Exploring Complexity Reduction in Deep Learning

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Outline

Introduction

Pre-Defined Sparsity

Reduce complexity of neural networks with minimal performance degradation

Deep-n-Cheap

Automated search framework to explore performance-complexity tradeoffs in CNN design

Dataset Engineering

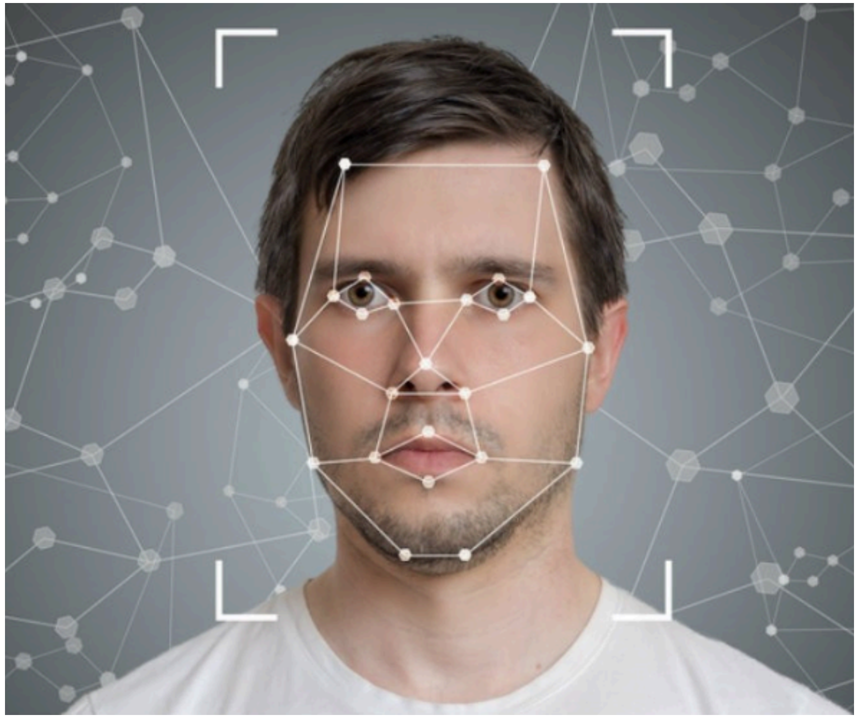
A family of synthetic datasets of customizable difficulty for ML classification problems

Introduction

Overview

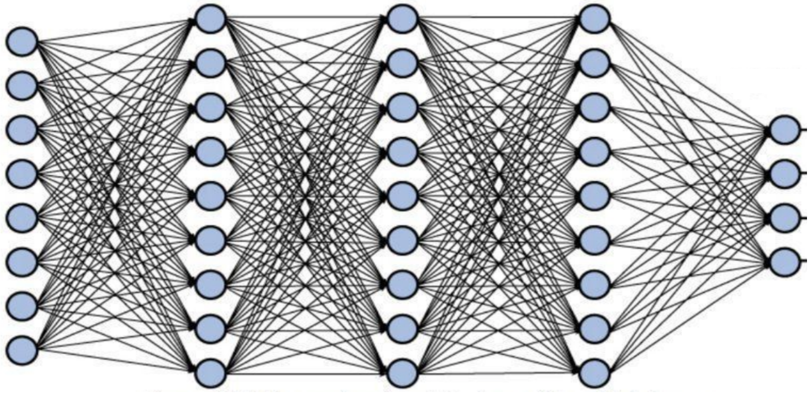
Neural networks (NNs) are key machine learning technologies

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



Motivation behind complexity reduction

Modern neural networks suffer from parameter explosion



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

Training can take weeks on CPU

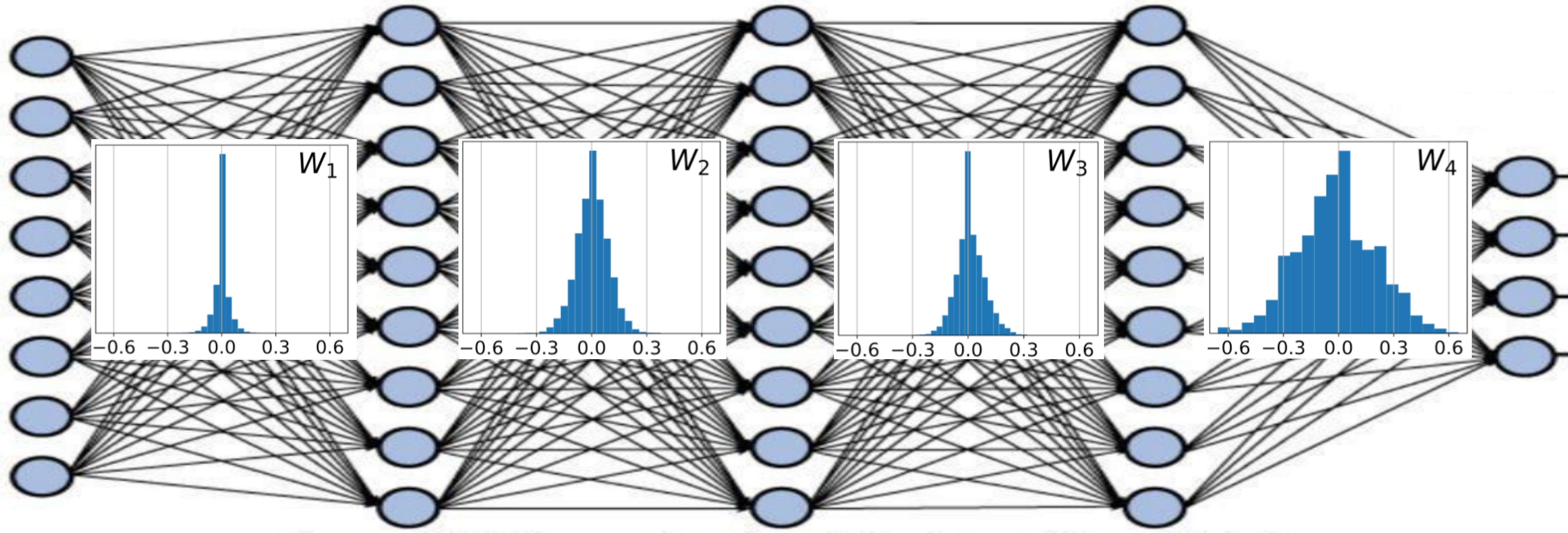
Cloud GPU resources are expensive

Typical deep **CNN**

Pre-Defined Sparsity

Reduce complexity of neural networks with minimal performance degradation

Motivation behind pre-defined sparsity



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

Pre-defined Sparsity

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

Use this sparse network for both training and inference

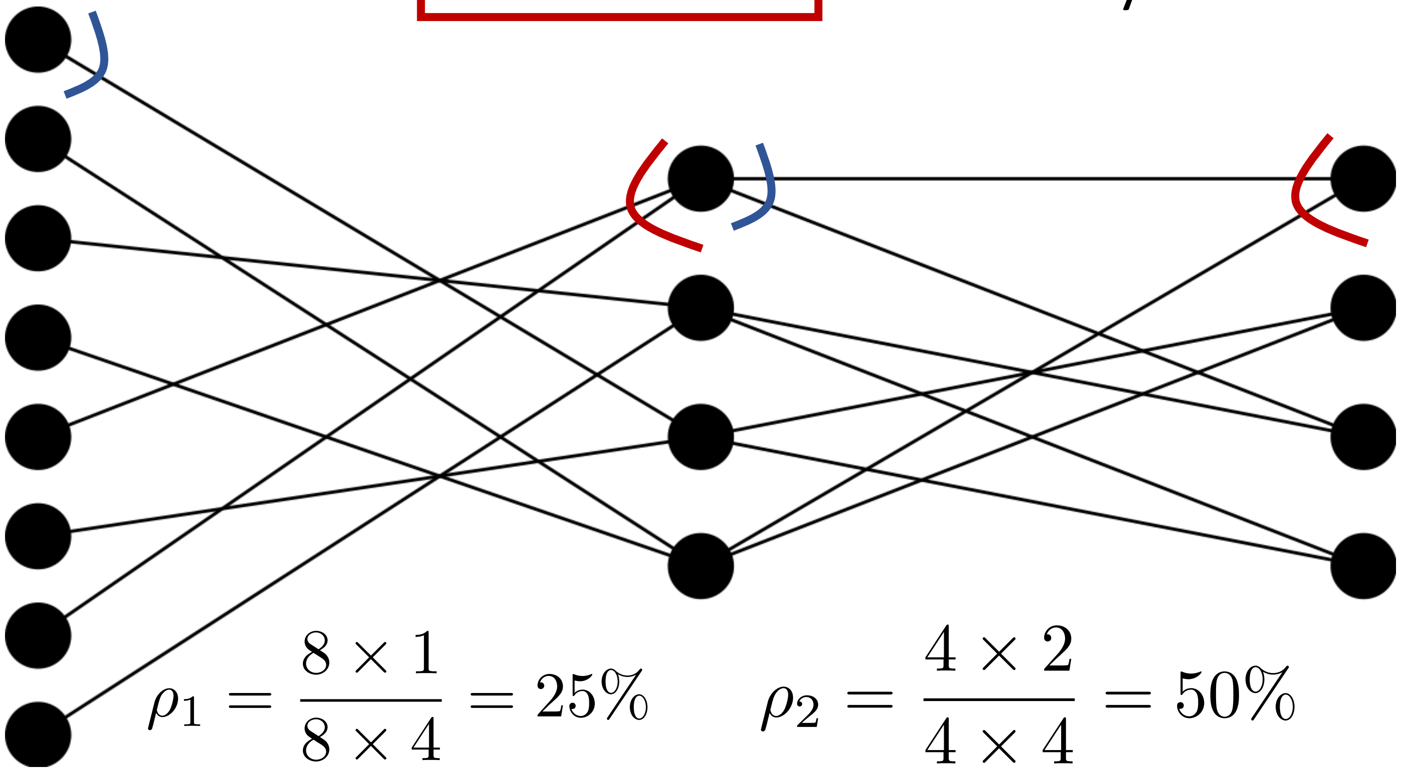
Reduced training *and* inference complexity

