Brain MRI Tissue Segmentation with a Continuous Restricted Boltzmann Machine

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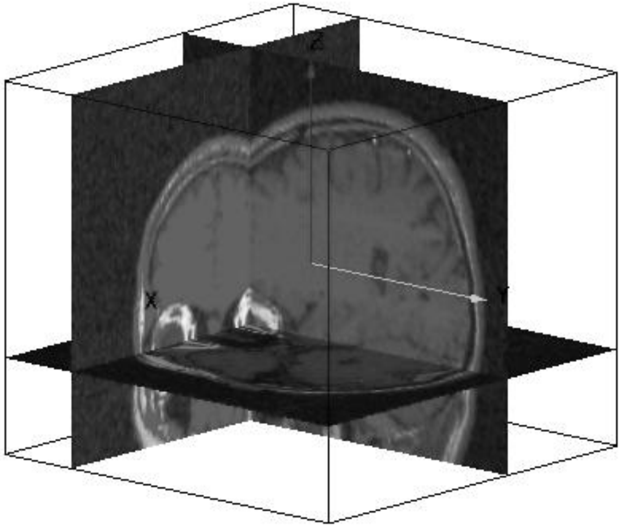
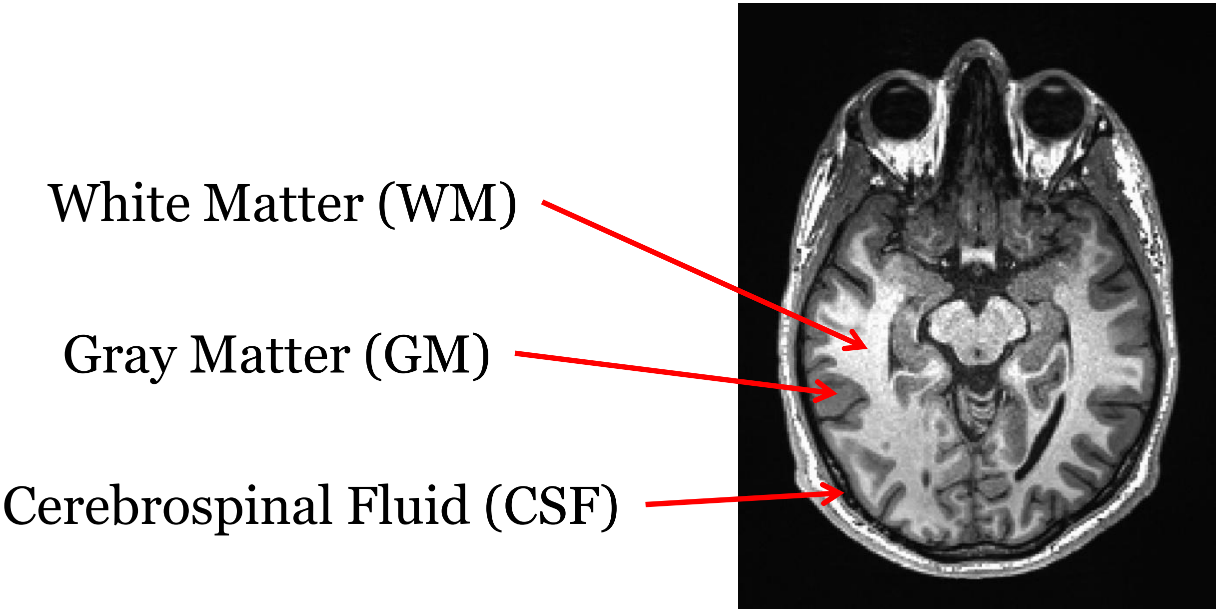
MRI Brain Scans

- 3D volumes - many 2D slices
- Only contain intensity data



MRI Brain Scans

- Three tissue types of interest



Why Perform Tissue Segmentation?

