

A low-poly Corgi and a rubber duck are the central focus of the slide. The Corgi is on the left, rendered in a low-poly style with yellow and white facets. The rubber duck is on the right, rendered in a smooth, realistic style. They are surrounded by several smaller rubber ducks in the background. A semi-transparent white box is centered over the image, containing the title and author information.

## Proximal gradient method

**Daniil Merkulov**

Optimization methods. MIPT

## Subgradient method

# Non-smooth problems

$\ell_1$  induces sparsity

$\ell_2$  regularization.  $\|Xw - y\|_2^2 \rightarrow \min_{\|w\|_2 \leq 1}$



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@fminxyz

# Subgradient method

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$$\min_{x \in \mathbb{R}^n} f(x)$$

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$$f(x_k) - f^* \sim \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$$
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## Theorem

Assume that  $f$  is  $G$ -Lipschitz and convex, then  
Subgradient method converges as:

$$f(\bar{x}) - f^* \leq \frac{GR}{\sqrt{k}},$$

where

- $\alpha = \frac{R}{G\sqrt{k}}$

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# Non-smooth convex optimization lower bounds

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- One can use Mirror Descent (a generalization of the subgradient method to a possibly non-Euclidian distance) with the same convergence rate to better fit the geometry of the problem.
- However, we can achieve standard gradient descent rate  $\mathcal{O}\left(\frac{1}{k}\right)$  (and even accelerated version  $\mathcal{O}\left(\frac{1}{k^2}\right)$ ) if we will exploit the structure of the problem.

## Proximal operator

# Proximal mapping intuition

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$$\frac{dx}{dt} = -\nabla f(x)$$

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Implicit Euler discretization:

$$\begin{aligned}\frac{x_{k+1} - x_k}{\alpha} &= -\nabla f(x_{k+1}) \\ \frac{x_{k+1} - x_k}{\alpha} + \nabla f(x_{k+1}) &= 0\end{aligned}$$

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! Proximal operator

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# Proximal operator visualization

$$\text{Prox}_f(x) = \underset{x'}{\operatorname{argmin}} \frac{1}{2} \|x - x'\|^2 + f(x')$$



Figure 1: Source

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Thus, we have a usual gradient descent with  $\alpha \rightarrow 0$ :  $x_{k+1} = x_k - \alpha \nabla f(x_k)$

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$$x_{k+1} = \text{prox}_{f_{x_k}^{II}, \alpha}(x_k) = \arg \min_{x \in \mathbb{R}^n} \left[ f(x_k) + \langle \nabla f(x_k), x - x_k \rangle + \frac{1}{2} \langle \nabla^2 f(x_k)(x - x_k), x - x_k \rangle + \frac{1}{2\alpha} \|x - x_k\|_2^2 \right]$$

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## From projections to proximity

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Proximity: Replace  $\mathbb{I}_S$  by some convex function!

$$\text{prox}_r(y) = \text{prox}_{r,1}(y) := \arg \min \frac{1}{2} \|x - y\|^2 + r(x)$$

## Composite optimization

# Regularized / Composite Objectives

Many nonsmooth problems take the form

$$\min_{x \in \mathbb{R}^n} \varphi(x) = f(x) + r(x)$$

- **Lasso, L1-LS, compressed sensing**

$$f(x) = \frac{1}{2} \|Ax - b\|_2^2, r(x) = \lambda \|x\|_1$$



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$$f(x) = \frac{1}{2} \|Ax - b\|_2^2, r(x) = \lambda \|x\|_1$$

- **L1-Logistic regression, sparse LR**

$$f(x) = -y \log h(x) - (1-y) \log(1-h(x)), r(x) = \lambda \|x\|_1$$





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$$x_{k+1} = \text{prox}_{r,\alpha}(x_k - \alpha \nabla f(x_k))$$

And this method converges at a rate of  $\mathcal{O}(\frac{1}{k})$ !



