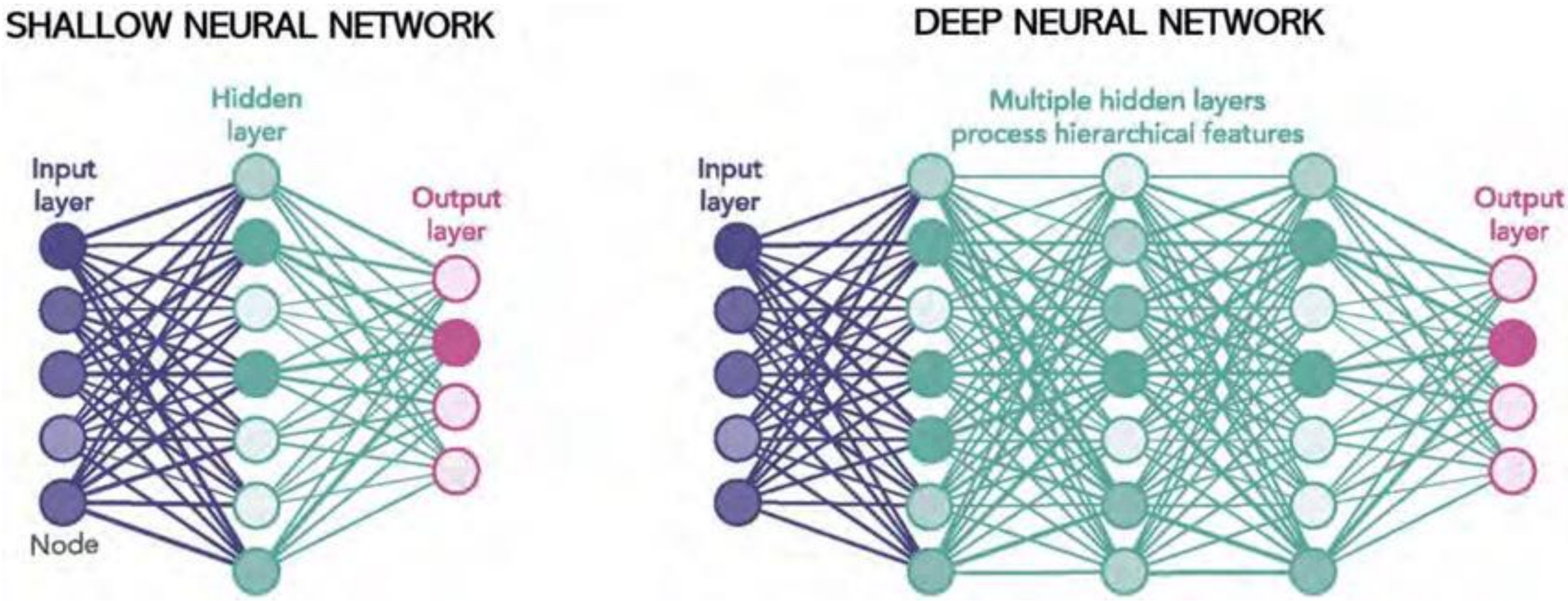
Redes Neuronales y Aprendizaje Profundo

Bloque1: Feedforward Neural Networks

From Shallow to Deep NN



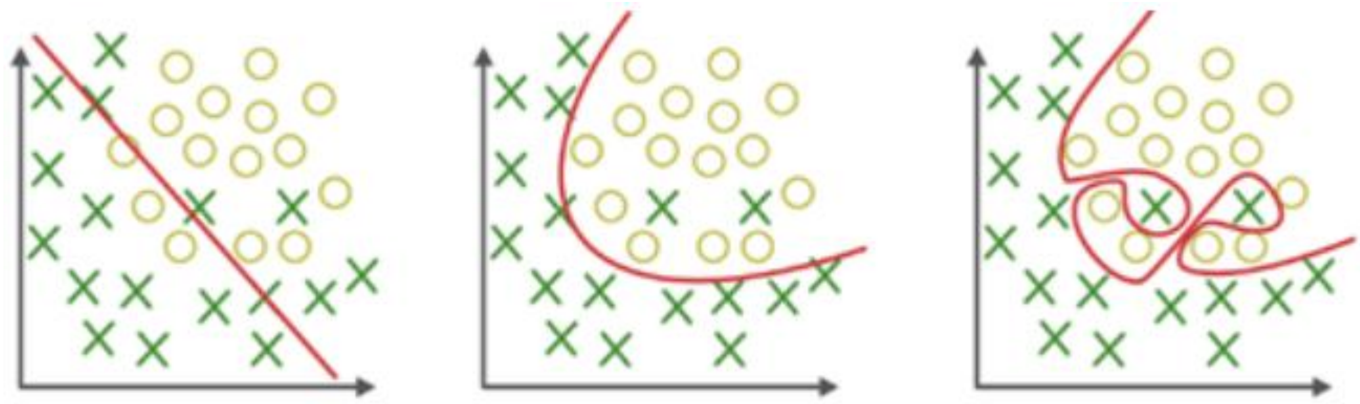
- **Objectives**
  - To analyze the phenomena of **Overfitting and Underfitting** to understand how model complexity affects generalization performance.
  - To investigate regularization techniques for preventing poor generalization.
  - To evaluate the role of **Parameter Initialization** in maintaining gradient flow and preventing numerical instability in deep architectures

