Introduction to Unconstraint Optimization

Maximise or Minimize $z(x_1, x_2, ..., x_n)$

First-order conditions

If (\mathbf{x}^*) is the solution to the above problem, we must have

$$\frac{\partial z(\mathbf{x}^*)}{\partial x_1} = \mathbf{0}$$
$$\cdot$$
$$\frac{\partial z(\mathbf{x}^*)}{\partial x_n} = \mathbf{0}$$

Second-order conditions

1) For maximization problem:

Formally, the Hessian of z w.r.t. \mathbf{x} at (\mathbf{x}^*) , denoted by $D^2 z(\mathbf{x}^*)$,

is negative semidefinite, i.e. $\mathbf{h}^T D^2 z(\mathbf{x}^*) \mathbf{h} \leq \mathbf{0}$ for all $\mathbf{h} \neq \mathbf{0}$.

or negative definite, i.e. $\mathbf{h}^T D^2 z(\mathbf{x}^*) \mathbf{h} < \mathbf{0}$ for all $\mathbf{h} \neq \mathbf{0}$. (for a strict local max)

2) For minimization problem:

Formally, the Hessian of z w.r.t. \mathbf{x} at (\mathbf{x}^*) , denoted by $D^2 z(\mathbf{x}^*)$,

is positive semidefinite,i.e. $\mathbf{h}^T D^2 z(\mathbf{x}^*) \mathbf{h} \geq \mathbf{0}$ for all $\mathbf{h} \neq \mathbf{0}$

or positive definite, i.e. $\mathbf{h}^T D^2 z(\mathbf{x}^*) \mathbf{h} > \mathbf{0}$ for all $\mathbf{h} \neq \mathbf{0}$ (for a strict local min)

Checking for SOC.

1) For maximization problem:

For negative semidefinite: check that all nonzero principal minors of the Hessian matrix of order k has the sign $(-1)^k$ for k = 1, 2, ..., n

For negative definite: check that the leading principal minors of the Hessian matrix of order k has the sign $(-1)^k$ for k = 1, 2, ..., n

2) For minimization problem:

For positive semidefinite: check that all the principal minors of the Hessian matrix are nonnegative

For positive definite: check that the leading principal minors of the Hessian matrix are all positive. Profit Maximization

For Profit Maximization with 2 inputs,

$$\max \pi = pf(x_1, x_2) - w_1 x_1 - w_2 x_2$$

F.O.C.s are

$$p\frac{\partial f(\mathbf{x}^*)}{\partial x_1} - w_1 = \mathbf{0}$$

$$p\frac{\partial f(\mathbf{x}^*)}{\partial x_2} - w_2 = \mathbf{0}$$

S.O.C. is

$$D^{2}\pi(\mathbf{x}^{*}) = \begin{pmatrix} \frac{\partial^{2}\pi(\mathbf{x}^{*})}{\partial x_{1}^{2}} & \frac{\partial^{2}\pi(\mathbf{x}^{*})}{\partial x_{2}\partial x_{1}} \\ \frac{\partial^{2}\pi(\mathbf{x}^{*})}{\partial x_{1}\partial x_{2}} & \frac{\partial^{2}\pi(\mathbf{x}^{*})}{\partial x_{2}^{2}} \end{pmatrix} = p \begin{pmatrix} \frac{\partial^{2}f(\mathbf{x}^{*})}{\partial x_{1}^{2}} & \frac{\partial^{2}f(\mathbf{x}^{*})}{\partial x_{2}\partial x_{1}} \\ \frac{\partial^{2}f(\mathbf{x}^{*})}{\partial x_{1}\partial x_{2}} & \frac{\partial^{2}f(\mathbf{x}^{*})}{\partial x_{2}^{2}} \end{pmatrix}$$

is negative definite