BE 521 - Homework 7

Spring 2015

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Objective: Motor Prediction

0 Setup

```
clf; close all; clear; clc;
addpath(genpath('./libsvm-3.20/matlab/'));
me = 'mlautman';
pass_file = 'mla_ieeglogin.bin';

dataset1 = 'I521_A0007_D001';
dataset2 = 'I521_A0007_D002';
[T, session1] = evalc('IEEGSession(dataset1, me, pass_file)');
[T, session2] = evalc('IEEGSession(dataset2, me, pass_file)');
data1 = session1.data;
data2 = session2.data;
sr1 = data1.sampleRate;     % Hz
Nvals1 = data1.channels(1).get_tsdetails.getNumberOfSamples;
Nvals2 = data2.channels(1).get_tsdetails.getNumberOfSamples;
neurons = data1.getvalues(1:Nvals1, 1:40);
positions = data2.getvalues(1:Nvals2, 1:2);
```

1 Motor Predictions

1.1 R size

The correct size of R is $1972x801$ since there are 1972 x-y position values and $40neurons * 20timebins + 1forbias$

```
N = 20; % backwards looking time stamps for each neuron for feature vect
d = 40 * N + 1; % 40 neurons by 20 time steps plus a ones vect for bias
M = 1972; % last timestamp for positions

R = zeros(M, d);
size(R)
```

```
ans =

        1972         801
```

1.2 Generate the R matrix

```
% We create the R matrix
for i=1:M
    e = i + N - 1;
    row = neurons(i:e, :);
    R(i, :) = [1, row(:)'];
end

mean(mean(R))
```

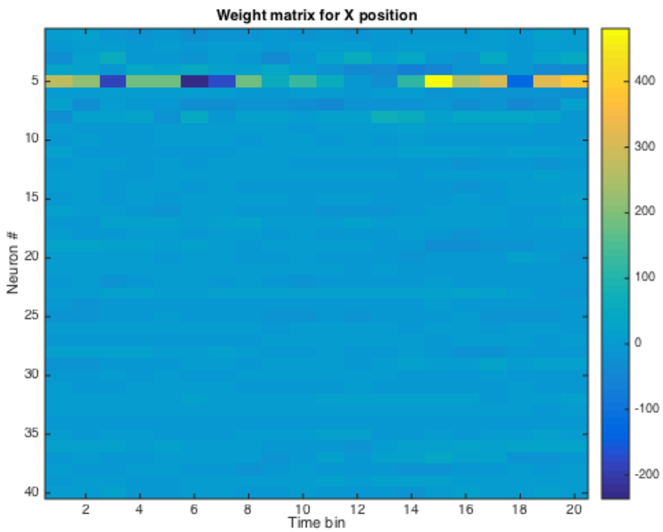
```
ans =

    1.5096
```

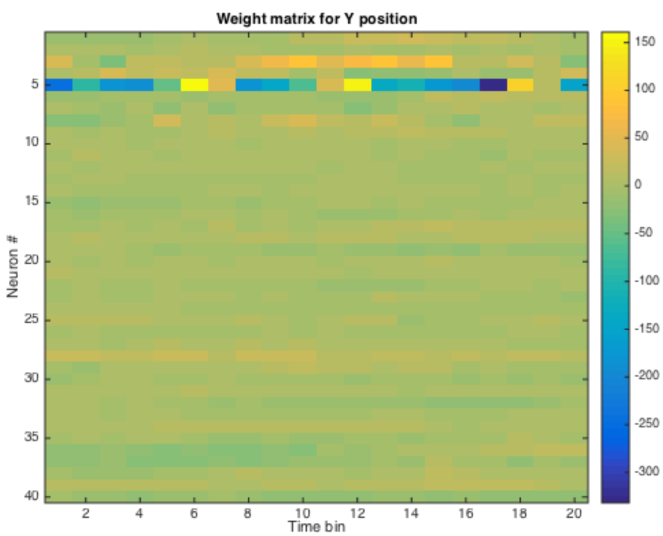
1.3 linear filter

```
% Training data
s = positions;

% Linear regression explicit solution
f = (R' * R) \ (R' * s);
```

