

Detecting FMRI Brain Activation Via Neural Network

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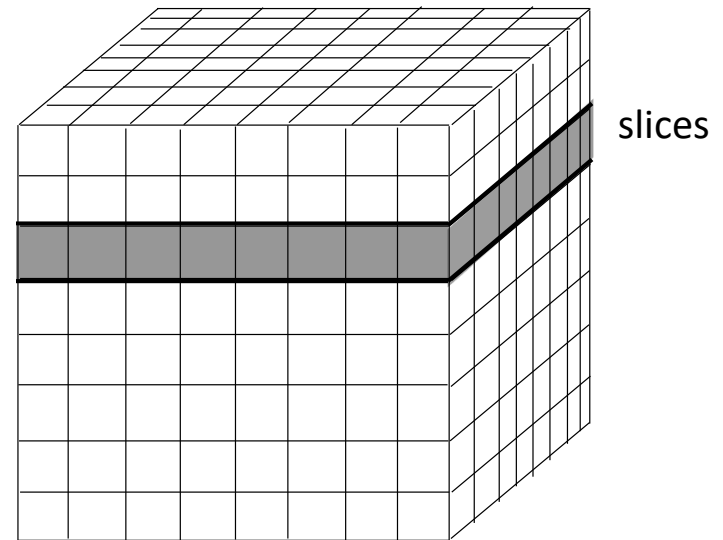
July 29, 2019
8:35 – 8:50 am

Outline

- 1. The fMRI Problem**
- 2. Artificial Neural Nets**
- 3. ANNs and fMRI**
- 4. Results**
- 5. Discussion**

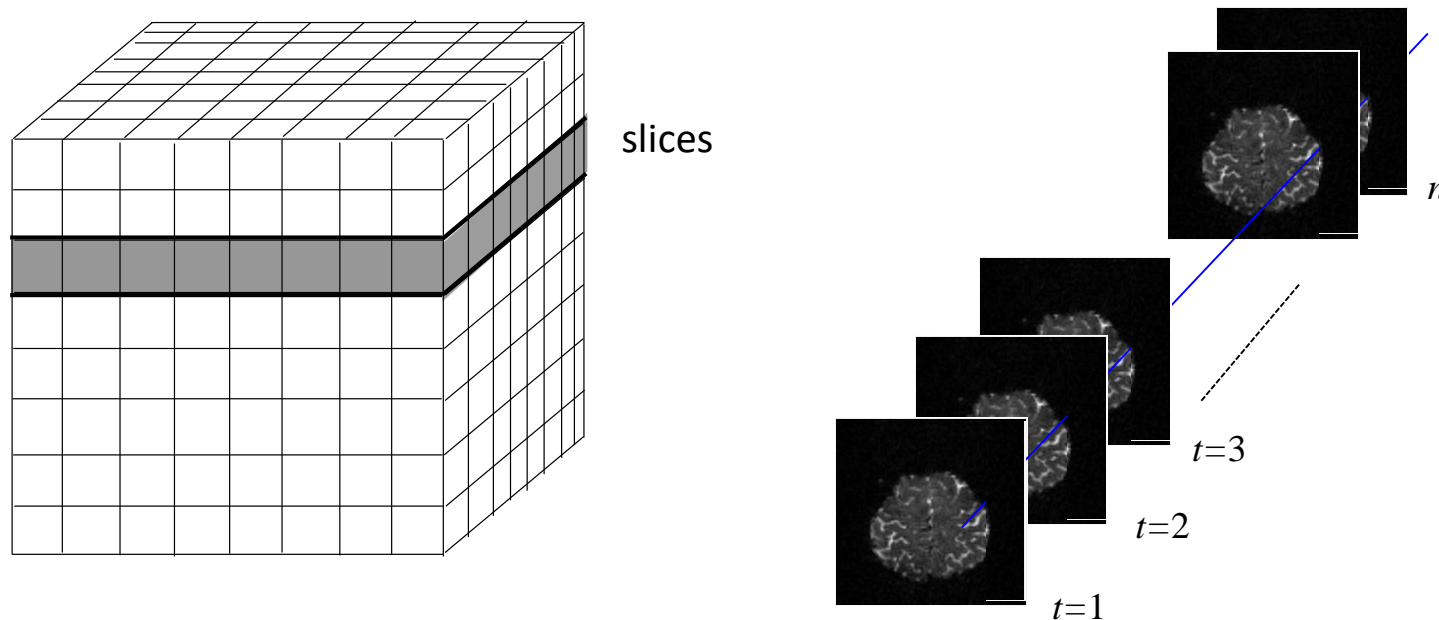
1. The fMRI Problem

In fMRI, a subject is placed in the MRI machine and volume images of their brain measured



