Large Language Models Under the Hood
Part 1: Training Deep Neural Networks

Andrey Kutuzov

University of Oslo

NLDL 2025

Contents

Tutorial technicalities

Welcome to the NLDL 2025 tutorial on large language models!

Andrey Kutuzov, Egil Rønningstad, David Samuel

Tutorial technicalities

Welcome to the NLDL 2025 tutorial on large language models!

Andrey Kutuzov, Egil Rønningstad, David Samuel

Schedule

- 13:00 - Part 1, Training Deep Neural Networks
- 14:00 - Part 2, Modern Generative Language Models
- 15:00 - Part 3, Hands-on with open-weights LLMs for Norwegian

Supported by NAIC

Tutorial technicalities

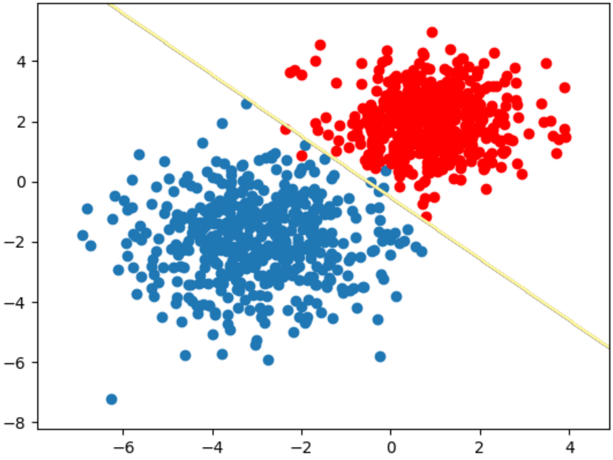
Materials for the hands-on session

- Test whether you can access `https://github.com/ltgoslo/nldl_llm_tutorial`
- You are allocated Linux virtual machines for the hands-on session
- Connect via `ssh` and run Python; can also use Jupyter Lab.
- Find the ip address and the username for your virtual machine (VM) at the spreadsheet below:

(here goes QR code leading to the spreadsheet)

Contents

Basics of supervised machine learning



Basics of supervised machine learning

- Input 1: a training set of *n* training instances $x_{1:n} = x_1, x_2, \ldots x_n$

Basics of supervised machine learning

- Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \ldots x_n$
  - for example, e-mail messages.

Basics of supervised machine learning

- Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \ldots x_n$
  - for example, e-mail messages.
- Input 2: corresponding 'gold' labels for these instances $y_{1:n} = y_1, y_2, \ldots y_n$

Basics of supervised machine learning

- Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \ldots x_n$
  - for example, e-mail messages.
- Input 2: corresponding 'gold' labels for these instances $y_{1:n} = y_1, y_2, \ldots y_n$
  - for example, whether the message is spam (1) or not (0).

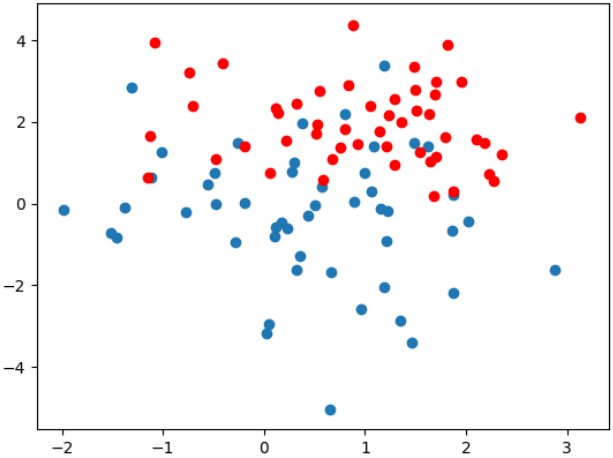
Basics of supervised machine learning

- Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \ldots x_n$
  - for example, e-mail messages.
- Input 2: corresponding 'gold' labels for these instances $y_{1:n} = y_1, y_2, \ldots y_n$
  - for example, whether the message is spam (1) or not (0).
- The trained models allow to make label predictions for unseen instances.

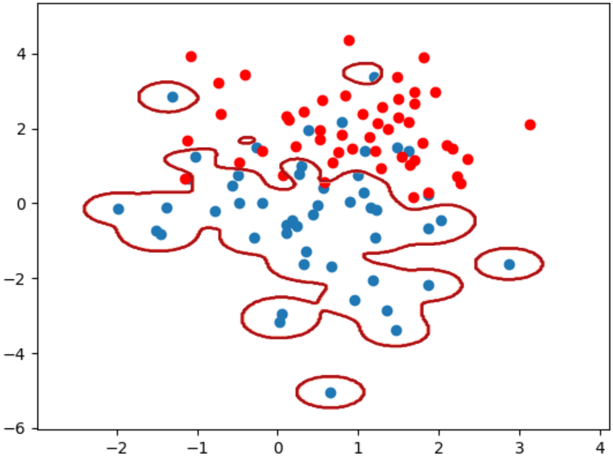
Basics of supervised machine learning

- Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \ldots x_n$
  - for example, e-mail messages.
- Input 2: corresponding 'gold' labels for these instances $y_{1:n} = y_1, y_2, \ldots y_n$
  - for example, whether the message is spam (1) or not (0).
- The trained models allow to make label predictions for unseen instances.
- Generally: some program for mapping instances to labels.

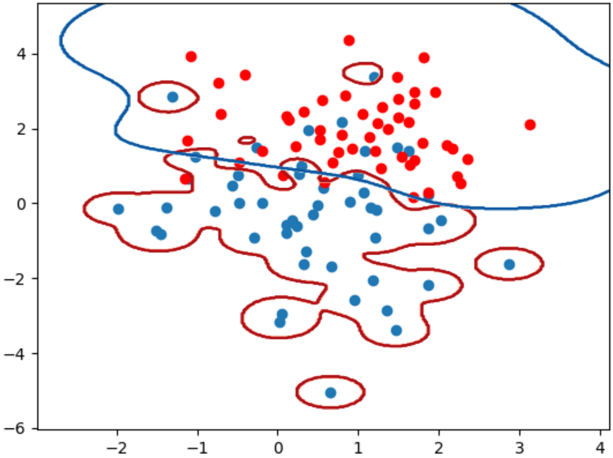
What do you think a good model would look like for this data?



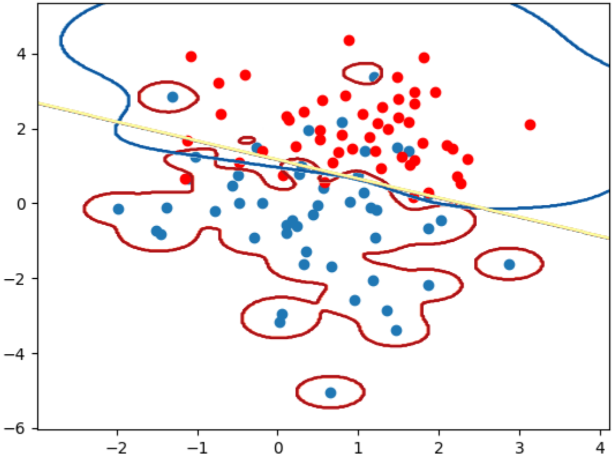
What do you think a good model would look like for this data?



What do you think a good model would look like for this data?



What do you think a good model would look like for this data?



Linear functions: a popular hypothesis class

Simple linear function

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b} \tag{1}$$

$$\theta = \boldsymbol{W}, \boldsymbol{b} \tag{2}$$

- Function input:
  - feature vector $\boldsymbol{x} \in \mathbb{R}^{d_{in}}$;
  - each training instance is represented with d_{in} features;
  - for example, some properties of the documents.

Basics of supervised machine learning

Simple linear function

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b} \quad (1)$$

$$\theta = \boldsymbol{W}, \boldsymbol{b} \quad (2)$$

- Function input:
  - feature vector $\boldsymbol{x} \in \mathbb{R}^{d_{in}}$;
  - each training instance is represented with d_{in} features;
  - for example, some properties of the documents.
- Function parameters θ:
  - matrix $\boldsymbol{W} \in \mathbb{R}^{d_{in} \times d_{out}}$
    - d_{out} is the dimensionality of the desired prediction (number of classes)
  - bias vector $\boldsymbol{b} \in \mathbb{R}^{d_{out}}$
    - bias 'shifts' the function output to some direction.

Training of a linear classifier

$$f(\boldsymbol{x};\boldsymbol{W},\boldsymbol{b}) = \boldsymbol{x}\cdot\boldsymbol{W}+\boldsymbol{b}$$

$$\theta = \boldsymbol{W},\boldsymbol{b}$$

- Training is finding the optimal θ.

Basics of supervised machine learning

Training of a linear classifier

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

$$\theta = \boldsymbol{W}, \boldsymbol{b}$$

- Training is finding the optimal θ.
- 'Optimal' means '*producing predictions* $\hat{\boldsymbol{y}}$ *closest to the gold labels* $\boldsymbol{y}$ *on our n training instances*'.

Basics of supervised machine learning

Training of a linear classifier

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

$$\theta = \boldsymbol{W}, \boldsymbol{b}$$

- Training is finding the optimal θ.
- 'Optimal' means '*producing predictions $\hat{\boldsymbol{y}}$ closest to the gold labels $\boldsymbol{y}$ on our n training instances*'.
- Ideally, $\hat{\boldsymbol{y}} = \boldsymbol{y}$

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of binary classification

Binary decision ($d_{out} = 1$):

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of binary classification

Binary decision ($d_{out} = 1$):

- '*Is this message spam or not?*'

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of binary classification

Binary decision ($d_{out} = 1$):

- '*Is this message spam or not?*'
- $\boldsymbol{W}$ is a vector, $\boldsymbol{b}$ is a scalar.

Basics of supervised machine learning

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of binary classification

Binary decision ($d_{out} = 1$):

- '*Is this message spam or not?*'
- $\boldsymbol{W}$ is a vector, $\boldsymbol{b}$ is a scalar.
- The prediction $\hat{\boldsymbol{y}}$ is also a scalar: either 1 ('yes') or -1 ('no').

Basics of supervised machine learning

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of binary classification

Binary decision ($d_{out} = 1$):

- '*Is this message spam or not?*'
- $\boldsymbol{W}$ is a vector, $\boldsymbol{b}$ is a scalar.
- The prediction $\hat{\boldsymbol{y}}$ is also a scalar: either 1 ('yes') or -1 ('no').
- NB: the model can output any number, but we convert all negatives to -1 and all positives to 1 (*sign* function).

$$\theta = (\boldsymbol{W} \in \mathbb{R}^{d_{in}}, \boldsymbol{b} \in \mathbb{R}^1)$$

$$f(x; W, b) = x \cdot W + b$$

$$\begin{array}{ccccccc} x & & W & & b & & \hat{y} \\ \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} & \cdot & \begin{bmatrix} 0 & 0 & 1 & 1 & 1 \end{bmatrix} & + & 0.5 & = & \text{sign}(1.5) = 1 \end{array}$$

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of multi-class classification

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of multi-class classification

Multi-class decision ($d_{out} = k$)

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of multi-class classification

Multi-class decision ($d_{out} = k$)

- '*Which languages appear in this tweet?*'

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of multi-class classification

Multi-class decision ($d_{out} = k$)

- '*Which languages appear in this tweet?*'
- $\boldsymbol{W}$ is a matrix, $\boldsymbol{b}$ is a vector of k components.

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of multi-class classification

Multi-class decision ($d_{out} = k$)

- '*Which languages appear in this tweet?*'
- $\boldsymbol{W}$ is a matrix, $\boldsymbol{b}$ is a vector of k components.
- The prediction $\hat{\boldsymbol{y}}$ is also a one-hot vector of k components.

Basics of supervised machine learning

$$f(\boldsymbol{x}; \boldsymbol{W}, \boldsymbol{b}) = \boldsymbol{x} \cdot \boldsymbol{W} + \boldsymbol{b}$$

Output of multi-class classification

Multi-class decision ($d_{out} = k$)

- '*Which languages appear in this tweet?*'
- $\boldsymbol{W}$ is a matrix, $\boldsymbol{b}$ is a vector of k components.
- The prediction $\hat{\boldsymbol{y}}$ is also a one-hot vector of k components.
- The component corresponding to the correct language has the value of 1, others are zeros, for example:
  $\hat{\boldsymbol{y}} = [0, 0, 1, 0]$ (for $k = 4$)

$$\theta = (\boldsymbol{W} \in \mathbb{R}^{d_{in} \times d_{out}}, \boldsymbol{b} \in \mathbb{R}^{d_{out}})$$

$$f(x; W, b) = x \cdot W + b$$

$$\begin{array}{ccccccc} x & & W & & b & & \hat{y} \\ \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} & \cdot & \begin{bmatrix} 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 \end{bmatrix} & + & \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} & = & \text{argmax}(\begin{bmatrix} 2 & 2 & 4 \end{bmatrix}) \\ & & & & & = & 3 \end{array}$$

Log-linear classification

If we care about how confident is the classifier about each decision:

Log-linear classification

If we care about how confident is the classifier about each decision:

- Map the predictions to the range of $[0, 1]$...

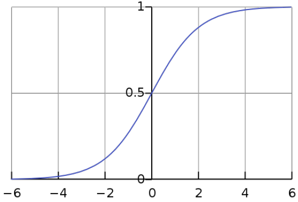
Log-linear classification

If we care about how confident is the classifier about each decision:

- Map the predictions to the range of $[0, 1]$...
- ...by a squashing function, for example, sigmoid:

$$\hat{y} = \sigma(f(\boldsymbol{x})) = \frac{1}{1 + e^{-(f(\boldsymbol{x}))}} \tag{3}$$

- The result is the probability of the prediction!



$\sigma(\boldsymbol{x})$

Basics of supervised machine learning

- For multi-class cases, log-linear models produce probabilities for all classes, for example:
  $\hat{\boldsymbol{y}} = [0.4, 0.1, 0.9, 0.5]$ (for $k = 4$)

Basics of supervised machine learning

- For multi-class cases, log-linear models produce probabilities for all classes, for example:
  $\hat{\boldsymbol{y}} = [0.4, 0.1, 0.9, 0.5]$ (for $k = 4$)
- We choose the one with the highest score:

$$\hat{y} = \arg\max_{i} \hat{\boldsymbol{y}}_{[i]} = \hat{\boldsymbol{y}}_{[2]} \tag{4}$$

Basics of supervised machine learning

- For multi-class cases, log-linear models produce probabilities for all classes, for example:
  $\hat{\boldsymbol{y}} = [0.4, 0.1, 0.9, 0.5]$ (for $k = 4$)
- We choose the one with the highest score:

$$\hat{y} = \arg\max_i \hat{\boldsymbol{y}}_{[i]} = \hat{\boldsymbol{y}}_{[2]} \tag{4}$$

- But often it is more convenient to transform scores into a probability distribution, using the softmax function:

$$\hat{\boldsymbol{y}} = softmax(\boldsymbol{x}\boldsymbol{W} + \boldsymbol{b}) \tag{5}$$

$$\hat{\boldsymbol{y}}_{[i]} = \frac{e^{(\boldsymbol{x}\boldsymbol{W}+\boldsymbol{b})_{[i]}}}{\sum_j e^{(\boldsymbol{x}\boldsymbol{W}+\boldsymbol{b})_{[j]}}} \tag{6}$$

Basics of supervised machine learning

- For multi-class cases, log-linear models produce probabilities for all classes, for example:
  $\hat{\boldsymbol{y}} = [0.4, 0.1, 0.9, 0.5]$ (for $k = 4$)
- We choose the one with the highest score:

$$\hat{y} = \arg\max_i \hat{\boldsymbol{y}}_{[i]} = \hat{\boldsymbol{y}}_{[2]} \tag{4}$$

- But often it is more convenient to transform scores into a probability distribution, using the softmax function:

$$\hat{\boldsymbol{y}} = softmax(\boldsymbol{xW} + \boldsymbol{b}) \tag{5}$$

$$\hat{\boldsymbol{y}}_{[i]} = \frac{e^{(\boldsymbol{xW}+\boldsymbol{b})_{[i]}}}{\sum_j e^{(\boldsymbol{xW}+\boldsymbol{b})_{[j]}}} \tag{6}$$

- $\hat{\boldsymbol{y}} = softmax([0.4, 0.1, 0.9, 0.5]) = [0.22, 0.16, 0.37, 0.25]$
  - (all scores sum to 1)

Basics of supervised machine learning

$$f(x; W, b) = x \cdot W + b$$

$$\overset{x}{\begin{bmatrix}0\\1\\0\\1\\1\end{bmatrix}} \cdot \overset{W}{\begin{bmatrix}0&0&1&1&1\\1&0&1&1&1\\1&1&0&1&1\end{bmatrix}} + \overset{b}{\begin{bmatrix}0&0&1\end{bmatrix}} = \overset{\hat{y}}{\begin{bmatrix}2&2&4\end{bmatrix}}$$

softmax

$$\begin{bmatrix}.1&.1&.8\end{bmatrix}$$

(expect this to be used for language modeling: it is secretly classification!)

Basics of supervised machine learning

- The goal of the training is to find the optimal values of parameters in θ.

- The goal of the training is to find the optimal values of parameters in θ.
- Formally, it means to minimize the loss $\mathcal{L}(\theta)$ on training or development dataset.

Basics of supervised machine learning

- The goal of the training is to find the optimal values of parameters in θ.
- Formally, it means to minimize the loss $\mathcal{L}(\theta)$ on training or development dataset.
- Conceptually, loss is a measure of how 'far away' the model predictions $\hat{\boldsymbol{y}}$ are from gold labels $\boldsymbol{y}$.

Basics of supervised machine learning

- The goal of the training is to find the optimal values of parameters in θ.
- Formally, it means to minimize the loss $\mathcal{L}(\theta)$ on training or development dataset.
- Conceptually, loss is a measure of how 'far away' the model predictions $\hat{\boldsymbol{y}}$ are from gold labels $\boldsymbol{y}$.
- It can be any function $\mathcal{L}(\hat{\boldsymbol{y}}, \boldsymbol{y})$ returning a scalar value:
  - for example, $\mathcal{L} = (\boldsymbol{y} - \hat{\boldsymbol{y}})^2$ (square error)

Basics of supervised machine learning

- The goal of the training is to find the optimal values of parameters in θ.
- Formally, it means to minimize the loss $\mathcal{L}(\theta)$ on training or development dataset.
- Conceptually, loss is a measure of how 'far away' the model predictions $\hat{\boldsymbol{y}}$ are from gold labels $\boldsymbol{y}$.
- It can be any function $\mathcal{L}(\hat{\boldsymbol{y}}, \boldsymbol{y})$ returning a scalar value:
  - for example, $\mathcal{L} = (\boldsymbol{y} - \hat{\boldsymbol{y}})^2$ (square error)
- It is averaged over all training instances and gives us estimation of the model 'fitness'.

Basics of supervised machine learning

- The goal of the training is to find the optimal values of parameters in θ.
- Formally, it means to minimize the loss $\mathcal{L}(\theta)$ on training or development dataset.
- Conceptually, loss is a measure of how 'far away' the model predictions $\hat{\boldsymbol{y}}$ are from gold labels $\boldsymbol{y}$.
- It can be any function $\mathcal{L}(\hat{\boldsymbol{y}}, \boldsymbol{y})$ returning a scalar value:
  - for example, $\mathcal{L} = (\boldsymbol{y} - \hat{\boldsymbol{y}})^2$ (square error)
- It is averaged over all training instances and gives us estimation of the model 'fitness'.
- $\hat{\theta}$ is the best set of parameters:

$$\hat{\theta} = \arg\min_{\theta} \mathcal{L}(\theta) \tag{7}$$

Now we can measure model performance. How can we change our parameters θ to improve?

Optimizing with gradient

- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.

Basics of supervised machine learning

Optimizing with gradient

- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.
- Commonly solved using gradient methods:
  1. compute the loss,

Optimizing with gradient

- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.
- Commonly solved using gradient methods:
  1. compute the loss,
  2. compute gradient of θ parameters with respect to the loss,

Optimizing with gradient

- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.
- Commonly solved using gradient methods:
  1. compute the loss,
  2. compute gradient of θ parameters with respect to the loss,
  3. *(gradient here is the collection of partial derivatives, one for each parameter of θ)*

Optimizing with gradient

- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.
- Commonly solved using gradient methods:
  1. compute the loss,
  2. compute gradient of θ parameters with respect to the loss,
  3. *(gradient here is the collection of partial derivatives, one for each parameter of θ)*
  4. move the parameters in the opposite direction (to decrease the loss),

Basics of supervised machine learning

Optimizing with gradient

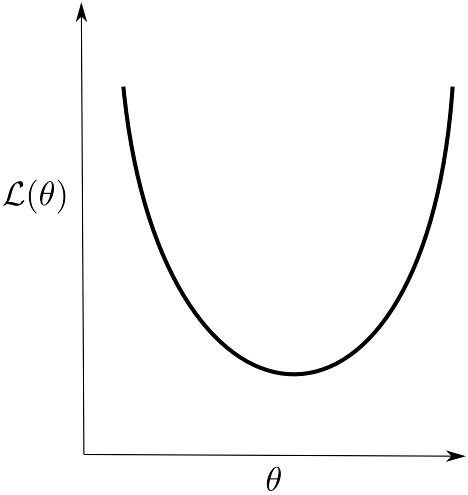
- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.
- Commonly solved using gradient methods:
  1. compute the loss,
  2. compute gradient of θ parameters with respect to the loss,
  3. *(gradient here is the collection of partial derivatives, one for each parameter of θ)*
  4. move the parameters in the opposite direction (to decrease the loss),
  5. repeat until the optimum is found (the derivative is 0) or until the pre-defined number of iterations (epochs) is achieved.

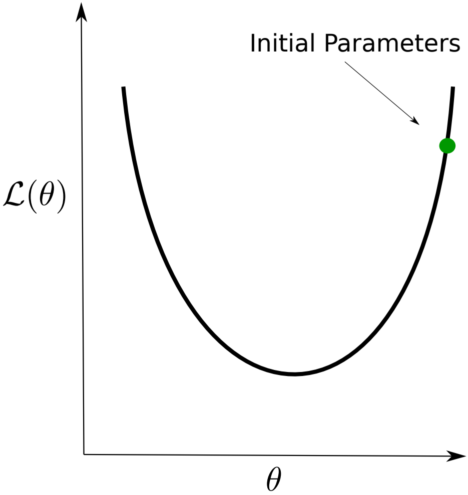
Optimizing with gradient

- $\hat{\theta} = \arg\min_{\theta}(\mathcal{L}(\theta) + \lambda R(\theta))$ is an optimization problem.
- Commonly solved using gradient methods:
  1. compute the loss,
  2. compute gradient of θ parameters with respect to the loss,
  3. *(gradient here is the collection of partial derivatives, one for each parameter of θ)*
  4. move the parameters in the opposite direction (to decrease the loss),
  5. repeat until the optimum is found (the derivative is 0) or until the pre-defined number of iterations (epochs) is achieved.

Convexity

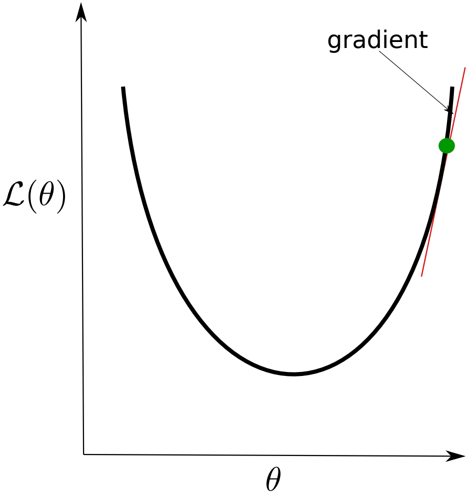
- Convex functions: a single optimum point.
- Non-convex functions: multiple optimum points.


$\mathcal{L}(\theta)$
θ

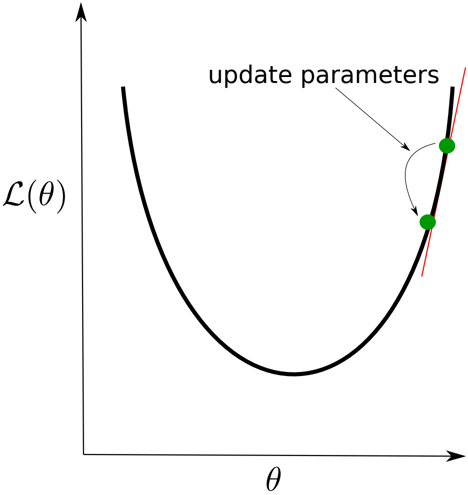


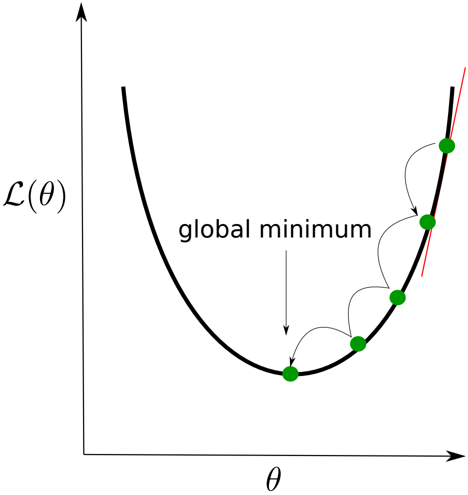
Initial Parameters
$\mathcal{L}(\theta)$
θ

Basics of supervised machine learning

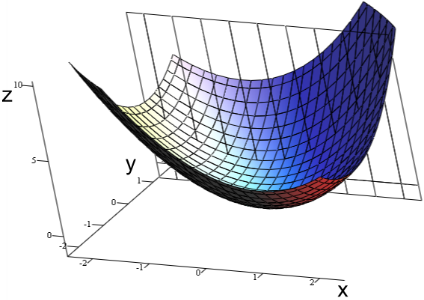


Basics of supervised machine learning

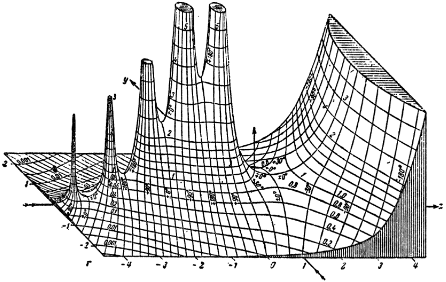



$\mathcal{L}(\theta)$
global minimum
θ

Error surfaces of convex and not-convex functions:

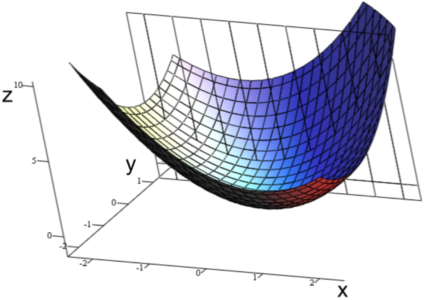


Convex function

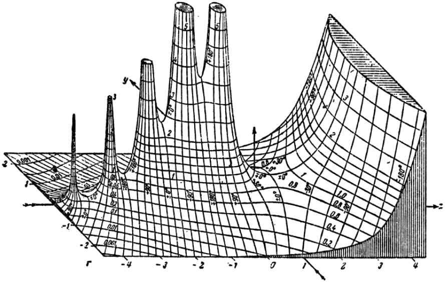


Non-convex function

Error surfaces of convex and not-convex functions:



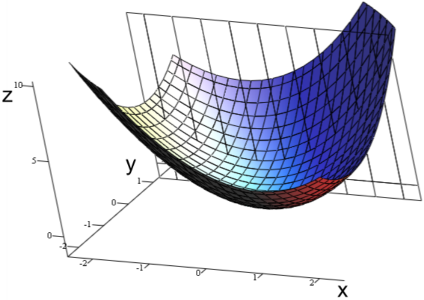
Convex function



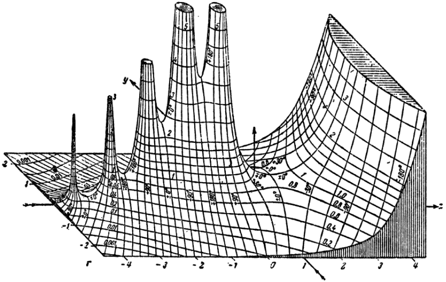
Non-convex function

- Convex functions can be easily minimized with gradient methods, reaching the global optimum.
- With non-convex functions, optimization can end up in a local optimum.

Error surfaces of convex and not-convex functions:



Convex function



Non-convex function

- Convex functions can be easily minimized with gradient methods, reaching the global optimum.
- With non-convex functions, optimization can end up in a local optimum.
- Linear and log-linear models as a rule have convex error functions.
- ...unlike non-linear models (e.g., used in 'deep learning').

Contents

Advantages and limitations of linear models

- Linear models are efficient and effective.

Advantages and limitations of linear models

- Linear models are efficient and effective.
- They are interpretable to a degree: you can find the most important features by looking at the weights

Advantages and limitations of linear models

- Linear models are efficient and effective.
- They are interpretable to a degree: you can find the most important features by looking at the weights
- Can be used on their own (often enough in practice)...
- ...or as building blocks for non-linear neural classifiers.

Advantages and limitations of linear models

- Linear models are efficient and effective.
- They are interpretable to a degree: you can find the most important features by looking at the weights
- Can be used on their own (often enough in practice)...
- ...or as building blocks for non-linear neural classifiers.

Unfortunately, linear models can represent only linear relations in the data

Advantages and limitations of linear models

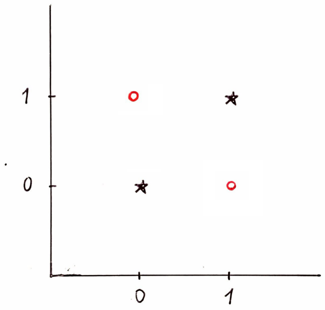
- Are there non-linear functions that linear models can't deal with?

Advantages and limitations of linear models

- Are there non-linear functions that linear models can't deal with?
- Yes, there are.

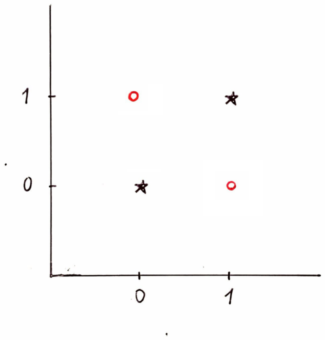
Advantages and limitations of linear models

- Are there non-linear functions that linear models can't deal with?
- Yes, there are.
- One example is the XOR ('excluding OR') function:



Advantages and limitations of linear models

- Are there non-linear functions that linear models can't deal with?
- Yes, there are.
- One example is the XOR ('excluding OR') function:



It is clearly not linearly separable.

Advantages and limitations of linear models

Possible solutions

- We can transform the input so that it becomes linearly separable.

Advantages and limitations of linear models

Possible solutions

- We can transform the input so that it becomes linearly separable.
- Linear transformations will not be able to do this.

Advantages and limitations of linear models

Possible solutions

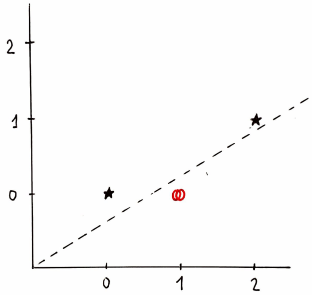
- We can transform the input so that it becomes linearly separable.
- Linear transformations will not be able to do this.
- We need non-linear transformations.

Advantages and limitations of linear models

Possible solutions

- We can transform the input so that it becomes linearly separable.
- Linear transformations will not be able to do this.
- We need non-linear transformations.

For example, $\phi(x_1, x_2) = [x_1 + x_2, x_1 \times x_2]$ maps the instances to another representation and makes the XOR problem linearly separable:



Advantages and limitations of linear models

Training mapping functions

- But how to find the transformation function ϕ suitable for the task at hand?

Advantages and limitations of linear models

Training mapping functions

- But how to find the transformation function ϕ suitable for the task at hand?
- Idea: leave it for the algorithm to train a suitable representation mapping function!

Advantages and limitations of linear models

Training mapping functions

- But how to find the transformation function ϕ suitable for the task at hand?
- Idea: leave it for the algorithm to train a suitable representation mapping function!

$$\phi(\boldsymbol{x}) = g(\boldsymbol{x}\boldsymbol{W}' + \boldsymbol{b}') \tag{8}$$

$$\hat{\boldsymbol{y}} = \phi(\boldsymbol{x})\boldsymbol{W} + \boldsymbol{b} \tag{9}$$

- ...where g is a non-linear activation function, and $\boldsymbol{W}', \boldsymbol{b}'$ are its trainable parameters.

Training mapping functions

- But how to find the transformation function ϕ suitable for the task at hand?
- Idea: leave it for the algorithm to train a suitable representation mapping function!

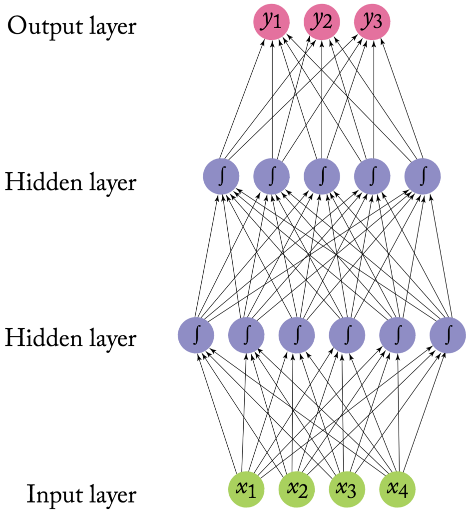
$$\phi(\boldsymbol{x}) = g(\boldsymbol{x}\boldsymbol{W}' + \boldsymbol{b}') \tag{8}$$

$$\hat{\boldsymbol{y}} = \phi(\boldsymbol{x})\boldsymbol{W} + \boldsymbol{b} \tag{9}$$

- ...where g is a non-linear activation function, and $\boldsymbol{W}', \boldsymbol{b}'$ are its trainable parameters.
- The equation above defines a simple multi-layer perceptron (MLP): a neural model.

Contents

Going deeply non-linear: multi-layered perceptrons



A simple feed-forward neural network (perceptron) with 2 hidden layers.

Going deeply non-linear: multi-layered perceptrons

The nature of perceptrons

- Input data goes through successive transformations at each layer.

Going deeply non-linear: multi-layered perceptrons

The nature of perceptrons

- Input data goes through successive transformations at each layer.
- The transformations are linear, but followed with a non-linear activation at each hidden layer.

Going deeply non-linear: multi-layered perceptrons

The nature of perceptrons

- Input data goes through successive transformations at each layer.
- The transformations are linear, but followed with a non-linear activation at each hidden layer.
- At the last layer, the prediction $\hat{y}$ is produced.

Going deeply non-linear: multi-layered perceptrons

The nature of perceptrons

- Input data goes through successive transformations at each layer.
- The transformations are linear, but followed with a non-linear activation at each hidden layer.
- At the last layer, the prediction $\hat{y}$ is produced.
- Representation functions and the linear classifiers are trained simultaneously.

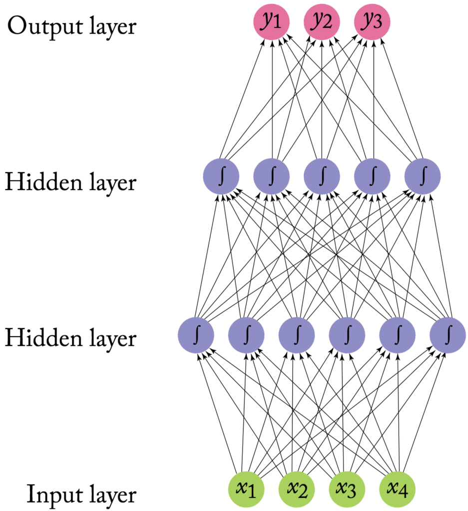
Going deeply non-linear: multi-layered perceptrons

The nature of perceptrons

- Input data goes through successive transformations at each layer.
- The transformations are linear, but followed with a non-linear activation at each hidden layer.
- At the last layer, the prediction $\hat{y}$ is produced.
- Representation functions and the linear classifiers are trained simultaneously.

Important: **neural networks with hidden layers can theoretically approximate any function** [Leshno et al., 1993].

Going deeply non-linear: multi-layered perceptrons

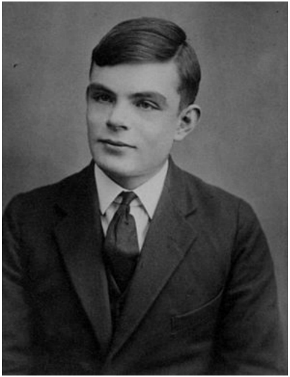


A simple feed-forward neural network (perceptron) with 2 hidden layers.

'Machines of this character can behave in a very complicated manner when the number of units is large.'

Alan Turing, 'Intelligent Machinery'

[Turing, 1948]



Brain metaphor

- Why ‘artificial neural networks’?

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,
  - each neuron accepts electrical signals (inputs) from other neurons,

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,
  - each neuron accepts electrical signals (inputs) from other neurons,
  - processes (weighs) them differently, depending on their source,

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,
  - each neuron accepts electrical signals (inputs) from other neurons,
  - processes (weighs) them differently, depending on their source,
  - and then passes own electrical signals (outputs) to other neurons;

Going deeply non-linear: multi-layered perceptrons

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,
  - each neuron accepts electrical signals (inputs) from other neurons,
  - processes (weighs) them differently, depending on their source,
  - and then passes own electrical signals (outputs) to other neurons;
  - depending on input signals, a neuron can be more or less activated,

Going deeply non-linear: multi-layered perceptrons

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,
  - each neuron accepts electrical signals (inputs) from other neurons,
  - processes (weighs) them differently, depending on their source,
  - and then passes own electrical signals (outputs) to other neurons;
  - depending on input signals, a neuron can be more or less activated,
  - ... or completely relaxed ('silent');

Brain metaphor

- Why 'artificial neural networks'?
- ...because it seems neurons in human brain act similarly:
  - Connected into a large network,
  - each neuron accepts electrical signals (inputs) from other neurons,
  - processes (weighs) them differently, depending on their source,
  - and then passes own electrical signals (outputs) to other neurons;
  - depending on input signals, a neuron can be more or less activated,
  - ... or completely relaxed ('silent');
  - the whole system is distributed across many neurons.

Going deeply non-linear: multi-layered perceptrons

...But brain metaphor is not optimal

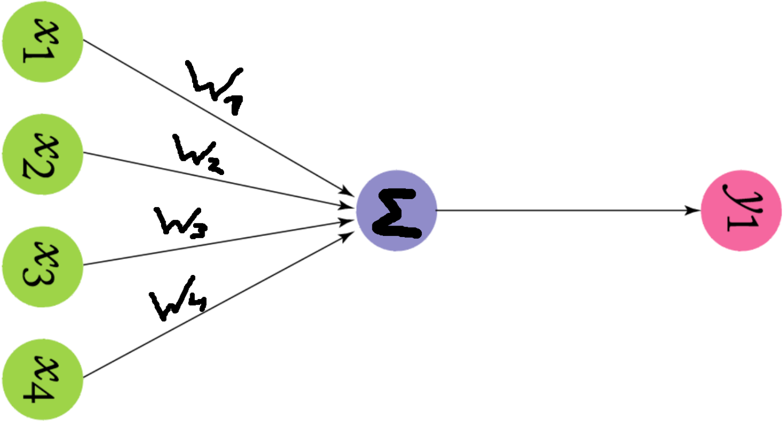
- Although the first neural networks were based loosely on knowledge of neural activation at the time, we have long abandoned any real connection to neuroscience.

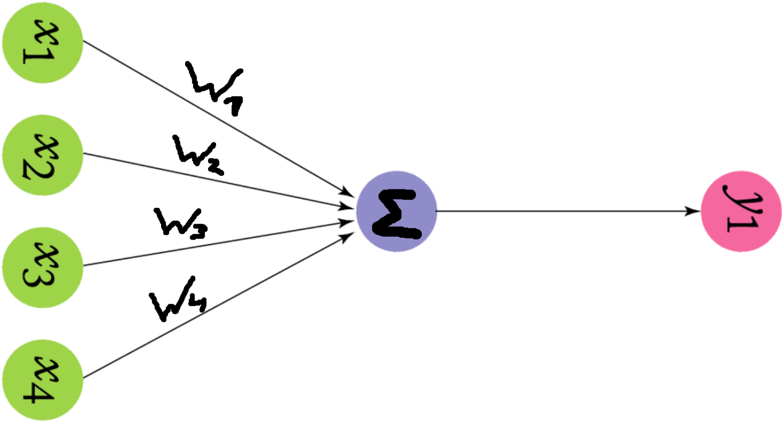
...But brain metaphor is not optimal

- Although the first neural networks were based loosely on knowledge of neural activation at the time, we have long abandoned any real connection to neuroscience.
- Thus, it's less cool but more convenient to think about artificial neural networks in terms of linear algebra concepts:

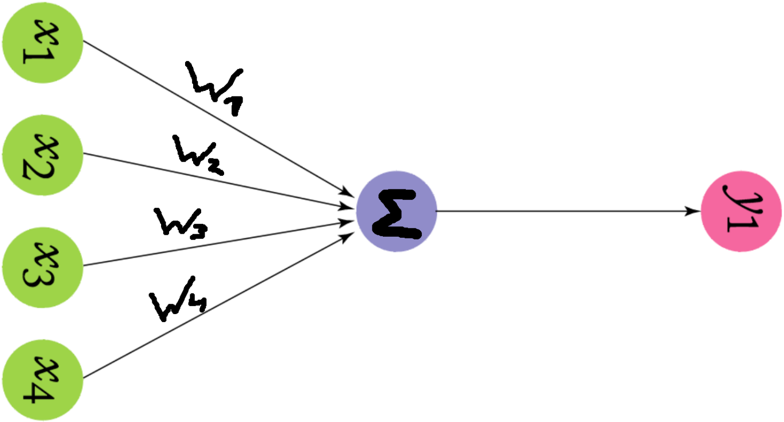
…But brain metaphor is not optimal

- Although the first neural networks were based loosely on knowledge of neural activation at the time, we have long abandoned any real connection to neuroscience.
- Thus, it's less cool but more convenient to think about artificial neural networks in terms of linear algebra concepts:
  - vectors,
  - matrices,
  - sequential algebraic operations on them.

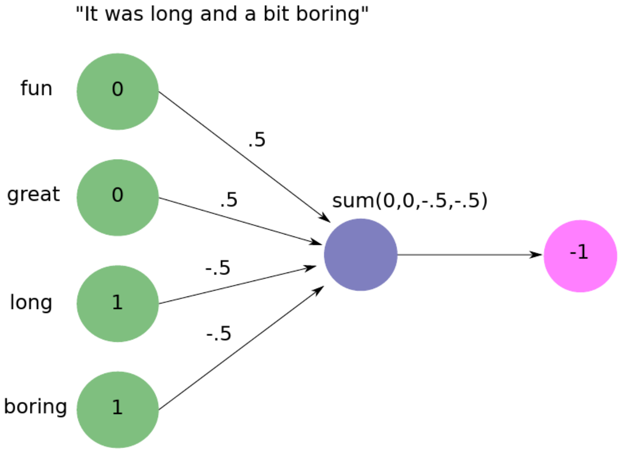

x_1
x_2
x_3
x_4
W_1
W_2
W_3
W_4
Σ
y_1



- In fact this is already a simple neural network...
- with one neuron Σ as a computational unit.



- In fact this is already a simple neural network...
- with one neuron Σ as a computational unit.
- Σ takes 4 input values and returns their weighted sum as output value.



Sentiment analysis with only one neuron and binary bag-of-words.

Stack of linear classifiers

We can stack classifiers...

Stack of linear classifiers

We can stack classifiers...

- by feeding the prediction of one classifier to another one:

Stack of linear classifiers

We can stack classifiers...

- by feeding the prediction of one classifier to another one:
- $\hat{\boldsymbol{y}} = (\boldsymbol{x}\boldsymbol{W}^{\mathbf{0}})\boldsymbol{W}^{\mathbf{1}}$

Stack of linear classifiers

We can stack classifiers...

- by feeding the prediction of one classifier to another one:
- $\hat{\boldsymbol{y}} = (\boldsymbol{x}\boldsymbol{W}^{0})\boldsymbol{W}^{1}$
- $\hat{\boldsymbol{y}} = ((\boldsymbol{x}\boldsymbol{W}^{0})\boldsymbol{W}^{1})\boldsymbol{W}^{2}$

Going deeply non-linear: multi-layered perceptrons

Stack of linear classifiers

We can stack classifiers...

- by feeding the prediction of one classifier to another one:
- $\hat{\boldsymbol{y}} = (\boldsymbol{x}\boldsymbol{W}^{\mathbf{0}})\boldsymbol{W}^{\mathbf{1}}$
- $\hat{\boldsymbol{y}} = ((\boldsymbol{x}\boldsymbol{W}^{\mathbf{0}})\boldsymbol{W}^{\mathbf{1}})\boldsymbol{W}^{\mathbf{2}}$
- ...etc. Can be arbitrarily deep

Going deeply non-linear: multi-layered perceptrons

Stack of linear classifiers

We can stack classifiers...

- by feeding the prediction of one classifier to another one:
- $\hat{\boldsymbol{y}} = (\boldsymbol{x}\boldsymbol{W}^{\mathbf{0}})\boldsymbol{W}^{\mathbf{1}}$
- $\hat{\boldsymbol{y}} = ((\boldsymbol{x}\boldsymbol{W}^{\mathbf{0}})\boldsymbol{W}^{\mathbf{1}})\boldsymbol{W}^{\mathbf{2}}$
- ...etc. Can be arbitrarily deep
- each subsequent row of neurons (layer) is a vector;

Going deeply non-linear: multi-layered perceptrons

Stack of linear classifiers

We can stack classifiers...

- by feeding the prediction of one classifier to another one:
- $\hat{\boldsymbol{y}} = (\boldsymbol{x}\boldsymbol{W^0})\boldsymbol{W^1}$
- $\hat{\boldsymbol{y}} = ((\boldsymbol{x}\boldsymbol{W^0})\boldsymbol{W^1})\boldsymbol{W^2}$
- ...etc. Can be arbitrarily deep
- each subsequent row of neurons (layer) is a vector;
- it is multiplied by the next weight matrix (shapes must match).

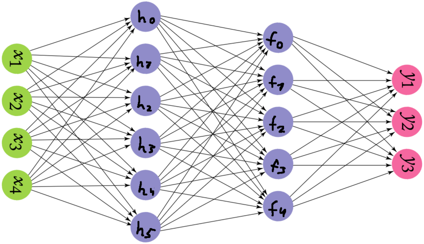
Stack of linear classifiers

We can stack classifiers...

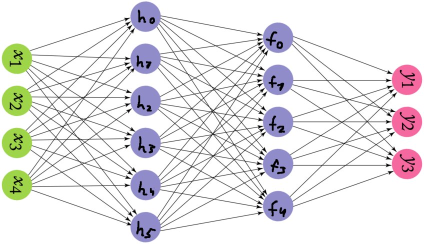
- by feeding the prediction of one classifier to another one:
- $\hat{\boldsymbol{y}} = (\boldsymbol{x}\boldsymbol{W}^{\boldsymbol{0}})\boldsymbol{W}^{\boldsymbol{1}}$
- $\hat{\boldsymbol{y}} = ((\boldsymbol{x}\boldsymbol{W}^{\boldsymbol{0}})\boldsymbol{W}^{\boldsymbol{1}})\boldsymbol{W}^{\boldsymbol{2}}$
- ...etc. Can be arbitrarily deep
- each subsequent row of neurons (layer) is a vector;
- it is multiplied by the next weight matrix (shapes must match).

Can even use both multiple neurons and multiple layers.

Going deeply non-linear: multi-layered perceptrons



Going deeply non-linear: multi-layered perceptrons



Looks much like a 'deep neural network'

Stacked linear classifier with multiple computational units at each layer:

$$h = \boldsymbol{x}\boldsymbol{W^0} \tag{10}$$

$$f = \boldsymbol{h}\boldsymbol{W^1} \tag{11}$$

$$\hat{\boldsymbol{y}} = \boldsymbol{f}\boldsymbol{W^2} \tag{12}$$

- But any stack of linear classifiers is still a linear classifier :-(

Going deeply non-linear: multi-layered perceptrons

- But any stack of linear classifiers is still a linear classifier :-(
- Still can't handle XOR and other non-linear problems.

Contents

Non-linearities

- Differentiable non-linear transformations (activations) are the core reason of deep learning's substantial results, including in NLP.

Non-linearities

- Differentiable non-linear transformations (activations) are the core reason of deep learning's substantial results, including in NLP.
- They help induce good input data representations.

Non-linearities

- Differentiable non-linear transformations (activations) are the core reason of deep learning's substantial results, including in NLP.
- They help induce good input data representations.
- These representations are processed with a linear classifier in the end.

Non-linearities

- Differentiable non-linear transformations (activations) are the core reason of deep learning's substantial results, including in NLP.
- They help induce good input data representations.
- These representations are processed with a linear classifier in the end.

Popular activation functions

- Sigmoid (logistic function):
  $\sigma(x) = \frac{1}{1+e^{-x}} \to [0, 1]$

Non-linearities

- Differentiable non-linear transformations (activations) are the core reason of deep learning's substantial results, including in NLP.
- They help induce good input data representations.
- These representations are processed with a linear classifier in the end.

Popular activation functions

- Sigmoid (logistic function):
  $\sigma(\boldsymbol{x}) = \frac{1}{1+e^{-\boldsymbol{x}}} \rightarrow [0,1]$
- REctified Linear Unit (**ReLU**) [Glorot et al., 2011]:

$$relu(\boldsymbol{x}) = \begin{cases} \boldsymbol{x}, & \text{if } \boldsymbol{x} \geq 0 \\ 0, & \text{otherwise} \end{cases} \rightarrow [0, \infty]$$

Non-linearities

- Differentiable non-linear transformations (activations) are the core reason of deep learning's substantial results, including in NLP.
- They help induce good input data representations.
- These representations are processed with a linear classifier in the end.

Popular activation functions

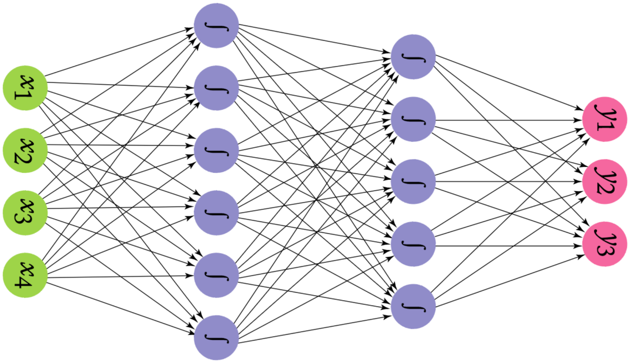
- Sigmoid (logistic function):
  $\sigma(\boldsymbol{x}) = \frac{1}{1+e^{-\boldsymbol{x}}} \rightarrow [0, 1]$
- REctified Linear Unit (**ReLU**) [Glorot et al., 2011]:

$$relu(\boldsymbol{x}) = \begin{cases} \boldsymbol{x}, & \text{if } \boldsymbol{x} \geq 0 \\ 0, & \text{otherwise} \end{cases} \rightarrow [0, \infty]$$

- Hyperbolic tangent:

$$\tanh(\boldsymbol{x}) = \frac{e^{2\boldsymbol{x}} - 1}{e^{2\boldsymbol{x}} + 1} \rightarrow [-1, 1]$$

Non-linearities



The only difference between this deep neural network and a stack of linear classifiers: non-linearities ($\int$) between linear transformations.

Non-linearities

What exactly is ‘deep’ in deep neural networks?

- Input data goes through successive transformations ϕ at each layer.

Non-linearities

What exactly is 'deep' in deep neural networks?

- Input data goes through successive transformations ϕ at each layer.
- The transformations themselves are still linear...

Non-linearities

What exactly is ‘deep’ in deep neural networks?

- Input data goes through successive transformations ϕ at each layer.
- The transformations themselves are still linear...
- ...but followed with some non-linear operation g at each layer.

Non-linearities

What exactly is 'deep' in deep neural networks?

- Input data goes through successive transformations ϕ at each layer.
- The transformations themselves are still linear...
- ...but followed with some non-linear operation g at each layer.
- At the last layer, the prediction $\hat{\boldsymbol{y}}$ is produced.

Non-linearities

What exactly is 'deep' in deep neural networks?

- Input data goes through successive transformations ϕ at each layer.
- The transformations themselves are still linear...
- ...but followed with some non-linear operation g at each layer.
- At the last layer, the prediction $\hat{\boldsymbol{y}}$ is produced.
- The whole system is trained end-to-end.

$$\phi(\boldsymbol{x}) = g(\boldsymbol{x}\boldsymbol{W}') \tag{13}$$

$$\hat{\boldsymbol{y}} = \phi(\boldsymbol{x})\boldsymbol{W} \tag{14}$$

Non-linearities

Feed-forward neural networks

- ‘Feed-forward neural network’ is a more precise name for a multi-layer perceptron with non-linearities.

Feed-forward neural networks

- ‘Feed-forward neural network’ is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.

Non-linearities

Feed-forward neural networks

- 'Feed-forward neural network' is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.
- Outputs from neurons in each layer are passed to neurons in the next layer, multiplied by the correspondent weights.

Non-linearities

Feed-forward neural networks

- 'Feed-forward neural network' is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.
- Outputs from neurons in each layer are passed to neurons in the next layer, multiplied by the correspondent weights.
- A non-linear function is applied element-wise after each layer.

Non-linearities

Feed-forward neural networks

- 'Feed-forward neural network' is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.
- Outputs from neurons in each layer are passed to neurons in the next layer, multiplied by the correspondent weights.
- A non-linear function is applied element-wise after each layer.
- No outputs are passed back to previous layers.

Non-linearities

Feed-forward neural networks

- 'Feed-forward neural network' is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.
- Outputs from neurons in each layer are passed to neurons in the next layer, multiplied by the correspondent weights.
- A non-linear function is applied element-wise after each layer.
- No outputs are passed back to previous layers.

1. The first layer contains input units,

Non-linearities

Feed-forward neural networks

- 'Feed-forward neural network' is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.
- Outputs from neurons in each layer are passed to neurons in the next layer, multiplied by the correspondent weights.
- A non-linear function is applied element-wise after each layer.
- No outputs are passed back to previous layers.

1. The first layer contains input units,
2. the last layer contains output units,

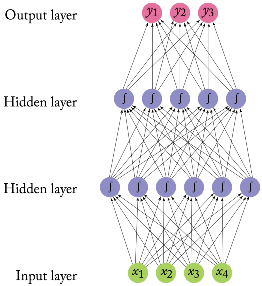
Non-linearities

Feed-forward neural networks

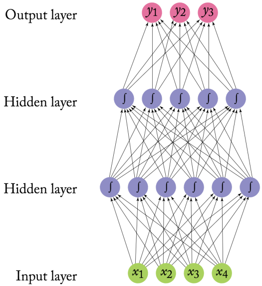
- 'Feed-forward neural network' is a more precise name for a multi-layer perceptron with non-linearities.
- A network in which the neurons/units are connected without cycles.
- Outputs from neurons in each layer are passed to neurons in the next layer, multiplied by the correspondent weights.
- A non-linear function is applied element-wise after each layer.
- No outputs are passed back to previous layers.

1. The first layer contains input units,
2. the last layer contains output units,
3. all layers in between (hidden layers) contain hidden units, which form hidden representations of the input data.

Non-linearities

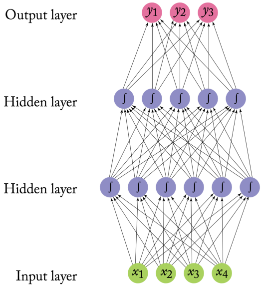


Non-linearities



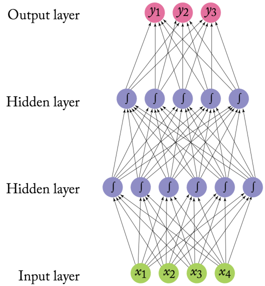
- Feed-forward network with 2 hidden layers;

Non-linearities



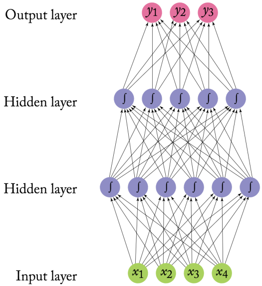
- Feed-forward network with 2 hidden layers;
- Before the transition to the l^{n+1}, the output vector of l^n goes through a non-linear function (instead of simple weighted sum).

