

# A Quick Math Review

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This short note provides a quick review of some of the essential mathematical tools used in this course. Most results are stated without proofs. For a more rigorous and complete treatment, see, for example, *Mathematics for Economists* by Simon and Blume.

## 1. Functions

A function  $f$  from a set  $X$  (the domain of  $f$ ) to a set  $Y$ , denoted as  $f : X \rightarrow Y$ , maps each  $x$  in  $X$  to a unique element  $f(x)$  in  $Y$ . If for each  $y \in Y$ , there exists  $x \in X$  such that  $y = f(x)$ , then we say  $f$  is a function onto  $Y$  (or,  $f$  is *surjective*).  $f$  is called *one-to-one* (or,  $f$  is *injective*) if  $f(x_1) = f(x_2)$  implies  $x_1 = x_2$ . If  $f$  is a one-to-one function from  $X$  onto  $Y$ , then it is *bijective*.

Let  $\mathbb{N} = \{1, 2, 3, \dots\}$  denote the set of *natural numbers*. An (infinite) *sequence* is a function whose domain is  $\mathbb{N}$ , often denoted as  $\{x^n\}_{n=1}^{\infty}$ , or simply  $\{x^n\}$ . A set  $S$  is called *countable* if there exists a one-to-one function  $f : S \rightarrow \mathbb{N}$ .

## 2. Real numbers

Denote the set of *real numbers* as  $\mathbb{R}$  and the set of *rational numbers* as  $\mathbb{Q}$ . There are much more reals than rationals.

**Theorem**  $\mathbb{R}$  is not countable;  $\mathbb{Q}$  is countable.

But between any two different real numbers, there exists a rational number.

**Theorem** For any  $x, y \in \mathbb{R}$  with  $x < y$ , there exists  $z \in \mathbb{Q}$  such that  $x < z < y$ .

Given a set of real numbers  $S \subseteq \mathbb{R}$ ,  $b \in \mathbb{R}$  is an *upper bound* of  $S$  if  $x \leq b$  for each  $x \in S$ .  $c \in \mathbb{R}$  is a *least upper bound* of  $S$  if it is an upper bound of  $S$  and  $c \leq b$  for each upper bound  $b$  of  $S$ . From this definition, it is clear that a least upper bound, if it exists, is unique. While a set of real numbers with an upper bound may not include a maximum element (e.g. think of the open interval  $(0, 1)$ ), a nice property of real numbers is that the least upper bound of such a set always exists.

**Completeness Axiom** Every non-empty set  $S$  of real numbers which has an upper bound has a least upper bound.

The least upper bound of  $S$  is denoted as " $\sup S$ ". Similarly,  $b$  is a *lower bound* of  $S$  if  $b \leq x$  for each  $x \in S$ .  $c$  is a *greatest lower bound* of  $S$ , denoted as " $\inf S$ ", if it is a lower bound of  $S$  and  $c \geq b$  for each lower bound  $b$  of  $S$ . From the completeness axiom, it can be seen that each non-empty set of real numbers which has a lower bound has a greatest lower bound.<sup>1</sup> In the simple example given above, we have  $\sup(0, 1) = 1$  and  $\inf(0, 1) = 0$ .

### 3. Convergence and continuity

From now on, let us focus on the Euclidean space  $\mathbb{R}^N$ , which is of most interest in Economics. For any  $x, y \in \mathbb{R}^N$ , their distance is the usual Euclidean norm

$$\|x - y\| = \sqrt{\sum_{n=1}^N (x_n - y_n)^2}$$

**Definition** A sequence  $\{x^n\}$  in  $\mathbb{R}^N$  converges to  $x \in \mathbb{R}^N$ , denoted as  $x^n \rightarrow x$ , if for every  $\epsilon > 0$ , there exists  $N \in \mathbb{N}$  such that  $\|x^n - x\| < \epsilon$  for all  $n > N$ .

**Proposition** If  $x^n \rightarrow x$ ,  $y^n \rightarrow y$  and  $x^n \geq y^n$  for all  $n$ , then  $x \geq y$ .

**Definition** A set  $S \subseteq \mathbb{R}^N$  is *open* if for every  $x \in S$  there exists some  $\epsilon > 0$  such that for all  $y$  with  $\|y - x\| < \epsilon$ ,  $y \in S$ .  $S \subseteq \mathbb{R}^N$  is *closed* if for any  $\{x^n\} \subseteq S$  with  $x^n \rightarrow x$ , we have  $x \in S$ .

**Proposition** A set  $S$  is closed if and only if  $\mathbb{R}^N \setminus S$  is open.

We are mostly interested in properties of *real-valued* functions.

