Zero Cost Deep-Learning for Microscopy

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Content

1. What is ZeroCostDL4Mic?
2. Experience Report Noise2Void
3. Conclusions

1.1 Spoiler

- Is it really for free?
  - yes
  - some restrictions, but usable

1.2 What problem does it solve?

- We've seen a lot of publications applying deep-learning for microscopy
- But difficult to use for most, because they need to be trained on our data
  - need cloud/GPU/cluster access
  - need to get the images to the cloud/GPU/cluster
  - need programming skills
  - need DL basics to select the training parameters

1.3 How does it help?

- prepared jupyter notebooks
- start them on google colab by clicking on a button
- the text walks you through the process step by step
- you don’t have to touch any code
  - everything is done via a graphical user interface in the notebook
- access to your data via your google-drive

1.4 What can I do with it?

- There are currently 5 models:

model	application
UNet	segmentation, EM, brightfield images
Stardist (2D/3D)	nuclei segmentation, DAPI, Hoechst
Noise2Void (2D/3D)	denoising, unsupervised - no ground truth images needed
CARE (2D/3D)	image restoration, low SNR to high SNR
fnet	create fluorescent image from brightfield image

1.5 How to get started?

- Start at the project's wiki
  - ZeroCostDL4Mic/wiki
- You need
  - a google account
  - enough free space in your google-drive
- Click on the "Open in colab"-button to start a notebook in colab
- Follow the instructions in the notebook

1.6 What are the restrictions?

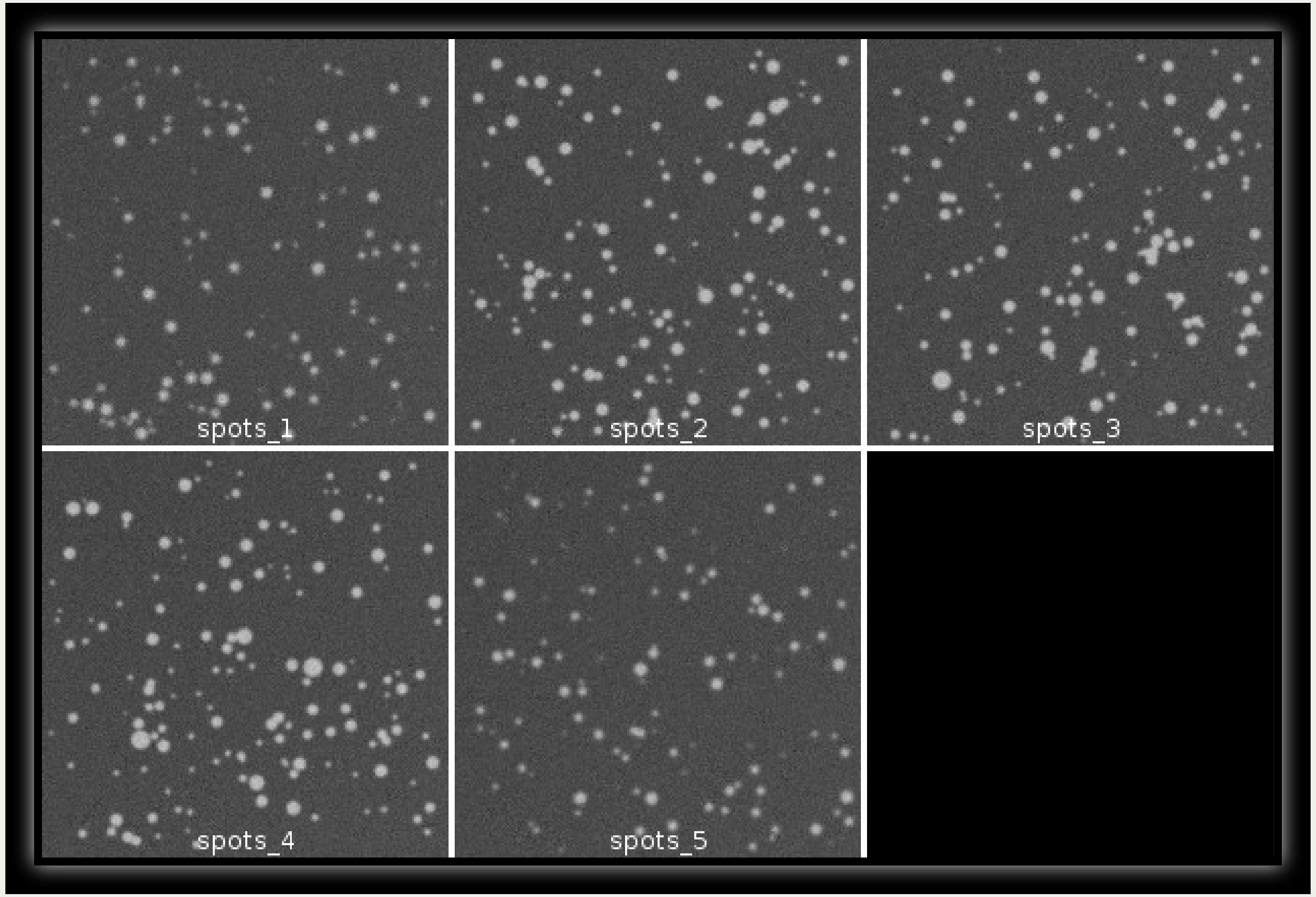
- One training/prediction unit can max. take 12h
  - colab disconnects every 12 hours
    - to make crypto-currency mining impossible
- free google-drive provides 15GB of disk-space
- colab distributes GPUs/TPUs according to availability
  - you get access to GPUs/TPUs according to
    - availability
    - your previous usage