1.3.a Show Weights

```
% plotting
f_len = length(f);
f_x = f(2:f_len,1);
f_x2 = reshape(f_x, [20,40])';
figure(1)
imagesc(f_x2)
colorbar()
title('Weight matrix for X position')
xlabel('Time bin')
ylabel('Neuron #')

f_y = f(2:f_len,2);
f_y2 = reshape(f_y, [20,40])';
figure(2)
imagesc(f_y2)
colorbar()
title('Weight matrix for Y position')
xlabel('Time bin')
ylabel('Neuron #')
```





1.3.b Notes on the Weight Vector

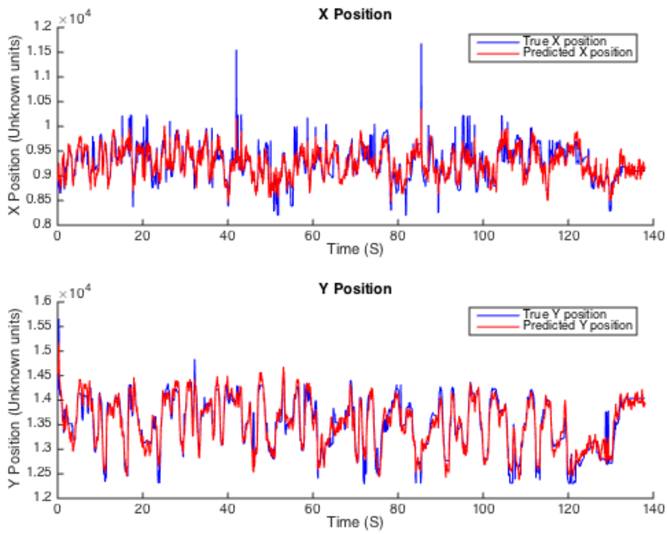
We can clearly see that our linear regression is very heavily dependent on neuron 5 to predict the correct position of the hand. We can also see that the variance in weight is very evenly spread out among the rest of the neurons. This leads us to believe that either neuron 5 by far the most important neuron for predicting the position of the monkey's hand or our linear regression model is overfitting. Overfitting might occur if the true decision function is too complex for us to get a good generalizable prediction function from a simple model such as linear regression.

1.4 Predictions

```
% predictions
u = R * f;
```

1.4.a Plot Predictions

```
% plotting
figure(3)
subplot(2,1,1)
hold on
plot((1:length(s(:,1))) * .070, s(:,1), 'b')
plot((1:length(u(:,1))) * .070, u(:,1), 'r')
title('X Position')
legend('True X position', 'Predicted X position', 'Location', 'best')
xlabel('Time (S)')
ylabel('X Position (Unknown units)')

subplot(2,1,2)
hold on
plot((1:length(s(:,2))) * .070, s(:,2), 'b')
plot((1:length(u(:,2))) * .070, u(:,2), 'r')
title('Y Position')
legend('True Y position', 'Predicted Y position', 'Location', 'best')
xlabel('Time (S)')
ylabel('Y Position (Unknown units)')
```



1.4.b ρx and ρ_y

```
rho_x = corr(s(:,1),u(:,1))
rho_y = corr(s(:,2),u(:,2))
```

```
rho_x =
    0.8389


rho_y =
    0.9556
```

1.5 Animating Motion (commented out for convenience)

```
figure(4)
for i=1:length(s)
   scatter(s(i,1), s(i,2), 'ro')
   hold on
   scatter(u(i,1), u(i,2), 'b.')
   hold off
   xlim([8000 12000])
   ylim([12000 16000])
   pause(.035)
end
```

2 A More Realistic Setting

2.1 Test Set Accuracy

```
N = 20; % backwards looking time stamps for each neuron for feature vect
d = 40 * N + 1; % 40 neurons by 20 time steps plus a ones vect for bias
M = 1972; % last timestamp for positions
tst_len = 400;

% We create the R matrix
R = zeros(M, d);
for i=1:M
    e = i + N - 1;
    row = neurons(i:e, :);
    R(i, :) = [1, row(:)'];
end

% Turn on or off randomization
perm = randperm(size(R,1));
% perm = 1:size(R,1);

Rshuff = R(perm, :);
R_tst = Rshuff(1:tst_len,:);
R_trn = Rshuff(tst_len+1:size(Rshuff,1),:);

% Training data
s = positions(perm, :);
s_tst = s(1:tst_len,:);
s_trn = s(tst_len+1:length(s),:);

% Linear regression explicit solution
f_trn = pinv(R_trn' * R_trn) * (R_trn' * s_trn);

% predictions
u_trn = R_trn * f_trn;
u_tst = R_tst * f_trn;

% Solving for the correlation scores
rho2_x = corr(s_tst(:,1),u_tst(:,1))
rho2_y = corr(s_tst(:,2),u_tst(:,2))
```

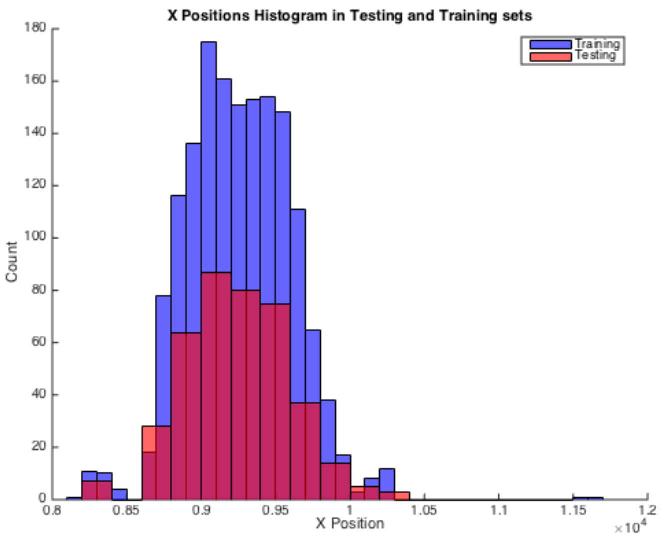
```
rho2_x =

    0.5149


rho2_y =
```

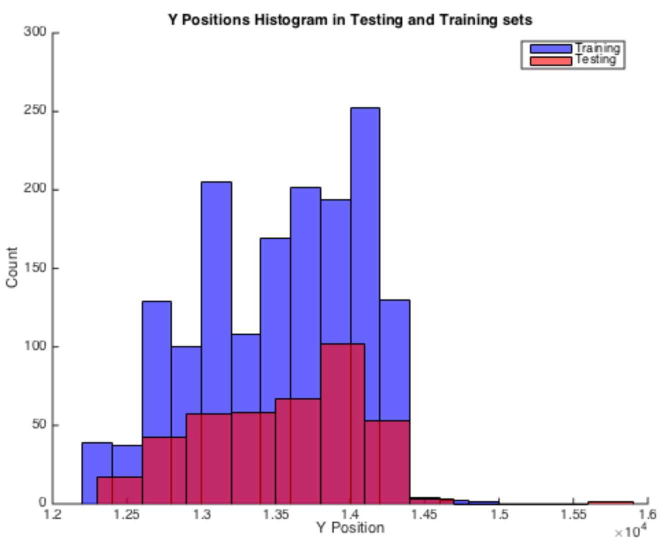
```
0.8396
```

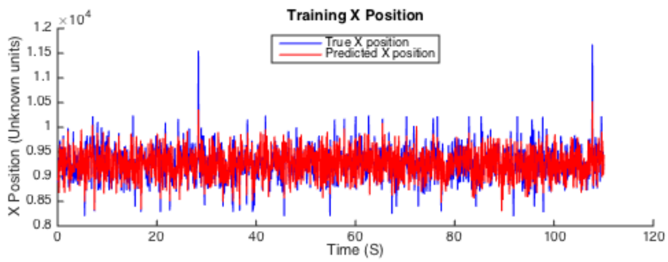
We see a large drop in the ρ_x score while the ρ_y score only drops a little. This is expected since validating your model on the testing set will inevitably give a higher accuracy than validating against an unseen testing set. However, there are still issues with this method. Since we did not randomize the rows for the training and test sets, we could run into issues if moving average position of the hand changes with time. (ie his hand was up for the first half and down for the second) We would see an effect from such a bias in the histograms for position in the testing and training sets. (shown below) Furthermore, by plotting the predicted and true positions for the test data, we can see a clear overfitting problem caused by the high variance of our predictions.

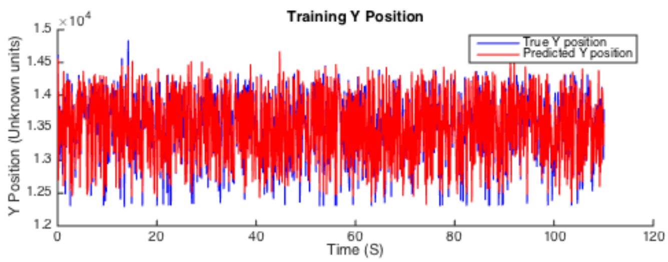
```
figure(5)
hold on
histogram(s_trn(:,1), 'FaceColor', 'b')
histogram(s_tst(:,1), 'FaceColor', 'r')
title('X Positions Histogram in Testing and Training sets')
xlabel('X Position')
ylabel('Count')
legend('Training','Testing','Location', 'best')

figure(6)
hold on
histogram(s_trn(:,2), 'FaceColor', 'b')
histogram(s_tst(:,2), 'FaceColor', 'r')
title('Y Positions Histogram in Testing and Training sets')
xlabel('Y Position')
ylabel('Count')
legend('Training','Testing','Location', 'best')


% plotting
figure(7)
subplot(2,1,1)
hold on
plot((1:length(s_trn(:,1))) * .070, s_trn(:,1), 'b')
plot((1:length(u_trn(:,1))) * .070, u_trn(:,1), 'r')
title('Training X Position')
legend('True X position', 'Predicted X position', 'Location', 'best')
xlabel('Time (S)')
ylabel('X Position (Unknown units)')

subplot(2,1,2)
hold on
plot((1:length(s_trn(:,2))) * .070, s_trn(:,2), 'b')
plot((1:length(u_trn(:,2))) * .070, u_trn(:,2), 'r')
title('Training Y Position')
legend('True Y position', 'Predicted Y position', 'Location', 'best')
xlabel('Time (S)')
ylabel('Y Position (Unknown units)')

figure(8)
subplot(2,1,1)
hold on
plot((1:length(s_tst(:,1))) * .070, s_tst(:,1), 'b')
plot((1:length(u_tst(:,1))) * .070, u_tst(:,1), 'r')
title('Test X Position')
legend('True X position', 'Predicted X position', 'Location', 'best')
xlabel('Time (S)')
ylabel('X Position (Unknown units)')

subplot(2,1,2)
hold on
```

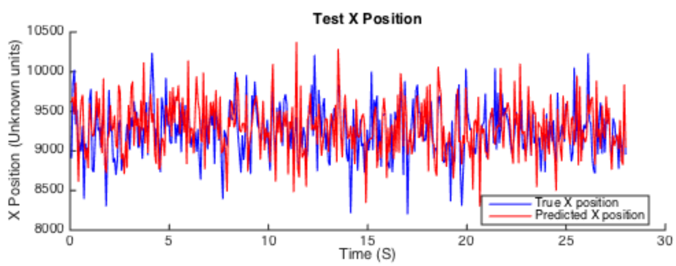
```
plot((1:length(s_tst(:,2))) * .070, s_tst(:,2), 'b')
plot((1:length(u_tst(:,2))) * .070, u_tst(:,2), 'r')
title('Test Y Position')
legend('True Y position', 'Predicted Y position', 'Location', 'best')
xlabel('Time (S)')
ylabel('Y Position (Unknown units)')
```