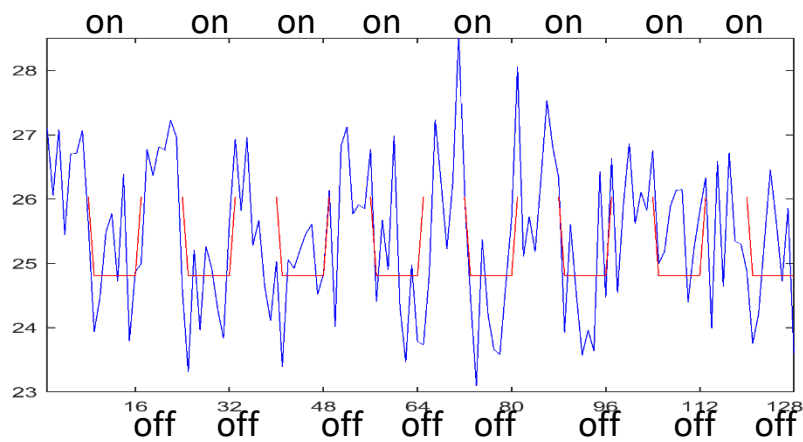
1. The fMRI Problem

... at n time points while they are generally performing a designed cognitive task

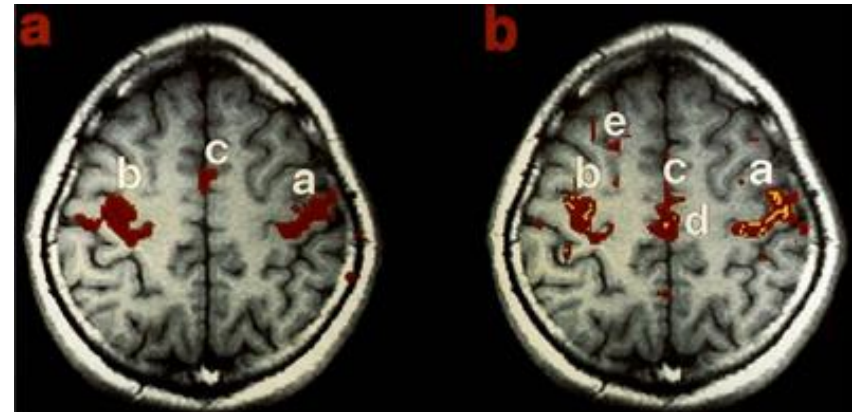


1. The fMRI Problem

... and a regression based measure of association between the task timing and voxel time series computed.



r, t
→



2. Artificial Neural Nets

An ANN maps inputs variables (x 's) to output variables (y 's) through activation a and probabilistic score functions Q .

Unsupervised Learning: input x and output y pairs and make inferences using one data set.

Supervised Learning: output “training” data” γ 's with class labels c_γ 's to “learn” (γ, c_γ) relationship, then apply this relationship to the current data y .

2. Artificial Neural Nets

ANNs can be used to classify voxel time series as active (1) or inactive (0) after having been trained.

In order to train the ANN, we need to have the observed time series y along with its known class assignment c .

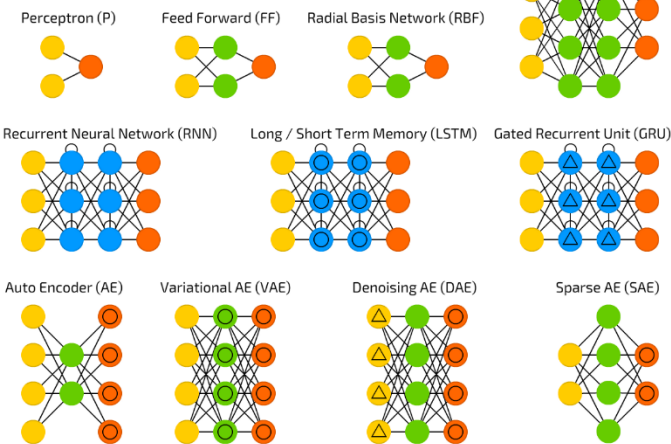
2. Artificial Neural Nets

ANNs can take on many exotic forms!

A mostly complete chart of Neural Networks

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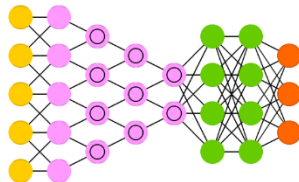
- Backfed Input Cell
- Input Cell
- △ Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- △ Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- △ Different Memory Cell
- Kernel
- Convolution or Pool



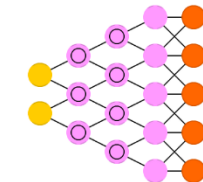
Deep Feed Forward (DFF)



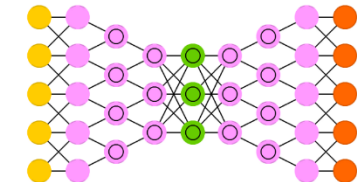
Deep Convolutional Network (DCN)



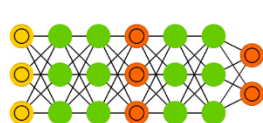
Deconvolutional Network (DN)



