Where we are in the course

- Fundamentals and History
  - neuroscience, **neural networks**, coding and information theory, dynamical systems
- Modeling Cognitive Phenomena
- Dynamics and Cognition, Embodiment
- Dynamics and Neuroscience
- Issues in Coding and Representation
  - Synchronization, correlation, transients

Simulating Networks

- Using detailed computational models of phenomena mentioned in Gettig, Abbot & Dayan not practical to
  - Dynamics time scales range over orders of magnitude
  - Large networks computationally infeasible or at least require heroic parallel processing efforts
- Solution: simpler rate coded models (varieties of connectionism)

Network Characteristics

- Topology or Structure
- Coding: Spatial Aspects
- Coding: Temporal Aspects
- Functional Taxonomy and Learning
- Activation Function
- Synchronous / Asychronous Update

Topologies

- Non-spatial networks
  - Feedforward
  - Recurrent
- Maps (spatial organization preserved)
  - Self Organizing Map
  - Cellular Neural Networks
  - Coupled Map* Lattices
    - Map here refers to a kind of computation within the lattice spatial structure (which also happens to be called a map)

Coding: What do we mean?

- In classical coding and information theory, a code is an *invertible mapping* from a stream in some alphabet . Coding serves functions of compression and reliable transmission through noisy channel.
- In neural networks, coding is often not invertible; mapping from input to output for some functional behavior - association, recall, categorization. Can associate invertible code if desired.

Network Structure

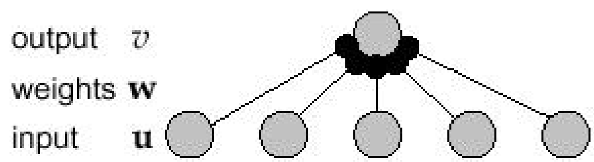


Figure 7.1: Feedforward inputs to a single neuron. Input rates $\mathbf{u}$ drive a neuron at an output rate v through synaptic weights given by the vector $\mathbf{w}$.

From Abbot and Dyan

Network Structure

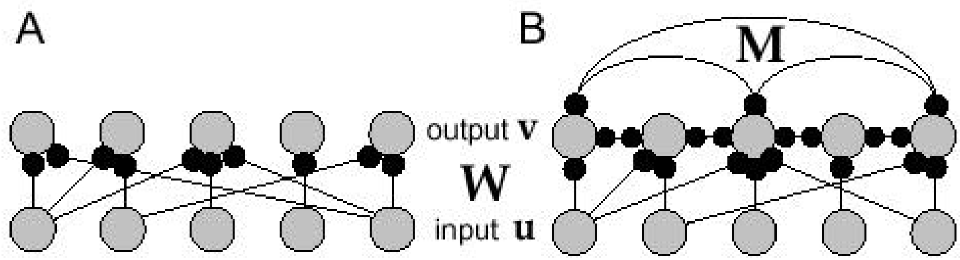
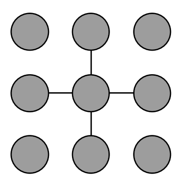


Figure 7.3: Feedforward and recurrent networks. A) A feedforward network with input rates **u**, output rates **v**, and a feedforward synaptic weight matrix **W**. B) A recurrent network with input rates **u**, output rates **v**, a feedforward synaptic weight matrix **W**, and a recurrent synaptic weight matrix **M**. Although we have drawn the connections between the output neurons as bidirectional, this does not necessarily imply connections of equal strength in both directions.