$$\boldsymbol{N}_{\text{net}} = (8,4,4)$$

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

$$\boxed{\boldsymbol{d}_{\text{net}}^{\text{in}} = (2,2)}$$

Structured Constraints:
Fixed in-, out-degrees for every node

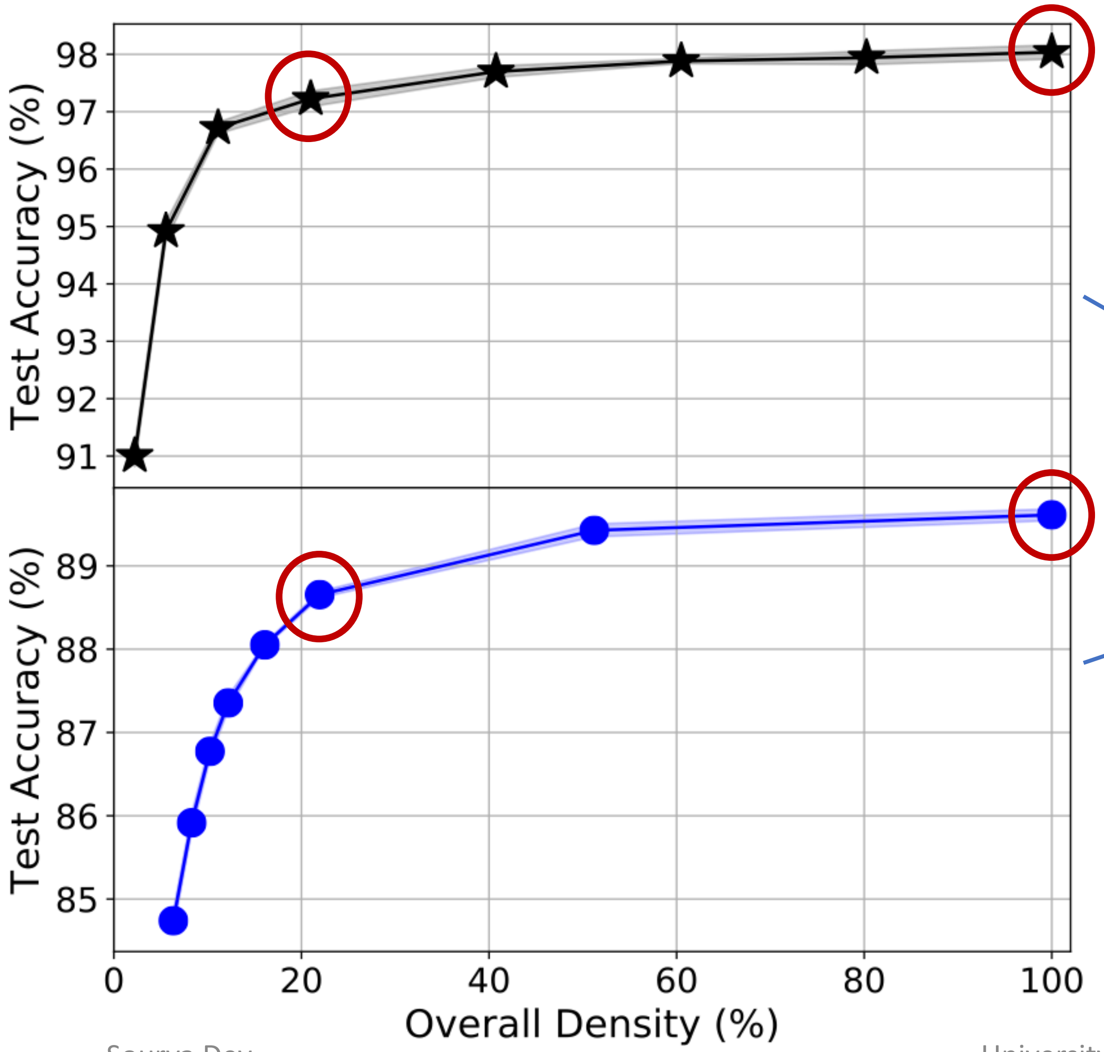


$$\rho_1 = \frac{8\times 1}{8\times 4} = 25\% \qquad \rho_2 = \frac{4\times 2}{4\times 4} = 50\%$$

