Intro to Neural Networks

Lisbon Machine Learning School
8 July 2021
What’s in this tutorial

• We will learn about
  – What is a neural network: historical perspective
  – What can neural networks model
  – What do they actually learn
Instructor

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Part 1: What is a neural network
Neural Networks are taking over!

• Neural networks have become one of the major thrust areas recently in various pattern recognition, prediction, and analysis problems

• In many problems they have established the state of the art
  – Often exceeding previous benchmarks by large margins
Breakthrough successes with neural networks
Breakthrough successes with neural networks

Found in translation: More accurate, fluent sentences in Google Translate

Barak Tuovsky
PRODUCT LEAD, GOOGLE TRANSLATE

In 10 years, Google Translate has gone from supporting just a few languages to 103, connecting strangers, reaching across language barriers and even helping
Breakthrough successes with neural networks
Breakthrough successes with neural networks

Explore the AlphaGo Games

Delve deeper into AlphaGo's fascinatingly innovative playing style, with commentary on the Lee Sedol match and self-play games by Fan Hui 2p. Featuring expert analysis by Gu Li 9p and Zhou Ruiyang 9p, these games will prove an enlightening read for Go players of all levels.
Breakthrough successes with neural networks
Successes with neural networks

• And a variety of other problems:
  – Image analysis
  – Natural language processing
  – Speech processing
  – Even predicting stock markets!
Neural nets and the employment market

This guy didn’t know about neural networks (a.k.a deep learning)

This guy learned about neural networks (a.k.a deep learning)
So what are neural networks??

• What are these boxes?
So what are neural networks??

• It begins with this..
So what are neural networks??

• Or even earlier.. with this..

“The Thinker!”
by Augustin Rodin
The magical capacity of humans

• Humans can
  – Learn
  – Solve problems
  – Recognize patterns
  – Create
  – Cogitate
  – ...

• Worthy of emulation

• But how do humans “work“?
Cognition and the brain..

• “If the brain was simple enough to be understood - we would be too simple to understand it!”
  — Marvin Minsky
Early Models of Human Cognition

- **Associationism**
  - Humans learn through association
- **400BC-1900AD**: Plato, David Hume, Ivan Pavlov..
What are “Associations”

- Lightning is generally followed by thunder
  - Ergo – “hey here’s a bolt of lightning, we’re going to hear thunder”
  - Ergo – “We just heard thunder; did someone get hit by lightning”?

- Associations!
  - Actually a pretty good theory that still applies

- But where and how do we store these associations?
Observation: The Brain

• Mid 1800s: The brain is a mass of interconnected neurons
Brain: Interconnected Neurons

- Many neurons connect *in* to each neuron
- Each neuron connects *out* to many neurons
Enter **Connectionism**

- Alexander Bain, philosopher, mathematician, logician, linguist, professor
- 1873: The information is in the *connections*
  - *The mind and body* (1873)
Bain’s Idea: Neural Groupings

- Neurons excite and stimulate each other
- Different combinations of inputs can result in different outputs
Bain’s Idea: Neural Groupings

- Different intensities of activation of A lead to the differences in when X and Y are activated
Bain’s Idea 2: Making Memories

• “when two impressions concur, or closely succeed one another, the nerve currents find some bridge or place of continuity, better or worse, according to the abundance of nerve matter available for the transition.”

• Predicts “Hebbian” learning (half a century before Hebb!)
Bain’s Doubts

• “The fundamental cause of the trouble is that in the modern world the stupid are cocksure while the intelligent are full of doubt.”
  – Bertrand Russell

• In 1873, Bain postulated that there must be one million neurons and 5 billion connections relating to 200,000 “acquisitions”

• In 1883, Bain was concerned that he hadn’t taken into account the number of “partially formed associations” and the number of neurons responsible for recall/learning

• By the end of his life (1903), recanted all his ideas!
  – Too complex; the brain would need too many neurons and connections
Connectionism lives on..

• The human brain is a connectionist machine

• Neurons connect to other neurons. The processing/capacity of the brain is a function of these connections

• Connectionist machines emulate this structure
Connectionist Machines

- Network of processing elements
- All world knowledge is stored in the connections between the elements
Connectionist Machines

• Neural networks are *connectionist* machines
  – As opposed to Von Neumann Machines

  ![Diagram of a Von Neumann/Harvard Machine and a Neural Network]

• The machine has many non-linear processing units
  – The program is the connections between these units
    • Connections may also define memory
Recap

• Neural network based AI has taken over most AI tasks
• Neural networks originally began as computational models of the brain
  – Or more generally, models of cognition
• The earliest model of cognition was associationism
• The more recent model of the brain is connectionist
  – Neurons connect to neurons
  – The workings of the brain are encoded in these connections
• Current neural network models are connectionist machines
Connectionist Machines

- Network of processing elements
- All world knowledge is stored in the *connections* between the elements
Connectionist Machines

• Connectionist machines are networks of units..

• We need a model for the units
Modelling the brain

- What are the units?
- A neuron:
  - Signals come in through the dendrites into the Soma
  - A signal goes out via the axon to other neurons
    - Only one axon per neuron
  - Factoid that may only interest me: Neurons do not undergo cell division
  - Factoid that may only interest me: Being called a “fathead” may be a compliment
• The Doctor and the Hobo..
  – Warren McCulloch: Neurophysician
  – Walter Pitts: Homeless wannabe logician who arrived at his door
The McCulloch and Pitts model

• A mathematical model of a neuron
  • Pitts was only 20 years old at this time

  – Threshold Logic
Synaptic Model

• *Excitatory synapse*: Transmits weighted input to the neuron

• *Inhibitory synapse*: Any signal from an inhibitory synapse forces output to zero
  – The activity of any inhibitory synapse absolutely prevents excitation of the neuron at that time.
    • Regardless of other inputs
Simple “networks” of neurons can perform Boolean operations.

**Figure 1.** Diagrams of McCulloch and Pitts nets. In order to send an output pulse, each neuron must receive two excitatory inputs and no inhibitory inputs. Lines ending in a dot represent excitatory connections; lines ending in a hoop represent inhibitory connections.
Criticisms

• Several..
  – Claimed their machine could emulate a Turing machine

• Didn’t provide a learning mechanism..
Donald Hebb

• “Organization of behavior”, 1949
• A learning mechanism:
  – Neurons that fire together wire together
Hebbian Learning

- If neuron $x_i$ repeatedly triggers neuron $y$, the synaptic knob connecting $x_i$ to $y$ gets larger.
- In a mathematical model:
  \[
  w_i = w_i + \eta x_i y
  \]
  Weight of $i^{th}$ neuron’s input to output neuron $y$.
- This simple formula is actually the basis of many learning algorithms in ML.
A better model

• Frank Rosenblatt
  – Psychologist, Logician
  – Inventor of the solution to everything, aka the Perceptron (1958)
Simplified mathematical model

• Number of inputs combine linearly
  – Threshold logic: Fire if combined input exceeds threshold

\[
Y = \begin{cases} 
  1 & \text{if } \sum_i w_i x_i + b > 0 \\
  0 & \text{else}
\end{cases}
\]
His “Simple” Perceptron

- Originally assumed could represent any Boolean circuit and perform any logic
  - “the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence,” New York Times (8 July) 1958
  - “Frankenstein Monster Designed by Navy That Thinks,” Tulsa, Oklahoma Times 1958
Also provided a learning algorithm

\[ \mathbf{w} = \mathbf{w} + \eta (d(x) - y(x)) \mathbf{x} \]

**Sequential Learning:**
- \( d(x) \) is the desired output in response to input \( x \)
- \( y(x) \) is the actual output in response to \( x \)

- Boolean tasks
- Update the weights whenever the perceptron output is wrong
- Proved convergence
Perceptron

- Easily shown to mimic any Boolean gate
- But...
Perceptron

No solution for XOR!
Not universal!

