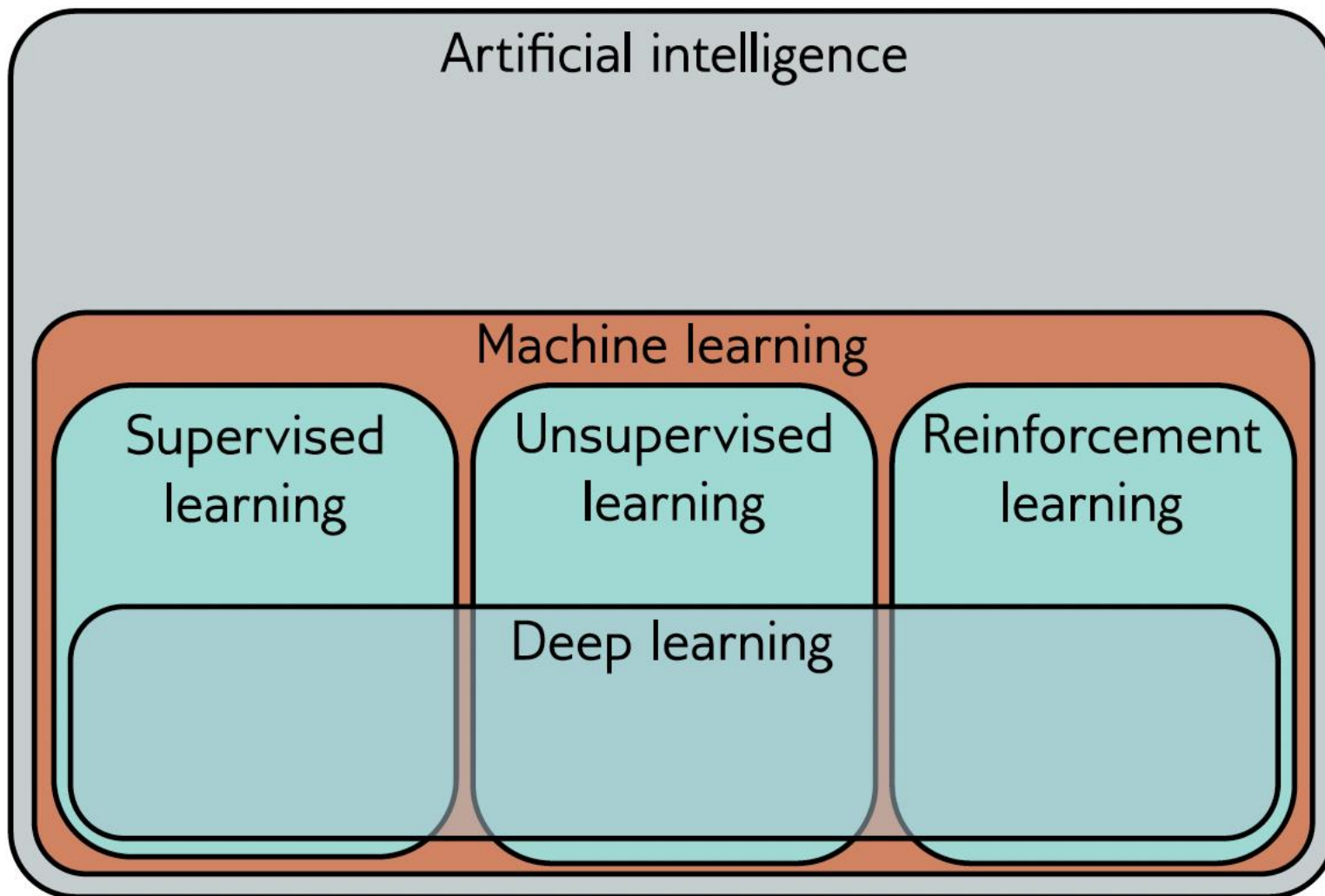
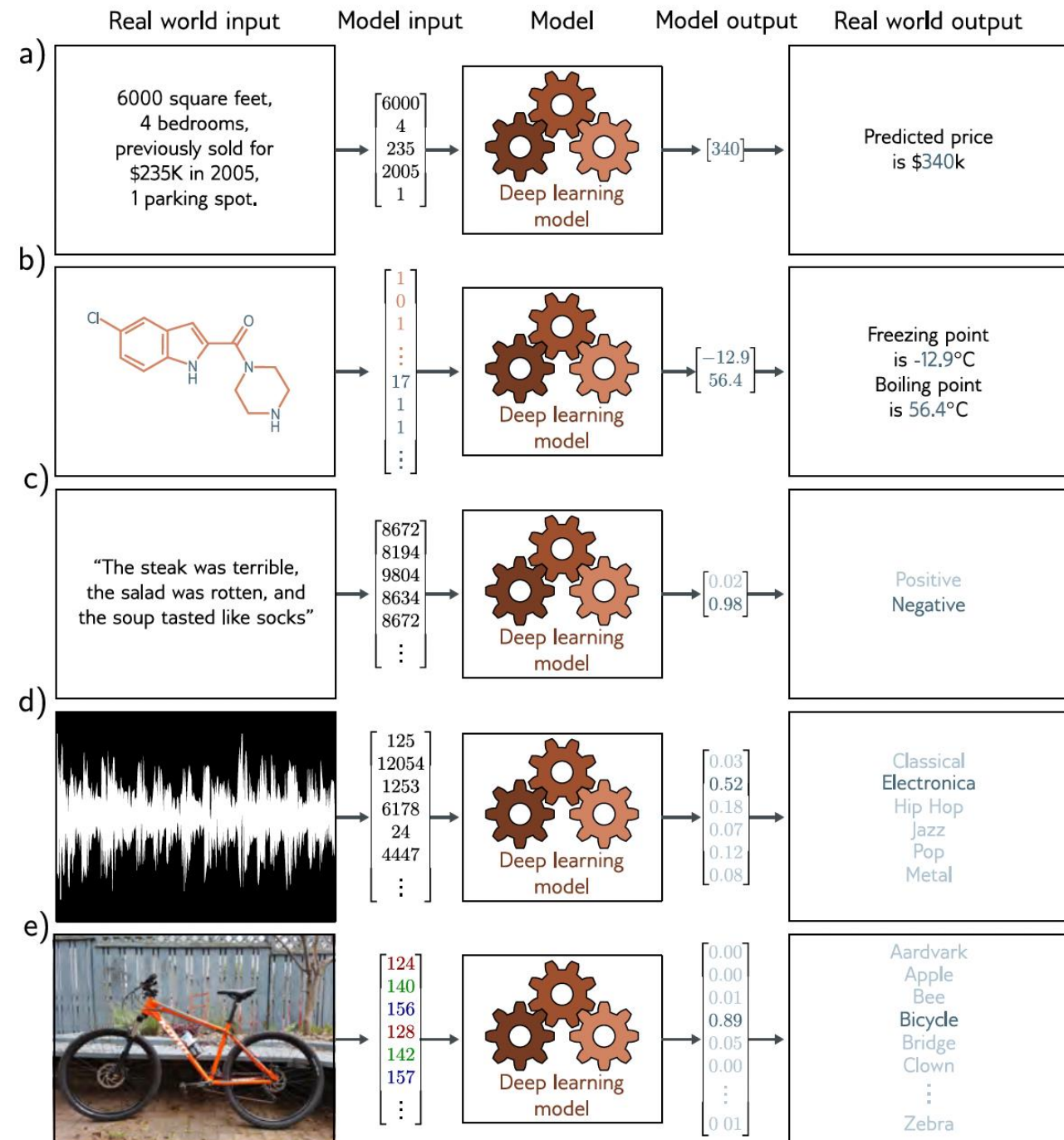
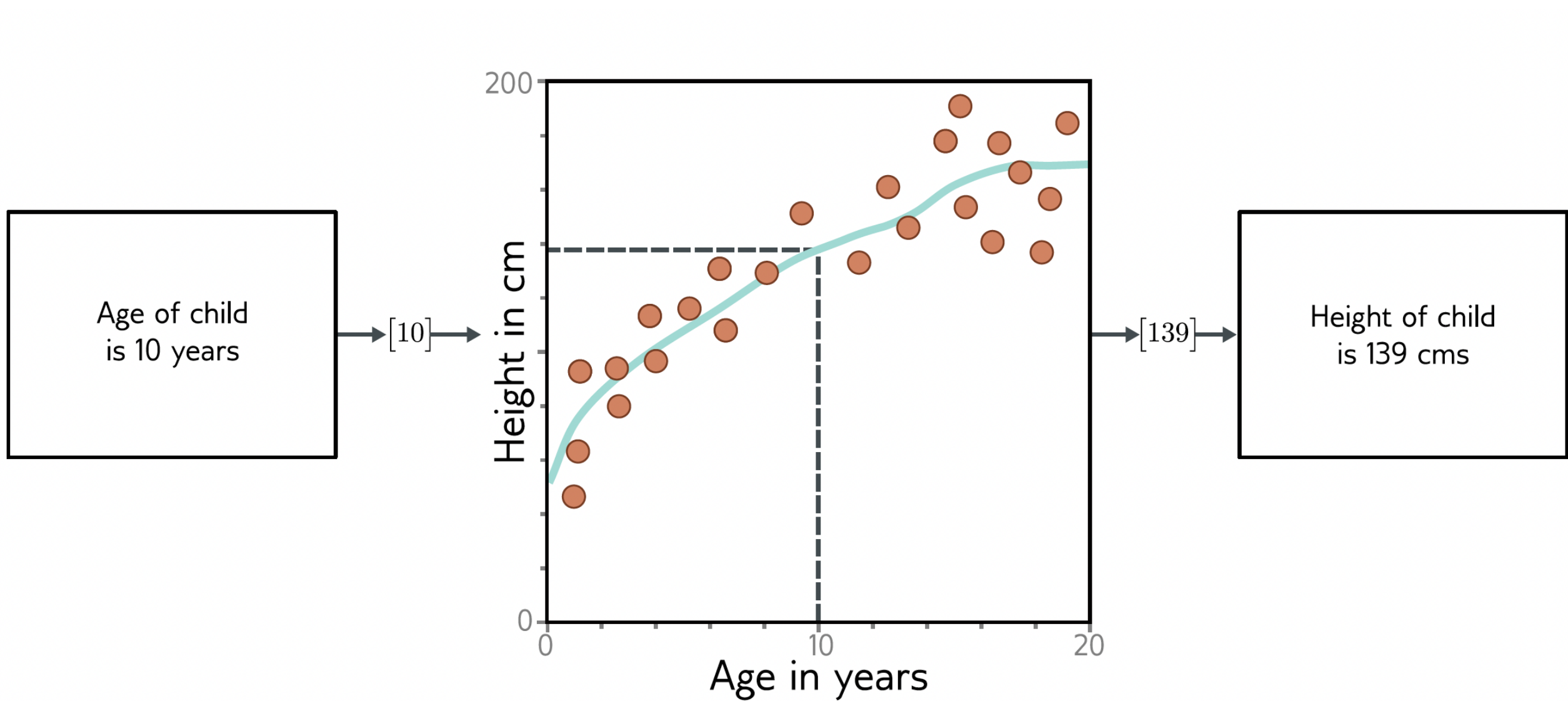


