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last modified: 03/30/2014

Problem Category

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

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:

$$P(\omega_1) = \frac{2}{3}, \quad P(\omega_2) = \frac{1}{3}$$

$$\sigma_1^2 = \sigma_2^2 = 1$$

$$\mu_1 = 4, \quad \mu_2 = 10$$

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.

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

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

$$\Rightarrow \frac{p(x|\omega_1)}{p(x|\omega_2)} > \left(\frac{\frac{1}{3}}{\frac{2}{3}}\right)$$

$$\Rightarrow \frac{p(x|\omega_1) \cdot \frac{2}{3}}{p(x|\omega_2) \cdot \frac{1}{3}} > 1$$

$$\Rightarrow \frac{2}{3} \cdot \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu_1}{\sigma_1}\right)^2\right] > \frac{1}{3} \cdot \frac{1}{\sqrt{2\pi\sigma_2^2}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu_2}{\sigma_2}\right)^2\right]$$

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

$$\Rightarrow \frac{2}{3} \cdot \exp\left[-\frac{1}{2}\left(\frac{x-\mu_1}{\sigma_1}\right)^2\right] > \frac{1}{3} \cdot \exp\left[-\frac{1}{2}\left(\frac{x-\mu_2}{\sigma_2}\right)^2\right] \quad \Bigg| ln, \quad \mu_1 = 4, \quad \mu_2 = 10, \quad \sigma = 1$$

$$\Rightarrow ln(2) - ln(3) - \frac{1}{2}(x-4)^2 > ln(1) - ln(3) - \frac{1}{2}(x-10)^2 \quad \Bigg| + ln(3), \ \cdot(-2) \Rightarrow -2ln(2) + (x-4)^2 < (x-10)^2$$

$$\Rightarrow x^2 - 8x + 14.6137 < x^2 - 20x + 100$$

$$\Rightarrow 12x < 85.3863$$

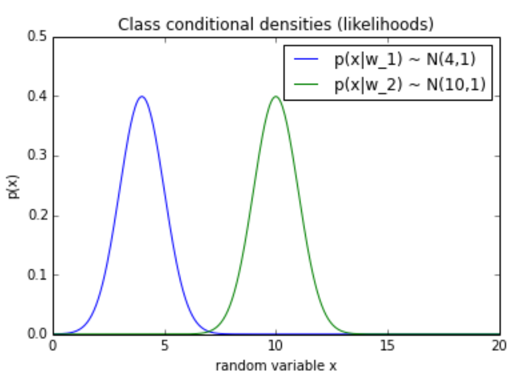
$$\Rightarrow x < 7.1155$$

Plotting the Class Conditional Densities and Decision Boundary

In [2]:

```
%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()
```

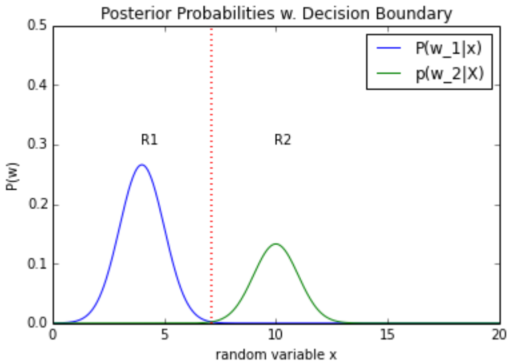
```
Populating the interactive namespace from numpy and matplotlib
```



In [4]:

```
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), 2/3.0)
posterior2 = posterior(pdf(x, mu=10, sigma=1), 1/3.0)

# 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(7.1155, color='r', alpha=0.8, linestyle=':', linewidth=2)
plt.annotate('R1', xy=(4, 0.3), xytext=(4, 0.3))
plt.annotate('R2', xy=(10, 0.3), xytext=(10, 0.3))
plt.show()
```



In [ ]: