Can we learn **compact** Neural Network Architectures, in a way that is **general purpose**?

Learning Compact, General Purpose Neural Network Architectures

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Introduction

In this work, we propose a unique approach to learning neural network architectures, by attempting to learn **compact, problem agnostic architectures.**

We hypothesize that the performance of sparse neural networks are not dependant on specific connections, but rather on the **number of connections** (weights), which define their capacity.

Motivation

- Current Methods → Primitive, limited by our biases.
- Wrong Focus → Optimizing weights θ, correct architecture f?
- Architectures → Extremely complicated.

Problems - Current NAS Methods

- **Computationally intensive** & **millions of parameters** [2,4,5].
- Still require **domain engineering** [4,5].
- **Restrictive search space** - only convolutional layers [1,2,3,5].

Methodology

1. Define a concept called **Density** - percentage of active weights in a layer.
2. Allow specification of a **maximum depth** and **width** of a neural network and learn an efficient architecture within those bounds.
3. Use **Random Search** and **Bayesian Hyperparameter** optimisation to find the correct architectures using the above mentioned search space.
4. Use performance estimation techniques to **efficiently estimate** the performance of similar architectures.

References

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3. Suganuma, M., Shirakawa, S., and Nagao, T. (2017). A genetic programming approach to designing convolutional neural network architectures. In Proceedings of the Genetic and Evolutionary Computation Conference, pages 497–504. ACM.
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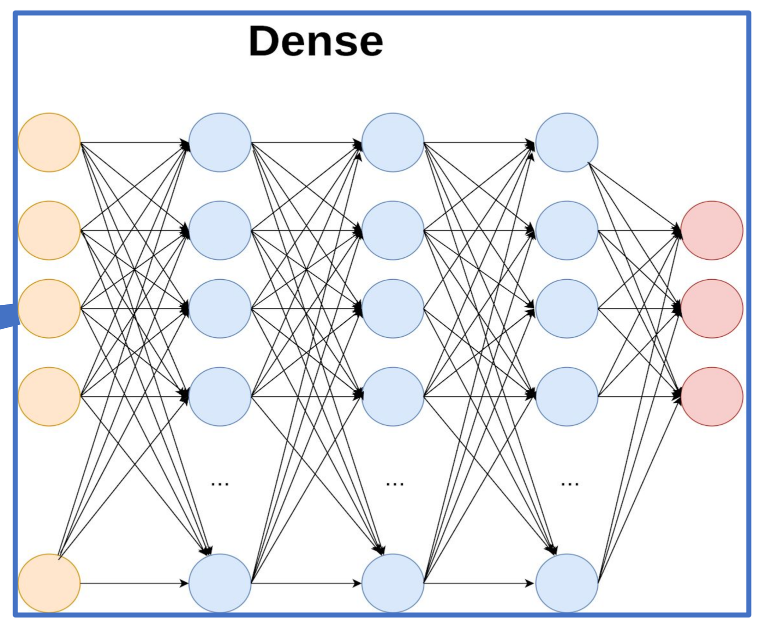
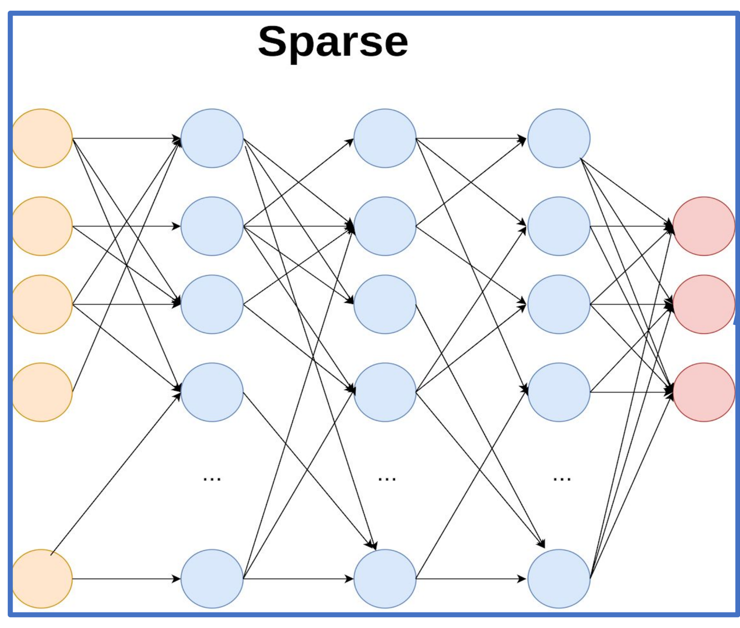
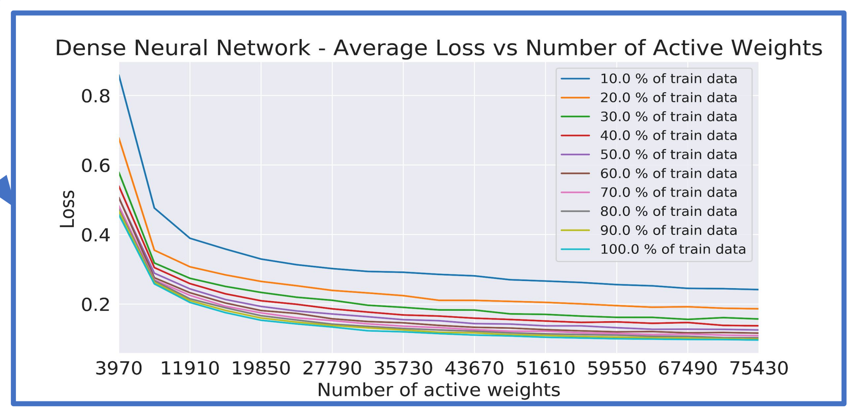
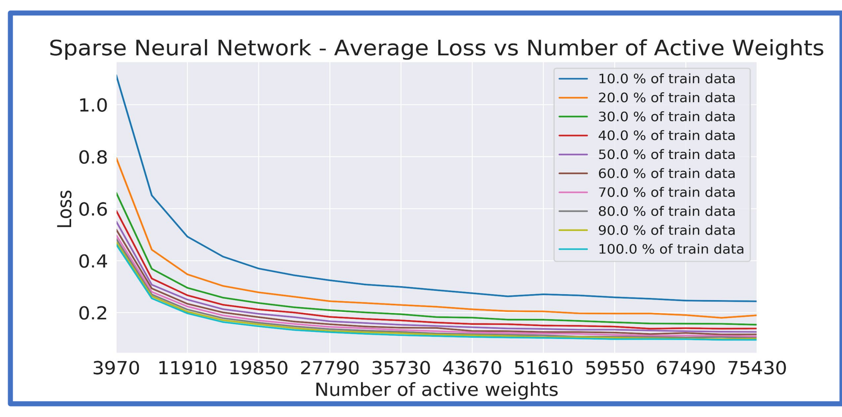
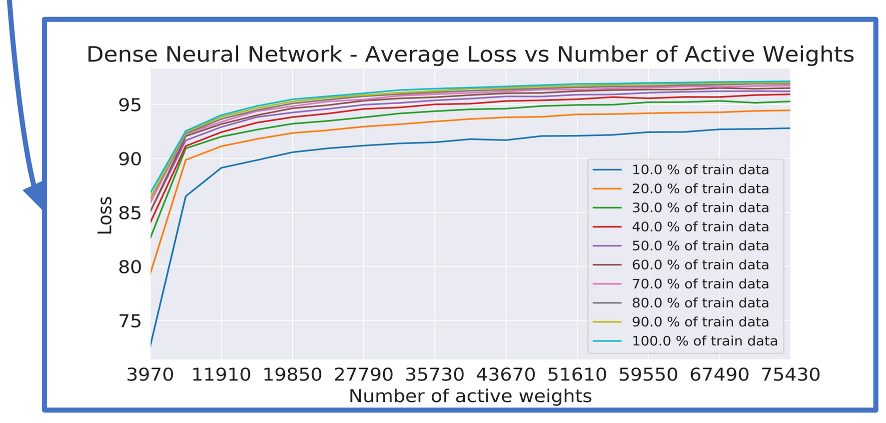