Recap and beyond

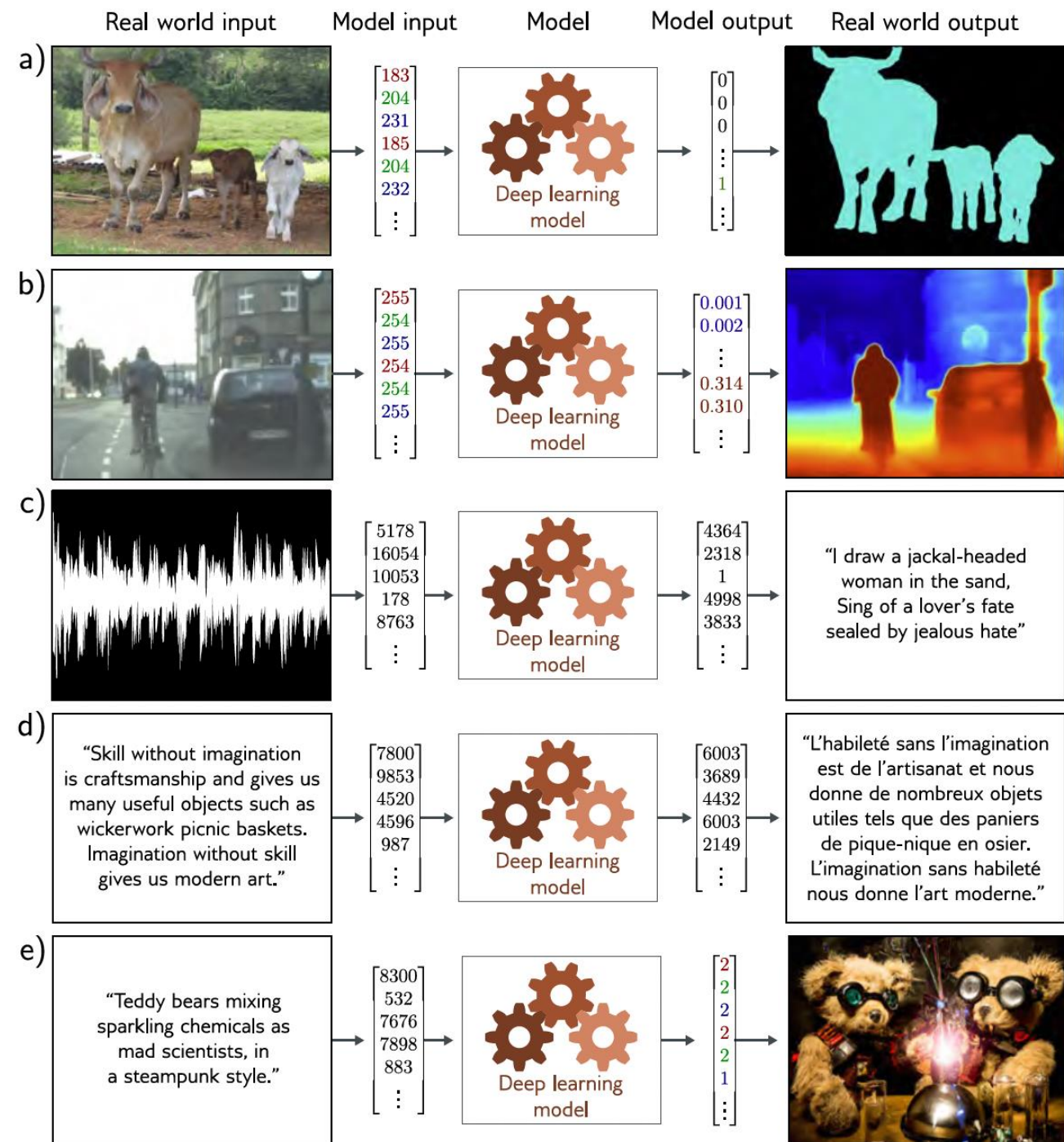


Regression VS classification problems





More complex cases *let that sink in*



Supervised Learning – General Formulation

In supervised learning, we aim to build a model that takes an input x and outputs a prediction y

$$\mathbf{y} = \mathbf{f}[\mathbf{x}]$$

Supervised Learning – General Formulation

Regardless of the approach: neural networks, random forest, support-vector machines, etc. Our model have parameters

$$\mathbf{y} = \mathbf{f}[\mathbf{x}, \phi]$$

Supervised Learning – General Formulation

When we talk about learning or training, we are saying we are fitting the model to find parameters that make good predictions. In other words, we are minimizing the model prediction against the data. Which implies in minimizing the *loss function*.

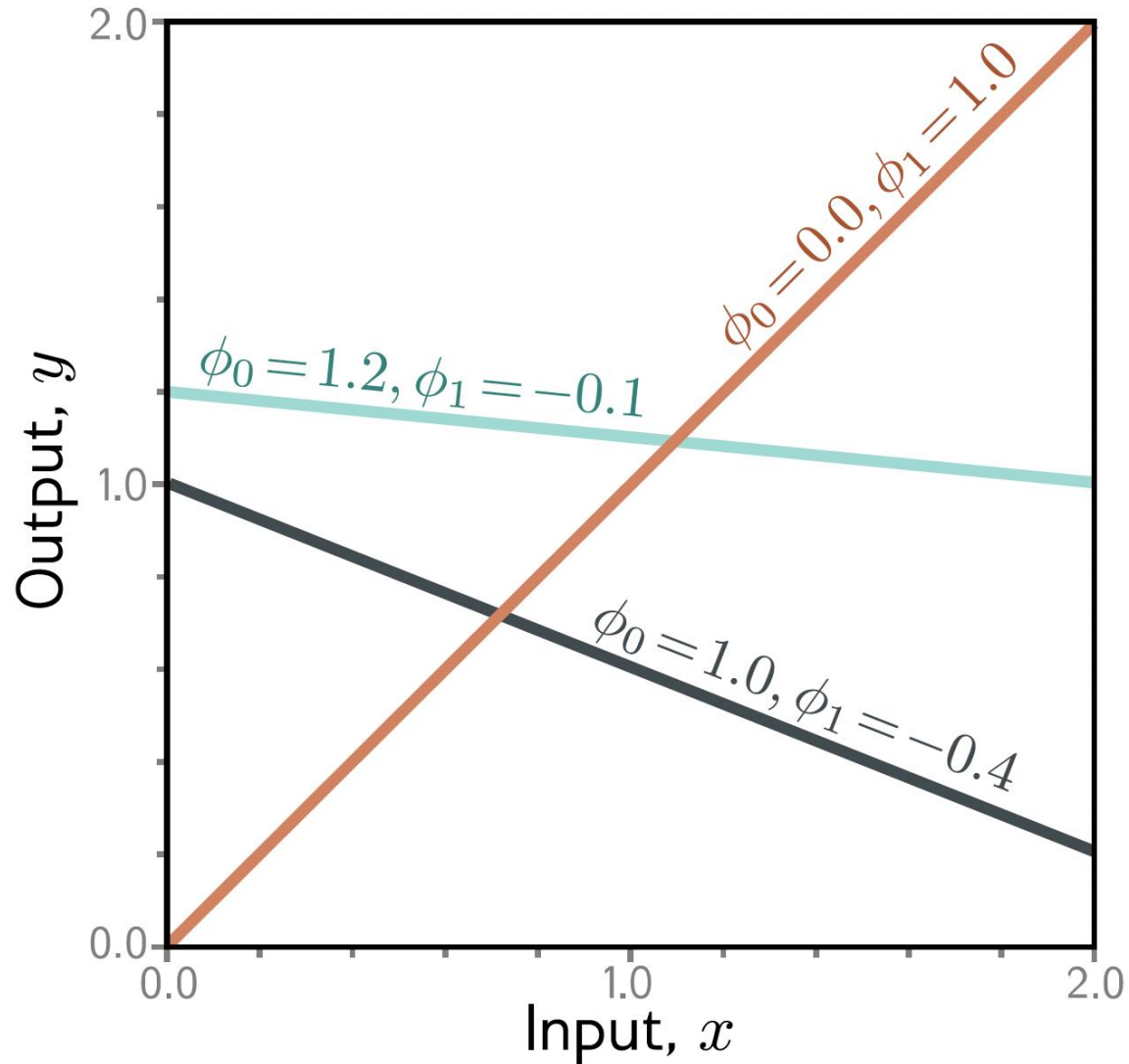
$$\hat{\phi} = \underset{\phi}{\operatorname{argmin}} \left[L[\phi] \right]$$

The case of Linear Regression

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

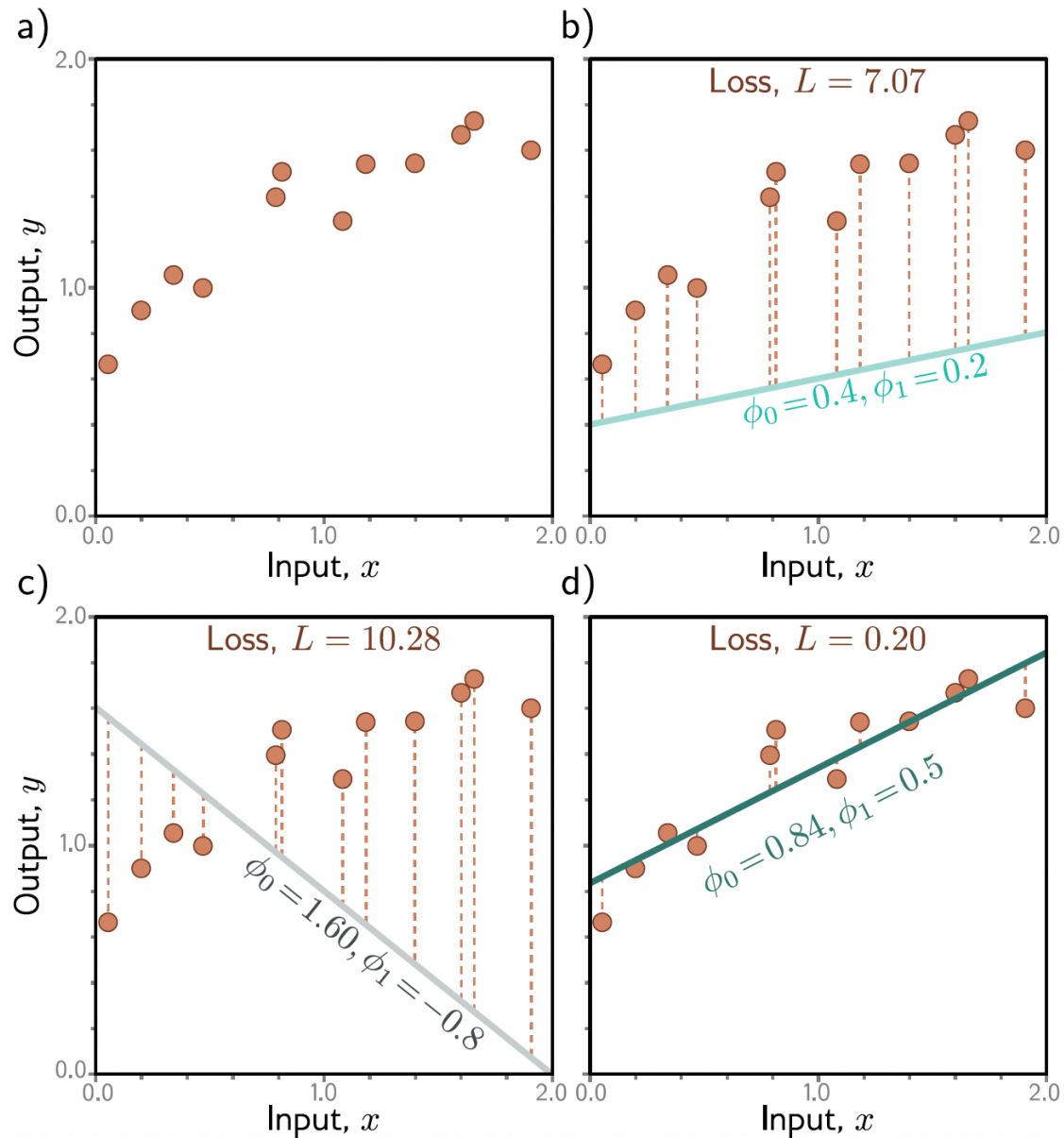
On this simple case, the function f is known, but not the parameters.

