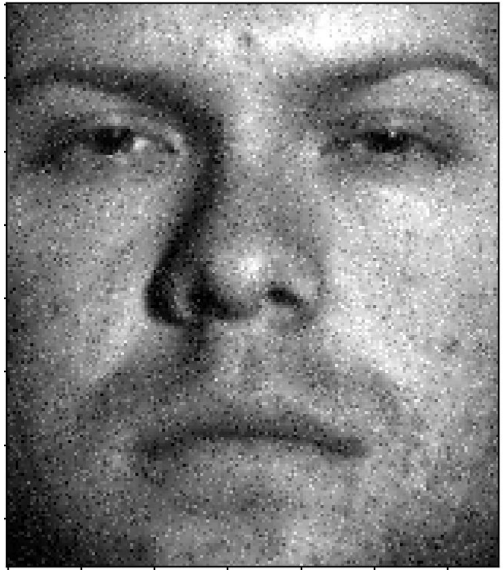


Image Denoising

Group: Xu Han, Han Yang, Jiarui Wang, Rowy Zhong

Dataset(s)

Our dataset is the Yale Face Database for facial recognition, which contains 2452 grayscale images in PNG format of 38 individuals.

- 64 images per person, one per different lighting condition
- pre-processed our data by cropping it in the center



Problem Definition

- Restore original images from noisy ones.

Why is this an interesting problem?

- Real world application: medical image denoising

Methods

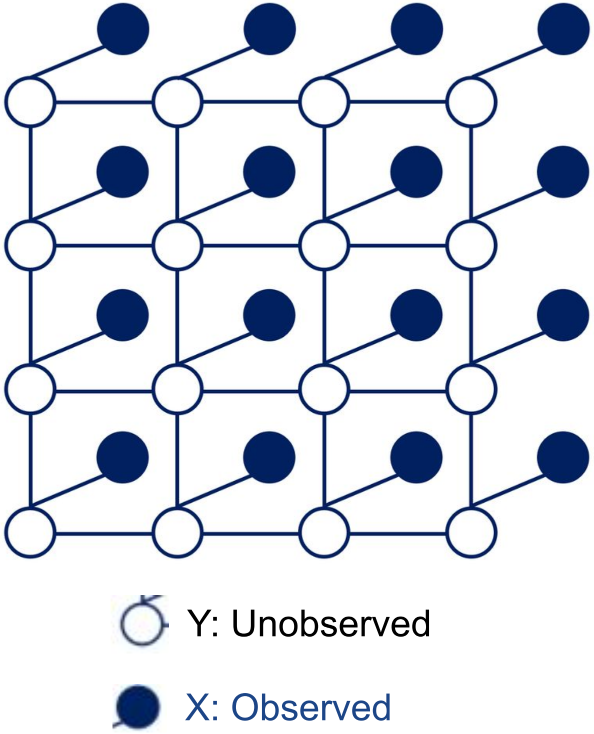
- Markov Random Field
- Total Variation Minimization
- Low rank representation
- Deep Learning
- Deep Image prior

Optimization-based algorithms

Deep learning and its related algorithms

Markov Random Field

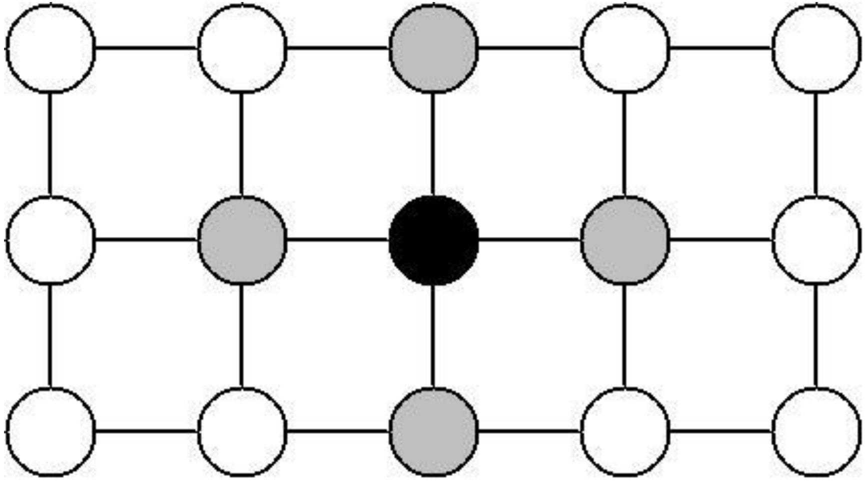
$$
\begin{aligned}
P(X,Y) &= \frac{1}{Z} exp(-E(X,Y)) \\
&= \frac{1}{Z} exp\Bigg(\alpha \underbrace{\sum_i \sum_j ||X_{ij} - Y_{ij}||_1}_{\text{Truth-observation potential}} \\
&\quad + \beta \underbrace{\sum_{k \in \mathcal{N}(ij)} ||Y_{ij} - Y_k|||_1}_{\text{Neighborhood potential}}\Bigg)
\end{aligned}
$$



