Deep Learning:
Architectures, algorithms, applications

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Outline

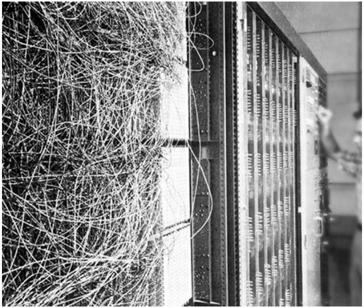
Part I:

1. Intro, motivation
2. Machine learning 101
3. Neural nets, backprop, RNNs
4. Applications

Part II:

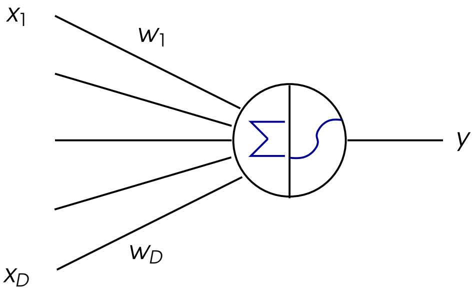
1. Structured prediction
2. Unsupervised learning
3. Attention $\rightarrow$ Reasoning $\rightarrow$ "Neural programs"
4. Architecture exploration
5. Towards hardware-friendlier DL
6. Software

Rosenblatt’s perceptron (1957)



pictures from http://www.rutherfordjournal.org/article040101.html

Rosenblatt's perceptron (1957)



$y(\sum_i w_i x_i) = y(\mathbf{w}^{\mathrm{T}}\mathbf{x})$

- *"the embryo of an electronic computer that (the Navy) expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence"*

(in NYT according to wikipedia)

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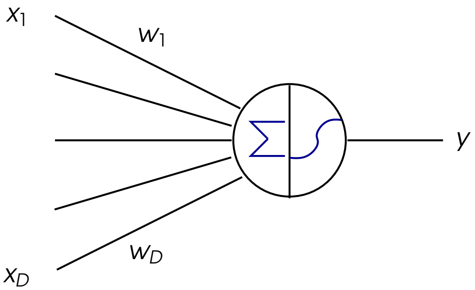

$y(\sum_i w_i x_i) =$
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- *"the embryo of an electronic computer that (the Navy) expects will be able to* **walk***,* **talk***,* **see***,* **write***, reproduce itself and be conscious of its existence"*

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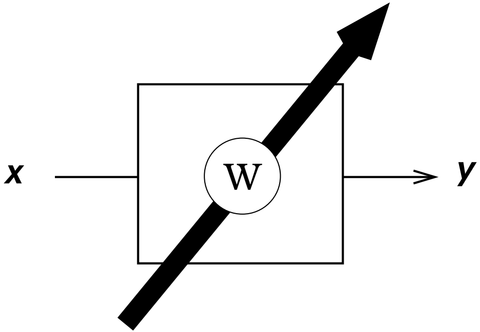
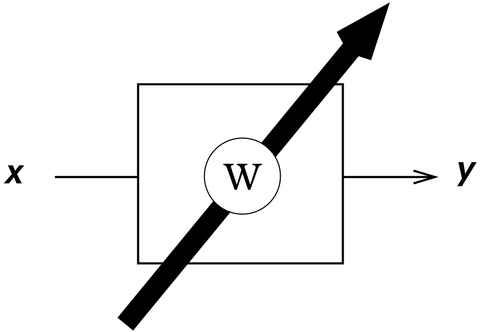
Machine Learning

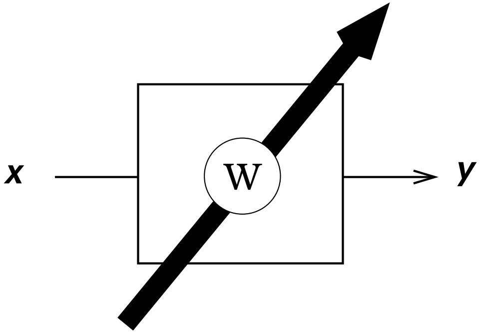


Machine Learning



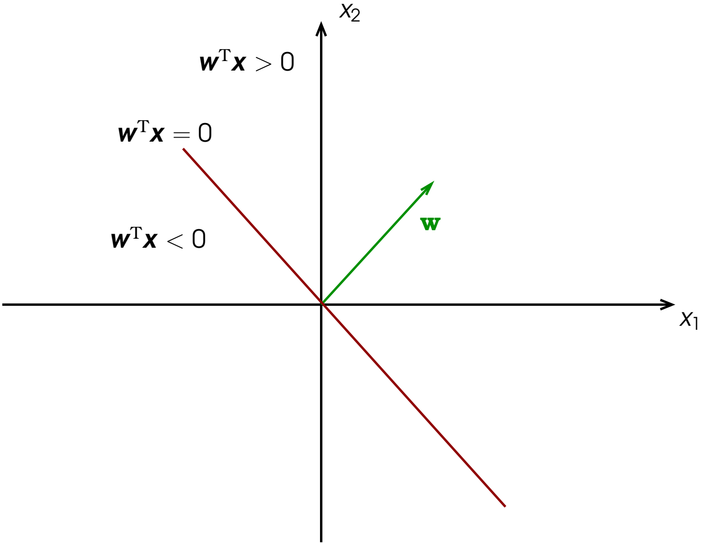
- ML allows us to harness **training data** $(\boldsymbol{x}_n, \boldsymbol{t}_n)_{n=1 \ldots N}$

Machine Learning



- ML allows us to harness **training data** $(\boldsymbol{x}_n, \boldsymbol{t}_n)_{n=1 \ldots N}$
- ML allows us to harness **parallelization**

Machine Learning



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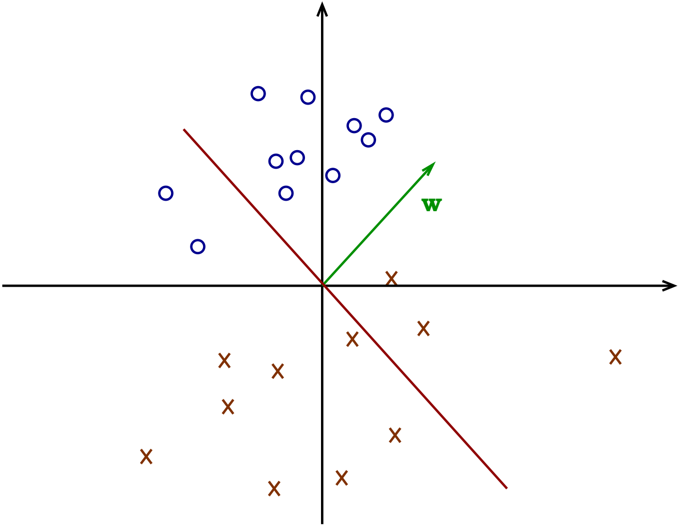
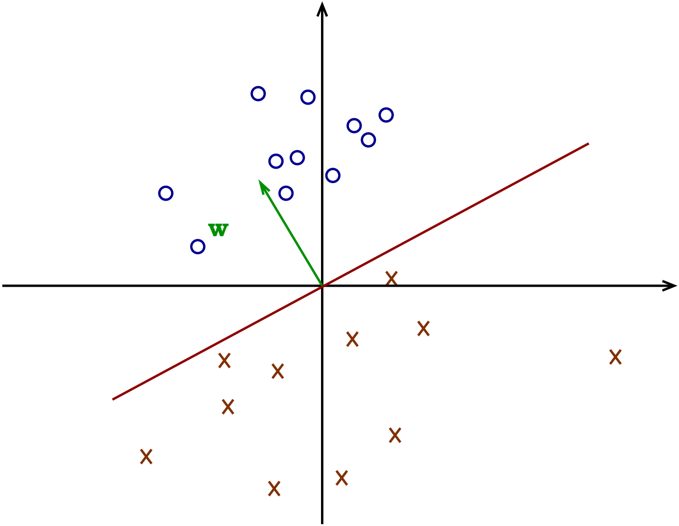
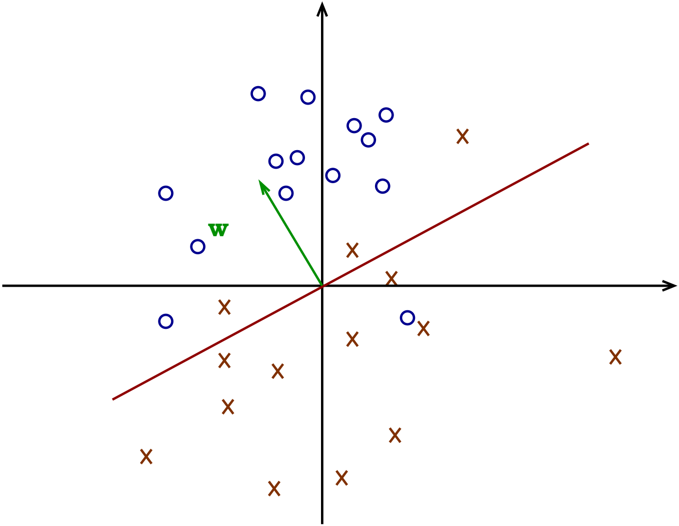


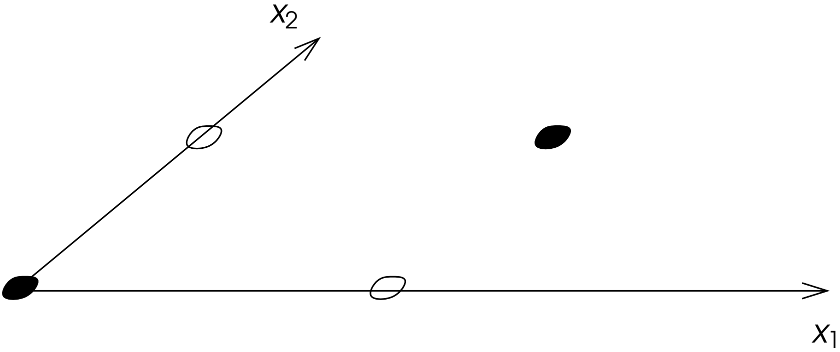
Machine Learning



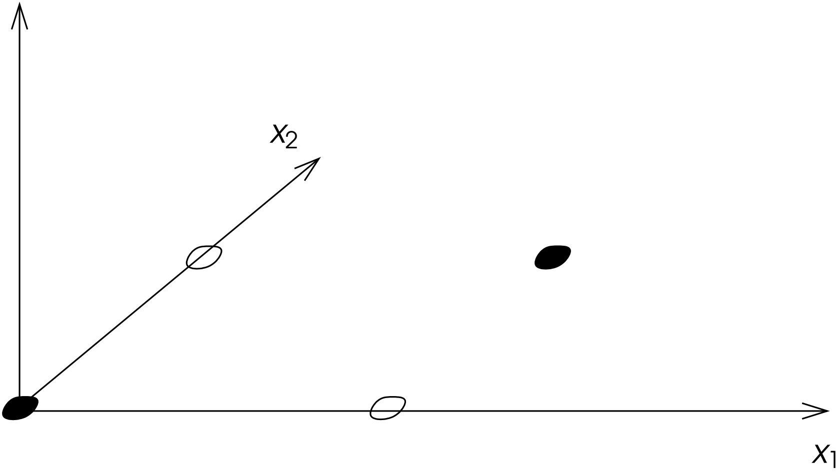
Machine Learning



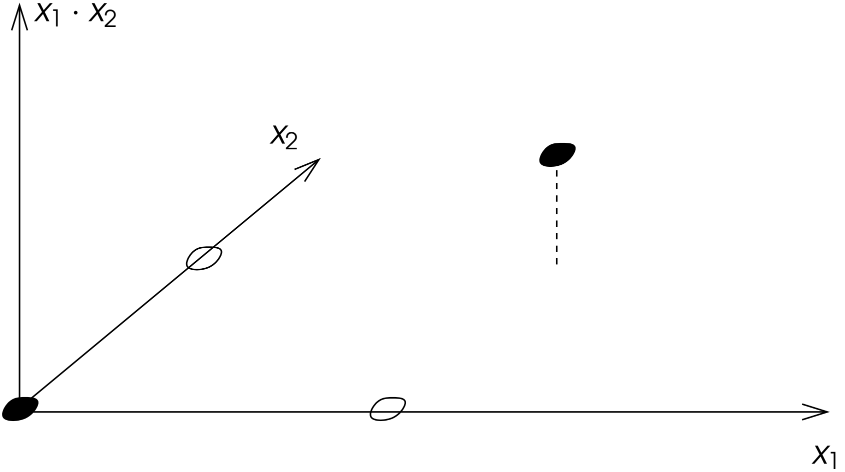
The XOR problem



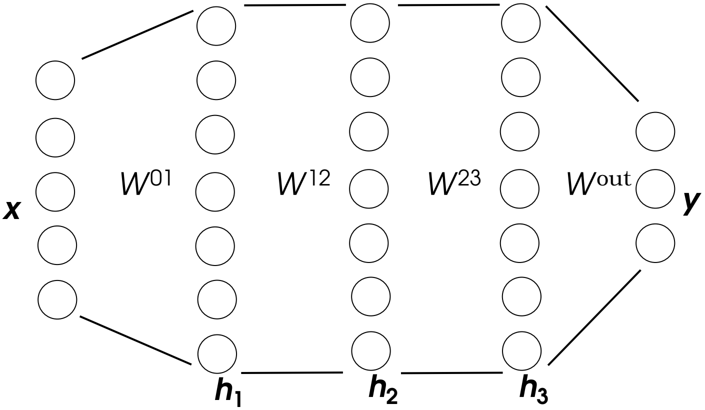
The XOR problem and multi-stage processing



The XOR problem and multi-stage processing



Multi-stage processing



“It’s the features, stupid!”

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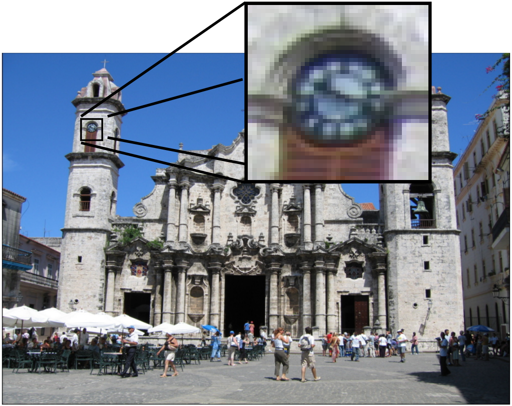
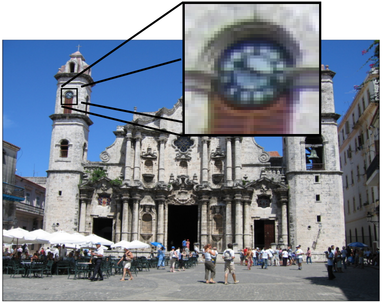


“It’s the features, stupid!”

A common computer vision pipeline before 2012

1. Find interest points.

"It's the features, stupid!"



A common computer vision pipeline before 2012

1. Find interest points.
2. Crop patches around them.

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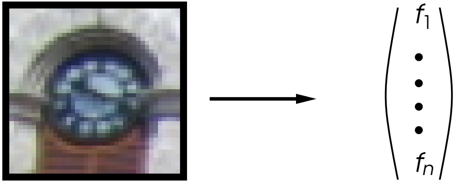


A common computer vision pipeline before 2012

1. Find interest points.
2. Crop patches around them.
3. Represent each patch with a sparse local descriptor.

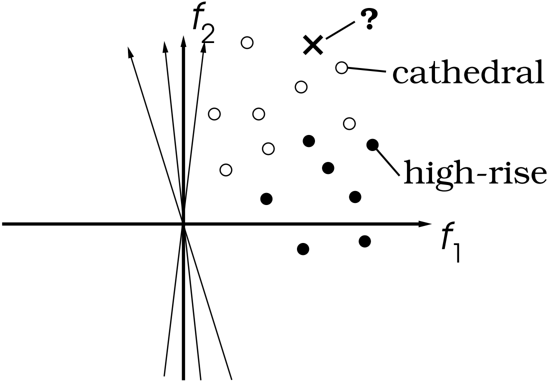
“It’s the features, stupid!”

$$\begin{pmatrix} f_1^1 \\ \vdots \\ f_n^1 \end{pmatrix} + \cdots\cdots + \begin{pmatrix} f_1^M \\ \vdots \\ f_n^M \end{pmatrix}$$

A common computer vision pipeline before 2012

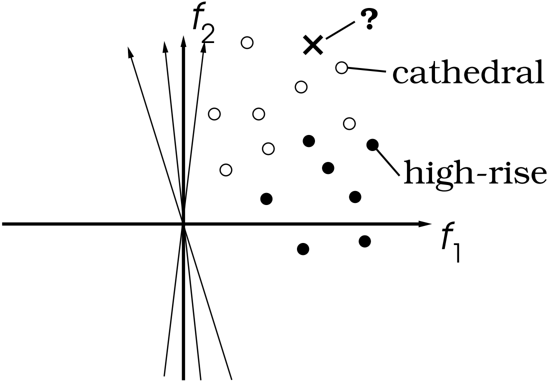
1. Find interest points.
2. Crop patches around them.
3. Represent each patch with a sparse local descriptor.
4. Combine the descriptors into a representation of the image.

“It’s the features, stupid!”



- This creates a representation that even a linear classifier can deal with.

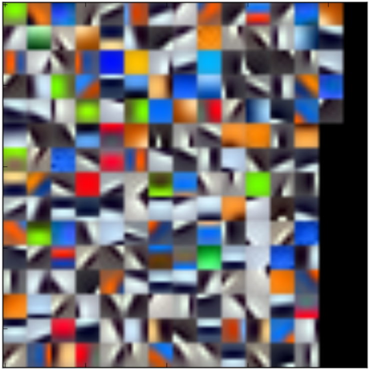
“It’s the features, stupid!”



- This creates a representation that even a linear classifier can deal with.

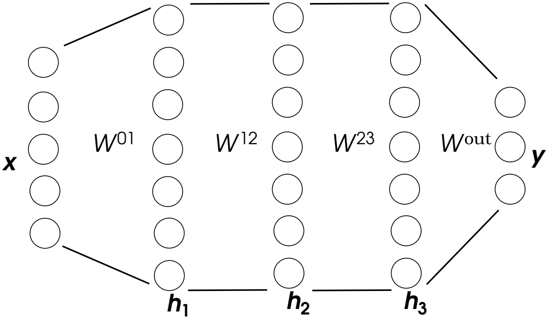
bottom line: **non-linear pipelines are useful**
(aka *“the representation matters”*)

What do good low-level features look like?

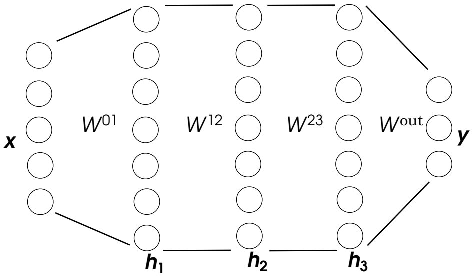


- Local features that are often found to work well are based on oriented structure (such as Gabor features)
- These were discovered again and again (also in other areas) and are closely related to the Short Time Fourier Transform.

Neural networks are *trainable* pipelines



Neural networks are *trainable* pipelines

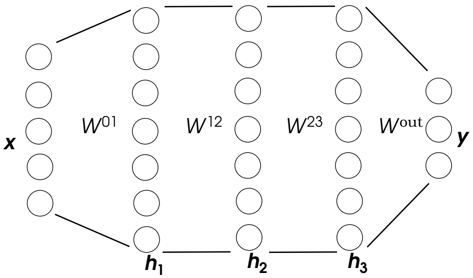


Most common networks interleave **matrix multiplies** with **element-wise non-linearities**:

$$\boldsymbol{y}(\mathbf{x}) = W^{\text{out}} h(W^{23} h(W^{12} h(W^{01} \boldsymbol{x})))$$

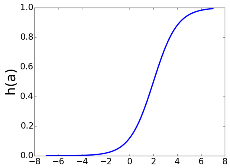
Usually there are constant "bias"-terms as well.

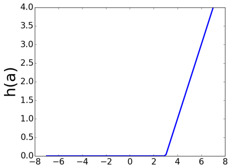
Neural networks are *trainable* pipelines

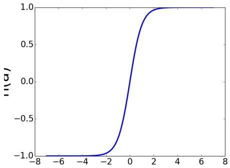


Common non-linearities:

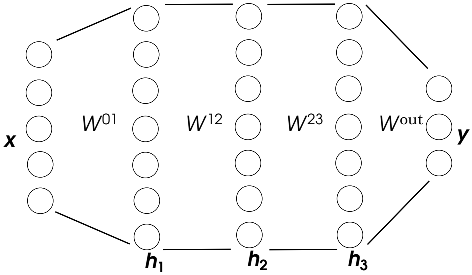
sigmoid: $h(a) = \frac{1}{1+\exp(a)}$ ReLU: $h(a) = a \cdot [a > 0]$ tanh: $h(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}$







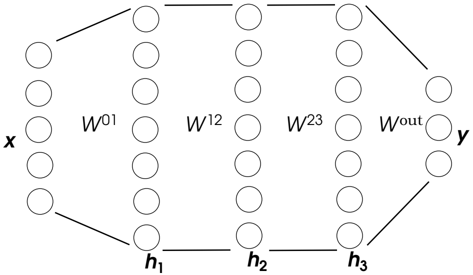
Neural networks are *trainable* pipelines



For classification tasks, turn class outputs into probabilities using the "softargmax" function:

$$p(\mathcal{C}_k|\boldsymbol{x}) = \frac{\exp(y_k(\boldsymbol{x}))}{\sum_j \exp(y_j(\boldsymbol{x}))}$$

Neural networks are *trainable* pipelines



For training, use a (large) training set $(\boldsymbol{x}_n, \boldsymbol{t}_n)_{n=1...N}$ and minimize a suitable *cost*-function.
The minimization is usually done using stochastic gradient descent (SGD).

The most common choices of cost function

- **Regression** (predict real values):

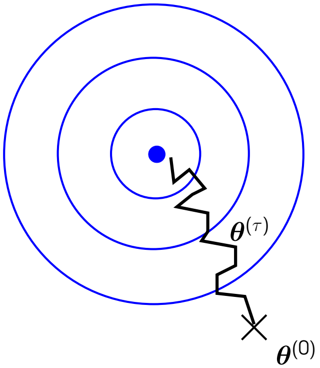
$$\text{cost} = \frac{1}{2}\sum_{n=1}^{N} \|\boldsymbol{y}(\boldsymbol{x}_n) - \boldsymbol{t}_n\|^2$$

- **Classification** (predict discrete labels):

$$\text{cost} = -\sum_{n=1}^{N}\sum_{k=1}^{K} t_{nk} \log p(\mathcal{C}_k|\boldsymbol{x}_n)$$

where $t_{nk} = 1$ iff training case n belongs to class k.

Stochastic gradient descent (SGD)



new parameter value

$$\boldsymbol{\theta}^{(\tau+1)} = \boldsymbol{\theta}^{(\tau)} - \eta \frac{\partial \mathrm{cost}(\boldsymbol{x}_n, \boldsymbol{t}_n)}{\partial \boldsymbol{\theta}}$$

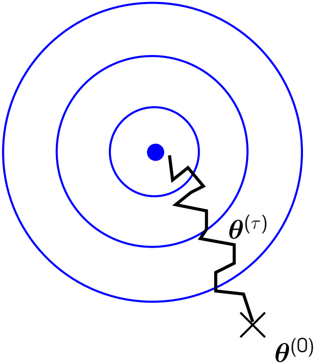
old parameter value

learning rate

For one or several training cases at a time, iterate:

1. compute cost (forward pass)
2. compute derivatives (backward pass)
3. update parameters

Stochastic gradient descent (SGD)



new parameter value

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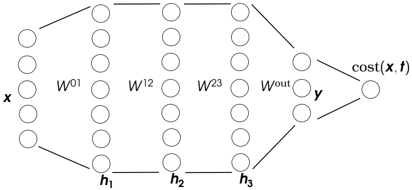
old parameter value

learning rate

- Most operations performed on each training example will be matrix-vector products.
- To get a higher arithmetic intensity it is common to use **mini-batches** (often of size $\approx$ 100, currently...).
- Each full pass through the training set is called an **epoch**.

Computing derivatives: Error back-propagation (backprop): Rumelhart, Hinton, Williams 1986



- **Use the chainrule!** For regression and classification we get:

$$\frac{\partial \text{cost}}{\partial \boldsymbol{y}(\boldsymbol{x}_n)} = \boldsymbol{y}(\boldsymbol{x}_n) - \boldsymbol{t}_n$$

- Next: If $\boldsymbol{y}$ has any parameters, W^{out}, collect them using:

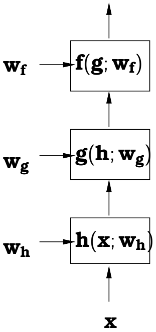
$$\frac{\partial \text{cost}}{\partial W^{\text{out}}} = (\boldsymbol{y}(\boldsymbol{x}_n) - \boldsymbol{t}_n) \cdot \frac{\partial \boldsymbol{y}(\boldsymbol{x}_n)}{\partial W^{\text{out}}}$$

- Next: Descend to the next layer by computing

$$\frac{\partial \text{cost}}{\partial \boldsymbol{h}_3} = \frac{\partial \text{cost}}{\partial \boldsymbol{y}(\boldsymbol{x}_n)} \cdot \frac{\partial \boldsymbol{y}(\boldsymbol{x}_n)}{\partial \boldsymbol{h}_3(\boldsymbol{x}_n)}$$

...and so on...

Backprop general form



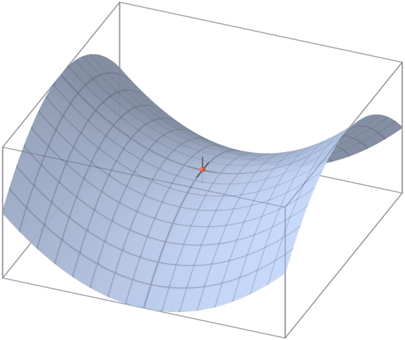
$\mathbf{f}$	$\frac{\partial \mathbf{f}}{\partial \mathbf{g}}$	$\frac{\partial \mathbf{f}}{\partial \mathbf{w_f}}$
fprop	bprop	grad

- Backprop can be thought of as an engineering principle, that prescribes how to design an end-to-end train-able system from differentiable components:
- Use components which provide the methods **fprop**, **bprop** and **grad**. Then backprop can be automated.
- Well-suited for support by software frameworks

Potential Issues

- “But what about local minima?”
- “But what about overfitting?”
- Vanishing gradients

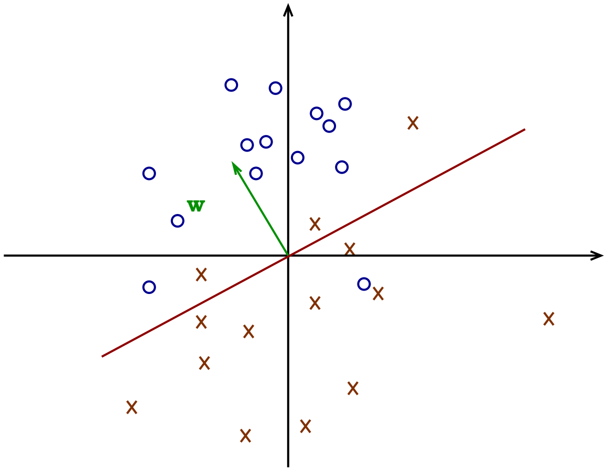
The cost surface/local optima



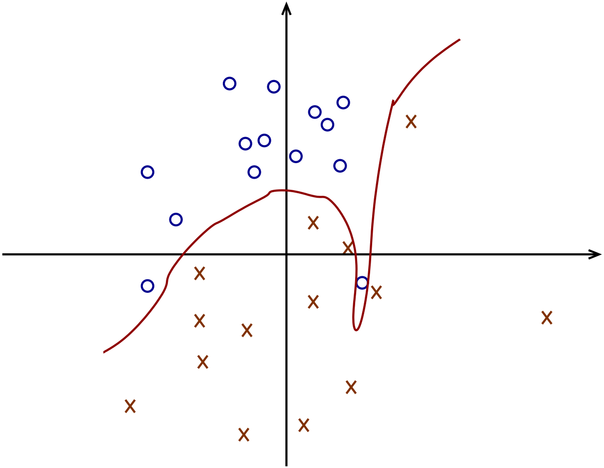
- Local minima not an issue in practice
- This is probably due to high dimensional parameter space, which causes most critical points to be **saddle points** not local optima.
- Some recent theoretical work supports this view (Choromanska et al. 2014); (Dauphin, et al. 2014)

figure from wikipedia

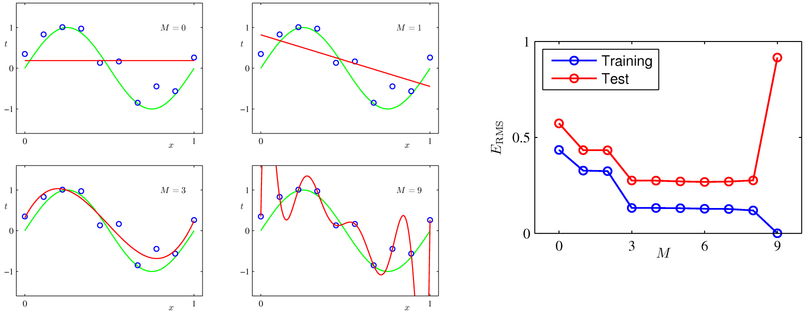
Overfitting



Overfitting



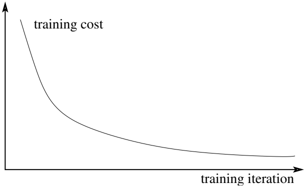
Overfitting in regression

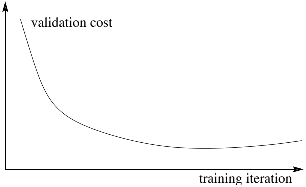


(Bishop 2006: Pattern recognition and machine learning)

Preventing overfitting in neural networks

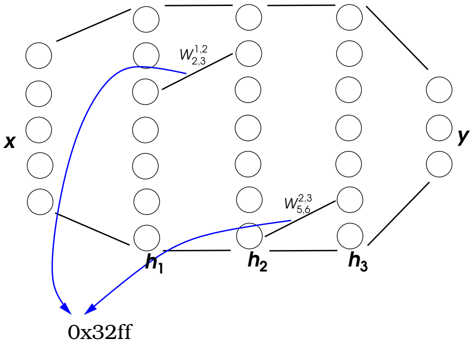
- **Early stopping**:





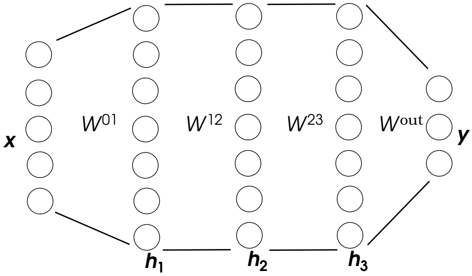
- **Weight decay** (somewhat outdated): add a weight penalty to the training objective (weight constraints now more common)
- **Dropout (Hinton et al., 2012)**: Corrupt hidden unit activations during training
- **More data**
- **Weight sharing (reduce the number of parameters):**

Weight sharing



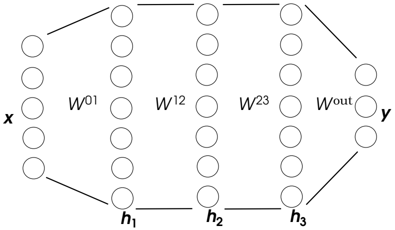
- Parameters can be shared by having them point to the same memory location.
- Very common way to reduce parameters and encode prior knowledge.
- Central ingredient in conv-nets (CNNs) and recurrent nets (RNNs).
- *Caveat: It requires long-range communication.*

The vanishing gradients problem



- The backward-pass is a sequence of matrix multiplies.
- Depending on the magnitude of the eigenvalues, initial values can blow up or decay to zero.
- This can may learning difficult or slow.
- Potential solutions: architectural tricks (for example, the "LSTM" unit)

Neural nets learn distributed representations



- Neural networks encode information as vectors of real values.
- This makes it easy to encode conceptual similarities. In a text processing task, for example:
  - If user searches for **Dell notebook battery size**, we would like to match documents with "Dell laptop battery capacity"
  - If user searches for **Seattle motel**, we would like to match documents containing "Seattle hotel"

(Example from Chris Manning)

Summary so far

1. Non-linear pipelines are good
2. It is easy to train non-linear pipelines end-to-end using back-prop + SGD
3. Local minima are a non-issue
4. Overfitting is an issue, but it can be solved

- The two crucial changes that made deep learning work on real-world tasks $\approx$ 2010:

$$\text{GPUs} + \text{Large datasets}$$

DL impact in speech recognition

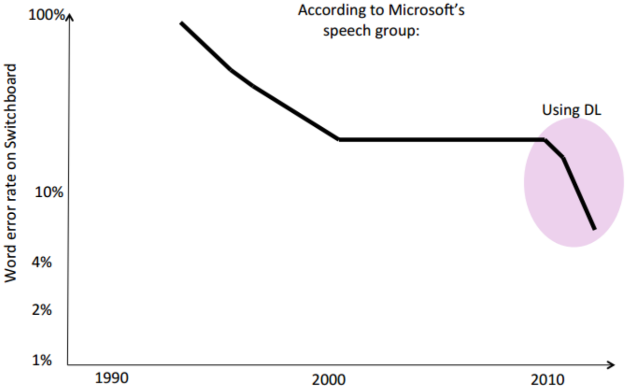
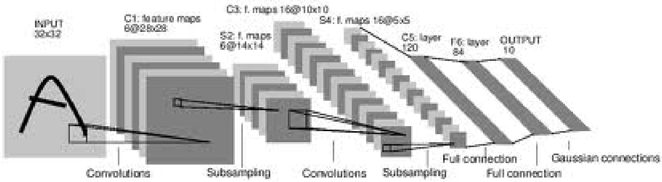


figure from Yoshua Bengio

Convolutional networks (CNN)



- LeCun et al. 1998
- The gist: Instead of feeding a large image to the network, feed small patches to the network.
- $\rightarrow$ dramatic reduction of parameters
- CNNs also have subsampling layers, so higher layers see more of the image.

ImageNet challenge 2012

ImageNet Large Scal ×

www.image-net.org/challenges/LSVRC/2012/results.html

IMAGENET **Large Scale Visual Recognition Challenge 2012 (ILSVRC2012)**

Held in conjunction with PASCAL Visual Object Classes Challenge 2012 (VOC2012)

Back to Main page

All results

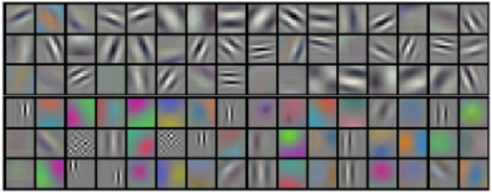
- Task 1 (classification)
- Task 2 (localization)
- Task 3 (fine-grained classification)
- Team information and abstracts

Task 1

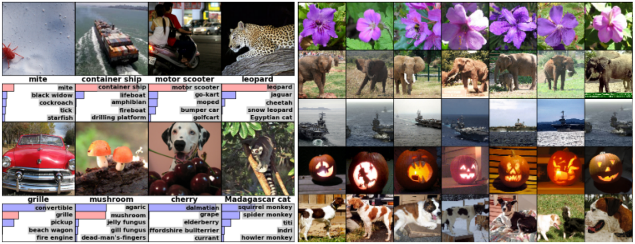
Team name	**Filename**	**Error (5 guesses)**	**Description**
SuperVision	test-preds-141-146.2009-131-137-145-146.2011-145f.	0.15315	Using extra training data from ImageNet Fall 2011 release
SuperVision	test-preds-131-137-145-135-145f.txt	0.16422	Using only supplied training data
ISI	pred_FVs_wLACs_weighted.txt	0.26172	Weighted sum of scores from each classifier with SIFT+FV, LBP+FV, GIST+FV, and CSIFT+FV, respectively.
ISI	pred_FVs_weighted.txt	0.26602	Weighted sum of scores from classifiers using each FV.
ISI	pred_FVs_summed.txt	0.26646	Naive sum of scores from classifiers using each FV.
ISI	pred_FVs_wLACs_summed.txt	0.26952	Naive sum of scores from each classifier with SIFT+FV, LBP+FV,

ImageNet challenge 2012

some first-layer features



some results



Krizhevsky, Sutskever, Hinton; 2012

High-level features

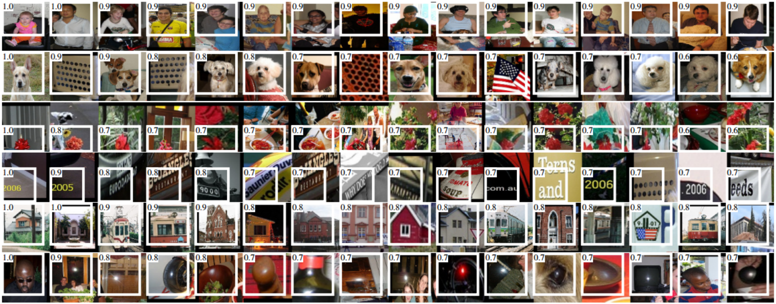
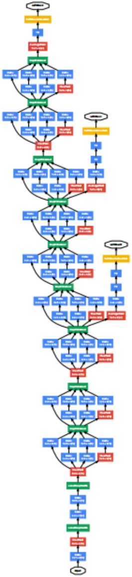


Figure 4: Top regions for six pool$_5$ units. Receptive fields and activation values are drawn in white. Some units are aligned to concepts, such as people (row 1) or text (4). Other units capture texture and material properties, such as dot arrays (2) and specular reflections (6).

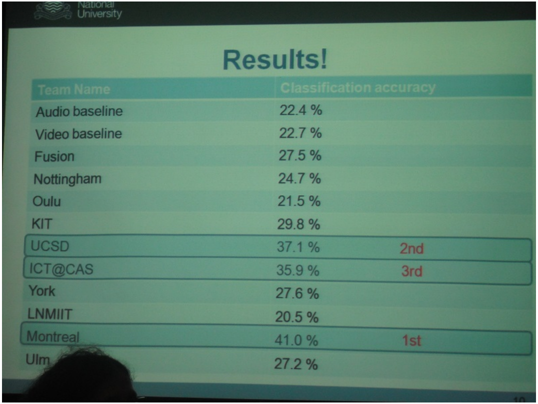
Girshick et al., 2014

GoogLeNet (Szegedy et al. 2014)

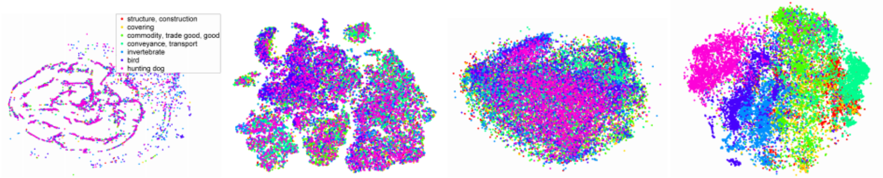


- Exercise in (a) scaling up, (b) unconventional architectures
- Won ImageNet 2014 with **6.66%** top-5 error rate
- A variation of this network including BatchNormalization (Ioffe, Szegedy, 2015) achieves **4.8%** top-5 error rate, surpassing the accuracy of human raters

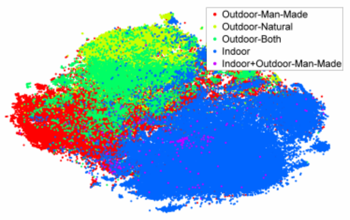
Emotion recognition in the wild Challenge 2013



Conv-nets learn good *generic* features



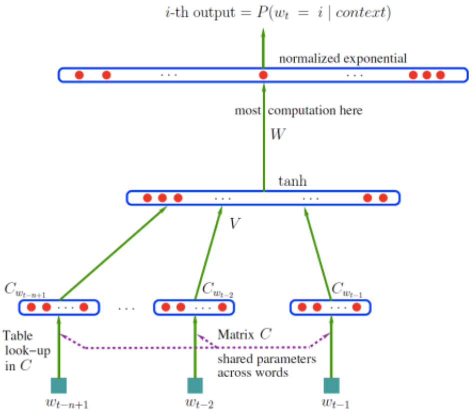
(a) LLC (b) GIST (c) DeCAF$_1$ (d) DeCAF$_6$



non-imagenet classes:

(Donahue et al, 2013)

Word embeddings



- Bengio et al 2000
- This is a way to learn **distributed representations** for symbols (words).

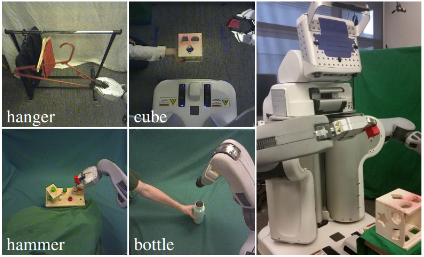
Word embeddings

King - Man + Woman = Queen

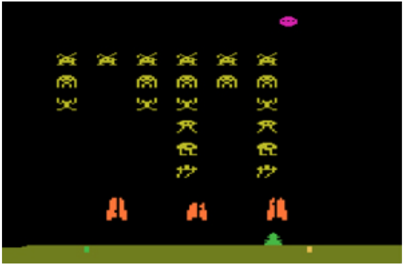
Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Mikolov et al. 2013

Robotics/Reinforcement Learning

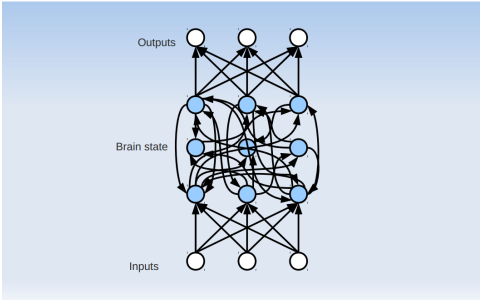


Levine et al. 2015



Mnih et al. 2013

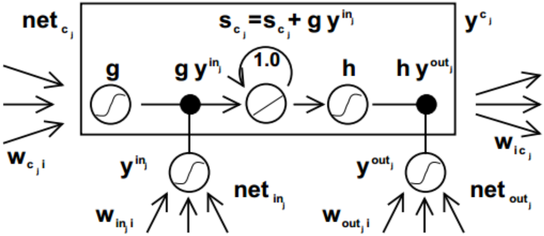
Recurrent networks (RNN)



picture from http://www.cs.toronto.edu/ asamir/cifar/Ilya_slides.pdf

- Stepping the network T time steps yields the equivalent of a T-layer feedforward net with weights that are shared between layers.
- Training the network by unrolling it in time is called back-prop-through-time (BPTT).
- Vanishing gradients especially problematic here.

Long-Short Term Memory (LSTM)

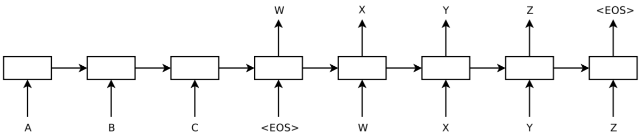


(Hochreiter, Schmidthuber; 1997)

RNN applications (thanks mainly to LSTM)

- Machine Translation (Sutskever et al. NIPS 2014), (Cho et al. Arxiv 2014)
- Speech synthesis (Fan et al. INTERSPEECH 2014)
- Speech recognition (Hannun et al., 2014)
- Handwriting generation http://www.cs.toronto.edu/ graves/handwriting.html
- Text generation
- Caption generation

The encoder-decoder architecture



Machine translation examples:

Type	Sentence
Our model	Ulrich UNK , membre du conseil d' administration du constructeur automobile Audi , affirme qu' il s' agit d' une pratique courante depuis des années pour que les téléphones portables puissent être collectés avant les réunions du conseil d' administration afin qu' ils ne soient pas utilisés comme appareils d' écoute à distance .
Truth	Ulrich Hackenberg , membre du conseil d' administration du constructeur automobile Audi , déclare que la collecte des téléphones portables avant les réunions du conseil , afin qu' ils ne puissent pas être utilisés comme appareils d' écoute à distance , est une pratique courante depuis des années .
Our model	" Les téléphones cellulaires , qui sont vraiment une question , non seulement parce qu' ils pourraient potentiellement causer des interférences avec les appareils de navigation , mais nous savons , selon la FCC , qu' ils pourraient interférer avec les tours de téléphone cellulaire lorsqu' ils sont dans l' air " , dit UNK .
Truth	" Les téléphones portables sont véritablement un problème , non seulement parce qu' ils pourraient éventuellement créer des interférences avec les instruments de navigation , mais parce que nous savons , d' après la FCC , qu' ils pourraient perturber les antennes-relais de téléphonie mobile s' ils sont utilisés à bord " , a déclaré Rosenker .
Our model	Avec la crémation , il y a un " sentiment de violence contre le corps d' un être cher " , qui sera " réduit à une pile de cendres " en très peu de temps au lieu d' un processus de décomposition " qui accompagnera les étapes du deuil " .
Truth	Il y a , avec la crémation , " une violence faite au corps aimé " , qui va être " réduit à un tas de cendres " en très peu de temps , et non après un processus de décomposition , qui " accompagnerait les phases du deuil " .

Sutskever et al. NIPS 2014, Bahdanau et al. 2014

Caption generation (Xu et al 2015)

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

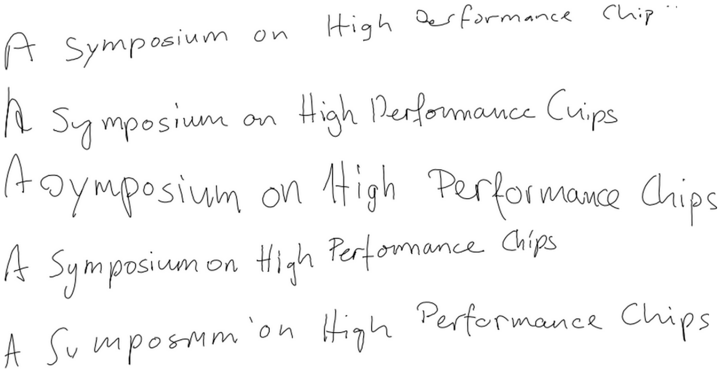
A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Handwriting generation



http://www.cs.toronto.edu/ graves/handwriting.html

Generating text

```
Naturalism and decision for the majority of Arab countries' capitalide was grounded
by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated
with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal
in the [[Protestant Immineners]], which could be said to be directly in Cantonese
Communication, which followed a ceremony and set inspired prison, training. The
emperor travelled back to [[Antioch, Perth, October 25|21]] to note, the Kingdom
of Costa Rica, unsuccessful fashioned the [[Thrales]], [[Cynth's Dajoard]], known
in western [[Scotland]], near Italy to the conquest of India with the conflict.
Copyright was the succession of independence in the slop of Syrian influence that
was a famous German movement based on a more popular servicious, non-doctrinal
and sexual power post. Many governments recognize the military housing of the
[[Civil Liberalization and Infantry Resolution 265 National Party in Hungary]],
that is sympathetic to be to the [[Punjab Resolution]]
(PJS)[http://www.humah.yahoo.com/guardian.
cfm/7754800786d17551963s89.htm Official economics Adjoint for the Nazism, Montgomery
was swear to advance to the resources for those Socialism's rule,
was starting to signing a major tripad of aid exile.]]
```

from: Andrej Kaparthy:
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Generating text

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
  return segtable;
}
```

from: Andrej Kaparthy:
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Generating text

For $\bigoplus_{n=1,\ldots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \mathrm{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example ??. It may replace S by $X_{spaces,\acute{e}tale}$ which gives an open subspace of X and T equal to S_{Zar}, see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

Lemma 0.1. *Assume (3) and (3) by the construction in the description.*

Suppose $X = \lim |X|$ (by the formal open covering X and a single map $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ over U compatible with the complex

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \to \mathcal{C}_{Z/X}$ is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S. Moreover there exists a closed subspace $Z \subset X$ of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1) f is locally of finite type. Since $S = \mathrm{Spec}(R)$ and $Y = \mathrm{Spec}(R)$.

Proof. This is form all sheaves of sheaves on X. But given a scheme U and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\ldots,n} U_i$ be the scheme X over S at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X},\ldots,0}$.

Lemma 0.2. *Let X be a locally Noetherian scheme over S, $E = \mathcal{F}_{X/S}$. Set $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. Since $\mathcal{I}^n \subset \mathcal{I}^n$ are nonzero over $i_0 \leq \mathfrak{p}$ is a subset of $\mathcal{J}_{n,0} \circ \overline{A}_2$ works.*

Lemma 0.3. *In Situation ??. Hence we may assume $\mathfrak{q}' = 0$.*

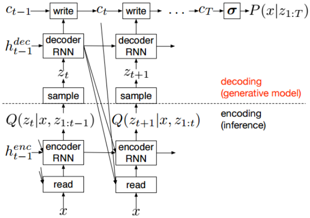
Proof. We will use the property we see that $\mathfrak{p}$ is the mext functor (??). On the other hand, by Lemma ?? we see that

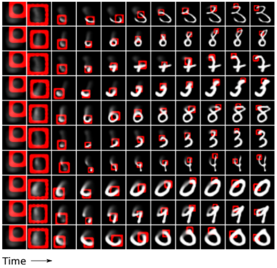
$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

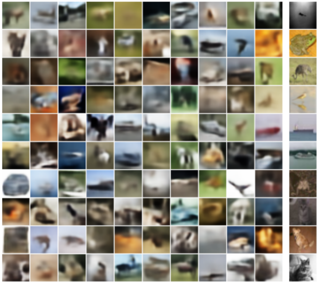
where K is an F-algebra where δ_{n+1} is a scheme over S. □

from: Andrej Kaparthy:
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

DRAWing (Gregor et al., 2015)

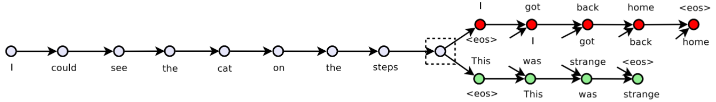






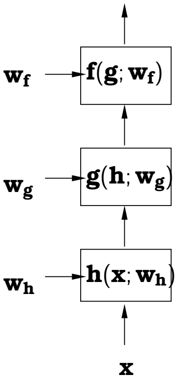
Sentence embeddings (Kiros et al 2015)

- A natural generalization of a word embedding is a sentence embedding:



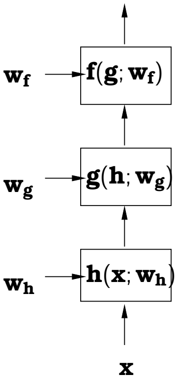
Query and nearest sentence
he ran his hand inside his coat , double-checking that the unopened letter was still there . he slipped his hand between his coat and his shirt , where the folded copies lay in a brown envelope .
im sure youll have a glamorous evening , she said , giving an exaggerated wink . im really glad you came to the party tonight , he said , turning to her .
although she could tell he had n't been too invested in any of their other chitchat , he seemed genuinely curious about this . although he had n't been following her career with a microscope , he 'd definitely taken notice of her appearances .
an annoying buzz started to ring in my ears , becoming louder and louder as my vision began to swim . a weighty pressure landed on my lungs and my vision blurred at the edges , threatening my consciousness altogether .
if he had a weapon , he could maybe take out their last imp , and then beat up errol and vanessa . if he could ram them from behind , send them sailing over the far side of the levee , he had a chance of stopping them .
then , with a stroke of luck , they saw the pair head together towards the portaloos . then , from out back of the house , they heard a horse scream probably in answer to a pair of sharp spurs digging deep into its flanks .
" i 'll take care of it , " goodman said , taking the phonebook . " i 'll do that , " julia said , coming in .
he finished rolling up scrolls and , placing them to one side , began the more urgent task of finding ale and tankards . he righted the table , set the candle on a piece of broken plate , and reached for his flint , steel , and tinder .

Deep Learning as a compute paradigm



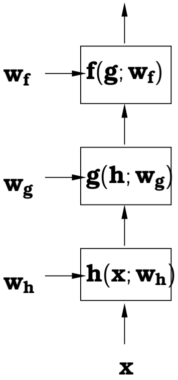
- perform a *series of operations* to solve a task
- $+$ use *learning* to define the computations

Deep Learning as a compute paradigm



- perform a *series of operations* to solve a task
- $+$ use *learning* to define the computations
- $+$ make each computation *parallel*

Deep Learning as a compute paradigm



- perform a *series of operations* to solve a task
- + use **learning** to define the computations
- + make each computation **parallel**

Dense, parallel computations are easy, if we don't need to program them.

Deep learning needs parallel hardware.

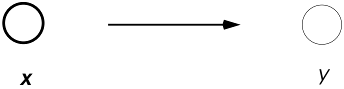
Parallel hardware needs deep learning.

Part II: Research directions, software tools, outlook

Structured prediction

Structured prediction

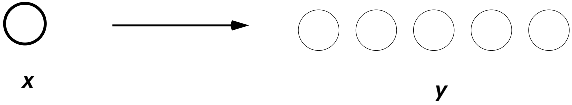
Prediction:



Structured prediction

Prediction:

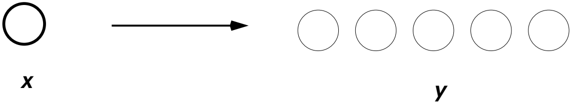
Structured prediction:



Structured prediction

Prediction:

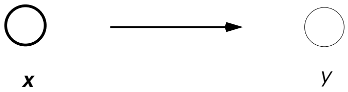
Structured prediction:



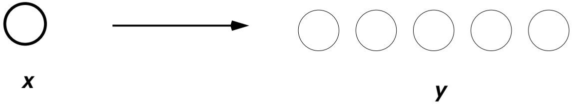
Problem: combinatorial explosion

Structured prediction

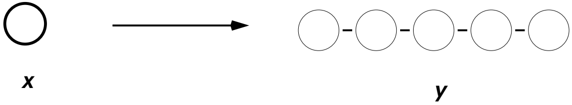
Prediction:



Structured prediction:

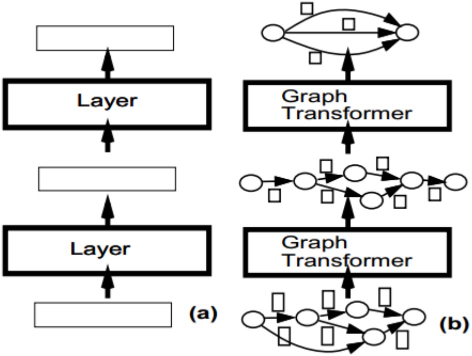


Problem: combinatorial explosion
Solution: Impose tractable dependency structure



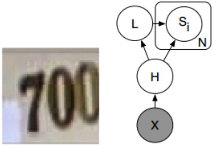
- Applications: Scene labeling, text, speech, ...

Solution proposed in 1998



- Main insight: When layers are complex *graphs*, back-prop still works (LeCun et al 1998)
- This observation was recycled in 2001 under the name *Conditional Random Field*

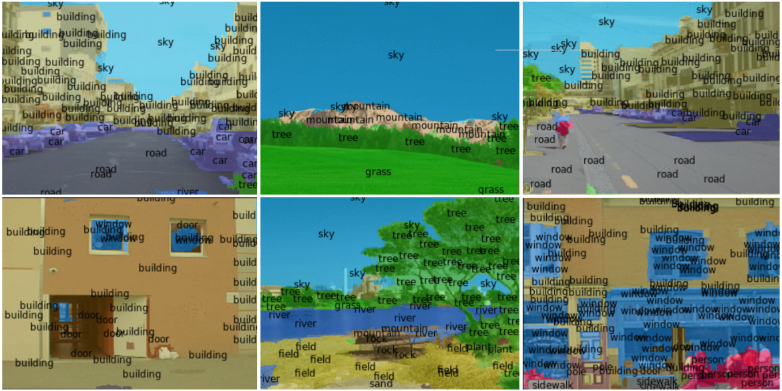
Streetview (Goodfellow et al, ICLR 2014)



a) b)

- recent extension to recognizing text in images: eg. Jaderberg et al. ICLR 2015

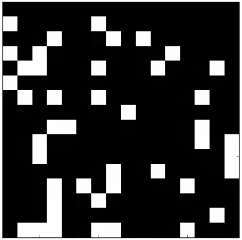
Towards scene understanding



Farabet et al, 2013

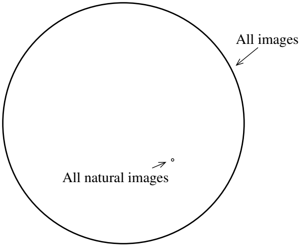
Unsupervised learning

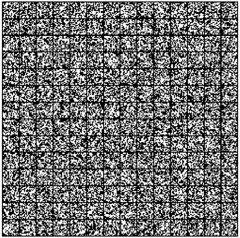
The curse of dimensionality

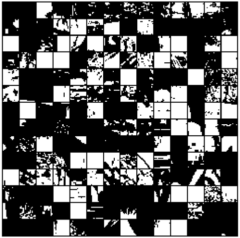


- There are 2^{16*16} tiny binary images of size 16×16 pixels.
- A child of age 3 has seen less than 10 billion images and much fewer labeled images.
- How is it possible we can do any vision?

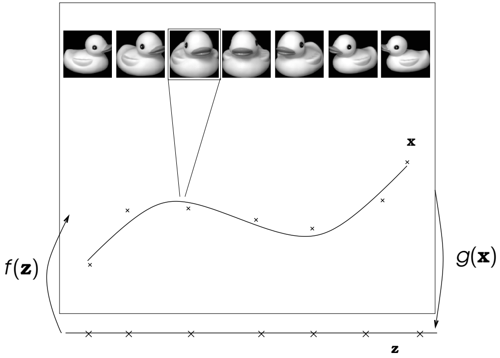
The curse of dimensionality





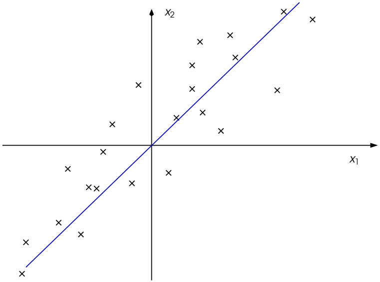


Unsupervised learning



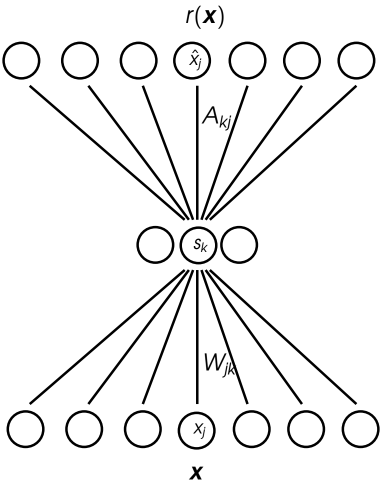
- Data may be distributed along some lower-dimensional *manifold* in the dataspace.

Principal Components Analysis (PCA)



- If that manifold is *linear*, learning is easy and it can done in closed form: Compute the eigenvectors of the data covariance matrix.

Autoencoders

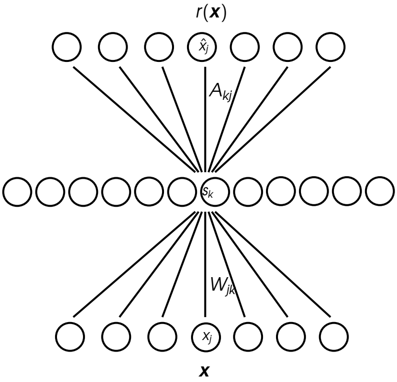


- If the manifold is non-linear (or not a really a manifold) we can use autoencoders.
- Autoencoders are simple neural networks that are trained to reconstruct their input:

$$\mathrm{cost} = \|r(\boldsymbol{x}) - \boldsymbol{x}\|^2$$

- The hidden layer is a bottleneck that forces the model to *compress* the inputs.

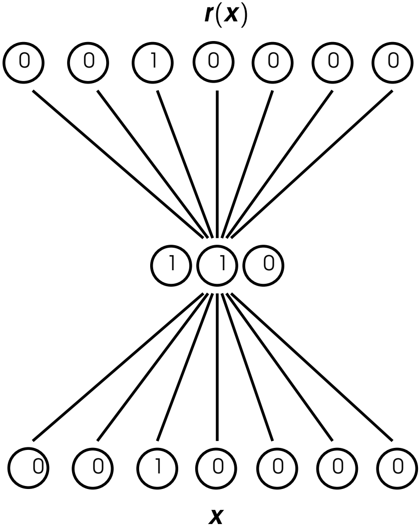
Autoencoders



- In practice, it is more common to use overcomplete hiddens and to enforce compression in other ways (for example, by making the hidden activations sparse).

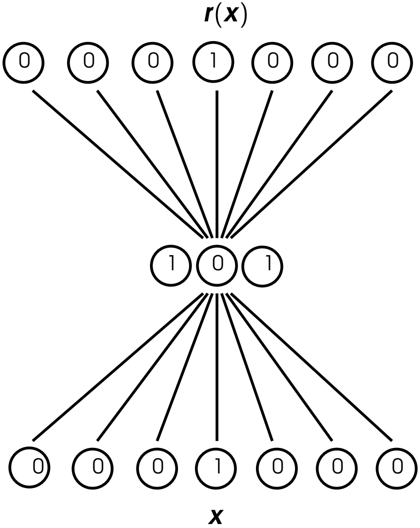
Autoencoders learn to do compression

$$\boldsymbol{r}(\boldsymbol{x}) = Wh\big(W^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{b}\big)$$

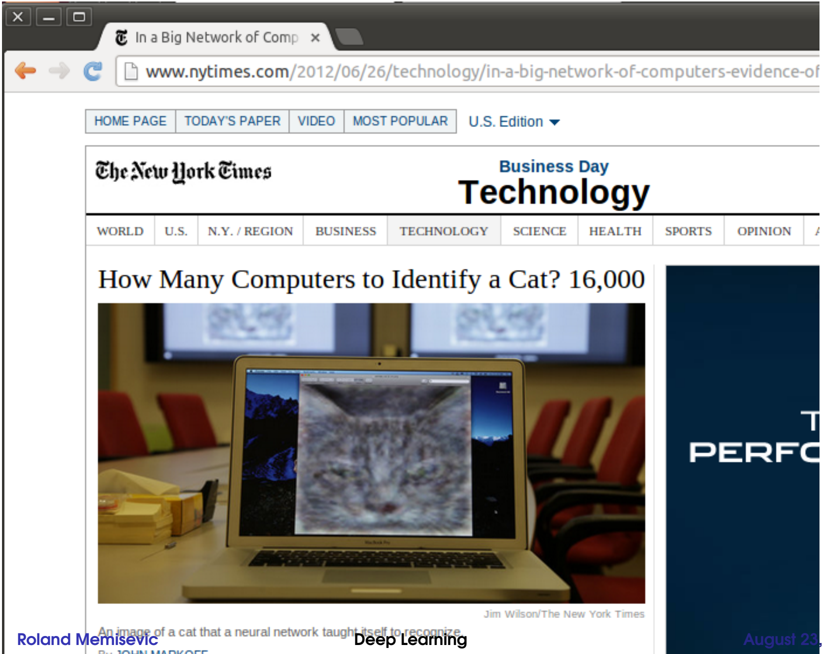


Autoencoders learn to do compression

$$\boldsymbol{r}(\boldsymbol{x}) = Wh\big(W^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{b}\big)$$



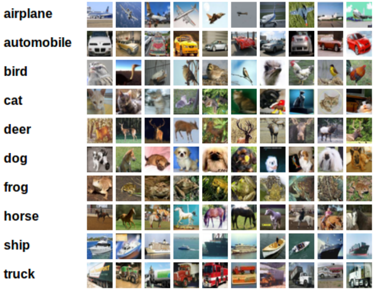
Stacked autoencoders (Le et al. 2012)

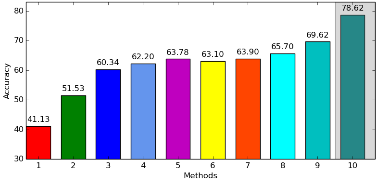


Other unsupervised methods

- Restricted Boltzmann machines
- Independent components analysis
- Sparse coding
- K-means clustering
- Most of these models can be implemented as a form of autoencoder, or trained using their own, specialized learning criteria.

The utility of unsupervised learning

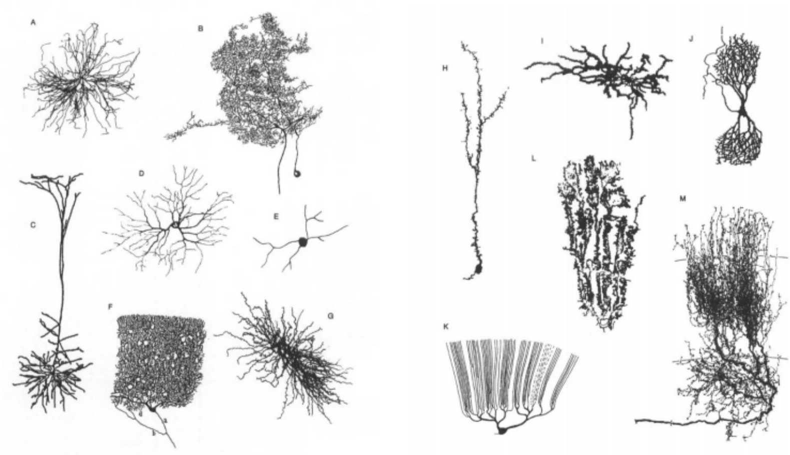




- Unsupervised learning helps when the amount of labeled data is small.
- But its utility pales in comparison to supervised back-prop on lots of data.
- Possible reasons:
  - (i) reconstruction may be the wrong objective
  - (ii) we need to scale up more
  - (iii) we need to rethink unsupervised learning

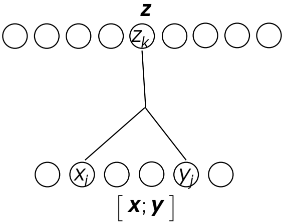
Architecture/non-linearities

$w^{\mathrm{T}}x$?

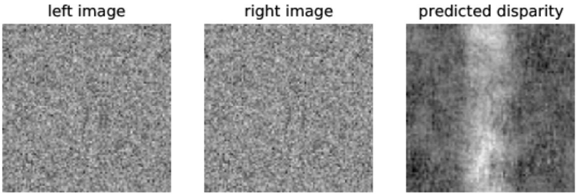


Mel, 1994

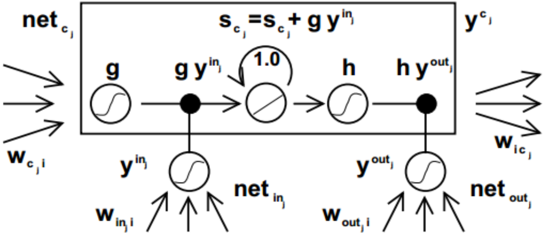
"Transistor neurons"



- Many tasks are based on encoding *relations* not *things*: Analogy making, motion understanding, invariance, depth estimation
- Multiplicative neurons may be a way to efficiently learn and encode such structure.



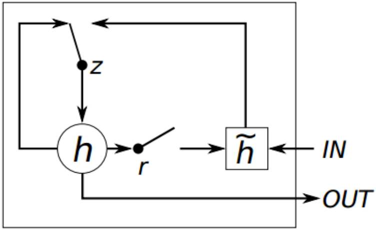
LSTM uses gating to address vanishing gradients



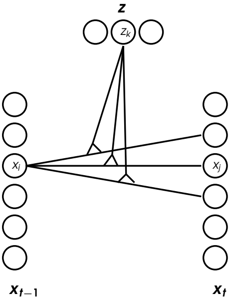
(Hochreiter, Schmidthuber; 1997)

- LSTM addresses the vanishing gradients problem by introducing a **constant unit** (with self-connection 1.0) surrounded by **"control logic"** (gating units).

Other RNN gating mechanisms



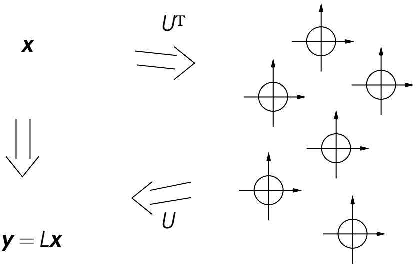
Cho et al 2014



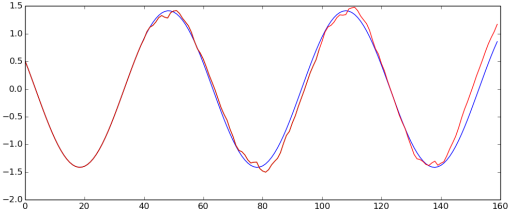
Michalski et al 2014

Orthogonal transformations

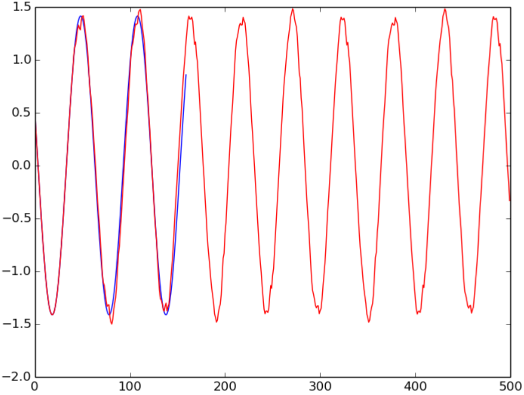
$$U^{\mathrm{T}} L U = \begin{bmatrix} R_1 & & \\ & \ddots & \\ & & R_k \end{bmatrix} \qquad R_i = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix}$$



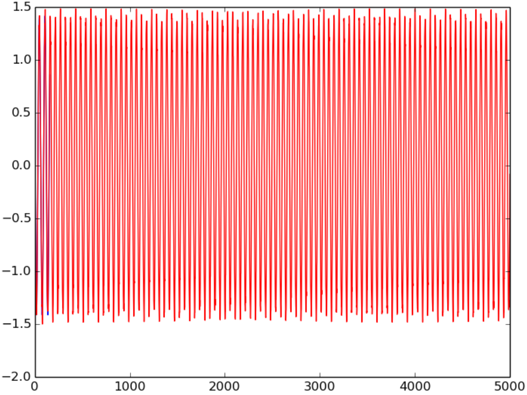
sine waves



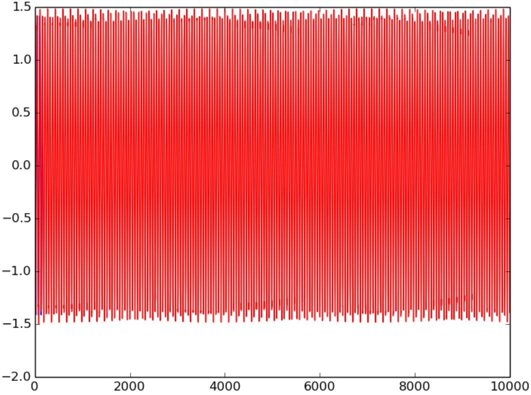
sine waves



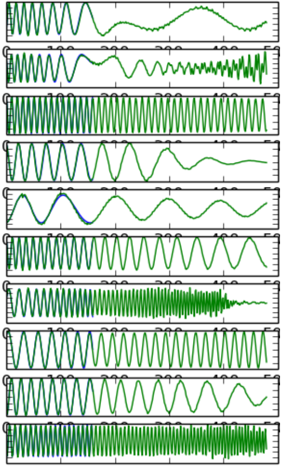
sine waves

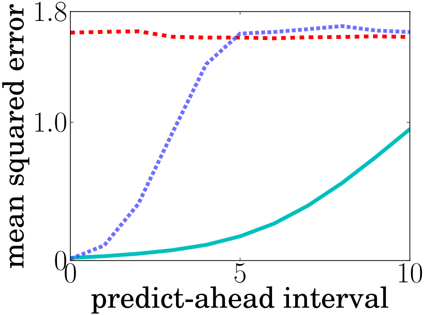


sine waves



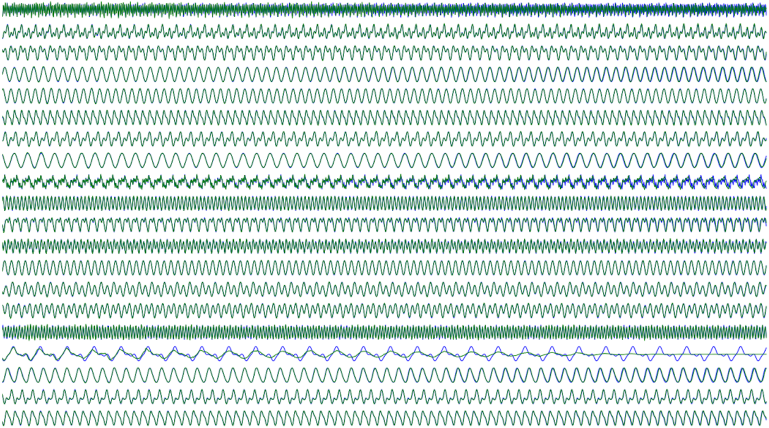
chirps





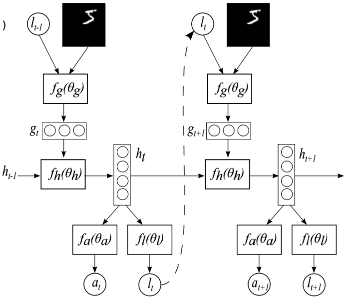
(CRBM vs RNN vs grammar cells)

Harmonics

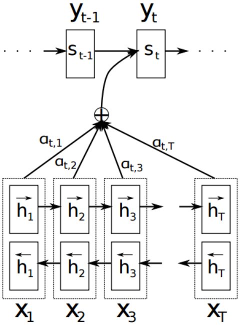


Form attention to differentiable models of computation and “neural programs”

Attention



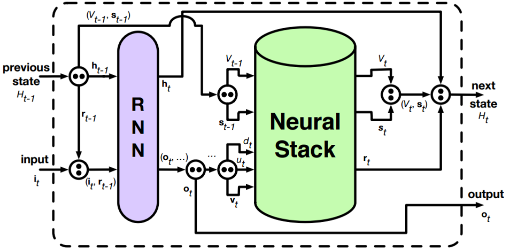
Hard attention
(Mnih et al, 2014)



Soft attention
(Bahdanau et al, 2014)

Differentiable models of computation

- Neural Turing Machine (Graves et al, 2014)
- Memory Networks (Weston et al, 2014)
- Learning to Transduce with Unbounded Memory (Grefenstette et al. 2015)



- To be able to back-propagate, all operations have to be based on differentiable operations
- (But sampling-based methods may work otherwise)

Learning to execute (Zaremba, Sutskever; 2014)

Input:

```
j=8584
for x in range(8):
  j+=920
b=(1500+j)
print((b+7567))
```

Target: 25011.

Input:

```
i=8827
c=(i-5347)
print((c+8704) if 2641<8500 else 5308)
```

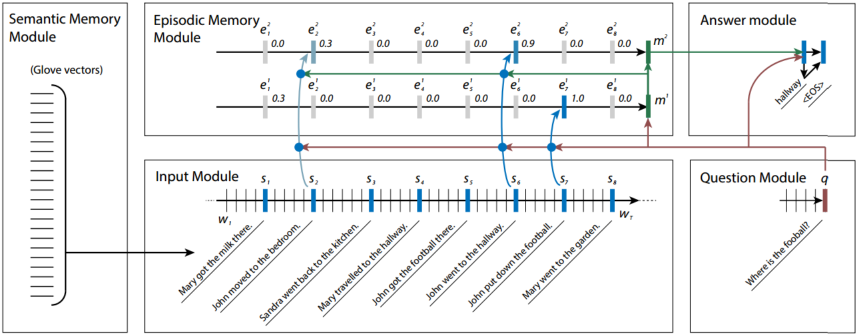
Target: 12184.

From neural networks to "neural programs"

I:	Jane went to the hallway.	I:	Everybody is happy.
I:	Mary walked to the bathroom.	Q:	What's the sentiment?
I:	Sandra went to the garden.	A:	positive
I:	Daniel went back to the garden.	Q:	What are the POS tags?
I:	Sandra took the milk there.	A:	NN VBZ JJ .
Q:	Where is the milk?	I:	The answer is far from obvious.
A:	garden	Q:	In French?
		A:	La réponse est loin d'être évidente.

Kumar et al 2015

From neural networks to "neural programs"



Kumar et al 2015

Von Neumann via Deep Learning

- In the past we simulated neural nets on classic hardware and it didn't work
- Today we simulate classic hardware on neural nets and it works beautifully

The benefit of today's way: Add parallelization and your "program" may run faster and faster and faster...

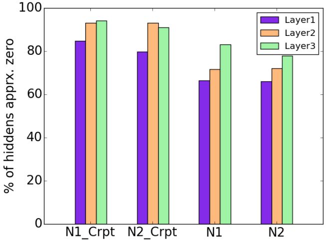
Towards hardware-friendlier deep learning

Deep learning with limited precision

- Gupta et al, 2015
- **Courbariaux et al, 2015:**

Format	Prop.	Up.	PI MNIST	MNIST	CIFAR10	SVHN
Single float	32	32	1.05%	0.51%	14.05%	2.71%
Half float	16	16	1.10%	0.51%	14.14%	3.02%
Fixed point	20	20	1.39%	0.57%	15.98%	2.97%
Dynamic fxp.	10	12	1.28%	0.59%	14.82%	4.95%

Spiking networks

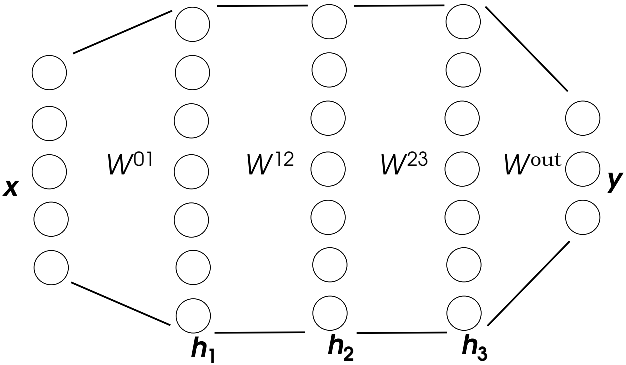


Sparsity levels in two networks trained on CIFAR-10. N1=(1000-2000-3000), N2=(2000-2000-2000 units). (N1_Crpt, N2_Crpt trained with dropout).

figure by Kishore Konda

- Neural network activations (real and artificial) tend to be **sparse**.
- So we are sending around, and multiplying by, lots of floating-point zeros.
- We are also applying synchronization and logic, although real brains don't seem to.
- The logical conclusion: **spiking networks** (but it is not clear yet how to train them)

Back-prop using asynchronous, local computations?



In the brain, where is the backward channel?

Towards back-prop using local computations

- Hinton 2007: Use the **temporal derivative** to encode the error derivative!
- (see also: Bengio et al. 2015)
- Recall that the derivative of most common cost functions is, conveniently, given by

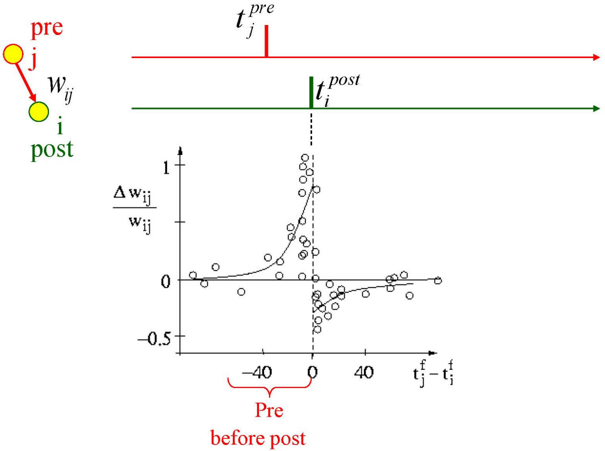
$$\frac{\partial \text{cost}}{\partial \boldsymbol{y}(\boldsymbol{x}_n)} = \boldsymbol{y}(\boldsymbol{x}_n) - \boldsymbol{t}_n$$

How local back-prop may work

- Let top-layer drive the activations towards the correct value.
- Let feedback weights transport that change downward.
- Make weight changes proportional to the *rate of change* of a postsynaptic neuron and the *value* of the pre-synaptic neuron.

Is the brain doing local back-prop?

- (Hinton 2007): "What would neuro-scientists see if this is what's happening in the brain?"
- They should see this (and they do!):



picture from http://www.scholarpedia.org/article/Spike-timing_dependent_plasticity

Research directions

- Applications
- Architectures (attention, vanishing gradients, **neural programs**)
- Reinforcement learning
- Theory
- Scaling up, **hardware**
- Multimodality and **grounding**: vision, language, speech, robotics

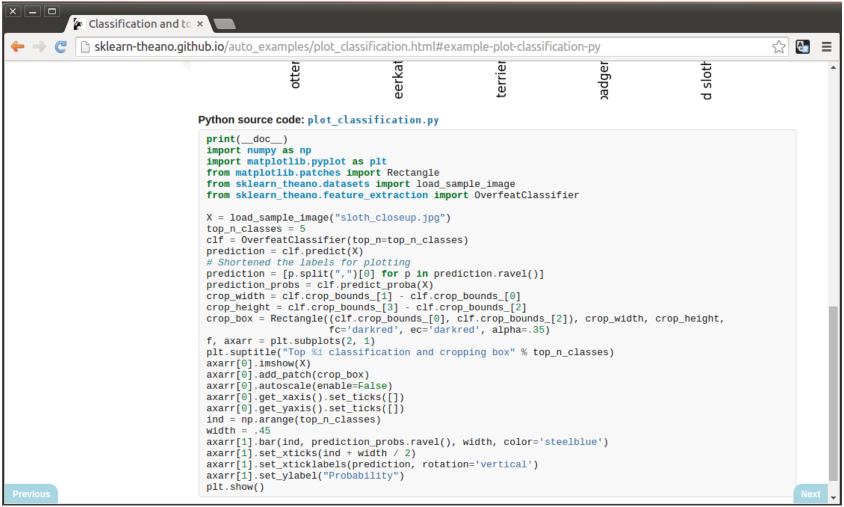
Tricks and facts

- Do not be afraid of non-differentiabilities (or even discontinuities). They don't matter.
- Gradient clipping (constraining the norm of the gradients) helps avoid getting thrown out by NaNs too often (especially for recurrent nets).
- Batch-normalization (Ioffe, Szegedy; 2015) helps training: Normalize hidden unit activations to have fixed means/standard deviations during training, by drawing the statistics form the current mini-batch.
- Adding a "momentum-term" to your SGD updates can have a very strong influence on convergence speed.
- You rarely successfully "try out" a model on a new task, you *make the model work* on the task.

Deep Learning Software/Frameworks

- Back-prop: torch, theano
- Add-ons: blocks, fuel, lasagne
- Low-level: cuDNN, nervanagpu, cudamat
- Convnets: caffe, overfeat, cuda-convnet, sklearn-theano
- Word embeddings: word2vec (available in gensim)

sklearn-theano



Classification and to

sklearn-theano.github.io/auto_examples/plot_classification.html#example-plot-classification-py

otter eerkat terrier adger d sloth

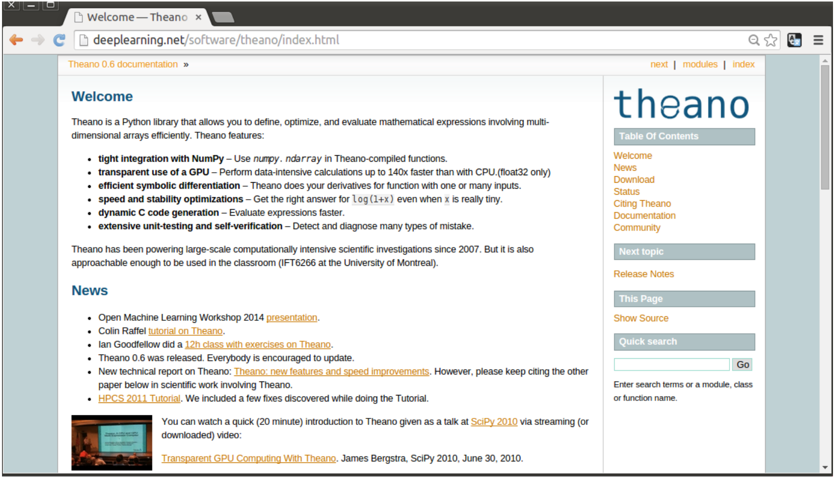
Python source code: `plot_classification.py`

```
print(__doc__)
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.patches import Rectangle
from sklearn_theano.datasets import load_sample_image
from sklearn_theano.feature_extraction import OverfeatClassifier

X = load_sample_image("sloth_closeup.jpg")
top_n_classes = 5
clf = OverfeatClassifier(top_n=top_n_classes)
prediction = clf.predict(X)
# Shortened the labels for plotting
prediction = [p.split(",")[0] for p in prediction.ravel()]
prediction_probs = clf.predict_proba(X)
crop_width = clf.crop_bounds_[1] - clf.crop_bounds_[0]
crop_height = clf.crop_bounds_[3] - clf.crop_bounds_[2]
crop_box = Rectangle((clf.crop_bounds_[0], clf.crop_bounds_[2]), crop_width, crop_height,
                     fc='darkred', ec='darkred', alpha=.35)
f, axarr = plt.subplots(2, 1)
plt.suptitle("Top %i classification and cropping box" % top_n_classes)
axarr[0].imshow(X)
axarr[0].add_patch(crop_box)
axarr[0].autoscale(enable=False)
axarr[0].get_xaxis().set_ticks([])
axarr[0].get_yaxis().set_ticks([])
ind = np.arange(top_n_classes)
width = .45
axarr[1].bar(ind, prediction_probs.ravel(), width, color='steelblue')
axarr[1].set_xticks(ind + width / 2)
axarr[1].set_xticklabels(prediction, rotation='vertical')
axarr[1].set_ylabel("Probability")
plt.show()
```

Previous Next

theano


Welcome — Theano

deeplearning.net/software/theano/index.html

Theano 0.6 documentation » next | modules | index

Welcome

Theano is a Python library that allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays efficiently. Theano features:

- **tight integration with NumPy** – Use *numpy.ndarray* in Theano-compiled functions.
- **transparent use of a GPU** – Perform data-intensive calculations up to 140x faster than with CPU.(float32 only)
- **efficient symbolic differentiation** – Theano does your derivatives for function with one or many inputs.
- **speed and stability optimizations** – Get the right answer for `log(1+x)` even when `x` is really tiny.
- **dynamic C code generation** – Evaluate expressions faster.
- **extensive unit-testing and self-verification** – Detect and diagnose many types of mistake.

Theano has been powering large-scale computationally intensive scientific investigations since 2007. But it is also approachable enough to be used in the classroom (IFT6266 at the University of Montreal).

News

- Open Machine Learning Workshop 2014 presentation.
- Colin Raffel tutorial on Theano.
- Ian Goodfellow did a 12h class with exercises on Theano.
- Theano 0.6 was released. Everybody is encouraged to update.
- New technical report on Theano: Theano: new features and speed improvements. However, please keep citing the other paper below in scientific work involving Theano.
- HPCS 2011 Tutorial. We included a few fixes discovered while doing the Tutorial.

You can watch a quick (20 minute) introduction to Theano given as a talk at SciPy 2010 via streaming (or downloaded) video:

Transparent GPU Computing With Theano. James Bergstra, SciPy 2010, June 30, 2010.

theano

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Release Notes

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Enter search terms or a module, class or function name.

http://www.deeplearning.net/tutorial/

theano code snippet (from deeplearning.net)

```
import theano
from theano import tensor

a = tensor.dscalar()
b = tensor.dscalar()

c = a + b

f = theano.function([a,b], c)

assert 4.0 == f(1.5, 2.5)
```

theano code snippet: linear regression

```
import theano
import theano.tensor as T

#define computational graph:
W = T.dmatrix()
inputs = T.dmatrix()
targets = T.dmatrix()
outputs = T.dot(W.T, inputs)
cost_theano = ((outputs - targets)**2).mean()
grad_theano = T.grad(cost_theano, W)

#compile functions:
cost = theano.function([W,inputs,targets], cost_theano)
grad = theano.function([W,inputs,targets], grad_theano)

#try on some _random_ data:
my_w = 0.01*randn(10,1).astype("float32")
my_inputs = randn(100,10).T.astype("float32")
my_targets = randn(1,100).astype("float32")
print cost(my_w, my_inputs, my_targets)
my_w -= 0.1*grad(my_w, my_inputs, my_targets)
print cost(my_w, my_inputs, my_targets)
```

theano code snippet: autoencoder

```
.
.
.
prehiddens = T.dot(inputs, W)
hiddens = (prehiddens > selectionthreshold) * prehiddens
outputs = T.dot(hiddens, W.T) + bvis

cost = T.mean(T.sum(0.5 * ((inputs - outputs)**2), axis=1))
grad = T.grad(cost, params)
.
.
.
```

Thank you

Questions?

www-labs.iro.umontreal.ca/˜ memisevr/talks/memisevicHotchips2015.pdf

Deep learning needs parallel hardware.

Parallel hardware needs deep learning.

www-labs.iro.umontreal.ca/˜ memisevr/talks/memisevicHotchips2015.pdf