The case of Linear Regression



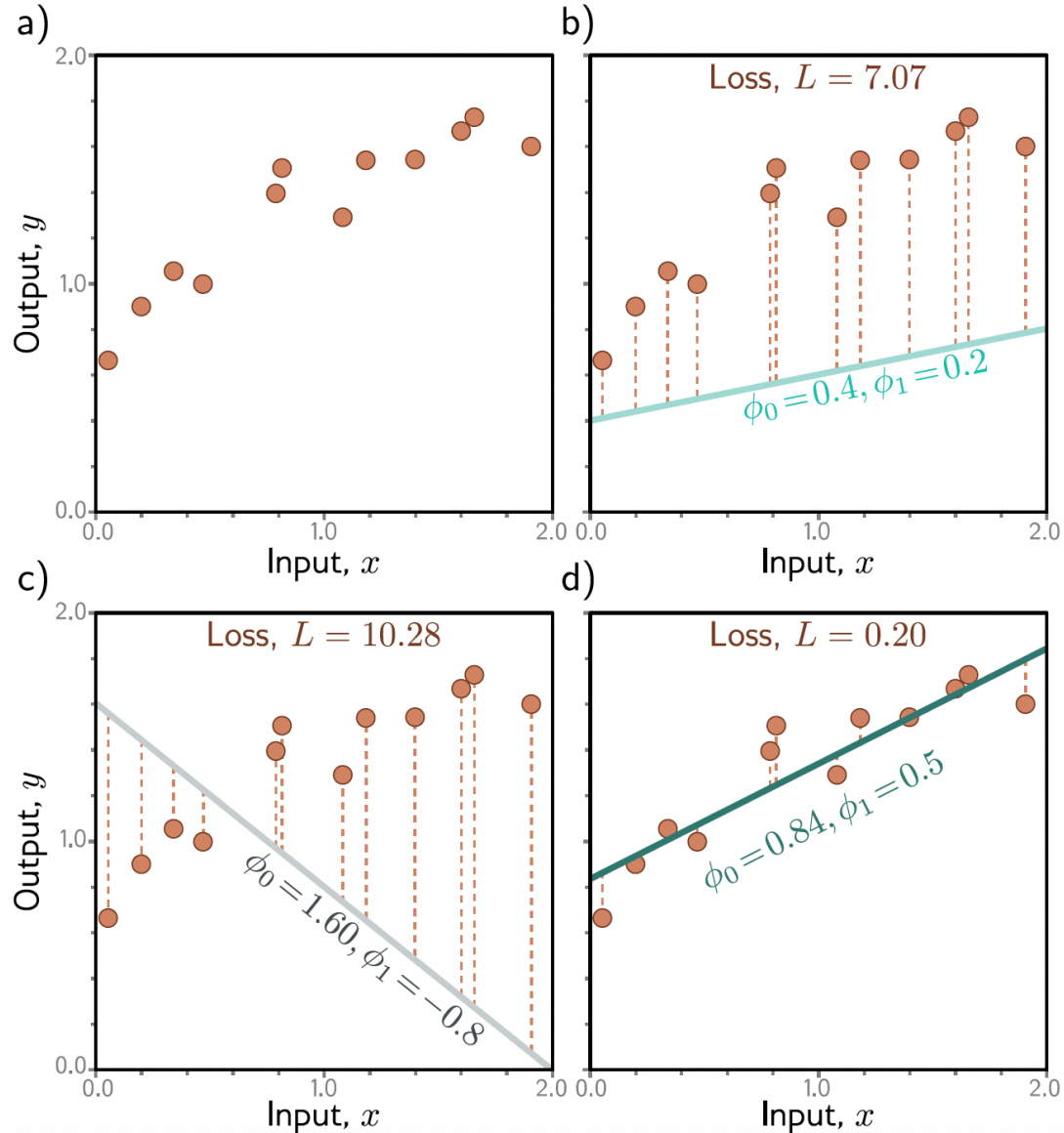
Linear regression model. For a given choice of parameters $\phi = [\phi_0, \phi_1]^T$, the model makes a prediction for the output (y-axis) based on the input (x-axis). Different choices for the y-intercept ϕ_0 and the slope ϕ_1 change these predictions (cyan, orange, and gray lines). The linear regression model (equation 2.4) defines a family of input/output relations (lines) and the parameters determine the member of the family (the particular line).

Loss Function



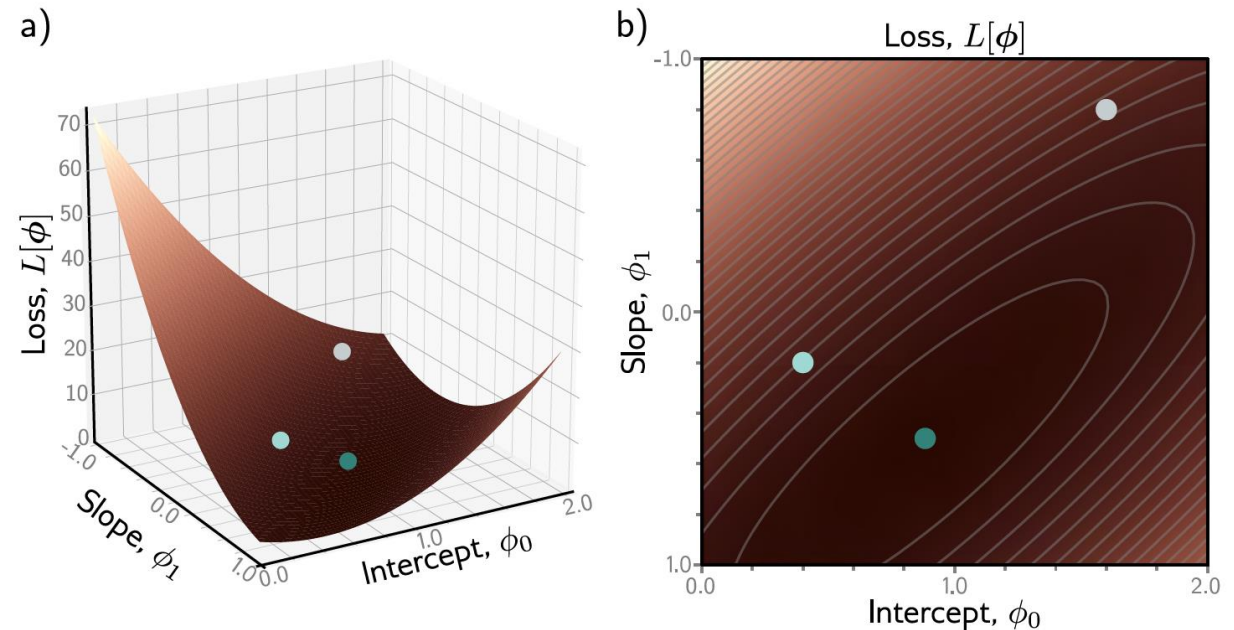
$$\begin{aligned} L[\phi] &= \sum_{i=1}^I (f[x_i, \phi] - y_i)^2 \\ &= \sum_{i=1}^I (\phi_0 + \phi_1 x_i - y_i)^2. \end{aligned}$$

Let's appreciate this for a moment.
 Now it's a good time for questions.

