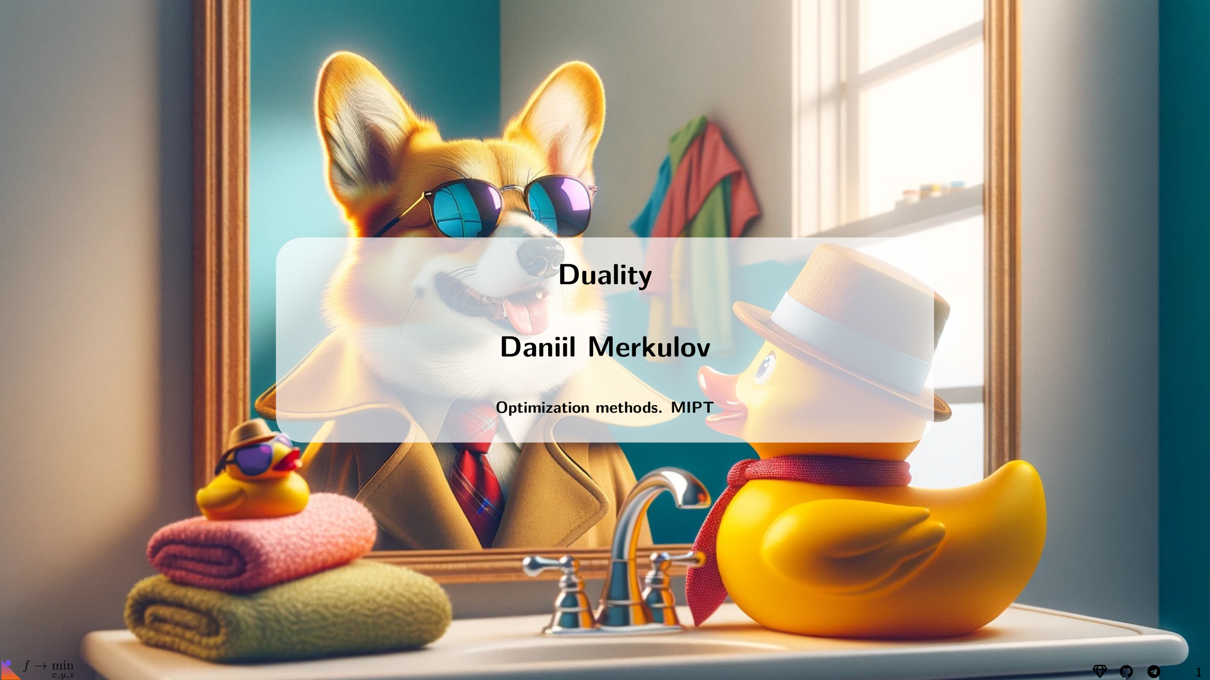

Duality

Daniil Merkulov

Optimization methods. MIPT

Duality

Motivation

Duality lets us associate to any constrained optimization problem a concave maximization problem, whose solutions lower bound the optimal value of the original problem. What is interesting is that there are cases, when one can solve the primal problem by first solving the dual one. Now, consider a general constrained optimization problem:

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Primal: $f(x) \to \min\limits_{x \in S}$ Dual: $g(y) \to \max\limits_{y \in \Omega}$

двойственная задача

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We'll build $g(y)$, that preserves the uniform bound:

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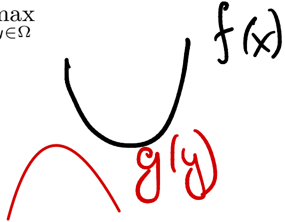

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двойств. переменная

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As a consequence:

$$
\boxed{\max_{y \in \Omega} g(y) \leq \min_{x \in S} f(x)}
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Lagrange duality

We'll consider one of many possible ways to construct $g(y)$ in case, when we have a general mathematical programming problem with functional constraints:

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And the Lagrangian, associated with this problem:

$$L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$$

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p \nu_i h_i(x) = f_0(x) + \lambda^\top f(x) + \nu^\top h(x)$$

