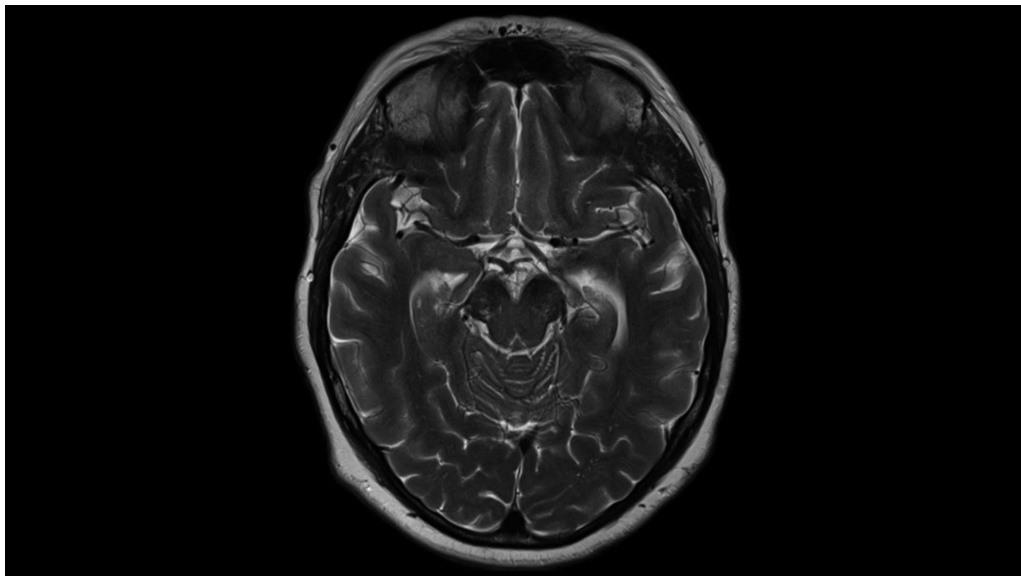
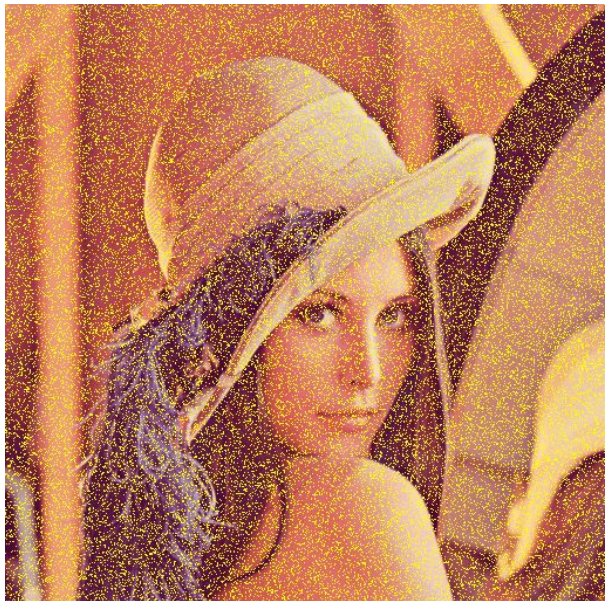


