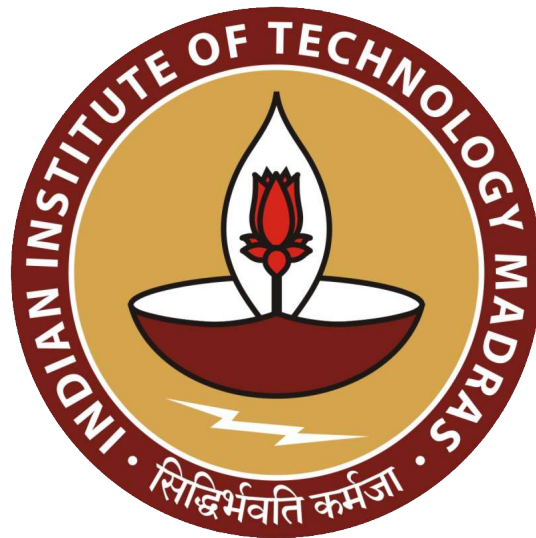


Assignment: 2

Mathematical Modelling in Industry



Name:	Lokendra Kumar
Roll No:	MA23M008
Submitted to:	Dr. Sundar S
Date of Sub:	14/09/2023

1 Assignment

Q.3 Implement Linear Isotropic Diffusion using inbuilt Gaussian filter function.

Sol. For Linear Isotropic Diffusion using inbuilt Gaussian filter function, MATLAB code is following.

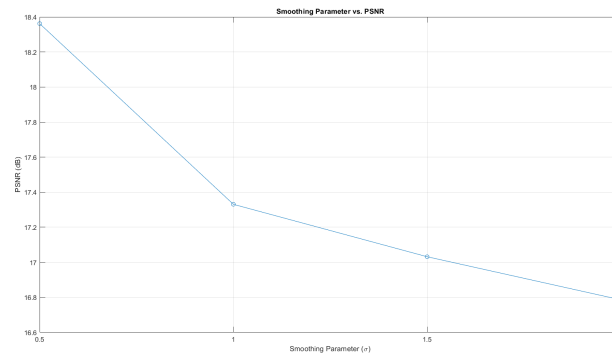
```
1      % Load the image
2      image = imread('logo1.png');
3
4      % Add Gaussian noise to the image
5      sigma = 25;
6      noisy_image = imnoise(image, 'gaussian', 0, (sigma/255)^2);
7
8      % Display the original and noisy images
9      subplot(2, 3, 1);
10     imshow(image);
11     title('Original Image');
12
13     subplot(2, 3, 2);
14     imshow(noisy_image);
15     title('Noisy Image');
16
17     % Define different values of sigma (smoothing parameter)
18     sigmas = [0.5, 1, 1.5, 2];
19
20     % Number of diffusion iterations
21     num_iterations = 5;
22
23     % Initialize a table to store PSNR values
24     psnr_table = zeros(length(sigmas), 1);
25
26     % Clean the noisy image for different sigma values
27     for i = 1:length(sigmas)
28         sigma = sigmas(i);
29
30         % Apply Gaussian filter for smoothing
31         cleaned_image = noisy_image; % Initialize cleaned_image with
            noisy_image
32         for j = 1:num_iterations
33             cleaned_image = imgaussfilt(cleaned_image, sigma);
34         end
35
36         % Calculate PSNR
37         mse = mean((double(image(:)) - double(cleaned_image(:))).^2);
38         max_pixel_value = double(max(image(:)));
39         psnr = 10 * log10((max_pixel_value^2) / mse);
40
41         % Store PSNR in the table
42         psnr_table(i) = psnr;
43
44         % Display the cleaned image
45         subplot(2, 3, i + 2);
46         imshow(uint8(cleaned_image));
47         title(['\sigma = ', num2str(sigma), ', PSNR = ', num2str(psnr)]);
48     end
```

```

49
50 % Create a table of Smoothing Parameter vs. PSNR
51 table_data = table(sigmas', psnr_table, 'VariableNames',
52     {'SmoothingParameter', 'PSNR'});
53 disp('PSNR_Table:');
54 disp(table_data);
55
56 % Plot Smoothing Parameter vs. PSNR
57 figure;
58 plot(sigmas, psnr_table, '-o');
59 xlabel('Smoothing_Parameter_(\sigma)');
60 ylabel('PSNR_(dB)');
61 title('Smoothing_Parameter_vs._PSNR');
62 grid on;
63
64 % Ensure subplots are properly displayed
65 set(gcf, 'Position', get(0,'Screensize'));

