LEARING FROM DATA

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CONTENTS

1	Perceptron A	Algorithm	2
2	Logistic Reg	ression	3
3	Methods		3
LI	ST OF FI	GURES	
Fig	gure 1	Sigmoid function with a single variant x, various choice of parameter w	2
Fig	gure 2	Sigmoid function with a single variant <i>x</i> , various choice	
		of bias b	3

LIST OF TABLES

ABSTRACT

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PERCEPTRON ALGORITHM 1

The perceptron algorithm is the most simple learning algorithm for classification problem. It works as follows

$$h(x) = sign\left(\left(\sum_{i=1}^{d} w_i x_i\right) + b\right)$$
 (1)

where w_i is the weight for feature x_i and b is a bias term. We can easily rewrite it in terms of linear algebra. We will treat bias b as a constant weight $w_0 = b$. With this convention $\mathbf{w}^\mathsf{T} \mathbf{x} = \sum_{i=0}^d w_i x_i$. From this notation, it looks like there is no difference between weights and bias in perceptron model. A natural question is that if weight and bias are similar, why we even borther to introduce both weight and bias?

LOGISTIC REGRESSION 2

The logistic regression utitilizes logistic function.

$$f(x) = \frac{L}{1 + e^{-k(x - x_0)}}$$
 (2)

where L defines the curve's maximum value and k specifies steepness of the curve and x_0 is the centre of the curve. Sigmoid function is a special case of logistic function. The logistic regression is also a classification algorithm.

To answer this question, let take a look at the property of sigmoid function in Figure 1 and 2. In a nutshell, the weight w controls its steepness of sigmoid functions and bias b enables to shift the entire curve to left and right. Let take back and take glimpse at its properity.

- Sigmoid has a nearly linear range around its centre o and becomes non-linear at two ends.
- Sigmoid has finite limits at negative infinity and infinity, most often going either from 0 to 1 or from -1 to 1 depending on convention.
- Sigmoid can model many natural processes, such as those of complex system learning curves, exhibit a progression from small beginings that accelebrates and approaches a climax over time.
- Sigmoid is differentiable. Its derivative is $\frac{1}{dx}y = y(1-y)$.

The key difference between

METHODS

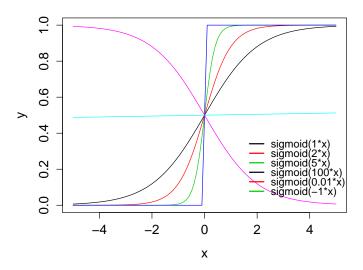


Figure 1: Sigmoid function with a single variant *x*, various choice of parameter *w*.

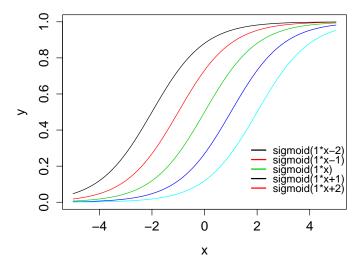


Figure 2: Sigmoid function with a single variant *x*, various choice of bias b.