Neural Networks



MIC Conference

Data: TBA

Project ideas:

Signup:



Brief Recap:

- Data-driven learning

.



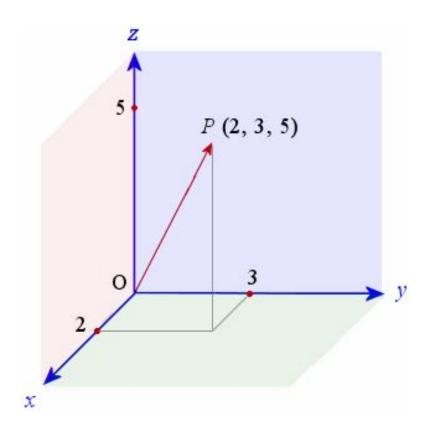
What's a Neural Network?

hidden layer 1 hidden layer 2 hidden layer 3 input layer output layer



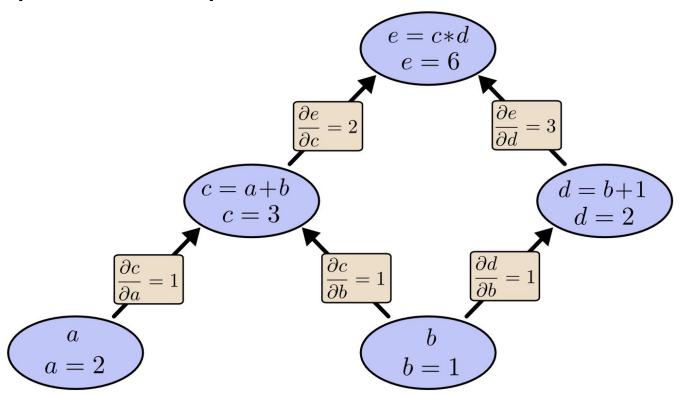
Vectors and Vectorization

- Data is represented in arrays, with each term representing one dimension
- Vectorization is essentially using
 built-in functions to take
 advantage of parallel computing
 capabilities (reduces training time)



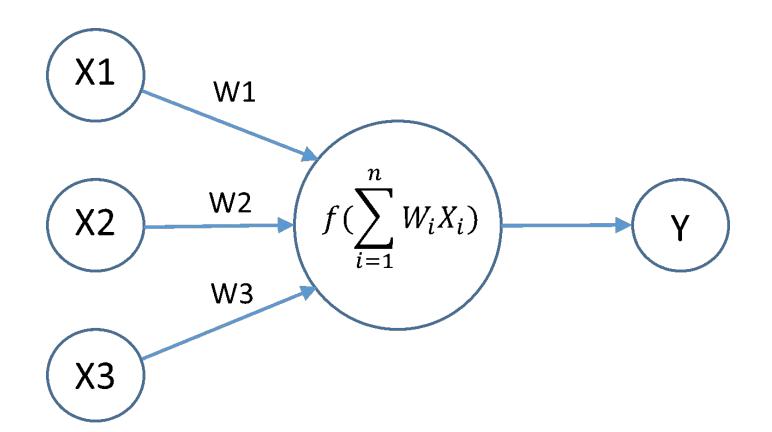


Computation Graph



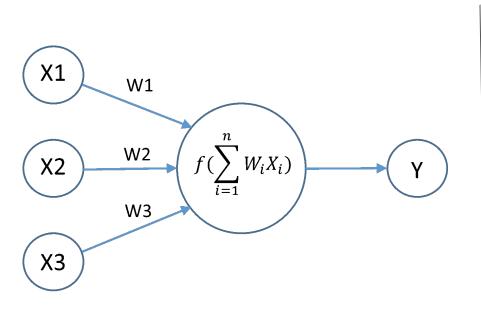


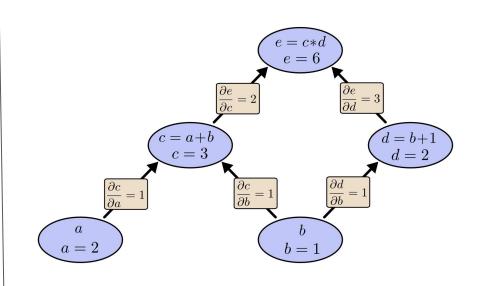
Neural Network (who decides function f)





Neural Networks as Computational Graphs



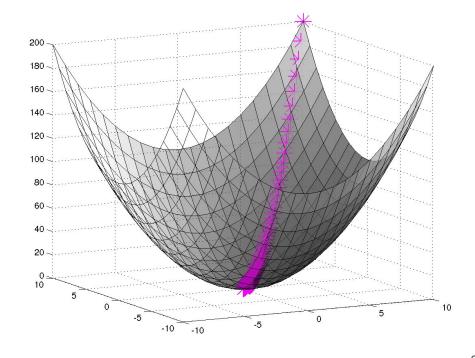




Gradient Descent

- The process by which your neural net is trained to be accurate
- Through numerousIterations of logisticregression
- Reach the global minima!

