From Biology to Learning Algorithms and back: 
*Distributed Local Rules for Behavioral Learning*

Wulfram Gerstner, EPFL, Lausanne
10,000 neurons
3 km wires

(10^{10} proc. elements/neurons)
10,000 links per neuron
Highly connected net

10 000 neurons
3 km wires

(10^{10} proc. elements/neurons)
10 ’000 links per neuron
Hodgkin-Huxley type models
Integrate-and-fire type models

- spikes are events
- threshold
- spike/reset/refractoriness

Spike emission

Spike reception
Background: What is brain-style computation?

Brain

Computer
Systems for computing and information processing

**Brain**

**Computer**

**Distributed architecture**

\(10^{10}\) proc. Elements/neurons

No separation of processing and memory

**Von Neumann architecture**

1 CPU

\(10^{10}\) transistors
Systems for computing and information processing

Brain

Tasks:
slow
Mathematical
\[ \sqrt{5 \cos \left( \frac{7\pi}{5} \right)} \]

fast
Real world
E.g. complex scenes

Computer

slow

fast
How fast is neuronal signal processing?

animal -- no animal

Simon Thorpe
Nature, 1996

psychophysical experiment
30 images in 30 seconds

Visual processing

Memory/association

eye
Systems for computing and information processing

Brain

Where is the program?

Where is the memory?

Computer

Von Neumann architecture

Clear separation:
software (program)/hardware

Clear separation:
memory/processing

In the synaptic connections
Highly connected net
10,000 neurons
3 km wires

$10^{10}$ proc. elements/neurons
10,000 links per neuron
... but these connections change strength all the time!

Connection = synapse
Change in connection = synaptic plasticity
Connections are directed
Models of synaptic Plasticity

Synapse

Synaptic changes = basis of learning
Computational Neuroscience

Learning

- behavior memory
- computational model
- Neurons
  - synapses
- molecules
- ion channels
From Biology to Learning Algorithms and back: *Distributed Local Rules for Behavioral Learning*

- Biology background: the brain
- What is learning? [behavioral learning]
- How could learning be? [neuronal level]
- An example of an algorithm
- The big questions
Unsupervised Learning

- Background tunes in the department store

- Different trees – you get better at seeing them, concepts are formed

- Learn your password for credit card?
Reward-based learning, conditioning

Reinforcement learning

Learn how to ride a bike
Supervised Learning

- Unsupervised learning
- Reinforcement learning
- Supervised learning

Learning = optimize Parameters using labeled data

Class L
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Hebbian Learning

When an axon of cell $j$ repeatedly or persistently takes part in firing cell $i$, then $j$’s efficiency as one of the cells firing $i$ is increased

Hebb, 1949
Hebbian learning and LTP

Changes
- induced over 3 sec
- persist over hours and days
Hebbian Learning
Hebbian Learning

item memorized
Hebbian Learning

Recall:
Partial info

item recalled
Hebbian Learning: Functional Postulates

1) Useful for memory

Examples: Hopfield model, associative memory models

My problem: WHEN do we form new memories? Always?

Examples: Hopfield model, attractor networks – learning happens in a separate epoch, then connections fixed

Existing models of Hebbian learning and associative memory describe only induction of synaptic changes but not consolidation/maintenance
Hebbian Learning
= unsupervised learning

\[ \Delta w_{ij} \propto F(\text{pre, post}) \]
3-factor learning rules:
= \text{global} \ast (\text{local Hebb})

\text{SUCCESS/Shock/Attention}

Functional Postulate (2)
Useful for learning the important stuff

\[ \Delta w_{ij} \propto F(\text{pre, post, SUCCESS}) \]

My problem (2): Existing models of learning and memory do not take into account Neuromodulators/cannot describe success/shock/attention

Examples: learn to bike; car on highway trip; credit card number
Function (3): Synaptic changes for development

Initial: random connections

unselective neurons

Receptive field development: many plasticity models do this!
My problem (3): how about recurrent connections?

