6.036/6.862: Introduction to Machine Learning

Lecture: starts Tuesdays 9:35am (Boston time zone)

Course website: introml.odl.mit.edu

Who's talking? Prof. Tamara Broderick

Questions? discourse.odl.mit.edu ("Lecture 6" category)

Materials: Will all be available at course website

Last Time(s)

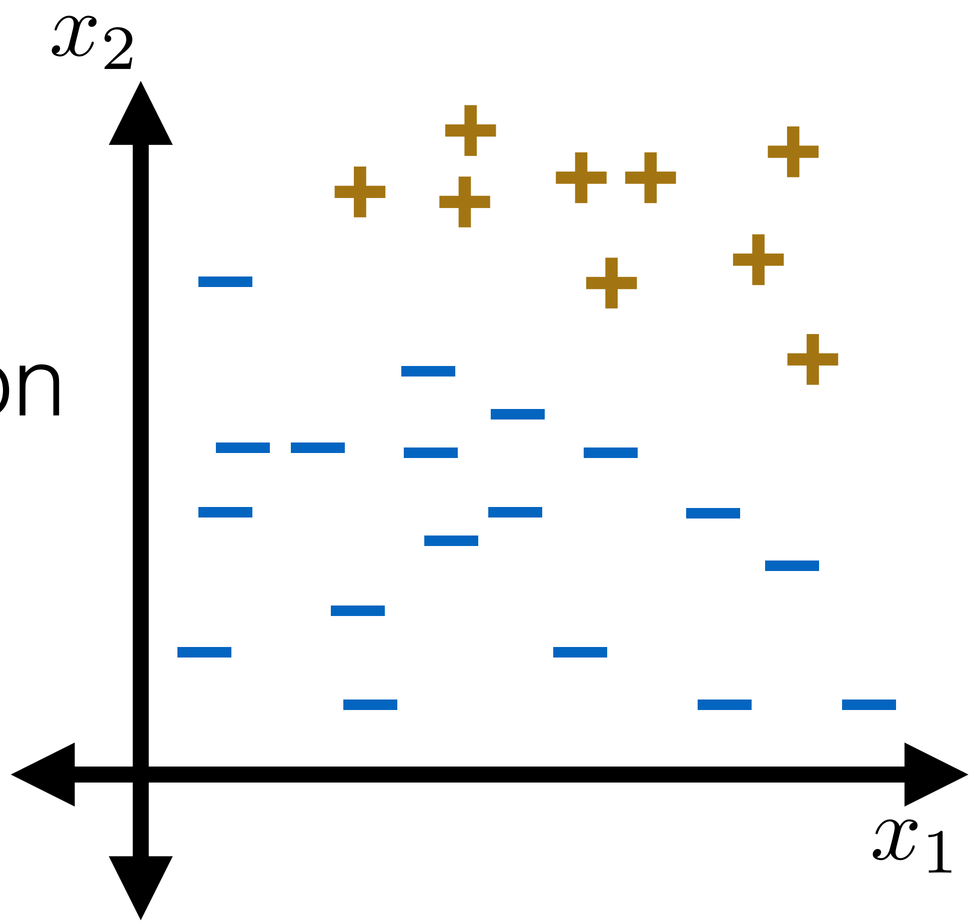
I. Linear classification
II. Linear regression
III. Choosing features

Today's Plan

I. Step-function features
II. Neural nets: hypothesis class
III. Neural nets: learning

Recall

- Linear classification with default features:



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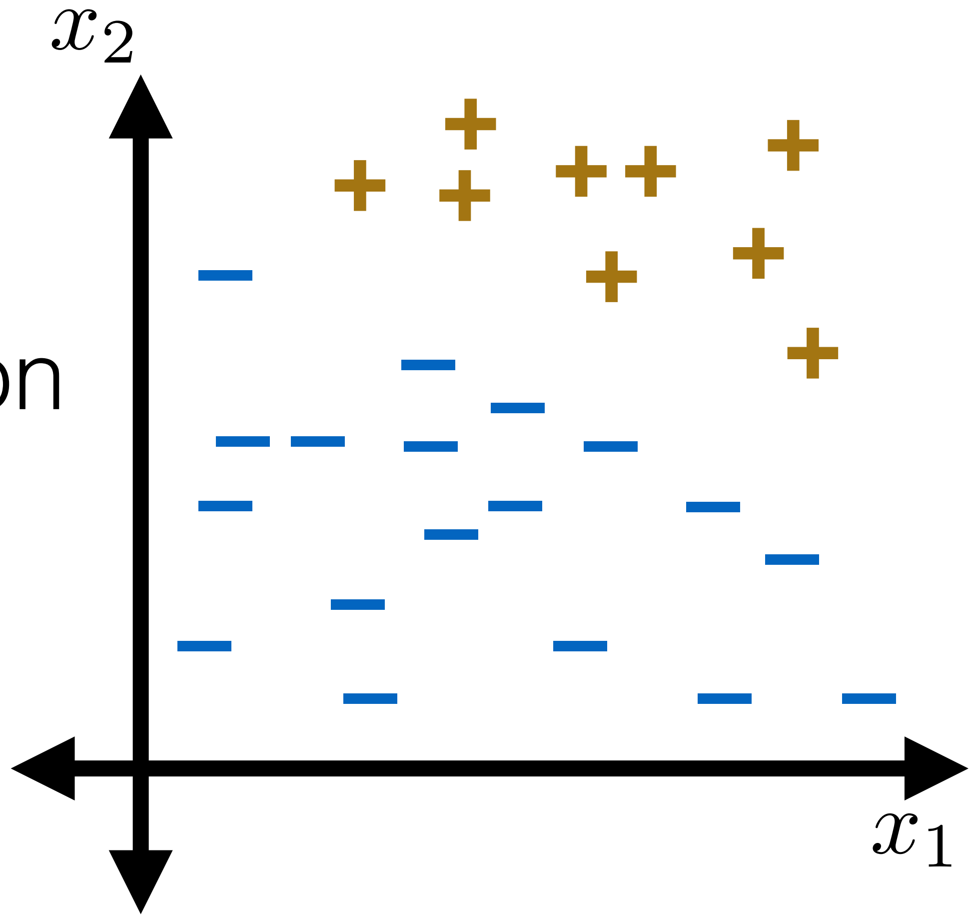

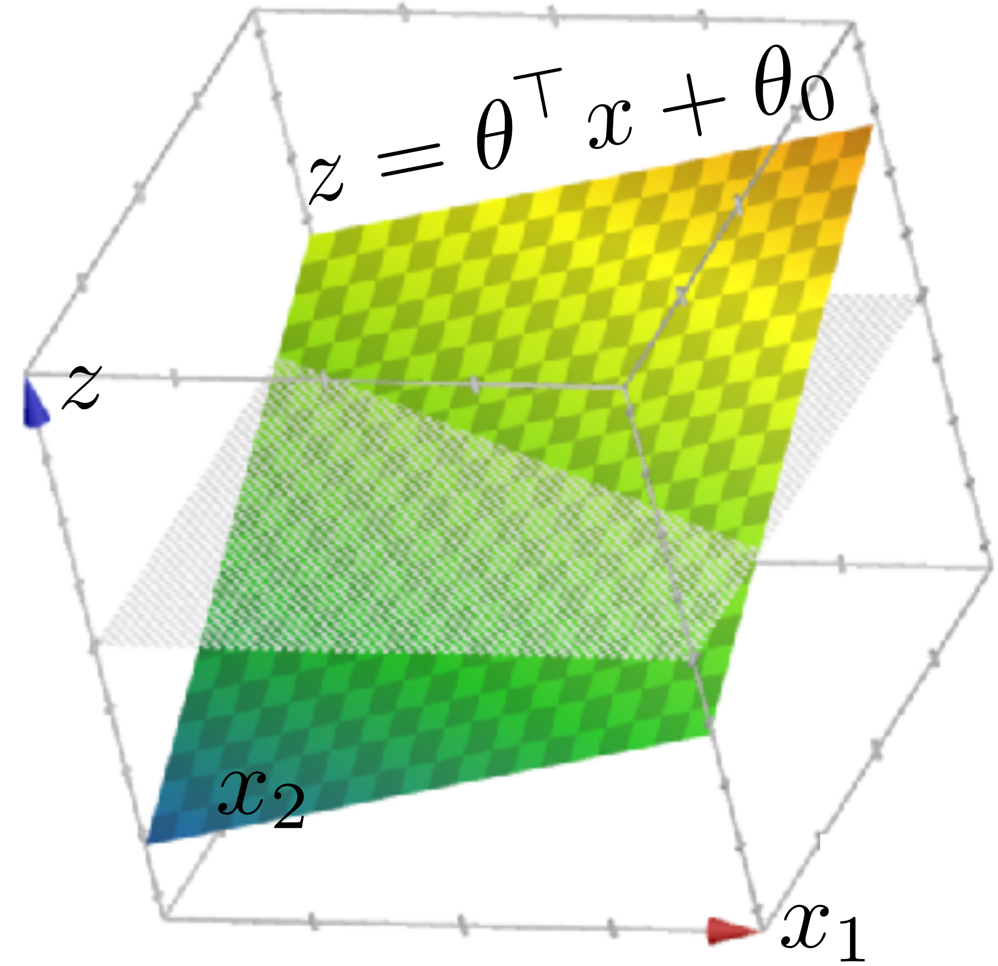

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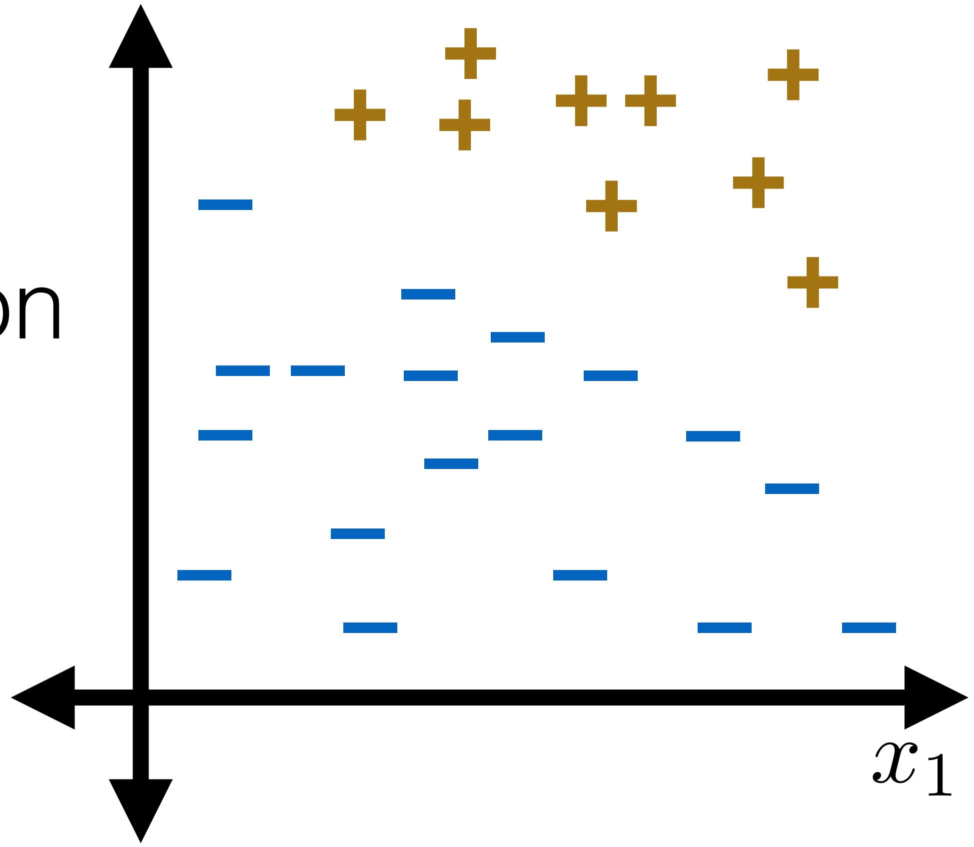

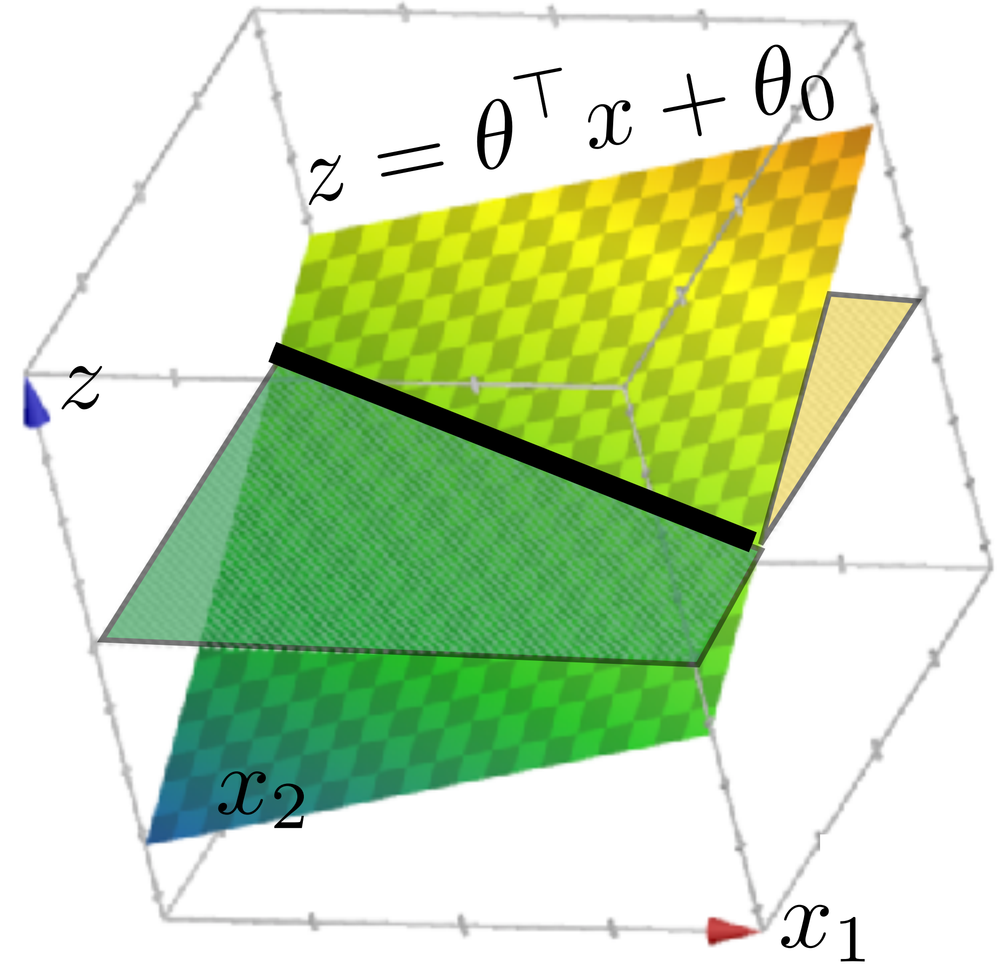

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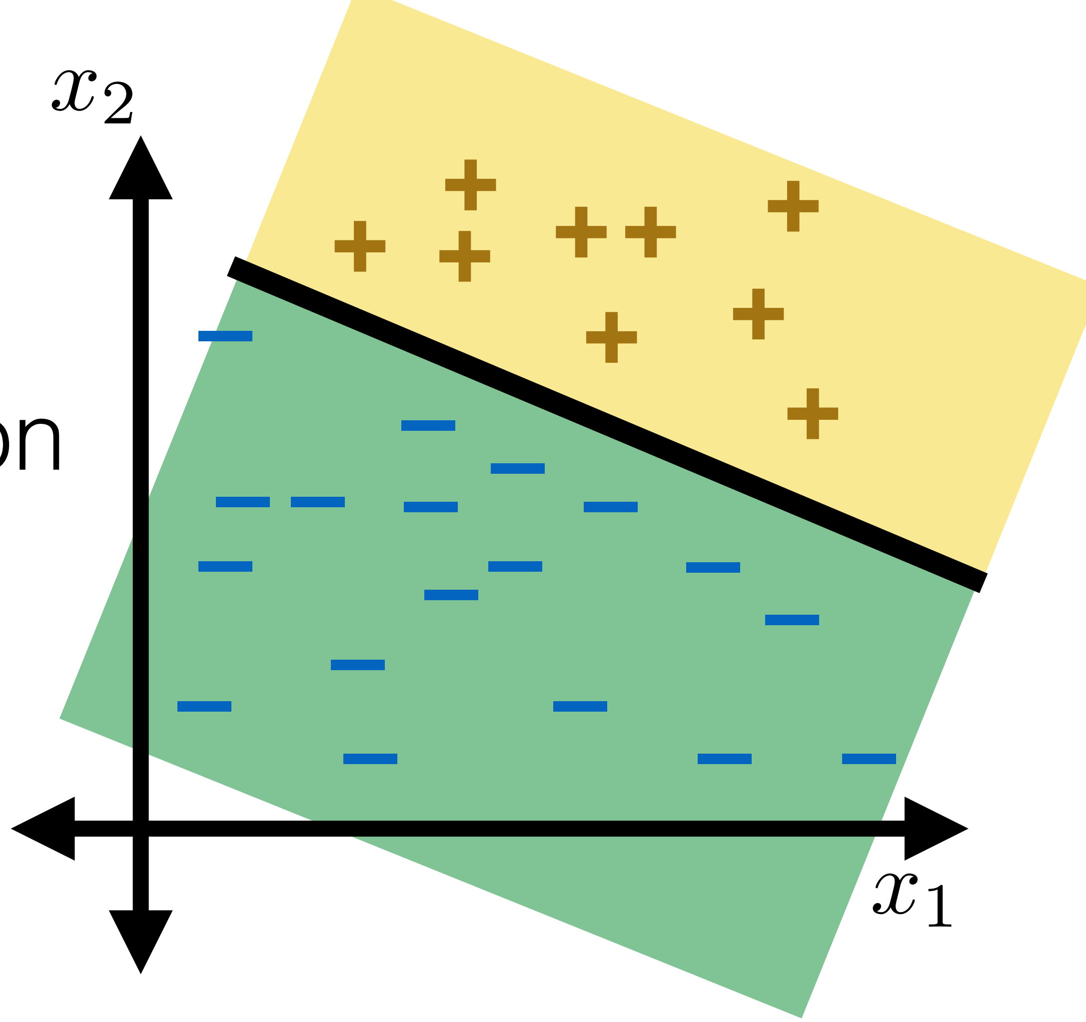

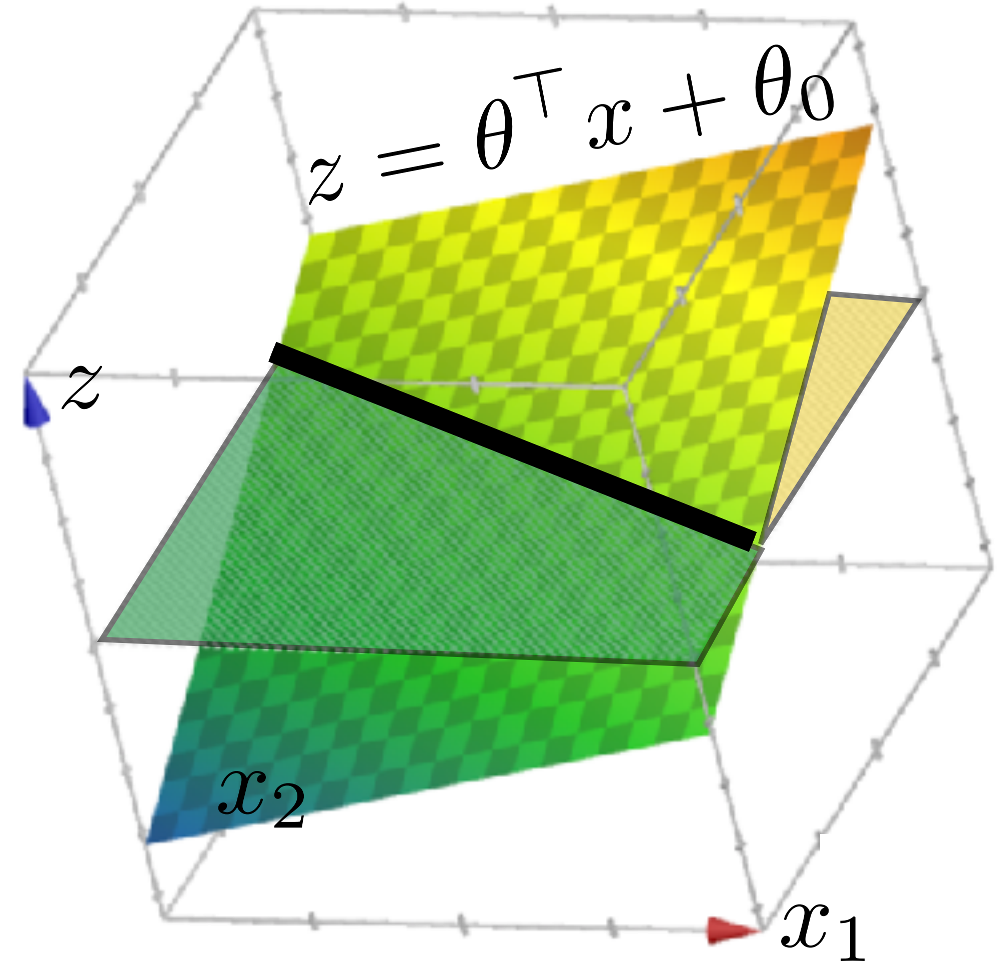

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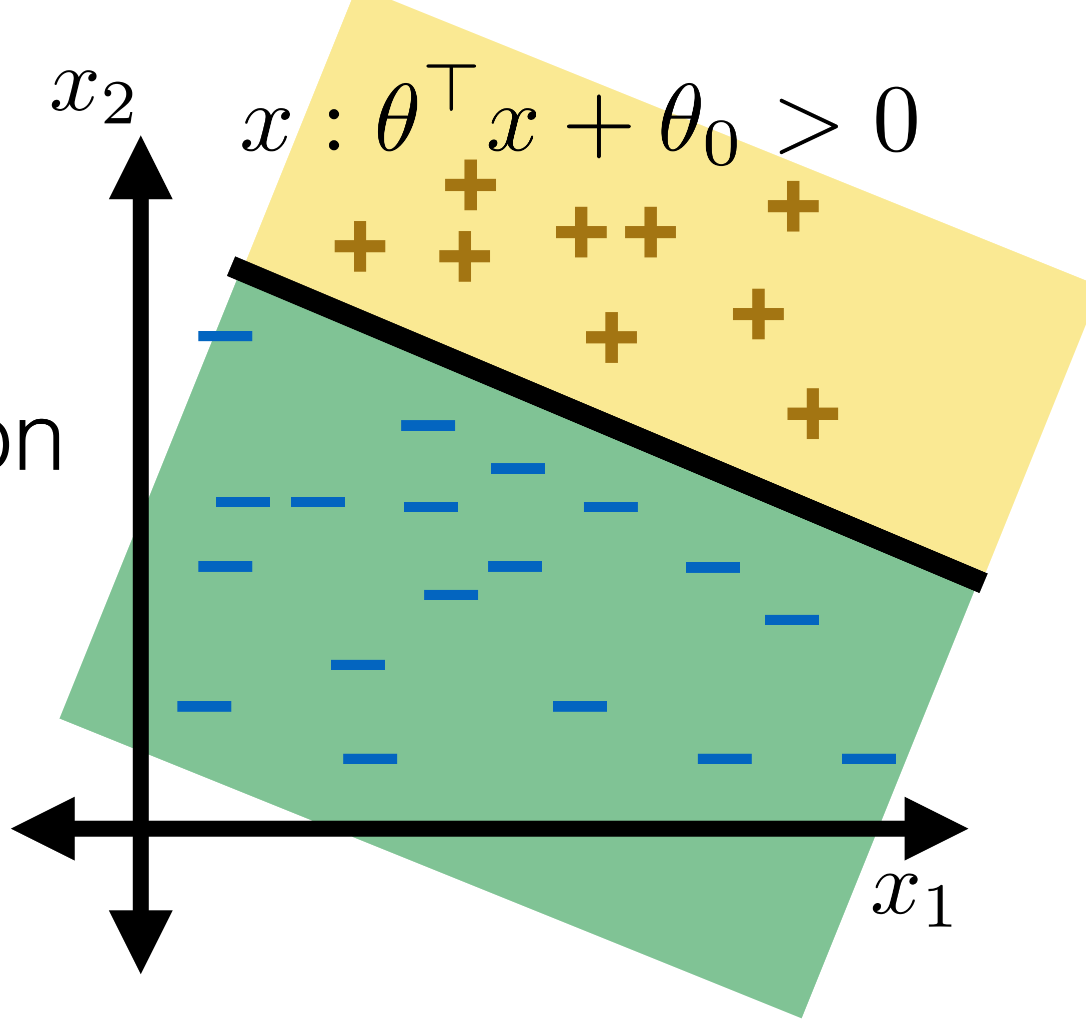

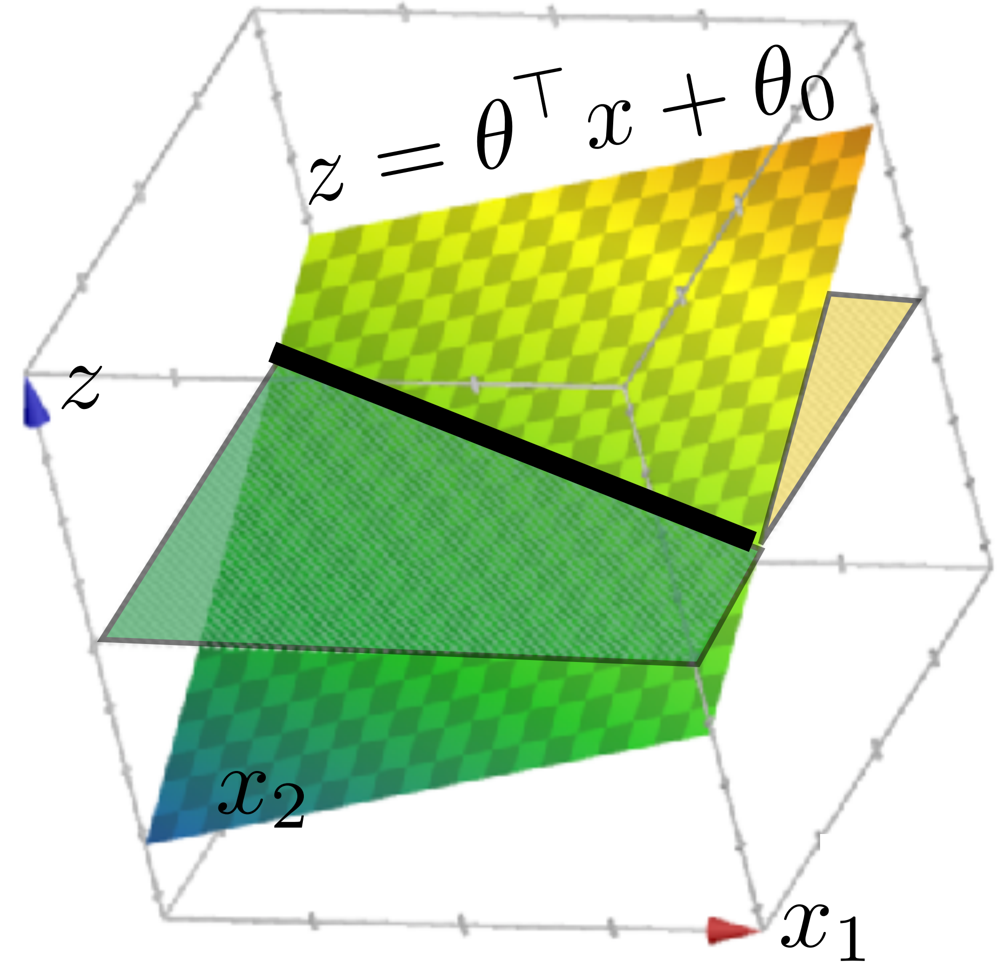

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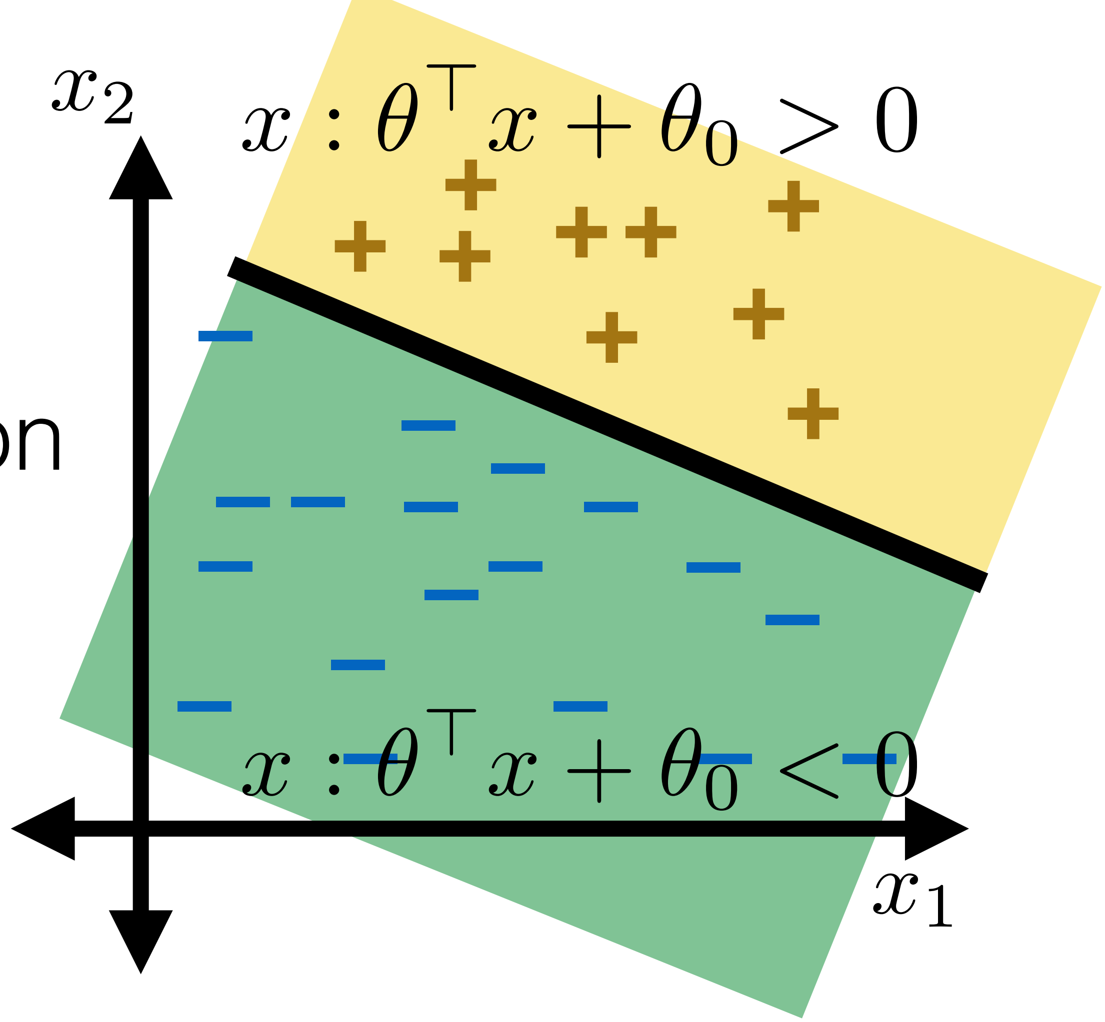

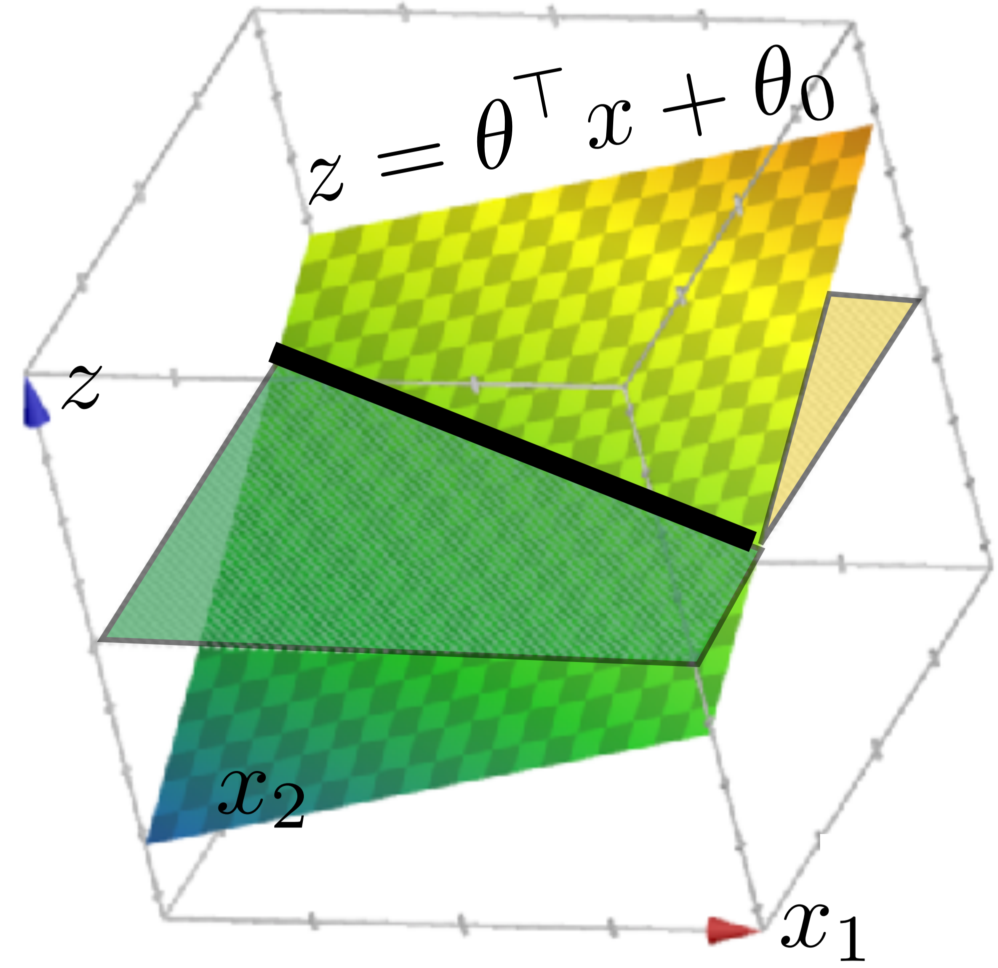

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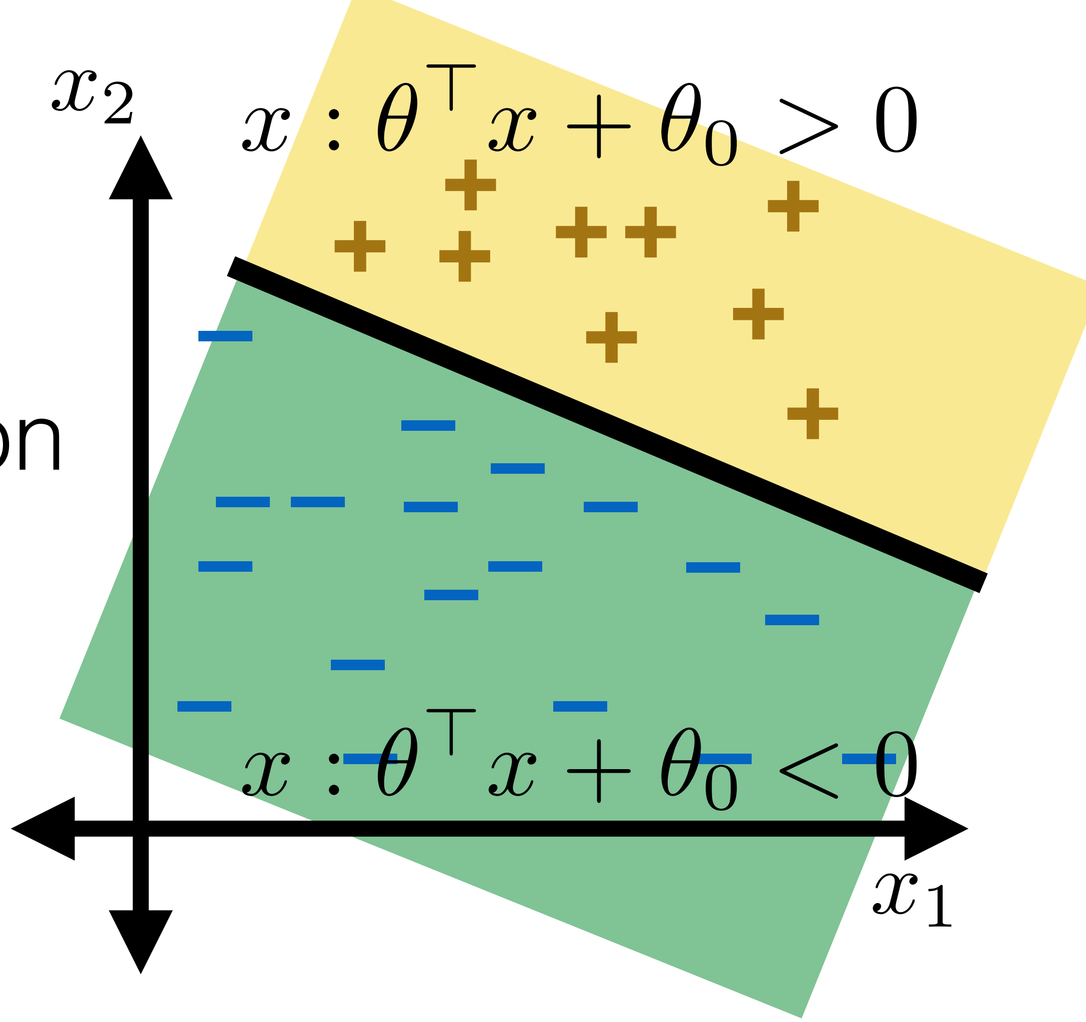

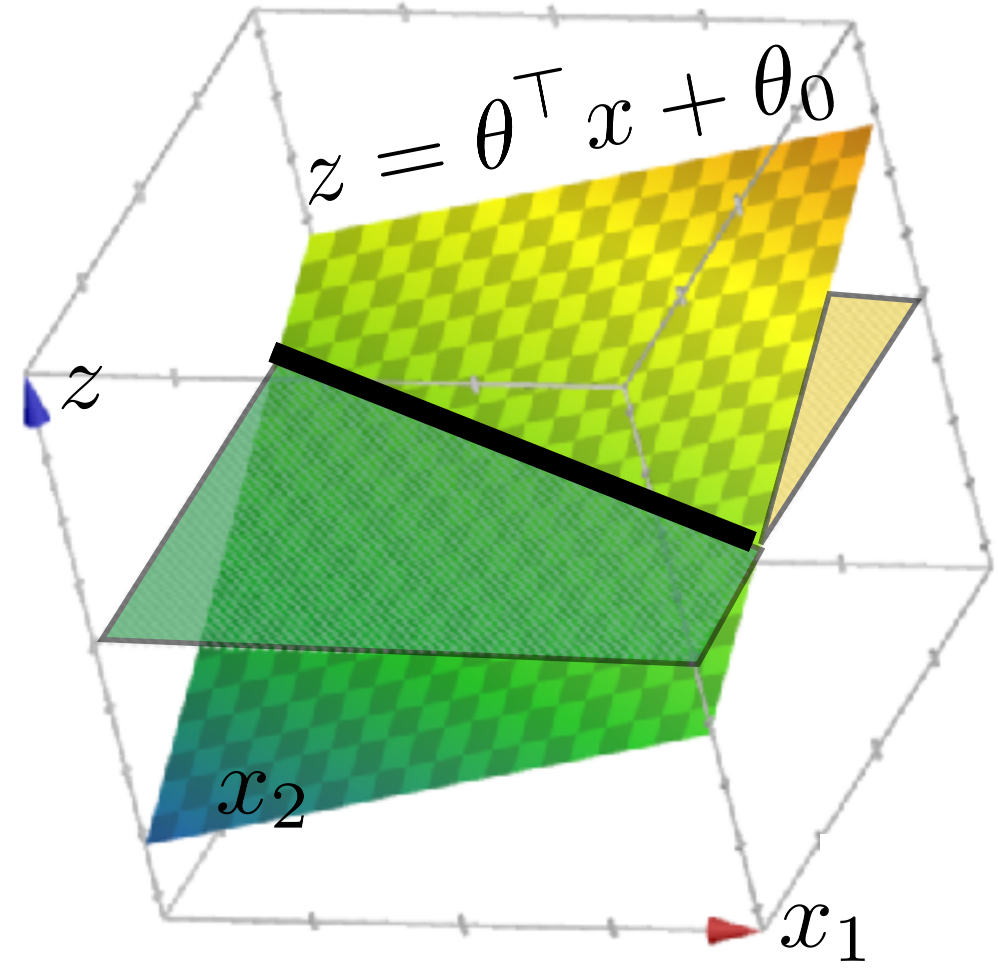

- Linear classification with polynomial features:

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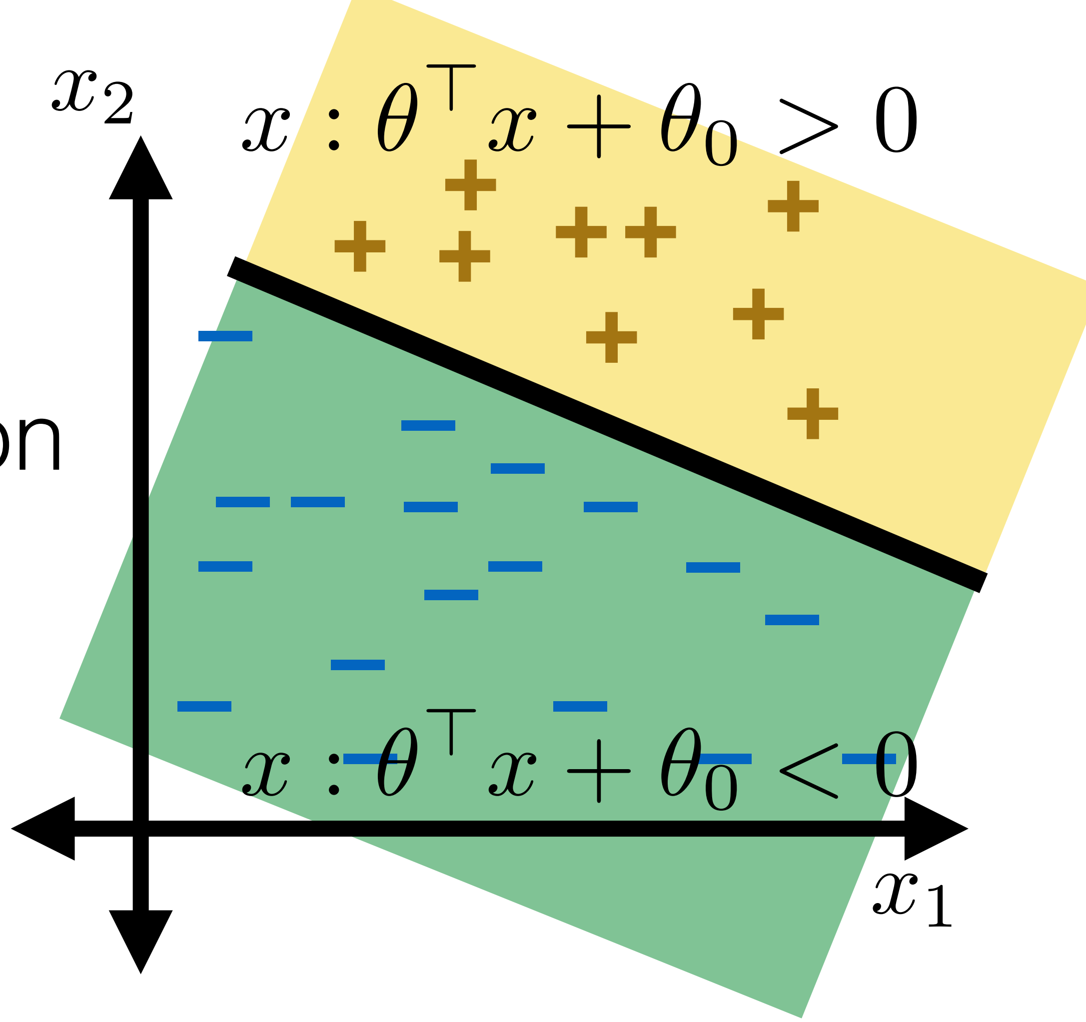

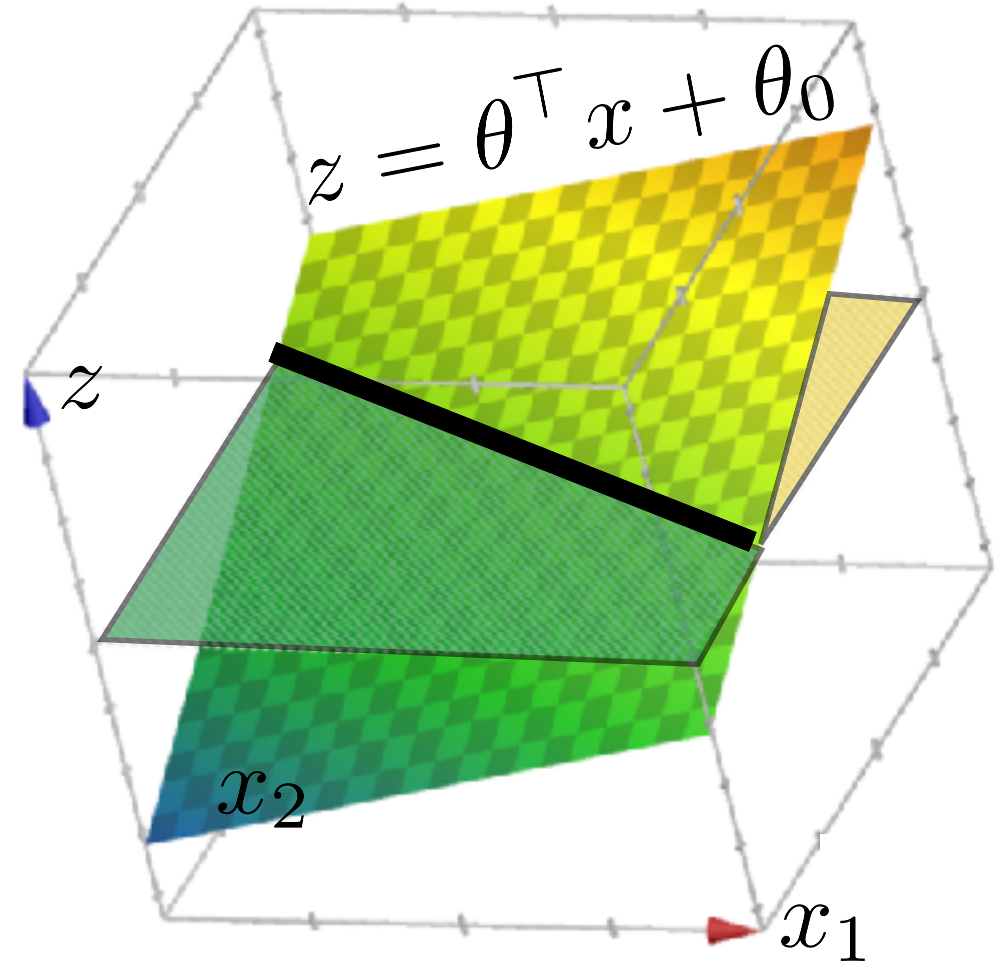

- Linear classification with default features:

- Linear classification with polynomial features:

$\phi(x)$
$= [x_1, x_2, x_1^2,$
$x_1 x_2, x_2^2]^\top$

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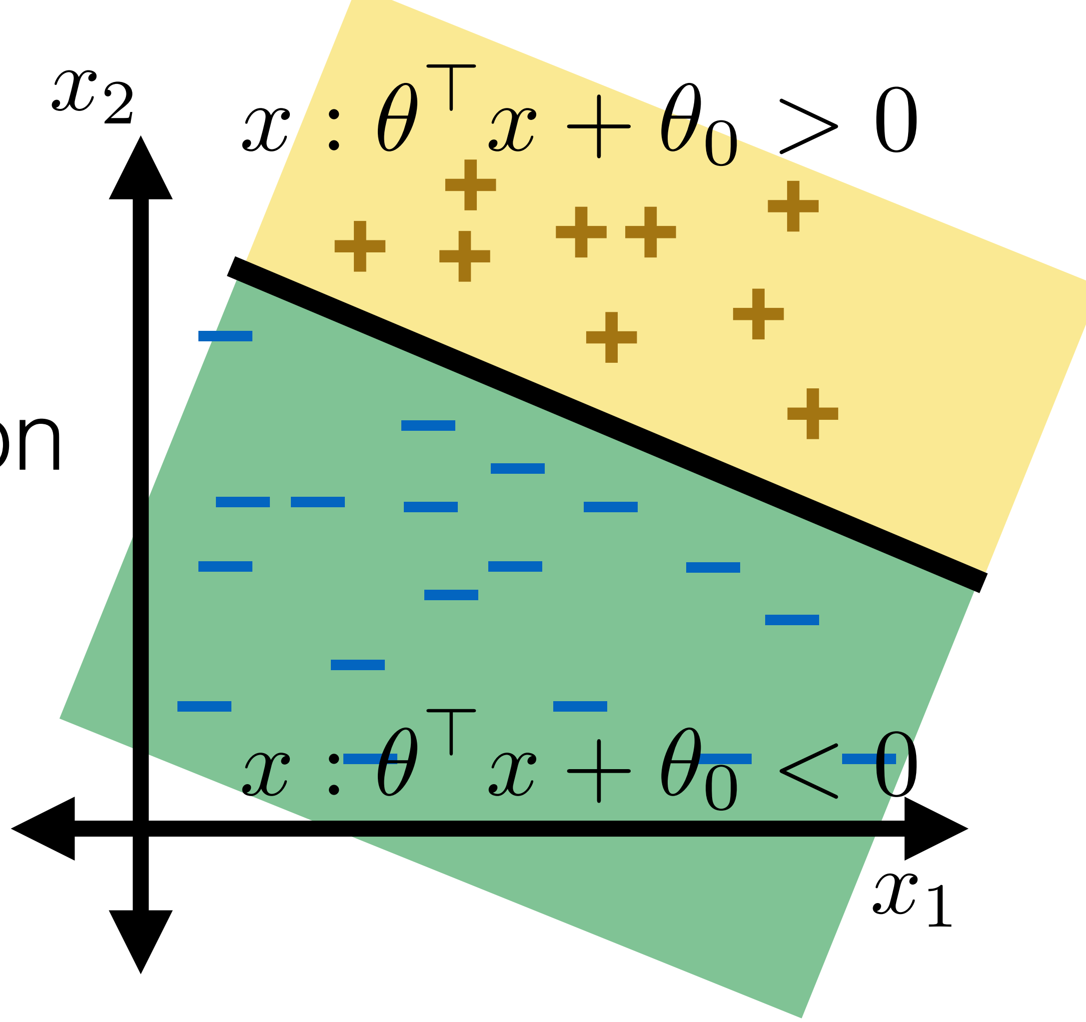

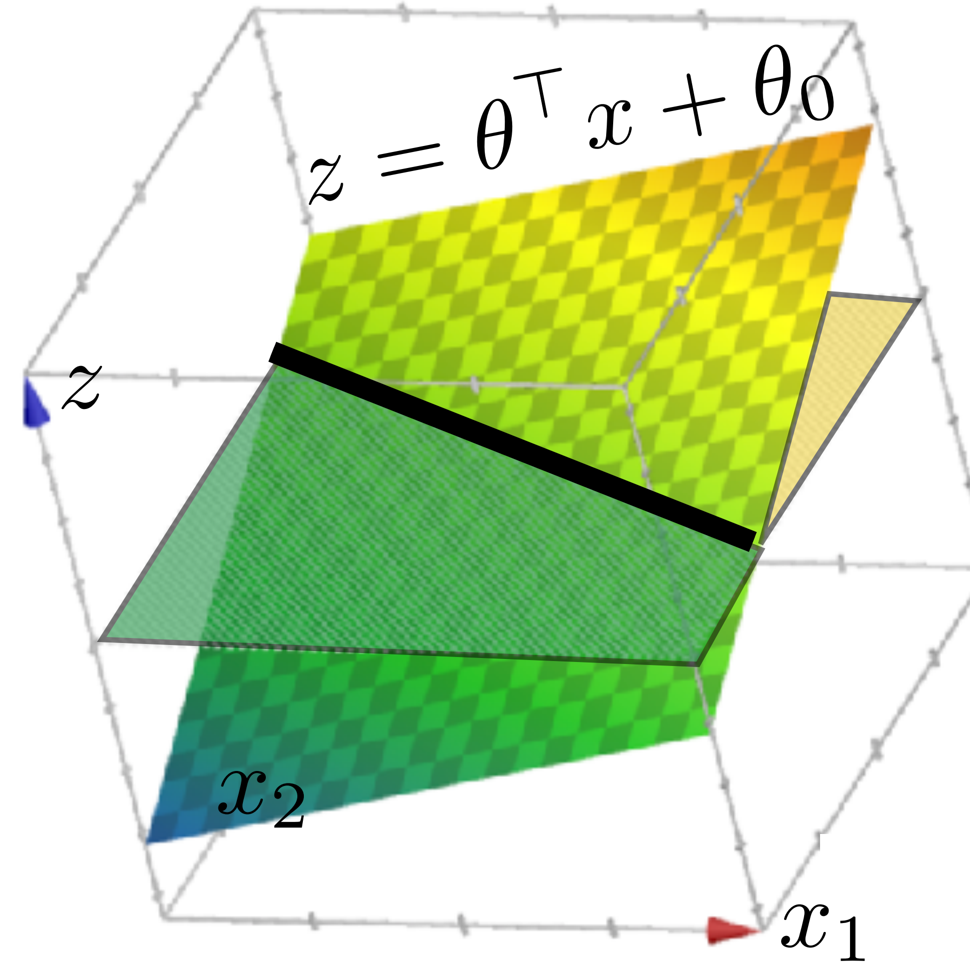

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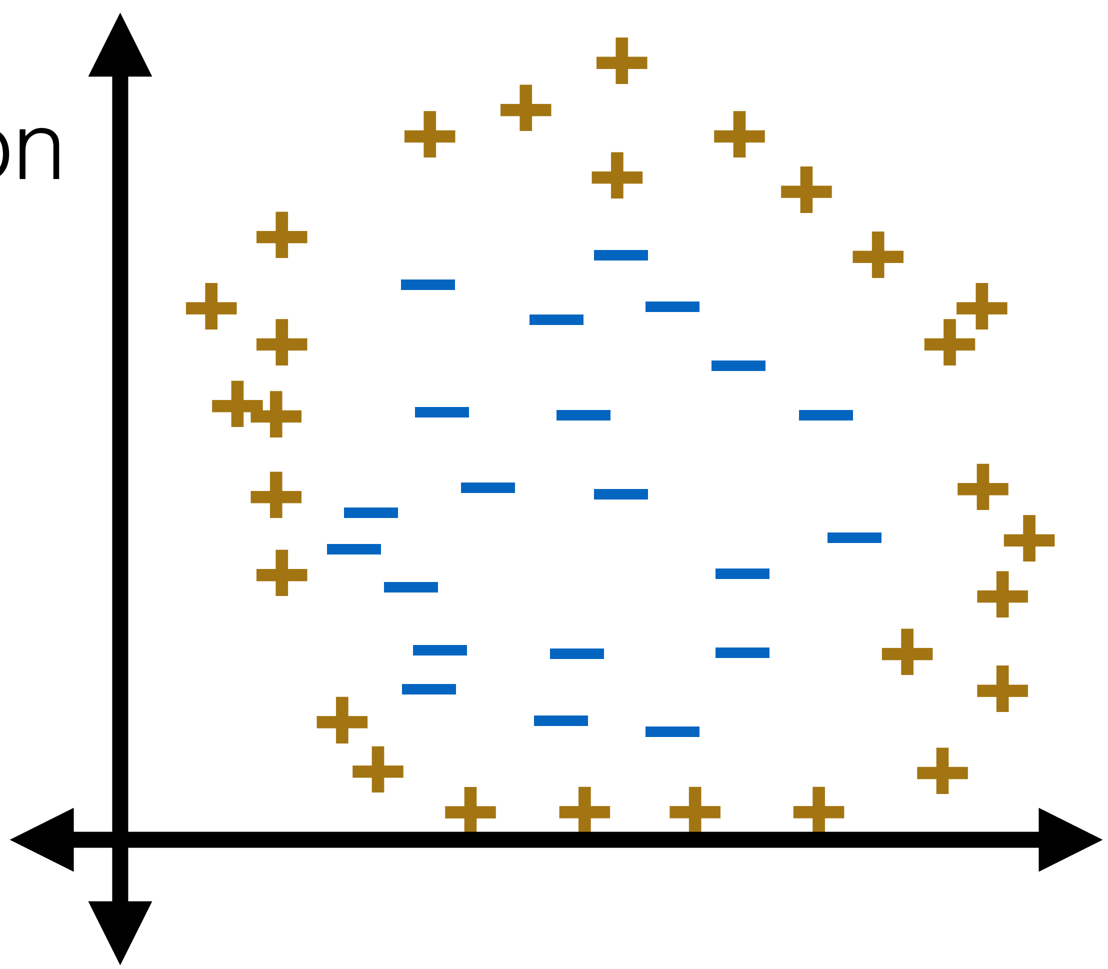

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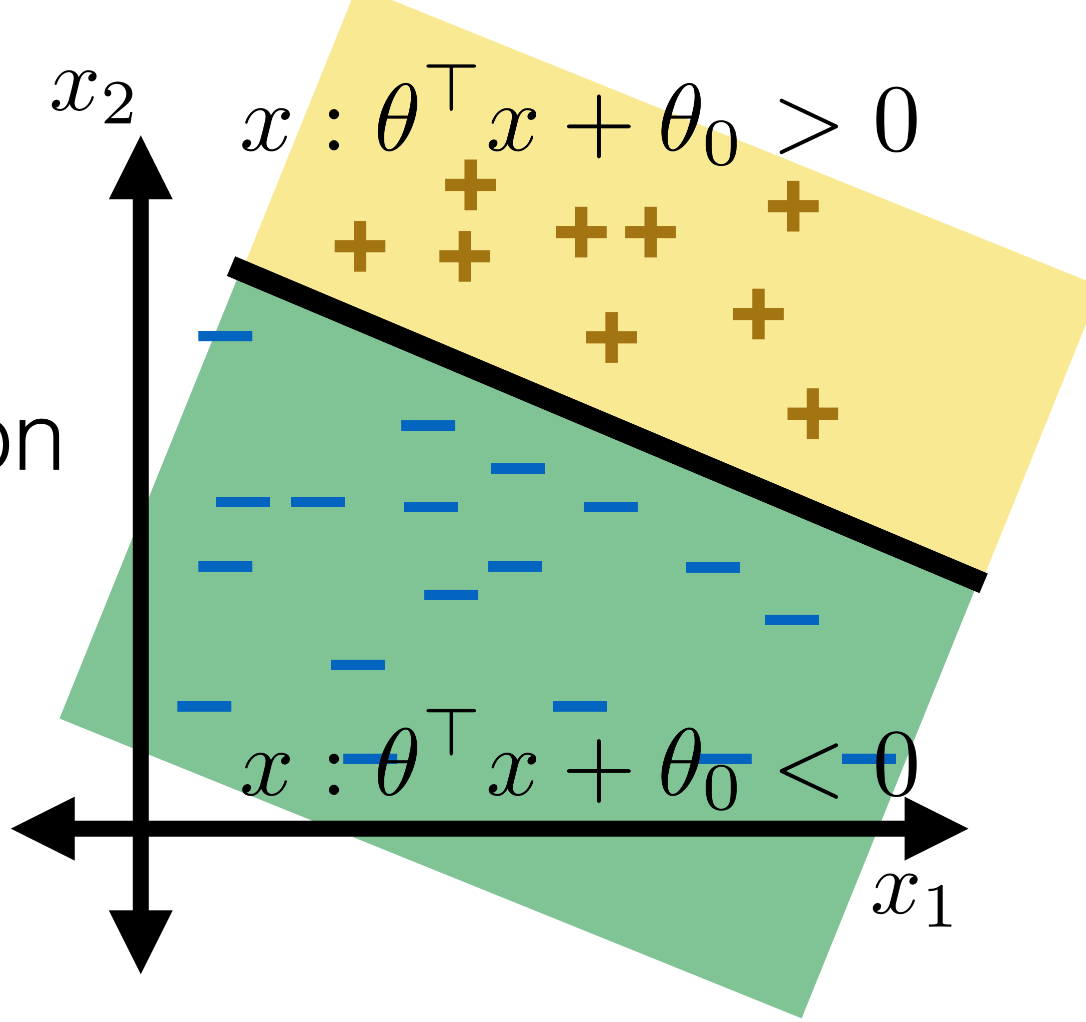

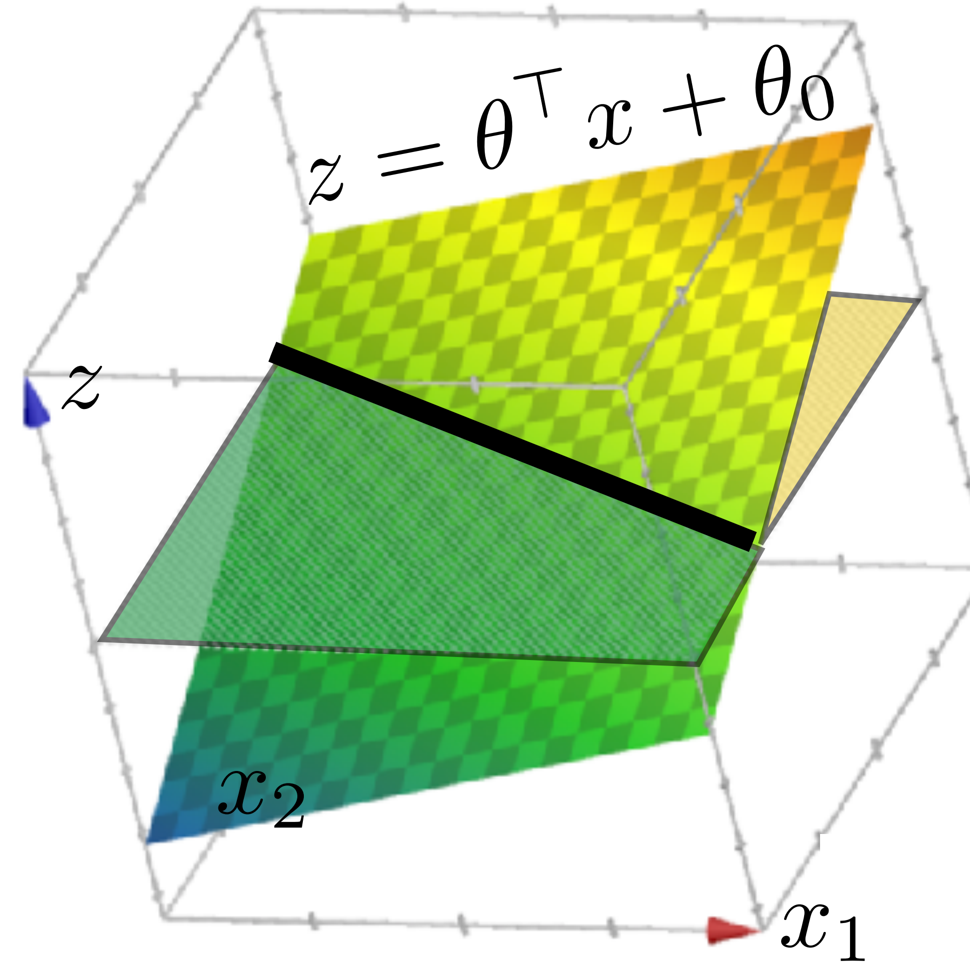

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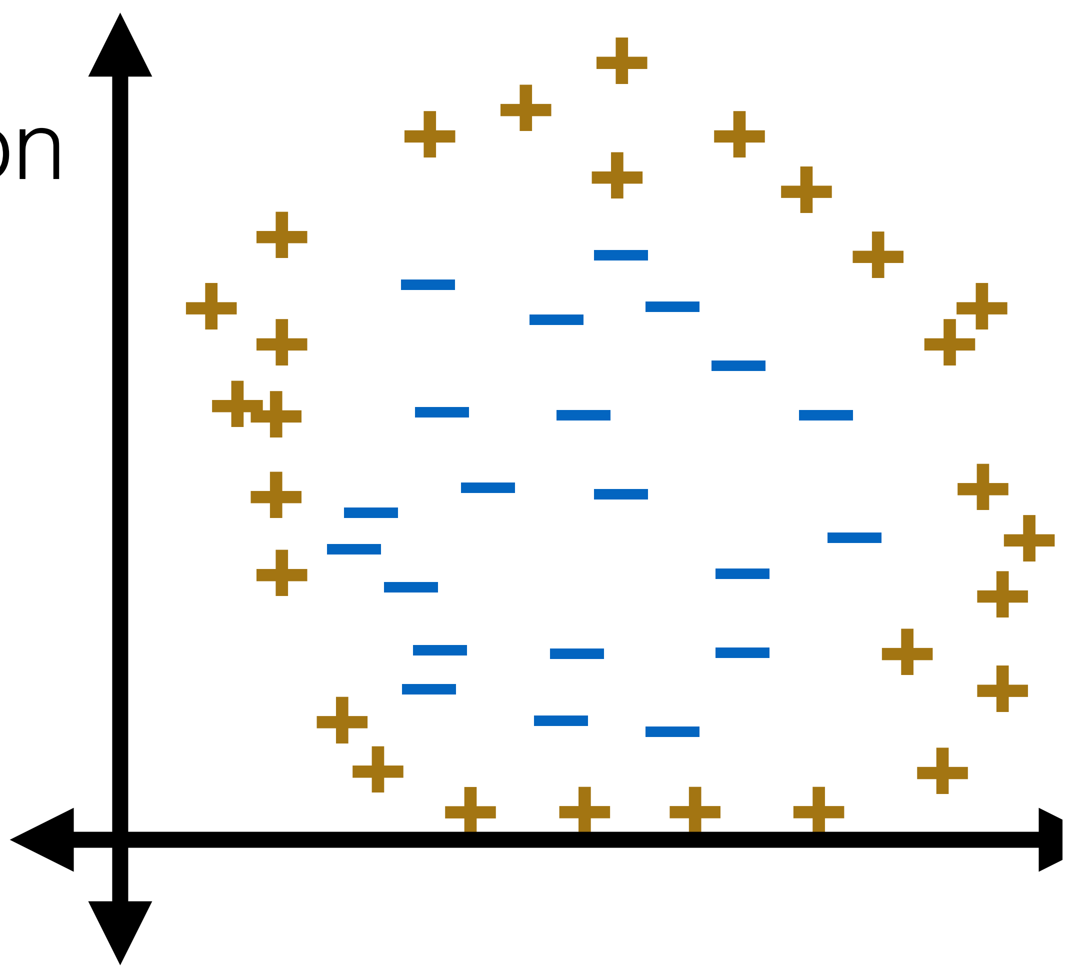

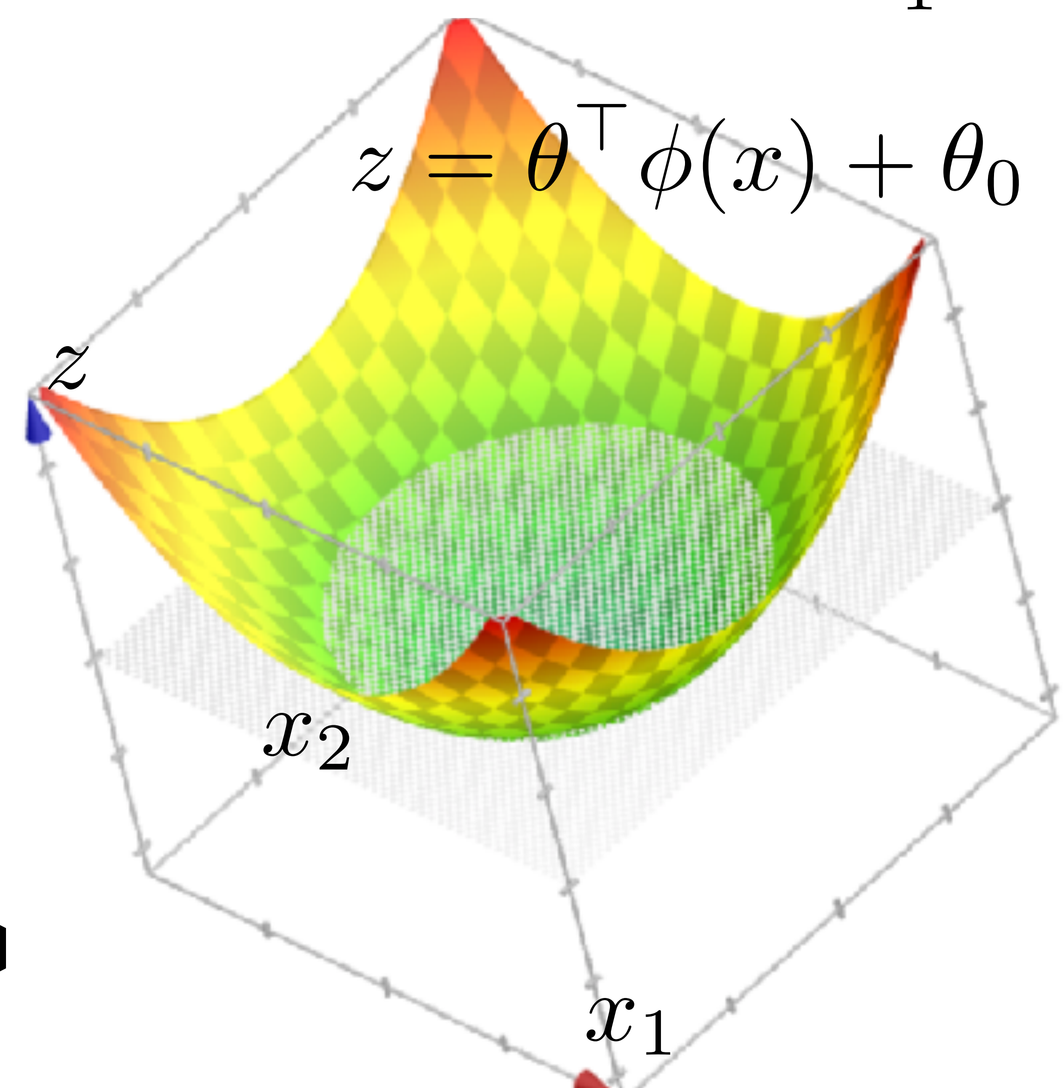

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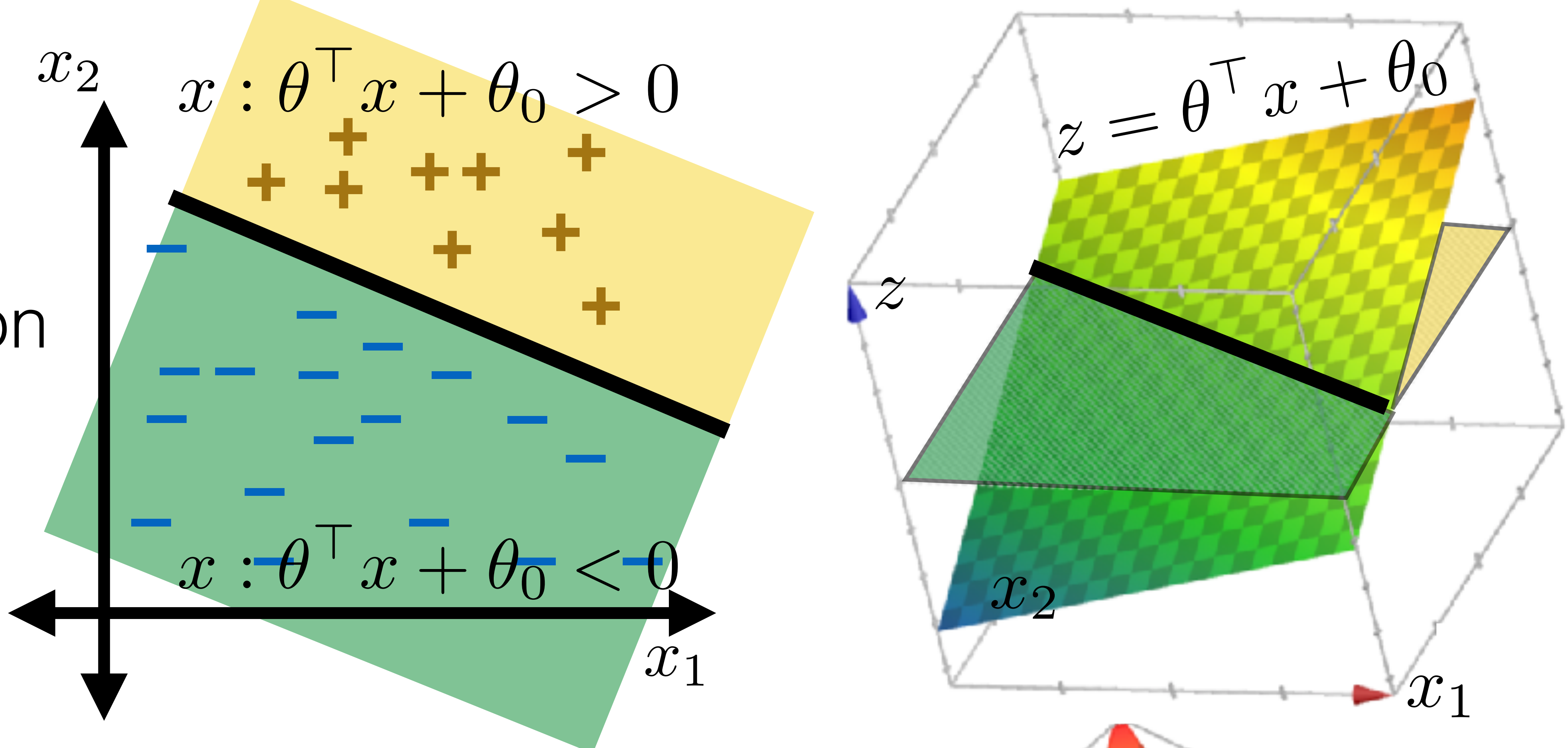

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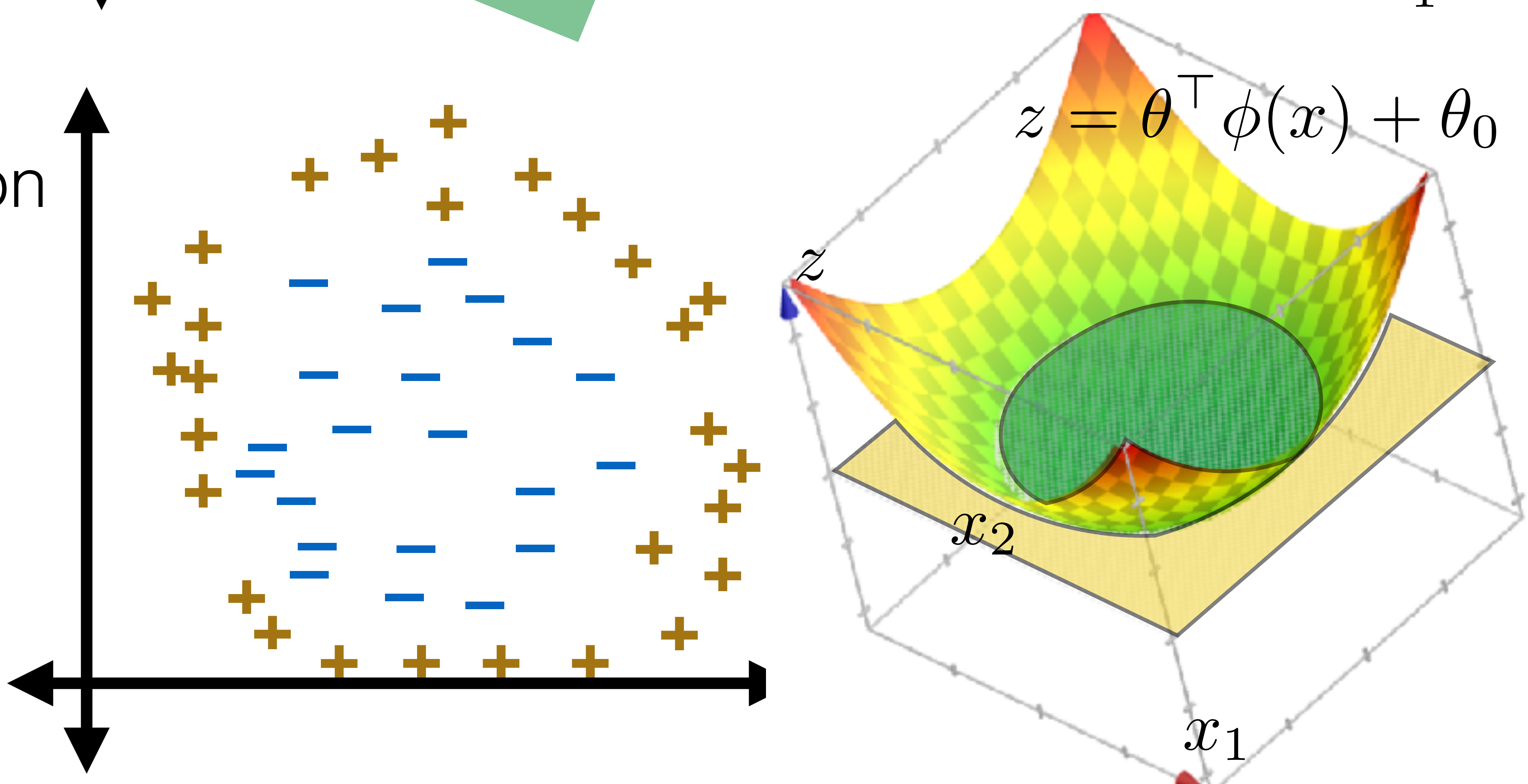

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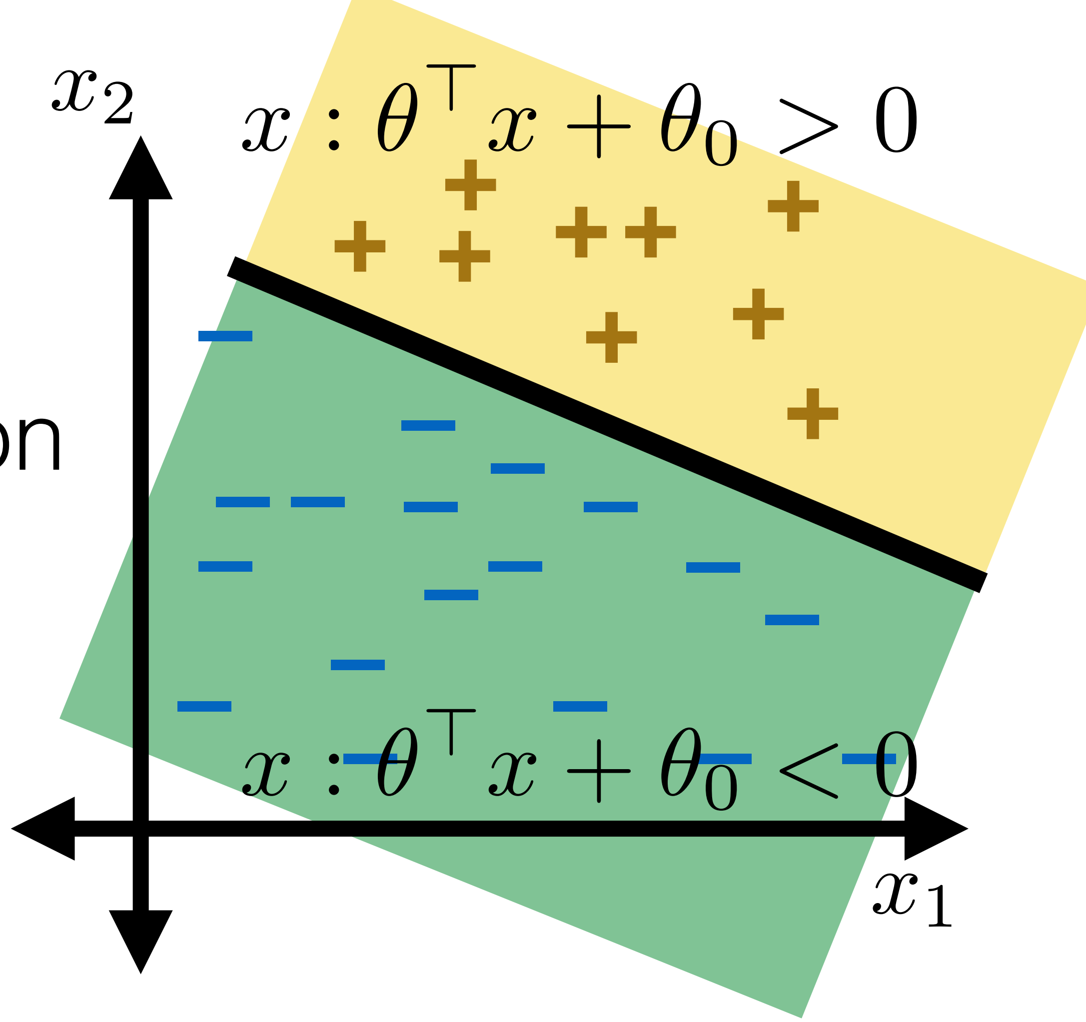

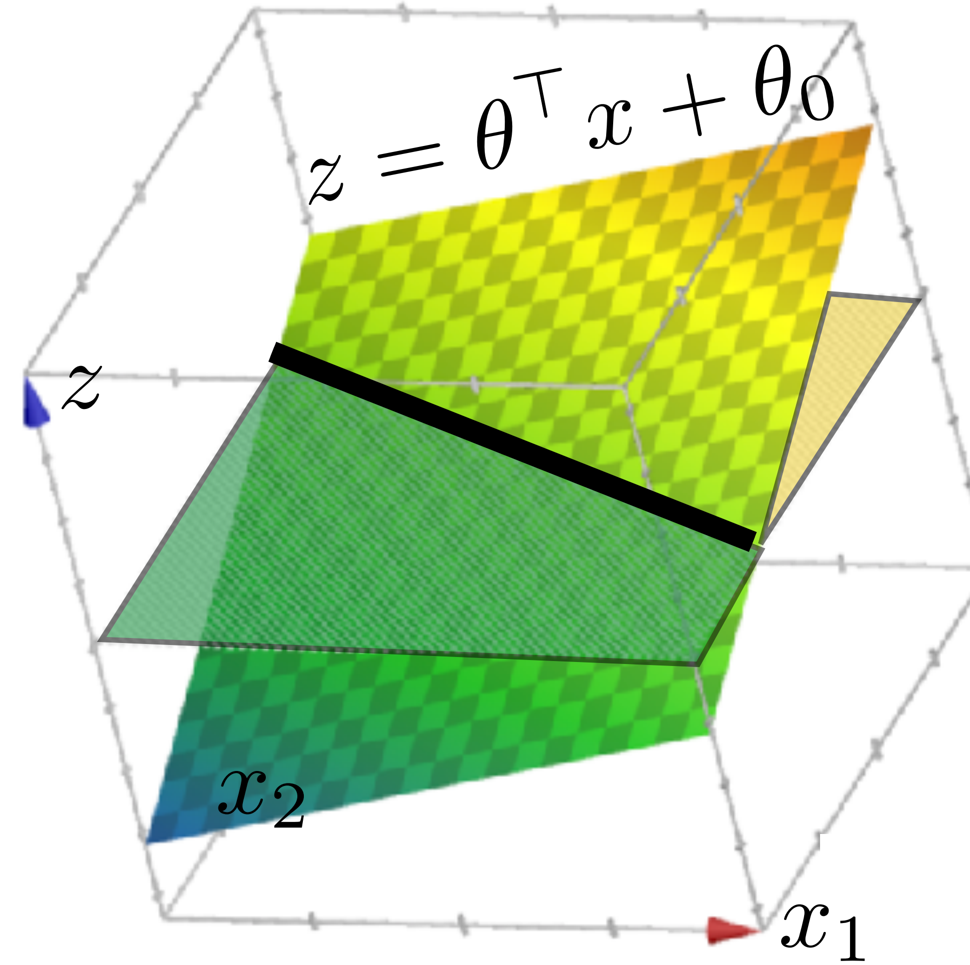

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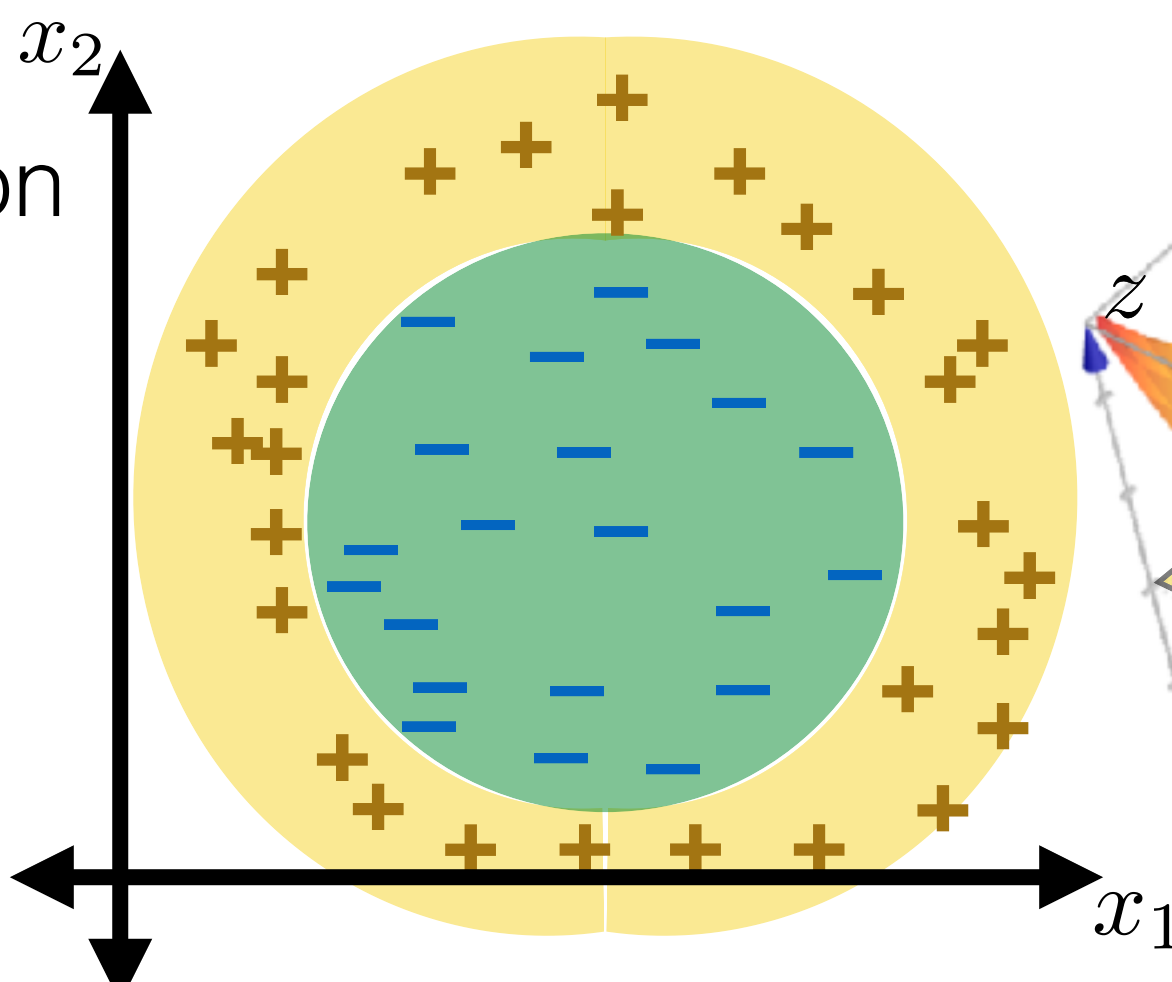

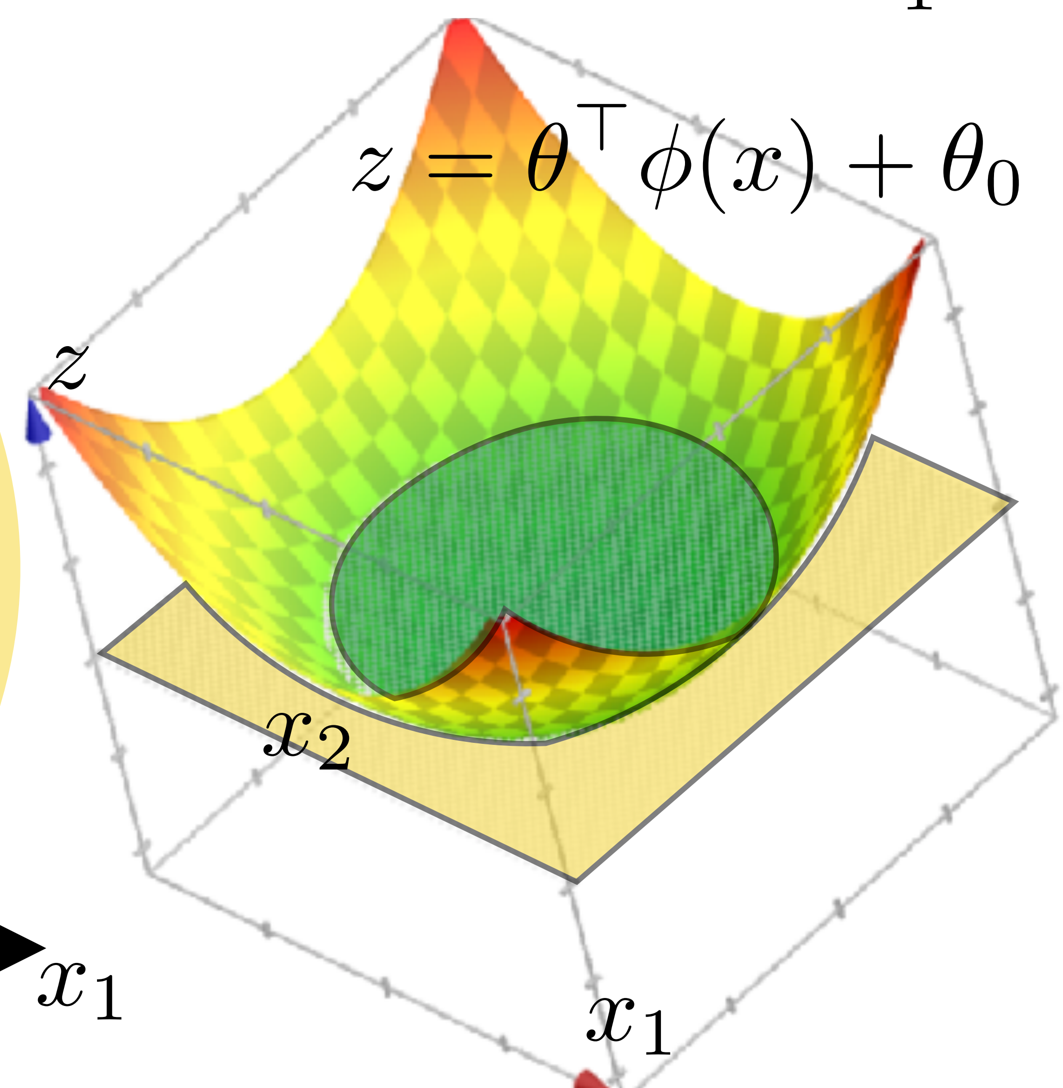

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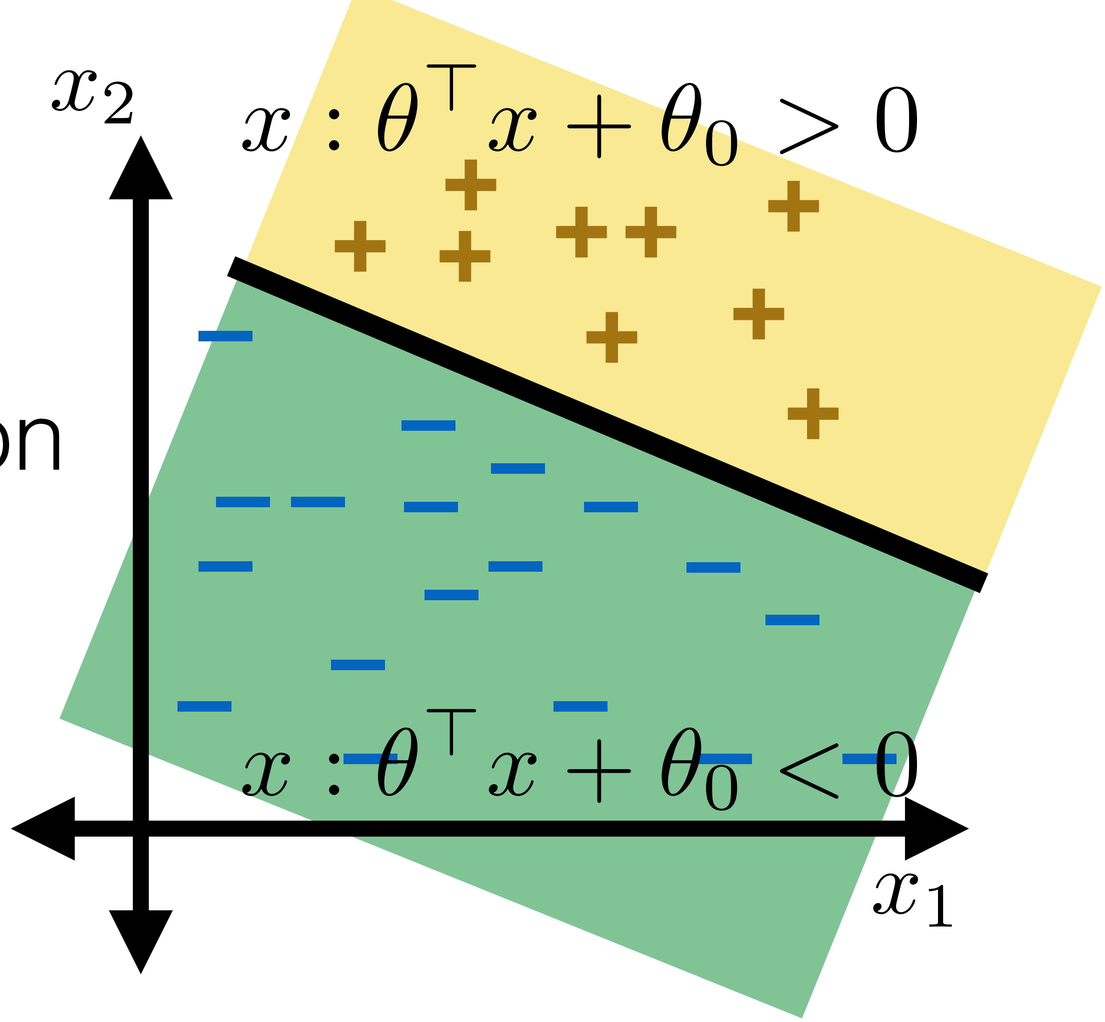

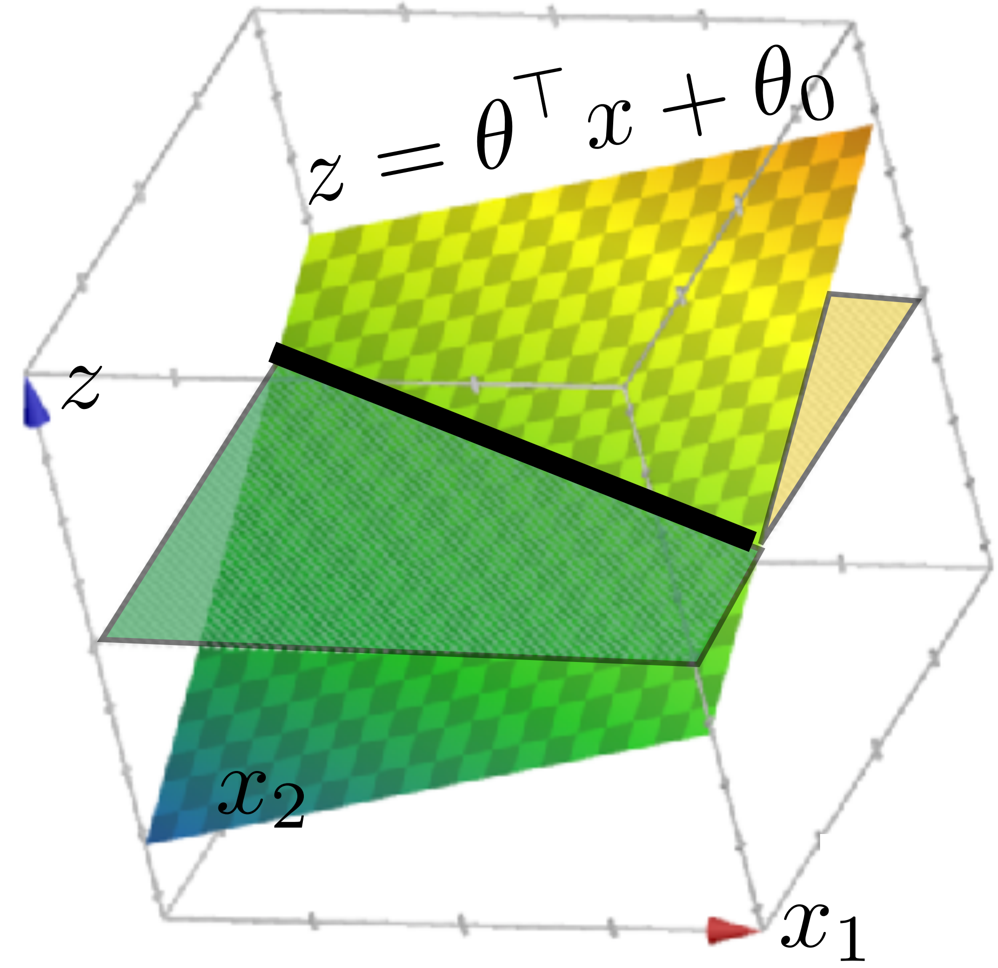

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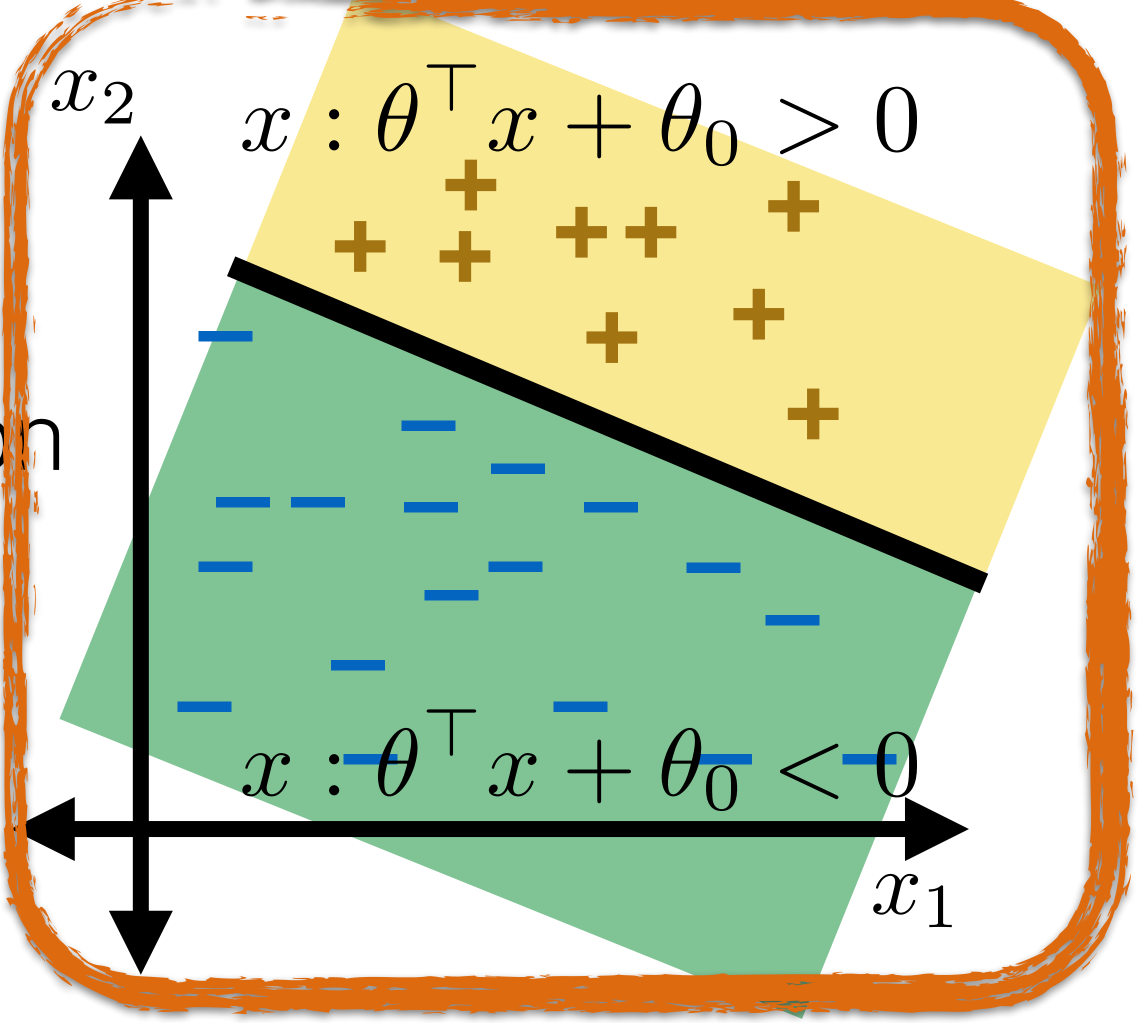

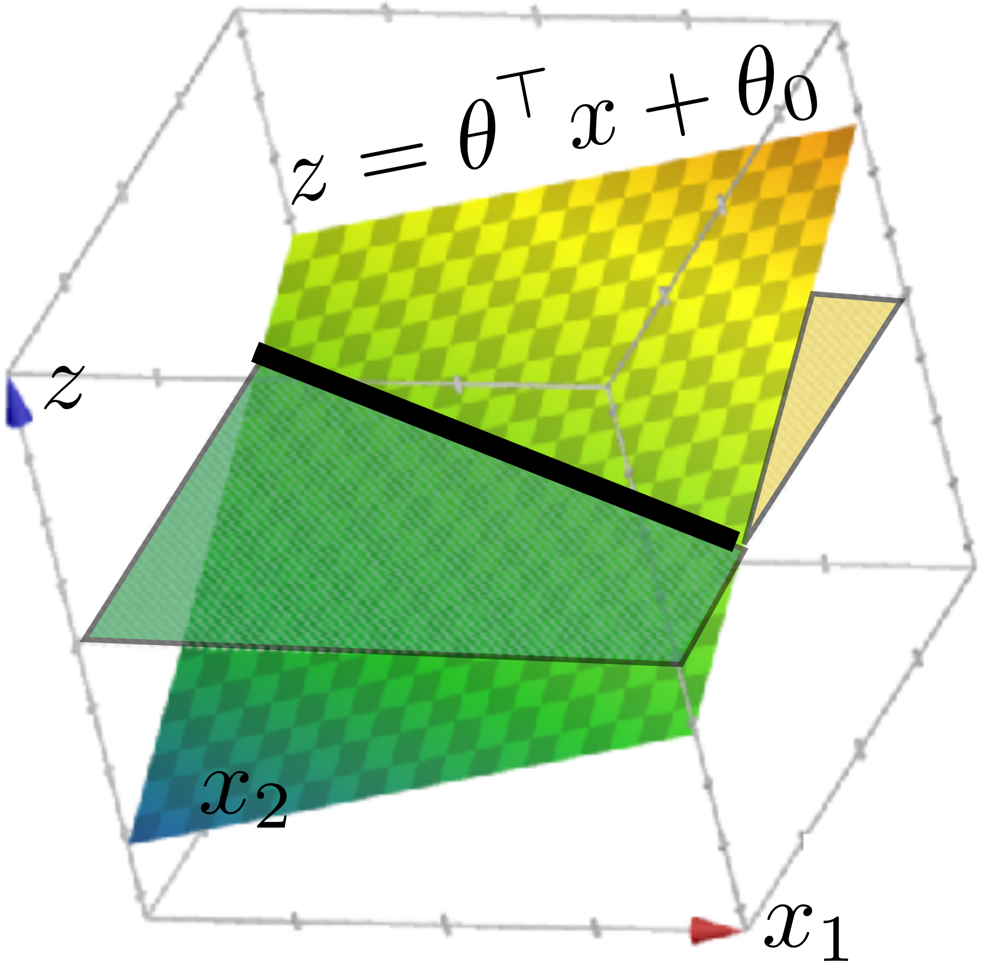

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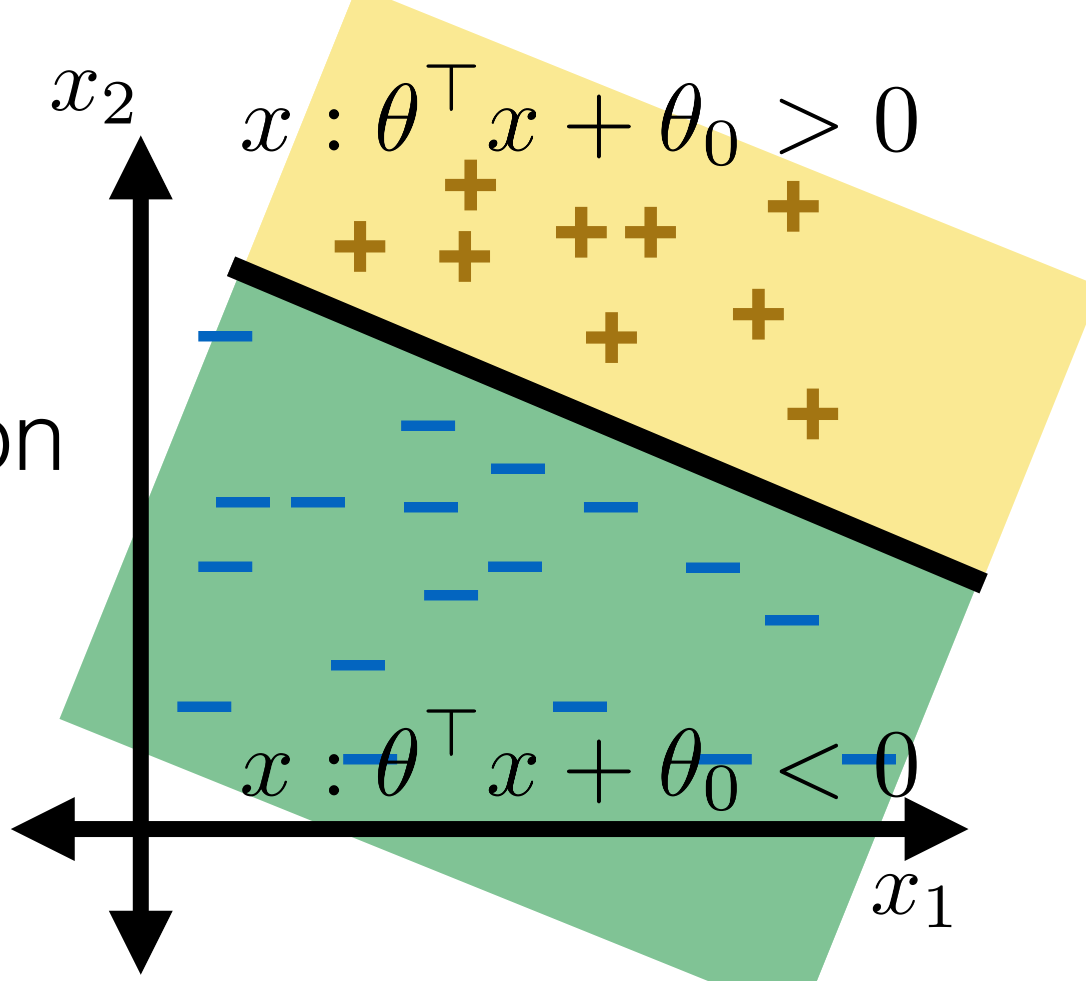

