Lecture 2

Introduction to Deep Neural Networks

OUTLINE

- Introduction to multi-layered neural network
- Optimization (back-propagation)
- Regularization and Dropout
- The vanishing gradient issue
- Toolkit

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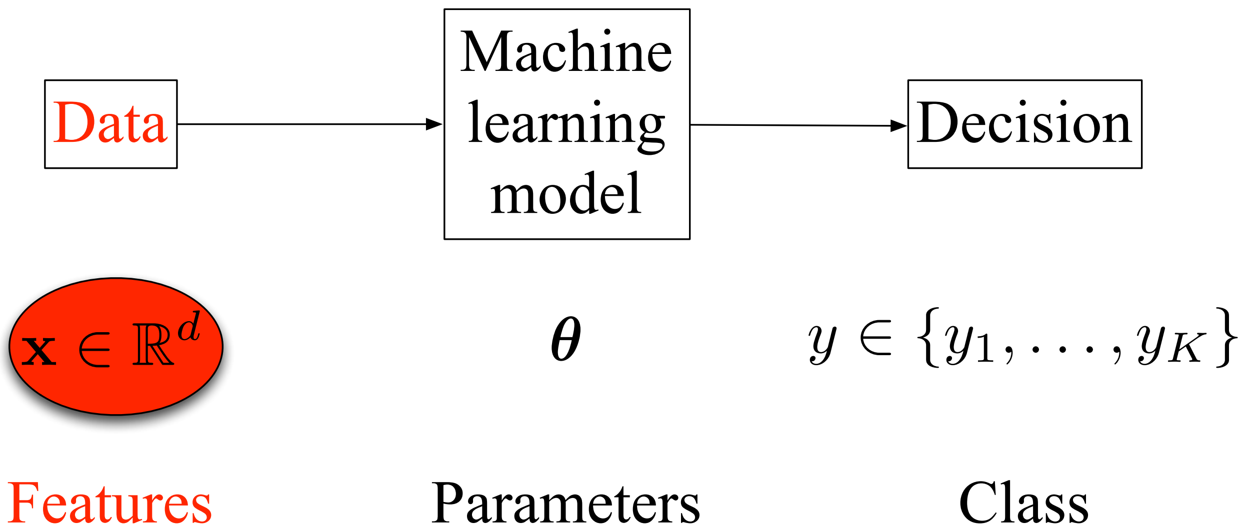
FEATURE ENGINEERING

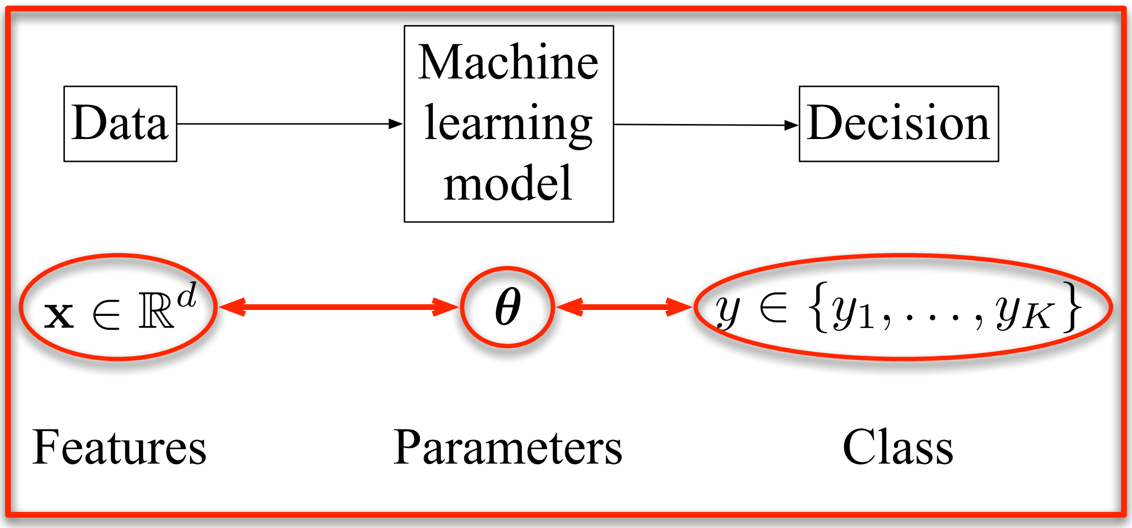
Most current machine learning works well because of human-designed representations and input features



- Time consuming and task/domain dependant
- Features are often both over-specified and incomplete
- Machine learning $\Leftrightarrow$ optimizing parameters to make the best prediction

REPRESENTATION LEARNING AND DEEP NETWORKS

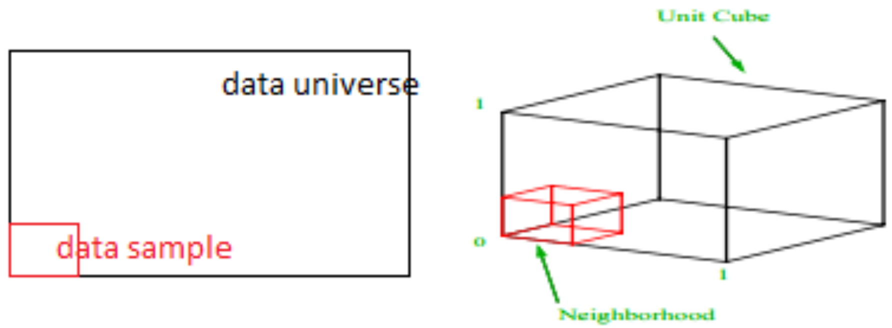
Representation learning attempts to automatically learn useful features



- Learning a hierarchical and abstract representation
- That can be shared among tasks
- Almost all data is unlabeled $\Rightarrow$ unsupervised learning

THE CURSE OF DIMENSIONALITY

In high-dimensional space, training data becomes sparse



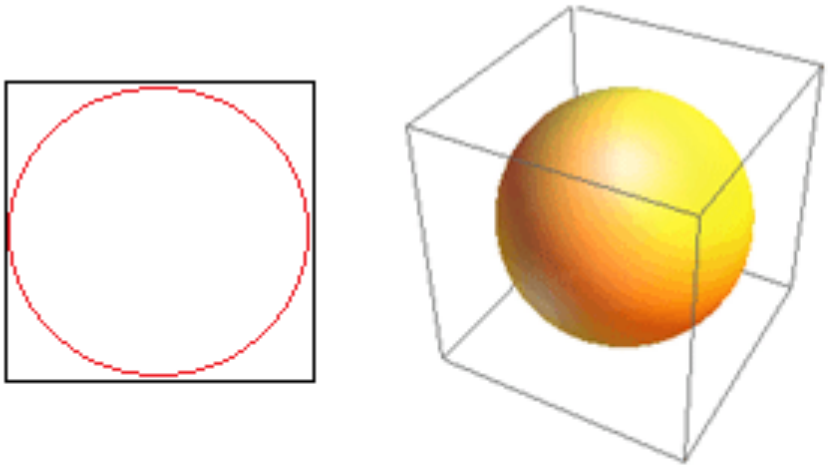
http ://www.edupristine.com/blog/curse-dimensionality

To generalize :

- Use the distance to define some sort of “near-ness”
- Spread the probability mass around training examples (smooth the empirical distribution)

THE CURSE OF DIMENSIONALITY (DIMENSION=3)

In 2-dimensions, two points are near if one falls within a certain radius of another.



http://www.edupristine.com/blog/curse-dimensionality

In 2-d, which proportion of uniformly spaced points within black square fall inside the red circle ?

$$\frac{\pi r^2}{4r^2} = \frac{\pi}{4} \approx 78\%$$

This proportion drops to 52% in 3-d, and to 0.24% in 10-d.

Consequence

In high-dimensional space, the distance does not define a useful similarity.

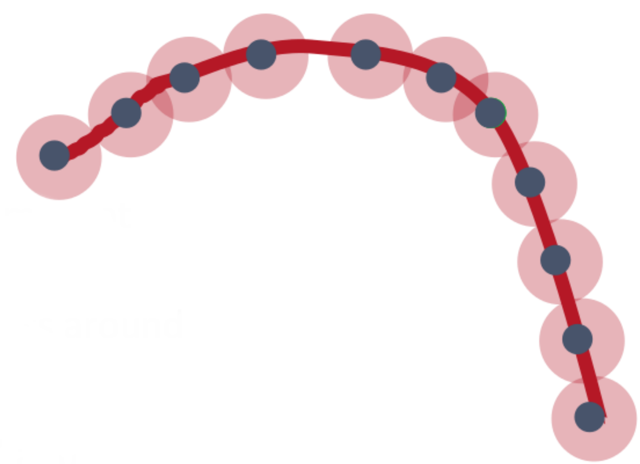
THE CURSE OF DIMENSIONALITY (DIMENSION=3)

Smoothing distribution

- The mass is spread around the examples.
- While plausible in this 2-dimensional case, in higher dimensions, the balls will leave holes or be too large in high probability regions.

Manifold

- If we can discover a representation of the probability concentration,
- a lower dimensional (non-linear) manifold,
- we can "flatten" it by changing the representation
- for which the distance is useful for density estimation, interpolation, ...



