Advanced ICT approaches
Machine learning

Hands-on deep learning

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Slides from http://udlbook.com, by Simon J.D. Prince

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Machine learning – introduction

1. (Linear) regression
2. Approximation with shallow neural network
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4. Neural Networks: Playground Exercises
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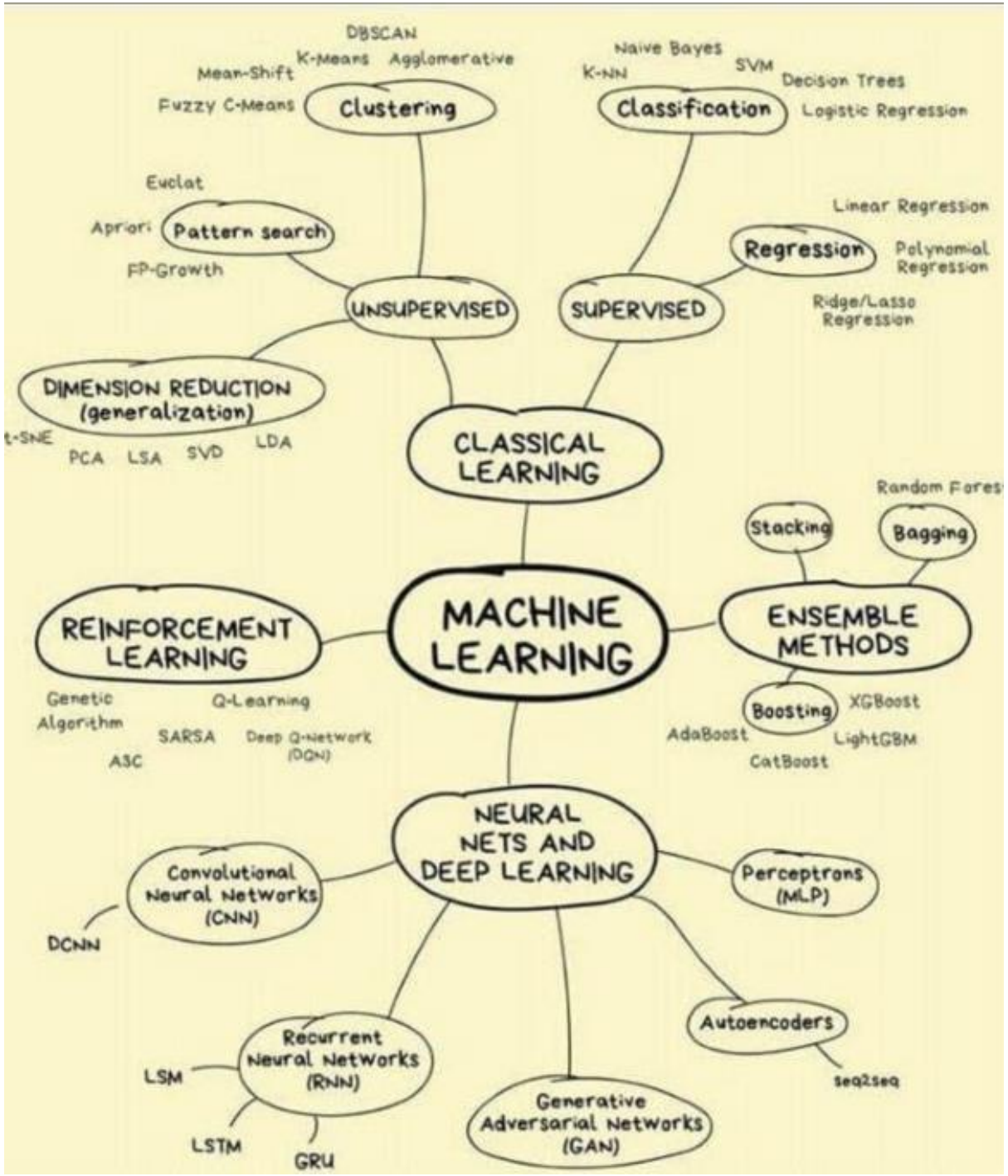
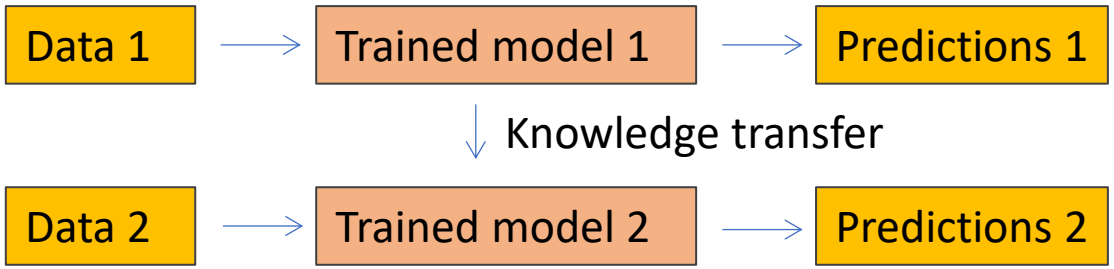
Machine Learning (ML)

- Developing algorithms and models that enable machines to learn from data
- Key concepts:
  - **Supervised learning**: ML algorithms learn from labeled data (input-output pairs) to make predictions about new, unseen data
  - **Unsupervised learning**: ML algorithms learn from unlabeled data to identify patterns, relationships, or structures in the data
  - **Reinforcement learning**: ML algorithms learn by interacting with an environment and receiving feedback as rewards or penalties
  - **Transfer learning**: ML algorithms focus on storing knowledge gained while solving one problem and applying it to a different but related problem



Transfer learning

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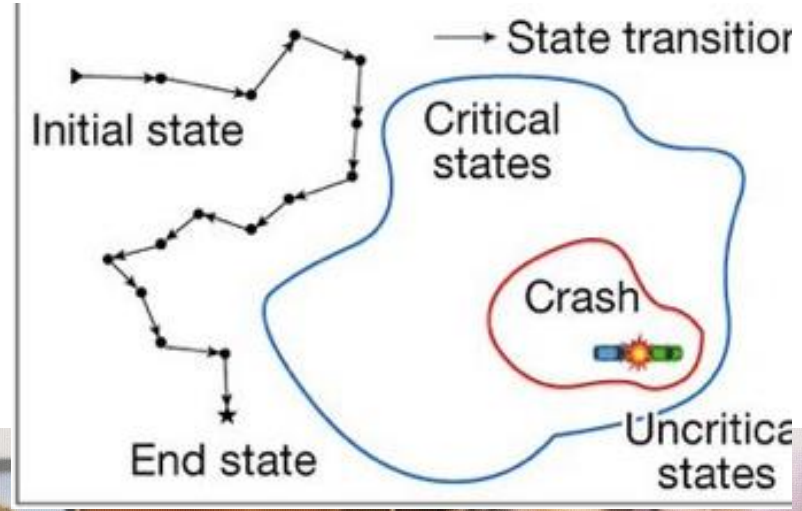
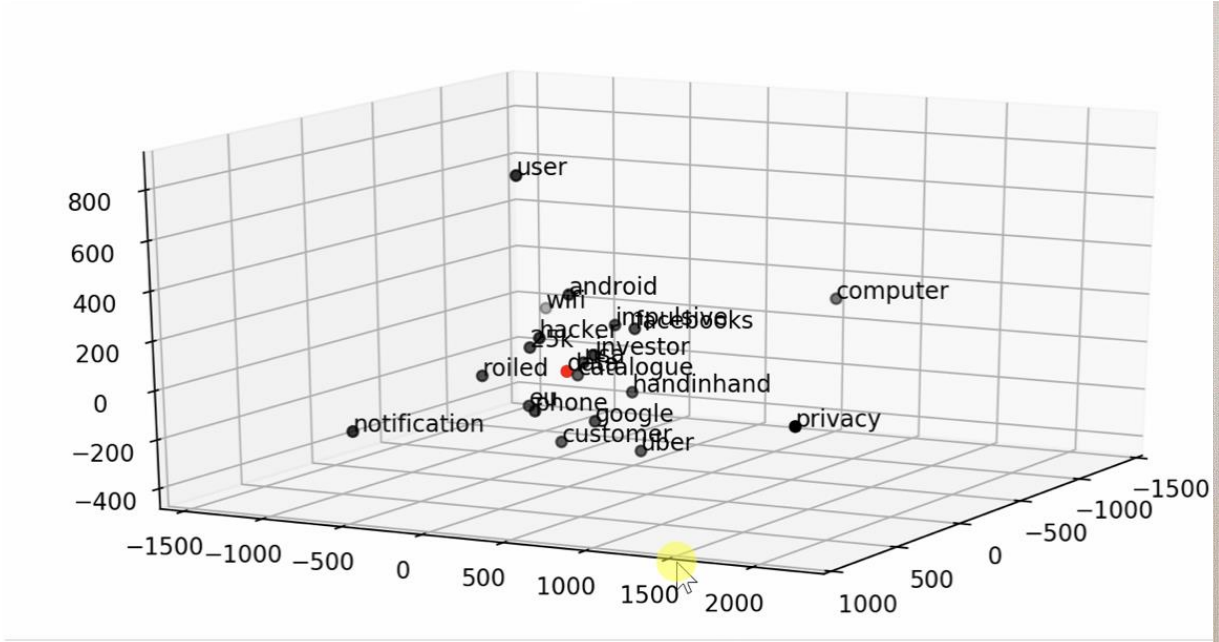

State transition
Initial state
Critical states
Crash
End state
Uncritical states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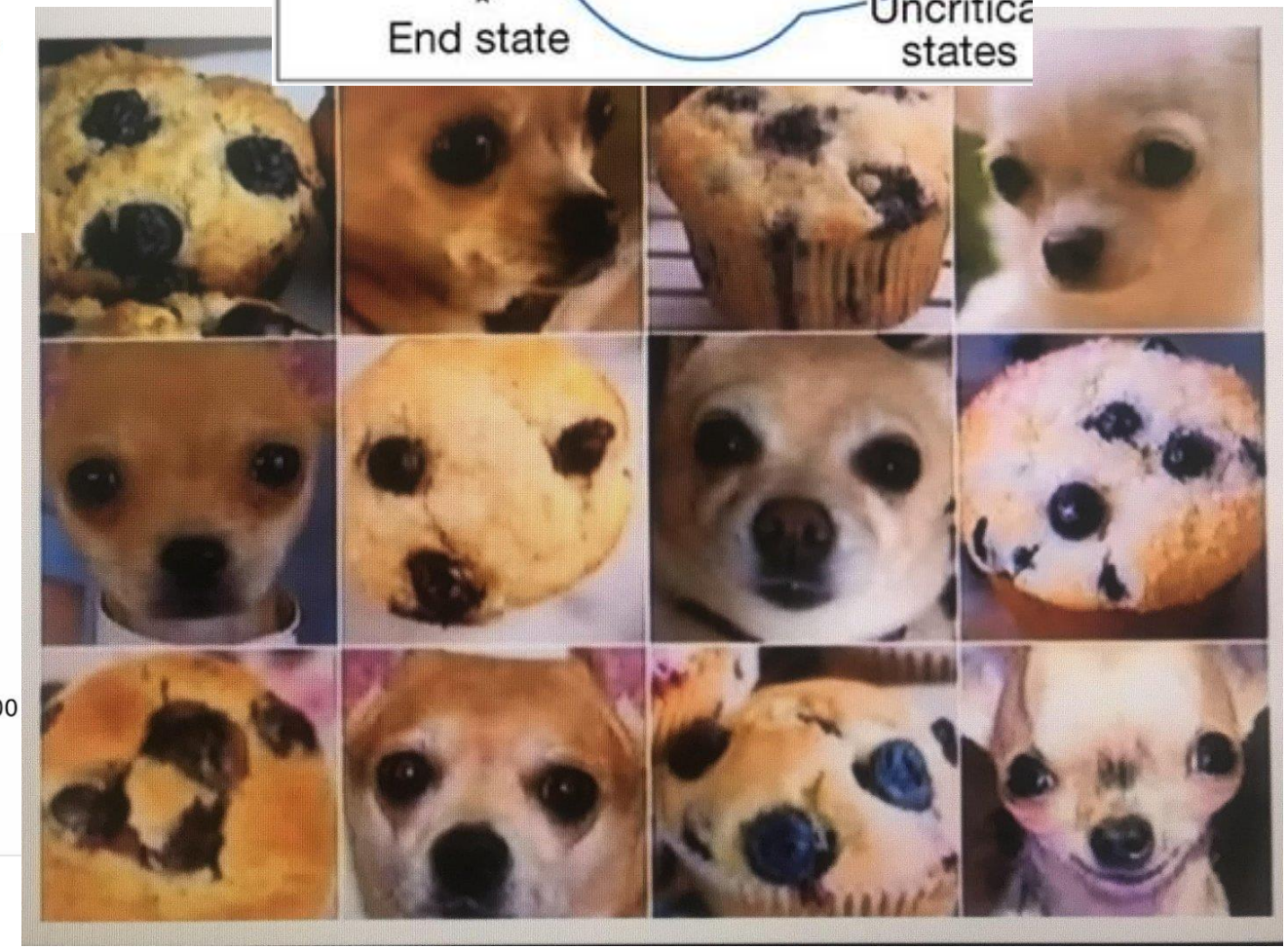
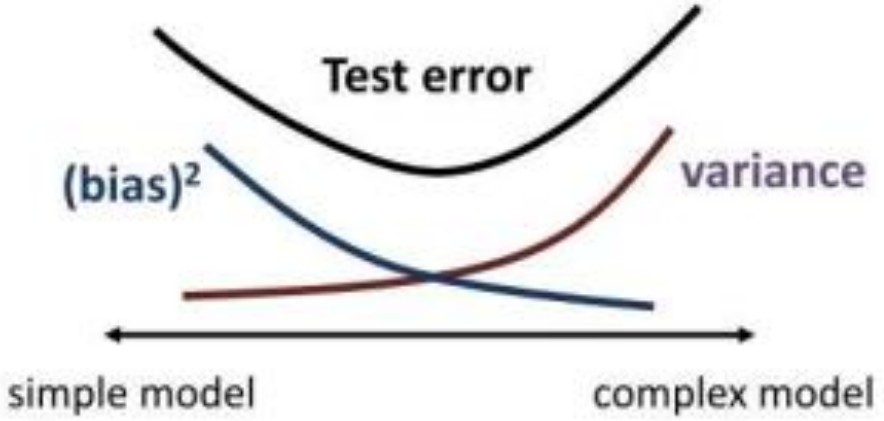
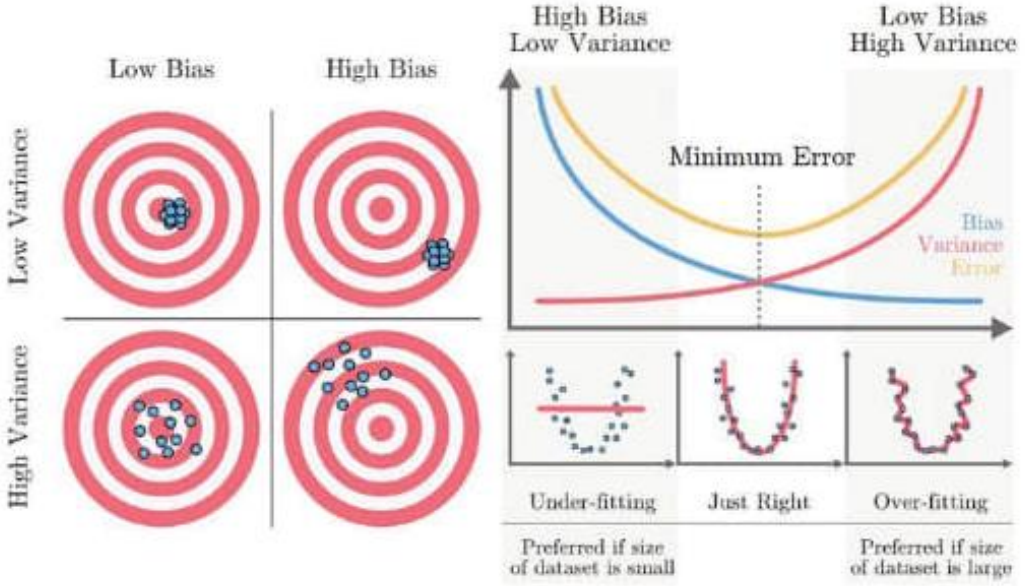


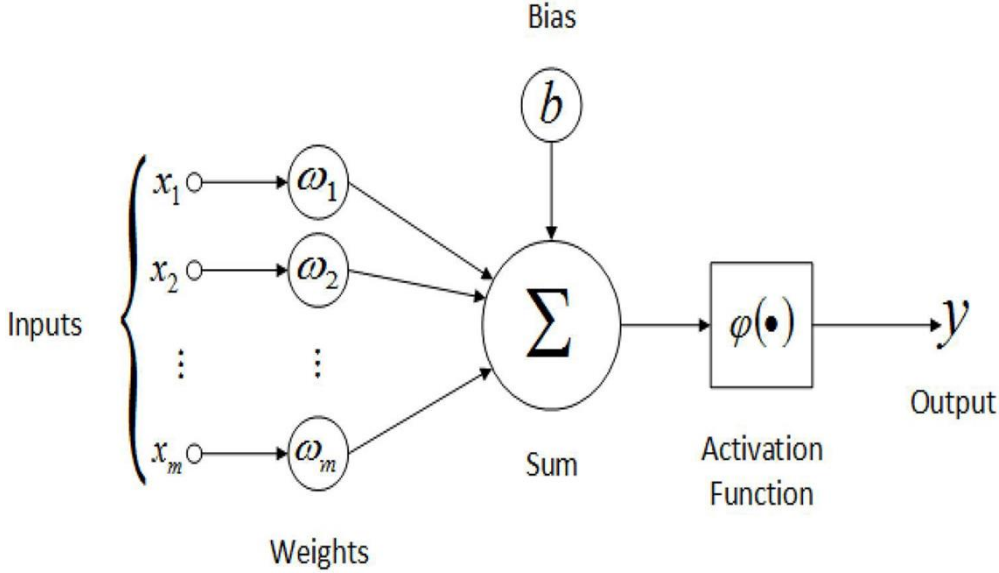
Machine Learning (ML)

- Learning models from training data (generalization)
- Measuring performance on unseen test data
- Model overfitting: too specialized on its training data
- Model underfitting: overly simplistic, inadequate capture of underlying patterns in the data
- Result: poor performance on unseen data