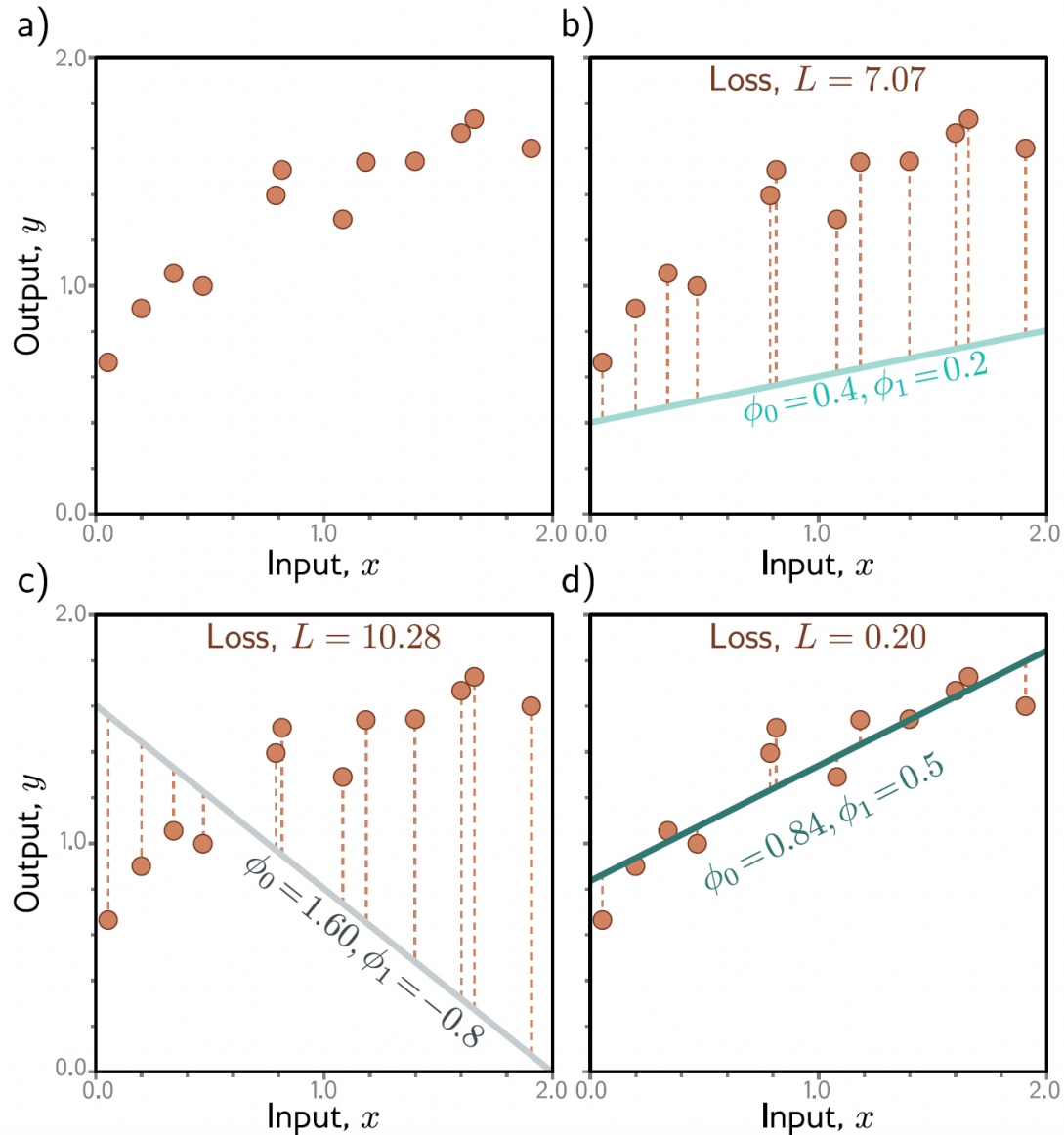


$$L[\phi] = \sum_{i=1}^I (f[x_i, \phi] - y_i)^2$$

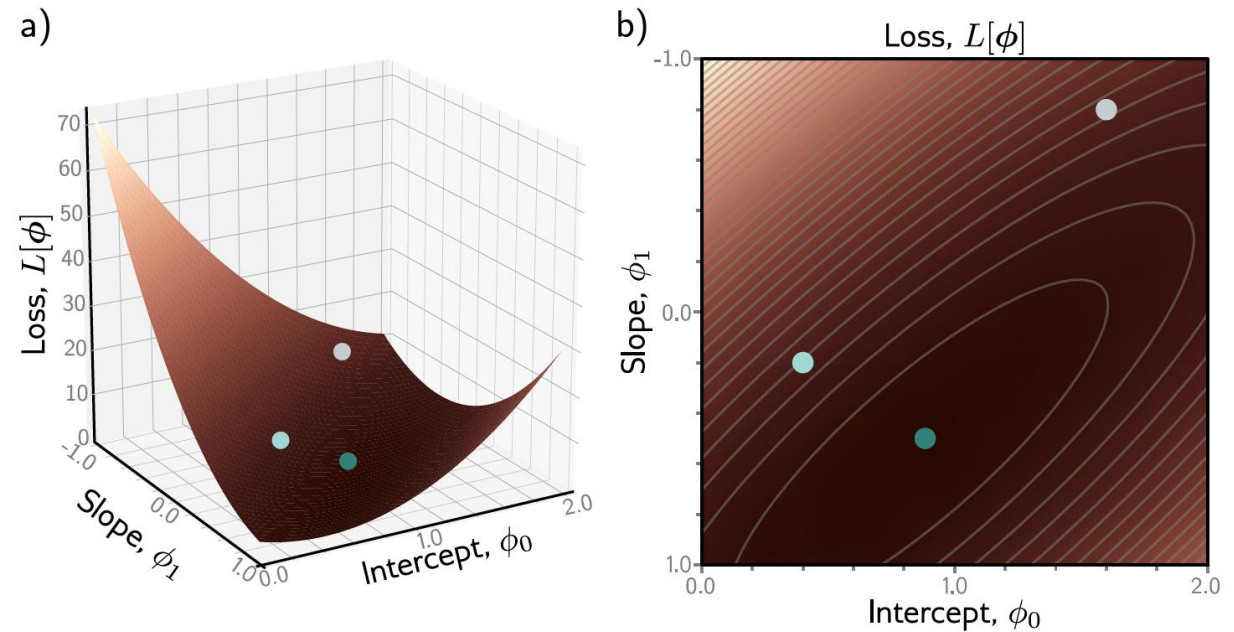
$$= \sum_{i=1}^I (\phi_0 + \phi_1 x_i - y_i)^2.$$

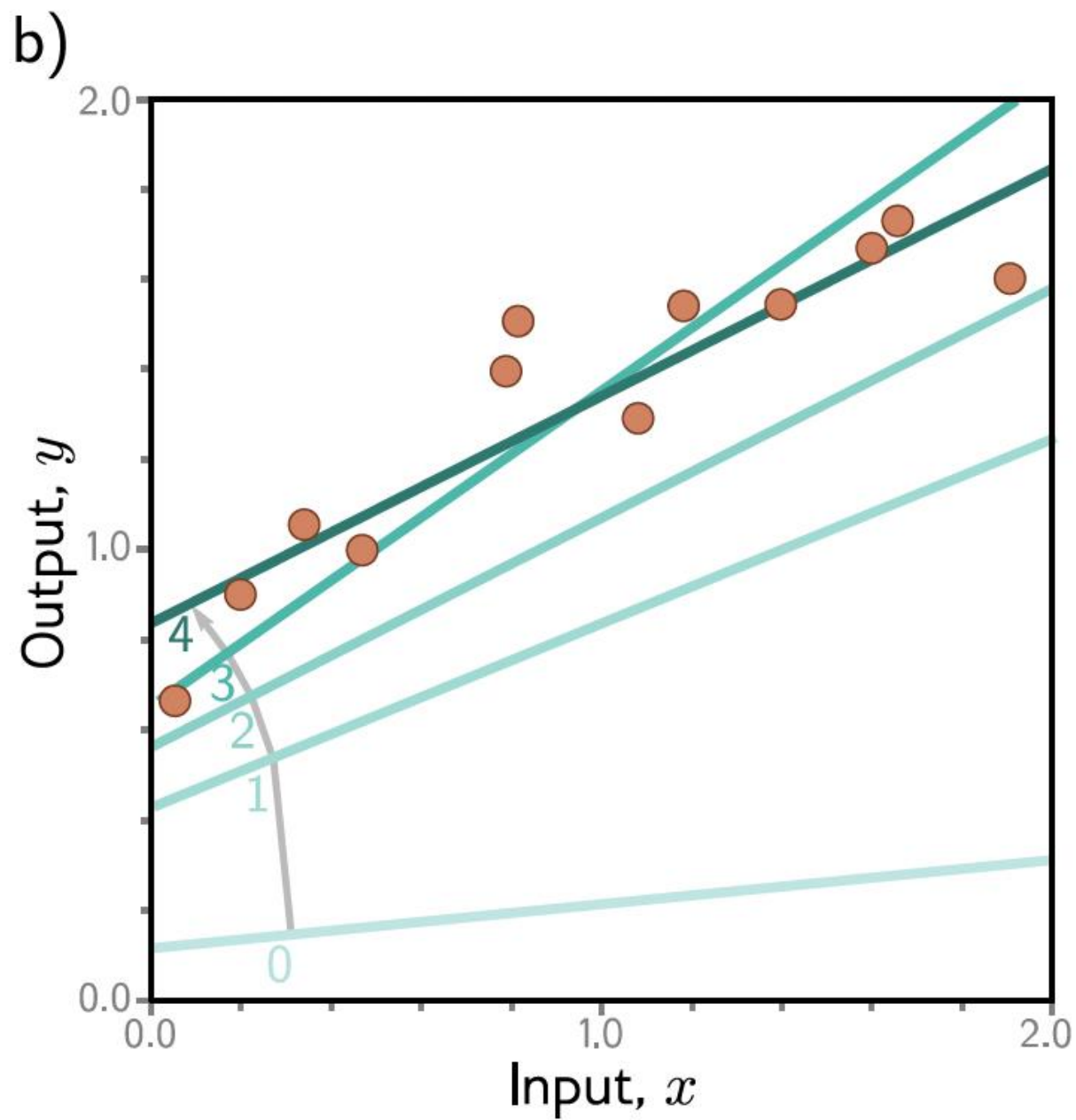
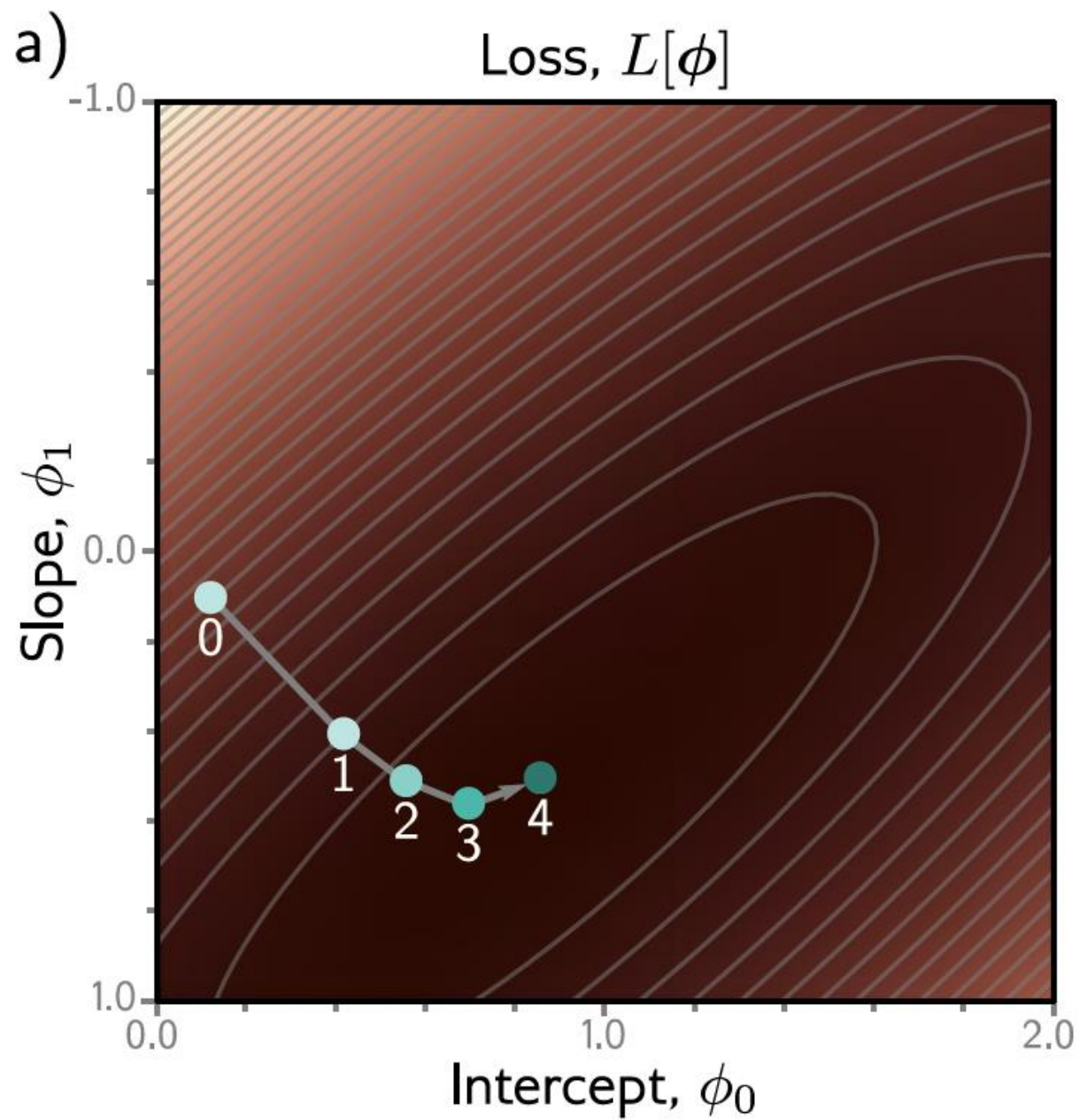


