0.611

freeSulfurDioxide: 1599×1 double

    Properties:
        Description:  free sulfur dioxide
    Values:

        Min           1
        Median       14
        Max          72

totalSulfurDioxide: 1599×1 double

    Properties:
        Description:  total sulfur dioxide
    Values:

        Min           6
        Median       38
        Max         289

density: 1599×1 double

    Properties:
        Description:  density
    Values:

        Min       0.99007
```

```
        Median    0.99675
        Max        1.0037

    pH: 1599×1 double

        Properties:
            Description:  pH
        Values:

            Min         2.74
            Median      3.31
            Max         4.01

    sulphates: 1599×1 double

        Properties:
            Description:  sulphates
        Values:

            Min         0.33
            Median      0.62
            Max            2

    alcohol: 1599×1 double

        Properties:
            Description:  alcohol
        Values:

            Min          8.4
            Median      10.2
            Max         14.9

    quality: 1599×1 cell array of character vectors

        Properties:
            Description:  quality
```

```
X(1:5,:) % 5 first examples of data set
```

```
ans = 5×12 table
```

...

	fixedAcidity	volatileAcidity	citricAcid	residualSugar	chlorides
1	7.4000	0.7000	0	1.9000	0.0760
2	7.8000	0.8800	0	2.6000	0.0980
3	7.8000	0.7600	0.0400	2.3000	0.0920
4	11.2000	0.2800	0.5600	1.9000	0.0750
5	7.4000	0.7000	0	1.9000	0.0760

2. Pre-processing

2.1 Label encoding

We start with encoding the labels of our classification, 'bad' quality is encoded as 0 and 'good' quality as 1.

```
[~, n] = size(X);
X.quality = categorical(X.quality);
```

```
% Seperate labels
y = (X{:,"quality"} == 'good');
X = X(:,1:n-1);
n = n-1; % Number of features
```

2.2 Cross-Validation

The data is splitted to 3 parts as follows : 60% training set, 20% validation set and 20% test set.

```
% Training, 60% of dataset
TrainX = X{1:960,:};
Trainy = y(1:960,:);
Trainm = size(TrainX,1); % Number of examples in training set

% Cross-Validation, 20% of dataset
ValidationX = X{961:1280,:};
Validationy = y(961:1280,:);
Validm = size(ValidationX,1); % Number of examples in validation set

% Test, 20% of dataset
TestX = X{1281:end,:};
Testy = y(1281:end,:);
Testm = size(TestX,1); % Number of examples in test set
```

2.3 Feature standardization

By looking at the values of features, we note that there are much differences between orders of magnitudes . Feature standardization can make gradient descent converge much more quickly.

```
[TrainX, mu, sigma] = featureStandardize(TrainX); % Scale training set features and se
% Add intercept term to TrainX
TrainX = [ones(Trainm, 1) TrainX];
```

It is important to store the values used for standardization of training test - the mean value and the standard deviation - in order to be able to standardize validation and test set.

```
ValidationX = (ValidationX - mu)./sigma; % Scale validation set features and set them
% Add intercept term to TrainX
ValidationX = [ones(Validm, 1) ValidationX];