Correlated input

output neurons

Receptive field and cortical map formation: e.g. v.d. Malsburg; Kohonen; Bienenstock
Synaptic Plasticity: Functional Postulates

1) Useful for memory

2) Useful for learning the important stuff

3) Useful for developmental learning:
   Recept. fields AND recurrent connections

4) Useful for activity control:
   - avoid blow-up of synaptic weights,
   - avoid blow-up of network activity
From Biology to Learning Algorithms and back:
Distributed Local Rules for Behavioral Learning

✓ - Biology background: the brain
✓ - What is learning? [behavioral learning]
✓ - How could learning be? [neuronal level]
  - An example of an algorithm
    (from unsupervised to 3-factor)
✓ - The big questions
Hebbian Learning (rate models)

When an axon of cell \( j \) repeatedly or persistently takes part in firing cell \( i \), then \( j \)'s efficiency as one of the cells firing \( i \) is increased

- local rule
- simultaneously active (correlations)

Rate model:
active = high rate = many spikes per second

Hebb, 1949
Synaptic Plasticity (rate models)

\[ \frac{dW_{ij}}{dt} = F(W_{ij}, v_j^{\text{pre}}, v_i^{\text{post}}) \]

- local rule
- simultaneously active

\[ \frac{dW_{ij}}{dt} = a_0 + a_1^{\text{pre}} v_j^{\text{pre}} + a_1^{\text{post}} v_i^{\text{post}} + a_2^{\text{corr}} v_j^{\text{pre}} v_i^{\text{post}} \]

depend on \( W_{ij} \)

\[
\frac{dw_{ij}}{dt} = a_2^{corr} v_j^{pre} v_i^{post}
\]

\[
\frac{dw_{ij}}{dt} = a_2^{corr} v_j^{pre} v_i^{post} - c
\]

\[
\frac{dw_{ij}}{dt} = a_2^{corr} v_j^{pre} (v_i^{post} - \theta)
\]

**all are Hebbian models**

**all are local models**
Rate-based Hebbian Learning: BCM

\[
\frac{d}{dt} w_{ij} = a^\text{corr}_2 (v_i^{\text{post}} - \mathcal{G}) v_j^{\text{pre}}
\]

presynaptically gated

\[
\frac{d}{dt} w_{ij} = \Phi(v_i^{\text{post}} - \mathcal{G}) v_j^{\text{pre}}
\]

BCM

\[
\mathcal{G} = f(\overline{v}_i^{\text{post}})
\]

Rate-based plasticity models can be classified in framework

Control loop for network activity
Detour: Receptive field development
Detour: Receptive field development
Function (3): Synaptic changes for development

Initial: random connections

\[ \text{unselective neurons} \]

Correlated input

\[ \text{output neurons} \]

Receptive field and cortical map formation:

\[ \text{output neurons specialize} \]
Receptive field development

Localized receptive fields

Plasticity yields ICA

Wavelets, computer vision
Lateral and forward connectivity
feedforward/lateral onto neuron 4

before

10 excitatory
4 inhibitory

after

Unsupervised learning/development of connectivity
from unsupervised to 3-factor rules
= global * local Hebb

\[ \Delta w_{ij} \propto F(\text{pre, post, SUCCESS}) \]

Memorize at specific moments:
Protein synthesis depends on neuromodulators,
in particular dopamine \(\rightarrow\) success signal
TagTriC Model

Early LTP  Protein synthesis  consolidation

Induction model  SUCCESS/attention/shock

Tag: synapse is preliminarily strengthened, decays spontaneously
hypothesis of the TagTriC Model

- long-term stability requires that synapse has 2 stable states
  → synaptic weight can be maintained over weeks

\[ E \rightarrow Z \]
hypothesis of the TagTriC Model

- long-term stability requires that synapse has 2 stable states
  → synaptic weight can be maintained over weeks
hypothesis of the TagTriC Model

- How does it get from one well to the other?

For this to happen we need:
- LTP tag \( h=1 \)
- protein \( p>0.5 \)
from unsupervised to 3-factor rules
= global * local Hebb

\[ \Delta w_{ij} \propto F(\text{pre}, \text{post}, \text{SUCCESS}) \]

local \hspace{1cm} global

Memorize at specific moments:
Protein synthesis depends on neuromodulators,
in particular dopamine \(\rightarrow\) learn now!!!!

Example: car on highway ; marriage ceremony
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✓ What is learning? [behavioral learning]
✓ How could learning be? [neuronal level]
✓ An example of an algorithm
✓ Another example of an algorithm

-The big questions
Reward-based learning, conditioning

Reinforcement learning

Learn how to ride a bike

$h$
Behavior: Navigation to a hidden goal (Morris water maze)

- Invisible platform in the water pool
- Distal visual cues

Morris 1981
Space representation: place cells

- Code for position of the animal

O’Keefe & Dostrovsky 1971
Space representation: place cells

- Code for position of the animal
- Learn action towards goal

O’Keefe & Dostrovsky 1971
Biological mechanisms: place cells

- Code for position of the animal

**Cell recording**

**Activity map**

**Place cells**

*O’Keefe & Dostrovsky 1971*
Reward-based Action Learning

Connection reinforced if action $a$ at state $s$ is successful.