Y. Bengio, 2015

NEURAL NETWORKS

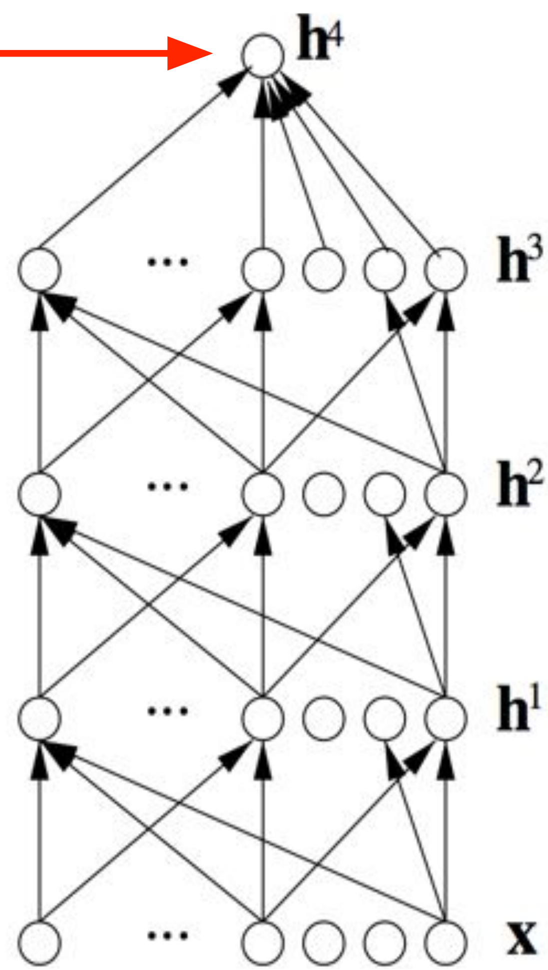
Output layer

prediction of the supervised target

Hidden Layers

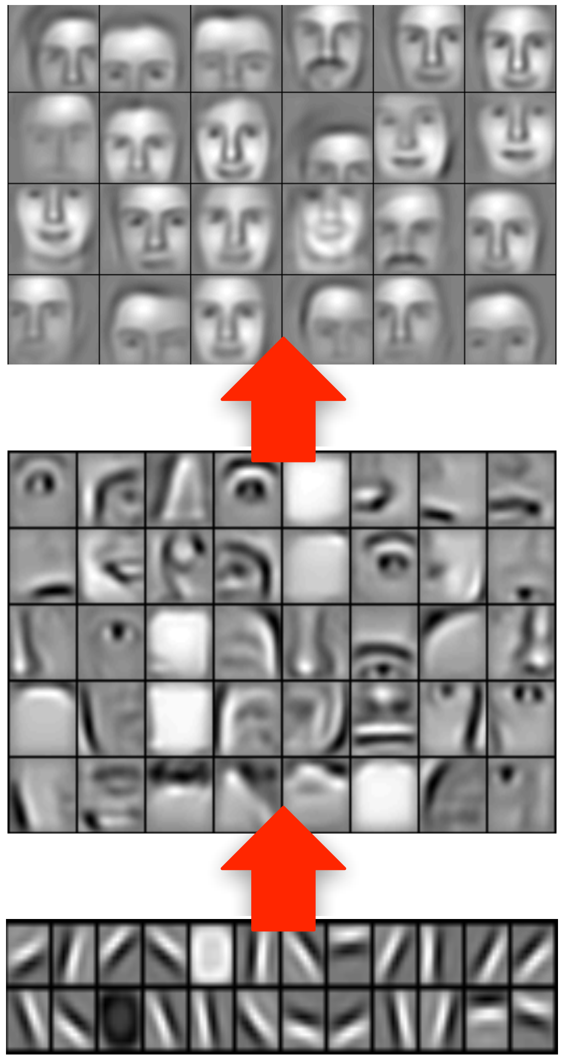
learn more abstract features as you head up

Raw inputs



(from Bengio, 2015)

ILLUSTRATION AT DIFFERENT LAYERS?

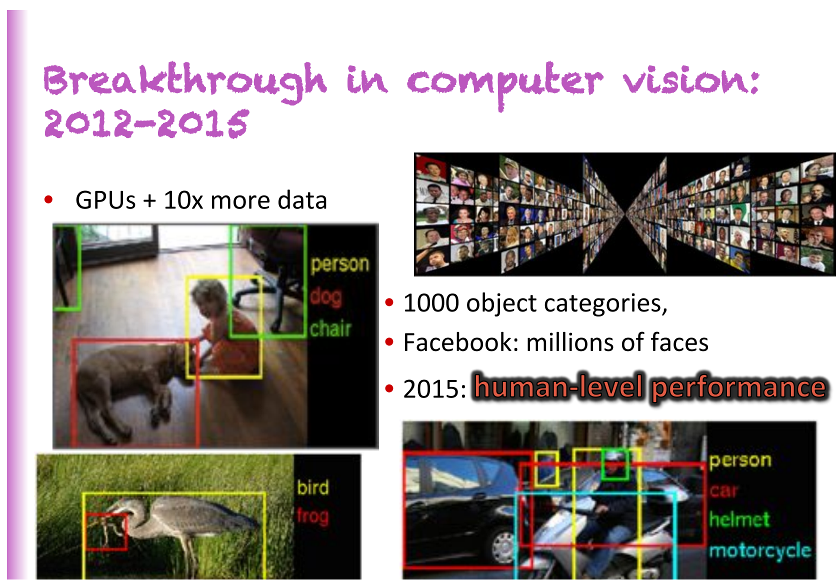


(Lee et al.2009)

DEEP LEARNING AND NEURAL NETWORKS: A SUCCESS STORY

Since 2009, deep learning approaches won several challenges

- ImageNet since 2012 (Krizhevsky et al.2012)
- Traffic signs recognition : superhuman performance in 2011 (Ciresan et al.2012) based on (LeCun et al.1989)
- Handwritting recognition since 2009 (Graves and Schmidhuber2009) based on (Hochreiter and Schmidhuber1997)
- Automatic Speech recognition (Hinton et al.2012)



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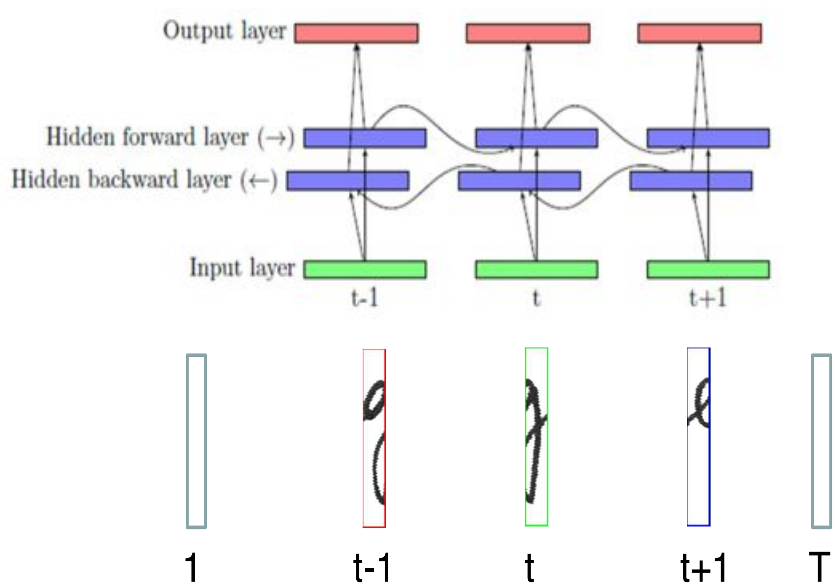


DEEP LEARNING AND NEURAL NETWORKS: A LONG STORY

The breakthrough of 2006

The expression *Deep Learning* was coined around 2006 with papers on unsupervised pre-training of neural nets (Hinton et al.2006; Hinton and Salakhutdinov2006; Bengio et al.2007)

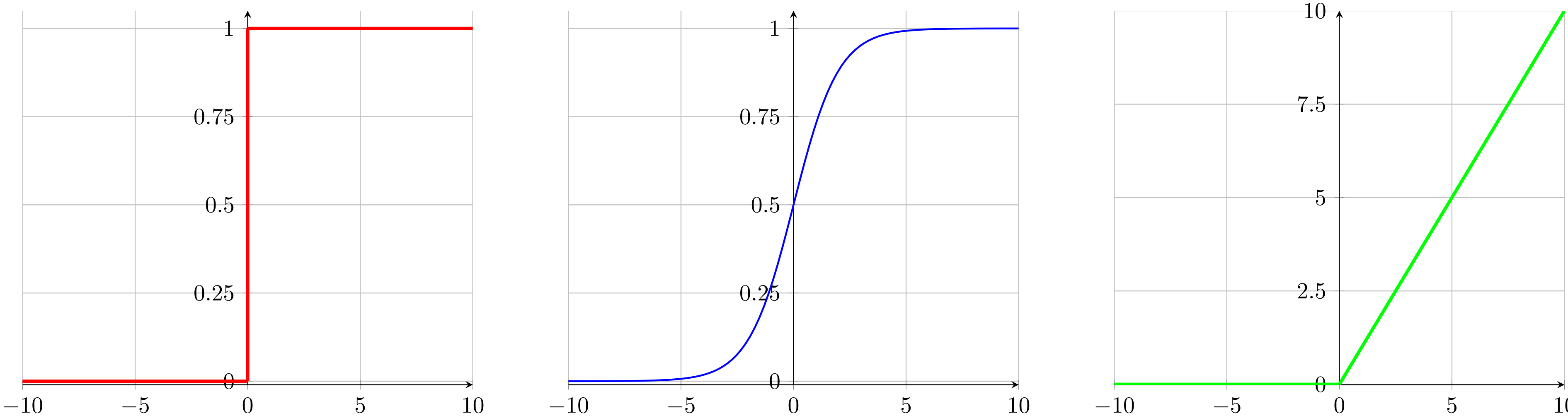
And before ? (just a few dates)

- 1958 Rosenblatt proposed the perceptron (Rosenblatt1958), following the work of McCulloch and Pitts in 1943 and Hebb in 1949.
- 1980 Neocognitron (Fukushima1980) or the multilayered NNets
- 1982 Hopfield network with memory and recurrence (Hopfield1982), the unsupervised SOM (Kohonen1982), Neural PCA (Oja1982)
- 1986 Multilayer perceptrons and backpropagation (Rumelhart et al.1986b)
- 1989 Autoencoders (Baldi and Hornik1989), Convolutional network (LeCun et al.1989)
- 1993 Sparse coding (Field1993)

BUT, WHAT IS NEW?

