Using Machine Learning to tell if a Spider Died

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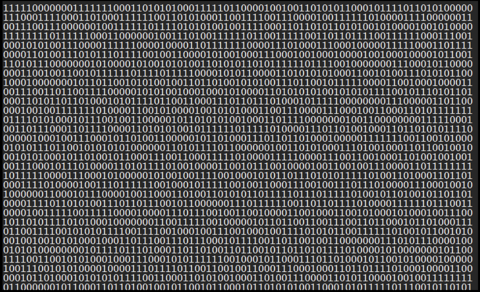
Goal

- 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



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```

Problem

Null Character

Inaction (spider not doing anything) is coded similarly to sleeping.
Actually, its exactly the same

- As is, no human can look at this data and determine if a spider was affected by change in day/night cycle or if it died overnight
- This biases the data, rendering tons of information inconclusive

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...

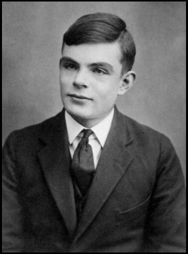
- Action Space: n. We should be able to point (somewhat accurately) to the moment when the spider died.
- State Space: 2^n. Every possible arrangement of 0s and 1s needs to be classifiable. This number is HUGE.

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



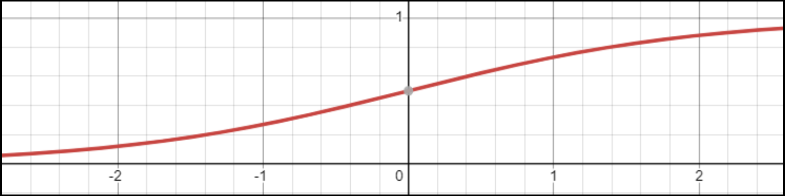
Not So Fast...

Just because it can doesn't mean it won't take forever

So not only do we need to train an algorithm that solves this problem, we need to be smart about it as to not end up spending $1,345,232,923 on AWS.

Solution 1: ‘Meh’ Classifier

Multilayered Perception (MLP)



- a sigmoidal (non-linear) activation function
- outputs on a gradient
  - 0.0 → The spider died (earlier)
  - 1.0 → The the spider is totally still alive
  - $0.25 < x < 0.75$ → ‘Meh’

Solution 1: ‘Meh’ Classifier

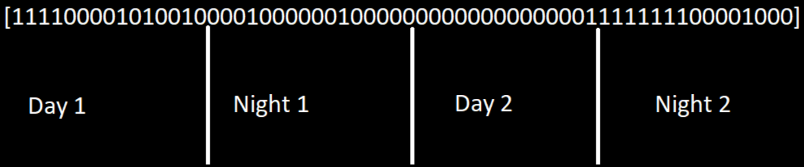
Pros

- 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



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Day 1

Night 1

Day 2

Night 2

- 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

- Solve vanishing gradient problem → more hidden layers!
- unlock more sophisticated 'deep' learning algorithms (CNN, A2C)

Solution 2: We Go Deeper

Pros	Cons
▪ more informative and reliable output ▪ I can still code this myself (with numpy)	▪ more hidden layers are more expensive to train

PyTorch

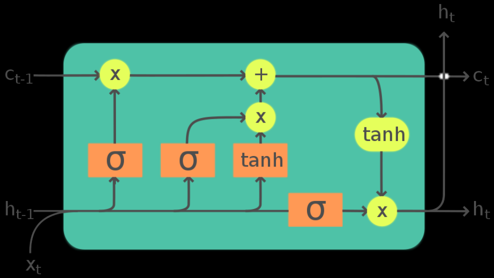
PyTorch Package for Python

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

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

- A2C - Actor Critic
  - value-based actor (Q-learning)
  - policy-based critic (perceptron)
- CNN - Convolution Neural Net
  - multilayered sparsely connected perceptron
  - GoTo choice for image classification
- LSTM - Long-Short Term Memory
  - recursive neural net with variable-time weight updates

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

- invented in 1995
- Bill Gates likes it
- OpenAI and Deepmind use it
- made for problems like ours

Cons

- might be expensive
- going to require more research
- I definitely couldn't make this without PyTorch