



Planar 3D Transfer Learning for End to End Unimodal MRI Unbalanced Data Segmentation

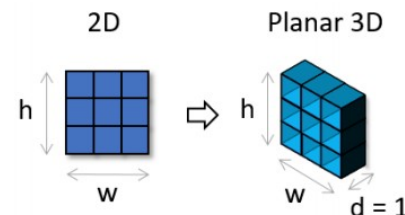
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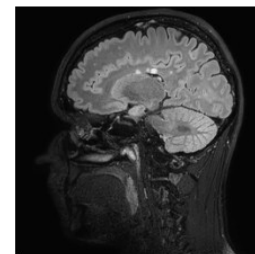


Introduction

- Paper presents novel 2D \rightarrow 3D transfer learning method for semantic segmentation
- Experiments evaluated on Multiple sclerosis lesion segmentation from unimodal MRI Flair scan
 - Heavily unbalanced segmentation
- Complete source code published:
 - <https://github.com/mrkolarik/transfer2d3d>



(a) Convolutional kernel mapping from 2D to 3D



(b) Raw MRI Sagittal scan

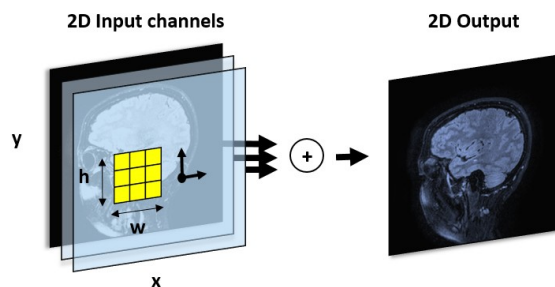


(c) Segmentation mask

Motivation 1# – 2D vs 3D convolutional nets

2D Convolutional networks

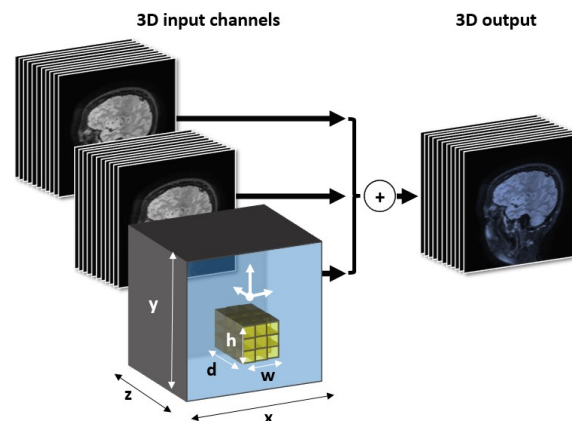
- + Suitable for 2D data
- Processing 3D volume slice by slice
- + Availability of transfer learning



VS

3D Convolutional networks

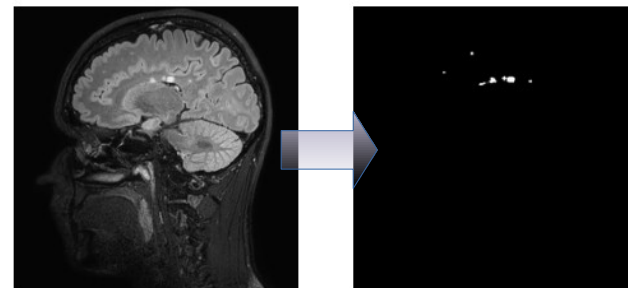
- + Suitable for 3D data
- + Processing 3D data as volumes
- Lack of sources of transfer learning



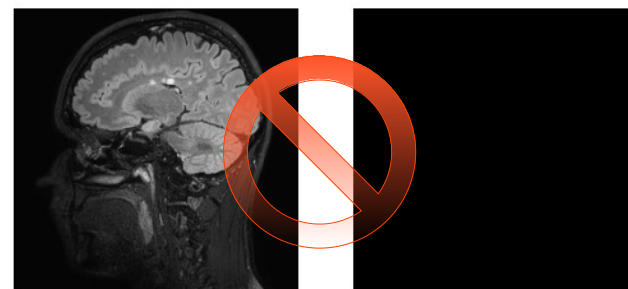
Motivation 2# – segmenting unbalanced data

