

# Multi-Dimensional Gated Recurrent Units for the Segmentation of Biomedical 3D-Data

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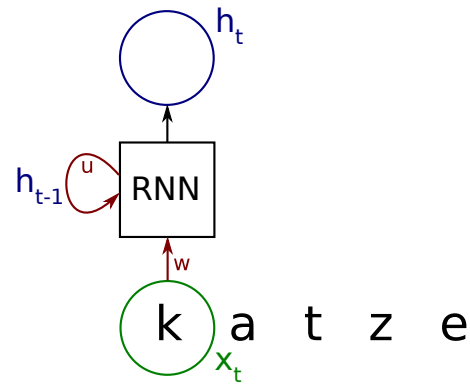
2nd Workshop on Deep Learning in Medical Image Analysis in Conjunction  
with MICCAI 2016

# RNN (Example)

text to text: translation

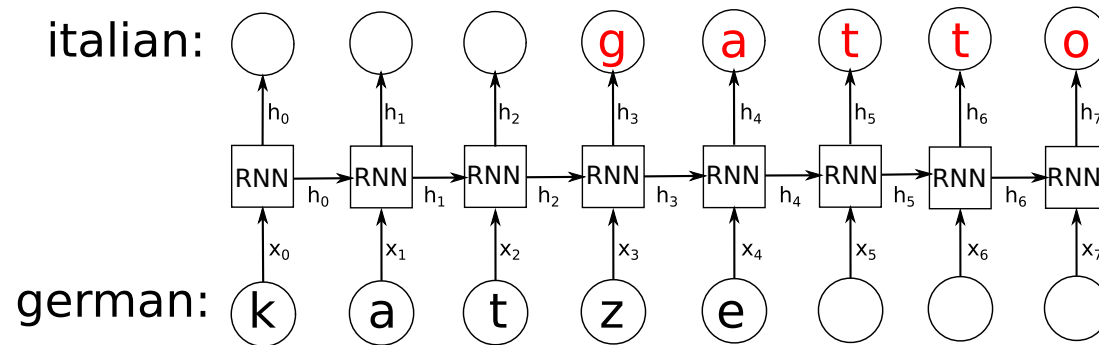
italian:

german:



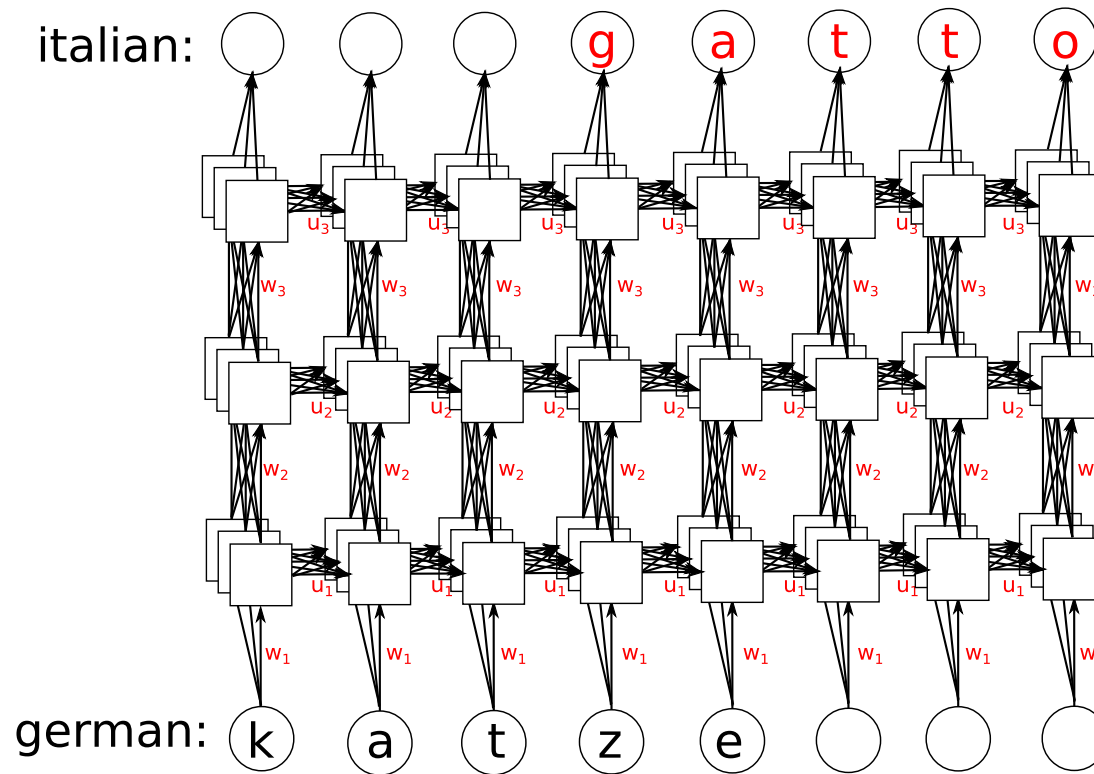
# RNN (Example)