Dual function

мн-во определения задачи

$\min x^2 + y^2$

$x + y = 2$

$h(x,y) = x + y - 2$

$D = \mathbb{R}^2$

We assume $\mathcal{D} = \bigcap_{i=0}^{m} \textbf{dom } f_i \cap \bigcap_{i=1}^{p} \textbf{dom } h_i$ is nonempty. We define the Lagrange dual function (or just dual function) $g : \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ as the minimum value of the Lagrangian over x: for $\lambda \in \mathbb{R}^m, \nu \in \mathbb{R}^p$

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двойственная функция

$$
\boxed{g(\lambda, \nu) = \inf_{x \in \mathcal{D}} L(x, \lambda, \nu)} = \inf_{x \in \mathcal{D}} \left(f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x) \right)
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When the Lagrangian is unbounded below in x, the dual function takes on the value $-\infty$. Since the dual function is the pointwise infimum of a family of affine functions of (λ, ν), it is concave, even when the original problem is not convex.

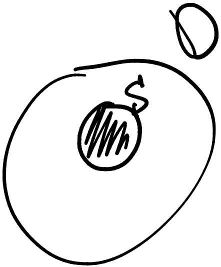
Dual function as a lower bound

Пусть $\tilde{x} \in S \subseteq D$

$h(\tilde{x}) = 0$

$f(\tilde{x}) \leq 0$

Let us show, that the dual function yields lower bounds on the optimal value p^* of the original problem for any $\lambda \succeq 0, \nu$. Suppose some $\hat{x}$ is a feasible point for the original problem, i.e., $f_i(\hat{x}) \leq 0$ and $h_i(\hat{x}) = 0$, $\lambda \succeq 0$. Then we have:



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$\forall \tilde{x} \in S: \quad L(\hat{x}, \lambda, \nu) \leq f_0(\hat{x})$ [illegible] $\qquad \lambda^* \cdot f(x^*) = 0$

$$
L(\hat{x}, \lambda, \nu) = f_0(\hat{x}) + \underbrace{\lambda^\top f(\hat{x})}_{\leq 0} + \underbrace{\nu^\top h(\hat{x})}_{= 0} \leq f_0(\hat{x})
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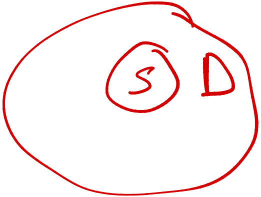

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$f_0(x^*) = p^*$

Hence

$$g(\lambda, \nu) = \boxed{\inf_{x \in \mathcal{D}} L(x, \lambda, \nu) \leq L(\hat{x}, \lambda, \nu)} \leq f_0(\hat{x})$$

$\hat{x} = x^*$

$\forall \hat{x} \in S: \; g(\lambda, \nu) \leq f_0(\hat{x})$

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The term "dual feasible", to describe a pair (λ, ν) with $\lambda \succeq 0$ and $g(\lambda, \nu) > -\infty$, now makes sense. It means, as the name implies, that (λ, ν) is feasible for the dual problem. We refer to (λ^*, ν^*) as dual optimal or optimal Lagrange multipliers if they are optimal for the above problem.

Summary

$d^* \le p^*$ всегда вогнутая

	Primal	Dual
Function	$f_0(x)$	$g(\lambda, \nu) = \min\limits_{x \in \mathcal{D}} L(x, \lambda, \nu)$
Variables	$x \in S \subseteq \mathbb{R}^n$	$\lambda \in \mathbb{R}^m_+, \nu \in \mathbb{R}^p$
Constraints	$f_i(x) \le 0,\ i = 1, \ldots, m$ $h_i(x) = 0,\ i = 1, \ldots, p$	$\lambda_i \ge 0, \forall i \in \overline{1, m}$
задача Problem	$f_0(x) \to \min\limits_{x \in \mathbb{R}^n}$ s.t. $f_i(x) \le 0,\ i = 1, \ldots, m$ $h_i(x) = 0,\ i = 1, \ldots, p$	$g(\lambda, \nu) \to \max\limits_{\lambda \in \mathbb{R}^m, \nu \in \mathbb{R}^p}$ s.t. $\lambda \succeq 0$
Optimal	x^* if feasible, $p^* = f_0(x^*)$	λ^*, ν^* if $\max$ is achieved, $d^* = g(\lambda^*, \nu^*)$

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with the matrix $A \in \mathbb{R}^{m \times n}$.