• Minsky and Papert, 1968
A single neuron is not enough

• Individual elements are weak computational elements
  – Marvin Minsky and Seymour Papert, 1969, *Perceptrons: An Introduction to Computational Geometry*

• *Networked* elements are required
Multi-layer Perceptron!

- **XOR**
  - The first layer is a “hidden” layer
  - Also originally suggested by Minsky and Papert, 1968
A more generic model

- A “multi-layer” perceptron
- Can compose arbitrarily complicated Boolean functions!
  - More on this in the next part

[((A&\bar{X}&Z)|(A&\bar{Y}))&(X & Y)|(X&Z))
• Neural networks began as computational models of the brain
• Neural network models are *connectionist machines*
  – The comprise networks of neural units
• McCullough and Pitt model: Neurons as Boolean threshold units
  – Models the brain as performing propositional logic
  – But no learning rule
• Hebb’s learning rule: Neurons that fire together wire together
  – Unstable
• Rosenblatt’s perceptron: A variant of the McCulloch and Pitt neuron with a provably convergent learning rule
  – But individual perceptrons are limited in their capacity (Minsky and Papert)
• Multi-layer perceptrons can model arbitrarily complex Boolean functions
But our brain is not Boolean

- We have real inputs
- We make non-Boolean inferences/predictions
The perceptron with *real* inputs

- $x_1 \ldots x_N$ are real valued
- $W_1 \ldots W_N$ are real valued
- Unit “fires” if weighted input exceeds a threshold
The perceptron with *real* inputs and a real *output*

- \( x_1 \ldots x_N \) are real valued
- \( W_1 \ldots W_N \) are real valued
- The output \( y \) can also be real valued
  - Sometimes viewed as the “probability” of firing
  - *Is useful to continue assuming Boolean outputs though*
A Perceptron on Reals

A perceptron operates on real-valued vectors

– This is a linear classifier
• Boolean perceptrons are also linear classifiers
  – Purple regions have output 1 in the figures
  – What are these functions
  – Why can we not compose an XOR?
Composing complicated “decision” boundaries

- Build a network of units with a single output that fires if the input is in the coloured area

Can now be composed into “networks” to compute arbitrary classification “boundaries”
Booleans over the reals

- The network must fire if the input is in the coloured area
Booleans over the reals

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Booleans over the reals

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Booleans over the reals

• The network must fire if the input is in the coloured area
More complex decision boundaries

- Network to fire if the input is in the yellow area
  - “OR” two polygons
  - A third layer is required
Complex decision boundaries

• Can compose very complex decision boundaries
  – How complex exactly? More on this in the next part
Complex decision boundaries

• Classification problems: finding decision boundaries in high-dimensional space

784 dimensions (MNIST)
Story so far

• **MLPs are connectionist computational models**
  – Individual perceptrons are computational equivalent of neurons
  – The MLP is a layered composition of many perceptrons

• **MLPs can model Boolean functions**
  – Individual perceptrons can act as Boolean gates
  – Networks of perceptrons are Boolean functions

• **MLPs are Boolean machines**
  – They represent Boolean functions over linear boundaries
  – They can represent arbitrary decision boundaries
  – They can be used to classify data
So what does the perceptron really model?

- Is there a “semantic” interpretation?
• What do the weights tell us?
  – The neuron fires if the inner product between the weights and the inputs exceeds a threshold

\[
y = \begin{cases} 
1 & \text{if } \sum_i w_i x_i \geq T \\
0 & \text{else}
\end{cases}
\]

\[
y = \begin{cases} 
1 & \text{if } x^T w \geq T \\
0 & \text{else}
\end{cases}
\]
The weight as a “template”

- The perceptron fires if the input is within a specified angle of the weight.
- Neuron fires if the input vector is close enough to the weight vector.
  - If the input pattern matches the weight pattern closely enough.

\[ x^T W > T \]
\[ \cos \theta > \frac{T}{|X|} \]
\[ \theta < \cos^{-1} \left( \frac{T}{|X|} \right) \]
The weight as a template

If the correlation between the weight pattern and the inputs exceeds a threshold, fire

The perceptron is a correlation filter!

\[ y = \begin{cases} 
1 & \text{if } \sum_i w_i x_i \geq T \\
0 & \text{else}
\end{cases} \]

• If the correlation between the weight pattern and the inputs exceeds a threshold, fire
• The perceptron is a correlation filter!
The MLP as a Boolean function over feature detectors

• The input layer comprises “feature detectors”
  – Detect if certain patterns have occurred in the input
• The network is a Boolean function over the feature detectors
• I.e. it is important for the first layer to capture relevant patterns
The MLP as a cascade of feature detectors

- The network is a cascade of feature detectors
  - Higher level neurons compose complex templates from features represented by lower-level neurons
Story so far

• Multi-layer perceptrons are connectionist computational models
• MLPs are Boolean \textit{machines}
  – They can model Boolean functions
  – They can represent arbitrary decision boundaries over real inputs
• Perceptrons are \textit{correlation filters}
  – They detect patterns in the input
• MLPs are Boolean formulae over patterns detected by perceptrons
  – Higher-level perceptrons may also be viewed as feature detectors
• Extra: MLP in classification
  – The network will fire if the combination of the detected basic features matches an “acceptable” pattern for a desired class of signal
  • E.g. Appropriate combinations of (Nose, Eyes, Eyebrows, Cheek, Chin) \rightarrow Face
MLP as a continuous-valued regression

- A simple 3-unit MLP with a “summing” output unit can generate a “square pulse” over an input
  - Output is 1 only if the input lies between $T_1$ and $T_2$
  - $T_1$ and $T_2$ can be arbitrarily specified
MLP as a continuous-valued regression

• A simple 3-unit MLP can generate a “square pulse” over an input

• **An MLP with many units can model an arbitrary function over an input**
  – To arbitrary precision
    • Simply make the individual pulses narrower

• This generalizes to functions of any number of inputs (next part)
Story so far

• **Multi-layer perceptrons are connectionist computational models**

• **MLPs are classification engines**
  – They can identify classes in the data
  – Individual perceptrons are feature detectors
  – The network will fire if the combination of the detected basic features matches an “acceptable” pattern for a desired class of signal

• **MLP can also model continuous valued functions**
Neural Networks:
Part 2: What can a network represent
Recap: The perceptron

• A threshold unit
  – “Fires” if the weighted sum of inputs and the “bias” $T$ is positive

$$z = \sum_i w_i x_i - T$$

$$y = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{else} \end{cases}$$
The “soft” perceptron

- A “squashing” function instead of a threshold at the output
  - The sigmoid “activation” replaces the threshold

- **Activation:** The function that acts on the weighted combination of inputs (and threshold)
Other “activations”

- Does not always have to be a squashing function
- We will continue to assume a “threshold” activation in this lecture

