Neural networks

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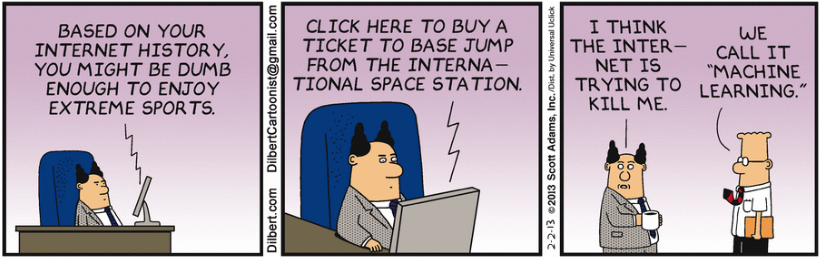

BASED ON YOUR INTERNET HISTORY, YOU MIGHT BE DUMB ENOUGH TO ENJOY EXTREME SPORTS.
Dilbert.com DilbertCartoonist@gmail.com
CLICK HERE TO BUY A TICKET TO BASE JUMP FROM THE INTERNA– TIONAL SPACE STATION.
2-2-13 ©2013 Scott Adams, Inc./Dist. by Universal Uclick
I THINK THE INTER– NET IS TRYING TO KILL ME.
WE CALL IT "MACHINE LEARNING."

Neural networks

Our learning algorithms so far:

$$\text{Training data: } (x_i, y_i)_{i=1}^n \longrightarrow \text{Machine Learning} \longrightarrow y = \hat{f}(x)$$

All of the procedures directly work on input features.
What if the input features are not informative?

Neural networks

Feature engineering — handcrafting transformations

$$\text{Training data: } (x_i, y_i)_{i=1}^n \longrightarrow \Phi \longrightarrow (\Phi_x(x_i), \Phi_y(y_i))_{i=1}^n$$

Here Φ is designed by a human.

$$(\Phi_x(x_i), \Phi_y(y_i))_{i=1}^n \longrightarrow \text{Machine Learning} \longrightarrow \Phi_y(y) = \hat{f}(\Phi_x(x))$$

This process is expensive and time consuming.

Example: Handwritten Digit Recognition

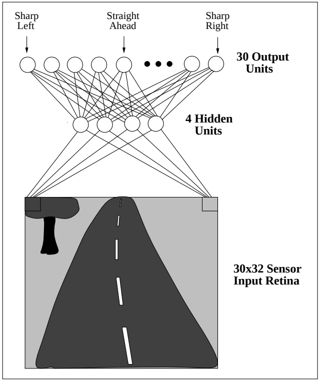
$P(y = 2 \mid$  $, b)$

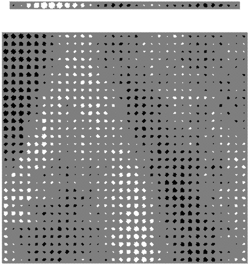
$P(y = 9 \mid$  $, b)$

How to represent image?
How informative is each pixel?
Logistic regression trainned on pixel values gives ~90% accuracy.

Example: ALVINN

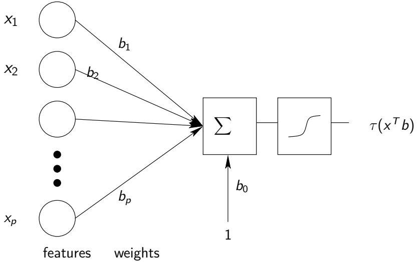
Autonomous Land Vehicle In a Neural Network



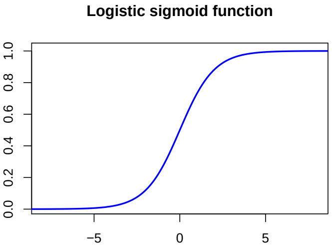


Video: `http://watson.latech.edu/book/intelligence/intelligenceOverview5b4.html`

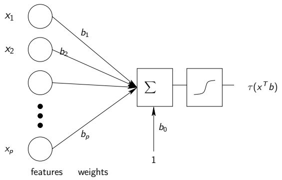
Model of a neuron



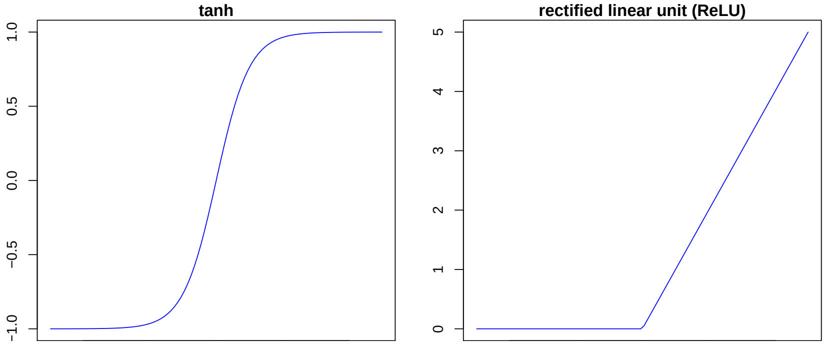
A close couising to perceptron. Think about putting a rug over the threshold.



