3D CNN for inverse EEG problem

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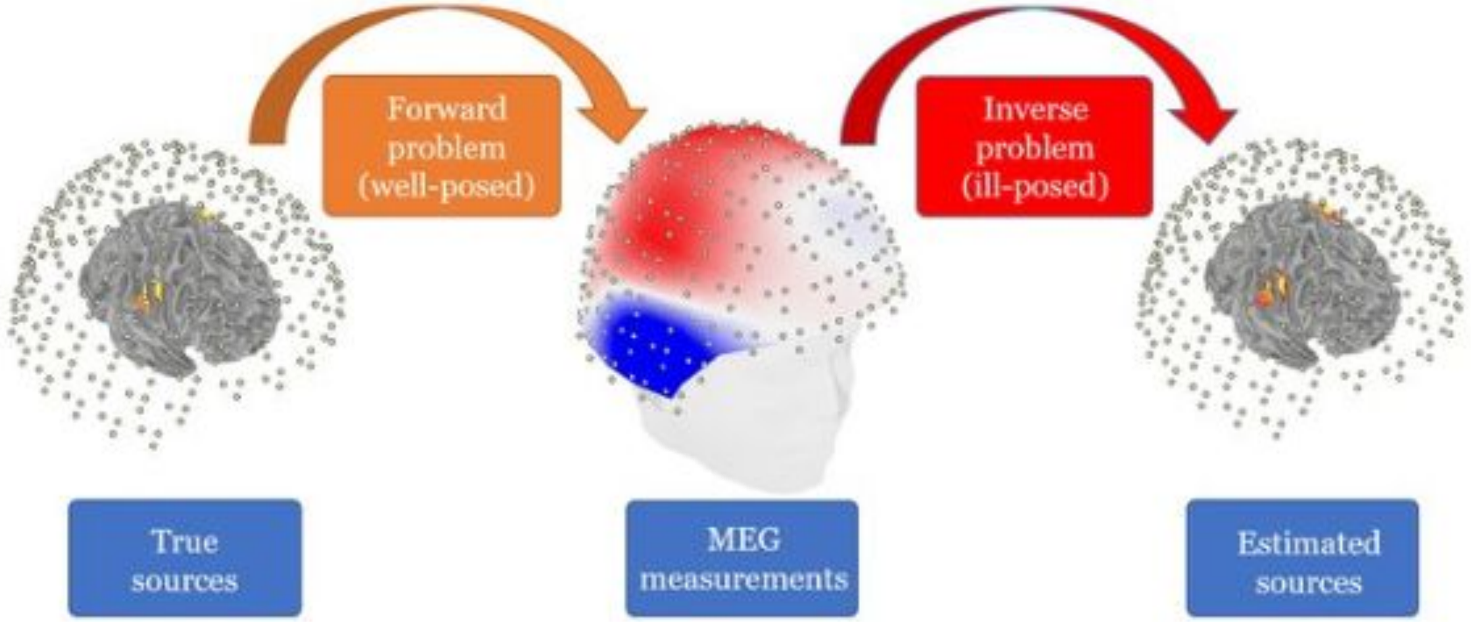
Andrei Kalinichenko
Victor Kozhevnikov
Pavel Tikhonov

Problem

Inverse problem of encephalography is
- ill posed
- underdetermined (more dipoles then measurements/sensors)



[MEG forward and inverse problems]

