Logistic Regression

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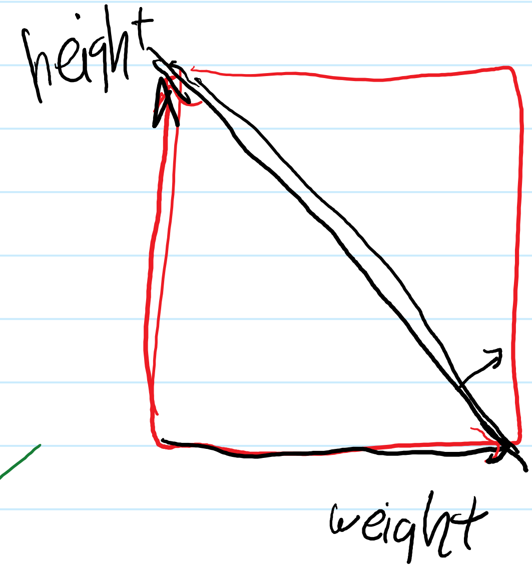
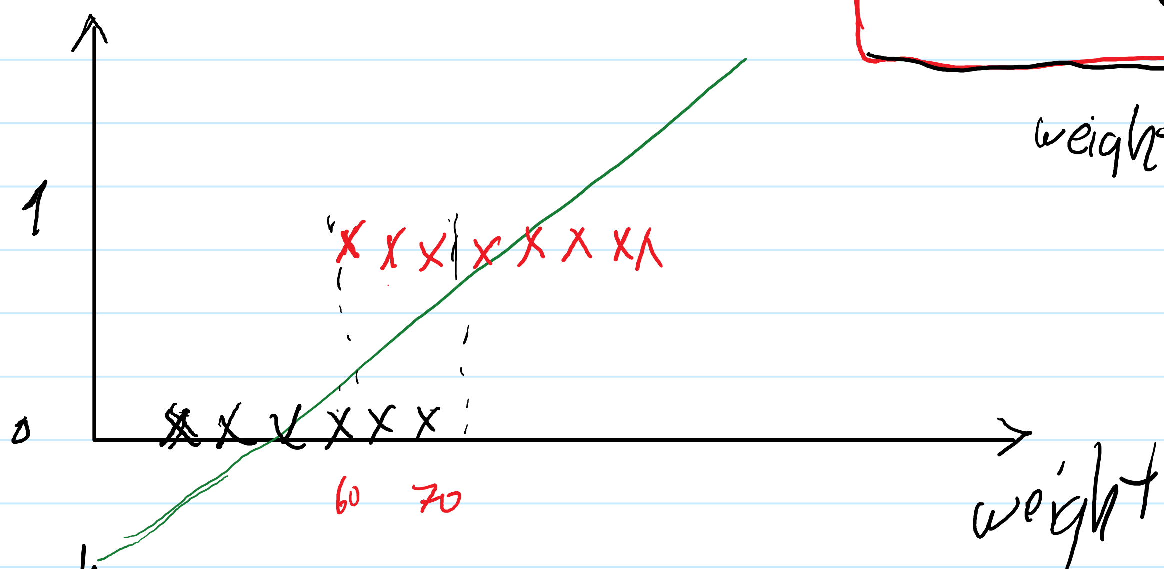
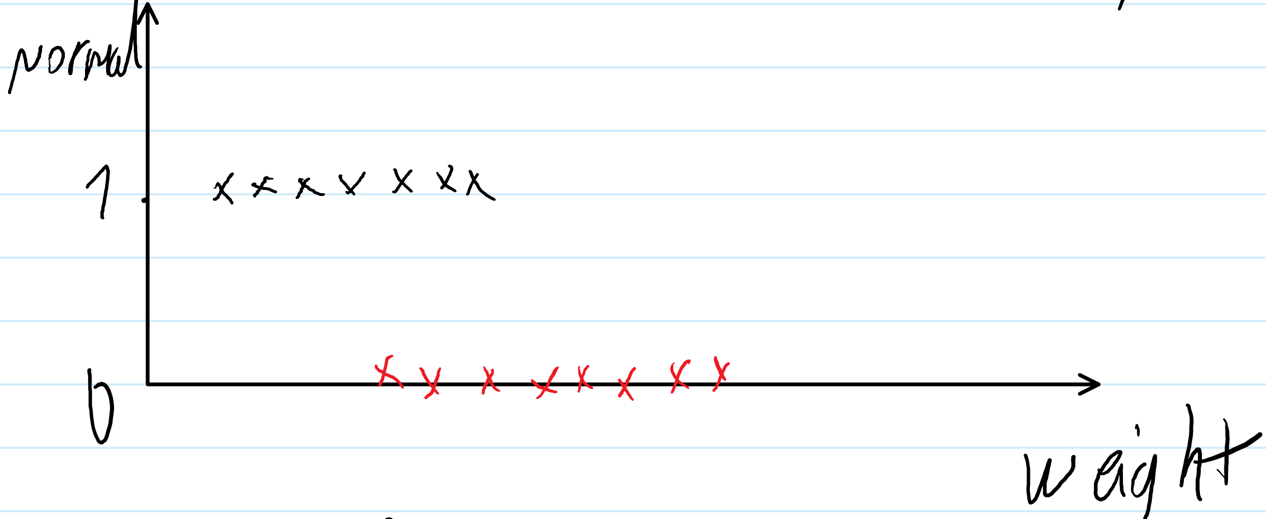
supervised learning

