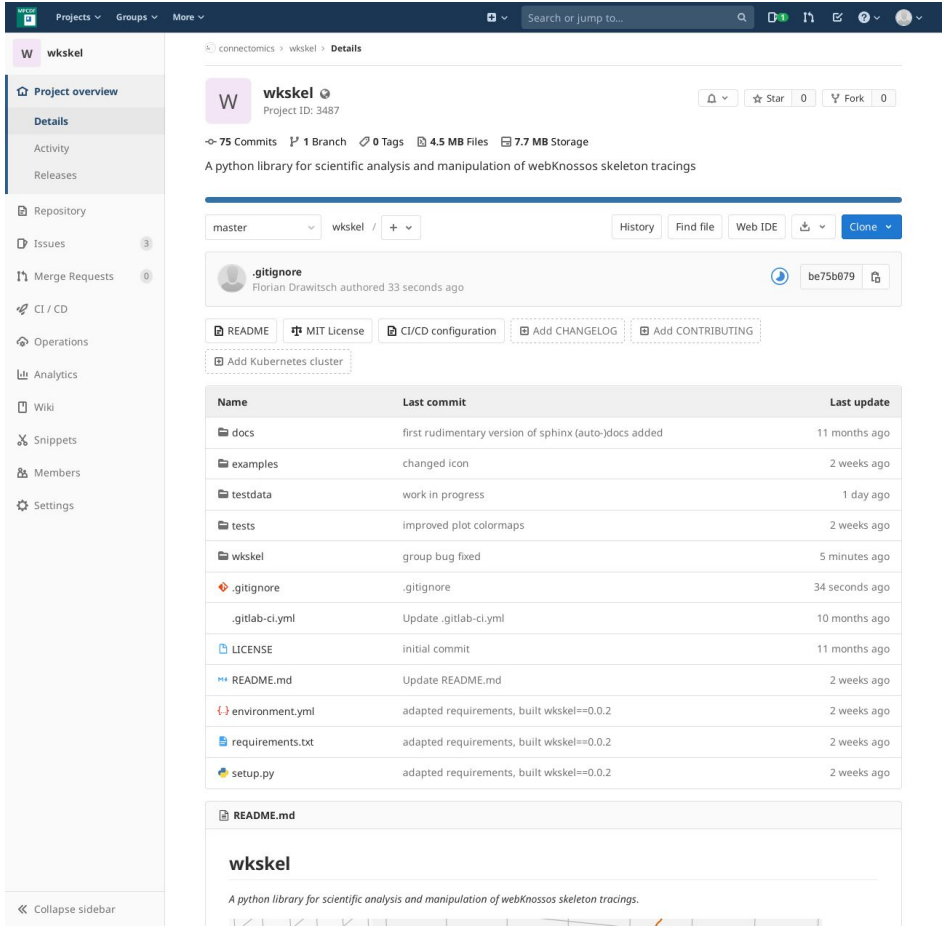
Autoencoders for mSEM artifact detection

Call for contributions: wkskel



wkskel: python library for skeleton manipulation

- Developed on the side from scratch
- Most important functionality is there
- Porting full functionality & performance of matlab skeleton class is a lot of work
- Please help by using, improving & documenting it
- Two contribution strategies possible:
  - Direct commits to master: Please write test for your method (repo has gitlab ci/cd set up)
  - Pull requests

How to install it:
$ pip install wkskel
How to use it:
Jupyter notebook tutorial:
https://gitlab.mpcdf.mpg.de/connectomics/wkskel:examples

Autoencoders for mSEM artifact detection

mSEM artifacts: general

- mSEM artifacts are a problem for automated downstream analysis -> hinder classification / segmentation / agglomeration
- mSEM artifacts come in various forms and are difficult to detect reliably using humans or hand-designed algorithms
- Variety of artifacts and large data size
  ➔ Problematic situation for classical supervised approaches (e.g. U-net)
- Training a *naive* U-net or similar (>E6 params) in a supervised fashion would require HUGE amount of labeled training data

mSEM artifacts: data situation

- Huge amount of unlabeled data (even in mag-8-8-1 ~1TB)
- Much less labeled data (> 500 training patches ~ 10MB):
  - Lablog Summary: https://mhlablog.net/2020/02/05/training-data-for-artefact-detection-in-msem-data/
  - Circular Artifact: https://webknossos.brain.mpg.de/annotations/Explorational/5e387a00010000501b1a41bd#25238,20546,3546,0,0.513,1
  - Horse shoe Artifact: https://webknossos.brain.mpg.de/annotations/Explorational/5e387a00010000501b1a41bd#19895,15530,3732,0,0.513,12
  - Scratch Artifact: https://webknossos.brain.mpg.de/annotations/Explorational/5e387a00010000501b1a41bd#20088,16049,3925,0,0.513,17

Supervised CNN vs. unsupervised autoencoder (AE)

CNN

$f: X \rightarrow Y$

$y = f'(x) + \varepsilon$

$\text{Min}_p \text{Loss}(f'_p(x) - y)$

```
class CNN:
  def predict(x):
    y_hat = f(x)
    return y_hat
```

AE

$e: X \rightarrow L$

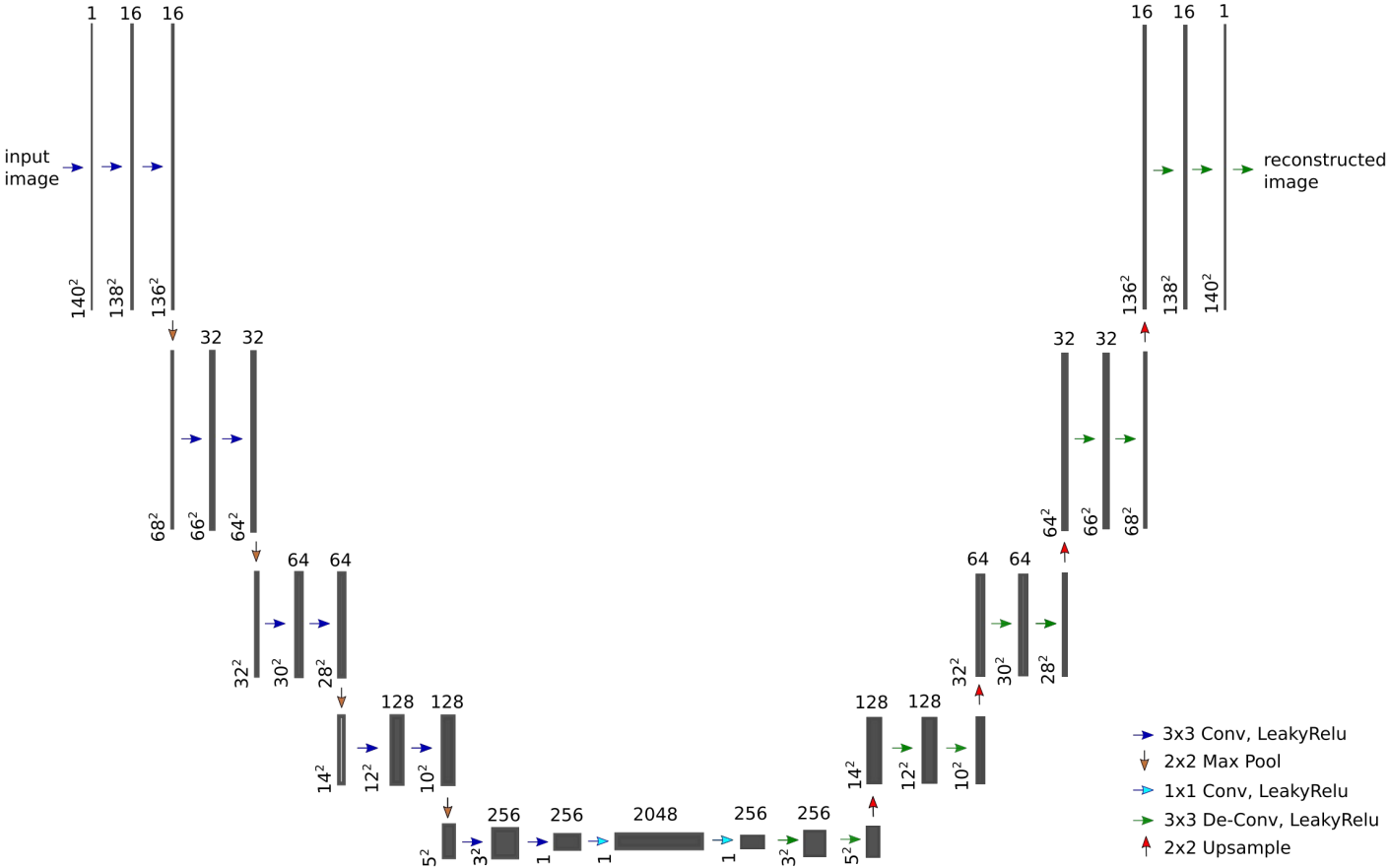
$d: L \rightarrow X$

$x = d'(e'(x)) + \varepsilon$

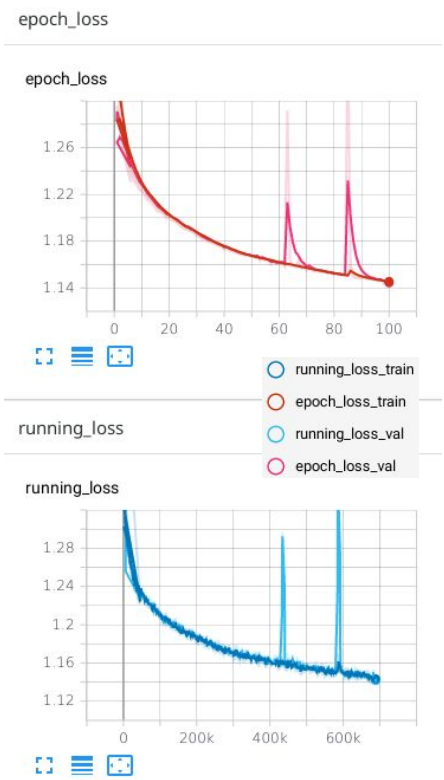
$\text{Min}_p \text{Loss}(d'_p(e'_p(x)) - x)$

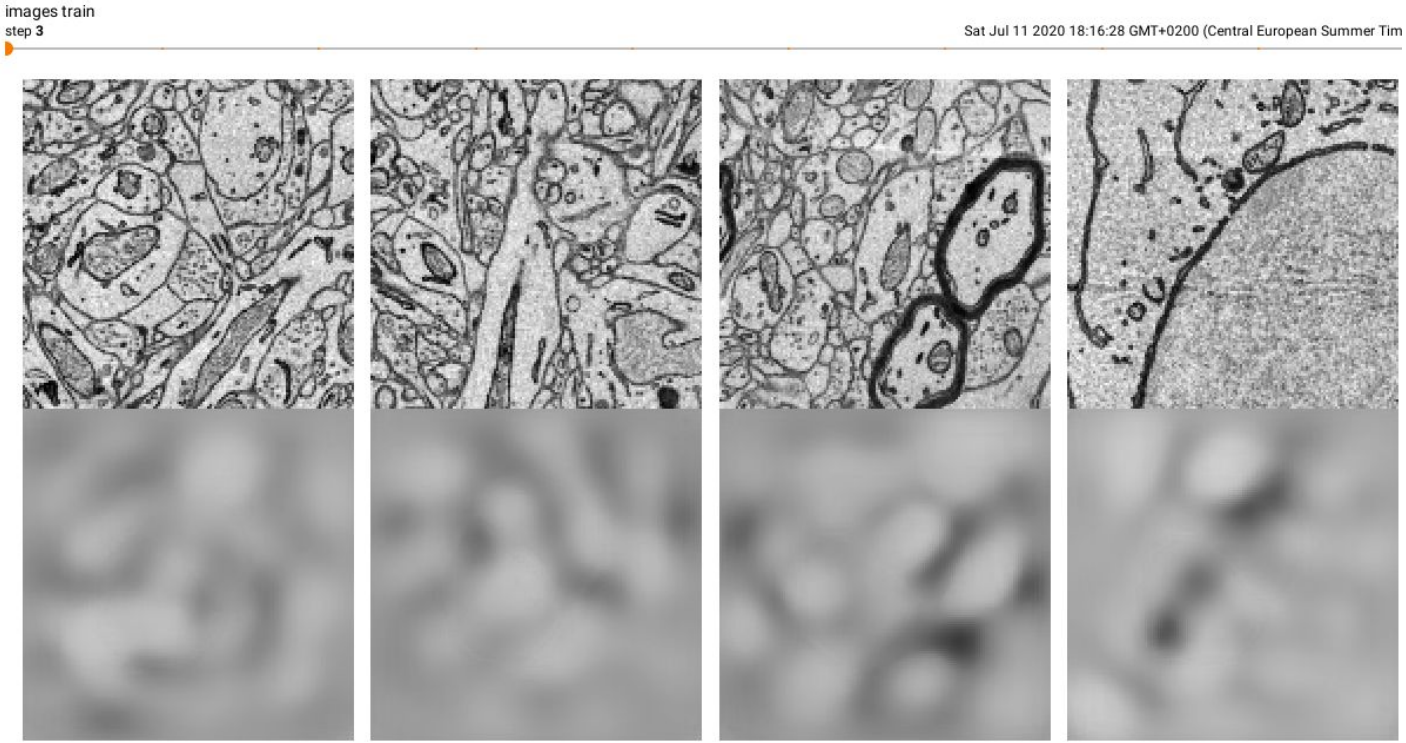
```
class AE:
  def predict(x)
      x_hat = d(e(x))
      return x_hat
```

Basic multi-res AE for mSEM data



Basic multi-res AE for mSEM data





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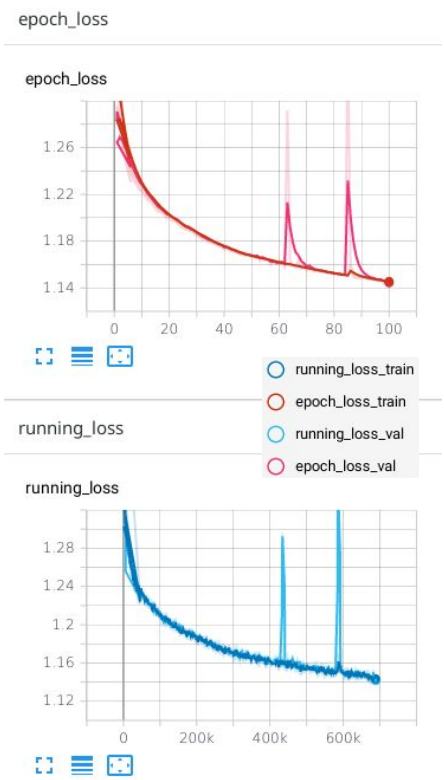

