Exploring Complexity Reduction in Deep Learning

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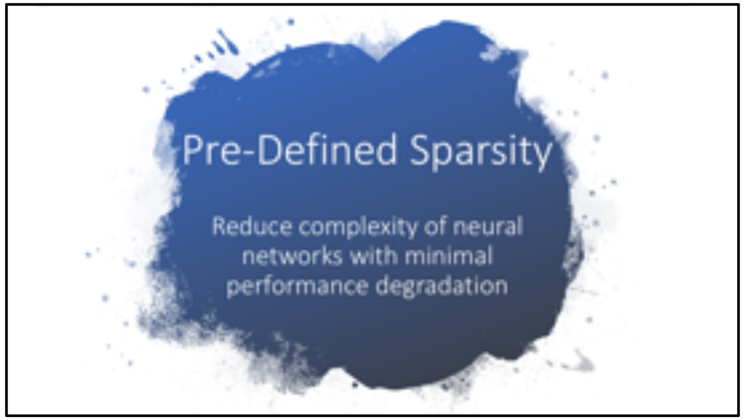
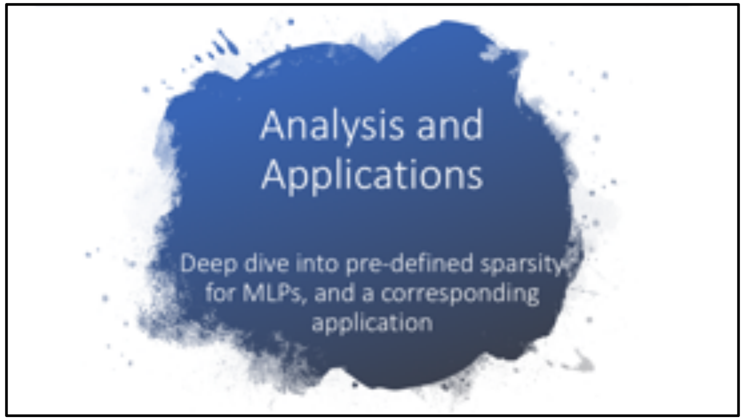
Outline


Pre-Defined Sparsity
Reduce complexity of neural networks with minimal performance degradation


Analysis and Applications
Deep dive into pre-defined sparsity for MLPs, and a corresponding application


Model Search
Automate the design of CNNs with good performance and low complexity

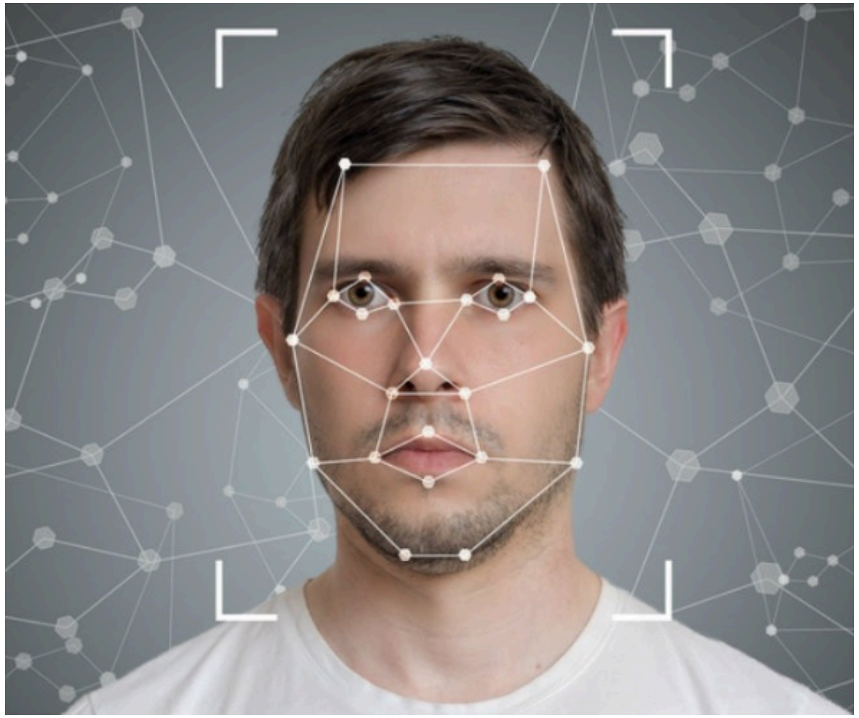
Pre-Defined Sparsity

Reduce complexity of neural networks with minimal performance degradation

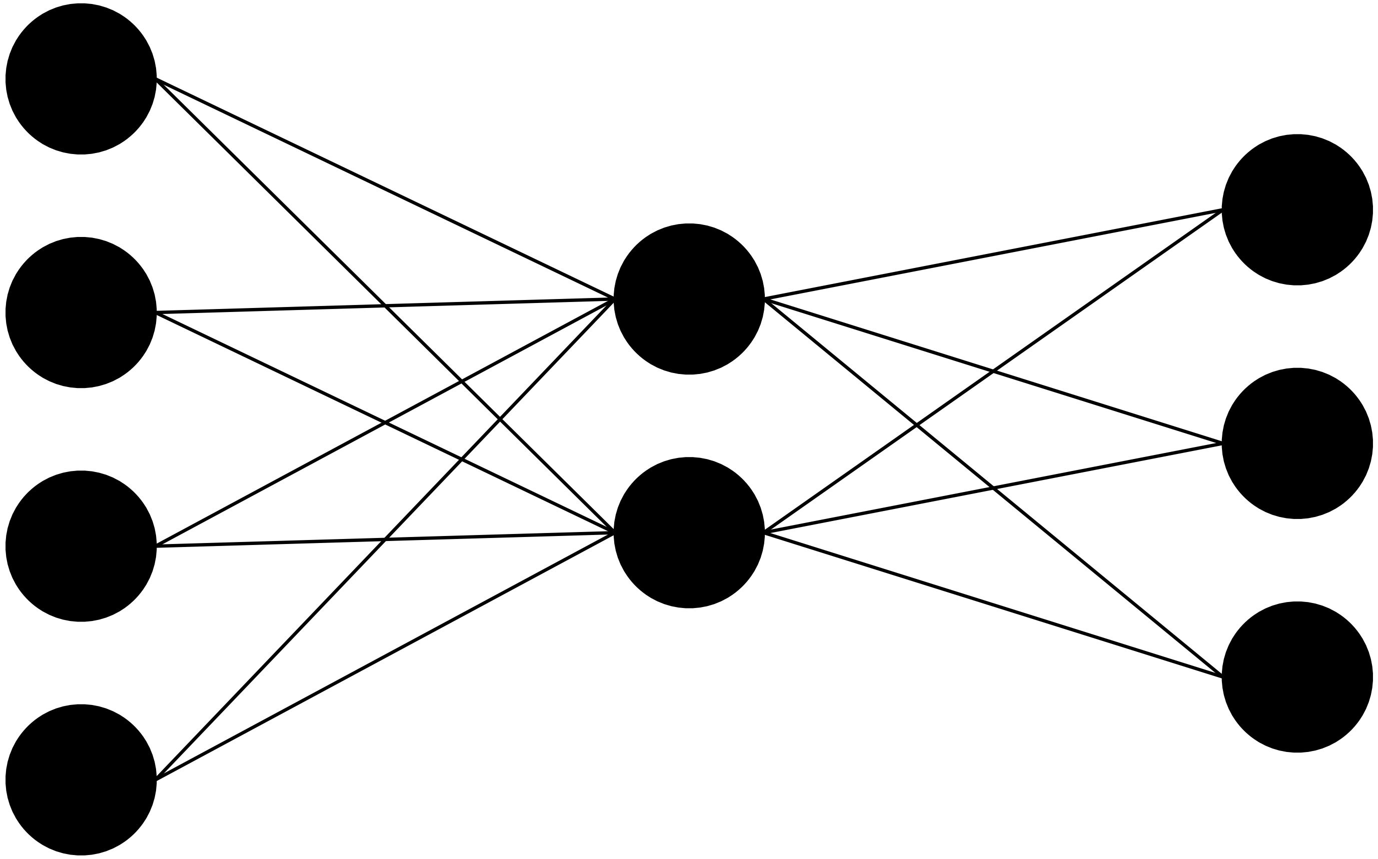
Overview

Neural networks (NNs) are key machine learning technologies

- ➢ Artificial intelligence
- ➢ Self-driving cars
- ➢ Speech recognition
- ➢ Face ID
- ➢ and more smart stuff …



Basic working of an artificial neural network



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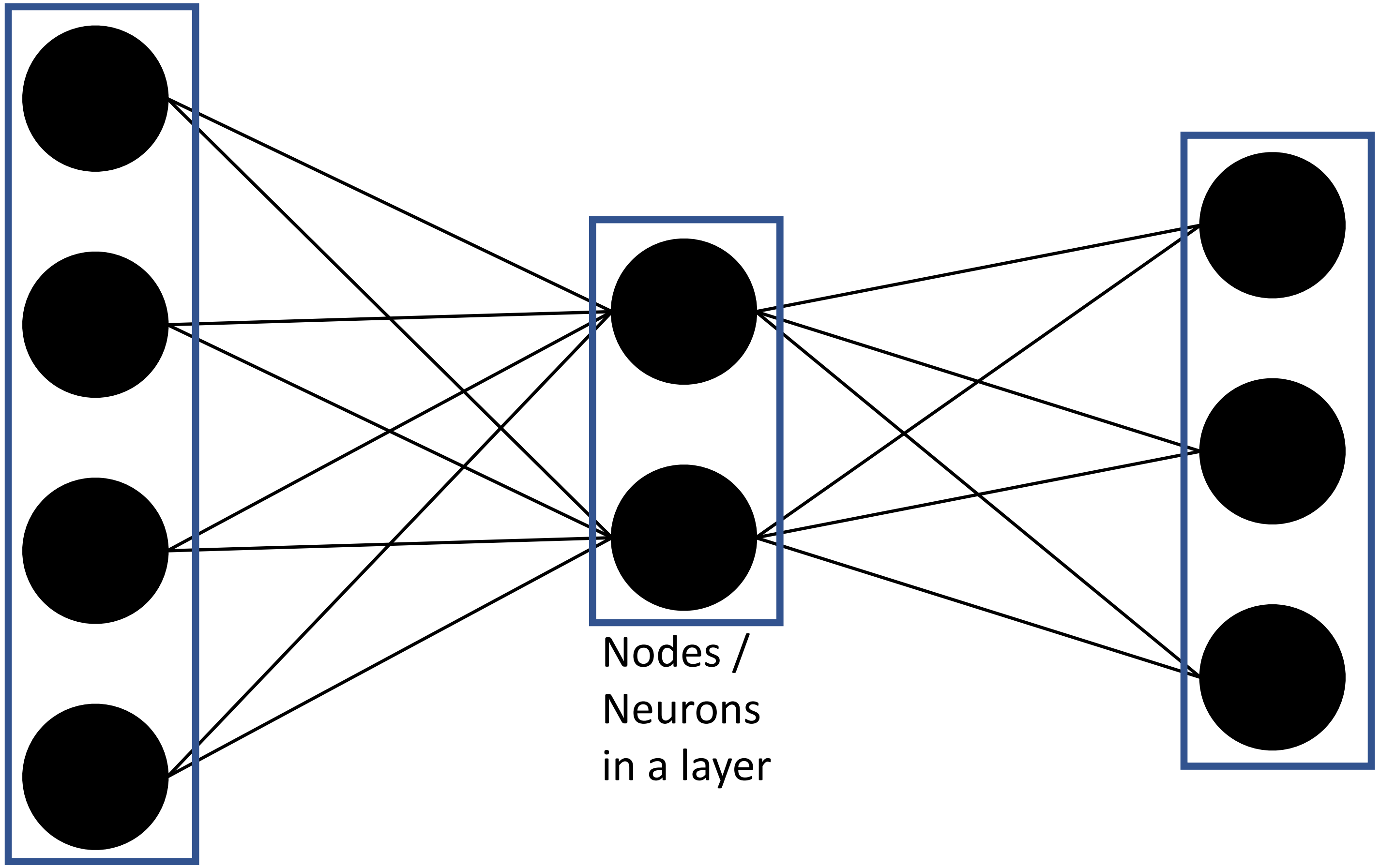

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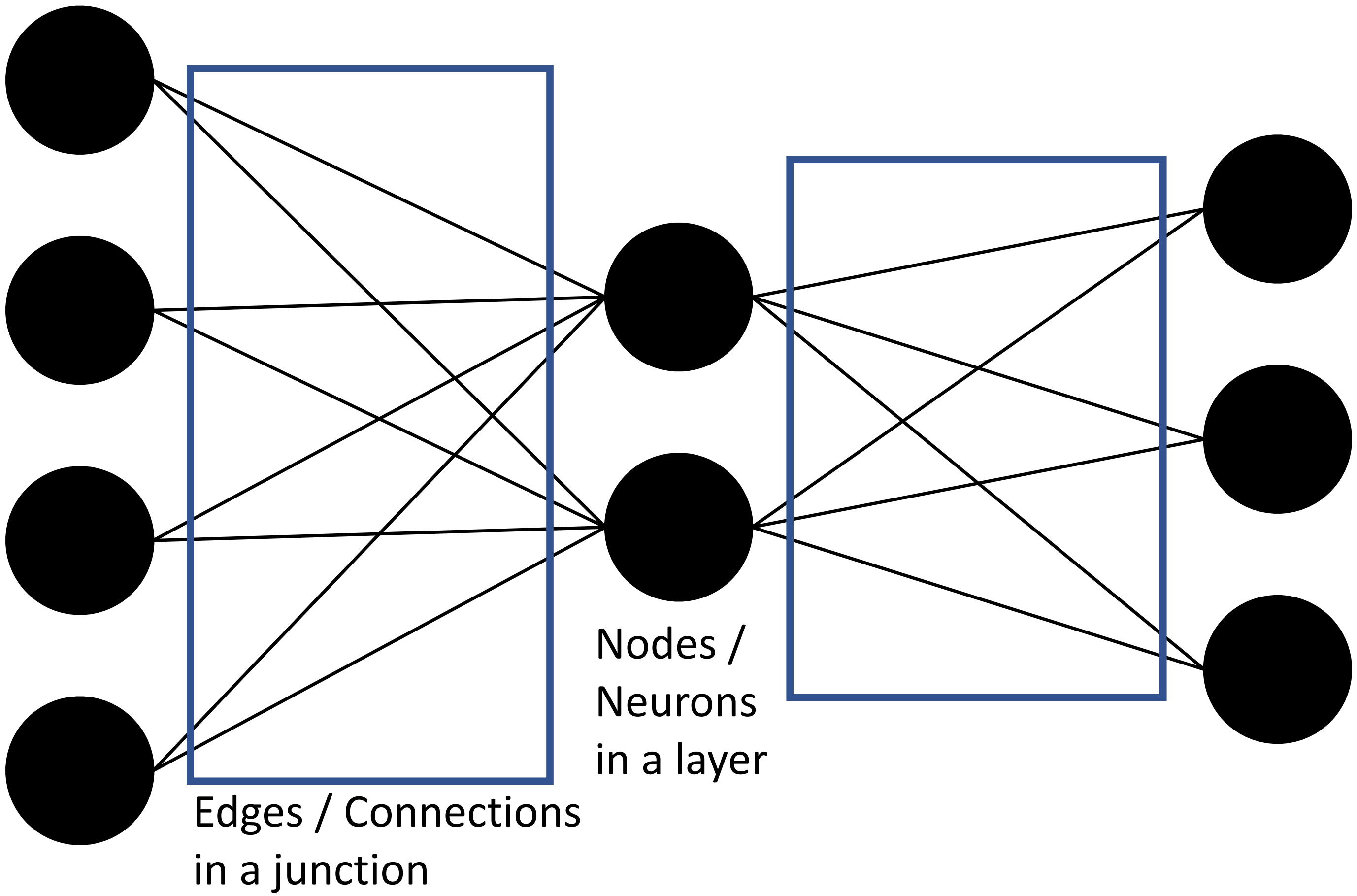

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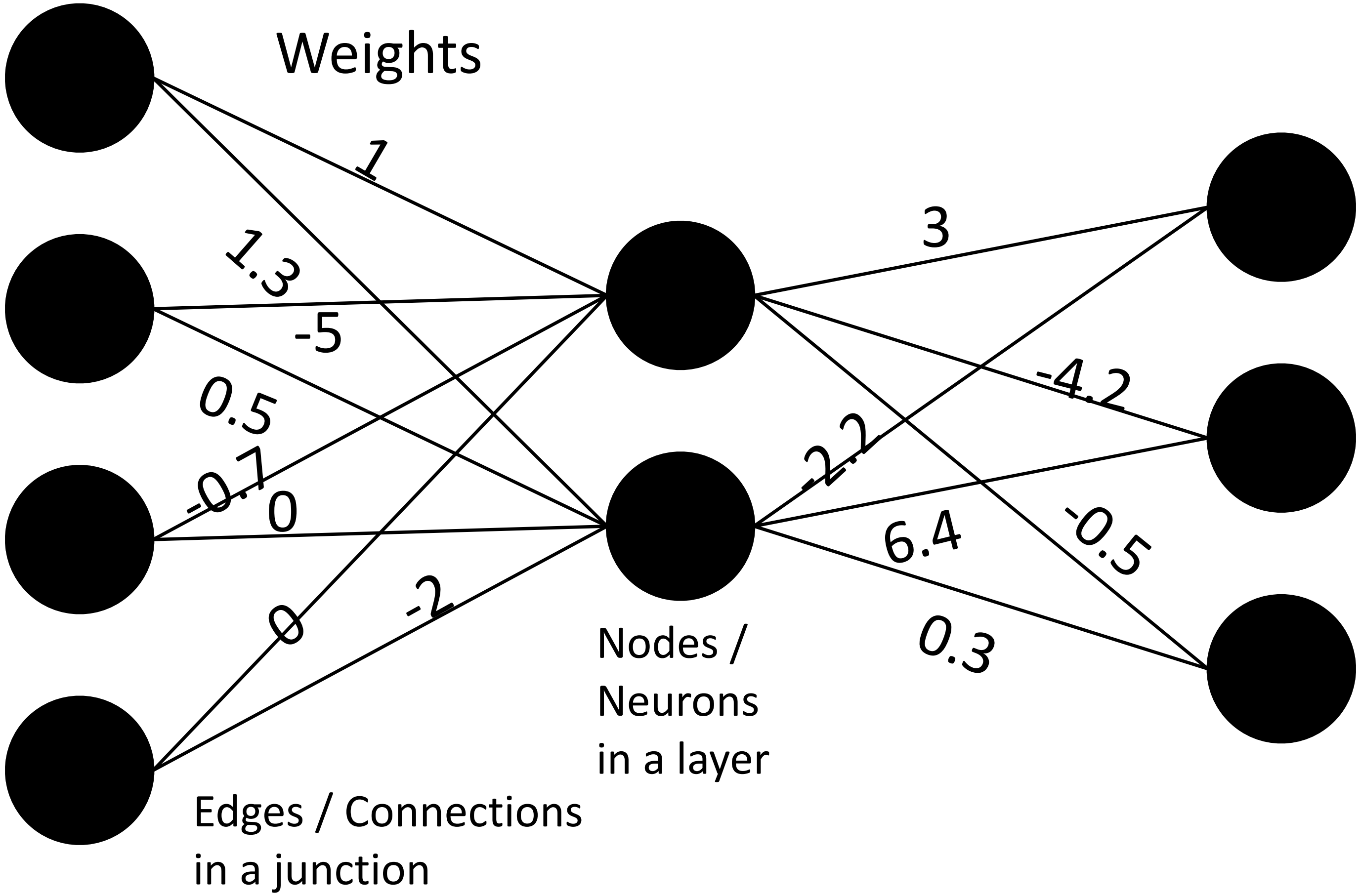

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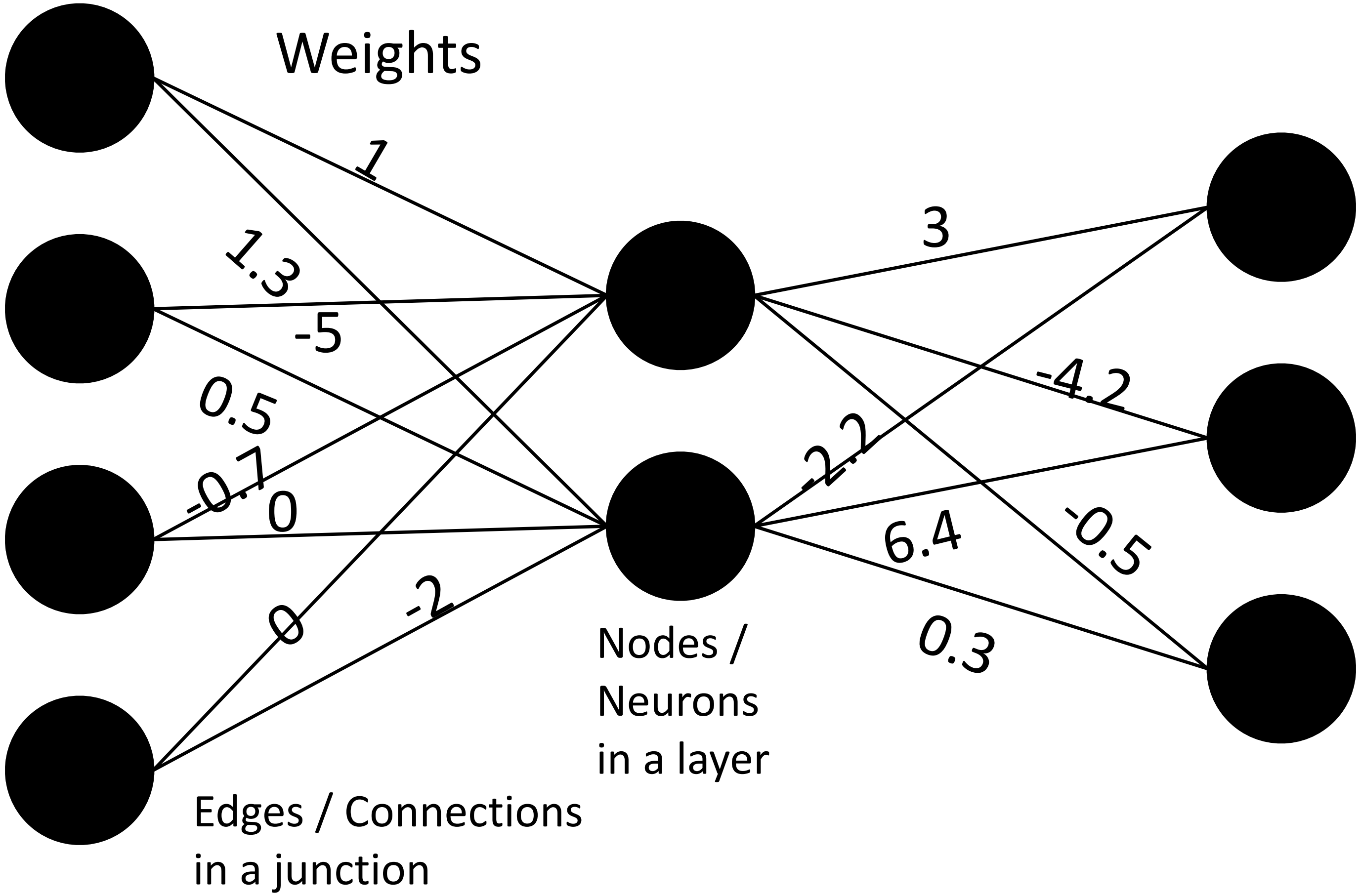

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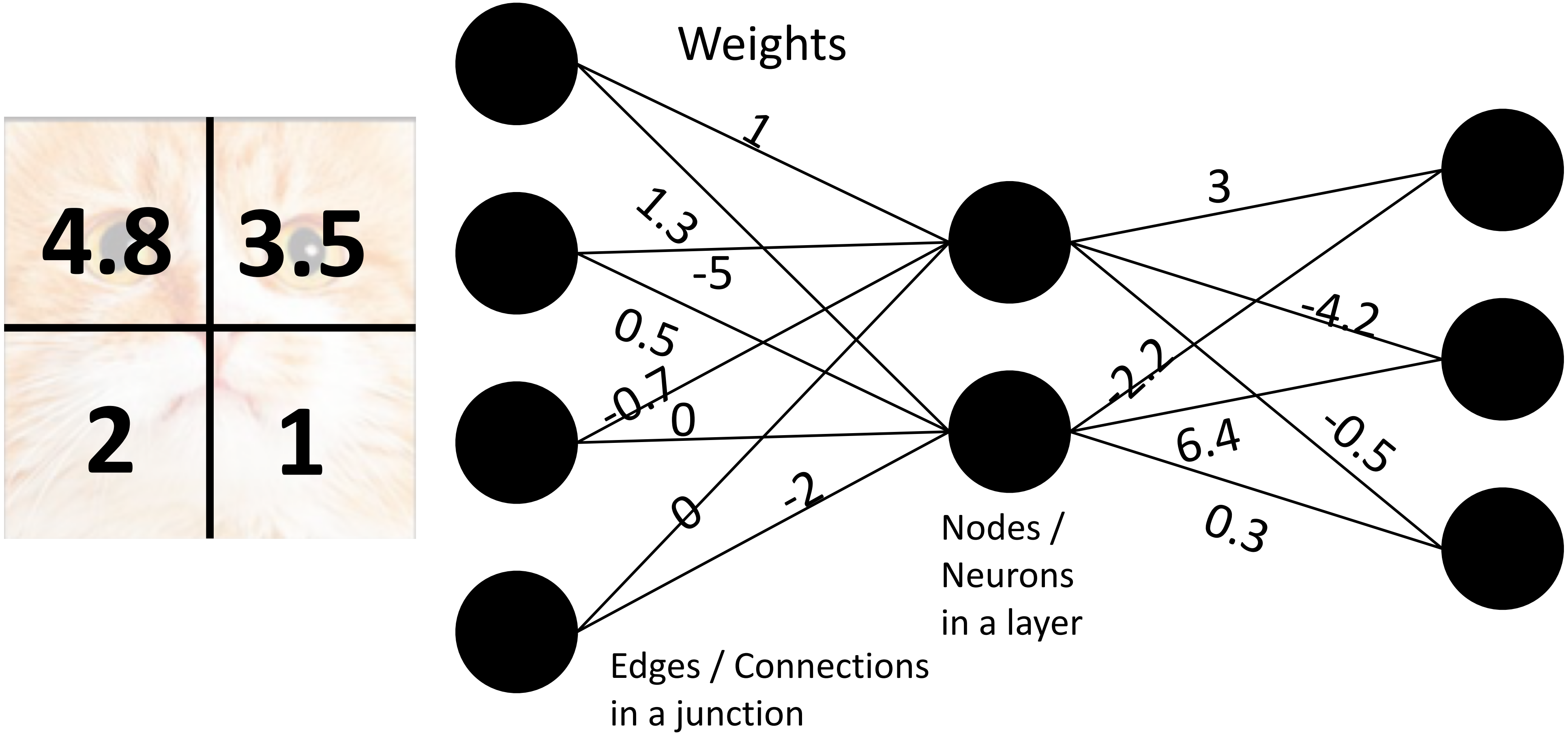

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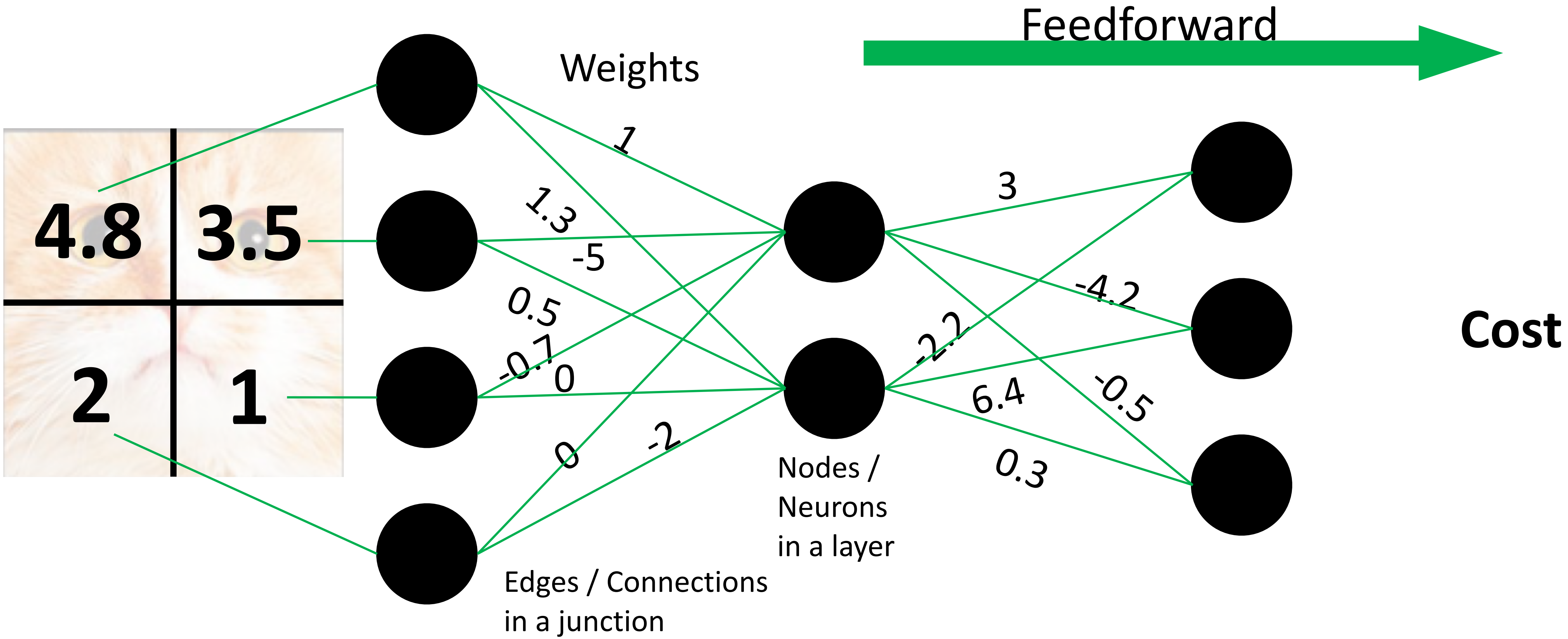
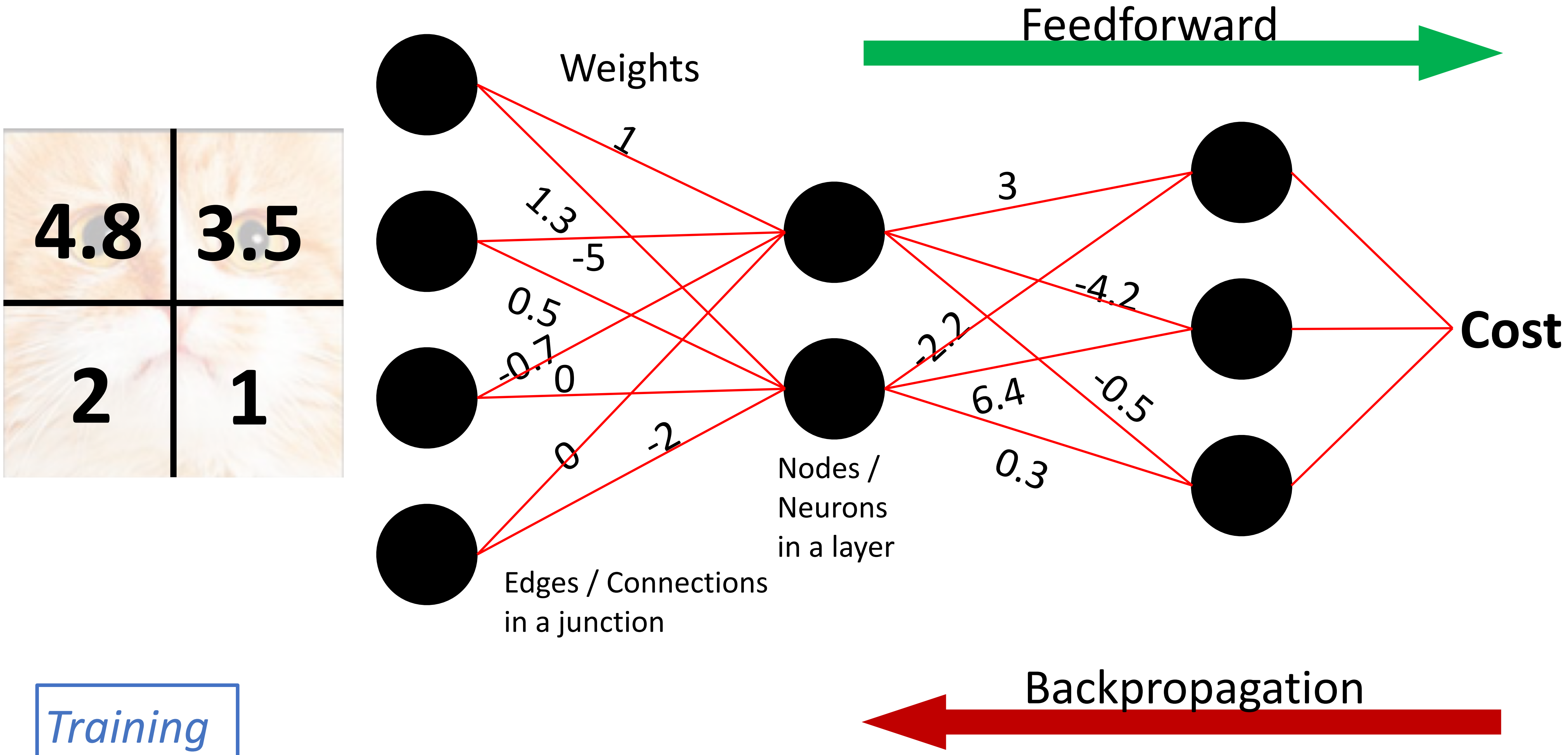


Training

Inference

Basic working of an artificial neural network



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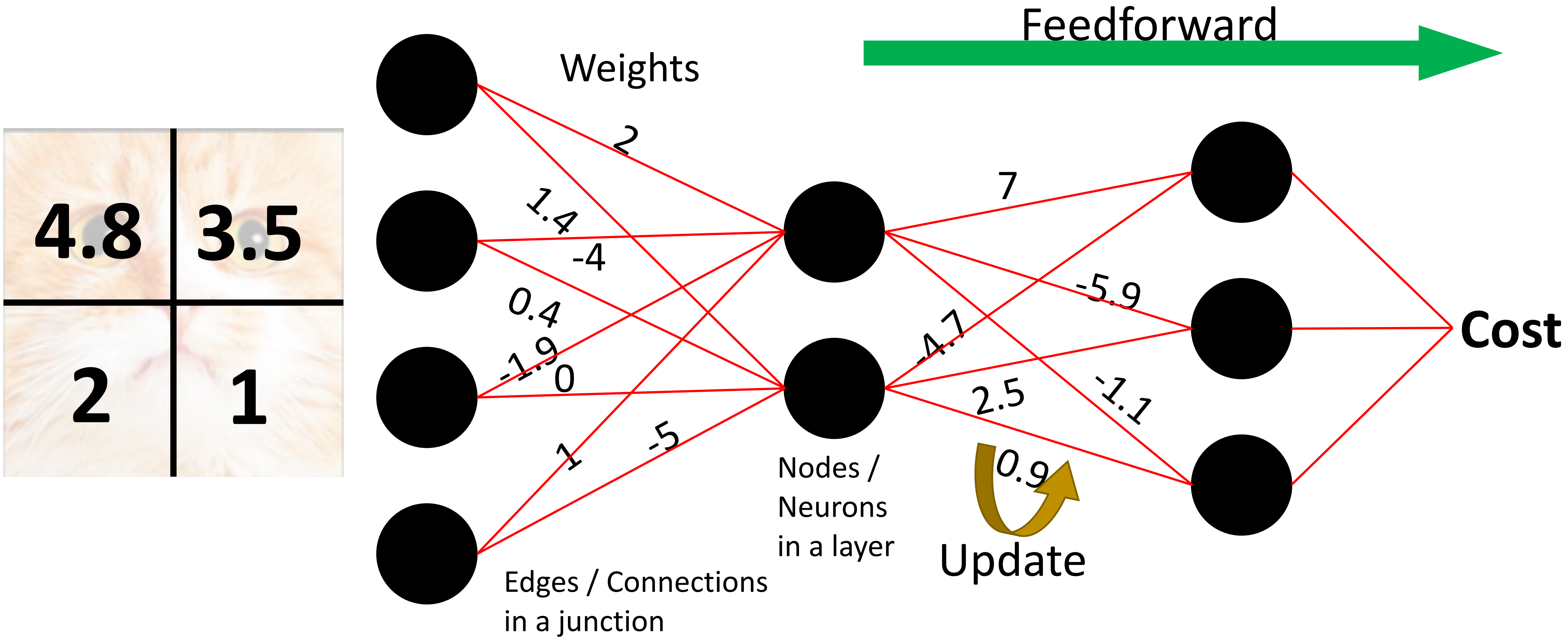

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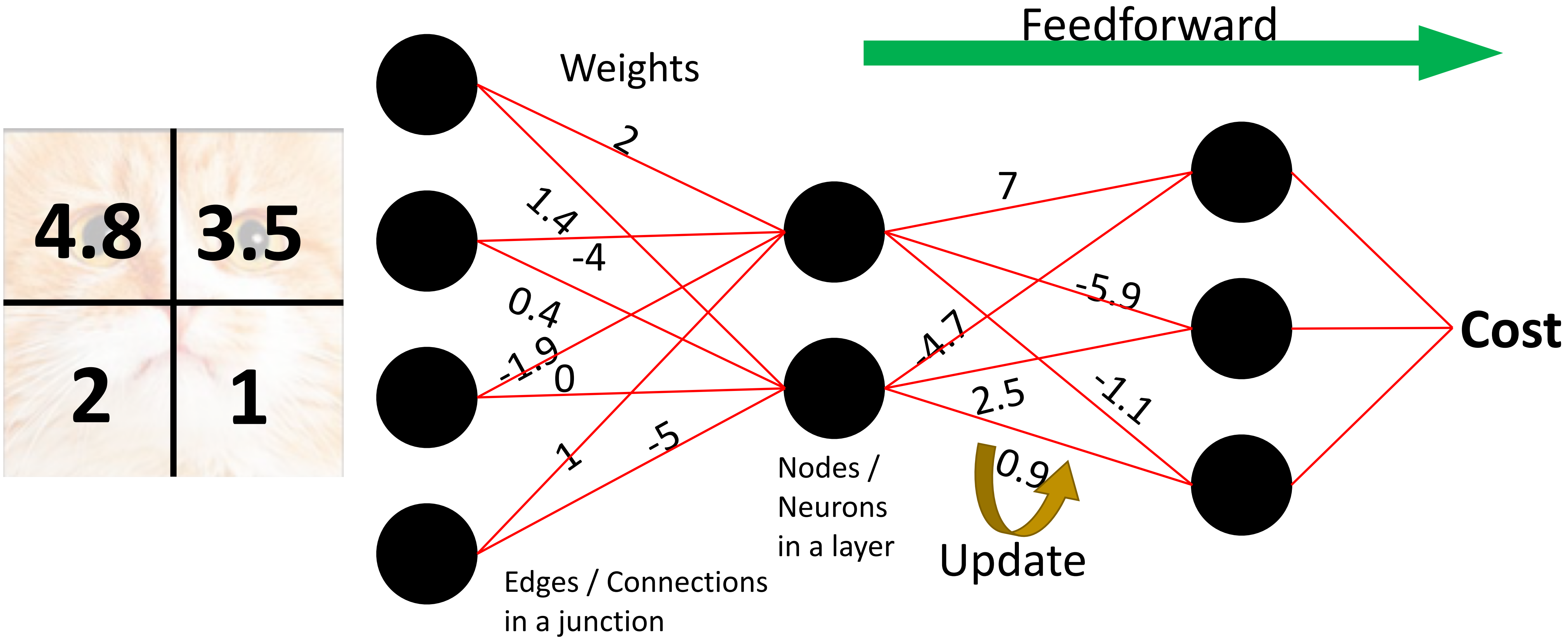
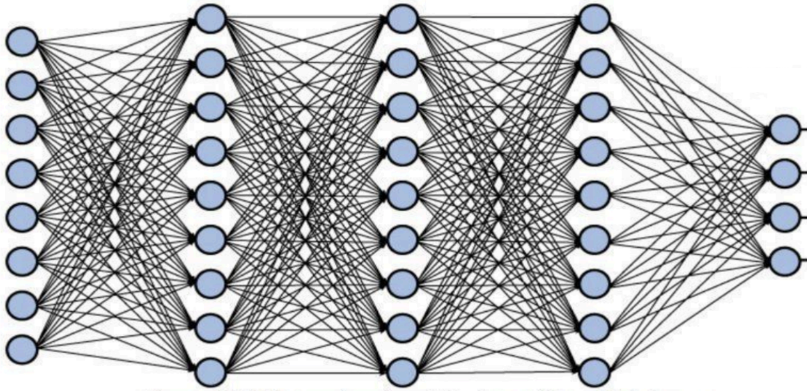


Weights dominate complexity – they are all used in all 3 operations

Motivation behind our work

Modern neural networks suffer from parameter explosion

Typical deep **CNN**



Fully connected **(FC)** Multilayer Perceptron **(MLP)**

Training can take weeks on CPU

Cloud GPU resources are expensive

amazon web services

Microsoft Azure

Google Cloud Platform

Our Work: Pre-defined Sparsity

Pre-define a sparse connection pattern **prior to training**

Use this sparse network for both training and inference

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$$\boldsymbol{N}_{\text{net}} = (8, 4, 4)$$
$$\boldsymbol{d}_{\text{net}}^{\text{out}} = (1, 2)$$
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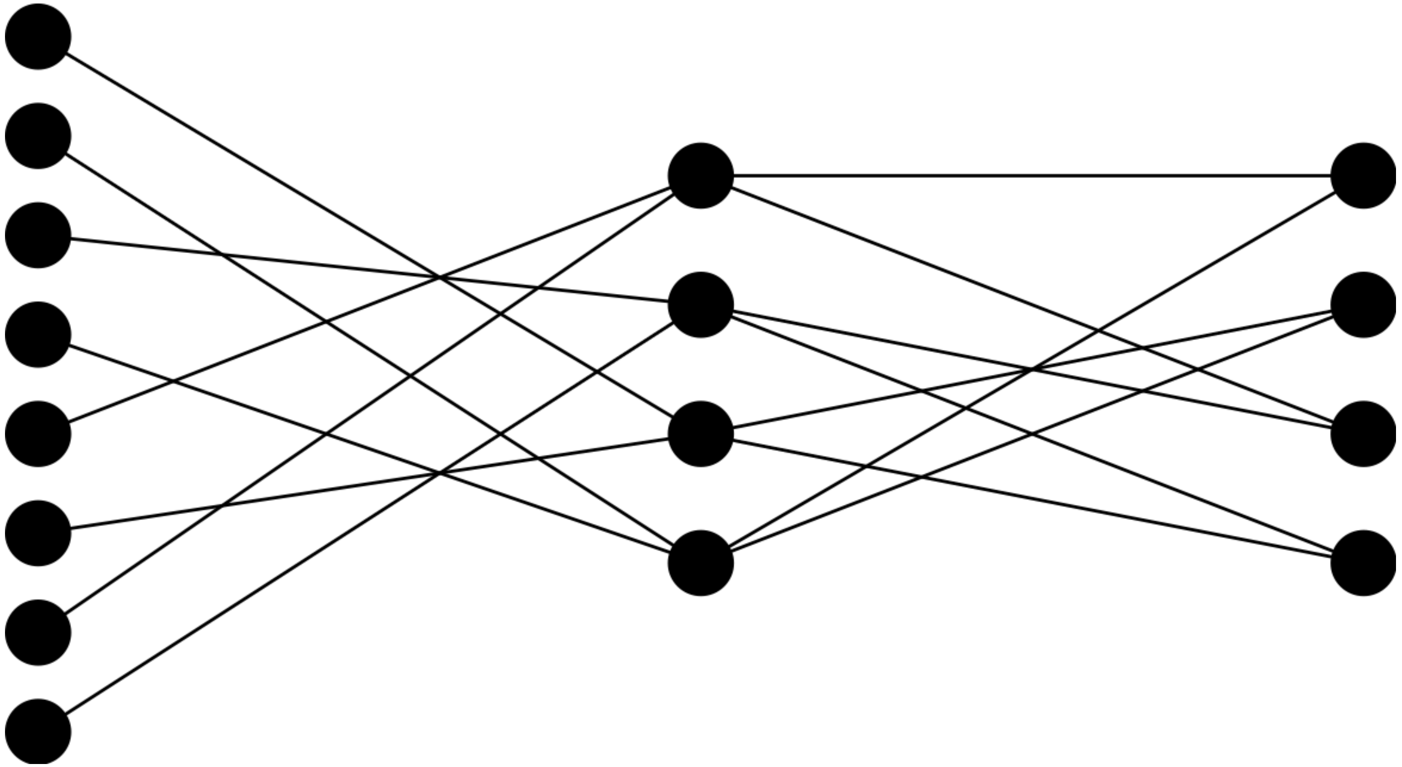

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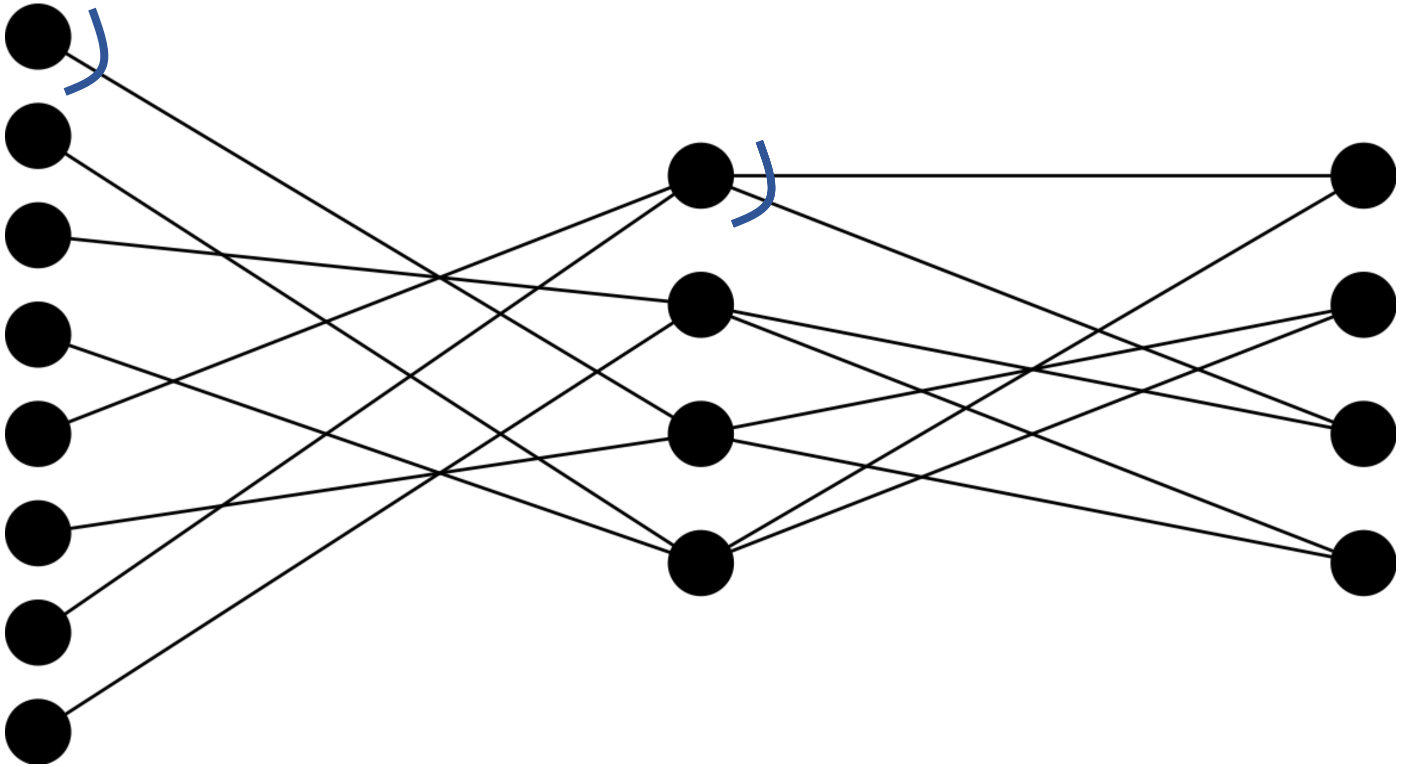

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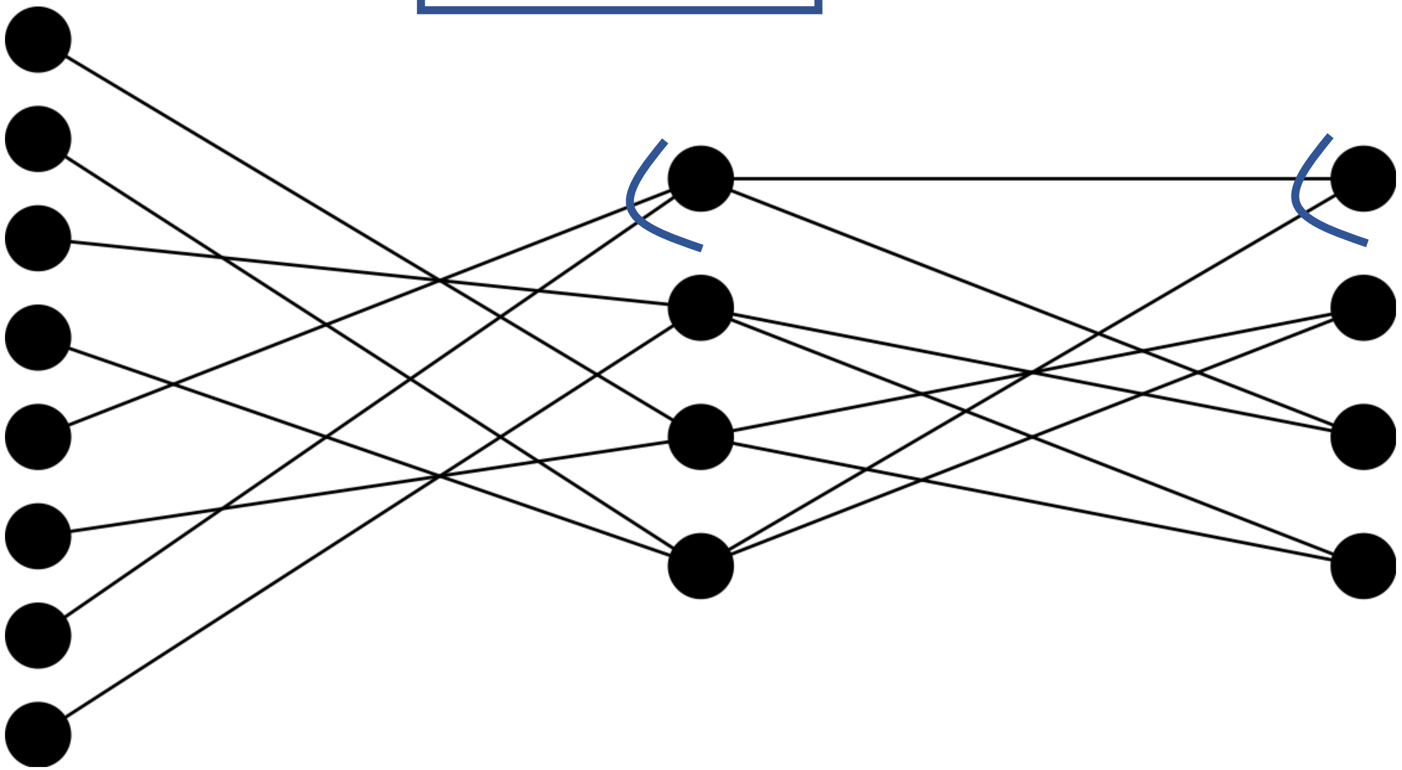

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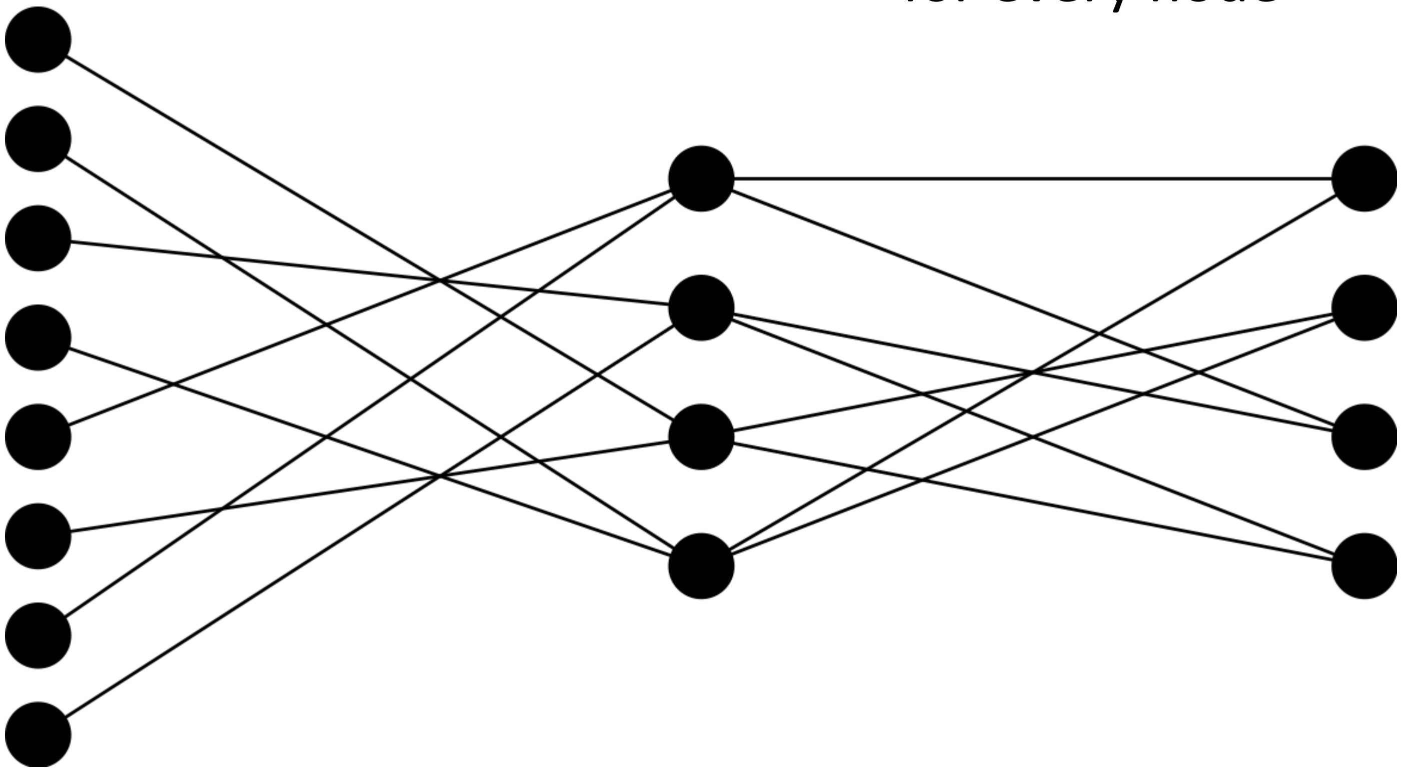
Structured Constraints:

Fixed in-, out-degrees for every node



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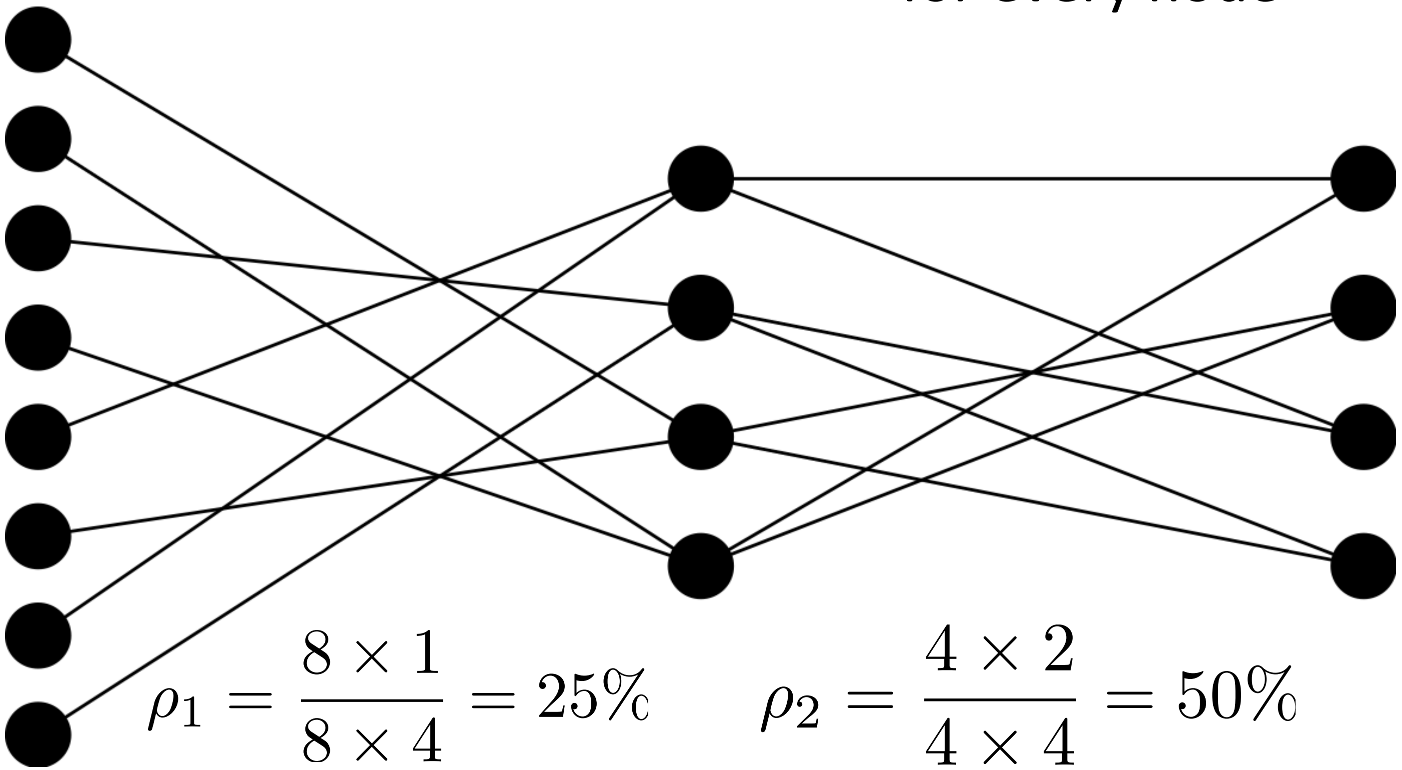

$$\rho_1 = \frac{8\times 1}{8\times 4} = 25\% \qquad \rho_2 = \frac{4\times 2}{4\times 4} = 50\%$$

$$\rho_{\text{net}} = \frac{8+8}{32+16} = 33\%$$

Overall Density compared to FC

Our Work: Pre-defined Sparsity

Pre-define a sparse connection pattern **prior to training**

Use this sparse network for both training and inference

Reduced training *and* inference complexity

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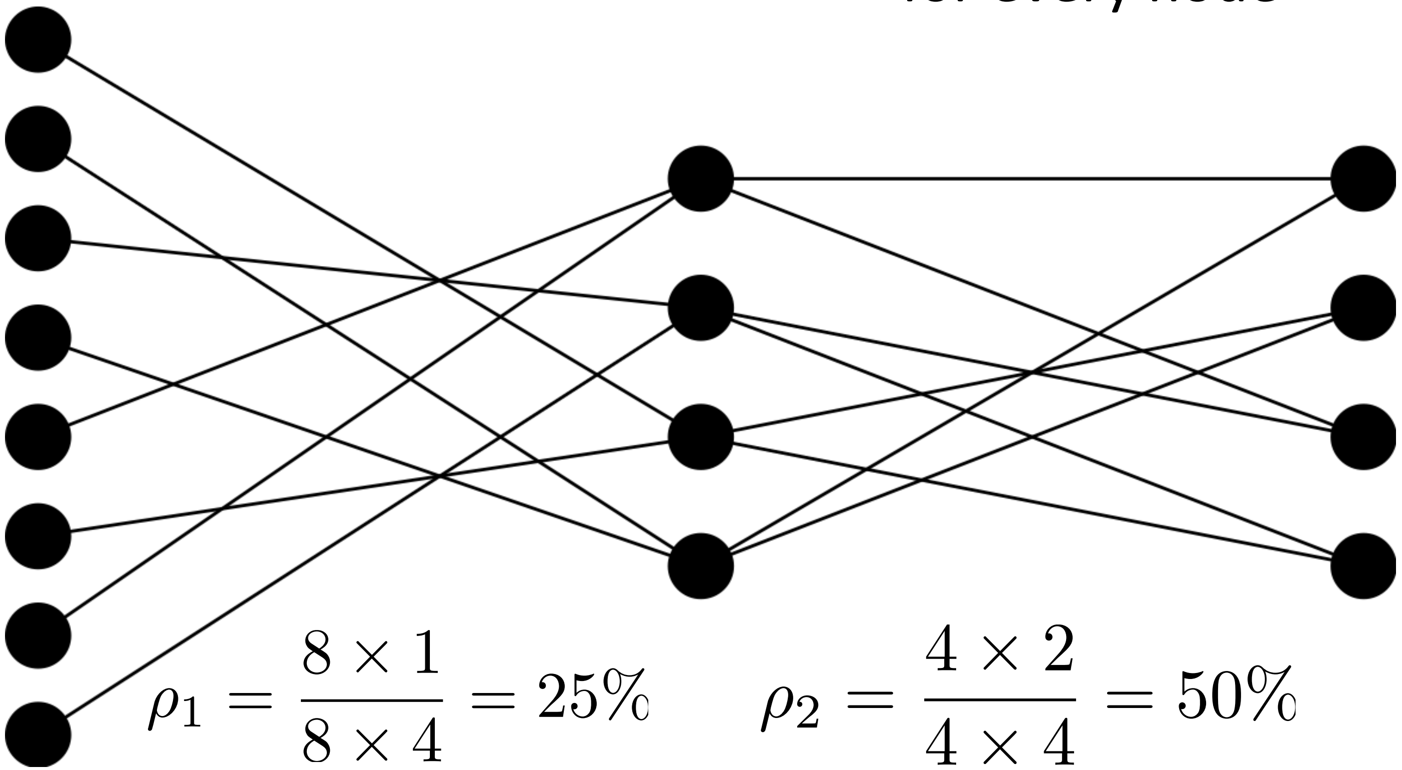

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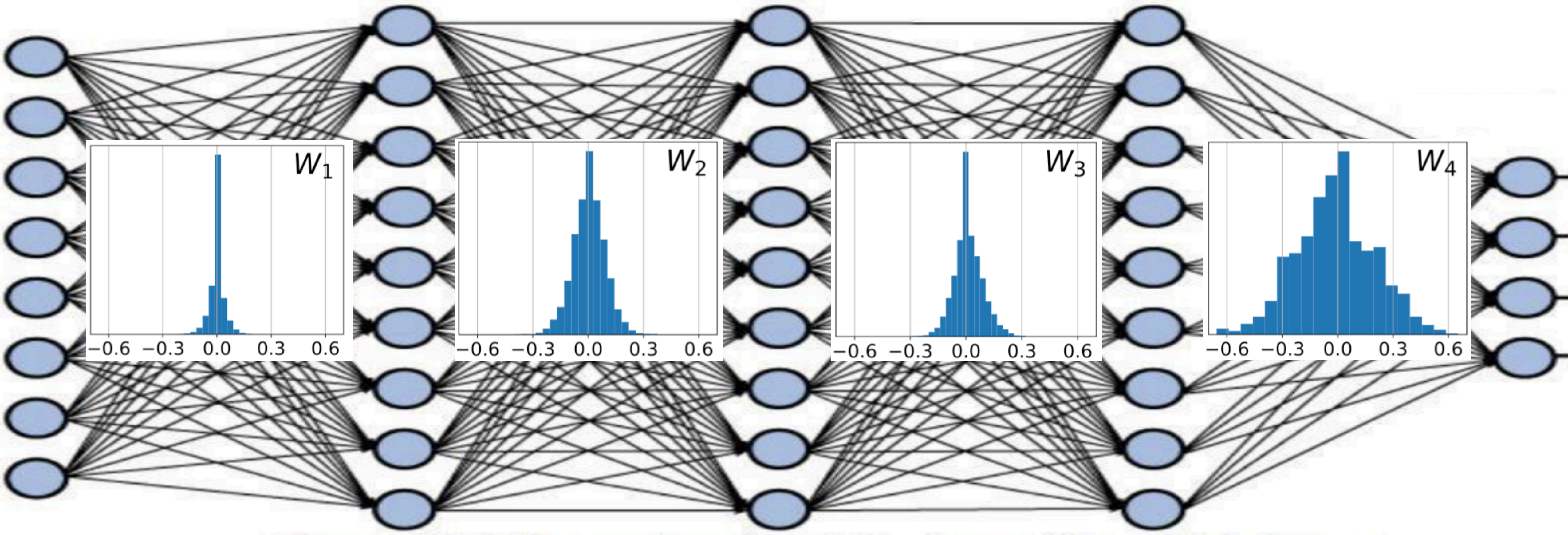
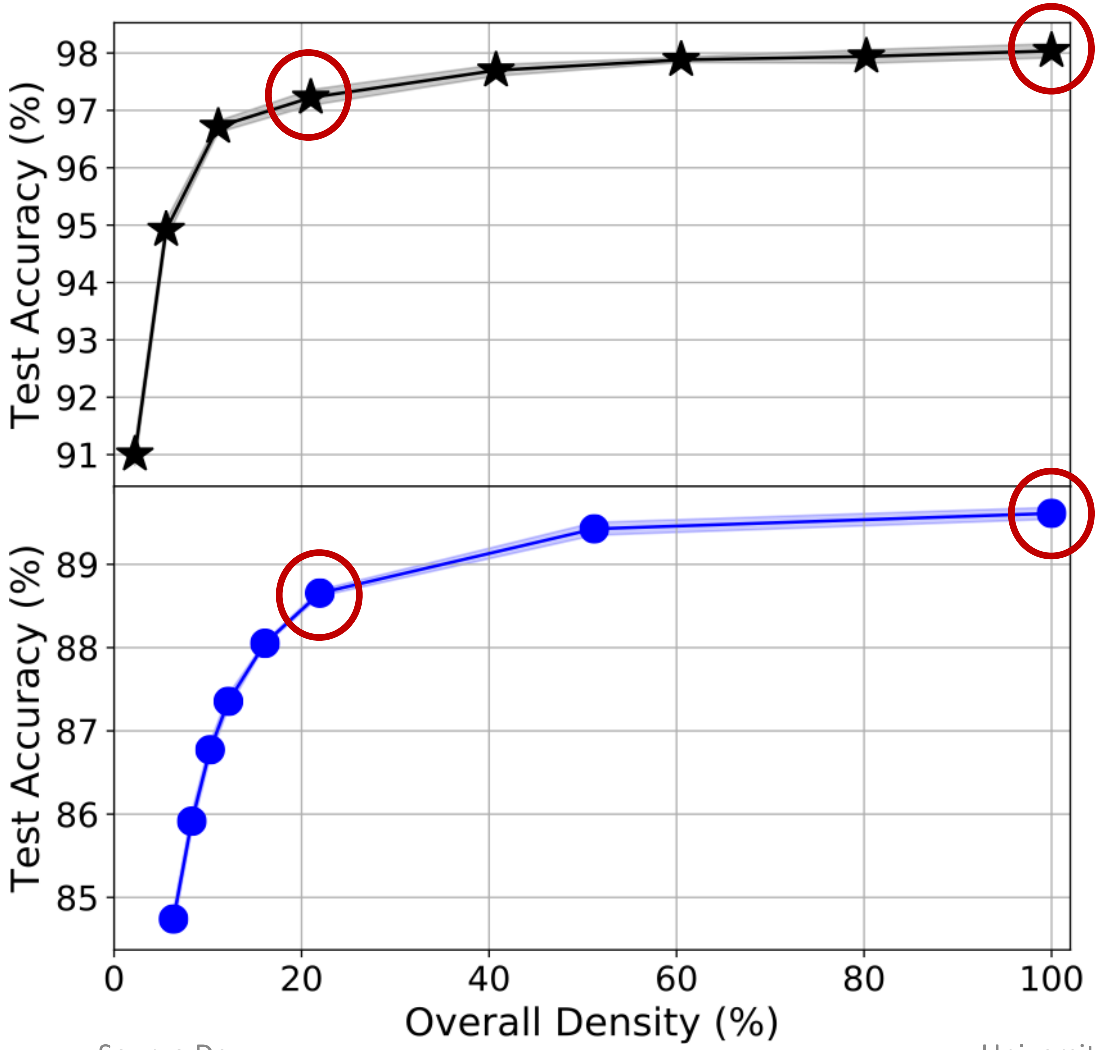
Overall Density compared to FC