# Total variation method for image reconstruction

Nikita Belousov  
Dmitrii Masnyi

# Why denoising is important?

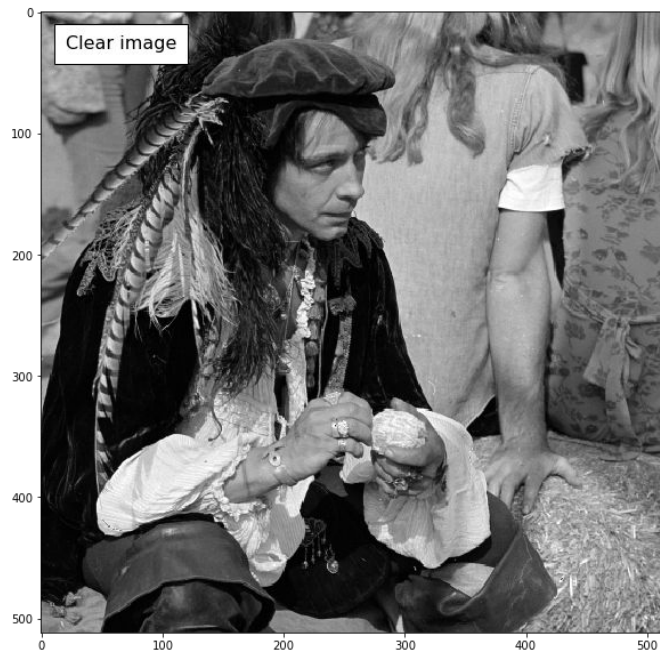


# Classical methods

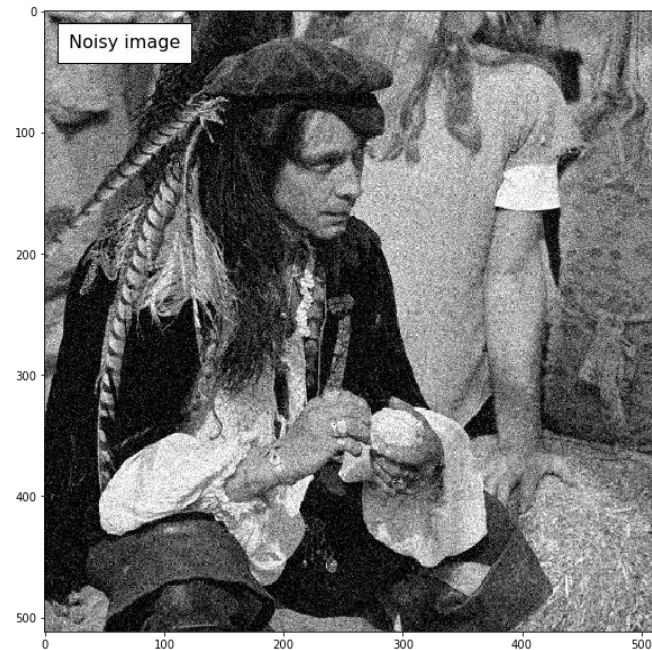
- Spatial domain filtering
- **Total variation regularization**
- Sparse representation
- Low-rank minimization

# Notation

$X$



$$B = X + N$$



# Total variation denoising problem

Primal problem:

$$\begin{aligned} &\text{minimize } \sum_{i=1}^m \sum_{j=1}^n \|D_{(ij)} x\|_2 \\ &\text{subject to } \|x - b\|_2 \leq \delta, \end{aligned}$$

Dual problem:

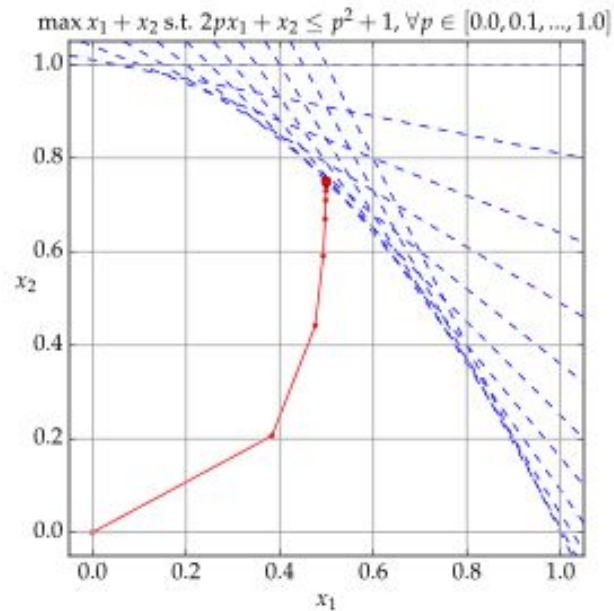
$$\begin{aligned} &\text{maximize } -\delta \|D^T u\|_2 + b^T D^T u \\ &\text{subject to } \|u_{(ij)}\|_2 \leq 1, \quad i = 1, \dots, m, \quad j = 1, \dots, n, \end{aligned}$$

Discrete TV function:

$$T(x) = \sum_{i=1}^m \sum_{j=1}^n \|D_{(ij)} x\|_2,$$

**Second-order cone programming problem  
(SOCP)**

# Classical method



Interior-point algorithm

Useless for large scale problems.

