Harvey Mudd College

CS 152
Neural Networks
Fall 2012

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MTW 2:45-4:00
By drop-in (as available, simply knock)

By appointment:
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Grading:
  Homework problems (some computational): 40%
  Final project: 50%
  Participation: 10%
Categories Represented in the wikipedia Neuroscience Portal


Neural Networks: Possible Reasons for Studying

**Biology:**
To understand workings of nervous systems

**Computer Science:**
To build artificially intelligent systems

**Engineering:**
To understand and apply unique problem-solving techniques

**Psychology:**
To understand modes of learning
In computer science, biological explanations of networks are admired and desired, but not required.

For example, even though a given structural model might be biologically plausible, we don't always have a clear biological learning method for such a model.

Why is this not necessarily bad?

What Kinds of Problems Can Neural Networks Solve?

**Classification Problems**: Determine whether or not an input is a member of a certain class (Example: Differentiate some class of faces from others.)

**Transformation Problems**: Transform one kind of input into an output. The transformation is learned, rather than programmed explicitly. (Example: Inverse control problems: Transform a desired behavior into a control input.)

**Association Problems**: Cluster a space of inputs according to similarity. (Example: Learn similarities of countries according to their economic attributes.)
**Biological Intelligence**

**Intelligence**: the ability to make decisions based upon input from the environment that aid individual survival.

Intelligence is **realized** by *networks* of *neurons*, for example the brain and the attendant sensory and motor neurons.

*figure source: http://en.wikipedia.org/wiki/Intelligence*

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**“Neurons R Us”**

Not only our intelligence, but most aspects of our behavior, are the result of *neural* activity:

- reflexes
- emotions
- memory
- preferences
- habits
- addictions
Complexity of Natural Neural Networks

In a Human:

- $10^{11}$ neurons
- $10^{15}$ connections (average of $10^4$ connections per neuron)

- $10^{10}$ neurons in the brain alone
- $10^{13}$ connections in the brain

S. Seung estimates millions of miles of connections total.

“If the human brain were so simple that we could understand it, we would be so simple that we couldn’t.”
Emerson Pugh

Speed of Neural Networks

Neurons switch on the order of **milliseconds** max (tenths of a second is typical).

In contrast, computer gates switch on the order of **nanoseconds**.

The transmission speed in axons is on the order of **100 m/s** max, vs. speed of light, for electronics: **300 million m/s**.

Where neural networks “win” is that there is a higher degree of **parallelism** (millions of neurons firing concurrently) and a higher degree of **connectivity**.

**Energy Consumed**

The brain represents
2% of the body weight,
15% of the cardiac output,
20% of total body oxygen consumption,
25% of total body glucose utilization.

http://www.acnp.org/g4/gn401000064/ch064.html

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**Neuro-Computational Levels of Abstraction**

<table>
<thead>
<tr>
<th>Sub-systems</th>
<th>Anatomically distinct collections of maps</th>
<th>10 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maps</td>
<td>Large-scale collections of circuits</td>
<td>1 cm</td>
</tr>
<tr>
<td>Circuits</td>
<td>Collections of neurons organized with a specific function</td>
<td>1 mm</td>
</tr>
<tr>
<td>Neuron</td>
<td>Basic long-range signaling unit</td>
<td>10 μ</td>
</tr>
<tr>
<td>Synapses</td>
<td>Charge regulation in a neuron</td>
<td>1 μ</td>
</tr>
</tbody>
</table>

In 2005, Dr. Olaf Sporns at Indiana U. and Dr. Patric Hagmann at Lausanne U. Hospital introduced the term “connectome” (analogous to genome) to mean the totality of an individual’s neural connections.

http://en.wikipedia.org/wiki/Connectome

Brief video by Sebastian Seung at MIT:
http://www.amazon.com/gp/product/0547508182/ref=pd_1ctyhuc__top_sim_04_01

A longer TED talk: http://www.youtube.com/watch?v=HA7GwKXfJB0

(The human connectome is several orders of magnitude more complex than the human genome.)

http://www.humanconnectome.org/

Neuroimaging project at Washington University in St. Louis
Brain Imaging

Diffusion spectrum image shows brain wiring in a healthy human adult. The thread-like structures are nerve bundles, each containing hundreds of thousands of nerve fibers.
Source: Source: Van J. Wedeen, M.D., MGH/Harvard U.