Why today ?

- The huge amount of data and the growth of computational power.
- Regularization
- and ...



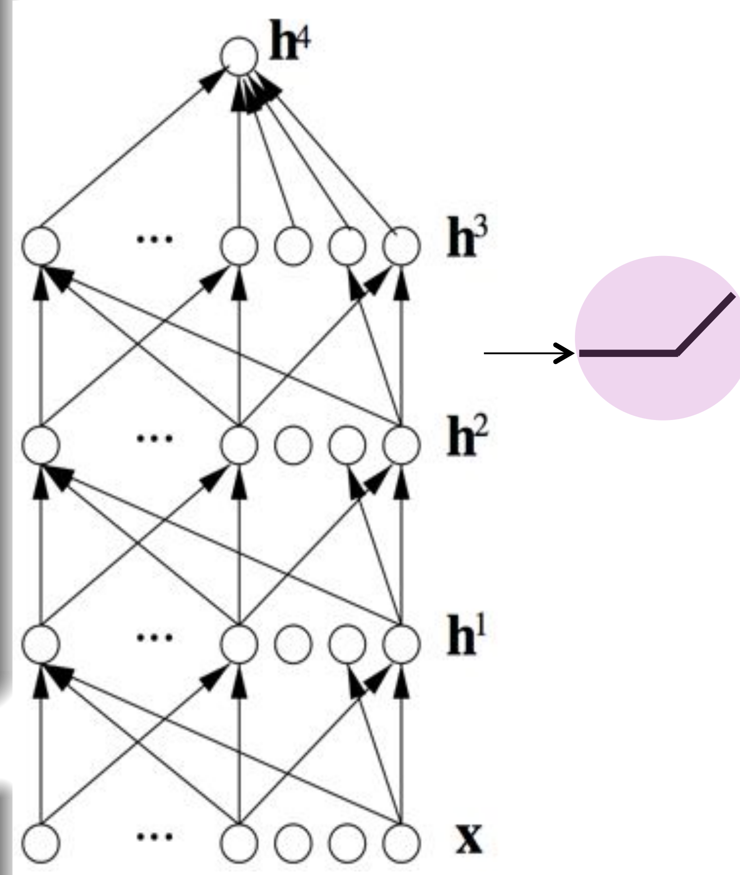
BUT, WHAT IS NEW?

Why today ?

- We have connected the dots, e.g. (Probabilistic) PCA / Neural PCA / Autoencoder
- We understand learning better (regularization, architecture)
- No need to be scared of non-convex optimization (initialization)
- The huge amount of data and the growth of computational power.

What is the difference between a NNet and a Deep Network ?

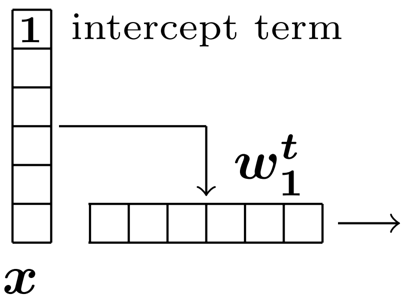
An intensive empirical exploration of different issues



Y. Bengio, 2015

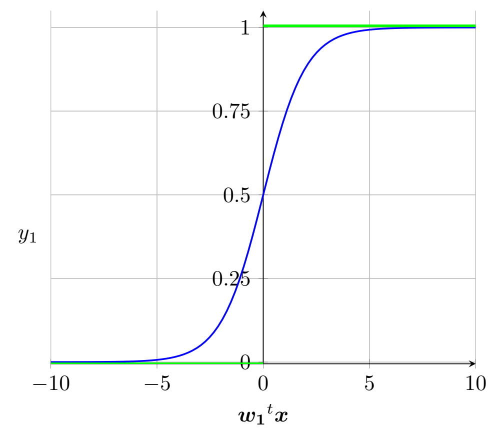
LOGISTIC REGRESSION

Logistic regression (binary classification)

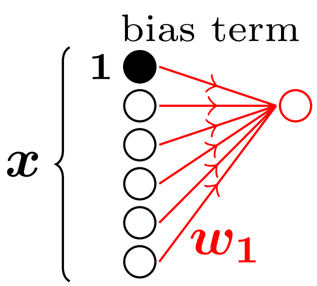


$$y_1 = f(\boldsymbol{w_1}^t \boldsymbol{x})$$

$$f(a = \boldsymbol{w_1}^t \boldsymbol{x}) = \frac{1}{1 + e^{-a}}$$



A single artificial neuron

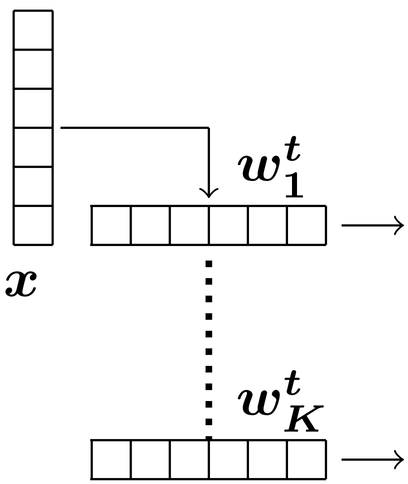


pre-activation : $a_1 = \boldsymbol{w_1}^t \boldsymbol{x}$

$y_1 = f(\boldsymbol{w_1}^t \boldsymbol{x})$, f is the activation function of the neuron

LOGISTIC REGRESSION

From binary classification to K classes (Maxent)

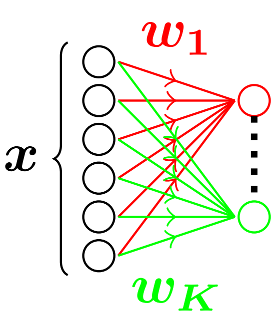


$$y_1 = f(\boldsymbol{w_1}^t \boldsymbol{x})$$

$$y_K = f(\boldsymbol{w_K}^t \boldsymbol{x})$$

$$f(a_k = \boldsymbol{w_k}^t \boldsymbol{x}) = \frac{e^{a_k}}{\sum_{k'=1}^{K} e^{a_{k'}}} = \frac{e^{a_k}}{Z(\boldsymbol{x})}$$

A simple neural network

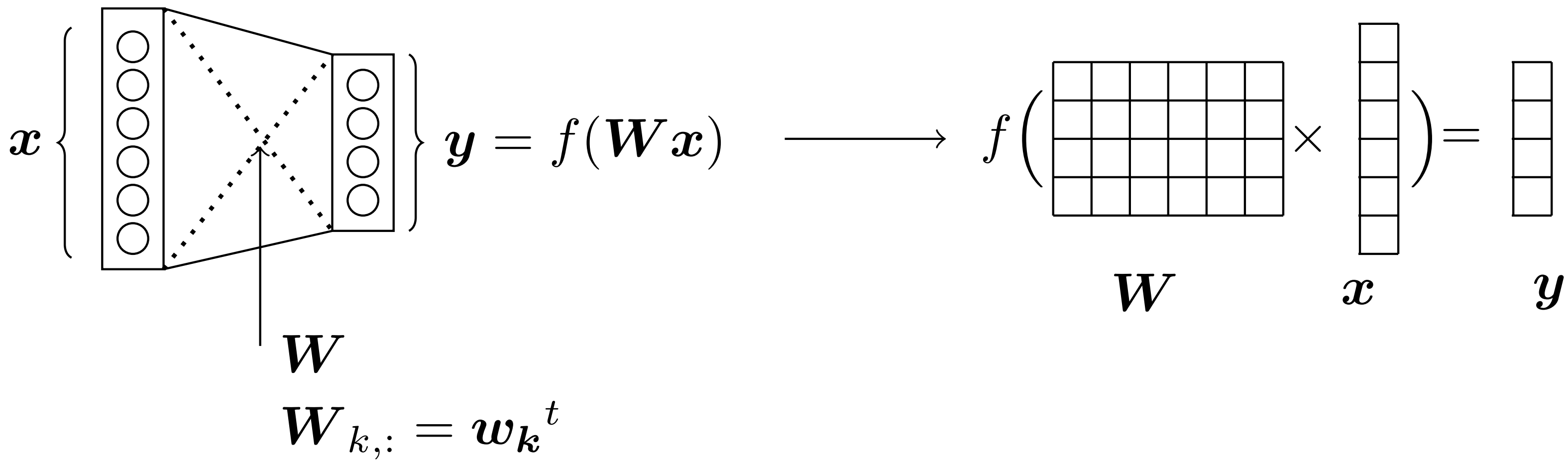


$$y_1 = f(\boldsymbol{w_1^t x})$$

$$y_K = f(\boldsymbol{w_K^t x})$$

- $\boldsymbol{x}$: *input layer*
- $\boldsymbol{y}$: *output layer*
- each y_k has its parameters $\boldsymbol{w}_k$
- f is the softmax function

LOGISTIC REGRESSION

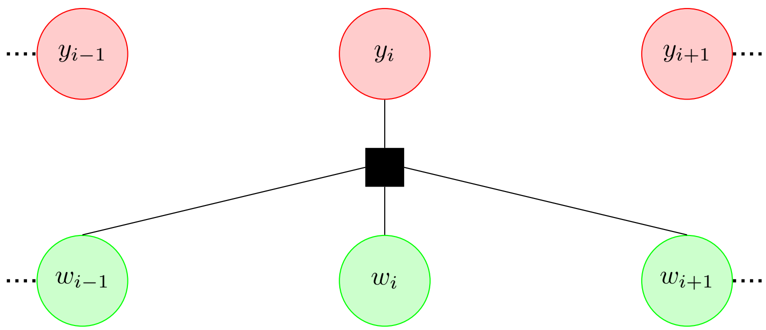


- f is usually a non-linear function
- f is a component wise function
- $e.g$ the softmax function :

$$y_k = P(c = k|\boldsymbol{x}) = \frac{e^{\boldsymbol{w_k}^t \boldsymbol{x}}}{\sum_{k'} e^{\boldsymbol{w_{k'}}^t \boldsymbol{x}}} = \frac{e^{\boldsymbol{W}_{k,:}\boldsymbol{x}}}{\sum_{k'} e^{\boldsymbol{W}_{k',:}\boldsymbol{x}}}$$

- tanh, sigmoid, relu, ...