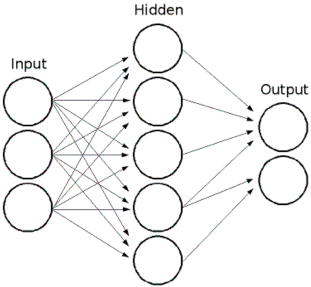
Model of a neuron



Other nonlinear activations



Multilayer Perceptron



2 Layers of Neurons

- 1st layer takes input x
- 2nd layer takes output of 1st layer
- The last layer is the output

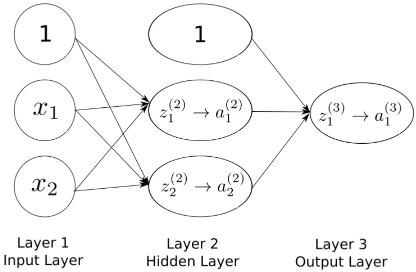
Multilayer Perceptron

The activities of the neurons in each layer are a non-linear function of the activities in the layer below.

Can approximate arbitrary functions

- Provided hidden layer is large enough
- "fat" 2-layer network

1 hidden layer details



$$z_1^{(2)} = b_{10}^{(1)} + b_{11}^{(1)} x_1 + b_{12}^{(1)} x_2 \longrightarrow a_1^{(2)} = g(z_1^{(2)})$$

$$z_2^{(2)} = b_{20}^{(1)} + b_{21}^{(1)} x_1 + b_{22}^{(1)} x_2 \longrightarrow a_2^{(2)} = g(z_2^{(2)})$$

$$z_1^{(3)} = b_{10}^{(2)} a_0^{(2)} + b_{11}^{(2)} a_1^{(2)} + b_{12}^{(2)} a_2^{(2)} \longrightarrow a_1^{(3)} = g(z_1^{(3)})$$

Example: Simulated XOR

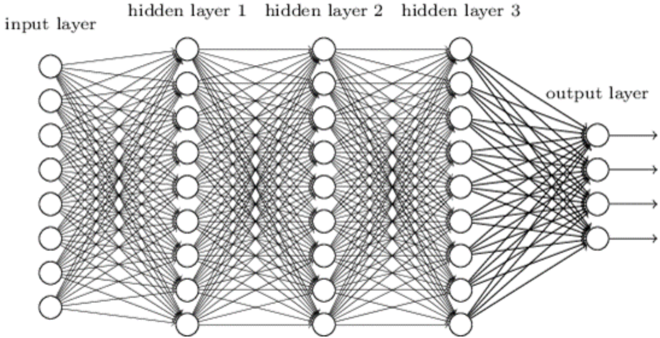
- See *xor.h2o.R*

Example: Regularization in logistic regression

Example: Tabloid data

- See *tabloid.h2o.R*

Deep neural network



If there is more than one hidden layer, networks are called “deep” neural networks.

Fitting neural networks

Gradient descent + chain rule + lot of tricks

- We will not provide details
- The procedure is called backpropagation

Difficult to train because there are many local minima

- Train multiple nets with different initial weights
- Initialize weights near zero
- Therefore, initial networks near-linear
- Increasingly non-linear functions possible as training progresses

Fitting neural networks

Adaptive Learning Rate

- Automatically set learning rate for each neuron based on its training history
- ADADELTA:
  http://www.matthewzeiler.com/pubs/googleTR2012/googleTR2012.pdf

Momentum

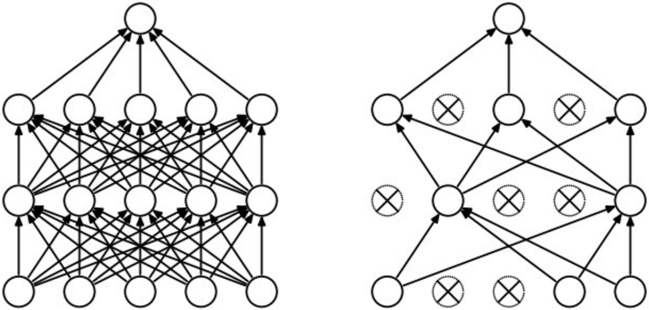
- $b^{t+1} = b^t - \eta \cdot \nabla J(b) + \alpha(b^t - b^{t-1})$
- α is the momentum parameter
- helps avoiding stuck in a local optimum

