Mathematics for Economists: Lecture 6

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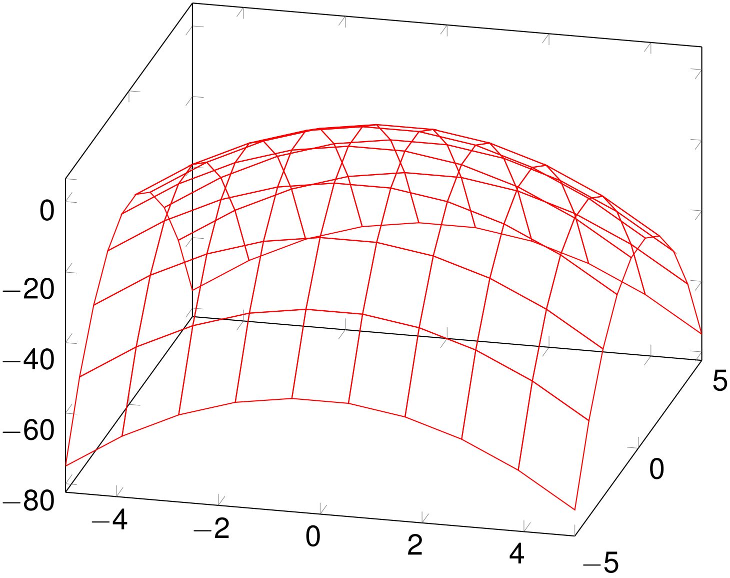
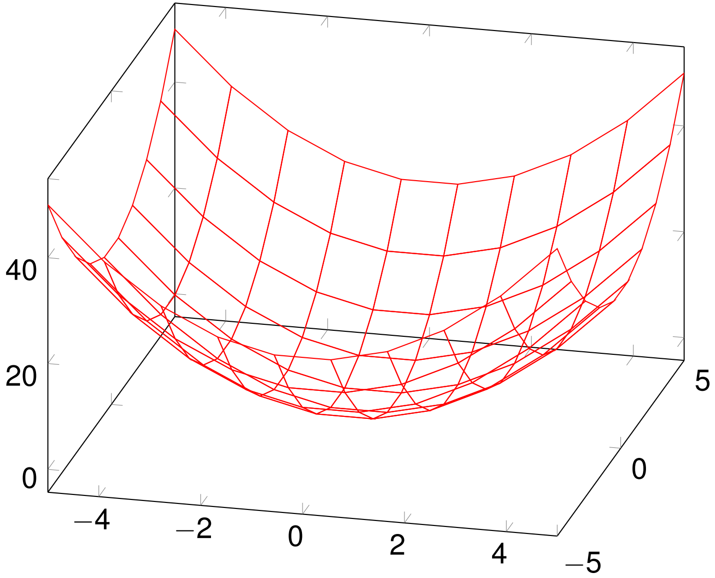
This lecture covers

1. Economic applications of unconstrained optimization
   1.1 Finding extrema of quadratic functions
   1.2 Ordinary least squares
   1.3 Profit maximizing firm
2. Convex sets
3. Concave and convex functions
4. Quasiconcave functions

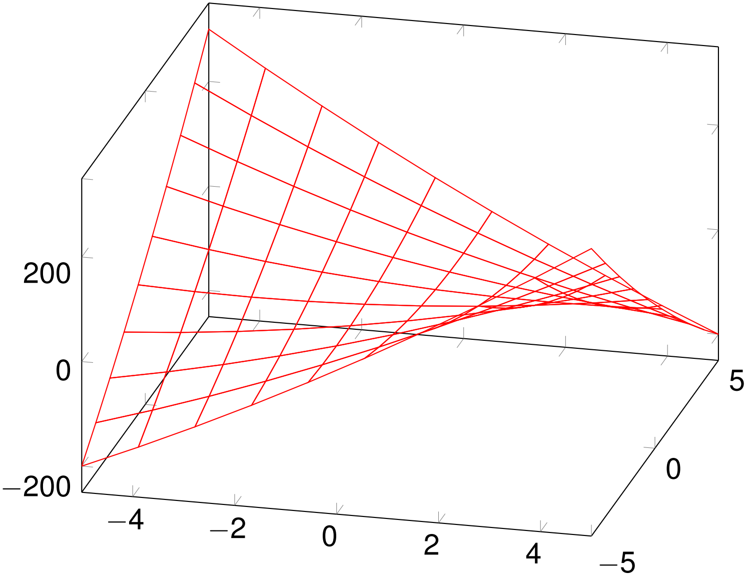
$f(x_1, x_2) = -x_2^2 - 2x_1^2$: maximum at $(0, 0)$



