Deep Learning and Neural Nets

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Return Path

- Worldwide leader in email intelligence
- Collect and aggregate enormous amounts of email data, including *raw text data*
- Help receivers improve spam filtering with whitelists, blacklist, reputation scoring
- Help senders improve their email sending program
- Great place to work!

Supervised/Unsupervised Learning

- ***Supervised learning (classification/regression):*** start with a *training set* of *labeled* observations (x1, y1), …, (x_N, y_N), where *x’s* are *inputs*, *y’s* are outputs
  - Create algorithm to “learn” pattern from observations to make predictions on new inputs (like generalized curve-fitting)
    - Example: given a *labeled* training set of pictures of dogs and other animals, create an algorithm to recognize pictures of dogs
- ***Unsupervised learning (clustering, feature extraction, dimensionality reduction):*** automatically find patterns, groupings, useful variables in an *un*labeled dataset
  - Example: given an *unlabeled* set of pictures of animals, create an algorithm to automatically distinguish between different types of animals
- Supervised learning is typically easier
  - **BUT** you need a labeled training set, often a BIG one

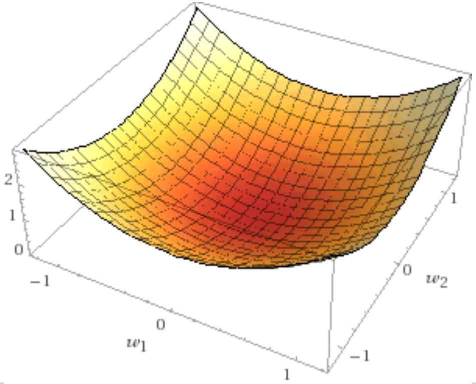
How to train a learning algorithm

1. Initialize ***parameters*** of model
2. Run data through algorithm
3. Compute ***cost function*** based on model run-through
    a. Supervised learning: cost function computed based on how close model output is to training set labels
        i. Example: RMSE = sqrt(mean((outputs - labels)^2))
    b. Unsupervised learning: usually problem-specific
        i. Example: how well-separated are the clusters?
4. Adjust the parameters to reduce the value of the cost function
    a. Usual method: gradient descent
5. Repeat the process until the cost function reaches a *threshold* (usually defined by the *gradient* of the cost function being *small*)

Gradient descent

- **Gradient descent:** adjust parameters of cost function according to direction of gradient
- **Gradient:** If *f* is a function of *N* parameters *w_1, w_2, …, w_N*, then the *gradient* of *f* is the vector **grad** *f = [∂f/(∂w_1), … , ∂f/(∂w_N)]*, where *∂f/(∂w_i)* is the rate of change of f with respect to a change in the variable *w_i* – called the partial derivative of f *with re*spect to *w_i*

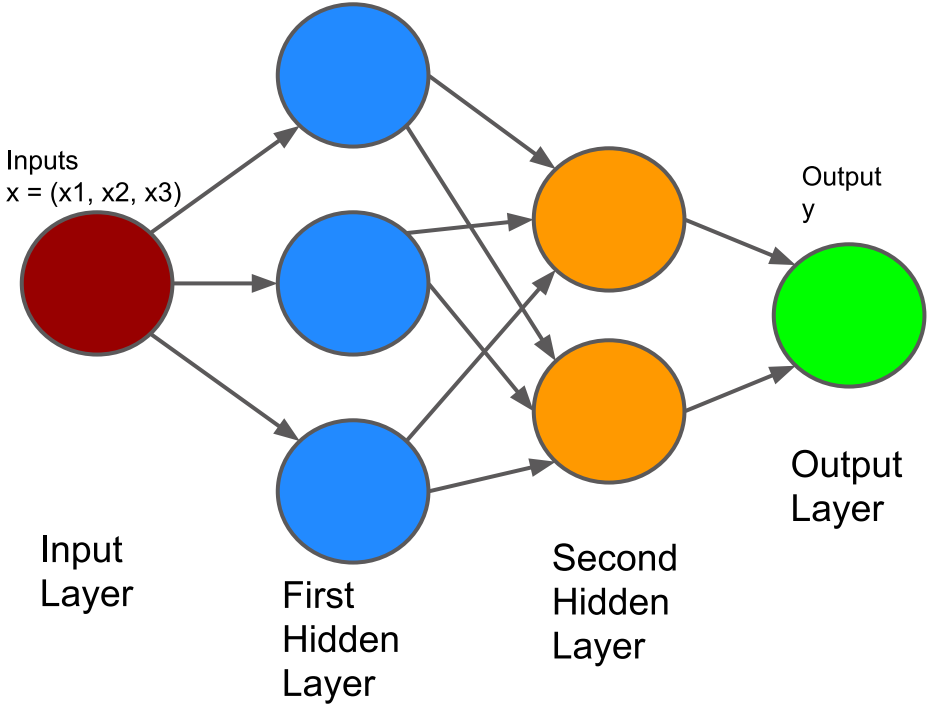
Cost function at a minimum ⇒ **grad** *f* = 0 (does *not* work the other way!!)



