(https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning#cs-229---machine-learning)CS 229 - Machine Learning (teaching/cs-229)

English

Supervised Learning | Unsupervised Learning | **Deep Learning** | Tips and tricks

(https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning#cheatsheet)Deep Learning cheatsheet

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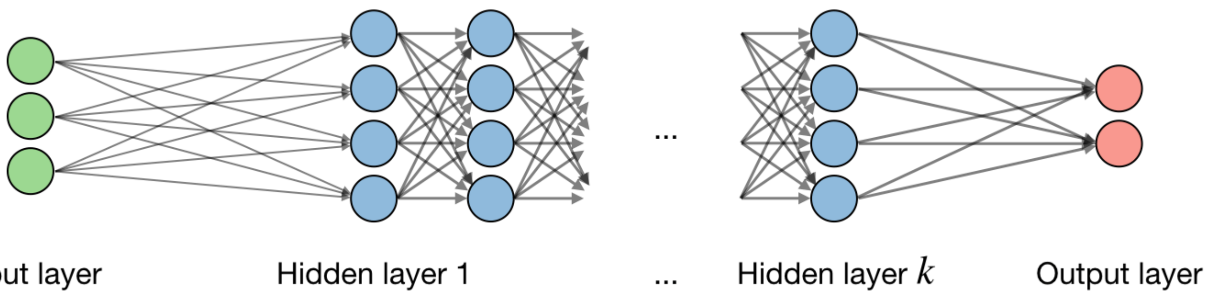
(https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning#nn) Neural Networks

Neural networks are a class of models that are built with layers. Commonly used types of neural networks include convolutional and recurrent neural networks.

❐ **Architecture** — The vocabulary around neural networks architectures is described in the figure below:

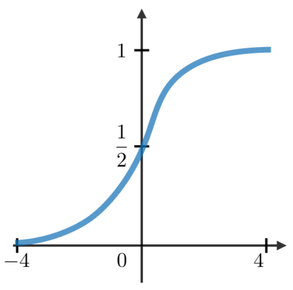
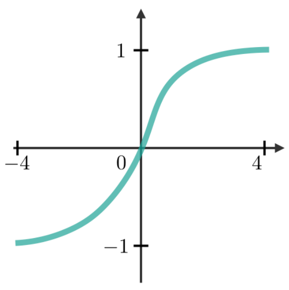
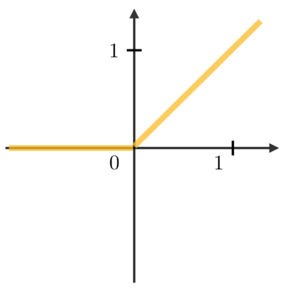
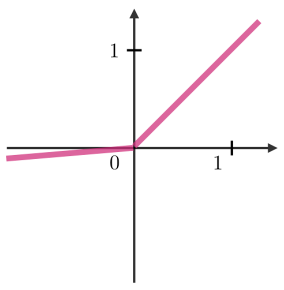


By noting i the i^{th} layer of the network and j the j^{th} hidden unit of the layer, we have:

$$\boxed{z_j^{[i]} = {w_j^{[i]}}^T x + b_j^{[i]}}$$

where we note w, b, z the weight, bias and output respectively.

❒ **Activation function** — Activation functions are used at the end of a hidden unit to introduce non-linear complexities to the model. Here are the most common ones:

Sigmoid	Tanh	ReLU	Leaky ReLU
$g(z)=\dfrac{1}{1+e^{-z}}$	$g(z)=\dfrac{e^z-e^{-z}}{e^z+e^{-z}}$	$g(z)=\max(0,z)$	$g(z)=$ $\max(\epsilon z,z)$ with $\epsilon\ll1$
			

❒ **Cross-entropy loss** — In the context of neural networks, the cross-entropy loss $L(z,y)$ is commonly used and is defined as follows:

$$\boxed{L(z,y)=-\Big[y\log(z)+(1-y)\log(1-z)\Big]}$$

❒ **Learning rate** — The learning rate, often noted α or sometimes η, indicates at which pace the weights get updated. This can be fixed or adaptively changed. The current most popular method is called Adam, which is a method that adapts the learning rate.

❒ **Backpropagation** — Backpropagation is a method to update the weights in the neural network by taking into account the actual output and the desired output. The derivative with respect to weight w is computed using chain rule and is of the following form:

$$\boxed{\frac{\partial L(z,y)}{\partial w}=\frac{\partial L(z,y)}{\partial a}\times\frac{\partial a}{\partial z}\times\frac{\partial z}{\partial w}}$$

As a result, the weight is updated as follows:

$$\boxed{w\longleftarrow w-\alpha\frac{\partial L(z,y)}{\partial w}}$$

❒ **Updating weights** — In a neural network, weights are updated as follows:

- Step 1: Take a batch of training data.
- Step 2: Perform forward propagation to obtain the corresponding loss.
- Step 3: Backpropagate the loss to get the gradients.
- Step 4: Use the gradients to update the weights of the network.