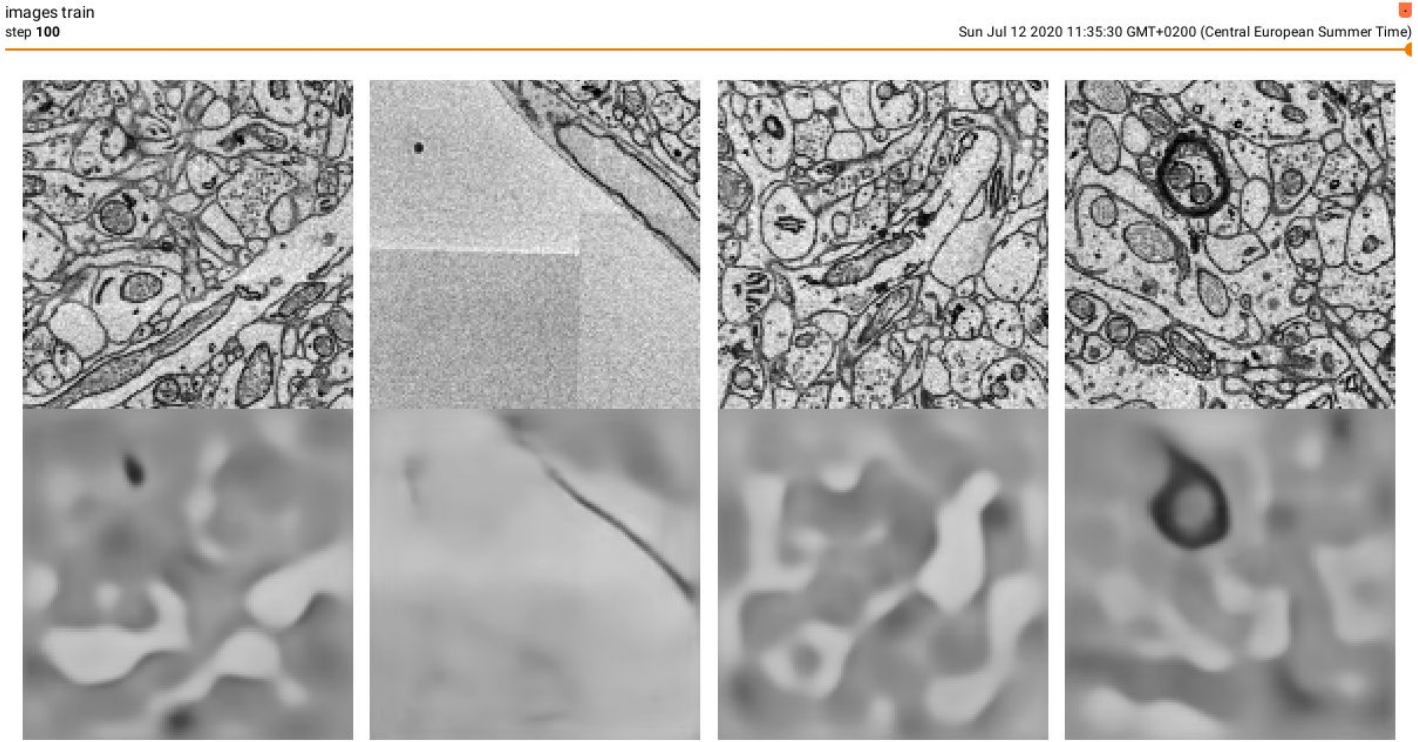

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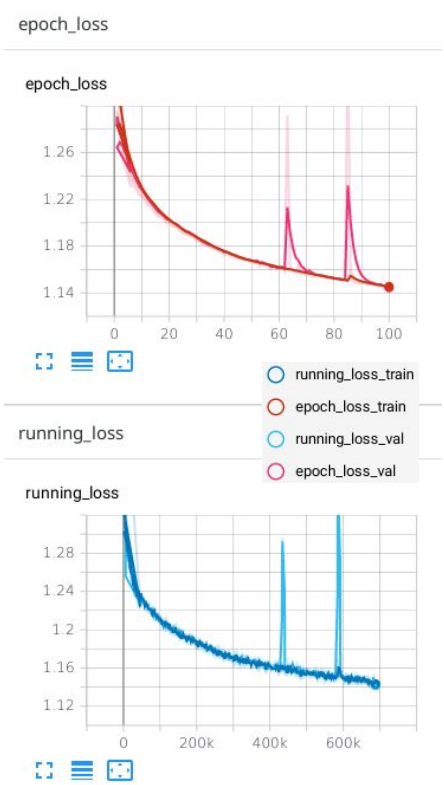
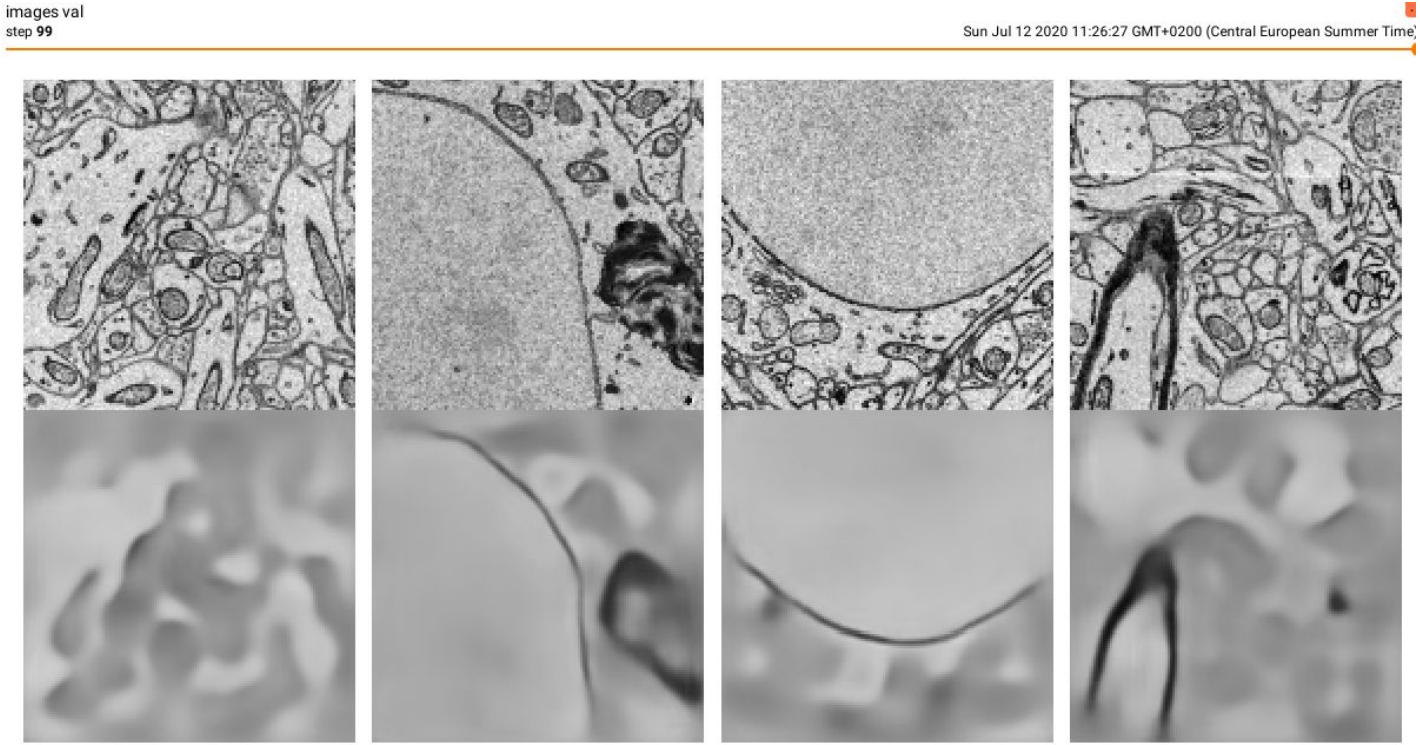
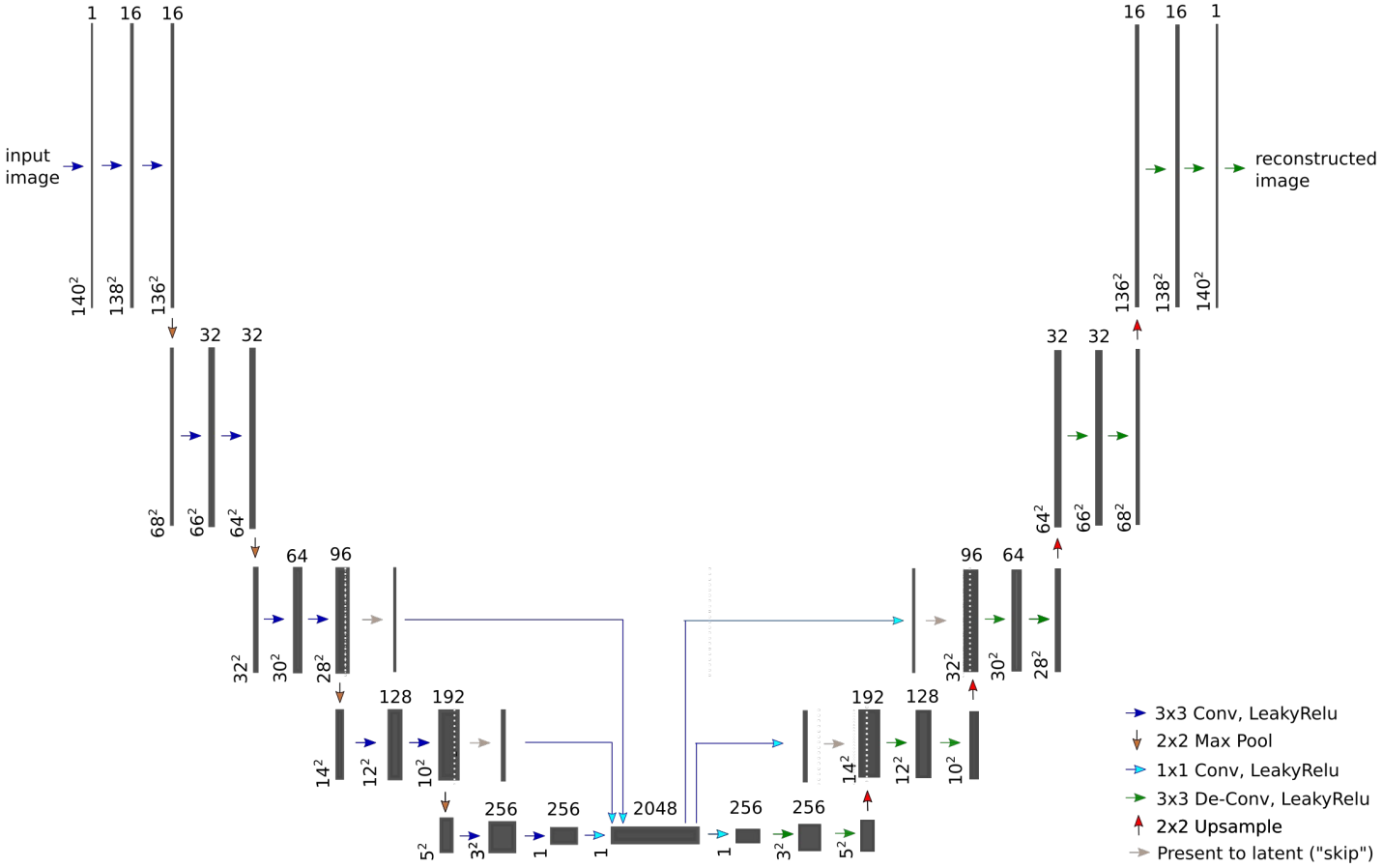




Multi-res “skip” AE for mSEM data



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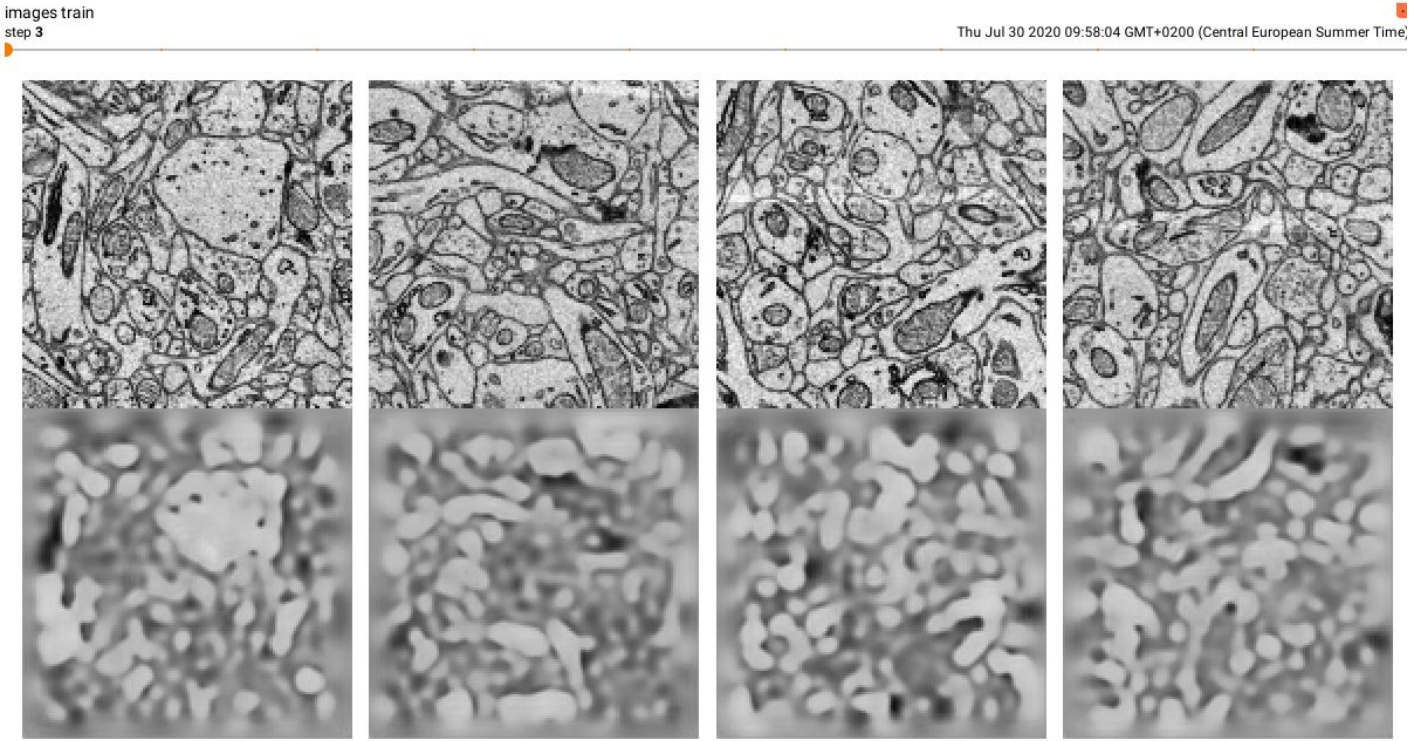