1 reg

2 clf







$$0 < f(w) < 1$$

LR

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$$0 < f(x) < 1$$

$$f(x, \beta) = \frac{1}{1 + e^{-\beta x}}$$

$y = 1$: $p(x) \longrightarrow 1$ $\hat{\beta}$

$y = 0$ $1 - p(x) \longrightarrow 1$

LR

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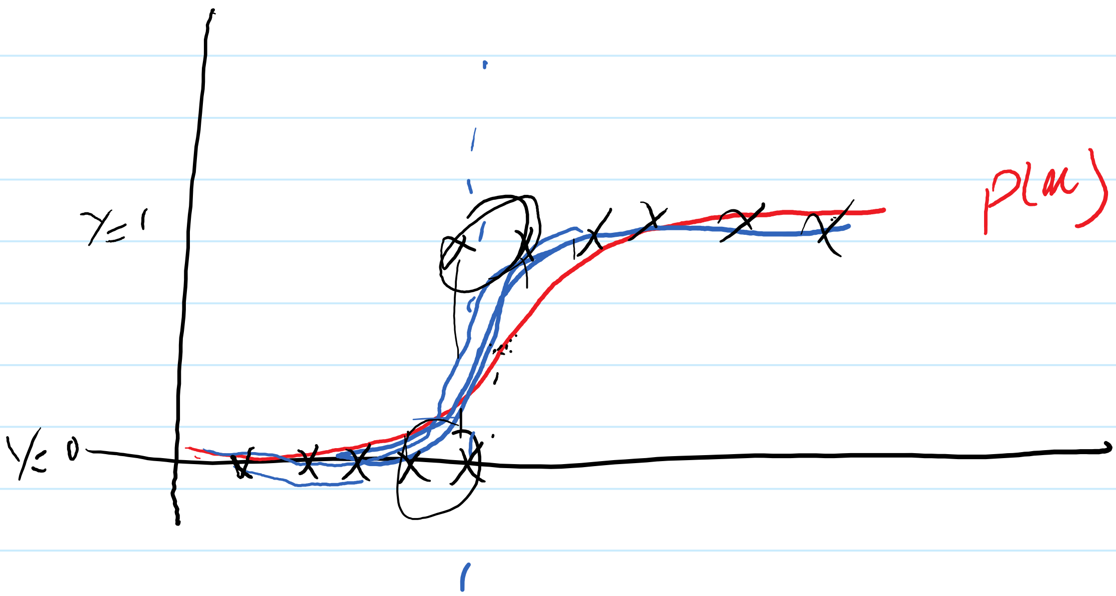

$\hat{\beta}$

$y=1 \quad p(x) \to 1$

$y=0 \quad 1-p(x) \to 1$

$$\boxed{P(y,x) = p_x^{y}(1-p_x)^{1-y}}$$

$$L(\beta) = \prod_{y=1} p(x) \cdot \prod_{y=0} (1-p(x))$$

$$\boxed{L(\beta) = \prod P_x^{y}[1-P_x]^{1-y}}$$

LR

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$$l(\beta) = \sum y_i \log P_x + (1 - y_i) \log(1 - P_x)$$

$$P = \frac{1}{1 + e^{-\beta x}}$$

$$\hat{\beta} = \operatorname{argmax} l(\beta)$$

$$l(\beta) = \sum y_i \beta x_i - \log(1 + e^{\beta x})$$

$$\left\{ \begin{aligned} \beta^{t+1} &= \beta^{t} + (X^T W X)^{-1} X(Y - \hat{Y}(t)) \\ W &= P \cdot (1 - P) \end{aligned} \right.$$

