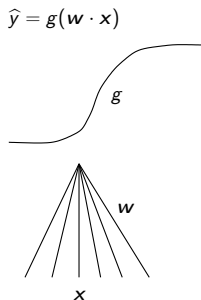


Learning with a single neuron



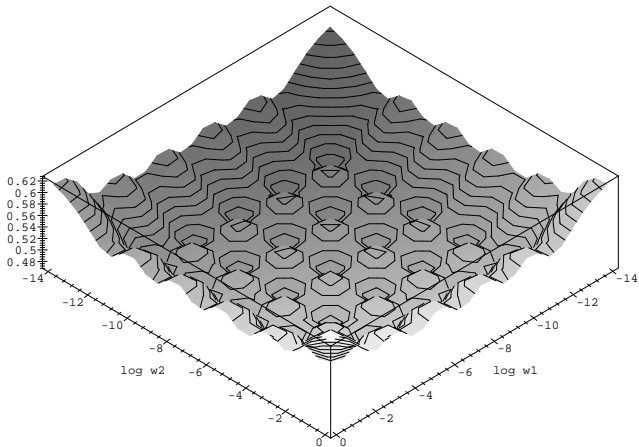
- Sigmoid function $g(z) = \frac{1}{1+e^{-z}}$
- For set of examples $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$

total loss $\sum_{n=1}^N (g(\mathbf{w} \cdot \mathbf{x}_n) - y_n)^2 / 2$

can have **exponentially # of minima** in weight space



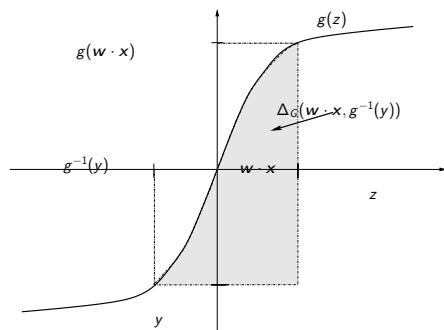
[Bu,AHW]



Want loss that is **convex** in \mathbf{w}
Convex plus convex is convex!



Bregman Divergences lead to good loss functions



transfer function $g = \nabla G$

$$\begin{aligned} \int_{g^{-1}(y)}^{w \cdot x} (g(z) - y) dz &= G(w \cdot x) - G(g^{-1}(y)) - (w \cdot x - g^{-1}(y)) y \\ &= \Delta_G(w \cdot x, g^{-1}(y)) \end{aligned}$$

$$\frac{\partial \Delta_G(w \cdot x, g^{-1}(y))}{\partial w} = \underbrace{(g(w \cdot x))}_{\hat{y}} - \underbrace{(g(g^{-1}(y)))}_y x$$

Use $\Delta_G(\mathbf{w} \cdot \mathbf{x}, g^{-1}(y))$ as loss of \mathbf{w} on (\mathbf{x}, y)

Called **matching loss** for g

[AHW,HKW]

transfer func. $g(z)$	$G(z)$	match. loss $d_G(\mathbf{w} \cdot \mathbf{x}, g^{-1}(y))$
z	$\frac{1}{2}z^2$	$\frac{1}{2}(\mathbf{w} \cdot \mathbf{x} - y)^2$ square loss
$\frac{e^z}{1+e^z}$	$\ln(1 + e^z)$	$y \ln y + (1 - y) \ln(1 - y)$ $+ \ln(1 + e^{\mathbf{w} \cdot \mathbf{x}}) - y \mathbf{w} \cdot \mathbf{x}$ logistic loss

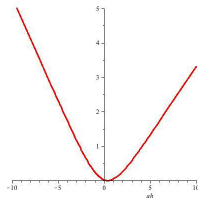
In all cases, $\frac{\partial \text{match.loss}}{\partial \mathbf{w}} = (\hat{y} - y)\mathbf{x}$, where $\hat{y} = g(\mathbf{w} \cdot \mathbf{x})$

Matching loss always **convex** in \mathbf{w}

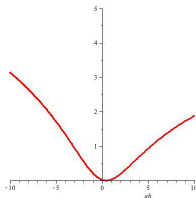


But convex losses **NON-ROBUST TO OUTLIERS**

Convex losses can't handle outliers



- Any convex loss grows at least linearly



- We need the "wings to bend down", i.e. *forget / give up on* examples
- Non-convexity is needed to achieve robustness !!!**

