CLASSIFICATION OF AUTISM SPECTRUM DISORDER USING MACHINE LEARNING

Andrew Bender

Mentors: Dr. Mark Wallace and David Tovar

Thesis committee: Dr. Mark Wallace, Dr. Ramnarayan Ramachandran, Dr. Randolph Blake, and Dr. Eli Zimmerman

April 18, 2019

OUTLINE

- Chapter 1: Introduction to Classification and Machine Learning
  - Classification
  - A Few Basic Classifiers
  - Artificial Neural Networks
- Chapter 2: Classification of Autism Spectrum Disorder Using Machine Learning
  - Introduction
  - Methods
  - Results
  - Discussion

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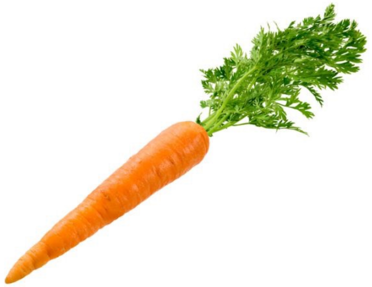
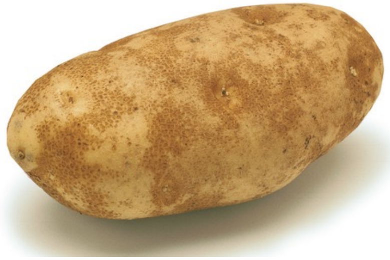
CLASSIFICATION





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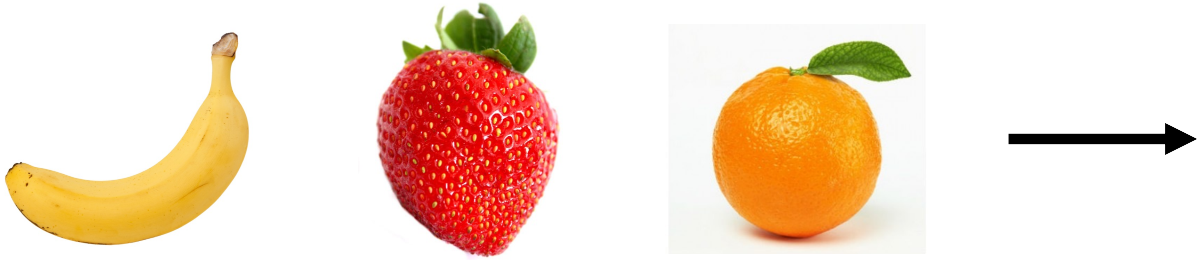

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Fruits

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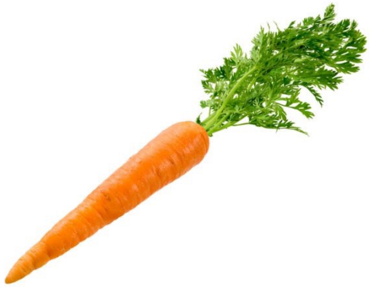 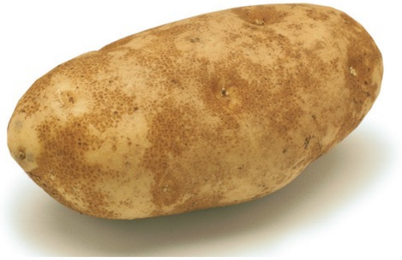 

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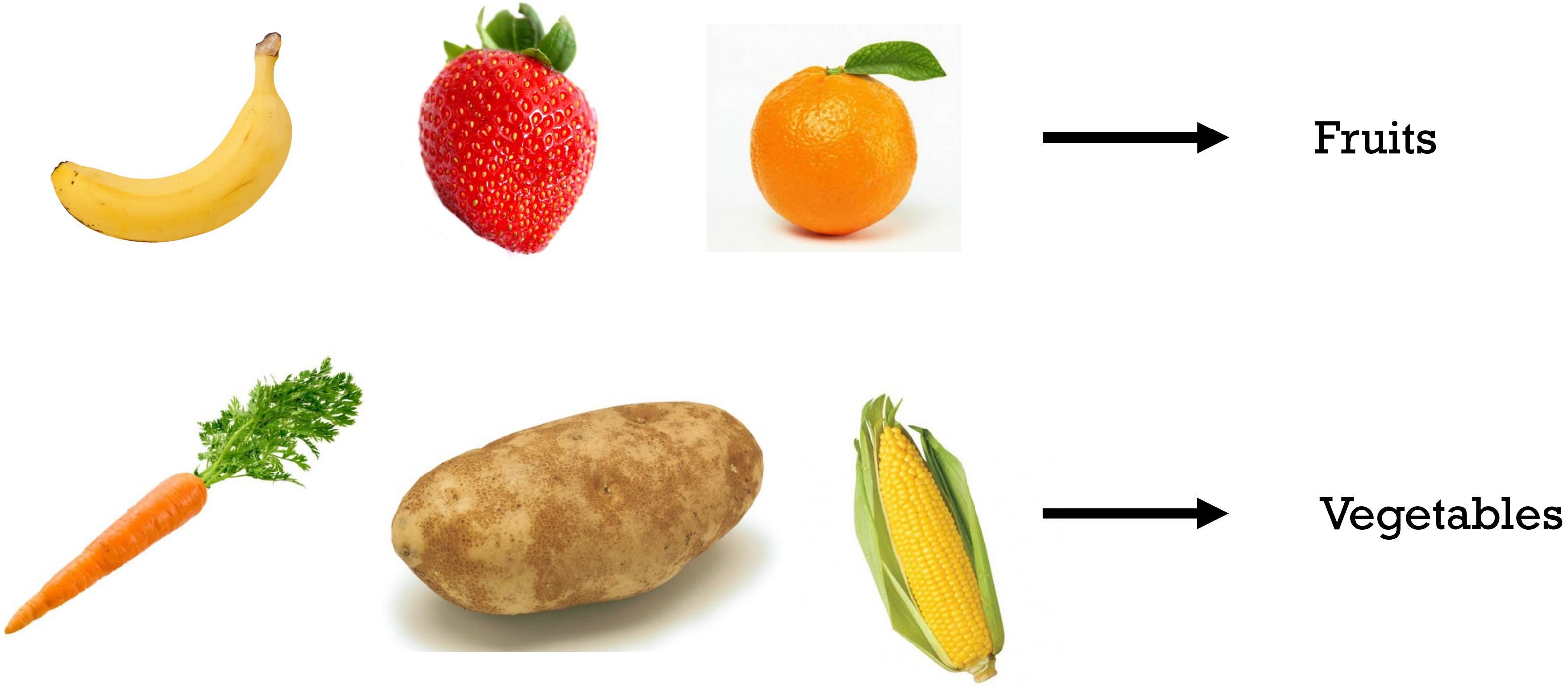

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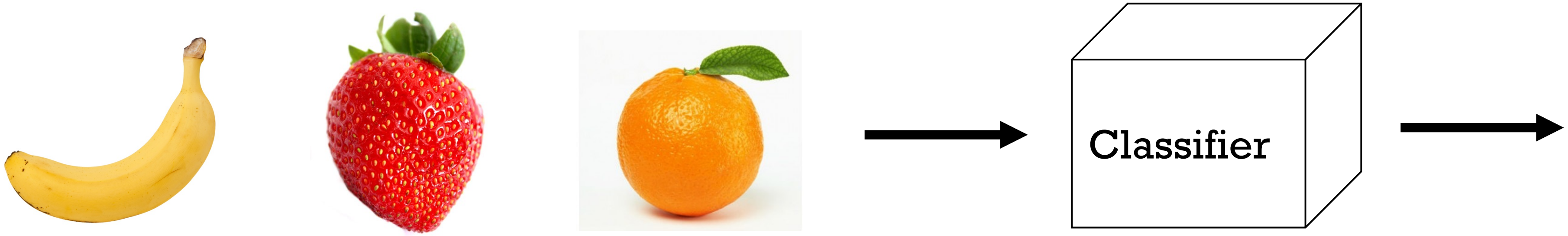

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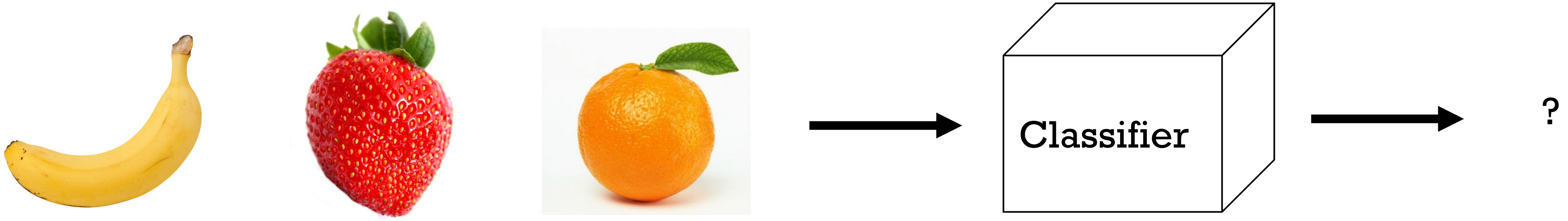

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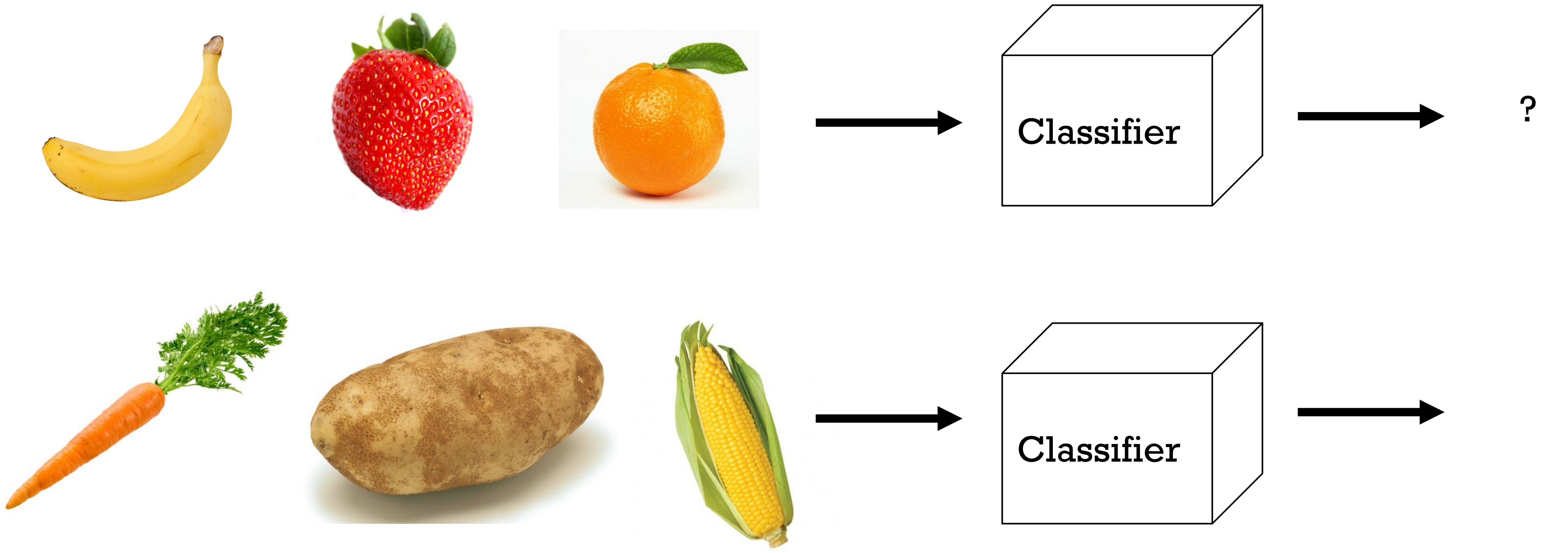

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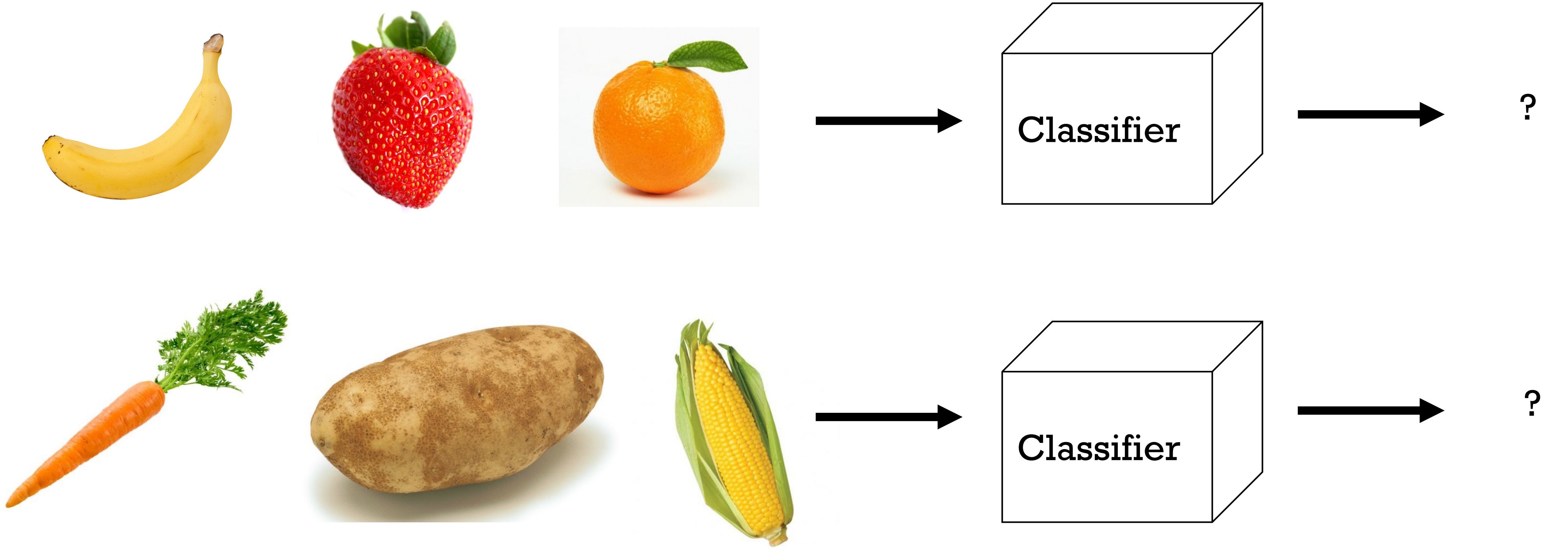
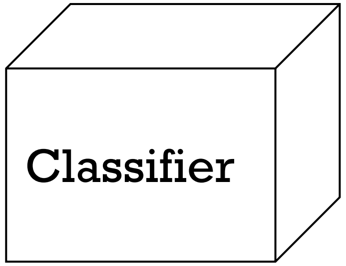
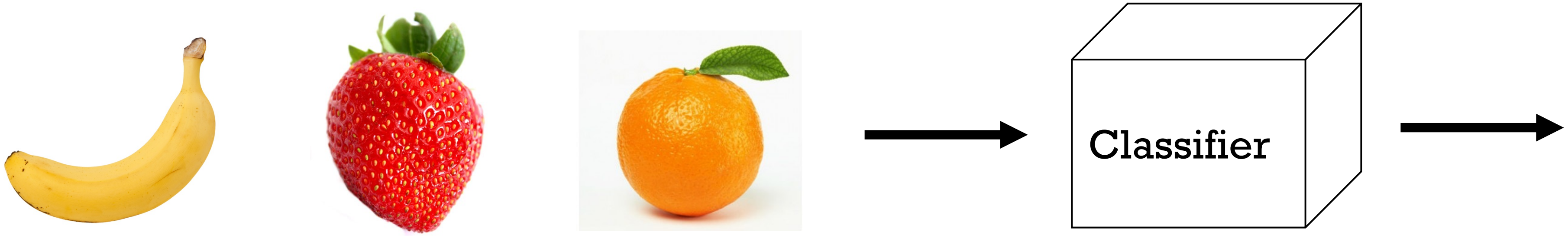


CLASSIFIER TRAINING



Picture from muscleandfitness.com

CLASSIFICATION AFTER TRAINING



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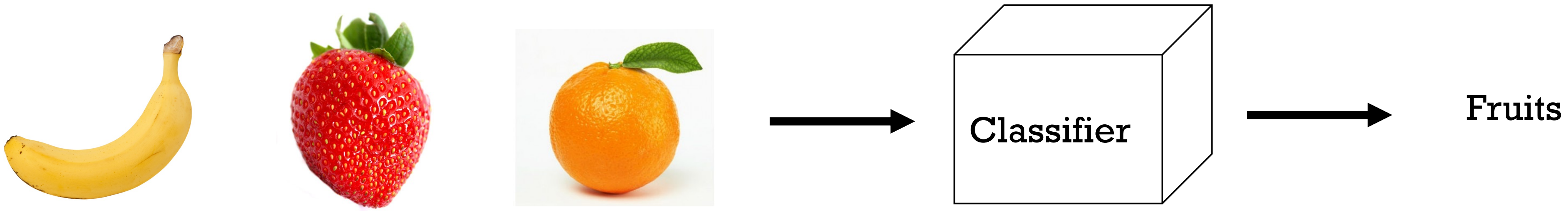

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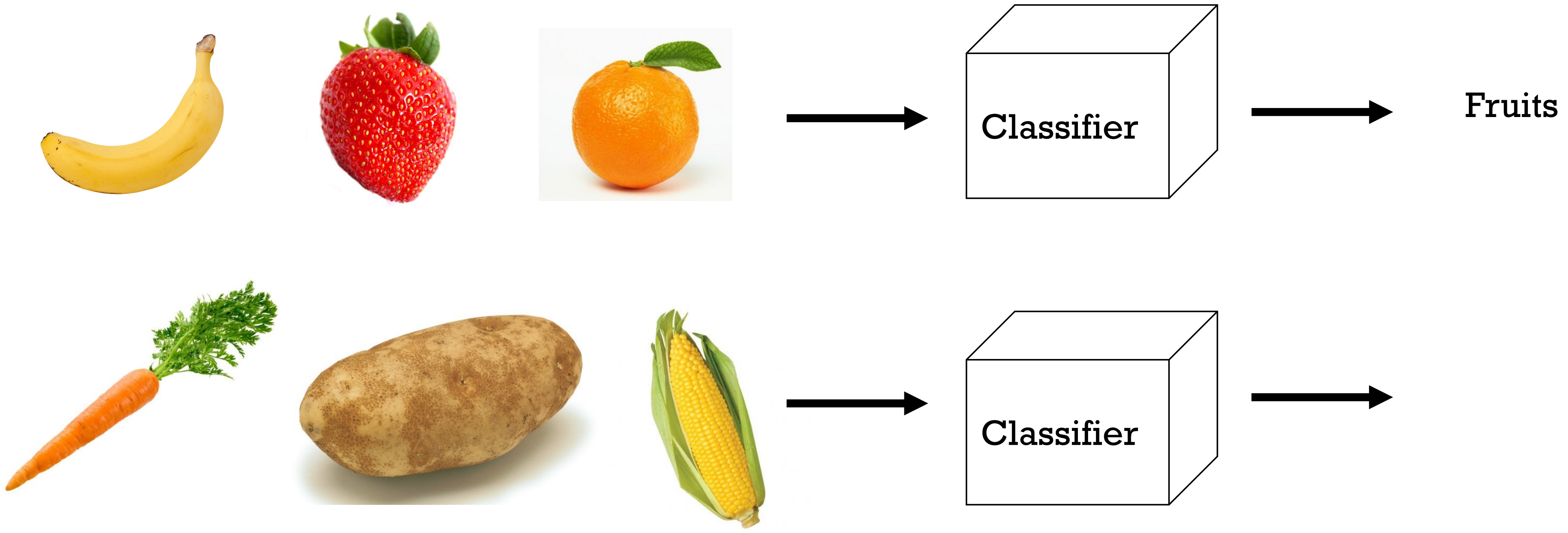

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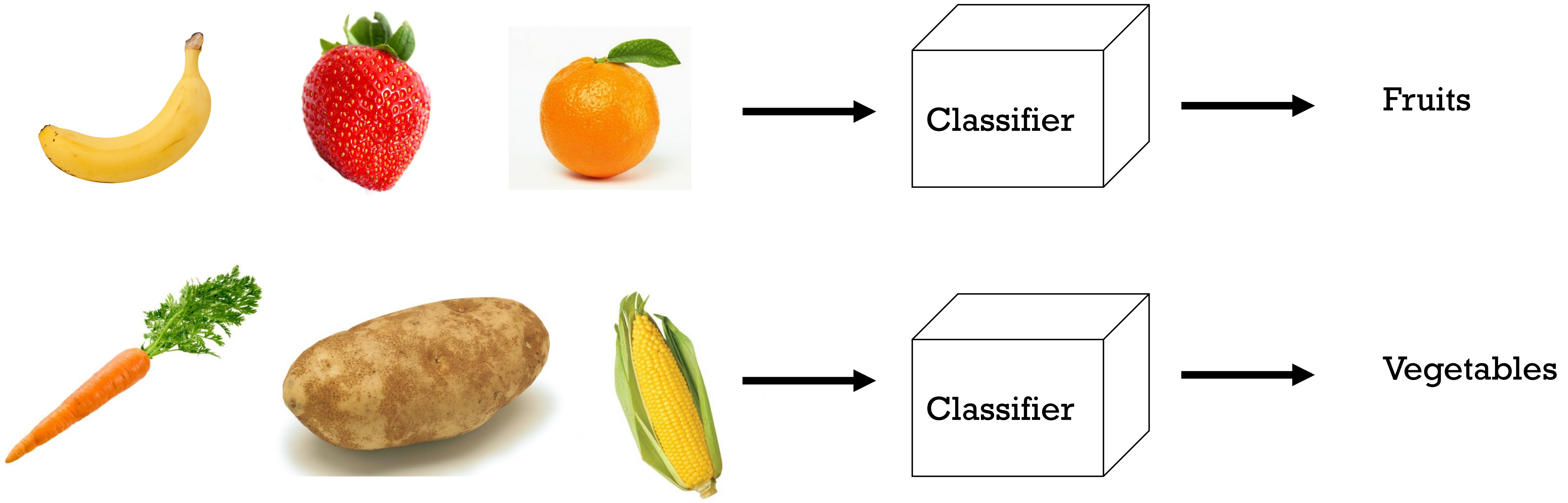
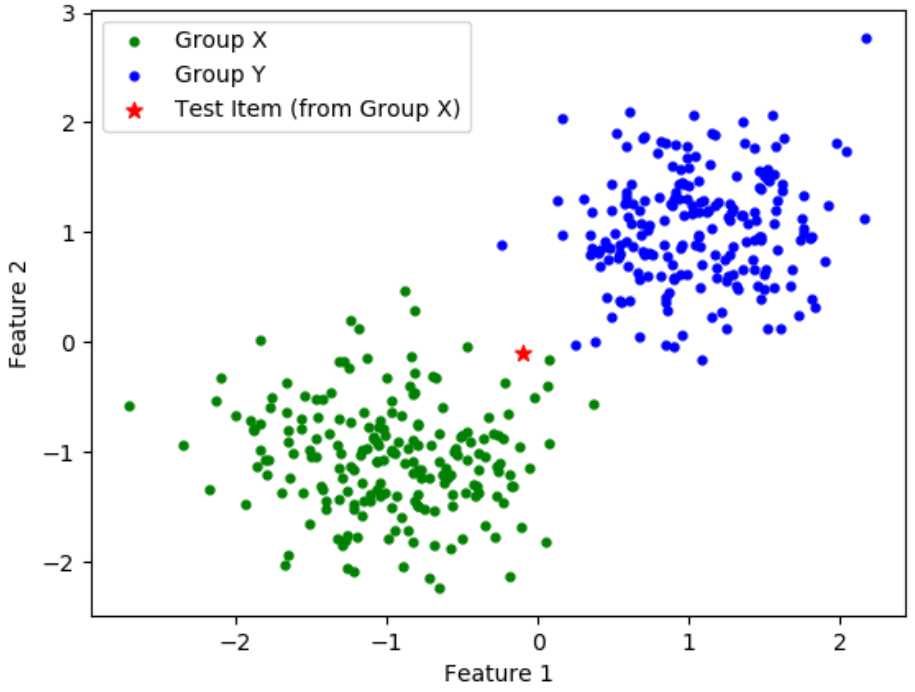


CLASSIFICATION TERMINOLOGY

- Observations
- Classes
- Features
- Feature space



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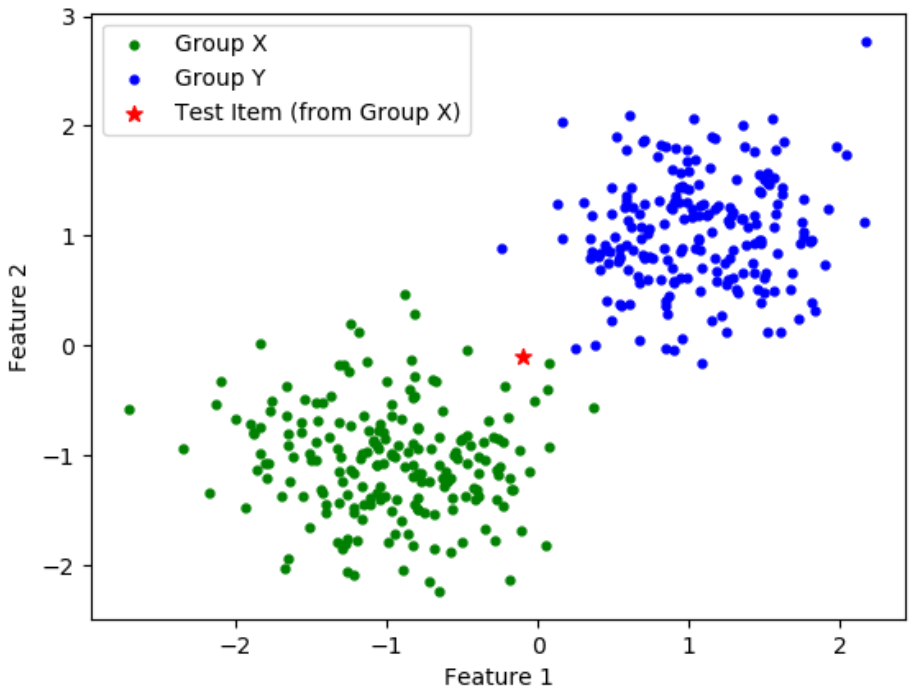

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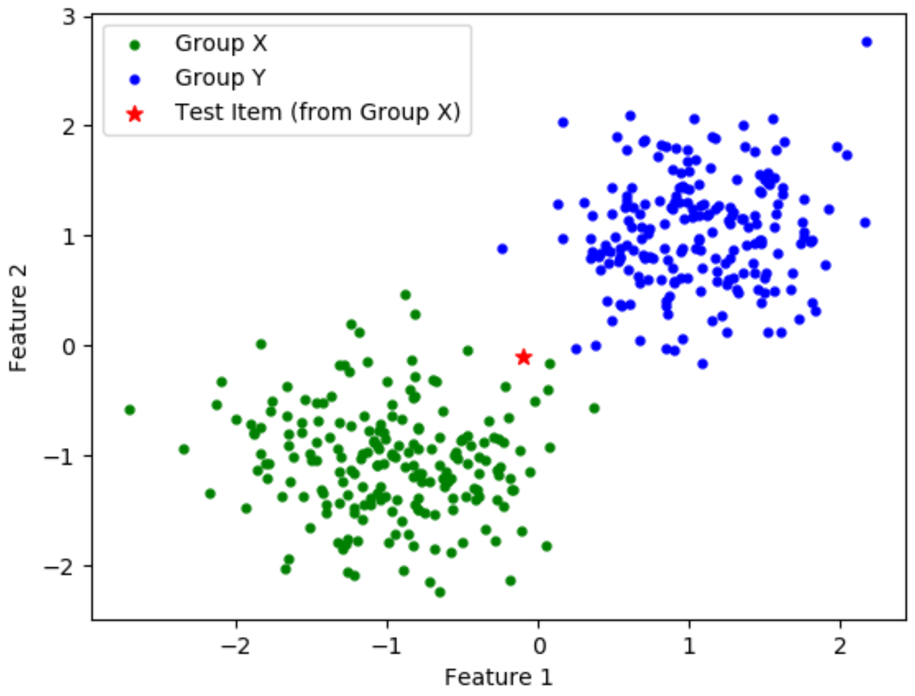

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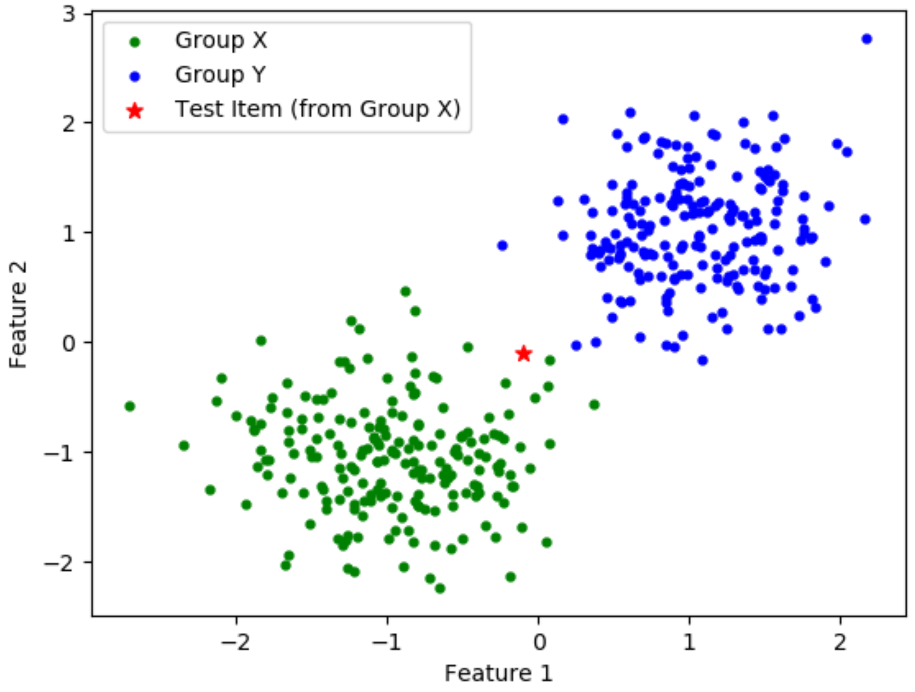

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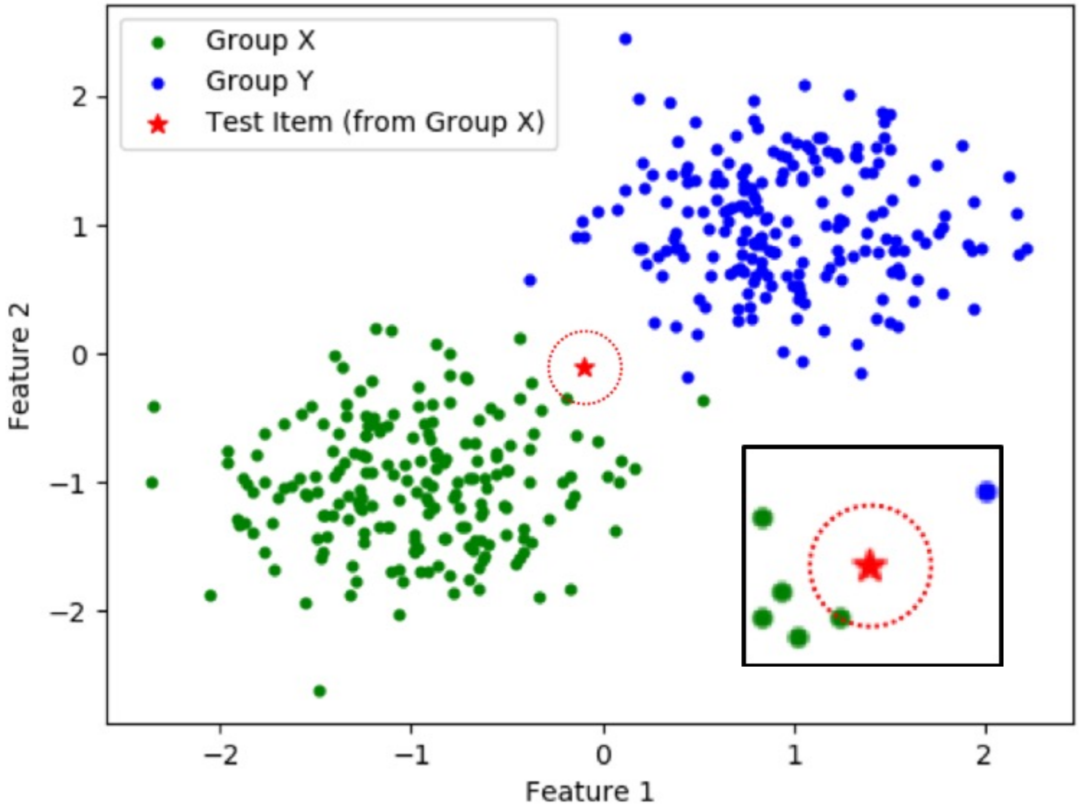
K-NEAREST NEIGHBORS

- No training required
- Euclidean distance between test item and every item in training set
- K = 1: nearest neighbor determines class label
- K > 1: k-nearest neighbors determine class label
  - Majority
  - Weighting



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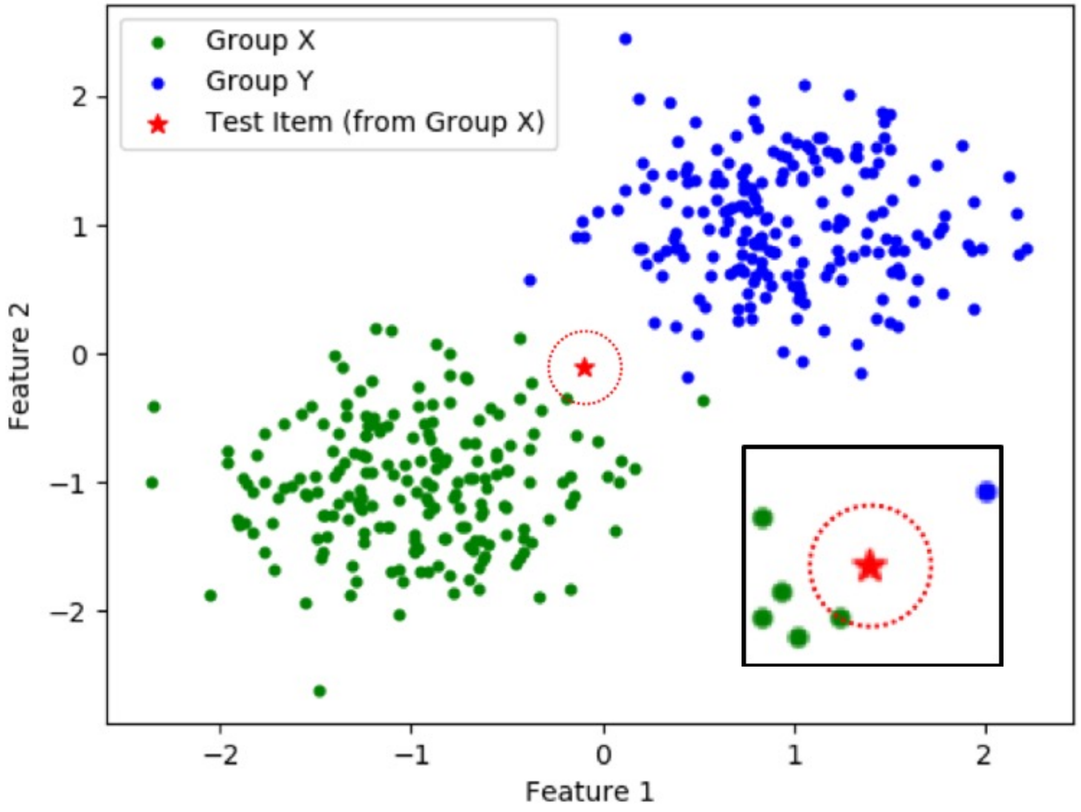

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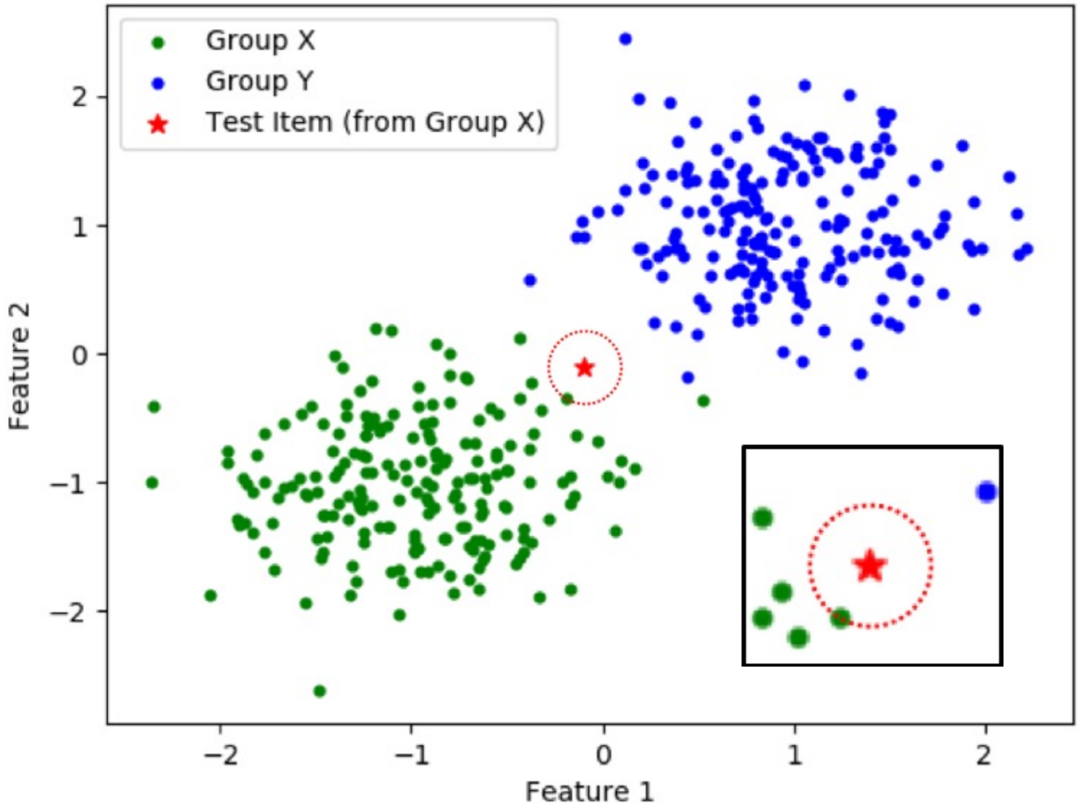

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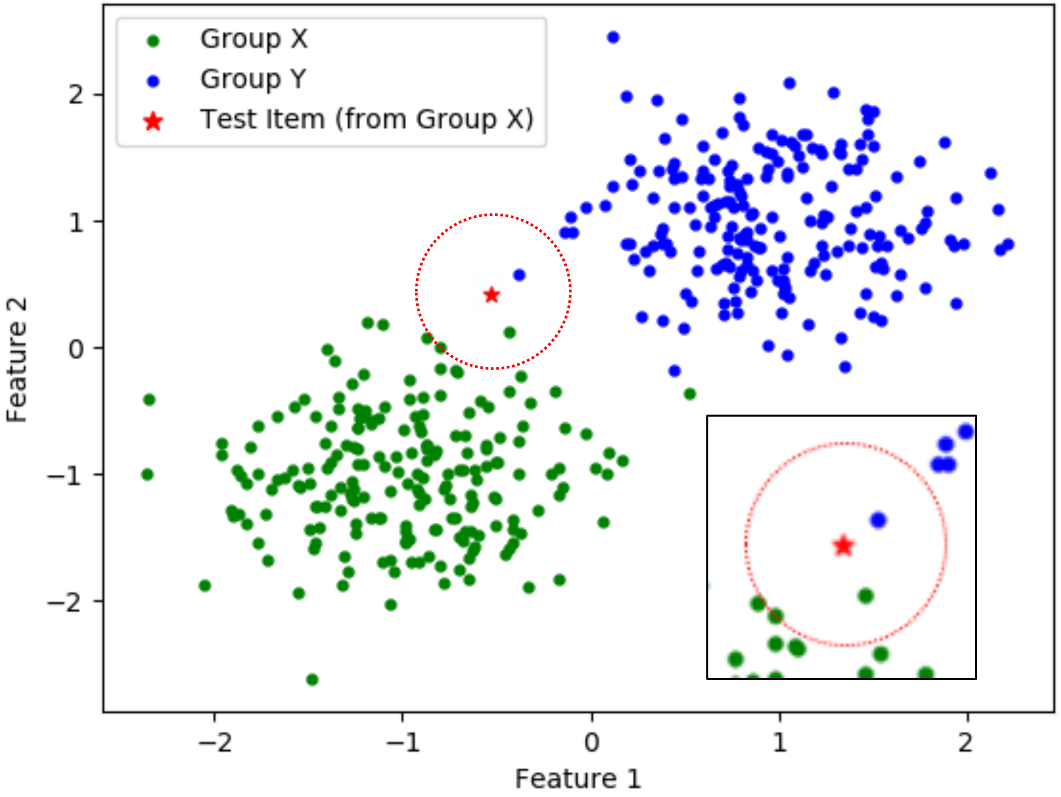

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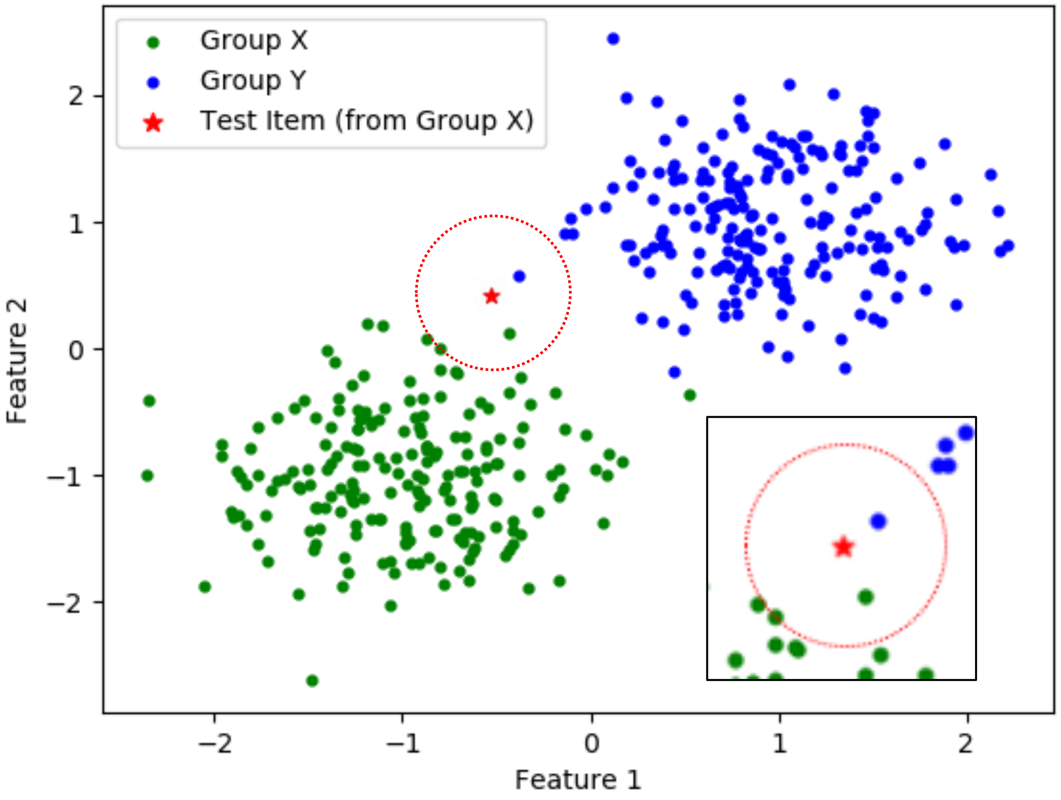

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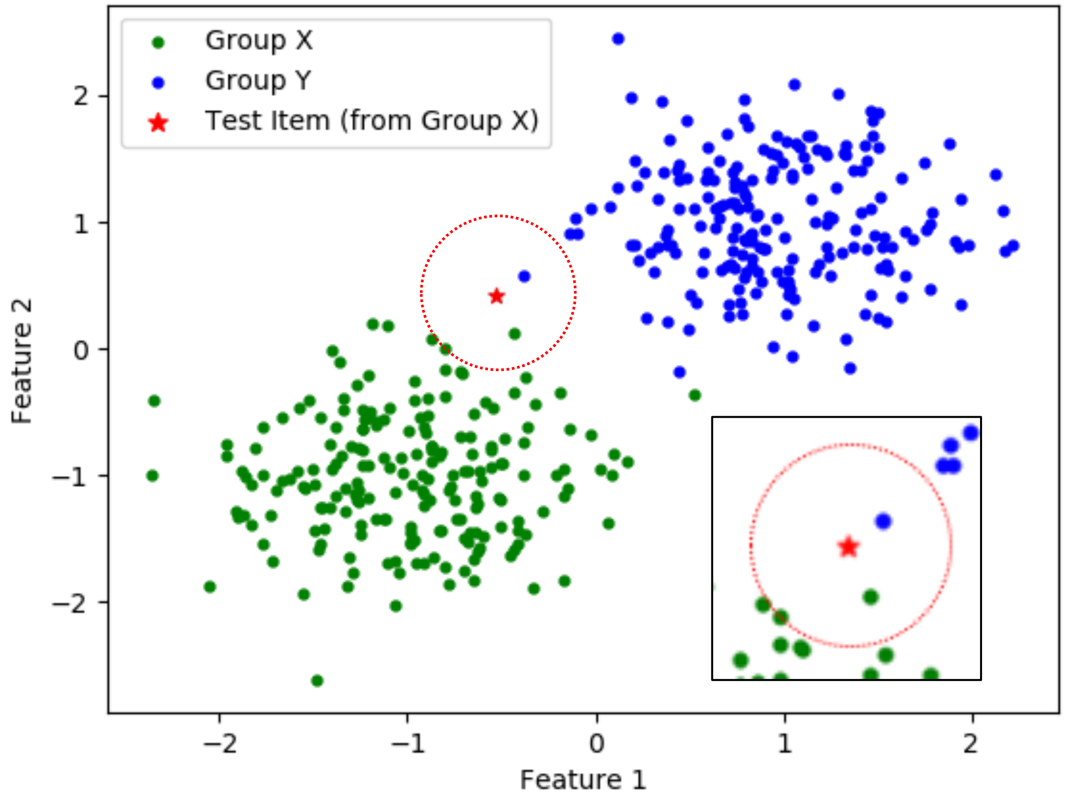
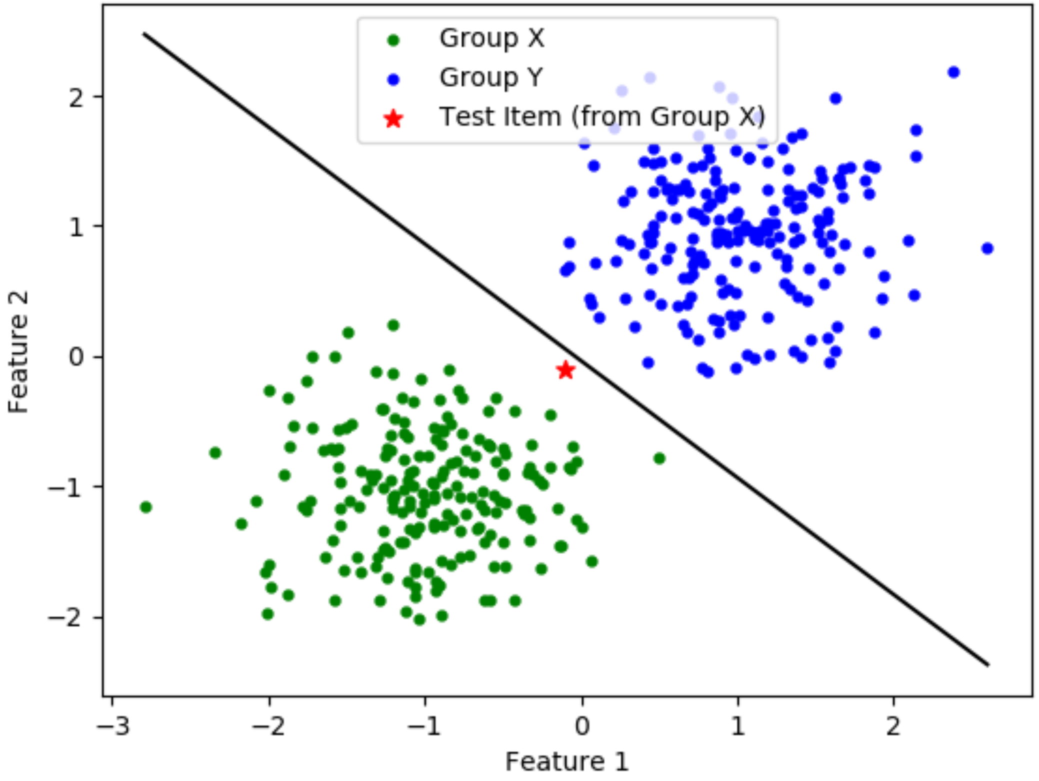