**Definition** Let  $S \subseteq \mathbb{R}^N$  and  $f : S \rightarrow \mathbb{R}$ .  $f$  is *continuous* at  $x \in S$  if for any  $\epsilon > 0$ , there exists  $\delta > 0$  such that for any  $y \in S$  with  $\|y - x\| < \delta$  we have  $|f(y) - f(x)| < \epsilon$ .

We say  $f$  is continuous on  $S$  if it is continuous at every  $x \in S$ . The continuity of a function can also be defined using convergent sequences.

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<sup>1</sup>This can be shown by considering the set " $-S$ ",  $-S = \{-x : x \in S\}$

**Proposition** Let  $S \subseteq \mathbb{R}^N$  and  $f : S \rightarrow \mathbb{R}$ .  $f$  is continuous at  $x \in S$  if and only if for any  $\{x^n\} \subseteq S$  with  $x^n \rightarrow x \in S$ , we have  $f(x^n) \rightarrow f(x)$ .

#### 4. Convex analysis

A set  $S \subseteq \mathbb{R}^N$  is *convex* if for any  $x, y \in S$  and  $\alpha \in [0, 1]$  we have  $\alpha x + (1 - \alpha)y \in S$ .

**Definition** Let  $S \subseteq \mathbb{R}^N$  be convex and  $f : S \rightarrow \mathbb{R}$ .  $f$  is *concave* if for any  $x, y \in S$  and  $\alpha \in [0, 1]$ , we have  $f(\alpha x + (1 - \alpha)y) \geq \alpha f(x) + (1 - \alpha)f(y)$ . If the inequality is strict for all  $x \neq y$  and  $\alpha \in (0, 1)$ , then  $f$  is *strictly concave*.

*Convexity* and *strict convexity* of a function are defined analogously by reversing the inequalities. Note that the concavity of a function  $f$  may not be preserved under a strictly increasing transformation. For example,  $f(x) = \sqrt{x}$  is concave, and  $g(x) = x^4, x \geq 0$ , is a strictly increasing function, but  $g \circ f(x) = x^2$  is not concave. It is tempting to think about what a strictly increasing transformation of a concave function looks like.

Let  $f : S \rightarrow \mathbb{R}$  be concave and  $g : \mathbb{R} \rightarrow \mathbb{R}$  a strictly increasing function. Consider any  $x, y \in S$  and  $\alpha \in [0, 1]$ . We have

$$\begin{aligned} g \circ f(\alpha x + (1 - \alpha)y) &\geq g[\alpha f(x) + (1 - \alpha)f(y)] \\ &\geq g[\alpha \cdot \min\{f(x), f(y)\} + (1 - \alpha) \cdot \min\{f(x), f(y)\}] \\ &= g(\min\{f(x), f(y)\}) \\ &= \min\{g \circ f(x), g \circ f(y)\} \end{aligned}$$

In fact,  $g \circ f$  is *quasiconcave*:

**Definition** Let  $S \subseteq \mathbb{R}^N$  be convex and  $f : S \rightarrow \mathbb{R}$ .  $f$  is *quasiconcave* if for any  $x, y \in S$  and  $\alpha \in [0, 1]$ , we have  $f(\alpha x + (1 - \alpha)y) \geq \min\{f(x), f(y)\}$ . If the inequality is strict for all  $x \neq y$  and  $\alpha \in (0, 1)$ , then  $f$  is *strictly quasiconcave*.

Quasiconcavity is also often characterized by convex upper contour sets.

**Proposition** Let  $S \subseteq \mathbb{R}^N$  be convex and  $f : S \rightarrow \mathbb{R}$ .  $f$  is quasiconcave if and only if for any  $t \in \mathbb{R}$ , the set  $\{x \in S : f(x) \geq t\}$  is convex.  $f$  is strictly quasiconcave if and only if

for any  $x, y \in S$  with  $x \neq y$ ,  $\alpha \in (0, 1)$  and  $t \in \mathbb{R}$ , we have:  $f(x) \geq t$  and  $f(y) \geq t$  imply  $f(\alpha x + (1 - \alpha)y) > t$ .

*Quasiconvexity* can be defined analogously. Let  $S \subseteq \mathbb{R}^N$  be convex.  $f : S \rightarrow \mathbb{R}$  is quasiconvex if for any  $x, y \in S$  and  $\alpha \in [0, 1]$ , we have  $f(\alpha x + (1 - \alpha)y) \leq \max \{f(x), f(y)\}$ . If the inequality is strict for all  $x \neq y$  and  $\alpha \in (0, 1)$ , then  $f$  is strictly quasiconvex.  $f$  is quasiconvex if and only if for any  $t \in \mathbb{R}$ , the set  $\{x \in S : f(x) \leq t\}$  is convex.