Example Connectome: C. Elegans

Caenorhabditis Elegans, 302 neurons

http://www.brainpickings.org/index.php/2012/03/22/connectome-sebastian-seung/
Is knowing structure enough to simulate a brain?

Complete knowledge of *structure* enough to simulate a brain?

No. Not all neurons are alike and there are multiple varieties.

So be wary when someone says he/she has simulated a mouse brain, cat brain, etc. on a supercomputer.

Even C. Elegans has not been accurately simulated.

http://lesswrong.com/lw/88g/whole_brain_emulation_looking_at_progress_on_c/

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Early Neural Network Chronology

1943: McCulloch and Pitts (U of Chicago),
**Linear Threshold Logic Gate models**

1949: Hebb (Yerkes Primate Research Center)
**Learning Postulate**

1957: Rosenblatt (Cornell Aeronautical)
**Perceptron**

1960: Widrow & Hoff (Stanford EE)
**Adaline**

1969: Minsky & Papert (MIT CS),
**Limitations of perceptrons**

1969-1986: Bryson & Ho; Werbos; Le Cun; Rumelhart, Hinton, & Williams
**Backpropagation: Overcoming limitations**
conjectured by Minsky & Papert
## Some Approaches to Artificial Intelligence

<table>
<thead>
<tr>
<th>Approach</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reverse-Engineer Biology</td>
<td>Understand <strong>real</strong> neurons well enough to model accurately</td>
</tr>
<tr>
<td></td>
<td><strong>Simulate</strong> neural behavior, including learning aspects</td>
</tr>
<tr>
<td>Simulate Evolution</td>
<td>Provide basic evolutionary mechanism for neurons</td>
</tr>
<tr>
<td></td>
<td><strong>Evolve</strong> the parameters</td>
</tr>
<tr>
<td>Artificial Neural Networks</td>
<td>Develop a parameterized <strong>model</strong> for a class of problems</td>
</tr>
<tr>
<td></td>
<td><strong>Learn</strong> the parameters</td>
</tr>
</tbody>
</table>

**Combinations of the above**

Scientists pursuing AI using neural network models are sometimes called “connectionists”.

## Fundamental Problems for Any Given Neural Model

<table>
<thead>
<tr>
<th>Problem</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>How to <strong>represent</strong> information?</td>
<td></td>
</tr>
<tr>
<td>How to characterize the <strong>computational capability</strong> of the model?</td>
<td></td>
</tr>
<tr>
<td>How to achieve <strong>learning</strong> in the model?</td>
<td></td>
</tr>
</tbody>
</table>

From the computer science angle, these issues come under the heading of “**soft computing**” (which includes neural networks, fuzzy logic, and evolutionary programming).
Early Drawings of Neurons

Ramón y Cajal (1909) relied on Golgi’s method of staining, which highlights a subset of the neurons.

Histologie du système nerveux de l'homme et des vertébré. A. Maloine, Paris.

Neural Network Segment

The Golgi method of staining brain tissue renders the neurons and their interconnecting fibers visible in silhouette.

Golgi and Cajal won the 1906 Nobel prize in Physiology or Medicine.

Camillo Golgi

Photomicrograph of three neurons, in a human brain

source: http://www.scienceclarified.com/Mu-Oi/Nervous-System.html#b

Growth of Neural Density in a Human Brain

After 2 years, some pruning has occurred.

Inter-Neural Communication

Communication is:

**Electrical** (via ions) along axons

**Chemical** (via molecules) across synapse

http://en.wikipedia.org/wiki/Neurons

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Zooming in on a Neuron

1. First we start with a diagram of a Purkinje cell dendritic tree, perhaps a millimeter or two in size. Then we magnify a tiny "twig" of the dendritic tree about 5 times.

2. Next the tiny twig is magnified about 10 more times, and we can see that it has lumpy protrusions. These are the dendritic spines. They vastly increase the surface area available for synaptic contact.

3. If we slice through two of the dendritic spines, we get a cross-section of the dendrite. The slice occurs at thin line.

4. Here is how such a slice would look. The odd shape is approximately what would be produced by slicing through the dendrite and two of the spines.

http://www.intropsych.com/ch02_human_nervous_system/real_neuron.html
Micrograph of Axon, Synapses, Dendrites

Here is an actual electron micrograph from a rat's cerebellum. Can you find the shape from the diagrams on the previous page?

http://www.intropsych.com/ch02_human_nervous_system/real_neuron.html

In this diagram the "slice" through the dendrite is light gray; the dark gray is an axon passing by.

Synaptic Vesicles carry Neurotransmitters

The "slice" is already magnified 44,000 times, but let's keep going. We zoom in on a synapse and see a vesicle releasing its contents (transmitter substances) into the synaptic cleft. The thickening on post-synaptic side is typical and probably consists of massive numbers of receptor sites for the transmitters.

http://www.intropsych.com/ch02_human_nervous_system/real_neuron.html
Neuro-Transmitters crossing Synaptic Cleft

http://www.intropsych.com/ch02_human_nervous_system/transmitter_substances.html

Chemical Synapse Structure

http://www.daviddarling.info/encyclopedia/N/neurotransmitter.html
Neurotransmitter Conveyance

Depolarization potential at synapse

Ca ions enter cell

Vesicles move to membrane, spill contents into cleft

causing voltage change on dendrite of next neuron


Animation of Synaptic Behavior

http://youtu.be/HXx9qlJetSU
Animation of Action Potential

http://youtu.be/7EyhsOewnH4

Wave Action along Axon Animation

http://youtu.be/U0NpTdge3aw
### Classifying the Neuro-Transmitters (around 100 discovered so far)

<table>
<thead>
<tr>
<th>Neurotransmitter systems</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>System</strong></td>
</tr>
<tr>
<td>Noradrenaline system</td>
</tr>
<tr>
<td>Dopamine system</td>
</tr>
<tr>
<td>Serotonin system</td>
</tr>
<tr>
<td>Cholinergic system</td>
</tr>
</tbody>
</table>

http://en.wikipedia.org/wiki/Neurotransmitter

### 3 Distinct Types of Neurons

**Sensory Neuron**: Senses the environment.

**Motor Neuron** (or *motoneuron*): Effects muscular activity.

**Intra-Neuron**: In between sensory and motor.
Reflex exemplifies Direct Sensor-Motor Neural Connection
Neural Systems, Neural Networks, and Brain Function

Operation and Habituation of the Gill Withdrawal Reflex of Aplysia

The Dynamics of a Single Neural Unit with Positive Feedback

Neural Networks: Neural Systems with Multiple Interconnected Units

Neurons transform information. Information is conveyed between neurons by electrical signals.

Information is encoded in the form of a series of impulses or “spikes”, also called action potentials.

Facets of this encoding are still being researched.

Spikes result when integrated inputs are above some (nebulous) threshold.

Meanwhile, it is possible to make some modeling progress by abstracting the encoded information, representing it as a single real number.

Spiking Output of a Single Neuron when Excited


Modes of Spiking Explainable by an underlying Dynamical System

Note: Spiking frequency, rather than amplitude, conveys the information.

Figure 1.9: Resting, excitable, and periodic spiking activity correspond to a stable equilibrium (a and b) or limit cycle (c), respectively.

Dynamical Systems in Neuroscience:
The Geometry of Excitability and Bursting.
The MIT press
The neuron acts roughly like an “leaky” integrator in accumulating the effect of input spikes.

The accumulation cannot go on forever:
- If the accumulation is sufficiently high in a short time period, the neuron spikes.
- Over a longer time period without spiking, the neuron gradually leaks the built-up potential.