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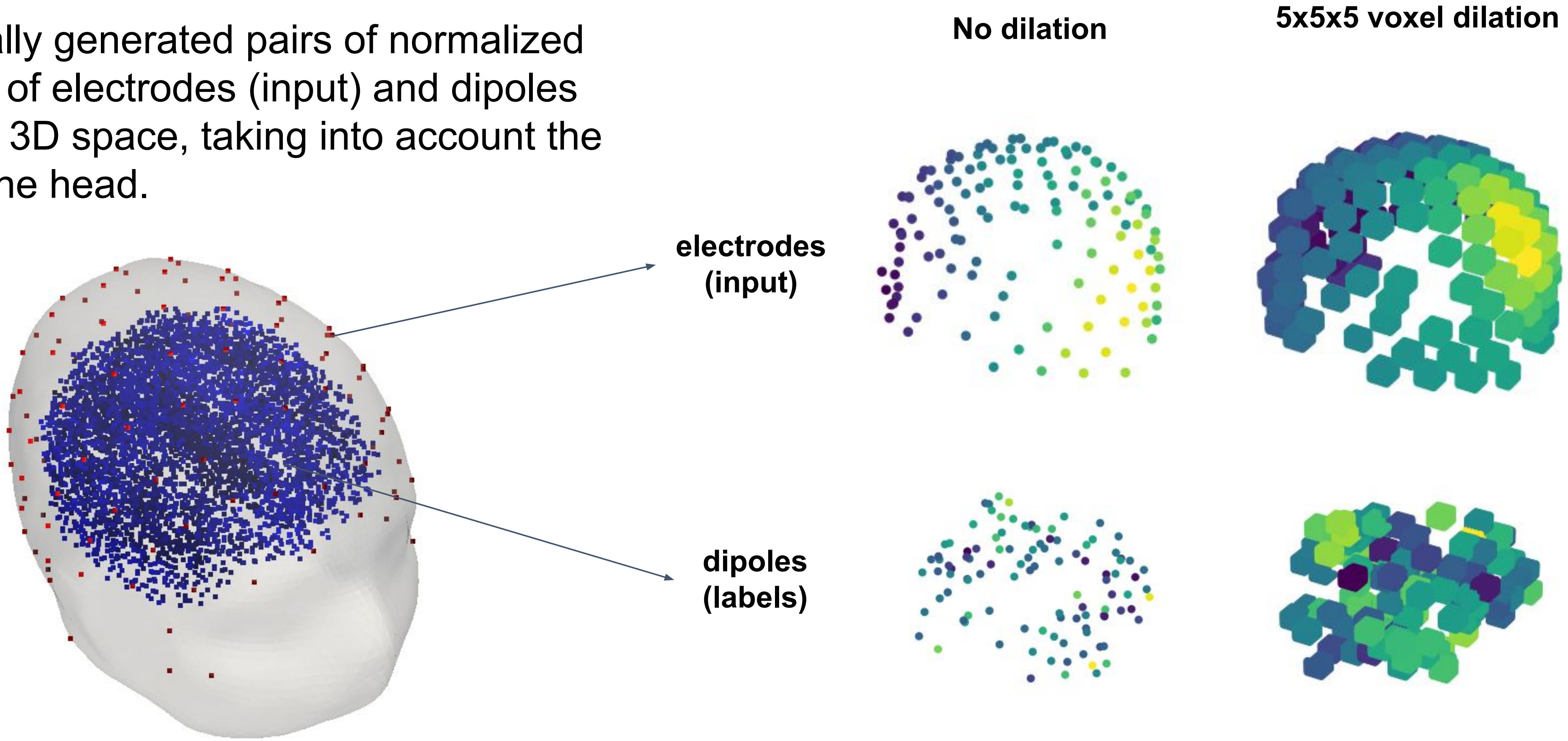
Methods