Let's appreciate this for a moment.
 Now it's a good time for questions.



$$\begin{aligned}\hat{\phi} &= \operatorname{argmin}_{\phi} [L[\phi]] \\ &= \operatorname{argmin}_{\phi} \left[\sum_{i=1}^I (f[x_i, \phi] - y_i)^2 \right] \\ &= \operatorname{argmin}_{\phi} \left[\sum_{i=1}^I (\phi_0 + \phi_1 x_i - y_i)^2 \right].\end{aligned}$$



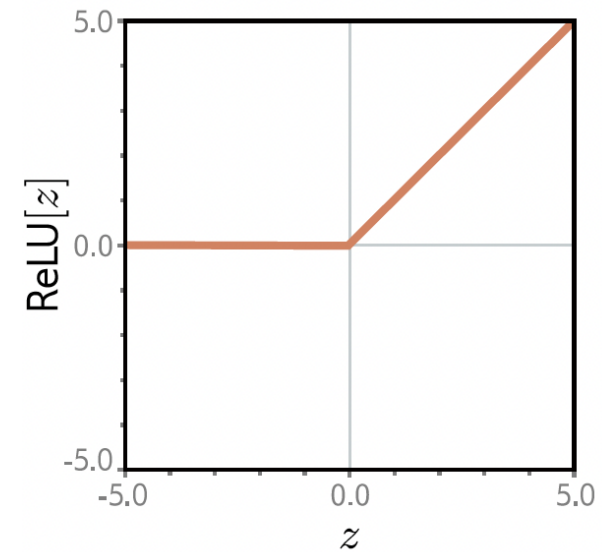


The case of neural networks

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

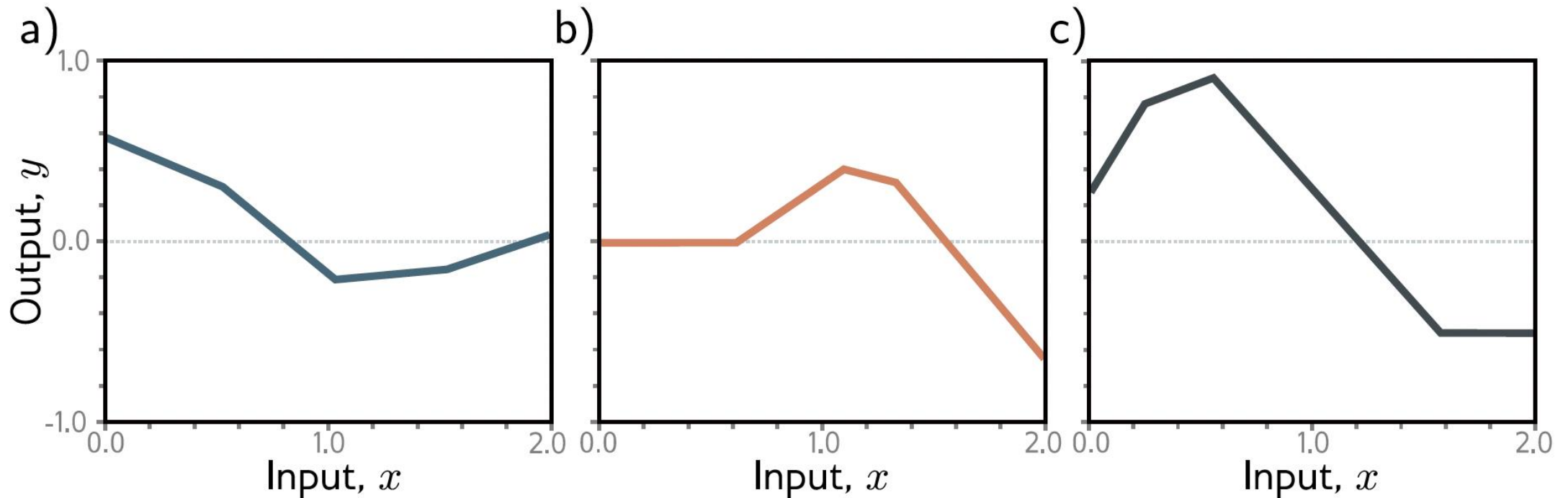
$$\phi = \{\phi_0, \phi_1, \phi_2, \phi_3, \theta_{10}, \theta_{11}, \theta_{20}, \theta_{21}, \theta_{30}, \theta_{31}\}$$

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



The case of neural networks

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



Different values of the parameters

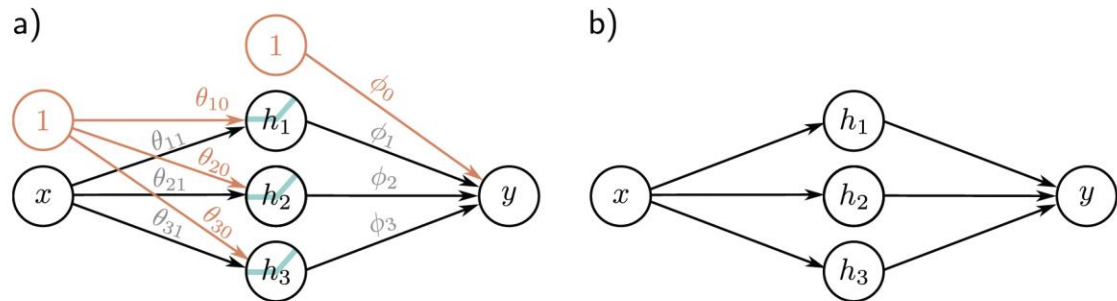
Neural Network Intuition

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

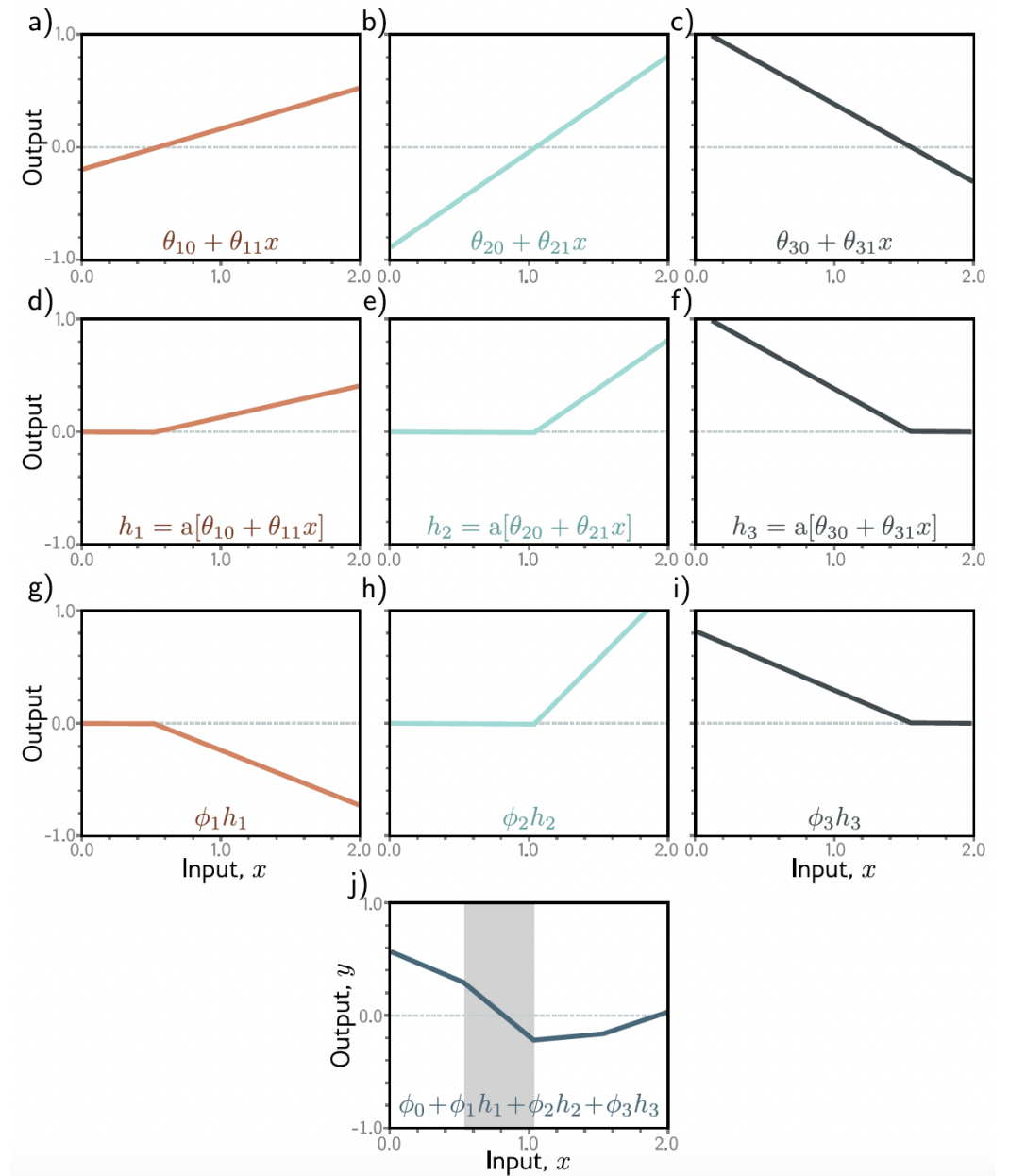
$$\begin{aligned} h_1 &= a[\theta_{10} + \theta_{11}x] \\ h_2 &= a[\theta_{20} + \theta_{21}x] \\ h_3 &= a[\theta_{30} + \theta_{31}x], \end{aligned}$$

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

Hidden Units

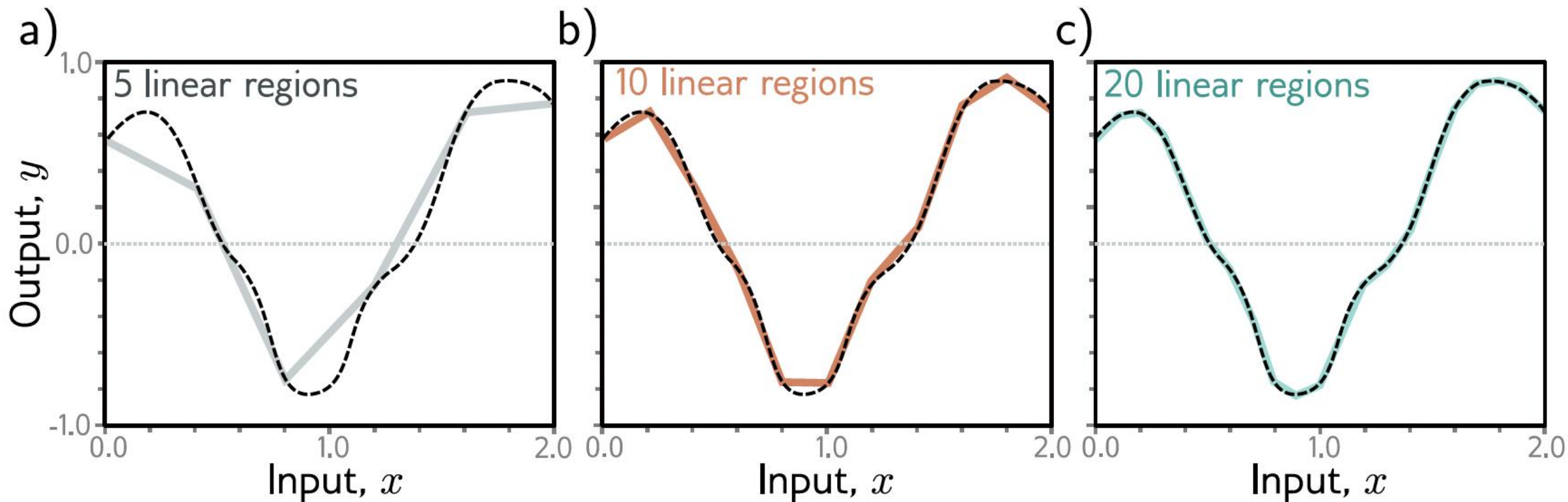


$$y = \phi_0 + \phi_1 h_1 + \phi_2 h_2 + \phi_3 h_3.$$

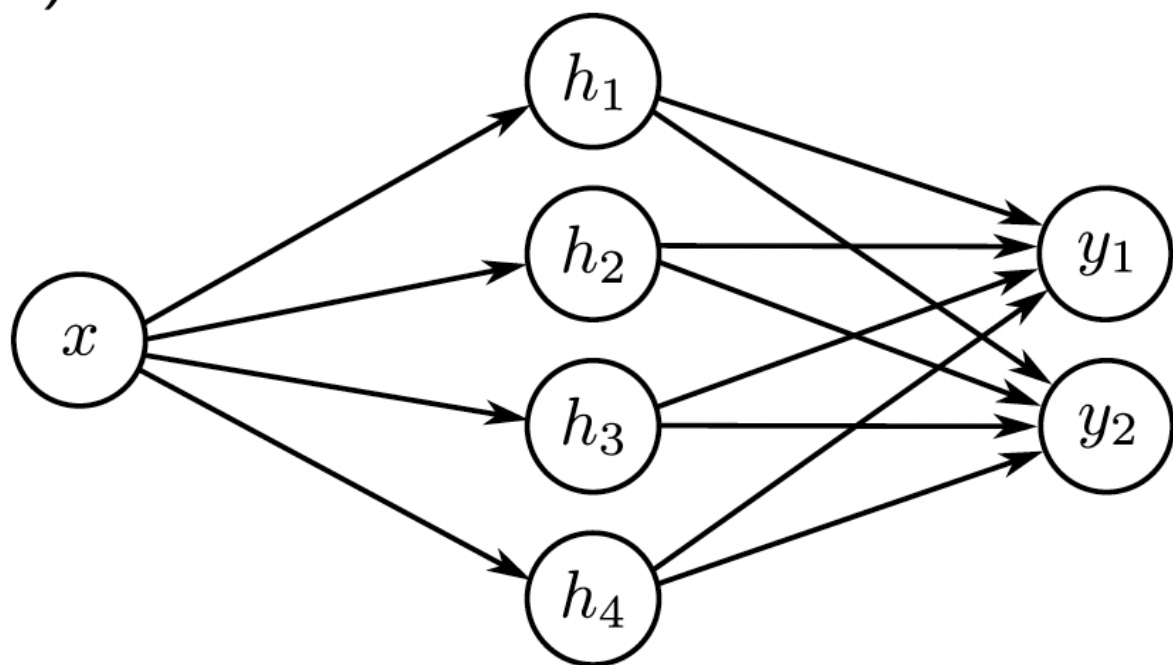


$$h_d = a[\theta_{d0} + \theta_{d1}x], \quad y = \phi_0 + \sum_{d=1}^D \phi_d h_d.$$

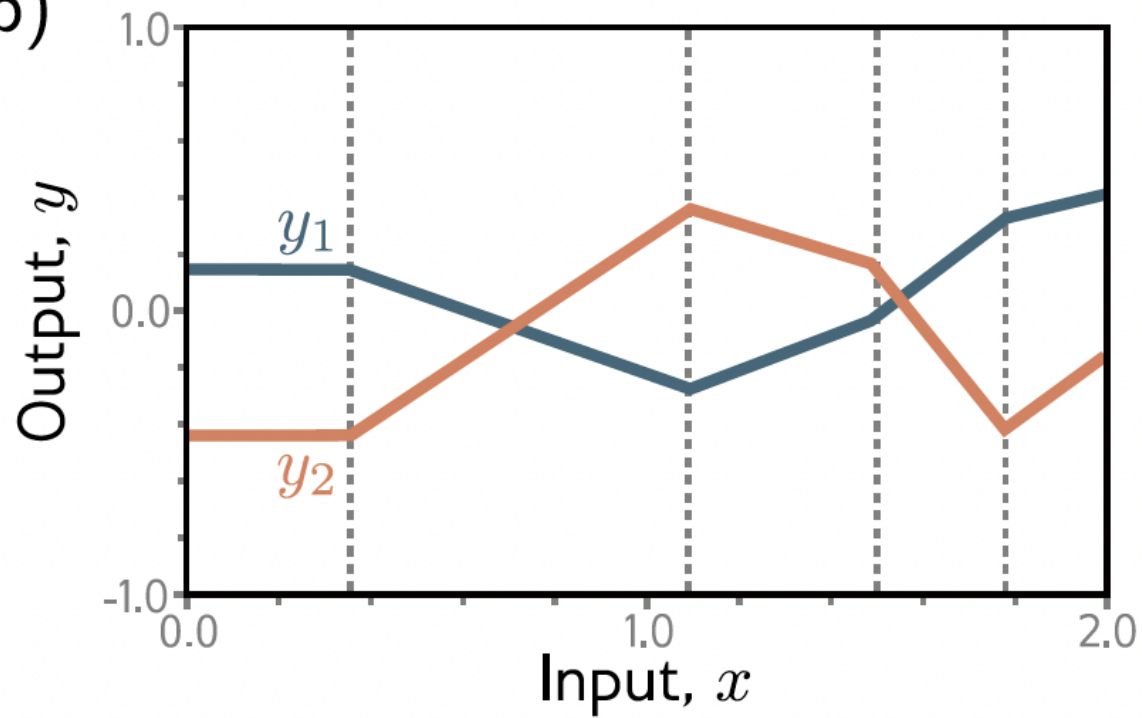
The number of hidden layers is a measure of the network flexibility

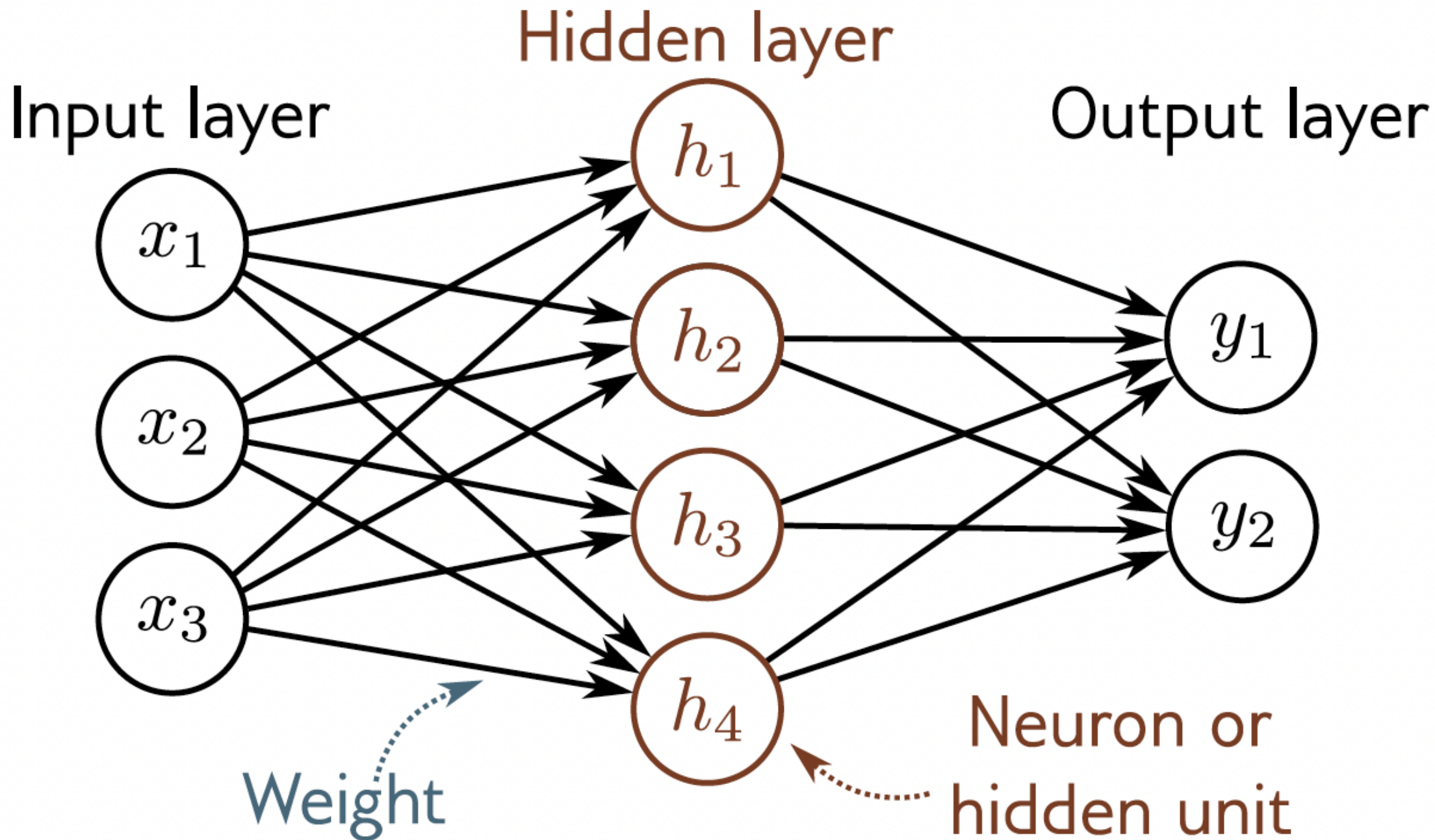


a)