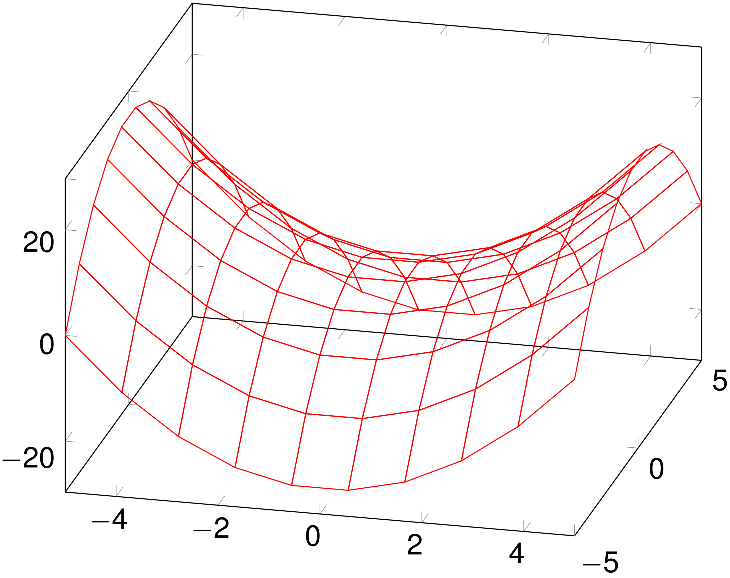
$f(x_1, x_2) = x_2^2 + x_1^2$: minimum at $(0, 0)$



$f(x_1, x_2) = x_2^2 + x_1^2 - 10x_1x_2$: saddle at $(0,0)$



$f(x_1, x_2) = x_2^2 - x_1^2$: saddle at $(0, 0)$



Quadratic forms and classifying extrema of $f : \mathbb{R}^n \to \mathbb{R}$

- A quadratic form is a second-degree polynomial whose terms are all of second order. They can be written as:

  $$\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x},$$

  for some symmetric matrix $\boldsymbol{A}$.
- A quadratic form is *positive definite* if for all $\boldsymbol{x} \neq 0$, $\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x} > 0$. It is *positive semidefinite* if for all $\boldsymbol{x}$, $\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x} \geq 0$.
- A quadratic form is *negative definite* if for all $\boldsymbol{x} \neq 0$, $\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x} < 0$. It is *negative semidefinite* if for all $\boldsymbol{x}$, $\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x} \leq 0$. In all other cases, we say that the quadratic form is indefinite.
- It may be helpful to write out the matrix products as summations:

  $$\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x} = \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j.$$

Classifying quadratic forms

- The general case is tedious. We need to consider the leading principal minors $M(k)$ of $\boldsymbol{A}$:

$$
\begin{aligned}
M_1 &= \det a_{11}, M_2 = \det \begin{pmatrix} a_{11} & a_{12} \\ a_{12} & a_{22} \end{pmatrix}, \\
M_3 &= \det \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{12} & a_{22} & a_{23} \\ a_{13} & a_{23} & a_{33} \end{pmatrix}, \ldots
\end{aligned}
$$

Classifying quadratic forms

- A quadratic form
$$\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x}$$
is positive definite if $M_i > 0$ for all i. It is negative definite if $M_i \, (-1)^i > 0$ for all i, i.e. M_i is negative for odd i and positive for even i.
- A quadratic form
$$\boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x}$$
is positive definite (semidefinite) if all eigenvalues of $\boldsymbol{A}$ are strictly positive (non-negative). It is negative definite (semidefinite) if all eigenvalues of $\boldsymbol{A}$ are strictly negative (non-positive).

