Statistical Machine Learning: SVM [Assignment #01]

by José Ananías Hilario Reyes

Contents

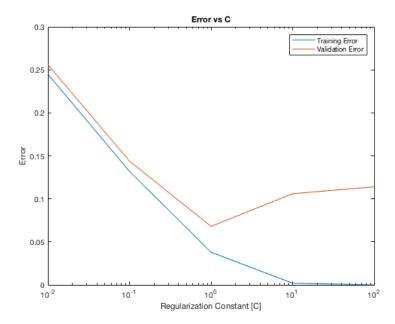
- Task #1
- Task #2
- Task #3

Task #1

```
load('dns_data_kernel.mat');
C = [0.01, 0.1, 1, 10, 100];
s = struct('Parameters',0,'nr_class',0,'totalSV',0,'rho',0,'Label',0,'sv_indices',0,'ProbA',0,'ProbB',0,'nSV',0,'sv coef',0,'SVs',0);
Svm_trn = repmat(s, 1, length(C));
m_trn = length(Trn.Y);
m_val = length(Val.Y);
bias_trn = zeros(size(C));
alpha_trn = zeros(length(C), m_trn);
nSV_trn = zeros(size(C));
scores trn = zeros(length(C), m trn);
predY_trn = zeros(length(C), m_trn);
trnErr trn = zeros(size(C));
scores_val = zeros(length(C), m_val);
predY_val = zeros(length(C), m_val);
trnErr val = zeros(size(C));
t_columns = zeros(length(C), 3);
for i = 1:length(C)
    m = length(Trn.Y);
    Svm_trn(i) = svmtrain(Trn.Y, [[1:m]' Trn.K], ['-s 0 -t 4 -c ' num2str(C(i))]);
    bias_trn(i)
                      = -Svm_trn(i).rho;
                      = zeros(m, 1);
    a(Svm_trn(i).SVs) = Svm_trn(i).sv_coef(:);
    alpha_trn(i,:)
                     = a';
    nSV_trn(i) = Svm_trn(i).totalSV;
    % Trn
    scores_trn(i,:) = (Trn.K*alpha_trn(i,:)' + bias_trn(i))';
    predY_trn(i,:) = 2*double(scores_trn(i,:) >= 0) - 1;
    trnErr_trn(i) = mean(predY_trn(i,:)' ~= Trn.Y(:));
    % Val
    scores_val(i,:) = (Val.K*alpha_trn(i,:)' + bias_trn(i))';
    predY_val(i,:) = 2*double(scores_val(i,:) >= 0) - 1;
    trnErr_val(i) = mean(predY_val(i,:)' ~= Val.Y(:));
    t_columns(i,:) = [trnErr_trn(i) trnErr_val(i) nSV_trn(i)];
t = cell2table(cell(3,length(C)), 'VariableNames', {'C_001', 'C_01', 'C_1', 'C_10', 'C_100'});
t.Properties.RowNames = {'R_trn', 'R_val', 'nSV'};
t.C_001 = t_columns(1,:)';
t.C 01 = t columns(2,:)';
t.C_1 = t_columns(3,:)';
t.C_10 = t_columns(4,:)';
t.C_100 = t_columns(5,:)';
writetable(t, 'errors vs c.xls');
f = figure;
plot(C, trnErr_trn);
hold on;
plot(C, trnErr_val);
title('Error vs C');
xlabel('Regularization Constant [C]');
ylabel('Error');
legend('Training Error', 'Validation Error');
set(gca,'xscale','log');
saveas(f, 'errors_vs_c.png');
```

```
optimization finished, #iter = 500
nu = 1.000000
obj = -9.583942, rho = -0.143882
nSV = 1000, nBSV = 1000
Total nSV = 1000
optimization finished, #iter = 501
nu = 0.856651
obj = -67.442877, rho = -0.491564
nSV = 876, nBSV = 834
Total nSV = 876
*.*
optimization finished, #iter = 1360
nu = 0.424782
obj = -288.313362, rho = -0.124357
nSV = 543, nBSV = 305
Total nSV = 543
optimization finished, #iter = 4689
nu = 0.120007
obj = -628.558518, rho = -0.021492
nSV = 386, nBSV = 14
Total nSV = 386
..*...*
optimization finished, #iter = 5293
nu = 0.012860
obj = -643.027774, rho = -0.019940
nSV = 376, nBSV = 0
Total nSV = 376
t. =
  3×5 table
```

