TRAINING VERY DEEP NETWORKS

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Some Background Details

- **Authors**
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- **Location**
  - **The Swiss AI Lab** is a part of
    - IDSIA Institution (Istituto Dalle Molle di Studi sull'Intelligenza Artificiale)
    - USI University (Università della Svizzera Italiana)
    - SUPSI University (Scuola Universitaria Professionale della Svizzera Italiana)

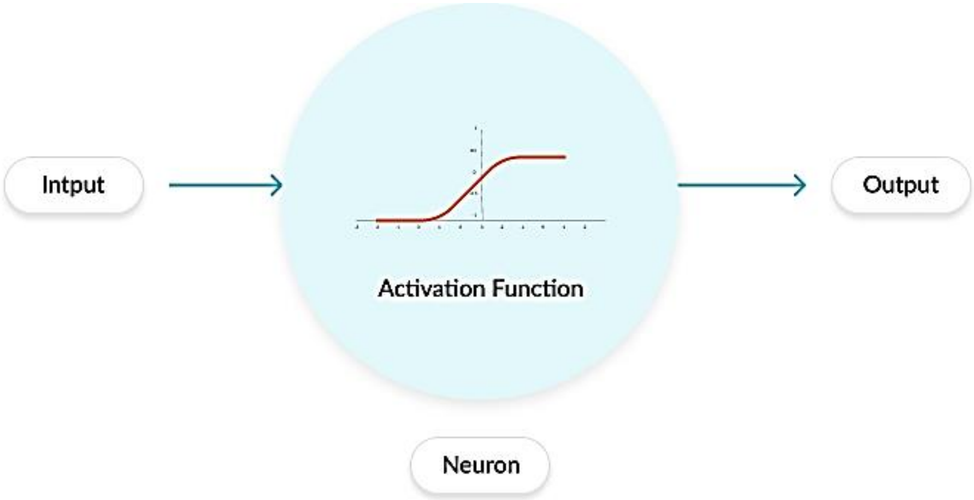
- **Published in**
  - International Conference on Machine Learning (ICML) 2015 (+600 citations)

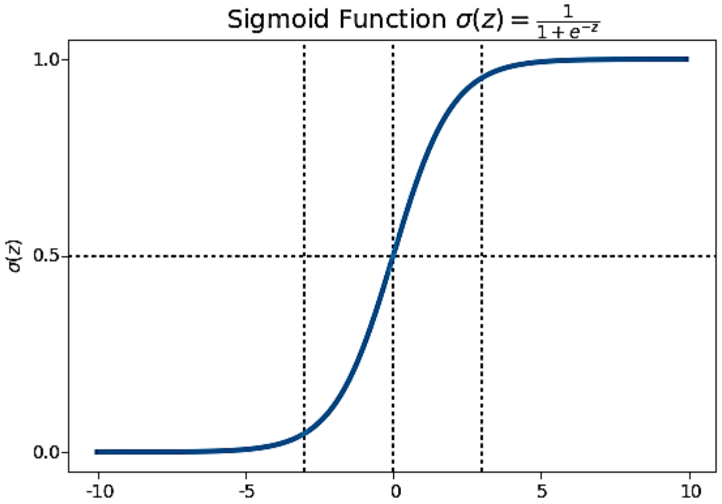
- **Conference location and date**
  - Lille, France, 6 - 11 July 2015

Professor Jürgen Schmidhuber
Main Contributor to LSTM / Backpropagation

Addressing The Problem

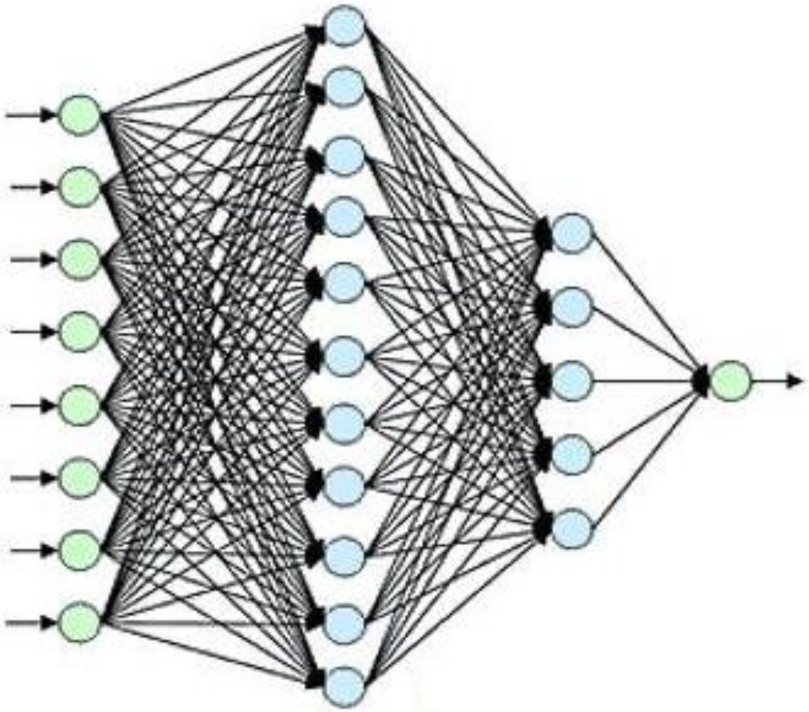
- It is still an open problem why training becomes more difficult as depth of the neural network increases
- As number of hidden layers increases, number of inputs in each hidden layers increases
- This will make activation function less sensitive and become difficult to train neural network
- This problem is identified as **Vanishing Gradient Problem** in machine learning

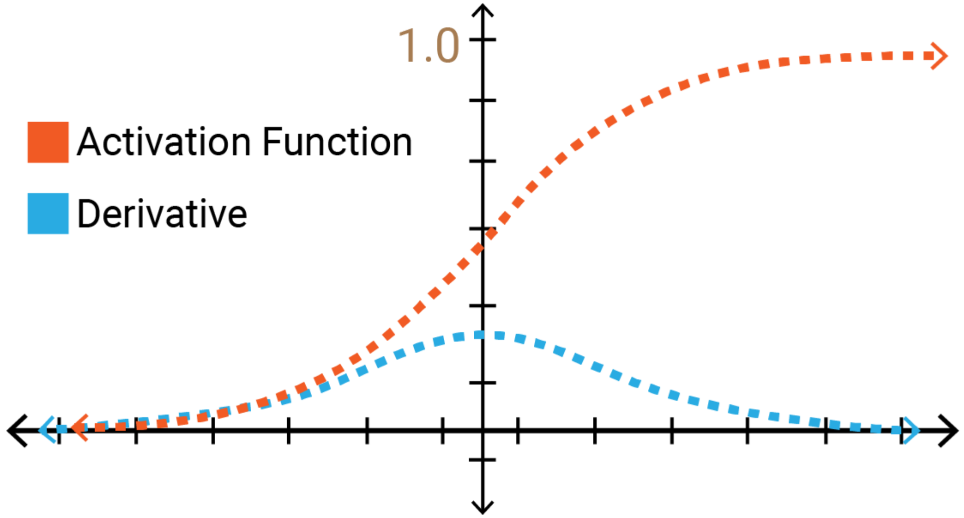




Vanishing Gradient Problem

- As more layers using certain activation functions are added to neural networks, the rate of the change of each activation function approaches zero



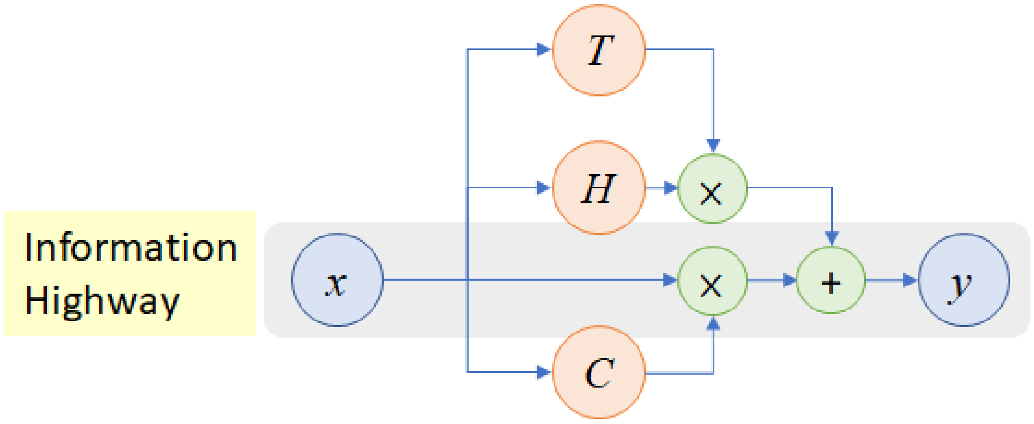


$$\text{Activation Function (Sigmoid)} = \frac{1}{1+e^{-z}}$$

$$\text{Derivative} = \frac{e^{-z}}{(1+e^{-z})^2}$$

Introduction to Highway Networks

- It is a LSTM-inspired gating mechanism that information can flow across many layers without attenuation (more than 1000 layers)
- Highway Networks allow unimpeded information flow across many layers due to the Transform Gate (T) and Carry Gate (C)

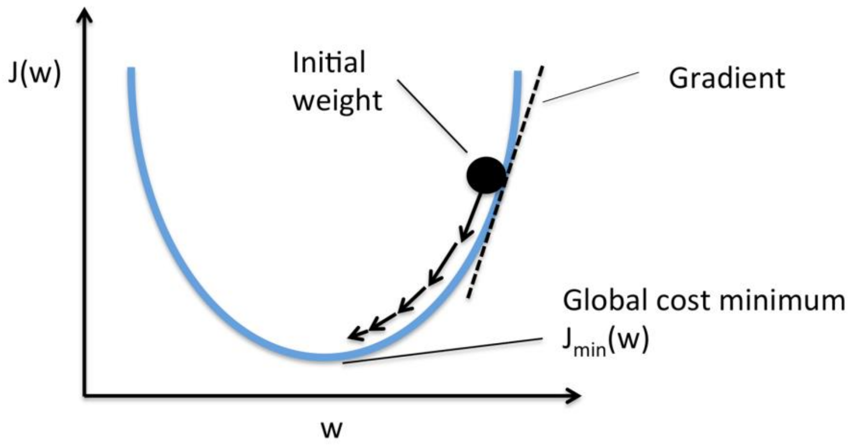


x = Input
T = Transform Gate
H = Transform Function
C = Carry gate
y = Output

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}) \cdot T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x} \cdot (1 - T(\mathbf{x}, \mathbf{W_T}))$$

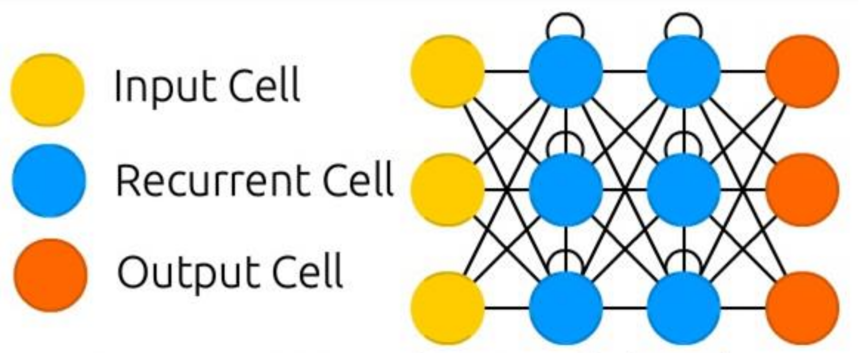
Introduction to Highway Networks

- It is based on **RNN** and **LSTM** neural network architectures
- Highway networks can be trained directly using **Stochastic Gradient Descent (SGD)** and does not stall for networks more than 1000 layer of network depth
- **Gradient Descent** is an iterative algorithm that start from a random point on a function and travels down its slope in steps until it reaches the lowest point of that function
- **Stochastic Gradient Descent** minimizes computations by picking data points randomly

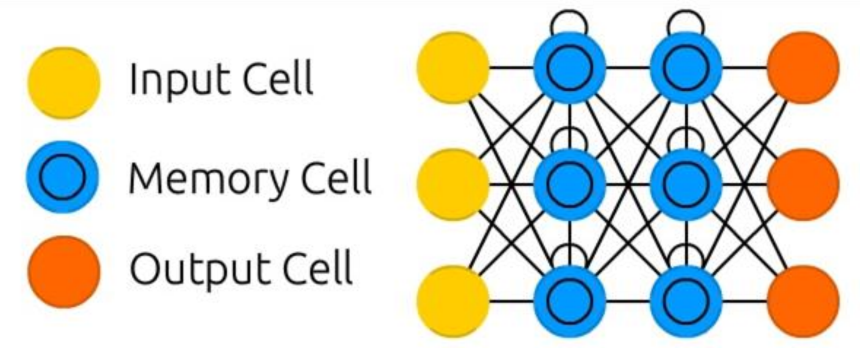


RNN and LSTM Architectures

- Recurrent neural network architecture allows previous output to be used as input while having hidden states
- RNN includes “Recurrent Cells” which can store information while processing new inputs
- Long-Short term memory is the further developed RNN architecture
- LSTM includes “Memory Cells” which can maintain information for long period of time



Recurrent Neural Network (RNN)



Long / Short Term Memory (LSTM)

Previous Work

- The top-5 (probability to be in top 5 predictions) image classification accuracy on the 1000-class ImageNet dataset has increased from 84% to 95% using deeper networks within just a few years due to the recent breakthrough
- To deal with difficulties of training deep networks, some researchers have focused on developing better optimizers such as Hessian-free optimization (James Martens, Ilya Sutskeverg, 2012)
- Initialization strategies for activation functions, Improvements in flow of information (shallow teacher network, Neural history compressor, Credit assignment problem) have been developed in recent years

Contribution of This Research Paper

- To show that extremely deep highway networks can be trained directly using **Stochastic Gradient Descent (SGD)**
- Deep network with limited computational budget, such as training deeper student network in multiple stages, can be directly trained in a single stages

Highway Networks

Highway Networks

It is found that there are difficulties optimizing a very deep neural network. However, it’s still an open problem why it is difficult to optimize a deep network. Inspired by Long Short-Term Memory (LSTM), authors thereby make use of gating function to adaptively transform or bypass the signal so that the network can go deeper.

Highway Networks

Notation

Boldface letters :- vectors and matrices

Italicized capital letters :-transformation functions

0 and 1 denote vectors of zeros and ones respectively

I - Identity matrix

The dot operator (·) :- element-wise multiplication.

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Plain network

Consider a plain feed forward neural network with L layers.

lth layer applies a non linear transformation H

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H})$$

$\mathbf{x}$ is input, $\mathbf{W_H}$ is the weight, H is the transform function followed by an activation function and $\mathbf{y}$ is the output.

For ith unit;

$$\mathbf{y}_i = H_i(\mathbf{x})$$

We compute the y_i and pass it to next layer.

Highway Networks

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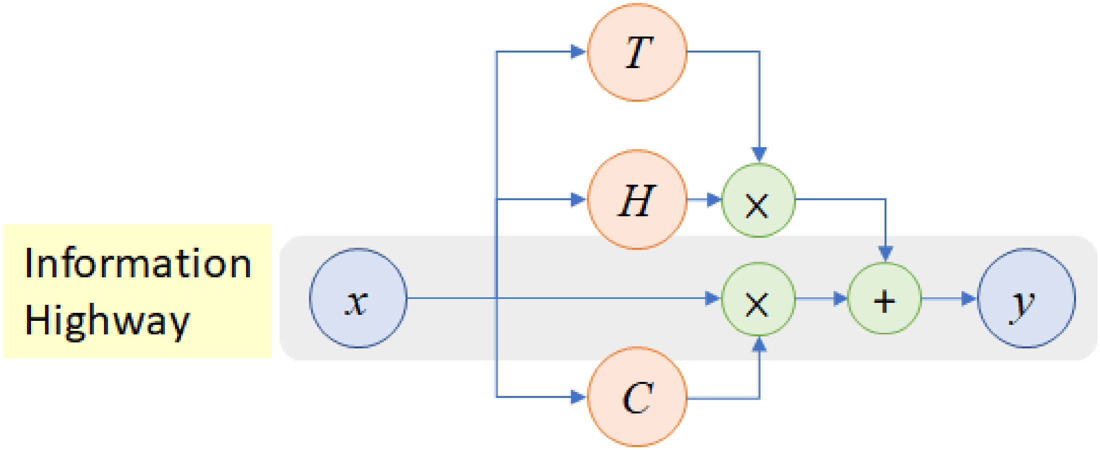
Highway network



In highway network, two non-linear transforms ***T*** and ***C*** are introduced

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W}_H).\ T(\mathbf{x}, \mathbf{W}_T) + \mathbf{x}.\ C(\mathbf{x}, \mathbf{W}_C)$$

Where ***T*** **is the Transform Gate** and **C is the Carry Gate**.

Highway Networks

Notation

Boldface letters :- vectors and matrices

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For simplicity , ***C* = 1 - *T***

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}).\ T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x}.\ (1 - T(\mathbf{x}, \mathbf{W_T}))$$

The dimensionality of $\mathbf{x}$, $\mathbf{y}$, $H(\mathbf{x}, \mathbf{W_H})$ and $T(\mathbf{x}, \mathbf{W_T})$ must be same

Below conditions can be haven for particular *T* values

$$\mathbf{y} = \mathbf{x}, \quad \text{if } T(\mathbf{x}, \mathbf{W_T}) = 0$$

$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}), \quad \text{if } T(\mathbf{x}, \mathbf{W_T}) = 1$$

When *T*=0, we pass the input as output directly which creates an information highway. That’s why it is called Highway Network !!!

Highway Networks

Notation

Boldface letters :- vectors and matrices

Italicized capital letters :-transformation functions

0 and 1:- vectors of zeros and ones respectively

I - Identity matrix

Dot operator $(\cdot)$:- element-wise multiplication.

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When T=1, we use the non-linear activated transformed input as output

Highway network consists of multiple blocks such that i_{th} block computes a block state $H_i(\mathbf{x})$ and transform gate output $T_i(\mathbf{x})$ and block output as;

$$\mathbf{y}_i = H_i(\mathbf{x}) * T_i(\mathbf{x}) + \mathbf{x}_i * (1 - T_i(\mathbf{x}))$$

Highway Networks

$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}).\ T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x}.\ (1\text{-}T(\mathbf{x}, \mathbf{W_T}))$

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Constructing highway networks

The dimensionality of $\mathbf{x}$, $\mathbf{y}$, $H(\mathbf{x}, \mathbf{W_H})$ and $T(\mathbf{x}, \mathbf{W_T})$ must be same

To change the size of intermediate representation;

- Can replace x with x obtain by sub sampling
- Use a plain layer

Convolutional highway layers utilize weight-sharing and local receptive field for both H and T

Same sized receptive fields for both and zero-padding are used to ensure that sizes will not change

Highway Networks

$\sigma(x) = \frac{1}{1+e^{-x}}$, $x \in$ R

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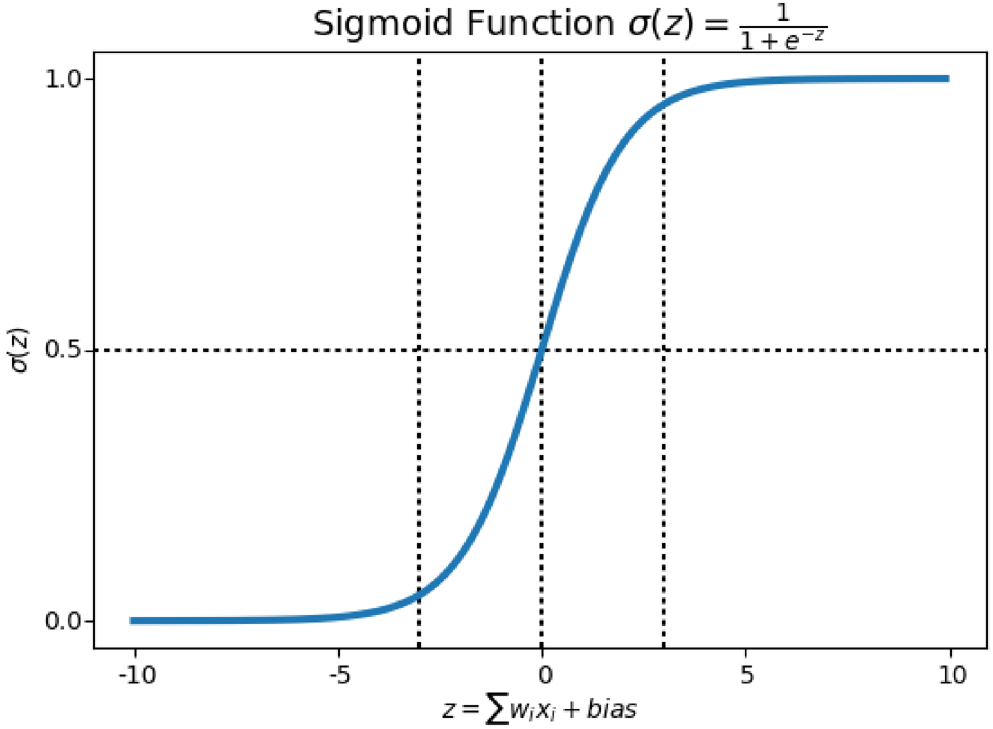
Training deep highway networks

Formally, $T(x)$ is the sigmoid function

$$T(\mathbf{x}) = \sigma\,(\mathbf{W}_T\,.\mathbf{x} + \mathbf{b}_T)$$



Highway Networks

$$\sigma(x) = \frac{1}{1+e^{-x}}, \quad x \in \mathrm{R}$$

sigmoid function caps the output between 0 to 1. When the input has too small value, it becomes 0. When the input has too large value, it becomes 1. Therefore, by learning $\mathbf{W_T}$ and $\mathbf{b_T}$, the network can adaptively pass $\boldsymbol{H(x)}$ or just pass $\boldsymbol{x}$ to next layer.

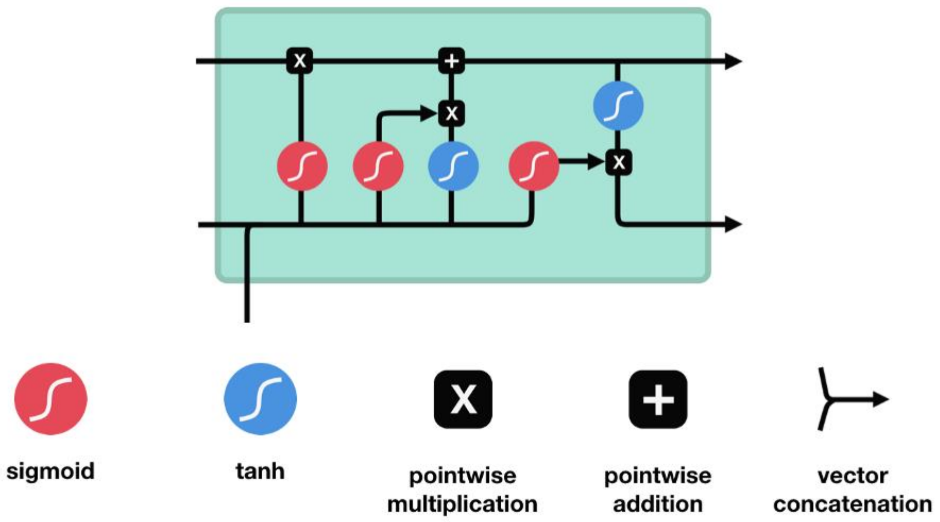
Here $\mathbf{W_T}$ is the weight matrix and $\mathbf{b_T}$ is the bias vector for the transform gates. This suggests a simple initialization scheme which is independent of the nature of *H*.

$\mathbf{b_T}$ can be initialized with a negative value (e.g. -1, -3 etc.) such that the network is initially biased towards carry behavior.

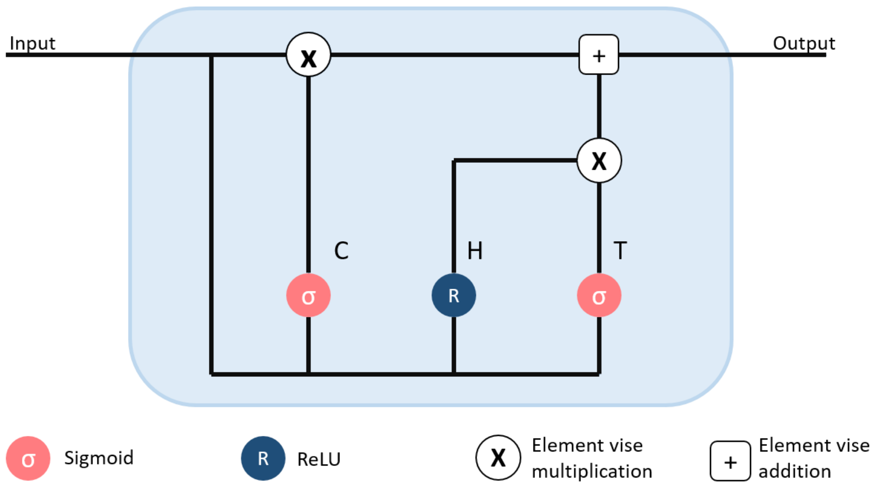
This idea is inspired by LSTM as authors mentioned.

LSTM and Information Highways

LSTM



INFORMATION HIGHWAY

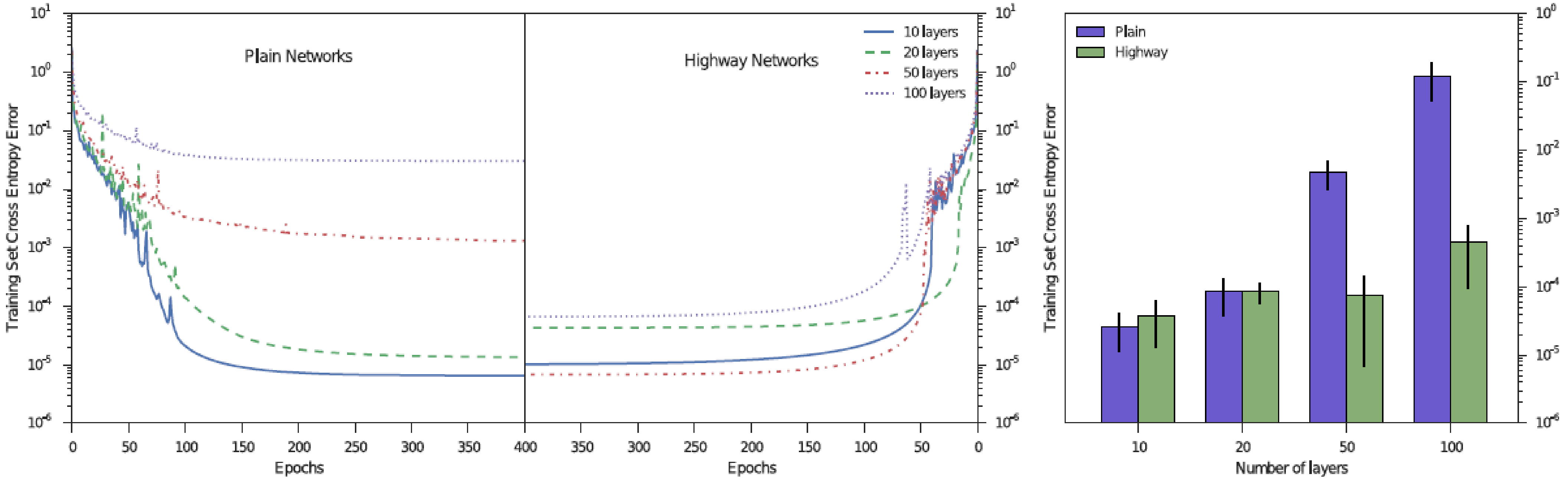


Experiment

Optimization

- All networks were trained using SGD with momentum
- An exponentially decaying learning rate was used in optimization
  - Learning rate starts at a value λ and decays according to a fixed schedule by factor ϒ
  - λ,ϒ and schedule were selected once based on validation performance on the CIFAR-10 and kept fixed for others
- All convolutional highway networks utilize the ReLU activation function to compute H.
- Caffe and Brainstorm were used as frameworks

- Trained both plain and highway networks of varying depths on the MNIST digit classification dataset
- All networks are thin:
  - Each layer has 5 blocks for highway networks and 71 units for plain networks
  - Yielding roughly identical number of parameters per layer
- The first layer is a fully connected plain layer followed by 9, 19, 49, or 99 fully connected plain or highway layers. Finally, the network output is produced by a softmax layer.



- ➢ Plain networks exhibits very good performance at 10 and 20 layers but it significantly degrades with depth increases
- ➢ Highway networks performs similar to the 10/20 layers networks at 50/100 layers
- ➢ It also consistently converged significantly faster than plain networks