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**i** Another form of proximal operator

$$\text{prox}_{f,\alpha}(x_k) = \text{prox}_{\alpha f}(x_k) = \arg \min_{x \in \mathbb{R}^n} \left[ \alpha f(x) + \frac{1}{2} \|x - x_k\|_2^2 \right] \quad \text{prox}_f(x_k) = \arg \min_{x \in \mathbb{R}^n} \left[ f(x) + \frac{1}{2} \|x - x_k\|_2^2 \right]$$

## Proximal operators examples

- $r(x) = \lambda \|x\|_1, \lambda > 0$

$$[\text{prox}_r(x)]_i = [|x_i| - \lambda]_+ \cdot \text{sign}(x_i),$$

which is also known as soft-thresholding operator.

# Proximal operators examples

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$$[\text{prox}_r(x)]_i = [|x_i| - \lambda]_+ \cdot \text{sign}(x_i),$$

which is also known as soft-thresholding operator.

- $r(x) = \frac{\lambda}{2} \|x\|_2^2, \lambda > 0$

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- $r(x) = \mathbb{I}_S(x).$

$$\text{prox}_r(x_k - \alpha \nabla f(x_k)) = \text{proj}_r(x_k - \alpha \nabla f(x_k))$$

# Proximal operator properties

## **i** Theorem

Let  $r : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$  be a convex function for which  $\text{prox}_r$  is defined. If there exists such an  $\hat{x} \in \mathbb{R}^n$  that  $r(\hat{x}) < +\infty$ . Then, the proximal operator is uniquely defined (i.e., it always returns a single unique value).

**Proof:**

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It is strongly convex, meaning it has exactly one unique minimum (the existence of  $\hat{x}$  is necessary for  $r(\hat{x}) + \frac{1}{2}\|x - \hat{x}\|_2^2$  to take a finite value somewhere).



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1. Let's establish the equivalence between the first and second conditions. The first condition can be rewritten as

$$y = \arg \min_{\tilde{x} \in \mathbb{R}^d} \left( r(\tilde{x}) + \frac{1}{2} \|x - \tilde{x}\|^2 \right).$$

From the optimality condition for the convex function  $r$ , this is equivalent to:

$$0 \in \partial \left( r(\tilde{x}) + \frac{1}{2} \|x - \tilde{x}\|^2 \right) \Big|_{\tilde{x}=y} = \partial r(y) + y - x.$$

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2. From the definition of the subdifferential, for any subgradient  $g \in \partial f(y)$  and for any  $z \in \mathbb{R}^d$ :

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$$\langle g, z - y \rangle \leq r(z) - r(y).$$

In particular, this holds true for  $g = x - y$ .

Conversely, it is also clear: for  $g = x - y$ , the above relationship holds, which means  $g \in \partial r(y)$ .

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The operator  $\text{prox}_r(x)$  is firmly nonexpansive (FNE)

$$\|\text{prox}_r(x) - \text{prox}_r(y)\|_2^2 \leq \langle \text{prox}_r(x) - \text{prox}_r(y), x - y \rangle$$

and nonexpansive:

$$\|\text{prox}_r(x) - \text{prox}_r(y)\|_2 \leq \|x - y\|_2$$

## Proof

1. Let  $u = \text{prox}_r(x)$ , and  $v = \text{prox}_r(y)$ . Then, from the previous property:

$$\langle x - u, z_1 - u \rangle \leq r(z_1) - r(u)$$

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2. Substitute  $z_1 = v$  and  $z_2 = u$ . Summing up, we get:

$$\langle x - u, v - u \rangle + \langle y - v, u - v \rangle \leq 0,$$

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4. The last point comes from simple Cauchy-Bunyakovsky-Schwarz for the last inequality.

