# ECE 313 Final Project Report

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#### Task 0:

```
clear all;
      clc;
      load 1_a41178.mat;
      patient1_data = floor(all_data);
       patient1_labels = all_labels;
      training1 = patient1_data(:,1:(2*length(patient1_data)/3));
      testing1 = patient1_data(:,(2*length(patient1_data)/3):length(
      patient1_data));
      label_training1 = patient1_labels(1:(2*length(patient1_labels)
      label\_testing1 = patient1\_labels((2*length(patient1\_labels)/3):
      length(patient1_labels));
      load 2_a42126.mat;
      patient2_data = floor(all_data);
13
       patient2_labels = all_labels;
      training2 = patient2_data(:,1:floor(2*length(patient2_data)/3))
      testing2 = patient2_data(:, floor(2*length(patient2_data)/3):
      length(patient2_data));
      label_training2 = patient2_labels(1:floor(2*length(
      patient2_labels)/3));
      label\_testing 2\ =\ patient 2\_labels \, (\,floor\, (2*length\, (\,patient 2\_labels\,
      )/3):length(patient2_labels));
19
      load 3_a40076.mat;
      patient3_data = floor(all_data);
21
      patient3_labels = all_labels;
      training 3 = patient 3\_data (:, 1: (2*length (patient 3\_data)/3));
23
      testing3 = patient3_data(:,(2*length(patient3_data)/3):length(
      patient3_data));
      label_training3 = patient3_labels(1:(2*length(patient3_labels)
25
       /3));
      label_testing3 = patient3_labels((2*length(patient3_labels)/3):
      length(patient3_labels));
27
      load 4_a40050.mat;
      patient4_data = floor(all_data);
29
      patient4_labels = all_labels;
      training4 = patient4_data(:,1:floor(2*length(patient4_data)/3))
```

```
testing4 = patient4_data(:, floor(2*length(patient4_data)/3):
      length(patient4_data));
      label_training4 = patient4_labels(1:floor(2*length(
33
      patient4_labels)/3));
      label_testing4 = patient4_labels(floor(2*length(patient4_labels
      )/3):length(patient4_labels));
      load 5_a41287.mat;
      patient5_data = floor(all_data);
      patient5_labels = all_labels;
      training5 = patient5_data(:,1:(2*length(patient5_data)/3));
39
      testing5 = patient5_data(:,(2*length(patient5_data)/3):length(
      patient5_data));
      label_training5 = patient5_labels(1:(2*length(patient5_labels)
41
      /3));
      label\_testing5 = patient5\_labels((2*length(patient5\_labels)/3):
      length(patient5_labels));
43
      load 6_a41846.mat;
      patient6_data = floor(all_data);
45
      patient6_labels = all_labels;
      training6 = patient6_data(:,1:floor(2*length(patient6_data)/3))
47
      testing6 = patient6_data(:, floor(2*length(patient6_data)/3):
      length(patient6_data));
      label_training6 = patient6_labels(1:floor(2*length()))
      patient6_labels)/3));
      label_testing6 = patient6_labels(floor(2*length(patient6_labels
      )/3):length(patient6_labels));
      load 7_a41846.mat;
      patient7_data = floor(all_data);
53
      patient7_labels = all_labels;
      training7 = patient7_data(:,1:floor(2*length(patient7_data)/3))
      testing7 = patient7_data(:, floor(2*length(patient7_data)/3):
      length(patient7_data));
      label_training7 = patient7_labels(1:floor(2*length(
      patient7_labels)/3));
      label_testing7 = patient7_labels(floor(2*length(patient7_labels
      )/3):length(patient7_labels));
59
      load 8_a42008.mat;
      patient8_data = floor(all_data);
61
      patient8_labels = all_labels;
      training8 = patient8_data(:,1:(2*length(patient8_data)/3));
      testing8 = patient8_data(:,(2*length(patient8_data)/3):length(
      patient8_data));
      label_training8 = patient8_labels(1:(2*length(patient8_labels)
65
      /3));
      label\_testing8 = patient8\_labels((2*length(patient8\_labels)/3):
      length(patient8_labels));
67
      load 9_a41846.mat;
      patient9_data = floor(all_data);
      patient9_labels = all_labels;
      training9 = patient9_data(:,1:floor(2*length(patient9_data)/3))
```

```
;
testing9 = patient9_data(:,floor(2*length(patient9_data)/3):
length(patient9_data));
label_training9 = patient9_labels(1:floor(2*length(
patient9_labels)/3));
label_testing9 = patient9_labels(floor(2*length(patient9_labels)/3):length(patient9_labels));
```

For task 0 we took the raw patient and gold data and partitioned it into testing and training segments.