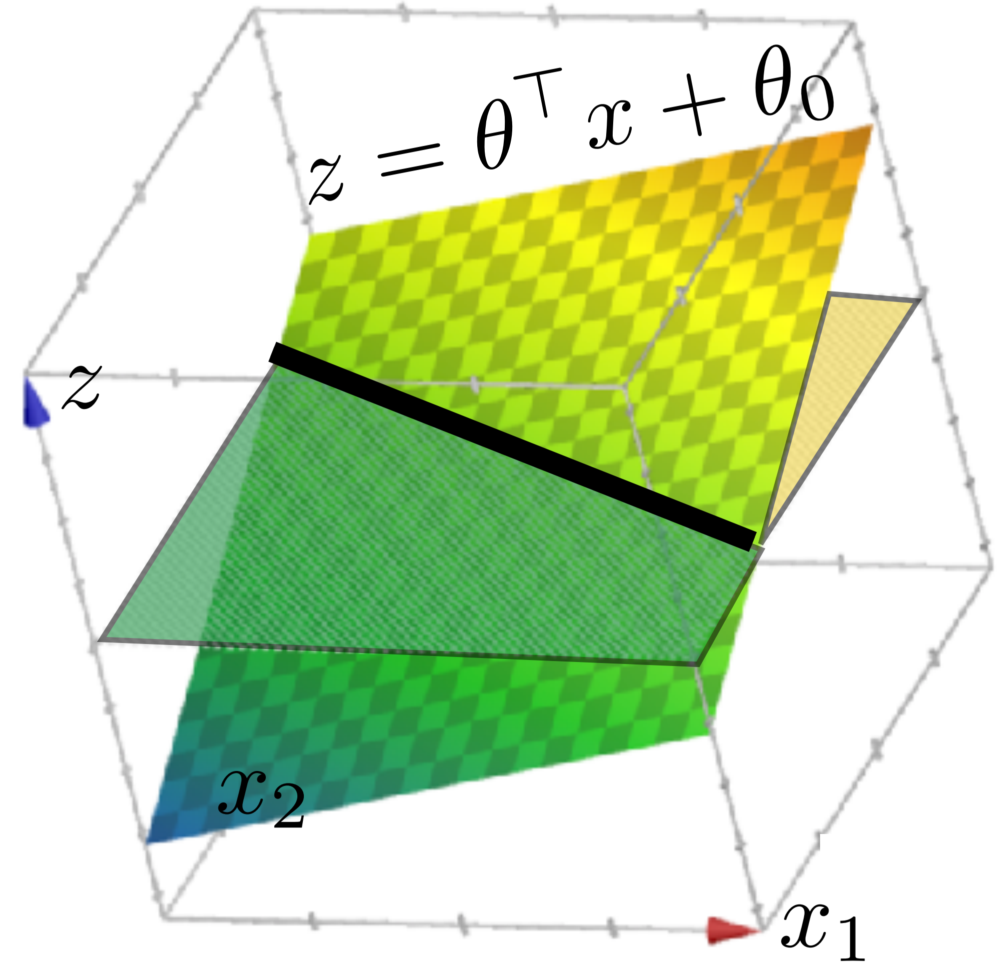

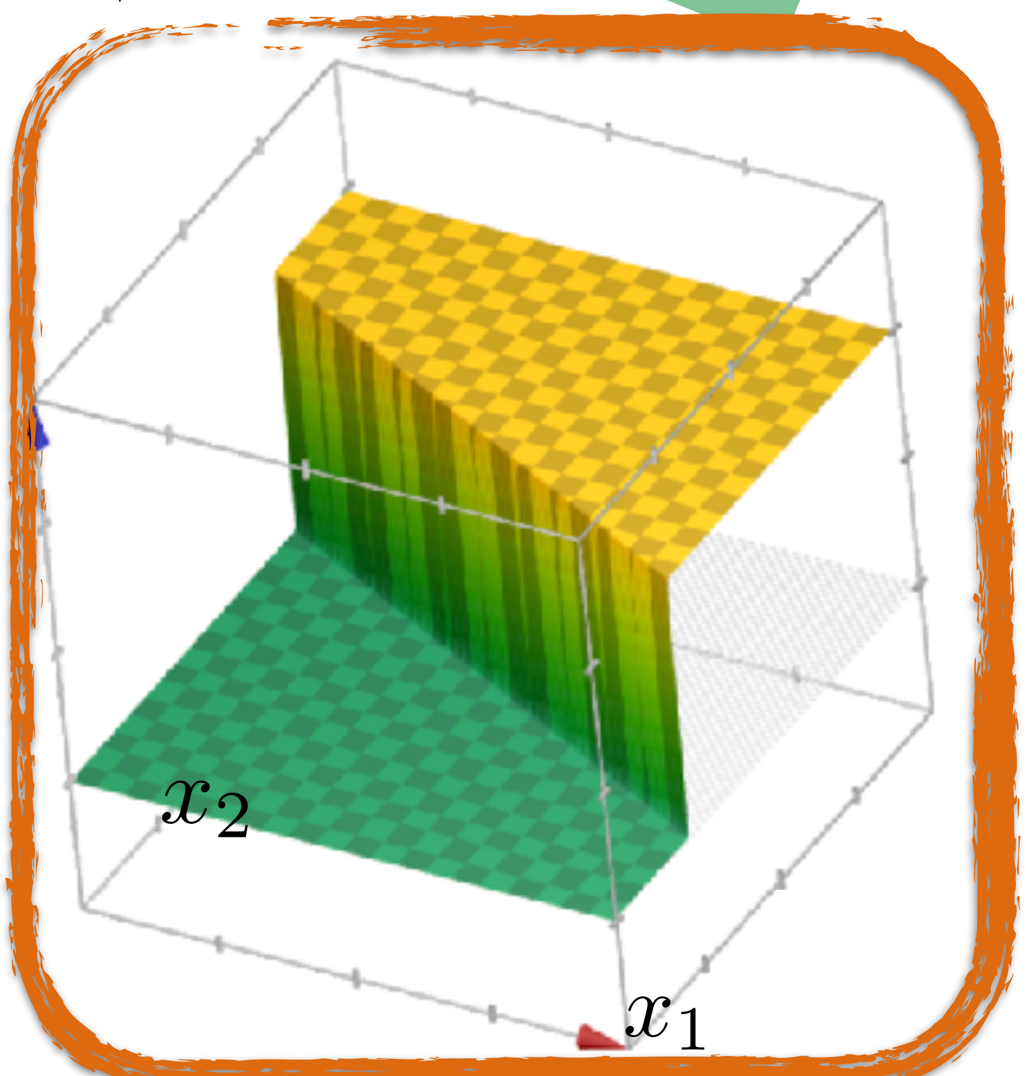

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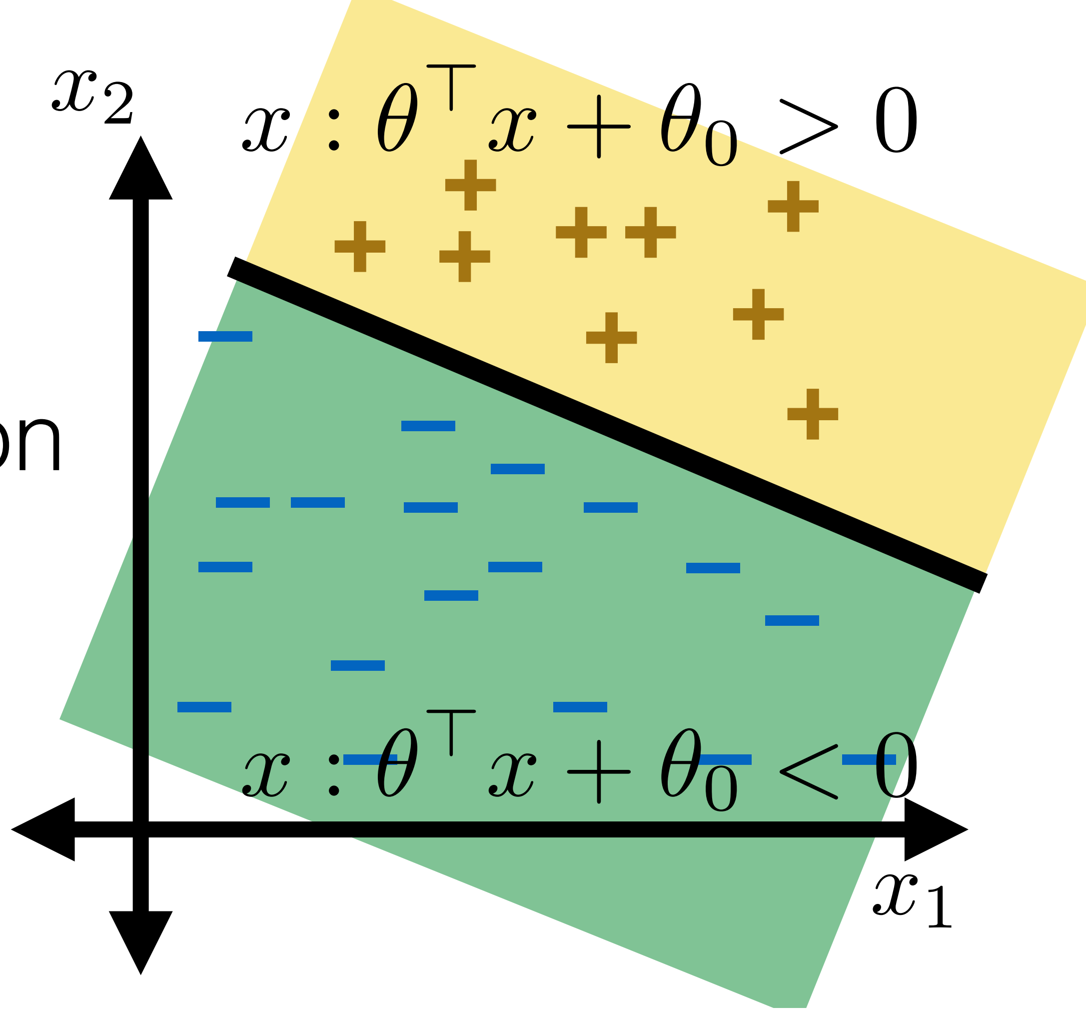

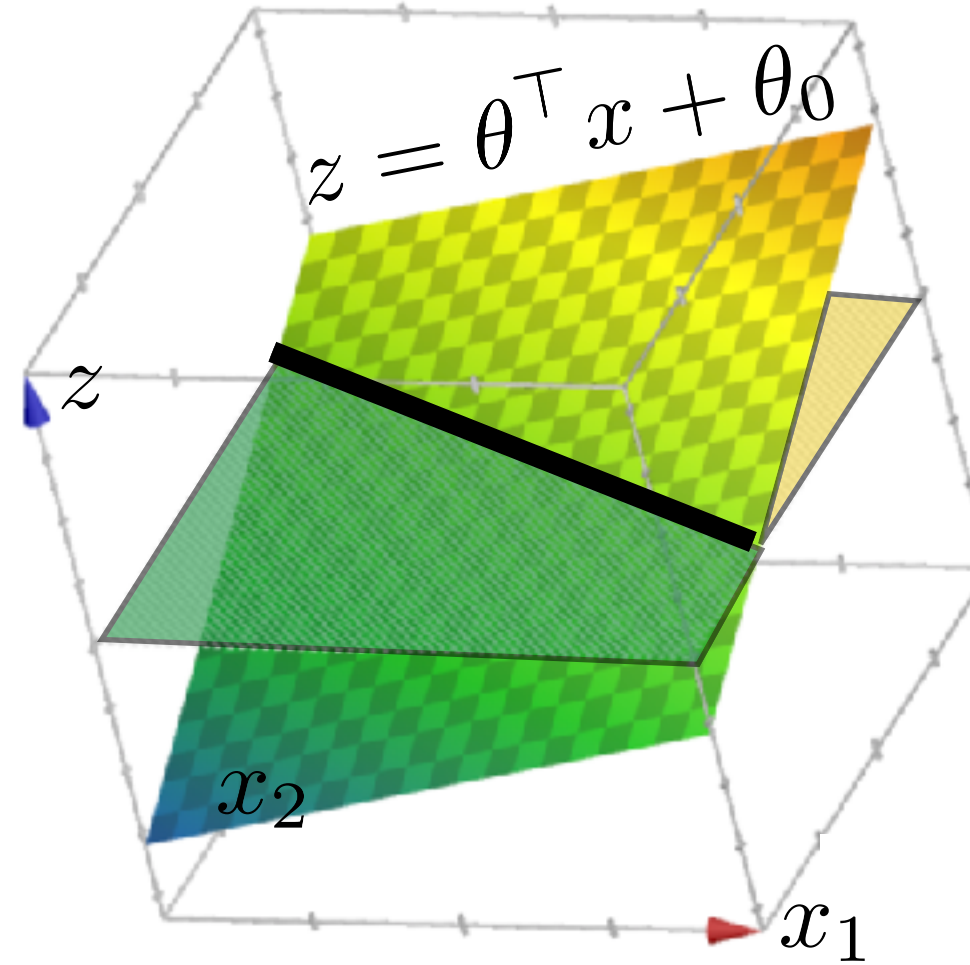

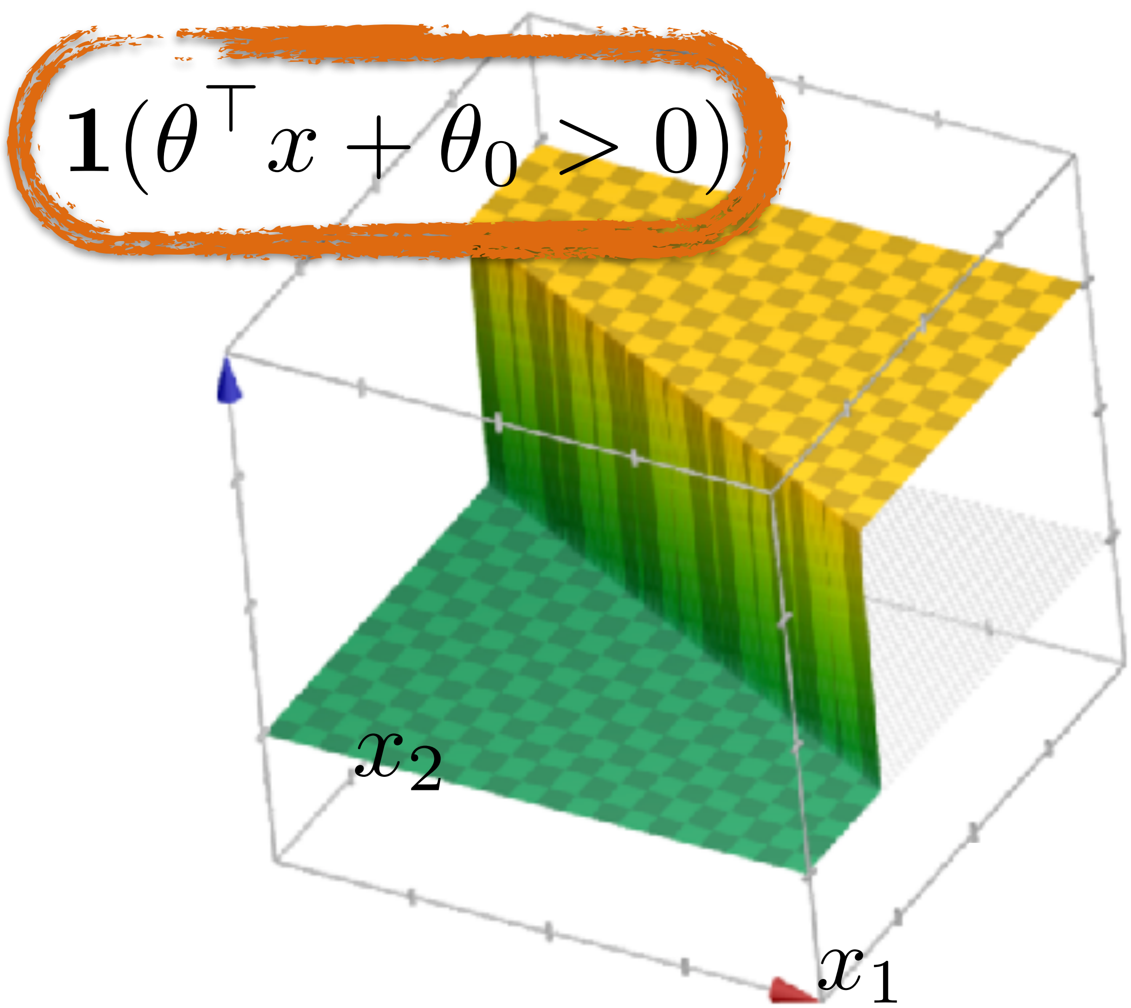

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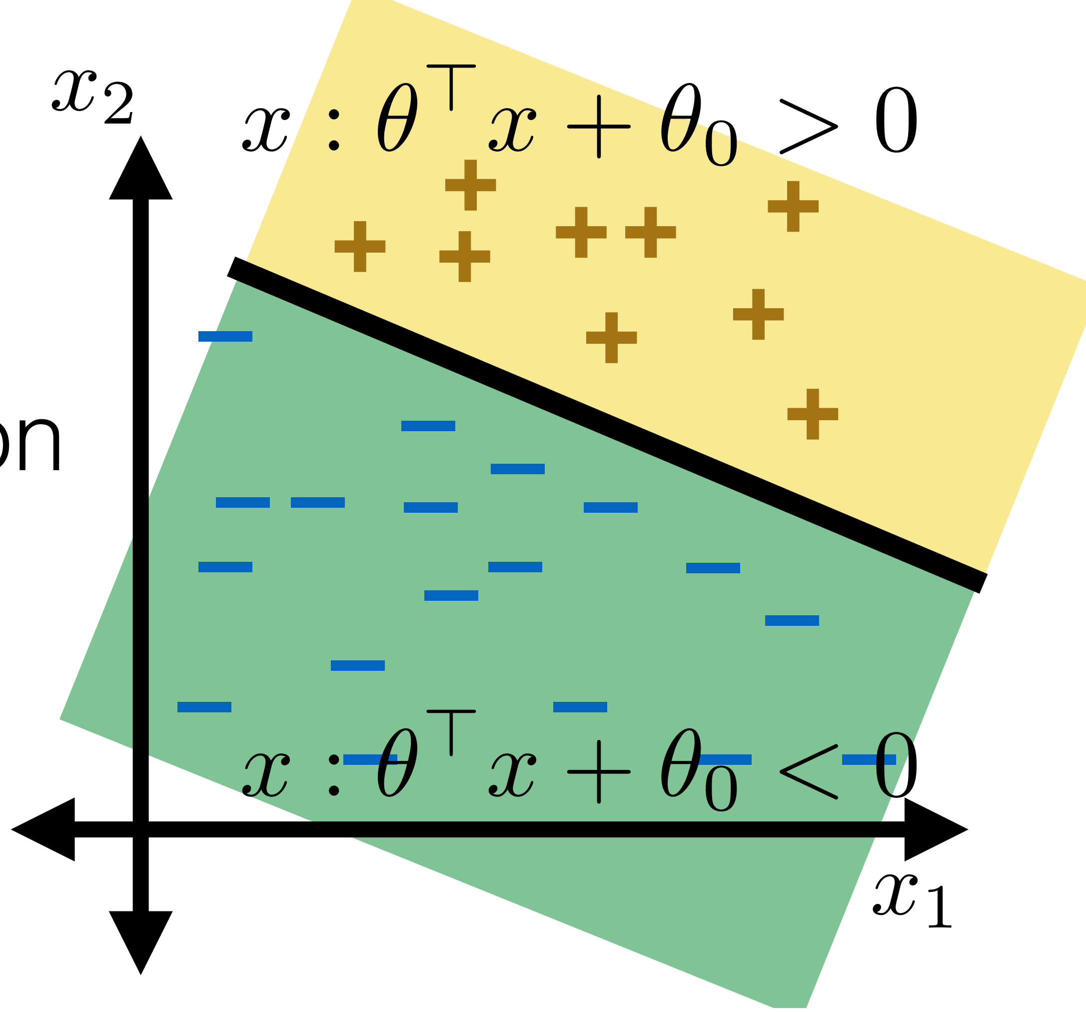

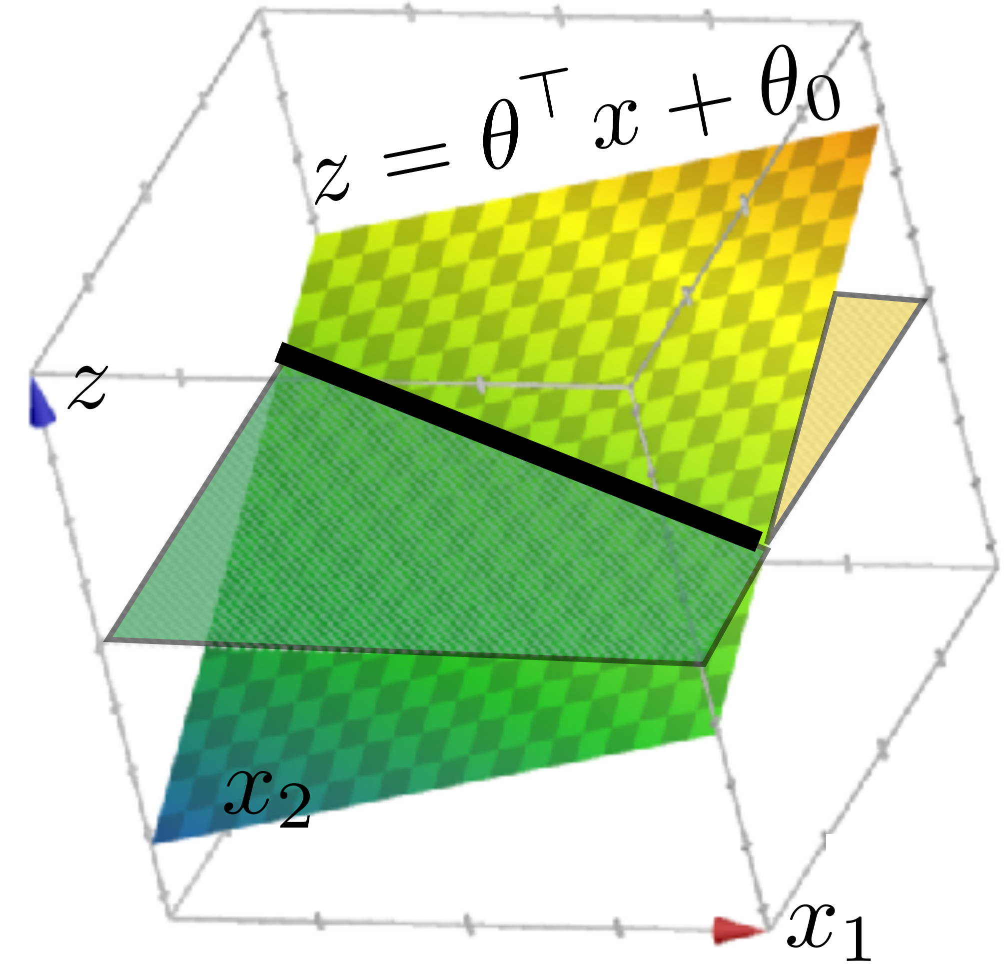

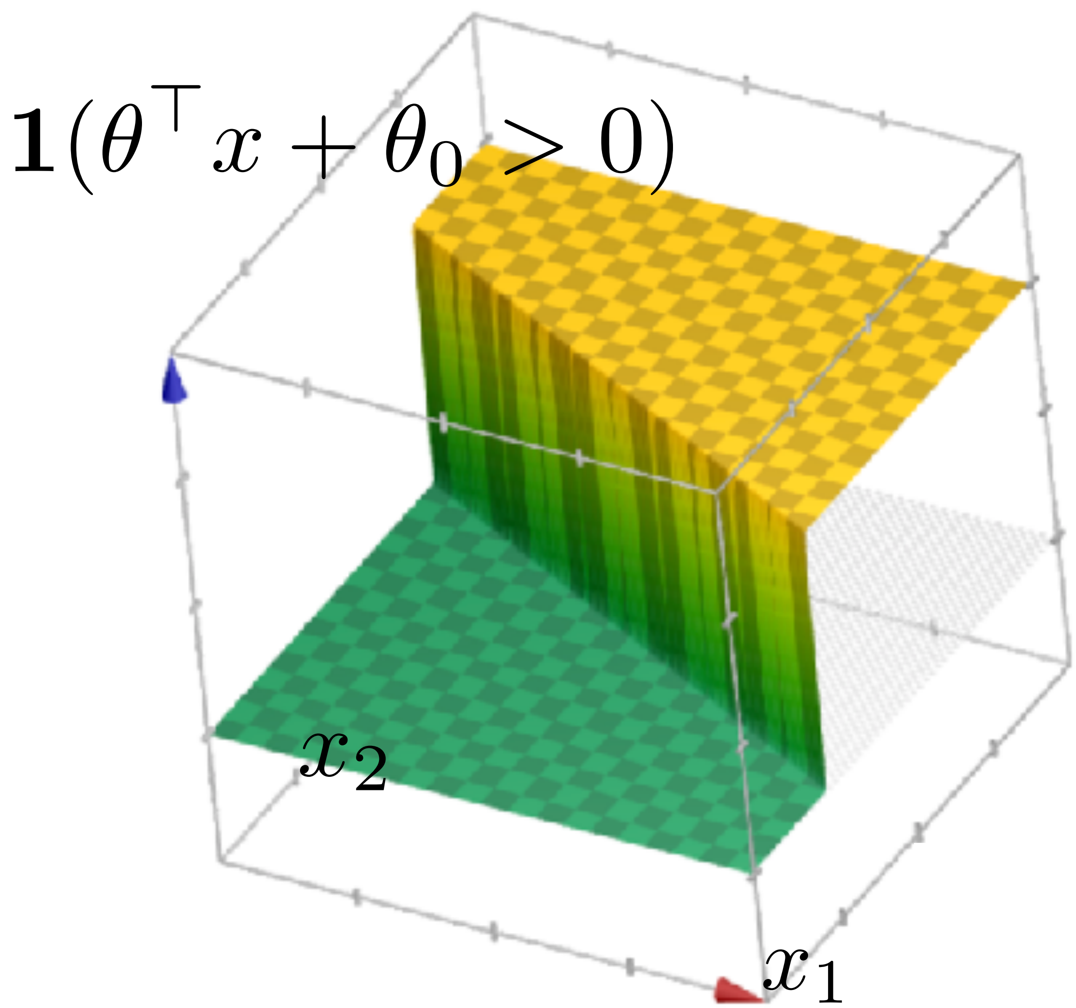

- We're used to using step functions to classify

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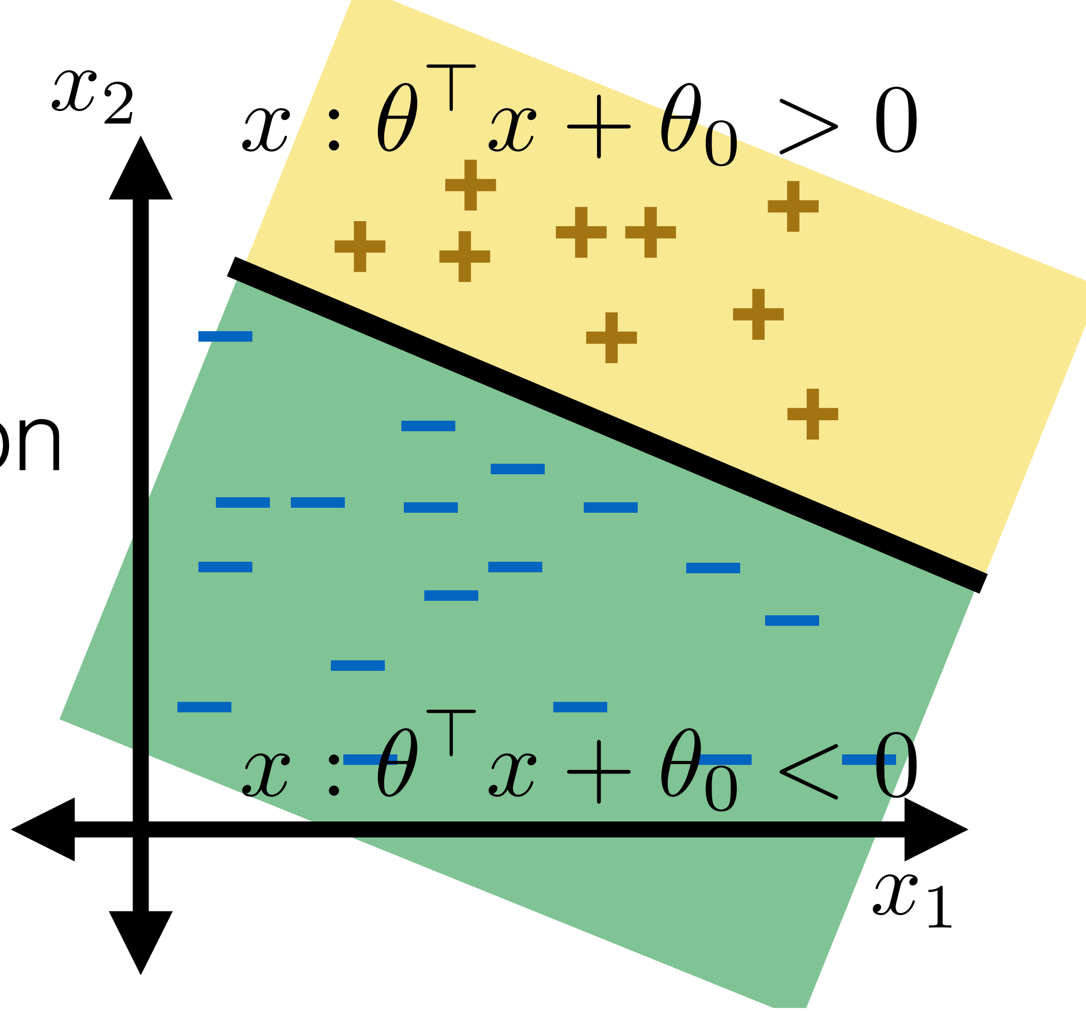

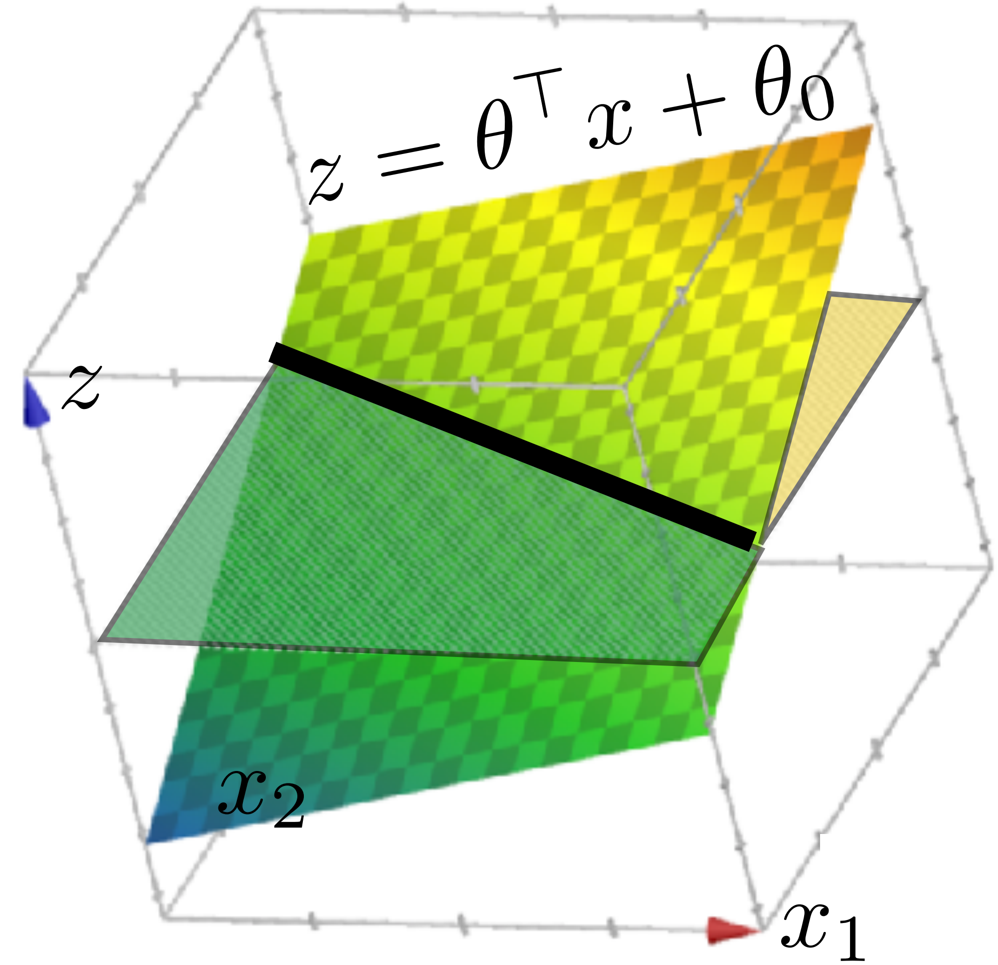

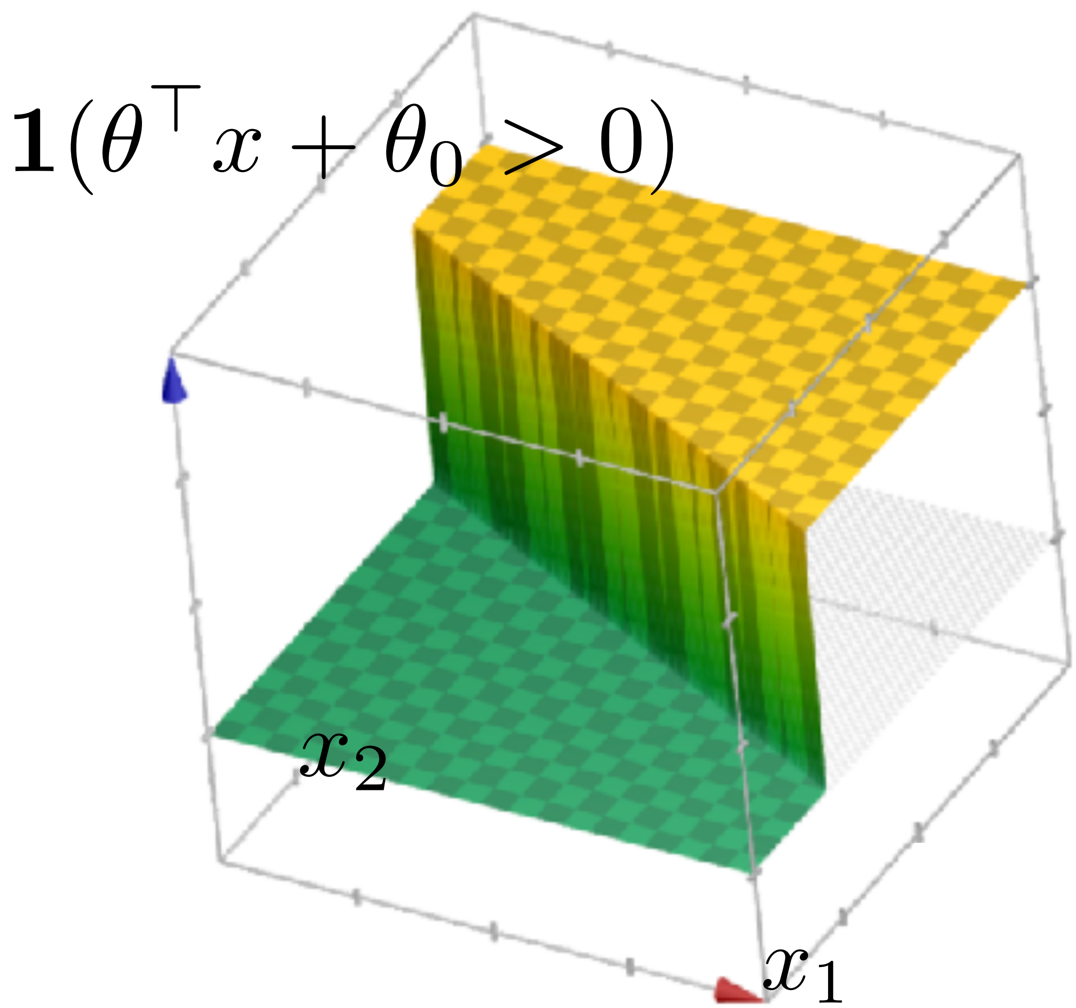

- We're used to using step functions to classify
- New idea today: we'll use step functions as *features*, with their own parameters

New features: step functions!

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$$\phi_1(x) = \mathbf{1}\{w^\top x + w_0 \geq 0\}$$

New features: step functions!

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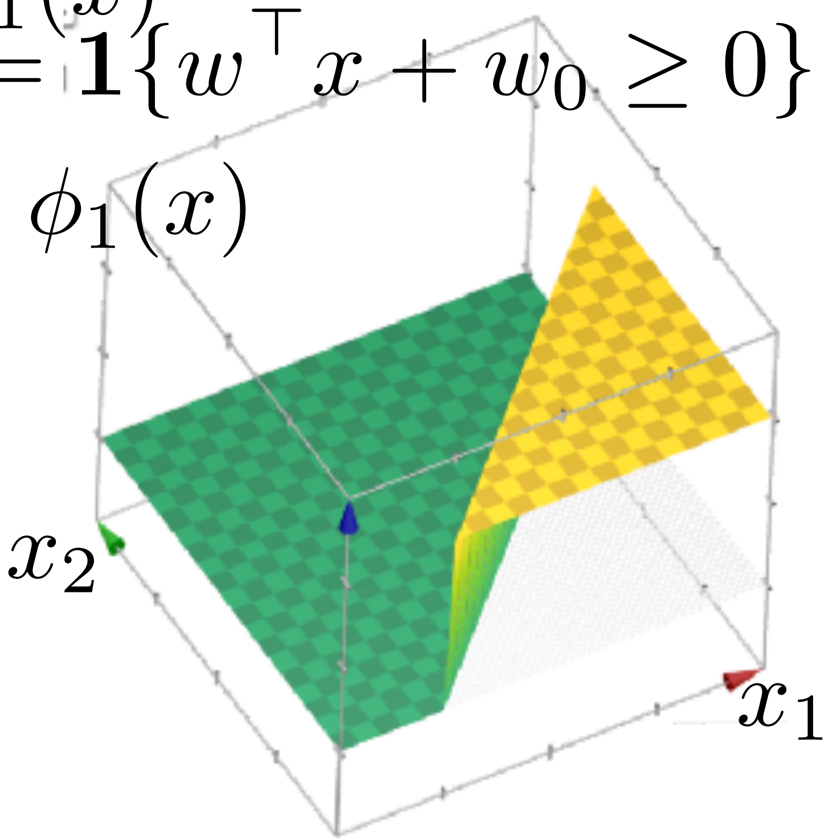

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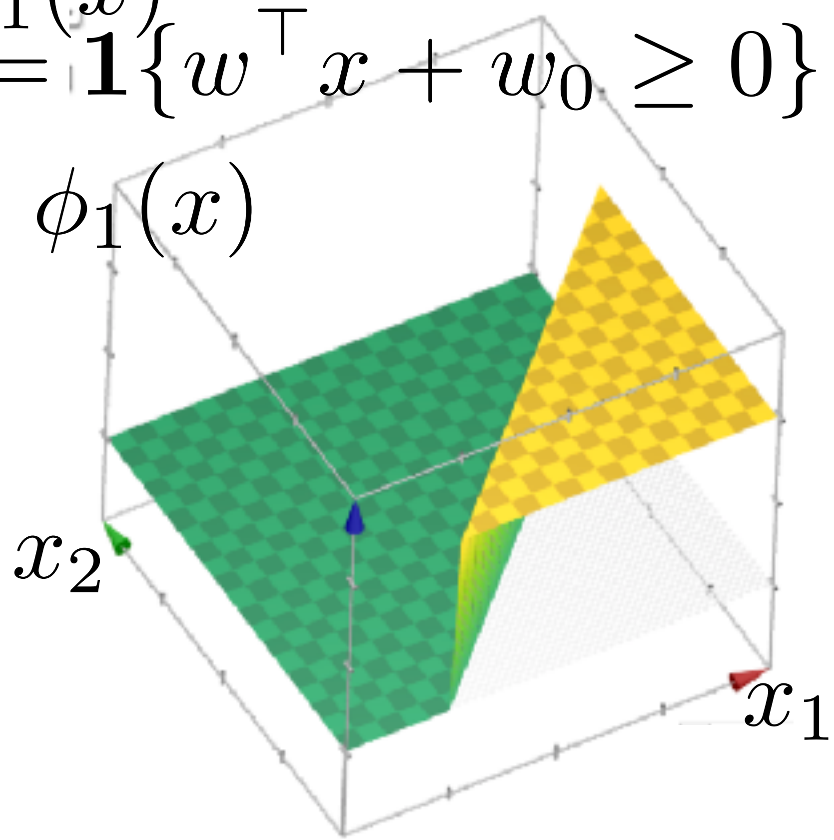

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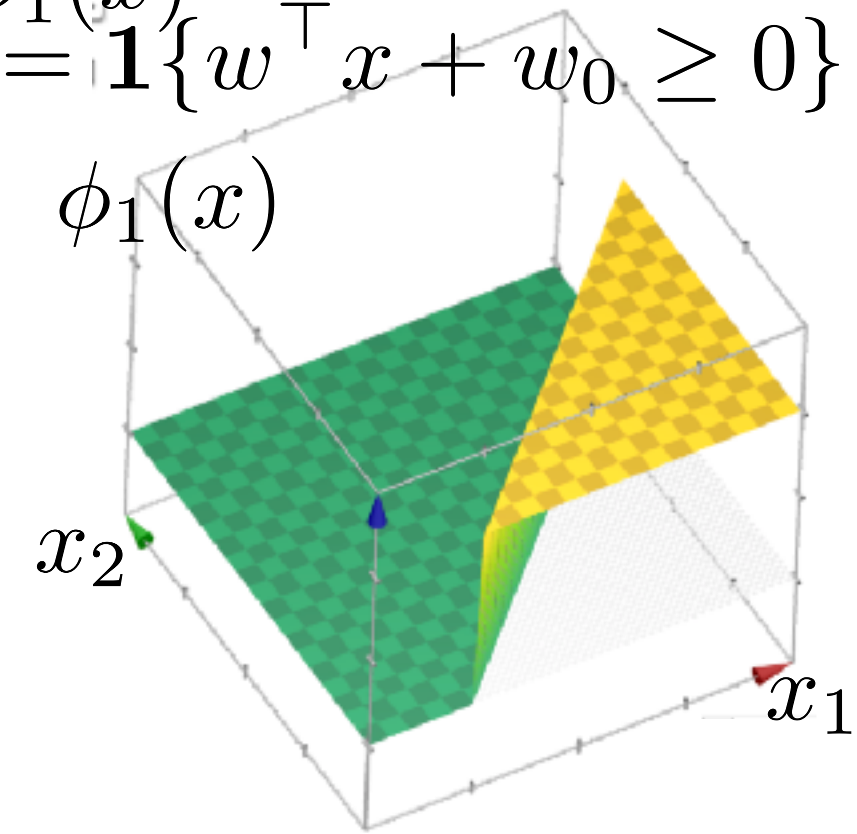

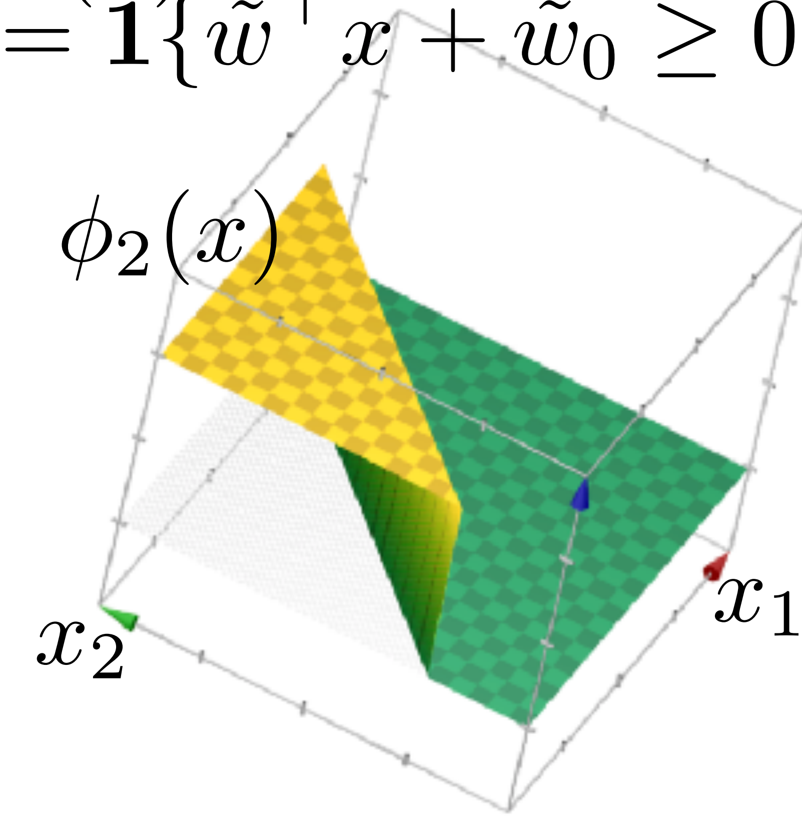

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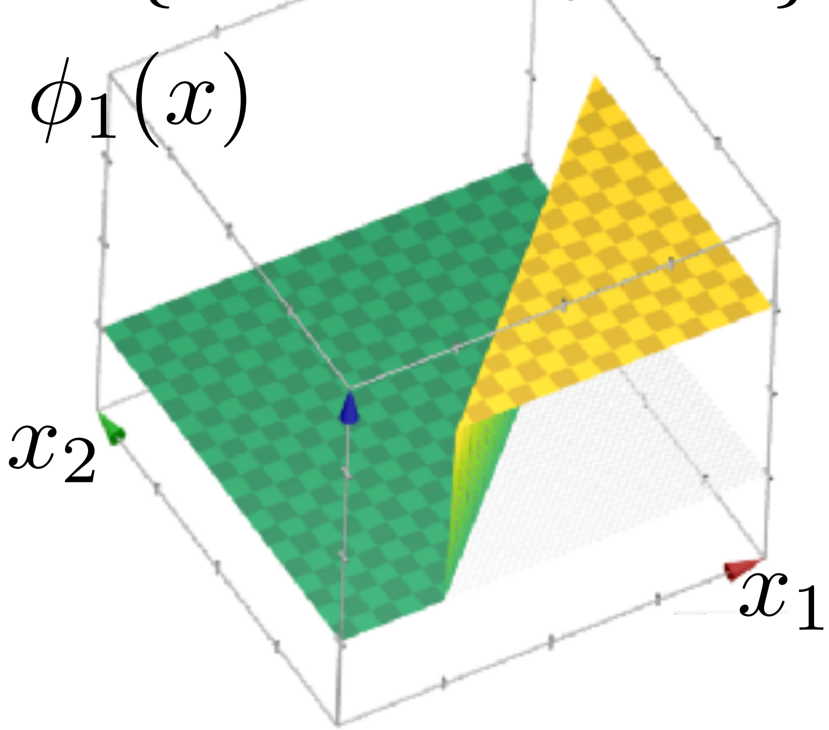

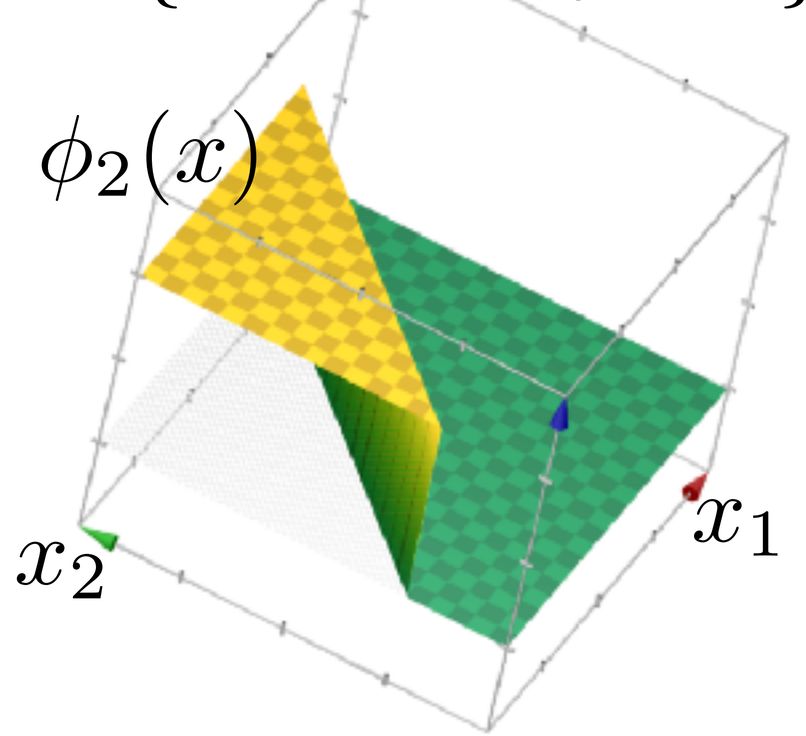

$$z = \theta^\top \phi(x) + \theta_0$$

New features: step functions!

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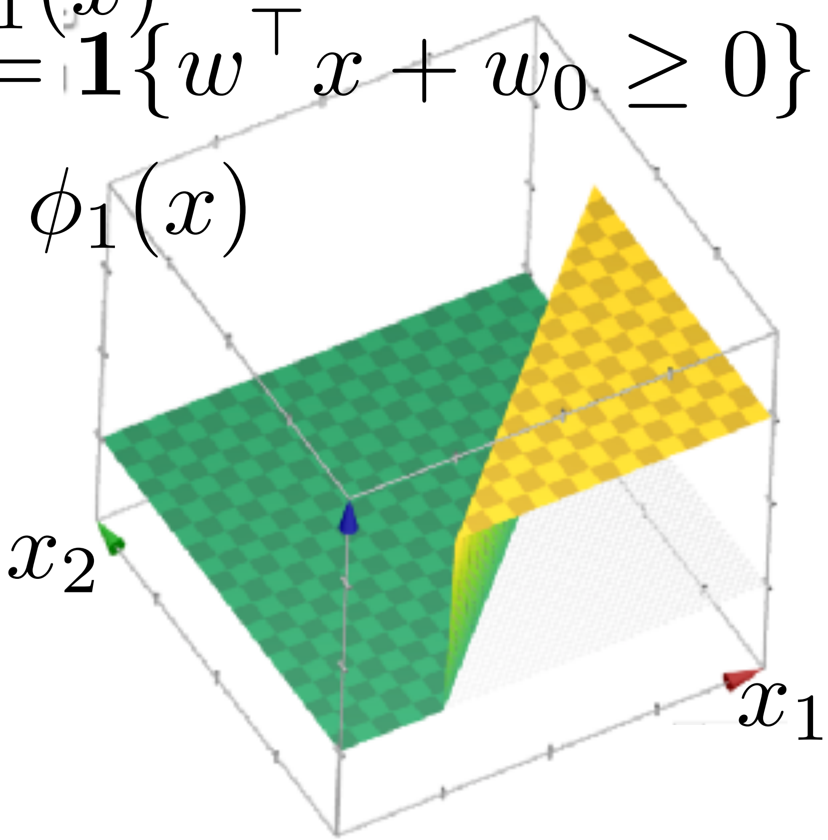

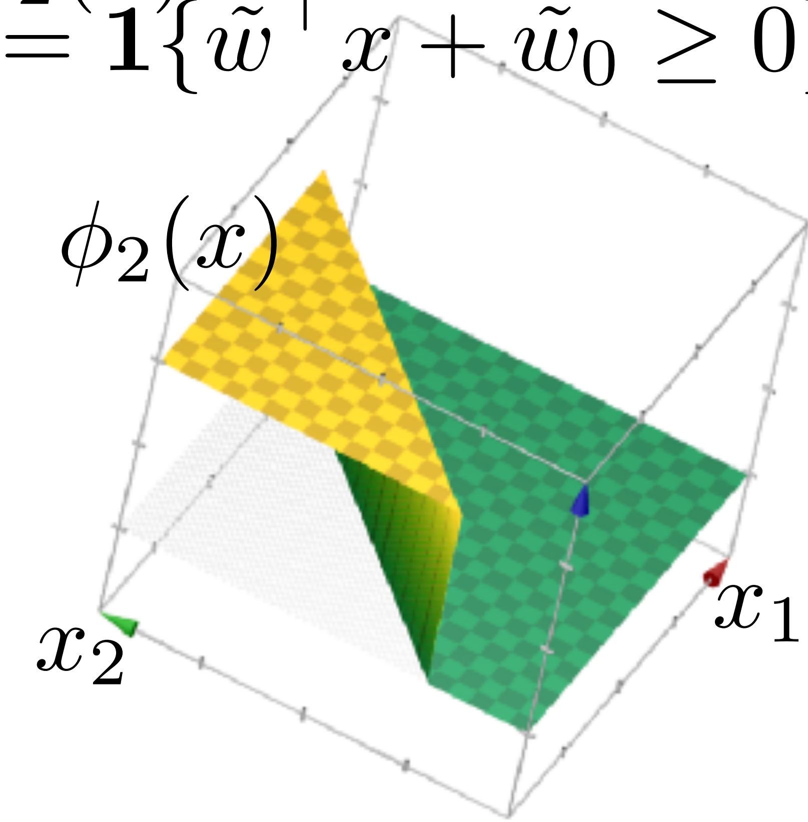

$$z = \theta^\top \phi(x) + \theta_0$$
$$= \theta_1\phi_1(x) + \theta_2\phi_2(x) + \theta_0$$

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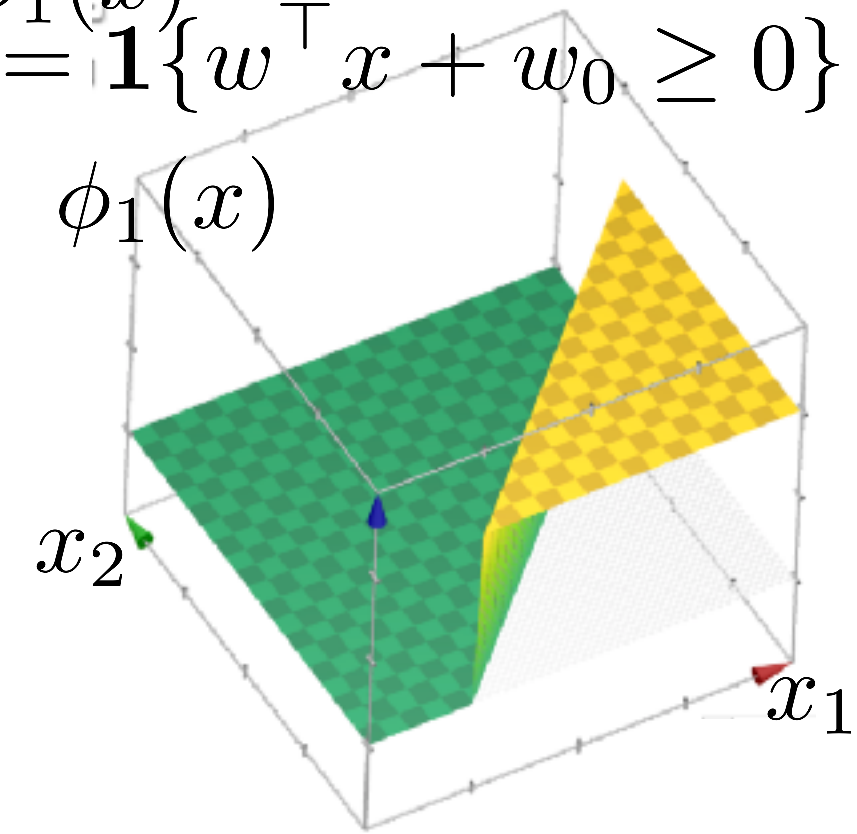

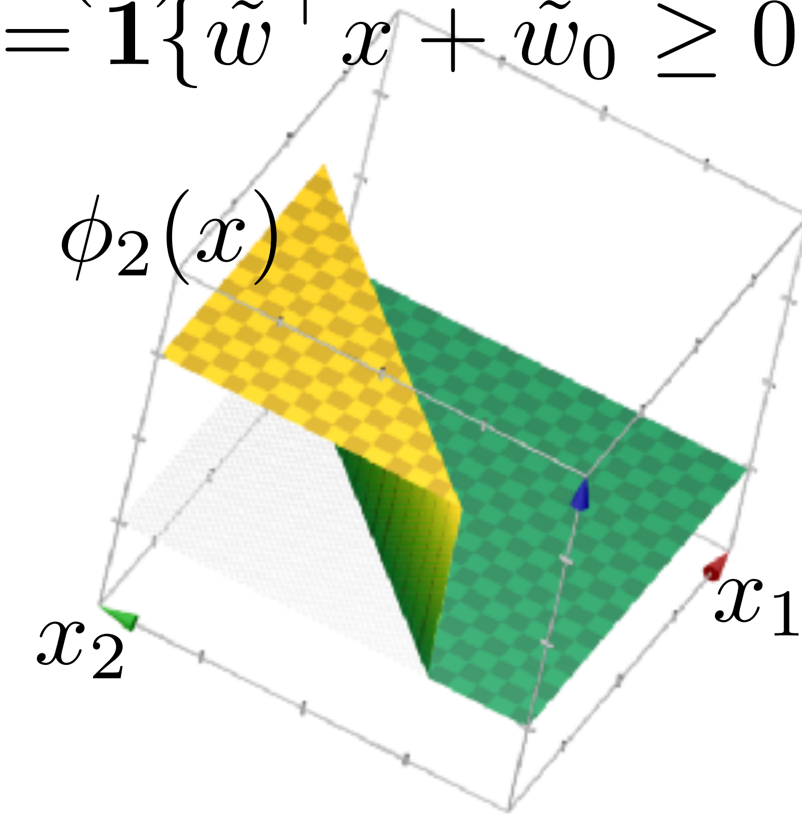

$$z = \theta^\top \phi(x) + \theta_0$$

$$= \theta_1 \phi_1(x) + \theta_2 \phi_2(x) + \theta_0$$

$$= 1 \cdot \phi_1(x) + 1 \cdot \phi_2(x) + (-0.5)$$

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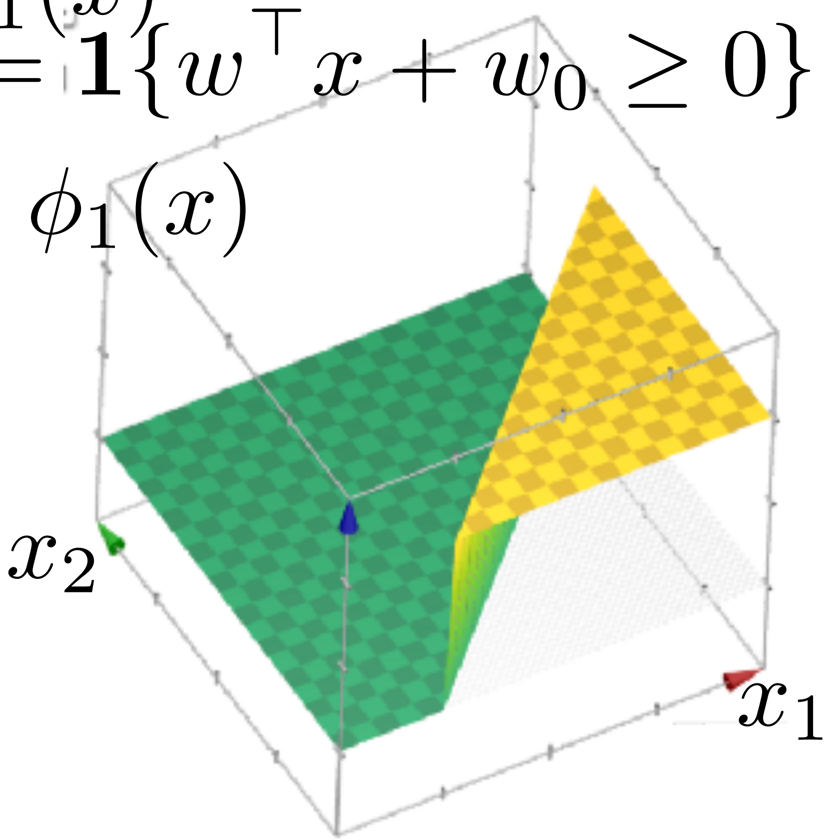
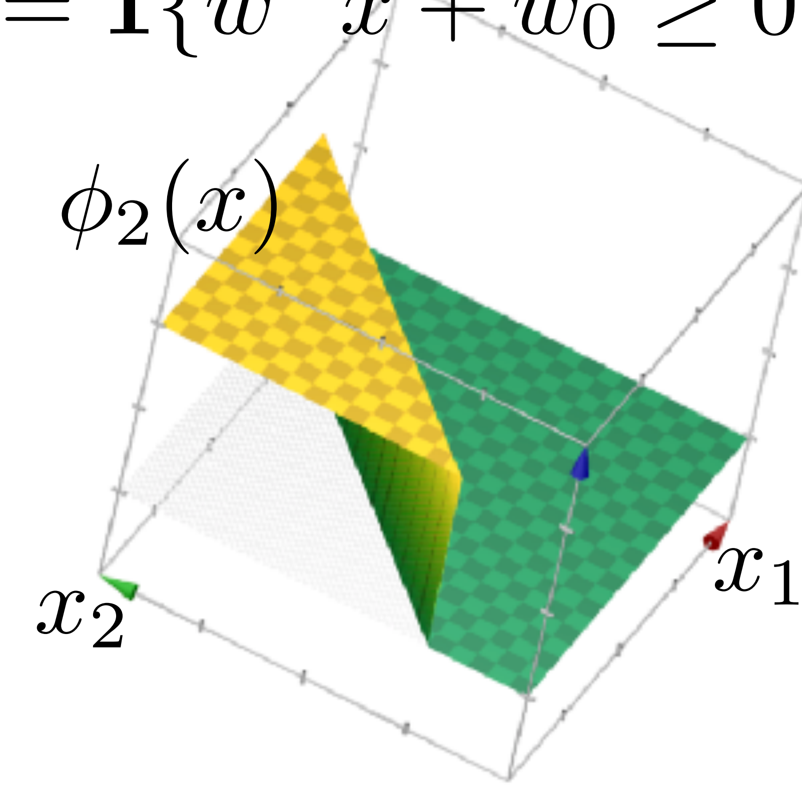
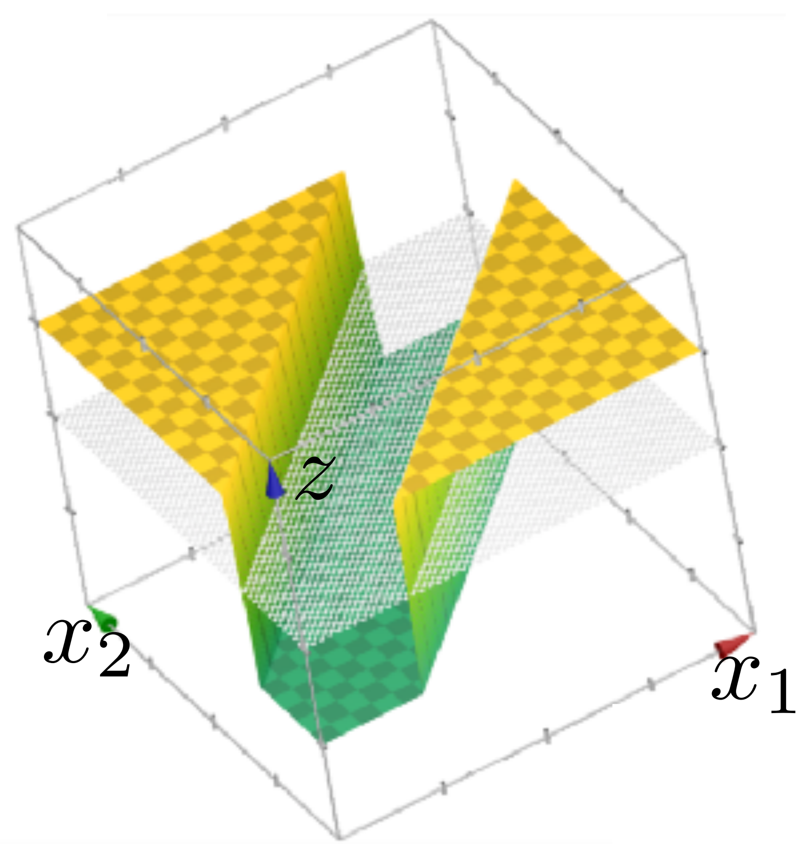




$$\begin{aligned}
z &= \theta^\top \phi(x) + \theta_0 \\
&= \theta_1 \phi_1(x) + \theta_2 \phi_2(x) \\
&\quad + \theta_0 \\
&= 1 \cdot \phi_1(x) + 1 \cdot \phi_2(x) \\
&\quad + (-0.5)
\end{aligned}$$



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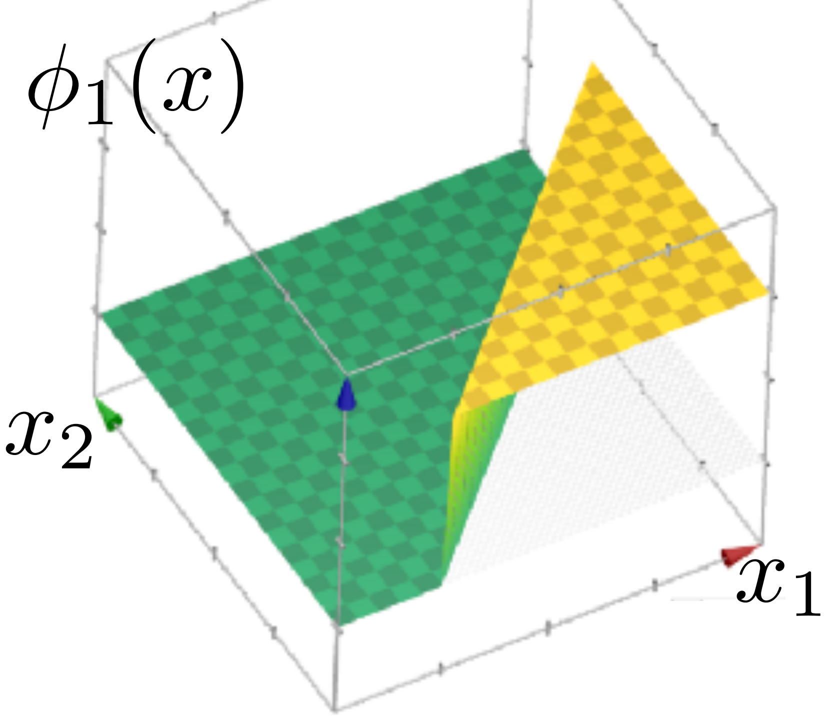

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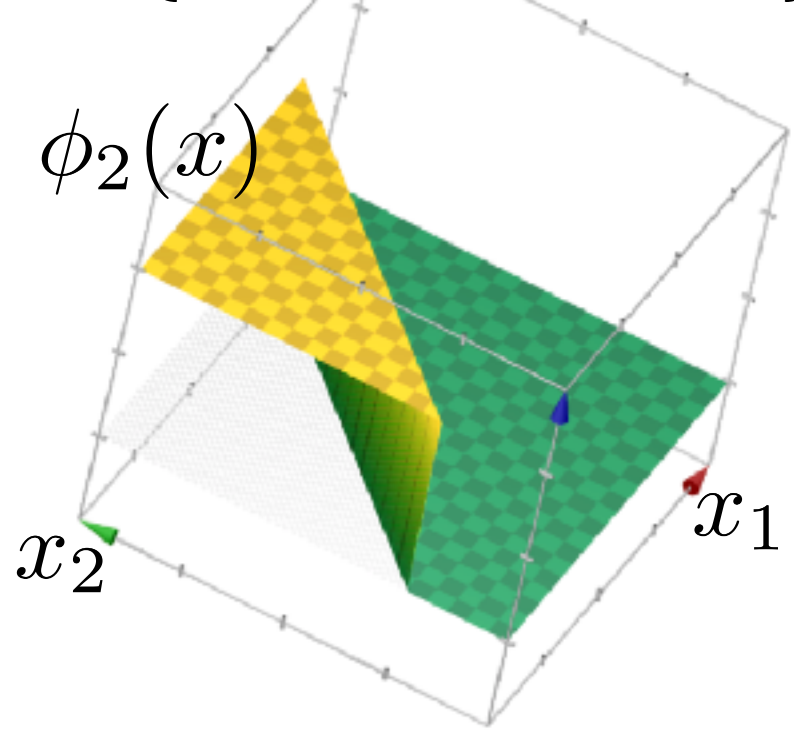

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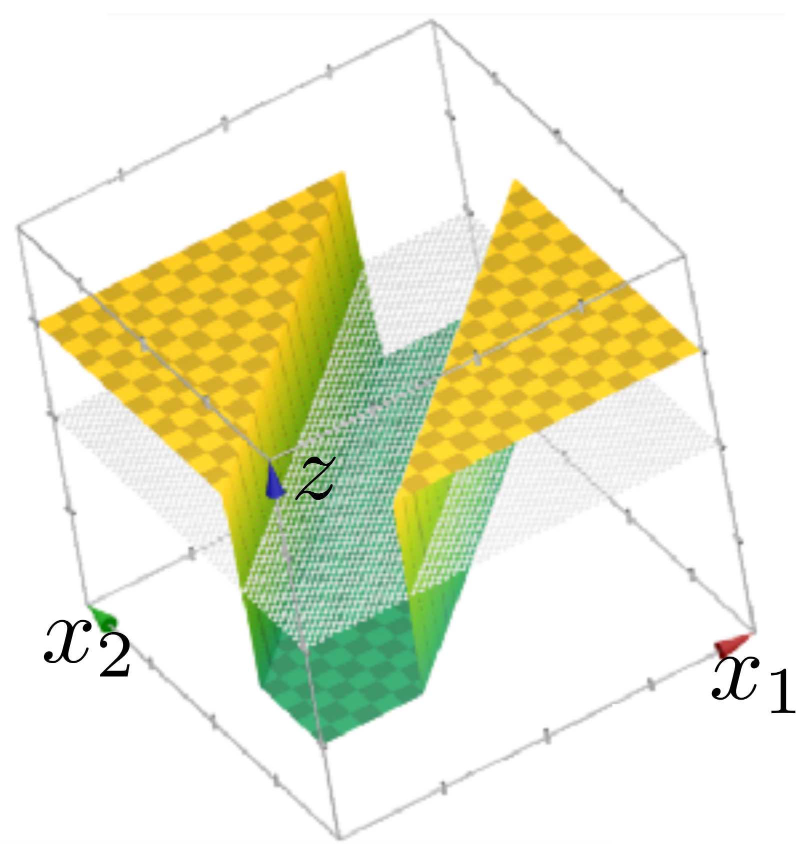

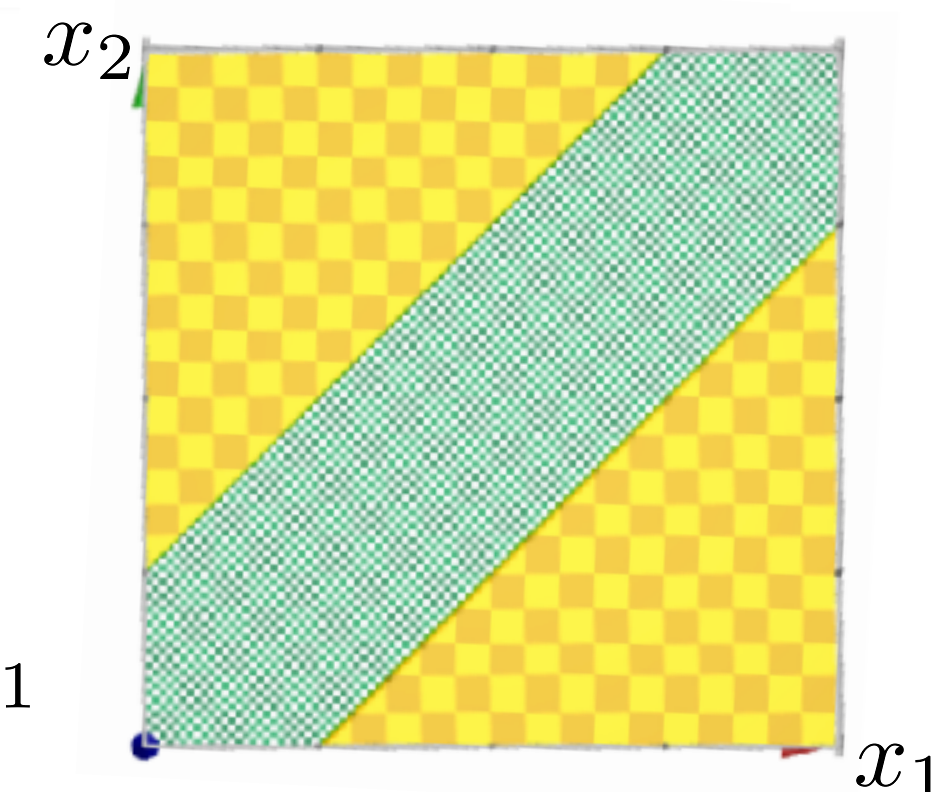

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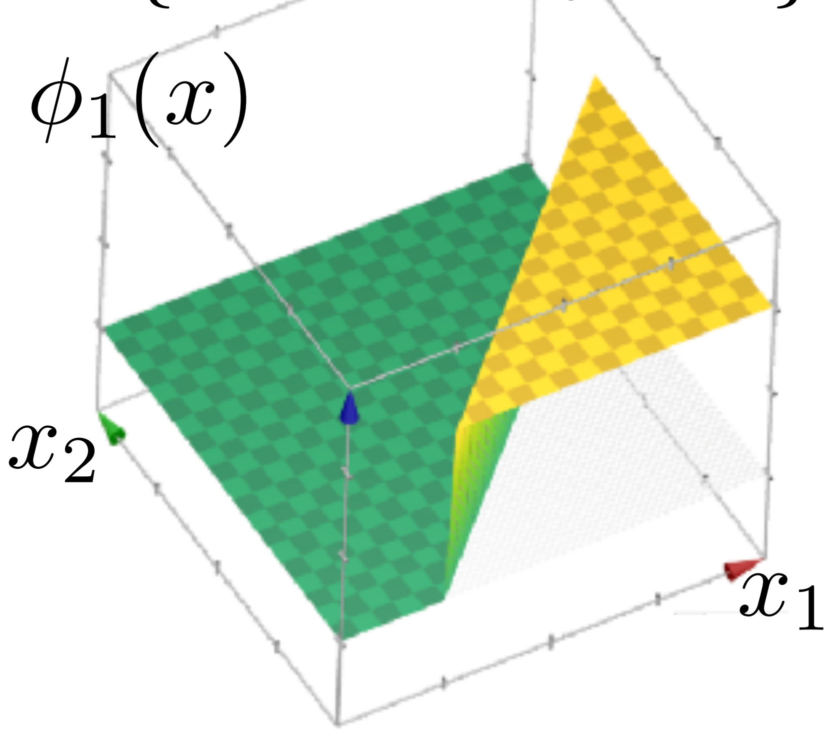

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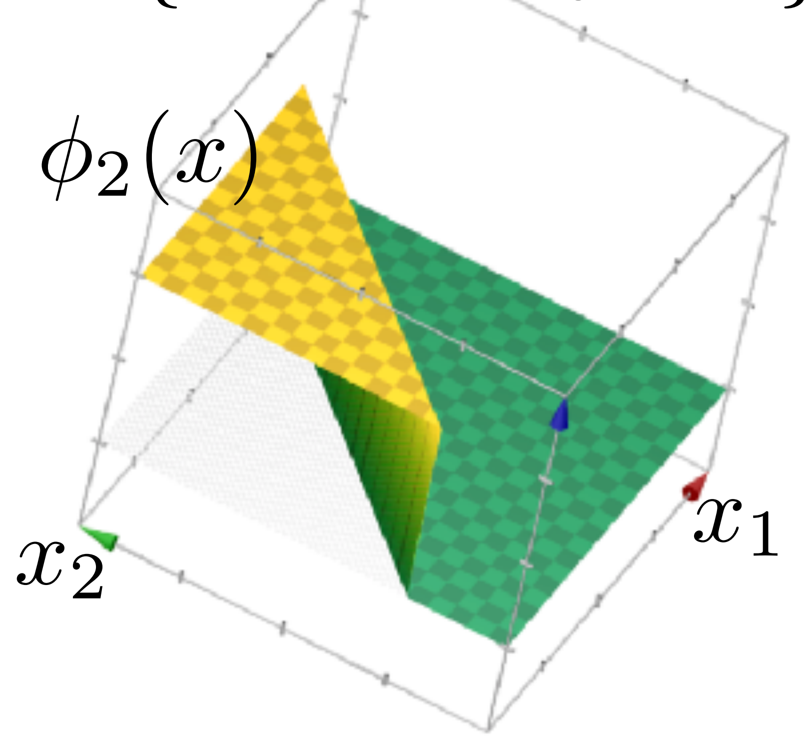

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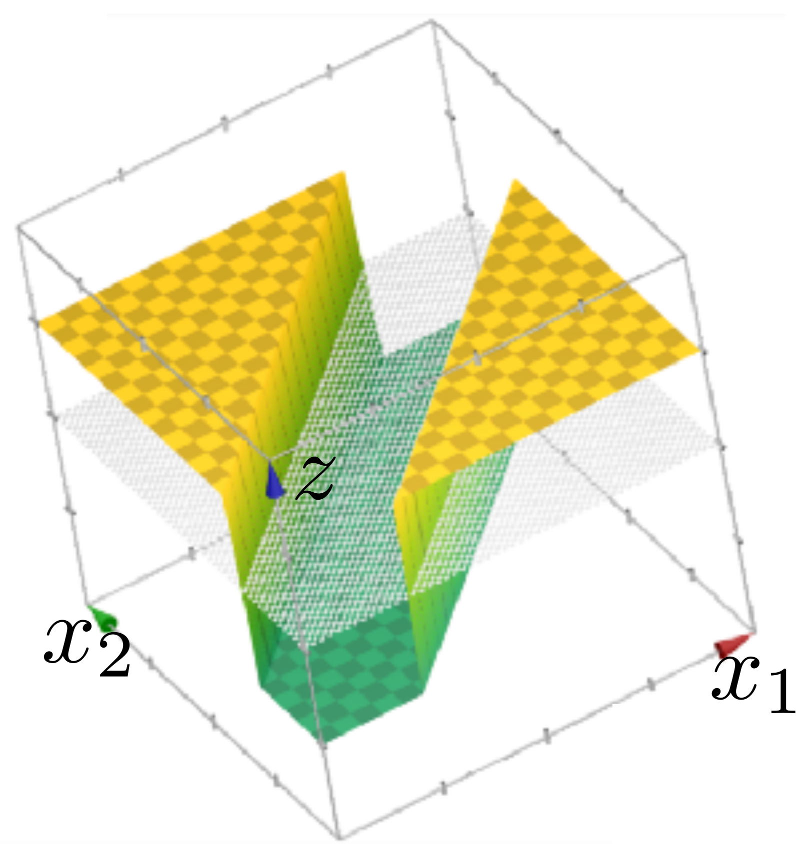

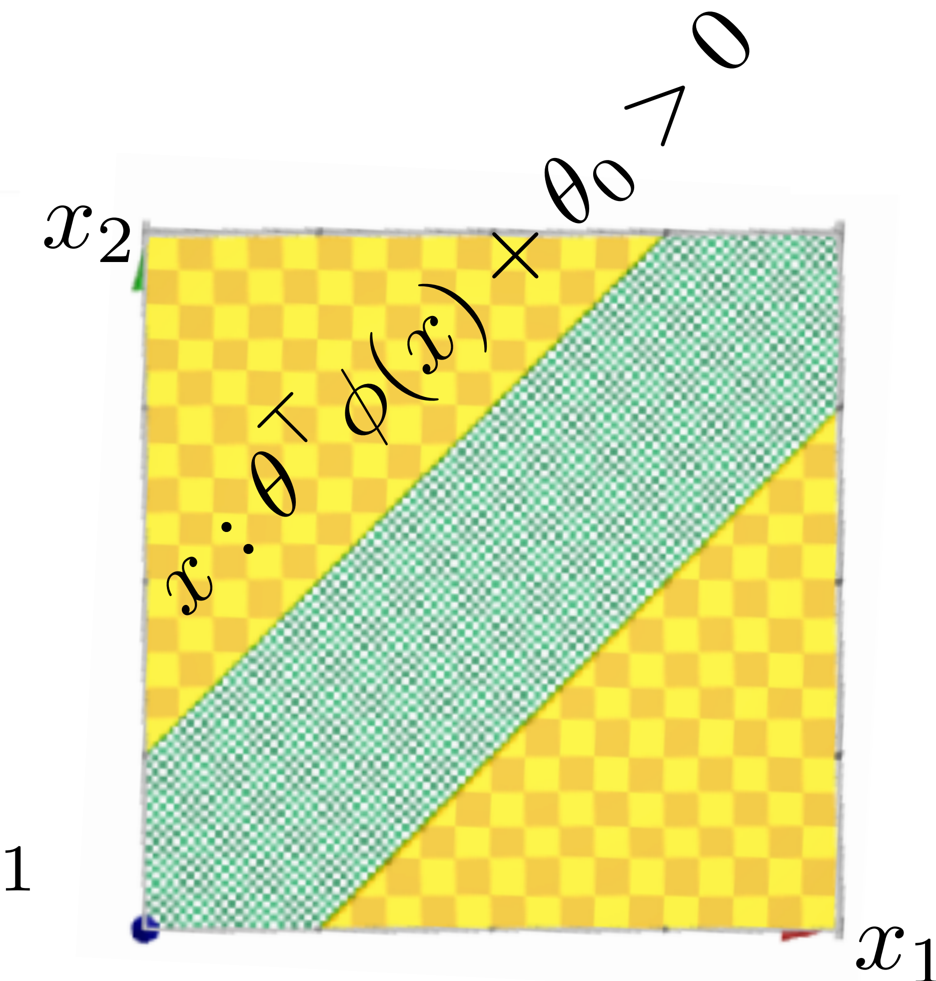

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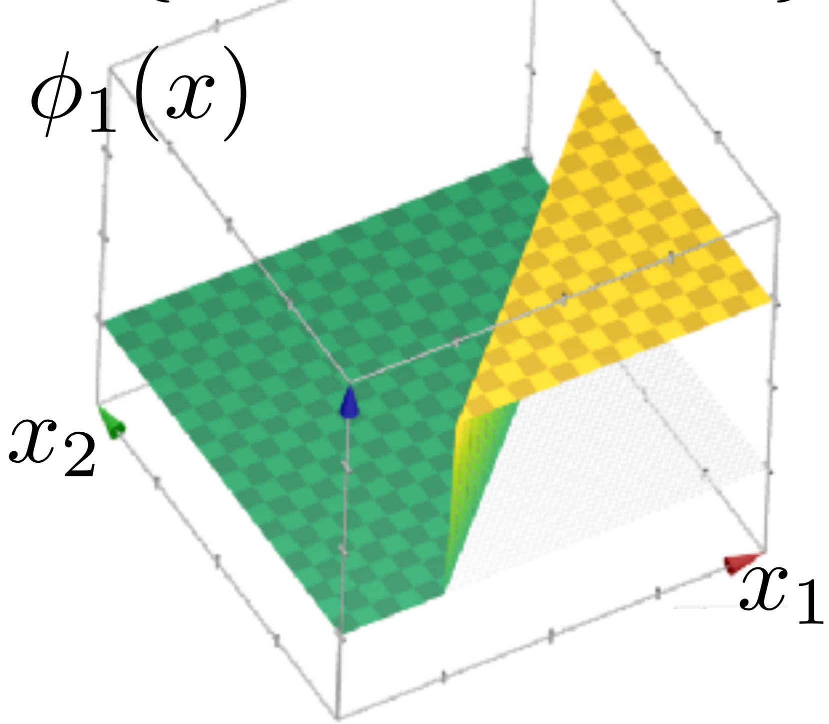

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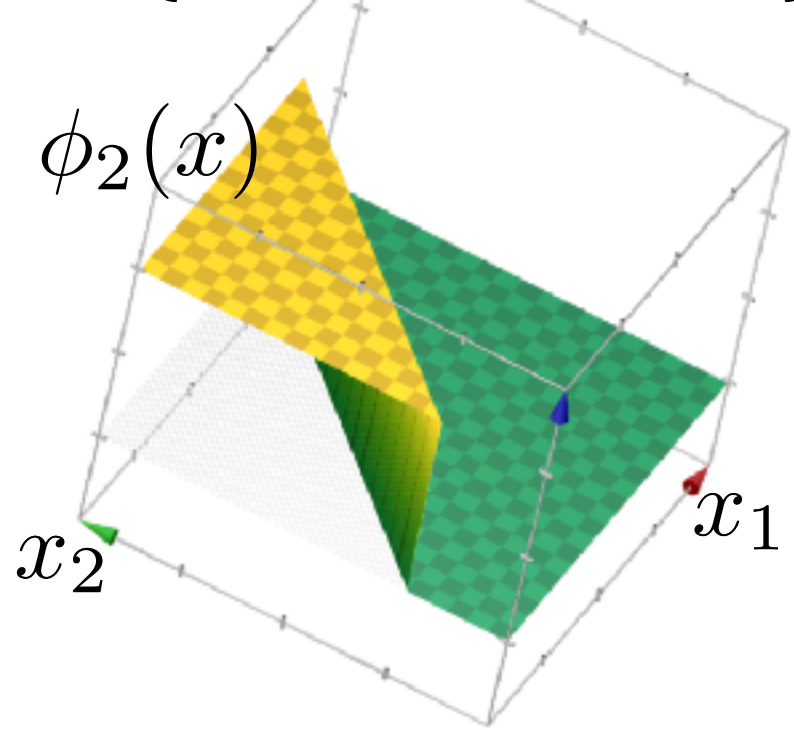

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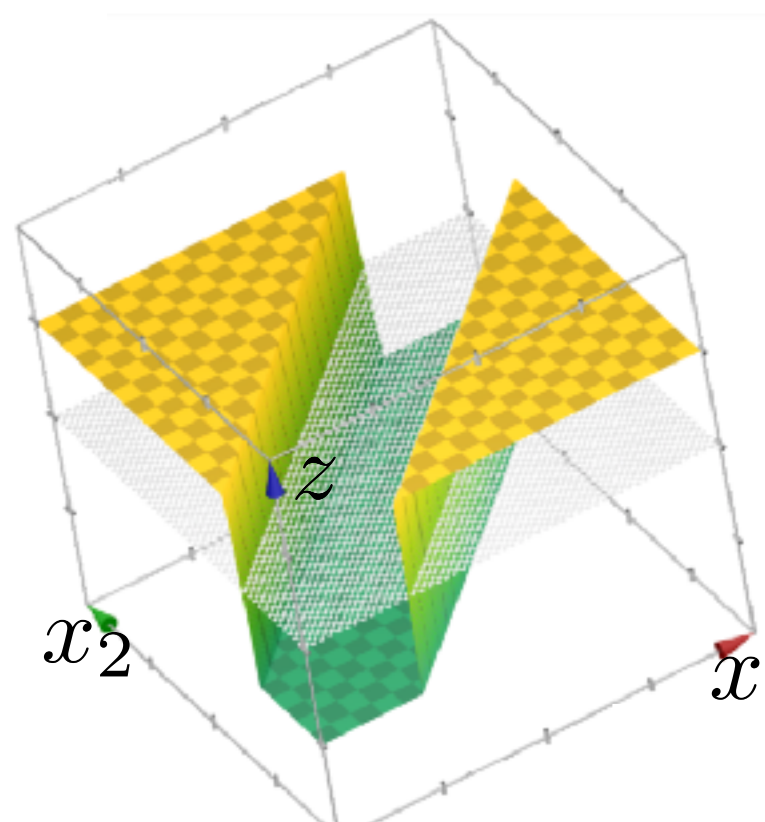

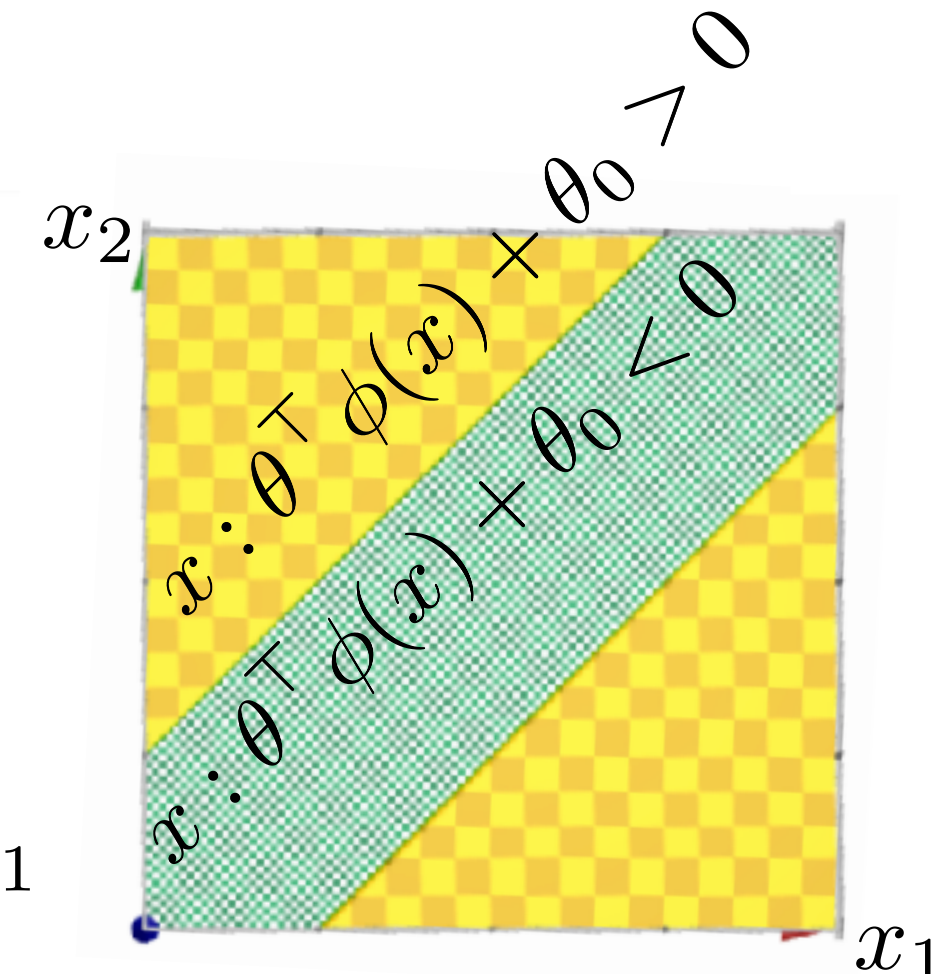

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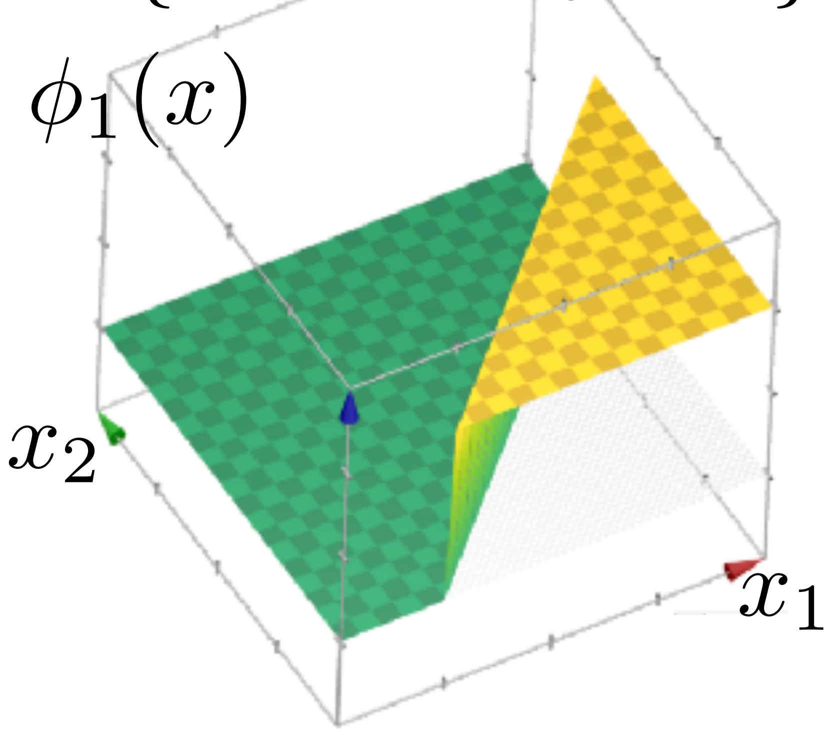

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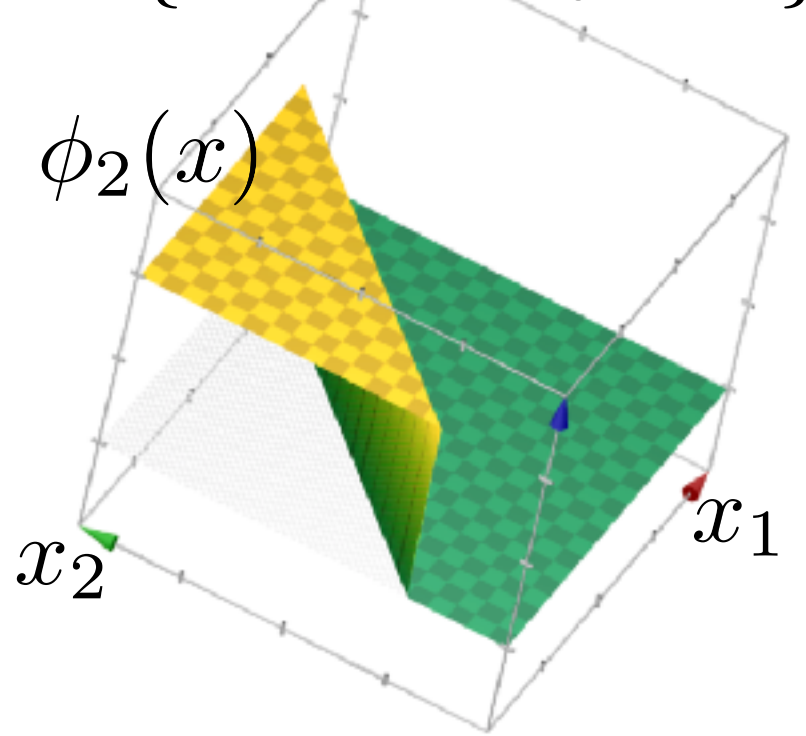

Is an exoplanet in the habitable zone?

