

Functional connectivity magnetic resonance imaging classification of autism spectrum disorder using the multisite ABIDE dataset

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Agenda

1 Introduction

2 ABIDE Datasets

3 Experiments

4 Results

5 Discussion

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1 Introduction

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4 Results

5 Discussion

Autism Spectrum Disorder (ASD)

- Autism spectrum disorder (ASD) is a brain disorder that is characterized by social and communication impairments as well as restricted interests and repetitive behaviors.
- According to the Centers for Disease Control, autism affects an estimated 1 in 59 children in the United States today.

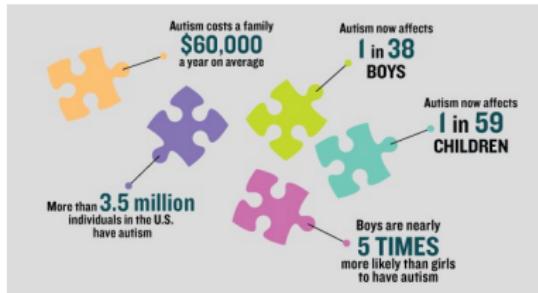


Figure: Early intervention can change a life.

Autism Spectrum Disorder (ASD)

- Indicators of autism usually appear by age 2 or 3. Some associated development delays can appear even earlier, and often, it can be diagnosed as early as 18 months.
- Research shows that early intervention leads to positive outcomes later in life for people with autism.



Figure: World Autism Awareness Day is on 2 April every year

What cause Autism?

- Research suggests that autism develops from a combination of genetic and nongenetic, or environmental, influences.

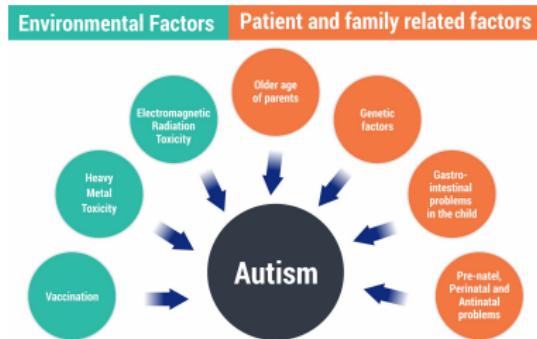


Figure: These mentioned are a few probable causes of autism

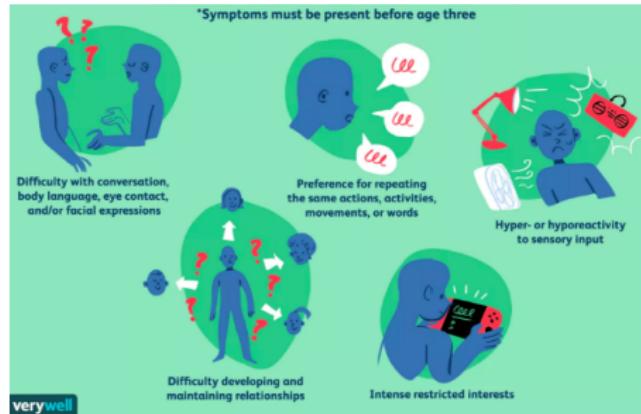
- Although ASD has been identified since the early 1960s, its exact cause is still unknown.

Main goals of Autism Research

- Seek the causes and types of autism.
- Lower the average age of diagnosis to under 2 years.
- Enhance medical treatment of autism's health conditions.

Symptom-based Diagnosis of Autism

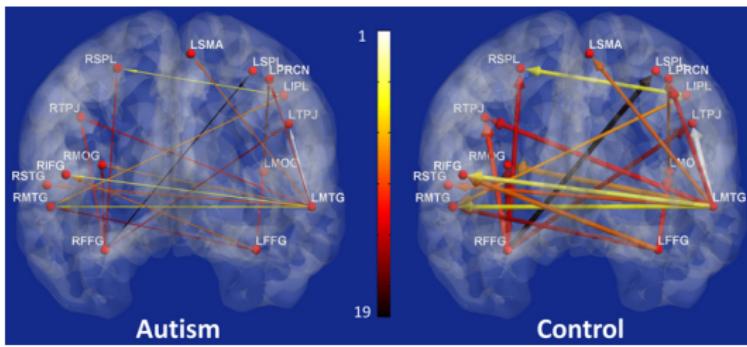
- Generally, the symptom-based diagnosis of ASD requires a very significant amount of time behavioral assessments under the guidance of a highly experienced multidisciplinary team.



- However, symptom-based diagnosis often results in poor treatment due to lack of knowledge of neuropathology.

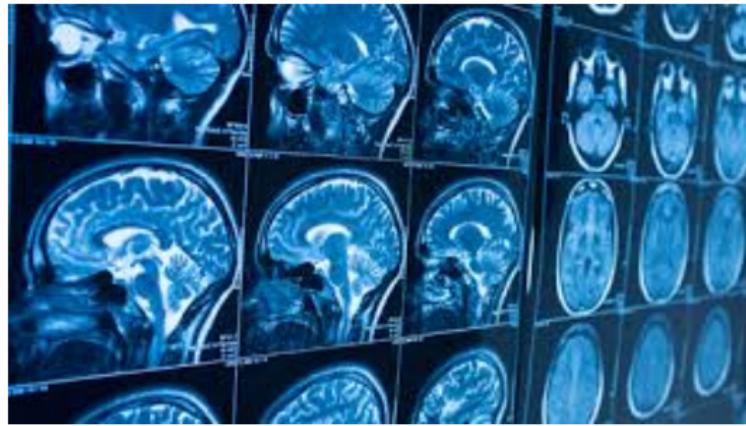
Data-driven Diagnosis of Autism

- In the past few years, an increasing number of neuroscience research studies have used machine learning to implement neuroimaging data-driven diagnosis of ASD, which would lead to more effective treatment outcomes.



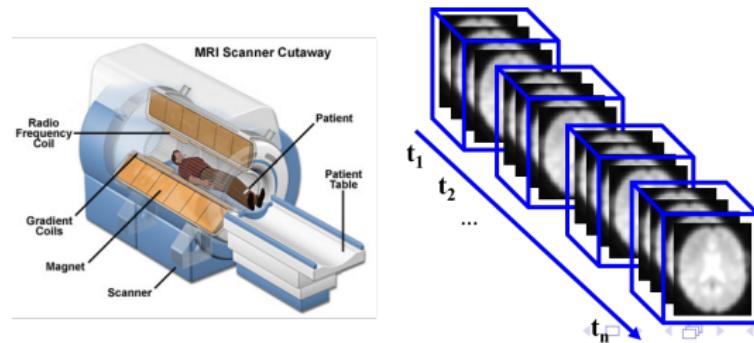
Neuroimaging Techniques

- **Anatomical Technique:** track the normal and abnormal development of the brain of the patients.
- **Functional Technique:** track the brain activity.



Magnetic resonance imaging (MRI)

- MRI provides good contrast between the different soft tissues of the body based on the facts that the human body is largely composed of water molecules.
- Most of the disease tissue are tend to have higher water molecules than normal tissue.
- MRI is a **3D** data cube, which is usually composed of a lot of **MRI slices**. Each MRI slice is a 2D image.



Magnetic resonance imaging (MRI)