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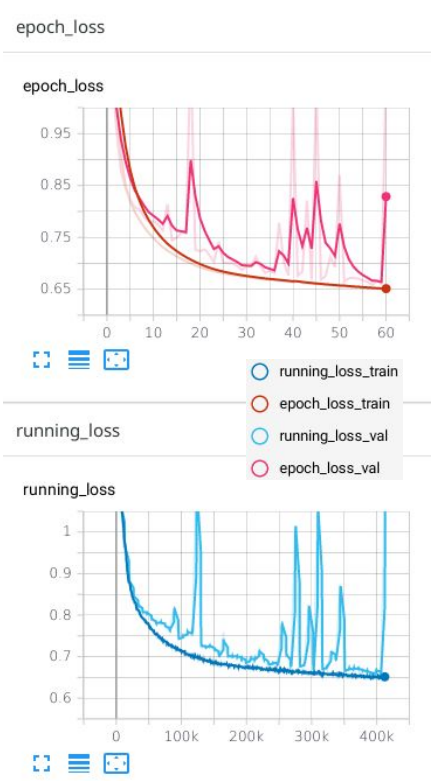

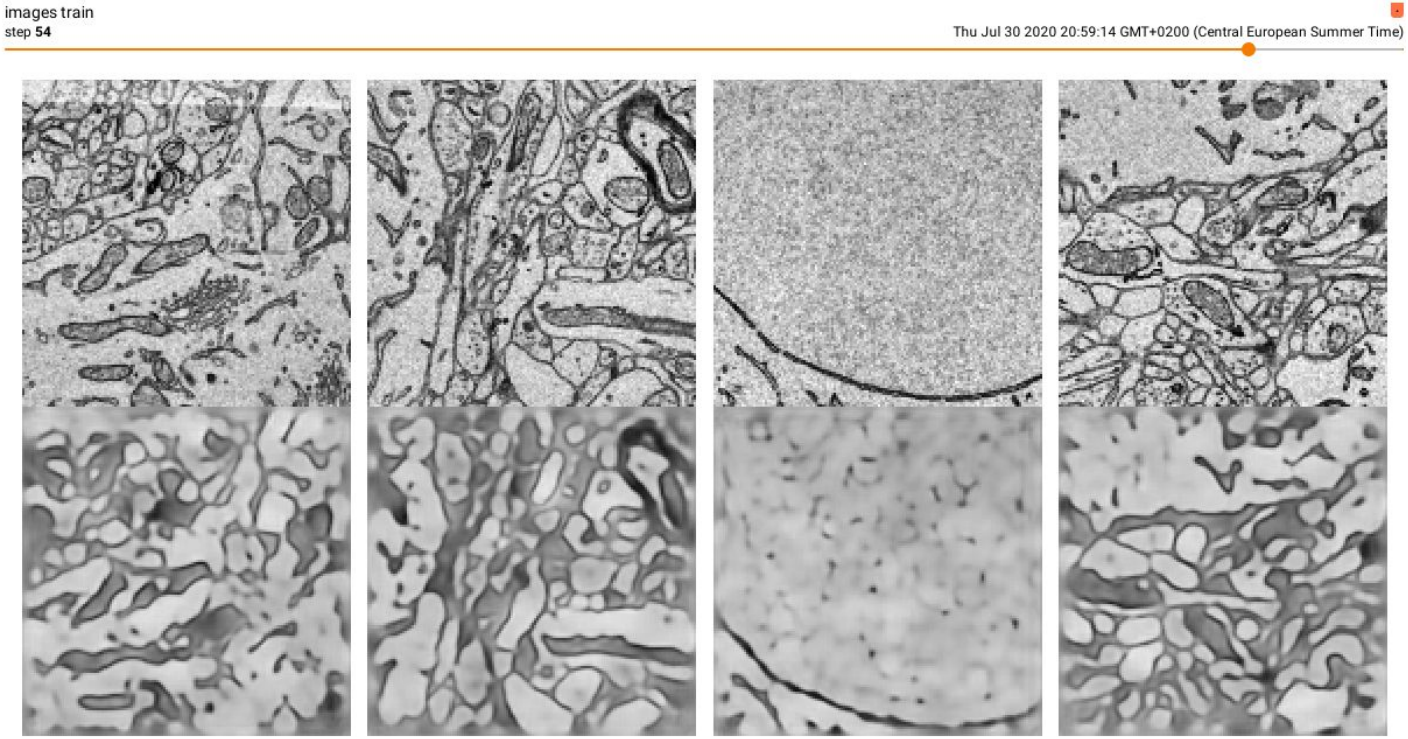

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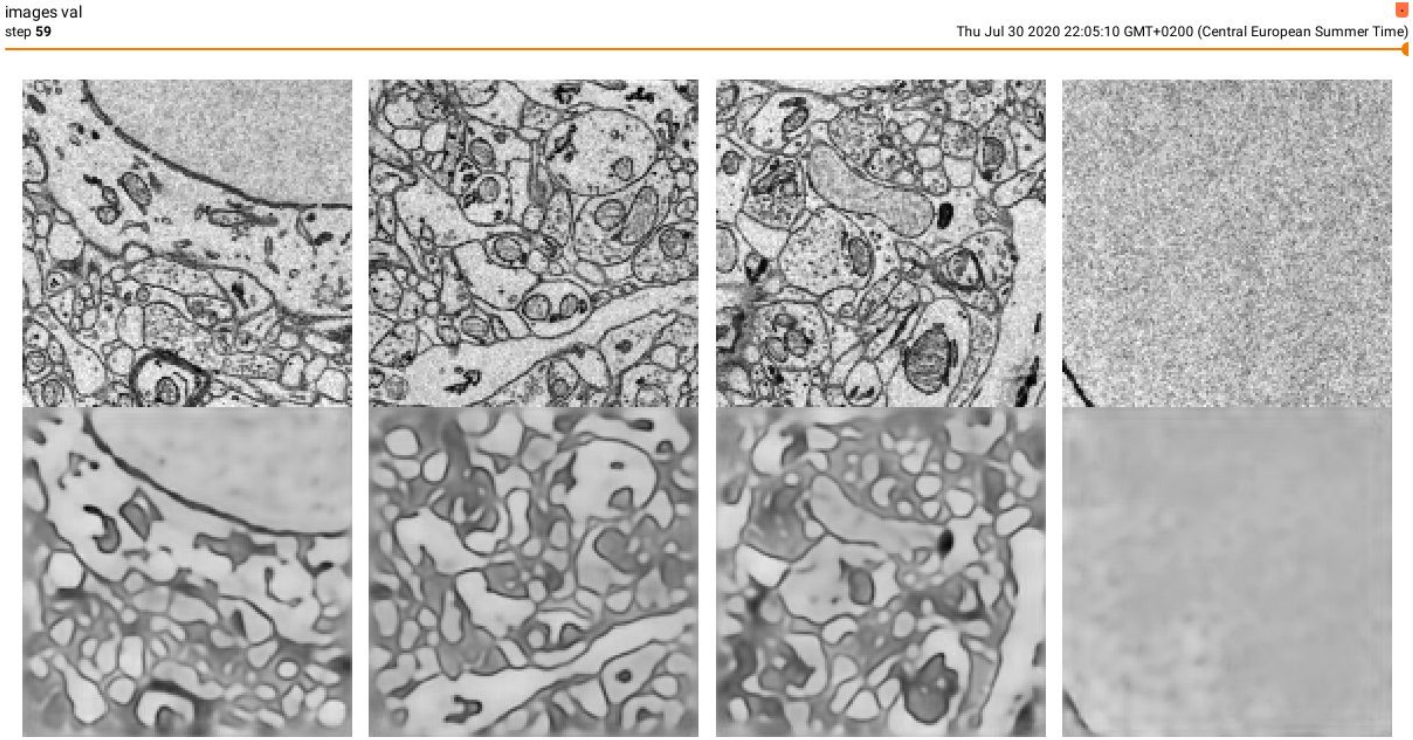

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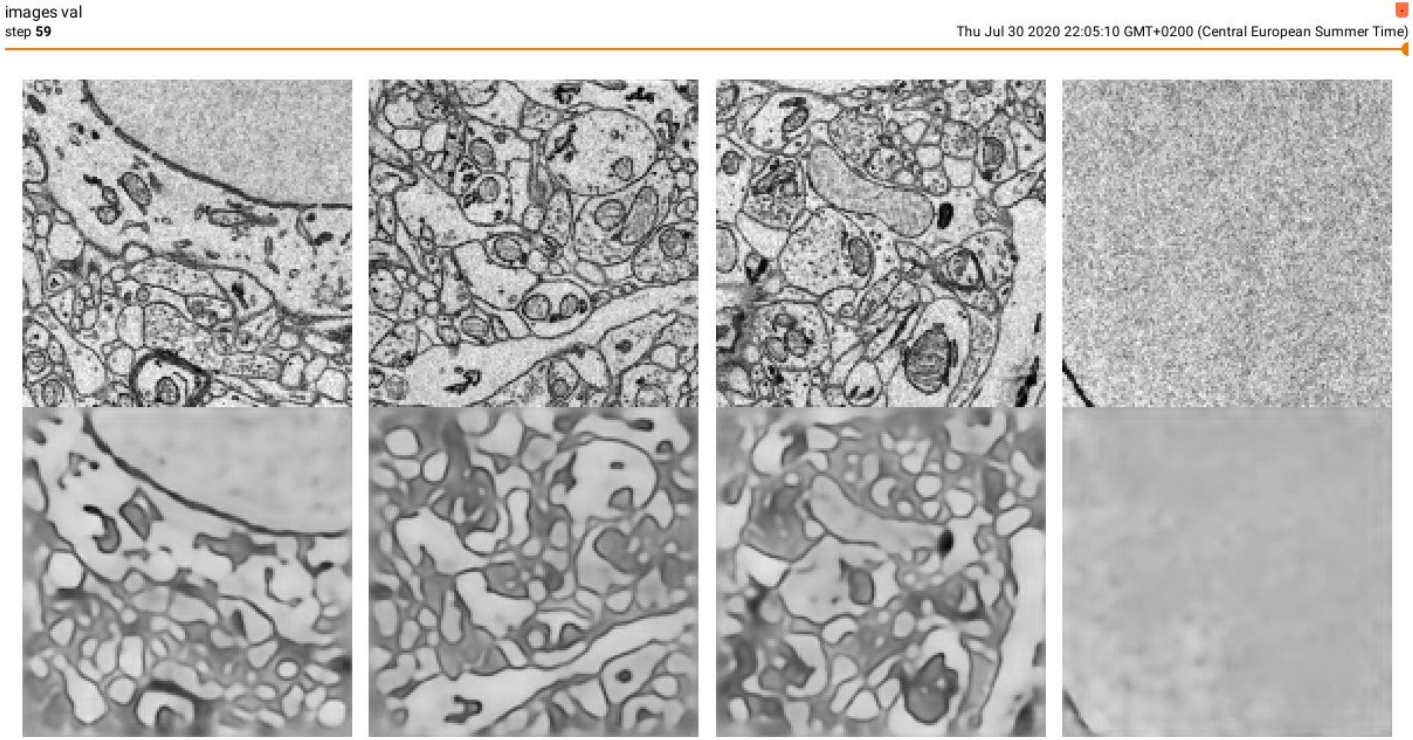


Unsupervised AE vs. semi-supervised encoder + classifier

AE

$e: X \rightarrow L$

$d: L \rightarrow X$

$x = d'(e'(x)) + \varepsilon$

$\text{Min}_p \text{Loss}(d'_p(e'_p(x)) - x)$

```
class AE:
  def predict(x)
      x_hat = d(e(x))
      return x_hat
```