## unfolded



# RNN (Example)

more likely setup



# Vanishing Gradient Problem

TanH	LSTM	GRU
<ul style="list-style-type: none"><li>• only one activation</li></ul>	<ul style="list-style-type: none"><li>• 3 gates, 1 state, 1 activation</li></ul>	<ul style="list-style-type: none"><li>• 2 gates, 1 state and activation</li></ul>

<http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

# Generalization to Multiple Dimensions

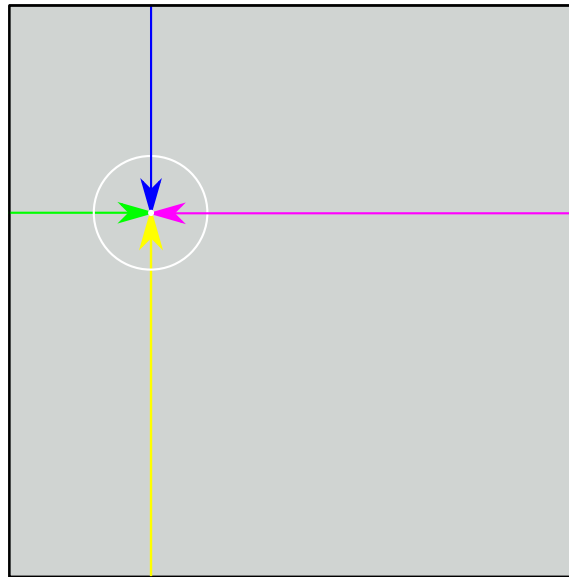
⚡ Time is one-dimensional

- Each dimension individually as time dimension! [1]
- For each RNN layer:
  - Apply RNN along each dimension in each direction
  - Sum intermediate results

[1] Stollenga, M.F., Byeon, W., Liwicki, M., Schmidhuber, J.: *Parallel Multi- Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation*. Advances in Neural Information Processing Systems 28, pp. 2998–3006. (2015)

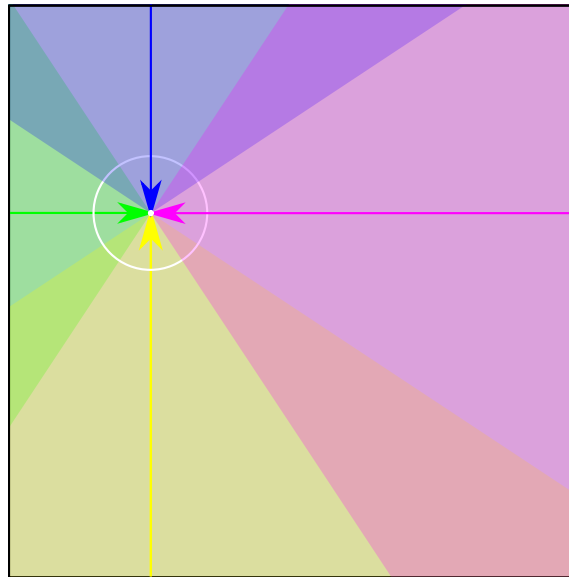
# MD-RNN Recurrent Connections (2D)