$m < n$

1) $L(x, \nu) = x^T x + \nu^T (Ax - b)$

2) Двойственная функция:

$$g(\nu) = \inf_{x \in \mathbb{R}^n} L(x, \nu) = \inf_{x \in \mathbb{R}^n} [x^T x + \nu^T A x] - \nu^T b$$

$\varphi(x, \nu)$

$\nabla_x \varphi(x, \nu) = 0$

$2\bar{x} + A^T \nu = 0 \Rightarrow \bar{x} = -\frac{1}{2} A^T \nu$

$\Rightarrow g(\nu) = L(\bar{x}, \nu) = \; =$

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$O(n^3)$

$n^2 = 10^{14}$ $n = 10^7$

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$p^* \geq g(\nu)$

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$$
-(1/4)\nu^T A A^T \nu - b^T \nu \leq \inf\{x^T x \mid Ax = b\}.
$$

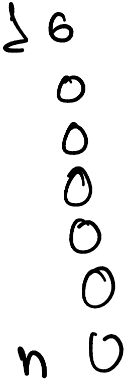
Which is a simple non-trivial lower bound without any problem solving.

Example. Two-way partitioning problem

$x_i = \pm 1$

We are examining a (nonconvex) problem:

$$\begin{aligned} \text{minimize} \quad & x^T W x \\ \text{subject to} \quad & x_i^2 = 1, \quad i = 1, \ldots, n, \end{aligned}$$



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w_{ij} - стоимость нах. i-ого и j-ого объекта в группе

$x_i \cdot w_{ij} \cdot x_j$

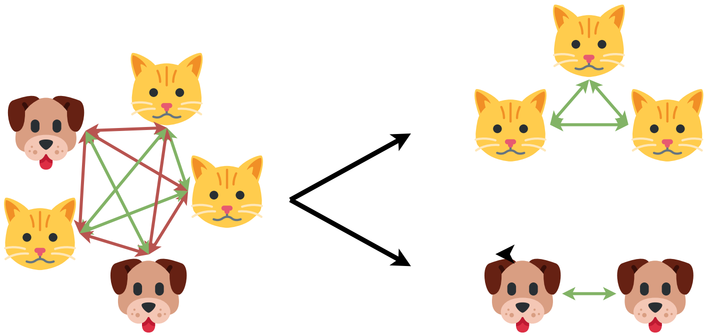

Figure 1: Illustration of two-way partitioning problem

$W_{кк} = 1e-3$

$W_{кп} = 100$

$W_{пп} = 1e-3$

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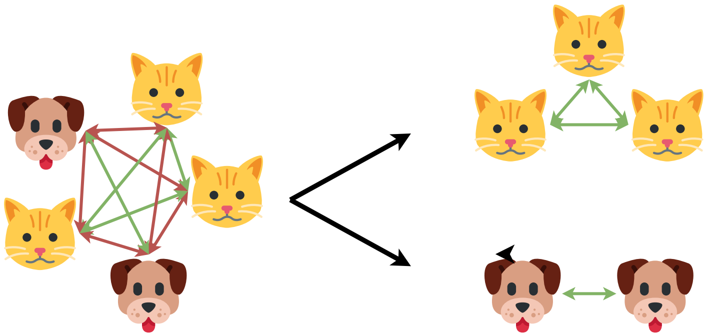

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This problem can be construed as a two-way partitioning problem over a set of n elements, denoted as $\{1, \ldots, n\}$: A viable x corresponds to the partition

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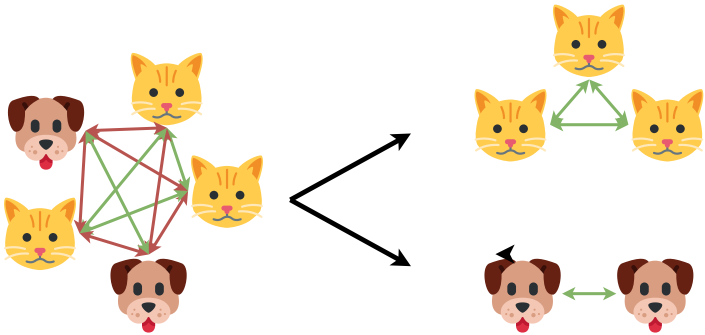

