

## B. Stochastic Neural Networks

(in particular, the stochastic Hopfield network)

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### Trapping in Local Minimum

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### Escape from Local Minimum

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### Escape from Local Minimum

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### Motivation

- **Idea:** with low probability, go against the local field
  - move up the energy surface
  - make the “wrong” microdecision
- **Potential value for optimization:** escape from local optima
- **Potential value for associative memory:** escape from spurious states
  - because they have higher energy than imprinted states

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### The Stochastic Neuron

Deterministic neuron:  $s'_i = \text{sgn}(h_i)$

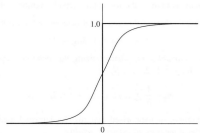
$\Pr\{s'_i = +1\} = \Theta(h_i)$   
 $\Pr\{s'_i = -1\} = 1 - \Theta(h_i)$

Stochastic neuron:  
 $\Pr\{s'_i = +1\} = \sigma(h_i)$   
 $\Pr\{s'_i = -1\} = 1 - \sigma(h_i)$

Logistic sigmoid:  $\sigma(h) = \frac{1}{1 + \exp(-2h/T)}$

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### Properties of Logistic Sigmoid

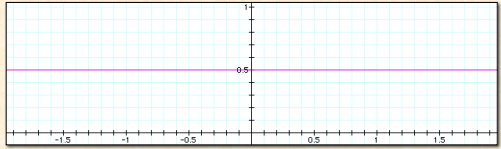


$$\sigma(h) = \frac{1}{1 + e^{-2h/T}}$$

- As  $h \rightarrow +\infty$ ,  $\sigma(h) \rightarrow 1$
- As  $h \rightarrow -\infty$ ,  $\sigma(h) \rightarrow 0$
- $\sigma(0) = 1/2$

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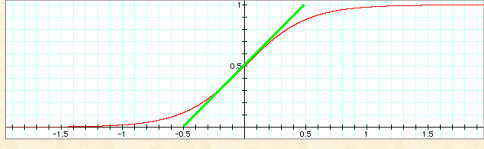
### Logistic Sigmoid With Varying $T$



$T$  varying from 0.05 to  $\infty$  ( $1/T = \beta = 0, 1, 2, \dots, 20$ )

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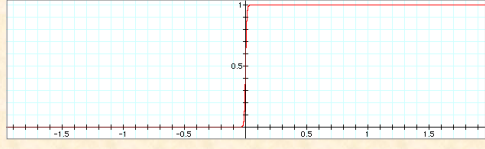
### Logistic Sigmoid $T = 0.5$



Slope at origin =  $1 / 2T$

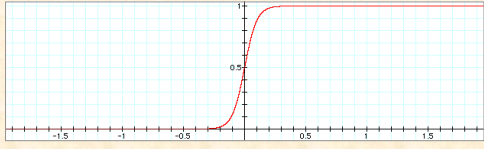
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### Logistic Sigmoid $T = 0.01$




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### Logistic Sigmoid $T = 0.1$



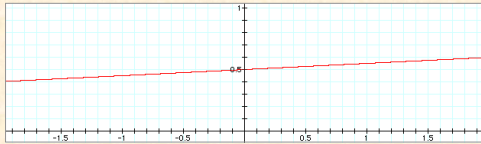
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### Logistic Sigmoid $T = 1$



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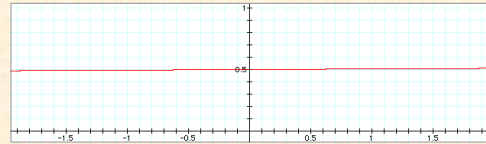
### Logistic Sigmoid $T = 10$



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### Logistic Sigmoid $T = 100$



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### Pseudo-Temperature

- Temperature = measure of thermal energy (heat)
- Thermal energy = vibrational energy of molecules
- A source of random motion
- Pseudo-temperature = a measure of nondirected (random) change
- Logistic sigmoid gives same equilibrium probabilities as Boltzmann-Gibbs distribution

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### Transition Probability

Recall, change in energy  $\Delta E = -\Delta s_k h_k$   
 $= 2s_k h_k$

$$\Pr\{s'_k = \pm 1 | s_k = \mp 1\} = \sigma(\pm h_k) = \sigma(-s_k h_k)$$

$$\Pr\{s_k \rightarrow -s_k\} = \frac{1}{1 + \exp(2s_k h_k / T)}$$

$$= \frac{1}{1 + \exp(\Delta E / T)}$$

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### Stability

- Are stochastic Hopfield nets stable?
- Thermal noise prevents absolute stability
- But with symmetric weights:  
average values  $\langle s_i \rangle$  become time - invariant

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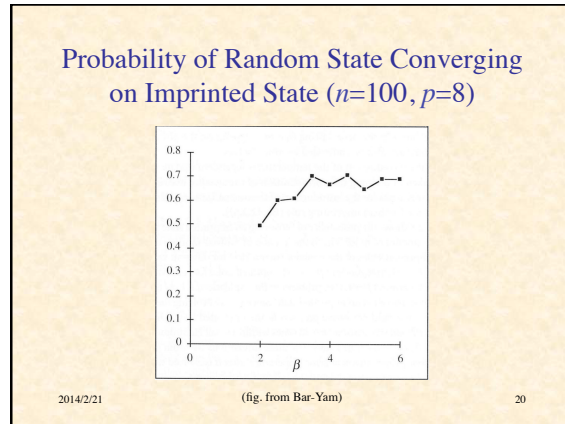
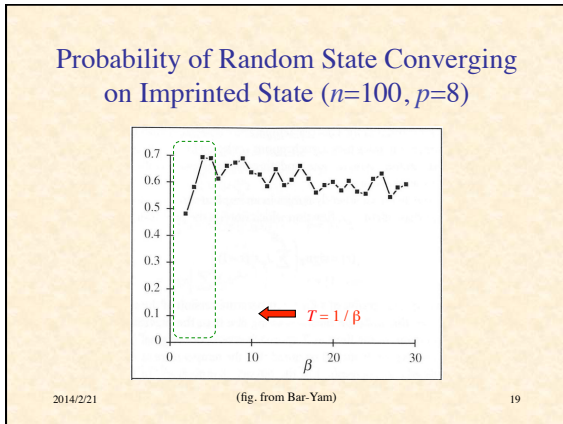
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### Does “Thermal Noise” Improve Memory Performance?

- Experiments by Bar-Yam (pp. 316-20):
  - $n = 100$
  - $p = 8$
- Random initial state
- To allow convergence, after 20 cycles set  $T = 0$
- How often does it converge to an imprinted pattern?

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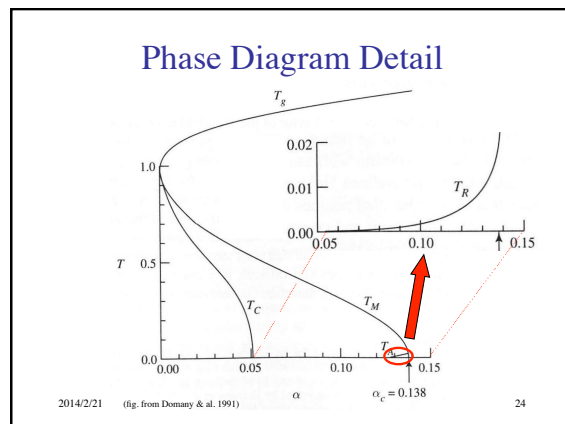
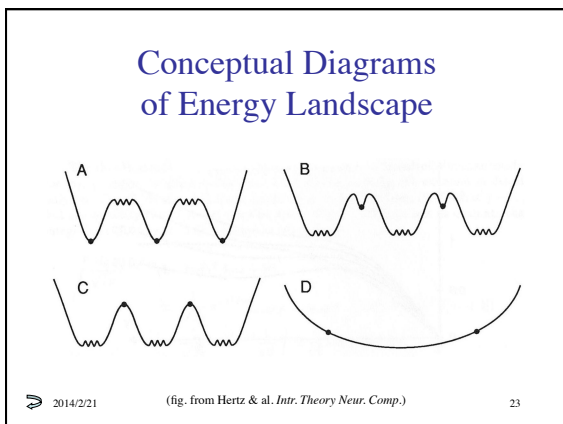
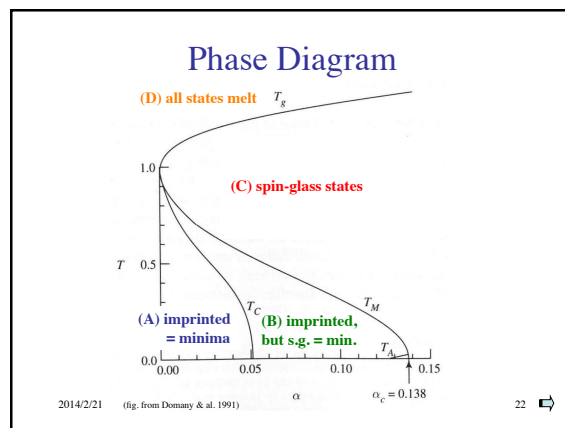
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### Analysis of Stochastic Hopfield Network