Motivation behind pre-defined sparsity



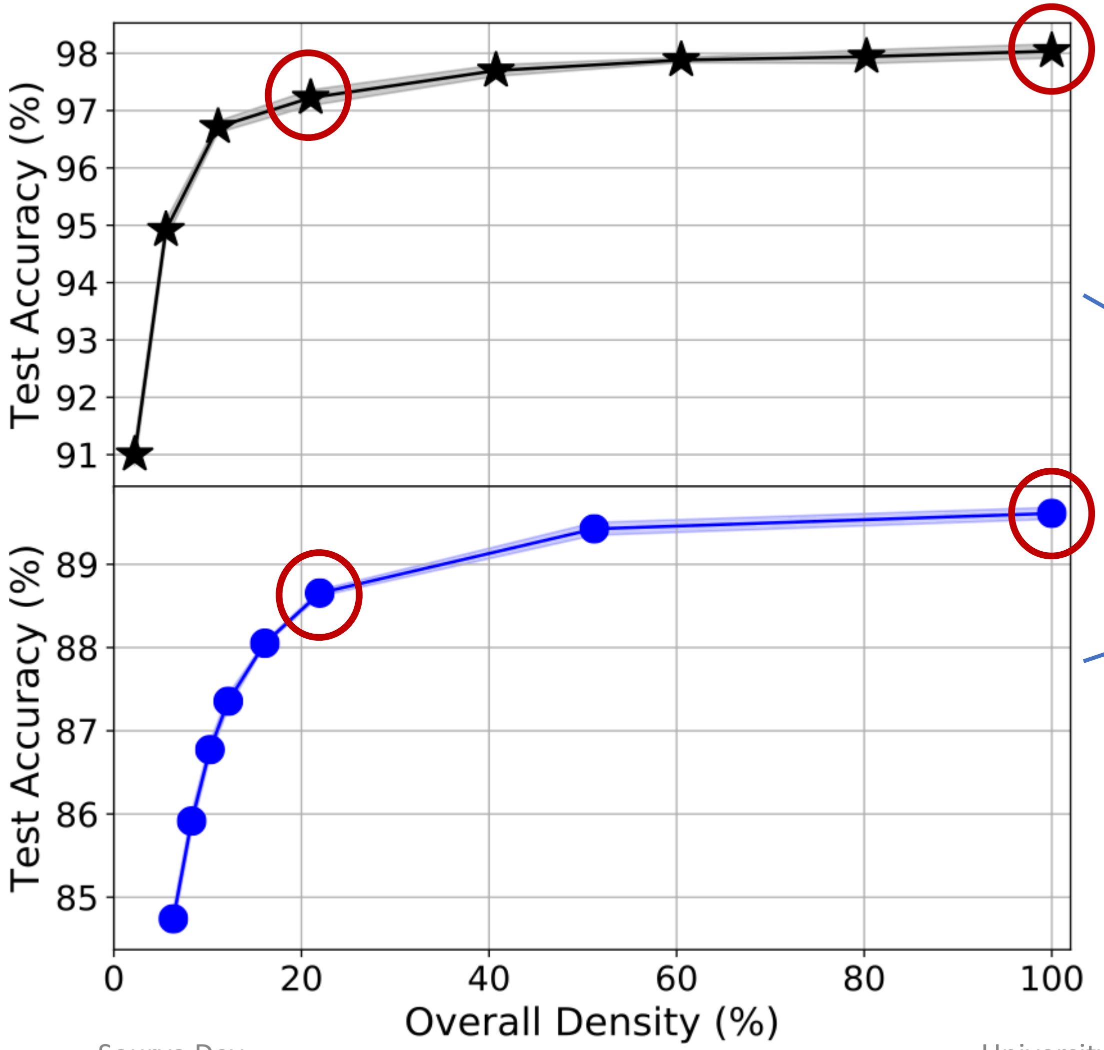
In a FC network, most weights are very small in magnitude after training

Pre-defined sparsity performance on MLPs



Starting with only 20% of parameters reduces test accuracy by just 1%

Pre-defined sparsity performance on MLPs



Starting with only 20% of parameters reduces test accuracy by just 1%

MNIST handwritten digits

Reuters news articles

TIMIT phonemes

CIFAR images

Morse symbols

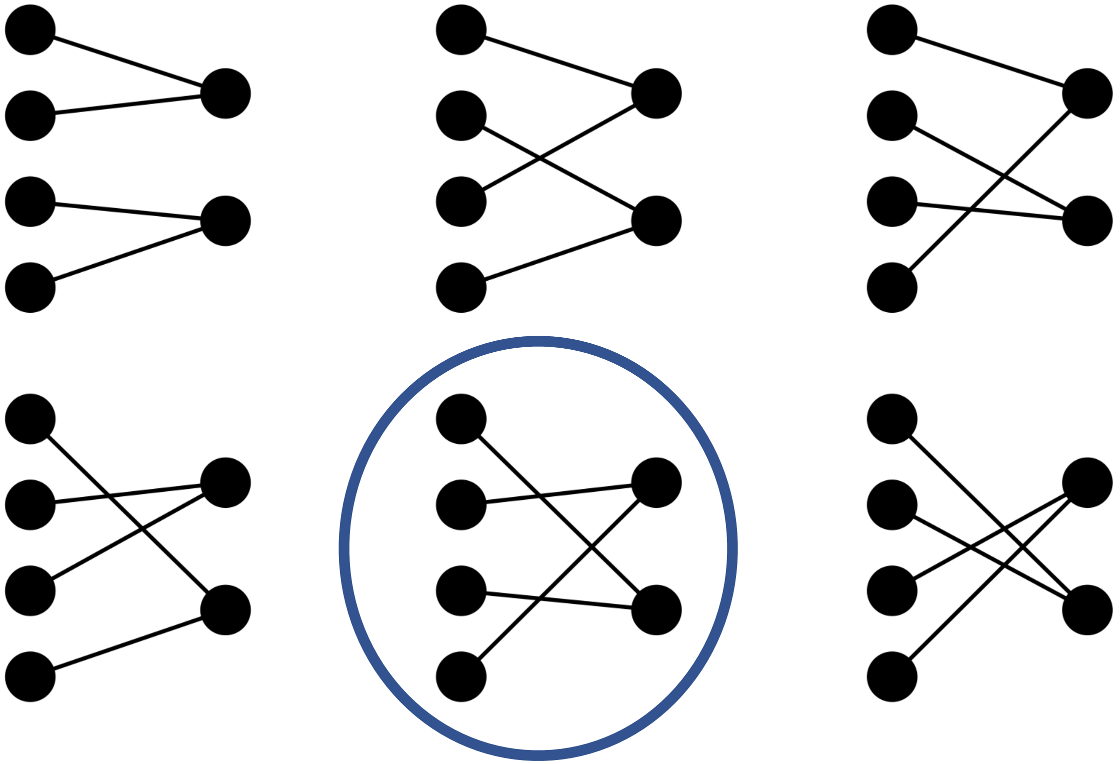
S. Dey, K. M. Chugg and P. A. Beerel, “Morse Code Datasets for Machine Learning,” in ICCCNT 2018. **Won Best Paper award.** https://github.com/usc-hal/morse-dataset

Analysis and Applications

Deep dive into pre-defined sparsity for MLPs, and a corresponding application

Designing pre-defined sparse networks

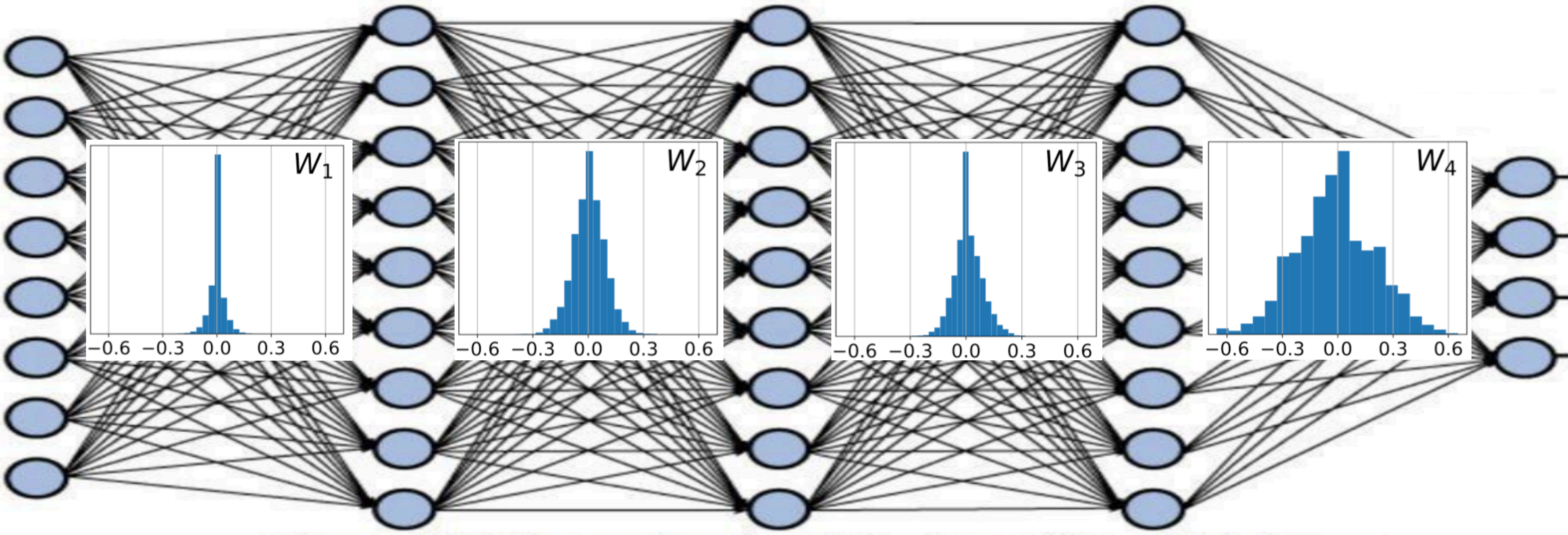
*A pre-defined sparse connection pattern is a **hyperparameter** to be set prior to training*



Find trends and guidelines to optimize pre-defined sparse patterns

S. Dey, K. Huang, P. A. Beerel and K. M. Chugg, "Pre-Defined Sparse Neural Networks with Hardware Acceleration," in *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 9, no. 2, pp. 332-345, June 2019.

Individual junction densities



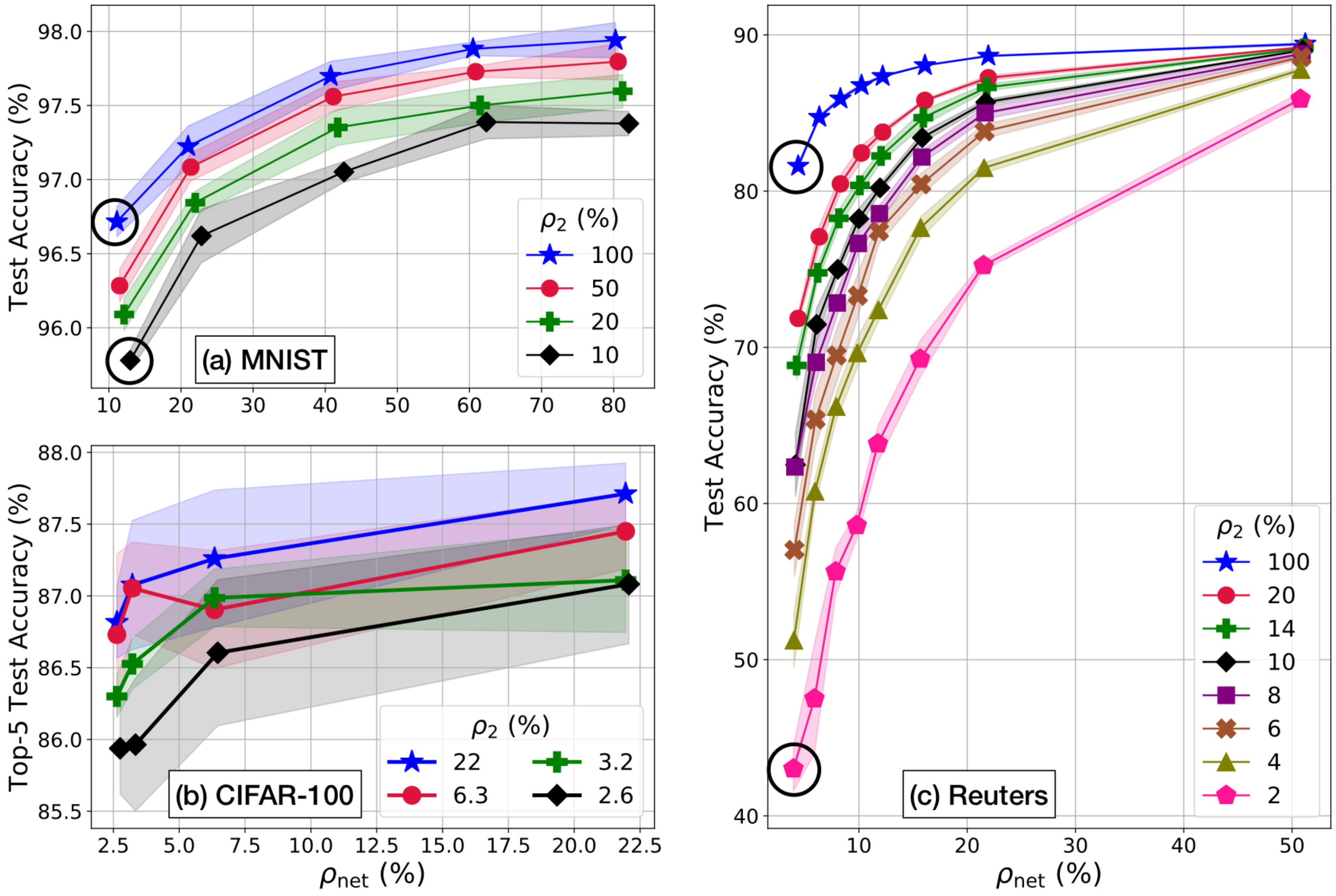
Latter junctions (closer to the output) need to be denser