TestX = (TestX - mu)./sigma; % Scale validation set features and set them to zero mean
% Add intercept term to TestX
TestX = [ones(Testm, 1) TestX];
```

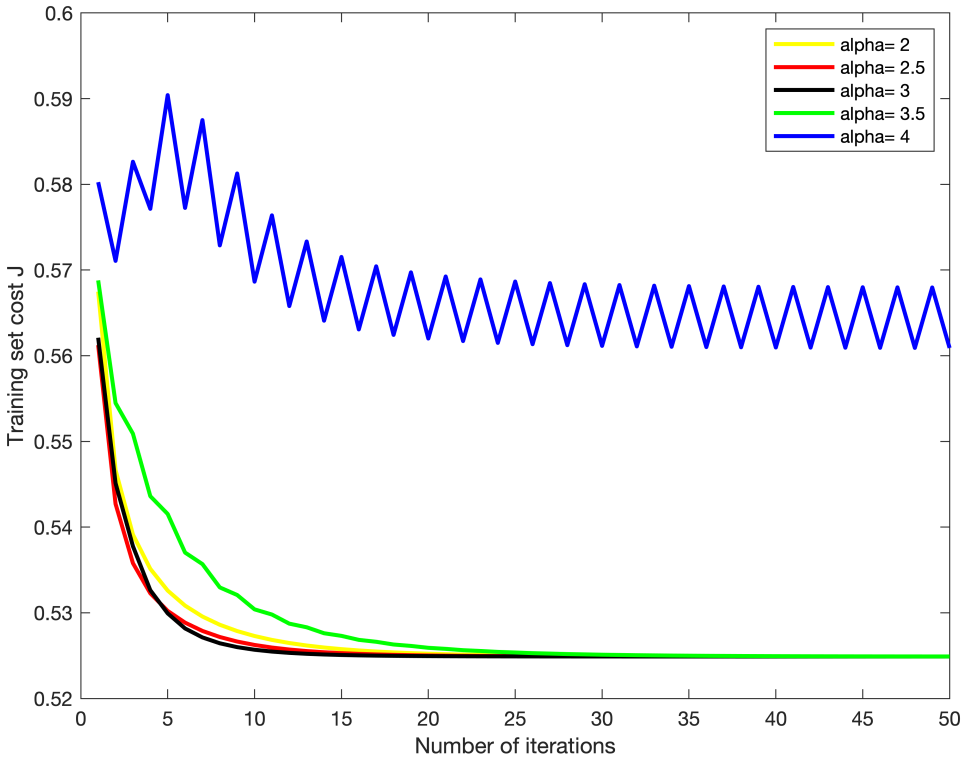
3. Selecting hyper-parameters

3.1 Selecting best learning rate

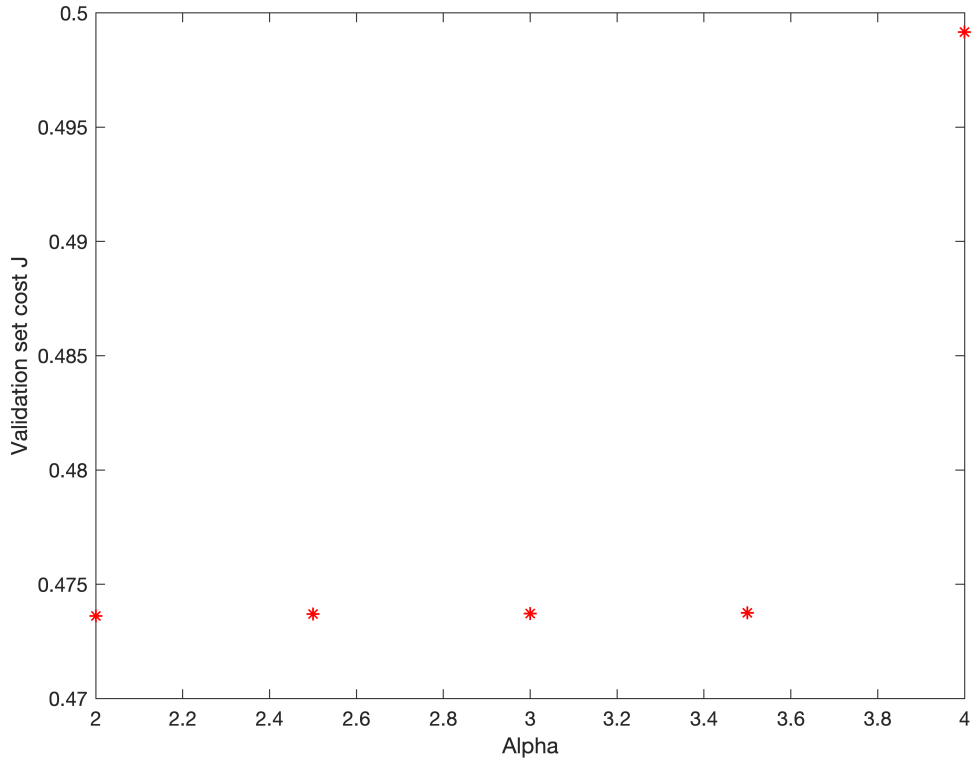
In order to find the best learning rate, we train a few models with different learning rate in parallel. Then only we select the one that works better at the end on our validation set.