1.7 Related resources

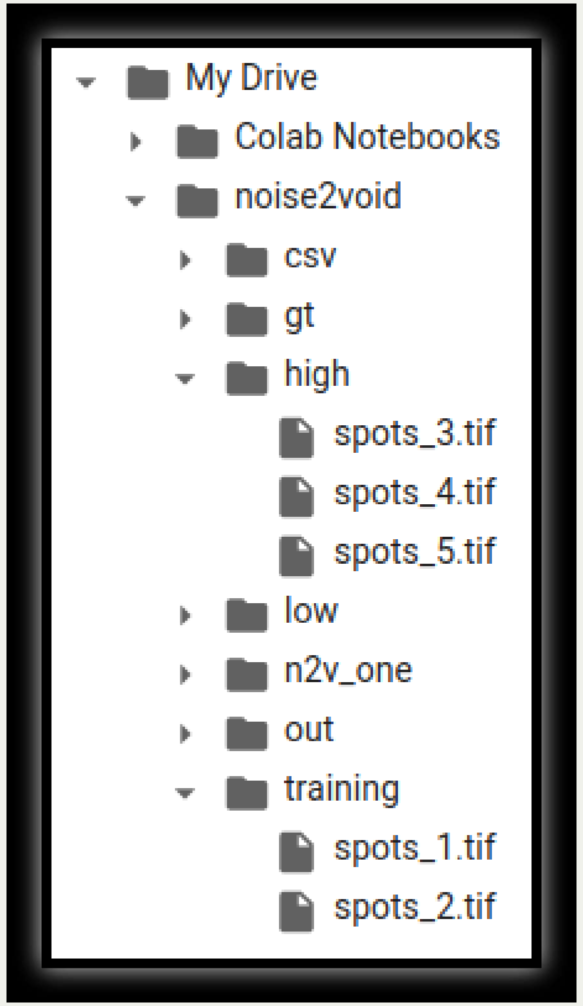
- Look here for the paper and some videos
  - ZeroCostDL4Mic
- A simple example of training and using a network
  - DL_EXP_PC/
- The slides of day 2 of the MRI workshop
  - mri-workshop-machine-learning

2.1 Noise2Void Experience

- the images (800x800 8-bit)



2.2 Image Upload

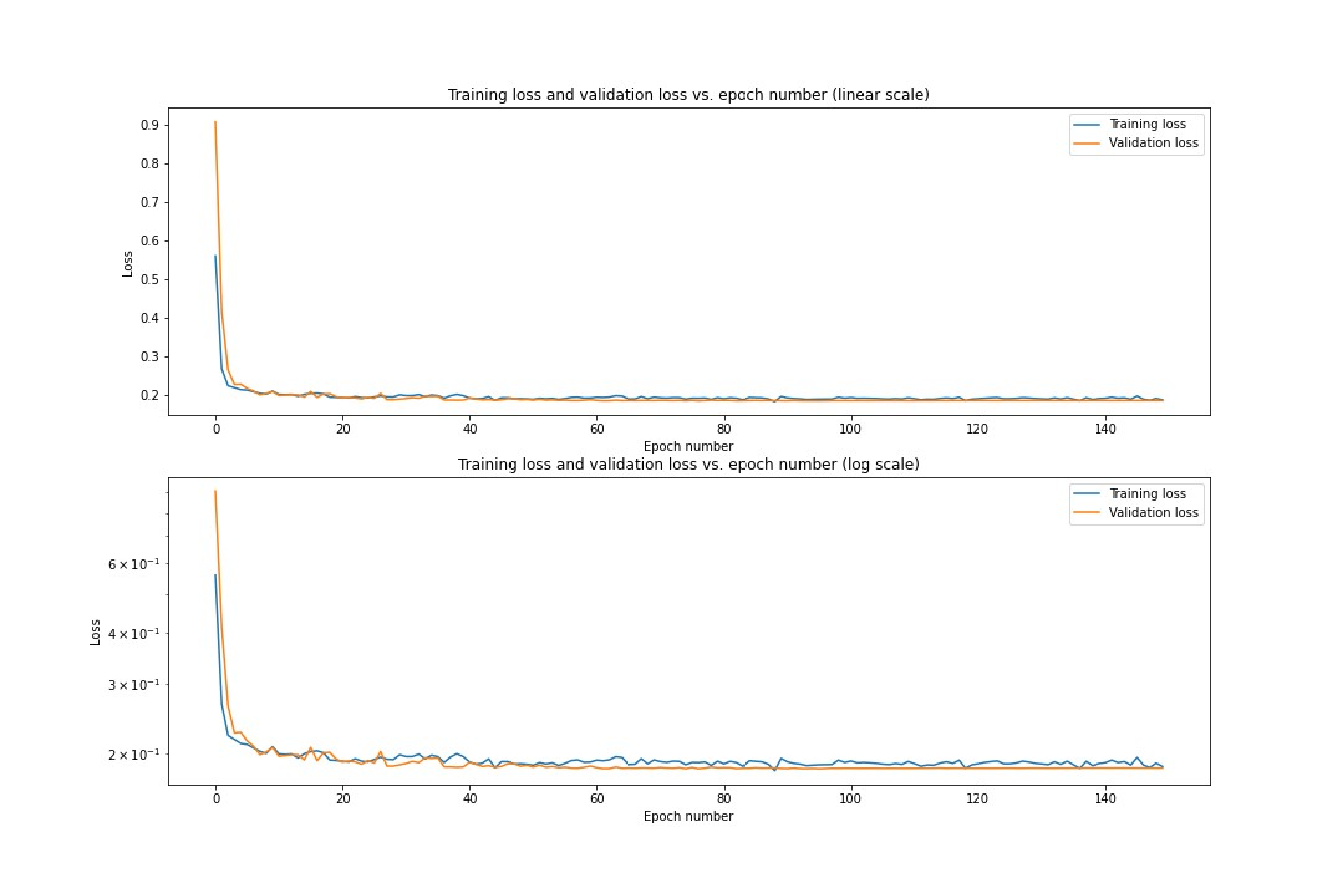


- upload to google-drive
  - 2 images for training, 3 images for predictions

2.3 Running the noise2void

- run Noise2VOID_2D_ZeroCostDL4Mic.ipynb
- follow the instructions
- parameters used:
  - number_of_epochs: 150
  - patch_size: 64
- training duration: 12min