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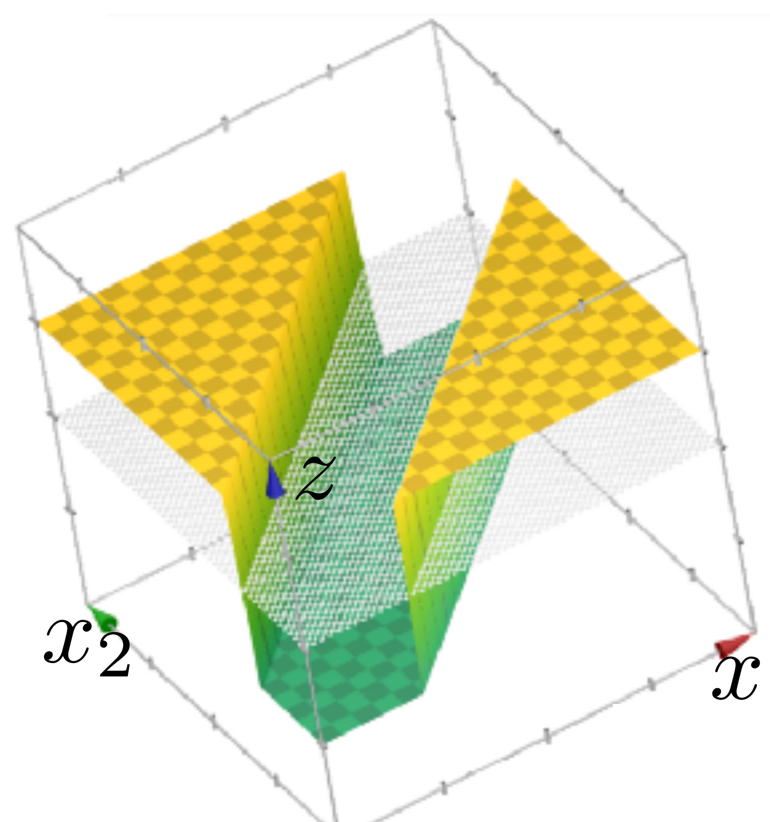

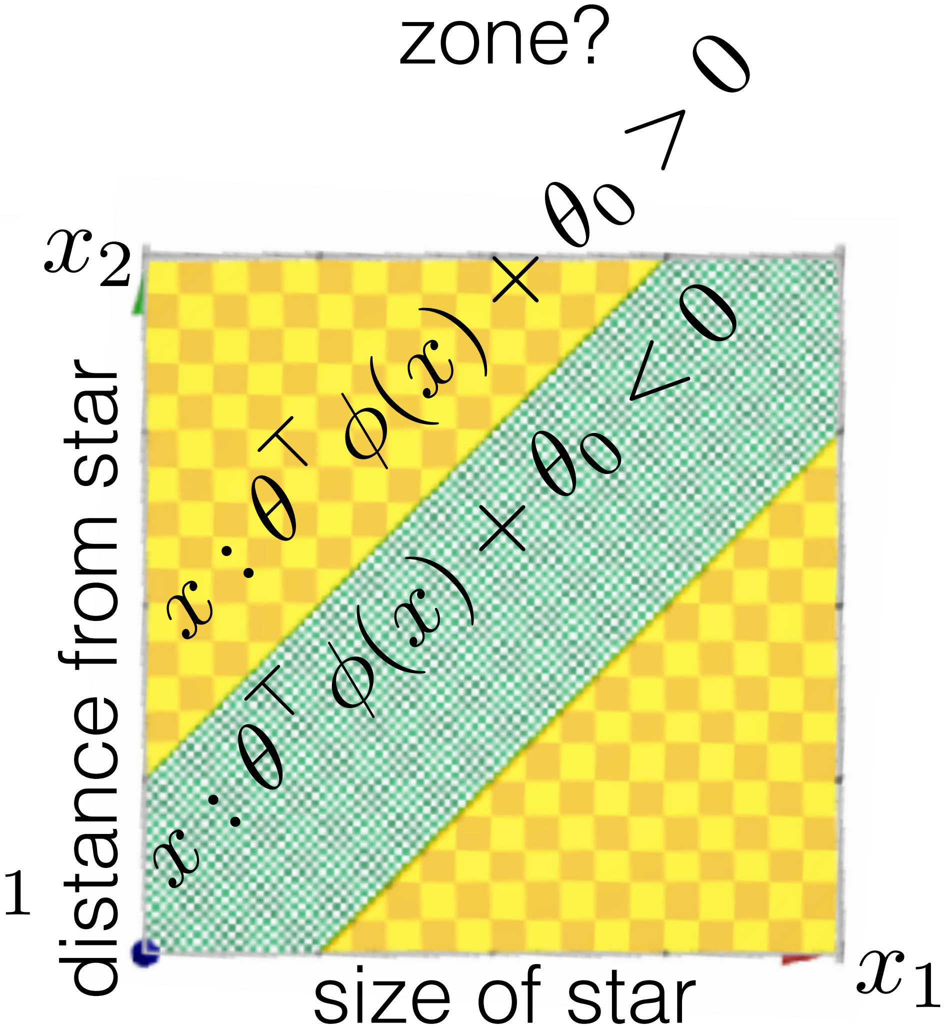

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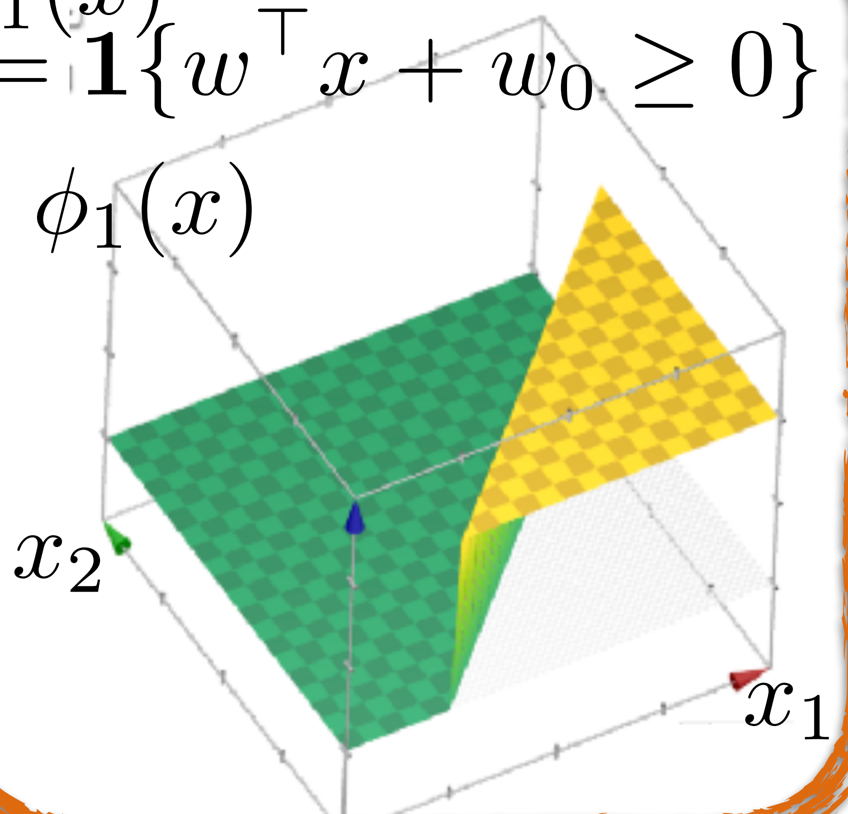

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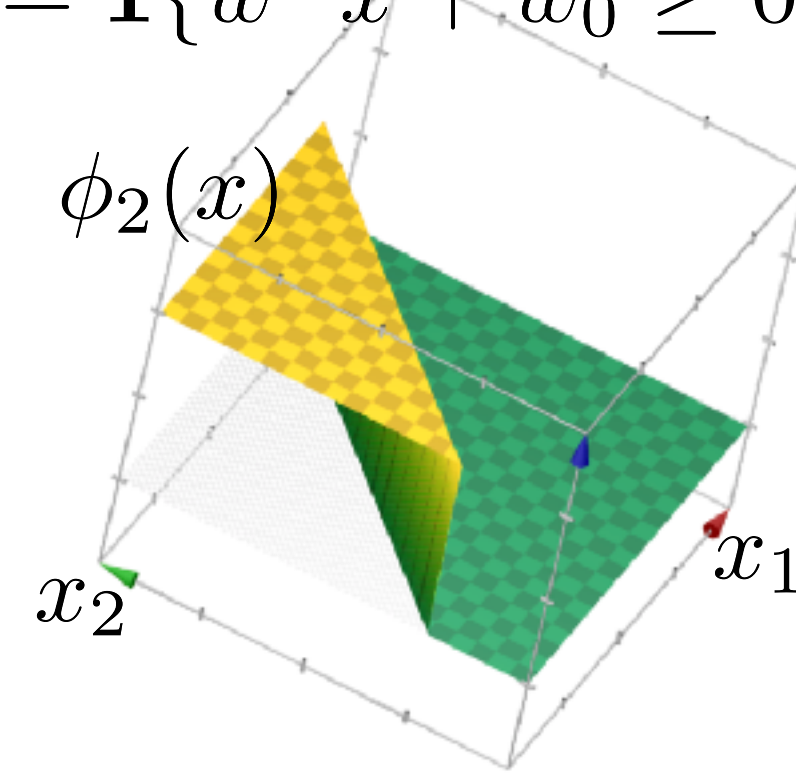

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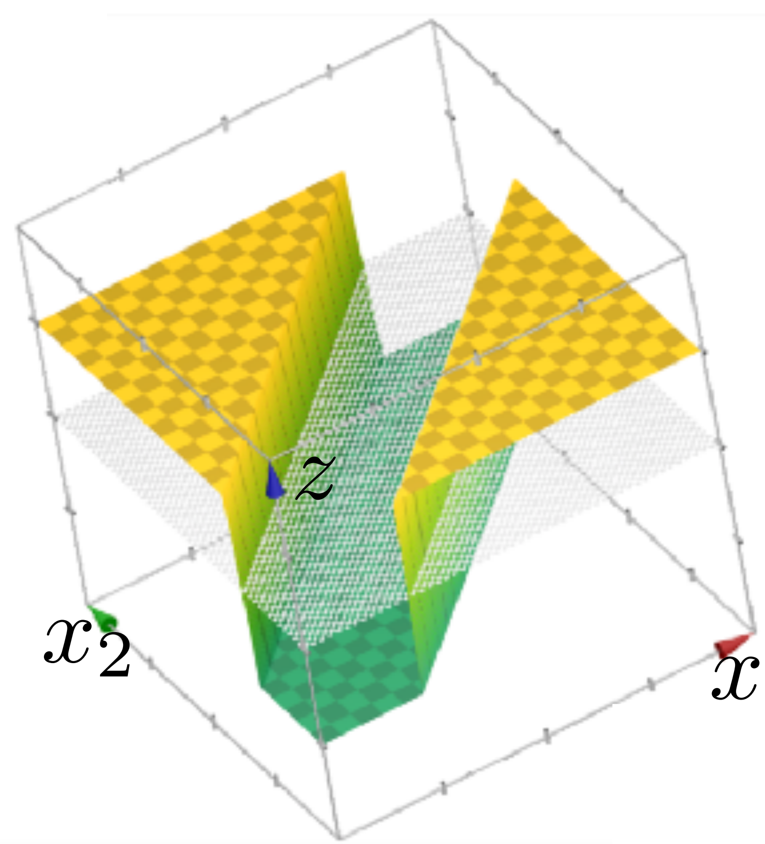

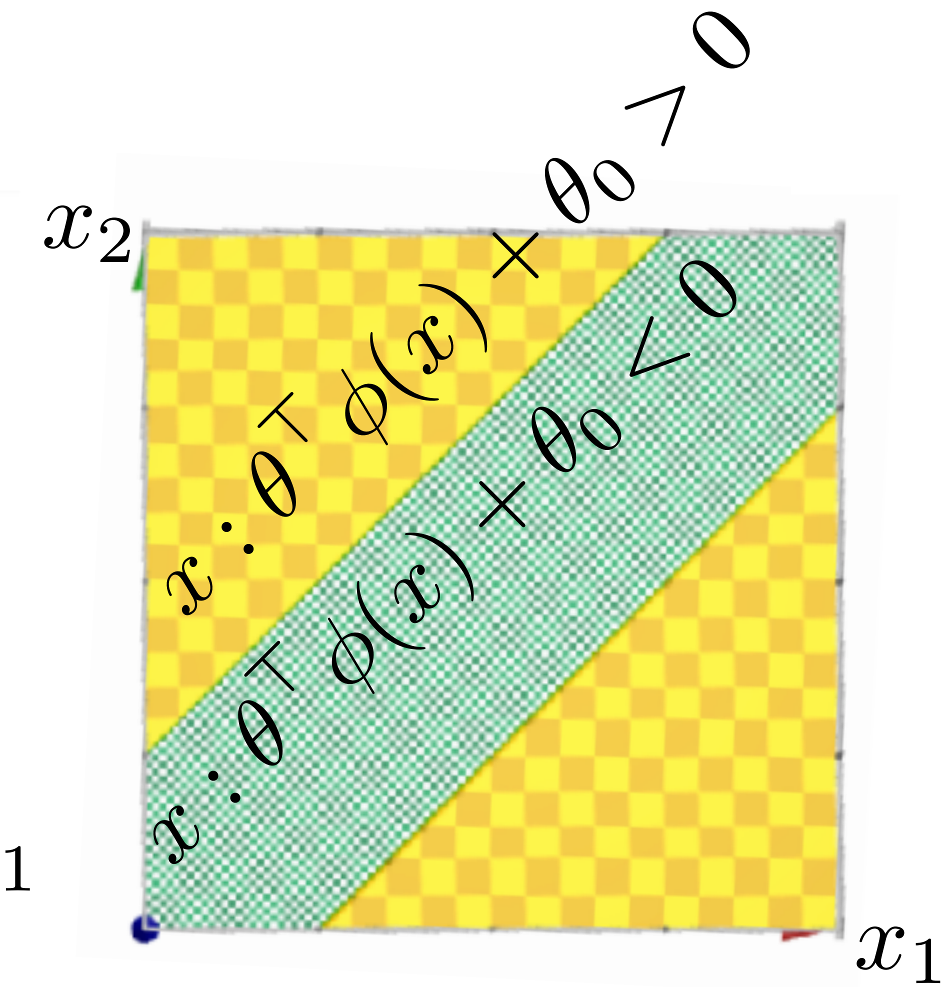

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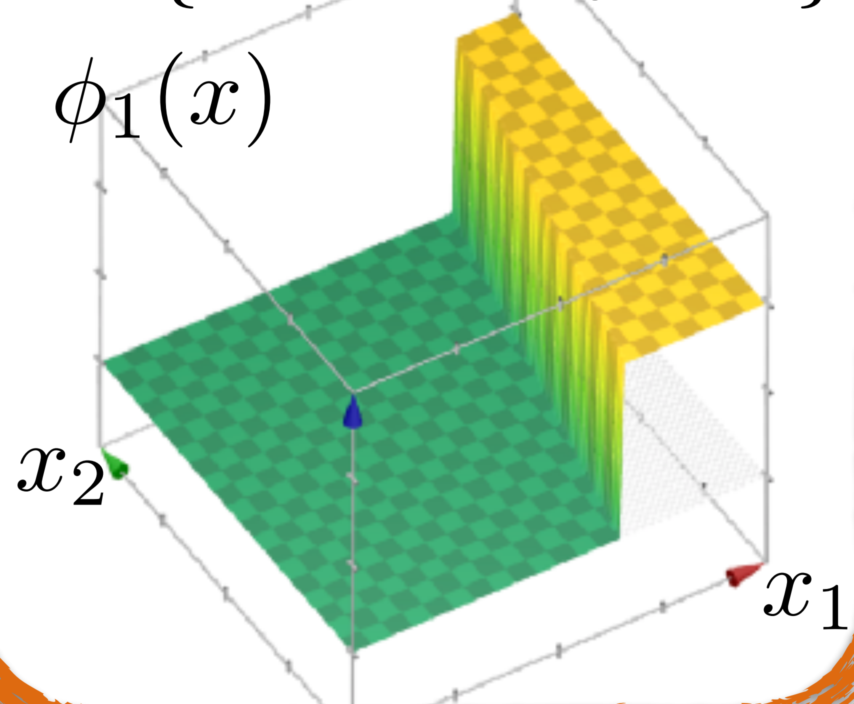

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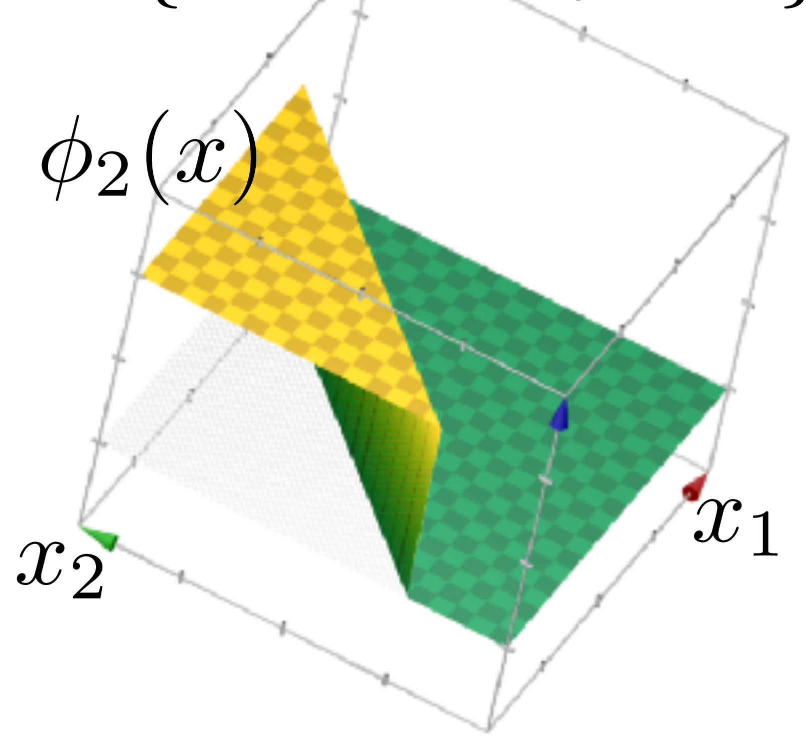

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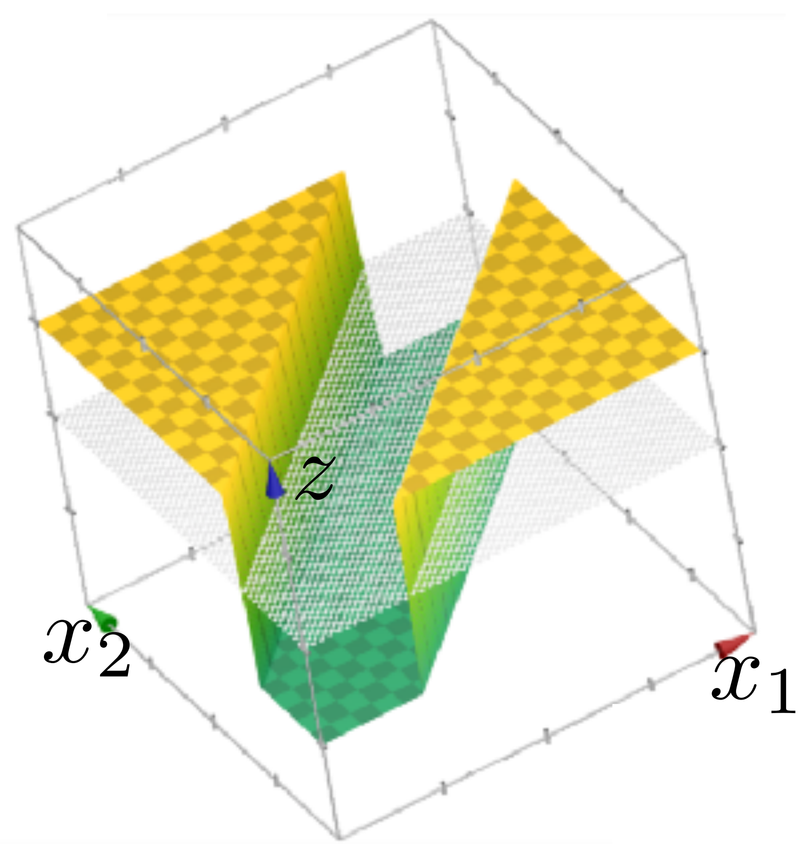

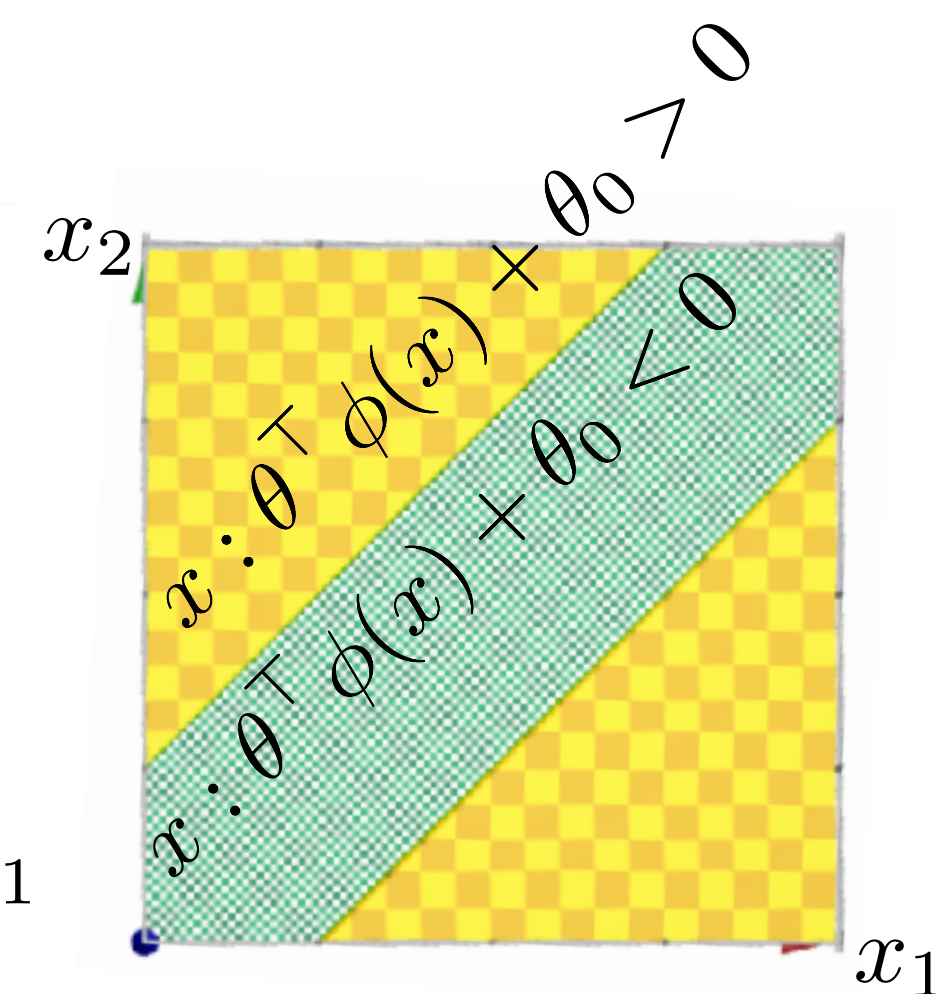

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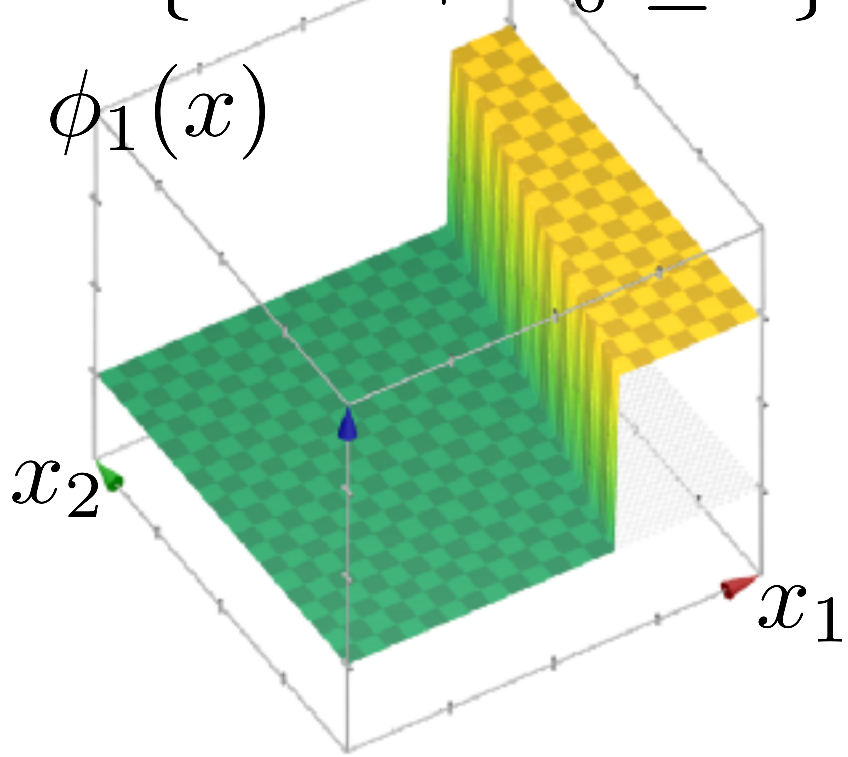

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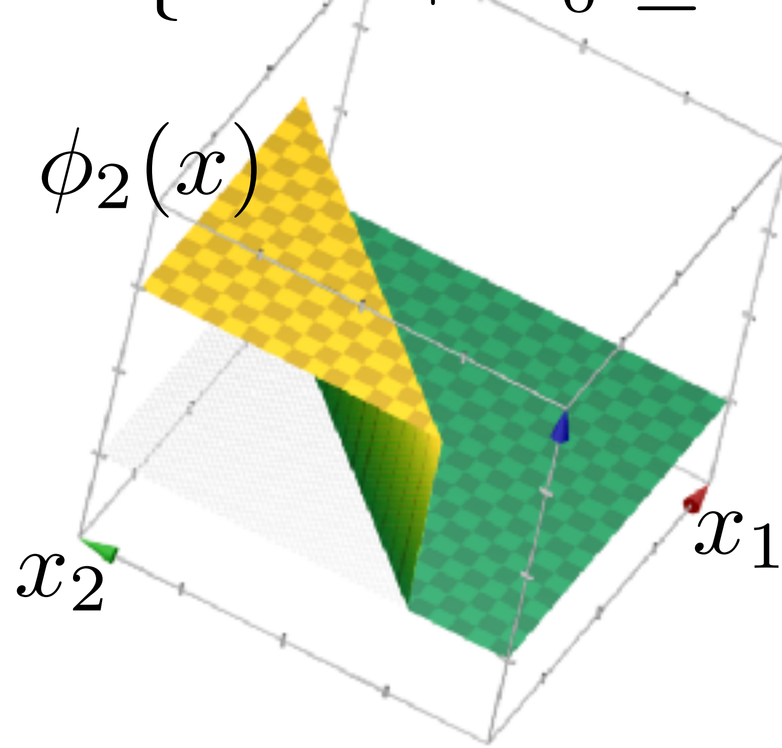

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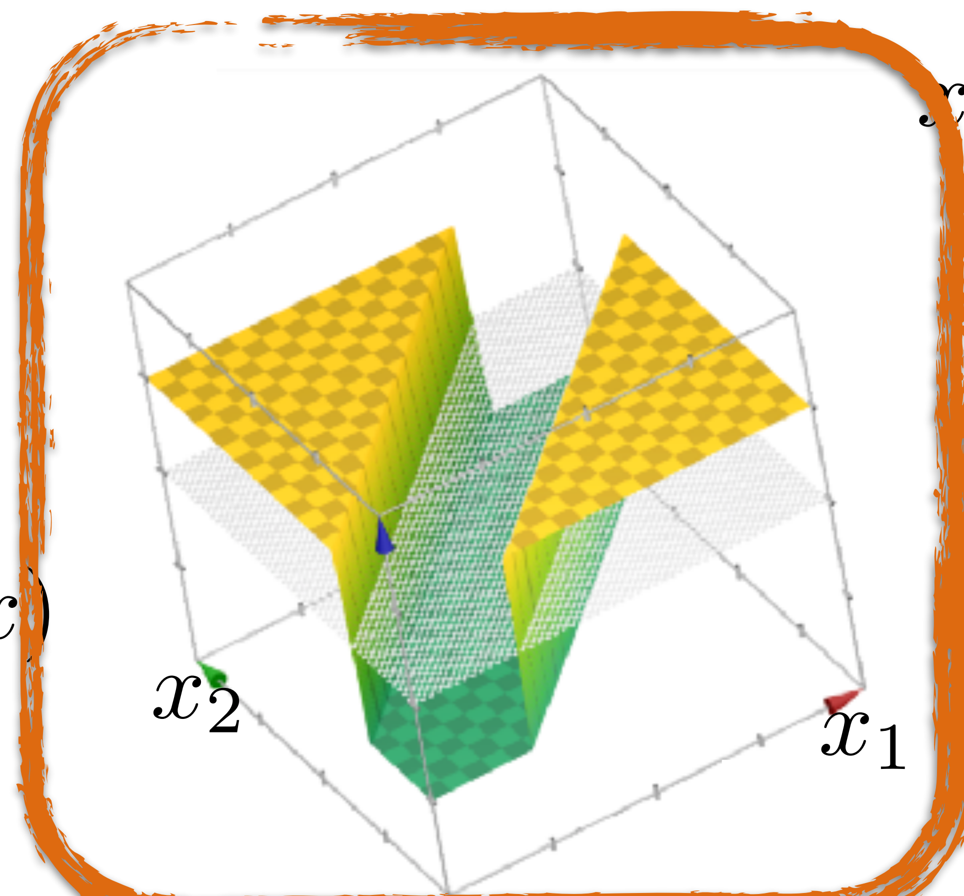

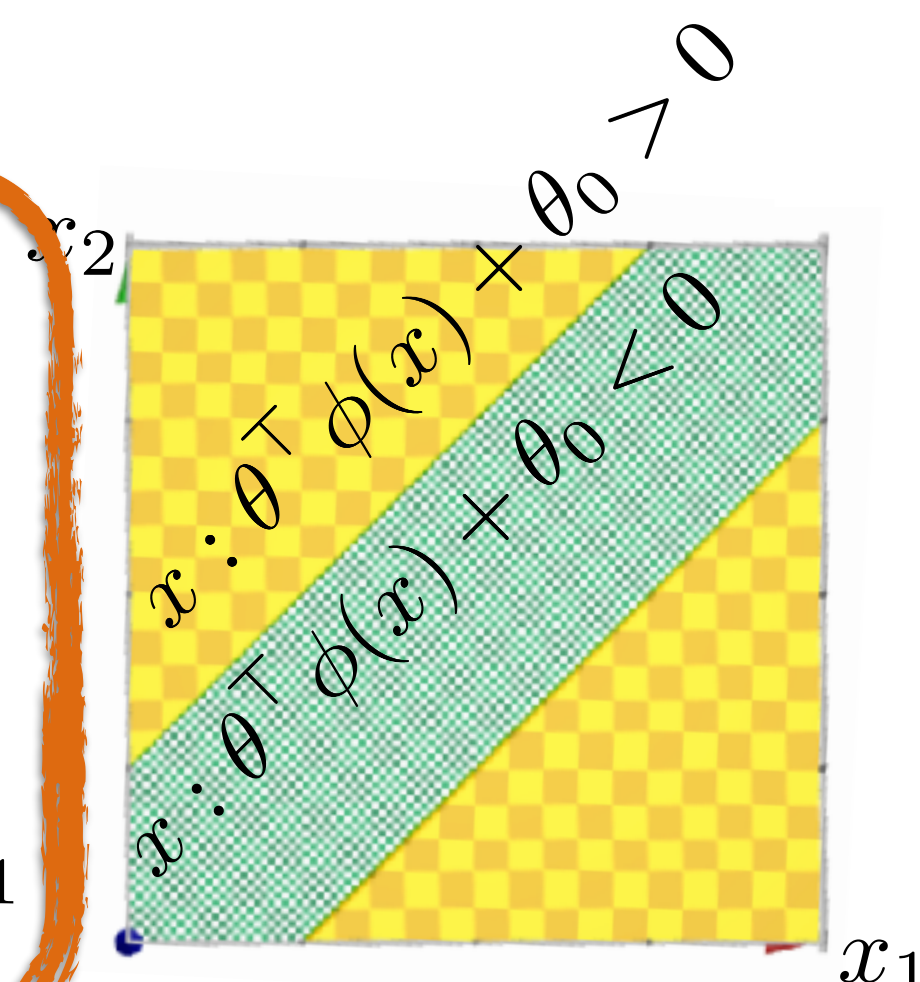

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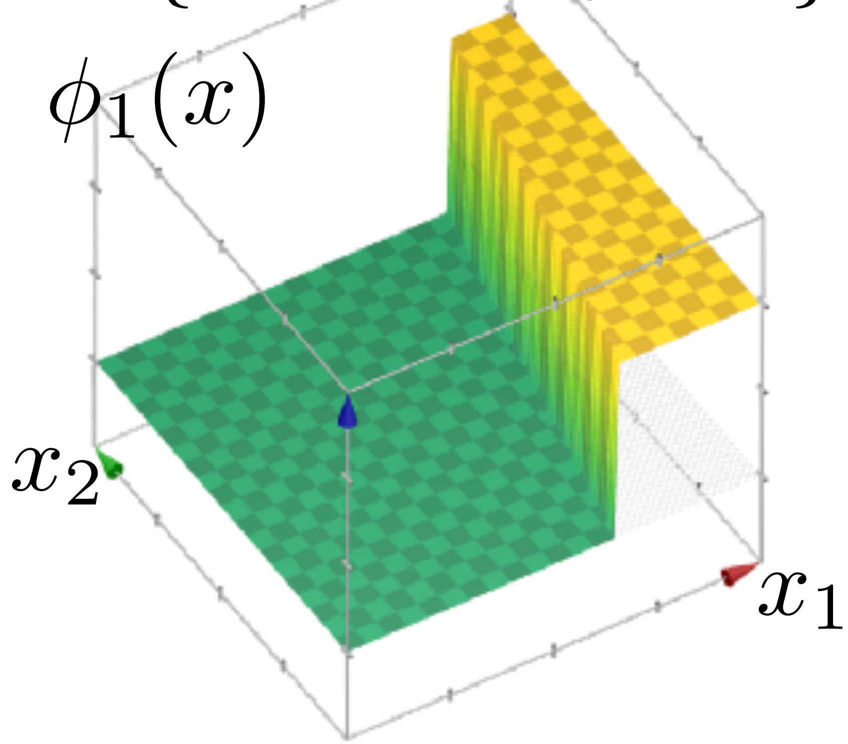

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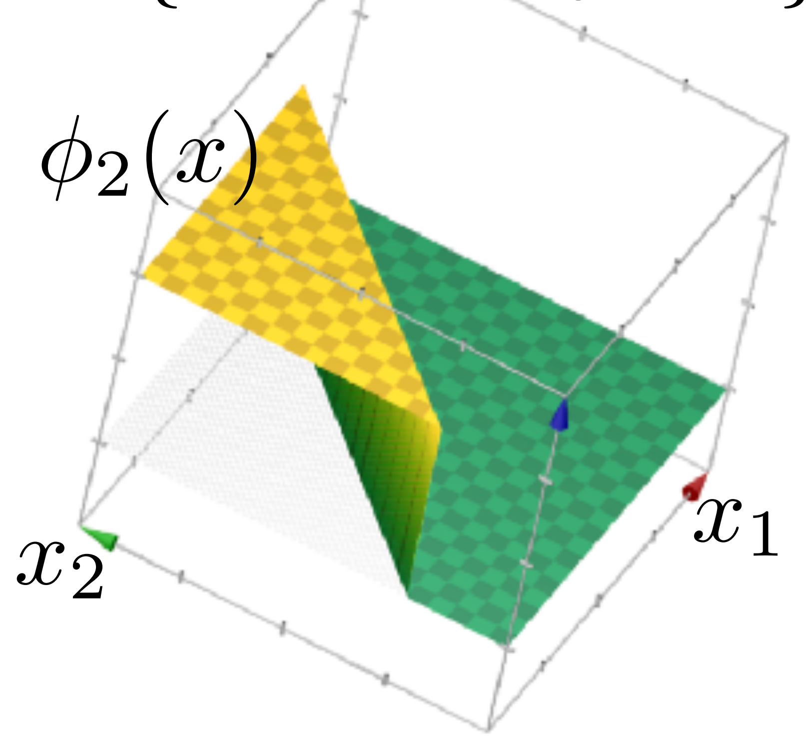

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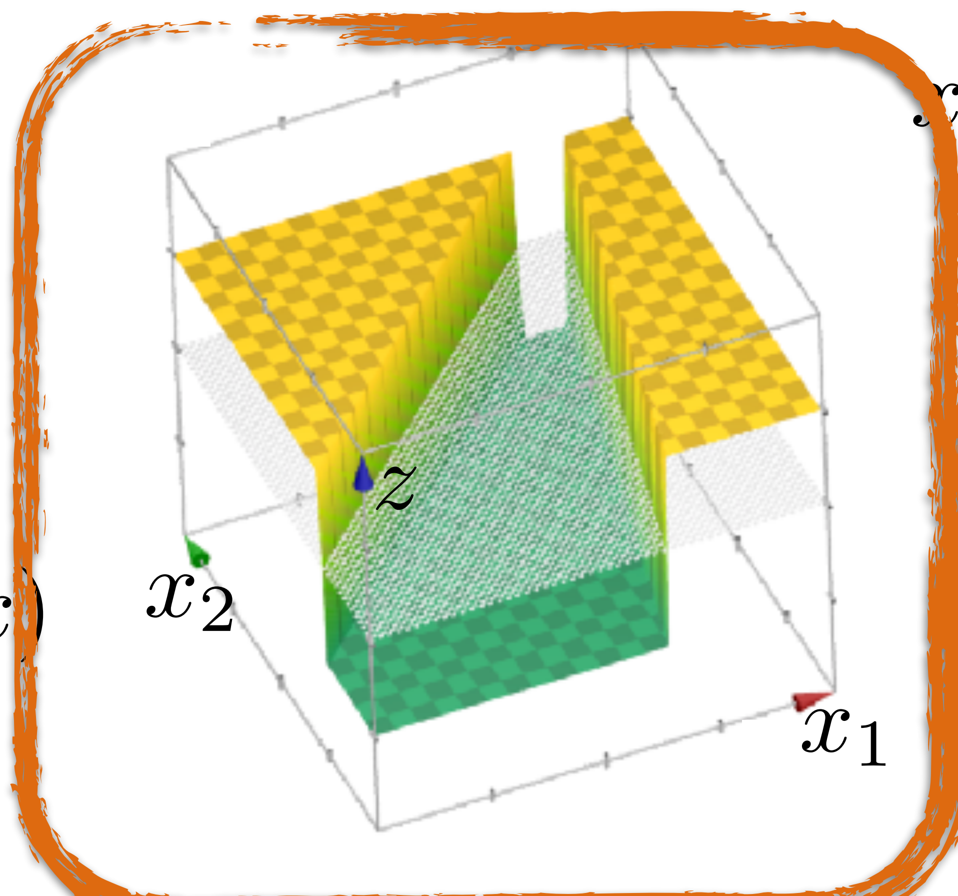

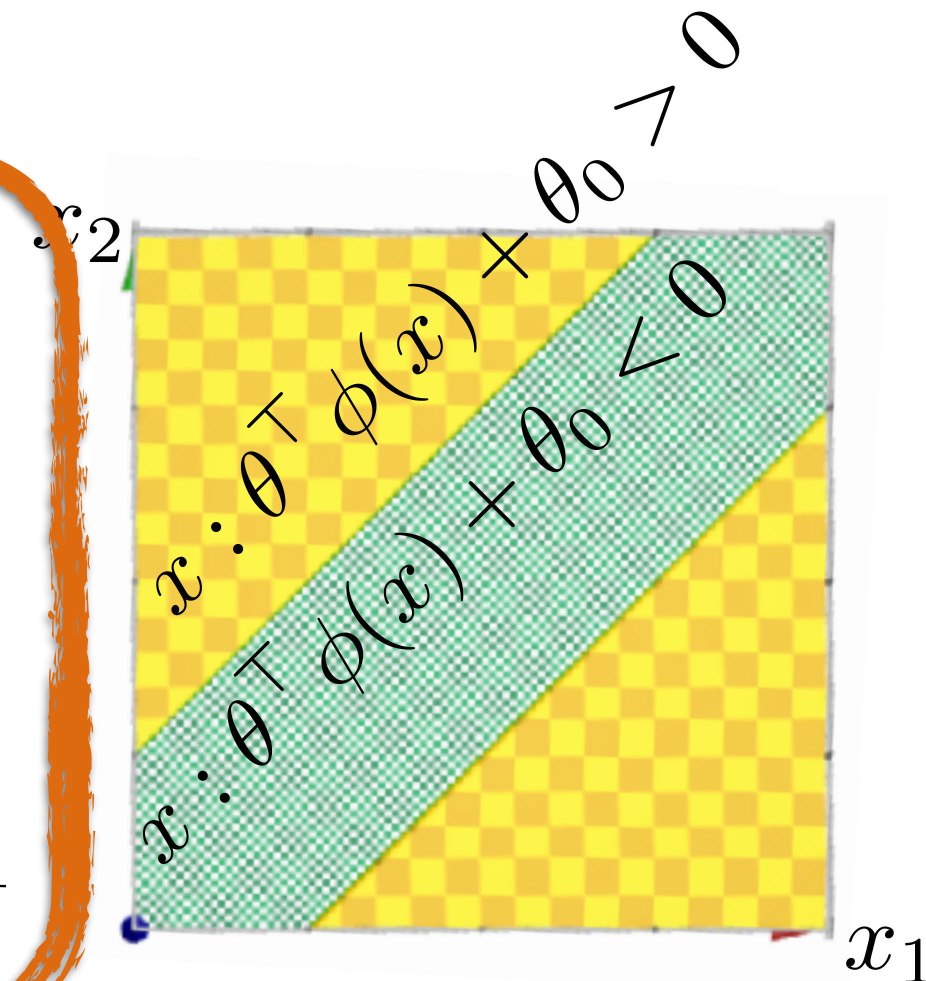

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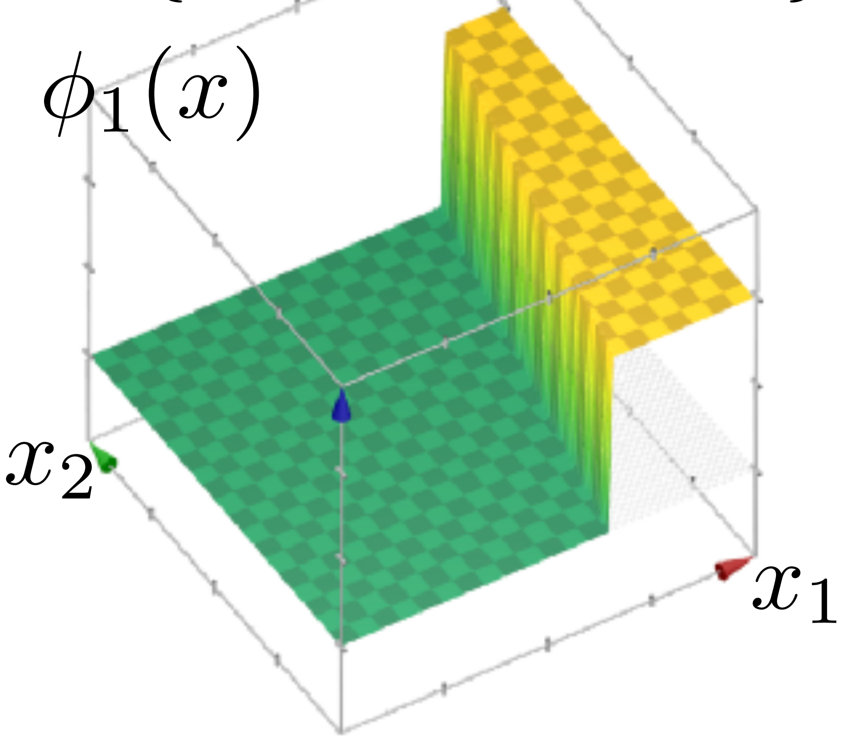

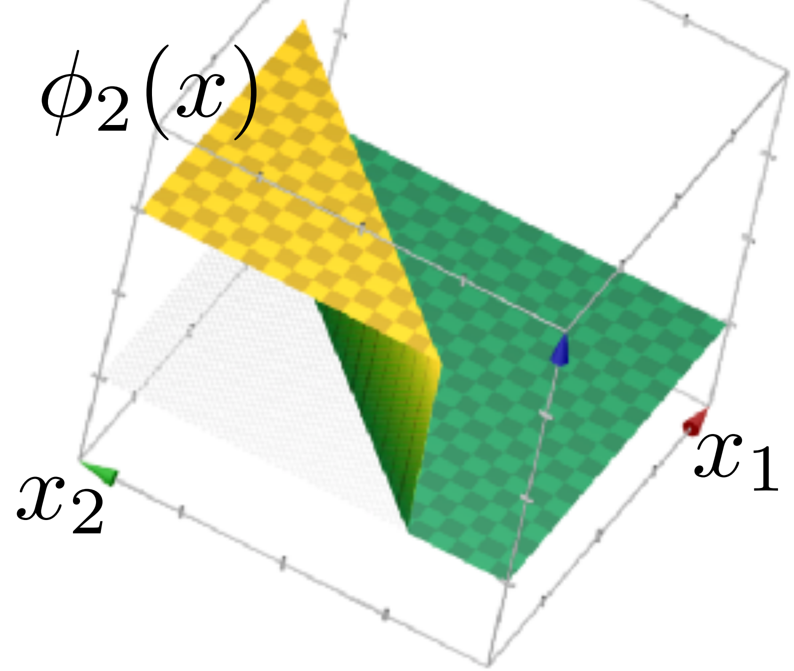

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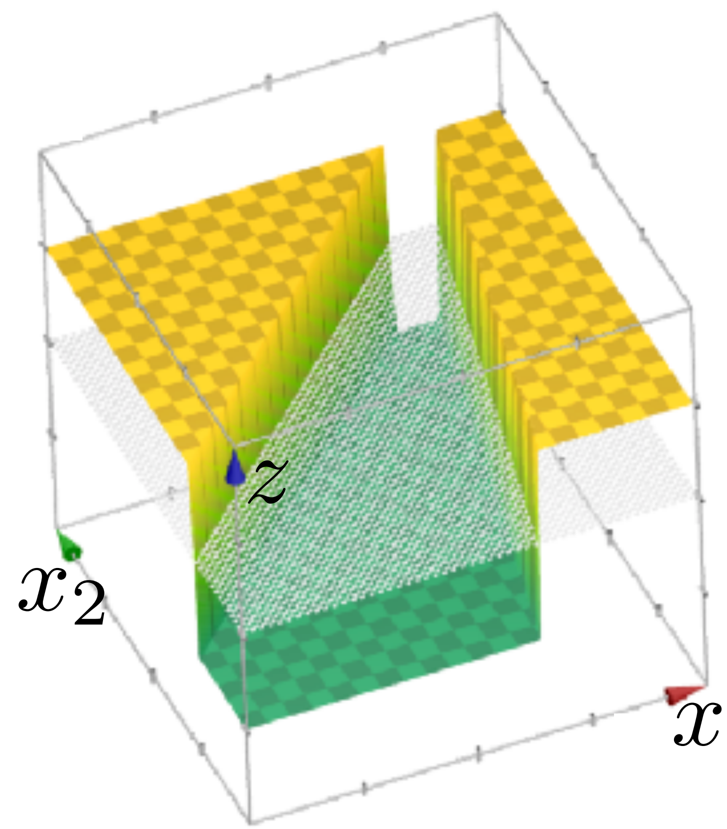

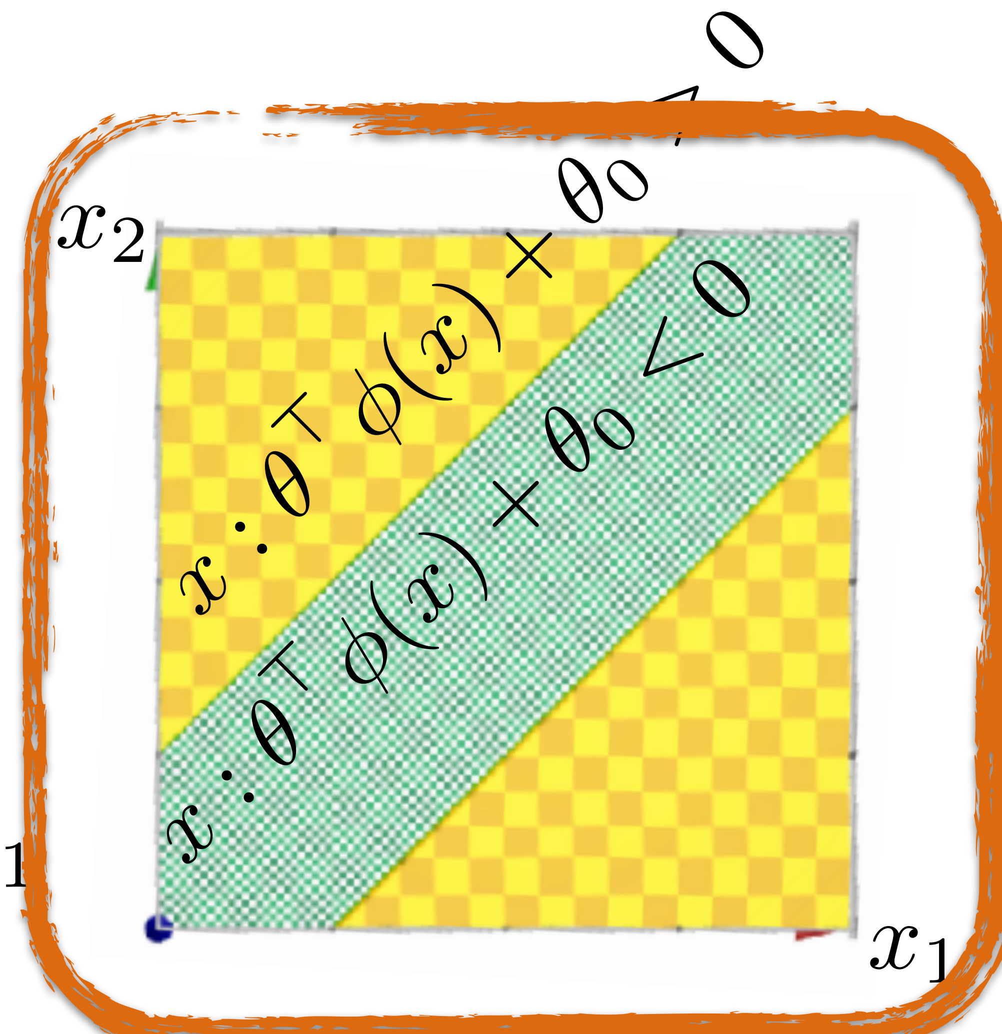

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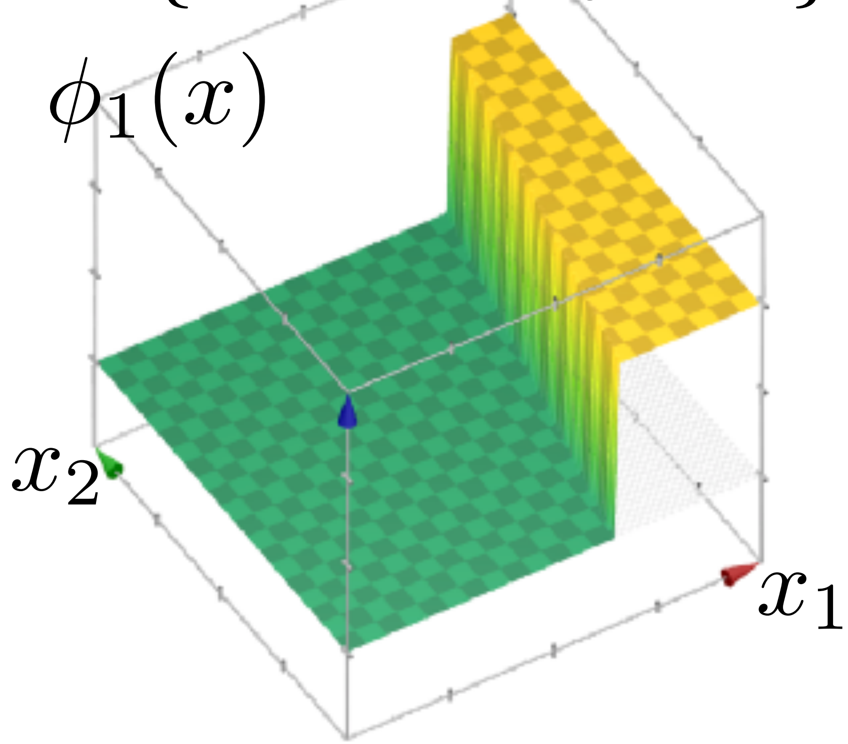

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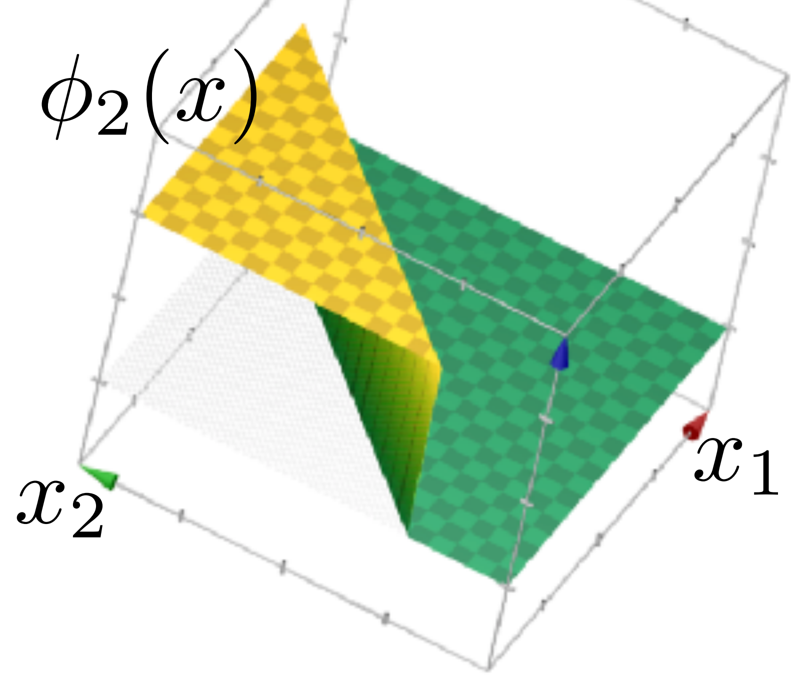

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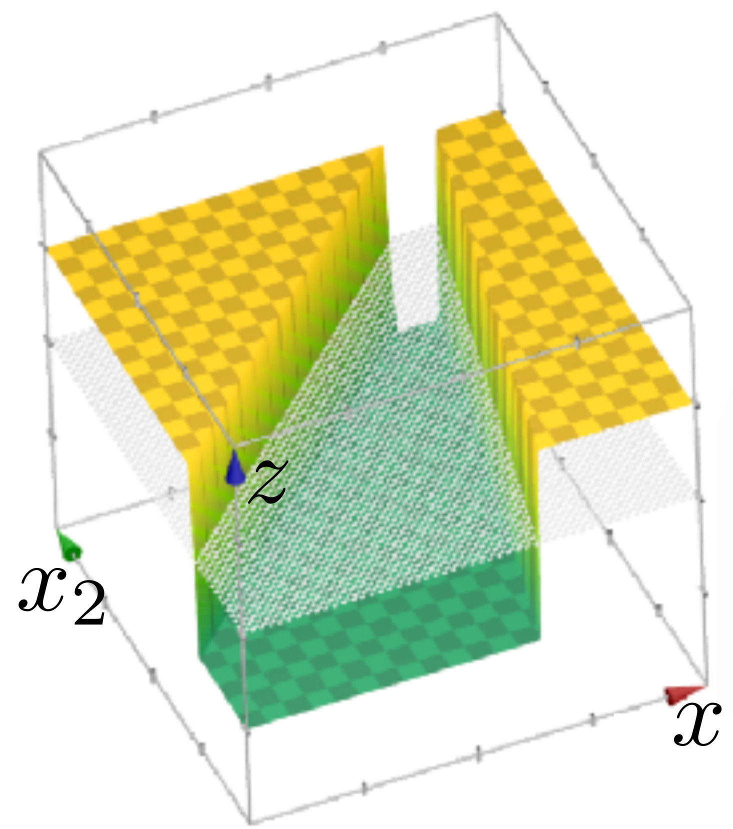

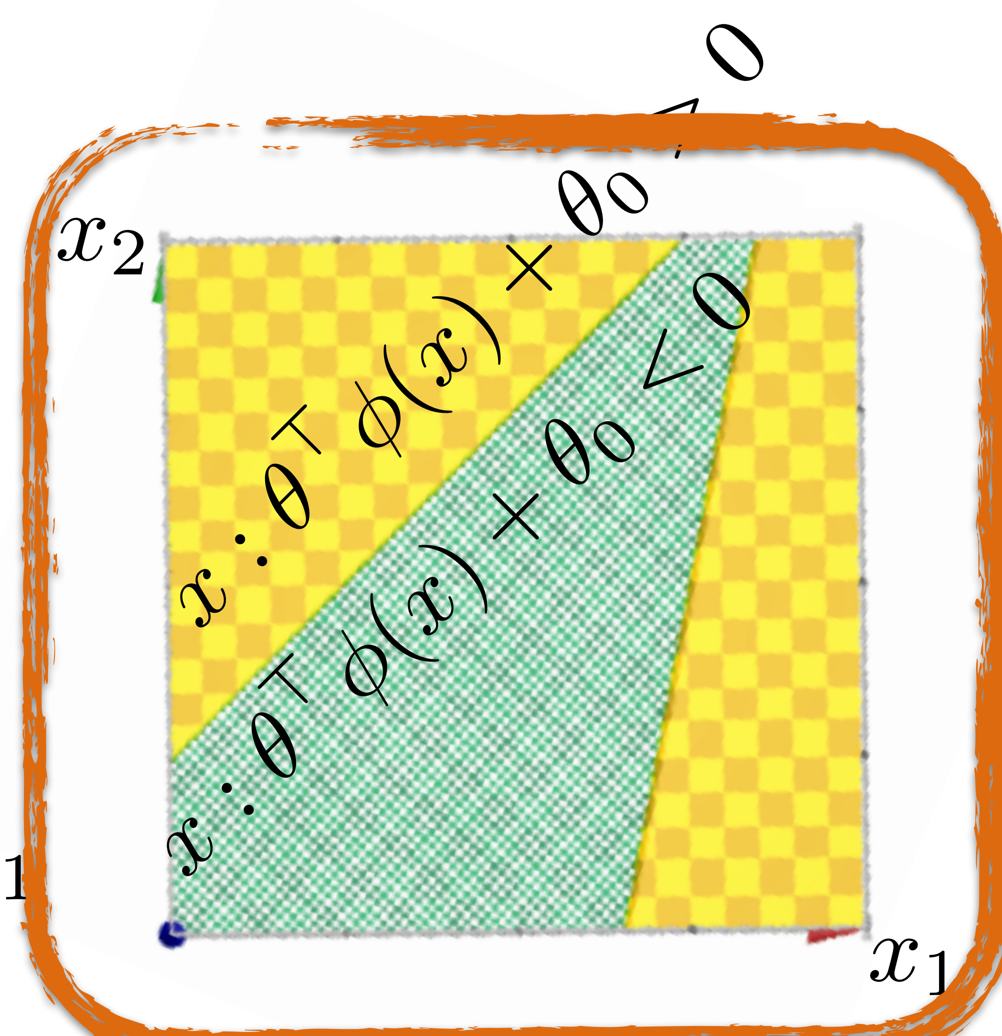

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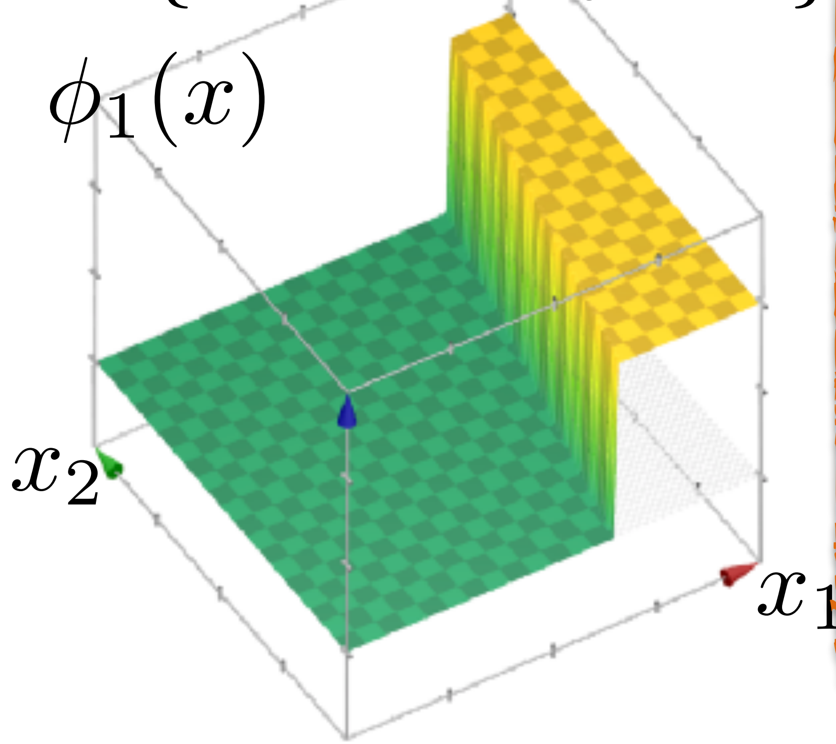

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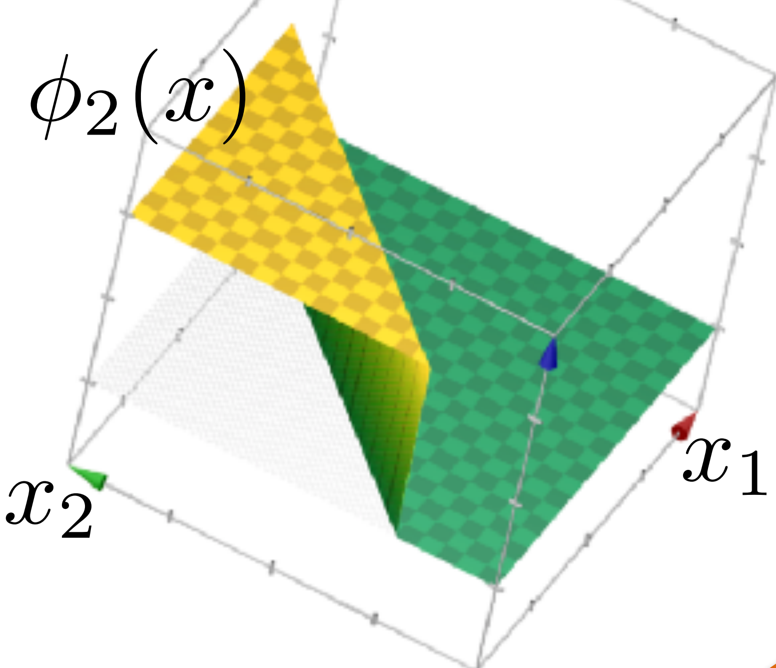

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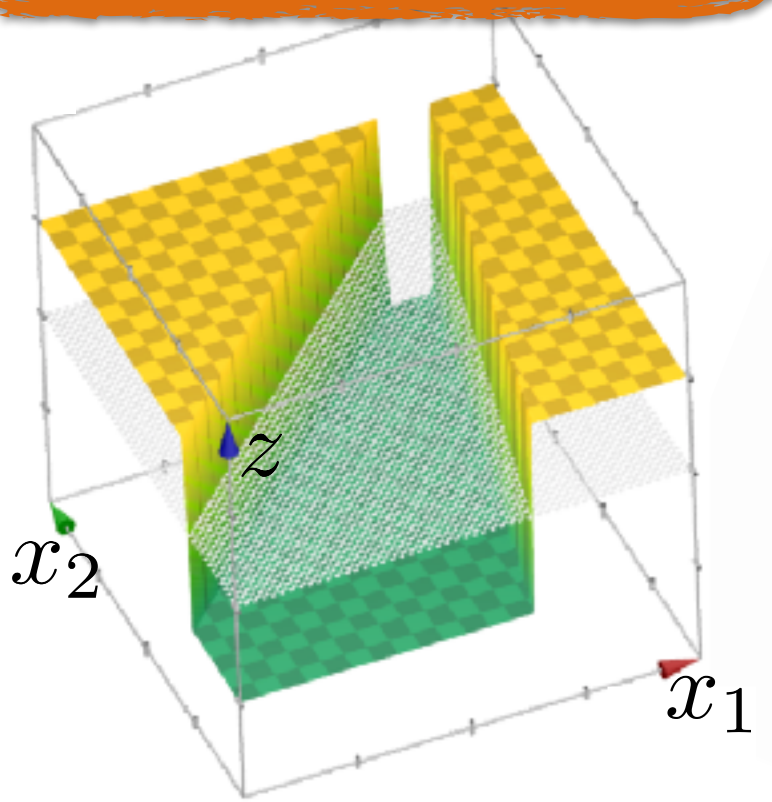

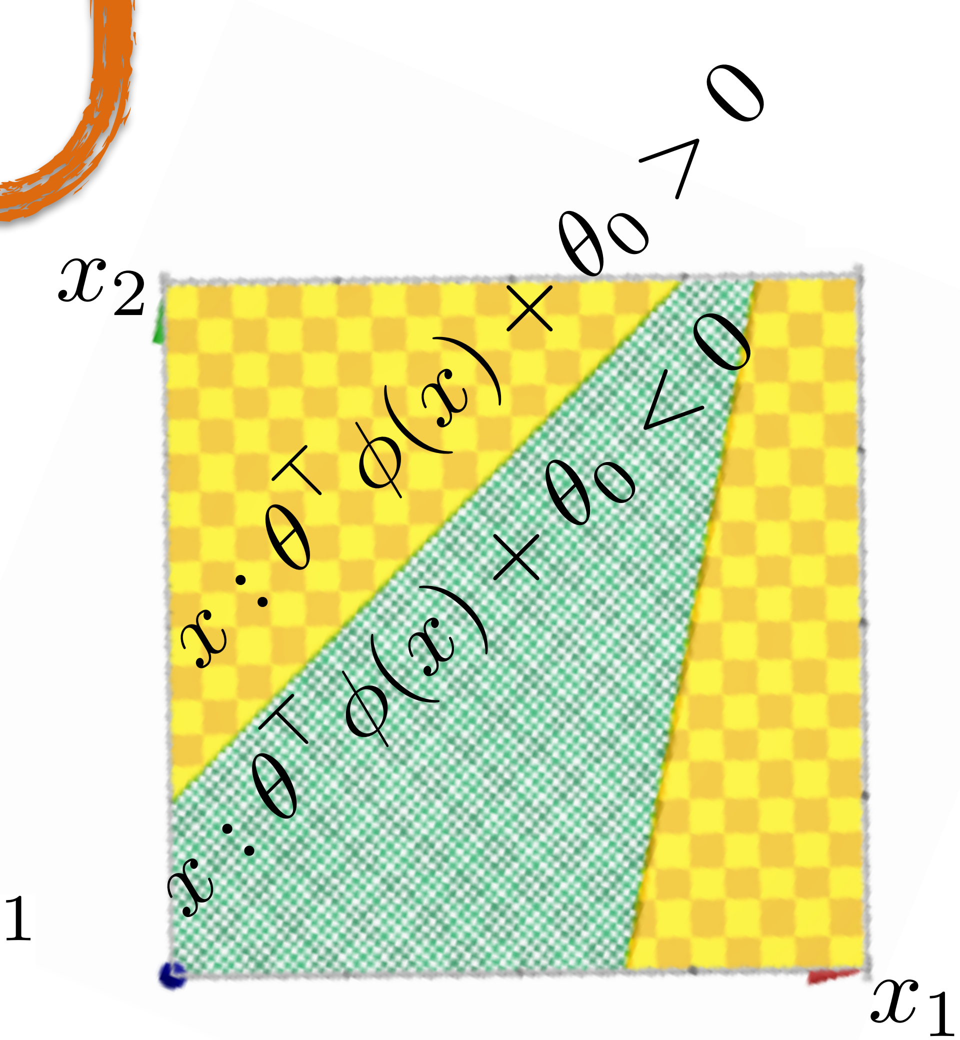

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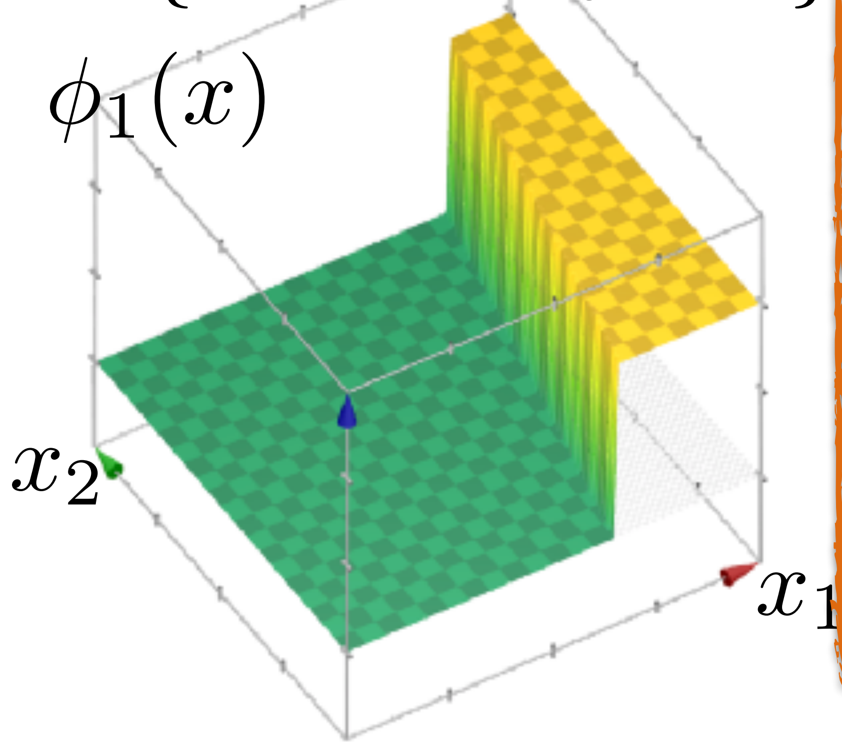

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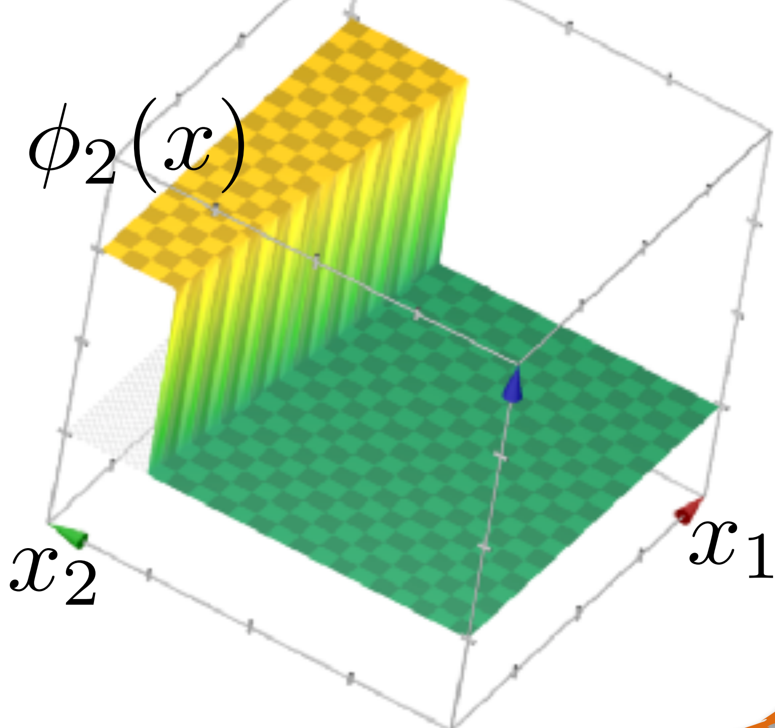

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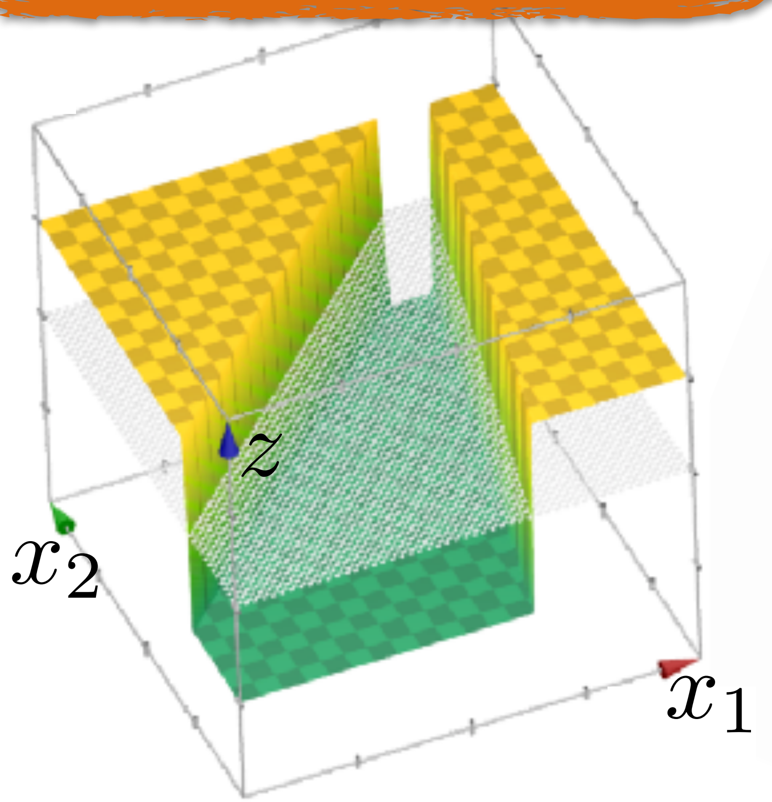

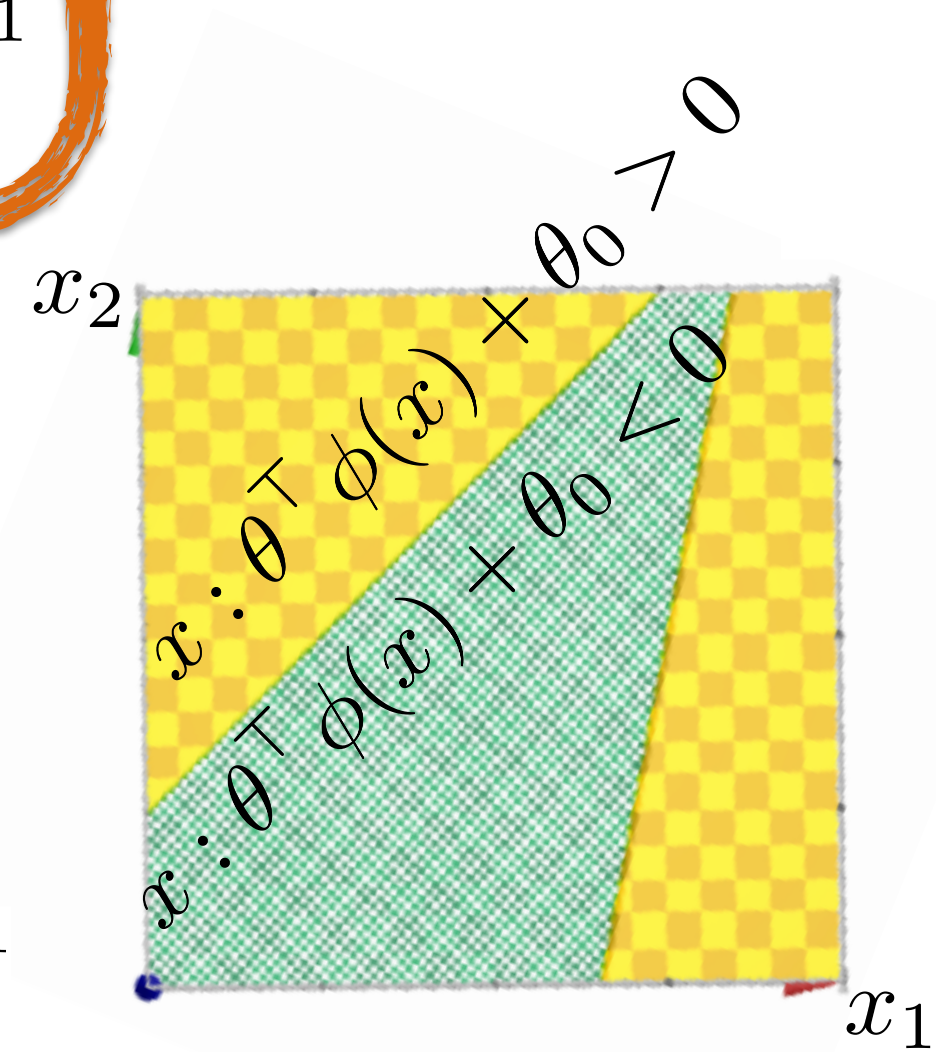

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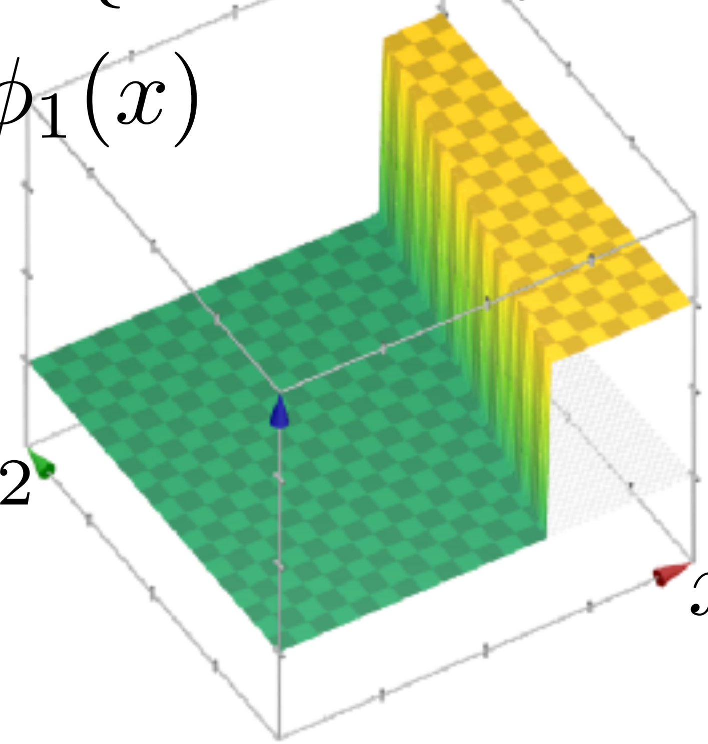

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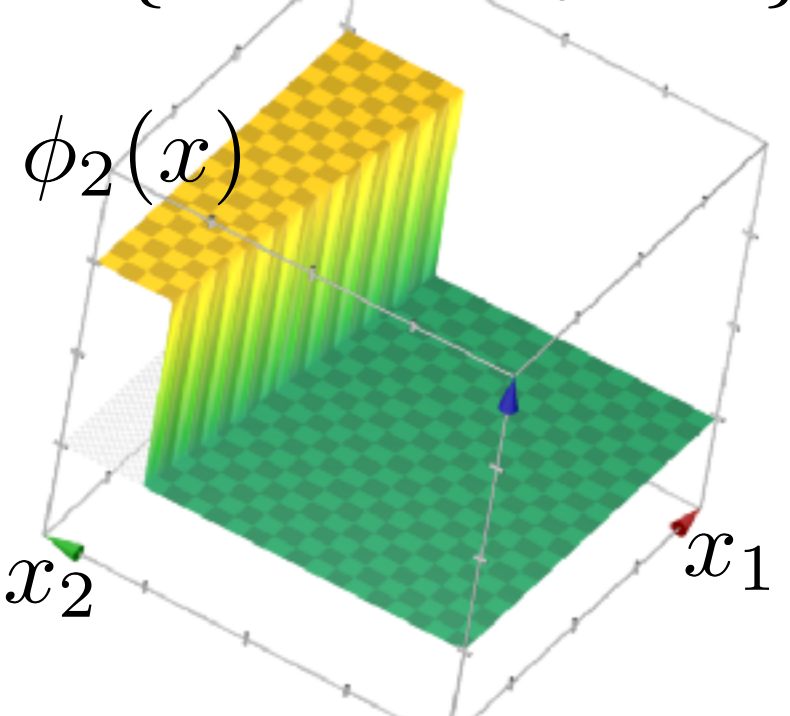

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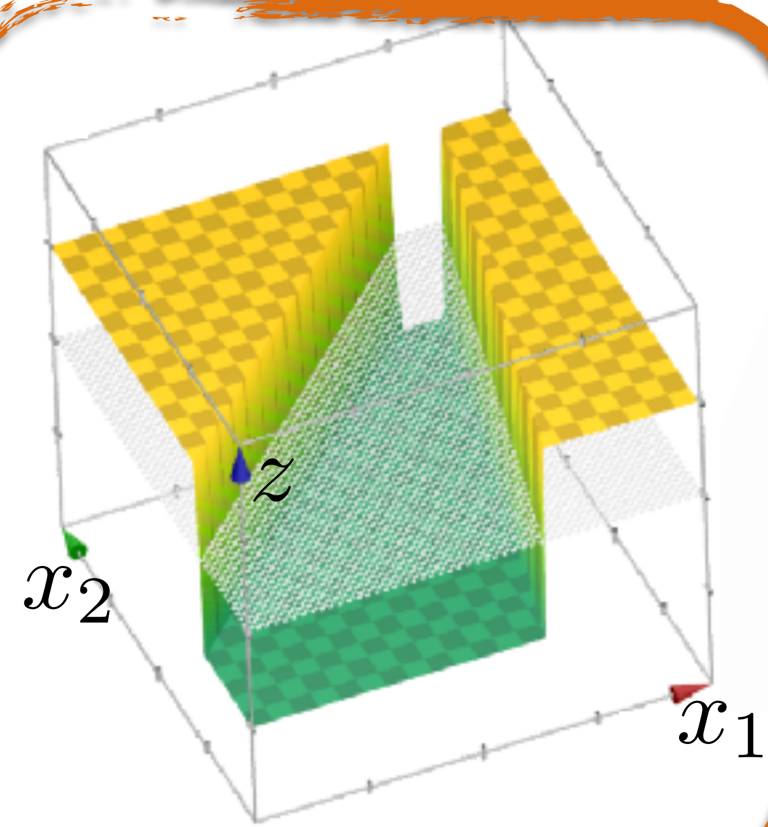

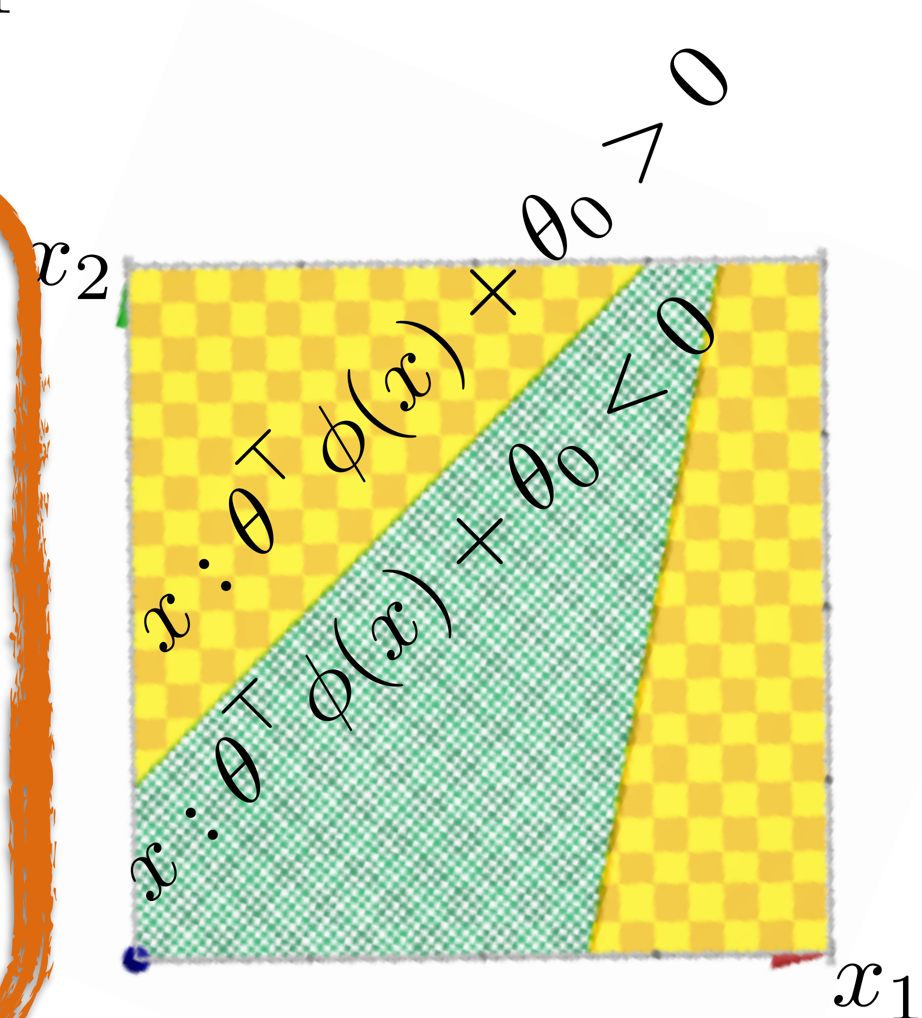

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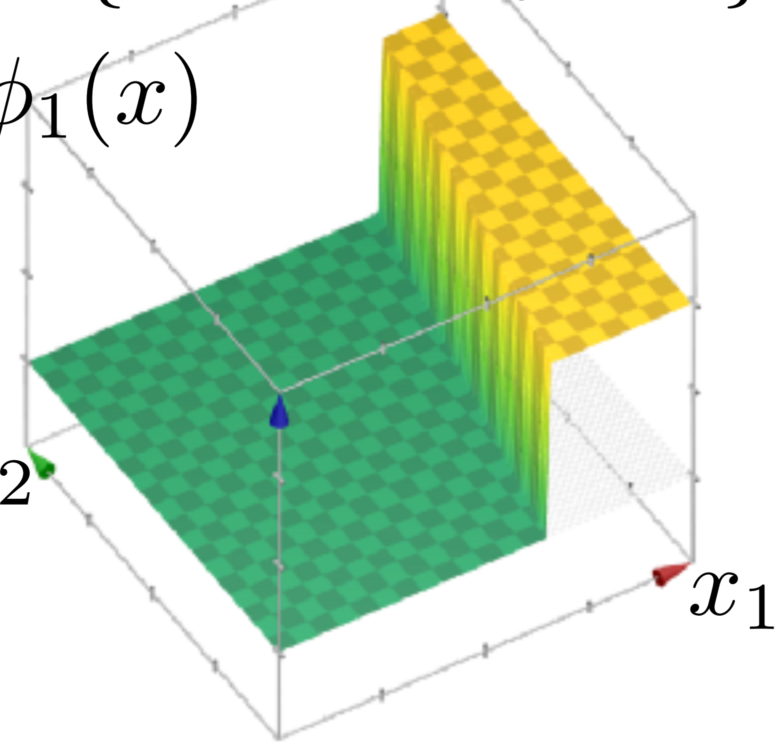

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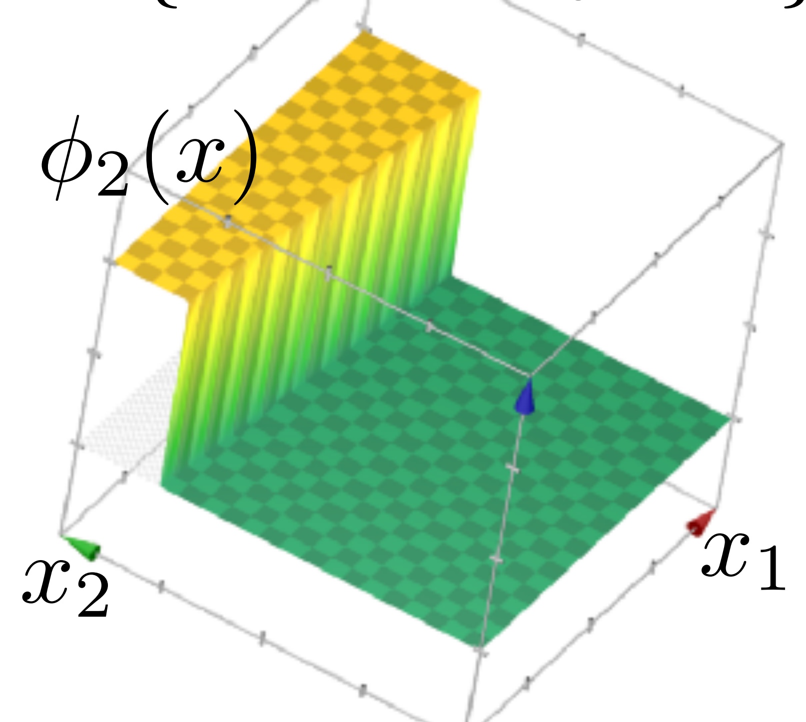

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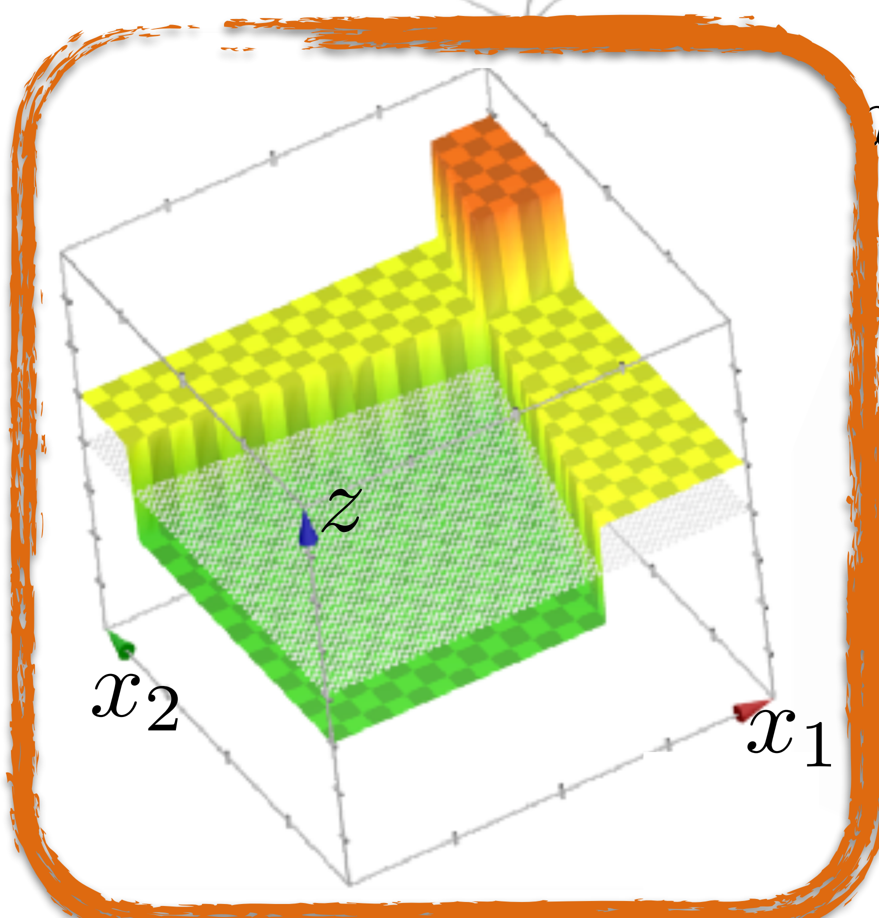

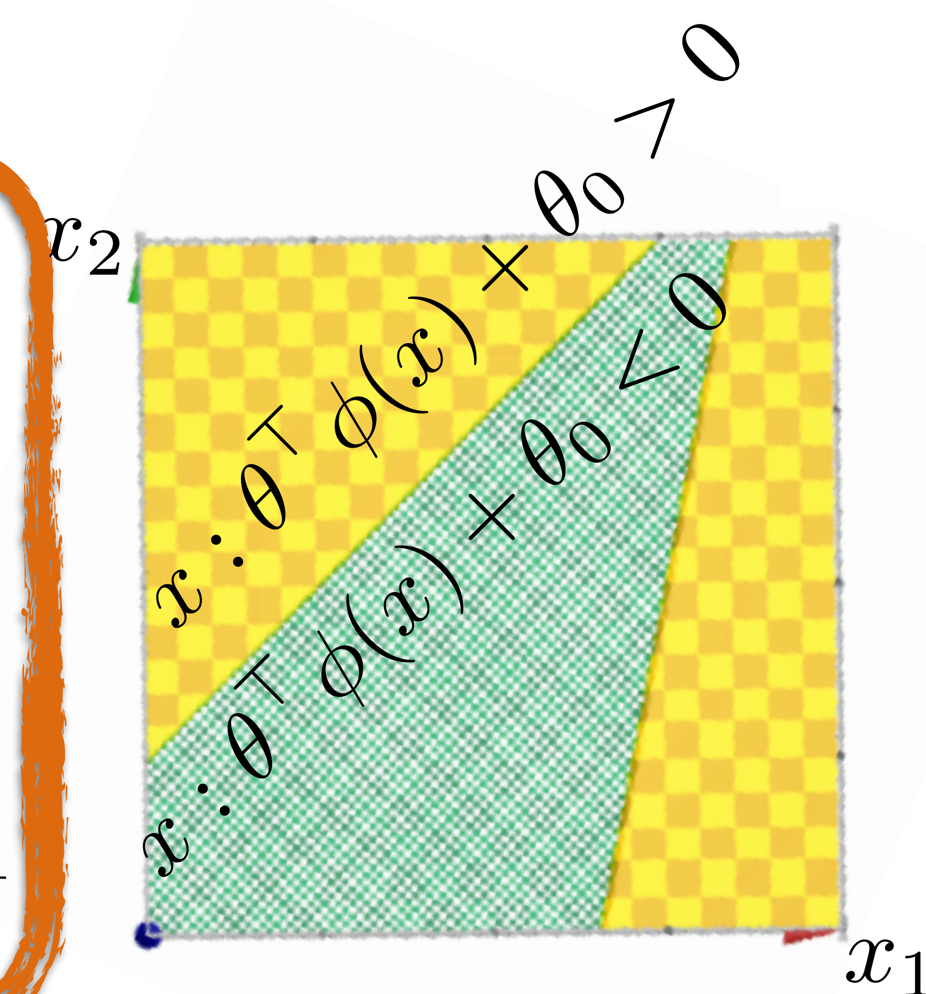

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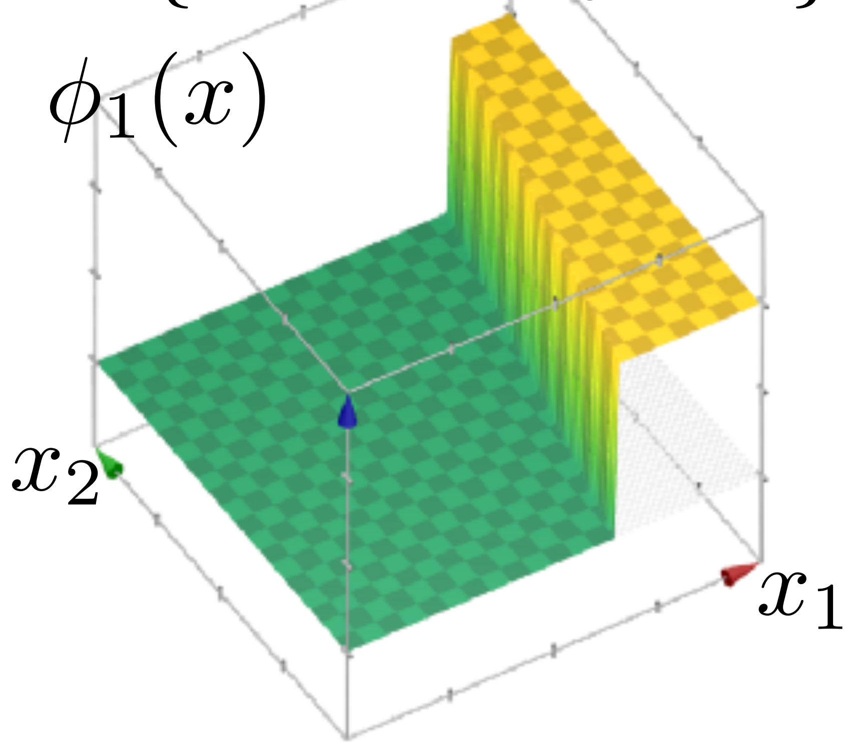

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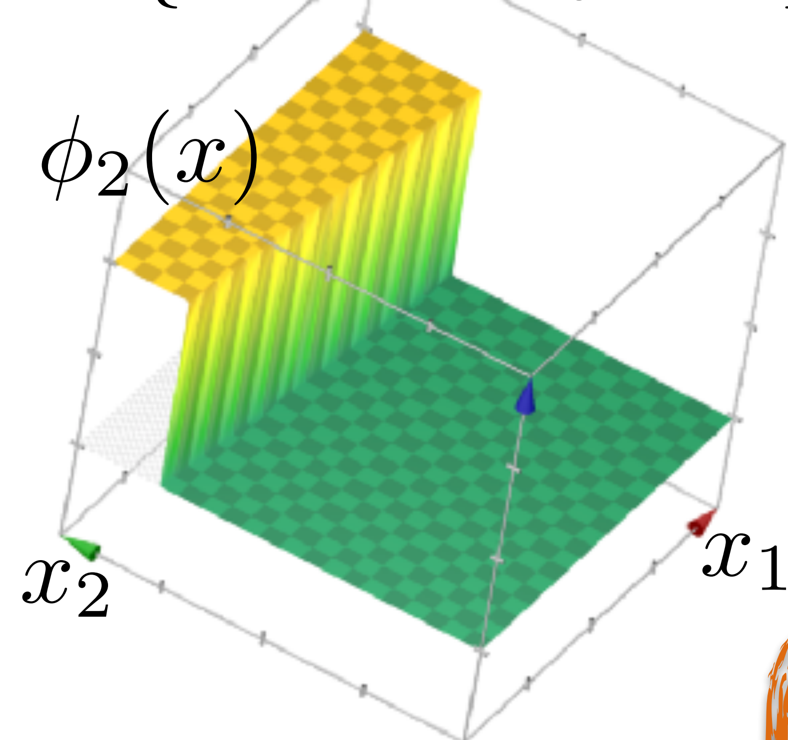

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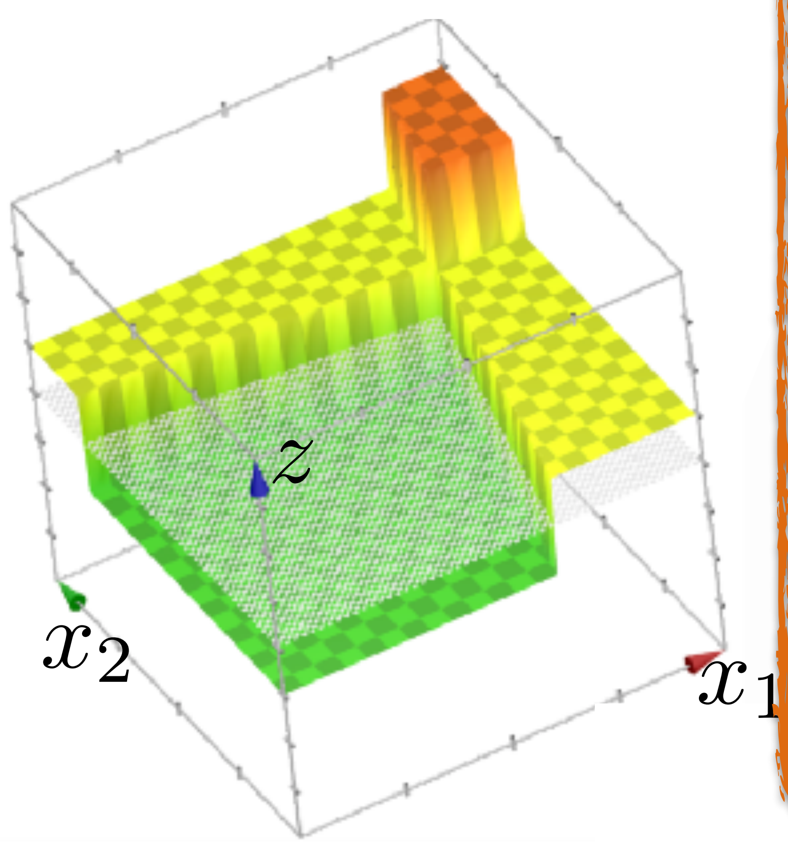

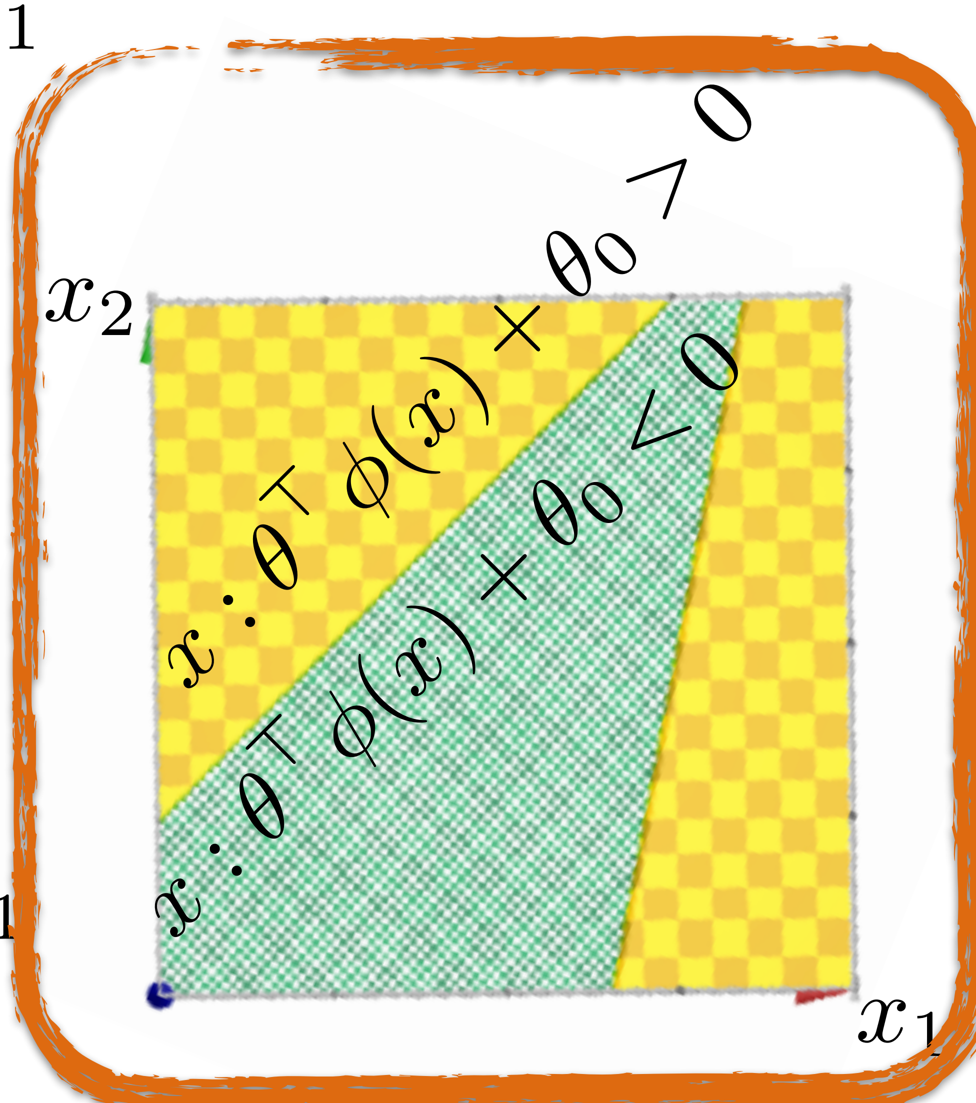

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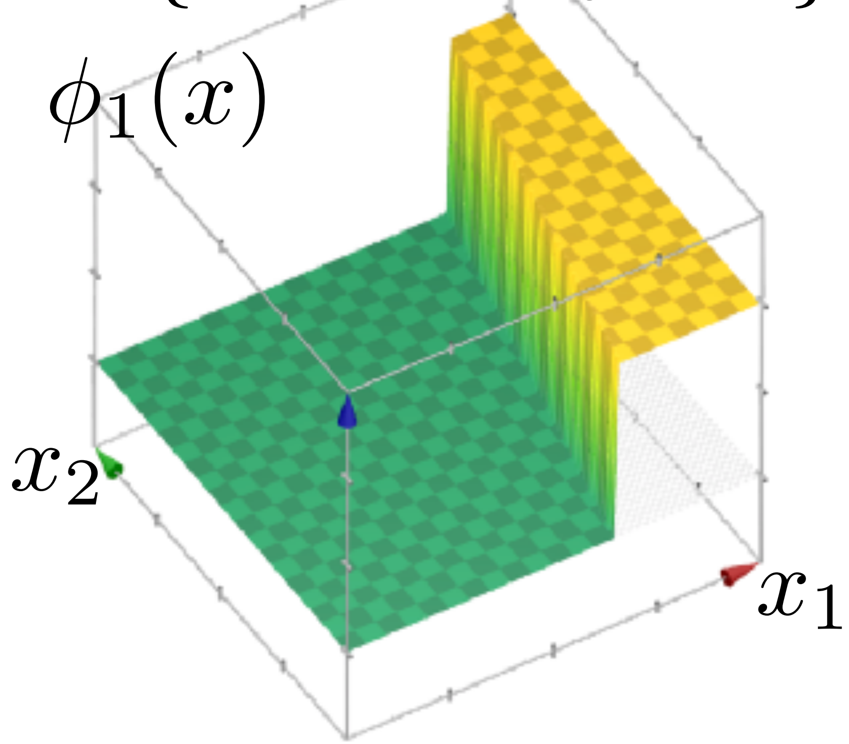

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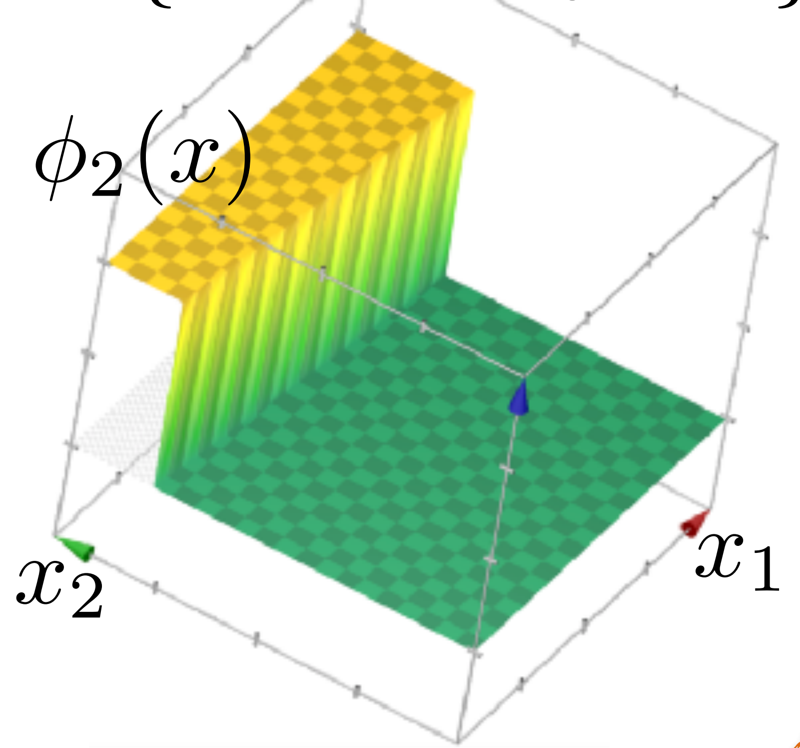

$$z = \theta^\top \phi(x) + \theta_0$$
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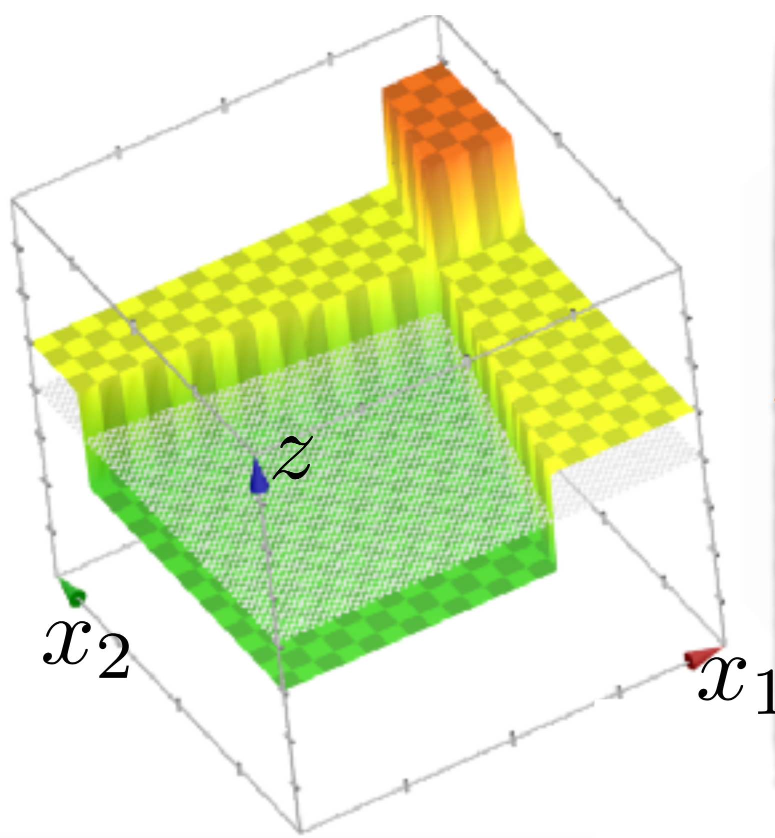
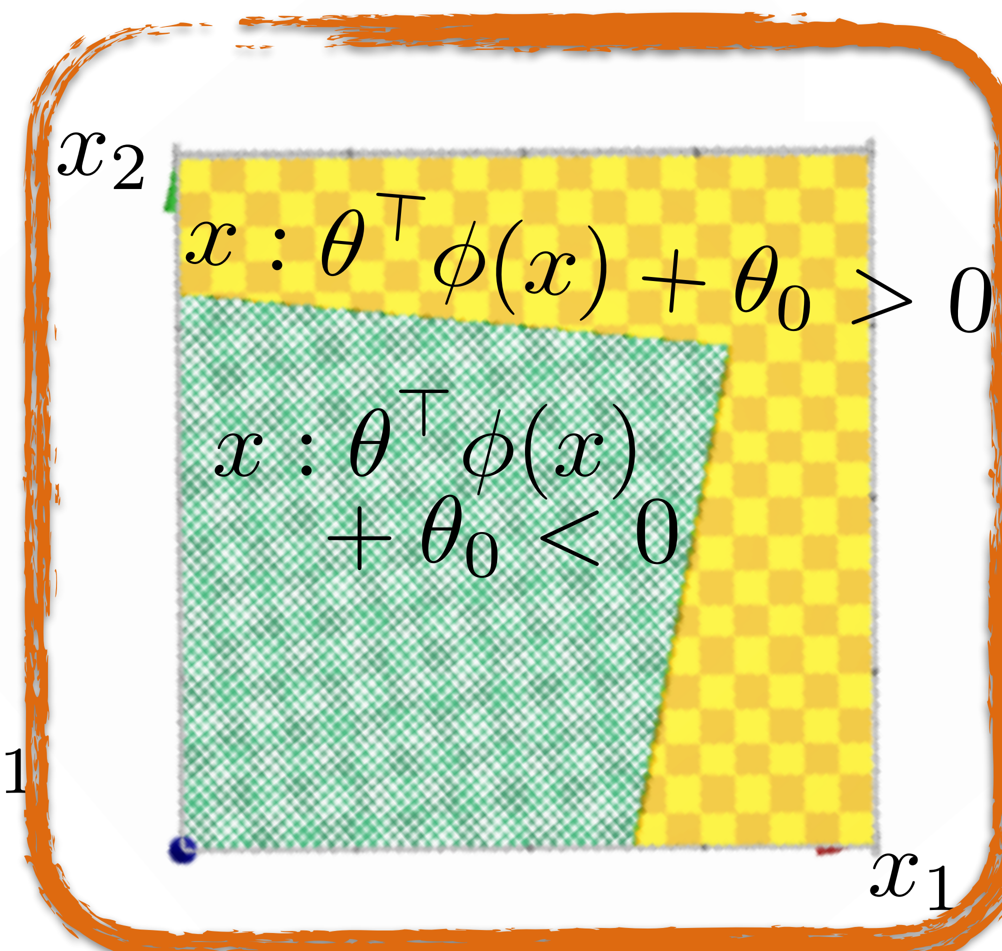
$$= 1 \cdot \phi_1(x) + 1 \cdot \phi_2(x) + (-0.5)$$