```

Listing 1: Your MATLAB code caption here



Original Image



Noisy Image



$\sigma = 0.5$, PSNR = 18.3618



$\sigma = 1$, PSNR = 17.3307



$\sigma = 1.5$, PSNR = 17.0317



$\sigma = 2$, PSNR = 16.7856



Output:PSNR Table to understand the quality of cleaning.

SmoothingParameter	PSNR
-----	-----
0.5	18.362
1	17.331
1.5	17.032
2	16.786

Listing 2: PSNR Table

Q.2 A series of cups of equal capacity have been filled with water and arranged one below another. Pour into the first cup a quantity of wine equal to the capacity of the cup at a constant rate and let the overflow in each cup, go into the cup just below. Assuming that complete mixing of wine and water takes place instantaneously. Find the amount of wine in each cup at any time t and at the end of the process at time T . For this question formulate the model as Black box model.

Sol. First we fix $T = 10$ and generate a the values randomly considering a normal distribution and generate 50 iid samples of q , and t (where $0 < t \leq T, q > 0$) from it. Let x_n be the amount of wine in the n th cup where

$$x_n = q \left(1 - \frac{\left(1 + \frac{1}{1!} + \frac{1}{2!} + \frac{1}{3!} + \dots + \frac{1}{(n-1)!} \right) \frac{t}{T}}{e^{\frac{t}{T}}} \right).$$

Now using regression(machine learning method) we are going to solve it.

```

1 T = 100; % Maximum value of t
2 num_samples = 100; % Number of samples
3
4 % Generate random values for t and q
5 mu_t = T / 2; % Mean of t
6 sigma_t = T / 3; % Standard deviation of t
7
8 mu_q = 50; % Mean of q
9 sigma_q = 20; % Standard deviation of q
10
11 % Generate random samples
12 t_samples = max(0, min(T, t_samples)); % To get only +ve values
13 q_samples = normrnd(mu_q, sigma_q, 1, num_samples);
14
15 % Ensure that generated values are within the specified range
16 t_samples = max(0, min(T, t_samples));
17 q_samples = max(0, q_samples);
18
19 % Display the generated samples
20 disp("Generated t samples:");
21 disp(t_samples);
22
23 disp("Generated q samples:");
24 disp(q_samples);
25
26 % Split the generated dataset into train and test datasets
27 train_ratio = 0.8; % 80% of data for training, 20% for testing
num_train_samples = round(num_samples * train_ratio);

```

```

28 num_test_samples = num_samples - num_train_samples;
29
30 % Split the t_samples and q_samples into train and test sets
31 t_train = t_samples(1:num_train_samples);
32 q_train = q_samples(1:num_train_samples);
33
34 t_test = t_samples(num_train_samples+1:end);
35 q_test = q_samples(num_train_samples+1:end);
36
37 % Initialize an array to store the predicted values x_n
38 x_n_train = zeros(size(t_train));
39
40 % Calculate the predicted variable x_n for the train dataset
41 for i = 1:num_train_samples
42 x_n_train(i) = q_train(i) * (1 - sum(1 ./ factorial(0:i-1)) * (t_train(i)
    / T) / exp(t_train(i) / T));
43 end
44
45 % Display the predicted x_n for the train dataset
46 disp("Predicted x_n for the train dataset:");
47 disp(x_n_train);
48
49
50 % Define a custom equation for curve fitting
51 eqn = @(a, t) a(1) * (1 - sum(1 ./ factorial(0:length(a)-2)) * (t / T) ./
    exp(t / T));
52
53 % Initial guess for fitting parameters
54 a0 = [1];
55
56 % Fit the curve to the training data using lsqcurvefit
57 fit_params = lsqcurvefit(eqn, a0, t_train, x_n_train);
58
59 % Calculate the fitted values for the training dataset
60 fitted_values_train = eqn(fit_params, t_train);
61
62 % Display the fitted parameters
63 disp("Fitted parameters:");
64 disp(fit_params);
65
66 % Use a linear regression model to predict on the test dataset (same as
    before)
67 X_train = [t_train', q_train']; % Predictors
68 X_test = [t_test', q_test']; % Test predictors
69
70 % Add a constant term to the predictors for regression
71 X_train = [ones(num_train_samples, 1), X_train];
72 X_test = [ones(num_test_samples, 1), X_test];
73
74 % Fit a linear regression model to the training data
75 regression_model = fitlm(X_train, x_n_train);
76
77 % Make predictions on the test dataset
78 predicted_x_n_test = max(0, predict(regression_model, X_test));