What is a Neural Network?

- Artificial Neural Networks are machine-learning algorithms (loosely) based on the human brain
- Network of nodes (“neurons”) that perform computations
- Can be used for supervised or unsupervised learning

A simple neural net



1. Inputs enter first **hidden layer** “neurons”, and are transformed by **activation function**, then
2. passed to second hidden layer, and transformed again by activation function, then passed to **output layer**
3. **Cost function** calculated based on outputs
4. **Parameters** of activation function adjusted to reduce value of cost function (*gradient descent*)
5. Process repeated until gradient reaches small enough *tolerance*

Activation and Cost Functions

- **Activation Function (one at each node of each hidden layer):**
  - *logistic function*: $f(x) = 1/(1 + exp(-x))$
    - $x = w\_1\ x\_1 + w\_2\ x\_2 + \ldots + w\_n\ x\_n$ (weighted sum of inputs from previous layer)
    - *parameters:* w_1, …, w_n
  - *ReLU* (rectified linear units): approx. linear combo of logistic functions
    - prevents *local minimum problem* in gradient descent (more later)
- **Cost Function:**
  - Supervised learning (classification, regression): often RMSE = sqrt (mean((outputs - labels)^2))
  - Unsupervised learning (clustering, feature extraction): problem specific

What is Deep Learning?

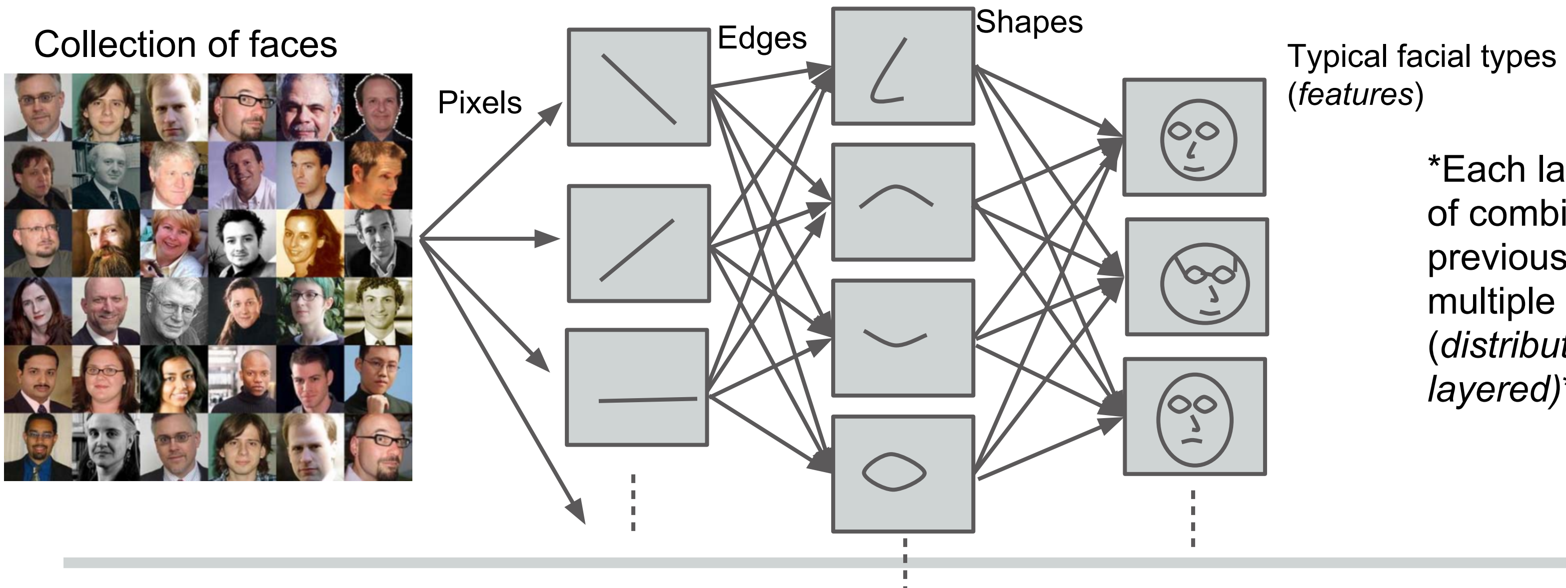
- *Deep learning* is a collection of methods based on training neural nets with *many* hidden layers
- Advantages:
  - State of the art for machine translation, image recognition, speech recognition tasks
  - Accurate at classification and regression (supervised learning) with much smaller *labeled* training sets than typical ML algorithms
  - Automatically *learns* useful features of dataset
- Disadvantages:
  - Slow to train
  - Prone to *overfitting*
  - Prone to *local minimum problem*

Feature learning

- A *feature* of a dataset is a carefully-selected combination of the original variables
  - Ex: edges or colors in a collection of nature pictures
  - Ex: noses or eyes in a collection of pictures of faces
  - Ex: meaningful, common phrases in a collection of documents
  - Ex: chords or repeated rhythms in a collection of songs
- ML algorithms work better when you feed in the *right* features to the training algorithm
- The problem: typically, humans have to engineer useful features *by hand*
- The solution: deep learning algorithms (just like our brain) *learn* useful features *automatically*

Layered feature representations

- In the human brain, images are represented as a *distributed*, *multi-layered*, *feature* representation
  - Humans see *features*, not just *pixels*



*Each layer is made up of combinations of the previous layer, using multiple nodes (*distributed*, *multi-layered*)*

One learning algorithm hypothesis

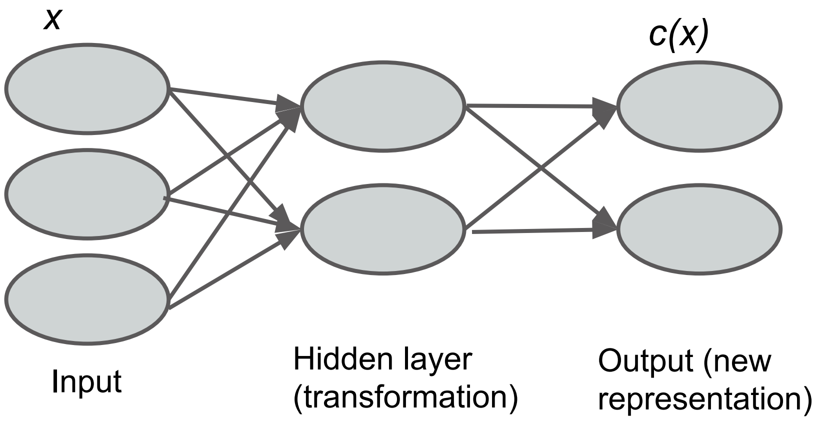
- Sight, hearing, touch all seem to use the *same* distributed multi-layered feature representation learning algorithm
- How do we know?
    - Experiments “rewiring” the vision and sound centers of animal brains
    - In humans: “seeing” with your tongue, feeling the direction North
- Deep learning neural nets perform well on image recognition, speech recognition, text processing, etc.
    - Same architecture, same algorithm, same results -- on different tasks!

How does deep learning work?

