

LP and simplex algorithm

optimization
US
+ ... = PROGRAMMING
UK

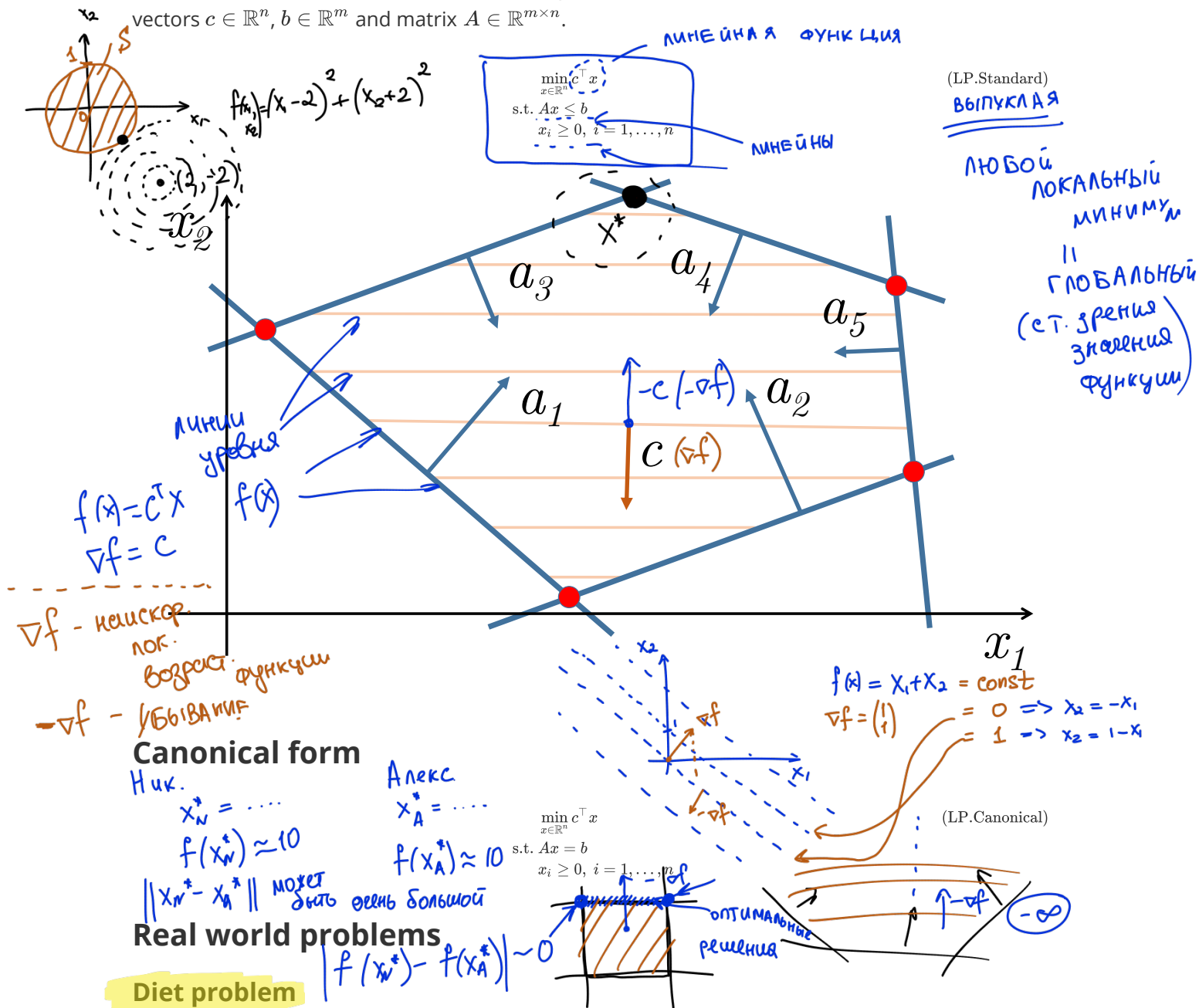
What is LP

Linear Programming

Generally speaking, all problems with linear objective and linear equalities/inequalities constraints could be considered as Linear Programming. However, there are some widely accepted formulations.

Standard form

This form seems to be the most intuitive and geometric in terms of visualization. Let us have vectors $c \in \mathbb{R}^n$, $b \in \mathbb{R}^m$ and matrix $A \in \mathbb{R}^{m \times n}$.