Slice 6

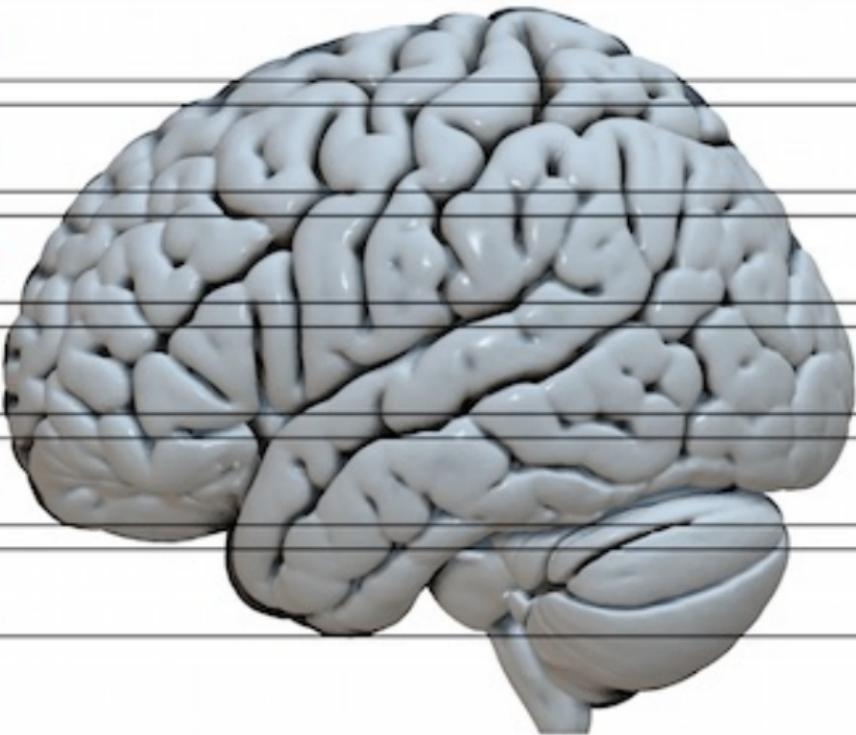
Slice 5

Slice 4

Slice 3

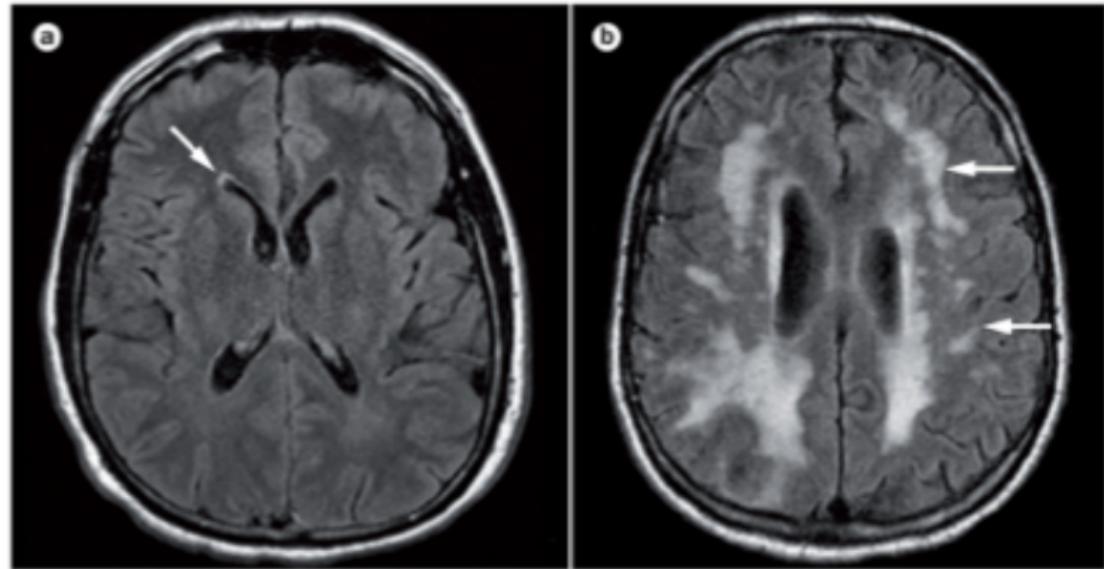
Slice 2

Slice 1



Magnetic resonance imaging (MRI)

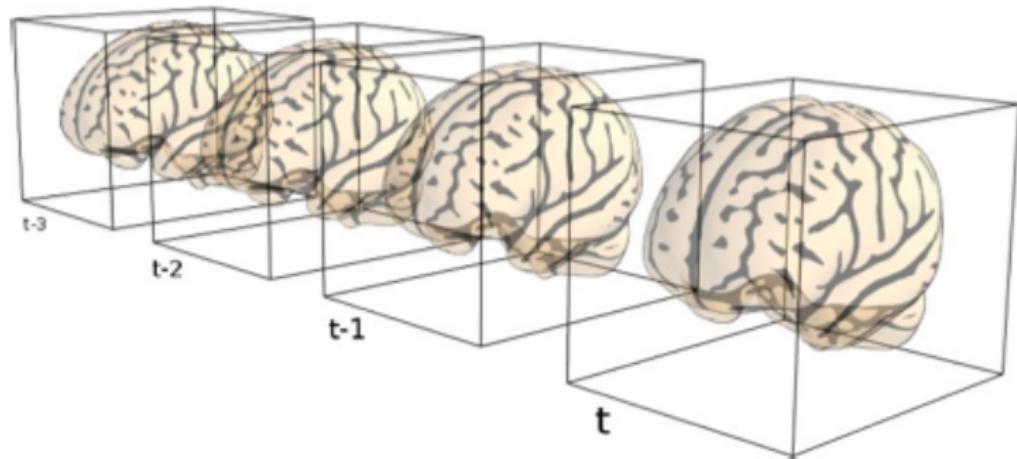
Go to page 2



Nature Reviews | Neurology

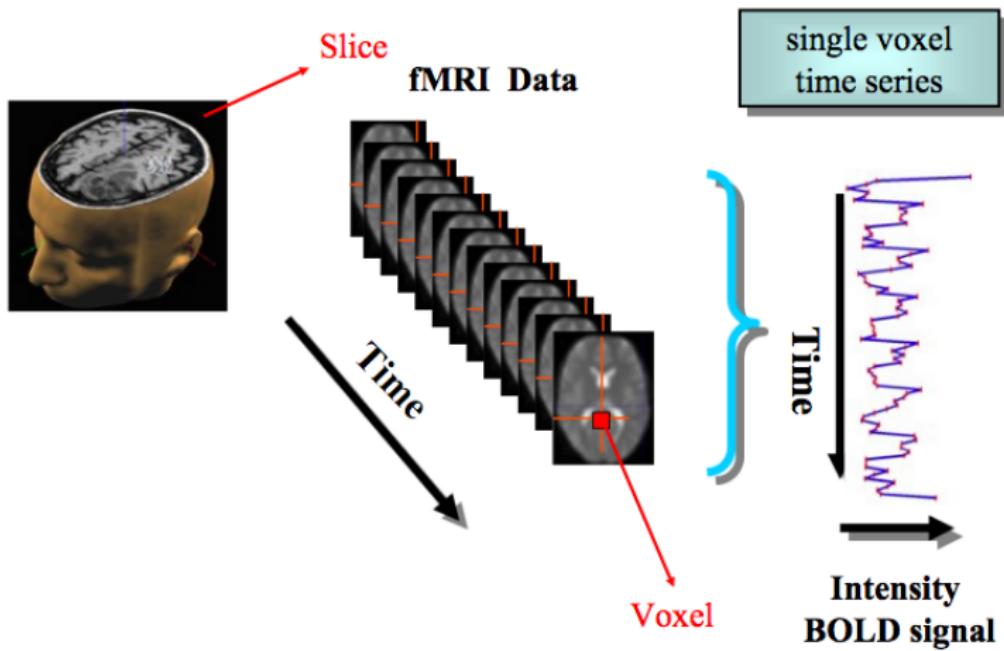
functional Magnetic resonance imaging (fMRI)

- During the course of an fMRI experiment, a series of brain images are acquired while the subject performs a set of tasks.



functional Magnetic resonance imaging (fMRI)

fMRI time series

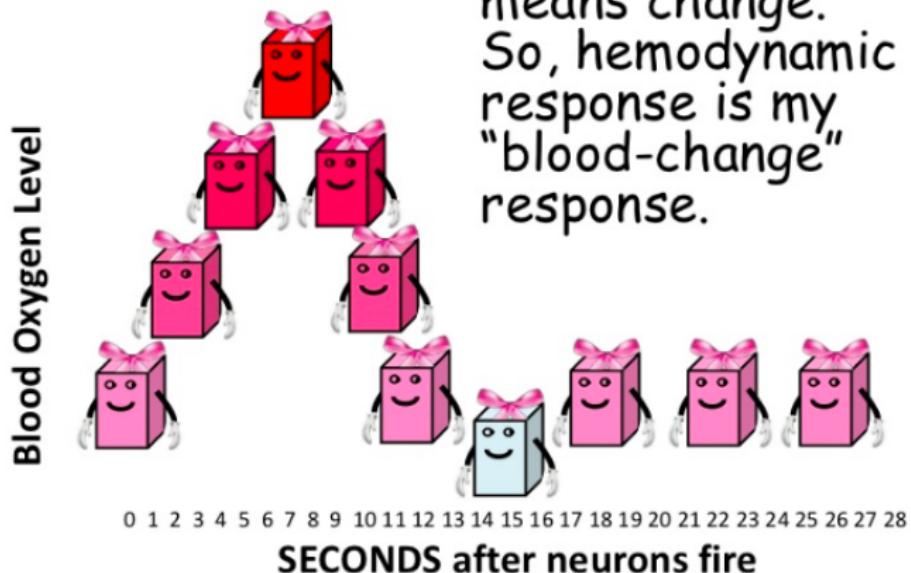


functional Magnetic resonance imaging (fMRI)

- The general purpose of fMRI data studies is to analyze the brain voxel's time series data to detect whether the Blood Oxygen Level Dependent (BOLD) signal changes in response to a particular stimulus and hence to infer neuronal activity of the human brain.

functional Magnetic resonance imaging (fMRI)

"Hemo" means blood. "Dynamic" means change. So, hemodynamic response is my "blood-change" response.



functional Magnetic resonance imaging (fMRI)

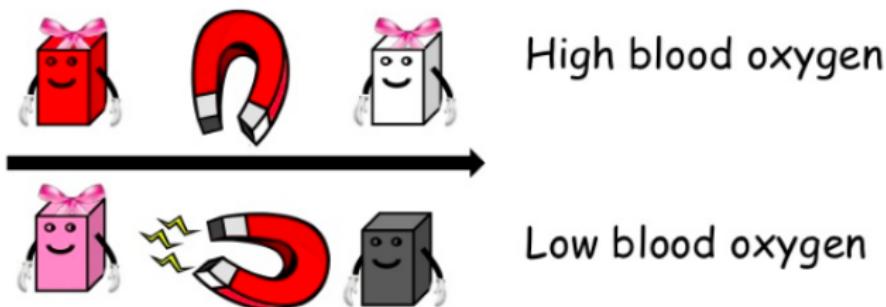
The fMRI machine can see my color change because blood with a lot of oxygen (red) is less attracted to magnets than blood without much oxygen (pink or blue).



functional Magnetic resonance imaging (fMRI)

The fMRI machine is measuring a BOLD signal because the color is

Blood
Oxygen
Level
Dependent



Resting state fMRI

- Resting state fMRI (rs-fMRI) is a method of functional magnetic resonance imaging (fMRI) that is used in brain mapping to evaluate regional interactions that occur in a resting state.
- Because brain activity is intrinsic, present even in the absence of an externally prompted task, any brain region will have spontaneous fluctuations in BOLD signal .
- The resting state approach is useful to explore the brain's functional organization and to examine if it is altered in neurological or mental disorders .