Direct predecessor only



# MD-RNN Recurrent Connections (2D)

Including **neighborhood** of predecessor (convolution)



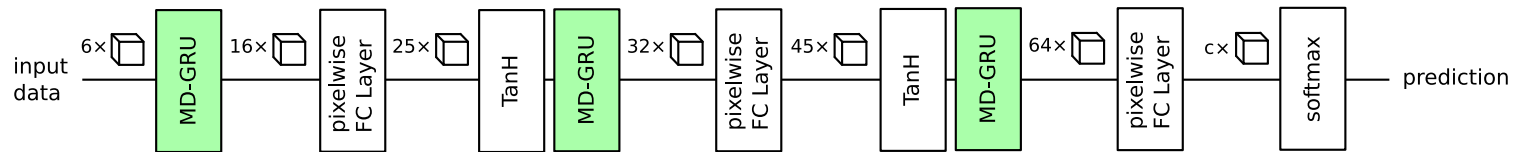


# Convolutional Gated Recurrent Unit (C-GRU)

MD-GRU Layer: 1 C-GRU for each direction & dimension

$$\begin{aligned} r^j &= \sigma \left( \sum_i^I (x^i * w_r^{i,j}) + \sum_k^J (h_{t-1}^k * u_r^{k,j}) + b_r^j \right), \\ z^j &= \sigma \left( \sum_i^I (x^i * w_z^{i,j}) + \sum_k^J (h_{t-1}^k * u_z^{k,j}) + b_z^j \right), \\ \tilde{h}_t^j &= \phi \left( \sum_i^I (x^i * w^{i,j}) + r^j \odot \sum_k^J (h_{t-1}^k * u^{k,j}) + b^j \right), \\ h_t^j &= z^j \odot h_{t-1}^j + (1 - z^j) \odot \tilde{h}_t^j. \end{aligned}$$

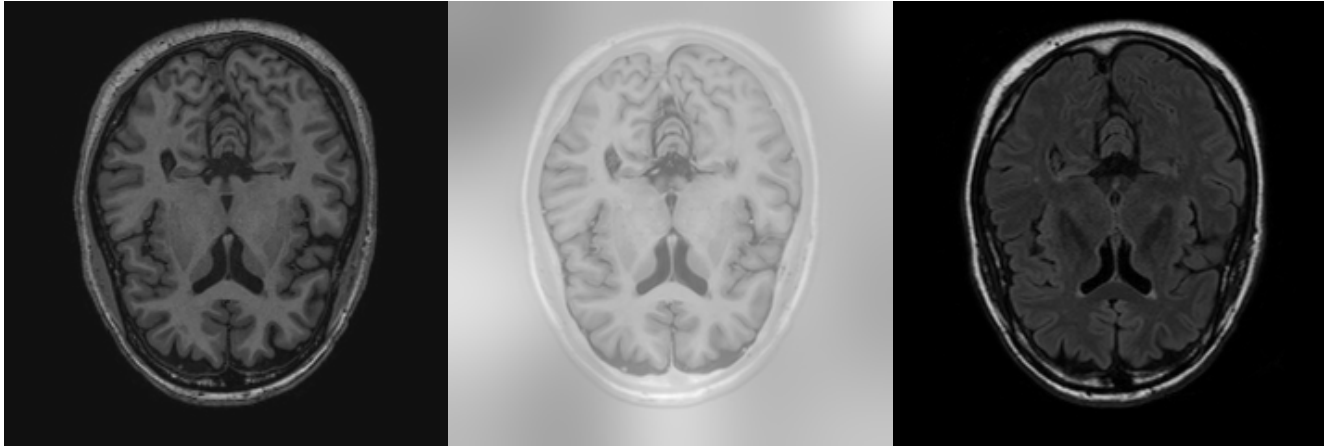
# Network



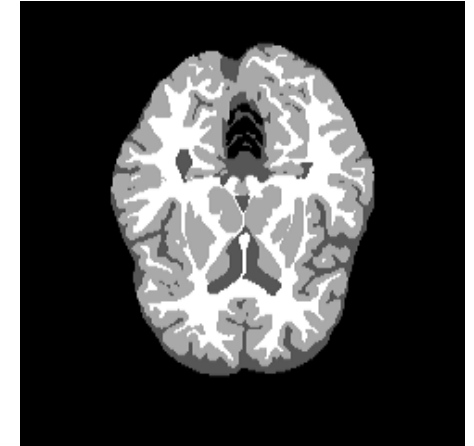
- Caffe 1.0 rc3
- Custom layers using CuDNN v5

# MrBrains13 challenge

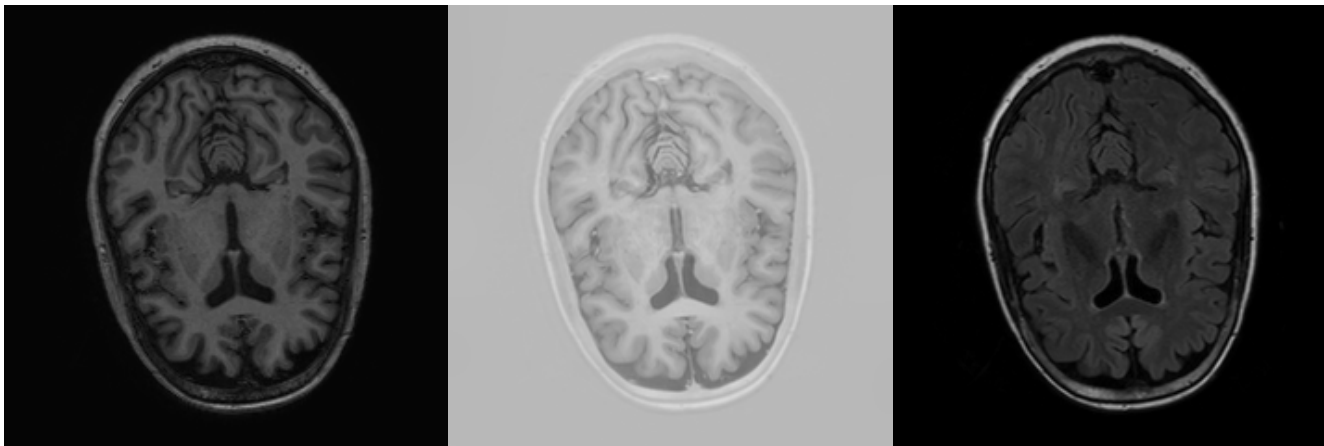
Training data (5 patients)



Training labels



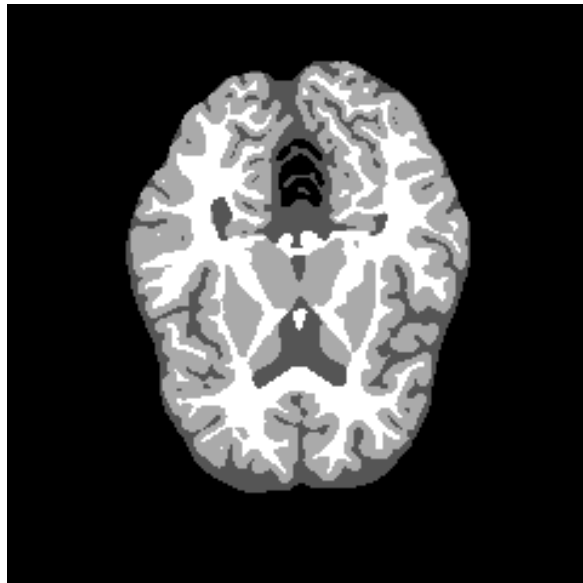
Testing data (15 patients)



