

# Subgradient method with Polyak's step in transformed space

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# Outline

- 1 Polyak's subgradient method ( $m = 1$ )
- 2 Method A ( $m \geq 1$ )
- 3 Method B ( $m \geq 1$ , matrix  $B$ )
- 4 Comparison of the methods A and B

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# Formulation of the problem

We consider the following problem

$$\text{to find } x^* = \arg \min_{x \in R^n} f(x) \quad \text{if } f^* \text{ is known,} \quad (1)$$

where  $f(x)$  is a convex function and  $f^* = f(x^*) = \min_{x \in R^n} f(x)$ .

# Main inequality for the subgradient

For convex function  $f(x)$  the following inequality is valid

$$(x - x^*, g_f(x)) \geq f(x) - f^*, \quad \forall x \in R^n, \quad (2)$$

where  $g_f(x)$  is a subgradient (gradient) of the function  $f(x)$ .

Inequality (2) is used for the calculation of the step in subgradient method, which B.T. Polyak offered in 1969.



Polyak B.T. Minimization of unsmooth functionals // *USSR Comput. Math. Math. Phys.* 1969. Vol. 9, No. 3, pp. 14-29.

# Polyak's subgradient method

Polyak's subgradient method has the iterative form

$$x_{k+1} = x_k - h_k \frac{g_f(x_k)}{\|g_f(x_k)\|}, \quad h_k = \frac{f(x_k) - f^*}{\|g_f(x_k)\|}, \quad k=0, 1, \dots \quad (3)$$

Step  $h_k$  is called Polyak's step.

# Decrease of the distance to the minimum point

## Theorem 1 (Polyak, 1969)

The sequence  $\{x_k\}_{k=0}^{\infty}$ , generated by the method (3), satisfies the inequalities

$$\|x_{k+1} - x^*\|^2 \leq \|x_k - x^*\|^2 - \frac{(f(x_k) - f^*)^2}{\|g_f(x_k)\|^2}, \quad k = 0, 1, 2, \dots$$

**Remark.** Theorem 1 guarantees that in Polyak's method the distance to the minimum point decreases monotonically.

# $m$ -inequality for the subgradient

We consider methods A and B for convex functions  $f(x)$ , subgradients  $g_f(x)$  of which satisfy the following condition:

$$(x - x^*, g_f(x)) \geq m(f(x) - f^*), \quad \forall x \in R^n, \quad (4)$$

where parameter  $m \geq 1$ .

The method A uses the step  $h_k$  in **original space**, the method B uses  $h_k$  in **transformed space** of variables.

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# Method A

**Initialization.**  $f^*$ ,  $m \geq 1$ ,  $x_0 \in R^n$ ,  $\varepsilon > 0$ .

**A1.** Calculate  $f(x_k)$  and  $g_f(x_k)$ .

If  $f(x_k) - f^* \leq \varepsilon$ , then STOP ( $k^* = k$ ,  $x_\varepsilon^* = x_k$ ).

**A2.** Calculate the next point

$$x_{k+1} = x_k - h_k \frac{g_f(x_k)}{\|g_f(x_k)\|}, \quad h_k = \frac{m(f(x_k) - f^*)}{\|g_f(x_k)\|}.$$

**A3.** Go to the  $(k + 1)$ -th iteration with  $x_{k+1}$ .

# Decrease of the distance to the minimum point

## Theorem 2.1 (Stetsyuk, 2012)

*The sequence  $\{x_k\}_{k=0}^{k^*-1}$ , generated by the method A, satisfies the inequalities*

$$\|x_{k+1} - x^*\|^2 \leq \|x_k - x^*\|^2 - \frac{m^2(f(x_k) - f^*)^2}{\|g_f(x_k)\|^2}, \quad k = 0, 1, 2, \dots$$

**Remark.** Theorem 2.1 guarantees that in Polyak's subgradient method the distance to the minimum point decreases monotonically if the inequality (4) is used.

# Convergence rate of the method A

## Theorem 2.2 (general case)

If a convex function  $f(x)$  satisfies the inequality (4) the following inequality is true:

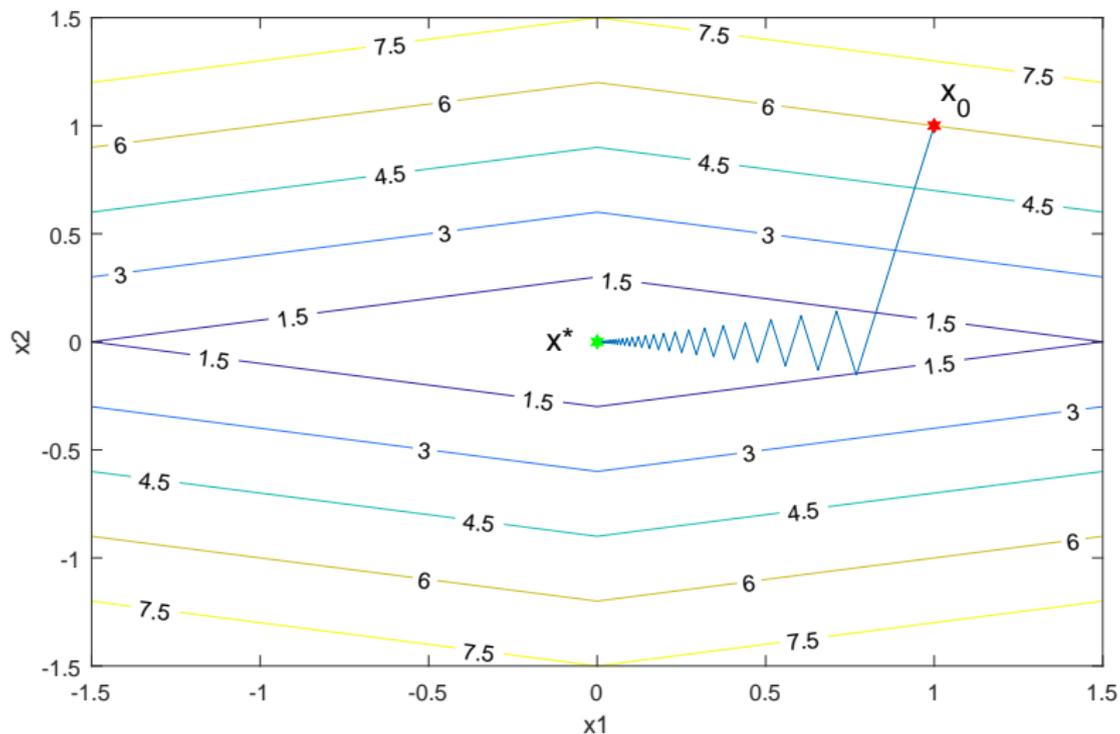
$$\lim_{k \rightarrow \infty} \sqrt{k}(f(x_k) - f^*) = 0 \quad (5)$$

## Theorem 2.3 (acute minimum case)

Let function  $f(x)$  satisfy the inequality  $f(x) - f^* \geq \alpha \|x - x^*\|$ . Then the method A converges with geometric progression rate with common ratio  $q_1 = 1 - \left(\frac{m\alpha}{c_1}\right)^2$ , where  $c_1$  is the constant that bounds subgradient  $g_f(x)$  norm.

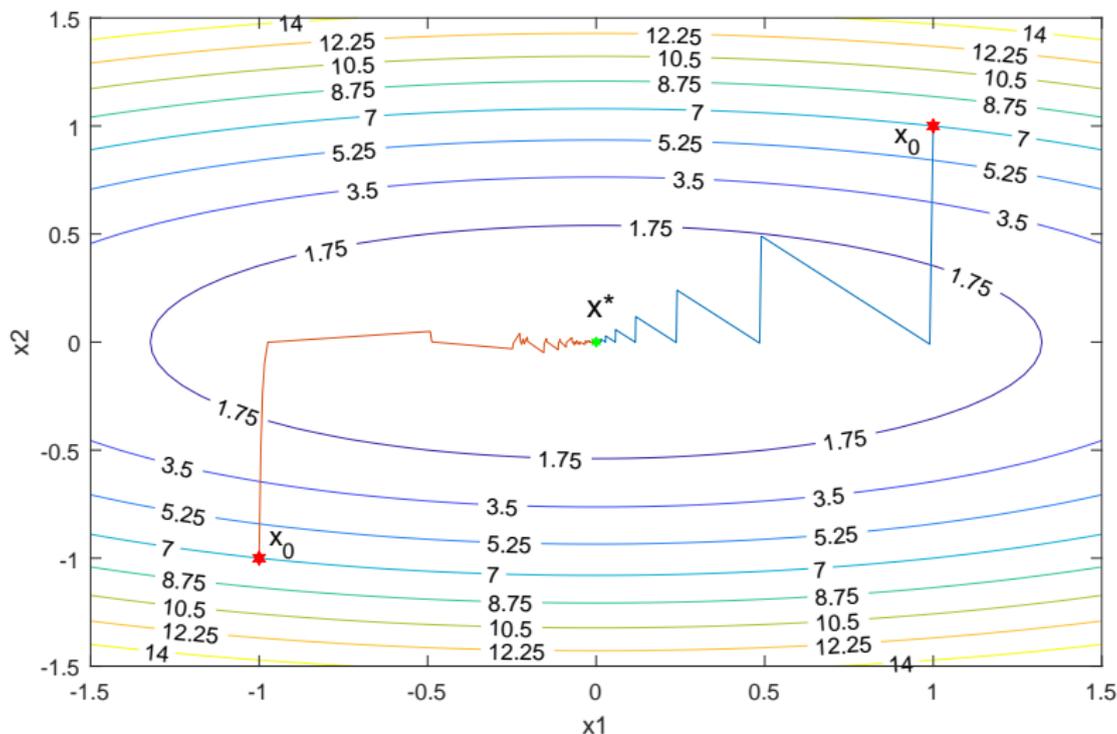
# Method A for $f_1(x_1, x_2) = |x_1| + 5|x_2|$