- Build population atlases
- Guide surgeons
- Monitor anatomical changes

(Chung, Dinov, Toga & Vese, 2010)

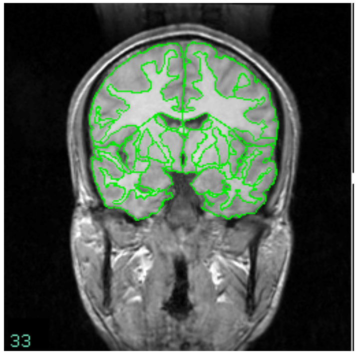
Why Perform Tissue Segmentation?

- Build population atlases
- Guide surgeons
- Monitor anatomical changes

- Traditionally done **manually**

(Chung, Dinov, Toga & Vese, 2010)

Existing Segmentation Algorithms



- Edge Detection
- Region Growing
- K Nearest Neighbours

- Hidden Random Markov Field (FAST)
- Gaussian Probability Model (SPM5)

(Zhang, Brady & Smith, 2001)

Justification

- There are already several good MRI tissue segmentation algorithms…

  Why investigate another one?

(cma.mgh.harvard.edu/ibsr)

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  Why investigate another one?

- Successful only under narrow conditions
- Require large datasets and extensive training
- Require additional 'backend' information

(cma.mgh.harvard.edu/ibsr)

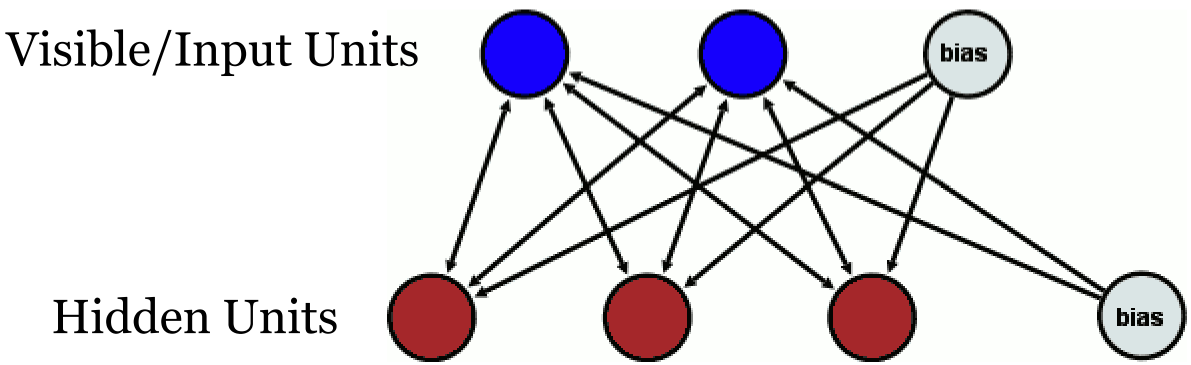
Ideal Algorithm:

- Robust to noise
- Require few training cases
- Trained quickly
- Store all information implicitly

The Continuous Restricted Boltzmann Machine

(CRBM)