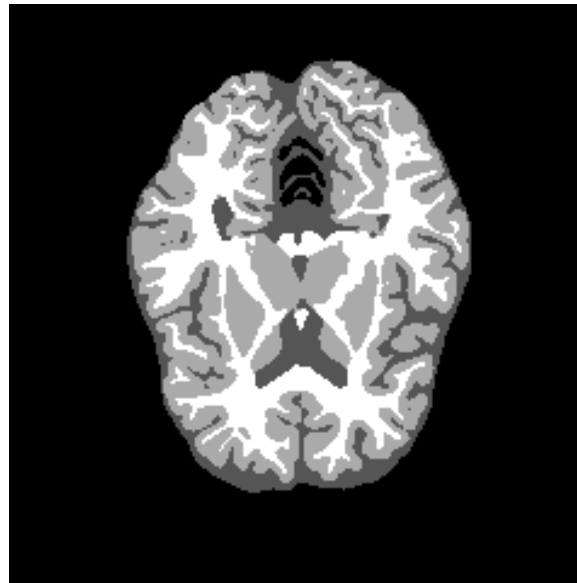
Estimation



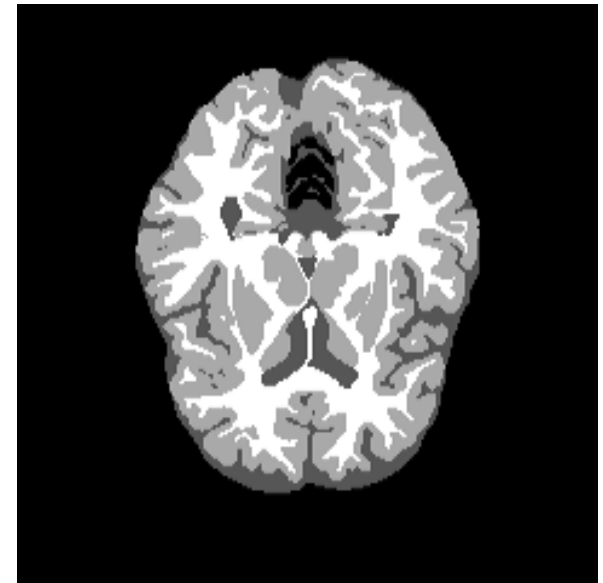
# MD-GRU / MD-LSTM [1]