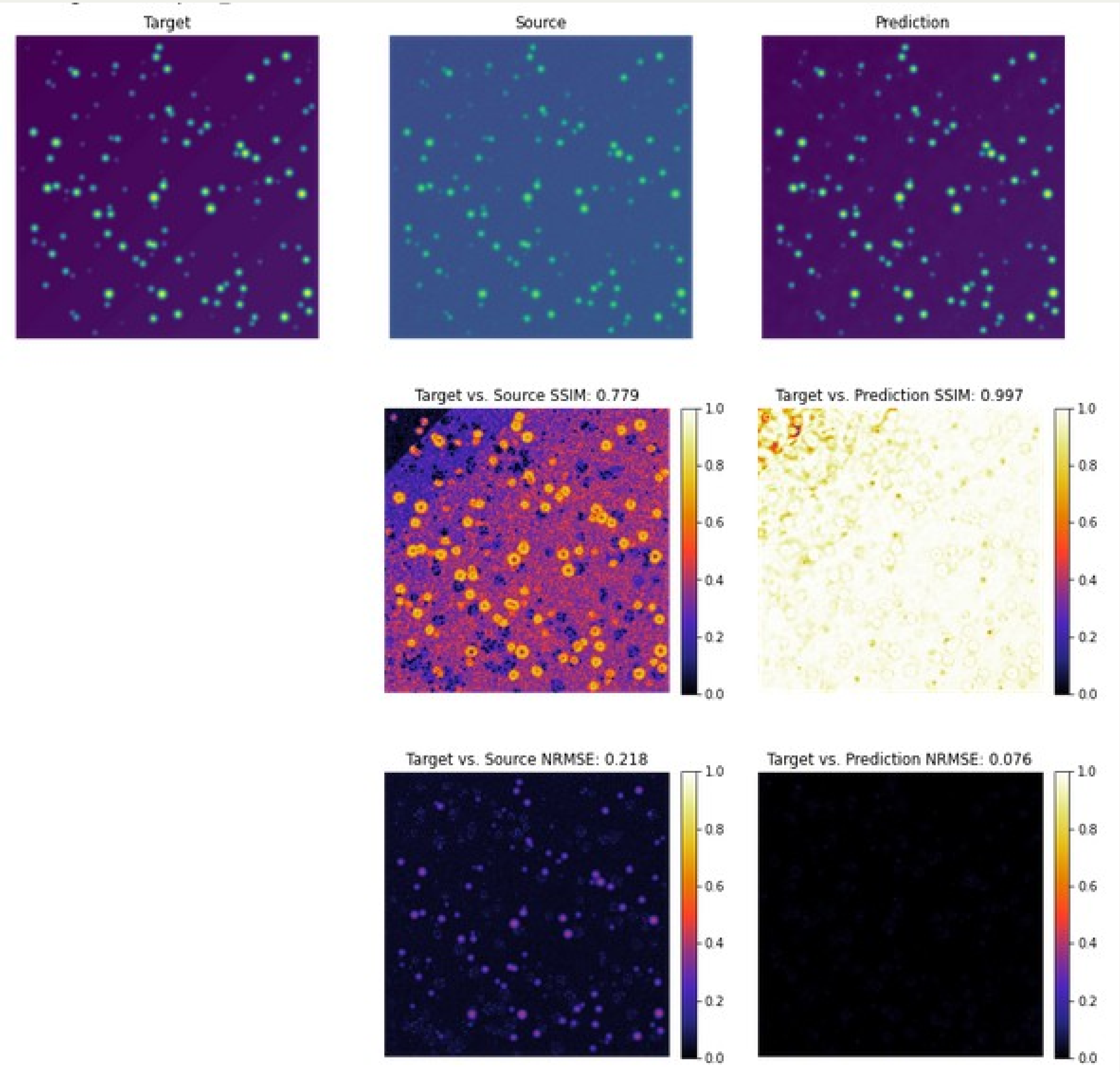
2.4 Training Loss



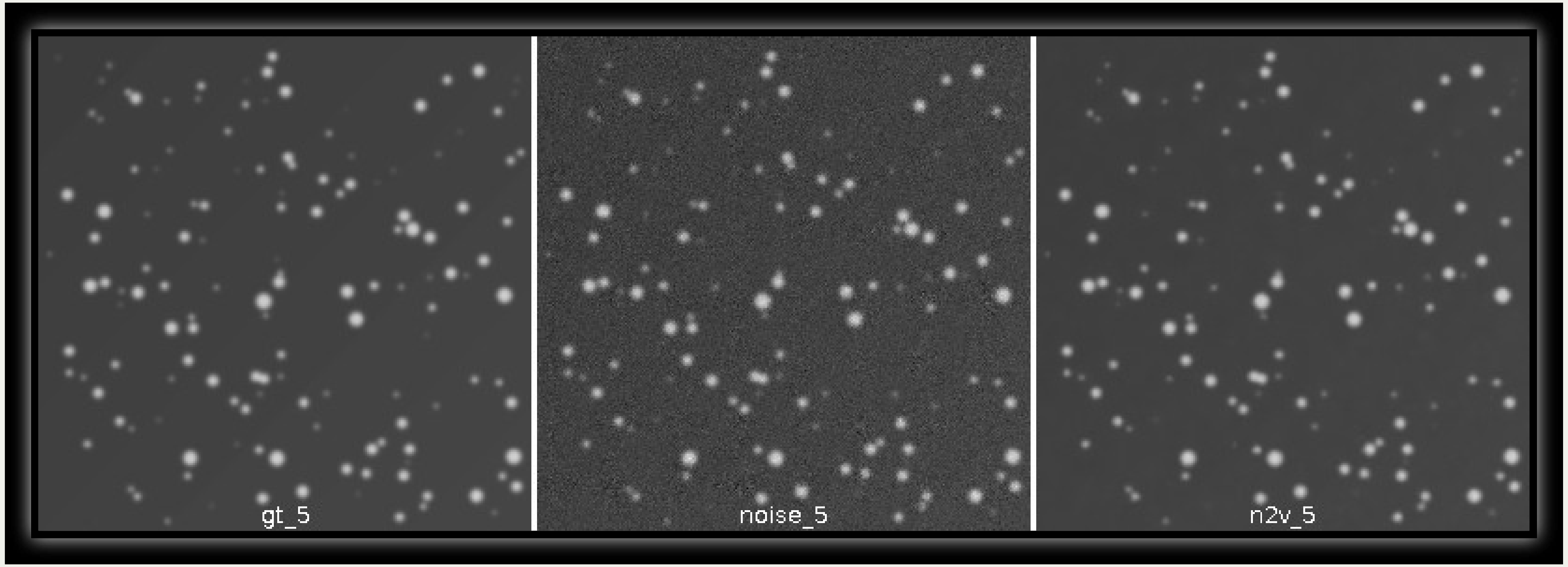
2.5 Quality control

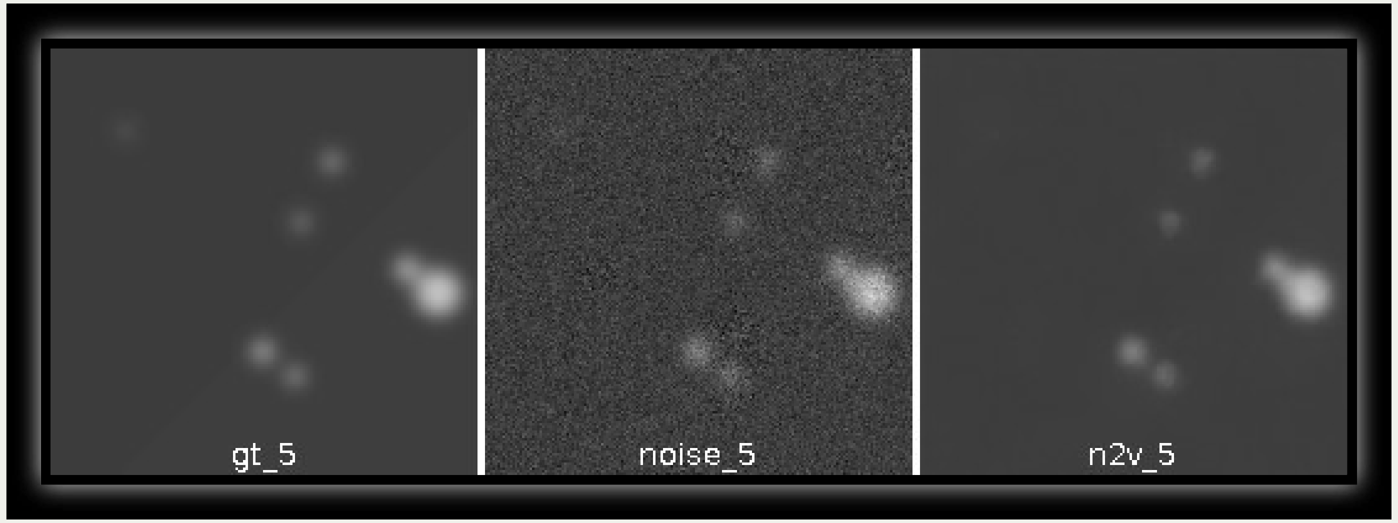
- You need ground-truth images to do the quality estimation
- In this case the images are synthetic
- low noise images created with MRI_Create_Synthetic_Spots_Tool
- noise added separately for foreground and background with ImageJ