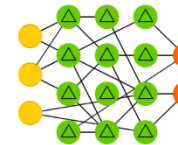
Deep Convolutional Inverse Graphics Network (DCIGN)



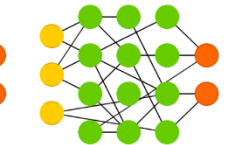
Generative Adversarial Network (GAN)



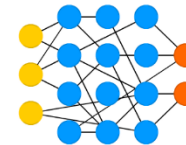
Liquid State Machine (LSM)



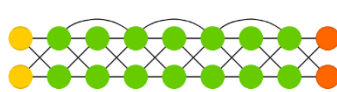
Extreme Learning Machine (ELM)



Echo State Network (ESN)



Deep Residual Network (DRN)



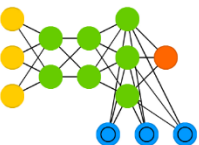
Kohonen Network (KN)



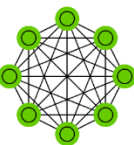
Support Vector Machine (SVM)



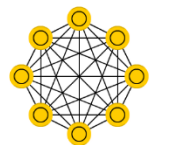
Neural Turing Machine (NTM)



Markov Chain (MC)



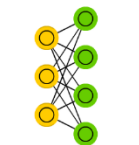
Hopfield Network (HN)



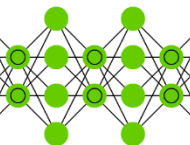
Boltzmann Machine (BM)



Restricted BM (RBM)



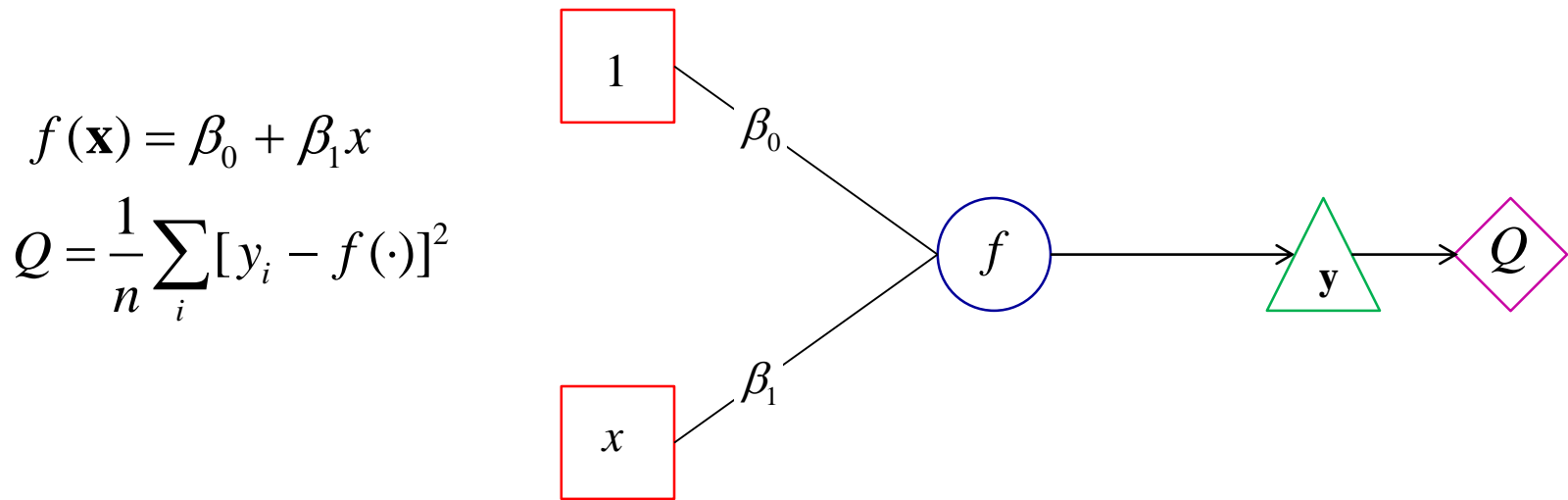
Deep Belief Network (DBN)