LINEAR DISCRIMINANT ANALYSIS

- Provides a line that best separates the two features
- Linear decision boundary
- Importance of linear separability



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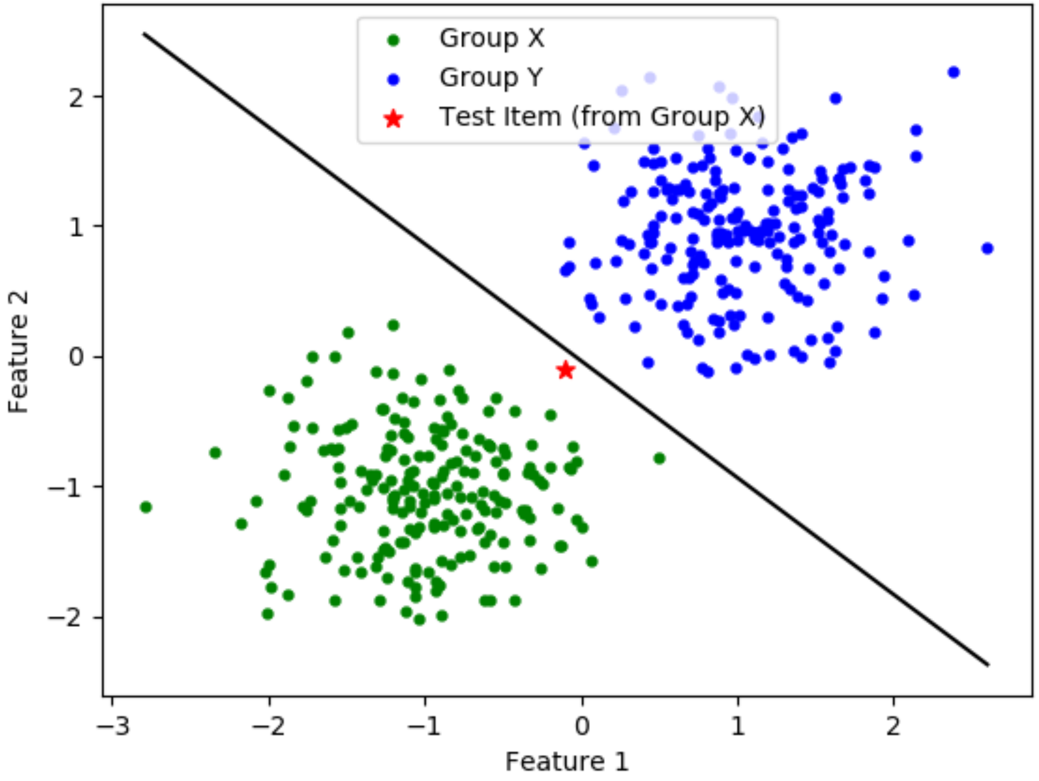

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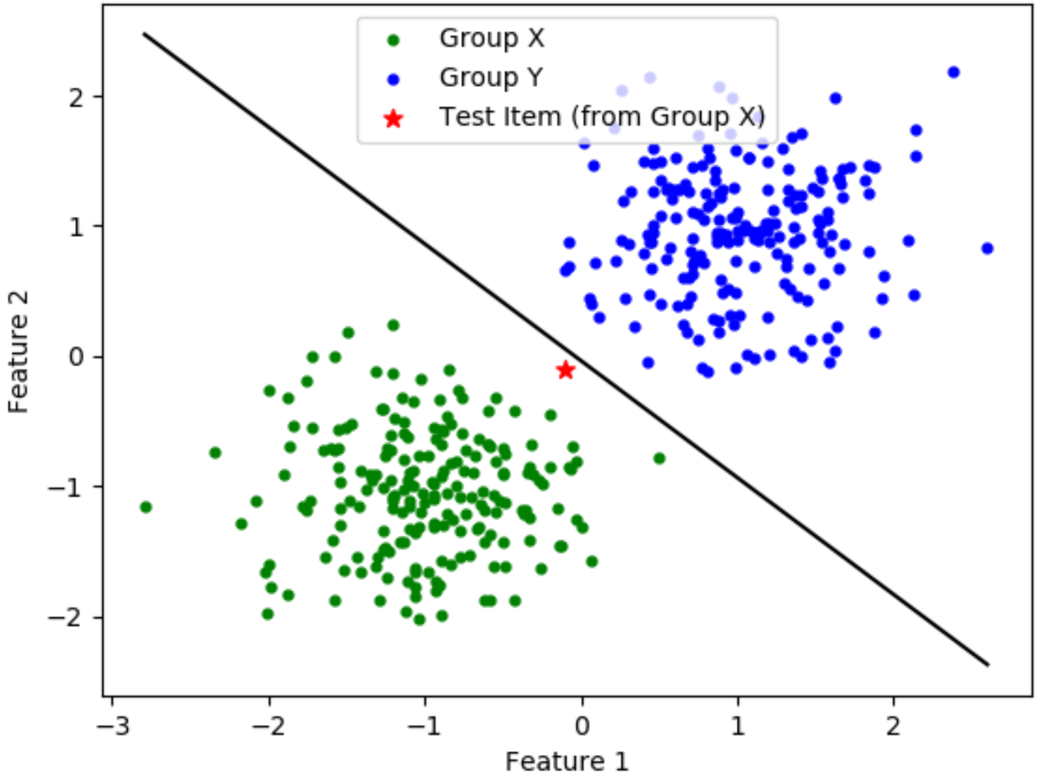

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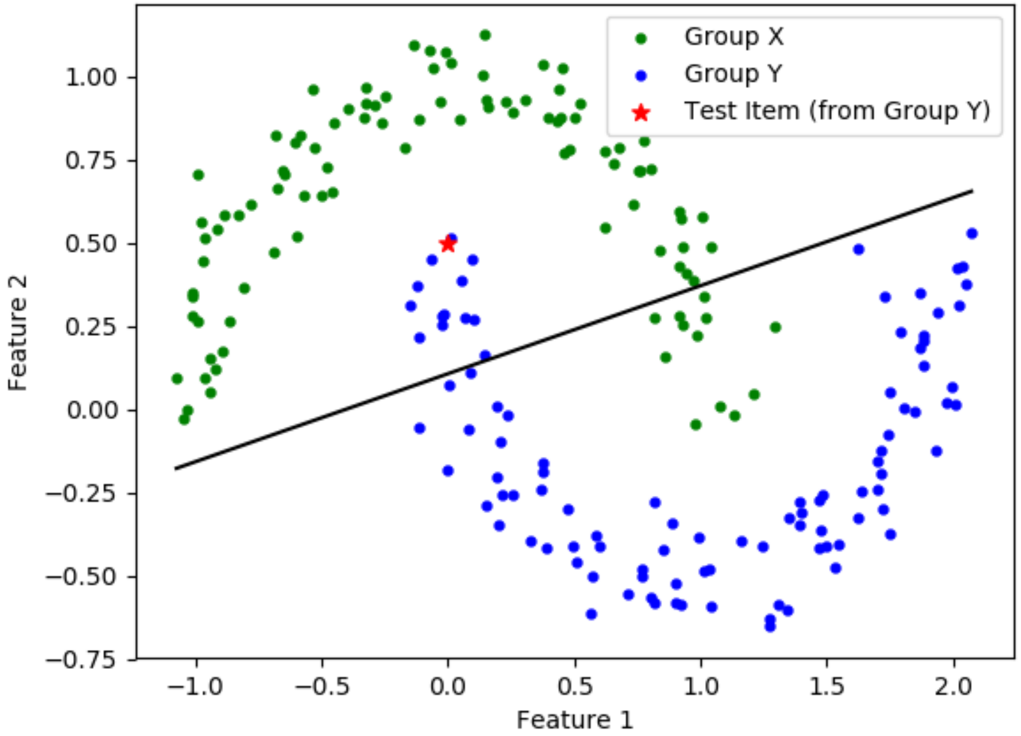

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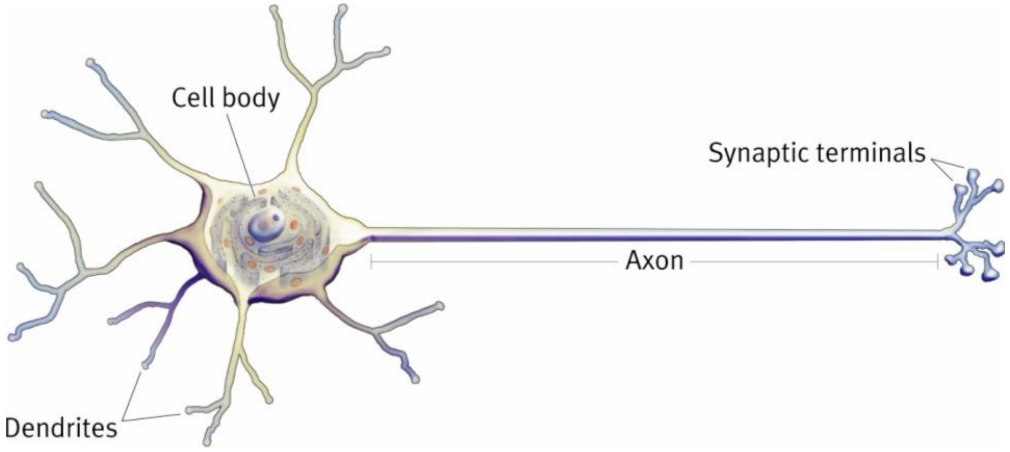
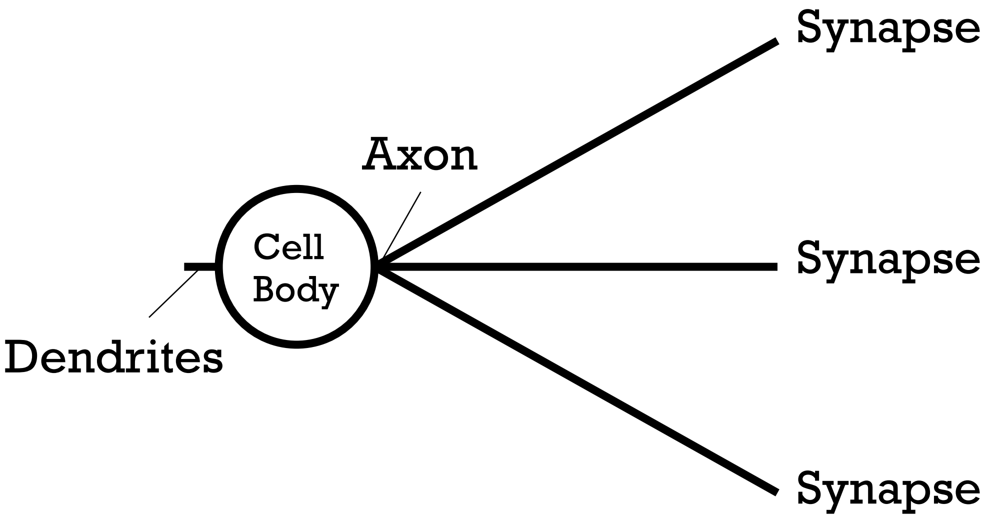
NEURON → NODE IN NEURAL NETWORK

Neuron

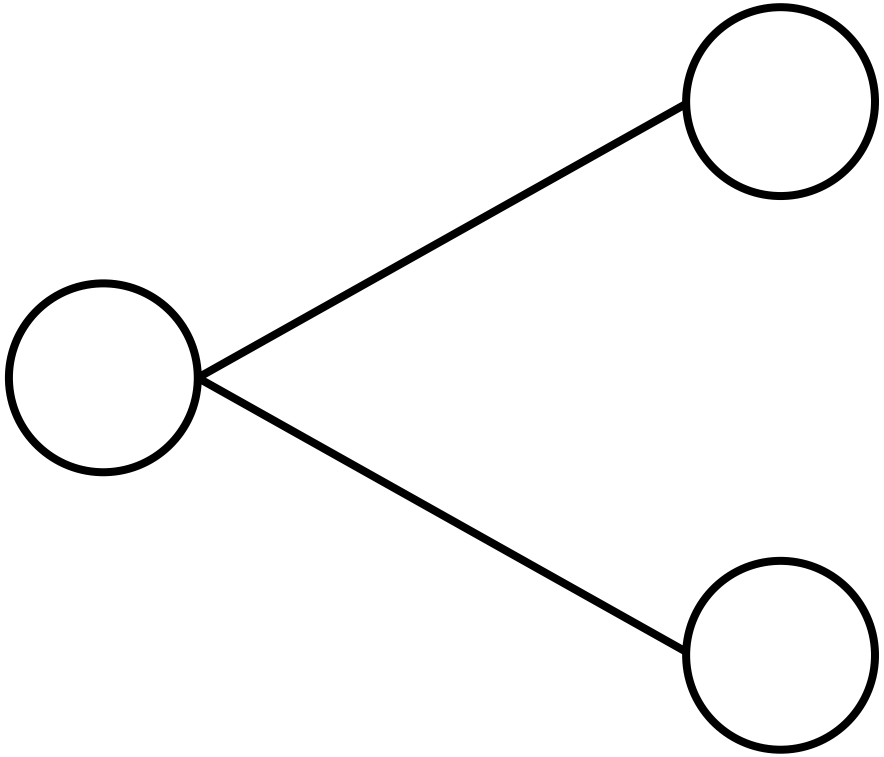


From Memorang

Node in NN

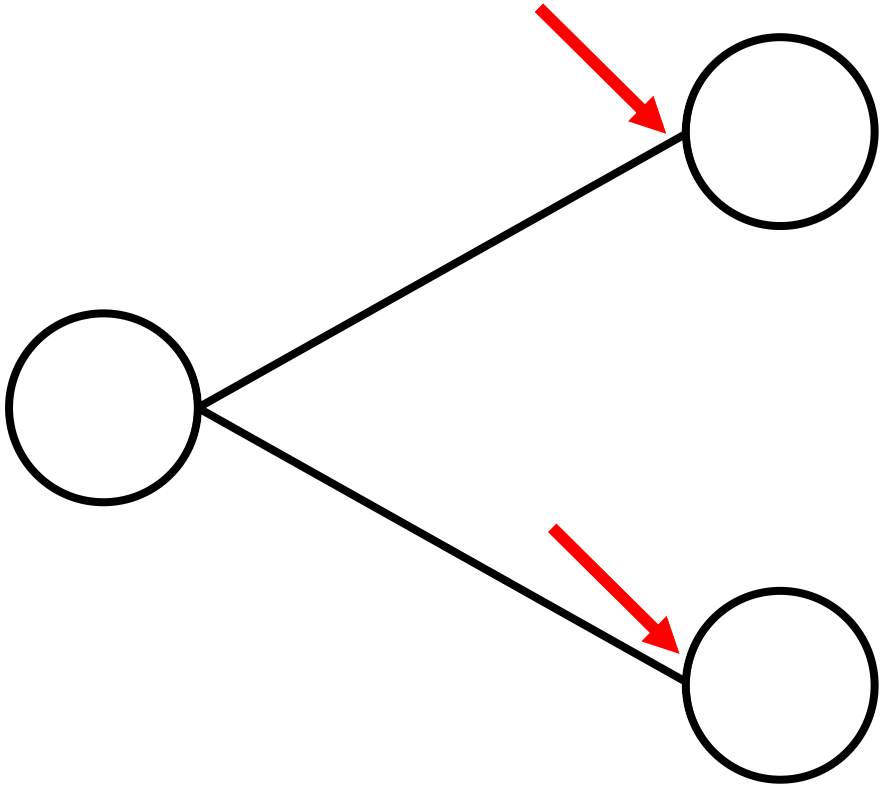


ARTIFICIAL NEURAL NETWORK – 3 NEURONS



NEURAL NETWORK TERMINOLOGY

- Inputs
- Weights
- Activation
- Outputs
- Layers



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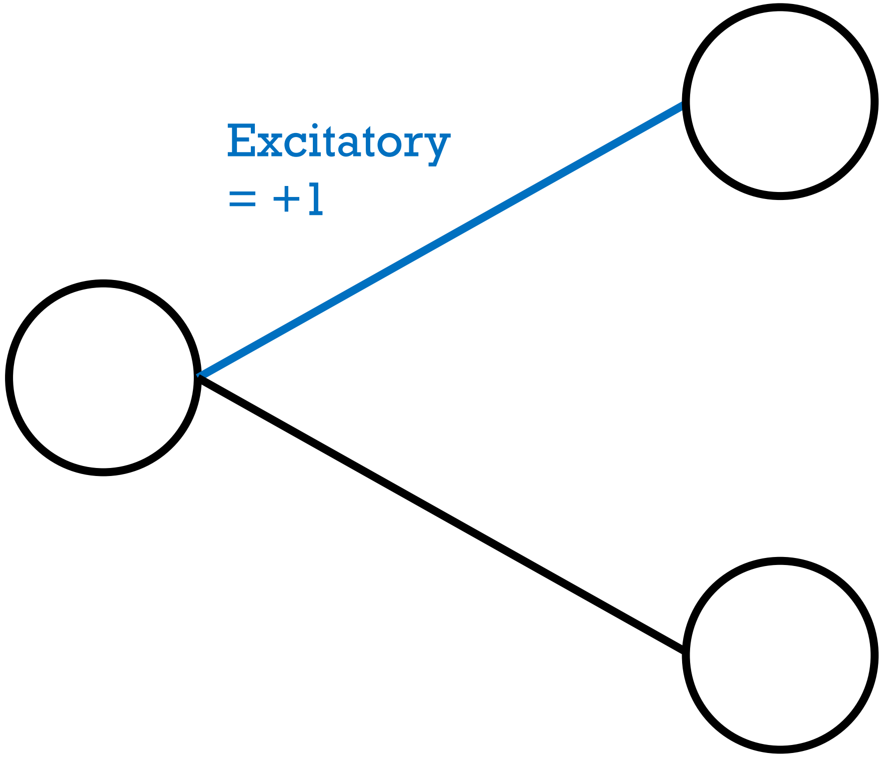

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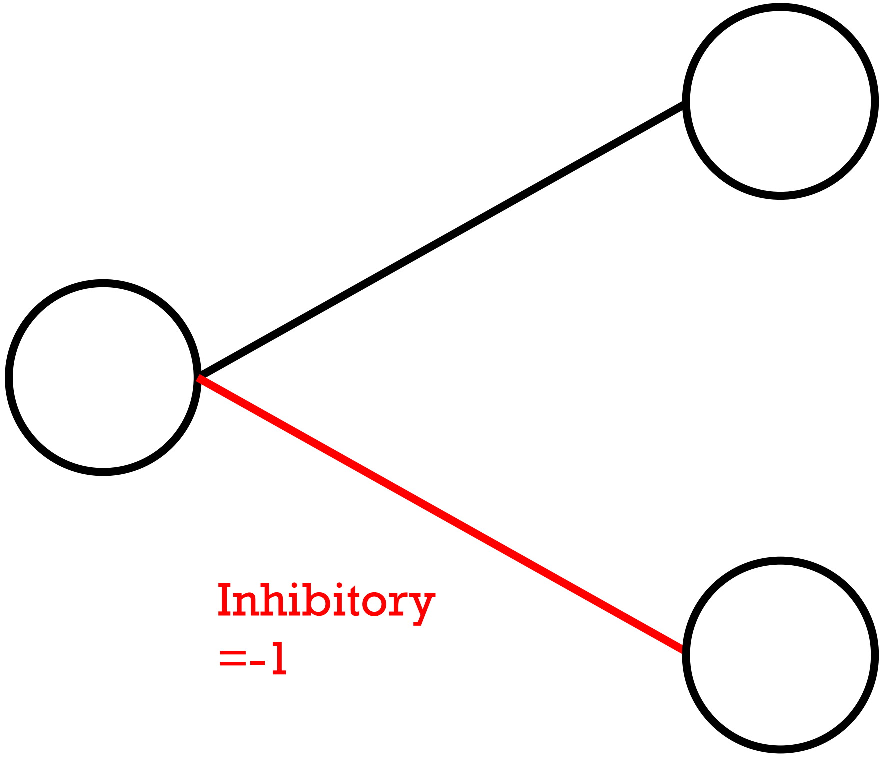

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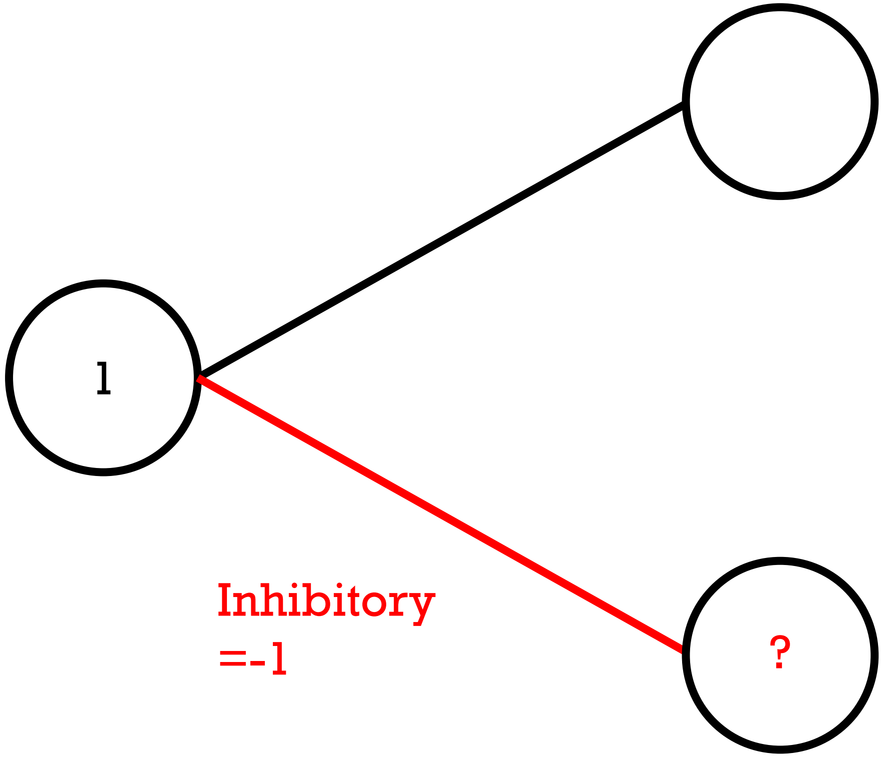
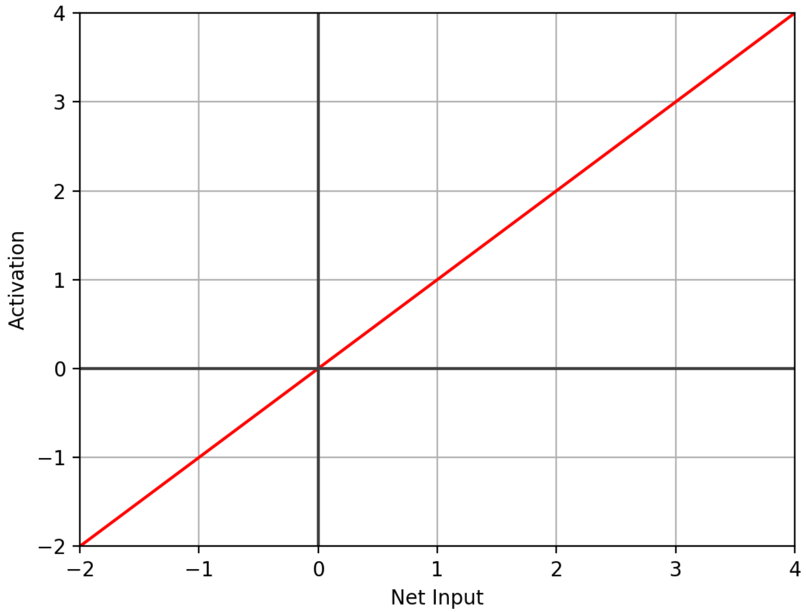
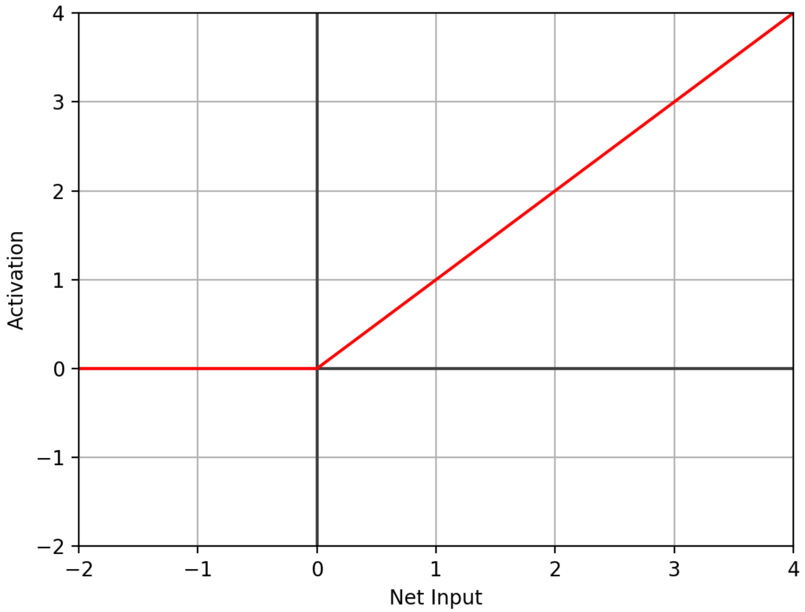


ACTIVATION FUNCTIONS

Linear



Rectified Linear Unit (ReLU)



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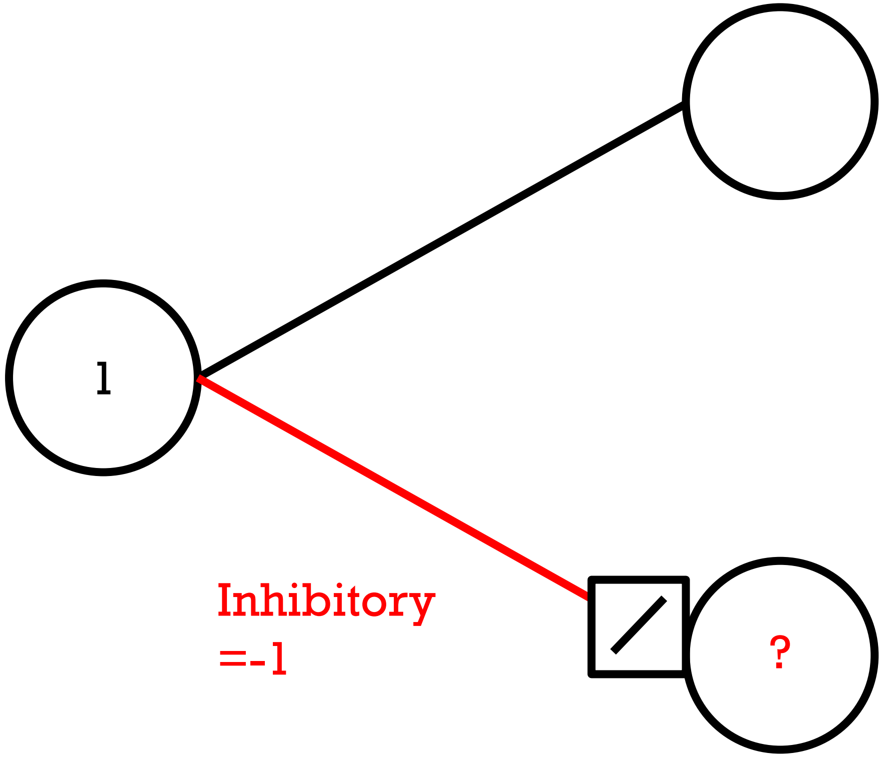

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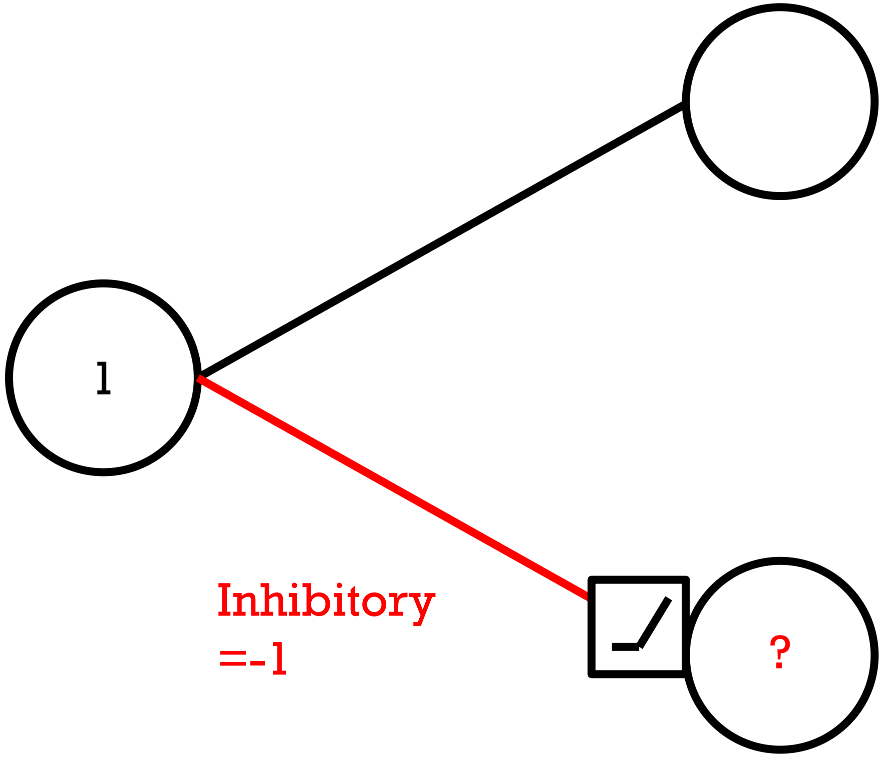

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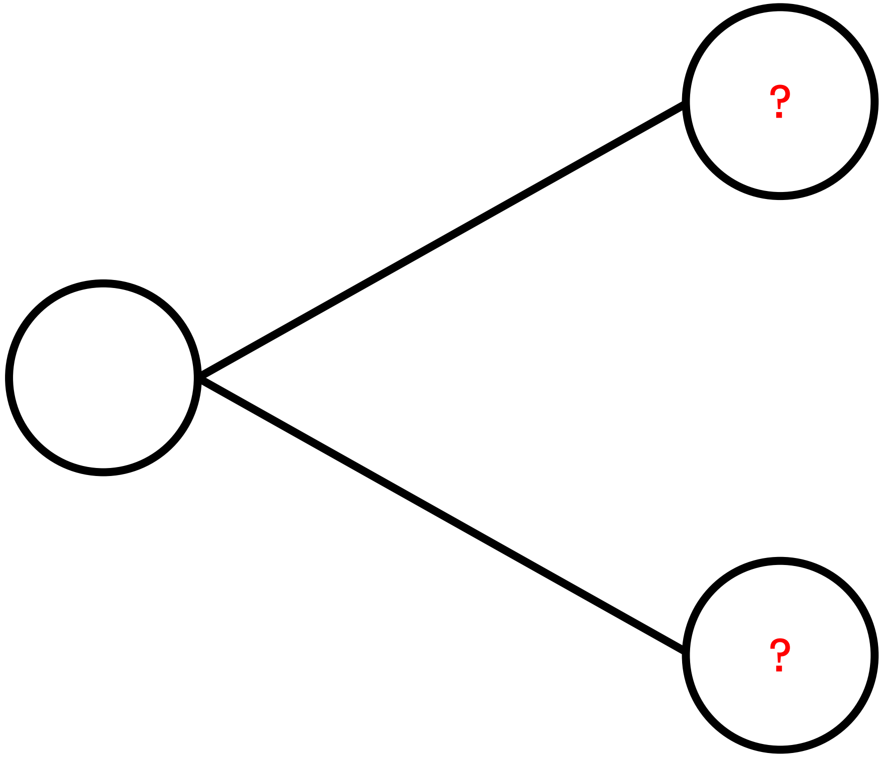

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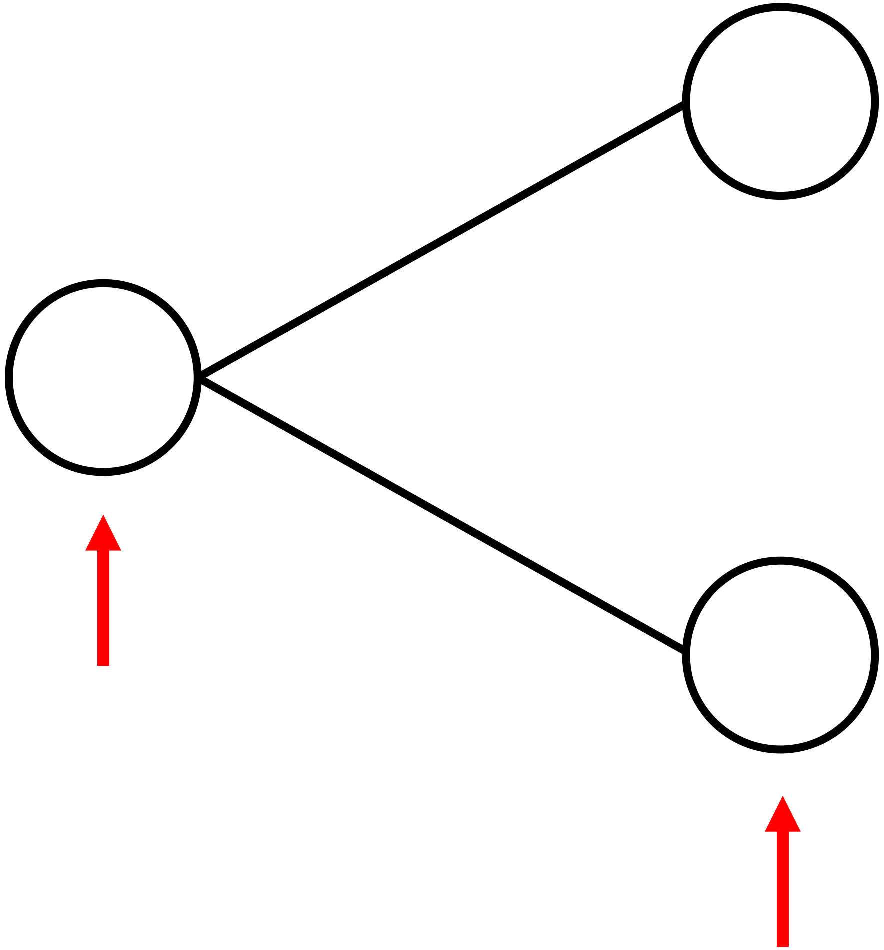
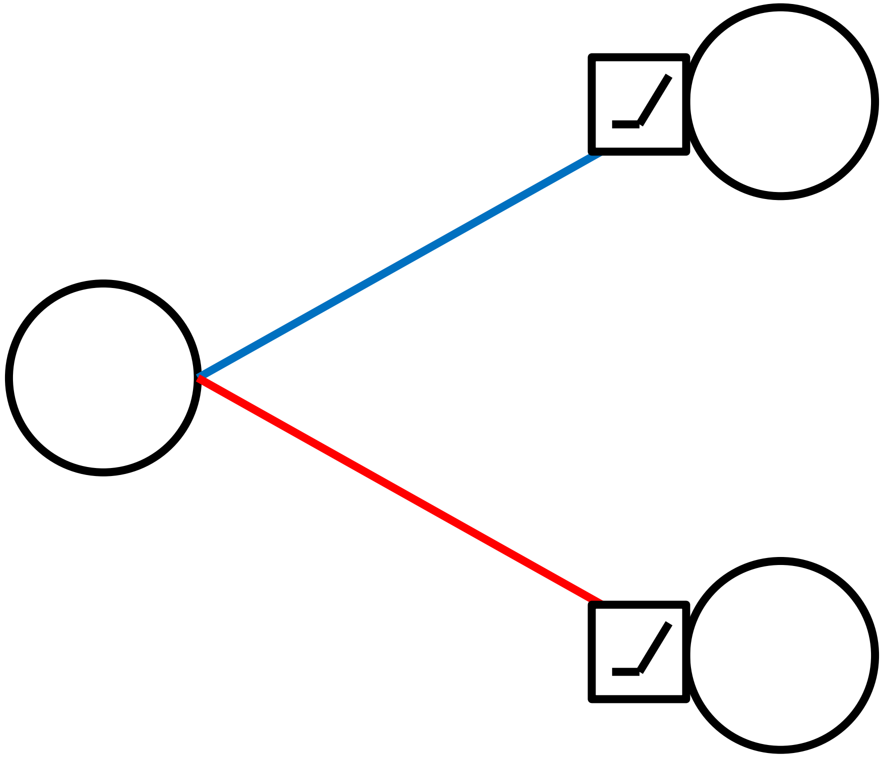


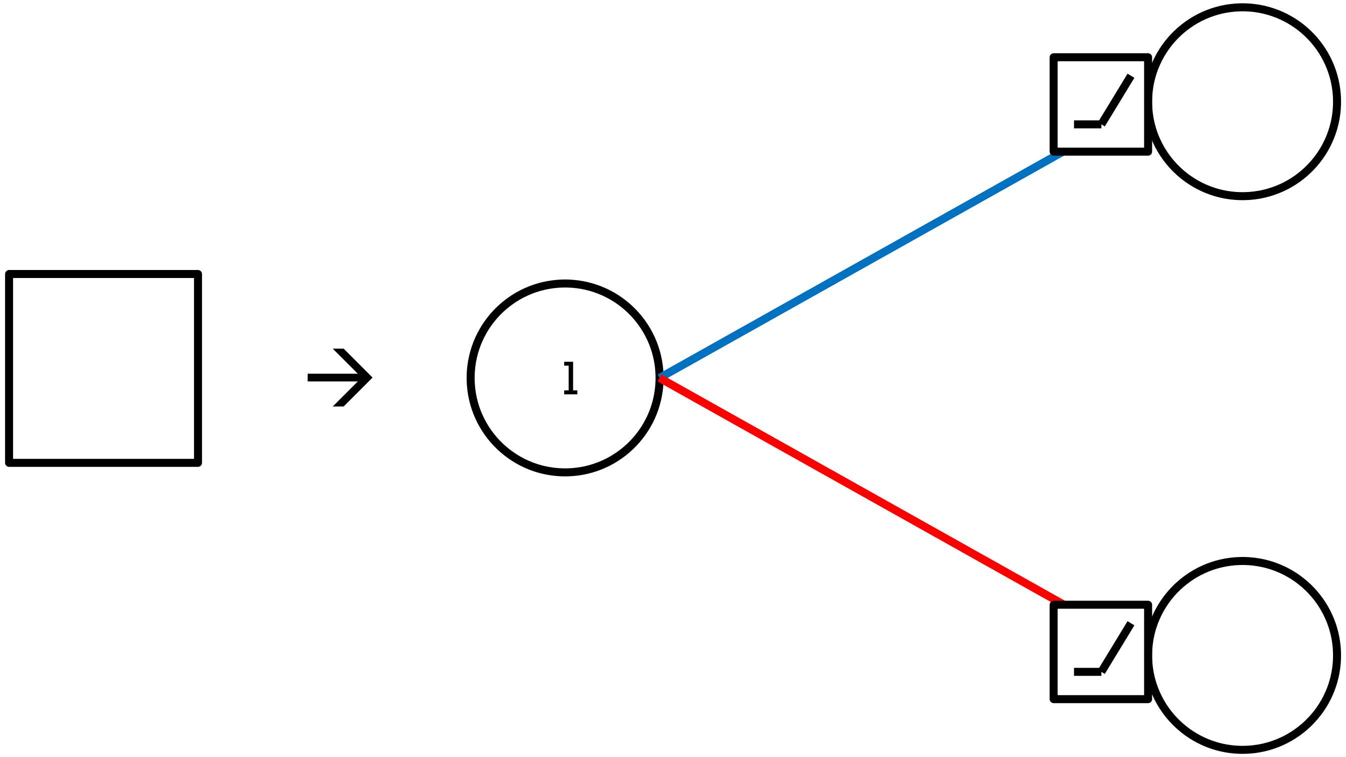
OVERVIEW

- Why ASDNet?
- Neurons → Neural Network
- Basic Neural Network Examples
- Weight Tuning/Optimization
- ASDNet
- Visualization
- Results

BASIC NEURAL NETWORK



BASIC NEURAL NETWORK – 1 PIXEL



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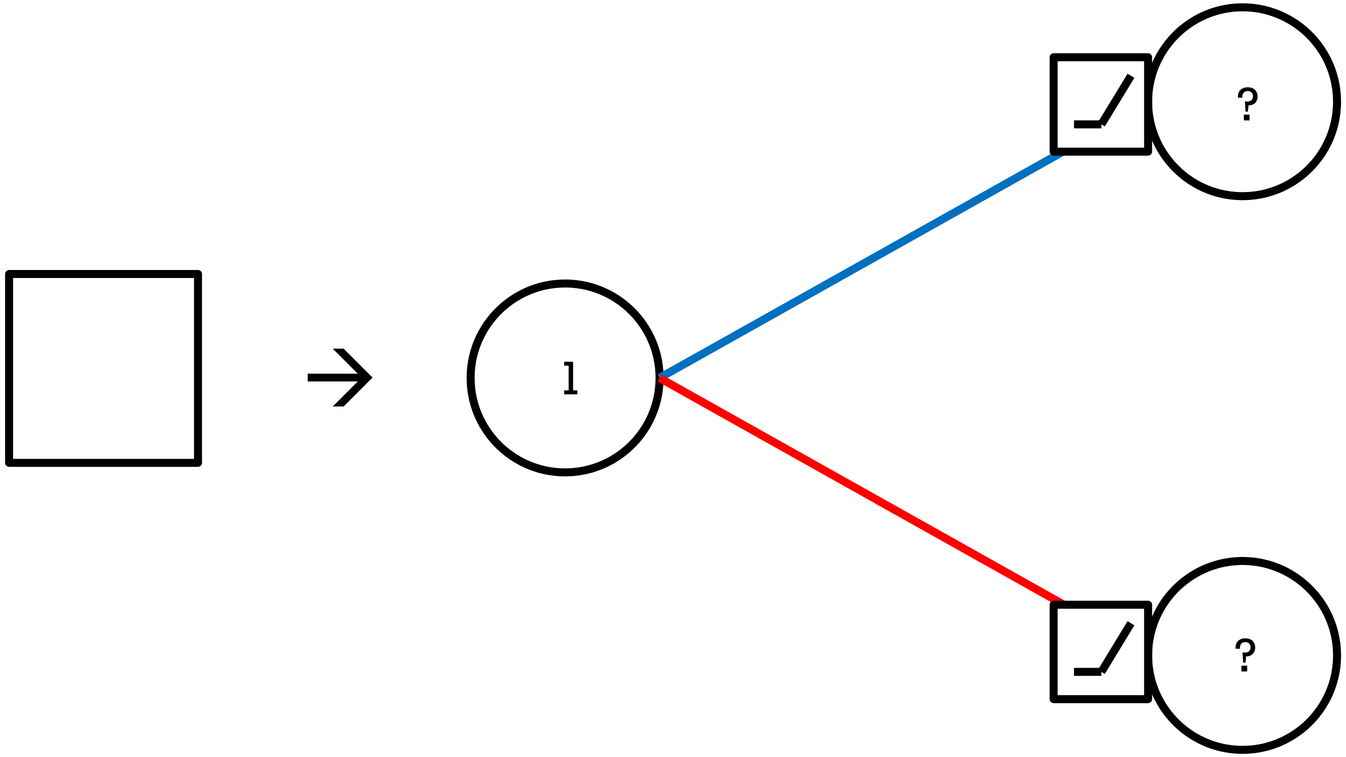

