Basis Of Learning _ Brain & Cognitive Society

Timeline :
Week 1: Introduction to Python, Anaconda, jupyter notebooks & libraries
Week 2: Exploratory data analysis, intuition about Neural Networks, Deep learning vs Machine learning
Week 3: Introduction to Neural Networks, FNN, Backpropagation, gradient Descent

Week 1 - Team Learners

Anaconda

Anaconda basically takes python and makes it more work-oriented toward data science. Where python would be a general-purpose programming language, Anaconda is utilized for deep learning, machine learning, etc.

Jupyter Notebook:

Jupyter Notebook can be opened after installing Anaconda.
It has code cells in which we can write our code and the output will be shown right after the code cell. This is what makes Jupyter Notebook attractive as compared to a normal python file. It makes data easier to visualize.

Environments:

An Environment contains a certain python version and library which are all compatible with each other. The advancements many a time make it do that the libraries ain't compatible, in this case, we make an Environment and run our code in there.

Links to Notebooks created by mentees: here
Tasks given: Create documentation of Python installation, curate a jupyter tutorial based on your understanding, mention your choice of module used to create and manage virtual environments and create a markdown explaining it in detail. Learn pandas, numpy, and matplotlib, and make a notebook describing major things you can do with it.

Week 3: Team Beluga & Team Noobs

Multi-layer perceptron

Steps

- creating a **fully connected** neural network architecture
- apply neural nets to two classic ML problems: **regression** and **classification**
- train neural nets with **stochastic gradient descent**, and
- improve performance of network with **dropout**, **batch normalization**

What is Deep Learning?

Deep learning is an approach to machine learning characterized by deep stacks of computations.

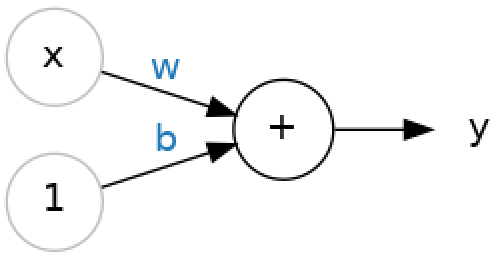
- This depth of computation is what has enabled deep learning models to disentangle the kinds of complex and hierarchical patterns found in the most challenging real-world datasets.

Neural networks are composed of neurons, where each neuron individually performs only a simple computation.

The `power` of a neural network comes from the complexity of the connections these neurons form.

The Linear Unit

the individual neuron. As a diagram, a **neuron** (or **unit**) with one input looks like:

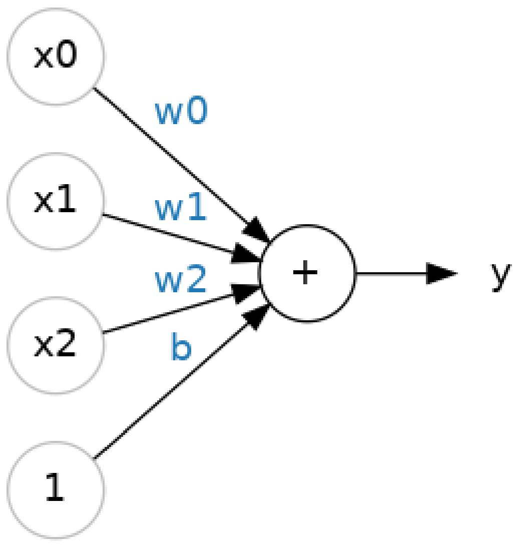


The Linear Unit: y = wx + b

- The input is x. Its connection to the neuron has a **weight** which is `w`.
- The b is a special kind of weight we call the **bias**.
- The y is the value the neuron ultimately outputs.
- This neuron's activation is `y = w * x + b`, or as a formula $y = wx + b$.

Multiple Inputs

Rather than single Input there might have multipleinputs.For these We can just add more input connections to the neuron, one for each additional feature.



A linear unit with three inputs.

The formula for this neuron would be $y = w_0x_0 + w_1x_1 + w_2x_2 + b$. A linear unit with two inputs will fit a plane, and a unit with more inputs than that will fit a hyperplane.

Creating multiple units

The easiest way to create a model in Keras is through `keras.Sequential`, which creates a neural network as a stack of *layers*. We can create models like those above using a *dense* layer

SYNTAX:

model = keras.Sequential([layers.Dense(units(output units)=1,input_shape=3)])

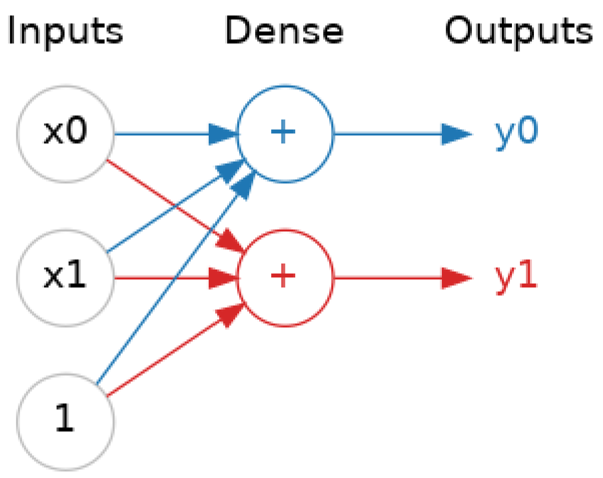
Complex Networks

The key idea here is `modularity`, building up a complex network from simpler functional units.

We've seen how a linear unit computes a linear function – now we'll see how to combine and modify these single units to model more complex relationships.

Layers

Neural networks typically organize their neurons into **layers**. When we collect together linear units having a common set of inputs we get a **dense** layer.



A dense layer of two linear units receiving two inputs and a bias.

You could think of each layer in a neural network as performing some kind of relatively simple transformation.

Through a deep stack of layers, a neural network can transform its inputs in more and more complex ways.

In a well-trained neural network, each layer is a transformation getting us a little bit closer to a solution.

Many Kinds of Layers

A “layer” in Keras is a very general kind of thing. A layer can be, essentially, any kind of data transformation.

Many layers, like the convolutional and recurrent layers, transform data through use of neurons and differ primarily in the pattern of connections they form.

Others though are used for feature engineering or just simple arithmetic.

The Activation Function

Two dense layers with nothing in between are no better than a single dense layer by itself.

Dense layers by themselves can never move us out of the world of lines and planes.

What we need is something *nonlinear*,These are activation functions.

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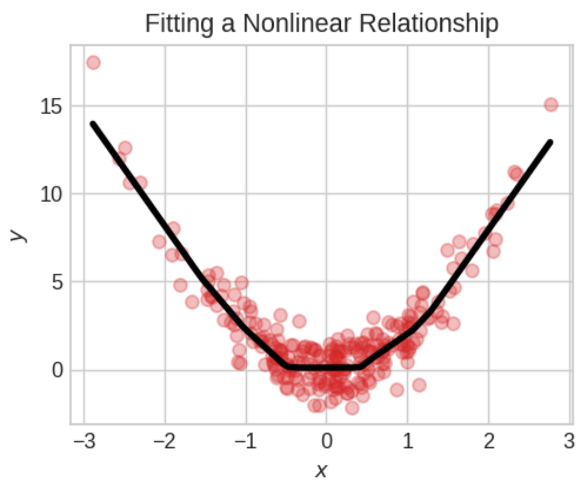
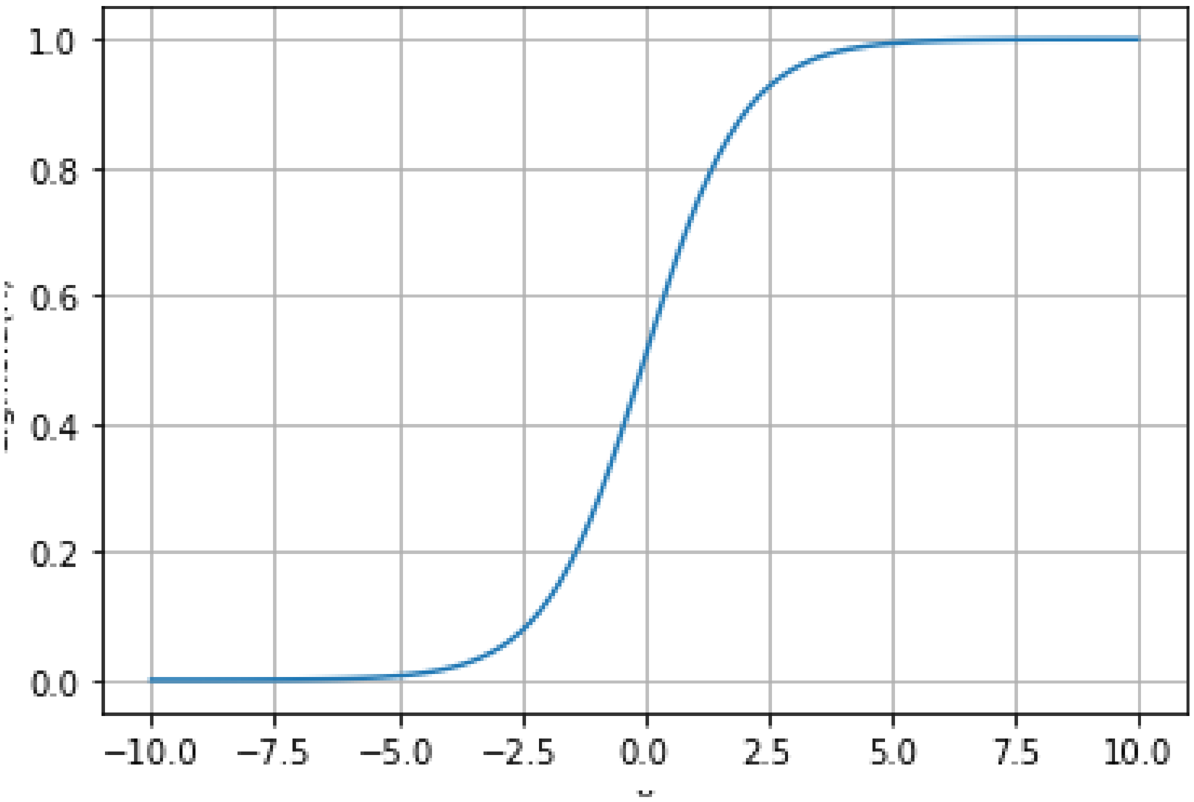
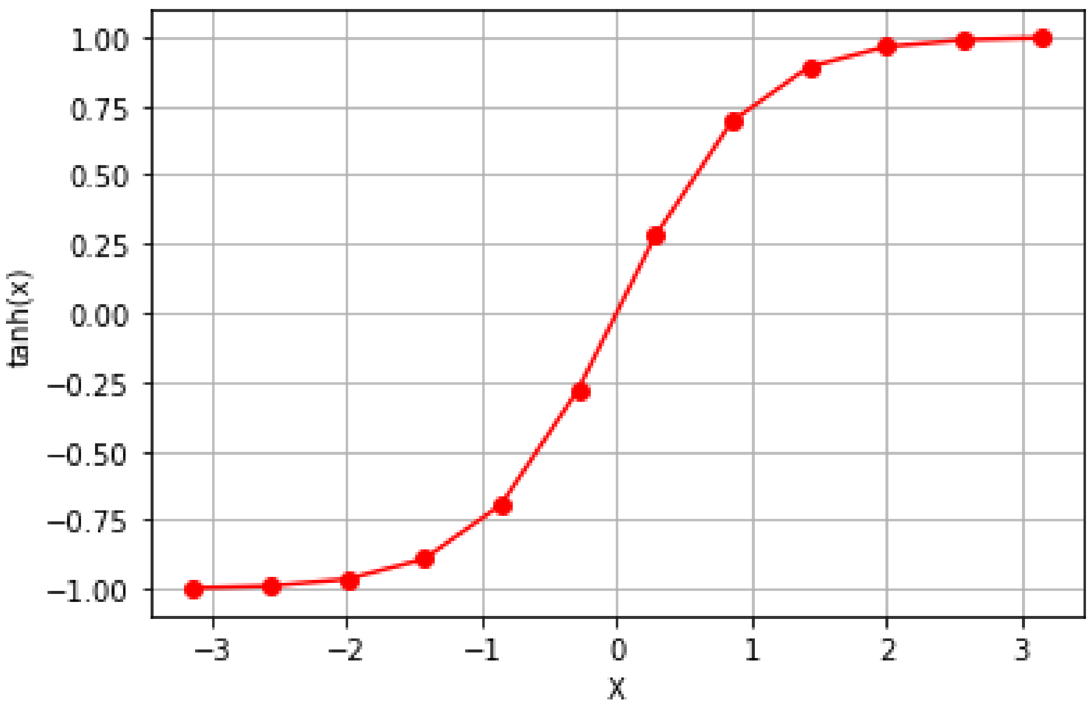