2.6 Quality control results

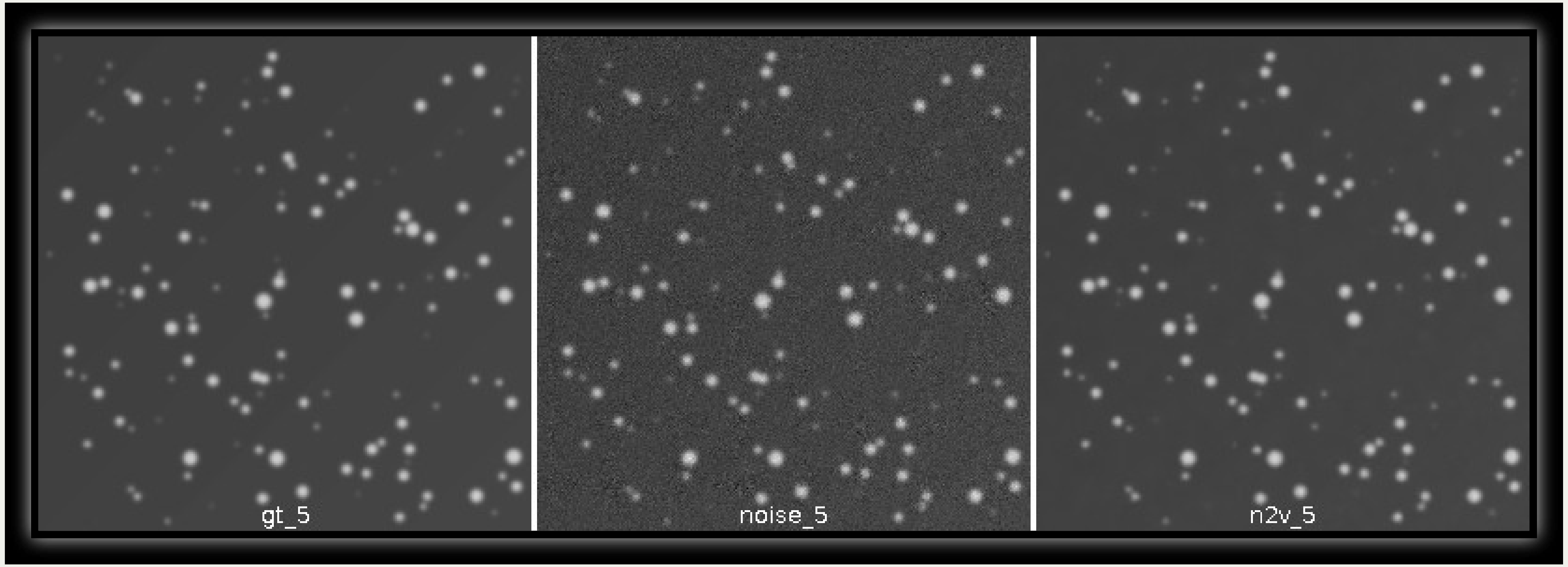


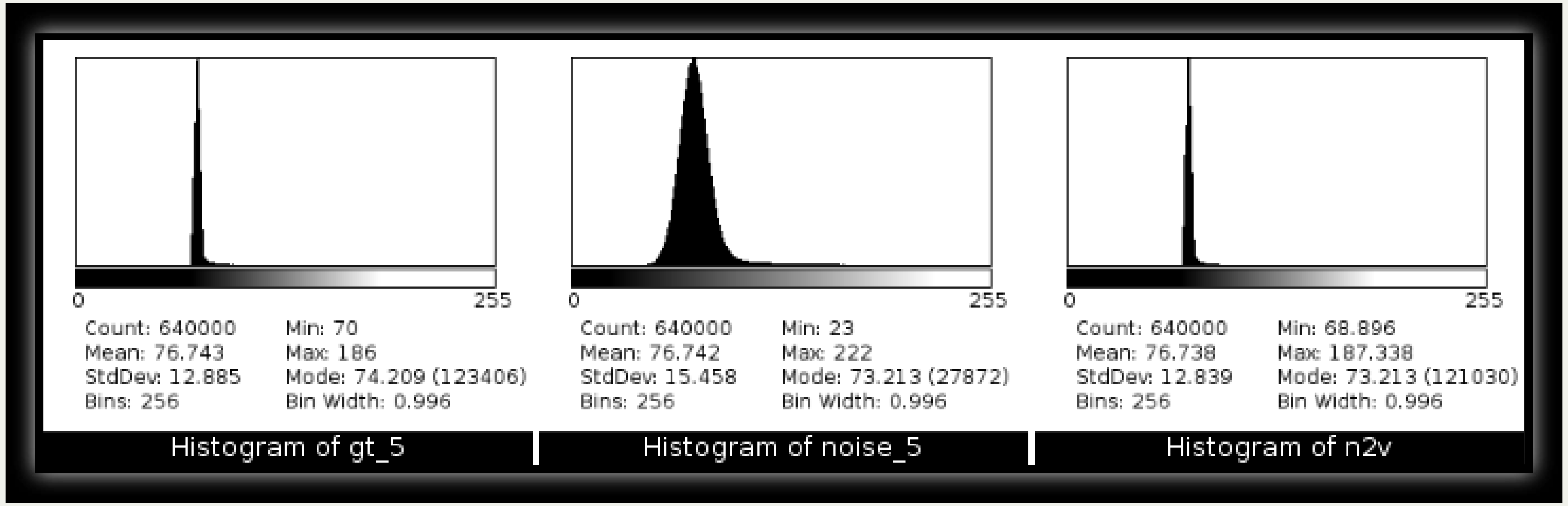
2.7 Results - Images



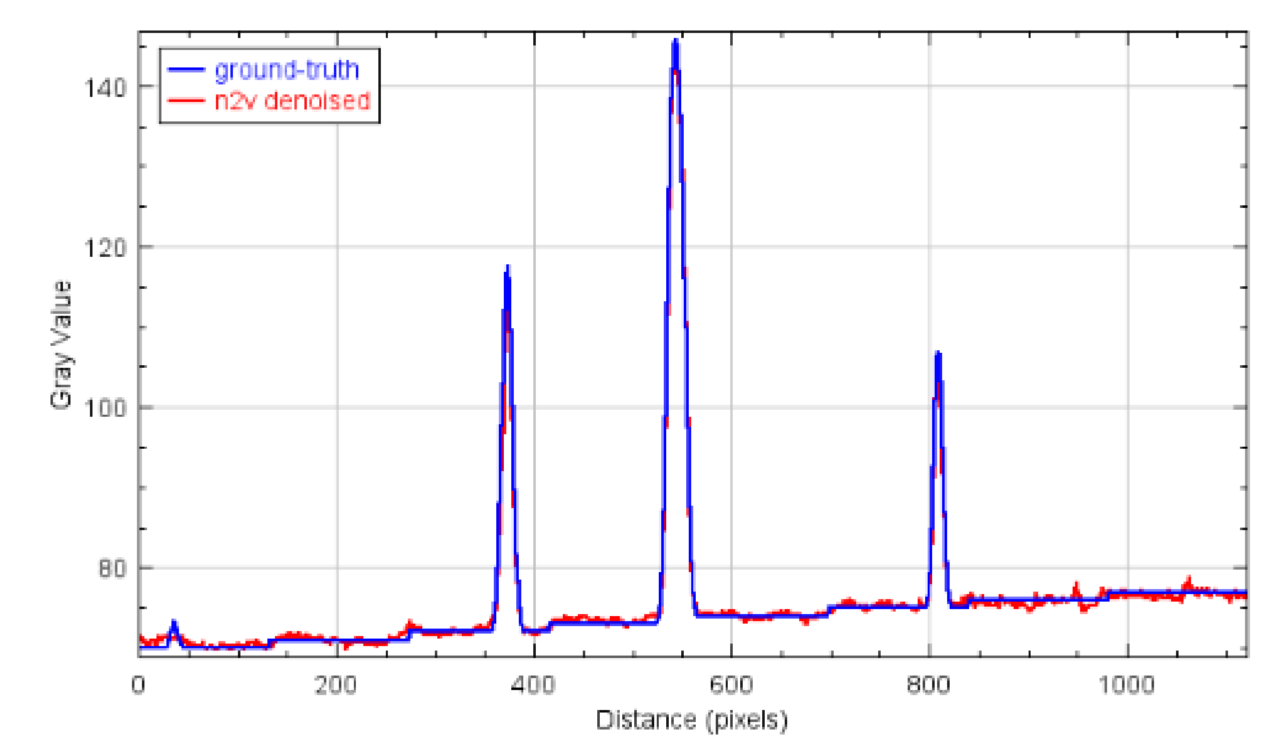


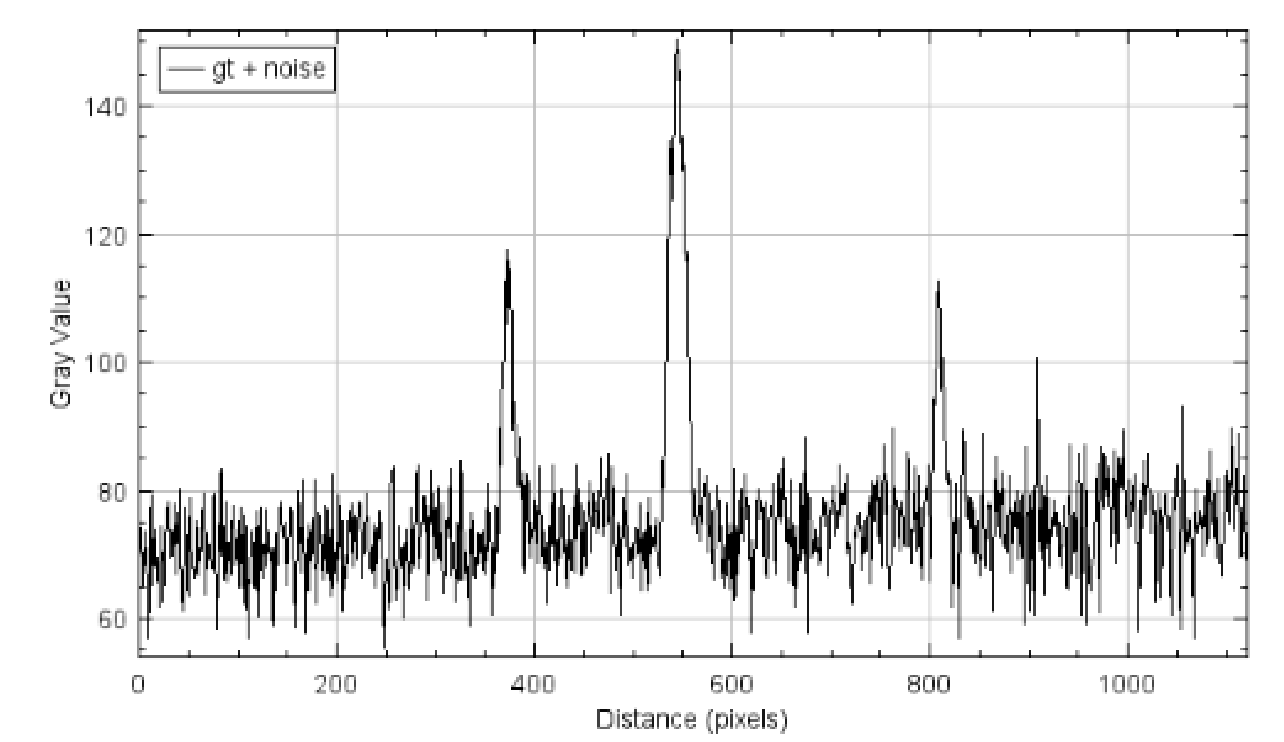
2.8 Results - Histograms





2.9 Results - Plots





2.10 Results - Metrics

(N°) Reference Image	(N°) Test Image	SNR [dB]	PSNR [dB]	RMSE	MAE
(1) gt	(1) noise	19.20405144	26.77276932	8.52853583	6.72216094
(1) gt	(1) n2v-denoised	38.72119838	46.28991626	0.90160670	0.58652819

Calculated with the SNR-Plugin [1]

