

## 8. Saddle points and duality

**Idea:** Squeeze more information out of the Lagrange function and define a dual optimization problem, which can help in finding the solution to the original one.

Let  $X \subseteq \mathbb{R}^n$  and assume that  $f, g, h \in C^1(X)$  if  $X$  is open, otherwise  $C^1$  in a neighbourhood of  $X$ . The **primal problem** is

$$(P) \quad \begin{aligned} & \text{minimize} && f(\mathbf{x}) \\ & \text{subject to} && \mathbf{x} \in S = \{\mathbf{x} \in X; \mathbf{g}(\mathbf{x}) \leq \mathbf{0}, \mathbf{h}(\mathbf{x}) = \mathbf{0}\}. \end{aligned}$$

We define the *Lagrange function*

$$L(\mathbf{x}; \mathbf{u}, \mathbf{v}) := f(\mathbf{x}) + \mathbf{u}^\top \mathbf{g}(\mathbf{x}) + \mathbf{v}^\top \mathbf{h}(\mathbf{x}), \quad \mathbf{x} \in X, \quad (\mathbf{u}, \mathbf{v}) \in U := \{(\mathbf{u}, \mathbf{v}) : \mathbf{u} \geq \mathbf{0}\},$$

and use the terminology:

$$\begin{aligned} \bar{\mathbf{x}} \text{ is feasible} &\iff \bar{\mathbf{x}} \in S, \\ \bar{\mathbf{x}} \text{ solves } (P) &\iff \bar{\mathbf{x}} \text{ is a global solution of } (P) \iff f(\bar{\mathbf{x}}) \leq f(\mathbf{x}) \quad \forall \mathbf{x} \in S. \end{aligned}$$

The *Karush-Kuhn-Tucker* conditions are

$$(KKT) \quad \left\{ \begin{array}{l} \nabla_{\mathbf{x}} L(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) = \mathbf{0}, \\ \bar{\mathbf{u}}^\top \mathbf{g}(\bar{\mathbf{x}}) = 0, \quad (\text{complementary slackness; CS}) \\ (\bar{\mathbf{u}} \geq \mathbf{0}). \end{array} \right.$$

A **convex problem** is defined as

(CP) (P) with  $X$  convex set and the functions  $f, g$  convex and  $h$  affine.

LEMMA A.  $\mathbf{x}$  is feasible  $\implies L(\mathbf{x}; \mathbf{u}, \mathbf{v}) \leq f(\mathbf{x})$ .

PROOF:  $L(\mathbf{x}; \mathbf{u}, \mathbf{v}) = f(\mathbf{x}) + \underbrace{\mathbf{u}^\top \mathbf{g}(\mathbf{x})}_{\geq 0} + \underbrace{\mathbf{v}^\top \mathbf{h}(\mathbf{x})}_{\leq 0} + \underbrace{0}_{=0} \leq f(\mathbf{x}) \quad \forall (\mathbf{x}; \mathbf{u}, \mathbf{v}) \in S \times U$ .

THEOREM (FIRST-ORDER SUFFICIENT CONDITIONS) (Ch. 7, pp 264–265).

$$\bar{\mathbf{x}} \text{ feasible for (CP) and (KKT)} \implies \bar{\mathbf{x}} \text{ solves (CP)}$$

PROOF: Conditions (KKT) imply that  $\bar{\mathbf{x}}$  is stationary point of the convex function  $L(\cdot; \bar{\mathbf{u}}, \bar{\mathbf{v}})$  (positive linear combination of convex functions); hence,  $\bar{\mathbf{x}}$  is a global minimizer of  $L(\cdot; \bar{\mathbf{u}}, \bar{\mathbf{v}})$  and we get

$$(2) \quad f(\bar{\mathbf{x}}) = f(\bar{\mathbf{x}}) + \underbrace{\bar{\mathbf{u}}^\top \mathbf{g}(\bar{\mathbf{x}})}_{=0 \text{ (CS)}} + \underbrace{\bar{\mathbf{v}}^\top \mathbf{h}(\bar{\mathbf{x}})}_{=0} = L(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) \leq L(\mathbf{x}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) \stackrel{\substack{\leq \\ \uparrow \\ \text{Lemma A}}}{\leq} f(\mathbf{x}) \quad \forall \mathbf{x} \in S. \quad \square$$