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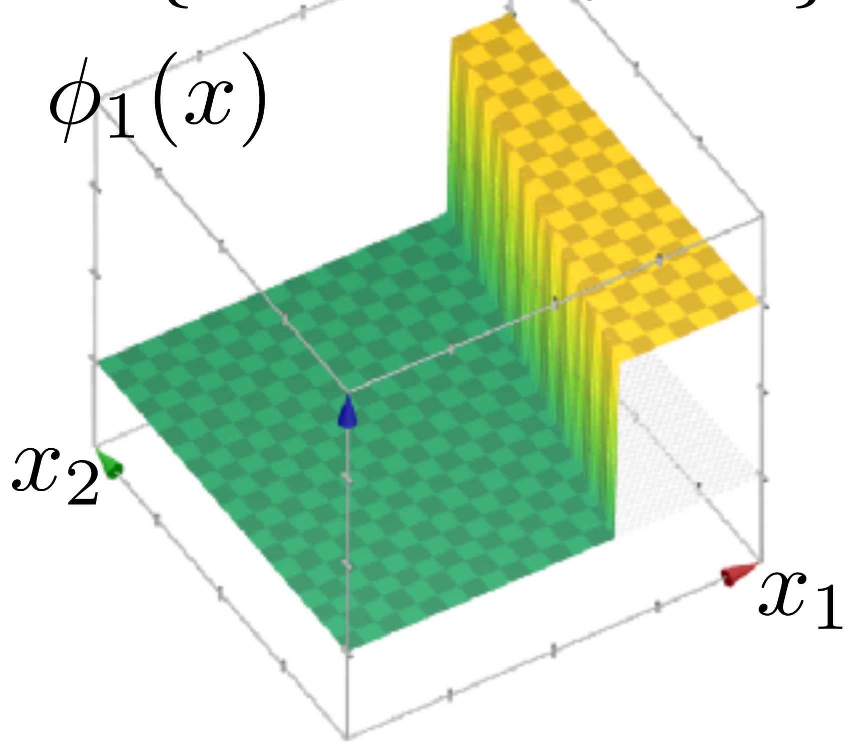

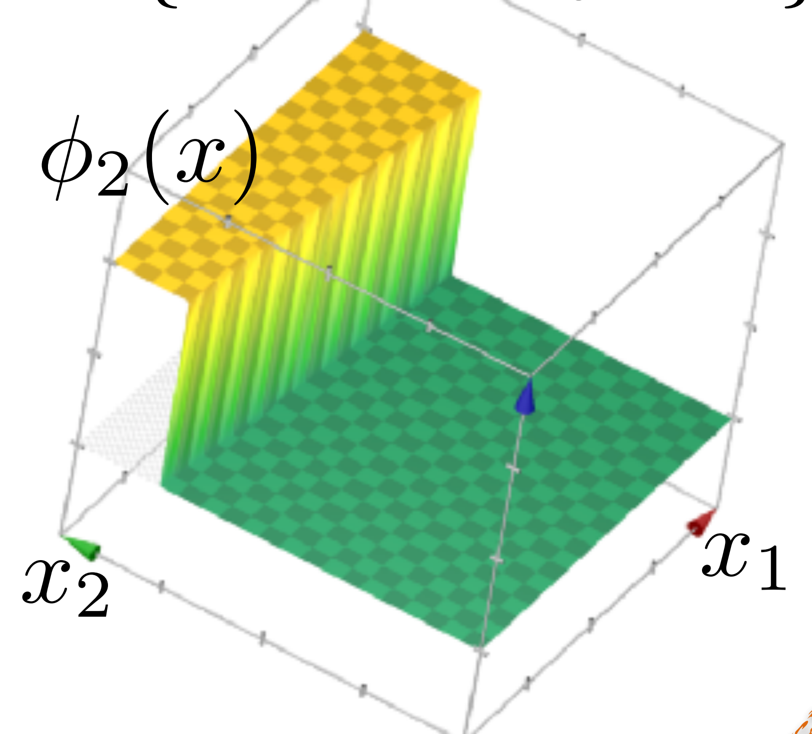

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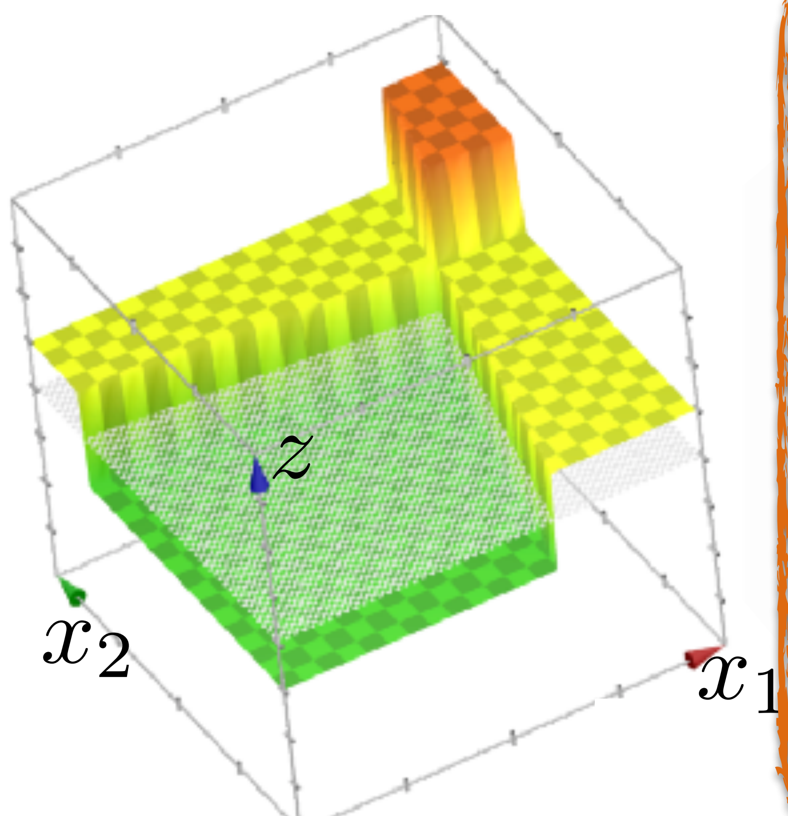

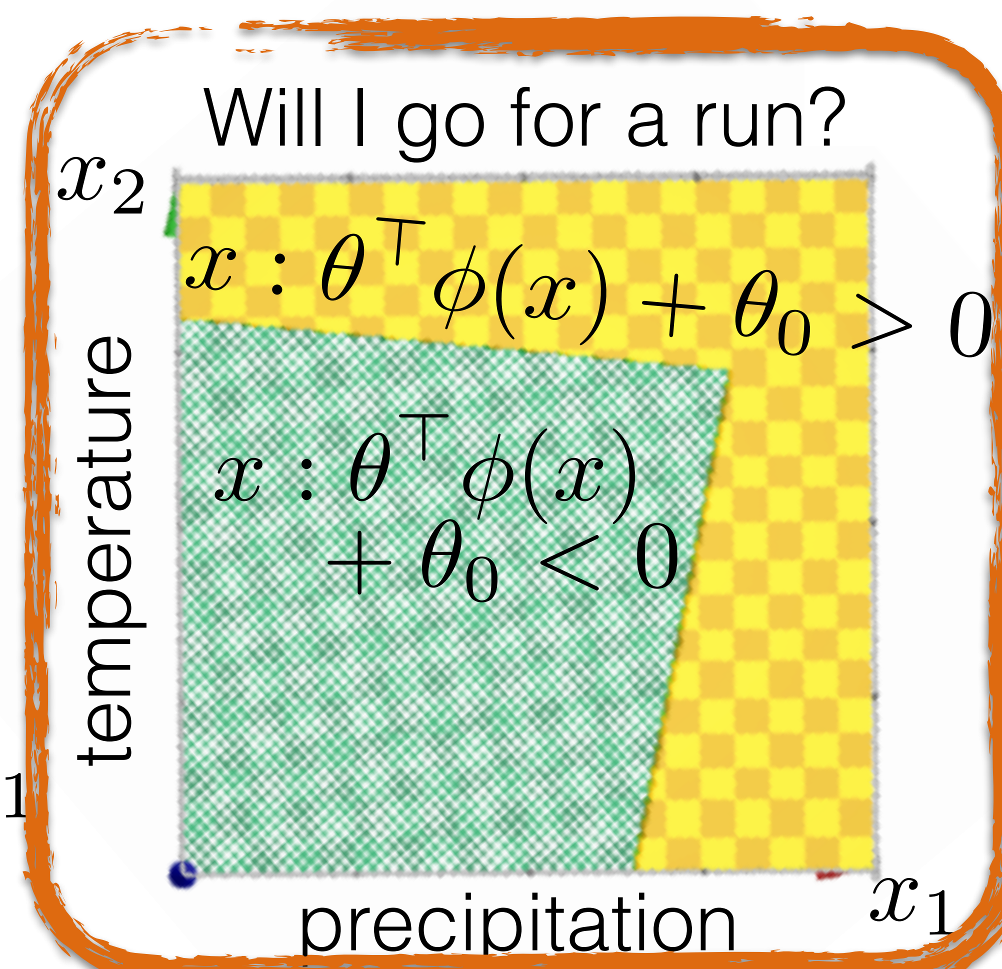

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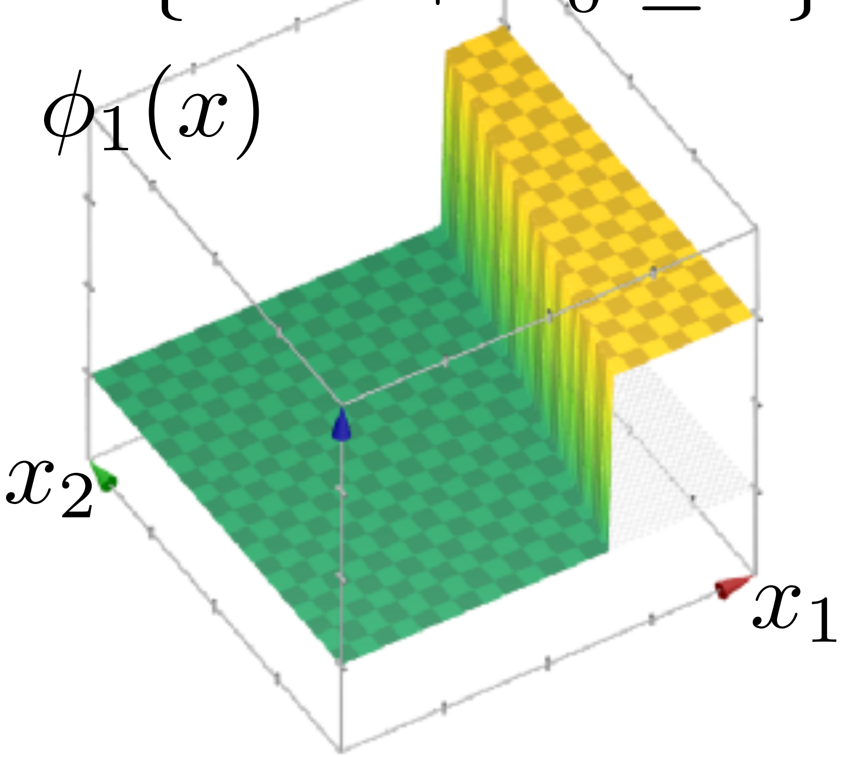

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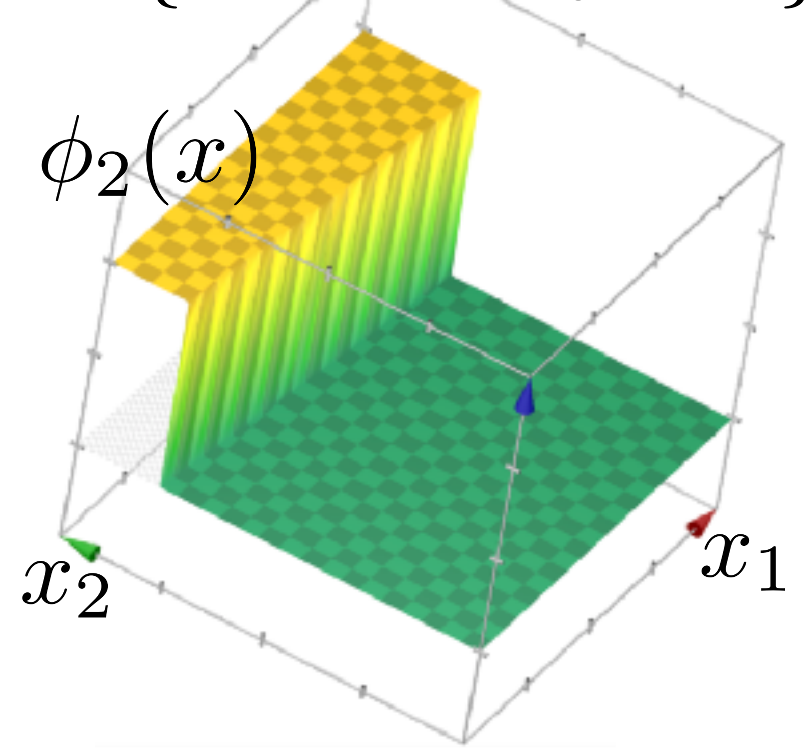

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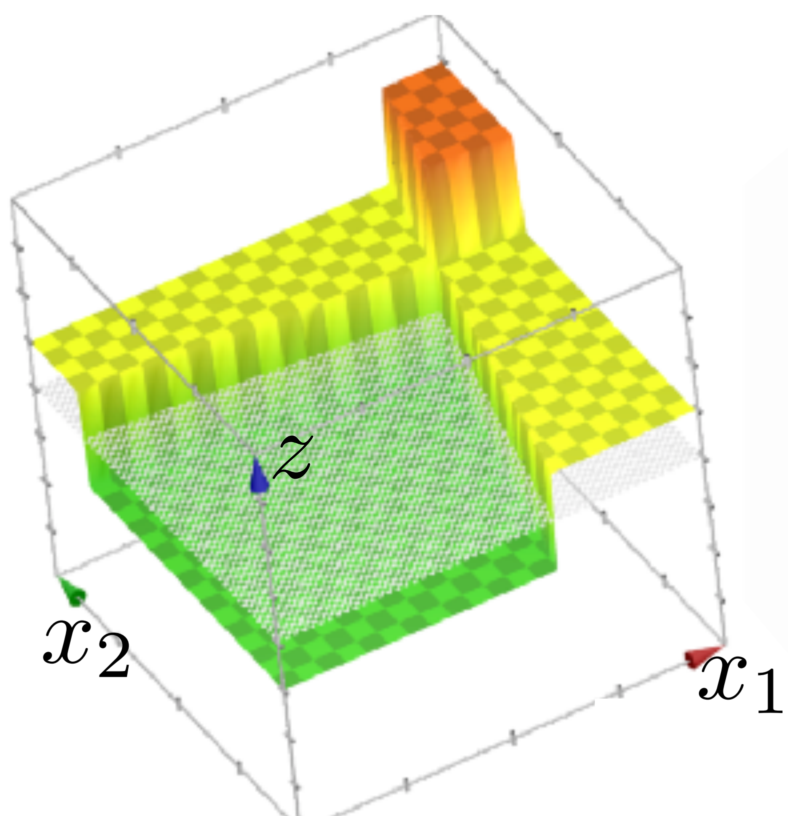
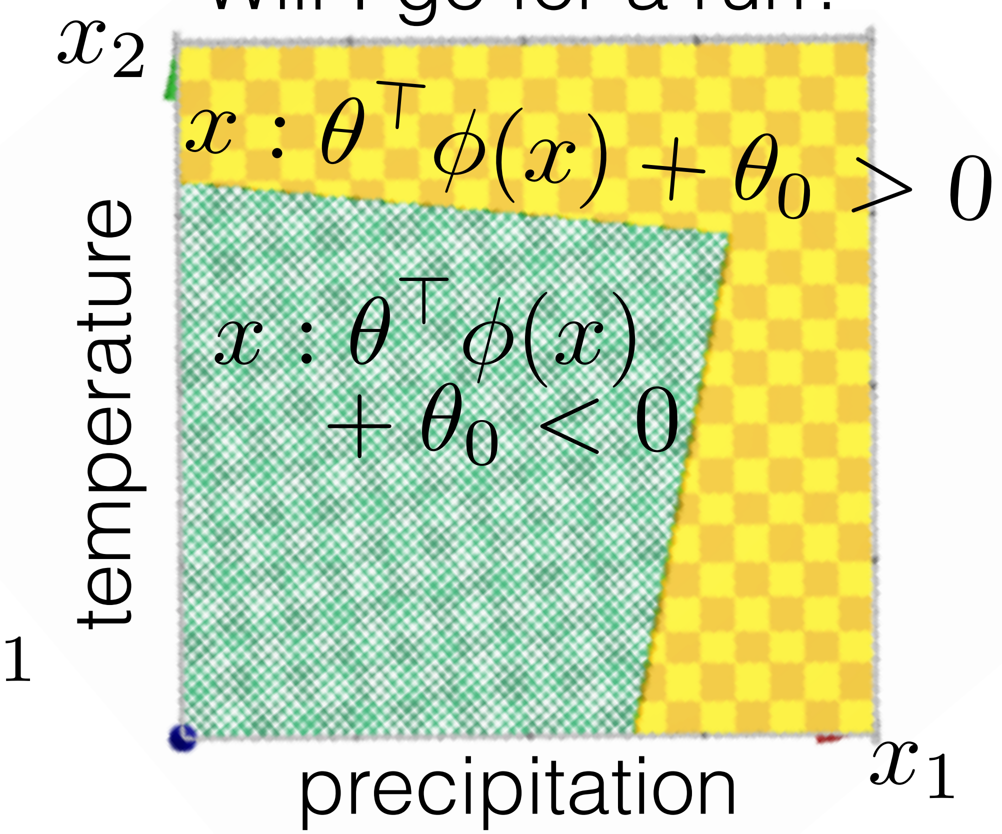


Will I go for a run?



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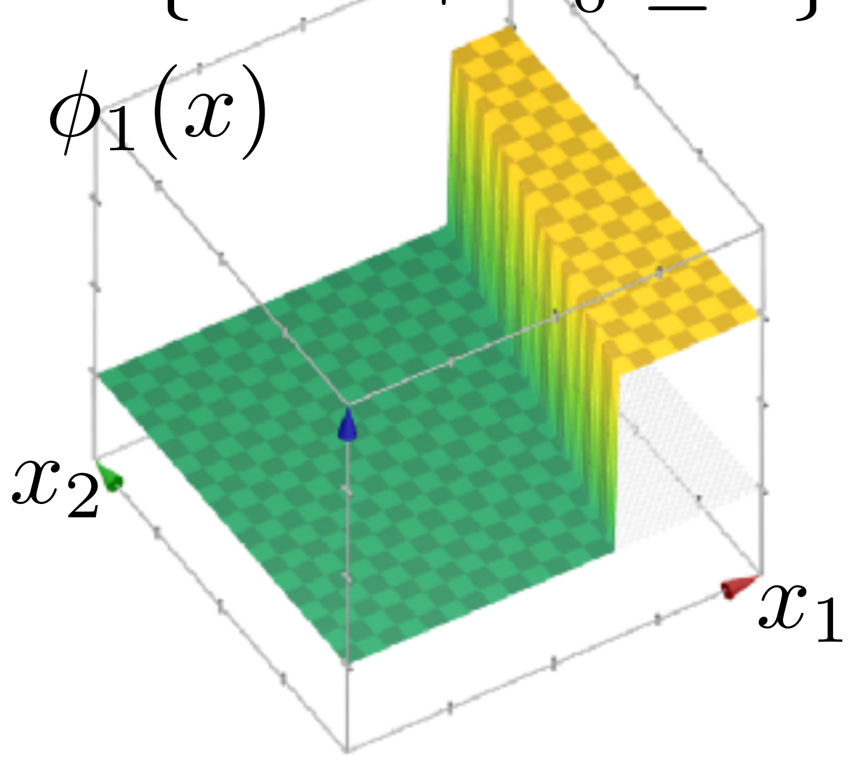

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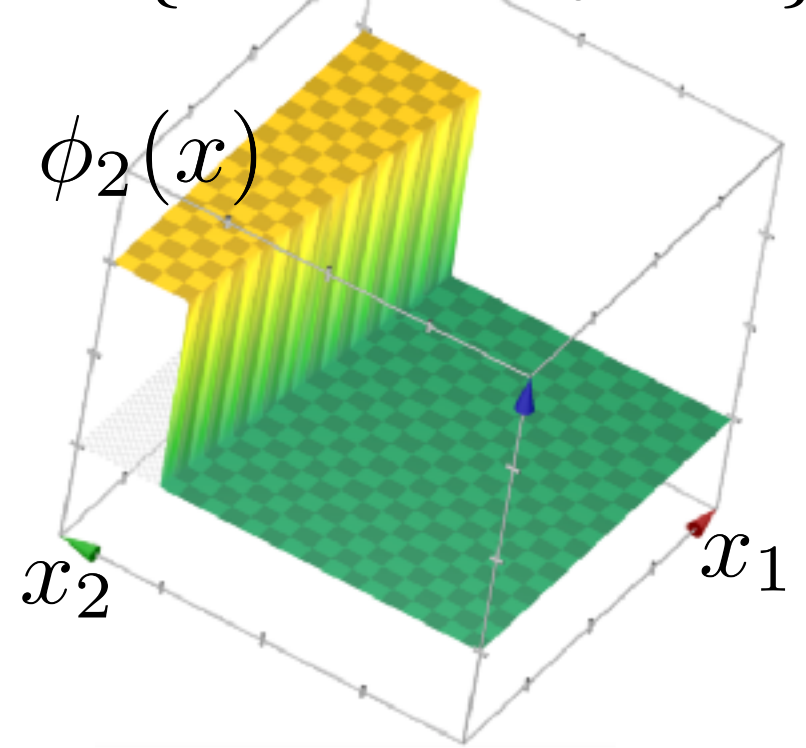

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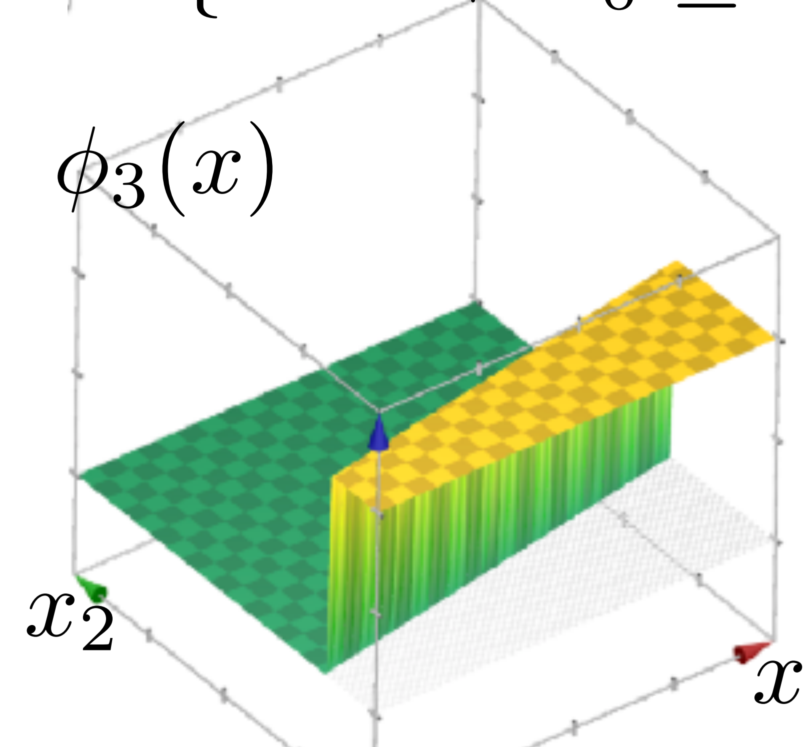

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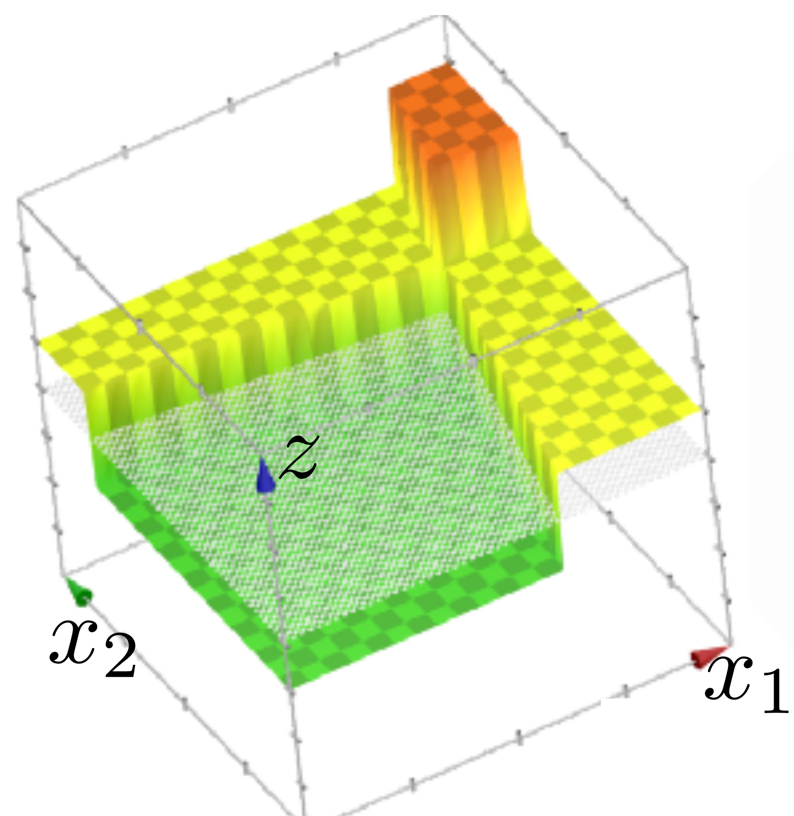

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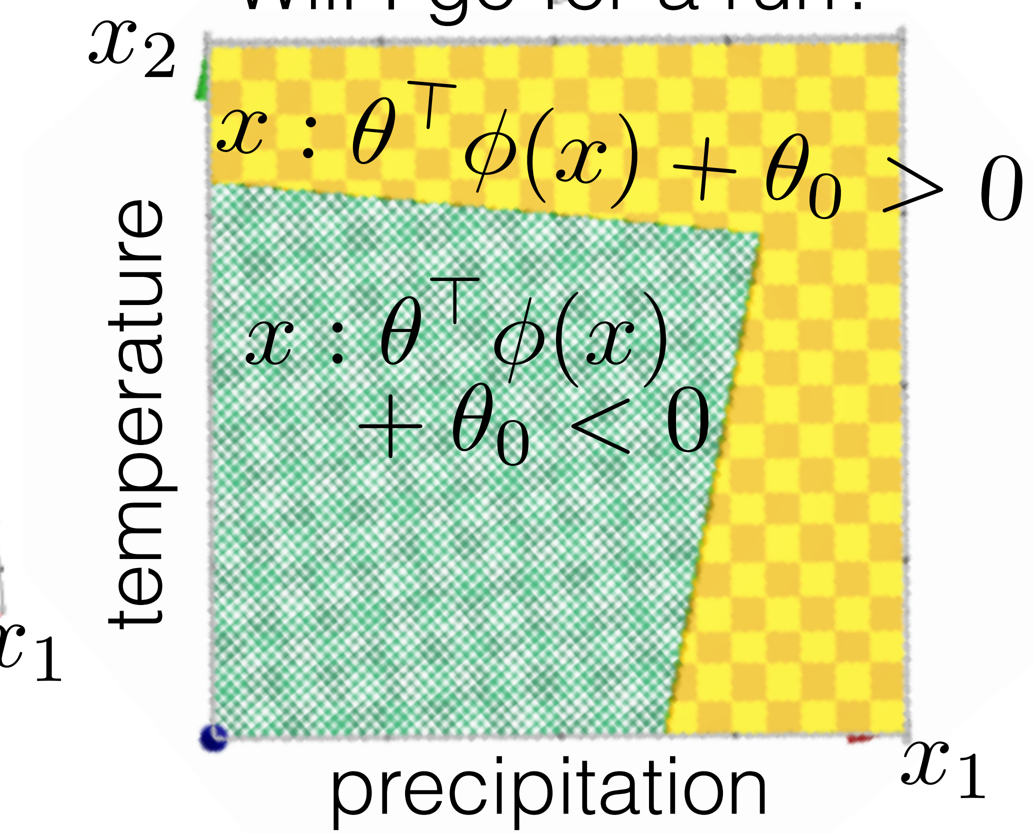

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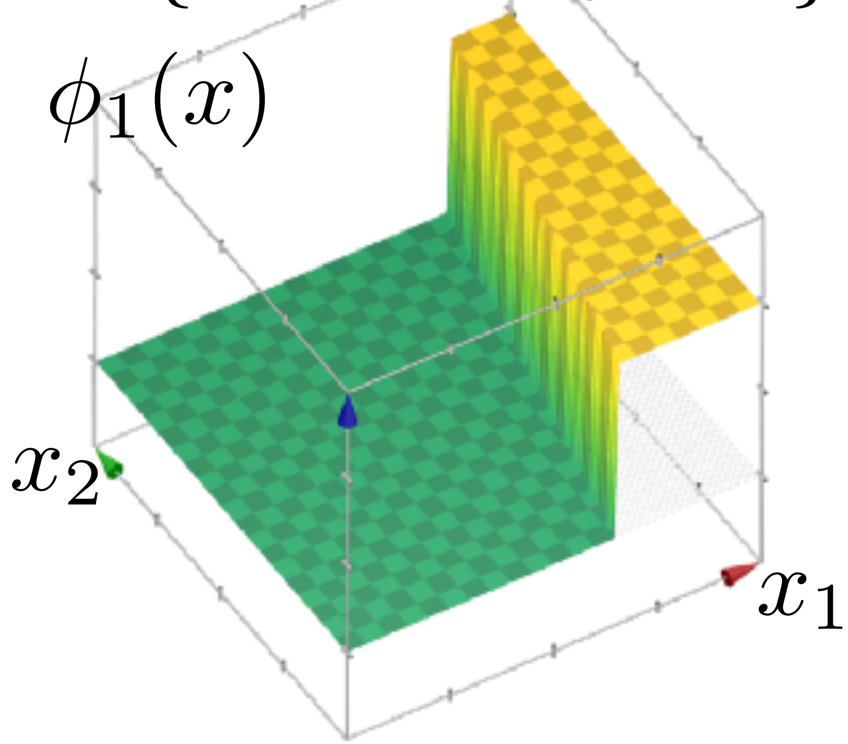

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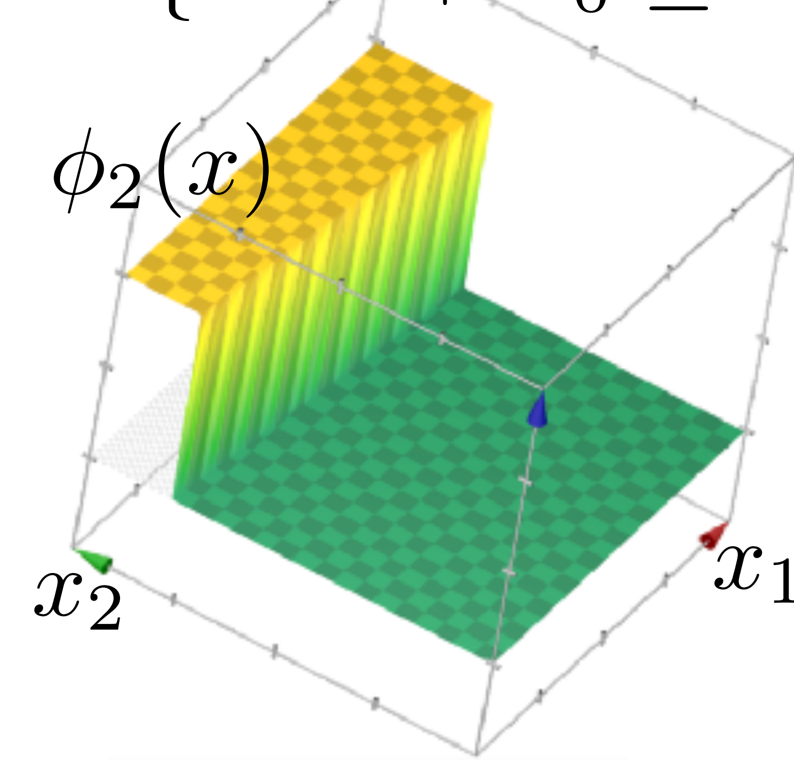

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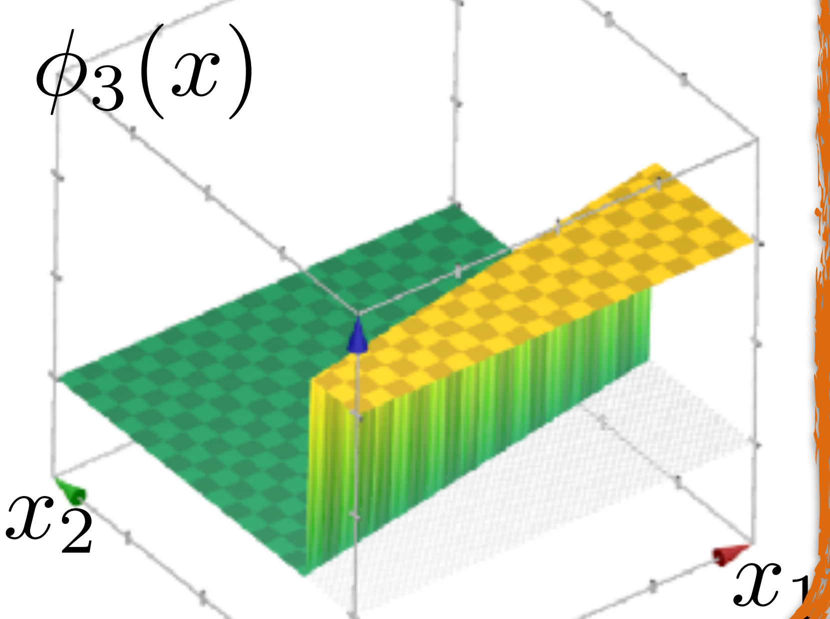

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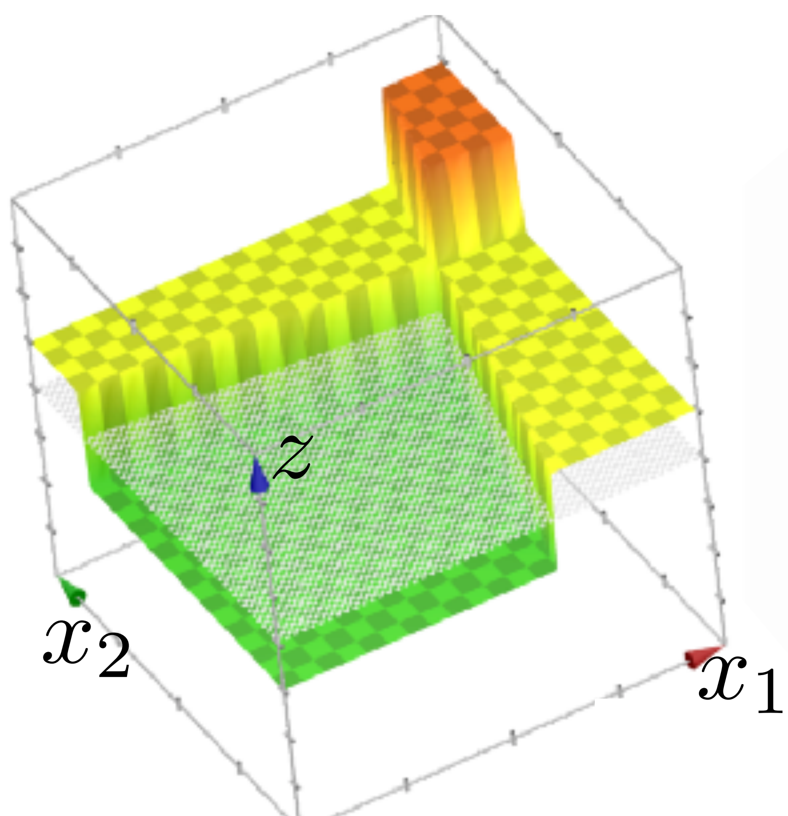

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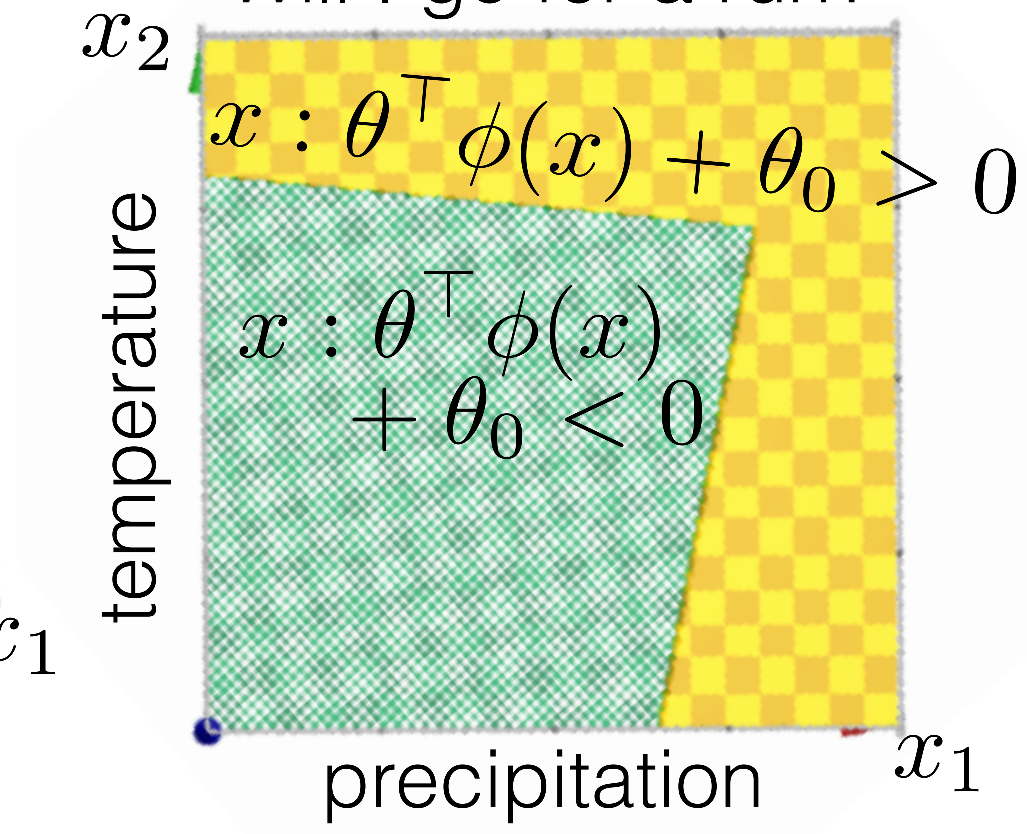

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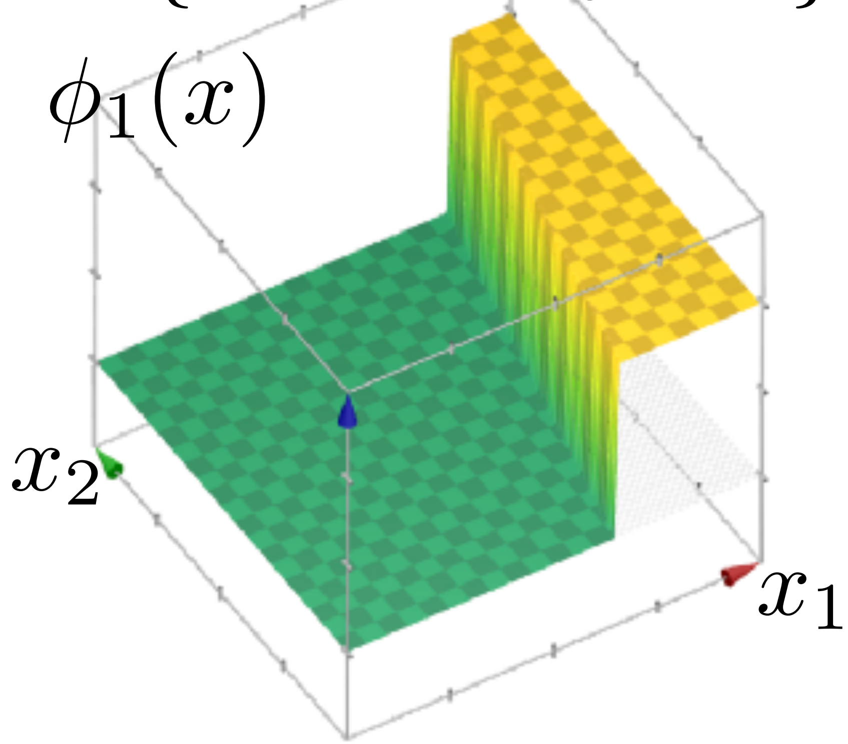

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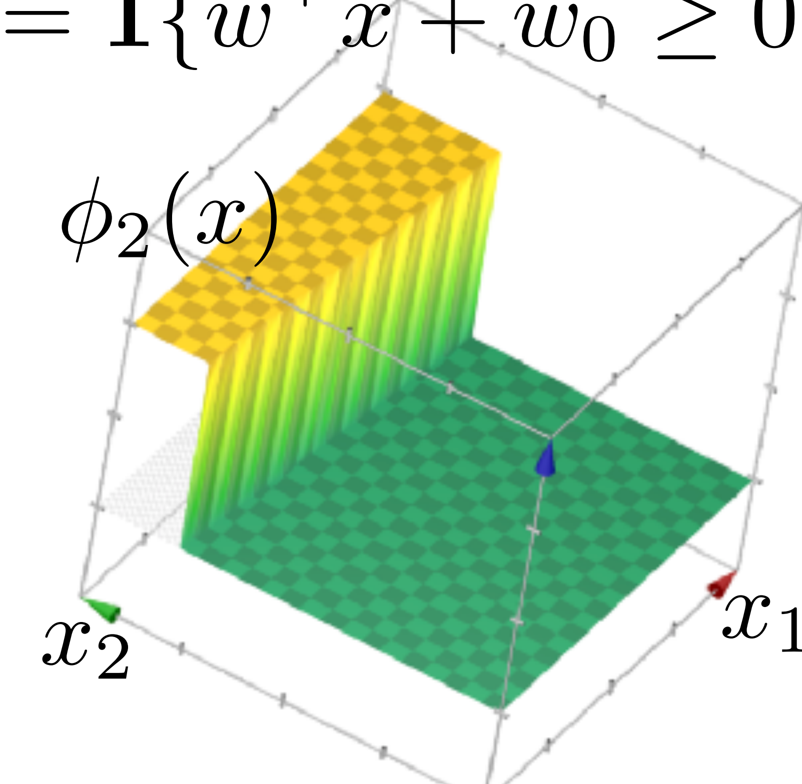

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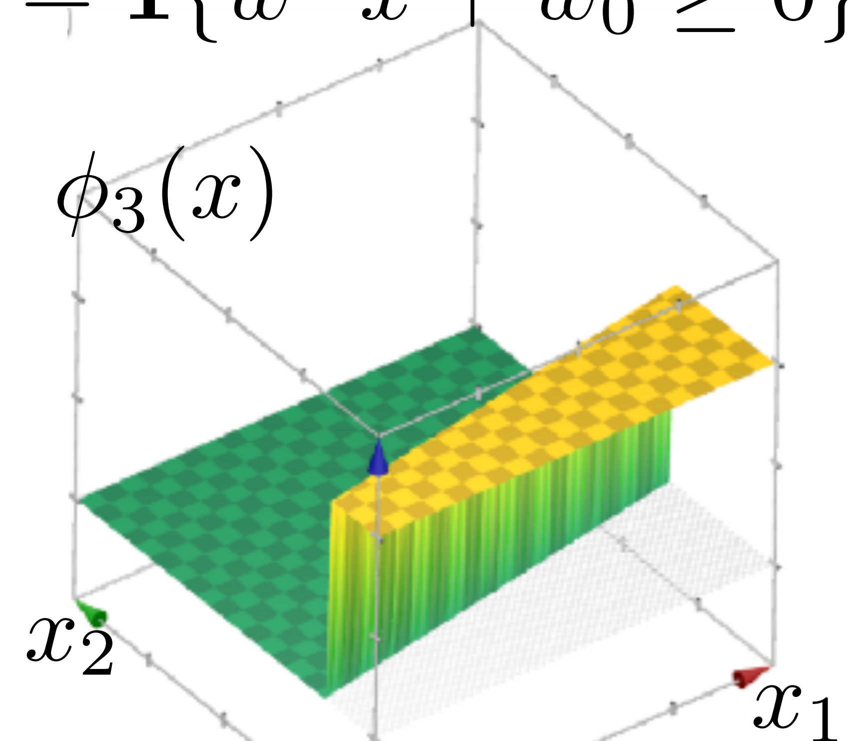

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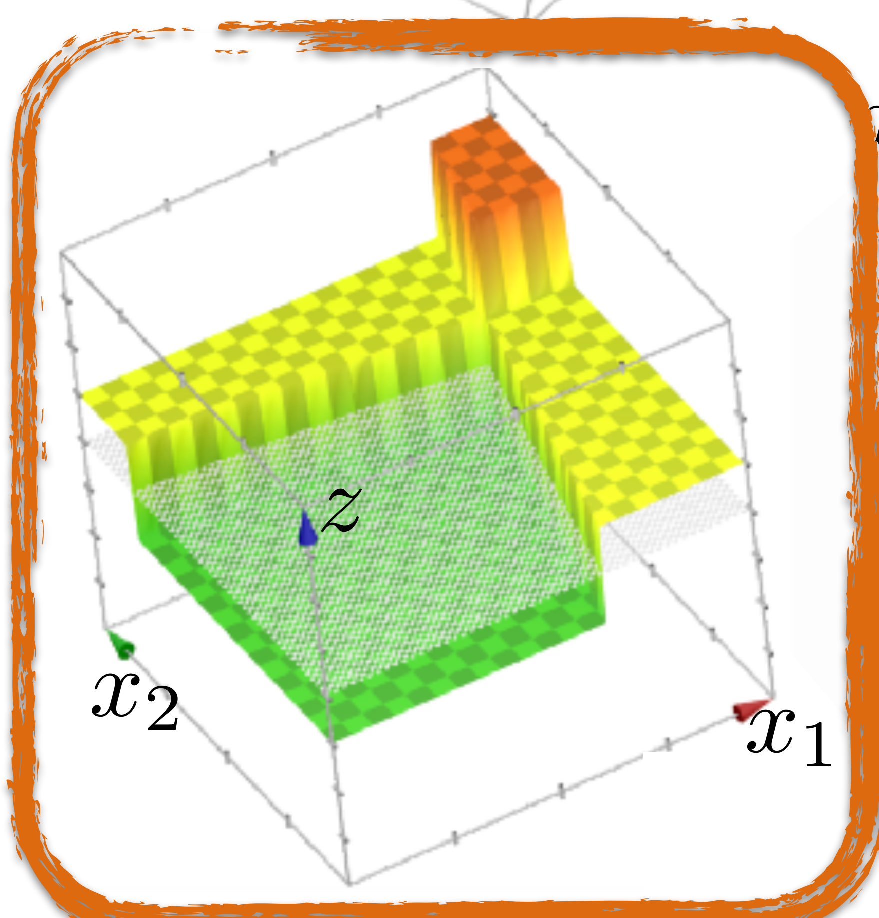

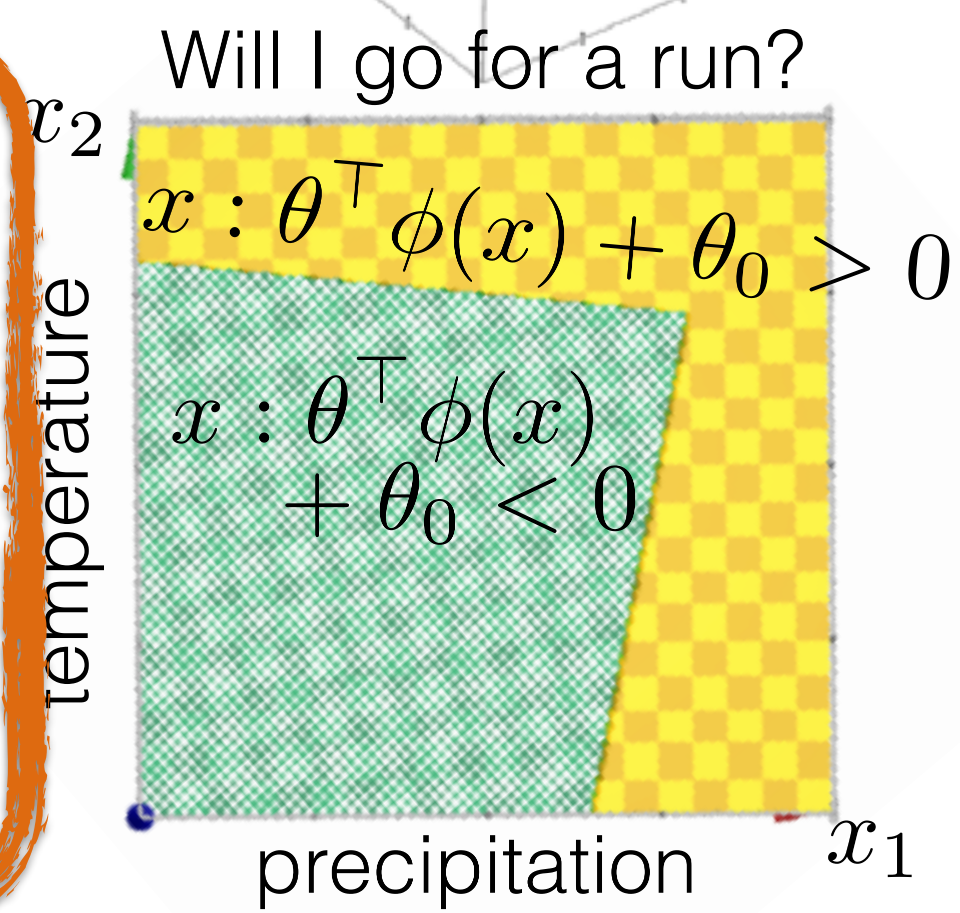

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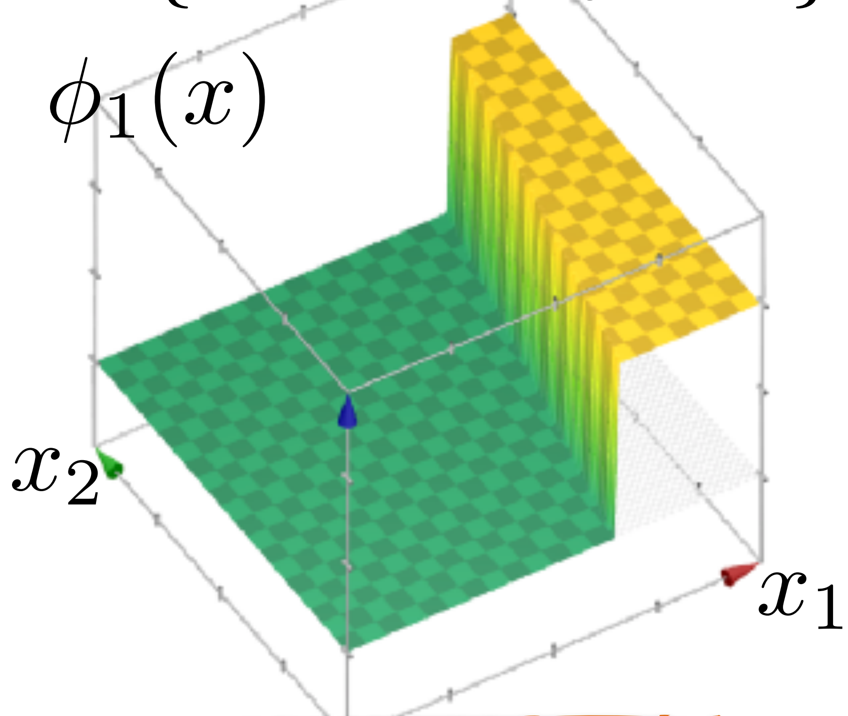

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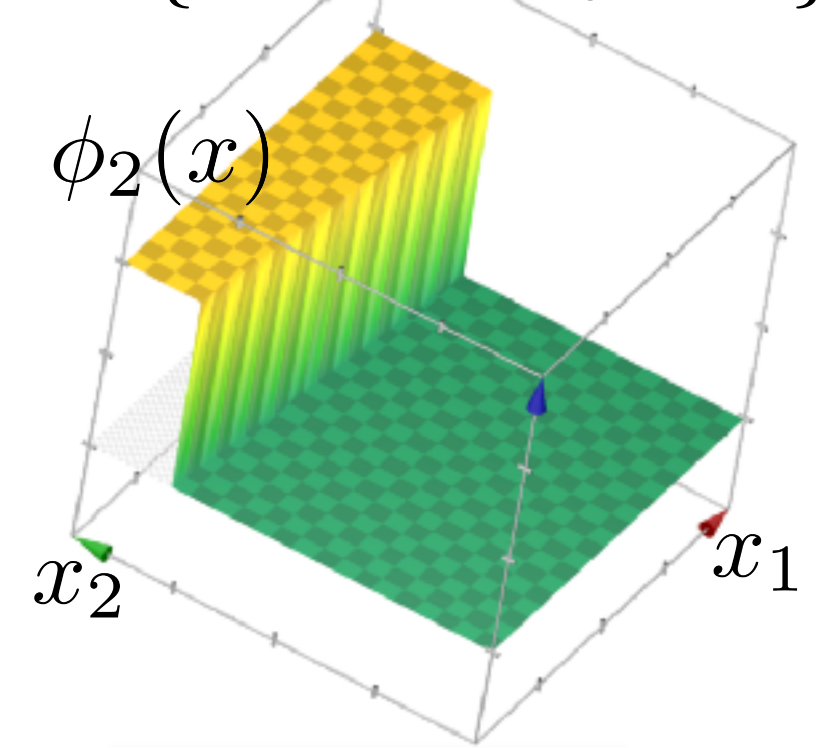

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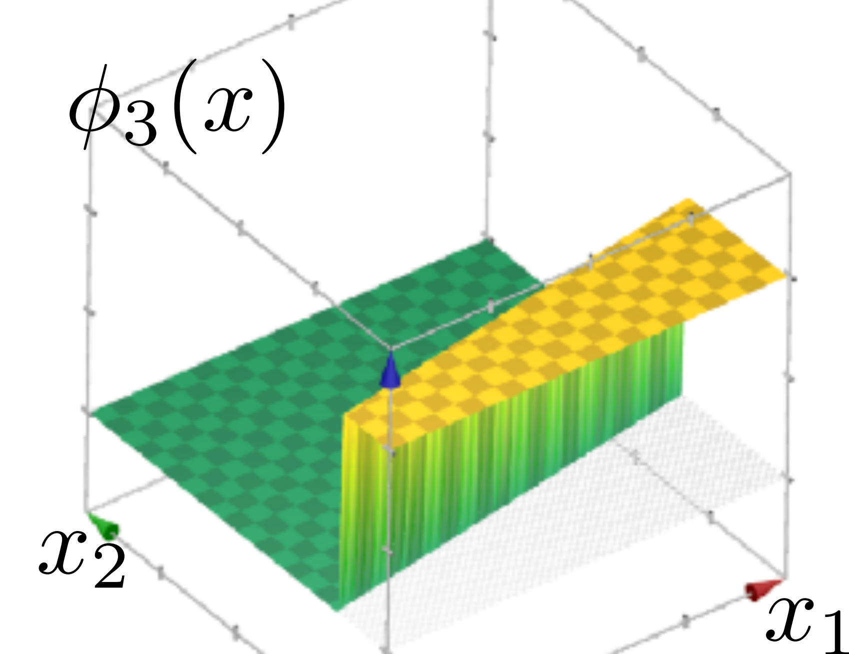
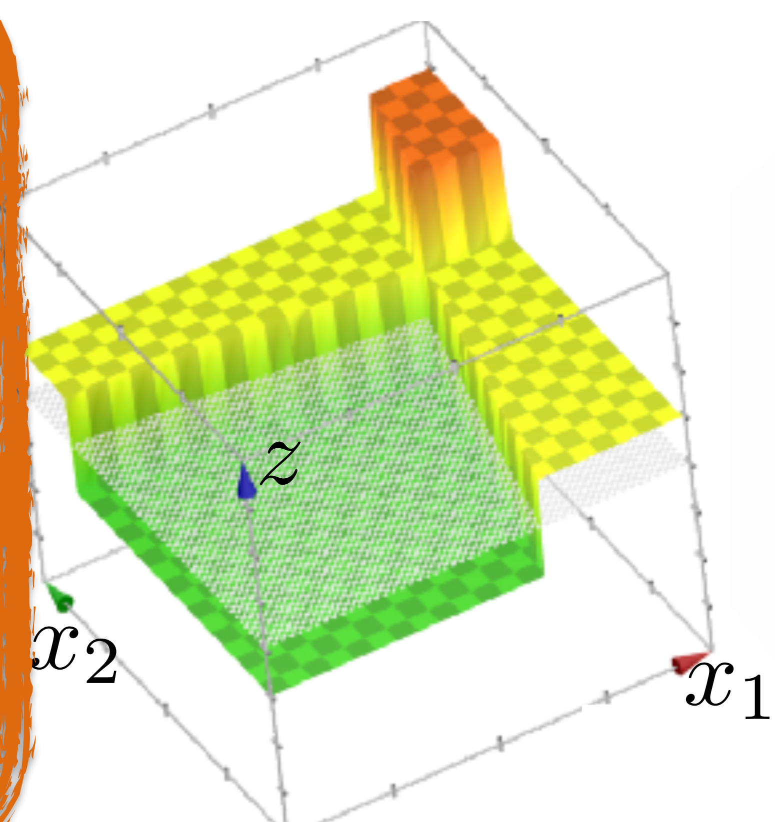
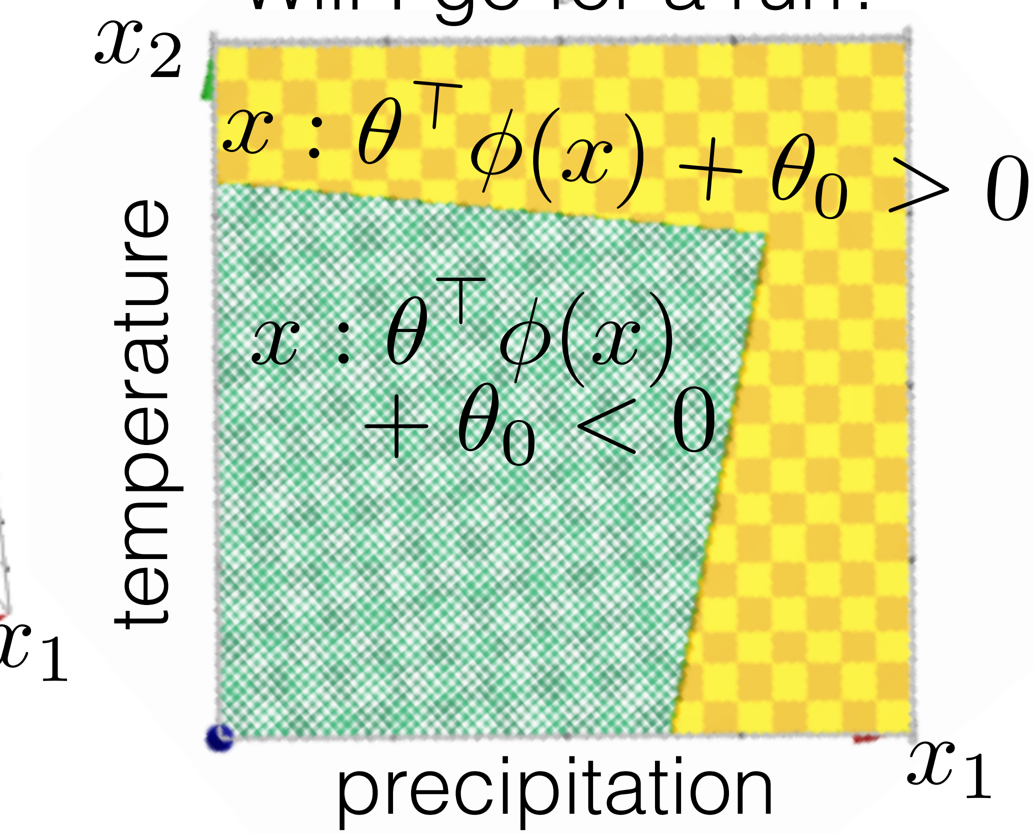


$$\boxed{\begin{aligned} z &= \theta^\top \phi(x) + \theta_0 \\ &= \theta_1\phi_1(x) + \theta_2\phi_2(x) \\ &\quad + \theta_0 \\ &= 1 \cdot \phi_1(x) + 1 \cdot \phi_2(x) \\ &\quad + (-0.5) \end{aligned}}$$



Will I go for a run?



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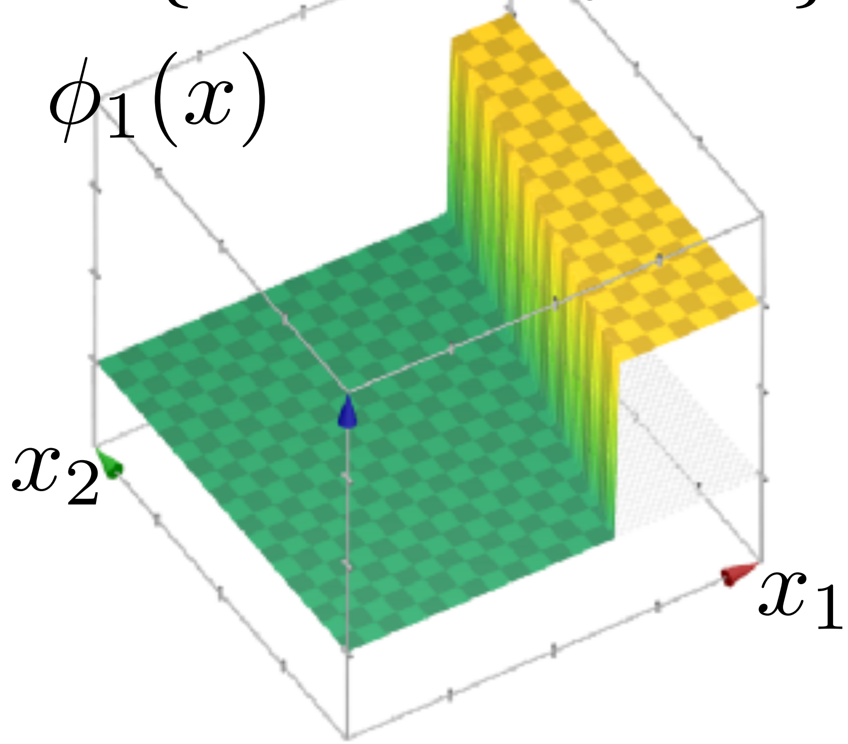

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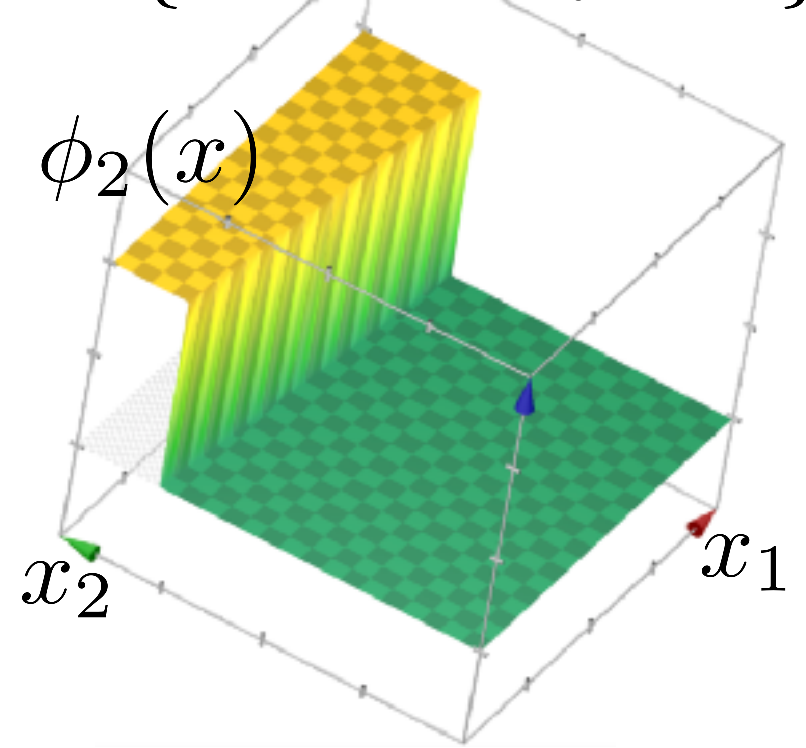

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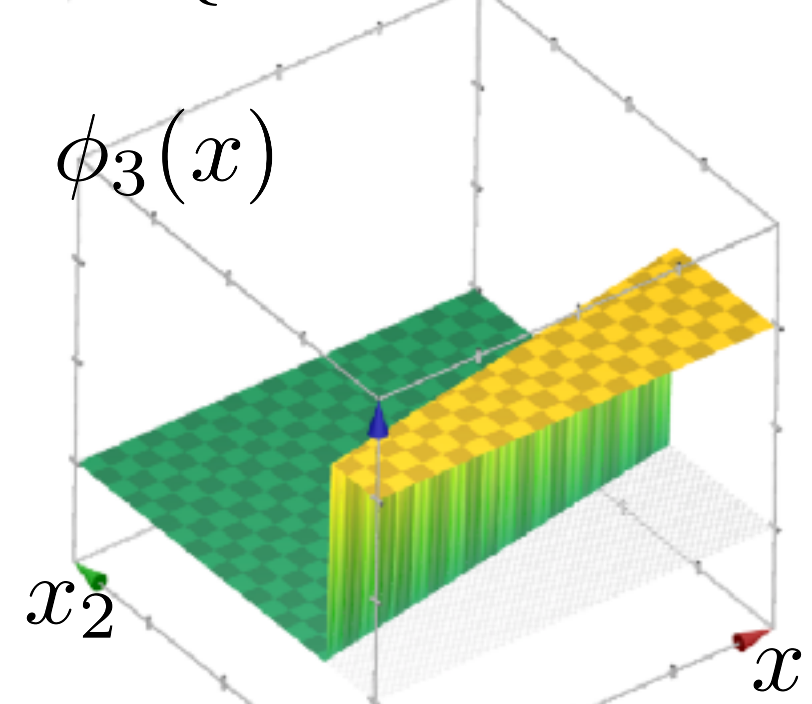

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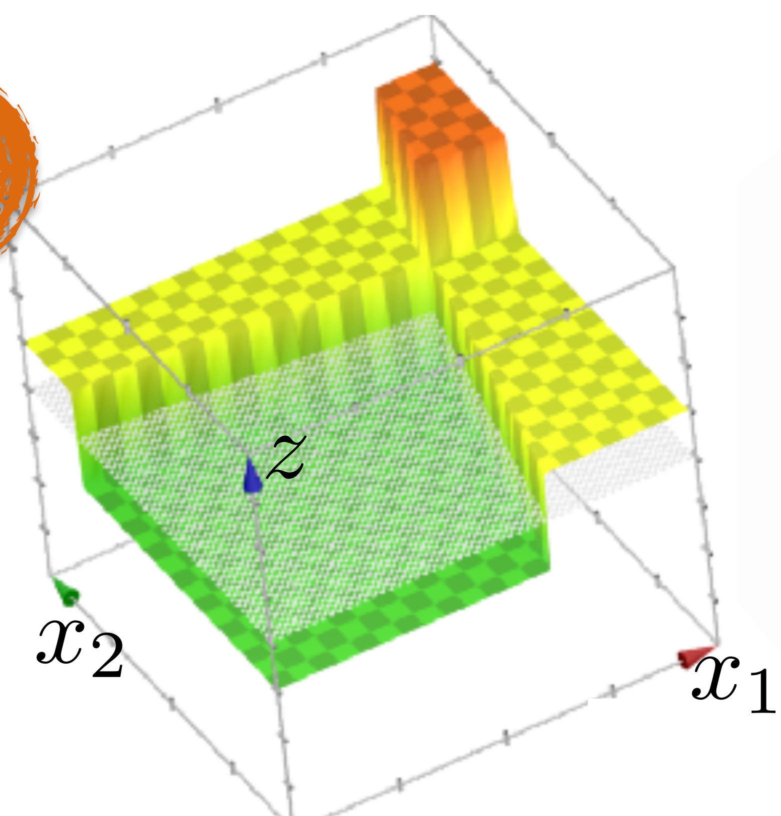

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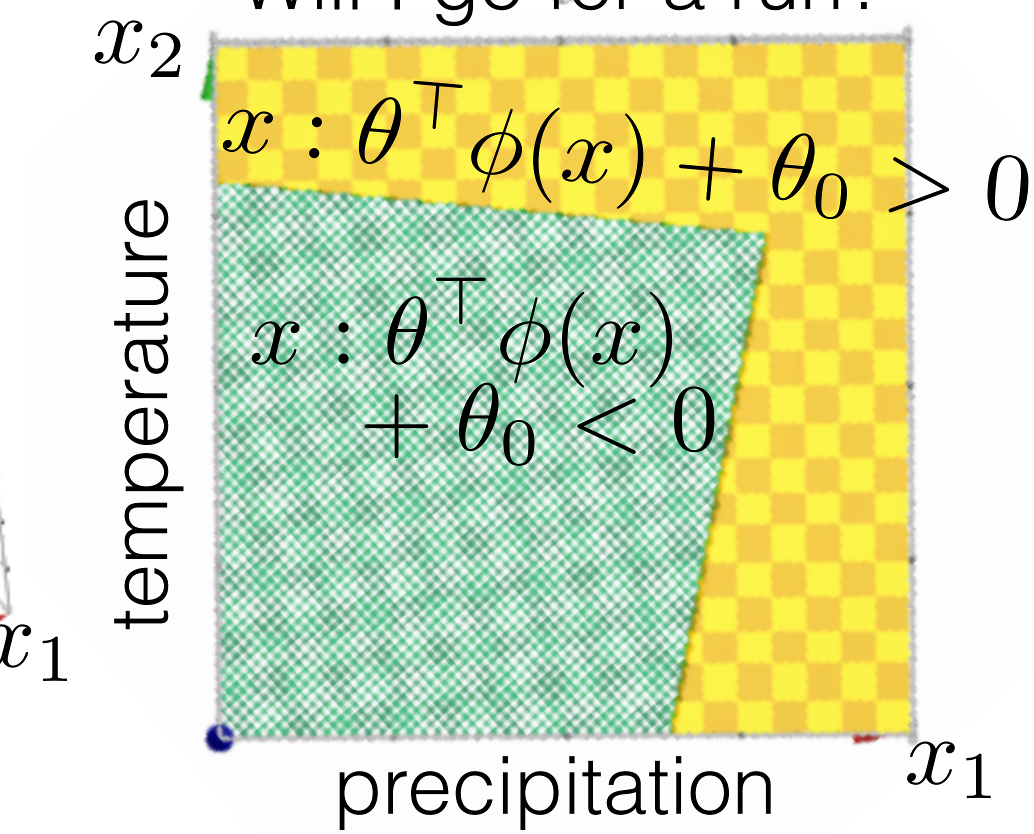

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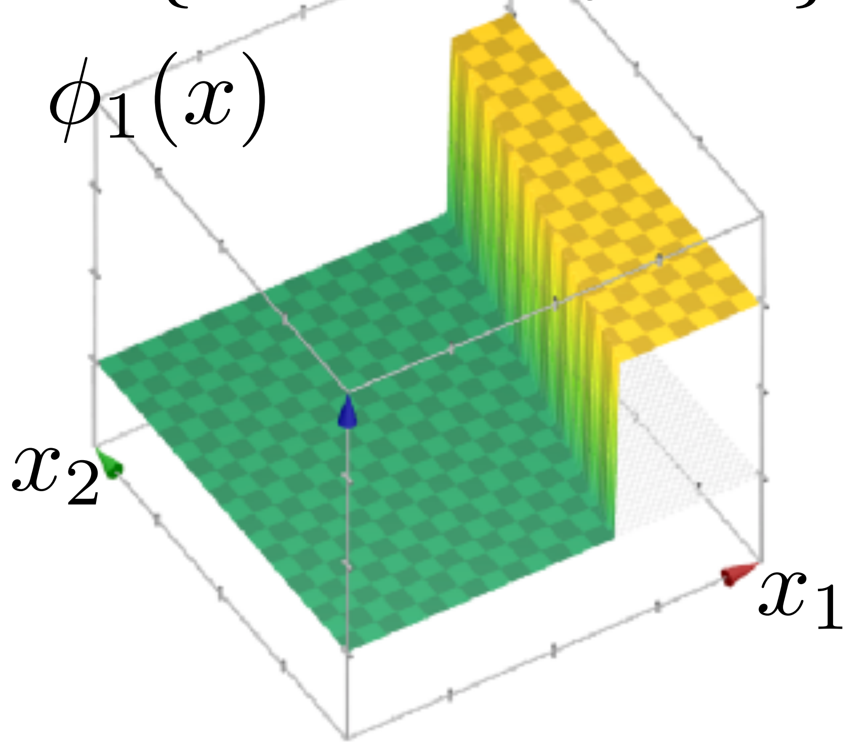

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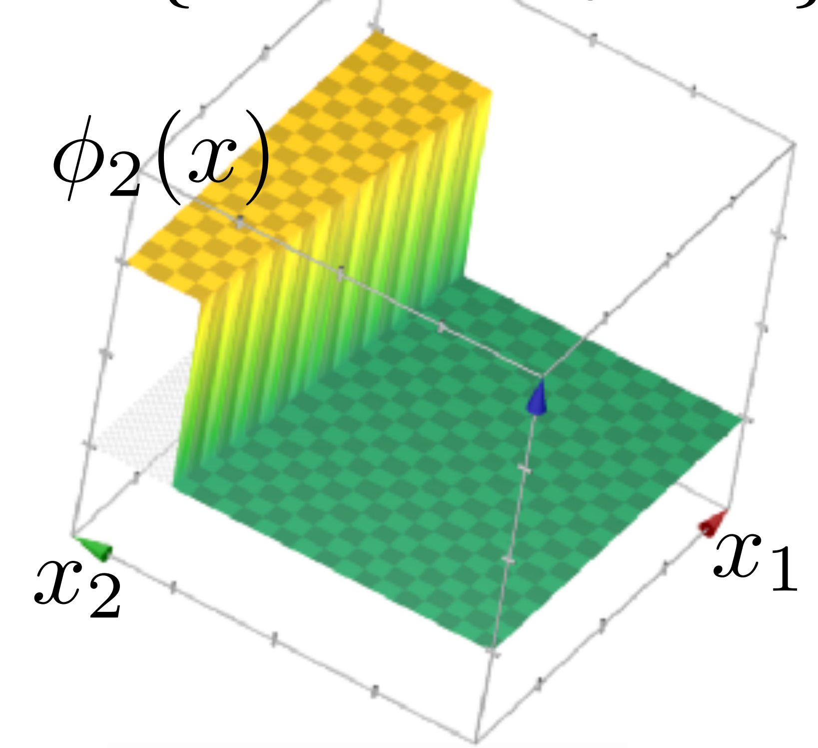

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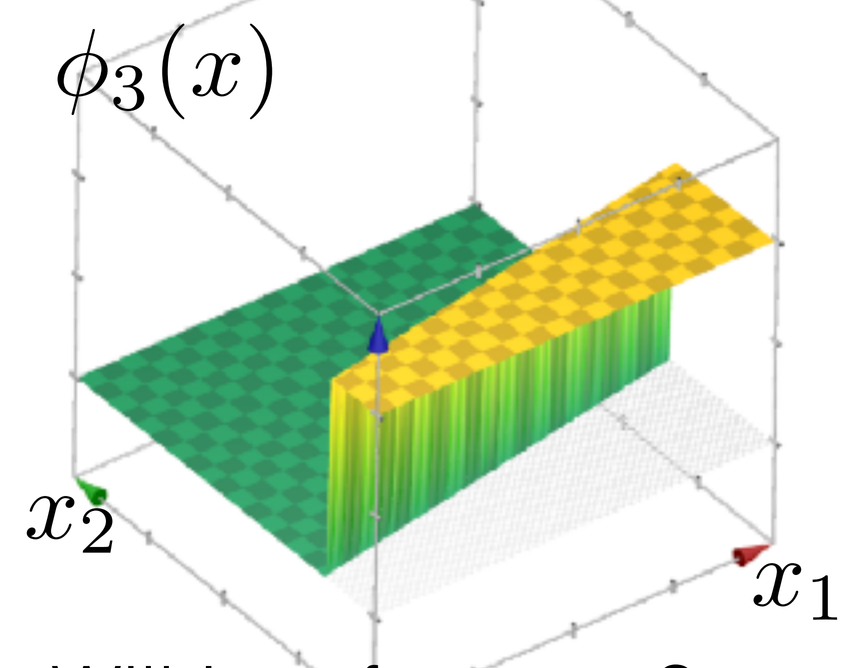

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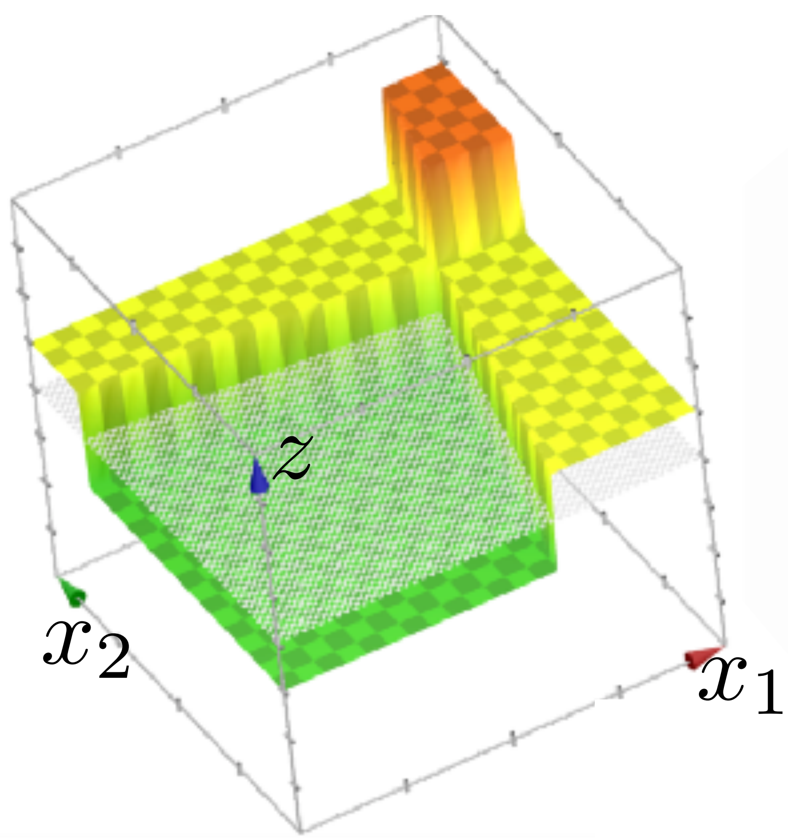

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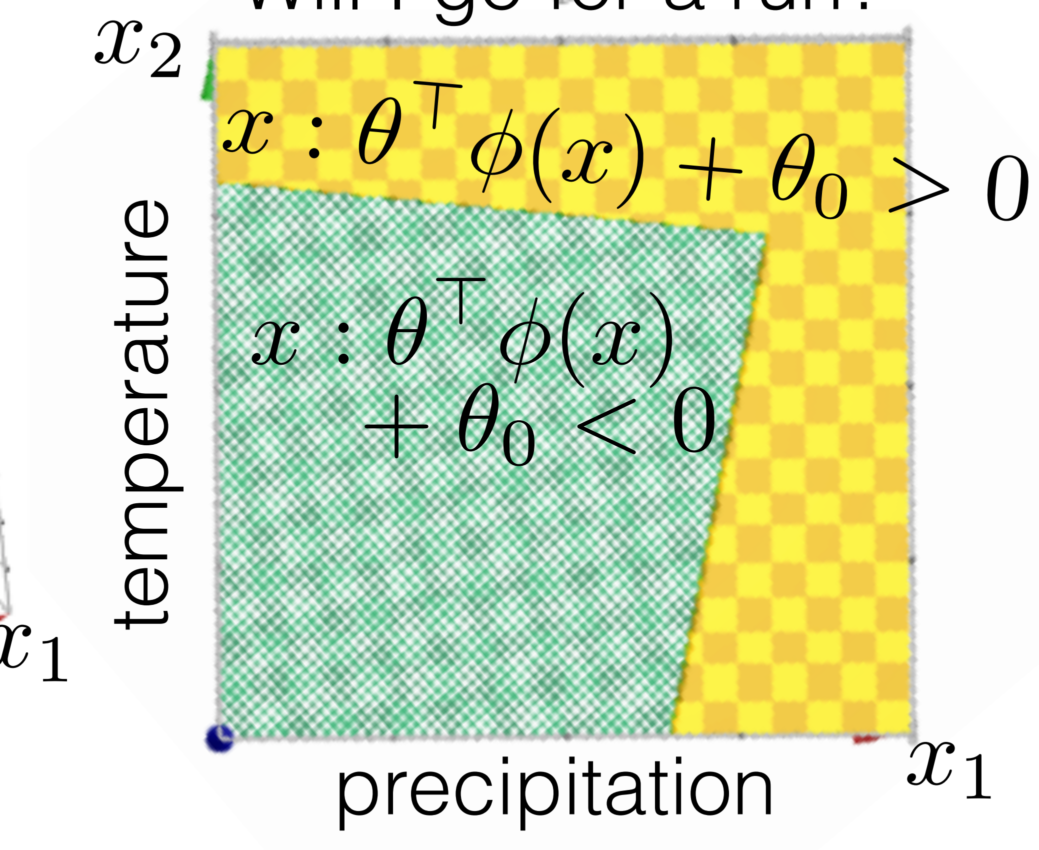

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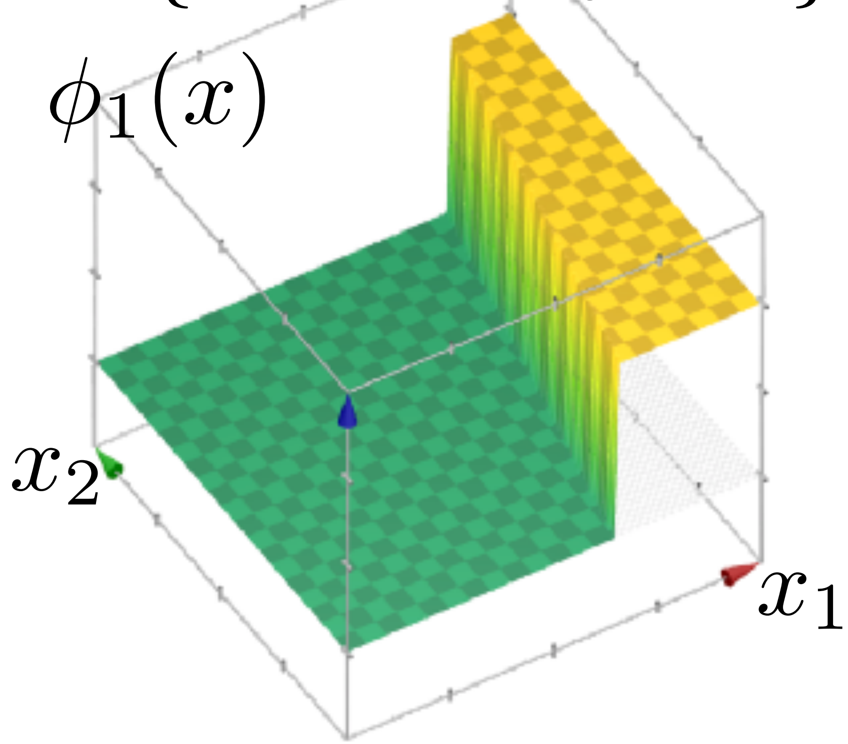

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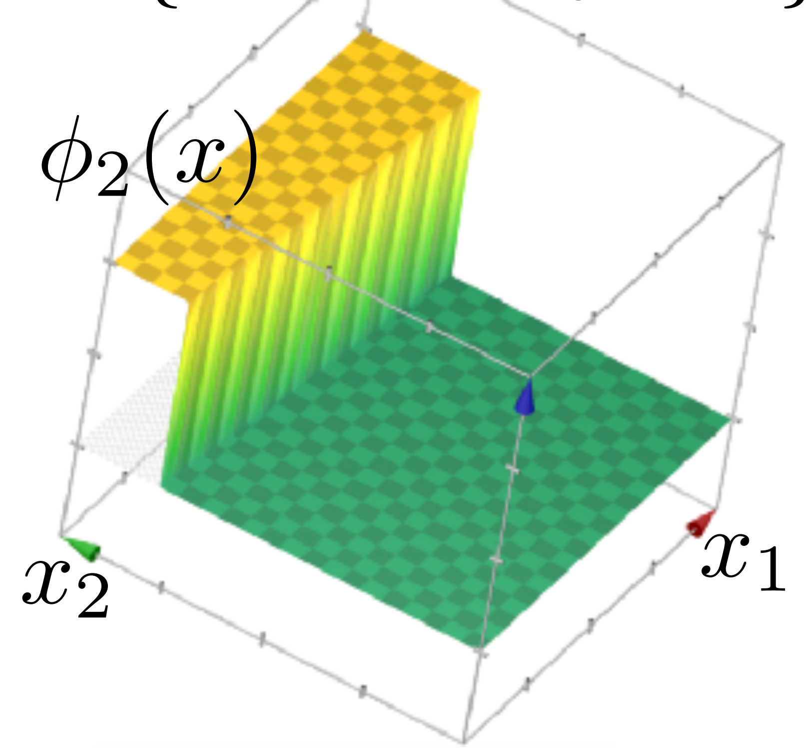

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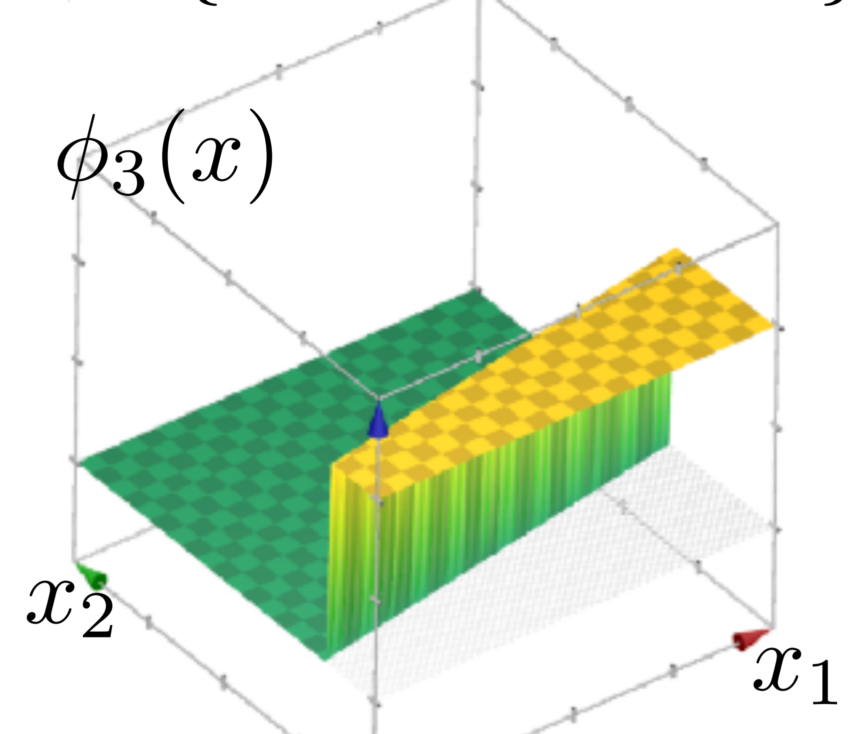

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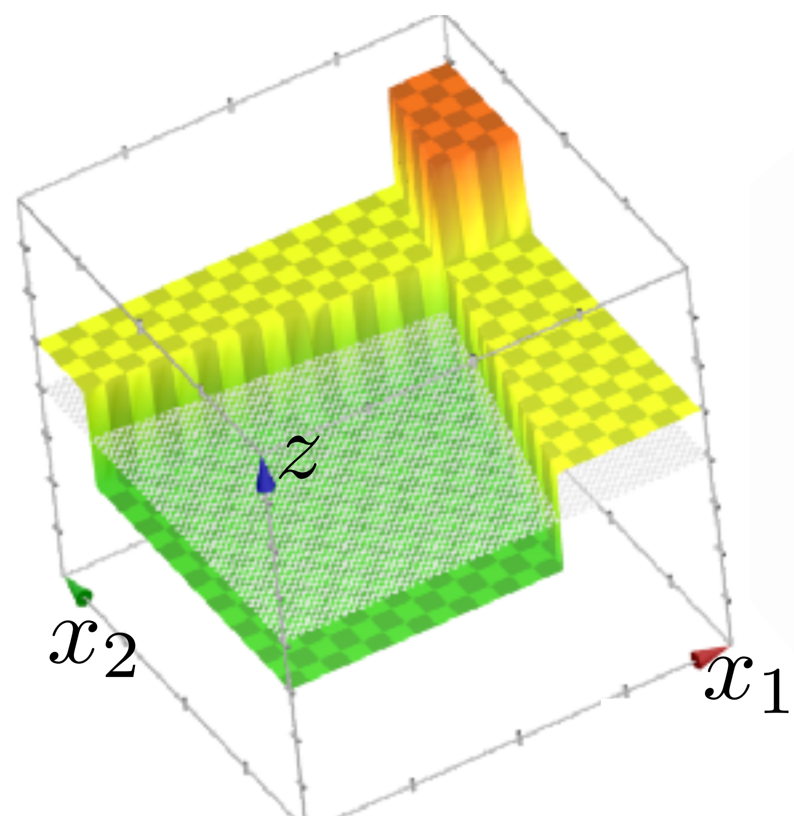

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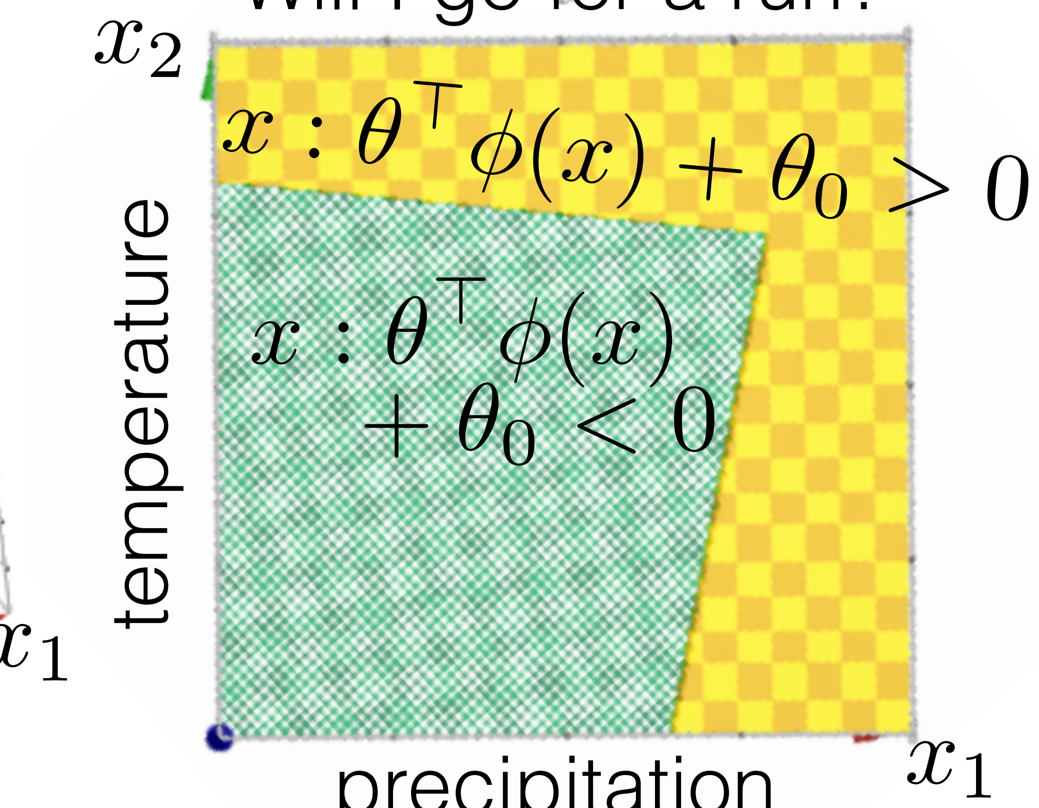

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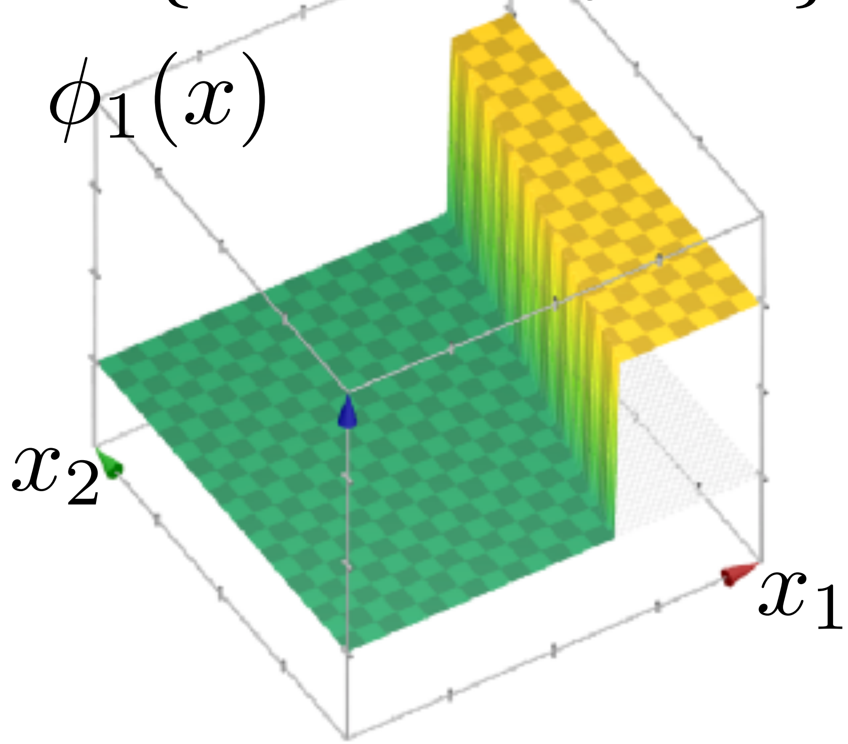

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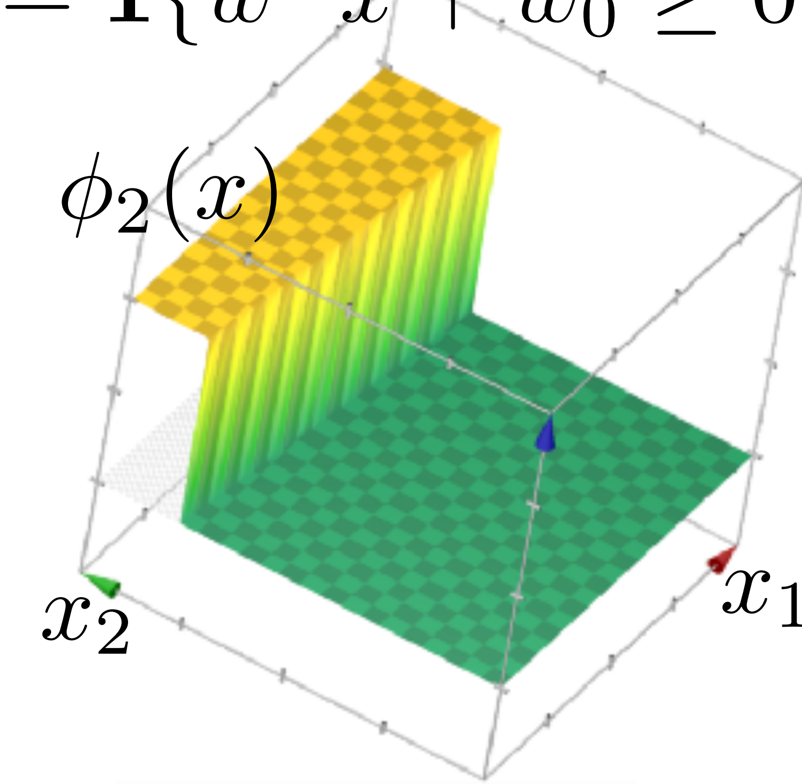

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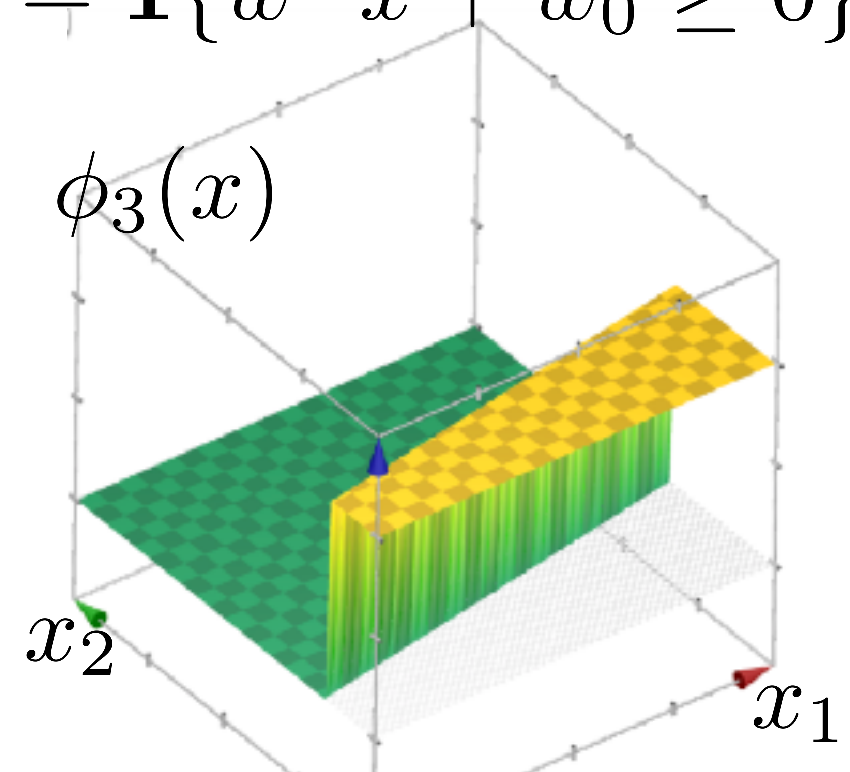

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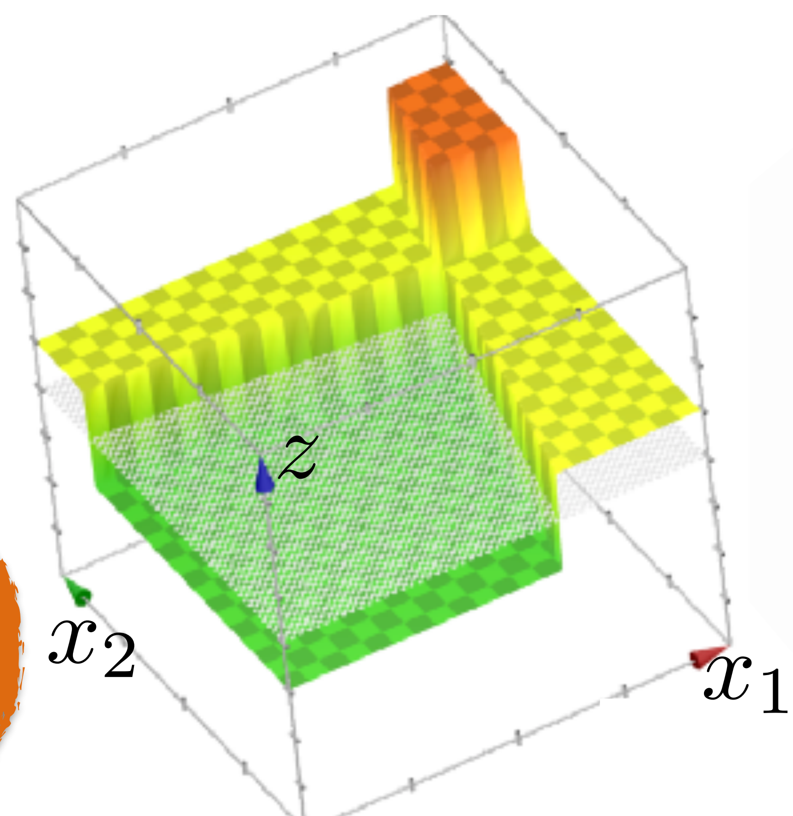

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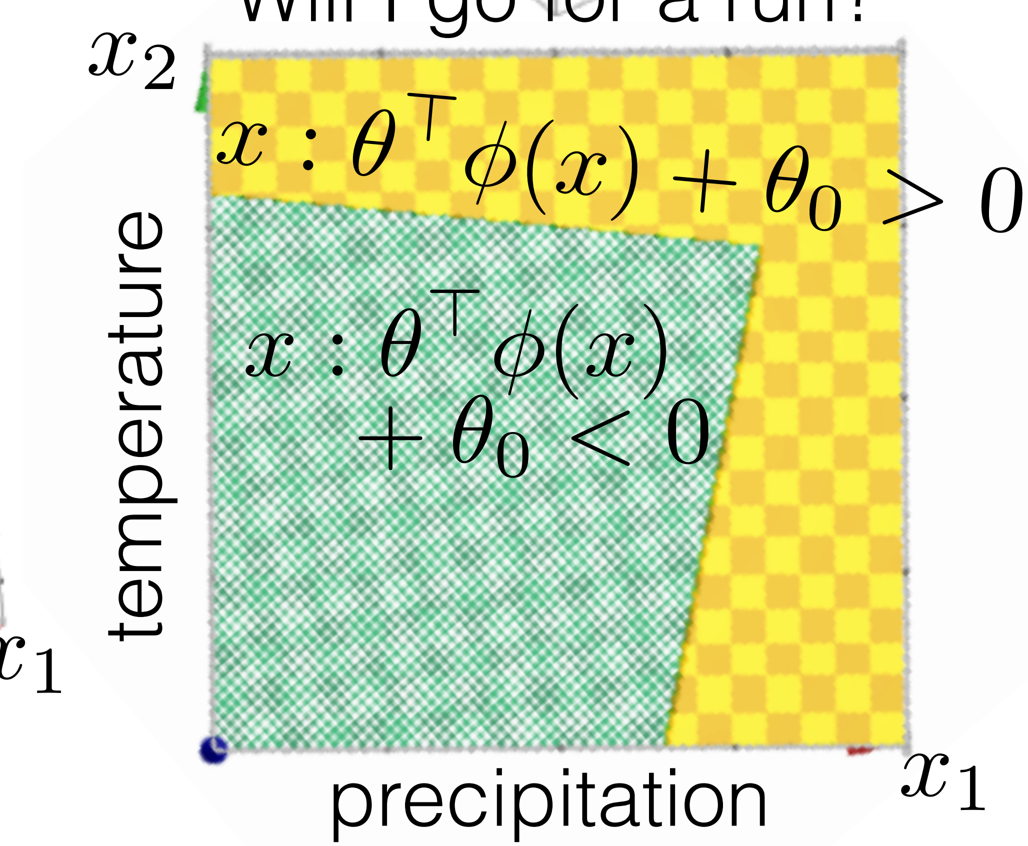

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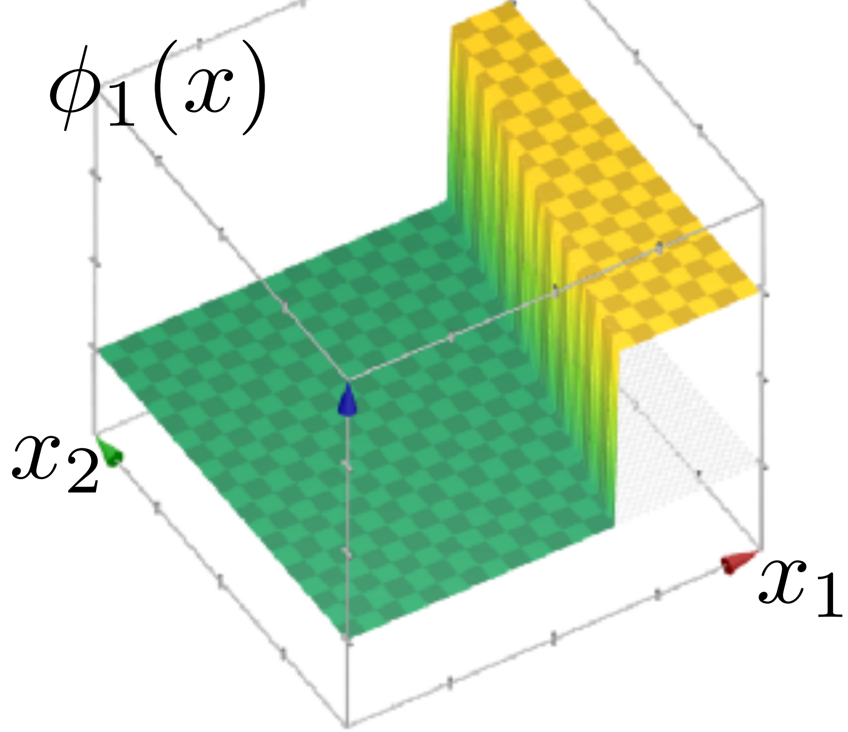

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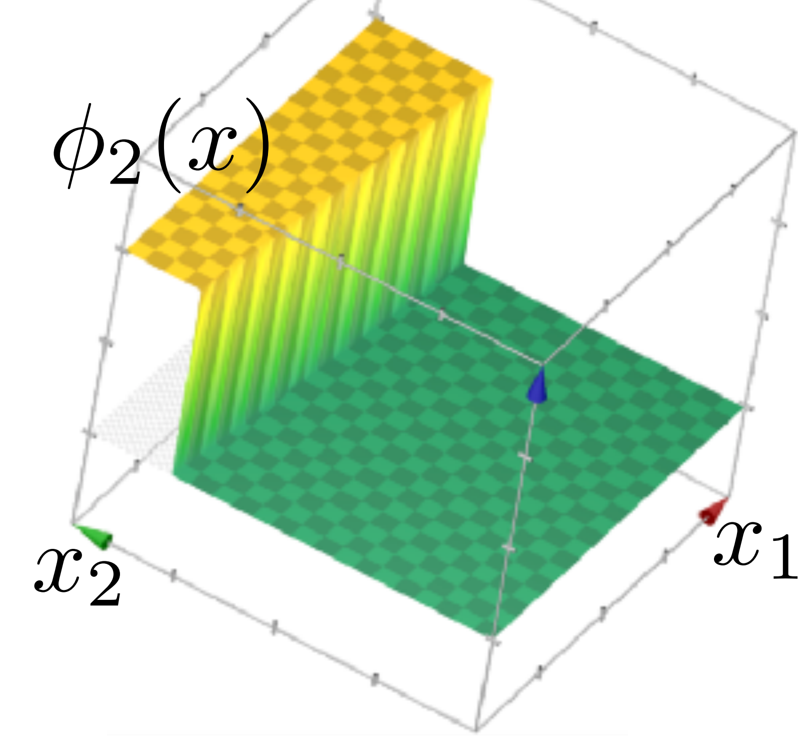

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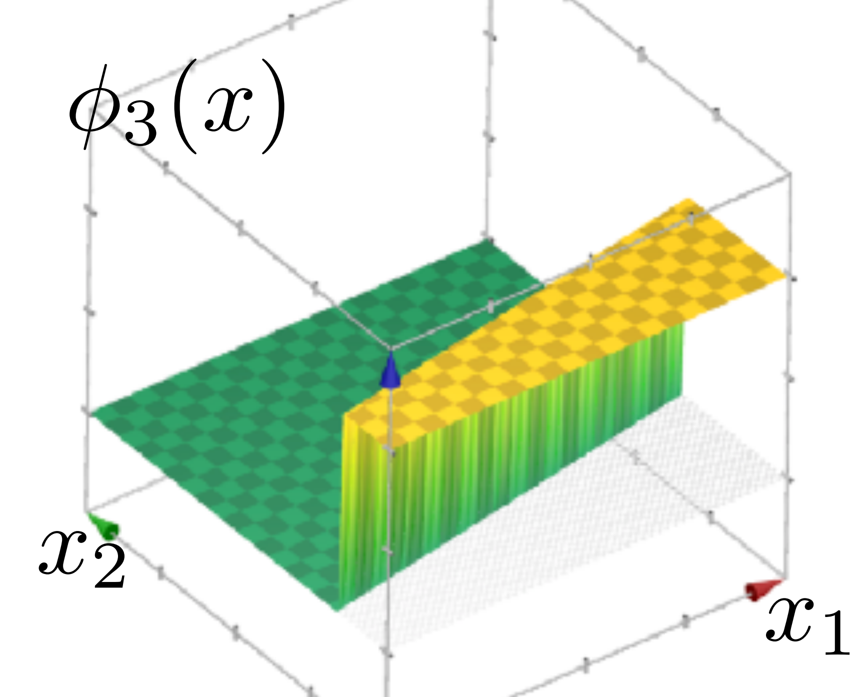

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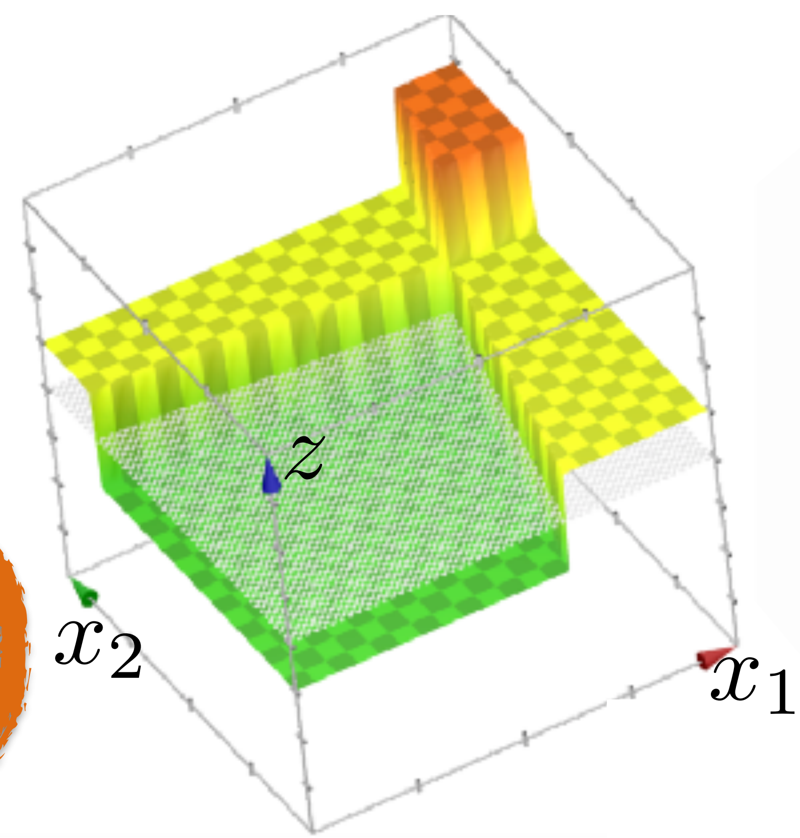

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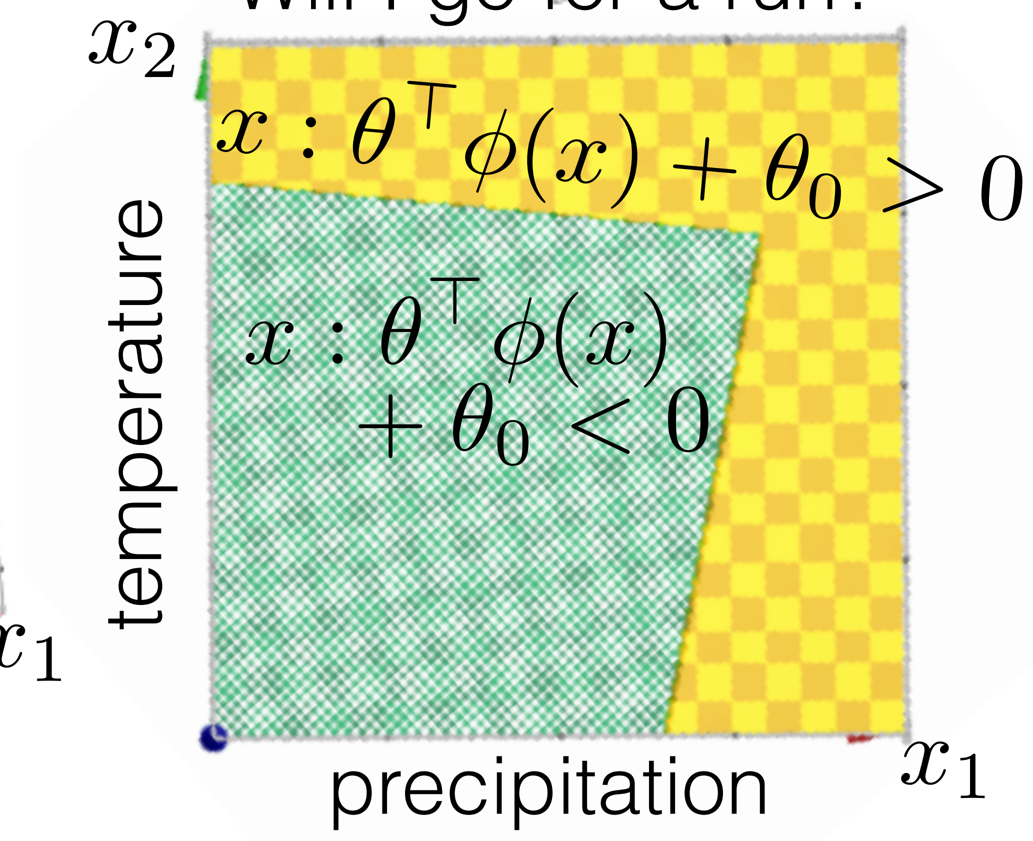

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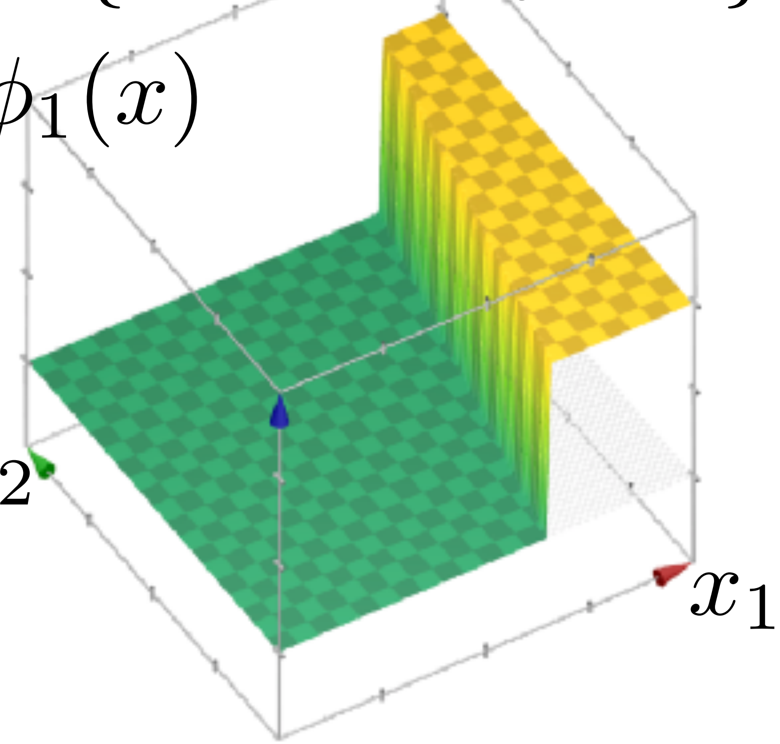
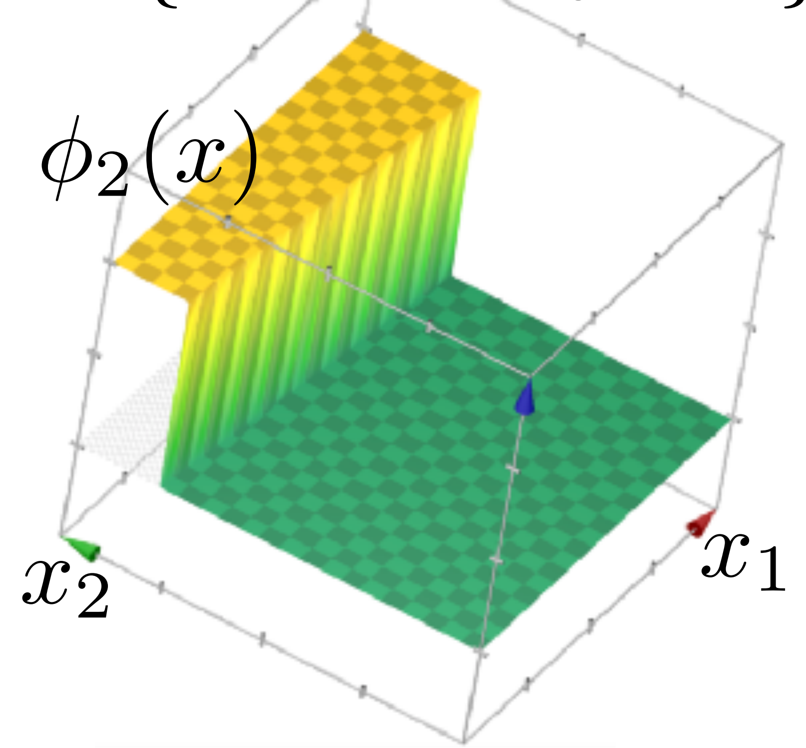
$\phi_1(x) = \mathbf{1}\{w^\top x + w_0 \geq 0\}$



$\phi_2(x) = \mathbf{1}\{\tilde{w}^\top x + \tilde{w}_0 \geq 0\}$



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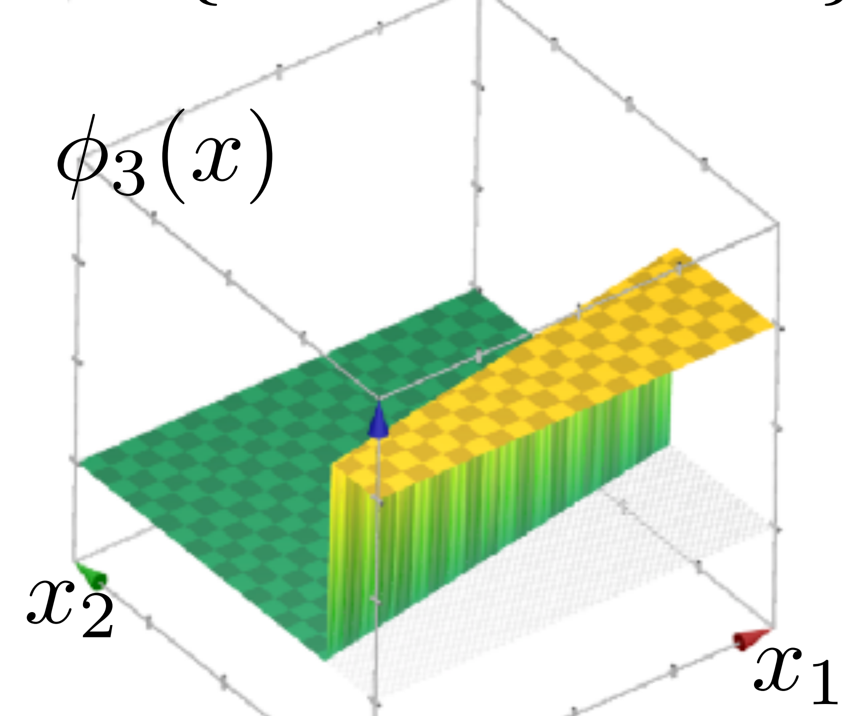

$$
\begin{aligned}
z &= \theta^\top \phi(x) + \theta_0 \\
&= \theta_1 \phi_1(x) + \theta_2 \phi_2(x) \\
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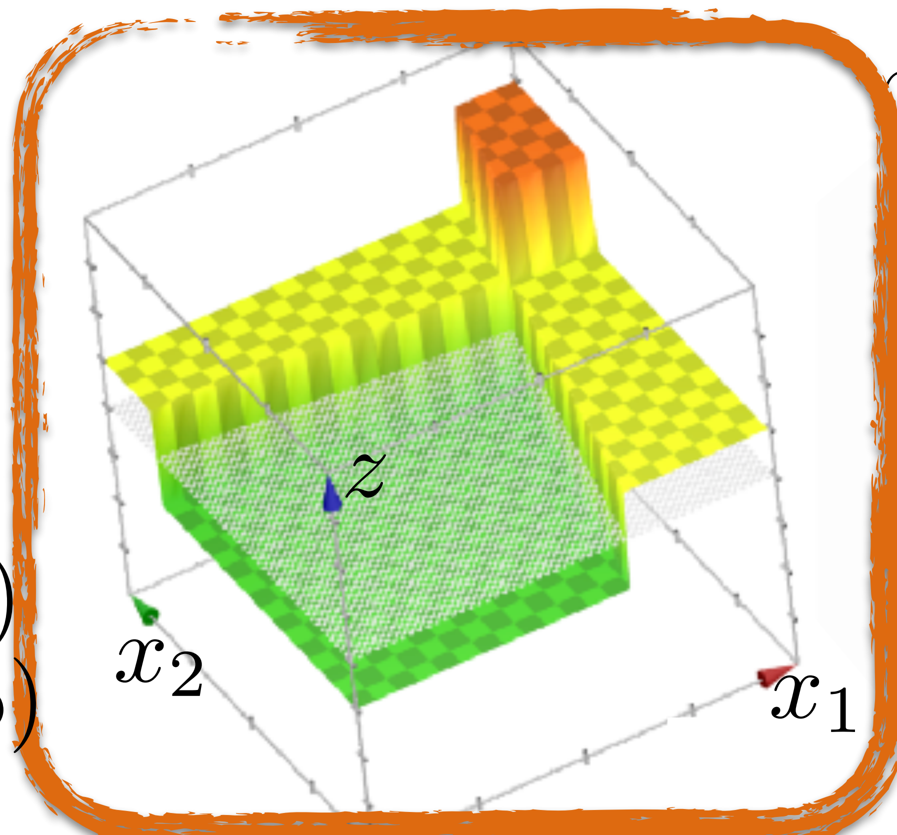
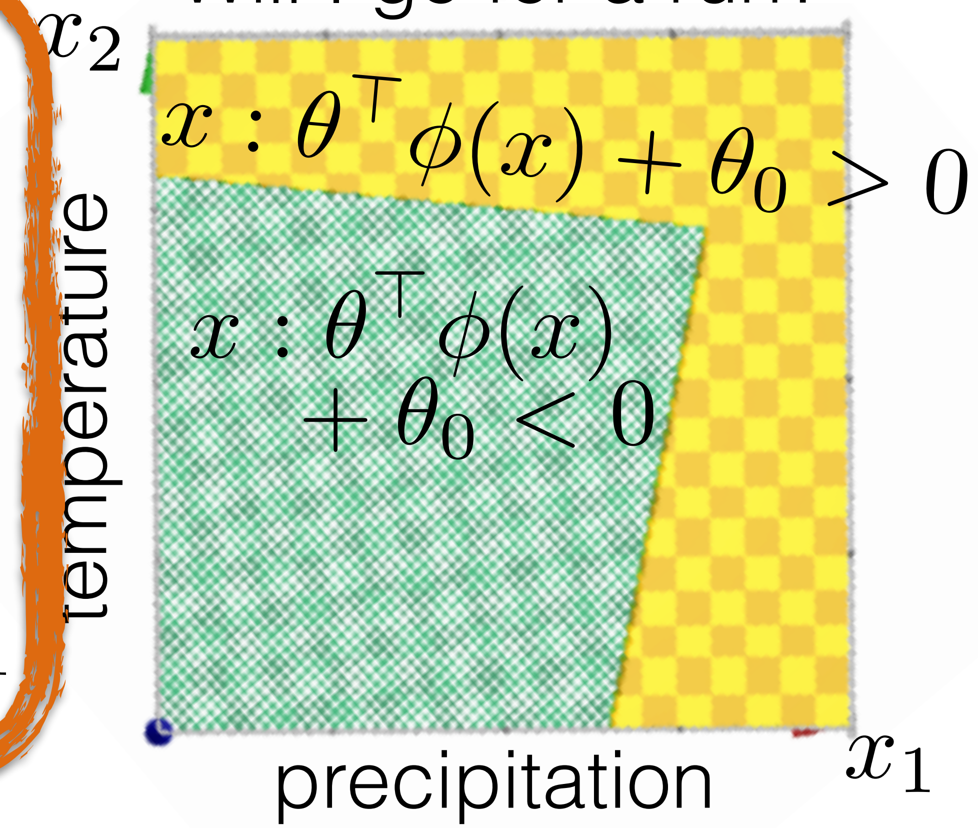


Will I go for a run?



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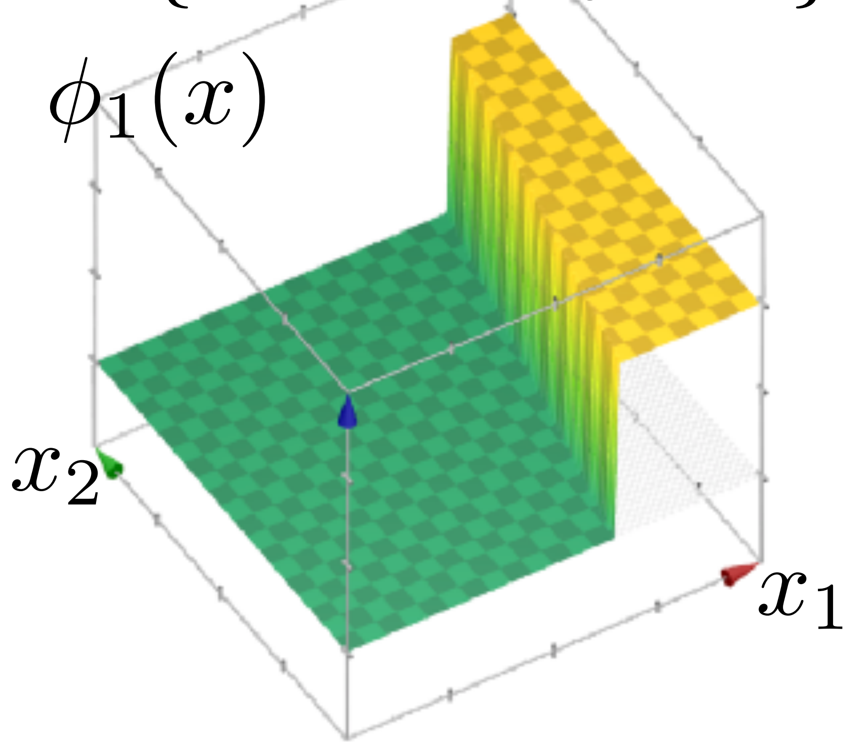

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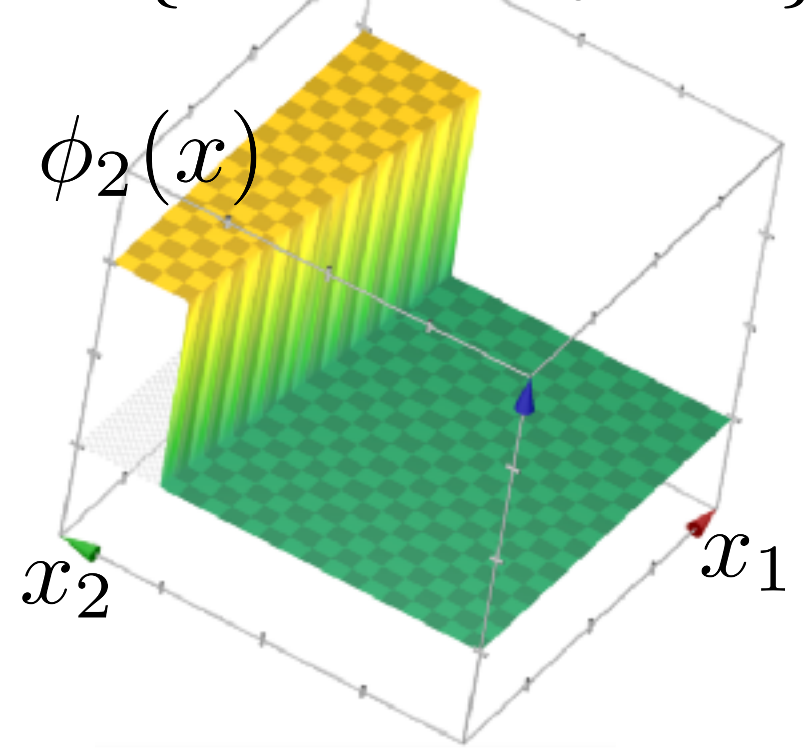

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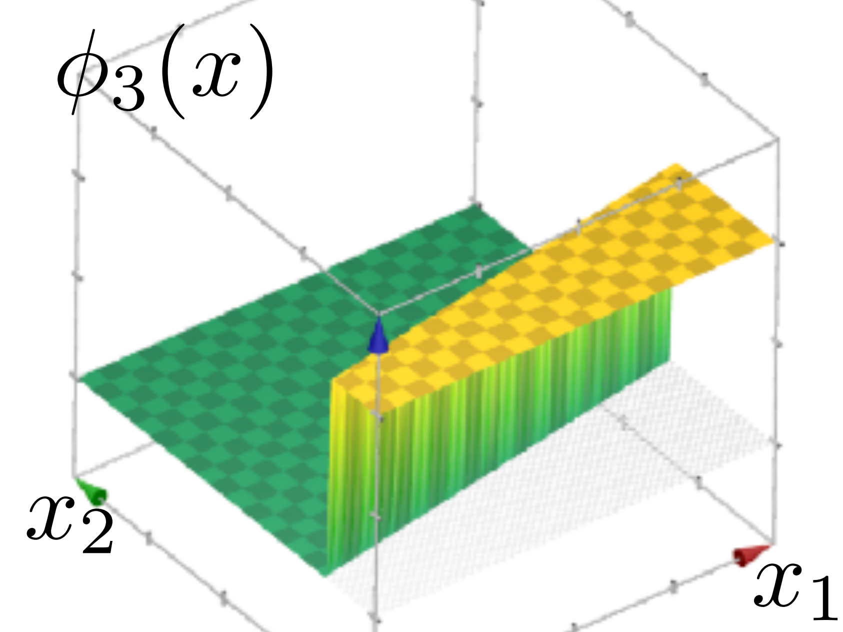

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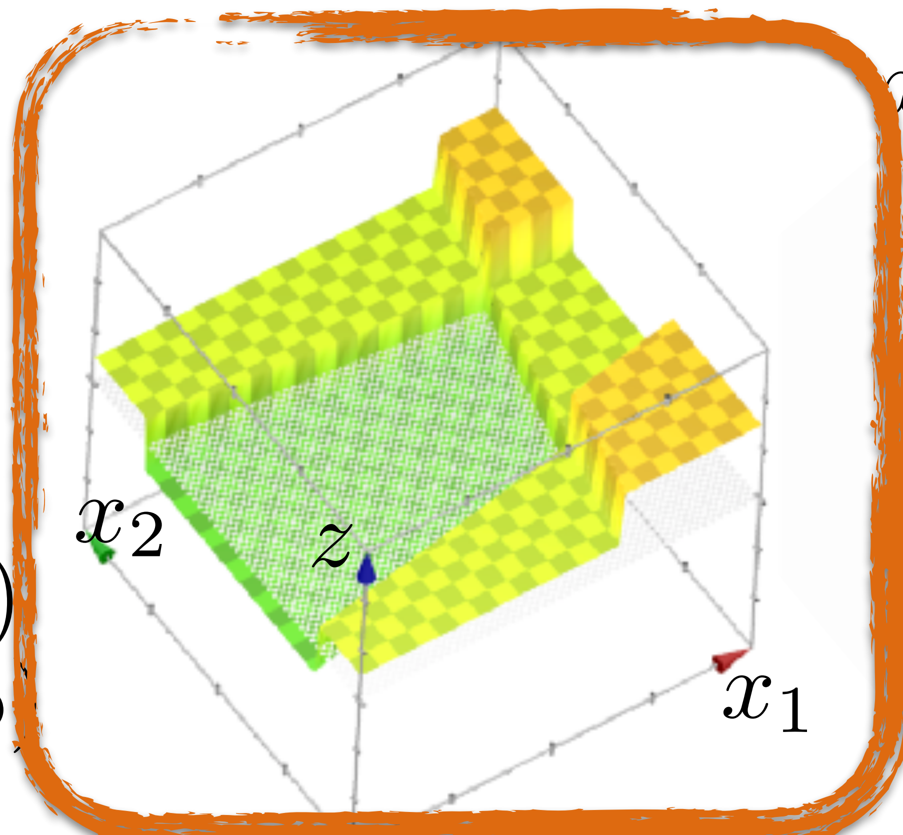

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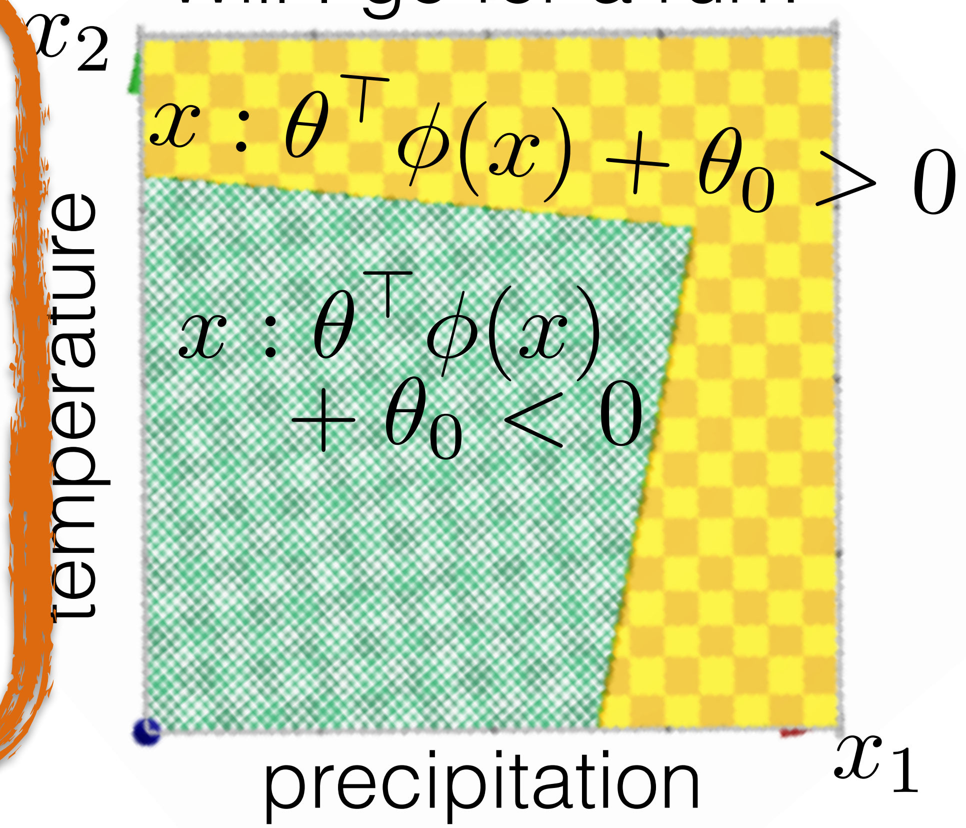

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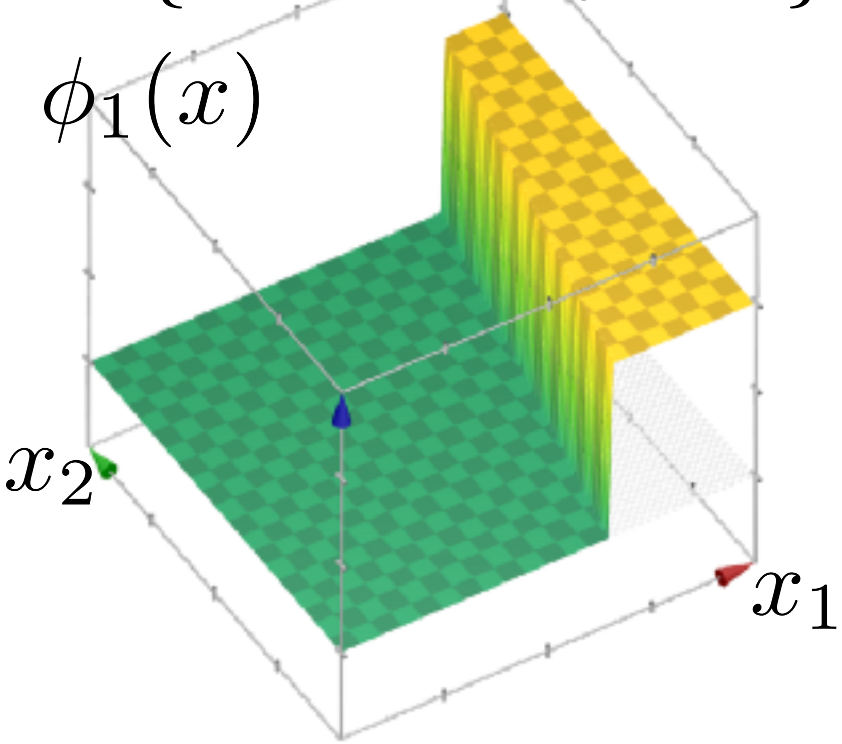

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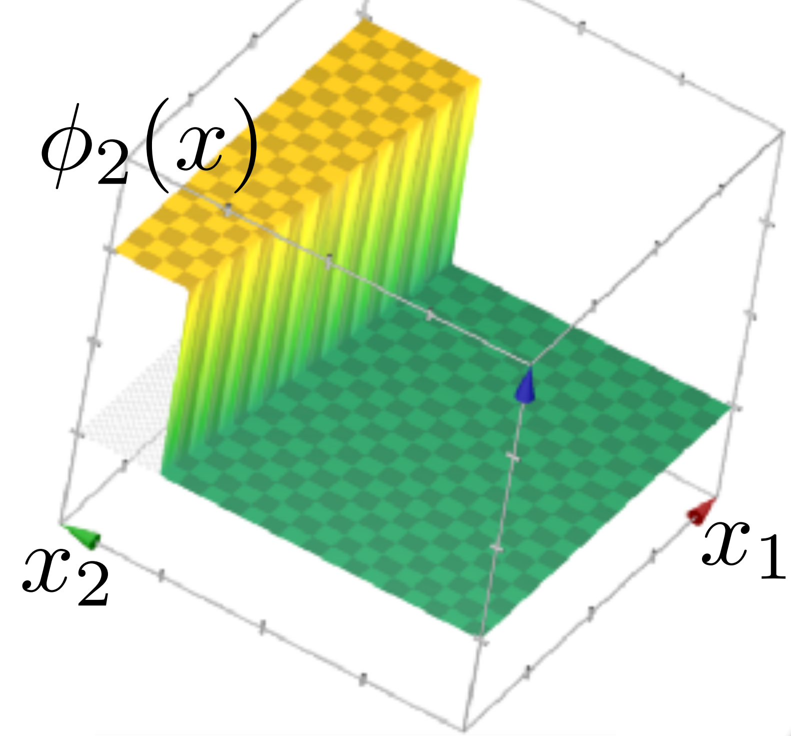

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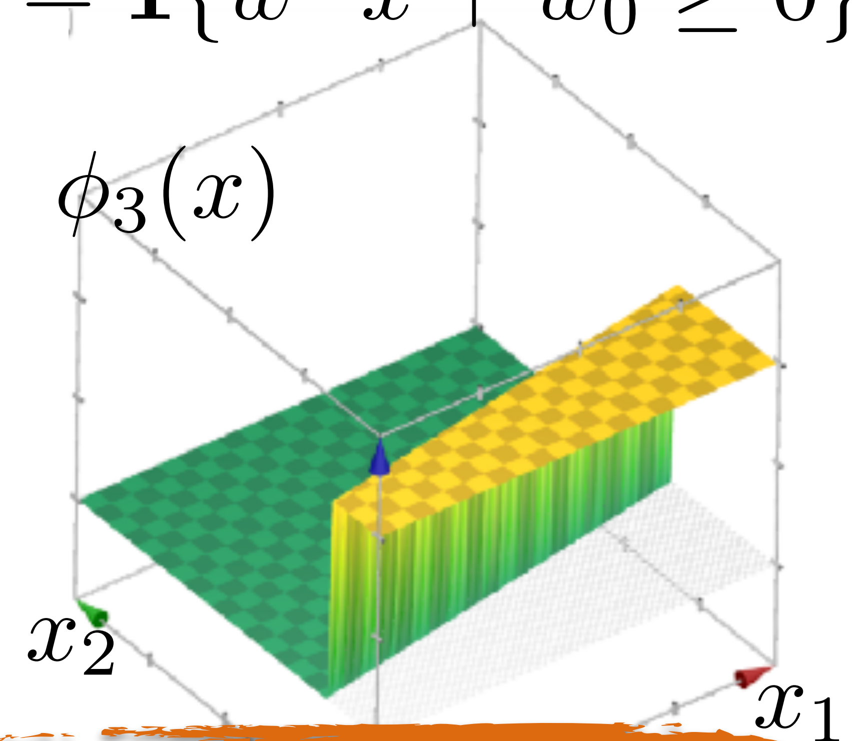

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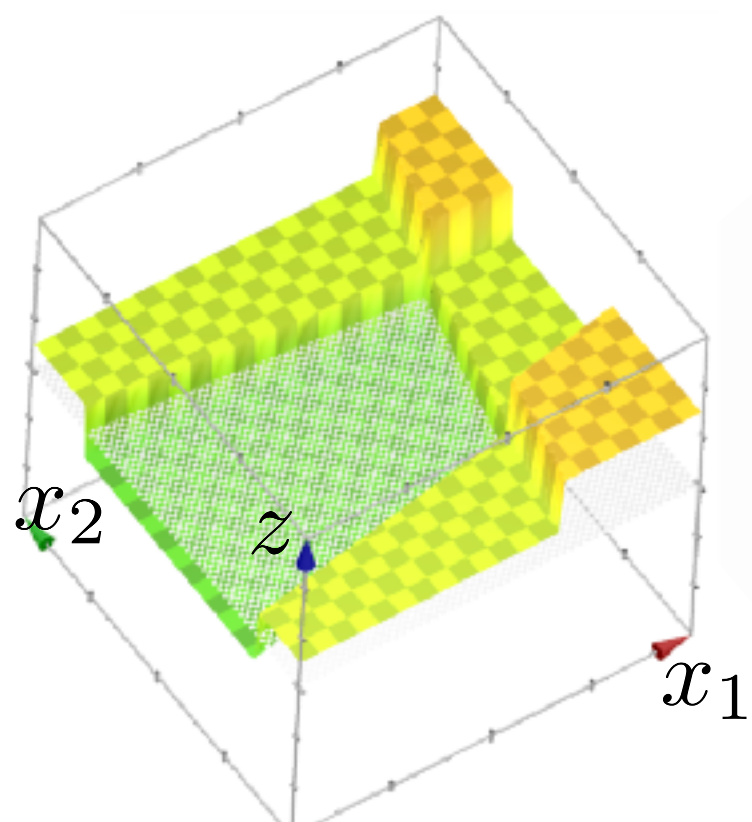

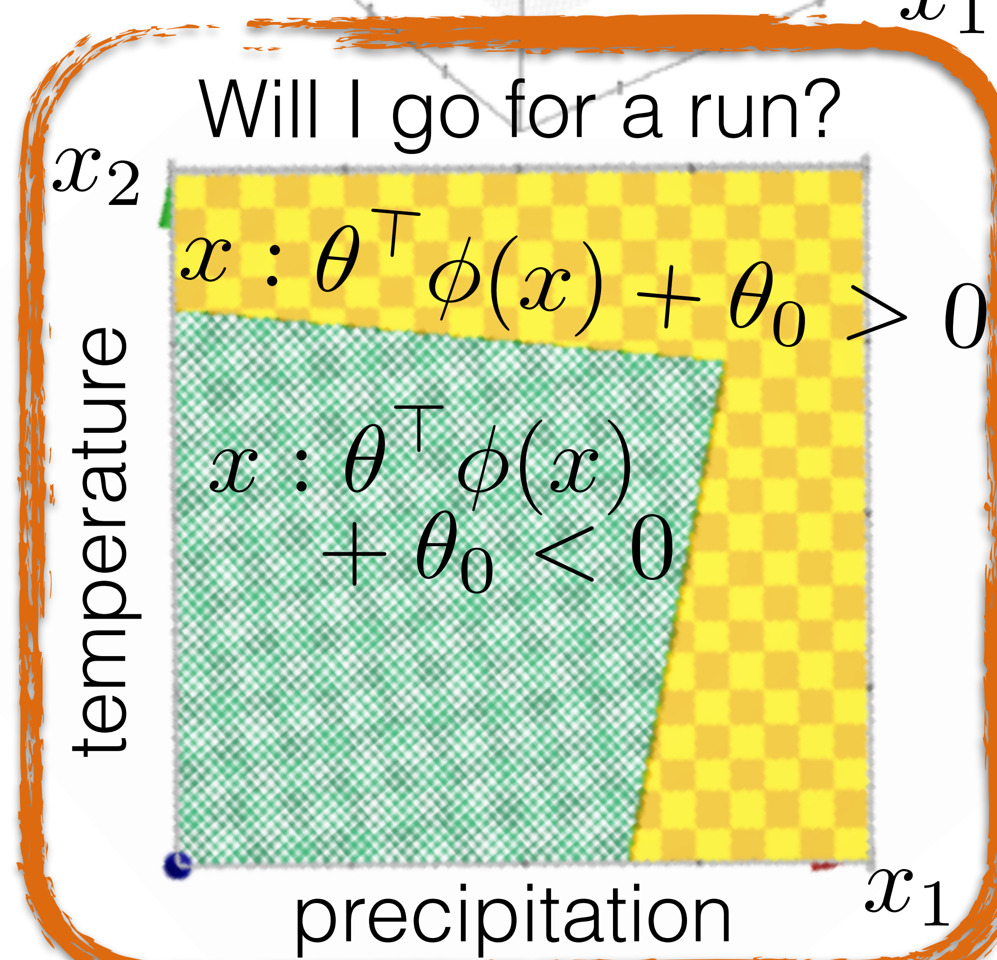

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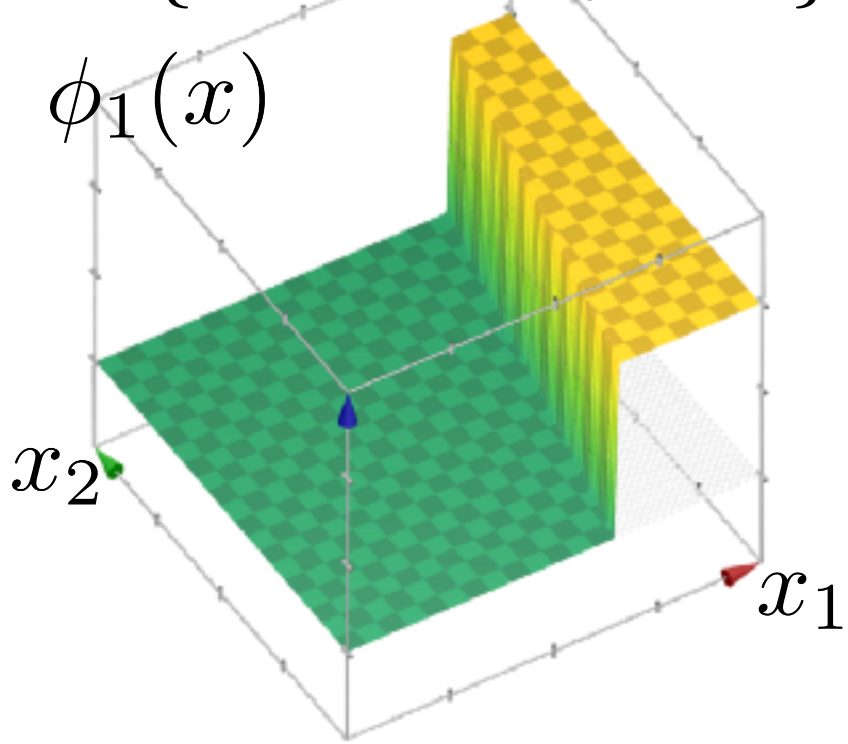

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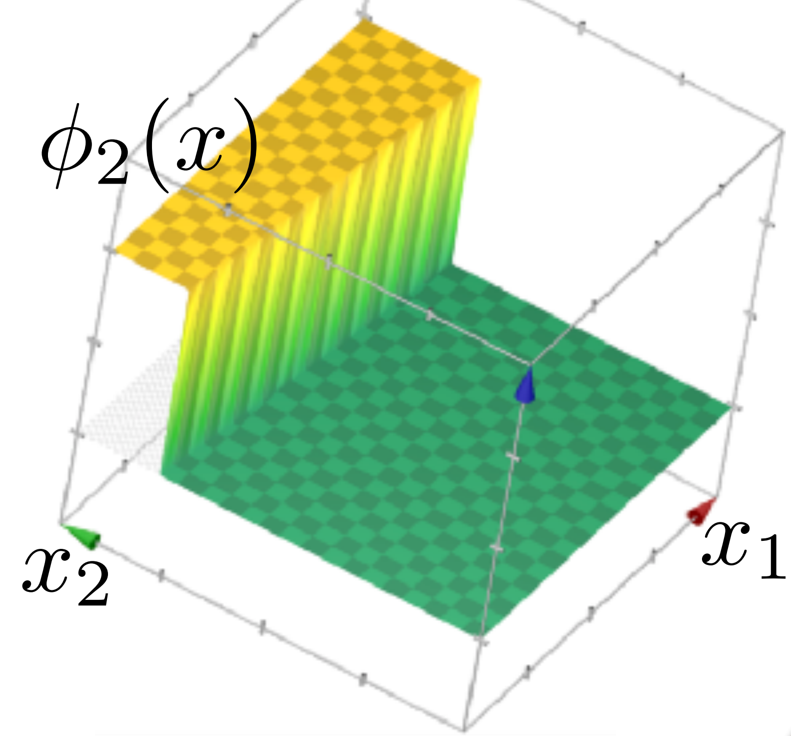

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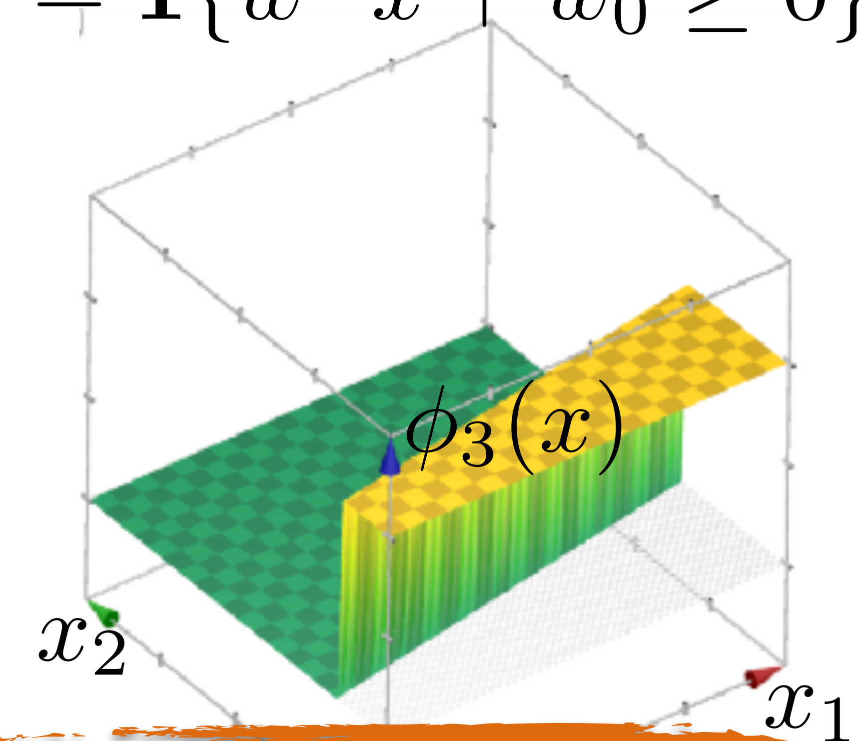

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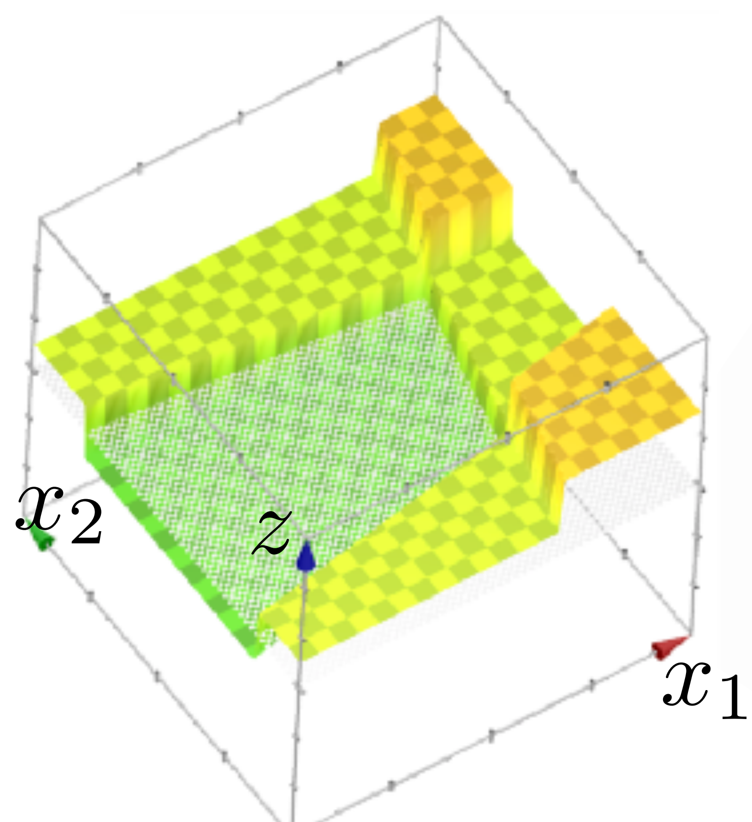

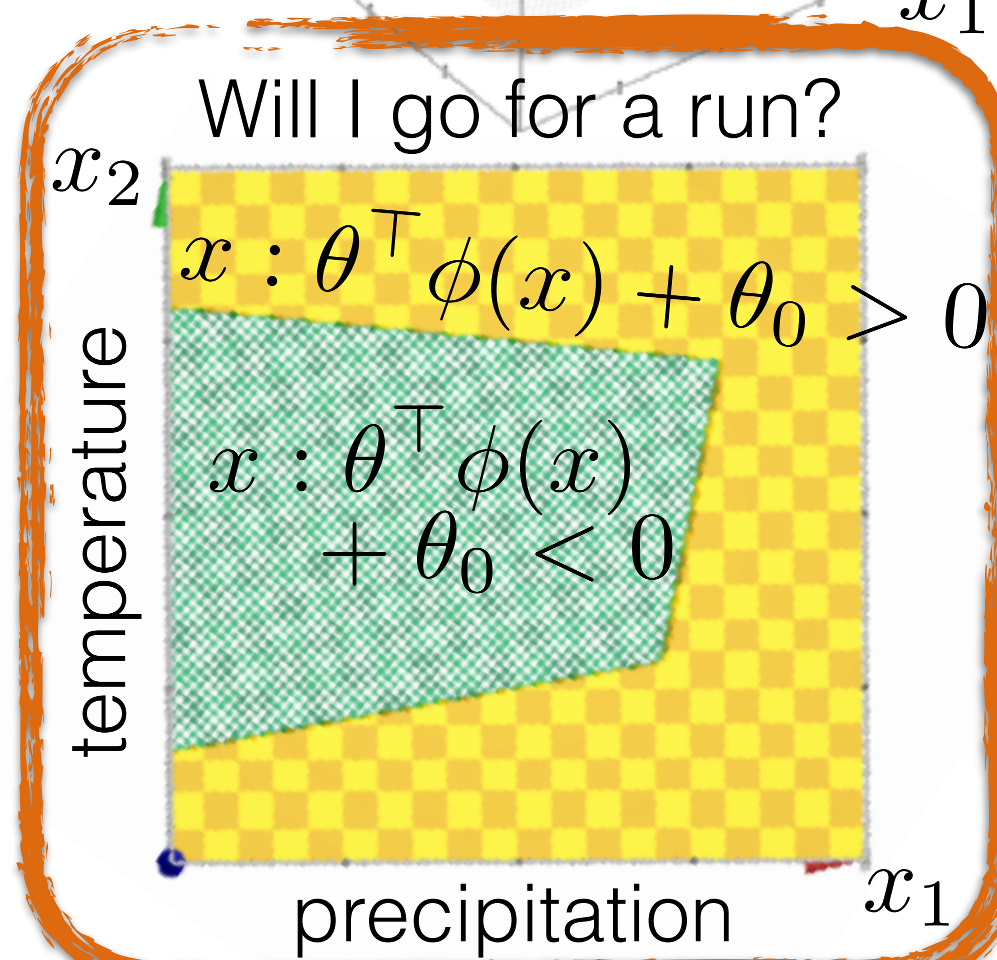

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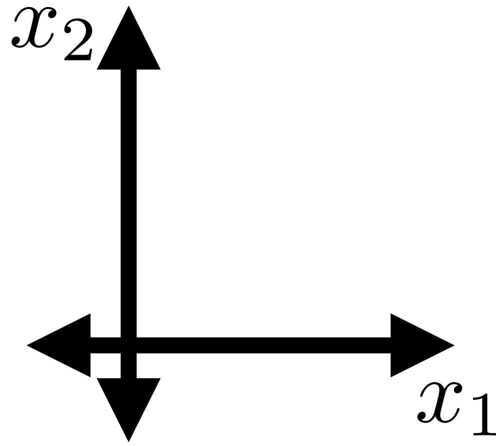

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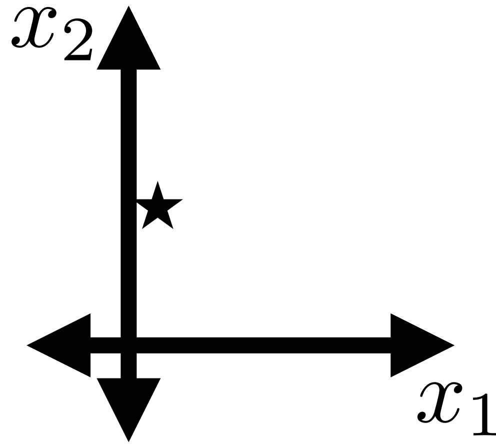

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- 1st layer, constructing the features:
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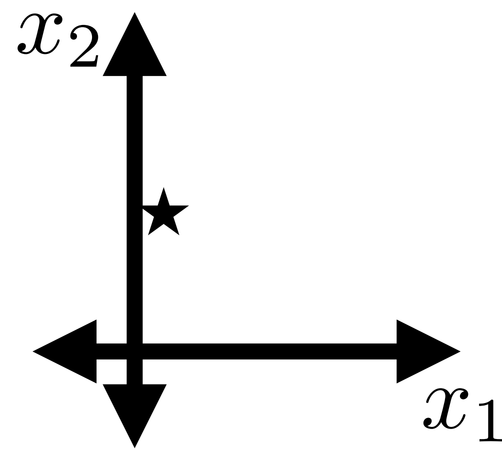

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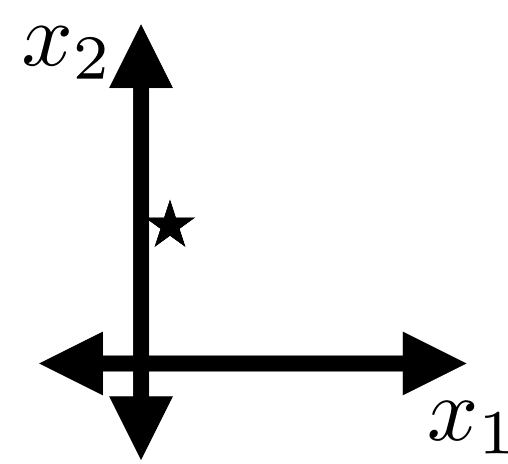
- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$

$m^{(1)} = d$



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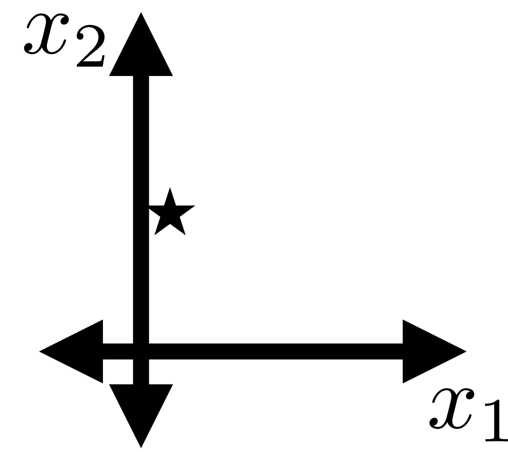

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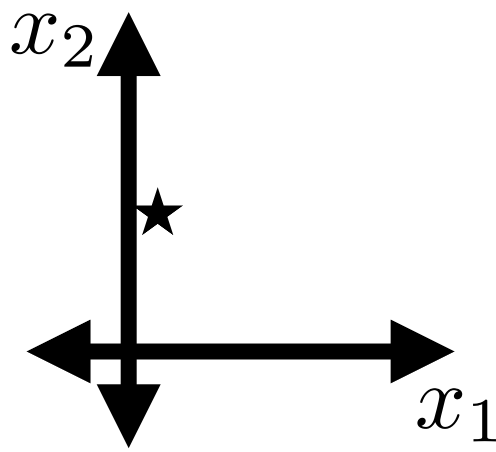

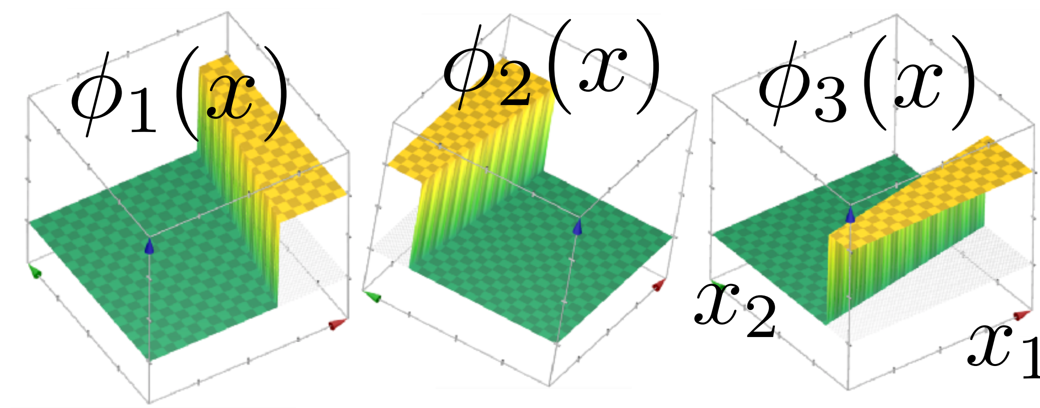

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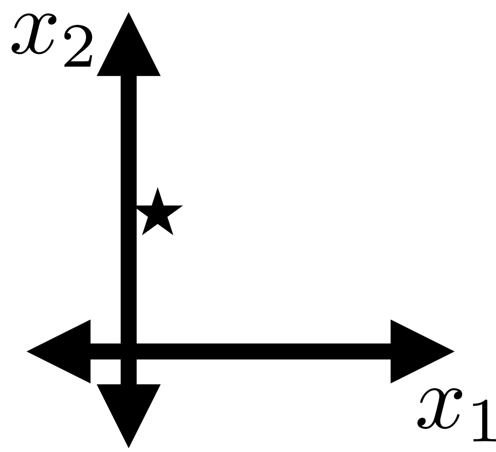

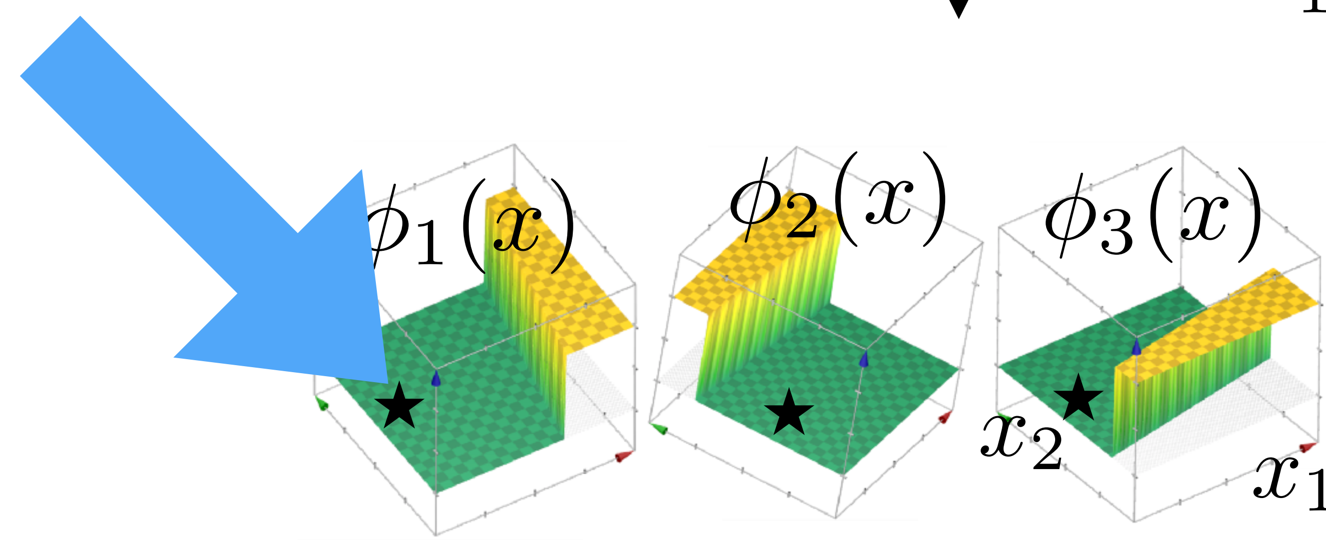

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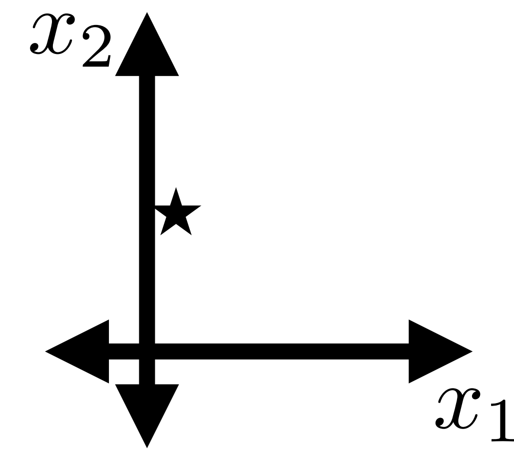

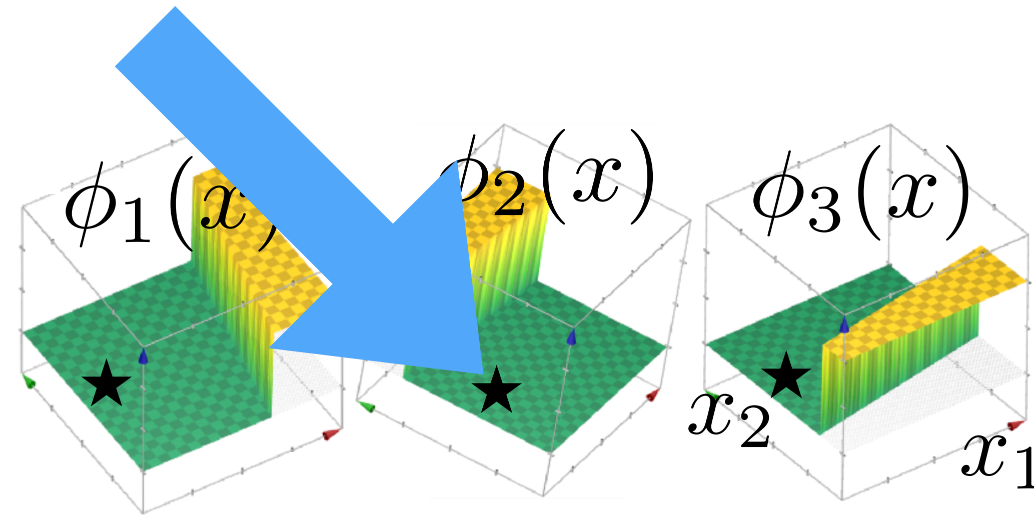

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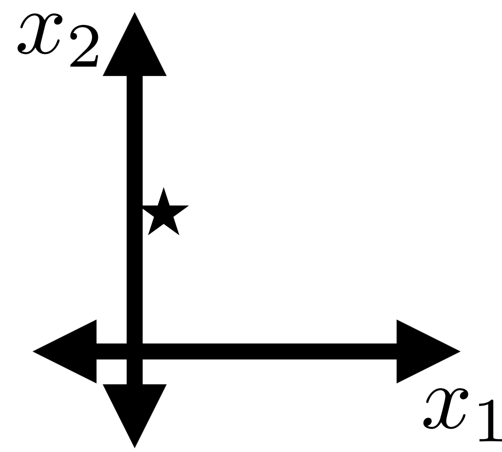

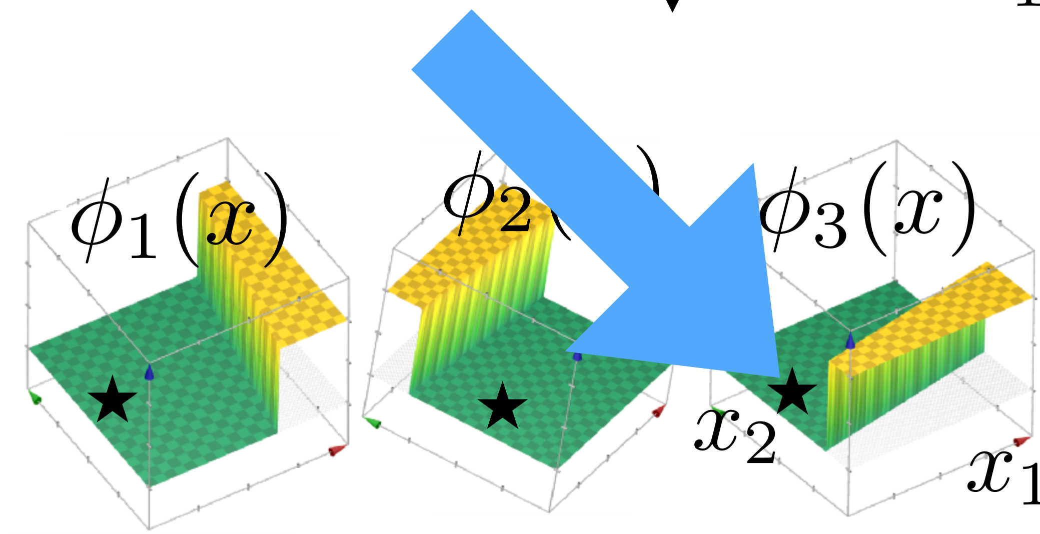

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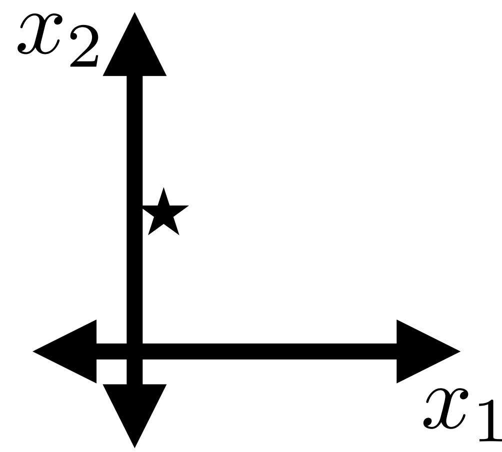

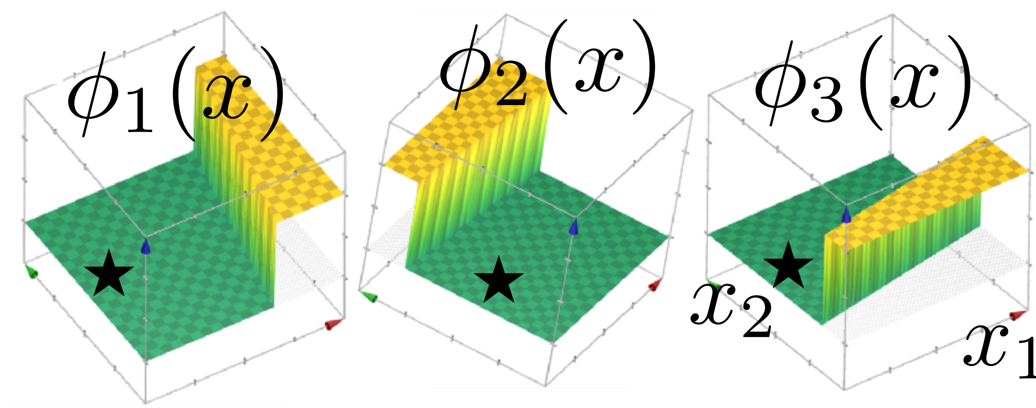

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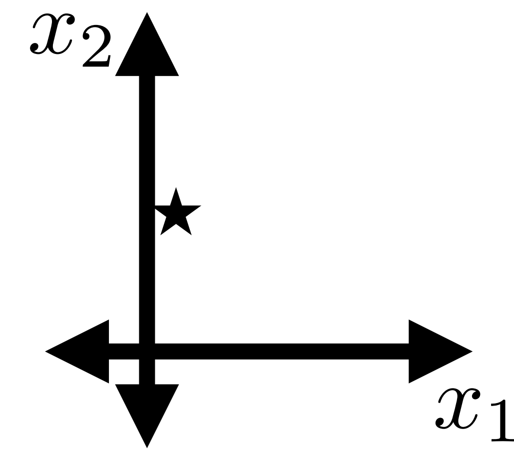

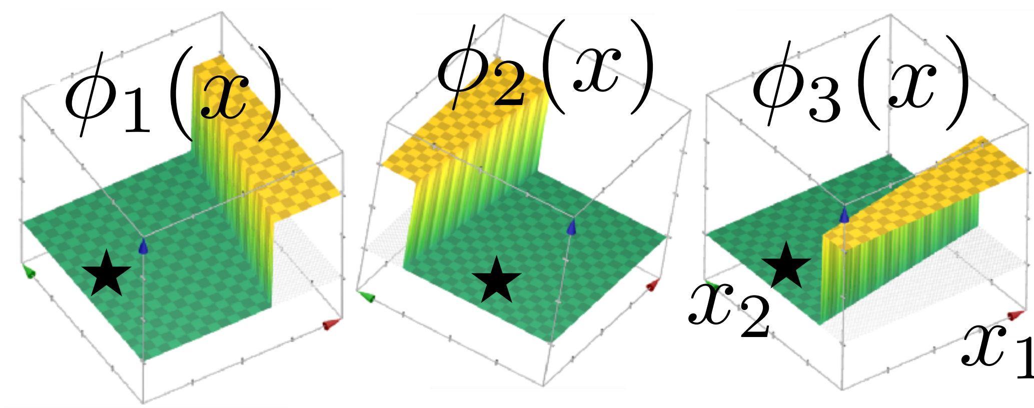

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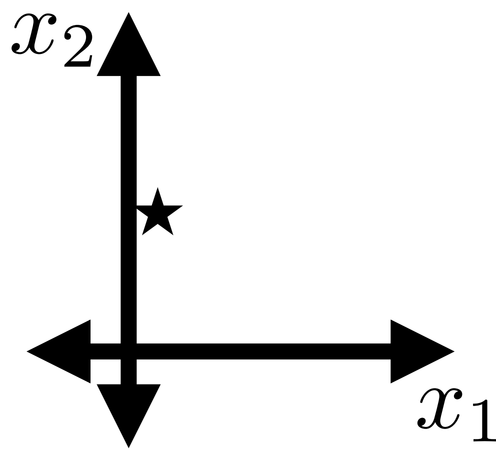

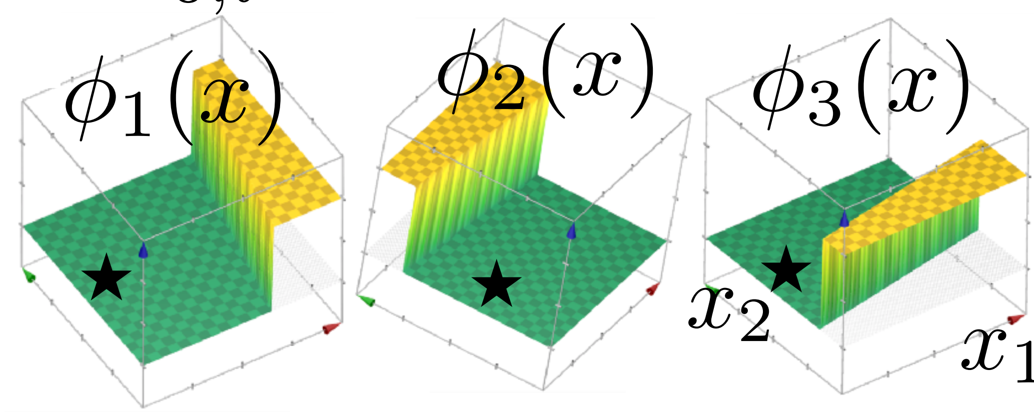

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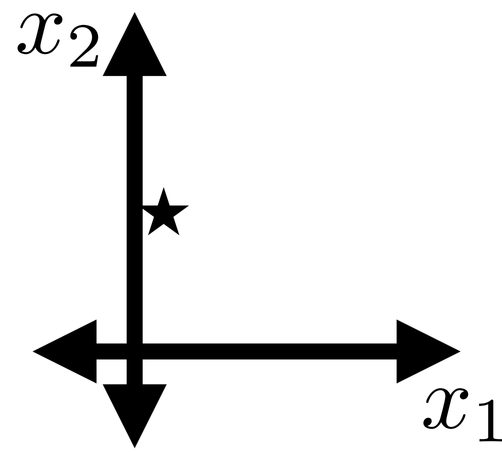

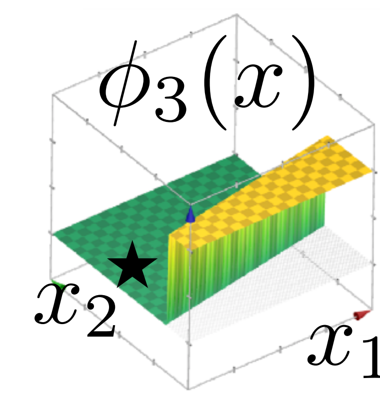

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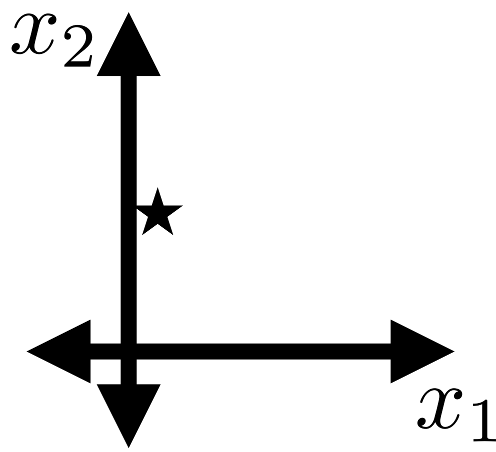

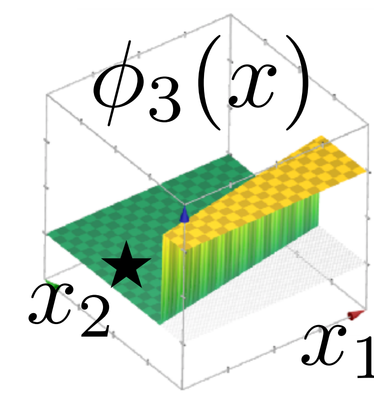

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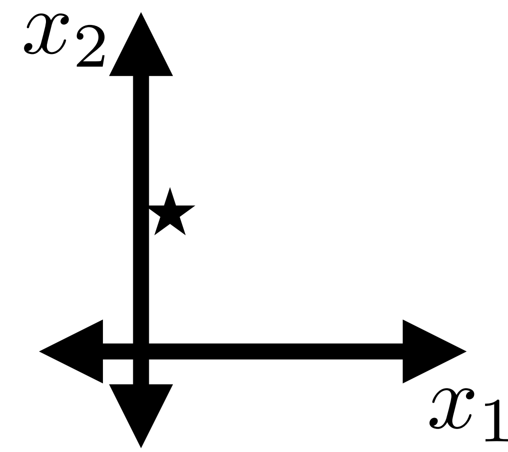

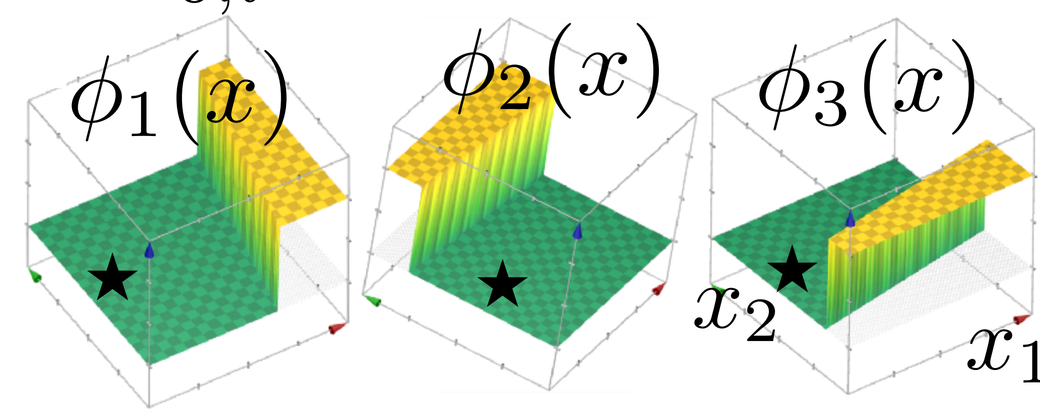

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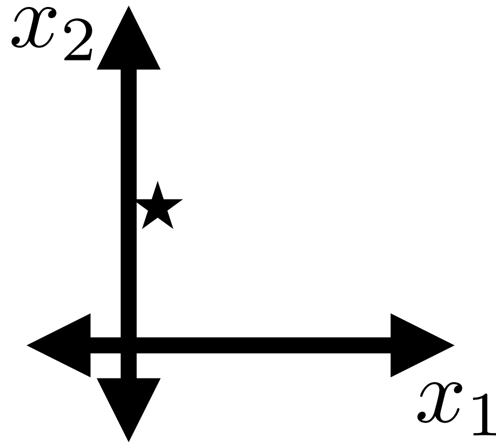
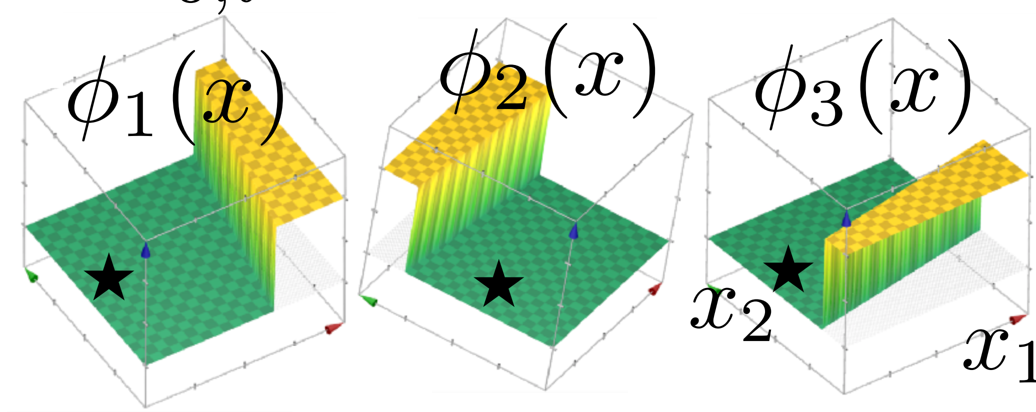
    - All the features at once:





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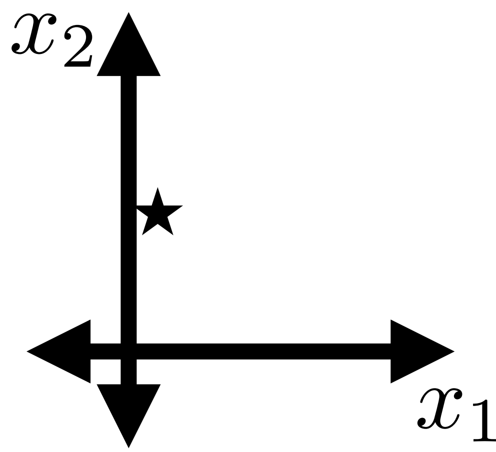

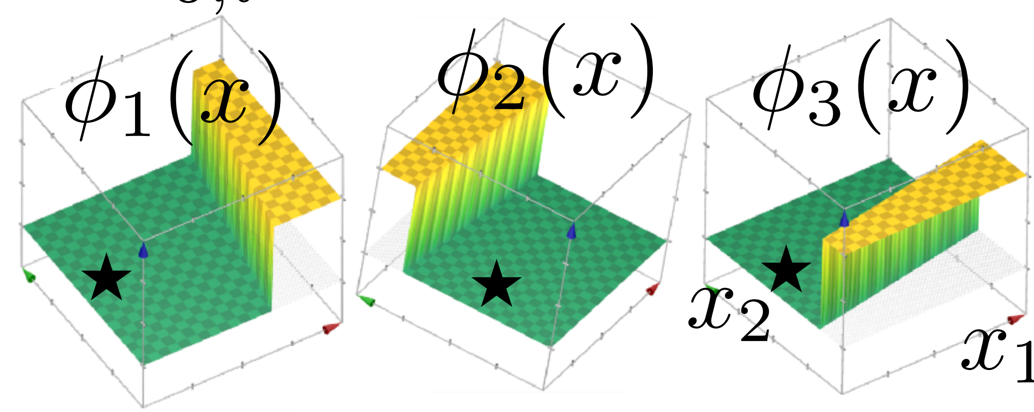

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      - $W^{(1)} : m^{(1)} \times n^{(1)}$

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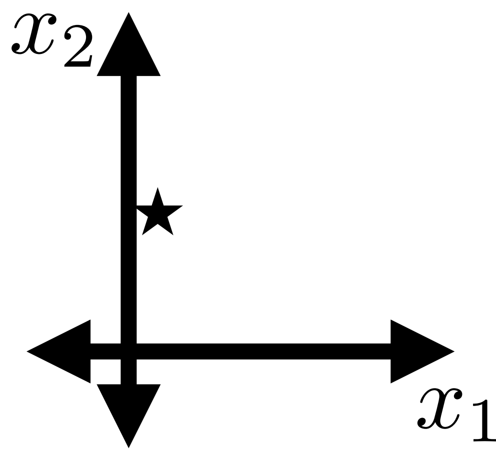

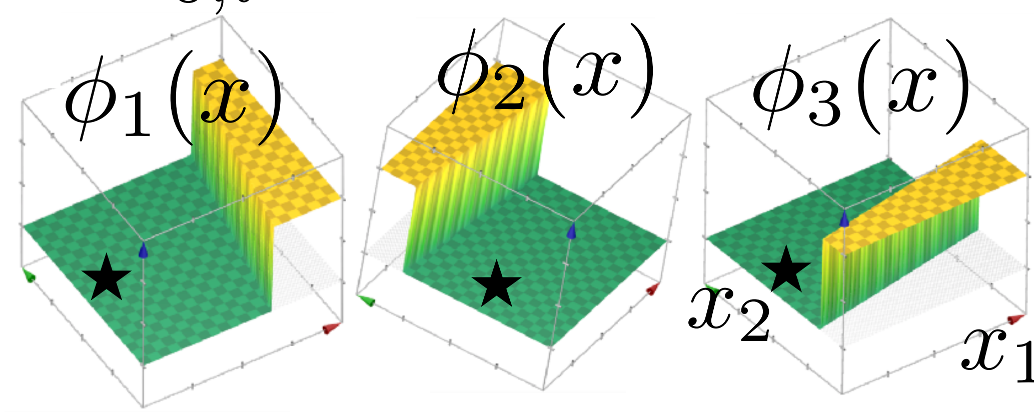

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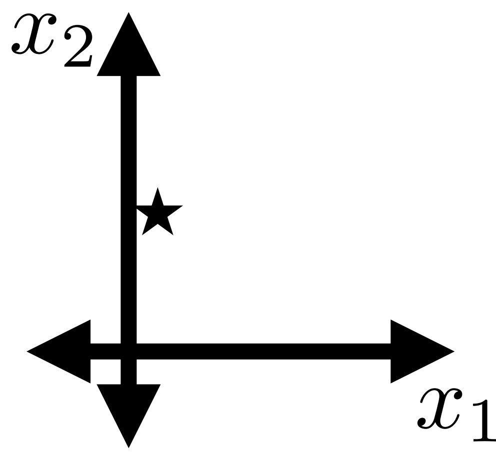

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    - All the features at once:
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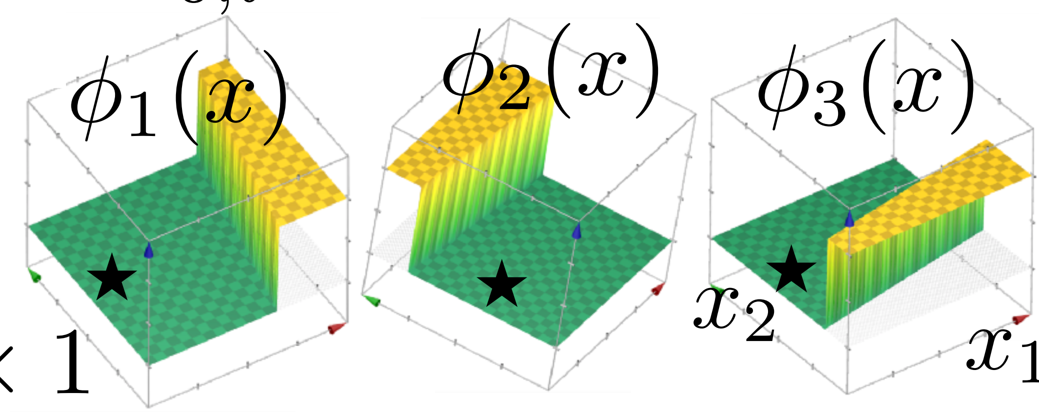
      - $W^{(1)} : m^{(1)} \times n^{(1)}; W_0^{(1)} : n^{(1)} \times 1$



Let's get some new notation

- 1st layer, constructing the features:
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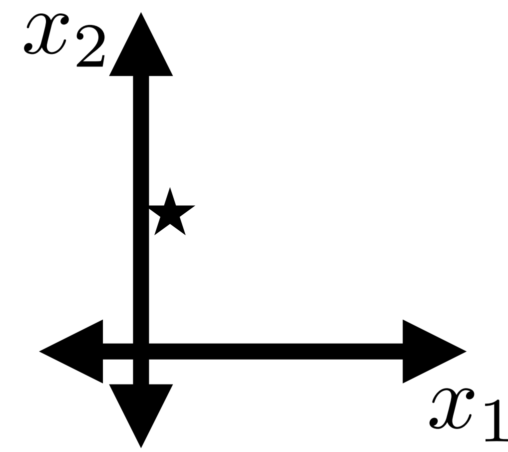
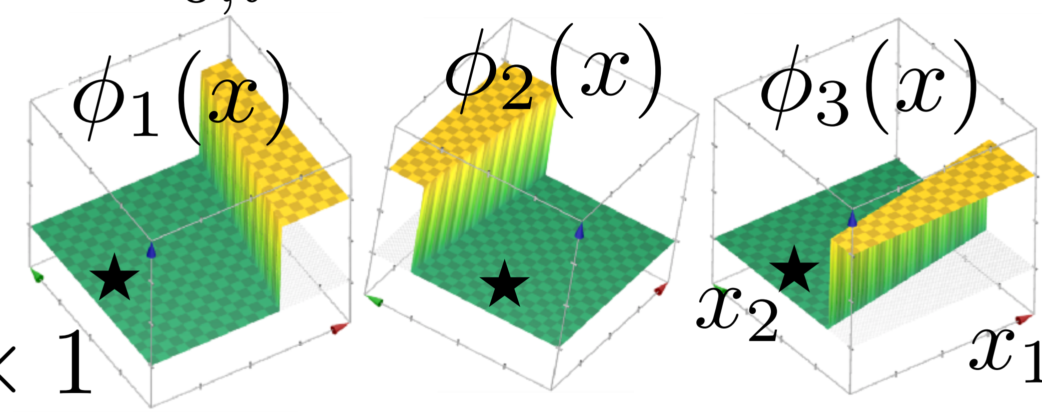
$m^{(1)} = d$





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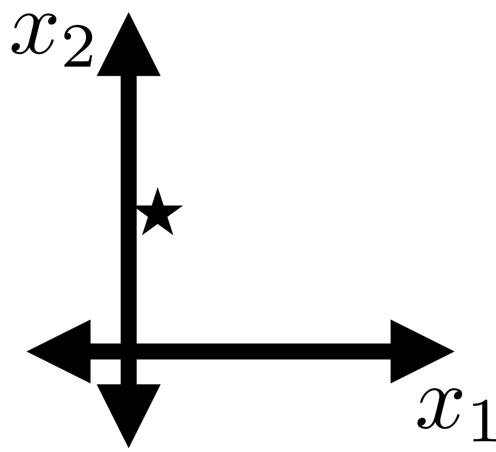

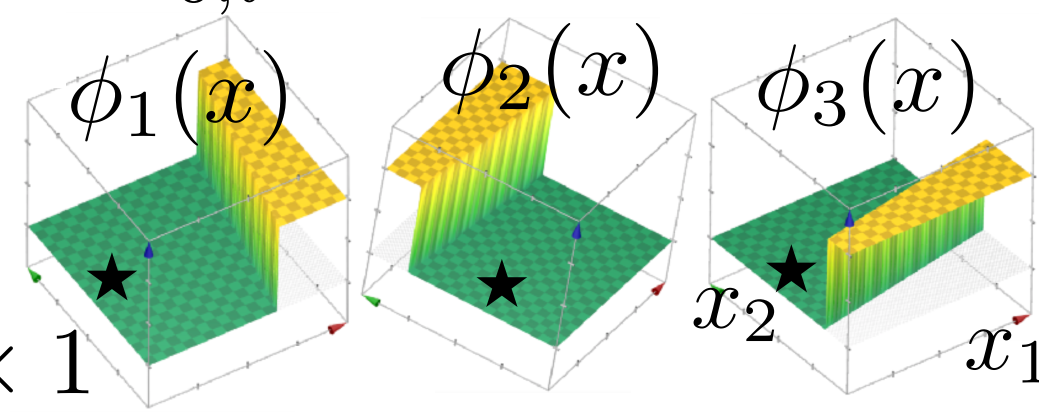

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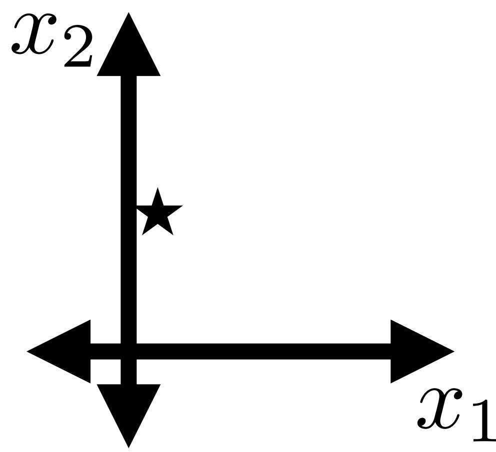
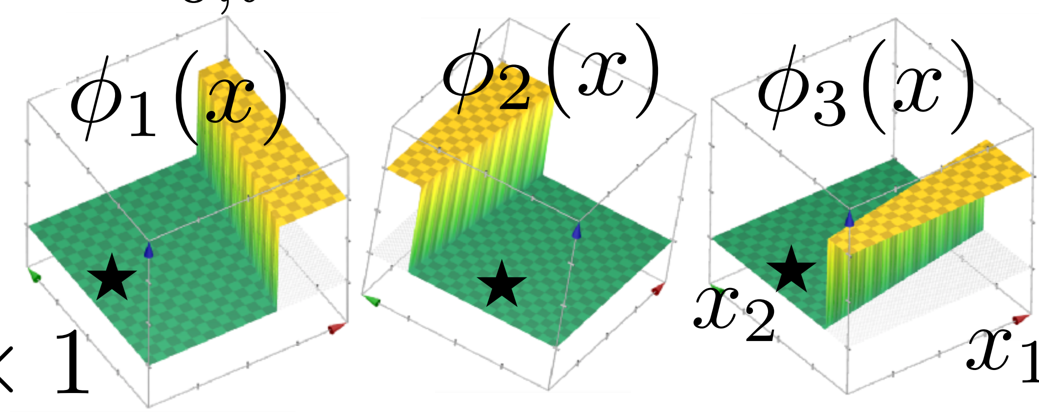
$\boxed{m^{(1)} = d}$





$\boxed{f^{(1)} \text{ is applied componentwise!}}$

Let's get some new notation

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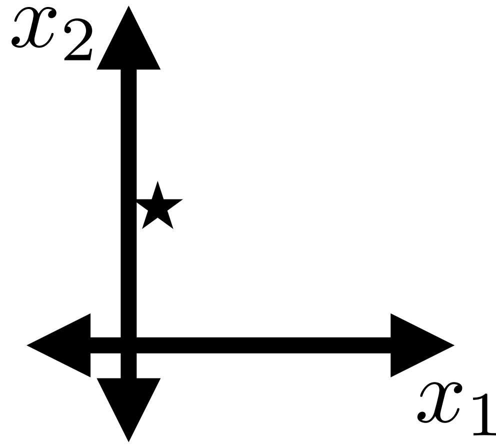
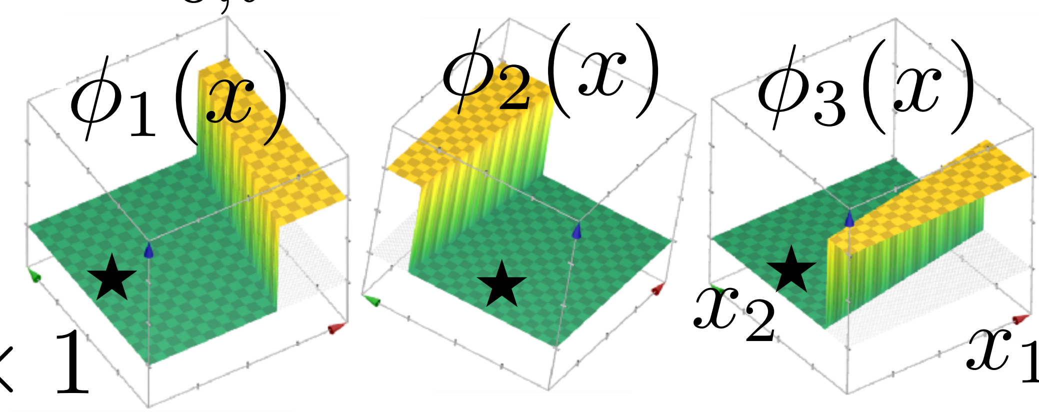
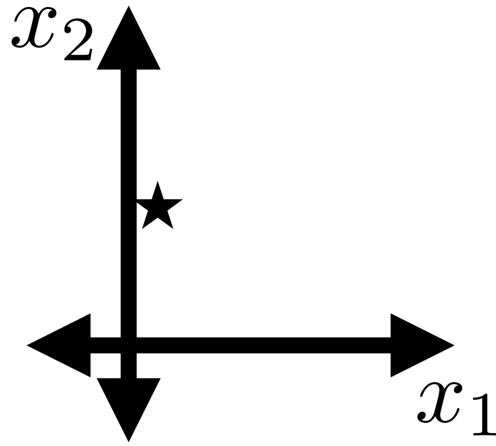




Let's get some new notation

$\boxed{m^{(1)} = d}$



- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The *i*th feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
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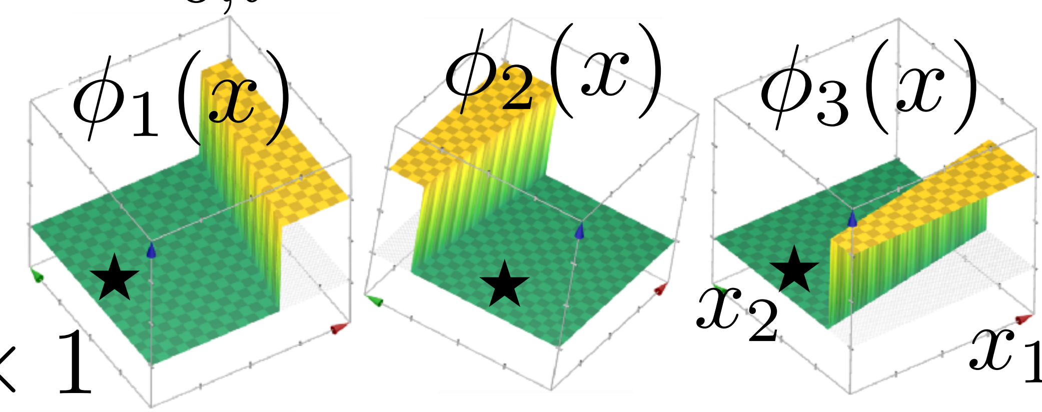
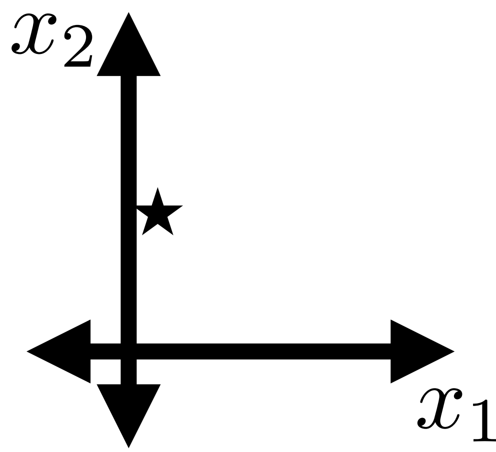


- 2nd layer, assigning a label (or labels):

Let's get some new notation

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$

$m^{(1)} = d$



  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The *i*th feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
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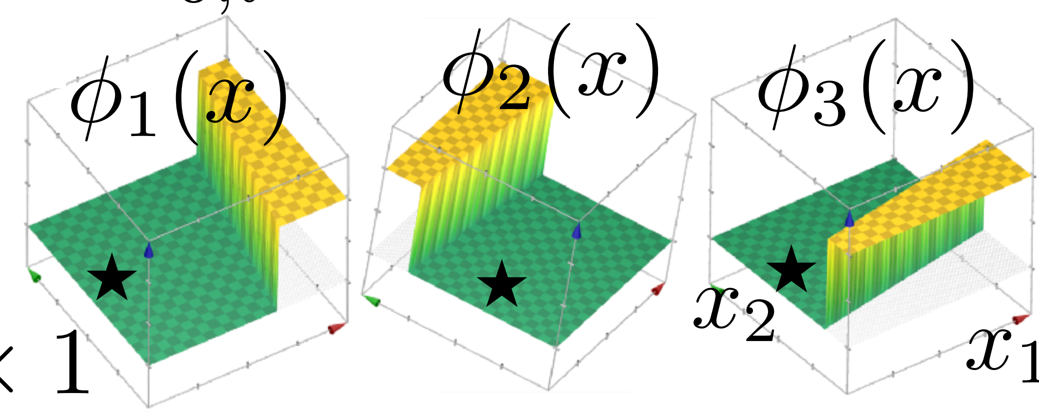

- 2nd layer, assigning a label (or labels):
  - Input (the features)

Let's get some new notation

$m^{(1)} = d$

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The *i*th feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
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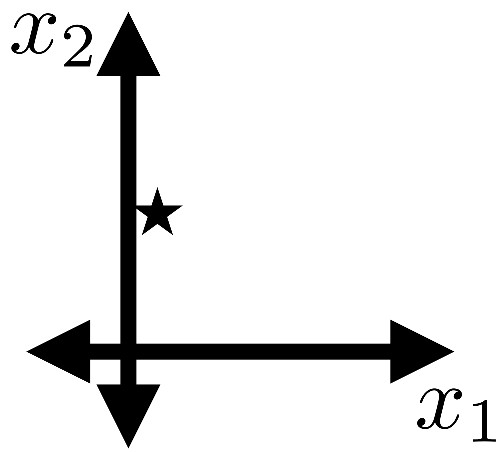
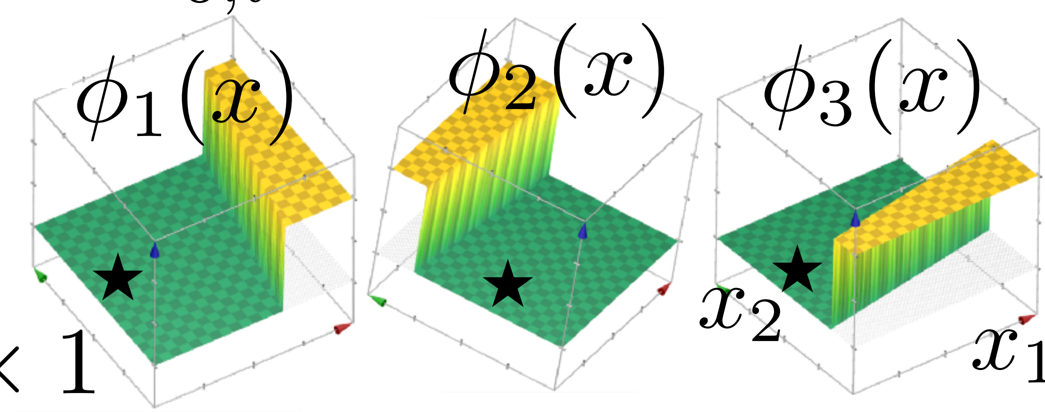
      - $A^{(1)} = f^{(1)}(W^{(1)\top} x + W_0^{(1)})$
      - $W^{(1)} : m^{(1)} \times n^{(1)}; W_0^{(1)} : n^{(1)} \times 1$
- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$





Let's get some new notation

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$ $\boxed{m^{(1)} = d}$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The *i*th feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
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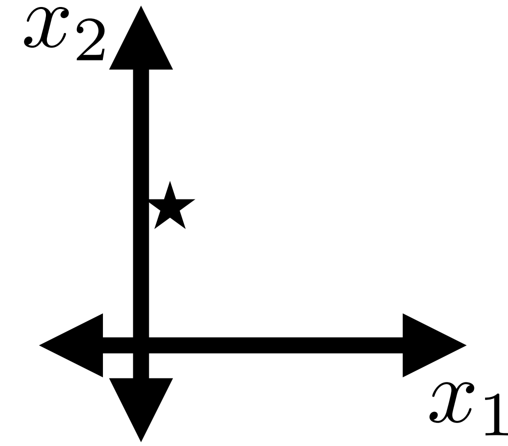

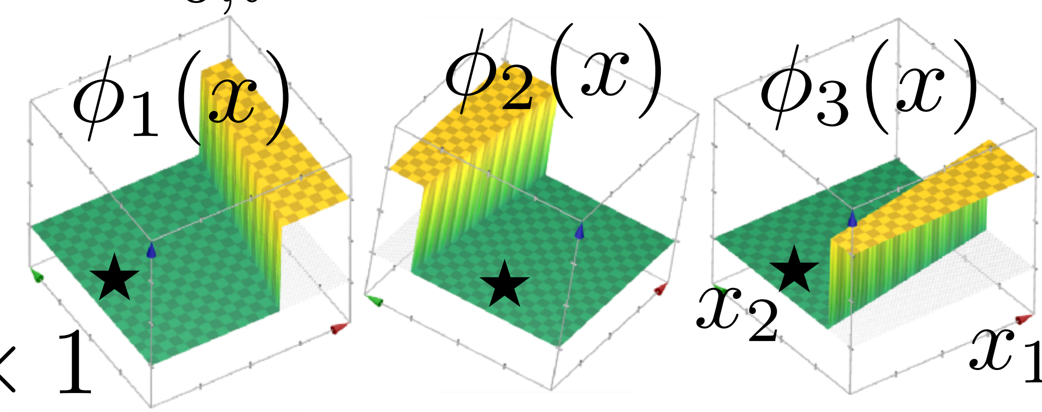

- 2nd layer, assigning a label (or labels):
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- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$ $m^{(1)} = d$
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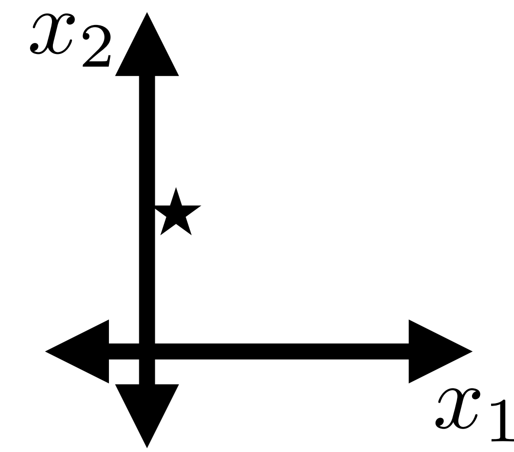

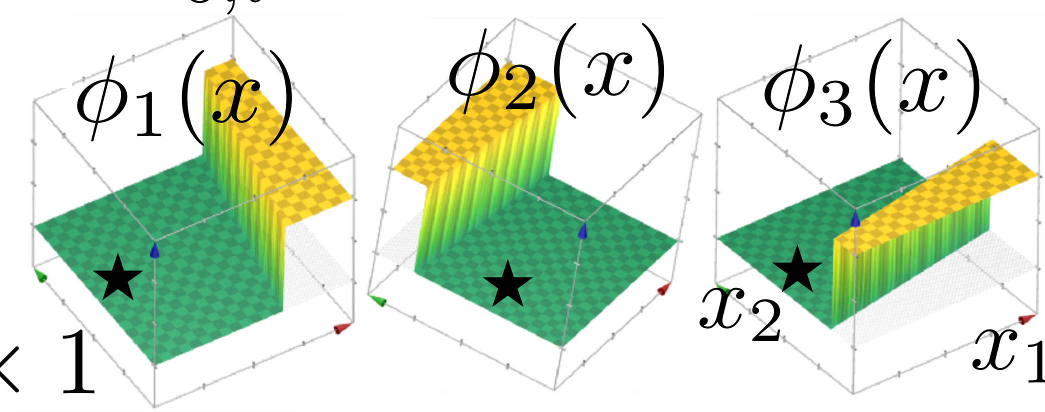

- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$ $m^{(2)} = n^{(1)}$
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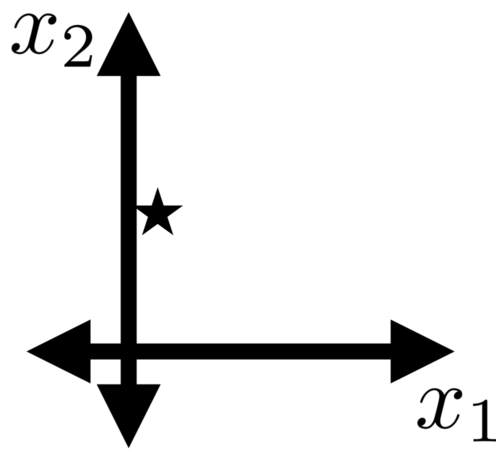
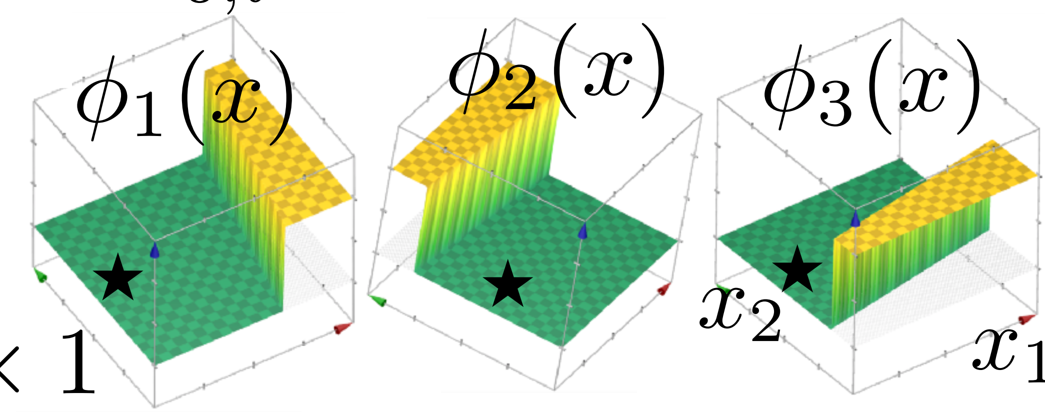
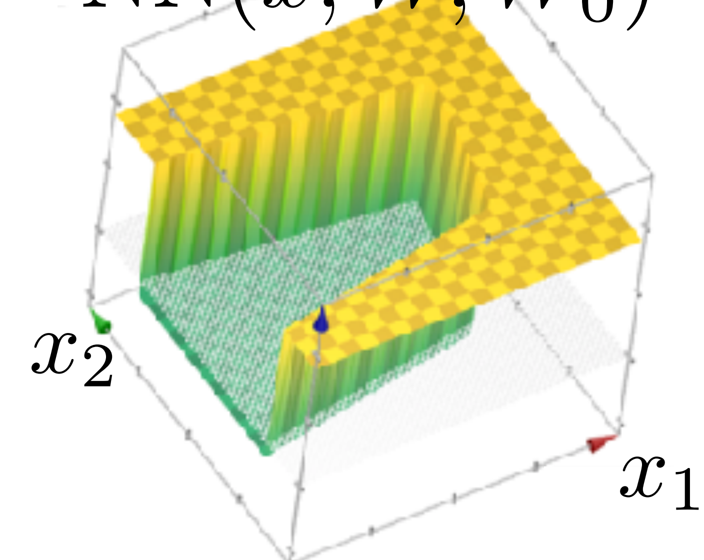




