Neural Networks

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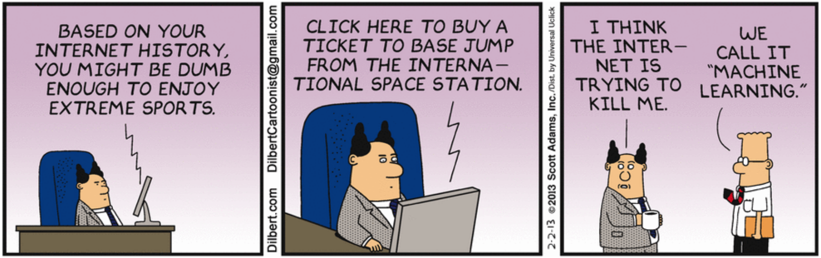
BASED ON YOUR INTERNET HISTORY, YOU MIGHT BE DUMB ENOUGH TO ENJOY EXTREME SPORTS.
CLICK HERE TO BUY A TICKET TO BASE JUMP FROM THE INTERNATIONAL SPACE STATION.
I THINK THE INTERNET IS TRYING TO KILL ME.
WE CALL IT "MACHINE LEARNING."
Dilbert.com DilbertCartoonist@gmail.com
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Neural 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

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

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

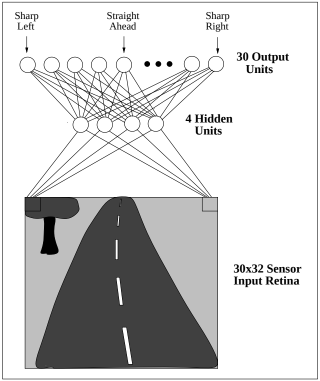
How to represent image?

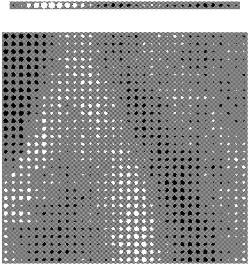
How informative is each pixel?

Logistic regression trainned on pixel values gives ~90% accuracy.

Example: ALVINN

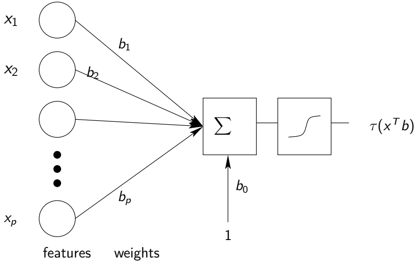
Autonomous Land Vehicle In a Neural Network