Imagine, that you have to construct a diet plan from some set of products: 🍌 🍷 🥛 🥩 🥦. Each of the products has its own vector of nutrients. Thus, all the food information could be processed through the matrix W . Let also assume, that we have the vector of requirements for each of nutrients $r \in \mathbb{R}^n$. We need to find the cheapest configuration of the diet, which meets all the requirements:

$$\begin{aligned} \min_{x \in \mathbb{R}^p} c^T x \\ \text{s.t. } Wx \geq r \\ x_i \geq 0, i = 1, \dots, n \end{aligned}$$

p штук разных продуктов

n нутриентов, о которых мы беспокоимся



данные

Requirements

$W \in \mathbb{R}^{n \times p}$,

Proteins	3	20
Carbs	25	5
Fats	25	15
Calories	400	200
Vitamin D	100	50
Вкусность	1000	100

$c \in \mathbb{R}^p$ cost per 100 g
cost

$$r \in \mathbb{R}^n \quad K_1 x_1 + K_2 x_2 + \dots + K_p x_p \geq r$$

x - кол-во продукта, которое мы хотим купить
 $x \in \mathbb{R}^p$

$$\begin{aligned} \min_{x \in \mathbb{R}^p} c^T x \\ x \geq 0 \\ Wx \geq r_{\min} \end{aligned}$$

$$c_1 x_1 + \dots + c_p x_p \leftarrow \text{стоимость заказа}$$

$$c^T x$$

Radiation treatment

How to retrieve LP

$$Wx \leq r_{\max}$$

Basic transformations

Inequality to equality by increasing the dimension of the problem by m .

$$Ax \leq b \leftrightarrow \begin{cases} Ax + z = b \\ z \geq 0 \end{cases}$$

unsigned variables to nonnegative variables.

$$x \leftrightarrow \begin{cases} x = x_+ - x_- \\ x_+ \geq 0 \\ x_- \geq 0 \end{cases}$$

Chebyshev approximation problem

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_{\infty} \leftrightarrow \min_{x \in \mathbb{R}^n} \max_i |a_i^T x - b_i|$$

$$\begin{aligned} \min_{t \in \mathbb{R}, x \in \mathbb{R}^n} t \\ \text{s.t. } a_i^T x - b_i \leq t, i = 1, \dots, n \\ -a_i^T x + b_i \leq t, i = 1, \dots, n \end{aligned}$$

l_1 approximation problem

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_1 \leftrightarrow \min_{x \in \mathbb{R}^n} \sum_{i=1}^n |a_i^T x - b_i|$$

$$\begin{aligned} \min_{t \in \mathbb{R}^n, x \in \mathbb{R}^n} \quad & \mathbf{1}^\top t \\ \text{s.t.} \quad & a_i^\top x - b_i \leq t_i, \quad i = 1, \dots, n \\ & -a_i^\top x + b_i \leq t_i, \quad i = 1, \dots, n \end{aligned}$$

Idea of simplex algorithm

- The Simplex Algorithm walks along the edges of the polytope, at every corner choosing the edge that decreases $c^\top x$ most
- This either terminates at a corner, or leads to an unconstrained edge ($-\infty$ optimum)

We will illustrate simplex algorithm for the simple inequality form of LP:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & c^\top x \\ \text{s.t.} \quad & Ax \leq b \end{aligned} \quad (\text{LP.Inequality})$$

Definition: a **basis** B is a subset of n (integer) numbers between 1 and m , so that $\text{rank} A_B = n$.

