AI & Companies Week

MSGI (Mathematics Study Group with Industry)

Industry: **CEA**

Topic: Deblurring Images by deconvolution for high-energy scanner

Members:

Jérémy Grebot

Georgios Kopanas

Giulia Marchello

Louis Ohl

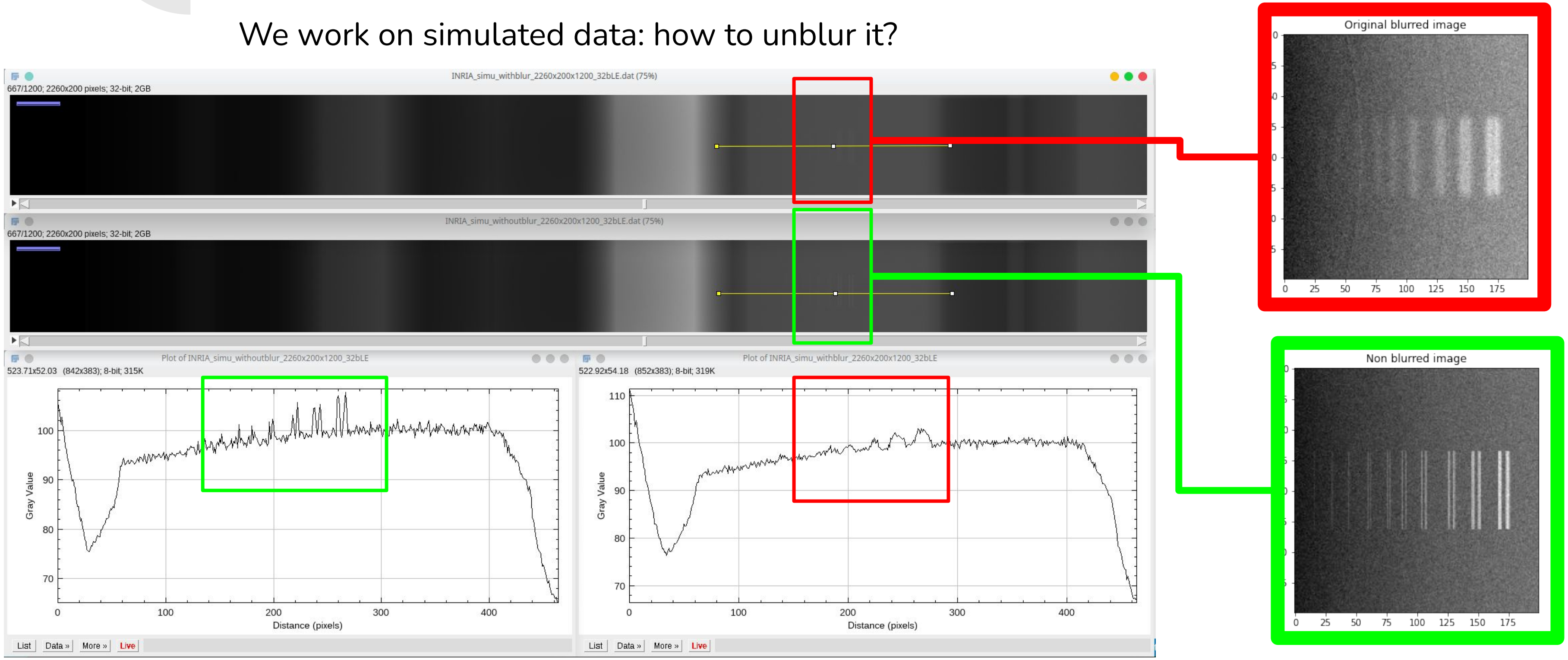
Vasiliki Stergiopoulou

Table of contents

A. Introduction

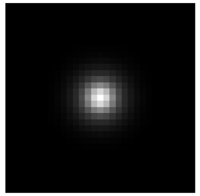
Let’s talk data

We work on simulated data: how to unblur it?

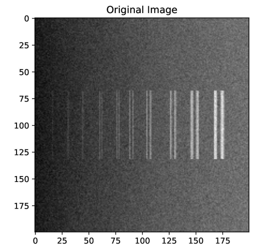


Inverse problem

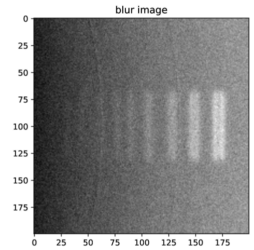
Observation Model: $\mathbf{g} = \mathbf{H}\mathbf{u} + \mathbf{n}$



$\mathbf{H}$



$\mathbf{u}$



$\mathbf{g}$

- $\mathbf{g}$: Observed Image
- $\mathbf{H}$: Convolution Kernel or Point Spread Function (PSF) - **provided**
- $\mathbf{u}$: Original Image (without degradation)
- $\mathbf{n}$: Noise

It is an *ill-posed inverse problem*. We search for an estimation $\hat{\mathbf{u}}$ of the original image $\mathbf{u}$.

Find an estimation of the original image

Least Square Solution: $\hat{\mathbf{u}} = \arg\min_{\mathbf{u}} ||\mathbf{g} - \mathbf{H}\mathbf{u}||_2^2$

→ Reduce the set of solution by introducing constraints - **Regularization**

With regularization: $\hat{\mathbf{u}} = \arg\min_{\mathbf{u}} ||\mathbf{g} - \mathbf{H}\mathbf{u}||_2^2 + R(\mathbf{u})$ $\begin{cases} \lambda||\mathbf{u}||_1 \\ \lambda||\mathbf{u}||_2^2 \\ \lambda||\nabla\mathbf{u}||_1 \\ \lambda||\nabla\mathbf{u}||_2^2 \\ \lambda||\mathbf{\Psi}\mathbf{u}||_1 \\ \textbf{Combination} \end{cases}$