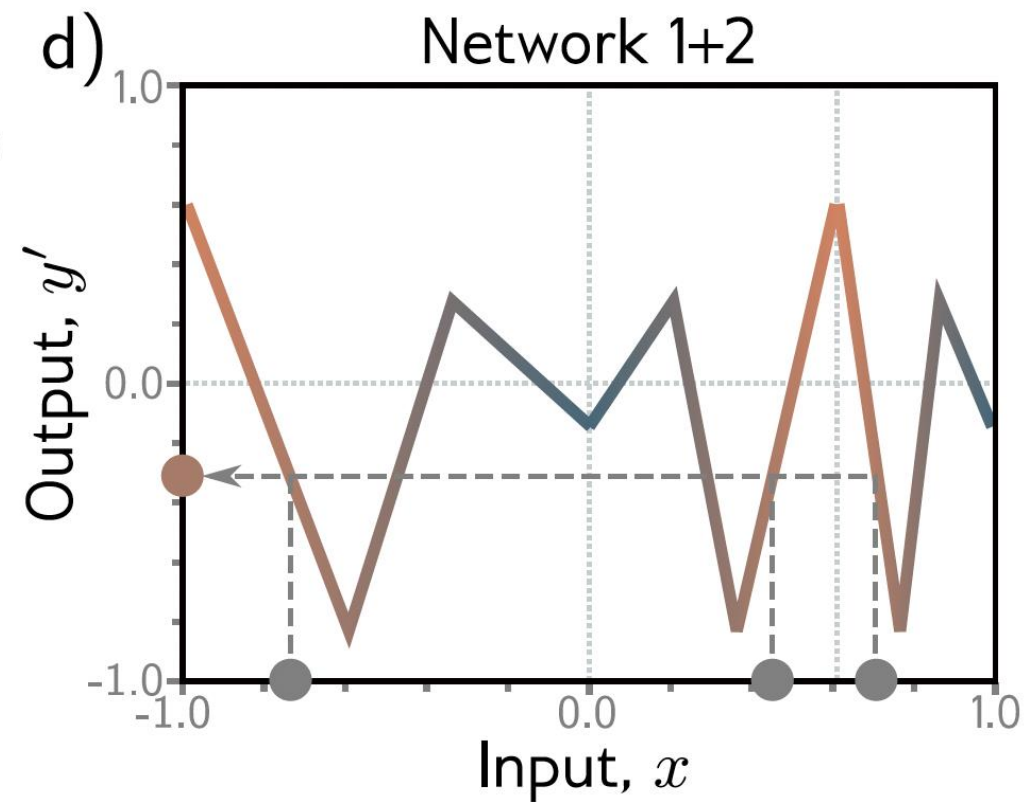
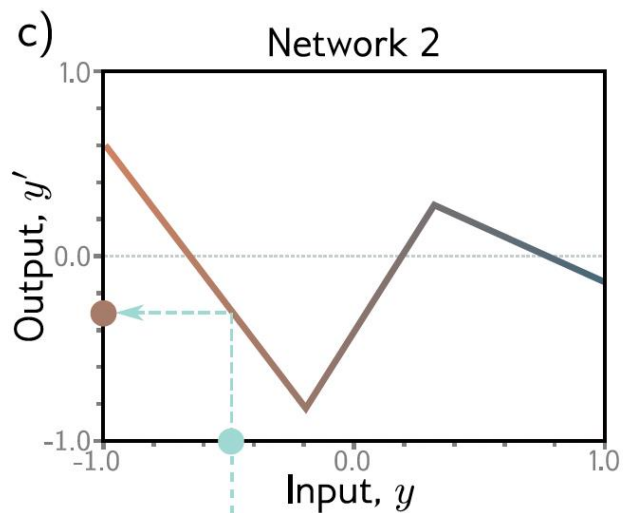
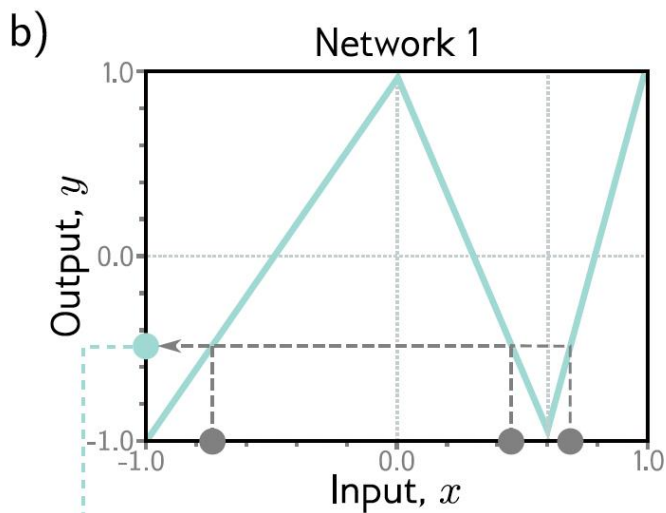
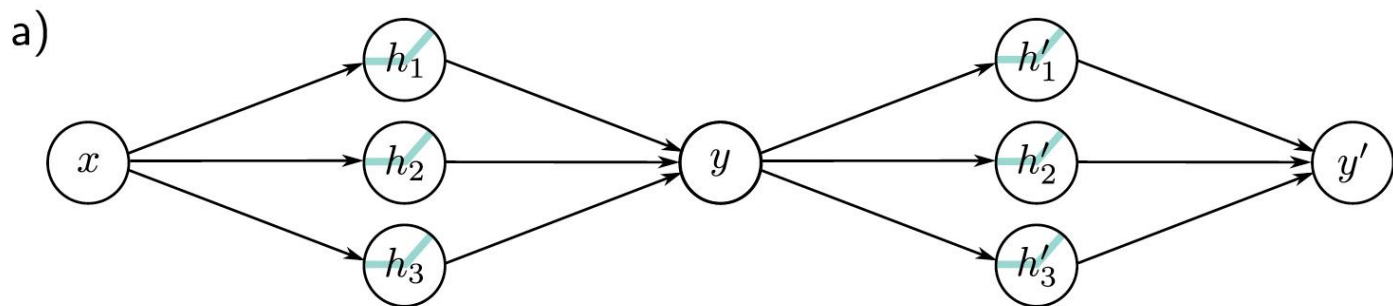


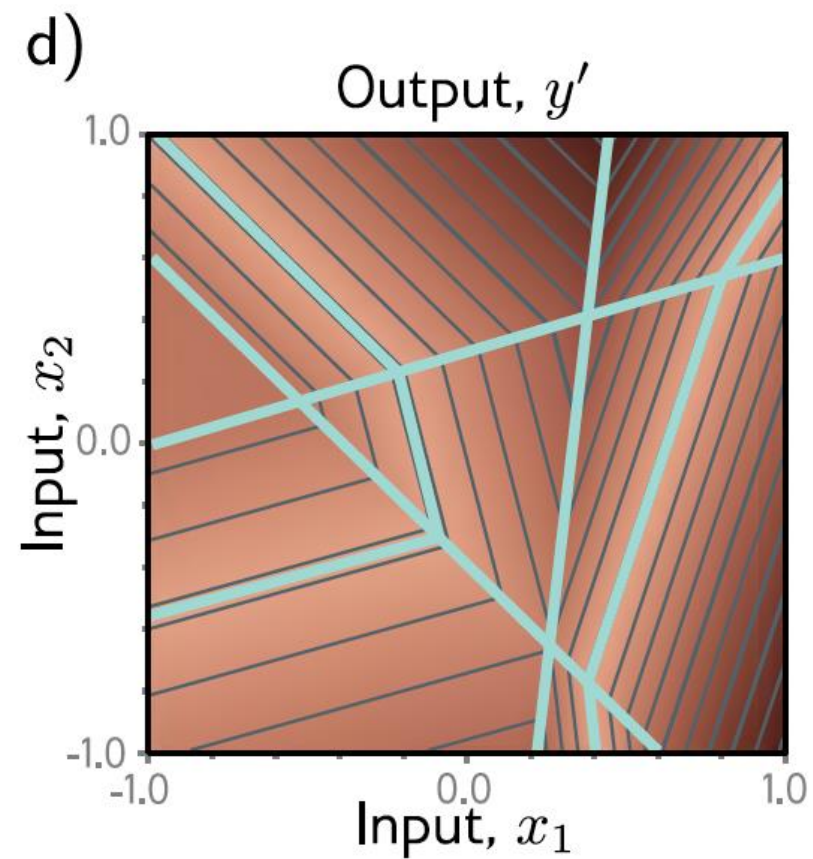
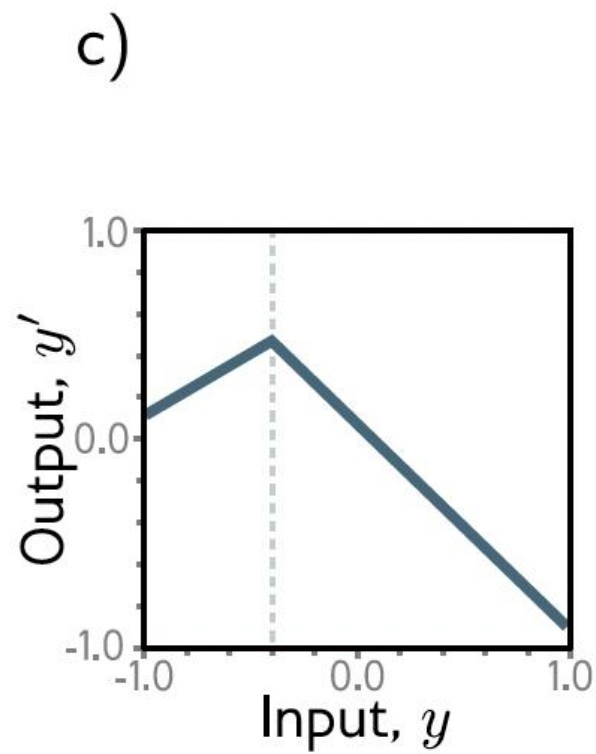
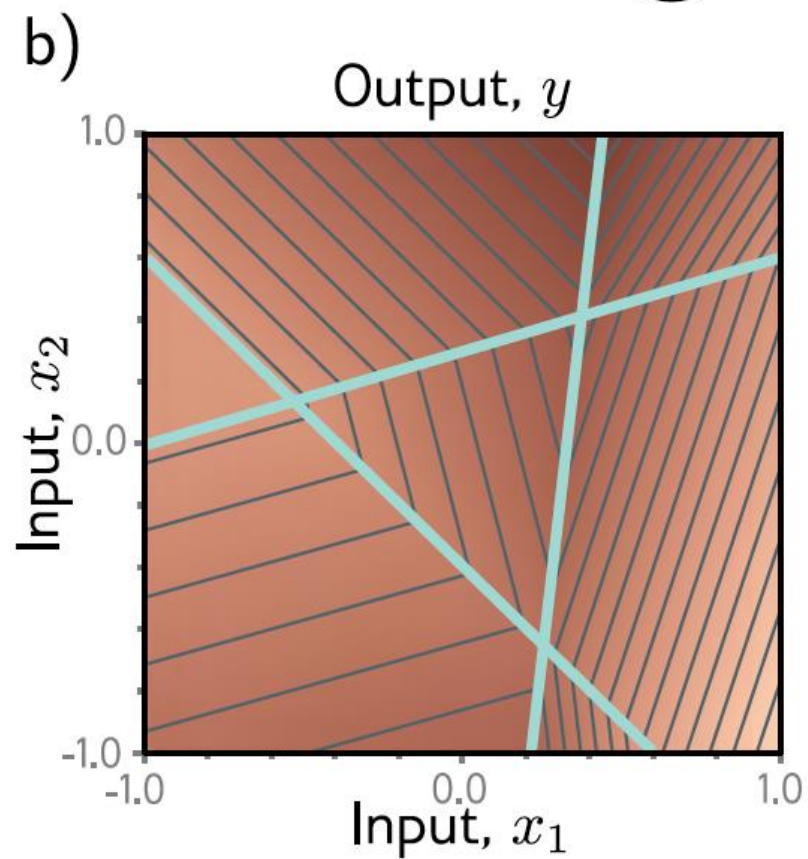
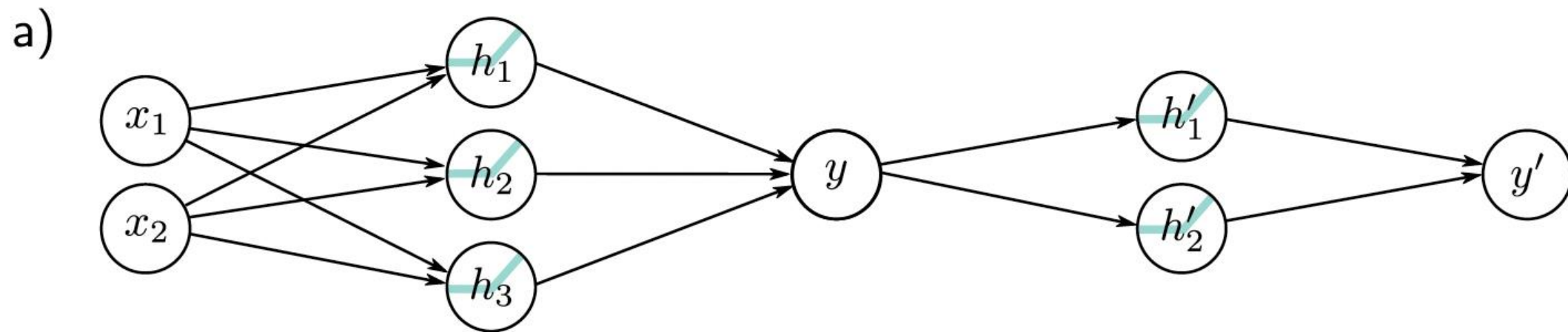
b)