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

Overall Density compared to FC

Pre-defined sparsity performance on MLPs



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

MNIST handwritten digits

Reuters news articles

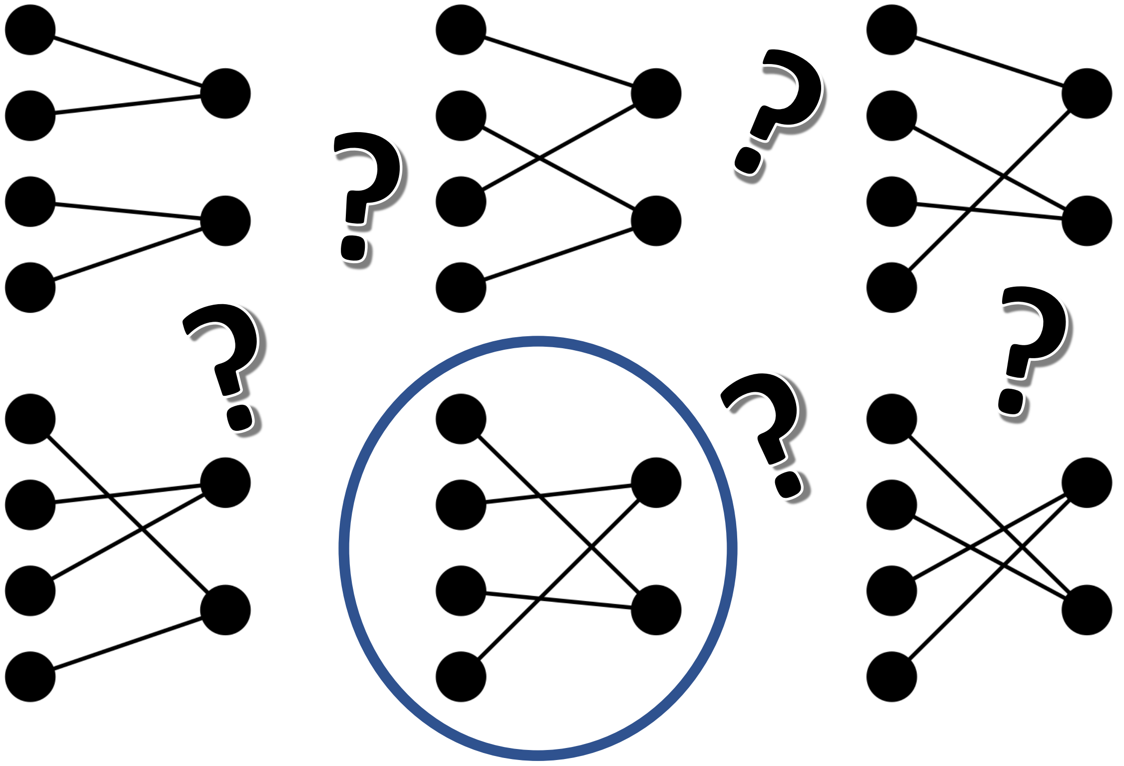
TIMIT phonemes

CIFAR images

Morse symbols

Designing pre-defined sparse networks

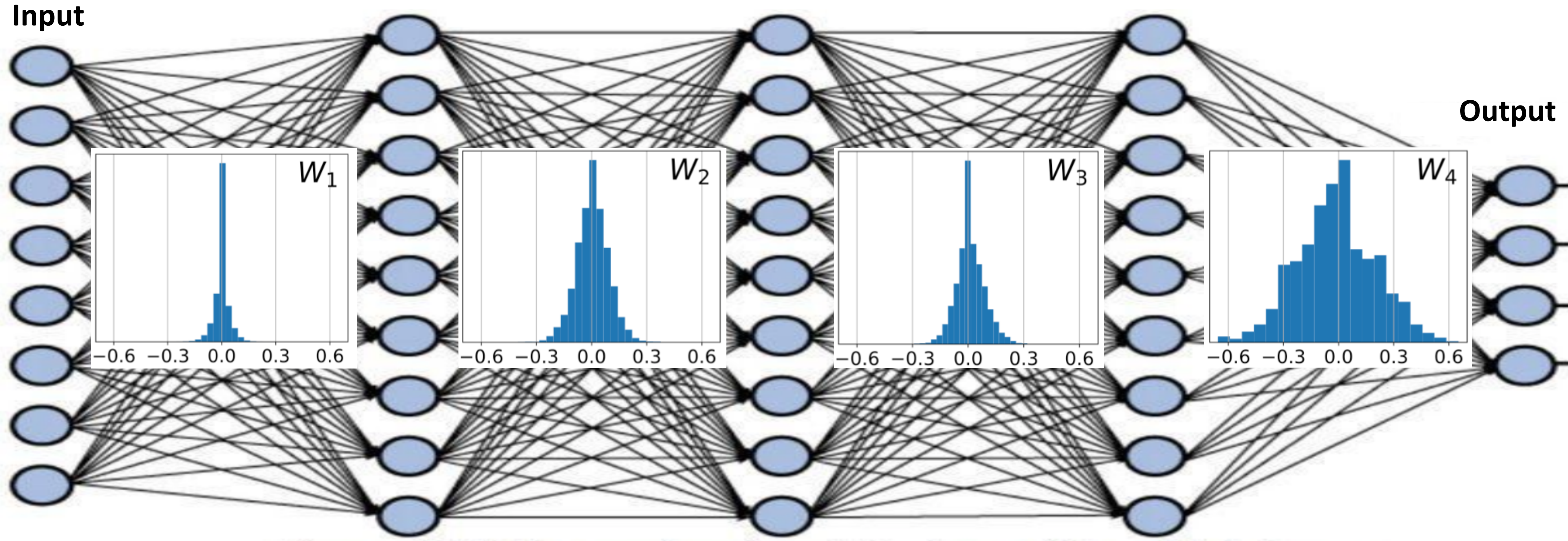
*A pre-defined sparse connection pattern is a **hyperparameter** to be set prior to training*



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.

1. Individual junction densities



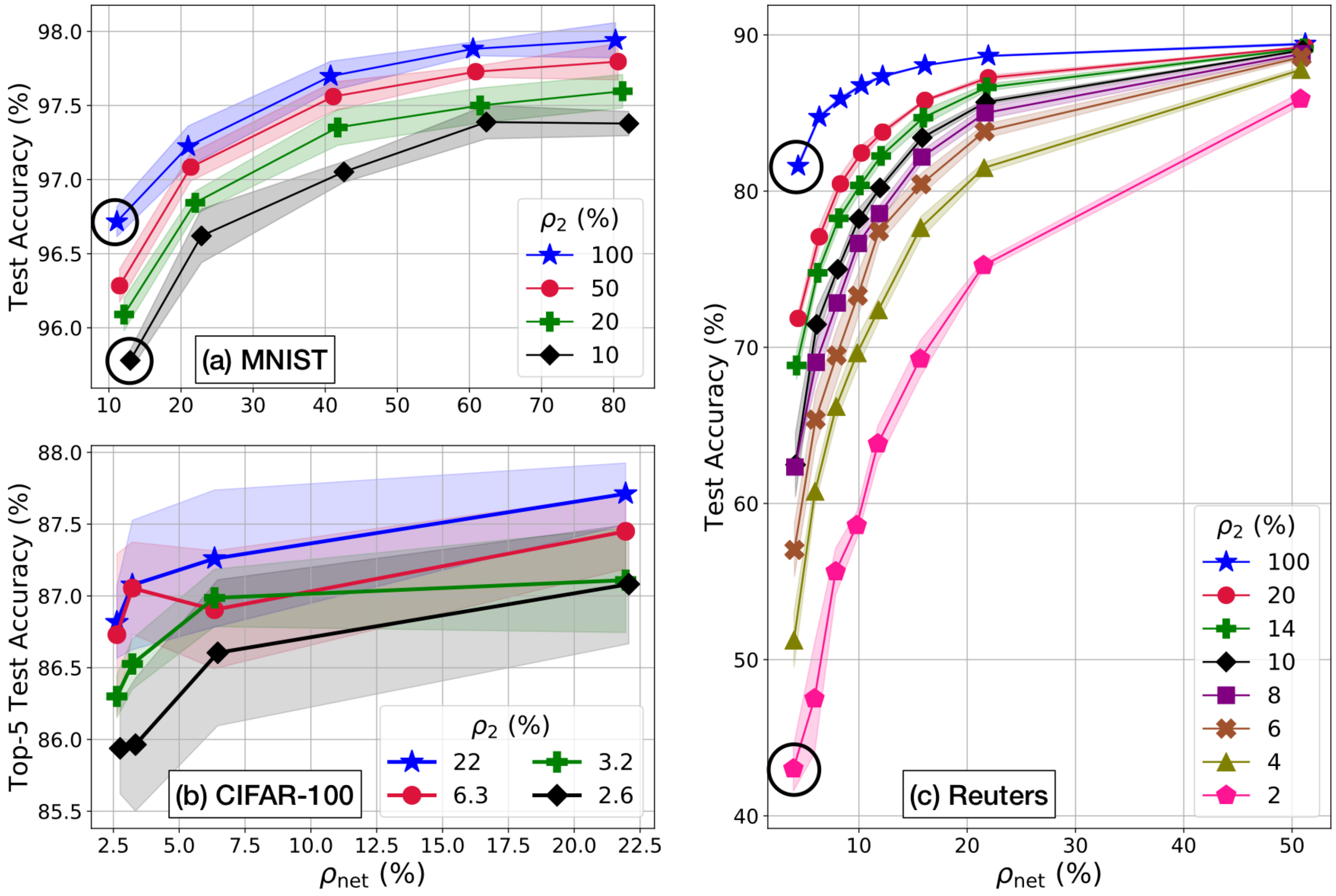
Latter junctions (closer to the output) learn higher-order, more complicated representations => They need to be denser

Results

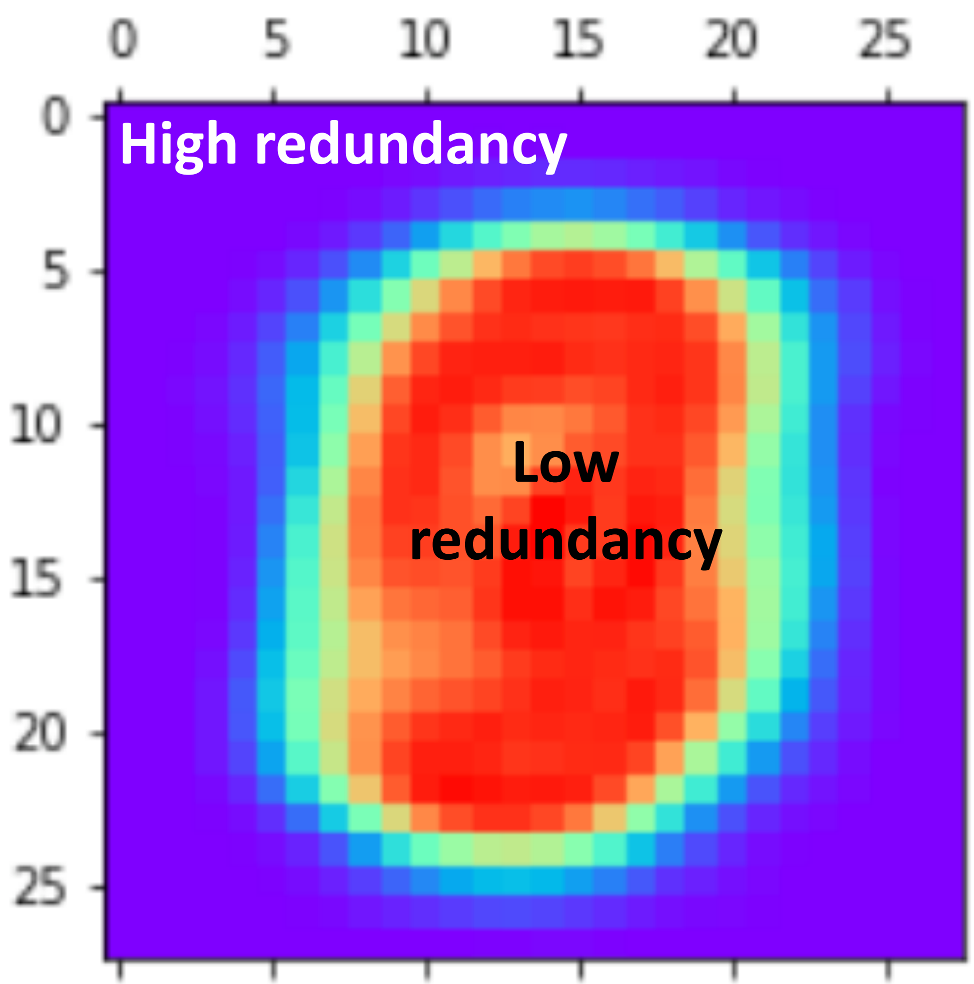
Each curve keeps ρ_2 fixed and varies ρ_{net} by varying ρ_1