Restricted Boltzmann Machine

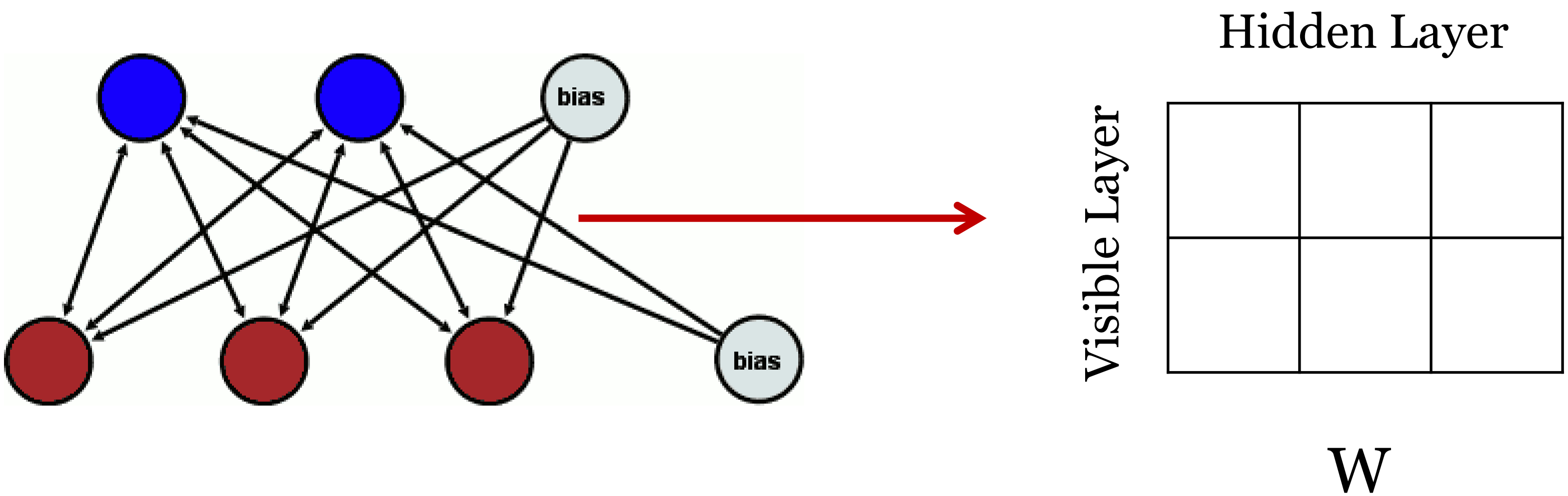


- Invented in 1986 by Paul Smolensky
- Popularized recently by Geoffrey Hinton

(Image: imonad.com)

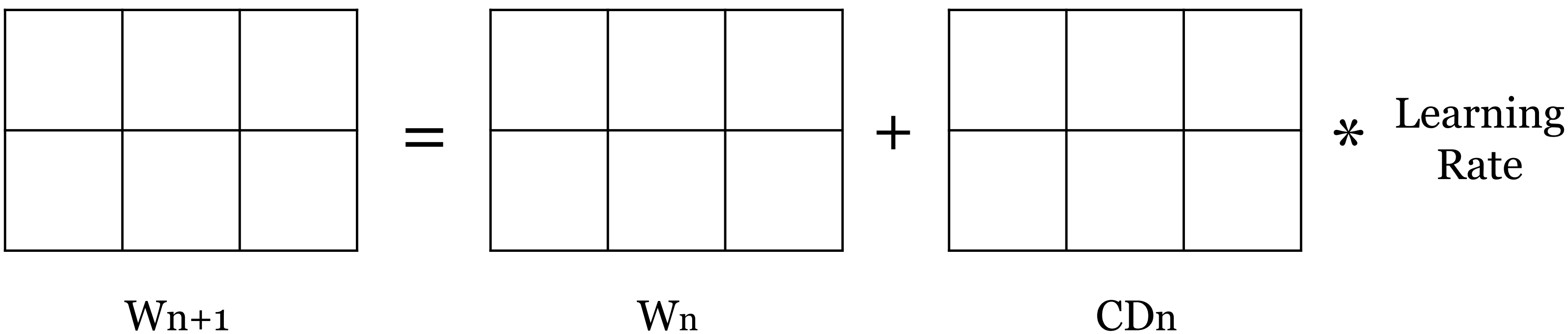
CRBM: Learning

- Let matrix W be the weights between each pair of nodes in the machine



CRBM: Learning

- Iteratively change the weights in W
- Reflect the input states in the training data