It can be easily shown that (strict) concavity implies (strict) quasiconcavity, and any strictly increasing transformation of a quasiconcave function is quasiconcave. Analogous results hold for quasiconvexity.

## 5. Optimization

We consider the problem of maximizing a real-valued function. We first present an existence result. A set  $S \subseteq \mathbb{R}^N$  is *bounded* if there exists  $r \in \mathbb{R}$  such that  $\|x\| < r$  for all  $x \in S$ . A set  $S \subseteq \mathbb{R}^N$  is *compact* if it is closed and bounded.

**Theorem** Let  $S \subseteq \mathbb{R}^N$  be compact.  $f : S \rightarrow \mathbb{R}$  is continuous on  $S$ . Then there exists  $x \in S$  such that  $f(x) \geq f(y)$  for all  $y \in S$ .

Next, we consider unconstrained optimization, i.e., maximizing a function  $f : \mathbb{R}^N \rightarrow \mathbb{R}$ .

**Definition**  $\bar{x} \in \mathbb{R}^N$  is a *local maximizer* of  $f$  if there exists  $\epsilon > 0$  such that for any  $y \in \mathbb{R}^N$  with  $\|y - \bar{x}\| < \epsilon$  we have  $f(\bar{x}) \geq f(y)$ .  $\bar{x} \in \mathbb{R}^N$  is a *global maximizer* of  $f$  if  $f(\bar{x}) \geq f(y)$  for every  $y \in \mathbb{R}^N$ .

*Local* and *global minimizers* are defined analogously. The next theorem gives the necessary, or first-order, conditions.

**Theorem** If  $f$  is differentiable and  $\bar{x}$  is a local maximizer or a local minimizer of  $f$ , then  $\nabla f(\bar{x}) = 0$ , i.e.,  $\frac{\partial f(\bar{x})}{\partial x_n} = 0$  for  $n = 1, \dots, N$ .

A common sufficient condition is concavity.

**Theorem** If  $f$  is differentiable, concave and  $\nabla f(\bar{x}) = 0$ , then  $\bar{x}$  is a global maximizer of  $f$ .

Finally, we consider a general constrained optimization problem:

$$\begin{aligned} & \text{Max}_{x \in \mathbb{R}^N} f(x) \\ & s.t. \quad g_1(x) = b_1, \dots, g_M(x) = b_M \\ & \quad \quad h_1(x) \leq c_1, \dots, h_K(x) \leq c_K \end{aligned}$$

$f$ ,  $g_m$ ,  $m = 1, \dots, M$ , and  $h_k$ ,  $k = 1, \dots, K$ , are all mappings from  $\mathbb{R}^N$  to  $\mathbb{R}$ . There are  $M$  equality constraints and  $K$  inequality constraints. Assume that  $N \geq M + K$ .

$$C = \{x \in \mathbb{R}^N : g_1(x) = b_1, \dots, g_M(x) = b_M, h_1(x) \leq c_1, \dots, h_K(x) \leq c_K\}$$

is the set of points satisfying all the constraints.

**Definition**  $\bar{x} \in C$  is a *local constrained maximizer* of  $f$  if there exists  $\epsilon > 0$  such that for any  $y \in C$  with  $\|y - \bar{x}\| < \epsilon$  we have  $f(\bar{x}) \geq f(y)$ .  $\bar{x} \in C$  is a *global constrained maximizer* of  $f$  if  $f(\bar{x}) \geq f(y)$  for every  $y \in C$ .

Given  $\bar{x} \in C$ , the *constraint qualification* is satisfied if the vectors in

$$\{\nabla g_m(\bar{x}) : m = 1, \dots, M\} \cup \{\nabla h_k(\bar{x}) : h_k(\bar{x}) = c_k\}$$

are linearly independent.

The next theorem presents the first-order conditions. All of the involved functions are assumed to be differentiable.

**Theorem: Kuhn-Tucker conditions** Suppose that  $\bar{x}$  is a local constrained maximizer and the constraint qualification is satisfied. Then there are multipliers  $\lambda_m \in \mathbb{R}$ , one for each equality constraint, and  $\mu_k \in \mathbb{R}_+$ , one for each inequality constraint, such that after setting up the Lagrangian

$$\mathcal{L}(x, \lambda, \mu) = f(x) + \sum_{m=1}^M \lambda_m (b_m - g_m(x)) + \sum_{k=1}^K \mu_k (c_k - h_k(x))$$

we have

$$\frac{\partial \mathcal{L}(\bar{x}, \lambda, \mu)}{\partial x_n} = 0, \quad n = 1, \dots, N \quad (\text{first-order conditions of the Lagrangian})$$

and,

$$\mu_k(c_k - h_k(\bar{x})) = 0, \quad k = 1, \dots, K \quad (\text{complementary slackness conditions})$$

