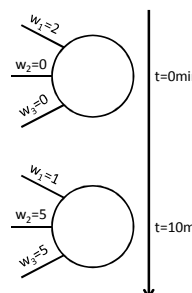


## CISC 3250 Systems Neuroscience

**Neuroplasticity:  
Learning in Neurons**

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JMH 328A



t=0min

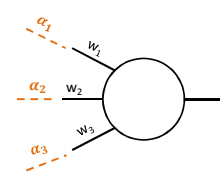
t=10min

## Review of weights


$R_i(t) = \sum_j w_j \alpha_j(t)$

Weights indicate


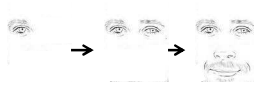
- Connection (0 or not)
- NT effect
  - $w > 0$  excitatory
  - $w < 0$  inhibitory
- Magnitude of impact of input



## Association

- We recall information through associations with other information
- Pneumonics:
  - Roy G. Biv
  - Please Excuse My Dear Aunt Sally ( ) Exp x / + -
- Memories of experiences:
  - Lake -> Summer vacation 2012 
  - Dealy -> Final exam Fall 2014 
- Complex objects
  - ::Bark:: -> Dog, fur, happy/fear 

## Features of associators



- Pattern completion/ generalization 
- Fault tolerance
  - Selected dendrites miss input, post-synaptic neuron still fires
- Learning prototypes
  - Neuron firing for common combinations 

## Pattern completion

Activation requires only a subset of desired inputs

$r^{in}$	w
leg1	0.5
leg2	0.5
body	0.5
ears	0.5
mouth	0.5
tail	0.5

How many inputs needed to fire?


Define input  $h = \sum_i w_i r_i^{in}$   
 Neuron fires at rate  $r^{out}=1$  when  $h > 1.5$   
 Assume  $r^{in}=1$  when active,  $r^{in}=0$  when inactive

## Fault tolerance

Activation requires only a subset of desired inputs

$r^{in}$	w
moo	2
quack	0
woof	0
moo	2
woof	0
moo	2

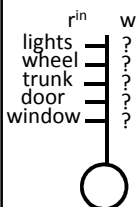
How many inputs needed to fire?



$h = \sum_i w_i r_i^{in}$   
 Neuron fires at rate  $r^{out}=1$  when  $h > 1.5$

### Prototypes

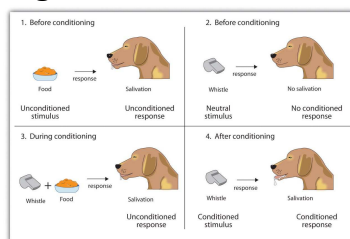
Activation requires all desired inputs



$$h = \sum_i w_i r_i^{in}$$

Neuron fires at rate  $r^{out}=1$  when  $h > 1.5$

### Learning to associate: Conditioning

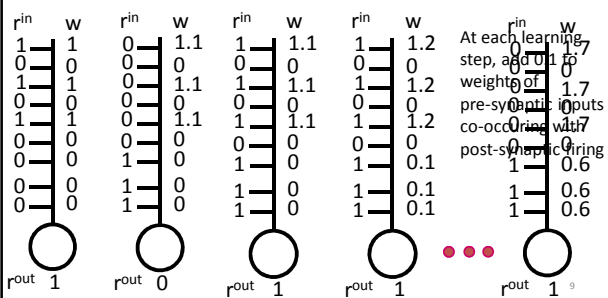


Associating both smell and whistle with food

- **Unconditioned stimulus:** smell – already associated with food
- **Conditioned stimulus:** whistle – indicates food coming

### Computing level: Associator network

Define input  $h = \sum_i w_i r_i^{in}$   
Neuron fires at rate  $r^{out}=1$  when  $h > 1.5$



### Two forms of plasticity

- **Structural plasticity:** generation of new connections between neurons
- **Functional plasticity:** changing strength of connections between neurons

**Hebbian plasticity:**  
“cells that fire together, wire together”

### Chemical level: NT receptors

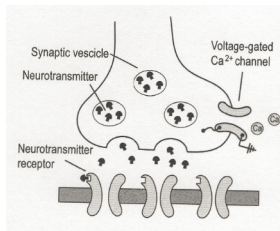
Increase weight by improving NT detection

Post-synaptic:

- Insert more receptors into dendrite membrane
- Improve performance of receptors

Pre-synaptic:

- Increase amount of NT released



### Marr's levels of analysis

- **Computational theory:** Learn associations among sensations
- **Representation and algorithm:** Associate each sense with set of neural outputs, adjust weights on these outputs into another neuron
- **Hardware implementation:** Insert/remove NT receptors from dendrites

### Math of Hebbian rate learning

“Cells that fire together, wire together”

$r_i \rightarrow r^{out}$   
 $r_j \rightarrow r^{in}$   
 $\epsilon$  learning speed

$$\Delta w_{ij} = \epsilon(w) r_i r_j$$

Time (sec)

### Using the learning rule

Define input  $h = \sum_i w_i r_i^{in}$   
 Neuron fires at rate  $r^{out}=1$  when  $h > 1$

$$\epsilon(w) = \begin{cases} -0.5 & w < 0 \\ 0.5 & w \geq 0 \end{cases}$$

$$\Delta w_{ij} = \epsilon(w) r_i r_j$$

### Weight control and decay

- Synaptic weights are finite
- Propose learning rules that keep weights bounded

$$\Delta w_{ij} = r_i r_j - c w_{ij}$$

$$\Delta w_{ij} = r_i (r_j - w_{ij}) - \text{Willshaw}$$

- Or, preserve total synaptic weight across network:

$$w_{ij} \leftarrow \frac{w_{ij}}{\sum_j w_{ij}}$$

### Using weight control and decay

Define input  $h = \sum_i w_i r_i^{in}$   
 Neuron fires at rate  $r^{out}=1$  when  $h > 1$

$$\Delta w_{ij} = r_i (r_j - w_{ij})$$

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