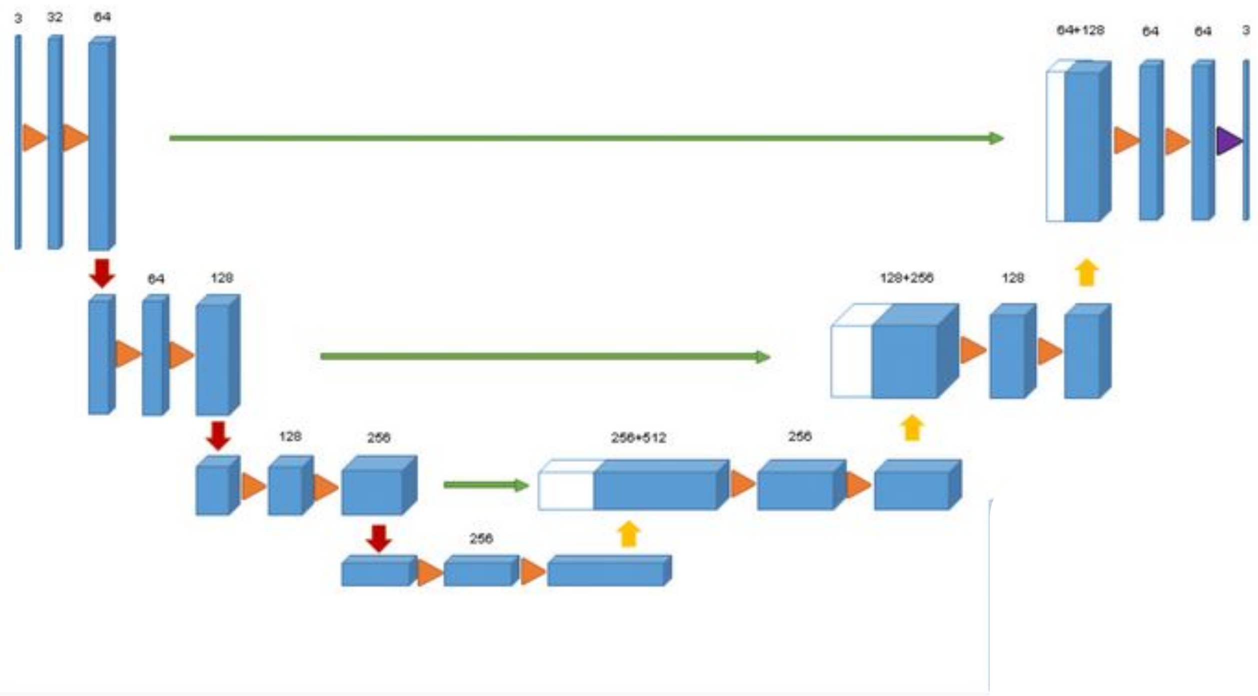
	Advantages	Disadvantages
Numerical solutions: - equivalent current dipole - distributed dipole model *Sarvas J., 1987*	- theoretically proven - can be interpreted	- requires explicit regularization
2D CNN *Razorenova A. et al. , 2020* *Hecker L. et al. , 2021*	- stability with respect to noise - in some problem statements outperform classical approach	- a lot of training data that can only be modeled - interpretation problem
3D CNN (proposed)	- preserving spatial information about the distribution of the dipoles - taking into account anatomical differences in different subjects	

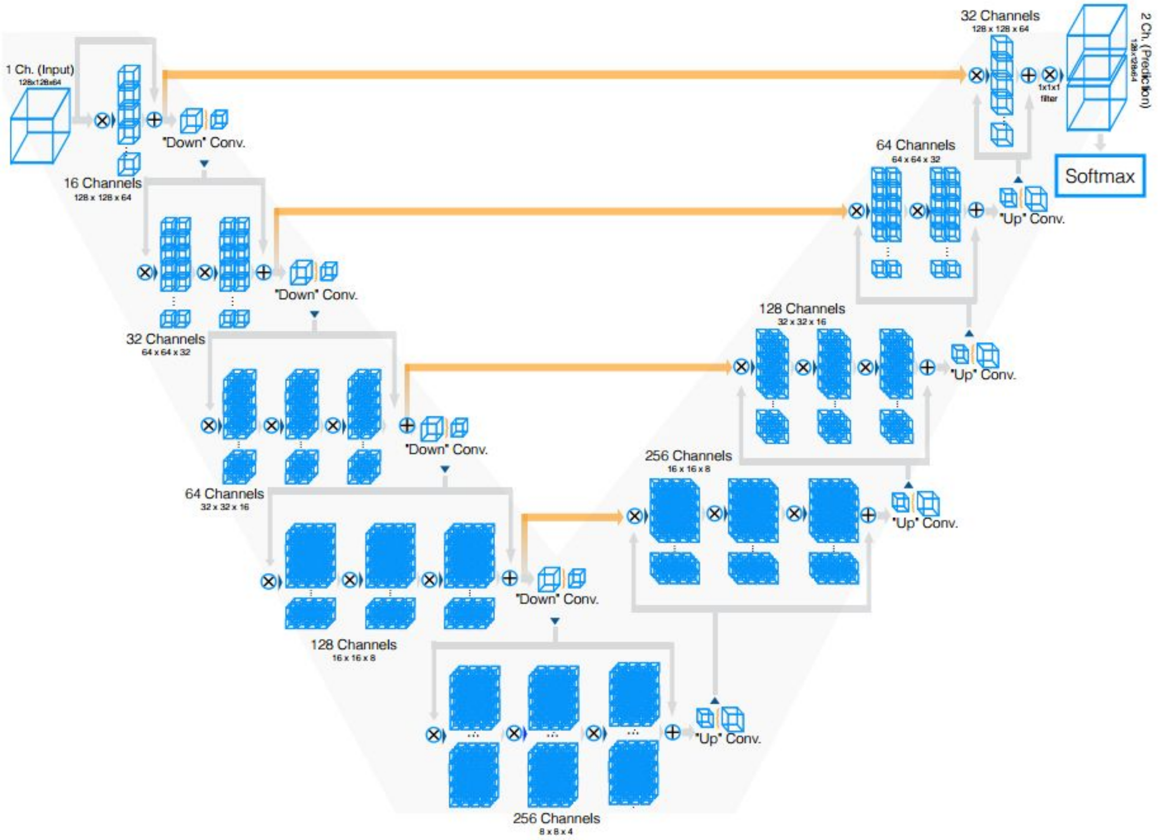
Data and preprocessing

Synthetically generated pairs of normalized intensities of electrodes (input) and dipoles (output) in 3D space, taking into account the shape of the head.