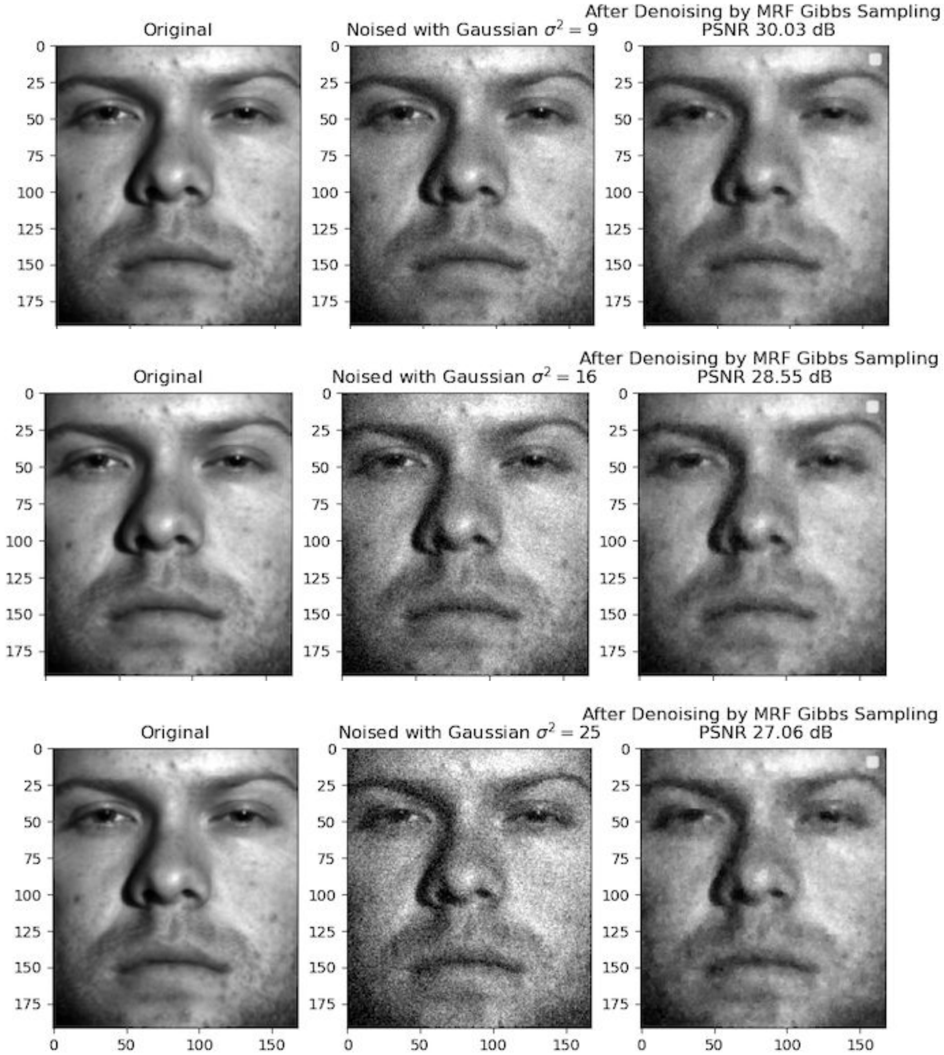
Gibbs Sampling For Markov Random Field

For each Y_{ij}
Sample $Y_{ij} \sim P(Y_{ij}|\text{others})$

It will eventually converge to P(Y|X)