Neural Networks

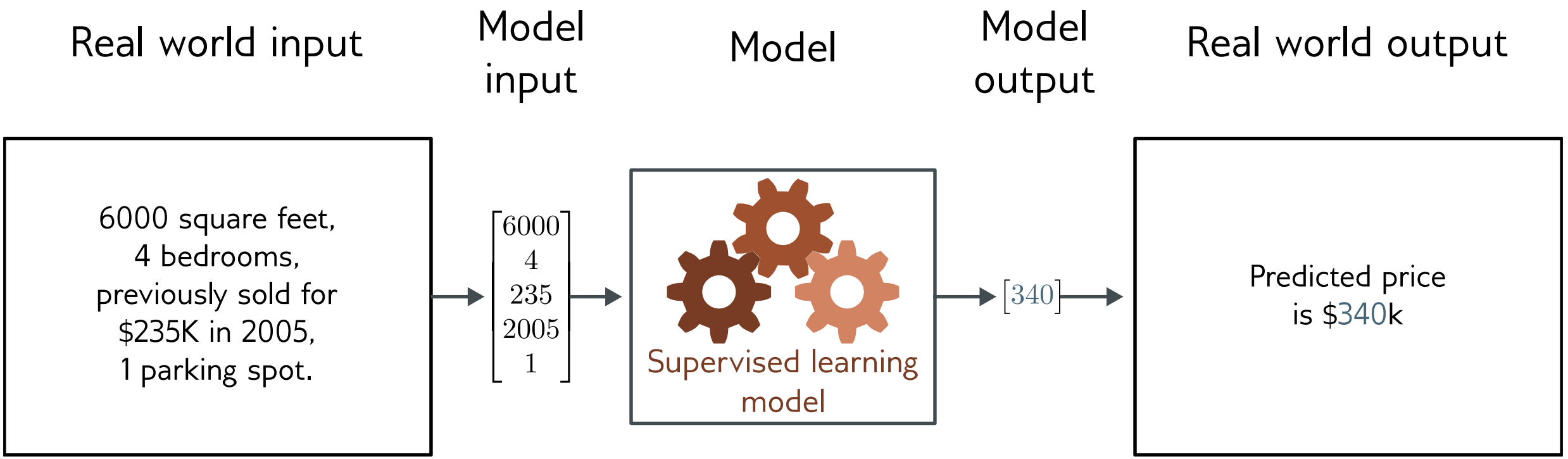


- **Inspired by the structure and function of biological neurons and neural systems**
- Designed to process, learn, and represent complex patterns in data
- Key concepts:
  - **Neurons**: the basic building blocks of neural networks, which receive input signals, process them, and produce output signals
  - **Activation functions**: nonlinear functions applied to the weighted sum of a neuron's inputs to determine its output signal
  - **Backpropagation**: an algorithm used to train neural networks by minimizing the error between predicted outputs and actual outputs through gradient descent and weight adjustments

1. Linear regression

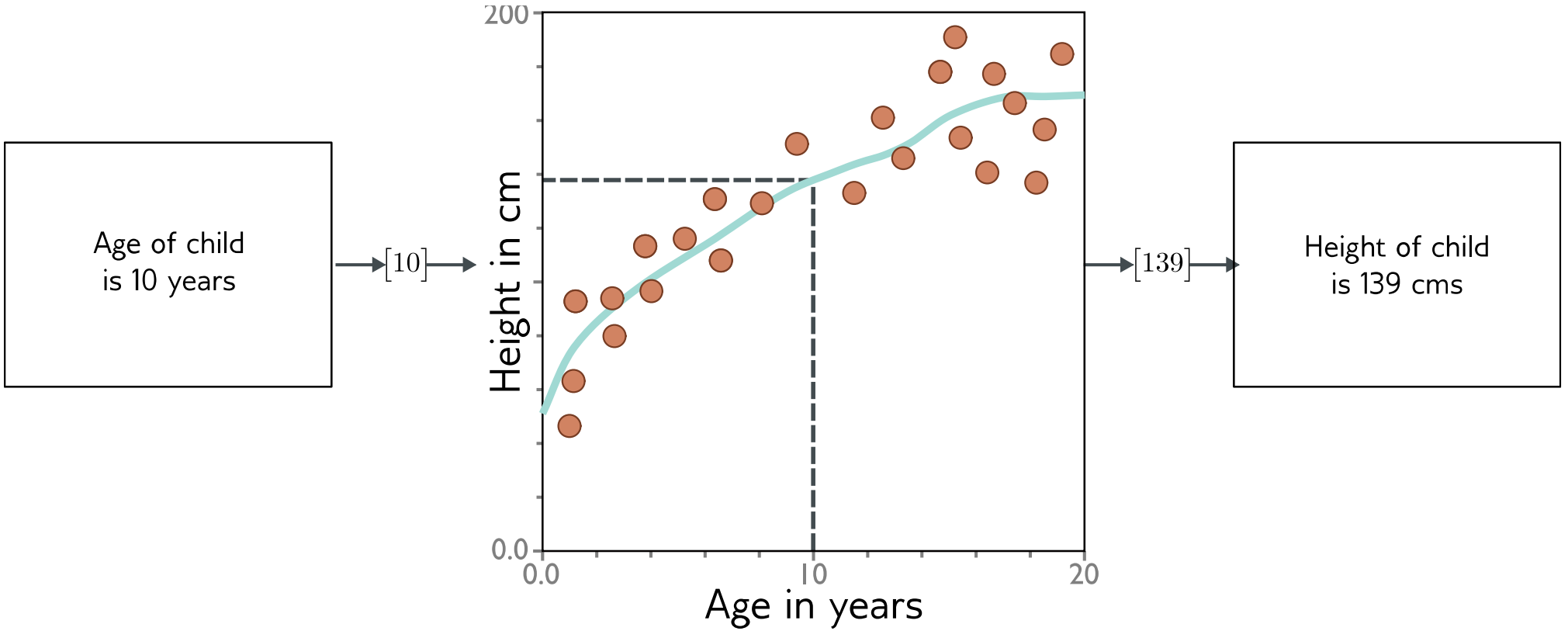
- Data points (x_1, y_1), (x_2, y_2), (x_3, y_3), … (x_{n-1}, y_{n-1}), (x_n, y_n)
- $y = k * x + n$
- Loss function
- Estimation of k and n from data

Regression



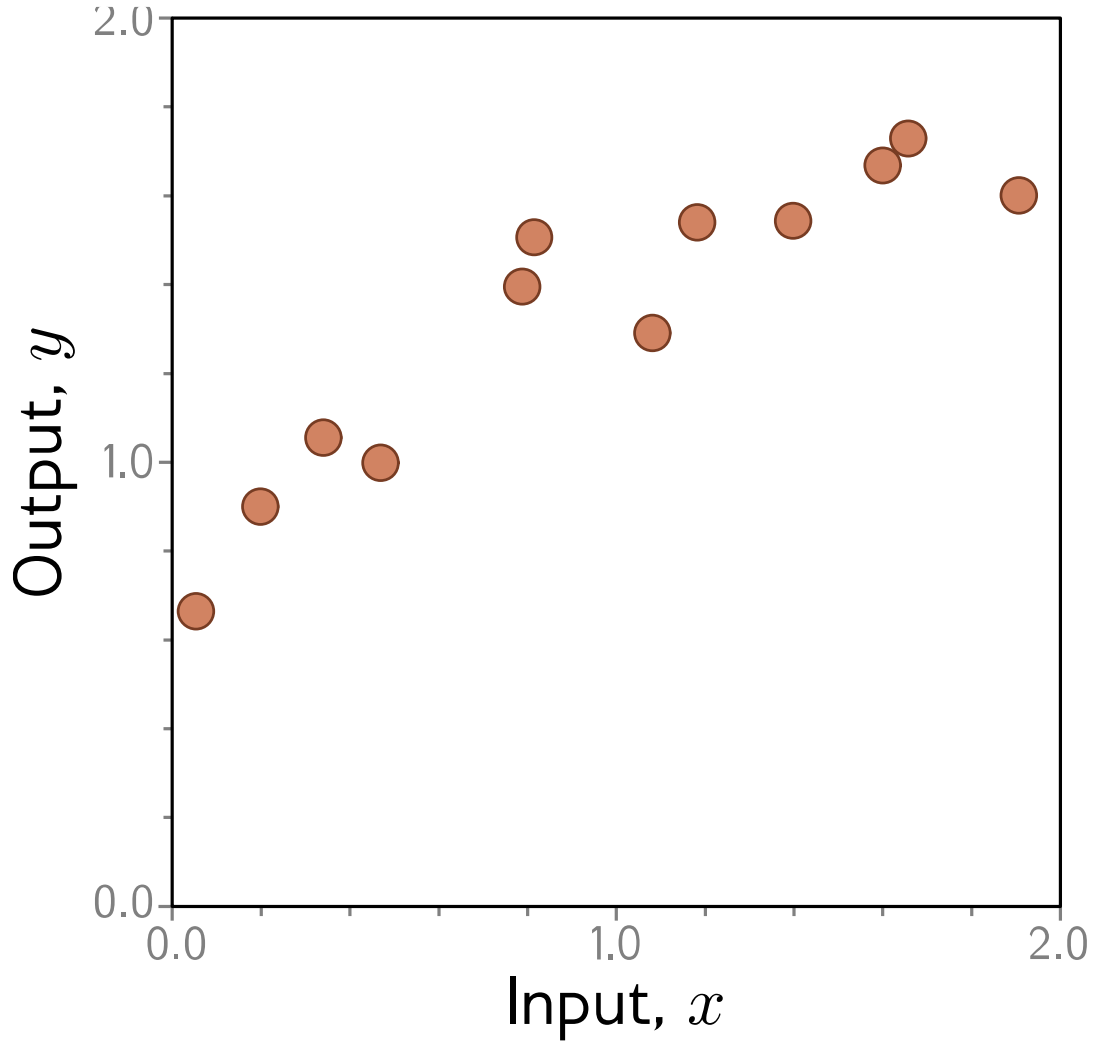
- Univariate regression problem (one output, real value)
- Fully connected network

What is a supervised learning model?



- An equation relating input (age) to output (height)
- Search through family of possible equations to find one that fits training data well

Example: 1D Linear regression training data



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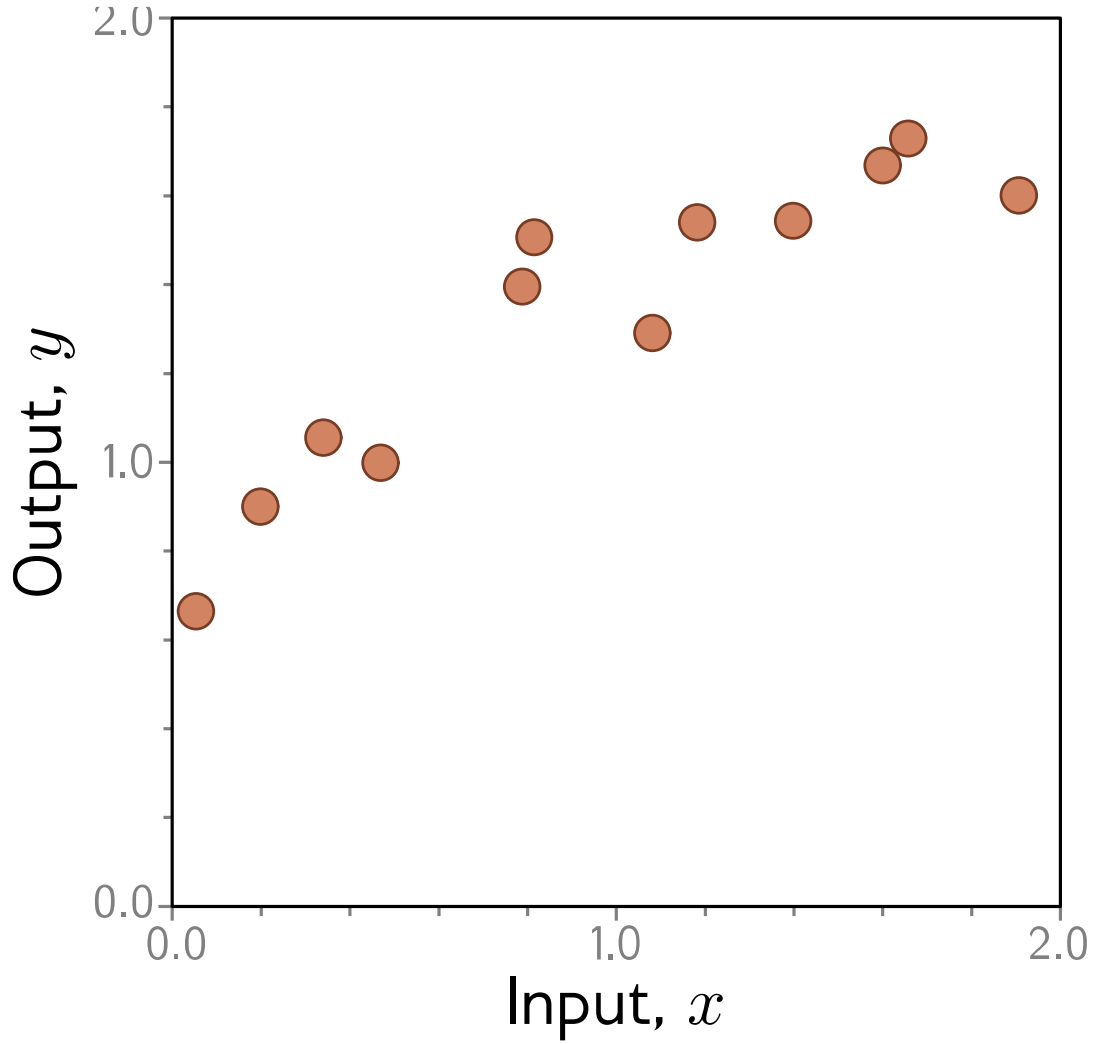


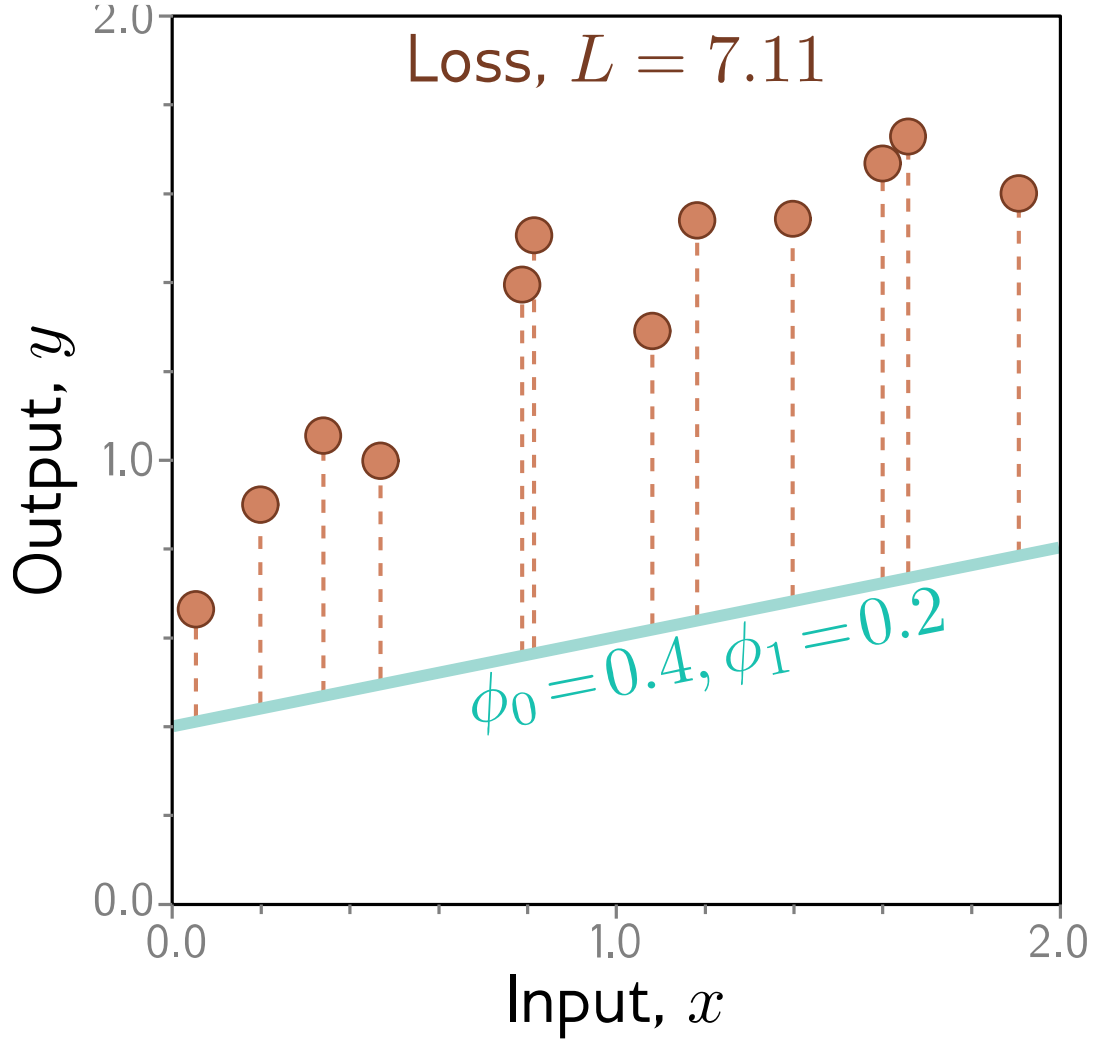
Loss function:

$$L[\boldsymbol{\phi}] = \sum_{i=1}^{I} (\mathrm{f}[x_i, \boldsymbol{\phi}] - y_i)^2$$

$$= \sum_{i=1}^{I} (\phi_0 + \phi_1 x_i - y_i)^2$$

"Least squares loss function"

Example: 1D Linear regression loss function



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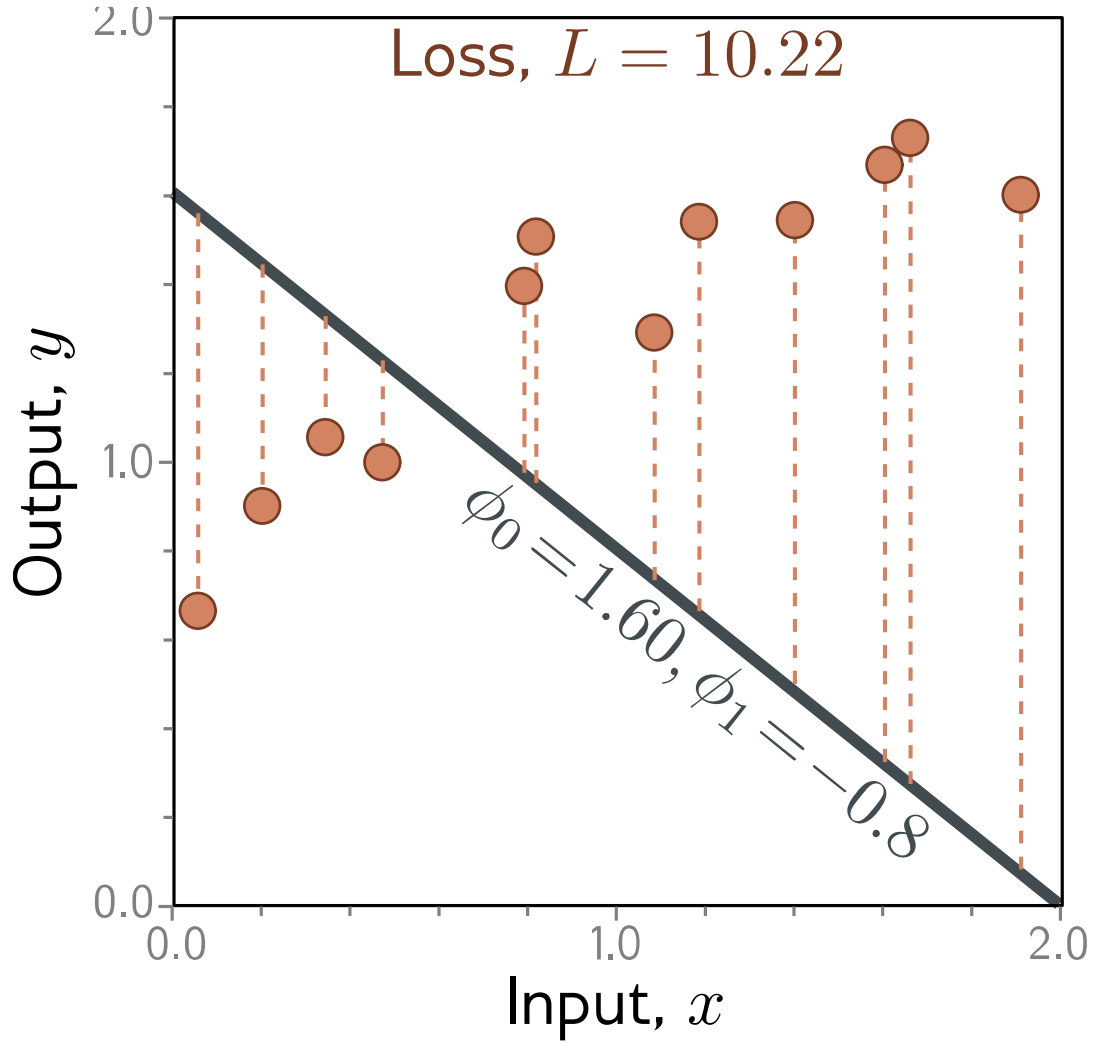