3D UNet and VNet encoders architecture that proposed to solve the inverse problem

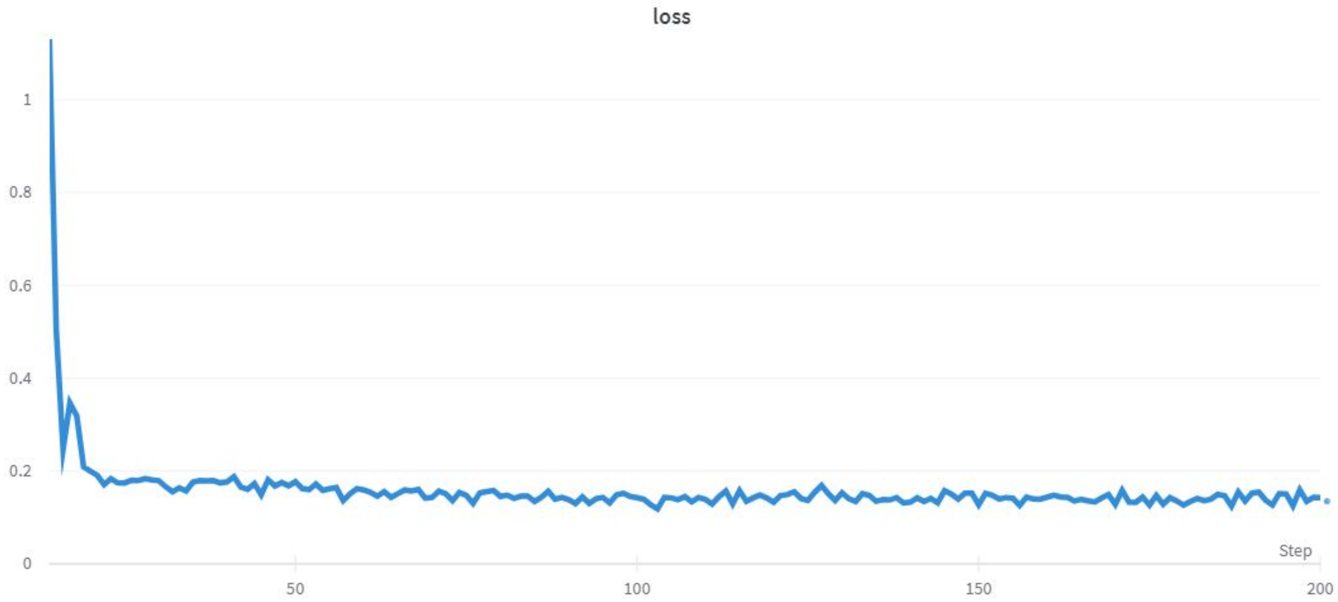




Source:
- 3DUnet description: *Çiçek Ö. et al., 2016*
- model realization: https://github.com/wolny/pytorch-3dunet

Source:
- VNet description: *Milletari F., et al., 2016*
- model realization: https://github.com/Dootmaan/VNet.PyTorch