Result



Small noise
PSNR: 30.03

Medium noise
PSNR: 28.55

Large noise
PSNR: 27.06

Total Variation Minimization

$$\min_{\hat{X},E} \; TotalVariation(\hat{X}) + \lambda||E||_1$$

$$s.t. \quad X = \hat{X} + E$$

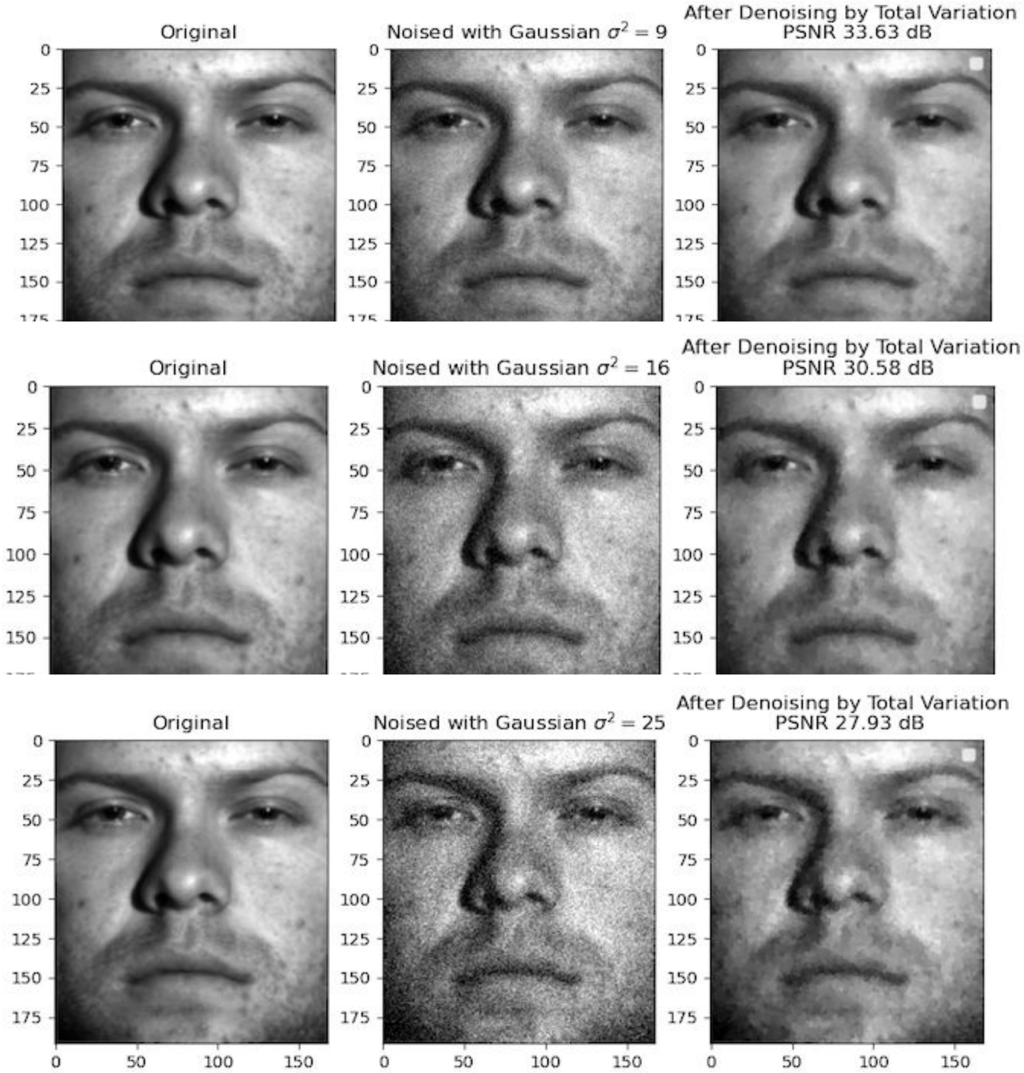
Error

Data

Low variation

$$TotalVariation(X) = ||X[:, 1:] - X[:, :-1]||_1 + ||X[1:, :] - X[:-1, :]||_1$$