- Complete analysis by Daniel J. Amit & colleagues in mid-80s
- See D. J. Amit, *Modeling Brain Function: The World of Attractor Neural Networks*, Cambridge Univ. Press, 1989.
- The analysis is beyond the scope of this course

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## Simulated Annealing

(Kirkpatrick, Gelatt & Vecchi, 1983)

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## Dilemma

- In the early stages of search, we want a high temperature, so that we will explore the space and find the basins of the global minimum
- In the later stages we want a low temperature, so that we will relax into the global minimum and not wander away from it
- **Solution:** decrease the temperature gradually during search

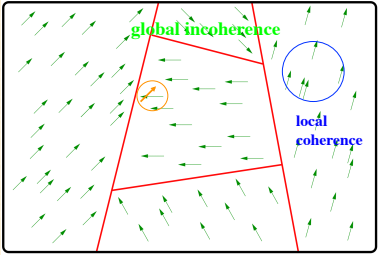
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## Quenching vs. Annealing

- **Quenching:**
  - rapid cooling of a hot material
  - may result in defects & brittleness
  - local order but global disorder
  - locally low-energy, globally frustrated
- **Annealing:**
  - slow cooling (or alternate heating & cooling)
  - reaches equilibrium at each temperature
  - allows global order to emerge
  - achieves global low-energy state

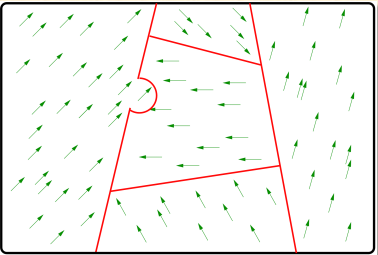
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## Multiple Domains



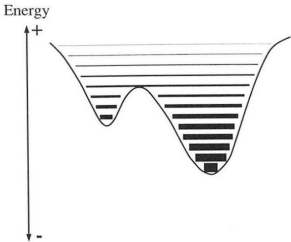
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## Moving Domain Boundaries



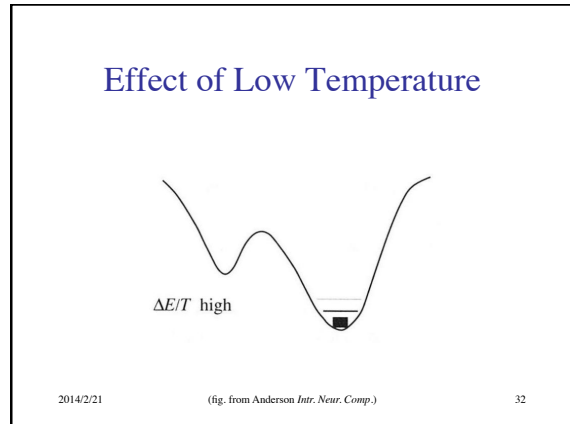
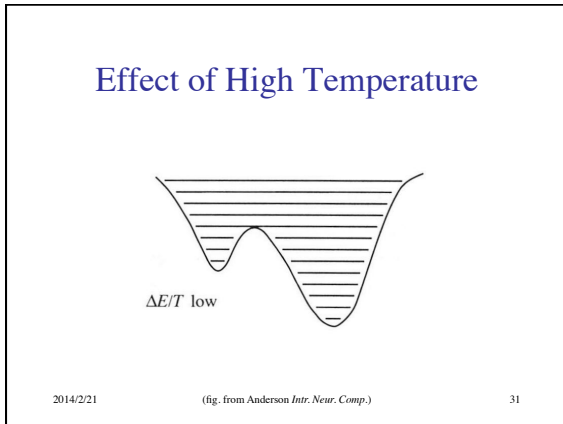
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## Effect of Moderate Temperature



