

Mathematical Preliminaries

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1 Convexity

1.1 Convex Sets

Formally, we define a convex set as follows.

Definition 1 A set A is **convex** if $\forall a, b \in A, \forall \lambda \in [0, 1], (1 - \lambda)a + \lambda b \in A$.

Intuitively, a set is convex if, whenever you take any two points in it, the line segment connecting these two points is completely contained within it.

Examples:

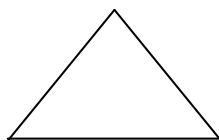


Figure 1: Convex set in two dimensions.

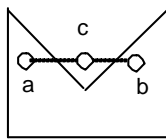


Figure 2: Non-convex set in two dimensions.

Note that the set in Figure 2 is not convex because we can find an $a \in A$ and a $b \in A$ as well as a $\lambda \in [0, 1]$ such that $c = (1 - \lambda)a + \lambda b \notin A$.

1.2 Concave Functions

Definition 2 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **concave** if for any $x_0, x_1 \in \text{Dom}(f)$ and for any $\lambda \in [0, 1]$, we have the following inequality

$$f((1 - \lambda)x_0 + \lambda x_1) \geq (1 - \lambda)f(x_0) + \lambda f(x_1)$$

To connect the idea of a concave function with that of a convex set, we have the following proposition, which I will not prove here.

Proposition 3 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is concave if and only if the set $\{(x, y) : y \leq f(x)\} \subset \mathbb{R}^n \times \mathbb{R}$ is convex.

Definition 4 We refer to the set $\{(x, y) : y \leq f(x)\}$ as the **hypograph** of the function f .

Intuitively, the hypograph of f is "the area under the curve." A function is concave if this area is a convex set.

1.3 Quasiconcave Functions

Definition 5 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **quasiconcave** if for all $x_0, x_1 \in \text{Dom}(f)$ and for all $\lambda \in [0, 1]$, we have the following inequality

$$f((1 - \lambda)x_0 + \lambda x_1) \geq \min\{f(x_0), f(x_1)\}$$

We can connect this definition to the idea of convex sets as well with the following proposition (whose proof I will omit).

Proposition 6 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is quasiconcave if and only if the set $\{x : f(x) \geq a\} \subset \mathbb{R}^n$ is convex for all $a \in \mathbb{R}$.

Definition 7 We refer to the set $\{x : f(x) \geq a\} \subset \mathbb{R}^n$ as the **upper contour set** for the function f at the value a .

2 Supremum

2.1 Supremum of a Set

Definition 8 Let $A \subset \mathbb{R}$. We say that b is an **upper bound** for A if for all $a \in A$, $a \leq b$.

Definition 9 A point b is said to be a **maximal point** for A if $b \in A$ and for all $a \in A$, $a \leq b$.

We write $b = \max_{a \in A} a \equiv \max A$.

The critical distinction between an upper bound and a maximal point of a set is that the definition of the maximal point calls for b to be in A . This can be problematic, though, since there are (many) sets for which no such point exists. (i.e. $(0, 1), \mathbb{R}$). This leads us to the following definition.

Definition 10 A point b is said to be the **least upper bound (supremum)** for the set A if b is an upper bound (i.e. $\forall a \in A, a \leq b$) and it is the smallest upper bound (i.e. $\forall b'$ satisfying $a \leq b'$ for all $a \in A$, we have that $b \leq b'$).

We write $b = \sup_{a \in A} a \equiv \sup A$.

This definition is much more robust since every set in \mathbb{R} has a supremum. In addition, the supremum may take on the values $\pm\infty$. (i.e. $\sup(0, 1) = 1$ and $\sup \mathbb{R} = +\infty$) By convention, we say that if a set contains no elements, its supremum is $-\infty$. That is, $\sup \emptyset = -\infty$.

2.2 Supremum of a Function

Definition 11 Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$. The **supremum** of f on $\text{Dom}(f)$ is defined as $\sup_{x \in \text{Dom}(f)} f(x) = \sup\{f(x) : x \in \text{Dom}(f)\}$.

Note that the definition of the supremum of a function ends up being exactly the same as that of the definition of the supremum of a set.

3 Homogeneity, Additivity

3.1 Homogeneity

Definition 12 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **positively homogeneous** (of degree one) if for all $\lambda > 0$, $f(\lambda x) = \lambda f(x)$.