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$$\{1, \ldots, n\} = \{i | x_i = -1\} \cup \{i | x_i = 1\}.$$

The coefficient W_{ij} in the matrix represents the expense associated with placing elements i and j in the same partition, while $-W_{ij}$ signifies the cost of segregating them. The objective encapsulates the aggregate cost across all pairs of elements, and the challenge posed by problem is to find the partition that minimizes the total cost.

Example. Two-way partitioning problem

We now derive the dual function for this problem. The Lagrangian is expressed as

$$L(x,\nu) = x^T W x + \sum_{i=1}^{n} \nu_i (x_i^2 - 1) = x^T (W + \text{diag}(\nu)) x - \mathbf{1}^T \nu.$$

$$g(\nu) = \inf_{x \in \mathbb{R}^n} x^T (W + \text{diag}(\nu)) x - \mathbf{1}^T \nu =$$

$$= \begin{cases} -\mathbf{1}^T \nu, & W + \text{diag}(\nu) \succeq 0 \\ -\infty, & \text{иначе} \end{cases}$$

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By minimizing over x, we procure the Lagrange dual function:

$$g(\nu) = \inf_x x^T(W + \text{diag}(\nu))x - \mathbf{1}^T\nu = \begin{cases} -\mathbf{1}^T\nu & \text{if } W + \text{diag}(\nu) \succeq 0 \\ -\infty & \text{otherwise,} \end{cases}$$

$g(\nu) \to \max$

$W + \text{diag}(\nu) \succeq 0$

p^* невозможно посчитать для $n > 100$

$\forall \nu: \; g(\nu) \le p^*$

Example. Two-way partitioning problem

We now derive the dual function for this problem. The Lagrangian is expressed as

$$L(x,\nu) = x^T W x + \sum_{i=1}^{n} \nu_i (x_i^2 - 1) = x^T (W + \text{diag}(\nu)) x - \mathbf{1}^T \nu.$$

By minimizing over x, we procure the Lagrange dual function:

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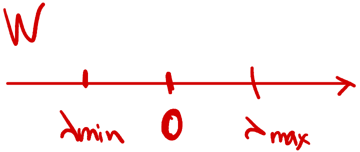
This dual function furnishes lower bounds on the optimal value of the problem. For instance, we can adopt the particular value of the dual variable

$$\nu = -\lambda_{\text{min}}(W)\mathbf{1}$$



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The code for the problem is available here Open in Colab

Strong duality

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It is common to name this relation between optimals of primal and dual problems as **weak duality**. For problem, we have:

СЛАБАЯ двойственность выполнена всегда

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p^* \geq d^*
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Note, that we always have weak duality, if we've formulated primal and dual problem. It means, that if we have managed to solve the dual problem (which is always concave, no matter whether the initial problem was or not), then we have some lower bound. Surprisingly, there are some notable cases, when these solutions are equal.

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Strong duality happens if duality gap is zero:

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- Several sufficient conditions known!

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- "Easy" necessary and sufficient conditions: unknown.

Strong duality in linear least squares

$f_0(x) = x^T x \to \min_{Ax = b}$, $m < n$

$g(\nu) \to \max_{\nu \in \mathbb{R}^m}$

$g(\nu) = -\frac{1}{4}\nu^T A A^T \nu - b^T \nu$

AA^T: $m\times n$, $n \times m$ → $m \times m$

Exercise

In the Least-squares solution of linear equations example above calculate the primal optimum p^* and the dual optimum d^* and check whether this problem has strong duality or not.

