Neural Networks with Temporal Behavior

- Inclusion of feedback gives temporal characteristics to neural networks: **recurrent networks**.
- Two ways to add feedback:
  - Local feedback
  - Global feedback
- Recurrent networks can become unstable or stable.
- Main interest is in recurrent network’s **stability**: neurodynamics.
- Stability is a property of the whole system: coordination between parts is necessary.

Stability in Nonlinear Dynamical System

- **Lyapunov stability**: more on this later.
- Study of neurodynamics:
  - Deterministic neurodynamics: expressed as nonlinear differential equations.

Preliminaries: Dynamical Systems

- A **dynamical system** is a system whose state varies with time.
- **State-space model**: values of state variables change over time.
- Example: \( x_1(t), x_2(t), \ldots, x_N(t) \) are state variables that hold different values under independent variable \( t \). This describes a system of order \( N \), and \( \mathbf{x}(t) \) is called the **state vector**. The dynamics of the system is expressed using ordinary differential equations:
  \[
  \frac{d}{dt} x_j(t) = F_j(x_j(t)), \quad j = 1, 2, \ldots, N.
  \]
  or, more conveniently
  \[
  \frac{d}{dt} \mathbf{x}(t) = \mathbf{F}(\mathbf{x}(t)).
  \]
Autonomous vs. Non-autonomous Dynamical Systems

- Autonomous: $F(\cdot)$ does not explicitly depend on time.
- Non-autonomous: $F(\cdot)$ explicitly depends on time.

$F$ as a Vector Field

- Since $\frac{dx}{dt}$ can be seen as velocity, $F(x)$ can be seen as a velocity vector field, or a vector field.
- In a vector field, each point in space ($x$) is associated with one unique vector (direction and magnitude). In a scalar field, one point has one scalar value.

State Space

- It is convenient to view the state-space equation $\frac{dx}{dt} = F(x)$ as describing the motion of a point in N-dimensional space (Euclidean or non-Euclidean). Note: $t$ is continuous!
- The points traversed over time is called the trajectory or the orbit.
- The tangent vector shows the instantaneous velocity at the initial condition.

Conditions for the Solution of the State Space Equation

- A unique solution to the state space equation exists only under certain conditions, which restricts the form of $F(x)$.
- For a solution to exist, it is sufficient for $F(x)$ to be continuous in all of its arguments.
- For uniqueness, it must meet the Lipschitz condition.
  - Lipschitz condition:
    - Let $x$ and $u$ be a pair of vectors in an open set $\mathcal{M}$ in a normal vector space. A vector function $F(x)$ that satisfies:
      \[ \|F(x) - F(u)\| \leq K\|x - u\| \]
      for some constant $K$, the above is said to be Lipschitz, and $K$ is called the Lipschitz constant for $F(x)$.
    - If $\frac{\partial F_i}{\partial x_j}$ are finite everywhere, $F(x)$ meet the Lipschitz condition.
Stability of Equilibrium States

• \( \bar{x} \in \mathcal{M} \) is said to be an equilibrium state (or singular point) of the system if

\[
\frac{dx}{dt} \bigg|_{x=\bar{x}} = F(\bar{x}) = 0.
\]

• How the system behaves near these equilibrium states is of great interest.

• Near these points, we can approximate the dynamics by linearizing \( F(x) \) (using Taylor expansion) around \( \bar{x} \), i.e., \( x(t) = \bar{x} + \Delta x(t) \):

\[
F(x) \approx \bar{x} + A \Delta x(t)
\]

where \( A \) is the Jacobian:

\[
A = \frac{\partial}{\partial x} F(x) \bigg|_{x=\bar{x}}
\]

Eigenvalues/Eigenvectors

• For a square matrix \( A \), if a vector \( x \) and a scalar value \( \lambda \) exists so that

\[
(A - \lambda I)x = 0
\]

then \( x \) is called an eigenvector of \( A \) and \( \lambda \) an eigenvalue.

• Note, the above is simply

\[
Ax = \lambda x
\]

• An intuitive meaning is: \( x \) is the direction in which applying the linear transformation \( A \) only changes the magnitude of \( x \) (by \( \lambda \)) but not the angle.

• There can be as many as \( n \) eigenvector/eigenvalue for an \( n \times n \) matrix.