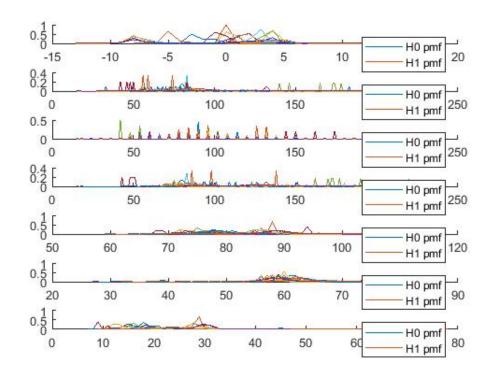
#### Task 1.1:

```
HT_table_array_pat_1 = Get_HT_table(1, training1, label_training1);
HT_table_array_pat_2 = Get_HT_table(2, training2, label_training2);
HT_table_array_pat_3 = Get_HT_table(3, training3, label_training3);
HT_table_array_pat_4 = Get_HT_table(4, training4, label_training4);
HT_table_array_pat_5 = Get_HT_table(5, training5, label_training5);
HT_table_array_pat_6 = Get_HT_table(6, training6, label_training6);
HT_table_array_pat_7 = Get_HT_table(7, training7, label_training7);
HT_table_array_pat_8 = Get_HT_table(8, training8, label_training8);
HT_table_array_pat_9 = Get_HT_table(9, training9, label_training9);

HT_table_array_pat_3, HT_table_array_pat_4,
HT_table_array_pat_5, HT_table_array_pat_6,
HT_table_array_pat_7, HT_table_array_pat_8,
HT_table_array_pat_9);
```

```
function HT_table_array_pat = Get_HT_table(patient_index,
      patient_data, patient_labels)
3 % Prior probablities, alarms/total
  P_H1 = sum(patient_labels)/length(patient_labels);
_{5}|P_{H0} = 1 - P_{H1};
7 HT_table_array_pat = cell(1, 7);
9 | % name = strcat('Patient_', int2str(patient_index), '_Features');
  % figure ('name', name, 'unit', 'normalized', 'outerposition', [.1
      .1 .8 .8]);
  for i = 1:7
    [feature_mat, x_mat] = Get_Feat_Mat(patient_data(i:i, :),
13
      patient_labels);
    ML\_vector = zeros(1, length(feature\_mat(1:1, :)));
    MAP\_vector = zeros(1, length(feature\_mat(1:1, :)));
17
    for k = 1: length (feature_mat(1:1, :))
      P_H1_i = feature_mat(1, k);
19
      P_H0_i = feature_mat(2, k);
       if (P_H1_i) >= P_H0_i
21
        \% if H1_pmf >= H0_pmf
```

```
ML_{vector}(k) = 1;
23
       end
       if (P_H1*P_H1_i) = P_H0*P_H0_i)
25
         \% \text{ if } H1_pmf*P(H1) >= H0_pmf*P(H0)
         MAP_vector(k) = 1;
27
       end
    end
29
     HT_{table} = cat(1, x_{mat}, feature_{mat}(1:1, :), feature_{mat}(2:2, :)
31
    , ML_vector, MAP_vector);
HT_table = rot90 (HT_table, -1);
    HT_table = fliplr(HT_table);
    % Have to flip the table so that it matches with the given format
    HT_table_array_pat {1, i} = num2cell(HT_table);
35
     subplot(7, 1, i);
     hold on;
37
     plot(x_mat, feature_mat(1:1, :));
     plot (x_mat, feature_mat(2:2, :));
39
     legend('H0 pmf', 'H1 pmf');
     hold off;
41
  end
```