Individual junction densities

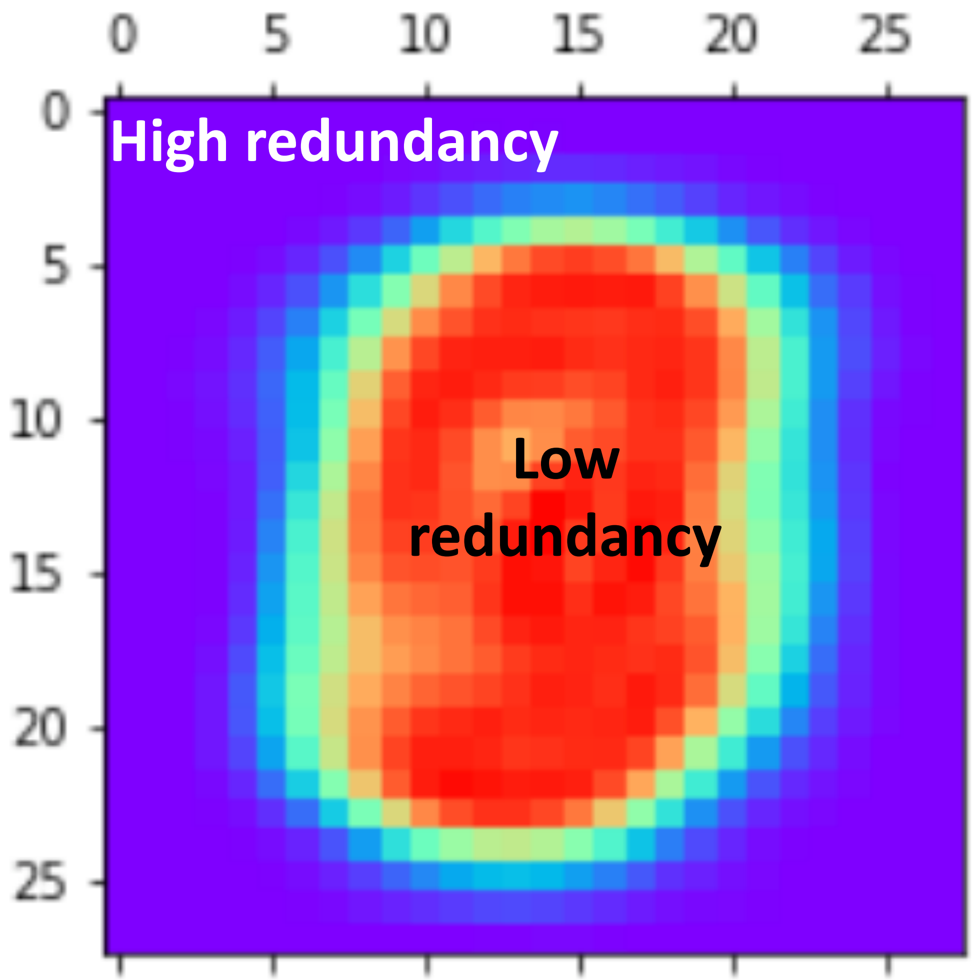
Each curve keeps ρ_2 fixed and varies ρ_{net} by varying ρ_1

For the same ρ_{net}, $\rho_2 > \rho_1$ improves performance

Mostly similar trends observed for deeper networks



Dataset redundancy



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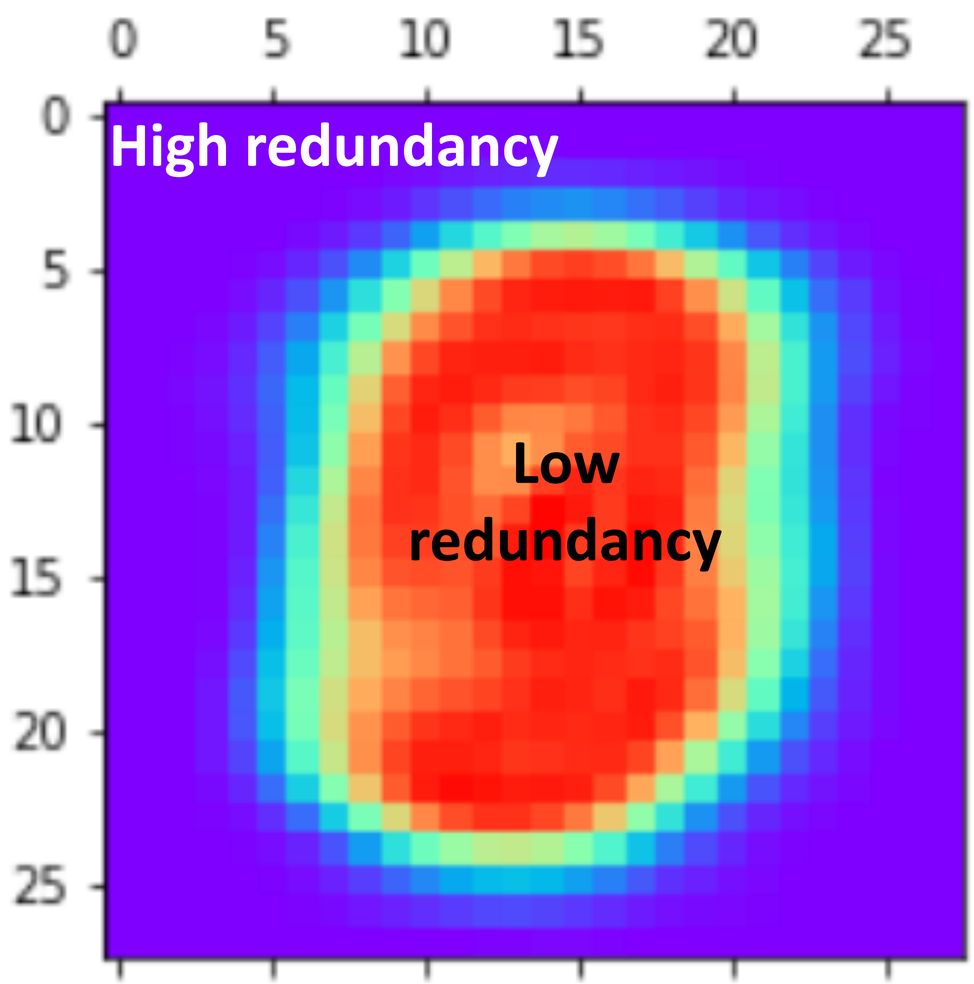
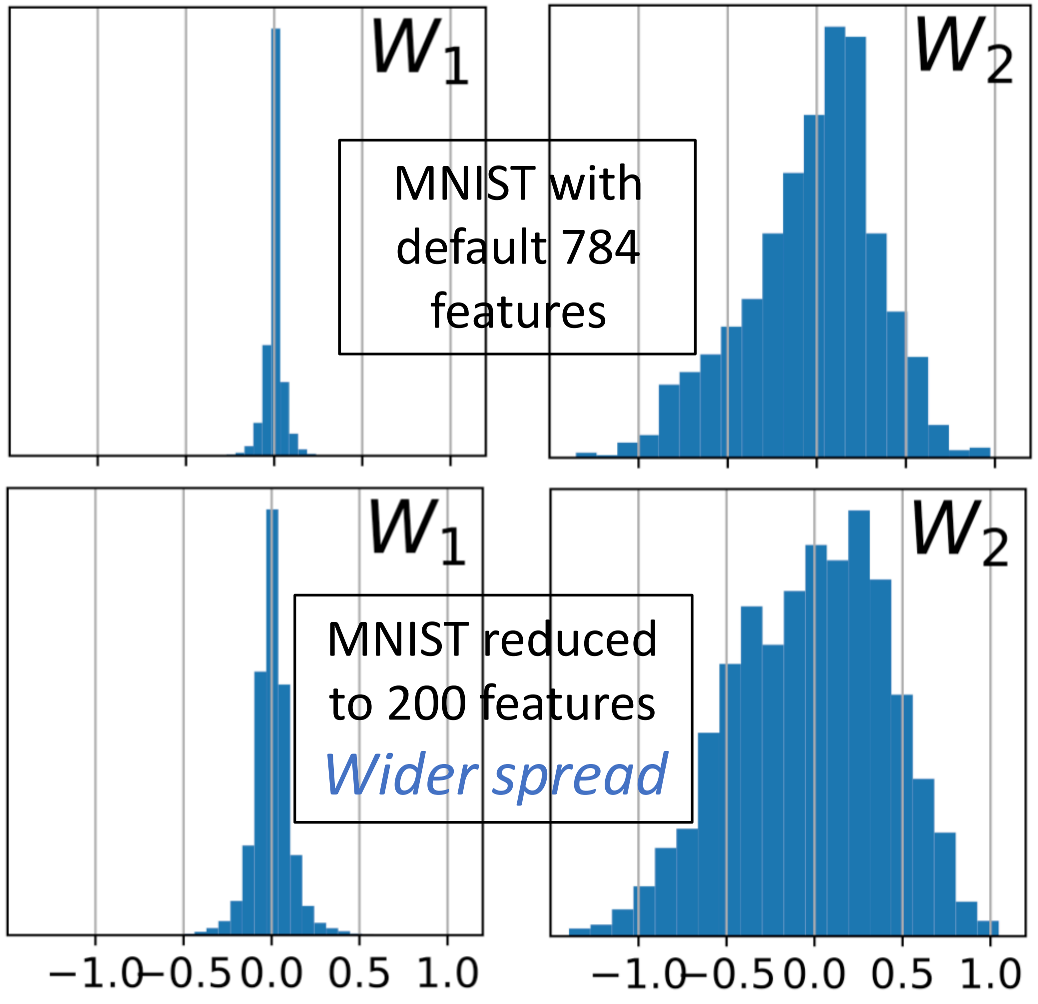
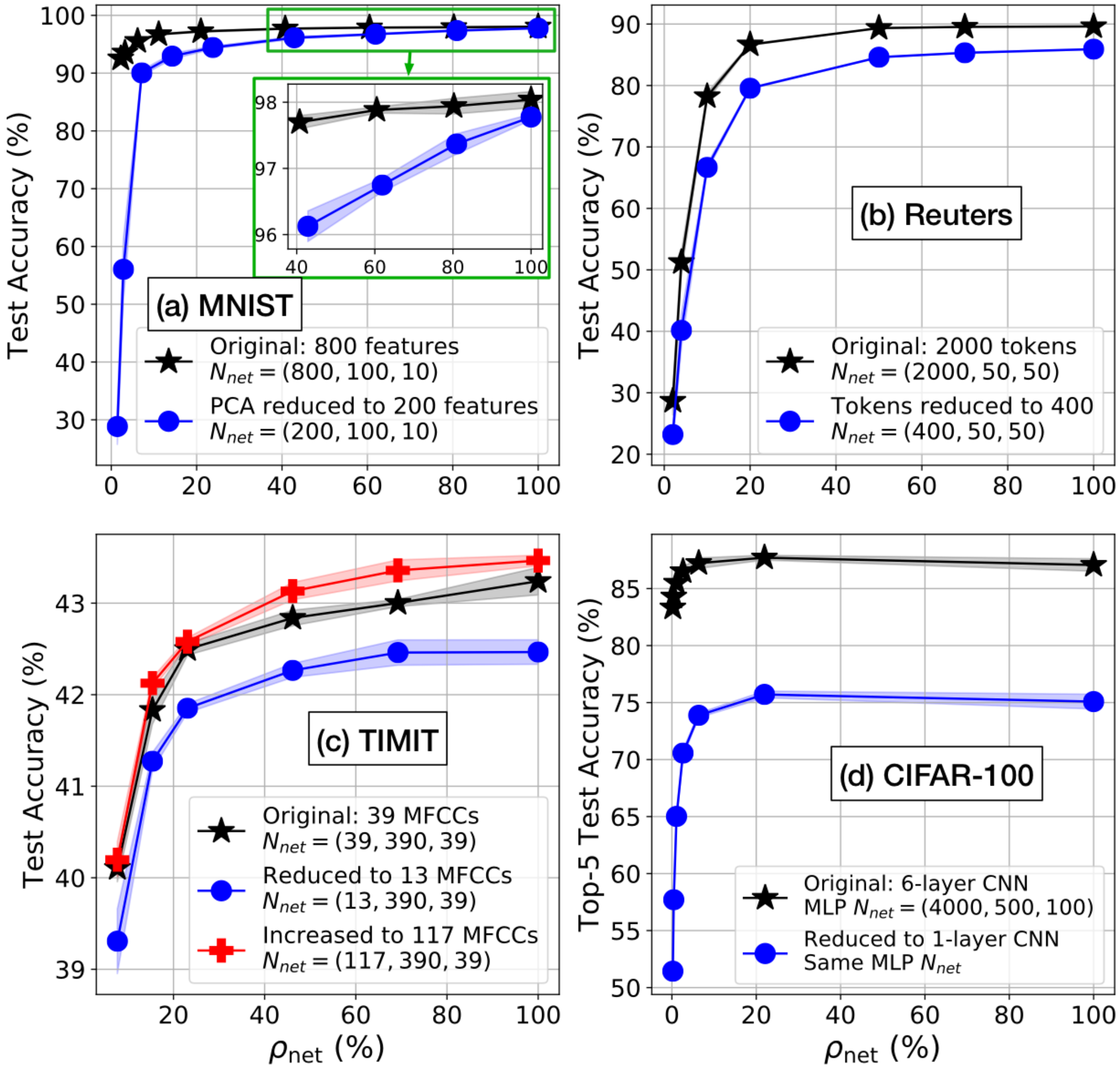




