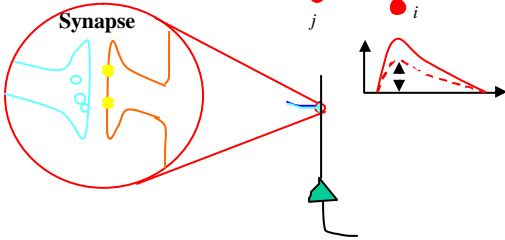
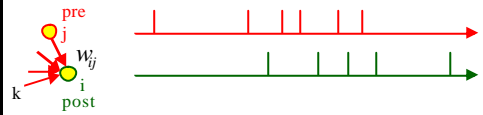


## Models of synaptic Plasticity

Wulfram Gerstner  
EPFL, Lausanne



## Hebbian Learning

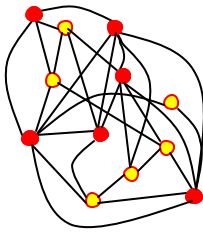


When an axon of cell  $j$  repeatedly or persistently takes part in firing cell  $i$ , then  $j$ 's efficiency as one of the cells firing  $i$  is increased

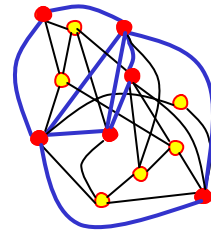
Hebb, 1949

- local rule
- simultaneously active (correlations)

## Hebbian Learning



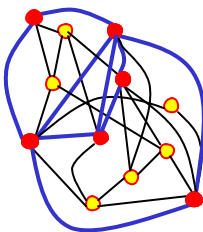
## Hebbian Learning



item memorized

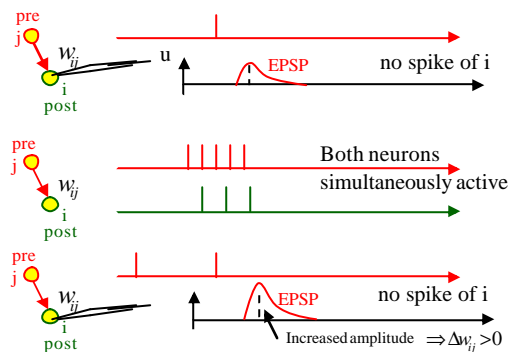
## Hebbian Learning

Recall:  
Partial info



item recalled

## Hebbian Learning in experiments (schematic)



# Synaptic Dynamics

## Induction of changes

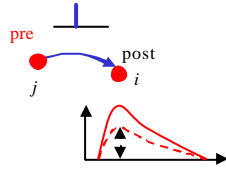
- fast (if stimulated appropriately)
- slow (homeostasis)

## Persistence of changes

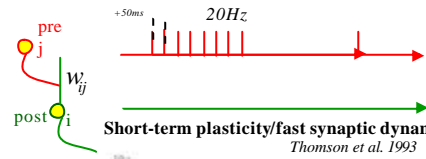
- long (LTP/LTD)
- short (short-term plasticity)

## Functionality

- useful for learning a new behavior
- useful for development (e.g., wiring for receptive field development)
- useful for activity control in network
- useful for coding



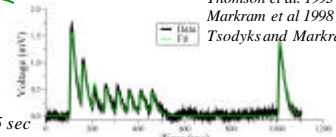
# Classification of plasticity: short-term vs. Long-term



## Short-term plasticity/fast synaptic dynamics

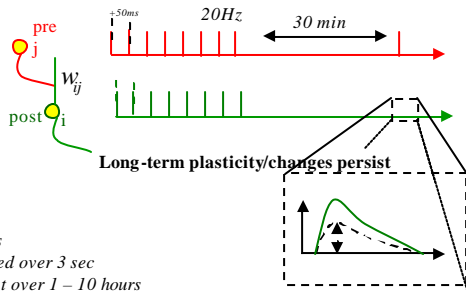
Thomson et al. 1993  
Markram et al. 1998  
Tsodyks and Markram 1997

- Changes
- induced over 0.5 sec
  - recover over 1 sec



Data: Silberberg, Markram  
Fit: Richardson (Tsodyks-Markram model)

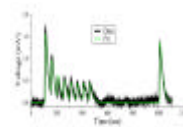
# Classification of plasticity: short-term vs. Long-term



## Long-term plasticity/changes persist

- Changes
- induced over 3 sec
  - persist over 1 - 10 hours

# Classification of plasticity: short-term vs. Long-term



- Changes
- induced over 0.1-0.5 sec
  - recover over 1 sec

Protocol

- presynaptic spikes

Model

- well established (Tsodyks, Senn, Markram)

## LTP/LTD/Hebb

- Changes
- induced over 0.5-5sec
  - remains over hours

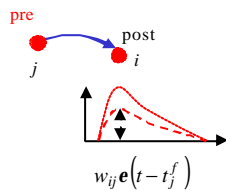
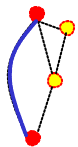
Protocol

- presynaptic spikes + ...

Model

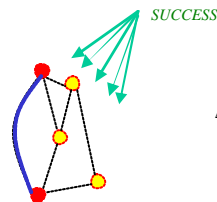
- we will see

# Hebbian Learning = unsupervised learning



$$\Delta w_{ij} \propto F(\text{pre}, \text{post})$$

# Reinforcement Learning = reward + Hebb



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

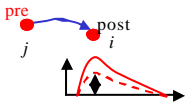
↑ local    ↑ global

# Classification of plasticity: unsupervised vs reinforcement

## LTP/LTD/Hebb

### Theoretical concept

- passive changes
- exploit statistical correlations



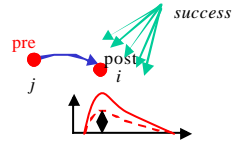
### Functionality

- useful for development
- (wiring for receptive fields)

## Reinforcement Learning

### Theoretical concept

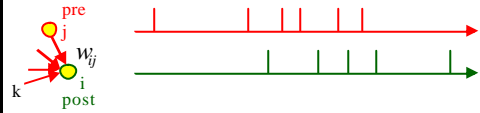
- conditioned changes
- maximise reward



### Functionality

- useful for learning a new behavior

# 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

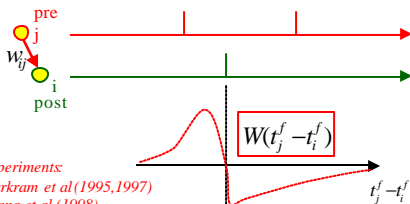
Hebb, 1949

- local rule
- simultaneously active (correlations)