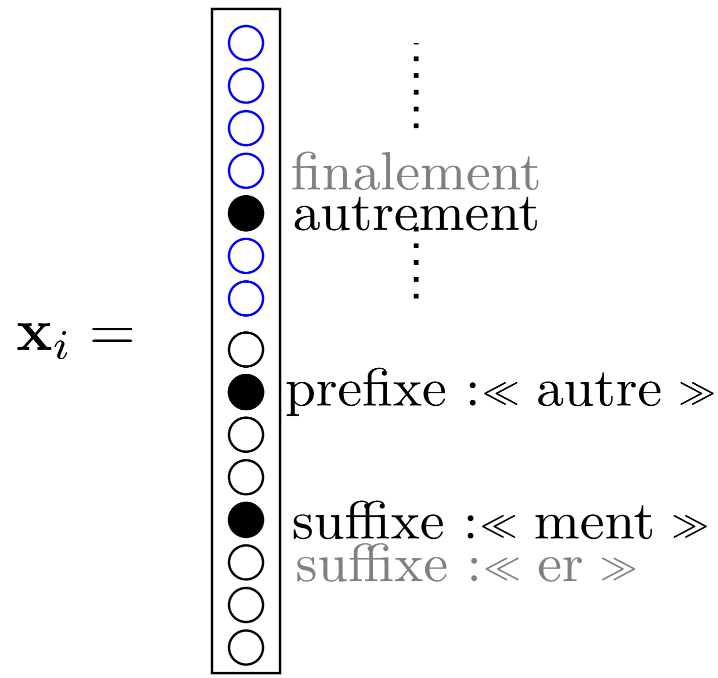
MAXENT CLASSIFIERS



Word representation

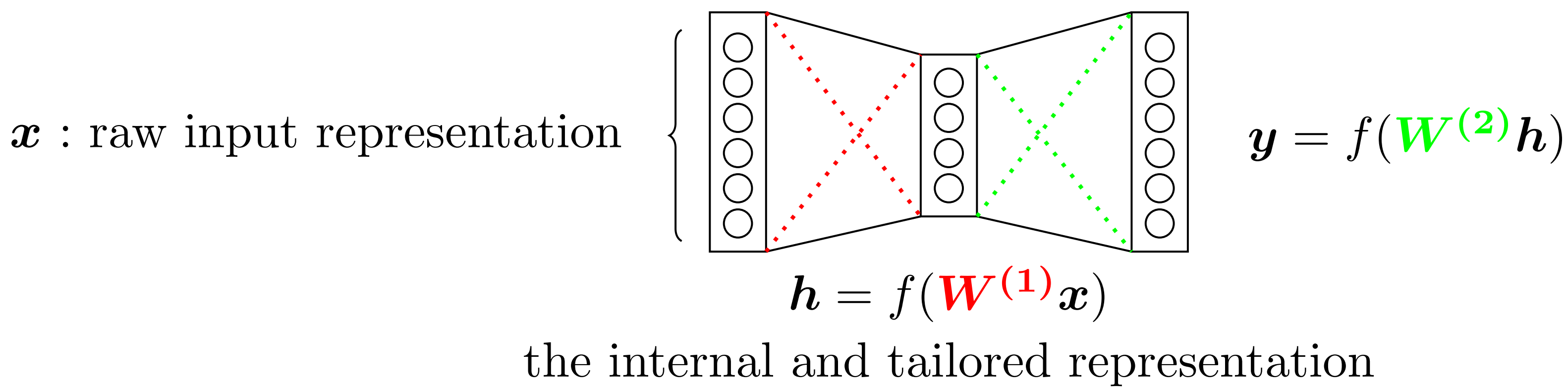
For each word in the context

- surface form (one-hot vector)
- prefix
- suffix
- ...



A rich representation of the input for a better generalization.

NEURAL NETWORKS WITH A HIDDEN LAYER



Intuitions

- Learn an internal representation of the raw input
- Apply a non-linear transformation
- The input representation $\boldsymbol{x}$ is transformed/compressed in a new representation $\boldsymbol{h}$
- Adding more layers to obtain a more and more abstract representation

HOW DO WE LEARN THE PARAMETERS ?

For a supervised single layer neural net

Just like a maxent model :

- Calculate the gradient of the objective function and use it to iteratively update the parameters.
- Conjugate gradient, L-BFGS, ...
- In practice : **Stochastic gradient descent (SGD)**

With one hidden layer

- The internal ("hidden") units make the function non-convex ... just like other models with hidden variables :
  - hidden CRFs (Quattoni et al.2007), ...
- But we can use the same ideas and techniques
- Just without guarantees ⇒ **backpropagation** (Rumelhart et al.1986b)

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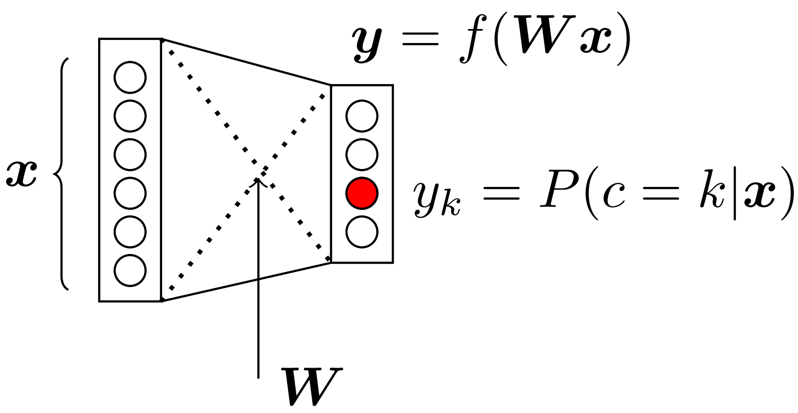
OPTIMIZATION OF A SINGLE LAYER NETWORK FOR CLASSIFICATION



The set of parameters is denoted $\boldsymbol{\theta}$, in this case :

$$\boldsymbol{\theta} = (\boldsymbol{W})$$

The log-loss (conditional log-likelihood)

Assume the dataset $\mathcal{D} = (\boldsymbol{x}_{(i)}, c_{(i)})_{i=1}^{N}$, $c_{(i)} \in \{1, 2, \ldots, C\}$

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{i=1}^{N} l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)}) = \sum_{i=1}^{N} \Big(- \sum_{c=1}^{C} \mathbb{I}\{c = c_{(i)}\} \log(P(c|\boldsymbol{x}_{(i)})) \Big) \quad (1)$$

$$l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)}) = - \sum_{k=1}^{C} \mathbb{I}\{k = c_{(i)}\} \log(y_k) \quad (2)$$

OPTIMIZATION USING SGD

Stochastic Gradient Descent (Bottou2010)

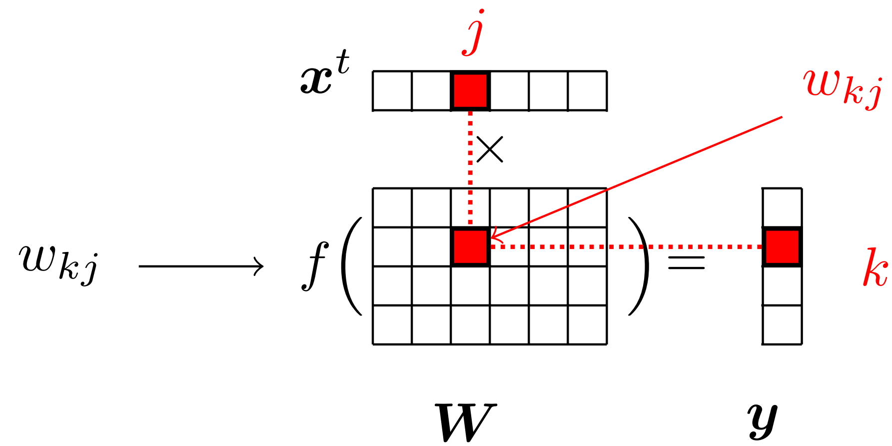
For ($t = 1$; until convergence ; $t++$) :