```

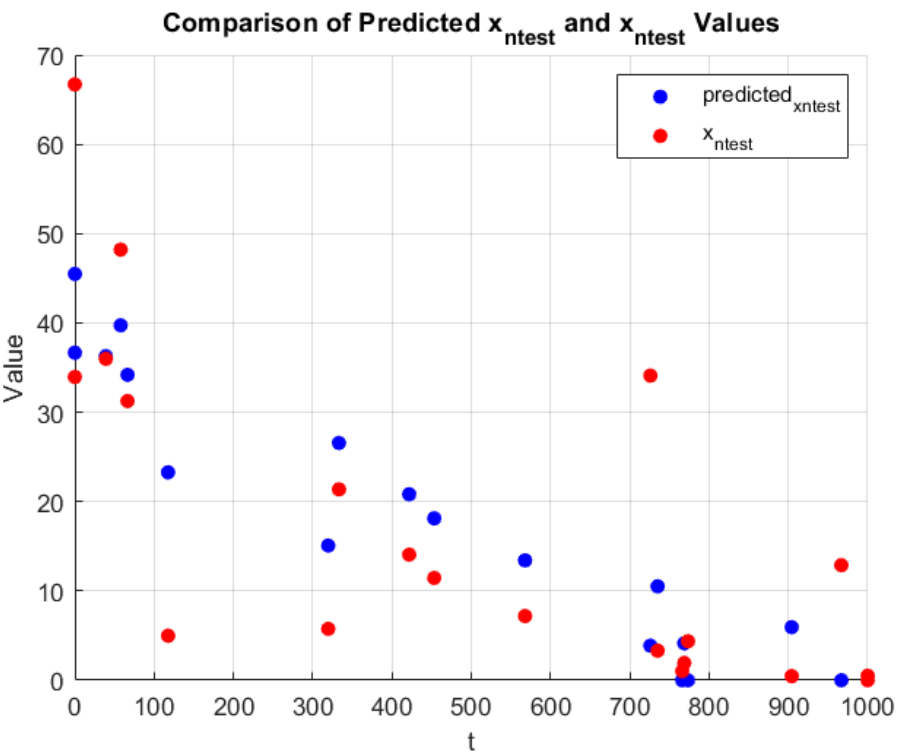
```

79
80 % Display the predicted values on the test dataset
81 disp("Predicted x_n for the test dataset:");
82 disp(predicted_x_n_test);
83 % Initialize an array to store the predicted values x_n for the test
    dataset
84 x_n_test_formula = zeros(size(t_test));
85
86 % Calculate the predicted variable x_n for the test dataset using the
    formula
87 for i = 1:num_test_samples
88     sum_term = 0;
89     for j = 0:(i-1)
90         sum_term = sum_term + 1 / factorial(j);
91     end
92     x_n_test_formula(i) = q_test(i) * (1 - sum_term * (t_test(i) / T) /
        exp(t_test(i) / T));
93 end
94 % Determine the minimum number of rows among the variables
95 rows = 20;
96
97 data = cell(rows, 5); % 5 columns: t, T, q, x_n_test, predicted_x_n_test
98
99 % Fill in the cell array with the available data
100 for i = 1:rows
101     data{i, 1} = t_test(i);
102     data{i, 2} = T;
103     data{i, 3} = q_test(i);
104     data{i, 4} = x_n_test_formula(i);
105     data{i, 5} = predicted_x_n_test(i);
106 end
107
108 % Create the table using cell2table
109 test_data_table = cell2table(data, 'VariableNames', {'t', 'T', 'q',
    'x_n_test', 'predicted_x_n_test'});
110
111 % Display the table
112 disp(test_data_table);
113
114 % Create a figure
115 figure;
116
117 % Scatter plot for predicted_x_n_test values in blue
118 scatter(t_test, predicted_x_n_test, 'b', 'filled');
119
120 hold on;
121
122 % Scatter plot for x_n_test values in red
123 scatter(t_test, x_n_test_formula, 'r', 'filled');
124
125 % Add labels and a legend
126 xlabel('t');
127 ylabel('Value');
128 title('Comparison of Predicted x_n {test} and x_n {test} Values');

