

## 書目計量學

### Lecture 02 -- 基本數學

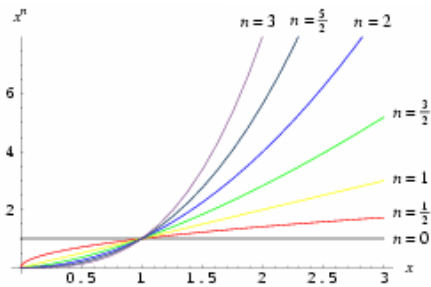
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## Declaration

- The content of this slide is extracted from MathWorld (<http://mathworld.wolfram.com>)

## Exponent

- An exponent is the **power**  $n$  in an expression of the form  $x^n$ .



## Exponent Laws

$$\begin{aligned}x^m \cdot x^n &= x^{m+n} & \left(\frac{x}{y}\right)^n &= \frac{x^n}{y^n} \\ \frac{x^m}{x^n} &= x^{m-n} & x^{-n} &= \frac{1}{x^n} \\ (x^m)^n &= x^{mn} & \left(\frac{x}{y}\right)^{-n} &= \left(\frac{y}{x}\right)^n \\ (xy)^m &= x^m y^m & & \end{aligned}$$

## Logarithm

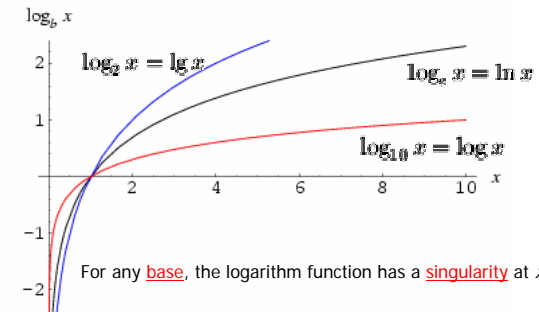
The logarithm  $\log_b x$  for a **base**  $b$  and a number  $x$  is defined to be the **inverse function** of taking  $b$  to the **power**  $x$ , i.e.,  $b^x$ . Therefore, for any  $x$  and  $b$ ,

$$x = \log_b(b^x),$$

or equivalently,

$$x = b^{\log_b x}.$$

## Logarithm Curve



For any **base**, the logarithm function has a **singularity** at  $x = 0$ .

Source: <http://mathworld.wolfram.com/Logarithm.html>

## Some Properties of Logarithm

$$xy = b^{\log_b x} b^{\log_b y} = b^{\log_b x + \log_b y}$$

$$\log_b x + \log_b y = \log_b xy$$

$$\log_b x - \log_b y = \log_b (x / y)$$

$$n \log_b x = \log_b x^n$$

## Some Properties of Logarithm

(continued)

$$\begin{aligned} a &= a^{\log_a b / \log_a b} \\ &= (a^{\log_a b})^{1 / \log_a b} \\ &= b^{1 / \log_a b} \\ \log_b a &= \frac{1}{\log_a b} \end{aligned}$$

## Some Properties of Logarithm (continued)

$$\begin{aligned}\log_b x &= \log_b (y^{\log_y x}) \\ &= \log_y x \log_b y \\ \log_b x &= \frac{\log_n x}{\log_n b} \\ a^x &= b^{x/\log_a b} \\ &= b^{x \log_b a}\end{aligned}$$

## Basic Calculus

導數的定義	$f'(x) = \frac{d}{dx} f(x) = \lim_{\Delta x \rightarrow 0} \frac{f(x+\Delta x) - f(x)}{\Delta x}$
冪法則	$\frac{d}{dx} x^n = nx^{n-1}$
函數和差之導數	$\frac{d}{dx} [f(x) \pm g(x)] = \frac{d}{dx} f(x) \pm \frac{d}{dx} g(x)$
積法則	$\frac{d}{dx} [f(x)g(x)] = f(x) \frac{d}{dx} g(x) + g(x) \frac{d}{dx} f(x)$
商法則	$\frac{d}{dx} \frac{f(x)}{g(x)} = \frac{g(x) \frac{d}{dx} f(x) - f(x) \frac{d}{dx} g(x)}{[g(x)]^2}$