Stability of in Linearized System

• In the linearized system, the property of the Jacobian matrix \( A \) determine the behavior near equilibrium points.

• This is because

\[
\frac{d}{dt} \Delta x(t) \approx A \Delta x(t).
\]

• If \( A \) is nonsingular, \( A^{-1} \) exists and this can be used to describe the local behavior near the equilibrium \( \bar{x} \).

• The eigenvalues of the matrix \( A \) characterize different classes of behaviors.

Example: 2nd-Order System

Positive/negative, real/imaginary character of eigenvalues of Jacobian determine behavior.

• Stable node (real -), unstable focus (Complex, + real)
• Stable focus (Complex, - real), Saddle point (real + -)
• Unstable node(real +), Center (Complex, 0 real)
Definitions of Stability

- **Uniformly stable** for an arbitrary $\epsilon > 0$, if there exists a positive $\delta$ such that $\|x(0) - \bar{x}\| < \delta$ implies $\|x(t) - \bar{x}\| < \epsilon$ for all $t > 0$.

- **Convergent** if there exists a positive $\delta$ such that $\|x(0) - \bar{x}\| < \delta$ implies $x(t) \to \bar{x}$ as $t \to \infty$.

- **Asymptotically stable** if both stable and convergent.

- **Globally asymptotically stable** if stable and all trajectories of the system converge to $\bar{x}$ as time $t$ approaches infinity.

Lyapunov’s Theorem

- **Theorem 1**: The equilibrium state $\bar{x}$ is stable if in a small neighborhood of $\bar{x}$ there exists a positive definite function $V(x)$ such that its derivative with respect to time is negative semidefinite in that region.

- **Theorem 2**: The equilibrium state $\bar{x}$ is asymptotically stable if in a small neighborhood of $\bar{x}$ there exists a positive definite function $V(x)$ such that its derivative with respect to time is negative definite in that region.

- A scalar function $V(x)$ that satisfies these conditions is called a Lyapunov function for the equilibrium state $\bar{x}$.

Attractors

- Dissipative systems are characterized by attracting sets or manifolds of dimensionality lower than that of the embedding space. These are called attractors.

- Regions of initial conditions of nonzero state space volume converge to these attractors as time $t$ increases.

Types of Attractors

- Point attractors (left)

- Limit cycle attractors (right)

- Strange (chaotic) attractors (not shown)
Neurodynamical Models

We will focus on state variables are continuous-valued, and those with dynamics expressed in differential equations or difference equations.

Properties:

- Large number of degree of freedom.
- Nonlinearity
- Dissipative (as opposed to conservative), i.e., open system.
- Noise

Manipulation of Attractors as a Recurrent Nnet Paradigm

- We can identify attractors with computational objects (associative memories, input-output mappers, etc.).
- In order to do so, we must exercise control over the location of the attractors in the state space of the system.
- A learning algorithm will manipulate the equations governing the dynamical behavior so that a desired location of attractors are set.
- One good way to do this is to use the energy minimization paradigm (e.g., by Hopfield).

Discrete Hopfield Model

- Based on McCulloch-Pitts model (neurons with +1 or -1 output).
- Energy function is defined as

\[ E = -\frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} x_i x_j (i \neq j). \]

- Network dynamics will evolve in the direction that minimizes \( E \).
- Implements a content-addressable memory.
**Content-Addressable Memory**

- Map a set of patterns to be memorized $\xi_\mu$ onto fixed points $x_\mu$ in the dynamical system realized by the recurrent network.
- **Encoding**: Mapping from $\xi_\mu$ to $x_\mu$
- **Decoding**: Reverse mapping from state space $x_\mu$ to $\xi_\mu$.

**Hopfield Model: Storage**

- The learning is similar to Hebbian learning:
  \[ w_{ji} = \frac{1}{N} \sum_{\mu=1}^{M} \xi_{\mu,j} \xi_{\mu,i} \]
  with $w_{ji} = 0$ if $i = j$. (Learning is one-shot.)
- In matrix form the above becomes:
  \[ W = \frac{1}{N} \sum_{\mu=1}^{M} \xi_{\mu} \xi_{\mu}^T - M I \]
- The resulting weight matrix $W$ is symmetric: $W = W^T$.

**Spurious States**

- The weight matrix $W$ is symmetric, thus the eigenvalues of $W$ are all real.
- For large number of patterns $M$, the matrix is degenerate, i.e., several eigenvectors can have the same eigenvalue.
- These eigenvectors form a subspace, and when the associated eigenvalue is 0, it is called a null space.
- This is due to $M$ being smaller than the number of neurons $N$.
- Hopfield network as content addressable memory:
  - Discrete Hopfield network acts as a vector projector (project probe vector onto subspace spanned by training patterns).
  - Underlying dynamics drive the network to converge to one of the corners of the unit hypercube.
- **Spurious states** are those corners of the hypercube that do not belong to the training pattern set.

**Hopfield Model: Activation (Retrieval)**

- Initialize the network with a probe pattern $\xi_{\text{probe}}$.
  \[ x_j(0) = \xi_{\text{probe},j} \]
- Update output of each neuron (picking them by random) as
  \[ x_j(n + 1) = \text{sgn} \left( \sum_{i=1}^{N} w_{ji} x_i(n) \right) \]
  until $x$ reaches a fixed point.
Storage Capacity of Hopfield Network

- Given a probe equal to the stored pattern $\xi_\nu$, the activation of the $j$th neuron can be decomposed into the signal term and the noise term:

\[
v_j = \frac{1}{N} \sum_{\mu=1}^{M} \xi_{\mu,j} \sum_{i=1}^{N} \xi_{\mu,i} \xi_{\nu,i} = \underbrace{\xi_{\nu,j}}_{\text{signal}} + \frac{1}{N} \sum_{\mu=1,\mu\neq\nu}^{M} \xi_{\mu,j} \sum_{i=1}^{N} \xi_{\mu,i} \xi_{\nu,i} \underbrace{\sum_{i=1}^{N} \xi_{\mu,i} \xi_{\nu,i}}_{\text{noise}}.
\]

- The signal-to-noise ratio is defined as

\[
\rho = \frac{\text{variance of signal}}{\text{variance of noise}} = \frac{1}{(M-1)/N} \approx \frac{N}{M}.
\]

- The reciprocal of $\rho$, called the load parameter is designated as $\alpha$.

According to Amit and others, this value needs to be less than 0.14 (critical value $\alpha_c$). 25

Storage Capacity of Hopfield Network (cont’d)

- Given $\alpha = 0.14$, the storage capacity becomes

\[
M_c = \alpha_c N = 0.14 N
\]

when some error is allowed in the final patterns.

- For almost error-free performance, the storage capacity becomes

\[
M_c = \frac{N}{2 \log_e N}
\]

- Thus, storage capacity of Hopfield network scales less than linearly with the size $N$ of the network.

- This is a major limitation of the Hopfield model.

Cohen-Grossberg Theorem

- Cohen and Grossberg (1983) showed how to assess the stability of a certain class of neural networks:

\[
\frac{d}{dt} u_j = a_j(u_j) \left[ b_j(u_j) - \sum_{i=1}^{N} c_{ji} \varphi_i(u_i) \right], \ j = 1, 2, \ldots, N
\]

- Neural network with the above dynamics admits a Lyapunov function defined as:

\[
E = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ji} \varphi_i(u_i) \varphi_j(u_j) - \sum_{j=1}^{N} \int_{0}^{u_j} b - j(\lambda) \varphi_j'(\lambda) d\lambda,
\]

where

\[
\varphi'(\lambda) = \frac{d}{d\lambda} (\varphi_j(\lambda)).
\]

Cohen-Grossberg Theorem (cont’d)

- For the definition in the previous slide to be valid, the following conditions need to be met.

  - The synaptic weights are symmetric.
  - The function $a_j(u_j)$ satisfies the condition for nonnegativity.
  - The nonlinear activation function $\varphi_j(u_j)$ needs to follow the monotonicity condition:

\[
\varphi'_j(u_j) = \frac{d}{du_j} \varphi_j(u_j) \geq 0.
\]

- With the above

\[
\frac{dE}{dt} \leq 0
\]

ensuring global stability of the system.

- Hopfield model can be seen as a special case of the Cohen-Grossberg theorem.
Demo

- Noisy input
- Partial input
- Capacity overload