We note that (CQ) is not needed. The proof gives that ~~we~~ the convexity assumption can be replaced by the weaker blue inequality, which says “ $\bar{\mathbf{x}}$  is a minimizer of  $L(\cdot; \bar{\mathbf{u}}, \bar{\mathbf{v}})$ ”. Then we need not the condition  $\nabla_{\mathbf{x}} L(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) = \mathbf{0}$  of (KKT), but only (CS) and that  $\bar{\mathbf{x}}$  is feasible. The latter two conditions are important and are in fact equivalent to another inequality of the Lagrange function.

LEMMA B.  $\bar{x}$  is feasible and (CS)  $\implies f(\bar{x}) = L(\bar{x}; \bar{u}, \bar{v}).$

PROOF: See (2).

LEMMA C.  $\bar{x}$  is feasible and (CS)  $\iff L(\bar{x}; \mathbf{u}, \mathbf{v}) \leq L(\bar{x}; \bar{u}, \bar{v}) \quad \forall (\mathbf{u}, \mathbf{v}) \in U.$

PROOF:  $\Rightarrow$

$$L(\bar{x}; \mathbf{u}, \mathbf{v}) = f(\bar{x}) + \mathbf{u}^\top \underbrace{\mathbf{g}(\bar{x})}_{\leq 0} + \mathbf{v}^\top \underbrace{\mathbf{h}(\bar{x})}_{=0} \leq f(\bar{x}) = L(\bar{x}; \bar{u}, \bar{v}).$$

$\Leftarrow$

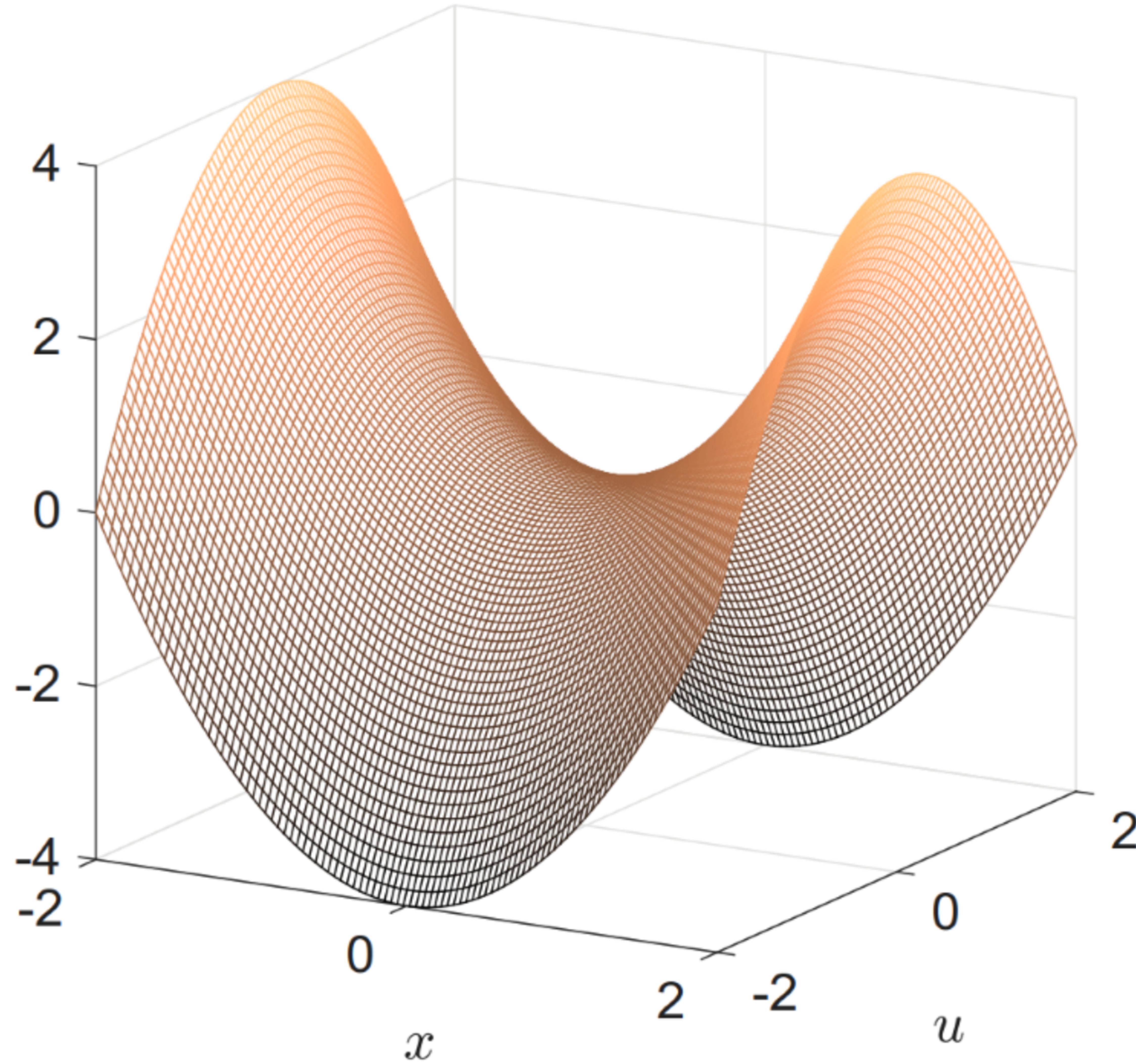
$$L(\bar{x}; \mathbf{u}, \mathbf{v}) - L(\bar{x}; \bar{u}, \bar{v}) = (\mathbf{u} - \bar{u})^\top \mathbf{g}(\bar{x}) + (\mathbf{v} - \bar{v})^\top \mathbf{h}(\bar{x}) \leq 0 \quad \forall (\mathbf{u}, \mathbf{v}) \in U.$$

Firstly, we choose  $\mathbf{u} = \bar{u}$  and  $\mathbf{v} = \bar{v} + \mathbf{h}(\bar{x})$  and get  $\|\mathbf{h}(\bar{x})\|^2 = \mathbf{h}(\bar{x})^\top \mathbf{h}(\bar{x}) \leq 0 \Leftrightarrow \mathbf{h}(\bar{x}) = \mathbf{0}.$  Secondly, we choose  $\mathbf{v} = \bar{v}$  and  $\mathbf{u} = \bar{u} + \mathbf{e}_1 \geq 0,$  where  $\mathbf{e}_1 = (1, 0, \dots, 0)^\top$  to obtain  $g_1(\bar{x}) \leq 0,$  and repeat the same for  $\mathbf{e}_i, i = 2, \dots, m;$  hence,  $\mathbf{g}(\bar{x}) \leq \mathbf{0}.$  Thirdly, with  $\mathbf{v} = \bar{v},$  the choice  $\mathbf{u} = \mathbf{0}$  implies  $-\bar{u}^\top \mathbf{g}(\bar{x}) \leq 0$  and the choice  $\mathbf{u} = 2\bar{u} \geq 0$  implies  $\bar{u}^\top \mathbf{g}(\bar{x}) \leq 0;$  hence,  $\bar{u}^\top \mathbf{g}(\bar{x}) = 0.$   $\square$

DEFINITION.  $(\bar{x}; \bar{u}, \bar{v}) \in X \times U$  is a **saddle point** of  $L$  iff

$$L(\bar{x}; \mathbf{u}, \mathbf{v}) \leq L(\bar{x}; \bar{u}, \bar{v}) \leq L(x; \bar{u}, \bar{v}) \quad \forall (x; \mathbf{u}, \mathbf{v}) \in X \times U.$$

Graph of  $L(x; u) = x^2 - u^2$



Now we can reformulate the theorem on first-order sufficient conditions without convexity.

**THEOREM 1.**  $(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) \in X \times U$  is a saddle point  $\implies \bar{\mathbf{x}}$  solves (P) and (KKT) holds.

**PROOF:** Lemma C gives that  $\bar{\mathbf{x}}$  is feasible and (CS) holds. The remaining KKT condition is  $\nabla_{\mathbf{x}} L(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) = \mathbf{0}$ , which is implied by the fact that  $\bar{\mathbf{x}}$  is a minimizer of  $L(\cdot; \bar{\mathbf{u}}, \bar{\mathbf{v}})$ . Lemmas B and A now give

$$f(\bar{\mathbf{x}}) = L(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) \leq L(\mathbf{x}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) \leq f(\mathbf{x}) \quad \forall \mathbf{x} \in S,$$

i.e.,  $\bar{\mathbf{x}}$  solves (P).  $\square$

The right inequality of the saddle-point property “ $\bar{\mathbf{x}}$  is a minimizer of  $L(\cdot; \bar{\mathbf{u}}, \bar{\mathbf{v}})$ ” can be written

$$L(\bar{\mathbf{x}}; \bar{\mathbf{u}}, \bar{\mathbf{v}}) = \min_{\mathbf{x} \in X} L(\mathbf{x}; \bar{\mathbf{u}}, \bar{\mathbf{v}}).$$

**DEFINITION.** We define the function

$$\theta(\mathbf{u}, \mathbf{v}) := \inf_{\mathbf{x} \in X} L(\mathbf{x}; \mathbf{u}, \mathbf{v}), \quad (\mathbf{u}, \mathbf{v}) \in U,$$

which may attain  $-\infty$  if  $L(\cdot; \mathbf{u}, \mathbf{v})$  is unbounded, and the (Lagrange) **dual problem** to (P):

$$(D) \quad \begin{aligned} &\text{maximize} && \theta(\mathbf{u}, \mathbf{v}) \\ &\text{subject to} && (\mathbf{u}, \mathbf{v}) \in U. \end{aligned}$$

For feasible points  $\mathbf{x} \in S$  and  $(\mathbf{u}, \mathbf{v}) \in U$ , we have

$$(*) \quad \theta(\mathbf{u}, \mathbf{v}) = \inf_{\mathbf{y} \in X} L(\mathbf{y}; \mathbf{u}, \mathbf{v}) \leq L(\mathbf{x}; \mathbf{u}, \mathbf{v}) \stackrel{\substack{\leq \\ \uparrow \\ \text{Lemma A}}}{=} f(\mathbf{x})$$

For any fixed  $(\mathbf{u}, \mathbf{v})$ , we can take the infimum over  $\mathbf{x} \in S \neq \emptyset$  and get

$$\theta(\mathbf{u}, \mathbf{v}) \leq \inf_{\mathbf{x} \in S} f(\mathbf{x}).$$

Thus, any feasible point for the dual problem gives a lower bound of the primal one. If (P) is unbounded (below), then (D) has no solution. If (P) has a solution, we take the supremum of the left-hand side over  $(\mathbf{u}, \mathbf{v}) \in U$  to get the duality inequality

$$(DI) \quad \sup_{\mathbf{u} \geq 0} \theta(\mathbf{u}, \mathbf{v}) \leq \inf_{\mathbf{x} \in S} f(\mathbf{x}).$$

(If we analogously start from (\*) and see that the supremum of  $\theta(\mathbf{u}, \mathbf{v})$  is infinity, then the primal problem has no solution.) A positive difference between the right- and left-hand sides in (DI) is called a *duality gap*. If this is zero, we have *strong duality*.