Classifying quadratic forms

- To analyze semidefiniteness of $\boldsymbol{A}$, more is needed. Define for all $1 \leq i_1 < i_2 < ... < i_n \leq n$

$$\boldsymbol{A}^n_{\{i_1,i_2,\ldots,i_n\}} = \begin{pmatrix} a_{i_1 i_1} & a_{i_1 i_2} \cdots & a_{i_1 i_n} \\ \cdot & & \cdot \\ \cdot & & \cdot \\ \cdot & & \cdot \\ a_{i_n i_1} & a_{i_n i_2} \ldots & a_{i_n i_n} \end{pmatrix}.$$

and

$$M^n_{\{i_1,i_2,\ldots,i_n\}} = \det\left(\boldsymbol{A}^n_{\{i_1,i_2,\ldots,i_n\}}\right).$$

Classifying quadratic forms

- The matrix $\boldsymbol{A}$ is positive semidefinite if
$$M^n_{\{i_1,i_2,\ldots,i_n\}} \geq 0 \text{ for all } n \text{ and for all } \{i_1, i_2, \ldots, i_n\}.$$
It is negative semidefinite if
$$M^n_{\{i_1,i_2,\ldots,i_n\}} \leq 0 \text{ for all odd } n \text{ and for all } \{i_1, i_2, \ldots, i_n\},$$
$$M^n_{\{i_1,i_2,\ldots,i_n\}} \geq 0 \text{ for all even } n \text{ and for all } \{i_1, i_2, \ldots, i_n\}.$$

An example

- Consider the definiteness of

$$\boldsymbol{A} = \begin{pmatrix} 2 & 1 & 1 \\ 1 & 2 & -1 \\ 1 & -1 & 1 \end{pmatrix}.$$

1. $M^1 = \det(a_{11}) = 2.$
2. $M^2 = \det \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} = 3.$
3. $M^3 = \det \begin{pmatrix} 2 & 1 & 1 \\ 1 & 2 & -1 \\ 1 & 1 & 1 \end{pmatrix} = (-1)^{3+3} \det \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix} +$
   $(-1)^{3+2}(-1) \det \begin{pmatrix} 2 & 1 \\ 1 & -1 \end{pmatrix} + (-1)^{3+1} \det \begin{pmatrix} 1 & 1 \\ 2 & -1 \end{pmatrix} = 3 - 3 - 3 = -3.$

Therefore $\boldsymbol{A}$ is indefinite.

Quadratic functions

- A multivariate quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ takes the form:

  $$f(\boldsymbol{x}) = c + \boldsymbol{b} \cdot \boldsymbol{x} + \boldsymbol{x} \cdot \boldsymbol{A}\boldsymbol{x},$$

  where $c \in \mathbb{R}$ is the constant term, the inner product $\boldsymbol{b} \cdot \boldsymbol{x}$ is the linear term for some $\boldsymbol{b} \in \mathbb{R}^n$, and $\boldsymbol{A}$ is a non-zero symmetric matrix defining a quadratic form.
- Note that for all $n \times n$ matrices $\boldsymbol{B}$, the matrix $\frac{1}{2}(\boldsymbol{B}^\top + \boldsymbol{B})$ is a symmetric matrix, and

  $$\boldsymbol{x} \cdot \boldsymbol{B}\boldsymbol{x} = \boldsymbol{x} \cdot (\frac{1}{2}(\boldsymbol{B}^\top + \boldsymbol{B}))\boldsymbol{x}.$$

- Writing out the inner products and matrix products, we see that:

  $$f(\boldsymbol{x}) = c + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j.$$

Derivatives of quadratic functions

- The partial derivative of f with respect to x_k is:

$$\frac{\partial f(\boldsymbol{x})}{\partial x_k} = b_k + \sum_{i=1}^{n} a_{ik} x_i + \sum_{j=1}^{n} a_{kj} x_j.$$

- Since $\boldsymbol{A}$ is symmetric, $\sum_{i=1}^{n} a_{ik} x_i = \sum_{j=1}^{n} a_{kj} x_j$ and:

$$\frac{\partial f(\boldsymbol{x})}{\partial x_k} = b_k + 2\sum_{i=1}^{n} a_{ik} x_i.$$

- This means that we can write the gradient of f as

$$\nabla f(\boldsymbol{x}) = \boldsymbol{b} + 2\boldsymbol{A}\boldsymbol{x}.$$

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Quadratic functions

- Therefore we can solve for the critical points (by finding the inverse matrix $\boldsymbol{A}^{-1}$, by Gaussian elimination or by Cramer's rule) from the linear system :

$$2\boldsymbol{A}\boldsymbol{x} = -\boldsymbol{b}.$$

- Because of this linearity in the first-order necessary conditions, quadratic functions are manageable.
- The Hessian matrix of f is $2\boldsymbol{A}$. Hence classifying the critical points depends on the definiteness of $\boldsymbol{A}$.
- Quadratic models in economics: mean-variance preferences in finance, interdependent markets with linear demand curves, capacity expansion with quadratic adjustment costs, incentive problems with Normally distributed noise, ordinary least squares...

Application of quadratic optimization: ordinary least squares

- Statistics Finland has register data on N individuals living in Finland.
- Let y_i denote the income of individual i.
- Let $\boldsymbol{x}_i = (x_{i1}, x_{i2}, ..., x_{iK})$ be a vector of numerical covariates that characterize individual i (e.g. age, years of schooling, years in continuous employment, etc.)
- Your total data: vector $\boldsymbol{y} = (y_1, ..., y_N)$ and $N \times K$ matrix of observables $\boldsymbol{X}$ with element x_{ik} for individual $i's$ characteristic k.
- How would you find the best linear model to predict y_i if you only know $\boldsymbol{x}_i$?

Application of quadratic optimization: ordinary least squares

- If the number of individuals N is large in comparison to the number of observable characteristics, K, you will not be able to find a perfect linear fit i.e. a vector $\boldsymbol{\beta} = (\beta_1, ..., \beta_K)$ such that:

$$y_i = \sum_{k=1}^{K} \beta_k x_{ki} = \boldsymbol{x}_i \cdot \boldsymbol{\beta} \text{ for all } i.$$

- Allow an individual random term ϵ_i that accounts for the discrepancy and find the vector $\boldsymbol{\beta}$ that 'minimizes the size' of the error vector $\boldsymbol{\epsilon} = (\epsilon_1, ..., \epsilon_N)$.
- How to measure the size? Ordinary least squares minimizes norm:

$$\boldsymbol{\epsilon} \cdot \boldsymbol{\epsilon} = \sum_{i=1}^{N} \epsilon_i^2.$$

Minimizing the sum of squared errors

- If $y_i = \sum_{k=1}^{K} \beta_k x_{ki} + \epsilon_i$, then $\epsilon_i = y_i - \sum_{k=1}^{K} \beta_k x_{ki} = y_i - \boldsymbol{x}_i \cdot \boldsymbol{\beta}$. But then:

$$\boldsymbol{\epsilon} \cdot \boldsymbol{\epsilon} = \sum_{i=1}^{N} \epsilon_i^2 = \sum_{i=1}^{N} (y_i - \boldsymbol{x}_i \boldsymbol{\beta})^2.$$

- Writing in vector form, we have:

$$\boldsymbol{\epsilon} \cdot \boldsymbol{\epsilon} = (\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}) \cdot (\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}) = \boldsymbol{y} \cdot \boldsymbol{y} - \boldsymbol{y} \cdot \boldsymbol{X}\boldsymbol{\beta} - \boldsymbol{X}\boldsymbol{\beta} \cdot \boldsymbol{y} + \boldsymbol{\beta} \cdot \boldsymbol{X}^\top \boldsymbol{X}\boldsymbol{\beta}$$

$$= \boldsymbol{y} \cdot \boldsymbol{y} - 2\boldsymbol{X}^\top \boldsymbol{y} \cdot \boldsymbol{\beta} + \boldsymbol{\beta} \cdot \boldsymbol{X}^\top \boldsymbol{X}\boldsymbol{\beta}$$

Minimizing the sum of squared errors

- We see that this is a quadratic function and therefore we can use our result from above to conclude that its critical points are found at the solution to:

$$-2\boldsymbol{X}^\top \boldsymbol{y} + 2\boldsymbol{X}^\top \boldsymbol{X}\beta = 0,$$

or the critical point $\hat{\beta}$ satisfies:

$$\hat{\beta} = (\boldsymbol{X}^\top \boldsymbol{X})^{-1}\boldsymbol{X}^\top \boldsymbol{y}.$$

- This is the OLS-estimator for the linear model $\boldsymbol{y} = \boldsymbol{X}\beta$.

Profit maximization with CES - production function

- Consider profit maximization

$$\max_{k,l>0} f(k,l) - \frac{r}{p}k - \frac{w}{p}l,$$

with the production function $f : \mathbb{R}^2 \to \mathbb{R}$:

$$f(k,l) = (k^\rho + l^\rho)^{\frac{1}{\rho}}.$$

- Form the gradient of profit:

$$\nabla\pi(k,l) = \begin{pmatrix} p\frac{\partial f(k,l)}{\partial k} - \frac{r}{p} \\ p\frac{\partial f(k,l)}{\partial l} - \frac{w}{p} \end{pmatrix} = \begin{pmatrix} p(k^\rho + l^\rho)^{\frac{1}{\rho}-1} k^{\rho-1} - \frac{r}{p} \\ p(k^\rho + l^\rho)^{\frac{1}{\rho}-1} l^{\rho-1} - \frac{w}{p} \end{pmatrix}.$$