<https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464>

2. Artificial Neural Nets

A linear perceptron ANN with Gradient Descent



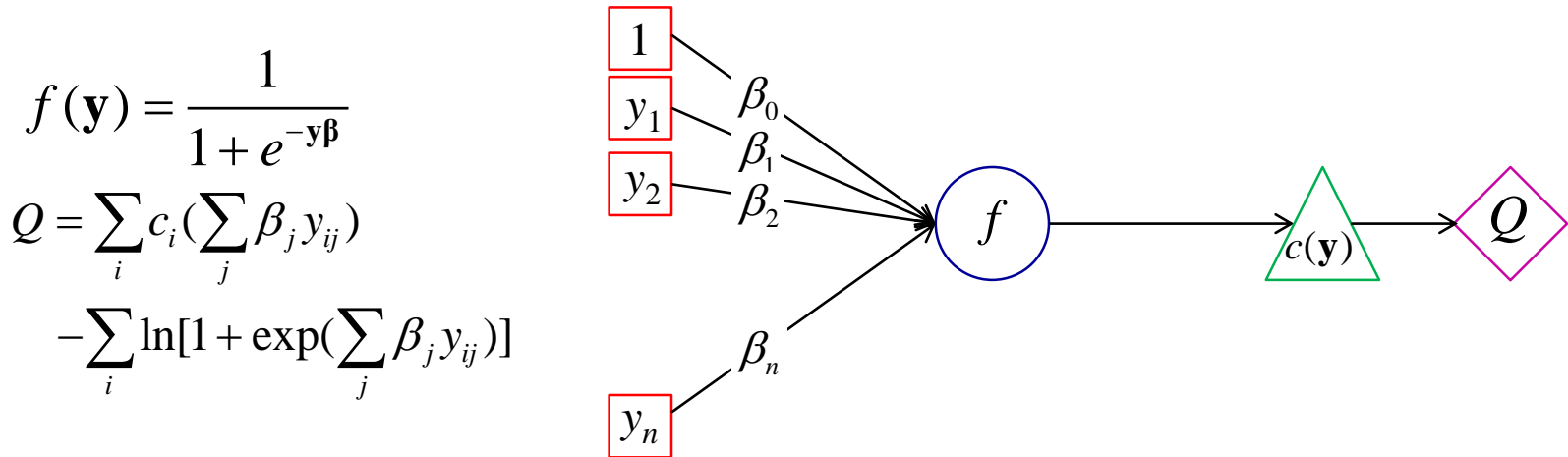
$t=0$
 → Run data through with $\hat{\beta}^{(t)} = (\hat{\beta}_0^{(t)}, \hat{\beta}_1^{(t)})'$ → $\hat{\beta} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix}$
 Calculate $\nabla Q(\hat{\beta}^{(t)}) = -\frac{2}{n} (X' \mathbf{y} - X' X \hat{\beta}^{(t)})$, → $t(\hat{\beta}_1)$
 Calculate new $\hat{\beta}^{(t+1)} = \hat{\beta}^{(t)} - \gamma \nabla Q(\hat{\beta}^{(t)})$, $t=t+1$ → $c(\mathbf{y})$

2. Artificial Neural Nets

$$\frac{\partial Q}{\partial \beta_j} = \frac{2}{n} \sum_i \left[\frac{x_{ij} [y_i - \ln(1 + A)] A}{1 + A} \right]$$

$$A = \exp\left(\sum_j \beta_j x_{ij}\right)$$

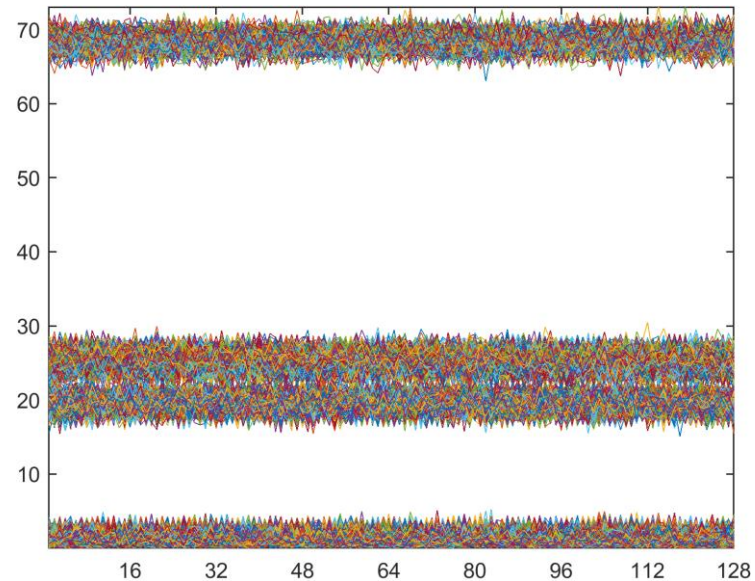
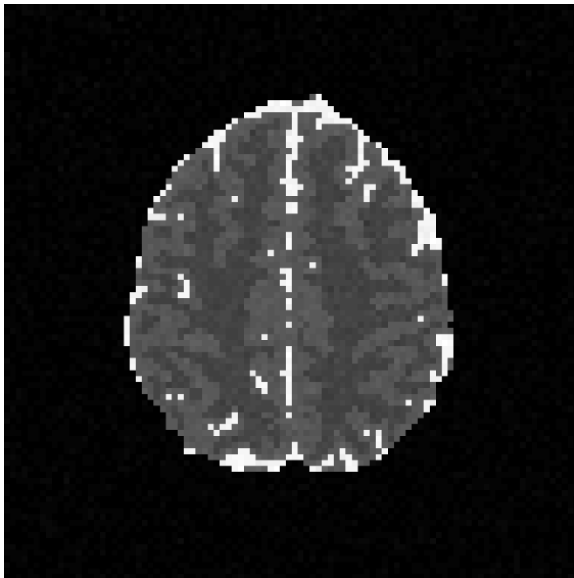
A Softmax classifying ANN with Gradient Descent