Решим двойств.: $-\frac{1}{4}\nu^T A A^T \nu - b^T \nu \to \max_\nu$

$-\frac{1}{4}\cdot 2 AA^T\nu - b = 0 \Rightarrow -\frac{1}{2}AA^T\nu = b \Rightarrow \nu^* = -2(AA^T)^{-1}b$

Найдём $d^* = g(\nu^*) = -\frac{1}{4}(-2)b^T(AA^T)^{-1}\cdot AA^T\cdot(-2(AA^T)^{-1})b - b^T(-2(AA^T)^{-1})b$

Strong duality in linear least squares

$$d^* = b^T (AA^T)^{-1} b$$

сильная двойств.

$x^T x \to \min$

$Ax = b$

$L = x^T x + \nu^T (Ax - b)$

$\frac{\partial L}{\partial x} = 2x + A^T \nu = 0$

$x = -\frac{1}{2} A^T \nu$

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$Ax = b$

$A \cdot \left(-\frac{1}{2} A^T \nu\right) = b$

$\nu = -2 (AA^T)^{-1} b$

$$p^* = x^{*T} x^* = b^T (AA^T)^{-1} A A^T (AA^T)^{-1} b = b^T (AA^T)^{-1} b$$

$$x = -\frac{1}{2} A^T \cdot (-2)(AA^T)^{-1} b = A^T (AA^T)^{-1} b$$

Useful features of duality

- **Construction of lower bound on solution of the primal problem.**

  It could be very complicated to solve the initial problem. But if we have the dual problem, we can take an arbitrary $y \in \Omega$ and substitute it in $g(y)$ - we'll immediately obtain some lower bound.

$$p^* \geq \ldots$$

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- **Checking for the problem's solvability and attainability of the solution.**

  From the inequality $\max\limits_{y \in \Omega} g(y) \leq \min\limits_{x \in S} f_0(x)$ follows: if $\min\limits_{x \in S} f_0(x) = -\infty$, then $\Omega = \varnothing$ and vice versa.

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  $\boxed{f_0(x) - f_0^* \leq f_0(x) - g(y)}$ for an arbitrary $y \in \Omega$ (suboptimality certificate). Moreover, $p^* \in [g(y), f_0(x)], d^* \in [g(y), f_0(x)]$

$\forall y, x: \; f_0(x) \geq g(y)$

$f_0^* = p^*$

хотим достичь ε-точности

$f_0(x) - f^* \leq \varepsilon$

если

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- **Dual function is always concave**

  As a pointwise minimum of affine functions.

Slater's condition

Theorem

If for a convex optimization problem (i.e., assuming minimization, f_0, f_i are convex and h_i are affine), there exists a point x such that $h(x) = 0$ and $f_i(x) < 0$ (existance of a strictly feasible point), then we have a zero duality gap and KKT conditions become necessary and sufficient.

An example of convex problem, when Slater's condition does not hold

Example

$$\min\{f_0(x) = x \mid f_1(x) = \frac{x^2}{2} \leq 0\},$$

An example of convex problem, when Slater's condition does not hold

Example

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\min\{f_0(x) = x \mid f_1(x) = \frac{x^2}{2} \leq 0\},
$$

The only point in the budget set is: $x^* = 0$. However, it is impossible to find a non-negative $\lambda^* \geq 0$, such that

$$
\nabla f_0(0) + \lambda^* \nabla f_1(0) = 1 + \lambda^* x = 0.
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A nonconvex quadratic problem with strong duality

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where $A \in \mathbb{S}^n, A \nsucceq 0$ and $b \in \mathbb{R}^n$. Since $A \nsucceq 0$, this is not a convex problem. This problem is sometimes called the trust region problem, and arises in minimizing a second-order approximation of a function over the unit ball, which is the region in which the approximation is assumed to be approximately valid.

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& -\sum_{i=1}^n \frac{(q_i^\top b)^2}{\lambda_i + \lambda} - \lambda \to \max_{\lambda \in \mathbb{R}} \\
\text{s.t. } & \lambda \geq -\lambda_{min}(A)
\end{aligned}
$$

Applications

Solving the primal via the dual

$L : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ $\quad g : \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$

$f_0 : \mathbb{R}^n \to \mathbb{R}$

An important consequence of stationarity: under strong duality, given a dual solution λ^*, ν^*, any primal solution x^* solves

решение двойств. задачи

$$\min_{x \in \mathbb{R}^n} f_0(x) + \sum_{i=1}^{m} \lambda_i^* f_i(x) + \sum_{i=1}^{p} \nu_i^* h_i(x)$$

Often, solutions of this unconstrained problem can be expressed **explicitly**, giving an explicit characterization of primal solutions from dual solutions.