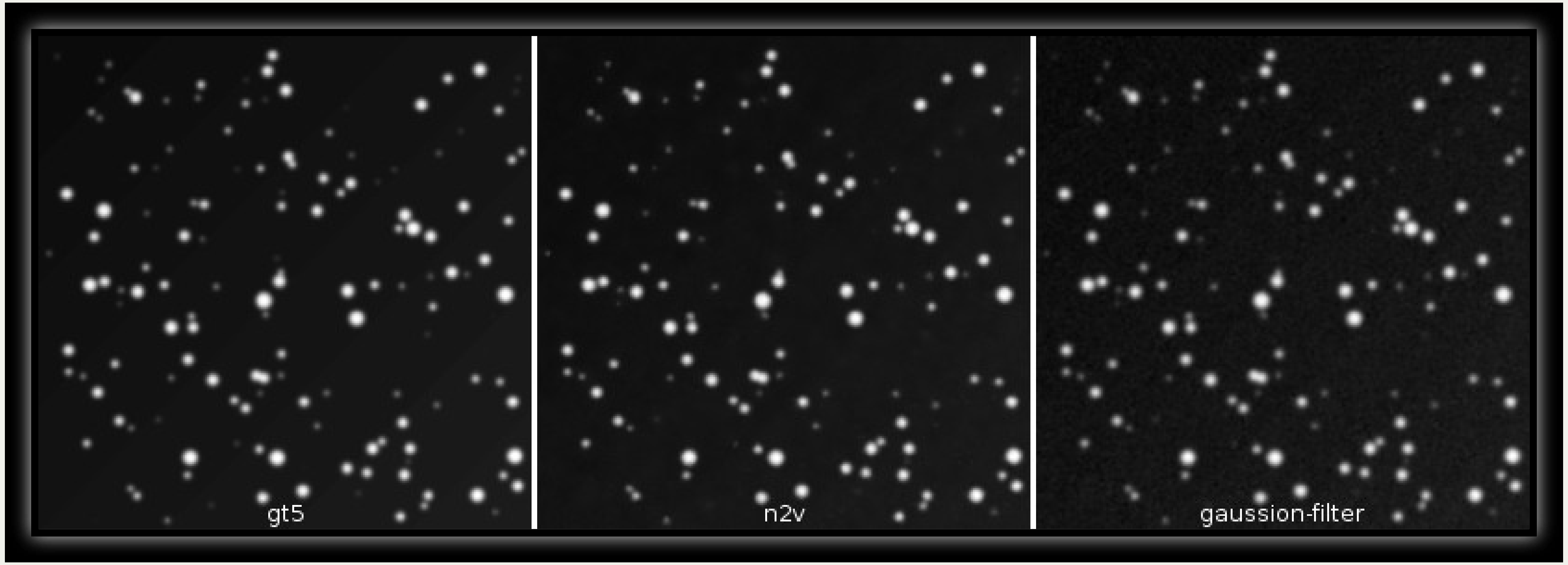
metric	long name
SNR	Signal to Noise Ratio
PSNR	Peak Signal to Noise Ratio
RMSE	Root Mean Square Error
MAE	Mean Absolute Error

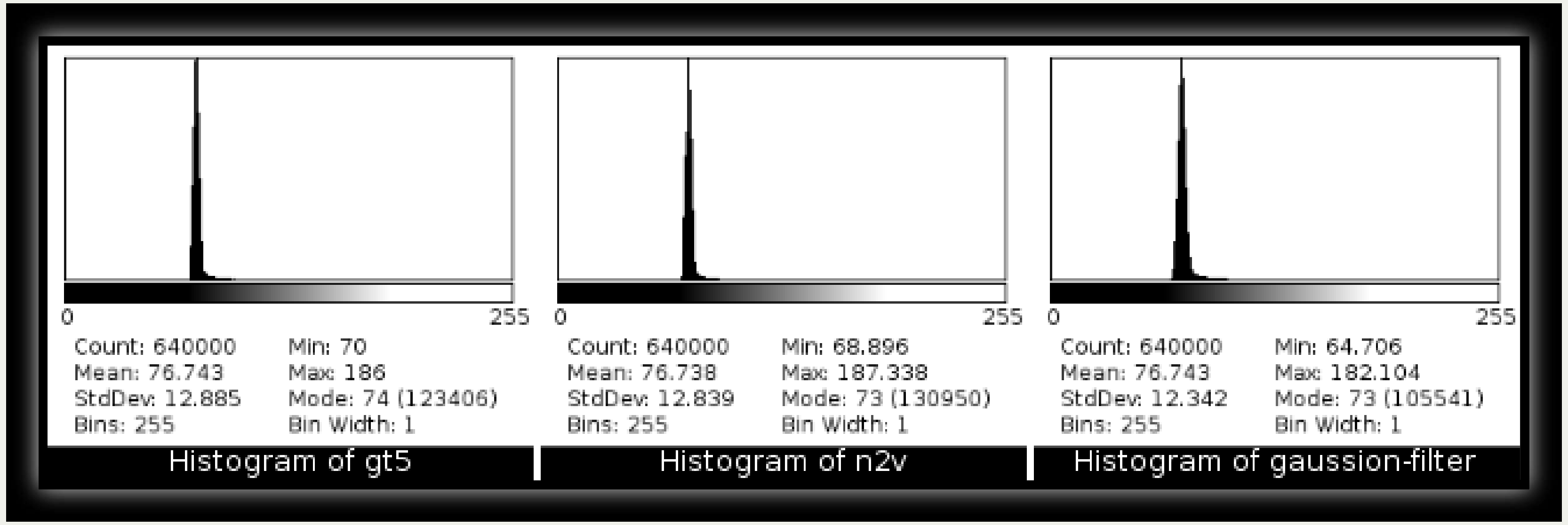
[1] D. Sage, M. Unser, Teaching Image-Processing Programming in Java, IEEE Signal Processing Magazine, vol. 20, no. 6, pp. 43-52, November 2003.