- Network's aim is to minimize loss function during training
 - Segmenting heavily unbalanced data is problematic
 - Network easily converges to wrong solution (negative output)
- Solutions:
 - Specialized loss functions
 - Class / sample weighting
- Problematic when using large 3D feature size (our case 16x256x256)

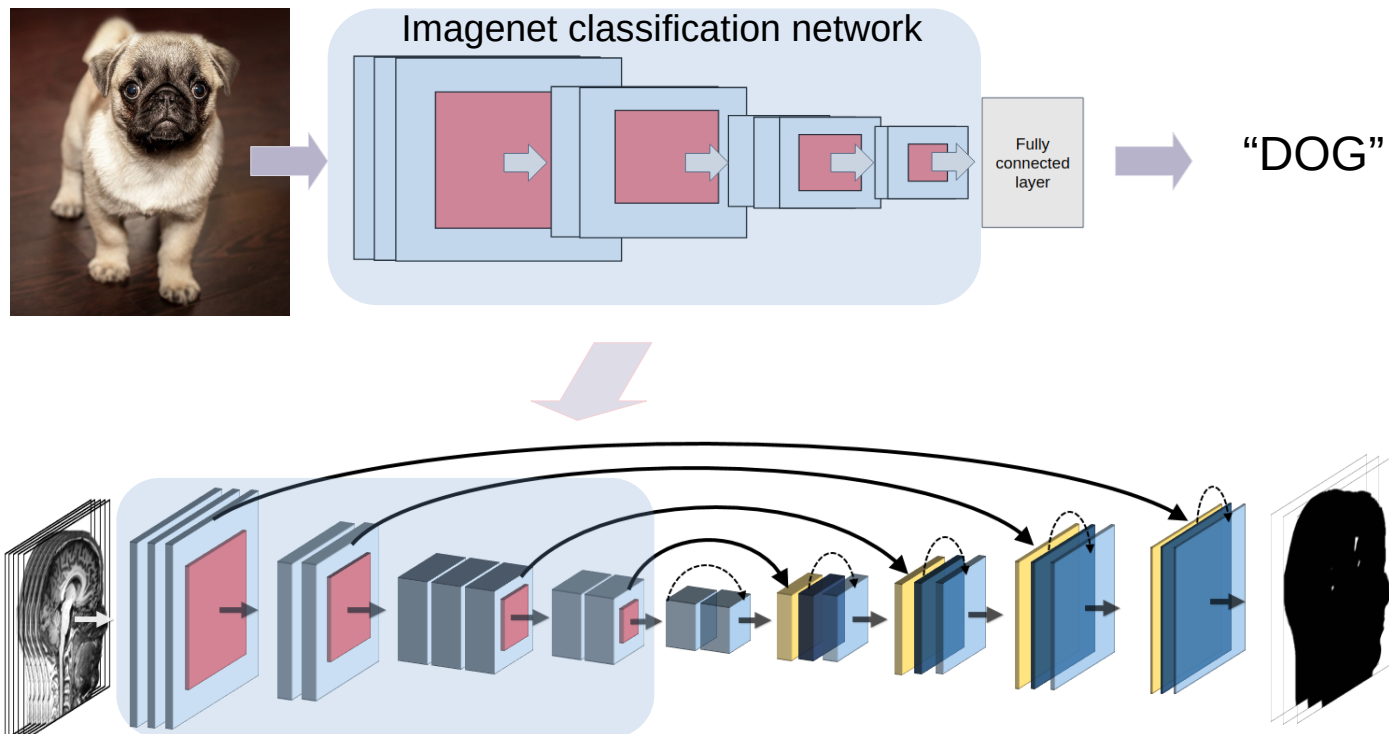
Correct result



Wrong segmentation

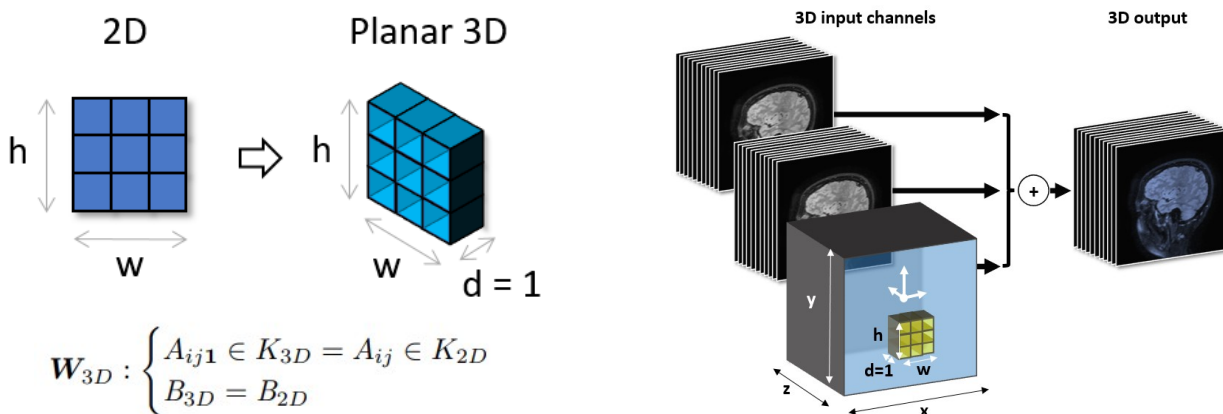


