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

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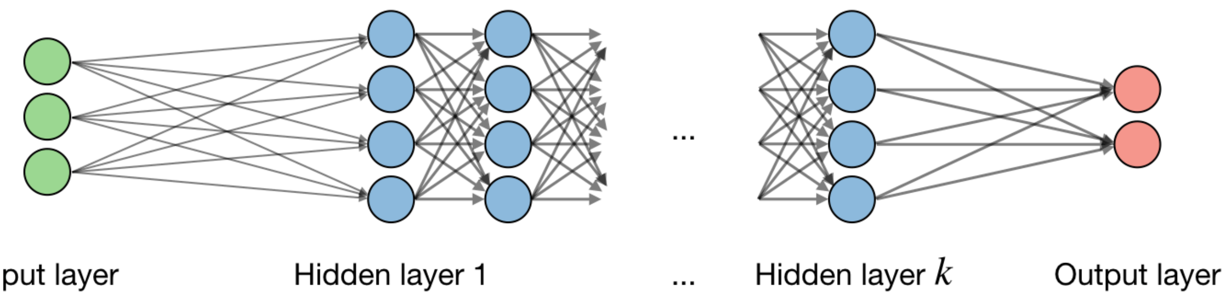
(https://stanford.edu/~shervine/teaching/cs-229/cheatsheet-deep-learning#nn) Neural Networks

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:

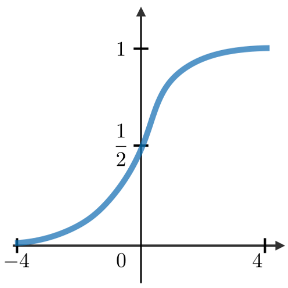
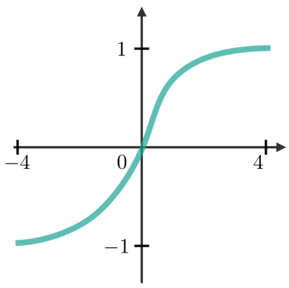
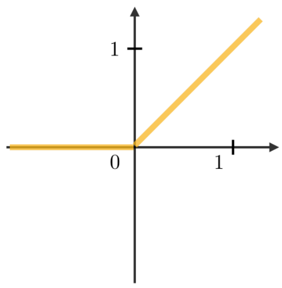
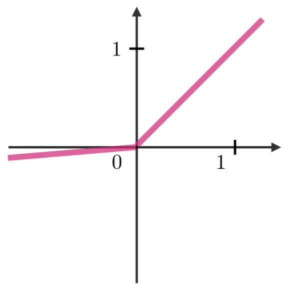


By noting i the i^{th} layer of the network and j the j^{th} hidden unit of the layer, we have:

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

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 $\epsilon \ll 1$
			

❐ **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-deep-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:

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

❐ **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:

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

❐ **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:

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

❐ **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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