Deep Learning
Image Classification

BMI701 Introduction of Biomedical Informatics
Lab Session 10

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HMS DBMI — MGH LCS

Google @ JAMA

JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

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IMPORTANCE Deep learning is a family of computational methods that allow an algorithm to program itself by learning from a large set of examples that demonstrate the desired behavior, removing the need to specify rules explicitly. Application of these methods to medical imaging requires further assessment and validation.

OBJECTIVE To apply deep learning to create an algorithm for automated detection of diabetic retinopathy and diabetic macular edema in retinal fundus photographs.

DESIGN AND SETTING A specific type of neural network optimized for image classification called a deep convolutional neural network was trained using a retrospective development data set of 128 175 retinal images, which were graded 3 to 7 times for diabetic retinopathy,

Editorial

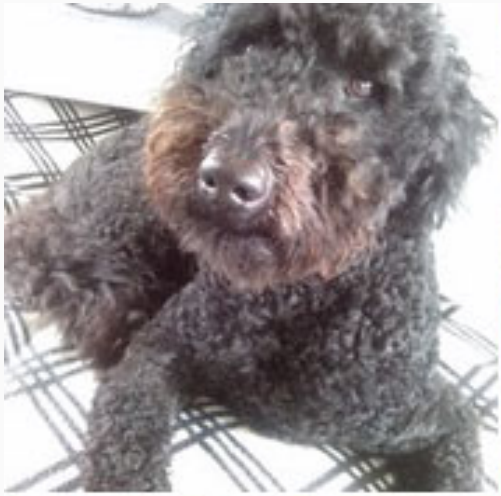
Supplemental content

Gulshan 2016

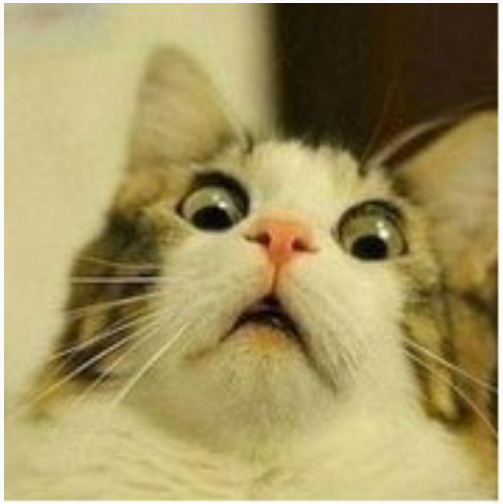
Deep Learning?

