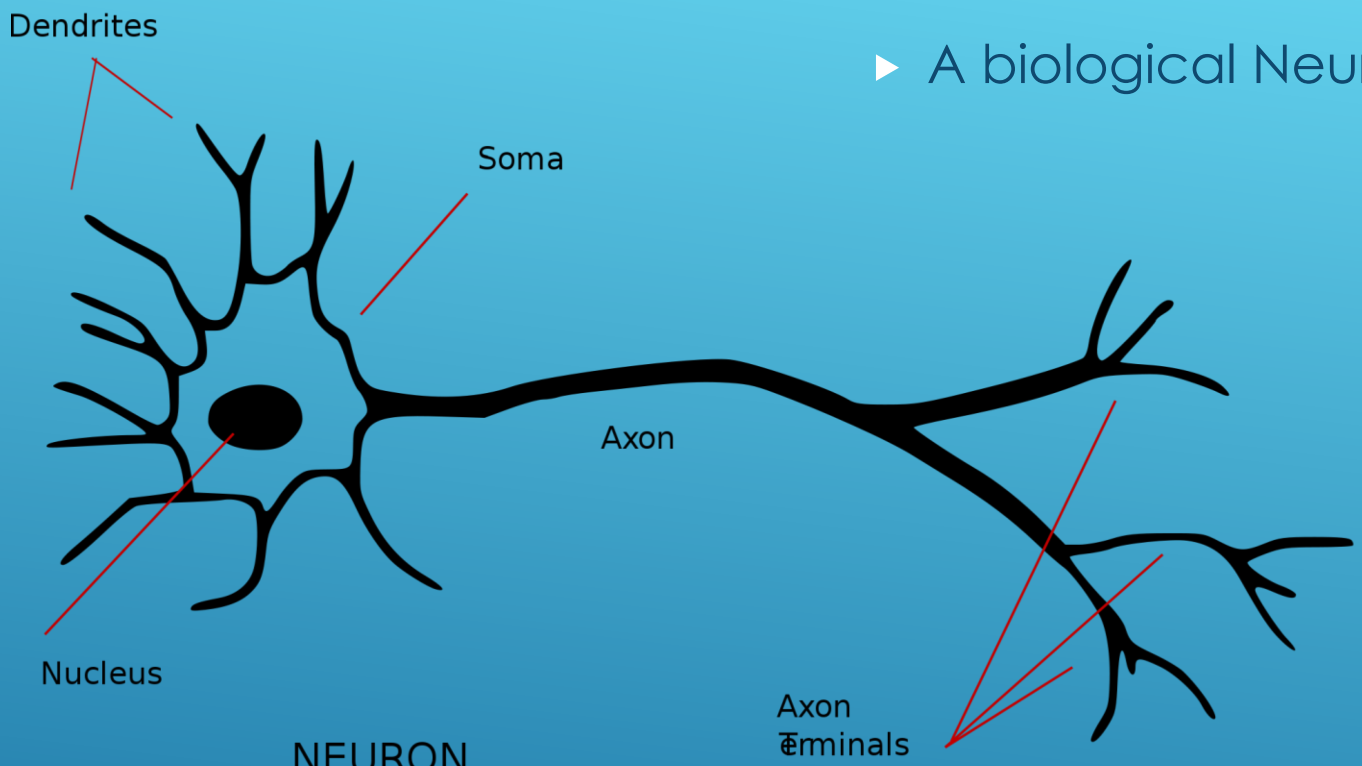
NEURAL NETWORKS

Power Hidden in Obscurity

“I'M GOING TO TEACH YOU IN THIS LECTURE HOW TO ANSWER QUESTIONS ABOUT NEUROBIOLOGY WITH AN 80% PROBABILITY THAT YOU WILL GIVE THE SAME ANSWER AS A NEUROBIOLOGIST.”

PROFESSOR PATRICK HENRY WINSTON

Comment to his class on Artificial Intelligence at Massachusets Institute of Technology.



NEURON

- A biological Neuron

THE BASIC BUILDING BLOCK OF THE BRAIN

“AND NOW, I’M GOING TO SHOW YOU HOW TO ANSWER A QUESTION ABOUT NEUROBIOLOGY WITH 80% PROBABILITY YOU’LL GET IT RIGHT. JUST SAY, WE DON’T KNOW!”