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Let  $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$  and  $r : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$  be convex functions. Additionally, assume that  $f$  is continuously differentiable and  $L$ -smooth, and for  $r$ ,  $\text{prox}_r$  is defined. Then,  $x^*$  is a solution to the composite optimization problem if and only if, for any  $\alpha > 0$ , it satisfies:

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## Proof

1. Optimality conditions:

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### 2. Recall from the previous lemma:

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2. Recall from the previous lemma:

$$\text{prox}_r(x) = y \Leftrightarrow x - y \in \partial r(y)$$

3. Finally,

$$x^* = \text{prox}_{\alpha r}(x^* - \alpha \nabla f(x^*)) = \text{prox}_{r,\alpha}(x^* - \alpha \nabla f(x^*))$$

## Theoretical tools for convergence analysis



# Convergence tools

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Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be an  $L$ -smooth convex function. Then, for any  $x, y \in \mathbb{R}^n$ , the following inequality holds:

$$f(x) + \langle \nabla f(x), y - x \rangle + \frac{1}{2L} \|\nabla f(x) - \nabla f(y)\|_2^2 \leq f(y) \text{ or, equivalently,}$$
$$\|\nabla f(y) - \nabla f(x)\|_2^2 = \|\nabla f(x) - \nabla f(y)\|_2^2 \leq 2L (f(x) - f(y) - \langle \nabla f(y), x - y \rangle)$$

## Proof

1. To prove this, we'll consider another function  $\varphi(y) = f(y) - \langle \nabla f(x), y \rangle$ . It is obviously a convex function (as a sum of convex functions). And it is easy to verify, that it is an  $L$ -smooth function by definition, since  $\nabla \varphi(y) = \nabla f(y) - \nabla f(x)$  and  $\|\nabla \varphi(y_1) - \nabla \varphi(y_2)\| = \|\nabla f(y_1) - \nabla f(y_2)\| \leq L\|y_1 - y_2\|$ .

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$$x:=y, y:=y - \frac{1}{L} \nabla \varphi(y) \quad \varphi\left(y - \frac{1}{L} \nabla \varphi(y)\right) \leq \varphi(y) + \left\langle \nabla \varphi(y), -\frac{1}{L} \nabla \varphi(y) \right\rangle + \frac{1}{2L} \|\nabla \varphi(y)\|_2^2$$

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## Convergence tools

3. From the first order optimality conditions for the convex function  $\nabla\varphi(y) = \nabla f(y) - \nabla f(x) = 0$ . We can conclude, that for any  $x$ , the minimum of the function  $\varphi(y)$  is at the point  $y = x$ . Therefore:

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The lemma has been proved. From the first view it does not make a lot of geometrical sense, but we will use it as a convenient tool to bound the difference between gradients.

# Convergence tools

## i Theorem

Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be continuously differentiable on  $\mathbb{R}^n$ . Then, the function  $f$  is  $\mu$ -strongly convex if and only if for any  $x, y \in \mathbb{R}^d$  the following holds:

$$\text{Strongly convex case } \mu > 0 \quad \langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \mu \|x - y\|^2$$

$$\text{Convex case } \mu = 0 \quad \langle \nabla f(x) - \nabla f(y), x - y \rangle \geq 0$$

## Proof

1. We will only give the proof for the strongly convex case, the convex one follows from it with setting  $\mu = 0$ . We start from necessity. For the strongly convex function

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|x - y\|_2^2$$

$$f(x) \geq f(y) + \langle \nabla f(y), x - y \rangle + \frac{\mu}{2} \|x - y\|_2^2$$

$$\text{sum} \quad \langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \mu \|x - y\|^2$$

## Convergence tools

2. For the sufficiency we assume, that  $\langle \nabla f(x) - \nabla f(y), x - y \rangle \geq \mu \|x - y\|^2$ . Using Newton-Leibniz theorem  $f(x) = f(y) + \int_0^1 \langle \nabla f(y + t(x - y)), x - y \rangle dt$ :

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$$f(x) - f(y) - \langle \nabla f(y), x - y \rangle = \int_0^1 \langle \nabla f(y + t(x - y)), x - y \rangle dt - \langle \nabla f(y), x - y \rangle$$