[Diagram of neural network with sigmoid and tanh activation functions]
Recap: the multi-layer perceptron

- A network of perceptrons
  - Generally “layered”
Aside: Note on “depth”

- What is a “deep” network
  - And what is a “layer”?
Deep Structures

• In any directed network of computational elements with input source nodes and output sink nodes, “depth” is the length of the longest path from a source to a sink
  – A “source” node in a directed graph is a node that has only outgoing edges
  – A “sink” node is a node that has only incoming edges

• Left: Depth = 2. Right: Depth = 3
Deep Structures

• **Layered deep structure**
  – The input is the “source”,
  – The output nodes are “sinks”

• “Deep” → Depth greater than 2
• “Depth” of a layer – the depth of the neurons in the layer w.r.t. input

**Diagram:**
- Input: Black
- Layer 1: Red
- Layer 2: Green
- Layer 3: Yellow
- Layer 4: Blue
The multi-layer perceptron

• Inputs are real or Boolean stimuli
• Outputs are real or Boolean values
  – Can have multiple outputs for a single input
• What can this network compute?
  – What kinds of input/output relationships can it model?
MLPs approximate functions

- MLPs can compose Boolean functions
- MLPs can compose real-valued functions
- What are the limitations?
The MLP as a Boolean function

• How well do MLPs model Boolean functions?
The perceptron as a Boolean gate

- A perceptron can model any simple binary Boolean gate
Perceptron as a Boolean gate

- The universal AND gate
  - AND any number of inputs
    - Any subset of who may be negated

Will fire only if $X_1 \ldots X_L$ are all 1 and $X_{L+1} \ldots X_N$ are all 0
Perceptron as a Boolean gate

The universal OR gate

- OR any number of inputs
  - Any subset of who may be negated

\[
\begin{align*}
\text{Will fire only if any of } X_1 \ldots X_L & \text{ are 1} \\
\text{or any of } X_{L+1} \ldots X_N & \text{ are 0}
\end{align*}
\]
Perceptron as a Boolean Gate

- Universal OR:
  - Fire if any K-subset of inputs is "ON"

Will fire only if the total number of of $X_1 \ldots X_N$ that are 1 is at least $K$
The perceptron is not enough

• Cannot compute an XOR
Multi-layer perceptron

MLPs can compute the XOR

• MLPs can compute the XOR
Multi-layer perceptron

MLPs can compute more complex Boolean functions

MLPs can compute *any* Boolean function
  – Since they can emulate individual gates

MLPs are *universal Boolean functions*
MLP as Boolean Functions

- MLPs are universal Boolean functions
  - Any function over any number of inputs and any number of outputs
- But how many “layers” will they need?
How many layers for a Boolean MLP?

• Expressed in disjunctive normal form

Truth Table

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Truth table shows all input combinations for which output is 1.
How many layers for a Boolean MLP?

• Expressed in disjunctive normal form

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$Y = \bar{X}_1 \bar{X}_2 X_3 X_4 \bar{X}_5 + \bar{X}_1 X_2 \bar{X}_3 X_4 X_5 + \bar{X}_1 X_2 X_3 \bar{X}_4 \bar{X}_5 + \bar{X}_1 \bar{X}_2 \bar{X}_3 \bar{X}_4 \bar{X}_5 + X_1 \bar{X}_2 X_3 \bar{X}_4 X_5 + X_1 \bar{X}_2 X_3 X_4 X_5 + X_1 X_2 \bar{X}_3 \bar{X}_4 X_5$
How many layers for a Boolean MLP?

• Expressed in disjunctive normal form

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How many layers for a Boolean MLP?

- Expressed in disjunctive normal form

Truth table shows *all* input combinations for which output is 1

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- Expressed in disjunctive normal form
How many layers for a Boolean MLP?

- Expressed in disjunctive normal form

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<tr>
<th>X₁</th>
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Truth table shows all input combinations for which output is 1

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• Expressed in disjunctive normal form
How many layers for a Boolean MLP?

- Any truth table can be expressed in this manner!

A one-hidden-layer MLP is a Universal Boolean Function

Truth table shows all input combinations for which output is 1

\[ Y = X_1 \bar{X}_2 X_3 X_4 \bar{X}_5 + X_1 X_2 \bar{X}_3 X_4 X_5 + \bar{X}_1 X_2 X_3 \bar{X}_4 \bar{X}_5 + X_1 \bar{X}_2 \bar{X}_3 \bar{X}_4 X_5 + X_1 \bar{X}_2 X_3 X_4 X_5 + X_1 X_2 \bar{X}_3 \bar{X}_4 X_5 + \]

But what is the largest number of perceptrons required in the single hidden layer for an N-input-variable function?
Reducing a Boolean Function

- **DNF form:**
  - Find groups
  - Express as reduced DNF

This is a “Karnaugh Map”

It represents a truth table as a grid.

Filled boxes represent input combinations for which output is 1; blank boxes have output 0.

Adjacent boxes can be “grouped” to reduce the complexity of the DNF formula for the table.
Reducing a Boolean Function

Basic DNF formula will require 7 terms
Reducing a Boolean Function

- Reduced DNF form:
  - Find groups
  - Express as reduced DNF

\[ O = \overline{Y} \overline{Z} + \overline{W} X \overline{Y} + \overline{X} Y \overline{Z} \]
Reducing a Boolean Function

- Reduced DNF form:
  - Find groups
  - Express as reduced DNF

\[ O = \overline{Y} \overline{Z} + \overline{W}XY + \overline{X}YZ \]
Largest irreducible DNF?

- What arrangement of ones and zeros simply cannot be reduced further?
Largest irreducible DNF?

- What arrangement of ones and zeros simply cannot be reduced further?
Largest irreducible DNF?

- What arrangement of ones and zeros simply cannot be reduced further?

How many neurons in a DNF (one-hidden-layer) MLP for this Boolean function?
• How many neurons in a DNF (one-hidden-layer) MLP for this Boolean function of 6 variables?
• **How many neurons in a DNF (one-hidden-layer) MLP for this Boolean function**

**Width of a single-layer Boolean MLP**

*Can be generalized: Will require $2^{N-1}$ perceptrons in hidden layer*

*Exponential in $N$*
How many neurons in a DNF (one-hidden-layer) MLP for this Boolean function?

Can be generalized: Will require $2^{N-1}$ perceptrons in hidden layer

Exponential in $N$

How many units if we use multiple layers?

- How many neurons in a DNF (one-hidden-layer) MLP for this Boolean function
Width of a deep MLP

\[ O = W \bigoplus X \bigoplus Y \bigoplus Z \]

\[ O = U \bigoplus V \bigoplus W \bigoplus X \bigoplus Y \bigoplus Z \]
Multi-layer perceptron XOR

- An XOR takes three perceptrons
An XOR needs 3 perceptrons.

This network will require $3 \times 3 = 9$ perceptrons.

$$O = W \oplus X \oplus Y \oplus Z$$
An XOR needs 3 perceptrons

This network will require $3 \times 5 = 15$ perceptrons

Width of a deep MLP

$O = U \oplus V \oplus W \oplus X \oplus Y \oplus Z$

15 perceptrons
• An XOR needs 3 perceptrons
• This network will require 3x5 = 15 perceptrons
Width of a single-layer Boolean MLP

Single hidden layer: Will require $2^{N-1} + 1$ perceptrons in all (including output unit)

Exponential in $N$

Will require $3(N-1)$ perceptrons in a deep network

Linear in $N$!!!

Can be arranged in only $2\log_2(N)$ layers
A better representation

- Only $2 \log_2 N$ layers
  - By pairing terms
  - 2 layers per XOR

$$O = X_1 \oplus X_2 \oplus \ldots \oplus X_N$$
The challenge of depth

- Using only $K$ hidden layers will require $O(2^{(N-K/2)})$ neurons in the $K$th layer
  - Because the output can be shown to be the XOR of all the outputs of the $K-1$th hidden layer
  - I.e. reducing the number of layers below the minimum will result in an exponentially sized network to express the function fully
  - A network with fewer than the required number of neurons cannot model the function

\[
\begin{align*}
O &= X_1 \oplus X_2 \oplus \ldots \oplus X_N \\
&= Z_1 \oplus Z_2 \oplus \ldots \oplus Z_M
\end{align*}
\]
Recap: The need for depth

• Deep Boolean MLPs that scale linearly with the number of inputs ...
• ... can become exponentially large if recast using only one layer
• It gets worse..
The need for depth

- The wide function can happen at any layer
- Having a few extra layers can greatly reduce network size
Depth vs Size in Boolean Circuits

• The XOR is really a parity problem

• Any Boolean circuit of depth $d$ using AND, OR and NOT gates with unbounded fan-in must have size $2^{n^{1/d}}$
  

  – Alternately stated: $parity \notin AC^0$
    • Set of constant-depth polynomial size circuits of unbounded fan-in elements
Caveat: Not all Boolean functions..

- Not all Boolean circuits have such clear depth-vs-size tradeoff

- Shannon’s theorem: For $n > 2$, there is Boolean function of $n$ variables that requires at least $2^n/n$ gates
  - More correctly, for large $n$, almost all $n$-input Boolean functions need more than $2^n/n$ gates

- Note: If all Boolean functions over $n$ inputs could be computed using a circuit of size that is polynomial in $n$, P = NP!
Network size: summary

• An MLP is a universal Boolean function

• But can represent a given function only if
  – It is sufficiently wide
  – It is sufficiently deep
  – Depth can be traded off for (sometimes) exponential growth of the width of the network

• Optimal width and depth depend on the number of variables and the complexity of the Boolean function
  – Complexity: minimal number of terms in DNF formula to represent it
Multi-layer perceptrons are *Universal Boolean Machines*

Even a network with a *single* hidden layer is a universal Boolean machine
  - But a single-layer network may require an exponentially large number of perceptrons

Deeper networks may require far fewer neurons than shallower networks to express the same function
  - Could be *exponentially* smaller
Caveat

• Used a simple “Boolean circuit” analogy for explanation
• We actually have threshold circuit (TC) not, just a Boolean circuit (AC)
  – Specifically composed of threshold gates
    • More versatile than Boolean gates
      – E.g. “at least K inputs are 1” is a single TC gate, but an exponential size AC
      – For fixed depth, Boolean circuits ⊂ threshold circuits (strict subset)
  – A depth-2 TC parity circuit can be composed with $O(n^2)$ weights
    • But a network of depth log$(n)$ requires only $O(n)$ weights
  – But more generally, for large $n$, for most Boolean functions, a threshold circuit that is polynomial in $n$ at optimal depth $d$ becomes exponentially large at $d − 1$

• Other formal analyses typically view neural networks as arithmetic circuits
  – Circuits which compute polynomials over any field

• So lets consider functions over the field of reals
The MLP as a classifier

- MLP as a function over real inputs
- MLP as a function that finds a complex “decision boundary” over a space of reals

784 dimensions (MNIST)

2

Not 2

784 dimensions
A Perceptron on Reals

A perceptron operates on real-valued vectors — This is a linear classifier
Booleans over the reals

- The network must fire if the input is in the coloured area
More complex decision boundaries

• Network to fire if the input is in the yellow area
  – “OR” two polygons
  – A third layer is required
Complex decision boundaries

• Can compose *arbitrarily* complex decision boundaries
Complex decision boundaries

- Can compose *arbitrarily* complex decision boundaries
Complex decision boundaries

- Can compose arbitrarily complex decision boundaries
  - With only one hidden layer!
  - How?
Exercise: compose this with one hidden layer

• How would you compose the decision boundary to the left with only one hidden layer?
Composing a Square decision boundary

- The polygon net

\[
\sum_{l=1}^{4} y_l \geq 4?
\]
Composing a pentagon

- The polygon net
Composing a hexagon

• The polygon net

\[ \sum_{i=1}^{N} y_i \geq 6? \]
How about a heptagon

• What are the sums in the different regions?
  – A pattern emerges as we consider $N > 6$. ..
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  – A pattern emerges as we consider $N > 6$. 

1000 sides
Polygon net

- Increasing the number of sides reduces the area outside the polygon that have $N/2 < \text{Sum} < N$
In the limit

\[ \sum_{i=1}^{N} y_i \geq N? \]

- For small radius, it’s a near perfect cylinder
  - N in the cylinder, N/2 outside
Composing a circle

- The circle net
  - Very large number of neurons
  - *Sum is N inside the circle, N/2 outside everywhere*
  - Circle can be of arbitrary diameter, at any location

\[
\sum_{i=1}^{N} y_i \geq N?
\]
Composing a circle

• The circle net
  – Very large number of neurons
  – *Sum is $N/2$ inside the circle, 0 outside everywhere*
  – Circle can be of arbitrary diameter, at any location
• The “sum” of two circles sub nets is exactly $N/2$ inside either circle, and 0 outside
Composing an arbitrary figure

- Just fit in an arbitrary number of circles
  - More accurate approximation with greater number of smaller circles
  - Can achieve arbitrary precision
MLP: Universal classifier

- MLPs can capture *any* classification boundary
- A *one-layer MLP* can model any classification boundary
- *MLPs are universal classifiers*
Depth and the universal classifier

• Deeper networks can require far fewer neurons
Optimal depth..

- Formal analyses typically view these as a category of *arithmetic circuits*
  - Compute polynomials over any field
    - Valiant et. al: A polynomial of degree $n$ requires a network of depth $\log^2(n)$
      - Cannot be computed with shallower networks
      - Nearly all functions are very high or even infinite-order polynomials..
    - Bengio et. al: Shows a similar result for sum-product networks
      - But only considers two-input units
      - Generalized by Mhaskar et al. to all functions that can be expressed as a binary tree
  - Depth/Size analyses of arithmetic circuits still a research problem
Optimal depth in *generic* nets

- We look at a different pattern:
  - “worst case” decision boundaries

- For *threshold-activation* networks
  - Generalizes to other nets
Optimal depth

\[ \sum_{i=1}^{N} y_i - \frac{N}{2} > 0? \]

- A one-hidden-layer neural network will require infinite hidden neurons.
Optimal depth

- Two-layer network: 56 hidden neurons
Optimal depth

- Two-layer network: 56 hidden neurons
  - 16 neurons in hidden layer 1
Optimal depth

- Two-layer network: 56 hidden neurons
  - 16 in hidden layer 1
  - 40 in hidden layer 2
  - 57 total neurons, including output neuron
Optimal depth

- But this is just $Y_1 \oplus Y_2 \oplus \cdots \oplus Y_{16}$
• But this is just $Y_1 \bigoplus Y_2 \bigoplus \cdots \bigoplus Y_{16}$
  – The XOR net will require $16 + 15 \times 3 = 61$ neurons
  • Greater than the 2-layer network with only 52 neurons
Optimal depth

\[ \sum_{i=1}^{KN} y_i - \frac{KN}{2} > 0? \]

- A one-hidden-layer neural network will require infinite hidden neurons
Actual linear units

• 64 basic linear feature detectors
Optimal depth

- Two hidden layers: 608 hidden neurons
  - 64 in layer 1
  - 544 in layer 2
- 609 total neurons (including output neuron)
Optimal depth

- XOR network (12 hidden layers): 253 neurons
- The difference in size between the deeper optimal (XOR) net and shallower nets increases with increasing pattern complexity
Network size?