- **Objectives**
  - To understand **Early Stopping** to strategically halt the optimization process at the point of maximum generalization
  - To explore **Quantization** as a technique to map high-precision parameters to discrete spaces for efficient edge-device inference.

- **Contents**
  - Overfitting and Underfitting
  - Regularization techniques
  - Parameter initialization
  - Early Stopping
  - Quantization

Overfitting and Underfitting

- **Gradient Descent. Epochs**
  - **Epochs**
  - In training a neural network if too many epochs are used the model may have “overfitting” with the training data set.



under-fitting **appropiate-fitting** **over-fitting**

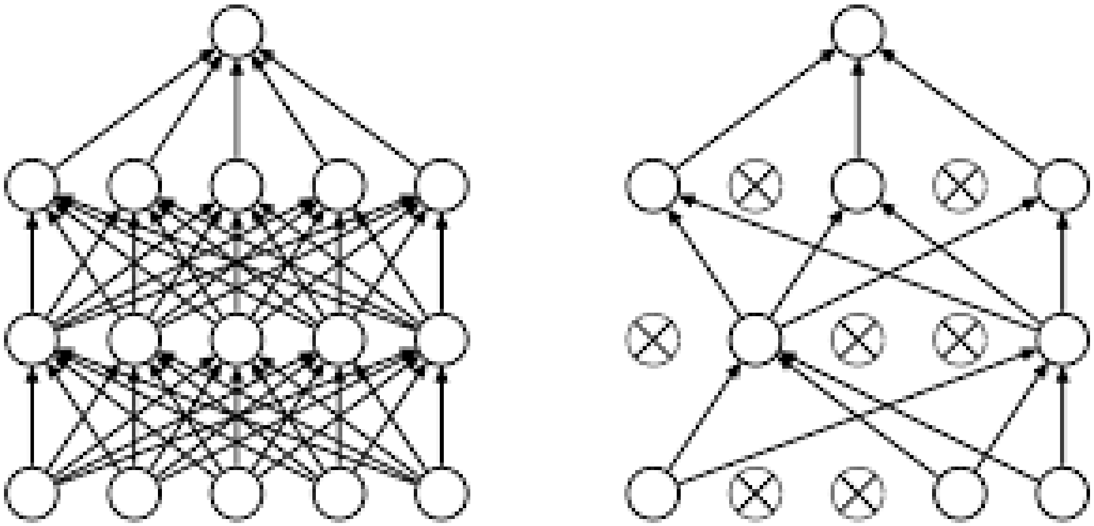
Overfitting and Underfitting

- **Overfitting and Underfitting**
  - **Overfitting:** Learns training data too well but has poor generalization in inference.
  - **Underfitting:** Does not learn training data and misses characteristics and patterns of the data, leading to poor performance in both training and test datasets.
  - Possible solutions:

- K-fold cross-validation
- Data augmentation
- Model selection
- Hyperparameters selection

Regulatization techniques

- ## Dropout
  - Dropout is a **regularization technique** used in neural networks **to prevent overfitting**.
  - It works by **randomly deactivating** (or "**dropping out**") a **fraction of neurons during training**, forcing the model to learn more robust and generalizable features.



(a) Standard Neural Net (b) After applying dropout.

- ## Weight Decay
  - Weight Decay penalizes the sum of squared weights.
  - Prevents weights from **becoming too large** and leads to more **stable models**.