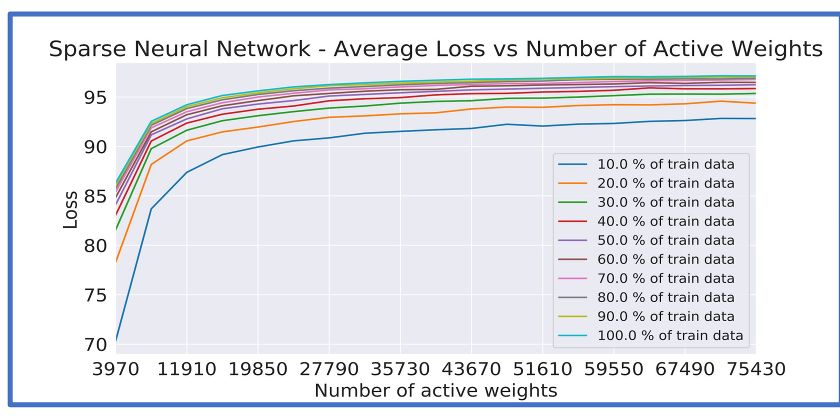




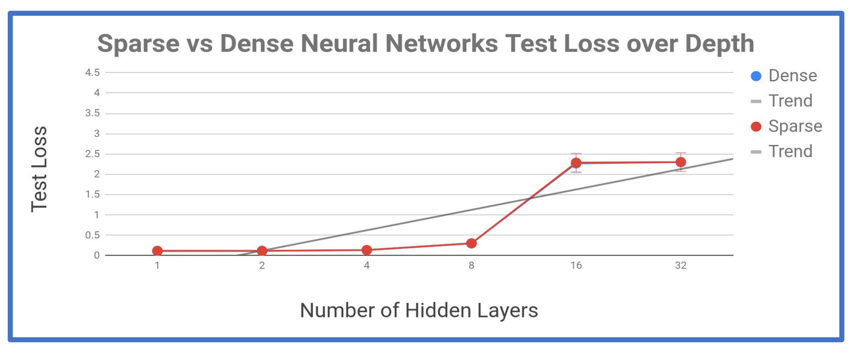


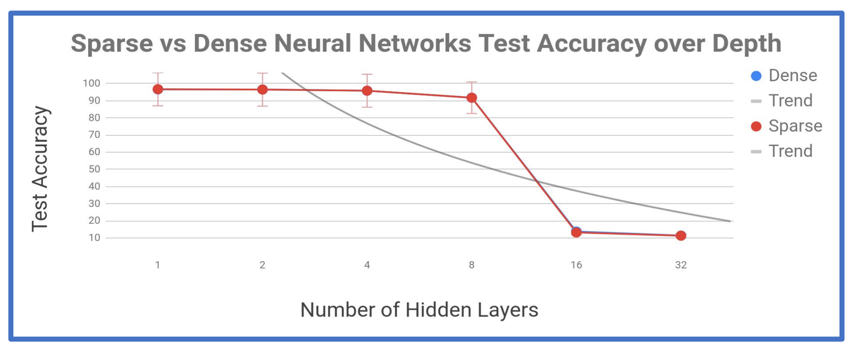
1. Similarity of Dense and Sparse Networks with 1 hidden layer.



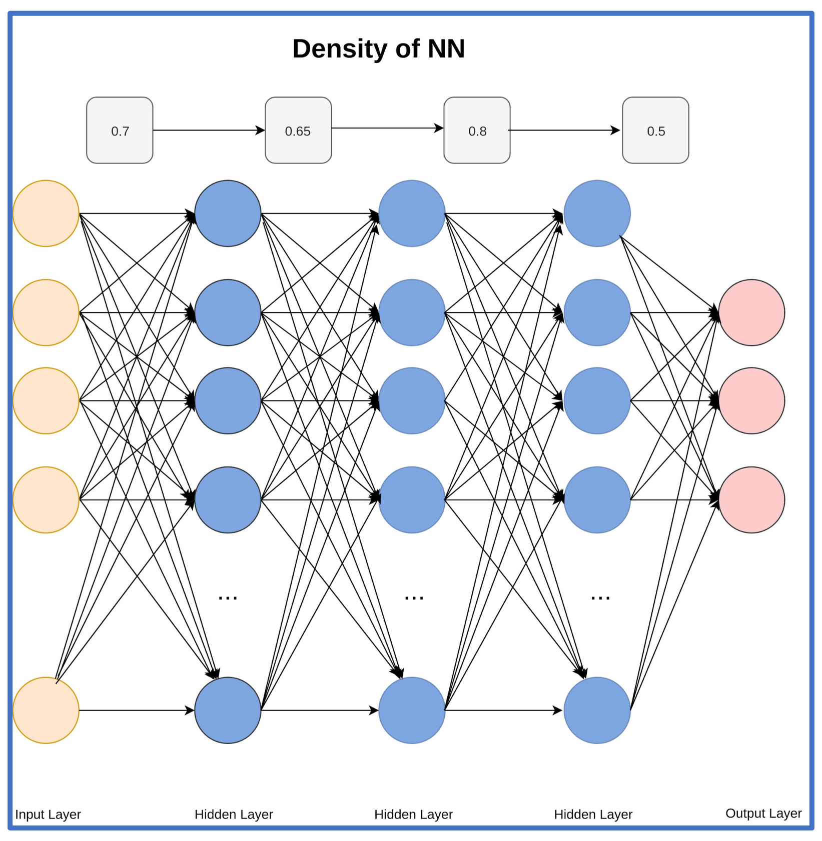


2. Similarity of Dense and Sparse Networks with 1 - 32 hidden layers.





3. Define Density.



4. Results achieved via Random Search.

Results - Mnist

- **97.86%** Accuracy.
- **0.072** Test Loss.
- Approx. **60 000 active weights**.
- **No tuning of non-architectural hyperparameters!**

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