Encoder + classifier

$e: X \rightarrow L$

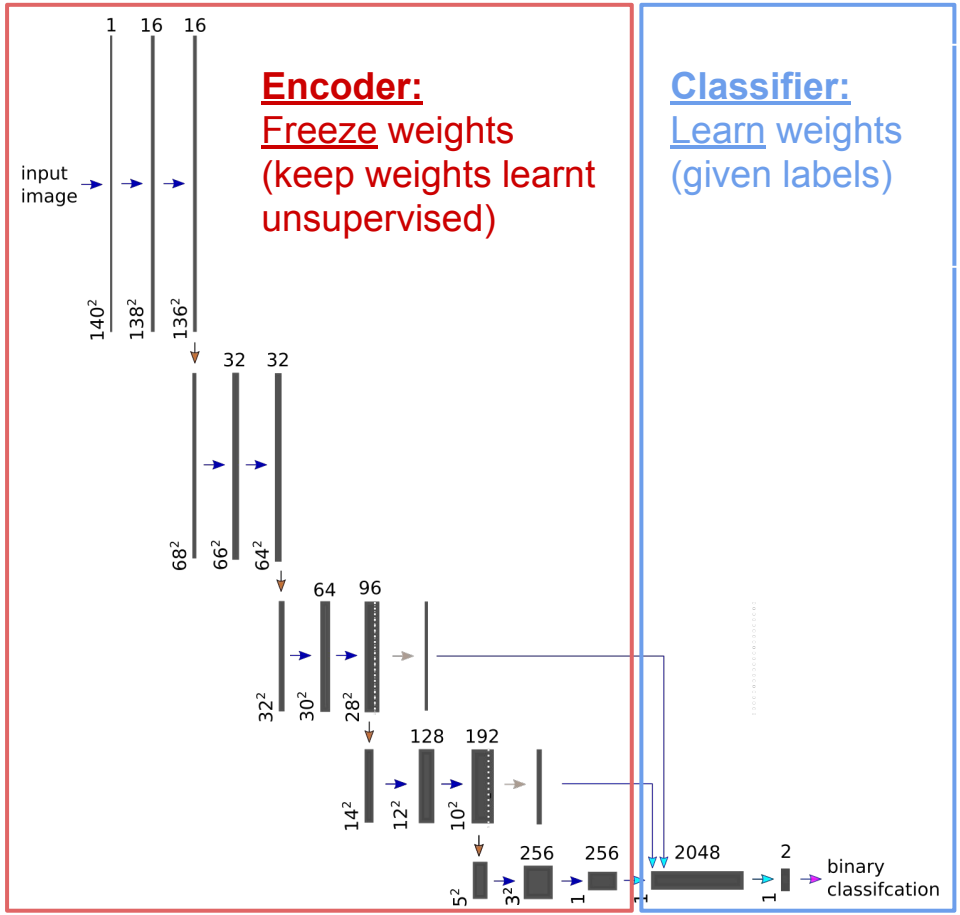
$c: L \rightarrow Y$

$y = c'(e'(x)) + \varepsilon$

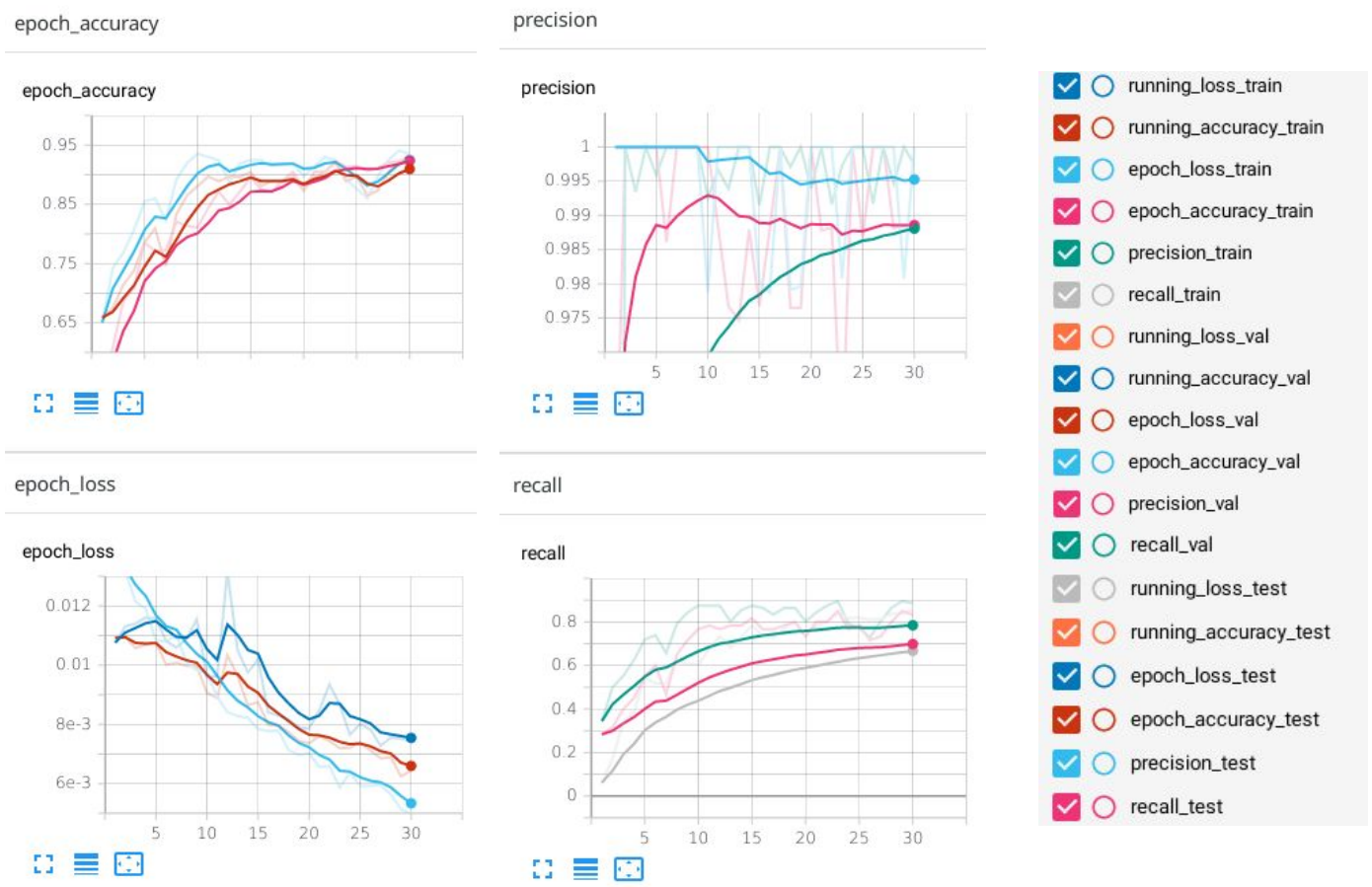
$\text{Min}_p \text{Loss}(c'_p(e'(x)) - x)$

```
class EncoderClassifier:
  def predict(x)
      y_hat = c(e(x))
      return y_hat
```

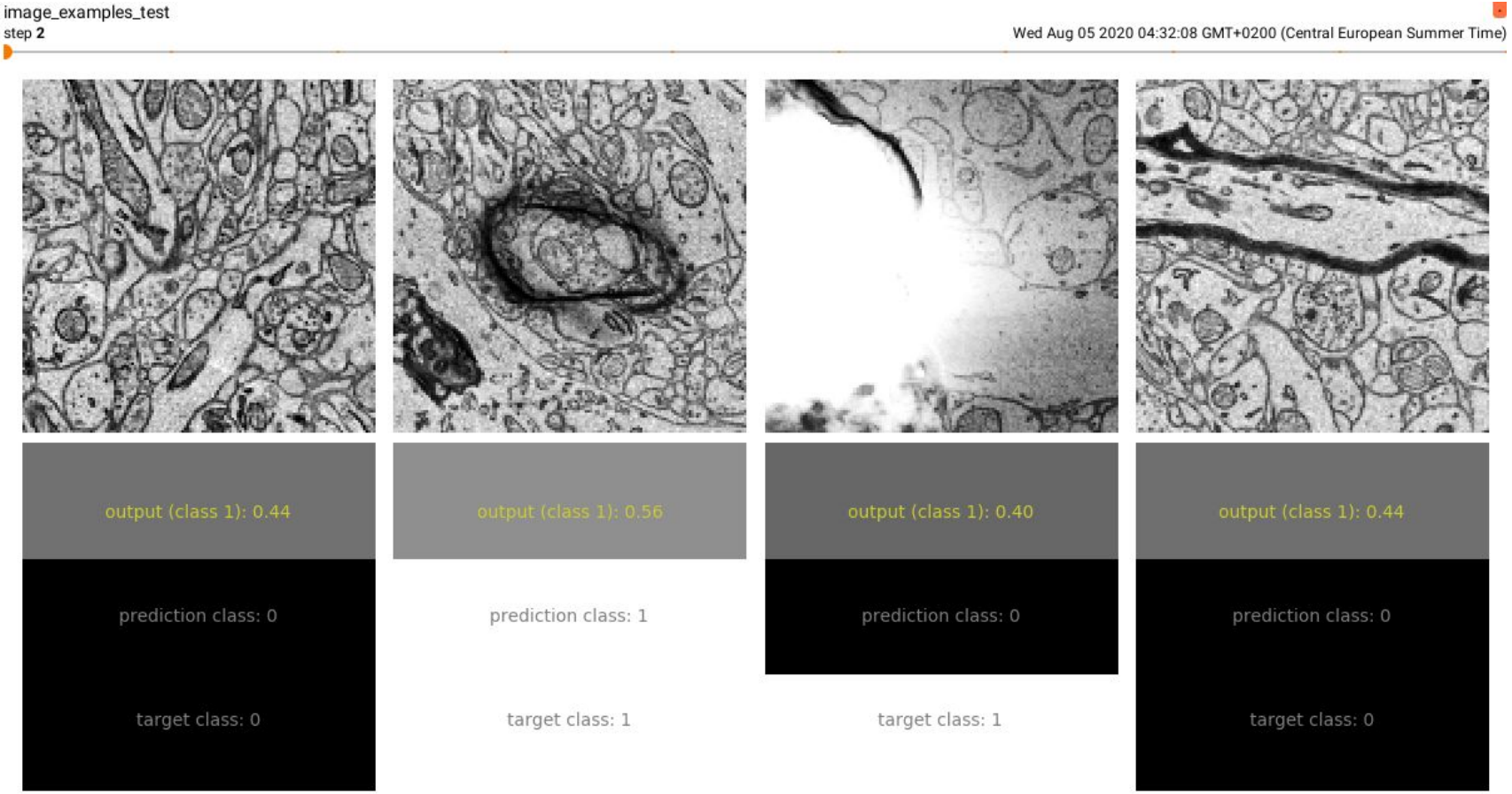
Multi-res “skip” encoder + binary classifier for mSEM data



Multi-res “skip” encoder + binary classifier for mSEM data



Multi-res “skip” encoder + binary classifier for mSEM data



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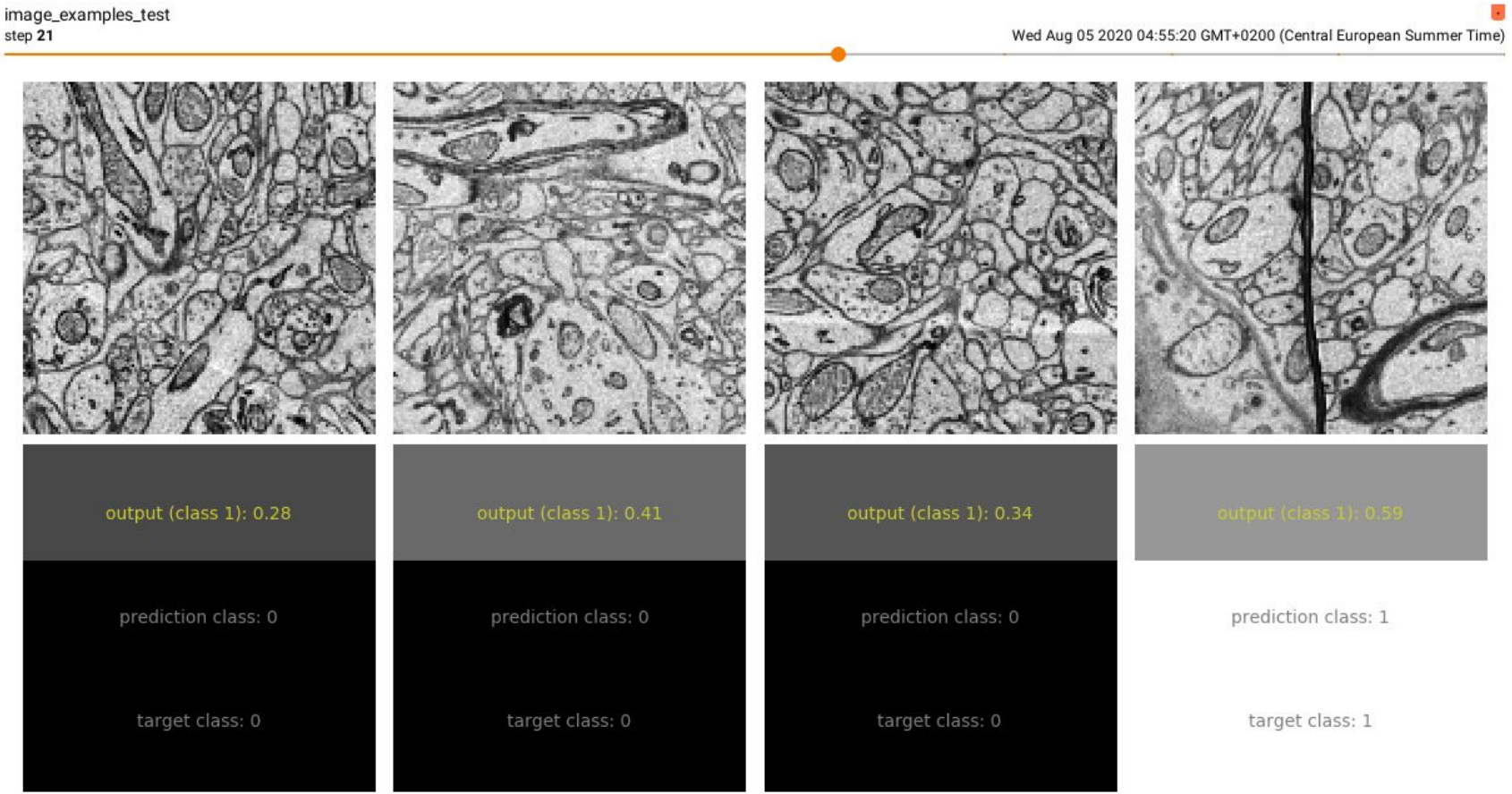

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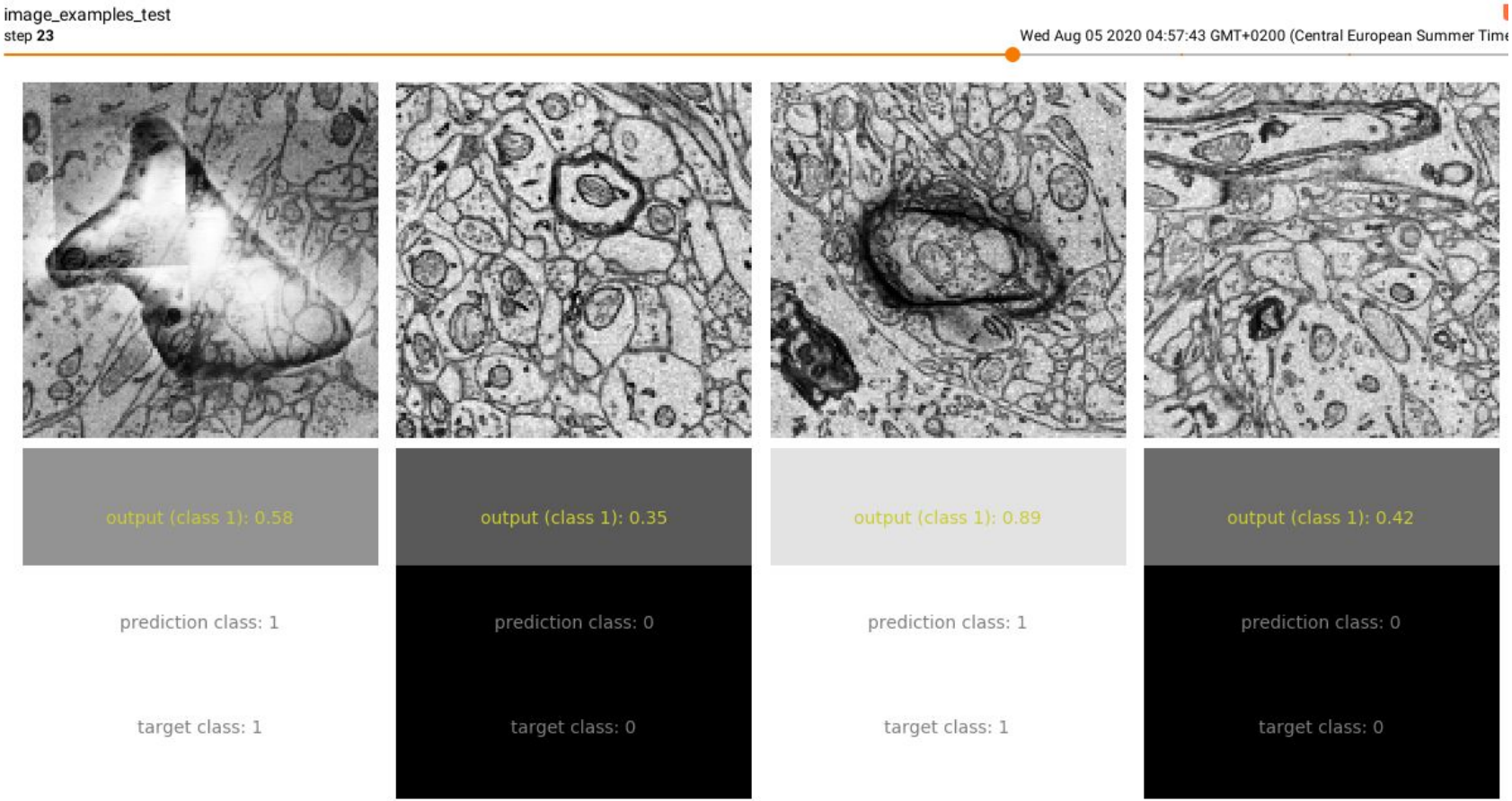

