Neural networks and visual processing

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Overview

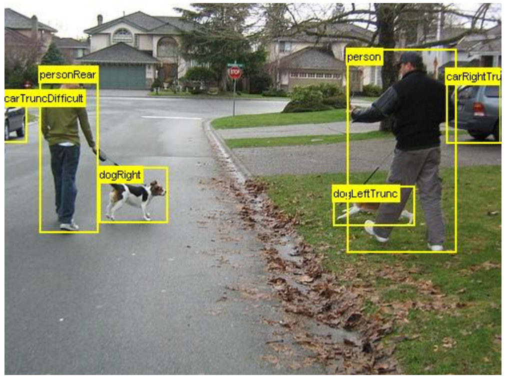
- So far we have discussed unsupervised learning up to V1
- For most technology applications (except perhaps compression), V1 description is not enough. Yet it is not clear how to proceed to higher areas.
- At some point supervised learning will be necessary to attach labels. Hopefully this can be postponed to very high levels.

Neurobiology of Vision

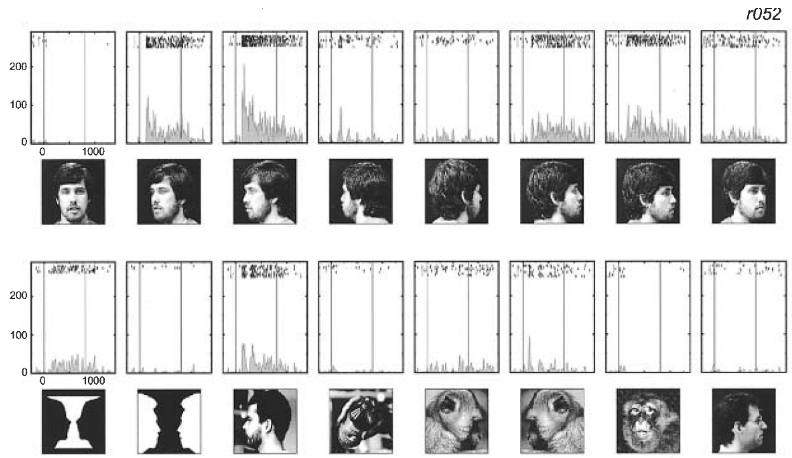
- WHAT pathway: V1 $\to$ V2 $\to$ V4 $\to$ IT (focus of our treatment)
- WHERE pathway: V1 $\to$ V2 $\to$ V3 $\to$ MT/V5 $\to$ parietal lobe
- IT (Inferotemporal cortex) has cells that are
  - Highly selective to particular objects (e.g. face cells)
  - Relatively invariant to size and position of objects, but typically variable wrt 3D view
- What and where information must be combined somewhere ('throw the ball at the dog')

Example tasks

- Classification
  - Is there a dog in this image?
- Detection
  - Localize all the people (if any) in this image
- etc..

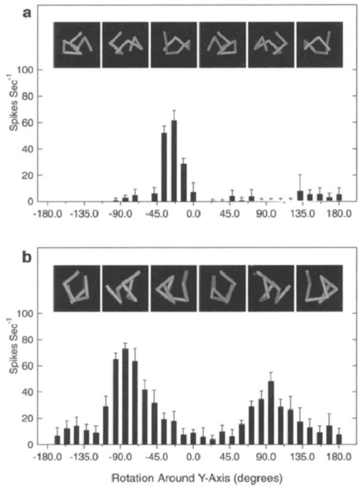


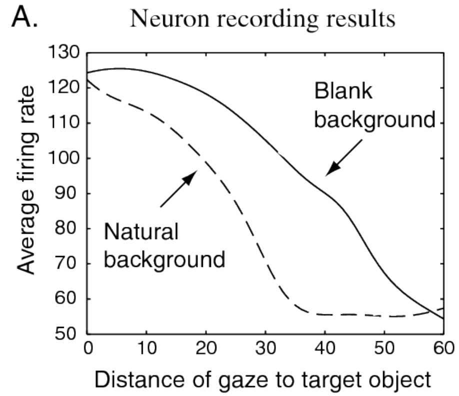
Invariances in higher visual cortex



[Logothetis and Sheinberg, 1996]

Invariance is however limited



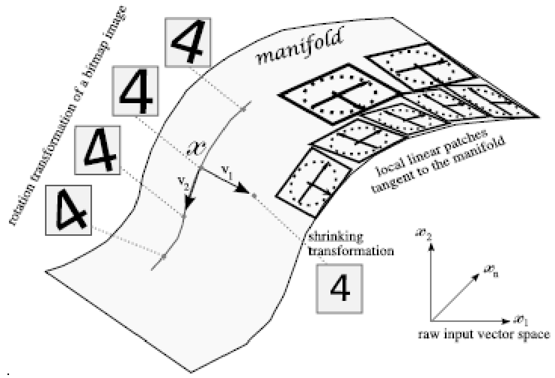


Left: partial rotation invariance [Logothetis and Sheinberg, 1996].
Right: clutter reduces translation invariance [Rolls and Deco, 2002].

Computational Object Recognition

- The big problem is creating *invariance* to scaling, translation, rotation (both in-plane and out-of-plane), and partial occlusion, yet at the same time being selective.
- Large input dimension, need enormous (labelled) training set + tricks
- Objects are not generally presented against a neutral background, but are embedded in *clutter*
- Within class variation of objects (e.g. cars, handwritten letters, ..)

Geometrical picture



[From Bengio 2009 review]
Pixel space. Same objects form manifold (potentially discontinuous, and disconnected).

Some Computational Models

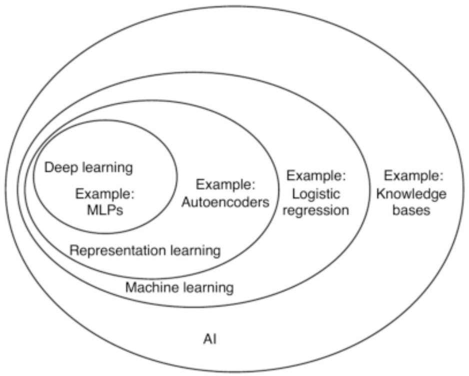
Two extremes:

- Extract 3D description of the world, and match it to stored 3D structural models (e.g. human as generalized cylinders)
- Large collection of 2D views (templates)

Some other methods

- 2D structural description (parts and spatial relationships)
- Match image features to model features, or do pose-space clustering (Hough transforms))
  - What are good types of features?
- Feedforward neural network
- Bag-of-features (no spatial structure; but what about the "binding problem"?)
- Scanning window methods to deal with translation/scale

AI



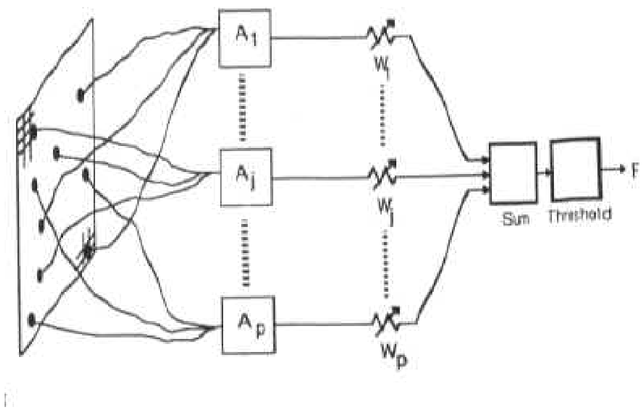
[Bengio et al., 2014]

History

- McCullough & Pitts (1943): Binary neurons can implement any finite state machine. Von Neumann used this for his architecture.
- Rosenblatt (1962): Perceptron learning rule: Learning of (some) binary classification problems.
- Backprop (1980s): Universal function approximator. Generalizes, but has local maxima.
- Boltzmann machines (1980s): Probabilistic models. Long ignored for being exceedingly slow.

Perceptrons

- Supervised binary classification of K N-dimensional $\mathbf{x}^\mu$ pattern vectors.
- $y = H(h) = H(\mathbf{w}.\mathbf{x} + b)$, H is step function, $h = \mathbf{w}.\mathbf{x} + b$ is net input ('field')



[ignore A_i in figure for now, and assume x_i is pixel intensity]

Perceptron learning rule

- Denote desired binary output for pattern μ as d^μ. Rule:

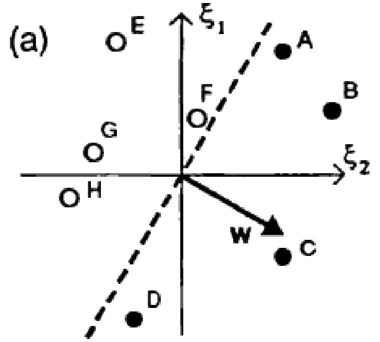
$$\Delta w_i^\mu = \eta x_i^\mu (d^\mu - y^\mu)$$

  or, to be more robust, with margin κ

$$\Delta w_i^\mu = \eta H(N\kappa - h^\mu d^\mu) d^\mu x_i^\mu$$

- note, if patterns correct then $\Delta w_i^\mu = 0$ (stop-learning).
- *If* learnable, rule converges in polynomial time.

Perceptron learning rule



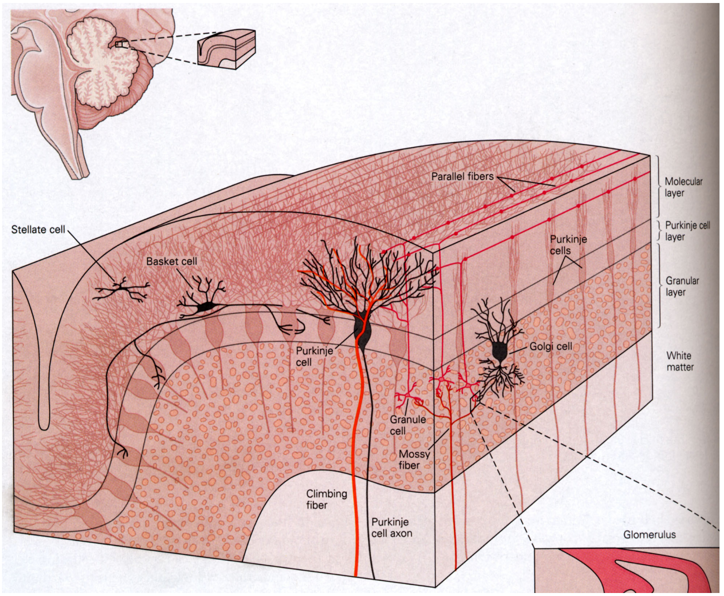
- Learnable if patterns are linearly separable.
- Random patterns are typically learnable if $\#patterns < 2.\#inputs$, $K < 2N$.
- Mathematically solves set of inequalities.
- General trick: replace bias $b = w_b.1$ with 'always on' input.

Perceptron biology

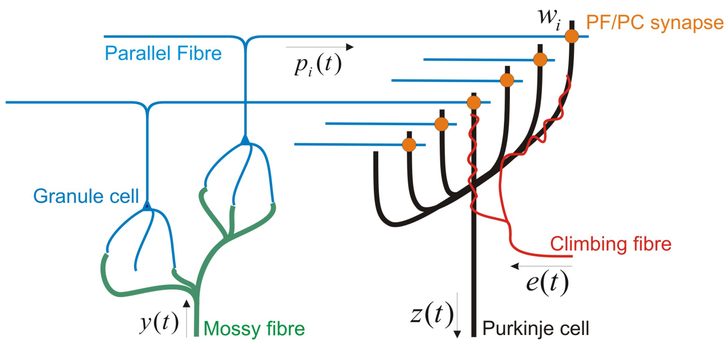
Tricky questions

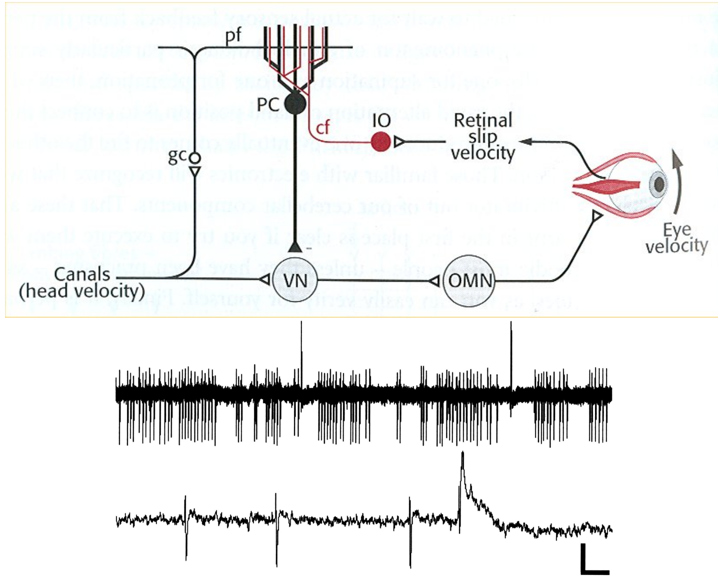
- How is the supervisory signal coming into the neuron?
- How is the stop-learning implemented in Hebbian model where $\Delta w_i \propto x_i y$?
- Perhaps related to cerebellar learning (Marr-Albus theory)

Perceptron and cerebellum



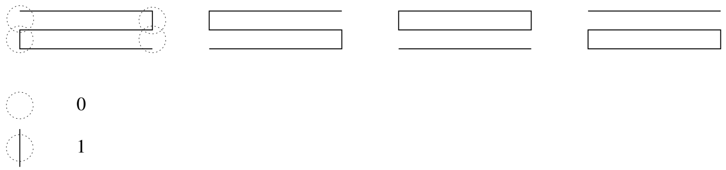
Perceptron and cerebellum





[Purkinje cell spikes recorded extra-cellularly + zoom]
Simple spikes: standard output. Complex spikes: IO feedback, trigger plasticity.

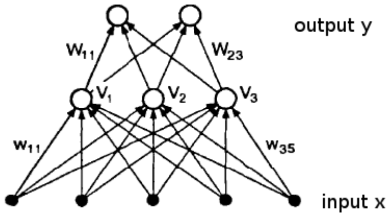
Perceptron limitation



- Perceptron with limited receptive field cannot determine connectedness (give output 1 for connected patterns and 0 for dis-connected).
- This is the XOR problem, $d = 1$ if $x_1 \neq x_2$. This is the simplest parity problem, $d = (\sum_i x_i) mod 2$.
- Equivalently, identity function problem, $d = 1$ if $x_1 = x_2$.
- In general: categorizations that are not linearly separable cannot be learned (weight vector keeps wandering).

Multi-layer perceptron (MLP)

- Supervised algorithm that overcomes limited functions of the single perceptron.
- With continuous units and large enough single hidden layer, MLP can approximate any continuous function! (and two hidden layers approximate any function). Argument: write function as sum of localized bumps, implement bumps in hidden layer.
- Ultimate goal is not the learning of the patterns (after all we could just make a database), but a sensible generalization. The performance on test-set, not training set, matters.



- $y_i^\mu(\mathbf{x}^\mu; w, W) = g(\sum_j W_{ij} v_j) = g\left(\sum_j W_{ij} g(\sum_k w_{jk} x_k)\right)$
- Learning: back-propagation of errors. Mean squared error of P training patterns:

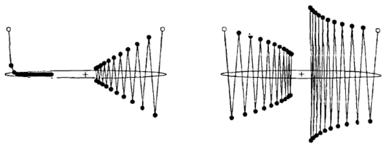
$$E = \sum_{\mu=1}^{P} E_\mu = \frac{1}{2}\sum_{\mu=1}^{P}[d_i^\mu - y_i^\mu(\mathbf{x}^\mu; w, W)]^2$$

  Gradient descent (batch) "$\Delta w \propto -\eta \frac{\partial E}{\partial w}$" where w are all the weights (input $\to$ hidden, hidden $\to$ output, biases).

- Stochastic descent: Pick arbitrary pattern, use $\Delta w = -\eta \frac{\partial E_\mu}{\partial w}$ instead of $\Delta w = -\eta \frac{\partial E}{\partial w}$. Quicker to calculate, and randomness helps learning.
- $\frac{\partial E^\mu}{\partial W_{ij}} = (y_i - d_i) g'(\sum_k W_{ik} v_k) v_j \equiv \delta_i v_j$
- $\frac{\partial E^\mu}{\partial w_{jk}} = \sum_i \delta_i W_{ij} g'(\sum_l w_{jl} x_l) x_k$
- Start from random, smallish weights. Convergence time depends strongly on lucky choice.
- If $g(x) = [1 + exp(-x)]^{-1}$, one can use $g'(x) = g(x)(1 - g(x))$.
- Normalize input (e.g. z-score)

MLP tricks

Learning MLPs is slow and local maxima are present.

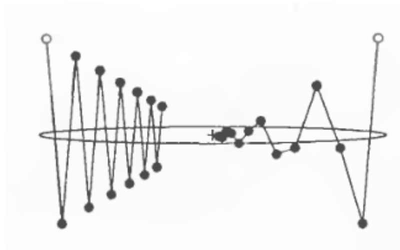


[from HKP, increasing learning rate. 2nd: fastest, 4th: too big]

- Learning rate often made adaptive (first large, later small).
- Sparseness priors are often added to prevent large negative weights cancelling large positive weights.
  e.g $E = \frac{1}{2}\sum_\mu (d^\mu - y^\mu(\mathbf{x}^\mu; w))^2 + \lambda \sum_{i,j} w_{ij}^2$
- Other cost functions are possible.
- Traditionally one hidden layer. More layers do not enhance repertoire and slow down learning (but see below).

MLP tricks

Momentum: previous update is added, hence wild direction fluctuations in updates are smoothed.



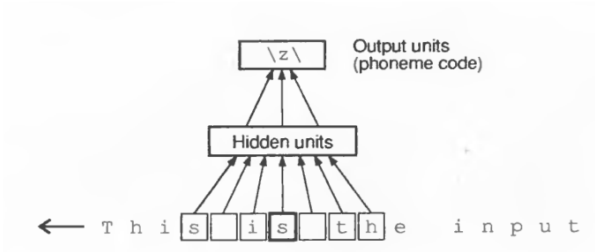
[from HKP. Same learning rate but with (right) and without momentum (left)].

MLP examples

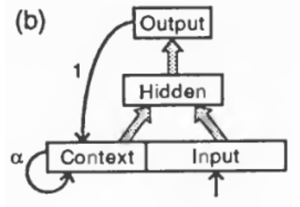
Essentially curve fitting. Best on problems that are not fully understood / hard to formulate.

- Hand-written postcodes.
- Self-driving car at 5km/h ($\sim$ 1990)
- Backgammon game

MLP sequence data

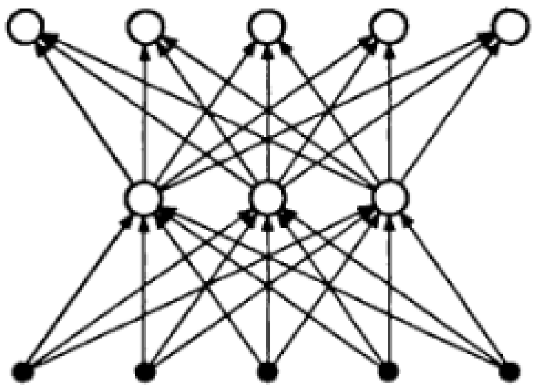


- Temporal patterns by for instance setting input vector as $\{s_1(t), s_2(t), \ldots s_n(t), s_1(t-1), \ldots s_n(t-1)\}$.



- Context units that decay over time (Ellman net)

Auto-encoders



Autoencoders: Minimize $E(input, output)$
Fewer hidden units than input units: find optimal compression (PCA when using linear units).

Biology of back-propagation?

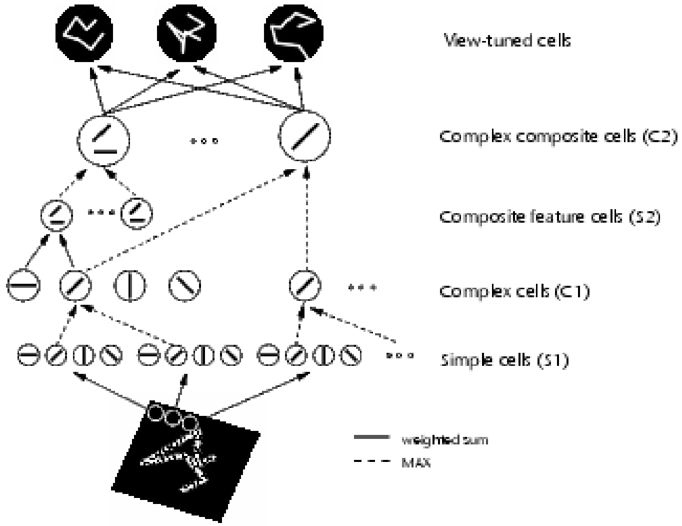
- How to back-propagate in biology?
- O'Reilly (1996) Adds feedback weights (do not have to be exactly symmetric).
- Uses 2-phases. -phase: input clamped; +phase: input and output clamped.
- Approximate $\Delta w_{ij} = \eta(post_i^+ - post_i^-)pre_j^-$
- more when doing Boltzmann machines...

Convolutional networks

Neocognitron
[Fukushima, 1980, Fukushima, 1988, LeCun et al., 1990]

- To implement location invariance, “clone” (or replicate) a detector over a region of space (weight-sharing), and then pool the responses of the cloned units
- This strategy can then be repeated at higher levels, giving rise to greater invariance and faster training

HMAX model



[Riesenhuber and Poggio, 1999]

HMAX model

- Deep, *hard-wired* network
- S1 detectors based on Gabor filters at various scales, rotations and positions
- S-cells (simple cells) convolve with local filters
- C-cells (complex cells) pool S-responses with maximum
- No learning between layers !
- Object recognition: Supervised learning on the output of C2 cells.

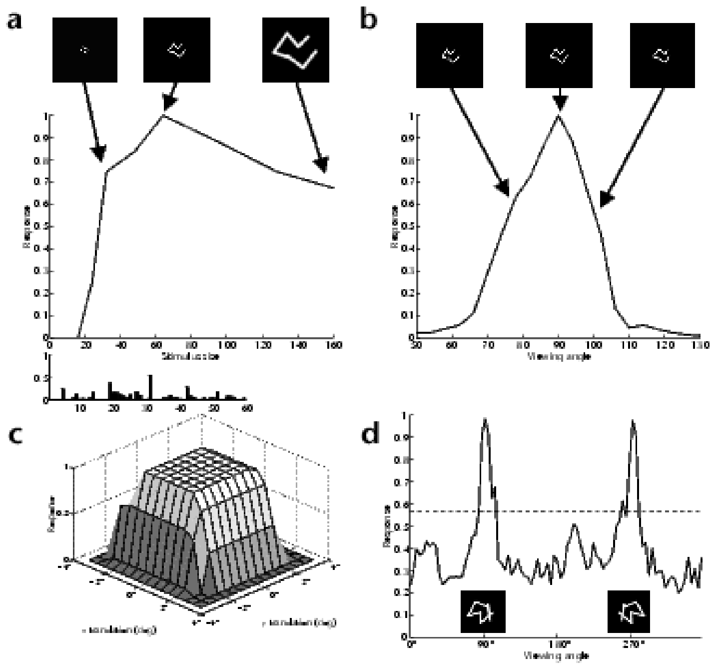
Rather than learning, take refuge in having many, many cells.
(Cover, 1965)*A complex pattern-classification problem, cast in a high-dimensional space non-linearly, is more likely to be linearly separable than in a low-dimensional space, provided that the space is not densely populated.*

Infinite monkey theorem

From Wikipedia, the free encyclopedia

The **infinite monkey theorem** states that a monkey hitting keys at random on a typewriter keyboard for an infinite amount of time will almost surely type a given text, such as the complete works of William Shakespeare.

Given enough time, a hypothetical chimpanzee typing at random would, as part of its output, almost surely produce all of Shakespeare's plays.

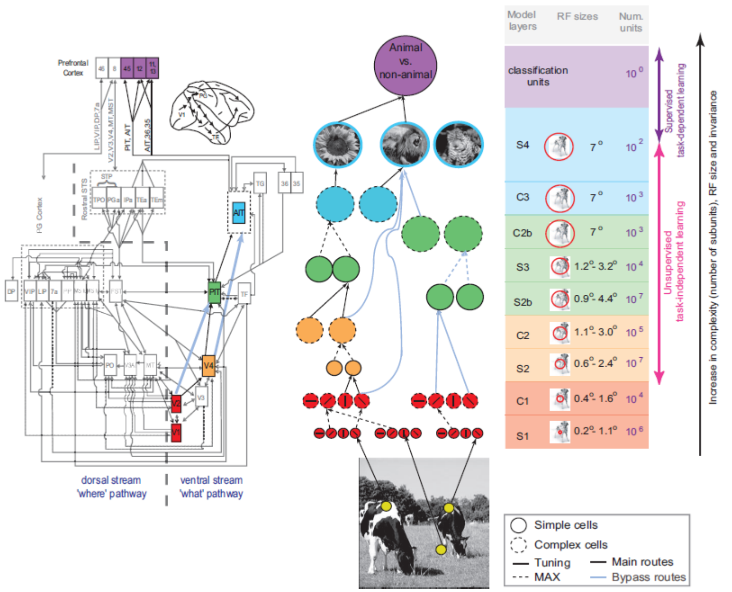


[Riesenhuber and Poggio, 1999]

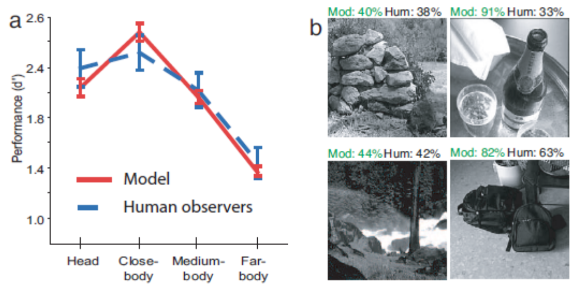
HMAX model: Results

- “paper clip” stimuli
- Broad tuning curves wrt size, translation
- Scrambled input image does not give rise to object detections: not all conjunctions are preserved

More recent version



[Serre et al., 2007]



- Use real images as inputs
- S-cells convolution,e.g. $h = (\frac{\sum_i w_i x_i}{\kappa + \sqrt{\sum_i w_i^2}})$, $y = g(h)$.
- C-cell soft-max pooling $h = \frac{\sum x_i^{q+1}}{\kappa + \sum_k x_i^q}$ (some support from biology for such pooling)
- Some unsupervised learning between layers [Serre et al., 2005]

HMAX model: Results

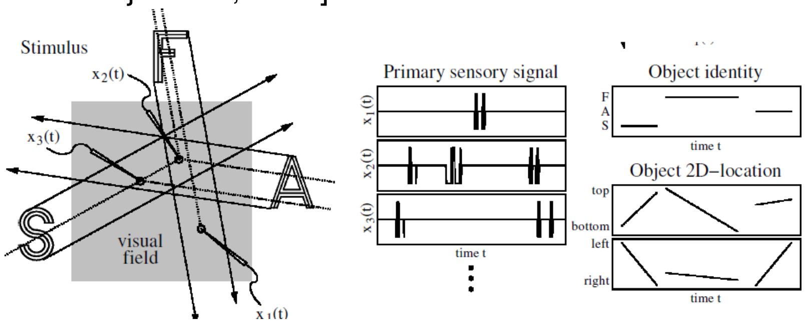
- Localization can be achieved by using a sliding-window method
- Claimed as a model on a “rapid categorization task”, where back-projections are inactive
- Performance similar to human performance on flashed (20ms) images
- The model doesn’t do segmentation (as opposed to bounding boxes)

Learning invariances

- Hard-code (convolutional network) http://yann.lecun.com/exdb/lenet/
- Supervised learning (show samples and require same output)
- Use temporal continuity of the world. Learn invariance by seeing object change, e.g. it rotates, it changes colour, it changes shape.
  Algorithms: trace rule[Földiák, 1991]
  E.g. replace
  $\Delta w = x(t).y(t)$ with $\Delta w = x(t).\tilde{y}(t)$
  where $\tilde{y}(t)$ is temporally filtered $y(t)$.
- Similar principles: VisNet [Rolls and Deco, 2002], Slow feature analysis.

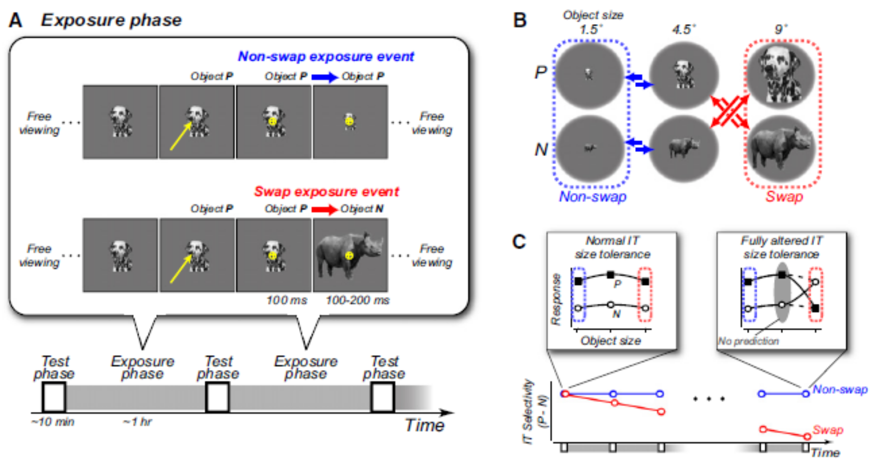
Slow feature analysis

Find slow varying features, these are likely relevant [Wiskott and Sejnowski, 2002]



Find output y for which: $\langle (\frac{dy(t)}{dt})^2 \rangle$ minimal,
while $\langle y \rangle = 0, \langle y^2 \rangle = 1$

Experiments: Altered visual world [Li and DiCarlo, 2010]



Including top-down interaction

- Extensive top-down connections everywhere in the brain
- One known role: attention. For the rest: many theories

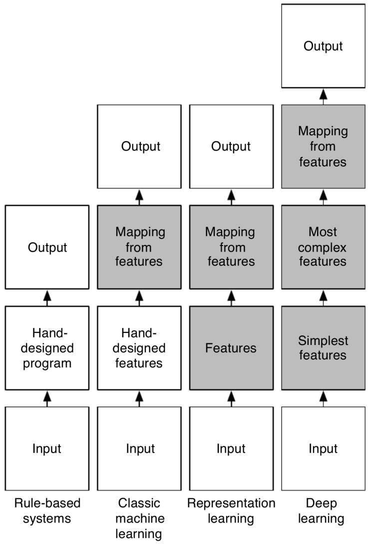
[Epshtein et al., 2008]

Local parts can be ambiguous, but knowing global object at helps.
Top-down to set priors.
Improvement in object recognition is actually small,
but recognition and localization of parts is much better.

Deep MLPs

- Traditional MLPs are also called shallow (1 or 2 hidden layers).
- While deeper nets do not have more computational power. 1) Some tasks require less nodes (e.g. 1 hidden layer: parity requires exp. many hidden layer units) 2) they can lead to better representations. Better representations lead to better generalization and better learning.
- Learning slows down in deep networks, as transfer functions $g()$ saturate at 0 or 1. ($\Delta w \propto g'() \to 0$) So:
  - Pre-training, e.g. with Boltzmann machines (see below)
  - Convolutional networks
  - Use non-saturating activation function.
- Better representation by adding noisy/partial stimuli. This artificially increases the training set and forces invariances.

AI



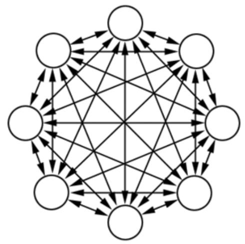
[Bengio et al., 2014]

Role of representation

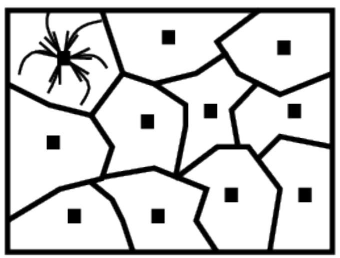
- Finding good representation solves most problems 90%
- Similarly, bad representation can make problem very hard.
- E.g. odd/even number categorization using base-2 (only last bit matters) vs base-3 (all bits matter) representation.
- E.g. recognition of images after fixed, random scrambling is difficult for humans. This is the task naive MLPs are faced with.

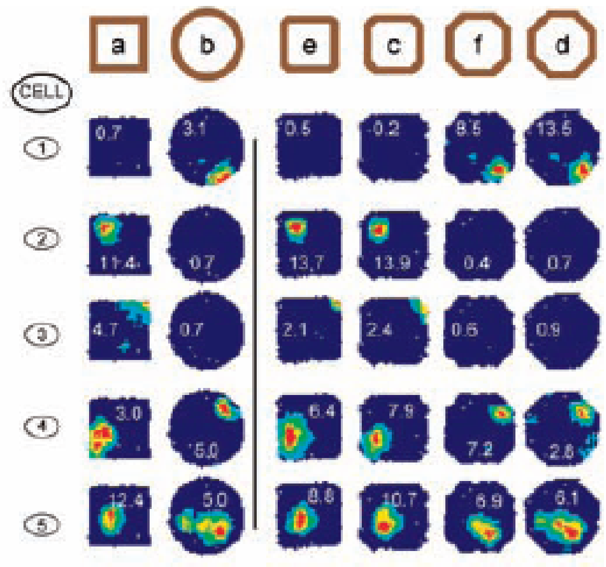
- MLPs have no dynamics
- Recurrent networks are dynamic. Could be steady state(s), periodic, or chaotic. With symmetric weights there can only be fixed points (point or line attractors).
- In recurrent networks it is much harder to find weights to be altered. Often restrict to cases where dynamics has fixed points.

- All to all connected network (can be relaxed)
- Binary units $s_i = \pm 1$, or rate with sigmoidal transfer.
- Dynamics $s_i(t+1) = sign[\sum_j w_{ij} s_j(t)]$ or continuous version $\frac{d\mathbf{r}(t)}{dt} = -\mathbf{r} + g(W\mathbf{r}(t))$.
- Using symmetric weights $w_{ij} = w_{ji}$, we can define energy $E = -\frac{1}{2}\sum_{ij} s_i w_{ij} s_j$.



- Under these conditions network moves from initial condition (stimulus, $\mathbf{s}(t=0) = \mathbf{x}$) into the closest attractor state ('memory') and stays there.
- Auto-associative, pattern completion
- Simple (suboptimal) learning rule: $w_{ij} = \sum_\mu^M x_i^\mu x_j^\mu$ (μ indexes patterns $\mathbf{x}^\mu$).

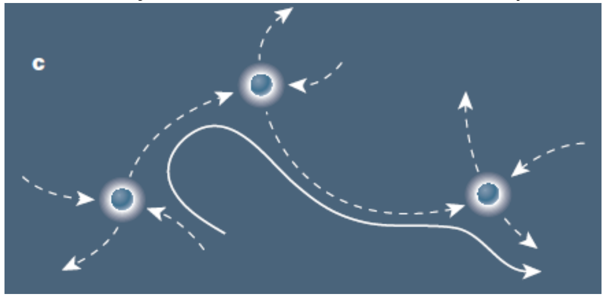




Indirect experimental evidence using maze deformation[Wills et al., 2005]

Winner-less competition

How to escape from attractor states?
Noise, asymmetric connections, adaptation.

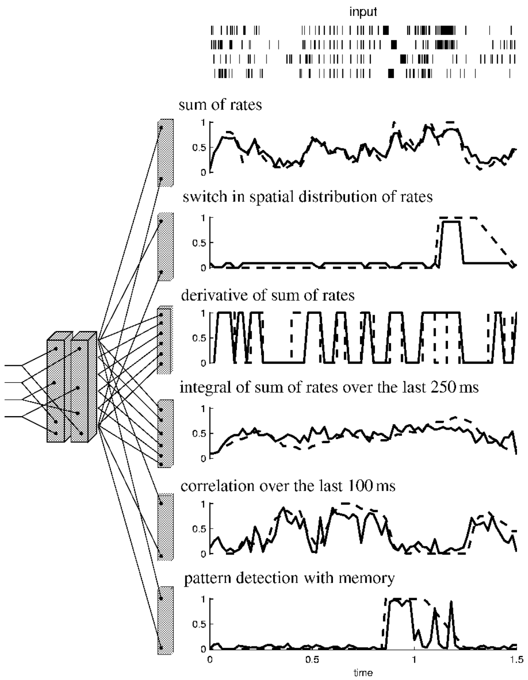


From [Ashwin and Timme, 2005].

Liquid state machines

[Maass et al., 2002]

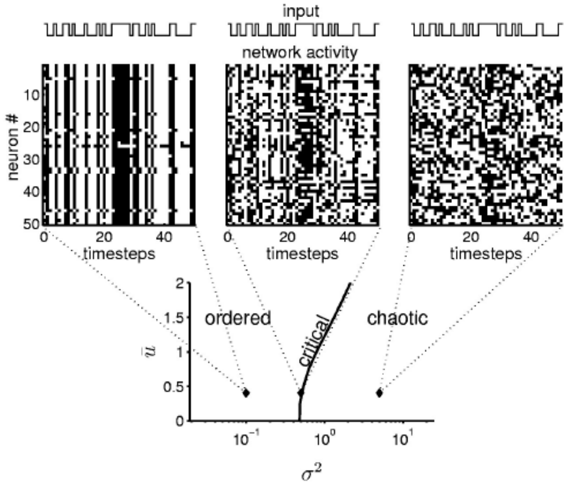
- Motivation: arbitrary spatio-temporal computation without precise design.
- Create pool of spiking neurons with random connections.
- Results in very complex dynamics if weights are strong enough
- Similar to echo state networks (but those are rate based).
- Both are known as reservoir computing
- Similar theme as HMAX model: create rich repetoire and only learn at the output layer.



Various functions can be implemented by varying readout.

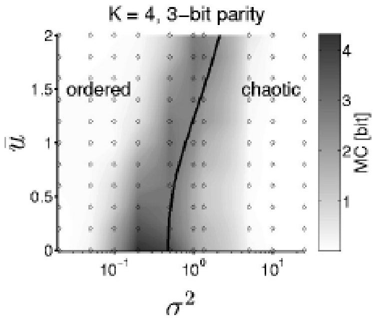
Optimal reservoir?

Best reservoir has rich yet predictable dynamics.
Edge of Chaos [Bertschinger and Natschlaeger, 2004]



Network 250 binary nodes, $w_{ij} = \mathcal{N}(0, \sigma^2)$
(x-axis is recurrent strength)

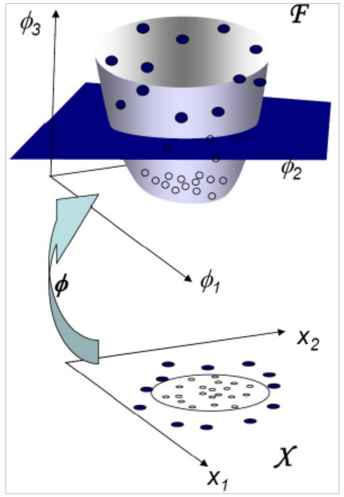
Optimal reservoir?



Task: $Parity(in(t), in(t-1), in(t-2))$
Best (darkest in plot) at edge of chaos.
Does chaos exist in the brain?

- In spiking network models: yes [van Vreeswijk and Sompolinsky, 1996]
- In real brains: ?

Relation to Support Vector Machines

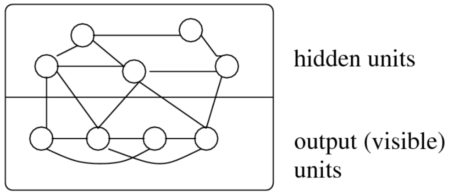


Map problem in to high dimensional space $\mathcal{F}$; there it often becomes linearly separable.
This can be done without much computational overhead (kernel trick).

Boltzmann machines

Hopfield network is not perfect. It is impossible to learn only $(1,1,-1),(-1,-1,-1),(1,-1,1),(-1,1,1)$ but not $(-1,-1,1),(1,1,1),(-1,1,-1),(1,-1,1)$ (XOR again)...
Because $\langle x_i \rangle = \langle x_i x_j \rangle = 0$
Boltmann machines have ± 1 units and include two, somewhat unrelated, modifications:

- Introduce hidden units, these can extract abstract features.



Boltzmann machines

- Stochastic updating: $p(s_i = 1) = \frac{1}{1+e^{-2\beta E_i}}$
  $E_i = \sum_j w_{ij} s_j - \theta_i$, $E = \sum_i E_i$.
  $T = 1/\beta$ is temperature (set to some arbitrary value).
- Boltzmann distribution

$$P(\mathbf{s}) = \frac{\exp(-\beta E(\mathbf{s}))}{Z}$$

where $Z = \sum_{\mathbf{s}} \exp(-\beta E(\mathbf{s}))$

Boltzmann machines

- Boltzmann machine learns arbitrary $P(\mathbf{v})$.
- Can thus be used for auto-association (pattern completion)
- Or, by labelling some visible units as inputs and others as output, can be used as if it were a associator like an MLP.

Learning in Boltzmann machines

The generated probability for state $\mathbf{s}_\alpha$, after equilibrium is reached, is given by the Boltzmann distribution

$$P_\alpha = \frac{1}{Z} \sum_\gamma e^{-\beta H_{\alpha\gamma}}$$

$$H_{\alpha\gamma} = -\frac{1}{2} \sum_{ij} w_{ij} s_i s_j$$

$$Z = \sum_{\alpha\beta} e^{-\beta H_{\alpha\gamma}}$$

where α labels states of visible units, γ the hidden states.

As in other generative models, we match true distribution to generated one. Minimize KL divergence between input and generated distribution.

$$KL = \sum_\alpha G_\alpha \log \frac{G_\alpha}{P_\alpha}$$

Minimize to get [Ackley et al., 1985, Hertz et al., 1991]

$$\Delta w_{ij} = \eta\beta[\langle s_i s_j \rangle_{clamped} - \langle s_i s_j \rangle_{free}]$$

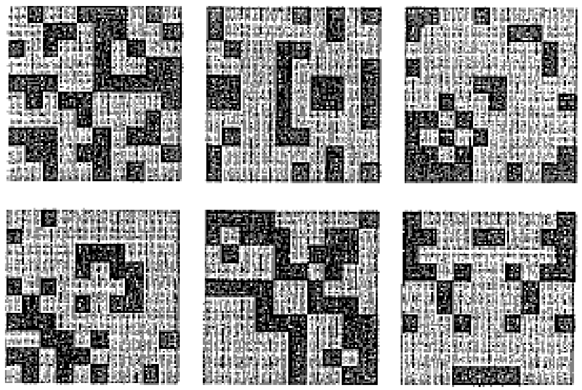
(note, $w_{ij} = w_{ji}$)
Wake ('clamped') phase vs. sleep ('dreaming') phase

- Clamped phase: Hebbian type learning. Average over input patterns and hidden states.
- Sleep phase: unlearn erroneous correlations.

