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Machine Learning Algorithms: exercise 2

Answer: 1

-1.6510

```
% Load data from file
data = load(['D:\TUNI\Courses\Period-4\DATA.ML.210 [Machine Learning Algorithms]' ...
     '\Exercises 1\Data.txt']);
data
data = 212 \times 2
   0.8028
           -1.6510
   0.9140
            0.9831
   1.5186
            0.9786
   1.8732
            -0.1436
           0.8740
   1.4445
  -0.7420
           0.0806
   1.7561
           -1.0257
   1.3040 0.1644
  -2.5543
           0.5886
   -1.1737 -0.4639
size(data)
ans = 1 \times 2
  212
X = data(:, 1:2);
Χ
X = 212 \times 2
   0.8028
           -1.6510
   0.9140
            0.9831
           0.9786
   1.5186
           -0.1436
   1.8732
           0.8740
   1.4445
  -0.7420
           0.0806
          -1.0257
   1.7561
   1.3040
           0.1644
   -2.5543
           0.5886
   -1.1737 -0.4639
y = data(:, 2);
У
y = 212 \times 1
```

```
0.9831
0.9786
-0.1436
0.8740
0.0806
-1.0257
0.1644
0.5886
-0.4639
```

```
% Define the classifier parameters
w = 1/sqrt(2) * [1; -1];
p = [2; 2];
% Classify the points using the classifier
n = size(X, 1);
X_{diff} = X - repmat(p', n, 1);
y_pred = sign(X_diff * w);
% Evaluate the performance of the classifier
accuracy = sum(y_pred == y) / length(y);
TP = sum(y_pred == 1 \& y == 1);
FN = sum(y_pred == -1 \& y == 1);
if TP + FN == 0
    sensitivity = 0;
else
    sensitivity = TP / (TP + FN);
end
TN = sum(y_pred == -1 \& y == -1);
FP = sum(y pred == 1 \& y == -1);
if TN + FP == 0
    specificity = 0;
else
    specificity = TN / (TN + FP);
end
if TP + TN == 0
    accuracy = 0;
else
    accuracy = (TP + TN) / (TP + TN + FP + FN);
end
% Display the results
fprintf('Accuracy: %.2f\n', accuracy);
```

```
Accuracy: 0.00
```

```
fprintf('Sensitivity: %.2f\n', sensitivity);
```

Sensitivity: 0.00

```
fprintf('Specificity: %.2f\n', specificity);
Specificity: 0.00
```

Answer: 2

```
if TP + TN + FP + FN == 0
    P_error = 0;
else
    P_error = (FP + FN) / (TP + TN + FP + FN);
end

% Display the results
fprintf('Accuracy: %.2f\n', accuracy);
```

Accuracy: 0.00

```
fprintf('Sensitivity: %.2f\n', sensitivity);
```

Sensitivity: 0.00

```
fprintf('Specificity: %.2f\n', specificity);
```

Specificity: 0.00

```
fprintf('Probability of error: %.2f\n', P_error);
```

Probability of error: 0.00

Answer: 3

```
% Define the class-conditional probabilities
p_x_given_w1 = @(x) double(0 <= x & x <= 1);
p_x_given_w2 = @(x) double(1/2 <= x & x <= 5/2) * 1/2;

% Define the prior probabilities
p_w1 = 1/2;
p_w2 = 1/2;

% Define the range of x values to consider
x_min = 0;
x_max = 3;
dx = 0.01;
x_range = x_min:dx:x_max;

% Compute the conditional probabilities
p_w2_given_w1 = integral(@(x) p_x_given_w2(x) * p_w1 ./ max(p_x_given_w1(x) ...
    * p_w1 + p_x_given_w2(x) * p_w2, eps), x_min, x_max);
p_w1_given_w2 = 0;</pre>
```

```
% Compute the probability of error
p_error = p_w1 * p_w2_given_w1 + p_w2 * p_w1_given_w2;

% Display the result
fprintf('Probability of error: %.2f\n', p_error);
```

Probability of error: 0.83

Answer: 5

```
% Define the class-conditional densities
p_x_given_w1 = @(x) 1 / sqrt(2 * pi) * exp(-x.^2 / 2);
p_x_given_w2 = @(x) 1 / sqrt(4 * pi) * exp(-(x - 3).^2 / 8);
% Define the prior probabilities
p_w1 = 0.3;
p_w2 = 0.7;
% Define the range of x values to consider
x min = -1;
x_max = 6;
dx = 0.01;
x_range = x_min:dx:x_max;
% Compute the probabilities of each class
p_w1_given_x = p_x_given_w1(x_range) * p_w1 ./ (p_x_given_w1(x_range) ...
    * p_w1 + p_x given_w2(x_range) * p_w2);
p_w2_given_x = 1 - p_w1_given_x;
% Estimate the probability of error
p_error = sum(min(p_w1_given_x, p_w2_given_x)) * dx;
% Display the result
fprintf('Probability of error: %.4f\n', p_error);
```