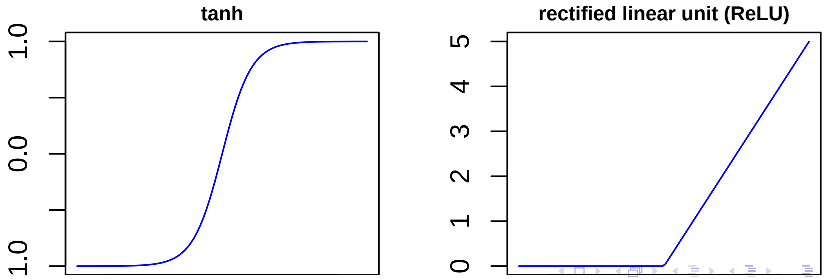


Video: `http://watson.latech.edu/book/intelligence/intelligenceOverview5b4.html`

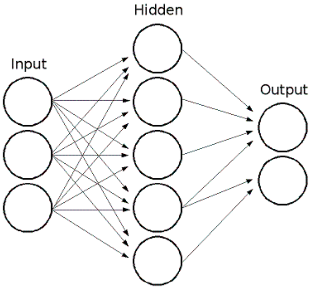
Model of a neuron



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

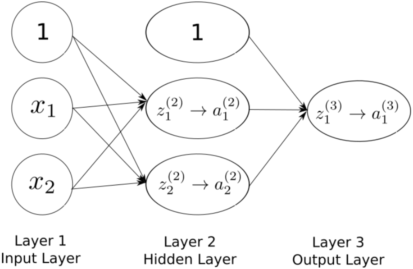
Multilayer Perceptron

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

Can approximate arbitrary functions

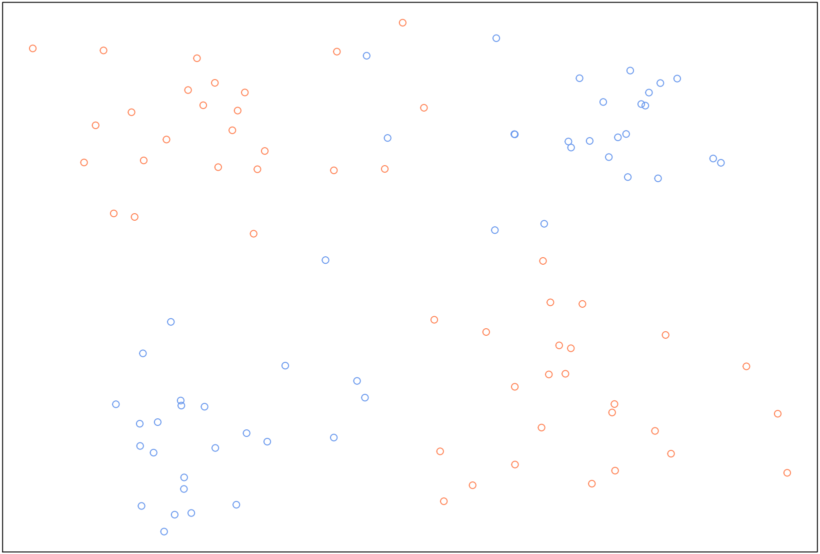
- Provided hidden layer is large enough
- "fat" 2-layer network

1 hidden layer details

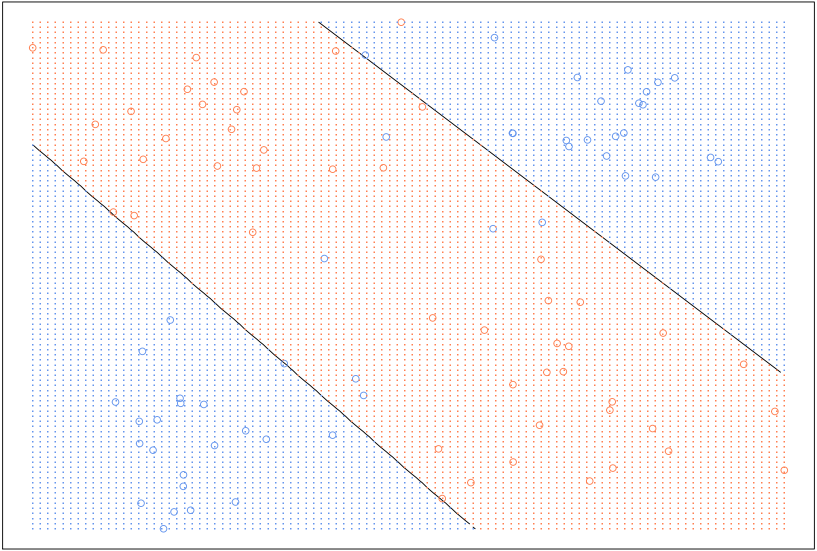


$$
\begin{aligned}
z_1^{(2)} &= b_{10}^{(1)} + b_{11}^{(1)} x_1 + b_{12}^{(1)} x_2 & \longrightarrow \quad & a_1^{(2)} = g(z_1^{(2)}) \\
z_2^{(2)} &= b_{20}^{(1)} + b_{21}^{(1)} x_1 + b_{22}^{(1)} x_2 & \longrightarrow \quad & a_2^{(2)} = g(z_2^{(2)}) \\
z_1^{(3)} &= b_{10}^{(2)} a_0^{(2)} + b_{11}^{(2)} a_1^{(2)} + b_{12}^{(2)} a_2^{(2)} & \longrightarrow \quad & a_1^{(3)} = g(z_1^{(3)})
\end{aligned}
$$

Example: Simulated XOR



neural network –– 1 hidden layer with 2 neurons



Weights in hidden layer

```
h2o.biases(model, vector_id = 1)
```

```
##              C1
## 1   -7.657945
## 2  -14.447970
```

```
h2o.weights(model, matrix_id = 1)
```

```
##          x.1        x.2
## 1  -9.006323   8.071541
## 2  16.291693 -17.266787
```