The goal of this study

- The goal of this study is to apply machine learning algorithms to classify autism spectrum disorder (ASD) patients and typically developing (TD) participants using resting-state functional MRI (rs-fMRI) data from a large multisite data repository ABIDE (Autism Brain Imaging Data Exchange)

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Datasets

ABIDE Datasets

- The preprocessed rs-fMRI data with ASD and TD are downloaded from a large multisite data repository ABIDE (Autism Brain Imaging Data Exchange).
- ABIDE is a multisite platform that has aggregated functional and structural brain imaging data collected from 17 different laboratories around the world.



Autism Brain Imaging
Data Exchange

ABIDE data Phenotypical Information

ABIDE Datasets

- In total, there are 1112 subjects consist of structural and preprocessed resting state functional MRI data along with phenotypic information.
- From these 1112 subjects, 1035 subjects are screened for our study since only 1035 subjects have been given the corresponding completed phenotypic information.
- In these 1035 subjects, there are 505 ASD and 530 TD, 157 females and 878 males .

Data Summary

TABLE I
ABIDE DATA PHENOTYPICAL INFORMATION

| site | ASD | TD | M | F | <i>Age Range</i> |
|----------|-----|-----|-----|-----|------------------|
| CALTECH | 19 | 18 | 29 | 8 | 17~56 |
| CMU | 14 | 13 | 21 | 6 | 19~40 |
| KKI | 20 | 28 | 36 | 12 | 8~13 |
| LEUVEN | 29 | 34 | 55 | 8 | 12~32 |
| MAX_MUN | 24 | 28 | 48 | 4 | 7~58 |
| NYU | 75 | 100 | 139 | 36 | 6~39 |
| OHSU | 12 | 14 | 26 | 0 | 8~15 |
| OLIN | 19 | 15 | 29 | 5 | 10~24 |
| PITT | 29 | 27 | 48 | 8 | 9~35 |
| SBL | 15 | 15 | 30 | 0 | 20~64 |
| SDSU | 14 | 22 | 29 | 7 | 9~17 |
| STANFORD | 19 | 20 | 31 | 8 | 8~13 |
| TRINITY | 22 | 25 | 47 | 0 | 12~26 |
| UCLA | 54 | 44 | 86 | 12 | 8~18 |
| UM | 66 | 74 | 113 | 27 | 8~29 |
| USM | 46 | 25 | 71 | 0 | 9~50 |
| YALE | 28 | 28 | 40 | 16 | 7~18 |
| TOTAL | 505 | 530 | 157 | 878 | 6~64 |

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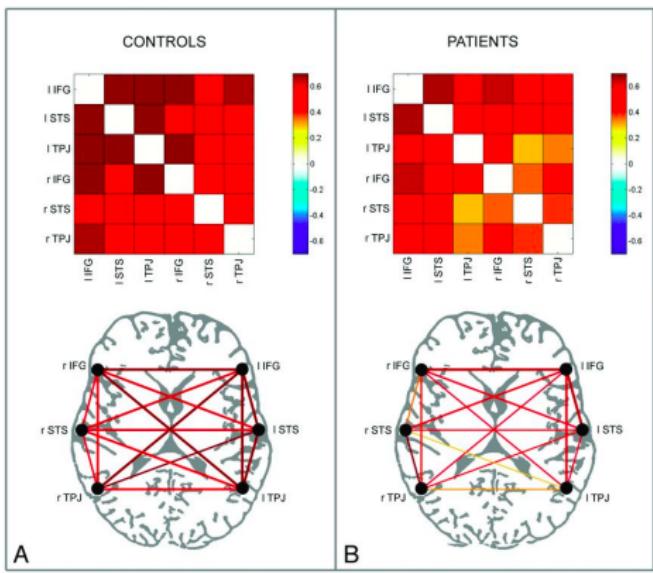
Feature Extraction

Keywords

- resting state functional magnetic resonance imaging (rs-fMRI)
- function connectivity (rsfc-fMRI)
- region of interests (ROIs)
- craddock 400 (cc400, 400 ROIs)

Feature Extraction

- Since the functional connectivity is a manifestation of the co-activation level of the brain regions, in this study, we use functional connectivity of ROIs to classify ASD patients and TD participants.



Brain Atlas

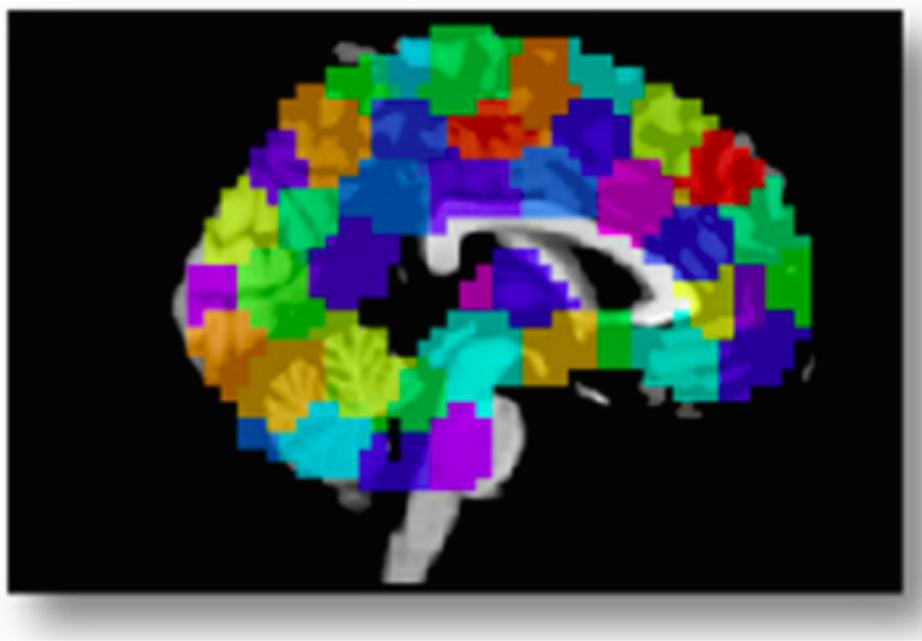
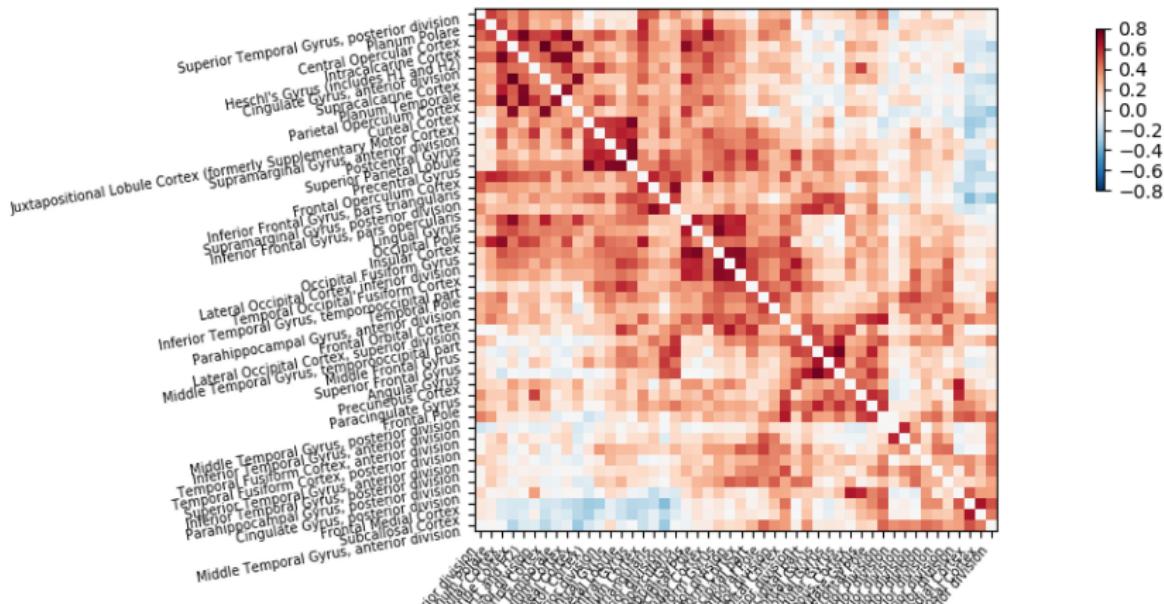


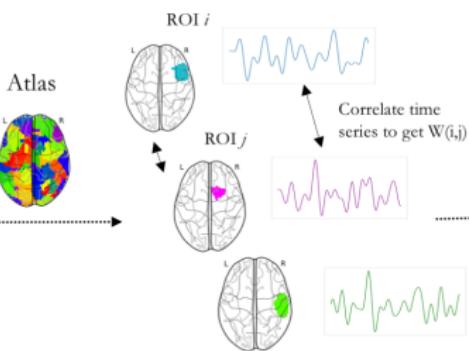
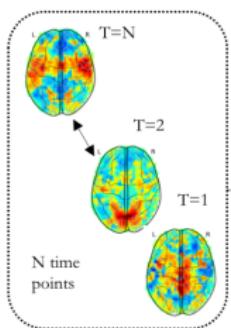
Figure: craddock 400 (cc400, 400 ROIs)

Connectivity Matrix

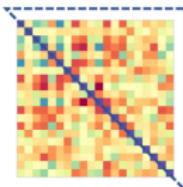


Preprocess and feature extraction

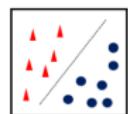
Preprocessed 4D rs-fMRI data



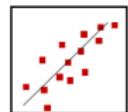
Functional Connectivity matrix (W)



(a) Classification

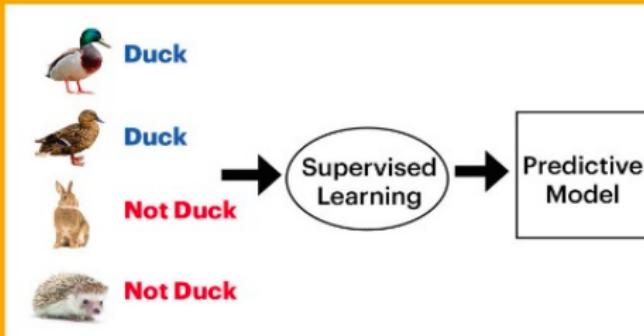


(b) Regression



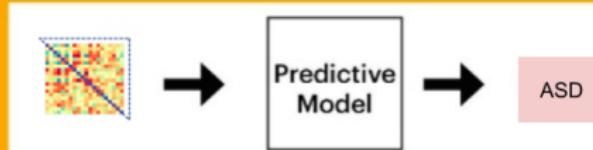
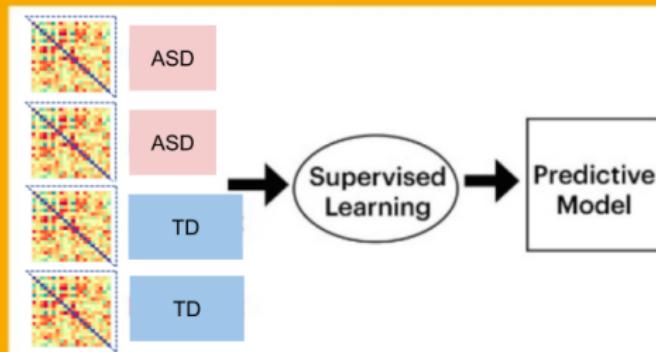
Classification

Supervised Learning (Classification Algorithm)



Classification

Supervised Learning (Classification Algorithm)

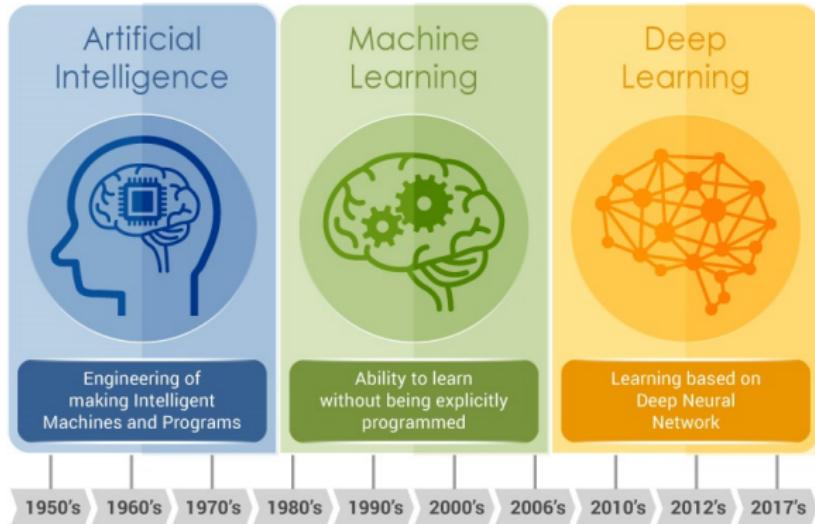


Machine Learning Models

Classifiers

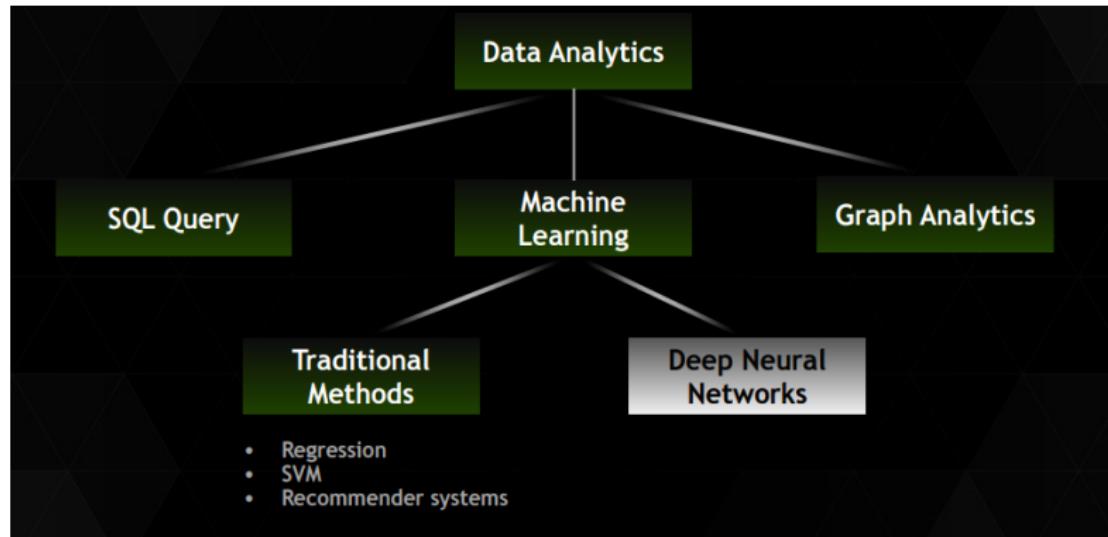
- Ridge
- Logistic Regression
- linear Support Vector Machine
- Kernel Support Vector Machine
- Deep Neural Network

AI v.s. Machine Learning v.s. Deep Learning



- Figure courtesy of www.embedded-vision.com

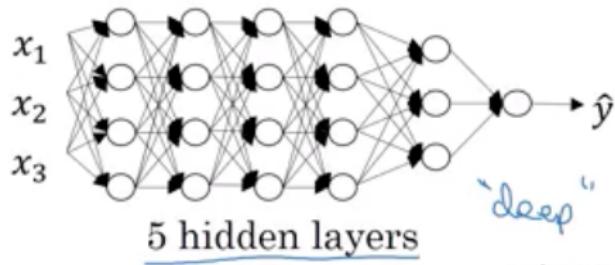
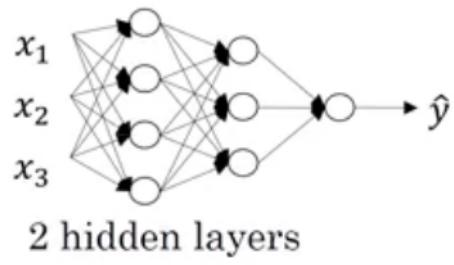
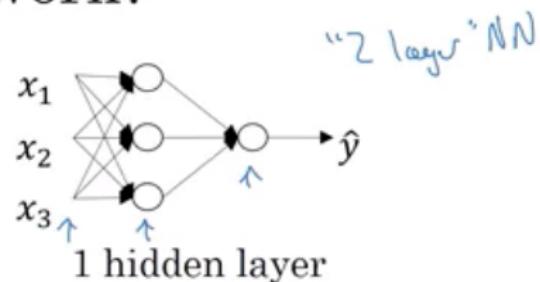
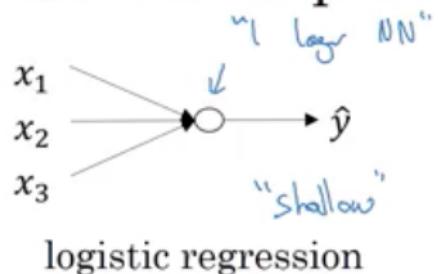
Deep Neural Networks



- Slide courtesy of Larry Brown, NVIDIA.com

What make Deep Neural Networks **deep**?