2.11 Comparison with Gaussian-Filter

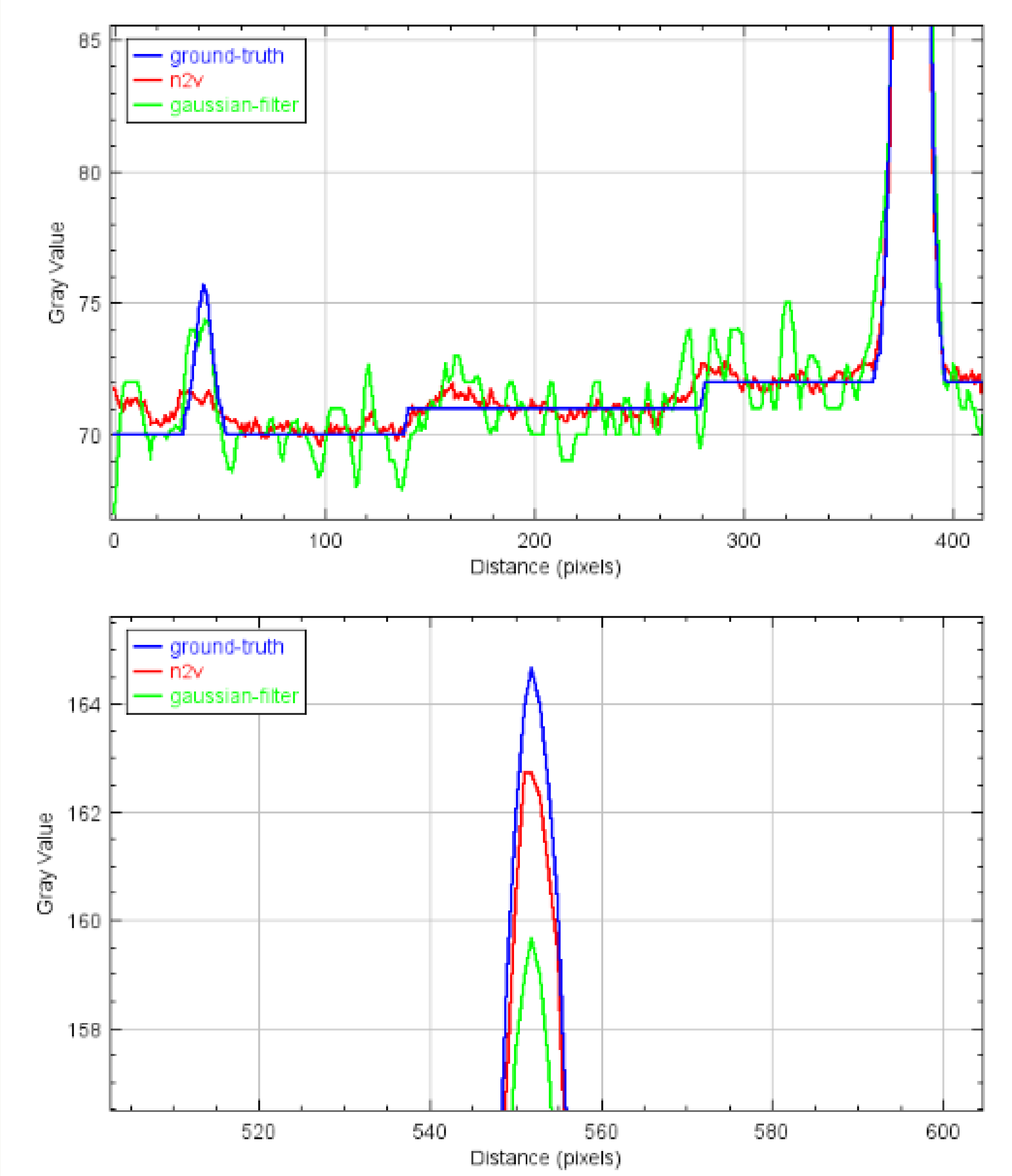
- Is the n2v denoising better than a simple solution?

2.12 Comparison - Histograms





2.13 Comparison - Plots



2.14 Comparison - Metrics

(N°) Reference Image	(N°) Test Image	SNR [dB]	PSNR [dB]	RMSE	MAE
(1) gt5	(1) noise	19.20405144	26.77276932	8.52853583	6.72216094
(1) gt5	(1) n2v	38.72119838	46.28991626	0.90160670	0.58652819
(1) gt5	(1) gaussian-filter	34.12542003	41.69413791	1.53040385	1.08228281

Calculated with the SNR-Plugin [1]

metric	long name
SNR	Signal to Noise Ratio
PSNR	Peak Signal to Noise Ratio
RMSE	Root Mean Square Error
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3.1 Conclusions noise2void experiment

- Training was fast
- The result “looks” very good
- Higher SNR than the Gaussian-blur filter
- Low intensity spots are lost with n2v
  - For segmentation Gaussian-blur filter might be better (in this case)

3.2 Conclusions

- We can use Zero Cost Deep-Learning for Microscopy (all)
- We can setup other DeepLearning-models in the same way (the ML-team)
- We can train and apply the model
  - on colab
  - on analysis pcs (with or without gpus, depending on the model)
  - on our own server (we do not have it yet)
  - possibly on the meso@lr cluster (not setup yet)
- We can apply the trained models from ImageJ

=> Try it on colab to get started

3.3 An alternative

- ImJoy [1]
  - nice environment for deploying DL-models
  - also a number of DL-models for microscopy already available
  - for cloud computing it uses mybinder (only demo)
    - but could use other services
  - more complex for setup and data-access
  - user friendly gui for training and predictions

[1] Ouyang, W., Mueller, F., Hjelmare, M. *et al.* ImJoy: an open-source computational platform for the deep learning era. *Nat Methods* 16, 1199–1200 (2019)