From Abbot and Dyan

Spatial Map Network (cellular neural net, coupled map lattice



Typically these are **recurrent** and **coupled to neighborhood** by a **coupling function.**

This is not the same as **weights -** implies a degree of **synchronization not multiplication.**

Coding Taxonomy: Spatial aspects

- Local
  - Activation of specific output node is code
- Fully distributed
  - Each output node contributes to coding
- Sparse distributed
  - Only a few active nodes contribute to code

Taxonomy of Networks: temporal characteristics of code

- Asymptotic value
  - Output for feedforward
  - attractor for recurrent networks
- Population Statistics averaged over time
  - Important for complex attractors, oscillations
- Populations Statistics at an instant
  - Sampling of transients of a network, rather than asymptotic state

Activation Functions

- Modeling single neurons or tuned receptor group
  - Binary Threshold
  - Linear
  - Sigmoidal (Non-linear)
- Modeling Oscillatory behavior of ensemble
  - Non-Monotonic
  - Chaotic

Functional Taxonomy of Networks (Rolls &Treves: Neural networks & brain function, 1998)

- Pattern Association (Feedforward, Backpropagation)
- Autoassociative (Hopfield recurrent network)
- Competitive (Self Organizing Map, Radial Basis Function)

Types of Learning

- Supervised (pattern association)
  - Desired network output is known and characteristics (weights) changed to match desired output
- Unsupervised
  - Network doesn’t get taught answer explicitly, but learns via correlations (Hebbian or anti-Hebbian), competitive interactions

Activation Functions

- Binary Threshold
- Linear
- Sigmoidal (Non-linear)
- Non-Monotonic
- Chaotic

Activation Functions

- Usually with Feedforward topology
  - Binary Threshold
  - Sigmoidal
- Usually with Recurrent topology
  - Sigmoidal (Non-linear)
  - Oscillating (Non-monotonic
    - Chaotic

Activation Functions and Computational Power

- Different activation functions, topology impart more or less computational power
  - Ability to handle temporal data
  - Ability to recognize languages of increasing complexity in Chomsky hierarchy given recurrent analog dynamics
    - Moore, C. Finite-Dimensional Analog Computers: Flows, Maps, and Recurrent NeuralNetworks First International Conference on Unconventional Models of Computation. C.S. Calude, J. Casti, and M.J. Dinneen, Eds., Springer-Verlag (1998).
    - http://www.santafe.edu/~moore/pubs/umc.html

Oscillatory Behavior

- Normally we think of oscillations as *periodic* change in some values. In nonlinear dynamics, we also refer to *irregular* changing values as oscillations.
- **Oscillating units** stand in for **ensembles** of real neurons - coupled groups of excitatory and inhibitory populations with monotonic activation functions -> non-monotic population dynamics

Linear, Nonlinear, Chaotic

- Linear systems
  - Solutions combine to make new solution
  - Nearby input - Nearby output (Lifschitz cond.)
- Nonlinear
  - Solutions don’t combine additively
  - Many inputs may give same output
    - Saturation - most common nonlinearity
    - Dissipative or contracting dynamics
  - Sudden changes in output (bifurcation) with small changes in control, input

Linear, Nonlinear, Chaotic

- Chaotic system
  - Nearby input gives very different output especially after time
  - So: linear-nonlinear is *not* a binary distinction
  - We can speak of more and less nonlinear
    - - Lyaponov exponents are a measure of divergence or convergence of nearby inputs over time

Fundamental Operations: Weights and Coupling

- Weights on connections to units with monotonic activation functions
  - Multiplication (scaling, gain control) is basic operation
- Coupling on connections to units with non-monotonic activation functions
  - Synchronization (desynchronization) is basic operation
  - Cooperative processing

Biological Networks: Differences from Artificial Neural Networks

- Separation of learning epochs and recall or association behavior is not the normal mode
- Background activity
- Response may have complex time course and correlation behavior; not necessarily simple activation or asymptotic behavior (fixed point attractor neural network)
- Same network may compute differently at different times - non-stationary

What is a good neural model?

- Doesn’t violate anatomy, experimental data
- Simpler - fewer parameters
- Easier learning - online learning
- Easier for evolution to find
  - Example: with recurrent chaotic activation function networks - simpler network connection structure, complex structure in graph characterizing the state transitions