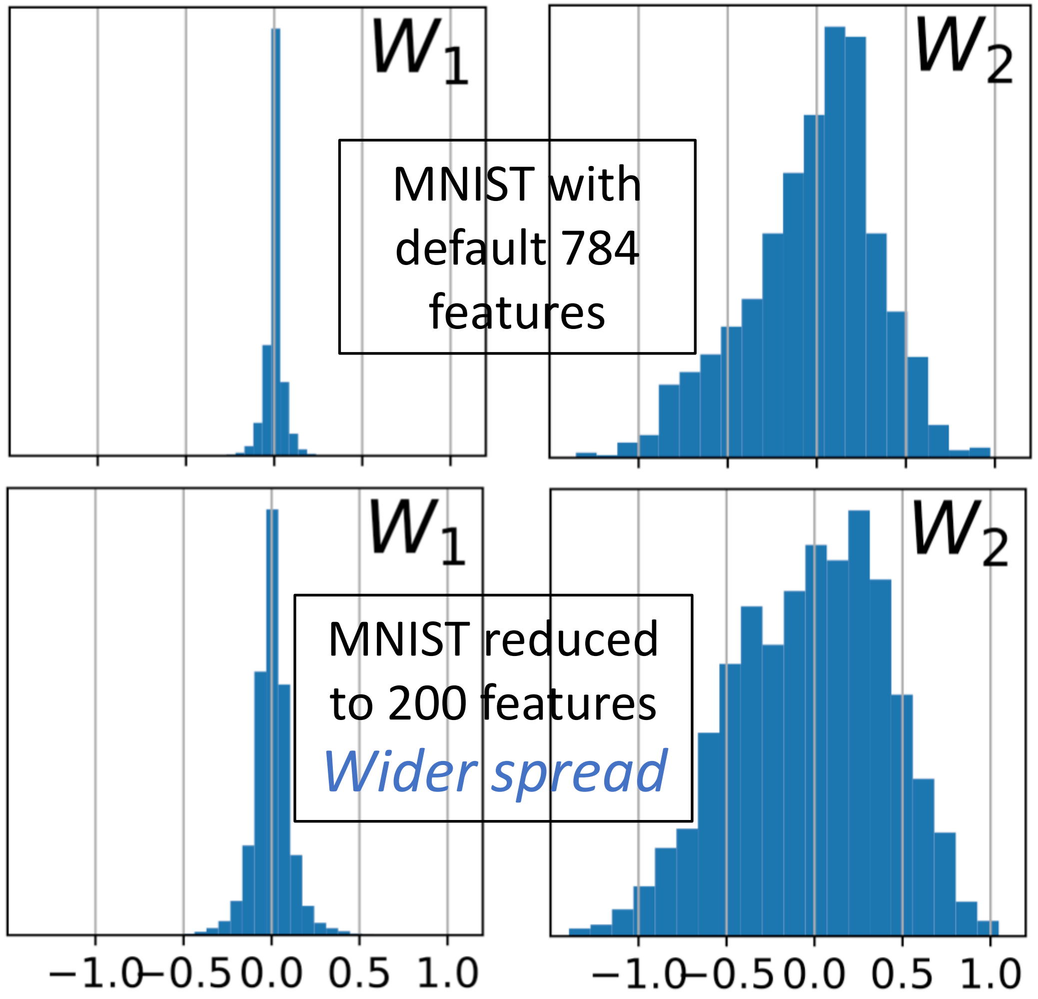
For the same ρ_{net}, $\rho_2 > \rho_1$ improves performance