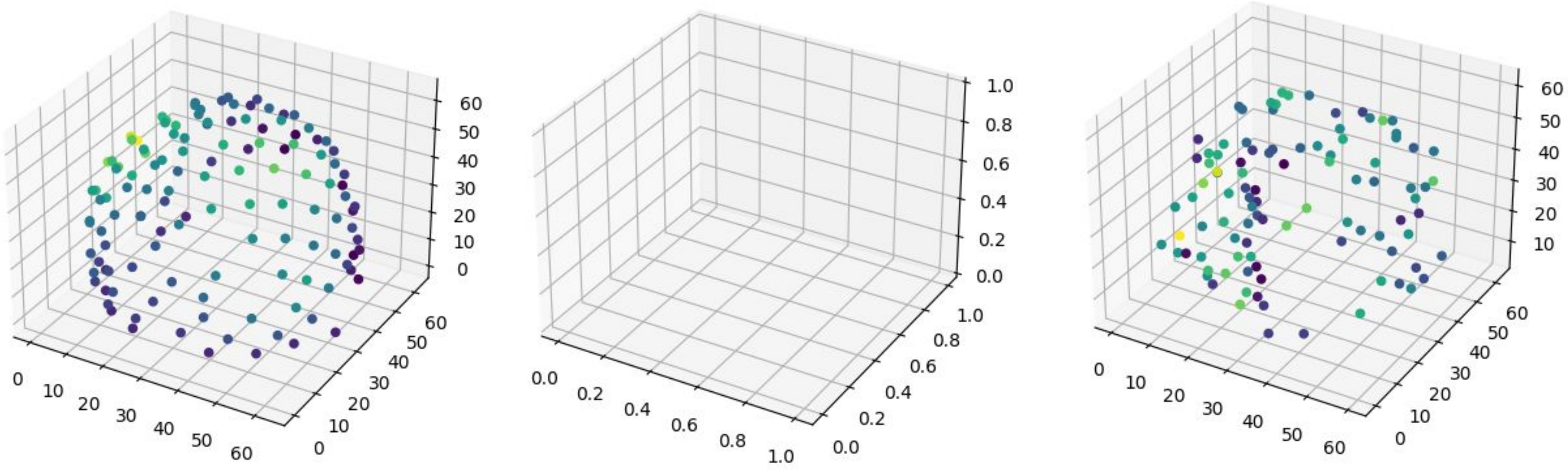
Parameters search results for 3D U-Net



Problem: data is very sparse -> the model predicts zero background

Proposed solutions:

- increase the value of true labels
- increase the volume of true region
- reformulate the task as a classification problem



Parameters search results for V-Net

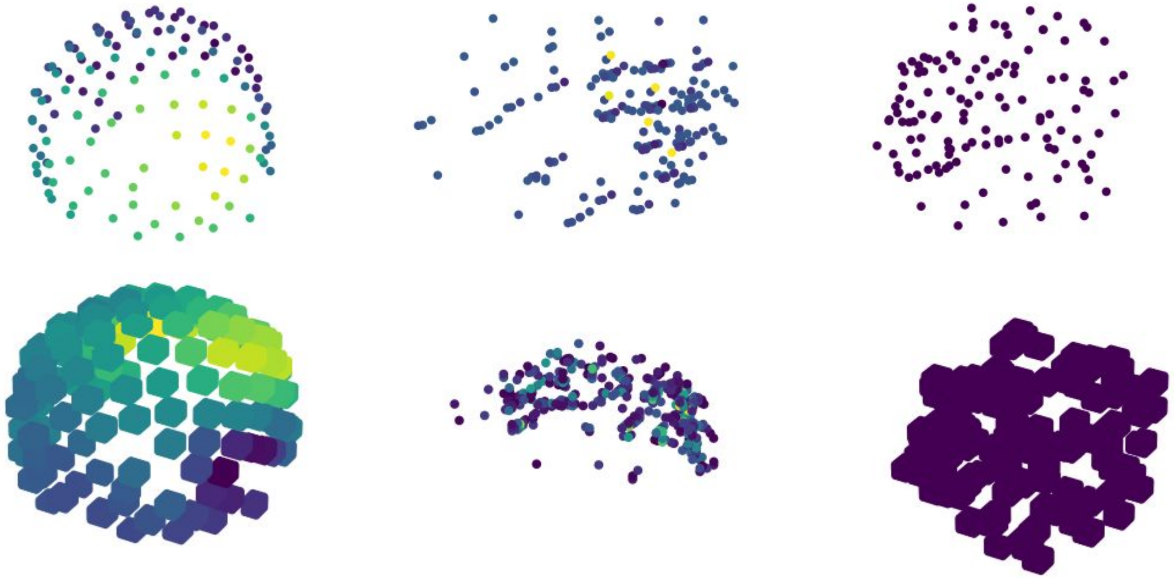
Parameters for classification:

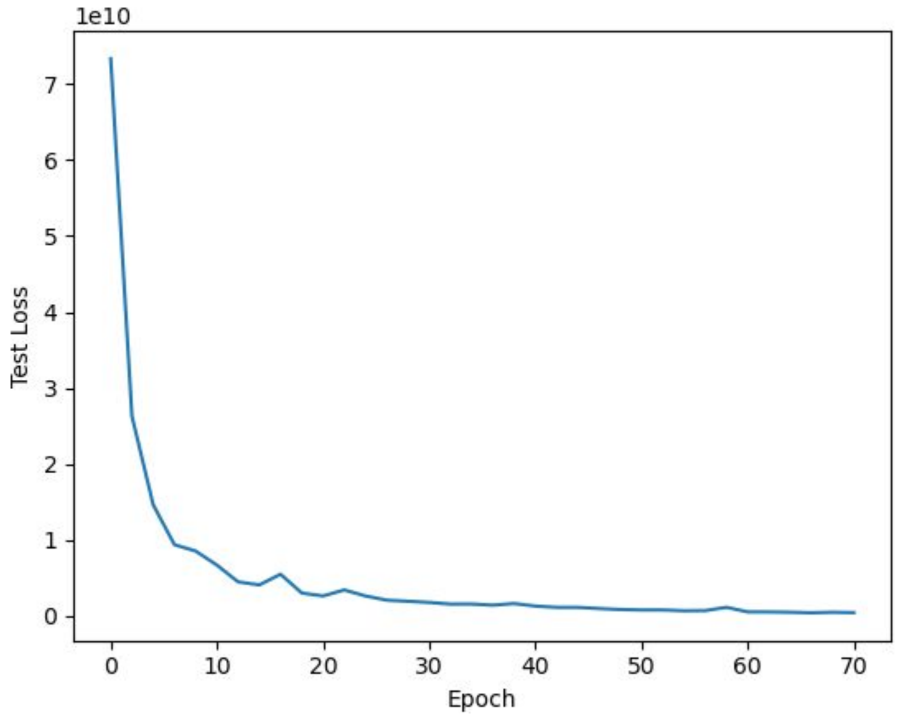
loss: CrossEntropyLoss
weights: 1e-7 - background, 1 - signals
optimizer: Adam
learning_rate: 1e-3
weight_decay: 1e-4

