Lagrangian Optimization

- For optimization with constraints
- Equality constraints
- Inequality constraint

1. Lagrange Optimization with One Equality constraint

Use typical math notation:

Problem: find an extremum of $f(\underline{x})$ ($=J(w)$ for us), subject to constraint:

$g(\underline{x})=0$ → new constraint

Solution:

1. set up Lagrangian function

$$L(\underline{x},\lambda)=f(\underline{x})+\lambda g(\underline{x})$$

$f(\underline{x})$: original function to minimize; $g(\underline{x})=0$: new constraint

Note: when $g(\underline{x})=0$ (constraint satisfied) $L(\underline{x},\lambda)=f(\underline{x})$

2. Lagrange method $\nabla_{\underline{x},\lambda} L(\underline{x},\lambda)=\underline{0}$

$$\Rightarrow (*)\begin{cases}\nabla_{\underline{x}} L(\underline{x},\lambda)=\nabla_{\underline{x}} f(\underline{x})+\nabla_{\underline{x}}\lambda g(\underline{x})=0\\ \nabla_{\lambda} L(\underline{x},\lambda)=g(\underline{x})=0\end{cases}$$

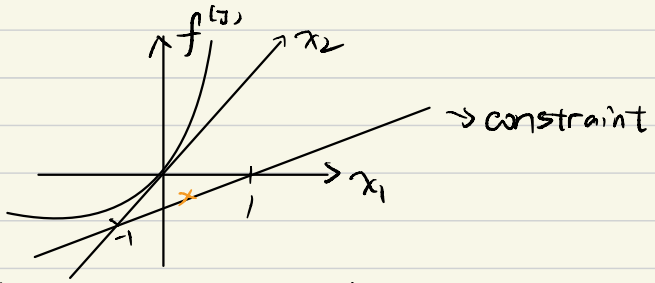
If $\underline{x}$ has d dimension $\Rightarrow$ $d+1$ unknowns, $d+1$ equations

Example of Lagrangian Optimization with 1 Equality Constraint

Let $f(\underline{x})=\|\underline{x}\|_2^2=x_1^2+x_2^2$ $(d=2)$

Minimize $f(\underline{x})$ subject to (s.t.) constraint: $x_2-x_1=-1$

$\Rightarrow g(\underline{x})=x_2-x_1+1=0$



Lagrange method:

Let $L(\underline{x},\lambda)=f(\underline{x})+\lambda g(\underline{x})$

$=\|\underline{x}\|_2^2+\lambda(x_2-x_1+1)$

$\nabla_{\underline{x},\lambda} L(\underline{x},\lambda)=\underline{0}$

$$\Rightarrow\begin{cases}\nabla_{\underline{x}} L=\begin{bmatrix}2x_1-\lambda\\ 2x_2+\lambda\end{bmatrix}=\begin{bmatrix}0\\0\end{bmatrix} & \leftarrow ①\\ \nabla_{\lambda} L=x_2-x_1+1=0 & \leftarrow ②\end{cases}$$

$$\therefore\begin{cases}x_1=\frac{1}{2}\\ x_2=-\frac{1}{2}\\ \lambda=1\end{cases}$$

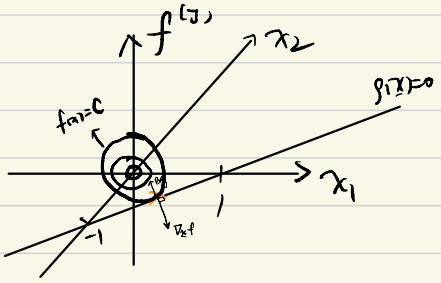
$\therefore \underline{x}^*=\begin{bmatrix}\frac{1}{2}\\ -\frac{1}{2}\end{bmatrix}$ $\lambda=1$.

Intuitive explanation of Lagrange example.

In $x_1 x_2$-plane. $f(\underline{x}) = \|\underline{x}\|_2^2$

$f(\underline{x}) = d_E^2(\underline{0}, \underline{x}) = r^2$

(f = constant) is a circle, about origin.



