#### Contents

- Liam Jackson HW1 BE700 ML
- Question 1
- Part 1
- Importing / Sorting Data
- Bessel Approx
- Polynomial Approximations
- Calculate Residuals
- Plotting LS Poly fits
- Part 2
- 20 rounds of (k = 5) Cross Validation
- Plotting PE values for each CV Round
- Part 3
- Part /

### Liam Jackson HW1 BE700 ML

#### Question 1

```
%{
Ok, honestly this code is overcomplicated. I had to rewrite it 5
times because MATLAB didn't save my changes a couple days in a row. So
in the interest of time, I tried writing functions to accomplish the
analysis for question 1 that I could then recycle for question 2. It's
ugly, I switch data structure types all over the place. But hopefully I
approached the correct answers in the end.
%}
```

#### Part 1

```
close all, clear all, clc;
warning('off','MATLAB:polyfit:RepeatedPointsOrRescale')
warning('off','MATLAB:nearlySingularMatrix')
```

# Importing / Sorting Data

```
[x1, x2, y] = textread('besseldata.txt', ' %f%f%f', 'headerlines', 1);
r = sqrt(x1.^2 + x2.^2);
r_norm = normalize(r);

data_arr = sortrows([x1, x2, r, r_norm, y], 3);
data_table = array2table(data_arr,...
    'VariableNames', {'x1','x2','r','r_norm','y'});
```

### **Bessel Approx**

```
k_bes = 1;
bes_approx = besselj(0, k_bes*data_table.r);

fig1 = figure(1);
dot_sz = 0.2;
line_w = 2.5;
scatter(data_table.r, data_table.y, dot_sz, '.');
hold on;
plot(data_table.r, bes_approx, 'LineWidth', line_w);
hold off;
title({'Timpanic Memb Displacement', 'approximated by Bessel Fxn (J_0)'});
xlabel('r');
ylabel('Intensity');
legend({'Real Data', 'J_0'});
```

#### **Polynomial Approximations**

```
max_poly_order = 14;
model_data = poly_model_vals(data_table, max_poly_order);
ry_polyvals_table = model_data.ry_polyvals_table;
```

### Calculate Residuals

```
residuals_table = res_table(ry_polyvals_table)
```

## Plotting LS Poly fits

```
data_labels = ry_polyvals_table.Properties.VariableNames;

fig2 = figure(2);
    sgtitle({\text{"Membrane Displacement Data', 'vs. OLS Polynomial Fits'});
    number_of_plots = max_poly_order;

for plot_id = 1:number_of_plots
    subplot(number_of_plots / 2, 2, plot_id);
    scatter(ry_polyvals_table.r, ry_polyvals_table.y, dot_sz, '.');
    hold on;
    plot(ry_polyvals_table.r, ry_polyvals_table.(string(data_labels(plot_id + 2))), 'LineWidth', line_w)
    hold off;
    xlabel('r');
    ylabel('Displacement');
    legend({'y real', string(data_labels(plot_id + 2))});
end
```

