

(Non-examinable)

Probability estimation question

Iain is juggling.



Assume he has a 1% chance of dropping each catch.

(not really independent,
but let's pretend)

Estimate without a computer/calculator
the probability he manages

100 catches in a row
on first attempt.

$N=100$ catches, $f=0.01$ drop prob.

$$P(N \text{ catches}) = \prod_{n=1}^N (1-f)$$
$$= (1-f)^N$$

$\approx 1-Nf$?
 $\Rightarrow 0$ here $\times$

$$\log P(N \text{ catches}) = N \log(1-f)$$

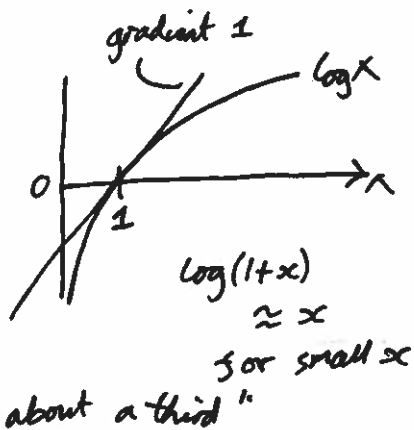
$$\approx -Nf$$

$$\approx -1 \text{ here}$$

$$P(100 \text{ catches}) \approx e^{-1}$$

$$= 1/e$$

$$\approx \underline{\underline{0.37}}$$



In Matlab/Octave or Numpy 10^{-20}

$$\log(1 - 1e-20) \approx 0$$

$$\log 1p(-1e-20) = 1e-20$$

$\uparrow$ " $\log(1+x)$ "

Recipe: fit parameters to data

Loss and function: $L(y^{(n)}, f(x^{(n)}, \underline{w})) = L_n$

Square loss: $(y^{(n)} - f_n)^2$

Negative log probability: $-\log p(y^{(n)} | x^{(n)}, \underline{w})$

Cost

$$C = \sum_n L_n \quad \text{sum over training set}$$

Learning direction

$$-\frac{1}{N} \nabla_{\underline{w}} C = -\frac{1}{N} \sum_n \nabla_{\underline{w}} L_n$$

Monte Carlo approx:

$-\nabla_{\underline{w}} L_n$ for random n

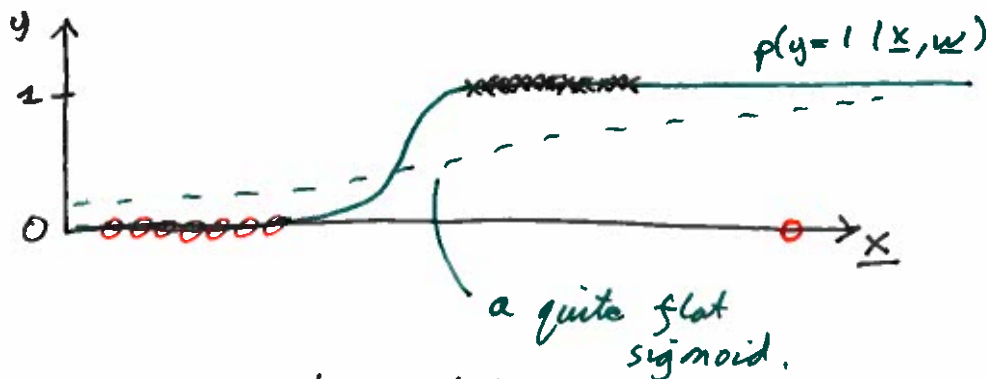
$\Rightarrow$ Identify probabilistic model of y , $p(y | x, \underline{w})$

$\Rightarrow$ Update parameters:

$$\underline{w} \leftarrow \underline{w} + \eta \nabla_{\underline{w}} \log p(y^{(n)} | x^{(n)}, \underline{w})$$

S.G.D. on loss. S.G. Ascent on log likelihood

Robust Logistic Regression



Each example has a binary variable

$$m^{(n)} \in \{0, 1\} \quad \text{hidden variable}$$

/ latent variable

I will assume:

$$P(m | \epsilon) = \begin{cases} 1 - \epsilon & m=1 \\ \epsilon & m=0 \end{cases}$$

↖ $\epsilon \approx 0.01?$

Model for labels:

$$P(y=1 | \underline{x}, \underline{w}, m) = \begin{cases} \sigma(\underline{w}^T \underline{x}) & m=1 \\ 1/2 & m=0 \end{cases}$$