Transfer learning in semantic segmentation



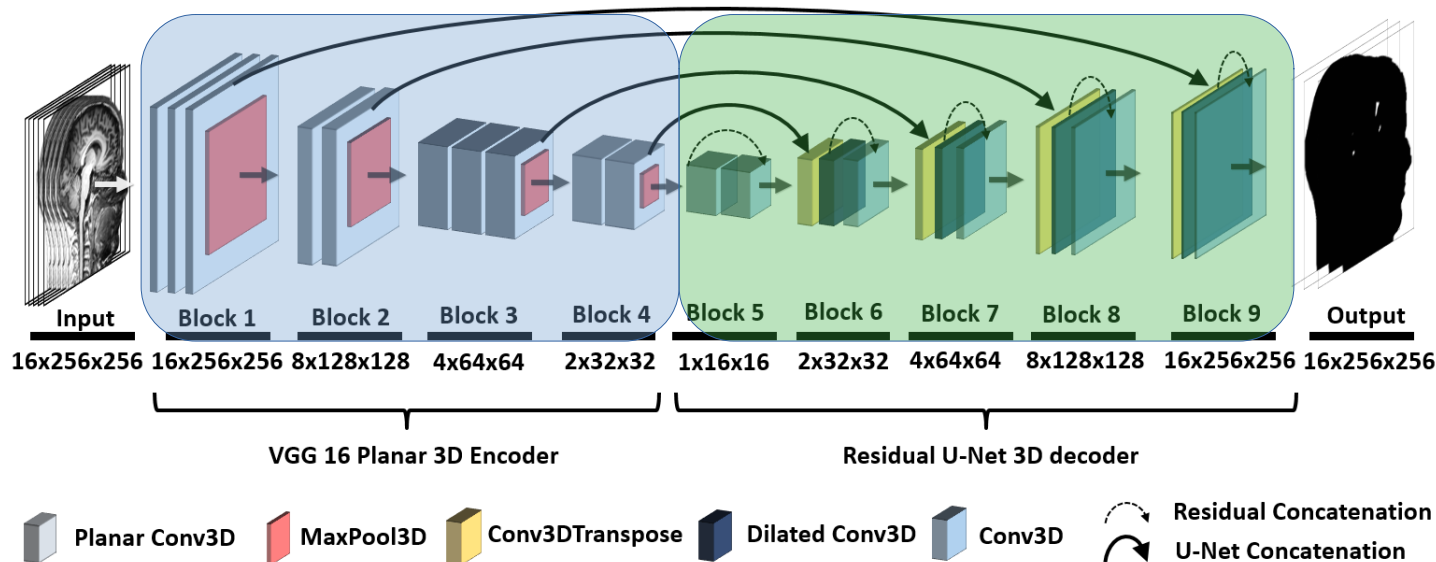
Weights transformation 2D → Planar 3D

- Aim is to combine the 3D data processing capability of 3D neural networks with 2D domain transfer learning sources availability
- We present a mapping operation of convolutional neural network weights from 2D to Planar 3D
 - application in transfer learning for semantic segmentation