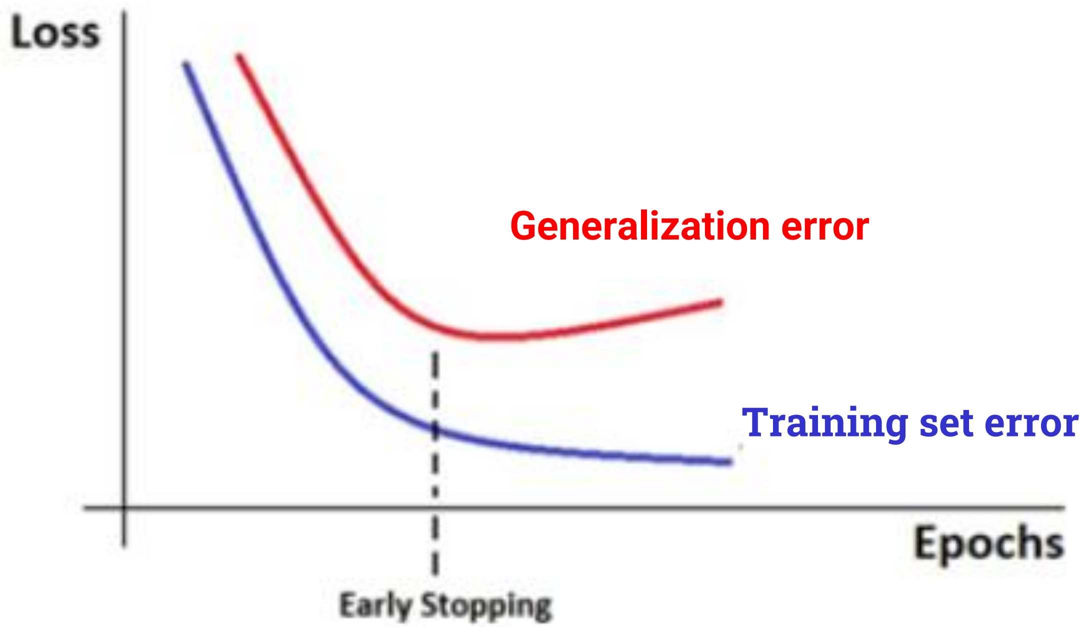
$$\boldsymbol{w} = (\boldsymbol{1} - \lambda)\boldsymbol{w} - \boldsymbol{\alpha}\Delta \boldsymbol{C_0}$$

  - Useful if we do not want the model to focus on local noise of new inputs. Force the network to learn only relevant features in the training set.

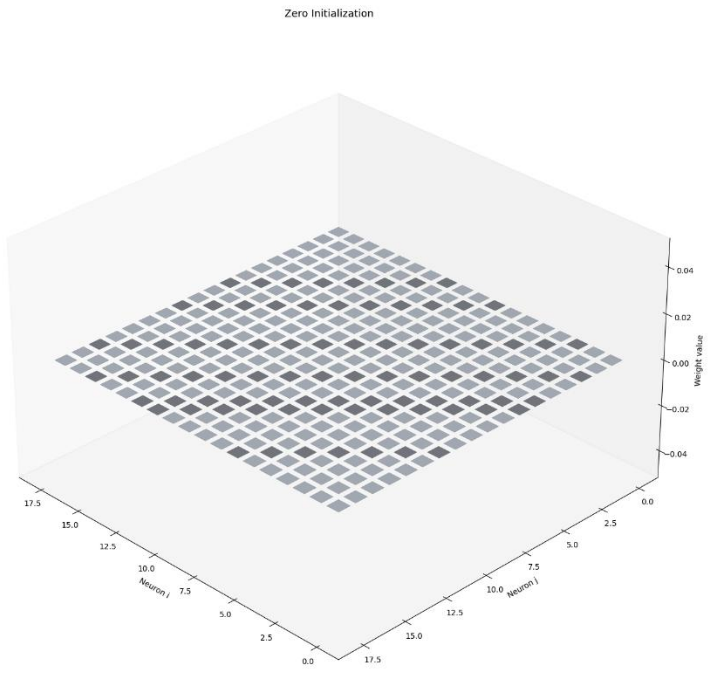
Regularization techniques

- **Data Augmentation**
  - Generates **additional** examples and reduces overfitting **increasing the variability** of the dataset
  - In small tabular datasets we can apply data augmentation by generating samples with the same distribution or adding noise.