Mostly similar trends observed for deeper networks



2. Dataset redundancy



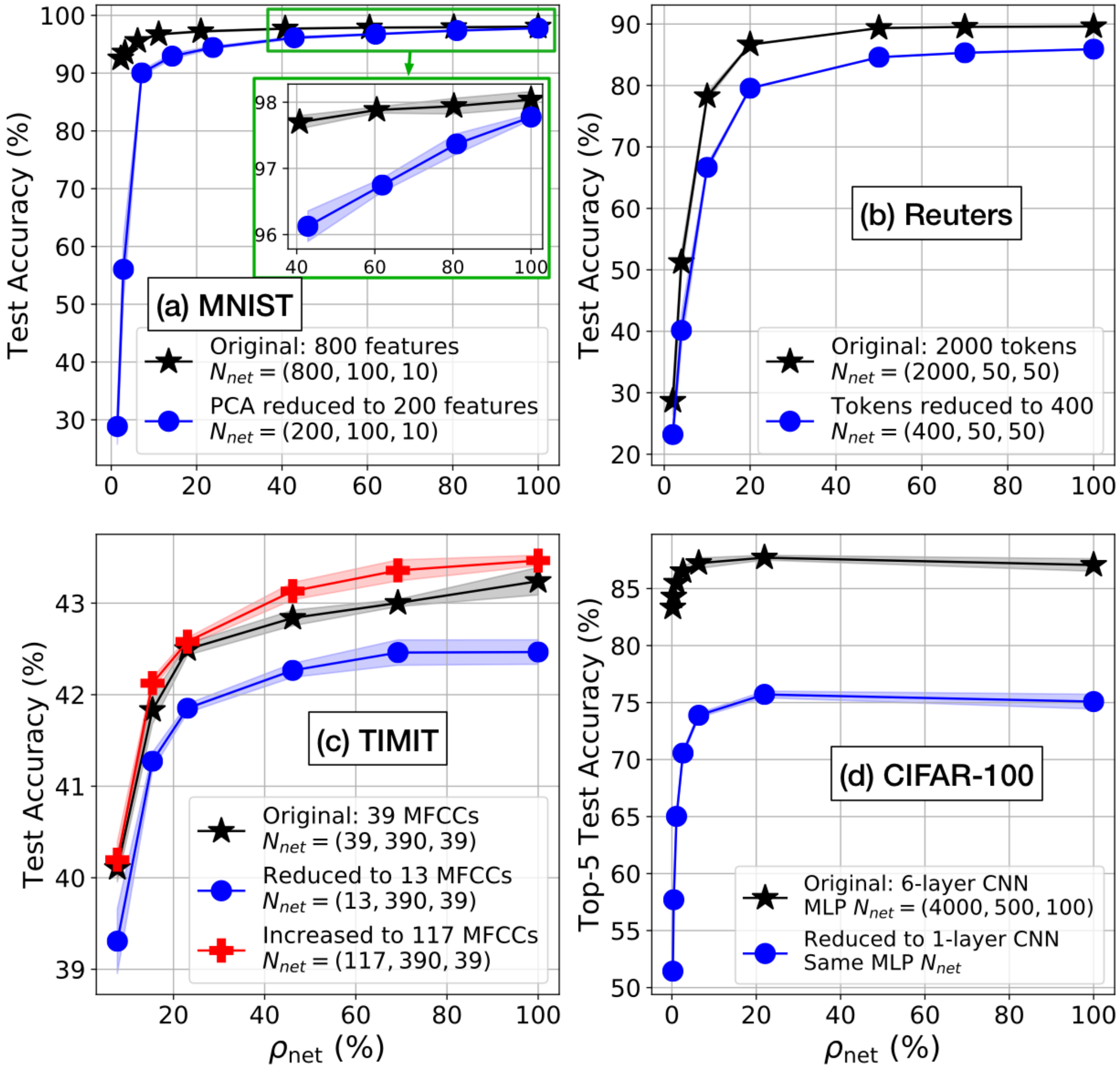


Less redundancy => Less sparsification possible

Results

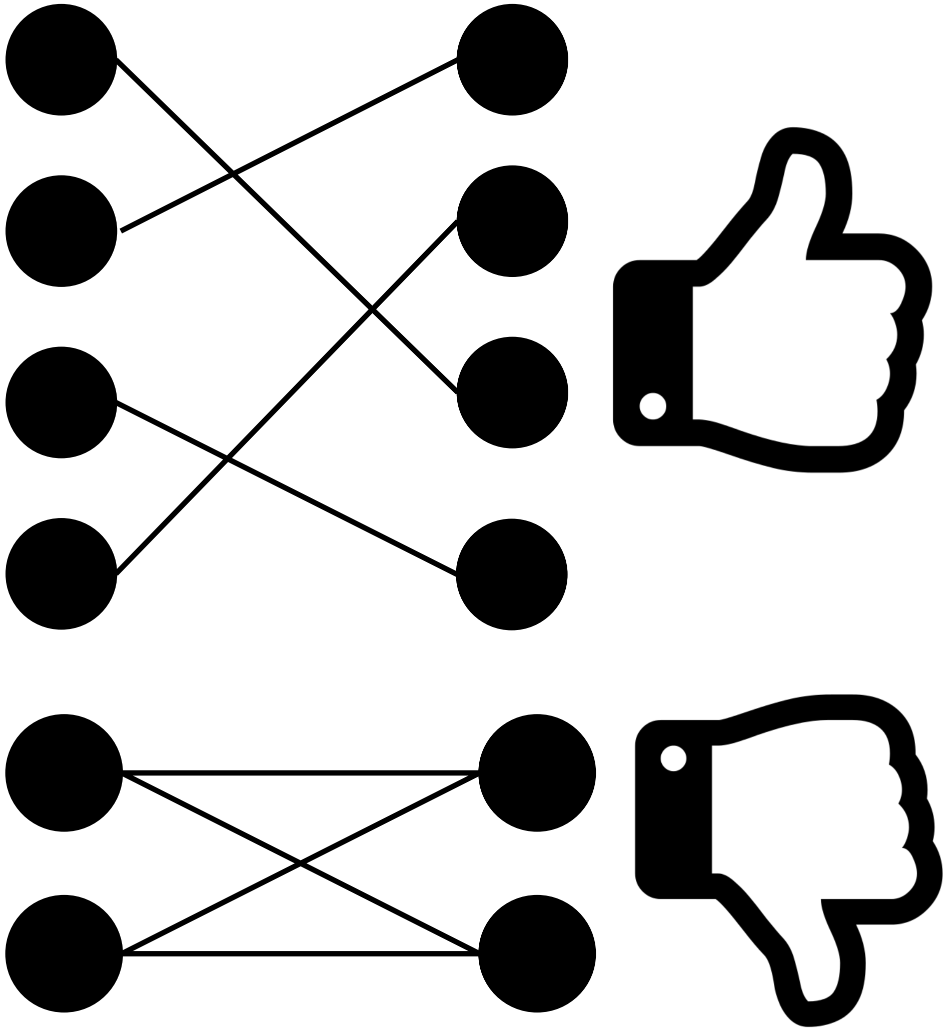
Reducing redundancy leads to increased performance degradation on sparsification

Pre-defined sparse design is problem-dependent



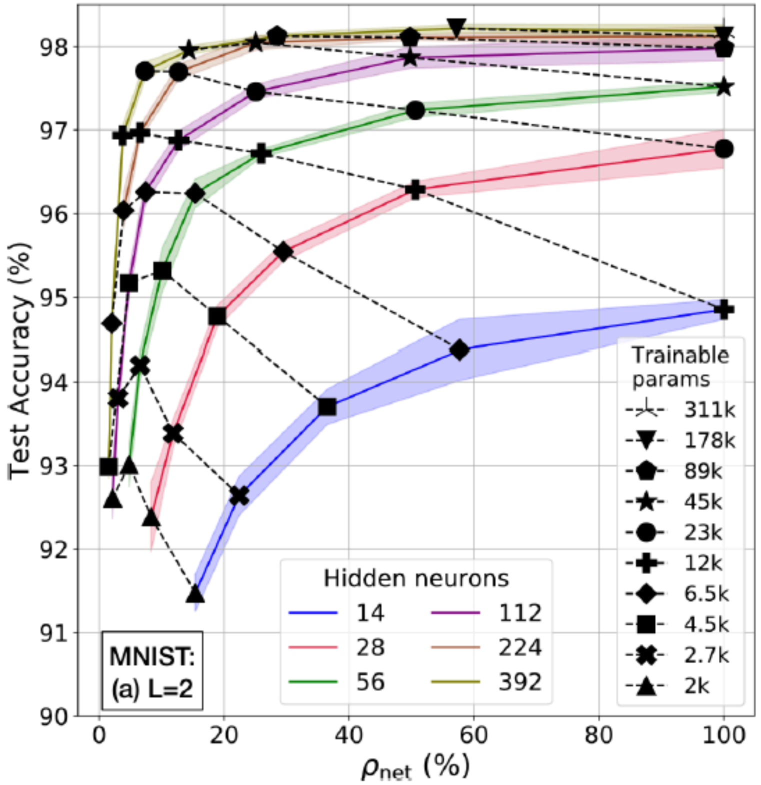
3. ‘Large sparse’ vs ‘small dense’ networks

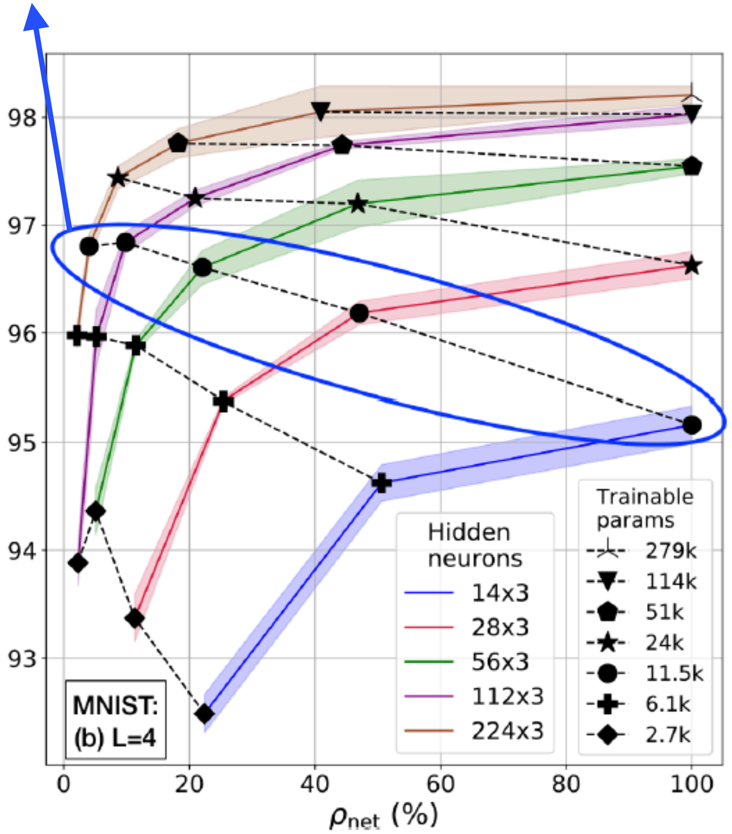
A sparser network with more hidden nodes will outperform a denser network with less hidden nodes, when both have same number of weights