$$m = 1, f^* = 0, x_0 = (1, 1)^T$$



# Method A for $f_2(x_1, x_2) = x_1^2 + 6x_2^2$

Blue -  $m = 2$ ,  $x_0 = (1, 1)^T$     Red -  $m = 1$ ,  $x_0 = (-1, -1)^T$



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# Method B

**Initialization.**  $f^*$ ,  $m \geq 1$ ,  $x_0 \in R^n$ ,  $n \times n$  matrix  $B$ ,  $\varepsilon > 0$ .

**A1.** Calculate  $f(x_k)$  and  $g_f(x_k)$ .

If  $f(x_k) - f^* \leq \varepsilon$ , then STOP ( $k^* = k$ ,  $x_{\varepsilon}^* = x_k$ ).

**A2.** Calculate the next point

$$x_{k+1} = x_k - h_k B \frac{B^T g_f(x_k)}{\|B^T g_f(x_k)\|}, \quad h_k = \frac{m(f(x_k) - f^*)}{\|B^T g_f(x_k)\|}.$$

**A3.** Go to the  $(k + 1)$ -th iteration with  $x_{k+1}$ .

Here  $h_k$  is the Polyak's step in the **transformed** space of variables.

If  $B$  is an identity matrix, the method B turns into the method A.

# Decrease of the distance to the minimum point

## Theorem 3.1 (Stetsyuk, Stovba, Chernousova, 2018)

*The sequence  $\{x_k\}_{k=0}^{k^*-1}$ , generated by the method B, satisfies the inequalities*

$$\|A(x_{k+1} - x^*)\|^2 \leq \|A(x_k - x^*)\|^2 - \frac{m^2(f(x_k) - f^*)^2}{\|B^T g_f(x_k)\|^2}, \quad k = 0, 1, \dots$$

**Remark.** Theorem 3.1 guarantees that in the method B the distance to the minimum point decreases monotonically in the transformed space if the inequality (4) is used.

# Convergence rate of the method B

## Theorem 3.2 (general case)

If a convex function  $\varphi(y) = f(By) = f(x)$  satisfies the inequality  $(y - y^*, g_\varphi(y)) \geq m(\varphi(x) - \varphi^*)$  for any  $y$ , the following inequality is true:

$$\lim_{k \rightarrow \infty} \sqrt{k}(\varphi(y_k) - \varphi^*) = 0 \quad (6)$$

## Theorem 3.3 (acute minimum case)

Let function  $\varphi(y)$  satisfy the inequality  $\varphi(y) - \varphi^* \geq \alpha \|y - y^*\|$ . Then the method B converges with geometric progression rate with common ratio  $q_2 = 1 - (\frac{m\alpha}{c_2})^2$ , where  $c_2$  is the constant that bounds subgradient  $g_\varphi(y)$  norm.

# Method B for $f_1(x_1, x_2) = |x_1| + 10|x_2|$

$$B = \begin{pmatrix} 1 & 0 \\ 0 & 1/\alpha \end{pmatrix}, \quad x_0 = (1, 1)^T$$

$\varepsilon_f$	$\alpha = 1$	$\alpha = 1.5$	$\alpha = 2$	$\alpha = 3$	$\alpha = 4$	$\alpha = 5$
1.0e-02	262	114	62	19	17	13
1.0e-04	492	216	119	44	31	22
<b>1.0e-06</b>	<b>722</b>	<b>319</b>	<b>177</b>	<b>70</b>	<b>45</b>	<b>31</b>
1.0e-08	952	421	234	95	60	40
1.0e-10	1183	523	292	121	74	49

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# Functions used to compare the methods A and B