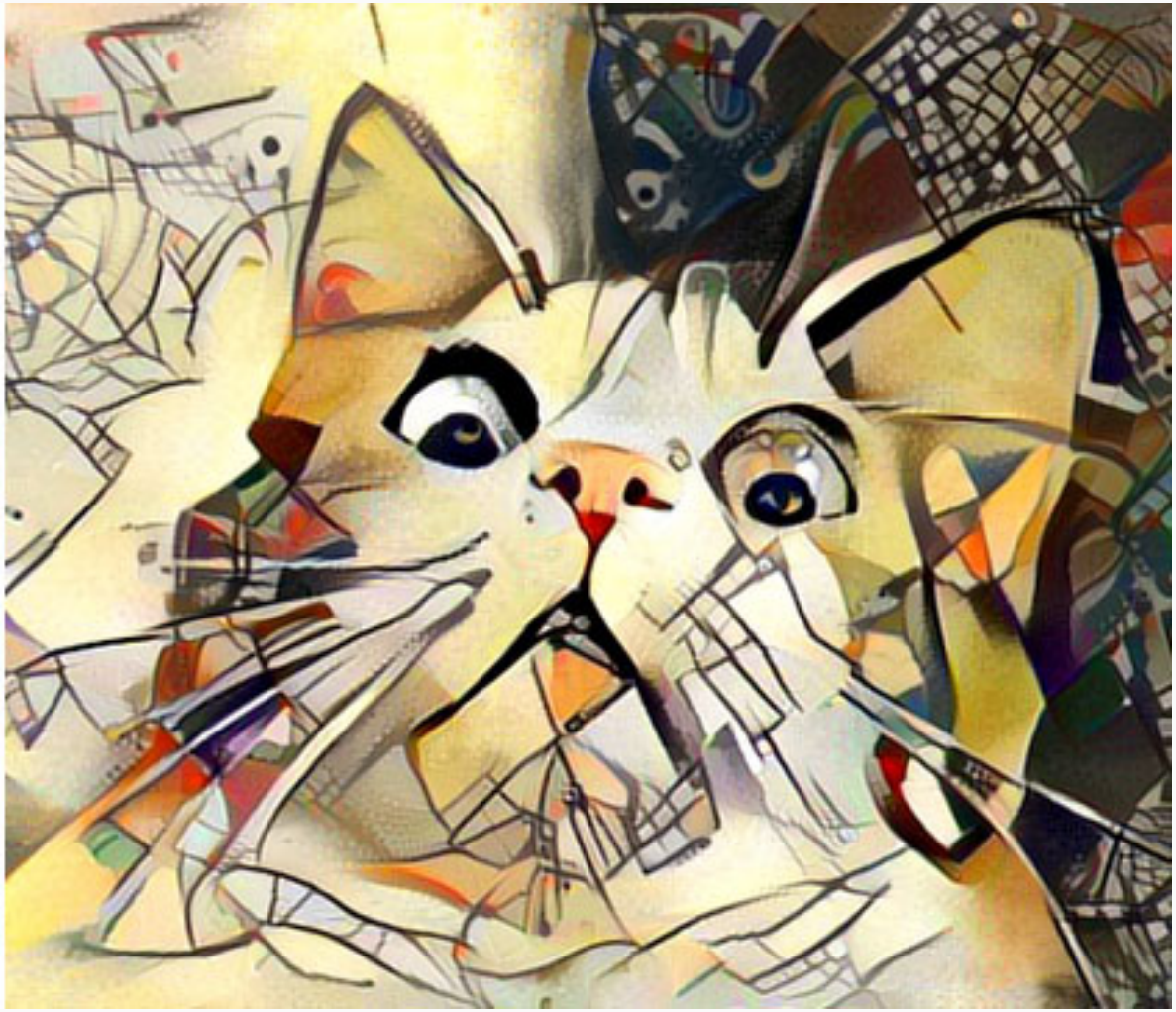
- As Go master
- As an artist
- Deep style
- Deep dream
- How DNN think about your selfie
- Deep learning Google trend
- Simply to say, less feature engineering by hand
- Multiple layers perceptron
- IDEA! Rebrand Neural Nets $\rightarrow$ Deep Nets
- $\uparrow$ Computational power
- Very good Nature review paper by three big names (LeCun, Bengio, Hinton)

Vincent Van Dog



Kandinsky Cat





Outline

- Brief introduction of deep learning
- Algorithms
- Using R to do image classification

Why Deep Learning?

- Shallow vs. deep?
  - Shallow network can represent any function (given enough hidden neurons), but deep structure is more effective
  - Less parameteres
  - Less training data and hand-crafted features
  - More machine learning
- Modularization

Step by Step

- Network Structure: A set of function
- Learning Target: Define the goodness of a function
- Learn: Pick the best function f

Network Structure

- Neuron
- Input layer
- Hidden layers
- Output layer (softmax)
- Weight / bias $\rightarrow$ network parameters θ
- Activation function: sigmoid / ReLU
- Fully connected feedforward network

Learning Target?

- Make your **loss** as small as possible
- Find a function f and parameters θ to
- $argminL = \sum_{r=1}^{R} l_r$

Learn

- Gradient descent
- Randomly pick up w
- Compute $\partial L/\partial w$
  - Negative $\rightarrow$ increase w
  - Positive $\rightarrow$ decrease w
  - $w \leftarrow w - \eta \partial L/\partial w$
  - η is so called learning rate
- Repeat and repeat until $\partial L/\partial w \rightarrow 0$
- Do gradient decent on all w and $b \rightarrow \nabla L$
- Sometimes it goes to local minimum when you assign different initial w
- Using backpropagation to compute $\partial L/\partial w$
- Don't use your hand, use the developed tools...
  - Theano, Tensorflow, Caffe, Torch, ...
  - Keras

Some Tips

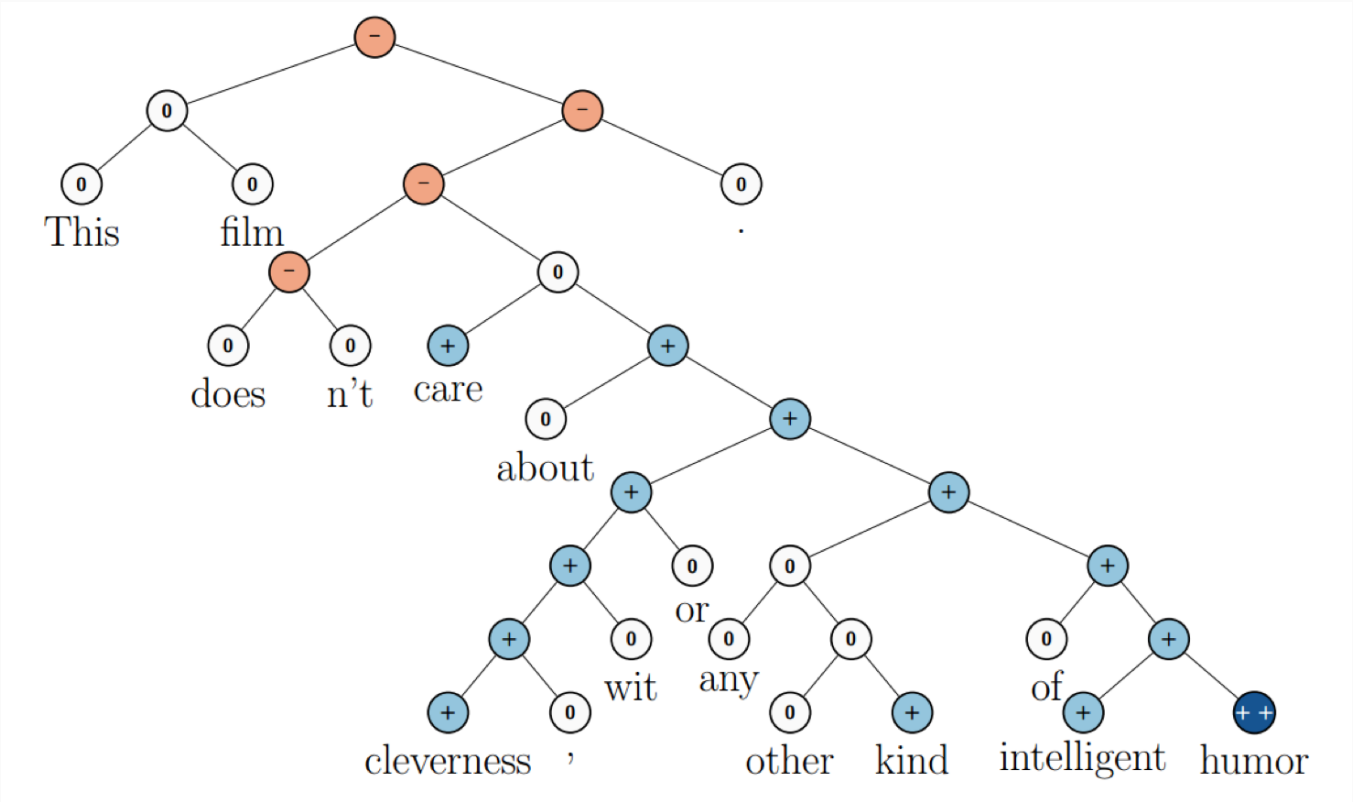
- Choose proper loss: square error vs. cross entropy
  - Use CE when you use softmax output
- Mini-batch
  - Update once after going through all sample
  - Update 100 times in one epoch if you have 100 batches
  - Fast convergence
- New activation function
  - When you have too many layers
  - GD will almost disappear, learn very slow and almost randomly
  - Use ReLU / maxout instead of sigmoid
- Adaptive learning rate
  - Adagrad ($\eta_w = \frac{\eta}{\sqrt{\sum_{i=0}^{t}(g^i)^2}}$)
- Momentum
  - Add some momentum to get out of local minimum
  - Adam algorithm (Advanced Adagrad + Momentum)

Some Tips

- Early stopping
- Regularization / weight decay
  - $w \leftarrow$ smaller and smaller...$w - \eta \partial L / \partial w$
- Dropout
  - Remove x% neurons in each mini-batch (resampling)
  - Network structure will be different
  - Do better job?
  - Sort of emsemble method (different batch, different network, average them)
- Different network structures
- Deep Playground by Google Tensorflow

