



Deep Learning

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Deep Learning: Caption generation

Generate caption automatically from images

Xu, K., Lei Ba, J., Kiros, R., Cho, K., Courville, A., Salakhutdinov, R. Richard S. Zemel, R. S., and Bengio, Y. **Show, attend and tell: neural image caption generation with visual attention.** In *Proceedings of the 32nd International Conference on Machine Learning (ICML)*, Lille, France, July, 2015.

Deep learning: AI Go player

An AI defeated a human professional for the first time in the game of Go



Silver, D. et al. **Mastering the game of Go with deep neural networks and tree search**, *Nature*, Vol 529, 484–489 (2016)



Outline

1. What is a neural network (NN)?
2. Why do deep neural networks work so well?
 - a) Why neural networks?
 - b) Why deep?
3. Some comment, pointers and summary



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Skin cancer – background

One recent result on the use of deep learning in medicine - Detecting skin cancer (February 2017)

Andre Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M. and Thrun, S. **Dermatologist-level classification of skin cancer with deep neural networks.** *Nature*, 542, 115–118, February, 2017.

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Some background figures (from the US) on skin cancer:

- ▶ Melanomas represents less than 5% of all skin cancers, **but** accounts for 75% of all skin-cancer-related deaths.
- ▶ Early detection absolutely critical. Estimated 5-year survival rate for melanoma: Over 99% if detected in its earlier stages and 14% is detected in its later stages.



Skin cancer – taxonomy used

Image copyright Nature doi:10.1038/nature21056)



Skin cancer – task

Image copyright Nature ([doi:10.1038/nature21056](https://doi.org/10.1038/nature21056))



Skin cancer – solution (ultrabrief)

Start from a neural network trained on 1.28 million images
(**transfer learning**).

Make minor modifications to this model, specializing to present situation.



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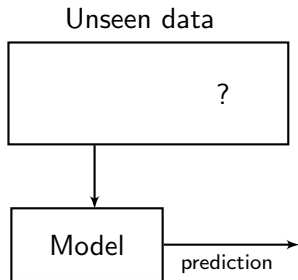
Learn new model parameters
using 129 450 clinical images
(~ 100 times more images than
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Skin cancer – indication of the results

$$\text{sensitivity} = \frac{\text{true positive}}{\text{positive}}$$

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Image copyright Nature (doi:10.1038/nature21056)

Constructing an NN for regression

A **neural network (NN)** is a nonlinear function $\hat{y} = \mathbf{g}_{\theta}(\varphi)$ from an input variable φ to an output variable \hat{y} parameterized by θ .

Linear regression models the relationship between a continuous target variable \hat{y} and an input variable φ ,

$$\hat{y} = \sum_{i=1}^n \varphi_i \theta_i + \theta_0 = \varphi^T \theta,$$

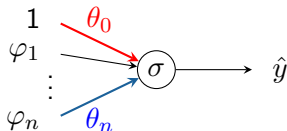
where θ is the parameters composed by the “weights” θ_i and the offset (“bias”) term θ_0 ,

$$\theta = (\theta_0 \quad \theta_1 \quad \theta_2 \quad \cdots \quad \theta_n)^T,$$
$$\varphi = (1 \quad \varphi_1 \quad \varphi_2 \quad \cdots \quad \varphi_n)^T.$$

Generalized linear regression

We can generalize this by introducing nonlinear transformations of the predictor $\varphi^T \theta$,

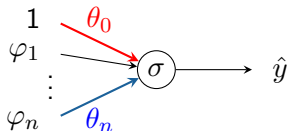
$$\hat{y} = \sigma(\varphi^T \theta).$$



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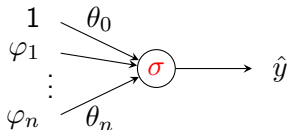


We call $\sigma(x)$ the *activation function*. Two common choices are:

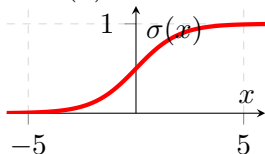
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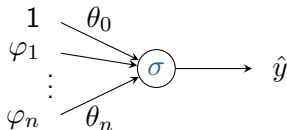


Sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$

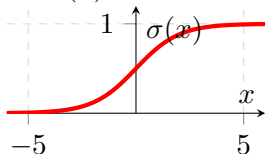
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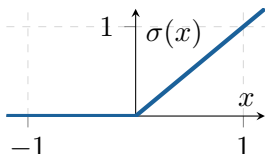
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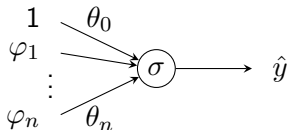
ReLU: $\sigma(x) = \max(0, x)$

Let us consider an example of a **feed-forward NN**, indicating that the information flows from the input to the output layer.

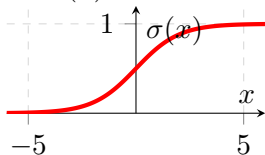
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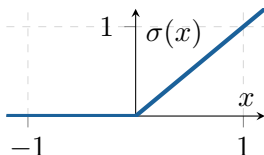
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Neural network - construction

A NN is a sequential construction of several linear regression models.

Inputs

Hidden units

Outputs

1

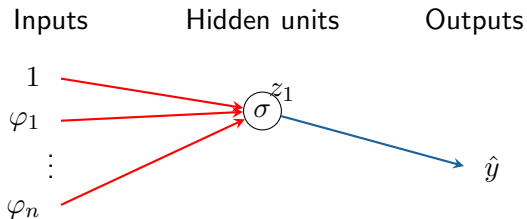
φ_1

\vdots

φ_n

Neural network - construction

A NN is a sequential construction of **several** linear regression models.

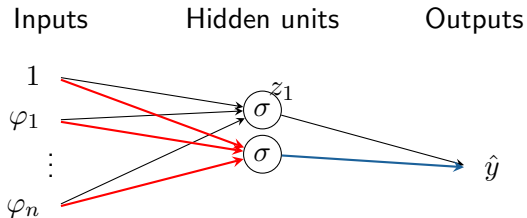


$$z_1 = \sigma \left(\theta_{01}^{(1)} + \sum_{j=1}^n \theta_{j1}^{(1)} \varphi_j \right)$$

$$y = \theta_1^{(2)} z_1$$

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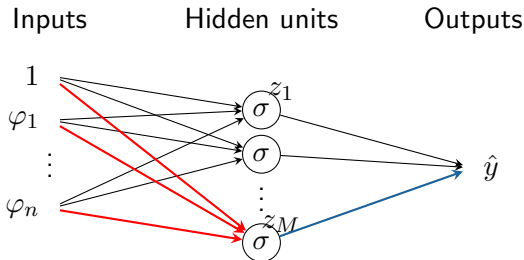
$$z_1 = \sigma \left(\theta_{01}^{(1)} + \sum_{j=1}^n \theta_{j1}^{(1)} \varphi_j \right)$$

$$z_2 = \sigma \left(\theta_{02}^{(1)} + \sum_{j=1}^n \theta_{j2}^{(1)} \varphi_j \right)$$

$$y = \sum_{m=1}^2 \theta_m^{(2)} z_m$$

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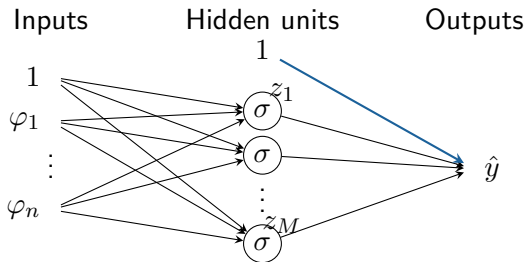
$$\vdots$$