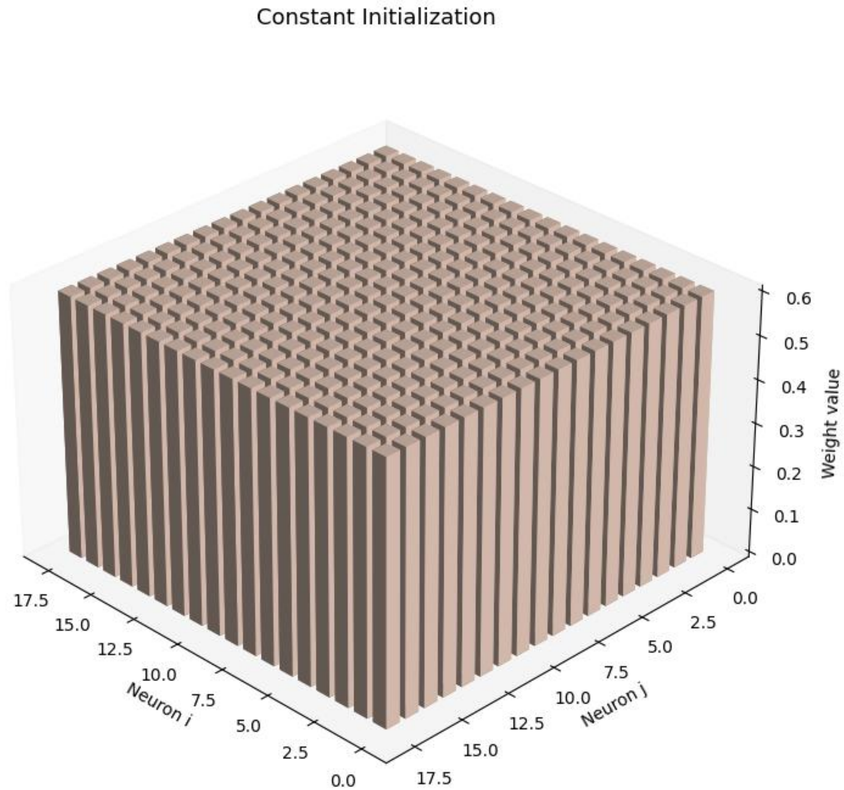
- **Early stopping**
  - A very high number of epochs can reduce the training error but increase the generalization error.



- **Zero initialization**
  - **Zero initialization** initializes weights with 0. This produces that the all the neurons of the NN learns the same.

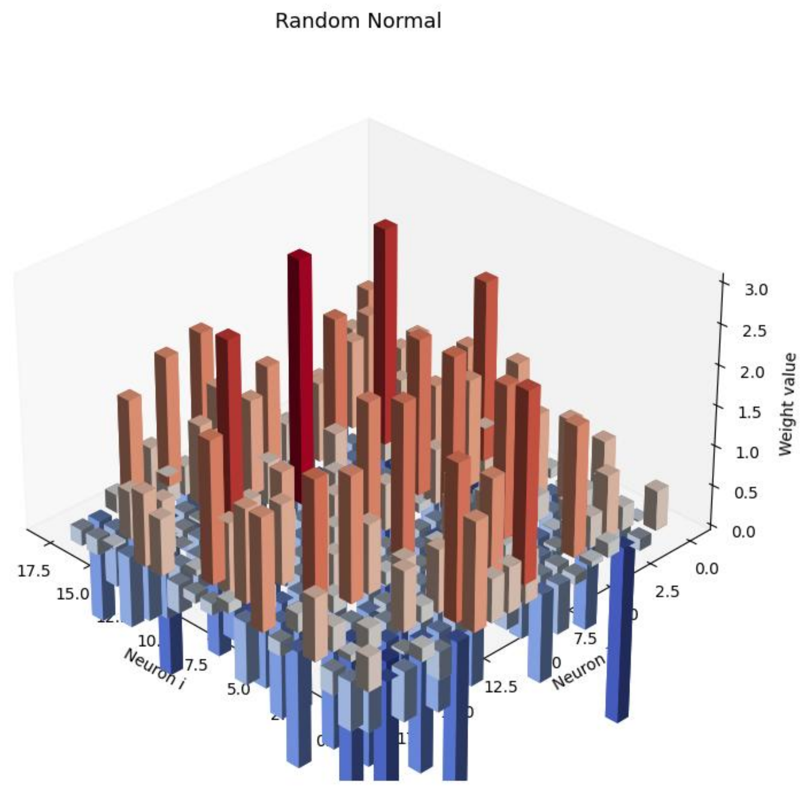


- **Constant initialization**
  - **Constant initialization** initializes weights with the same value. Has the same problem of Zero initialization.