Regularization

- L1 penalty on the parameters
- L2 penalty on the parameters (weight decay parameter)
- Early stopping

Fitting neural networks

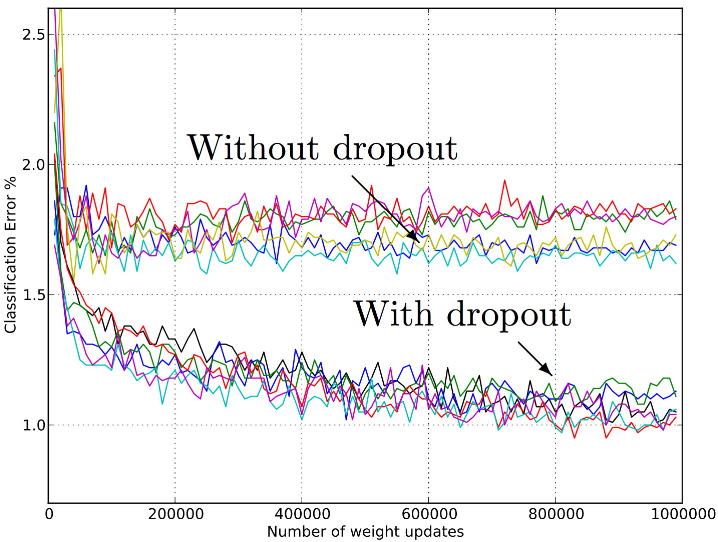
Dropout:



(a) Standard Neural Net (b) After applying dropout.

https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf

Fitting neural networks



https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf

Fitting neural networks: Tips from H_2O

- more layers for more complex functions (more non-linearity)
- more neurons per layer to fit finer structure in data
- add regularization (max_w2=50 or L1=1e-5)
- do a grid search do get a feel for parameters
- try "Tanh," then "Rectifier"
- try dropout (input 20%, hidden 50%)

See also `http://yyue.blogspot.com/2015/01/a-brief-overview-of-deep-learning.html`

Example: MNIST

Famous data set in machine learning community

- http://yann.lecun.com/exdb/mnist/

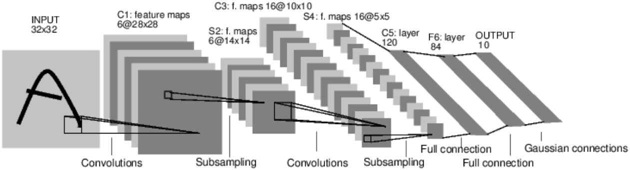
Kaggle competition (recent competition)

- https://www.kaggle.com/c/digit-recognizer

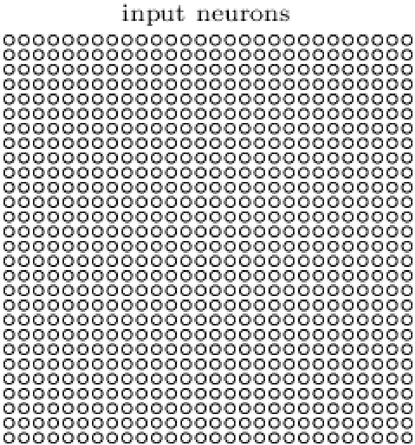
Online demo

- http://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

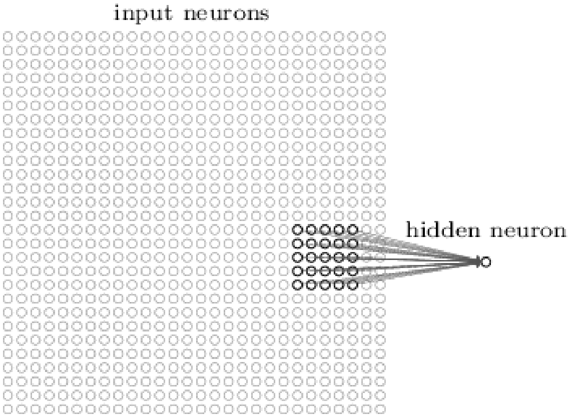
LeNet5: convolutional neural network



See `http://yann.lecun.com/exdb/lenet/`



From: http://neuralnetworksanddeeplearning.com/chap6.html



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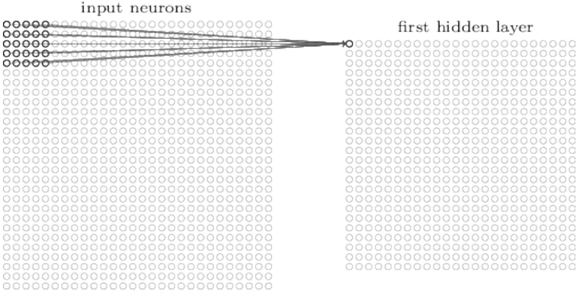