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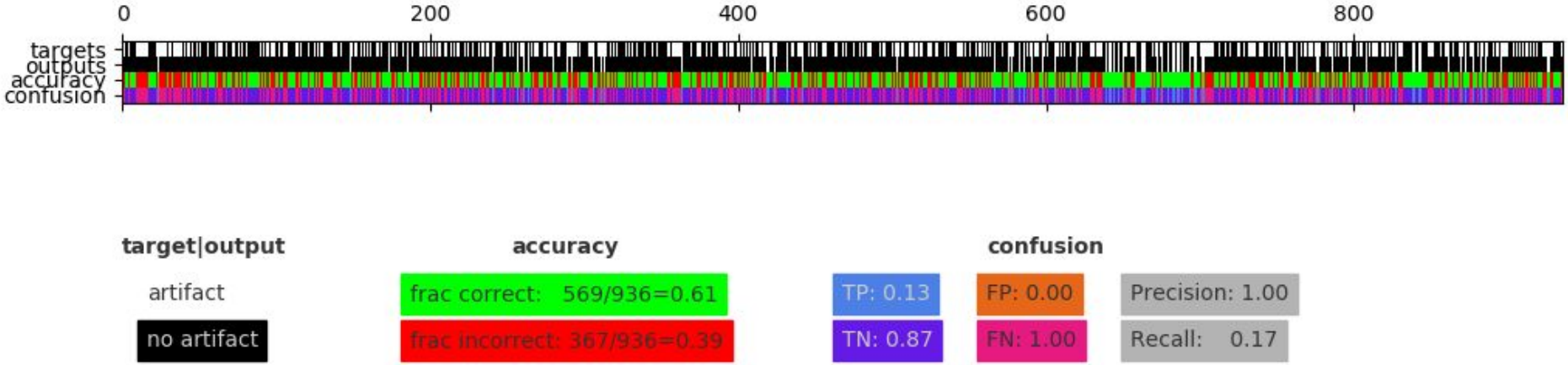

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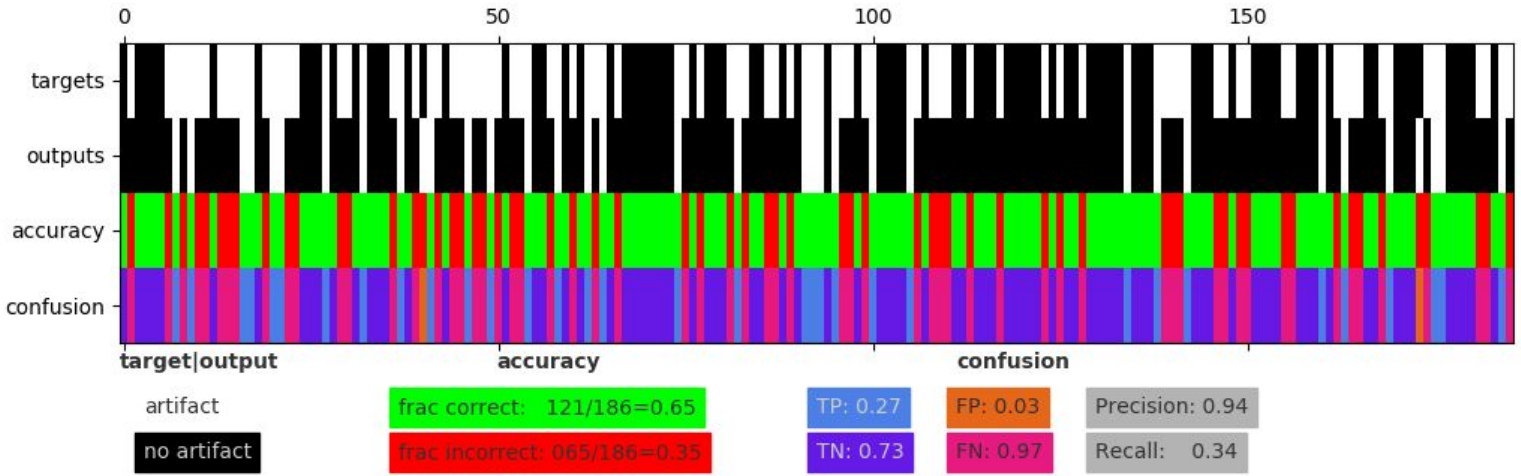

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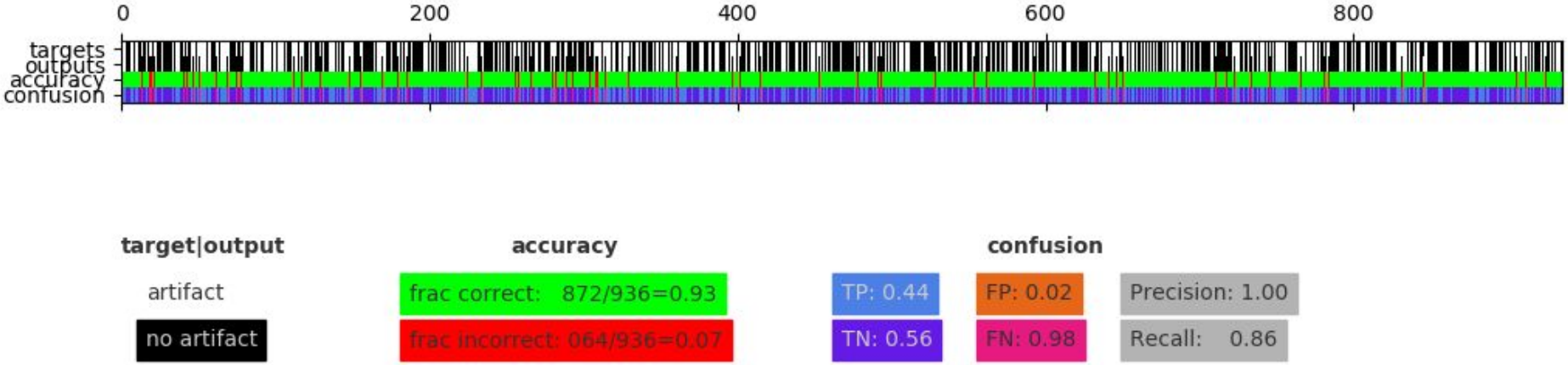

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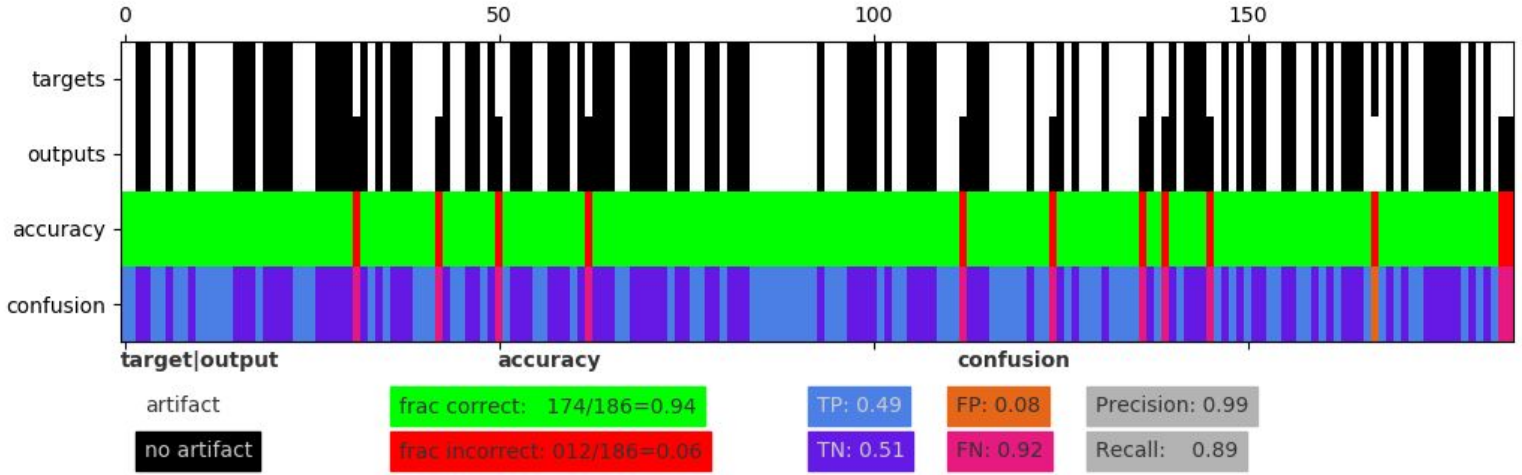

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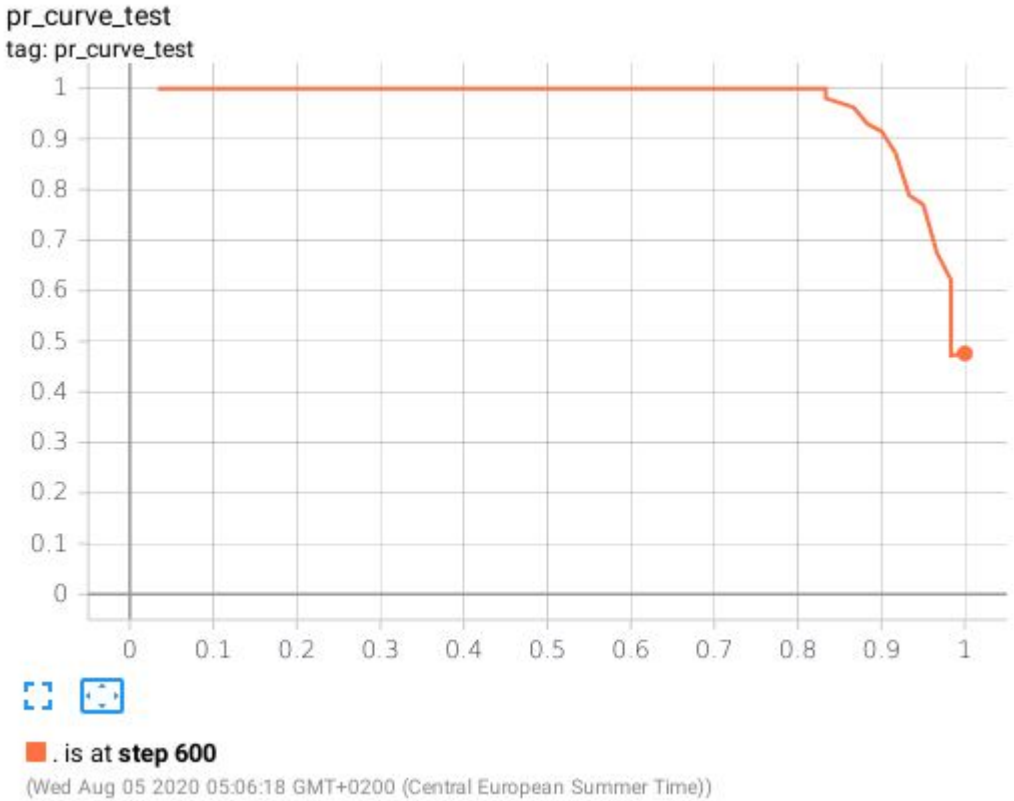
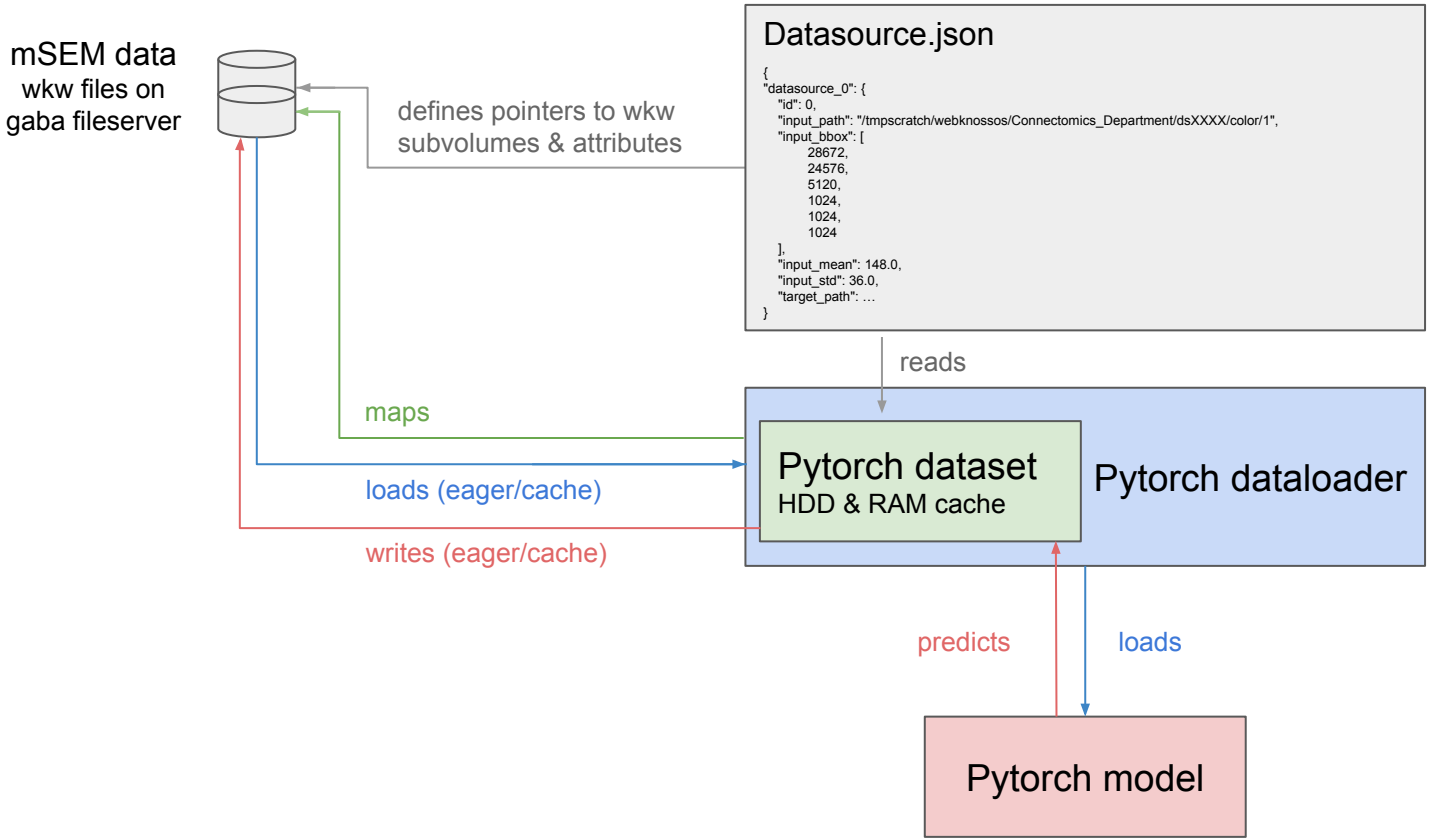


