Common Mathematical Tools

CHEN Si

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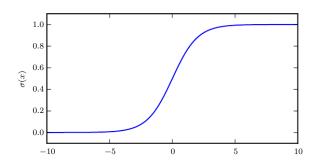
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Part I

Common Functions

1 Logistic Sigmoid

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$



Formulas

1.
$$\sigma(x) = \frac{\exp(x)}{\exp(x) + \exp(0)}$$

2.
$$\frac{\mathrm{d}}{\mathrm{d}x}\sigma(x) = \sigma(x)(1 - \sigma(x))$$

$$3. 1 - \sigma(x) = \sigma(-x)$$

4.
$$\log \sigma(x) = -\zeta(-x)$$

5.
$$\sigma(x) = \frac{\mathrm{d}}{\mathrm{d}x}\zeta(x)$$

6.
$$\forall x \in (0,1), \ \sigma^{-1}(x) = \log\left(\frac{x}{1-x}\right)$$

• The function $\sigma^{-1}(x)$ is called the **logit** in statistics.

Properties

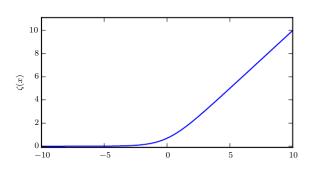
- 1. Saturates when its argument is very positive or very negative.
 - very flat
 - insensitive to small changes in its input

Applications

1. Produce the parameter of a Bernoulli distribution.

2 Softplus Function

 $\zeta(x) = \log(1 + \exp(x))$



Formulas

1.
$$-\zeta(-x) = \log \sigma(x)$$

$$2. \ \frac{\mathrm{d}}{\mathrm{d}x}\zeta(x) = \sigma(x)$$

3.
$$\forall x > 0, \ \zeta^{-1}(x) = \log(\exp(x) - 1)$$

4.
$$\zeta(x) = \int_{-\infty}^{x} \sigma(y) dy$$

5.
$$\zeta(x) - \zeta(-x) = x$$

Properties

1.
$$\zeta(x) \in (0, \infty)$$

2.
$$\zeta(x)$$
 is a smoothed (or "softened") version of

$$x^+ = \max(0, x)$$

 $\zeta(-x)$ is a smoothed (or "softened") version of

$$x^- = \max(0, -x)$$

Similar to $x^+ - x^- = x$, we also have

$$\zeta(x) - \zeta(-x) = x$$

Applications

1. Produces the β or σ parameter of a normal distribution.

Part II

Common Probability Distributions

3 Gaussian Distribution

Introduction

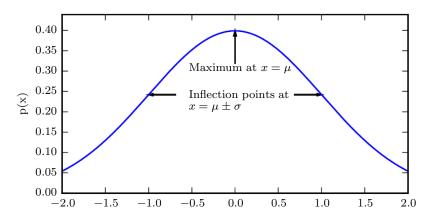
- Also known as the **Normal Distribution**.
- The most commonly used distribution over real numbers.

Definition

For real numbers

$$\mathcal{N}(x; \mu, \sigma^2) = \sqrt{\frac{1}{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right)$$

- $\mu \in \mathbb{R}$
- $\sigma \in (0, \infty)$



For \mathbb{R}^n

$$\mathcal{N}(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sqrt{\frac{1}{(2\pi)^n \det(\boldsymbol{\Sigma})}} \exp\left(-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^\top \boldsymbol{\Sigma}^{-1}(\boldsymbol{x} - \boldsymbol{\mu})\right)$$

- Also known as Multivariate Normal Distribution.
- The covariance matrix Σ is positive definite symmetric.

Variant

For real numbers If we need to frequently evaluate the PDF with diffrent parameter values, a more efficient way of parametrizing the distribution is to use a parameter $\beta \in (0, \infty)$ to control the **precision** (or inverse variance) of the distribution

$$\mathcal{N}(x; \mu, \beta^{-1}) = \sqrt{\frac{\beta}{2\pi}} \exp\left(-\frac{1}{2}\beta(x-\mu)^2\right)$$

For \mathbb{R}^n We can use a precision matrix $\boldsymbol{\beta}$

$$\mathcal{N}(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\beta}^{-1}) = \sqrt{\frac{\det(\boldsymbol{\beta})}{(2\pi)^n}} \exp\left(-\frac{1}{2}(\boldsymbol{x} - \boldsymbol{\mu})^{\top} \boldsymbol{\beta}(\boldsymbol{x} - \boldsymbol{\mu})\right)$$

We often fix the covariance matrix to be a diagonal matrix. An even simpler version is the **isotropic** Gaussian distribution, whose covariance matrix is a scalar times the identity matrix.

Properties

• $\mathbb{E}[x] = \mu$

Advantages

- 1. The **central limit theorem** shows that the sum of many independent random variables is approximately normally distributed.
- 2. Out of all possible probability distributions with the same variance, the normal distribution encodes the maximum amount of uncertainty over the real numbers.
 - We can thus think of the normal distribution as being the one that inserts the least amount of prior knowledge into a model.