

March 26, 2021

Norms:  $\|A\|_2 = \max_x \|Ax\|_2 = \sigma_1(A) \quad x \geq v_1$   
s.t.  $\|x\|_2 = 1$

Least squares:  $\arg \min_x \|Ax - b\|_2^2 (+ \beta \|x\|_2^2)$   
 $\hat{x} = R^{-1} Q^T b$   
 $\begin{pmatrix} A \\ \sqrt{\beta} I \end{pmatrix} = QR$

Eigenvalues / Eigenvectors  $\min_x x^T A x$   
s.t.  $\|x\|_2 = 1 \quad \lambda_n \quad Ax = \lambda_n x$

optimization variable  $\rightarrow \arg \min (x)$   
s.t.  $x^T L x$  objective function  
 $\|x\|_2^2 = n$  constraints  
 $\{ e^T x = 0 \}$  linear const.

unconstrained

$$\min_x f(x)$$

$$\Leftrightarrow \max_x -f(x)$$

constrained

$$\min_x f(x)$$
$$\text{s.t. } g(x) = 0$$



$$f: \mathbb{R} \rightarrow \mathbb{R} \quad \min_{x \in \mathbb{R}} f(x)$$

Taylor expansion: 
$$f(x) = \sum_{j=0}^{\infty} \frac{f^{(j)}(a)}{j!} (x-a)^j$$

Example:  $e^{-x}$  ( $a=0$ ):  $1 - x + \frac{x^2}{2} - \frac{x^3}{6} + \dots$

$$f(x+h) = \sum_{j=0}^{\infty} \frac{f^{(j)}(x)}{j!} h^j \approx f(x) + \underline{f'(x)h} + \frac{1}{2} f''(x) h^2$$







$$= (b_0 - a_0) / 2^k$$