```

```
129 legend('predicted_x_n_{test}', 'x_n_{test}');
130
131 % Display the grid
132 grid on;
133
134 % Show the plot
135 hold off;
```

Listing 3: Your MATLAB code caption here



Output table:

t	q	x_n_test	predicted_x_n_test
-----	-----	-----	-----
90.153	13.462	8.5353	0
3.1961	60.718	56.959	39.206
56.852	63.857	12.454	14.233
0	36.249	36.249	34.631
50.947	56.352	9.6355	15.194
100	53.257	0.031644	0
81.371	73.182	1.4451	4.7911
49.769	52.568	9.3338	14.814
38.725	70.789	20.198	24.665
67.609	47.665	3.1121	5.0268
85.23	37.034	0.44602	0
50.491	49.24	8.4506	13.637
100	46.014	2.9264e-09	0

22.805	67.633	34.257	31.519
0	48.877	48.877	37.784
25.06	33.175	15.586	21.834
43.357	46.903	11.072	16.478
37.575	73.772	22.024	25.962
21.754	41.702	21.863	25.55
94.575	36.828	0.056202	0

Q.1 How many cherries each of radius r can be packed in a can of radius R and height h ? Obtain upper and lower bounds. For this question formulate the model as Black box model.

Sol. first we are generating the 100 iid sample values of r, R and h randomly, considering a normal distribution. Now using regression(machine learning method) we are going to solve it.

```

1 % Number of samples
2 n = 100;
3
4
5 % Generate random values for r, R, and h following a normal distribution
6 r = abs(normrnd(5, 1, [1, n])); % r > 0
7 R = abs(normrnd(10, 2, [1, n])); % r < R
8 h = max(2*r, abs(normrnd(15, 3, [1, n]))); % h >= 2*r
9
10 % Create a dataset matrix
11 data = [r; R; h]';
12
13 % Split the dataset into train and test sets (e.g., 80% train, 20% test)
14 train_ratio = 0.8;
15 n_train = floor(n * train_ratio);
16 n_test = n - n_train;
17
18 % Shuffle the dataset
19 data = data(randperm(n), :);
20
21 % Split into train and test sets
22 train_data = data(1:n_train, :);
23 test_data = data(n_train+1:end, :);
24
25 % Calculate min and max cherries packed using the formula for the train
    dataset
26 minCherriesPacked_train = floor(train_data(:, 2).^2 .* train_data(:, 3)
    ./ (2 .* train_data(:, 1).^3));
27 maxCherriesPacked_train = floor(0.74 * 3 * train_data(:, 2).^2 .*
    train_data(:, 3) ./ (4 .* train_data(:, 1).^3));
28
29 % Display the min and max cherries packed for the train dataset
30 fprintf('Min Cherries Packed (Train): %s\n',
    mat2str(minCherriesPacked_train));
31 fprintf('Max Cherries Packed (Train): %s\n',
    mat2str(maxCherriesPacked_train));
32
33 % Fit a polynomial curve to the train data for minCherriesPacked
34 x = train_data(:, 1); % r values
35 y = minCherriesPacked_train;