• In this problem the 2-layer net was \emph{quadratic} in the number of lines
  – \(\lfloor (N + 2)^2 / 8 \rfloor\) neurons in 2\textsuperscript{nd} hidden layer
  – Not exponential
  – Even though the pattern is an XOR
  – Why?

• The data are two-dimensional!
  – Only two \emph{fully independent} features
  – The pattern is exponential in the \emph{dimension of the input (two)!}

• For general case of \(N\) mutually intersecting hyperplanes in \(D\) dimensions, we will need \(O\left(\frac{N^D}{(D-1)!}\right)\) weights (assuming \(N \gg D\)).
  – Increasing input dimensions can increase the worst-case size of the shallower network exponentially, but not the XOR net
    • The size of the XOR net depends only on the number of first-level linear detectors \(N)\)
Depth: Summary

• The number of neurons required in a shallow network is
  – Polynomial in the number of basic patterns
  – Exponential in the dimensionality of the input
  – (this is the worst case)
Story so far

• Multi-layer perceptrons are *Universal Boolean Machines*
  – Even a network with a *single* hidden layer is a universal Boolean machine

• Multi-layer perceptrons are *Universal Classification Functions*
  – Even a network with a single hidden layer is a universal classifier

• But a single-layer network may require an exponentially large number of perceptrons than a deep one

• Deeper networks may require exponentially fewer neurons than shallower networks to express the same function
  – Could be *exponentially* smaller
  – Deeper networks are more *expressive*
A simple 3-unit MLP with a “summing” output unit can generate a “square pulse” over an input

- Output is 1 only if the input lies between $T_1$ and $T_2$
- $T_1$ and $T_2$ can be arbitrarily specified
MLP as a continuous-valued regression

- A simple 3-unit MLP can generate a “square pulse” over an input
- **An MLP with many units can model an arbitrary function over an input**
  - To arbitrary precision
    - Simply make the individual pulses narrower
- **A one-layer MLP can model an arbitrary function of a single input**
For higher-dimensional functions

• An MLP can compose a cylinder
  – N in the circle, N/2 outside
A “true” cylinder

• An MLP can compose a *true* (almost) cylinder
  – N/2 in the circle, 0 outside
  – By adding a “bias”
  – We will encounter bias terms again
    • They are standard components of perceptrons
MLP as a continuous-valued function

- MLPs can actually compose arbitrary functions
  - Even with only one layer
    - As sums of scaled and shifted cylinders
  - To arbitrary precision
    - By making the cylinders thinner
  - The MLP is a universal approximator!
Caution: MLPs with additive output units are universal approximators

- MLPs can actually compose arbitrary functions
- But explanation so far only holds if the output unit only performs summation
  - i.e. does not have an additional “activation”
“Proper” networks: Outputs with activations

- Output neuron may have actual “activation”
  - Threshold, sigmoid, tanh, softplus, rectifier, etc.
- What is the property of such networks?
The network as a function

\[ f: \{0,1\}^N \rightarrow \{0,1\} \quad \text{Boolean} \]

\[ f: R^N \rightarrow \{0,1\} \quad \text{Threshold} \]

\[ f: R^N \rightarrow (0,1) \quad \text{Sigmoid} \]

\[ f: R^N \rightarrow (-1,1) \quad \text{Tanh} \]

\[ f: R^N \rightarrow (0,\infty) \quad \text{Softrectifier, Rectifier} \]

- Output unit with activation function
  - Threshold or Sigmoid, or any other
- The network is actually a map from the set of all possible input values to all possible output values
  - All values the activation function of the output neuron
The network as a function

- Output unit with activation function:
  - Threshold or Sigmoid, or any other

- The network is actually a map from the set of all possible input values to all possible output values:
  - All values the activation function of the output neuron

The MLP is a Universal Approximator for the entire class of functions (maps) it represents!

- $f: \{0,1\}^N \rightarrow \{0,1\}$ Boolean
- $f: \mathbb{R}^N \rightarrow \{0,1\}$ Threshold
- $f: \mathbb{R}^N \rightarrow (0,1)$ Sigmoid
- $f: \mathbb{R}^N \rightarrow (-1,1)$ Tanh
- $f: \mathbb{R}^N \rightarrow (0,\infty)$ Softmax, Rectifier
The issue of depth

- Previous discussion showed that a single-layer MLP is a universal function approximator
  - Can approximate any function to arbitrary precision
  - But may require infinite neurons in the layer

- More generally, deeper networks will require far fewer neurons for the same approximation error
  - The network is a generic map
    - The same principles that apply for Boolean networks apply here
  - Can be exponentially fewer than the 1-layer network
Sufficiency of architecture

- A neural network *can* represent any function provided it has sufficient *capacity*
  - I.e. sufficiently broad and deep to represent the function
- Not all architectures can represent any function
Sufficiency of architecture

A neural network can represent any function provided it has sufficient capacity – i.e. sufficiently broad and deep to represent the function

• Not all architectures can represent any function

Why?

A network with 16 or more neurons in the first layer is capable of representing the figure to the right perfectly

A network with less than 16 threshold neurons in the first layer cannot represent this pattern exactly

With caveats..
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Not all architectures can represent any function.
Sufficiency of architecture

A network with 16 or more threshold neurons in the first layer is capable of representing the figure to the right perfectly.

A network with less than 16 neurons in the first layer cannot represent this pattern exactly.

With caveats..

Why?
Sufficiency of architecture

This effect is because we use the threshold activation

It *gates* information in the input from later layers

The pattern of outputs within any colored region is identical

Subsequent layers do not obtain enough information to partition them
Sufficiency of architecture

This effect is because we use the threshold activation gates information in the input from later layers.

Continuous activation functions result in graded output at the layer. The gradation provides information to subsequent layers, to capture information “missed” by the lower layer (i.e. it “passes” information to subsequent layers).
Sufficiency of architecture

This effect is because we use the threshold activation gates information in the input from later layers.

Continuous activation functions result in graded output at the layer.

The gradation provides information to subsequent layers, to capture information “missed” by the lower layer (i.e. it “passes” information to subsequent layers).

Activations with more gradation (e.g. RELU) pass more information.
Width vs. Activations vs. Depth

• Narrow layers can still pass information to subsequent layers if the activation function is sufficiently graded.

• But will require greater depth, to permit later layers to capture patterns.
Sufficiency of architecture

- The capacity of a network has various definitions
  - *Information* or *Storage* capacity: how many patterns can it remember
  - VC dimension
    - bounded by the square of the number of weights in the network
    - From our perspective: largest number of disconnected convex regions it can represent

- A network with insufficient capacity *cannot* exactly model a function that requires a greater minimal number of convex hulls than the capacity of the network
  - But can approximate it with error
The “capacity” of a network

• VC dimension

• A separate lecture
  – Koiran and Sontag (1998): For “linear” or threshold units, VC dimension is proportional to the number of weights
    • For units with piecewise linear activation it is proportional to the square of the number of weights
    • For any \( W, L \) s.t. \( W > CL > C^2 \), there exists a RELU network with \( \leq L \) layers, \( \leq W \) weights with VC dimension \( \geq \frac{WL}{C} \log_2\left(\frac{W}{L}\right) \)
  – Friedland, Krell, “A Capacity Scaling Law for Artificial Neural Networks” (2017):
    • VC dimension of a linear/threshold net is \( O(MK) \), \( M \) is the overall number of hidden neurons, \( K \) is the weights per neuron
Lessons

- MLPs are universal Boolean function
- MLPs are universal classifiers
- MLPs are universal function approximators

- A *single-layer* MLP can approximate anything to arbitrary precision
  - But could be exponentially or even infinitely wide in its inputs size
- Deeper MLPs can achieve the same precision with far fewer neurons
  - Deeper networks are more expressive
Learning the network

- The neural network can approximate *any* function
- But only if the function is known *a priori*
• In reality, we will only get a few *snapshots* of the function to learn it from

• We must learn the entire function from these “training” snapshots
General approach to training

• Define an error between the actual network output for any parameter value and the desired output
  – E.g. error defined as the sum of the squared error over individual training instances

\[ E = \sum_i (y_i - f(x_i, W))^2 \]
General approach to training

- Problem: Network may just learn the values at the inputs
  - Learn the red curve instead of the dotted blue one
    - Given only the red vertical bars as inputs
  - Need “smoothness” constraints
Data under-specification in learning

• Consider a binary 100-dimensional input
• There are $2^{100}=10^{30}$ possible inputs
• Complete specification of the function will require specification of $10^{30}$ output values
• A training set with only $10^{15}$ training instances will be off by a factor of $10^{15}$
Data under-specification in learning

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Data under-specification in learning

• MLPs naturally impose constraints

• MLPs are universal approximators
  – Arbitrarily increasing size can give you arbitrarily wiggly functions
  – The function will remain ill-defined on the majority of the space

• For a given number of parameters deeper networks impose more smoothness than shallow ones
  – Each layer works on the already smooth surface output by the previous layer
Smoothness through network structure

- Smoothness constraints can also be imposed through the network structure.
- For a given number of parameters, deeper networks impose more smoothness than shallow ones.
  - Each layer works on the already smooth surface output by the previous layer.
Even when we get it all right

• Typical results (varies with initialization)
• 1000 training points
  – Many orders of magnitude more than you usually get
• All the training tricks known to mankind
But depth and training data help

- Deeper networks seem to learn better, for the same number of total neurons
  - Implicit smoothness constraints
    - As opposed to explicit constraints from more conventional classification models
- Similar functions not learnable using more usual pattern-recognition models!!

10000 training instances
Part 3: What does the network learn?
Learning in the net

• Problem: Given a collection of input-output pairs, learn the function
Learning for classification

- When the net must learn to classify..
  - Learn the classification boundaries that separate the training instances
Learning for classification

- In reality
  - In general, not really cleanly separated
    - So, what is the function we learn?
A trivial MLP: a single perceptron

• Learn this function
  – A step function across a hyperplane
• Learn this function
  – A step function across a hyperplane
  – Given only samples form it
Learning the perceptron

- Given a number of input output pairs, learn the weights and bias

\[
y = \begin{cases} 
1 & \text{if } \sum_{i=1}^{N} w_i x_i - b \geq 0 \\
0 & \text{otherwise}
\end{cases}
\]

- Learn \( W = [w_1..w_N] \) and \( b \), given several \((X, y)\) pairs
Restating the perceptron equation by adding another dimension to $X$

$$y = \begin{cases} 
1 & \text{if } \sum_{i=1}^{N+1} w_i x_i \geq 0 \\
0 & \text{otherwise} 
\end{cases}$$

where $X_{N+1} = 1$
The Perceptron Problem

- Find the hyperplane $\sum_{i=1}^{N+1} w_i X_i = 0$ that perfectly separates the two groups of points
Perceptron Learning Algorithm

- Given $N$ training instances $(X_1, Y_1), (X_2, Y_2), ..., (X_N, Y_N)$
  - $Y_i = +1$ or $-1$

- Initialize $W$

- Cycle through the training instances:

- While more classification errors
  - For $i = 1 \ldots N_{\text{train}}$
    
    \[ O(X_i) = \text{sign}(W^T X_i) \]
    
    - If $O(X_i) \neq Y_i$
      
      \[ W = W + Y_i X_i \]

Using a +1/-1 representation for classes to simplify notation
A simple learner: Perceptron Algorithm

• Given $N$ training instances $(X_1, Y_1), (X_2, Y_2), \ldots, (X_N, Y_N)$
  – $Y_i = +1$ or $-1$ (instances are either positive or negative)

• Cycle through the training instances
• Only update $W$ on misclassified instances
• If instance misclassified:
  – If instance is positive class
    \[ W = W + X_i \]
  – If instance is negative class
    \[ W = W - X_i \]
The Perceptron Algorithm

- **Initialize:** Randomly initialize the hyperplane
  - i.e. randomly initialize the normal vector $W$
  - Classification rule $\text{sign}(W^T X)$
  - The random initial plane will make mistakes
Perceptron Algorithm
Perceptron Algorithm

Misclassified positive instance
Perceptron Algorithm

+1 (blue)
-1 (Red)
Perceptron Algorithm

Misclassified positive instance, add it to W
Perceptron Algorithm

Updated hyperplane

+1 (blue)  -1 (Red)
Perceptron Algorithm

Misclassified instance, negative class
Perceptron Algorithm

+1 (blue)  -1 (Red)
Perceptron Algorithm

Misclassified negative instance, subtract it from W
Perceptron Algorithm

Updated hyperplane
Perceptron Algorithm

Perfect classification, no more updates
Convergence of Perceptron Algorithm

• Guaranteed to converge if classes are linearly separable
  – After no more than \( \left( \frac{R}{\gamma} \right)^2 \) misclassifications
    • Specifically, when \( W \) is initialized to 0
  – \( R \) is length of longest training point
  – \( \gamma \) is the best-case closest distance of a training point from the classifier
    • Same as the margin in an SVM
  – Intuitively – takes many increments of size \( \gamma \) to undo an error resulting from a step of size \( R \)
In reality: Trivial linear example

- Two-dimensional example
  - Blue dots (on the floor) on the “red” side
  - Red dots (suspended at Y=1) on the “blue” side
  - No line will cleanly separate the two colors
Non-linearly separable data: 1-D example

- One-dimensional example for visualization
  - All (red) dots at $Y=1$ represent instances of class $Y=1$
  - All (blue) dots at $Y=0$ are from class $Y=0$
  - The data are not linearly separable
    - In this 1-D example, a linear separator is a threshold
    - No threshold will cleanly separate red and blue dots
Undesired Function

• One-dimensional example for visualization
  – All (red) dots at $Y=1$ represent instances of class $Y=1$
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  – The data are not linearly separable
    • In this 1-D example, a linear separator is a threshold
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What if?