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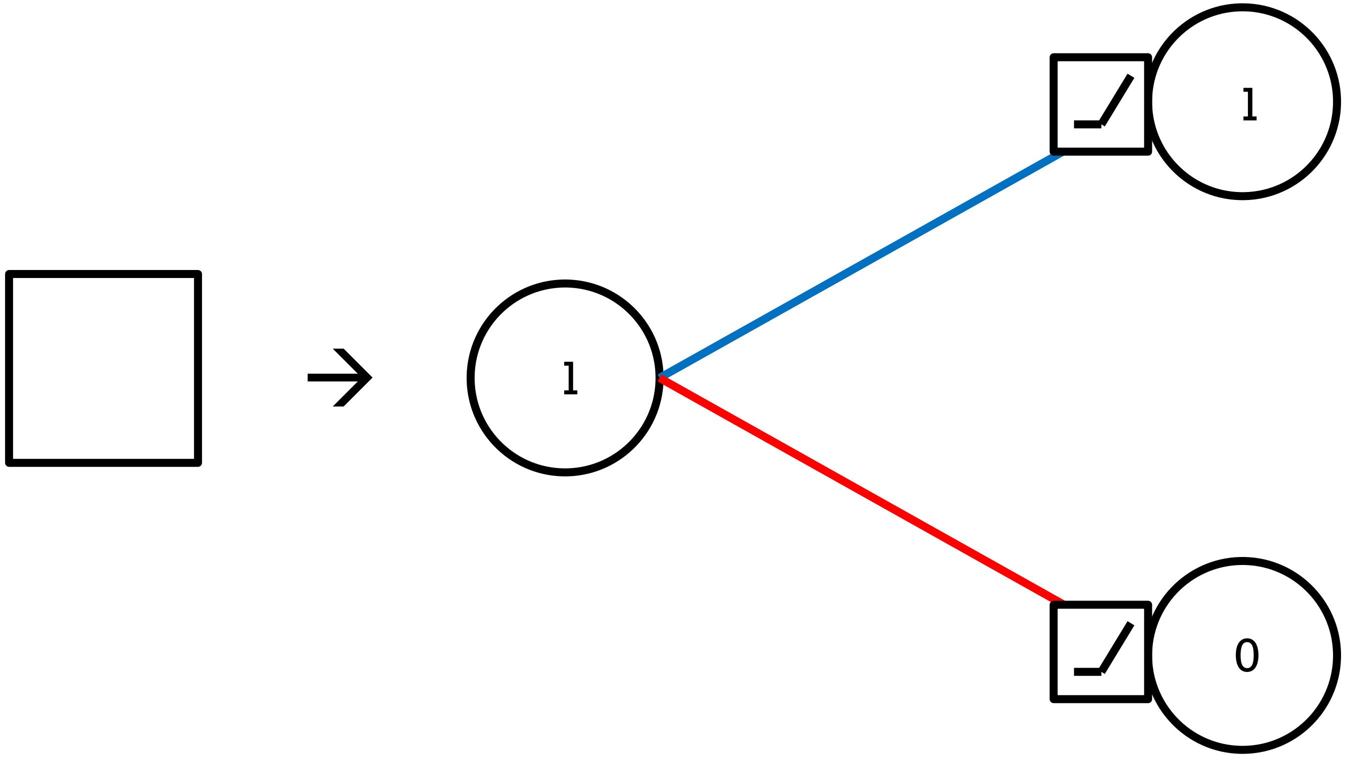

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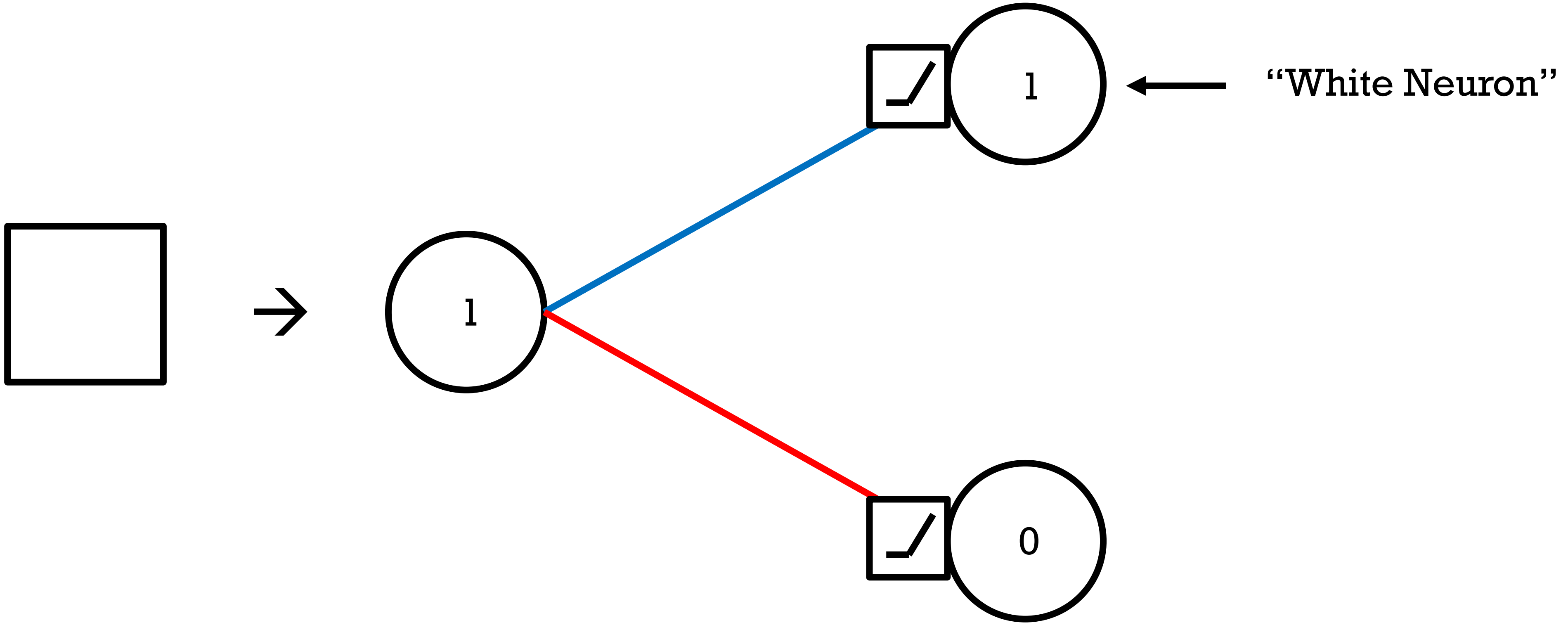

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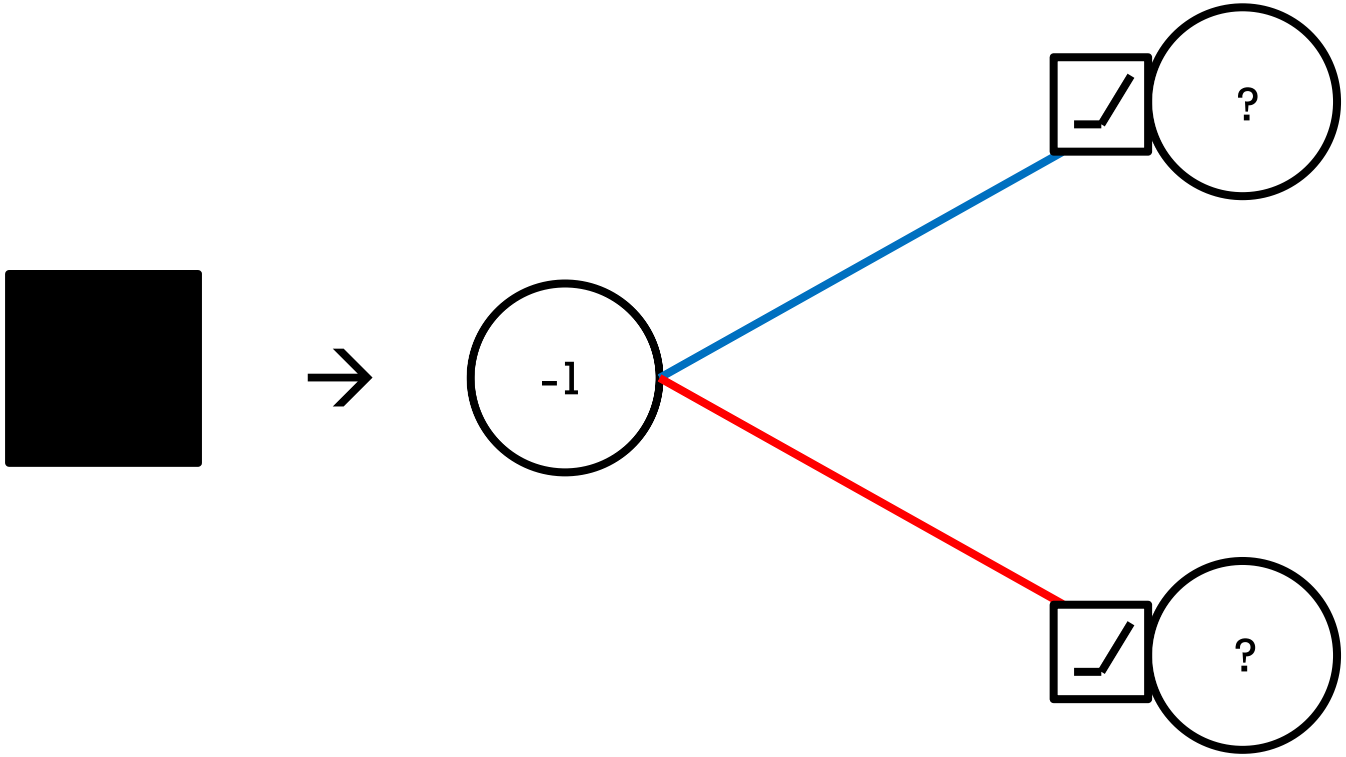

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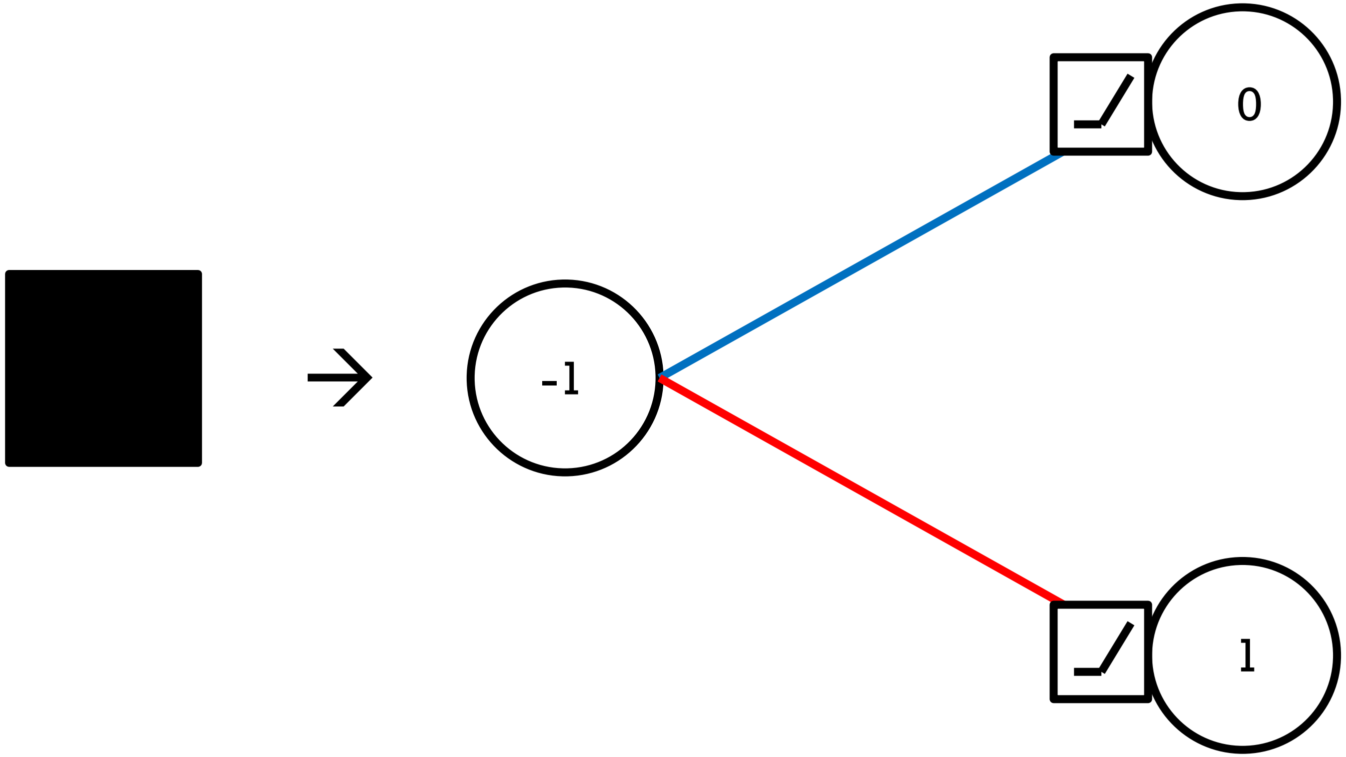

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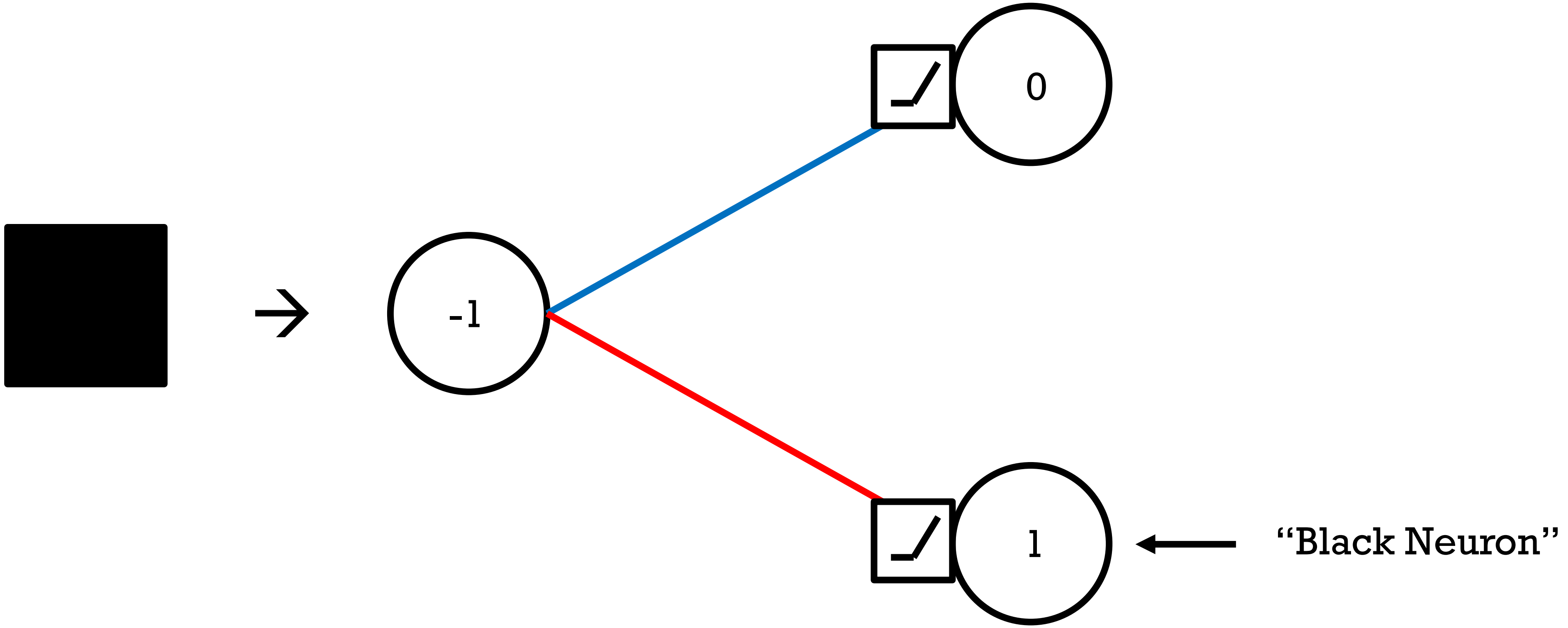

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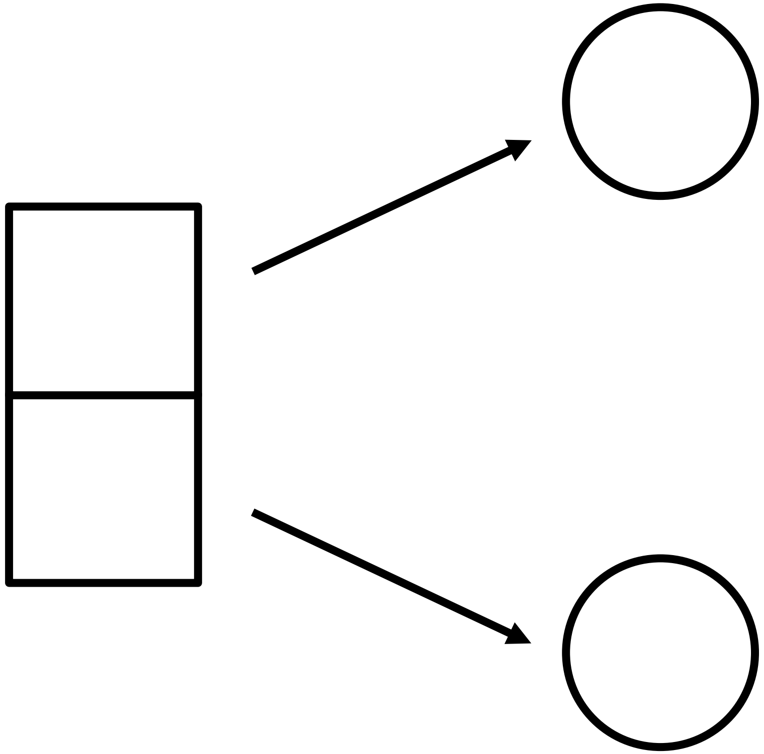

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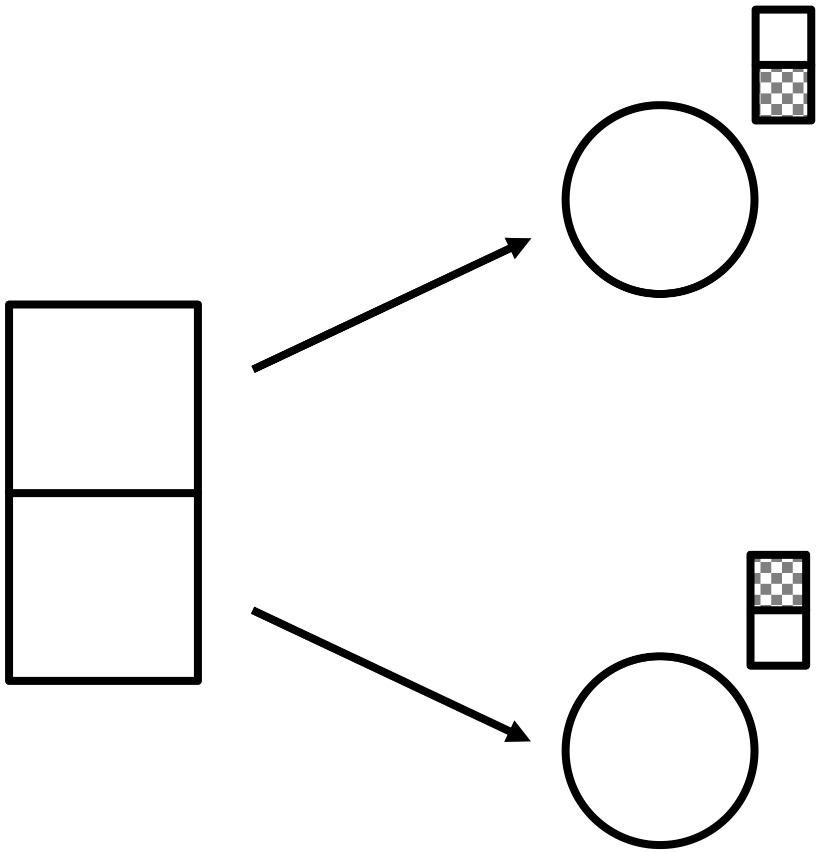

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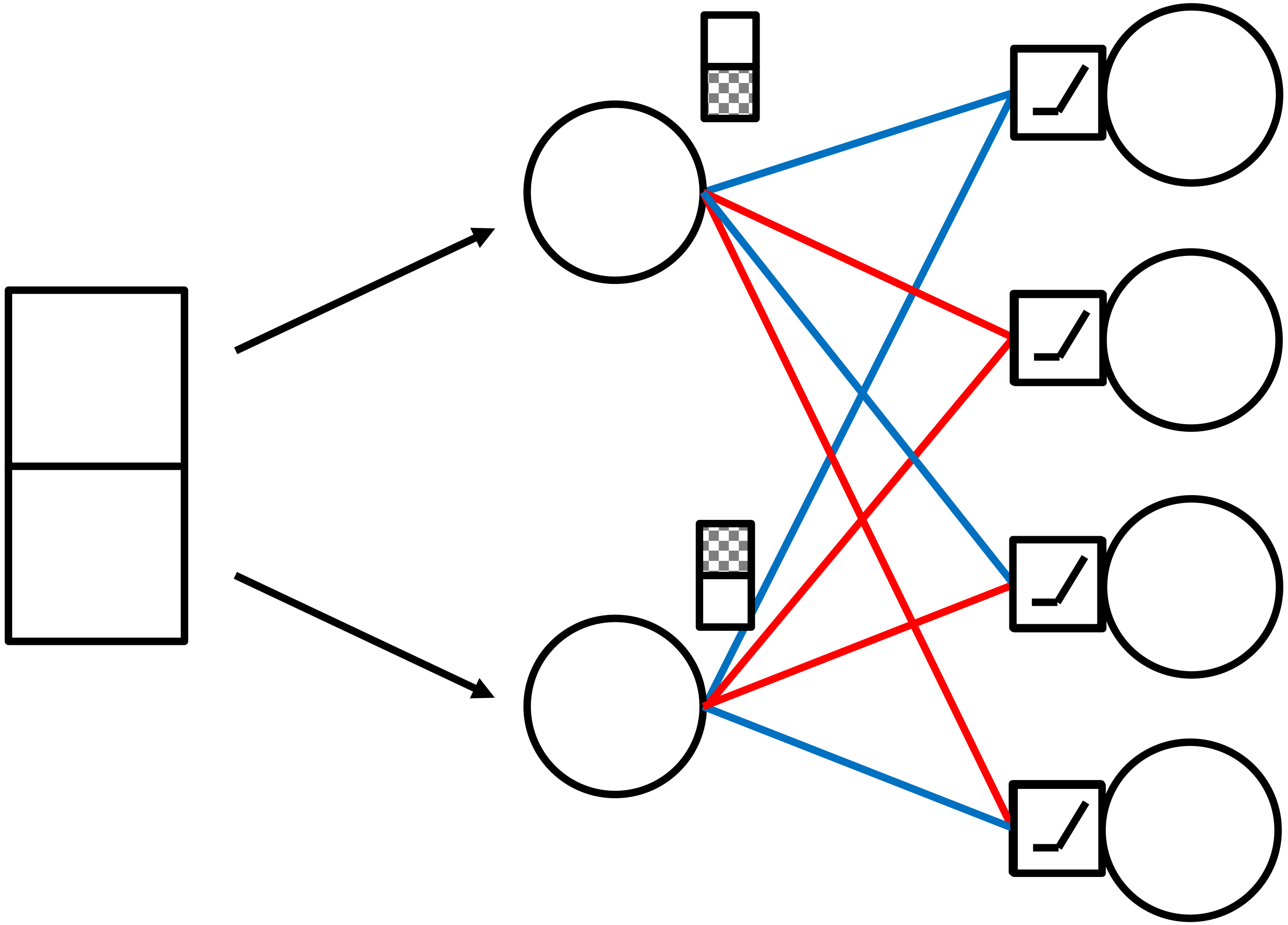

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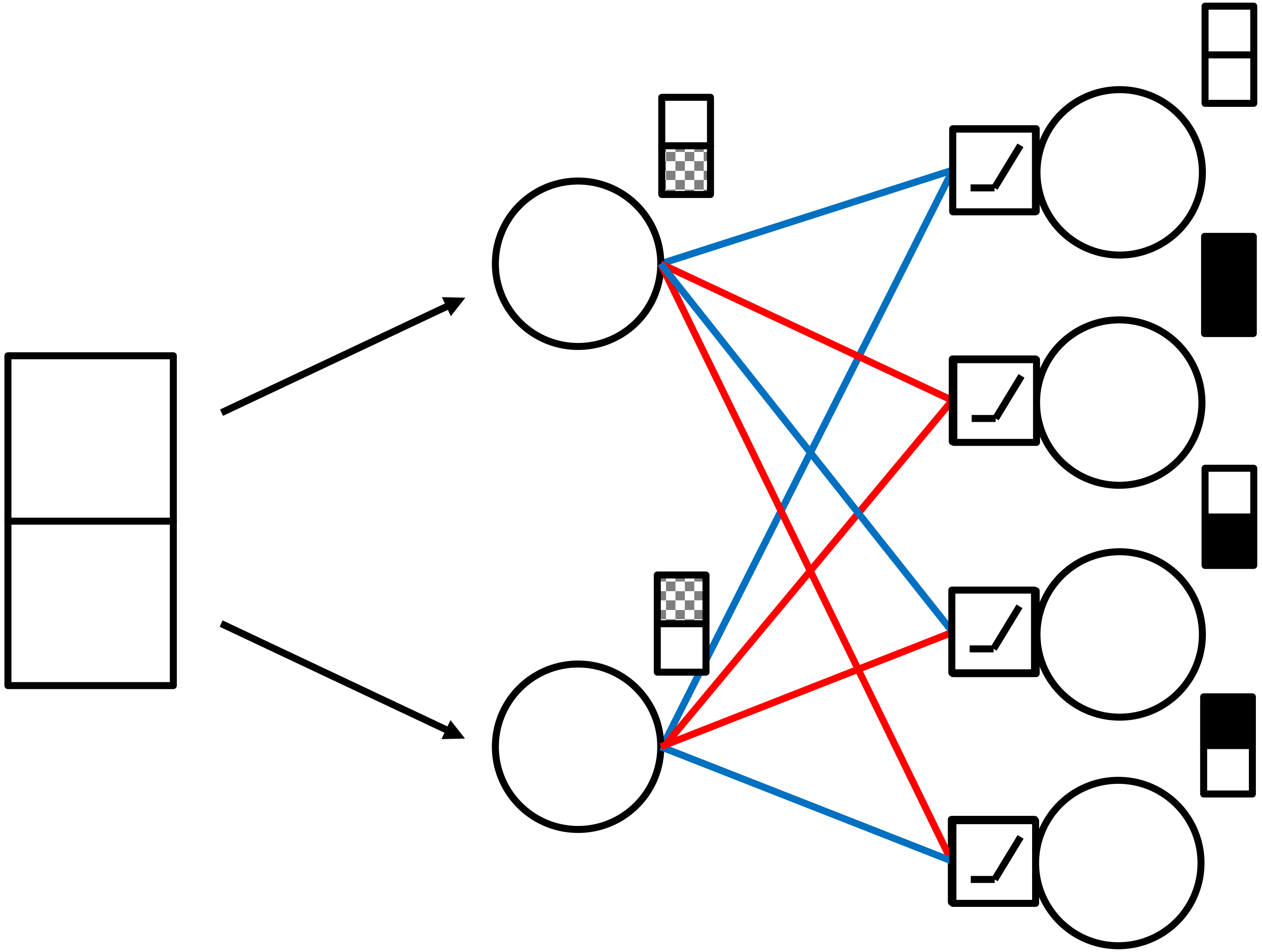

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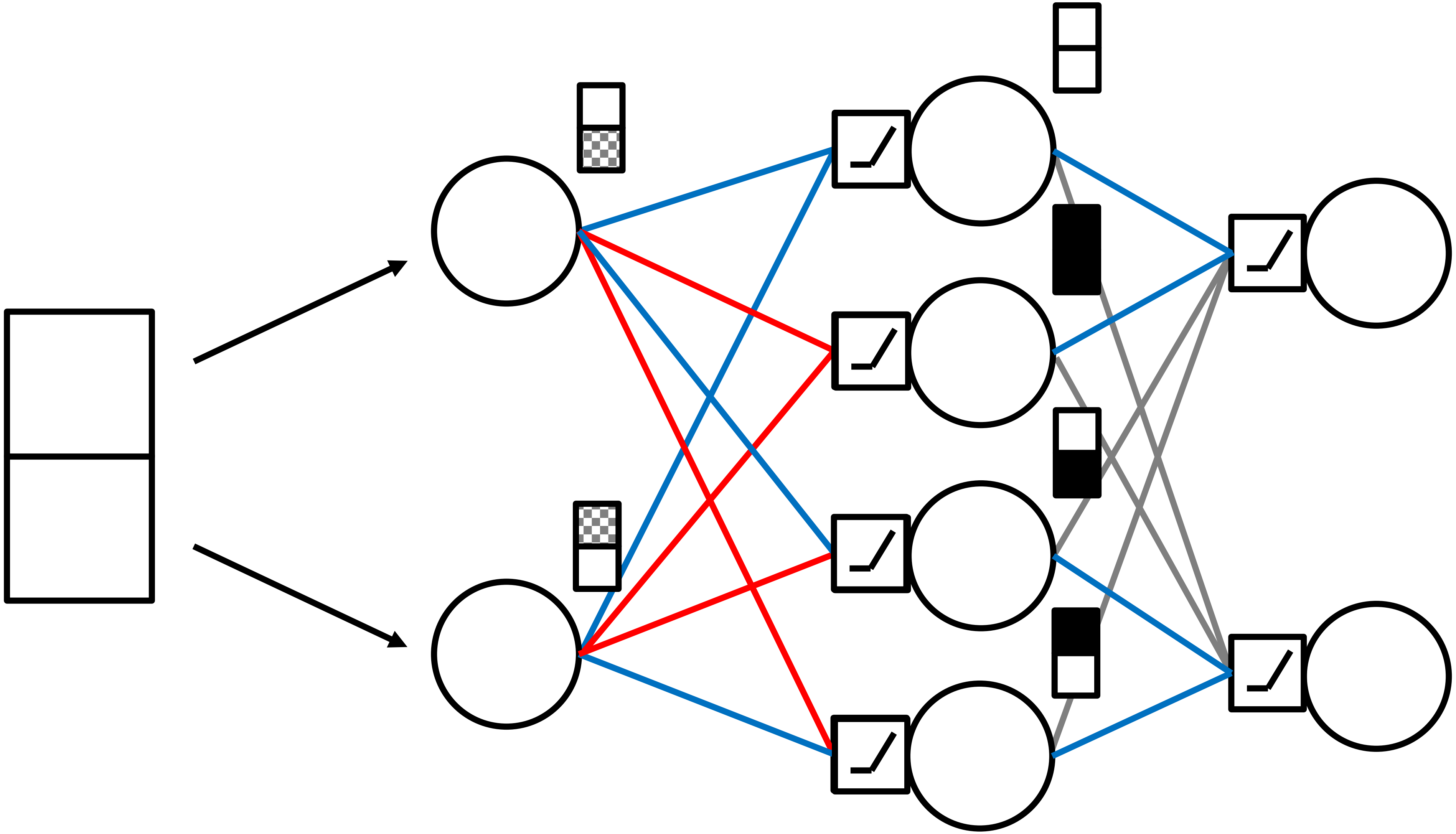

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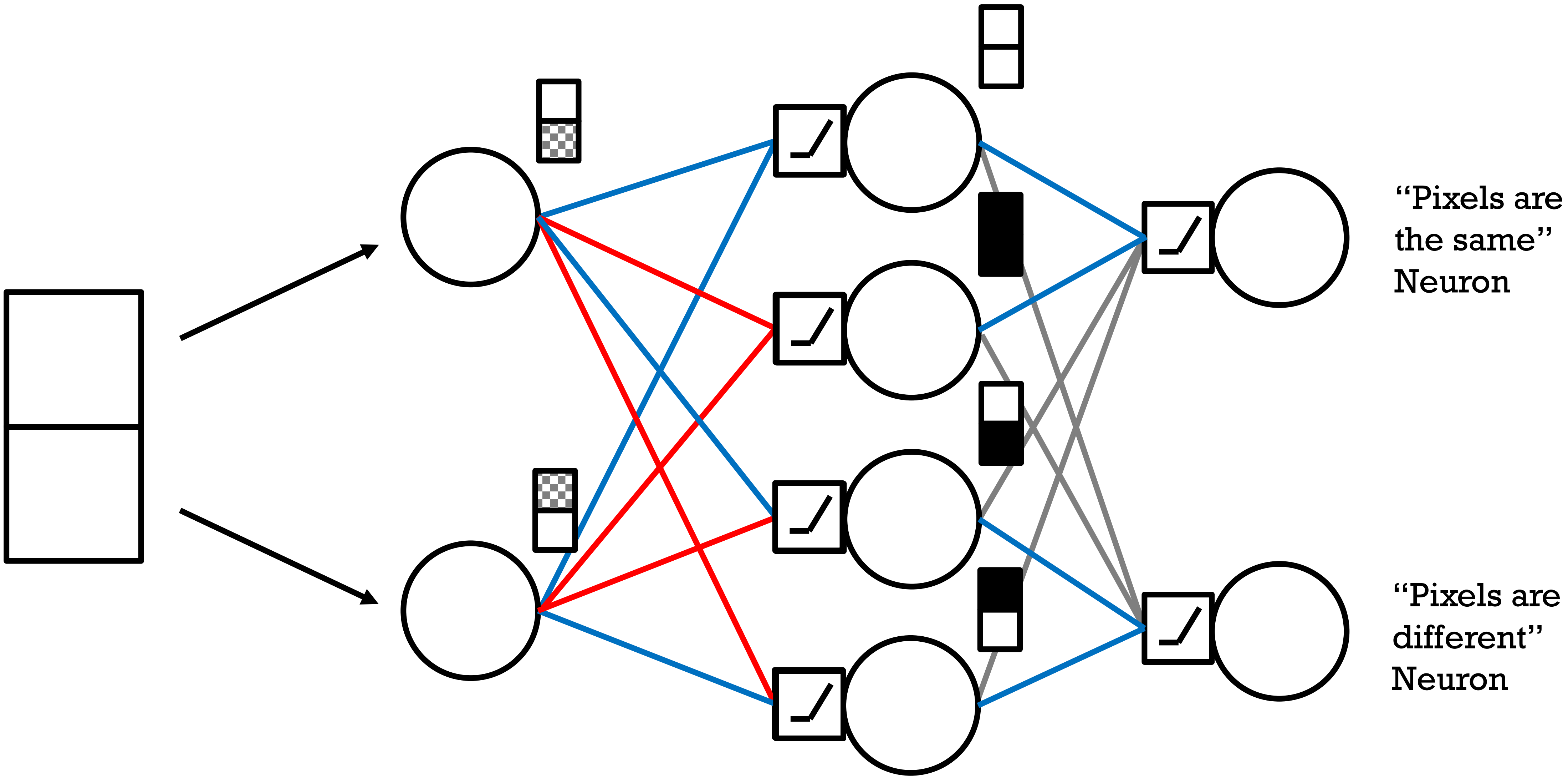

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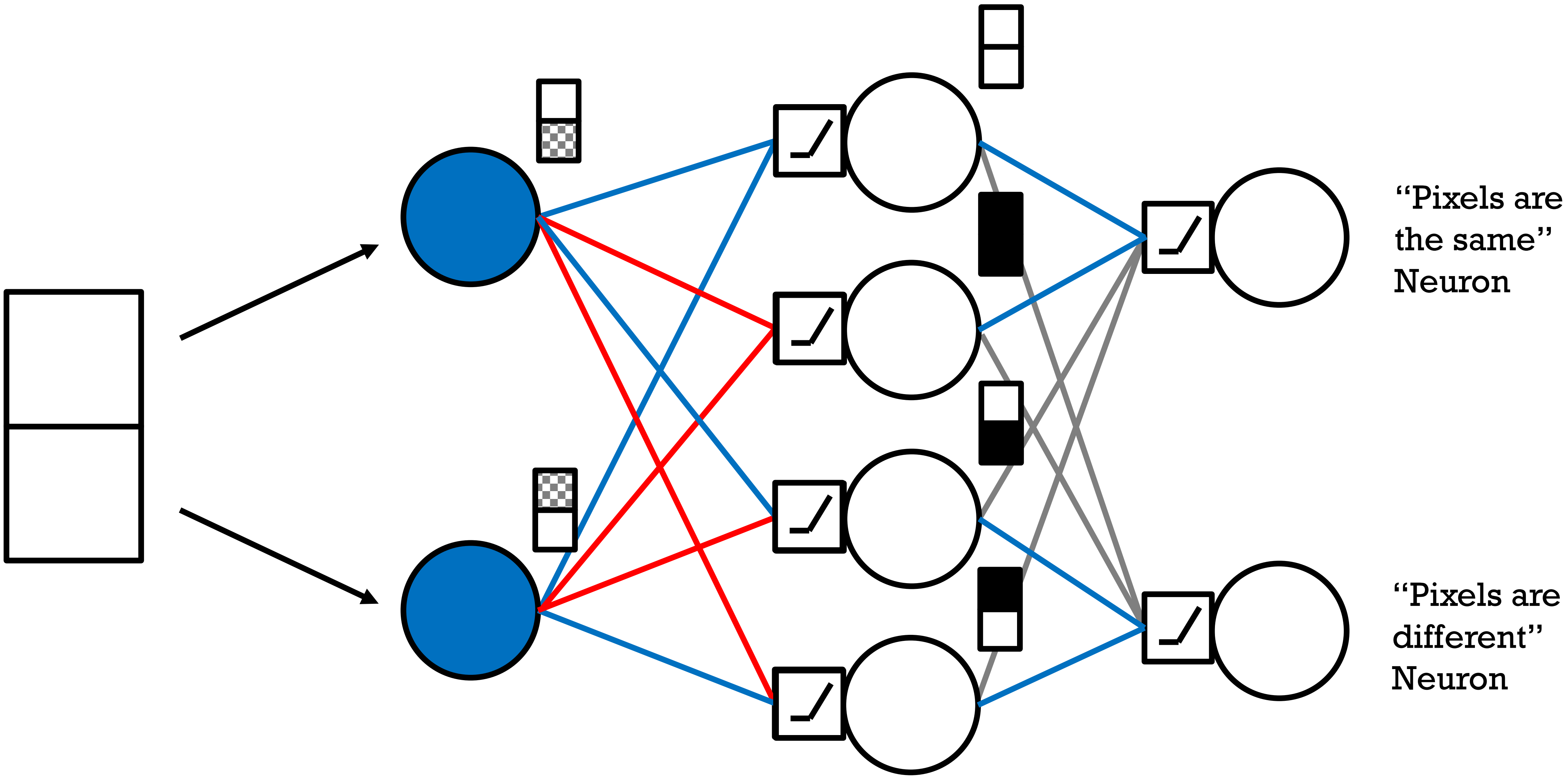

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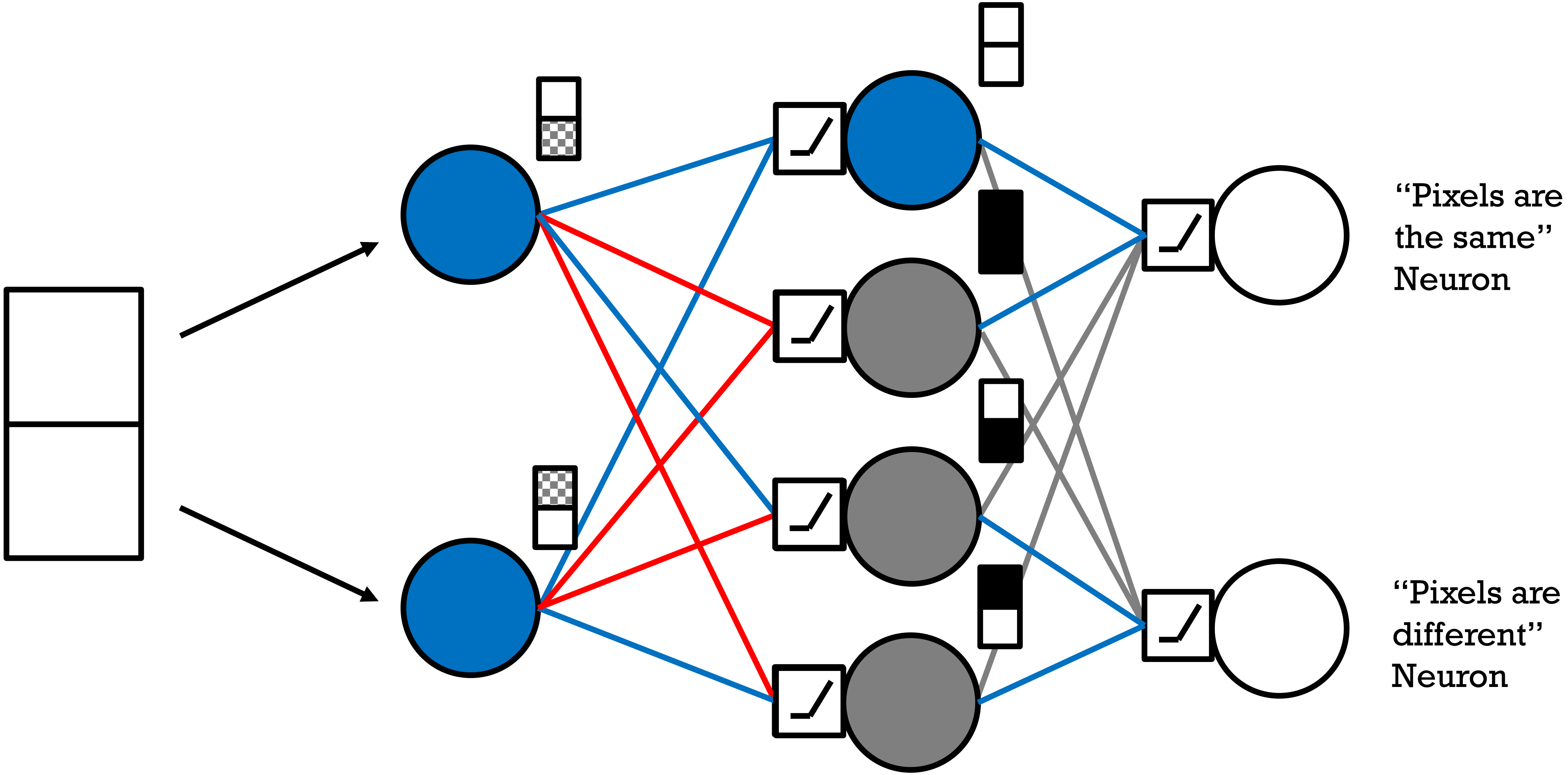

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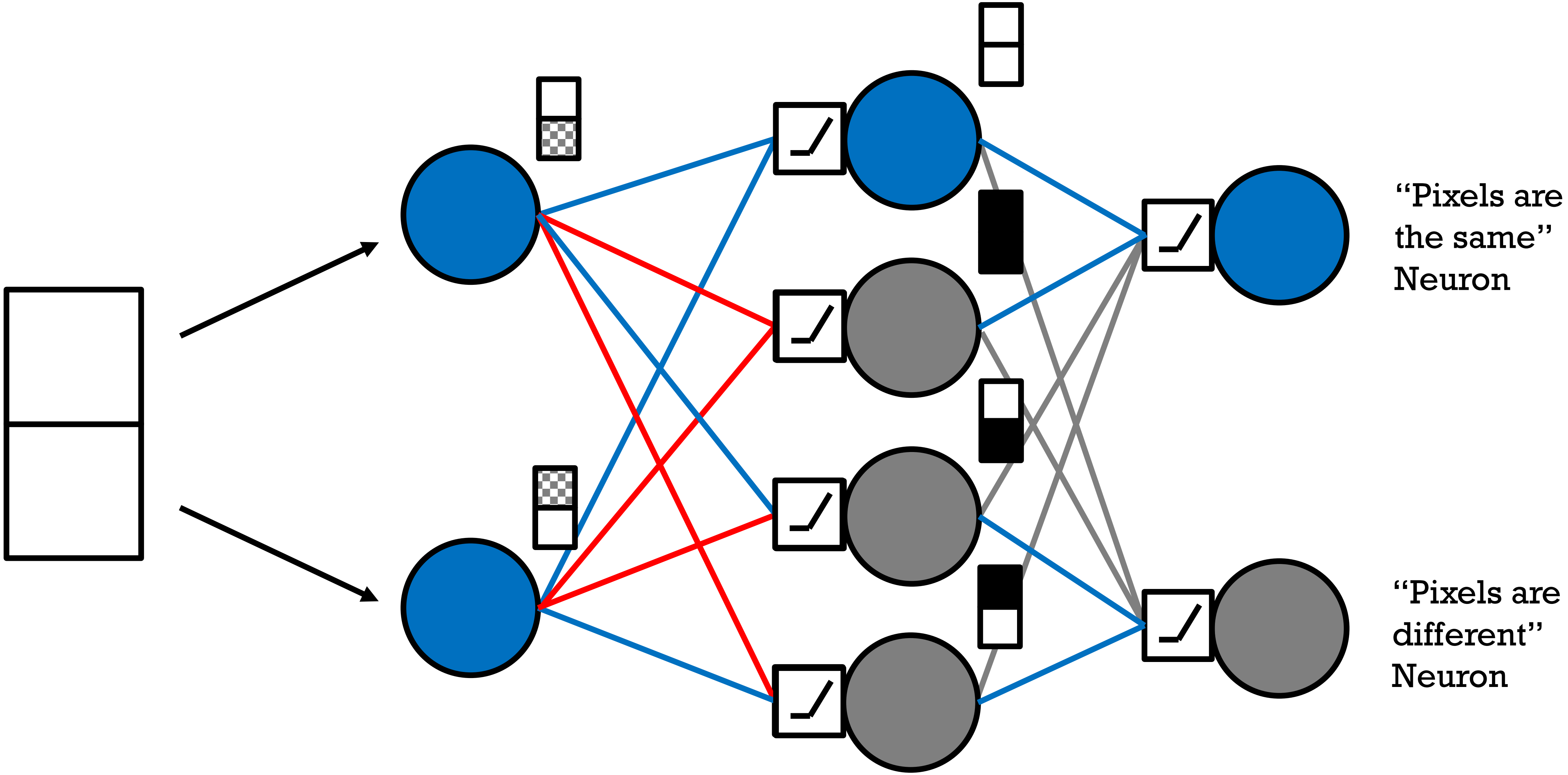

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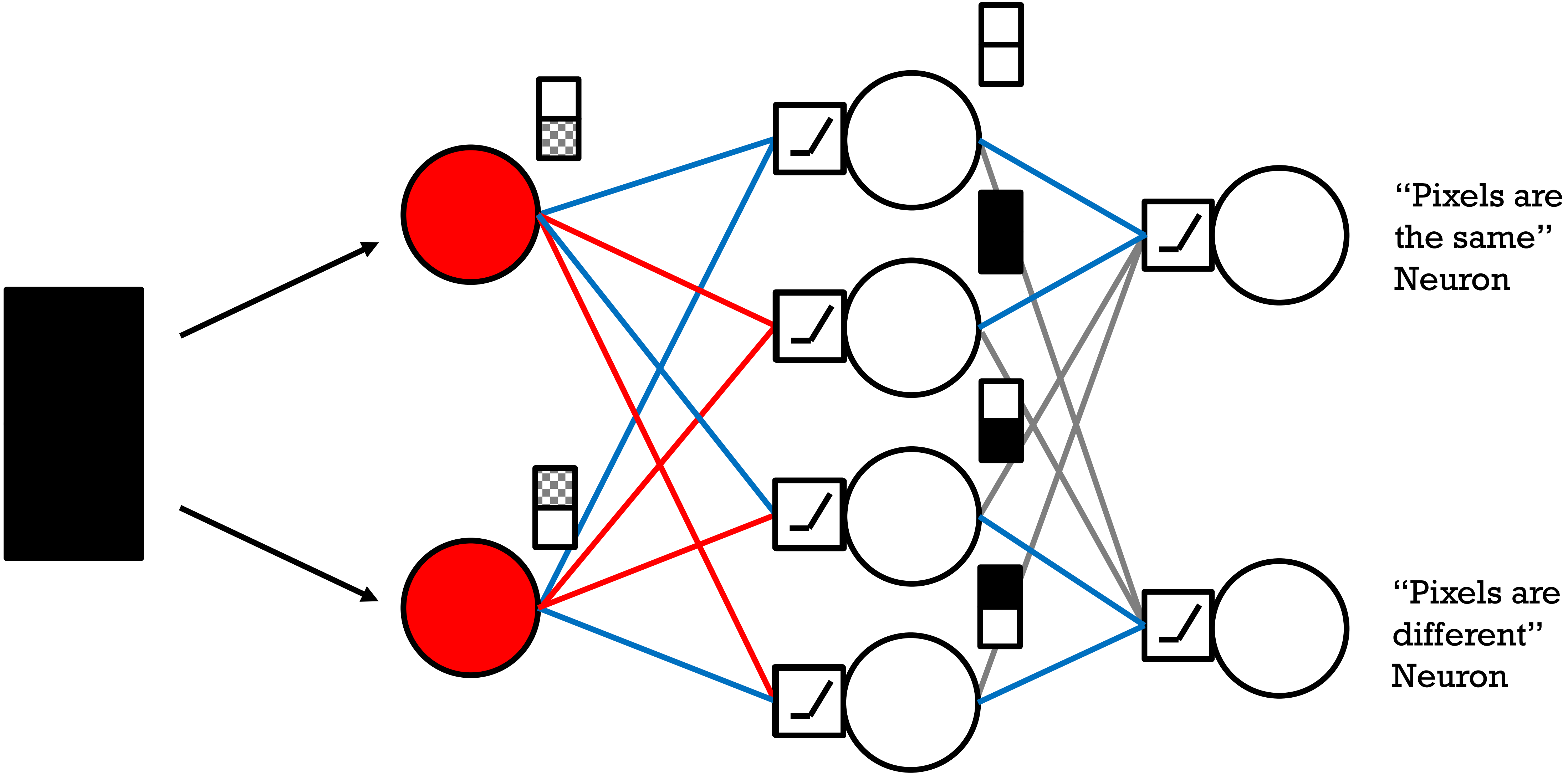

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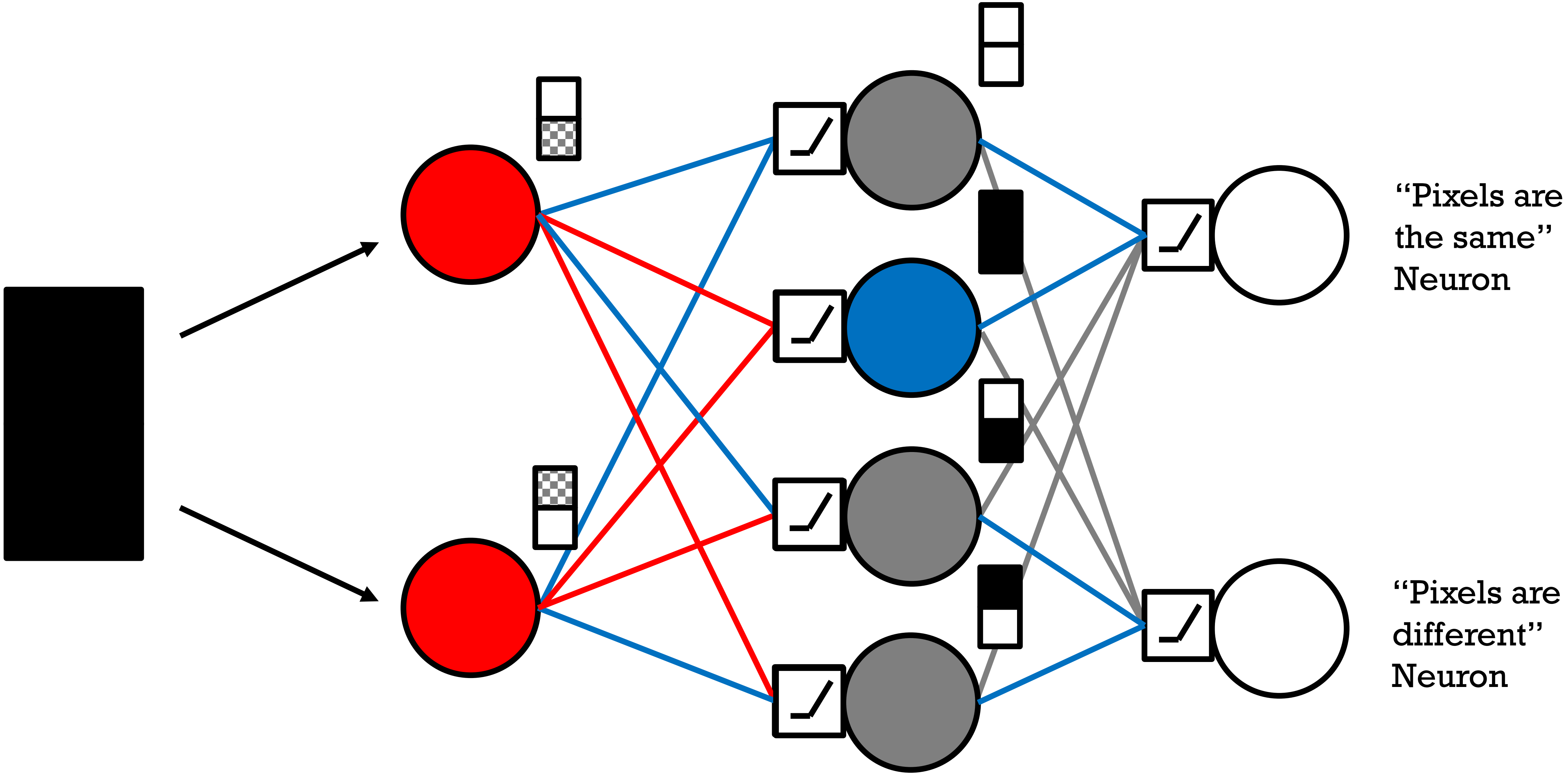

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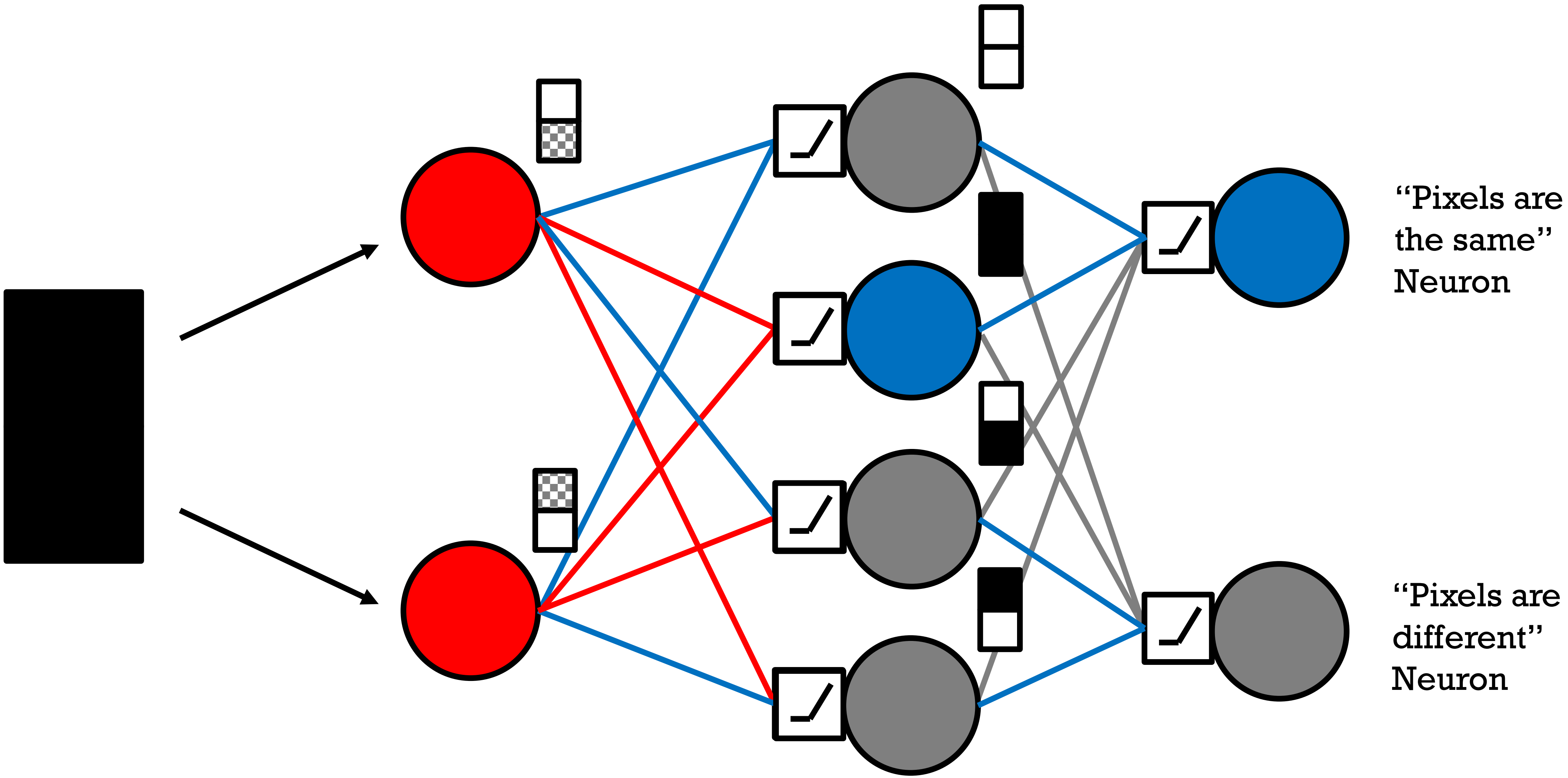

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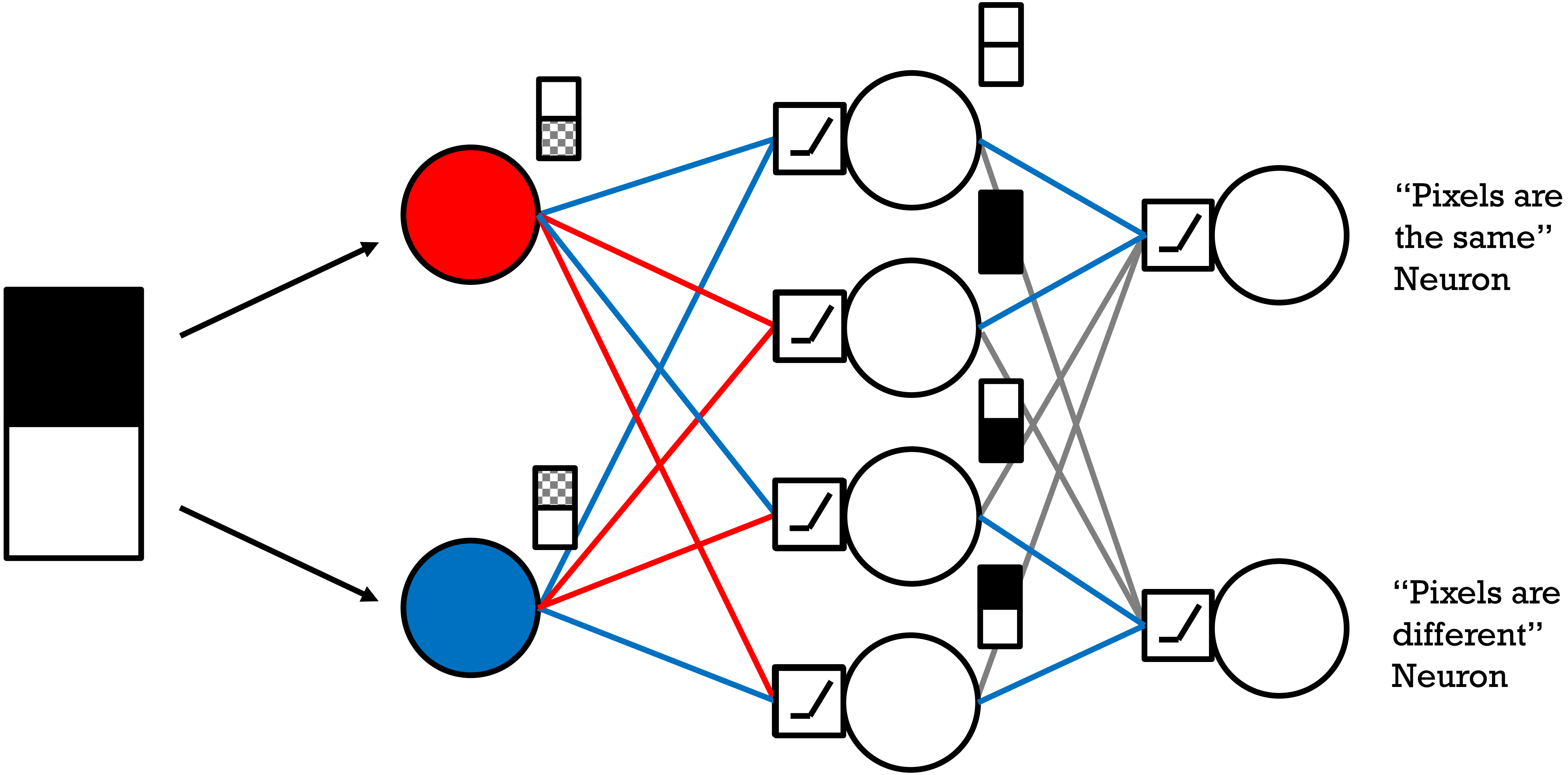

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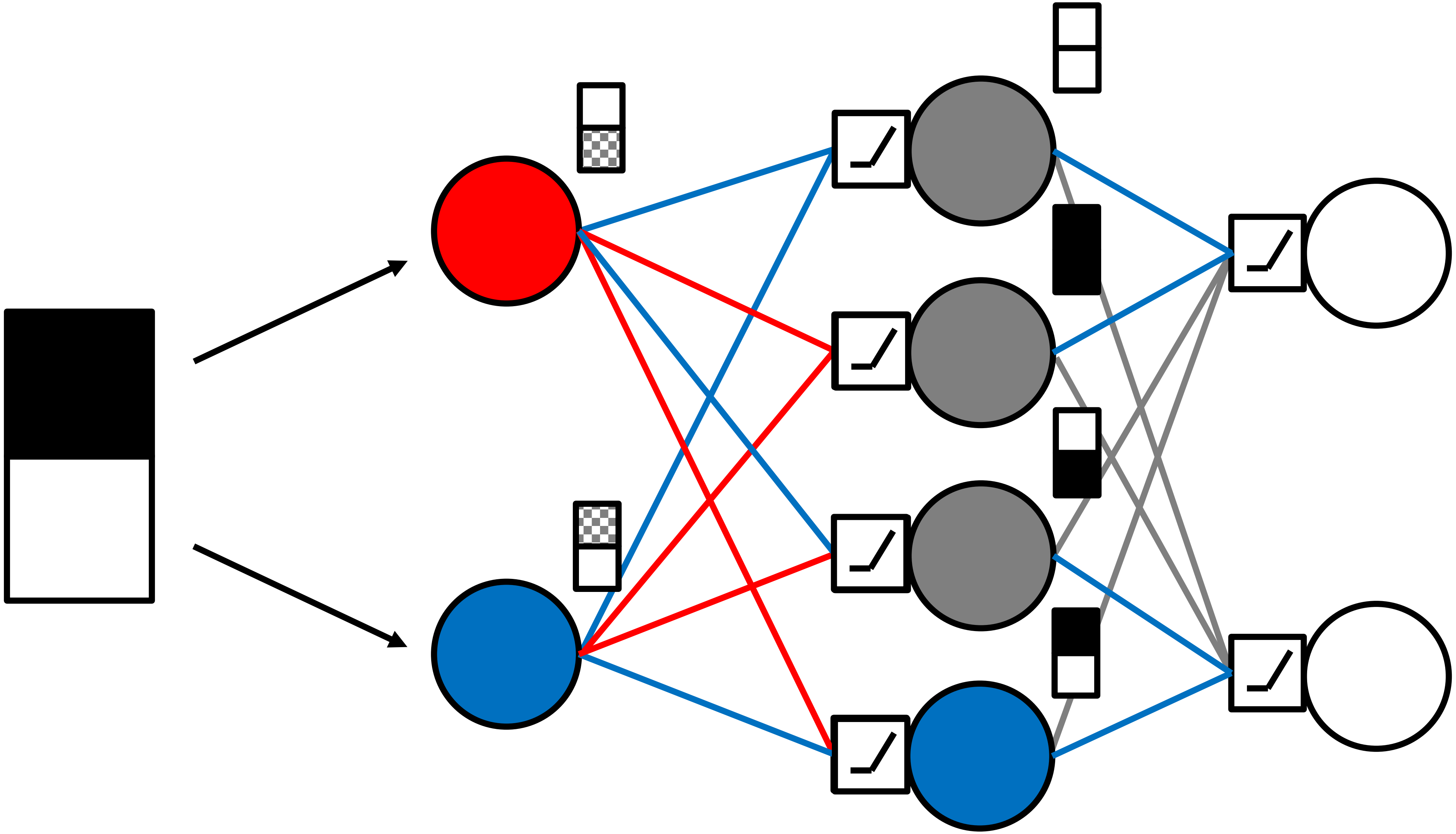
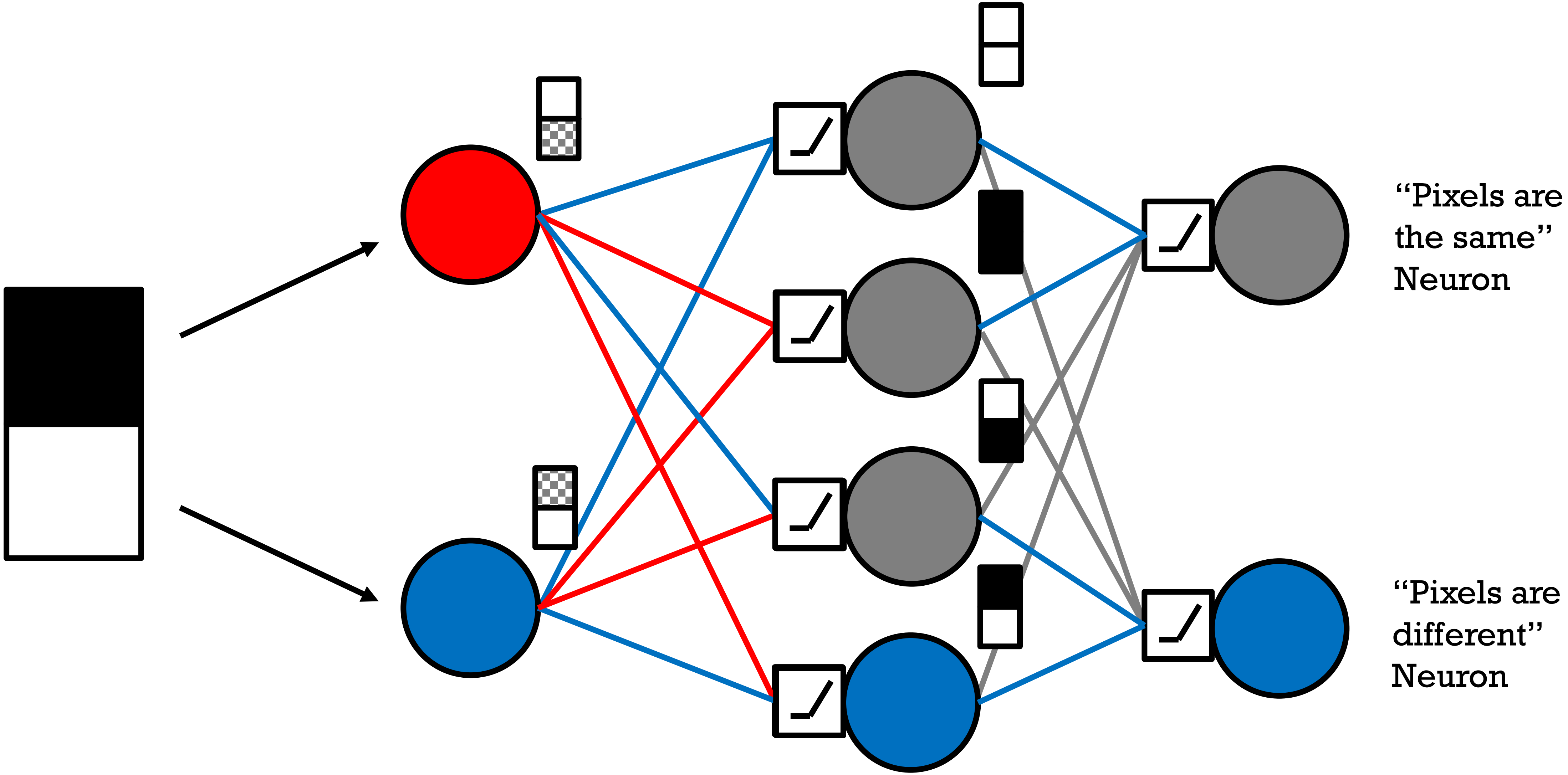


"Pixels are the same" Neuron

"Pixels are different" Neuron

BASIC NEURAL NETWORK – 2 PIXELS



OVERVIEW

- Why ASDNet?
- Neurons → Neural Network
- Basic Neural Network Examples
- Weight Tuning/Optimization
- ASDNet
- Visualization
- Results
- Future Directions

IN REALITY

- Best answer is not given
- Weights are not just -1, 0, or 1
- Many more pixels/inputs
- Many more layers
- Many more nodes within each layer

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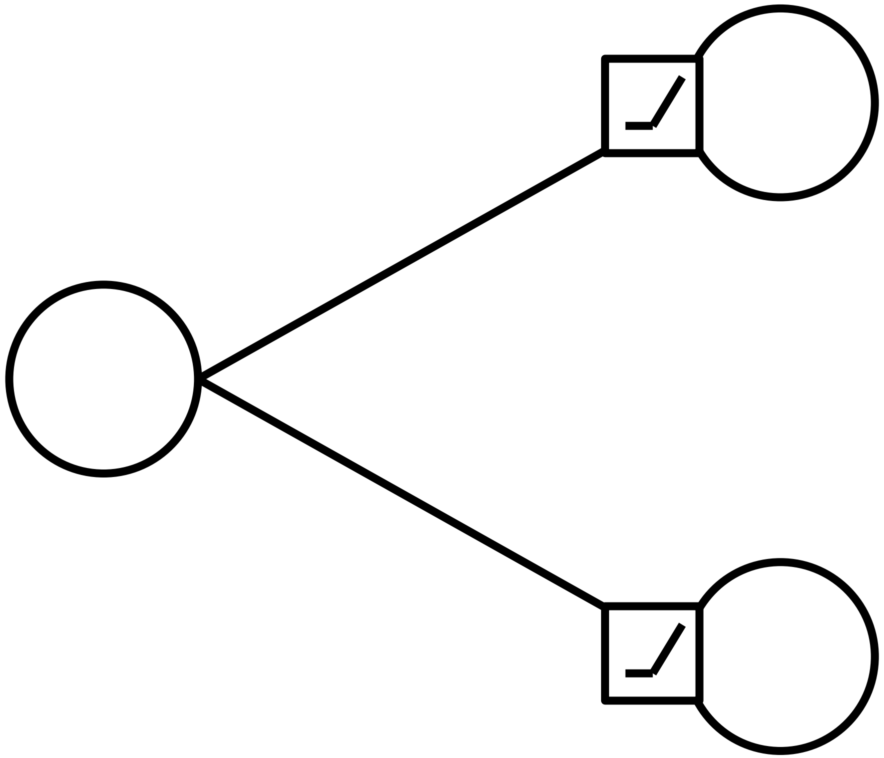
HOW IT REALLY WORKS

1. Set up neural network architecture
2. Initialize weights to small values with mean 0
3. TRAINING



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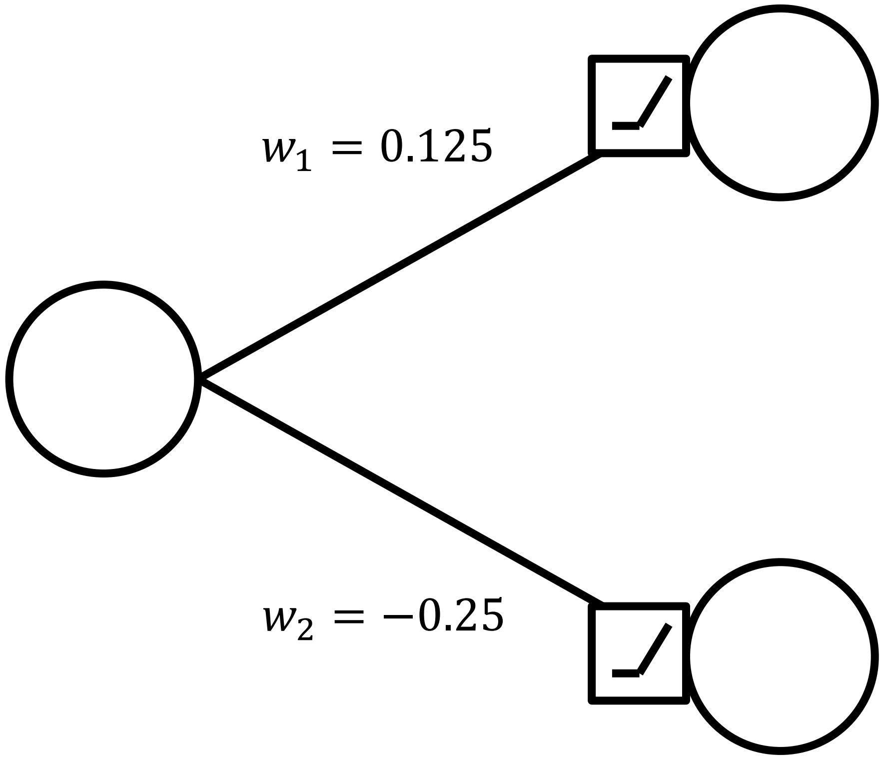

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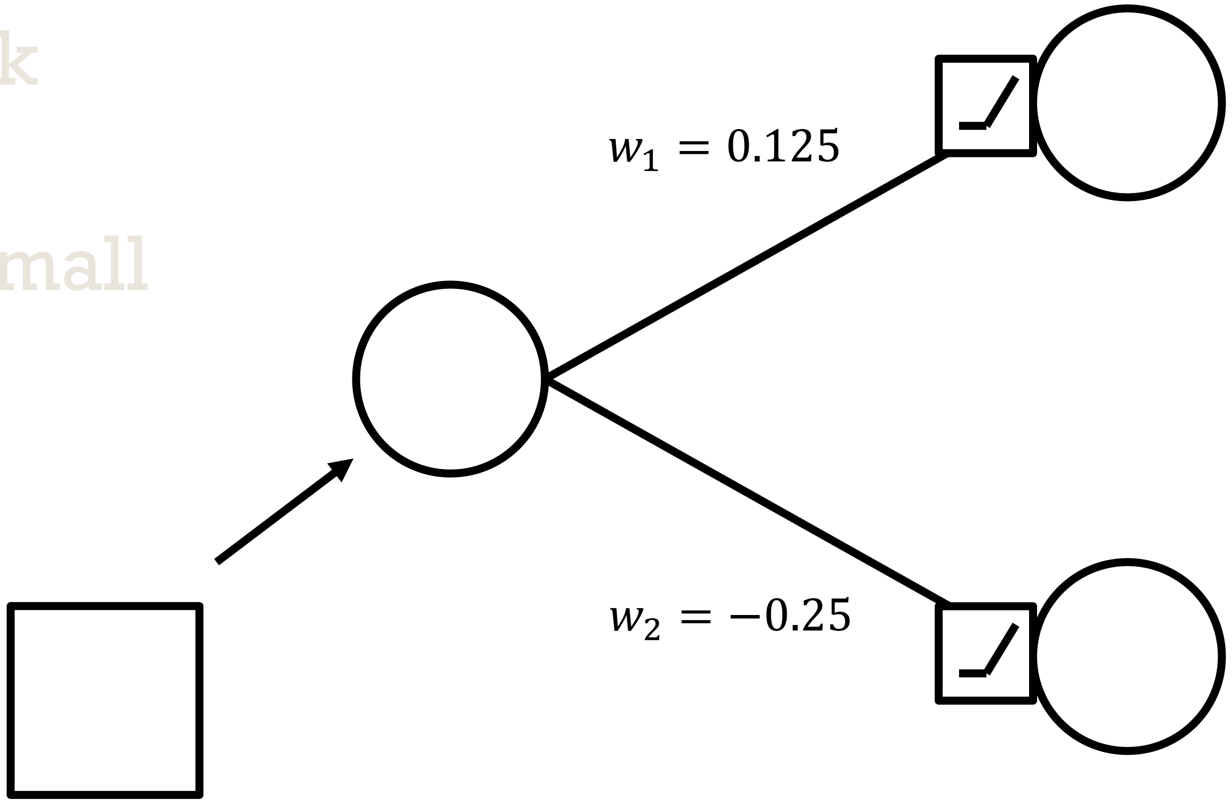

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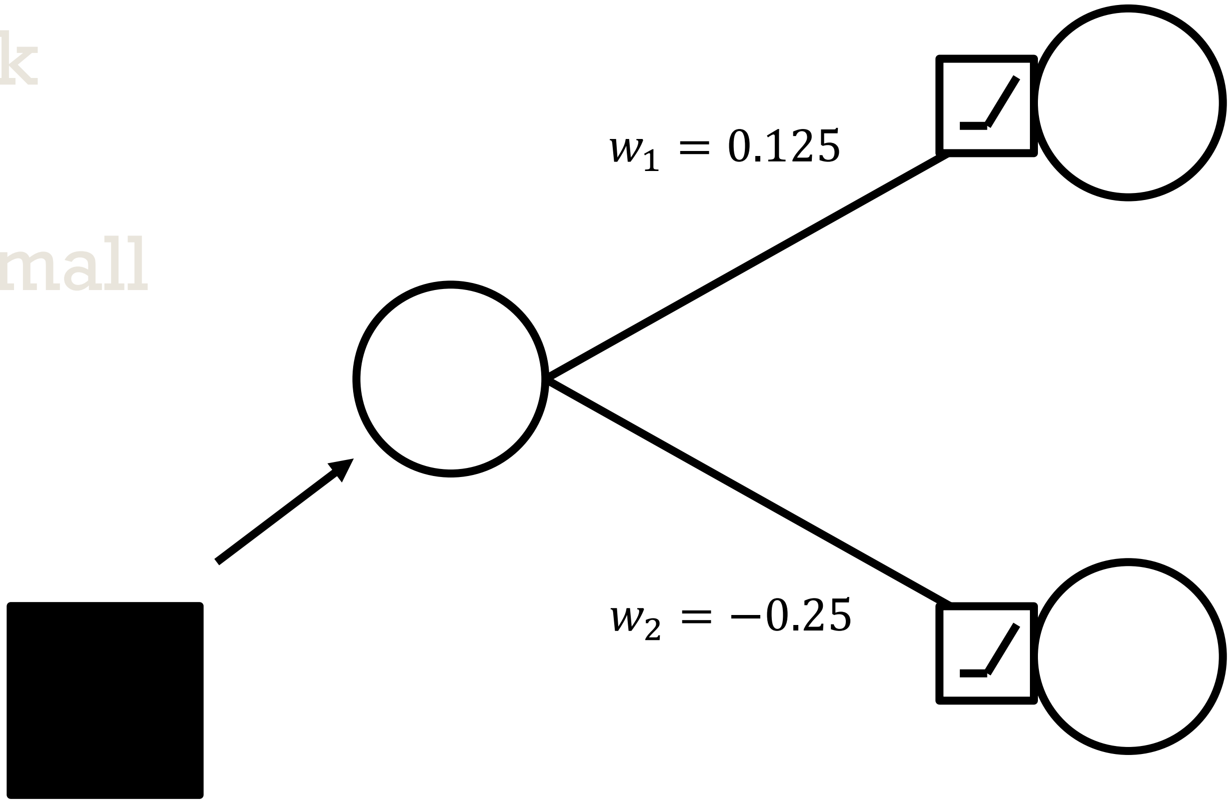

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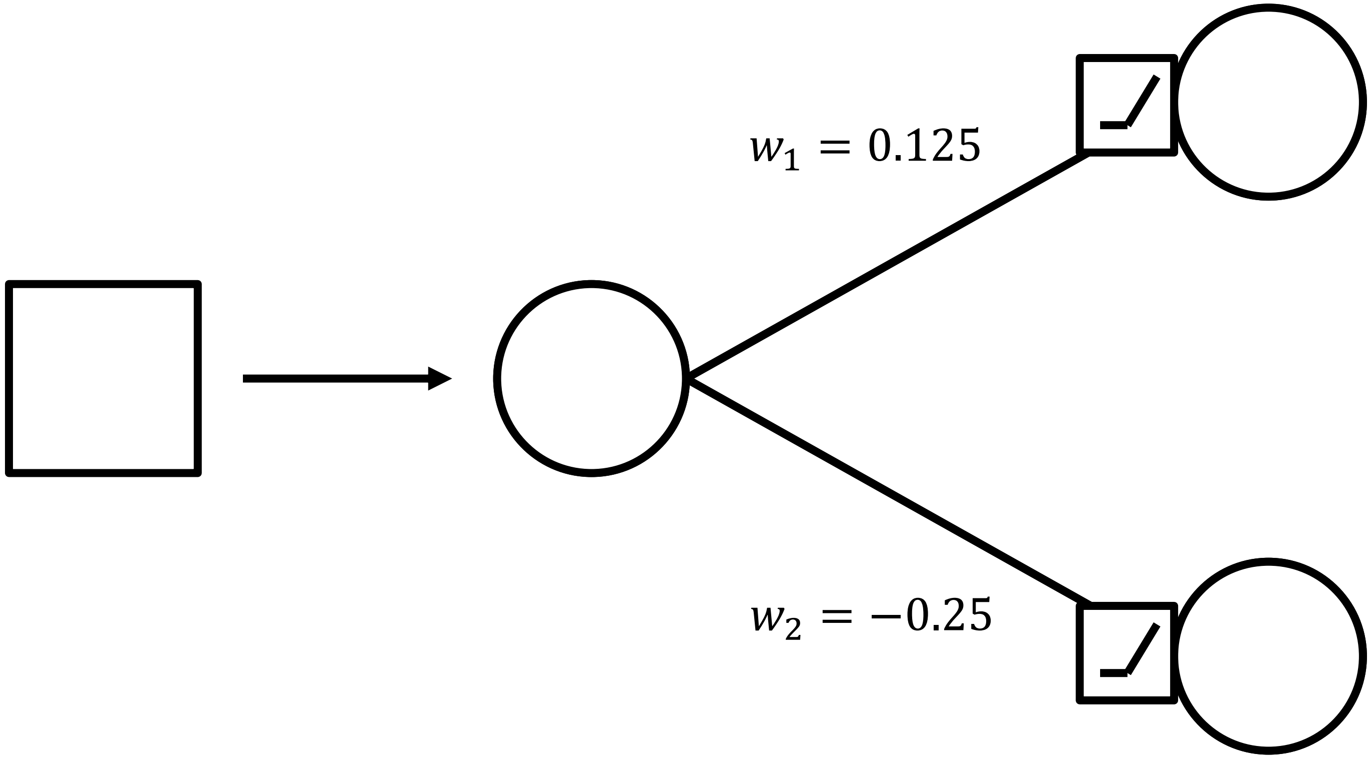

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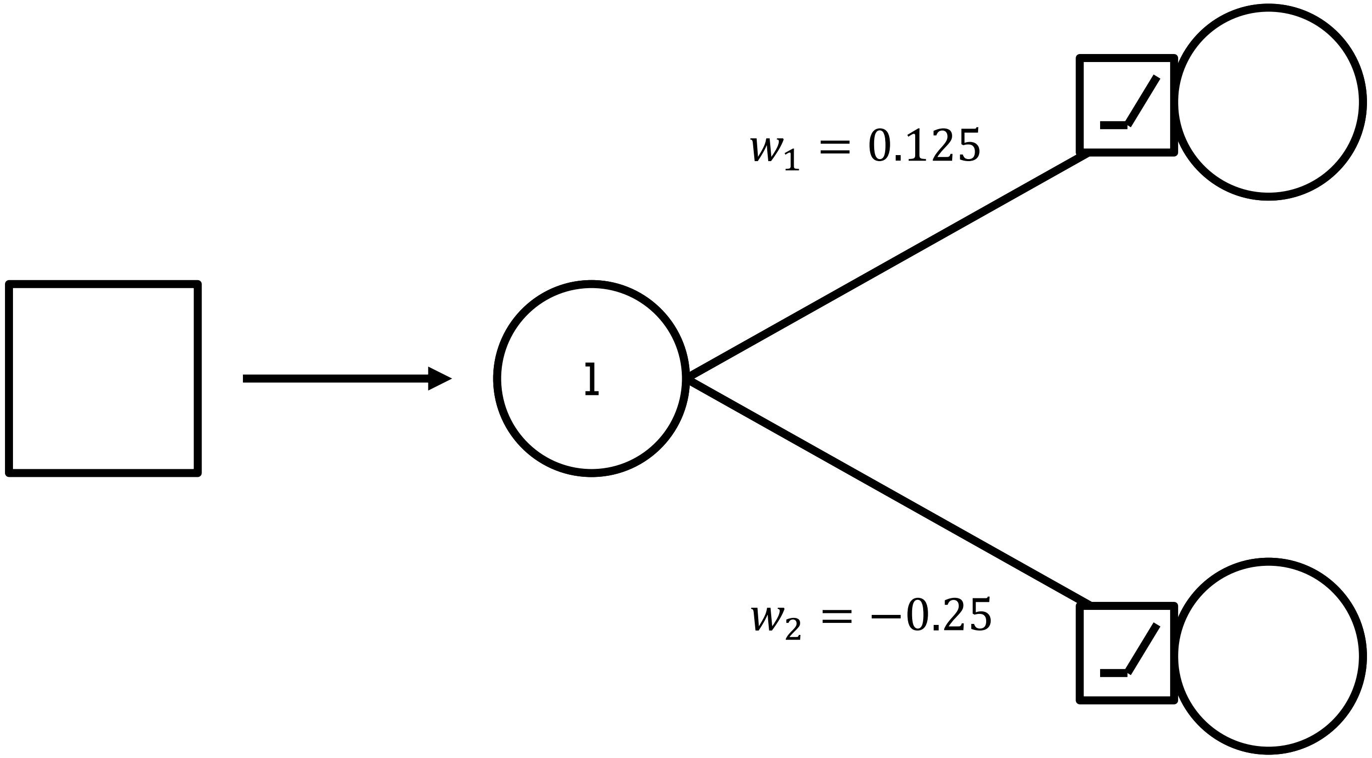

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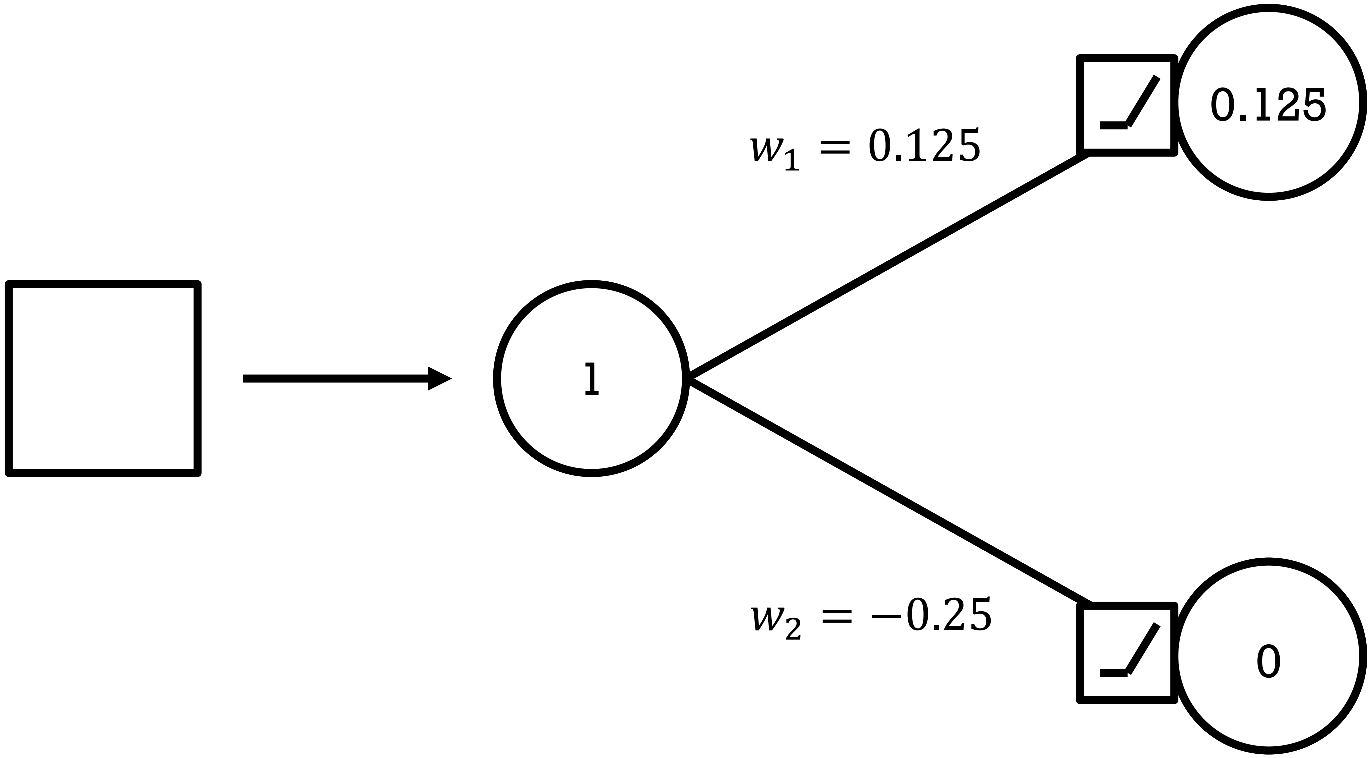

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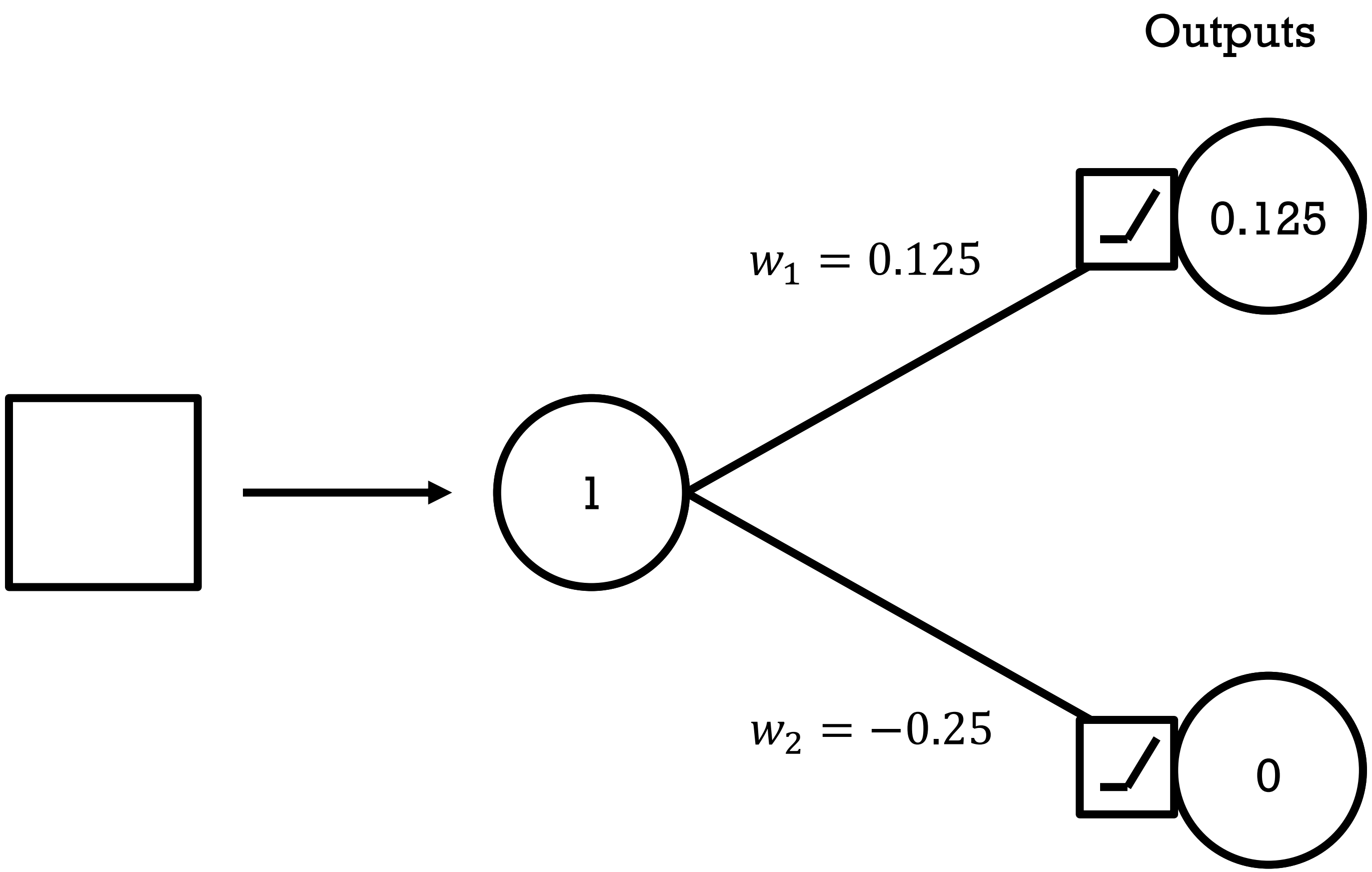