	C_001	C_01	C_1	C_10	C_100
R_trn	0.245	0.132	0.038	0.002	0
R_val	0.256	0.144	0.068	0.106	0.114
nSV	1000	876	543	386	376



Task #2

Since we have a test set that is independent from training set, we can use Hoeffding

```
min = inf;
for i = 1:length(C)
    if min > t_columns(i,2)
        min = t_columns(i,2);
    bestC = C(i);
```

```
alpha = alpha_trn(i,:);
        weights = Svm_trn(i).sv_coef;
        bias = bias_trn(i);
end
bestC
scores tst = (Tst.K*alpha' + bias)';
predY_tst = 2*double(scores_tst >= 0) - 1;
R tst = mean(predY tst' ~= Tst.Y(:))
m = length(Tst.Y);
conf = 0.99;
eps = sqrt((log(2) - log(1 - conf)) / (2 * m))
R true = [R tst - eps, R tst + eps]
% In case we don't have independent test samples and in turn you need to account for infinite number of hypothesis
  - Kernel defines Hilbert space, but this does it affect VC dimension?
용
  - Turns out it does. Growth function approx is bad upper bound.
  - Instead use margin to calculate VC dimension.
  - margin = 2 / norm(weights);
용
  - dvc = 1 + 1/margin^2; % Features generated by similarities between strings (kernel)
  - m = length(Trn.Y);
  - delta = 1 - conf;
  - eps = sqrt(8*(dvc * log(2 * m * exp(1) / dvc) + log(4 / delta)) / m);
```

```
bestC =
    1

R_tst =
    0.0785

eps =
    0.0364

R_true =
    0.0421    0.1149
```

Task #3

```
urls = [{'google.com'}, {'facebook.com'}, {'atqgkfauhuaufm.com'}, {'vopydum.com'}];
kernel = zeros(length(urls));
normalized_kernel = zeros(length(urls));
lambda = 0.4;
q = 3;
for i = 1:length(urls)
   for j = 1:length(urls)
        kernel(i,j) = subseq_kernel(char(urls(i)), char(urls(j)), q, lambda);
   end
end
for i = 1:length(urls)
   for j = 1:length(urls)
        normalized_kernel(i,j) = kernel(i,j)/(sqrt(kernel(i,i))*sqrt(kernel(j,j)));
end
k_table = array2table(kernel, 'VariableNames', {'google_com', 'facebook_com', 'atqgkfauhuaufm_com', 'vopydum_com'});
k_table.Properties.RowNames = {'google_com', 'facebook_com', 'atqgkfauhuaufm_com', 'vopydum_com'}
writetable(k_table, 'subsequence_string_kernel.xls');
nk_table = array2table(normalized_kernel, 'VariableNames', {'google_com', 'facebook_com', 'atqgkfauhuaufm_com', 'vopydum_com'});
nk table.Properties.RowNames = {'google com', 'facebook com', 'atqqkfauhuaufm com', 'vopydum com'}
writetable(nk_table, 'subsequence_string_normalized_kernel.xls');
k_table =
  4×4 table
```

```
google_com facebook_com atqgkfauhuaufm_com vopydum_com
```

Statistical Machine Learning : SVM [Assignment #01]

13	com 2.4428 uaufm_com 1.5209	2.4428 21.115 2.5464	1.5209 2.5464 168.25	1.681 1.8473 2.0194
<pre>vopydum_c nk_table =</pre>	com 1.681	1.8473	2.0194	8.6267
4×4 table				
	google_	com facebook_c	om atqgkfauhuau:	fm_com vopydum_com

0.20351

0.20351

0.053005 atqgkfauhuaufm_com 0.044888 0.042722 0.053005 vopydum_com 0.21911 0.13687

0.21911

0.13687

0.044888

0.042722

Published with MATLAB® R2017b

google_com

facebook_com