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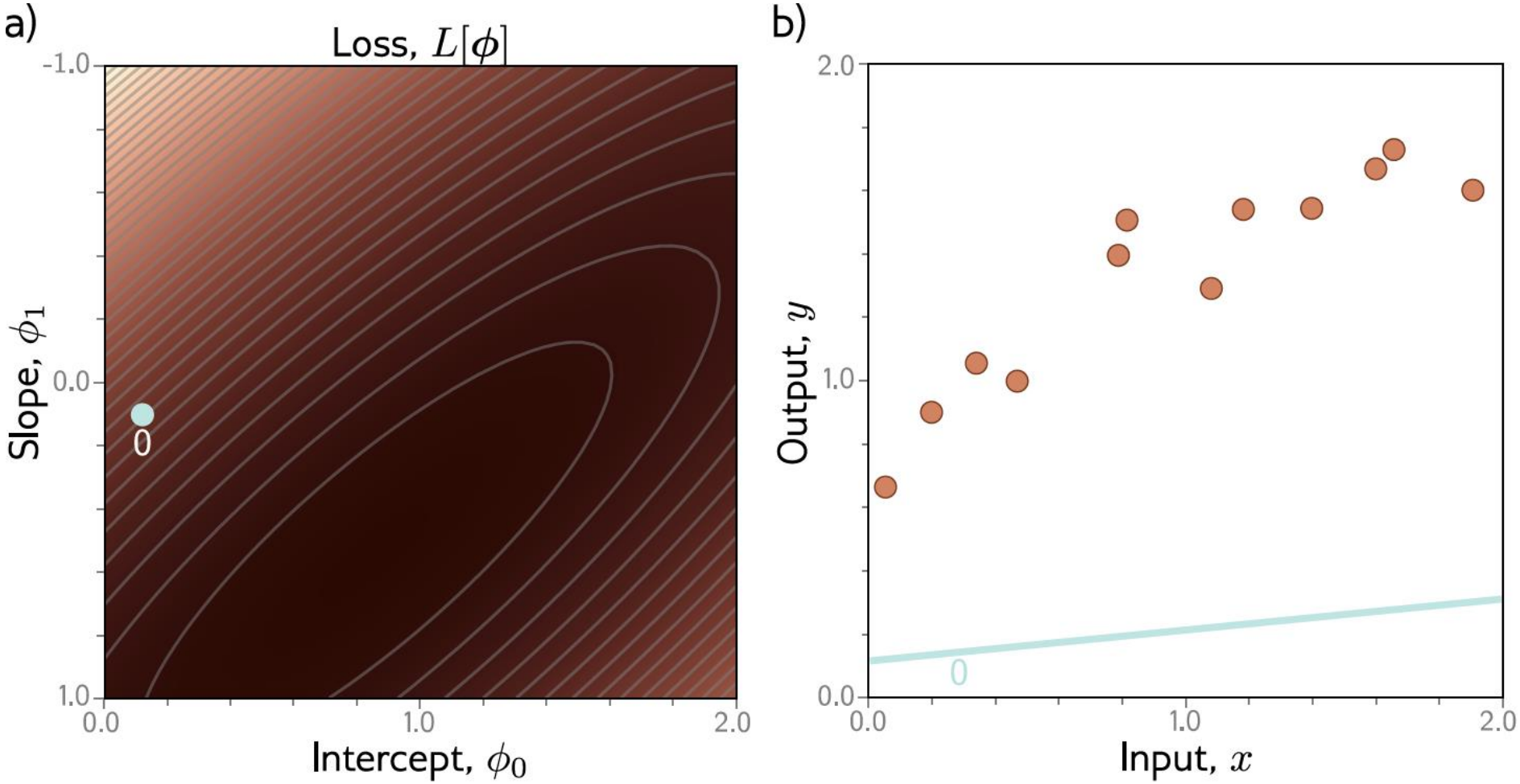

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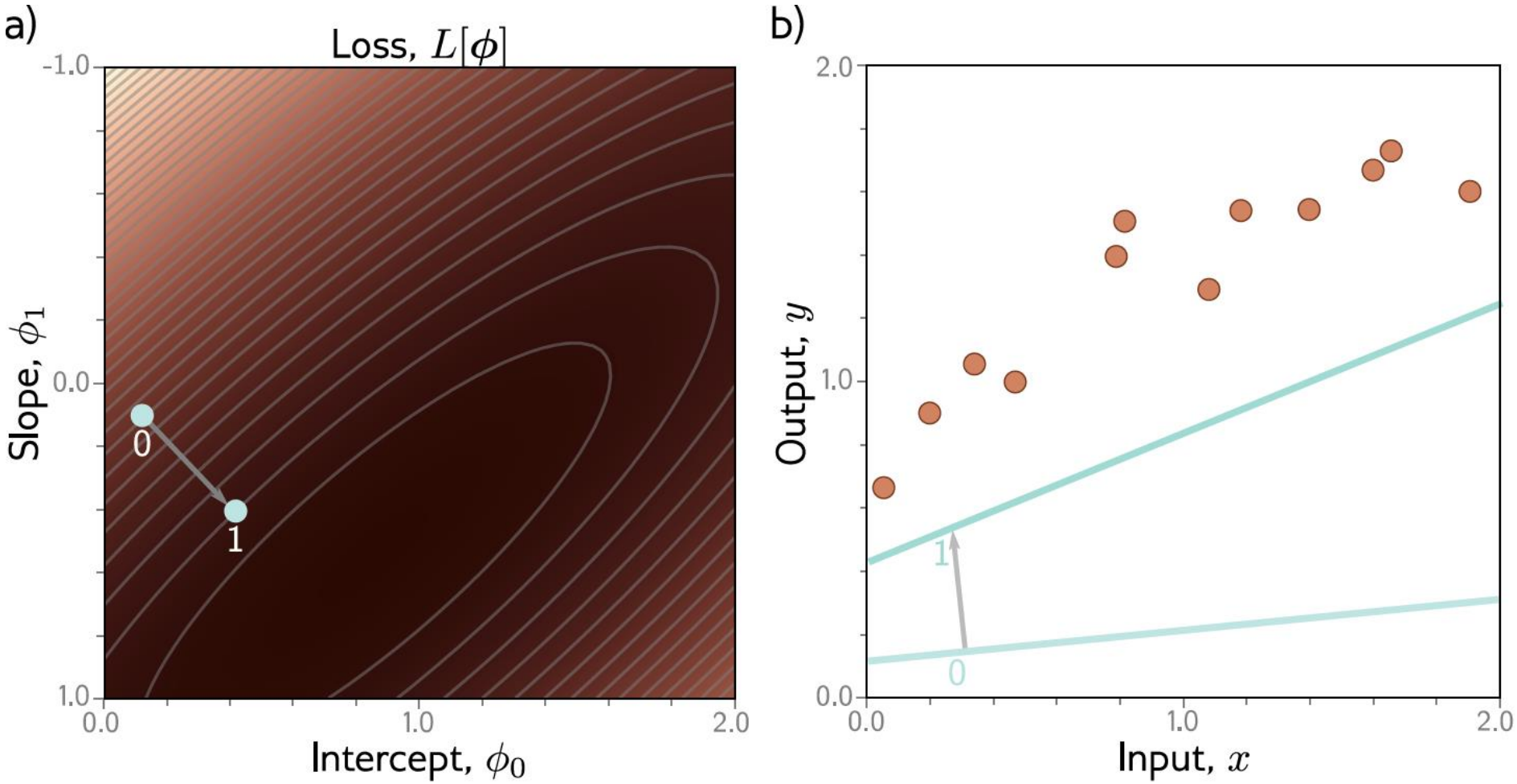

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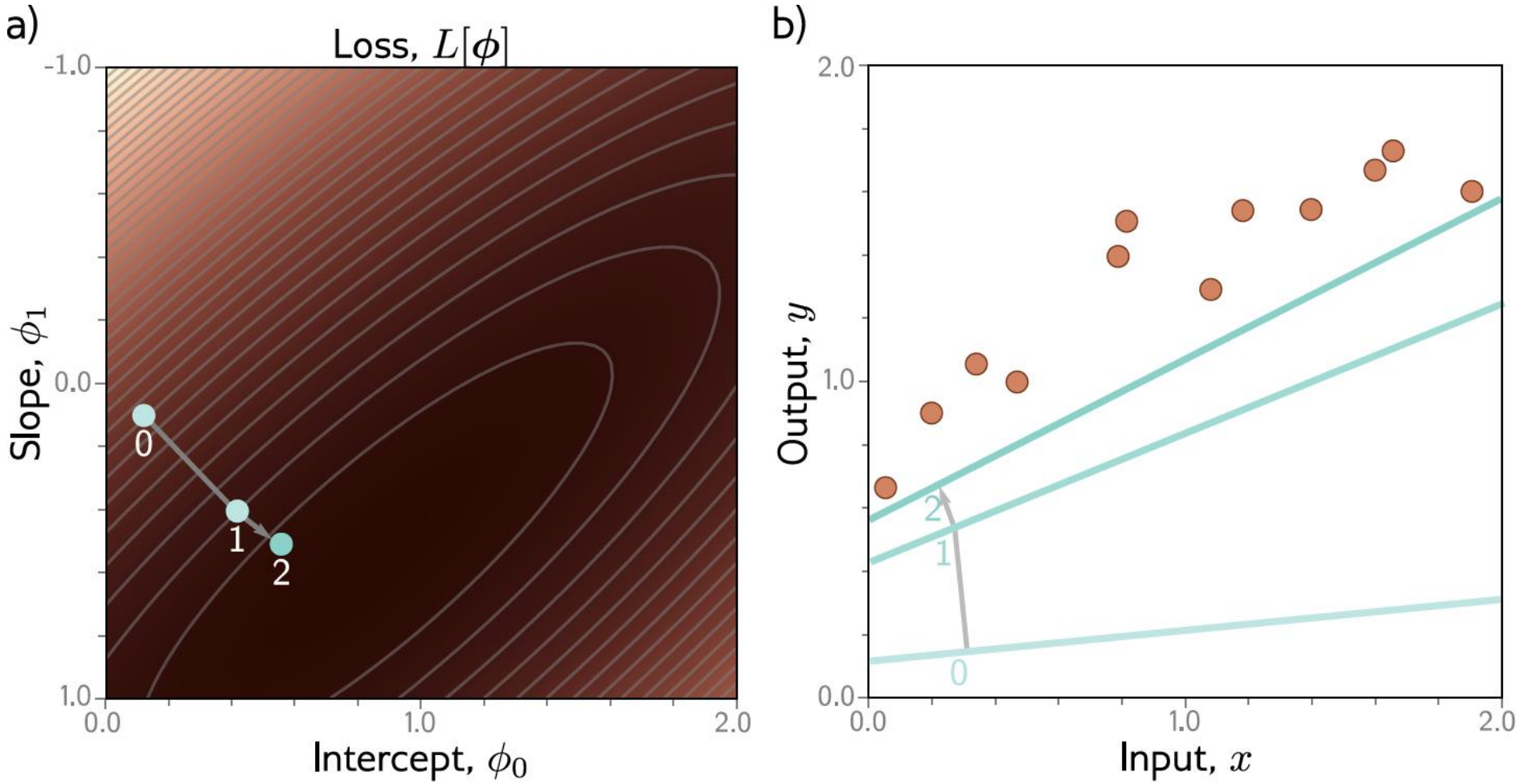

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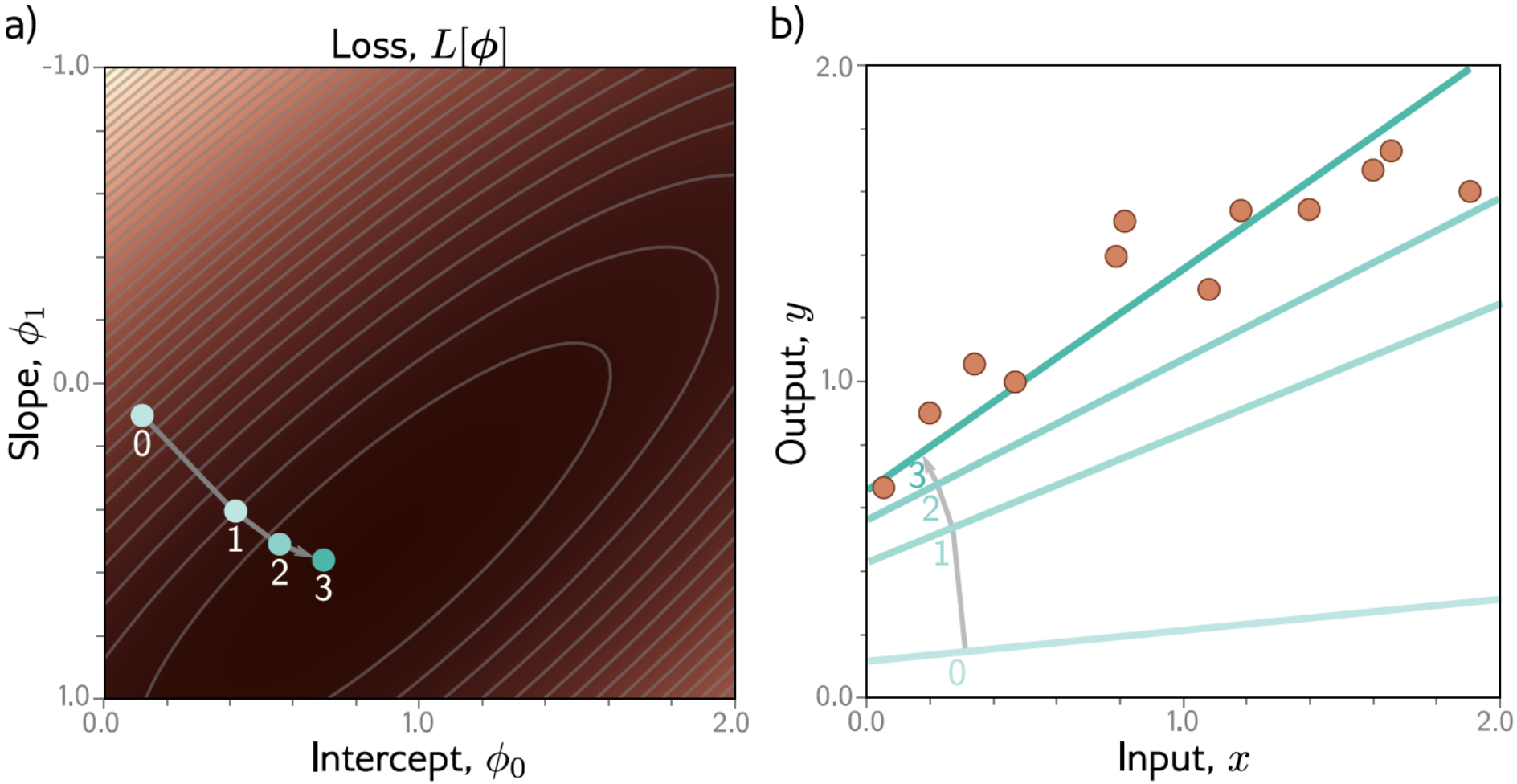

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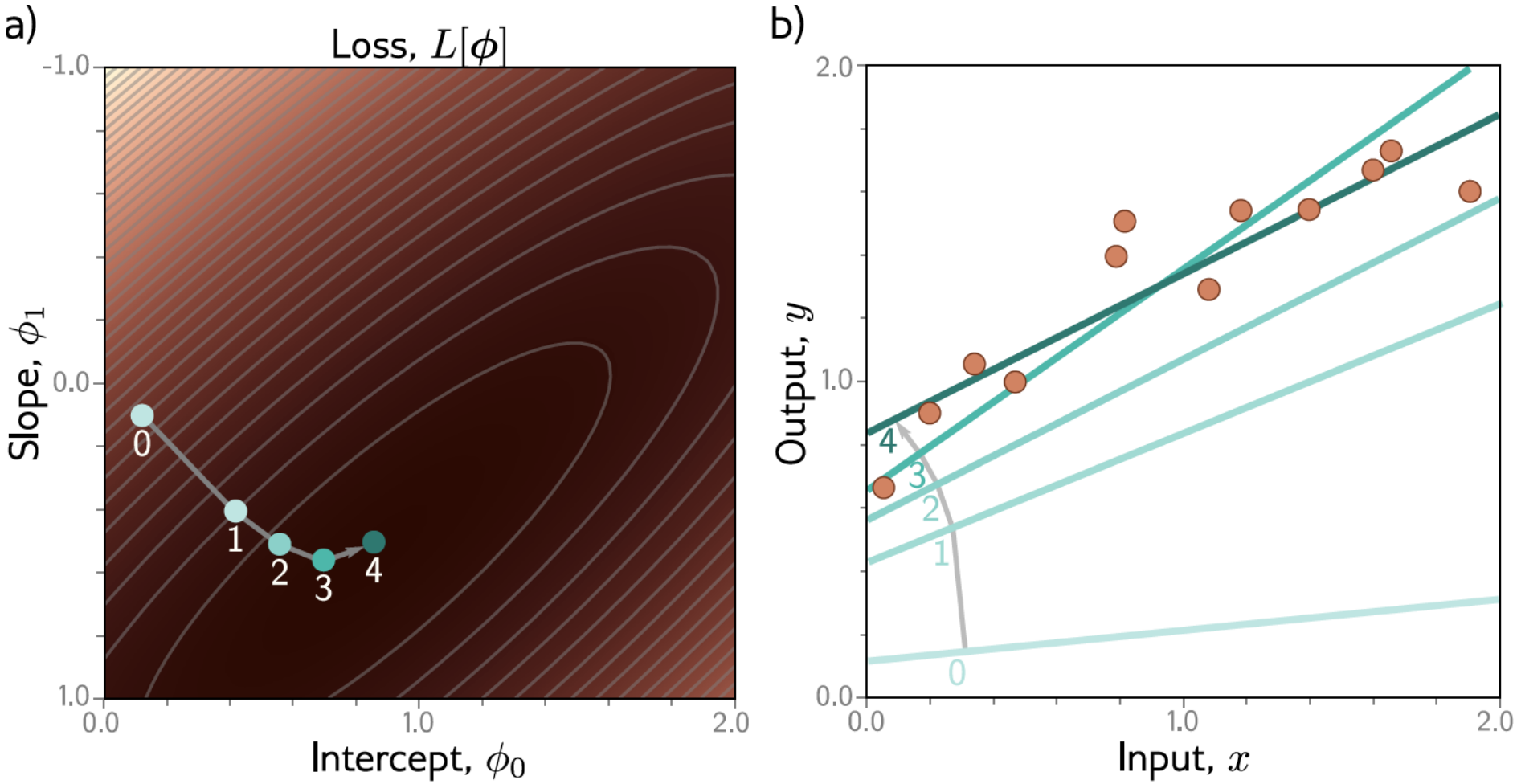


This technique is known as gradient descent

Possible objections

- But you can fit the line model in closed form!
  - Yes – but we won't be able to do this for more complex models
- But we could exhaustively try every slope and intercept combo!
  - Yes – but we won't be able to do this when there are a million parameters

Example in python notebook

- Notebook 2.1 Supervised Learning

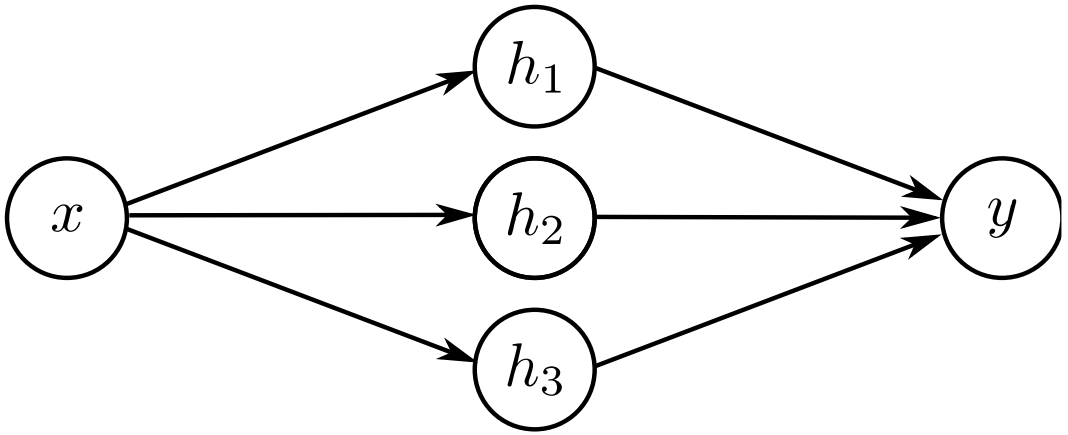
2. Approximation with shallow neural network

- Data points (x_1, y_1), (x_2, y_2), (x_3, y_3), … (x_{n-1}, y_{n-1}), (x_n, y_n)
- Loss function
- Estimation of parameters (from training data)

Depicting neural networks

$$h_1 = \mathrm{a}[\theta_{10} + \theta_{11}x]$$
$$h_2 = \mathrm{a}[\theta_{20} + \theta_{21}x]$$
$$h_3 = \mathrm{a}[\theta_{30} + \theta_{31}x]$$

$$y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3$$



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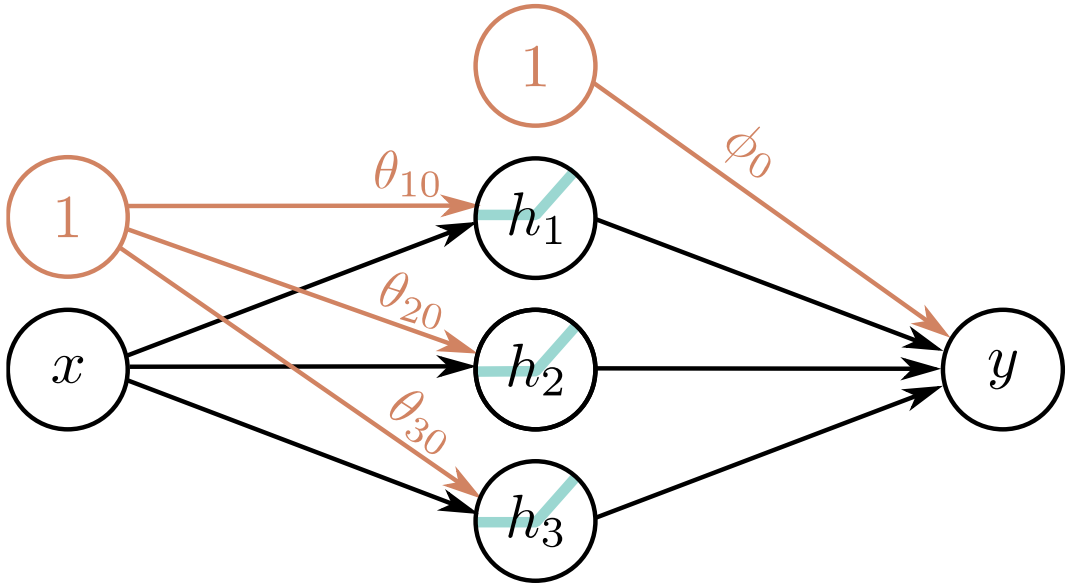

Each parameter multiplies its source and adds to its target

1D Linear Regression

$$
\begin{aligned}
y &= \mathrm{f}[x, \boldsymbol{\phi}] \\
&= \phi_0 + \phi_1 x
\end{aligned}
$$

Example shallow network

$$
\begin{aligned}
y &= \mathrm{f}[x, \boldsymbol{\phi}] \\
&= \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11} x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21} x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31} x]
\end{aligned}
$$

Example shallow network

$$
\begin{aligned}
y &= \mathrm{f}[x, \boldsymbol{\phi}] \\
&= \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11} x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21} x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31} x]
\end{aligned}
$$

Example shallow network

Activation function

$$y = \mathrm{f}[x, \boldsymbol{\phi}]$$
$$= \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11} x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21} x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31} x]$$

Example shallow network

Activation function

$$y = \mathrm{f}[x, \boldsymbol{\phi}]$$
$$= \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11}x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21}x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31}x]$$

$$\mathrm{a}[z] = \mathrm{ReLU}[z] = \begin{cases} 0 & z < 0 \\ z & z \geq 0 \end{cases}.$$

Rectified Linear Unit

(particular kind of activation function)

Example shallow network

Activation function

$$y = \mathrm{f}[x, \boldsymbol{\phi}]$$
$$= \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11}x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21}x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31}x]$$

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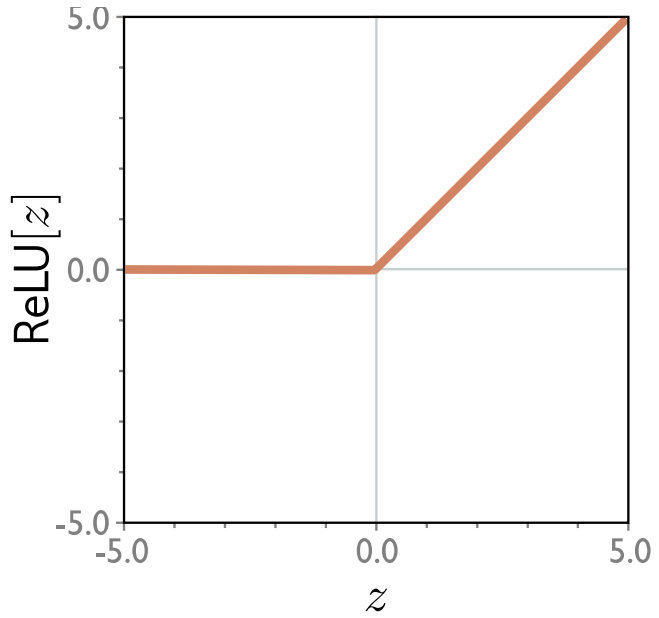
Rectified Linear Unit

(particular kind of activation function)



Example shallow network

$$y = \mathrm{f}[x, \boldsymbol{\phi}]$$
$$= \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11} x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21} x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31} x]$$

This model has 10 parameters:

$$\boldsymbol{\phi} = \{\phi_0, \phi_1, \phi_2, \phi_3, \theta_{10}, \theta_{11}, \theta_{20}, \theta_{21}, \theta_{30}, \theta_{31}\}$$

- Represents a family of functions
- Parameters determine particular function
- Given parameters can perform inference (run equation)
- Given training dataset $\{\mathbf{x}_i, \mathbf{y}_i\}_{i=1}^{I}$
- Define loss function $L[\boldsymbol{\phi}]$ (least squares)
- Change parameters to minimize loss function

Example shallow network

$$y = \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11}x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21}x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31}x].$$

Hidden units

$$y = \phi_0 + \phi_1 \mathrm{a}[\theta_{10} + \theta_{11}x] + \phi_2 \mathrm{a}[\theta_{20} + \theta_{21}x] + \phi_3 \mathrm{a}[\theta_{30} + \theta_{31}x].$$

Break down into two parts:

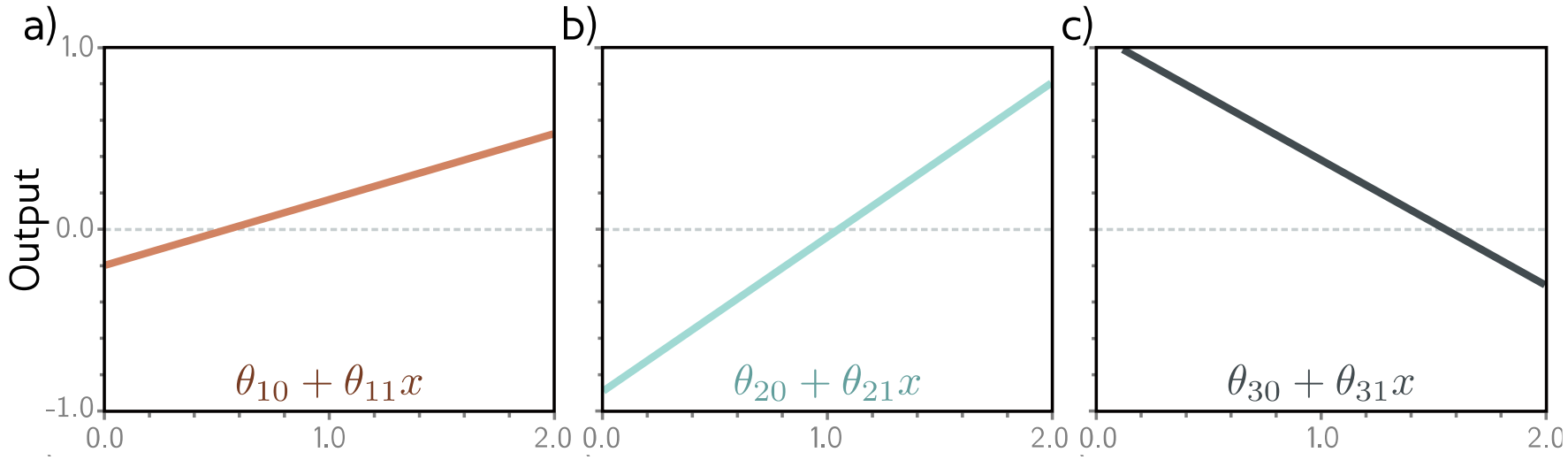
$$y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3$$

where:

Hidden units

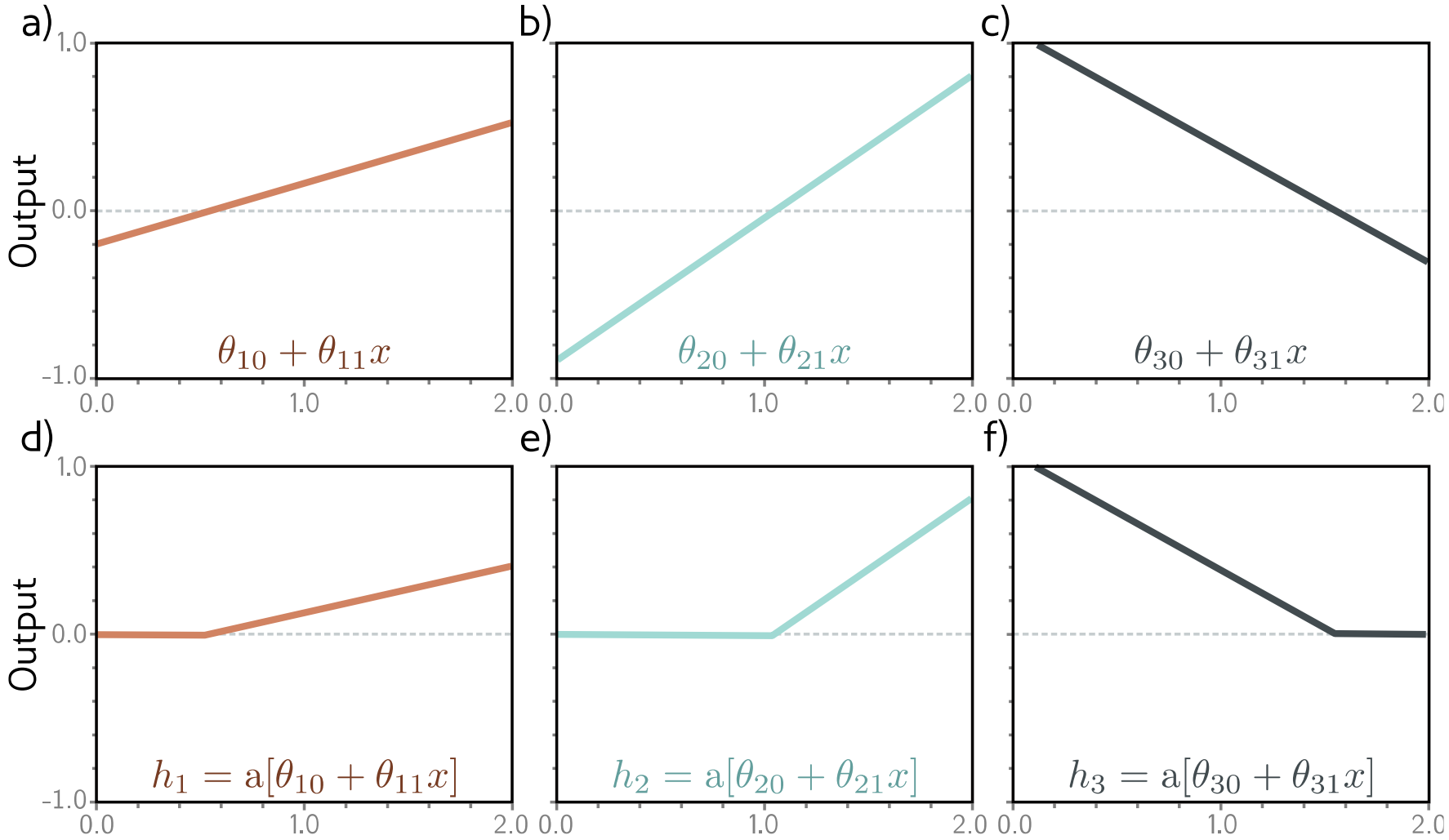
$$\begin{aligned} h_1 &= \mathrm{a}[\theta_{10} + \theta_{11}x] \\ h_2 &= \mathrm{a}[\theta_{20} + \theta_{21}x] \\ h_3 &= \mathrm{a}[\theta_{30} + \theta_{31}x] \end{aligned}$$

1. compute three
linear functions

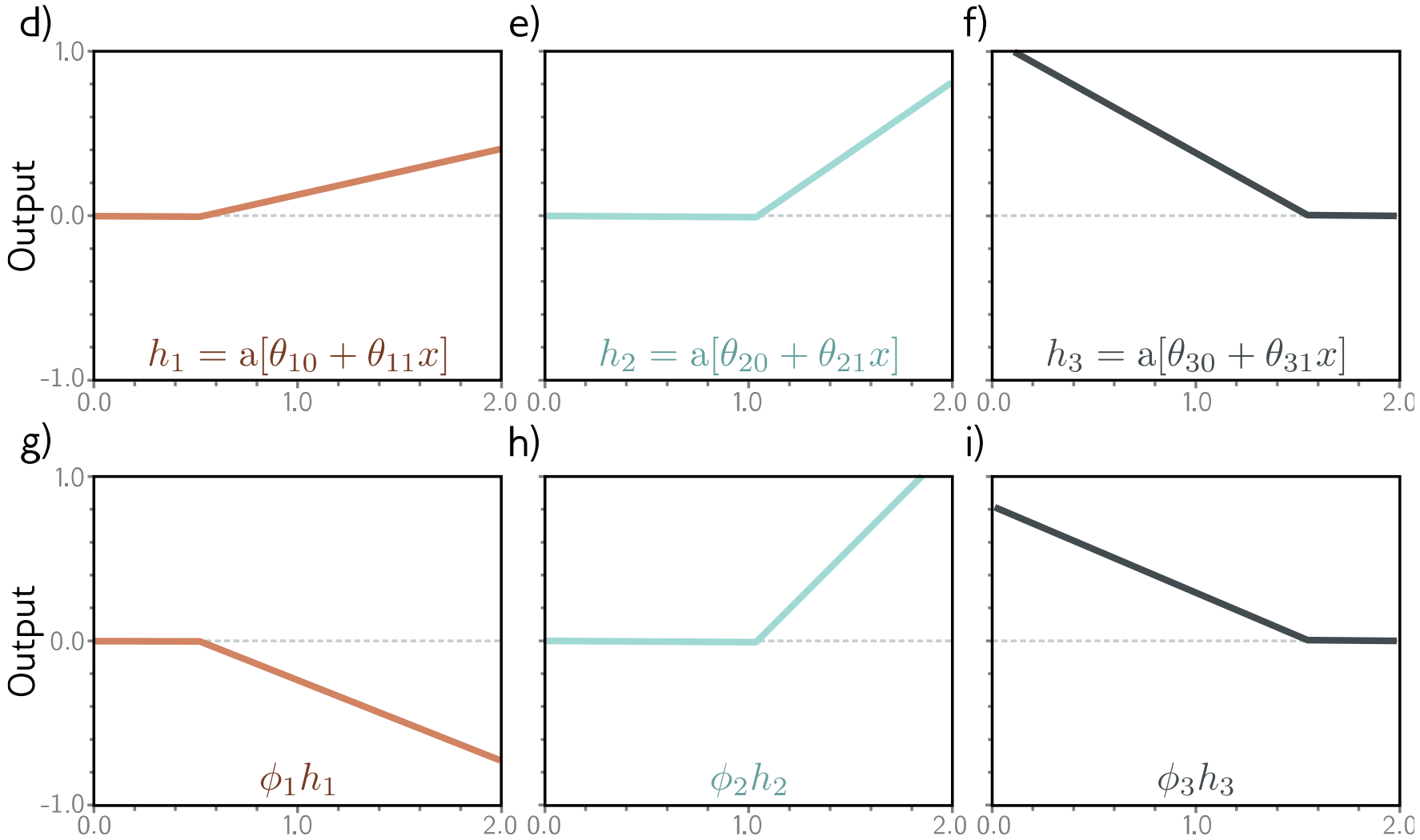


2. Pass through ReLU functions (creates hidden units)

$$h_1 = \mathrm{a}[\theta_{10} + \theta_{11}x]$$
$$h_2 = \mathrm{a}[\theta_{20} + \theta_{21}x]$$
$$h_3 = \mathrm{a}[\theta_{30} + \theta_{31}x],$$