#### Part 2

### 20 rounds of (k = 5) Cross Validation

```
cv_rounds = 20;
k_{cv} = 5;
PE_arr = zeros([cv_rounds, max_poly_order]);
MSE_arr = zeros([max_poly_order, k_cv, cv_rounds]);
all_cv_poly_coeffs = zeros([max_poly_order + 1, max_poly_order, k_cv, cv_rounds]);
for cv round = 1:cv rounds
    binned_data_struct = bin_this_data(data_arr, k_cv);
    binned_data_cell = binned_data_struct.cell;
    bin indices = 1:k cv;
    for test bin = 1:k cv
        train_bins = bin_indices(1:end ~= test_bin);
        train_data_cell = binned_data_cell(train_bins);
        train_data_arr = sortrows(cat(1, train_data_cell{:}), 3);
        test_data_arr = sortrows(cell2mat(binned_data_cell(test_bin)), 3);
        train_data_table = array2table(train_data_arr,.
            'VariableNames', {'x1','x2','r','r_norm','y'});
        test_data_table = array2table(test_data_arr,..
            'VariableNames', {'x1', 'x2', 'r', 'r_norm', 'y'});
        model_train_struct = poly_model_vals(train_data_table, max_poly_order);
        cv_ry_polyvals_table = model_train_struct.ry_polyvals_table;
        cv_coeffs_arr = model_train_struct.coeffs_arr;
        all_cv_poly_coeffs(:, :, test_bin, cv_round) = cv_coeffs_arr;
        poly_zeros_pad = zeros([size(test_data_arr, 1), max_poly_order]);
        model_poly_vals = [test_data_arr, poly_zeros_pad];
        for poly_ord_ind = 1:max_poly_order
            n_coeffs = poly_ord_ind + 1;
            temp_coeffs = cv_coeffs_arr(1:n_coeffs, poly_ord_ind);
            model_poly_vals(:, poly_ord_ind + 5) = polyval(temp_coeffs, model_poly_vals(:, 4));
        temp\_ry\_polyvals\_table = array2table([model\_poly\_vals(:, 3), model\_poly\_vals(:, 5), model\_poly\_vals(:, 6:end)], \dots \\
             'VariableNames', cv_ry_polyvals_table.Properties.VariableNames);
        temp_residuals_table = res_table(temp_ry_polyvals_table);
        MSE_arr(:, test_bin, cv_round) = temp_residuals_table.MSE;
    PE_col = mean(squeeze(MSE_arr(:, :, cv_round)), 2);
    PE_arr(cv_round, :) = PE_col';
PE_var_labels = cv_ry_polyvals_table.Properties.VariableNames;
PE_var_labels = PE_var_labels(3:end);
PE_row_nums = 1:cv_rounds;
PE_row_labels = "rnd" + PE_row_nums;
PE_table = array2table(PE_arr,..
    'VariableNames', PE_var_labels,...
    'RowNames', PE_row_labels)
```

# Plotting PE values for each CV Round

```
fig3 = figure(3);
plot(PE_table{:,:}.');
title('PE values for 20 rounds of (k=5)-CV');
xlabel('Polynomial Model Order');
ylabel('Predictive Error');
legend(PE_table.Properties.RowNames, 'location', 'eastoutside');
```

```
%{
A polynomial OLS-fit of order 10 seems to have the best compromise of accuracy and economy of variables. A substantial reduction in error occurs from order-9 to order-10, with no substantial decrease with additional (11, 12, 13, 14) order terms.

%}
Char({'A polynomial OLS-fit of order 10 seems to have the best',...
'compromise of accuracy and economy of variables. A substantial',...
'reduction in error occurs from order-9 to order-10, with no',...
'substantial decrease with additional (11, 12, 13, 14) order terms.'})
```

### Part 4

```
data_table_opt = data_table;
x1 = data_table_opt.x1;
x2 = data_table_opt.x2;
r = data_table_opt.r;
y = data_table_opt.y;
opt_ord = 10;
beta_deg10 = ols_coeffs_data(r, y, opt_ord).beta;
beta_ud = flipud(beta_deg10);
[X1, X2] = meshgrid(-20:.2:20);
Y_opt = polyval(beta_ud, sqrt(X1.^2 + X2.^2));
\mbox{\% I'm} removing the "wall" of the surf that approaches inf so the figure is easier to see
Y_opt(1:75, 1:75) = NaN;
J0 = besselj(k\_bes, sqrt(X1.^2 + X2.^2));
fig4 = figure(4);
scatter3(x1, x2, y, 15, '.');
hold on;
opt = surf(X1, X2, Y_opt, 'EdgeColor', 'none');
colorbar
colormap(spring)
caxis([-1 1.5])
hold off;
title({'Polynomial (p=10) Model', 'vs. Real Displacement Data'});
xlabel('x1');
ylabel('x2');
zlabel('Displacement');
zlim([-.8, 1.5]);
fig5 = figure(5);
scatter3(x1, x2, y, 15, '.');
hold on;
surf(X1, X2, J0, 'EdgeColor', 'none');
title({'Bessel Fxn J_0', 'vs. Real Displacement Data'});
xlabel('x1');
ylabel('x2');
zlabel('Displacement');
```

residuals\_table =

14×3 table

Residual Sum	MSE			
	<del></del>			
425.17	0.085034			
412.42	0.082483			
369.4	0.073879			
268.61	0.053722			
168.66	0.033733			
164.73	0.032945			
105.34	0.021069			
47.384	0.0094768			
43.922	0.0087844			
28.828	0.0057656			
28.809	0.0057619			
27.775	0.0055551			
27.718	0.0055437			
27.697	0.0055394			
	425.17 412.42 369.4 268.61 168.66 164.73 105.34 47.384 43.922 28.828 28.809 27.775 27.718			

