2018

Intro to Data Science - Guest Lecture on Deep Learning (Week Thirteen)

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Deep Learning.

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Course - **homepage** - **github**

Tom Sercu - **homepage** - **twitter** - **github**.

This guest lecture - **Preface** - **Main slides** - **Figure** - **lab (github)**

Recapping part 1 (pdf)

DL: Successes

Object recognition

Speech recognition

Machine Translation

"simple" Input->Output ML problems!

DL: Frontiers

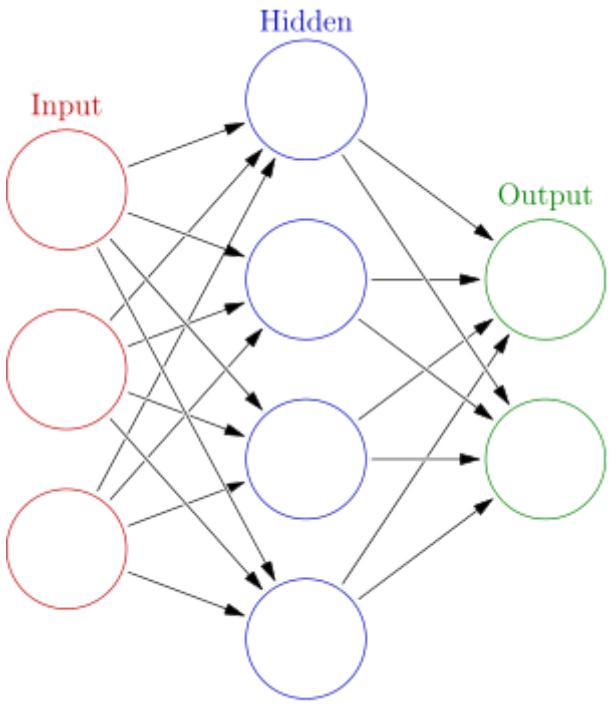
Common sense

What is deep learning? opening the black box

- Forward propagation
  - A bad picture
  - A better picture
- Backward propagation
  - Need to change the weights
  - What is $\nabla_\theta \mathcal{L}(\theta)$
- What's the big deal

Somewhat based on https://campus.datacamp.com/courses/deep-learning-in-python

Forward propagation



$$h(x) = g(W_1 x + b_1)$$
$$y(h(x)) = W_2 h(x) + b_2$$
$$x \in \mathbb{R}^3 \quad h \in \mathbb{R}^4 \quad y \in \mathbb{R}^2$$
$$W_1 \in \mathbb{R}^{4\times 3} \quad b_1 \in \mathbb{R}^4$$
$$W_2 \in \mathbb{R}^{2\times 4} \quad b_2 \in \mathbb{R}^2$$

DL: better picture

Figure

DL: better picture

- All weights/parameters: $\theta = [W_1, b_1, W_2, b_2]$
- The loss = scalar measure how bad $y(x)$ is.
  - For a single sample: $\ell(y(x), y_t; \theta)$
  - For a dataset: $\mathcal{L}(\theta) = \sum_{x,y \in D} \ell(y(x), y_t; \theta)$
- We need to change the weights θ to improve loss $\mathcal{L}(\theta)$.

- How to change weights θ to improve loss $\mathcal{L}(\theta)$?
- Backprop: compute $\nabla_\theta \mathcal{L}(\theta) = \left[\frac{\partial \mathcal{L}}{\partial W_1}, \frac{\partial \mathcal{L}}{\partial b_1}, \frac{\partial \mathcal{L}}{\partial W_2}, \frac{\partial \mathcal{L}}{\partial b_2} \right]$
- $\nabla_\theta \mathcal{L}(\theta)$ = what happens to the loss if I wiggle θ
- Backprop: the chain rule on an arbitrary graph

DL: What's the big deal?

- Stack more layers: **deep** learning...
- Universal function approximator
- Parametrization: build in prior knowledge
  - convolutional: locality and translation invariance
  - recurrent: sequential nature of data
- BUT
  - non-convex optimization: all bets are off
  - no bounds, no guarantees
  - hard to proof anything
- It works

Deep Learning: TLDR

Learn a hierarchy of features

The framework ecosystem

The framework ecosystem

- Old times
  - theano (U Montreal, Y Bengio group)
  - torch (NYU, Yann LeCun group)
  - MATLAB (U Toronto, Geoff Hinton ;)
- Now
  - tensorflow (Google, conceptually close to theano)
    - keras will become new standard
  - pytorch (FAIR, directly descending from torch)
  - ONNX <- one standard to rule them all
    - caffe2, chainer, mxnet, etc.

theano / tensorflow design

- First define the graph
- Then run it multiple times (Session)
- tf: Too low-level for most users
- Many divergent high level libraries on top
  - tf.slim, tf.keras, sonnet, tf.layers, ...
- Recently Keras was adopted as standard
  - Torch-like design

pytorch design

- Construct the computational graph on the go
  (while doing the forward pass)
- "define by run"
- Reduces boilerplate code *a lot*
- Flexibility: forward pass can be different every iteration (depending on input)
- tf tries to imitate this model with "eager mode"

Andrej Karpathy
@karpathy

I've been using PyTorch a few months now and I've never felt better. I have more energy. My skin is clearer. My eye sight has improved.

1,564 2:56 PM - May 26, 2017

436 people are talking about this

my advice for learning DL

Just Do It

“ What I cannot create,
I do not understand ”

Richard Feyman

actual advice

- Work in two stages
  - Fast iteration (playground) -> notebooks
  - Condense it -> version controlled python scripts
- 1. Fast iteration stage:
  - take everything apart
  - no structure, no abstractions
- 2. Condense it
  - carefully think about the right abstractions
- github repo's can be a great starting point
  - ..but start from scratch a couple times

DL: math

- ML = optimization
- Gradient descent
- SGD = Stochastic gradient descent
- Backpropagation revisited
- Beyond SGD

ML = optimization

This is all of ML:

$$\arg\min_{\theta} \mathcal{L}(\theta)$$

Gradient descent

Find argmin by taking little steps α along :

$\nabla_\theta \mathcal{L}(\theta)$

$\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}(\theta)$

Stochastic Gradient descent

Oops $\nabla_\theta \mathcal{L}(\theta)$ is expensive, sums over all data.

Ok instead of $\mathcal{L}(\theta) = \sum_{x,y \in D} \ell(x, y; \theta)$

Let us use $\mathcal{L}^{mb}(\theta) = \sum_{x,y \in mb} \ell(x, y; \theta)$

$\mathcal{L}^{mb}(\theta)$ is the loss for one minibatch.

Backpropagation

Compute $\nabla_\theta \mathcal{L}^{mb}(\theta)$ by chain rule:

reverse the computation graph.

Beyond SGD

- SGD is the simplest thing you can do.
  What else is out there?
- Second order optimization.. meh
- Adaptive learning rate methods

A word about overfitting

with deep learning,
you can (over)fit anything you want