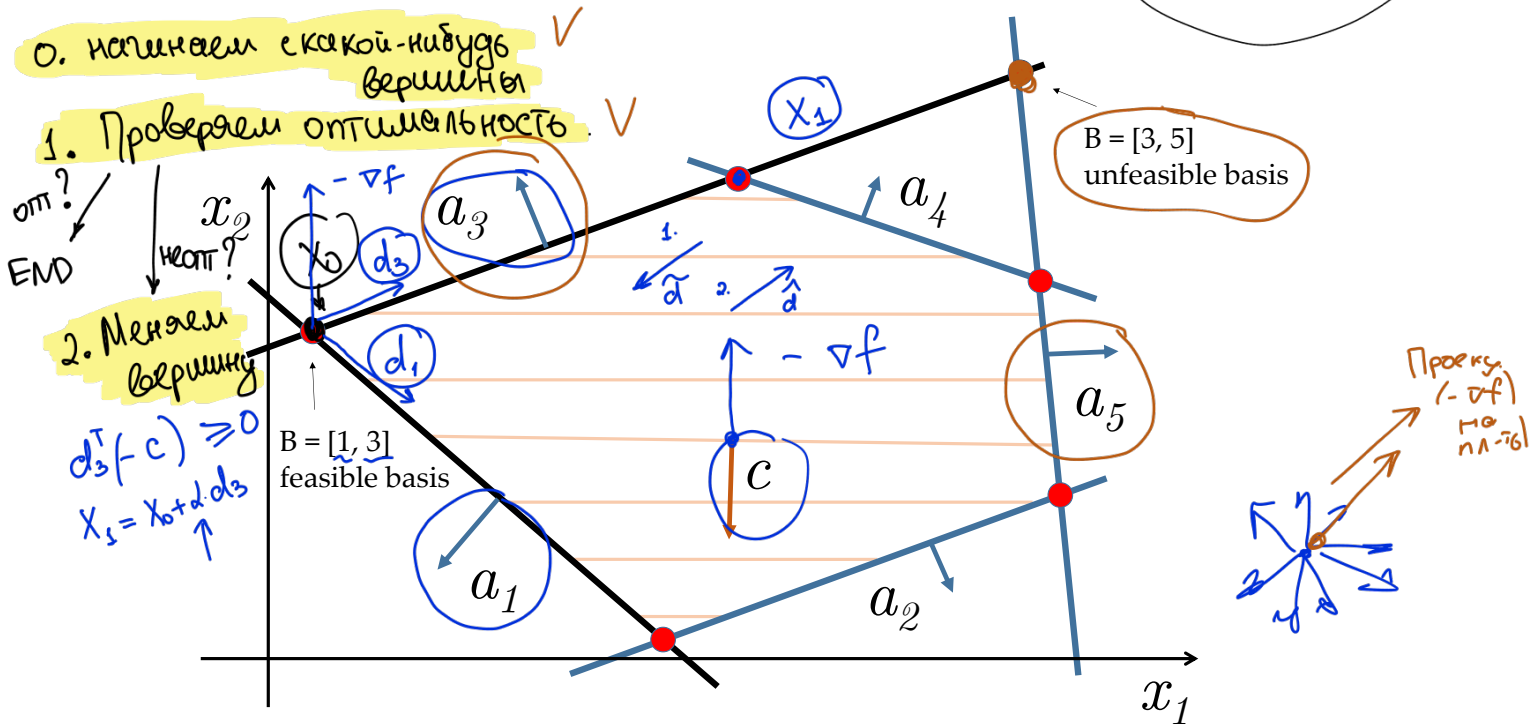
Note, that we can associate submatrix A_B and corresponding right-hand side b_B with the basis B .

Also, we can derive a point of intersection of all these hyperplanes from basis: $x_B = A_B^{-1} b_B$.

If $Ax_B \leq b$, then basis B is **feasible**.

A basis B is optimal if x_B is an optimum of the LP.Inequality.

$$Ax \leq b$$



Since we have a basis, we can decompose our objective vector c in this basis and find the scalar coefficients λ_B :

$$\begin{aligned} \lambda_B^\top A_B = c^\top & \Leftrightarrow \lambda_B^\top = c^\top A_B^{-1} \\ c & \approx a_1 + \dots + a_3 \end{aligned}$$

Main lemma

If all components of λ_B are non-positive and B is feasible, then B is optimal.

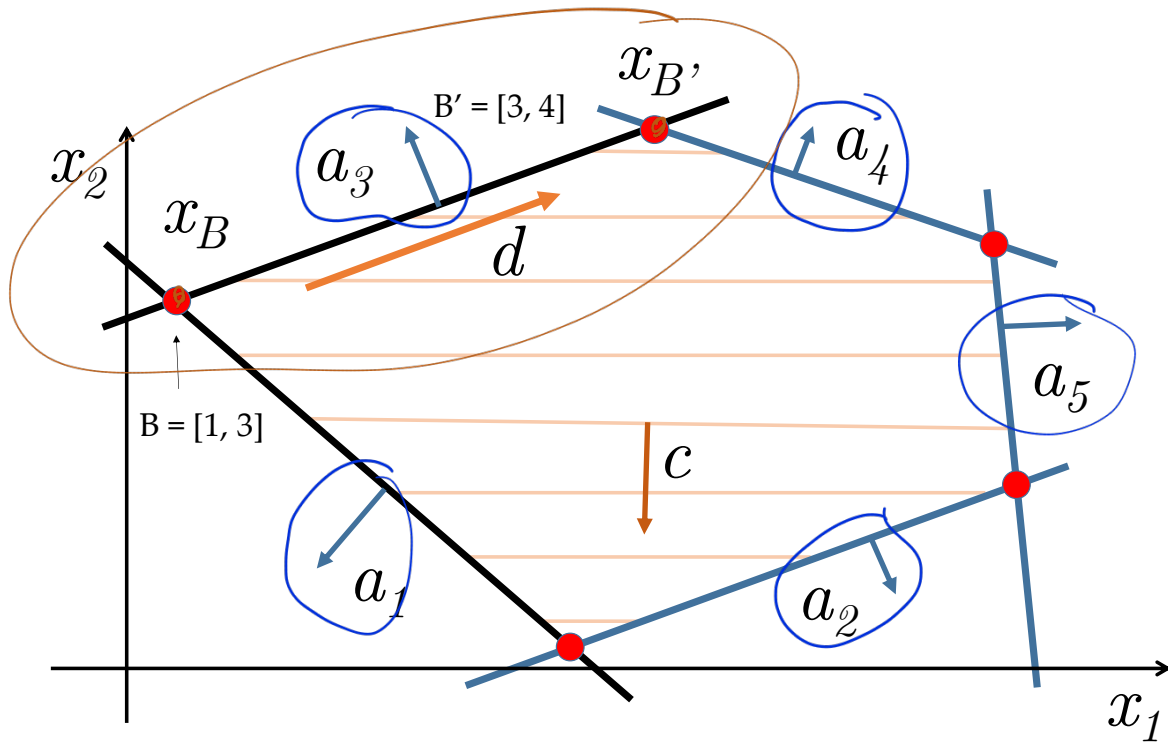
Proof:

Суммарно
АЛГОРИТМ

$$\begin{aligned}
\exists x^* : Ax^* &\leq b, c^\top x^* < c^\top x_B \\
A_B x^* &\leq b_B \\
\lambda_B^\top A_B x^* &\geq \lambda_B^\top b_B \\
c^\top x^* &\geq \lambda_B^\top A_B x_B \\
c^\top x^* &\geq c^\top x_B
\end{aligned}$$

Changing basis

Suppose, some of the coefficients of λ_B are positive. Then we need to go through the edge of the polytope to the new vertex (i.e., switch the basis)



$$x_{B'} = x_B + \mu d = A_B^{-1} b_{B'}$$

About convergence

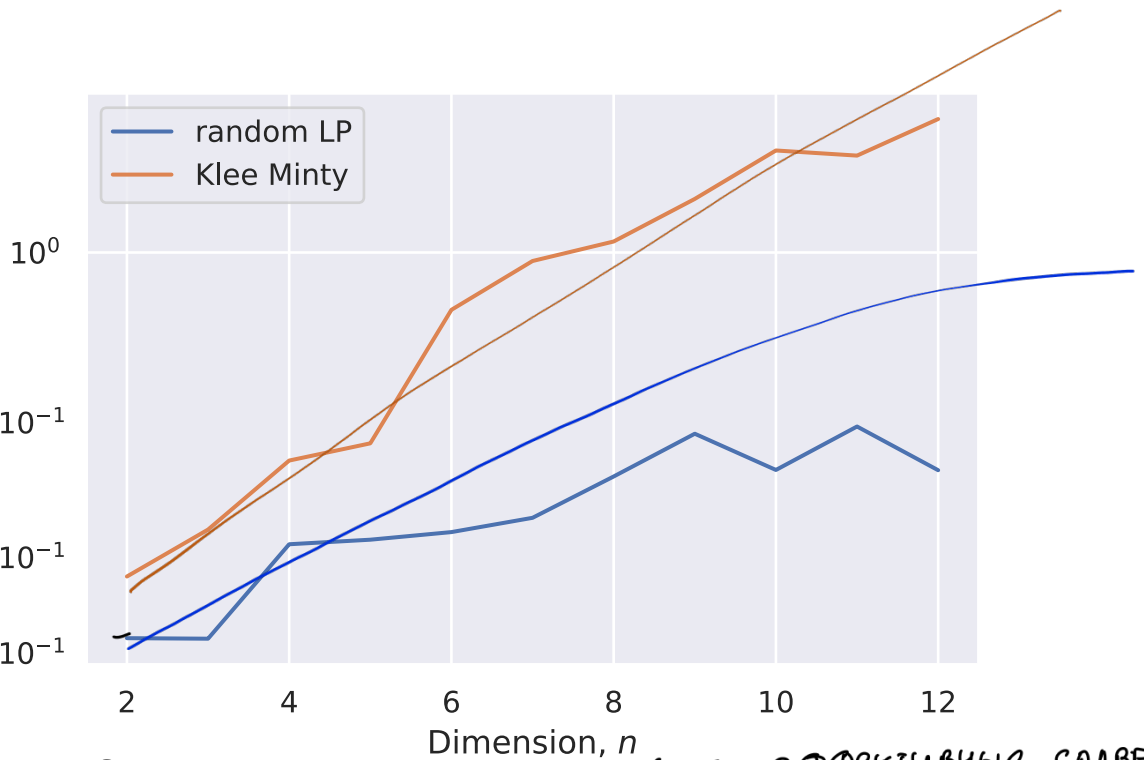
Klee Minty example

In the following problem simplex algorithm needs to check $2^n - 1$ vertices with $x_0 = 0$.

