peaks2maps: reconstructing unthresholded statistical maps from peak coordinates using deep neural networks

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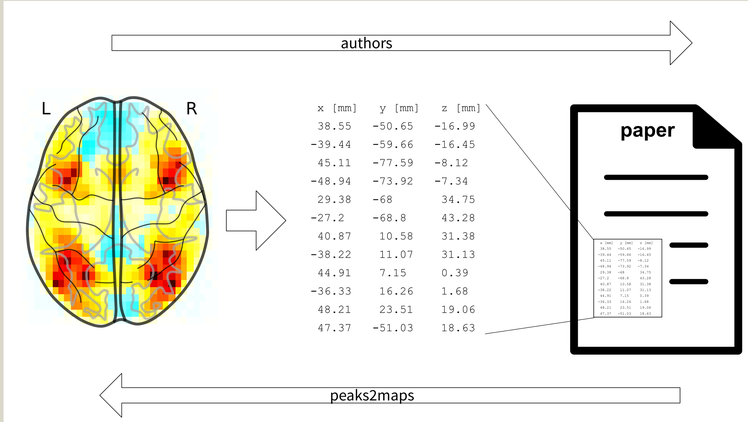
The problem

Meta analysis is a way of statistically **evaluating if results across multiple studies are consistent**.

In brain mapping meta analysis looks at **consistency of brain patterns reported in the literature**.

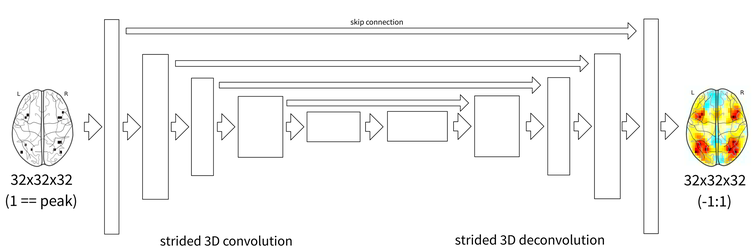
Most papers only **report locations of peak coordinates** instead of a full brain pattern.

Can we train a model **reconstructing brain patterns (unthresholded maps) from just coordinates of peaks**?



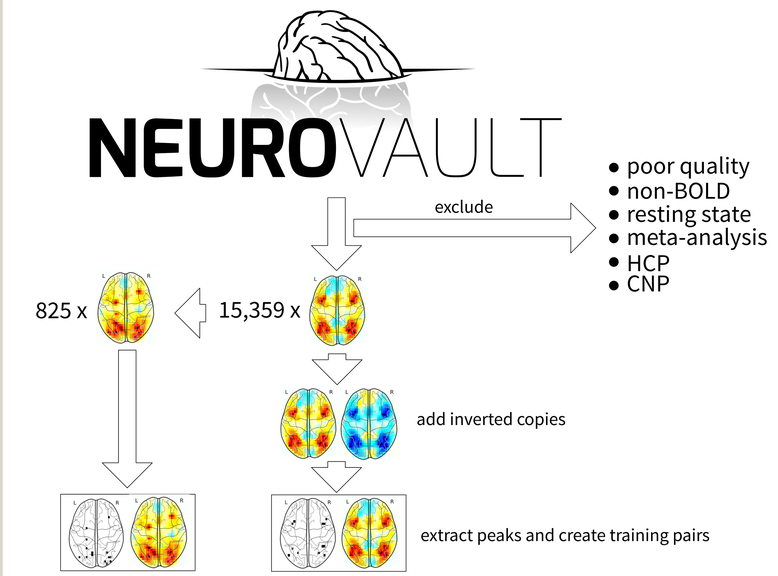
Data reduction problem. Through statistical inference otherwise known as thresholding, brain patterns are reduced to a set of regions or groups of voxels. Coordinates in a standardized space of peaks in those regions are then reported in the literature. peaks2maps is a model that reverses this process reconstructing maps from peak coordinates.