- Modeled after multi-layer, distributed feature representation in brain
- Multiple hidden layers in neural nets
    - Each layer *learns* a new feature representation of previous layer (ie. pixels -> edges -> shapes -> typical face types)
        - uses an *autoencoder* or *Restricted Boltzmann Machine* (more on this later)
    - Feature representation is learned *one layer at a time*, starting with the simplest representation (pixels -> edges)
        - called *layerwise pre-training*

Autoencoders

- An *autoencoder* is a neural network that attempts to learn an efficient, *distributed, feature representation* of its inputs
    - tries to learn a new *encoding c(x)* of the input *x*
    - Cool aside: an autoencoder with a *linear* activation function does the same transformation as PCA



Layerwise pre-training

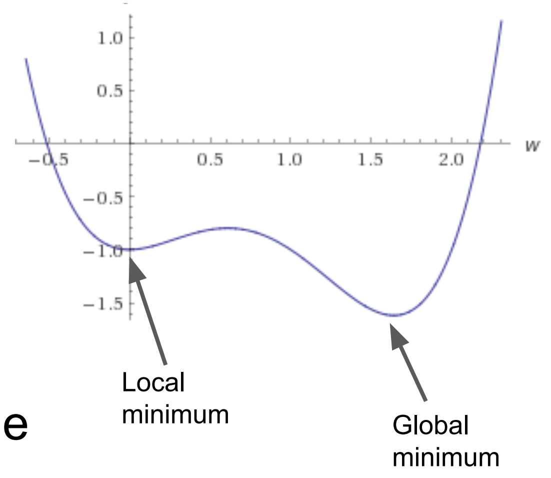
- Each hidden layer of a deep neural net is itself an autoencoder
- At each layer, a new representation of the the inputs from previous layer is learned
- This automatically *learns* useful features from dataset

Why does deep learning work?

- The features deep-learning networks automatically learn are often *much* more useful than human-engineered features (and take *much* less work to create)
- Useful features means
  - Faster training time
  - Fewer examples needed for training (smaller *training set*)
  - Easier to recognize similar examples, distinguish different examples
- Ex: a child only needs to see a few trucks before learning the typical features of a truck
  - Can generalize the feature representation of “truck” to bulldozers and army tanks, and even see the relationship to planes or boats
  - Deep learning neural nets attempt to do essentially the same thing

The local minimum problem

- **grad** *f* = 0 does not imply *f* is at a *global* minimum!
- Why: a cost function could have multiple local minima
- Training can get *stuck* at a *local* minimum that is not a *global* minimum if the gradient gets really *small*, because:
    - parameters are adjusted less when the gradient is small
    - algorithm is stopped when the gradient reaches small enough *tolerance*
- Why is this bad?
    - Algorithm is not as accurate as it *could* be if the cost function is not as *low* as it could be

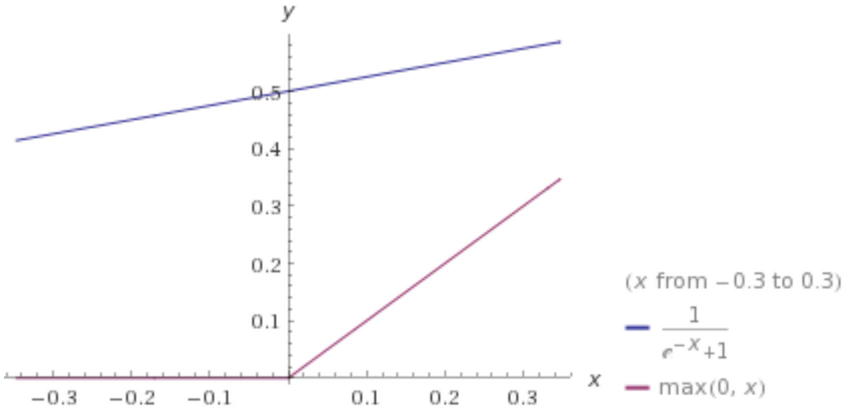


ReLU

- Deep learning is prone to *local minimum problem*
  - can get "stuck" at a low point of the gradient of the cost function
- Problem: *logistic* activation function has very *small* gradient (rate of change) for small values of *x*
- Solution: instead of using *tanh* function, use activation function called *ReLU*: "rectified linear units"