CRBM: Learning

- Iteratively change the weights in W
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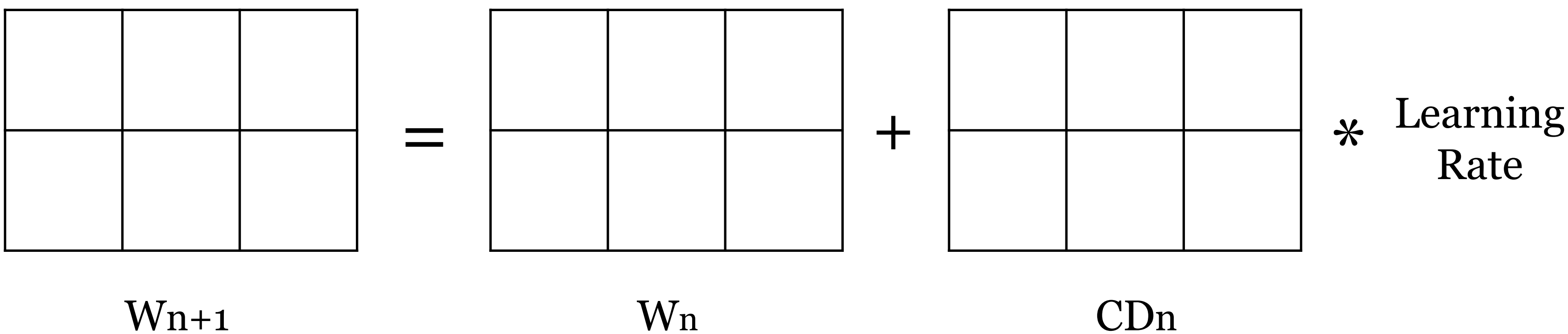
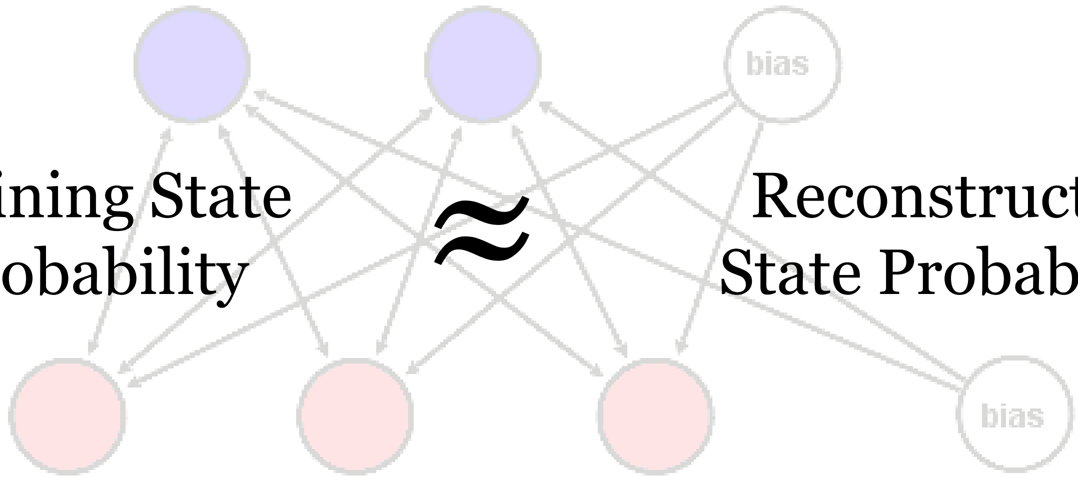


$$\sum (\text{input states} - \text{reconstructed states})^2 < (\text{threshold})$$