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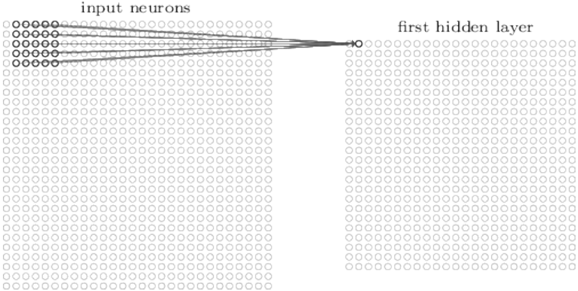

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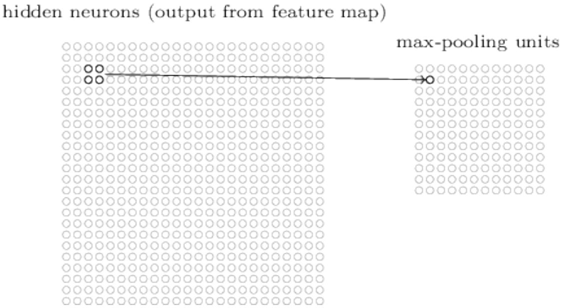
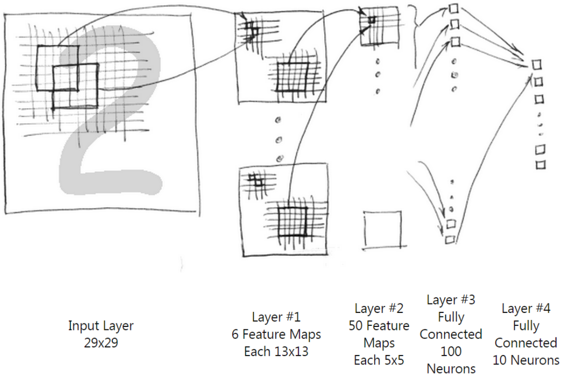


From: http://neuralnetworksanddeeplearning.com/chap6.html

Mistakes made by LeNet5

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, november 1998.

A simpler architecture



From: http://www.codeproject.com/Articles/16650/Neural-Network-for-Recognition-of-Handwritten-Digi

Practical consideration

Standard trick — expand the set of examples

- small distortions, scaling, rotation, ...

What else needs to be done to make system useful?

Advantages and disadvantages

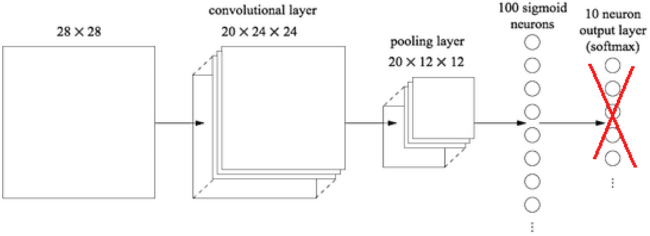
Pros:

- Tolerance to noise
- Able to capture complex signals
- In some applications lead to the state-of-the-art performance
- Fast at test time

Cons:

- Very hard/impossible to interpret (black box method)
- Can easily overfit
- Need a large amount of data to train
- Slow to train

Learning representation



Use the output of the last layer as a representation of your data.
Fit a model with this representation.

Some success stories

- Google voice transcription

  http://googleresearch.blogspot.com/2015/08/the-neural-networks-behind-google-voice.html

- Google voice search

  http://googleresearch.blogspot.com/2015/09/google-voice-search-faster-and-more.html

- Google translate app

  http://googleresearch.blogspot.com/2015/07/how-google-translate-squeezes-deep.html

Some success stories

- Facebook face recognition

  http://www.technologyreview.com/news/525586/facebook-creates-software-that-matches-faces-almost-as-well-as-you-do

- Paypal fraud detection

  http://www.slideshare.net/0xdata/paypal-fraud-detection-with-deep-learning-in-h2o-presentationh2oworld2014

Additional resources

- Deep Learning by Ian Goodfellow and Yoshua Bengio and Aaron Courville `http://www.deeplearningbook.org/`
- Free online book by Michael Nielsen
  `http://neuralnetworksanddeeplearning.com/`
  (explains backpropagation well)
- `http://deeplearning.net/tutorial/`
  Excellent tutorial using Theano library in Python