Fitting a Nonlinear Relationship
y
x
15
10
5
0
−3
−2
−1
0
1
2
3

Sigmoid(x):

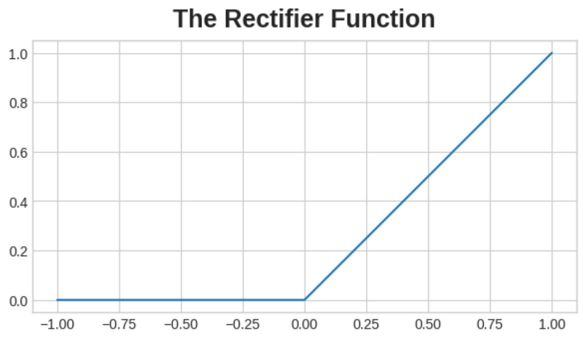

1.0
0.8
0.6
0.4
0.2
0.0
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0

Tanh(x):



- **Without activation functions, neural networks can only learn linear relationships.**
- **In order to fit curves, we'll need to use activation functions.**

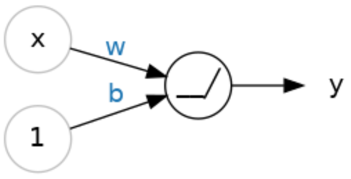
An **activation function** is simply some function we apply to each of a layer's outputs (its *activations*). The most common is the *rectifier* function $max(0, x)$.



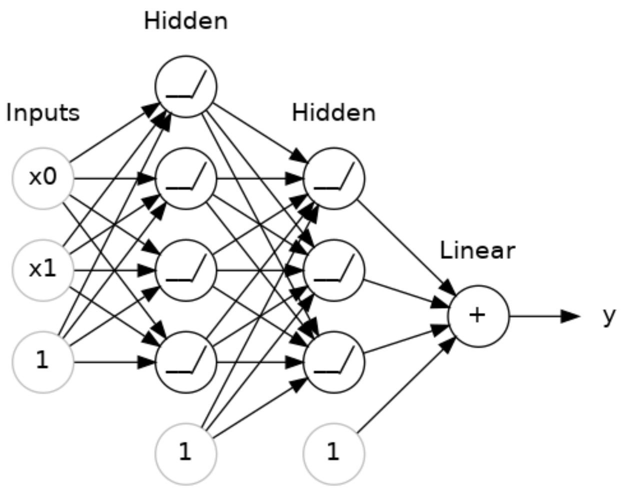
The rectifier function has a graph that's a line with the negative part "rectified" to zero. Applying the function to the outputs of a neuron will put a *bend* in the data, moving us away from simple lines.

When we attach the rectifier to a linear unit, we get a **rectified linear unit** or **ReLU**

Applying a ReLU activation to a linear unit means the output becomes `max (0, w * x + b)`, which we might draw in a diagram like:



Stacking Dense Layers



A stack of dense layers makes a "fully-connected" network.

The layers before the output layer are called hidden** since we never see their outputs directly.**

Now, notice that the final (output) layer is a linear unit (meaning, no activation function).

That makes this network appropriate to a regression task, where we are trying to predict some arbitrary numeric value.

Other tasks (like classification) might require an activation function on the output.

Building Sequential Models

The `Sequential` model we've been using will connect together a list of layers in order from first to last: the first layer gets the input, the last layer produces the output. This creates the model in the figure above

In addition to the training data, we need two more things: - A "loss function" that measures how good the network's predictions are. - An "optimizer" that can tell the network how to change its weights.

The Loss Function

The **loss function** measures the disparity between the the target's true value and the value the model predicts.

Different problems call for different loss functions. - For **regression** problems, the task is to predict some numerical value

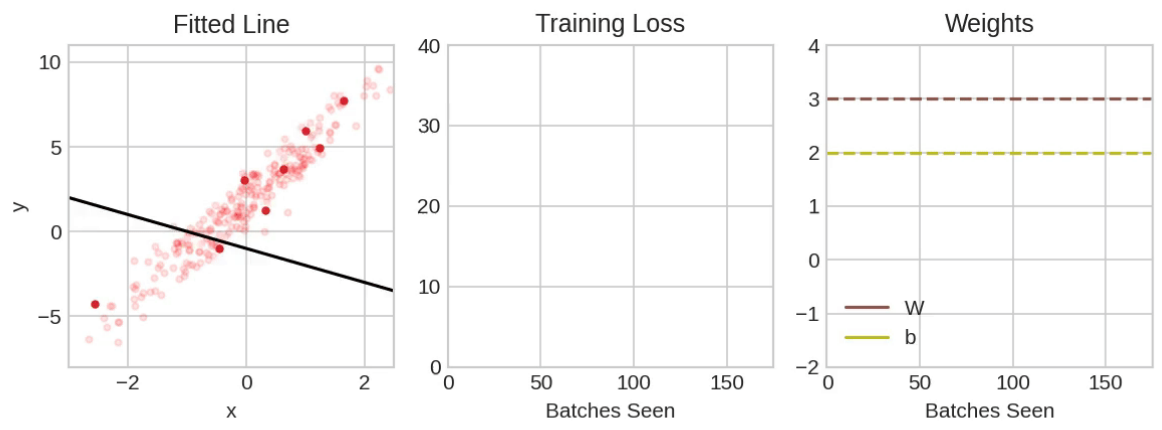
- A common loss function for regression problems is the **mean absolute error** or **MAE**.
- For each prediction `y_pred`, MAE measures the disparity from the true target `y_true` by an absolute difference `abs(y_true - y_pred)`.

The Optimizer - Stochastic Gradient Descent

The **optimizer** is an algorithm that adjusts the weights to minimize the loss.

The optimization algorithms used in deep learning belong to a family called **stochastic gradient descent**. They are iterative algorithms that train a network in steps. One **step** of training goes like this: 1. Sample some training data and run it through the network to make predictions. 2. Measure the loss between the predictions and the true values. 3. Finally, adjust the weights in a direction that makes the loss smaller.

Then just do this over and over until the loss is as small as you like (or until it won't decrease any further.)



Training a neural network with Stochastic Gradient Descent.

Each iteration's sample of training data is called a **minibatch** (or often just "batch"), while a complete round of the training data is called an **epoch** . The number of epochs you train for is how many times the network will see each training example.

Learning Rate and Batch Size

Notice that the line only makes a small shift in the direction of each batch (instead of moving all the way). The size of these shifts is determined by the **learning rate**. A smaller learning rate means the network needs to see more minibatches before its weights converge to their best values.

The learning rate and the size of the minibatches are the two parameters that have the largest effect on how the SGD training proceeds. Their interaction is often subtle and the right choice for these parameters isn't always obvious. (We'll explore these effects in the exercise.)

Fortunately, for most work it won't be necessary to do an extensive hyperparameter search to get satisfactory results. **Adam** is an SGD algorithm that has an adaptive learning rate that makes it suitable for most problems without any parameter tuning (it is "self tuning", in a sense).

d Adam is a great general-purpose optimizer.

Adding the Loss and Optimizer

After defining a model, you can add a loss function and optimizer with the model's `compile` method:

```
model.compile(
    optimizer="adam",
    loss="mae",
)
```

Forward Propagation, Backward Propagation, and Computational Graphs

- In training models with minibatch stochastic gradient descent the calculations involved in *forward propagation* through the model are very computational.
- Hence,When it came time to calculate the gradients, the backpropagation function provided by the deep learning framework is very efficient.
- The automatic calculation of gradients (automatic differentiation) simplifies the implementation.

In this section, *backward propagation* (more commonly called *backpropagation*) is explained.

Forward Propagation

> *Forward propagation* means the calculation and storage of intermediate variables (including outputs) for a neural network in order from the input layer to the output layer.

