

Introduction to Neural Networks and Deep Learning

Deep Forward Neural Networks

Andres Mendez-Vazquez

June 22, 2020

Outline

1 Introduction

- Limitations of Shallow Architectures
- Highly-varying functions
- Local vs Non-Local Generalization
- From Simpler Features to More Complex Features

2 Deep Forward Architectures

- Introduction
- Convolutional Neural Networks
 - Image Processing
- Auto Encoders
- Boltzmann Machines
- Generative Adversarial Networks
- There Are Many More

3 The Vanishing and Exploding Gradients

- Introduction
- Reasoning Iteratively
- Fixed Points
- Stabilizing the Network
 - Gradient Clipping
 - Normalizing your Data
 - Normalization Layer AKA Batch Normalization

4 Problems with Deeper Architectures

- The Degradation Problem
- The Residual Networks
- Conclusions

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For this initial analysis

We will look at the paper by Bengio

- "Learning deep architectures for AI", Foundations and trends in Machine Learning 2, 1 (2009), pp. 1--127.

- After Shanon pointed out the fact they are useful to represent complex problems [1].

For this initial analysis

We will look at the paper by Bengio

- "Learning deep architectures for AI", Foundations and trends in Machine Learning 2, 1 (2009), pp. 1--127.

And for this, we will look at Boolean functions

- After Shanon pointed out the fact they are useful to represent complex problems [1].

Architecture

A two-layer circuit of logic gates can represent any boolean function
[2]

- Any boolean function can be written as a sum of products, disjunctive normal form:
 - ▶ AND gates on the first layer with optional negation of inputs,
 - ▶ And OR gate on the second layer

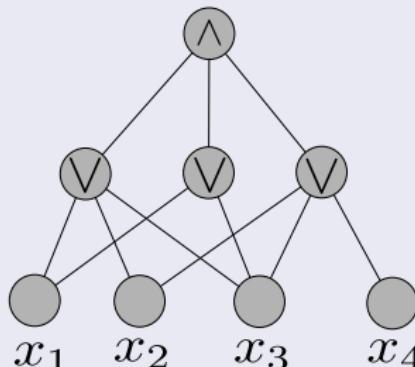
Example

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Example



The Exponential Width

Here, we have a small problem

- There are functions computable with a polynomial-size logic gates circuit of depth k that require **exponential size** when restricted to depth $k - 1$ [3]
 - ▶ For Example

$$\text{parity} : (b_1, \dots, b_d) \in \{0, 1\}^d \mapsto \begin{cases} 1 & \text{if } \sum_{i=1}^d b_i \text{ is even} \\ -1 & \text{otherwise} \end{cases}$$

↳ The input channel learning in Machine Learning

- Many of the results for boolean circuits can be generalized to architectures whose computational elements are linear threshold units

$$f(x) = 1_{wx+b>0}$$

- ▶ The fan-in of a circuit is the maximum number of inputs of a particular element.

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How this impact shallow learning in Machine Learning?

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- ▶ The fan-in of a circuit is the maximum number of inputs of a particular element.

Therefore

How this impact shallow learning in Machine Learning?

- First, we define the concept of f_k function

- The function f_k is a function of N^{2k-2} variables. It is defined by a depth k circuit that is a tree. At the leaves of the tree there are unnegated variable, The i^{th} level from the bottom consists of \wedge -gates if i is even and otherwise it consists of \vee -gates.

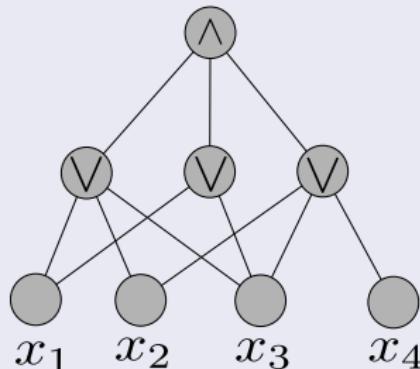
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An Important Theorem

Of particular interest is the following theorem

- Monotone weighted threshold circuits (i.e. multi-layer neural networks with linear threshold units and positive weights)

Theorem [1]

- A monotone weighted threshold circuit of depth $k - 1$ computing a function f_k has size at least 2^{cN} for some constant $c > 0$ and $N > N_0$.

An Important Theorem

Of particular interest is the following theorem

- Monotone weighted threshold circuits (i.e. multi-layer neural networks with linear threshold units and positive weights)

Theorem [4]

- A monotone weighted threshold circuit of depth $k - 1$ computing a function f_k has size at least 2^{cN} for some constant $c > 0$ and $N > N_0$.

Meaning

This theorem does not fail any type of architecture

- But the question arises, Are the depth 1, 2 and 3 architectures (many Machine Learning algorithms) too shallow to represent efficiently more complicated functions?

What happens in Deep Architectures?

- Bengio et al. argues that they can represent highly-varying functions

[5]

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Highly-varying functions

Meaning

- We say that a function is highly-varying when a piecewise approximation of that function would require a large number of pieces.

Observation

- Deeper Architectures can handle such functions in a easier way than shallow ones.

Example

- The polynomial $\prod_{i=1}^n \sum_{j=1}^m a_{ij}x_j$ can be represented as a product of sums with only $O(nm)$ elements

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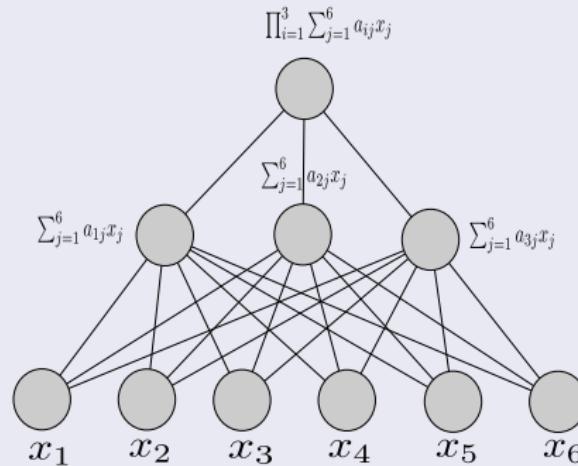
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Basically

We have a Perceptron Layer and a Product Second Layer

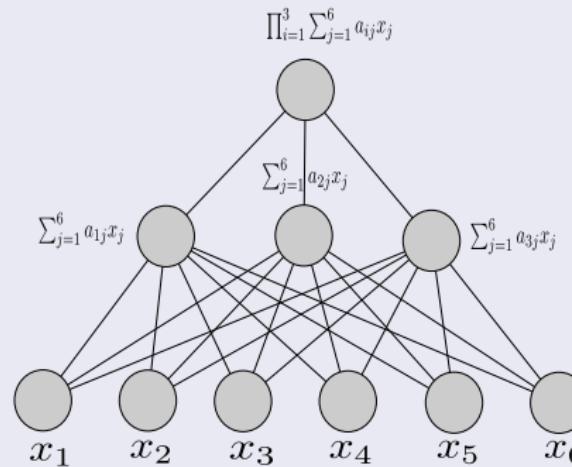


What will happen to the outputs?

- What will happen?

Basically

We have a Perceptron Layer and a Product Second Layer



What if I do a product of sums

- What will happen?

Ok, we have a problem

Because for our case

$$\prod_{i=1}^3 \sum_{j=1}^6 a_{ij} x_j = \sum_{j=1}^6 \prod_{i=1}^3 a_{ij} x_j$$

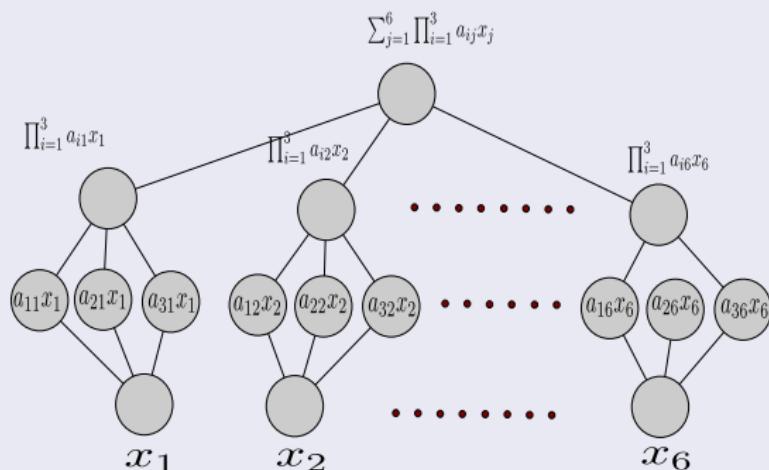
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$$\prod_{i=1}^3 \sum_{j=1}^6 a_{ij} x_j = \sum_{j=1}^6 \prod_{i=1}^3 a_{ij} x_j$$

We have the following problem $O(n^m)$



Actually

You could claim

- Machine Learning shallow learning depends on complex computational units to handle complex functions

Deep learning

- Proposes simpler units but deeper structures to handle complex functions

What about both facts together?

- Complex adaptive units
- Deeper architectures to help such units
 - ▶ It seems to be the case of the human brain...!!!

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Local vs Non-Local Generalization

Something Notable

- A local estimator partitions the input space in regions

❑ How local estimator can be based on matching local template?

- It can be thought of as having two levels..

❑ The first level

- It is made of a set of templates which can be matched to the input.

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The first level

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Then

A template unit will output a value that indicates the degree of matching

$$K(x|\Theta)$$

The overall loss function is then:

- Typically a simple linear combination or product combination

$$L(x) = \sum_{i=1}^k K(x|\Theta_i)$$

For example, the kernel machine

$$f(x) = b + \sum_{i=1}^k \alpha_i K(x, x_i)$$

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The second level combines these values

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Classic Example, the kernel machine

$$f(x) = b + \sum_{i=1}^k \alpha_i K(x, x_i)$$

As you can see

The Kernel has a local influence based on the support vectors

- For example the Gaussian Kernel

$$K(x, x_i) = \exp\left\{-\frac{\|x - x_i\|^2}{\sigma^2}\right\}$$

The Problem of Kernel

- The assumption that the target function is smooth or can be well approximated with a smooth function.

The Limitations of a fixed kernel Kernel like the Gaussian Kernel

- They have motivated a lot of research in designing kernels [6, 7]

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The limitations of a fixed generic kernel such as the Gaussian kernel

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For Example, in supervised learning

If we have the training example (x_i, y_i)

- We want to build predictor that output something near y_i when any other sample is near x_i

Especially when x_i is outlier

- Bengio and Le Cun claim this is not enough [8, 9]

Although it is possible to do this

- That such highly varying space is due to a lack of the correct feature selection process.

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Additional possible reason:

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Although, It is possible to argue

- That such highly varying space is due to a lack of the correct feature selection process.

However

If you look at the parity problem

$$\text{parity} : (b_1, \dots, b_d) \in \{0, 1\}^d \mapsto \begin{cases} 1 & \text{if } \sum_{i=1}^d b_i \text{ is even} \\ -1 & \text{otherwise} \end{cases}$$

Hard case

- Let $f(\mathbf{x}) = b + \sum_{i=1}^{2^d} \alpha_i K(\mathbf{x}_i, \mathbf{x})$ be an affine combination of Gaussian with the same width σ centered on points $\mathbf{x}_i \in \{-1, 1\}^d$. If f solve the parity problem, then there are at least 2^{d-1} non-zero support vectors.

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Theorem

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However

Although, this function is not a representative

- The kind of functions we are more interested in AI.

In suggest algorithm based systems

- They are not enough, but still not a conclusive result

What all

- More Memory could be added to those systems

However

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After all

- More Memory could be added to those systems

For example

Tensors have been used to add memory to SVM

$$\begin{aligned} \min_{U_i^{(m)}, \mathbf{K}^{(m)}, \boldsymbol{\beta}, b} \quad & \gamma \sum_{i=1}^N \left\| \mathcal{X}_i - \left[\mathbf{K}^{(1)} \mathbf{U}_i^{(1)}, \dots, \mathbf{K}^{(M)} \mathbf{U}_i^{(M)} \right] \right\|_F^2 + \dots \\ & \lambda \boldsymbol{\beta}^T \widehat{\mathbf{K}} \boldsymbol{\beta} + \sum_{i=1}^N \left[1 - y_i \left(\widehat{\mathbf{k}}_i^T \boldsymbol{\beta} + b \right) \right]_+ \end{aligned}$$

- $\mathbf{K}^{(m)}$ are kernel matrices defined on each mode to capture the nonlinear part.
- $\mathbf{U}^{(m)} = [\mathbf{u}_1^{(m)}, \dots, \mathbf{u}_R^{(m)}]$ are factor matrices of size $I_m \times R_m$

However

A Problem

- You are limiting the Machine Learning operations to matrix additions and products and non-linear operations.
 - ▶ In a shallow way...

We need to add more complexity to our models

- After all deeper architectures construct complex functions layer by layer

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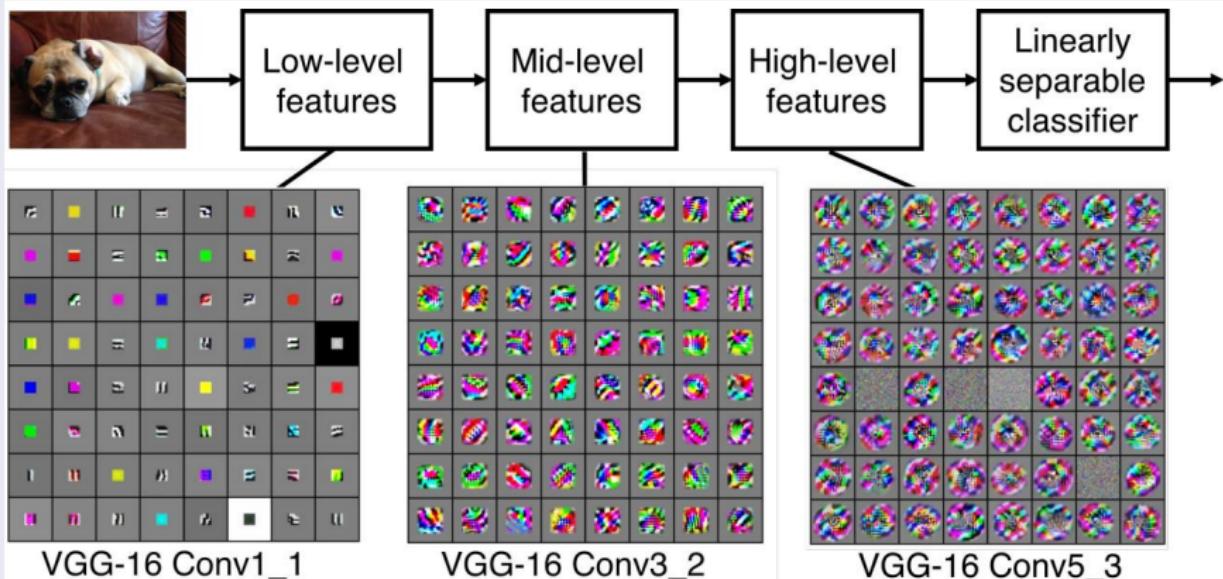
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By Using Weights in Certain Deep Learners

The Application of each Layer increase the complexity of the features



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Some of the Models to be Reviewed of Models

Convolutional Neural Networks

- The classic model that started the phenomena of Neural Networks.

Auto Encoder

- How to generate novel features by funneling.

Generative Models

- Energy Based Models.

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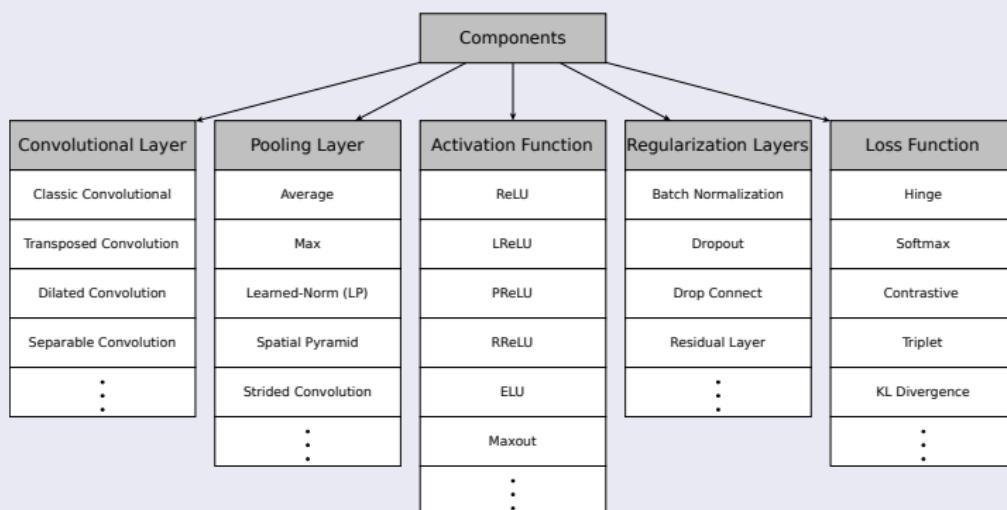
Boltzmann Machine

- Energy Based Models.

However

We will see that there are many possible architectures

- And more with the different layers
[10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20] :



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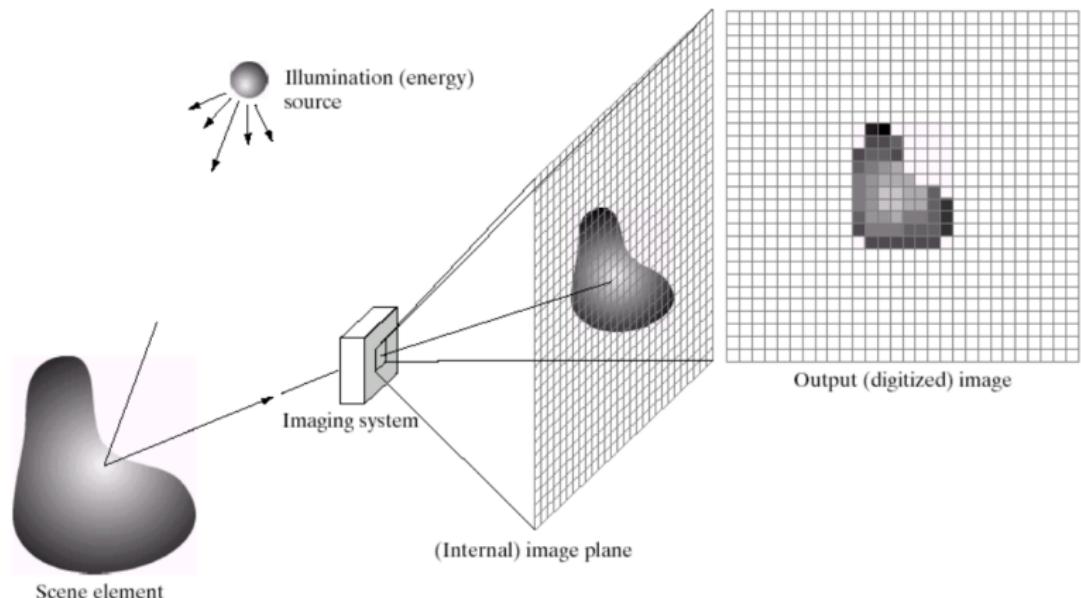
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Digital Images as pixels in a digitized matrix



Further

Pixel values typically represent

- Gray levels, colours, heights, opacities etc

Something Measurable

- Remember digitization implies that a digital image is an approximation of a real scene

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Therefore, we have the following process

Low Level Process

Input	Processes	Output
Image	Noise Removal	Improved Image
	Image Sharpening	

Example: Edge Detection

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Mid Level Process

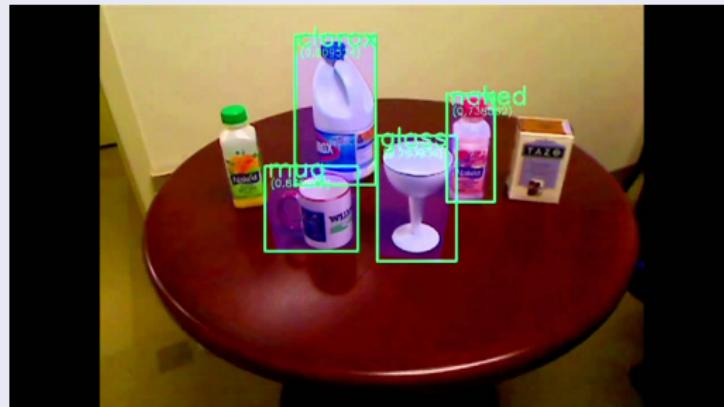
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Image	Object Recognition	Attributes
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Mid Level Process

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Object Recognition



Therefore

It would be nice to automatize all these processes

- We would solve a lot of headaches when setting up such process

What would we need?

- By using a Neural Networks that replicates the process.

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Why not to use the data sets

- By using a Neural Networks that replicates the process.

Convolutional Neural Networks History

Work by Hubel and Wiesel in the 1950s and 1960s

- They showed that cat and monkey visual cortices contain neurons that individually respond to small regions of the visual field.

- David H. Hubel and Torsten N. Wiesel (2005). Brain and visual perception: the story of a 25-year collaboration. Oxford University Press US, p. 106.

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After all more studies about the visual cortex happened

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Neurocognitron (Circa 1980)

Kunihiko Fukushima [21]

- Proposed a Hierarchical Network for image recognition with a convolution!!!

What is a Neurocognitron?

$$\varphi \left(\frac{1 + \sum_{k_{t-1}=1}^{K_{t-1}} \sum_{v \in S_t} a_t(k_{t-1}, v, k_t) u_{d-1}(k_{t-1}, n+v)}{1 + \frac{2}{1+r_t} b_t(k_t) v_{CI-1}(n)} - 1 \right)$$

What is a ReLU function?

$$\varphi(x) = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}$$

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But it used a function φ

$$\varphi \left(\frac{1 + \sum_{k_{t-1}=1}^{K_{t-1}} \sum_{v \in S_l} a_l(k_{t-1}, v, k_l) u_{cl-1}(k_{l=1}, n+v)}{1 + \frac{2r_l}{1+r_l} b_l(k_l) v_{Cl-1}(n)} - 1 \right)$$

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With a Relu function

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Furthermore (Circa 1993)

Weng et al. [22, 23]

- Proposed the use of Maxpooling to recognize 3D objects in 2D images

- The Beginning of the Dream!!!

Furthermore (Circa 1993)

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- Proposed the use of Maxpooling to recognize 3D objects in 2D images

Yan LeCunn finally proposed the use of backpropagation [24]

- The Beginning of the Dream!!!

Convolutional Neural Networks

Basically they are deep learners based in convolutions or its variants

$$(f * g)(i, j) = \sum_{k=-n}^{-n} \sum_{l=-n}^n f(k, l) \times g(i - k, j - l) \quad (1)$$

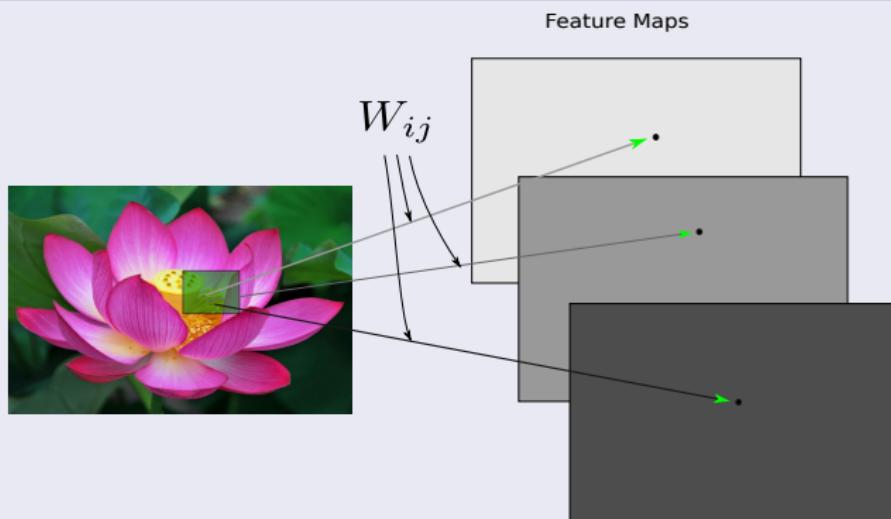
Kernel Filter

Convolutional Neural Networks

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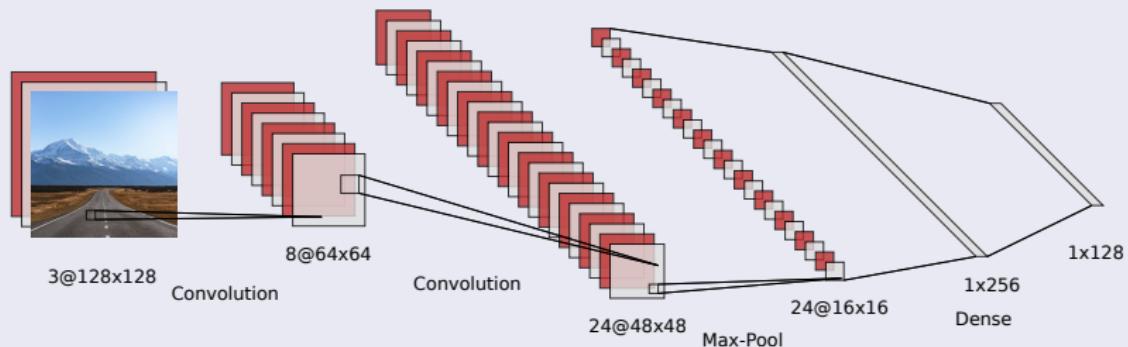
$$(f * g)(i, j) = \sum_{k=-n}^{+n} \sum_{l=-n}^{+n} f(k, l) \times g(i - k, j - l) \quad (1)$$

Basically Filters



Example of CNN

A Basic Convolutional Network



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We know that

Many of the existing machine learning algorithms

- They depend on the quality of the input characteristics to generate a good model.

- The amount of these variables is also important, given that performance tends to decline as the input dimensionality increases.

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Many of the existing machine learning algorithms

- They depend on the quality of the input characteristics to generate a good model.

Not only that

- The amount of these variables is also important, given that performance tends to decline as the input dimensionality increases.

We have several techniques for that

Principal Component Analysis

$$L(\mathbf{u}_1) = \mathbf{u}_1^T S \mathbf{u}_1 + \lambda_1 (1 - \mathbf{u}_1^T \mathbf{u}_1)$$

Linear discriminant analysis

$$\Phi(Y) = \sum_i \left| Y_i - \sum_j W_{ij} Y_j \right|^2$$

Other methods

- Uniform Manifold Approximation and Projection for Dimension Reduction [25]

We have several techniques for that

Principal Component Analysis

$$L(\mathbf{u}_1) = \mathbf{u}_1^T S \mathbf{u}_1 + \lambda_1 \left(1 - \mathbf{u}_1^T \mathbf{u}_1\right)$$

Linear Locally Embeddings

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And finally:

- Uniform Manifold Approximation and Projection for Dimension Reduction [25]

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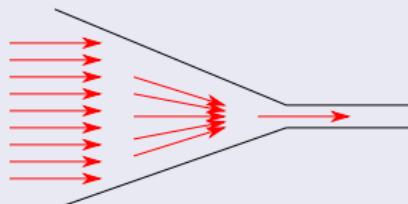
And recently

- Uniform Manifold Approximation and Projection for Dimension Reduction [25]

Therefore

We have the need to codify the original feature into better ones

- This can be done by a series of mappings that act as funnels, How?



Essentially, we have a series of mappings

$$x \in \mathbb{R}^{n_1} \rightarrow f_1(x) \in \mathbb{R}^{n_2} \rightarrow f_2(x_1) \in \mathbb{R}^{n_3} \dots \rightarrow f_m(x_{m-1}) \in \mathbb{R}^{n_{m+1}}$$

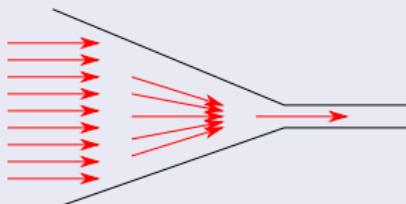
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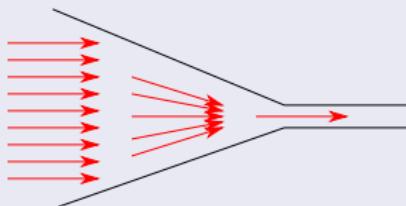
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Then, we can use linear mappings for this

With the following matrix functions

$$\sigma [f_{A_{i+1}}(x_i)] = \sigma(A_{i+1}x)$$

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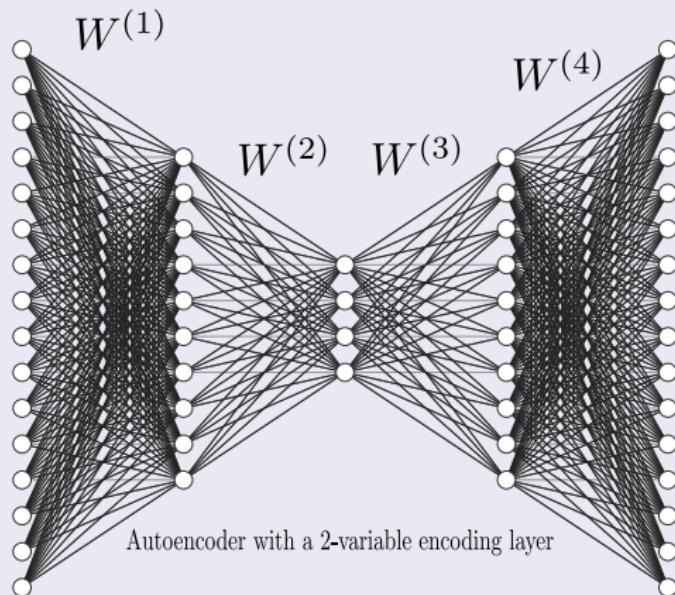
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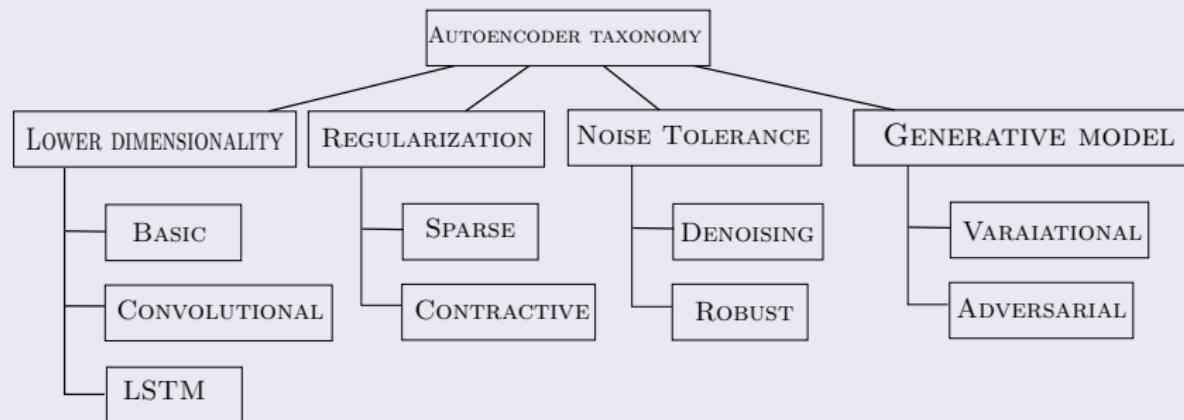
The Basic Auto Encoder Architecture

We have



Taxonomy

Most popular Auto Encoders



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The Basic Energy Models

We have that the Boltzmann Machines

- A Boltzmann machine is a network of units that are connected to each other

Binary values of the connected units

- Each unit takes a binary value in $\{0, 1\}$

Represented by a random variable X_i , $i = 1, \dots, N$.

Additional parameters

- Bias b_i

- Weight w_{ij} between unit i and unit j , $(i, j) \in [1, N - 1] \times [i + 1, N]$

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The Energy Based Structure

The energy of the Boltzmann machine is defined by

$$E_{W,b}[\mathbf{x}] = -\sum_{i=1}^N b_i x_i - \sum_{i=1}^{N-1} \sum_{j=i+1}^N w_{ij} x_i x_j = -\mathbf{b}^T \mathbf{x} - \mathbf{x}^T W \mathbf{x}$$

This allows us to define a probability distribution:

$$p_{W,b}(\mathbf{x}) = \frac{\exp(-E_{W,b}[\mathbf{x}])}{\sum_{\tilde{\mathbf{x}}} \exp(-E_{W,b}[\tilde{\mathbf{x}}])}$$

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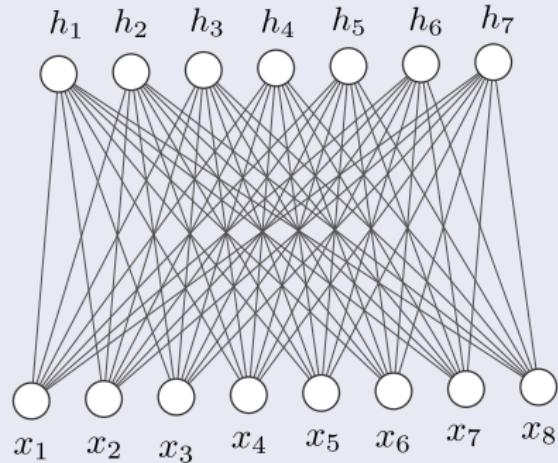
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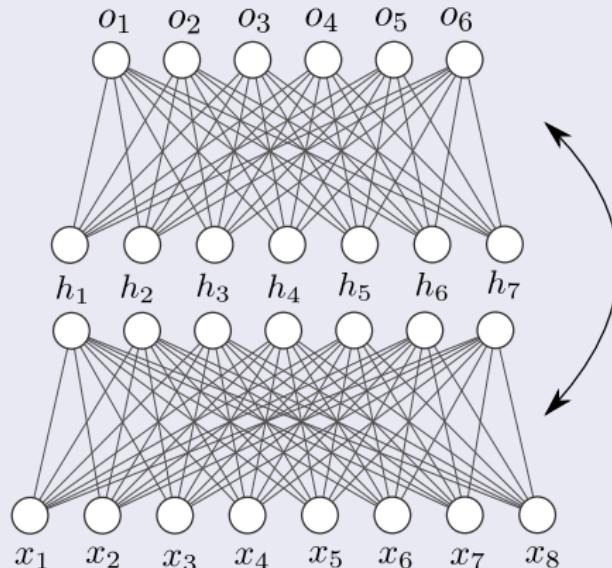
Example

Restricted Boltzmann Machines where the connectivity is layer by layer



Thus, using it as a basic model

We can stack them into a multiple layer model



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Generative Adversarial Networks

They can be seen as an Accept-Reject MCMC Model

- However, they do not require Markov Chains with the classic problem:
 - ▶ The independence between the samples to generate ergodic probabilities (The real one)

Both networks compete

- The generator network tries to produce realistic-looking samples
- The discriminator network tries to figure out whether an image came from the training set or the generator network

Generative Adversarial Networks

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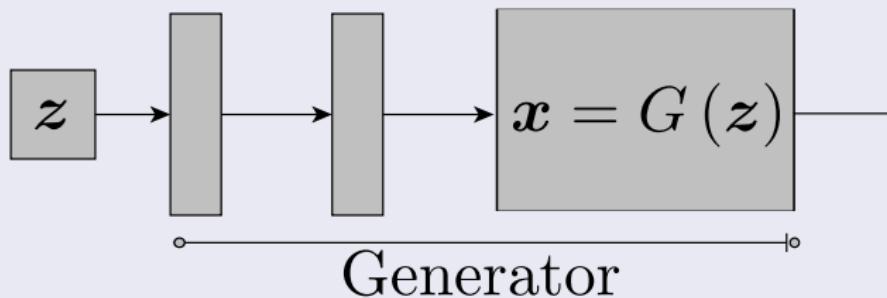
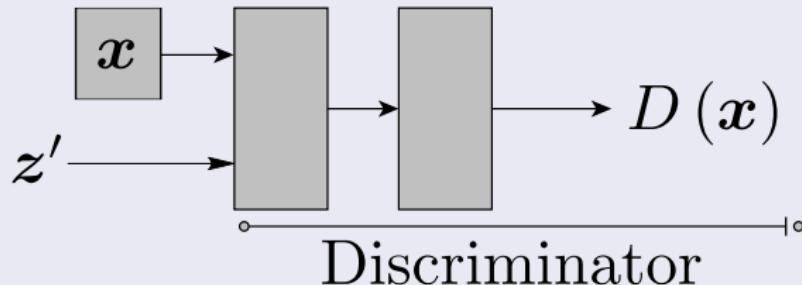
- However, they do not require Markov Chains with the classic problem:
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As in the Accept-Reject

- The **generator network** tries to produce realistic-looking samples
- The **discriminator network** tries to figure out whether an image came from the training set or the generator network

Graphically

We have the following Basic Model



Here

There is a need to join both functions

- So, we can use the idea of Backpropagation to obtain the desired minimization.

- We can define a sensible learning criterion when the dataset is not linearly separable

For this, we can use the logistic cross-entropy loss (We will explain more about this later)

$$\mathcal{L}_{LCE}(z, t) = LCE(\sigma(z), t) = t \log(1 + e^{-z}) + (1 - t) \log(1 + e^z)$$

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How can we do this?

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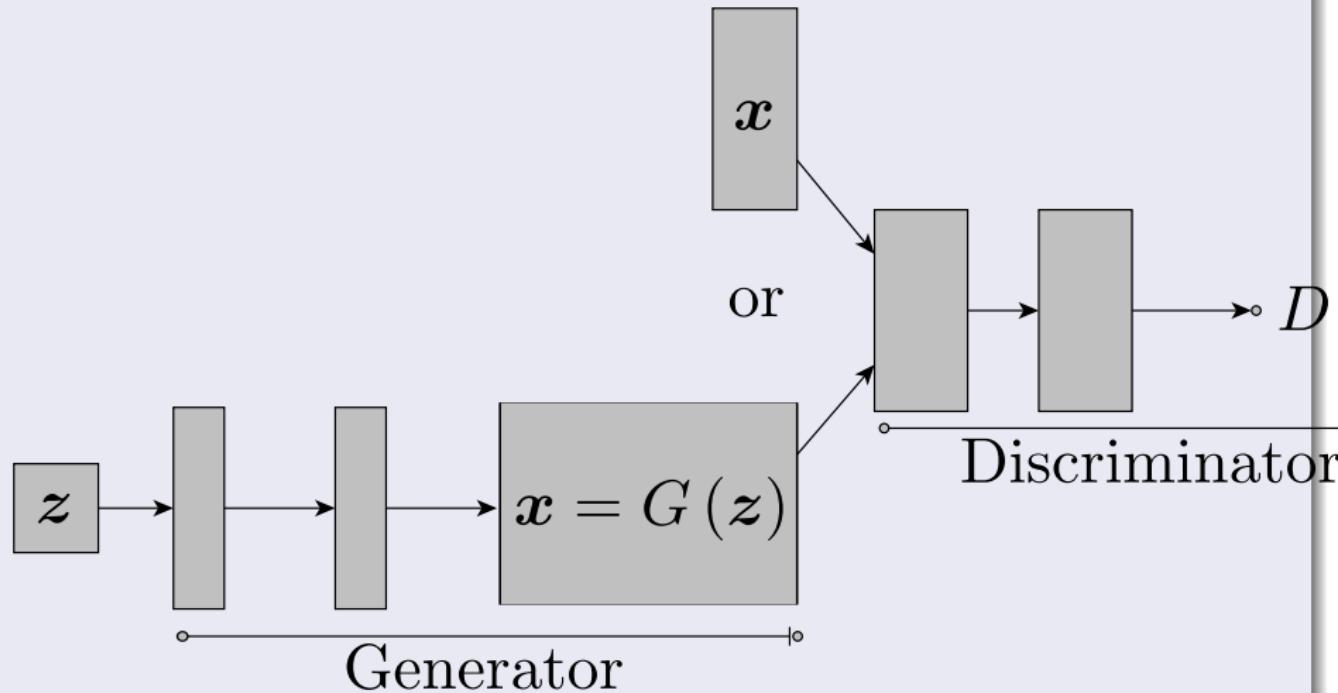
- We can define a sensible learning criterion when the dataset is not linearly separable

For this, we can use the **logistic cross-entropy loss** (We will explain more about this later)

$$\mathcal{L}_{LCE}(z, t) = L_{CE}(\sigma(z), t) = t \log(1 + e^{-z}) + (1 - t) \log(1 + e^z)$$

Therefore, we have

The following architecture use this idea



In this basic Generator

D denote the discriminator's predicted probability of being data

$$\mathcal{J}_D = E_{\mathbf{x} \sim \mathcal{D}} [-\log D(\mathbf{x})] + E_{\mathbf{z}} [-\log (1 - D(G(\mathbf{z})))]$$

Can't we do the same for the generator?

$$\mathcal{J}_G = -\mathcal{J}_D = const + E_{\mathbf{z}} [\log (1 - D(G(\mathbf{z})))]$$

In this basic Generator

D denote the discriminator's predicted probability of being data

$$\mathcal{J}_D = E_{\mathbf{x} \sim \mathcal{D}} [-\log D(\mathbf{x})] + E_{\mathbf{z}} [-\log (1 - D(G(\mathbf{z})))]$$

One possible cost function for the generator

$$\mathcal{J}_G = -\mathcal{J}_D = const + E_{\mathbf{z}} [\log (1 - D(G(\mathbf{z})))]$$

Then using both functions

The minimax formulation

- Since the generator and discriminator are playing a zero-sum game against each other.

Discriminator

$$\max_G \min_D \mathcal{J}_D$$

There are other examples using the LS [Eq.]

$$\mathcal{J}_G = \frac{1}{N} \sum_{i=1}^N [G(z) - x_i]^2$$

Then using both functions

The minimax formulation

- Since the generator and discriminator are playing a zero-sum game against each other.

Basically

$$\max_G \min_D \mathcal{J}_D$$

Let's take a look at the loss function

$$\mathcal{J}_G = \frac{1}{N} \sum_{i=1}^N [G(z) - x_i]^2$$

Then using both functions

The minimax formulation

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Basically

$$\max_G \min_D \mathcal{J}_D$$

There are other examples using the LSE [26]

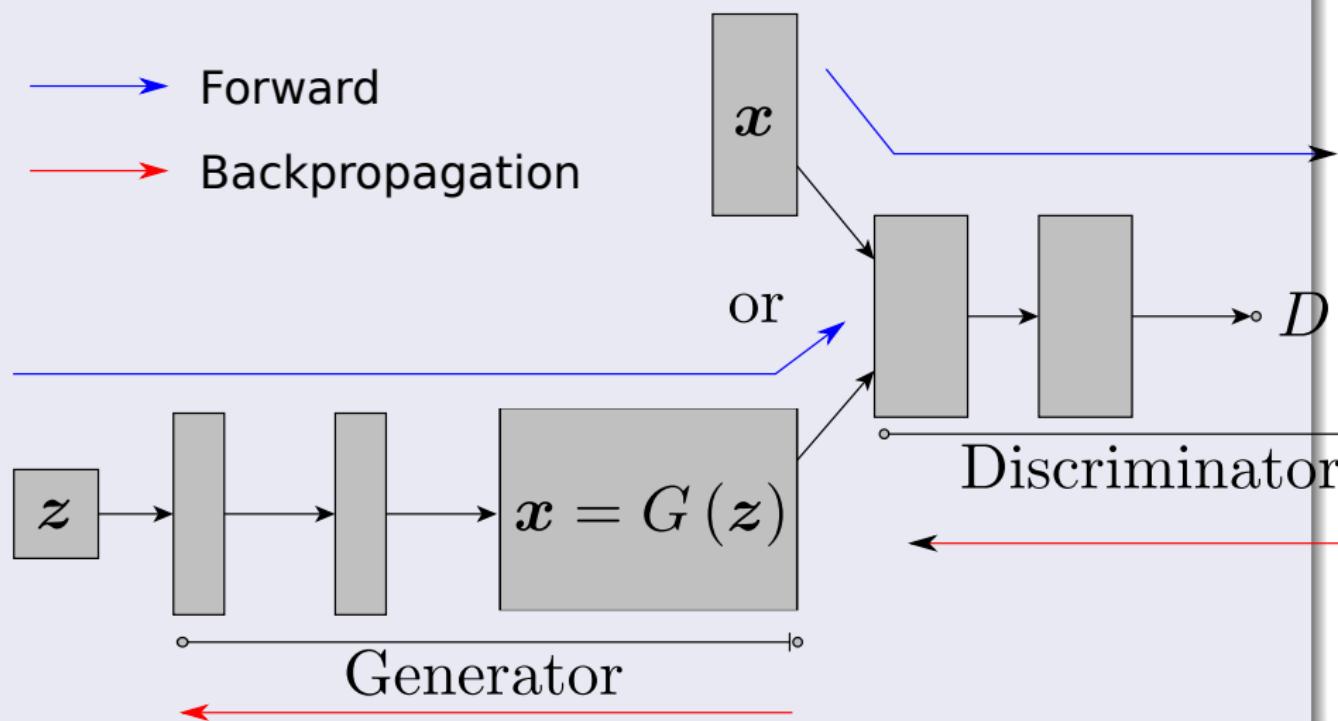
$$\mathcal{J}_G = \frac{1}{N} \sum_{i=1}^N [G(\mathbf{z}) - \mathbf{x}]^2$$

Therefore, we have two updates

First update the Discriminator

→ Forward

→ Backpropagation



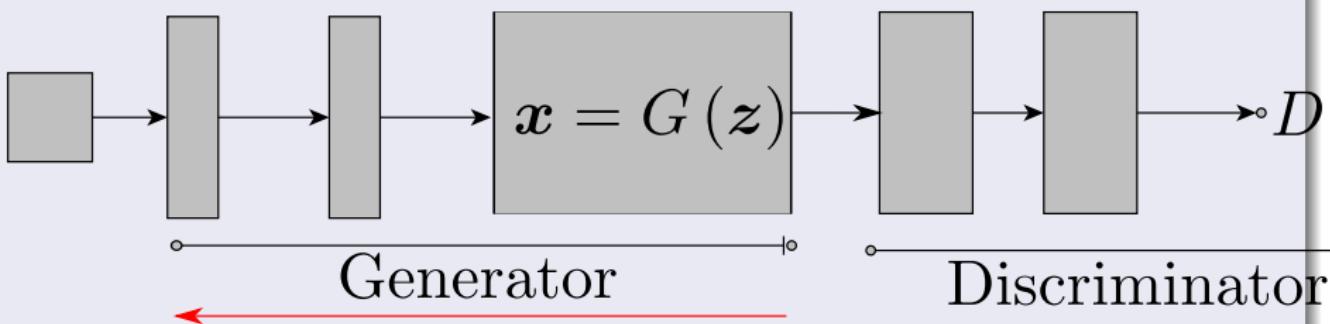
Now

Update the Generator

Backprop Derivatives Through the Discriminator, but do not change variables on it... only in the generator

→ Forward

→ Backpropagation



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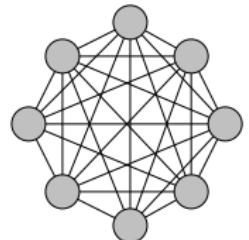
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4 Problems with Deeper Architectures

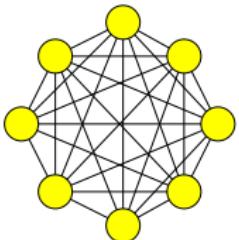
- The Degradation Problem
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There Are Many More!!! Here a few more...

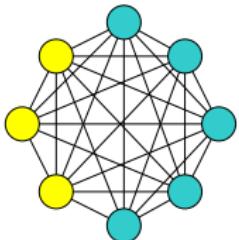
Markov Chain



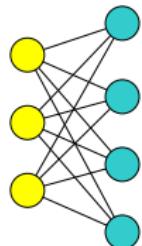
Hopfield Network



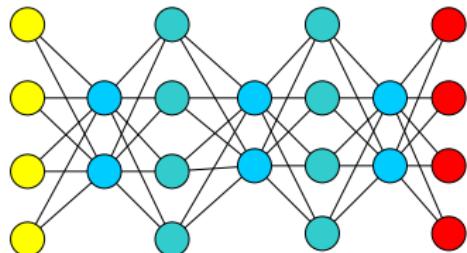
Boltzmann Machine



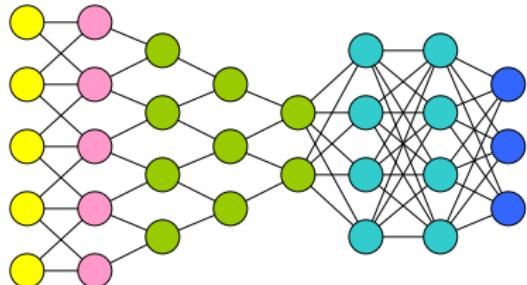
Restricted BM



Deep Belief Network

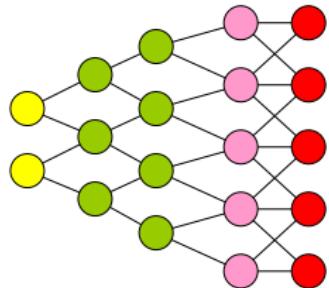


Convolutional Network

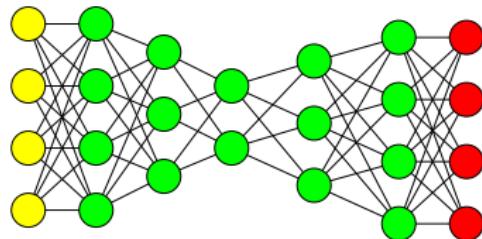


Furthermore

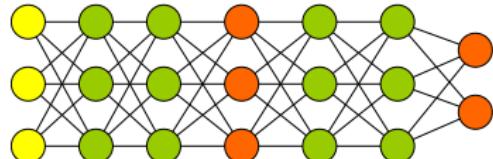
Deconvolutional Network



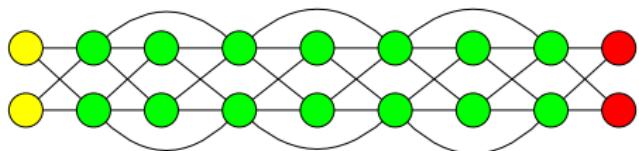
Autoencoder



Generative Adversarial Network



Deep Residual Network



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As We know

In Recurrent Neural Networks, we have the problem

- Vanishing and Exploding Gradients

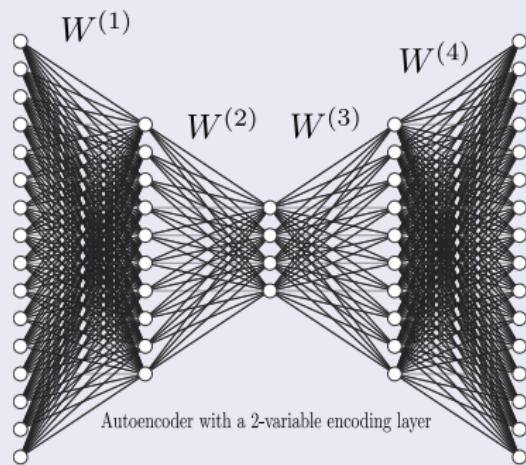
In this section, we will discuss some countermeasures to have much better training.

As We know

In Recurrent Neural Networks, we have the problem

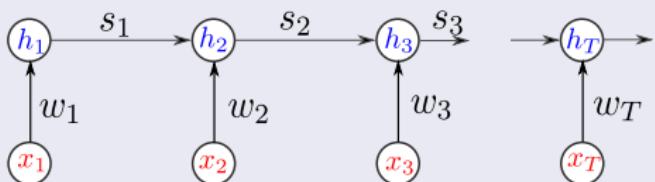
- Vanishing and Exploding Gradients

In the Deeper Architectures as encoder-decoder we have such phenomena



Consider a simple encoder encoder network

We have this simplified version

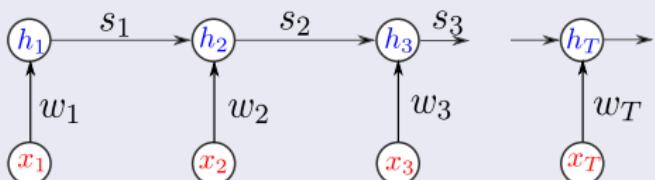


$$h_t = w_t x_t + z_{t-1}$$

$$z_t = s_t h_t$$

Consider a simple encoder encoder network

We have this simplified version



We have the following structure

$$h_t = w_t x_t + z_{t-1}$$

$$z_t = s_t h_t$$

Backpropagation Rules

Then, we get the following backpropagation rules

$$\frac{\partial h_t}{\partial w_i} = \frac{\partial h_t}{\partial h_{t-1}} \times \frac{\partial h_{t-1}}{\partial h_{t-2}} \times \dots \times \frac{\partial h_i}{\partial w_i}$$
$$\frac{\partial h_t}{\partial s_i} = \frac{\partial h_t}{\partial h_{t-1}} \times \frac{\partial h_{t-1}}{\partial h_{t-2}} \times \dots \times \frac{\partial h_{i+1}}{\partial s_i}$$

Then, we have

By Using Our simplifying assumption that

$$\frac{\partial h_t}{\partial h_{t-1}} = \frac{\partial (w_t x_t + s_{t-1} h_{t-1})}{\partial h_{t-1}} = s_{t-1}$$

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And for $\frac{\partial h_i}{\partial w_i}$

$$\frac{\partial h_i}{\partial w_i} = x_t$$

Finally, we have that

$$\frac{\partial h_i}{\partial w_i} = x_t \begin{bmatrix} & & & \\ & \vdots & & \\ & s_{t-1} & & \\ & & \ddots & \\ & & & s_k \end{bmatrix}$$

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Finally, we have that

$$\frac{\partial h_t}{\partial w_i} = x_t \left[\prod_{k=t-1}^{i-1} s_k \right]$$

It is clear that

Unless the s_k 's are near to 1

- You have the vanishing gradient if $s_k \in [0, 1)$ for all k .
- You have the exploding gradient if $s_k \in (1, +\infty]$ for all k .

Even with small learning rates

- These terms tend to appear in the Deep Learners when Backpropagation is done

Using backpropagation

- We have many activation function that squash the signal...

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In the case of Forward

- We have many activation function that squash the signal...

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Instead of doing this

Let us do the following

$$f(x) = 3.5x(1 - x)$$

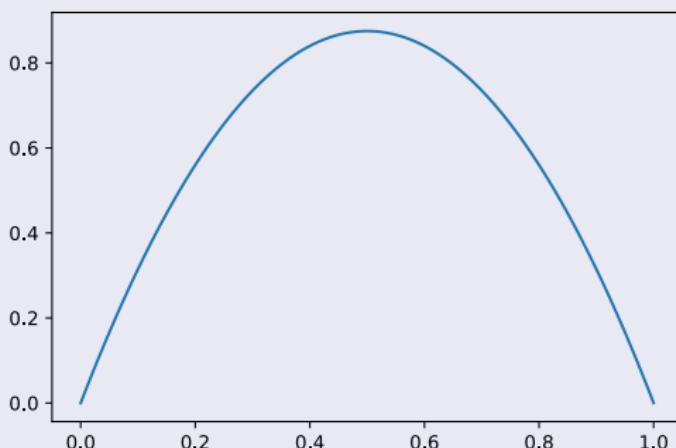
Find the composition of $f \circ f$

Instead of doing this

Let us do the following

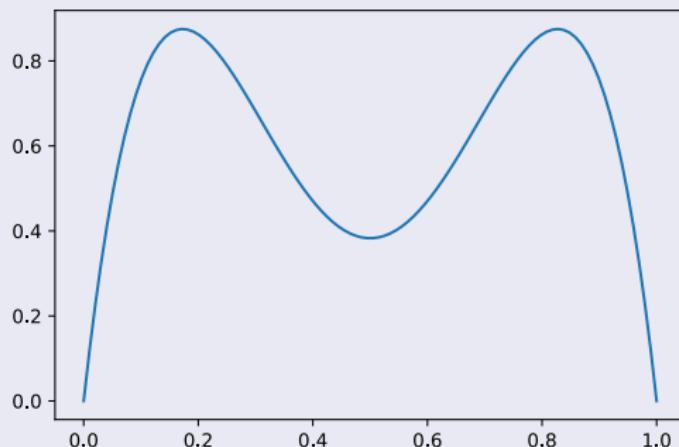
$$f(x) = 3.5x(1 - x)$$

In the first composition, we get



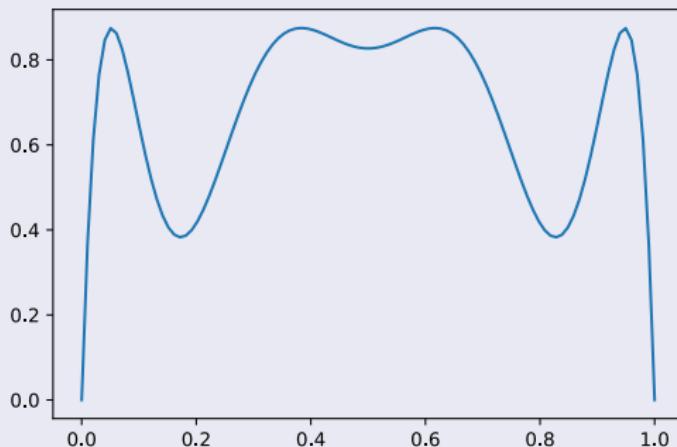
Now, as we compound the function

Second one, $y = f \circ f (x)$



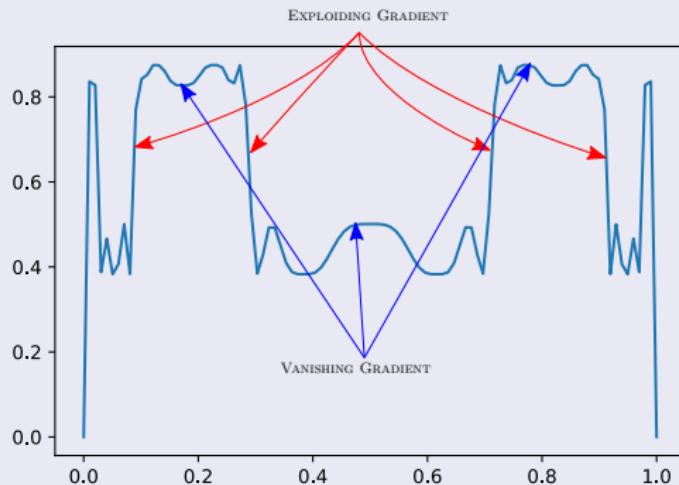
Now, as we increment iterations

Third one, $y = f \circ f \circ f (x)$



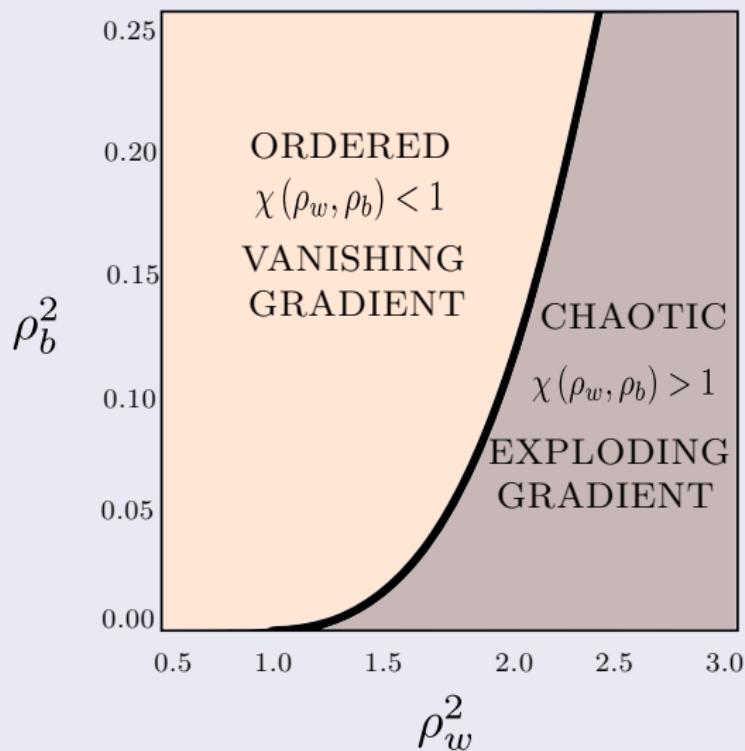
Finally

We see the increment in the gradient part negative or positive



Actually, we have

A Frontier defining the Vanishing and Exploding Gradient [27]



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Actually

Eventually, the iterates go to infinity or zero OR

- They wind up at a fixed point...

• Fixed Point

$$x = f(x)$$

Actually

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- They wind up at a fixed point...

A Fixed Point?

$$x = f(x)$$

Basically

The fixed points can be thought

- Some fixed points repel the iterates; **these are called sources.**
- Other fixed points attract the iterates; **these are called sinks.**

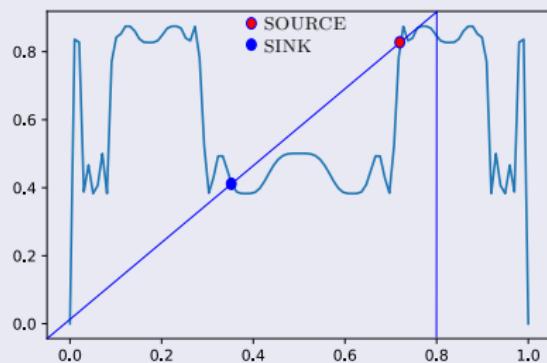
[Source: https://en.wikipedia.org/wiki/Attractor_(mathematics)]

Basically

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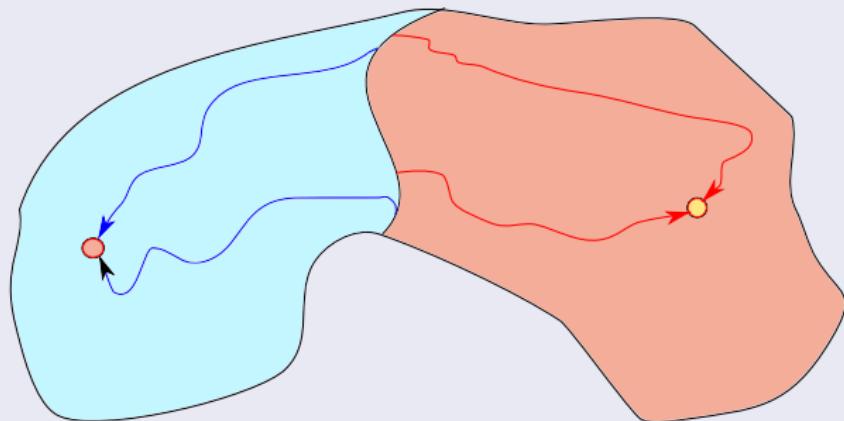
- Some fixed points repel the iterates; **these are called sources**.
- Other fixed points attract the iterates; **these are called sinks**.

Basically $f'(x) < 1$ are sinks and $f'(x) > 1$ are sources



Areas of attraction

Basically, we have that there are areas the pull in the iterations of the function



These fixed points

In Deep Structures as RNN without sigmoid functions

$$\begin{aligned}\mathbf{h}_t &= W_{sd} \mathbf{x}_t + U_{ss} \mathbf{h}_{t-1} \\ \mathbf{y}_t &= V_{os} \mathbf{h}_t\end{aligned}$$

We have

$$\mathbf{x}_t = V_{os} [W_{sd} \mathbf{x}_t + U_{ss} \mathbf{h}_{t-1}]$$

The eigenvalues of V_{os}

- Then, we have that

$$\mathbf{x}_t = V_{os} W_{sd} \mathbf{x}_t + V_{os} U_{ss} \mathbf{h}_{t-1} = I \mathbf{x}_t + 0$$

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Therefore if $\mathbf{b} = V_{os} U_{ss} \mathbf{h}_{t-1}$

- Then, we have that

$$\mathbf{x}_t = V_{os} W_{sd} \mathbf{x}_t + V_{os} U_{ss} \mathbf{h}_{t-1} = I \mathbf{x}_t + \mathbf{0}$$

Therefore

We have that

$$V_{os}W_{sd} \approx I \text{ and } \mathbf{h}_{t-1} \approx 0$$

They define an area

Where V_{os} and W_{sd}

- They are the inverse of each other

↳ [View the full document on my website](#)

- Basically they fixed point converts a RNN without activation functions in a linear model

They define an area

Where V_{os} and W_{sd}

- They are the inverse of each other

And the hidden state is almost zero

- Basically they fixed point converts a RNN without activation functions in a linear model

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Gradient Clipping

We prevent gradient from blowing up by rescaling to a certain value

$$\|\nabla_{\theta}L\| > \eta \implies \nabla_{\theta}L = \frac{\eta \nabla_{\theta}L}{\|\nabla_{\theta}L\|}$$

We have a series of slides on loss [23]

$$\min_{x \in \mathbb{R}^d} f(x)$$

Furthermore, we define a sphere

$$S = \{x | \exists y \text{ such that } f(y) \leq f(x_0), \text{ and } \|x - y\| \leq 1\}$$

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Furthermore, we define a space

$$S = \{x | \exists y \text{ such that } f(y) \leq f(x_o), \text{ and } \|x - y\| \leq 1\}$$

We have then for S

In \mathbb{R}^2 the following example

Assumptions

Assumption 1

- Function f is lower bounded by f^*

- Function f is twice differentiable

Assumptions

Assumption 1

- Function f is lower bounded by f^*

Assumption 2

- Function f is twice differentiable

Then, there are the following proposals

The ordinary gradient descent

$$x_{k+1} = x_k - \eta \nabla f(x_k)$$

The classical gradient descent algorithm:

$$x_{k+1} = x_k - h_c \nabla f(x_k), \text{ where } h_c = \min \left\{ \eta_c, \frac{\eta_c}{\|\nabla f(x)\|} \right\}$$

Normalized gradient descent algorithm:

$$x_{k+1} = x_k - h_n \nabla f(x_k), \text{ where } h_n = \frac{\eta_c}{\|\nabla f(x)\| + \beta}$$

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The Clipped Gradient Descent (CGD)

$$x_{k+1} = x_k - h_c \nabla f(x_k), \text{ where } h_c = \min \left\{ \eta_c, \frac{\gamma \eta_c}{\|\nabla f(x)\|} \right\}$$

Normalized gradient descent method

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Remark

Clipped GD and NGD are almost equivalent

- If we set $\gamma\eta_c = \eta_n$ and $\eta_c = \frac{\eta_n}{\beta}$ then

$$\frac{1}{2}h_c \leq h_n \leq 2h_c$$

A Natural Question

Definition

- The objective f is called L -smooth if
$$\|\nabla f(x) - \nabla f(y)\| \leq L \|x - y\| \text{ for all } x, y \in \mathbb{R}^d$$

This is equivalent under some differentiable

$$\|\nabla^2 f(x)\| \leq L$$

Then we have the following approximation

$$f(y) \approx f(x) + \nabla^T f(x)(y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(x)(y - x)$$

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$$\|\nabla^2 f(x)\| \leq L$$

Then, you get the following upper-bound

$$f(y) \approx f(x) + \nabla^T f(x)(y - x) + \frac{1}{2}(y - x)^T \nabla^2 f(x)(y - x)$$

Then, it is possible to use the 3 Assumption

We have that

$$f(y) \leq f(x) + \nabla^T f(x)(y - x) + \frac{1}{2}L\|y - x\|^2$$

Then taking all the other variables and assuming $y = x + h\mathbf{e}_1$

$$h^* = \arg \min_h \left[f(x) + h\|\nabla f(x)\|^2 + \frac{1}{2}Lh^2\|\nabla f(x)\|^2 \right] = \frac{1}{L}$$

Basically

- This choice of h leads to GD with a fixed step,

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Exercise

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Question

- “Is clipped gradient descent optimized for a different smoothness condition?”

$$f(y) \leq f(x) + \nabla^T f(x)(y - x) + \frac{1}{2}L\|y - x\|^2$$

Answer

$$\eta^* = \frac{\eta}{\|\nabla f(x)\| + \beta}$$

Now

Question

- “Is clipped gradient descent optimized for a different smoothness condition?”

Inspired in the equation

$$f(y) \leq f(x) + \nabla^T f(x)(y - x) + \frac{1}{2}L\|y - x\|^2$$

ANSWER

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Inspired in the equation

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Assume

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Then, we have

Assume that such value optimize the equation

$$f(x) - h \|\nabla f(x)\|^2 + \frac{1}{2} L h^2 \|\nabla f(x)\|^2$$

Then we have

$$L(x) = \frac{\|\nabla f(x)\| + \beta}{\eta}$$

Assumption 3: the function $L(x)$ is smooth.

- (L_0, L_1) -smoothness. f is (L_0, L_1) -smooth, if there exist positive L_0 and L_1 such that $\|\nabla^2 f(x)\| \leq L_0 + L_1 \|\nabla f(x)\|$
 - » $\nabla^2 f(x)$ is the Hessian

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Assumption 3 by using $\|\nabla^2 f(x)\| \leq L$

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 - ▶ $\nabla^2 f(x)$ is the Hessian

The final Theorem

Theorem (CGD) [28]

- Assume that Assumptions 1, 2, and 3 hold in set S . With parameters

$$\eta_c = \frac{1}{10L_o} \text{ and } \gamma = \min \left\{ \frac{1}{\eta_c}, \frac{1}{10L_o\eta_c} \right\},$$

- Then Clipped GD terminates in

$$\frac{20L_0(f(x_0) - f^*)}{\epsilon^2} + \frac{20 \max \{1, L_1^2\} (f(x_0) - f^*)}{L_0} \text{ iterations}$$

Remarks

The paper

- It points out to a high correlation between the Jacobian and the Hessian

Please read the paper...

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There are more work to be done

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Another way to stabilize the network

Data Normalization

- Standardization is the most popular form of preprocessing
 - ▶ Normally mean subtraction and subsequent scaling by the standard deviation.

Mean subtraction

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i \text{ then } x'_i = x_i - \mu$$

Final

- Standardization refers to altering the data dimensions such that they are of approximately the same scale.

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Therefore, we have that

Standardization

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \mu)^2$$
$$x_i^s = \frac{x_i - \mu}{\sigma}$$

However, there is one more step to do.

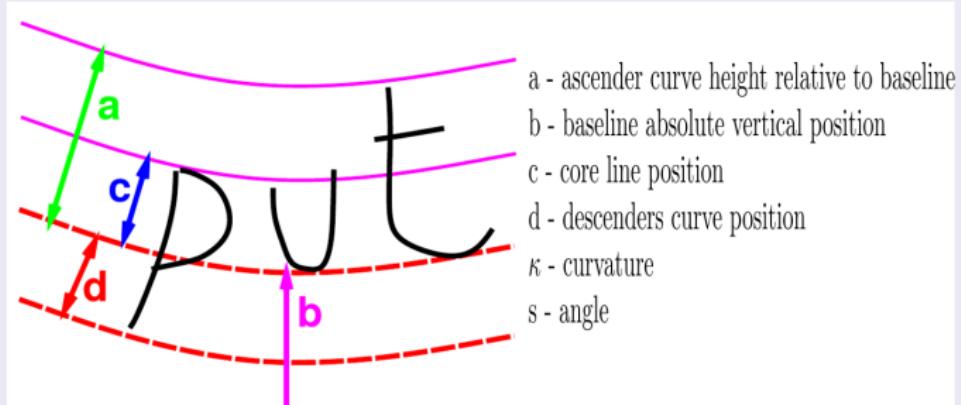
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However, there other tricks, Bengio et al [29]



Softmax Scaling

Thus

- All new features have zero mean and unit variance.

However

- Other linear techniques limit the feature values in the range of $[0, 1]$ or $[-1, 1]$ by proper scaling.

However

- We can non-linear mapping. For example the softmax scaling

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Steps of Softmax Scaling

Softmax Scaling

- It consists of two steps

1. Pre-scale

$$y_{ik} = \frac{x_{ik} - \bar{x}_k}{\sigma} \quad (2)$$

2. Compute softmax

$$\hat{x}_{ik} = \frac{1}{1 + \exp \{-y_{ik}\}} \quad (3)$$

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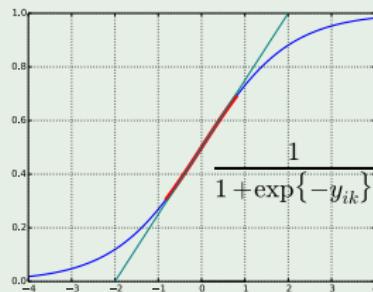
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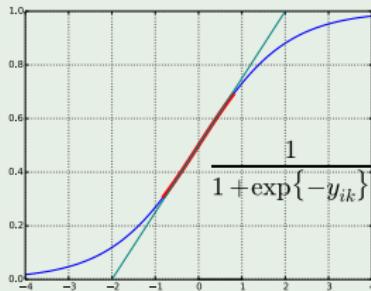
Explanation

Notice the red area is almost flat!!!



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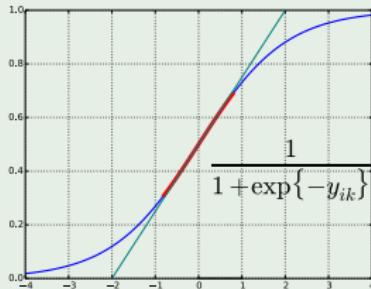
Thus, we have that

- The red region represents values of y inside of the region defined by the mean and variance (small values of y).

Then, if we have those values y behaves as a linear function.

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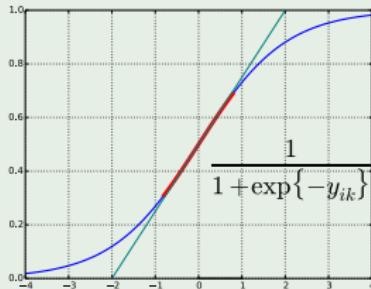
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Here, the people at Google [17] around 2015

They commented in the “Internal Covariate Shift Phenomena”

- Due to the change in the distribution of each layer’s input

Deep learning

- The min-batch forces to have those changes which impact on the learning capabilities of the network.

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In Neural Networks, they define this

- Internal Covariate Shift as the change in the distribution of network activations due to the change in network parameters during training.

They gave the following reasons

Consider a layer with the input u that adds the learned bias b

- Then, it normalizes the result by subtracting the mean of the activation over the training data:

$$\hat{x} = x - E[x]$$

- $\mathcal{X} = \{x, \dots, x_N\}$ the data samples and $E[x] = \frac{1}{N} \sum_{i=1}^N x_i$

Now, we can implement this. The dependent variable is y :

- Then $b = b + \Delta b$ where $\Delta b \propto -\frac{\partial L}{\partial x}$



$$u + (b + \Delta b) - E[u + (b + \Delta b)] = u + b - E[u + b]$$

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Now, if the gradient ignores the dependence of $E[x]$ on b

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Now, if the gradient ignores the dependence of $E[\mathbf{x}]$ on b

- Then $b = b + \Delta b$ where $\Delta b \propto -\frac{\partial l}{\partial \hat{\mathbf{x}}}$

Finally

$$u + (b + \Delta b) - E[u + (b + \Delta b)] = u + b - E[u + b]$$

Then

The following will happen

- The update to b leads to **no change** in the output of the layer.

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Normalization via Mini-Batch Statistic

It is possible to describe the normalization as a transformation layer

$$\hat{x} = \text{Norm}(x, \mathcal{X})$$

- Which depends on all the training samples \mathcal{X} which also depends on the layer parameters

For back-propagation we will need to compute the following terms

$$\frac{\partial \text{Norm}(x, \mathcal{X})}{\partial x} \text{ and } \frac{\partial \text{Norm}(x, \mathcal{X})}{\partial \mathcal{X}}$$

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Normalization via Mini-Batch Statistic

Problem!!!

- whitening the layer inputs is expensive, as it requires computing the covariance matrix

$$Cov[\mathbf{x}] = E_{\mathbf{x} \in \mathcal{X}} [\mathbf{x}\mathbf{x}^T] \text{ and } E[\mathbf{x}] E[\mathbf{x}]^T$$

- ▶ To produce the whitened activations

Therefore

A Better Options, we can normalize each dimension

$$\hat{\mathbf{x}}^{(k)} = \frac{\mathbf{x}^{(k)} - \mu}{\sigma}$$

- with $\mu = E [\mathbf{x}^{(k)}]$ and $\sigma^2 = Var [\mathbf{x}^{(k)}]$

• The effect of such normalization

- Simply normalizing each input of a layer may change what the layer can represent.

• One need to keep each standard deviation in the network

- Which can represent the identity transform

Therefore

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So, we need to insert a transformation in the network

- Which can represent the identity transform

The Transformation

The Linear transformation

$$\mathbf{y}^{(k)} = \gamma^{(k)} \hat{\mathbf{x}}^{(k)} + \beta^{(k)}$$

The Inverse transformation

- This allow to recover the identity by setting $\gamma^{(k)} = \sqrt{\text{Var}[\mathbf{x}^{(k)}]}$ and $\beta^{(k)} = E[\mathbf{x}^{(k)}]$ if necessary.

