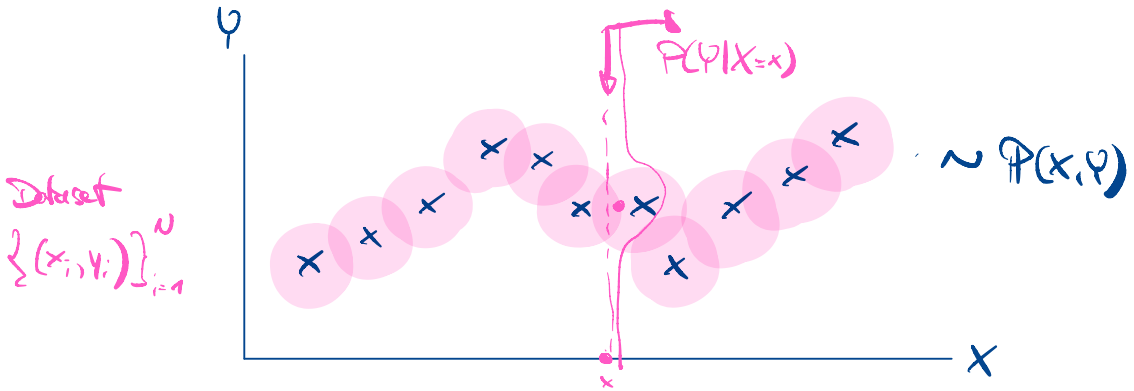


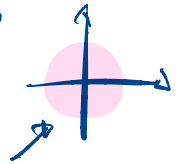
WATSON - WATSON



base
densities

$f(x)g(y)$ where f, g are unimodal, localized
with mean 0

(think of $\frac{e^{-(x^2+y^2)/(2\sigma^2)}}{2\pi\sigma^2}$)



model for
the joint
density

$$P(x, y) := \frac{1}{N} \sum_{i=1}^N f(x-x_i) g(y-y_i)$$

$$\left[\int P(x, y) dx dy = \frac{1}{N} \sum_{i=1}^N \underbrace{\int f(x-x_i) dx}_{\substack{x=x_i \\ \int f(x) dx = 1}} \underbrace{\int g(y-y_i) dy}_{=1} \right]$$

$$= 1$$

prediction $y_{\text{model}}(x) := \mathbb{E}_{P(Y|X=x)}[Y] = \int \frac{P(x, y) y}{\int P(x, \tilde{y}) d\tilde{y}} dy$

$$= \sum_{i=1}^N f(x-x_i) \int g(y-y_i) y dy \frac{1}{\sum_{j=1}^N f(x-x_j) \underbrace{\int g(\tilde{y}-y_j) d\tilde{y}}_{=1}}$$

$y' := y - y_i$

$$= \sum_{i=1}^N \frac{f(x-x_i)}{\sum_{j=1}^N f(x-x_j)} \underbrace{\int g(y') (y' + y_i) dy'}_{= \underbrace{\int g(y') y' dy'}_{=0} + y_i \underbrace{\int g(y') dy'}_{=1}}$$

$$= \sum_{i=1}^N y_i k(x, x_i)$$

$$\bullet \sum_{i=1}^N k(x, x_i) = \frac{\sum_{i=1}^N \cancel{f(x-x_i)}}{\sum_{j=1}^N \cancel{f(x-x_j)}} = 1$$

$$\bullet k(x, x_i) = \frac{f(x-x_i)}{f(x-x_i) + \sum_{j \neq i} f(x-x_j)} = \frac{1}{1 + \dots} \leq 1$$

$k(x, x_i)$
is a prob.
dist. over i

$$\Rightarrow y_{\text{model}}(x) = \text{expectation of } \underline{y_i} \text{ w.r.t } i \mapsto \underline{k(x, x_i)}$$

$$k(x, x_i) = \frac{f(x - x_i)}{\sum_{j=1}^N f(x - x_j)}$$

$\left. \begin{array}{l} \text{ } \end{array} \right\} \text{large if } x \approx x_i$
 $\left. \begin{array}{l} \text{ } \end{array} \right\} \text{more or less const w.r.t } x$