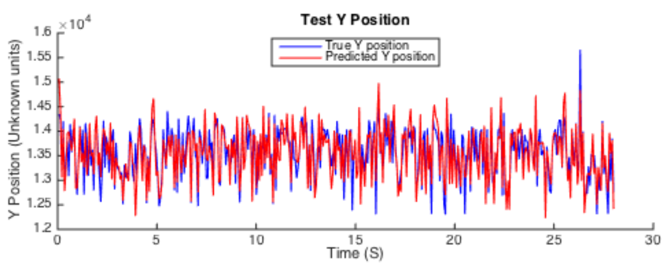






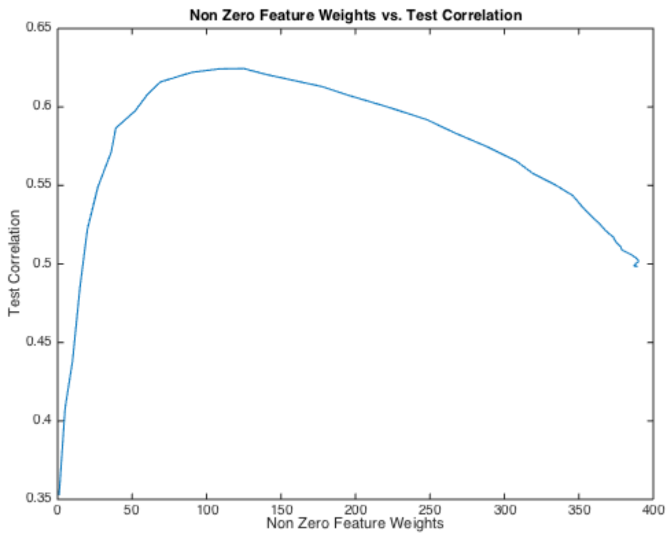






2.2.a Lasso

```
% predicting X positions
[f_lasso1, fit1]  = lasso(R_trn, s_trn(:,1), 'Lambda', 0.015);
non_zeros = sum(f_lasso1>0,1);
u_lasso1 = R_tst * f_lasso1;
rho_x_lasso = corr(s_tst(:,1),u_lasso1);

figure(9)
plot(non_zeros, rho_x_lasso);
title('Non Zero Feature Weights vs. Test Correlation')
xlabel('Non Zero Feature Weights')
ylabel('Test Correlation')
```



2.2.b How it works

The additional L1 penalty for complexity in the model forces the optimization to choose a set of coefficients that represent the ideal function as closely as possible using as few coefficients as possible. By increasing λ, we can increase the penalty for model complexity and reduce the number of non-zero coefficients. By reducing λ we can have the opposite effect.

3 Grand Challenge

I tried two methods for predicting monkey hand positions. The first method was linear regression with the lasso complexity penalty. This method was able to be tuned to yeild correlation scores up to aproximately 0.90 on the test set. The problem with this method is that a linear combination of the input variables is most likely not the ideal representation of the underlying system. In reality, the true function space is much more complex than a linear combination can allow for. For that reason, I applied a Nu-SVC regression with a radial basis function kernel. Since the Matlab builtin SVC implementation does not support regression I used an open source implementation initially written by Jun- Cheng Chen, Kuan-Jen Peng, Chih-Yuan Yang and Chih-Huai Cheng from Department of Computer Science, National Taiwan University. Using this method I was able to tune my implementation to achieve correlation scores upwards of 0.98 during cross validation.

Linear regression

```
load('HW7Data');
n_neur = size(test_count, 2);
N = 5; % backwards looking time stamps for each neuron for feature vect
d = n_neur * N + 1; % 40 neurons by 20 time steps plus a ones vect for bias
Mtrn = size(count,1) - N + 1;
R_trn = zeros(Mtrn, d);

Mtst = size(test_count,1) - N + 1; % last timestamp for positions
R_tst = zeros(Mtst, d);

scale = 1; % Scaling discretization bins
rand_test_set = false;
```

```
% We create the R trn matrix

for i=1:Mtrn
    e = i + N - 1;
    row = count(i:e, :);
    R_trn(i, :) = [1, row(:)'];
end

% We create the R tst matrix
for i=1:Mtst
    e = i + N - 1;
    row = test_count(i:e, :);
    R_tst(i, :) = [1, row(:)'];
end

% Randomize test set (or not)
if rand_test_set
    perm = randperm(size(R,1));
else
    perm = 1:size(R_trn,1);
end

% training set
R_trn = R_trn(perm, :);

% Training data NOT discretized
s_trn = angles(perm, :);

% Linear regression explicit solution
f_trn = pinv(R_trn' * R_trn) * (R_trn' * s_trn);

% predictions
u_tst = R_tst * f_trn;
u_trn = R_trn * f_trn;

% Solving for the correlation scores
rho2_x = corr(s_trn(:,1),u_trn(:,1));
rho2_y = corr(s_trn(:,2),u_trn(:,2));
rho2_z = corr(s_trn(:,3),u_trn(:,3));
c = corr(s_trn, u_trn);
```