Non-linearities



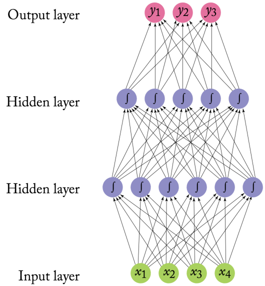
- Feed-forward network with 2 hidden layers;
- Before the transition to the l^{n+1}, the output vector of l^n goes through a non-linear function (instead of simple weighted sum).
- Fully-connected: transitions between layers are linear transformations:

Non-linearities



- Feed-forward network with 2 hidden layers;
- Before the transition to the l^{n+1}, the output vector of l^n goes through a non-linear function (instead of simple weighted sum).
- Fully-connected: transitions between layers are linear transformations:
  - each neuron in the layer l^n is connected to each neuron in the layer l^{n+1}

Non-linearities



- Feed-forward network with 2 hidden layers;
- Before the transition to the l^{n+1}, the output vector of l^n goes through a non-linear function (instead of simple weighted sum).
- Fully-connected: transitions between layers are linear transformations:
  - each neuron in the layer l^n is connected to each neuron in the layer l^{n+1}
  - ... mathematically, a vector-matrix multiplication $\boldsymbol{x^n W^n = x^{n+1}}$

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.
- Unlike in linear classifiers, the error/loss function is usually not convex...

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.
- Unlike in linear classifiers, the error/loss function is usually not convex...
- ...but gradient-based optimizers still work well in practice.

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.
- Unlike in linear classifiers, the error/loss function is usually not convex...
- ...but gradient-based optimizers still work well in practice.
- NB: one can balance between the number of layers and their sizes (number of neurons).

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.
- Unlike in linear classifiers, the error/loss function is usually not convex...
- ...but gradient-based optimizers still work well in practice.
- NB: one can balance between the number of layers and their sizes (number of neurons).
- Different layers learn different hidden representations
  - eliminates the need to manually design feature combinations:

Deep learning summary

Network parameters

- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.
- Unlike in linear classifiers, the error/loss function is usually not convex...
- ...but gradient-based optimizers still work well in practice.
- NB: one can balance between the number of layers and their sizes (number of neurons).
- Different layers learn different hidden representations
  - eliminates the need to manually design feature combinations:
  - the network is able to learn that '*not*' and '*good*' co-occurrence in a text is a powerful feature in itself...

Deep learning summary

Network parameters

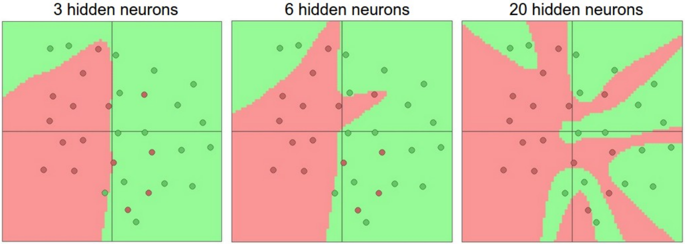
- Like in linear classifiers, weights and biases are parameters of the network;
- a.k.a. θ;
- the aim of the training is to learn optimal values for θ.
- Unlike in linear classifiers, the error/loss function is usually not convex...
- ...but gradient-based optimizers still work well in practice.
- NB: one can balance between the number of layers and their sizes (number of neurons).
- Different layers learn different hidden representations
  - eliminates the need to manually design feature combinations:
  - the network is able to learn that '*not*' and '*good*' co-occurrence in a text is a powerful feature in itself...
  - ...and reflect this in its hidden representations.

Model size

The deeper and wider the model is, the more capacity (parameters) it has, the more complex functions it can approximate.

Model size

The deeper and wider the model is, the more capacity (parameters) it has, the more complex functions it can approximate.

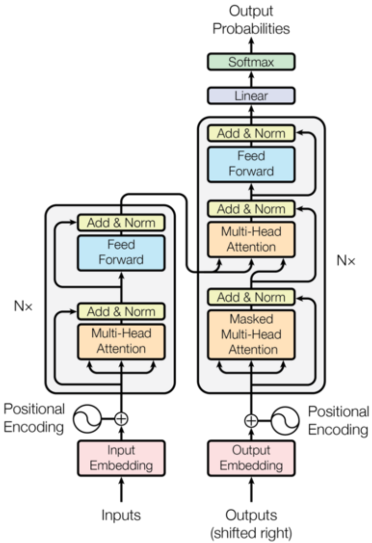


Contents

The One

Almost all modern large language models are invariably based in a variation of feed-forward neural network: Transformer architecture.

- BER**T**, RoBER**T**a, BAR**T**
- GP**T** variants
- Text-to-Text Transfer **T**ransformer (T5)
- PaLM, BARD, LaMDA, LLaMA bla bla bla
- Used for text-to-image in DALL-E, Stable Diffusion etc..



Attention is all you need

Attention: the way for the model to learn relative importance of tokens/words in different positions of the input.

Attention is all you need

Attention: the way for the model to learn relative importance of tokens/words in different positions of the input.

Transformer revolution

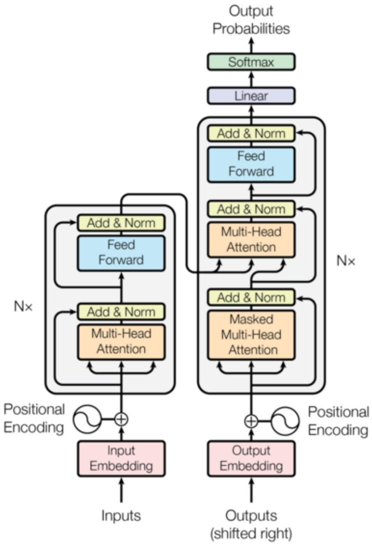
"The dominant sequence transduction models are based on complex recurrent or convolutional neural networks in an encoder and decoder configuration. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a novel, simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely."

– [Vaswani et al., 2017]

– Per 28.02.2023: cited 66,7k times

This simplification made Transformer a very parallelizable architecture. It makes very good use of modern computational hardware (GPUs and TPUs).

The Transformer, at a glance



The Transformer, at a glance

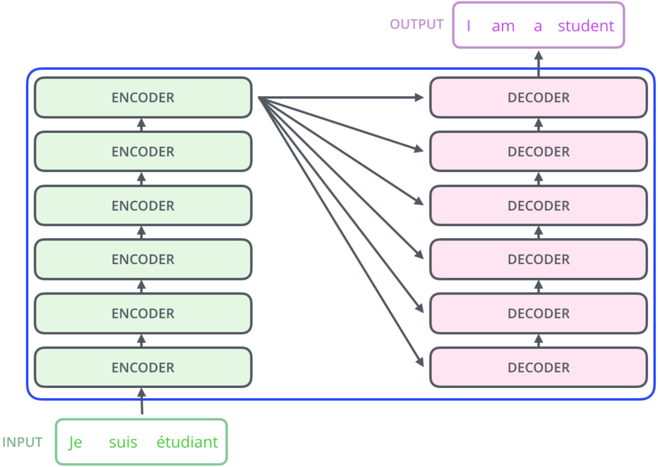


Figure from Jay Alammar's, *The Illustrated Transformer*[1]

[1] https://jalammar.github.io/illustrated-transformer/

Applications of Attention: high level explanation

Three different applications of attention in the Transformer:

1. In the Encoder-Decoder way: we use the 'hidden state' from the encoders and do some operation with the state in the decoder
2. Encoder Self-Attention: each position in the encoder can attend to previous positions
3. Decoder Self-Attention: each position can attend to all previous positions up to that point (autoregressive via masking)

Those are also the three types of modern large language models (LLMs).

So how good is it?

Transformer turned out to be extremely good in machine translation:

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

‘A small fraction of the training cost’

[Vaswani et al., 2017]

So how good is it?

Transformer turned out to be extremely good in machine translation:

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

'A small fraction of the training cost'

[Vaswani et al., 2017]

...not long after Transformer became the dominant architecture for language models, NLP models in general, and 'artificial intelligence' overall.

References I

Glorot, X., Bordes, A., and Bengio, Y. (2011).
Deep sparse rectifier neural networks.
In Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, pages 315–323.

Leshno, M., Lin, V. Y., Pinkus, A., and Schocken, S. (1993).
Multilayer feedforward networks with a nonpolynomial activation function can approximate any function.
Neural Networks, 6(6):861–867.

Turing, A. (1948).
Intelligent machinery.
Technical report, National Physical Laboratory.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017).
Attention is all you need.
In Advances in Neural Information Processing Systems, pages 5998–6008.