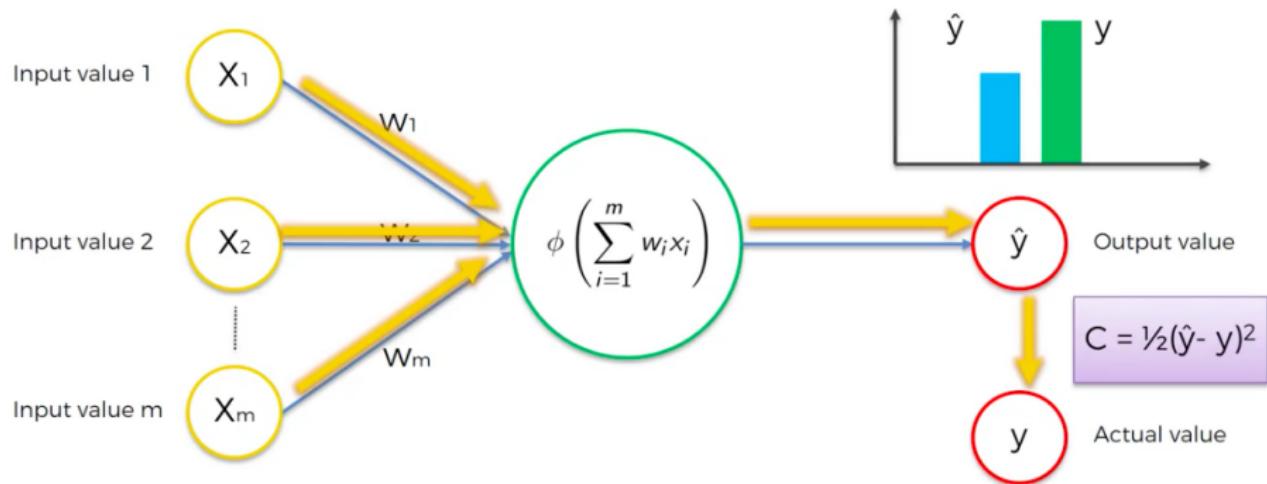
What is a deep neural network?



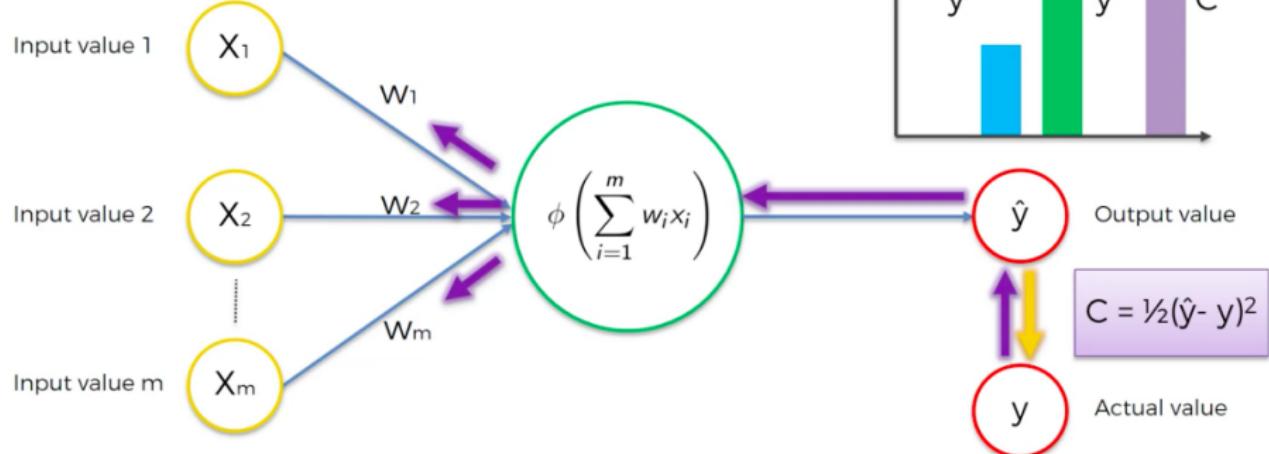
Naming Conventions

- The overall length of the chain gives the **depth** of the model. The name “deep learning” arose from this terminology.
- You may also hear these networks interchangeably referred to as **“Artificial Neural Networks” (ANN)**.
- Many people do not like the analogies between Neural Networks and real brains and prefer to refer to neurons as **units**.

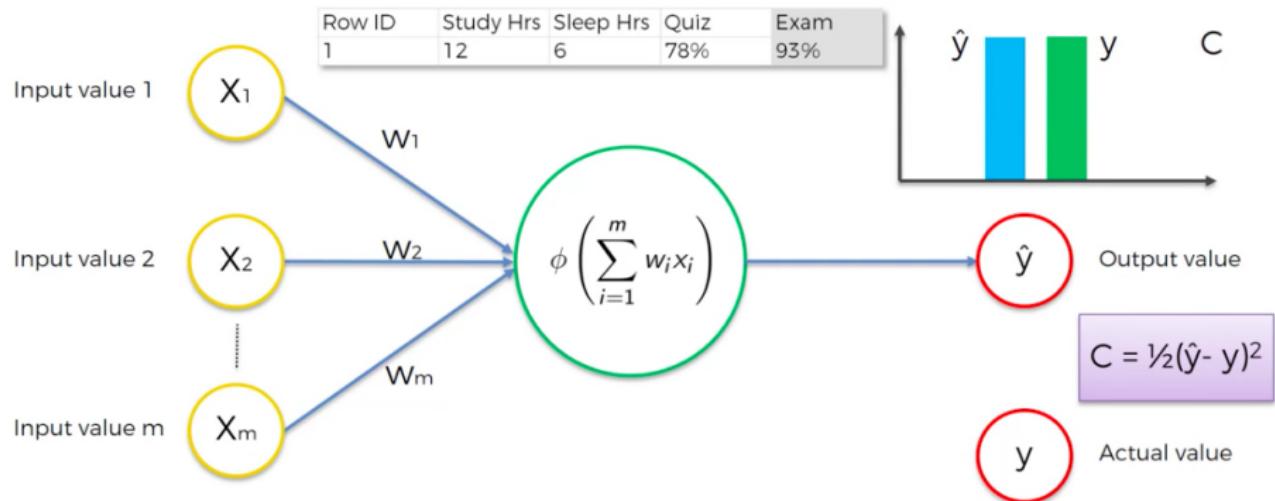
How do Neural Networks work ?



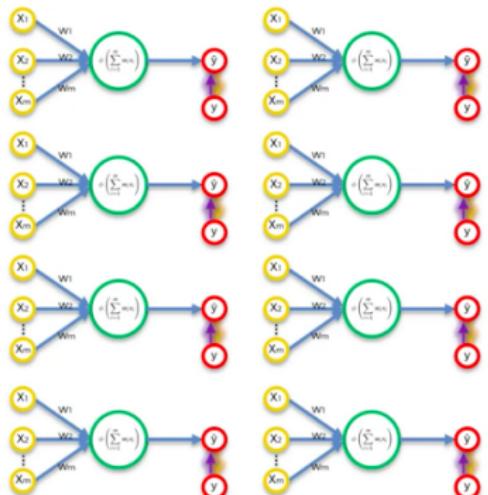
How do Neural Networks learn?



How do Neural Networks work ?



How do Neural Networks learn?



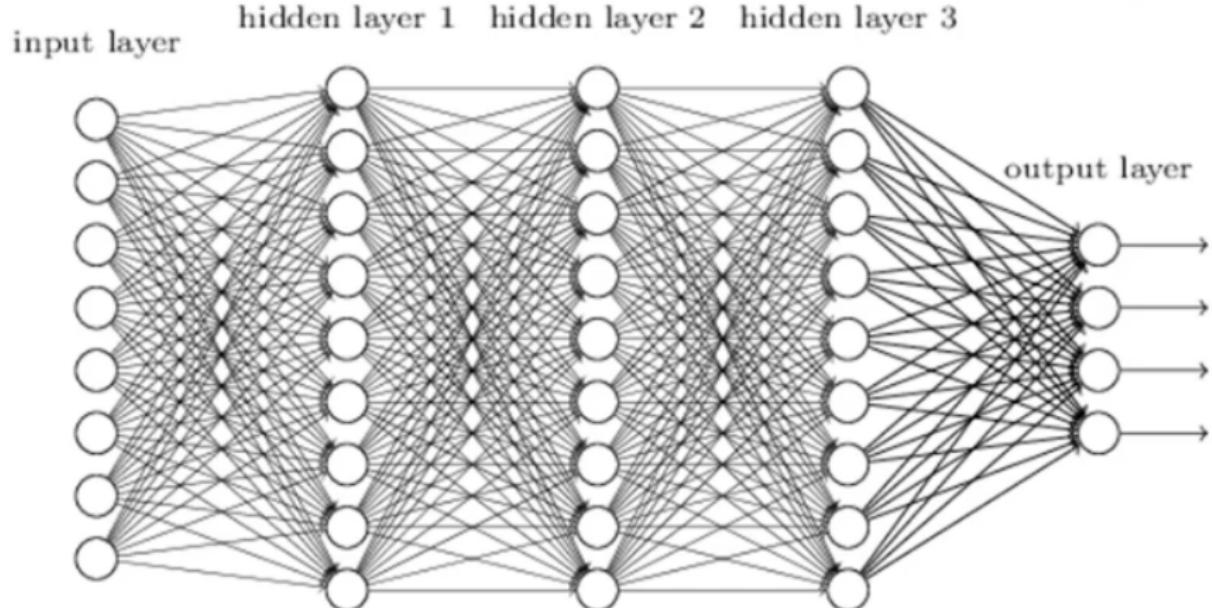
| Row ID | Study Hrs | Sleep Hrs | Quiz | Exam |
|--------|-----------|-----------|------|------|
| 1 | 12 | 6 | 78% | 93% |
| 2 | 22 | 6.5 | 24% | 68% |
| 3 | 115 | 4 | 100% | 95% |
| 4 | 31 | 9 | 67% | 75% |
| 5 | 0 | 10 | 58% | 51% |
| 6 | 5 | 8 | 78% | 60% |
| 7 | 92 | 6 | 82% | 89% |
| 8 | 57 | 8 | 91% | 97% |