*This is tedious than **Backpropoagation**,but we will look into its implementation.*

The input is —> $\mathbf{x} \in \mathbb{R}^d$

Here the intermediate variable is:

$$\mathbf{z} = \mathbf{W}^{(1)}\mathbf{x} + \mathbf{B}$$

Here,

weight : $\mathbf{W}^{(1)} \in \mathbb{R}^{h \times d}$

NOTE: Let us assume bias is zero for simplicity.

After running the intermediate variable $\mathbf{z} \in \mathbb{R}^h$ through the activation function ϕ we obtain our hidden activation vector of length h,

$$\mathbf{h} = \phi(\mathbf{z}).$$

The hidden variable $\mathbf{h}$ is also an intermediate variable. Assuming that the parameters of the output layer only possess a weight of $\mathbf{W}^{(2)} \in \mathbb{R}^{q \times h}$, we can obtain an output layer variable with a vector of length q:

$$\mathbf{o} = \mathbf{W}^{(2)}\mathbf{h}.$$

Assuming that the loss function is l and the example label is y, we can then calculate the loss term for a single data example,

$$L = l(\mathbf{o}, y).$$

According to the definition of L_2 regularization, given the hyperparameter λ, the regularization term is

$$s = \frac{\lambda}{2}\left(\| \mathbf{W}^{(1)} \|_F^2 + \| \mathbf{W}^{(2)} \|_F^2\right),$$

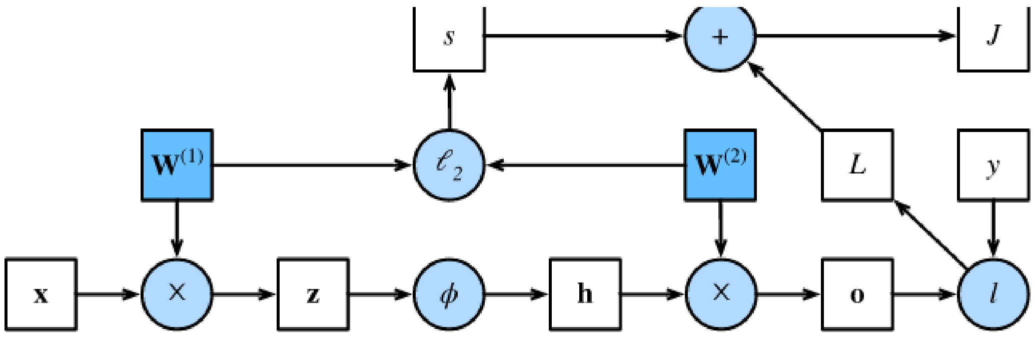
the Frobenius norm of the matrix is simply the L_2 norm applied after flattening the matrix into a vector.

Finally, the model's regularized loss on a given data example is:

$$J = L + s.$$

We refer to J as the *objective function* in the following discussion.

Computational Graph of Forward Propagation



Backpropagation

Backpropagation is the method of calculating the gradient of neural network parameters.

- this method traverses the network in reverse order:

```
output  ----->  input layer
```

It follows *chain rule* from calculus.

- The algorithm stores any intermediate variables(partial derivatives)required while calculating the gradient with respect to some parameters.

method

Let us take:

1. $\mathsf{Y} = f(\mathsf{X})$ and $\mathsf{Z} = g(\mathsf{Y})$
2. The input and the output $\mathsf{X}, \mathsf{Y}, \mathsf{Z}$ are tensors of arbitrary shapes.
3. By using the chain rule, we can compute the derivative of Z with respect to X via

$$\frac{\partial \mathsf{Z}}{\partial \mathsf{X}} = \text{prod}\left(\frac{\partial \mathsf{Z}}{\partial \mathsf{Y}}, \frac{\partial \mathsf{Y}}{\partial \mathsf{X}}\right).$$

Here,

- The prod operator is used to multiply its arguments after the necessary operations, such as transposition and swapping input positions, have been carried out.
- For vectors, this is straightforward: it is simply matrix-matrix multiplication. For higher dimensional tensors, we use the appropriate counterpart. The operator prod hides all the notation overhead.
- the parameters of the simple network with one hidden layer, whose computational graph is given above are $\mathbf{W}^{(1)}$ and $\mathbf{W}^{(2)}$.
- The objective of backpropagation is to calculate the gradients $\partial J/\partial \mathbf{W}^{(1)}$ and $\partial J/\partial \mathbf{W}^{(2)}$.