Net stimulus (integrated inputs)

Response

A Glimpse at the Future: Computer Science & Neuroscience Integration

Image: Charles M. Lieber
BRAINS AND TRANSISTORS: Rat brain cells grown in a 3-D nanowire scaffolding interact with electronics.

http://spectrum.ieee.org/biomedical/devices/nanowire-mesh-links-cells-and-electronics/

Figure 1.2 The simplest neural system model

One-Input, One-Output

Synapse (Excitatory)

Dendrite Axon

TUTORIAL ON NEURAL SYSTEMS MODELING, Figure 1.2
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### Neuroscience Terminology

- **neurotransmitters**: molecules that traverse from synapse to dendrite through ion diffusion.
- **spiking**: abrupt change of output voltage
- **action potential**: a single spike
- **depolarization**: change in net input voltage toward a threshold value, at which it will “spike”
- **refractory period**: period immediately after firing during which neuron is temporarily not firable

### Text Example: Modeling Habituation

**Habituation**: Repeated exposure to a stimulus lessens the effect of an individual exposure.

This a special case of neural plasticity, where the behavior of the neuron changes as a result of stimuli. Habituation can be viewed as a simple form of **learning**.
Aplysia Californica, a Sea Slug

“The aplysia is handy for researchers because it is large (as big as an adult hand) but it has a simple nervous system with huge nerve cells cells that are easy to penetrate and monitor with microelectrodes. It has been the focus of an impressive research program stretching over 30 years headed by Eric Kandel. Researchers who spend time with the aplysia nervous system become able to predict what each neuron will do in specific situations.

When the sea slug is feeding, neuron #3 (let us say) will be very active, firing many nerve impulses. When a predator attacks the sea slug, neuron #4 will be very active. When a sea slug of the opposite sex appears, neurons #3 and #4 both fire lots of nerve impulses. So each neuron has a personality or perhaps multiple personalities (because a single neuron will perform several distinct functions). The neuron's behavior is consistent over time, like the personality of a human being.”

http://www.intropsych.com/ch02_human_nervous_system/neurons_are_people.html
Figure 1.3 A preparation to study habituation of the Aplysia gill-withdrawal reflex

Figure 1.4 Behavior of the simple reflex model

(A) Input

(B) Output
Matlab model for next figure

% habituationGWR.m
% this script sets up a very simple simulation of habituation of the Aplysia gill withdrawal reflex

stv=4; % set start weight value
dec=0.7; % set weight decrement (use 1.0 for previous figure)
pls=[0 0 1 0 0]; % set up a pulse
x=[pls pls pls pls pls pls]; % set up a series of pulses as the input
[dum nTs]=size(x); % find the size of the input time series
y=zeros(1,nTs); % set up (define) a vector for the output time series
v=stv; % set weight to start weight value
for t=1:nTs,
    y(t)=v*x(t); % find the output
    if x(t)>0, % if the input is present
        v=v*dec; % then decrement the weight
    end % end the conditional
end % end the for loop

Figure 1.5 Simulating a simple reflex undergoing habituation

(A)

(B)
Comment on this Model

We have only modeled the net effect.

This model says nothing about how the effect is actually accomplished biologically.

It would likely take more complex differential equations to model what is actually happening in the organism (e.g. the Hodgkin-Huxley model, 1952, derived from studying the neural behavior of the giant squid).

http://icwww.epfl.ch/~gerstner/SPNM/node14.html
Figure 1.7 Simple neural system with feedback

Figure 1.8 Behavior of the single-unit with positive-feedback model when the feedback weight is slightly less than 1
% oneUnitWithPosFB.m
% this script simulates a single model neuron with positive feedback

inFlag=1;  % set input flag (1 for impulse, 2 for step)
cut=-Inf;  % set cut-off
sat=Inf;   % set saturation (see Figure 1.10)
tEnd=100;  % set last time step
nTs=tEnd+1; % find the number of time steps
v=1;       % set the input weight
m=0.95;    % set the feedback weight

x=zeros(1,nTs);  % open (define) an input hold vector
start=11;        % set a start time for the input
if inFlag==1,    % if the input should be a pulse
    x(start)=1;  % then set the input at only one time point
elseif inFlag==2,
    x(start:nTs)=ones(1,nTs-start+1); % keep it up until the end
end

y=zeros(1,nTs);  % open (define) an output hold vector

for t=2:nTs,
    y(t)=w*y(t-1)+v*x(t-1); % compute the output
    if y(t)<cut, y(t)=cut; end   % impose the cut-off constraint
    if y(t)>sat, y(t)=sat; end   % impose the saturation constraint
end

Figure 1.9 Behavior of the single-unit with positive-feedback model when the feedback weight equals 1
Figure 1.10 Behavior of the single-unit with positive-feedback model when the feedback weight is slightly greater than 1 (exploits Saturation parameter)

(A) Input

(B) Output

Figure 1.11 A model of a single neuron with three inputs
Sometimes a Dot is used to Emphasize an Inhibitory Connection (Negative Weight)

Figure 1.12 A model of three neurons, each receiving three inputs
Figure 1.13 A model of three neurons, each receiving three inputs, and each feeding back on themselves and on each other.