$$C = \sum \frac{1}{2}(\hat{y} - y)^2$$



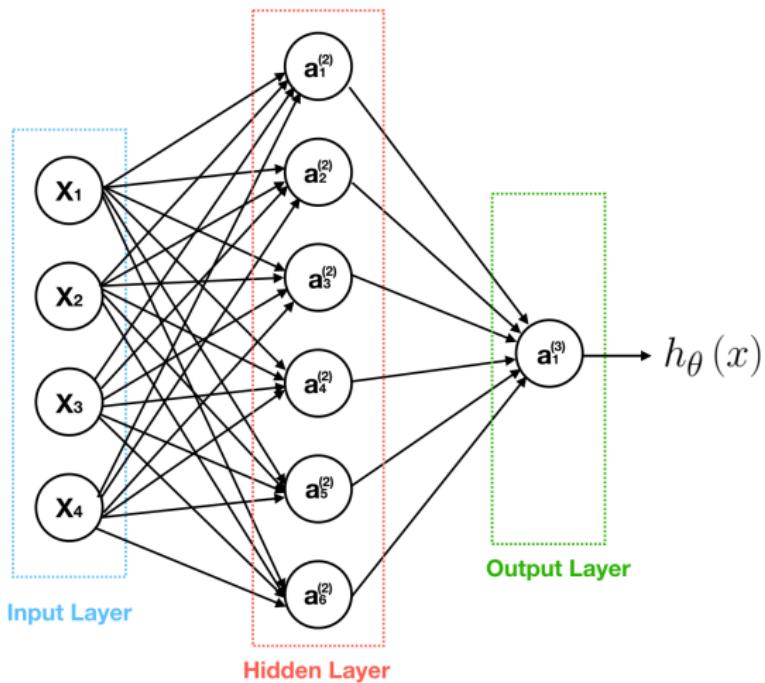
Forward Propagation

Forward Propagation



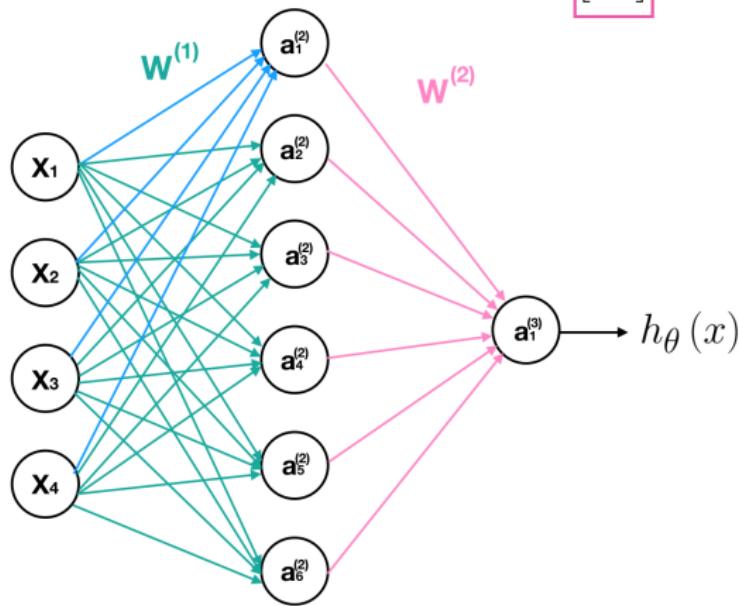
How do Neural Networks work ?

- Input Layer: 4 units, Output Layer: 1 units, Hidden Layer : 6 units



How do Neural Networks work ?

$$W^{(1)} = \begin{bmatrix} \theta_{11}^{(1)} & \theta_{21}^{(1)} & \theta_{31}^{(1)} & \theta_{41}^{(1)} & \theta_{51}^{(1)} & \theta_{61}^{(1)} \\ \theta_{12}^{(1)} & \theta_{22}^{(1)} & \theta_{32}^{(1)} & \theta_{42}^{(1)} & \theta_{52}^{(1)} & \theta_{62}^{(1)} \\ \theta_{13}^{(1)} & \theta_{23}^{(1)} & \theta_{33}^{(1)} & \theta_{43}^{(1)} & \theta_{53}^{(1)} & \theta_{63}^{(1)} \\ \theta_{14}^{(1)} & \theta_{24}^{(1)} & \theta_{34}^{(1)} & \theta_{44}^{(1)} & \theta_{54}^{(1)} & \theta_{64}^{(1)} \end{bmatrix}$$
$$W^{(2)} = \begin{bmatrix} \theta_{11}^{(2)} \\ \theta_{12}^{(2)} \\ \theta_{13}^{(2)} \\ \theta_{14}^{(2)} \\ \theta_{15}^{(2)} \\ \theta_{16}^{(2)} \end{bmatrix}$$

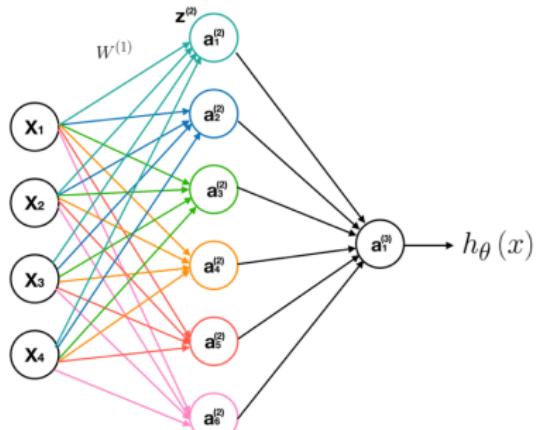


How do Neural Networks work ?

- From Input Layer to Hidden Layer

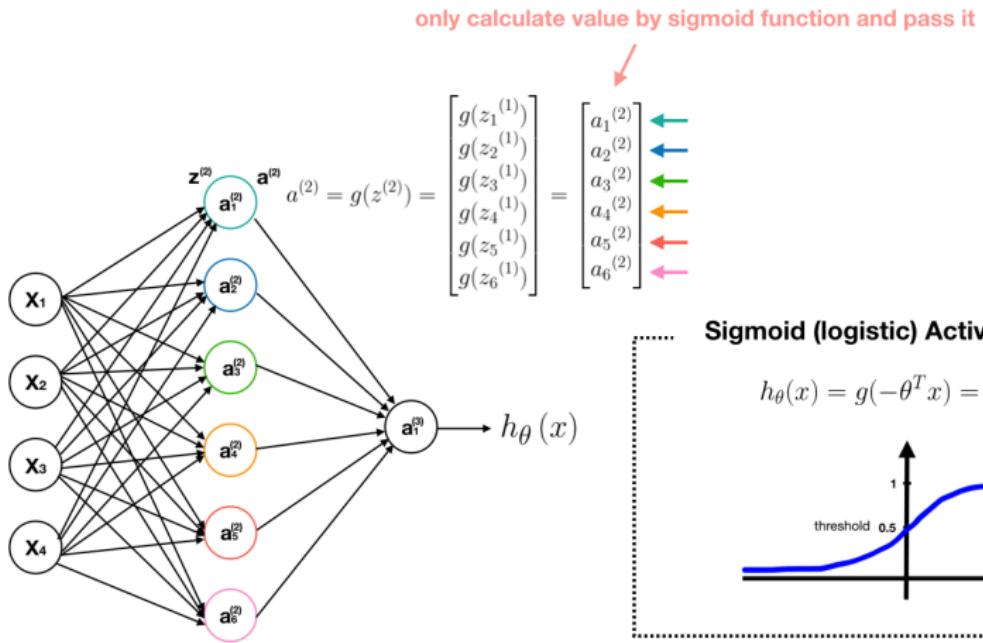
$$W^T X = \begin{bmatrix} \theta_{11}^{(1)} & \theta_{12}^{(1)} & \theta_{13}^{(1)} & \theta_{14}^{(1)} \\ \theta_{21}^{(1)} & \theta_{22}^{(1)} & \theta_{23}^{(1)} & \theta_{24}^{(1)} \\ \theta_{31}^{(1)} & \theta_{32}^{(1)} & \theta_{33}^{(1)} & \theta_{34}^{(1)} \\ \theta_{41}^{(1)} & \theta_{42}^{(1)} & \theta_{43}^{(1)} & \theta_{44}^{(1)} \\ \theta_{51}^{(1)} & \theta_{52}^{(1)} & \theta_{53}^{(1)} & \theta_{54}^{(1)} \\ \theta_{61}^{(1)} & \theta_{62}^{(1)} & \theta_{63}^{(1)} & \theta_{64}^{(1)} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{bmatrix} = \begin{bmatrix} z_1^{(1)} \\ z_2^{(1)} \\ z_3^{(1)} \\ z_4^{(1)} \\ z_5^{(1)} \\ z_6^{(1)} \end{bmatrix} = Z^{(2)}$$

$$\begin{aligned} z_1^{(2)} &= \theta_{11}^{(1)}x_1 + \theta_{12}^{(1)}x_2 + \theta_{13}^{(1)}x_3 + \theta_{14}^{(1)}x_4 \\ z_2^{(2)} &= \theta_{21}^{(1)}x_1 + \theta_{22}^{(1)}x_2 + \theta_{23}^{(1)}x_3 + \theta_{24}^{(1)}x_4 \\ z_3^{(2)} &= \theta_{31}^{(1)}x_1 + \theta_{32}^{(1)}x_2 + \theta_{33}^{(1)}x_3 + \theta_{34}^{(1)}x_4 \\ z_4^{(2)} &= \theta_{41}^{(1)}x_1 + \theta_{42}^{(1)}x_2 + \theta_{43}^{(1)}x_3 + \theta_{44}^{(1)}x_4 \\ z_5^{(2)} &= \theta_{51}^{(1)}x_1 + \theta_{52}^{(1)}x_2 + \theta_{53}^{(1)}x_3 + \theta_{54}^{(1)}x_4 \\ z_6^{(2)} &= \theta_{61}^{(1)}x_1 + \theta_{62}^{(1)}x_2 + \theta_{63}^{(1)}x_3 + \theta_{64}^{(1)}x_4 \end{aligned}$$