### Rate model:

active = high rate = many spikes per second

# Spike Timing Dependent Plasticity and Hebbian Learning



### Experiments:

- Markram et al (1995,1997)
- Zhang et al (1998)
- Bi&Poo (2001)

$$\Delta w_{ij} = W(t_j^f - t_i^f)$$

# Classification of plasticity standard LTP/LTD vs STDP

## LTP/LTD/Hebb

### exp. Protocol

- extracell. stimulation + ...
- postsyn. depol
- postsyn. activity

### Model

- we will see

$$\Delta w_{ij} \propto pre * post$$

## STDP

### exp. Protocol

- presyn spike + ...
- postsyn. spike

### Model

- we will see

$$\Delta w_{ij} \propto pre * post$$

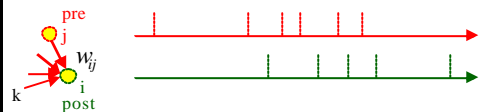
# Models of synaptic Plasticity

## 0. Introduction

### I. Hebbian Learning (unsupervised): review of rate-based theory

### II. Spike-Timing Dependent theory

# 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

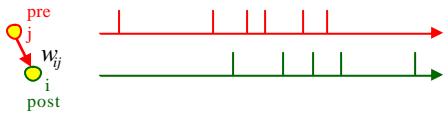
Hebb, 1949

- local rule
- simultaneously active (correlations)

### Rate model:

active = high rate = many spikes per second

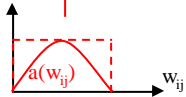
### Rate-based Hebbian Learning



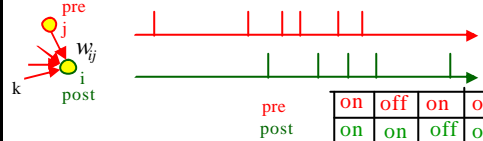
$$\frac{d}{dt} w_{ij} = F(w_{ij}; \mathbf{n}_j^{pre}, \mathbf{n}_i^{post})$$

$$\frac{d}{dt} w_{ij} = a_0 + a_1^{pre} \mathbf{n}_j^{pre} + a_1^{post} \mathbf{n}_i^{post} + a_2^{corr} \mathbf{n}_j^{pre} \mathbf{n}_i^{post} + \dots$$

$$a = a(w_{ij})$$



### Hebbian Learning: rate model



$$\frac{d}{dt} w_{ij} = a_2^{corr} \mathbf{n}_j^{pre} \mathbf{n}_i^{post}$$

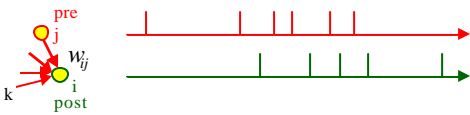
$$\frac{d}{dt} w_{ij} = a_2^{corr} \mathbf{n}_j^{pre} \mathbf{n}_i^{post} - c$$

$$\frac{d}{dt} w_{ij} = a_2^{corr} \mathbf{n}_j^{pre} (\mathbf{n}_i^{post} - J)$$

$$\frac{d}{dt} w_{ij} = a_2^{corr} (\mathbf{n}_j^{pre} - J)(\mathbf{n}_i^{post} - J)$$

	on	off	on	off
pre				
post				
+	0	0	0	0
+	-	-	-	-
+	0	-	0	0
+	-	-	-	+

### Exercise now: Hebbian Learning:



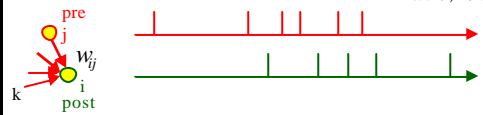
Show that

$$\frac{d}{dt} w_{ij} = a_2^{corr} (\mathbf{n}_i^{post} - J) \mathbf{n}_j^{pre}$$

Is a special case of

$$\frac{d}{dt} w_{ij} = a_0 + a_1^{pre} \mathbf{n}_j^{pre} + a_1^{post} \mathbf{n}_i^{post} + a_2^{corr} \mathbf{n}_j^{pre} \mathbf{n}_i^{post} + \dots$$

### Rate-based Hebbian Learning: BCM Bienenstock, Cooper Munro, 1982



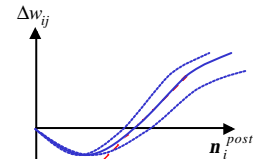
presynaptically gated

$$\frac{d}{dt} w_{ij} = a_2^{corr} (\mathbf{n}_i^{post} - J) \mathbf{n}_j^{pre}$$

BCM

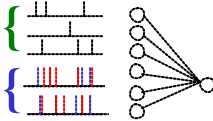
$$\frac{d}{dt} w_{ij} = a_2^{corr} \Phi(\mathbf{n}_i^{post} - J) \mathbf{n}_j^{pre}$$

$$J = f(\bar{\mathbf{n}}_i^{post})$$

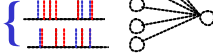


### Functional consequences of Hebbian Learning

Fixed rate

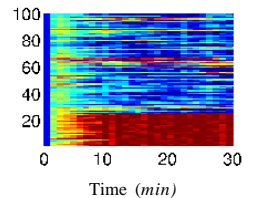
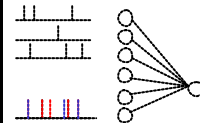