```
% Initialize theta
```

```
theta = zeros(n+1, 1);
iteration_max = 50;
lambda = 1;

% Choose some values for alpha
alpha_1 = 2;
alpha_2 = 2.5;
alpha_3 = 3;
alpha_4 = 3.5;
alpha_5 = 4;

% Train models with different learning rate in parallel
[theta_1, J1_history] = gradientDescent(TrainX, Trainy, theta, alpha_1, iteration_max,
[theta_2, J2_history] = gradientDescent(TrainX, Trainy, theta, alpha_2, iteration_max,
[theta_3, J3_history] = gradientDescent(TrainX, Trainy, theta, alpha_3, iteration_max,
[theta_4, J4_history] = gradientDescent(TrainX, Trainy, theta, alpha_4, iteration_max,
[theta_5, J5_history] = gradientDescent(TrainX, Trainy, theta, alpha_5, iteration_max,

% Plot the convergence graph
figure
plot(1:iteration_max, J1_history, '-y', 'LineWidth', 2);
hold on
plot(1:iteration_max, J2_history, '-r', 'LineWidth', 2);
plot(1:iteration_max, J3_history, '-k', 'LineWidth', 2);
plot(1:iteration_max, J4_history, '-g', 'LineWidth', 2);
plot(1:iteration_max, J5_history, '-b', 'LineWidth', 2);
legend('alpha= 2', 'alpha= 2.5','alpha= 3', 'alpha= 3.5', 'alpha= 4')
hold off
xlabel('Number of iterations');
ylabel('Training set cost J');
```




```
figure
plot(alpha_1, costFunction(theta_1, ValidationX, Validationy, lambda),'*r', 'LineWidth
hold on
plot(alpha_2, costFunction(theta_2, ValidationX, Validationy, lambda),'*r', 'LineWidth
plot(alpha_3, costFunction(theta_3, ValidationX, Validationy, lambda),'*r', 'LineWidth
plot(alpha_4, costFunction(theta_4, ValidationX, Validationy, lambda),'*r', 'LineWidth
plot(alpha_5, costFunction(theta_5, ValidationX, Validationy, lambda),'*r', 'LineWidth

hold off
xlabel('Alpha');
ylabel('Validation set cost J');
```



It can be noticed that the best learning rate is approximately 2.5 and with maximum iteration of 30, the curve reaches the minimum possible cost.

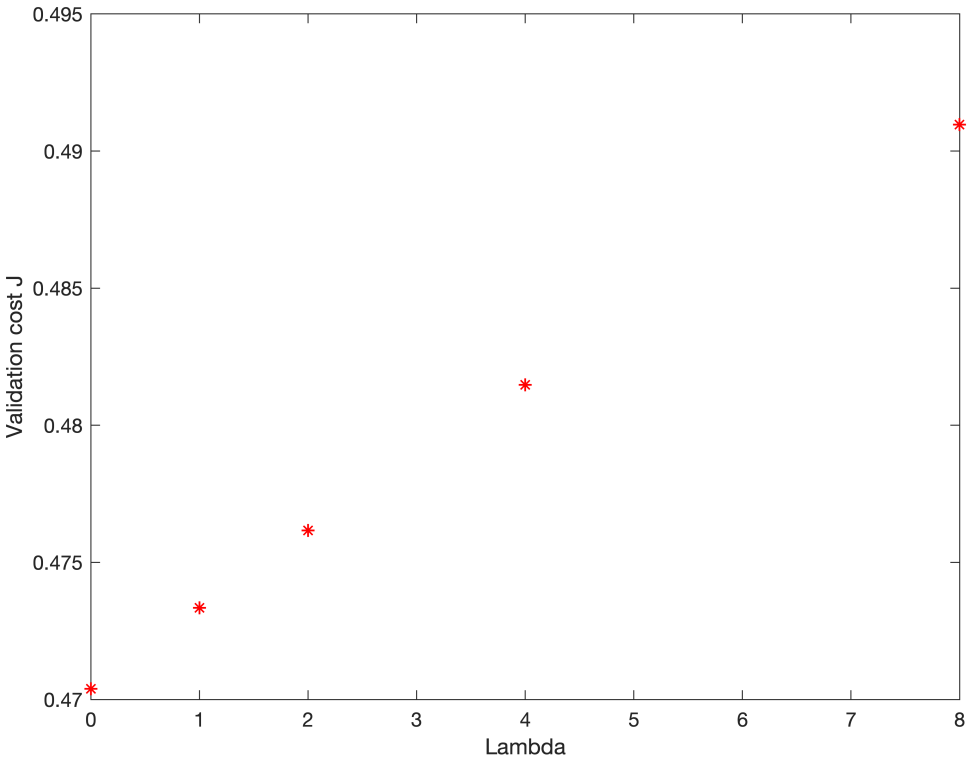
```
best_alpha = alpha_2;
iteration_max = 30;
```

3.2 Selecting best regularization rate

Same as finding the best learning rate, we train a few models with different regularization rate in parallel and select the one that works better on our validation set.