- Pick randomly a sample $(\boldsymbol{x}_{(i)}, c_{(i)})$
- Compute the gradient of the loss function w.r.t the parameters ($\nabla_{\boldsymbol{\theta}}$)
- Update the parameters : $\boldsymbol{\theta} = \boldsymbol{\theta} - \eta_t \nabla_{\boldsymbol{\theta}}$

Questions

- convergence : what does it mean ?
- what do you mean by η_t ?
  - convergence if $\sum_t \eta_t = \infty$ and $\sum_t \eta_t^2 < \infty$
  - $\eta_t \propto t^{-1}$
  - and lot of variants like Adagrad (Duchi et al.2011), Down scheduling, ... see (LeCun et al.2012)

GRADIENT COMPUTATION AT FIRST LAYER



Inference chain :

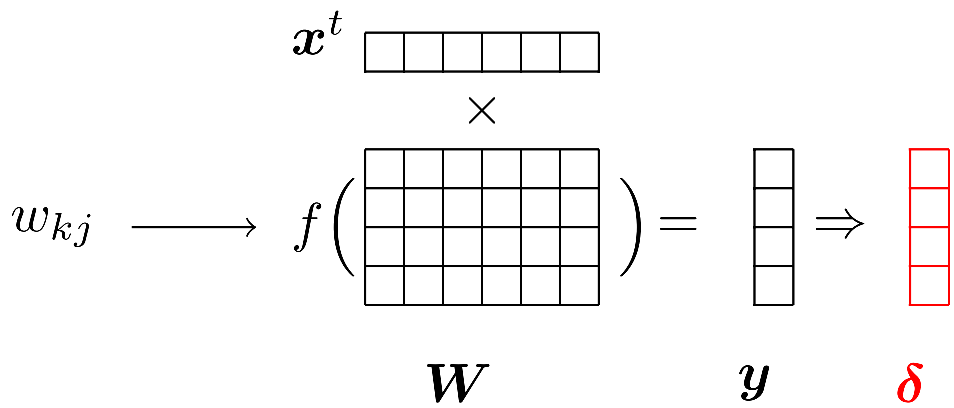
$$\boldsymbol{x}_{(i)} \longrightarrow (\boldsymbol{a} = \boldsymbol{W}\boldsymbol{x}_{(i)}) \longrightarrow (\boldsymbol{y} = f(\boldsymbol{a})) \longrightarrow l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)})$$

The gradient for w_{kj}

$$\nabla_{w_{kj}} = \frac{\partial l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)})}{\partial w_{kj}} = \frac{\partial l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)})}{\partial \boldsymbol{y}} \times \frac{\partial \boldsymbol{y}}{\partial \boldsymbol{a}} \times \frac{\partial \boldsymbol{a}}{\partial w_{kj}}$$

$$= -(\mathbb{I}\{k = c_{(i)}\} - y_k)x_j = \delta_k x_j$$

GRADIENT COMPUTATION AT SECOND LAYER



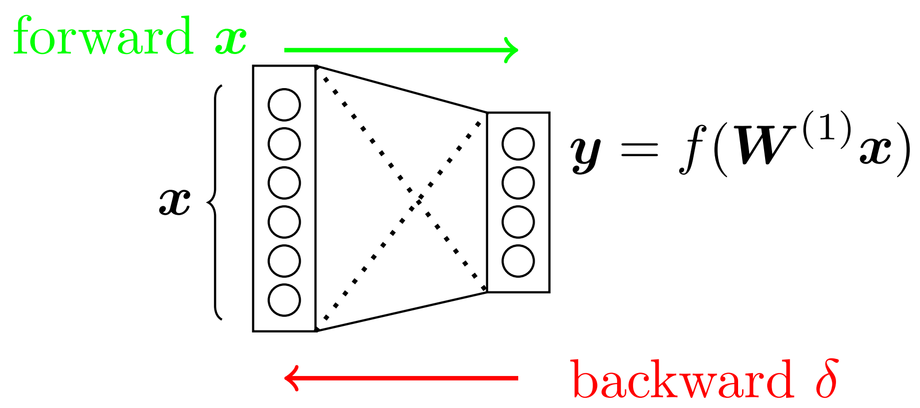
Generalization

$$\nabla_{\boldsymbol{W}} = \boldsymbol{\delta}\boldsymbol{x}^t$$

$$\delta_k = -(\mathbb{I}\{k = c_{(i)}\} - y_k)$$

with $\boldsymbol{\delta}$ the gradient at the pre-activation level.

ITERATIONS



Inference : a forward step

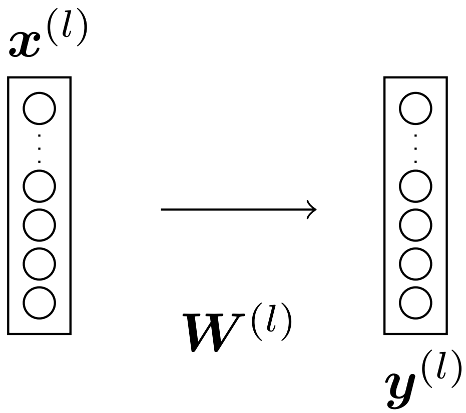
- matrice multiplication with the input $\boldsymbol{x}$
- Application of the activation function

One training step : forward and backward steps

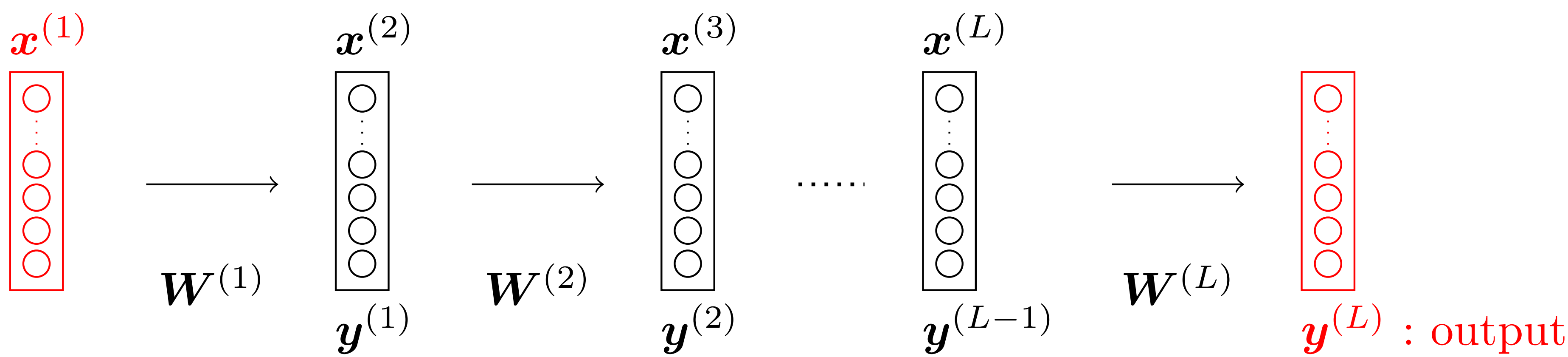
- Pick randomly a sample $(\boldsymbol{x}_{(i)}, c_{(i)})$
- Compute $\boldsymbol{\delta}$
- Update the parameters : $\boldsymbol{\theta} = \boldsymbol{\theta} - \eta_t \boldsymbol{\delta} \boldsymbol{x}^t$

FEED-FORWARD NETWORKS WITH A MULTI-LAYERS

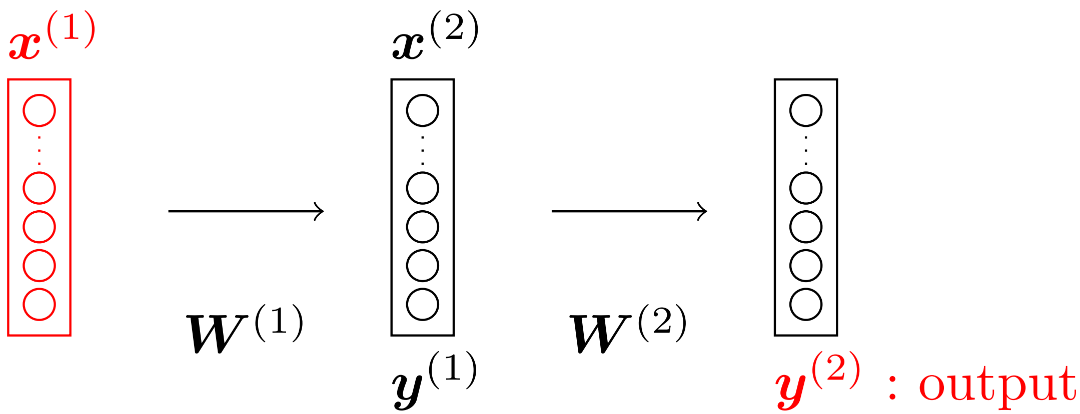
One layer, indexed by l



- $\boldsymbol{x}^{(l)}$: input of the layer l
- $\boldsymbol{y}^{(l)} = f^{(l)}(\boldsymbol{W}^{(l)}\ \boldsymbol{x}^{(l)})$
- stacking layers : $\boldsymbol{y}^{(l)} = \boldsymbol{x}^{(l+1)}$
- $\boldsymbol{x}^{(1)} =$ a data example