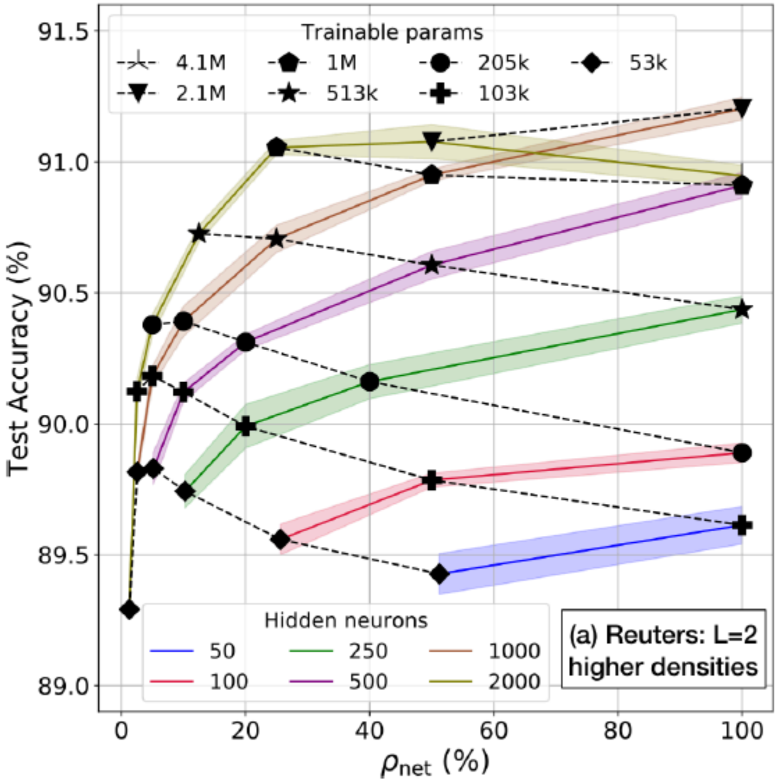


Results

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







4. 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

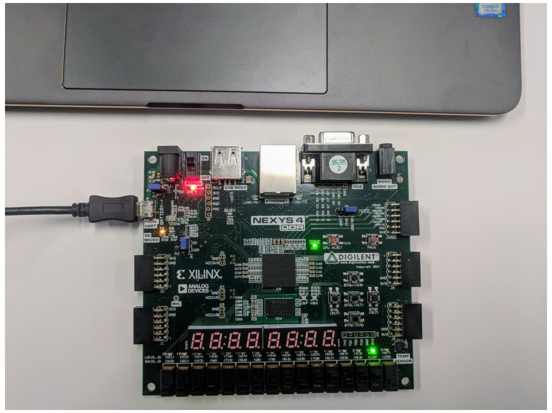
Pre-defined sparse networks need smaller λ (as determined by validation)

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

Applications and extensions of pre-defined sparsity



A hardware architecture for on-device training and inference, prototype implemented on FPGA

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.

Transferred to and currently being developed by team SAPIENT, in collaboration with DTRA and USC Information Sciences Institute (ISI).

W_{11}	W_{12}	W_{13}
W_{21}	W_{22}	W_{23}
W_{31}	W_{32}	W_{33}

Sparsifying kernels / filters in convolutional layers

S. Kundu, M. Nazemi, M. Pedram, K. M. Chugg and P. A. Beerel, “Pre-defined Sparsity for Low-Complexity Convolutional Neural Networks,” in *IEEE Transactions on Computers*, 2020.

Custom sparse libraries in software frameworks

- torch.sparse – Experimental API with room for improvement
- tensorflow.sparse

S. Dey, “Sparse Matrices in Pytorch,” in *Towards Data Science, Medium publication*, 2019. https://towardsdatascience.com/sparse-matrices-in-pytorch-be8ecaccae6

Deep-n-Cheap

Automated search framework to explore performance-complexity tradeoffs in CNN design

Objective

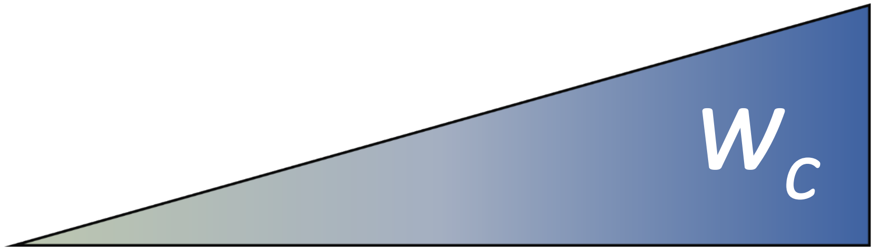
Find networks which optimize performance keeping in mind given complexity constraints

Loss function for search: $f = f_p(\text{Performance}) + w_c * f_c(\text{Complexity})$

1 – val accuracy

Wall clock time to train per epoch

w_c is like regularization



The optimization problem for *f*

Performance and complexity are both functions of overall config:

- Discrete architecture hyperparameters (#layers, type of layer, …), AND
- Continuous training hyperparameters (learning rate, weight decay, …)

Example: $\boldsymbol{x}_i$ = (10 conv layers, 6 batchnorm layers, lr=10^{-3}, weight_decay=10^{-4})

Approaches:

- **Bayesian optimization**
- *Grid search*

Bayesian optimization

Sample $f(\cdot)$ for n initial configs and model via a *Gaussian process*

$$f\left(\boldsymbol{X}_{1:n}\right) \sim \mathcal{N}\left(\underset{n\times 1}{\boldsymbol{\mu}}, \underset{n\times n}{\boldsymbol{\Sigma}}\right) \qquad \boldsymbol{\Sigma} = \begin{bmatrix} k(\boldsymbol{x}_1, \boldsymbol{x}_1) & \cdots & k(\boldsymbol{x}_1, \boldsymbol{x}_n) \\ \vdots & \text{Covariance kernel } k & \vdots \\ k(\boldsymbol{x}_n, \boldsymbol{x}_1) & \cdots & \kappa(\boldsymbol{x}_n, \boldsymbol{x}_n) \end{bmatrix}$$

Calculate *expected improvement* for new configs

$$EI\left(\boldsymbol{x}_{\text{new}}\right) = (\underbrace{f^*}_{\text{Current best}} - \mu)\, \underbrace{P}_{N(0,1)\text{ cdf}}\left(\frac{f^* - \mu}{\sigma}\right) + \sigma \underbrace{p}_{N(0,1)\text{ pdf}}\left(\frac{f^* - \mu}{\sigma}\right)$$

Expensive f evaluations are minimized

Designing the 'ramp' kernel function

Distance $$d\left(x_1, x_2\right) = \omega \left(\frac{|x_1 - x_2|}{u - l} \right)^r$$

Kernel $$k\left(x_1, x_2\right) = e^{-d^2/2}$$

<u>Example: batch_size</u>
Given: l=32 <= batch_size <= u=512

x_1 = 200, x_2 = 100, ω = 3, r = 1

=> k = 0.82

Kernel values for each search parameter are combined to get overall kernel between 2 configs

Search framework

- Step 1 – **Core architecture** using Bayesian optimization
  - Number of convolutional layers
  - Number of filters in each

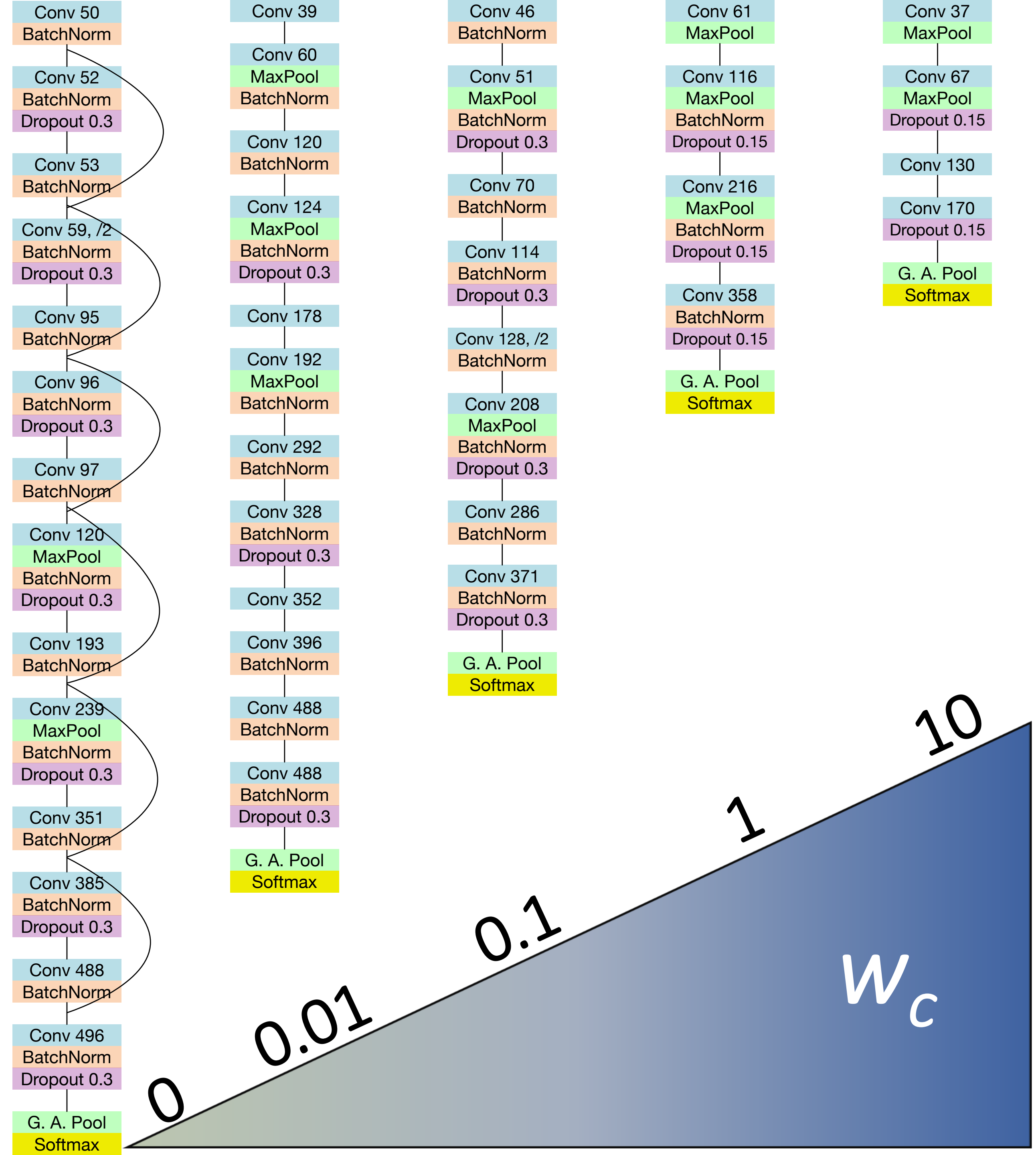
  Combined space

- Step 2 – **Remaining architecture** using grid search
  1. Strides vs max pooling
  2. Batch normalization locations
  3. Dropout locations and probabilities
  4. Shortcut connections