Furthermore, suppose the solution of this problem is unique; then it must be the primal solution x^*.

This can be very helpful when the dual is easier to solve than the primal.

Solving the primal via the dual

For example, consider:

$$\min_{x} \sum_{i=1}^{n} f_i(x_i) \quad \text{subject to} \quad a^T x = b$$

$\mathbb{R}^n$

$$L(x, \nu) = \sum_{i=1}^{n} f_i(x_i) + \nu(a^T x - b)$$

$$g(\nu) = \inf_{x \in \mathbb{R}^n} L(x, \nu)$$

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$$\min_x \sum_{i=1}^n f_i(x_i) \quad \text{subject to} \quad a^T x = b$$

where each $f_i(x_i) = \frac{1}{2} c_i x_i^2$ (smooth and strictly convex).
The dual function:

$$g(\nu) = \min_x \sum_{i=1}^n f_i(x_i) + \nu \left(b - a^T x \right)$$

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$$f^* = \sup\left(y^T x - f(x)\right)$$

$$f^* = -\min\left(f(x) - y^T x\right)$$

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f^* легко посчитать

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Solving the primal via the dual

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$c_i > 0$

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where each $\boxed{f_i^*(y) = \frac{1}{2c_i} y^2,}$ called the conjugate of f_i.

Solving the primal via the dual

For example, consider:

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очень простая DUAL PROBLEM

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This gives:

$$x_i^\star = \frac{a_i \nu^\star}{c_i}.$$

Sensitivity analysis

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\begin{split}
& f_0(x) \to \min_{x \in \mathbb{R}^n} \\
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One can even show, that when P is convex optimization problem, $p^*(u, v)$ is a convex function.

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Suppose, that strong duality holds for the orriginal problem and suppose, that x is any feasible point for the perturbed problem:

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And taking the optimal x for the perturbed problem, we have:

$$
p^*(u,v) \geq p^*(0,0) - {\lambda^*}^T u - {\nu^*}^T v \tag{1}
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In scenarios where strong duality holds, we can draw several insights about the sensitivity of optimal solutions in relation to the Lagrange multipliers. These insights are derived from the inequality expressed in equation above:

- **Impact of Tightening a Constraint (Large $\lambda_i^\star$)**:
  When the ith constraint's Lagrange multiplier, $\lambda_i^\star$, holds a substantial value, and if this constraint is tightened (choosing $u_i < 0$), there is a guarantee that the optimal value, denoted by $p^\star(u, v)$, will significantly increase.

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  then in either scenario, the optimal value $p^\star(u, v)$ is expected to increase greatly.
- **Consequences of Loosening a Constraint (Small $\lambda_i^\star$)**:
  If the Lagrange multiplier $\lambda_i^\star$ for the ith constraint is relatively small, and the constraint is loosened (choosing $u_i > 0$), it is anticipated that the optimal value $p^\star(u, v)$ will not significantly decrease.
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Sensitivity analysis

In scenarios where strong duality holds, we can draw several insights about the sensitivity of optimal solutions in relation to the Lagrange multipliers. These insights are derived from the inequality expressed in equation above:

- **Impact of Tightening a Constraint (Large $\lambda_i^\star$)**:
  When the ith constraint's Lagrange multiplier, $\lambda_i^\star$, holds a substantial value, and if this constraint is tightened (choosing $u_i < 0$), there is a guarantee that the optimal value, denoted by $p^\star(u, v)$, will significantly increase.
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These interpretations provide a framework for understanding how changes in constraints, reflected through their corresponding Lagrange multipliers, impact the optimal solution in problems where strong duality holds.