Improving the model

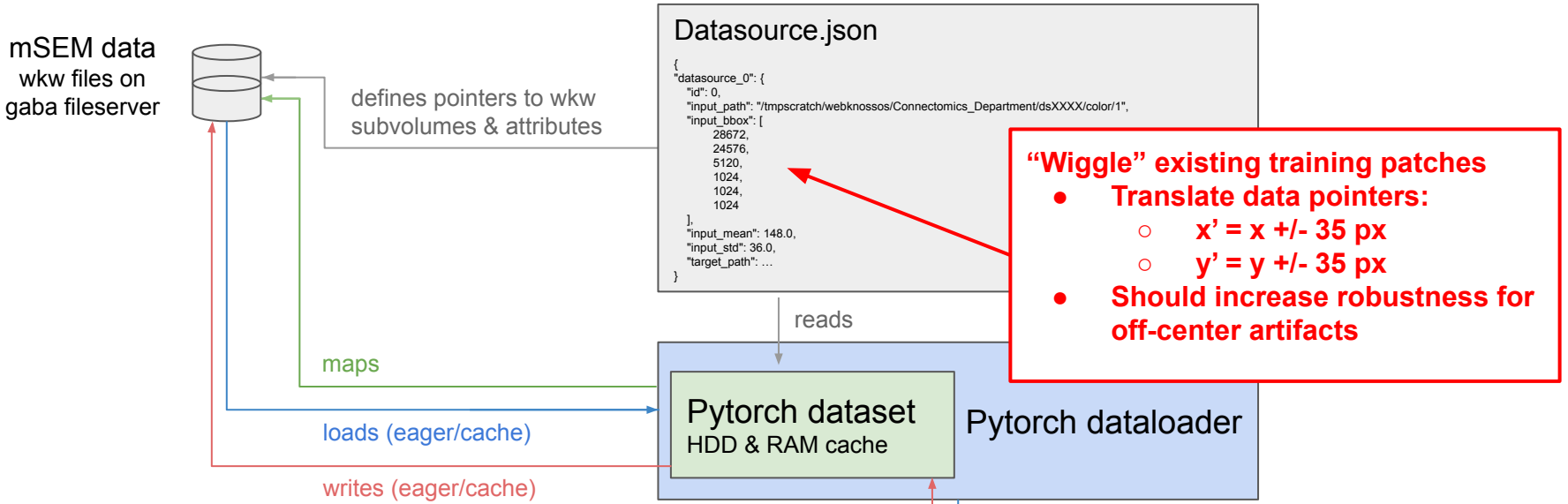
How to get pr curve up?

- Increase amount of training data
- Increase variation in training data / augmentation
- Increase complexity of classifier network

Interlude: Data architecture



Improving the model: Increase train data amount & variation



Dataset

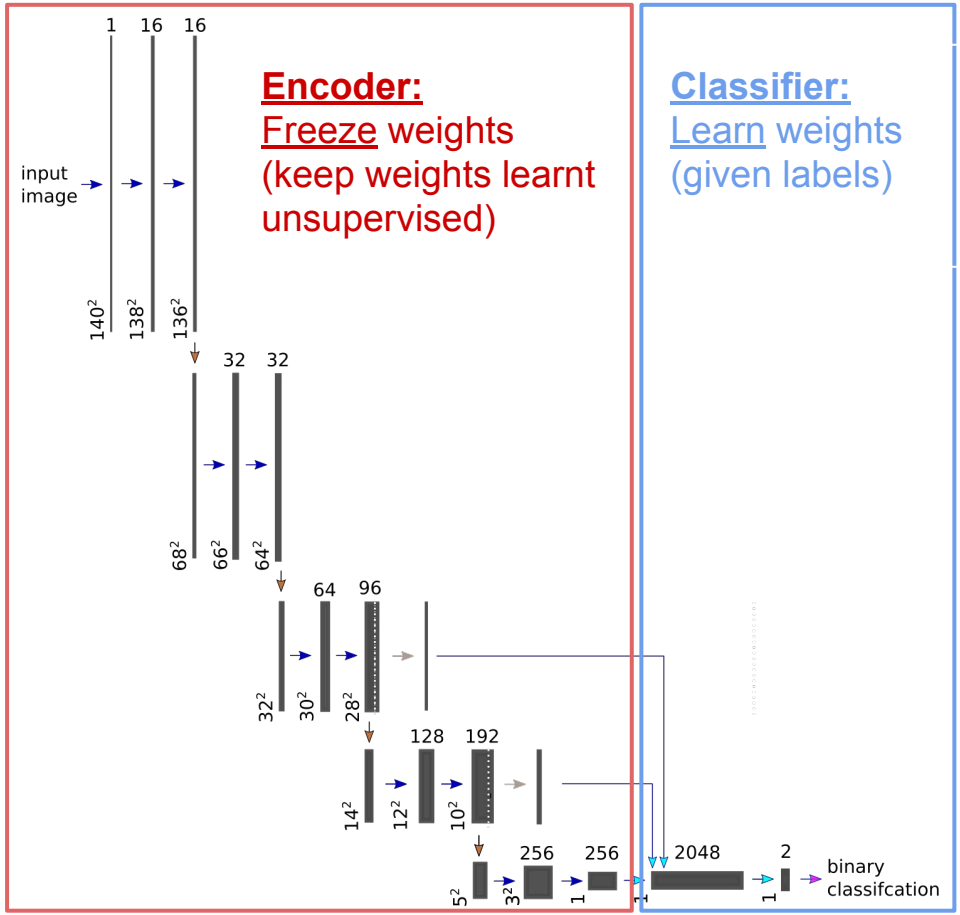
Total: 8562 (140x140x1) labelled samples

- Train: 7276 (2545 artifact, 4731 no artifact)
- Validation: 1284 (454 artifact, 829 no artifact)