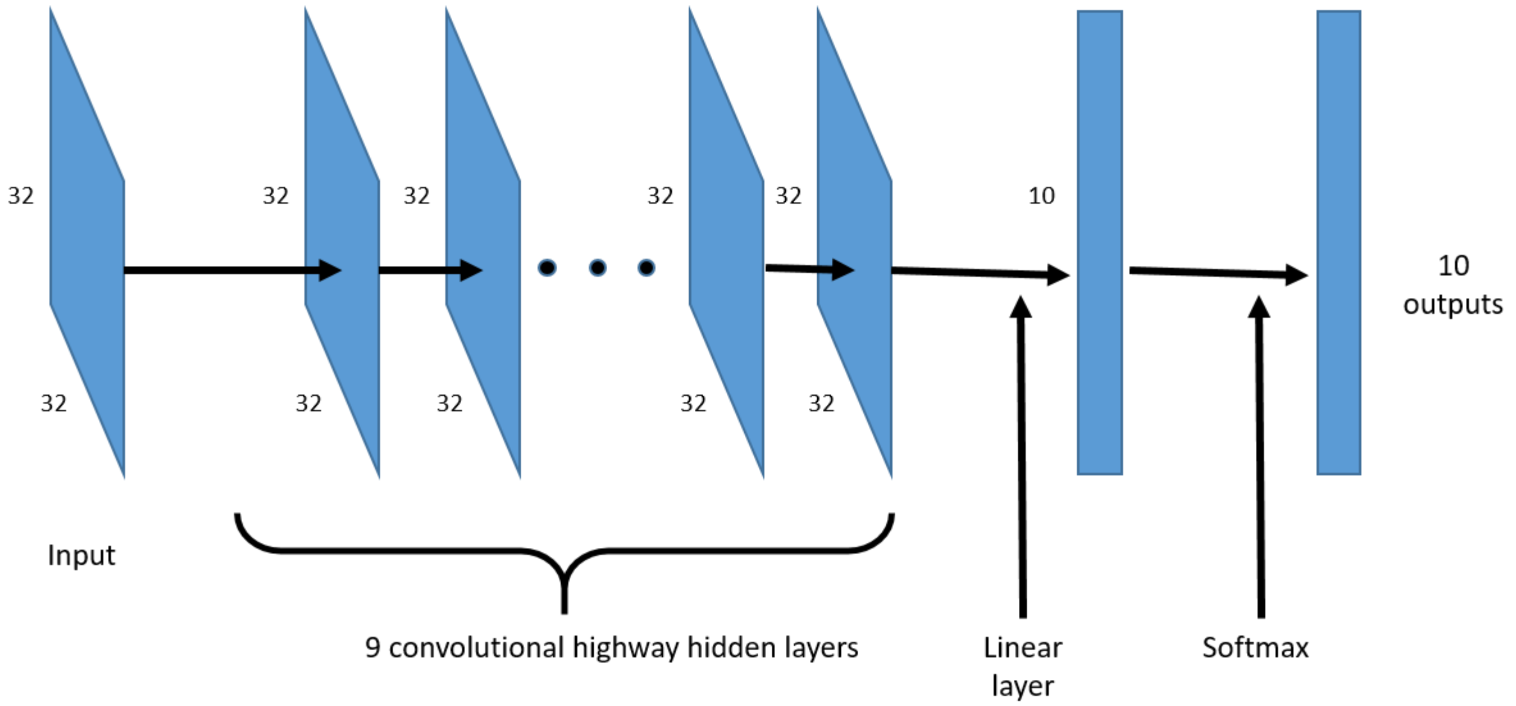
MNIST

- **10-layer convolutional highway networks** on MNIST are trained, using two architectures, each with 9 convolutional layers followed by a softmax output. The **number of filter maps (width) was set to 16 and 32** for all the layers.
- Compared with Maxout and DSN, **Highway Networks obtained similar accuracy but with much fewer number of parameters.**

Network	Highway Networks		Maxout [20]	DSN [24]
	10-layer (width 16)	10-layer (width 32)		
No. of parameters	39 K	151 K	420 K	350 K
Test Accuracy (in %)	99.43 (99.4$\pm$0.03)	99.55 (99.54$\pm$0.02)	99.55	99.61

MNIST

Architecture of highway network for MNIST digits dataset



CIFAR10 & CIFAR100

- Fitnet cannot optimize the networks directly when the networks are deep. It needs two-stage training
- **By using gating function, Highway can optimize the deep networks directly. In particular, Highway B obtains highest accuracy with 19 layers.**
- Though Highway C is inferior to Highway B, it stills can be optimized directly due to the existence of gating function.

Network	No. of Layers	No. of Parameters	Accuracy (in %)
Fitnet Results (reported by Romero et. al.[25])			
Teacher	5	~9M	90.18
Fitnet A	11	~250K	89.01
Fitnet B	19	~2.5M	91.61
Highway networks			
Highway A (Fitnet A)	11	~236K	89.18
Highway B (Fitnet B)	19	~2.3M	**92.46 (92.28±0.16)**
Highway C	32	~1.25M	91.20

- Here, the fully connected layer used in the networks in the previous experiment is replaced with a convolutional layer with a receptive field of size one and a global average pooling layer.
- Highway Network can obtain comparable performance on CIFAR-10 and highest accuracy on CIFAR-100

Network	**CIFAR-10 Accuracy (in %)**	**CIFAR-100 Accuracy (in %)**
Maxout [20]	90.62	61.42
dasNet [36]	90.78	66.22
NiN [35]	91.19	64.32
DSN [24]	92.03	65.43
All-CNN [37]	**92.75**	66.29
Highway Network	92.40 (92.31$\pm$0.12)	**67.76 (67.61$\pm$0.15)**

Comparison to Fitnets

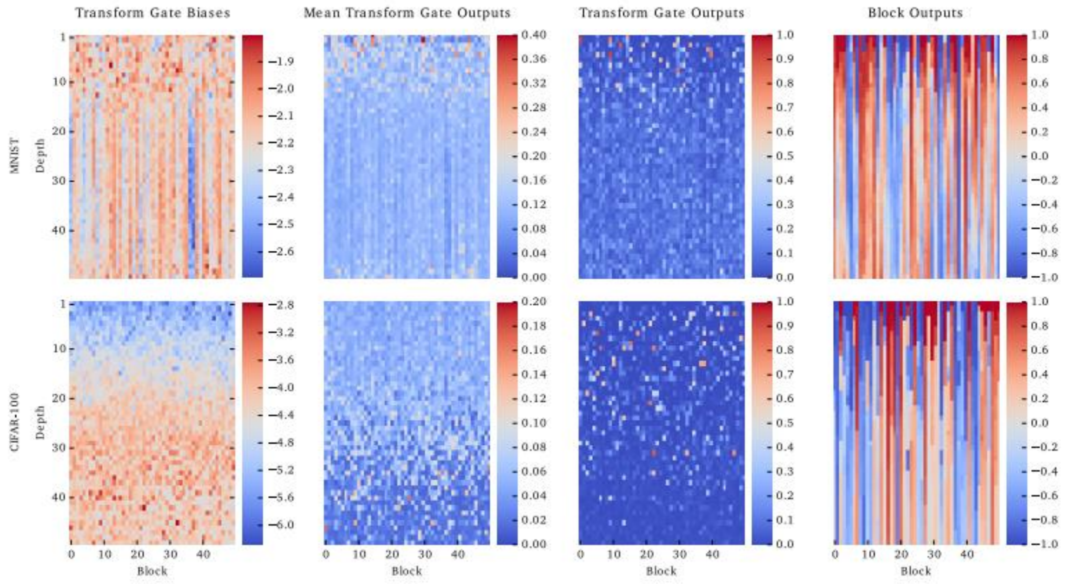
- A maxout layer is simply a layer where the activation function is the max of the inputs.

- Maxout networks can cope much better with increased depth than those with traditional activation functions .

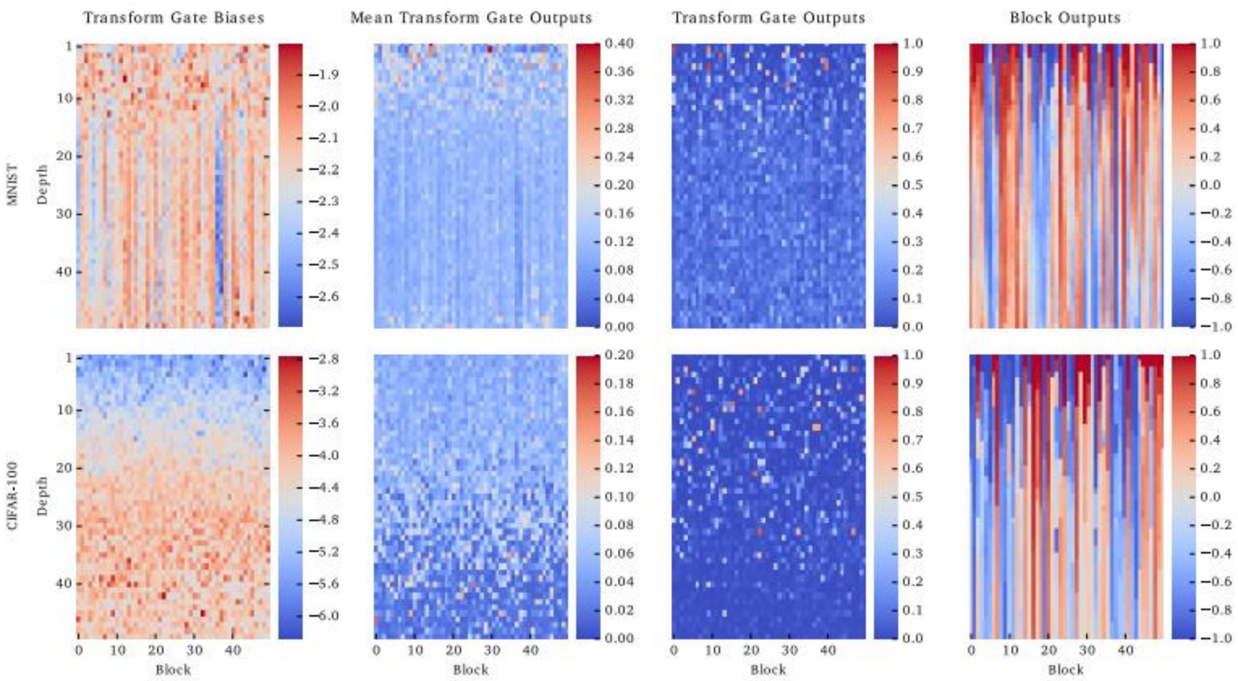
- Training on CIFAR-10 through plain backpropogation was only possible for maxout networks with a depth up to 5 layers when the number of parameters was limited to 250K .

- It is possible to obtain high performance on the CIFAR-10 and CIFAR-100 datasets by utilizing very large networks and extensive data augmentation.

VISUALIZATION OF BEST 50 HIDDEN-LAYER HIGHWAY NETWORKS



- The first hidden layer is a plain layer which changes the dimensionality of the representation to 50.
- Each of the 49 highway layers (y-axis) consists of 50 blocks
- Visualization of best 50 hidden-layer highway networks trained on MNIST (top row) and CIFAR-100 (bottom row)
- which were initialized to -2 and -4 respectively. In the second column the mean output of the transform gate over all training examples is depicted.
- The third and fourth columns show the output of the transform gates and the block outputs for a single random training sample. Best viewed in color.

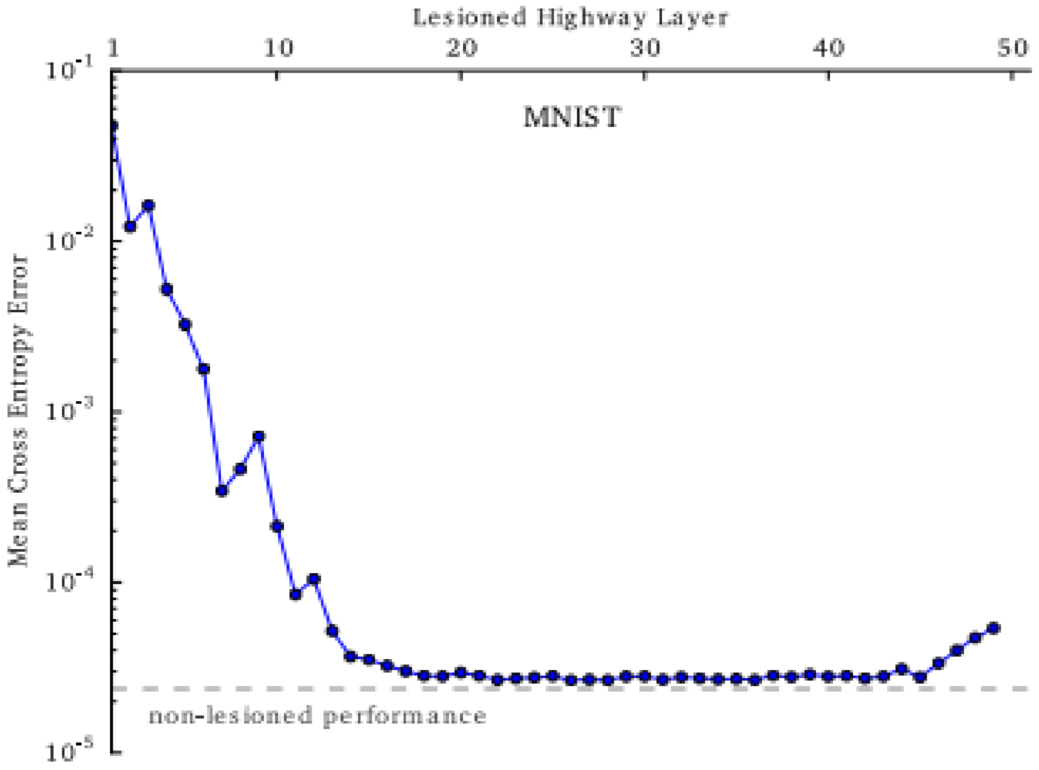


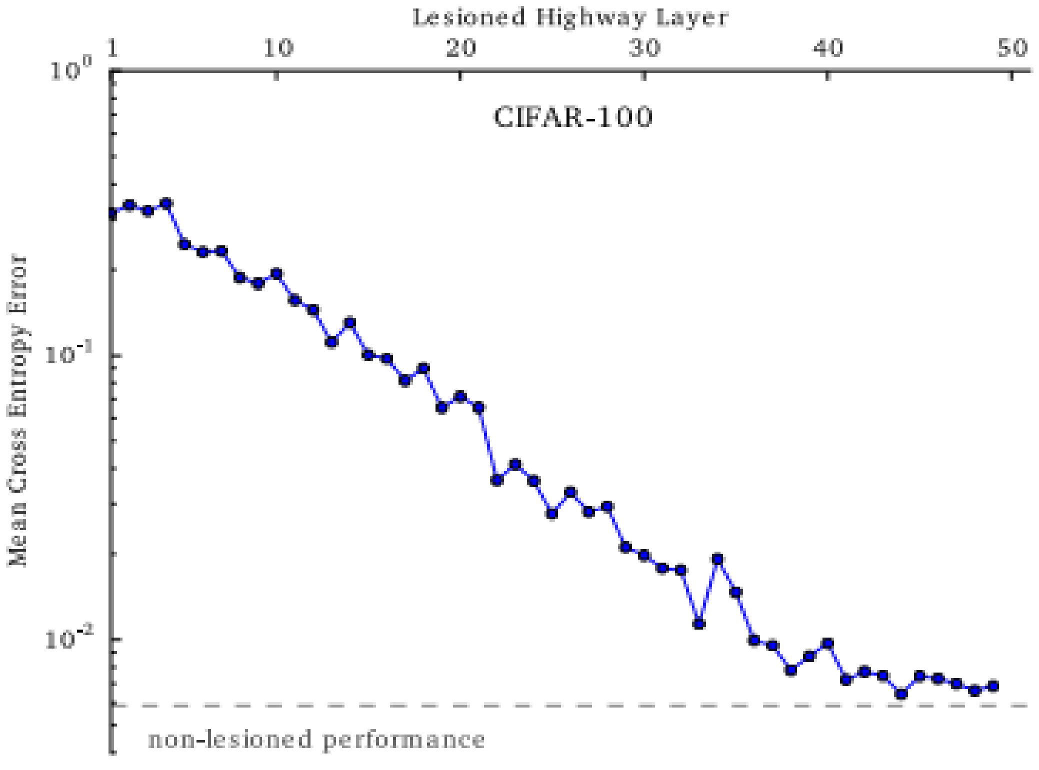
- For a single random sample for each transform gate respectively.
- Block outputs for the same single sample are displayed in the last column.
- The transform gate biases of the two networks were initialized to -2 and -4 respectively.

- The last column displays the block outputs and visualizes the concept of "information highways". Most of the outputs stay constant over many layers forming a pattern of stripes.
- Most of the change in outputs happens in the early layers

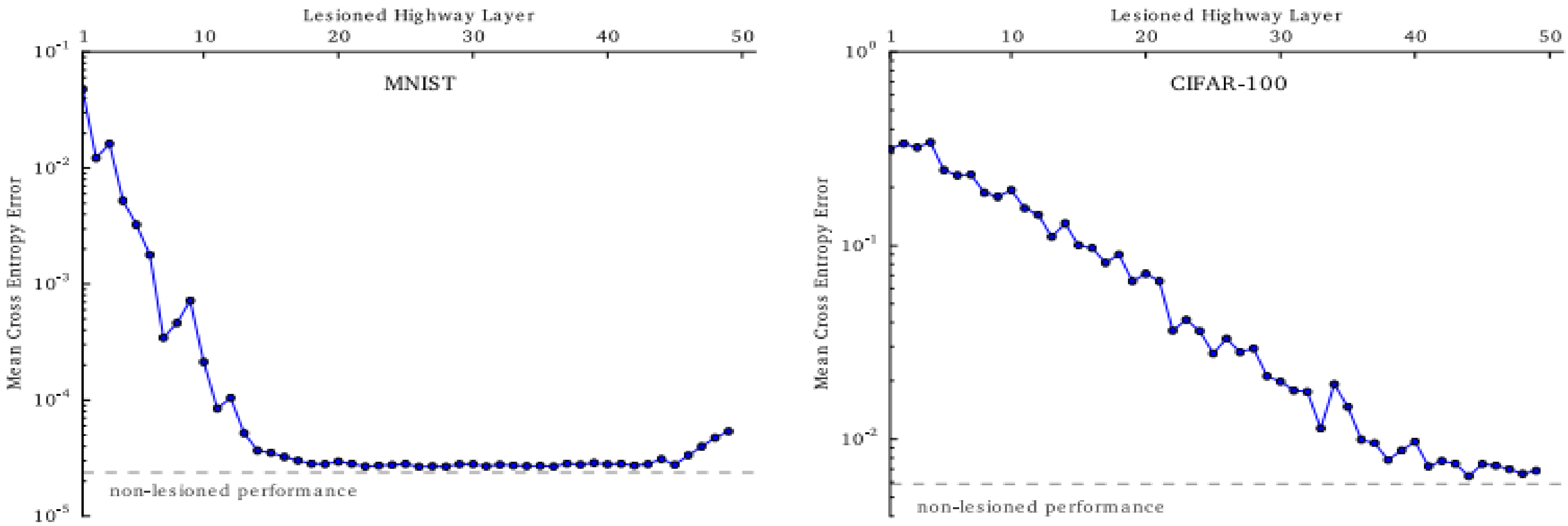
Routing of Information

- One possible advantage of the highway architecture over hard-wired shortcut connections is that the network can learn to dynamically adjust the routing of the information based on the current input.
- This behavior manifest itself in trained networks or do they just learn a static routing that applies to all inputs similarly
- Learning to route information through neural networks with the help of competitive interactions.
- Very deep highway networks, on the other hand, can directly be trained with simple gradient descent methods due to their specific architecture.





- Lesioned training set performance (y-axis) of the best 50-layer highway networks on MNIST (left) and CIFAR-100 (right).
- As a function of the lesioned layer (x-axis). Evaluated on the full training set while forcefully closing all the transform gates of a single layer at a time.
- The non-lesioned performance is indicated as a dashed line at the bottom.



- A possible objection is that many layers might remain unused if the transform gates stay closed.
- This experiments show that this possibility does not affect networks adversely—deep and narrow highway networks can match/exceed the accuracy of wide and shallow maxout networks