Network Structure

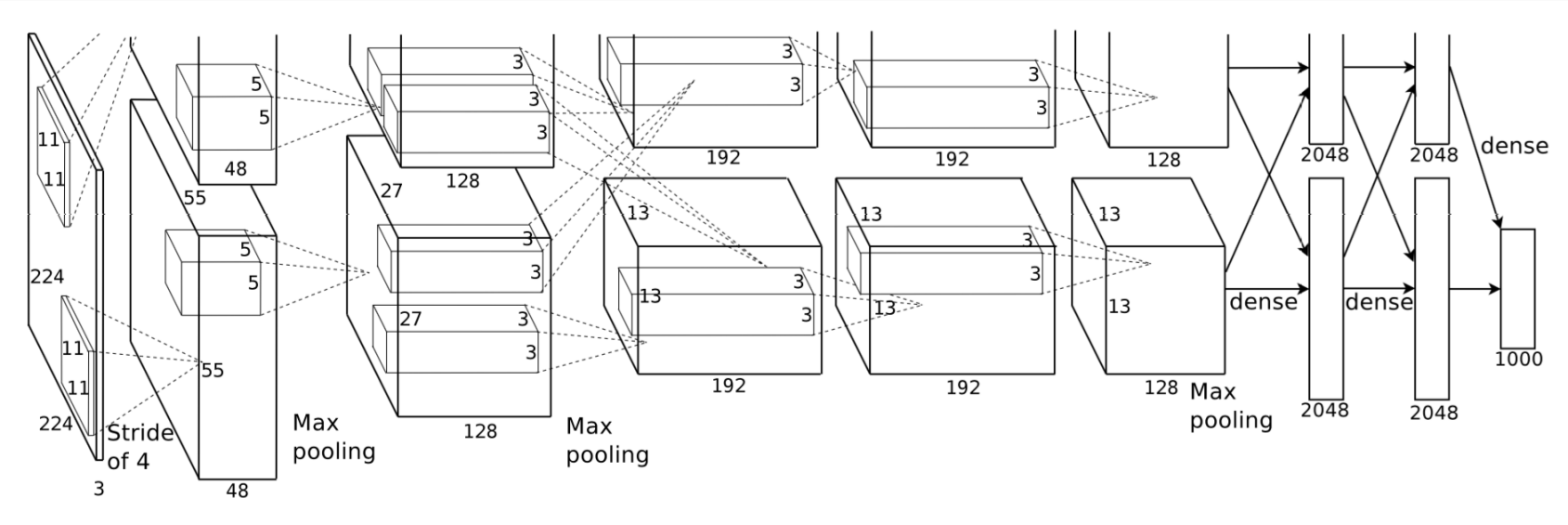
- RNN / LSTM



Socher 2012

Network Structure

- CNN
  - Convolution → max pooling → convolution → max pooling → ... → flatten → fully connected feedforward → softmax



Krizhevsky 2012

Why CNN?

- Some patterns are much smaller than the whole image: No need to use whole image as the input of the neuron
- Some patterns appear again and again in different places: Neurons do the almost same thing so they can share the same parameters
  - Convolution
- Subsampling will not change your perception
  - Max pooling
- So in fact, CNN is a simpler ANN architecture with less parameters
- But your input should have the features related to image recognition
  - AlphaGo use 5×5 for the first layer
  - But AlphaGo didn't do subsampling (no max pooling)

Network Structure of Alpha Go

Neural network architecture. The input to the policy network is a $19 \times 19 \times 48$ image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23×23 image, then convolves k filters of kernel size 5×5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21×21 image, then convolves k filters of kernel size 3×3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1×1 with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used $k = 192$ filters; Fig. 2b and Extended Data Table 3 additionally show the results of training with $k = 128$, 256 and 384 filters.

Silver, Huang 2016

What Does CNN Learn?

- 1st filter: Easy to understand
- 2nd filter: Input is the value after convulition and max pooling, NOT pixels!
- Degree of the activation of the k-th filter: use gradient ascent
- Filter before flatten: detect texture
- Filter after flatten: larger scale patterns
- But... DNN are easily fooled
    - Use regularization (e.g. LASSO)

Imaging Classification

- Using Theano
  - Courtesy by DeepLearning.net
  - Theano documentation
- Using H2O in R

Some Deep Learning Resource

- TED talk: Fei-Fei Li
- Theorerical deep learning: Yoshua Bengio
- Udacity: Deep learning course
- Stanford CS231n: CNN for Visual Recognition (Li)
- Stanford CS224d: Deep Learning for NLP (Socher)
- Deep Learning Book

Summary

- Thank you for coming to my lab sessions!
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