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Problem Category

- Statistical Pattern Recognition
 - Supervised Learning
 - Parametric Learning
 - Bayes Decision Theory
 - Univariate data
 - 2-class problem
 - equal variances
 - Gaussian model (2 parameters)
 - No Risk function
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Given Information:

model: continuous univariate normal (Gaussian) density

$$p(x|\omega_j) \sim N(\mu|\sigma^2)$$
$$p(x|\omega_j) \sim \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[-\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2 \right]$$

parameters:

$$P(\omega_1) = P(\omega_2) = 0.5$$
$$\sigma_1^2 = \sigma_2^2 = 1$$
$$\mu_1 = 4, \quad \mu_2 = 10$$

Bayes' Rule:

$$P(\omega_j|x) = \frac{p(x|\omega_j) * P(\omega_j)}{p(x)}$$

Bayes' Decision Rule:

Decide ω_1 if $P(\omega_1|x) > P(\omega_2|x)$ else decide ω_2 .

$$\Rightarrow \frac{p(x|\omega_1) * P(\omega_1)}{p(x)} > \frac{p(x|\omega_2) * P(\omega_2)}{p(x)}$$

We can drop $p(x)$ since it is just a scale factor.

$$\begin{aligned} \Rightarrow P(x|\omega_1) * P(\omega_1) &> p(x|\omega_2) * P(\omega_2) \\ \Rightarrow \frac{p(x|\omega_1)}{p(x|\omega_2)} &> \frac{P(\omega_2)}{P(\omega_1)} \\ \Rightarrow \frac{p(x|\omega_1)}{p(x|\omega_2)} &> \frac{0.5}{0.5} \\ \Rightarrow \frac{p(x|\omega_1)}{p(x|\omega_2)} &> 1 \\ \Rightarrow \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp \left[-\frac{1}{2} \left(\frac{x-\mu_1}{\sigma_1} \right)^2 \right] &> \frac{1}{\sqrt{2\pi\sigma_2^2}} \exp \left[-\frac{1}{2} \left(\frac{x-\mu_2}{\sigma_2} \right)^2 \right] \end{aligned}$$

Since we have equal variances, we can drop the first term completely.

$$\begin{aligned}
&\Rightarrow \exp \left[-\frac{1}{2} \left(\frac{x-\mu_1}{\sigma_1} \right)^2 \right] > \exp \left[-\frac{1}{2} \left(\frac{x-\mu_2}{\sigma_2} \right)^2 \right] \quad \left| \ln, \quad \mu_1 = 4, \quad \mu_2 = 10, \quad \sigma = 1 \right. \\
&\Rightarrow -\frac{1}{2} (x-4)^2 > -\frac{1}{2} (x-10)^2 \quad \left| \times (-2) \right. \\
&\Rightarrow (x-4)^2 < (x-10)^2 \\
&\Rightarrow x^2 - 8x + 16 < x^2 - 20x + 100 \\
&\Rightarrow 12x < 84 \\
&\Rightarrow x < 7
\end{aligned}$$

Plotting the Class Conditional Densities and Decision Boundary

```
In [11]: %pylab inline

import numpy as np
from matplotlib import pyplot as plt

def pdf(x, mu, sigma):
    """
    Calculates the normal distribution's probability density
    function (PDF).

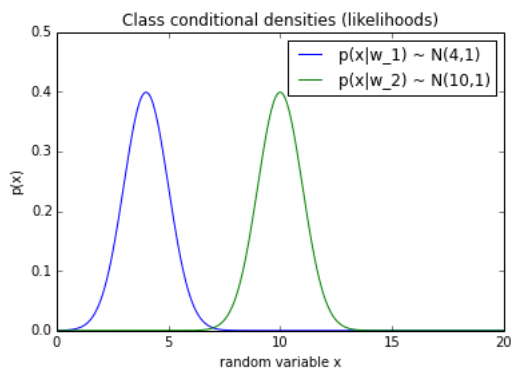
    """
    term1 = 1.0 / ( math.sqrt(2*np.pi) * sigma )
    term2 = np.exp( -0.5 * ( (x-mu)/sigma )**2 )
    return term1 * term2

# generating some sample data
x = np.arange(0, 100, 0.05)

# probability density functions
pdf1 = pdf(x, mu=4, sigma=1)
pdf2 = pdf(x, mu=10, sigma=1)

# Class conditional densities (likelihoods)
plt.plot(x, pdf1)
plt.plot(x, pdf2)
plt.title('Class conditional densities (likelihoods)')
plt.ylabel('p(x)')
plt.xlabel('random variable x')
plt.legend(['p(x|w_1) ~ N(4,1)', 'p(x|w_2) ~ N(10,1)'], loc='upper right')
plt.ylim([0,0.5])
plt.xlim([0,20])
plt.show()
```

Populating the interactive namespace from numpy and matplotlib



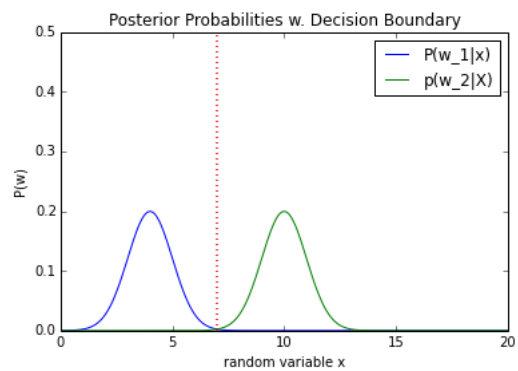
```
In [10]: def posterior(likelihood, prior):
    """
    Calculates the posterior probability (after Bayes Rule) without
    the scale factor p(x) (=evidence).

    """
    return likelihood * prior

# probability density functions
posterior1 = posterior(pdf(x, mu=4, sigma=1), 0.5)
posterior2 = posterior(pdf(x, mu=10, sigma=1), 0.5)

# Class conditional densities (likelihoods)
plt.plot(x, posterior1)
plt.plot(x, posterior2)
plt.title('Posterior Probabilities w. Decision Boundary')
plt.ylabel('P(w)')
plt.xlabel('random variable x')
```

```
plt.legend(['P(w_1|x)', 'p(w_2|X)'], loc='upper right')
plt.ylim([0,0.5])
plt.xlim([0,20])
plt.axvline(7, color='r', alpha=0.8, linestyle=':', linewidth=2)
plt.show()
```



In []: