# Lagrangian duality 2/2: strong duality

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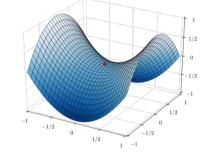
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# Saddle point

#### Definition: Saddle point

 $(x^*, \phi^*)$  is a saddle point of L if for all x and all  $\phi$ ,

$$L(x^*, \phi) \le L(x^*, \phi^*) \le L(x, \phi^*)$$



#### Proposition:

L has a saddle point  $(x^*, \phi^*)$  if and only if

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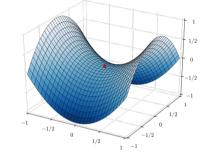
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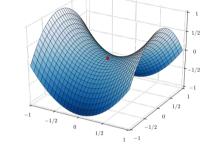
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- As  $\sup_{\phi}\inf_{x}L(x,\phi)=\inf_{x}\sup_{\phi}L(x,\phi)$ , we say that strong duality holds
- x\* is a minimizer of the primal problem
- $ightharpoonup \phi^*$  is a maximizer of the dual problem



## Karush-Kuhn-Tucker conditions

$$L(x,\phi_E,\phi_I) = f(x) + \langle \phi_E, A(x) \rangle + \langle \phi_I, g(x) \rangle - \iota_{\mathbb{R}^p_+}(\phi_I)$$

A saddle point verifies  $0 \in \partial_x L(x^*, \phi^*)$  and  $0 \in \partial_\phi(-L)(x^*, \phi^*)$ 

This gives the Karush-Kuhn-Tucker conditions

#### Theorem

 $(x^*, \phi_E^*, \phi_I^*)$  is a saddle point of L if and only if

$$0 \in \partial f(x^*) + \sum_{i=1}^n \phi_{E,i}^* \nabla A(x^*) + \sum_{j=1}^p \phi_{I,j}^* \partial g_j(x^*)$$

$$A(x^*) = 0$$

$$g(x^*) \le 0$$

$$\phi_I^* \ge 0$$

$$\forall j \in \{1, \dots, p\}, \ g_j(x^*) \phi_{I,j}^* = 0$$

# Strong duality theorem (Equality case)

How can we guarantee strong duality without computing a saddle point?

#### Theorem:

Consider the problem

$$\min_{x} f(x)$$
$$A(x) = 0$$

## Suppose that

- ▶ f is convex and A is affine
- ▶  $0 \in \text{relint}(A(\text{dom } f))$  (constraint qualification)

Then there exists a dual solution  $\phi_E^*$  and

$$\sup_{\phi_E} \inf_{x} L(x, \phi_E) = \inf_{x} \sup_{\phi_E} L(x, \phi_E)$$

# Strong duality theorem (Inequality case)

How can we guarantee strong duality without computing a saddle point?

#### Theorem:

Consider the problem

$$\min_{x} f(x)$$
$$g(x) \le 0$$

## Suppose that

- f is convex and  $g_i$  is convex for all j
- ▶  $\exists x_0 \in \text{dom } f \text{ such that } g_j(x_0) < 0 \text{ for all } j$  (Slater's constraint qualification)

Then there exists a dual solution  $\phi_I^*$  and

$$\sup_{\phi_I} \inf_{x} L(x, \phi_I) = \inf_{x} \sup_{\phi_I} L(x, \phi_I)$$