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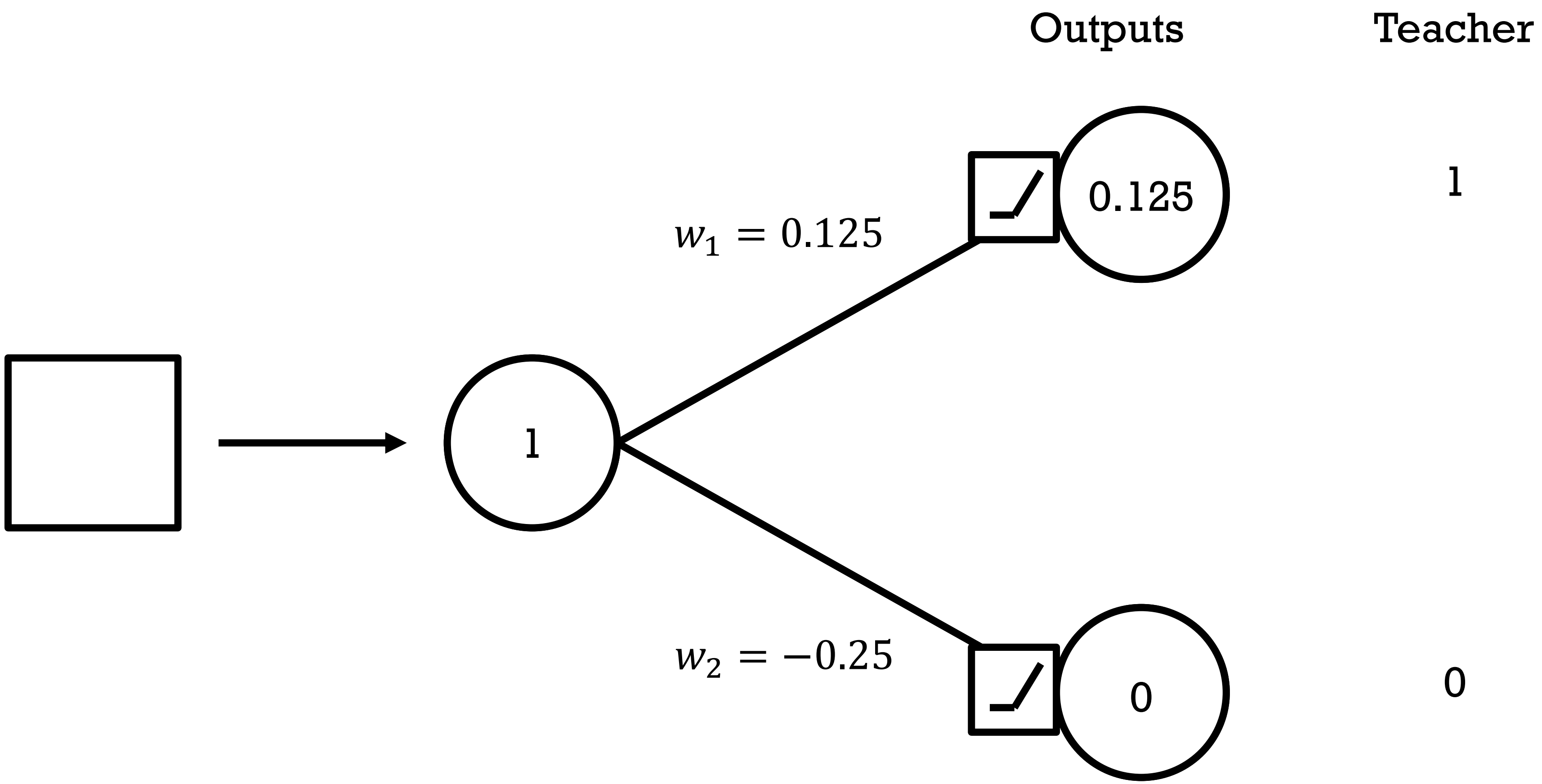


ERROR

- Sum of Squared Error

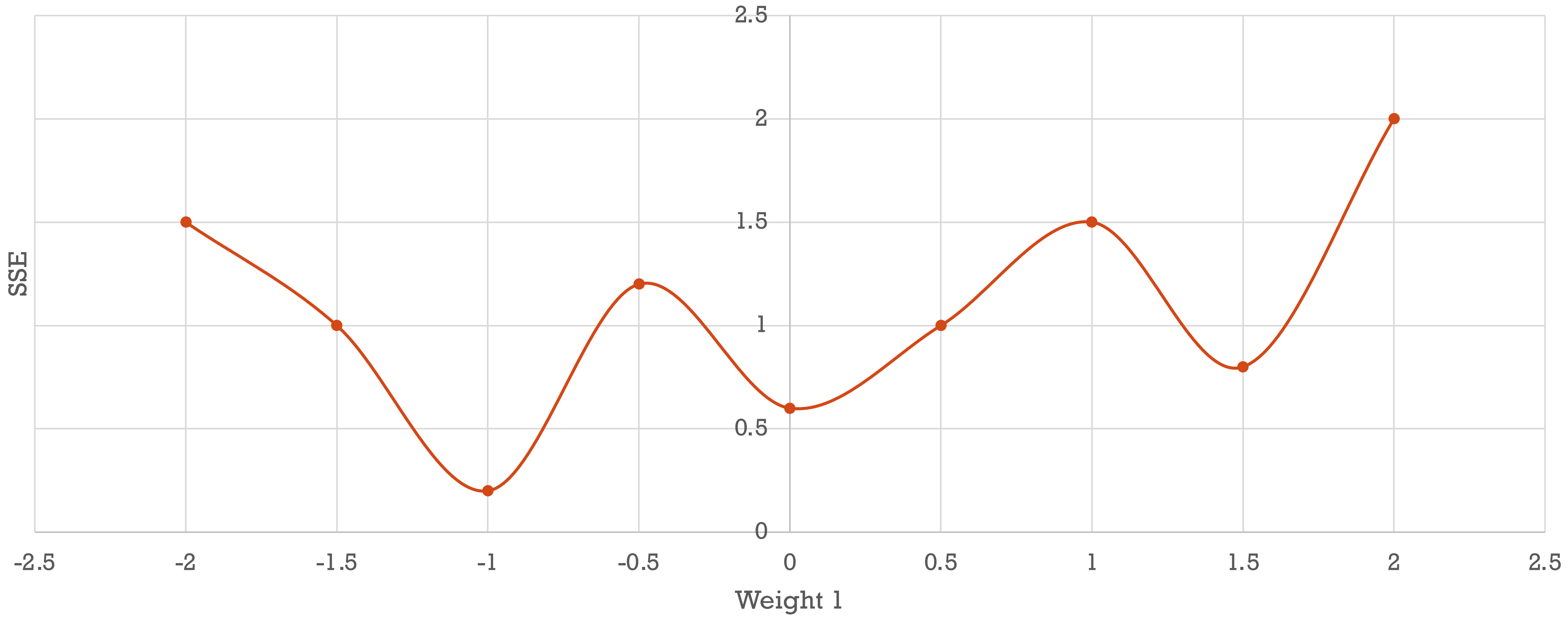
$$SSE = \sum (teacher - output)^2$$

ERROR CALCULATION

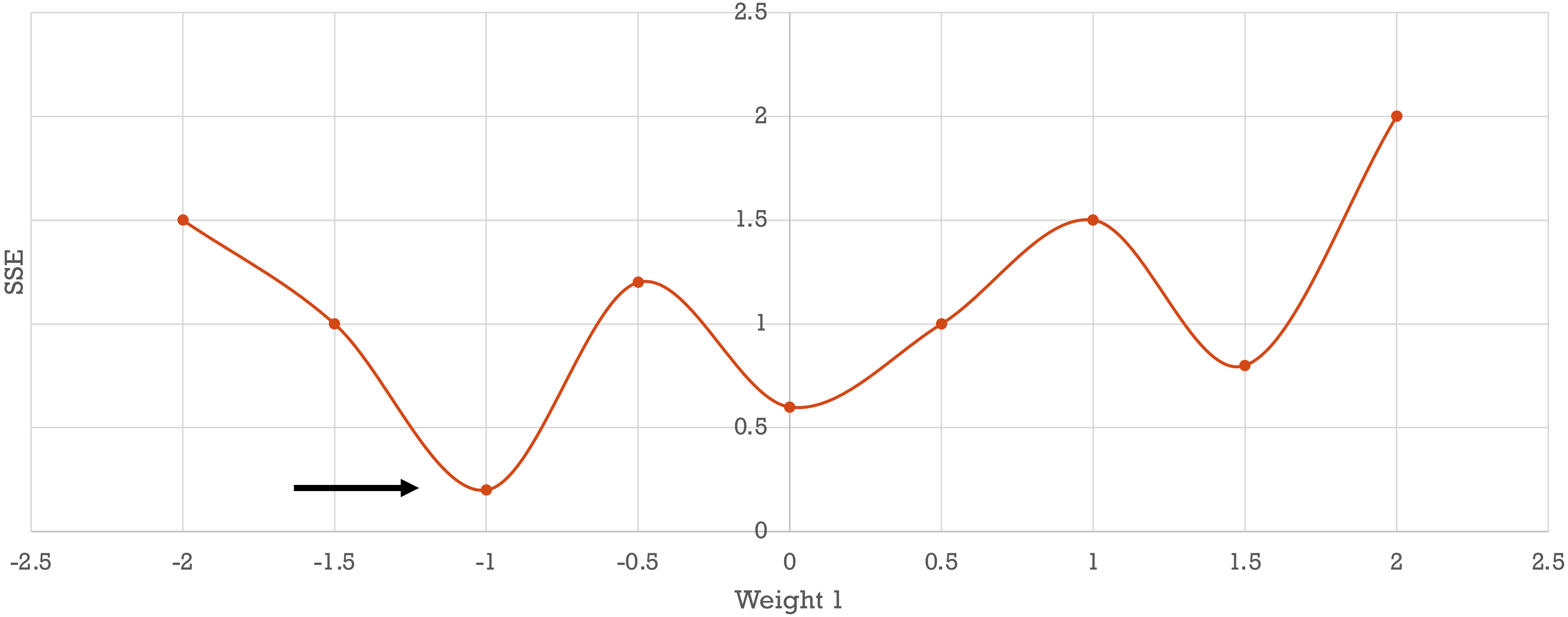
Output	Teacher	SE
0.125	1	(1 – 0.125) ^ 2 = 0.875 ^ 2 = 0.765625
0	0	(0 – 0)^2 = 0

SSE = 0.765625 + 0 = 0.765625

ERROR PLOT



WEIGHT TUNING AS OPTIMIZATION



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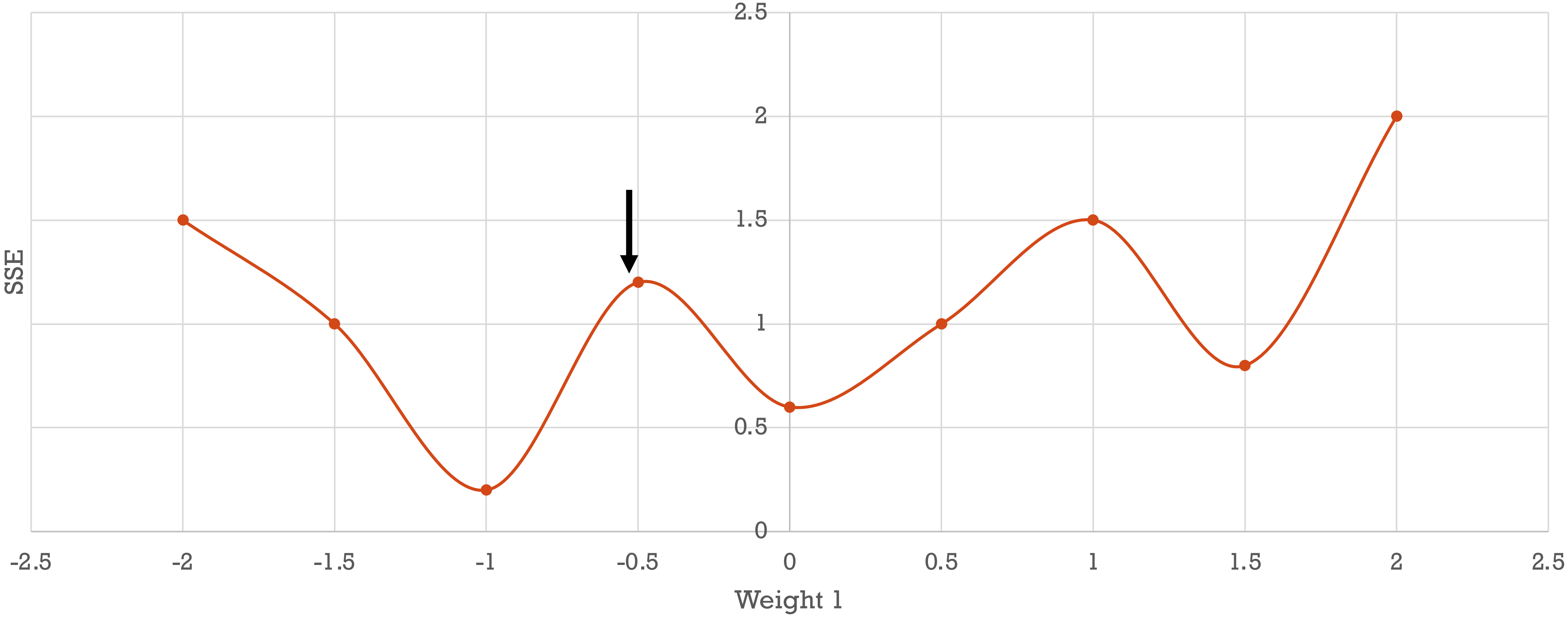
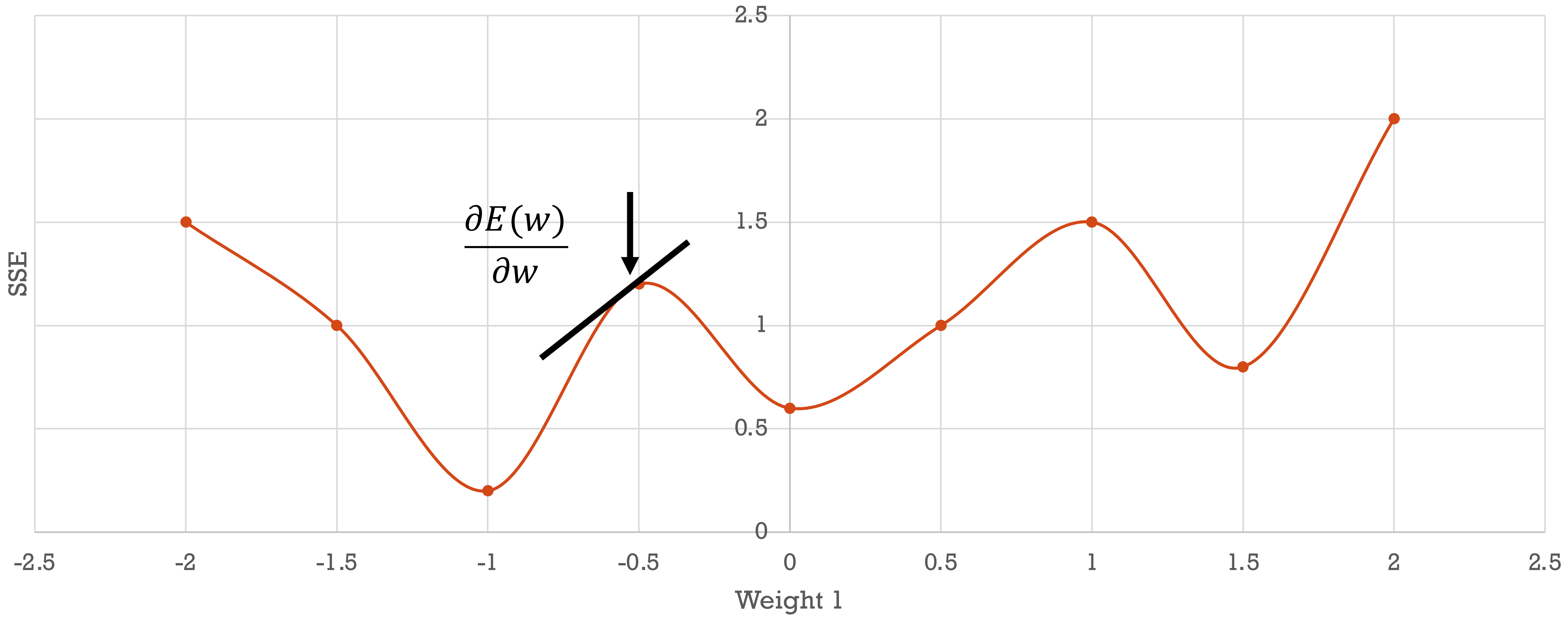


GRADIENT DESCENT



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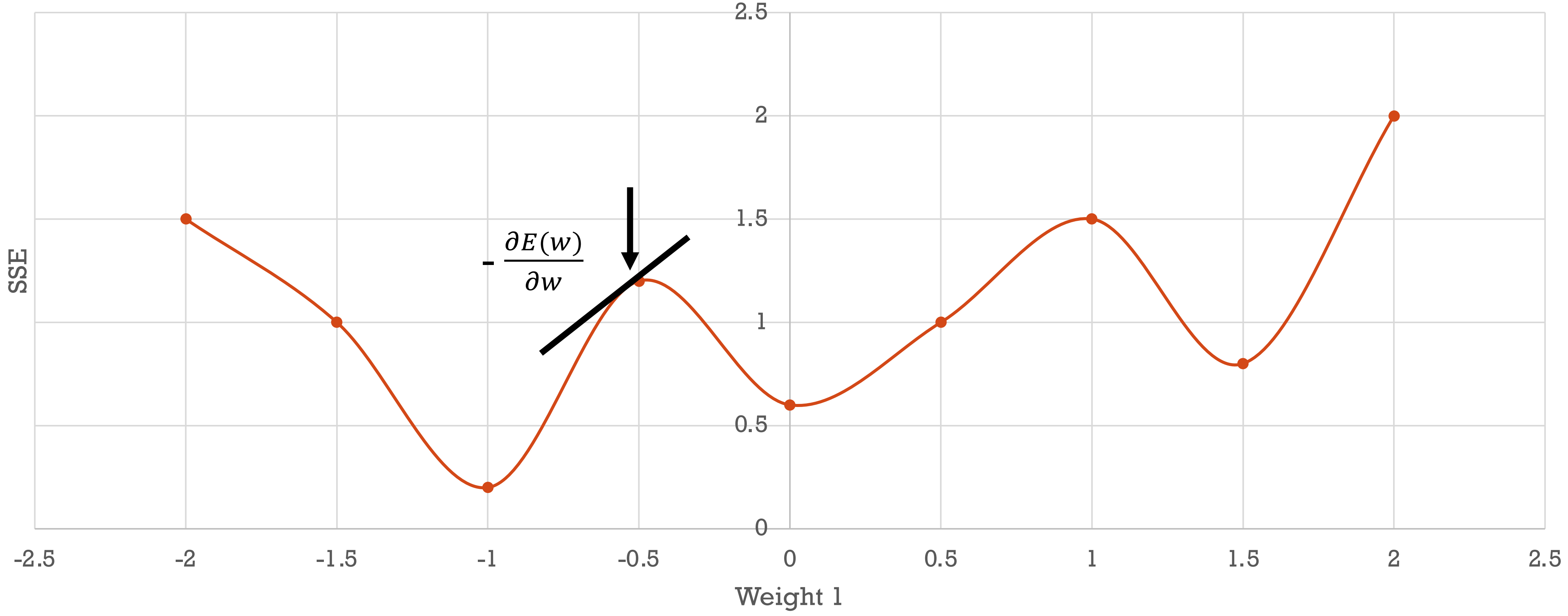
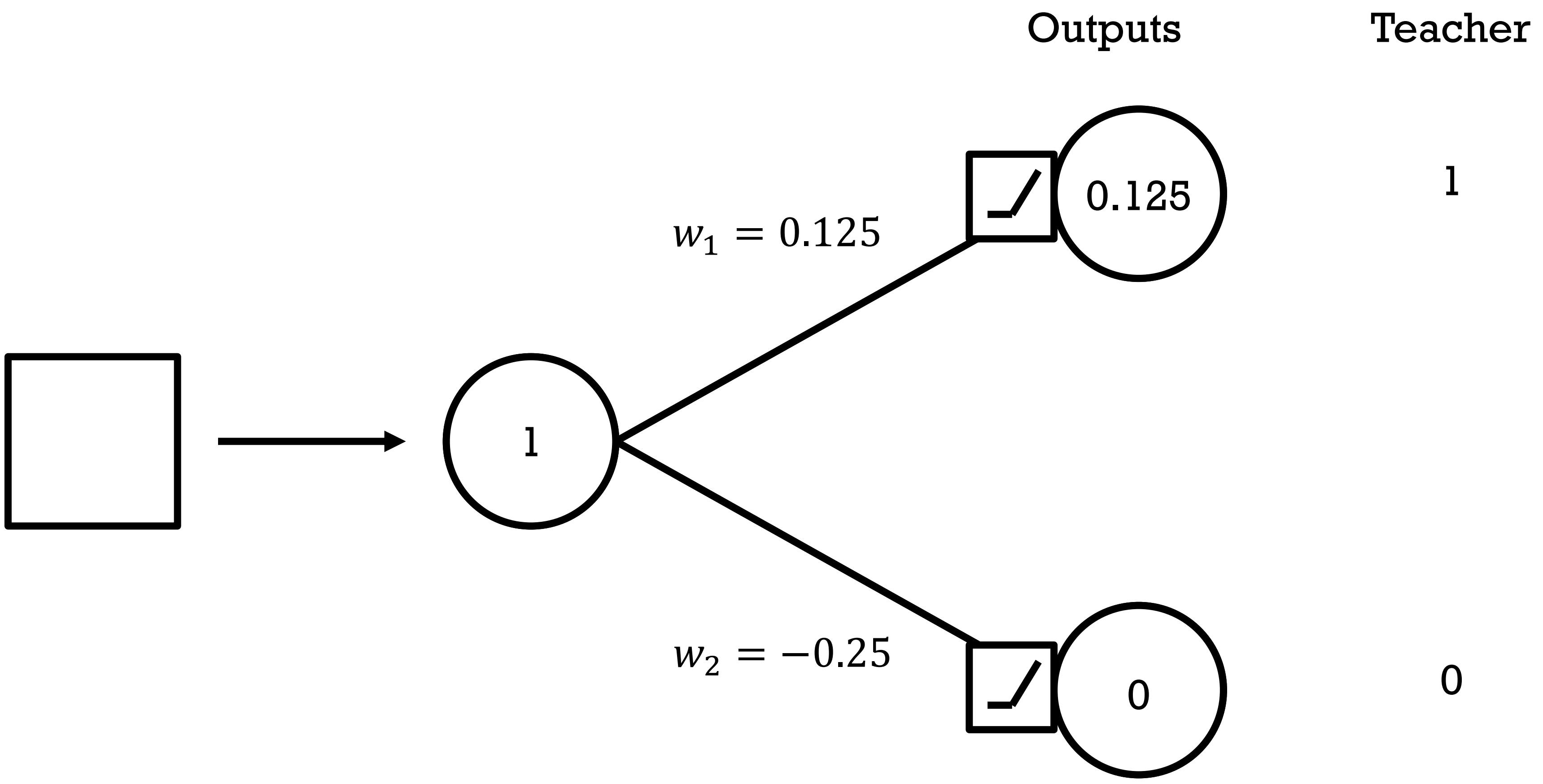
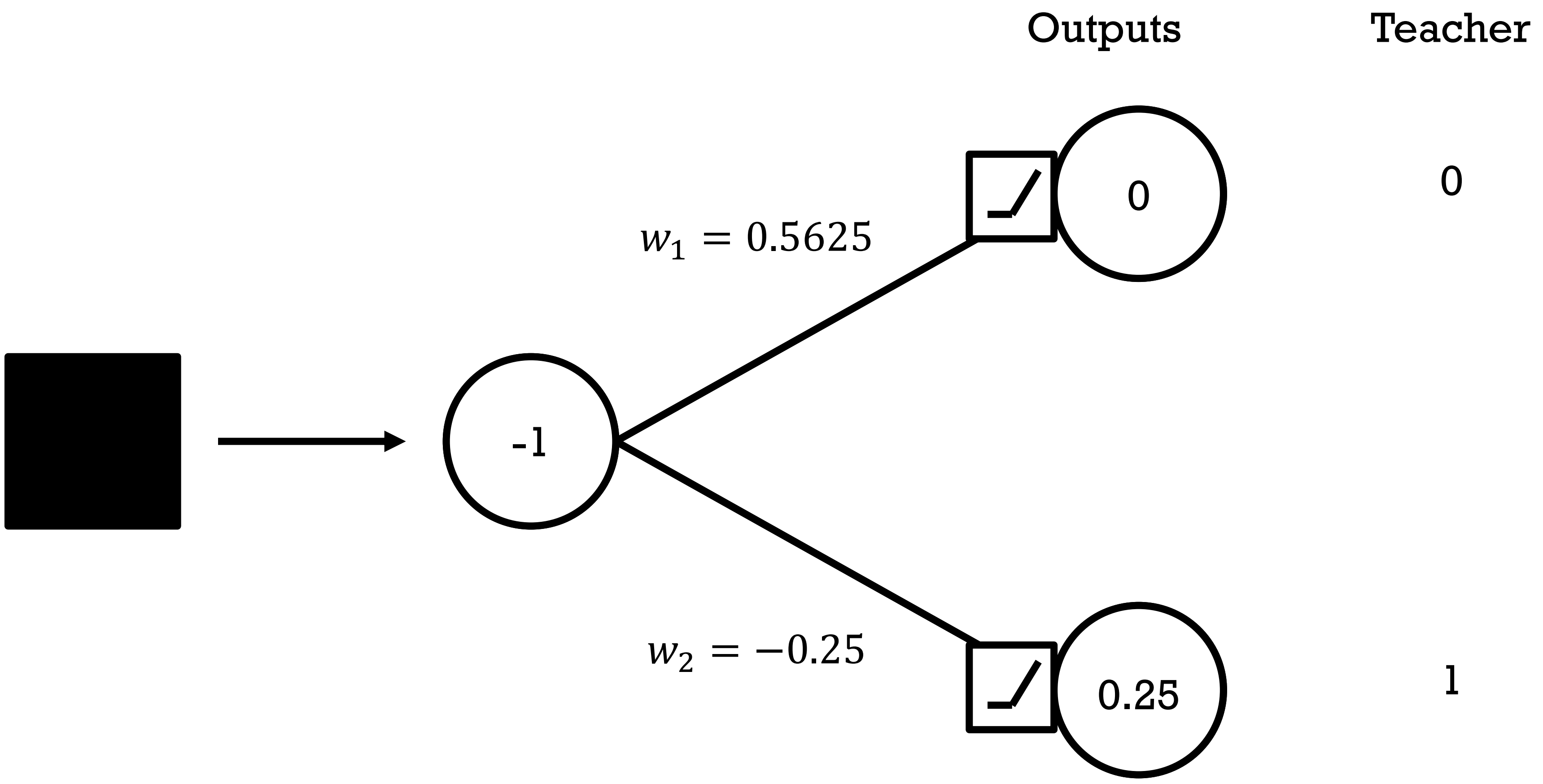