Less redundancy => Less sparsification possible

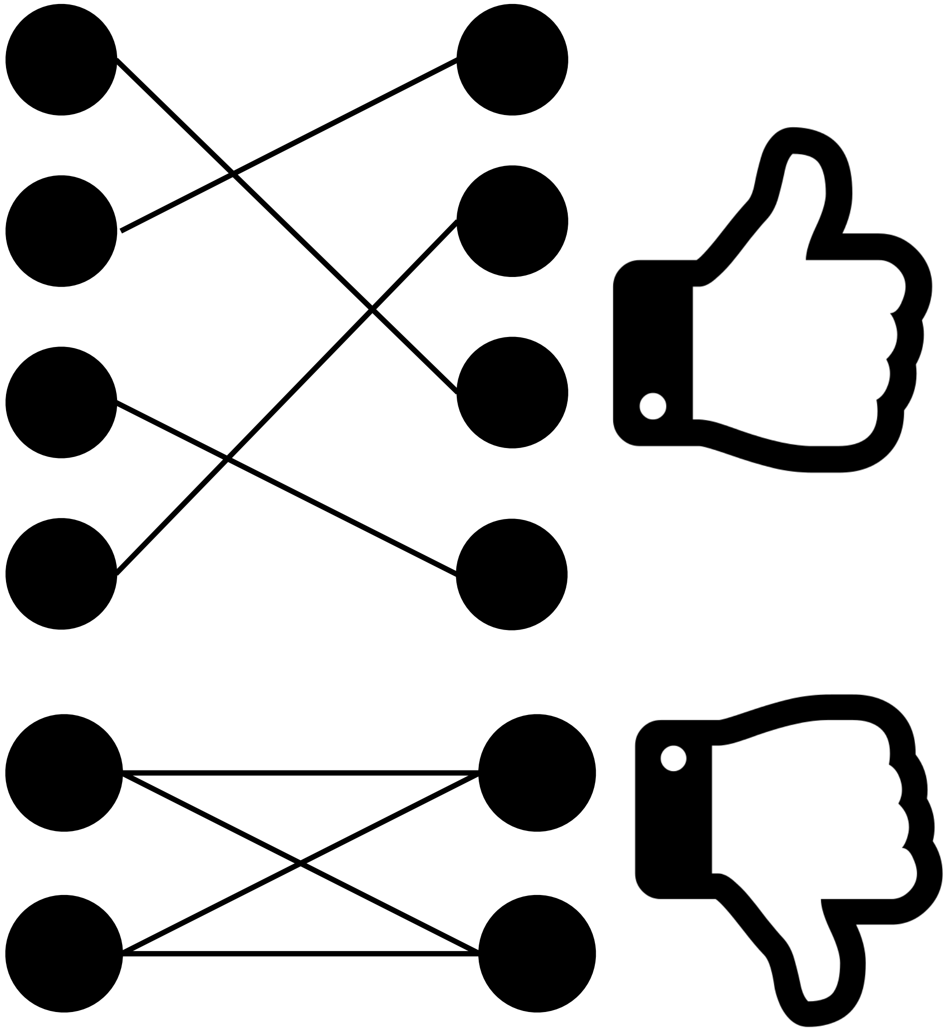
Effect of redundancy on sparsity



Reducing redundancy leads to increased performance degradation on sparsification

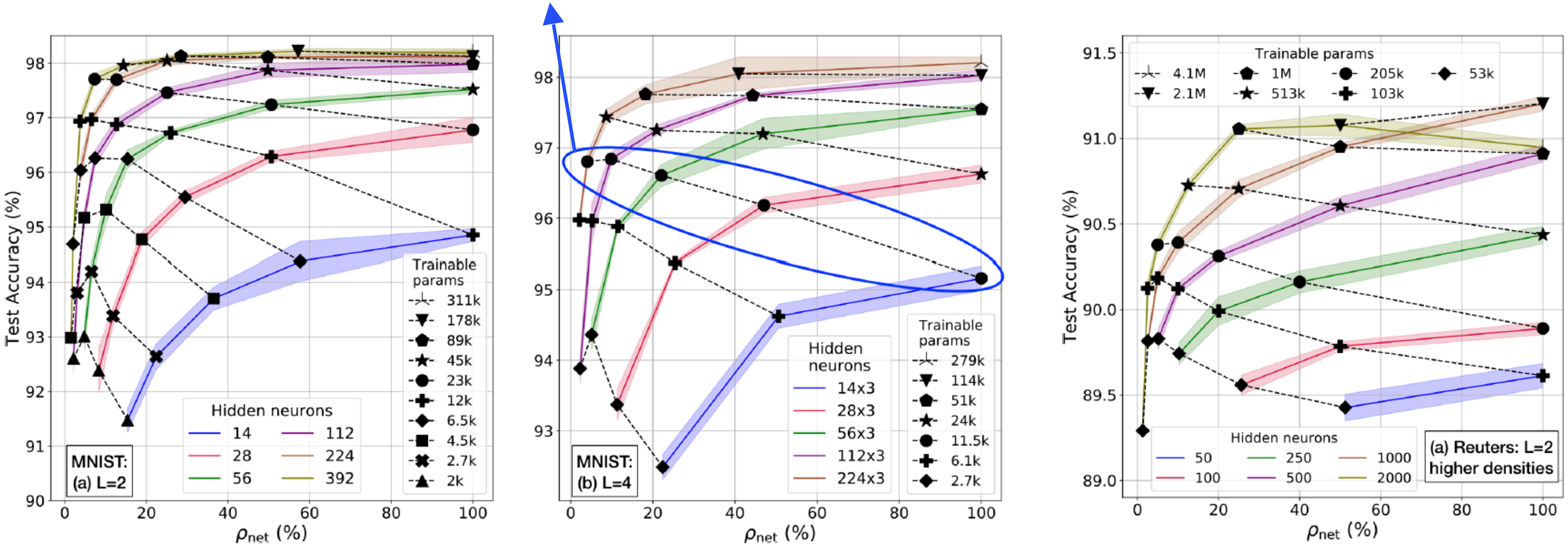
‘Large sparse’ vs ‘small dense’ networks

A sparser network with more hidden nodes will outperform a denser network with less hidden nodes, when both have same number of weights



‘Large sparse’ vs ‘small dense’ networks

Networks with same number of parameters go from bad to good as #nodes in hidden layers is increased



Regularization

$$C(\boldsymbol{w}) = C_0(\boldsymbol{w}) + \lambda \left\| \boldsymbol{w} \right\|_2^2$$

Regularized cost

Original unregularized
cost (like cross-entropy)

Regularization term

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Regularized cost

Original unregularized cost (like cross-entropy)

Regularization term

Pre-defined sparse networks need smaller λ (as determined by validation)

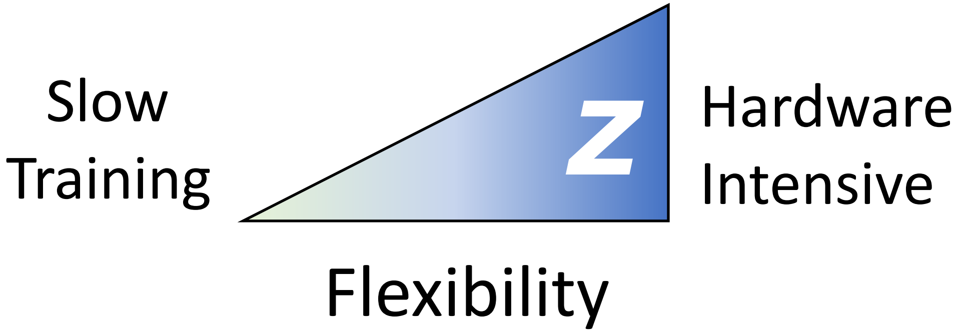
Overall Density	λ
100 %	1.1×10^{-4}
40 %	5.5×10^{-5}
11 %	0

Example for MNIST 2-junction networks

Pre-defined sparsity reduces the overfitting problem stemming from over-parametrization in big networks

Application: A hardware architecture for on-device training and inference

Degree of parallelism (z) = Number of weights processed in parallel in a junction



S. Dey, Y. Shao, K. M. Chugg and P. A. Beerel, "Accelerating training of deep neural networks via sparse edge processing," in *26th International Conference on Artificial Neural Networks (ICANN)* Part 1, pp. 273-280. Springer, Sep 2017.

Application: A hardware architecture for on-device training and inference

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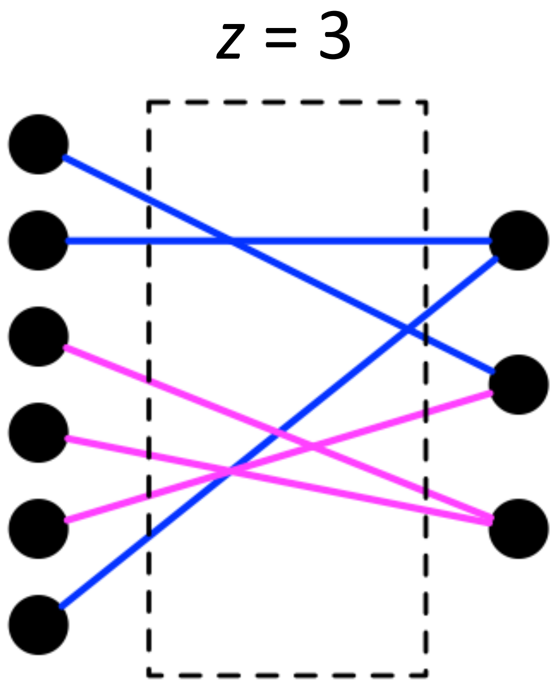
Connections designed for clash-free memory accesses to prevent stalling



S. Dey, P. A. Beerel and K. M. Chugg, "Interleaver design for deep neural networks," in *51st Annual Asilomar Conference on Signals, Systems, and Computers (ACSSC)*, pp. 1979-1983, Oct 2017.

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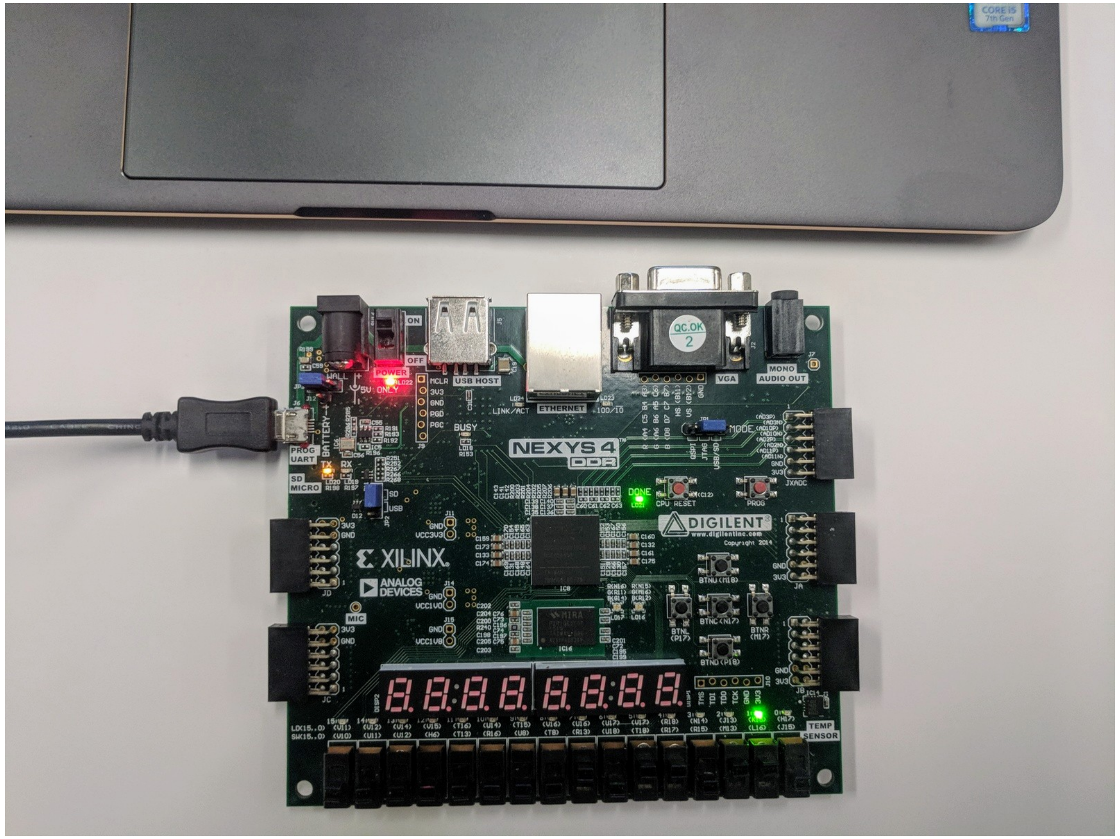
Prototype implemented on FPGA



S. Dey, D. Chen, Z. Li, S. Kundu, K. Huang, K. M. Chugg and P. A. Beerel, “A Highly Parallel FPGA Implementation of Sparse Neural Network Training,” in *2018 International Conference on Reconfigurable Computing and FPGAs (ReConFig)*, pp.1-4, Dec 2018. Expanded pre-print version available at arXiv:1806.01087.

Model Search

Automate the design of CNNs with good performance and low complexity

Model search is ongoing research, hence currently not available publicly

Thank you!

https://souryadey.github.io/