Opening the Black Box of Deep Neural Networks via Information

A paper by Ravid Schwarz-Ziv and Naftali Tishby

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Outline

Background

Motivation for the Paper

- There hasn't been a clear reason why deep neural networks **are generalizing** as well as they do.
- *DNNs* don't seem to have an overfitting problem.

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- There hasn't been a clear reason why deep neural networks **are generalizing** as well as they do.
- *DNNs* don't seem to have an overfitting problem.
- ...and there's a paper specifying a **maximal learning bound** named the **information bottleneck** for neural networks, written by the same *Tishby* as the paper presented here.

Theory – Machine Learning

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- In other words, trying to reproduce or *reverse-engineer the function* that would output the same results that exist in the data the algorithm is given.

Theory – Information Theory

- Aims to measure how much information can a **thing** (yes, everything) contain.
- Specific implementations include error correction, compression, RNGs and cryptoanalysis.

Theory – Information Theory – Mutual Information

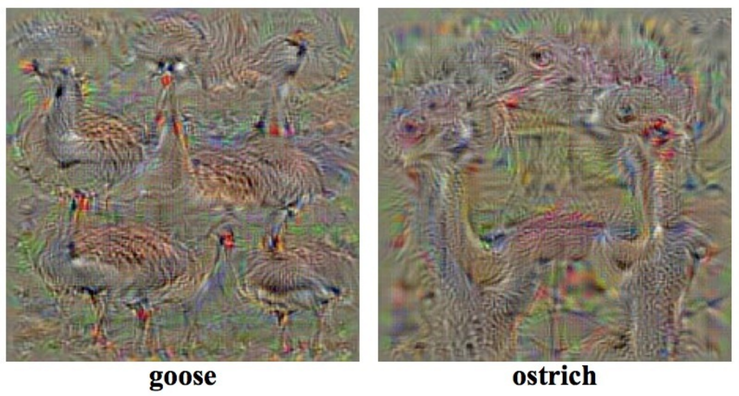
$$\mathrm{I(x,y)} = \sum_{x,y} P(x,y) \ln \frac{P(x,y)}{P(x)P(y)}$$

- Mutual information is defined with two entropies, shannon entropy and conditional entropy.
- It is a very robust *measurement of similarity*.

Looking at Neurons

- Last layer weights of a network – Closest representations of the classes
- In bigger networks, weights are somewhat recognizable. For example, in the case of Google's deep dream, they feed the network back the weights of the last neuron representing a dog, *and get snouts and drooping tongues everywhere*.

Looking at Neurons



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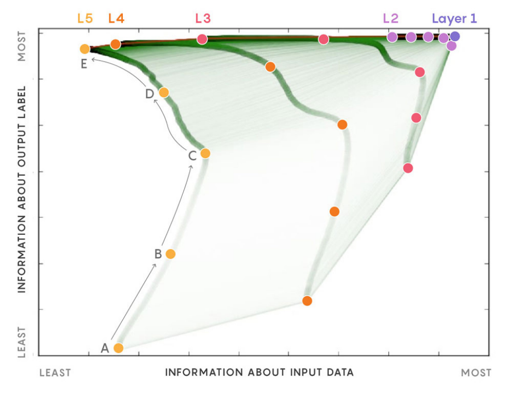
Looking at Neurons

- By iterating through a number of layers with filters, you **lose data on every one**.
- So what's basically happening is lossful compression of the whole input data!

Findings

Best-case Scenario

1. Network copies the training data, gaining information of the data and the labels
2. When the gradient gets smaller and smaller it starts to slowly lose information of the original training data, compressing the representation!



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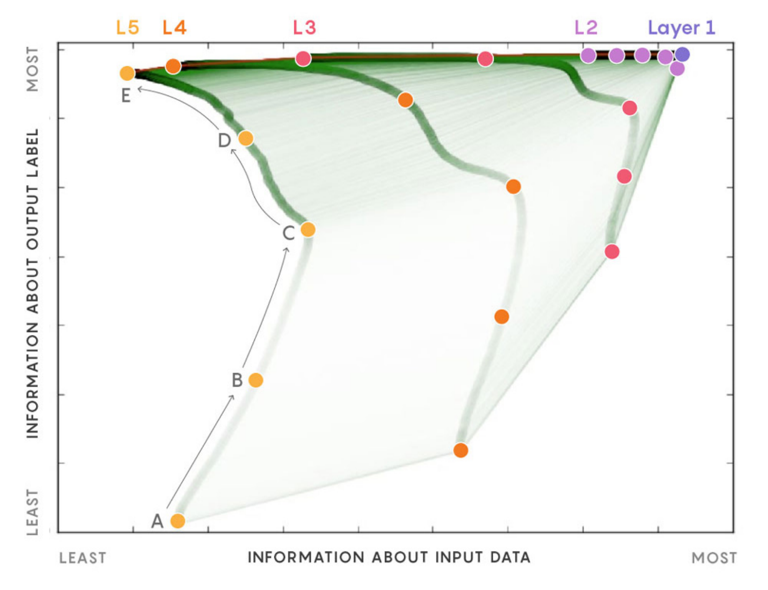
Best-case Scenario



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Video Time

Animation of the training progress in the information plane [2]

Why Does the Phase Change Happen?

- Stochastic gradient descent adds noise to the signal after a shallow gradient is reached.

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- This noise effectively *wipes out the irrelevant information* of the class, **compressing** the representation by relaxing the weights.

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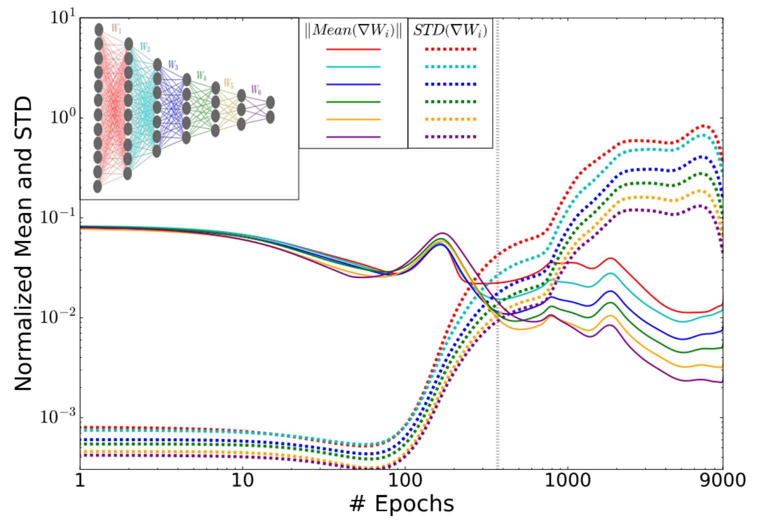

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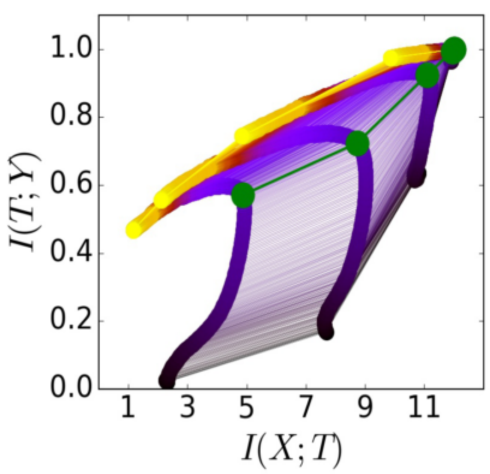
Training Gone Wrong

- The network copies the data well, but fails to generalize because it starts to lose information on the labels when compressing the representation on **shallow gradients**.
- Case: Too little data.



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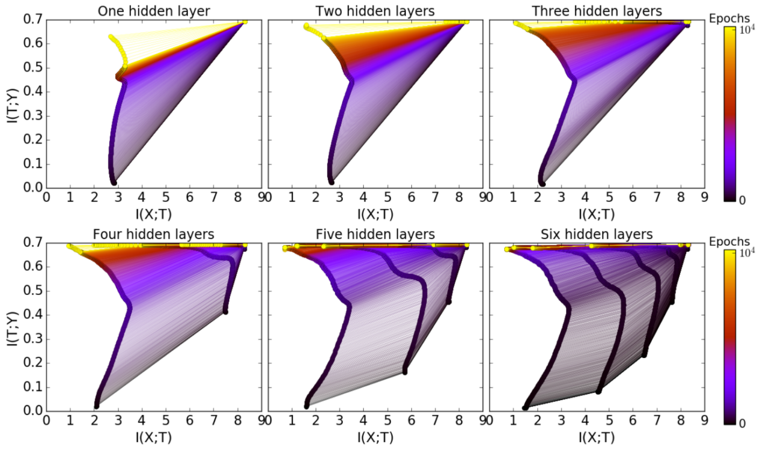
More Layers = Better Performance AND Speed



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- The paper helps us better understand with intuition and theory, what happens during training in modern neural networks.
- This might help us to define better hyperparameters (learning rate and such) for the network beforehand.
- In addition, the information bottleneck bound could be helpful in deciding if you need more data or a better network for a task.

Appendix

Sources i

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Opening the Black Box of Deep Neural Networks via Information
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