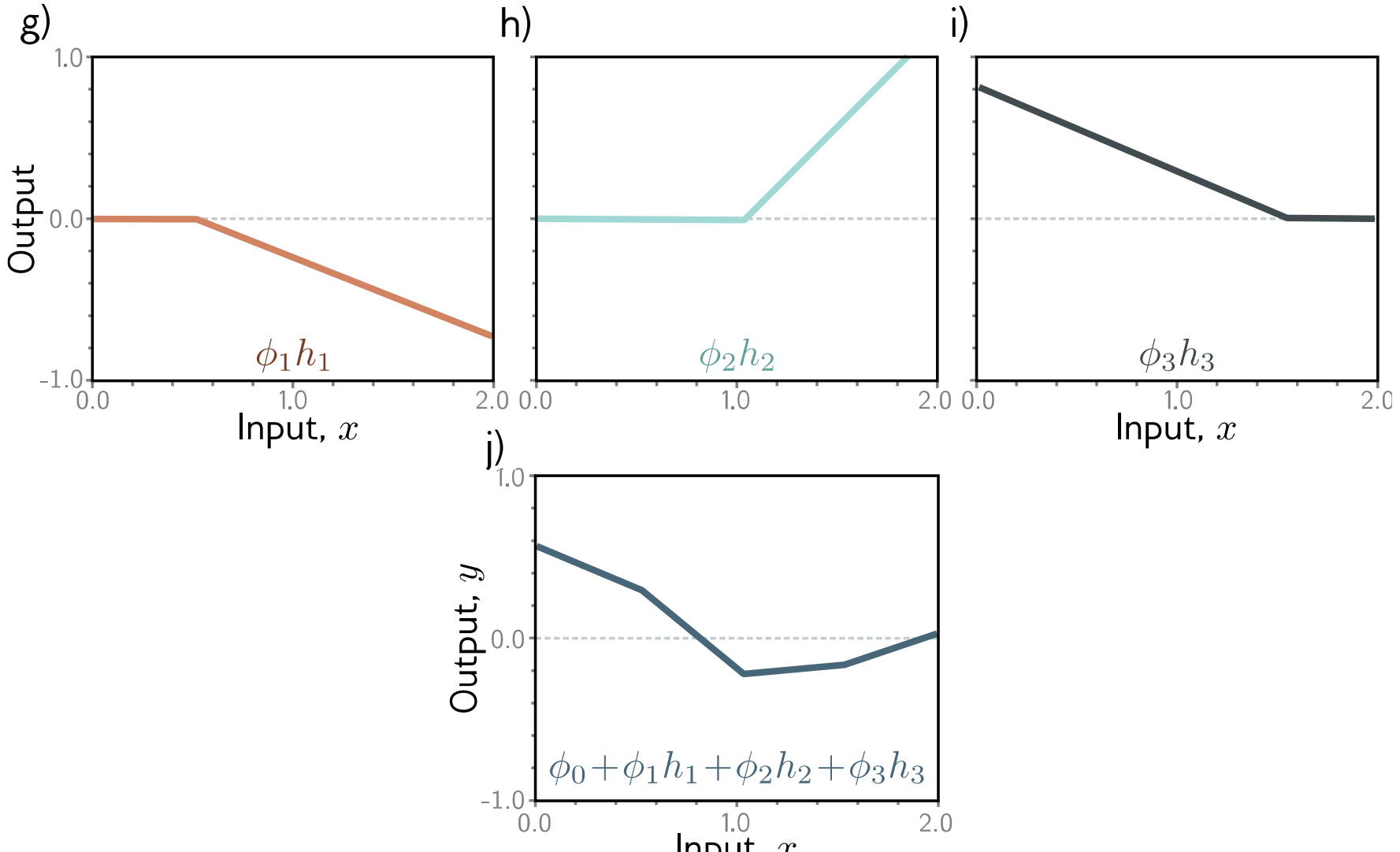


2. Weight the hidden units

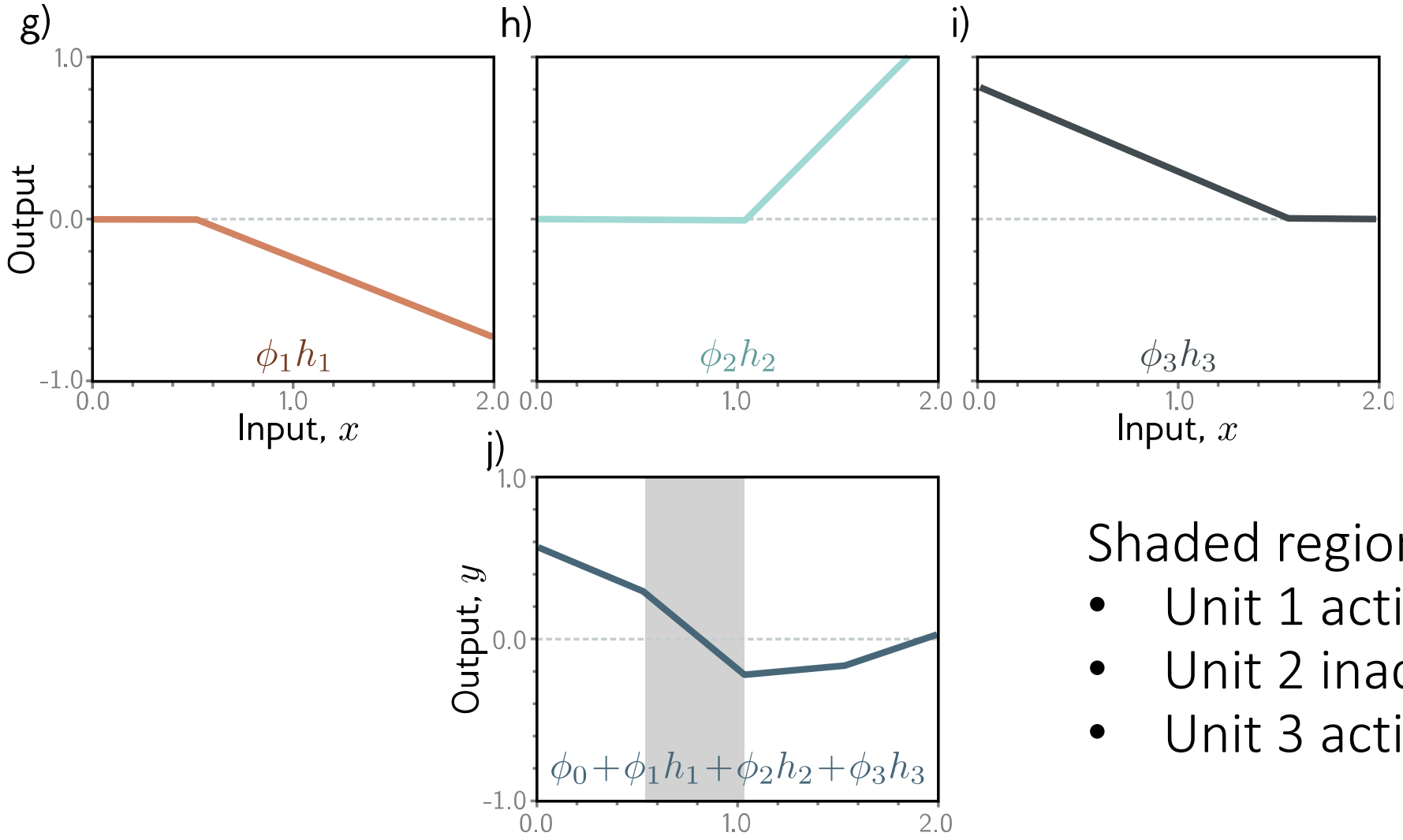


4. Sum the weighted hidden units to create output

$$y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3$$



Activation pattern = which hidden units are activated



Shaded region:

- Unit 1 active
- Unit 2 inactive
- Unit 3 active

Example in python notebook

- Notebook 3.1 Shallow neural networks I

3. Approximation with deep neural network

- Data points (x_1, y_1), (x_2, y_2), (x_3, y_3), … (x_{n-1}, y_{n-1}), (x_n, y_n)
- Loss function
- Estimation of parameters

Deep neural networks

- Networks with more than one hidden layer
- Intuition becomes more difficult

Composing two networks.

Network 1:

$$h_1 = \mathrm{a}[\theta_{10} + \theta_{11}x]$$
$$h_2 = \mathrm{a}[\theta_{20} + \theta_{21}x]$$
$$h_3 = \mathrm{a}[\theta_{30} + \theta_{31}x]$$

$$y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3$$

Network 2:

$$h'_1 = \mathrm{a}[\theta'_{10} + \theta'_{11}y]$$
$$h'_2 = \mathrm{a}[\theta'_{20} + \theta'_{21}y]$$
$$h'_3 = \mathrm{a}[\theta'_{30} + \theta'_{31}y]$$

$$y' = \phi'_0 + \phi'_1 h'_1 + \phi'_2 h'_2 + \phi'_3 h'_3$$

Composing two networks.

Network 1:

$$h_1 = \mathrm{a}[\theta_{10} + \theta_{11}x]$$
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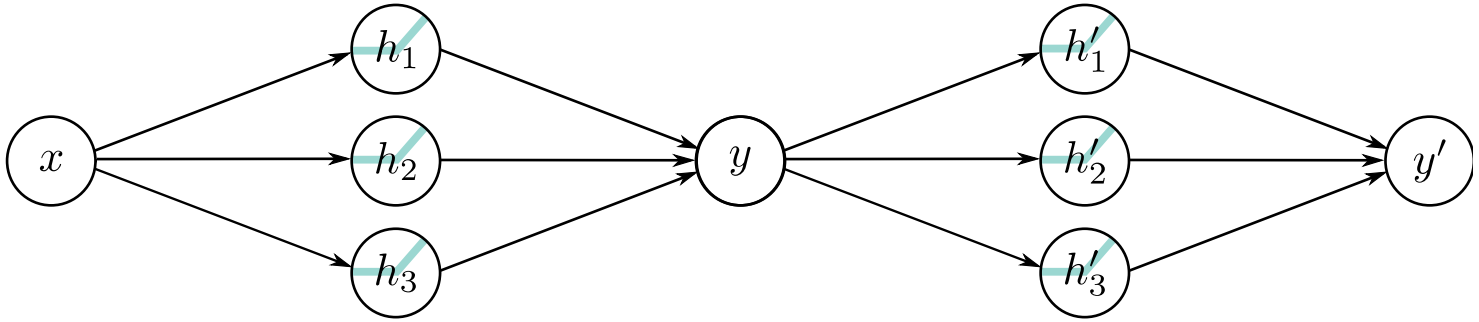
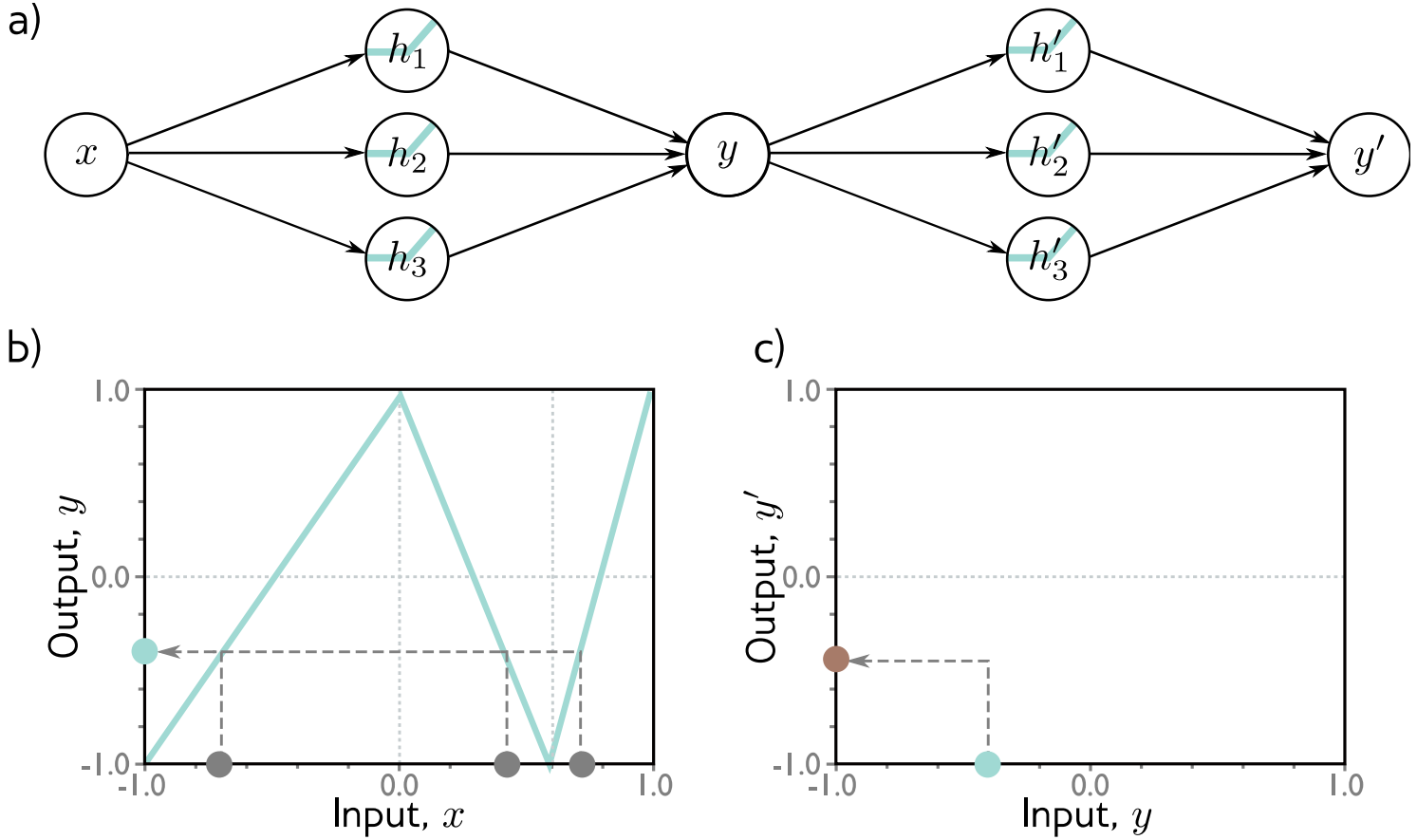
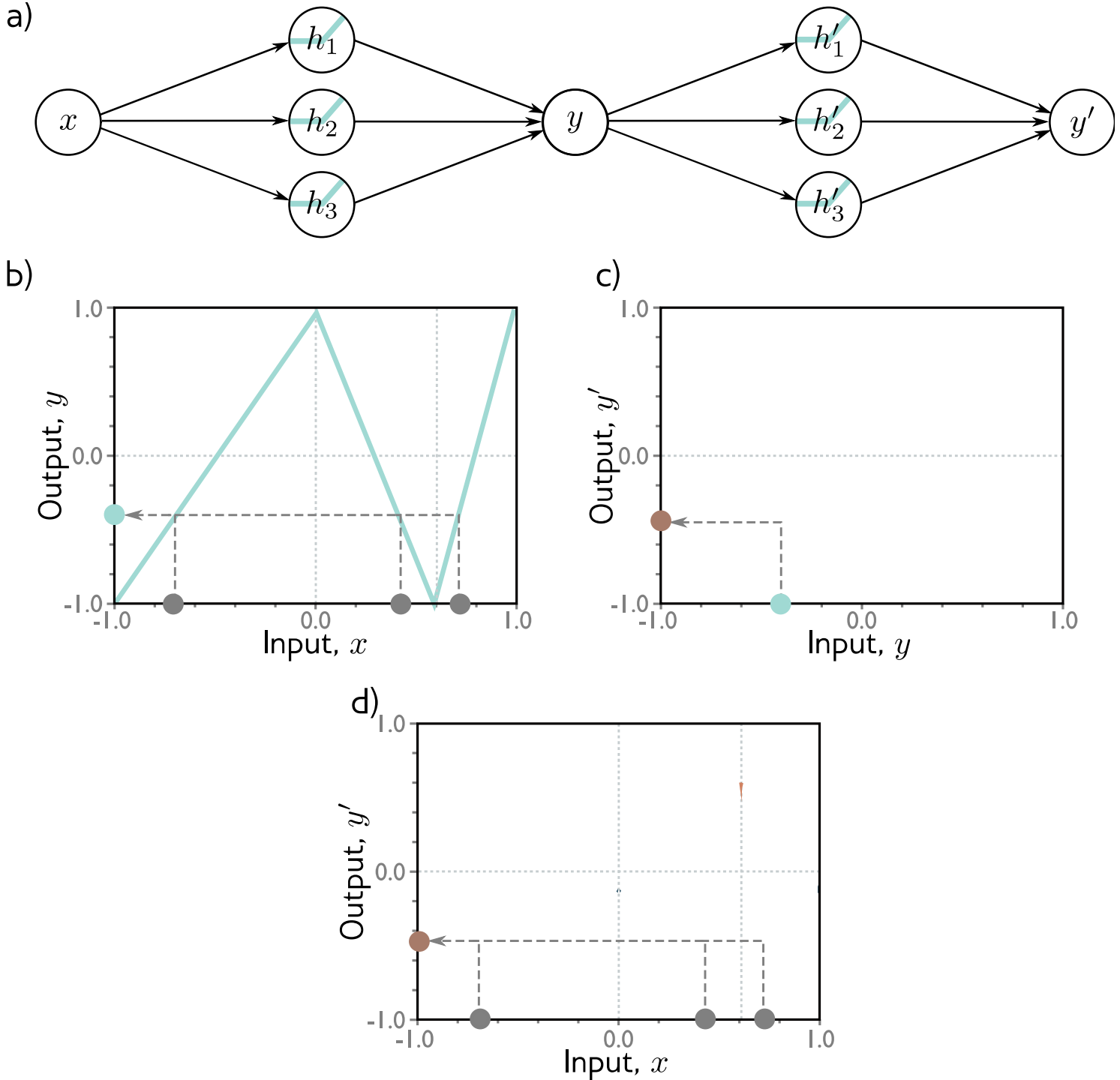
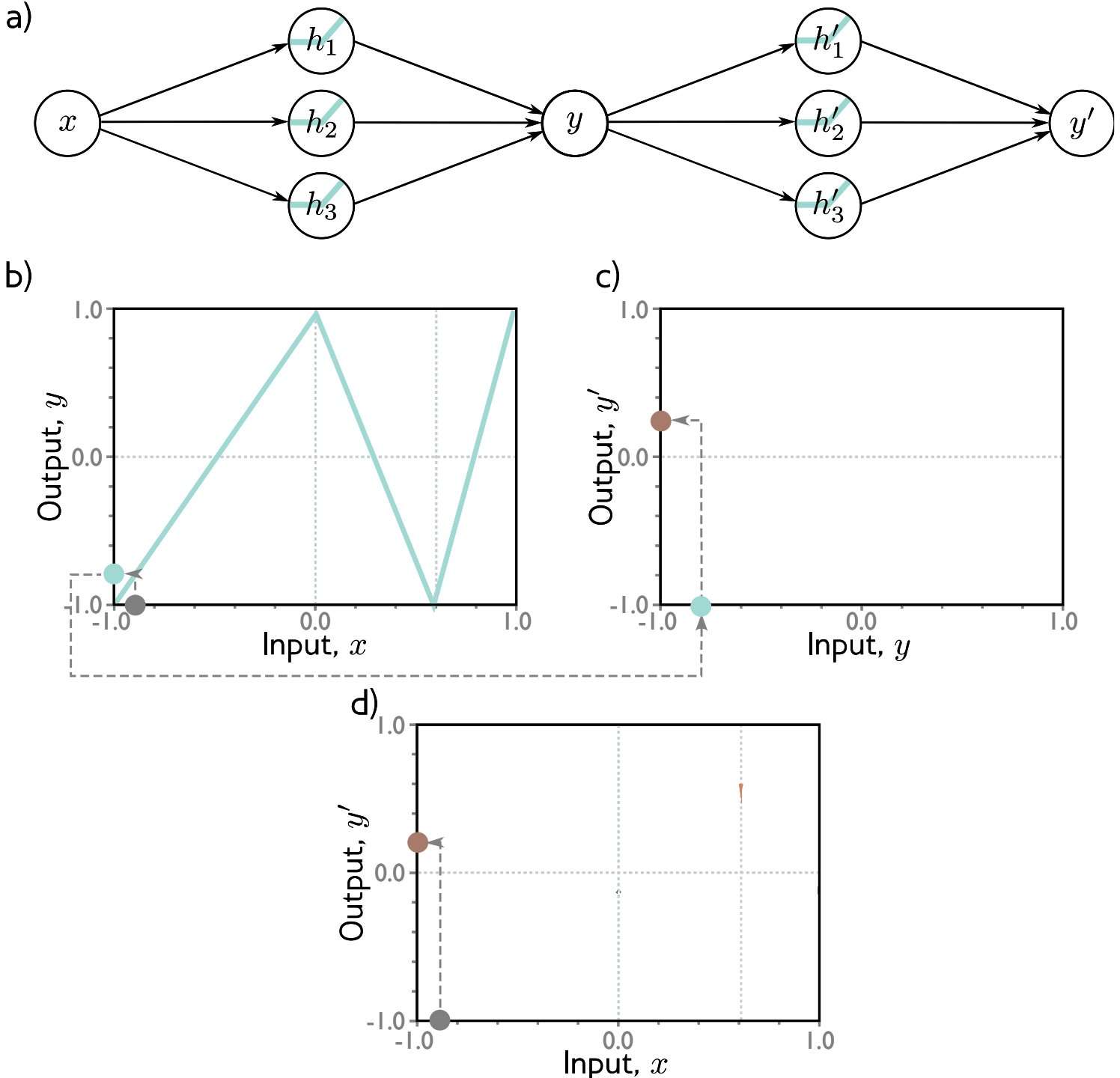