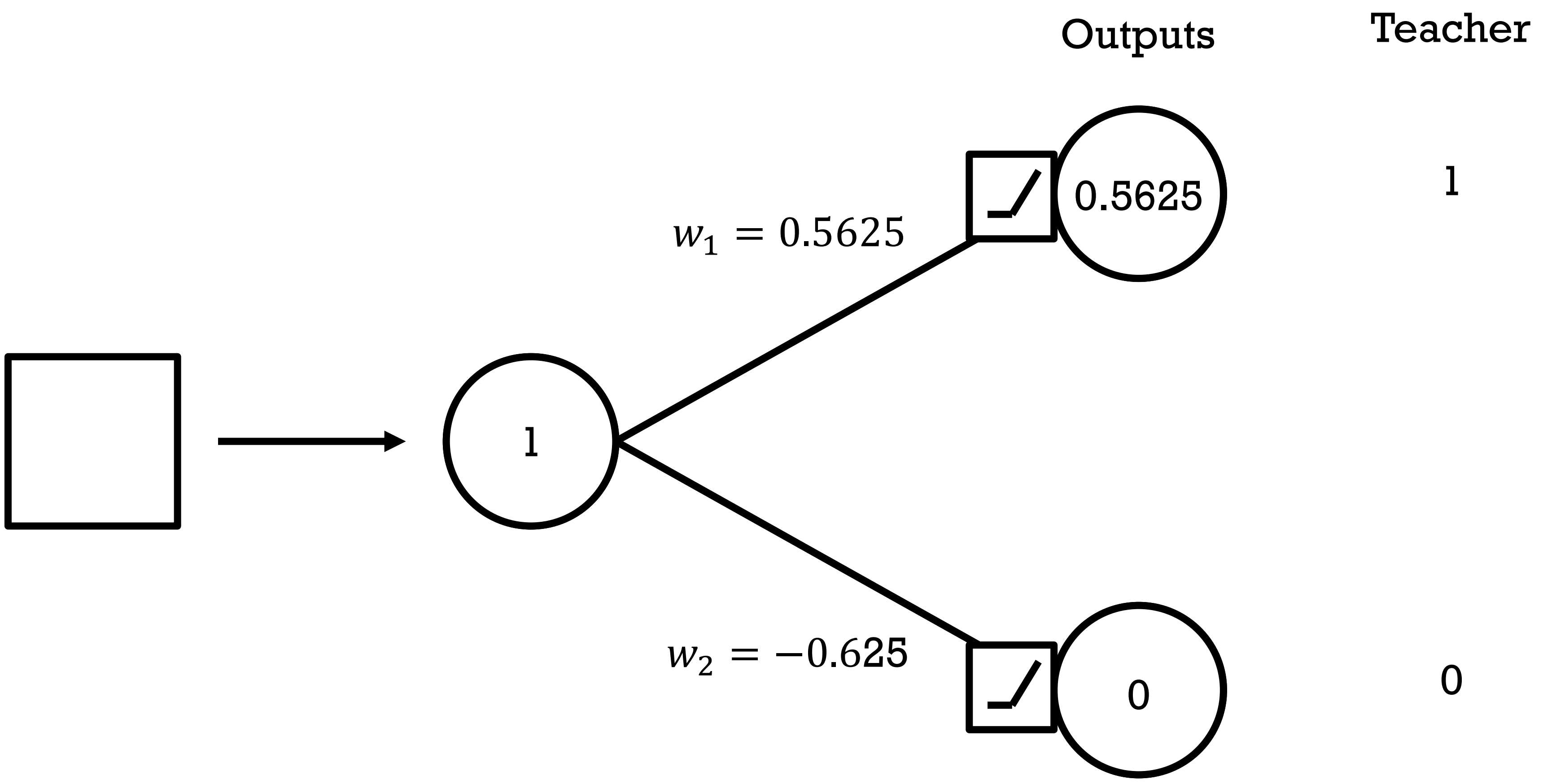
TRAINING – 1ST STEP



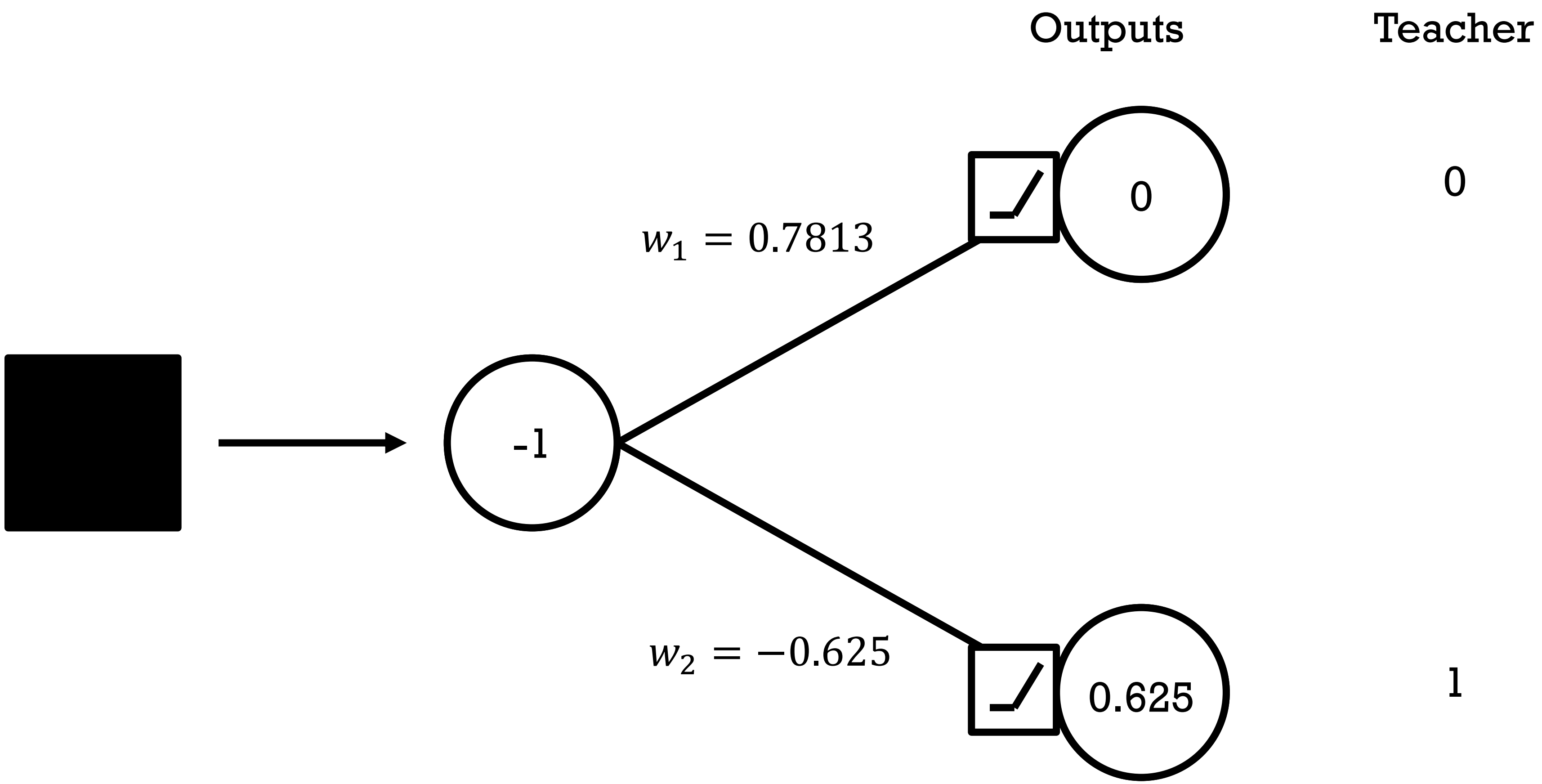
TRAINING – 2ND STEP



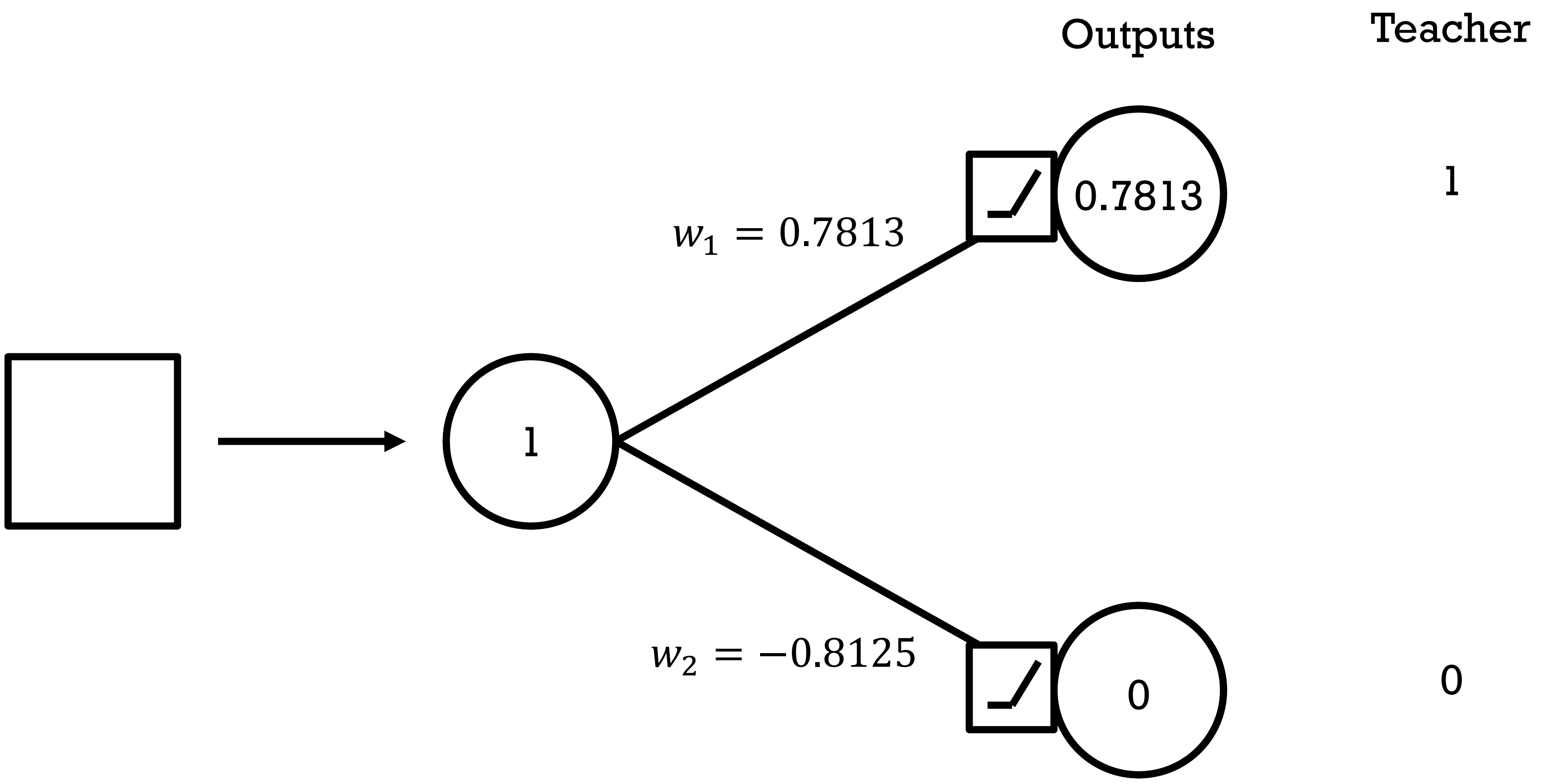
TRAINING – 1ST STEP OF 2ND EPOCH



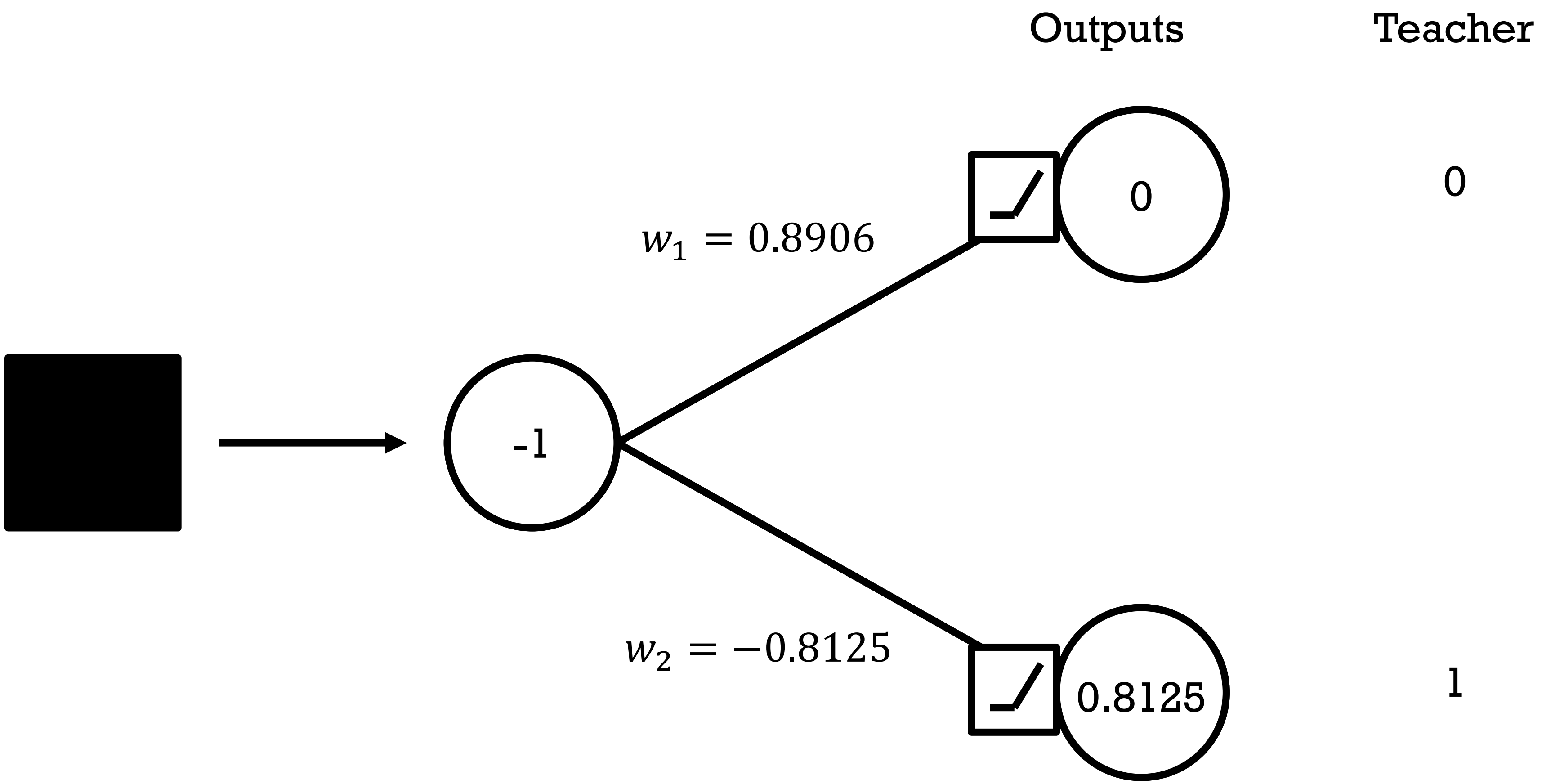
TRAINING – 2ND STEP OF 2ND EPOCH



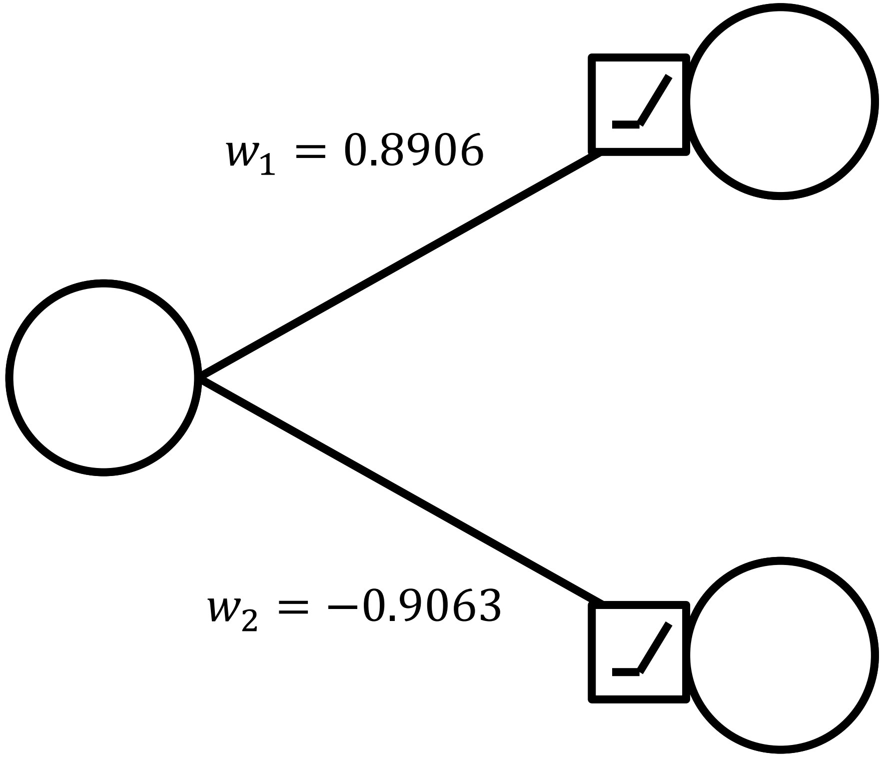
TRAINING – 1ST STEP OF 3RD EPOCH



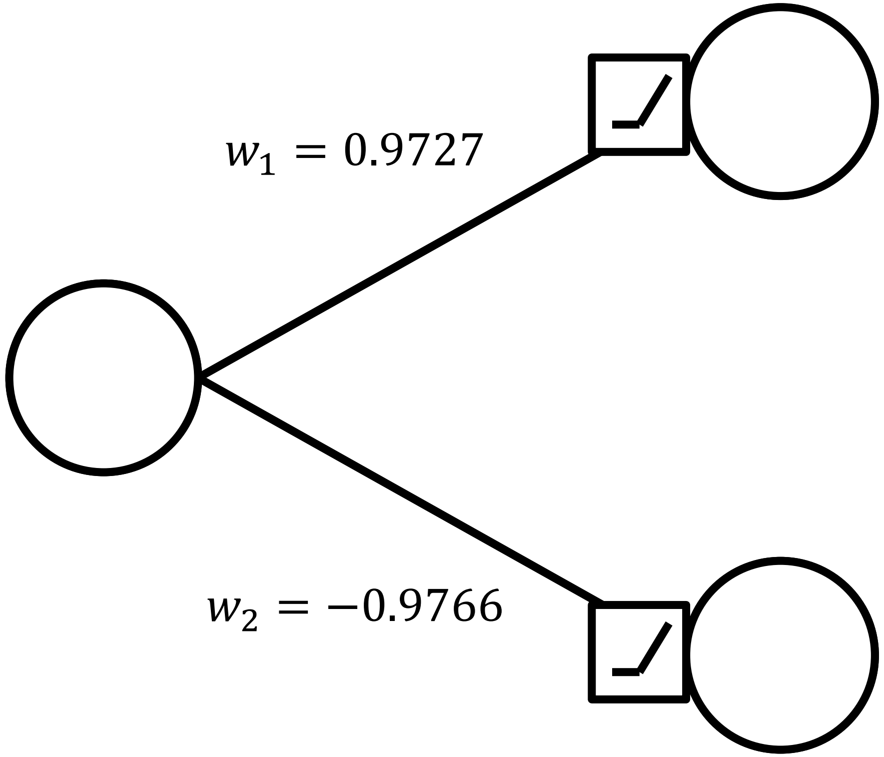
TRAINING – 2ND STEP OF 3RD EPOCH



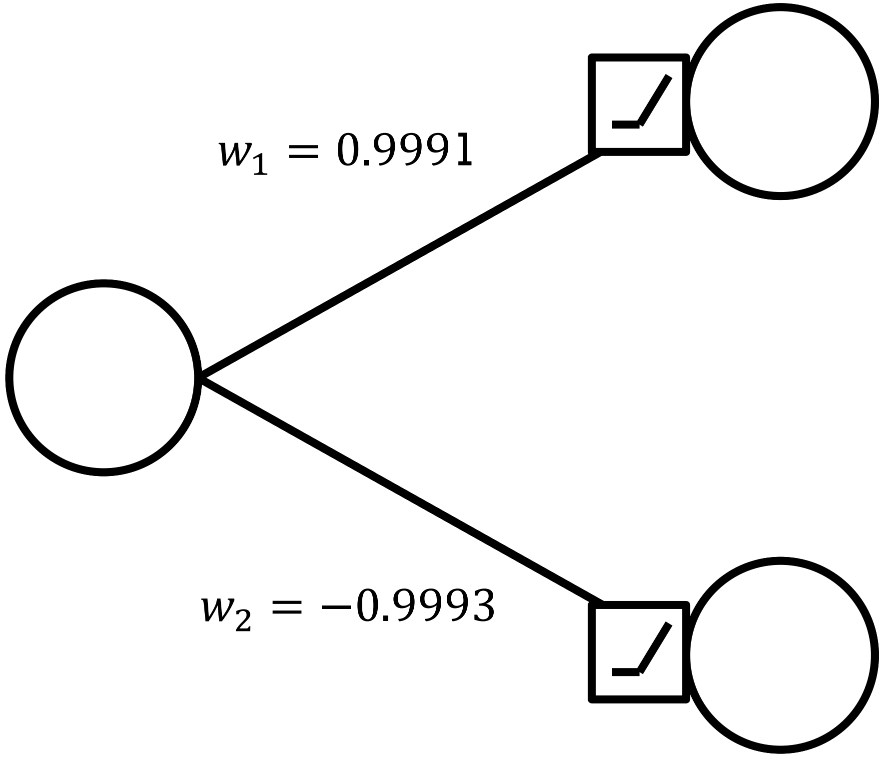
AFTER 3 EPOCHS



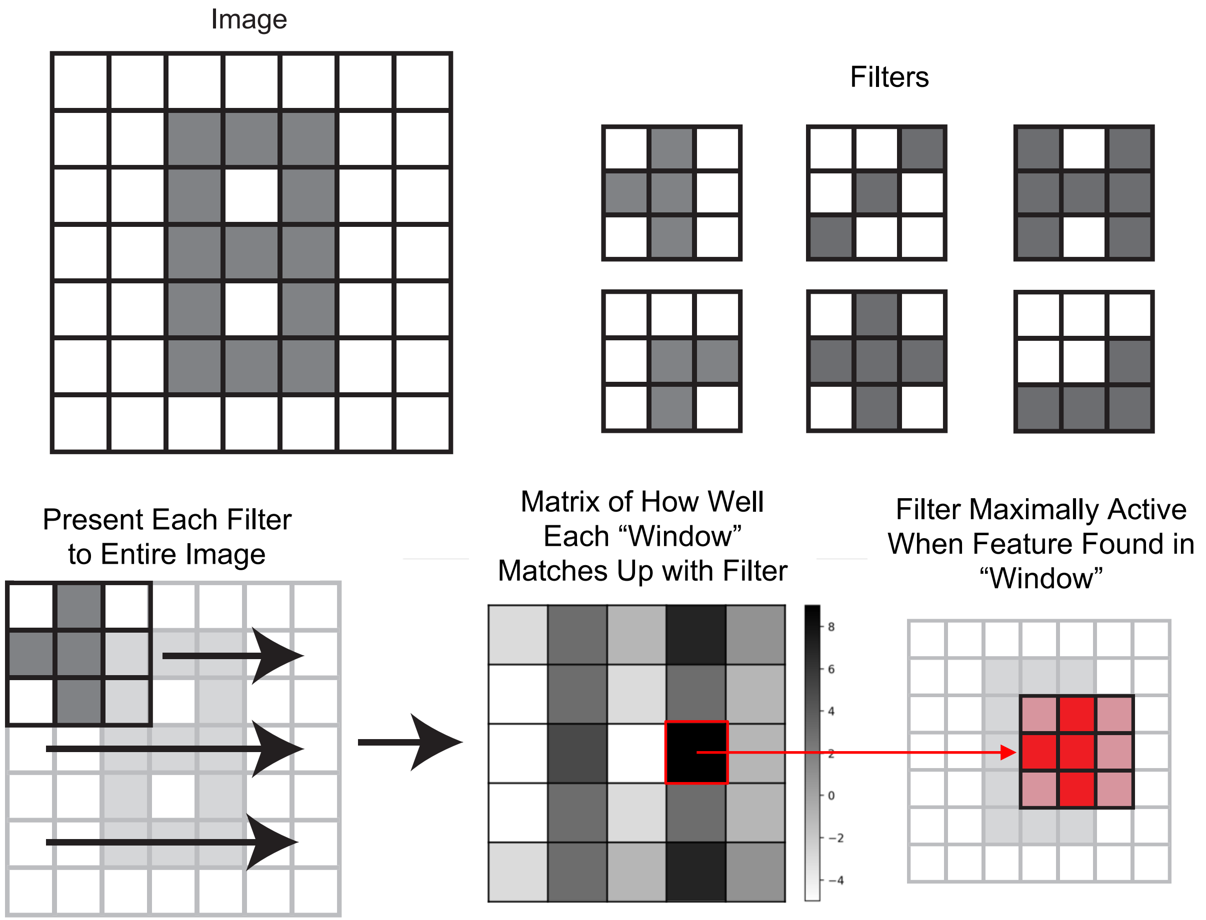
AFTER 5 EPOCHS



AFTER 10 EPOCHS

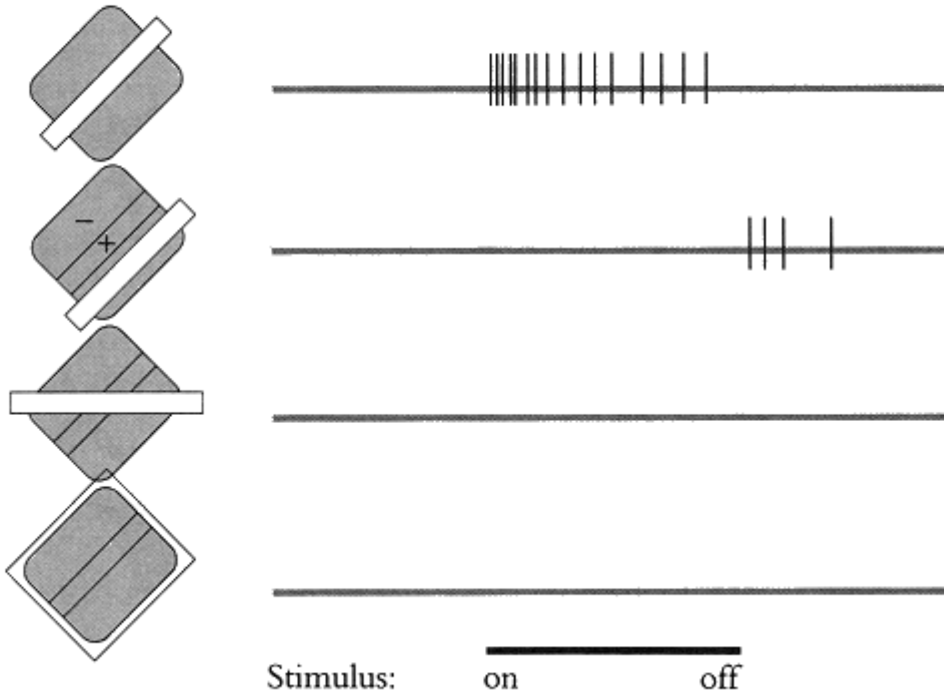


CONVOLUTION



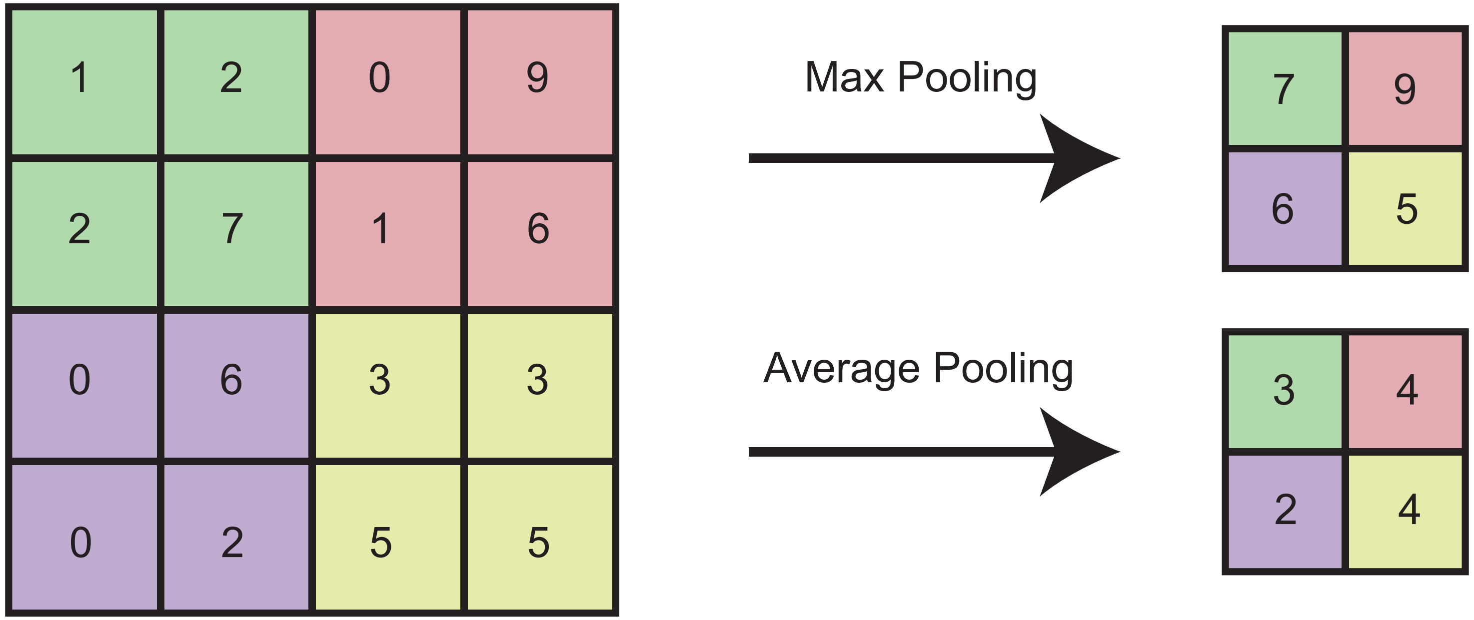
CONVOLUTION LAYERS

- Modeled after V1 simple cells



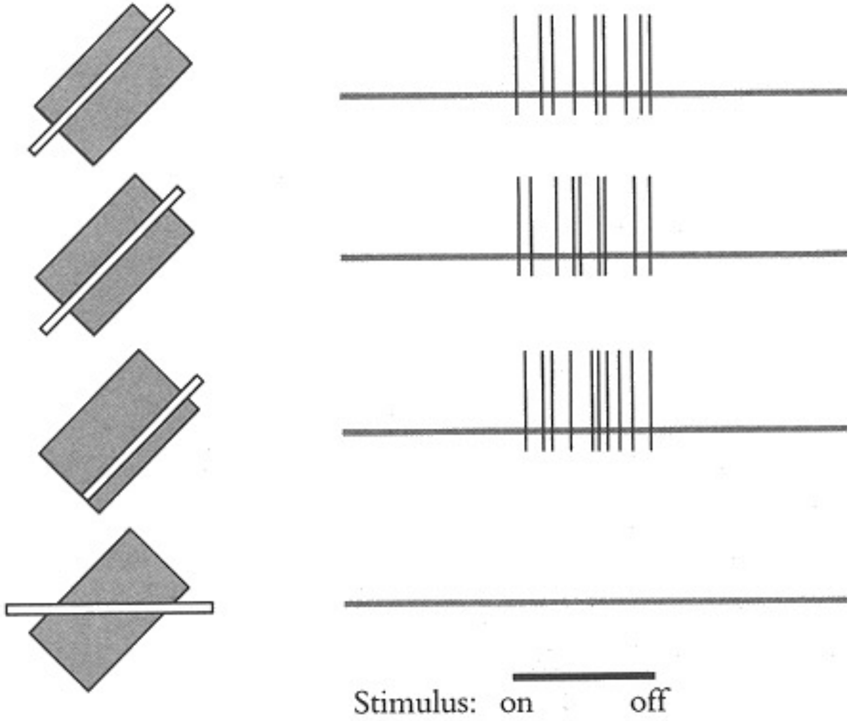
Picture from fourier.eng.hmu.edu

POOLING



POOLING AFTER CONVOLUTION

- Functions like V1 complex cells
- Shift invariance



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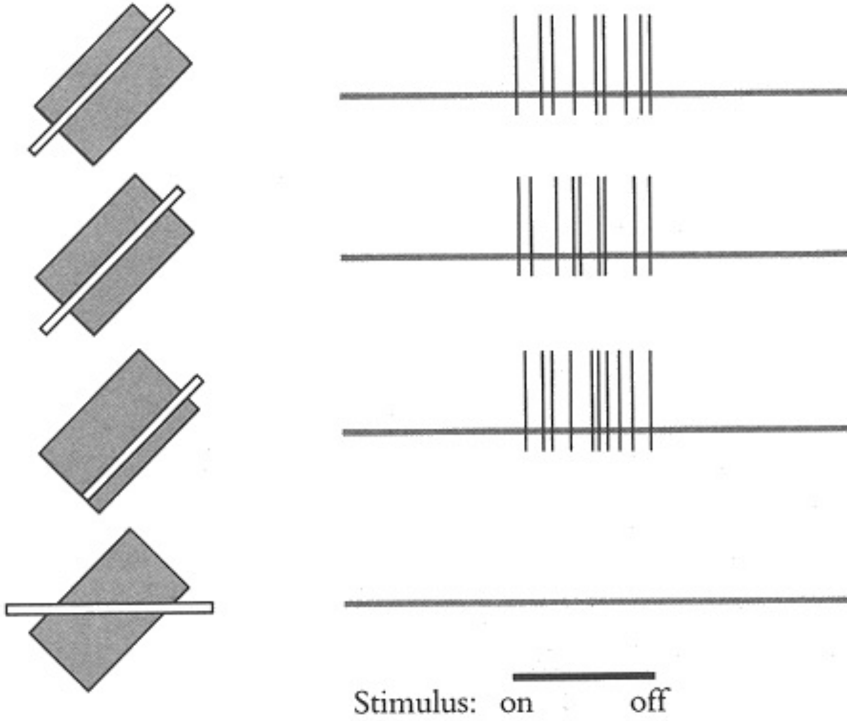

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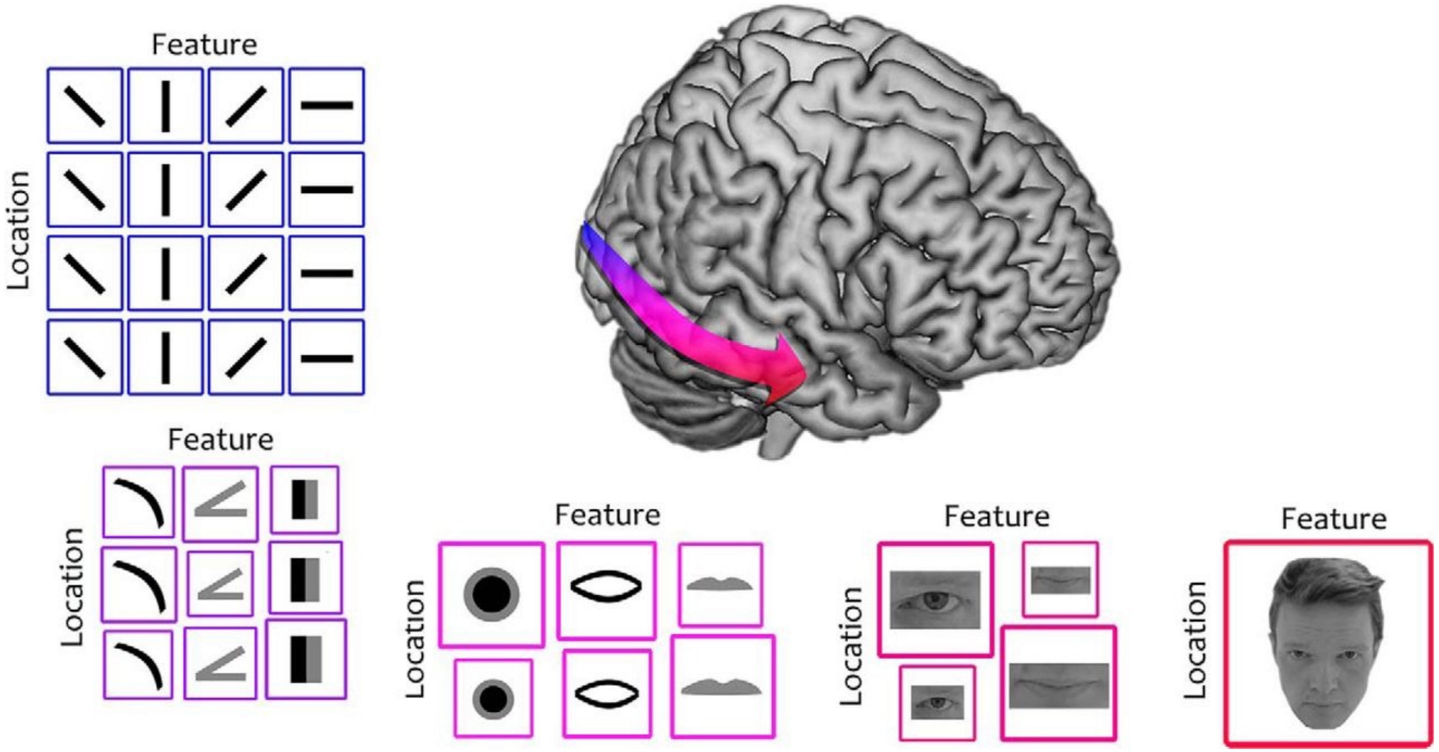
STACKING CONVOLUTION LAYERS

- Similar to ventral visual pathway
- Successive layers extract more complex features



Picture from Kaiser and Haselhahn (2017)

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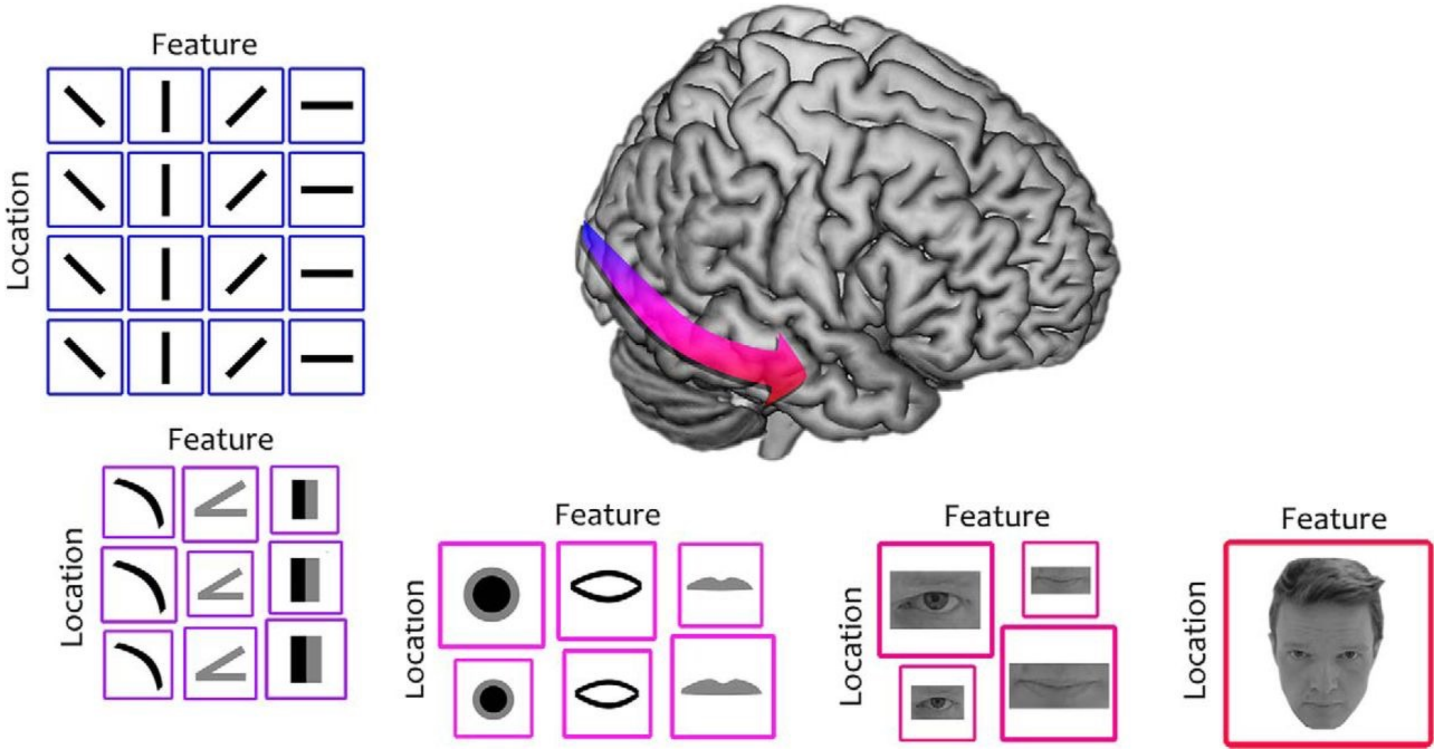

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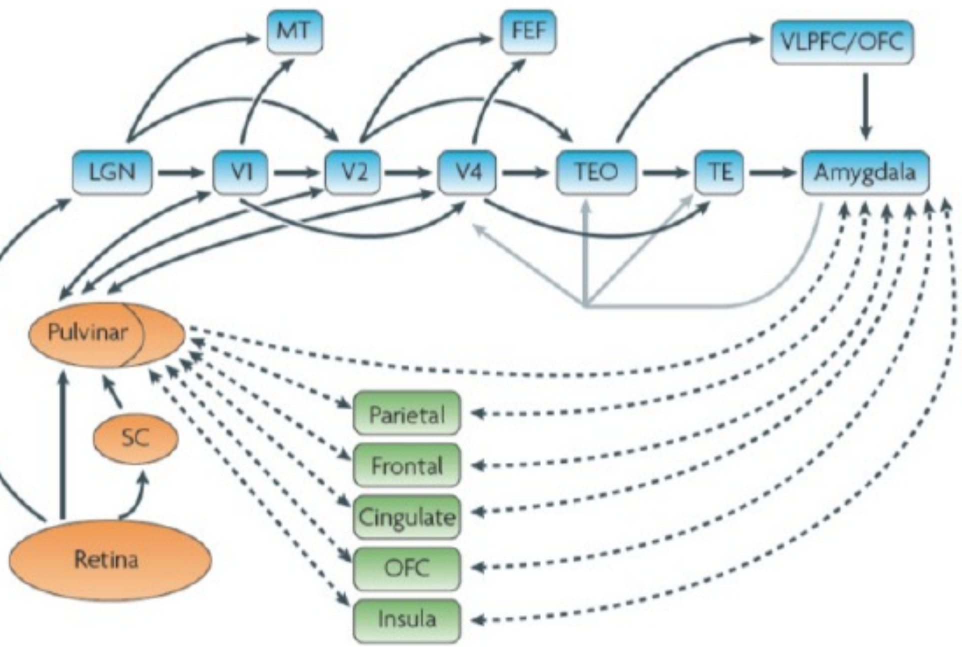
SKIP CONNECTIONS

- Similar to skip connections in brain
- Make training of networks easier



Picture from Peter Walla

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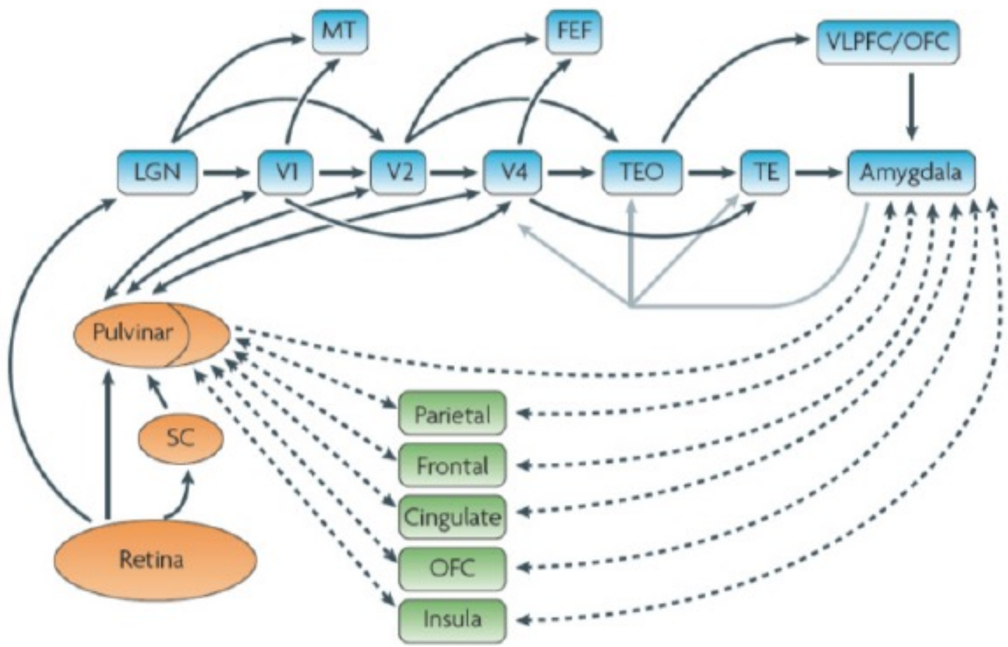
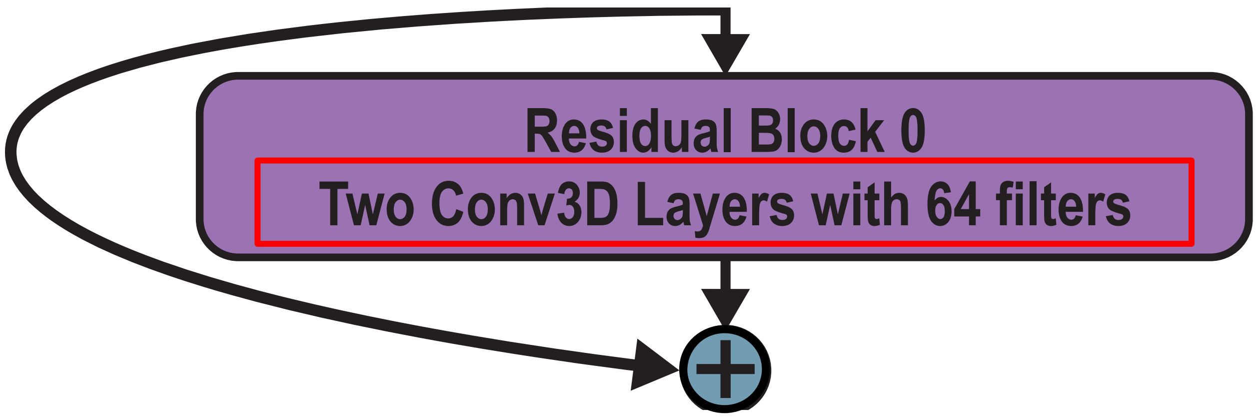


Picture from Peter Walla

RESIDUAL BLOCK

- Stack of 2 convolution layers
- Skip connection from beginning to end



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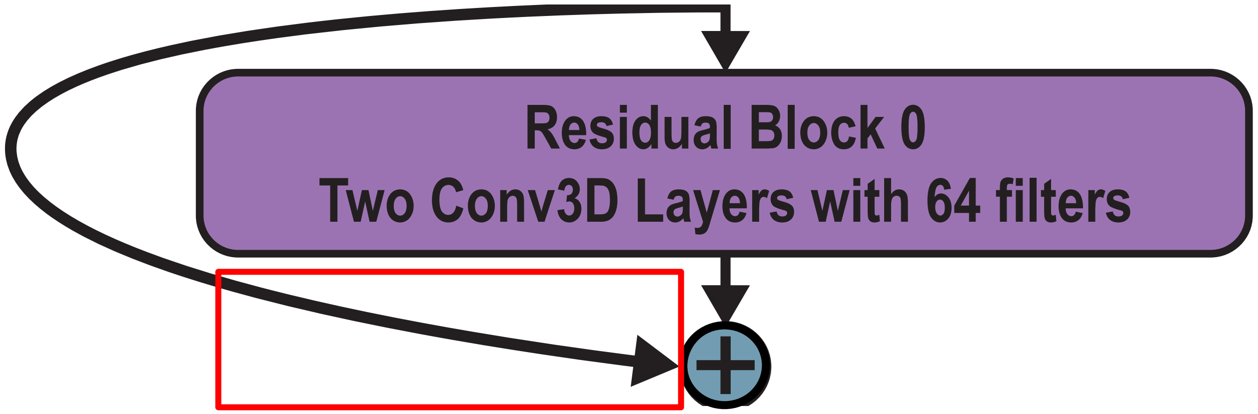
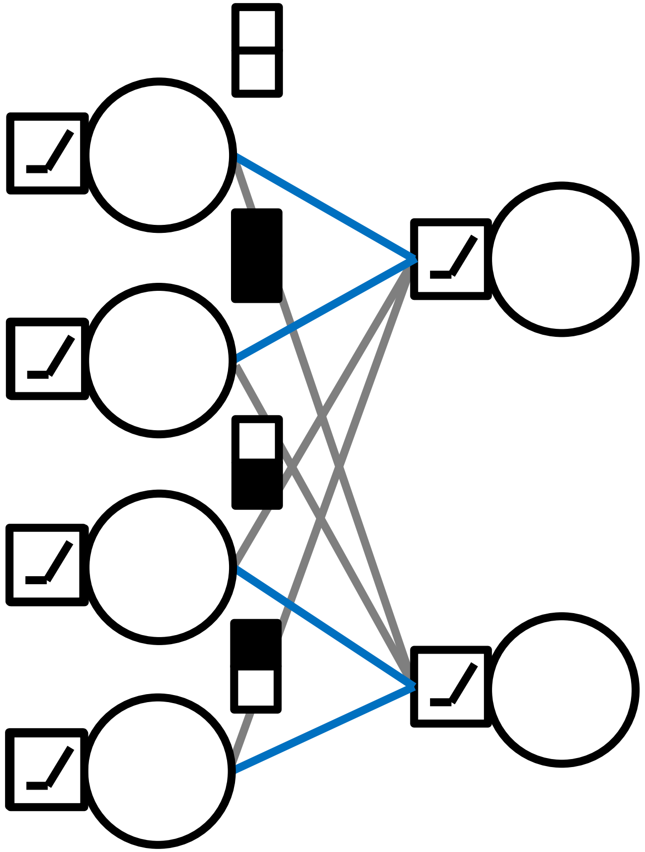


FULLY CONNECTED LAYER

- You already know about these!
- Utilize extracted features to make final prediction



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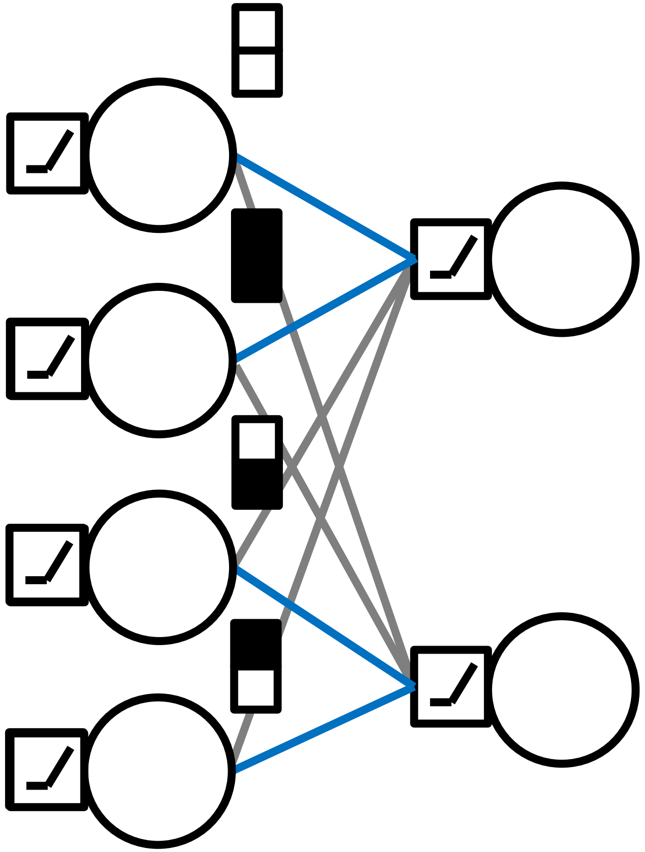
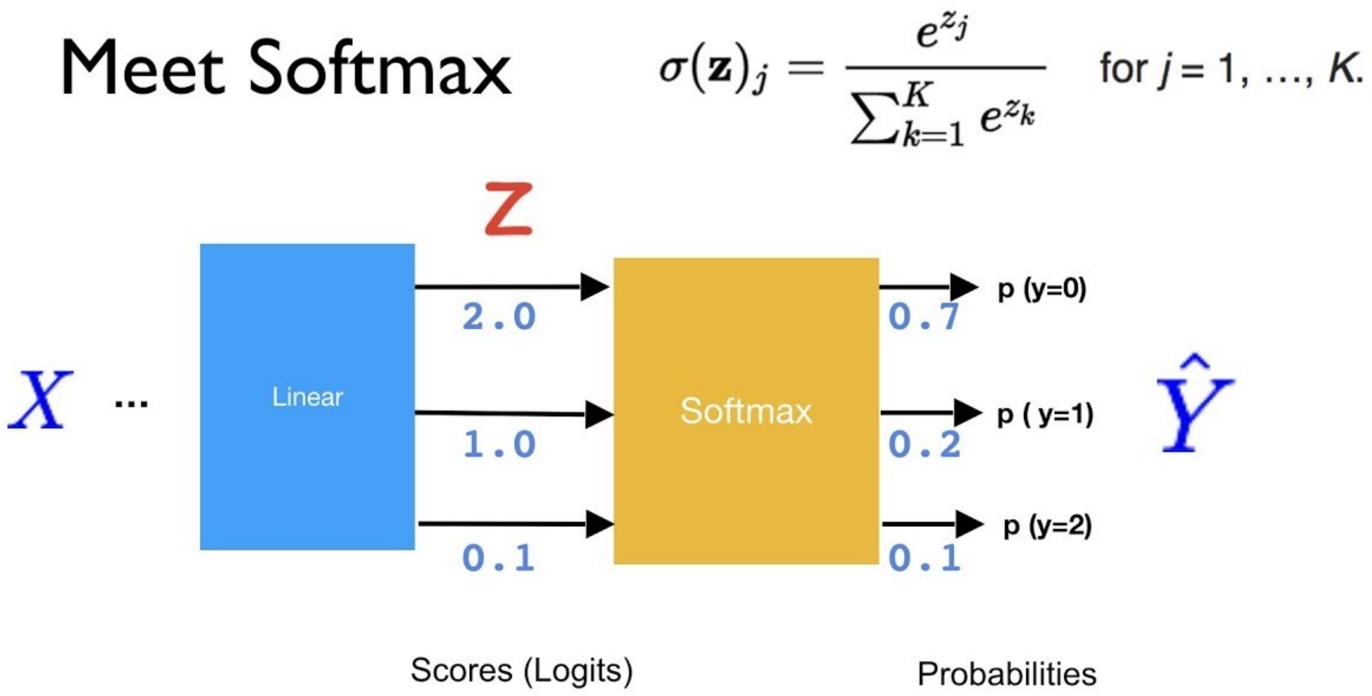


SOFTMAX



Picture from Sung Kim's YouTube video on Softmax Classifier

OUTLINE

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  - Classification
  - A Few Basic Classifiers
  - Artificial Neural Networks
  - Neural Network in Medical Imaging
- Chapter 2: Classification of Autism Spectrum Disorder Using Machine Learning
  - Introduction
  - Methods
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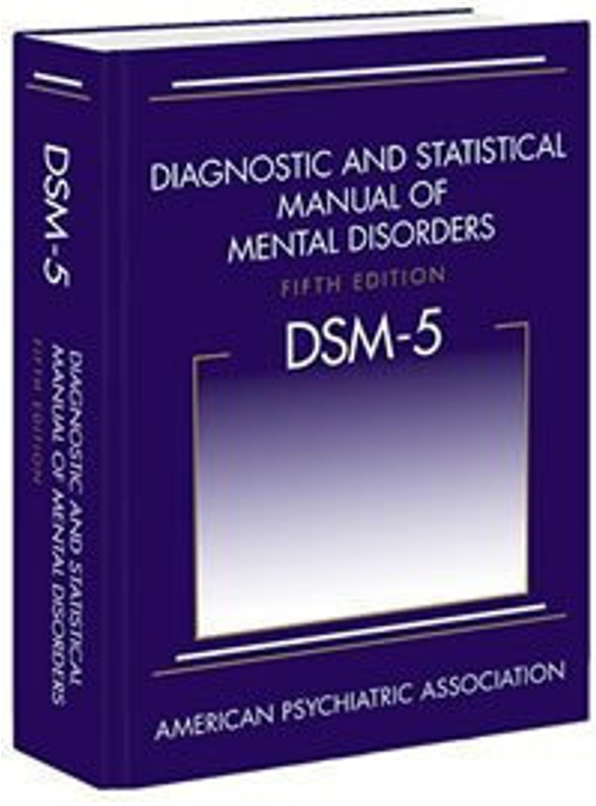
DIAGNOSIS

- Criteria from DSM-5
- Autism Diagnostic Interview-Revised (ADI-R)
- Autism Diagnostic Observation Schedule (ADOS)
- ADI-R and ADOS assess same clinical criteria
- Reliable specificity and sensitivity for ASD (Falkmer et al., 2013)
- ADOS has higher sensitivity than ADI-R (Randall et al., 2018)



Picture from etsy.com

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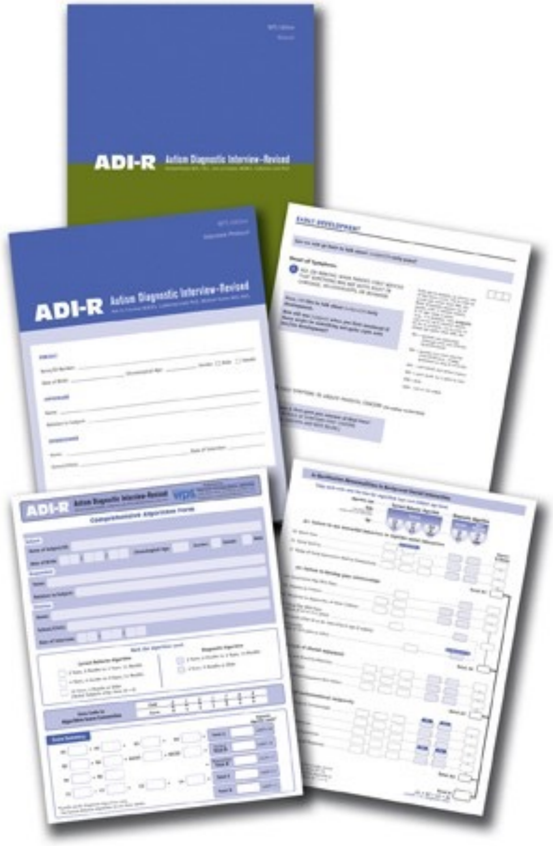

Picture from stoeltingco.com

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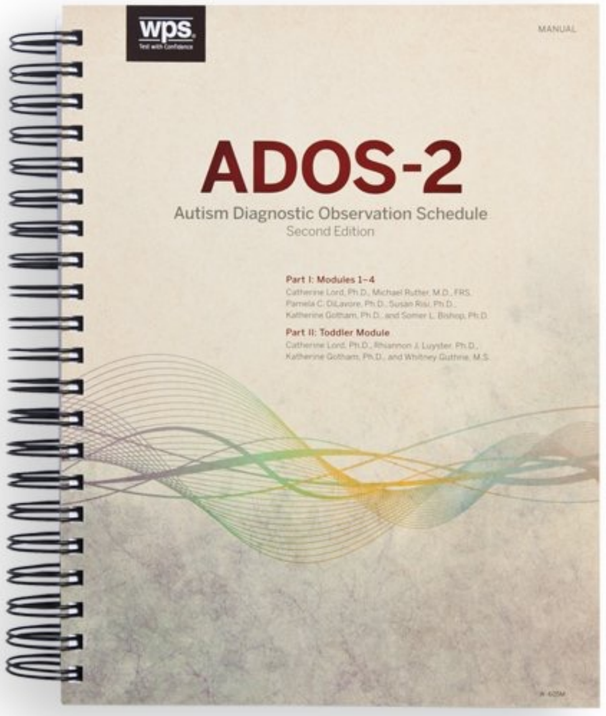

Picture from wpspublish.com

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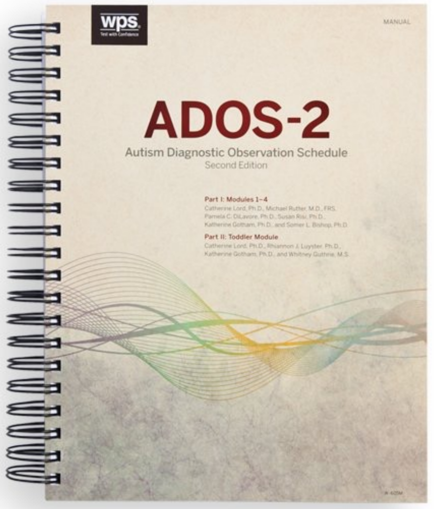

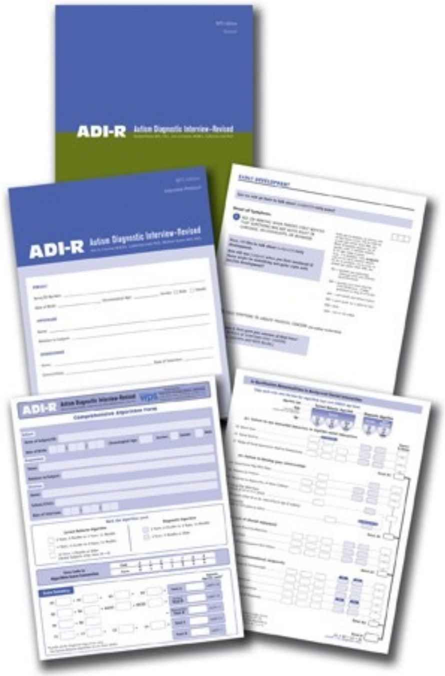

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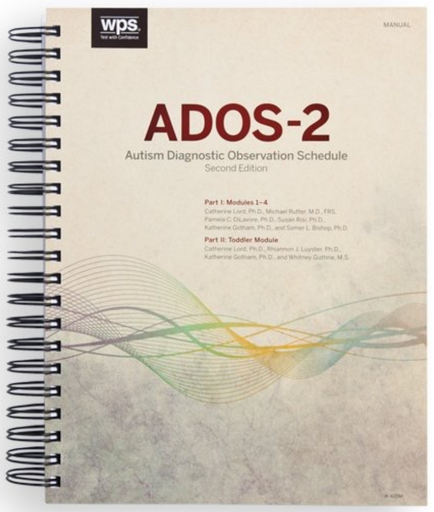

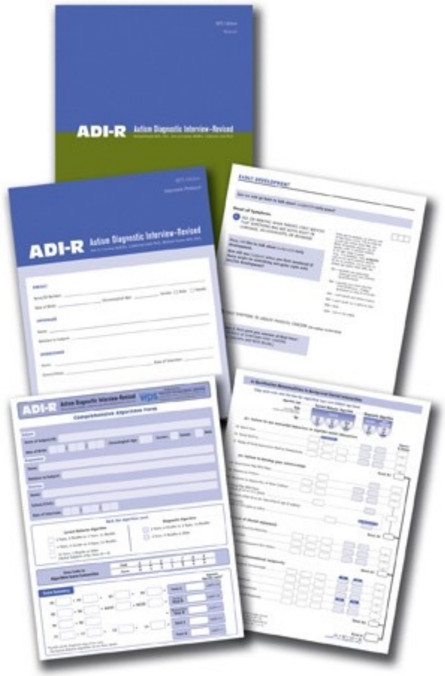

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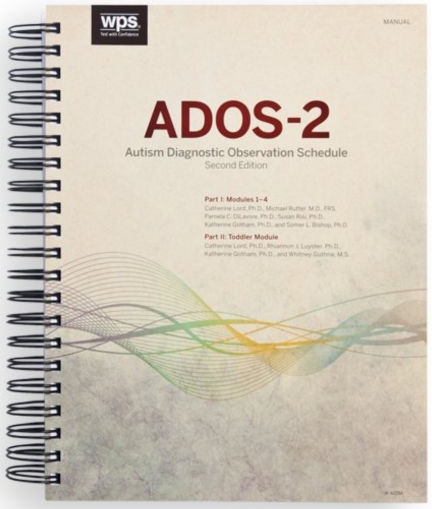

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EARLY DIAGNOSIS AND TREATMENT

- Current behavioral assessments require children to be 12 months and older (Esler et al. 2015)
- Improve quality of life for individuals and families (Elder et al., 2017)
- Estimated healthcare savings of $208,500/child (Chasson et al., 2007)
- Substantial sustained gains in IQ, language, academic performance, and adaptive behavior (Myers et al., 2007)

Picture from nashp.org

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FUNCTIONAL DIFFERENCES IN ASD

- Majority of changes seen in ASD (Rudie et al., 2013)
- Decreased functional connectivity throughout the brain
  - Resting-state network (Cherkassky et al., 2006)
  - Anterior-posterior connections (Cherkassky et al., 2006)
  - Fronto-parietal connections (Just et al., 2007)
  - Within functional systems (Rudie et al., 2013)
  - Interhemispheric connections (Anderson et al., 2011)
- No deactivation of resting-state network (Kennedy et al., 2006)