Network architecture

Based on 3D U-Net with implemented residual skip connections and Planar 3D VGG Encoder

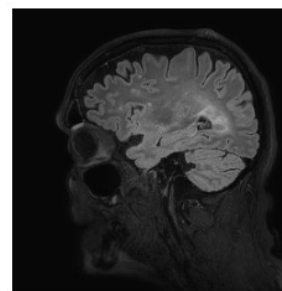


Data description

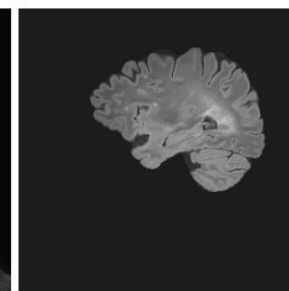
- MSSEG 2016 dataset
- The dataset consists of
 - 15 MRI head scans of
 - 15 different patients
 - Scanned from 3 different medical centers
- Data is heavily unbalanced
 - Lesion voxel ratio 0.2 %

Center	Lesion voxel ratio	Scans	Axial Resolution
01	0.311 %	5	144 × 512 × 512
07	0.141 %	5	128 × 224 × 256
08	0.144 %	5	261 × 336 × 336
Total	0.199 %	15	

Unprocessed scan



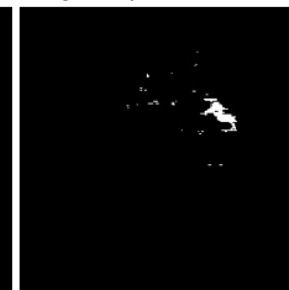
Pre-processed scan



Consensus mask



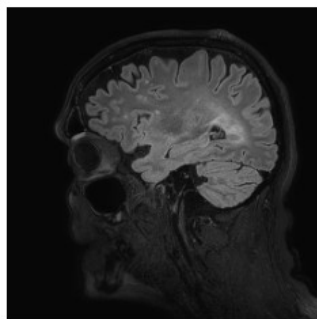
Single expert mask



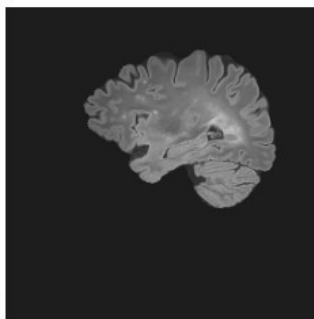
Results

- Our planar 3D res-u-net achieved a score of 0.611 for Dice coefficient
 - best published end to end method achieved score of 0.512
 - Best unimodal not end to end method achieved score of 0.598

Unimodal methods processing raw input data end-to-end			
Authors	End-to-end	Dice coef.	Sensitivity
Knight, et al. [42]	Yes	0.512 ± 0.014	0.45 ± 0.05
Our Result	Yes	0.611 ± 0.052	0.60 ± 0.10
Unimodal methods processing input data after brain extraction			
Authors	End-to-end	Dice coef.	Sensitivity
Mahbod, et al. [43]	No	0.448 ± 0.064	0.53 ± 0.03
McKinley, et al. [31]	No	0.598 ± 0.059	0.65 ± 0.03
Human expert results			
Expert annotation		Dice coef.	Sensitivity
Least precise human expert		0.670 ± 0.008	0.72 ± 0.06
Average human expert		0.705 ± 0.027	0.77 ± 0.02



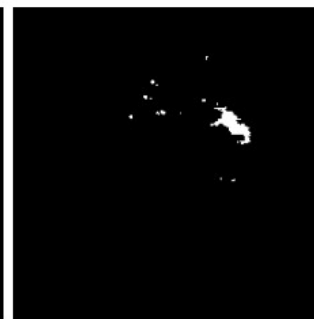
(a) Raw MRI FLAIR scan slice (our input)



(b) Pre-processed, brain extracted MRI



(c) Mask predicted by our system



(d) Consensus segmentation mask

Conclusion

- We presented a novel end-to-end learning approach to transfer learning utilizing mapping existing CNNs weights from 2D to planar 3D representation
- We have shown the effectiveness of our approach on the problem of heavily unbalanced data semantic segmentation
- We published complete source code under open-source license
 - Accompanying paper at the Reproducibility workshop

Thank you for your attention!