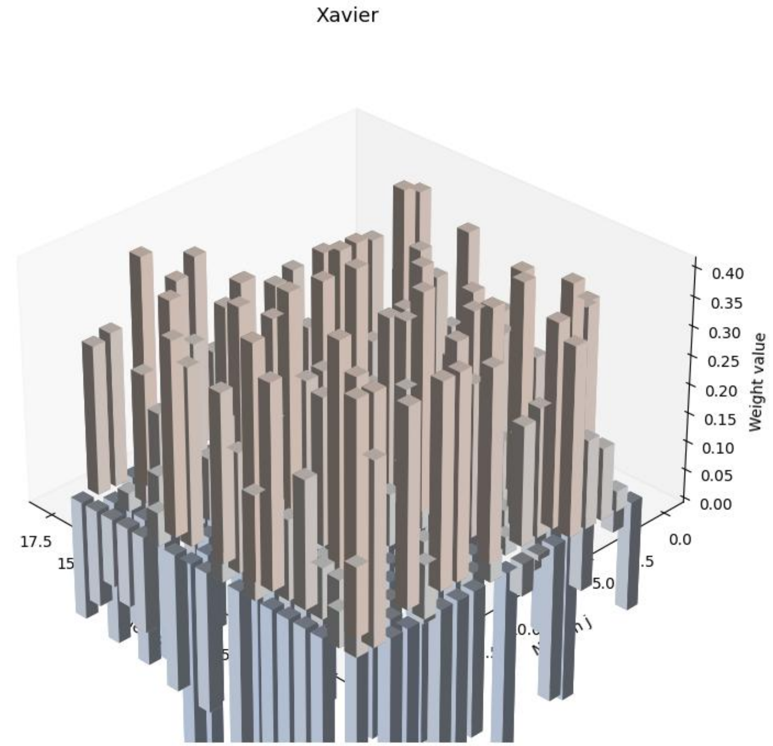


Parameter Initialization

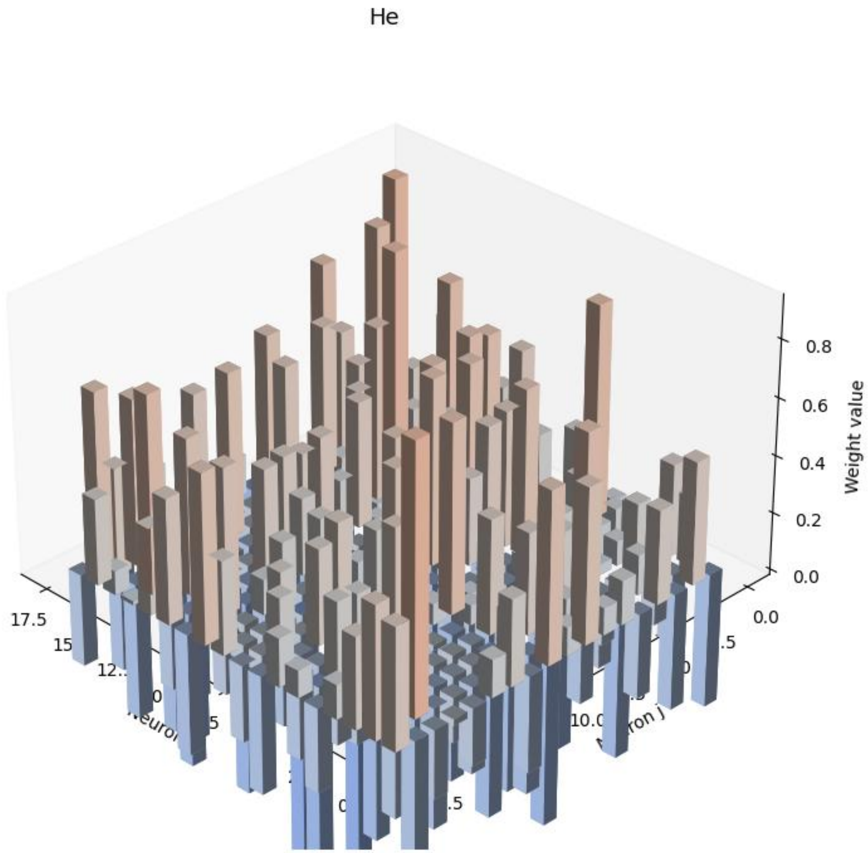
- **Random normal initialization**
  - **Random normal (Gaussian) initialization** initializes weights with the same value. Has the same problem of Zero initialization.