```



```

36 degree = 2; % Choose the degree of the polynomial curve
37
38 % Fit the polynomial curve
39 p_min = polyfit(x, y, degree);
40
41 % Predict minCherriesPacked on the test dataset
42 x_test = test_data(:, 1); % r values
43 minCherriesPacked_pred = floor(polyval(p_min, x_test));
44
45 % Fit a polynomial curve to the train data for maxCherriesPacked
46 y = maxCherriesPacked_train;
47
48 % Fit the polynomial curve
49 p_max = polyfit(x, y, degree);
50
51 % Predict maxCherriesPacked on the test dataset
52 maxCherriesPacked_pred = floor(polyval(p_max, x_test));
53
54 % Display predictions
55 fprintf('Predicted_minCherriesPacked_on_Test_Data: %s\n',
56         mat2str(minCherriesPacked_pred));
57 fprintf('Predicted_maxCherriesPacked_on_Test_Data: %s\n',
58         mat2str(maxCherriesPacked_pred));
59
60 % Calculate min and max cherries packed for the test dataset using the
61 % formulas
62 minCherriesPacked_test = floor(test_data(:, 2).^2 .* test_data(:, 3) ./
63     (2 .* test_data(:, 1).^3));
64 maxCherriesPacked_test = floor(0.74 * 3 * test_data(:, 2).^2 .*
65     test_data(:, 3) ./ (4 .* test_data(:, 1).^3));
66
67 % Predict minCherriesPacked and maxCherriesPacked using the fitted curves
68 minCherriesPacked_pred = floor(polyval(p_min, test_data(:, 1))); %
69     Predict minCherriesPacked
70 maxCherriesPacked_pred = floor(polyval(p_max, test_data(:, 1))); %
71     Predict maxCherriesPacked
72
73 % Create a table of values with the additional prediction columns
74 dataTable = table(test_data(:, 1), test_data(:, 2), test_data(:, 3), ...
75     minCherriesPacked_test, maxCherriesPacked_test, ...
76     minCherriesPacked_pred, maxCherriesPacked_pred, ...
77     'VariableNames', {'r', 'R', 'h', 'minCherriesPacked',
78         'maxCherriesPacked', 'minCherriesPacked_pred',
79         'maxCherriesPacked_pred'});
80
81 % Display the table
82 disp(dataTable);

```

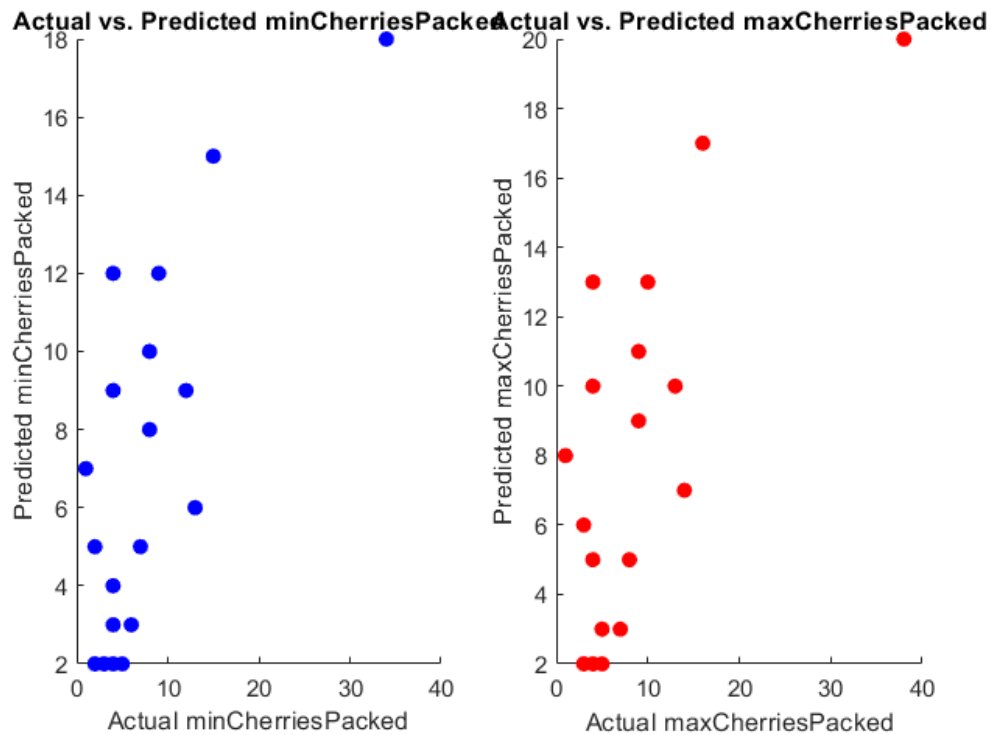
Listing 4: Your MATLAB code caption here

