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## 1 Learning Goals

By the end of the exercise, you should be able to

- Describe components of a perceptron.
- Construct a perceptron to represent simple linear functions such as AND, OR, and NOT.
- Represent the XOR function using a three-layer feed-forward perceptron network.
- Explain why the back-propagation algorithm can be interpreted as a version of the gradient descent optimization algorithm.
- Execute the back-propagation algorithm given the update rules of the weights.


## 2 Representing the XOR function using a three-layered feed-forward network

The XOR function is defined by the following truth table.

| $x_{1}$ | $x_{2}$ | y |
| :---: | :---: | :---: |
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |

XOR can be modeled by using a neural network with one hidden layer.

- Two input units.
- Two hidden units
- One output unit
- The activation function is the Sigmoid function.

To describe the back-propagation algorithm, we first introduce some notation.

- $x_{1}, x_{2}$ denotes the values of the input units.
$h_{1}, h_{2}$ denotes the values of the hidden units.
$o_{1}$ denotes the values of the output unit. $y$ denoted the actual value(true label).
- $w 1_{i j}$ is the weight on line between input unit $x_{i}$ and hidden unit $h_{j}$. $w 2_{j 1}$ is the weight on line between hidden unit $h_{j}$ and output unit $o_{1}$.

To measure the error between the desired output values and the actual output values, we will use the squared difference function.
error $=\frac{1}{2}\left(y-o_{1}\right)^{2}$.

## 3 Practice Questions

## Question 1:

Calculating the derivative of sigmoid function $f(x)=\frac{1}{1+e^{-x}}$ respect to x .
Solution:
$f^{\prime}(x)=-\frac{1}{\left(1+e^{-x}\right)^{2}} \times e^{-x} \times(-1)=\frac{e^{-x}}{\left(1+e^{-x}\right)^{2}}=\frac{1}{1+e^{-x}} \times \frac{e^{-x}}{1+e^{-x}}=\frac{1}{1+e^{-x}}\left(1-\frac{1}{1+e^{-x}}\right)=f(x)(1-f(x))$

Question 2: Consider a neural network with 2 input units, 2 hidden units and 1 output unit.
Derive the gradient of $w 2_{j 1}$, where $w 2_{j 1}$ represents the weight on line between the $j^{t h}$ hidden unit and the output unit $o_{1}$.

The predicted value from the output unit is $o_{1}$, the expected output(true label) is $y$, and the output from the $j^{\text {th }}$ hidden unit is $h_{j}$.

Solution: The gradient for $w 2_{j 1}$ :

$$
\begin{align*}
& \frac{\partial}{\partial w 2_{j 1}} \frac{1}{2}\left(y-o_{1}\right)^{2}  \tag{1}\\
& =-\left(y-o_{1}\right) \frac{\partial}{\partial w 2_{j 1}} o_{1}  \tag{2}\\
& =-\left(y-o_{1}\right) \frac{\partial}{\partial w 2_{j 1}} f\left(\sum_{j^{\prime}=0}^{B} w 2_{j^{\prime} 1} \cdot h_{j^{\prime}}\right)  \tag{3}\\
& =-\left(y-o_{1}\right) f^{\prime}\left(\sum_{j^{\prime}=0}^{B} w 2_{j^{\prime} 1} \cdot h_{j^{\prime}}\right) \frac{\partial}{\partial w 2_{j 1}}\left(\sum_{j^{\prime}=0}^{B} w 2_{j^{\prime} 1} \cdot h_{j^{\prime}}\right)  \tag{4}\\
& =-\left(y-o_{1}\right) f^{\prime}\left(o_{1}\right) \frac{\partial}{\partial w 2_{j 1}}\left(\sum_{j^{\prime}=0}^{B} w 2_{j^{\prime} 1} \cdot h_{j^{\prime}}\right)  \tag{5}\\
& =-\left(y-o_{1}\right) o_{1}\left(1-o_{1}\right) h_{j} \tag{6}
\end{align*}
$$

## Question 3:

We would like to learn the XOR function using a multi-layer neural network. We are running the back-propagation algorithm on the neural network and we are currently at the $n$-th iteration.

The current values of the parameters are as follows.

- $w 1_{01}=1, w 1_{11}=1, w 1_{21}=-1$
- $w 1_{02}=1, w 1_{12}=-1, w 1_{22}=1$
- $w 2_{01}=1, w 2_{11}=-1, w 2_{21}=-1$

The next set of inputs is $x_{1}=0, x_{2}=1$, and the true label is $y=1$. The learning rate is $\alpha=0.1$. Calculating the updated values of these parameters after this iteration.

Solution: Forward pass:
$h_{1}=\operatorname{sigmoid}\left(w 1_{01}+w 1_{11} * x_{1}+w 1_{21} * x_{2}\right)=\operatorname{sigmoid}(1+1 * 0+(-1) * 1)=0.5$
$h_{2}=\operatorname{sigmoid}\left(w 1_{02}+w 1_{12} * x_{1}+w 1_{22} * x_{2}\right)=\operatorname{sigmoid}(1+(-1) * 0+1 * 1)=0.88$
$o_{1}=\operatorname{sigmoid}\left(w 2_{01}+w 2_{11} * h_{1}+w 2_{21} * h_{2}\right)=\operatorname{sigmoid}(1+(-1) * 0.5+(-1) * 0.88)=0.406$

Backward pass:
$w 2_{j 1} \leftarrow w 2_{j 1}+\alpha\left(y-o_{1}\right) o_{1}\left(1-o_{1}\right) h_{j}$
$w 2_{01}=1+0.1 *(1-0.406) * 0.406 *(1-0.406) * 1=1.014$
$w 2_{11}=-1+0.1 *(1-0.406) * 0.406 *(1-0.406) * 0.5=-0.993$
$w 2_{21}=-1+0.1 *(1-0.406) * 0.406 *(1-0.406) * 0.88=-0.987$
$w 1_{i j} \leftarrow w 1_{i j}+\alpha h_{j}\left(1-h_{j}\right) x_{i}\left(y-o_{1}\right) o_{1}\left(1-o_{1}\right) w 2_{j 1}$
$w 1_{01}=1+0.1 * 0.5 *(1-0.5) * 1 *(1-0.406) * 0.406 *(1-0.406) *(-1)=0.996$
$w 1_{11}=1+0.1 * 0.5 *(1-0.5) * 0 *(1-0.406) * 0.406 *(1-0.406) *(-1)=1$

$$
\begin{aligned}
& w 1_{21}=-1+0.1 * 0.5 *(1-0.5) * 1 *(1-0.406) * 0.406 *(1-0.406) *(-1)=-1.004 \\
& w 1_{02}=1+0.1 * 0.88 *(1-0.88) * 1 *(1-0.406) * 0.406 *(1-0.406) *(-1)=0.998 \\
& w 1_{12}=-1+0.1 * 0.88 *(1-0.88) * 0 *(1-0.406) * 0.406 *(1-0.406) *(-1)=-1 \\
& w 1_{22}=1+0.1 * 0.88 *(1-0.88) * 1 *(1-0.406) * 0.406 *(1-0.406) *(-1)=0.998
\end{aligned}
$$

