



Recent Advances in Understanding and Interpreting the DNNs

Erfan Loweimi^{*} and Samira Loveyemi[†]

^{*} Research Associate, King's College London (KCL)

[†] Adjunct Lecturer, Shahid Chamran University of Ahvaz

Motivation ...

- Why is understanding DNNs important?

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 - Reliable validation → Safer practice
 - E.g., self-driving car ... no margin for error

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 - Reliable validation → Safer practice
 - E.g., self-driving car ... no margin for error
 - Extract new insights → Better practice
 - E.g., more efficient training ... with less data

Outlines

- Information Bottleneck
- Over-parameterisation and Generalisation
- Interpretation/Visualisation of Filters/Activations

Outlines

- Information Bottleneck *Why do DNNs generalise well?*
- Over-parameterisation and Generalisation
- Interpretation/Visualisation of Filters/Activations

Outlines (Part I)

- Information Bottleneck
- Over-parameterisation and Generalisation
- Interpretation/Visualisation of Filters/Activations

Information – Definition

- Information \equiv Average Surprise
- Information ... ≥ 0 , $\propto 1/P$, additive for independent RV*s

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$$H(X) = \mathbb{E} \left[\log \frac{1}{P(x)} \right] = \sum_{x \in \mathcal{X}} P(x) \log \frac{1}{P(x)}$$

Information – Definition

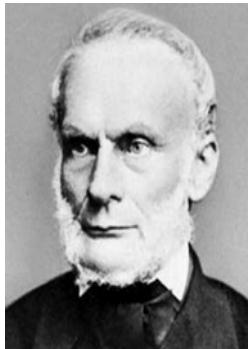
- Information \equiv Average Surprise
- Information ... ≥ 0 , $\propto 1/P$, additive for independent RV*s
- Quantitatively measured by **Entropy**

$$H(X) = \mathbb{E} \left[\log \frac{1}{P(x)} \right] = \sum_{x \in \mathcal{X}} P(x) \log \frac{1}{P(x)}$$

Entropy

Entropy over Time

R. Clausius



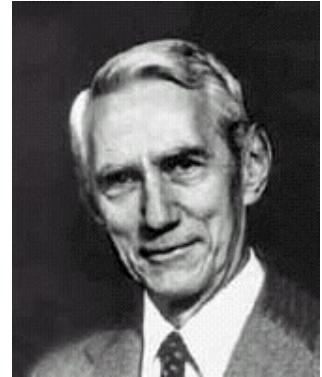
L. Boltzmann



J. Gibbs



C. Shannon



$$dS = \frac{dQ}{T}$$

$$S = k_B \log W$$

$$S = -k_B \sum_i p_i \log p_i$$

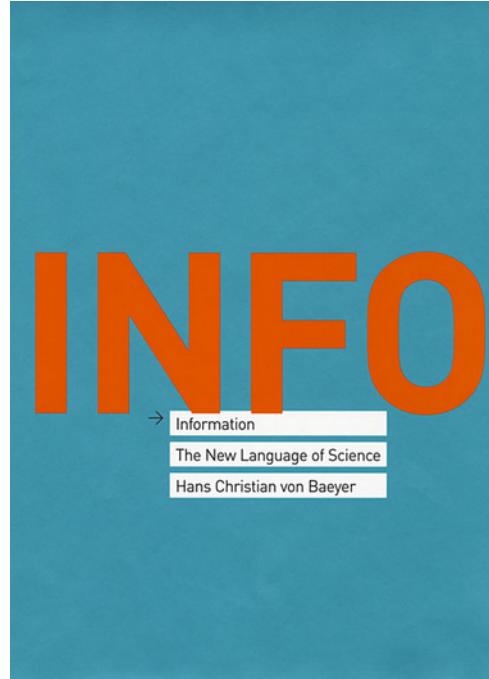
$$H = - \sum_i p_i \log_2 p_i$$

1865

1870

1876

1948



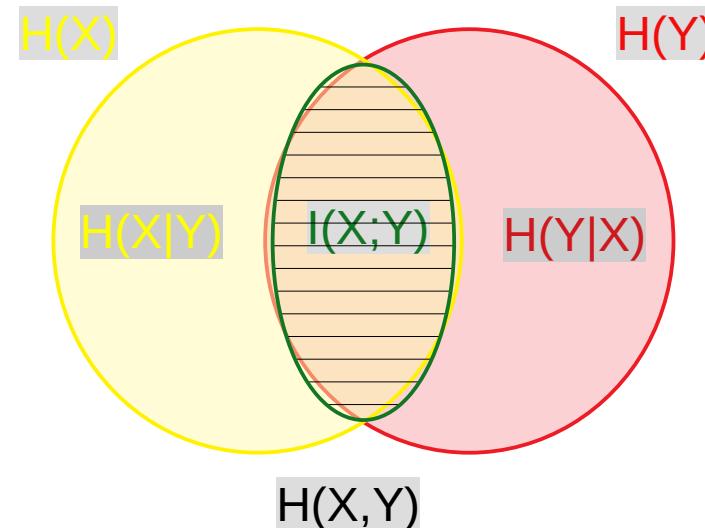
Claude Shannon, the founder of information theory, invented a way to measure 'the amount of information' in a message without defining the word 'information' itself, nor even addressing the question of the meaning of the message.

Information, The New Language of Science, Ch. 4, p. 28

Recent advances ...

Mutual Information (MI) ... Idea

- A measure for **Information X gives about Y** (or vice versa)

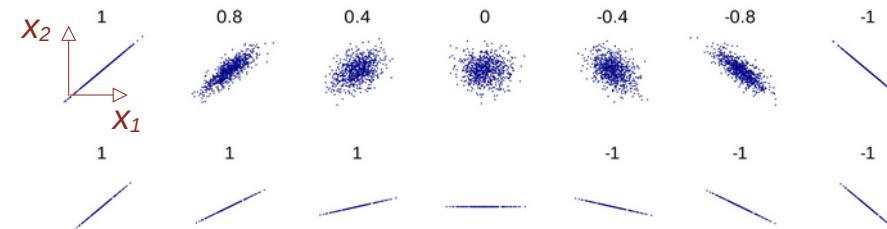


- * $I(X;Y)$: Mutual Information
- * $H(X)$: Entropy
- * $H(X|Y)$: Conditional entropy
- * $H(X,Y)$: Joint entropy

Mutual Information (MI) ... Idea

- Think of cross-correlation ...

Cross-correlation
(CC)

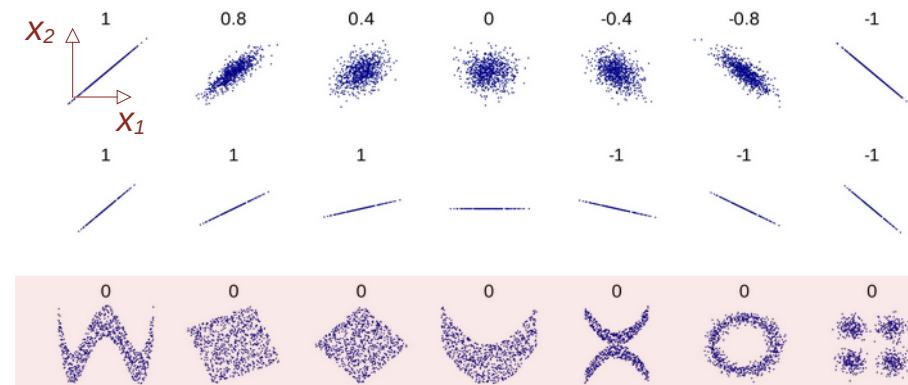


Recent advances ...

Mutual Information (MI) ... Idea

- Think of cross-correlation ... but *non-linear*

Cross-correlation
(CC)

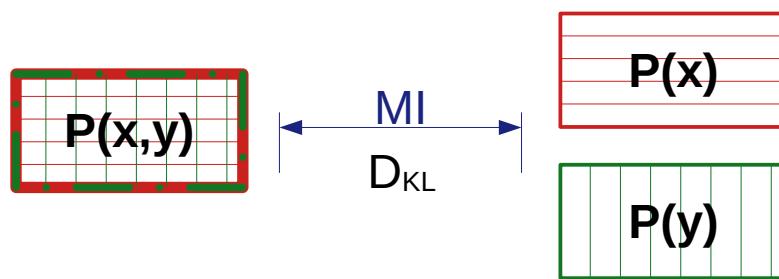


CC = 0 ... but ... MI != 0

Recent advances ...

MI ... Definition

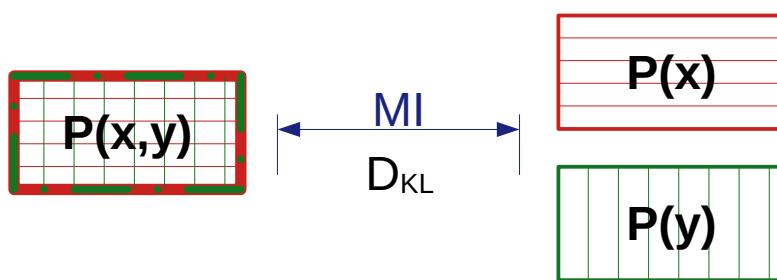
$$I(X;Y) = D_{KL}(P(x,y) || P(x)P(y))$$



Recent advances ...

MI ... Definition

$$I(X;Y) = D_{KL}(P(x,y) || P(x)P(y))$$



$$D_{KL}(P||Q) = - \sum_{x \in X} P(x) \log \frac{Q(x)}{P(x)} = H(P, Q) - H(P)$$

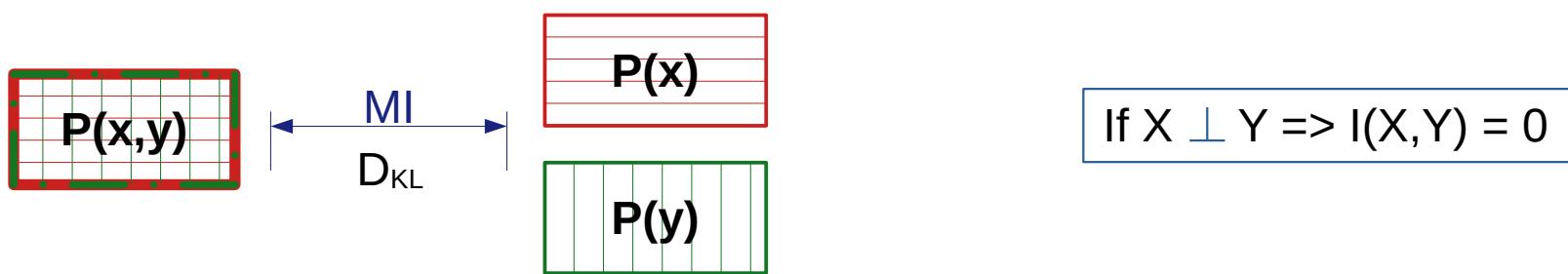
Cross-entropy Entropy

* D_{KL} : Kullback-Leibler Divergence

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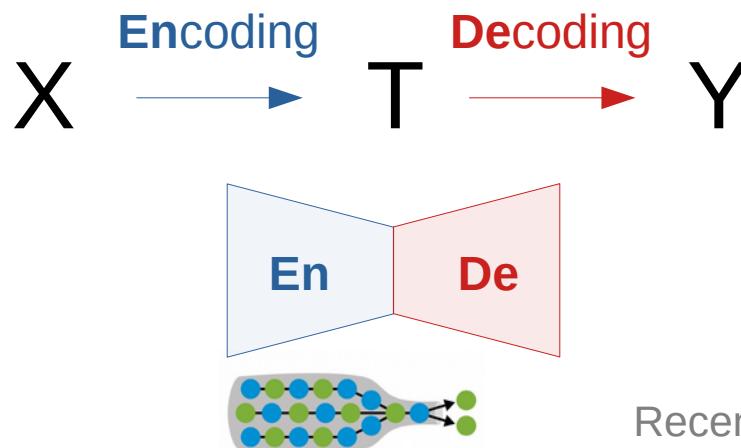
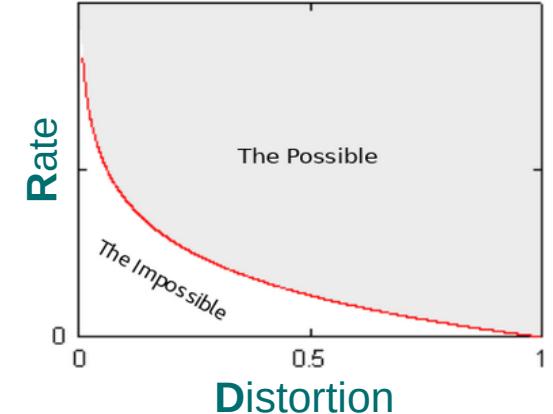
Recent advances ...

MI ... Properties

- **Data Processing Inequality (DPI)**
 - ... *Post-processing cannot increase information* ...
 - Markov Chain: $X \rightarrow T_1 \rightarrow T_2 \rightarrow T_3 \rightarrow \dots$
 - $I(X; T_1) \geq I(X; T_2); \quad I(T_1; T_2) \geq I(X; T_2)$
- **Transformation Invariance**
 - $I(X; Y) = I(f(X); g(Y))$ where f & g are *invertible* functions

Rate-Distortion Theory

- Encode X by T ...
 - Obj. Minimal Rate
 - s.t. Distortion $\leq D_{\max}$



Recent advances ...

X : Observation
 Y : Variable of interest
 T : Representation of X

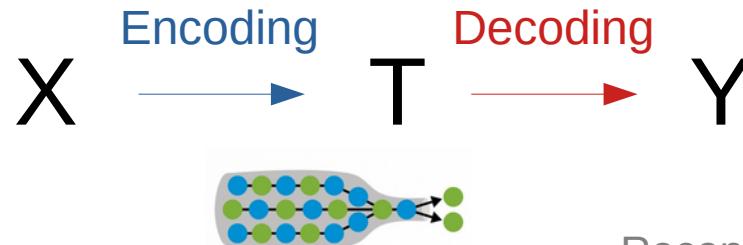
Information Bottleneck (IB)

- Turn finding T to a learning problem using MI ...

Compression/
Minimality/Complexity

Fidelity/
Sufficiency/Accuracy

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



Recent advances ...

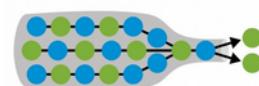
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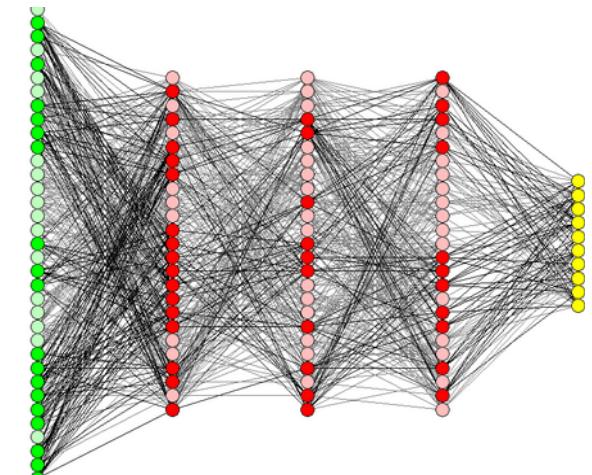
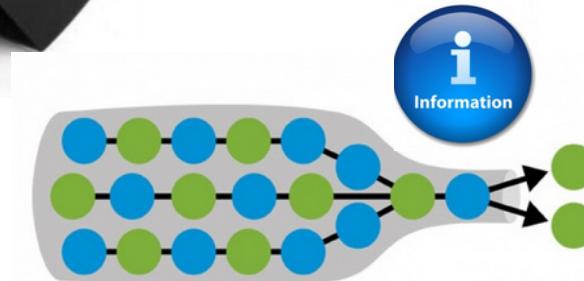
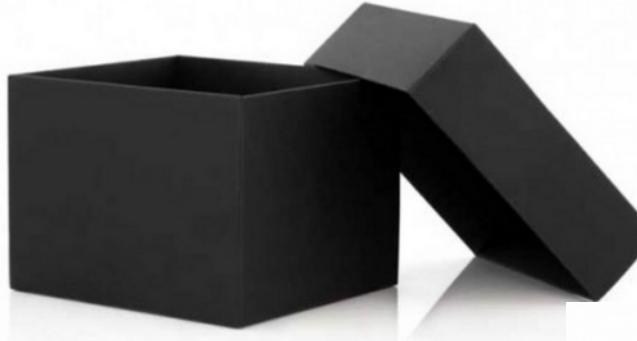


IDEALLY ... in coding ...

- $I(T; X) \leftrightarrow$ as LOW as possible (min Rate)
- $I(T; Y) \leftrightarrow$ as HIGH as possible (min Distortion)

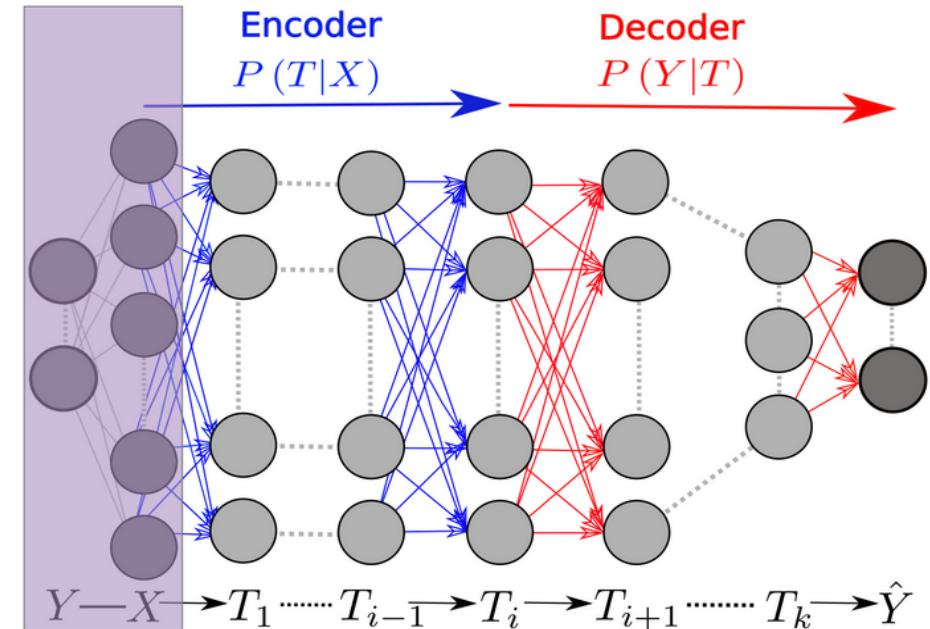
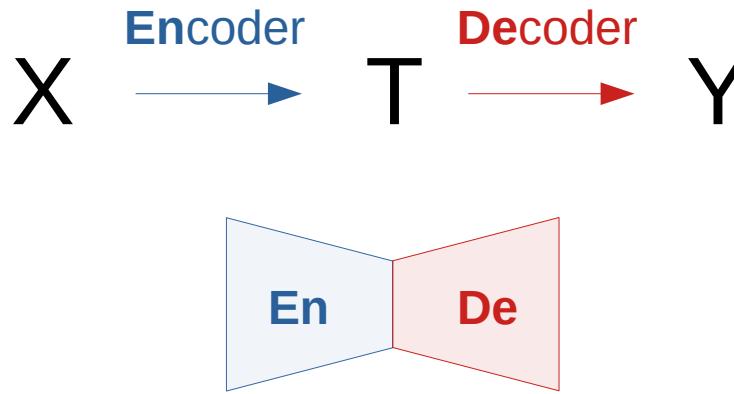
Recent advances ...

Opening the Black Box of DNNs via Information Bottleneck



Recent advances ...

Opening the black box ...

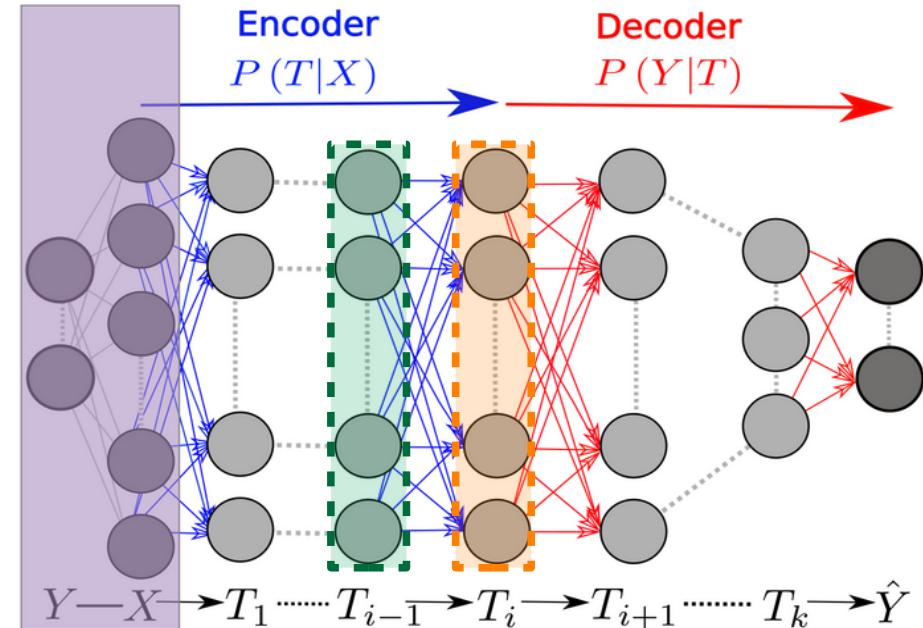
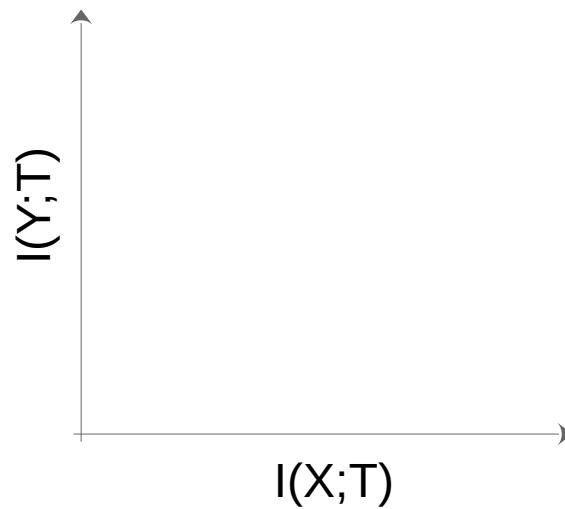


Markov Chain : $Y \leftrightarrow X \rightarrow T \rightarrow \hat{Y}$

Data : $\{(x_i, y_i)\}_{i=1}^N \sim p(x, y)$

Recent advances ...