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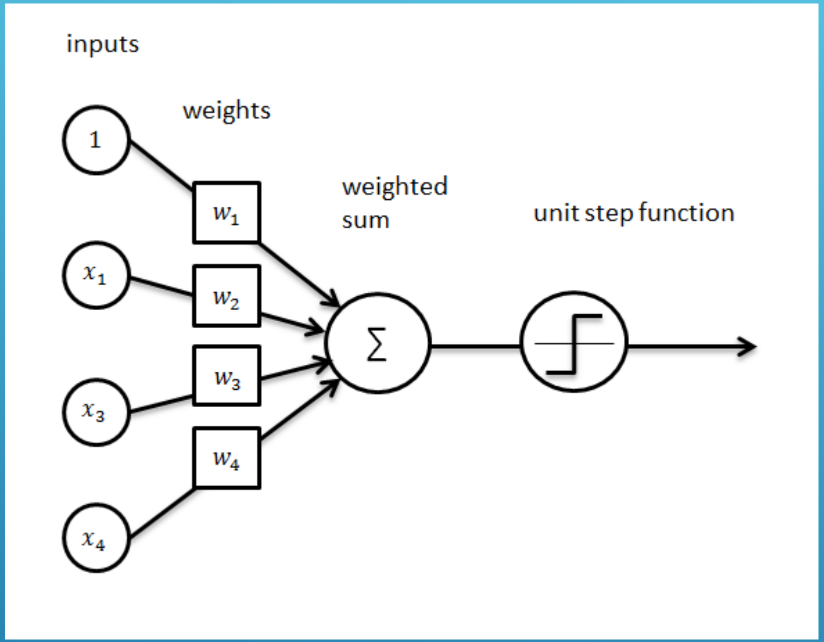
Comment to his class on Artificial Intelligence at Massachusets Institute of Technology.

IS NEURAL NETWORKS WORTH TEACHING.

- In 2010 MIT was considering dropping neural networks from the AI curriculum. The success was not very good.
- Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton from the University of Toronto brought neural networks back to the forefront with a neural net with 60 million parameters in it.
- It made some mistakes but was remarkably accurate and brought neural networks back from near extinction.

Image from Imagenet Classification With Deep Convolutional Neural Networks.pdf

Perceptron



Emulates Neuron

- Has *m* inputs corresponding to features of Data Set.
- Weights each input and sums the value.
- Includes a bias of 1 and a weight
- Passes output through a sigmoid function.

NEURAL NETWORK PERCEPTRON

[Ahmet Taspinar: The Perceptron]

CLASS DATA

- Normalize data and output to an list of inputs
- Each point of classification data is assigned a numerical value from 0 to 1.

Executable File | 36 lines (32 sloc) | 1.24 KB

Raw | Blame | History

```python
#! /usr/bin/python3
## reads in file and writes out normalized data

def class_array():
    f = open('class.csv', 'r')
    read_array = []
    for line in f:
        line = line.strip()
        read_array.append(line.split(','))
    f.close()

#day        weekday = 0, saturday = .33, sunday =.66, holiday = 1;
#seasons    summer = 0, autumn = .33, winter =.66, spring = 1;
#wind       none = 0, normal = .5, high = 1;
#Rain       none = 0, slight = .5, heavy = 1;
#answer     cancelled = 0, very late = .33, late = .66, on time = 1;
    normalized_array = []
    entry=[]
    for list in read_array:
        for s in list:
            if s == 'weekday' or s == 'summer' or s == 'none' or s == 'cancelled':
                entry.append(0)
            elif s == 'saturday' or s == 'autumn' or s == 'very late':
                entry.append(.33)
            elif s == 'normal' or s == 'slight':
                entry.append(.5)
            elif s == 'sunday' or s == 'winter' or s == 'late':
                entry.append(.66)
            elif s == 'holiday' or s == 'spring' or s == 'on time' or s == 'heavy' or s == 'high':
                entry.append(1)
        if entry:
            normalized_array.append(entry)
        entry = []

    return normalized_array
```

Executable File | 32 lines (28 sloc) | 952 Bytes

Raw | Blame | History

```
#! /usr/bin/python3
## reads in file and writes out normalized data
def weather_array():
    f = open('weather.csv', 'r')
    read_array = []
    for line in f:
        line = line.strip()
        read_array.append(line.split(','))
    f.close()


#outlook rain = 0, overcast = .5, sun = 1;
#temperature cool = 0, mild = .5, hot = 1;
#humidity normal = 0, high = 1;
#windy  False = 0, true = 1;
#answer no = 0, yes = 1;
    normalized_array = []
    entry=[]
    for list in read_array:
        for s in list:
            if s == 'rainy' or s == 'cool' or s == 'normal' or s == 'FALSE' or s == 'no':
                entry.append(0)
            elif s == 'overcast' or s == 'mild':
                entry.append(.5)
            elif s == 'sunny' or s == 'hot' or s == 'high' or s == 'TRUE' or s == 'yes':
                entry.append(1)
        if entry:
            normalized_array.append(entry)
        entry = []

    return normalized_array
```

WEATHER DATA

- Normalize data and output to an list of inputs
- Each point of classification data is assigned a numerical value from 0 to 1.

```python
#returns layer of weights ranomized -.5 <= w <= .5
def randomize_node_weights(num):
    node = []
    for i in range(0,num):
        node.append(random.uniform(-.5,.5))

    return node

#returns fully populated neural net of n layers by m nodes/layer
def define_neural_net(n,m):
    layers = []
    for i in range(0,n):
        layers.append(randomize_node_weights(4))
    return layers

```

```python
#returns entry passed through node
def return_weighted_input(node=[],input=[]):
    weighted_value = 0
    weighted_input = []
    for i in range(0,len(node)):
        weighted_value += BIAS_VALUE
        for j in range(0,len(node)):
            #summation of weights to each node.
            weighted_value += (node[i]*input[j])
        weighted_input.append(1/(1+math.exp(-1*weighted_value)))
    return weighted_input
```

MY NEURAL NETWORK WAS LACKING

MY UNDERSTANDING CAME MUCH TO LATE

In trying to finish my program and understand Backward Propagation I came upon a few flaws with my design. I miscalculated the number of weights for each layer. Structurally my code has to change some to allow for proper weighting of each synapse. The next couple slides make clear a simple walk through of a proper neural net.

Step 0: Read input and output

X				wh			bh			hidden_layer_input			hidden_layer_activations			wout	bout	output	y	E
1	0	1	0																1	
1	0	1	1																1	
0	1	0	1																0	

Step 1: Initialize weights and biases with random values (There are methods to initialize weights and biases but for now initialize with random values)

X				wh			bh			hidden_layer_input			hidden_layer_activations			wout	bout	output	y	E
1	0	1	0	0.42	0.88	0.55	0.46	0.72	0.08							0.30	0.69		1	
1	0	1	1	0.10	0.73	0.68										0.25			1	
0	1	0	1	0.60	0.18	0.47										0.23			0	
				0.92	0.11	0.52														

Borrowed from Analyticsvidhya.com

STEPS THROUGH THE METHODS

Step 2: Calculate hidden layer input:

hidden_layer_input= matrix_dot_product(X,wh) + bh

X				wh			bh			hidden_layer_input			hidden_layer_activations			wout	bout	output	y	E
1	0	1	0	0.42	0.88	0.55	0.46	0.72	0.08	1.48	1.78	1.10				0.30	0.69		1	
1	0	1	1	0.10	0.73	0.68				2.40	1.89	1.61				0.25			1	
0	1	0	1	0.60	0.18	0.47				1.48	1.56	1.27				0.23			0	
				0.92	0.11	0.52														

Step 3: Perform non-linear transformation on hidden linear input

hiddenlayer_activations = sigmoid(hidden_layer_input)

X				wh			bh			hidden_layer_input			hidden_layer_activations			wout	bout	output	y	E
1	0	1	0	0.42	0.88	0.55	0.46	0.72	0.08	1.48	1.78	1.10	0.81	0.86	0.75	0.30	0.69		1	
1	0	1	1	0.10	0.73	0.68				2.40	1.89	1.61	0.92	0.87	0.83	0.25			1	
0	1	0	1	0.60	0.18	0.47				1.48	1.56	1.27	0.81	0.83	0.78	0.23			0	
				0.92	0.11	0.52														

Step 4: Perform linear and non-linear transformation of hidden layer activation at output layer

output_layer_input = matrix_dot_product (hiddenlayer_activations * wout) + bout

output = sigmoid(output_layer_input)

X				wh			bh			hidden_layer_input			hidden_layer_activations			wout	bout	output	y	E
1	0	1	0	0.42	0.88	0.55	0.46	0.72	0.08	1.48	1.78	1.10	0.81	0.86	0.75	0.30	0.69	0.79	1	
1	0	1	1	0.10	0.73	0.68				2.40	1.89	1.61	0.92	0.87	0.83	0.25		0.80	1	
0	1	0	1	0.60	0.18	0.47				1.48	1.56	1.27	0.81	0.83	0.78	0.23		0.79	0	
				0.92	0.11	0.52														

Step 10: Update weight at both output and hidden layer

wout = wout + matrix_dot_product(hiddenlayer_activations.Transpose, d_output)*learning_rate

wh = wh+ matrix_dot_product(X.Transpose,d_hiddenlayer)*learning_rate

X				wh			bh			hidden_layer_input			hidden_layer_activations			wout	bout	output	y	E
1	0	1	0	0.42	0.88	0.55	0.46	0.72	0.08	1.48	1.78	1.10	0.81	0.86	0.75	0.29	0.69	0.79	1	0.21
1	0	1	1	0.10	0.73	0.68				2.40	1.89	1.61	0.92	0.87	0.83	0.25		0.80	1	0.20
0	1	0	1	0.60	0.18	0.47				1.48	1.56	1.27	0.81	0.83	0.78	0.23		0.79	0	-0.79
				0.92	0.11	0.51														

Slope hidden layer			error at hidden layer		
0.15	0.12	0.19	0.010	0.009	0.008
0.08	0.11	0.14	0.010	0.008	0.008
0.15	0.14	0.17	-0.039	-0.033	-0.031

Slope Output
0.17
0.16
0.17

E
0.21
0.20
-0.79

Learning Rate	0.1

delta hidden layer		
0.002	0.001	0.002
0.001	0.001	0.001
-0.006	-0.005	-0.005

delta output
0.035
0.033
-0.131

REFERENCES

- https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-fall-2010/lecture-videos/lecture-12a-neural-nets/uXt8qF2Zzfo.pdf
- http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf
- http://ataspinar.com/2016/12/22/the-perceptron/
- https://github.com/vfoley/neuralNet
- https://www.analyticsvidhya.com/blog/2017/05/neural-network-from-scratch-in-python-and-r/