$t=0$
 → Run data through with $\hat{\boldsymbol{\beta}}^{(t)} = (\hat{\beta}_0^{(t)}, \dots, \hat{\beta}_n^{(t)})'$ → $\hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \vdots \\ \hat{\beta}_n \end{pmatrix}$
 Calculate $\nabla Q(\hat{\boldsymbol{\beta}}^{(t)}) = \left(\frac{\partial Q}{\partial \beta_j} \right)$,
 Calculate new $\hat{\boldsymbol{\beta}}^{(t+1)} = \hat{\boldsymbol{\beta}}^{(t)} - \gamma \nabla Q(\hat{\boldsymbol{\beta}}^{(t)})$, $t=t+1$ → $c(\mathbf{y})$

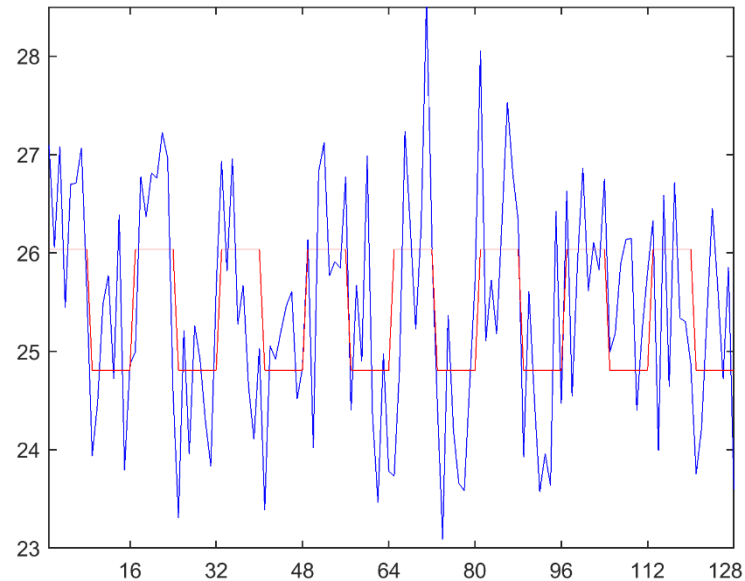
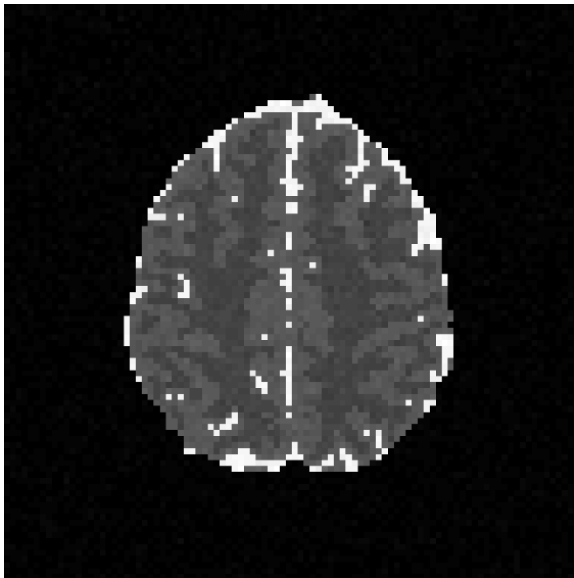
3. ANNs and fMRI

Simulated Training fMRI Data
Anatomical and voxel time series.