Jointly varying rate

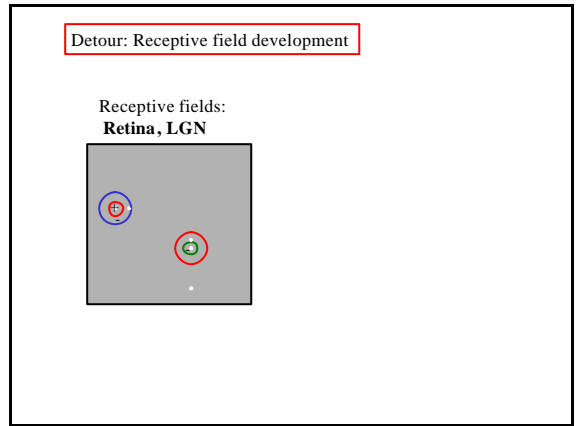
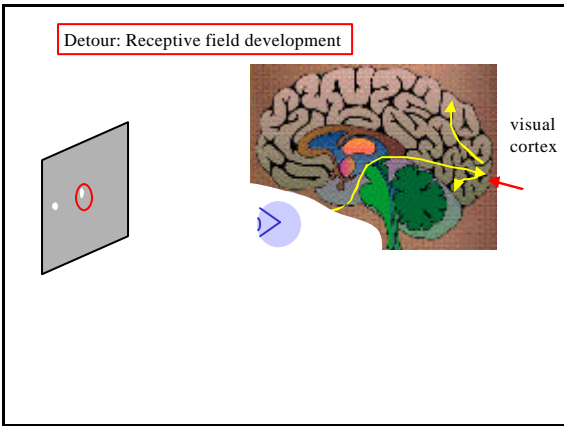
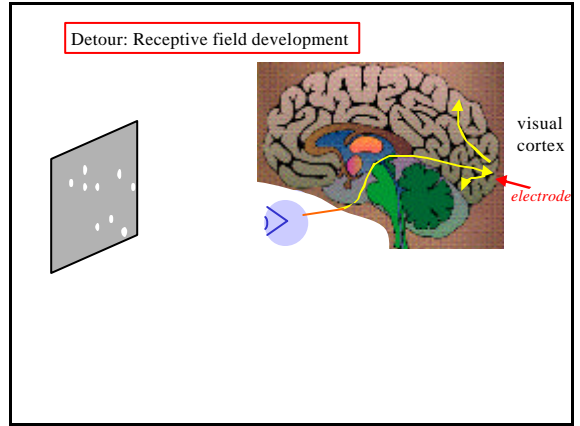
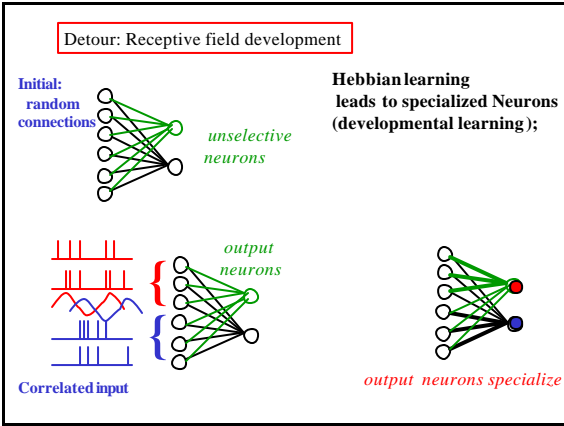
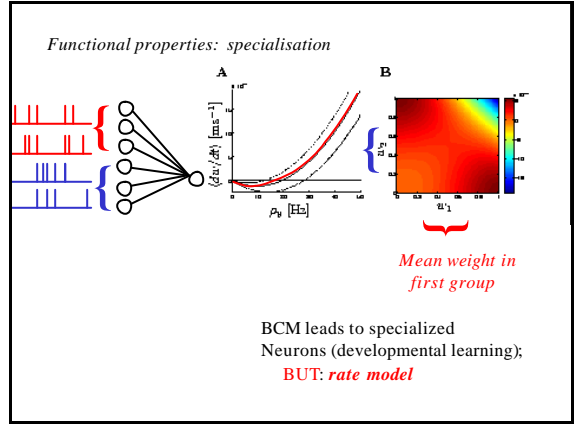
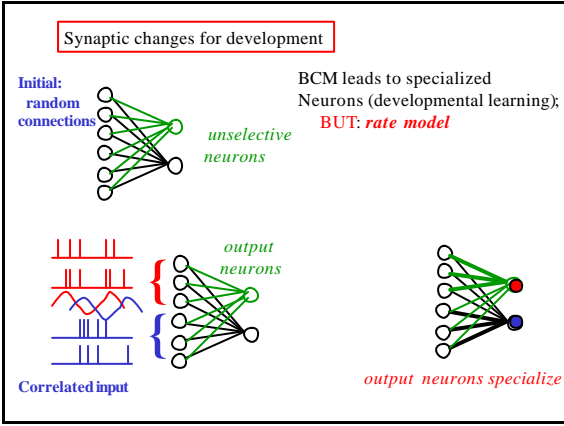


Detects correlations in the input

### Example: BCM

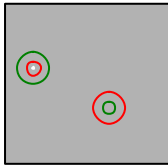


Plasticity rule detects where the 'interesting' input occurs  
-- some synapses strengthened at the expense of others

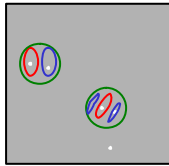


Detour: Receptive field development

Receptive fields:  
Retina, LGN



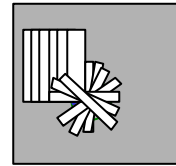
Receptive fields:  
visual cortex V1



Orientation selective

Detour: Receptive field development

Receptive fields:  
visual cortex V1

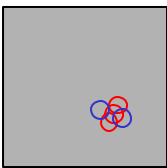


Orientation selective

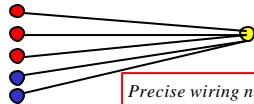
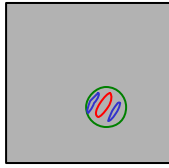
Detour: Receptive field development

What makes cells Orientation selective? - wiring

Receptive fields:  
in LGN



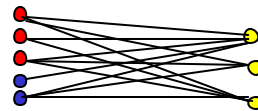
Receptive fields:  
visual cortex V1



Precise wiring necessary - how done?

Detour: Receptive field development

Precise wiring necessary - how done?

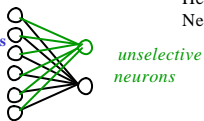


Make connections plastic:

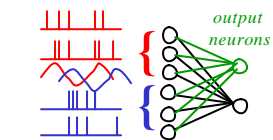
Hebbian (unsupervised) learning rule

Detour: Receptive field development

Initial:  
random  
connections



Hebbian learning leads to specialized  
Neurons (developmental learning);

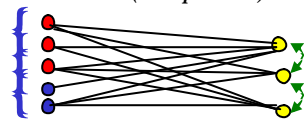


output neurons specialize

Detour: Receptive field development

Precise wiring necessary - how done?

Hebbian (unsupervised) learning rule



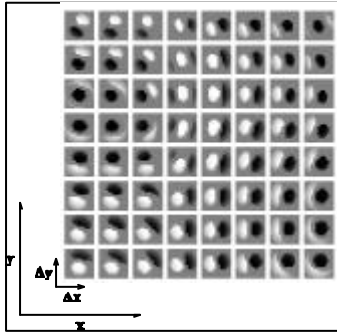
LGN neurons

cortical neurons

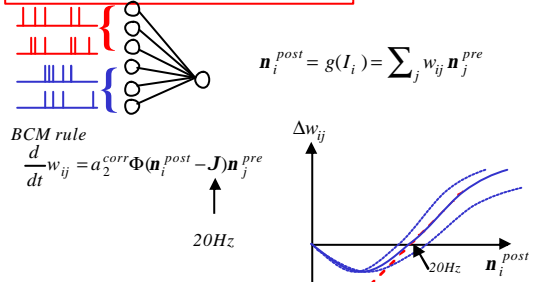
Stimulation with  
Locally correlated inputs

Wiring develops =  
receptive fields develop

**Detour: Receptive field development - model results**



**Exercise now: Hebbian Learning:**



Assume 2 groups of 10 neurons each. All weights equal 1.  
 a) Group 1 fires at 3 Hz, group 2 at 1 Hz. What happens?  
 b) Group 1 fires at 3 Hz, group 2 at 2.5 Hz. What happens?  
 c) As in b, but make theta a function of the averaged rate. What happens?

**Models of synaptic Plasticity**

0. Introduction

0.1 detour: short-term plasticity

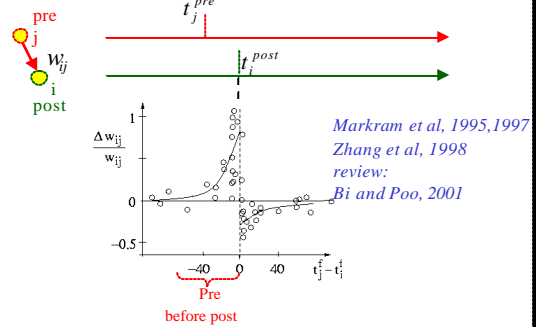
✓ I. Hebbian Learning (unsupervised): review of rate-based theory)

II. Spike-Timing Dependent theory

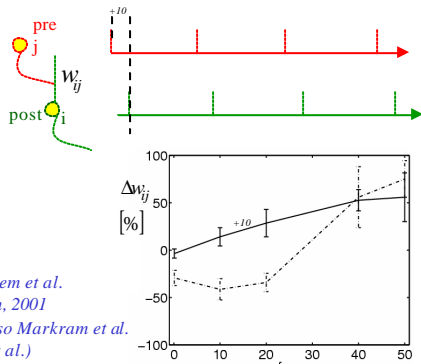
- -Experiments (basic)
- Functional models
- Detailed models
- Minimal models
- Optimal models

Swiss Federal Institute of Technology Lausanne, EPFL  
 Laboratory of Computational Neurosciences, CNRS, CHU, UNIL, Lausanne

**Spike-time dependent learning window**

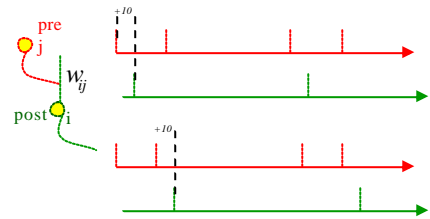


**Frequency dependence of STDP**



Sjöstroem et al.  
 Neuron, 2001  
 (see also Markram et al.  
 Senn et al.)

**Spike Triplets, quadruplets, ...**



Froemke and Dan, Nature, 2002  
 Wang, ..., and Bi, Nat. Neuroscience, 2005

# Models of synaptic Plasticity

0. Introduction

0.1 detour: short-term plasticity

✓ I. Hebbian Learning (unsupervised): review of rate-based theory)

II. Spike-Timing Dependent theory

- Experiments (basic)
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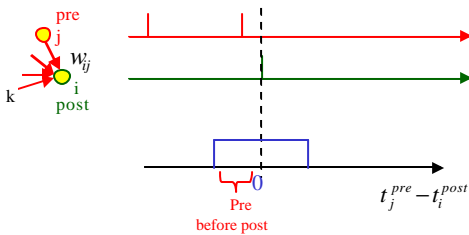


Swiss Federal Institute of Technology Lausanne - EPFL

Department of Computational Neuroscience, ECS, CH-1015 Lausanne

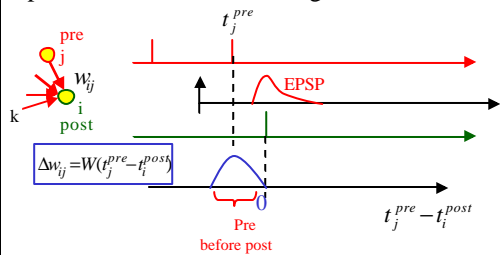
# Spike based models

## Spike-based Hebbian Learning



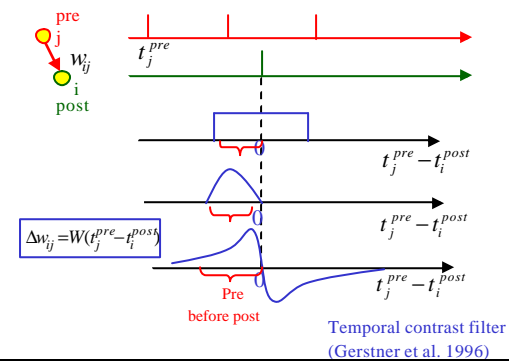
- local rule
- simultaneously active (correlations)

## Spike-based Hebbian Learning

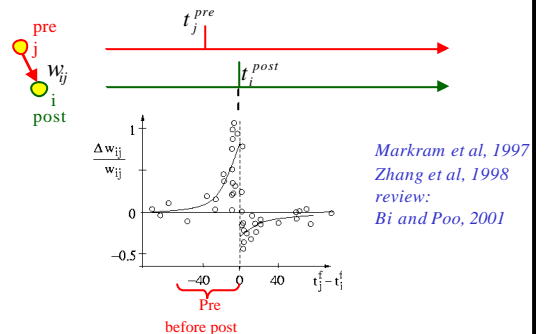


causal rule  
*'neuron j takes part in firing neuron'*  
*Hebb, 1949*

## Spike-time dependent learning window

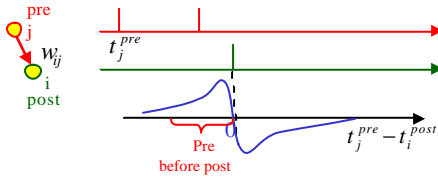


## Spike-time dependent learning window



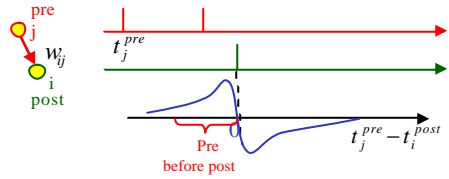


### Spike-time dependent learning: phenomenol. model



$$\Delta W_{ij} = \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} W(t_j^{pre} - t_i^{post}) + \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} b^{pre} + \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} b^{post} + b_0$$

### Spike-time dependent learning: voltage dependence



$$\Delta W_{ij} = \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} W(t_j^{pre} - t_i^{post}) + \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} b^{pre} + \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} b^{post} + b_0$$

$$\Delta W_{ij} = \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} W(t_i^{post} - t_j^{pre} - V_i^{post}) + \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} b^{pre} + \sum_{\substack{t_j^{pre}, t_i^{post} \\ t_j^{pre} < t_i^{post}}} b^{post} + b_0(V_i^{post})$$

### Which kind of model?

Descriptive Models

$$\Delta w = \begin{cases} A^+ \exp\left(-\frac{t_j - t_i}{\tau}\right), & \text{if } t_j < t_i \\ A^- \exp\left(-\frac{t_i - t_j}{\tau}\right), & \text{if } t_i > t_j \end{cases}$$

Gerstner et al. 1996  
Song et al. 2000  
Gütig et al. 2003

Mechanistic Models

$$\Delta w = g(a(t) \dot{b}(t) - a'(t) b(t))$$

Senn et al. 2000  
Abarbanel et al. 2002  
Shouval et al. 2000

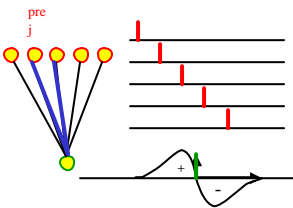
Optimal Models

Chechik, 2003  
Hopfield/Brody, 2004  
Dayan/London, 2004

### Functional consequences of STDP

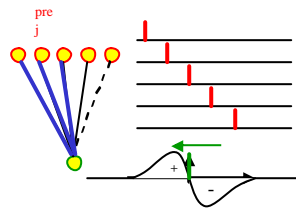
- Learning to be fast
- Learning spike patterns
- improving temporal precision

### Derivative filter and prediction



Mehta et al. 2000, 2002  
Song et al. 2000

### Derivative filter and prediction



Mehta et al. 2000, 2002  
Song et al. 2000

Postsynaptic firing shifts, becomes earlier

## Models of synaptic Plasticity

### 0. Introduction

#### 0.1 detour: short-term plasticity

### ✓ I. Hebbian Learning (unsupervised): review of rate-based theory)

#### II. Spike-Timing Dependent theory

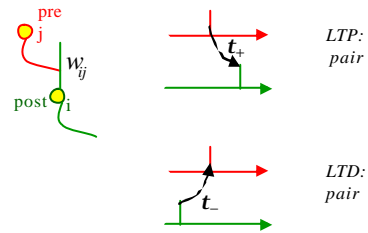
- Experiments (basic)
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- Detailed models
- Improved minimal model

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University of Computational Neuroscience, UCS, CNRS, EPFL Lausanne

## classical model of spike-based Hebbian Learning

Gerstner et al. 1996; Kempter et al. 1999

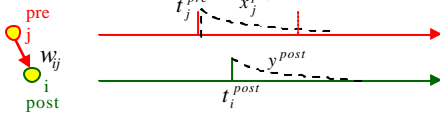


Minimal number of terms? --- only 2 terms.

Voltage dependent? --- no voltage dependence.

weight dependent? --- possible.

## Spike-time dependent plasticity by local variables

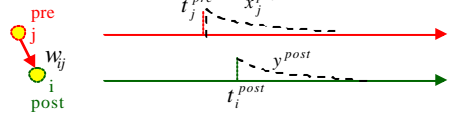


$$\dot{w}_+ \frac{d}{dt} x_j^{pre} = -x_j^{pre} + \mathbf{d}(t - t_j^{pre}) \quad \text{Update with pres. spike}$$

$$\dot{w}_- \frac{d}{dt} y_i^{post} = -y_i^{post} + \mathbf{d}(t - t_i^{post}) \quad \text{Update with posts. spike}$$

$$\frac{d}{dt} w_{ij} = a(w_{ij}) x_j^{pre} \mathbf{d}(t - t_i^{post}) + a(w_{ij}) y_i^{post} \mathbf{d}(t - t_j^{pre})$$

## Spike-timing dependent plasticity by local variables



$$\dot{w}_+ \frac{d}{dt} x_j^{pre} = -x_j^{pre} + \mathbf{d}(t - t_j^{pre}) \quad \text{Update with pres. spike}$$

$$\dot{w}_- \frac{d}{dt} y_i^{post} = -y_i^{post} + \mathbf{d}(t - t_i^{post}) \quad \text{Update with posts. spike}$$

Gerstner et al. 1996; 1997

Kempter et al. 1998, 1999

Abbott et al. 2000

Kistler et al. 2000

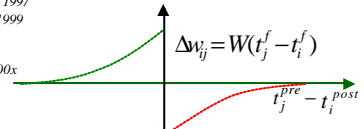
Van Rossum et al. 200x

Guetig et al. 200x

Roberts 1999, 2000

Karmarkar 200x

Senn Tsodyks Markram 1997, 2001



## Which kind of model?

### Descriptive Models

$$\Delta w = \begin{cases} A^+ \exp\left(\frac{t_j - t_i}{\tau}\right), & \text{if } t_j < t_i \\ A^- \exp\left(\frac{t_i - t_j}{\tau}\right), & \text{if } t_j > t_i \end{cases}$$