Find best lambda x using CV

```
[Bx2_n,FitInfo1] = lasso(R_trn(:,2:size(R_trn,2)),s_trn(:,1),'NumLambda',5, 'CV', 5);
lassoPlot(Bx2_n,FitInfo1,'PlotType','CV');

%% Build model for X
[Bx,FitInfo_x] = lasso(R_trn(:,2:size(R_trn,2)), s_trn(:,1),'Lambda', 0.015);
Bo = FitInfo_x.Intercept;
Bx = [Bo;Bx];
predX_trn = R_trn * Bx;
predX = R_tst * Bx;
% rho_x = corr(s_tst(:,1), predX)

%% Find best lambda y through CV
[By2_n,FitInfo1] = lasso(R_trn(:,2:size(R_trn,2)),s_trn(:,2),'NumLambda', 10, 'CV', 10);
lassoPlot(By2_n,FitInfo1,'PlotType','CV');

%% Build model for Y
[By,FitInfo_y] = lasso(R_trn(:, 2:size(R_trn,2)), s_trn(:,2),'Lambda', 0.015);
Bo = FitInfo_y.Intercept;
```

```
By = [Bo; By];
predY_trn = R_trn * By;
predY = R_tst * By;
% rho_y = corr(s_tst(:,2), predY)

%% Find best lambda z through CV
[By2_n,FitInfo1] = lasso(R_trn(:,2:size(R_trn,2)),s_trn(:,2),'NumLambda',10, 'CV', 10);
lassoPlot(By2_n,FitInfo1,'PlotType','CV');

%% Build model for Z
[Bz,FitInfo_z] = lasso(R_trn(:,2:size(R_trn,2)), s_trn(:,3),'Lambda',0.015);
Bo = FitInfo_z.Intercept; Bz = [Bo ;Bz];
predZ_trn = R_trn * Bz;
predZ = R_tst * Bz;
% rho_z = corr(s_tst(:,3), predZ)
```

```
%% Animate results

figure(10)
subplot(1,3,1);
hold on
axis([...
    min(s_trn(:,1)) max(s_trn(:,1)) ...
    min(s_trn(:,2)) max(s_trn(:,2)) ...
    min(s_trn(:,3)) max(s_trn(:,3)) ...
])
subplot(1,3,2);
hold on
axis([...
    min(predX_trn) max(predX_trn) ...
    min(predY_trn) max(predY_trn) ...
    min(predZ_trn) max(predZ_trn) ...
])
subplot(1,3,3);
hold on
axis([...
    min(predX) max(predX) ...
    min(predY) max(predY) ...
    min(predZ) max(predZ) ...
])
for i=1:min(length(predX), length(predX_trn))
    subplot(1,3,1);
    scatter3(s_trn(i,1), s_trn(i,2), s_trn(i,3))

    subplot(1,3,2);
    scatter3(predX_trn(i), predY_trn(i), predZ_trn(i))

    subplot(1,3,3);
    scatter3(predX(i), predY(i), predZ(i))
    pause(.01)
end
```