# Nesterov's first order algorithm

## Fast approach

$$\min_{x \in Q_p} \max_{u \in Q_d} u^T D x,$$

$$Q_p = \{x \mid \|x - b\|_2 \leq \delta\},$$

$$Q_d = \{u \mid \|u_{(ij)}\|_2 \leq 1, \ i = 1, \dots, m, \ j = 1, \dots, n\}.$$

$$f_p(x) = \frac{1}{2} \|x - b\|_2^2 \quad \text{and} \quad f_d(u) = \frac{1}{2} \|u\|_2^2.$$



# Fast approach

A smooth approximation

$$\mathcal{T}_\mu(x) = \max_{u \in Q_d} \{u^T D x - \mu f_d(u)\}.$$

Terminating criteria:

$$\sum_{i=1}^m \sum_{j=1}^n \|D_{(ij)} x\|_2 + \delta \|D^T u\|_2 - u^T D b < \epsilon.$$

# Nesterov's first order algorithm

Given data  $b$  and a tolerance  $\epsilon$ .

Set  $x^{[0]} = b$  (a feasible starting point),  $\mu = \frac{\epsilon}{2\Delta_d}$ , and  $\mathcal{L}_\mu = \frac{\|D\|_2^2}{\mu}$ .

For  $k = 0, 1, 2, \dots$

1) Evaluate  $g^{[k]} = \nabla \mathcal{T}_\mu(x^{[k]})$ .

2) Find  $y^{[k]} = \arg \min_{x \in Q_p} \left\{ (x - x^{[k]})^T g^{[k]} + \frac{1}{2} \mathcal{L}_\mu \|x - x^{[k]}\|_2^2 \right\}$ .

3) Find  $z^{[k]} = \arg \min_{x \in Q_p} \left\{ \mathcal{L}_\mu f_p(x) + \sum_{i=0}^k \frac{i+1}{2} (x - x^{[i]})^T g^{[k]} \right\}$ .

4) Update  $x^{[k+1]} = \frac{2}{k+3} z^{[k]} + \frac{k+1}{k+3} y^{[k]}$ .

# Modifications of the steps

## Step 1

$$\nabla \mathcal{T}_\mu(x^{[k]}) = D^T u^{[k]},$$

$$u^{[k]} = \arg \max_{u \in Q_d} u^T D x^{[k]} - \frac{\mu}{2} \|u\|_2^2.$$

$$u_{(ij)}^{[k]} = D_{(ij)} x^{[k]} / \max \{ \mu, \|D_{(ij)} x^{[k]}\|_2 \}.$$

# Modifications of the steps

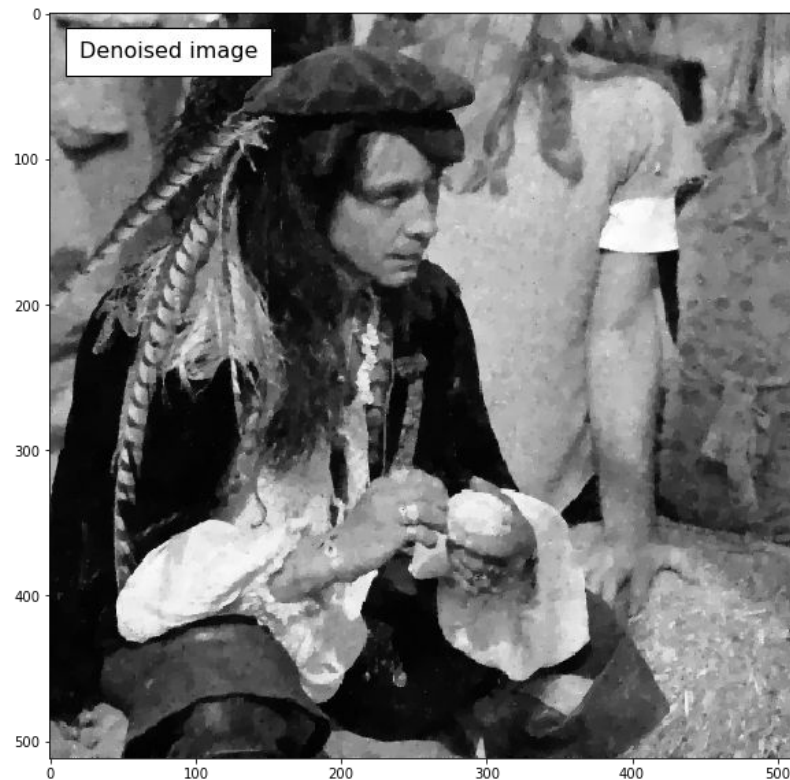
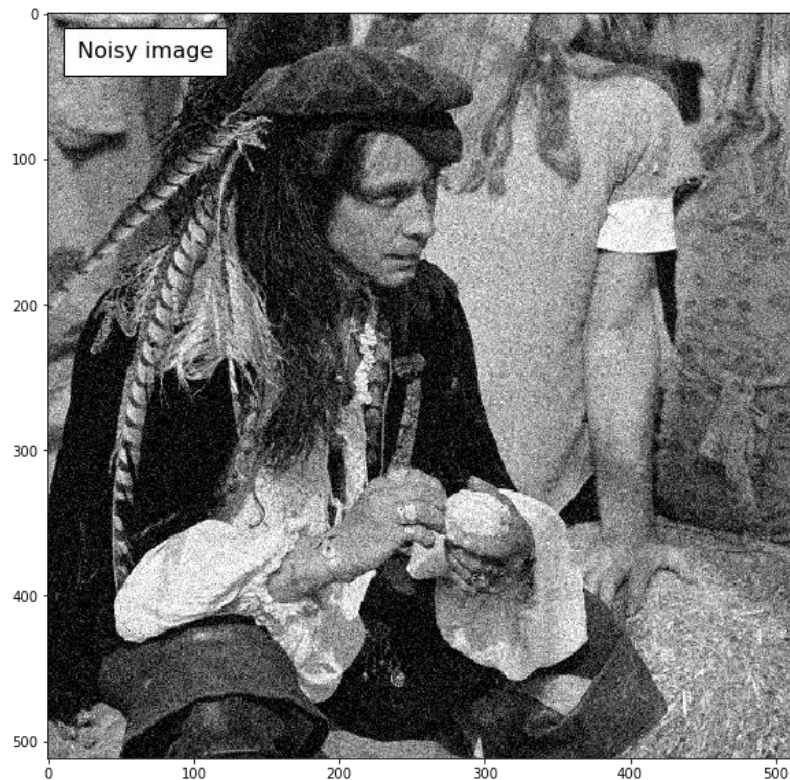
## Step 2