Above is our data after we created the probability matricies. **Task 1.2**:

```
Error_table_arrar_pat_1 = Get_Error_table(HT_table_array_pat_1,
  testing1, label_testing1);
Error_table_arrar_pat_2 = Get_Error_table(HT_table_array_pat_2,
  testing2, label_testing2);
Error\_table\_arrar\_pat\_3 = Get\_Error\_table(HT\_table\_array\_pat\_3,
 testing3, label_testing3);
Error_table_arrar_pat_4 = Get_Error_table(HT_table_array_pat_4,
 testing4 , label_testing4);
Error_table_arrar_pat_5 = Get_Error_table(HT_table_array_pat_5,
  testing5, label_testing5);
Error_table_arrar_pat_6 = Get_Error_table(HT_table_array_pat_6,
  testing6, label_testing6);
Error_table_arrar_pat_7 = Get_Error_table(HT_table_array_pat_7,
  testing7, label_testing7);
Error_table_arrar_pat_8 = Get_Error_table(HT_table_array_pat_8,
  testing8, label_testing8);
Error_table_arrar_pat_9 = Get_Error_table(HT_table_array_pat_9,
  testing9, label_testing9);
Error_table_arrar = cat(1, Error_table_arrar_pat_1, Error_table_arrar_pat_2, Error_table_arrar_pat_3,
  Error_table_arrar_pat_4, Error_table_arrar_pat_5,
   Error\_table\_arrar\_pat\_6 \ , \ Error\_table\_arrar\_pat\_7 \ , \\
  Error_table_arrar_pat_8 , Error_table_arrar_pat_9 );
```

```
function Error_table_pat = Get_Error_table(HT_table_array_pat,
       patient_data, patient_labels)
       Error_table_pat = cell(1, 7);
       for i = 1:7
           % Get feature from the parameter
         feature_table = HT_table_array_pat{1, i};
           feature_data = patient_data(i:i, :);
           % Offset the data
         feature_data_off = feature_data - min(feature_data) + 1;
           % Get the vectors and organize
         ML_vector = cell2mat(feature_table(:, 4:4));
         MAP_vector = cell2mat(feature_table(:, 5:5));
14
         ML_{\text{-}}vector = rot90 (ML_{\text{-}}vector);
         MAP\_vector = rot90 (MAP\_vector);
           ML_vector_off = zeros(1, max(feature_data_off));
         MAP_vector_off = zeros(1, max(feature_data_off));
18
         for k = 1:length (ML_vector)
           ML_vector_off(k) = ML_vector(k);
20
           MAP\_vector\_off(k) = MAP\_vector(k);
22
           % Alarms generated by vectors
         ML_vector_alarm = zeros(1, length(patient_labels));
MAP_vector_alarm = zeros(1, length(patient_labels));
         for k = 1:length(feature_data_off)
```

```
j = feature_data_off(k);
28
           if (ML\_vector\_off(j) == 1)
             ML_{vector\_alarm(k)} = 1;
           if (MAP_vector_off(j) == 1)
32
             MAP_{\text{-}}vector_{\text{-}}alarm(k) = 1;
          end
          end
          % count the errors
        FA_count_ML = 0;
38
        MD_count_ML = 0;
        FA_count_MAP = 0;
40
        MD_count_MAP = 0;
        for k = 1:length(patient_data)
           if (patient_labels(k) == 1)
             if (ML_vector_alarm(k) == 0)
               MD_count_ML = MD_count_ML + 1;
             end
             if (MAP_vector_alarm(k) == 0)
               MD_count_MAP = MD_count_MAP + 1;
             end
           else
             if (ML_vector_alarm(k) == 1)
               FA_count_ML = FA_count_ML + 1;
             if (MAP_vector_alarm(k) == 1)
               FA_count_MAP = FA_count_MAP + 1;
             end
          end
          end
          % Contruct the error table
60
           Error_table = zeros(2, 3);
        number_alarm = sum(patient_labels);
         total_alarm = length(patient_labels);
         64
         Error\_table(1, 2) = MD\_count\_ML/number\_alarm;
        \label{eq:energy_energy} \text{Error\_table}\left(1\,,\ 3\right) \,=\, \left(\text{FA\_count\_ML} \,+\, \text{MD\_count\_ML}\right)/\,\text{total\_alarm}\,;
66
         Error_table(2, 1) = FA_count_MAP/(total_alarm - number_alarm)
         68
        Error_table(2, 3) = (FA_count_MAP + MD_count_MAP)/total_alarm
        Error_table_pat {1, i} = num2cell(Error_table);
70
      end
```

Above you can see we created the Ml and map rule errors for the matrix.

#### Task 2.1:

```
patient_data_array = cell(1, 9);
patient_data_array{1, 1} = num2cell(patient1_data);
patient_data_array{1, 2} = num2cell(patient2_data);
patient_data_array{1, 3} = num2cell(patient3_data);
patient_data_array{1, 4} = num2cell(patient4_data);
```

```
patient_data_array {1, 5} = num2cell(patient5_data);
    patient_data_array {1, 6} = num2cell(patient6_data);
    patient_data_array {1, 7} = num2cell(patient7_data);
    patient_data_array {1, 8} = num2cell(patient8_data);
    patient_data_array {1, 9} = num2cell(patient9_data);
11
    corrcoef_array = cell(9, 9, 7);
    for i = 1:7
13
         for m = 1:9
1.5
             for n = 1:9
                 patient_data_m = cell2mat(patient_data_array{1, m});
                 patient_data_n = cell2mat(patient_data_array{1, n});
                 feature_table_m = patient_data_m(i:i, :);
                 feature_table_n = patient_data_n(i:i, :);
                 % Can't corrcoef if dimensions are different
                 % Expand the array by adding a zero to the right
21
      position
                 array_size = max(length(feature_table_m), length(
      feature_table_n));
                 feature_table_m (array_size) = 0;
                 feature\_table\_n(array\_size) = 0;
                 corr_coef = corrcoef(feature_table_m , feature_table_n
      );
                 corrcoef_array\{m, n, i\} = corr_coef(1, 2);
             end
27
        \quad \text{end} \quad
    end
```

Essentially for 2.1 we iterated through every possibility of patient and feature combination to see that the correlation between patient 6 and patient 9 is always 1 so they have the same data.