Information Plane

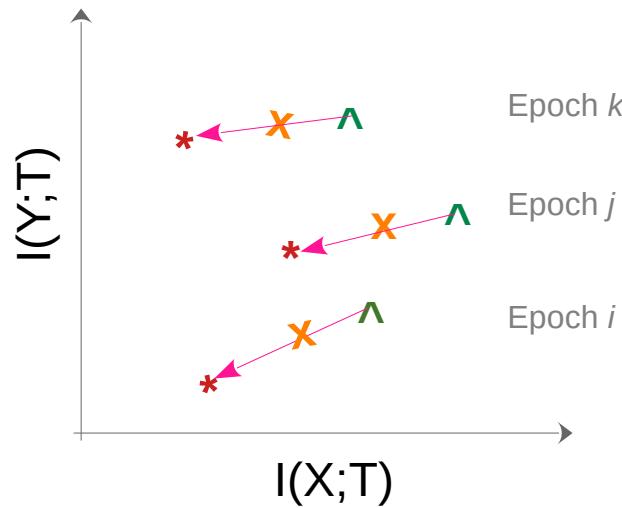


$$Y \rightarrow X \rightarrow \dots \rightarrow T_{i-1} \rightarrow \color{green}T_i\color{black} \rightarrow \color{red}T_{i+1}\color{black} \rightarrow \dots \rightarrow \hat{Y}$$

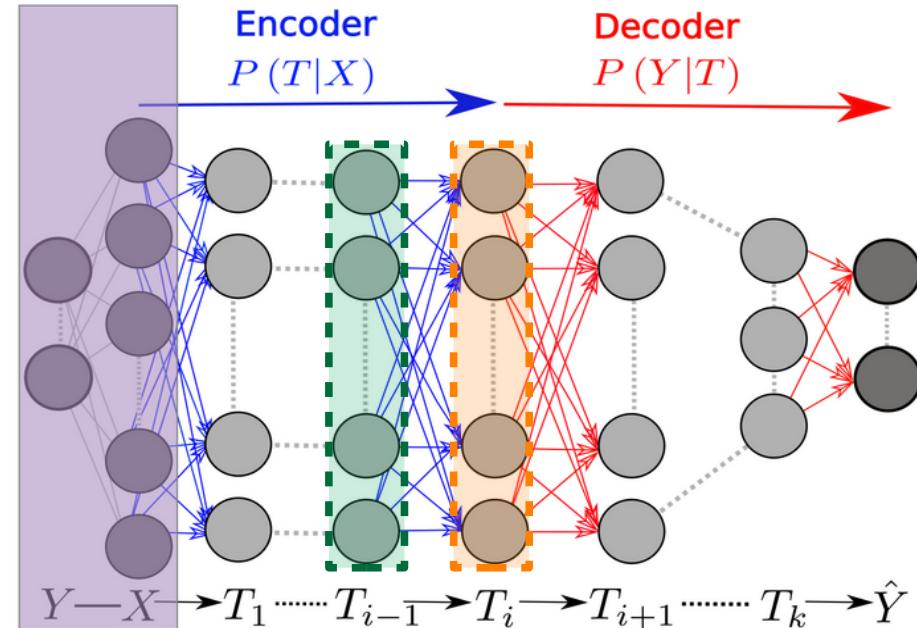
Recent advances ...

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A point for each epoch and $I_i \dots$

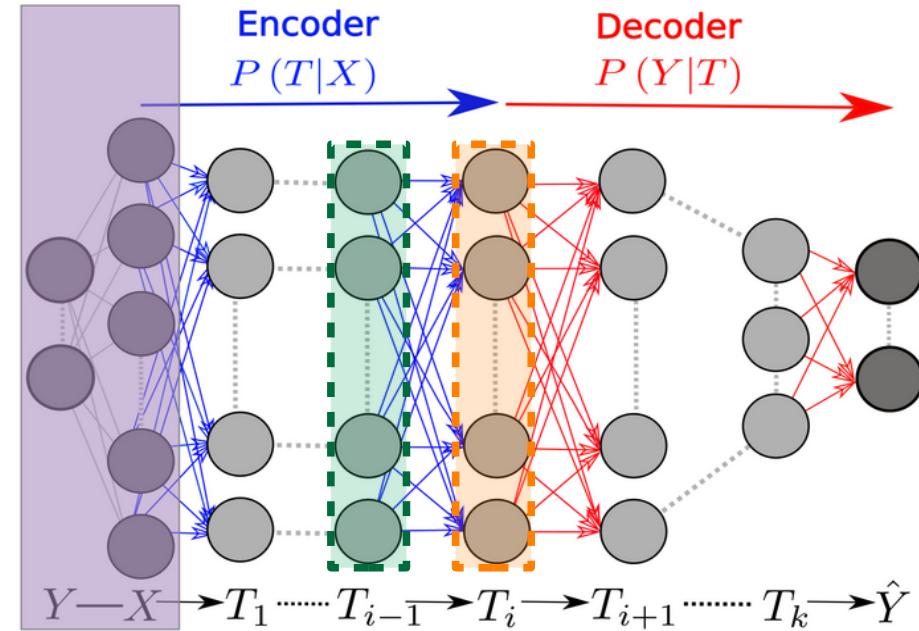
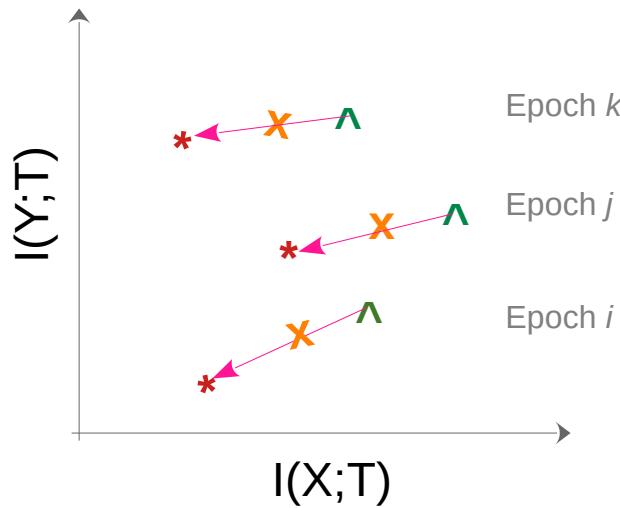


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MVIP 2022

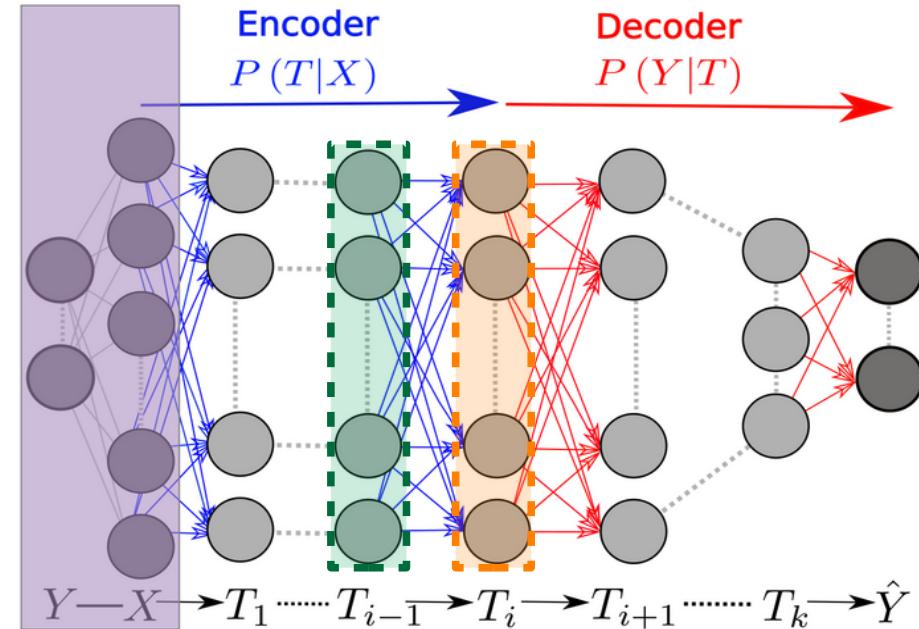
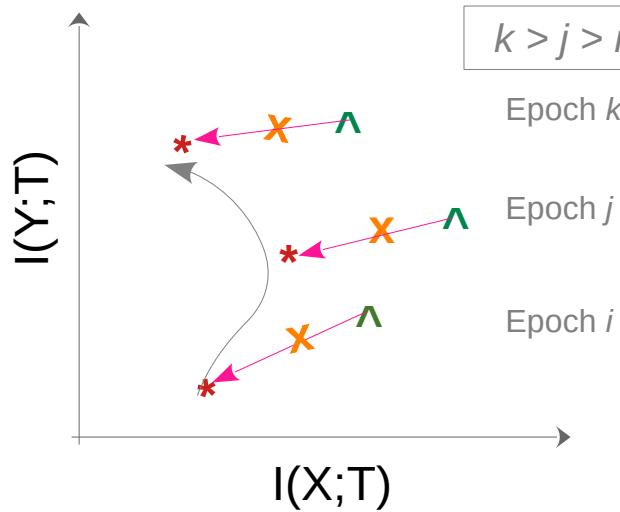
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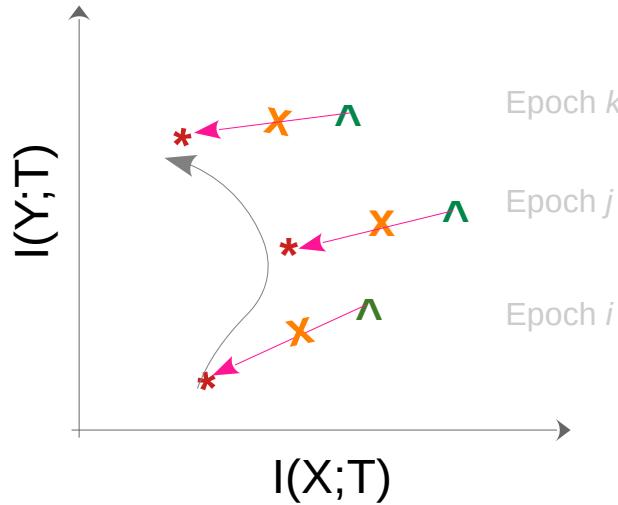
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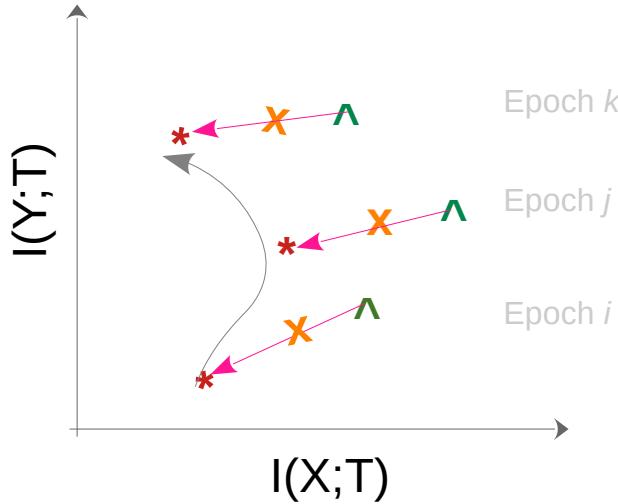
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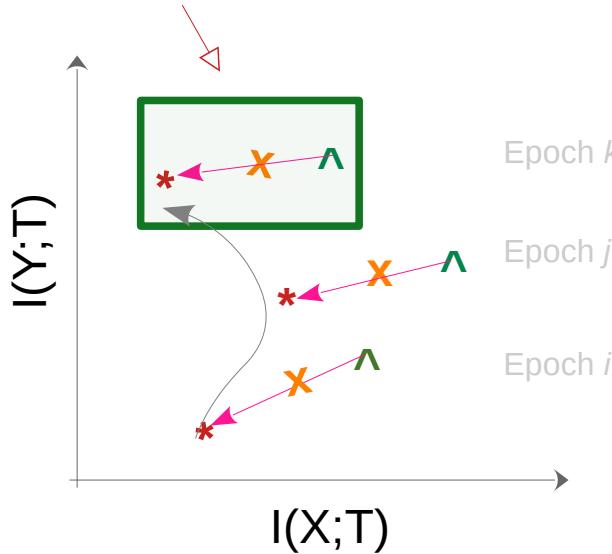
IDEALLY ... in learning ...

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Information Plane

Ideal solution



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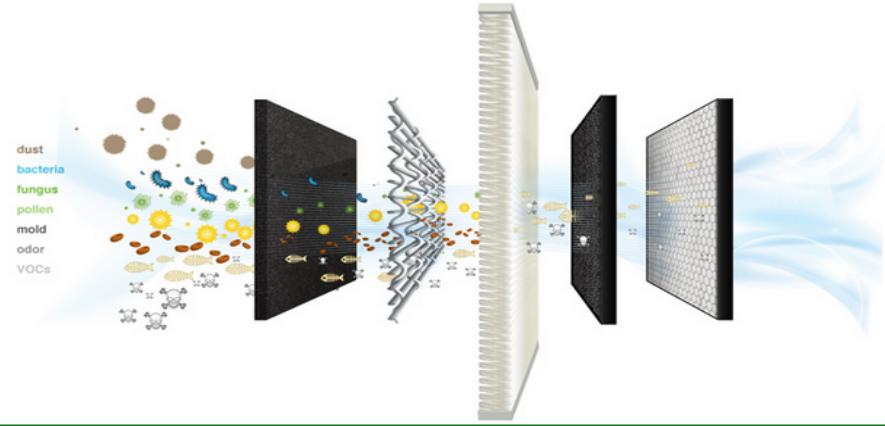
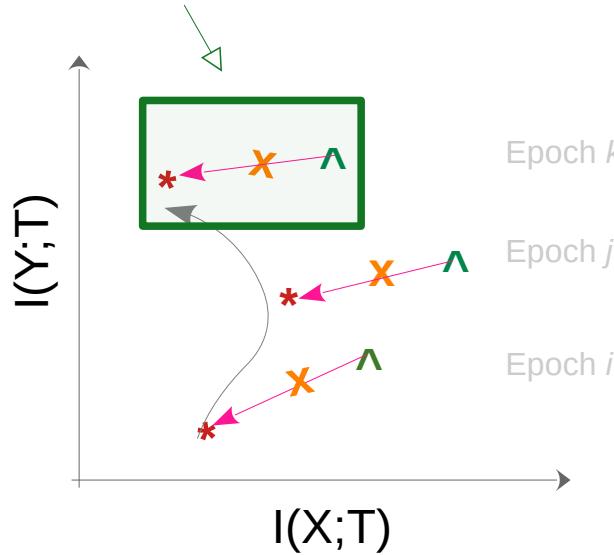
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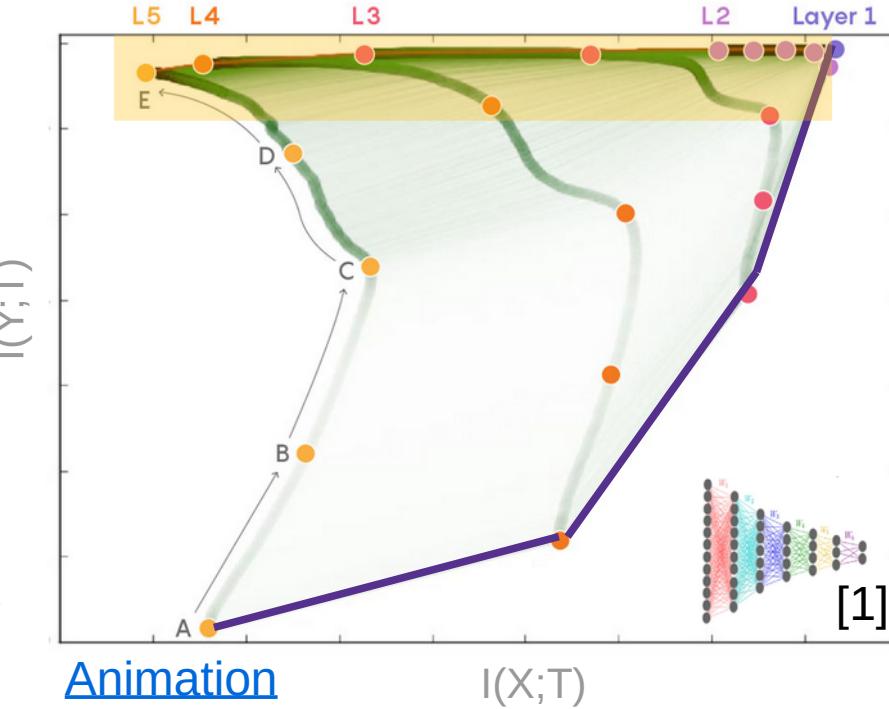
Recent advances ...

Learning from IB view



Epoch N

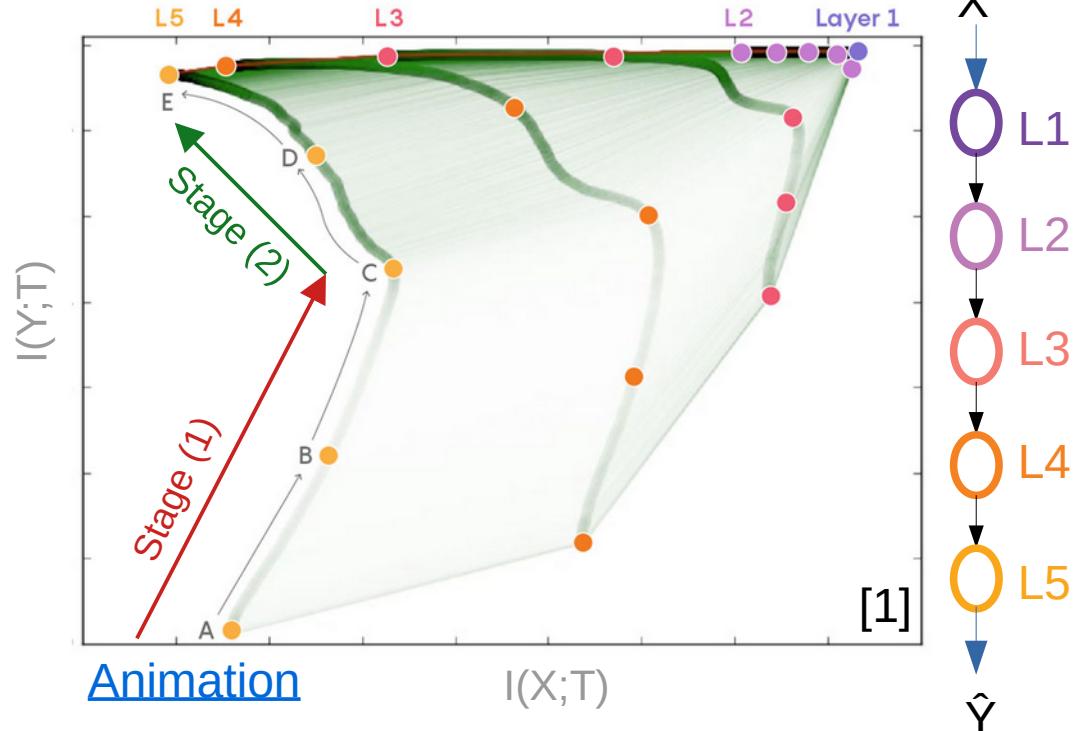
Epoch 1



Recent advances ...

Learning from IB view

- Two distinct stages ...
 - Stage (1): $A \rightarrow C$
 - Stage (2): $C \rightarrow E$



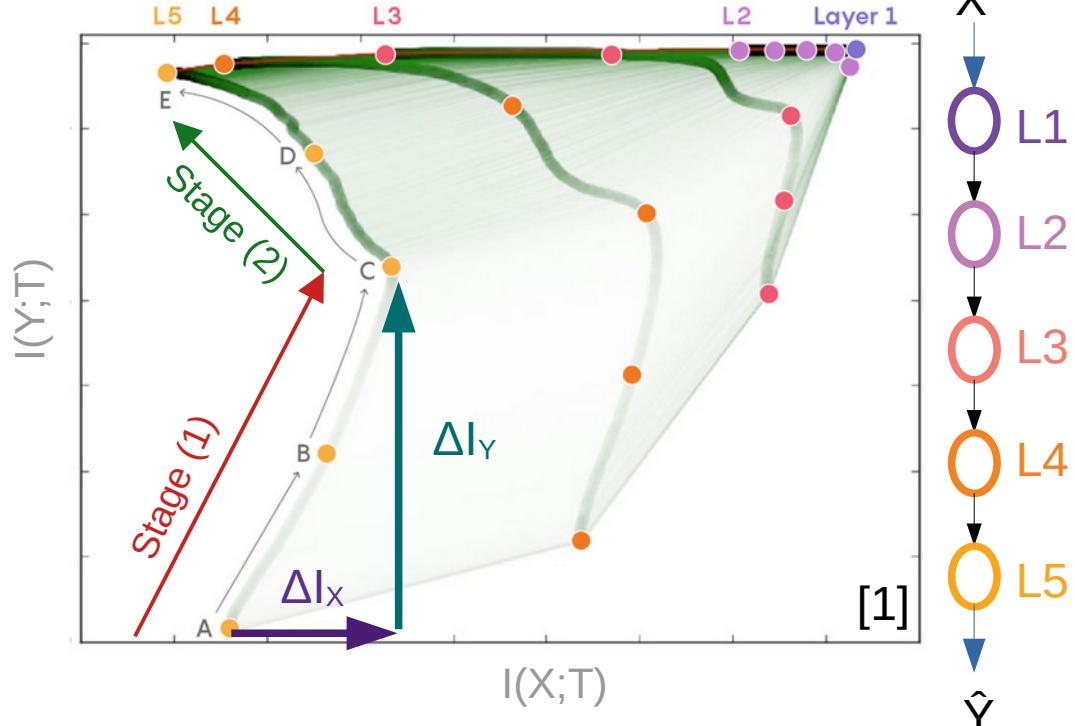
[Animation](#)

$I(X; T)$

Recent advances ...

Stage (1): A \rightarrow C

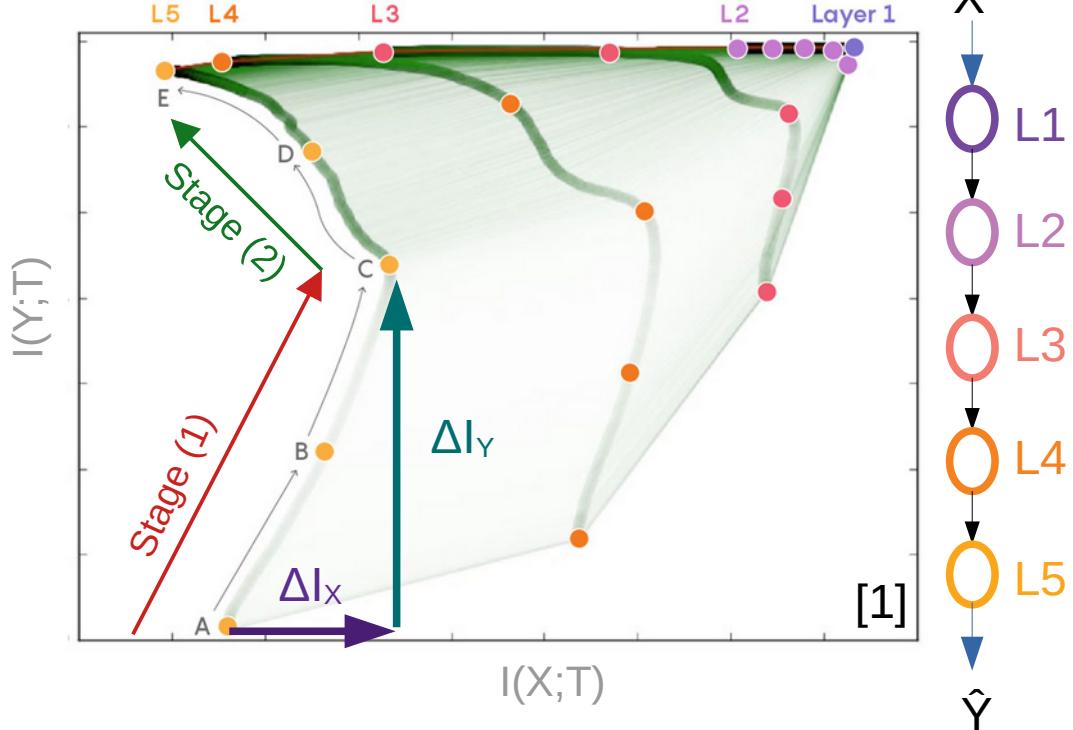
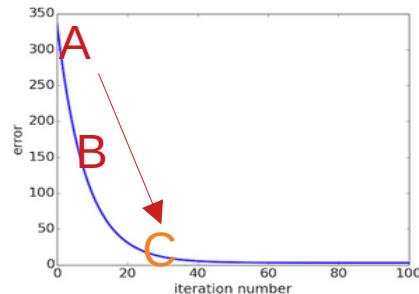
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 - Fitting
- $\Delta Empirical_risk \leq 0$
- Fast



Recent advances ...

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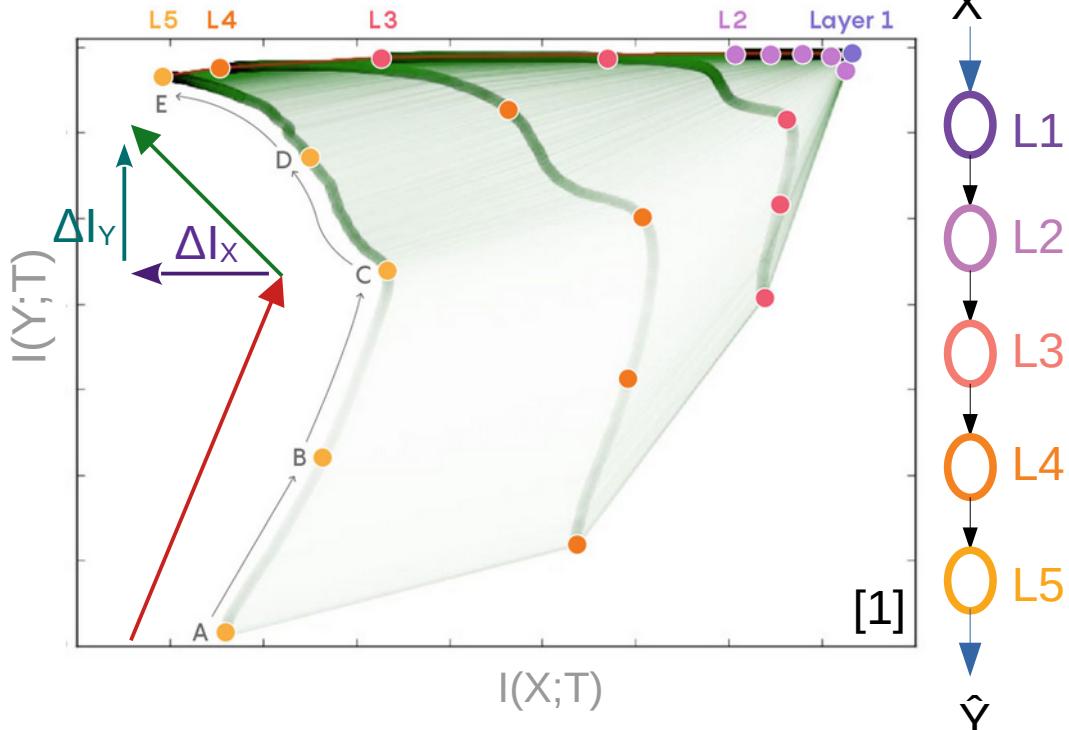
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Recent advances ...

Stage (2): C → E

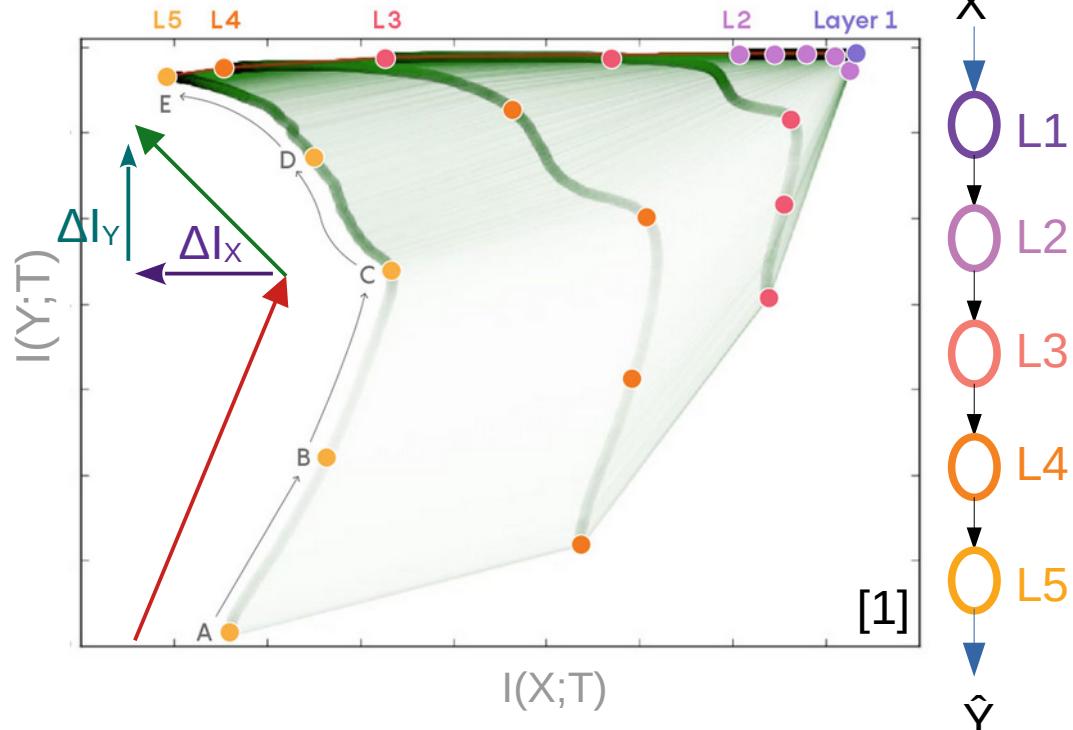
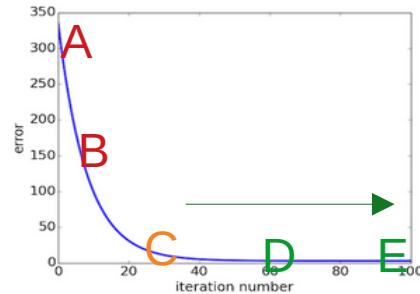
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Recent advances ...

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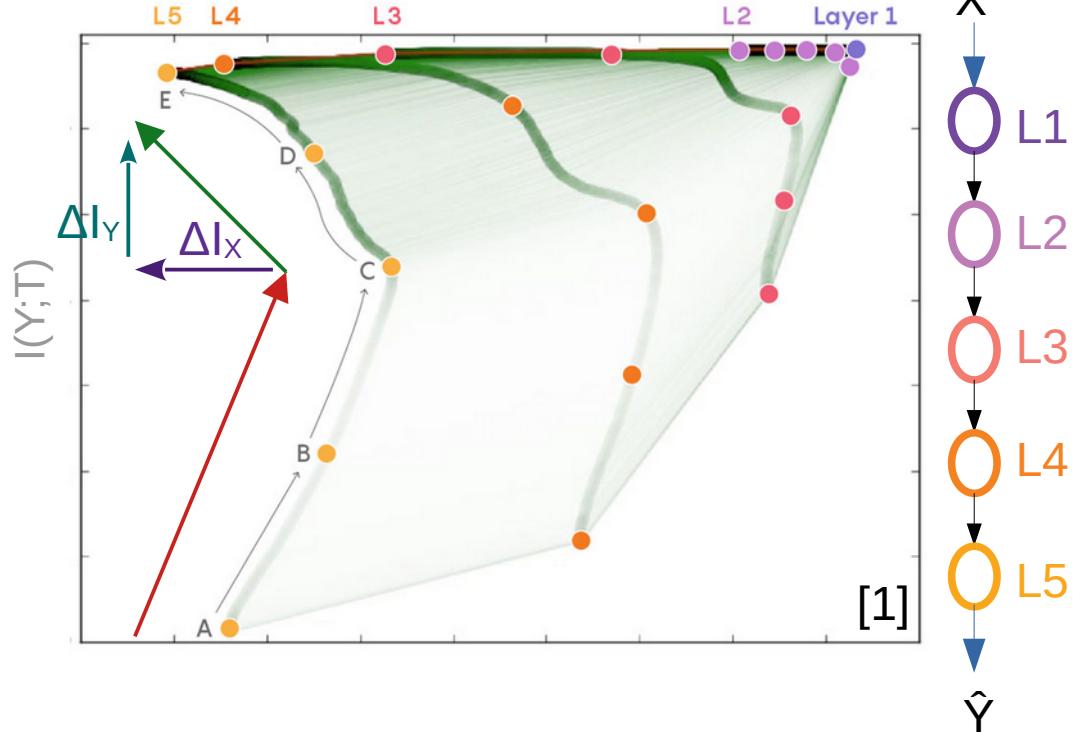
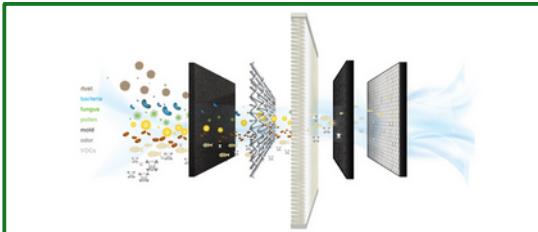
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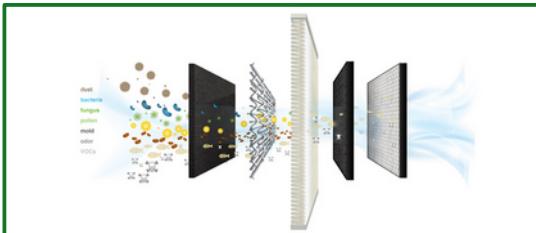
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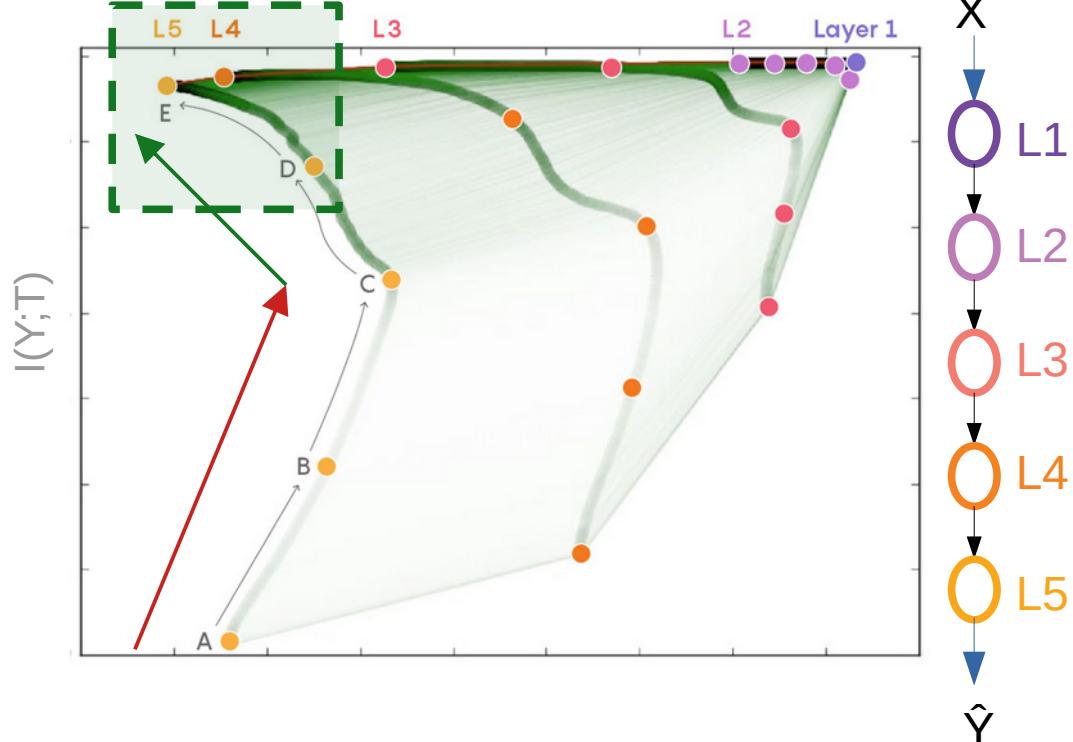
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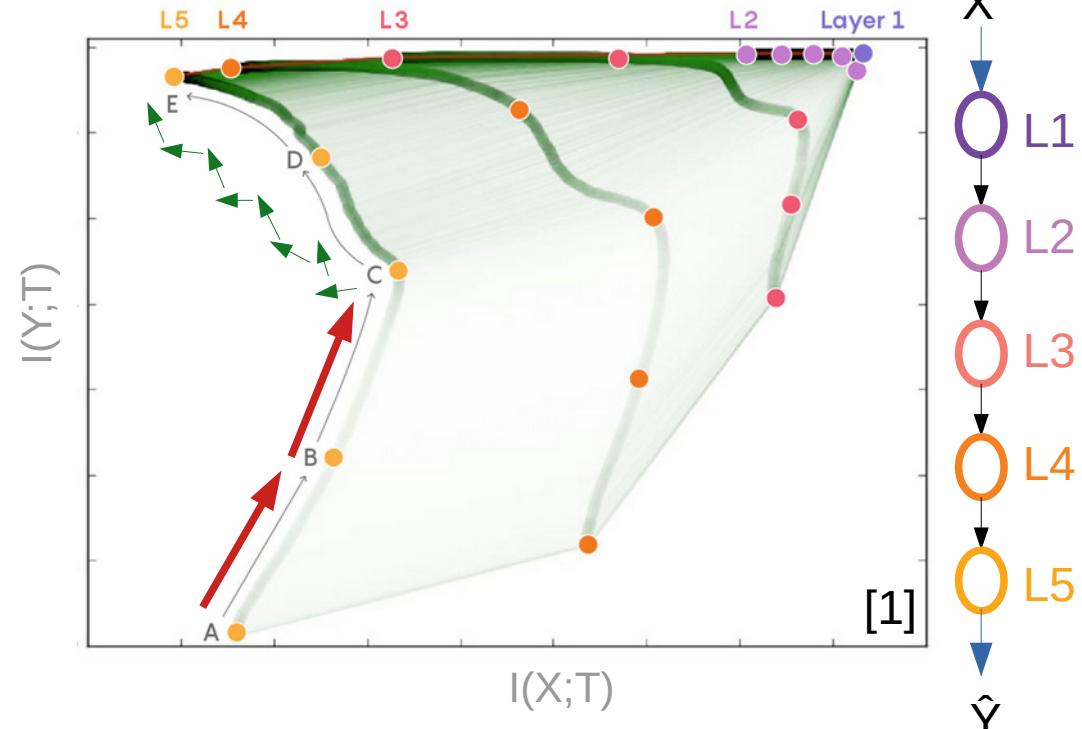
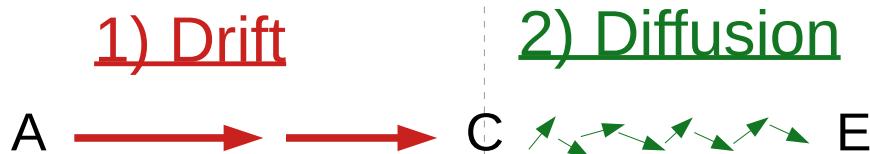


Ideal solution ...



Recent advances ...

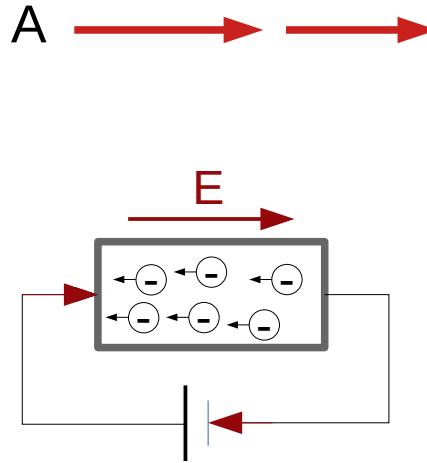
Learning has two stages ...



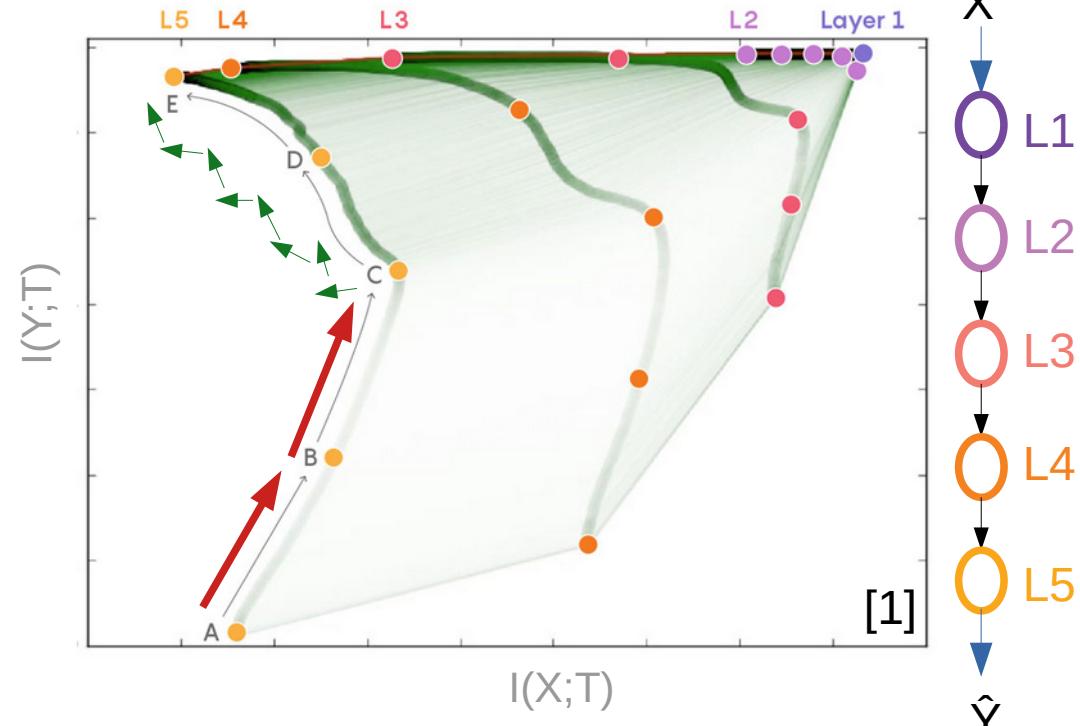
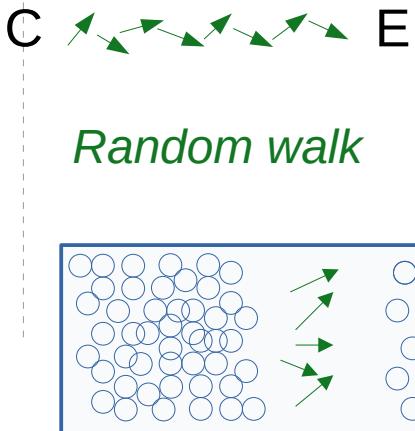
Recent advances ...

Learning has two stages ...

1) Drift

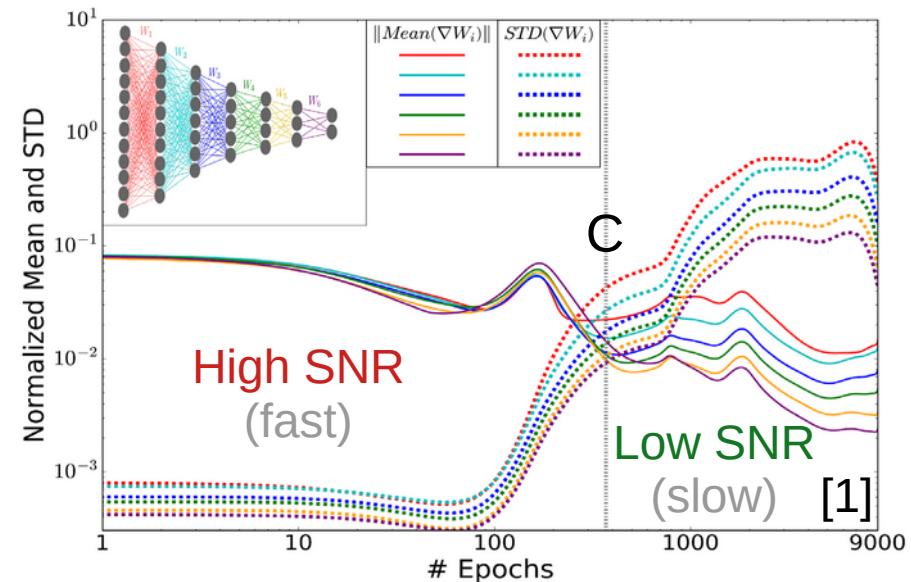
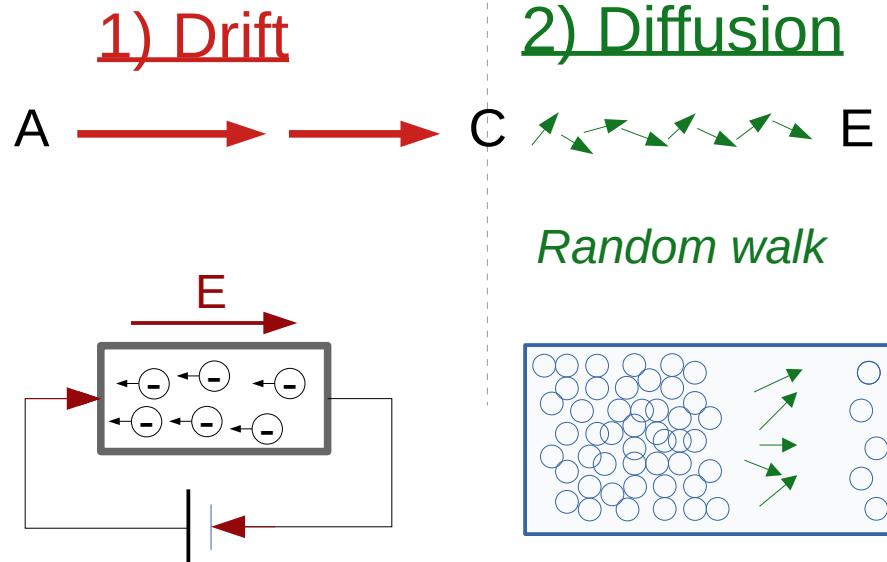


2) Diffusion



Recent advances ...

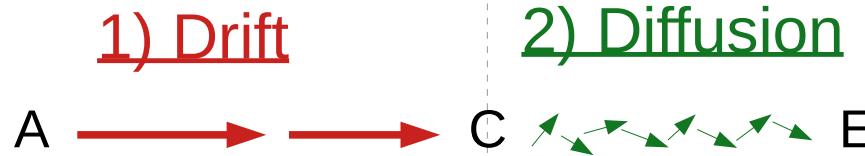
SNR of Gradient



$$\text{SNR} \triangleq \frac{\text{Mean}(\|\nabla W_l\|)}{\text{STD}(\|\nabla W_l\|)}$$

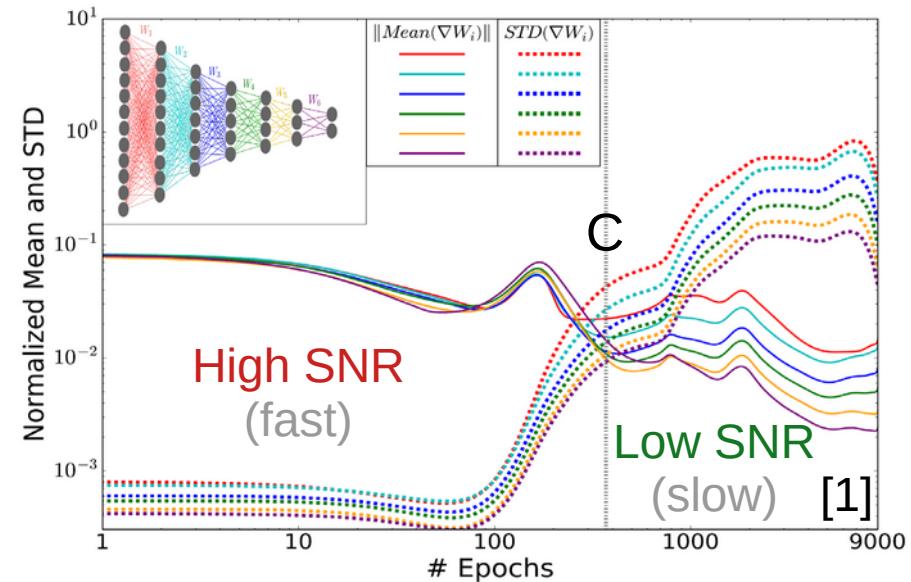
Recent advances ...

SNR of Gradient



Random walk

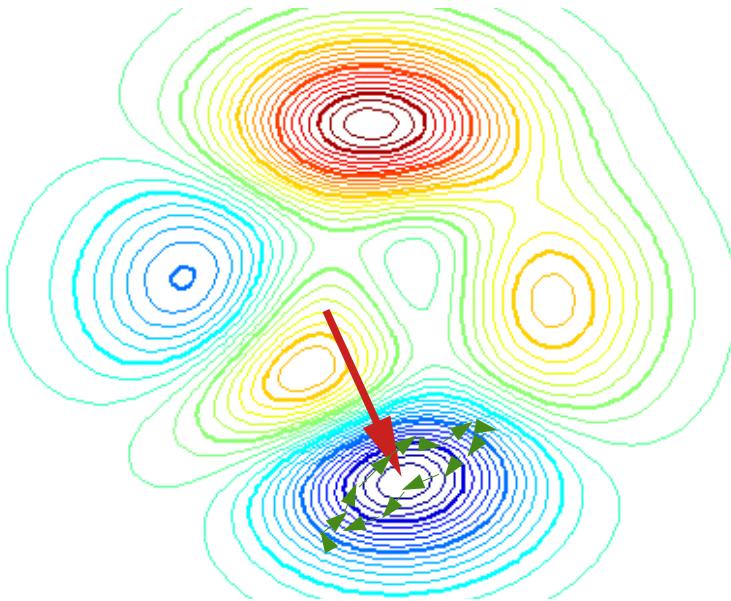
Stochasticity during **diffusion** is responsible for **generalisation** ...



$$SNR \triangleq \frac{Mean(\|\nabla W_l\|)}{STD(\|\nabla W_l\|)}$$

Recent advances ...

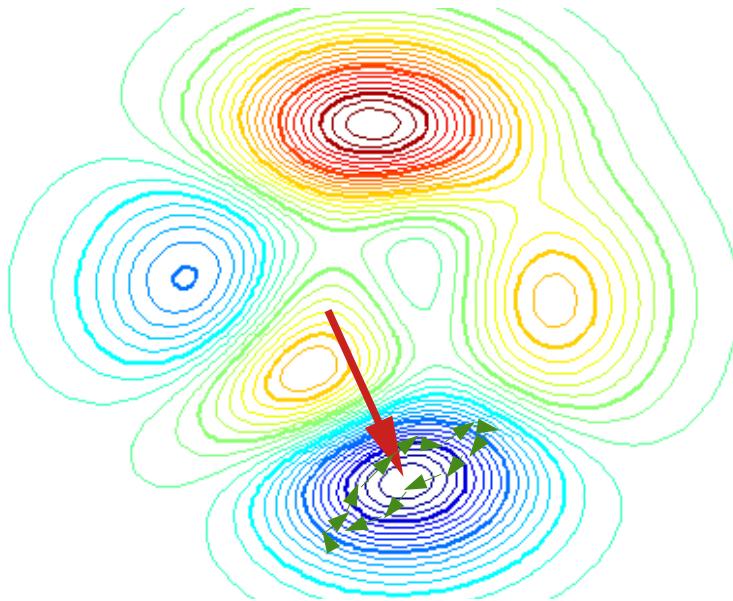
Stochasticity of the Diffusion Improves the Generalisation



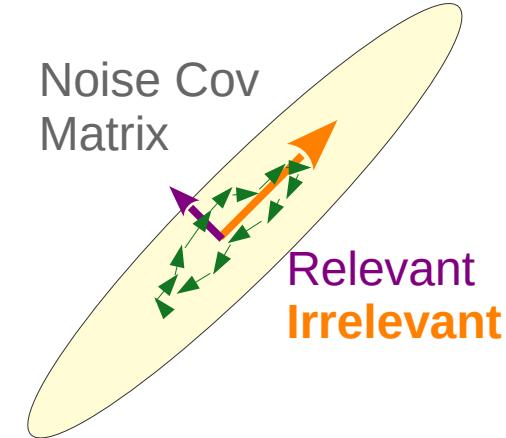
MVIP 2022
Drift (A → C) → High SNR
Diffusion (C → E) → Low SNR

Recent advances ...

Stochasticity of the Diffusion Improves the Generalisation



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Drift (A → C) → High SNR
Diffusion (C → E) → Low SNR

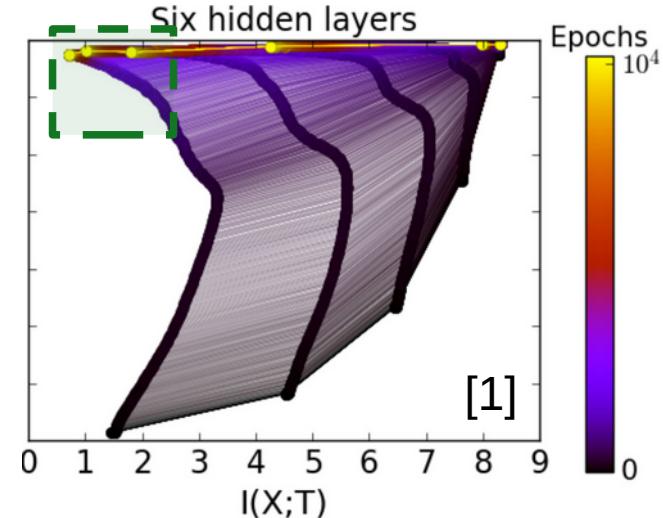
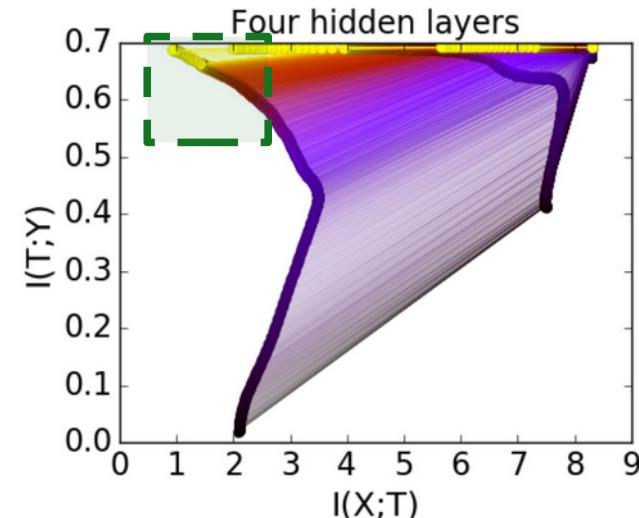
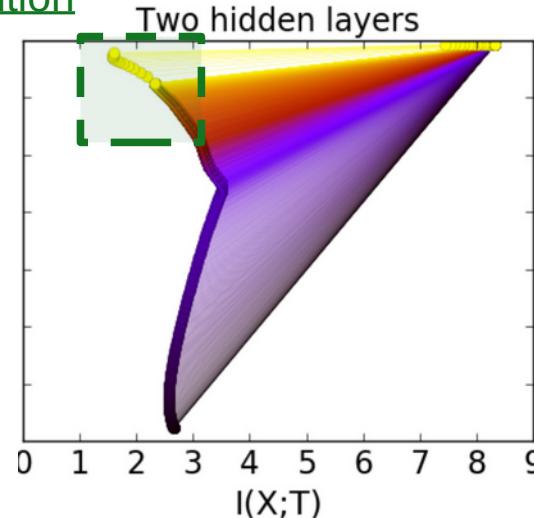


Diffusion's stochasticity ...

- Add noise to **irrelevant** features
- Forget irrelevant details

Effect of ... Depth

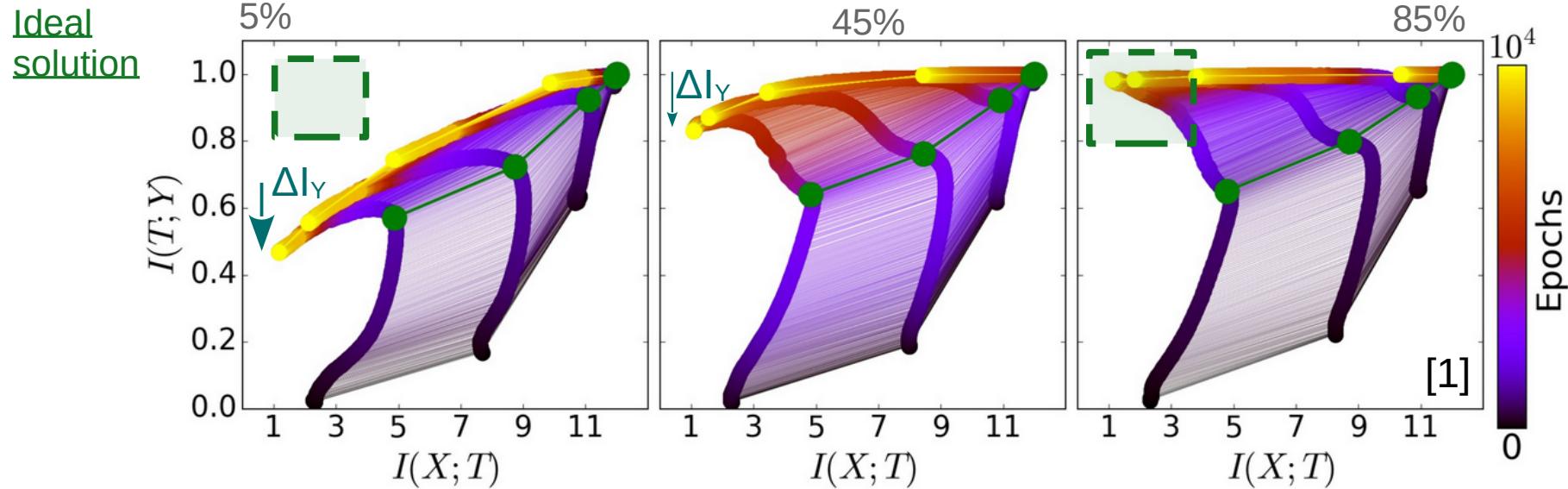
Ideal
solution



* Deeper network → Faster training ...
==>> Better generalisation with fewer epochs

Recent advances ...

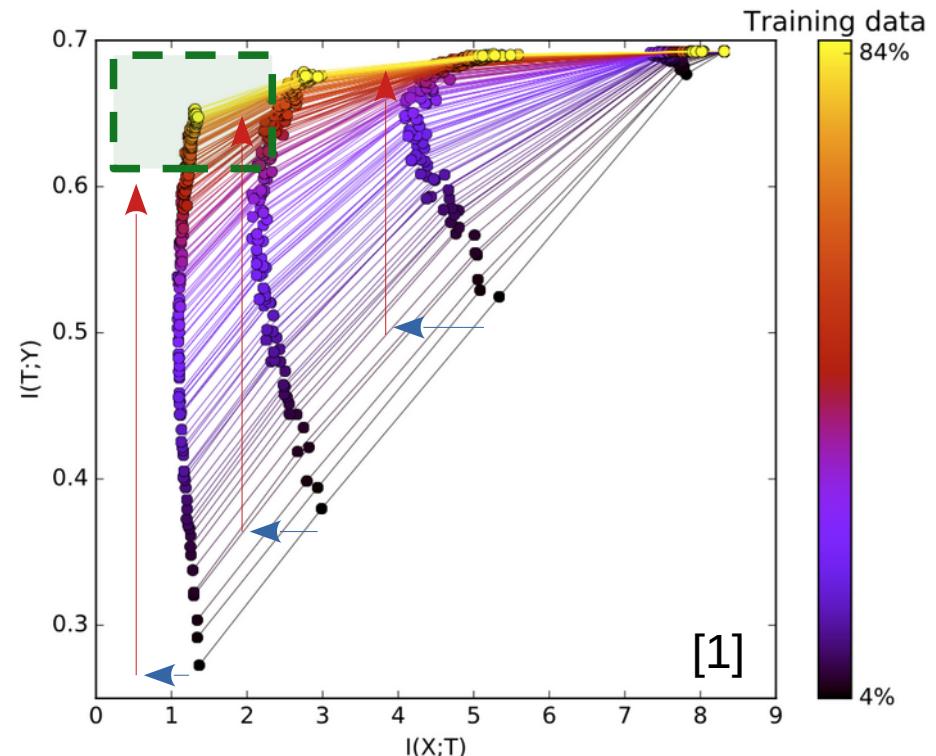
Effect of ... Training Data Amount (1)



* Less data ... may lead to $\Delta I_Y < 0$ & never reaching

Effect of ... Training Data Amount (2)

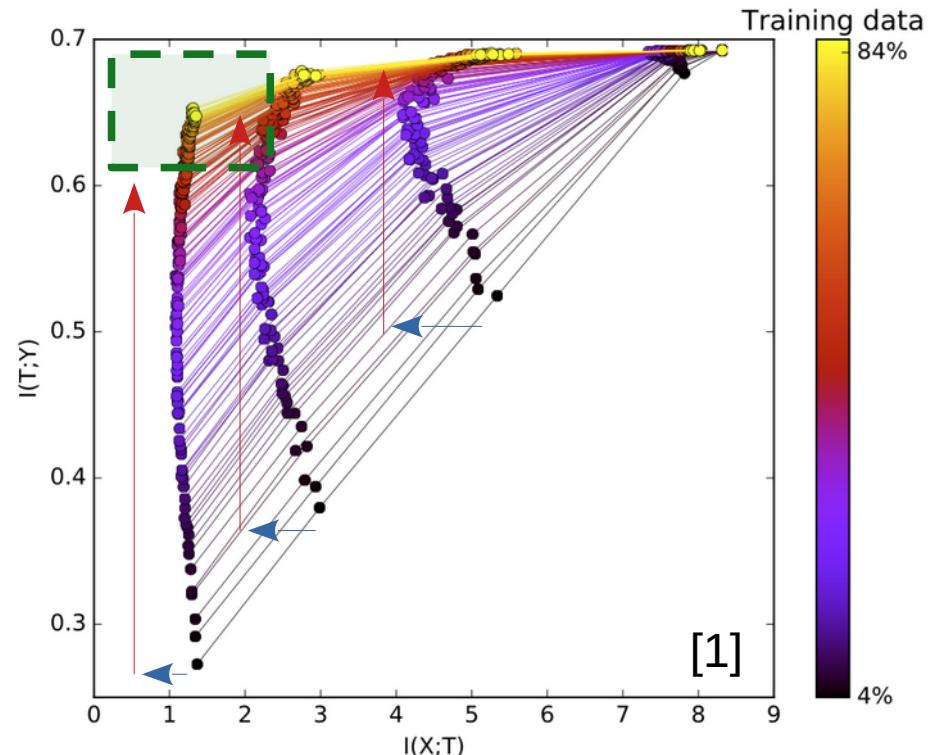
- More training data ...
 - I_X : Minor reduction ↓
 - I_Y : Major increase ↑



Recent advances ...

Effect of ... Training Data Amount (2)

- More training data ...
 - I_X : Minor reduction ↓
 - I_Y : Major increase ↑
- Good generalisation
 - I_X : low, I_Y : high



Recent advances ...

Effect of ... Batch Size (BS)

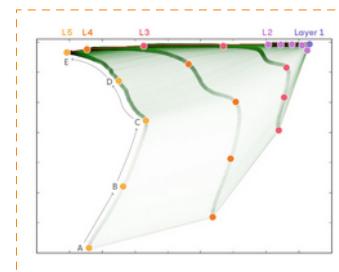
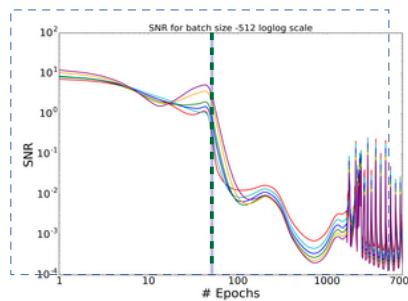
- The smaller the BS, the higher the stochasticity of GD

Effect of ... Batch Size (BS)

- The smaller the BS, the higher the stochasticity of GD

Drift to *diffusion* transition:

$$\operatorname{argmin} \frac{d}{dt} SNR \approx \operatorname{argmax} I(X; T)$$

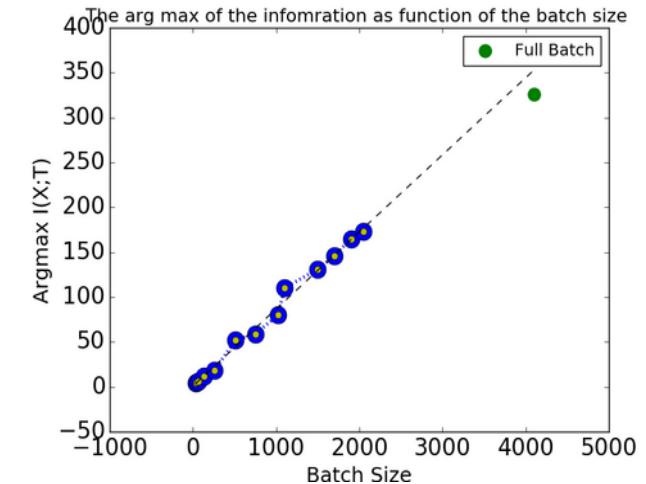
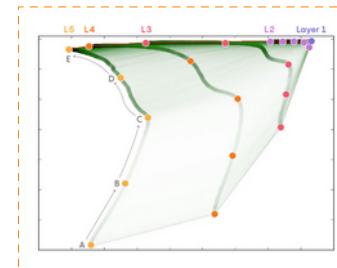
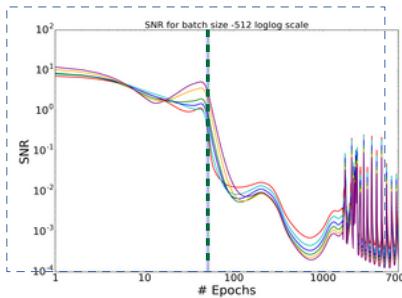


Effect of ... Batch Size (BS)

- The smaller the BS, the higher the stochasticity of GD

Drift to *diffusion* transition:

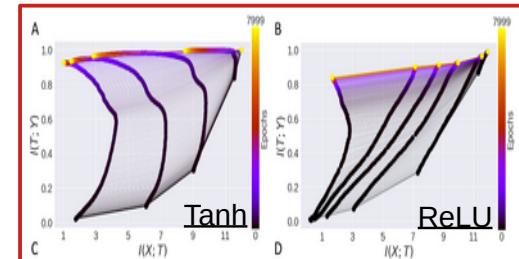
$$\operatorname{argmin} \frac{d}{dt} SNR \approx \operatorname{argmax} I(X; T)$$



* The smaller the BS, the faster the transition to diffusion ...

Criticisms

- Two-phase process is **NOT** generic [3]!
 - **ReLU** ... Adaptive binning helps [4] ...



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Adaptive Estimators Show Information Compression in Deep Neural Networks [PDF](#)

Ivan Chelombiev, Conor Houghton, Cian O'Donnell

27 Sept 2018 (modified: 21 Feb 2019) ICLR 2019 Conference Blind Submission Readers: [Everyone](#) Show Bibtex Show Revisions

Keywords: deep neural networks, mutual information, information bottleneck, noise, L2 regularization

TL;DR: We developed robust mutual information estimates for DNNs and used them to observe compression in networks with non-saturating activation functions

Abstract: To improve how neural networks function it is crucial to understand their learning process. The information bottleneck theory of deep learning proposes that neural networks achieve good generalization by compressing their representations to disregard information that is not relevant to the task. However, empirical evidence for this theory is conflicting, as compression was only observed when networks used saturating activation functions. In contrast, networks with non-saturating activation functions achieved comparable levels of task performance but did not show compression. In this paper we developed more robust mutual information estimation techniques, that adapt to hidden activity of neural networks and produce more sensitive measurements of activations from all functions, especially unbounded functions. Using these adaptive estimation techniques, we explored compression in networks with a range of different activation functions. With two improved methods of estimation, firstly, we show that saturation of the activation function is not required for compression, and the amount of compression varies between different activation functions. We also find that there is a large amount of variation in compression between different network initializations. Secondary, we see that L2 regularization leads to significantly increased compression, while preventing overfitting. Finally, we show that only compression of the last layer is positively correlated with generalization.

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On the Information Bottleneck Theory of Deep Learning [PDF](#)

Andrew Michael Saxe, Yamini Bansal, Joel Daepello, Madhu Advani, Artemy Kolchinsky, Brendan Daniel Tracey, David Daniel Cox

15 Feb 2018 (modified: 24 Feb 2018) ICLR 2018 Conference Blind Submission Readers: [Everyone](#) Show Bibtex Show Revisions

Abstract: The practical successes of deep neural networks have not been matched by theoretical progress that satisfactorily explains their behavior. In this work, we study the information bottleneck (IB) theory of deep learning, which makes three specific claims: first, that deep networks undergo two distinct phases consisting of an initial fitting phase and a subsequent compression phase; second, that the compression phase is causally related to the excellent generalization performance of deep networks; and third, that the compression phase occurs due to the diffusion-like behavior of stochastic gradient descent. Here we show that none of these claims hold true in the general case. Through a combination of analytical results and simulation, we demonstrate that the information plane trajectory is predominantly a function of the neural nonlinearity employed: double-sided saturating nonlinearities like tanh yield a compression phase as neural activations enter the saturation regime, but linear activation functions and single-sided saturating nonlinearities like the widely used ReLU in fact do not. Moreover, we find that there is no evident causal connection between compression and generalization: networks that do not compress are still capable of generalization, and vice versa. Next, we show that the compression phase, when it exists, does not arise from stochasticity in training by demonstrating that we can replicate the IB findings using full batch gradient descent rather than stochastic gradient descent. Finally, we show that when an input domain consists of a subset of task-relevant and task-irrelevant information, hidden representations do compress the task-irrelevant information, although the overall information about the input may monotonically increase with training time, and that this compression happens concurrently with the fitting process rather than during a subsequent compression period.

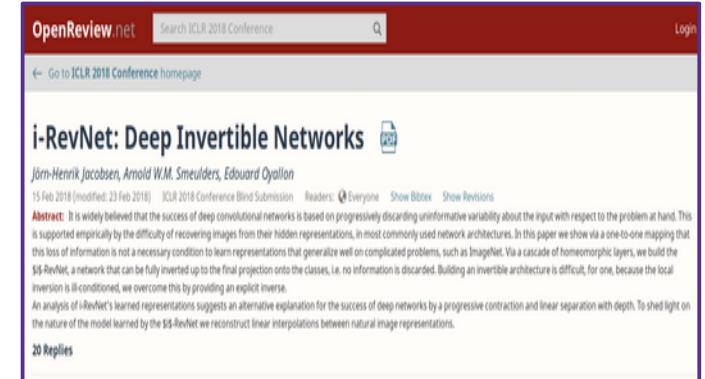
TL;DR: We show that several claims of the information bottleneck theory of deep learning are not true in the general case.

Keywords: information bottleneck, deep learning, deep linear networks

21 Replies

Criticisms

- Two-phase process is **NOT** generic [3]!
 - ReLU ... Adaptive binning helps [4] ...
- No causal relationship between stochasticity of SGD (compression/forgetting) & generalisation [3]
 - i-RevNet [5] ... good gen. w/o forgetting



The screenshot shows the OpenReview.net interface for the ICLR 2018 Conference. The title of the submission is "i-RevNet: Deep Invertible Networks". It includes the authors' names (Jörn-Henrik Jacobsen, Arnold W.M. Smeulders, Eduard Oyallon), the submission date (15 Feb 2018), and the fact that it is a blind submission. The abstract discusses the success of deep convolutional networks and how i-RevNet addresses this through a learned inverse mapping. It also mentions the reconstruction of linear interpolations between natural image representations. There are links for "Replies" and "Show Bitex".

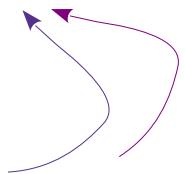
Recent advances ...

Criticisms

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 - ReLU ... Adaptive binning helps [4] ...
- No causal relationship between stochasticity of SGD (compression/forgetting) & generalisation [3]
 - i-RevNet [5] ... good gen. w/o forgetting
- Computing MI is challenging [6] ... especially for *random vectors*

Conclusion (Part I)

- Novelty: DNNs from Information Theory's perspective
 - $I(X;T_i)$ and $I(Y;T_i)$ plotted in *information plane*
 - Learning consists of two stages: 1) Drift, 2) Diffusion
-
- Why DNNs *generalise well*?
 - *Stochasticity of GD* → *Diffusion* → *forgetting irrelevant info*



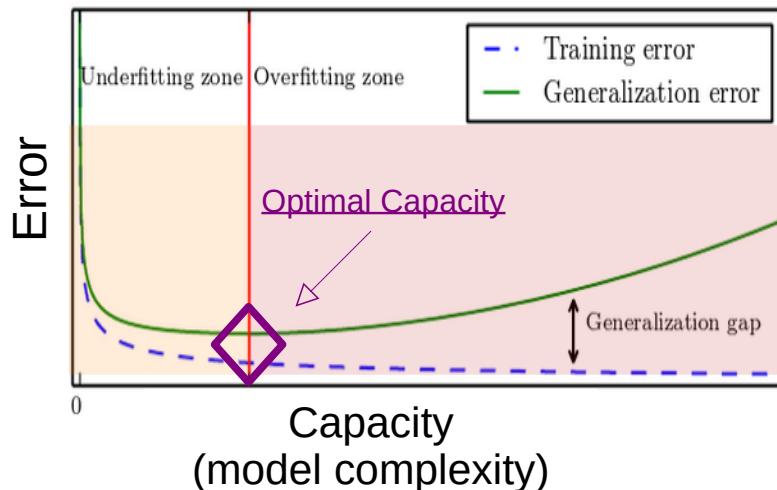
Outlines (Part II)

- Information Bottleneck
- Over-parameterisation and Generalisation
- Interpretation/Visualisation of Filters/Activations

DNNs ... Generalisation ...

- Why do DNNs generalise well?

Classic wisdom ...

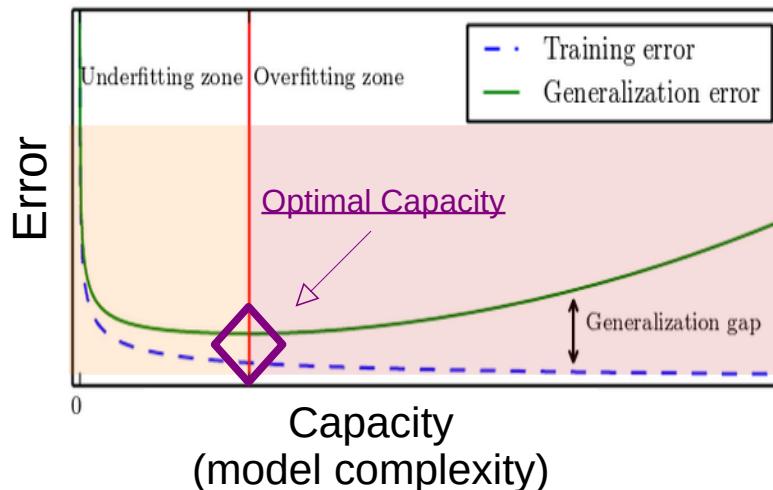


Recent advances ...

DNNs ... Generalisation ...

- Why do DNNs generalise well?

Classic wisdom ...

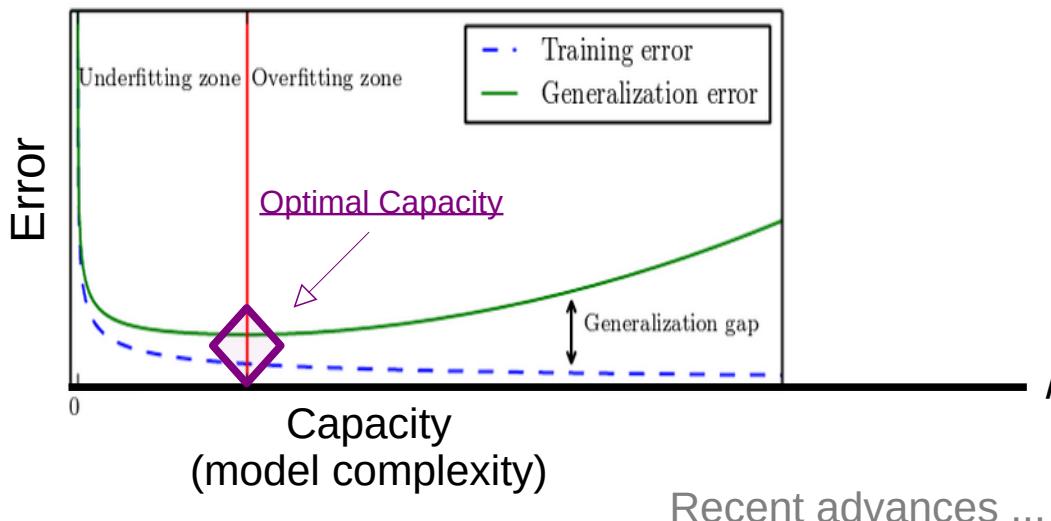


Underfitting: High Bias
Overfitting: High Variance

Recent advances ...

DNNs ... Generalisation ...

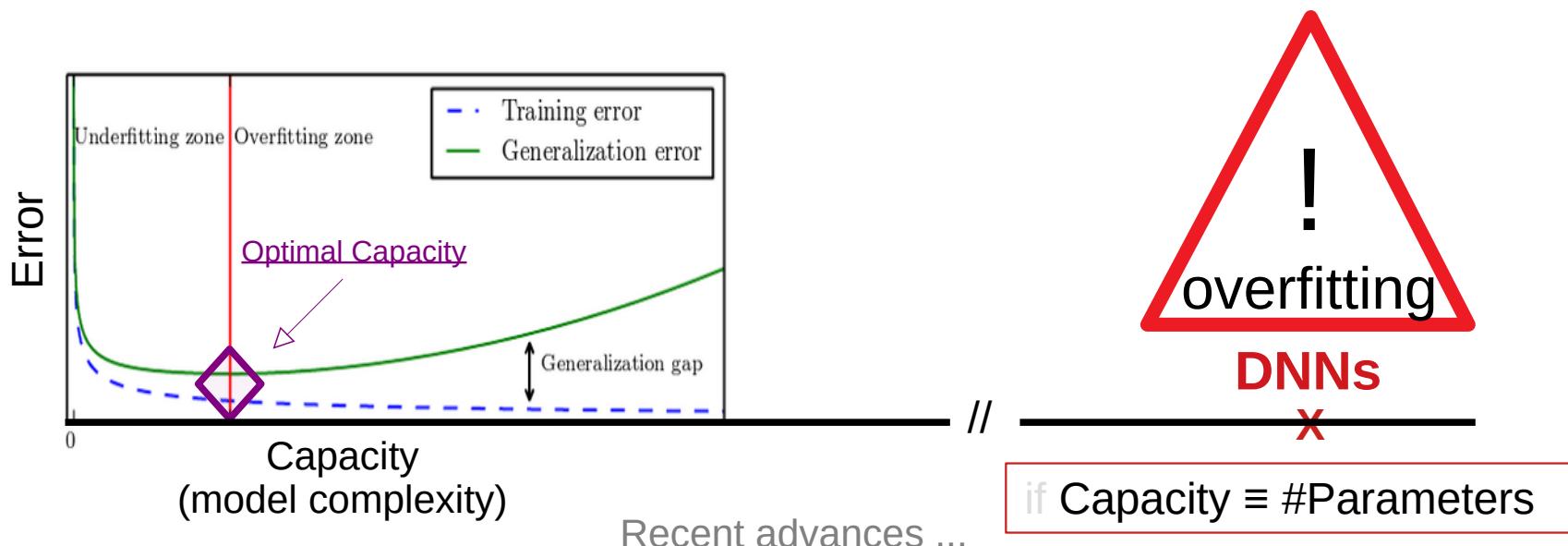
- Why do DNNs generalise well?



if $\text{Capacity} \equiv \#\text{Parameters}$

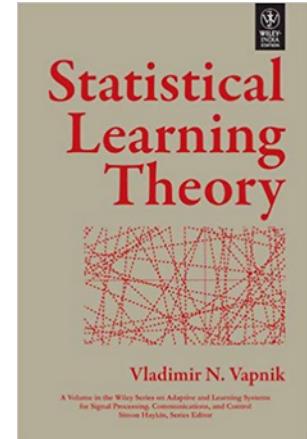
DNNs ... Generalisation ...

- Why do DNNs generalise well?
 - even when *over-parameterised* $\rightarrow P/N \gg 1$



Generalisation Error

- Classic statistical learning theory ...
 - Upper bound for $E_{gen} \leftrightarrow$ Capacity
 - Over-parameterisation ($P/N \gg 1$) is bad!



$$E_{gen} = E_{test} - E_{train} \underset{f_2(N)}{\propto} \frac{f_1(\#parameters)}{f_2(N)} \stackrel{\text{e.g.}}{=} \frac{f_1(VC\text{-dim})}{f_2(N)}$$

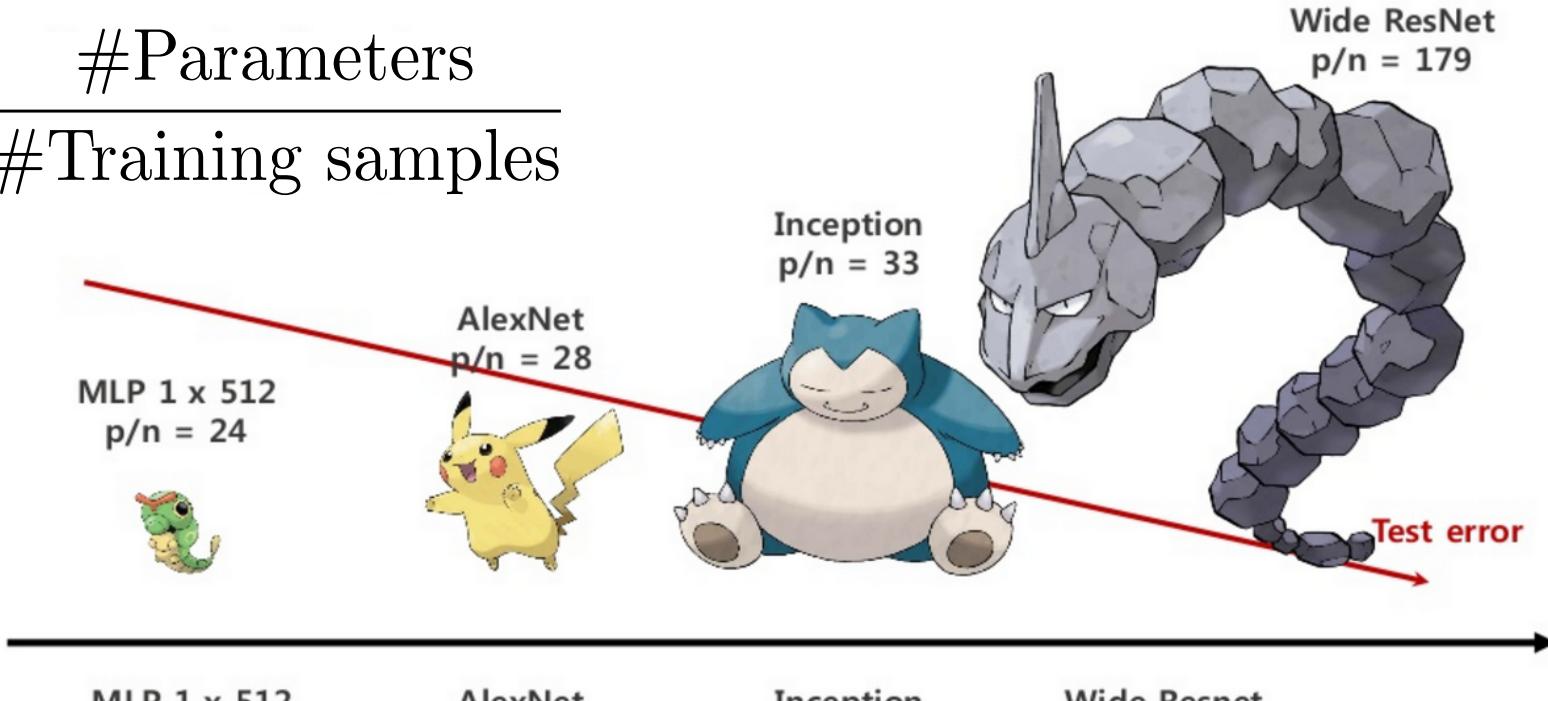
Over-parameterisation is good (1)

CIFAR-10	#train: 50,000	#parameter/#train
Inception	1,649,402	33
AlexNet	1,387,786	28
MLP 1x512	1,209,866	24
ImageNet	#train: 1,200,000	
Inception V3	23,885,392	20
AlexNet	61,100,840	51
ResNet-{18; 152}	11,689,512; 60,192,808	10; 50
VGG-{11;19}	132,863,336; 143,667,240	110; 120

[8]

Over-parameterisation is good (2)

$$p/n = \frac{\text{\#Parameters}}{\text{\#Training samples}}$$



[8]

Recent advances ...

If over-parametrisation is good ...

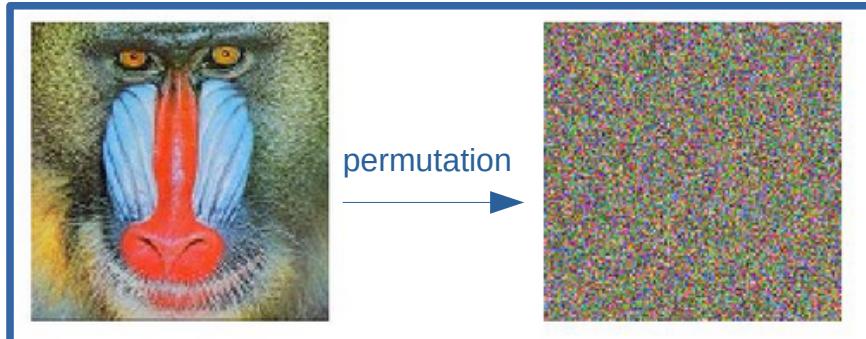
- *#parameters* does **NOT** represent *model complexity*
- *#parameters* does **NOT** upperbound E_{gen}
- Classic views to (*Capacity* \leftrightarrow E_{gen}) are **NOT** sufficient [8-12]

Why DNNs generalise well?

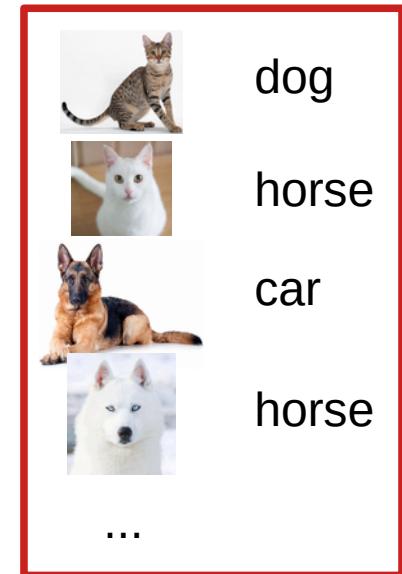
- Classic views ... $\#P$ & $\#N$... insufficient!
- DNNs generalise well because of ...
 - Optimisation?
 - Regularisation?
 - ...

Randomisation Test

- Training data: $\{x_i, y_i\}, i=1, 2, \dots, N$
- Break the (x_i, y_i) relationship by randomising x_i or y_i



Recent advances ...



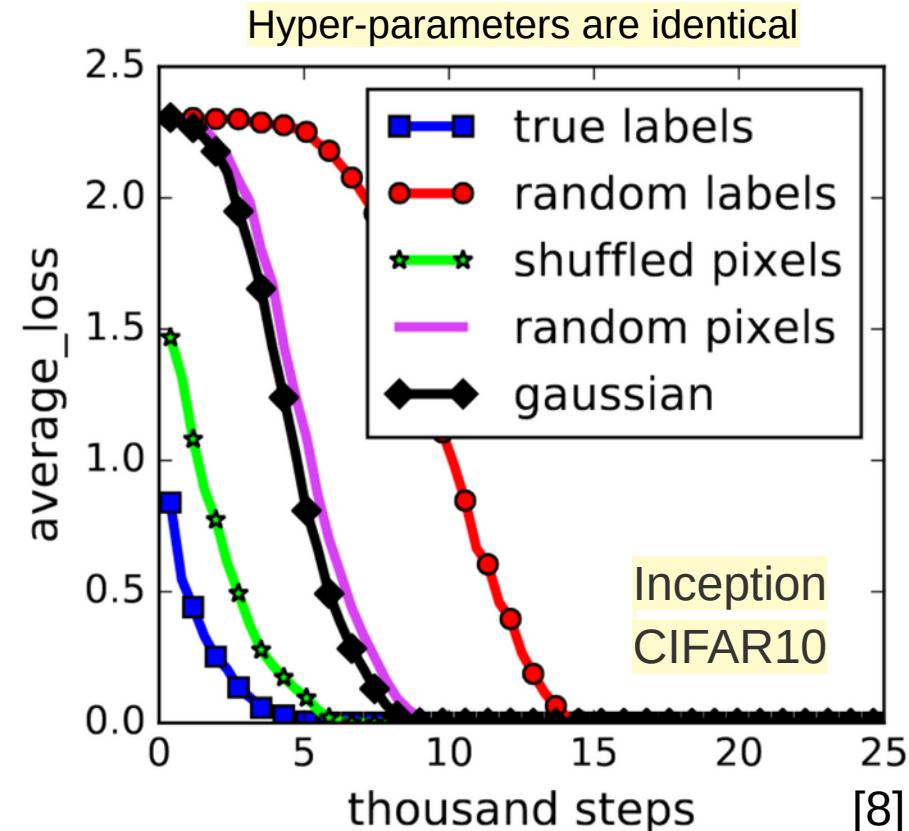
Randomisation Test

- Training data: $\{x_i, y_i\}, i=1, 2, \dots, N$
- Break the (x_i, y_i) relationship by randomising x_i or y_i
- Learning/Generalisation is **IMPOSSIBLE!**
- How about optimisation? (**IM**Possible?)

Randomisation Test – Results (1)

DNN **shatters** ($E_{train}=0$) training data, even with random data/labels.

This is **fitting** ...
agnostic to quality of **learning!**



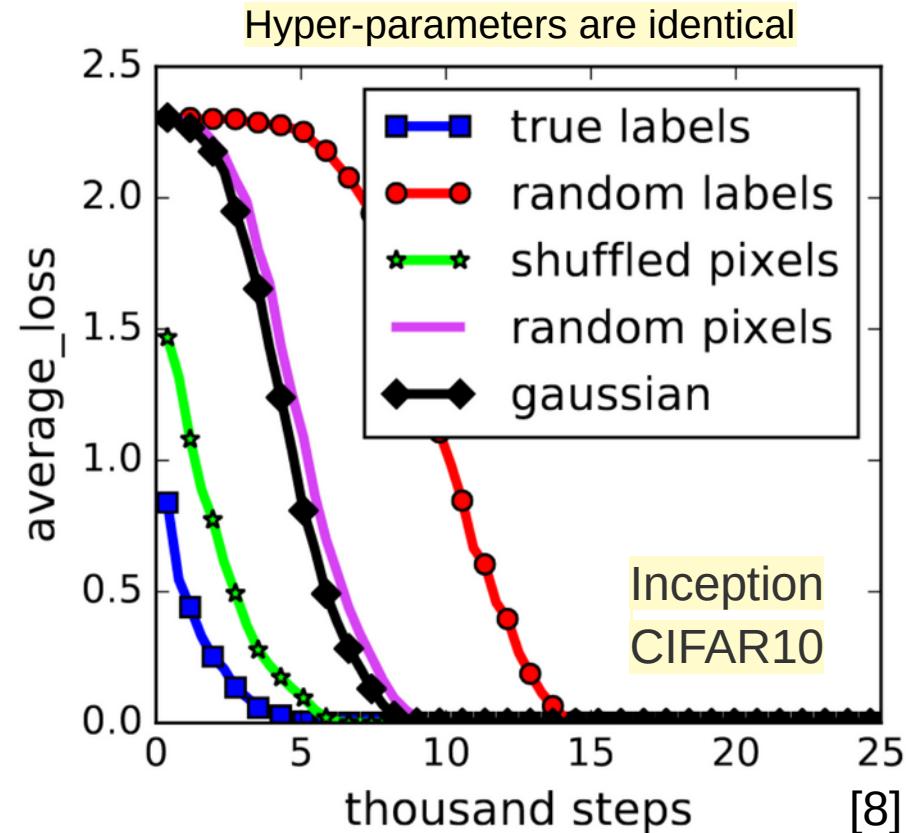
Recent advances ...

Randomisation Test – Results (2)

$$E_{gen} = E_{test} - E_{train} = <15, 90, 90, 90, 90>$$

E_{gen} is very different even when N, P and architecture are the same!

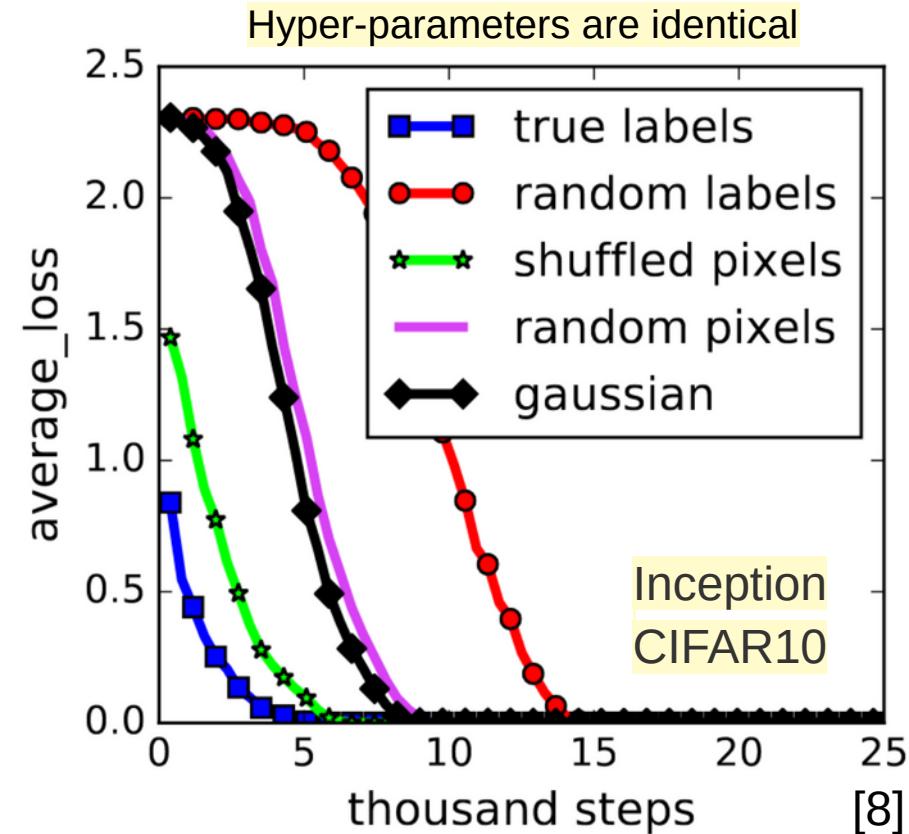
$$E_{gen} \Big|_{E_{train}=0} \leq O\left(\frac{VCdim}{N}\right)$$



Recent advances ...

Randomisation Test – Results (3)

Optimisation remains easy, ...
even when learning is impossible!
... Just slows down.



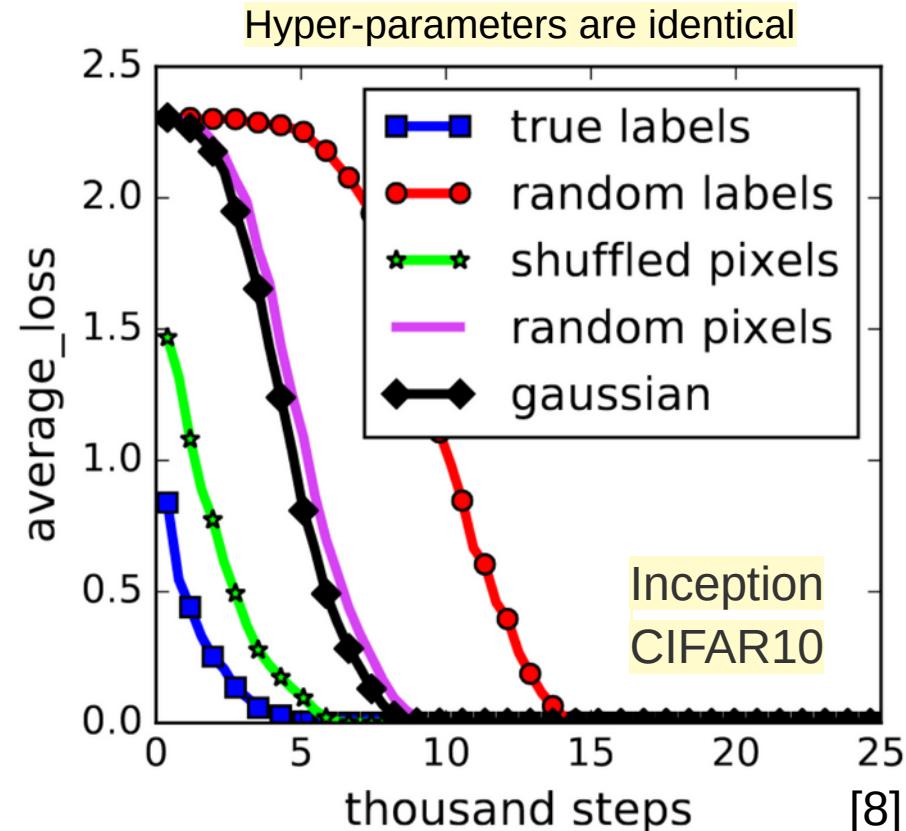
Recent advances ...

Randomisation Test – Results (3)

Optimisation remains easy, ...
even when learning is impossible!
... Just slows down.

Optimisation \leftrightarrow Fitting [YES]

Optimisation \leftrightarrow Learning [NO]



Recent advances ...

Local vs Global Optima ...

- Critical points ... local/global min/max or saddle
 - Positive/negative/in-definite Hessian → min/max/saddle

Local vs Global Optima ...

- Critical points ... local/global min/max or saddle
 - Positive/negative/in-definite Hessian → min/max/saddle
- In high dimensional spaces ...
 - Most of the critical points are **saddle** point [13]
 - **Local** minima are likely to be as good as **global** minima [14,15]

Local vs Global Optima ...

- Critical points ... local/global min/max or saddle
 - Positive/negative/in-definite Hessian → min/max/saddle
- In high dimensional spaces ...
 - Most of the critical points are saddle point [13]
 - Local minima are likely to be as good as global minima [14,15]
 - ✓ “... struggling to find the global minimum ... is not useful in practice and may lead to overfitting ... [15]”

Explicit Regularisation Effect

Max Performance Improvement ...

- By Reg.: **+3.56** (85.75 → 89.31)
- By Arch.: **+35.24** (50.51 → 85.75)

CIFAR-10		W/ Reg.		W/O Reg.	
model	# params	random crop	weight decay	train accuracy	test accuracy
Inception	1,649,402	yes	yes	100.0	89.05
		yes	no	100.0	89.31
		no	yes	100.0	86.03
		no	no	100.0	85.75
		no	no	100.0	9.78
Inception w/o BatchNorm	1,649,402	no	yes	100.0	83.00
		no	no	100.0	82.00
		no	no	100.0	10.12
		no	no	99.90	81.22
Alexnet	1,387,786	yes	yes	99.82	79.66
		yes	no	100.0	77.36
		no	yes	100.0	76.07
		no	no	99.82	9.86
		no	yes	100.0	53.35
MLP 3x512	1,735,178	no	no	100.0	52.39
		no	no	100.0	10.48
		no	no	99.80	50.39
MLP 1x512	1,209,866	no	yes	100.0	50.51
		no	no	99.34	10.61
		no	no	[8]	

Recent advances ...

Explicit Regularisation Effect

Max Performance Improvement ...

- By Reg.: **+3.56** (85.75 → 89.31)
- By Arch.: **+35.24** (50.51 → 85.75)

Regularisation helps ...
incrementally **NOT** fundamentally

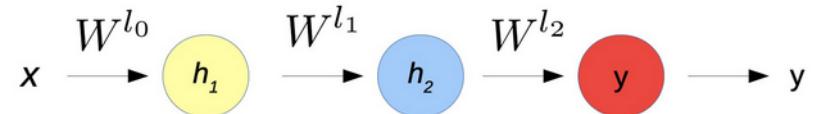
Architecture plays a critical role

CIFAR-10		W/ Reg.		W/O Reg.	
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		no	no	100.0	9.78
Inception w/o BatchNorm	1,649,402	no	yes	100.0	83.00
(fitting random labels)		no	no	100.0	82.00
		no	no	100.0	10.12
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		(fitting random labels)			[8]
MLP 1x512	1,209,866	no	yes	99.80	50.39
(fitting random labels)		no	no	100.0	50.51
		no	no	99.34	10.61

Recent advances ...

Implicit Regularisation in SGD ...

Back Propagation



$$W_{jk}^{(i)} = W_{jk}^{(i-1)} - \eta o_j \delta_k$$

$$\delta_k = \begin{cases} (o_k - t_k) o_k (1 - o_k) & , \text{ if } k \in y \\ (\sum_{l \in L} \delta_l W_{kl}) o_k (1 - o_k) & , \text{ if } k \in h_i \end{cases}$$

$$W^{l_2} = f(E)$$

$$W^{l_1} = f(E, W^{l_2})$$

$$W^{l_0} = f(E, W^{l_2}, W^{l_1})$$

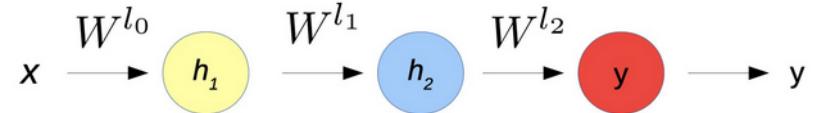
BP

Recent advances ...

Implicit Regularisation in SGD ...

Back Propagation

*Implicit regularisation ...
weights are tied together ...*



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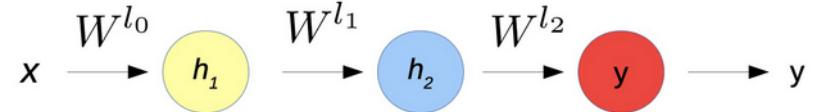
BP

Recent advances ...

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Capacity \equiv #Params_effective
#Params_effective \ll #Params

$$W^{l_2} = f(E)$$

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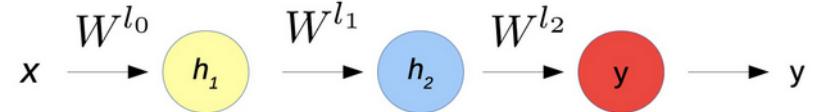
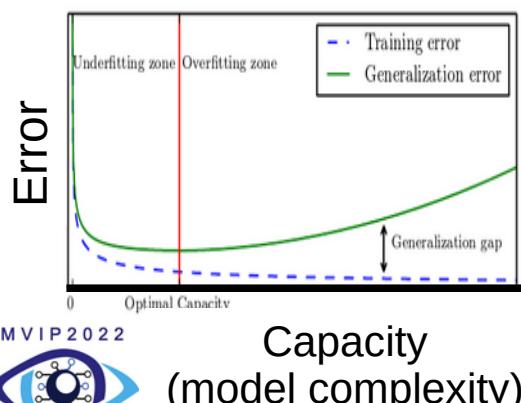
BP

Recent advances ...

Implicit Regularisation in SGD ...

Back Propagation

*Implicit regularisation ...
weights are tied together ...*



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Recent advances ...

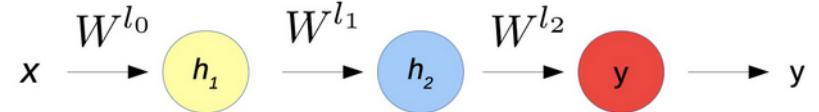
BP

Implicit Regularisation in SGD ...

Back Propagation

*Implicit regularisation ...
weights are tied together ...*

*... is responsible for good
generalisation of the DNNs.*



$$W_{jk}^{(i)} = W_{jk}^{(i-1)} - \eta o_j \delta_k$$

$$\delta_k = \begin{cases} (o_k - t_k) o_k (1 - o_k) & , \text{ if } k \in y \\ (\sum_{l \in L} \delta_l W_{kl}) o_k (1 - o_k) & , \text{ if } k \in h_i \end{cases}$$

$$W^{l_2} = f(E)$$

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$$W^{l_0} = f(E, W^{l_2}, W^{l_1})$$

BP

Recent advances ...

Conclusion (Part II)

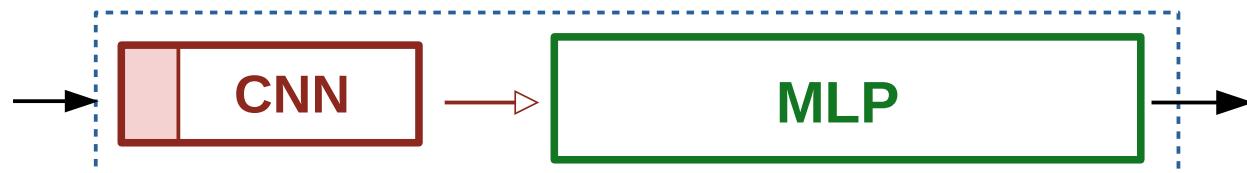
- Classic wisdom about generalisation is insufficient
- #Parameters does NOT represent model complexity
- Optimisation remains easy, even when learning is hard
- Explicit regularisation helps, incrementally NOT fundamentally
- Why do DNNs generalise well?
 - Implicit regularisation in SGD and ...

Outlines (Part III)

- Information Bottleneck
- Over-parameterisation and Generalisation
- Interpretation/Visualisation of Filters/Activations

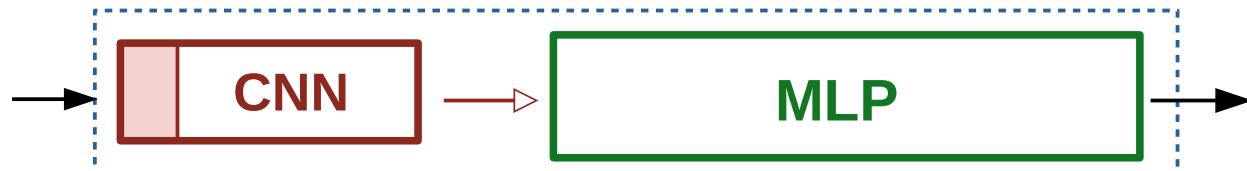
We will investigate ...

- Seriousness of gradient vanishing in low layers [16]
- Linear separability in high layers [17]



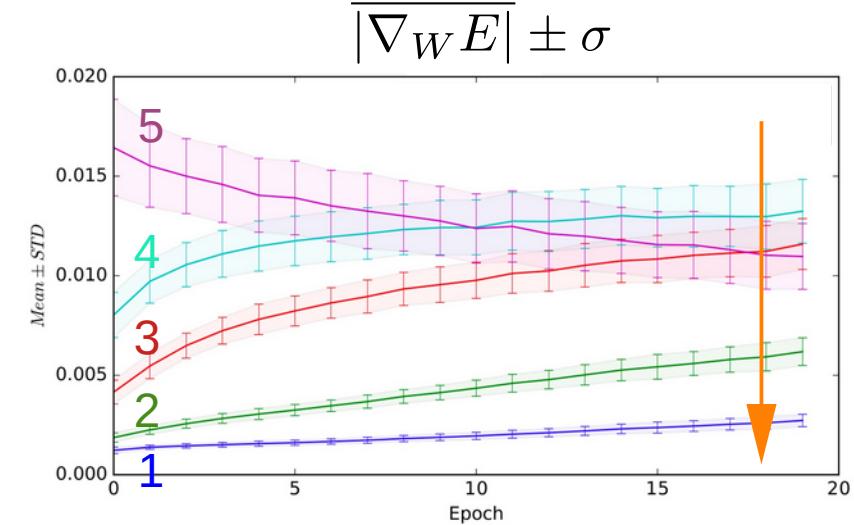
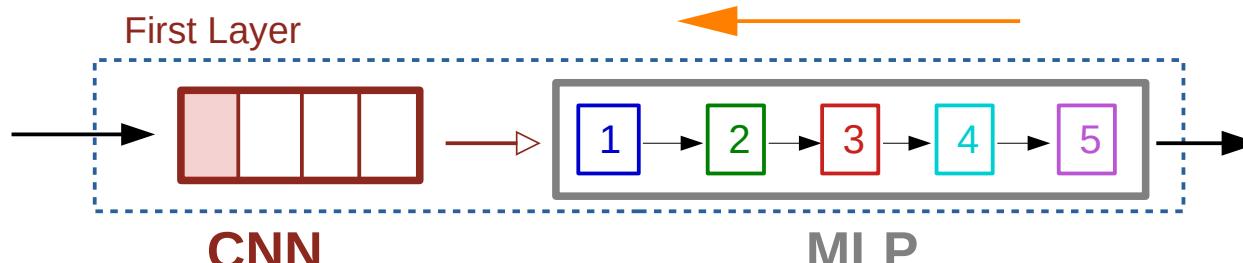
We will investigate ...

- Seriousness of gradient vanishing in low layers [16]
- Linear separability in high layers [17]



Seriousness of Gradient Vanishing

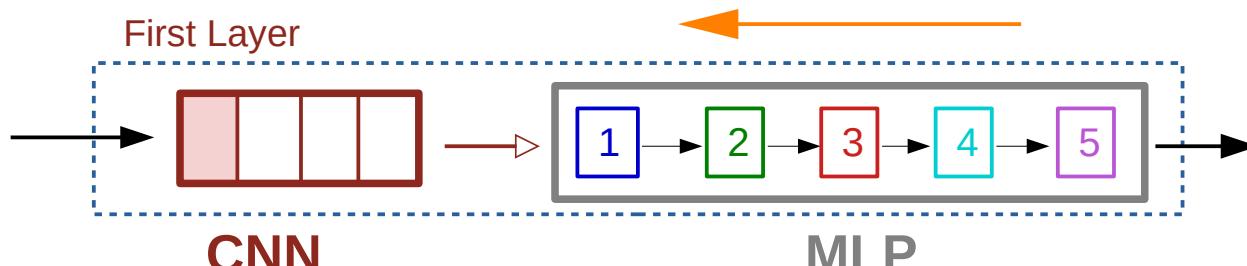
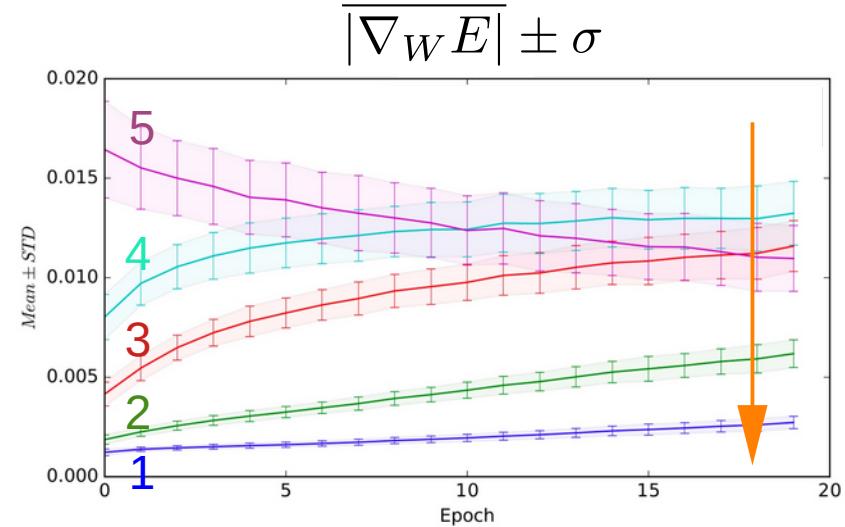
gradient vanishing ...



Recent advances ...

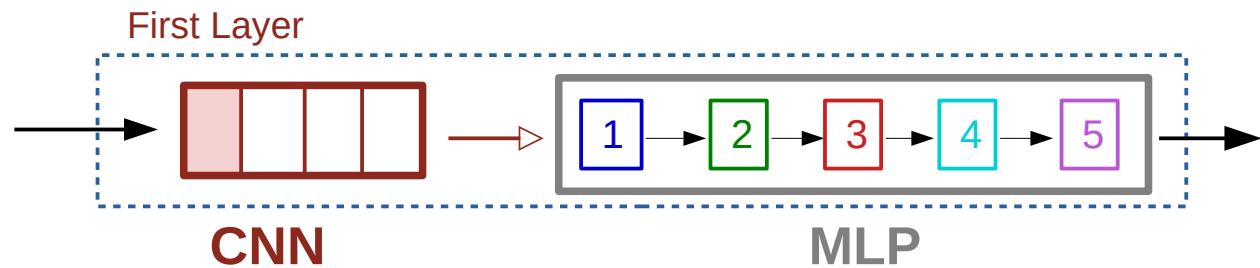
Seriousness of Gradient Vanishing

In light of gradient vanishing ...
How optimal the first layer is?



Recent advances ...

How to investigate it?



- * Error or accuracy reflect DNN's collective behaviour
- * *Layer-dependent* metric is needed ...

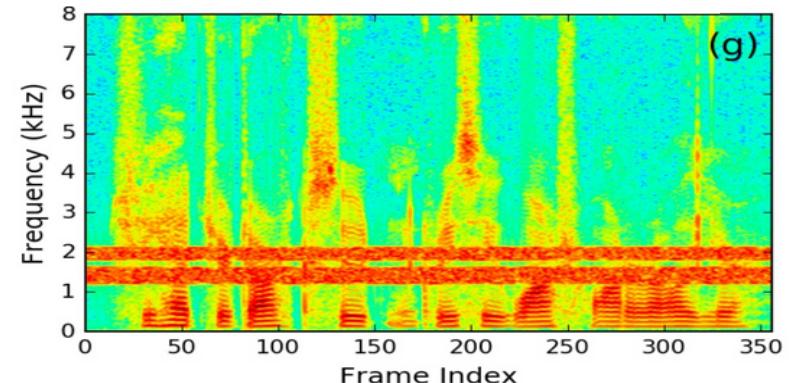
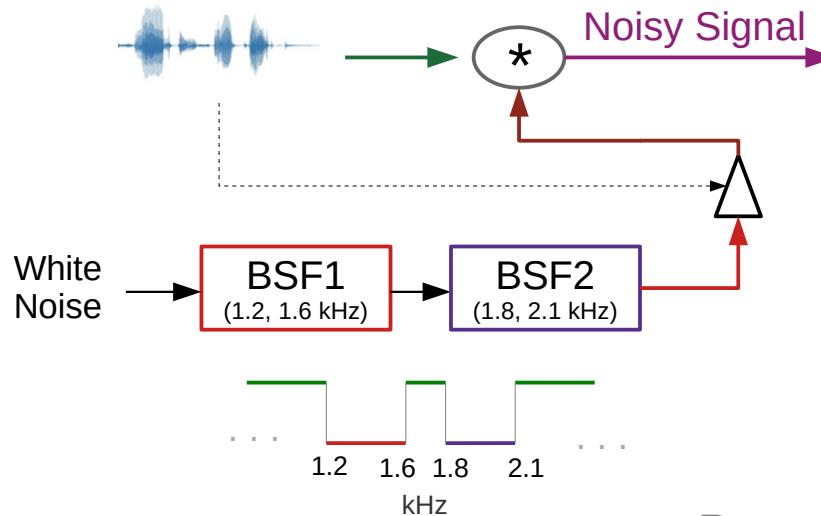
The proposed task ...

- Task: Phone recognition (TIMIT) using raw waveform



The proposed task ...

- Task: Phone recognition (TIMIT) using raw waveform
- How: add noise to training data ...



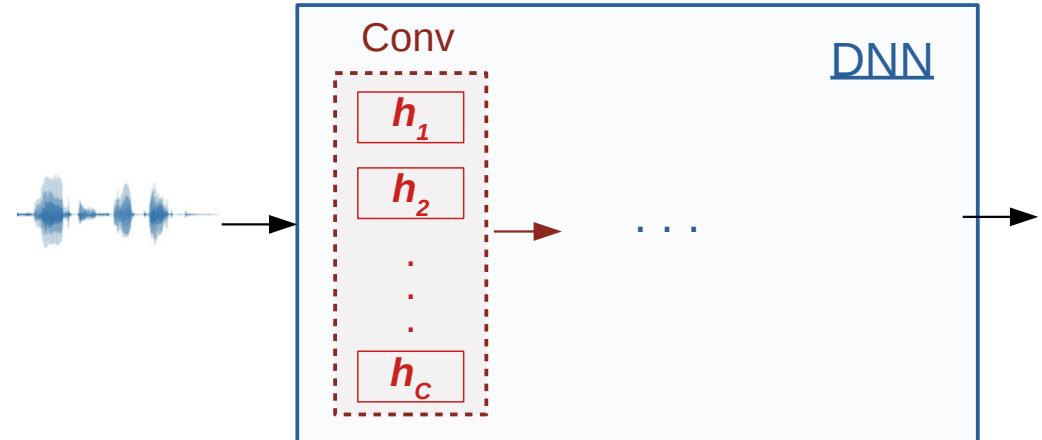
Recent advances ...

Gradient Vanishing Seriousness

- Task: Phone recognition (TIMIT) using raw waveform
- How: add noise to training data
- Metric: Average Frequency Response (AFR)

$$\text{AFR} = \frac{1}{C} \sum_{c=1}^C |H_c(\omega)|$$

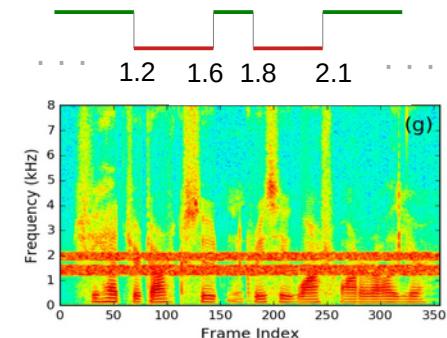
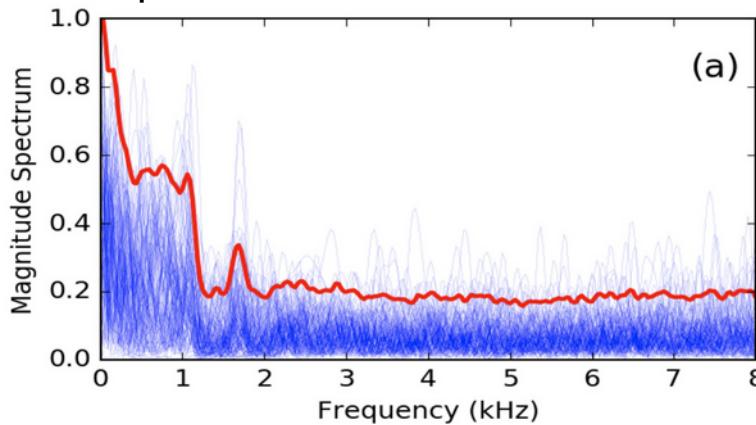
h: impulse response
H: frequency response
C: #channels



Recent advances ...

AFR Dynamics (1)

Epoch 1

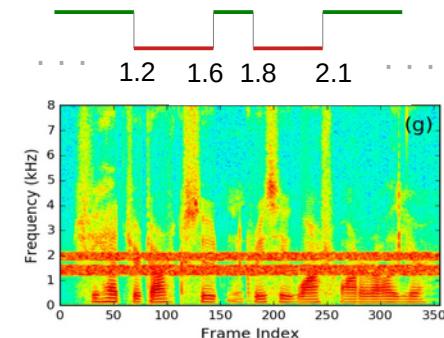
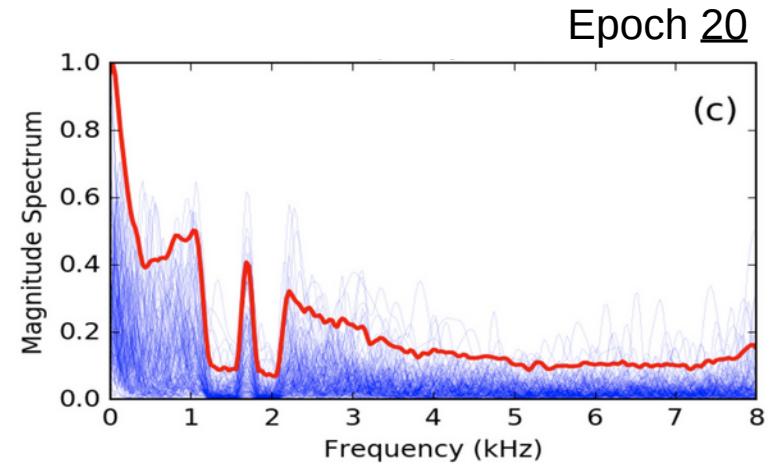
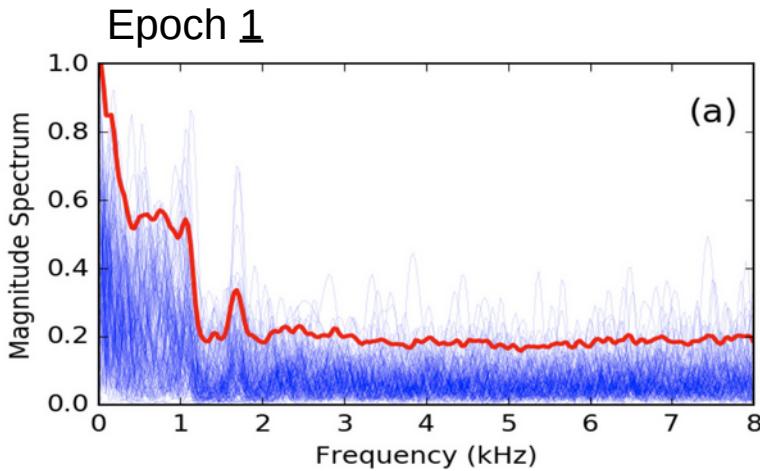


[16]

Recent advances ...

50/60

AFR Dynamics (1)

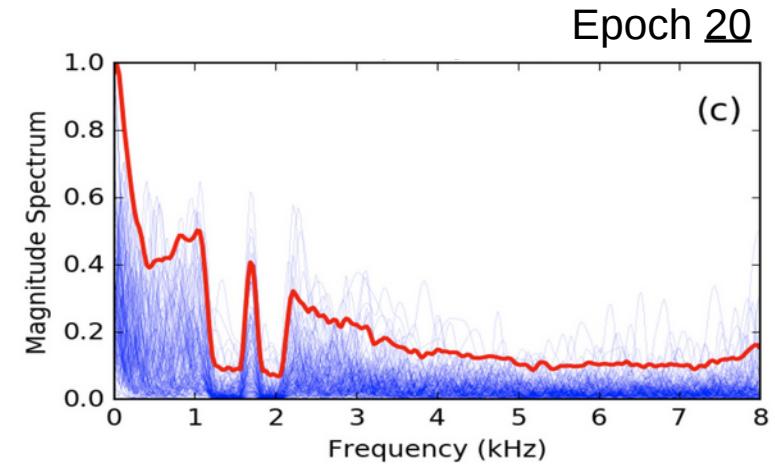
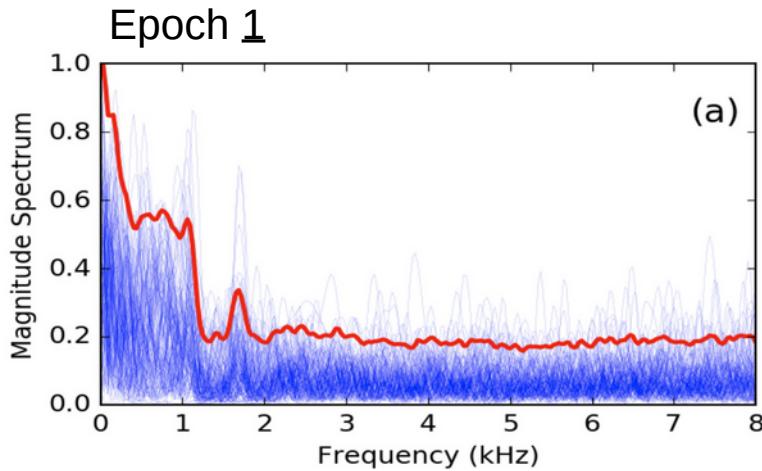


Recent advances ...

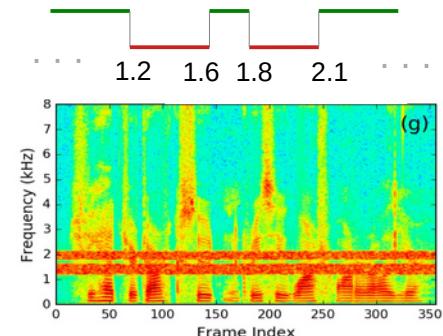
[16]

50/60

AFR Dynamics (2)



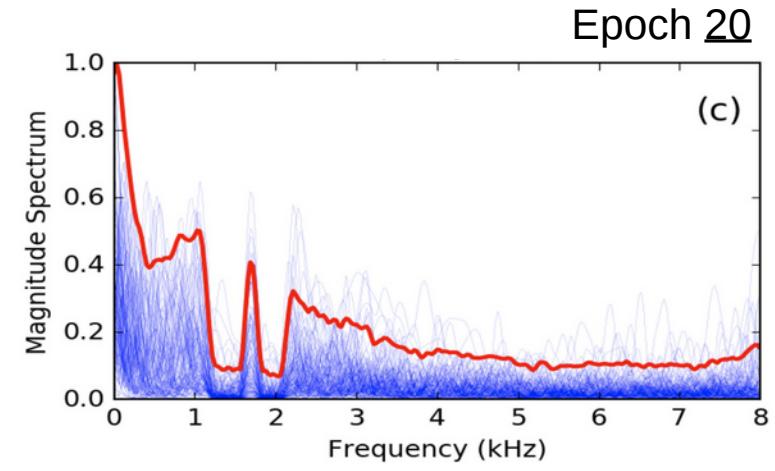
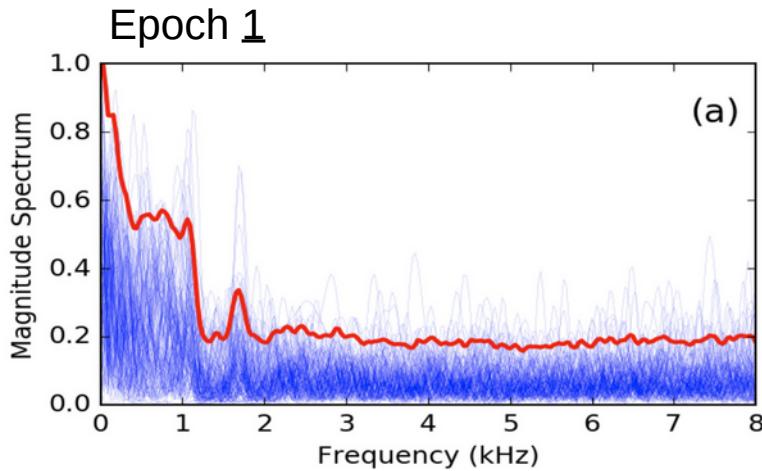
Using phone labels, the model finds the noisy sub-bands and filters them out.



[16]

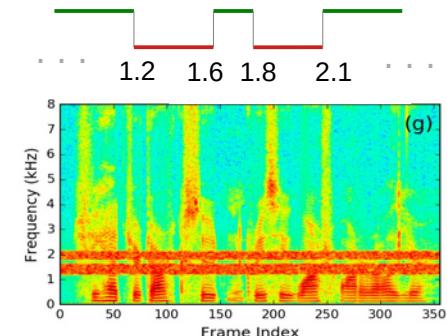
Recent advances ...

AFR Dynamics (2)



Using phone labels, the model finds the noisy sub-bands and filters them out.

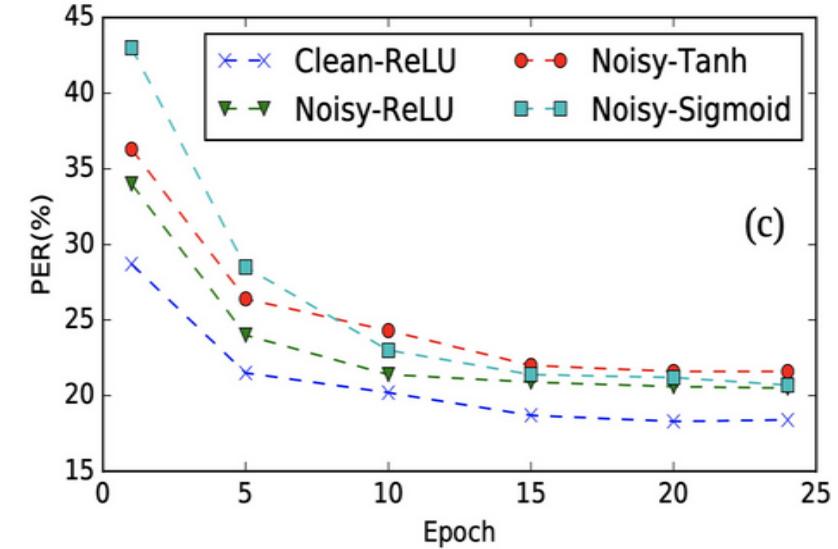
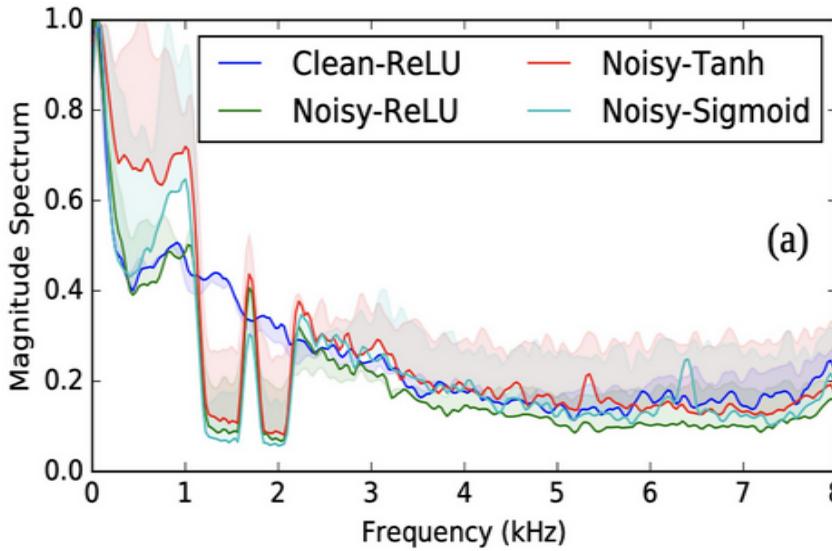
Gradient vanishing is NOT a serious problem ...



[16]

Recent advances ...

Effect of Activation Function

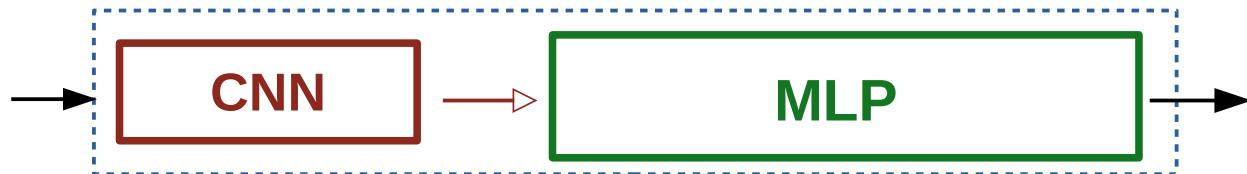


[16]

- * ... Sigmoid and Tanh ... Noisy sub-bands successfully found ...
- * Gradient vanishing is NOT a serious problem in a reasonable setup!

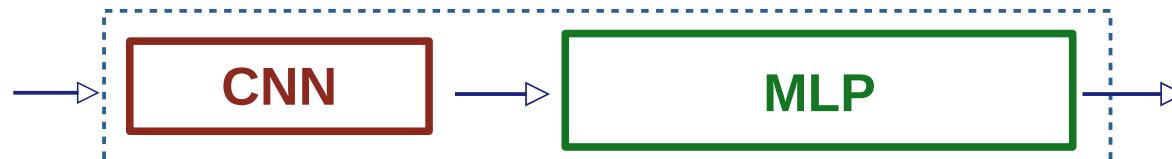
We will investigate ...

- Seriousness of gradient vanishing in low layers [16]
- Linear separability in high layers [17]



Towards output layer ...

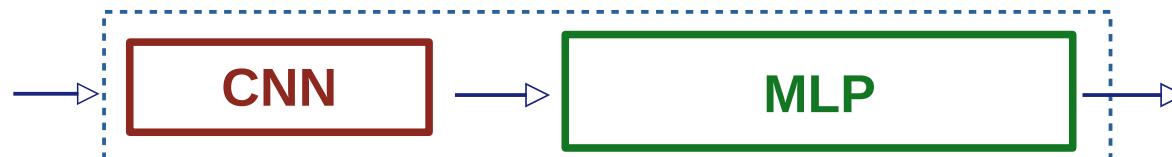
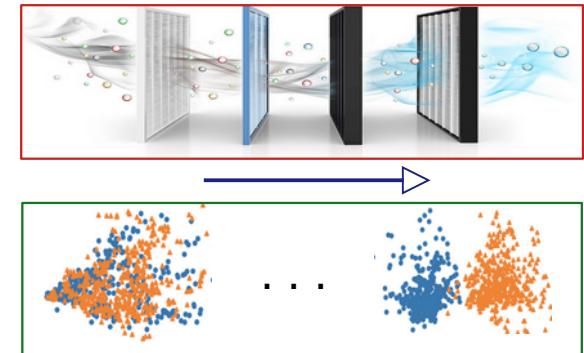
- DNN should ...
 - Filter out **irrelevant information**



Recent advances ...

Towards output layer ...

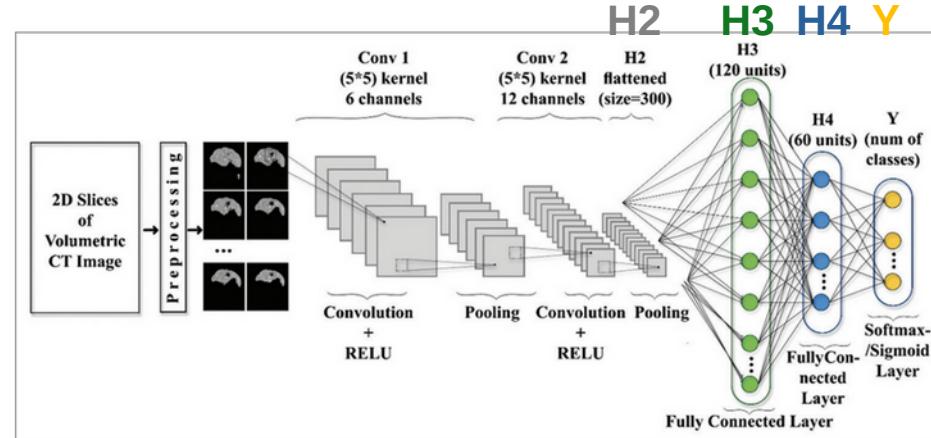
- DNN should ...
 - Filter out **irrelevant information**
 - Enhance **linear separability**
 - Softmax is a linear classifier



Recent advances ...