$$z_M = \sigma \left(\theta_{0M}^{(1)} + \sum_{j=1}^n \theta_{jM}^{(1)} \varphi_j \right)$$

$$y = \sum_{m=1}^M \theta_m^{(2)} z_m$$

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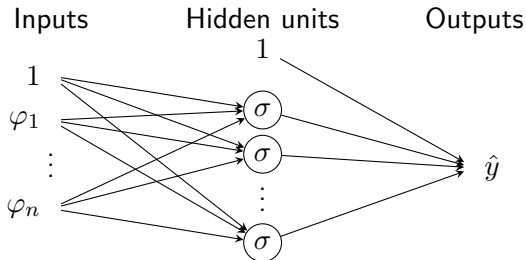
$$\vdots$$

$$z_M = \sigma \left(\theta_{0M}^{(1)} + \sum_{j=1}^n \theta_{jM}^{(1)} \varphi_j \right)$$

$$y = \theta_0^{(2)} + \sum_{m=1}^M \theta_m^{(2)} z_m$$

Neural network - construction

A NN is a sequential construction of **several** linear regression models.



$$\mathbf{z} = \sigma(W_1^T \boldsymbol{\varphi} + \mathbf{b}_1^T)$$

$$\mathbf{b}_1 = [\theta_{01}^{(1)} \dots \theta_{0M}^{(1)}]$$

$$W_1 = \begin{bmatrix} \theta_{01}^{(1)} & \dots & \theta_{0M}^{(1)} \\ \vdots & \dots & \vdots \\ \theta_{n1}^{(1)} & \dots & \theta_{nM}^{(1)} \end{bmatrix}$$

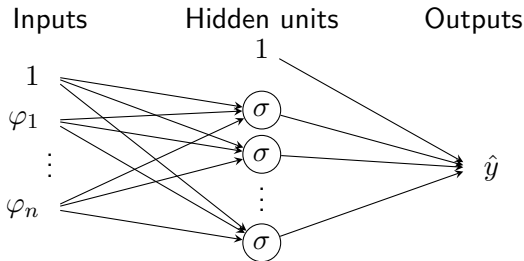
$$\hat{y} = W_2^T \mathbf{z} + \mathbf{b}_2^T$$

$$\mathbf{b}_2 = [\theta_0^{(1)}]$$

$$W_2 = \begin{bmatrix} \theta_0^{(2)} \\ \vdots \\ \theta_M^{(2)} \end{bmatrix}$$

Neural network - construction

A NN is a sequential construction of several **several** linear regression models.

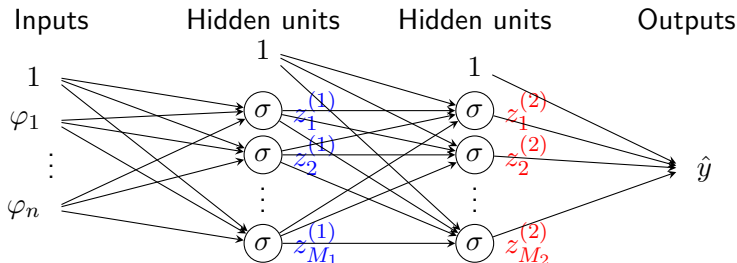


$$\mathbf{z} = \sigma(W_1^T \boldsymbol{\varphi} + \mathbf{b}_1^T)$$

$$y = W_2^T \mathbf{Z} + \mathbf{b}_2^T$$

Neural network - construction

A NN is a **sequential** construction of several linear regression models.



$$\mathbf{z}^{(1)} = \sigma(W_1^T \boldsymbol{\varphi} + \mathbf{b}_1^T)$$

$$\mathbf{z}^{(2)} = \sigma(W_2^T \mathbf{z}^{(1)} + \mathbf{b}_2^T)$$

$$y = W_3^T \mathbf{z}^{(2)} + \mathbf{b}_3^T$$

The model learns better using a deep network (several layers) instead of a wide and shallow network.



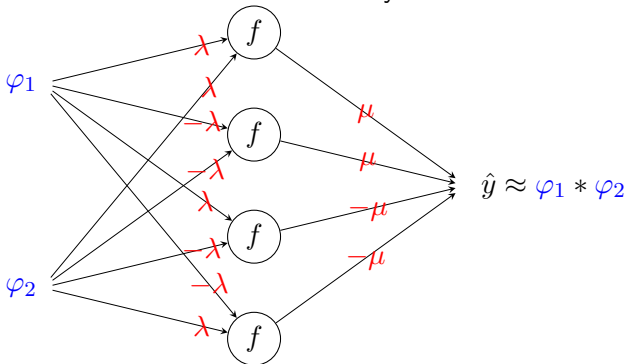
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Why neural networks?

Continuous multiplication gate

A neural network with only four hidden units can model multiplication of two numbers arbitrarily well.



If we choose $\mu = \frac{1}{4\lambda^2 f''(0)}$ then $\hat{y} \rightarrow \varphi_1 * \varphi_2$ when $\lambda \rightarrow 0$.

Henry W. Lin and Max Tegmark. (2016) **Why does deep and cheap learning work so well?**, *arXiv*



A regression example

Input: $\mathbf{u} \in \mathbb{R}^{1000}$

Output: $y \in \mathbb{R}$

Task: Model a quadratic relationship between y and \mathbf{u}

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Linear regression

$$\hat{y} = u_1 u_1 \theta_{1,1} + u_1 u_2 \theta_{1,2} + \dots + u_{1000} u_{1000} \theta_{1000,1000} = \boldsymbol{\varphi}^T \boldsymbol{\theta}$$

where

$$\boldsymbol{\varphi} = [u_1 u_1 \quad u_1 u_2 \quad \dots \quad u_{1000} u_{1000}]^T$$
$$\boldsymbol{\theta} = [\theta_{1,1} \quad \theta_{1,2} \quad \dots \quad \theta_{1000,1000}]^T$$

Requires $\approx \frac{1'000 * 1'000}{2} = 500'000$ parameters!

A regression example

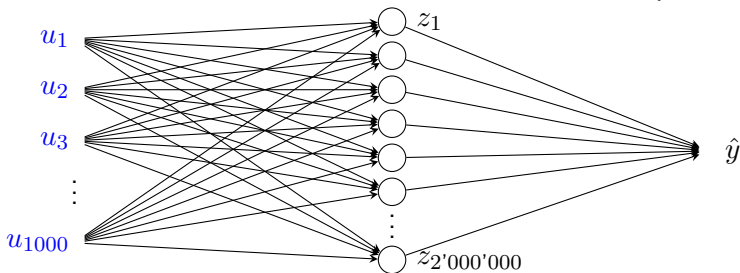
Input: $\mathbf{u} \in \mathbb{R}^{1000}$

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Task: Model a quadratic relationship between y and \mathbf{u}

Neural network

To model all products with a neural network we would need $4 * 500'000 = 2 * 10^6$ hidden units and hence 2 billion parameters...



$$1000 * (2 * 10^6) + 2 * 10^6 \approx 2 * 10^9 \text{ param.}$$

A regression example (cont.)

Input: $\mathbf{u} \in \mathbb{R}^{1000}$

Output: $y \in \mathbb{R}$

Task: Model a quadratic relationship between y and \mathbf{u}

Assume that only 10 of the regressors $u_i u_j$ are of importance

Linear regression

$$\hat{y} = u_1 u_1 \theta_{1,1} + u_1 u_2 \theta_{1,2} + \dots + u_{1000} u_{1000} \theta_{1000,1000} = \boldsymbol{\varphi}^T \boldsymbol{\theta}$$

where

$$\boldsymbol{\varphi} = [u_1 u_1 \quad u_1 u_2 \quad \dots \quad u_{1000} u_{1000}]^T$$
$$\boldsymbol{\theta} = [\theta_{1,1} \quad \theta_{1,2} \quad \dots \quad \theta_{1000,1000}]^T$$

You probably want to regularize, but 500'000 parameters are **still** required!

A regression example (cont.)

Input: $\mathbf{u} \in \mathbb{R}^{1000}$

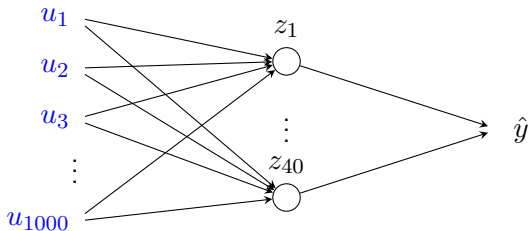
Output: $y \in \mathbb{R}$

Task: Model a quadratic relationship between y and \mathbf{u}

Assume that only 10 of the regressors $u_i u_j$ are of importance

Neural network

To model 10 products with a neural network we would need $4 \cdot 10$ hidden units, i.e. leading to only $\approx 40'000$ parameters!



$$1000 \cdot 40 + 40 = 40'040$$

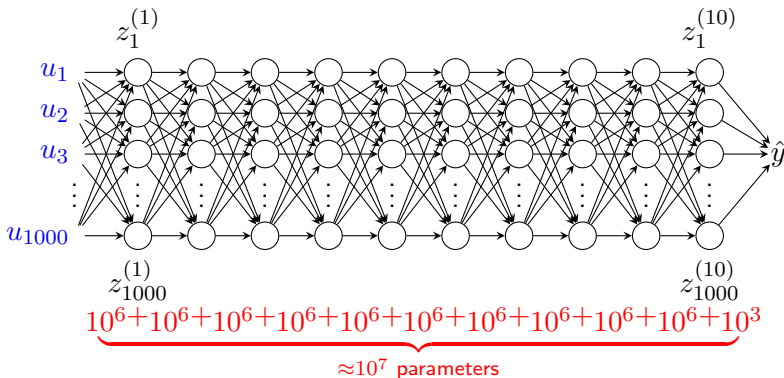


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Why deep? - A regression example

- ▶ Consider the same example. Now we want a model with complexity corresponding to polynomials of degree 1'000.
- ▶ Keep 250 products in each layer $\Rightarrow 250 \cdot 4 = 1'000$ hidden units.



Linear regression would require $\approx \frac{1000^{1000}}{1000!}$ parameters to model such a relationship...



Why deep? - Image classification

Example: Image classification

Input: pixels of an **image**

Output: **object identity**

Each hidden layer extracts
increasingly abstract
features.

Zeiler, M. D. and Fergus, R. **Visualizing and understanding convolutional networks**

Computer Vision - ECCV (2014).



Deep neural networks

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It is accomplished by using **multiple levels of representation**. Each level transforms the representation at the previous level into a new and more abstract representation,

$$\mathbf{z}^{(l+1)} = \mathbf{f} \left(\mathbf{W}^{(l+1)} \mathbf{z}^{(l)} + \mathbf{b}^{(l+1)} \right),$$

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Key aspect: The layers are **not** designed by human engineers, they are generated from (typically lots of) data using a learning procedure and lots of computations.



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Some comments - Why now?

Neural networks have been around for more than fifty years. Why have they become so popular now (again)?

To solve really interesting problems you need:

1. Efficient learning **algorithms**
2. Efficient computational **hardware**
3. A lot of labeled **data!**

These three factors have not been fulfilled to a satisfactory level until the last 5-10 years.



Some pointers

A book has recently been written

I. Goodfellow, Y. Bengio and A. Courville **Deep learning** *MIT Press*, 2016

<http://www.deeplearningbook.org/>



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You will also find more material than you can possibly want here

<http://deeplearning.net/>



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A deep NN is very **parameter efficient** when modelling high-dimensional, complex data.



Thank you!