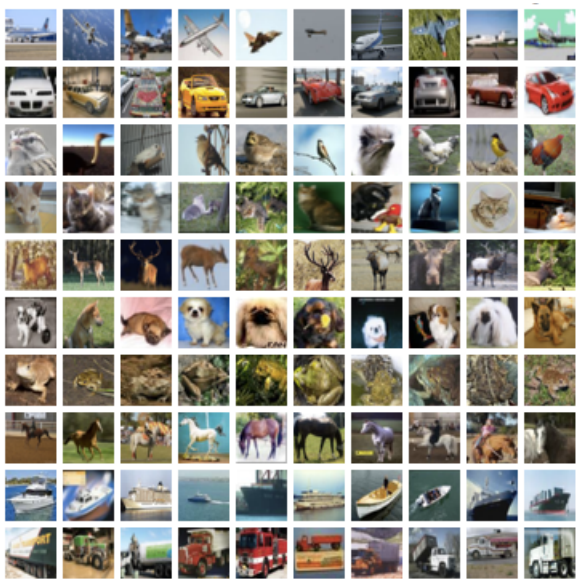
  Sequential, but order can be interchanged

- Step 3 – **Training hyperparameters** using Bayesian optimization
  - Initial learning rate
  - Weight decay
  - Batch size

  Combined space

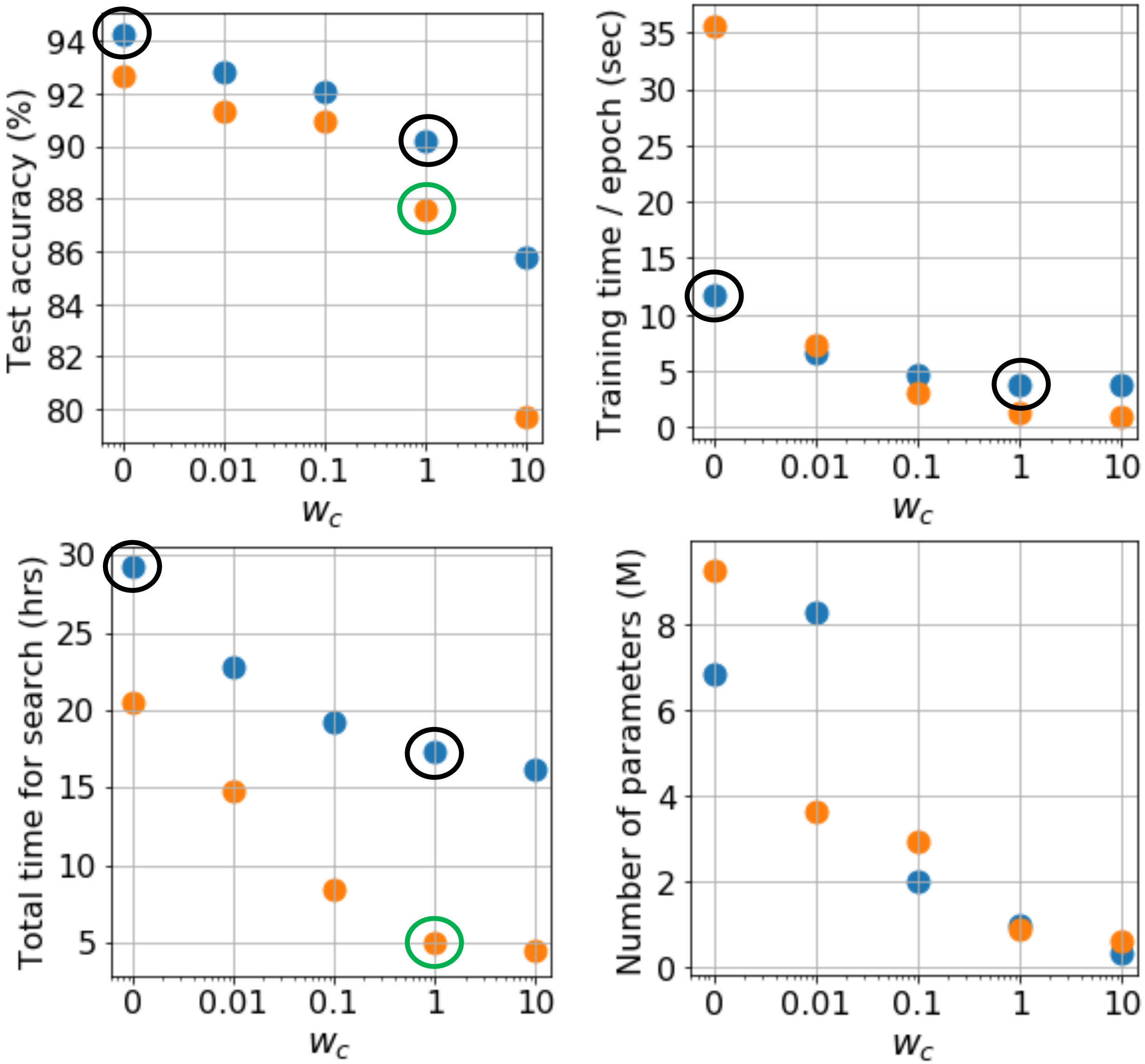


CIFAR-10 Results



w_c	Initial lr	Weight decay	Batch size
0	0.001	3×10^{-4}	195
0.01	0.001	8.3×10^{-5}	256
0.1	0.001	1.2×10^{-5}	459
1	0.003	0	452
10	0.001	0	256

Effect of w_c

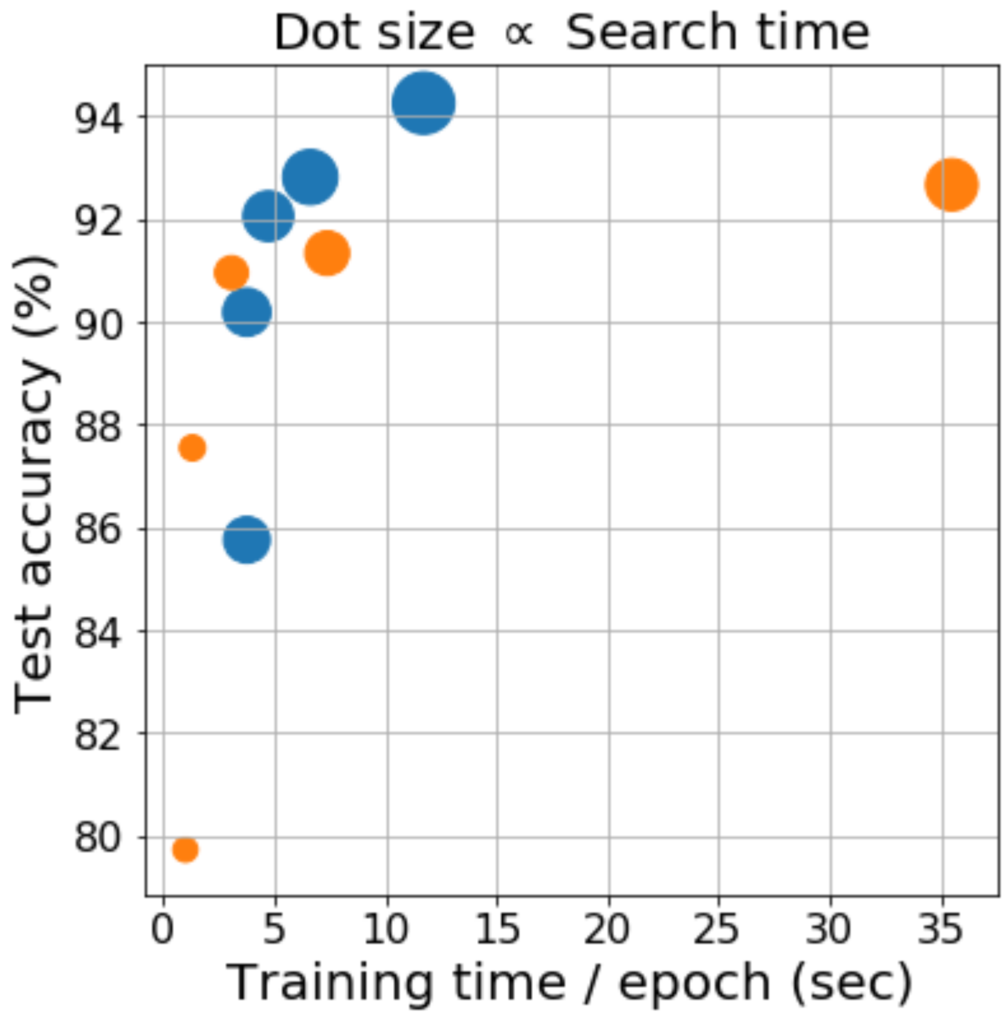


Legend:
CIFAR-10 with basic augmentation – normalization, flips, crops. Incurs data loading overheads!
CIFAR-10 without any preprocessing / augmentation. No data loading overheads!