EXAMPLE OF TWO LAYERS



$$\boldsymbol{\theta} = (\boldsymbol{W}^{(1)}, \boldsymbol{W}^{(2)})$$

Gradient for the output layer

As in the Ex. 1 :

$$\boldsymbol{y} \to \boldsymbol{y}^{(2)}$$

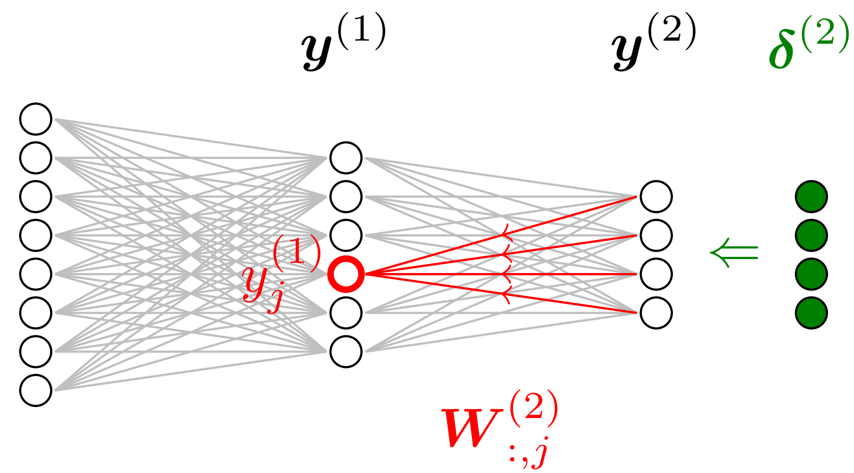
$$\boldsymbol{W} \to \boldsymbol{W}^{(2)}$$

$$\boldsymbol{x} \to \boldsymbol{x}^{(2)} = \boldsymbol{y}^{(1)}$$

$$\nabla_{\boldsymbol{W}^{(2)}} = \boldsymbol{\delta}^{(2)} {\boldsymbol{x}^{(2)}}^t, \text{ with}$$

$$\delta_k^{(2)} = -\mathbb{I}\left\{k = c_{(i)}\right\} - y_k$$

BACK-PROPAGATION OF THE LOSS GRADIENT



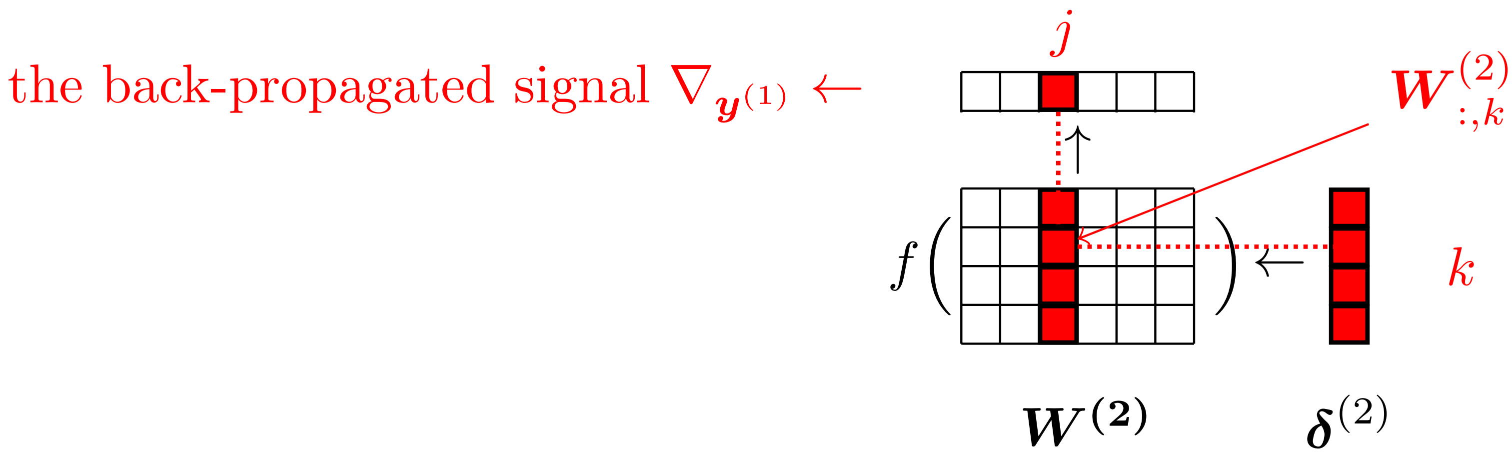
Inference chain part 1 :

$$\boldsymbol{y}^{(1)} = f^{(1)}(\boldsymbol{a}^{(1)}) \rightarrow \left(\boldsymbol{a}^{(2)} = \boldsymbol{W}^{(2)}\boldsymbol{y}^{(1)}\right) \rightarrow \left(\boldsymbol{y}^{(2)} = f^{(2)}(\boldsymbol{a}^{(2)})\right) \rightarrow l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)})$$

$$\nabla_{a_j^{(1)}} = \frac{\partial l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)})}{\partial a_j^{(1)}} = \frac{\partial l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)})}{\partial \boldsymbol{y}^{(2)}} \times \frac{\partial \boldsymbol{y}^{(2)}}{\partial \boldsymbol{a}^{(2)}} \times \frac{\partial \boldsymbol{a}^{(2)}}{\partial y_j^{(1)}} \times \frac{\partial y_j^{(1)}}{\partial a_j^{(1)}}$$

$$= \sum_k (\mathbb{I}\{k = c_{(i)}\} - y_k^{(2)}) w_{kj}^{(2)} f'^{(1)}(a_j) = f'^{(1)}(a_j)\left(\boldsymbol{W}_{:,j}^{(2)} \boldsymbol{\delta}^{(2)}\right)^t$$

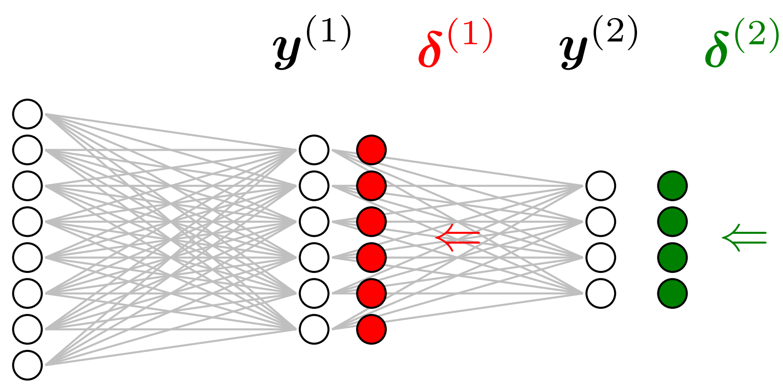
BACK-PROPAGATION OF THE LOSS GRADIENT (SECOND HIDDEN LAYER)



$$\nabla_{\boldsymbol{y}^{(1)}} = {\boldsymbol{W}^{(2)}}^t \boldsymbol{\delta}^{(2)}, \text{ then}$$

$$\boldsymbol{\delta}^{(1)} = \nabla_{\boldsymbol{a}^{(1)}} = {f^{(1)}}'(\boldsymbol{a}^{(1)}) \circ \left({\boldsymbol{W}^{(2)}}^t \boldsymbol{\delta}^{(2)}\right)$$

BACK-PROPAGATION OF THE LOSS GRADIENT (THIRD LAYER)



As for the output layer, the gradient is :

$$
\begin{aligned}
\nabla_{\boldsymbol{W}^{(1)}} &= \boldsymbol{\delta}^{(1)} {\boldsymbol{x}^{(1)}}^t, \text{ with} \\
\delta_j^{(1)} &= \nabla_{a_j^{(1)}} \\
\boldsymbol{\delta}^{(1)} &= {f'}^{(1)}(\boldsymbol{a}^{(1)}) \circ ({\boldsymbol{W}^{(2)}}^t \boldsymbol{\delta}^{(2)})
\end{aligned}
$$

The term $({\boldsymbol{W}^{(2)}}^t \boldsymbol{\delta}^{(2)})$ comes from the upper layer.

BACK-PROPAGATION : GENERAL CASE

For a hidden layer l :

- The gradient at the pre-activation level :

$$\boldsymbol{\delta}^{(l)} = f'^{(l)}(\boldsymbol{a}^{(l)}) \circ \left(\boldsymbol{W}^{(l+1)^t} \boldsymbol{\delta}^{(l+1)}\right)$$

- The update is as follows :

$$\boldsymbol{W}^{(l)} = \boldsymbol{W}^{(l)} - \eta_t \boldsymbol{\delta}^{(l)} \boldsymbol{x}^{(l)^t}$$

The layer should keep :

- $\boldsymbol{W}^{(l)}$: the parameters
- $f^{(l)}$: its activation function
- $\boldsymbol{x}^{(l)}$: its input
- $\boldsymbol{a}^{(l)}$: its pre-activation associated to the input
- $\boldsymbol{\delta}^{(l)}$: for the update and the back-propagation to the layer $l-1$

BACK-PROPAGATION : ONE TRAINING STEP

Pick a training example : $\boldsymbol{x}^{(1)} = \boldsymbol{x}_{(i)}$

Forward pass

For $l = 1$ to $(L-1)$

- Compute $\boldsymbol{y}^{(l)} = f^{(l)}(\boldsymbol{W}^{(l)}\boldsymbol{x}^{(l)})$
- $\boldsymbol{x}^{(l+1)} = \boldsymbol{y}^{(l)}$

$\boldsymbol{y}^{(L)} = f^{(L)}(\boldsymbol{W}^{(L)}\boldsymbol{x}^{(L)})$

Backward pass

Init : $\boldsymbol{\delta}^{(L)} = \nabla_{\boldsymbol{a}^{(L)}}$

For $l = L$ to 2 // all hidden units

- $\boldsymbol{\delta}^{(l-1)} = f'^{(l-1)}(\boldsymbol{a}^{(l-1)}) \circ \left(\boldsymbol{W}^{(l)^t}\boldsymbol{\delta}^{(l)}\right)$
- $\boldsymbol{W}^{(l)} = \boldsymbol{W}^{(l)} - \eta_t \boldsymbol{\delta}^{(l)} \boldsymbol{x}^{(l)^t}$

$\boldsymbol{W}^{(1)} = \boldsymbol{W}^{(1)} - \eta_t \boldsymbol{\delta}^{(1)} \boldsymbol{x}^{(1)^t}$

INITIALIZATION RECIPES

A difficult question with several empirical answers.