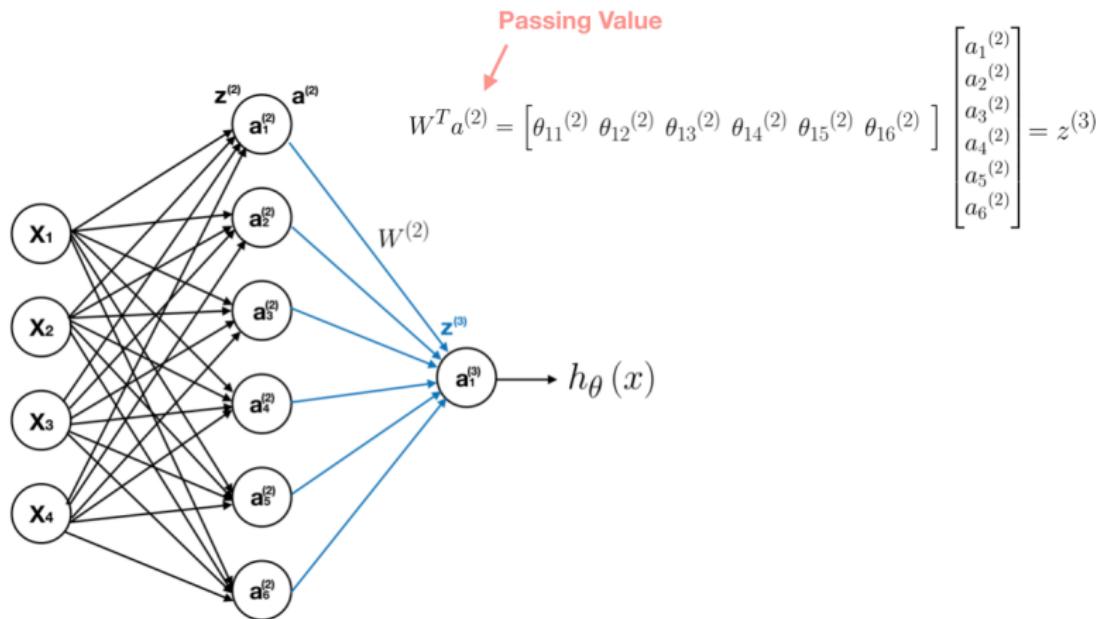
How do Neural Networks work ?

- From Input Layer to Hidden Layer



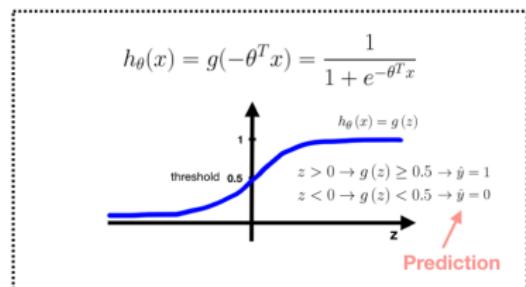
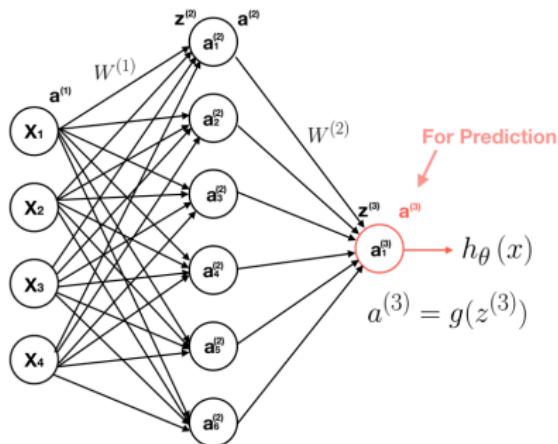
How do Neural Networks work ?

- From Hidden Layer to Output Layer



How do Neural Networks work ?

- From Hidden Layer to Output Layer



Loss Function

- **Loss Function** is also called **Cost Function**, but this name is used more commonly in NN.
- The goal of Loss Function is to measure the error that the model made.

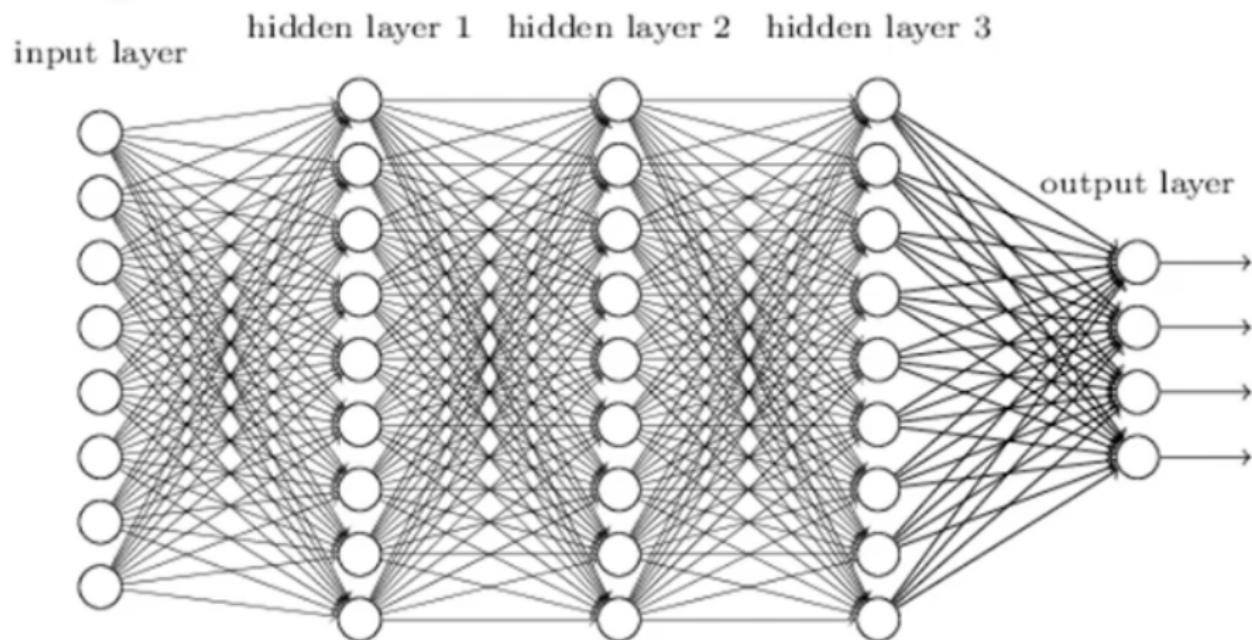
$$J(\Theta) = -\frac{1}{m} \left[\sum_{i=1}^m \sum_{k=1}^K y_k^{(i)} \log(h_\Theta(x^{(i)}))_k + (1 - y_k^{(i)}) \log(1 - (h_\Theta(x^{(i)}))_k) \right] + \boxed{\frac{\lambda}{2m} \sum_{l=1}^{L-1} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} (\Theta_{ji}^{(l)})^2}$$

↑
label number
↓
data number

Regularization Term

Back Propagation

Backpropagation



Back Propagation

- This procedure is for **minimizing Loss Function**, just like the technique – gradient descent.
- There are two steps:
 - Compute the partial derivative of $J(\Theta)$
 - Update each element of weighting matrix Θ

Repeat until converge {

$$\Theta_{ij}^{(l)} = \Theta_{ij}^{(l)} - \alpha \frac{\partial J(\Theta)}{\partial \Theta_{ij}^{(l)}}$$