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## Proximal Gradient Method. Convex case

# Convergence

## i Theorem

Consider the proximal gradient method

$$x_{k+1} = \text{prox}_{\alpha r}(x_k - \alpha \nabla f(x_k))$$

For the criterion  $\varphi(x) = f(x) + r(x)$ , we assume:

- $f$  is convex, differentiable,  $\text{dom}(f) = \mathbb{R}^n$ , and  $\nabla f$  is Lipschitz continuous with constant  $L > 0$ .
- $r$  is convex, and  $\text{prox}_{\alpha r}(x_k) = \arg \min_{x \in \mathbb{R}^n} [\alpha r(x) + \frac{1}{2} \|x - x_k\|_2^2]$  can be evaluated.

Proximal gradient descent with fixed step size  $\alpha = 1/L$  satisfies

$$\varphi(x_k) - \varphi^* \leq \frac{L \|x_0 - x^*\|^2}{2k},$$

Proximal gradient descent has a convergence rate of  $O(1/k)$  or  $O(1/\varepsilon)$ . This matches the gradient descent rate!  
(But remember the proximal operation cost)

# Convergence

## Proof

1. Let's introduce the **gradient mapping**, denoted as  $G_\alpha(x)$ , acts as a “gradient-like object”:

$$x_{k+1} = \text{prox}_{\alpha r}(x_k - \alpha \nabla f(x_k))$$

$$x_{k+1} = x_k - \alpha G_\alpha(x_k).$$

where  $G_\alpha(x)$  is:

$$G_\alpha(x) = \frac{1}{\alpha} (x - \text{prox}_{\alpha r}(x - \alpha \nabla f(x)))$$

Observe that  $G_\alpha(x) = 0$  if and only if  $x$  is optimal. Therefore,  $G_\alpha$  is analogous to  $\nabla f$ . If  $x$  is locally optimal, then  $G_\alpha(x) = 0$  even for nonconvex  $f$ . This demonstrates that the proximal gradient method effectively combines gradient descent on  $f$  with the proximal operator of  $r$ , allowing it to handle non-differentiable components effectively.

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7. Now it is easy to verify, that when  $x = x_k$  we have monotonic decrease for the proximal gradient algorithm:

$$\varphi(x_{k+1}) \leq \varphi(x_k) - \frac{\alpha}{2} \|G_\alpha(x_k)\|_2^2$$

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## Convergence

9. Now we write the bound above for all iterations  $i \in 0, k-1$  and sum them:

Which is a standard  $\frac{L\|x_0 - x^*\|_2^2}{2k}$  with  $\alpha = \frac{1}{L}$ , or,  $\mathcal{O}\left(\frac{1}{k}\right)$  rate for smooth convex problems with Gradient Descent!

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## Convergence

9. Now we write the bound above for all iterations  $i \in 0, k-1$  and sum them:

$$\begin{aligned}\sum_{i=0}^{k-1} [\varphi(x_{i+1}) - \varphi(x^*)] &\leq \frac{1}{2\alpha} [\|x_0 - x^*\|_2^2 - \|x_k - x^*\|_2^2] \\ &\leq \frac{1}{2\alpha} \|x_0 - x^*\|_2^2\end{aligned}$$

10. Since  $\varphi(x_k)$  is a decreasing sequence, it follows that:

$$\begin{aligned}\sum_{i=0}^{k-1} \varphi(x_k) &= k\varphi(x_k) \leq \sum_{i=0}^{k-1} \varphi(x_{i+1}) \\ \varphi(x_k) &\leq \frac{1}{k} \sum_{i=0}^{k-1} \varphi(x_{i+1}) \\ \varphi(x_k) - \varphi(x^*) &\leq \frac{1}{k} \sum_{i=0}^{k-1} [\varphi(x_{i+1}) - \varphi(x^*)] \leq \frac{\|x_0 - x^*\|_2^2}{2\alpha k}\end{aligned}$$

Which is a standard  $\frac{L\|x_0 - x^*\|_2^2}{2k}$  with  $\alpha = \frac{1}{L}$ , or,  $\mathcal{O}\left(\frac{1}{k}\right)$  rate for smooth convex problems with Gradient Descent!