$$y^{[k]} = (\mathcal{L}_\mu (x^{[k]} - b) - g^{[k]}) / \max \{ \mathcal{L}_\mu, \|\mathcal{L}_\mu (x^{[k]} - b) - g^{[k]}\|_2 / \delta \} + b,$$

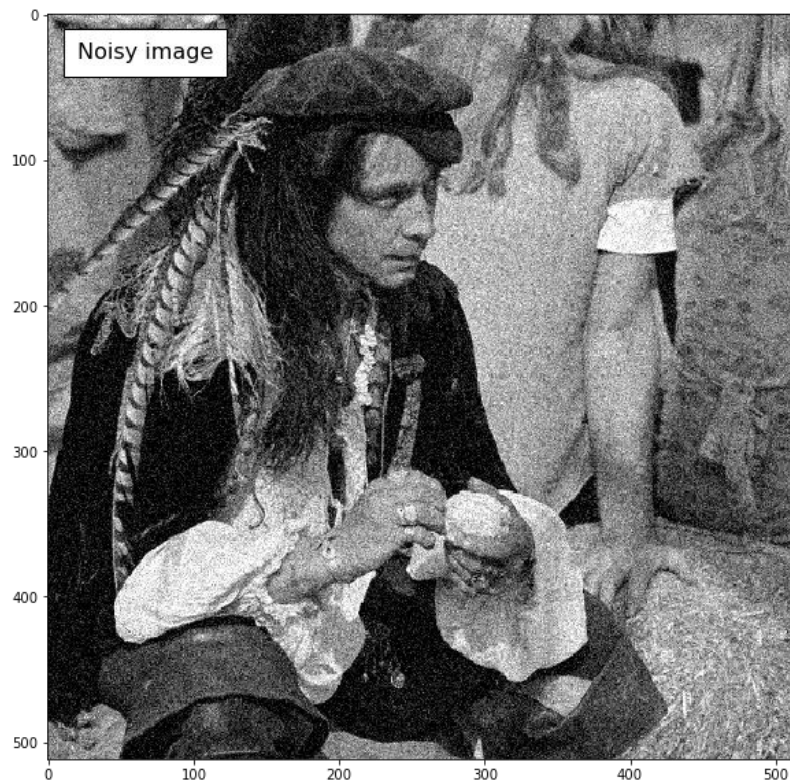
## Step 3

$$z^{[k]} = -w^{[k]} / \max \{ \mathcal{L}_\mu, \|w^{[k]}\|_2 / \delta \} + b, \quad w^{[k]} = \sum_{i=0}^k \frac{1}{2}(i+1) g^{[i]}.$$