Ψ: a wavelet basis

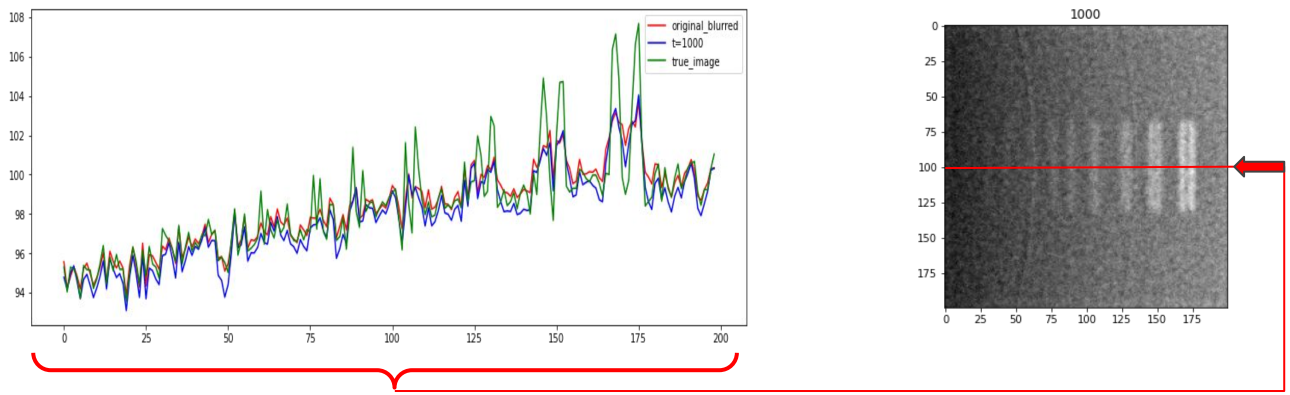
Popular algorithms to solve the minimization problems

Some examples:

- For $R(\mathbf{u}) = \lambda \|\nabla \mathbf{u}\|_2^2$
  - Tikhonov Regularization - Smooth contours
  - Smooth convex optimization
  - (Accelerated))Gradient Descent
- For $R(\mathbf{u}) = \lambda \|\nabla \mathbf{u}\|_1$
  - Total Variation (TV) - Piecewise constant regions
  - Non-smooth convex optimization
  - Primal-Dual, Alternate Direction Method of Multipliers (ADMM),..

Metrics

- 1D Profile:



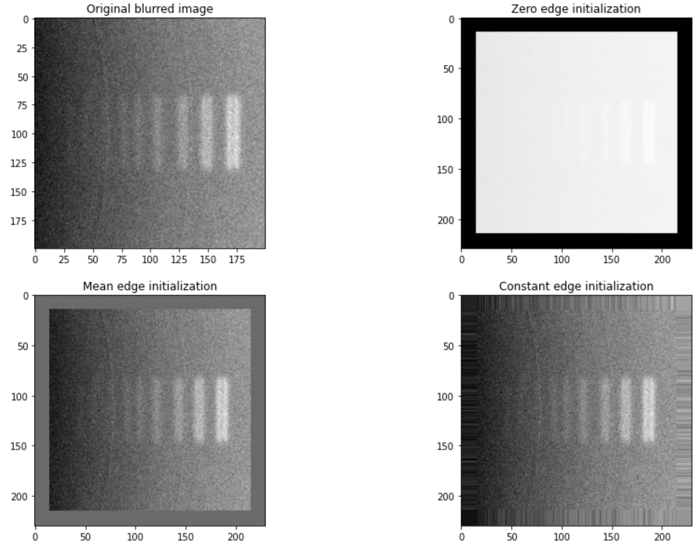
- The Peak-Signal-to-Noise-Ratio (PSNR):

$$PSNR(\boldsymbol{u},\boldsymbol{v}) = 10\log_{10}\left(\frac{K^2}{\frac{1}{N}\sum_{i=1}^{N}(\boldsymbol{u}_i-\boldsymbol{v}_i)^2}\right)$$

  - A log-scaled Mean Squared Error, measured in dB
  - The variables u,v are images of the same size and K is the maximum pixel value

Strategies to handle padding to avoid boundary effects

- Setting outer values to 0 (zero edge)
- Setting outer values to the mean of the picture (mean edge)
- Setting outer values equal to the edges (constant edge)



A. Introduction

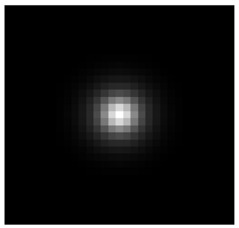
B. Preliminary investigations

C. Variational implementation with pytorch

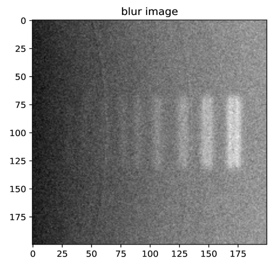
D. Deep Learning & Synthetic Degradation

Least square and regularization

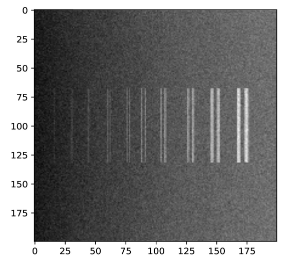
H



g



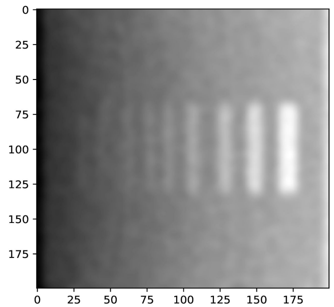
u (target)



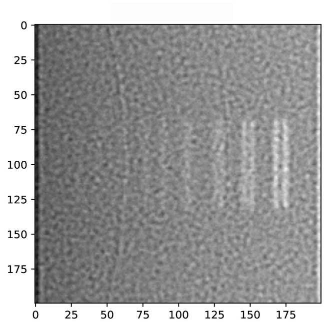
Regularization is with norm R:
(l2-norm of the gradient squared).

$$R(\mathbf{u}) = \lambda \|\nabla \mathbf{u}\|_2^2$$

Least square is with R=0.