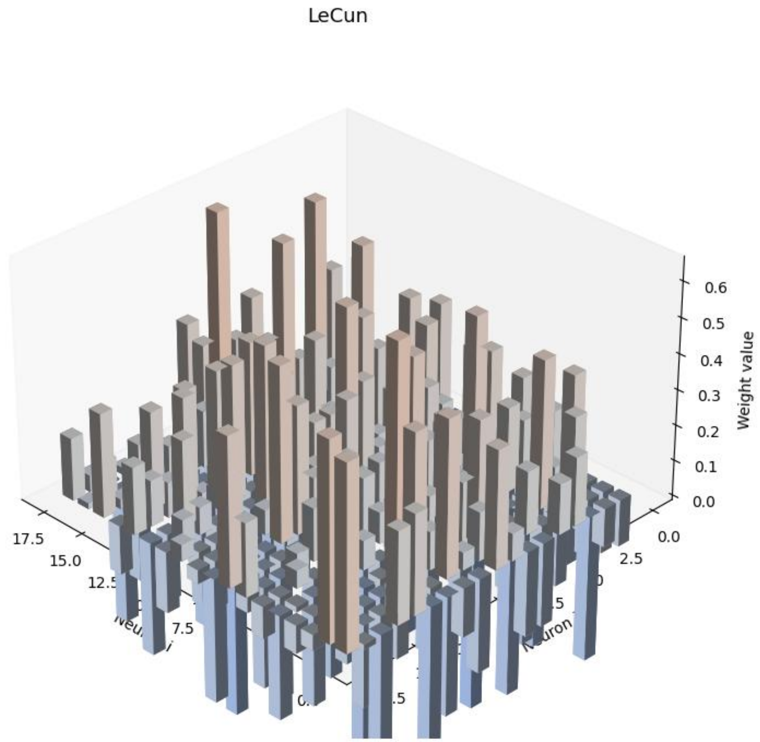
- **Xavier initialization**
  - One of the main objectives of **Xavier's initialization method** (also known as **Glorot initialization**) in a neural network is to ensure that the gradients during training are neither too large nor too small.



- **He initialization**
  - **He initialization (Normal)** is optimized for layers that use ReLU activation functions. Same variance for both inputs and outputs in NN.



- **Lecun initialization**
  - **Lecun initialization (Normal)** is optimized for layers that use SELU/sigmoid/tanh activation functions. Same variance for both inputs and outputs in NN.



Quantization

- ## Quantization
  - **Quantization** is a technique that **reduces** the precision of weights and activations. For instance, from Float32 to smaller formats such as INT8.
  - Some studies achieved good results although a quantization of **1.58 bits**.
  - Remember, 8 bits = 1 byte, FP32= 4 bytes = 32 bits. 32x times cheaper.

The Era of 1-bit LLMs: All Large Language Models are in 1.58 Bits

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Quantization

- **Quantization Types**
  - **Post-Training Quantization (PTQ)** quantizes a trained model.
  - **Quantization-Aware Training (QAT)** simulates quantization during training to reduce accuracy loss.
  - In **Weight Quantization** only weights are reduced in precision.
  - In **Activation Quantization** are reduced in precision.
  - **Bias Quantization** quantizes biases (less common).

Quantization

- **Exercise 1. Symmetric Uniform Quantization**

  - **Domain**

    $n = 8$, **number of bits for the representation**

    $q \in Z$, **quantized values are integers**

    $$\boxed{q_{min} = -2^{n-1} \qquad q_{max} = 2^{n-1} - 1}$$

  - **Scale**

    $\alpha =$ max(**abs(x)), max value in original data**

    $s = \dfrac{\alpha}{q_{max}}$, **scale factor that maps x**

  - **Input = x = [1.23, - 0.87]**

  - **Quantization**

    $q = round(\dfrac{x}{s})$, **rounds to nearest integer**