# Table of Contents



```
clear all
clc
```

# 5.1

```
N1 = normrnd(0, 1, 100, 1);
N2 = normrnd(2, 1, 100, 1);
tt1 = ttest2(N1, N2);

if tt1 > 0
 fprintf('N1 = 100, Mean = 0, Sigma = 1\nN2 = 100, Mean = 2, Sigma =
 1\n')
 fprintf('Significant difference\n\n')
end

N2 = normrnd(0.2, 1, 100, 1);
tt1 = ttest2(N1, N2);

if tt1 > 0
 fprintf('N1 = 100, Mean = 0, Sigma = 1\nN2 = 100, Mean = 0.2, Sigma =
 1\n')
 fprintf('Significant difference\n\n')
end

N1 = normrnd(0, 1, 150, 1);
N2 = normrnd(2, 1, 200, 1);
tt1 = ttest2(N1, N2);

if tt1 > 0
 fprintf('N1 = 150, Mean = 0, Sigma = 1\nN2 = 200, Mean = 2, Sigma =
 1\n')
 fprintf('Significant difference\n\n')
end


N2 = normrnd(.2, 1, 200, 1);
tt1 = ttest2(N1, N2);

if tt1 > 0
 fprintf('N1 = 150, Mean = 0, Sigma = 1\nN2 = 200, Mean = 0.2, Sigma =
 1\n')
 fprintf('Significant difference\n\n')
end
```

```
%{
There was a significant difference in the each experiment with a mean
 delta of 2.
The ttest attempts to determine the confidence that two data sets come
 from the
same normal distribution with a mean of 0 and an unknown sigma. From
 the experiment
it can be seen that data sets with a small difference in mean will be
 classified
under the same normal distribution. This can relate to any learning
 model that uses
mean as a feature, and may classify data similarly. Mean alone would
 not be a
good feature, but may provide insight as a support feature.

Table 5.1 is calculated using a Gaussian Kernel.
%}
```

```
N1 = 100, Mean = 0, Sigma = 1
N2 = 100, Mean = 2, Sigma = 1
Significant difference

N1 = 150, Mean = 0, Sigma = 1
N2 = 200, Mean = 2, Sigma = 1
Significant difference

N1 = 150, Mean = 0, Sigma = 1
N2 = 200, Mean = 0.2, Sigma = 1
Significant difference
```

# 5.2

```
clear all

I = [.2 0; 0 .2];
I(:,:,2) = I(:,:,1);
I(:,:,3) = I(:,:,1);
I(:,:,4) = I(:,:,1);

fprintf('Part a\n')
[N, classes] = genGaussClasses([-10 -10 10 10; -10 10 -10 10], I,
 [.25, .25, .25, .25], 400);
[Sw, Sb, Sm] = scatter_mat(N, classes)
j3 = J3_comp(Sw, Sm)
fprintf('\n')

fprintf('Part b\n')
[N, classes] = genGaussClasses([-1 -1 1 1; -1 1 -1 1], I,
 [.25, .25, .25, .25], 400);
[Sw, Sb, Sm] = scatter_mat(N, classes)
j3 = J3_comp(Sw, Sm)
```

```
fprintf('\n')

fprintf('Part c\n')
[N, classes] = genGaussClasses([-10 -10 10 10; -10 10 -10 10], I, [3,
 3, 3, 3], 400);
[Sw, Sb, Sm] = scatter_mat(N, classes)
j3 = J3_comp(Sw, Sm)
fprintf('\n')
```

```
Part a

Sw =

    0.2024   -0.0196
   -0.0196    0.2253


Sb =

  100.5171   -0.0374
   -0.0374   99.9764


Sm =

  100.7196   -0.0569
   -0.0569  100.2017


j3 =

  950.1088


Part b

Sw =

    0.2206   -0.0001
   -0.0001    0.2069


Sb =

    1.0329   -0.0056
   -0.0056    1.0966


Sm =

    1.2535   -0.0058
   -0.0058    1.3035
```

```
j3 =

   11.9826


Part c

Sw =

    0.1950   -0.0028
   -0.0028    0.1991


Sb =

  100.0586    0.0960
    0.0960  100.0653


Sm =

  100.2537    0.0932
    0.0932  100.2644


j3 =

   1.0179e+03
```

# Spectrel Learning

```
%{
 1) The kernel applied is the Gaussian Kernel. The kernel is applied
 to the
 higher dimensional data, which yields a similarity measure between
 each feature
 vector.

 2) The affinity matrix is a measure of similarity between data
 points, which
 is calculated by the Gaussian Kernel.

 3) The data that is clustered is the input data projected to a higher
 dimensionality.
%}
```

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