Need Likelihood of $\underline{w}, \epsilon$

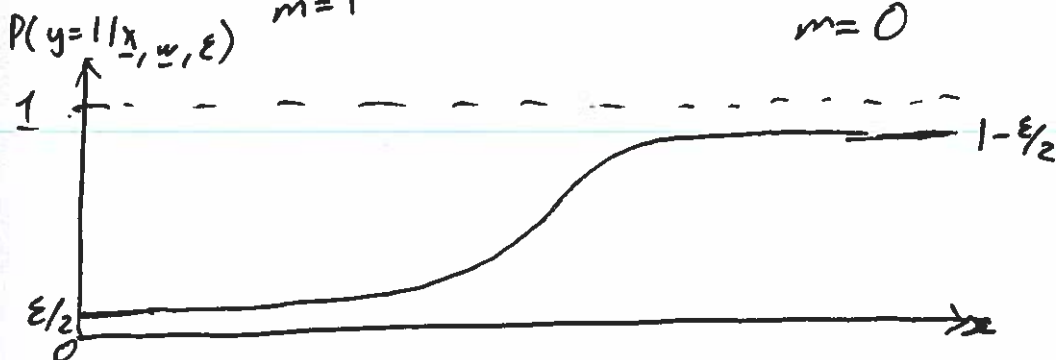
$$P(y=1 | \underline{x}, \underline{w}, \epsilon) = \sum_{m \in \{0,1\}} P(y=1, m | \underline{x}, \underline{w}, \epsilon)$$

(Sum Rule)

$$= \sum_m P(y=1 | \underline{x}, \underline{w}, \cancel{\epsilon}, m) P(\cancel{m} | \underline{x}, \underline{w}, \epsilon)$$

(Product Rule) For this model

$$= \underbrace{(1-\epsilon) \sigma(\underline{w}^T \underline{x})}_{m=1} + \underbrace{\epsilon/2}_{m=0}$$



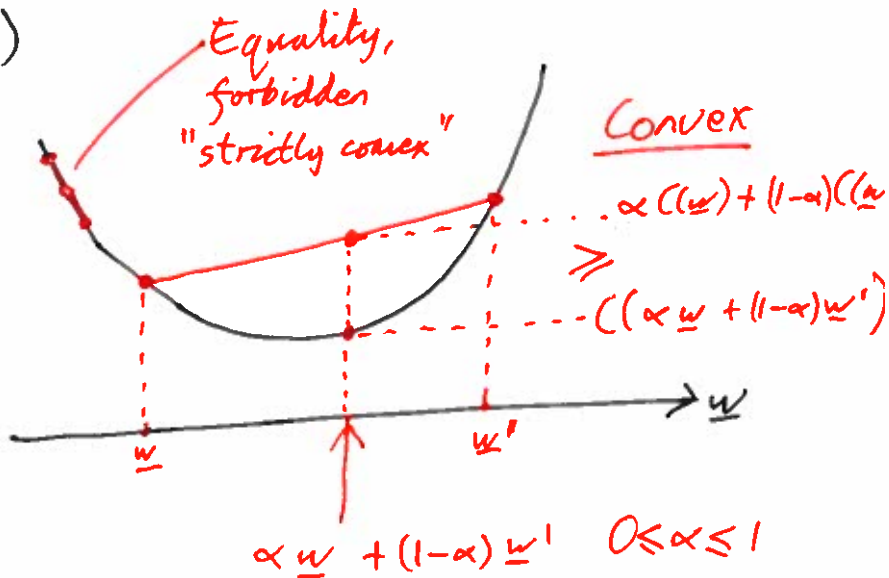
$$\nabla_{\underline{w}} \log P(y^{(n)} | \underline{x}^{(n)}, \underline{w}, \epsilon) = \dots \text{calculus/algebra}$$

$$= \frac{1}{1 + \frac{1}{2} \left(\frac{\epsilon}{1-\epsilon} \right) \frac{1}{\sigma_n}} \nabla_{\underline{w}} \log \sigma_n$$

($P(y^{(n)} | \underline{w}, \underline{x})$)
Logistic regression

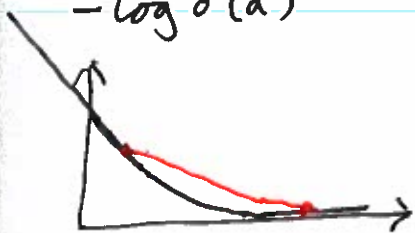
Convex Optimization Problem

Cost $C(\underline{w})$



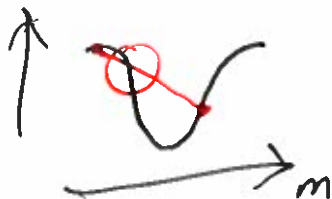
Logistic Regression

$-\log \sigma(a)$



Cost is sum
convex functions
 $\Rightarrow$ convex

$-N(x; m, \sigma^2)$



Robust logistic regression
NLL



How do we fit ε ?

By hand? Grid of settings $\varepsilon \in [0, 1]$

maybe on a log scale

0.1, 0.01, 0.001, ...

Jointly fit

$$\underline{\theta} = \begin{bmatrix} \underline{w} \\ \varepsilon \end{bmatrix}, \quad \nabla_{\underline{\theta}} \mathcal{L}$$

→ Do SGD

Doesn't work because $\varepsilon \in [0, 1]$

Trick: reparameterize model

$$\varepsilon = \sigma(b)$$

$$\uparrow -\infty < b < \infty$$

$$\frac{\partial \mathcal{L}}{\partial b} = \frac{\partial \mathcal{L}}{\partial \varepsilon} \underbrace{\frac{\partial \varepsilon}{\partial b}}_{\varepsilon(1-\varepsilon)}$$

Optimize $\begin{bmatrix} \underline{w} \\ b \end{bmatrix}$