❒ **Dropout** — Dropout is a technique meant to prevent overfitting the training data by dropping out units in a neural network. In practice, neurons are either dropped with probability p or kept with probability $1-p$.

https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-eep-learning#cnn) Convolutional Neural Networks

❒ **Convolutional layer requirement** — By noting W the input volume size, F the size of the convolutional layer neurons, P the amount of zero padding, then the number of neurons N that fit in a given volume is such that:

$$\boxed{N=\frac{W-F+2P}{S}+1}$$

❒ **Batch normalization** — It is a step of hyperparameter γ, β that normalizes the batch $\{x_i\}$. By noting μ_B, σ_B^2 the mean and variance of that we want to correct to the batch, it is done as follows:

$$\boxed{x_i\longleftarrow\gamma\frac{x_i-\mu_B}{\sqrt{\sigma_B^2+\epsilon}}+\beta}$$

It is usually done after a fully connected/convolutional layer and before a non-linearity layer and aims at allowing higher learning rates and reducing the strong dependence on initialization.

(https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning#rnn) Recurrent Neural Networks

❐ **Types of gates** — Here are the different types of gates that we encounter in a typical recurrent neural network:

Input gate	Forget gate	Gate	Output gate
Write to cell or not?	Erase a cell or not?	How much to write to cell?	How much to reveal cell?

❐ **LSTM** — A long short-term memory (LSTM) network is a type of RNN model that avoids the vanishing gradient problem by adding 'forget' gates.

For a more detailed overview of the concepts above, check out the **Deep Learning cheatsheets (teaching/cs-230)**!

(https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning#reinforcement) Reinforcement Learning and Control

The goal of reinforcement learning is for an agent to learn how to evolve in an environment.

Definitions

❐ **Markov decision processes** — A Markov decision process (MDP) is a 5-tuple $(\mathcal{S},\mathcal{A},\{P_{sa}\},\gamma,R)$ where:

- $\mathcal{S}$ is the set of states
- $\mathcal{A}$ is the set of actions
- $\{P_{sa}\}$ are the state transition probabilities for $s\in\mathcal{S}$ and $a\in\mathcal{A}$
- $\gamma\in[0,1[$ is the discount factor
- $R:\mathcal{S}\times\mathcal{A}\longrightarrow\mathbb{R}$ or $R:\mathcal{S}\longrightarrow\mathbb{R}$ is the reward function that the algorithm wants to maximize

❐ **Policy** — A policy π is a function $\pi:\mathcal{S}\longrightarrow\mathcal{A}$ that maps states to actions.

Remark: we say that we execute a given policy π if given a state s we take the action $a=\pi(s)$.

❒ **Value function** — For a given policy π and a given state s, we define the value function V^π as follows:

$$\boxed{V^\pi(s)=E\Big[R(s_0)+\gamma R(s_1)+\gamma^2R(s_2)+...|s_0=s,\pi\Big]}$$

❒ **Bellman equation** — The optimal Bellman equations characterizes the value function V^{π^*} of the optimal policy π^*:

$$\boxed{V^{\pi^*}(s)=R(s)+\max_{a\in\mathcal{A}}\gamma\sum_{s'\in S}P_{sa}(s')V^{\pi^*}(s')}$$

Remark: we note that the optimal policy π^* for a given state s is such that:

$$\boxed{\pi^*(s)=\underset{a\in\mathcal{A}}{\textrm{argmax}}\sum_{s'\in\mathcal{S}}P_{sa}(s')V^*(s')}$$

❒ **Value iteration algorithm** — The value iteration algorithm is in two steps:

1) We initialize the value:

$$\boxed{V_0(s)=0}$$

2) We iterate the value based on the values before:

$$\boxed{V_{i+1}(s)=R(s)+\max_{a\in\mathcal{A}}\left[\sum_{s'\in\mathcal{S}}\gamma P_{sa}(s')V_i(s')\right]}$$

❒ **Maximum likelihood estimate** — The maximum likelihood estimates for the state transition probabilities are as follows:

$$\boxed{P_{sa}(s')=\frac{\#\textrm{times took action }a\textrm{ in state }s\textrm{ and got to }s'}{\#\textrm{times took action }a\textrm{ in state }s}}$$

❒ **Q-learning** — Q-learning is a model-free estimation of Q, which is done as follows:

$$\boxed{Q(s,a)\leftarrow Q(s,a)+\alpha\Big[R(s,a,s')+\gamma\max_{a'}Q(s',a')-Q(s,a)\Big]}$$

For a more detailed overview of the concepts above, check out the **States-based Models cheatsheets (teaching/cs-221/cheatsheet-states-models)**!

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