The model

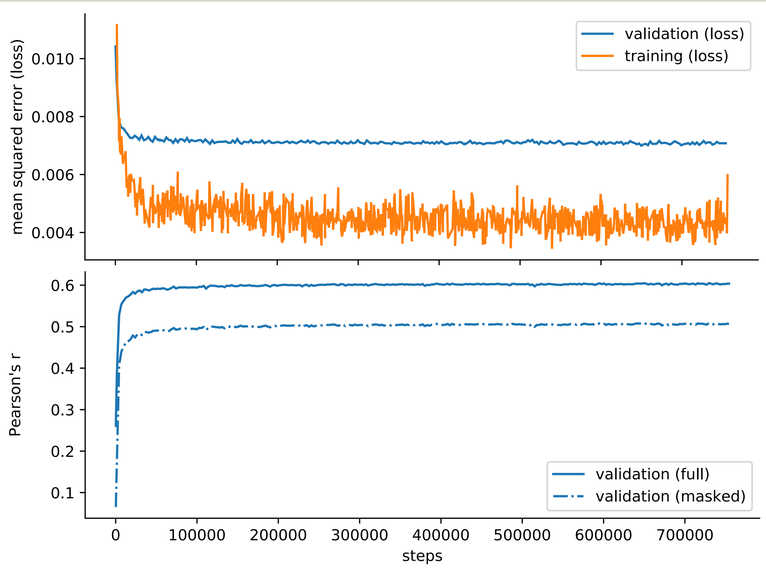


Model architecture. 10 layer U-Net 3D autoencoder with skip connections [1] was used to reconstruct unthresholded 3D maps (downsampled to 32x32x32) from a binary representation of the peak locations implemented via one hot encoding. Batch normalization was used to improve training speed and dropout (at 20% level) was used to avoid overfitting.

Training



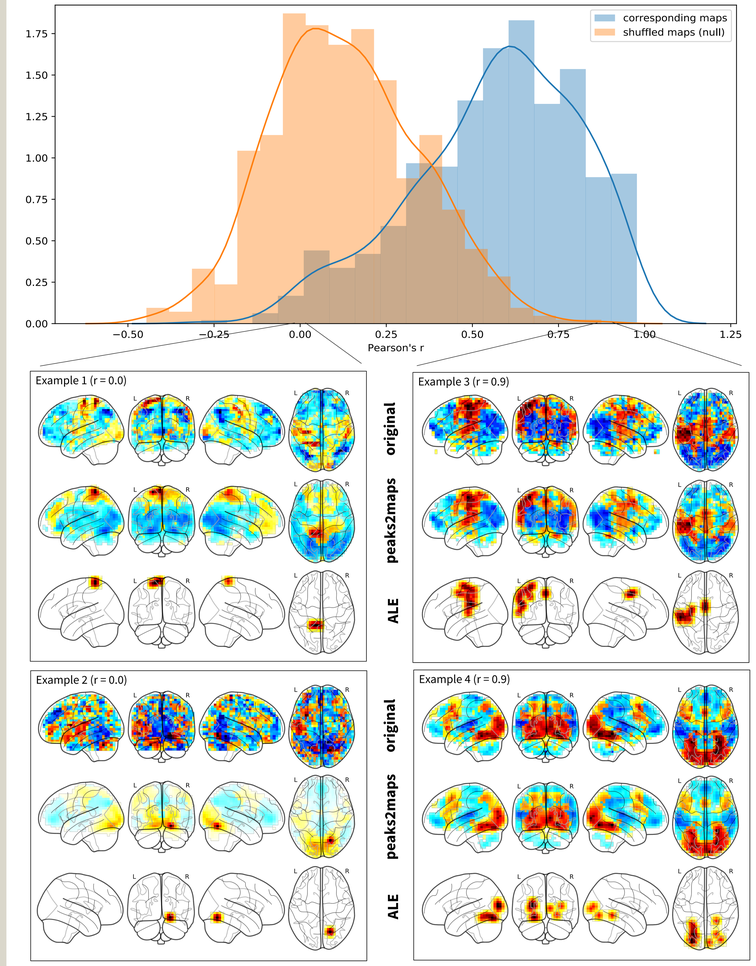
Data preprocessing pipeline. All training and evaluation data was obtained from the NeuroVault.org [2] repository. 15,359 maps survived data exclusion and 825 were set aside as validation set. Data augumentation in a form of intensity inversion was performed. All maps were resampled to 32x32x32 prior to training. Intensity of the maps was normalized so max(abs(x)) == 1. Maps with no supratrheshold voxels were excluded.



Training dynamics. Training was performed on a Titan Xp with batch size of 40 images and Adam optimizer. The loss function quickly converged, showing only minimal improvements with more training, but also no signs of overfitting. Spatial correlation with original image was high even after excluding immediate vicinity of the peaks (masked correlation).

Evaluation

Advanced evaluation. To check if the model is learning something more than an average map we performed a permutation test. We compared the distribution of pairwise correlation between original and reconstructed maps to a null distribution where each reconstructed map was correlated with a random original maps. Best and worst reconstructions (along original images and ALE [3] reconstructions) are shown below.



References

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