## Combined Model & Task Learning

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**Biology Says: Both** 

 $\vdash$ 

- 1. Pros and Cons: Use Both
- 2. Inhibition is also an Important Bias.

Mod  $Ca^{2+}$ 

 $\to LTD$ 

High  $Ca^{2+} \rightarrow LTP$ No  $Ca^{2+} \rightarrow$  no learning Minus Phase  $x_i^-, y_j^- \approx 0$   $x_i^-, y_j^- \approx 1$ 

0

0 +

Plus Phase

Only case disagreeing w/ Hebb is bottom left quadrant (LTD).

LTD

ightarrow Low  $Ca^{2+}$  (just minus phase) produces LTD ightarrow same mechanism as Hebb LTD for  $y_j$ =1,  $x_i$ =0.

### $\circ$ Other mechanisms for Error-driven Learning

- Neuromodulatory signals: Dopamine, Acetylcholine, etc.
- "Phasic" signals elicited by brain systems computing 'expected reward' and deviations from this expectation
- enhance contrast between two succeeding attractor states (what should have been expected) in subsequent state, can Resulting signals, when combined with target information
- Lots of evidence that LTP, LTD under neuromodulatory control
- (model learning, statistics) Hebbian learning always occurs locally, in every synapse
- changes during errors, leading to contrastive Hebbian learning (approximated by delta rule) Brain regions innervated by DA, ACh have enhanced weight

#### 4 Error-driven = Left-wing, Hebbian = Right-wing (?!) (local) Error-driven (remote) Hebbian autonomous, reliable task-driven, cooperative Pro**Functional: Pros and Cons** myopic, greedy co-dependent, lazy

#### $\mathfrak{Q}$

### Combining Error-driven + Hebbian

Get benefits of both:

$$\Delta w_{ij}pprox \Delta_{hebb} + \Delta_{err}$$

 $\exists$ 

$$\Delta_{hebb} = \epsilon a_j (a_i - w_{ij})$$

$$\Delta_{err} = \epsilon [(a_i^+ a_j^+) - (a_i^- a_j^-)]$$

$$\Delta w_{ij} = (k_{hebb}) \Delta_{hebb} + (1 - k_{hebb}) (\Delta_{err}) \tag{2}$$

Hebbian bias helps so that weights are constrained to smaller set of solutions (otherwise too interdependent in err-driven)

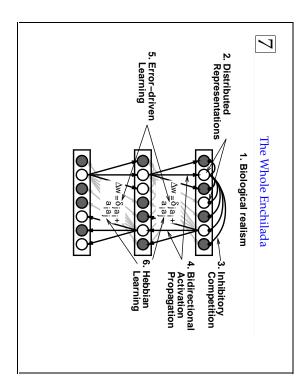
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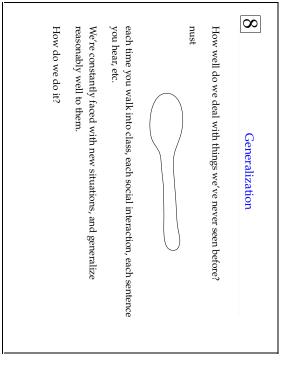
### Inhibitory Competition as a Bias

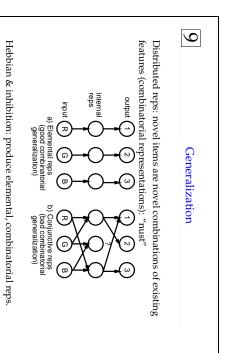
Inhibition:

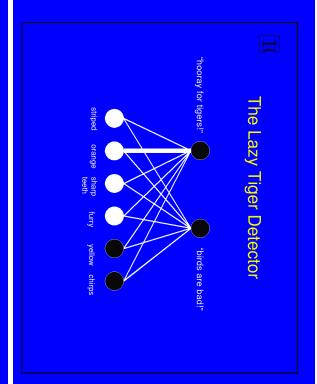
- Causes sparse, distributed representations (many alternatives, only a few relevant at any time).
- Competition and specialization: survival of fittest
- Self-organizing learning.

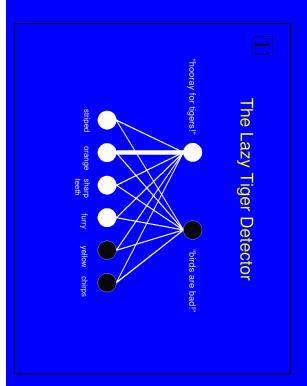
(Often more important than Hebbian bias)

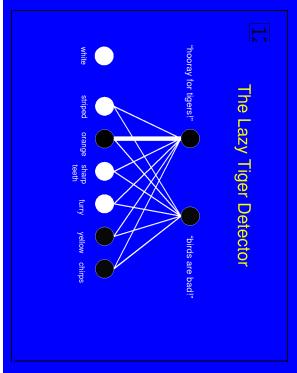




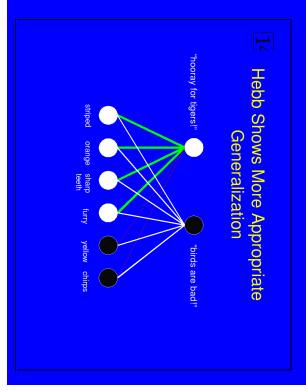


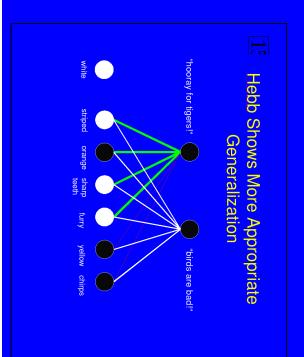


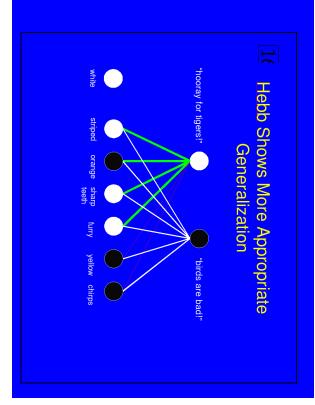




# Hebb Shows More Appropriate Generalization "hooray for tigers!" "birds are bad!" striped orange sharp furry yellow chirps









#### Hebb:

- Sometimes fails to learn the training set
- Represents meaningful "things" in the world (correlations)
- Shows good generalization

### Error (GeneRec):

- Always learns the training set
- Representations are "mushy"
- Can show poor generalization

### Error + Hebb:

- Learns the training set (more quickly than error alone)
- Represents meaningful features
- Shows good generalization!

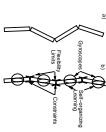


### Deep Networks en layers to achieve many stages of transforerresenting the problem).

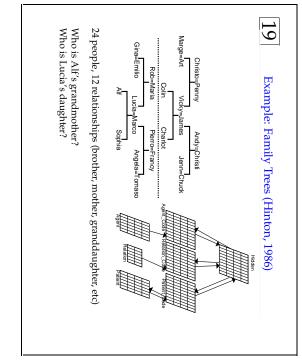
Need many hidden layers to achieve many stages of transformations (dramatically re-representing the problem).

But then the error signals are very remote & weak.

Need to add constraints and self-organizing learning:



- Hebb gives each layer local guidance on representations
- Inhib competition restricts flexibility (only certain states are valid)
- $\bullet \;$  Combined model + task  $\rightarrow$  fewer degrees of freedom to adapt



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