Gerstner et al. 1996  
Song et al. 2000  
Gütig et al. 2003

### Mechanistic Models

$$\Delta w = g(a(t) \mathcal{D}(t) - a^b(t) \mathcal{Y}(t))$$

Senn et al. 2000  
Abarbanel et al. 2002  
Shouval et al. 2000

### Optimal Models

Chechik, 2003  
Hopfield/Brody 2004  
Dayan/London, 2004



## Models of synaptic Plasticity

### 0. Introduction

#### 0.1 detour: short-term plasticity

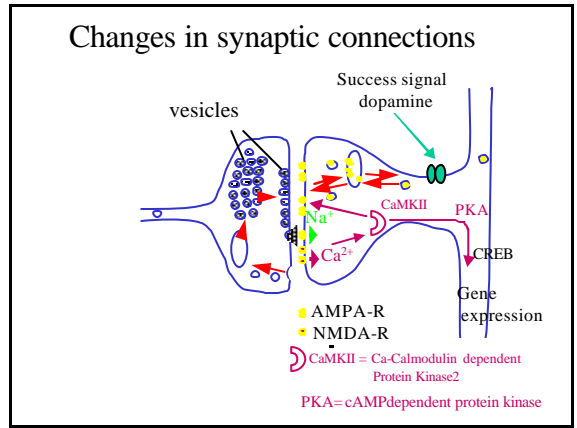
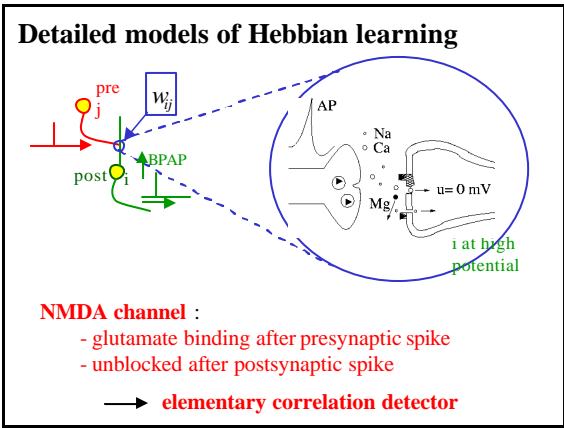
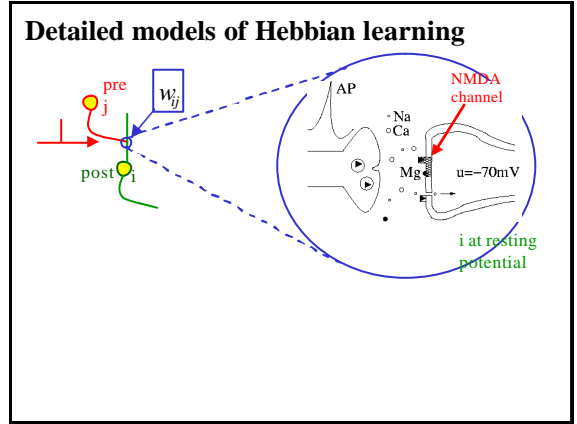
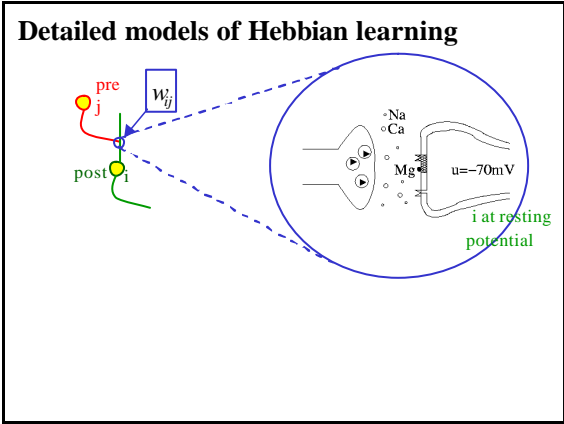
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- Experiments (basic)
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### Models of synaptic Plasticity

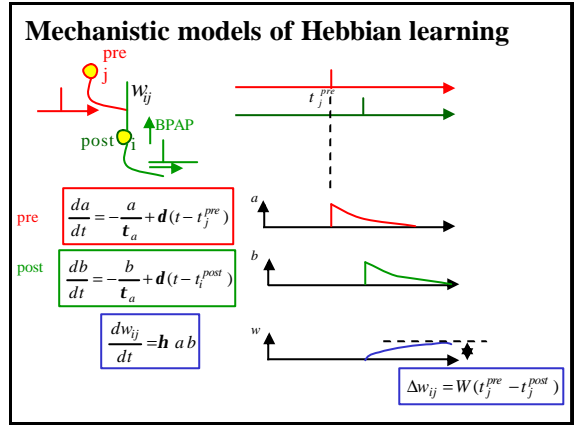
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 Institute of Neuroinformatics, University of Zurich and ETH Zurich



### Mechanistic models of Hebbian learning

4-factor model

$$\frac{dw_{ij}}{dt} = \mathbf{h} [a b - c d]$$

sophisticated 2-factor

$$\frac{dw_{ij}}{dt} = \mathbf{h} [a b^q - a^q b]$$

Gerstner et al. 1998  
Buonomano 2001  
Abarbanel et al. 2002

### Mechanistic models of Hebbian learning

1 pre, 1 post

$$\frac{dx}{dt} = -\frac{x}{\tau_a} + \mathbf{d}(t - t_j^{\text{pre}})$$

$$\frac{dy}{dt} = -\frac{y}{\tau_a} + \mathbf{d}(t - t_i^{\text{post}})$$

$$\frac{dw_{ij}}{dt} = a_+ x(t) \mathbf{d}(t - t_i^{\text{post}}) - a_- y(t) \mathbf{d}(t - t_j^{\text{pre}})$$

### Mechanistic models of Hebbian learning

Dynamics of NMDA receptor (Senn et al., 2001)

LTP

LTD

1 pre, 2 post; 1 post, 2 pre

### Which kind of model?

Descriptive Models

$$\Delta w = \begin{cases} A^+ \exp\left(-\frac{t_j - t_i}{\tau}\right), & \text{if } t_j < t_i \\ A^- \exp\left(-\frac{t_j - t_i}{\tau}\right), & \text{if } t_j > t_i \end{cases}$$