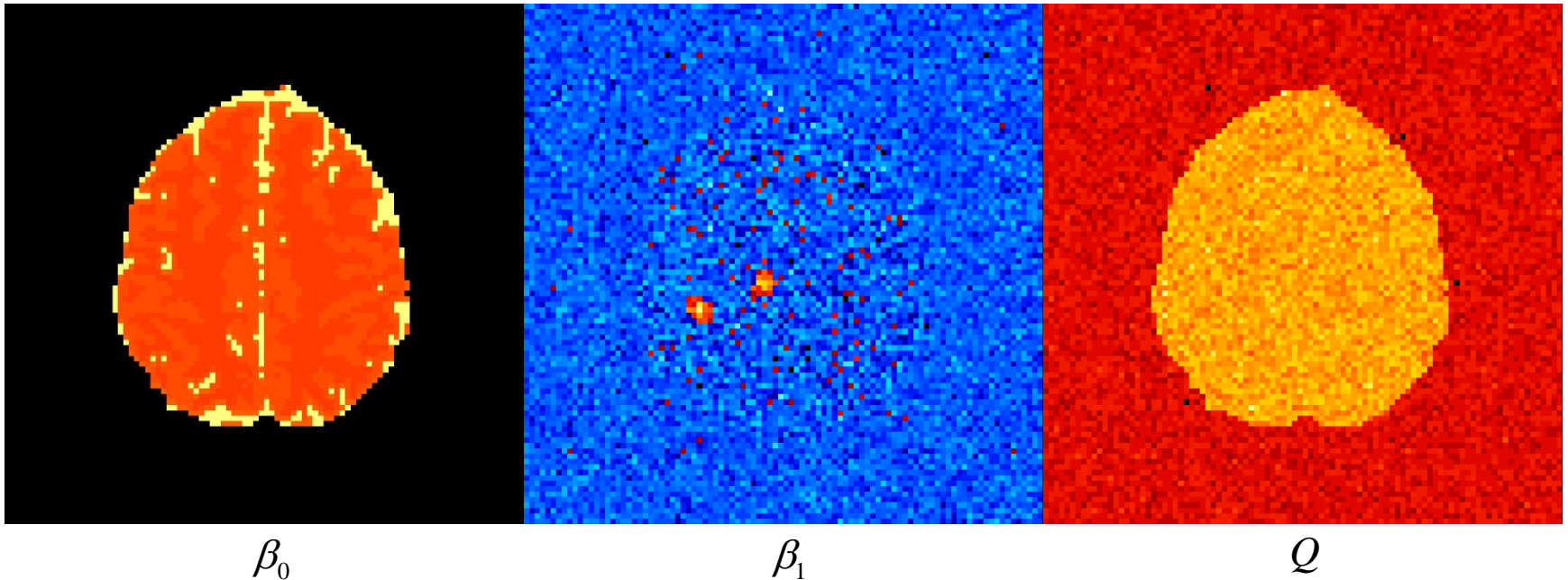
3. ANNs and FMRI

Train linear perceptron ANN to find the relationship between x design and y time series.



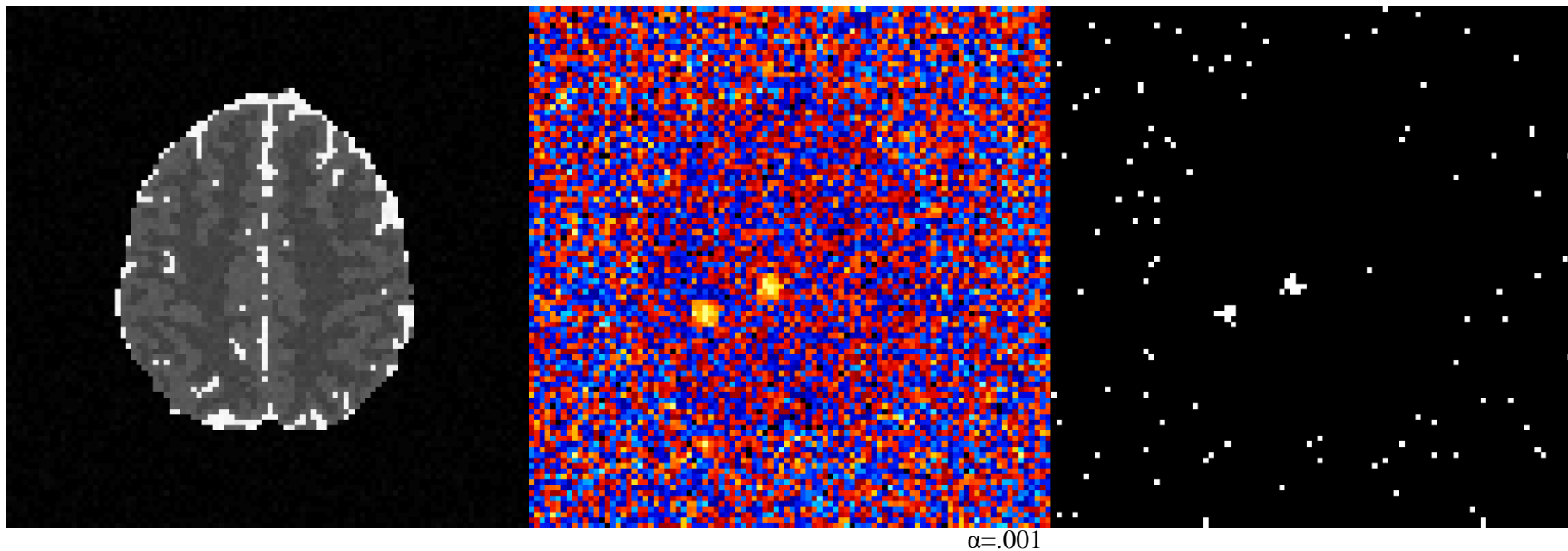
3. ANNs and FMRI

Train linear perceptron ANN to find the relationship between x design and y time series.



