

# 1 Math

## 2 Applied

Topics covered up to 31 October

Matrix / Vector differentiation

### 2.1 Linear Models

Least Squares Principle

$$\arg \min_{\beta} \|Y - X\beta\|^2$$

Normal Model

$$Y = X\beta + \epsilon, \quad \epsilon \sim N(0, \sigma^2 I)$$

Normal Equations - Any  $b$  satisfying this solves the least squares

$$X^T X b = X^T y$$

Gauss Markov Theorem -  $\hat{\beta}(X^T X)^{-1} y$  is Best Linear Unbiased Estimator (BLUE) of  $\beta$ .

### 2.2 General Techniques

Singular Value Decomposition (SVD) Any matrix  $X$  can be written

$$X = U D V^T$$

with  $U, V$  orthogonal, and  $D$  diagonal.

Moore Penrose Pseudoinverse  $A^+$  exists uniquely for every matrix  $A$ .

Projection matrix  $P$  are symmetric and idempotent. They have eigenvalues either 0 or 1.

$$P = P^T \quad P^2 = P$$

Multivariate Normal  $y \sim N(\mu, \Sigma)$ ,  $A$  an  $m \times n$  matrix, then

$$Ay \sim N(A\mu, A\Sigma A^t)$$