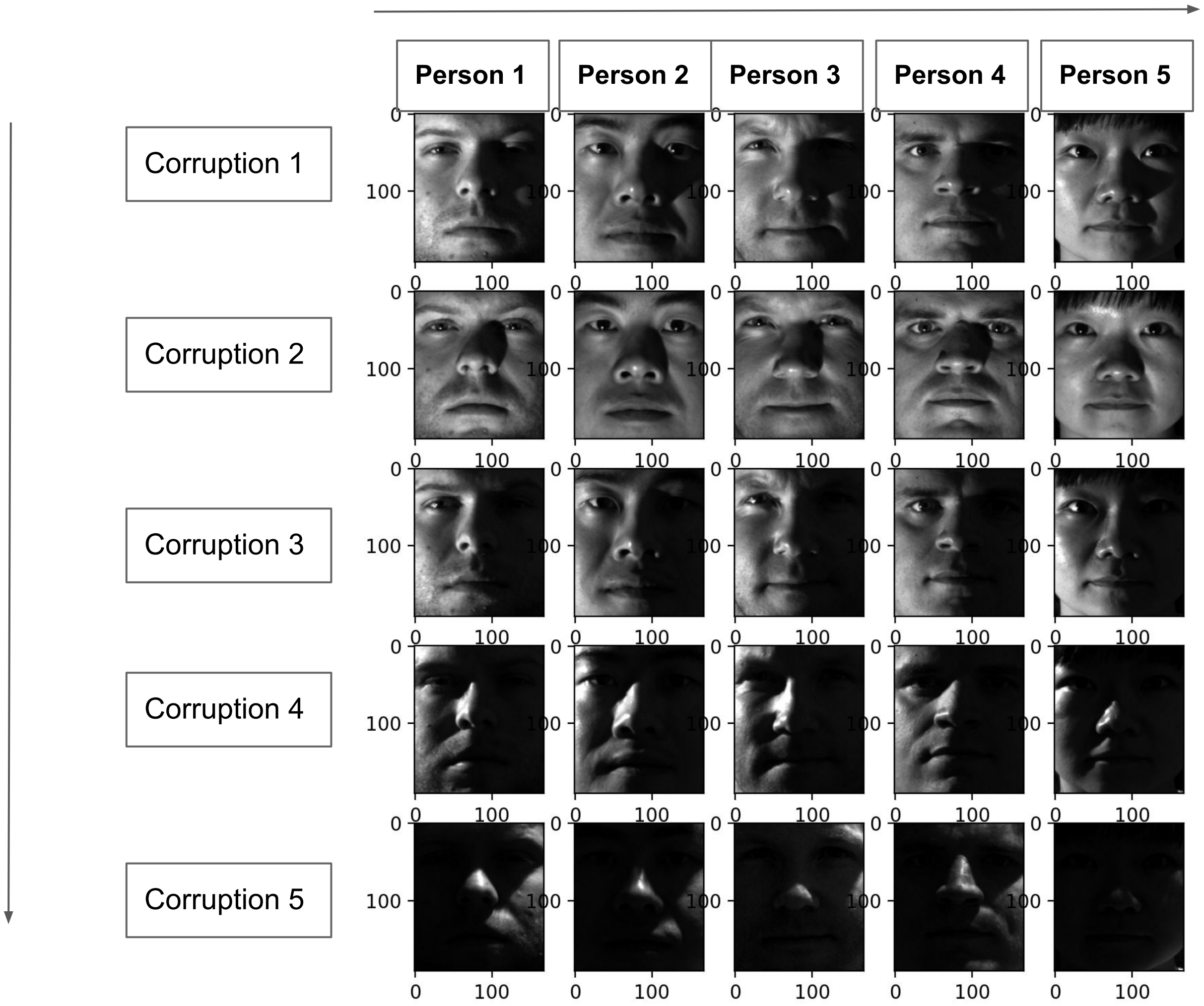
Result



Small noise
PSNR: 33.63

Medium noise
PSNR: 30.58

Large noise
PSNR: 27.93

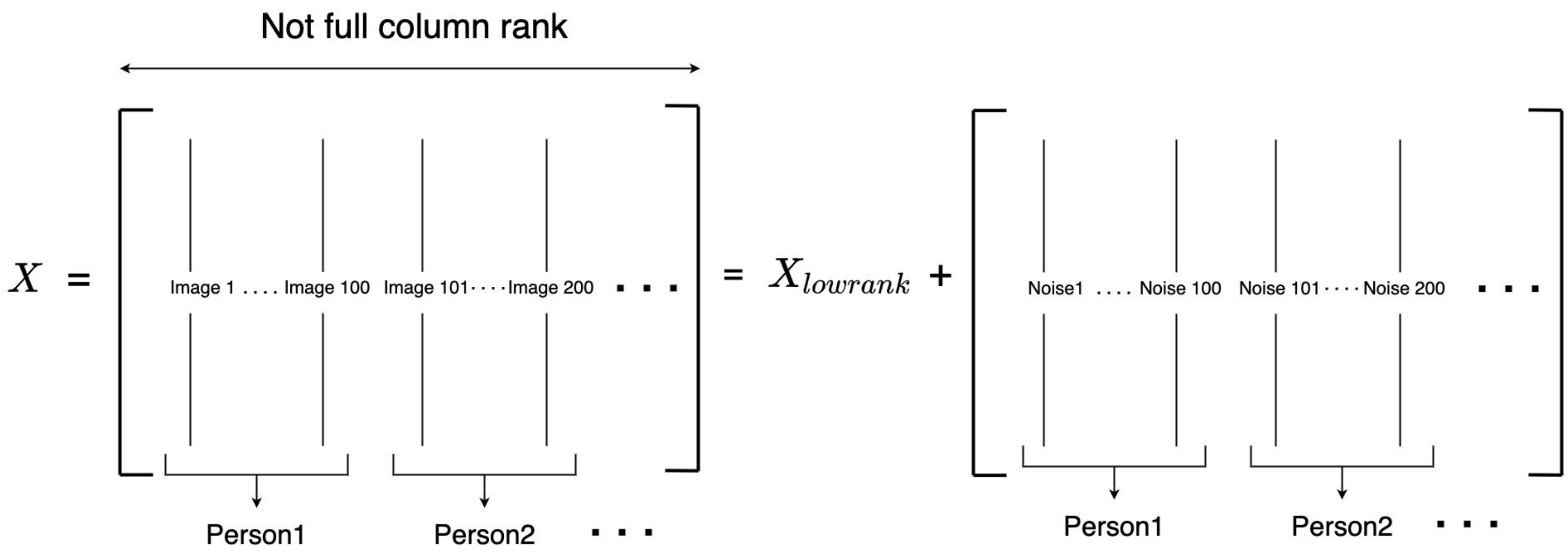


5 persons

5 ranks

Limited freedom!

Low Rank Representation



Low Rank Representation

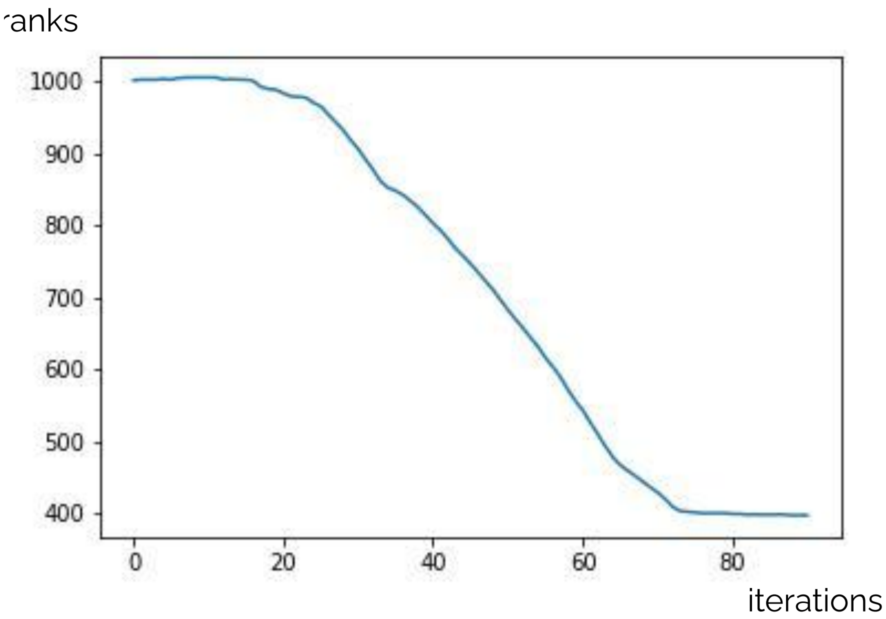
$$\min_{Z,E} \quad \mathrm{Rank}(Z) + \lambda ||E||_{2,1}$$
$$\text{s.t.} \quad X = XZ + E$$

Data **LR** **Error**

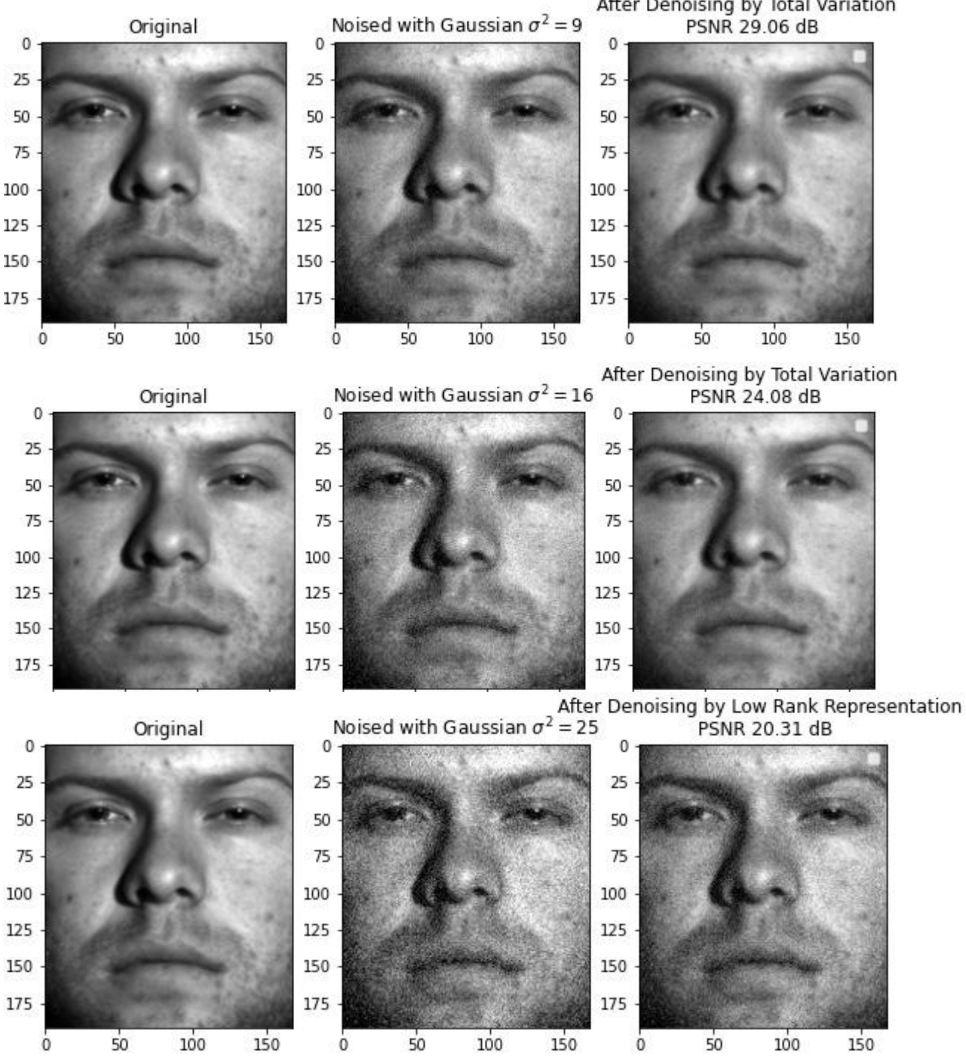
Relaxation

$$\min_{Z,E} \quad ||Z||_* + \lambda ||E||_{2,1}$$
$$\text{s.t.} \quad X = XZ + E$$

Optimize with Augmented Lagrangian



Result

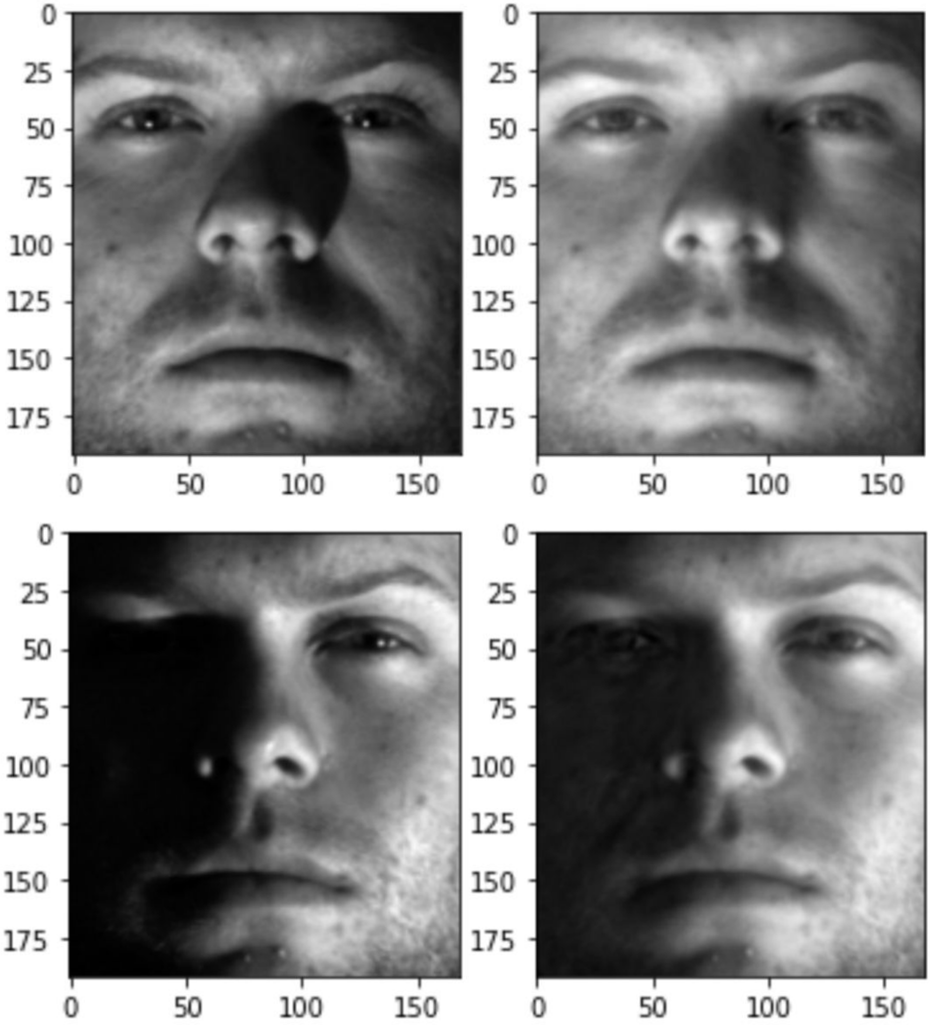


Small noise
PSNR: 29.06

Medium noise
PSNR: 24.08

Large noise
PSNR: 20.31

Result



Deep Learning - Noise2Noise

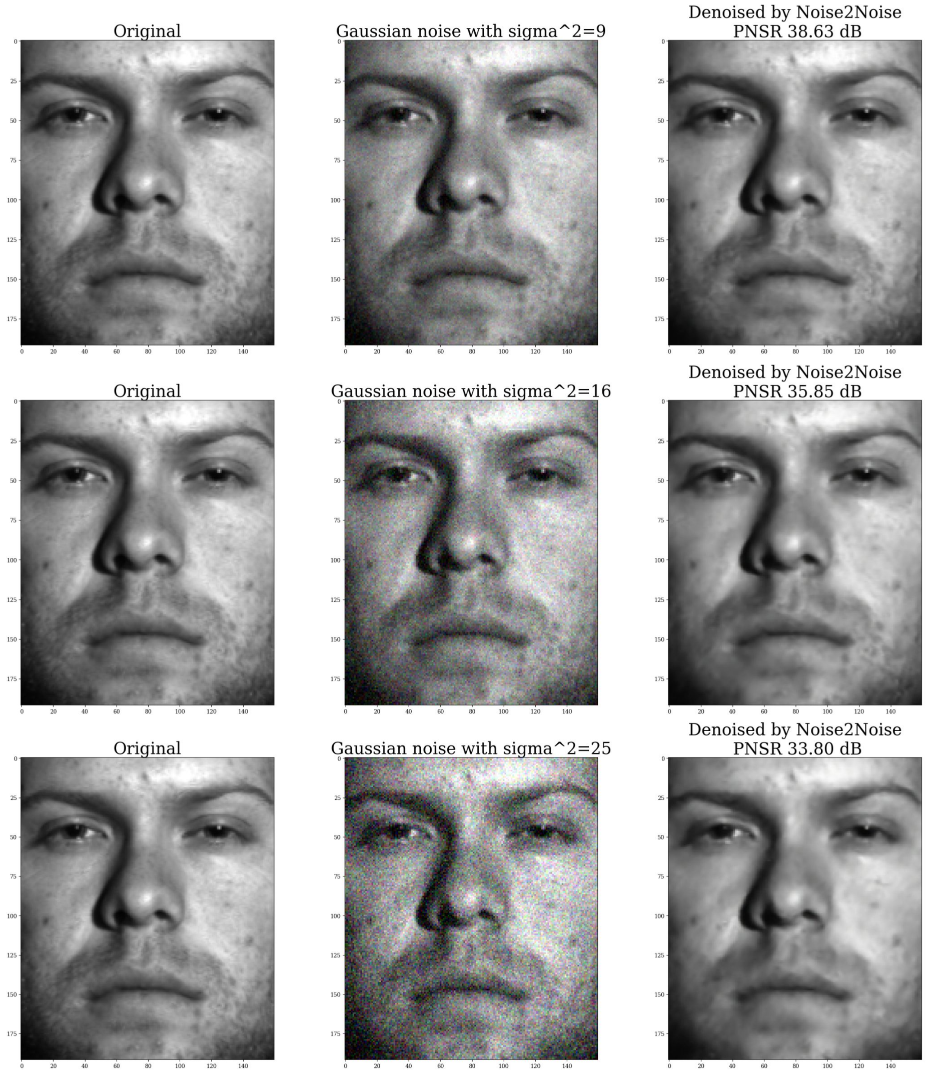
- **UNet Model, L2 loss:** $$\underset{\theta}{\operatorname{argmin}} \sum_i L\left(f_\theta(\hat{x}_i),\, \hat{y}_i\right)$$

  ,where $\hat{x}_i$ is the corrupted image with additional noise, f is a UNet model,

- **Train**: 2k images; **Dev**: 200 images

- randomize the noise standard deviation $\sigma \in [0,25]$ separately for each training example

Results



Small noise
PSNR: 38.63

Medium noise
PSNR: 35.85

Large noise
PSNR: 33.80

Deep Image Prior

- Image restoration: $\min_x E(x; x_0) + R(x)$

  data term ***image prior***

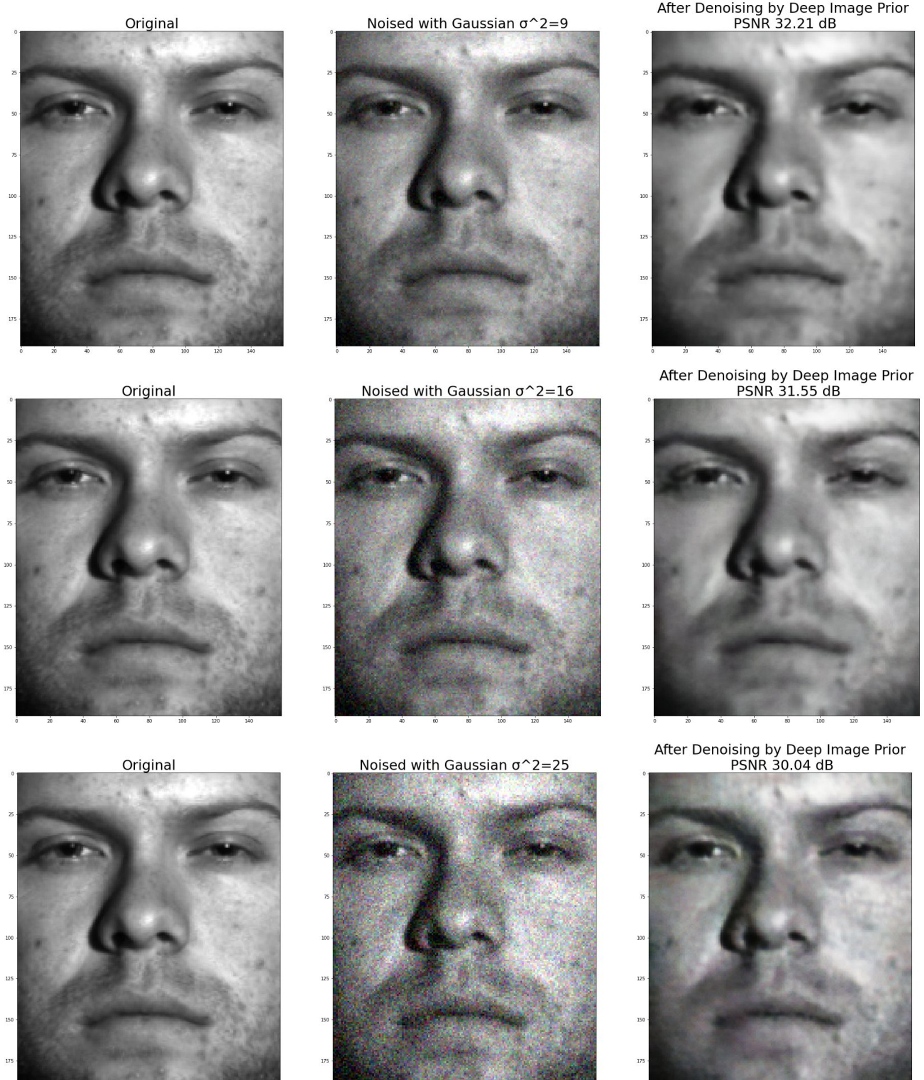
- Regularizer R(x) is replaced by a CNN:

$$\theta^\star = \min_\theta E(f_\theta(z), x_0), \quad x^\star = f_{\theta^\star}(z)$$

f(z) is a randomly initialized deep ConvNet.
Minimizer is optimized using a random z, starting from random initialization of θ.

Learning is NOT required for building good image priors! No large database or pre-trained network required.

Results

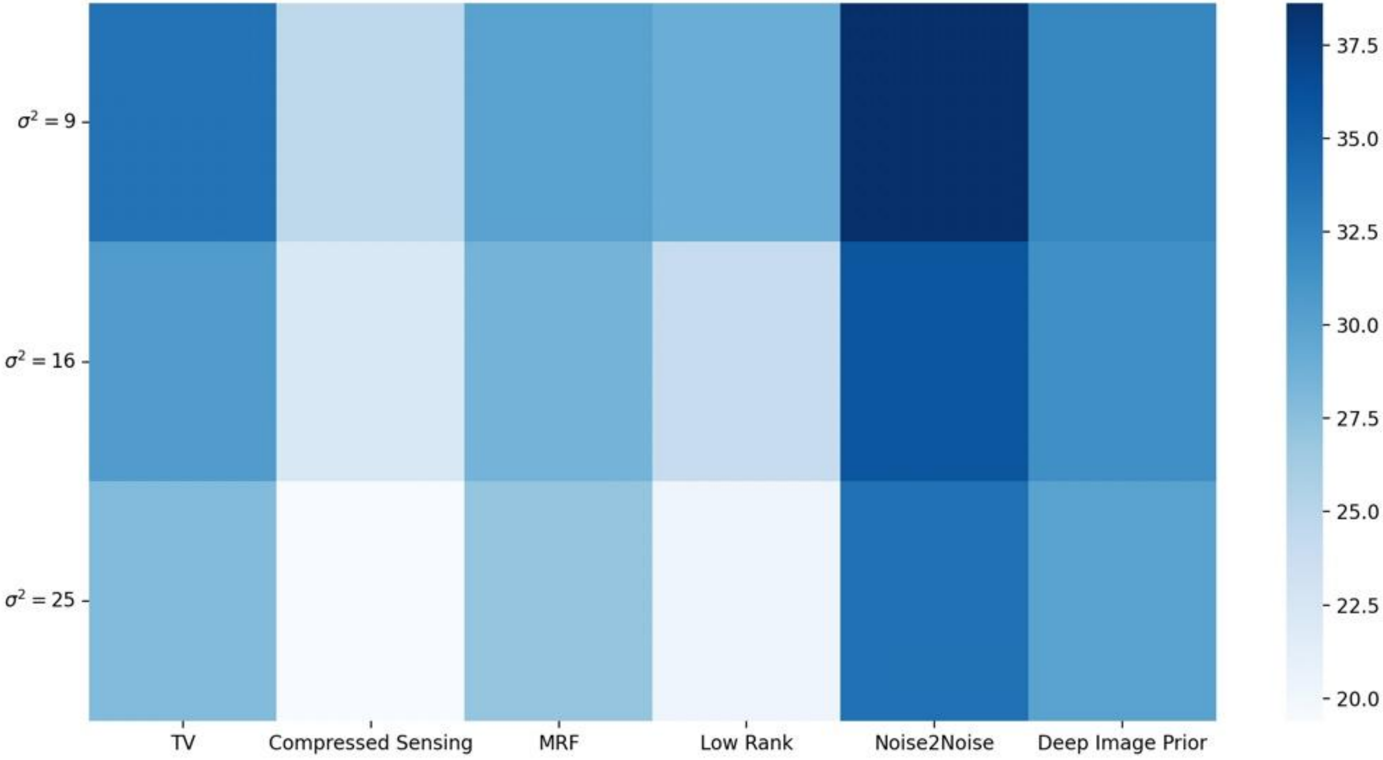


Small noise
PSNR: 32.21

Medium noise
PSNR: 31.55

Large noise
PSNR: 30.04

Summary



$\sigma^2 = 9$
$\sigma^2 = 16$
$\sigma^2 = 25$
TV
Compressed Sensing
MRF
Low Rank
Noise2Noise
Deep Image Prior
37.5
35.0
32.5
30.0
27.5
25.0
22.5
20.0

Deliverables

- How far have you made it on your project deliverables?

So far we finished all “Must accomplish” and parts of “Expect to accomplish”.

- Which deliverables were more difficult than you expected? Why?

We want to address the importance of traditional machine learning. However, deep learning methods outperform other methods, which makes our motivation unachievable.

We also tried to design a multi-noise factor analysis but it did not converge. And compressed sensing did not perform as well as we thought. But trying these method were still a lot of fun.

Deliverables

- Did you add, edit, or remove any of your deliverables? Why?

Yes. Since we have mentioned in last slide that deep learning outperform most of our optimization-based algorithm, we need to change parts of our deliverables as following:

In “Expect to accomplish” part, we change the third one “address the importance of traditional machine learning” to “improve our performance by combining deep learning and optimization-based method”

In “Would like to accomplish” part, we remove the first and the third one, since they are both under the assumption “low-rank”, which is a sharing property of Low-rank representation and compressed sensing model. Both of them have a relatively bad performance(kind of overturning our assumption). So we didn’t continue our work on them. As for second one, we remove it because the algorithm did not converge. However, in our deep image prior method, we used only one noisy image for the deep convnet and the result was surprisingly good, which is beyond our expectation.

What we've learned

- **Graphical model** and **deep learning** were most relevant to our project
- **What aspects of your project did you find most surprising?** When we use deep learning as prior, it can perform very well even if there is only one image as input and we don't need any pre-training. We might focus more on deep learning prior if we were going to start from beginning.
- **One question we still concern about:** is there any traditional machine learning/optimization-based algorithm can beat deep learning?
- **What would be the most helpful feedback to get from other groups?** Other more appropriate metric instead of PSNR score to evaluate the performance of image denoising.

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Thank you!