

Mathematics Handout

1. Derivatives

Let $f(x) = x^n$ and $g(x) = a + bx$ where n , a and b are constants.

$$\frac{d(x^n)}{dx} = nx^{n-1}$$

$$\frac{dg(x)}{dx} = b$$

$$\frac{d[f(x)+g(x)]}{dx} = nx^{n-1} + b$$

$$\frac{d[f(g(x))]}{dx} = n(a+bx)^{n-1}b$$

2. Summation notation

Let \bar{a} over a variable indicate the arithmetic mean or average value of that variable and k be a constant.

$$a_1 + a_2 + a_3 = \mathbf{E}_{i=1}^3 a_i$$

$$a_1 + a_2 + \dots + a_n = \mathbf{E}_{i=1}^n a_i$$

$$a + a + a = \mathbf{E}_{i=1}^3 a = 3a$$

$$\begin{aligned} \mathbf{E}[(y_i - \bar{y})(x_i - \bar{x})] &= \mathbf{E}(y_i x_i - \bar{y} x_i - \bar{x} y_i + \bar{x} \bar{y}) \\ &= \mathbf{E}(y_i x_i) - n \bar{x} \bar{y} \\ &= \mathbf{E}(y_i - \bar{y}) x_i \end{aligned}$$

$$\begin{aligned} \mathbf{E} \mathbf{E} x_i x_j &= \mathbf{E} x_i^2 + 2 \mathbf{E} \mathbf{E} x_i x_j \\ &= \left[\mathbf{E} x_i \right]^2 \end{aligned}$$

$$\mathbf{E} k a_i = k \mathbf{E} a_i$$

3. Derivatives in Summation Notation

Let $f(x)$ be any arbitrary function of x .

$$\frac{d(\mathbf{E}_i^n f(x))}{dx} = \mathbf{E}_i^n \frac{df(x)}{dx}$$

Suppose that $x = a + by$ and $f(x) = x^2$.

$$\frac{d(\mathbf{E}_i^n (a+by_i)^2)}{da} = 2\mathbf{E}_i^n (a+by_i)$$

$$\frac{d(\mathbf{E}_i^n (a+by_i)^2)}{db} = 2\mathbf{E}_i^n [(a+by_i)y_i]$$

4. Expectations, Means, and Variances

Recall from statistics that $E()$ is called the expectations operator and that the expected value of a random variable is its mean, or population average. Let x , y , z and \bar{x} be random variables where $\bar{x} = \frac{1}{n} \sum x_i$. If a bar appears over the variable it denotes the sample mean and s^2 is the sample variance. Let μ and σ^2 be the population mean and variance respectively.

$$\bar{x} = \frac{\mathbf{E}_{i=1}^n x_i}{n}$$

$$s_x^2 = \frac{\mathbf{E}_{i=1}^n (x_i - \bar{x})^2}{n-1}$$

$$E(x) = \mu_x$$

$$E[(x - \mu_x)(y - \mu_y)] = E(xy) - \mu_x \mu_y \\ = \mathbf{F}_{xy}$$

$$E(xz) = E(x(\mu_x + \mathbf{S}x, \dots)) = E[\mu_x + \mathbf{S}x^2 + \dots] \\ = \mu_x + \mathbf{S}E(x^2) + \dots \\ = \mu_x + \mathbf{S}E(x^2) + E(\dots, x)$$

$$E[(x - \mu_x)(y - \mu_y)] = E(xy) - \mu_x \mu_y \\ = \mathbf{F}_{xy}$$

$$E[x - E(x)]^2 = E[x - \mu_x]^2 \\ = E(x^2) - \mu_x^2 \\ = \mathbf{F}_x^2$$