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However, if $f_i(x^*) = 0$, meaning the constraint is precisely met at the optimum, then the situation is different. The value of the i-th optimal Lagrange multiplier, λ_i^*, gives us insight into how 'sensitive' or 'active' this constraint is. A small λ_i^* indicates that slight adjustments to the constraint won't significantly affect the optimal value. Conversely, a large λ_i^* implies that even minor changes to the constraint can have a significant impact on the optimal solution.

Mixed strategies for matrix games

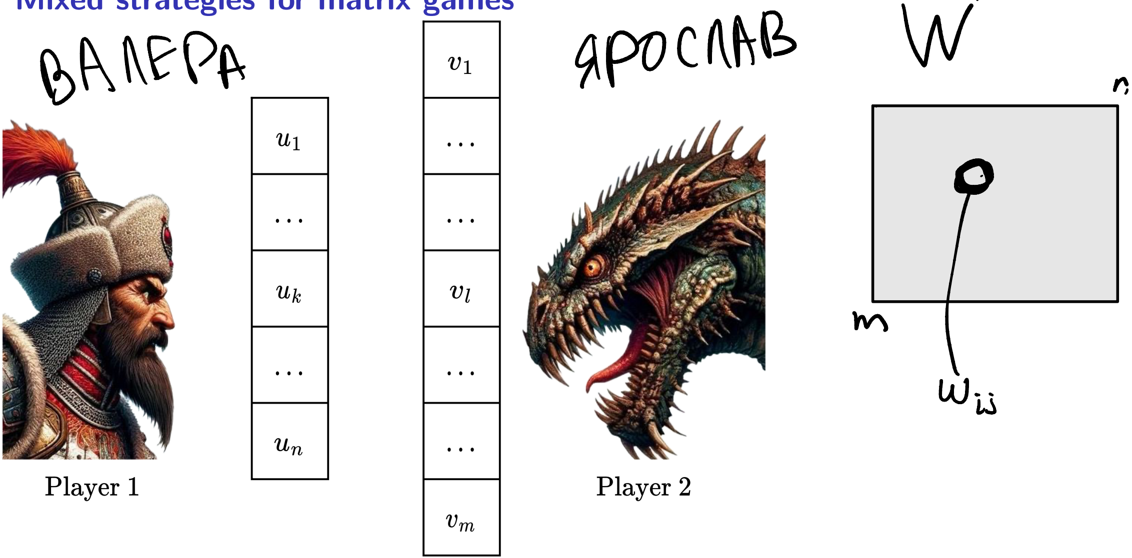

Figure 2: The scheme of a mixed strategy matrix game

Mixed strategies for matrix games

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In zero-sum matrix games, players 1 and 2 choose actions from sets $\{1, \dots, n\}$ and $\{1, \dots, m\}$, respectively. The outcome is a payment from player 1 to player 2, determined by a payoff matrix $P \in \mathbb{R}^{n \times m}$ Each player aims to use mixed strategies, choosing actions according to a probability distribution: player 1 uses probabilities u_k for each action i, and player 2 uses v_l.

$u \in \mathbb{R}^n \quad 1^T u = 1, \quad u \geq 0$

$v \in \mathbb{R}^m \quad 1^T v = 1, \quad v \geq 0$

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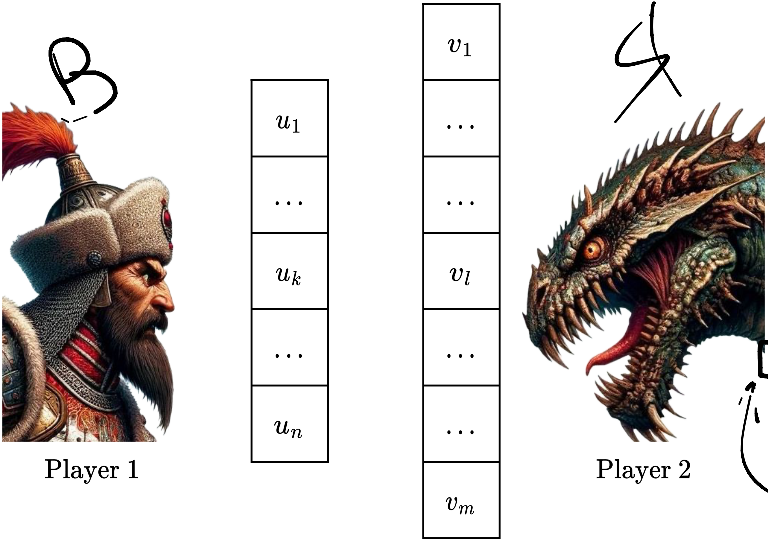

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МАТ. ОЖИДАНИЕ СУММЫ, КОТОРУЮ В→Я

Mixed strategies for matrix games. Player 1's Perspective

Валера!