$\Delta w_{aj} = \eta \cdot R_t \cdot e_{aj}$

Eligibility trace: $\frac{d}{dt} e_{aj}(t) = r(s_t) \cdot r_a(t) - g \cdot e_{aj}(t)$

State = activity $r(s)$

Action $a = \text{north}$
Theory

**Rate model**
\[
\frac{d}{dt} e_{aj}(t) = r(s_t) r_a(t) - g \cdot e_{aj}(t)
\]

**Spiking model**
\[
\frac{d}{dt} e_{aj}(t) = \epsilon(t - t_{j}^{pre})[\delta(t - t_{a}^{f}) - \rho(u(t))] - g \cdot e_{aj}(t)
\]

**EPSP spike potential**

\[
\frac{d}{dt} W_{aj} = \eta \ R_t \ e_{aj}
\]

Place cells
Neuronal model: Spike response model with stochastic threshold.

\[ u_i(t \mid x, y^i_t) = u_{\text{rest}} + \sum_{j=1}^{N} w_{ij} \sum_{t_j^f \in x_j} \varepsilon(t - t_j^f) + \sum_{t_i^f \in y_t^i} \eta(t - t_i^f) \]

\[ \rho_i(t \mid x, y^i_t) = \rho_0 \exp \left( \frac{u - \vartheta}{\Delta u} \right) = \rho(u(t)) \]
Theory

- Optimization of an objective function, i.e. Reward maximization.

\[
\langle R \rangle_{x,y} = \sum_{x,y} R(x, y) P(y|x) P(x)
\]

\[
\langle \Delta w \rangle_{x,y} = \alpha \left( R(x, y) \frac{\partial \log P(y|x)}{\partial w} \right)
\]

\[
\Delta w_{ij} = \alpha R(x, y) \int_0^T \frac{\rho_i'(s|x, y_s)}{\rho_i(s|x, y_s)} [Y(s) - \rho_i(s|x, y_s)] \sum_{t_i^f \in x_j} \epsilon(s - t_i^f) ds
\]

\[\text{reward} \quad \text{Hebb}\]

*Williams 1992
Xie and Seung, 20
Pfister et al. 2006
Florian 2007*
The learning rule

\[ \frac{d}{dt} e_{aj}(t) = \varepsilon(t - t_{j}^{pre})[\delta(t - t_{a}^{f}) - \rho(u(t))] - g \cdot e_{aj}(t) \]

EPSP spike potential

\[ \frac{d}{dt} W_{aj} = \eta R_{t} e_{aj} \]

very small decay
from unsupervised to 3-factor rules
= global * local Hebb

\[ \Delta w_{ij} \propto F(\text{pre, post, SUCCESS}) \]

Memorize when you get a reward:
Transient changes mark the synapse (eligibility trace),
Neuromodulator dopamine \(\rightarrow\) success signal
Escape latency vs. trials

- Simple square room

**Figure:**

*Escape latency = time to reach the platform from random starting point. Error bars represent 25% and 75% percentiles.*
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- Biology background: the brain
- What is learning? [behavioral learning]
- How could learning be? [neuronal level]
- An example of an algorithm
- Another example of an algorithm
- The big questions
from unsupervised to multi-factor rules
= global1 * gobal2 * (local Hebb)

\[ \Delta w_{ij} \propto F(\text{pre, post, SUCCESS}) \]

- Memorize when you get a reward
- And/or when you are attentive
- And/or after a shock

- what are useful global signals?
- how much can networks learn
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AND THE REALLY BIG QUESTIONS

(consciousness, human/animal brain, abstraction, emergence ...)

model

Neurons

behavior

molecules

ion channels
Spike based learning rule

Thanks!
Function (3): Synaptic changes for development

Receptive field development: many plasticity models do this! My problem (3): how about recurrent connections?

Recurrent Connectivity reflects Coding:
- Temporal code yields asymmetric connections
  → barrel cortex data (Lefort et al. 2009; Yadhav, Wolfe, Feldman 2009)
- Rate code yields symmetric connections
  → visual cortex data (Song et al. 2005)
Behavior: Navigation to a hidden goal (Morris water maze)

- Different starting positions
- Task learning depends on the hippocampus

*Foster, Morris & Dayan 2000*