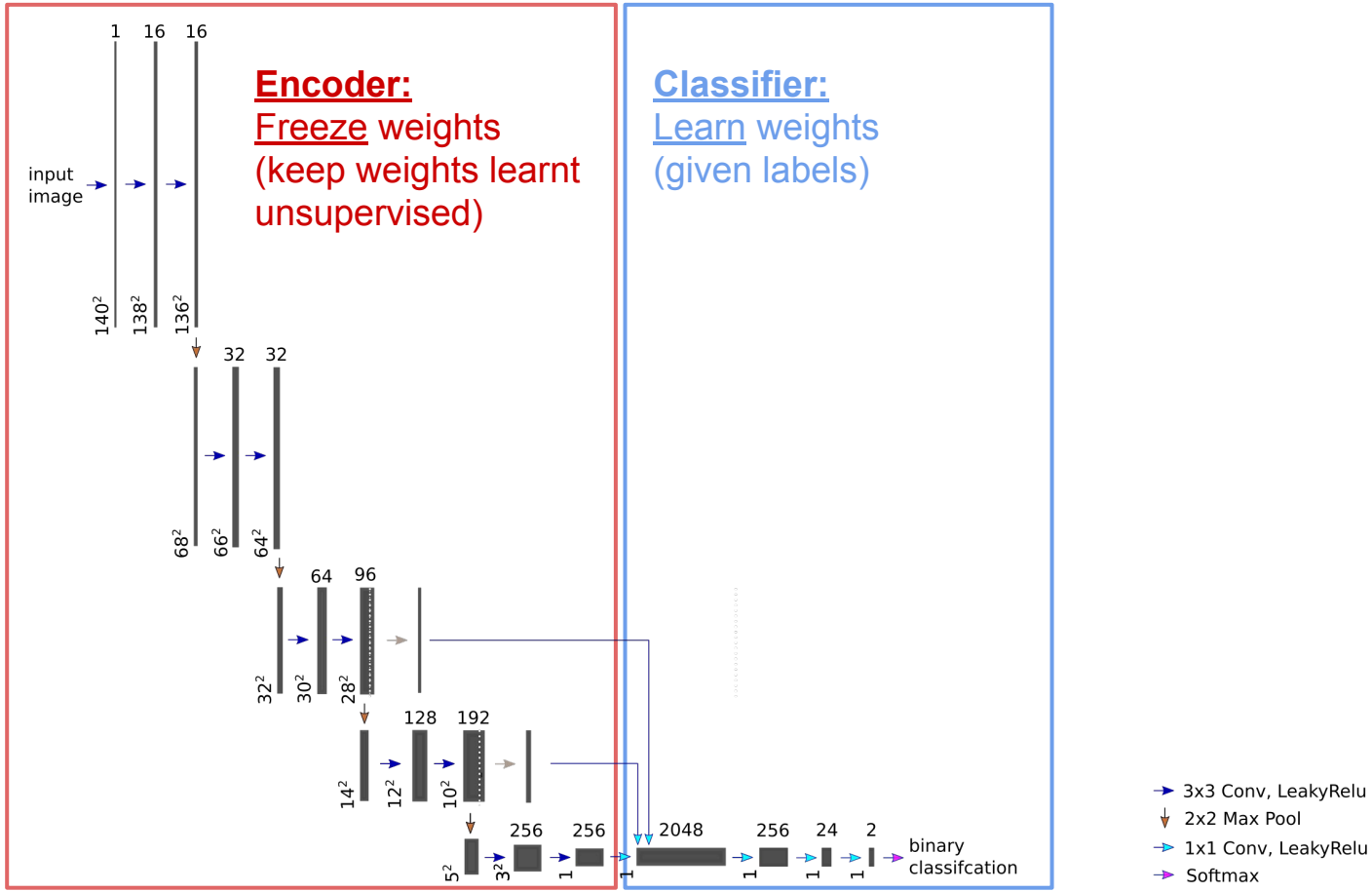
-> counts include wiggles

-> counts do not take into account random augmentations

Improving the model: previous classifier complexity

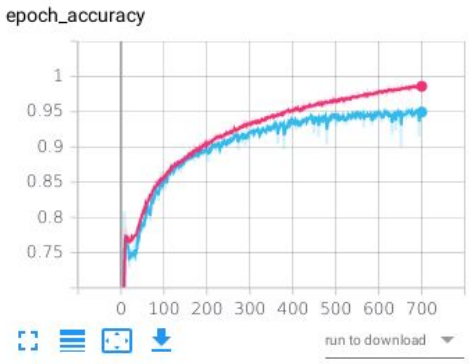


Improving the model: increased classifier complexity

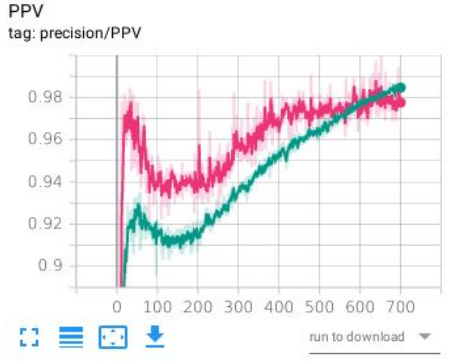


Improving the model: training performance

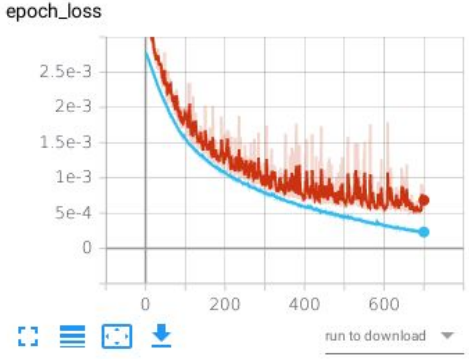
epoch_accuracy



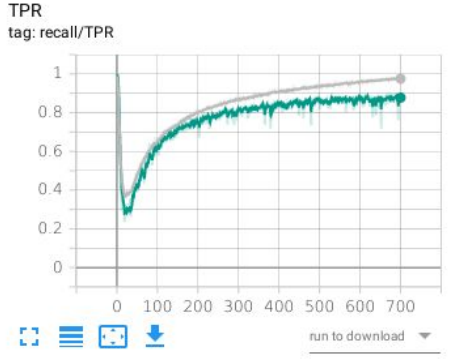
precision

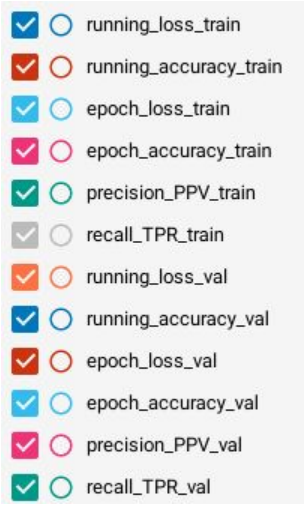


epoch_loss

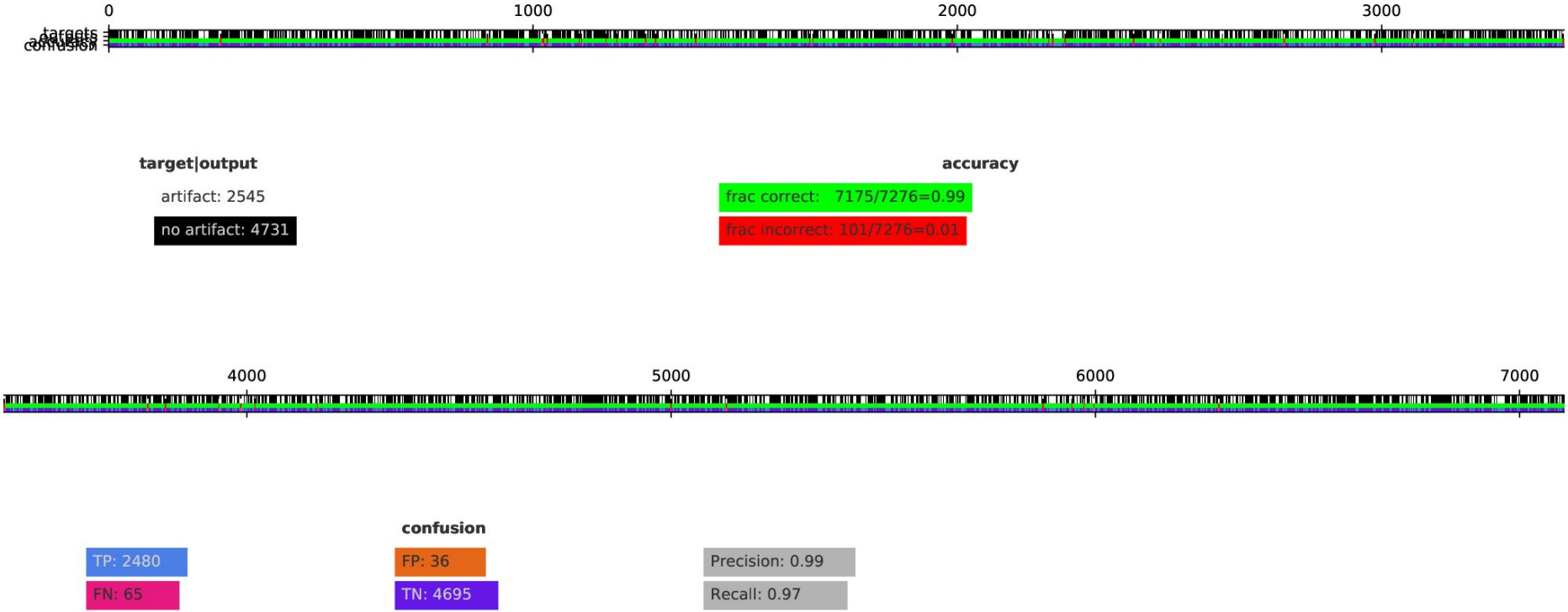


recall

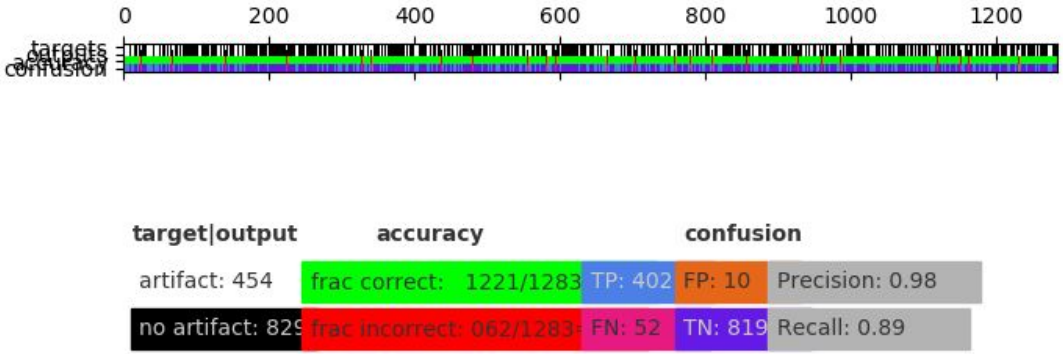




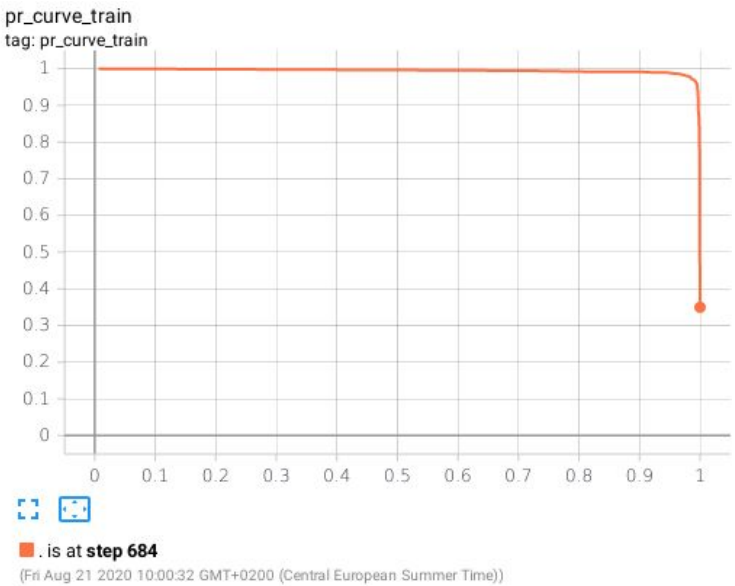
Improving the model: training performance (train set)

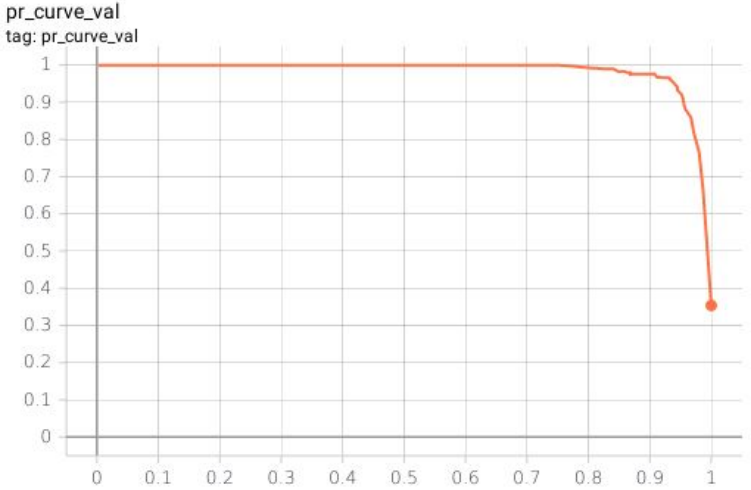


Improving the model: training performance (val set)



Improving the model: precision-recall curves





Inference on wk data

- Model input shape = (140, 140, 1), output_shape = (1, 1, 1)
  - predictions are sparse floats [0,1]
- Sparse floats can be written to compressed wkw files (20 mb instead of 4 gb), rendering in webknossos works
- Computational cost for predicting artifacts for a 1024^3 raw data cube with stride=(35,35,1)
  - cpu: ~ 60 min @ gabag; 16 cores
  - gpu: ~ 5 min @ gabag; tesla v100
- Mag8-8-1 of Meike's scMS109_1to7199 is comprised of ~ 3500 cubes:
  - cpu: 3500 * 60/60 * 16 = 65,000 core hours
  - gpu: 3500 * 5/60 = 290 gpu hours

Inference on wk data: examples

The good

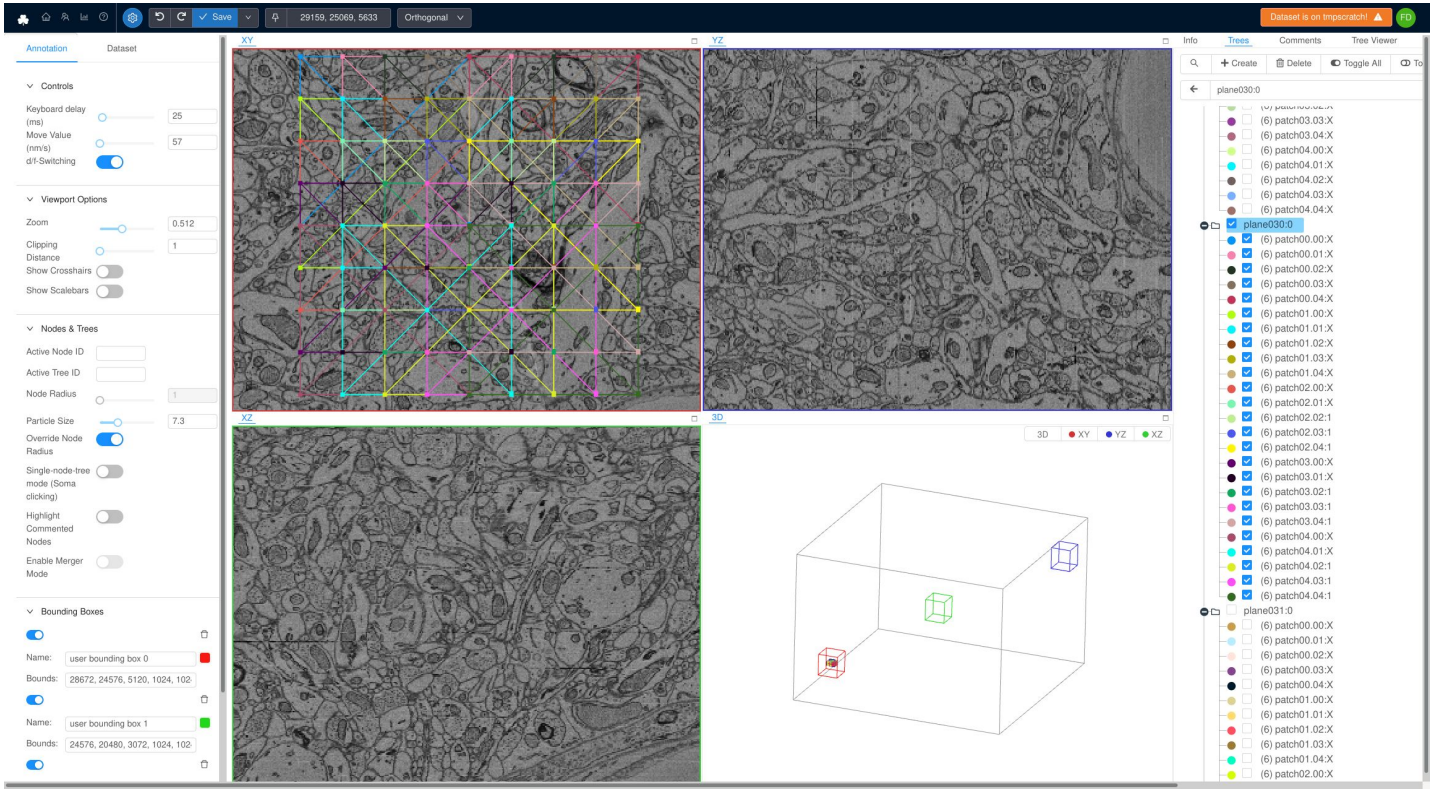
- Circular artifact
  https://webknossos.brain.mpg.de/datasets/Connectomics_Department/2018-11-13_scMS109_1to7199_v01_l4_06_24_fixed_mag8_artifact_pred/view#20952,15727,1336,0,0,467
- Fold
  https://webknossos.brain.mpg.de/datasets/Connectomics_Department/2018-11-13_scMS109_1to7199_v01_l4_06_24_fixed_mag8_artifact_pred/view#20725,15822,1362,0,0,467
- Horse shoe
  https://webknossos.brain.mpg.de/datasets/Connectomics_Department/2018-11-13_scMS109_1to7199_v01_l4_06_24_fixed_mag8_artifact_pred/view#20686,15980,1380,0,0,319

The bad & ugly

- Myelin (bad)
  https://webknossos.brain.mpg.de/datasets/Connectomics_Department/2018-11-13_scMS109_1to7199_v01_l4_06_24_fixed_mag8_artifact_pred/view#20795,15782,1389,0,0,263
- Blood vessel (bad)
  Not covered by current predictions but known from previous experience

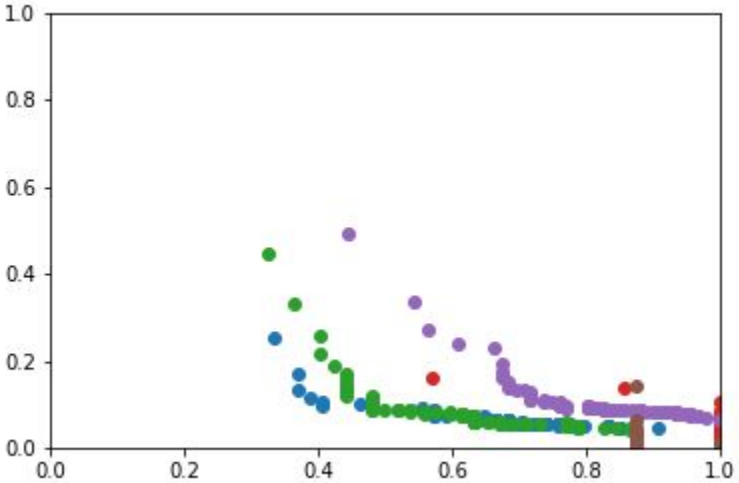
Inference on wk data: test data evaluation

- 3 distributed test boxes, each (10x10x2) um^3
- Used skeleton tracing for classification: Each prediction patch indicated by tree, all patch trees of one plane are part of one tree group
- -> comment hierarchy labels patches



Inference on wk data: test data evaluation

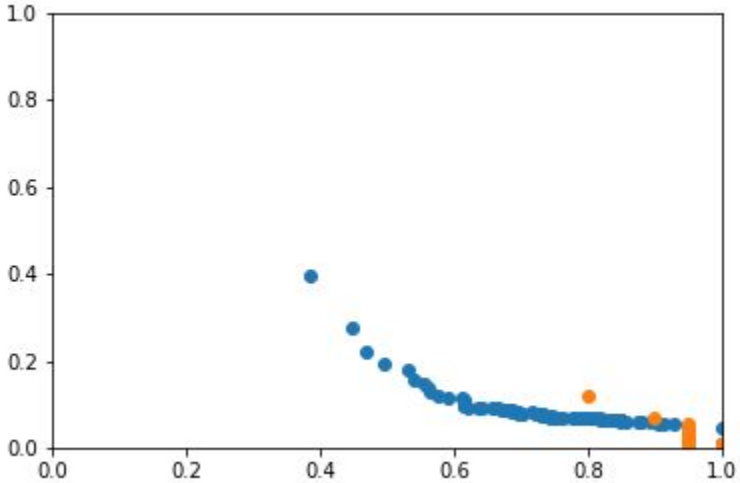
Pred test boxes separate



	condition_positive	condition_negative
predicted_positive	145	1784
predicted_negative	53	2293