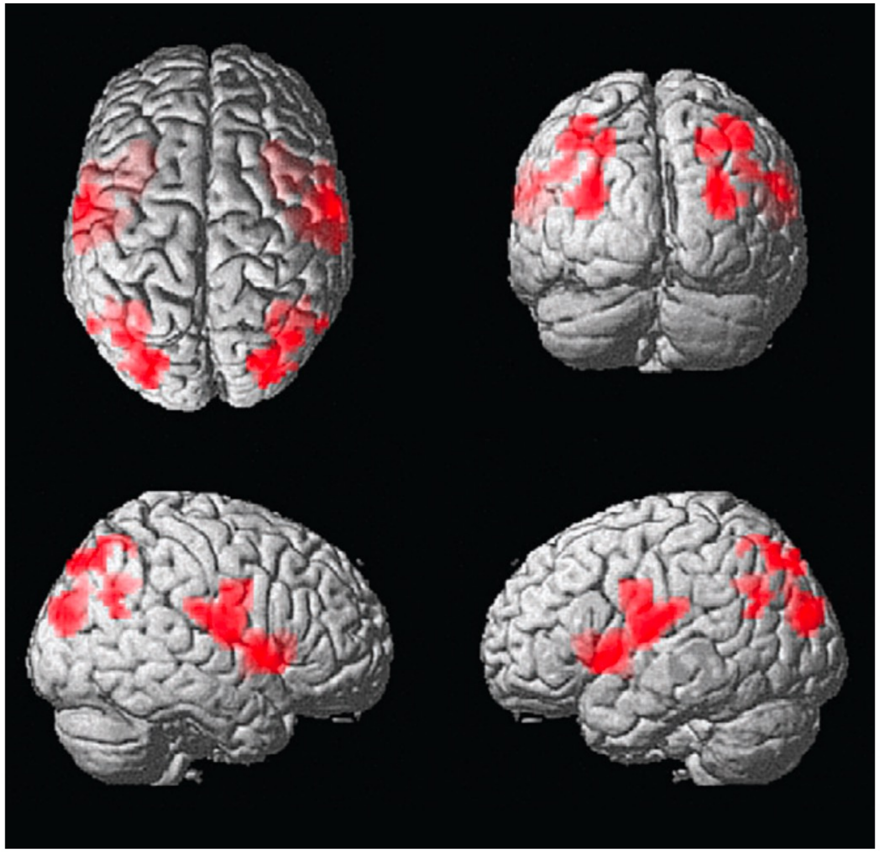

Figure from Anderson et al., 2011

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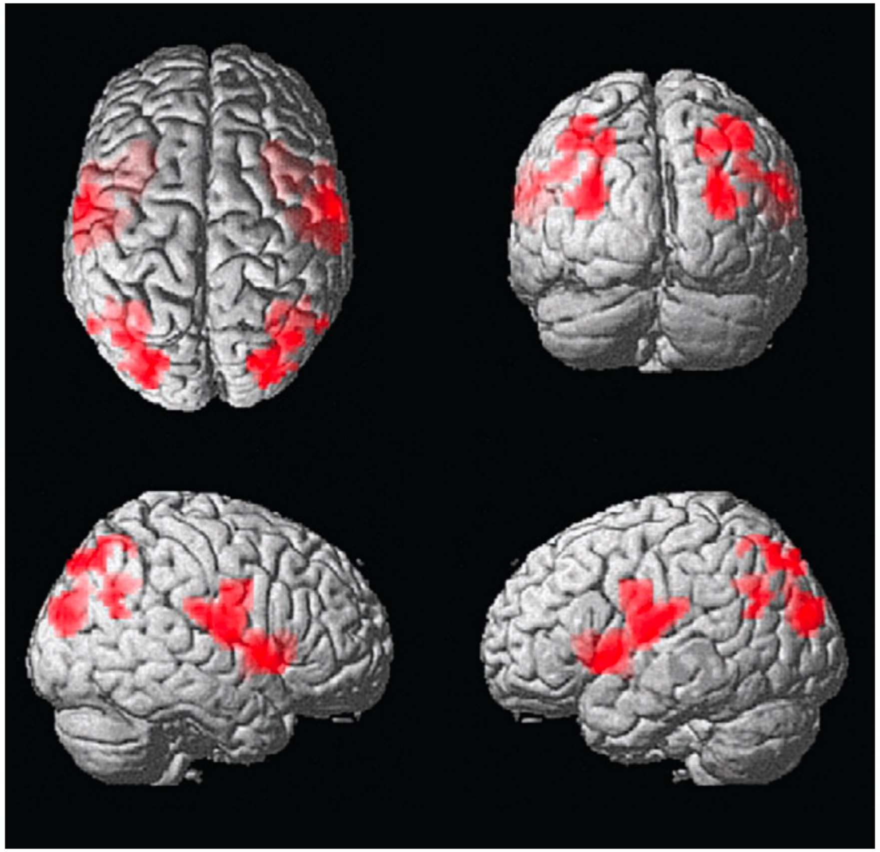

Figure from Anderson et al., 2011

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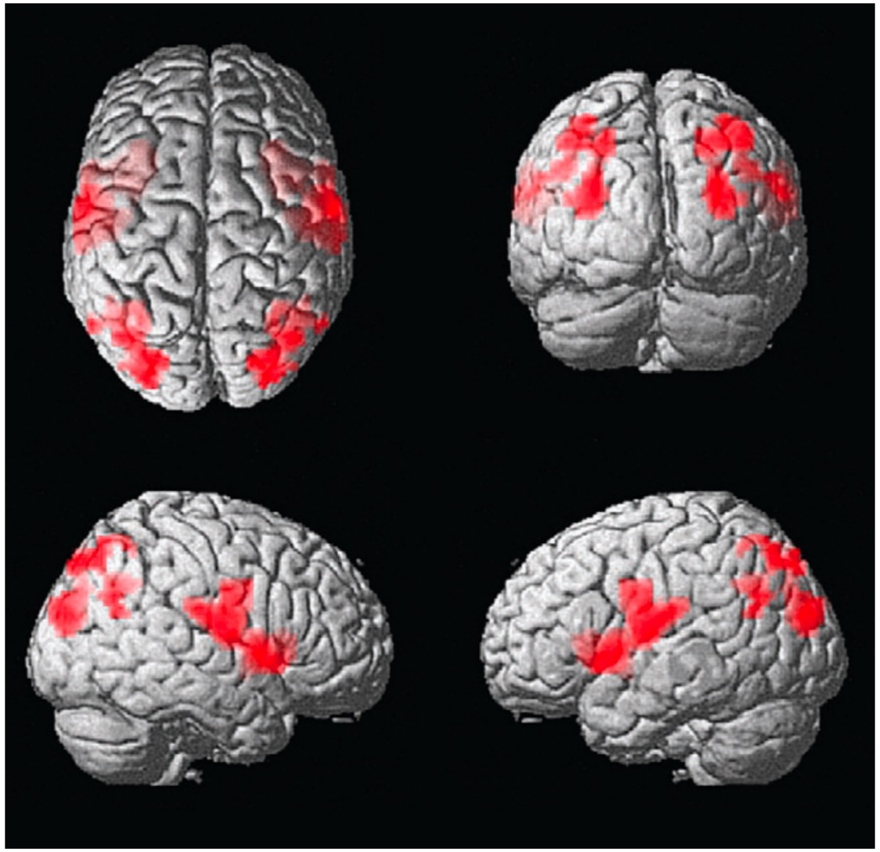

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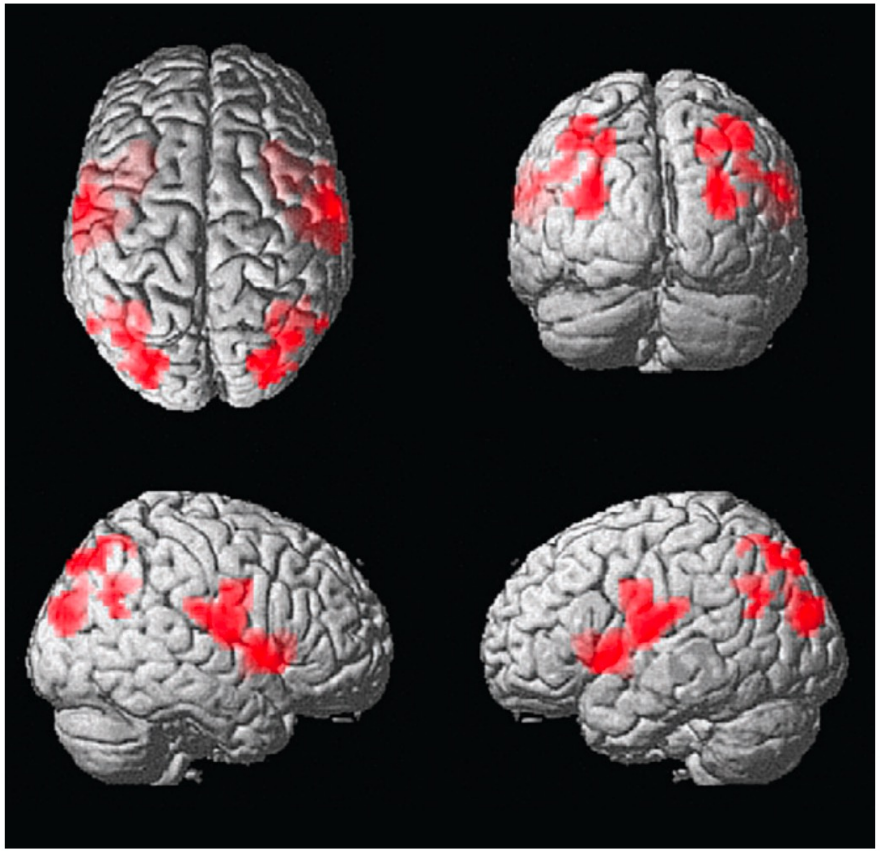

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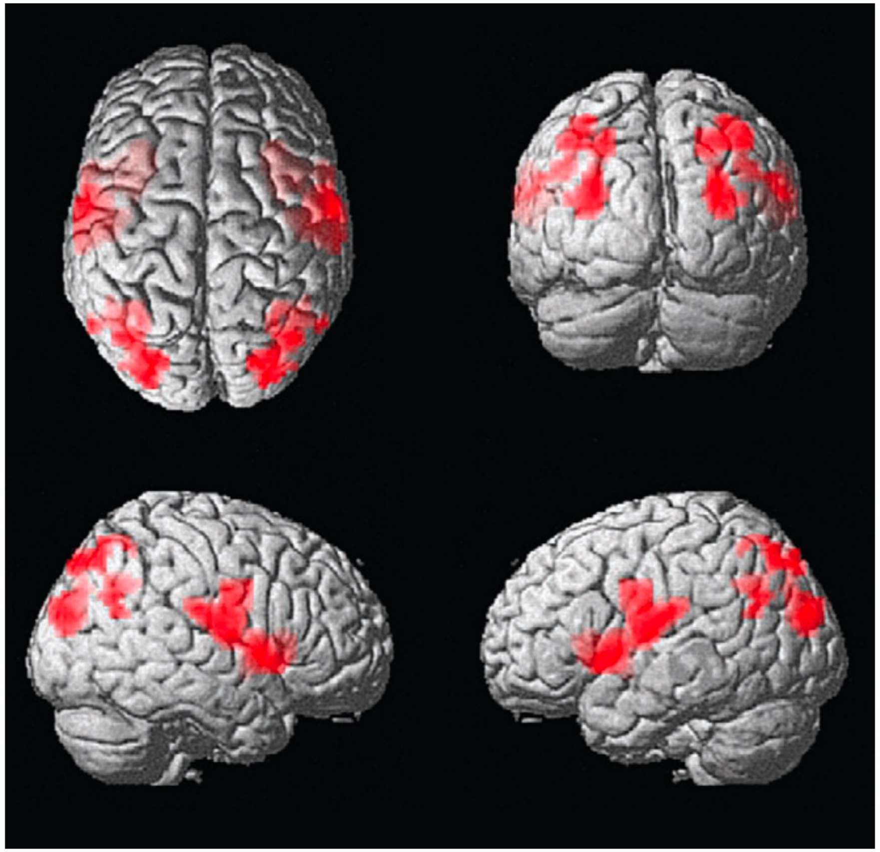

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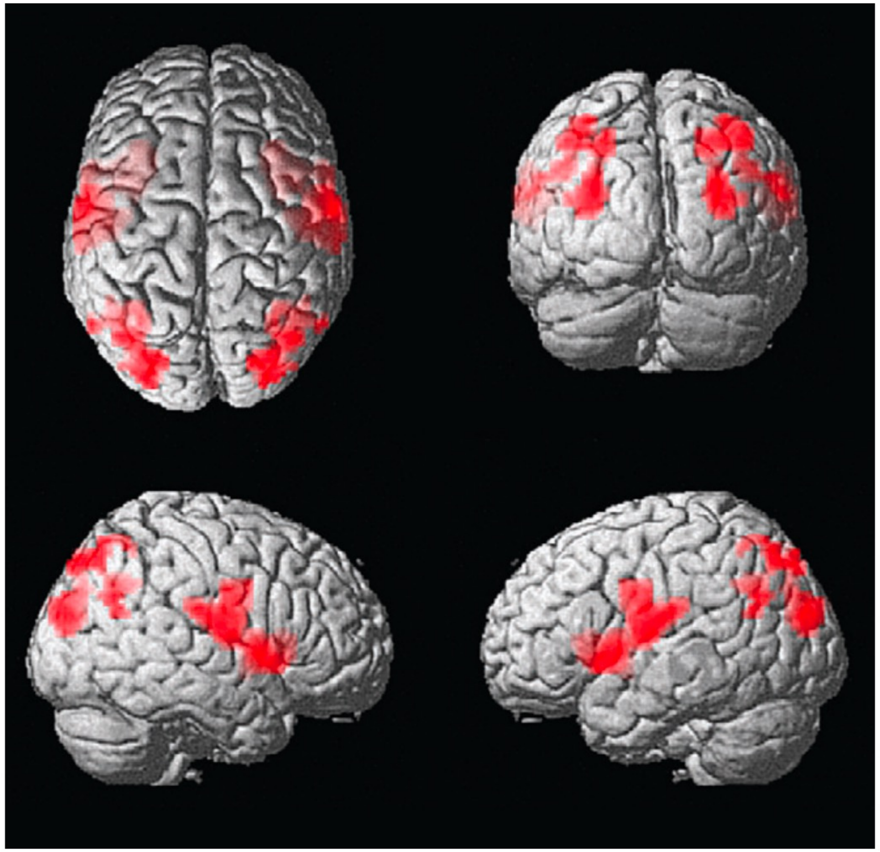

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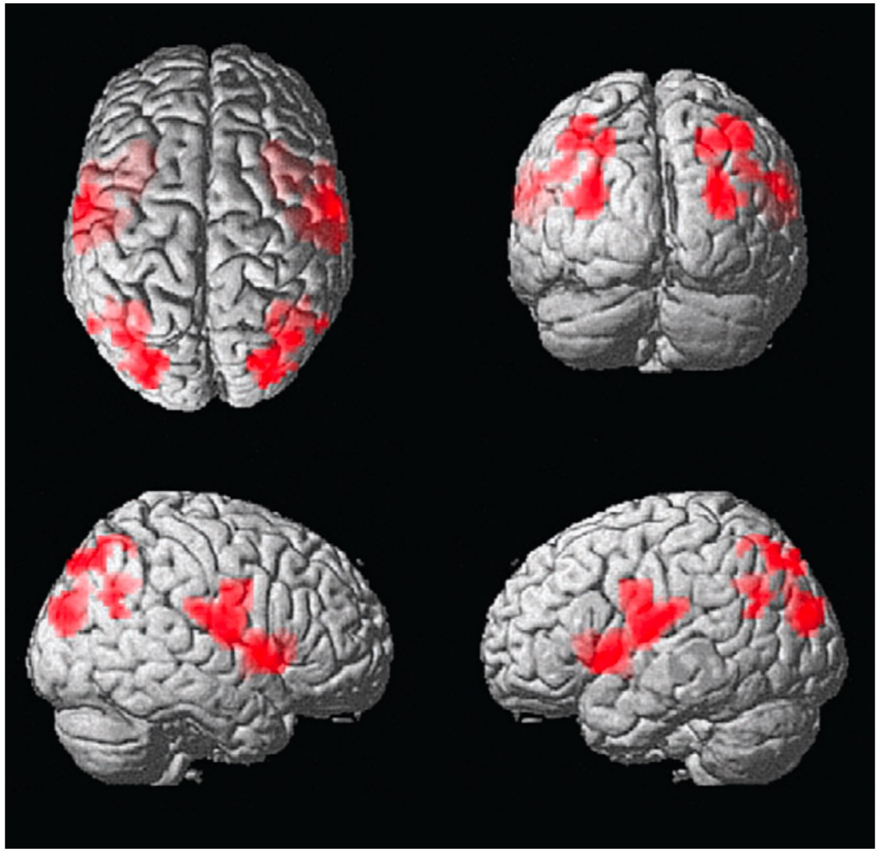

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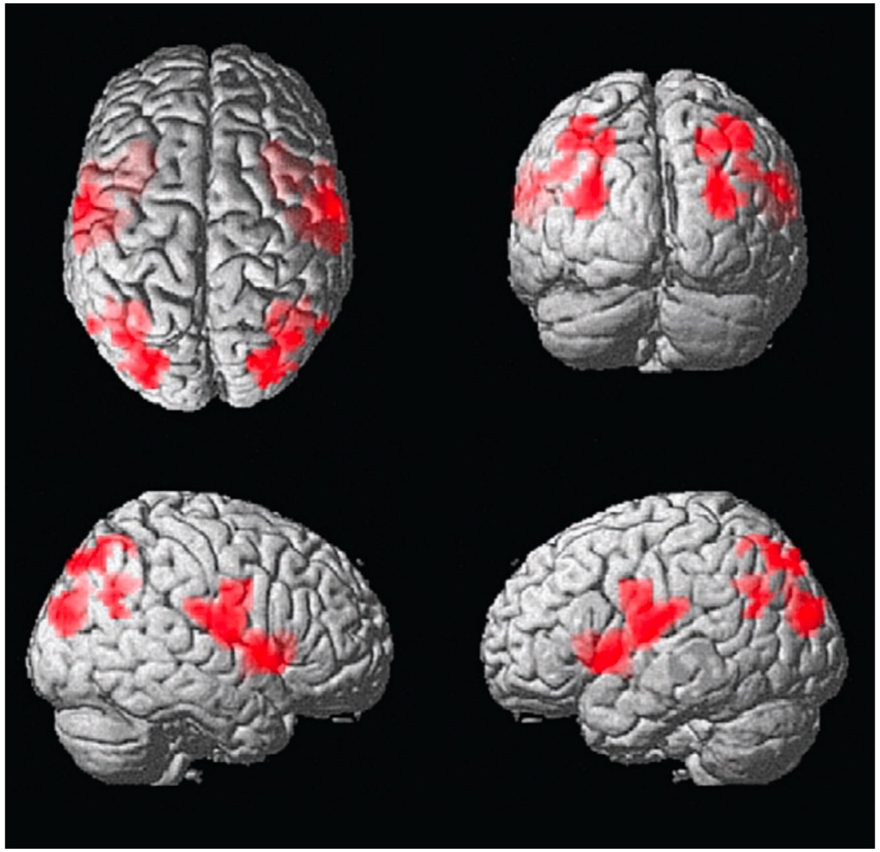

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STRUCTURAL DIFFERENCES IN ASD

- Reduced corpus callosum volume (Anderson et al., 2011; Chen et al., 2011; Pagnozzi et al., 2018)
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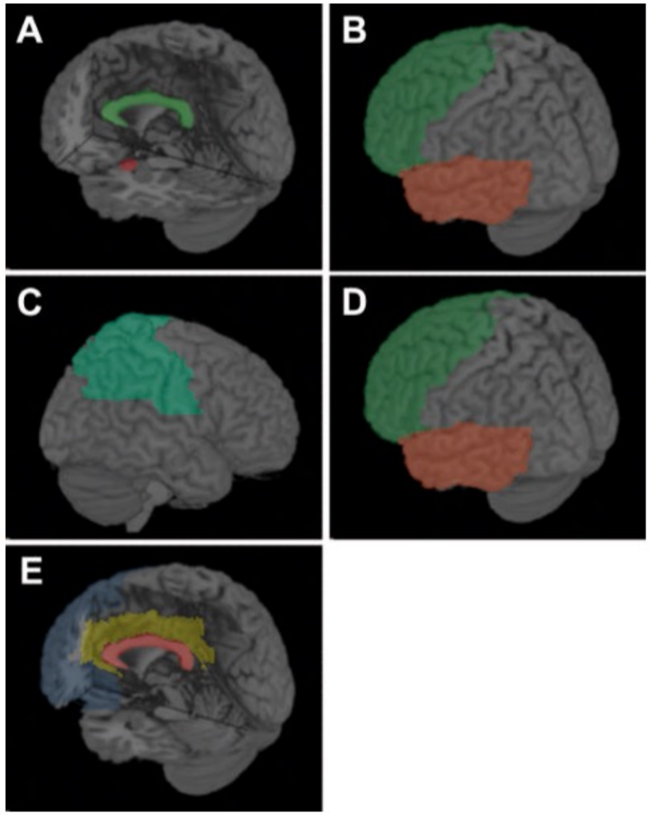

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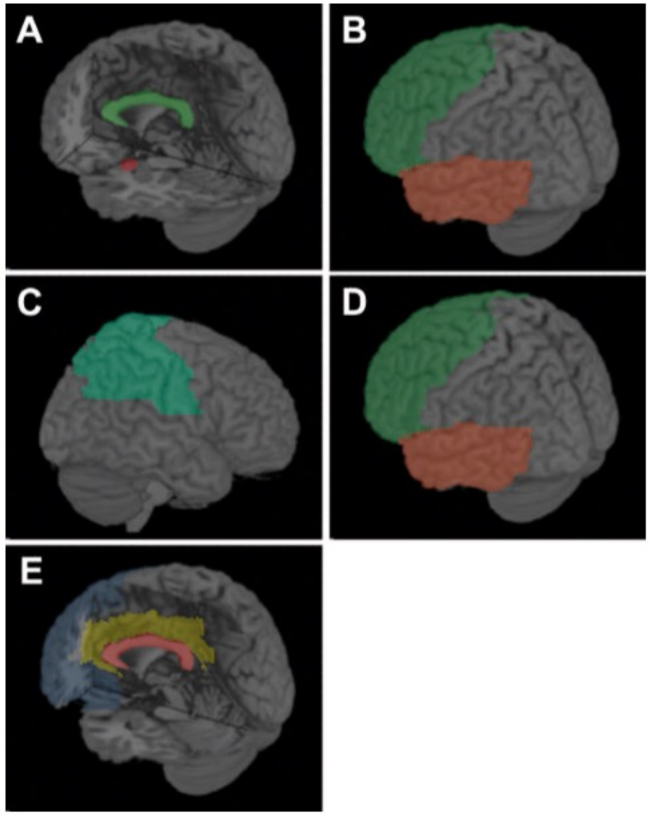

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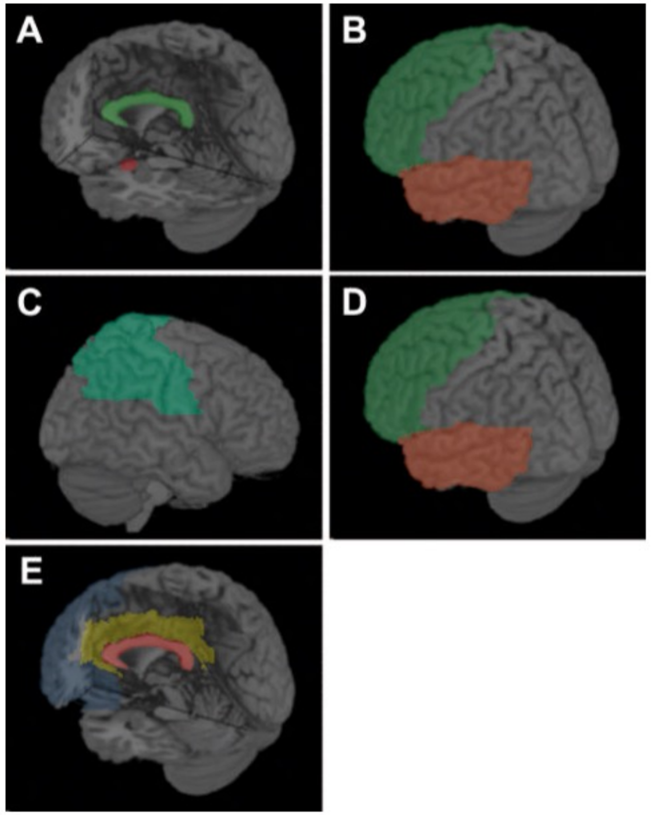

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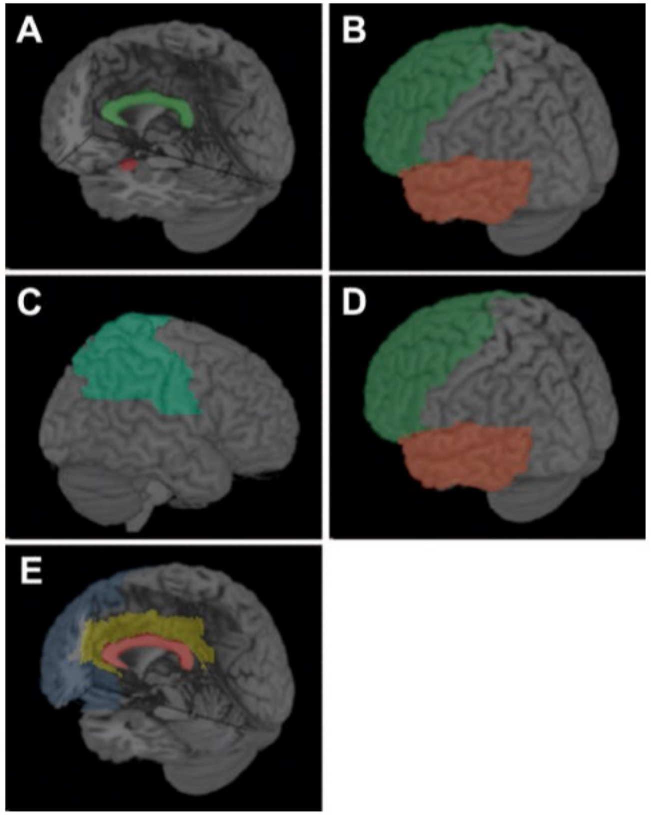

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ASD DIAGNOSIS USING MACHINE LEARNING

- Accuracy of 70% using 3-layer fully connected NN with functional connectivity features from fMRI
  - Autism Brain Imaging Data Exchange (ABIDE)

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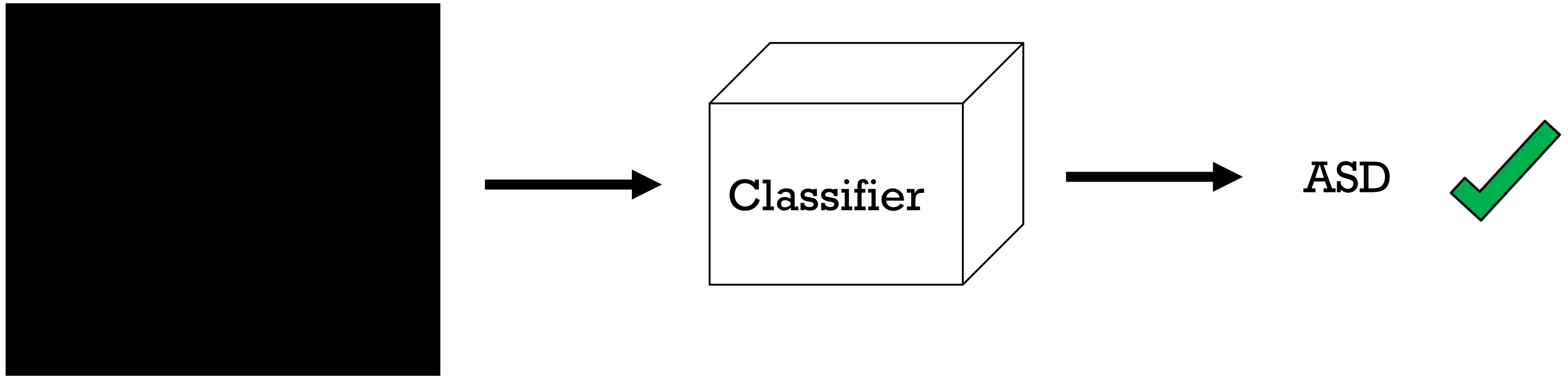
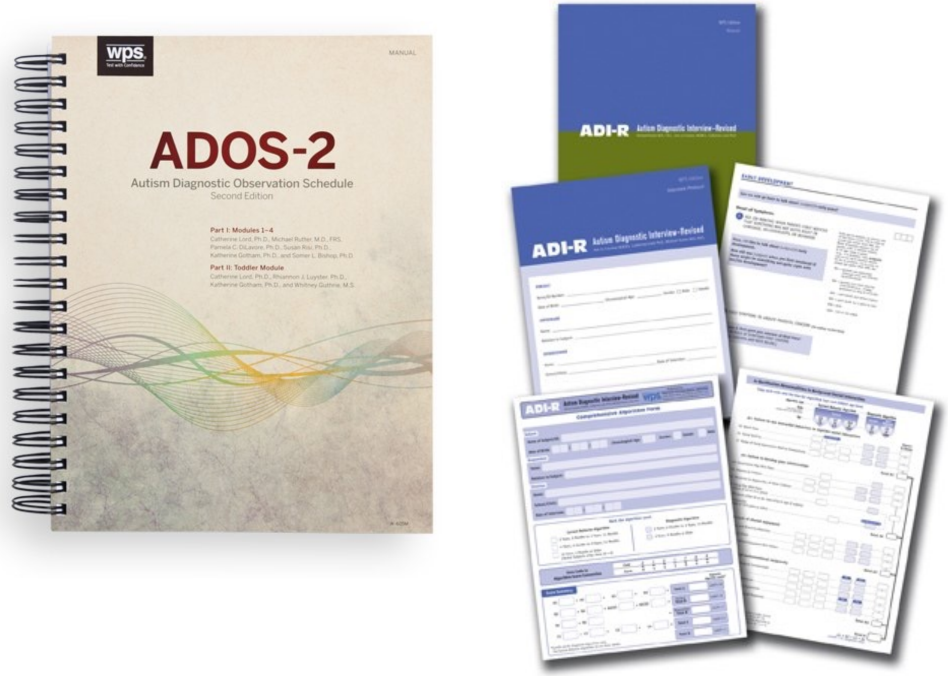
ASD DIAGNOSIS USING MACHINE LEARNING

- Aim 1: classify ASD from neuroimaging data using the following classification methods:
  - Nearest neighbor (NN)
  - Naïve-Bayes
  - Linear discriminant analysis (LDA)
  - Residual neural networks (RNNs)



ASD DIAGNOSIS USING MACHINE LEARNING

- Aim 2. link behavioral assessments scores to neuroimaging differences



Pictures from wpspublish.com and stoeltingco.com

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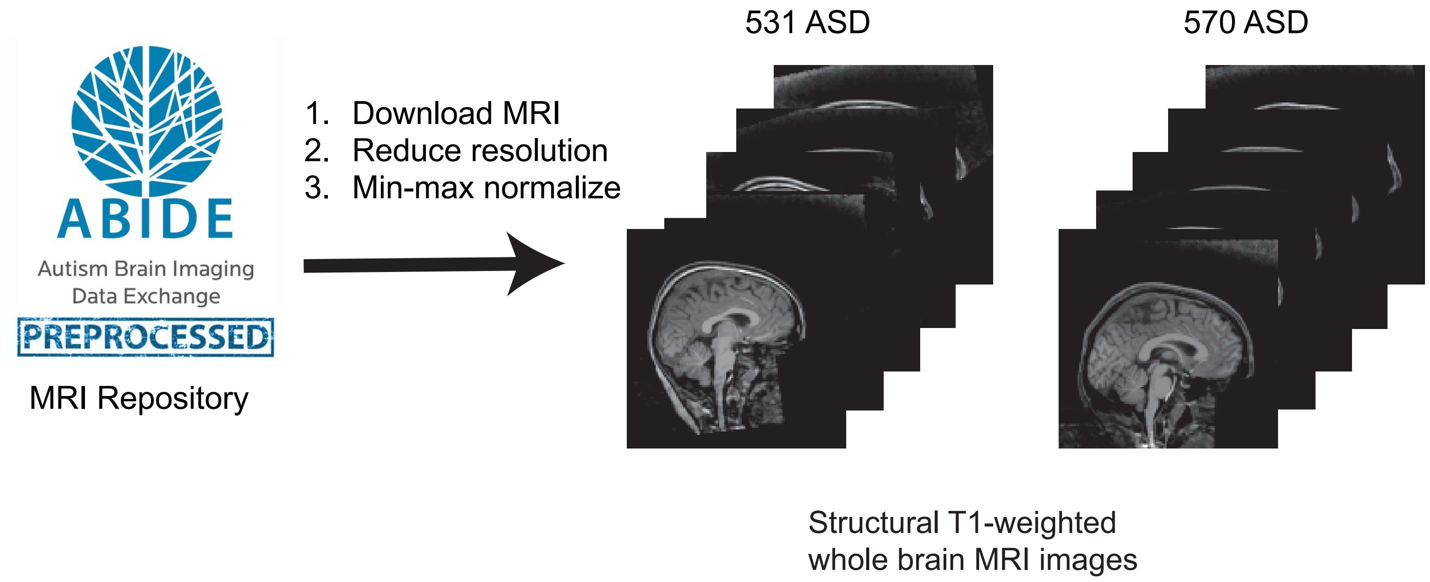
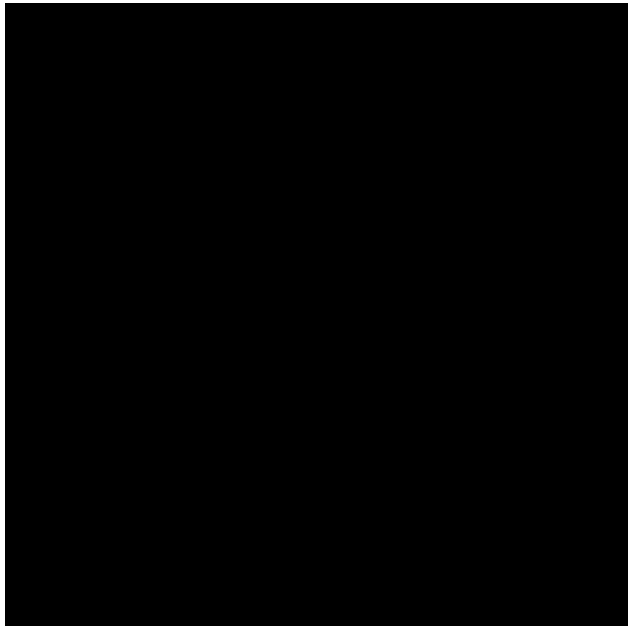


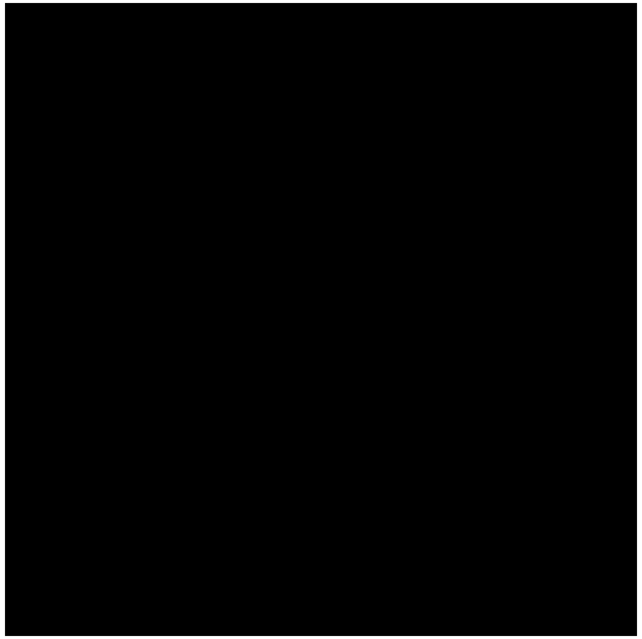
DOWNLOAD AND PREPROCESS

Cortical Thickness

Structural



Functional



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- PCA to 1100 features
- 8-fold cross validation
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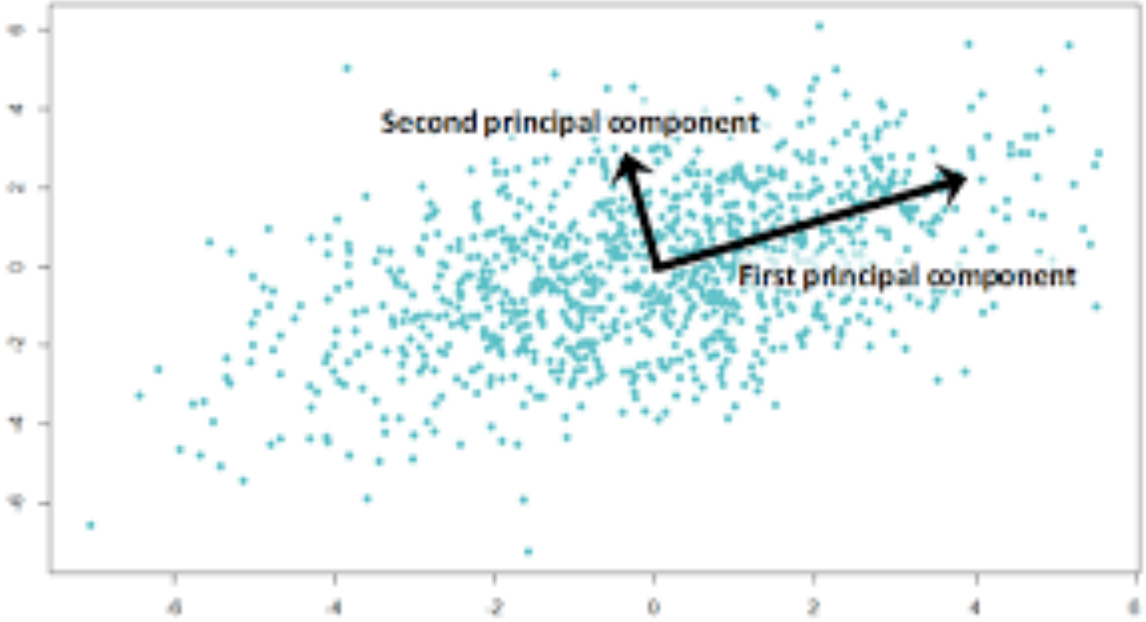

Figure from analyticsvidhya.com

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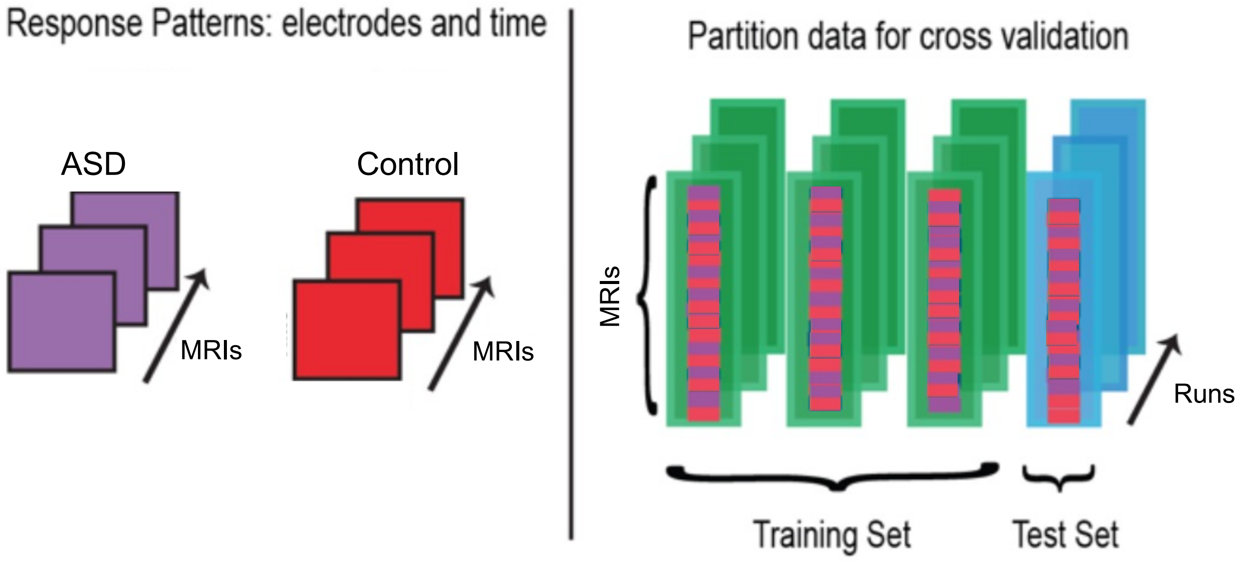

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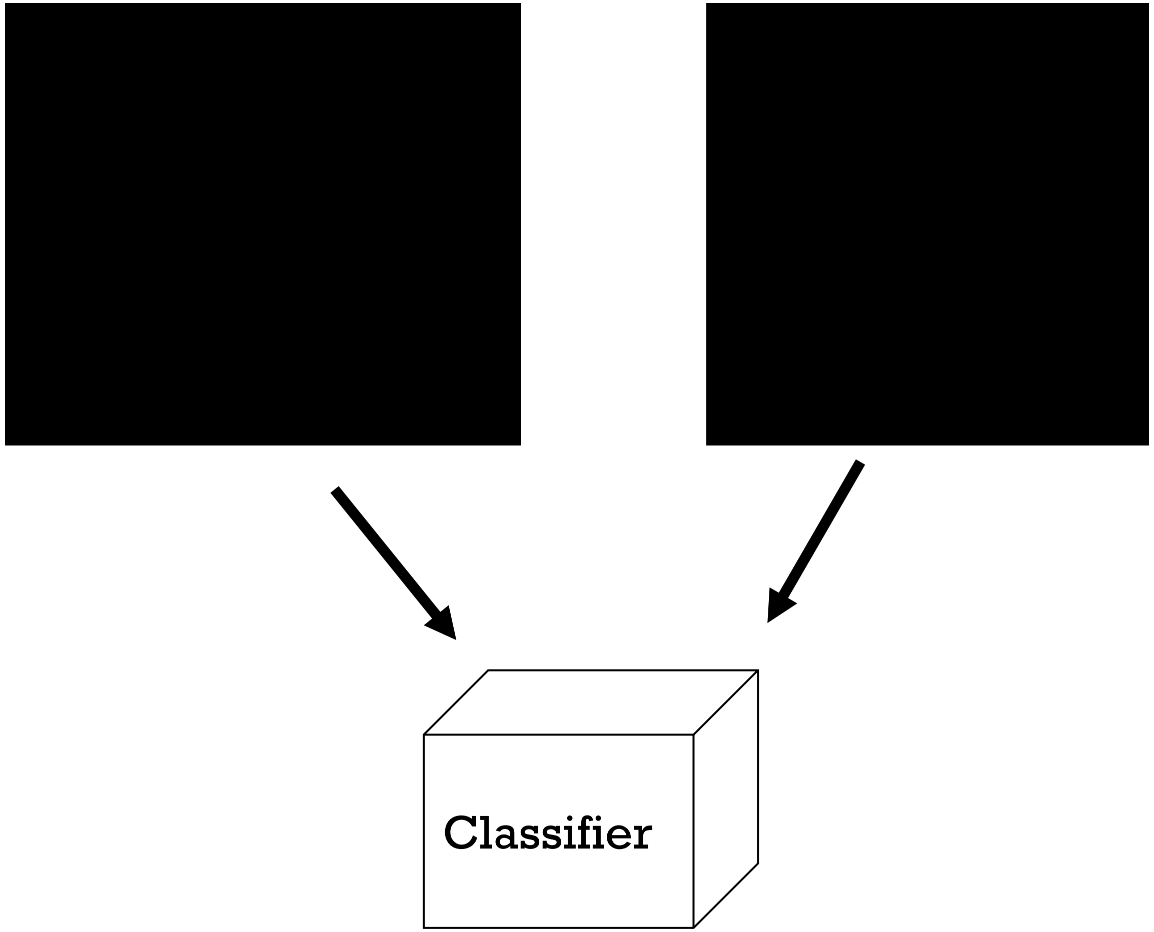

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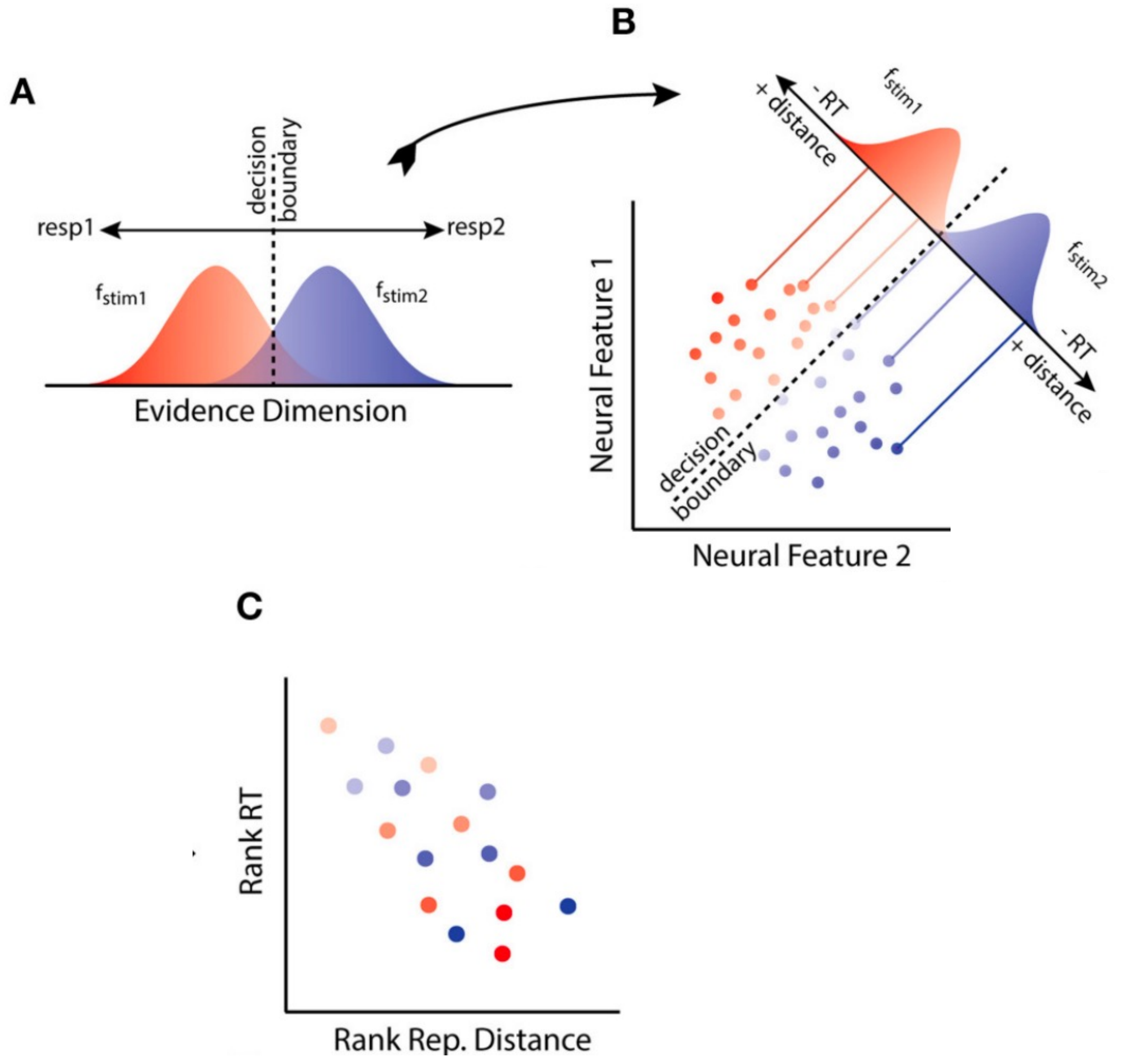
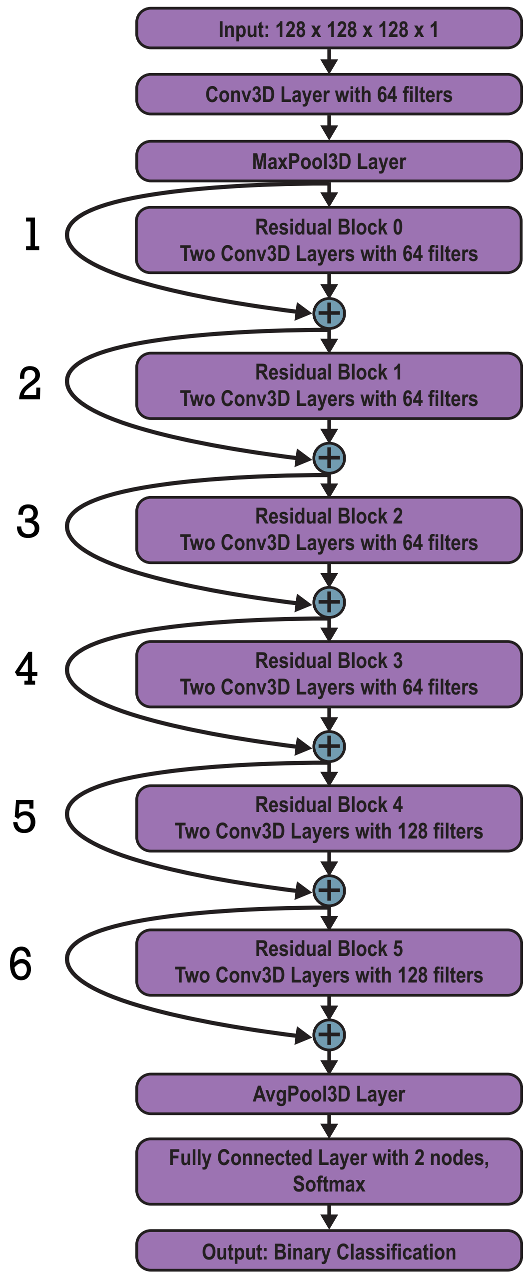