```
% Choose some values for lambda
lambda_1 = 0;
lambda_2 = 1;
lambda_3 = 2;
lambda_4 = 4;
lambda_5 = 8;

% Train models with different regularization rate in parallel
[theta_1, ~] = gradientDescent(TrainX, Trainy, theta, best_alpha, iteration_max, lambda
[theta_2, ~] = gradientDescent(TrainX, Trainy, theta, best_alpha, iteration_max, lambda
[theta_3, ~] = gradientDescent(TrainX, Trainy, theta, best_alpha, iteration_max, lambda
[theta_4, ~] = gradientDescent(TrainX, Trainy, theta, best_alpha, iteration_max, lambda
[theta_5, ~] = gradientDescent(TrainX, Trainy, theta, best_alpha, iteration_max, lambda


% Plot
```

```
figure
plot(lambda_1, costFunction(theta_1, ValidationX, Validationy, lambda_1),'*r', 'LineWi
hold on
plot(lambda_2, costFunction(theta_2, ValidationX, Validationy, lambda_2),'*r', 'LineWi
plot(lambda_3, costFunction(theta_3, ValidationX, Validationy, lambda_3),'*r', 'LineWi
plot(lambda_4, costFunction(theta_4, ValidationX, Validationy, lambda_4),'*r', 'LineWi
plot(lambda_5, costFunction(theta_5, ValidationX, Validationy, lambda_5),'*r', 'LineWi
hold off
xlabel('Lambda');
ylabel('Validation cost J');
```



It can be noticed that the lowest cost on the validation set is when regularization rate is equal to 0. In other words, fitting the parameters without regularization.

```
best_lambda = lambda_1;
theta = theta_1;
```

4. Computing accuracy

4.1 Training set accuracy

```
p = predict(theta, TrainX);
fprintf('Training Accuracy: %f\n', mean(double(p == Trainy)) * 100);
```

```
Training Accuracy: 74.062500
```

4.2 Validation set accuracy

```
p = predict(theta, ValidationX);
```

```
fprintf('Validation Accuracy: %f\n', mean(double(p == Validationy)) * 100);
```

```
Validation Accuracy: 78.437500
```

4.3 Test set accuracy

```
p = predict(theta, TestX);
fprintf('Test Accuracy: %f\n', mean(double(p == Testy)) * 100);
```

```
Test Accuracy: 74.294671
```

5. Conclusion

Knowing that we don't notice a considerable difference between the training set accuracy and test set accuracy, it can be deduced that there is no overfitting in our model.

However, the model suffers from underfitting (high-bias + low variance). This problem would be solved by adding polynomal features or using a more complex model such as Decision Tree.