#### **Task 2.2:**

```
feat1, feat2] = find_lowest_eror(Error_table_arrar); % find possible features using addition of errors [feat3, feat4] = find_lowest_corr(training1, training2, training3, training4, training5, training6, training7, training8, training9); % after the 2 data analysis runs, we have feat1 = 5, feat2 = 7, feat3 = 2, % feat4 = 7. the pair 5&7 has a error sum of 5: 2.2, 7:2.4, and a % correlation magnitude of .8346 which is terrrible. while the error sum of % 2: 3.6 is not terrible and the correlation of 2 and 7 is at a minimum of % the set at .0192
```

```
function [ feature1 , feature2 ] = find_lowest_eror( error_arr )

local_error = 0;
global_error = 1000000;
```

```
global_error2 = 1000000;
           local_feat1 = 0;
           local_feat2 = 0;
           for i=1:7
               for j=1:9
                   cel = error_arr{j,i};
                   error_feature = cel{1,3} + cel{2,3}; % sum up error
       for that feature in that patient
                   local_error = local_error + error_feature; % add to
       local sum and move to next patient
               if(local_error <= global_error)</pre>
                   global_error = local_error;
                   local_feat2 = local_feat1;
                   local_feat1 = i;
17
               else
                    if(local_error <= global_error2)</pre>
                        global_error2 = local_error;
                        local_feat2 = i;
               end
               local_error = 0;
25
          end
27
           feature1 = local_feat1;
29
           feature2 = local_feat2;
31
      end
```

```
function [ feature1 , feature2 ] = find_lowest_corr( pat1 , pat2 ,
       pat3, pat4, pat5, pat6, pat7, pat8, pat9)
             {\rm f1} \ = \ \cot \left( {2\,{\rm{,pat1}}\left( {1\,{\rm{,:}}} \right)\,{\rm{,pat2}}\left( {1\,{\rm{,:}}} \right)\,{\rm{,pat3}}\left( {1\,{\rm{,:}}} \right)\,{\rm{,pat4}}\left( {1\,{\rm{,:}}} \right)\,{\rm{,pat5}}
        (1,:), pat6 (1,:), pat7 (1,:), pat8 (1,:), pat9 (1,:));
             f2 = cat(2, pat1(2,:), pat2(2,:), pat3(2,:), pat4(2,:), pat5
        (2,:), pat6 (2,:), pat7 (2,:), pat8 (2,:), pat9 (2,:));
             f3 = cat(2, pat1(3,:), pat2(3,:), pat3(3,:), pat4(3,:), pat5
        (3,:), pat6 (3,:), pat7 (3,:), pat8 (3,:), pat9 (3,:));
             f4 = cat(2, pat1(4,:), pat2(4,:), pat3(4,:), pat4(4,:), pat5
        (4,:), pat6 (4,:), pat7 (4,:), pat8 (4,:), pat9 (4,:));
             f5 = cat(2, pat1(5,:), pat2(5,:), pat3(5,:), pat4(5,:), pat5
        (5,:), pat6 (5,:), pat7 (5,:), pat8 (5,:), pat9 (5,:));
             f6 = cat(2,pat1(6,:),pat2(6,:),pat3(6,:),pat4(6,:),pat5
        (6,:), pat6 (6,:), pat7 (6,:), pat8 (6,:), pat9 (6,:));
             f7 = cat(2, pat1(7,:), pat2(7,:), pat3(7,:), pat4(7,:), pat5
        (7,:), pat6 (7,:), pat7 (7,:), pat8 (7,:), pat9 (7,:));
             local_min = 0;
             global_min = 10;
             features = [f1;f2;f3;f4;f5;f6;f7]; % make 2d array of
        feature data for all patients
             for i = 1:6
12
```

```
for j = (i+1):7
                  corr = corrcoef(features(i,:), features(j,:)); %
      should be a 2x2 with flipped entries in each col so just sum
      column
                  local_min = abs(corr(1,2)); \% looking for smallest
      mag of correlation because this fits description better
                  if(global_min >= local_min)
                      global_min = local_min;
                      feature1 = i;
                      feature2 = j;
20
                  end
                  local_min = 0;
22
              end
          end
24
          % concatenate each feature data for each patient;
      end
```

After examining the output of the two functions and interpreting the data, we were left with the pairs of feature 5 and 7 or 2 and 7. If we analyze the error for each one and the correlation of them, the 2 and 7 pair is much better suited. so we have chosen those two features. However, we can use 5 and 7 for future hypothesis testing because of their low error.