In economics applications, we usually have non-negative constraints on the  $x$  variables. Suppose that we further require  $x_n \geq 0$  for some  $n$ . Then we only need *one* modification of the above Kuhn-Tucker conditions: instead of  $\frac{\partial \mathcal{L}(\bar{x}, \lambda, \mu)}{\partial x_n} = 0$ , we now have

$$\frac{\partial \mathcal{L}(\bar{x}, \lambda, \mu)}{\partial x_n} \leq 0, \quad \text{with equality if } \bar{x}_n > 0 \quad (1)$$

To see why this is true, we can explicitly add  $x_n \geq 0$  as an inequality constraint to the original problem, i.e., the  $(K+1)$ th inequality constraint is  $h_{K+1}(x) = -x_n \leq 0$ . The new Kuhn-Tucker conditions have two differences from before. First, the first order condition of the new Lagrangian,  $\widetilde{\mathcal{L}}$ , with respect to  $x_n$  is

$$\frac{\partial \widetilde{\mathcal{L}}(\bar{x}, \lambda, \mu)}{\partial x_n} = \frac{\partial \mathcal{L}(\bar{x}, \lambda, \mu)}{\partial x_n} + \mu_{K+1} = 0 \quad (2)$$

Second, there is one more complementary slackness condition

$$\mu_{K+1} \bar{x}_n = 0 \quad (3)$$

Recall that the multiplier corresponding to each inequality constraint must be non-negative, so  $\mu_{K+1} \geq 0$ . Then (2) and (3) imply

$$\frac{\partial \mathcal{L}(\bar{x}, \lambda, \mu)}{\partial x_n} \leq 0 \quad \text{and} \quad \frac{\partial \mathcal{L}(\bar{x}, \lambda, \mu)}{\partial x_n} \bar{x}_n = 0 \quad (4)$$

which is equivalent to (1).

**Example.**<sup>2</sup>

$$\text{Max } f(x) = x_1(x_2 + 3)$$

$$\text{s.t. } x_1 + x_2 \leq 2$$

$$x_1 \geq 0, x_2 \geq 0$$

$f$  is continuous on  $C = \{(x_1, x_2) : x_1 \geq 0, x_2 \geq 0, x_1 + x_2 \leq 2\}$  and  $C$  is compact, so a global constrained maximizer exists. Let  $\bar{x} \in C$  be a global constrained maximizer.

Set up the Lagrangian:

$$\mathcal{L}(x_1, x_2, \lambda) = x_1 x_2 + 3x_1 + \lambda(2 - x_1 - x_2)$$

$\bar{x}$  must satisfy Kuhn-Tucker conditions:<sup>3</sup>

$$\bar{x}_2 + 3 - \lambda \leq 0, \text{ with equality if } \bar{x}_1 > 0 \quad (5)$$

$$\bar{x}_1 - \lambda \leq 0, \text{ with equality if } \bar{x}_2 > 0 \quad (6)$$

$$\lambda \geq 0 \text{ and } \lambda(2 - \bar{x}_1 - \bar{x}_2) = 0 \quad (7)$$

In addition, we also know that  $\bar{x} \in C$ , i.e., it satisfies all the constraints.

From (5), we have  $\lambda > 0$  since  $\bar{x}_2 \geq 0$ . Then from (7)

$$\bar{x}_1 + \bar{x}_2 = 2 \quad (8)$$

If  $\bar{x}_1 > 0$  and  $\bar{x}_2 > 0$ , then (5) and (6) hold with equality. Together with (8), we can solve for  $\bar{x}_1$  and  $\bar{x}_2$ :  $\bar{x}_1 = 2.5$ ,  $\bar{x}_2 = -0.5 < 0$ , contradiction.

If  $\bar{x}_1 = 0$ , then by (8),  $\bar{x}_2 = 2$ . Then (6) implies  $\lambda = \bar{x}_1 = 0$ , contradiction.

We are only left with the case where  $\bar{x}_2 = 0$ . By (8),  $\bar{x}_1 = 2$ . Then (5) implies  $\lambda = 3$ . In this case, all of the Kuhn-Tucker conditions, as well as all the constraints, are satisfied.  $(\bar{x}_1 = 2, \bar{x}_2 = 0)$  is the unique global constrained maximizer.

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<sup>2</sup>This example is taken from Qianfeng Tang's notes.

<sup>3</sup>It can be verified that the constraint qualification is always satisfied at a global constrained maximizer in this problem.