- We apply the chain rule and calculate, in turn, the gradient of each intermediate variable and parameter.
- The order of calculations are reversed relative to those performed in forward propagation.

## STEPS

With Respect to $\mathbf{W}^{(1)}$

1. Calculate the gradients of the objective function $J = L + s$ with respect to the loss term L and the regularization term s.

$$\frac{\partial J}{\partial L} = 1 \text{ and } \frac{\partial J}{\partial s} = 1.$$

2. Compute the gradient of the objective function with respect to variable of the output layer $\mathbf{o}$ according to the chain rule:

$$\frac{\partial J}{\partial \mathbf{o}} = \text{prod}\left(\frac{\partial J}{\partial L}, \frac{\partial L}{\partial \mathbf{o}}\right) = \frac{\partial L}{\partial \mathbf{o}} \in \mathbb{R}^q.$$

3. Calculate the gradients of the regularization term with respect to both parameters:

$$\frac{\partial s}{\partial \mathbf{W}^{(1)}} = \lambda \mathbf{W}^{(1)} \text{ and } \frac{\partial s}{\partial \mathbf{W}^{(2)}} = \lambda \mathbf{W}^{(2)}.$$

— Now we are able to calculate the gradient $\partial J / \partial \mathbf{W}^{(2)} \in \mathbb{R}^{q \times h}$ of the model parameters closest to the output layer. Using the chain rule yields:

$$\frac{\partial J}{\partial \mathbf{W}^{(2)}} = \text{prod}\left(\frac{\partial J}{\partial \mathbf{o}}, \frac{\partial \mathbf{o}}{\partial \mathbf{W}^{(2)}}\right) + \text{prod}\left(\frac{\partial J}{\partial s}, \frac{\partial s}{\partial \mathbf{W}^{(2)}}\right) = \frac{\partial J}{\partial \mathbf{o}} \mathbf{h}^\top + \lambda \mathbf{W}^{(2)}.$$

with respect to $\mathbf{W}^{(1)}$

To obtain the gradient with respect to $\mathbf{W}^{(1)}$ we need to continue backpropagation along the output layer to the hidden layer. The gradient with respect to the hidden layer's outputs $\partial J / \partial \mathbf{h} \in \mathbb{R}^h$ is given by

$$\frac{\partial J}{\partial \mathbf{h}} = \text{prod}\left(\frac{\partial J}{\partial \mathbf{o}}, \frac{\partial \mathbf{o}}{\partial \mathbf{h}}\right) = {\mathbf{W}^{(2)}}^\top \frac{\partial J}{\partial \mathbf{o}}.$$

Since the activation function ϕ applies elementwise, calculating the gradient $\partial J / \partial \mathbf{z} \in \mathbb{R}^h$ of the intermediate variable $\mathbf{z}$ requires that we use the elementwise multiplication operator, which we denote by $\odot$:

$$\frac{\partial J}{\partial \mathbf{z}} = \text{prod}\left(\frac{\partial J}{\partial \mathbf{h}}, \frac{\partial \mathbf{h}}{\partial \mathbf{z}}\right) = \frac{\partial J}{\partial \mathbf{h}} \odot \phi'(\mathbf{z}).$$

Finally, we can obtain the gradient $\partial J/\partial \mathbf{W}^{(1)} \in \mathbb{R}^{h\times d}$ of the model parameters closest to the input layer. According to the chain rule, we get

$$\frac{\partial J}{\partial \mathbf{W}^{(1)}} = \text{prod}\left(\frac{\partial J}{\partial \mathbf{z}}, \frac{\partial \mathbf{z}}{\partial \mathbf{W}^{(1)}}\right) + \text{prod}\left(\frac{\partial J}{\partial s}, \frac{\partial s}{\partial \mathbf{W}^{(1)}}\right) = \frac{\partial J}{\partial \mathbf{z}}\mathbf{x}^\top + \lambda \mathbf{W}^{(1)}.$$

Training Neural Networks

```
When training neural networks, forward and backward propagation
depend on each other.
```

- In particular, for forward propagation, we traverse the computational graph in the direction of dependencies and compute all the variables on its path.
- These are then used for backpropagation where the compute order on the graph is reversed.