Feature transformation

```r
tmp.df = as.h2o(data.frame(x.1=c(-1, -1, 1, 1),
                           x.2=c(-1, 1, -1, 1)))
```

```r
trans.features = h2o.deepfeatures(model, tmp.df, layer = 1)
as.matrix( h2o.cbind(tmp.df, trans.features) )
```

```
##      x.1 x.2   DF.L1.C1 DF.L1.C2
## [1,]  -1  -1  0.9999927        1
## [2,]  -1   1  0.9926779       -1
## [3,]   1  -1  0.9903638       -1
## [4,]   1   1 -0.6600429       -1
```

Weights in output layer

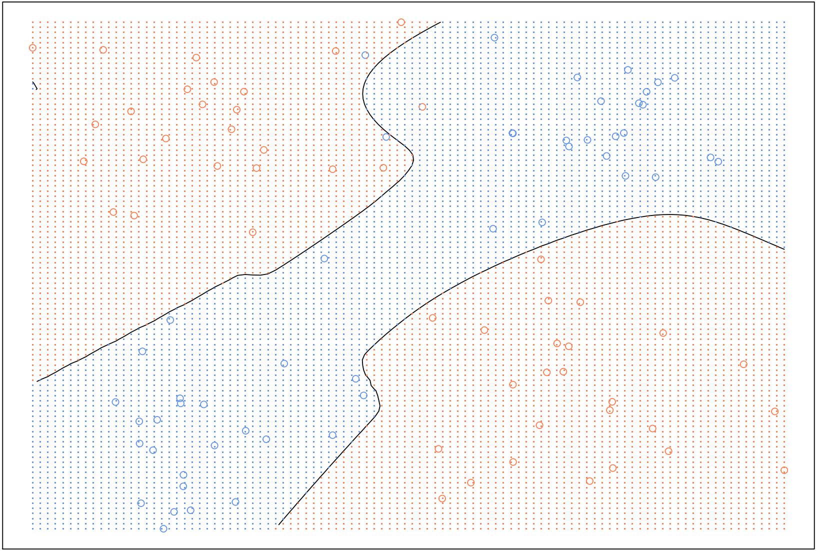
```r
h2o.biases(model, vector_id = 2)
```

```
##           C1
## 1   3.231547
## 2  -3.539516
```

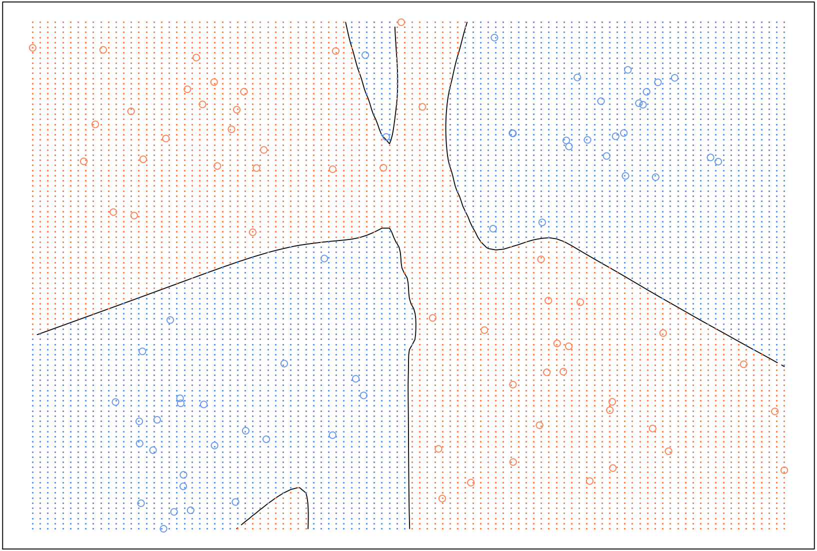
```r
h2o.weights(model, matrix_id = 2)
```

```
##           C1         C2
## 1  -2.574277   4.265737
## 2   0.814248  -1.587351
```