}

α ↑
learning rate

Back Propagation

$$\frac{\partial J(\Theta)}{\Theta^{(2)}} = \delta^{(3)} * a^{(2)}$$

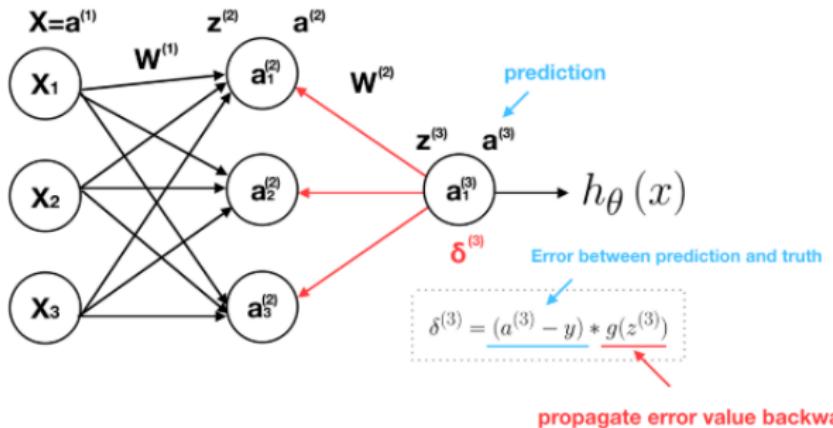
$$\frac{\partial J(\Theta)}{\Theta^{(1)}} = \delta^{(2)} * a^{(1)}$$

$$\delta^{(3)} = (a^{(3)} - y) * g'(z^{(3)})$$

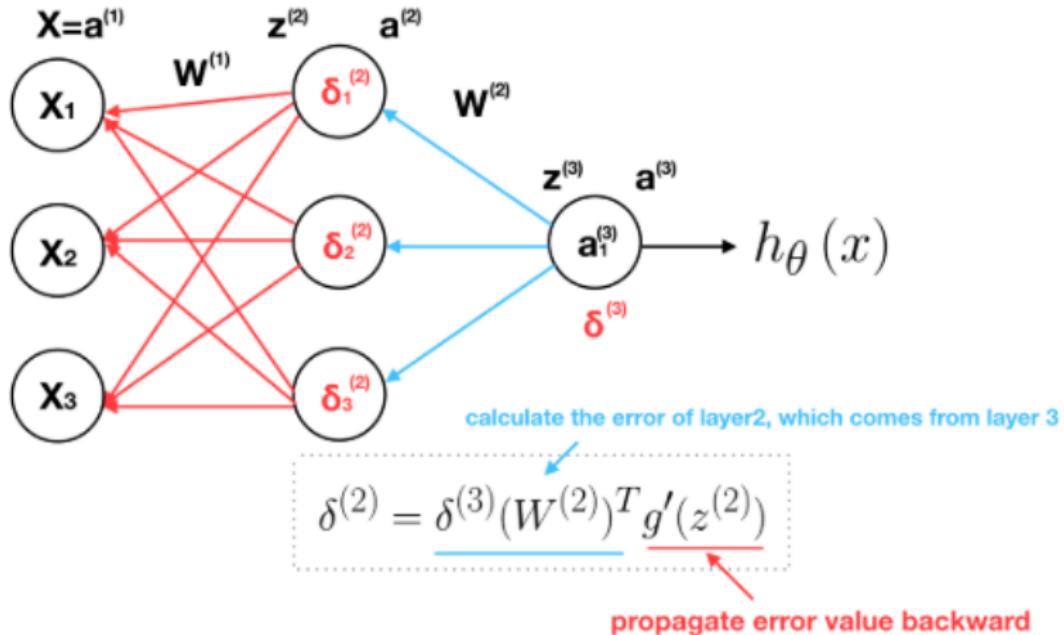
$$\delta^{(2)} = \delta^{(3)} (W^{(2)})^T g'(z^{(2)})$$

Back Propagation

- δ^3 is the error of layer3, the Output Layer in this example.
- δ^2 is the error of layer2, the Hidden Layer in this example.
- δ^1 is not exist since layer1 is the Input Layer.



Back Propagation



Warm Up

STEP 1: Randomly initialise the weights to small numbers close to 0 (but not 0).



STEP 2: Input the first observation of your dataset in the input layer, each feature in one input node.



STEP 3: Forward-Propagation: from left to right, the neurons are activated in a way that the impact of each neuron's activation is limited by the weights. Propagate the activations until getting the predicted result y .



STEP 4: Compare the predicted result to the actual result. Measure the generated error.



STEP 5: Back-Propagation: from right to left, the error is back-propagated. Update the weights according to how much they are responsible for the error. The learning rate decides by how much we update the weights



STEP 6: Repeat Steps 1 to 5 and update the weights after each observation (Reinforcement Learning). Or:

Repeat Steps 1 to 5 but update the weights only after a batch of observations (Batch Learning).



STEP 7: When the whole training set passed through the ANN, that makes an epoch. Redo more epochs.

Deep Learning Frameworks

Deep Learning Frameworks

- Caffe/Caffe2
- Keras
- TensorFlow
- Theano
- Torch

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Results

| Atlas | Classifier | Accuracy | Recall | Precision |
|-------|------------|----------|--------|-----------|
| CC400 | DNN | 72.95% | 74.76% | 71.96% |
| CC400 | Ridge | 71.98% | 70.89% | 71.53% |
| CC400 | LR | 71.79% | 70.69% | 71.29% |
| CC400 | linearSVM | 71.40% | 70.10% | 70.93% |
| CC400 | kernelSVM | 71.40% | 69.90% | 71.12% |

Table: 5 fold Cross-Validation Results

Deep Neural Network Results

| Layer | Accuracy | Recall | Precision |
|------------|----------|---------|-----------|
| 128-64-2 | 73.42% | 70.30 % | 75.00% |
| 256-128-2 | 72.95% | 74.76% | 71.96% |
| 512-256-2 | 71.98 % | 69.39% | 70.83% |
| 1024-512-2 | 72.46% | 68.37% | 72.53% |

Table: 5 fold Cross-Validation Results

Results

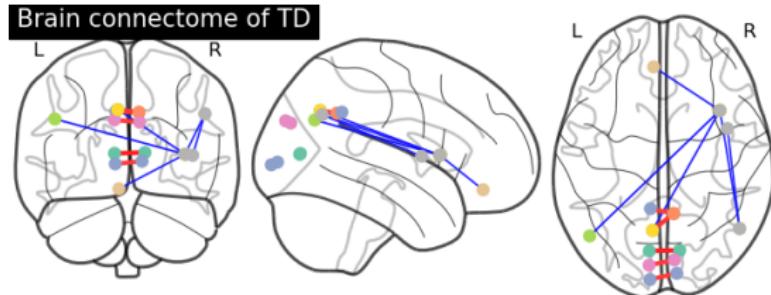


Figure: Top 5 correlated and anti-correlated ROIs of TD

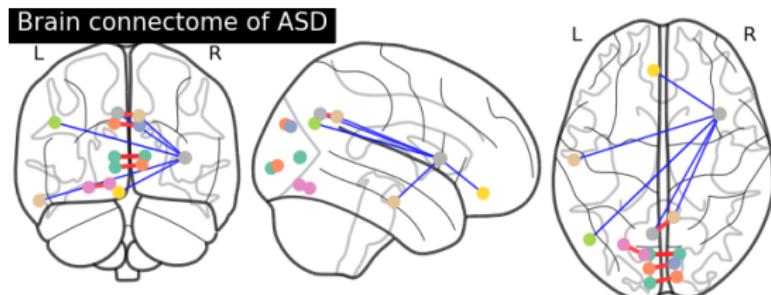


Figure: Top 5 correlated and anti-correlated ROIs of ASD

Results

Table: ROIs Analysis for CC400

| Top 5 Correlation Connectivity ROIs | |
|-------------------------------------|--|
| ASD | Left Intracalcarine Cortex → Right Intracalcarine Cortex |
| | Left Occipital Pole → Right Occipital Pole |
| | Left Cuneal Cortex → Right Cuneal Cortex |
| | Left Precuneous Cortex → Right Precuneous Cortex |
| | Left Occipital Fusiform Gyrus → Left Lingual Gyrus |
| TD | Left Intracalcarine Cortex → Right Intracalcarine Cortex |
| | Left Precuneous Cortex → Right Precuneous Cortex |
| | Left Cingulate Gyrus → Right Precuneous Cortex |
| | Left Occipital Pole → Right Occipital Pole |
| | Left Cuneal Cortex → Right Cuneal Cortex |

Results

Table: ROIs Analysis for CC400

Top 5 Anti-Correlation Connectivity ROIs

| ASD | |
|-----|---|
| ASD | Left Lateral Occipital Cortex → Right Frontal Operculum Cortex |
| | Right Frontal Medial Cortex → Right Frontal Operculum Cortex |
| | Left Middle Temporal Gyrus → Right Frontal Operculum Cortex |
| | Right Precuneous Cortex → Right Frontal Operculum Cortex |
| | Left Precuneous Corte → Right Frontal Operculum Cortex |
| TD | |
| TD | Left Lateral Occipital Cortex → Right Frontal Operculum Cortex |
| | Left Precuneous Cortex → Right Frontal Operculum Cortex |
| | Right Frontal Medial Cortex → Right Frontal Operculum Cortex |
| | Right Lateral Occipital Cortex → Right Frontal Operculum Cortex |
| | Right Lateral Occipital Cortex → Right Central Opercular Cortex |

Agenda

1 Introduction

2 ABIDE Datasets

3 Experiments

4 Results

5 Discussion

Future Work

- hyperparameter

How to find the best hyper-parameters?

Future Work

- more data samples

Can we get more data samples?

Future Work

- clinical application

Can fMRI research apply to the clinic?

End

Thank you! :)
Questions?

Functional connectivity magnetic resonance imaging classification of autism spectrum disorder using the multisite ABIDE dataset

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Jan 31st, 2020