Input volume | Prediction | True state

No dilation

5x5x5 voxel dilation





Loss dynamics for training with best parameters on non dilated small dataset

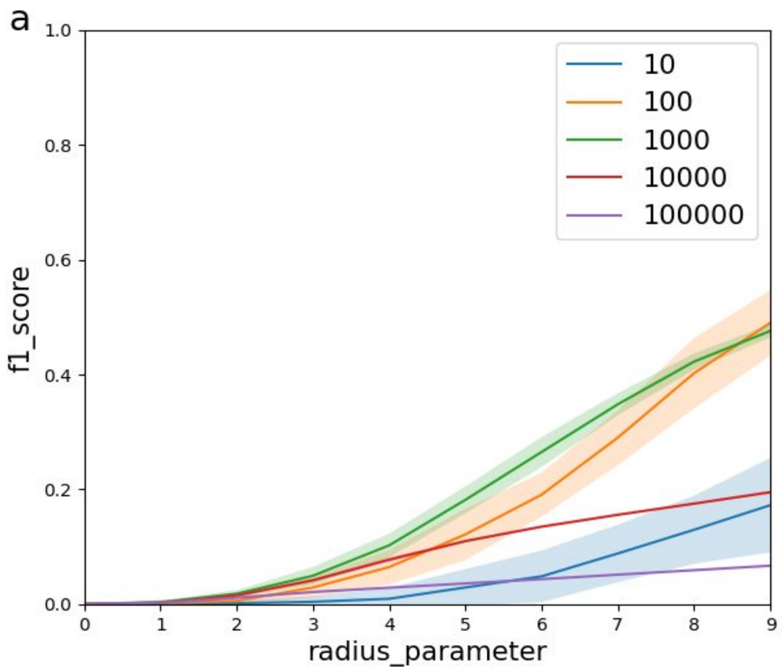
Metric

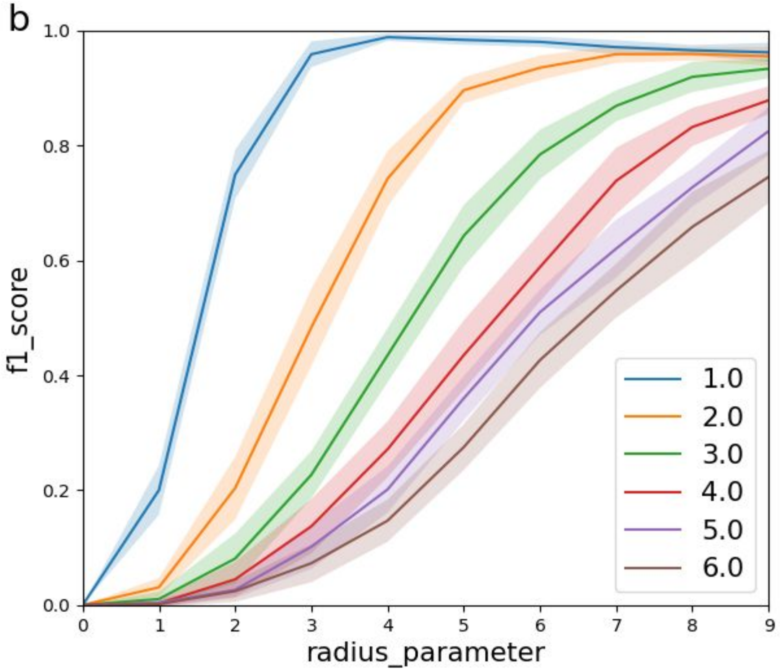
$$TP = \sum_{i=1}^{n} [\exists j \in [1, m] : |y_i - \hat{y}_j|_2 \leq r]$$

$$FP = m - TP$$

$$FN = n - TP$$

To evaluate the results with this metric we are comparing it with the results obtained on the same amount of predicted and true dots in the same space





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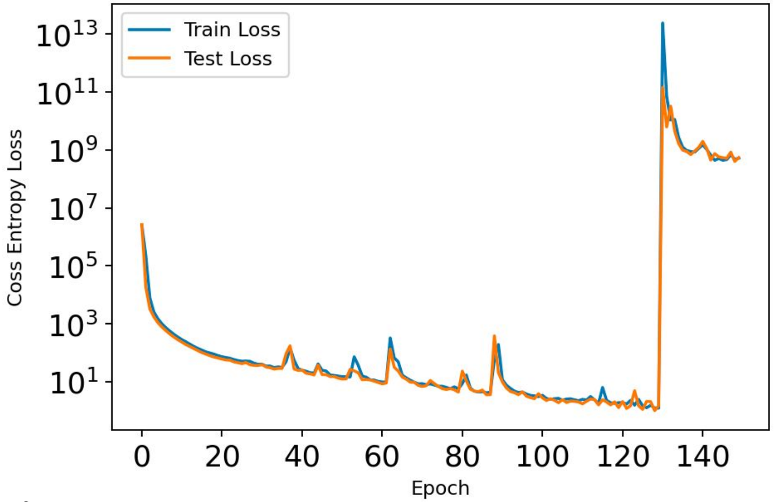
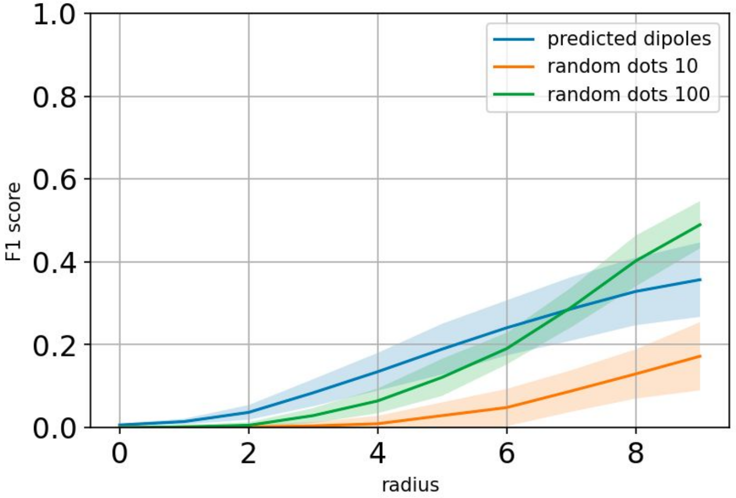
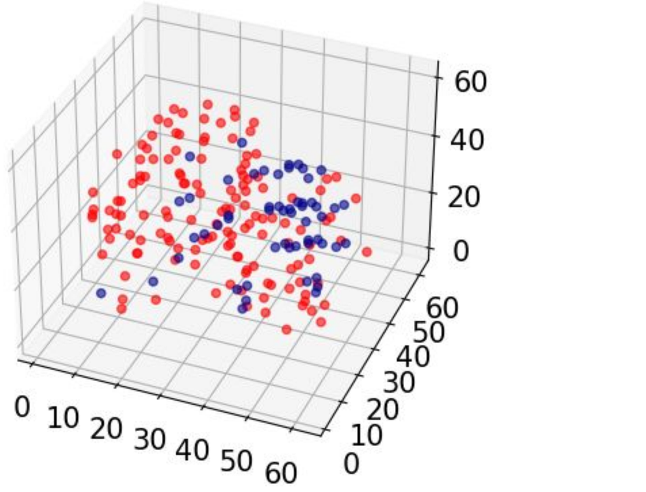
Training results for VNet on full dataset