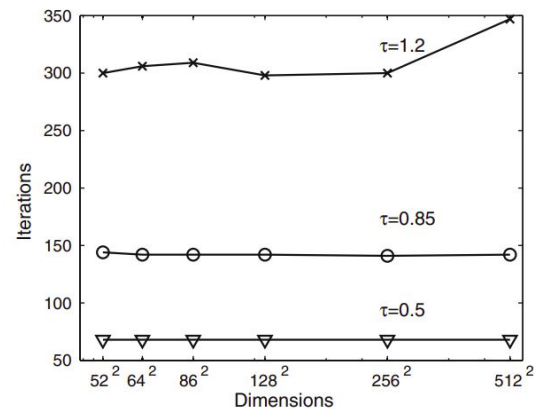
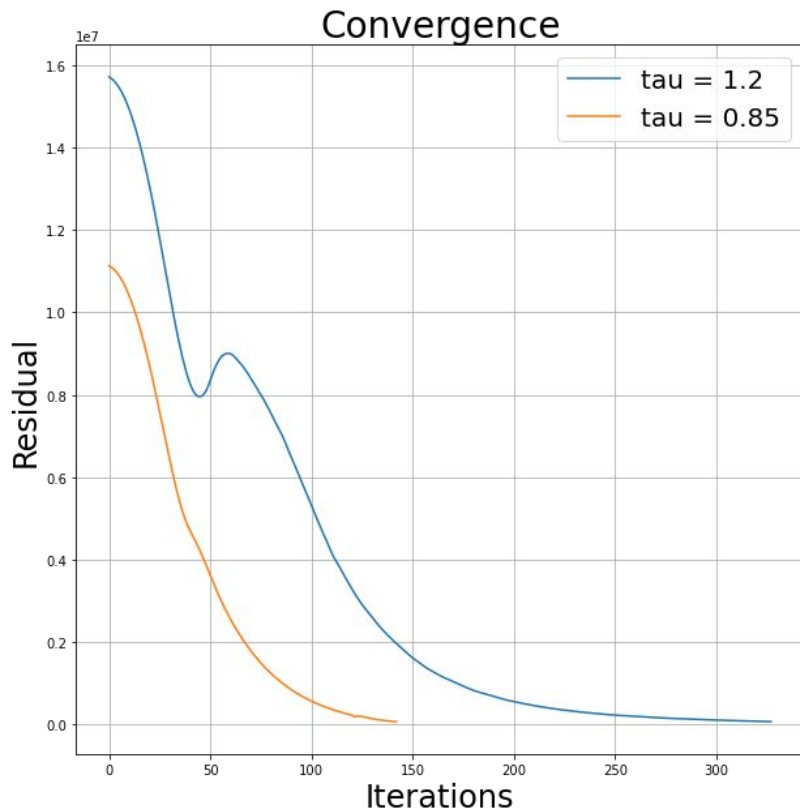
# Denoising results: $\tau = 0.85$ , $\sigma = 25$



# Denoising results: $\tau = 1.2$ , $\sigma = 25$



# Simulation results



	$\tau = 0.85$	$\tau = 1.2$
N iterations	142	327
Time	4:12	9:56

## Algorithm improvement

2) Find  $y^{[k]} = \arg \min_{x \in Q_p} \left\{ (x - x^{[k]})^T g^{[k]} + \frac{1}{2} \mathcal{L}_\mu \|x - x^{[k]}\|_2^2 \right\}.$

3) Find  $z^{[k]} = \arg \min_{x \in Q_p} \left\{ \mathcal{L}_\mu f_p(x) + \sum_{i=0}^k \frac{i+1}{2} (x - x^{[i]})^T g^{[k]} \right\}.$

	In parallel	Sequentially
Time	4:12	4:32



# Conclusion

- Image denoising is a hot research topic. Over the years many techniques of image denoising have been introduced.
- We studied one of the first efficient algorithms for this problem.
- We write the code for TV denoising algorithm from the scratch, so it is easy for user to understand how this algorithm works under-the-hood.
- Parallelizing the calculation of step 2 and step 3 decreased the time for computation.
- [https://github.com/dmasny99/cvx\\_opt\\_skoltech\\_project](https://github.com/dmasny99/cvx_opt_skoltech_project)

Thanks for your attention!