Tissue Segmentation with a CRBM

CRBM Tissue Segmentation: Theory

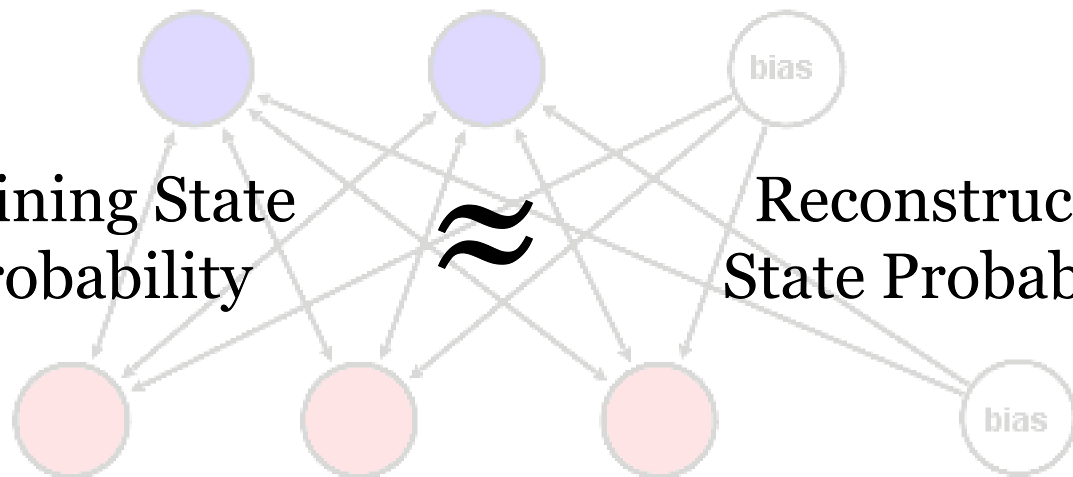
- “Learns” probable visible layer states



Training State Probability ≈ Reconstructed State Probability

CRBM Tissue Segmentation: Theory

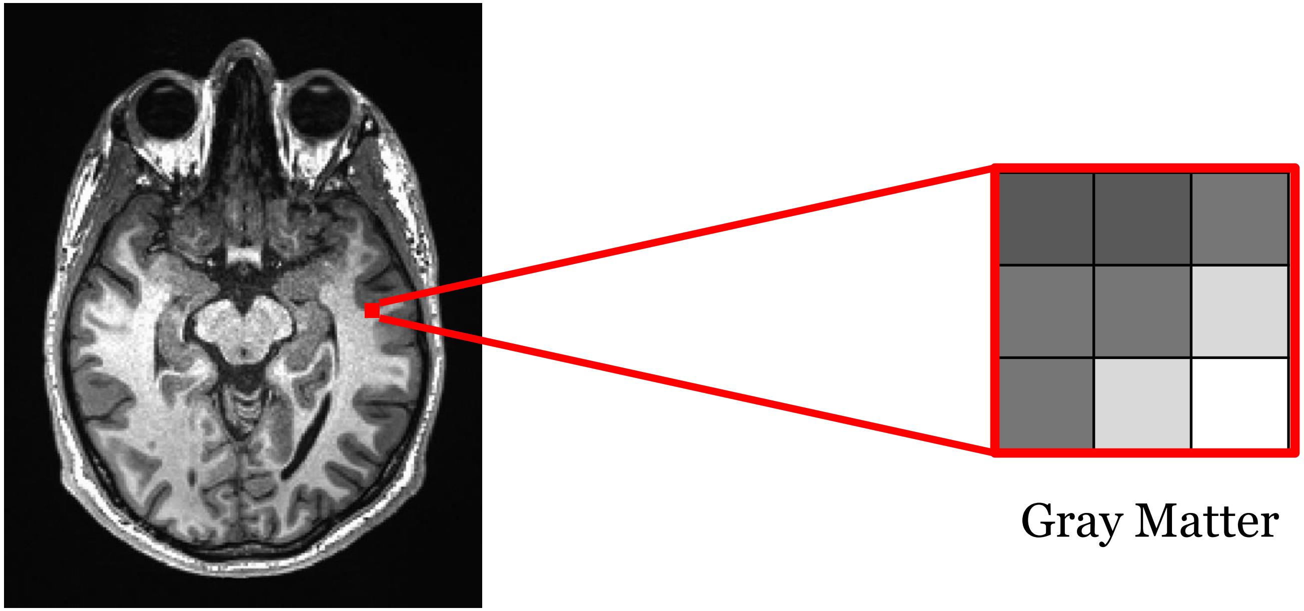
- “Learns” probable visible layer states