## Proximal Gradient Method. Strongly convex case

# Convergence

## i Theorem

Consider the proximal gradient method

$$x_{k+1} = \text{prox}_{\alpha r}(x_k - \alpha \nabla f(x_k))$$

For the criterion  $\varphi(x) = f(x) + r(x)$ , we assume:

- $f$  is  $\mu$ -strongly convex, differentiable,  $\text{dom}(f) = \mathbb{R}^n$ , and  $\nabla f$  is Lipschitz continuous with constant  $L > 0$ .
- $r$  is convex, and  $\text{prox}_{\alpha r}(x_k) = \arg \min_{x \in \mathbb{R}^n} [\alpha r(x) + \frac{1}{2} \|x - x_k\|_2^2]$  can be evaluated.

Proximal gradient descent with fixed step size  $\alpha \leq 1/L$  satisfies

$$\|x_{k+1} - x^*\|_2^2 \leq (1 - \alpha\mu)^k \|x_0 - x^*\|_2^2$$

This is exactly gradient descent convergence rate. Note, that the original problem is even non-smooth!

# Convergence

## Proof

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# Convergence

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1. Considering the distance to the solution and using the stationary point lemm:

$$\begin{aligned}\|x_{k+1} - x^*\|_2^2 &= \|\text{prox}_{\alpha f}(x_k - \alpha \nabla f(x_k)) - x^*\|_2^2 \\ \text{stationary point lemm} &= \|\text{prox}_{\alpha f}(x_k - \alpha \nabla f(x_k)) - \text{prox}_{\alpha f}(x^* - \alpha \nabla f(x^*))\|_2^2\end{aligned}$$

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$$\text{nonexpansiveness} \leq \|x_k - \alpha \nabla f(x_k) - x^* + \alpha \nabla f(x^*)\|_2^2$$



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$$\text{smoothness} \quad \|\nabla f(x_k) - \nabla f(x^*)\|_2^2 \leq 2L (f(x_k) - f(x^*) - \langle \nabla f(x^*), x_k - x^* \rangle)$$

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4. Due to convexity of  $f$ :  $f(x_k) - f(x^*) - \langle \nabla f(x^*), x_k - x^* \rangle \geq 0$ . Therefore, if we use  $\alpha \leq \frac{1}{L}$ :

$$\|x_{k+1} - x^*\|_2^2 \leq (1 - \alpha\mu) \|x_k - x^*\|^2,$$

which is exactly linear convergence of the method with up to  $1 - \frac{\mu}{L}$  convergence rate.



# Accelerated Proximal Method

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Let  $x_0 = y_0 \in \text{dom}(r)$ . For  $k \geq 1$ :

$$x_k = \text{prox}_{\alpha_k h}(y_{k-1} - \alpha_k \nabla f(y_{k-1}))$$

$$y_k = x_k + \frac{k-1}{k+2}(x_k - x_{k-1})$$

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- Uses extra “memory” for interpolation
- Same computational cost as ordinary prox-grad
- Convergence rate theoretically optimal

## Numerical experiments

## Quadratic case

$$f(x) = \frac{1}{2m} \|Ax - b\|_2^2 + \lambda \|x\|_1 \rightarrow \min_{x \in \mathbb{R}^n}, \quad A \in \mathbb{R}^{m \times n}, \quad \lambda \left( \frac{1}{m} A^T A \right) \in [\mu; L].$$

Linear Least Squares with  $\ell_1$  Regularization (LASSO).  
m=1000, n=100,  $\lambda=0$ ,  $\mu=0$ , L=10. Optimal sparsity: 0.0e+00



Figure 2: Smooth convex case. Sublinear convergence, no convergence in domain, no difference between subgradient and proximal methods

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Figure 3: Non-smooth convex case. Sublinear convergence. At the beginning, the subgradient method and proximal method are close.