a: MD-LSTM



b: MD-GRU



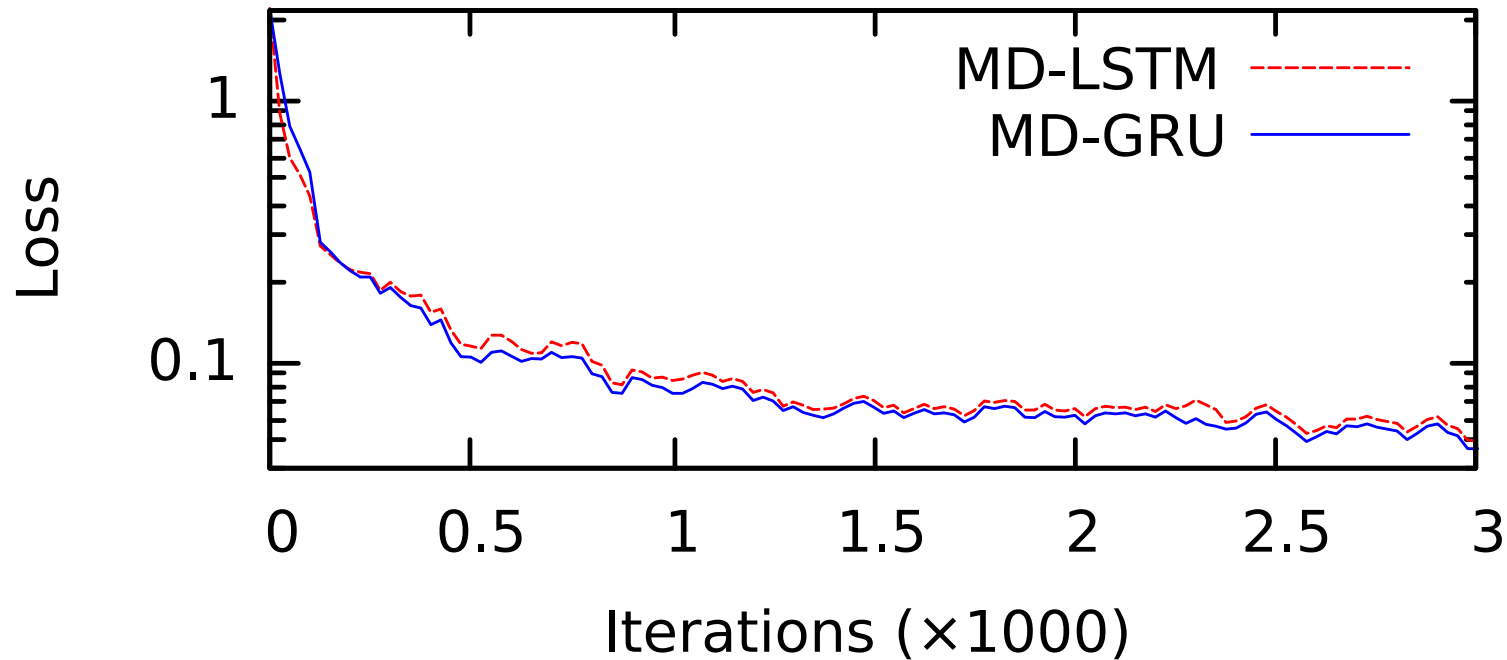
c: Training labels

[1] Stollenga, M.F., Byeon, W., Liwicki, M., Schmidhuber, J.: *Parallel Multi- Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation*. Advances in Neural Information Processing Systems 28, pp. 2998–3006. (2015)

# MD-GRU / MD-LSTM

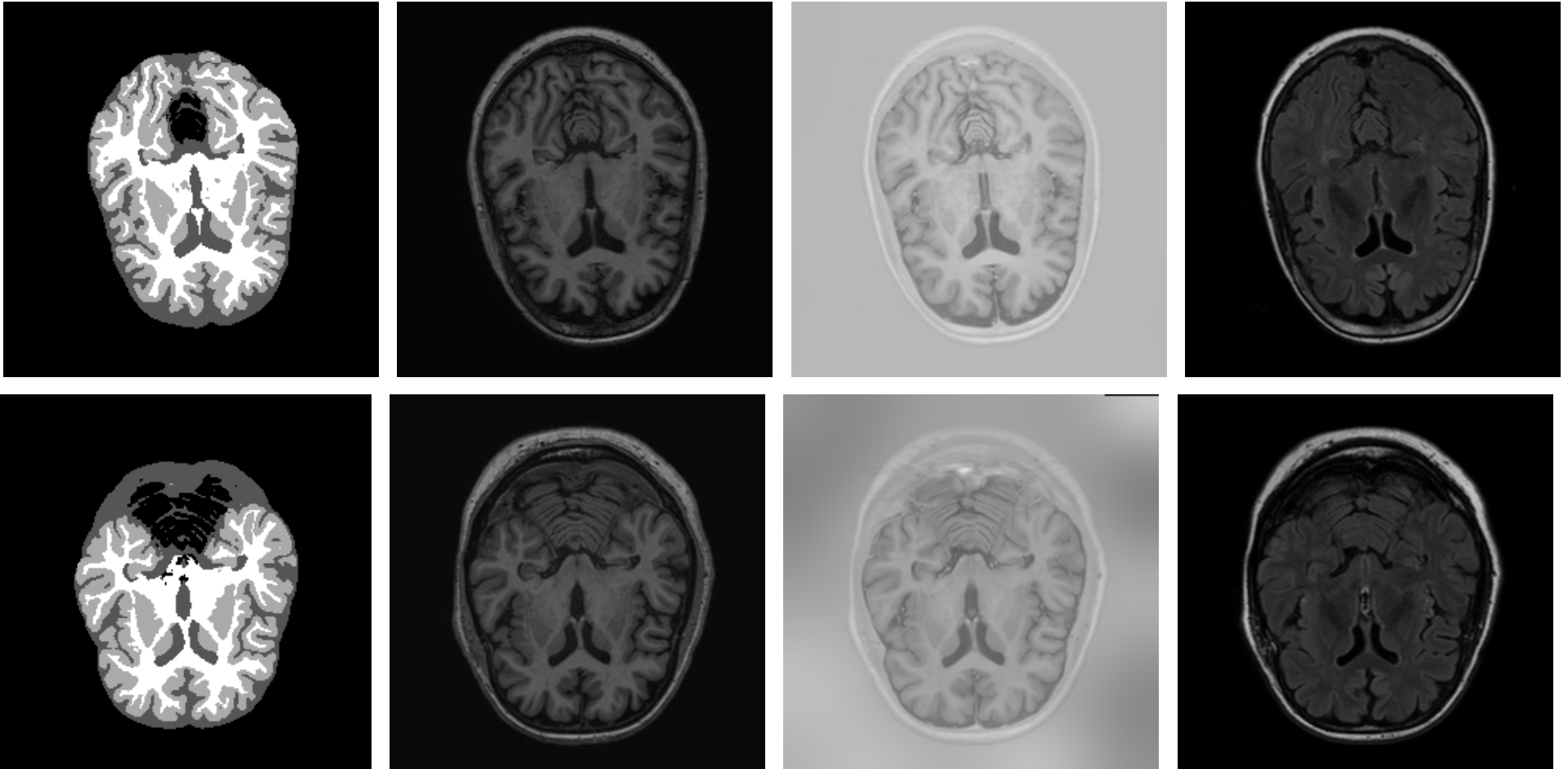
	GM	WM	CSF	ICV
MD-LSTM	<b>88.09</b>	90.08	82.62	97.56
MD-GRU	87.88	<b>90.15</b>	<b>83.19</b>	<b>97.73</b>