Probability of error: 0.9722

Answer: 6

```
% Read in the data
data2 = load(['D:\TUNI\Courses\Period-4\DATA.ML.210 [Machine Learning Algorithms]' ...
    '\Exercises 2\data2.txt']);

% Extract the x and y data
x = data2(:,1);
y = data2(:,2);

% Fit polynomial of order 1
fit1 = fitlm(x, y);
fit1
```

fit1 =
Linear regression model:
 y ~ 1 + x1

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.95134	0.035392	26.88	1.8495e-106
x1	-0.30298	0.0097573	-31.051	6.5516e-129

Number of observations: 629, Error degrees of freedom: 627

Root Mean Squared Error: 0.444

R-squared: 0.606, Adjusted R-Squared: 0.605

F-statistic vs. constant model: 964, p-value = 6.55e-129

```
% Fit polynomial of order 2
fit2 = fitlm(x, y, 'poly2');
fit2
```

fit2 = Linear regression model: $y \sim 1 + x1 + x1^2$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.94893	0.053025	17.896	3.7356e-58
x1	-0.30067	0.039002	-7.709	4.9995e-14
x1^2	-0.0003672	0.0060128	-0.06107	0.95132

Number of observations: 629, Error degrees of freedom: 626

Root Mean Squared Error: 0.445

R-squared: 0.606, Adjusted R-Squared: 0.605

F-statistic vs. constant model: 481, p-value = 2.55e-127

```
% Fit polynomial of order 3
fit3 = fitlm(x, y, 'poly3');
fit3
```

fit3 = Linear regression model: $y \sim 1 + x1 + x1^2 + x1^3$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	-0.2005	0.010586	-18.94	1.443e-63
x1	1.9045	0.01461	130.35	0
x1^2	-0.87891	0.0054085	-162.5	0
x1^3	0.093264	0.0005661	164.75	0

Number of observations: 629, Error degrees of freedom: 625

Root Mean Squared Error: 0.0668

R-squared: 0.991, Adjusted R-Squared: 0.991

F-statistic vs. constant model: 2.33e+04, p-value = 0

```
% Fit polynomial of order 4
fit4 = fitlm(x, y, 'poly4');
fit4
```

fit4 = Linear regression model: $y \sim 1 + x1 + x1^2 + x1^3 + x1^4$

Estimated Coefficients:

Estimate	SE	tStat	pValue
-0.19959	0.013196	-15.125	2.9319e-44
1.9015	0.029165	65.199	9.6805e-281
-0.87681	0.018908	-46.373	2.4247e-204
0.092741	0.0045254	20.494	9.2351e-72
4.162e-05	0.00035747	0.11643	0.90735
	-0.19959 1.9015 -0.87681 0.092741	-0.19959 0.013196 1.9015 0.029165 -0.87681 0.018908 0.092741 0.0045254	-0.19959 0.013196 -15.125 1.9015 0.029165 65.199 -0.87681 0.018908 -46.373 0.092741 0.0045254 20.494

Number of observations: 629, Error degrees of freedom: 624

Root Mean Squared Error: 0.0668

R-squared: 0.991, Adjusted R-Squared: 0.991

F-statistic vs. constant model: 1.74e+04, p-value = 0

```
% Fit polynomial of order 5
fit5 = fitlm(x, y, 'poly5');
fit5
```

fit5 = Linear regression model: $y \sim 1 + x1 + x1^2 + x1^3 + x1^4 + x1^5$

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	0.015498	0.0010264	15.1	3.9625e-44
x1	0.8625	0.0033118	260.44	0
x1^2	0.28506	0.0032744	87.058	0
x1^3	-0.40121	0.0013232	-303.22	0
x1^4	0.088563	0.00023234	381.17	0
x1^5	-0.0056383	1.4724e-05	-382.92	0

Number of observations: 629, Error degrees of freedom: 623

Root Mean Squared Error: 0.00435 R-squared: 1, Adjusted R-Squared: 1

F-statistic vs. constant model: 3.32e+06, p-value = 0

Answer: 4

```
function prob = normprob(mu, sigma2, a, b)
% Calculate the probability for an event that falls on the interval [a,b]
% in a one-dimensional normal distribution with mean mu and variance sigma2
% Define the standard deviation
sigma = sqrt(sigma2);
% Define the limits of integration
```

```
x = linspace(a, b, 1000);

% Calculate the probability density function
pdf = 1/(sigma*sqrt(2*pi)) * exp(-(x-mu).^2/(2*sigma^2));

% Approximate the integral using cumulative sum of the pdf
prob = sum(pdf)*(b-a)/length(x);
end
```