Training State Probability ≈ Reconstructed State Probability

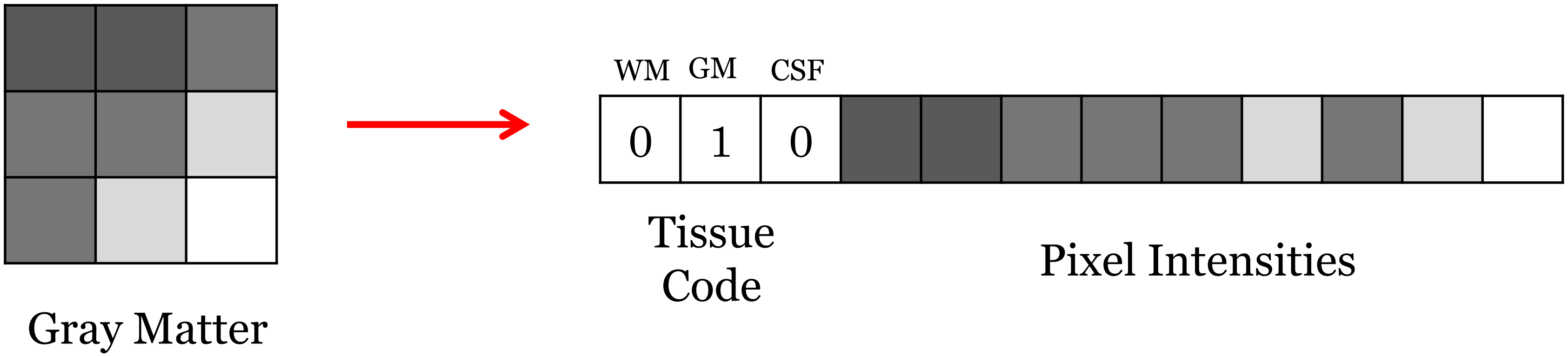
- Can reconstruct an **incomplete** input vector

CRBM Tissue Segmentation: Training



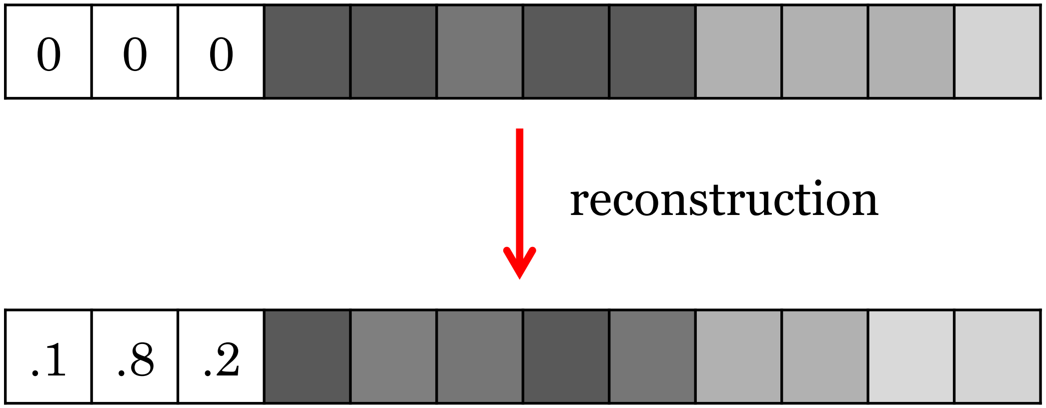
CRBM Tissue Segmentation: Training

Input Vector: [tissue type code + intensities]



CRBM Tissue Segmentation: Testing

- Present a partial input vector
- Reconstruct the missing tissue code

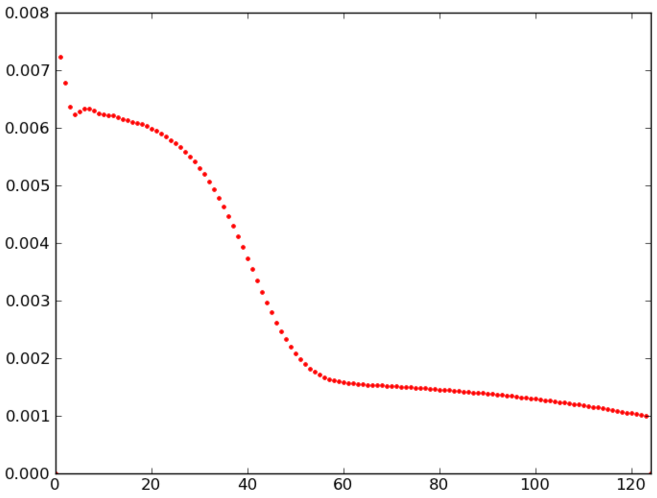


"Gray Matter"