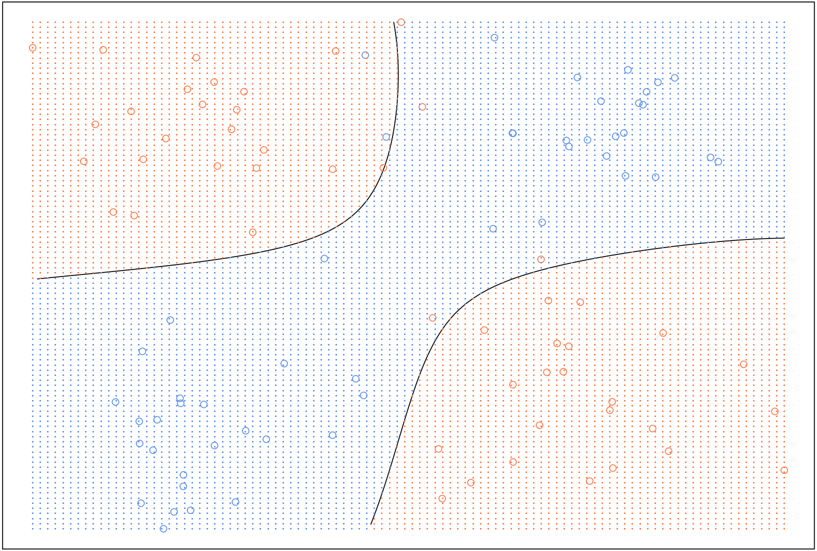
neural network -- 1 hidden layer with 5 neurons



neural network –– 1 hidden layer with 10 neurons



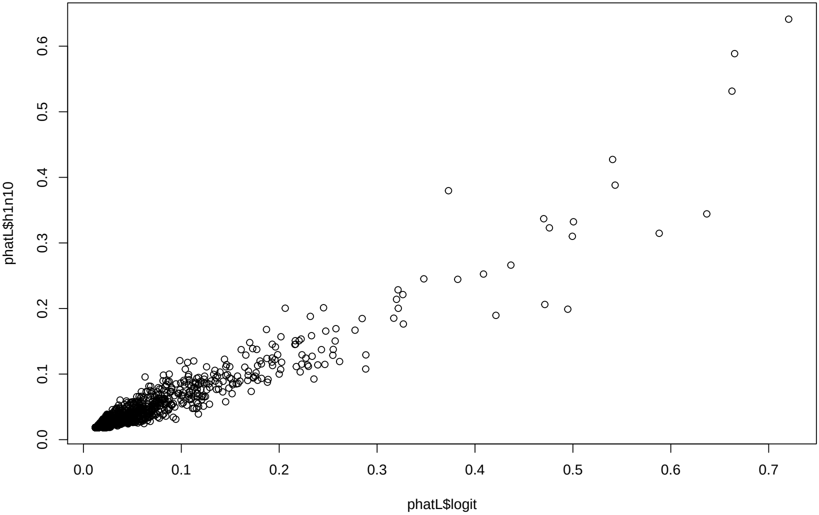
neural network –– 1 hidden layer with 10 neurons with regularization



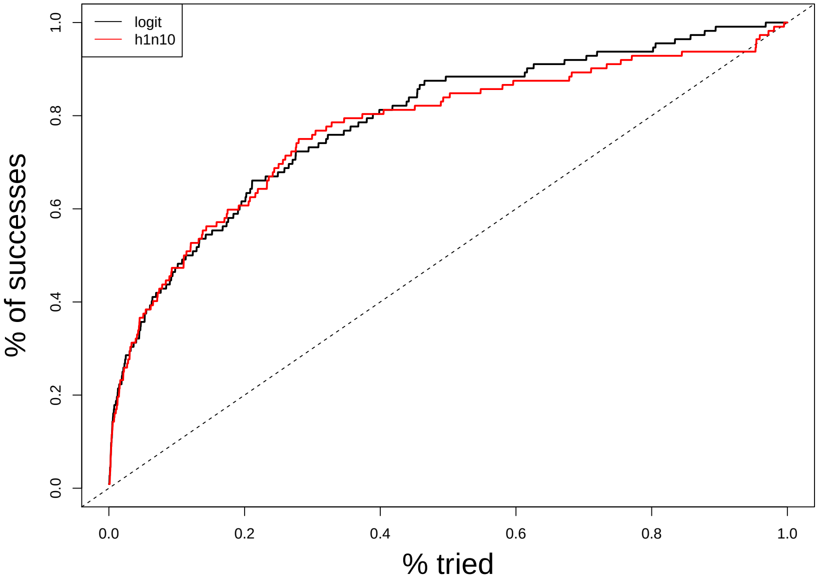
Example: Tabloid data

See *tabloid.h2o.R*

For example of how to use **nnet** package, see *tabloid.nnet.R*

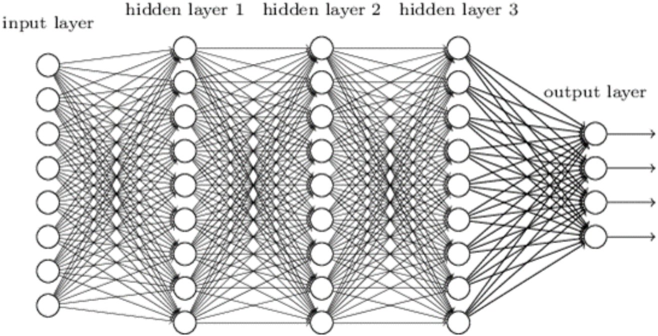


0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
phatL$logit
0.0
0.1
0.2
0.3
0.4
0.5
0.6
phatL$h1n10



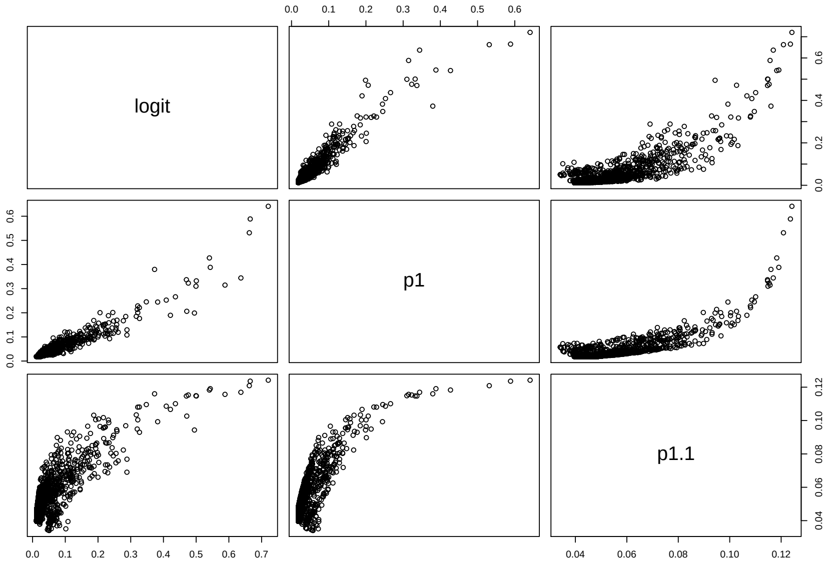
logit
h1n10
% of successes
% tried
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0