## 鏈式法則

$$\begin{aligned}\frac{dy}{dx} &= \frac{dy}{du} \cdot \frac{du}{dx} \\ \frac{dy}{dx} &= \frac{1}{\frac{dx}{dy}} \\ \frac{d}{dx} y^n &= ny^{n-1} \frac{dy}{dx}\end{aligned}$$

## 對數的導數

$$\begin{aligned}\frac{d}{dx} \log_a x &= \frac{\log_a e}{x} \\ \frac{d}{dx} \ln x &= \frac{1}{x}\end{aligned}$$

## 指數函數的導數

$$\frac{d}{dx} n^x = n^x \ln n$$

$$\frac{d}{dx} e^x = e^x$$

$$\frac{d}{dx} u^v = v u^{v-1} \frac{du}{dx} + u^v \ln u \frac{dv}{dx}$$

## Determine the Function

- Assume the function is  $Y=f(X)=a_0+a_1X+a_2X^2+\dots+a_mX^m$
- We have a set of points  $(x_1,y_1), (x_2,y_2), \dots, (x_n,y_n)$
- Sum of offsets is defined as
- $R^2=\sum[y_i-f(x_i)]^2$ ,  $1 \leq i \leq n$ , note  $a_0, a_1, \dots, a_m$  are unknown and will be determined through least square method
- The idea is to minimize  $R^2$ , i.e.,  $\frac{\partial(R^2)}{\partial a_i} = 0$

## Linear Regression

- When  $m$  is 1 in  $Y=f(X)=a_0+a_1X+a_2X^2+\dots+a_mX^m$ , we call this procedure linear regression
- $Y=f(X)=a_0+a_1X$ ,
- $R^2=\sum[y_i-f(x_i)]^2 = \sum[y_i-(a_0+a_1x_i)]^2$ ,  $1 \leq i \leq n$

$$\frac{\partial(R^2)}{\partial a_i} = 0$$

## Linear Regression (Continued)

$$R^2 = \sum_{i=1}^n [y_i - (a_0 + a_1x_i)]^2$$

$$\frac{\partial(R^2)}{\partial a_0} = -2 \sum_{i=1}^n [y_i - (a_0 + a_1x_i)] = 0$$

$$\frac{\partial(R^2)}{\partial a_1} = -2 \sum_{i=1}^n [y_i - (a_0 + a_1x_i)]x_i = 0$$

$$na_0 + a_1 \sum_{i=1}^n x_i = \sum_{i=1}^n y_i$$

$$a_0 \sum_{i=1}^n x_i + a_1 \sum_{i=1}^n x_i^2 = \sum_{i=1}^n x_i y_i$$

## Linear Regression (Continued)

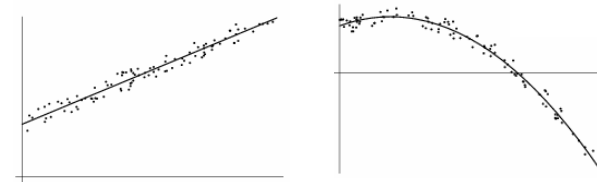
$$\begin{bmatrix} n & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n x_i^2 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i y_i \end{bmatrix}$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} n & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n x_i^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i y_i \end{bmatrix}$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = \frac{1}{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2} \begin{bmatrix} \sum_{i=1}^n y_i \sum_{i=1}^n x_i^2 - \sum_{i=1}^n x_i \sum_{i=1}^n x_i y_i \\ n \sum_{i=1}^n x_i y_i - \sum_{i=1}^n x_i \sum_{i=1}^n y_i \end{bmatrix}$$

## Least Square Method

- Find the best fitting curve to a given set of points by minimizing the sum of the squares of the offsets of the points from the curve.



## Residuals (offsets)