- The the Hessian matrix is the Hessian matrix of the production function:

$$Hf(k,l) = \begin{pmatrix} \frac{\partial^2 f(k,l)}{\partial k \partial k} & \frac{\partial^2 f(k,l)}{\partial k \partial l} \\ \frac{\partial^2 f(k,l)}{\partial l \partial k} & \frac{\partial^2 f(k,l)}{\partial l \partial l} \end{pmatrix}.$$

Example: CES -function

- By the product rule:

$$
\begin{aligned}
\frac{\partial^2 f(k,l)}{\partial k \partial k} &= (\rho - 1) k^{\rho-2} (k^\rho + l^\rho)^{\frac{1}{\rho}-1} \\
&\quad + \left(\frac{1}{\rho} - 1\right) (k^\rho + l^\rho)^{\frac{1}{\rho}-2} \rho k^{2\rho-2},
\end{aligned}
$$

$$
\frac{\partial^2 f(k,l)}{\partial k \partial l} = \left(\frac{1}{\rho} - 1\right) (k^\rho + l^\rho)^{\frac{1}{\rho}-2} \rho l^{\rho-1} k^{\rho-1},
$$

$$
\begin{aligned}
\frac{\partial^2 f(k,l)}{\partial l \partial l} &= (\rho - 1) l^{\rho-2} (k^\rho + l^\rho)^{\frac{1}{\rho}-1} \\
&\quad + \left(\frac{1}{\rho} - 1\right) (k^\rho + x_2^\rho)^{\frac{1}{\rho}-2} \rho l^{2\rho-2}.
\end{aligned}
$$

Example: CES -function

- By collecting the common terms, we get:

$$D^2 f(x_1, x_2) = \begin{pmatrix} \frac{\partial^2 f(k,l)}{\partial k \partial k} & \frac{\partial^2 f(k,l)}{\partial k \partial l} \\ \frac{\partial^2 f(k,l)}{\partial l \partial k} & \frac{\partial^2 f(k,l)}{\partial l \partial l} \end{pmatrix}$$

$$= (k^\rho + l^\rho)^{\frac{1}{\rho}-2} \begin{pmatrix} (\rho-1) k^{\rho-2} l^\rho & (1-\rho) l^{\rho-1} k^{\rho-1} \\ (1-\rho) l^{\rho-1} k^{\rho-1} & (\rho-1) l^{\rho-2} k^\rho \end{pmatrix}.$$

- When computing the determinant, we can separate the common factor:

$$\det(Hf(k,l)) =$$

$$(k^\rho + l^\rho)^{\frac{1}{\rho}-2} k^{2\rho-2} l^{2\rho-2} \det \begin{pmatrix} (\rho-1) & (1-\rho) \\ (1-\rho) & (\rho-1) \end{pmatrix} = 0.$$

- $Hf(x_1, x_2)$ is therefore negative semidefinite if $\rho < 1$ and positive semidefinite if$\rho > 1$.

Final comments on unconstrained optimization:

- Do local maxima or minima always exist?
- Are there economically meaningful cases where this could be problematic?
- If you find all local maxima of a function, can you be sure that one of them is a global maximum?
- How do you determine which one of the local maxima is the global maximum?

Convex and concave functions: Convex sets

Definition

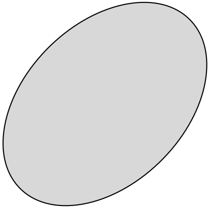
A set X *is convex* if for all $x, y \in X$ and for all $\lambda \in [0, 1]$, we have:

$$\lambda x + (1 - \lambda) y \in X.$$

We call $\lambda x + (1 - \lambda) y$ a *convex combination* of x and y.

- On the real line, convex sets are intervals $a \leq x \leq b$ for some $-\infty \leq a \leq b \leq \infty$.
- In $\mathbb{R}^n$, convex sets are sets X with the property that when you connect linearly two points in X, the entire connecting line is also in X.
- Hence a disk in the plane is convex and a cube in the three dimensional space are convex, but the circle in the plane is not, a disk with the center removed is not, a doughnut in three dimensions is not etc.

[Convex set]



[Non-convex set]

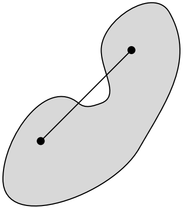


Figure: Illustration of convex sets.