LR

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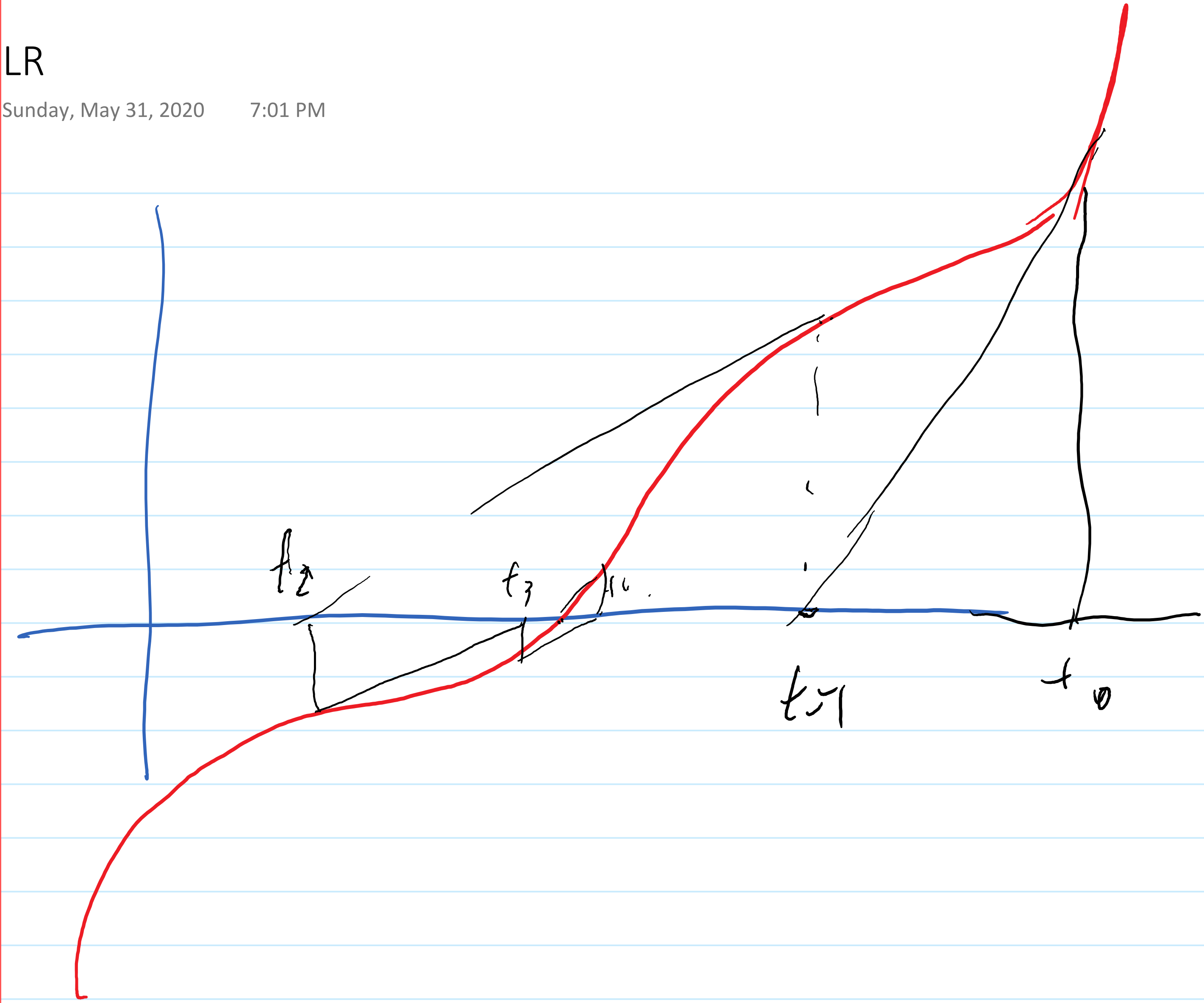

Multi LR

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