## 1. Piecewise quadratic function

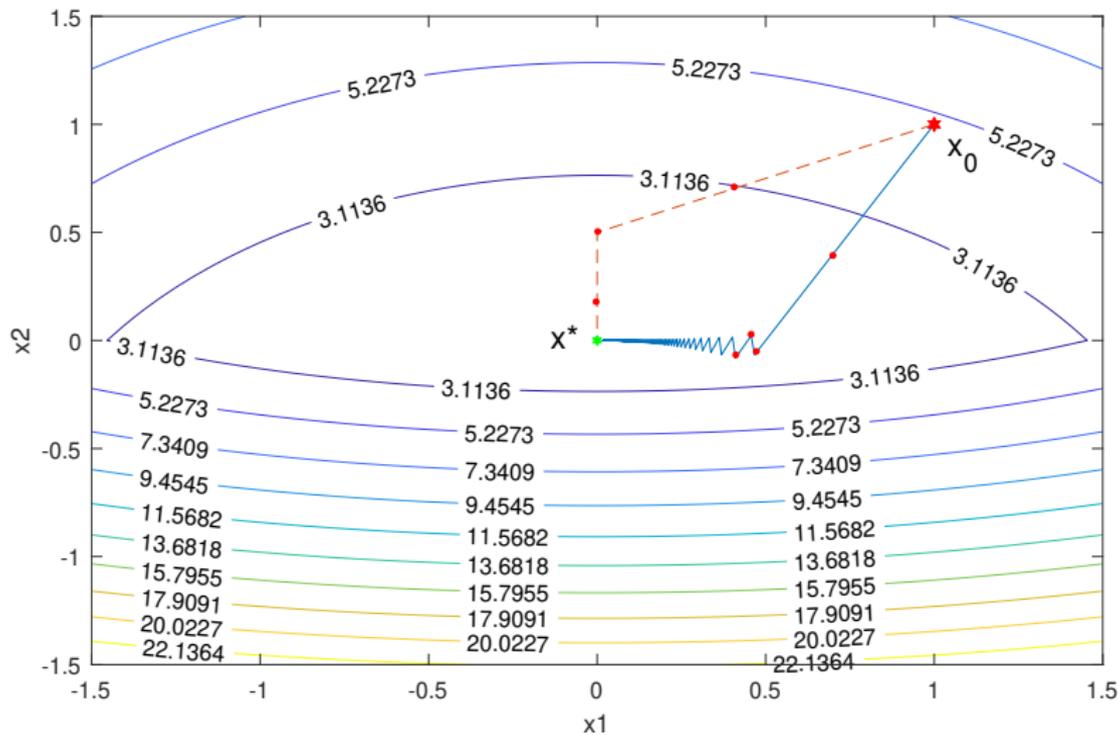
$$f_3(x_1, x_2) = \max \{x_1^2 + (2x_2 - 2)^2 - 3, x_1^2 + (x_2 + 1)^2\},$$
$$x^* = (0, 0), f^* = 1.$$

## 2. Quadratic function

$$f_4(x) = \|Ax - b\|^2, x^* = (1, 1, \dots, 1)^T, f^* = 0.$$

# Methods A and B for piecewise quadratic function

$x_0 = (1, 1)^T$ ,  $B = \text{diag}(1; 0.5)$ , method A - blue, method B - red



# Methods A and B for function $f_4(x) = \|Ax - b\|^2$

$$A = \|a_{ij}\|_{i,j=1}^{l,n} = \left\| \begin{array}{ccc} 100 & 0 & 0 \dots 0 \\ 0 & 100 & 0 \dots 0 \\ & & A_1 \end{array} \right\|, \quad b_i = \sum_{j=1}^n a_{ij}, \quad i = \overline{1, l},$$

$A_1$  -  $498 \times 100$  random matrix,  $m = 2$ .

$\varepsilon$	Method A		Method B	
	itnA	$\ x_\varepsilon^* - x^*\ $	itnB	$\ x_\varepsilon^* - x^*\ $
1.0e-04	695	8.0612e-04	86	1.2175e-04
1.0e-06	1085	8.2861e-05	108	1.1773e-05
1.0e-08	1491	8.3470e-06	130	1.1353e-06
<b>1.0e-10</b>	<b>1901</b>	<b>8.3881e-07</b>	<b>150</b>	<b>1.3526e-07</b>
1.0e-12	2313	8.3994e-08	172	1.3018e-08
1.0e-14	2725	8.4440e-09	194	1.2523e-09

# Conclusions

1. Using parameter  $m \geq 1$  in Polyak's subgradient method gives a possibility to minimize special classes of convex functions more effectively.
2. Application of space transformation can accelerate convergence of subgradient method with Polyak's step in the transformed space of variables.

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