Output Table:

r	R	h	minCherriesPacked	maxCherriesPacked	minCherriesPacked_pred	maxCherriesPacked_pred
5.9105	11.366	16.511	5	5	2	2

5.5894	9.4599	13.866	3	3	3	3
4.71	15.575	17.76	20	22	7	7
5.6125	9.4046	20.215	5	5	3	3
5.5712	10.311	22.526	6	7	3	3
5.9421	12.832	17.331	6	7	2	2
5.2296	7.6889	12.142	2	2	4	4
5.5954	6.7227	13.33	1	1	3	3
6.2616	7.6667	15.449	1	2	2	2
5.2495	8.9555	16.129	4	4	4	4
4.8682	10.288	16.665	7	8	6	6
5.5265	10.492	15.194	4	5	3	3
3.559	7.9356	14.887	10	11	17	19
4.9451	12.287	13.709	8	9	5	6
4.4592	11.502	15.639	11	12	8	9
4.507	7.4335	17.772	5	5	8	9
5.44	9.981	15.952	4	5	3	3
5.2696	9.8402	16.428	5	6	4	4
3.9484	12.059	9.8237	11	12	13	14
3.9797	10.582	14.856	13	14	13	14

Scatter Plots of Actual vs. Predicted Cherries Packed



Q.4 Formulate the Linear Isotropic Diffusion using inbuilt Gaussian filter function as Black box model.

Sol. First we are Generating random data for linearly independent variables d (diffusivity), t (diffusion time), and σ (Gaussian standard deviation). Then we are creating a black-box model using linear regression.

```

1 % Generate synthetic data for linearly independent variables
2 % Variables: d (diffusivity), t (diffusion time), and sigma
  (Gaussian standard deviation)
3 n_samples = 1000; % Number of data samples
4
5 % Generate random values for d, t, and sigma within specified
  ranges
6 d_min = 0.1;

```

```

7     d_max = 10;
8     t_min = 0.1;
9     t_max = 100;
10    sigma_min = 0.1;
11    sigma_max = 10;
12
13    d = d_min + (d_max - d_min) * rand(n_samples, 1);
14    t = t_min + (t_max - t_min) * rand(n_samples, 1);
15    sigma = sigma_min + (sigma_max - sigma_min) * rand(n_samples, 1);
16
17    % Calculate the corresponding output (result of Gaussian
18    % smoothing)
19    output = sqrt(2 * t) .* sigma;
20
21    % Create a black-box model using linear regression
22    X = [d, t]; % Independent variables
23    Y = output; % Dependent variable
24
25    % Fit a linear regression model
26    mdl = fitlm(X, Y);
27
28    % Display the model summary
29    disp(mdl);
30
31    % Predict the output for new data
32    % Example: Predict the output for d = 5 and t = 50
33    new_d = 5;
34    new_t = 50;
35    predicted_output = predict(mdl, [new_d, new_t]);
36    disp(['Predicted Output for d = ', num2str(new_d), ' and t = ',
37    num2str(new_t), ' is ', num2str(predicted_output)]);
38
39    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
40    % Load the image
41    image = imread('logo1.png');
42
43    % Generate synthetic data for d (diffusivity) and t (diffusion
44    % time)
45    % Example values:
46    d = 5; % Adjust as needed
47    t = 50; % Adjust as needed
48
49    % Apply Gaussian smoothing to the image using specified d and t
50    sigma = sqrt(2 * t);
51    smoothed_image = imgaussfilt(image, sigma, 'FilterSize', 5); %
52    You can adjust the filter size as needed
53
54    % Display the original and smoothed images
55    figure;
56    subplot(1, 2, 1);
57    imshow(image);
58    title('Original Image');

```

```
57 subplot(1, 2, 2);  
58 imshow(smoothed_image);  
59 title(['Smoothed Image (t=', num2str(t), ', d=', num2str(d),  
        ')']);
```

Listing 5: Your MATLAB code caption here