пусть Ярослав знает u

Player 1

u_1
$\dots$
u_k
$\dots$
u_n

Assuming player 2 knows player 1's strategy u, player 2 will choose v to maximize $u^T P v$. The worst-case expected payoff is thus:

$$\max_{v \geq 0, 1^T v = 1} u^T P v = \max_{i=1,\dots,m} (P^T u)_i$$

рац. стратегия Ярослава если он

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Player 1's optimal strategy minimizes this worst-case payoff, leading to the optimization problem:

$$\min_{u,t} t \quad u \geq 0 \quad 1^T u = 1 \quad P^T u \preceq t \cdot 1$$

$$\begin{aligned} &\min \max_{i=1,\ldots,m} (P^T u)_i \\ &\text{s.t. } u \geq 0 \\ &1^T u = 1 \end{aligned} \qquad p_1^* \tag{3}$$

This forms a convex optimization problem with the optimal value denoted as p_1^*.

Mixed strategies for matrix games. Player 2's Perspective

v_1
$\dots$
$\dots$
v_l
$\dots$
$\dots$
v_m

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Conversely, if player 1 knows player 2's strategy v, the goal is to minimize $u^T P v$. This leads to:

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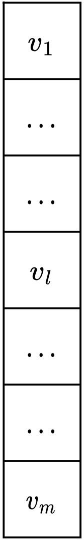

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Player 2 then maximizes this to get the largest guaranteed payoff, solving the optimization problem:

$$\begin{aligned} \max \ & \min_{i=1,\dots,n} (Pv)_i \\ \text{s.t. } & v \geq 0 \\ & 1^T v = 1 \end{aligned} \tag{4}$$

p_2^*

The optimal value here is p_2^*.

$p_1^* = p_2^*$

Mixed strategies for matrix games

Duality and Equivalence

It's generally advantageous to know the opponent's strategy, but surprisingly, in mixed strategy matrix games, this advantage disappears. The key lies in duality: the problems above are Lagrange duals. By formulating player 1's problem as a linear program and introducing Lagrange multipliers, we find that the dual problem matches player 2's problem. Due to strong duality in feasible linear programs, $p_1^* = p_2^*$, showing no advantage in knowing the opponent's strategy.

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We approach problem Equation 3 by setting it up as a linear programming (LP) problem. The goal is to minimize a variable t, subject to certain constraints:

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Solving the Dual Problem

The dual problem seeks to maximize ν under the following conditions:

1. $\lambda \geq 0$,

Mixed strategies for matrix games

Defining the Dual Function

The dual function $g(\lambda, \mu, \nu)$ is defined as:

$$g(\lambda, \mu, \nu) = \begin{cases} \nu & \text{if } 1^T\lambda = 1 \text{ and } P\lambda - \nu\mathbf{1} = \mu \\ -\infty & \text{otherwise} \end{cases}$$

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Upon eliminating μ, we obtain the Lagrange dual of Equation 3:

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Двойств. задача к ВАНере =

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\text{s.t. } &\lambda \geq 0 \\
&1^T\lambda = 1 \\
&P\lambda \geq \nu\mathbf{1}
\end{aligned}
$$

в точности совп. с зад. Ярослава

Conclusion

This formulation shows that the Lagrange dual problem is equivalent to problem Equation 4. Given the feasibility of these linear programs, strong duality holds, meaning the optimal values of Equation 3 and Equation 4 are equal.

References

- Lecture on KKT conditions (very intuitive explanation) in the course “Elements of Statistical Learning” @ KTH.

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- Duality Uses and Correspondences lecture by Ryan Tibshirani course.