Ex. in 1D.

$$(P) \quad \begin{aligned} & \text{minimize } f(x) = 4 - x^2 \\ & \text{subject to } g(x) = x^2 - 1 \leq 0 \end{aligned}$$

Solution:  $f(x) = 4 - x^2 \geq 4 - 1 = \boxed{3}$  with equality for  $x = \pm 1$ .

$$L(x; u) = 4 - x^2 + u(x^2 - 1) = -u + 4 + (u-1)x^2, \quad u \geq 0$$

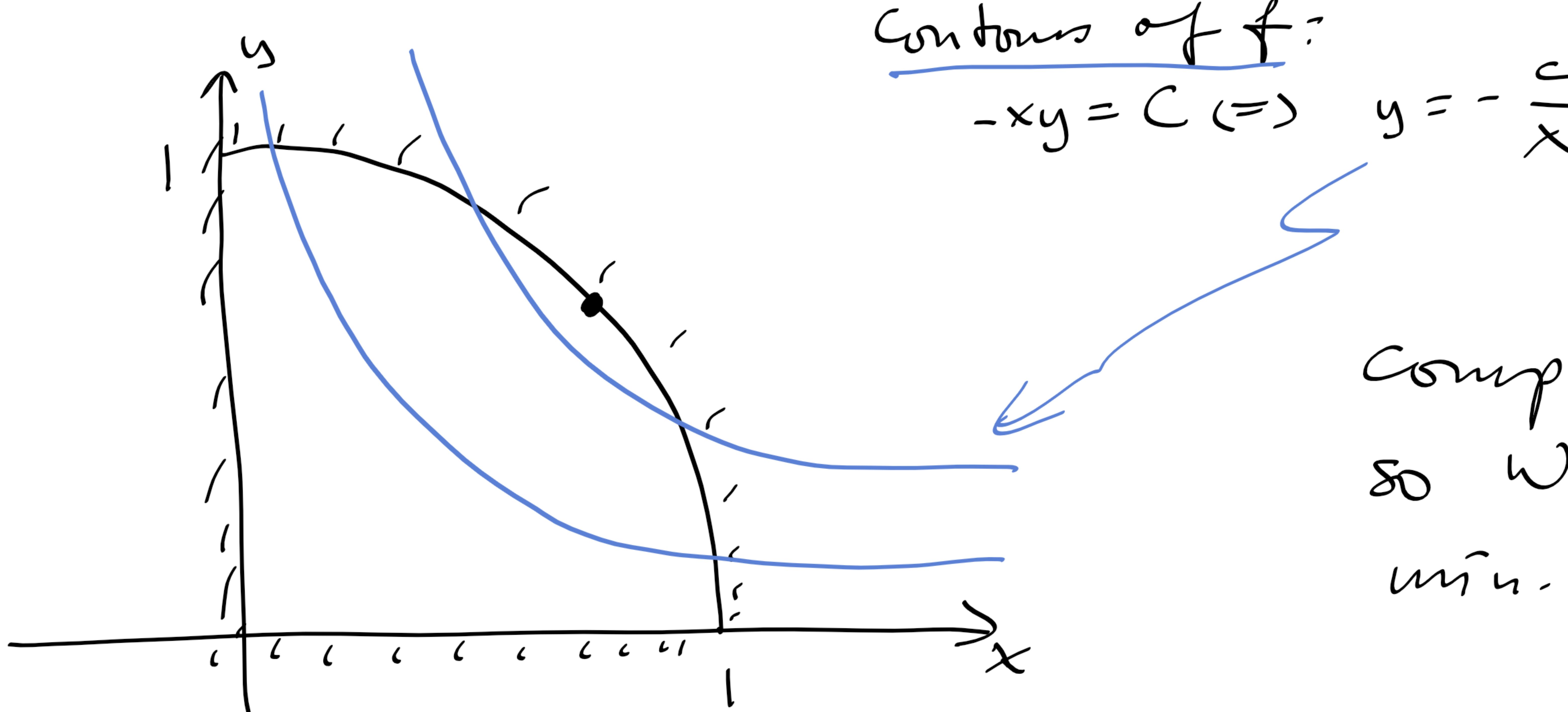
$$\Theta(u) = \inf_{x \in \mathbb{R}} L(x; u) = \begin{cases} -u + 4 & \text{if } u \geq 1 \\ -\infty & \text{if } 0 \leq u < 1 \end{cases}$$

$$(D) \quad \begin{aligned} & \text{maximize } \Theta(u) = -u + 4 = \boxed{3} \\ & u \geq 1 \end{aligned} \quad \begin{array}{l} \text{No duality gap} \\ (\text{strong duality}) \end{array}$$