Gerstner et al. 1996  
Song et al. 2000  
Gütig et al. 2003

Mechanistic Models

$$\Delta w = g(a(t) \theta(t) - a^h(t) \psi(t))$$

Senn et al. 2000  
Abarbanel et al. 2002  
Shouval et al. 2000

Optimal Models

Chechik, 2003  
Hopfield/Brody 2004  
Dayan/London, 2004

### Models of synaptic Plasticity

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- Detailed models
- Mechanistic models
- -A FRAMEWORK
- Minimal model(2)

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EPFL - Ecole Polytechnique Fédérale de Lausanne

### Stochastically spiking neuron model

$$x_j(t) = \sum_j \mathbf{d}(t - t_j^f)$$

$$y(t) = \sum_n \mathbf{d}(t - t_n)$$

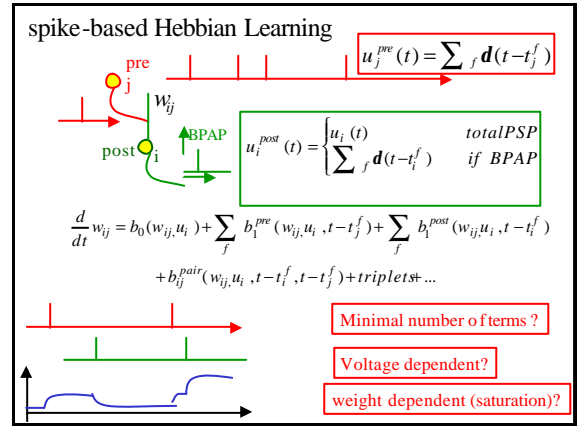
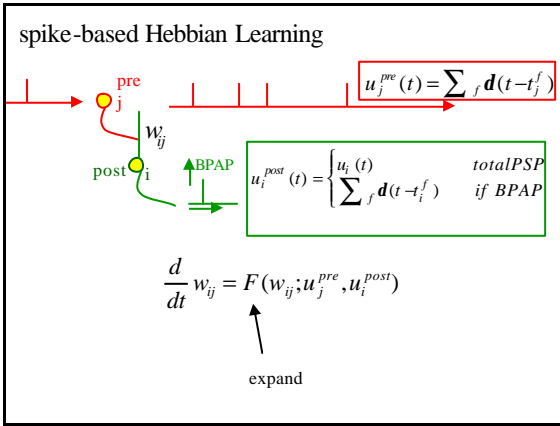
$$u(t) = \sum_{j,f} w_j \mathbf{e}(t - t_j^f)$$

$$\mathbf{r}(t) = g(u(t))$$

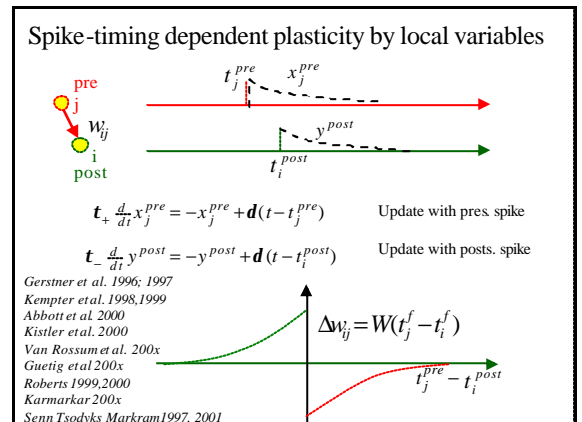
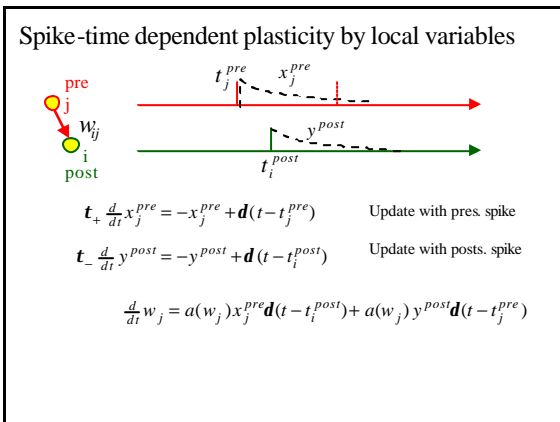
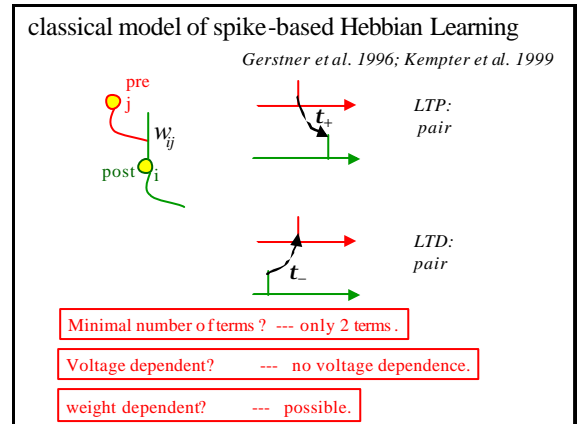
potential

stochastic firing

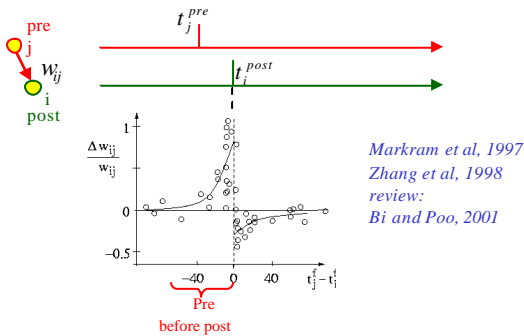
All spikes, all neurons



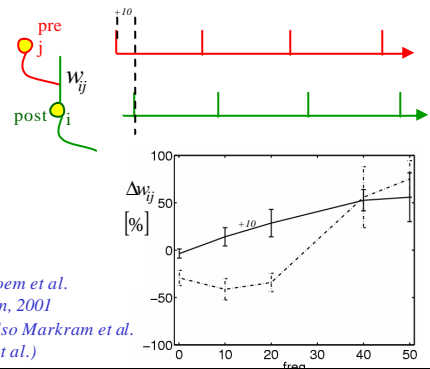
- ### Models of synaptic Plasticity
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    - -A Minimal model
    - Optimal models