Precision = tp/(tp+fp) = 145/(145+1784) = 0.10
Recall = tp/(tp+fn) = 145/(145+53) = 0.73

Pred test boxes combined

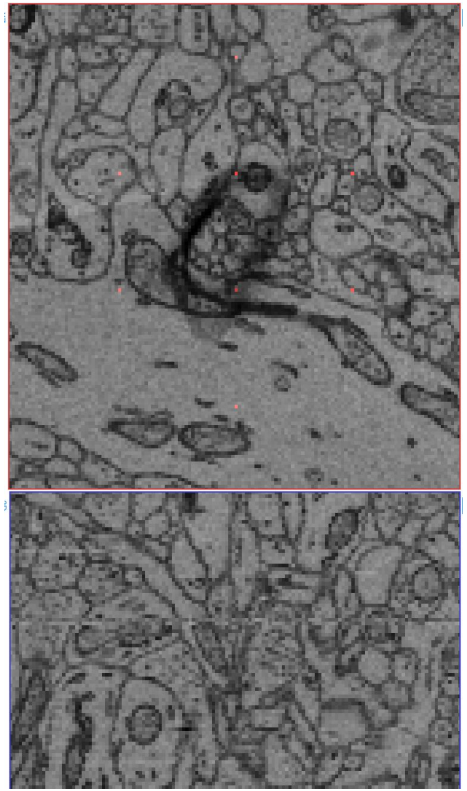


	condition_positive	condition_negative
predicted_positive	12	381
predicted_negative	3	3732

Precision = tp/(tp+fp) = 12/(12+381) = 0.03
Recall = tp/(tp+fn) = 12/(12+3) = 0.80

Inference on wk data: test data evaluation

- What we know about artifacts:
- Even small artifact spread (focally, xy-plane) over multiple prediction patches
- However, artifacts don't extend over multiple planes (axially). Instead, positive predictions extending over multiple planes might correspond to blood vessels, myelin etc.
- -> apply this geometrical prior to sparse predictions



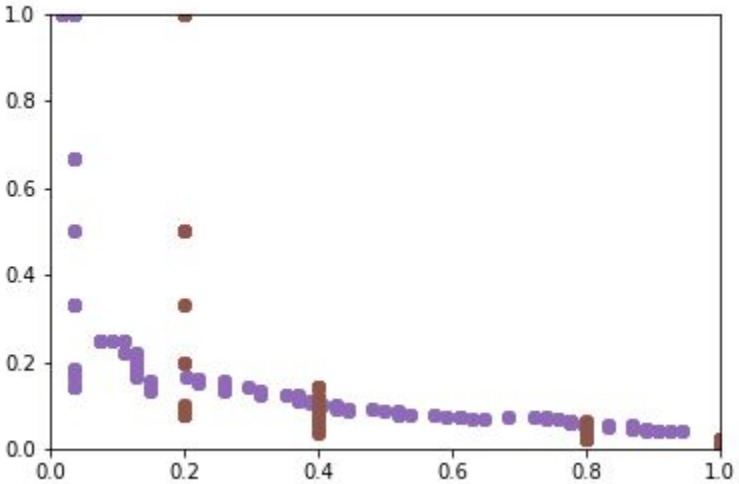
```
pred_filt = pred * kernel

kernel = array([
        [
            [-0.025, -0.05 , -0.025],
            [-0.05 ,   -0.2  , -0.05 ],
            [-0.025, -0.05 , -0.025]
        ],[
            [0.125,  0.25 ,  0.125],
            [ 0.25,    0.5  ,  0.25 ],
            [0.125,  0.25 ,  0.125]
        ],[
            [-0.025, -0.05 , -0.025],
            [-0.05 ,   -0.2  , -0.05 ],
            [-0.025, -0.05 , -0.025]
        ]])
```

- Problem: smears out bimodal probability distribution
- Instead: Morphological operations?

Inference on wk data: test data evaluation

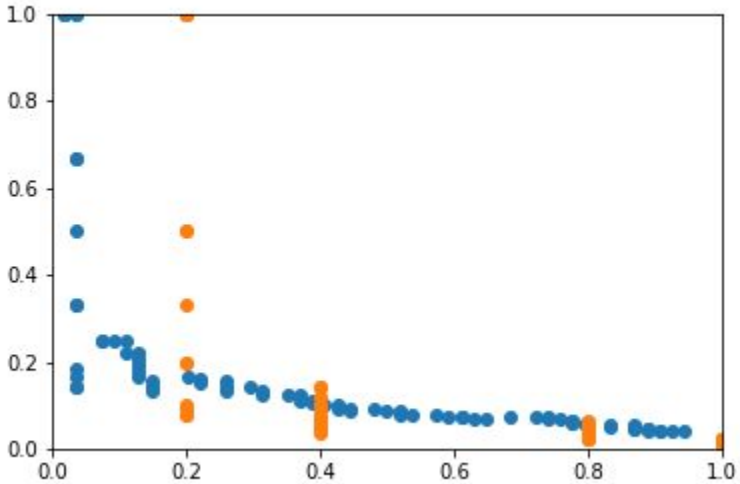
Pred filtered test boxes separate



	condition_positive	condition_negative
predicted_positive	51	381
predicted_negative	111	3732

Precision = tp/(tp+fp) = 51/(51+381) = 0.12
Recall = tp/(tp+fn) = 51/(51+111) = 0.31

Pred filtered test boxes combined



	condition_positive	condition_negative
predicted_positive	12	381
predicted_negative	3	3732

Precision = tp/(tp+fp) = 12/(12+381) = 0.03
Recall = tp/(tp+fn) = 12/(12+3) = 0.80

Inference on wk data: Todo

-> Explain extreme performance drop

- Validate by running inference on traindata
- If train metrics reproducible using inference code (model weight loading etc.):

<u>Problem could be real</u>

- Rooted in actual encoding + classification performance
  -> re-train network with much more artifact-free data

<u>Problem could be pseudo</u>

- Unexpected cause
  -> strange effect of batch norm
  -> inference bug
  -> metrics bug

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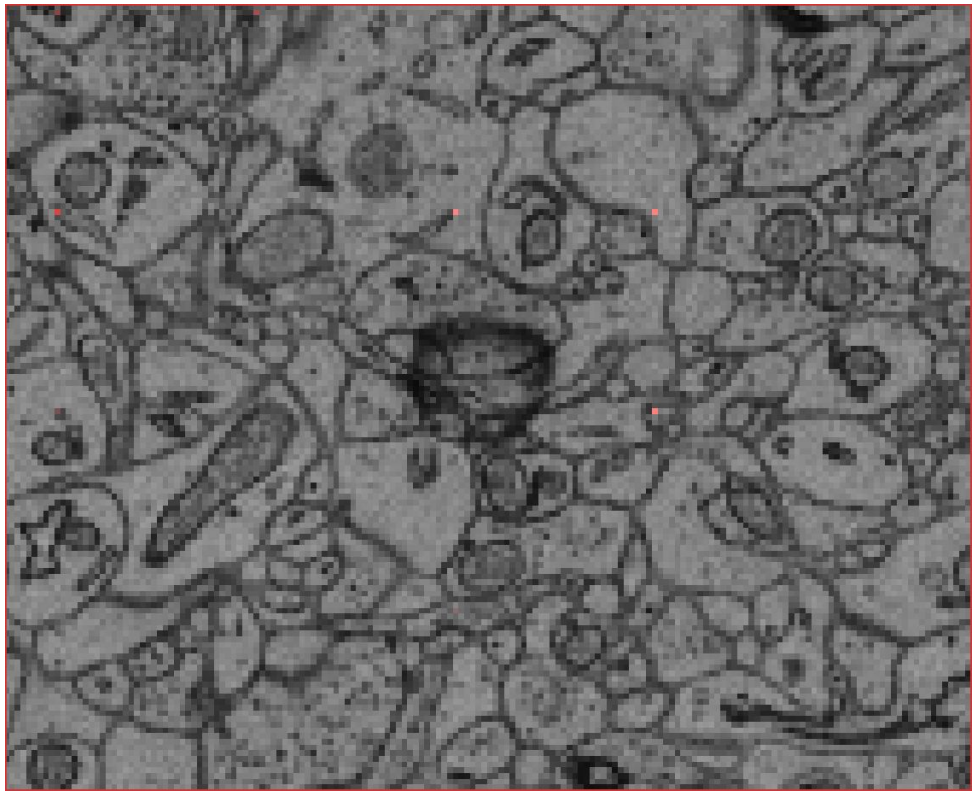
Philip Bastians

Appendix: Qualitative observations prediction quality



Observation

Prediction peak not centered on artifact

Possible cause

Artifact class not represented robustly enough in traindata (e.g. represented with low n + off-center)

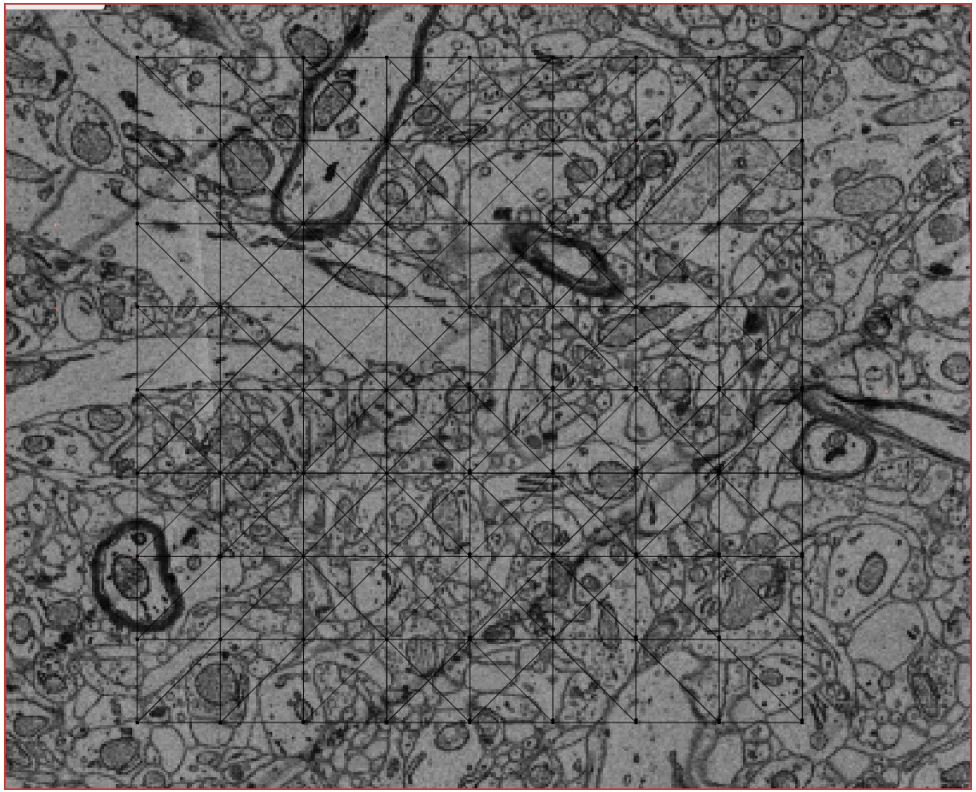
Possible alleviation

Increase availability in traindata

- Add more (e.g. selectively for certain artifact size ranges)
- Augment more (current wiggling with stride 35)

https://webknossos.brain.mpg.de/annotations/Explorational/5f5622a401000010004af1c6#29133,25108,5630,0,0,200,8034

Appendix: Ground truth for raw data fringe cases



Artifact or no artifact?

Equidistant dark stripes

https://webknossos.brain.mpg.de/annotations/Explorational/5f569d4001000050004afa25#20970,15849,1540,0,0,360

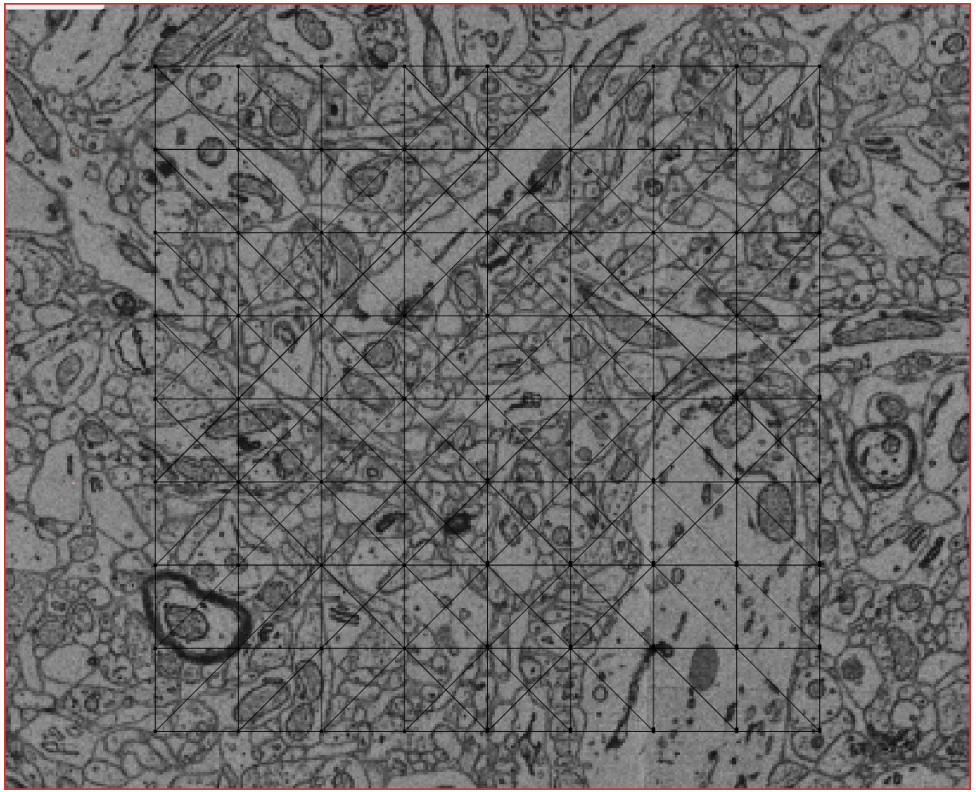
Appendix: Ground truth for raw data fringe cases

Artifact or no artifact?

Brightness variation

https://webknossos.brain.mpg.de/annotations/Explorational/5f569d4001000050004afa25#20970,15849,1540,0,0,360

Appendix: Ground truth for raw data fringe cases



Artifact or no artifact?

Out of focus

https://webknossos.brain.mpg.de/annotations/Explorational/5f569d4001000050004afa25#20970,15849,1552,0,0.360