# MD-GRU / MD-LSTM



MD-LSTM: 12.8 s / MD-GRU: 9.1 s per iteration  
(volume of  $192 \times 192 \times 14$ )

# MD-GRU Challenge Results



# MD-GRU Challenge Results

Team name	Rank	GM			WM			CSF			ICV		
		Dice	HD	AVD	Dice	HD	AVD	Dice	HD	AVD	Dice	HD	AVD
CU_DL2	1	<b>86.15</b>	<b>1.45</b>	6.60	<b>89.46</b>	<b>1.94</b>	6.05	<b>84.25</b>	2.19	7.69	98.10	2.75	1.54
CU_DL	2	86.12	1.47	6.42	89.39	<b>1.94</b>	<b>5.84</b>	83.96	2.28	7.44	97.99	3.16	1.83
MD-GRU [Ours]	3	85.40	1.55	<b>6.09</b>	88.98	2.02	7.69	84.13	2.17	7.44	<b>98.15</b>	<b>2.37</b>	0.86
PyraMiD-LSTM2	4	84.89	1.67	6.35	88.53	2.07	5.93	83.05	2.30	7.17	98.04	2.86	<b>0.69</b>
FBI/LMB Freiburg [2]	5	85.44	1.58	6.60	88.86	1.95	6.47	83.47	2.22	8.63	97.98	2.51	1.06
IDSIA [1]	6	84.82	1.70	6.77	88.33	2.08	7.05	83.72	<b>2.14</b>	<b>7.09</b>	<b>98.15</b>	2.44	0.95

[1] Stollenga, M.F., Byeon, W., Liwicki, M., Schmidhuber, J.: *Parallel Multi- Dimensional LSTM, With Application to Fast Biomedical Volumetric Image Segmentation*. Advances in Neural Information Processing Systems 28, pp. 2998–3006. (2015)

[2] Çiçek, Ö., Abdulkadir, A., Lienkamp, S.S., Brox, T., Ronneberger, O.: *3d U-Net: Learning Dense Volumetric Segmentation from Sparse Annotation*. arXiv:1606.06650 [cs] (Jun 2016)



# Acknowledgements