Convex and concave functions: Definitions

- Consider a real-valued function $f : X \to \mathbb{R}$, where X is a convex set.

Definition

The function f *is convex* if for all $\boldsymbol{x}, \boldsymbol{y} \in X$ and for all $\lambda \in [0, 1]$, we have:

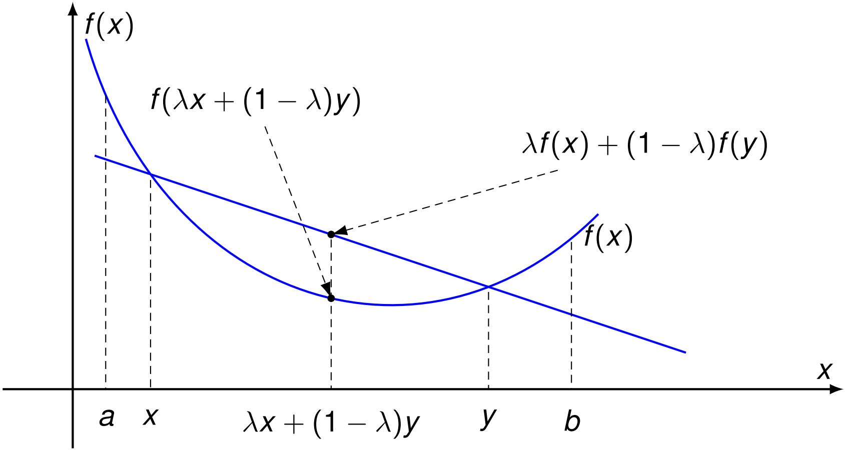
$$f\left(\lambda \boldsymbol{x} + (1-\lambda)\,\boldsymbol{y}\right) \leq \lambda f\left(\boldsymbol{x}\right) + (1-\lambda)\, f\left(\boldsymbol{y}\right).$$

f *is concave* if

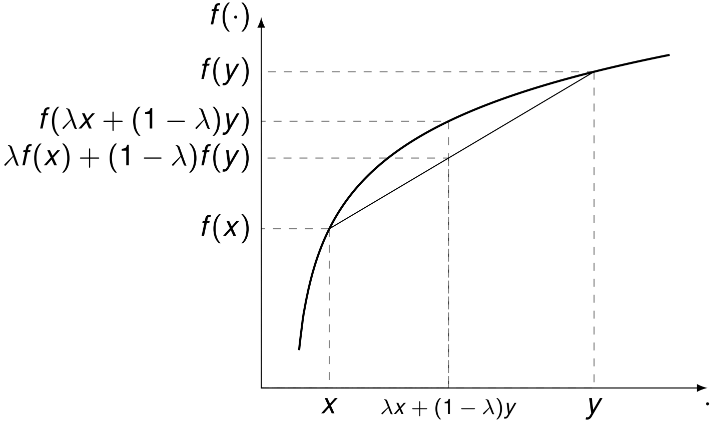
$$f\left(\lambda \boldsymbol{x} + (1-\lambda)\,\boldsymbol{y}\right) \geq \lambda f\left(\boldsymbol{x}\right) + (1-\lambda)\, f\left(\boldsymbol{y}\right).$$