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The Linear transformation

$$\mathbf{y}^{(k)} = \gamma^{(k)} \hat{\mathbf{x}}^{(k)} + \beta^{(k)}$$

The parameters $\gamma^{(k)}, \beta^{(k)}$

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Finally

Batch Normalizing Transform

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots m\}$, Parameters to be learned: γ, β

Output: $\{y_i = BN_{\gamma, \beta}(x_i)\}$

- ➊ $\mu_B = \frac{1}{m} \sum_{i=1}^m x_i$
- ➋ $\sigma_B^2 = \frac{1}{m} \sum_{i=1}^m (x_i - \mu)^2$
- ➌ $\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}$
- ➍ $y_i = \gamma^{(i)} \hat{x}_i + \beta = BN_{\gamma, \beta}(x_i)$

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$$③ \hat{\mathbf{x}} = \frac{\mathbf{x}_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}}$$

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Backpropagation

We have the following equations by using the loss function l

$$① \frac{\partial l}{\partial \hat{x}_i} = \frac{\partial l}{\partial y_i} \times \gamma$$

$$② \frac{\partial l}{\partial \mu_B} = \sum_{i=1}^m \frac{\partial l}{\partial x_i} \times (x_i - \mu_B) \times \left(-\frac{1}{2}\right) \times (\sigma_B^2 + \epsilon)^{-\frac{3}{2}}$$

$$③ \frac{\partial l}{\partial \sigma_B^2} = \left(\sum_{i=1}^m \frac{\partial l}{\partial x_i} \times \frac{-1}{\sqrt{\sigma_B^2 + \epsilon}} \right) + \frac{\partial l}{\partial \sigma_B^2} \times \frac{\sum_{i=1}^m -2 \times (x_i - \mu_B)}{m}$$

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$$\textcircled{3} \quad \frac{\partial l}{\partial \beta} = \sum_{i=1}^m \frac{\partial l}{\partial y_i}$$

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We have the following equations by using the loss function l

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Training Batch Normalization Networks

Input: Network N with trainable parameters Θ ; subset of activations $\{x^{(k)}\}_{k=1}^K$

Output: Batch-normalized network for inference N_{BN}^{inf}

- 1. $N_{BN}^{tr} = N // \text{Training BN network}$
- 2. for $k = 1..K$ do
 - 3. Add transformation $y^{(k)} = BN_{\gamma^{(k)}, \beta^{(k)}}(x^{(k)})$ to N_{BN}^{tr}
 - 4. Modify each layer in N_{BN}^{tr} with input $x^{(k)}$ to take $y^{(k)}$ instead
 - 5. Train N_{BN}^{tr} to optimize the parameters $\Theta \cup \{\gamma^{(k)}, \beta^{(k)}\}_{k=1}^K$
 - 6. $N_{BN}^{inf} = N_{BN}^{tr} // \text{Inference BN network with frozen parameters}$
 - 7. for $k = 1..K$ do
 - 8. Process multiple training mini-batches B , each of size m , and average over them
 - 9. $E[x] = E_B[\mu_B]$ and $Var[x] = \frac{m}{m-1} E_B[\sigma_B^2]$
 - 10. In N_{BN}^{inf} , replace the transform $y = BN_{\gamma, \beta}(x)$ with
 - 11. $y = \frac{\gamma}{\sqrt{Var[x]+\epsilon}} \times x + \left[\beta - \frac{\gamma E[x]}{\sqrt{Var[x]+\epsilon}} \right]$

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- ⑦ for $k = 1 \dots K$ do
- ⑧ Process multiple training mini-batches \mathcal{B} , each of size m , and average over them

⑨ $E[x] = \bar{x}_B$ [avg] and $Var[x] = \frac{m}{m-1} \bar{s}_B^2$

⑩ In N_{BN}^{tr} , replace the transform $y = BN_{\gamma, \beta}(x)$ with

⑪ $y = \frac{\gamma}{\sqrt{Var[x]+\epsilon}} \times x + \left[\beta - \frac{\gamma E[x]}{\sqrt{Var[x]+\epsilon}} \right]$

Training Batch Normalization Networks

Input: Network N with trainable parameters Θ ; subset of activations $\{\mathbf{x}^{(k)}\}_{k=1}^K$

Output: Batch-normalized network for inference N_{BN}^{inf}

- ① $N_{BN}^{tr} = N$ // Training BN network
- ② for $k = 1 \dots K$ do
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However

Santurkar et al. [18]

- They found that is not the covariance shift the one affected by it!!!

Batch Normalization

- Batch normalization has been arguably one of the most successful architectural innovations in deep learning.

ReLU vs. Standardized ReLU on CIFAR-10

- on CIFAR-10 with and without BatchNorm

However

Santurkar et al. [18]

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Santurkar et al. recognize that

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THEIR PAPER IS AVAILABLE AT <https://arxiv.org/abs/1801.04381>

• on CIFAR-10 with and without BatchNorm

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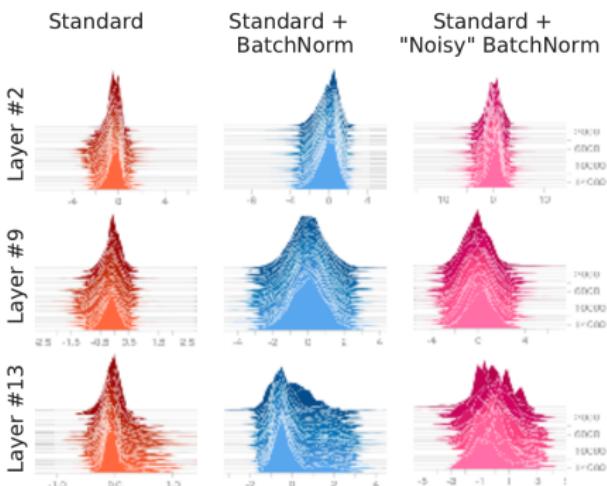
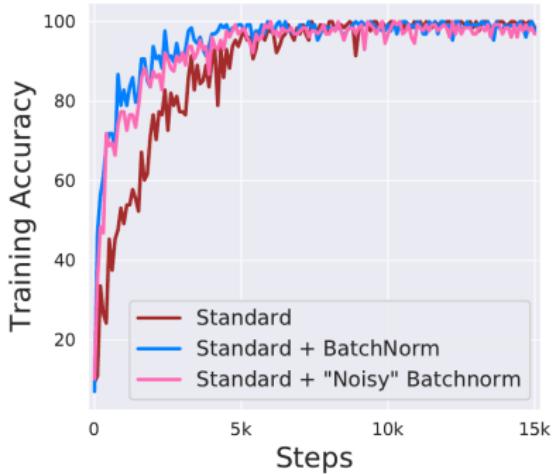
- Batch normalization has been arguably one of the most successful architectural innovations in deep learning.

They used a standard Very deep convolutional network

- on CIFAR-10 with and without BatchNorm

They found something quite interesting

The following facts



Actually Batch Normalization

It does not do anything to the Internal Covariate Shift

- Actually smooth the optimization manifold
 - ▶ It is not the only way to achieve it!!!

- "This suggests that the positive impact of BatchNorm on training might be somewhat serendipitous."

Actually Batch Normalization

It does not do anything to the Internal Covariate Shift

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They suggest that

- “This suggests that the positive impact of BatchNorm on training might be somewhat serendipitous.”

They actually have a connected result

To the analysis of gradient clipping!!!

- They are the same group

Lemma: The effect of BN differs on the Lipschitzness of the loss

- For a BatchNorm network with loss $\hat{\mathcal{L}}$ and an identical non-BN network with (identical) loss \mathcal{L} ,

$$\left\| \nabla_{y_j} \hat{\mathcal{L}} \right\|^2 \leq \frac{\gamma^2}{\sigma_j^2} \left[\left\| \nabla_{y_j} \mathcal{L} \right\|^2 + \frac{1}{m} \langle \mathbf{1}, \nabla_{y_j} \mathcal{L} \rangle^2 - \frac{1}{\sqrt{m}} \langle \nabla_{y_j} \mathcal{L}, \hat{y}_j \rangle^2 \right]$$

They actually have a connected result

To the analysis of gradient clipping!!!

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Theorem (The effect of BatchNorm on the Lipschitzness of the loss)

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1 Introduction

- Limitations of Shallow Architectures
- Highly-varying functions
- Local vs Non-Local Generalization
- From Simpler Features to More Complex Features

2 Deep Forward Architectures

- Introduction
- Convolutional Neural Networks
 - Image Processing
- Auto Encoders
- Boltzmann Machines
- Generative Adversarial Networks
- There Are Many More

3 The Vanishing and Exploding Gradients

- Introduction
- Reasoning Iteratively
- Fixed Points
- Stabilizing the Network
 - Gradient Clipping
 - Normalizing your Data
 - Normalization Layer AKA Batch Normalization

4 Problems with Deeper Architectures

● The Degradation Problem

- The Residual Networks
- Conclusions

Definition

Degradation Problem

- With the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly.

Something Mysterious

- Unexpectedly, such degradation is not caused by overfitting,

Something Else

- to a suitably deep model leads to higher training error,

Definition

Degradation Problem

- With the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly.

Something Notable

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Definition

Degradation Problem

- With the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly.

Something Notable

- Unexpectedly, such degradation is not caused by overfitting,

and adding more layers

- to a suitably deep model leads to higher training error,

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- The Degradation Problem
- **The Residual Networks**
- Conclusions

Therefore, we need to deal with such problems

The Residual Network [16]

- He, Kaiming et al. - "Deep Residual Learning for Image Recognition"

Basically, they propose to add residual connections to the network

$$\mathcal{F}(x) = A_2 A_1 x$$

Then, they introduce the residual connection

$$\mathcal{F}(x) = \mathcal{H}(x) - x \implies \mathcal{F}(x) + x = \mathcal{H}(x) \implies$$

Therefore, we need to deal with such problems

The Residual Network [16]

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Basically they got two layers doing something to an input

$$\mathcal{F}(\mathbf{x}) = A_2 A_1 \mathbf{x}$$

Then they add the original input back to it

$$\mathcal{F}(\mathbf{x}) = \mathcal{H}(\mathbf{x}) - \mathbf{x} \implies \mathcal{F}(\mathbf{x}) + \mathbf{x} = \mathcal{H}(\mathbf{x}) \implies$$

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$$\mathcal{F}(\mathbf{x}) = A_2 A_1 \mathbf{x}$$

Then imagine you have an ideal mapping $\mathcal{H}(\mathbf{x})$

$$\mathcal{F}(\mathbf{x}) = \mathcal{H}(\mathbf{x}) - \mathbf{x} \implies \mathcal{F}(\mathbf{x}) + \mathbf{x} = \mathcal{H}(\mathbf{x}) \implies$$

Basically

This allows to

- Motivation for skipping over layers is to avoid the problem of vanishing gradients.

- In the simplest case, only the weights for the adjacent layer's connection are adapted.

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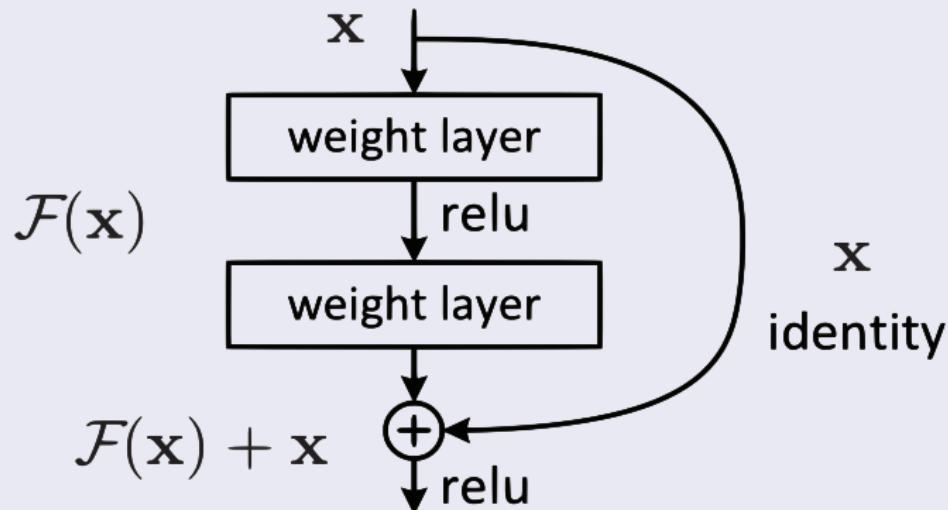
- Motivation for skipping over layers is to avoid the problem of vanishing gradients.

Something Notable

- In the simplest case, only the weights for the adjacent layer's connection are adapted.

Blocks of the Original RNN

We have



A Winner

Something Notable

- Winner of ILSVRC 2015 in image classification, detection, and localization, as well as Winner of MS COCO 2015 detection, and segmentation.

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We have seen many concepts

Deep Forward Networks

- Although a simple idea

The main idea is very simple:

- Basically... From Lower Complexity Features toward more complex more informative!!!

In conclusion

- Deep Forward Networks look to have more expressibility than shallow learners.

We have seen many concepts

Deep Forward Networks

- Although a simple idea

They represent a rich field of study

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