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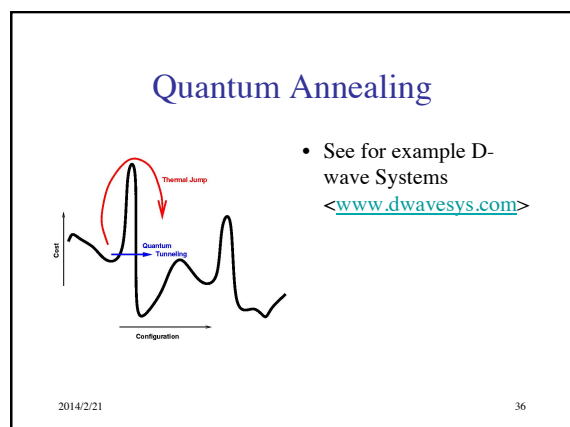
(fig. from Anderson *Intr. Neur. Comp.*)



- ### Annealing Schedule
- Controlled decrease of temperature
  - Should be sufficiently slow to allow equilibrium to be reached at each temperature
  - With sufficiently slow annealing, the global minimum will be found with probability 1
  - Design of schedules is a topic of research
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- ### Typical Practical Annealing Schedule
- **Initial temperature**  $T_0$  sufficiently high so all transitions allowed
  - **Exponential cooling:**  $T_{k+1} = \alpha T_k$ 
    - typical  $0.8 < \alpha < 0.99$
    - fixed number of trials at each temp.
    - expect at least 10 accepted transitions
  - **Final temperature:** three successive temperatures without required number of accepted transitions
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- ### Summary
- Non-directed change (random motion) permits escape from local optima and spurious states
  - Pseudo-temperature can be controlled to adjust relative degree of exploration and exploitation
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- See for example D-wave Systems  
<[www.dwavesys.com](http://www.dwavesys.com)>

### Hopfield Network for Task Assignment Problem

- Six tasks to be done (I, II, ..., VI)
- Six agents to do tasks (A, B, ..., F)
- They can do tasks at various rates
  - A (10, 5, 4, 6, 5, 1)
  - B (6, 4, 9, 7, 3, 2)
  - etc
- What is the optimal assignment of tasks to agents?

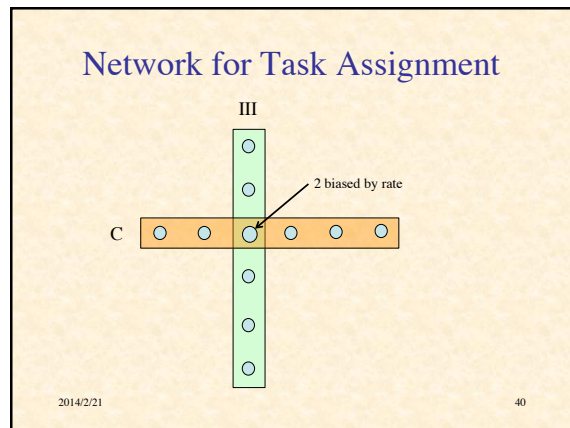
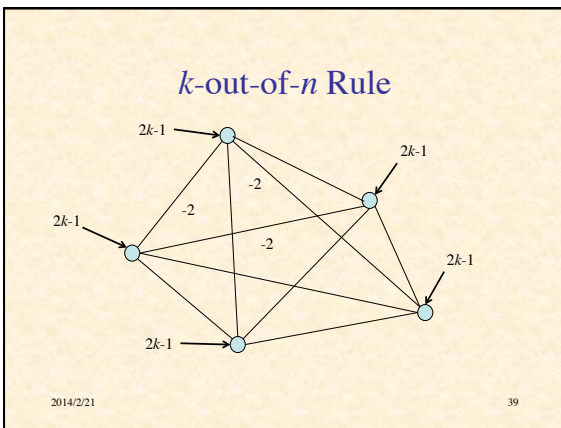
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### Continuous Hopfield Net

$$\dot{U}_i = \sum_{j=1}^n T_{ij} V_j + I_i - \frac{U_i}{\tau}$$

$$V_i = \sigma(U_i) \in (0,1)$$

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### NetLogo Implementation of Task Assignment Problem

[Run TaskAssignment.nlogo](#)

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