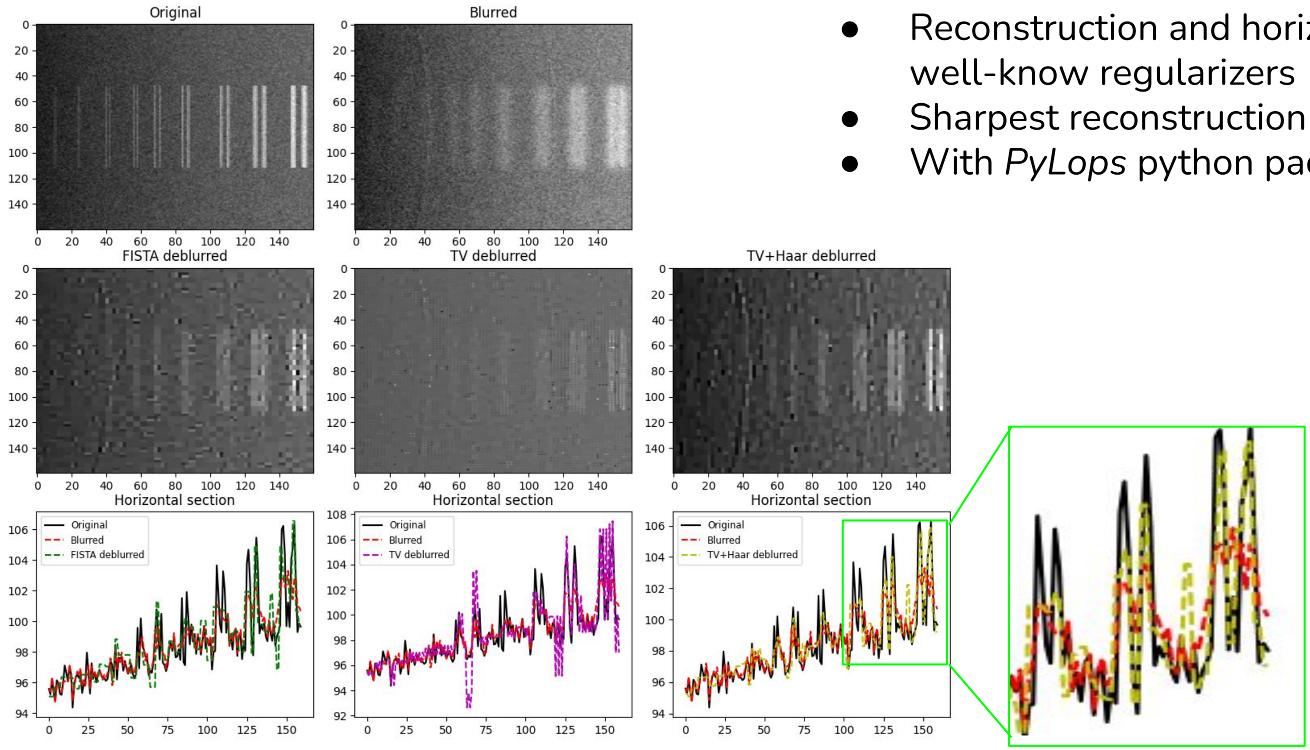
Restored image using **regularization** with l2-norm.



Restored image using **least square** (R = 0)

As a preliminary conclusion, regularization is promising.

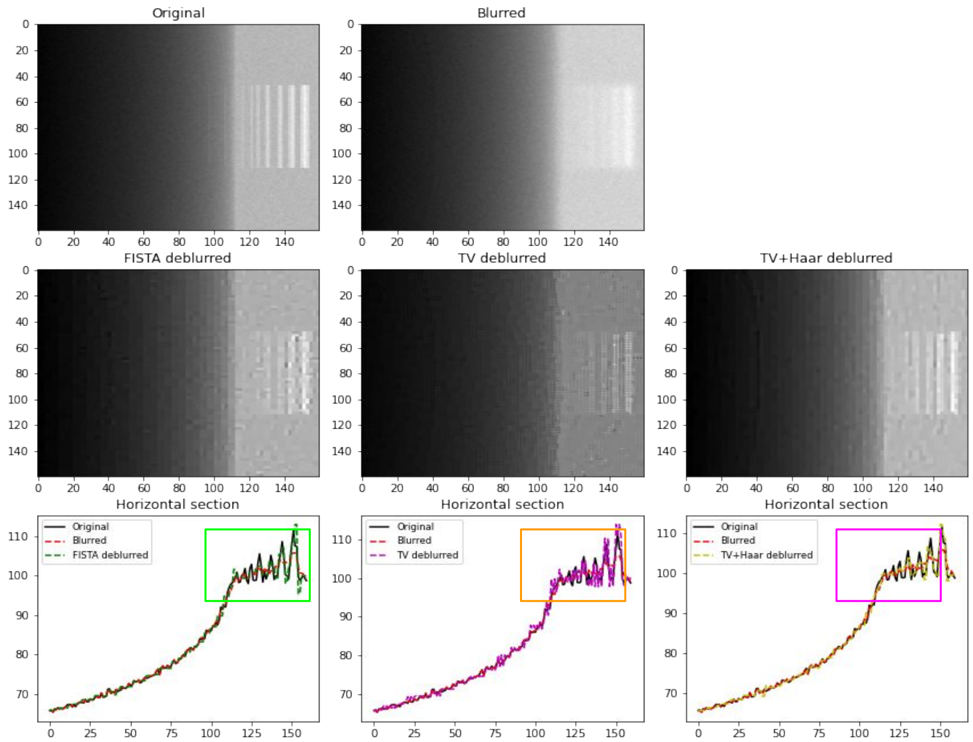
FISTA / TV / TV+Haar deblurred



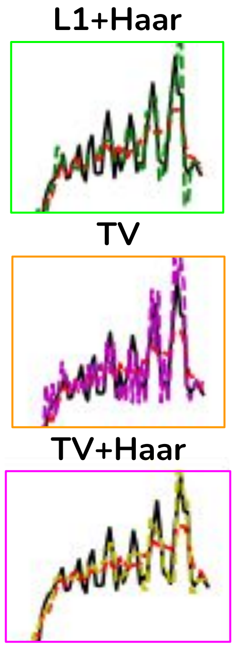
- Reconstruction and horizontal line profiles using three well-know regularizers
- Sharpest reconstruction using the TV+Haar regularizer
- With *PyLops* python package.

Regualarizer	PSNR (dB)
L1 + Haar Wavelet (FISTA)	39.58
TV	37.35
TV + Haar Wavelet	40.4

FISTA / TV / TV+Haar deblurred



- Another frame of the sequence,
- We recover **sharper** images
- With *PyLops* python package.



Regularizer	PSNR (dB)
L1 + Haar Wavelet (FISTA)	40.26
TV	37.86
TV + Haar Wavelet	41.47

Variational approach - use autograd

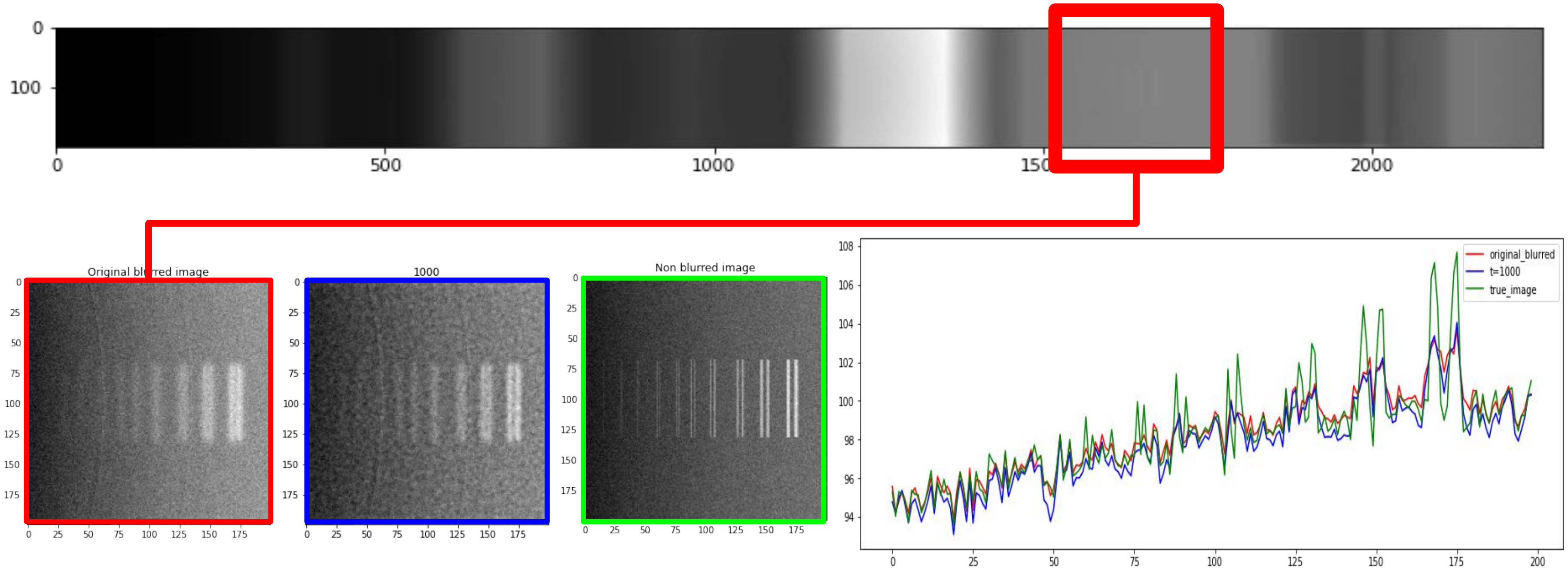
- Use the PyTorch framework to automatically compute the gradient of the cost J thanks to autograd
- Use the L1 regularisation

$$J(\hat{\boldsymbol{u}}) = \frac{1}{2}||\boldsymbol{g} - \boldsymbol{H}\hat{\boldsymbol{u}}||_2^2 + \lambda||\hat{\boldsymbol{u}}||_1$$

- Performing gradient descent with a learning rate of 0.01

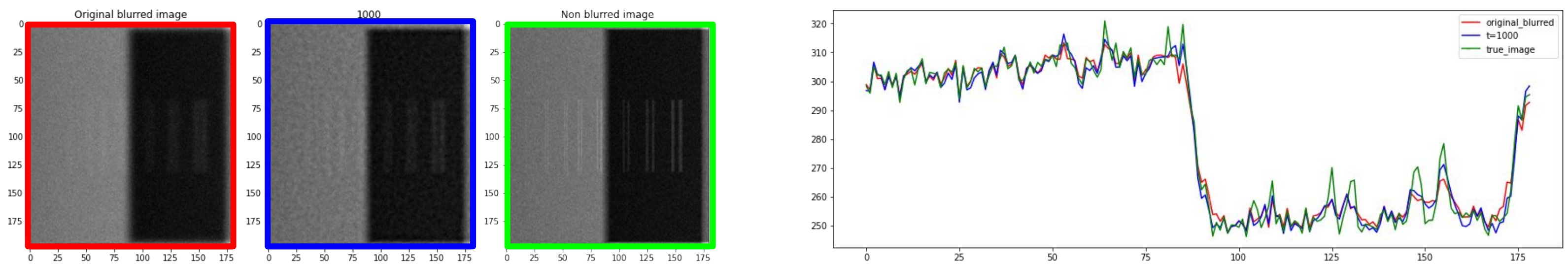
Variational approach - simulation results (1/3)

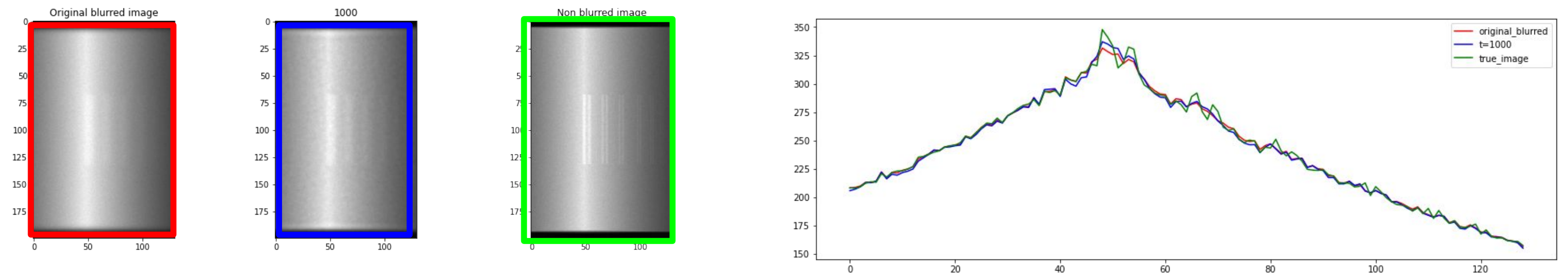
Variational approach - simulation results (2/3)



This shows better separation of the neighboring lines, but grain is also deconvolved (PSNR ≈ 45)

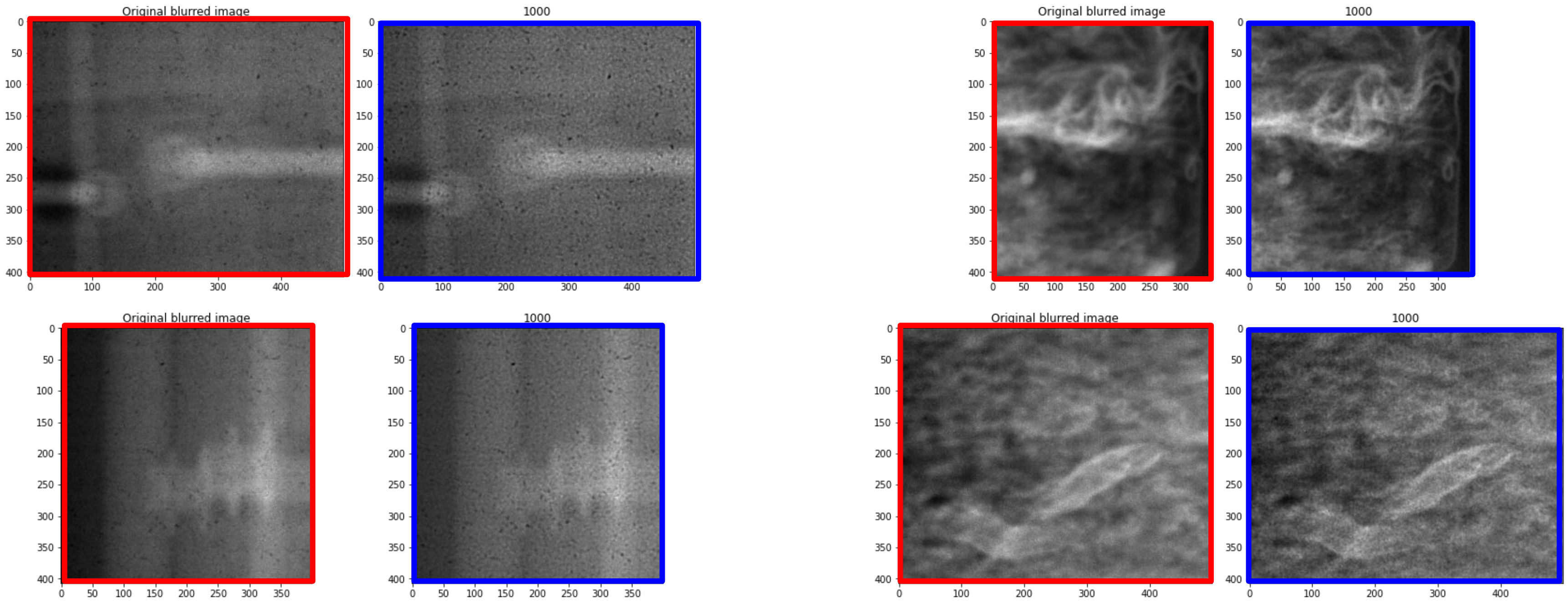
Variational approach - simulation results (3/3)





In the case of high gray-level variations, this method exhibits some drawbacks.

Variational approach - What about the *real* data?

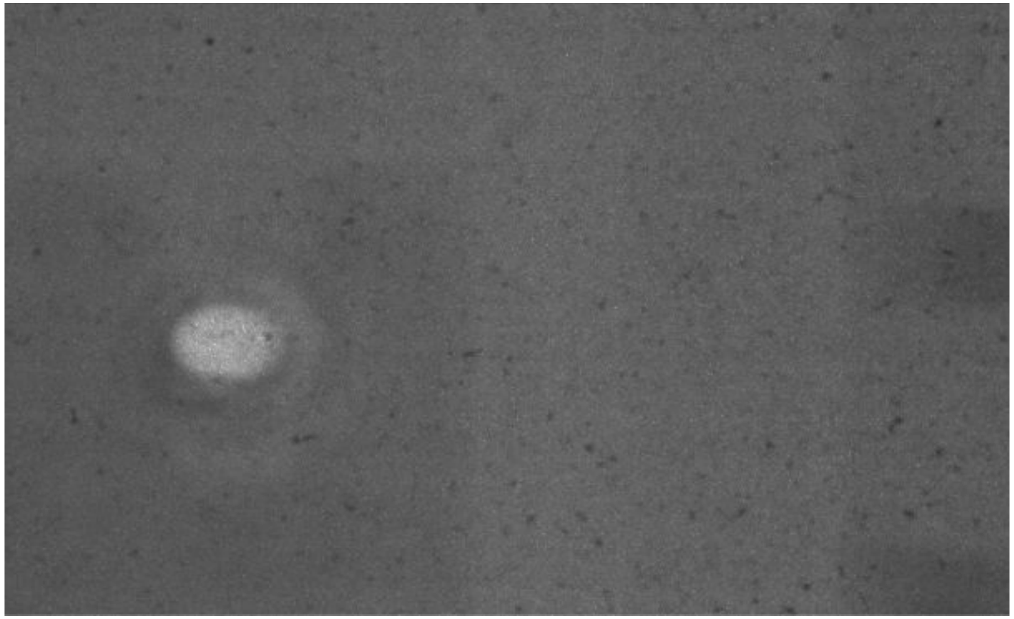


A. Introduction
B. Preliminary investigations
C. Variational implementation with pytorch

D. Deep Learning & Synthetic Degradation

Training Deep Learning Models

- Deep Learning models allow to solve jointly for noise and blur.



Real data sample

Training Deep Learning Models

- Model: Transformer-based SwinIR [1]
- Two ways to formulate input:
  a. Single Image
  b. Burst-Style denoising [2]

[1] Liang, J., Cao, J., Sun, G., Zhang, K., Van Gool, L. and Timofte, R., 2021. Swinir: Image restoration using swin transformer. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 1833-1844).
[2] Mildenhall, B., Barron, J.T., Chen, J., Sharlet, D., Ng, R. and Carroll, R., 2018. Burst denoising with kernel prediction networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 2502-2510).

Deep Learning for De-Noising & De-Blurring

- Common Practice: Creating data out of high quality images.
- Given a correct model for the stochastic process of the noise, all we need to create a dataset is HQ images.
- Available data: 360 CT tomography of one object.
- Train-Test Split: ¼ of the CT sequence withheld for testing.

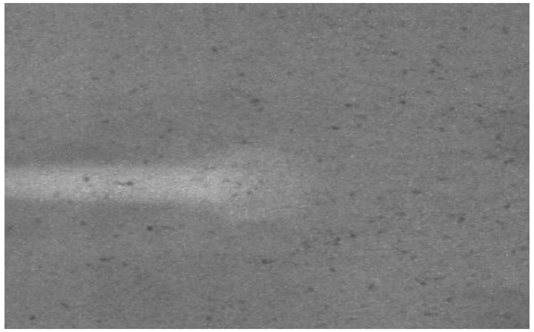
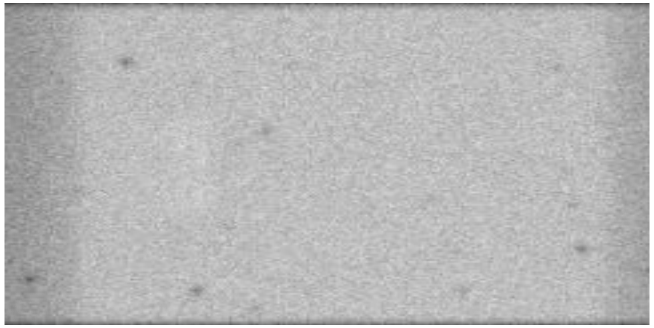


Image acquired from noisy capture

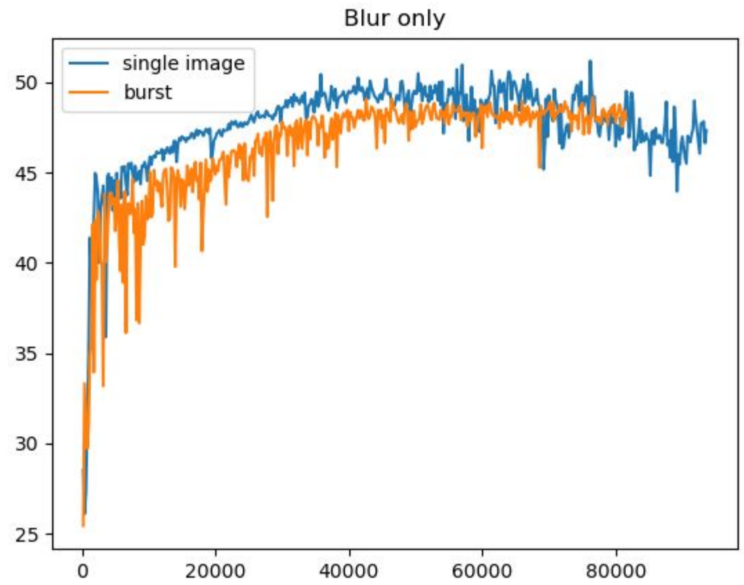
Clean acquiring capture



Synthetically simulated noisy capture

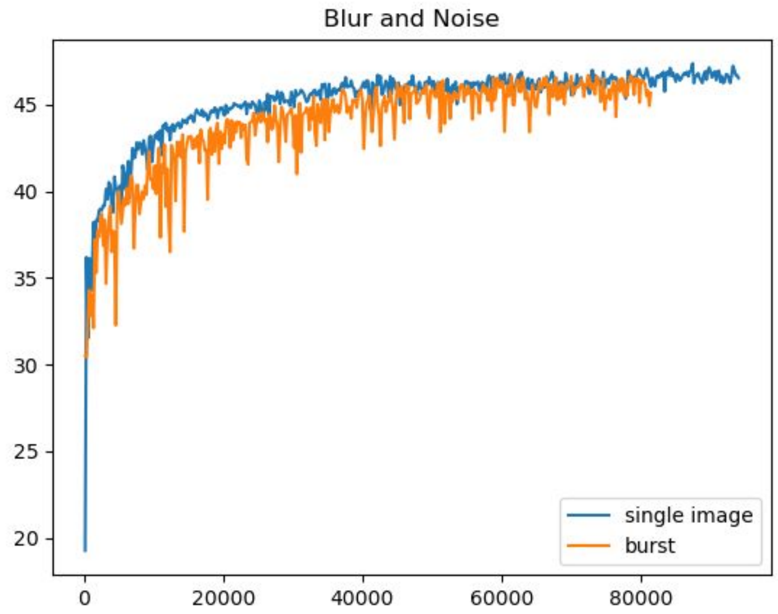
Training Deep Learning Models

P
S
N
R



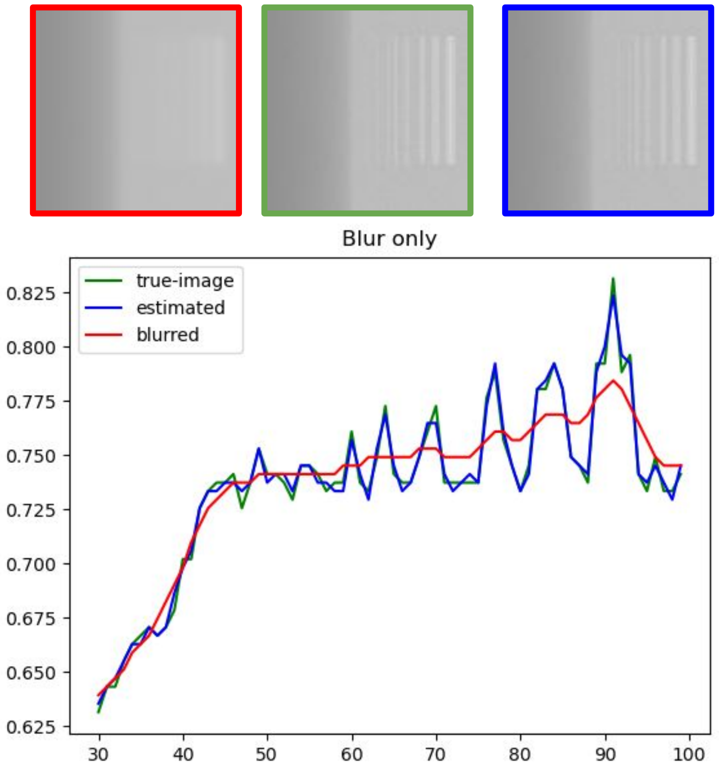
Iterations

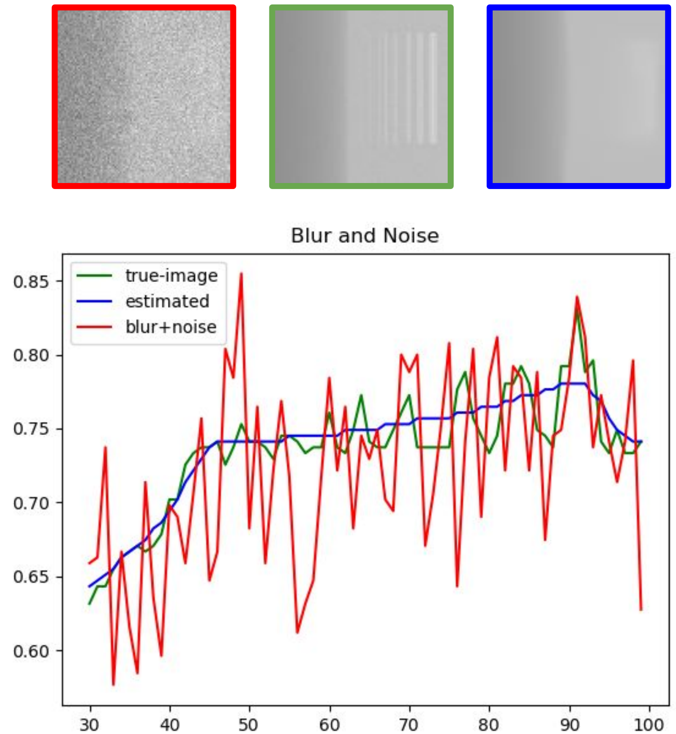
P
S
N
R



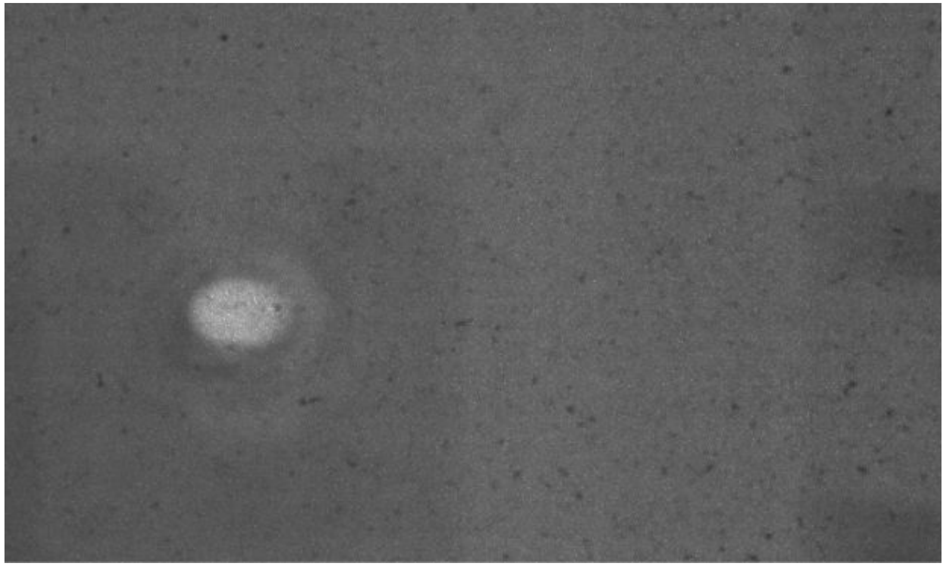
Iterations

Synthetic - Single Image





Real Examples



Noisy - Low Quality Input

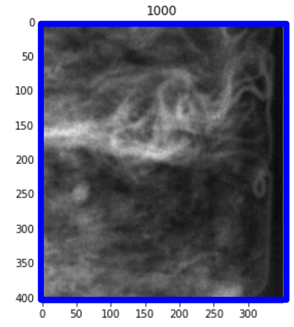
Output - Model trained on different object with synthetic Noise&Blur

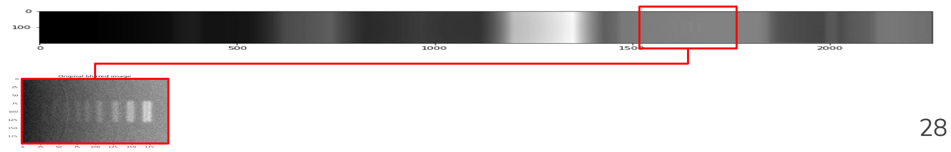
Conclusion

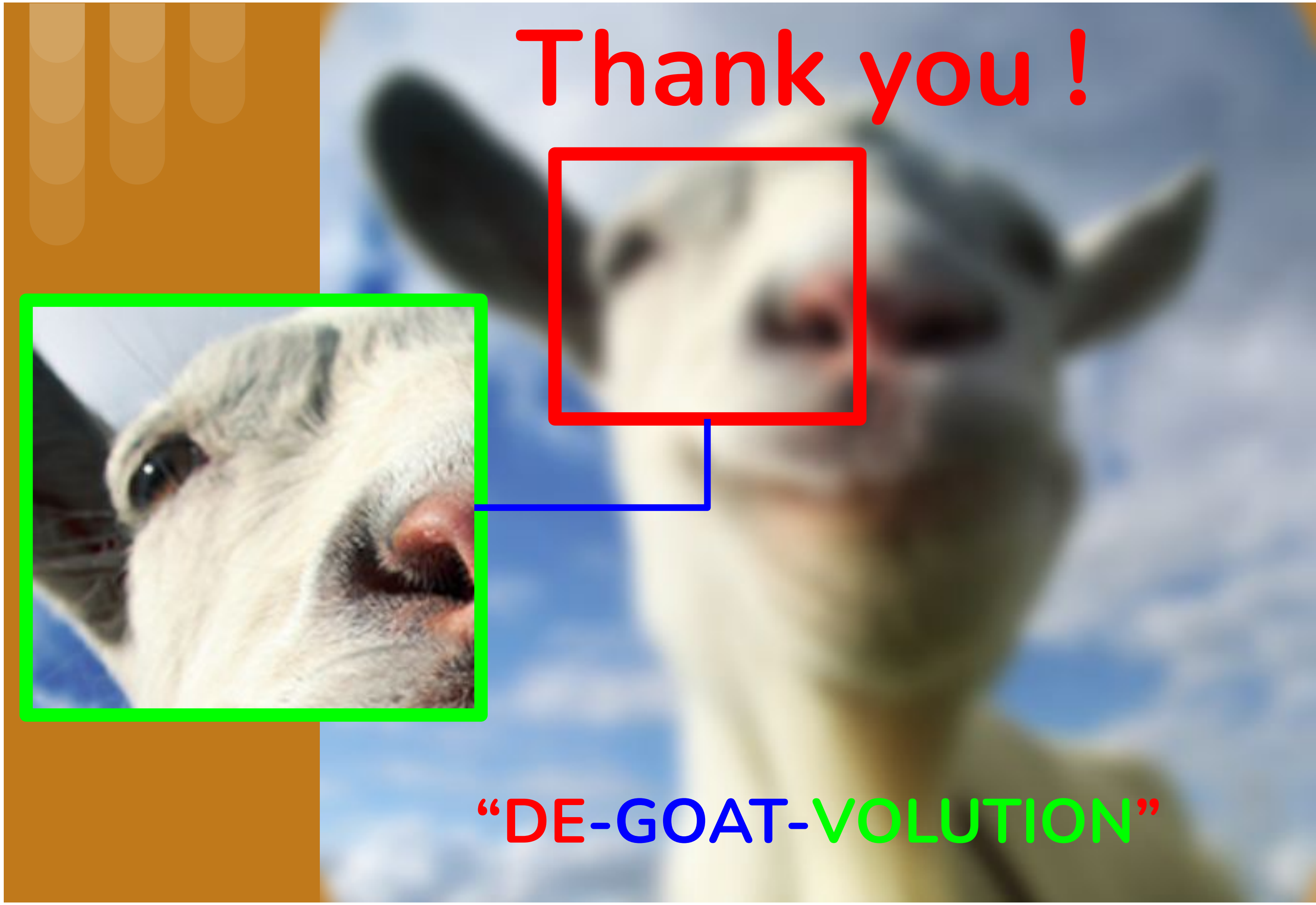
Conclusion and future steps

- The variational approach works best in case of images with high contrast
- The distribution of this data does not match that of pre-trained models: retraining from scratch must be privileged.
- Deep-learning trial still has room for improvements.

- Future Steps:
  - Replace the data fidelity term (least-square) by the Kullback–Leibler (KL) divergence to capture better the existence of Poisson noise
  - Make the training data more challenging. In the provided simulated data only a small part is challenging






Thank you !
“DE-GOAT-VOLUTION”