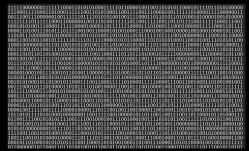
Using Machine Learning to tell if a Spider Died

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Goal

- Want to learn about circadian rhythms in spiders
 - How does a usual (12L:12D) cycle compare to a (12D:12D) cycle?
- We have large sets of data to help us determine this

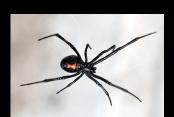


Problem

Null Character

Inaction (spider not doing anything) is coded similarly to sleeping.

Actually, its exactly the same



The spider is not Dead



The spider died

Problem Redefined

Dead | Not-Dead

A classification algorithm should be able to use pattern matching and see when or if a spider died.

For an input string of n 0s or 1s...

- Action Space: n. We should be able to point (somewhat accurately) to the moment when the spider died.
- State Space: 2ⁿ. Every possible arrangement of 0s and 1s needs to be classifiable. This number is HUGE.

Our state and action space makes training **Dead** Not-Dead non-trivial.



Can we do it?



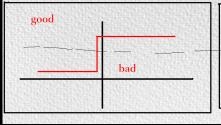
Yes

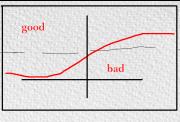
If the problem is solvable, then a perceptron can learn to solve it

But we need to be smart about it...

Solution 1: 'Meh' Classifier

Multilayered Perception (MLP)





- $lue{\sigma} o ext{outputs on a gradient}$
 - \bullet 0.0 \rightarrow The spider died (earlier)
 - $lue{}$ 1.0 ightarrow The the spider is totally still alive
 - $0.25 < x < 0.75 \rightarrow \text{'Meh'}$

Solution 1: 'Meh' Classifier

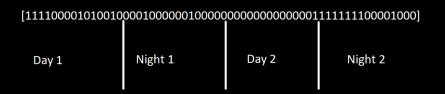
Pros

- Simple, understandable, we've had these since 1989
- I can (and have) implemented this with only numpy
- quick/inexpensive

Cons

- results may be uninformative
- Vanishing Gradient Problem
 - we can't to better than 'meh'

Pre-Classification



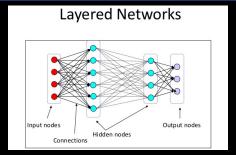
- split the dataset into m groups
- implement m hidden layers for the perception and do much better than 'meh'
- Unfortunately, with sigmoidals this is not possible (Vanishing Gradient)



Solution 2: We Go Deeper

Rectified Linear Activation Function (ReLU)

A piecewise function with constant derivative (linear). It's just a line with a cutoff!



Overhaul sigmoidals and use a ReLU instead

Solution 2: We Go Deeper

Pros

Cons

more informative and reliable output

I still have a thourough understanding of how it works

Cons

more hidden layers are more expensive to train

PyTorch

PyTorch Package for Python

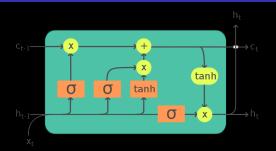
"An open source machine learning framework that accelerates the path from research prototyping to production deployment"



```
>>> rnn = nn.LSTM(10, 20, 2)
>>> input = torch.randn(5, 3, 10)
>>> h0 = torch.randn(2, 3, 20)
>>> c0 = torch.randn(2, 3, 20)
>>> output, (hn, cn) = rnn(input, (h0, c0))
```

PyTorch makes it easy to build things I don't understand!

Solution 3: LSTM



- Recursive (not feedforward) Neural Net
 - feedback connections allow for processing entire sequences of data - Wikipedia
- Sigmoidal but somehow still works
 - solves Vanishing Gradient problem by allowing gradients to flow unchanged - Wikipedia



Solution 3: LSTM

Pros	Cons
invented in 1995Bill Gates likes itOpenAl and Deepmind use itmade for problems like ours	 might be expensive going to require more research I definitely couldn't make this without PyTorch