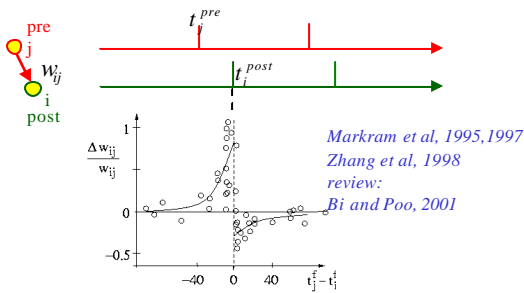
### Spike-time dependent learning window



### Frequency dependence of STDP

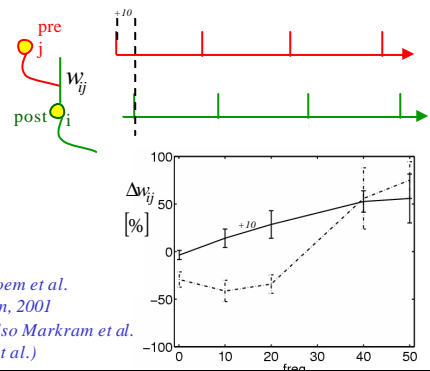


### Spike-time dependent learning window

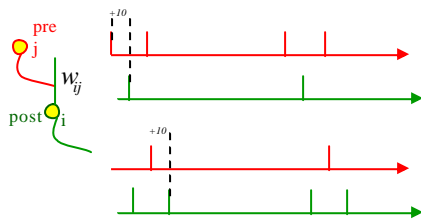


Pair-based STDP cannot account for frequency dependence

### Pair-based STDP cannot account for frequency dependence



### Spike Triplets, quadruplets, ...



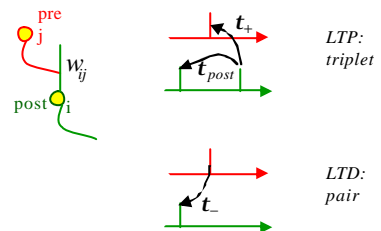
Experimental results show asymmetry

*Froemke and Dan, Nature, 2002  
Wang, ..., and Bi, Nat. Neuroscience, 2005*

Pair-based STDP cannot account for asymmetry

### Minimal model of spike-based Hebbian Learning

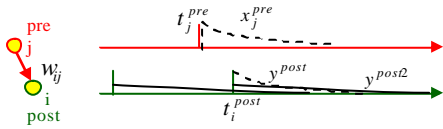
*(Pfister and Gerstner, J. Neuroscience, 2006)*



Minimal number of terms? --- only 2 terms.

Voltage dependent? --- no voltage dependence.

### Spike-time dependent plasticity by local variables



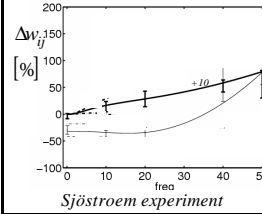
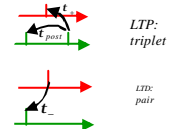
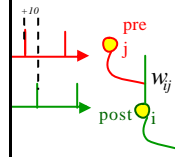
$$\dot{t}_+ \frac{d}{dt} x_j^{pre} = -x_j^{pre} + \mathbf{d}(t - t_j^{pre}) \quad \text{Update with pres. spike}$$

$$\dot{t}_- \frac{d}{dt} y_i^{post} = -y_i^{post} + \mathbf{d}(t - t_i^{post}) \quad \text{Update with posts. spike}$$

$$\dot{t}^{post} \frac{d}{dt} y_i^{post\Omega} = -y_i^{post\Omega} + \mathbf{d}(t - t_i^{post})$$

$$\frac{d}{dt} w_j = a_+ (w_j) x_j^{pre} \mathbf{d}(t - t_i^{post}) + a_- (w_j) y_i^{post} \mathbf{d}(t - t_j^{pre}) + a(w_j) x_j^{pre} y_i^{post\Omega} \mathbf{d}(t - t_i^{post})$$

### spike-based Hebbian Learning

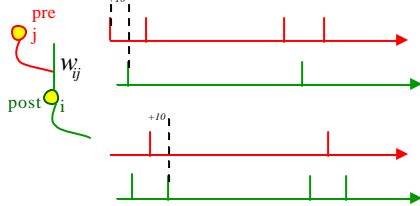


Minimal model reproduces Frequency dependence of STDP

(Pfister and Gerstner, *J. Neuroscience*, 2006)

### Spike Triplets, ...

Wang, ..., and Bi, *Nat. Neuroscience*, 2003

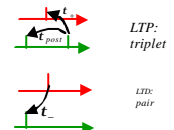
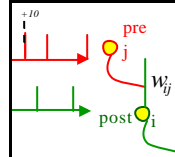


Our minimal models accounts for asymmetry

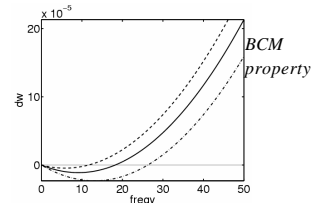
(Triplet experiment of Bi)

(Pfister and Gerstner, *J. Neuroscience*, 2006)

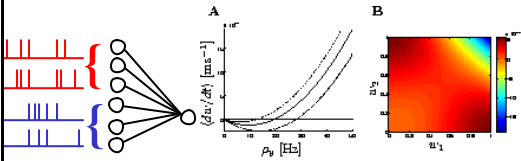
### spike-based Hebbian Learning



Poisson spike trains

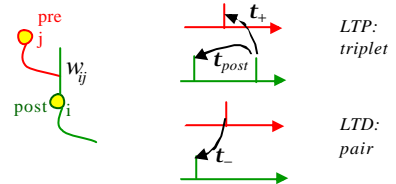


### Functional properties: receptive field development



(Pfister and Gerstner, *J. Neuroscience*, 2006)

### Minimal model of spike-based Hebbian Learning



With only 2 terms in expansion:

- BCM theory
- Sjöstroem experiment (frequency dependence of STDP)
- Bi's triplet experiment

(Pfister and Gerstner, *J. Neuroscience*, 2006)