Advanced Machine Learning

Paper: Shwartz-Ziv et al., *Opening the Black Box of Deep Neural Networks via Information* [5, 6, 7]

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Overview

1. Background
2. Opening the black box
3. Discussion

Overview

- **Information**

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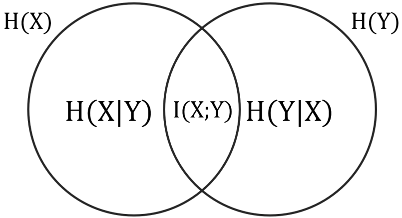
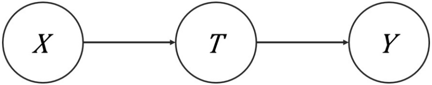
- **Mutual Information**

$$I(X;Y) = H(X) - H(X|Y)$$



- **Digital Processing Inequality:**

For a Markov Chain of the following form,



the inequality $I(X;T) \geq I(X;Y)$ is valid.

- **Minimal Sufficient Statistics:**

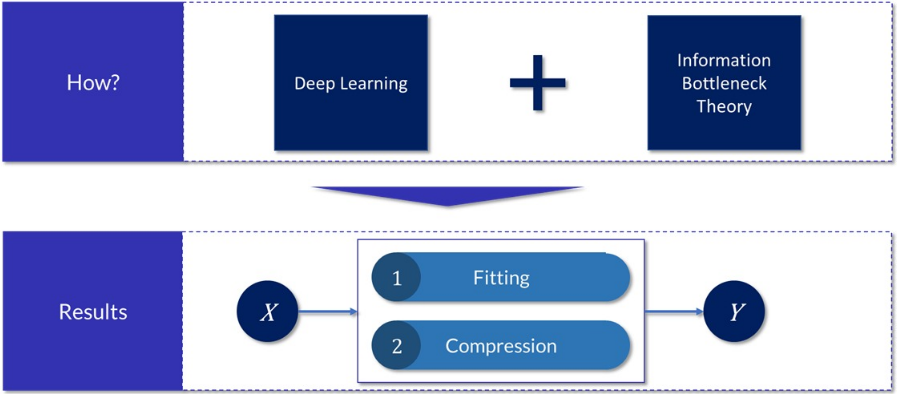
$$T(x) = \underset{S(X):\, I(S(X);Y) = I(X;Y)}{\arg\min} I(S(X);X)$$

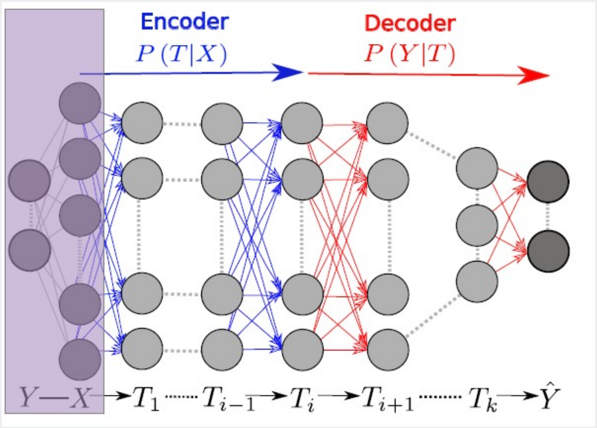
which can be rewritten with as the following Lagrangian,

$$\min_{p(x),p(y|t),p(t)} I(X;T) - \beta I(T;Y)$$

Overview

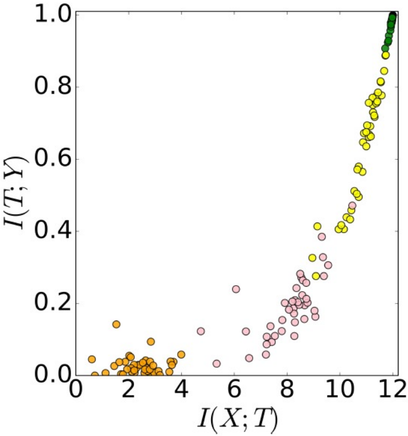
Opening the black box
Main idea



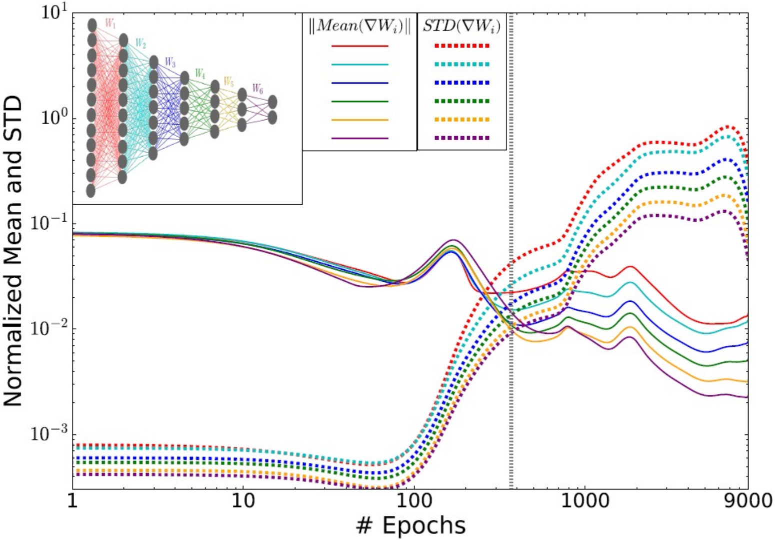


$$\text{Supervised Deep Learning} \stackrel{?}{=} \min\{I(X;T) - \beta I(T;Y)\}$$

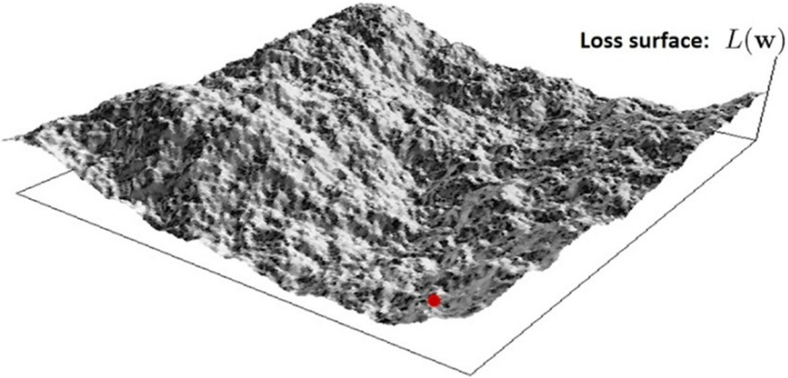
- Information plane (video)



Opening the black box
Norm and Variance of Gradients



Continuing SGD in local minima can be modelled as a Random Walk!



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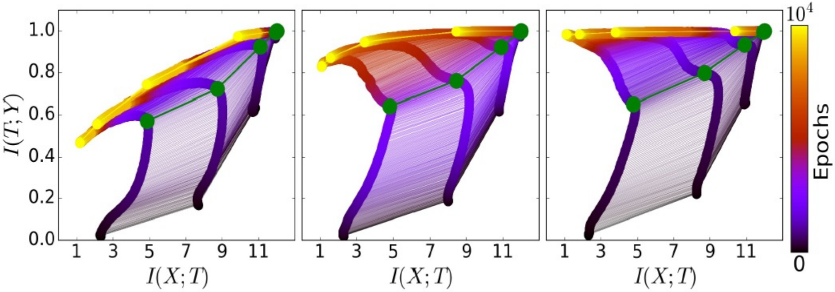
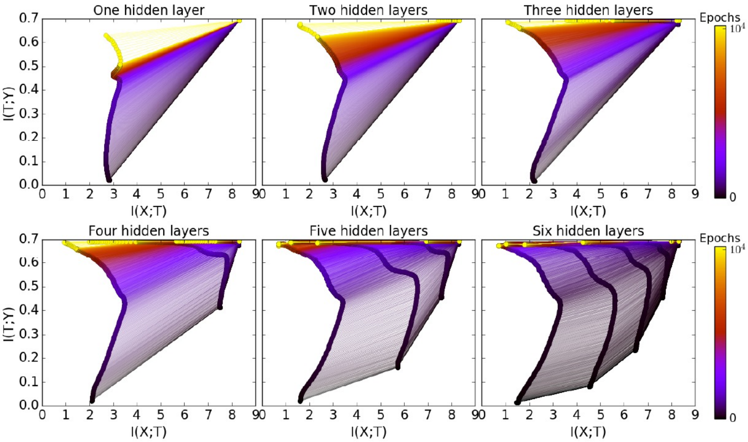
$\Rightarrow$ Minimizes $I(X;T_i) = \underbrace{H(X)}_{constant} - H(X|T_i)$

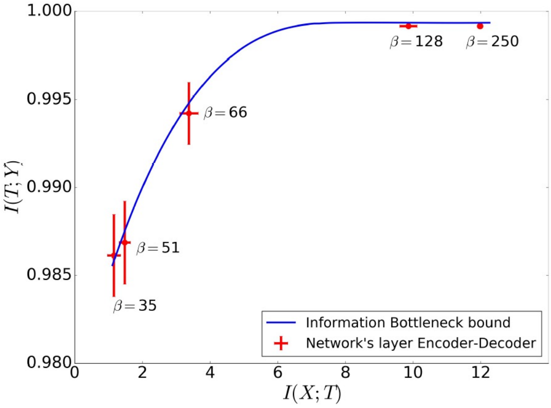
- Evolution in the information plane, for different training sample sizes. From left to right (5% of the data, 45% of the data, 85% of the data).





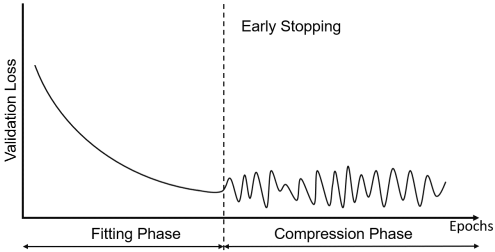
$$\text{Why?} \Rightarrow \boxed{exp(\sum_k \Delta I_X^k) \gg \sum_k exp(\Delta I_X^k)}$$

$$\text{Supervised Deep Learning} \approx \min\{I(X;T) - \beta I(T;Y)\}$$



Opening the black box
Summary

- Fitting then Compressing
- Overfitting = Overcompression
- Noise of SGD $\Rightarrow$ Generalization
- Do we need to adapt *Early Stopping* method?



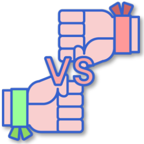
Overview

Discussion

Controversy

Advocates

- New MI estimators [3,6]
- Relationship with VAE [2]
- Train longer, Generalize better [4]



Detractors

- Saxe et al. [5]
- Hard to reproduce results

Pros:

- ✓ New insight of how DL works
- ✓ Led to various applications [1, 2]
- ✓ Justified Mathematically
- ✓ Available code

Cons:

- × Estimating MI is computationally expensive
- × Not tested on non-saturating functions and large networks
- × No verification of the results on challenging datasets

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