P(class): P(pos) / P(pos + neg), P(neg) / P(pos + neg)

P(Fi | class): sum(Feat x = a) / n(c)

classNB(x): max(P(class) prod(p(xi|class)))

$$P(x_i = a_i \mid c) = \frac{n(x_i = a_i, c)}{n(c)}$$

		+	-
F1	0		
	1		
F2	0		
	1		
F3	0		
	1		
F4	0		
	1		

P(prob x = a | given class) = <u>. sum(instances (feature x == a && class == C)) +1 .</u>
(instancs with class C) + k

Laplace where k is the number of possible values of attribute a

$$P(x_i = a_i \mid c_j) \approx \frac{n(x_i = a_i, c_j) + 1}{n(c_j) + k}$$

MAP ("maximum a posteriori") Learning

Bayes rule: $P(h \mid D) = \dfrac{P(D \mid h)P(h)}{P(D)}$

Goal of learning: Find maximum a posteriori hypothesis h_{MAP}:

$$h_{MAP} = \underset{h \in H}{\operatorname{argmax}} P(h \mid D)$$

$$= \underset{h \in H}{\operatorname{argmax}} \frac{P(D \mid h)P(h)}{P(D)}$$

$$= \underset{h \in H}{\operatorname{argmax}} P(D \mid h)P(h)$$

because $P(D)$ is a constant independent of h.

Note: If every $h \in H$ is equally probable, then

$$h_{MAP} = \underset{h \in H}{\operatorname{argmax}} P(D \mid h)$$

This is called the "maximum likelihood hypothesis".

GAUS

Mean: avg

sDev: sqrt(sum(V) / total)

F-1(pos) , F-1(neg)

M = , sDev =

M = , sDev =

F-2(pos) , F-2(neg)

M = , sDev =

M = , sDev =

X10 | 0.9 | 0.4 | ?

P(+) = p(f1=0.9 | +) * p(f2=0.4|+)

P(-) = p(f1=0.9 | -) * p(f2=0.4|-)

$$class_{NB}(\mathbf{x}) = \underset{class \in \{+1,-1\}}{\operatorname{argmax}} P(class) \prod_i P(x_i \mid class)$$

$$p(x_i = a_i \mid c_j) = N(x_i; \mu_{i, c_j}, \sigma_{i, c_j})$$

where

$$N(x; \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$