Figure 1.14 Behavior of a larger neural network model.

Weights

Response
Figure 1.14 Random weight assignment of a larger (recurrent) neural network model

(A) Feedforward weight

(B) Feedback weight

Output number 0 5 10
Input number 0 5 10

Figure 1.14 Possible behavior of a larger neural network model (random weight assignment)

(C) Input

(D) Output

Input number 0 5 10 Time step 50 100
Output number 0 10 Time step 50 100

TUTORIAL ON NEURAL SYSTEMS MODELING, Figure 1.14 (Part 1)
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Matlab Code for the Larger Network (called BigMess.m)

% BigMess.m
% this script will set up a single-layer network with
% random input and feedback connections and compute the
% output to a pulse or step input

nIn=10;  % set number of input units
nOut=10;  % set number of output units
scw=.5;  % enter scale for feedback weights
inFlag=1;  % set input flag (1 for pulse, 2 for step)
cut=8;  % set cut-off
sat=1000;  % set saturation
tEnd=100;  % set the last time step value
nTs=tEnd+1;  % find the number of time steps

x=zeros(nIn,nTs);  % open (define) an input hold matrix
if inFlag==1,  % if the input should be a pulse
    x(:,start)=ones(nIn,1);  % then set input at only one time point
elseif inFlag==2,  % if the input instead should be a step, then
    x(:,start:nTs)=ones(nIn,nTs-start+1);  % keep it up until the end
end  % end the conditional

y=zeros(nOut,nTs);  % open (define) an output hold vector
V=randn(nOut,nIn);  % construct random feed-forward weight matrix
W=randn(nOut)*scw;  % construct and scale random feedback weight matrix

for t=2:nTs,  % at every time step (skipping the first)
    y(:,t)=W*y(:,t-1) + V*x(:,t-1);  % compute the output
    y(:,t)=max(y(:,t),cut);  % impose the cut-off constraint
    y(:,t)=min(y(:,t),sat);  % impose the saturation constraint
end  % end the for loop

Table 1.2

| TABLE 1.2 Computing the inner (or dot) product between two vectors using MATLAB |
|---------------------------------|---------------------------------|---------------------------------|
| \[ \mathbf{v} = [1 \ 2 \ 3]' \] | \[ \mathbf{x} = [3 \ 2 \ 1]' \] | \[ \mathbf{y} = \mathbf{v}' \times \mathbf{x} \] |
| \[ \begin{bmatrix} 1 \\
| | 2 \\
| | 3 \end{bmatrix} \] | \[ \begin{bmatrix} 3 \\
| | 2 \\
| | 1 \end{bmatrix} \] | \[ \begin{bmatrix} 10 \\
| | 2 \\
| | 1 \end{bmatrix} \] |

TUTORIAL ON NEURAL SYSTEMS MODELING, Table 1.2
© 2010 Pearson Addison-Wesley.
### Table 1.3

**TABLE 1.3  Computing the product of a matrix and a vector using MATLAB**

\[
\begin{align*}
>> & V = [1 \ 2 \ 3 ; 4 \ 5 \ 6 ; 7 \ 8 \ 9] & \quad >> & x = [3 \ 2 \ 1]' & \quad >> & y = V \times x \\
V & = \\
\begin{bmatrix}
1 & 2 & 3 \\
4 & 5 & 6 \\
7 & 8 & 9
\end{bmatrix}
\quad x & = \\
\begin{bmatrix}
3 \\
2 \\
1
\end{bmatrix}
\quad y & = \\
10 & 28 & 46
\end{align*}
\]

TUTORIAL ON NEURAL SYSTEMS MODELING, Table 1.3
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