SVC

```
load('HW7Data');
n_neur = size(test_count, 2);
N = 20; % backwards looking time stamps for each neuron for feature vect
d = n_neur * N + 1; % 40 neurons by 20 time steps plus a ones vect for bias
Mtrn = size(count,1) - N + 1;
```

```
R_trn = zeros(Mtrn, d);

Mtst = size(test_count,1) ; % last timestamp for positions
R_tst = zeros(Mtst, d);

scale = 1; % Scaling discretization bins
rand_test_set = false;
% We create the R trn matrix


for i=1:Mtrn
    e = i + N - 1;
    row = count(i:e, :);
    R_trn(i, :) = [1, row(:)'];
end


% We create the R tst matrix
for i=1:Mtst
    e = i + N - 1;
    if e > Mtst
        e = Mtst;
    end
    row = test_count(i:e, :);
    r_h = size(row, 1);
    if r_h < N
        delta = N - r_h;
        for j = 1:delta
            row = [row; row(r_h,:)];
        end
    end
    R_tst(i, :) = [1, row(:)'];
end

% Randomize test set (or not)
if rand_test_set
    perm = randperm(size(R,1));
else
    perm = 1:size(R_trn,1);
end

% training set
R_trn = R_trn(perm, :);

% Training data NOT discretized
s_trn = angles(perm, :);
garbage_pred = ones(size(R_tst,1),1);
```

Useful functions for tuning parameters

```
svmX = svmtrain(round(s_trn(:,1)),R_trn, '-s 4 -t 2 -d 10 -c 100.5 -v 10 -q');
svmY = svmtrain(round(s_trn(:,2)),R_trn, '-s 4 -t 2 -d 10 -c 100.5 -v 10 -q');
svmZ = svmtrain(round(s_trn(:,3)),R_trn, '-s 4 -t 2 -d 10 -c 100.5 -v 10 -q');
```

```
Cross Validation Squared correlation coefficient = 0.975629
Cross Validation Mean squared error = 1.24202
Cross Validation Squared correlation coefficient = 0.989913
Cross Validation Mean squared error = 0.76548
Cross Validation Squared correlation coefficient = 0.987479
```

Train SVR X

```
svmX = svmtrain(round(s_trn(:,1)),R_trn, '-s 4 -t 2 -c 100.5 -q');
% make predictions on resulting set
predX_trn = svmpredict(s_trn(:,1), R_trn, svmX, '-q');
predX = svmpredict(garbage_pred, R_tst, svmX, '-q');
% svr_corr_X = corr(predX, s_tst(:,1))
% Train SVR Y
svmY = svmtrain(round(s_trn(:,2)),R_trn, '-s 4 -t 2 -c 100.5 -q');
% make predictions on resulting set
predY_trn = svmpredict(s_trn(:,2), R_trn, svmY, '-q');
predY = svmpredict(garbage_pred, R_tst, svmY, '-q');
% svr_corr_Y = corr(predY, s_tst(:,2))
% Train SVR Z
svmZ = svmtrain(round(s_trn(:,3)),R_trn, '-s 4 -t 2 -c 100.5 -q');
% make predictions on resulting set
predZ_trn = svmpredict(s_trn(:,3), R_trn, svmZ, '-q');
predZ = svmpredict(garbage_pred, R_tst, svmZ, '-q');
% svr_corr_Z = corr(predZ, s_tst(:,3))


%% Animate results
subplot(1,3,1);
hold on
axis([...
    min(s_trn(:,1)) max(s_trn(:,1)) ...
    min(s_trn(:,2)) max(s_trn(:,2)) ...
    min(s_trn(:,3)) max(s_trn(:,3)) ...
])
subplot(1,3,2);
hold on
axis([...
    min(predX_trn) max(predX_trn) ...
    min(predY_trn) max(predY_trn) ...
    min(predZ_trn) max(predZ_trn) ...
])
subplot(1,3,3);
hold on
axis([...
    min(predX) max(predX) ...
    min(predY) max(predY) ...
    min(predZ) max(predZ) ...
])
for i=1:min(length(predX), length(predX_trn))
    subplot(1,3,1);
    scatter3(s_trn(i,1), s_trn(i,2), s_trn(i,3))

    subplot(1,3,2);
    scatter3(predX_trn(i), predY_trn(i), predZ_trn(i))

    subplot(1,3,3);
    scatter3(predX(i), predY(i), predZ(i))
    pause(.01)
end

clf; clear all; close all;
```