Implementation

Test Case 1

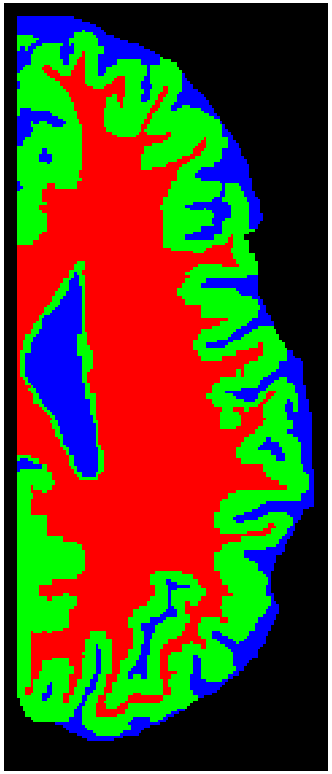
- Hidden Units: 1000
- Learning Rate: 0.65
- Error Threshold: 0.001
- Segments GM/WM/CSF



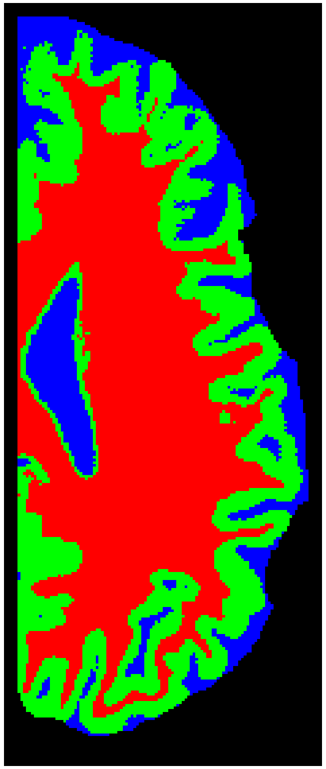
- Dataset from Western University
  - Naïve segmentation
  - 1 120x285 24bit PNG