a)
x
h_1
h_2
h_3
y
h'_1
h'_2
h'_3
y'
b)
1.0
0.0
-1.0
Output, y
-1.0
0.0
1.0
Input, x
c)
1.0
0.0
-1.0
Output, y'
-1.0
0.0
1.0
Input, y


a)
x
h_1
h_2
h_3
y
h'_1
h'_2
h'_3
y'
b)
Output, y
Input, x
1.0
0.0
-1.0
c)
Output, y'
Input, y
d)
Output, y'
Input, x


a)
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h_1
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h_3
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h'_2
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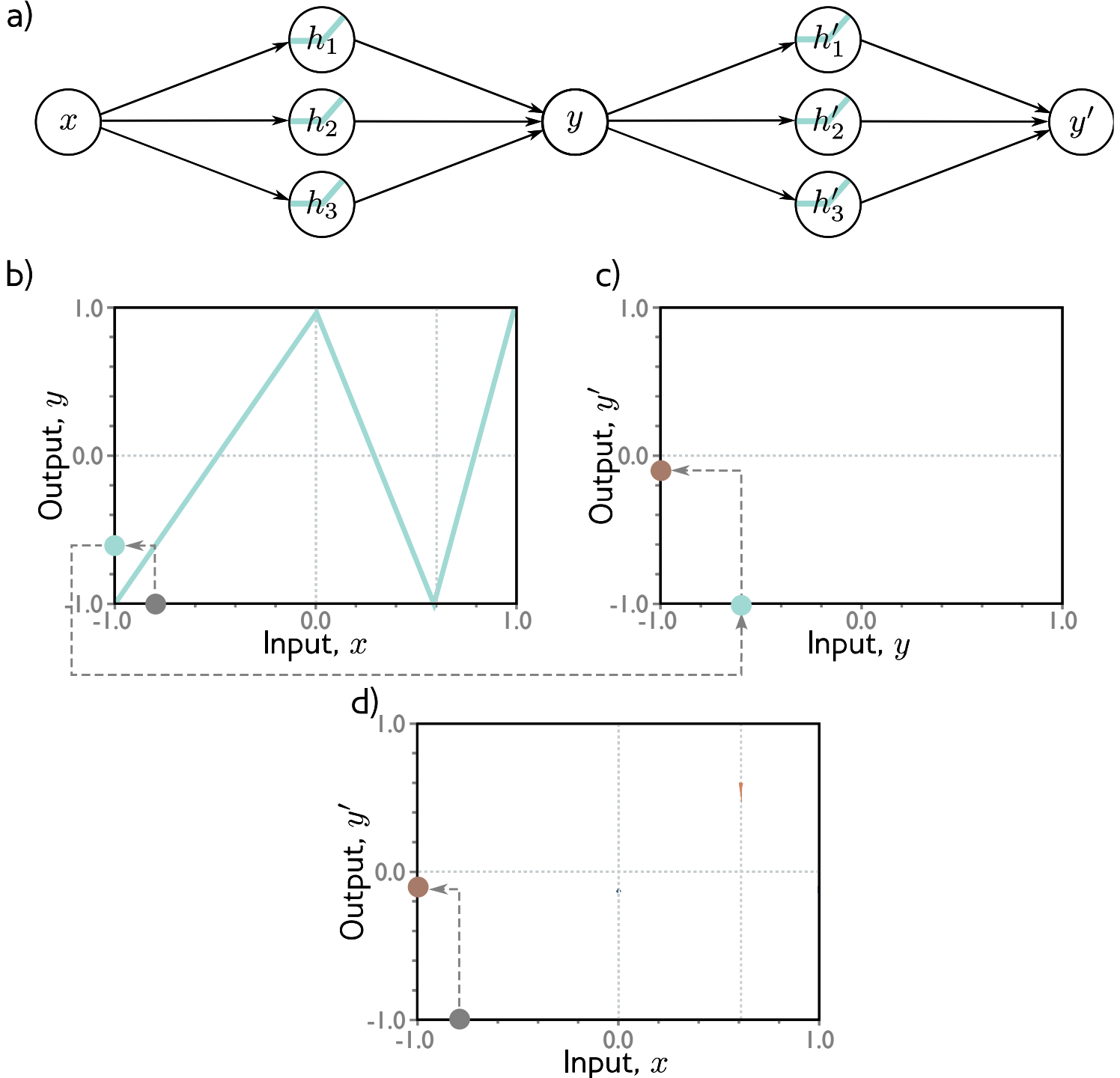
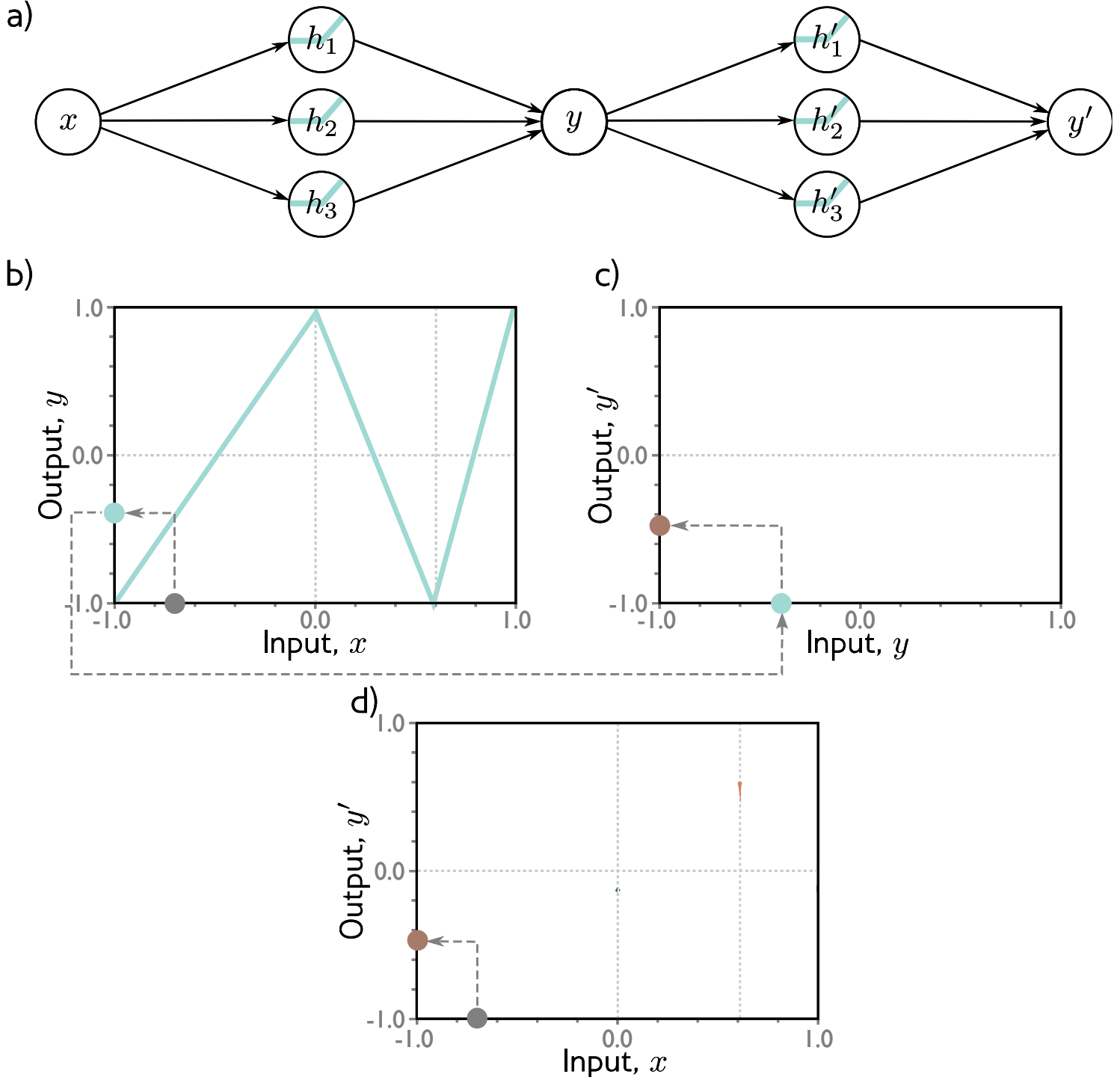
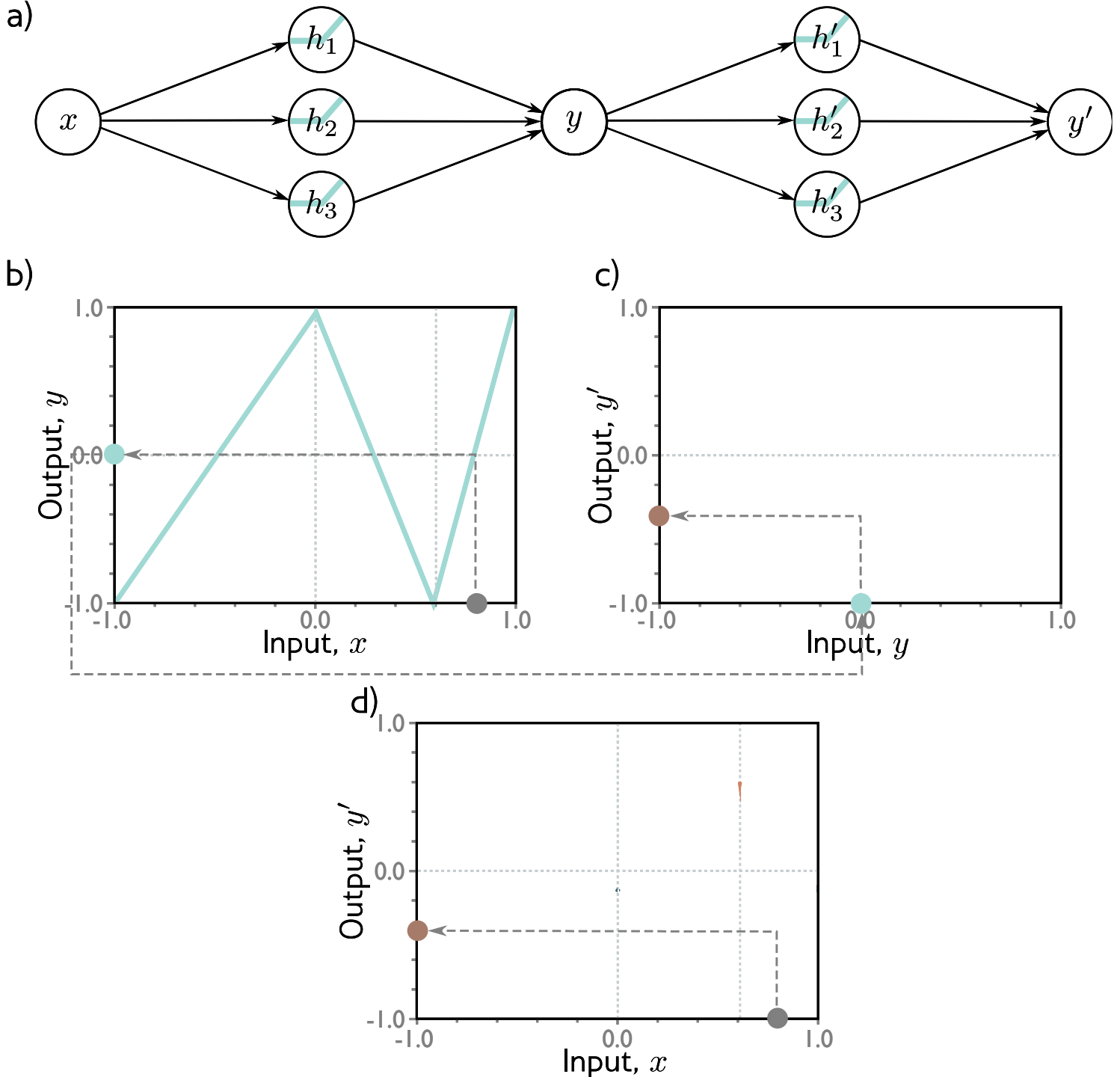
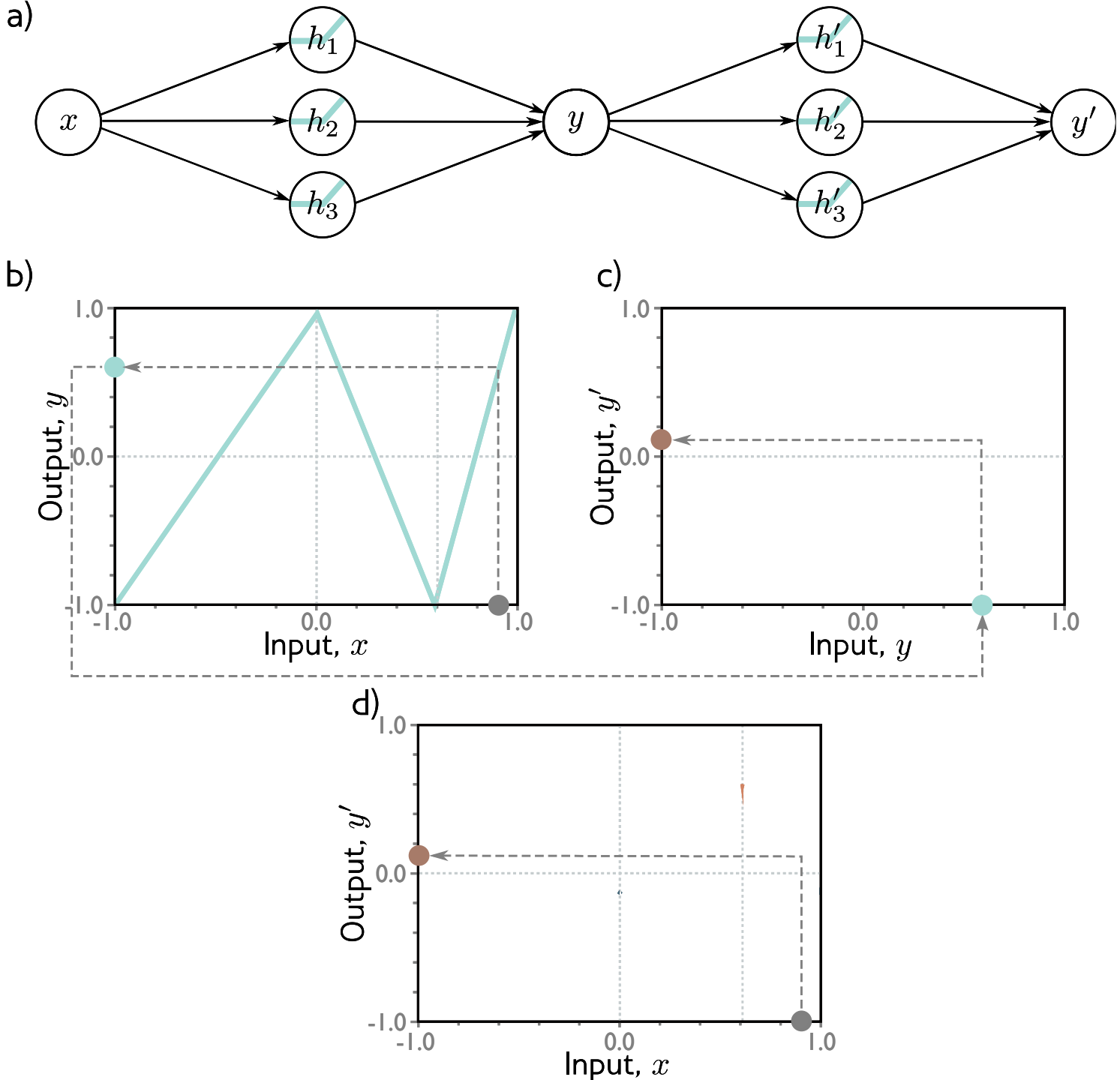
Input, x
1.0
0.0
-1.0
c)
Output, y'
Input, y
d)
Output, y'
Input, x