Some observations:

- *Tradeoffs when switching from w_c = 0 (14 layers) to w_c = 1 (4 layers) :* Per epoch training time reduces by 3X and overall search time by >10 hrs at the cost of 4% performance
- A 5 hr search yields a net with 88% accuracy on CIFAR-10.

Performance - Complexity Tradeoff

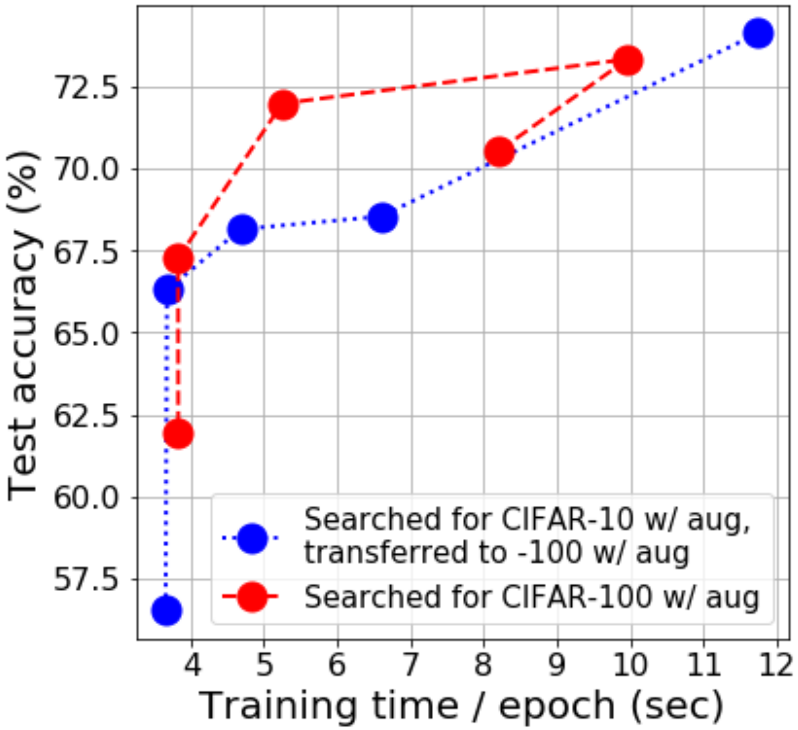


Spend a lot to get that last bit of performance!

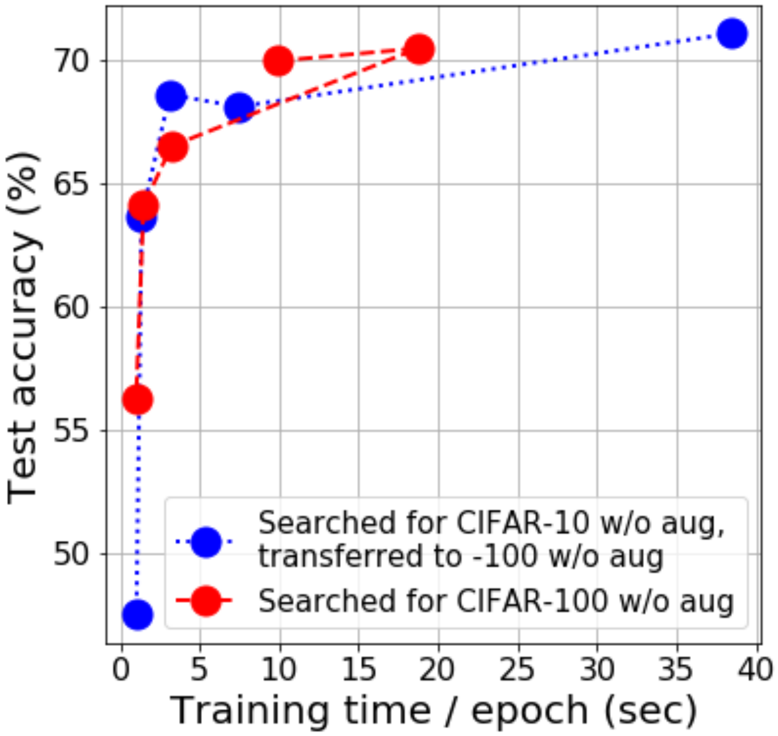
Transfer learning to CIFAR-100

Given a search process optimized for dataset A, how do the best configs perform on dataset B?

In other words, how do they compare with configs from a separate search optimized for B?



Best network for CIFAR-10 performs better on CIFAR-100 than the best network for CIFAR-100!



w_c varies through [10, 1, 0.1, 0.01, 0] along each line

Our upcoming work…

- We will release Deep-n-Cheap as an autoML framework for people to freely use to explore performance-complexity tradeoffs. (*ETA: On Github in April*)
    - Existing frameworks like AutoKeras and AutoGluon are limited in the architectures they search. For example, AutoGluon takes mins / epoch to try >50 layer networks on CIFAR-10.
    - Other existing frameworks like Auto-sklearn and Auto-PyTorch only support MLPs.

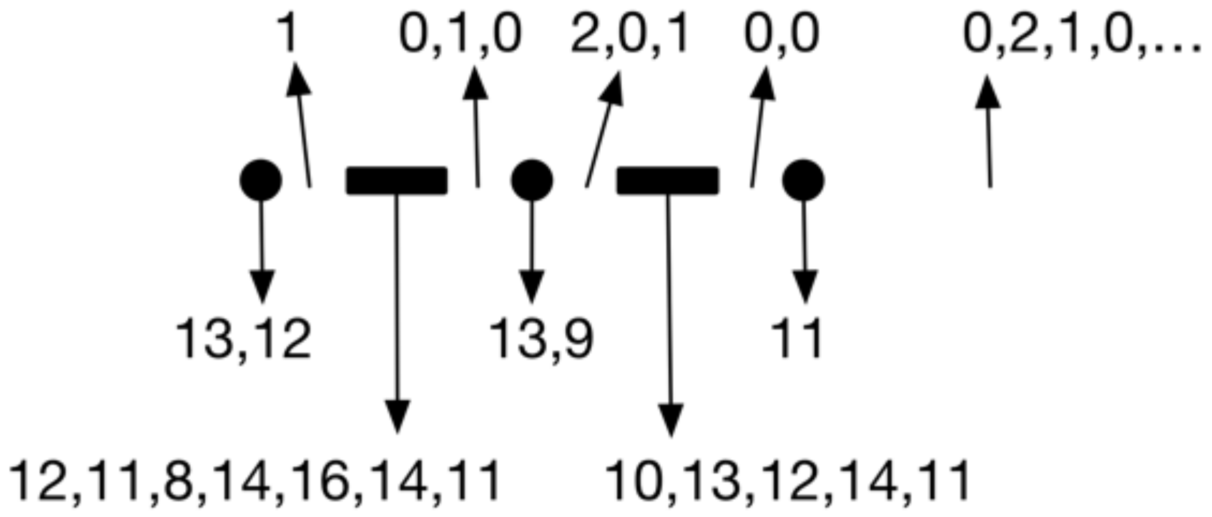
Dataset Engineering

A family of synthetic datasets of customizable difficulty for ML classification problems

Synthetic Datasets on Morse Code Classification

- Inputs: Intensity values for dots, dashes and spaces in Morse codewords
- Outputs: The actual symbol represented by the codeword
- Added features to customize difficulty such as noise and dataset size
- Cheaply generate large quantities of data

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



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... and others

Thank you!

I'll graduate soon and plan to conduct postdoctoral research

https://souryadey.github.io/