a - results for original dataset
b - results for dilated dataset

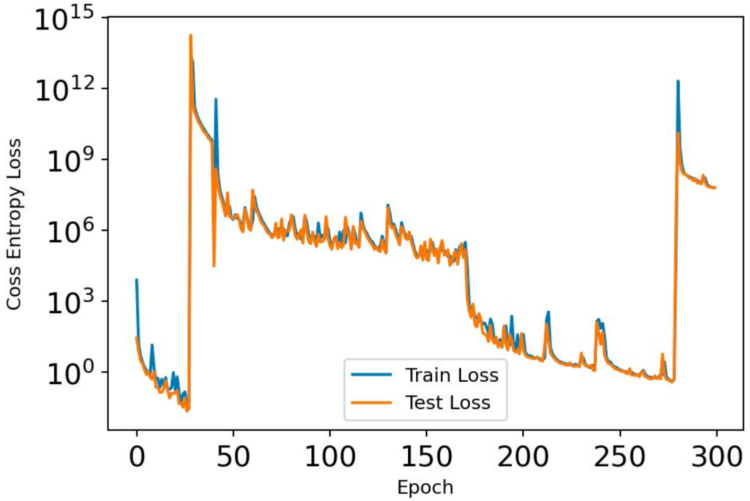
a

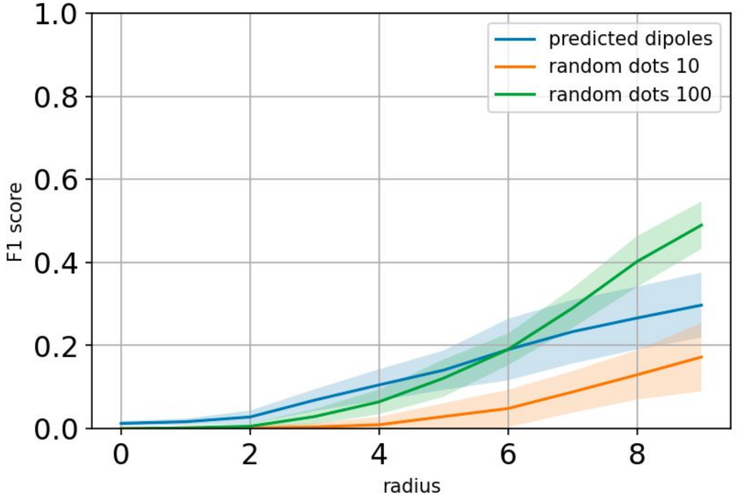


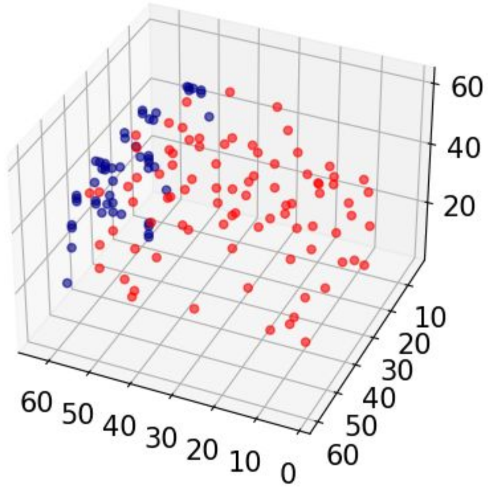




b







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Conclusions

- Only with VNet on the classification model for both datasets were we able to achieve any appreciable learning

- in all other cases, the prediction was an empty image. With the original dataset, we had a little bit more success in producing findings that were superior to random.

- Though it is insufficient to compete now with any current prediction method, we have discovered the optimal parameters to create the VNet model and train some pattern.

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Q&A

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