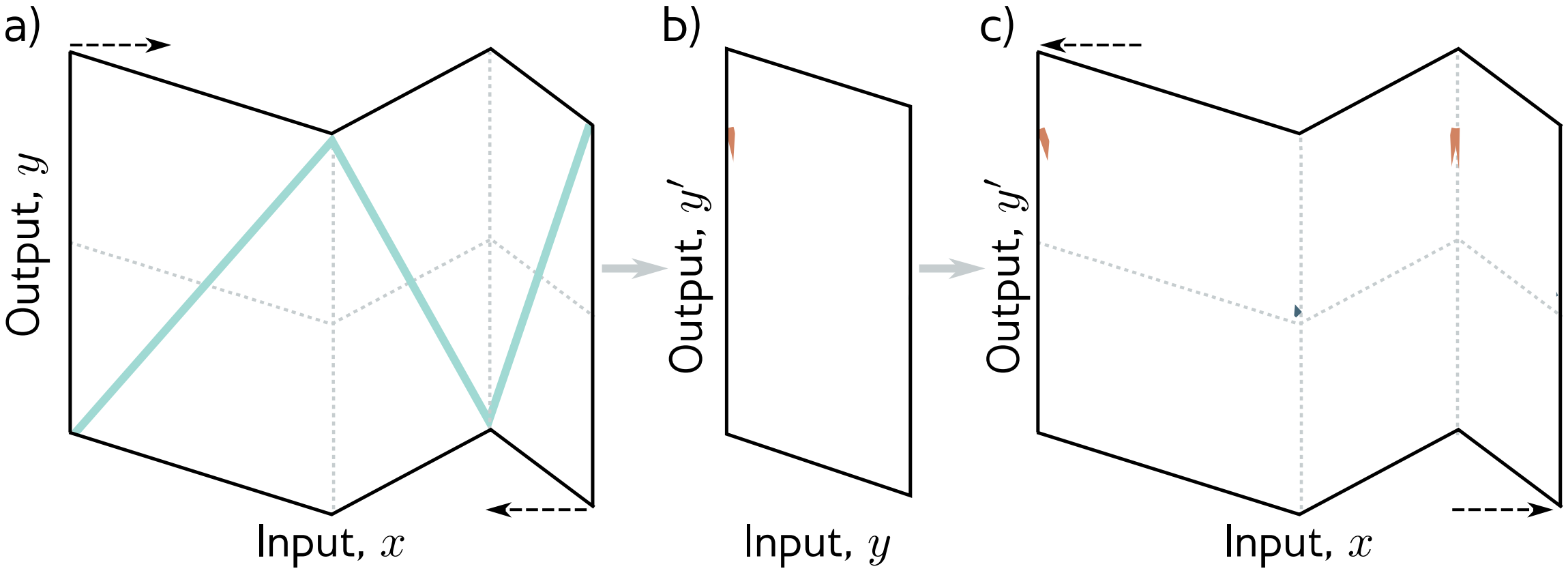

a)
x
h_1
h_2
h_3
y
h'_1
h'_2
h'_3
y'
b)
Output, y
Input, x
1.0
0.0
-1.0
c)
Output, y'
Input, y
d)
Output, y'
Input, x


a)
x
h_1
h_2
h_3
y
h'_1
h'_2
h'_3
y'
b)
Output, y
Input, x
1.0
0.0
-1.0
c)
Output, y'
Input, y
d)
Output, y'
Input, x

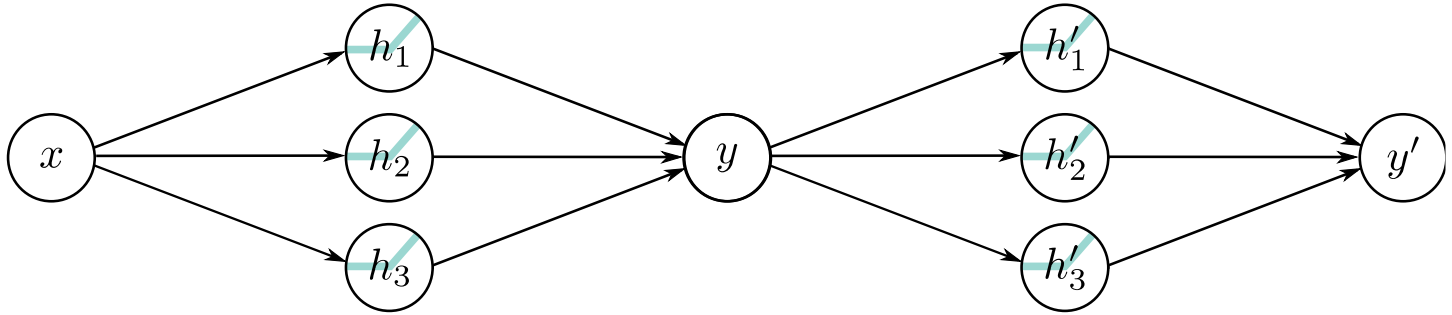

a)
x
h_1
h_2
h_3
y
h'_1
h'_2
h'_3
y'
b)
Output, y
Input, x
1.0
0.0
-1.0
c)
Output, y'
Input, y
d)
Output, y'
Input, x


a)
x
h_1
h_2
h_3
y
h'_1
h'_2
h'_3
y'
b)
Output, y
Input, x
1.0
0.0
-1.0
c)
Output, y'
Input, y
d)
Output, y'
Input, x

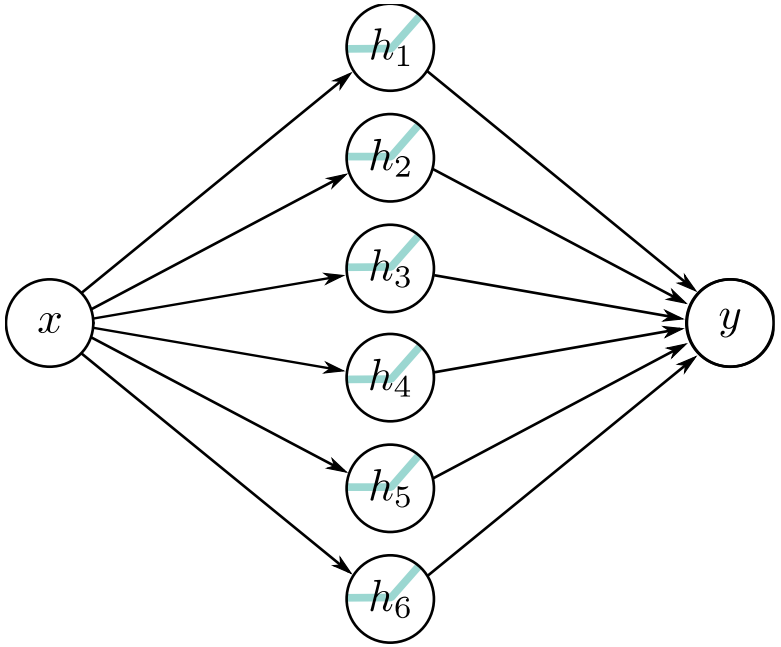
“Folding analogy”



Comparing to shallow with six hidden units



- 20 parameters
- (at least) 9 regions



- 19 parameters
- Max 7 regions

Combine two networks into one

Network 1:

$$h_1 = \mathrm{a}[\theta_{10} + \theta_{11}x]$$
$$h_2 = \mathrm{a}[\theta_{20} + \theta_{21}x]$$
$$h_3 = \mathrm{a}[\theta_{30} + \theta_{31}x]$$

$$y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3$$

Network 2:

$$h'_1 = \mathrm{a}[\theta'_{10} + \theta'_{11}y]$$
$$h'_2 = \mathrm{a}[\theta'_{20} + \theta'_{21}y]$$
$$h'_3 = \mathrm{a}[\theta'_{30} + \theta'_{31}y]$$

$$y' = \phi'_0 + \phi'_1 h'_1 + \phi'_2 h'_2 + \phi'_3 h'_3$$

Hidden units of second network in terms of first:

$$\begin{aligned}
h'_1 &= \mathrm{a}[\theta'_{10} + \theta'_{11}y] &&= \mathrm{a}[\theta'_{10} + \theta'_{11}\phi_0 + \theta'_{11}\phi_1 h_1 + \theta'_{11}\phi_2 h_2 + \theta'_{11}\phi_3 h_3] \\
h'_2 &= \mathrm{a}[\theta'_{20} + \theta'_{21}y] &&= \mathrm{a}[\theta'_{20} + \theta'_{21}\phi_0 + \theta'_{21}\phi_1 h_1 + \theta'_{21}\phi_2 h_2 + \theta'_{21}\phi_3 h_3] \\
h'_3 &= \mathrm{a}[\theta'_{30} + \theta'_{31}y] &&= \mathrm{a}[\theta'_{30} + \theta'_{31}\phi_0 + \theta'_{31}\phi_1 h_1 + \theta'_{31}\phi_2 h_2 + \theta'_{31}\phi_3 h_3]
\end{aligned}$$

Create new variables

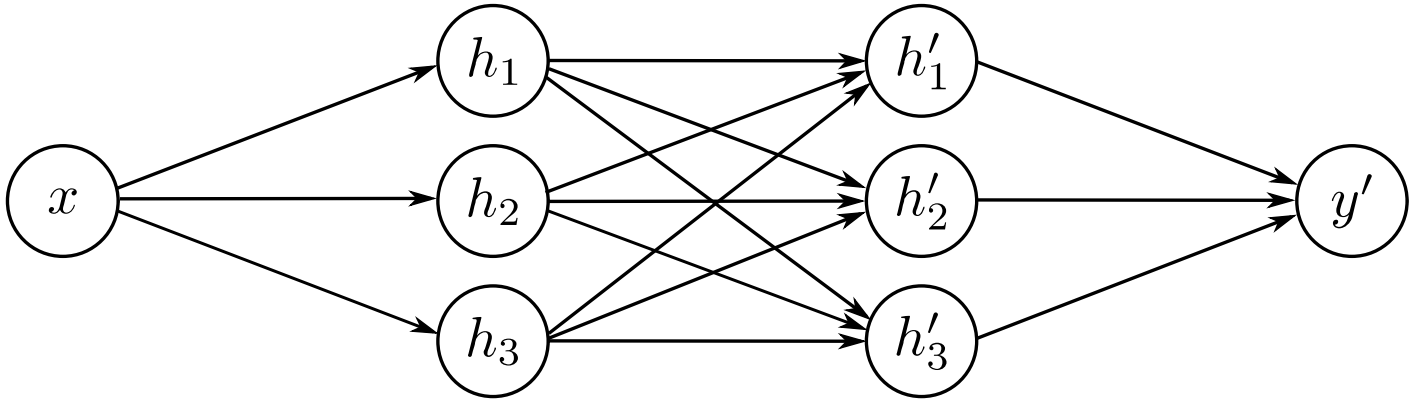
$$
\begin{aligned}
h_1' &= \mathrm{a}[\theta_{10}' + \theta_{11}' y] &&= \mathrm{a}[\theta_{10}' + \theta_{11}'\phi_0 + \theta_{11}'\phi_1 h_1 + \theta_{11}'\phi_2 h_2 + \theta_{11}'\phi_3 h_3] \\
h_2' &= \mathrm{a}[\theta_{20}' + \theta_{21}' y] &&= \mathrm{a}[\theta_{20}' + \theta_{21}'\phi_0 + \theta_{21}'\phi_1 h_1 + \theta_{21}'\phi_2 h_2 + \theta_{21}'\phi_3 h_3] \\
h_3' &= \mathrm{a}[\theta_{30}' + \theta_{31}' y] &&= \mathrm{a}[\theta_{30}' + \theta_{31}'\phi_0 + \theta_{31}'\phi_1 h_1 + \theta_{31}'\phi_2 h_2 + \theta_{31}'\phi_3 h_3]
\end{aligned}
$$

$$
\begin{aligned}
h_1' &= \mathrm{a}[\psi_{10} + \psi_{11} h_1 + \psi_{12} h_2 + \psi_{13} h_3] \\
h_2' &= \mathrm{a}[\psi_{20} + \psi_{21} h_1 + \psi_{22} h_2 + \psi_{23} h_3] \\
h_3' &= \mathrm{a}[\psi_{30} + \psi_{31} h_1 + \psi_{32} h_2 + \psi_{33} h_3]
\end{aligned}
$$

Two-layer network

$$h_1 = \mathrm{a}[\theta_{10} + \theta_{11}x] \qquad h'_1 = \mathrm{a}[\psi_{10} + \psi_{11}h_1 + \psi_{12}h_2 + \psi_{13}h_3]$$
$$h_2 = \mathrm{a}[\theta_{20} + \theta_{21}x] \qquad h'_2 = \mathrm{a}[\psi_{20} + \psi_{21}h_2 + \psi_{22}h_2 + \psi_{23}h_3]$$
$$h_3 = \mathrm{a}[\theta_{30} + \theta_{31}x] \qquad h'_3 = \mathrm{a}[\psi_{30} + \psi_{31}h_2 + \psi_{32}h_2 + \psi_{33}h_3]$$