Figure from Ritchie et al., 2016

ASDNET

- 6 residual blocks
- Max pooling before
- Average pooling after
- Fully connected at end
- Softmax
- 5-fold cross validation



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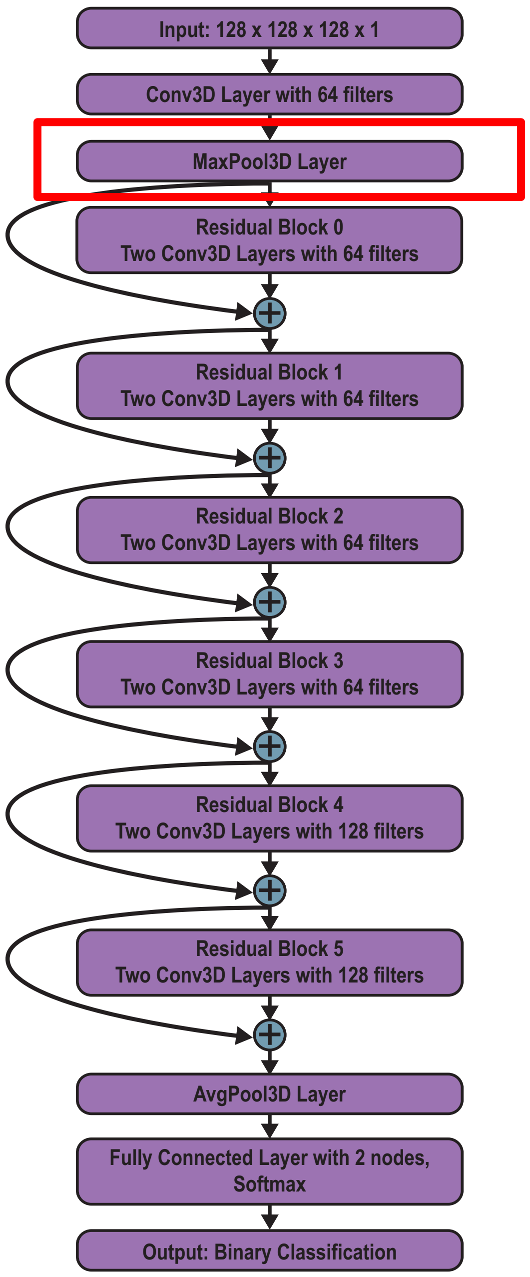

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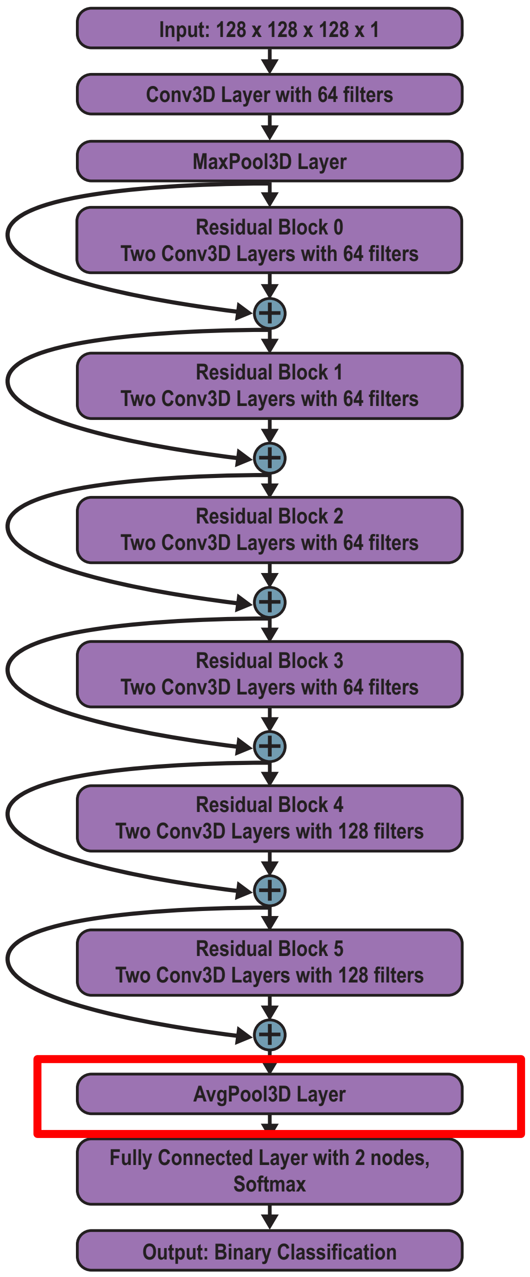

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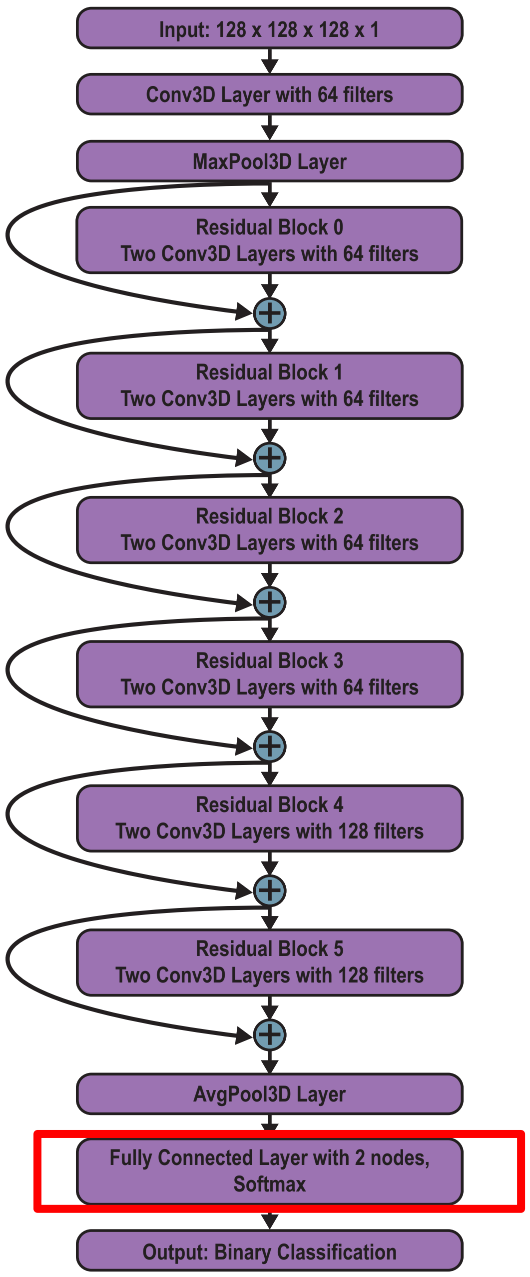

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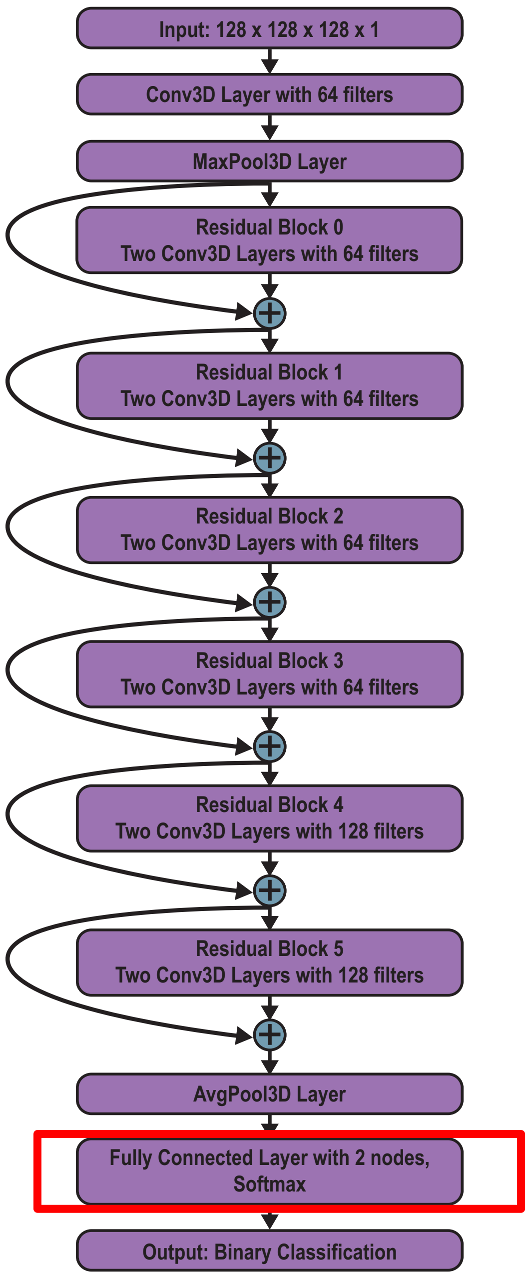

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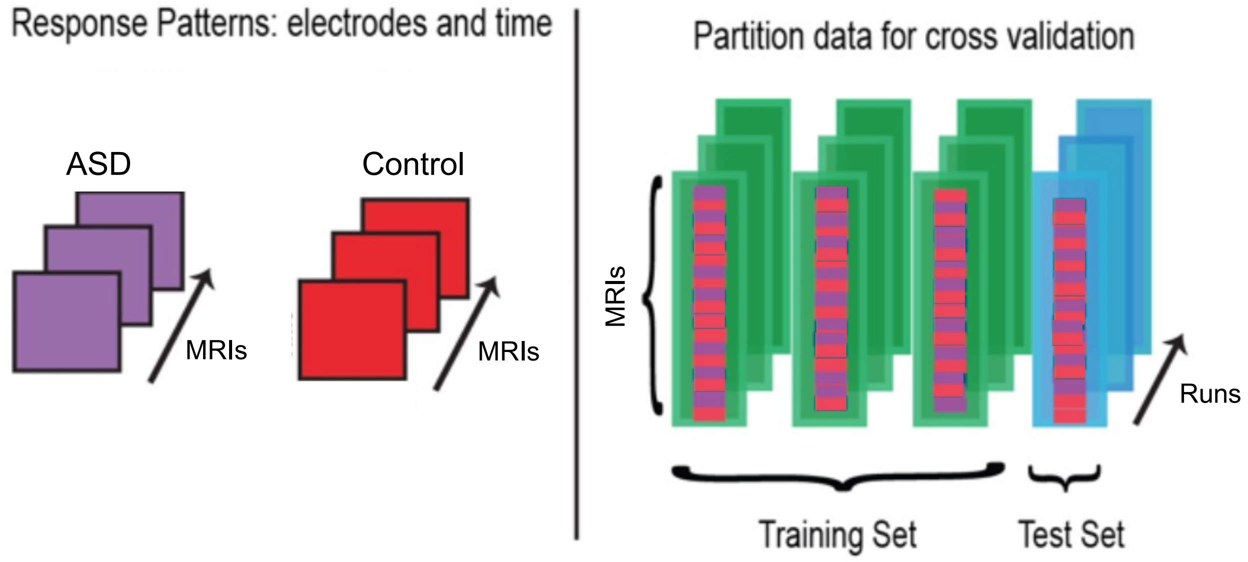

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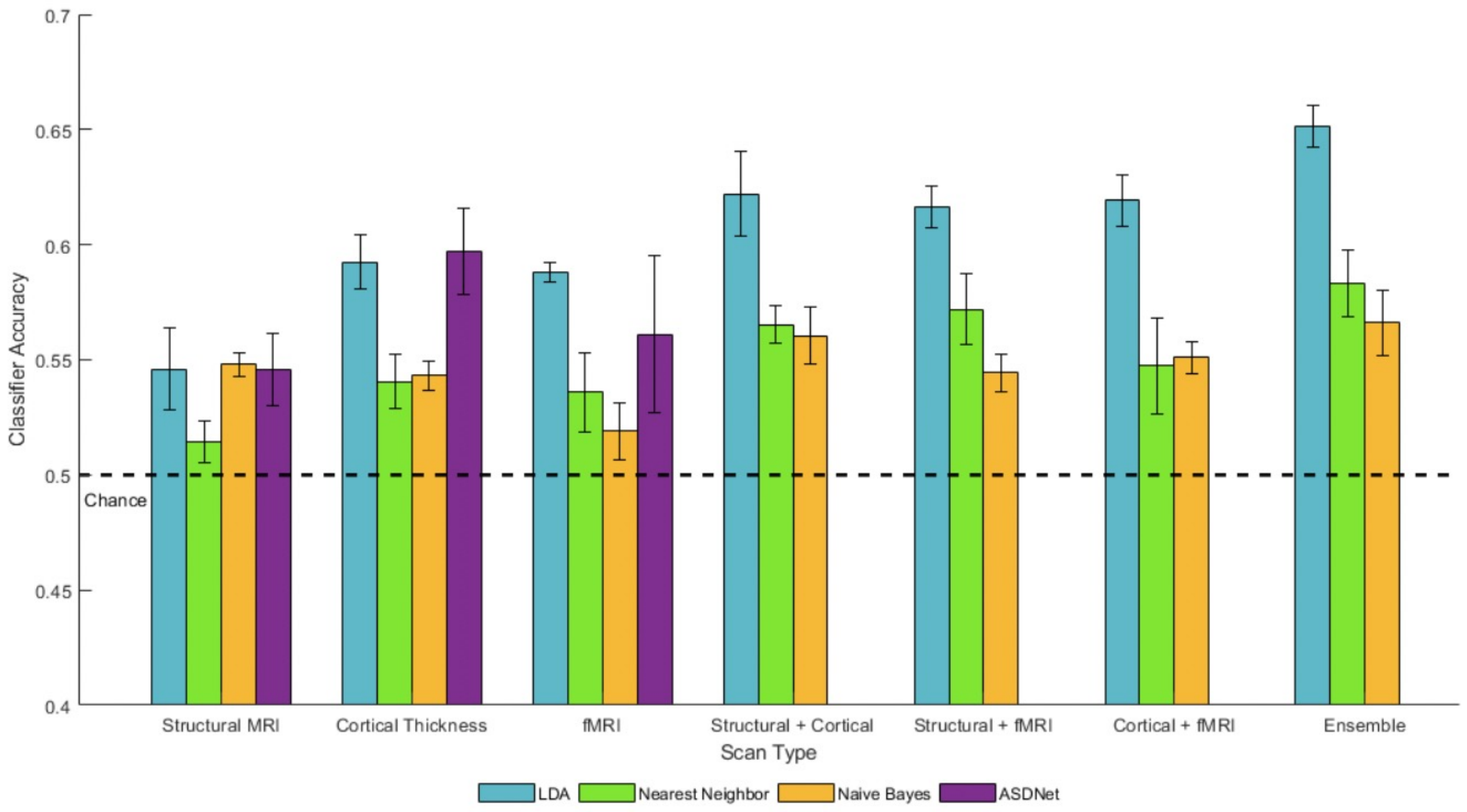
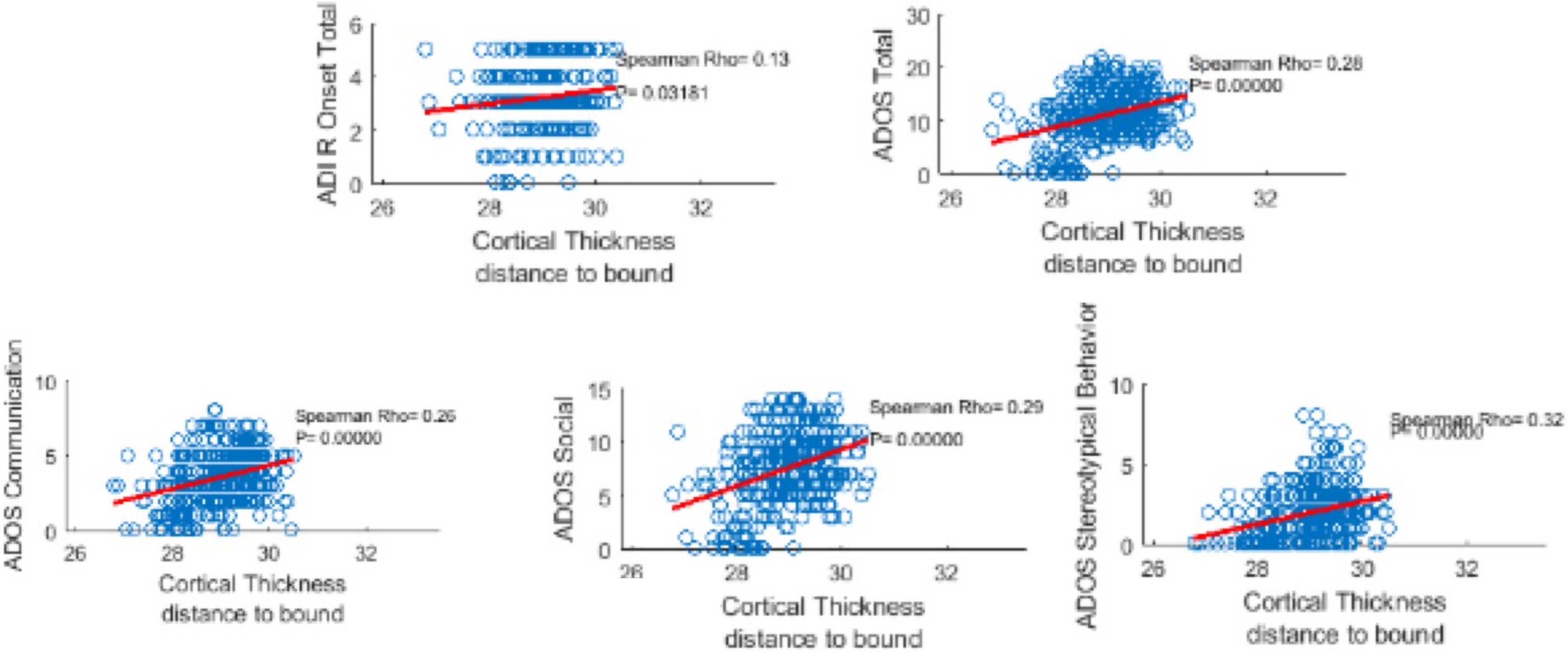
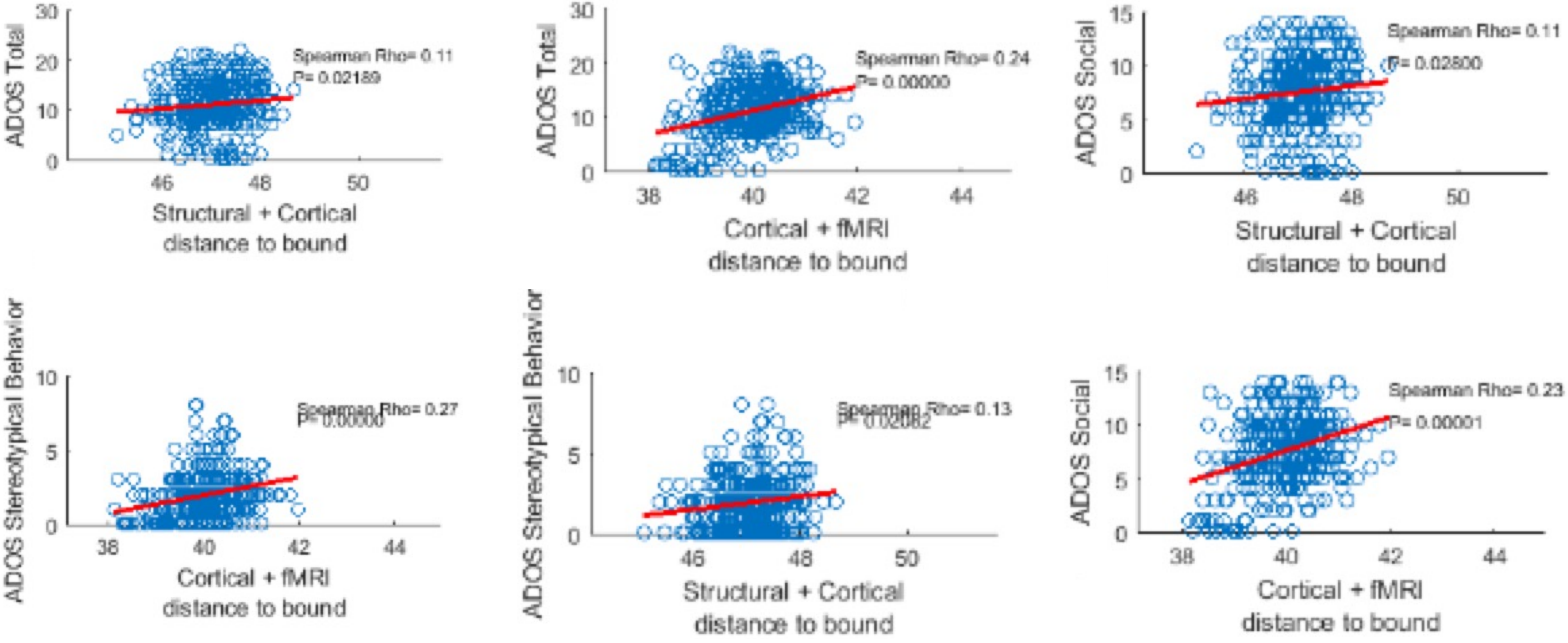
CLASSIFICATION PERFORMANCE



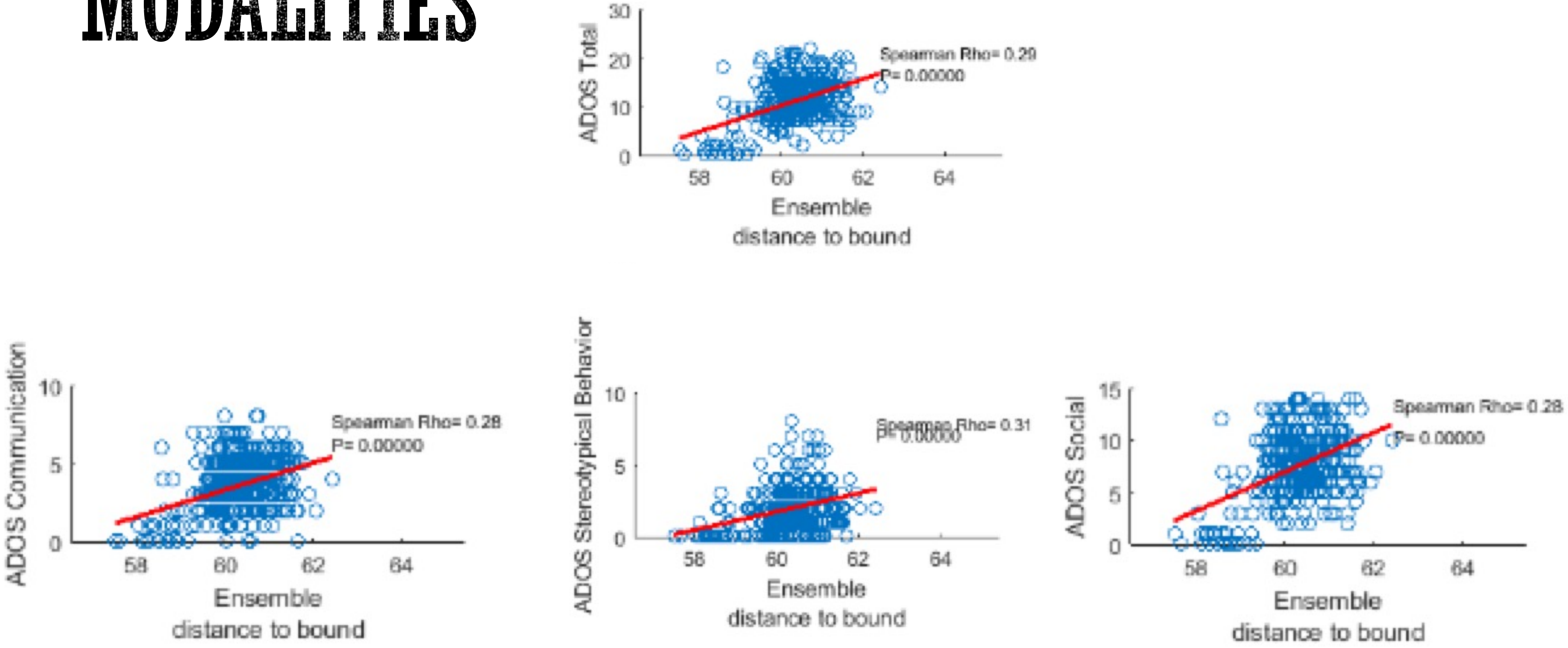
DISTANCE TO BOUND – ONE IMAGING MODALITY



DISTANCE TO BOUND – TWO IMAGING MODALITIES



DISTANCE TO BOUND – ALL IMAGING MODALITIES



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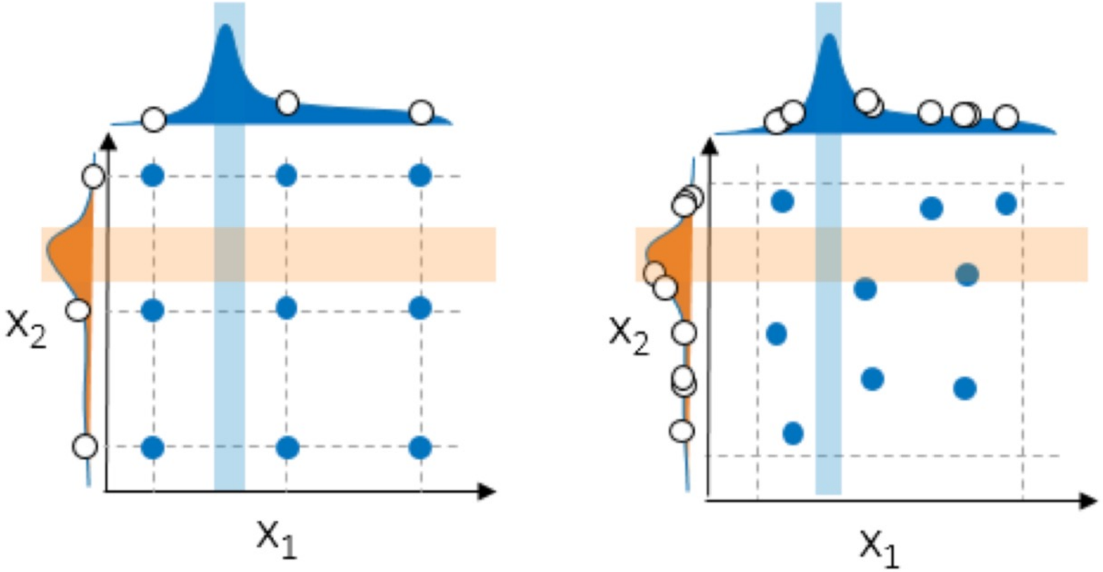

(a) Standard Grid Search (b) Random Search

Figure from support.sas.com

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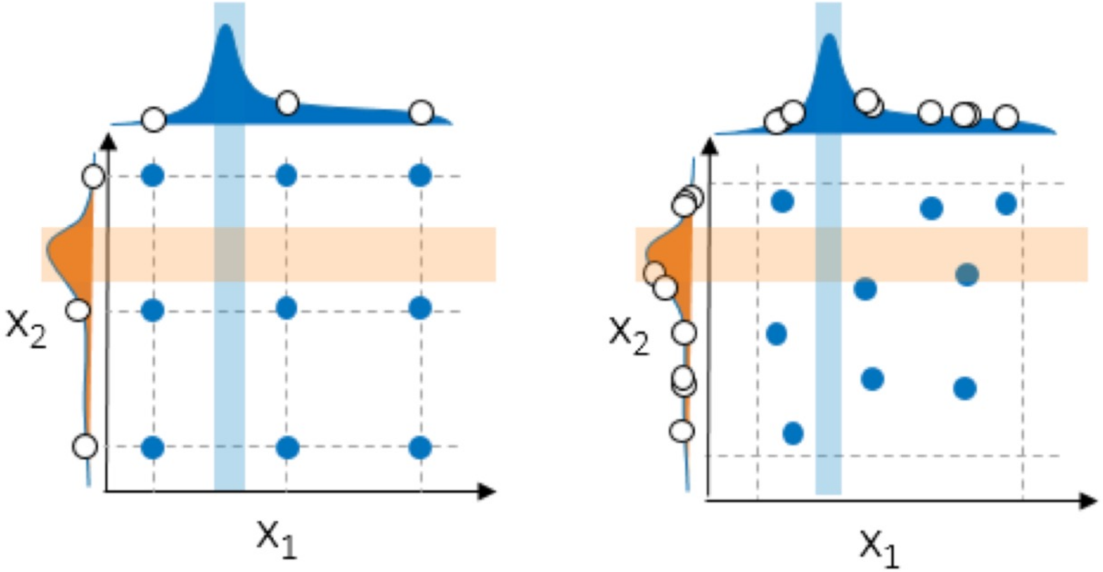

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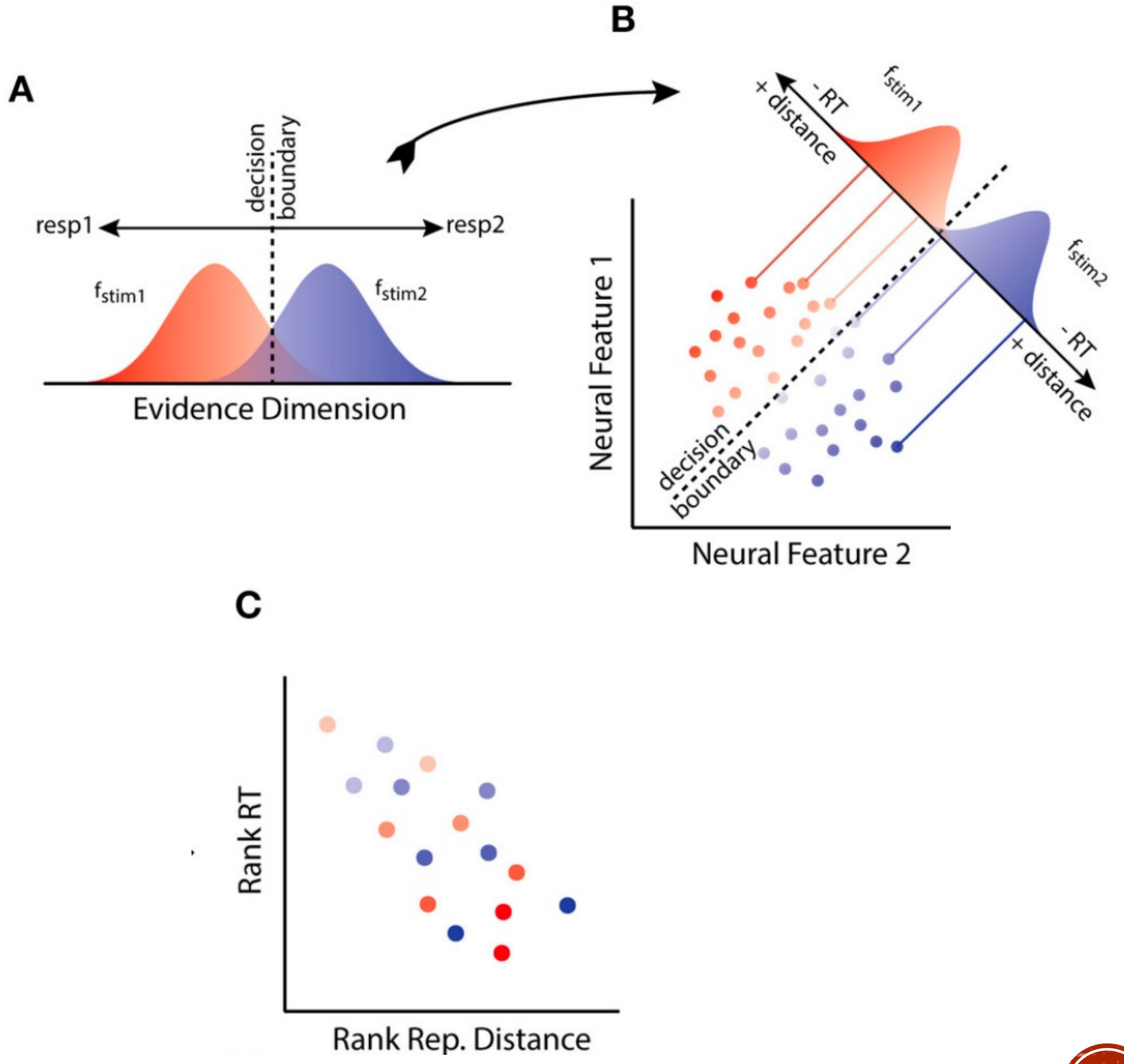

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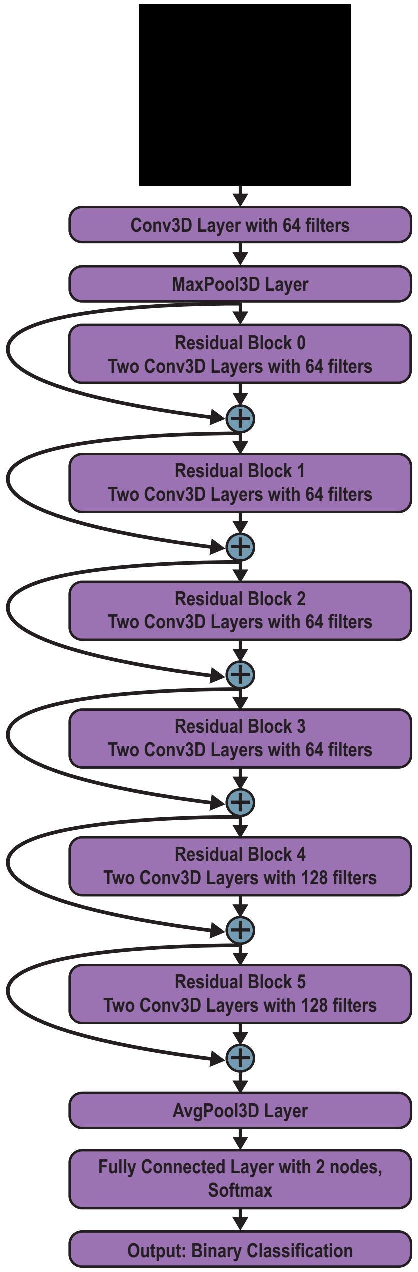

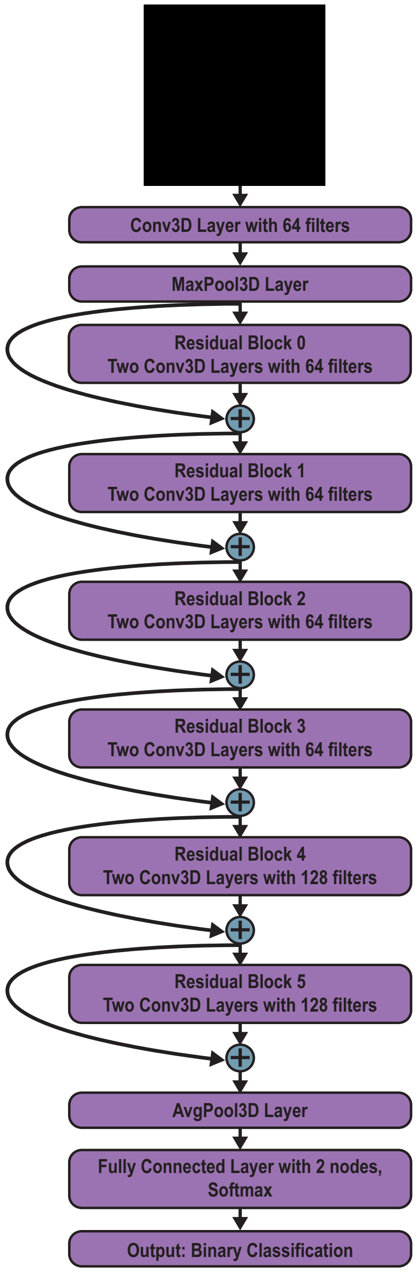

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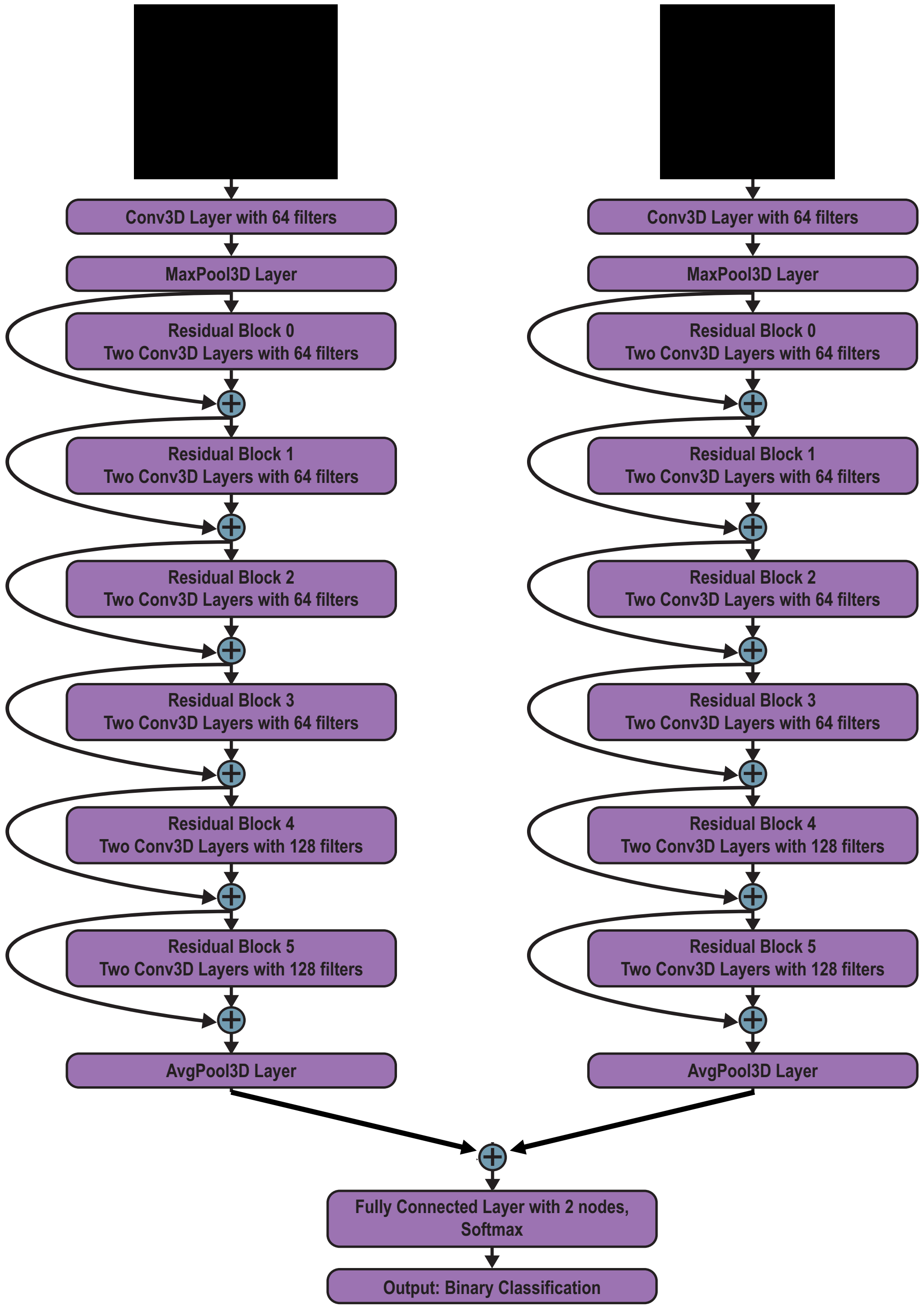
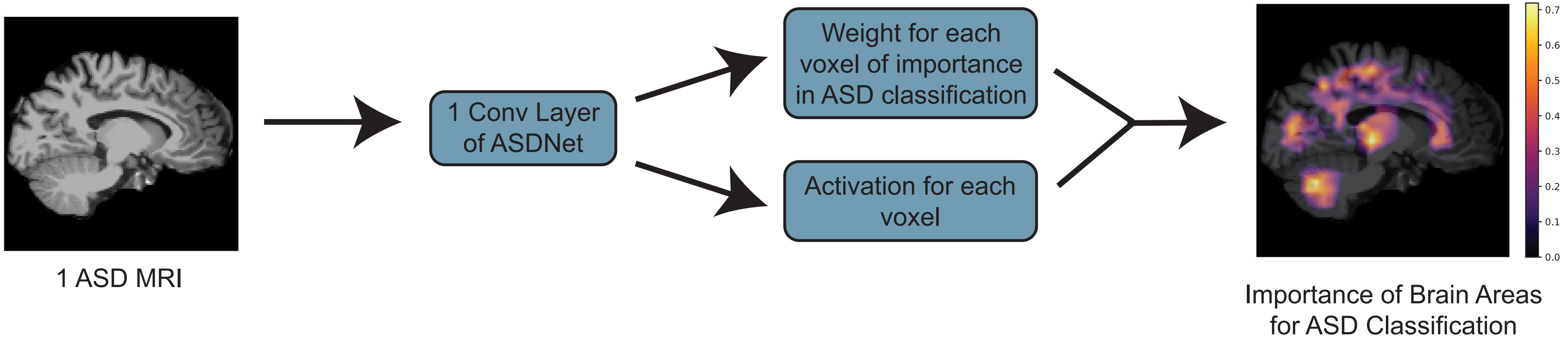


FUTURE DIRECTIONS – VISUALIZATION WITH 3D-GRAD-CAM



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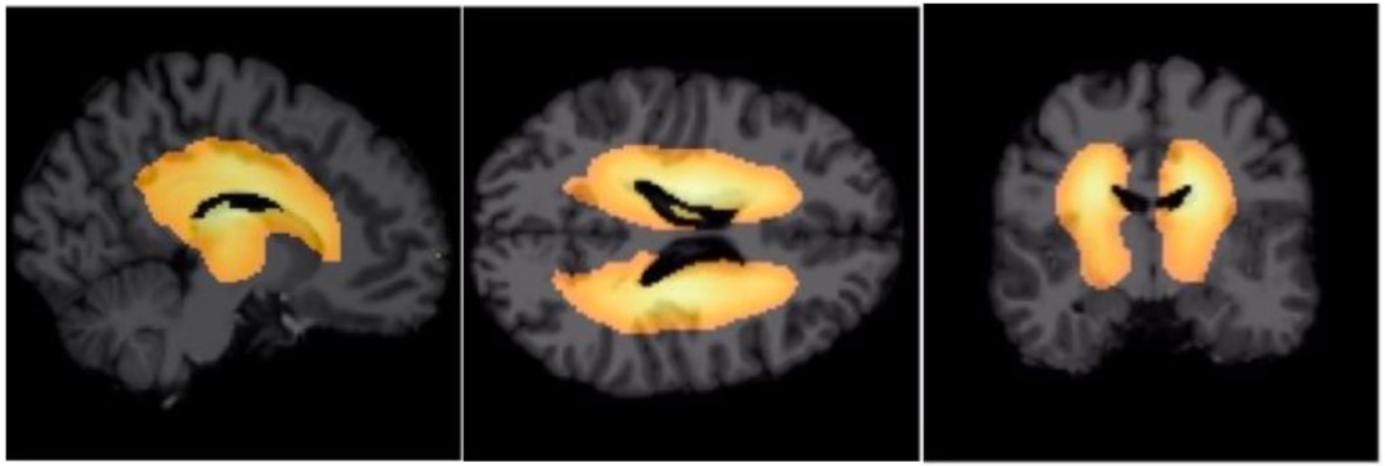

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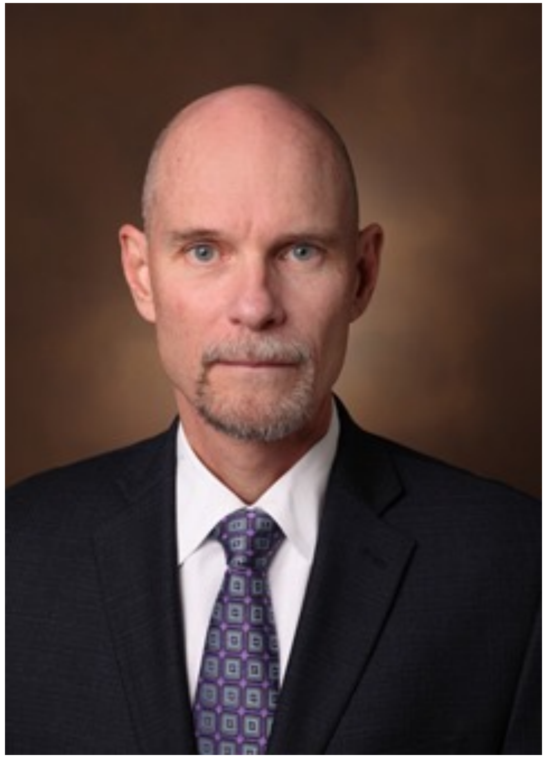

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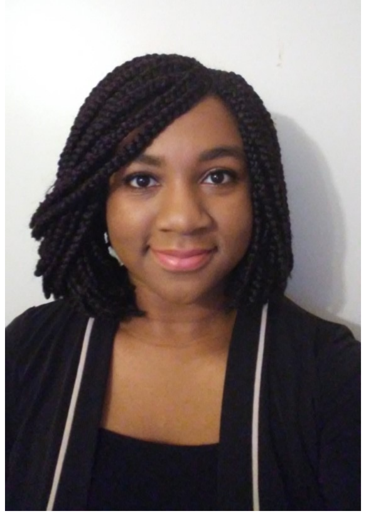

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QUESTIONS??