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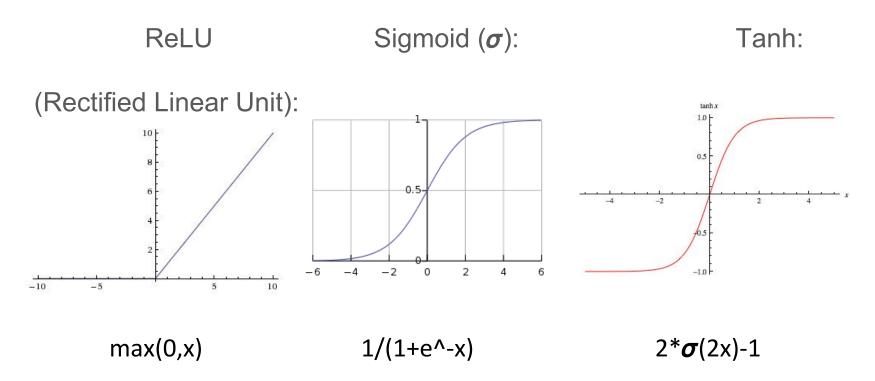


Logistic Regression Cost Function

- Used when output of neural network is 0 (false) or 1 (true)



Activation Functions





Levels of Supervision During Learning

Supervised Learning - you *have* labeled data; your data comes in pairs of input and desired output.

Unsupervised Learning - you *do not have* labeled data; your neural net looks to group different inputs based on similarities i.e. *clustering.*



Semi-supervised Learning - you have *some* labeled data; labeled data is expensive to generate, so you use a mix of labeled and unlabelled.

A Tidbit on the Universal Approximation Theorem

A multilayer perceptron can approximate *continuous functions* on a compact subset of real numbers with mild assumptions on the activation function. (Thanks Wikipedia)



A Basic Multilayer Perceptron with PyTorch

```
import torch
import torch.nn as nn
class MLP(nn.Module):
    def init (self, num inputs, num hiddens):
        super(MLP, self). init ()
        self.fc1 = nn.Linear(num_inputs, num_hiddens)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(num hiddens, 1)
    def forward(self, x):
        output = self.fc1(x)
        output = self.relu(output)
        output = self.fc2(output)
        return output
net = MLP(5, 3)
print(net)
parameters = list(net.parameters())
print(parameters)
print(len(parameters))
print(parameters[0].size())
```

Output:

```
MLP (
  (fc1): Linear (5 -> 3)
  (relu): ReLU ()
  (fc2): Linear (3 -> 1)
[Parameter containing:
-0.1721 0.0375 -0.4098 0.0769 -0.4214
 0.0392 -0.1720 0.3798 0.1420 -0.4239
 0.3698 0.3336 -0.4313 0.3198 0.2039
[torch.FloatTensor of size 3x5]
, Parameter containing:
-0.2104
 0.0990
 0.1316
[torch.FloatTensor of size 3]
, Parameter containing:
-0.2340 -0.2816 0.4150
[torch.FloatTensor of size 1x3]
, Parameter containing:
 0.1908
[torch.FloatTensor of size 1]
torch.Size([3, 5])
```

Paper Discussion Time!

http://cs.stanford.edu/~quocle/tutorial1.pdf

Read through, and we will reconvene in ~5minutes

**Feel free to start discussing with your peers if you finish beforehand!



Real World Applications

Image Identification (CNNs) (RNNs)

Natural Language Processing





Additional Resources

Andrew Ng's deeplearning.ai course (highly recommend!):

https://www.coursera.org/learn/neural-networks-deep-learning/lecture/Cuf2f/welcome

Segway for Next Workshop: PyTorch 60minute Blitz (with CNNs!):

http://pytorch.org/tutorials/beginner/deep_learning_60min_blitz.ht

Challenge Yourself: Efficient Backprop by Yann LeCun