• One-dimensional example for visualization
  – All (red) dots at $Y=1$ represent instances of class $Y=1$
  – All (blue) dots at $Y=0$ are from class $Y=0$
  – The data are not linearly separable
    • In this 1-D example, a linear separator is a threshold
    • No threshold will cleanly separate red and blue dots
• What must the value of the function be at this $X$?
  – 1 because red dominates?
  – 0.9 : The average?
• What must the value of the function be at this X?
  – 1 because red dominates?
  – 0.9: The average?

Estimate: \( \approx P(1|X) \)

Potentially much more useful than a simple 1/0 decision
Also, potentially more realistic
What if?

Should an infinitesimal nudge of the red dot change the function estimate entirely?

If not, how do we estimate $P(1|X)$?

(since the positions of the red and blue X Values are different)

- What must the value of the function be at this X?
  - 1 because red dominates?
  - 0.9 : The average?

Estimate: $\approx P(1|X)$

Potentially much more useful than a simple 1/0 decision
Also, potentially more realistic
The probability of $y=1$

- Consider this differently: at each point look at a small window around that point
- Plot the average value within the window
  - This is an approximation of the probability of $Y=1$ at that point
• Consider this differently: at each point look at a small window around that point

• Plot the average value within the window
  – This is an approximation of the probability of 1 at that point
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The probability of y=1

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The *probability of* $y=1$

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- Plot the average value within the window
  - This is an approximation of the *probability* of 1 at that point
The logistic regression model

- Class 1 becomes increasingly probable going left to right
  - Very typical in many problems
The logistic perceptron

A sigmoid perceptron with a single input models the \textit{a posteriori} probability of the class given the input:

\[
P(y|x) = \frac{1}{1 + e^{-(w_0 + w_1 x)}}
\]

- A sigmoid perceptron with a single input models the \textit{a posteriori} probability of the class given the input.
Non-linearly separable data

• Two-dimensional example
  – Blue dots (on the floor) on the “red” side
  – Red dots (suspended at $Y=1$) on the “blue” side
  – No line will cleanly separate the two colors
Logistic regression

\[ P(Y = 1|X) = \frac{1}{1 + \exp(- (\sum_i w_i x_i + w_0))} \]

• This the perceptron with a sigmoid activation
  – It actually computes the \textit{probability} that the input belongs to class 1
  – Decision boundaries may be obtained by comparing the probability to a threshold
    • These boundaries will be lines (hyperplanes in higher dimensions)
    • The sigmoid perceptron is a \textit{linear classifier}
Estimating the model

\[ P(y|x) = f(x) = \frac{1}{1 + e^{-(w_0 + w_1 x)}} \]

• Given the training data (many \((x, y)\) pairs represented by the dots), estimate \(w_0\) and \(w_1\) for the curve
Estimating the model

- Easier to represent using a $y = +1/-1$ notation

\[
P(y = 1 | x) = \frac{1}{1 + e^{-(w_0 + w_1 x)}}
\]

\[
P(y = -1 | x) = \frac{1}{1 + e^{(w_0 + w_1 x)}}
\]

\[
P(y | x) = \frac{1}{1 + e^{-y(w_0 + w_1 x)}}
\]
Estimating the model

• Given: Training data
  \((X_1, y_1), (X_2, y_2), \ldots, (X_N, y_N)\)

• \(Xs\) are vectors, \(ys\) are binary (0/1) class values

• Total probability of data

\[
P((X_1, y_1), (X_2, y_2), \ldots, (X_N, y_N)) = \prod_i P(X_i, y_i)
\]

\[
= \prod_i P(y_i|X_i) P(X_i) = \prod_i \frac{1}{1 + e^{-y_i(w_0 + w^TX_i)}} P(X_i)
\]
Estimating the model

- **Likelihood**

\[ P(\text{Training data}) = \prod_i \frac{1}{1 + e^{-y_i (w_0 + w^T X_i)}} P(X_i) \]

- **Log likelihood**

\[
\log P(\text{Training data}) = \\
\sum_i \log P(X_i) - \sum_i \log \left( 1 + e^{-y_i (w_0 + w^T X_i)} \right)
\]
Maximum Likelihood Estimate

\[ \hat{w}_0, \hat{w}_1 = \operatorname{argmax}_{w_0, w_1} \log P(\text{Training data}) \]

- Equals (note argmin rather than argmax)

\[ \hat{w}_0, \hat{w}_1 = \operatorname{argmin}_{w_0, w} \sum_i \log \left(1 + e^{-y_i (w_0 + w^T x_i)}\right) \]

- Identical to minimizing the cross entropy between the desired output \( y \) and actual output

\[ \frac{1}{1 + e^{-(w_0 + w^T x_i)}} \]

- Cannot be solved directly, needs gradient descent
So what about this one?

- Non-linear classifiers..
First consider the separable case..

- When the net must learn to classify..
First consider the separable case..

• For a “sufficient” net
First consider the separable case..

- For a “sufficient” net
- This final perceptron is a linear classifier
First consider the separable case..

• For a “sufficient” net
• This final perceptron is a linear classifier over the output of the penultimate layer
First consider the separable case..

- For perfect classification the output of the penultimate layer must be linearly separable.
First consider the separable case..

- The rest of the network may be viewed as a transformation that transforms data from non-linear classes to linearly separable features.
First consider the separable case..

- The rest of the network may be viewed as a transformation that transforms data from non-linear classes to linearly separable features
  - We can now attach *any* linear classifier above it for perfect classification
  - Need not be a perceptron
  - E.g. a max-margin classifier
First consider the separable case..

- This is true of any sufficient structure
  - Not just the optimal one
- For insufficient structures, the network may attempt to transform the inputs to linearly separable features
  - Will fail to separate
  - The learning algorithm will try to learn the most separating (or least error) boundaries
Mathematically..

\[ y_{out} = \frac{1}{1 + \exp(b + W^T y)} = \frac{1}{1 + \exp(b + W^T f(X))} \]

• The data are (almost) linearly separable in the space of \( Y \)
• The network until the second-to-last layer is a non-linear function \( f(X) \) that converts the input space of \( X \) into the feature space \( Y \) where the classes are maximally linearly separable
When the data are not separable and boundaries are not linear.

- More typical setting for classification problems
Inseparable classes with an output logistic perceptron

- The “feature extraction” layer transforms the data such that the posterior probability may now be modelled by a logistic
Inseparable classes with an output logistic perceptron

The “feature extraction” layer transforms the data such that the posterior probability may now be modelled by a logistic output.

- The output logistic computes the posterior probability of the class given the input.

\[ P(y|x) = f(x) = \frac{1}{1+e^{-(w_0 + w^T x)}} \]
When the data are not separable and boundaries are not linear.

- The output of the network is $P(y|x)$
  - For multi-class networks, it will be the vector of a posteriori class probabilities
Story so far

• A classification MLP actually comprises two components
  – A “feature extraction network” that converts the inputs into linearly separable features
    • Or *nearly* linearly separable features
  – A final linear classifier that operates on the linearly separable features
How about the lower layers?