One standard trick

$$\boldsymbol{W} \sim \mathcal{N}(0, \frac{1}{\sqrt{n_{in}}})$$

with n_{in} is the number of inputs

A more recent one

$$\boldsymbol{W} \sim \mathcal{U}\left[-\frac{\sqrt{6}}{\sqrt{n_{in} + n_{out}}}, \frac{\sqrt{6}}{\sqrt{n_{in} + n_{out}}}\right]$$

with n_{in} is the number of inputs

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REGULARIZATION L2 OR GAUSSIAN PRIOR OR WEIGHT DECAY

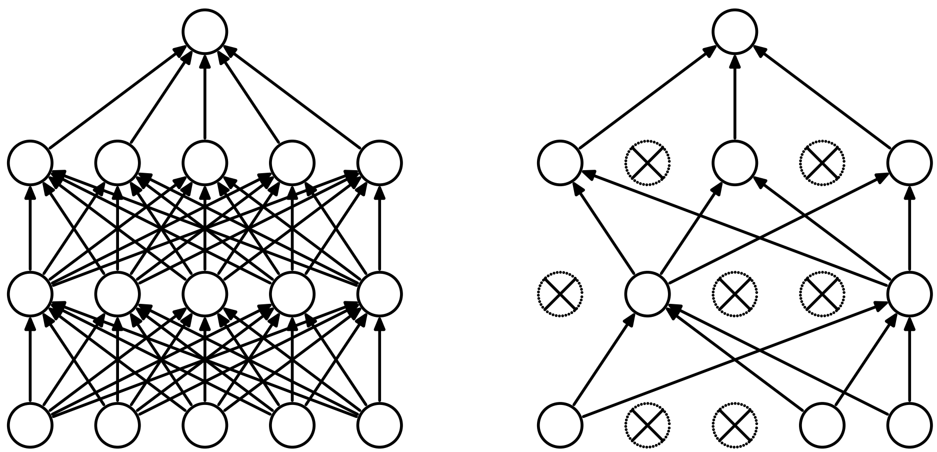
The basic way :

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{i=1}^{N} l(\boldsymbol{\theta}, \boldsymbol{x}_{(i)}, c_{(i)}) + \frac{\lambda}{2}||\boldsymbol{\theta}||^2$$

- The second term is the regularization term.
- Each parameter has a gaussian prior : $\mathcal{N}(0, 1/\lambda)$.
- λ is a hyperparameter.
- The update has the form :

$$\boldsymbol{\theta} = (1 + \eta_t \lambda)\boldsymbol{\theta} - \eta_t \nabla_{\boldsymbol{\theta}}$$

DROPOUT – A NEW REGULARIZATION SCHEME



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

- For each training example : randomly turn-off the neurons of hidden units (with $p = 0.5$)
- At test time, use each neuron scaled down by p

- Dropout serves to separate effects from strongly correlated features and
- prevents co-adaptation between units
- It can be seen as averaging different models that share parameters.
- It acts as a powerful regularization scheme.

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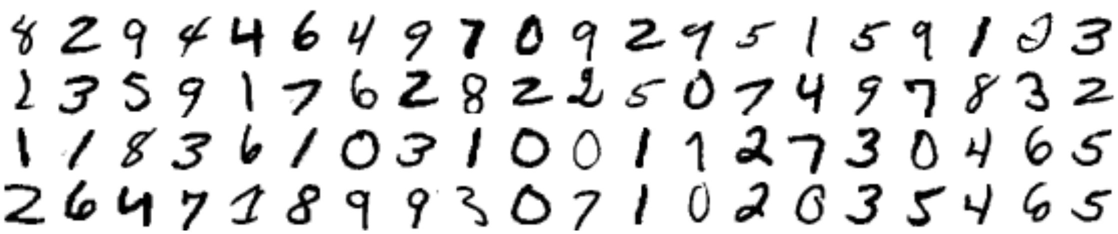
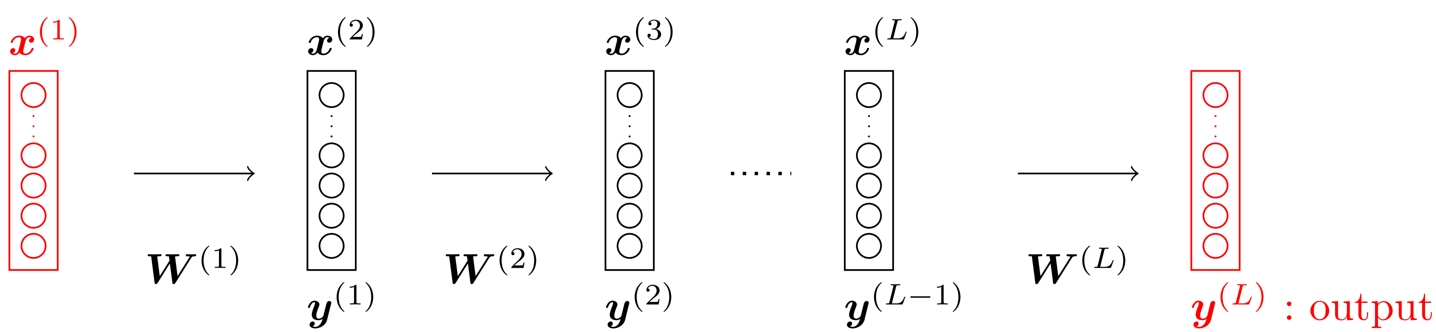
EXPERIMENTAL OBSERVATIONS (MNIST TASK) – ONE LAYER

The MNIST database



Comparison of different depth for feed-forward architecture

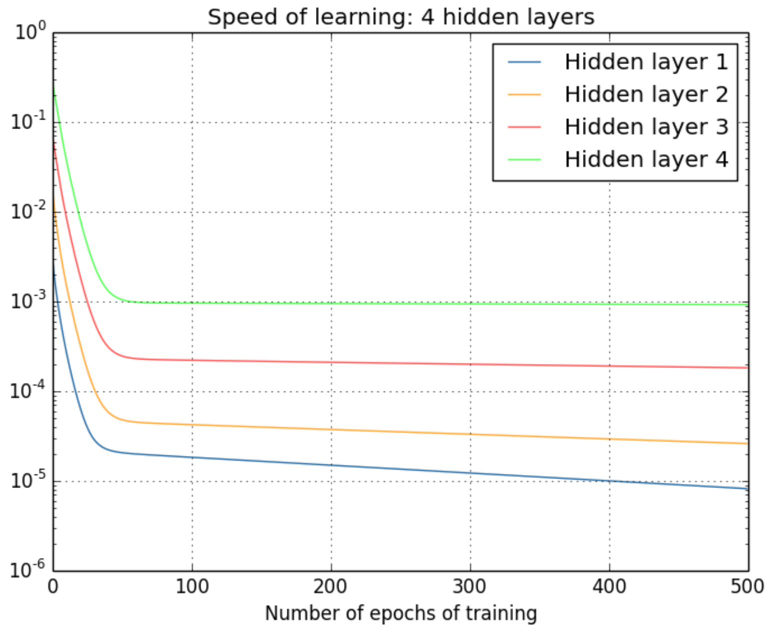


- Hidden layers have a sigmoid activation function.
- The output layer is a softmax.

EXPERIMENTAL OBSERVATIONS (MNIST TASK) - TWO LAYERS

Varying the depth

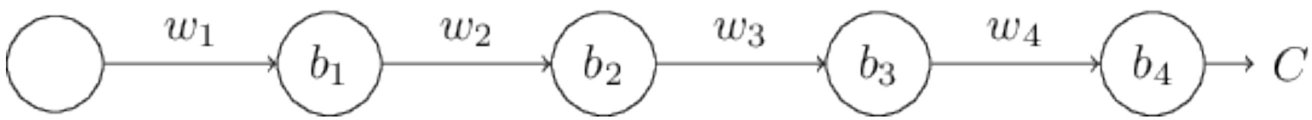
- Without hidden layer : $\approx 88\%$ accuracy
- 1 hidden layer (30) : $\approx 96.5\%$ accuracy
- 2 hidden layer (30) : $\approx 96.9\%$ accuracy
- 3 hidden layer (30) : $\approx 96.5\%$ accuracy
- 4 hidden layer (30) : $\approx 96.5\%$ accuracy



(From `http://neuralnetworksanddeeplearning.com/chap5.html`)

INTUITIVE EXPLANATION

Let consider the simplest deep neural network, with just a single neuron in each layer.



w_i, b_i are resp. the weight and bias of neuron i and C some cost function.