$\mathrm{NN}(x; W, W_0)$



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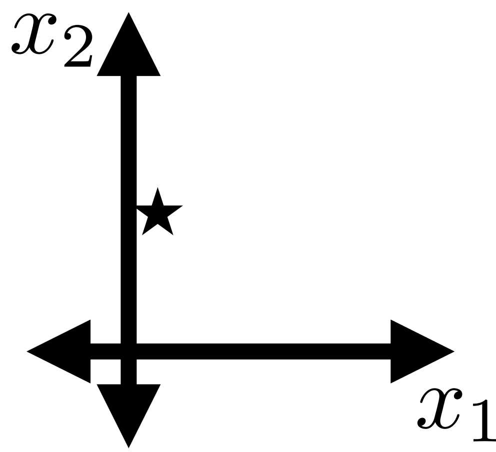

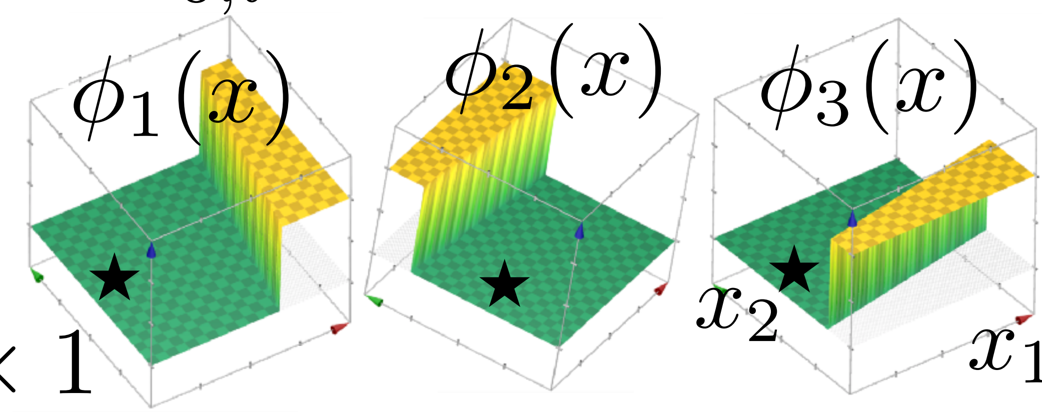

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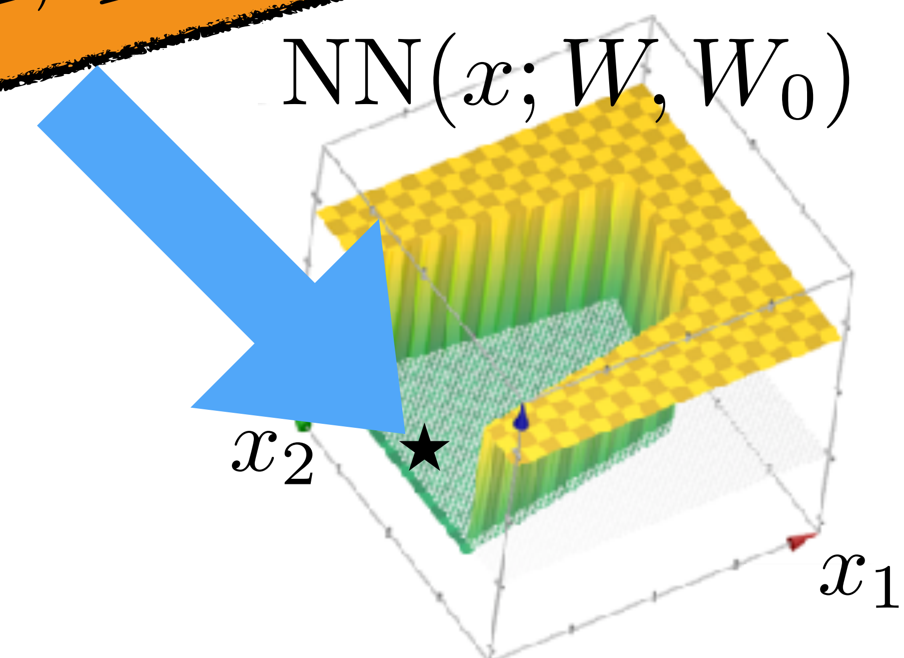

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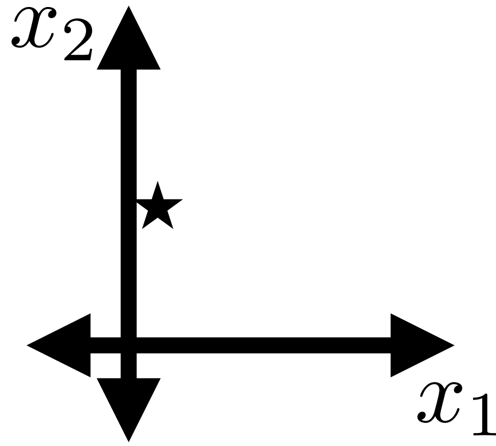

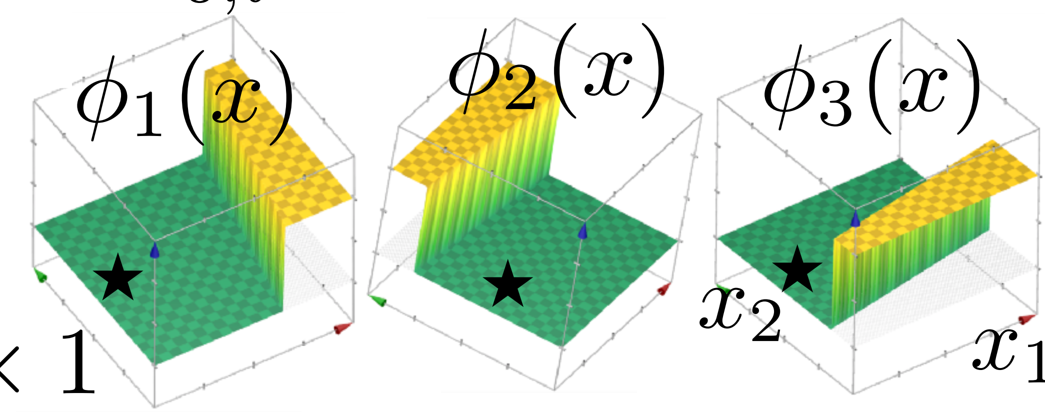

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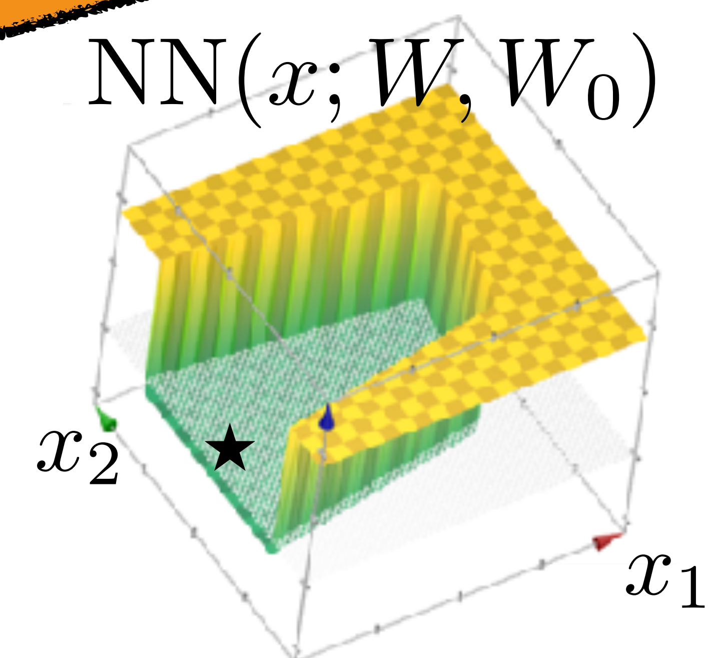

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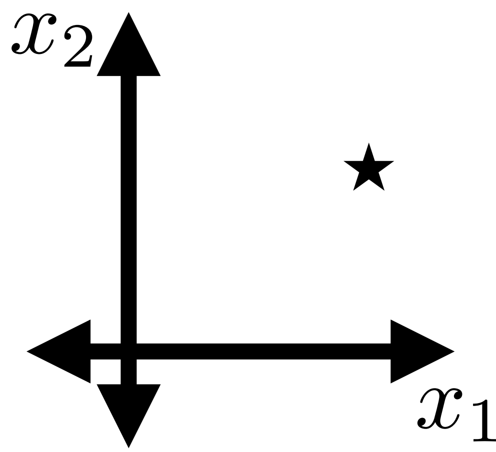

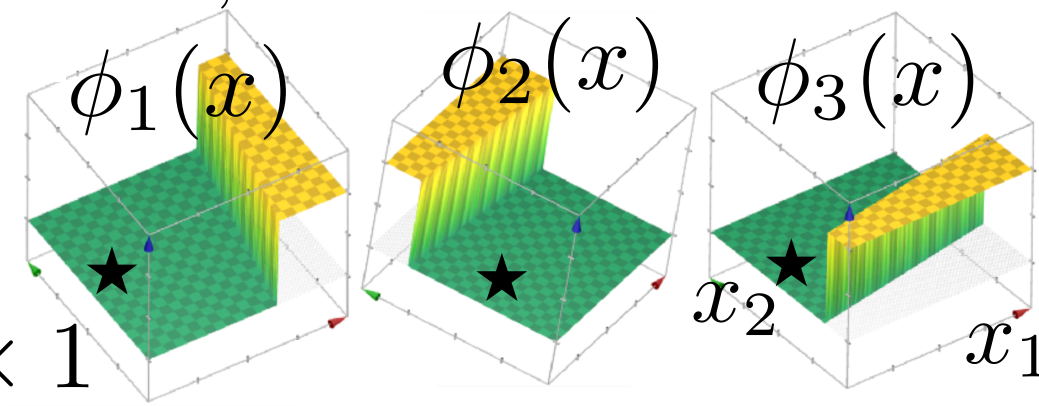

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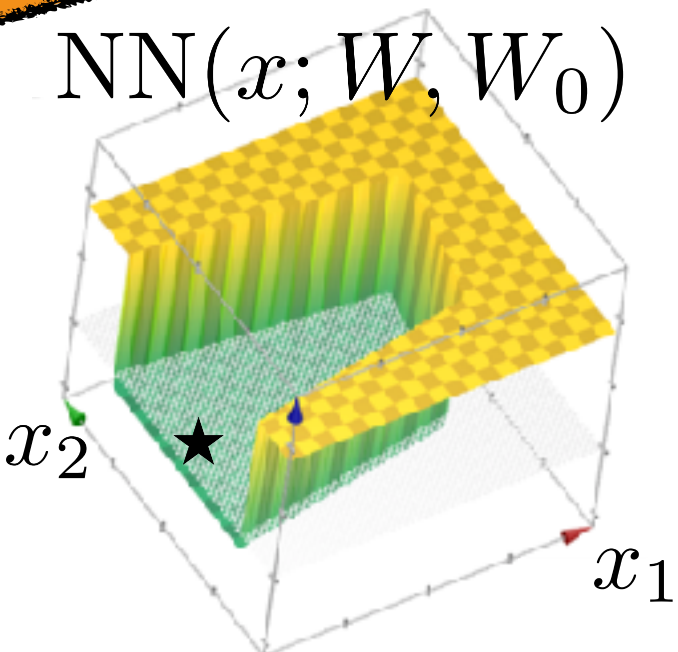

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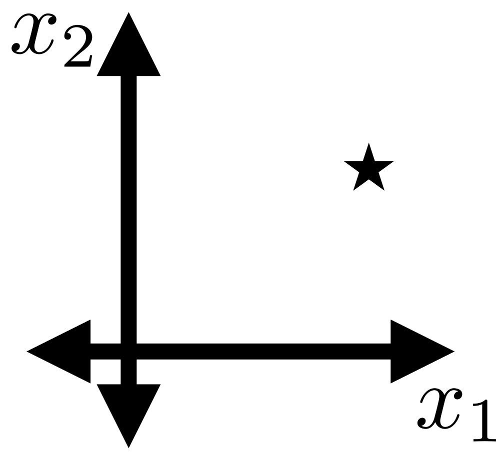
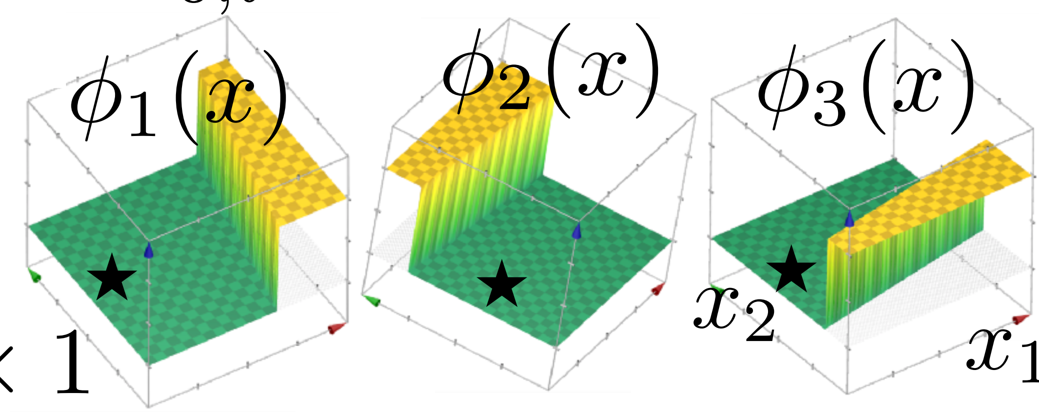
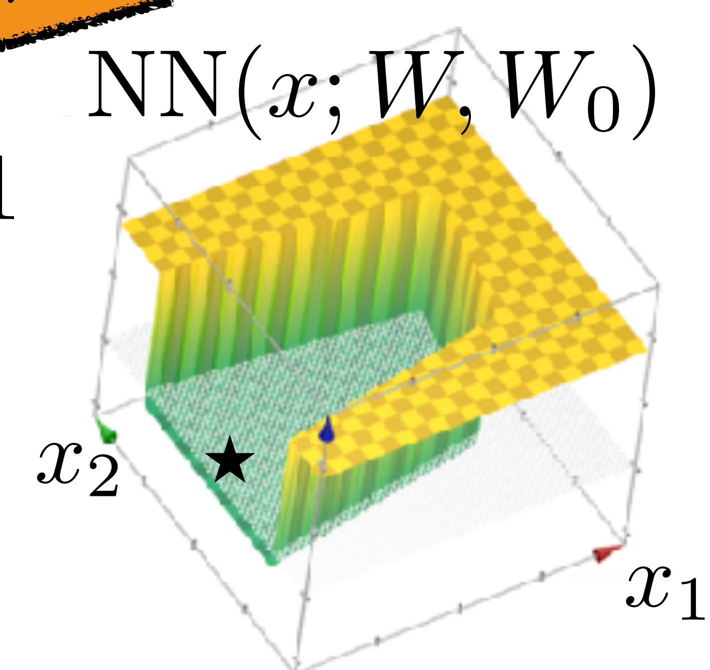




- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$ $\boxed{m^{(2)} = n^{(1)}}$
  - Output $A^{(2)}$(vector of labels): size $n^{(2)} \times 1$
  - The *i*th label:



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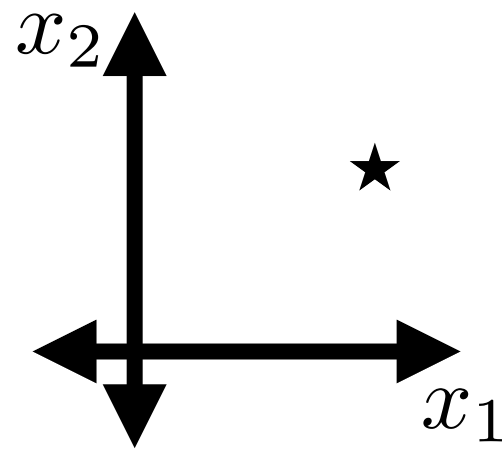

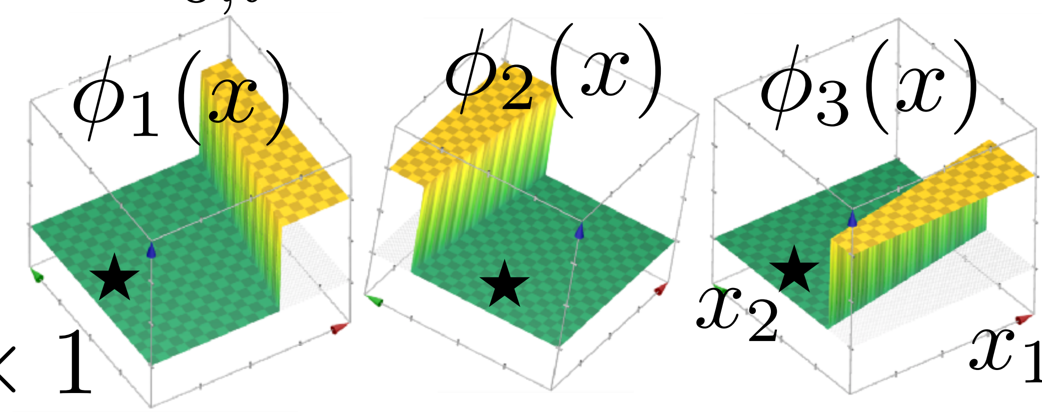

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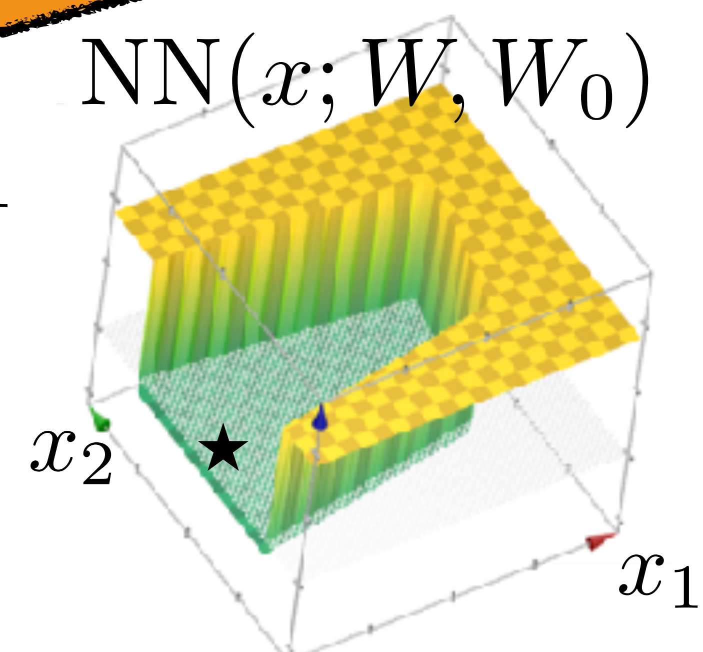
  - The *i*th label: $A_i^{(2)} = f^{(2)}(w_i^{(2)\top} A^{(1)} + w_{0,i}^{(2)})$



Let's get some new notation

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$ $m^{(1)} = d$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The ith feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
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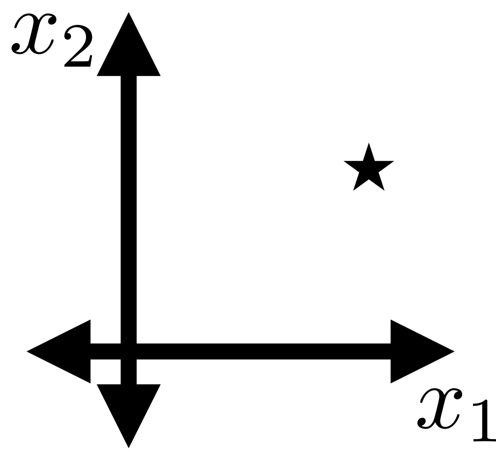
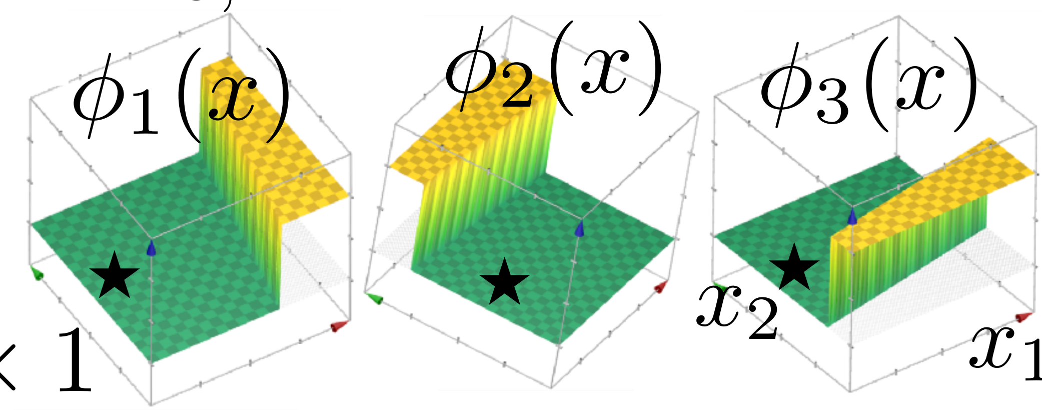
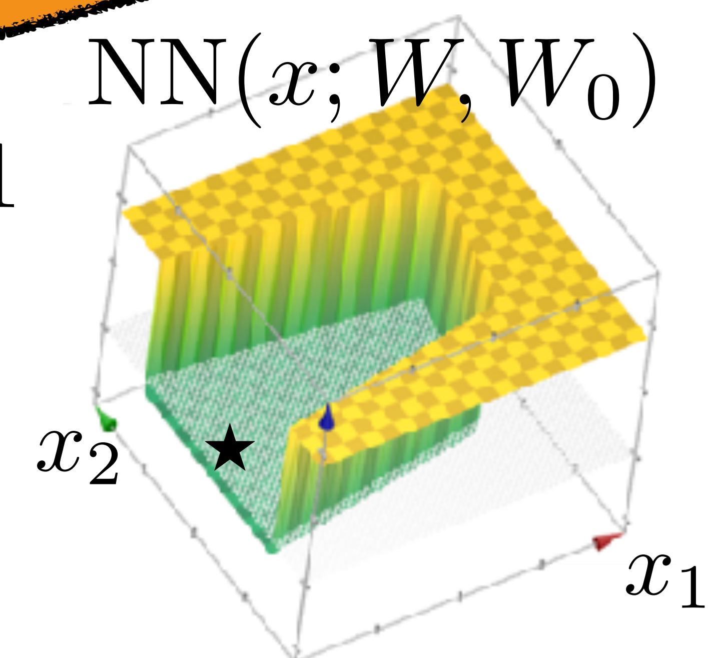




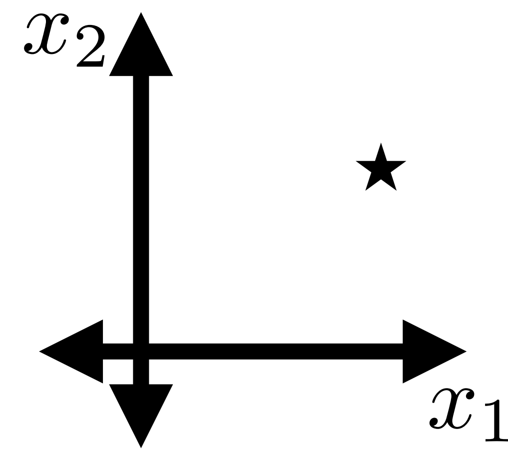
- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$ $m^{(2)} = n^{(1)}$
  - Output $A^{(2)}$(vector of labels): size $n^{(2)} \times 1$
  - The ith label: $A_i^{(2)} = f^{(2)}(w_i^{(2)\top} A^{(1)} + w_{0,i}^{(2)})$
    - All:

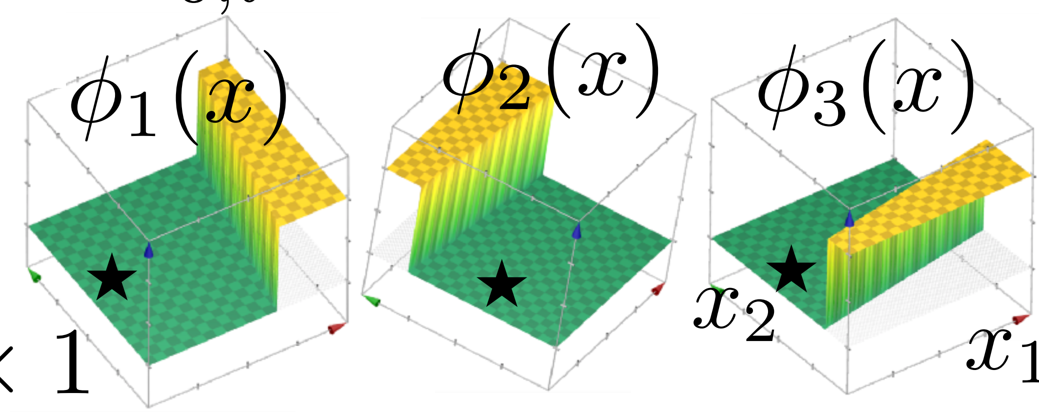


Let's get some new notation

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The ith feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
    - All the features at once:
      - $A^{(1)} = f^{(1)}(W^{(1)\top} x + W_0^{(1)})$
      - $W^{(1)} : m^{(1)} \times n^{(1)}; W_0^{(1)} : n^{(1)} \times 1$

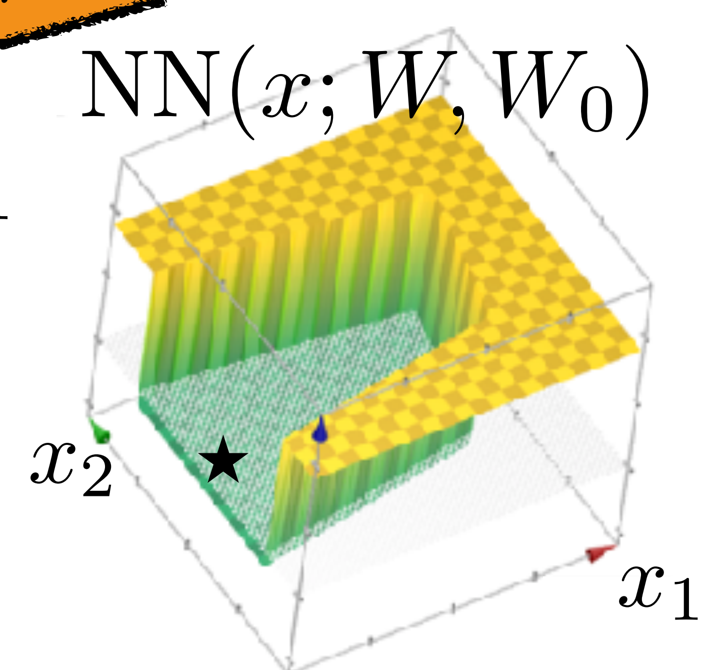
$\boxed{m^{(1)} = d}$





- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$
  - Output $A^{(2)}$(vector of labels): size $n^{(2)} \times 1$
  - The ith label: $A_i^{(2)} = f^{(2)}(w_i^{(2)\top} A^{(1)} + w_{0,i}^{(2)})$
    - All: $A^{(2)} = f^{(2)}(W^{(2)\top} A^{(1)} + W_0^{(2)})$

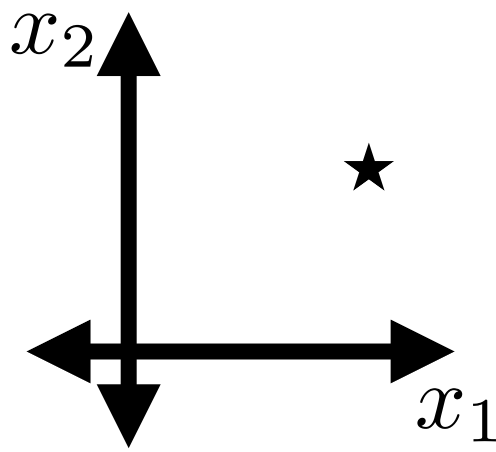
$\boxed{m^{(2)} = n^{(1)}}$

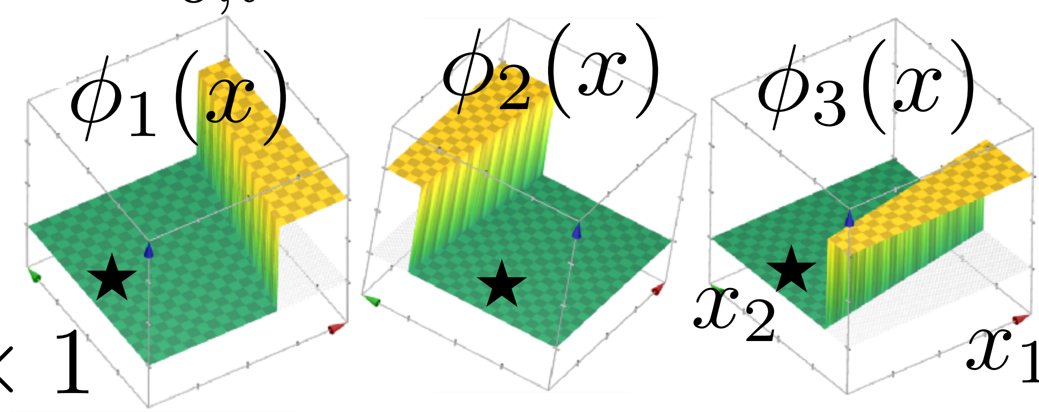


Let's get some new notation

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The *i*th feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
    - All the features at once:
      - $A^{(1)} = f^{(1)}(W^{(1)\top} x + W_0^{(1)})$
      - $W^{(1)} : m^{(1)} \times n^{(1)}; W_0^{(1)} : n^{(1)} \times 1$

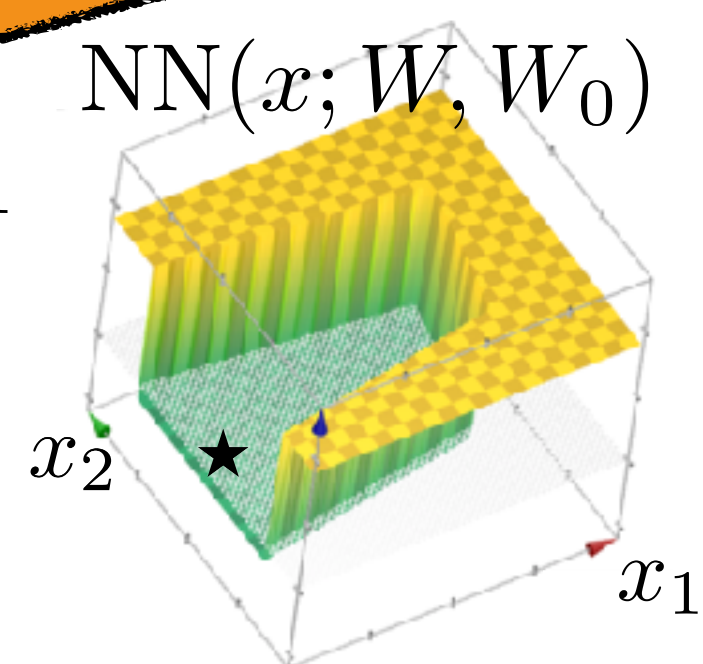
$m^{(1)} = d$





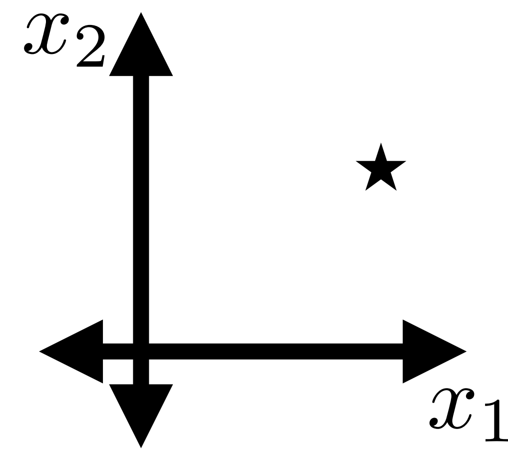
- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$
  - Output $A^{(2)}$(vector of labels): size $n^{(2)} \times 1$
  - The *i*th label: $A_i^{(2)} = f^{(2)}(w_i^{(2)\top} A^{(1)} + w_{0,i}^{(2)})$
    - All: $A^{(2)} = f^{(2)}(W^{(2)\top} A^{(1)} + W_0^{(2)})$
    - $W^{(2)} : m^{(2)} \times n^{(2)}$

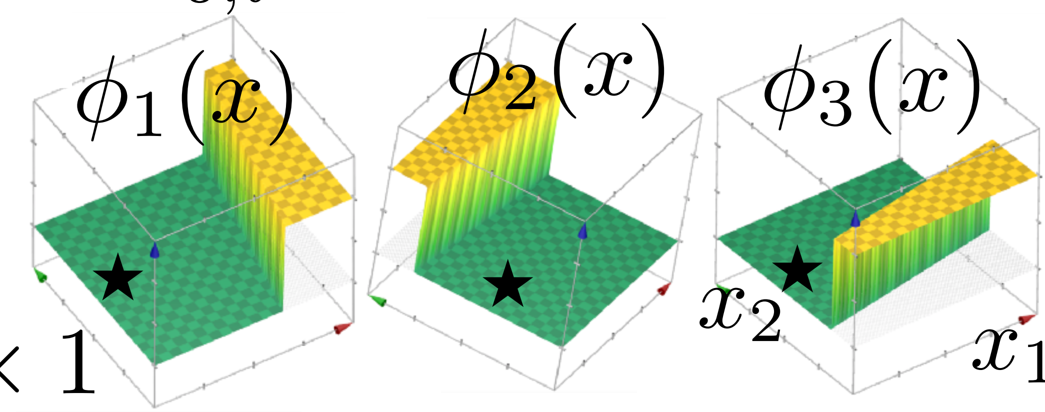
$m^{(2)} = n^{(1)}$



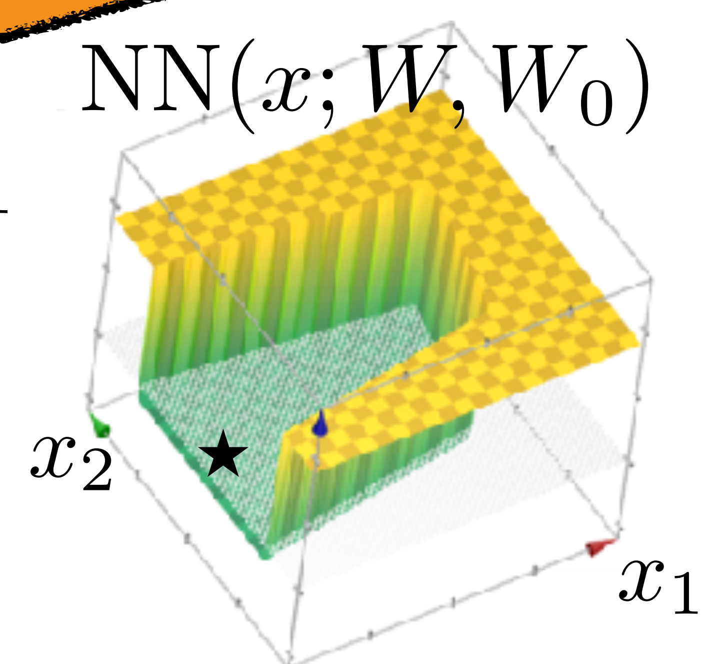
Let's get some new notation

- 1st layer, constructing the features:
  - Input x (a data point): size $m^{(1)} \times 1$ $\boxed{m^{(1)} = d}$
  - Output $A^{(1)}$ (vector of features): size $n^{(1)} \times 1$
  - The ith feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
    - All the features at once:
      - $A^{(1)} = f^{(1)}(W^{(1)\top} x + W_0^{(1)})$
      - $W^{(1)} : m^{(1)} \times n^{(1)}; W_0^{(1)} : n^{(1)} \times 1$





- 2nd layer, assigning a label (or labels):
  - Input (the features): size $m^{(2)} \times 1$ $\boxed{m^{(2)} = n^{(1)}}$
  - Output $A^{(2)}$(vector of labels): size $n^{(2)} \times 1$
  - The ith label: $A_i^{(2)} = f^{(2)}(w_i^{(2)\top} A^{(1)} + w_{0,i}^{(2)})$
    - All: $A^{(2)} = f^{(2)}(W^{(2)\top} A^{(1)} + W_0^{(2)})$
    - $W^{(2)} : m^{(2)} \times n^{(2)}; W_0^{(2)} : n^{(2)} \times 1$



Let's get some new notation

- 1st layer, constructing the features: $m^{(1)} = d$
  - Input x (a data point): size $m^{(1)} \times 1$
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  - The *i*th feature: $A_i^{(1)} = f^{(1)}(w_i^{(1)\top} x + w_{0,i}^{(1)})$
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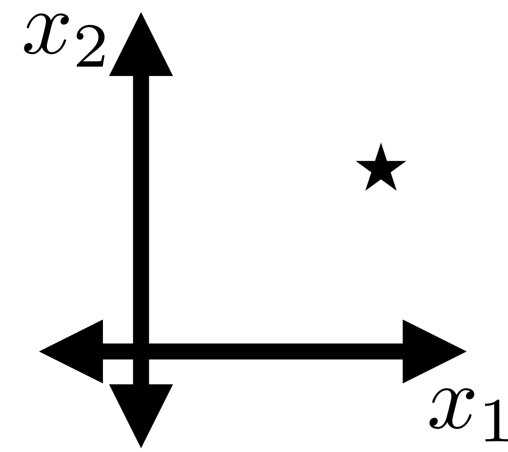
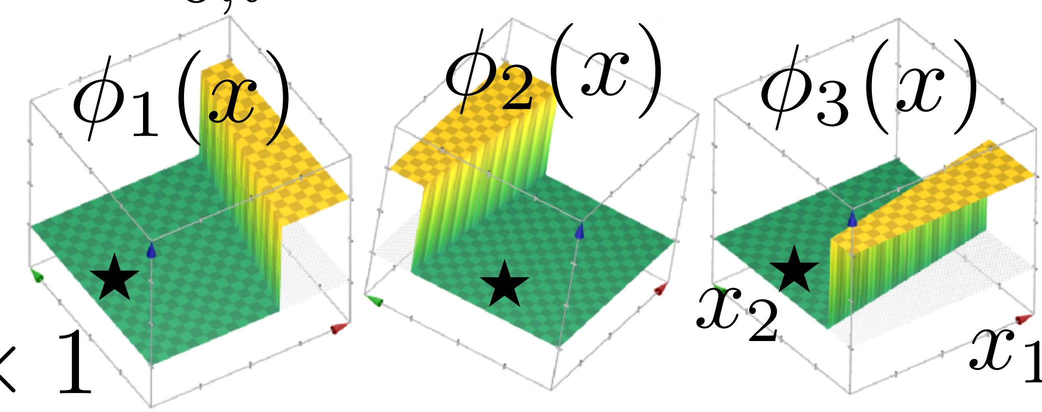
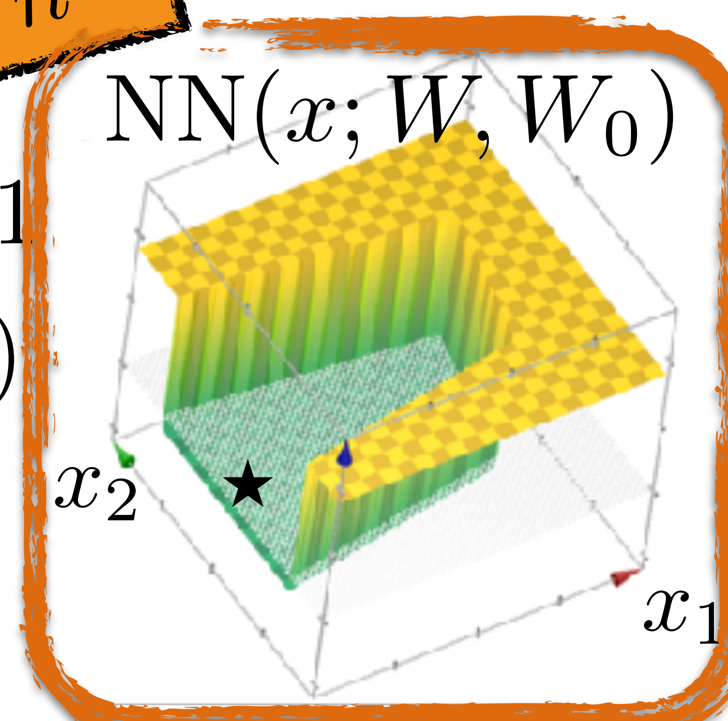




- 2nd layer, assigning a label (or labels): $m^{(2)} = n^{(1)}$
  - Input (the features): size $m^{(2)} \times 1$
  - Output $A^{(2)}$(vector of labels): size $n^{(2)} \times 1$
  - The *i*th label: $A_i^{(2)} = f^{(2)}(w_i^{(2)\top} A^{(1)} + w_{0,i}^{(2)})$
    - All: $A^{(2)} = f^{(2)}(W^{(2)\top} A^{(1)} + W_0^{(2)})$
    - $W^{(2)} : m^{(2)} \times n^{(2)}; W_0^{(2)} : n^{(2)} \times 1$



- 1st layer: $A^{(1)} = f^{(1)}(W^{(1)\top} x + W_0^{(1)})$
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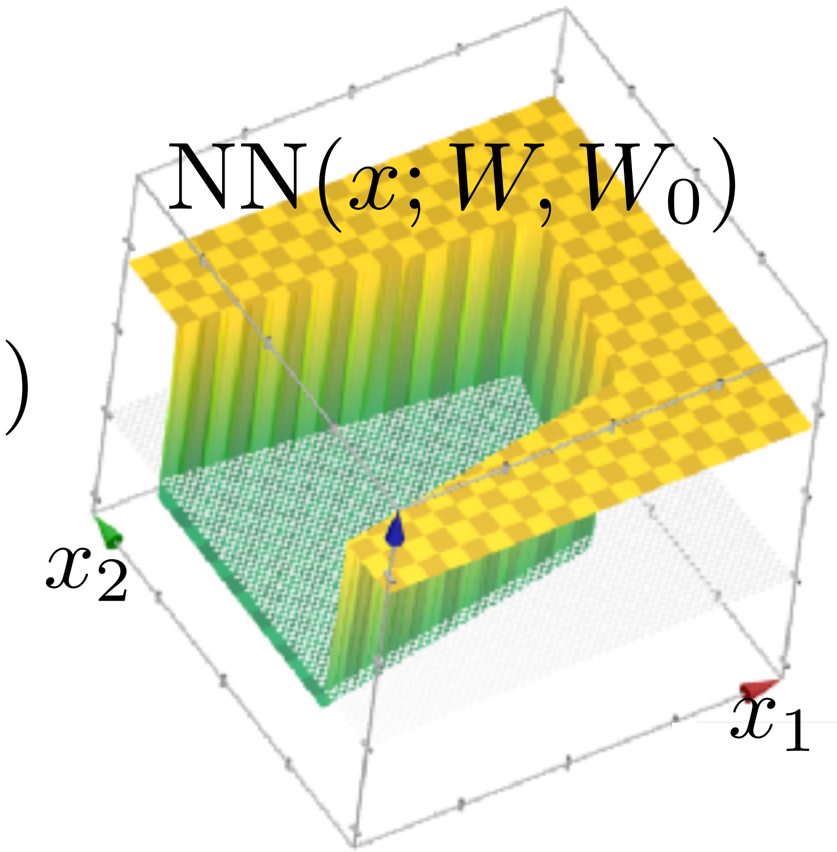

Function graph representation

- 1st layer: $A^{(1)} = f^{(1)}(W^{(1)\top}x + W_0^{(1)})$
- 2nd layer: $A^{(2)} = f^{(2)}(W^{(2)\top}A^{(1)} + W_0^{(2)})$
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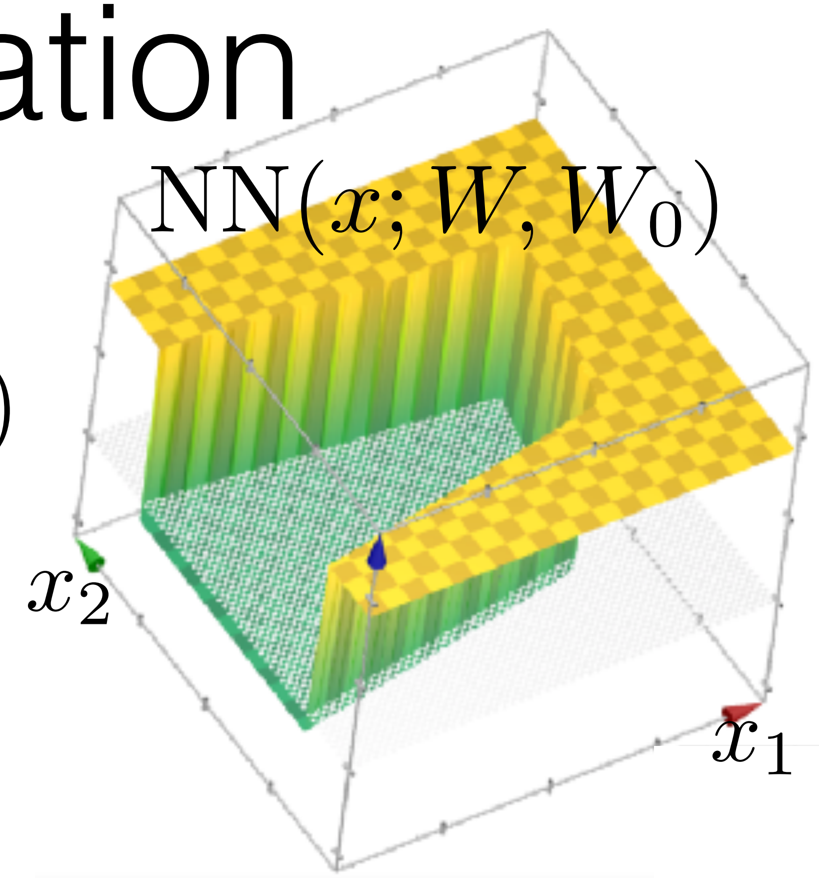

Function graph representation

- 1st layer: $A^{(1)} = f^{(1)}(W^{(1)\top}x + W_0^{(1)})$
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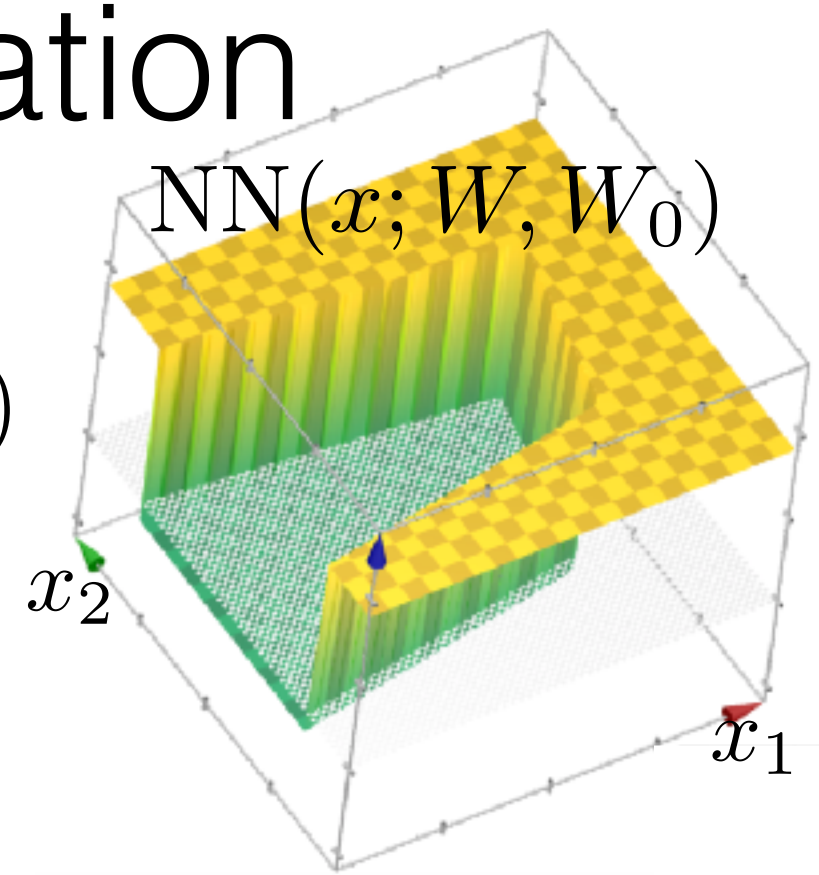

Function graph representation

- 1st layer: $\boxed{A^{(1)} = f^{(1)}(W^{(1)\top}x + W_0^{(1)})}$
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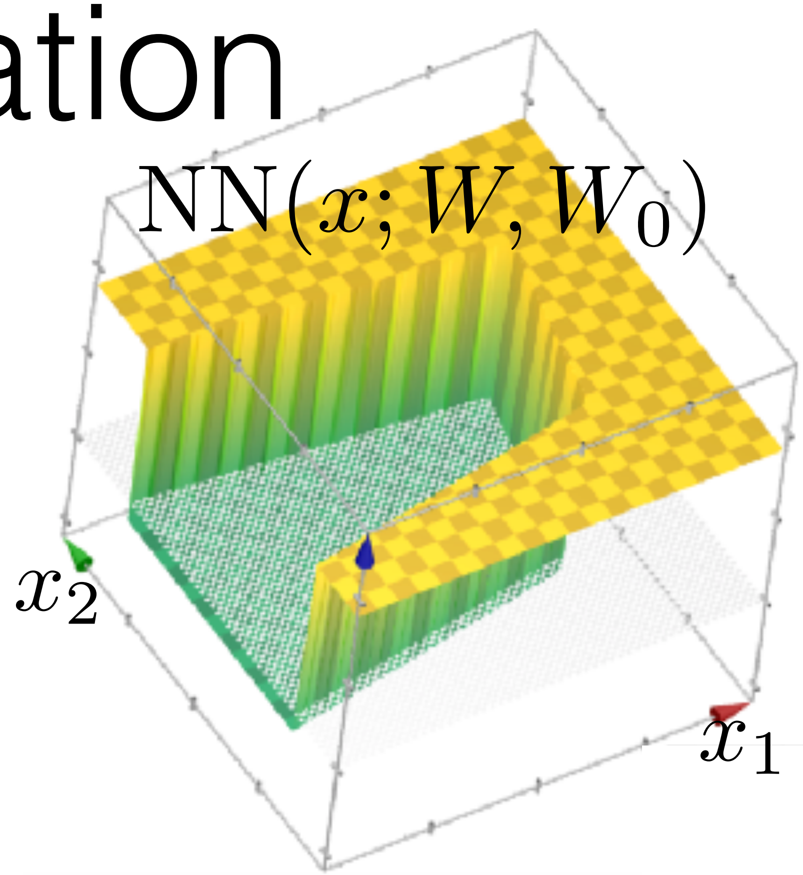
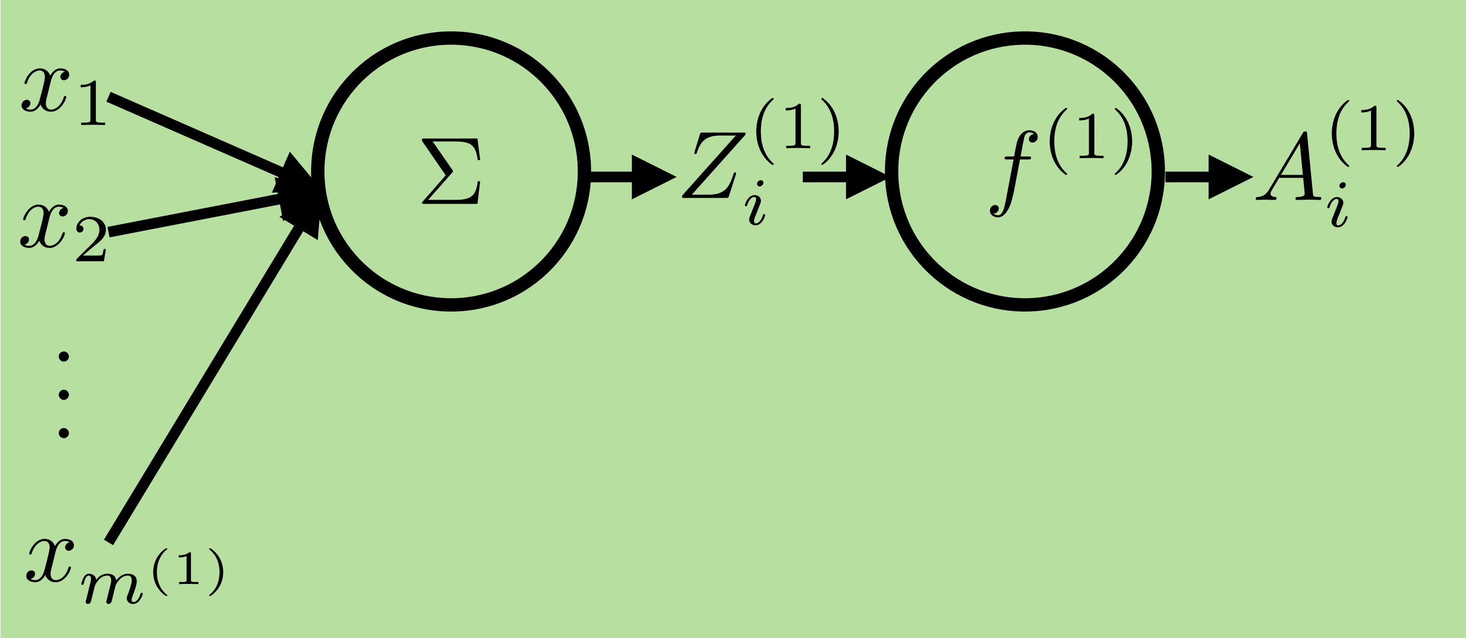
- Whole thing: $A^{(2)} = \mathrm{NN}(x; W, W_0)$





Function graph representation

- 1st layer: $A^{(1)} = f^{(1)}(W^{(1)\top} x + W_0^{(1)})$
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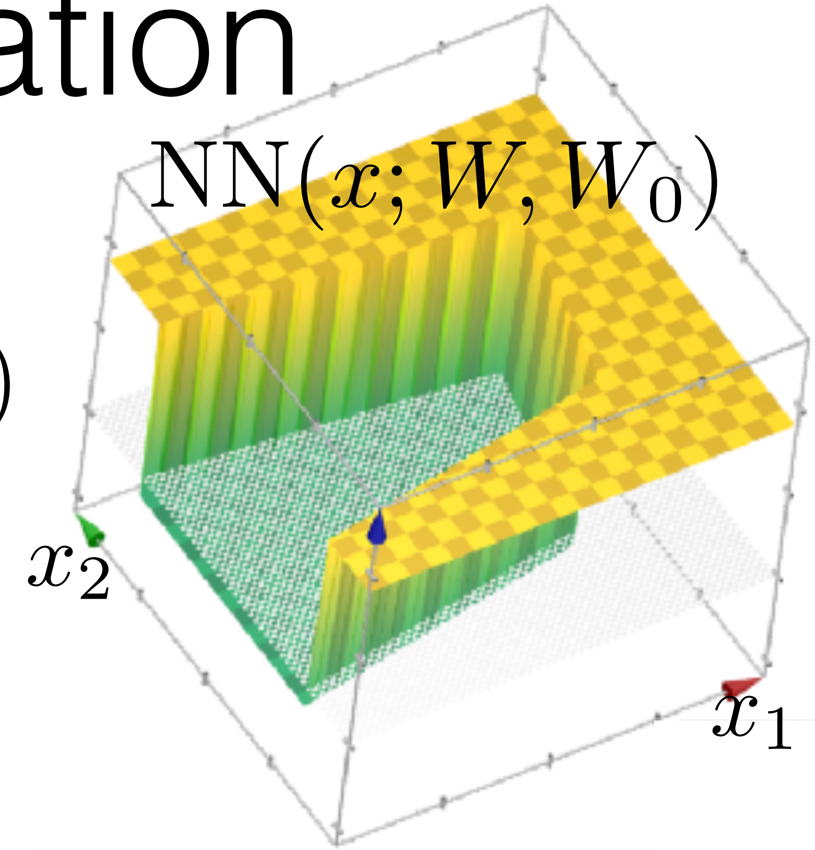

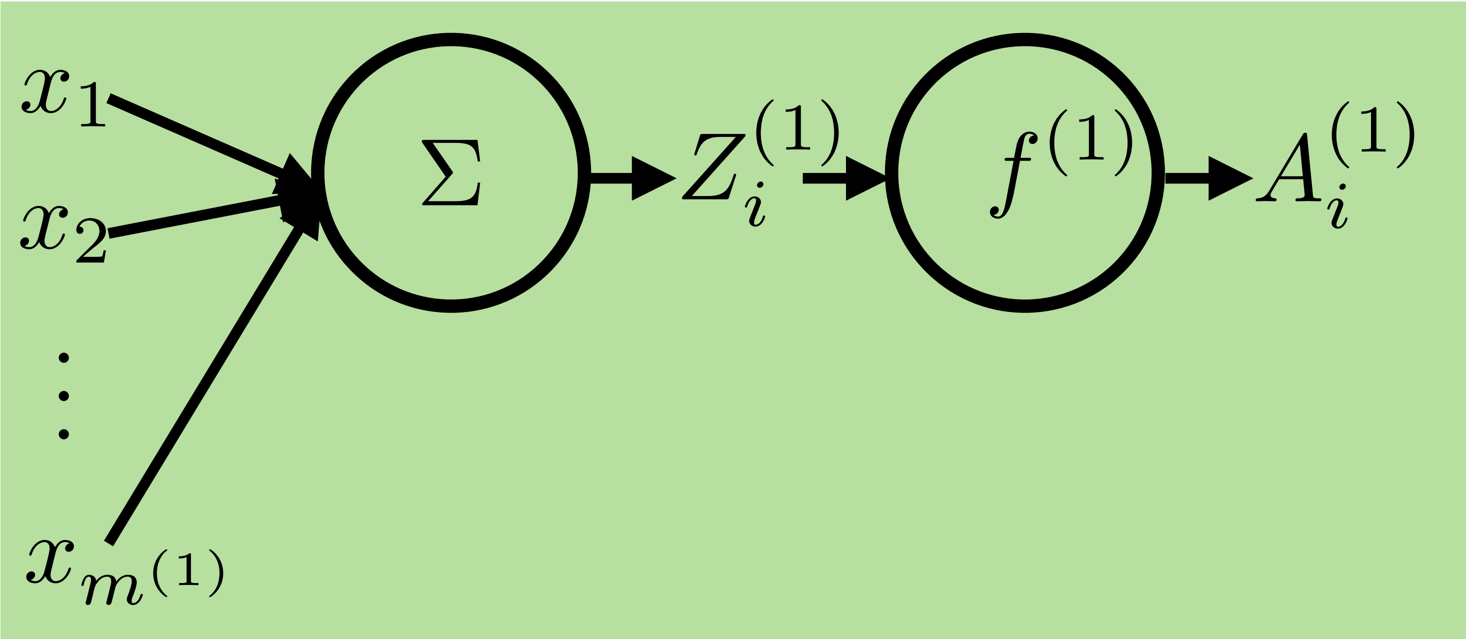

- Circle: function evaluation

Function graph representation

- 1st layer: $A^{(1)} = f^{(1)}(W^{(1)\top}x + W_0^{(1)})$
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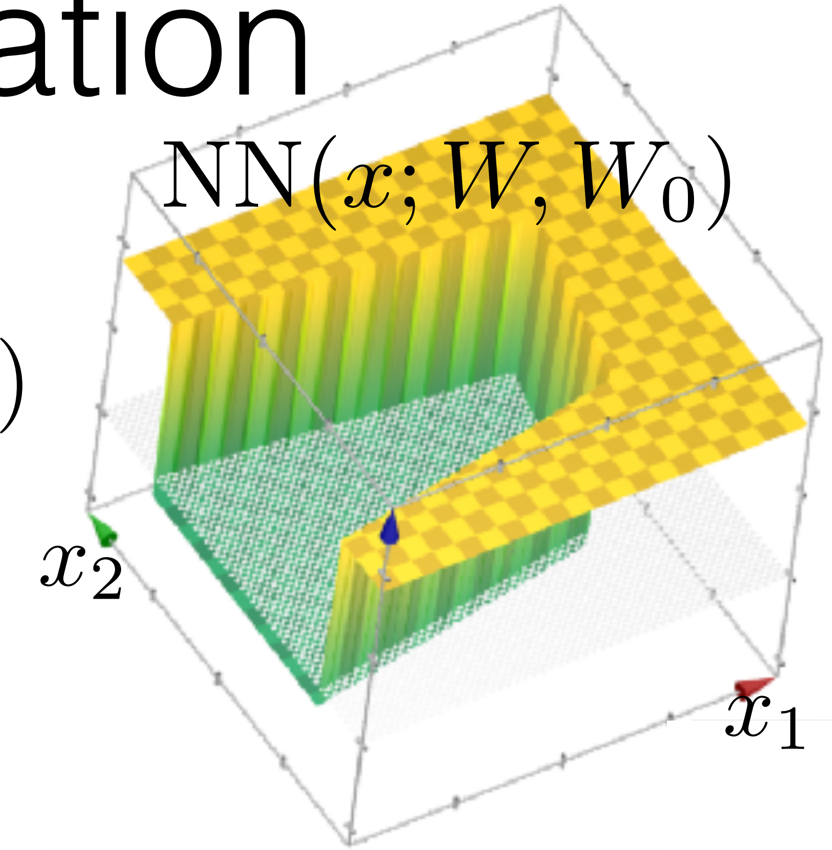

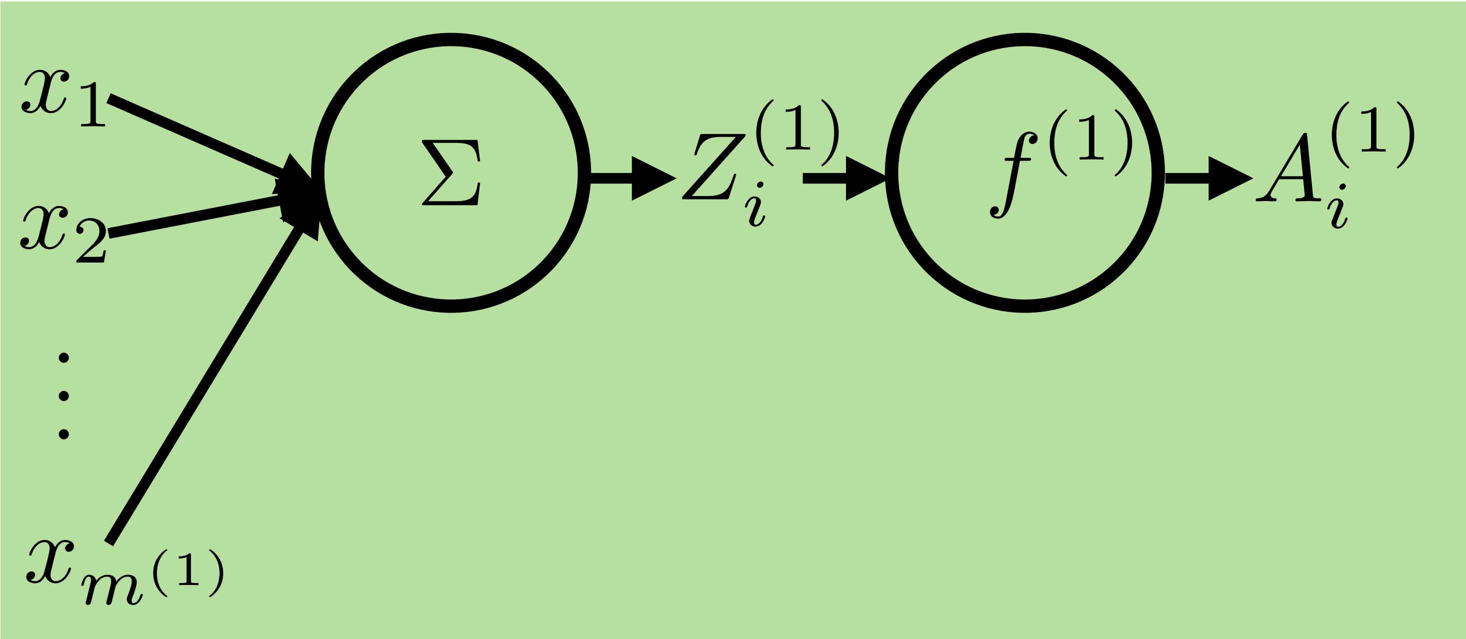

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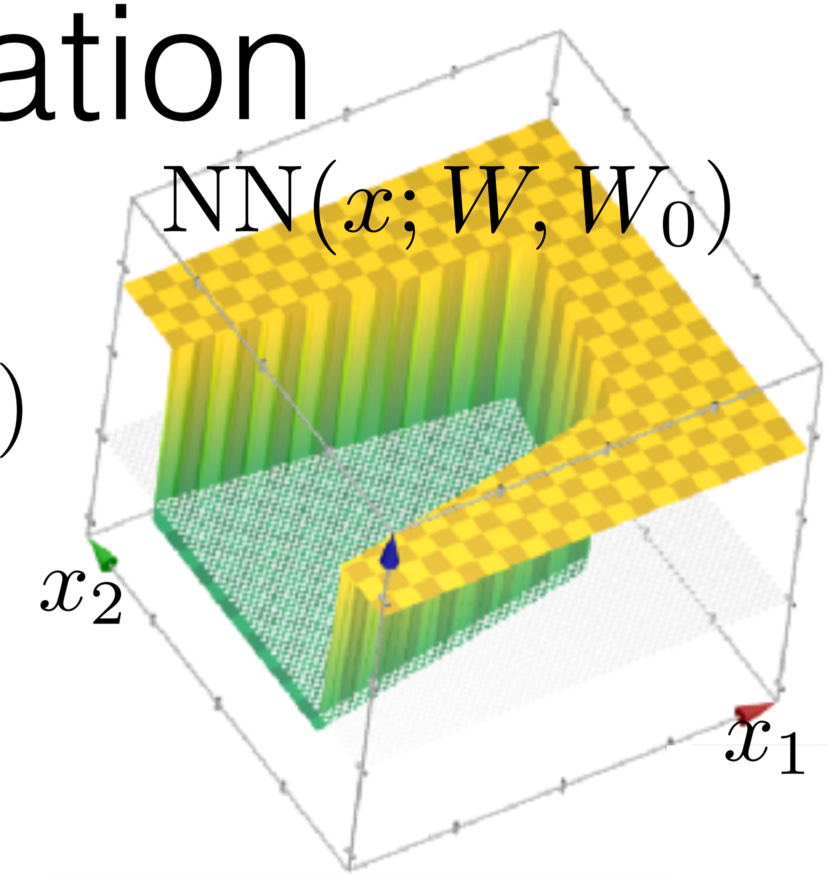

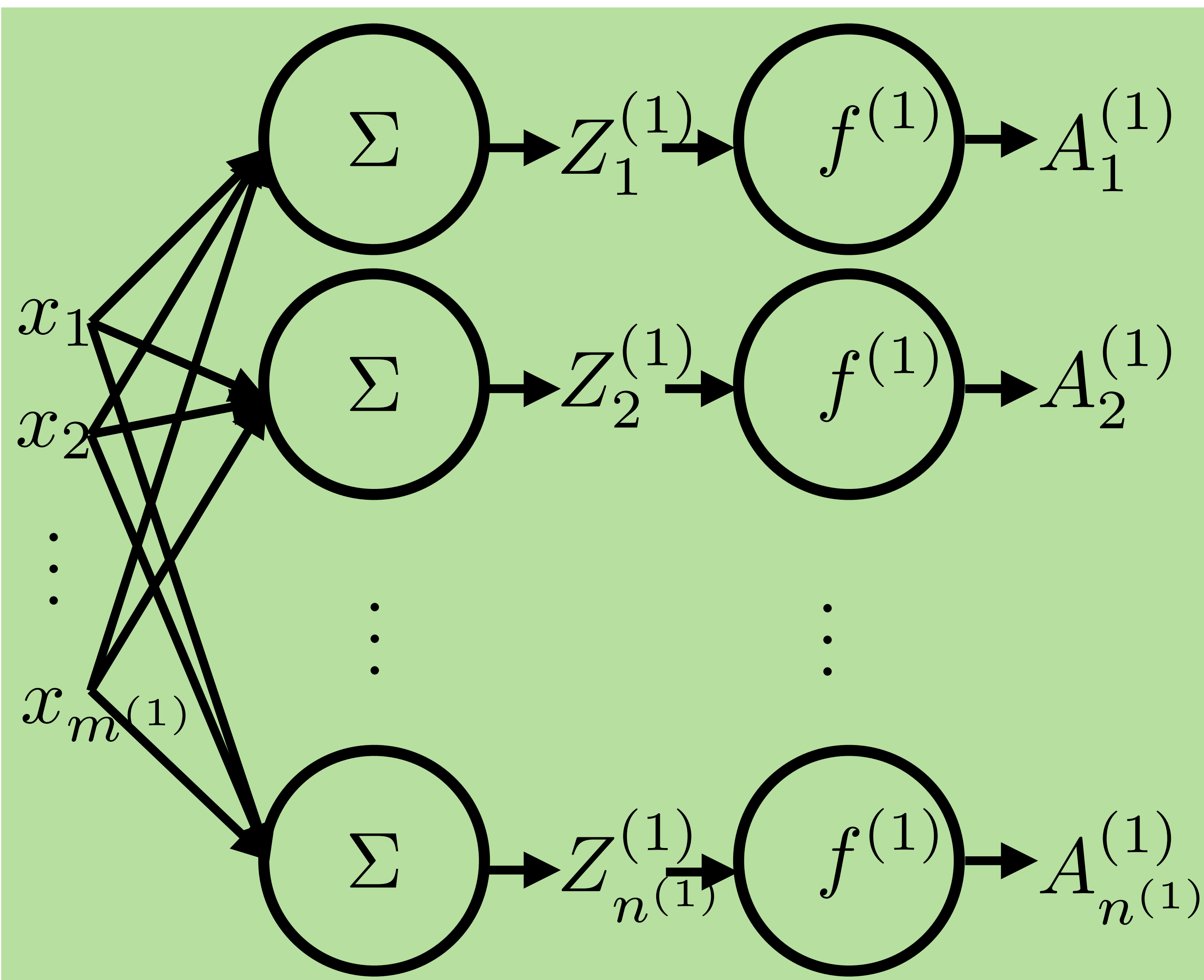

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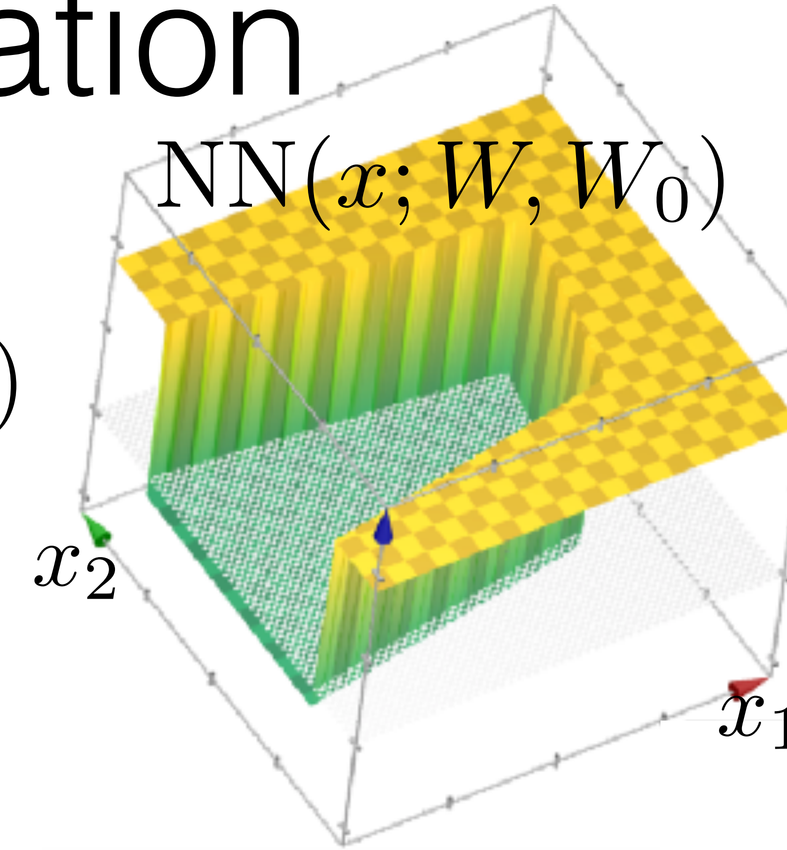

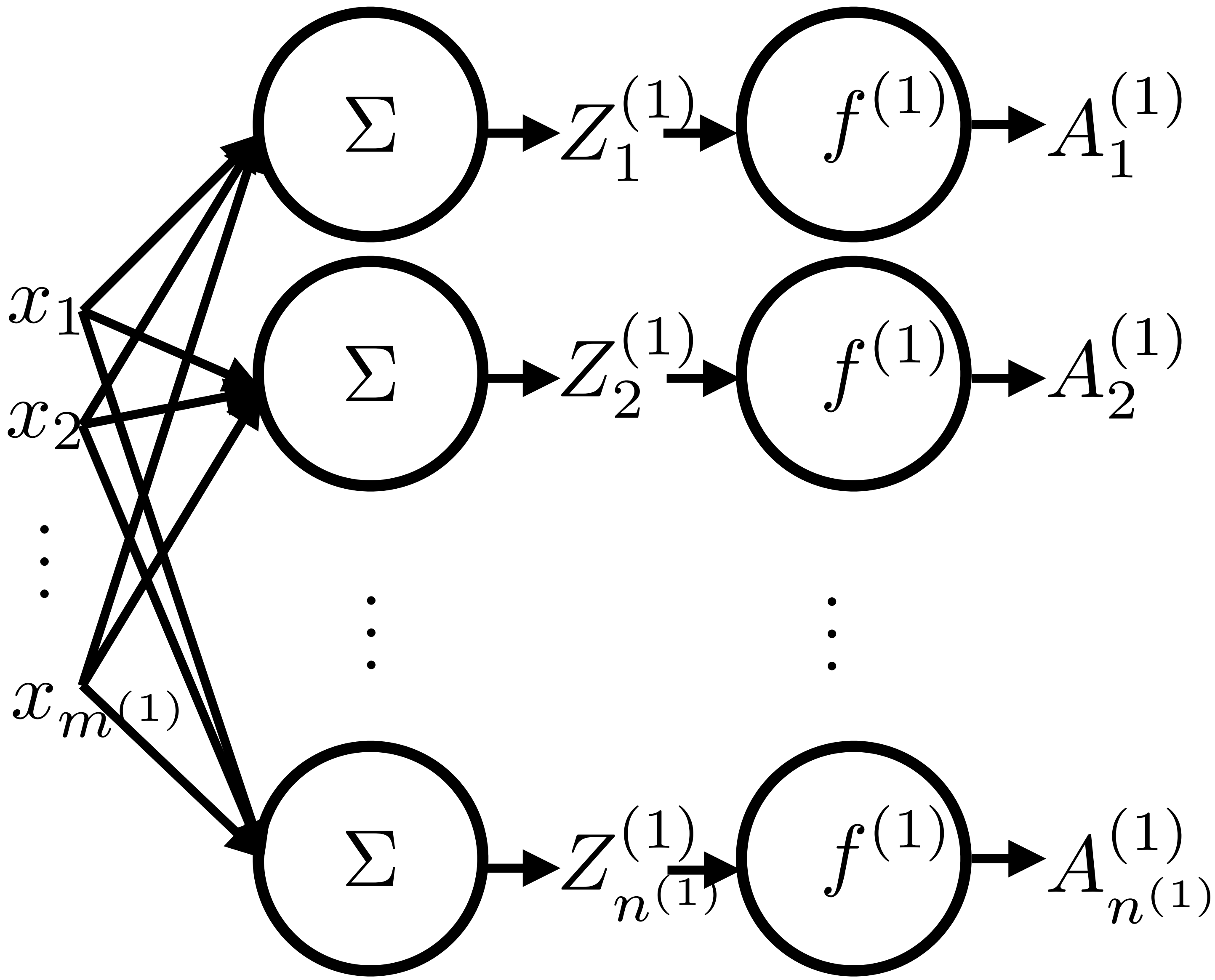

- Circle: function evaluation

Function graph representation

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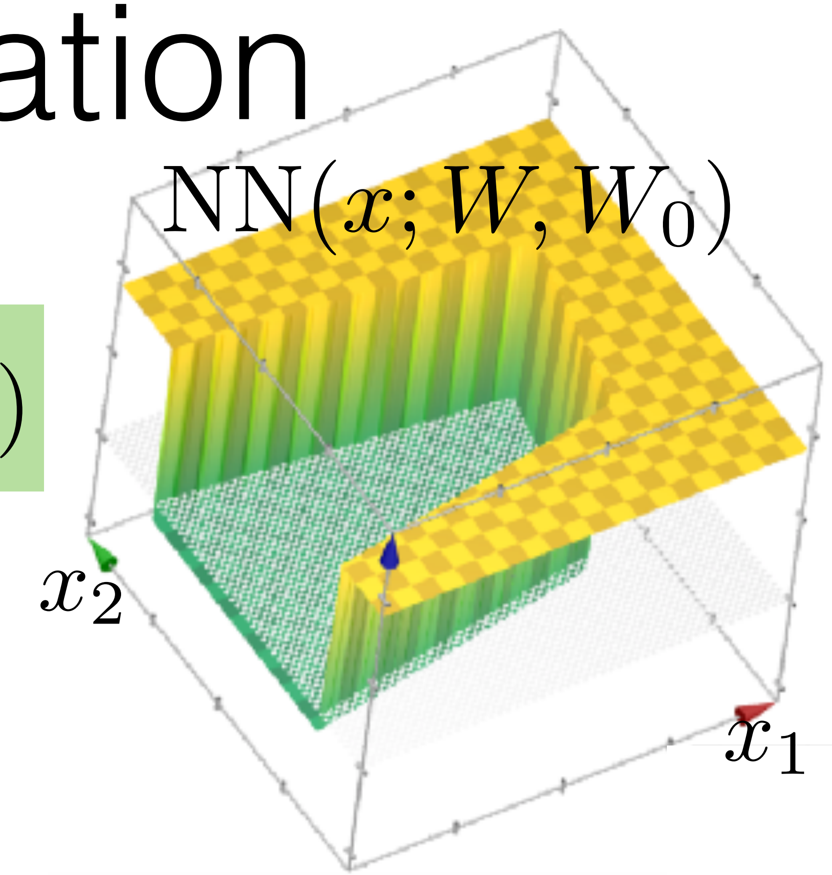

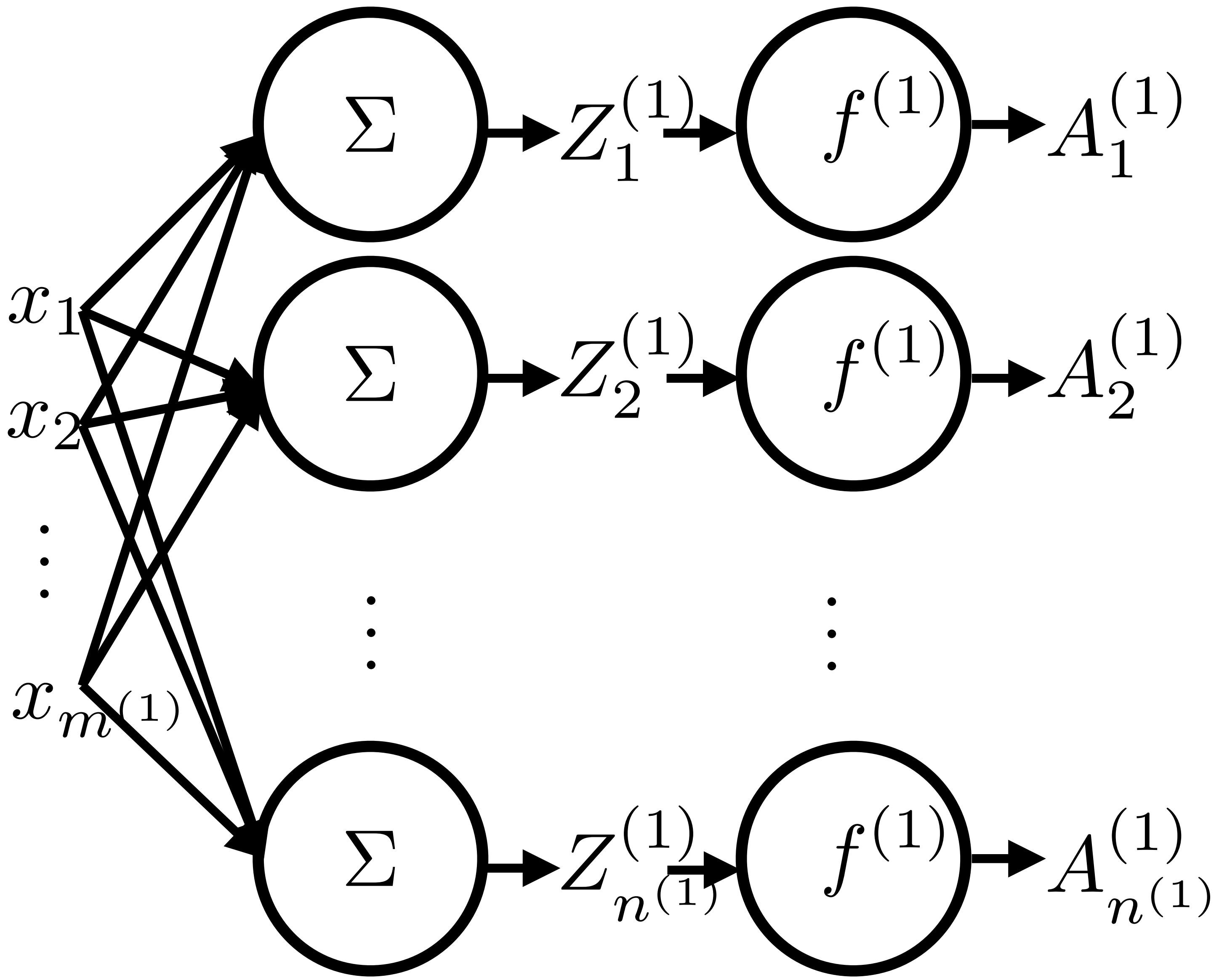

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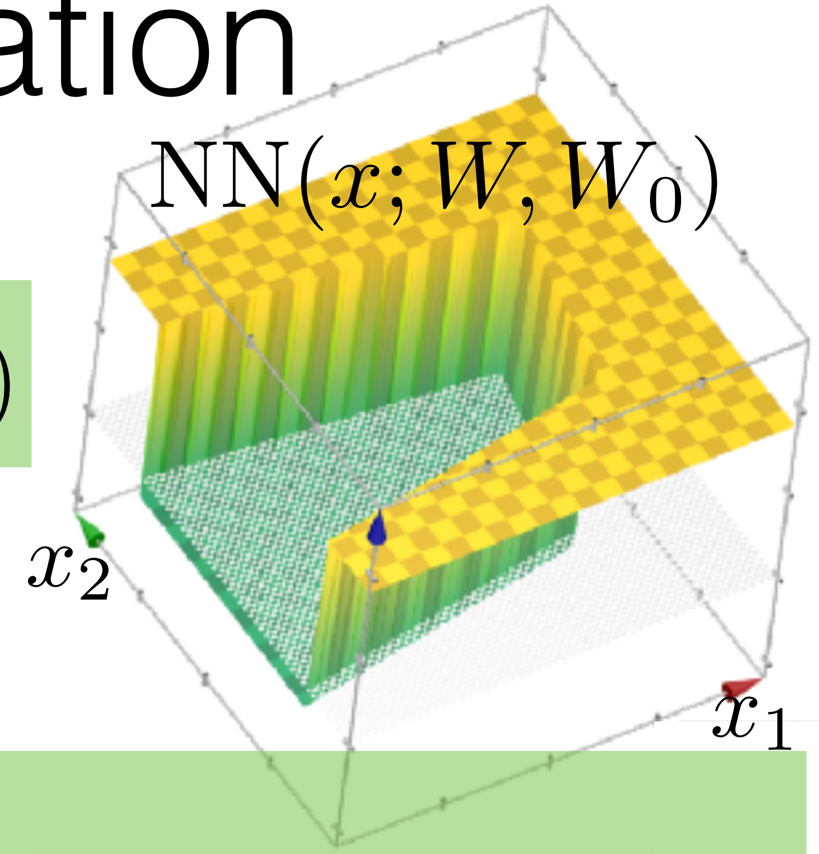

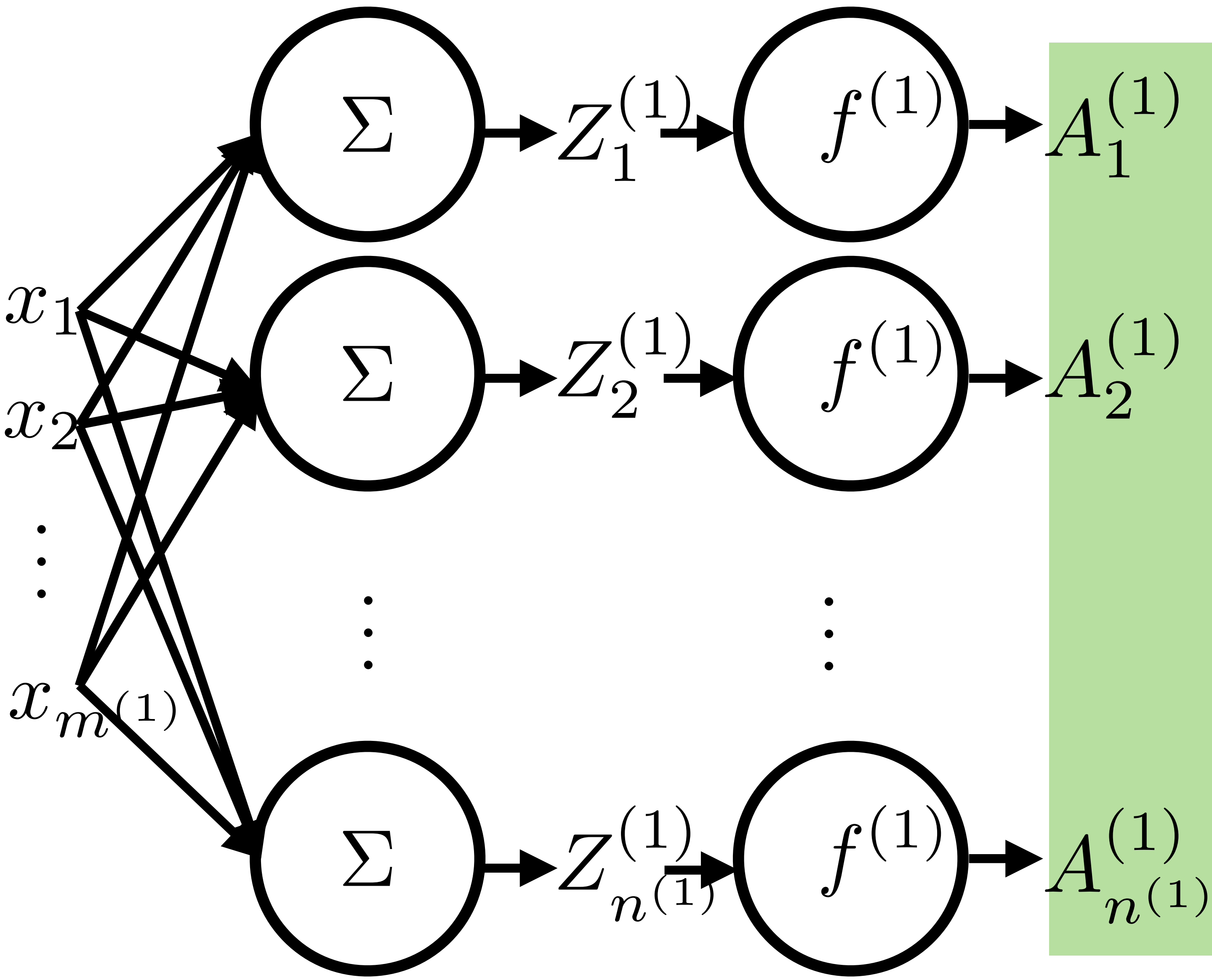

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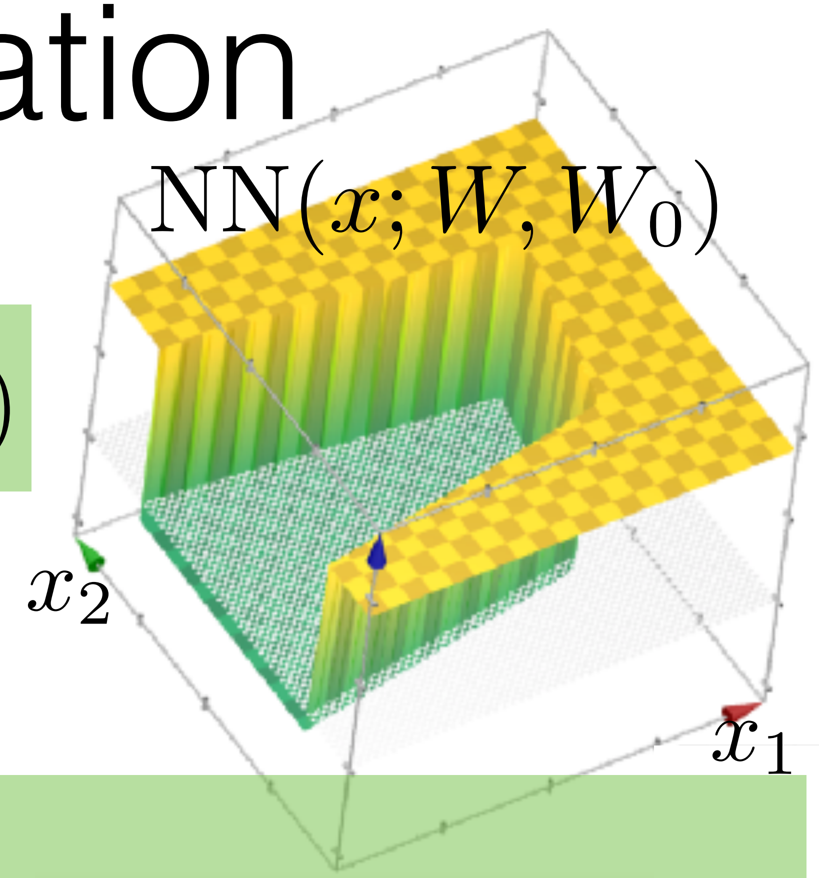

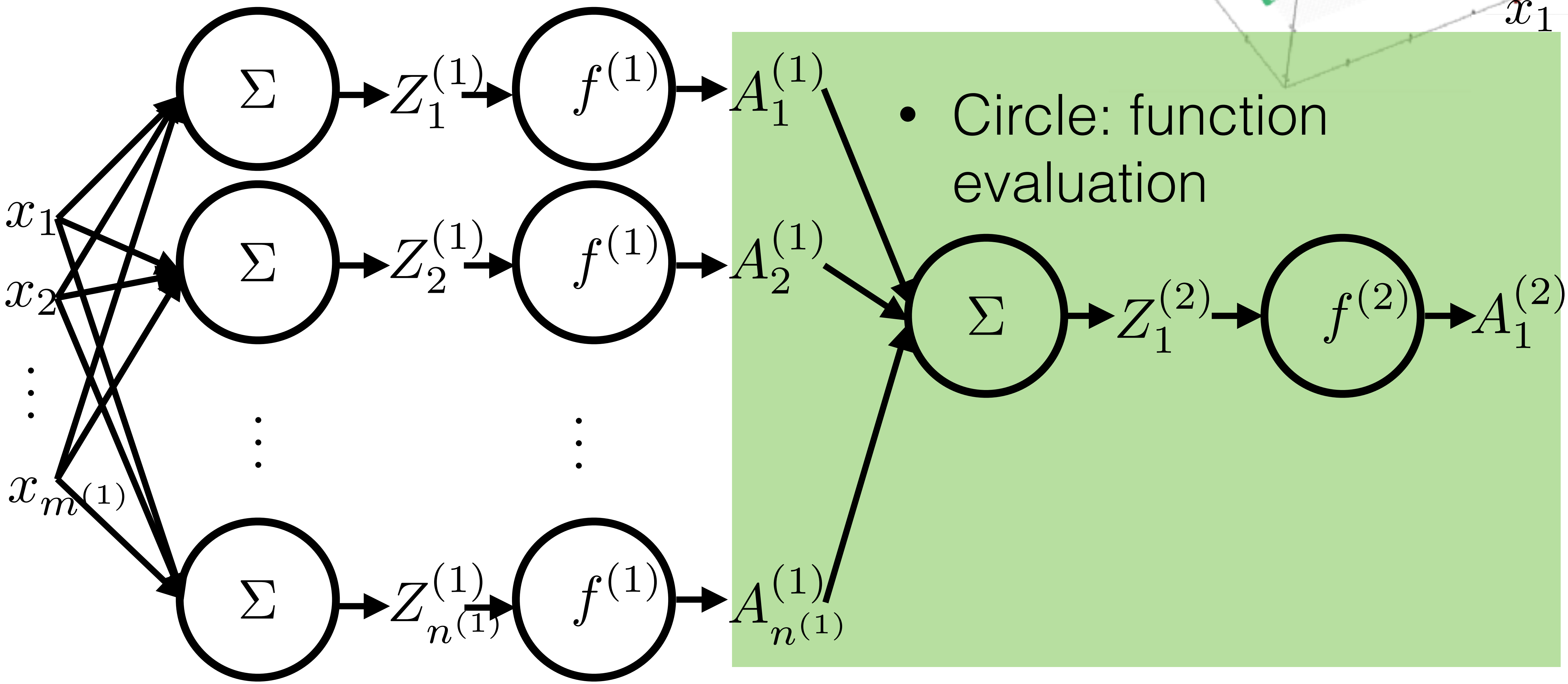

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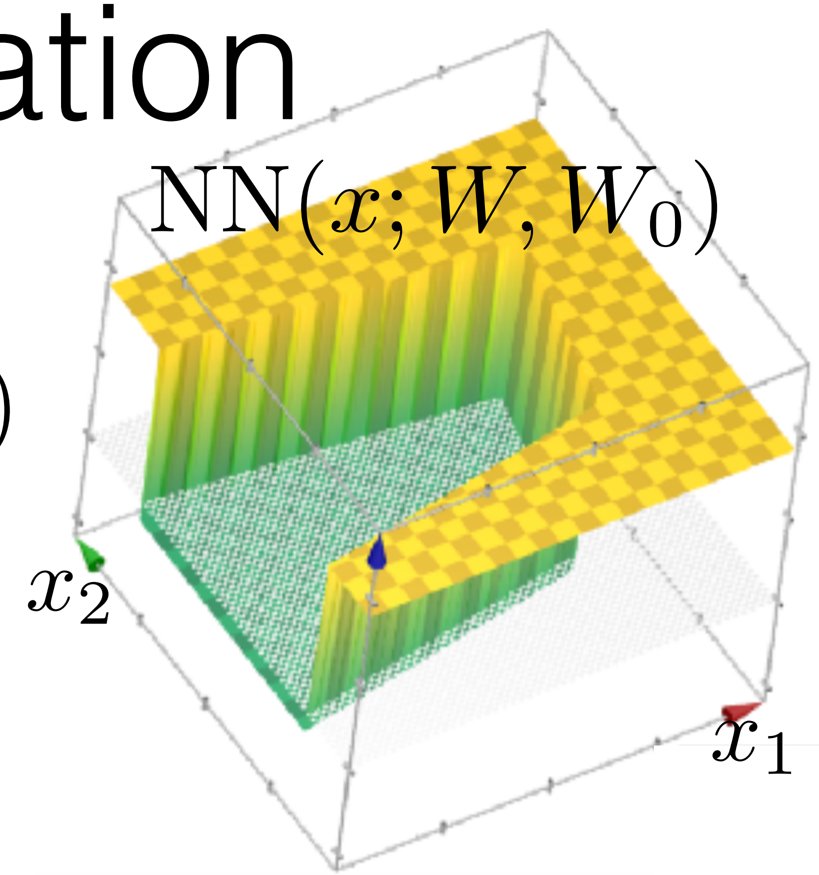
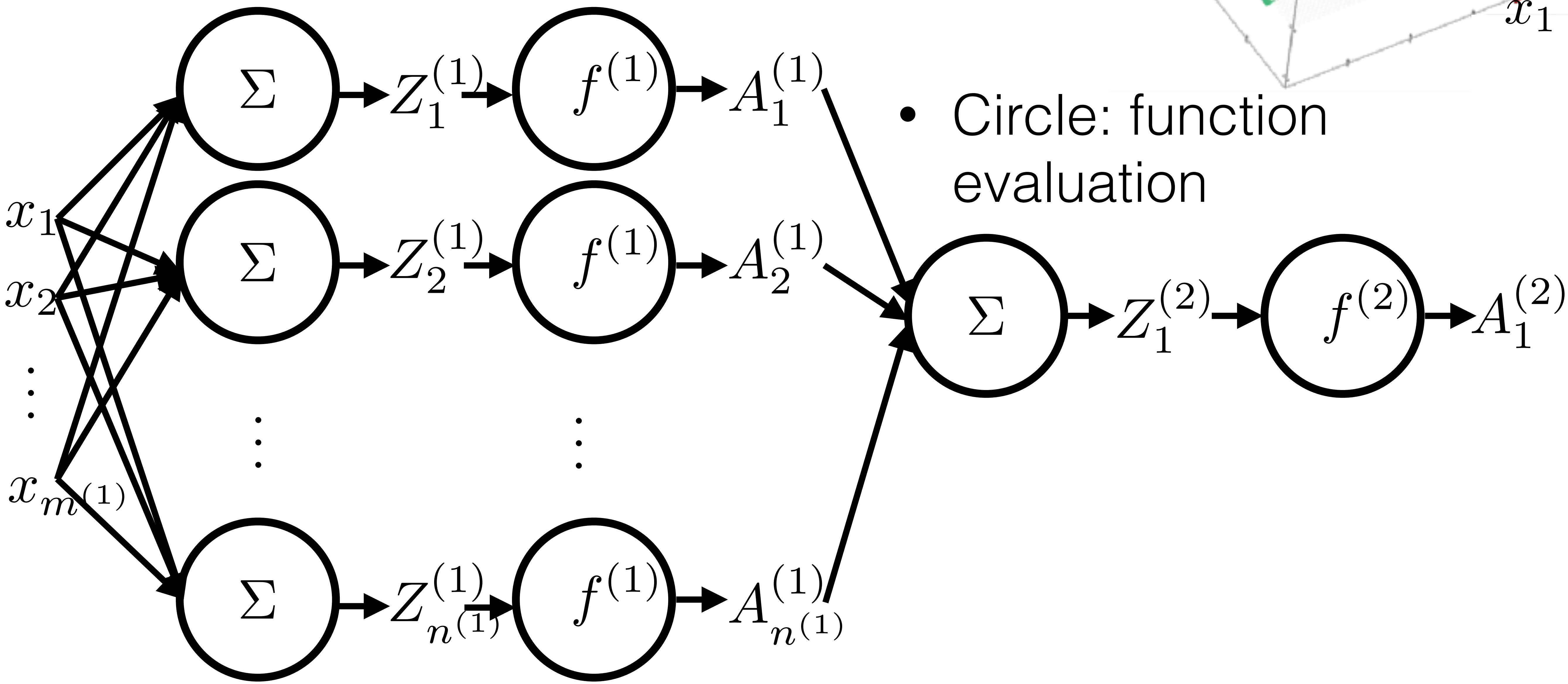
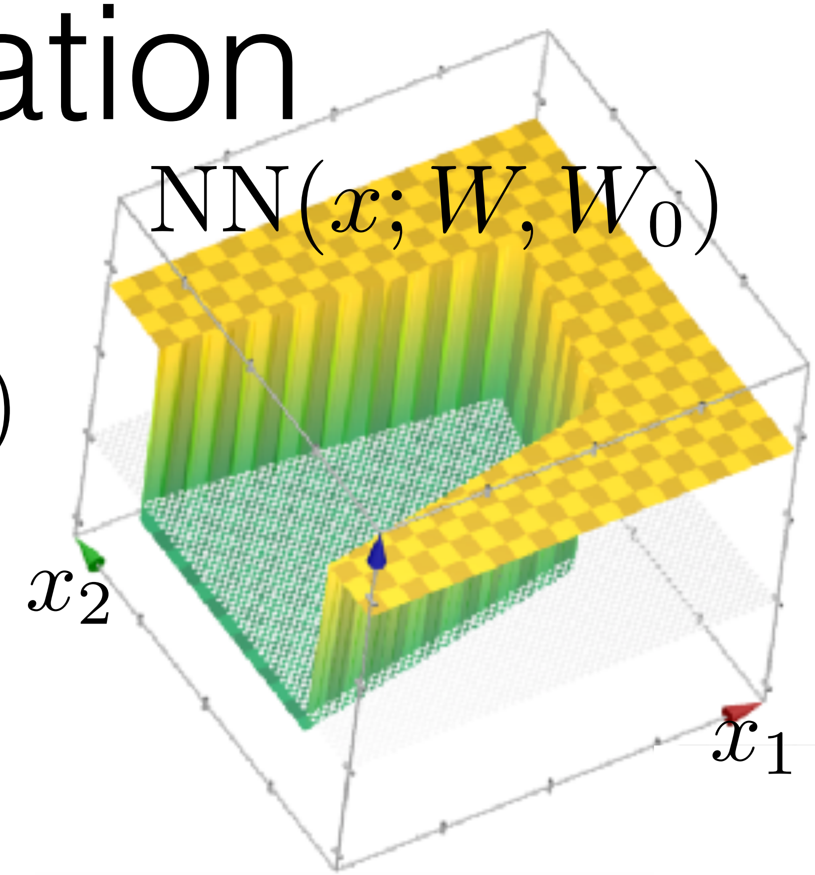




- Circle: function evaluation

Function graph representation



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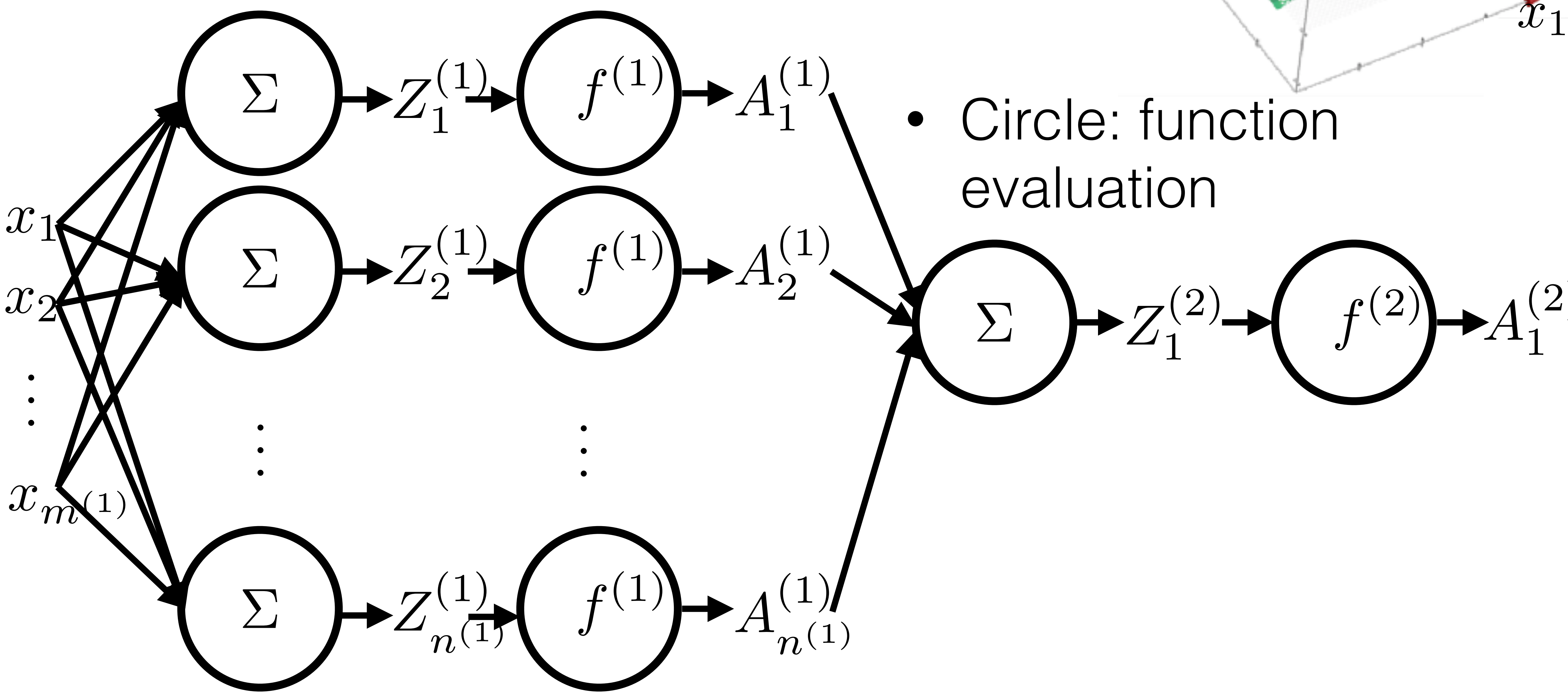
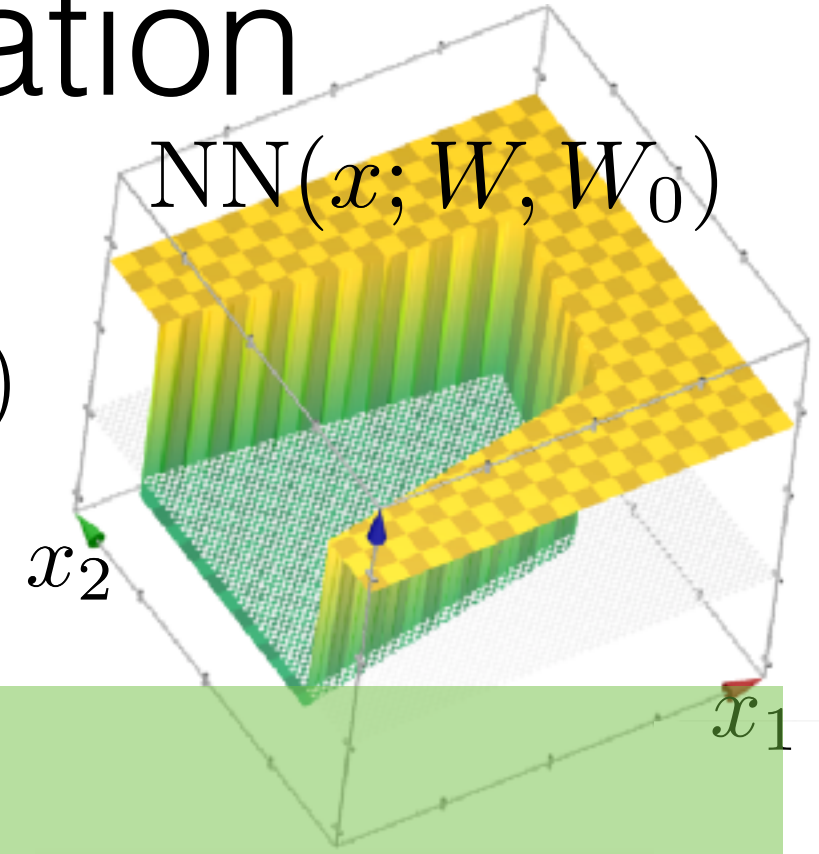


- Circle: function evaluation

Function graph representation



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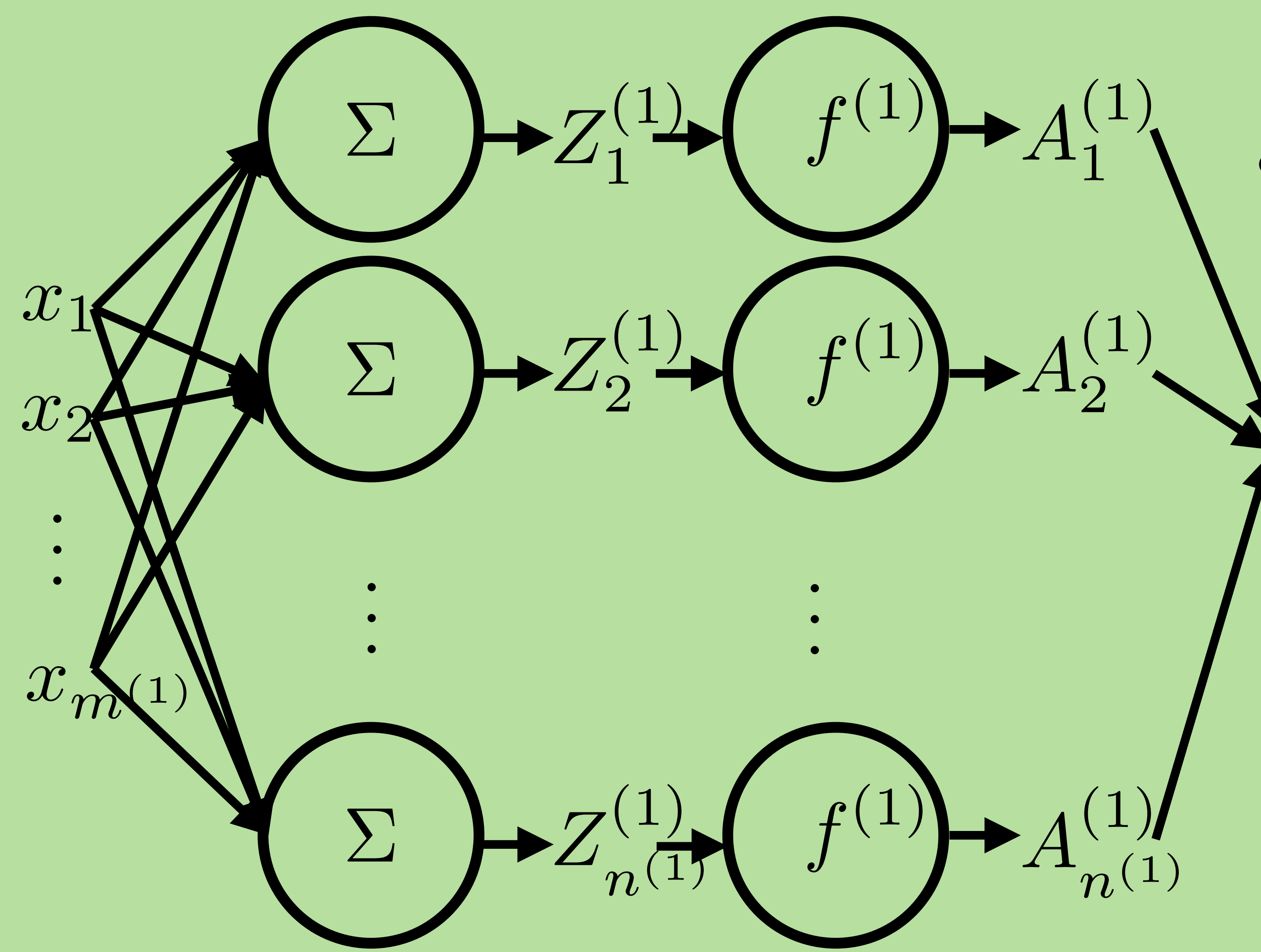

- Circle: function evaluation

Function graph representation

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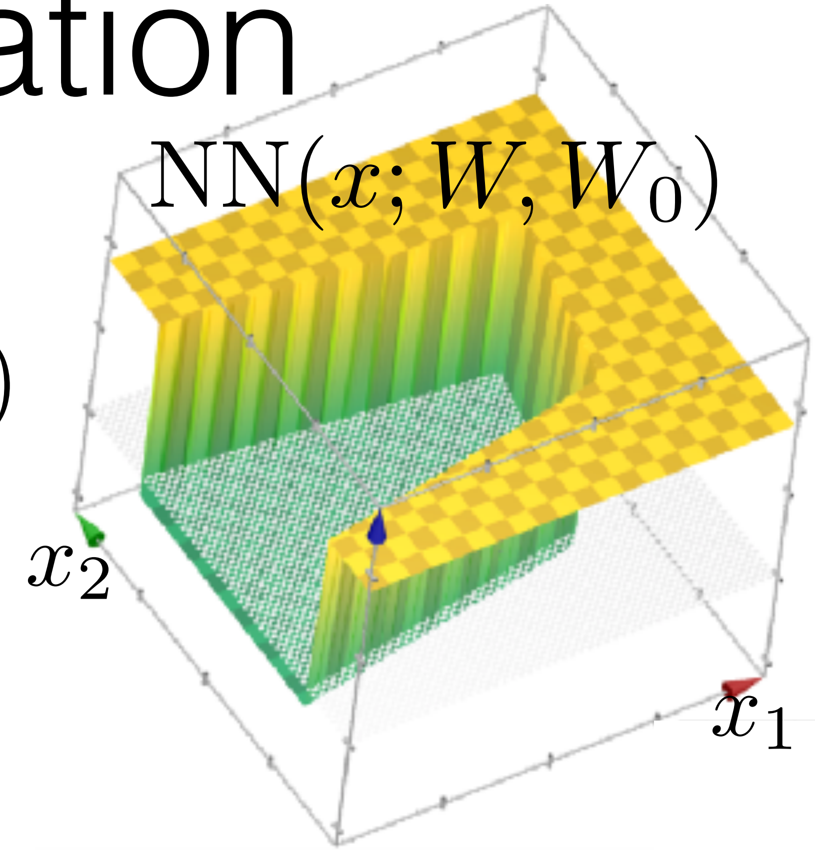
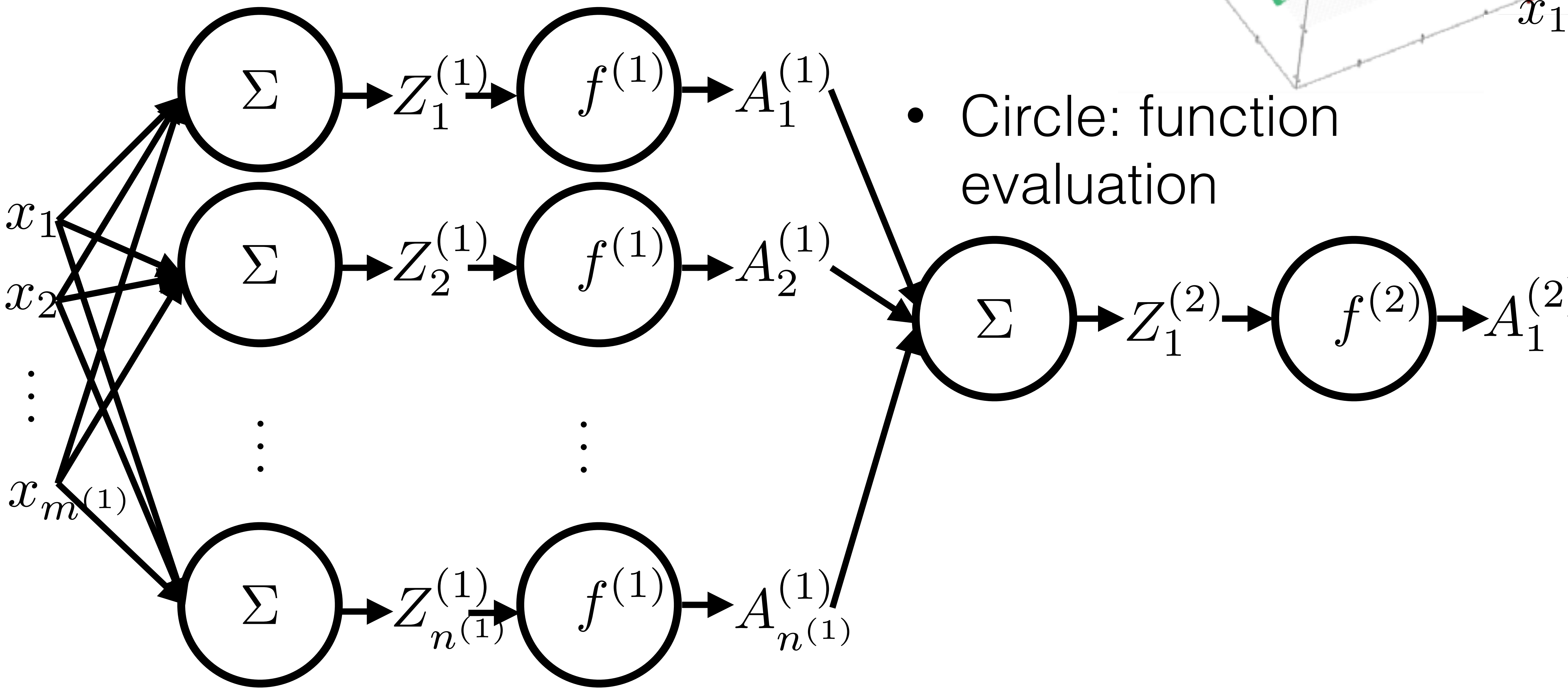
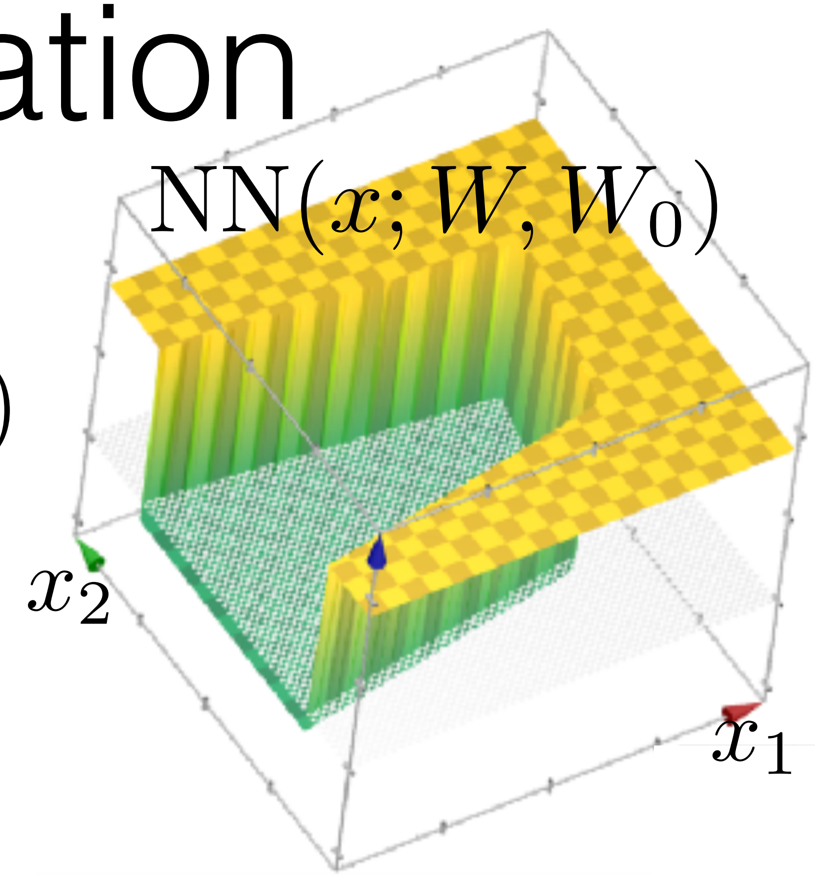




- Circle: function evaluation

Function graph representation



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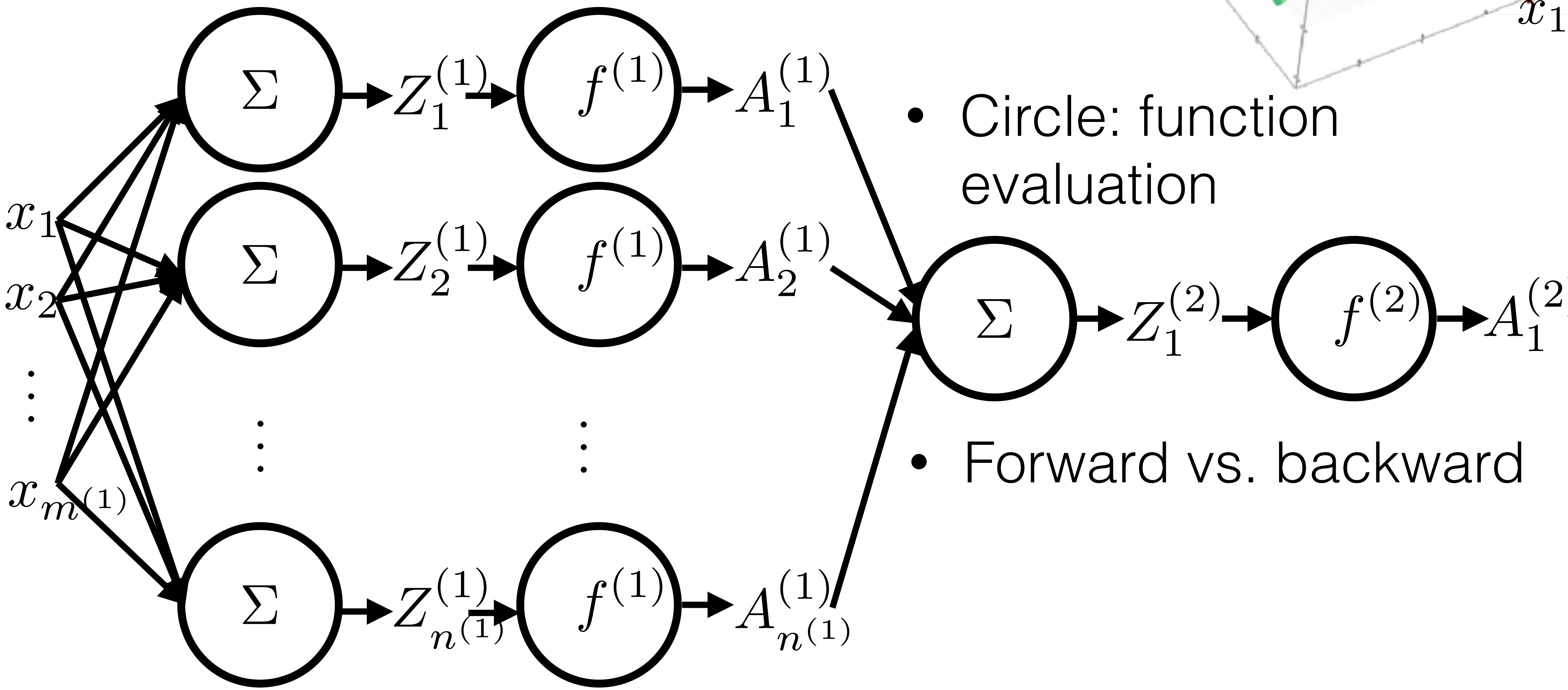

- Circle: function evaluation
- Forward vs. backward

Function graph representation

- 1st layer: $A^{(1)} = f^{(1)}(W^{(1)\top}x + W_0^{(1)})$
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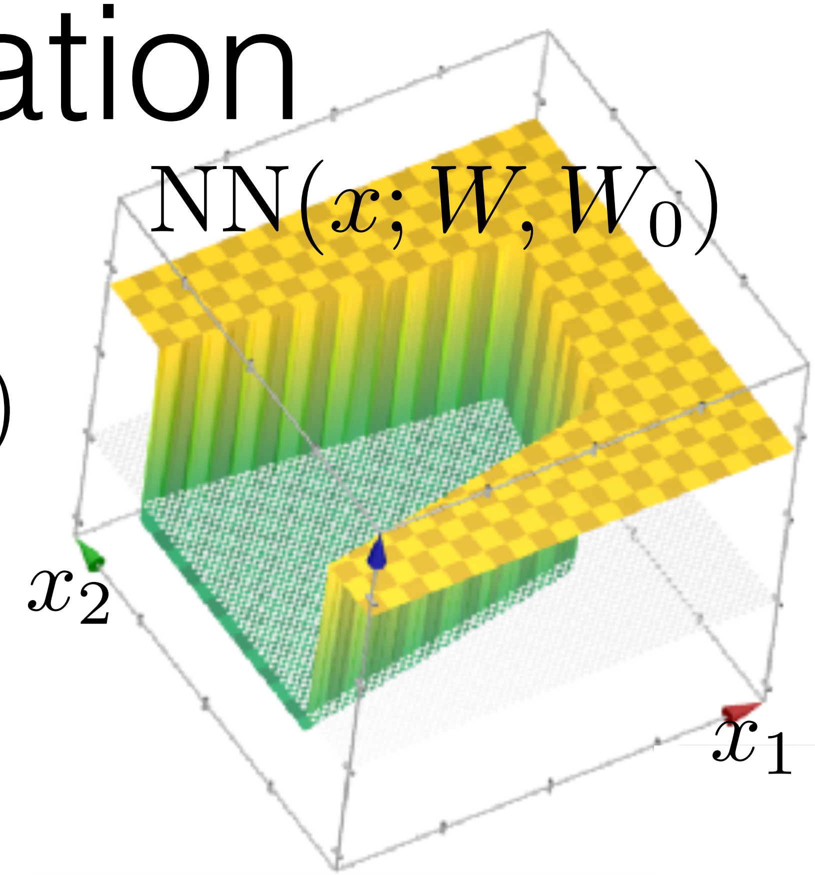
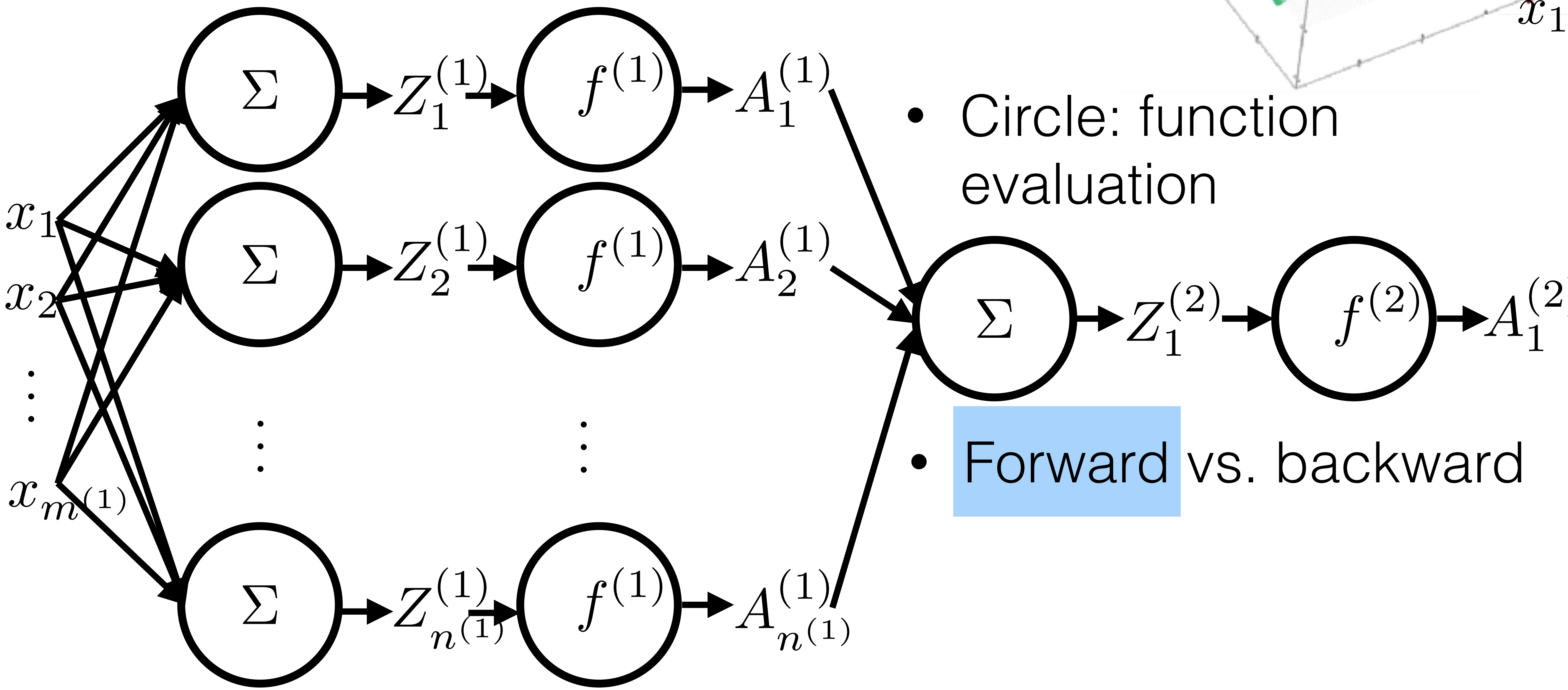
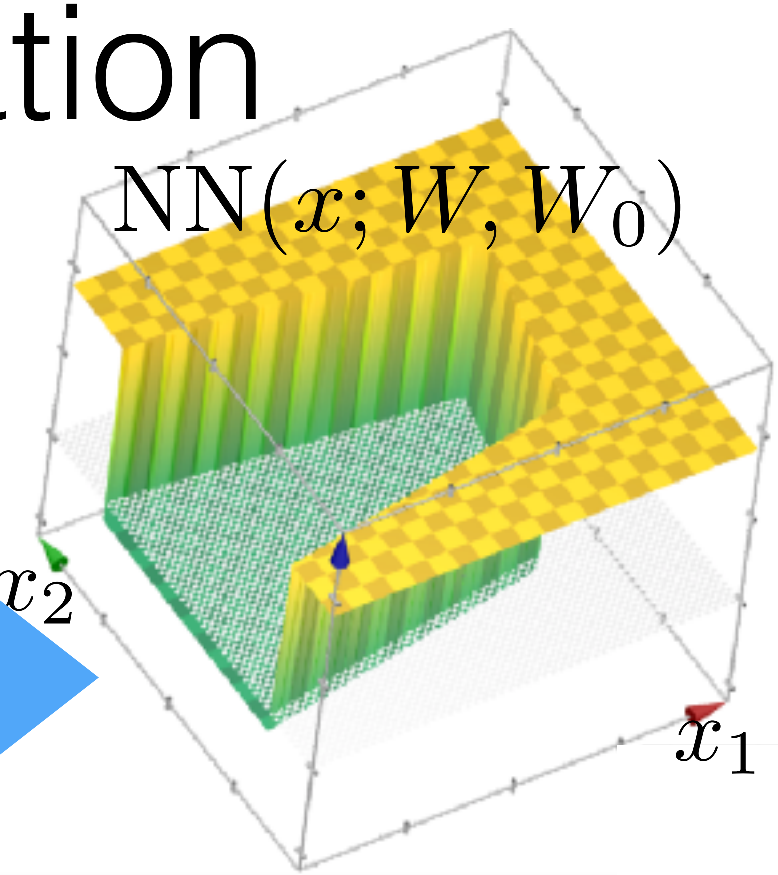




- Circle: function evaluation
- Forward vs. backward

Function graph representation



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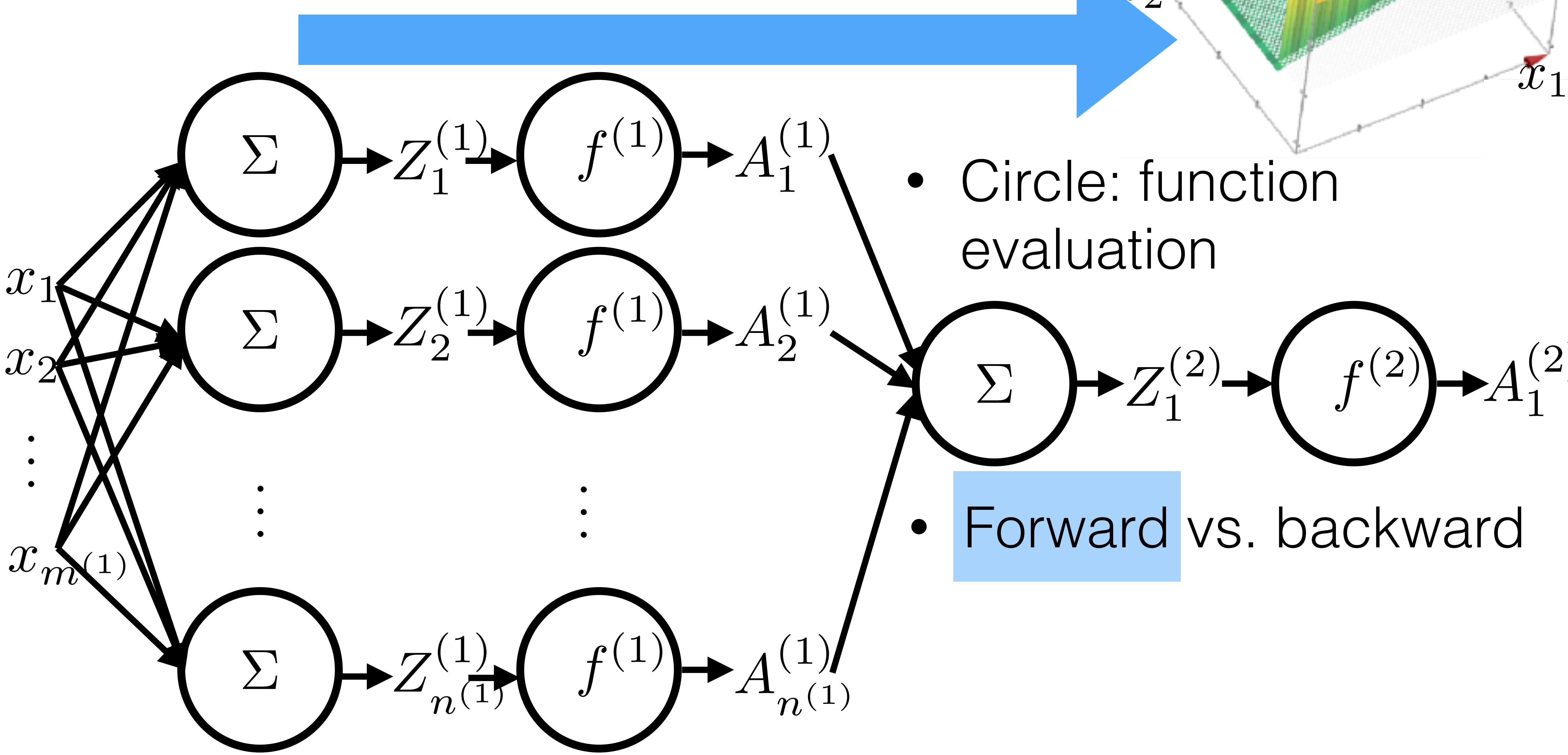

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Function graph representation

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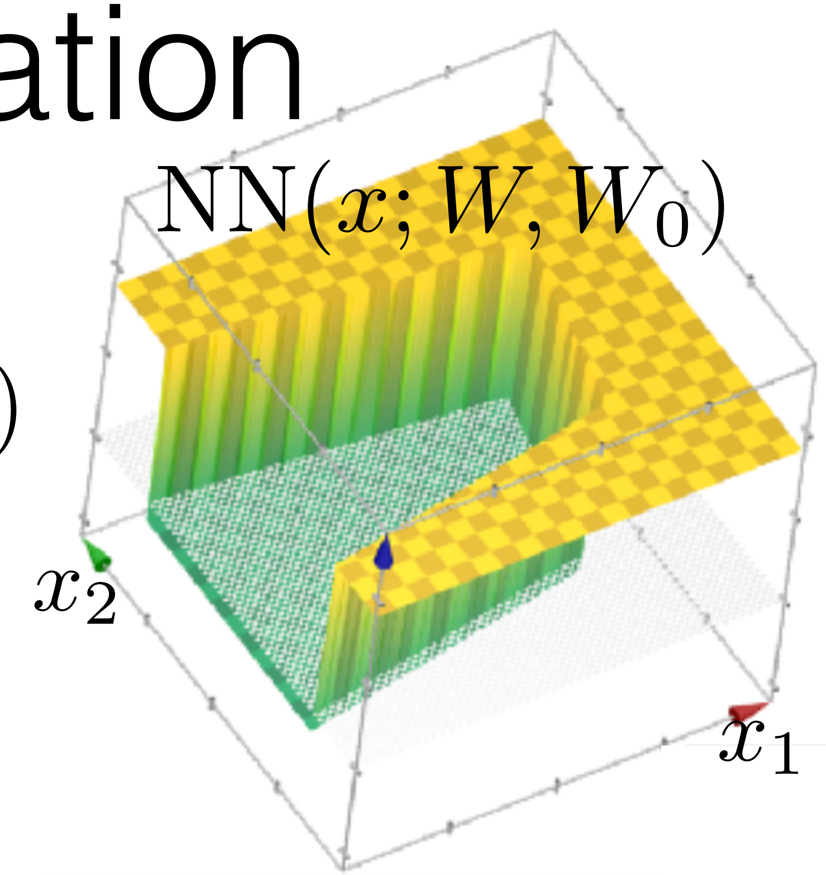

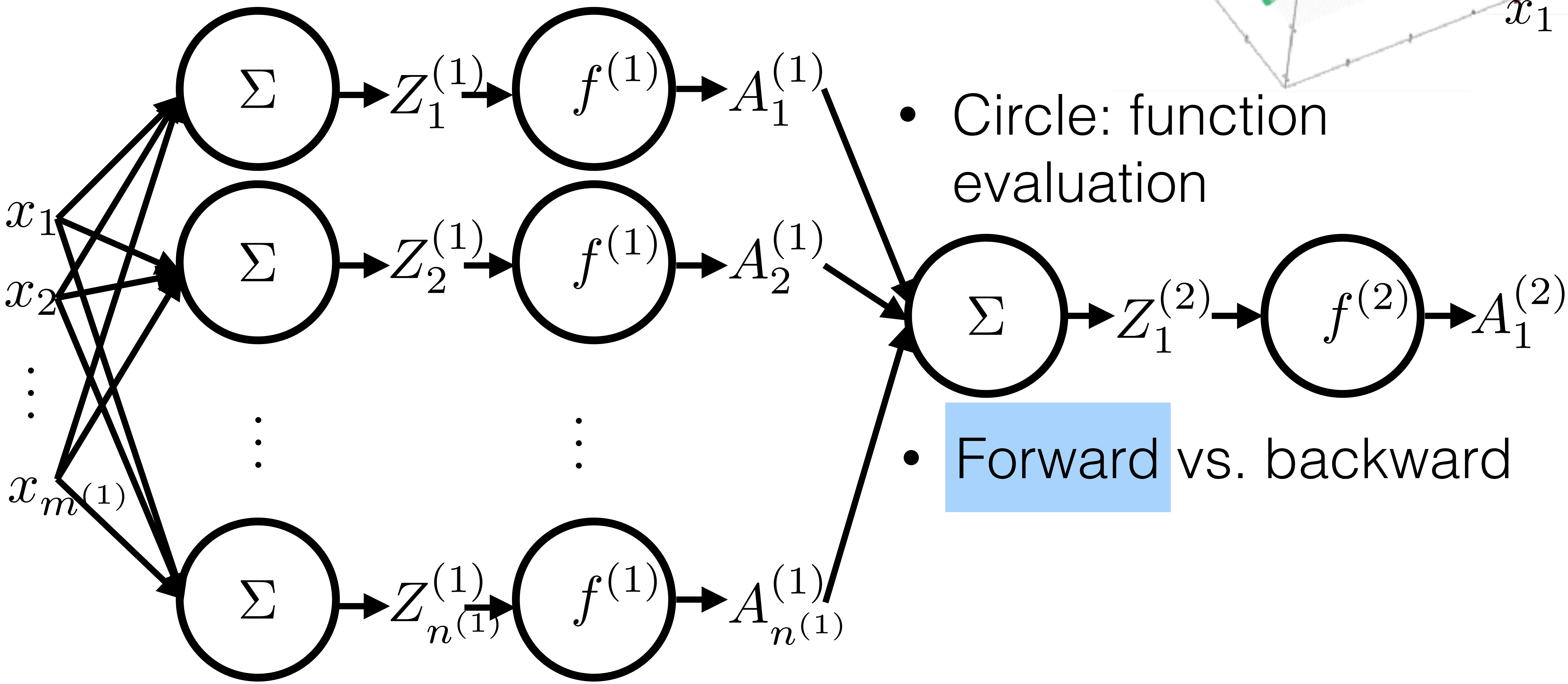

- Circle: function evaluation
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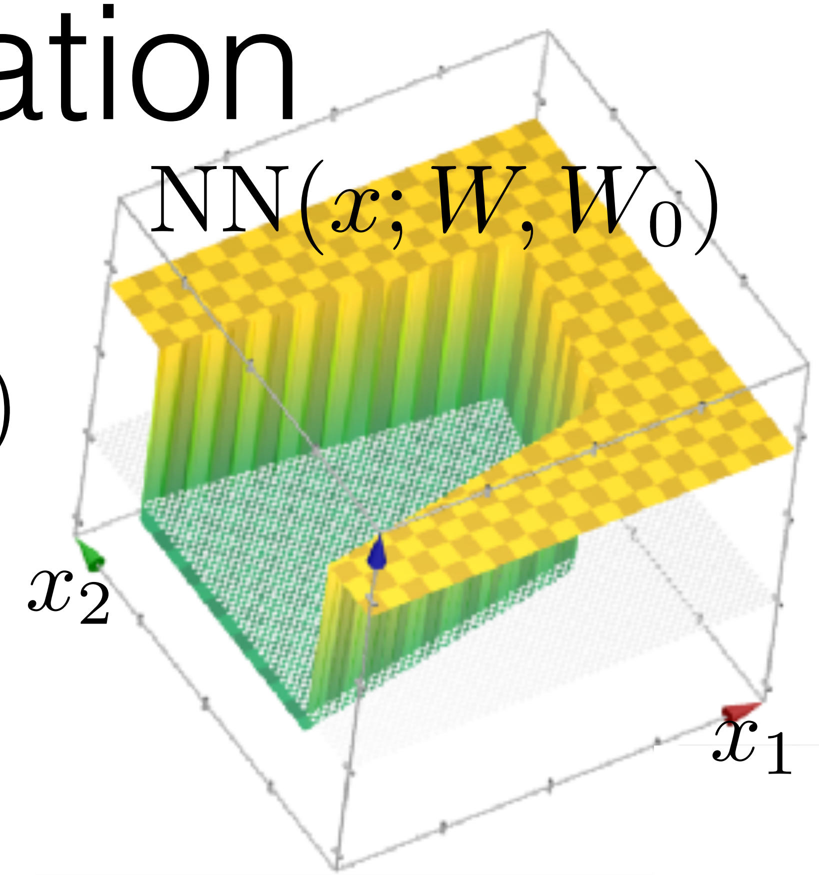

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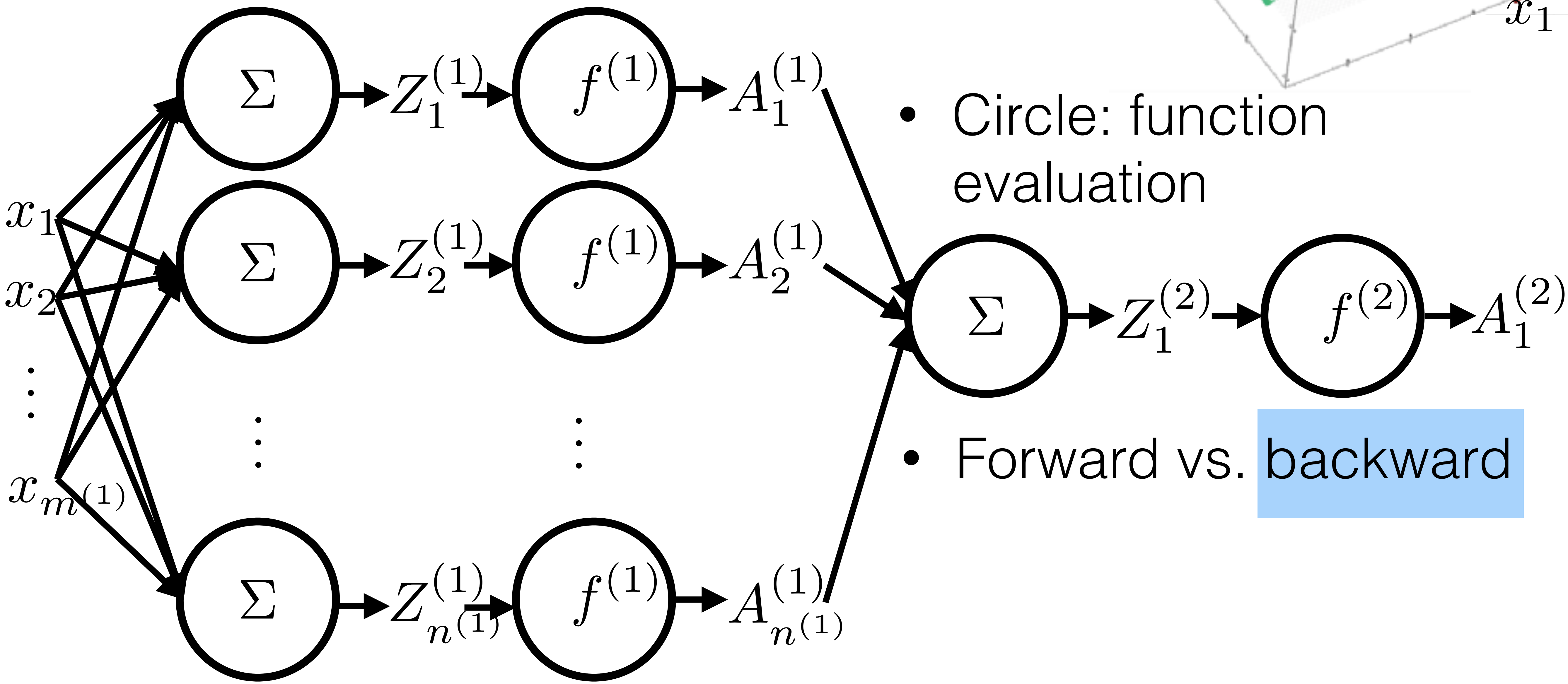

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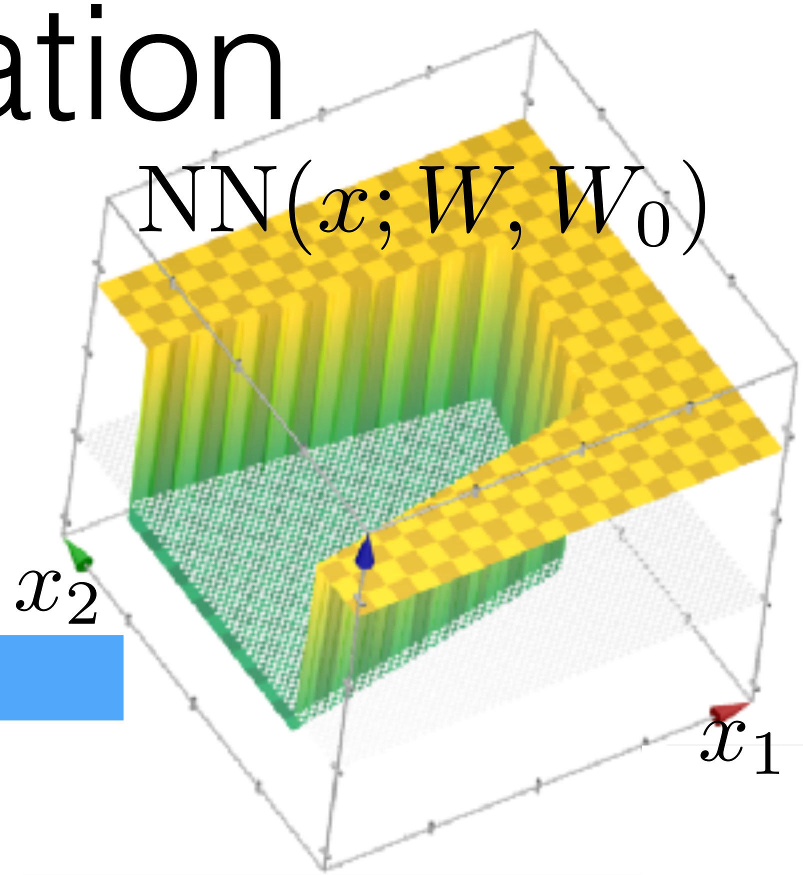

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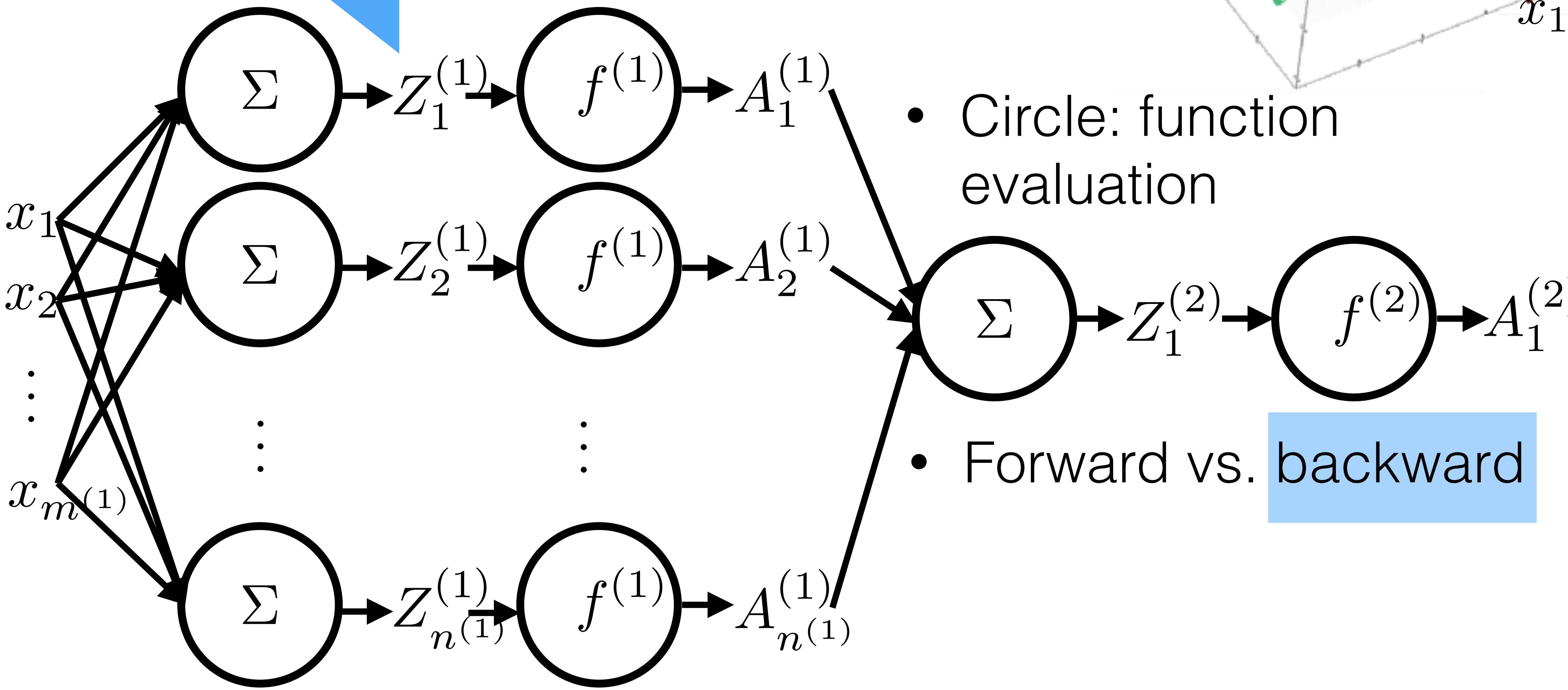

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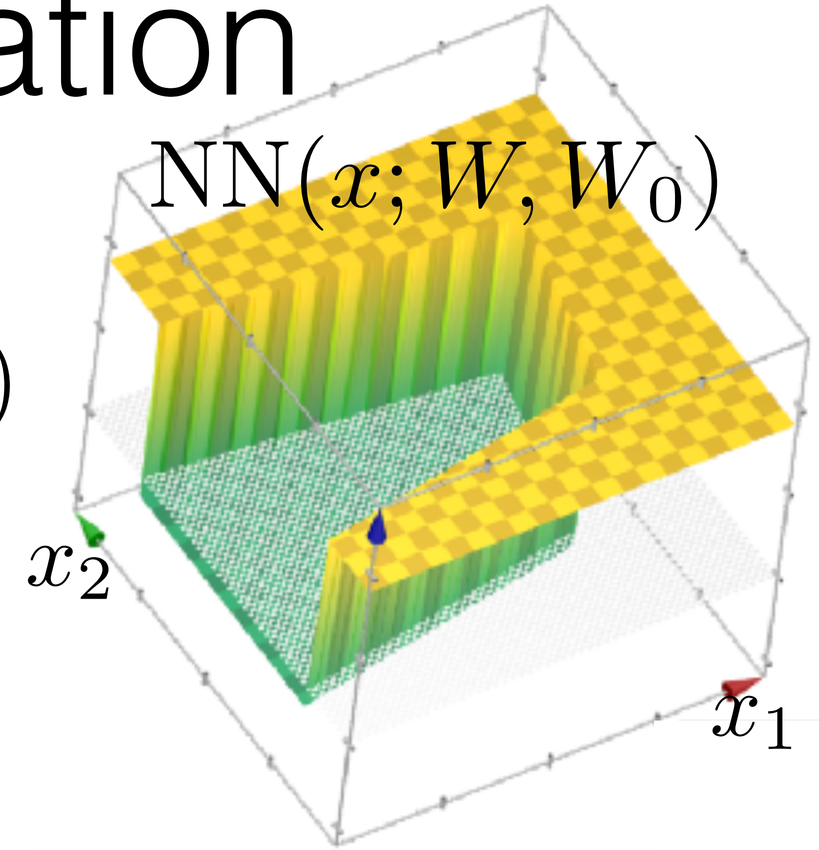

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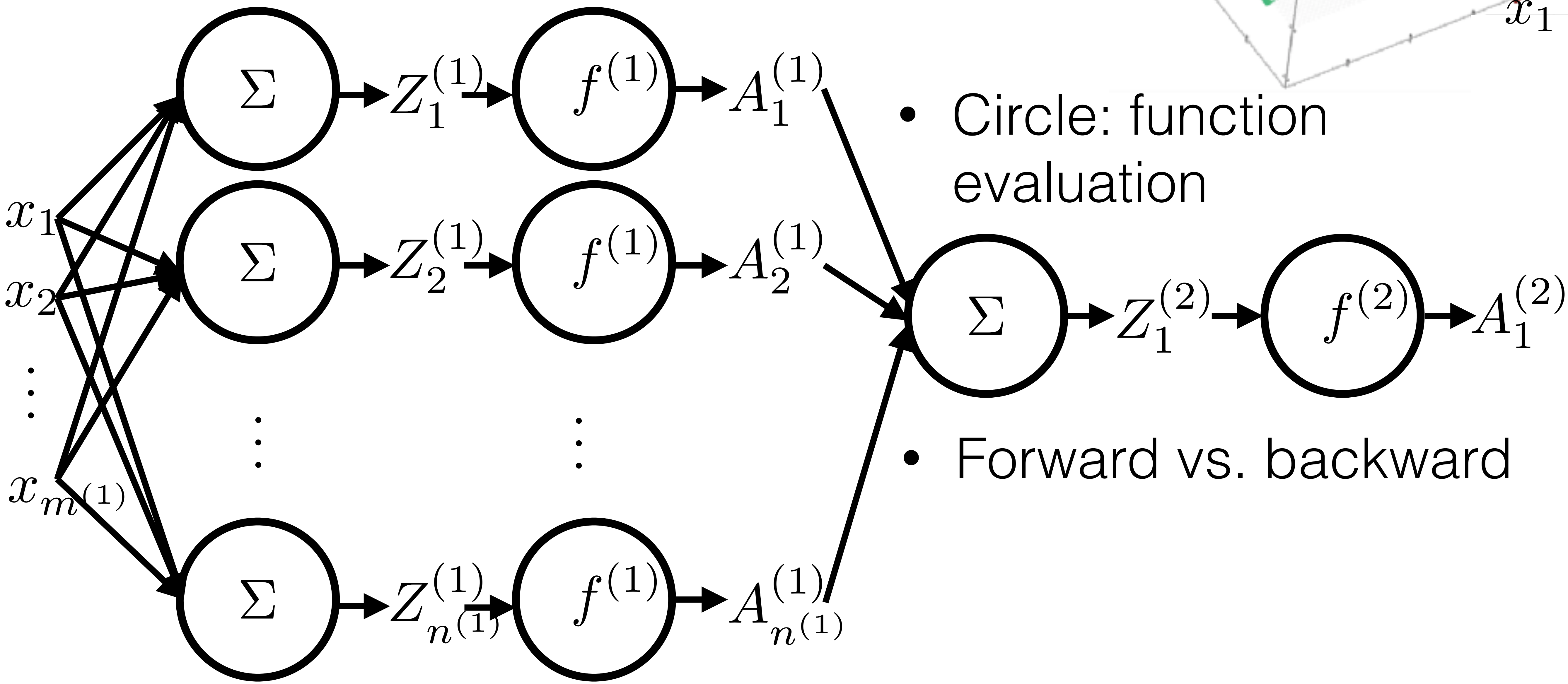

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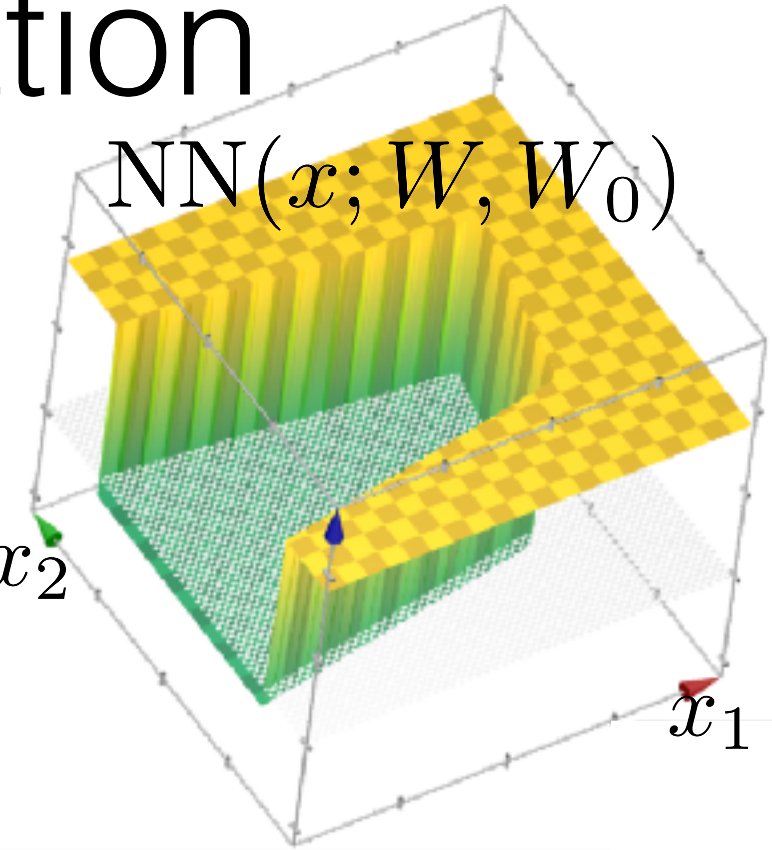

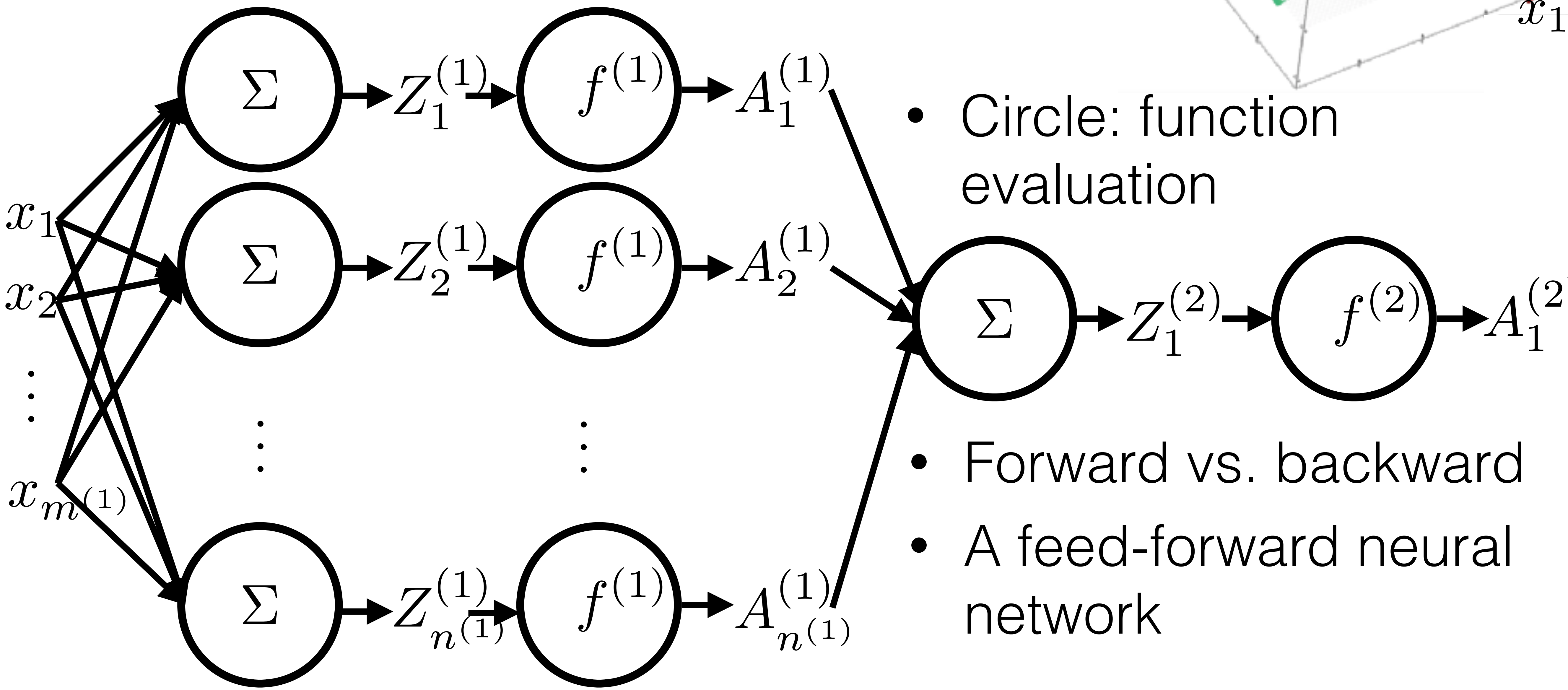

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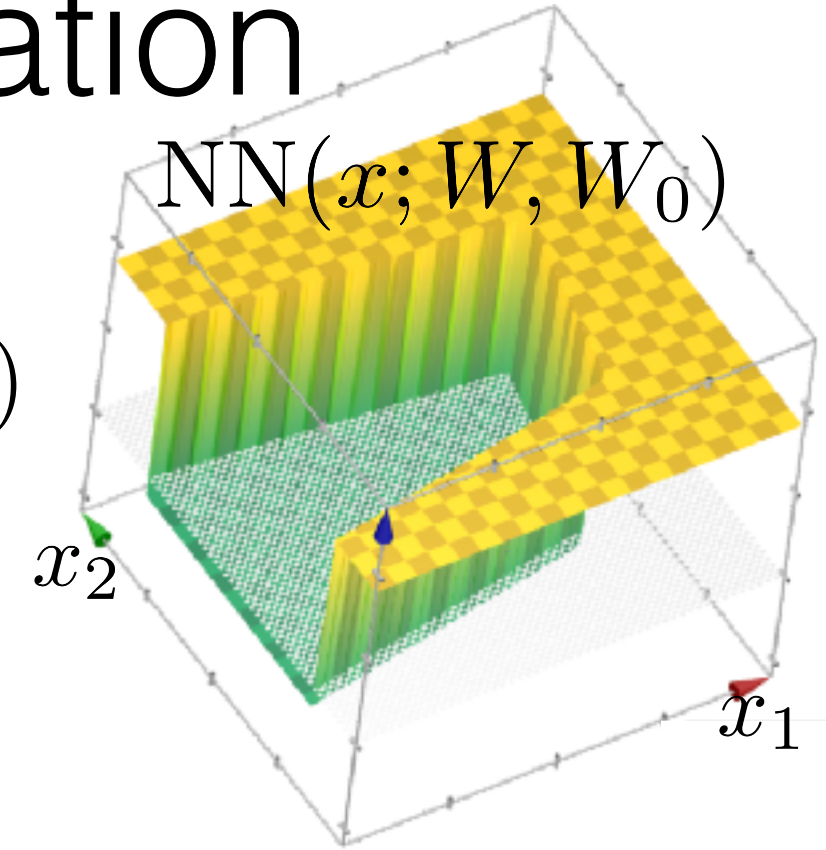

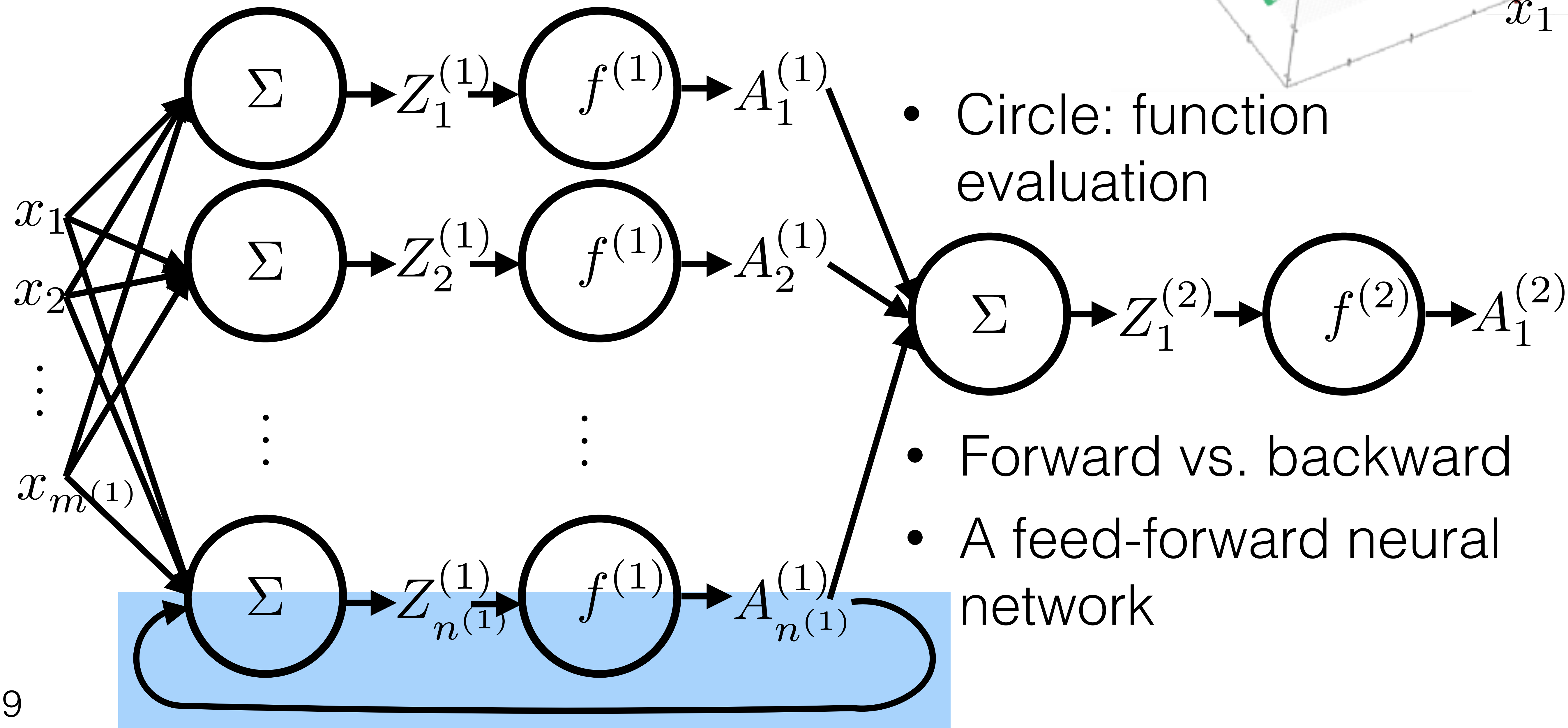

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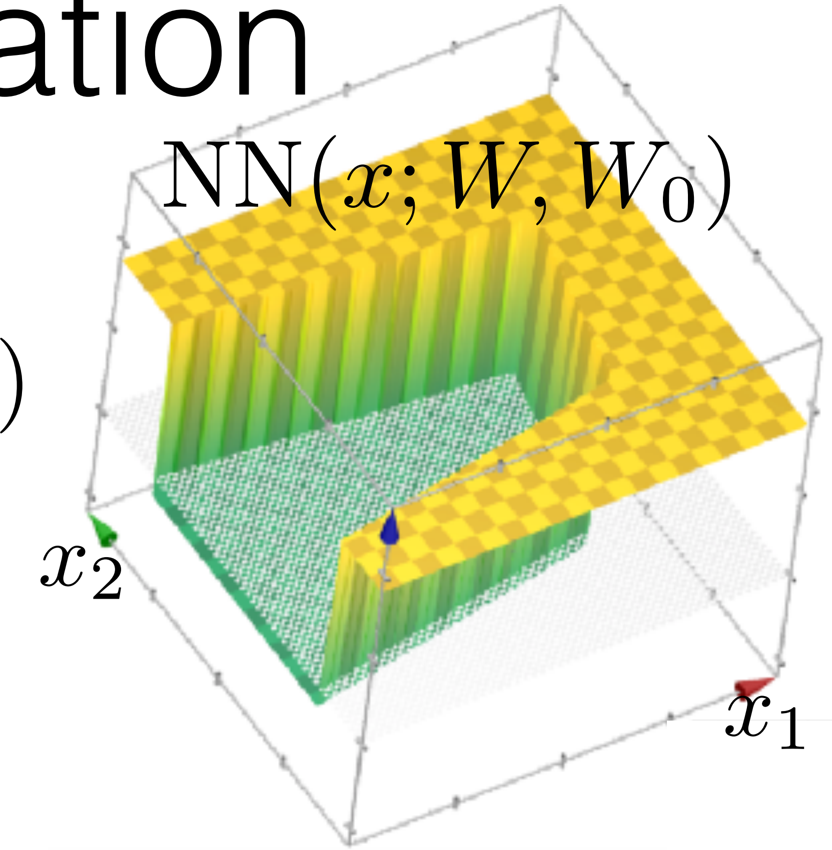

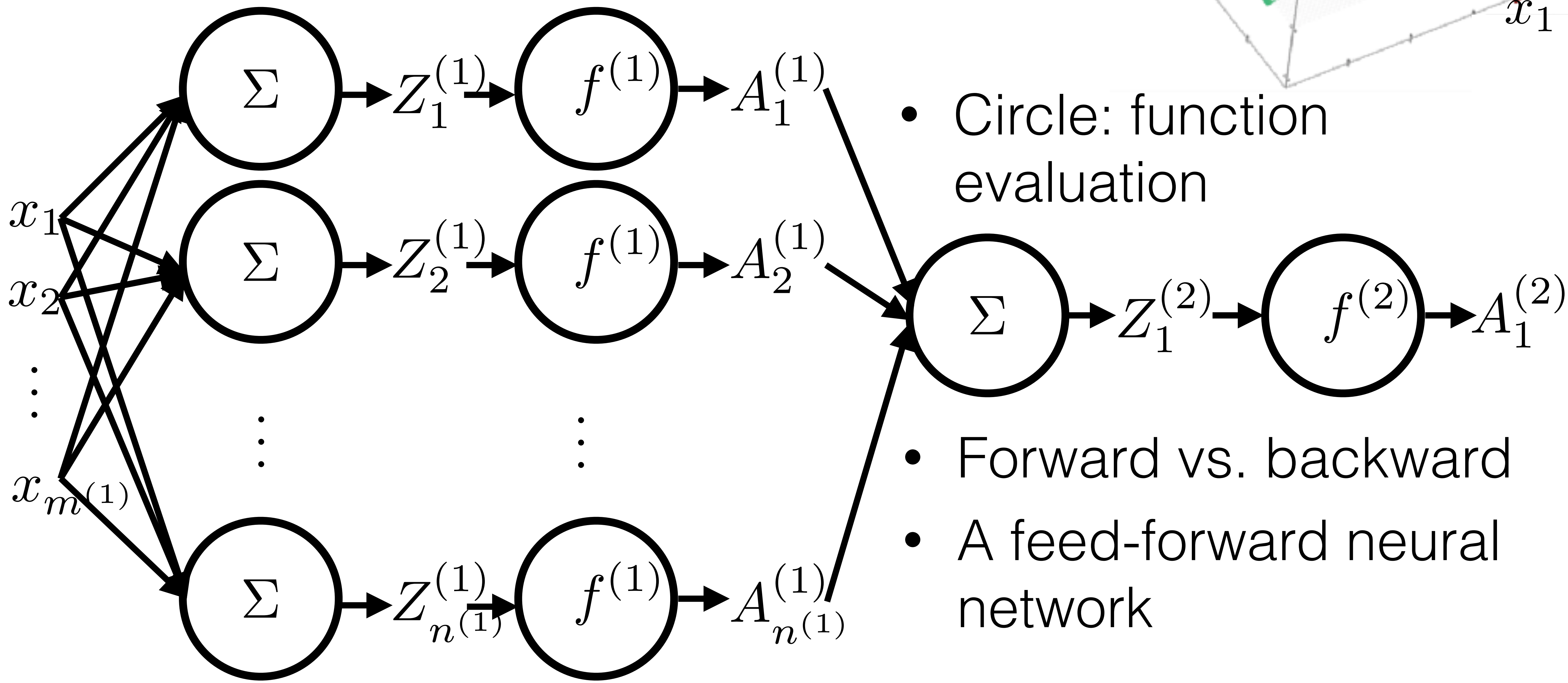

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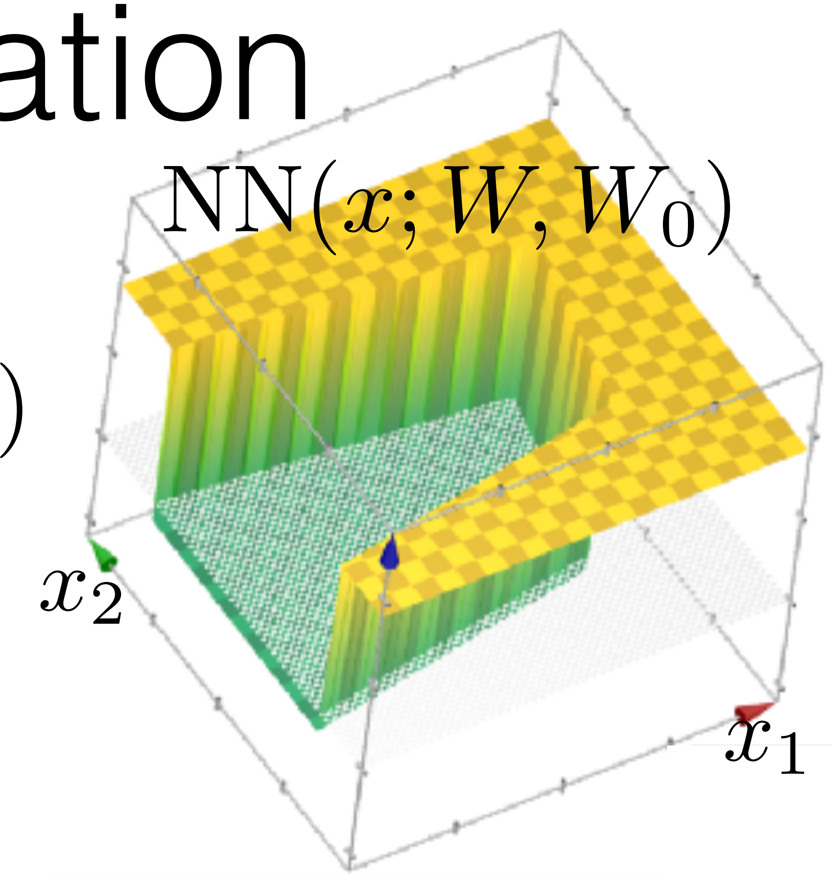

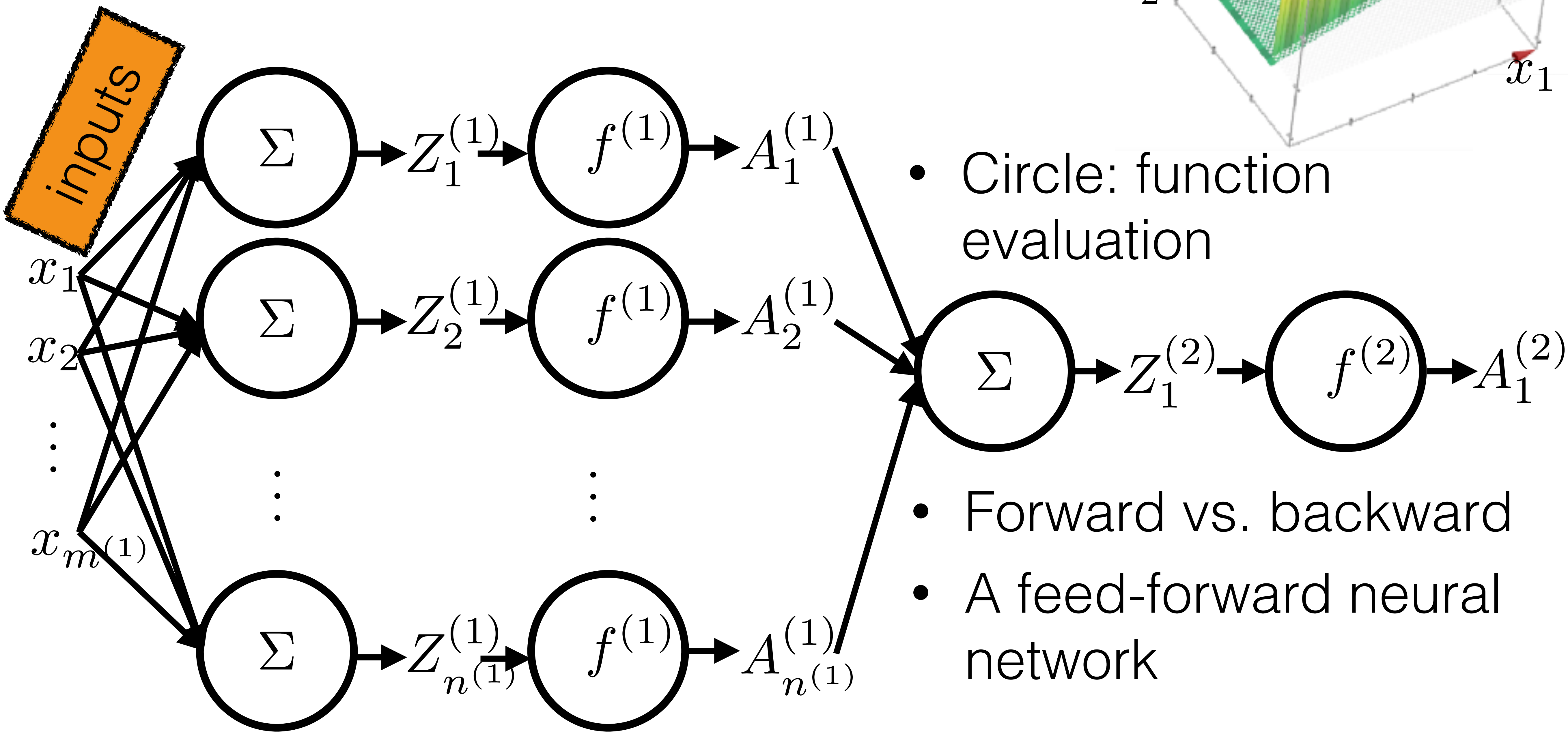

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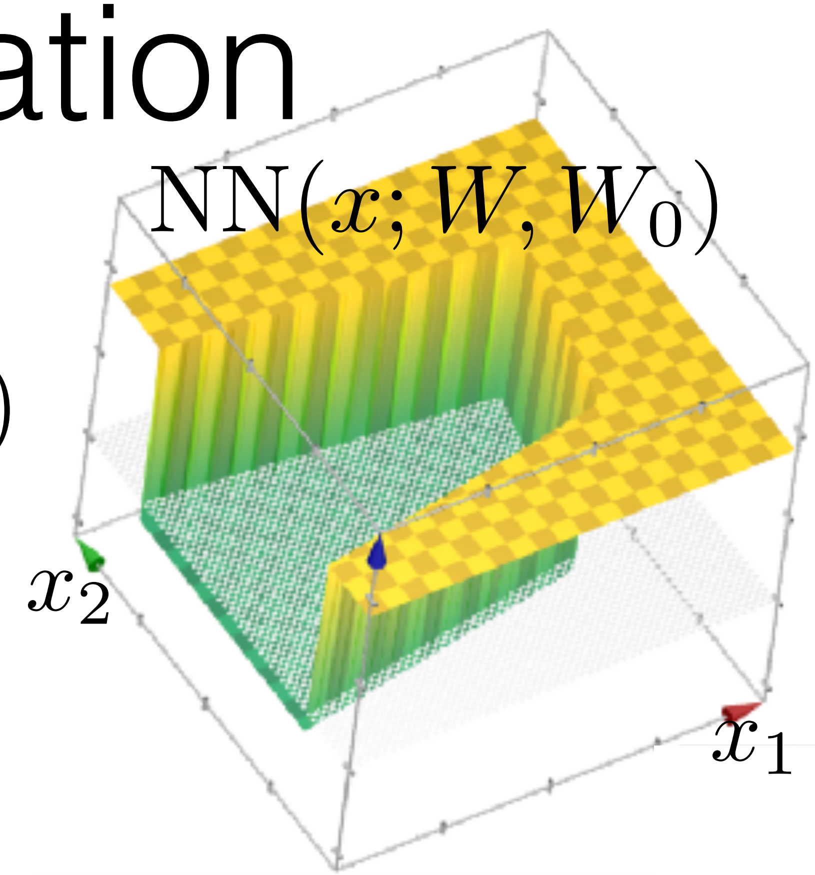
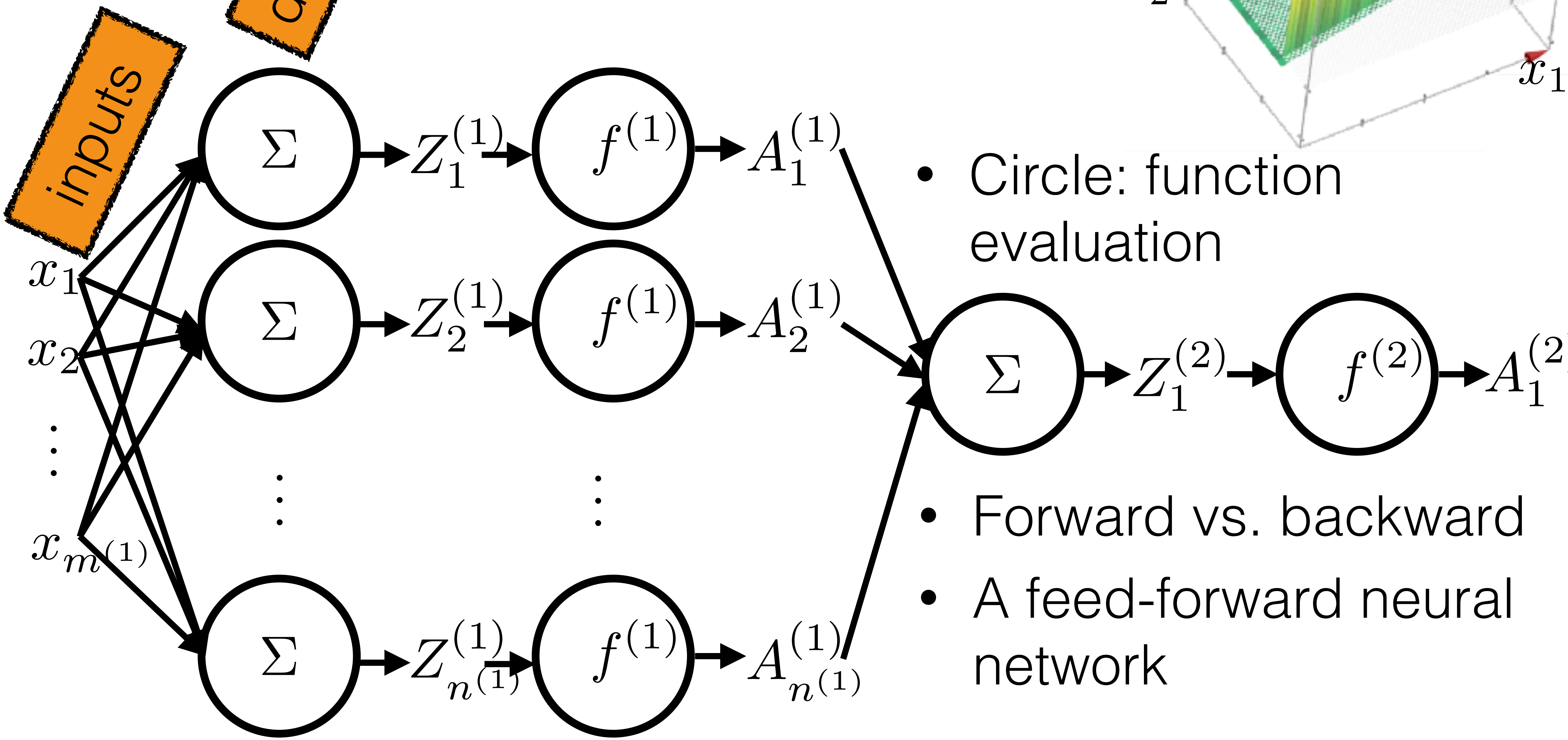
dot product





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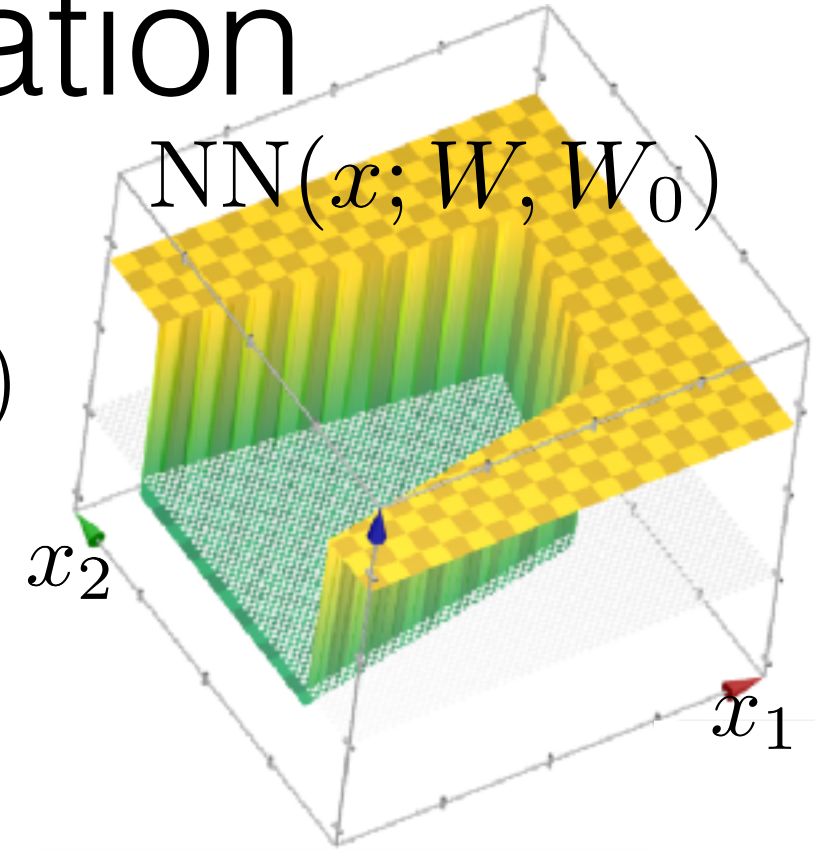

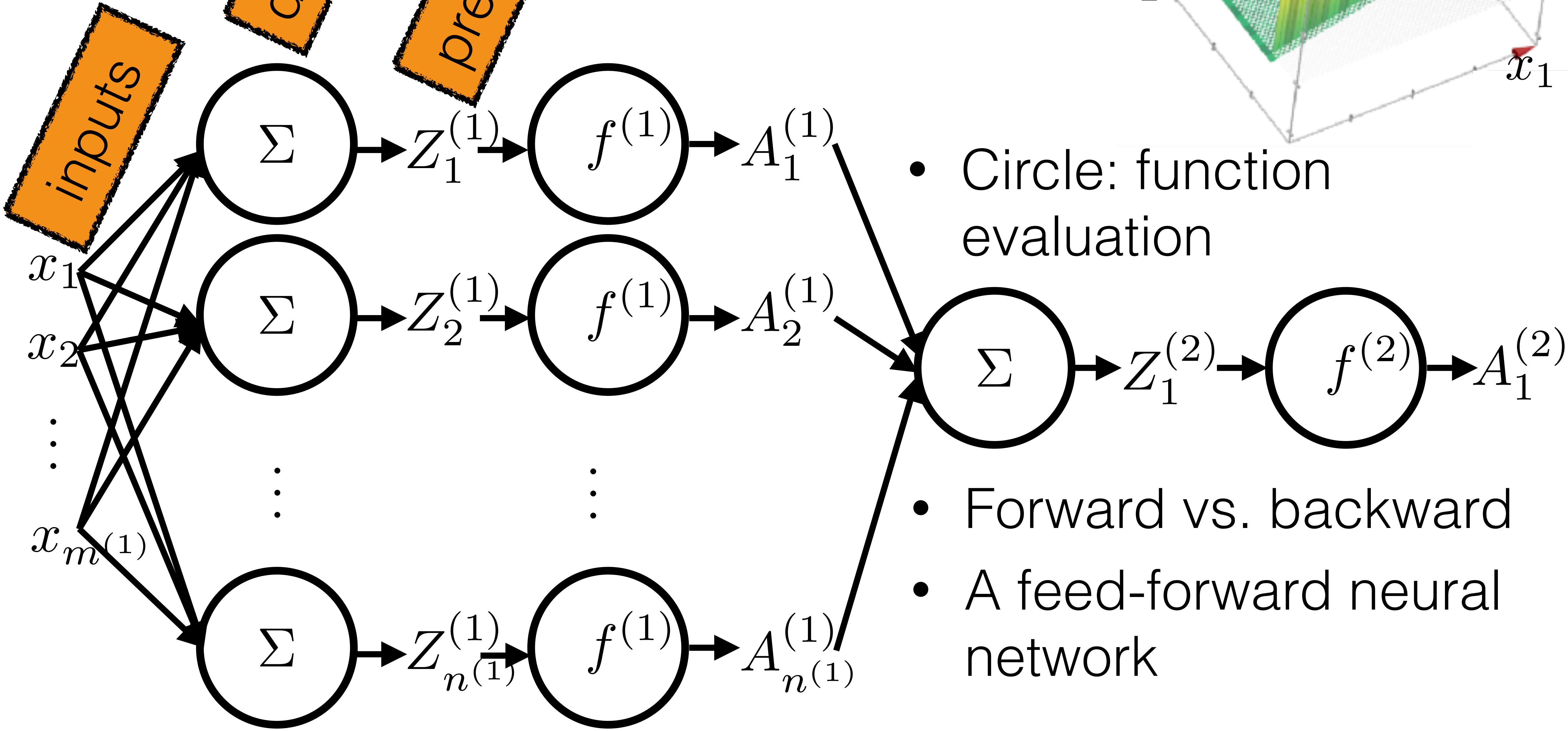

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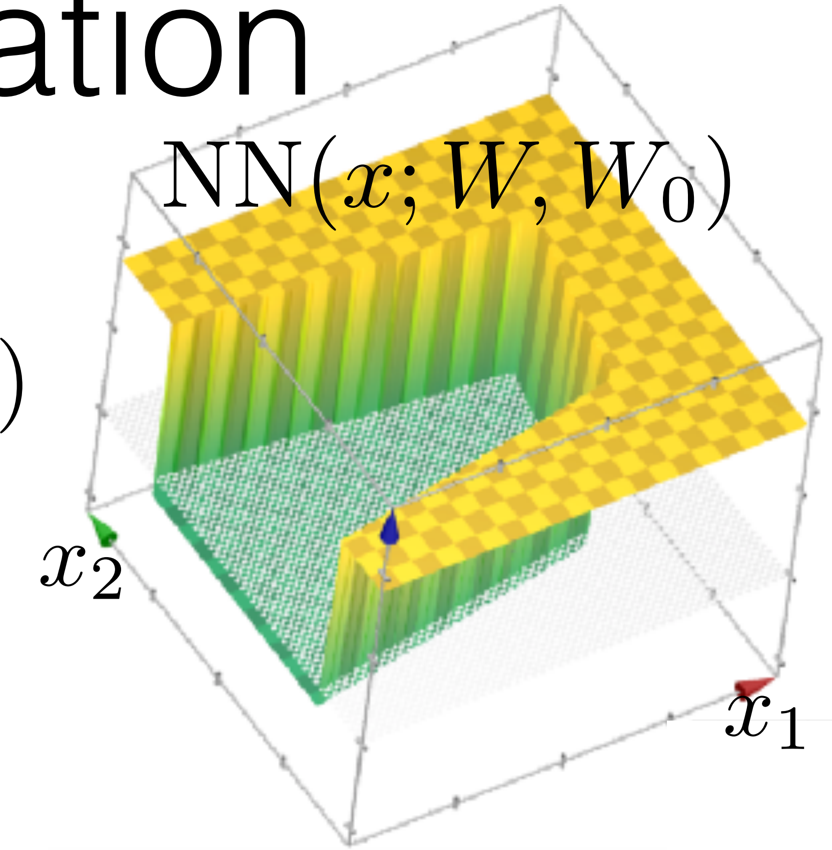

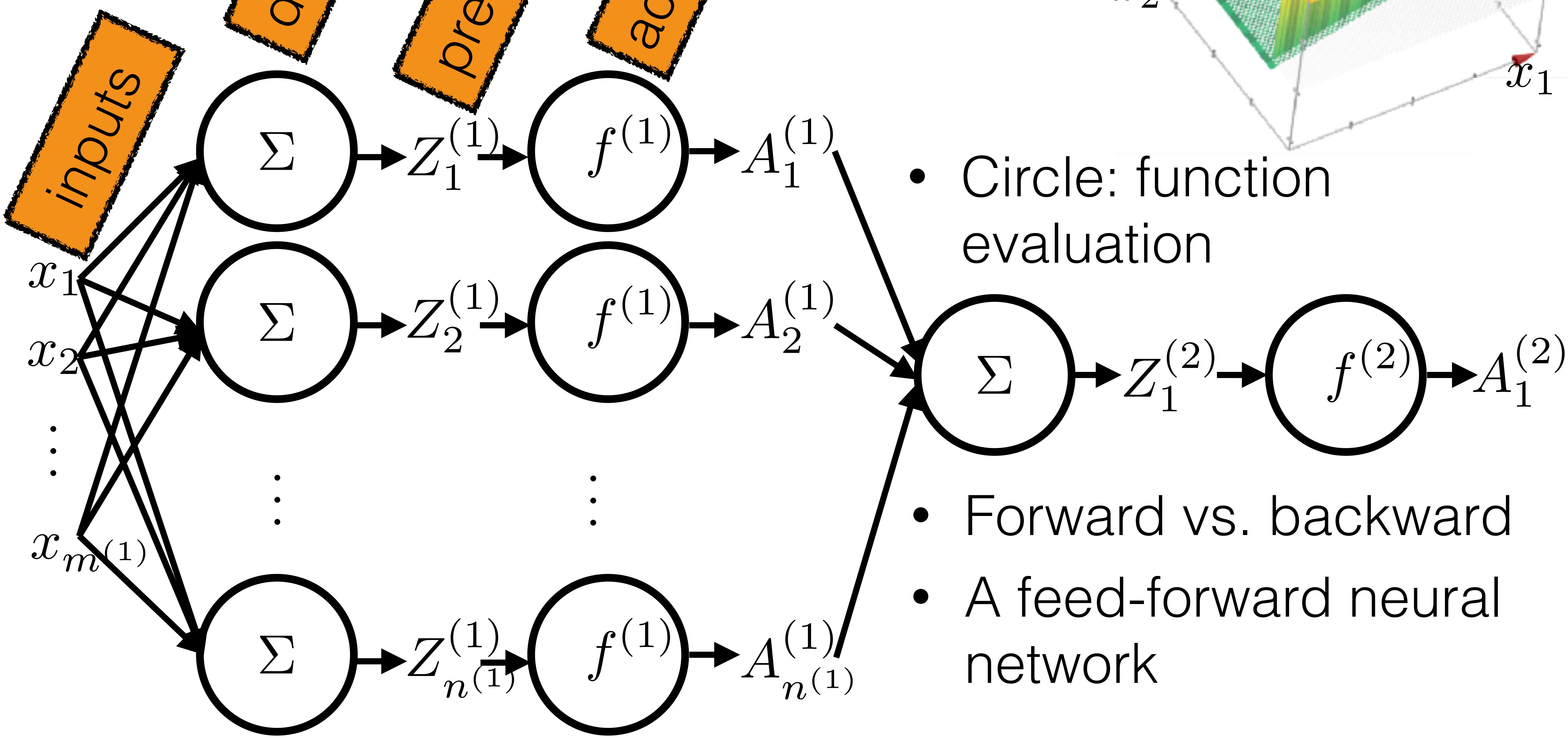

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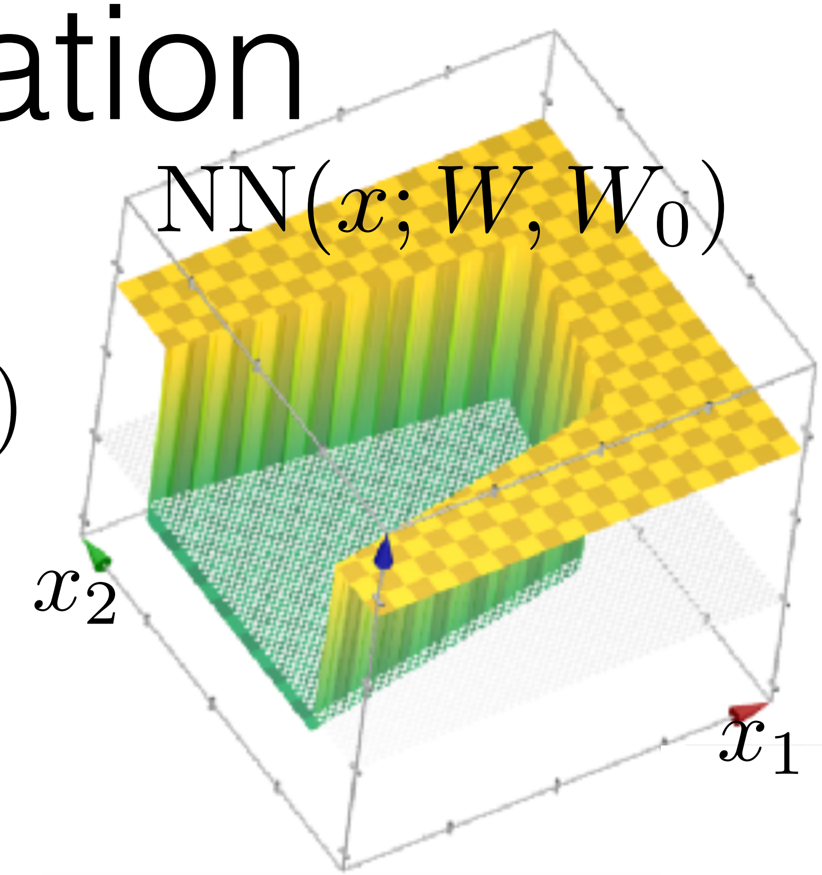

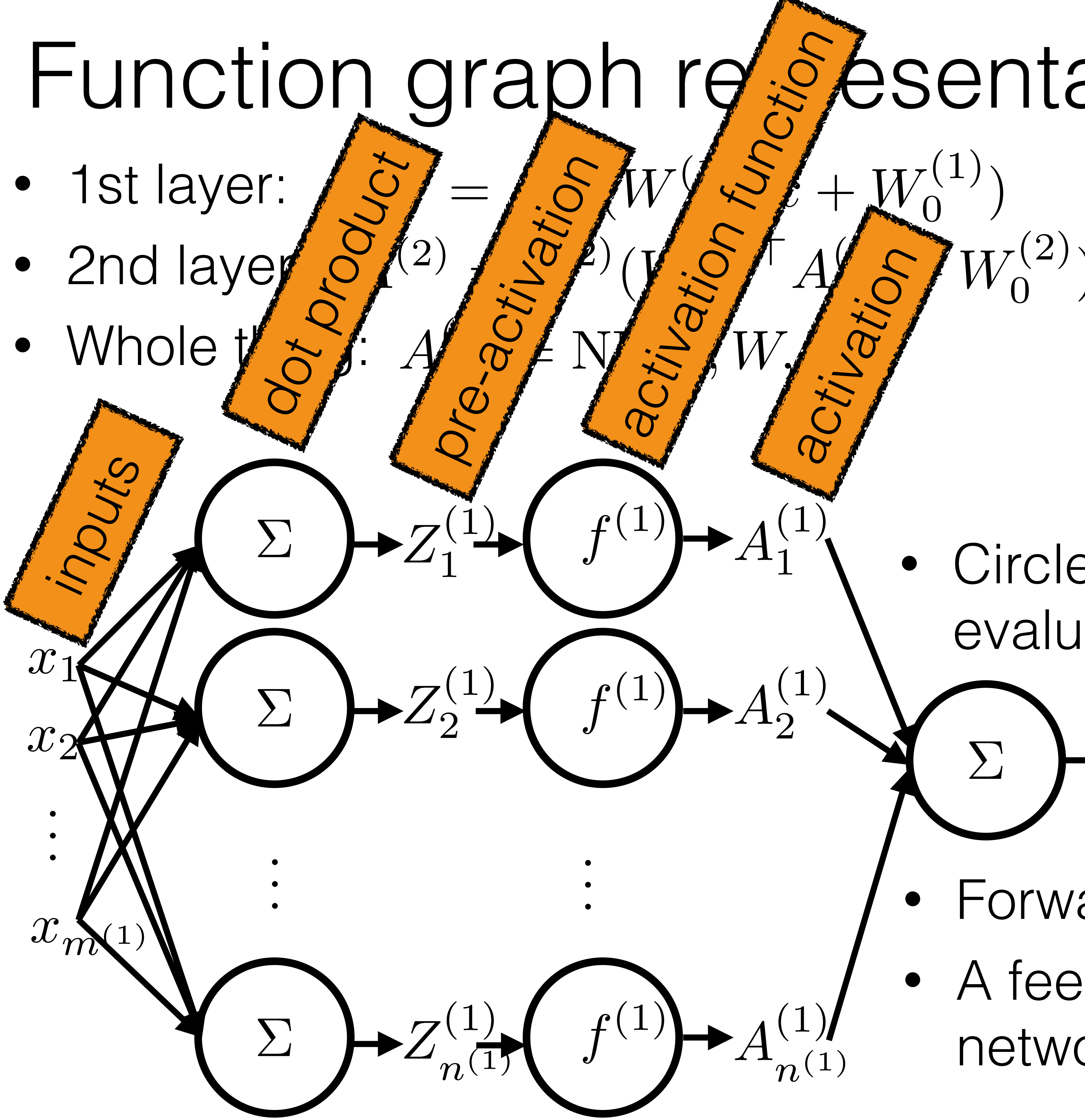

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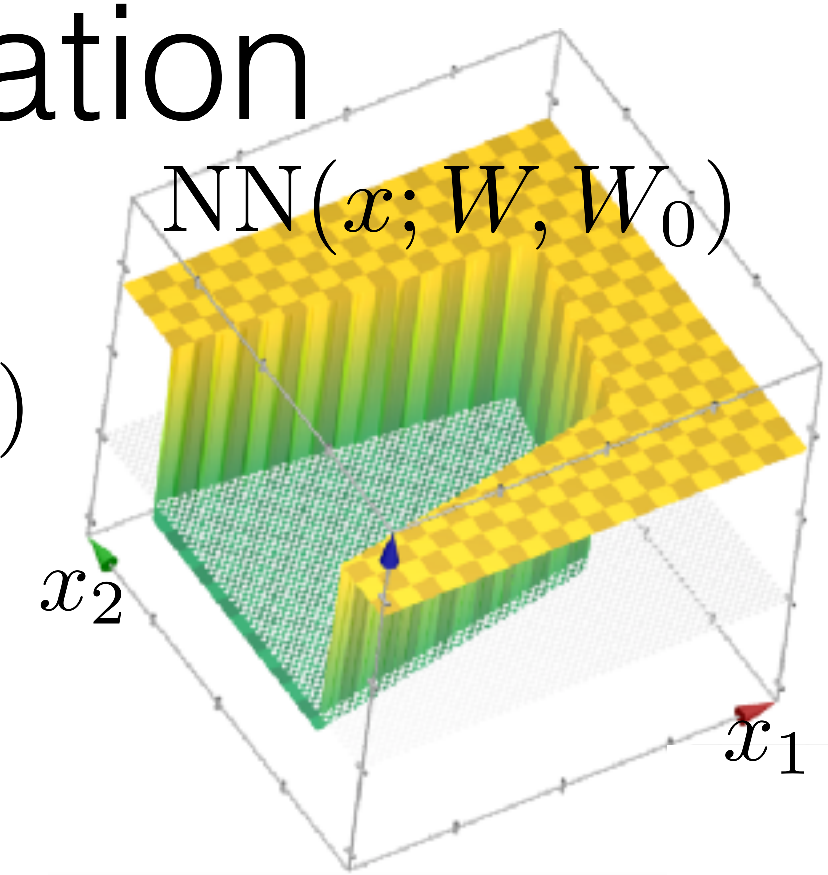

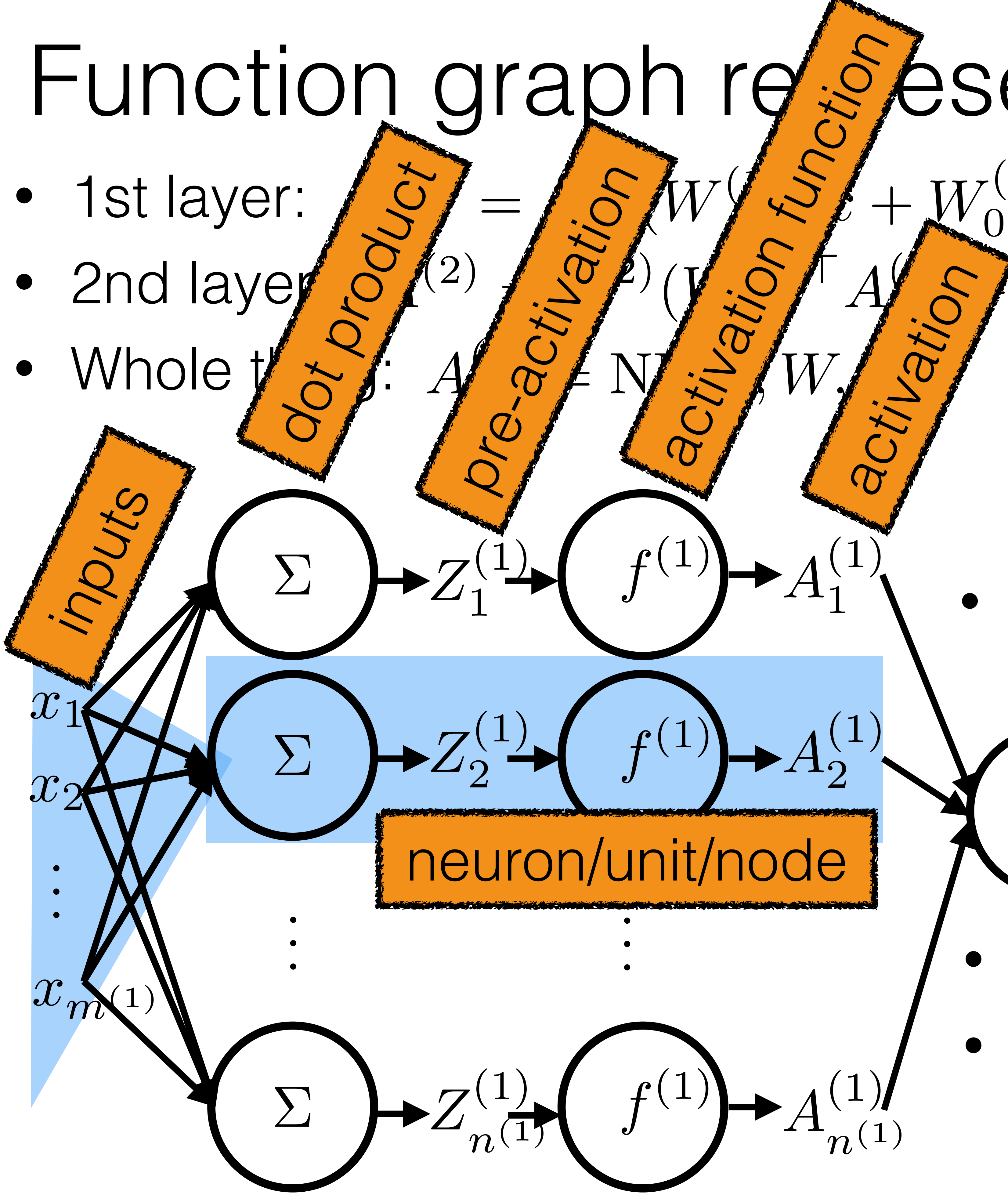

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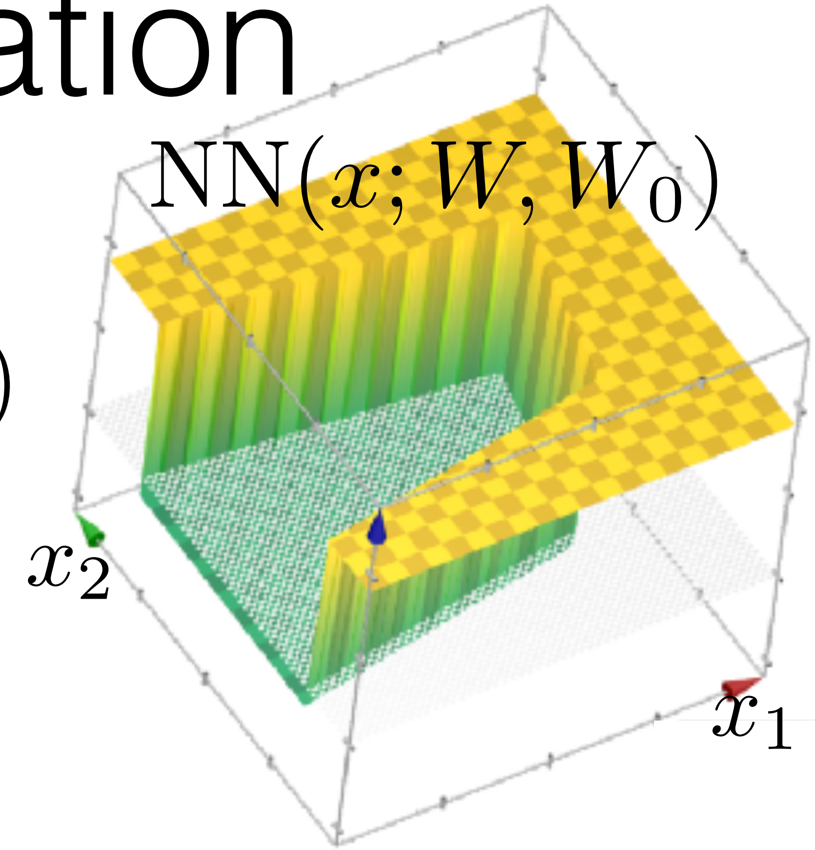