Definition 13 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **negatively homogeneous** (of degree one) if for all $\lambda < 0$, $f(\lambda x) = \lambda f(x)$.

Definition 14 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **homogeneous of degree one** if for all λ , $f(\lambda x) = \lambda f(x)$.

Example 15 (Cobb-Douglas) Consider the function $f(x, y) = x^\alpha y^{1-\alpha}$. Then

$$\begin{aligned} f(\lambda x, \lambda y) &= (\lambda x)^\alpha (\lambda y)^{1-\alpha} \\ &= \lambda^\alpha x^\alpha \lambda^{1-\alpha} y^{1-\alpha} \\ &= \lambda x^\alpha y^{1-\alpha} \\ &= \lambda f(x, y) \end{aligned}$$

Therefore, f is homogeneous of degree one.

More generally, we have the following definition.

Definition 16 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **homogeneous of degree k** if for all λ , $f(\lambda x) = \lambda^k f(x)$.

Example 17 (CES) Consider the function $f(x, y) = (x^{1/\rho} + y^{1/\rho})^{k\rho}$. Then

$$\begin{aligned} f(\lambda x, \lambda y) &= \left((\lambda x)^{1/\rho} + (\lambda y)^{1/\rho} \right)^{k\rho} \\ &= \left(\lambda^{1/\rho} x^{1/\rho} + \lambda^{1/\rho} y^{1/\rho} \right)^{k\rho} \\ &= \left(\lambda^{1/\rho} (x^{1/\rho} + y^{1/\rho}) \right)^{k\rho} \\ &= \left(\lambda^{1/\rho} \right)^{k\rho} (x^{1/\rho} + y^{1/\rho})^{k\rho} \\ &= \lambda^k (x^{1/\rho} + y^{1/\rho})^{k\rho} \\ &= \lambda^k f(x, y) \end{aligned}$$

3.2 Additivity

There are three definitions related to additivity.

Definition 18 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **superadditive** if for all a, a' , we have that $f(a + a') \geq f(a) + f(a')$.

Example 19 Let $f(x, y) = xy$, where $x, y \geq 0$. Then

$$\begin{aligned} f(x_1 + x_2, y_1 + y_2) &= (x_1 + x_2)(y_1 + y_2) \\ &= x_1 y_1 + x_2 y_2 + \underbrace{x_1 y_2}_{\geq 0} + \underbrace{x_2 y_1}_{\geq 0} \\ &\geq f(x_1, y_1) + f(x_2, y_2) \end{aligned}$$

Therefore, f is superadditive.

Definition 20 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **subadditive** if for all a, a' , we have that $f(a + a') \leq f(a) + f(a')$.

Example 21 Let $f(x) = \|x\|$, where $\|x\|$ is a norm. Then, we have that

$$\begin{aligned} f(x_1 + x_2) &= \|x_1 + x_2\| \leq \|x_1\| + \|x_2\| \\ &= f(x_1) + f(x_2) \end{aligned}$$

That is, f is subadditive.

Definition 22 A function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is said to be **additive** if for all a, a' , we have that $f(a + a') = f(a) + f(a')$.

Example 23 Any linear functional is additive. Let $f(x) = Ax$, where A is a matrix. Then we have

$$\begin{aligned} f(x_1 + x_2) &= A(x_1 + x_2) \\ &= Ax_1 + Ax_2 \\ &= f(x_1) + f(x_2) \end{aligned}$$

Therefore, f is additive.

3.3 Combining the two notions

Proposition 24 Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be superadditive and positively homogeneous. Then f is concave.

Proof. Let $\lambda \in [0, 1]$, $x, x' \in \mathbb{R}^n$ be arbitrary. Then

$$\begin{aligned} f((1 - \lambda)x + \lambda x') &\geq f((1 - \lambda)x) + f(\lambda x') \\ &= (1 - \lambda)f(x) + \lambda f(x') \end{aligned}$$

That is, f is a concave function. ■

Proposition 25 Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be subadditive and positively homogeneous. Then f is convex.

Proof. Let $\lambda \in [0, 1]$, $x, x' \in \mathbb{R}^n$ be arbitrary. Then

$$\begin{aligned} f((1 - \lambda)x + \lambda x') &\leq f((1 - \lambda)x) + f(\lambda x') \\ &= (1 - \lambda)f(x) + \lambda f(x') \end{aligned}$$

That is, f is a convex function. ■