$$\begin{aligned}
&\max_{x \in \mathbb{R}^n} 2^{n-1} x_1 + 2^{n-2} x_2 + \dots + 2 x_{n-1} + x_n \\
&\text{s.t. } x_1 \leq 5 \\
&\quad 4x_1 + x_2 \leq 25 \\
&\quad 8x_1 + 4x_2 + x_3 \leq 125 \\
&\quad \dots \\
&\quad 2^n x_1 + 2^{n-1} x_2 + 2^{n-2} x_3 + \dots + x_n \leq 5^n \quad x \geq 0
\end{aligned}$$

в худшем случае
алгоритм
работает
экспонен-
циально.

Average computation time on 100 runs



Code

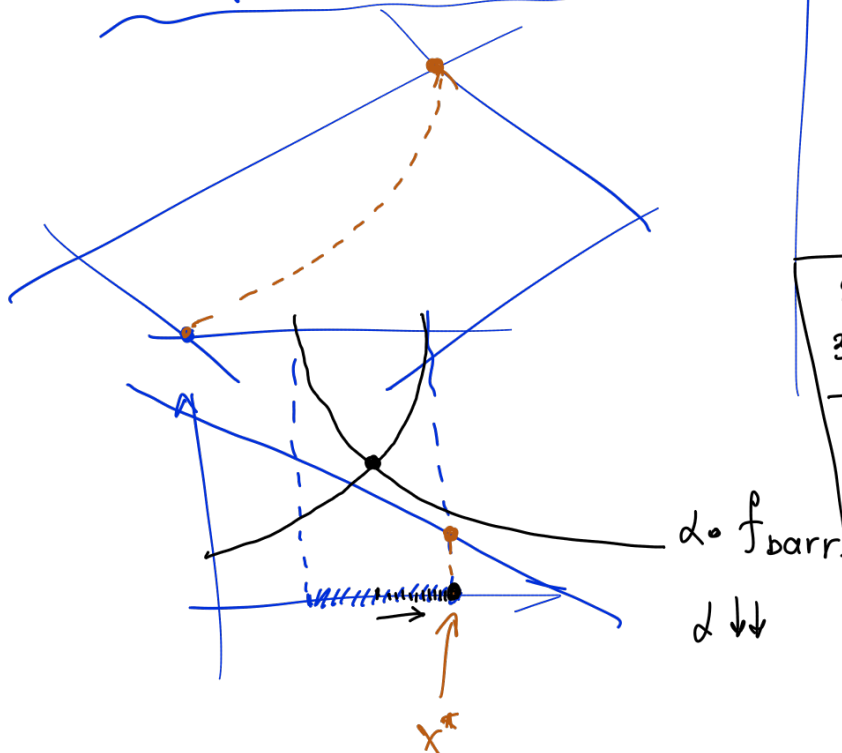
[Open in Colab](#)

Materials

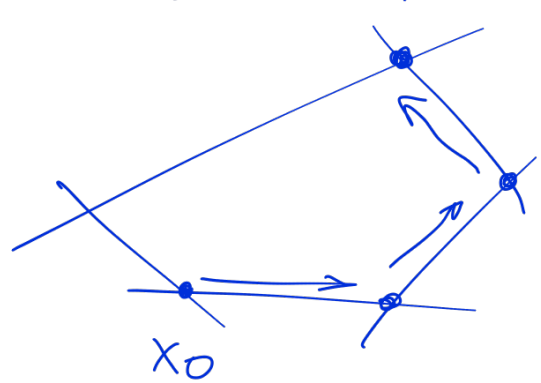
- ⊕ Довольно быстро решается (есть эффективные солверы)
- Отсутствует сильная выпуклость (НЕТ СХОДИМОСТИ) ПО АРГУМЕНТУ
- Симплекс метод прост, но в худшем случае работает экспоненциально долго.
- Есть много библиотек (scipy, pulp, pyomo)

- [Linear Programming](#) in V. Lempitsky optimization course.
- [Simplex method](#) in V. Lempitsky optimization course.
- [Overview of different LP solvers](#)
- [TED talks watching optimization](#)

Методы внутренней точки и



SIMPLEX x^*



Если есть переменные - дискретные. Задача сильно усложняется.