Increase r until circle tangent to $g(\underline{x})=0$
→ point x^*

∴ at x^*, we have
- $\nabla_{\underline{x}} f(\underline{x}) \perp f(\underline{x}) = C$ ← $\nabla_{\underline{x}} f(\underline{x}) = 0$
- $\nabla_{\underline{x}} g(\underline{x}) \perp g(\underline{x}) = 0$ ← $\nabla_{\underline{x}} g(\underline{x}) = 0$
- $f(\underline{x}) = C$ is tangent to $g(\underline{x}) = 0$

∴ $\nabla_{\underline{x}} f(x^*) \;//\; \nabla_{\underline{x}} g(x^*)$

∴ $\nabla_{\underline{x}} f(\underline{x}) = \pm\lambda \nabla_{\underline{x}} g(\underline{x})$ at $\underline{x} = x^*$ ← λ comes from here

∴ $\nabla_{\underline{x}} f(\underline{x}) \pm \lambda \nabla_{\underline{x}} g(\underline{x}) = 0$

→ Choose + sign

$\nabla_{\underline{x}} (f(\underline{x}) + \lambda g(\underline{x})) = 0 \Rightarrow \begin{cases} \nabla_{\underline{x}} (L(\underline{x}, \lambda)) = \underline{0} \\ \nabla_{\lambda} L(\underline{x}, \lambda) = \underline{0} \end{cases}$

2. Lagrangian Optimization with Multiple Equality Constraints

Find min of $f(\underline{x})$ s.t. $g_i(\underline{x}) = 0$ $i = 1, 2, \ldots$ $R < d$

$$L(\underline{x}, \underline{\lambda}) = f(\underline{x}) + \sum_{i=1}^{R} \lambda_i g_i(\underline{x})$$
$$\nabla_{\underline{x}, \underline{\lambda}} L(\underline{x}, \underline{\lambda}) = 0$$

λ_i = Lagragian multiplier
⇒ $d+R$ eqns, $d+R$ unknowns.

3. Lagrangian Optimization with 1 Inequality constraint

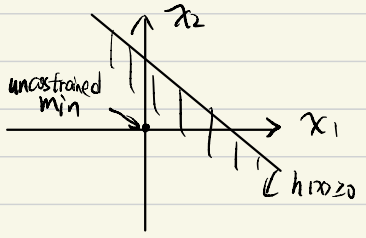
Extension of the equality constraint case

Find min of $f(\underline{x})$ s.t. $h(\underline{x}) \geq 0$

Let:

$$L(\underline{x}, \mu) = f(\underline{x}) - \mu h(\underline{x})$$

Find extremum of L over $\underline{x}$ and μ.



2 cases:

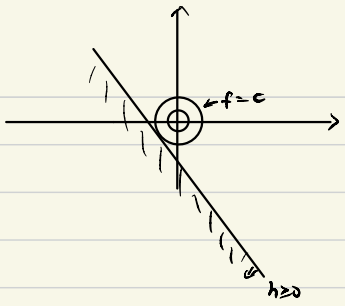
(a) unconstrained min is in region $h \geq 0$

⇒ Constrained min = unconstrained min

$\nabla_{\underline{x}} f(\underline{x}) = 0$

⇒ can solve using $L(\underline{x}, \mu)$ with $\mu = 0$

(b) unconstrained min is outside region $h \geq 0$



$\Rightarrow$ constrained min is on $h(\underline{x})=0$ curve
Same as equality constrained case

$L(\underline{x}, \mu)$ with $\mu \neq 0$
$\nabla_{\underline{x},\mu} L = \underline{0}$

$\Rightarrow \nabla_{\underline{x}} f = \mu \nabla_{\underline{x}} h \quad , \mu > 0$

$L(\underline{x}, \mu) = f(\underline{x}) - \mu h(\underline{x})$ with $h \geq 0$ (constraint)
In case (a): $\mu = 0$, $h(\underline{x}^*) > 0$
In case (b): $\mu > 0$, $h(\underline{x}^*) = 0$

in both case, $\mu h(\underline{x}^*) = 0$

Summary: Min $f(\underline{x})$ s.t. $h(\underline{x}) \geq 0$

$L(\underline{x}, \mu) = f(\underline{x}) - \mu h(\underline{x})$
$\nabla_{\underline{x},\mu} L(\underline{x}, \mu) = \underline{0}$
$h(\underline{x}^*) \geq 0$
$\mu \geq 0$
$\mu h(\underline{x}^*) = 0$
} KKT conditions

General case: multiple Equalities & multiple Inequalities constraints

Min $f(\underline{x})$ s.t. $g_i(\underline{x}) = 0 \ \forall i$, $h_j(\underline{x}) \geq 0 \ \forall j$.

$$L(\underline{x}, \underline{\lambda}, \underline{\mu}) = f(\underline{x}) + \sum_{i=1}^{R} \lambda_i g_i(\underline{x}) - \sum_{j=1}^{R'} \mu_j h_j(\underline{x})$$

$\nabla_{\underline{x},\underline{\lambda},\underline{\mu}} L(\underline{x}, \underline{\lambda}, \underline{\mu}) = \underline{0}$

Require: $\mu_j \geq 0 \ \forall j$
$\mu_j h_j(x^*) = 0 \ \forall j$
Given $g_i(x^*) = 0 \ \forall i$
$h_j(x^*) \geq 0 \ \forall j$