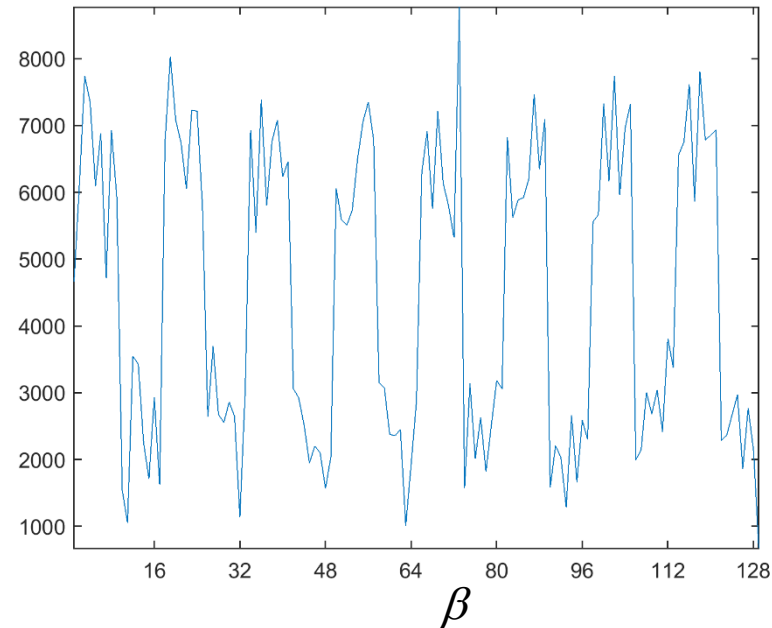
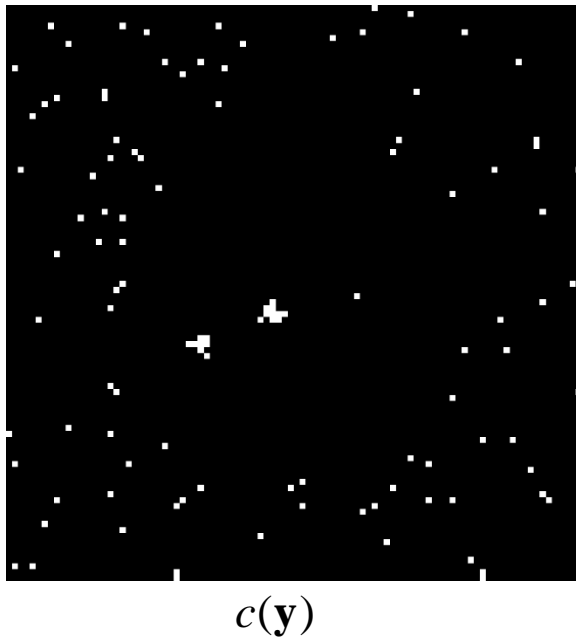
3. ANNs and FMRI

Translate trained x and y relationship to active vs. inactive classifications.



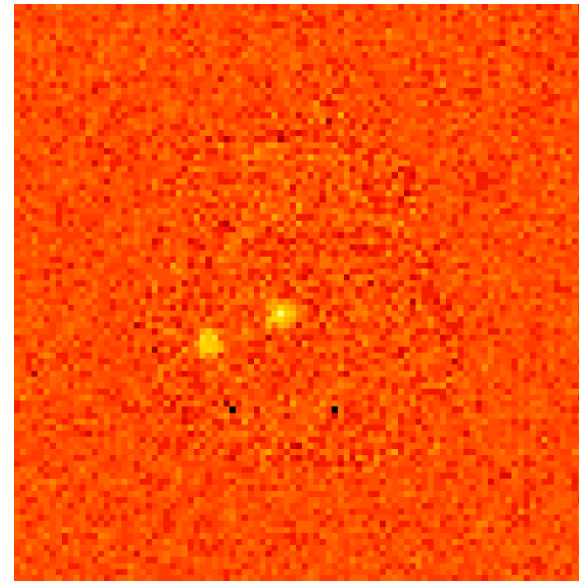
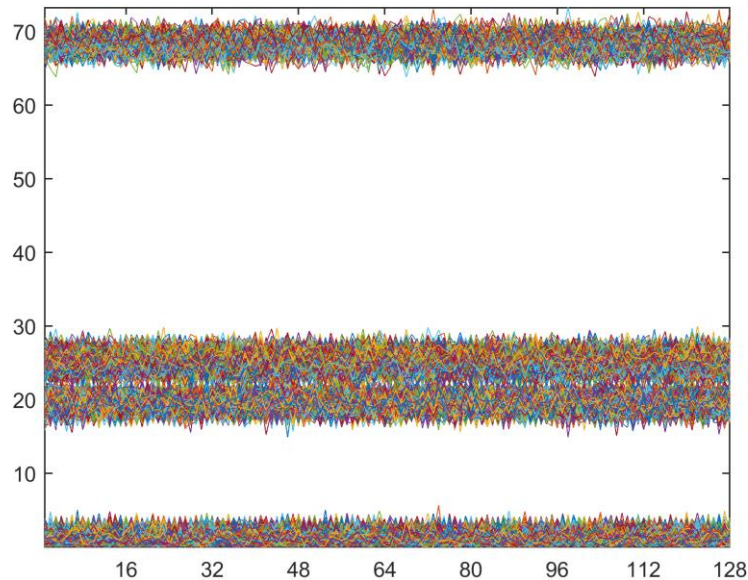
3. ANNs and FMRI