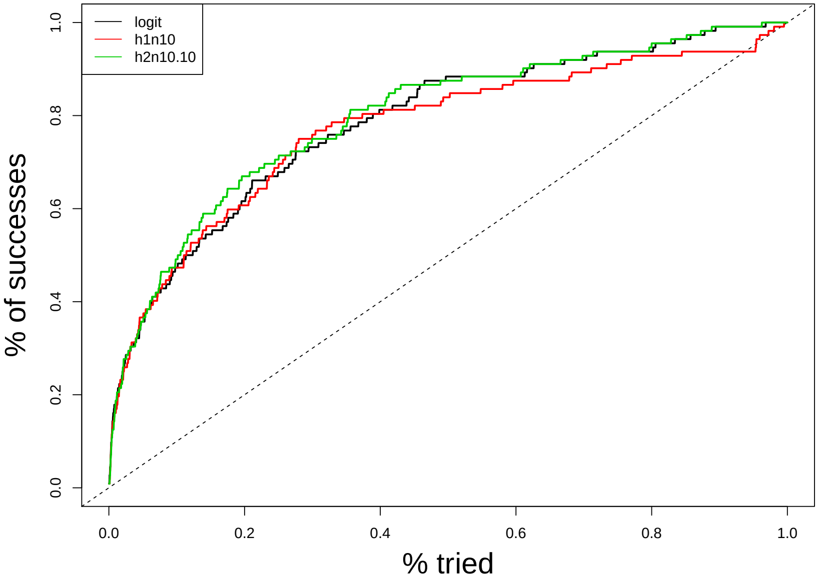
Deep neural network



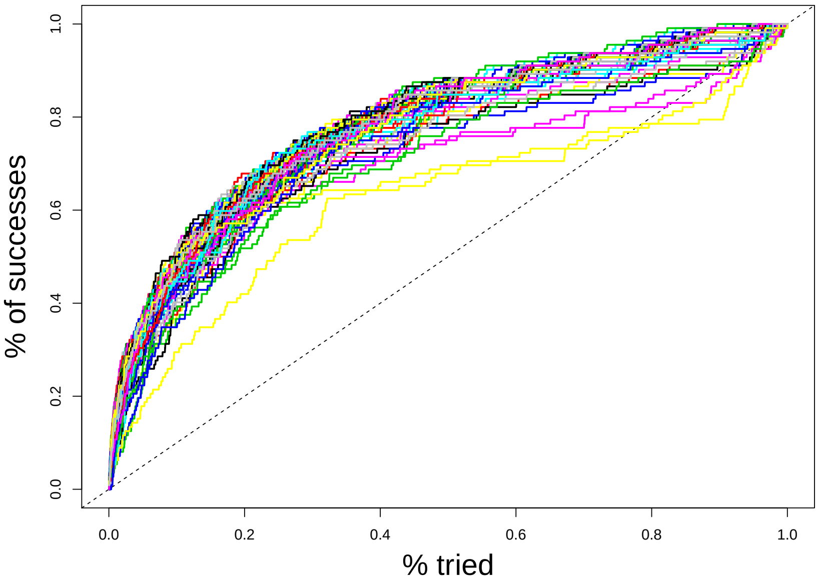
If there is more than one hidden layer, networks are called "deep" neural networks.

Tabloid again




logit
h1n10
h2n10.10
1.0
0.8
0.6
0.4
0.2
0.0
% of successes
0.0
0.2
0.4
0.6
0.8
1.0
% tried

Grid search



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 inital 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

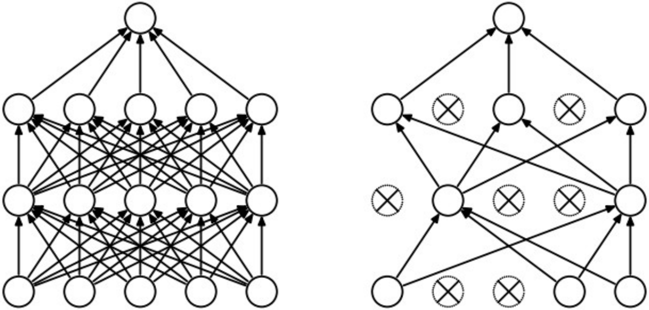
- $b^{t+1} = b^t - \eta \cdot \nabla J(b) + \alpha(b^t - b^{t-1})$
- α is the momentum parameter
- helps avoiding stuck in a local optimum

Regularization

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

Fitting neural networks

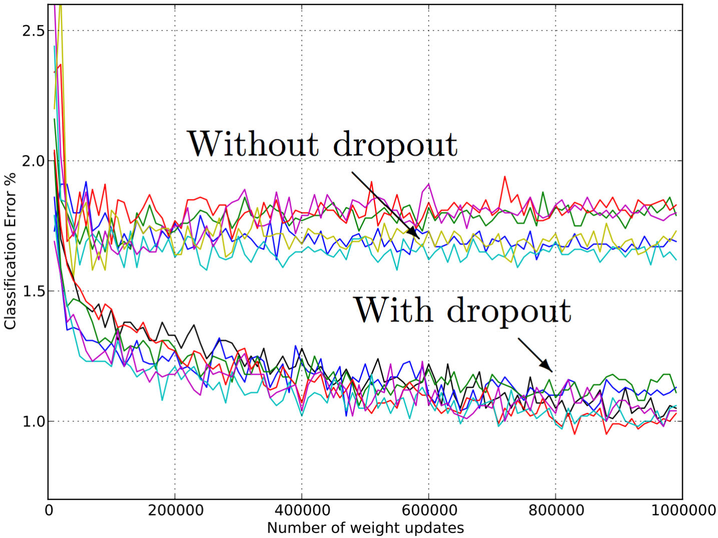
Dropout:



(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/

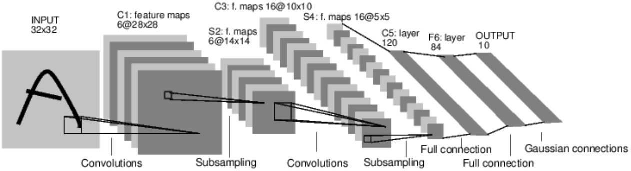
Even today: Kaggle competition

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

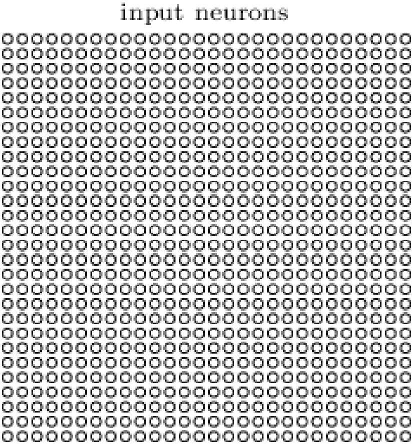
Online demo

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

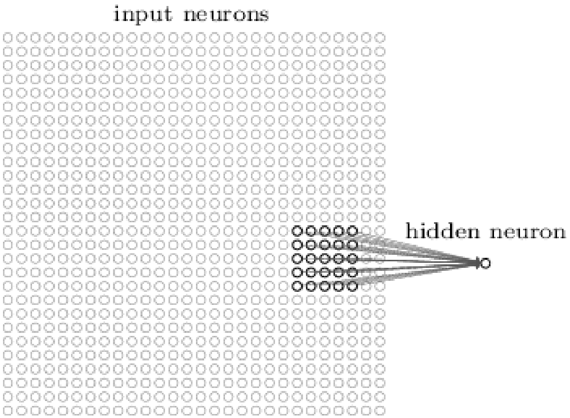
LeNet5: convolutional neural network



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



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



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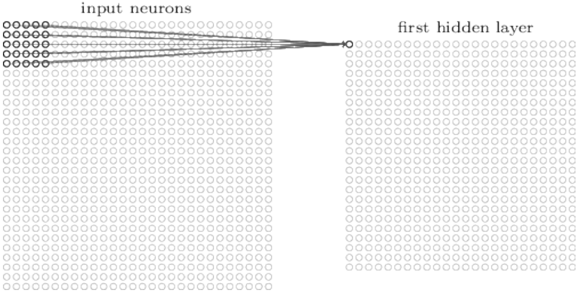
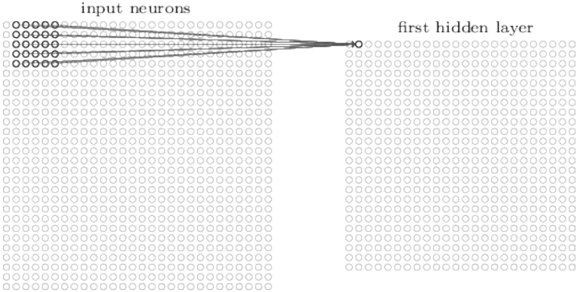
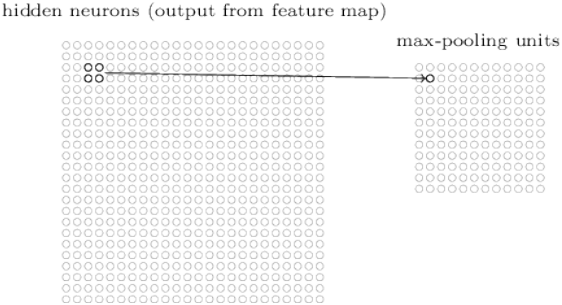


From: http://neuralnetworksanddeeplearning.com/chap6.html



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

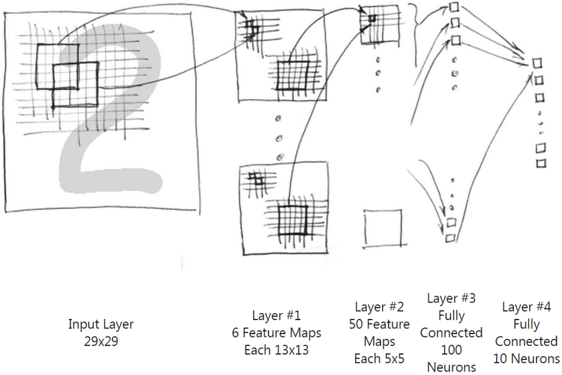


From: `http://neuralnetworksanddeeplearning.com/chap6.html`

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

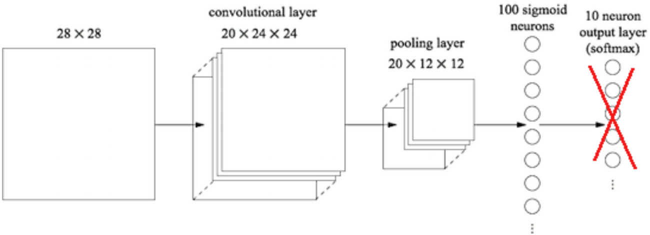
Pros:

- 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

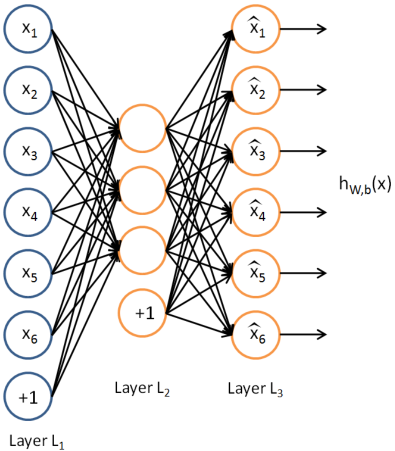
Learning representation



Use the output of the last layer as a representation of your data.

Fit a model with this representation.

Autoencoder



Network trained to reproduce its input at the output layer.

Usually tie the weights that go into and out of the hidden layer.

Autoencoder

Loss function

- For real valued inputs, try to find weights such that

$$\frac{1}{2}\sum_k (x_k - \hat{x}_k)^2$$

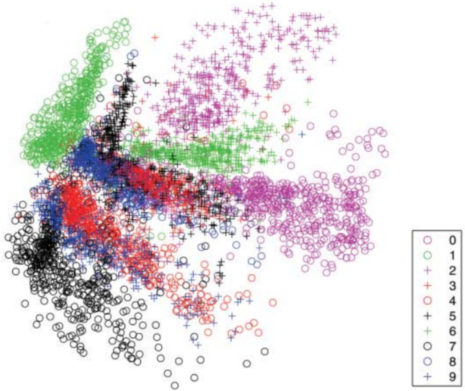
  is minimized
- For binary input cross entropy is used, which is similar to deviance

Fitting autoencoder

- Same tricks as before
- Greedy learning of stacked autoencoders
- https://www.cs.toronto.edu/~hinton/science.pdf

Autoencoder: Why are they useful?

Learning compressed representation of the input distribution (dimensionality reduction)

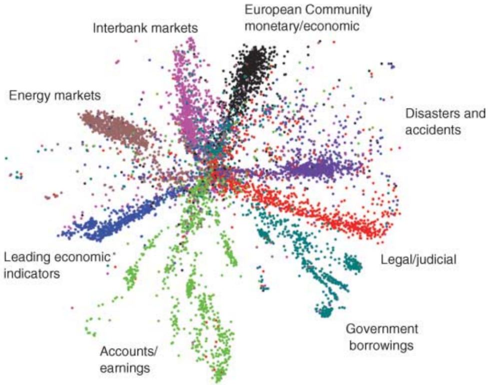


Autoencoder structure: 784 — 1000 — 500 — 250 — 2

https://www.cs.toronto.edu/~hinton/science.pdf

Autoencoder: Why are they useful?

Information retrieval: 804,414 newswire stories

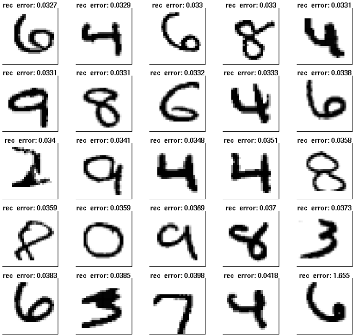


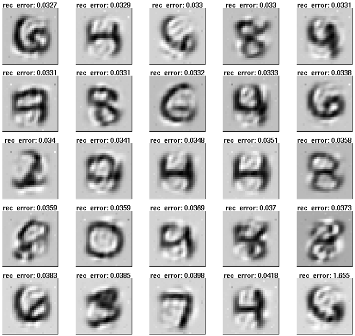
Autoencoder structure: 2000 — 500 — 250 — 125 — 2

https://www.cs.toronto.edu/~hinton/science.pdf

Autoencoder: Why are they useful?

- unsupervised pretraining of weights (many unlabeled images, but only few labeled)
- anomaly detection





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

- Free online book by Michael Nielsen
  `http://neuralnetworksanddeeplearning.com/`
  (explains backpropagation well)

- `http://deeplearning.net/tutorial/`
  Excellent tutorial using Theano library in Python