- How do the lower layers respond?
  - They too compute features
  - But how do they look
- Manifold hypothesis: For separable classes, the classes are linearly separable on a non-linear manifold
- Layers sequentially “straighten” the data manifold
  - Until the final layer, which fully linearizes it
The behavior of the layers

- Synthetic example: Feature space
The behavior of the layers

- CIFAR
The behavior of the layers

- CIFAR
Changing gears..
Intermediate layers

We’ve seen what the network learns here

But what about here?
Recall: The basic perceptron

- What do the weights tell us?
  - The neuron fires if the inner product between the weights and the inputs exceeds a threshold

\[
y = \begin{cases}
1 & \text{if } \sum_{i} w_i x_i \geq T \\
0 & \text{else}
\end{cases}
\]

\[
y = \begin{cases}
1 & \text{if } x^T w \geq T \\
0 & \text{else}
\end{cases}
\]

- Equation for output of the neuron
Recall: The weight as a “template”

- The perceptron fires if the input is within a specified angle of the weight
  - Represents a convex region on the surface of the sphere!
  - The network is a Boolean function over these regions.
    - The overall decision region can be arbitrarily nonconvex
- Neuron fires if the input vector is close enough to the weight vector.
  - If the input pattern matches the weight pattern closely enough

\[
X^T W > T \\
\cos \theta > \frac{T}{|X|} \\
\theta < \cos^{-1}\left(\frac{T}{|X|}\right)
\]
Recall: The weight as a template

- If the correlation between the weight pattern and the inputs exceeds a threshold, fire
- The perceptron is a correlation filter!

$$y = \begin{cases} 1 & \text{if } \sum_i w_i x_i \geq T \\ 0 & \text{else} \end{cases}$$
Recall: MLP features

• The lowest layers of a network detect significant features in the signal
• The signal could be (partially) reconstructed using these features
  – Will retain all the significant components of the signal
Making it explicit

• The signal could be (partially) reconstructed using these features
  – Will retain all the significant components of the signal

• Simply recompose the detected features
  – Will this work?
Making it explicit

- The signal could be (partially) reconstructed using these features
  - Will retain all the significant components of the signal
- Simply *recompose* the detected features
  - Will this work?

Not in this problem.

The network is optimized to recognize digits

Will only retain distinctly digit-like or obviously not-digit like features

Rest are irrelevant and will be lost
Making it explicit: an autoencoder

- A neural network can be trained to predict the input itself
- This is an autoencoder
- An encoder learns to detect all the most significant patterns in the signals
- A decoder recomposes the signal from the patterns
The Simplest Autencoder

• A single hidden unit
• Hidden unit has linear activation
• What will this learn?
The Simplest Autencoder

Training: Learning $W$ by minimizing L2 divergence

$$\hat{x} = w^Twx$$

$$div(\hat{x}, x) = \|x - \hat{x}\|^2 = \|x - w^Twx\|^2$$

$$\widehat{W} = \arg\min_W E[div(\hat{x}, x)]$$

$$\widehat{W} = \arg\min_W E[\|x - w^Twx\|^2]$$

- This is just PCA!
The Simplest Autencoder

- The autoencoder finds the direction of maximum energy
  - Variance if the input is a zero-mean RV
- All input vectors are mapped onto a point on the principal axis
The Simplest Autencoder

• Simply varying the hidden representation will result in an output that lies along the major axis
The Simplest Autencoder

• Simply varying the hidden representation will result in an output that lies along the major axis

• This will happen even if the learned output weight is separate from the input weight
  – The minimum-error direction is the principal eigen vector
For more detailed AEs without a non-linearity

\[ Y = WX \quad \hat{X} = W^T Y \quad E = \|X - W^T WX\|^2 \]

Find \( W \) to minimize \( \text{Avg}[E] \)

- This is still just PCA
  - The output of the hidden layer will be in the principal subspace
    - Even if the recomposition weights are different from the “analysis” weights
• Terminology:
  – **Encoder**: The “Analysis” net which computes the hidden representation
  – **Decoder**: The “Synthesis” which recomposes the data from the hidden representation
Introducing nonlinearity

• When the hidden layer has a linear activation the decoder represents the best linear manifold to fit the data
  – Varying the hidden value will move along this linear manifold

• When the hidden layer has non-linear activation, the net performs nonlinear PCA
  – The decoder represents the best non-linear manifold to fit the data
  – Varying the hidden value will move along this non-linear manifold
The AE

• With non-linearity
  – “Non linear” PCA
  – Deeper networks can capture more complicated manifolds
    • “Deep” autoencoders
Some examples

- 2-D input
- Encoder and decoder have 2 hidden layers of 100 neurons, but hidden representation is unidimensional
- Extending the hidden “z” value beyond the values seen in training does not continue along a helix
Some examples

- The model is specific to the training data..
  - Varying the hidden layer value only generates data along the learned manifold
    - *Any input* will result in an output along the learned manifold
  - But may not generalize beyond the manifold
When the hidden representation is of lower dimensionality than the input, often called a "bottleneck" network

- Nonlinear PCA
- Learns the manifold for the data
  - If properly trained
The AE

- The decoder can only generate data on the manifold that the training data lie on.
- This also makes it an excellent “generator” of the distribution of the training data.
  - Any values applied to the (hidden) input to the decoder will produce data similar to the training data.
The Decoder:

- The decoder represents a source-specific generative dictionary
- Exciting it will produce typical data from the source!
The decoder represents a source-specific generative *dictionary*

Exciting it will produce typical data from the source!
The Decoder:

- The decoder represents a source-specific generative dictionary
- Exciting it will produce typical data from the source!
A cute application..

• Signal separation...

• Given a mixed sound from multiple sources, separate out the sources
Dictionary-based techniques

- Basic idea: Learn a dictionary of “building blocks” for each sound source
- All signals by the source are composed from entries from the dictionary for the source
Dictionary-based techniques

- Learn a similar dictionary for all sources expected in the signal
Dictionary-based techniques

- A mixed signal is the linear combination of signals from the individual sources
  - Which are in turn composed of entries from its dictionary
• Separation: Identify the combination of entries from both dictionaries that compose the mixed signal
Dictionary-based techniques

• Separation: Identify the combination of entries from both dictionaries that compose the mixed signal
  • The composition from the identified dictionary entries gives you the separated signals
Learning Dictionaries

- Autoencoder dictionaries for each source
  - Operating on (magnitude) spectrograms

- For a well-trained network, the “decoder” dictionary is highly specialized to creating sounds for that source
Model for mixed signal

Estimate $I_1(t)$ and $I_2(t)$ to minimize cost function $J(.)$

• The sum of the outputs of both neural dictionaries
  – For some unknown input
Separation

Test Process

Given mixed signal and source dictionaries, find excitation that best recreates mixed signal

- Simple backpropagation

Intermediate results are separated signals

Cost function

\[ J = \sum \| X(f, t) - Y(f, t) \|^2 \]

Estimate \( I_1() \) and \( I_2() \) to minimize cost function \( J() \)

- Given mixed signal and source dictionaries, find excitation that best recreates mixed signal
  - Simple backpropagation

Intermediate results are separated signals
Example Results

5-layer dictionary, 600 units wide

- Separating music
Story for the day

• Classification networks learn to predict the *a posteriori* probabilities of classes
  – The network until the final layer is a feature extractor that converts the input data to be (almost) linearly separable
  – The final layer is a classifier/predictor that operates on linearly separable data

• Neural networks can be used to perform linear or non-linear PCA
  – “Autoencoders”
  – Can also be used to compose constructive dictionaries for data
    • Which, in turn can be used to model data distributions