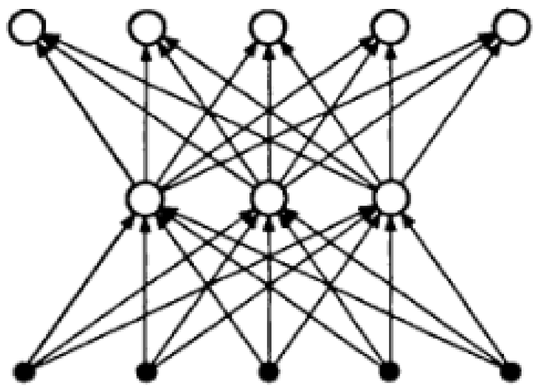
The hidden units will 'discover' statistical regularities.// Biology of phases unknown.

Boltzmann machines: applications

- Shifter circuit.
- Learning symmetry [Sejnowski et al., 1986]. Create a network that categorizes horizontal, vertical, diagonal symmetry (2nd order predicate).



Boltzmann machines: auto-encoders

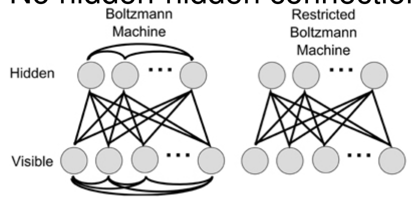


Autoencoders: Minimize $E(input, output)$
Fewer hidden units than input units: find optimal compression (PCA).
More hidden units: impose for instance sparseness.

Restricted Boltzmann

Need for multiple relaxation runs for every weight update (triple loop), makes training Boltzmann networks very slow.
Speed up learning in restricted Boltzmann:

- No hidden-hidden connections



- Don't wait for the sleep state to fully settle, one step is enough.
- Stack multiple layers (deep-learning)
- Application: high quality auto-encoder (i.e. compression) [Hinton and Salakhutdinov, 2006]

[also good webtalks/tutorials by Hinton on this]

Sparse deep belief net model for visual area V2

[Lee et al., 2008]

- Consider an RBM with Gaussian visible units

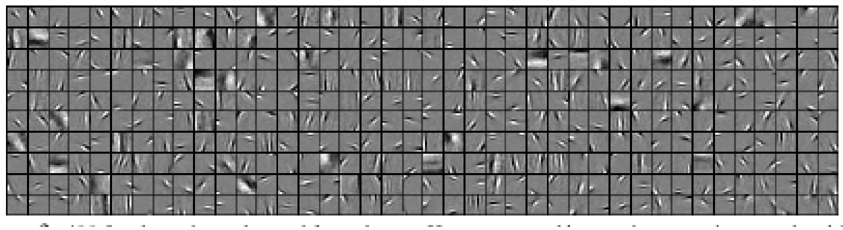
$$E(\mathbf{u}, \mathbf{v}) = \frac{1}{2\sigma^2} \sum_i u_i^2 - \frac{1}{\sigma^2} \left(\sum_i c_i u_i + \sum_j b_j v_j + \sum_{i,j} u_i v_j w_{ij} \right)$$

- $p(u_i|\mathbf{v}) \sim N(c_i + \sum_j w_{ij} v_j, \sigma^2)$
- Also impose a *sparsity prior* on the hidden units, with target sparseness p

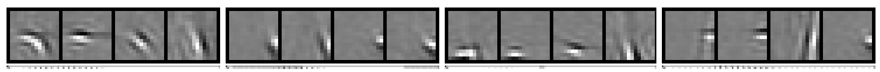
$$\sum_j ||p - \frac{1}{m} \sum_{k=1}^{m} \mathbb{E}[v_j^{(k)} | \mathbf{u}^{(k)}]||^2$$

- Layer 2 trained after layer 1 has learned (DBN)

First layer filters



Second layer: each unit "looks at" a small number of first layer units, e.g.



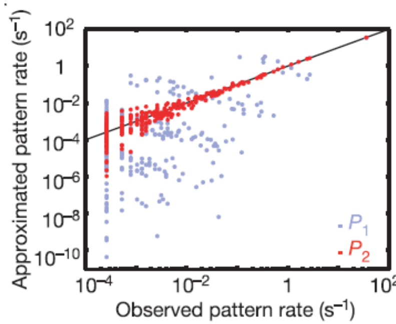
The leftmost patch in each group is a visualization of the model V2 basis, obtained by taking a weighted linear combination of the first layer bases to which it is connected.

Properties of "V2" units can be compared to neural data.

Recurrent models: Ising model of neural activity

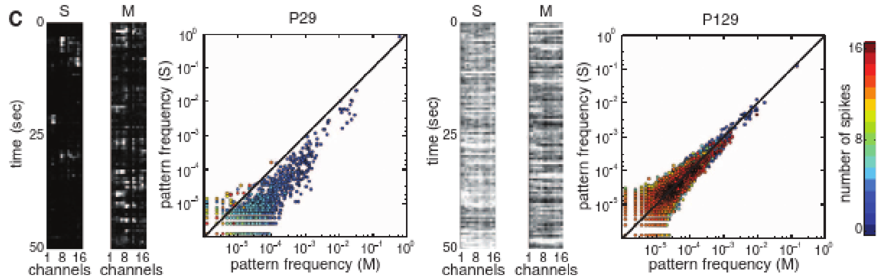
To describe data of retinal network, use Ising model
[Schneidman et al., 2006]

$$P(\mathbf{r}) = \frac{1}{Z} e^{(-\sum_i h_i r_i - \sum_{ij} w_{ij} r_i r_j)}$$



(But maybe it does not work well in large networks [Roudi et al., 2009])

Generative models



[Berkes et al., 2011]
During development spontaneous activity matched stimulus-evoked activity better and better.

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