PE\_table =

20×14 table

	p=1	p=2	p=3	p=4	p=5	p=6	p=7	p=8	p=9	p=10	p=11	p=12	р
										<del></del>			
rnd1	0.085065	0.082577	0.074357	0.054969	0.034563	0.033381	0.028947	0.0098362	0.01501	0.006425	0.0076866	0.0065539	

rnd2	0.085108	0.082569	0.074034	0.054003	0.034081	0.033134	0.02323	0.0098505	0.010745	0.0059828	0.0059781	0.0058127	0.0
rnd3	0.085127	0.082699	0.074457	0.054531	0.034317	0.03327	0.023955	0.0097887	0.010689	0.005926	0.0060101	0.0057978	0.0
rnd4	0.085134	0.082691	0.074525	0.054411	0.034338	0.033372	0.024019	0.010069	0.011438	0.0059981	0.0060173	0.0057865	0.0
rnd5	0.085151	0.082621	0.074146	0.054444	0.0343	0.033315	0.023954	0.0096891	0.010574	0.0059484	0.0061251	0.0057965	0.0
rnd6	0.085094	0.082574	0.07405	0.053968	0.034146	0.033214	0.024222	0.0098553	0.01086	0.0059703	0.0060338	0.0057492	0.0
rnd7	0.085065	0.082532	0.074127	0.054713	0.034718	0.033477	0.023915	0.010057	0.011002	0.0060462	0.0060709	0.0058321	0.0
rnd8	0.085165	0.08267	0.074137	0.054209	0.034092	0.033178	0.023494	0.0098238	0.010947	0.0059741	0.0060757	0.0058071	0.0
rnd9	0.085079	0.082579	0.074176	0.054251	0.034168	0.033249	0.023309	0.0098935	0.01112	0.0059834	0.0060462	0.0058289	0.0
rnd10	0.085113	0.08259	0.074421	0.05493	0.034551	0.03328	0.028994	0.0099285	0.015095	0.0063835	0.0071666	0.0062601	0.0
rnd11	0.085114	0.082641	0.074214	0.054661	0.034494	0.033468	0.030297	0.0097173	0.013768	0.0063214	0.0076979	0.0062456	0.0
rnd12	0.08514	0.082657	0.074335	0.054417	0.034287	0.03327	0.023885	0.0097416	0.010559	0.0059619	0.0060269	0.0057999	0.0
rnd13	0.085102	0.082591	0.074369	0.055	0.034708	0.033352	0.028202	0.010054	0.015138	0.006425	0.0074468	0.0063672	0.0
rnd14	0.085142	0.082635	0.074044	0.054013	0.034197	0.033606	0.023737	0.0099251	0.011152	0.0059168	0.0060737	0.0057321	0.0
rnd15	0.085182	0.082649	0.074122	0.054086	0.034096	0.033247	0.024024	0.0097745	0.01078	0.0059868	0.006066	0.0058092	0.0
rnd16	0.085159	0.082704	0.075006	0.055209	0.034545	0.033553	0.030413	0.0098368	0.014896	0.0065433	0.0082615	0.0060834	0.0
rnd17	0.08509	0.082586	0.074257	0.05483	0.034678	0.033489	0.029756	0.009869	0.014629	0.0062817	0.0070891	0.006335	0.0
rnd18	0.085052	0.082557	0.074247	0.05421	0.033971	0.033215	0.02378	0.0098048	0.011342	0.0059427	0.0060055	0.0058236	0.
rnd19	0.085087	0.082559	0.07409	0.054043	0.034102	0.033235	0.023818	0.0097457	0.010996	0.0059363	0.0060449	0.0057481	0.0
rnd20	0.085162	0.082648	0.074607	0.056379	0.035793	0.034067	0.039151	0.0099011	0.018097	0.0064823	0.0079107	0.0066796	0.0

ans

#### 4×66 char array

- 'A polynomial OLS-fit of order 10 seems to have the best
- 'compromise of accuracy and economy of variables. A substantial
- 'reduction in error occurs from order-9 to order-10, with no 'substantial decrease with additional (11, 12, 13, 14) order terms.'