- Note: If f is convex, then $-f$ is concave

A convex function of a real variable



A concave function of a real variable



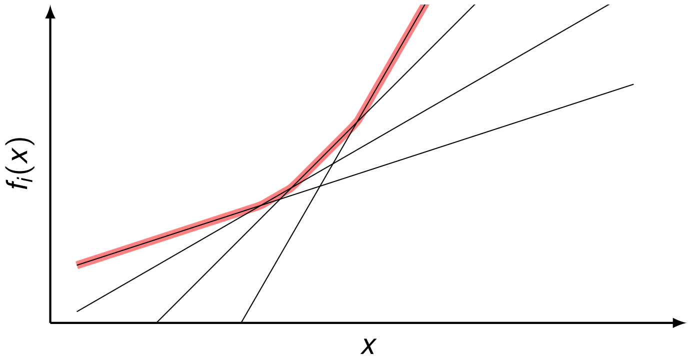
Properties of convex functions

- If $f(\boldsymbol{x})$ is convex, then $g(\boldsymbol{x}) = -f(\boldsymbol{x})$ is concave.
- If $f(\boldsymbol{x})$ is convex, then $af(\boldsymbol{x})$ is convex if $a > 0$.
- If $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$ are convex, then $h(\boldsymbol{x}) = f(\boldsymbol{x}) + g(\boldsymbol{x})$ is convex.
- If $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$ are convex, then $h(\boldsymbol{x}) = f(\boldsymbol{x})\, g(\boldsymbol{x})$ is not necessarily convex. (Give an example for both cases, i.e. where the product of convex functions is convex and where it is not).
- Exercise: Assume that $f : X \to \mathbb{R}$ is convex and $g : \mathbb{R} \to \mathbb{R}$ is also convex. Is $g(f(\boldsymbol{x}))$ convex? What if g is increasing and convex?
- (Optional Exercise): Assume that $f : X \to \mathbb{R}$ is a convex function. Show that the set

  $$\{(\boldsymbol{x}, y) \in \mathbb{R}^{n+1} \quad | \quad \boldsymbol{x} \in X, y \geq f(\boldsymbol{x})\}$$

  is a convex set.

Maximum of linear functions is convex



Properties of convex functions

One of the most important results is the following:

Proposition

If $f(\boldsymbol{x})$ *and* $g(\boldsymbol{x})$ *are convex, then* $h(\boldsymbol{x}) = \max\{f(\boldsymbol{x}), g(\boldsymbol{x})\}$ *is convex.*

Proof: In the notes.

Properties of convex functions

- The same result is true for an arbitrary set of convex functions. Let $f(\boldsymbol{x};\alpha)$ be convex in $\boldsymbol{x}$for all α. Then

$$g(\boldsymbol{x}) = \max_{\alpha} f(\boldsymbol{x};\alpha)$$

  is convex.
- Since linear functions are convex, this result holds for any set of linear functions.
- Since

$$\max\{f(\boldsymbol{x}), g(\boldsymbol{x})\} = -\min\{-f(\boldsymbol{x}), -g(\boldsymbol{x})\},$$

  and since $-f$ is concave when f is convex, we get:

$$g(\boldsymbol{x}) = \min_{\alpha} f(\boldsymbol{x};\alpha)$$

  is concave if $f(\boldsymbol{x};\alpha)$ is concave in $\boldsymbol{x}$ for all α.

Economic examples: profit maximization

- A competitive firm sells output y at price p_0 and buys inputs $\boldsymbol{x} = (x_1, ..., x_n)$ at input prices $\boldsymbol{p} = (p_1, ..., p_n)$. Its profit is

$$p_0 y - \Sigma_{i=1}^{n} p_i x_i.$$

- The maximization problem is then

$$\max_{y,x \in F} p_0 y - \Sigma_{i=1}^{n} p_i x_i,$$

  where F is the feasible set determined by technological possibilities.
- The profit function of the firm gives the maximum achievable profit amongst the feasible set at input and output prices $p_0, \boldsymbol{p}$.

$$\pi(p_0, \boldsymbol{p}) = \pi(p_0, p_1, ..., p_n) = \max_{y,x \in F} p_0 y - \Sigma_{i=1}^{n} p_i x_i$$

- Since the profit from a fixed feasible production is a linear function of the prices $p_0, \boldsymbol{p}$, the profit function is the maximum over linear functions and therefore convex in $p_0, \boldsymbol{p}$.

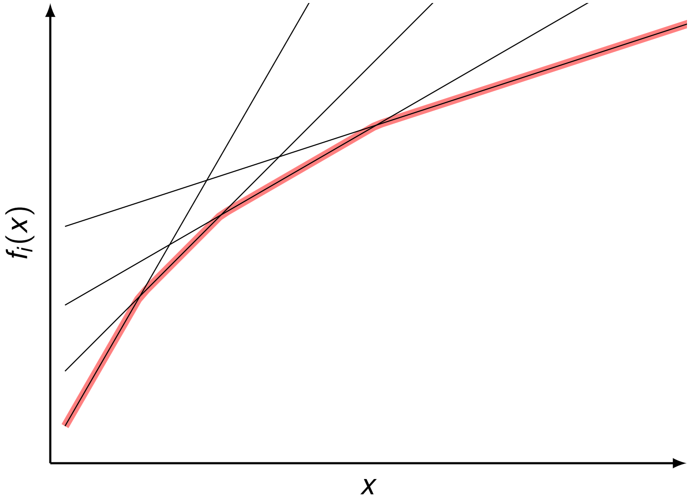
Economic examples: cost minimization

- Let X be the feasible set for inputs $\boldsymbol{x} = (x_1, ..., x_n)$ and $\boldsymbol{p} = (p_1, ..., p_n)$ be the input prices.
- The expenditure function

$$e(\boldsymbol{p}; X) = \min_{\boldsymbol{x} \in X} \boldsymbol{p} \cdot \boldsymbol{x} = \min_{\boldsymbol{x} \in X} \Sigma_{i=1}^{n} p_i x_i$$

  is a concave function by the same argument as above.
- These two examples show that convexity and concavity play a real role in economic applications.
- We shall see more applications when we discuss constrained optimization and value functions of optimization problems.