On one hand, - computing during forward propagation depends on the current values of model parameters $\mathbf{W}^{(1)}$ and $\mathbf{W}^{(2)}$.

- They are given by the optimization algorithm according to backpropagation in the latest iteration.

On the other hand, - the gradient calculation during backpropagation depends on the current value of the hidden variable $\mathbf{h}$, which is given by forward propagation.

> Therefore we should alternate forward propagation with backpropagation, updating model parameters using gradients given by backpropagation.
>
> `Note`

- backpropagation reuses the stored intermediate values from forward propagation to avoid duplicate calculations.
- One of the consequences is that we need to retain the intermediate values until backpropagation is complete.
- This is also one of the reasons why training requires significantly more memory than plain prediction.
- training deeper networks using larger batch sizes more easily leads to *out of memory* errors.

Vanishing and Exploding Gradients

> **Poor choices in initialization can cause us to encounter exploding or vanishing gradients while training.**

Considering a deep network with L layers, input $\mathbf{x}$ and output $\mathbf{o}$. With each layer l defined by a transformation f_l parameterized by weights $\mathbf{W}^{(l)}$, whose hidden variable is $\mathbf{h}^{(l)}$ (let $\mathbf{h}^{(0)} = \mathbf{x}$), our network can be expressed as:

$$\mathbf{h}^{(l)} = f_l(\mathbf{h}^{(l-1)}) \text{ and thus } \mathbf{o} = f_L \circ \ldots \circ f_1(\mathbf{x}).$$

If all the hidden variables and the input are vectors, we can write the gradient of $\mathbf{o}$ with respect to any set of parameters $\mathbf{W}^{(l)}$ as follows:

$$\partial_{\mathbf{W}^{(l)}} \mathbf{o} = \underbrace{\partial_{\mathbf{h}^{(L-1)}} \mathbf{h}^{(L)}}_{\mathbf{M}^{(L)} \overset{\text{def}}{=}} \cdot \ldots \cdot \underbrace{\partial_{\mathbf{h}^{(l)}} \mathbf{h}^{(l+1)}}_{\mathbf{M}^{(l+1)} \overset{\text{def}}{=}} \underbrace{\partial_{\mathbf{W}^{(l)}} \mathbf{h}^{(l)}}_{\mathbf{v}^{(l)} \overset{\text{def}}{=}}.$$

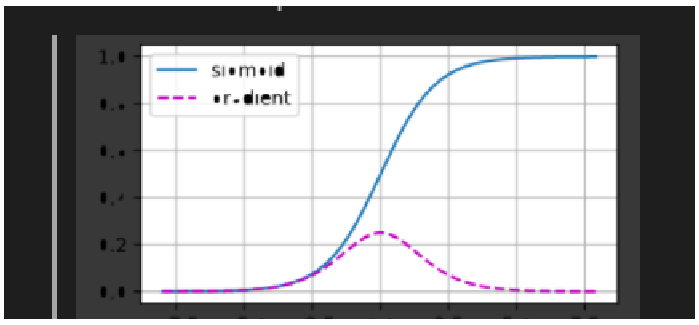
This gradient is the product of $L - l$ matrices $\mathbf{M}^{(L)} \cdot \ldots \cdot \mathbf{M}^{(l+1)}$ and the gradient vector $\mathbf{v}^{(l)}$.

- Thus, it leads to numerical underflow that often crop up when multiplying together too many probabilities.
- Gradients of unpredictable magnitude threaten the stability of our optimization algorithms.

We may be facing parameter updates that are either

1. excessively large, destroying our model (*exploding gradient*)

2. excessively small (*vanishing gradient*), rendering learning impossible as parameters hardly move on each update.



WE can see, **the sigmoid' s gradient vanishes both when its inputs are large and when they are small**

- Hence, `ReLUs`, which are more stable (but less neurally plausible), have emerged as the default choice for practitioners.

Parameter Initialization

One way of addressing—or at least mitigating—the issues raised above is through careful initialization.

Default Initialization

We use a normal distribution to initialize the values of our weights.

Xavier Initialization

- For each layer, variance of any output is not affected by the number of inputs, and variance of any gradient is not affected by the number of outputs.