Read Ex. 6 on p. 303: similar but with duality gap

Ex. in 2D. minimize  $f(x, y) = -xy$

$$(P) \quad \begin{aligned} & \text{subject to} \\ & \quad x^2 + y^2 \leq 1 \\ & \quad x \geq 0 \\ & \quad y \geq 0 \end{aligned}$$



Solution of (P): Set  $\bar{X} = \{(x, y) : x \geq 0, y \geq 0\}$

and

$$L(x, y; u) = -xy + u(\underbrace{x^2 + y^2 - 1}_{g(x, y)}), \quad (x, y, u) \in \bar{X} \times \{u \geq 0\}$$

$\nabla g = \begin{pmatrix} 2x \\ 2y \end{pmatrix}$  so (CQ) is satisfied except at  $(0, 0)$  where  $f(0, 0) = 0$

$$(KKT) \quad \left\{ \begin{aligned} \nabla_{(x,y)} L &= \begin{pmatrix} -y + u2x \\ -x + u2y \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \\ u(x^2 + y^2 - 1) &= 0 \\ u &\geq 0 \end{aligned} \right.$$

$u=0$   $\Rightarrow (x, y) = (0, 0)$  and  $f = 0$

$$\underline{u>0} \Rightarrow \begin{cases} \underbrace{\begin{pmatrix} 2u & -1 \\ -1 & 2u \end{pmatrix}}_A \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \\ x^2 + y^2 = 1 \end{cases}$$

Non-trivial solution iff  $\det A = 0 \Leftrightarrow$

$$4u^2 - 1 = 0 \Leftrightarrow u = \frac{1}{2}. \text{ Then}$$

$$\begin{cases} x - y = 0 \\ -x + y = 0 \\ x^2 + y^2 = 1 \end{cases} \Leftrightarrow \begin{cases} x = y \\ 2x^2 = 1 \end{cases} \Leftrightarrow x = y = \frac{1}{\sqrt{2}}$$

$$f\left(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right) = -\frac{1}{\sqrt{2}} \cdot \frac{1}{\sqrt{2}} = \boxed{-\frac{1}{2}}$$

Dual problem:

$$\mathcal{L}(x, y; u) = -xy + u(x^2 + y^2 - 1)$$

If  $u=0$ , then  $\mathcal{L} = -xy$  is unbounded below.

Otherwise  $u>0$ :

$$\mathcal{L} = -xy + ux^2 + uy^2 - u = -u + u\left(x^2 - \frac{1}{u}xy + y^2\right)$$

$$= -u + u\left(\left(x - \frac{y}{2u}\right)^2 - \frac{y^2}{4u^2} + y^2\right)$$

$$= -u + u\left(x - \frac{y}{2u}\right)^2 + u\left(1 - \frac{1}{4u^2}\right)y^2$$

$$\Theta(u) = \begin{cases} -u & \text{if } 1 - \frac{1}{4u^2} \geq 0 \Leftrightarrow u \geq \frac{1}{2} \\ -\infty & \text{if } 0 \leq u < \frac{1}{2} \quad (\text{by choosing } x = \frac{y}{2u} \text{ and } y \rightarrow \infty) \end{cases}$$

$$\Theta(u) = \inf_{(x,y) \in \bar{X}} \mathcal{L}(x, y; u) = \begin{cases} -u & \text{if } u \geq \frac{1}{2} \\ -\infty & \text{if } 0 \leq u < \frac{1}{2} \end{cases}$$

(D) maximize  $\Theta(u)$   
 $u \geq 0$

has the solution  $u = \frac{1}{2}$  and  $\Theta\left(\frac{1}{2}\right) = \boxed{-\frac{1}{2}}$

so no duality gap