Lower envelope of linear functions is concave



Convexity and concavity of differentiable functions

- When $f : \mathbb{R} \to \mathbb{R}$, and f is convex and differentable, it it is easy to see by drawing a picture that for all x, y we have:

$$f(y) - f(x) \geq f'(x)(y - x).$$

- This just says that the graph $(x, f(x))$ of a convex function f is above all of its tangent lines.
- Similarly, the graph of a concave function lies below its tangent line.
- The multivariate version of this is proved in the notes.

Second derivatives and convexity

- Start again with functions of a single variable. By Taylor's theorem without the remainder term,

$$f(y) = f(x) + f'(x)(y-x) + \frac{1}{2}f''(x)(y-x)^2 + \frac{1}{6}f'''(x)(y-x)^3 + \ldots$$

- In order to have

$$f(y) - f(x) \geq f'(x)(y-x)$$

  for $|y-x|$ small, we must have

$$f''(x) \geq 0.$$

- In other words, convex functions have a positive second derivative.

Second derivatives and convexity

- Taylor's theorem with a remainder term of second degree:

$$f(y) = f(x) + f'(x)(y - x) + \frac{1}{2} f''(z)(y - x)^2$$

  for some $z \in [x, y]$.
- If f'' is everywhere non-negative, we get:

$$f(y) - f(x) \geq f'(x)(y - x)$$

  for all y, x and f is therefore convex.
- Let's generalize now to $f : X \to \mathbb{R}$, where X is a convex subset of $\mathbb{R}^n$ n.
- Convexity corresponds to positive semidefiniteness of the Hessian matrix.
- Concavity corresponds to negative semidefiniteness of the Hessian matrix.
- Hence we see an immediate connection between convexity and the second order conditions for optimality.

Quasiconvex and quasiconcave functions

Even though the name suggests something extremely technical and tedious, quasiconcavity is actually one of the most important notions for functions in economic theory.

Definition

A function f on a convex set X is *quasiconcave* if for all $\boldsymbol{x}, \boldsymbol{y} \in X$ and for all $\lambda \in [0, 1]$

$$f(\lambda \boldsymbol{x} + (1-\lambda)\boldsymbol{y}) \geq \min\{f(\boldsymbol{x}), f(\boldsymbol{y})\}.$$

f is *quasiconvex* is for all $\boldsymbol{x}, \boldsymbol{y} \in X$ and for all $\lambda \in [0, 1]$

$$f(\lambda \boldsymbol{x} + (1-\lambda)\boldsymbol{y}) \leq \max\{f(\boldsymbol{x}), f(\boldsymbol{y})\}.$$

Exercise: f is quasiconcave, then $-f$ is quasiconvex.

Quasiconvex and quasiconcave functions: Observations

- If f is quasiconcave, then af is quasiconcave if $a > 0$.
- If f and g are quasiconcave $f + g$ is not necessarily quasiconcave.
- All monotone (i.e. all increasing and all decreasing) functions of a single variable are both quasiconcave and quasiconvex. This is NOT true for multidimensional functions
- All concave functions are quasiconcave. Show this as an exercise.
- Not all quasiconcave functions are concave.
- If f is a quasiconcave function and g is a strictly increasing function, then $h(\boldsymbol{x}) = g(f(\boldsymbol{x}))$ is a quasiconcave function.

Quasiconvex and quasiconcave functions: Observations

- An upper contour set of function f for value α is denoted by $U(f;\alpha)$ and defined as:
$$U(f;\alpha) := \{\boldsymbol{x} \in X | f(\boldsymbol{x}) \geq \alpha\}.$$
- Interpretation: if f is a utility function, $U(f;\alpha)$ is the better side of the indifference curve giving utility level α.

Proposition

A function f is quasiconcave if and only if $U(f;\alpha)$ is a convex set for all α.

Next Lecture:

- Introduction to constrained optimization
- Equality constraints and Lagrange's function
- Examples of constrained optimization problems