Train Softmax ANN classifier to input \mathbf{y} time series and class c then output classifier coefficients



4. Results

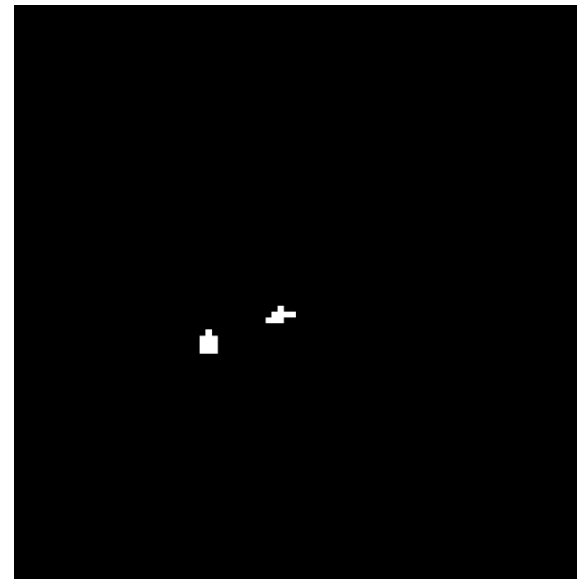
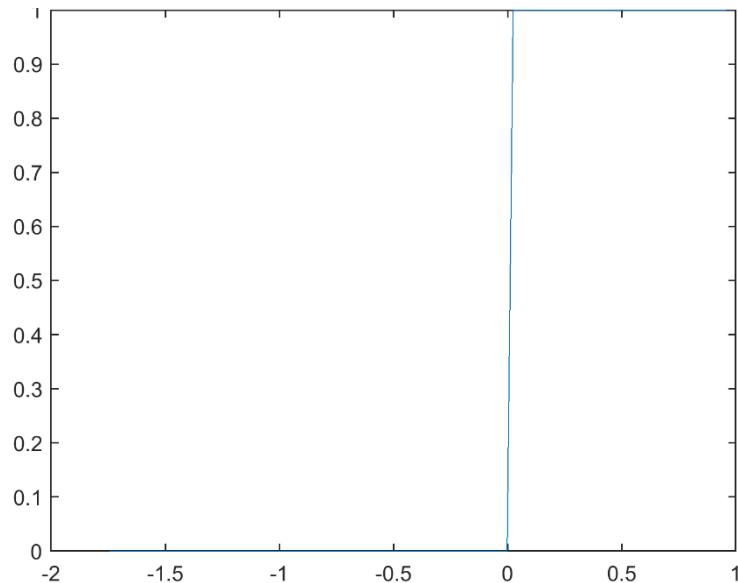
Simulated similar test data, calculated log odds using training data coefficients.



L

4. Results

Simulated similar training data.

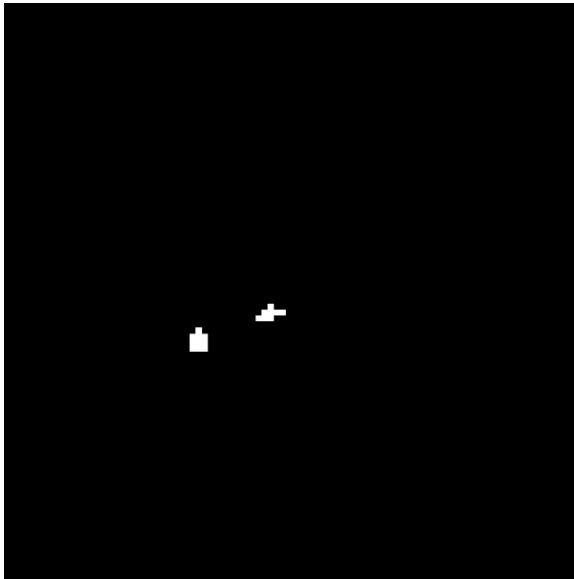


$$f(\mathbf{y}) = \frac{1}{1 + e^{-(\mathbf{y}\hat{\beta}-k)}}$$

$c(\mathbf{y})$

4. Results

Test data ANN classification vs. regression.



$c(\mathbf{y})$
ANN



$c(\mathbf{y})$ $\alpha=.001$
Regression

5. Discussion

Increase the number of layers.

Other activation functions.

More categories: OB NA, GM NA, WM NA, GM A.

Statistics vis Apply to experimental fMRI data.

Thank You!

Questions?

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