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Figure 4: Non-smooth convex case. If we take more iterations, the proximal method converges with the constant learning rate, which is not the case for the subgradient method. The difference is tremendous, while the iteration complexity is the same.



# Binary logistic regression

$$f(x) = \frac{1}{m} \sum_{i=1}^m \log(1 + \exp(-b_i(A_i x))) + \lambda \|x\|_1 \rightarrow \min_{x \in \mathbb{R}^n}, \quad A_i \in \mathbb{R}^n, \quad b_i \in \{-1, 1\}$$

Binary Logistic Regression with  $\ell_1$  Regularization.  
 $m=300$ ,  $n=50$ ,  $\lambda=0.1$ . Optimal sparsity:  $8.6e-01$



Figure 5: Logistic regression with  $\ell_1$  regularization

# Softmax multiclass regression

Convex multiclass regression. lam=0.01.



## Example: ISTA

### Iterative Shrinkage-Thresholding Algorithm (ISTA)

ISTA is a popular method for solving optimization problems involving L1 regularization, such as Lasso. It combines gradient descent with a shrinkage operator to handle the non-smooth L1 penalty effectively.

- **Algorithm:**

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- **Application:**

- Efficient for sparse signal recovery, image processing, and compressed sensing.



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### Fast Iterative Shrinkage-Thresholding Algorithm (FISTA)

FISTA improves upon ISTA's convergence rate by incorporating a momentum term, inspired by Nesterov's accelerated gradient method.

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- **Application:**

- Especially useful for large-scale problems in machine learning and signal processing where the L1 penalty induces sparsity.

# Example: Matrix Completion

## Solving the Matrix Completion Problem

Matrix completion problems seek to fill in the missing entries of a partially observed matrix under certain assumptions, typically low-rank. This can be formulated as a minimization problem involving the nuclear norm (sum of singular values), which promotes low-rank solutions.

- **Problem Formulation:**

$$\min_X \frac{1}{2} \|P_\Omega(X) - P_\Omega(M)\|_F^2 + \lambda \|X\|_*,$$

where  $P_\Omega$  projects onto the observed set  $\Omega$ , and  $\|\cdot\|_*$  denotes the nuclear norm.



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- **Algorithm:**

- Similar proximal gradient or accelerated proximal gradient methods can be applied, where the main computational effort lies in performing partial SVDs.

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where  $P_\Omega$  projects onto the observed set  $\Omega$ , and  $\|\cdot\|_*$  denotes the nuclear norm.

- **Proximal Operator:**

- The proximal operator for the nuclear norm involves singular value decomposition (SVD) and soft-thresholding of the singular values.

- **Algorithm:**

- Similar proximal gradient or accelerated proximal gradient methods can be applied, where the main computational effort lies in performing partial SVDs.

- **Application:**

# Example: Matrix Completion

## Solving the Matrix Completion Problem

Matrix completion problems seek to fill in the missing entries of a partially observed matrix under certain assumptions, typically low-rank. This can be formulated as a minimization problem involving the nuclear norm (sum of singular values), which promotes low-rank solutions.

- **Problem Formulation:**

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- **Application:**

- Widely used in recommender systems, image recovery, and other domains where data is naturally matrix-formed but partially observed.

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If we allow the proximal operator to be inexact (numerically), then it is true that we can solve any nonsmooth optimization problem. But this is not better from the point of view of theory than solving the problem by subgradient descent, because some auxiliary method (for example, the same subgradient descent) is used to solve the proximal subproblem.

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- Further reading: Proximal operator splitting, Douglas-Rachford splitting, Best approximation problem, Three operator splitting.