Compute the gradient of C $w.r.t$ the bias b_1

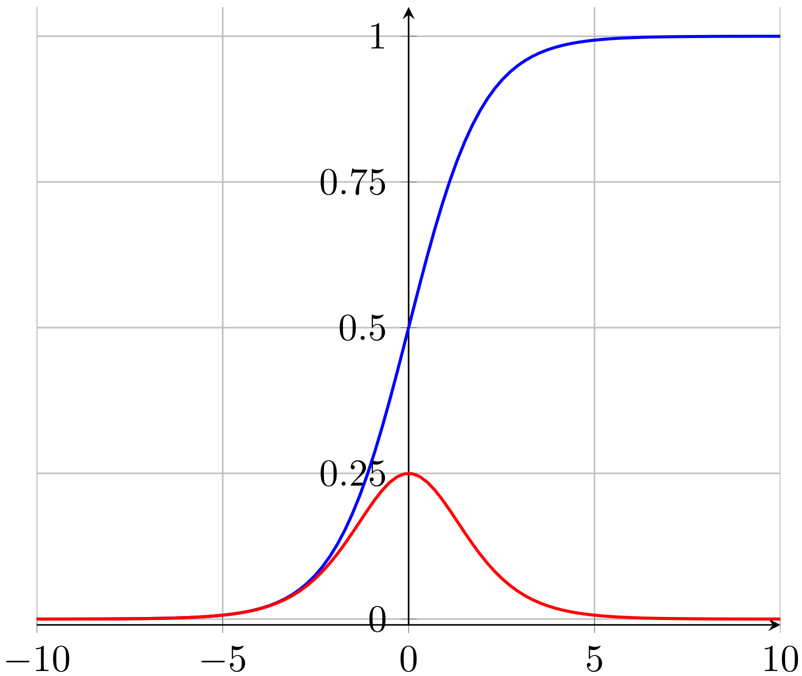
$$\frac{\partial C}{\partial b_1} = \frac{\partial C}{\partial y_4} \times \frac{\partial y_4}{\partial a_4} \times \frac{\partial a_4}{\partial y_3} \times \frac{\partial y_3}{\partial a_3} \times \frac{\partial a_3}{\partial y_2} \times \frac{\partial y_2}{\partial a_2} \times \frac{\partial a_2}{\partial y_1} \times \frac{\partial y_1}{\partial a_1} \times \frac{\partial a_1}{\partial b_1} \tag{3}$$

$$= \frac{\partial C}{\partial y_4} \times \sigma'(a_4) \times w_4 \times \sigma'(a_3) \times w_3 \times \sigma'(a_2) \times w_2 \times \sigma'(a_1) \tag{4}$$

(5)

INTUITIVE EXPLANATION

The derivative of the activation function : σ'



$$\sigma'(x) = \sigma(x)(1 - \sigma(x))$$

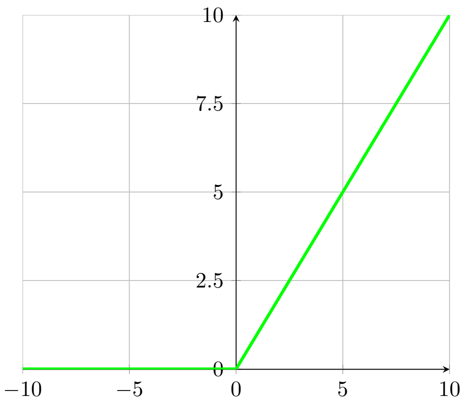
But weights are initialize around 0.

The different layers in our deep network are learning at vastly different speeds :

- when later layers in the network are learning well,
- early layers often get stuck during training, learning almost nothing at all.

SOME HEURISTICS

Change the activation function (Rectified Linear Unit or ReLU)



- Avoid the vanishing gradient
- Some units can "die"

See (Glorot et al.2011) for more details

Do pre-training when it is possible

See (Hinton et al.2006; Bengio et al.2007) :

when you cannot really escape from the initial (random) point, find a good starting point.

More details

See (Hochreiter et al.2001; Glorot and Bengio2010; LeCun et al.2012)

OUTLINE

- Introduction to multi-layered neural network
- Optimization (back-propagation)
- Regularization and Dropout
- The vanishing gradient issue
- Toolkit

USEFUL TOOLS

Theano : http://deeplearning.net/software/theano/

- in python, works on CPU and GPU and several wrappers
- http://lasagne.readthedocs.org/
- http://keras.io/
- https://www.cs.cmu.edu/~ymiao/pdnntk.html
- http://deeplearning.net/software/pylearn2/
- http://blocks.readthedocs.org/

Torch7 : http://torch.ch/

Lua interface to C/CUDA

TensorFlow https://www.tensorflow.org

API in C++ and Python

READINGS (PAPERS)

Basics of deep learning

- Intro to deep learning: http://www.deeplearningbook.org/contents/intro.htm
- Feedforward multi-layer nets: http://www.deeplearningbook.org/contents/r
-
- Learning deep architectures for AI
- Practical recommendations for gradient-based training of deep architectur
- Quick'n'dirty introduction to deep learning: Advances in Deep Learning
- A fast learning algorithm for deep belief nets
- Greedy Layer-Wise Training of Deep Networks
- Stacked denoising autoencoders: Learning useful representations in a dee network with a local denoising criterion
- Contractive auto-encoders: Explicit invariance during feature extraction
- Why does unsupervised pre-training help deep learning?
- An Analysis of Single Layer Networks in Unsupervised Feature Learning
- The importance of Encoding Versus Training With Sparse Coding and Vector Quantization
- Representation Learning: A Review and New Perspectives
- Deep Learning of Representations: Looking Forward
- Measuring Invariances in Deep Networks
- Neural networks course at USherbrooke [youtube]

READINGS (PAPERS)

Feedforward nets

- http://www.deeplearningbook.org/contents/mlp.html
- "Improving Neural Nets with Dropout" by Nitish Srivastava
- Batch Normalization
- "Fast Drop Out"
- "Deep Sparse Rectifier Neural Networks"
- "What is the best multi-stage architecture for object recognition?"
- "Maxout Networks"

MCMC

- Iain Murray's MLSS slides
- Radford Neal's Review Paper (old but still very comprehensive)
- Better Mixing via Deep Representations
- Bayesian Learning via Stochastic Gradient Langevin Dynamics

Restricted Boltzmann Machines

- Unsupervised learning of distributions of binary vectors using 2-layer networks
- A practical guide to training restricted Boltzmann machines
- Training restricted Boltzmann machines using approximations to the likelihood gradient
- Tempered Markov Chain Monte Carlo for training of Restricted Boltzmann Machine
- How to Center Binary Restricted Boltzmann Machines
- Enhanced Gradient for Training Restricted Boltzmann Machines
- Using fast weights to improve persistent contrastive divergence
- Training Products of Experts by Minimizing Contrastive Divergence

READINGS (PAPERS)

Boltzmann Machines

- Deep Boltzmann Machines (Salakhutdinov & Hinton)
- Multimodal Learning with Deep Boltzmann Machines
- Multi-Prediction Deep Boltzmann Machines
- A Two-stage Pretraining Algorithm for Deep Boltzmann Machines

Regularized Auto-Encoders

- The Manifold Tangent Classifier
- DL book chapter on autoencoders: http://www.deeplearningbook.org/contents/autoencoders.html
- DL book chapter on representation learning: http://www.deeplearningbook.org/contents/representation.html
- Representation Learning: A Review and New Perspectives, in particular section 7.

Regularization

Stochastic Nets & GSNs

- Estimating or Propagating Gradients Through Stochastic Neurons for Conditional Computation
- Learning Stochastic Feedforward Neural Networks
- Generalized Denoising Auto-Encoders as Generative Models
- Deep Generative Stochastic Networks Trainable by Backprop

READINGS (PAPERS)

Others

- Slow, Decorrelated Features for Pretraining Complex Cell-like Networks
- What Regularized Auto-Encoders Learn from the Data Generating Distribution
- Generalized Denoising Auto-Encoders as Generative Models
- Why the logistic function?

Recurrent Nets

- DL book chapter on recurrent nets
- Learning long-term dependencies with gradient descent is difficult
- Advances in Optimizing Recurrent Networks
- Learning recurrent neural networks with Hessian-free optimization
- On the importance of momentum and initialization in deep learning,
- Long short-term memory (Hochreiter & Schmidhuber)
- Generating Sequences With Recurrent Neural Networks
- Long Short-Term Memory in Echo State Networks: Details of a Simulation Study
- The "echo state" approach to analysing and training recurrent neural networks
- Backpropagation-Decorrelation: online recurrent learning with O(N) complexity
- New results on recurrent network training:Unifying the algorithms and accelerating convergence
- Audio Chord Recognition with Recurrent Neural Networks
- Modeling Temporal Dependencies in High-Dimensional Sequences: Application to Polyphonic Music Generation and Transcription

READINGS (PAPERS)

Convolutional Nets

- DL book chapter on convolutional nts: http://www.deeplearningbook.org/contents/convnets.html
- Generalization and Network Design Strategies (LeCun)
- ImageNet Classification with Deep Convolutional Neural Networks, Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, NIPS 2012.
- On Random Weights and Unsupervised Feature Learning

Optimization issues with DL

- Curriculum Learning
- Evolving Culture vs Local Minima
- Knowledge Matters: Importance of Prior Information for Optimization
- Efficient Backprop
- Practical recommendations for gradient-based training of deep architectures
- Batch Normalization
- Natural Gradient Works Efficiently (Amari 1998)
- Hessian Free
- Natural Gradient (TONGA)
- Revisiting Natural Gradient

READINGS (BOOKS)

- *Deep Learning Book* by Yoshua Bengio, Ian Goodfellow and Aaron Courville (`http://www.iro.umontreal.ca/~bengioy/dlbook/`)
- *Deep Learning for Natural Language Processing* by Stanford University `http://cs224d.stanford.edu/`
- *Deep Learning - Methods and Applications* by Li Deng and Dong Yu `http://research.microsoft.com/pubs/219984/BOOK2014.pdf`
- *Reading lists for new LISA students* by University of Montreal.