Investigating the Linear Separability ...

- **Task:** A binary classification (Question F, ImageCLEF2015)
- **How:** Dump activations → Dim. reduction to 2D (t-SNE, PCA, ...) →
→ Monitor linear separability across layers/epochs

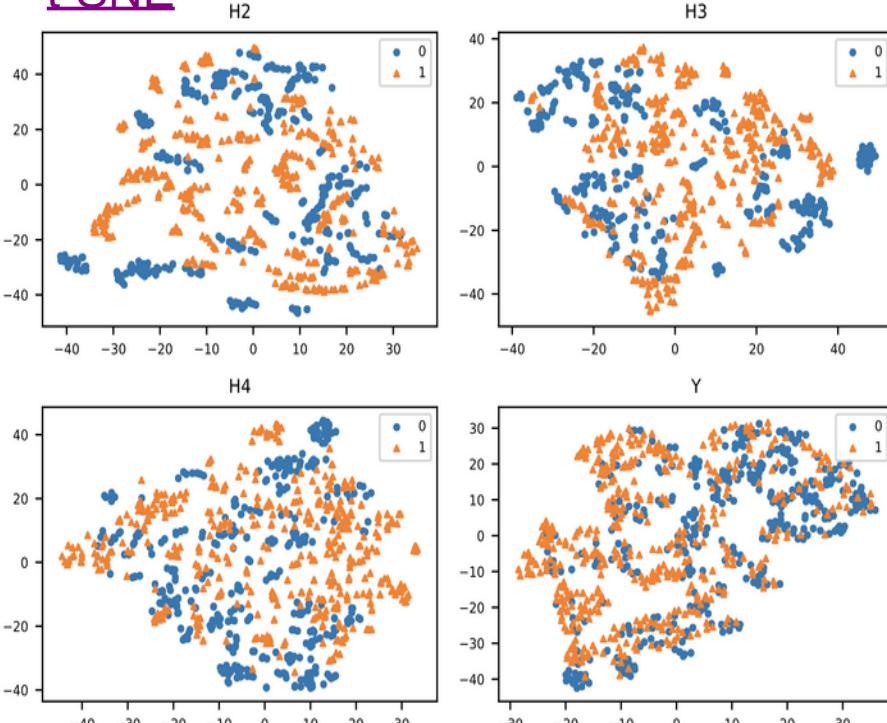


[17]

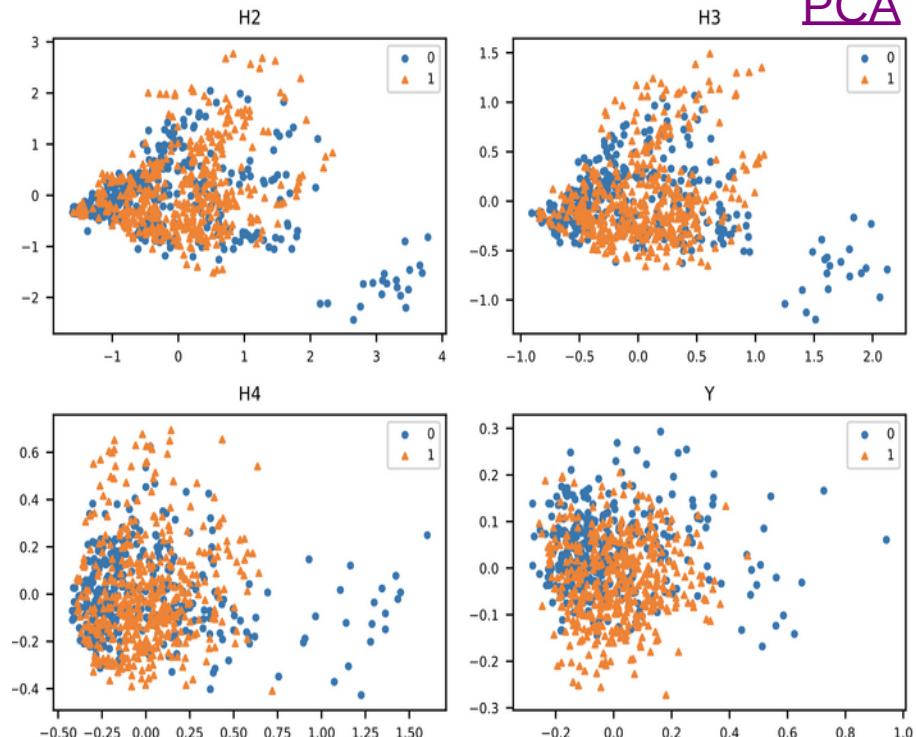
Recent advances ...

Epoch: 1

t-SNE



PCA



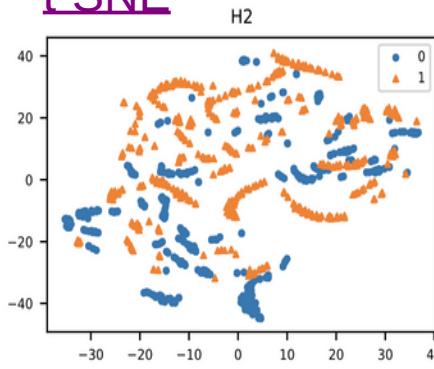
$X \rightarrow \text{CNN} \dots H2 \rightarrow H3 \rightarrow H4 \rightarrow Y$

Recent advances ...

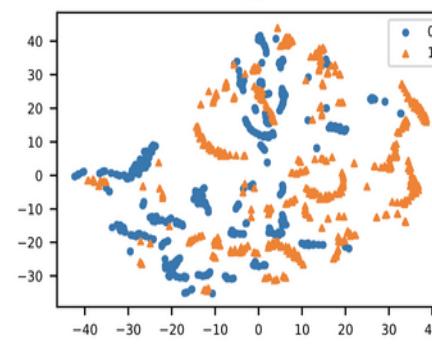
[17]

Epoch: 5

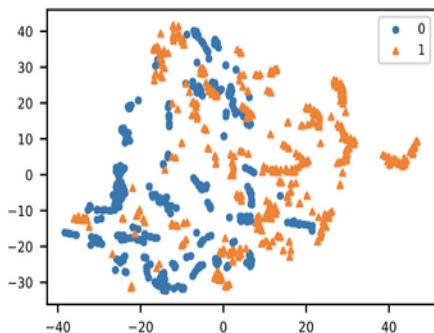
t-SNE



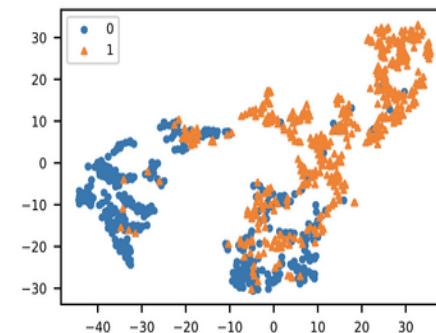
H3



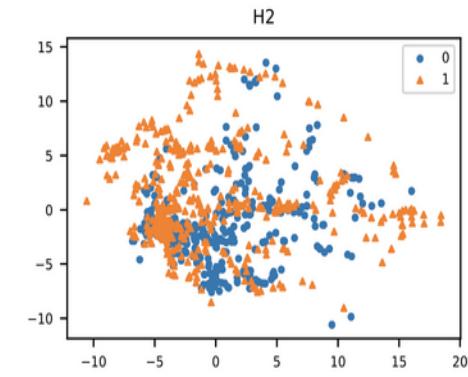
H4



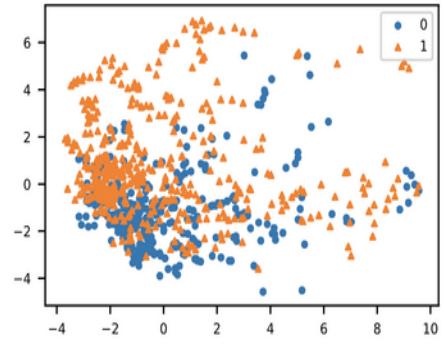
Y



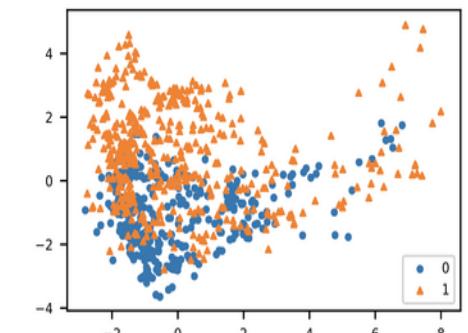
PCA



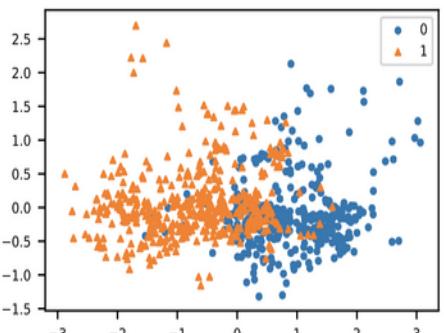
H3



H4



Y



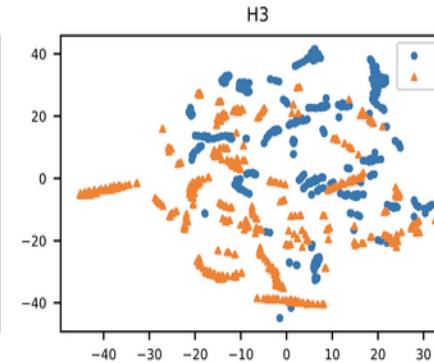
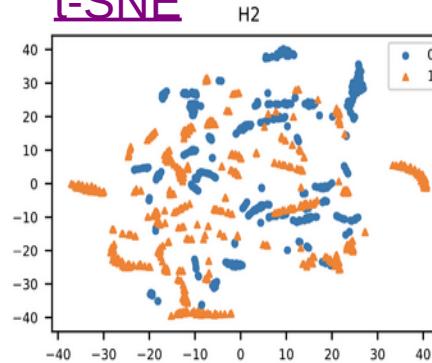
$X \rightarrow \text{CNN} \dots H2 \rightarrow H3 \rightarrow H4 \rightarrow Y$

Recent advances ...

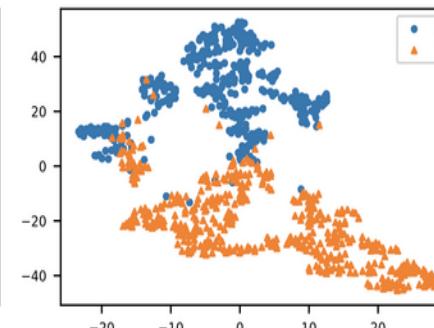
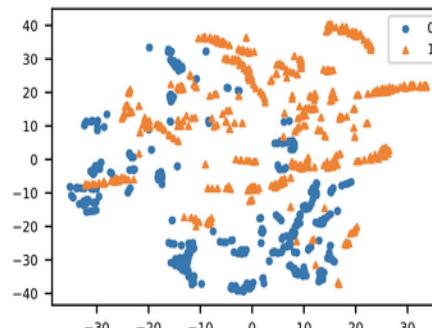
[17]

Epoch: 10

t-SNE

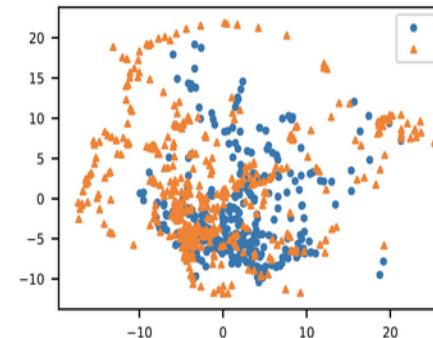


H4

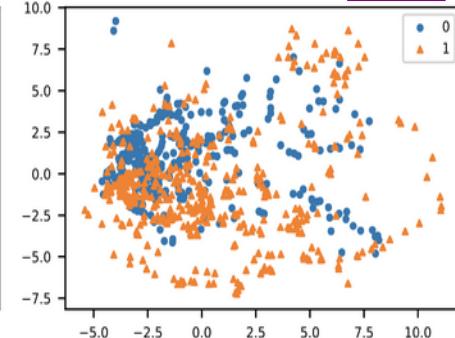


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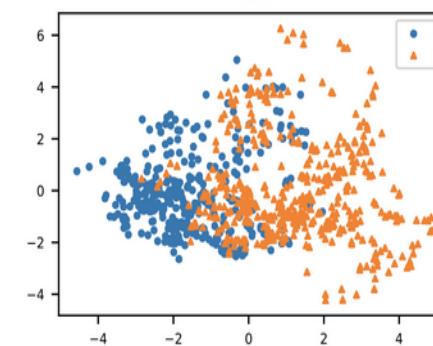
H2



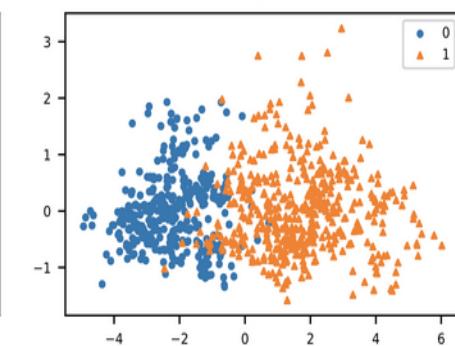
H3



H4



Y



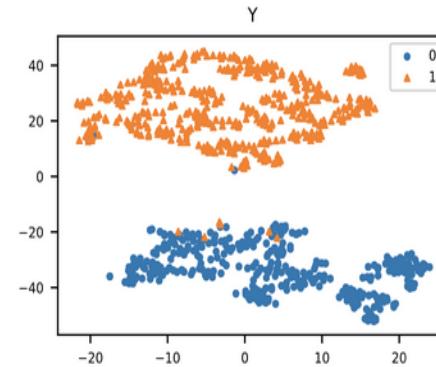
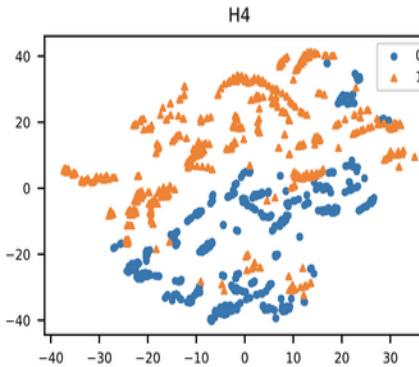
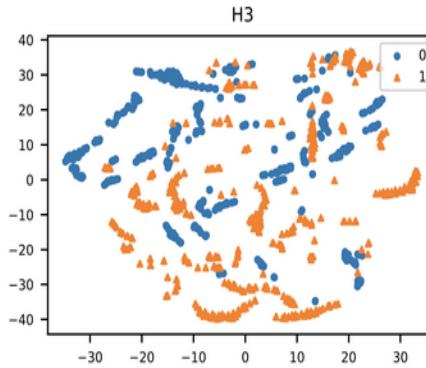
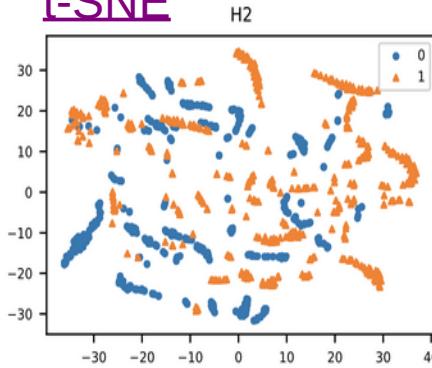
$X \rightarrow \text{CNN} \dots H2 \rightarrow H3 \rightarrow H4 \rightarrow Y$

Recent advances ...

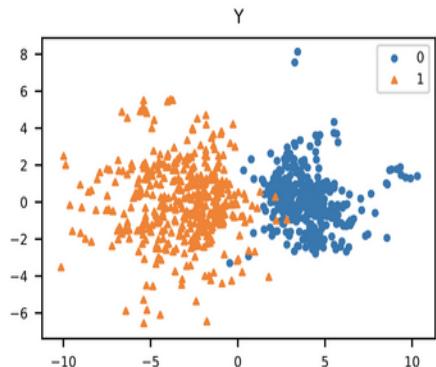
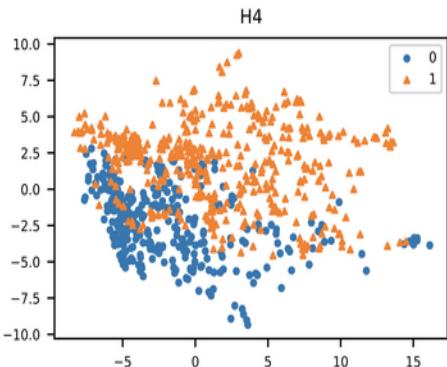
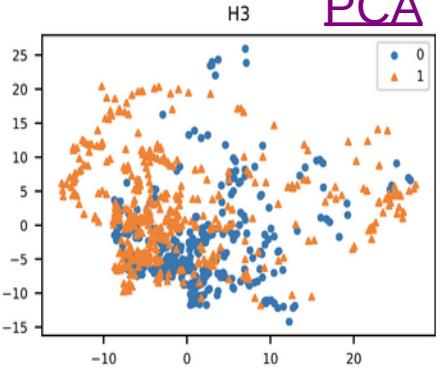
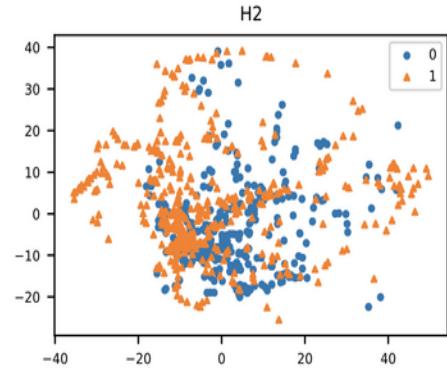
[17]

Epoch: 15

t-SNE



PCA



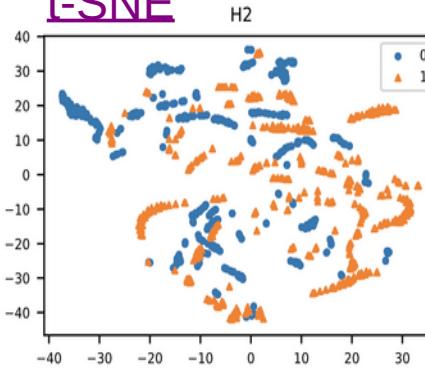
$X \rightarrow \text{CNN} \dots H2 \rightarrow H3 \rightarrow H4 \rightarrow Y$

Recent advances ...

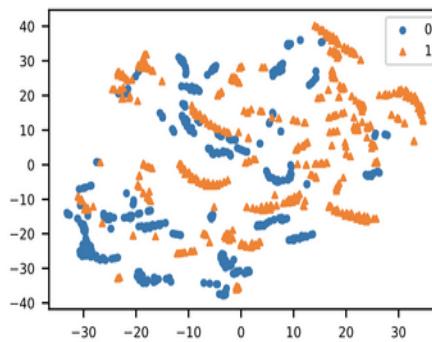
[17]

Epoch: 20

t-SNE

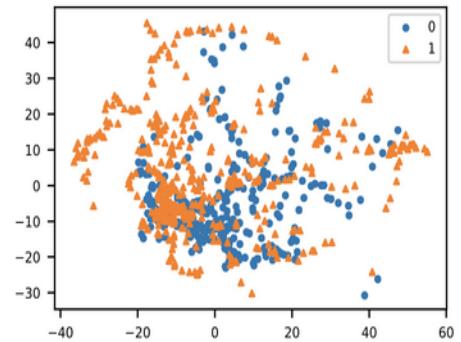


H3

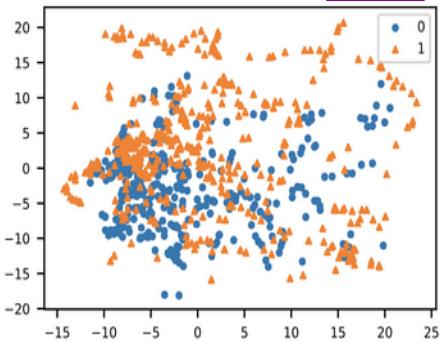


|

H2

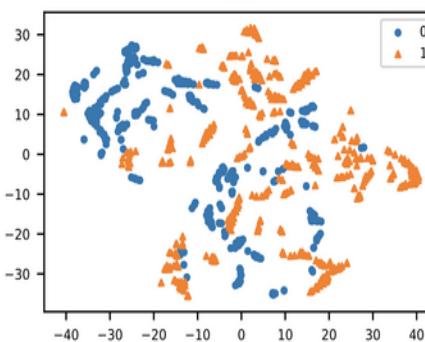


H3

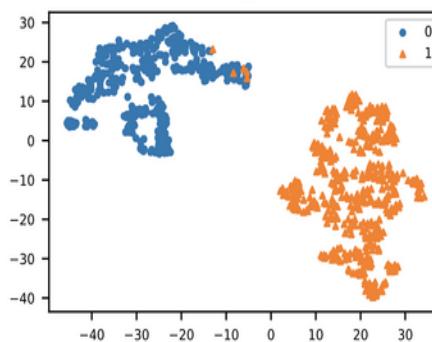


PCA

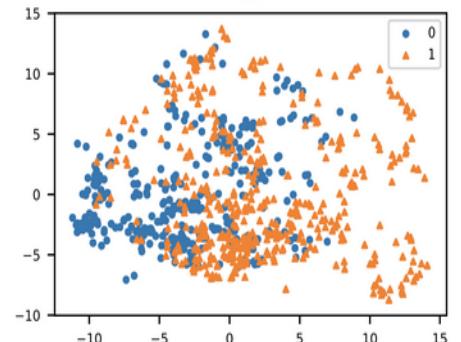
H4



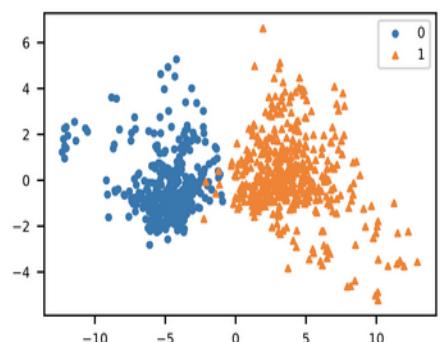
Y



H4



Y



[17]

$X \rightarrow \text{CNN} \dots H2 \rightarrow H3 \rightarrow H4 \rightarrow Y$

Recent advances ...

Conclusion (Part III)

- We studied/visualised the ...
 - Gradient vanishing seriousness
 - Linear separability across layers/epochs
- Providing interpretation/visualisation make the reviewer/readers happy :-), embed them into your work!

That's It!

- Thank you for Your Attention!
- Q&A
- References ↓

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