Test Case 1

MRI



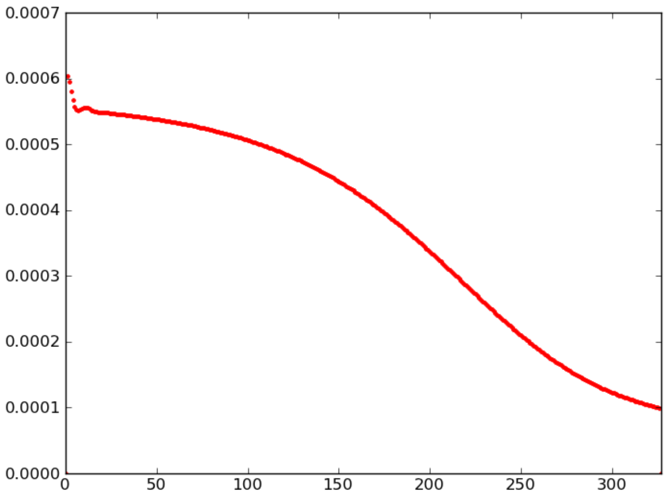
Manual Segmentation



CRBM Segmentation

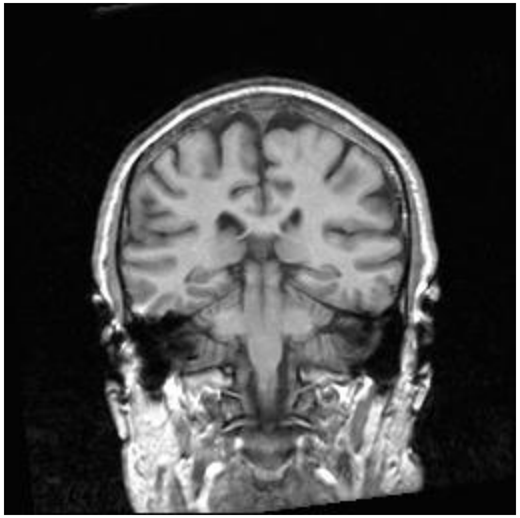
Test Case 2

- Hidden Units: 2000
- Learning Rate: 0.65
- Error Threshold: 0.0001
- Segments GM/WM

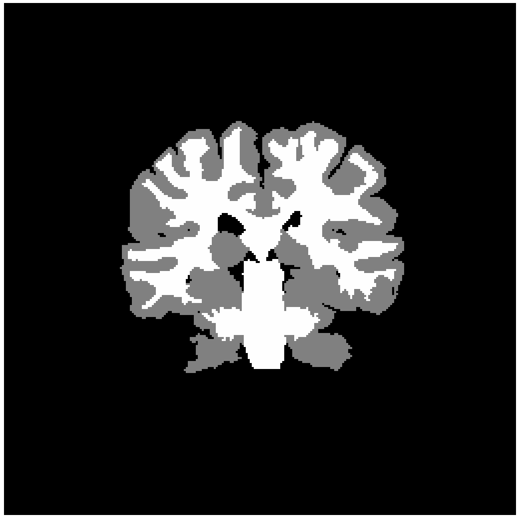


- Dataset from Massachusetts General Hospital
  - Expert segmentation
  - 28 256x256 24bit PNGs

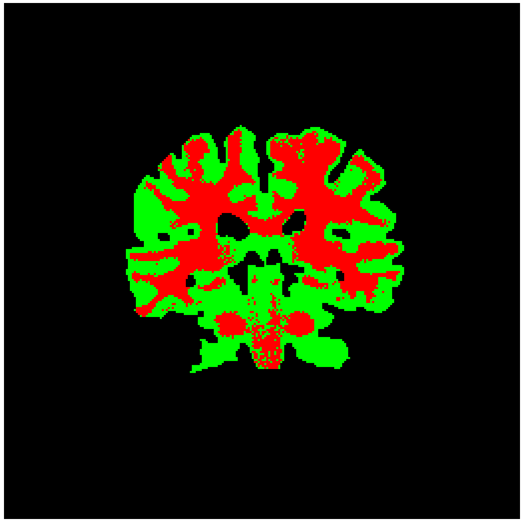
Test Case 2



MRI



Manual
Segmentation



CRBM
Segmentation

Results

- Test Case 1
  - DICE coefficient of 0.91
  - Jaccard index of 0.84

- Test Case 2
  - DICE coefficient of 0.76
  - Jaccard index of 0.61

Current Problems

- Sensitive to MRI noise and low-contrast scans
- Tissues outside cerebrum are misclassified
- Finding a good classification threshold is difficult

Future Improvements

- Improve input vectors
  - Normalize image contrast
  - Include in-volume neighbours
  - Include (x, y, z) coordinates
- Parallelize implementation
- Combine multiple datasets

References

Chung, G., Dinov, I. D., Toga, A. W., & Vese, L. A. (2010). MRI tissue segmentation using a variational multilayer approach. In K. Miller & P. Nielsen (Eds.), *Computational Biomechanics for medicine, doi: 10.1007/978-1-4419-5874-7_2 York: Psychology Press*.

MR brain data set 788 was provided by the Center for Morphometric Analysis at Massachusetts General Hospital and is available at *http://www.cma.mgh.harvard.edu/ibsr/*

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Zhang, Y., Brady, M., Smith, S. (2001). Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm. *IEEE TISSUE SEGMENTATION 13 Transactions on Image Processing, 20(1), 45–57*.