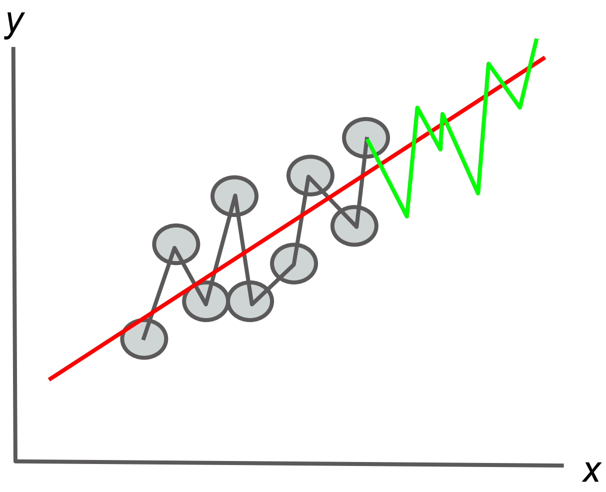
  f(x) = max(0,x)

Gradient of ReLU function does *not* get too small for small *x*



Overfitting

- **Overfitting:** *overfitting* occurs when a machine-learning algorithm fits "too well" to the training set, and does not generalize well to new data
- Example:



Line plus random Gaussian noise

$y = x + \nu$

$\nu \sim \mathcal{N}(0,1)$

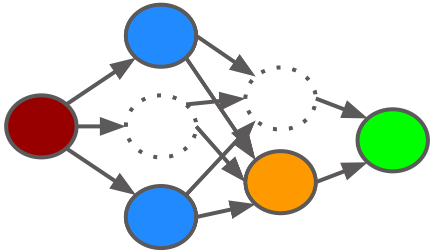
The *real* pattern is just a straight line. An *overfit* ML algorithm learns a pattern that is *simply not there*!

Preventing overfitting

- Cause: too many variables for the dataset
  - Ex: Fitting a 100-variable linear model to a dataset with only 3 relevant variables
- Solution: choose a number of variables appropriate to modeling task
- Cause: modeling algorithm too complicated for the dataset
  - Ex: Fitting a complex deep neural net to a linear dataset
- Solution: Test multiple types of modeling algorithms. Select model *hyperparameters* (like number of nodes of a neural network or number of variables in a tree-based model) with a *tuning grid*
- Specific to neural nets: *dropout* methods

Dropout

- Deep learning neural nets prone to *overfitting*
  - May learn features that are *not* important
    - Ex: may learn the logo “Ford” if looking at lots of trucks
- Solution: *dropout*
  - Randomly leave out neurons on each training example during training



- Works by not adjusting parameters *too much* on any given training example

The state of the art

- For supervised learning problems, “traditional” deep learning (from 2006 up until a few years ago) used layerwise unsupervised pre-training
  - Using ReLU and Dropout, it is possible to train deep learning models faster and more accurately, *without* using unsupervised pre-training
    - Caveat: you typically need a *lot* of training data for this to work
- Deep learning at (very) large scale: lots of top experts have moved to industry to implement deep learning for *huge* data business problems
  - Geoffrey Hinton works at Google
  - Yann LeCun works at Facebook
  - Andrew Ng works at Baidu
- Deep learning is getting easier to implement
  - Better documentation, better software libraries, Amazon GPU clusters, etc.

When to use deep learning

- When to use deep learning:
    - Complex, cognitive tasks with latent *deep structure*
        - Machine translation, image recognition, speech recognition, feature selection from a complex dataset
- When *not* to use deep learning:
    - Typical machine-learning tasks *without* deep structure: risk of overfitting
        - Deep learning is still difficult to implement compared to simpler methods

Implementing Deep Learning

- Python libraries: *theano* and *pylearn2*
- *theano*: a high-performance computing and computer-algebra system library
  - includes GPU computing functionality
- *pylearn2*: contains methods for training deep neural nets (uses *theano* for computation)
- Check out http://deeplearning.net

Questions?

- Thanks for listening, and thanks for inviting me to speak!
- Find me on my personal website: http://williamgstanton.com
- Connect with me on LinkedIn