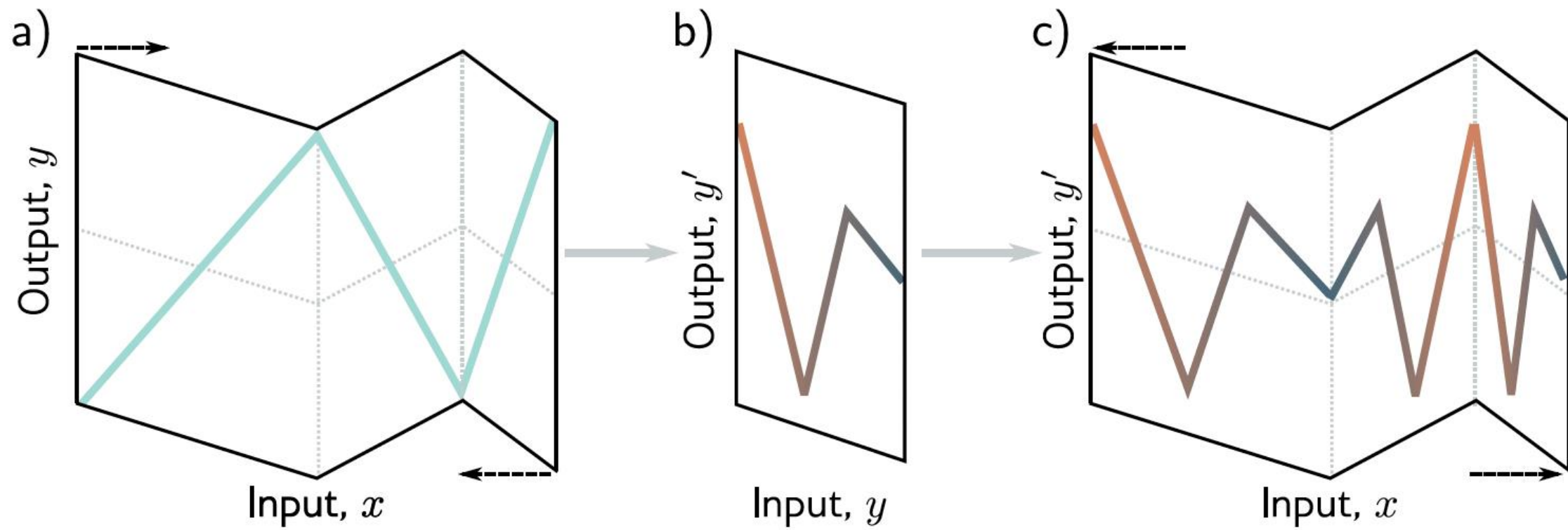




Deep neural networks

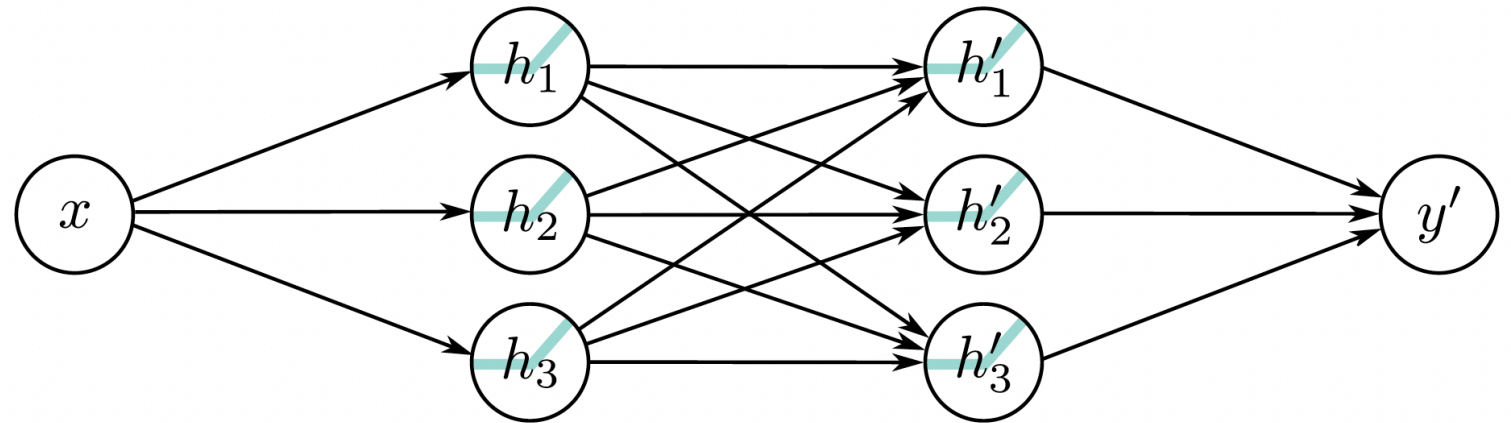




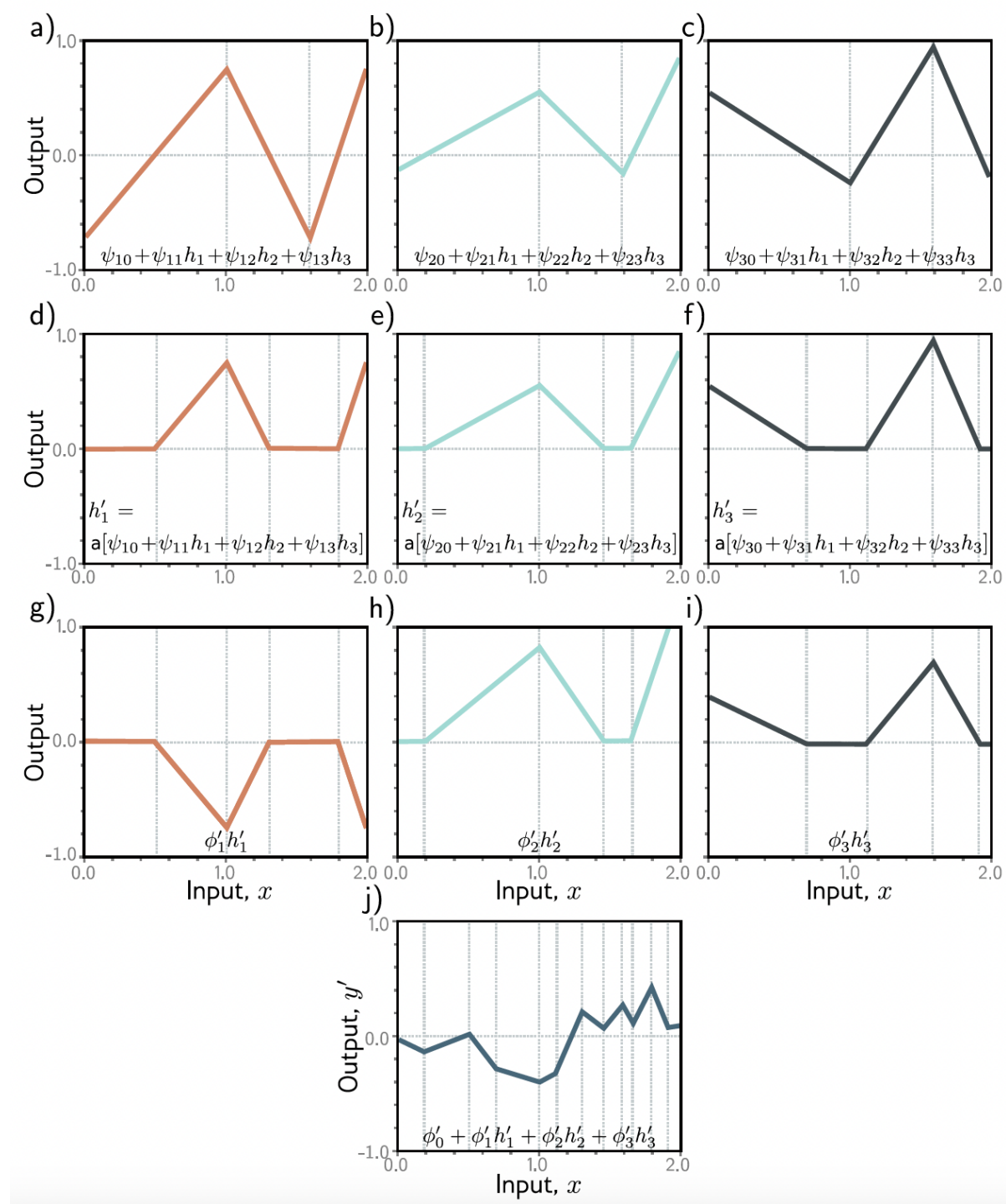


Deep neural Networks

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



$$\begin{aligned}h'_1 &= a[\psi_{10} + \psi_{11}h_1 + \psi_{12}h_2 + \psi_{13}h_3] \\h'_2 &= a[\psi_{20} + \psi_{21}h_1 + \psi_{22}h_2 + \psi_{23}h_3] \\h'_3 &= a[\psi_{30} + \psi_{31}h_1 + \psi_{32}h_2 + \psi_{33}h_3],\end{aligned} \quad y' = \phi'_0 + \phi'_1 h'_1 + \phi'_2 h'_2 + \phi'_3 h'_3.$$



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