$$y' = \phi'_0 + \phi'_1 h'_1 + \phi'_2 h'_2 + \phi'_3 h'_3$$

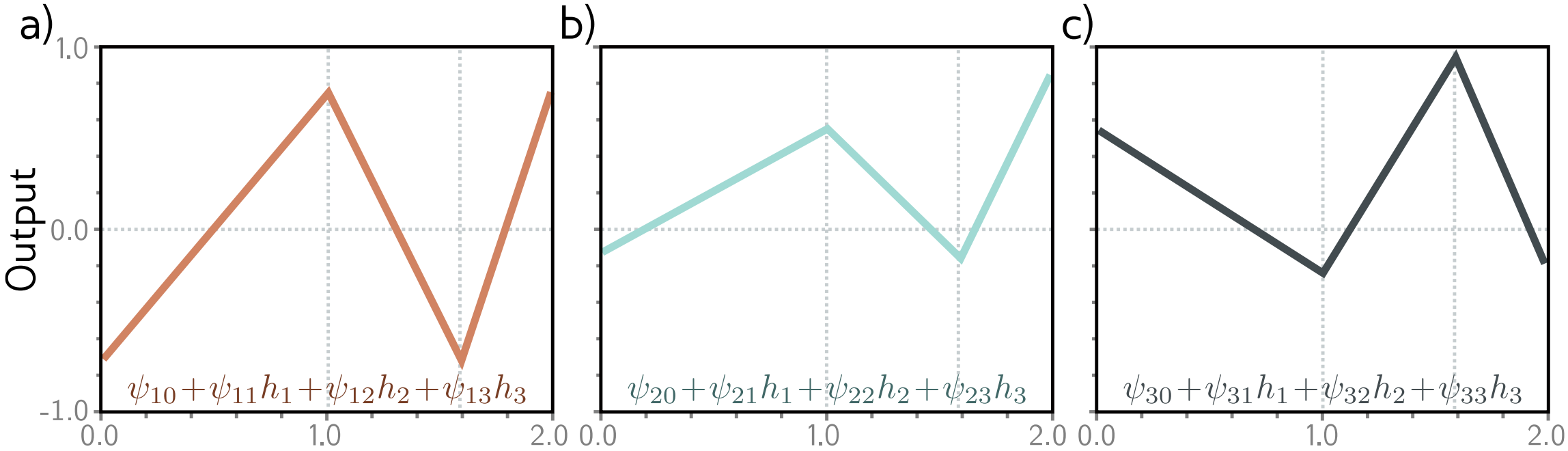


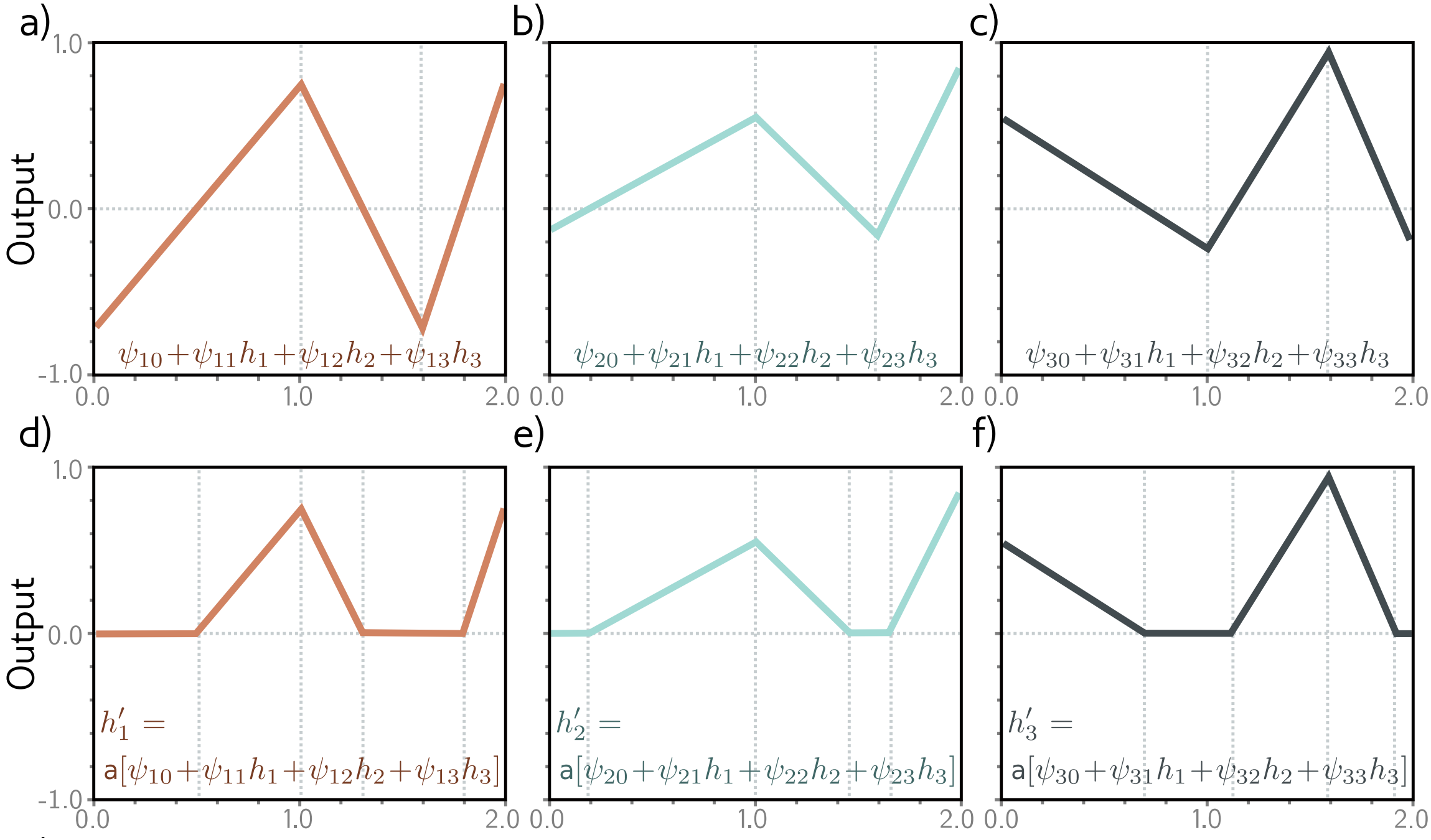
Two-layer network as one equation

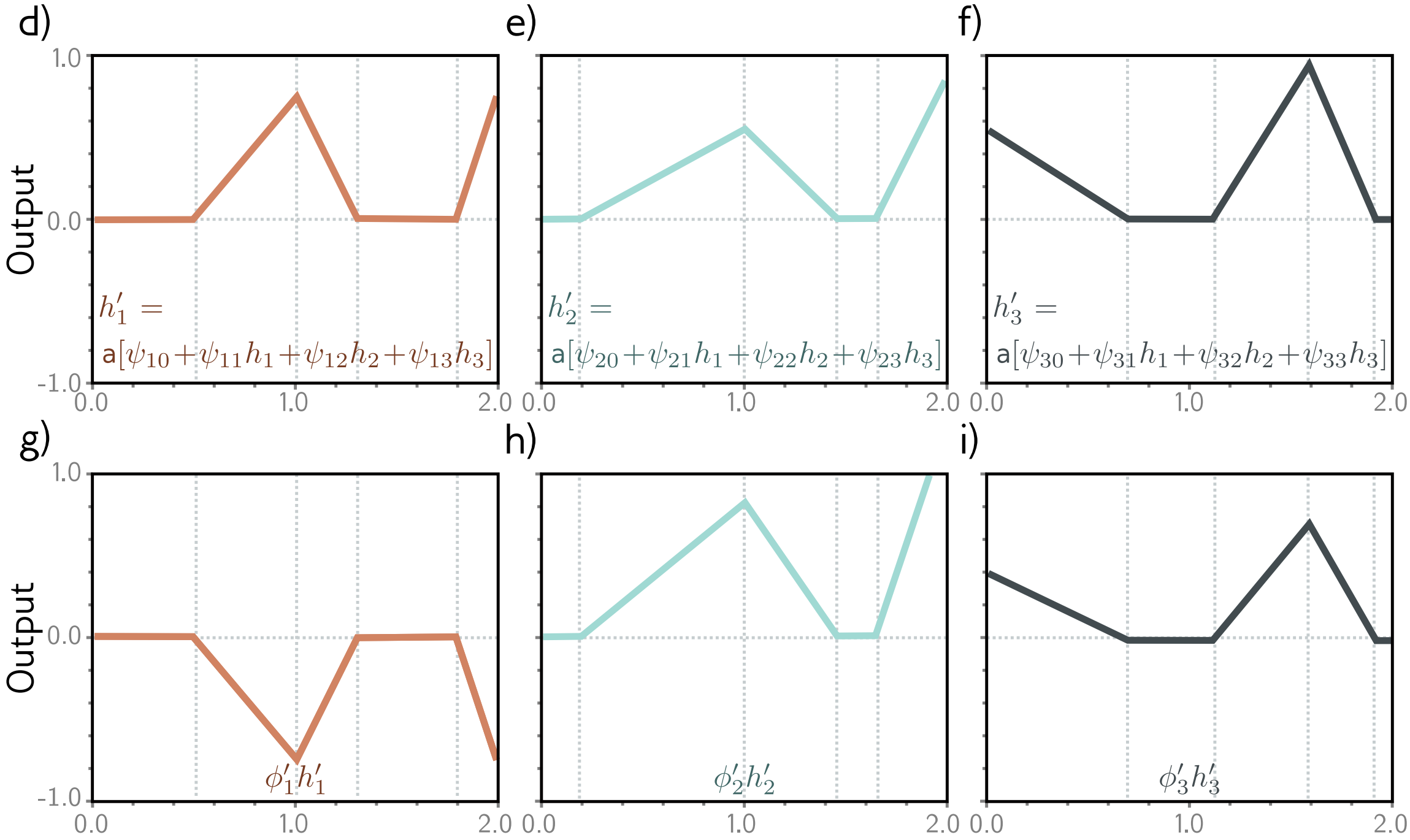
$$
\begin{aligned}
h_1 &= \mathrm{a}[\theta_{10} + \theta_{11}x] \\
h_2 &= \mathrm{a}[\theta_{20} + \theta_{21}x] \\
h_3 &= \mathrm{a}[\theta_{30} + \theta_{31}x]
\end{aligned}
\qquad
\begin{aligned}
h'_1 &= \mathrm{a}[\psi_{10} + \psi_{11}h_1 + \psi_{12}h_2 + \psi_{13}h_3] \\
h'_2 &= \mathrm{a}[\psi_{20} + \psi_{21}h_1 + \psi_{22}h_2 + \psi_{23}h_3] \\
h'_3 &= \mathrm{a}[\psi_{30} + \psi_{31}h_1 + \psi_{32}h_2 + \psi_{33}h_3]
\end{aligned}
$$

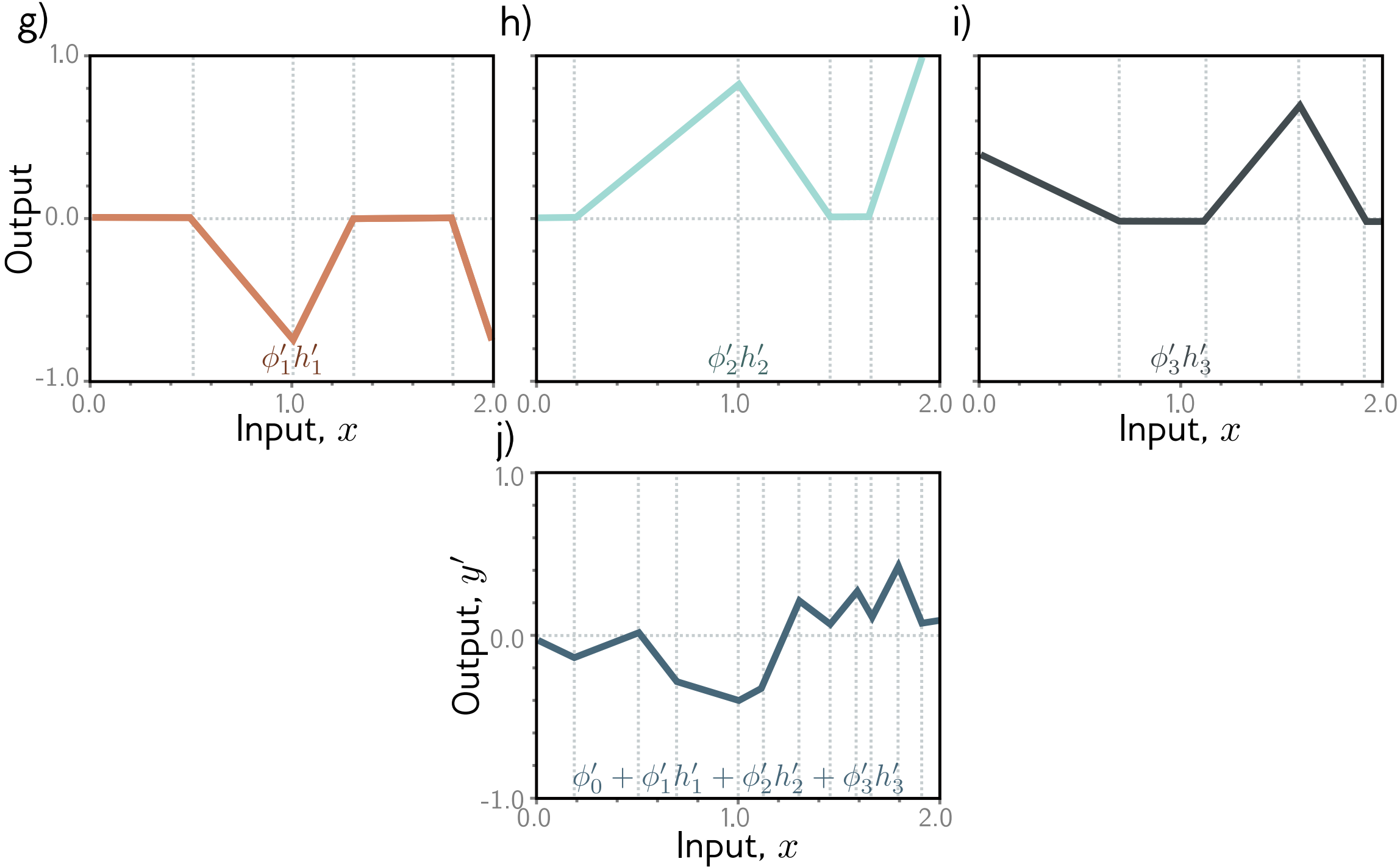
$$
y' = \phi'_0 + \phi'_1 h'_1 + \phi'_2 h'_2 + \phi'_3 h'_3
$$

$$
\begin{aligned}
y' = \phi'_0 &+ \phi'_1 \mathrm{a}\left[\psi_{10} + \psi_{11}\mathrm{a}[\theta_{10} + \theta_{11}x] + \psi_{12}\mathrm{a}[\theta_{20} + \theta_{21}x] + \psi_{13}\mathrm{a}[\theta_{30} + \theta_{31}x]\right] \\
&+ \phi'_2 \mathrm{a}[\psi_{20} + \psi_{21}\mathrm{a}[\theta_{10} + \theta_{11}x] + \psi_{22}\mathrm{a}[\theta_{20} + \theta_{21}x] + \psi_{23}\mathrm{a}[\theta_{30} + \theta_{31}x]] \\
&+ \phi'_3 \mathrm{a}[\psi_{30} + \psi_{31}\mathrm{a}[\theta_{10} + \theta_{11}x] + \psi_{32}\mathrm{a}[\theta_{20} + \theta_{21}x] + \psi_{33}\mathrm{a}[\theta_{30} + \theta_{31}x]]
\end{aligned}
$$


a)
b)
c)
Output
1.0
0.0
-1.0
0.0
1.0
2.0
$\psi_{10}+\psi_{11}h_1+\psi_{12}h_2+\psi_{13}h_3$
$\psi_{20}+\psi_{21}h_1+\psi_{22}h_2+\psi_{23}h_3$
$\psi_{30}+\psi_{31}h_1+\psi_{32}h_2+\psi_{33}h_3$


a)
b)
c)
d)
e)
f)
Output
Output
1.0
0.0
-1.0
0.0
1.0
2.0
$\psi_{10}+\psi_{11}h_1+\psi_{12}h_2+\psi_{13}h_3$
$\psi_{20}+\psi_{21}h_1+\psi_{22}h_2+\psi_{23}h_3$
$\psi_{30}+\psi_{31}h_1+\psi_{32}h_2+\psi_{33}h_3$
$h_1' =$
$\mathsf{a}[\psi_{10}+\psi_{11}h_1+\psi_{12}h_2+\psi_{13}h_3]$
$h_2' =$
$\mathsf{a}[\psi_{20}+\psi_{21}h_1+\psi_{22}h_2+\psi_{23}h_3]$
$h_3' =$
$\mathsf{a}[\psi_{30}+\psi_{31}h_1+\psi_{32}h_2+\psi_{33}h_3]$


d)
e)
f)
g)
h)
i)
Output
Output
1.0
0.0
-1.0
0.0
1.0
2.0
$h_1' = \mathrm{a}[\psi_{10}+\psi_{11}h_1+\psi_{12}h_2+\psi_{13}h_3]$
$h_2' = \mathrm{a}[\psi_{20}+\psi_{21}h_1+\psi_{22}h_2+\psi_{23}h_3]$
$h_3' = \mathrm{a}[\psi_{30}+\psi_{31}h_1+\psi_{32}h_2+\psi_{33}h_3]$
$\phi_1'h_1'$
$\phi_2'h_2'$
$\phi_3'h_3'$


g)
h)
i)
j)
1.0
0.0
-1.0
Output
$\phi_1' h_1'$
$\phi_2' h_2'$
$\phi_3' h_3'$
0.0
1.0
2.0
Input, x
Output, y'
$\phi_0' + \phi_1' h_1' + \phi_2' h_2' + \phi_3' h_3'$

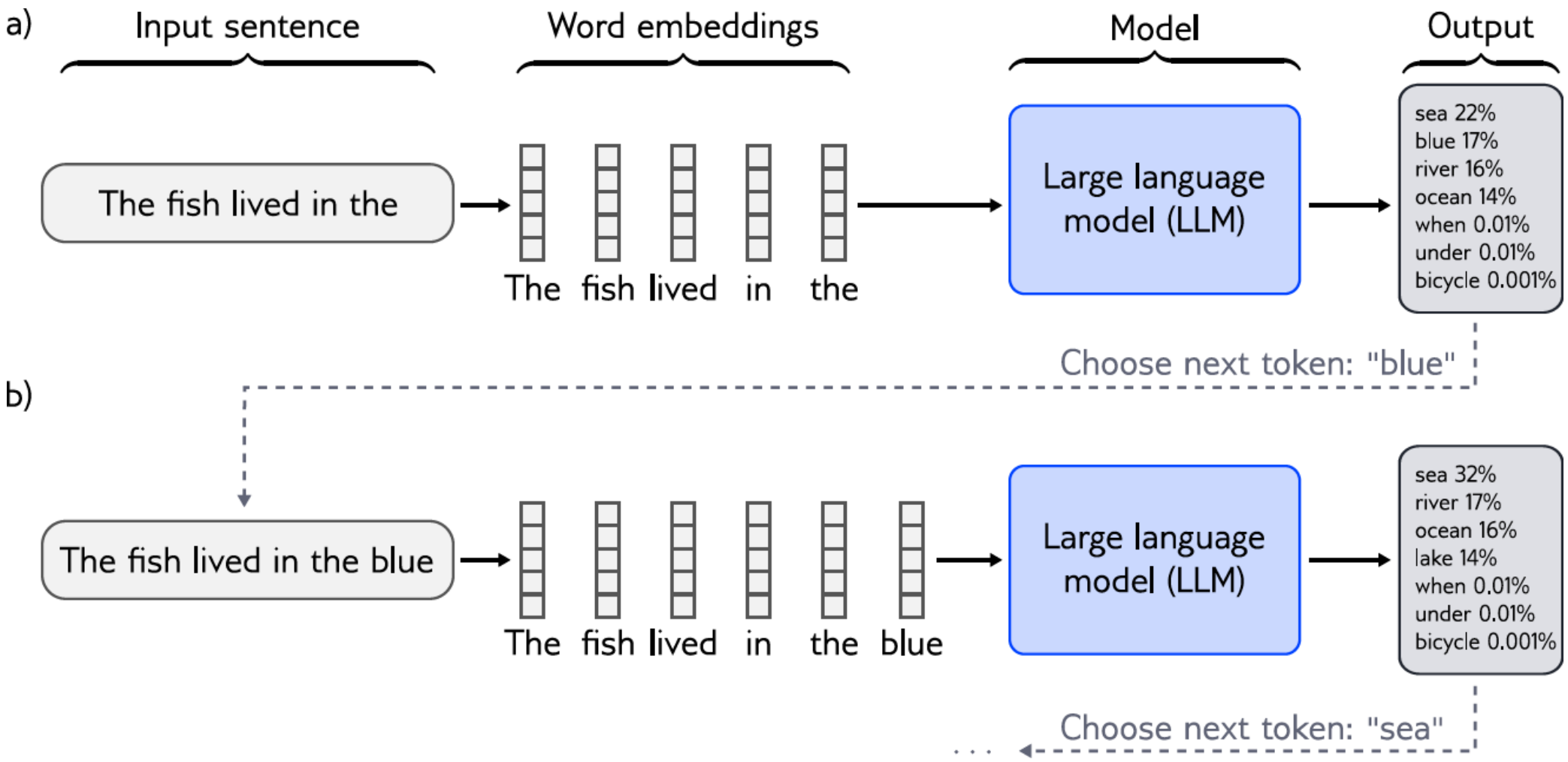
4. Neural Networks: Playground Exercises

- https://developers.google.com/machine-learning/crash-course/introduction-to-neural-networks/playground-exercises

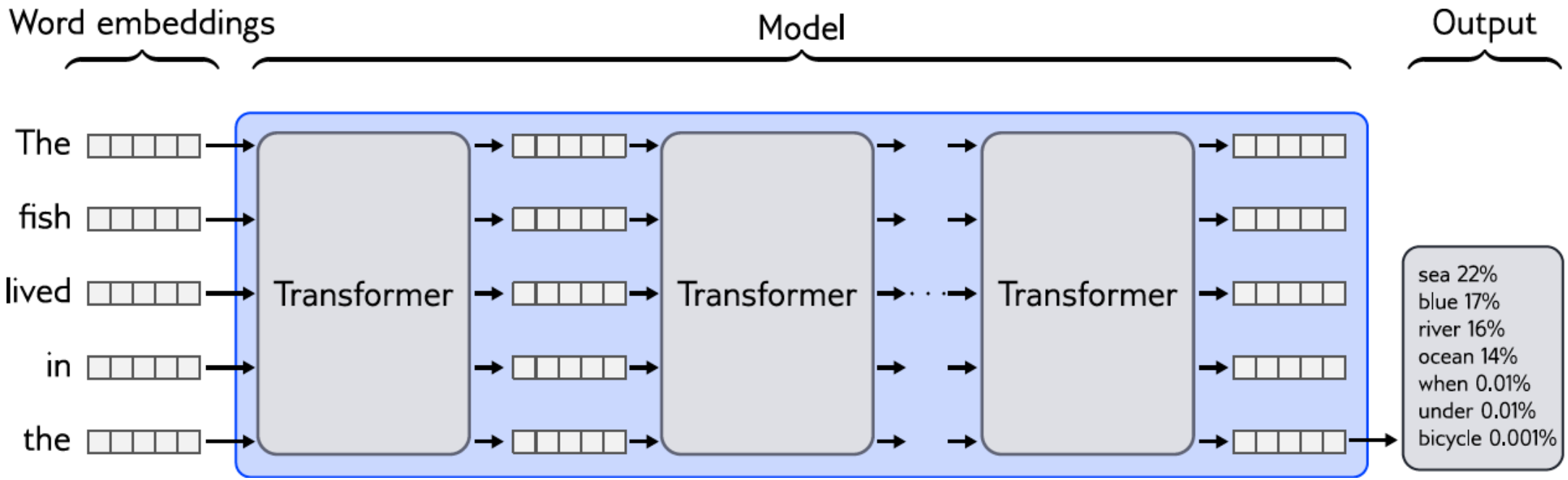
5. nanoGPT demo

- by Andrei Karpathy
- https://www.youtube.com/watch?v=kCc8FmEb1nY
- https://www.youtube.com/watch?v=6jTQ61tBeoQ

Decoder model



Predicting next



GPT3 (Brown et al. 2020)

- Sequence lengths are 2048 tokens long
- Batch size is 3.2 million tokens.
- 96 transformer layers (some of which implement a sparse version of attention), each of which processes a word embedding of size 12288.
- 96 heads in the self-attention layers and the value, query, and key dimension is 128.
- 300 billion tokens
- 175 billion parameters

Large Language Models are becoming very large indeed

Conclusion

- Demos of linear regression, shallow NN and deep NN
- NN training parameters
- Generative LLM