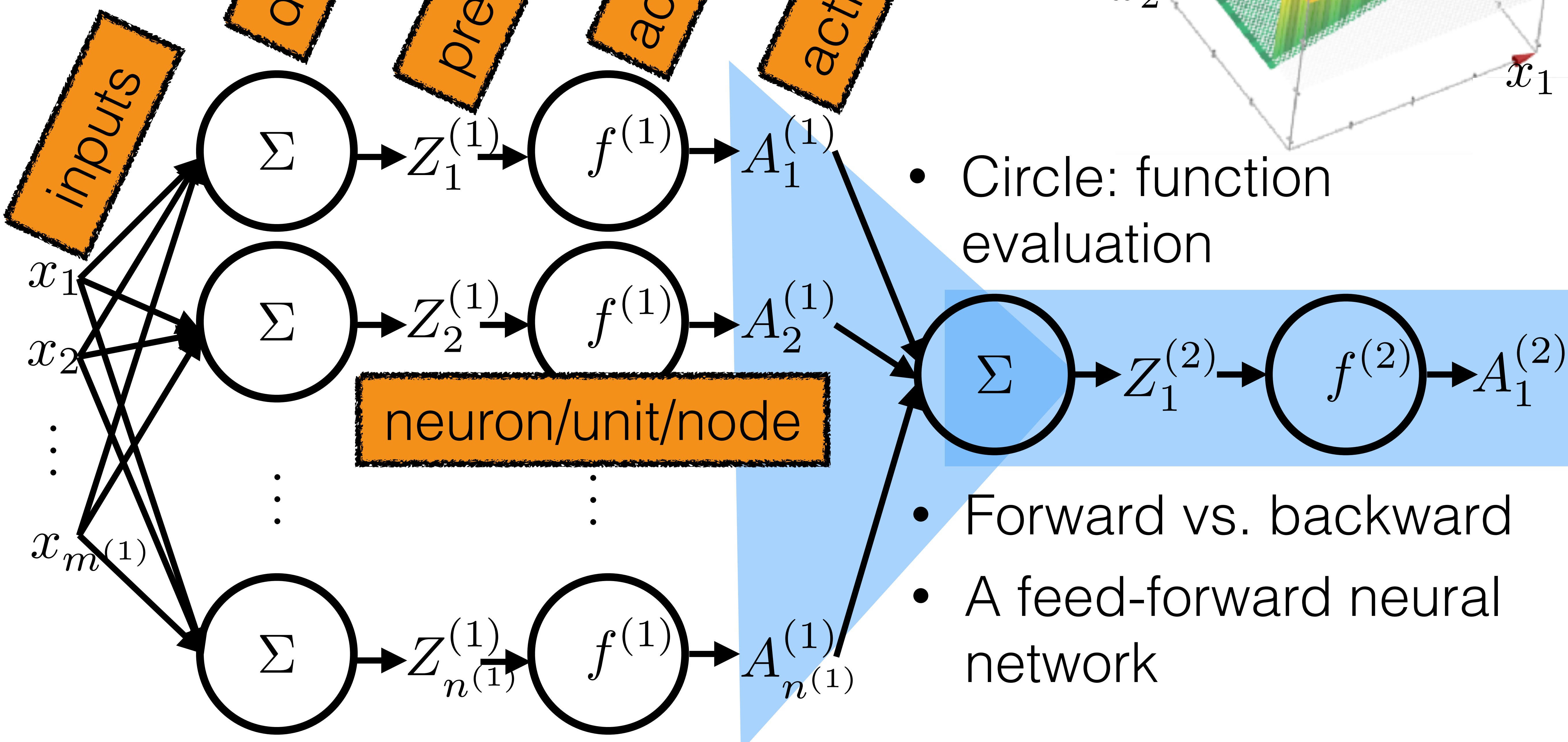

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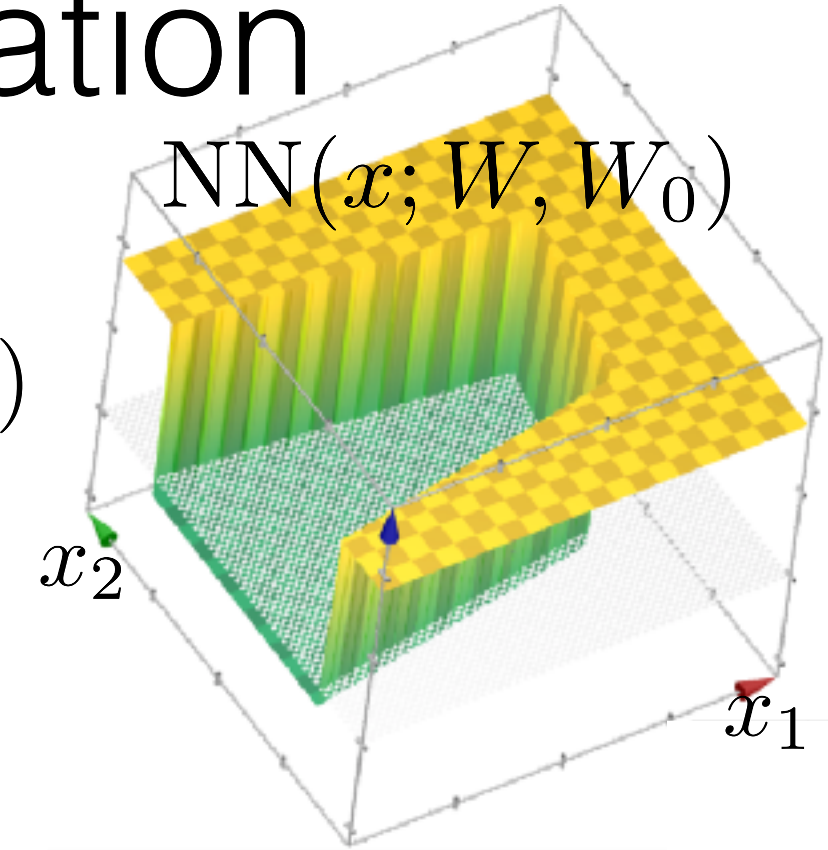

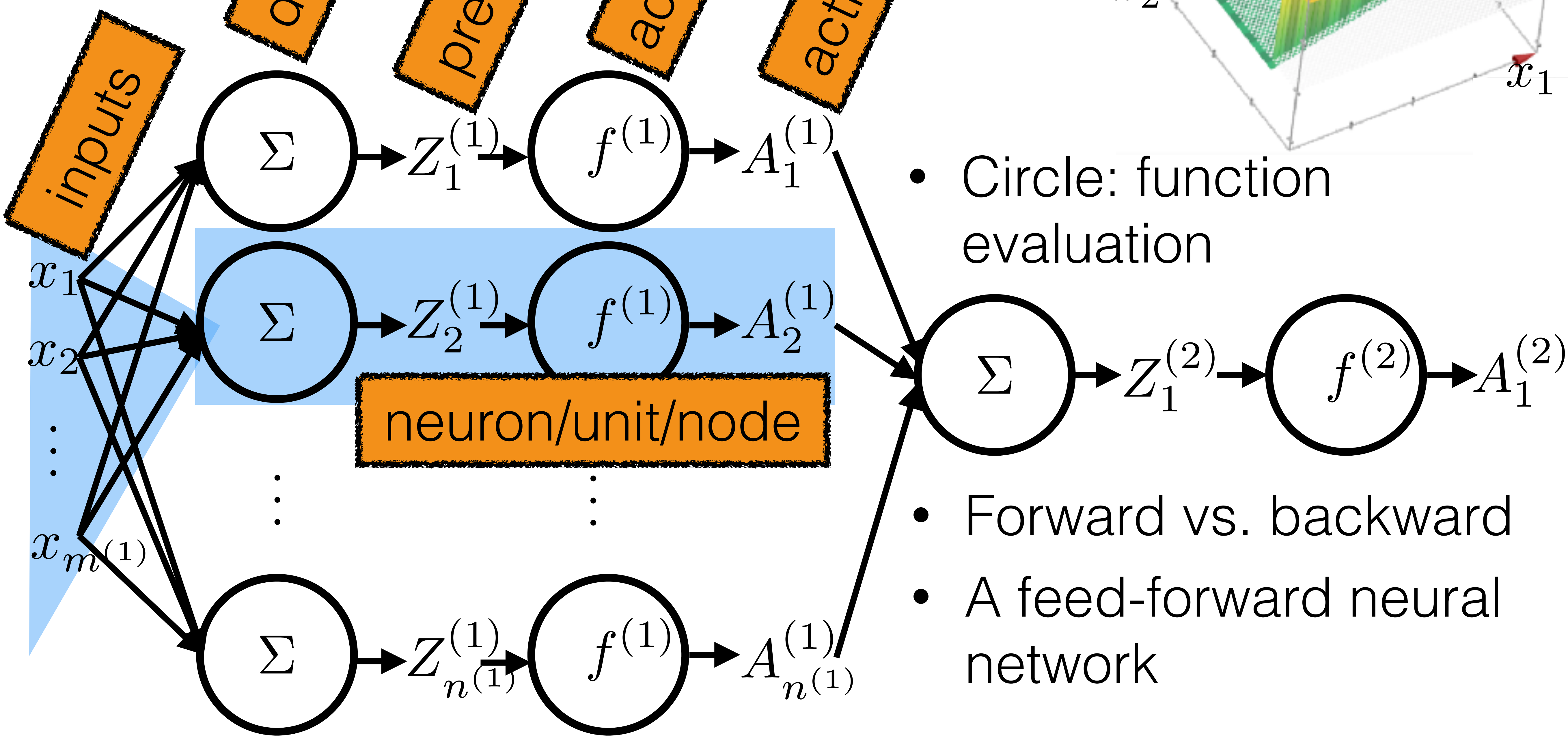

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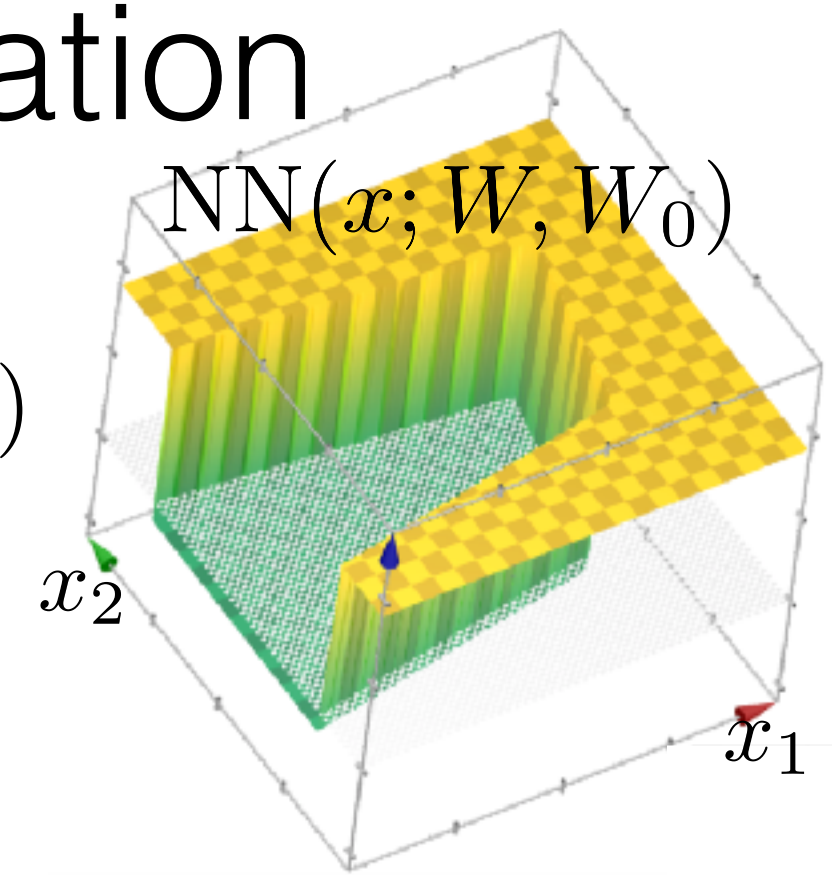

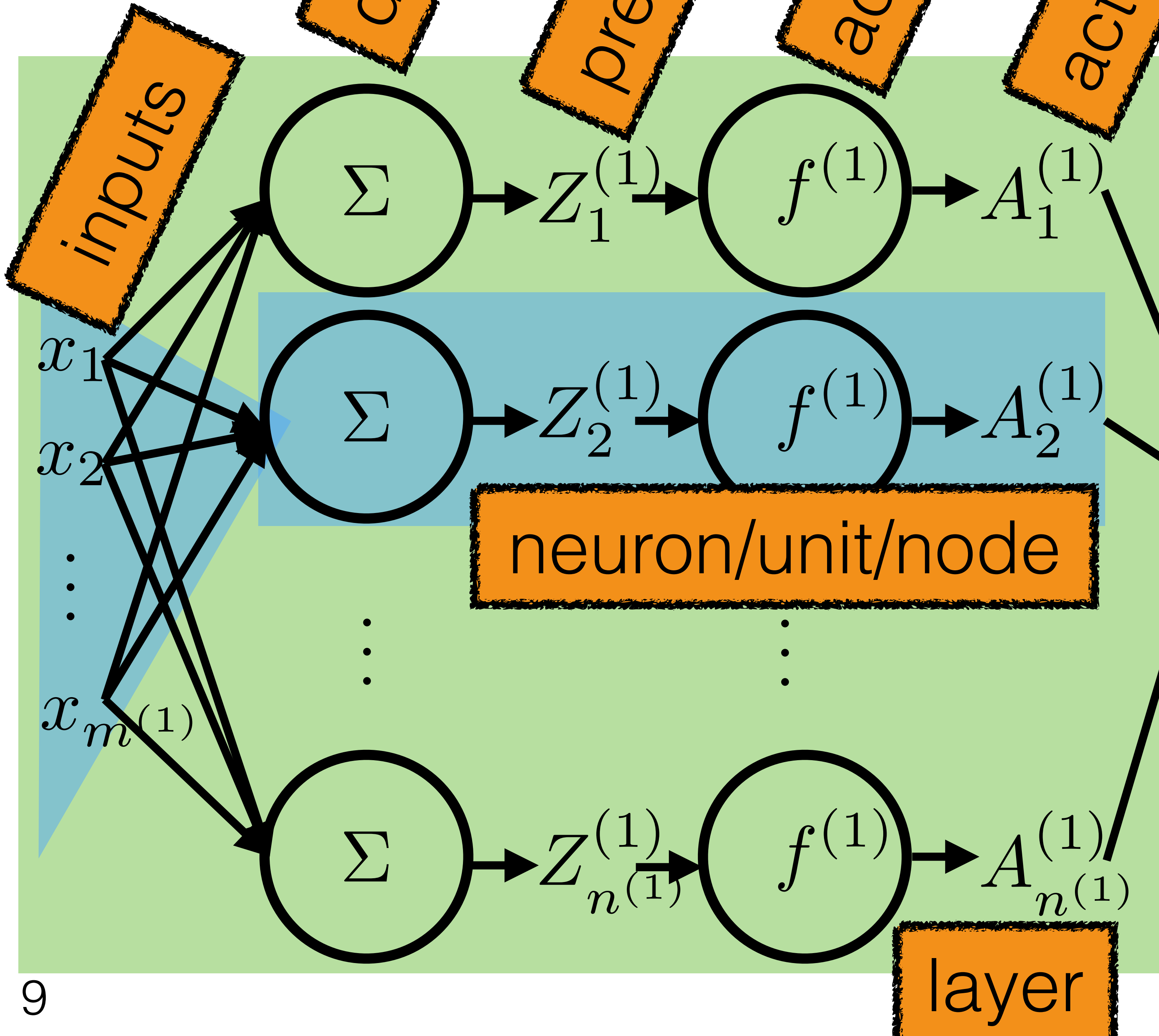

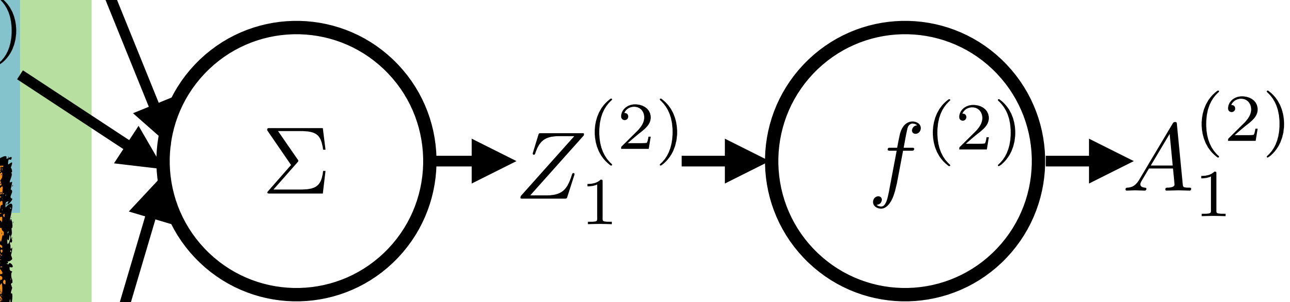

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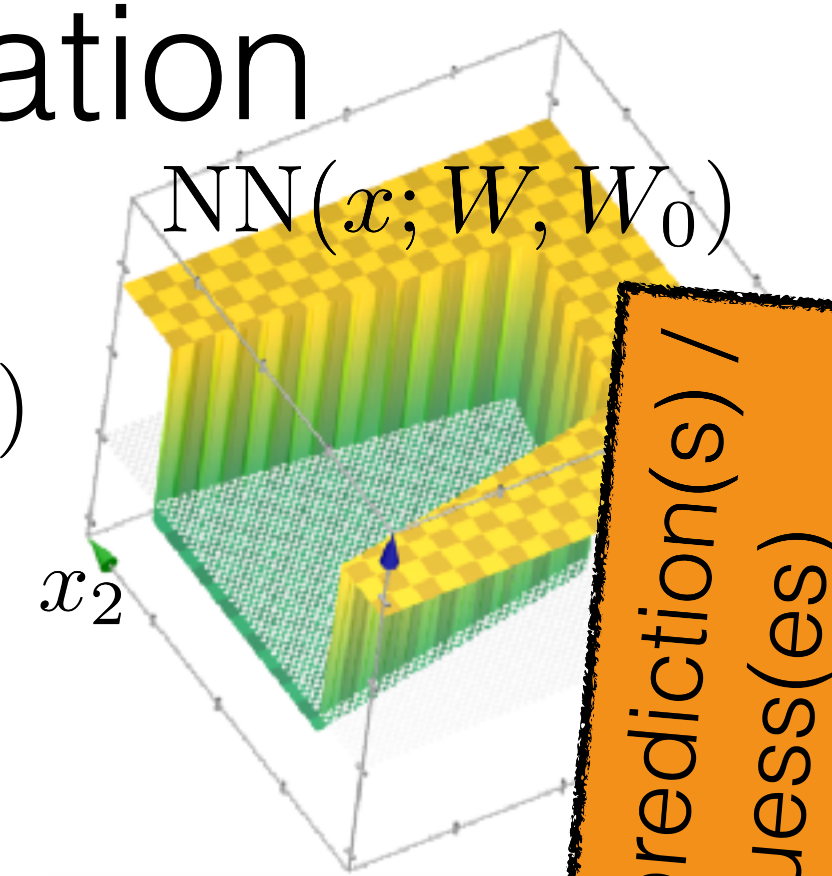

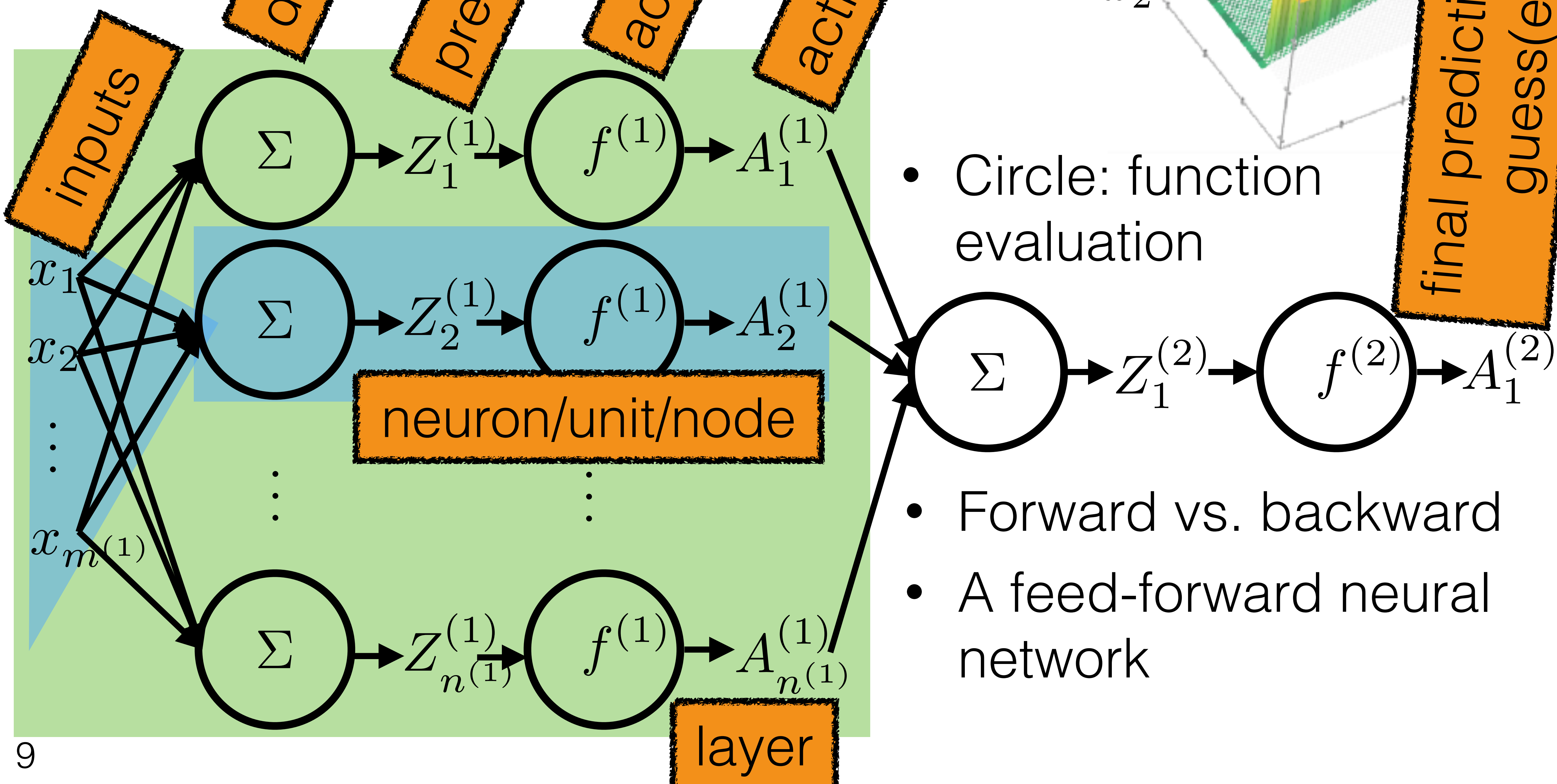

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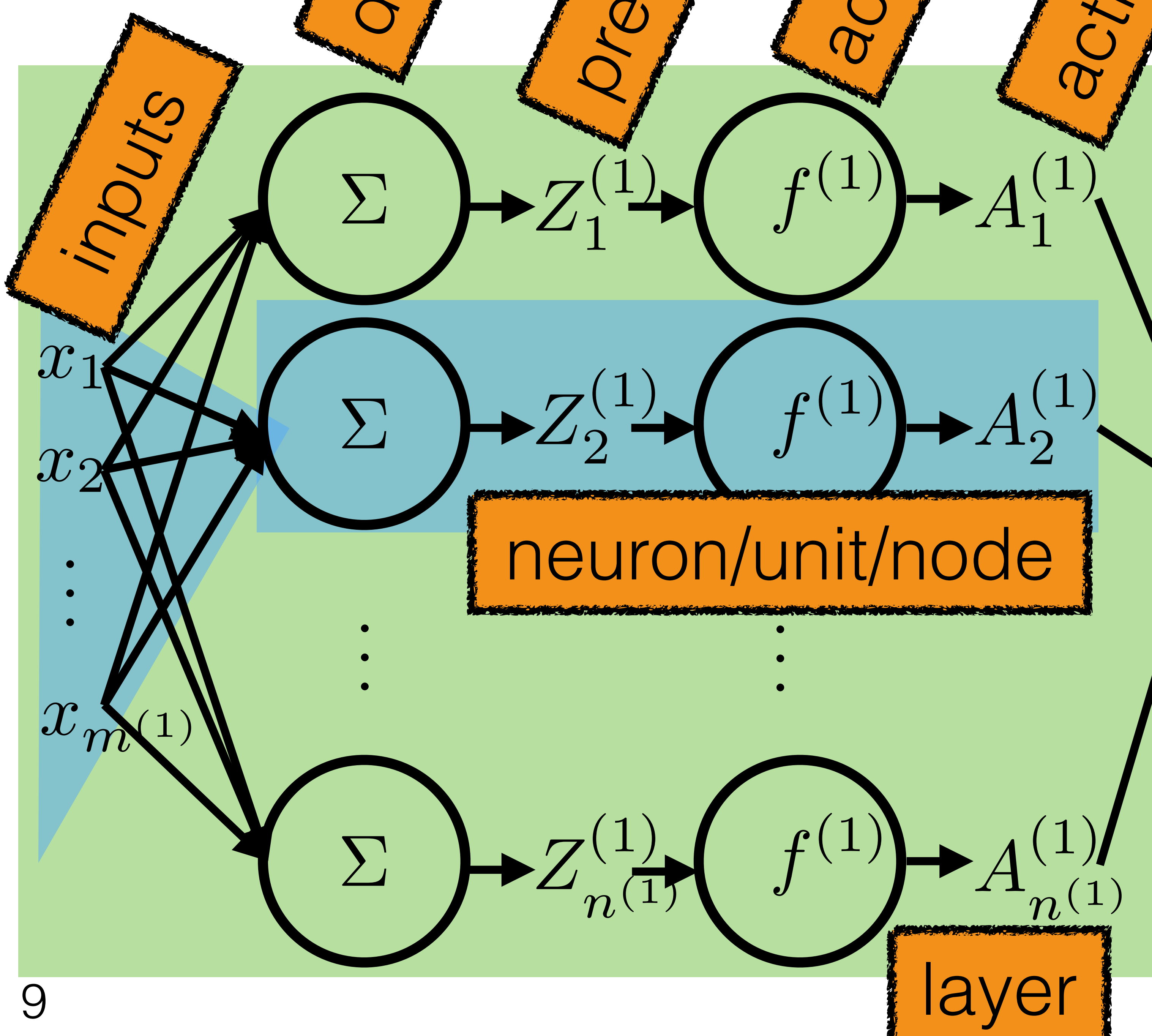

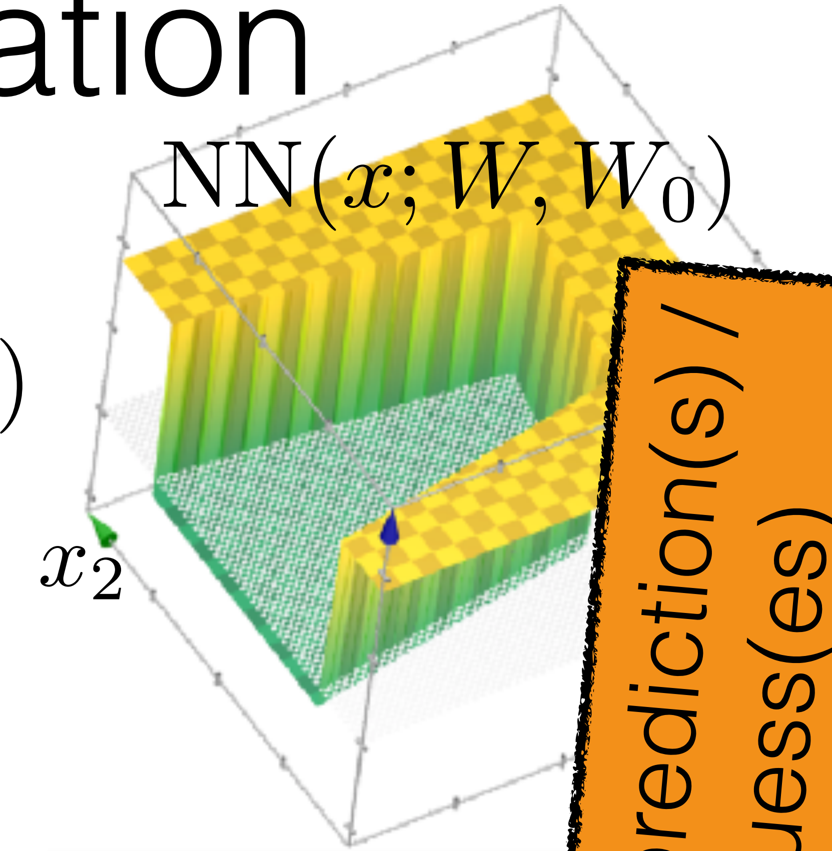

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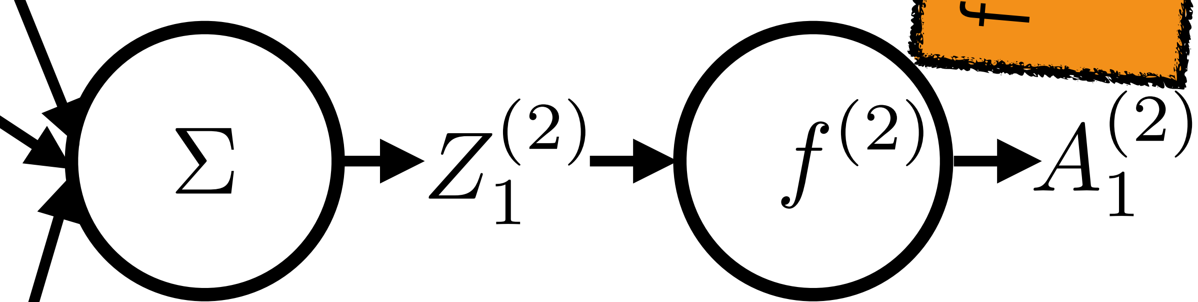

- Forward vs. backward
- A feed-forward neural network
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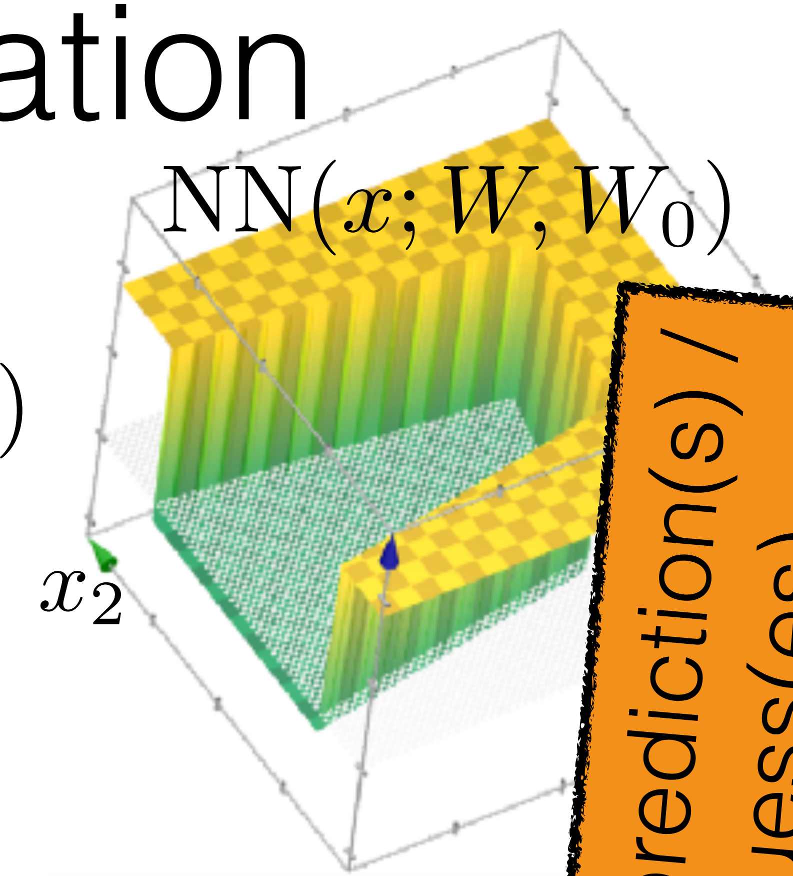

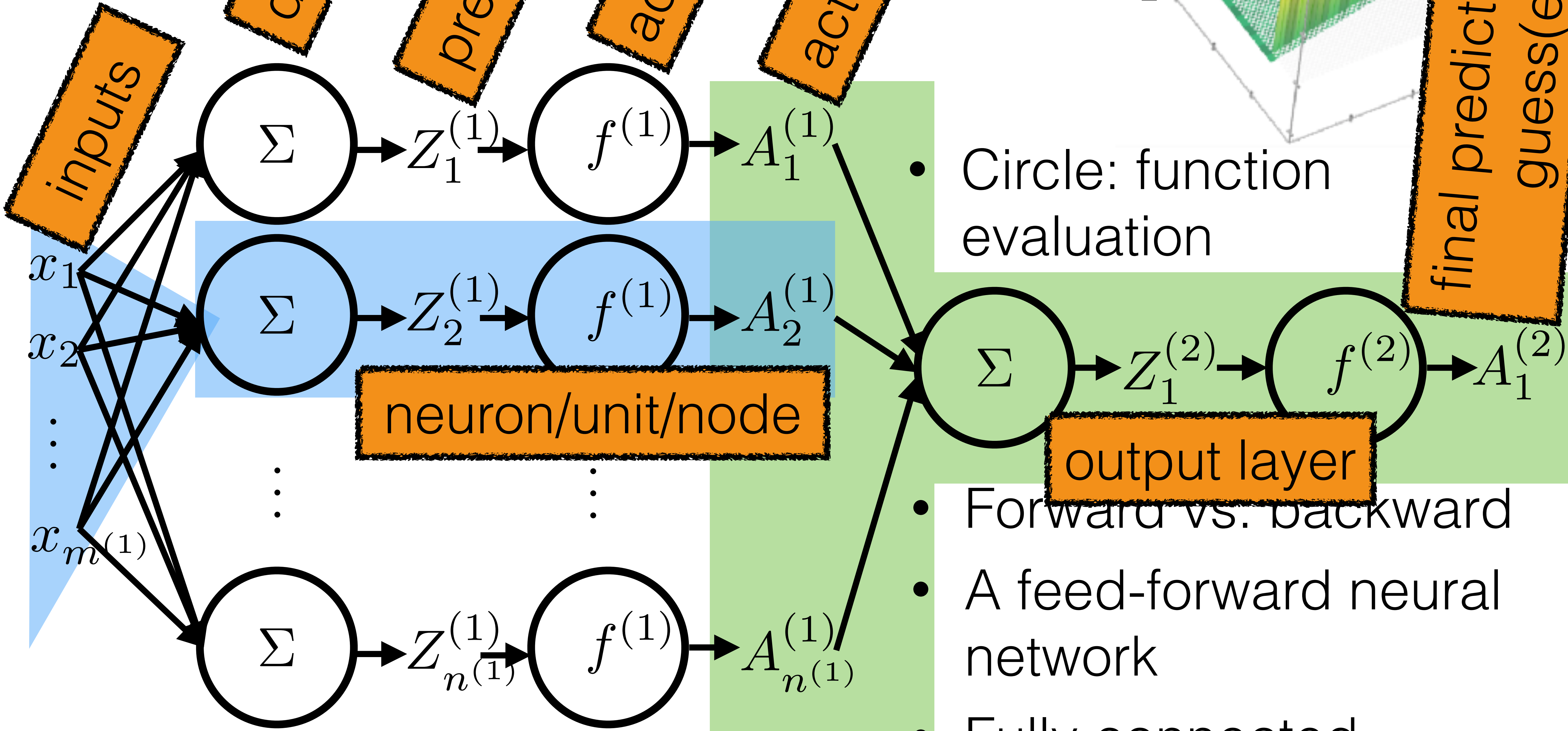

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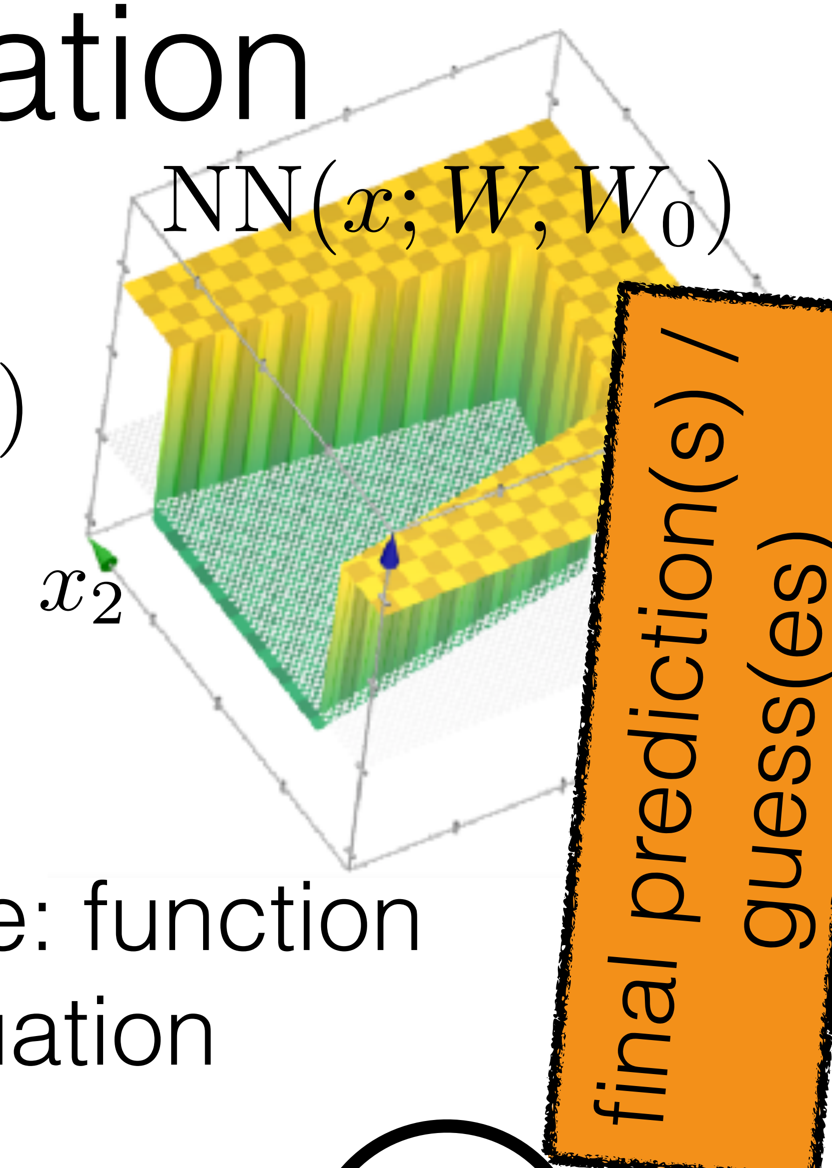

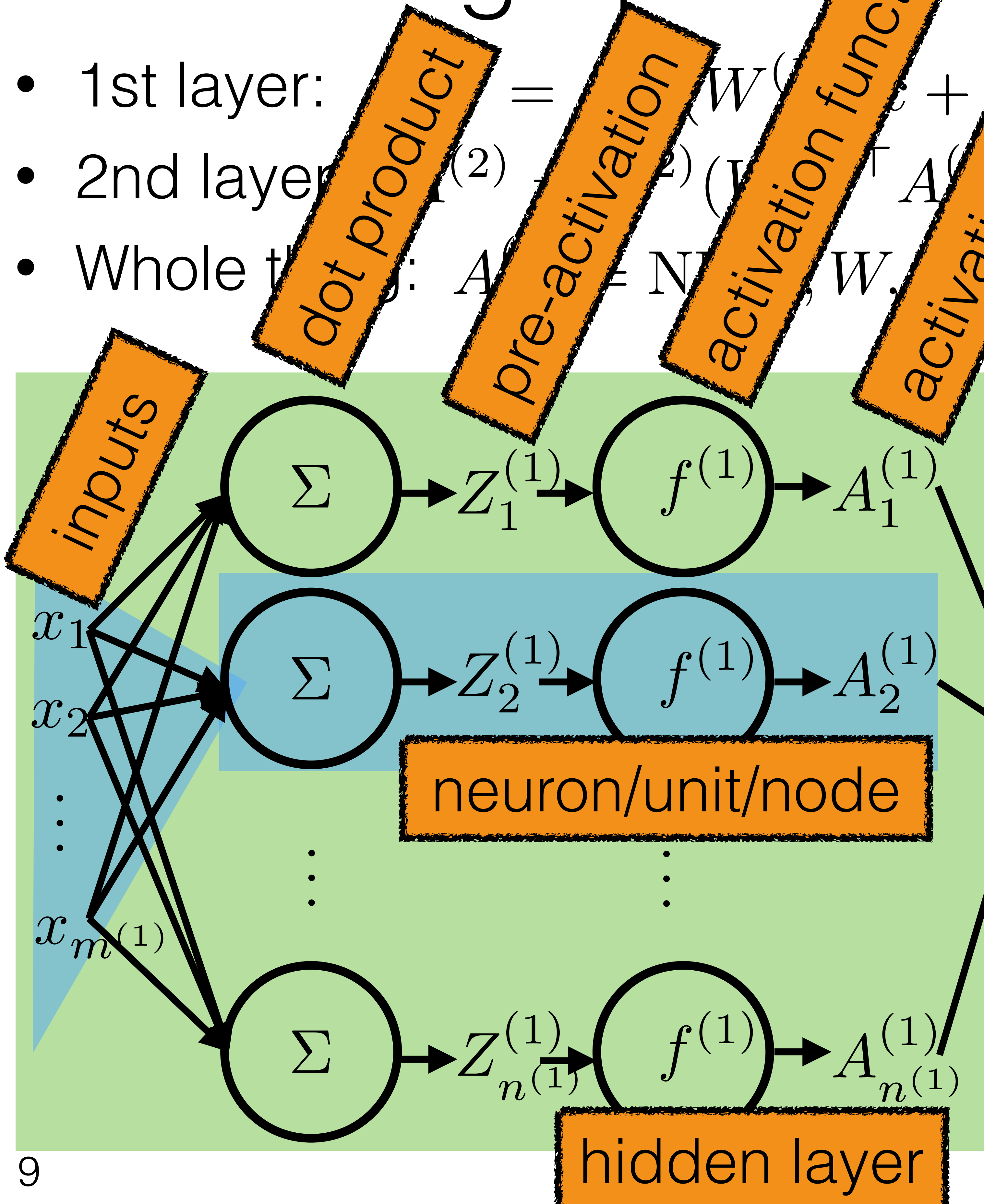

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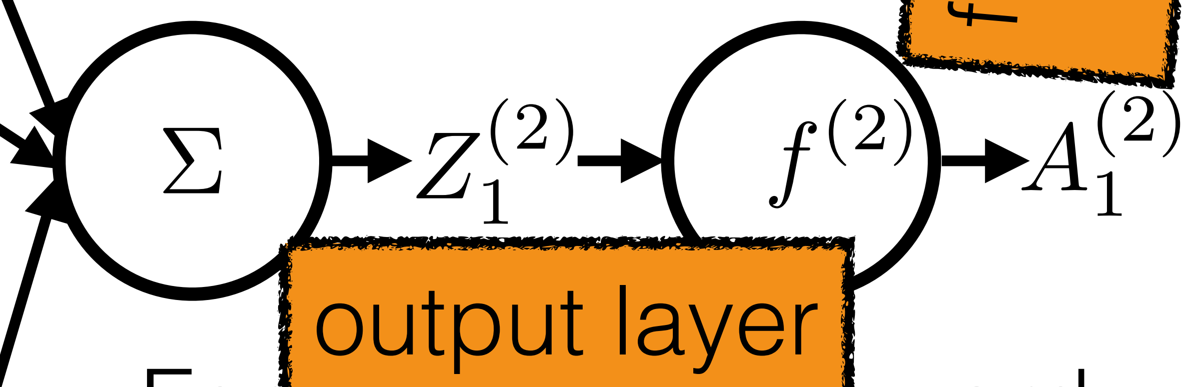

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- What if I want to do regression?

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2. Choose a loss. E.g. for classification: 0-1 loss, asymmetric, negative log likelihood
3. Learn the parameters. E.g. gradient descent or SGD
4. Predict on new data using these parameters

Issues:

- Derivatives are zero (or undefined) if we use the step function activation, so (S)GD won't do what we want
- What if I want to do regression?
- What if I want to use NLL loss?

Different activation functions

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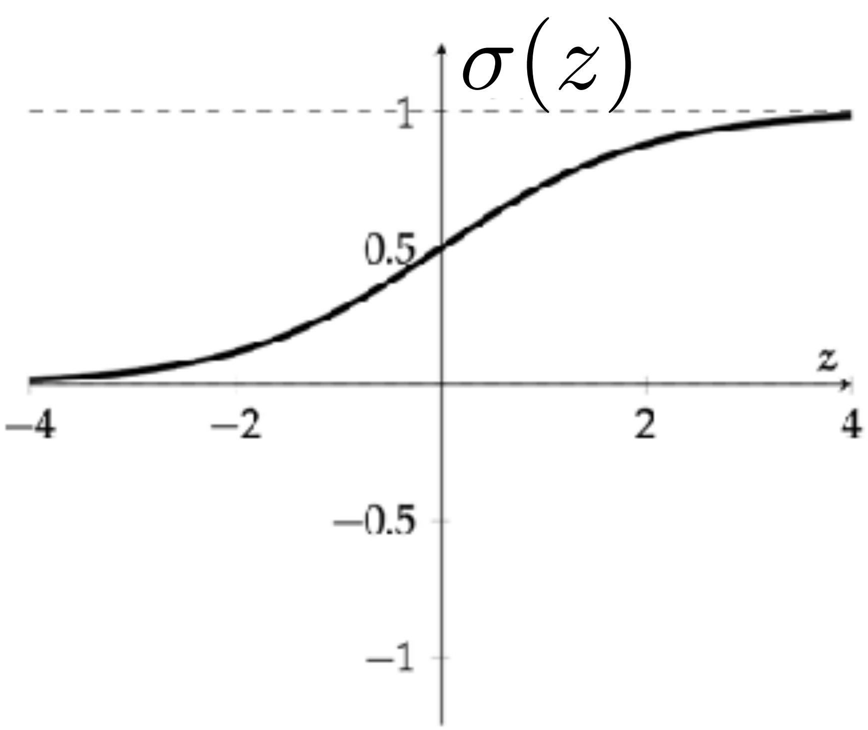

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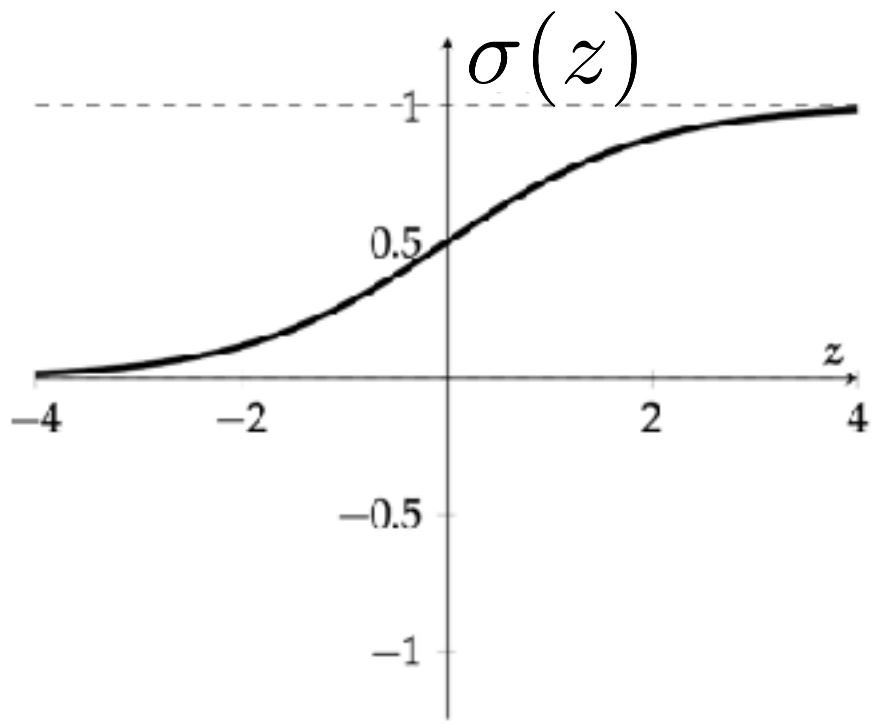

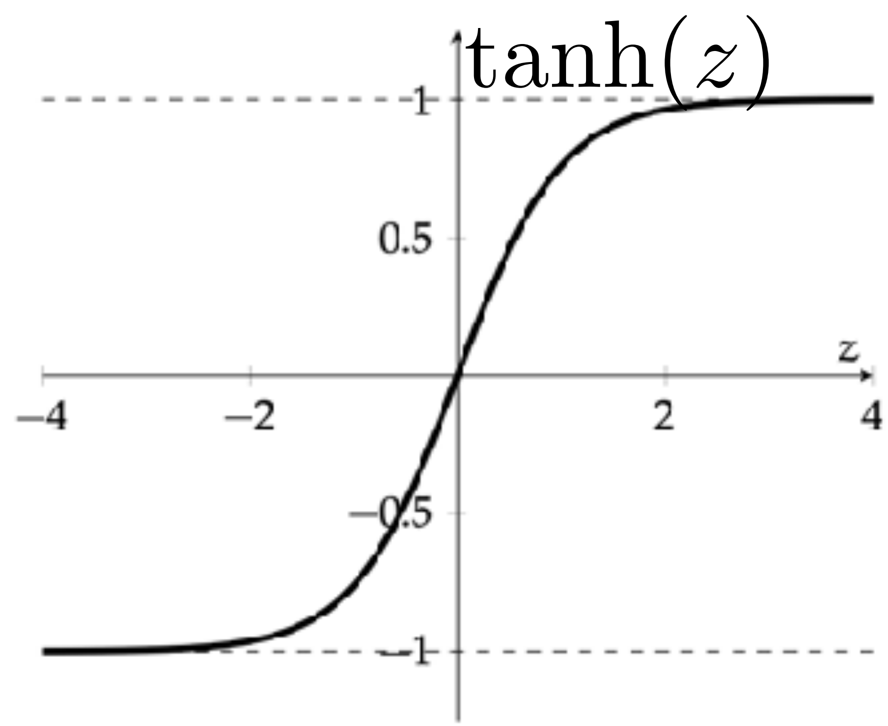

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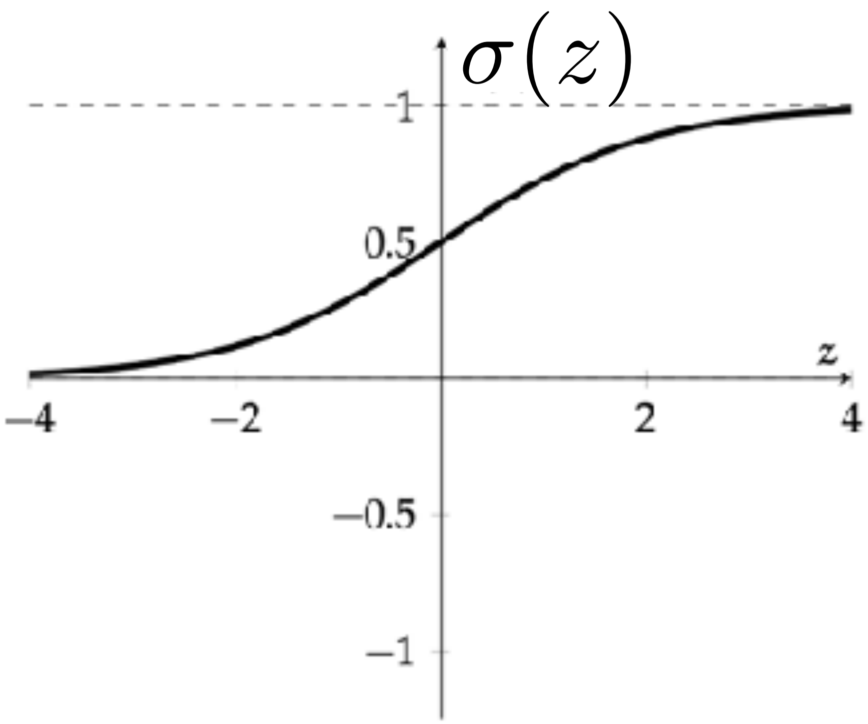

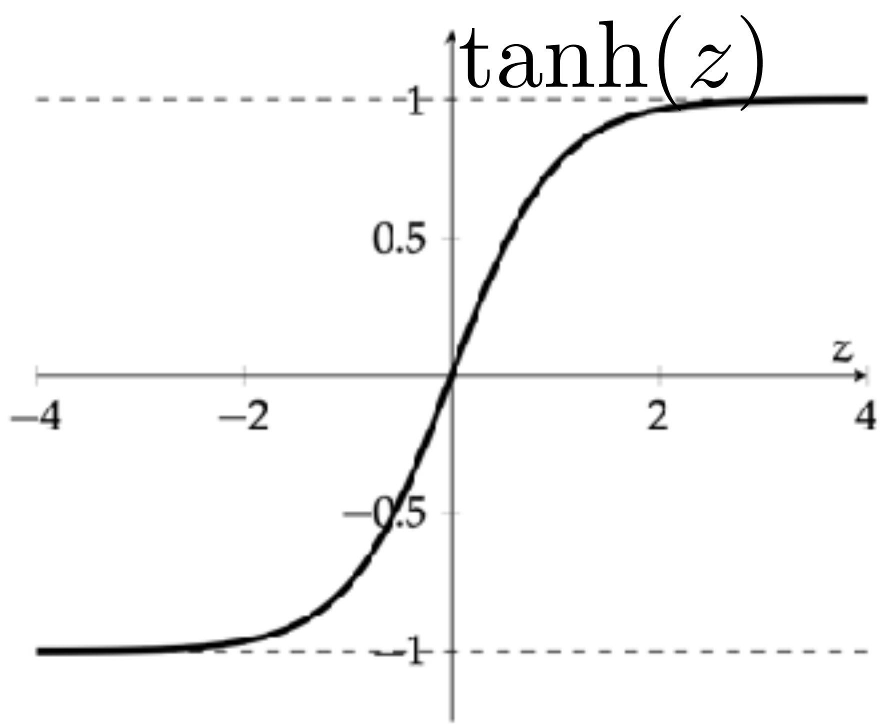

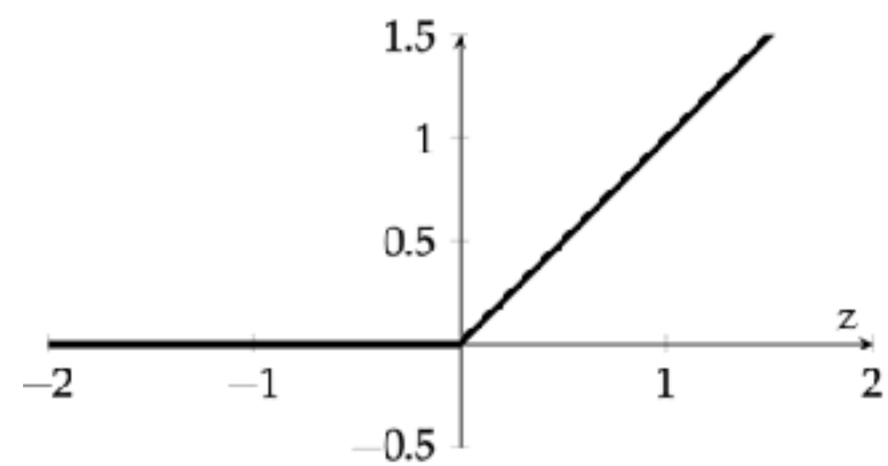

$\mathrm{ReLU}(z)$

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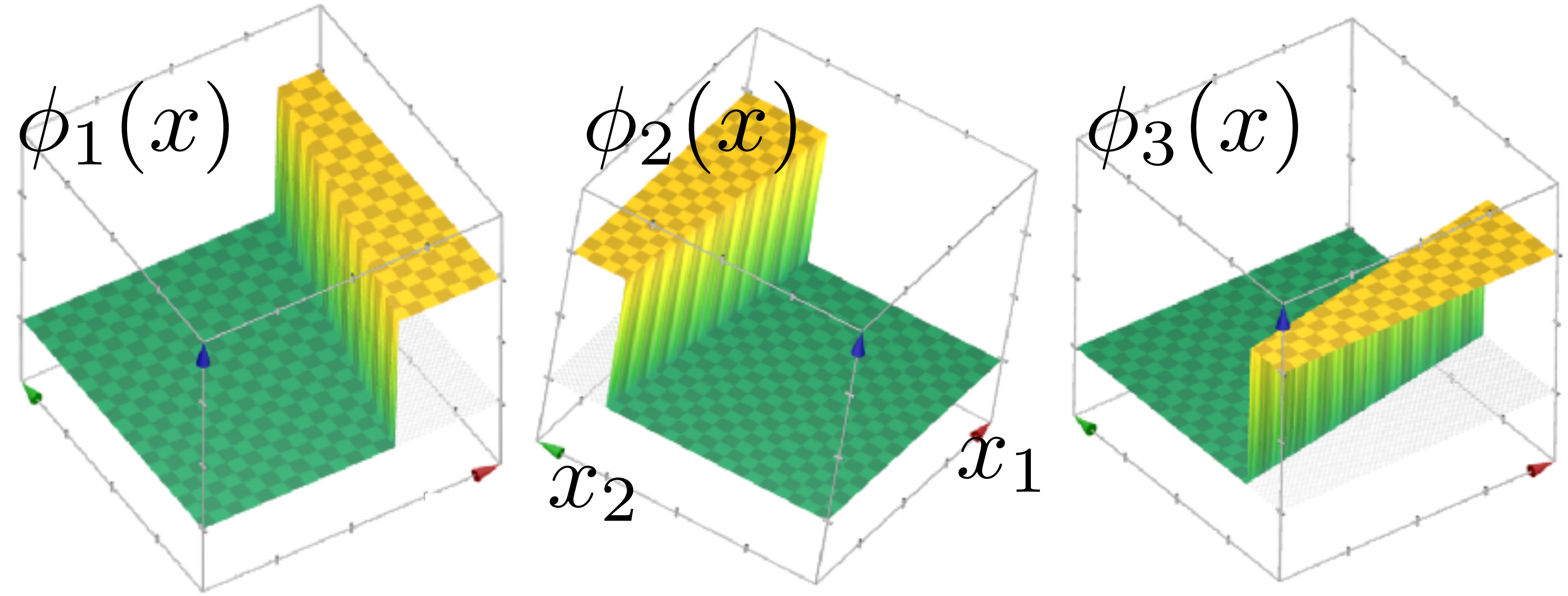

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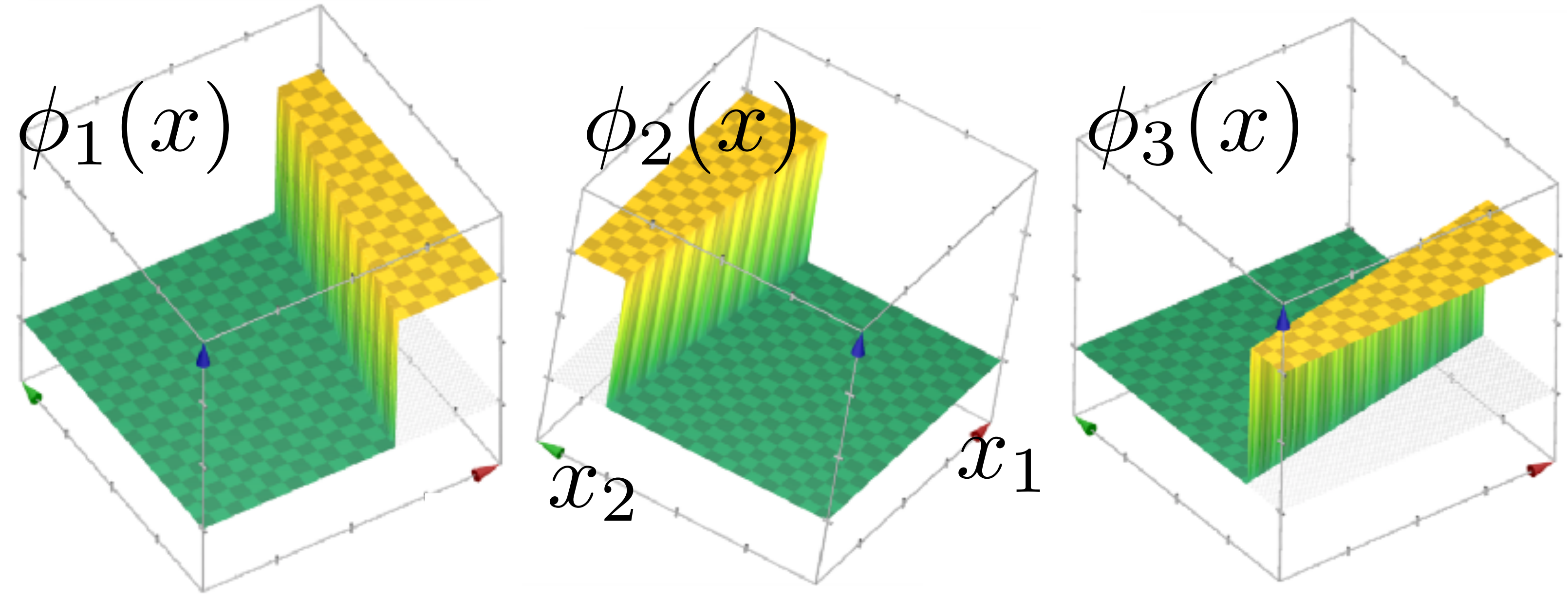

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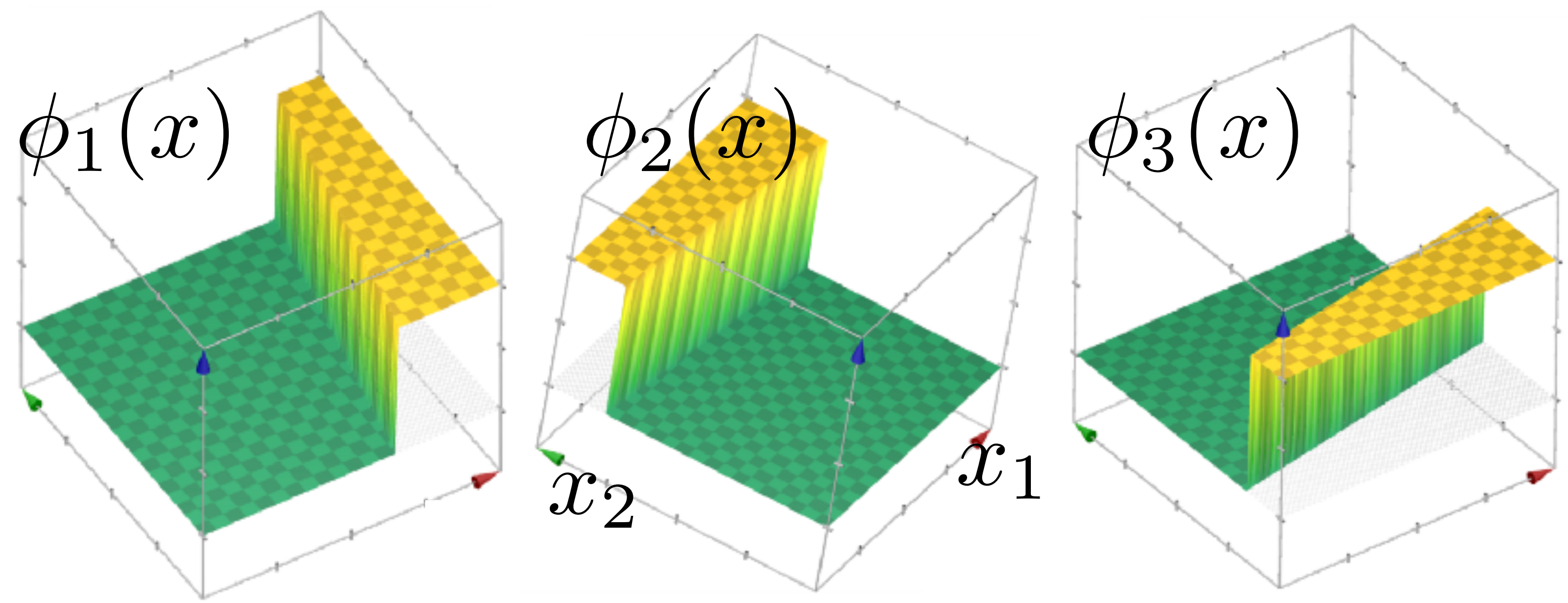

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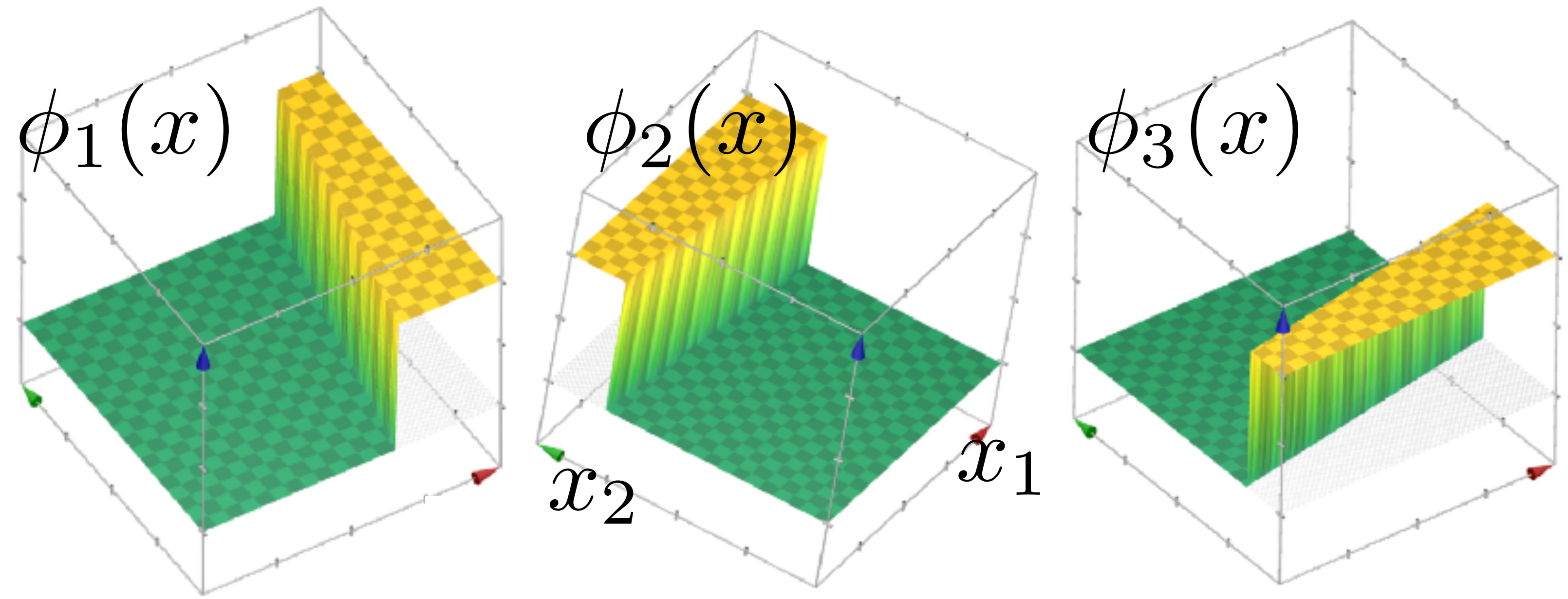

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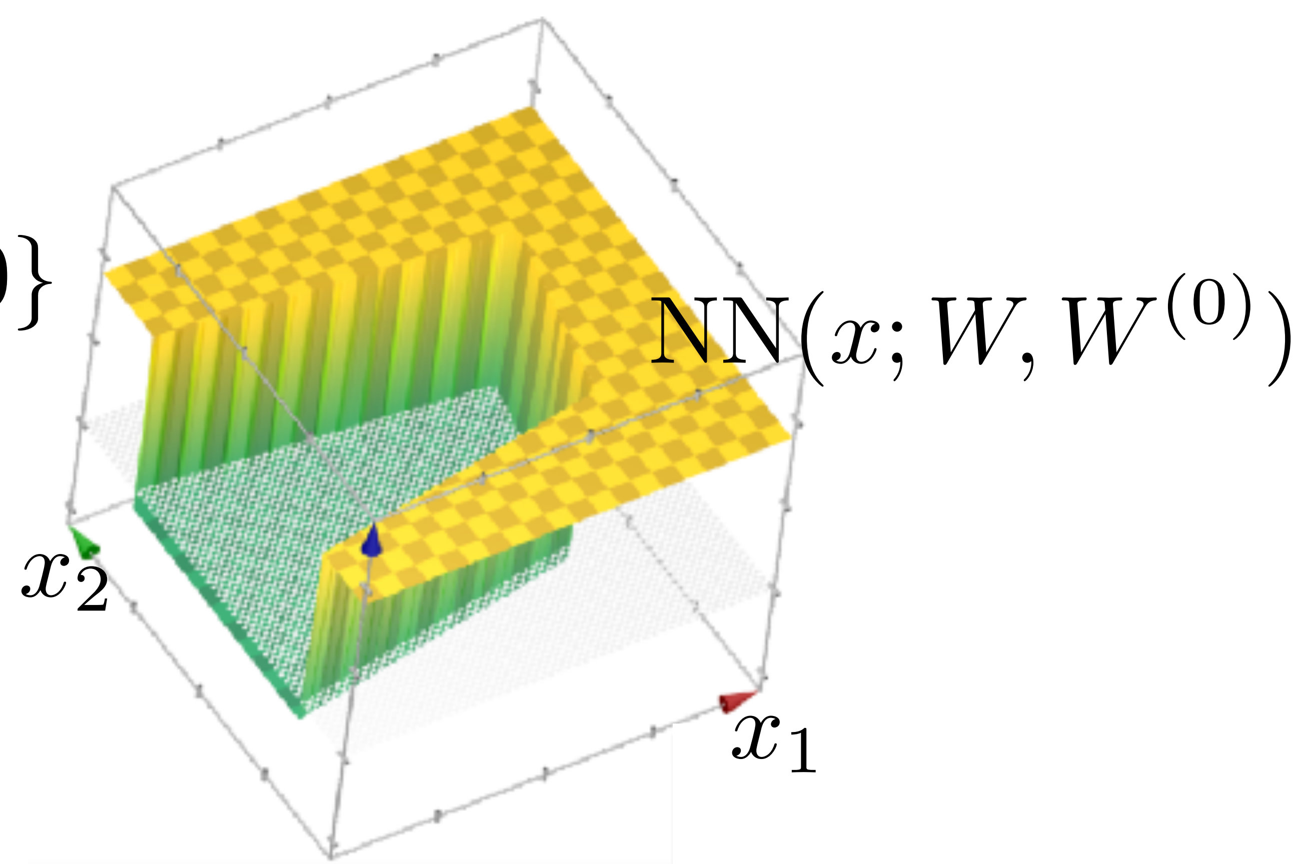

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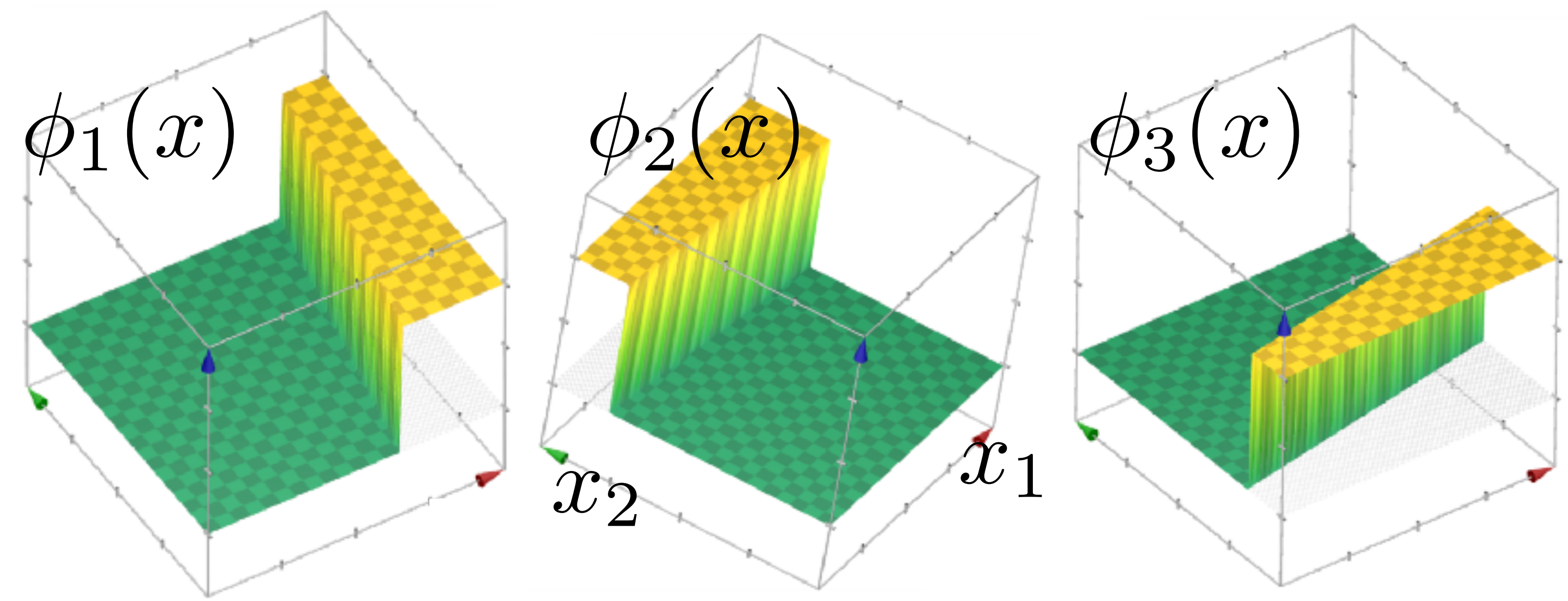

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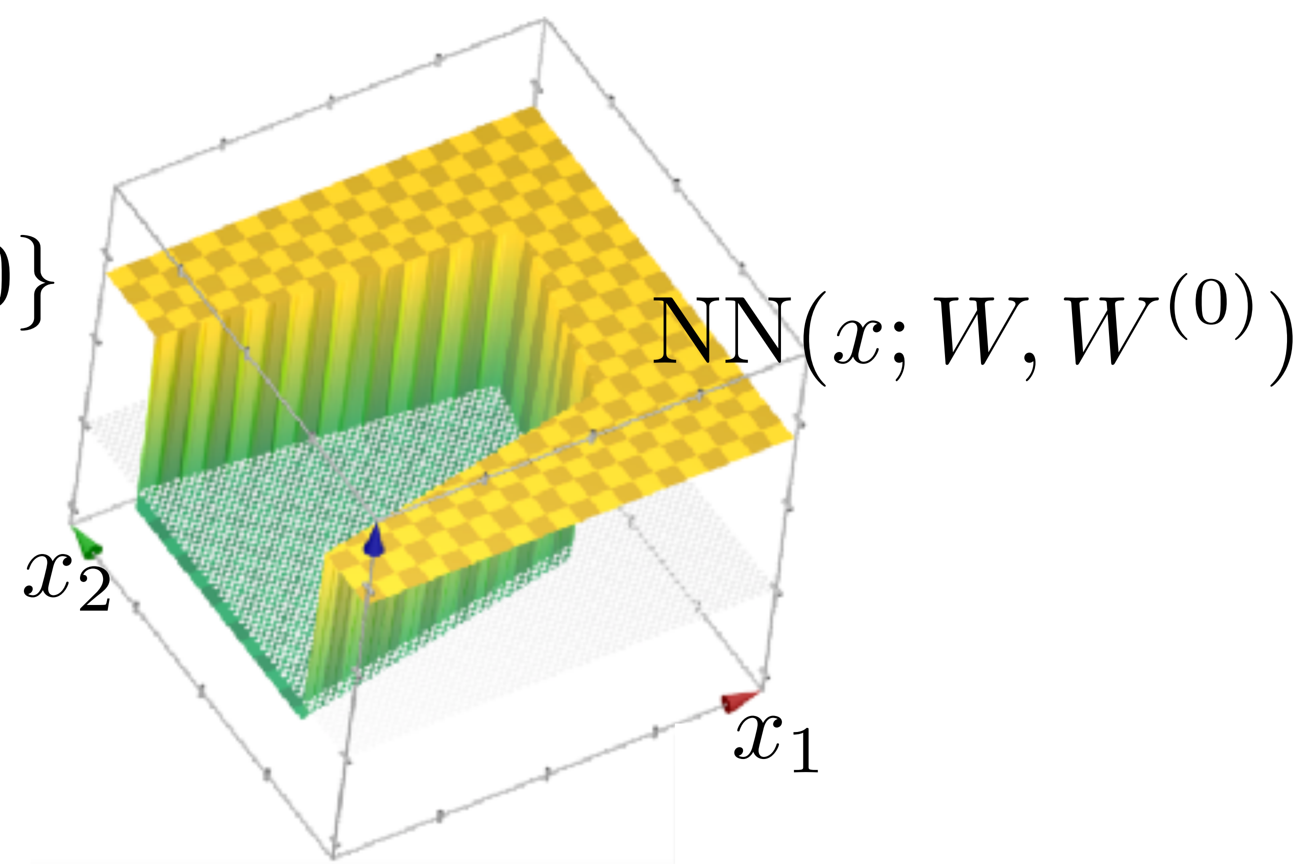

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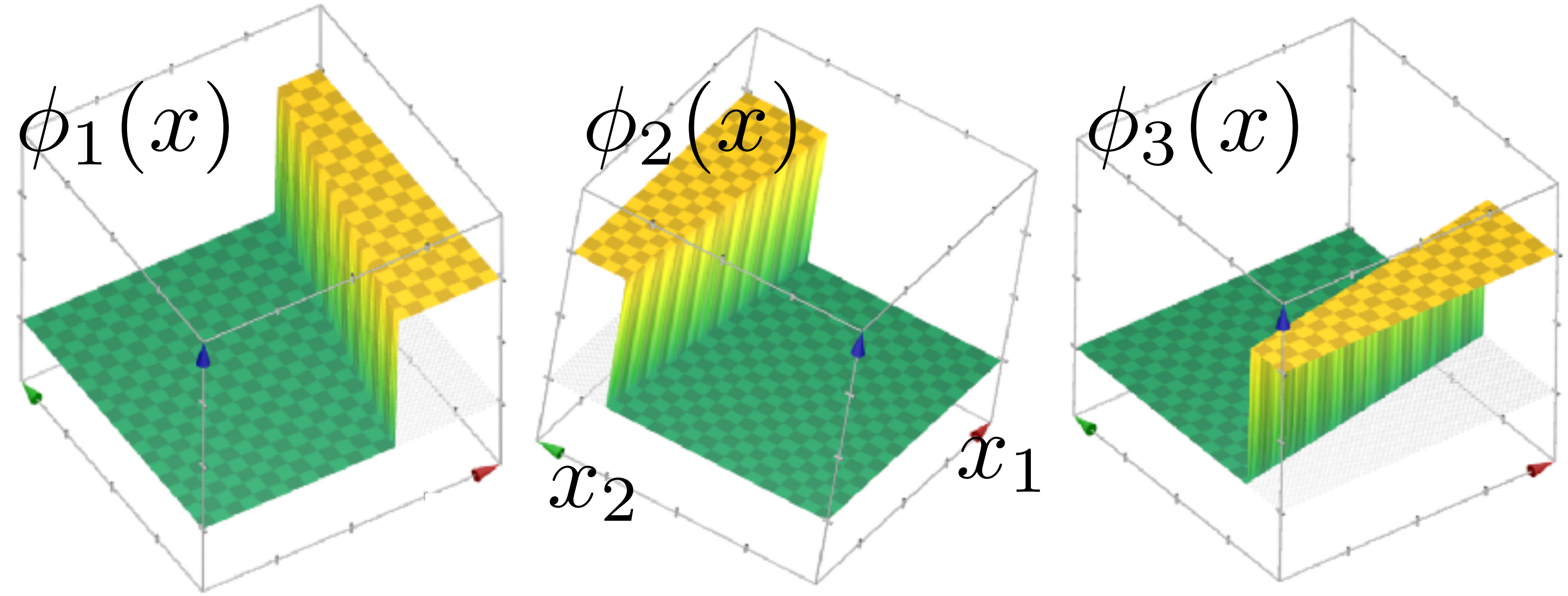

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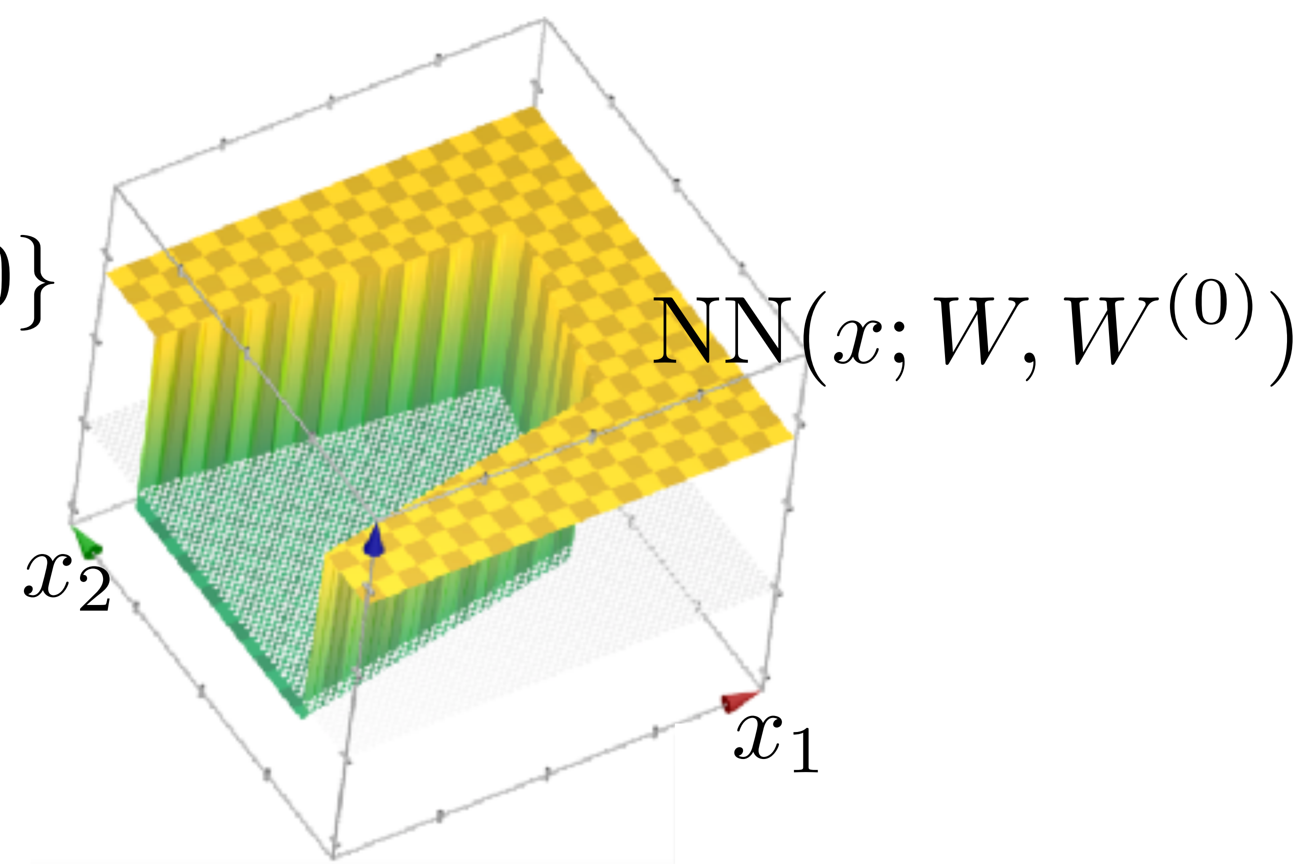

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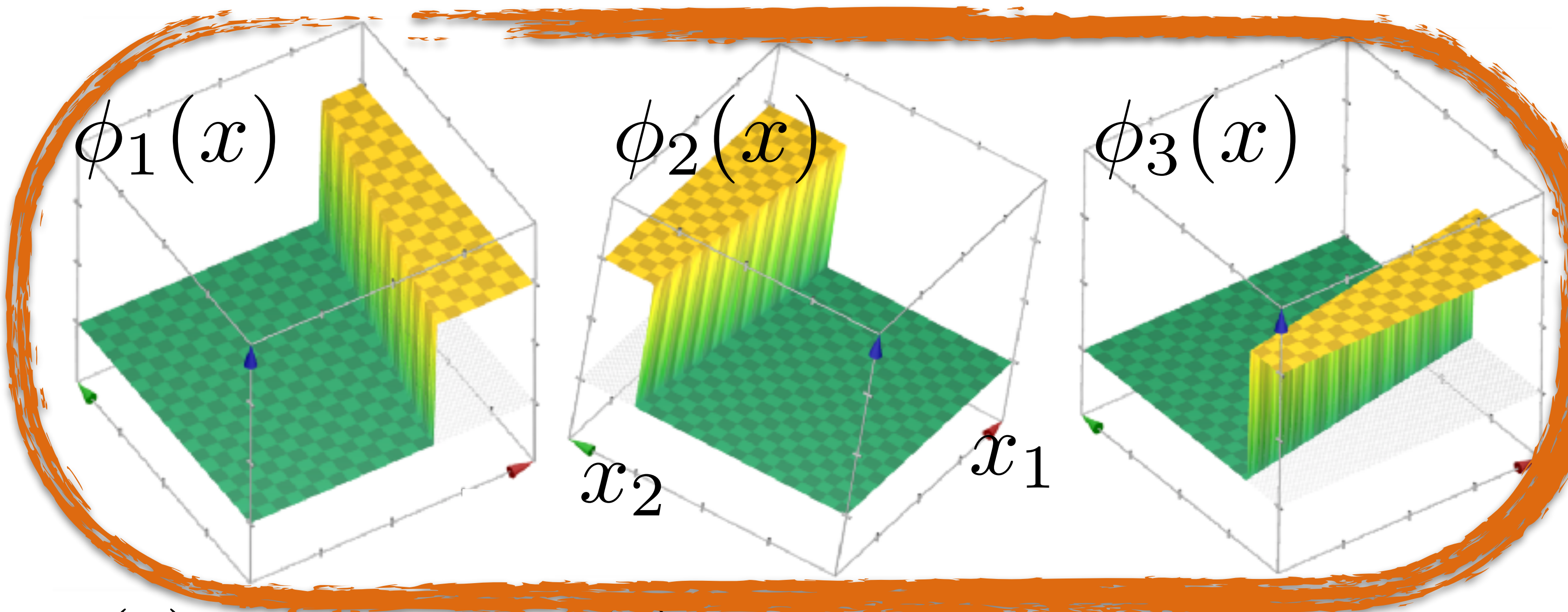

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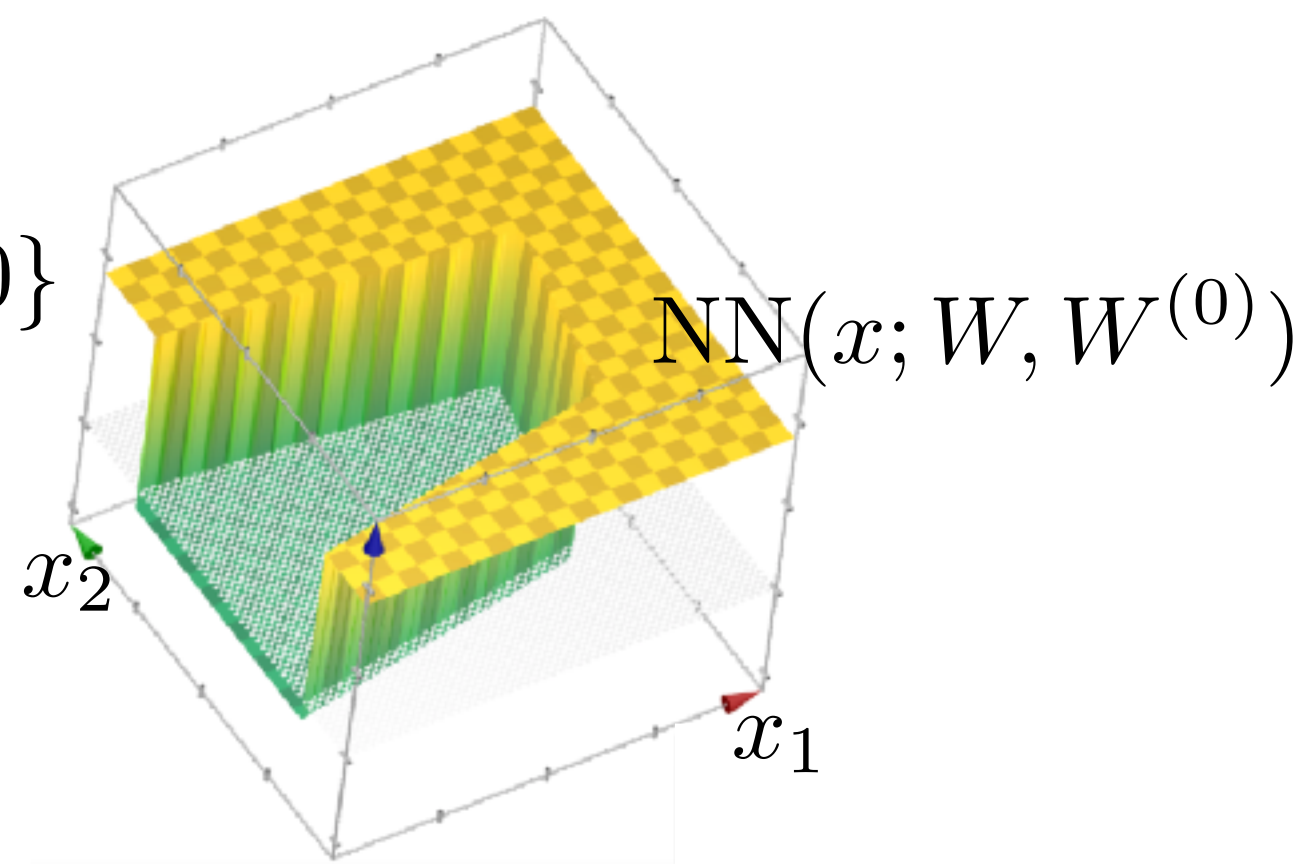

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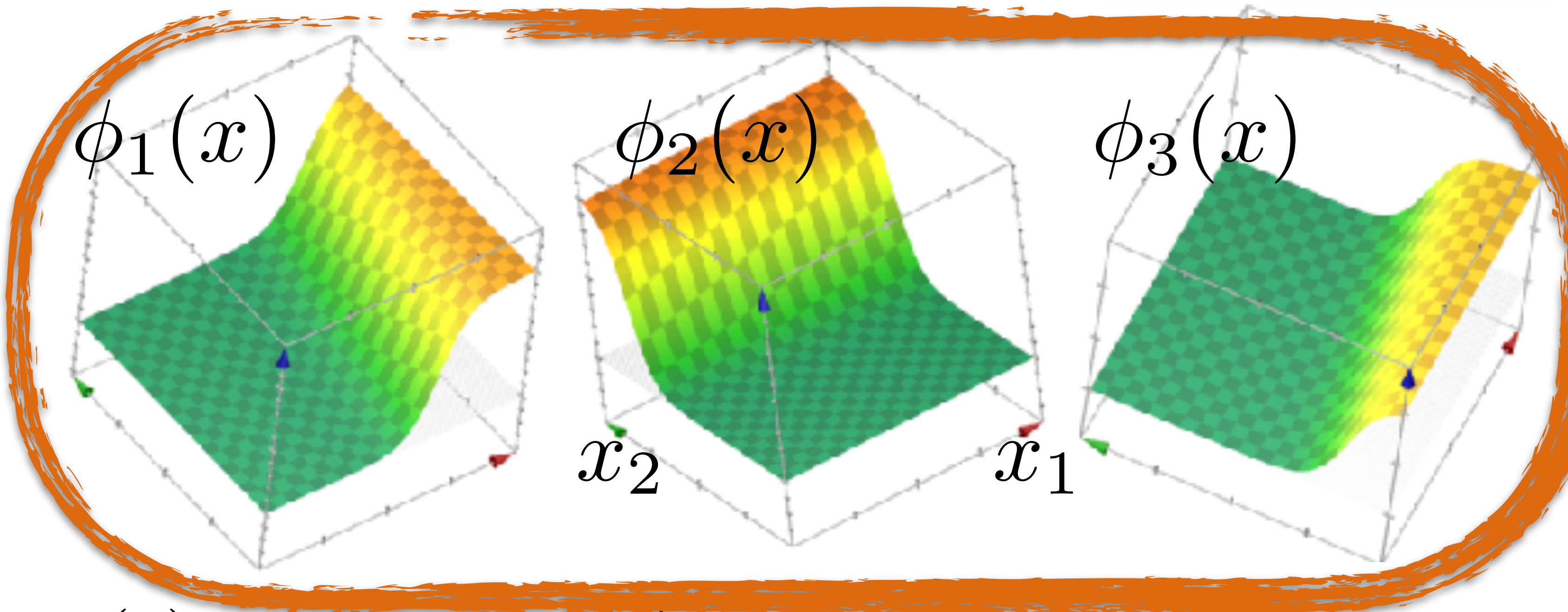

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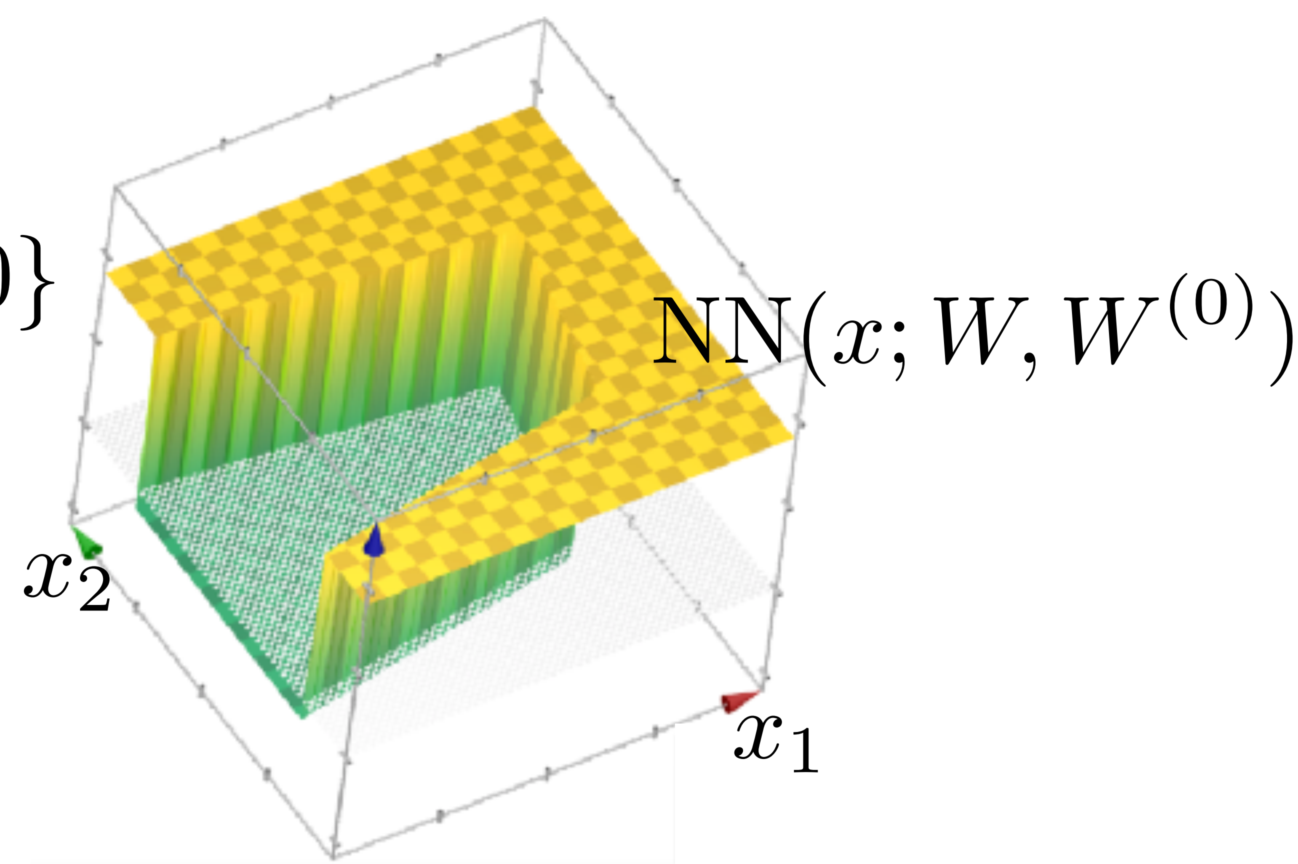

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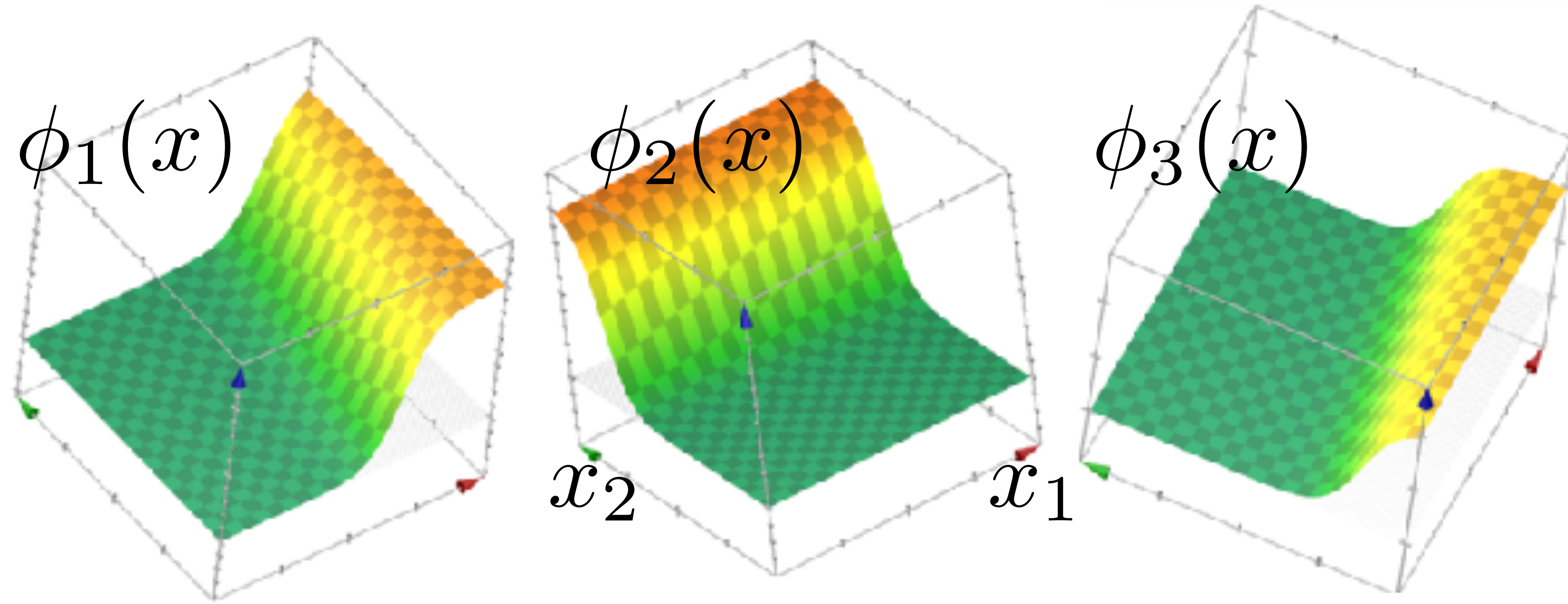

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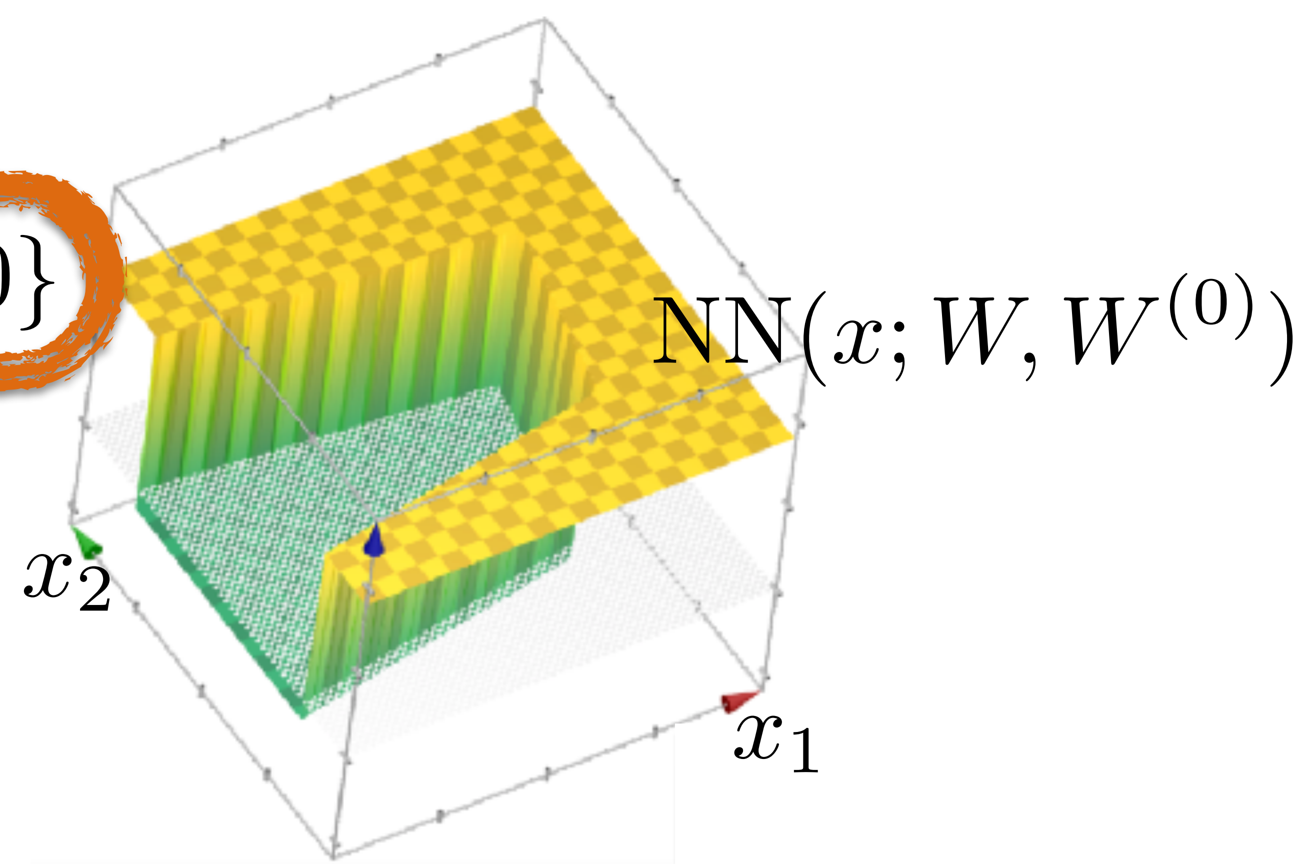

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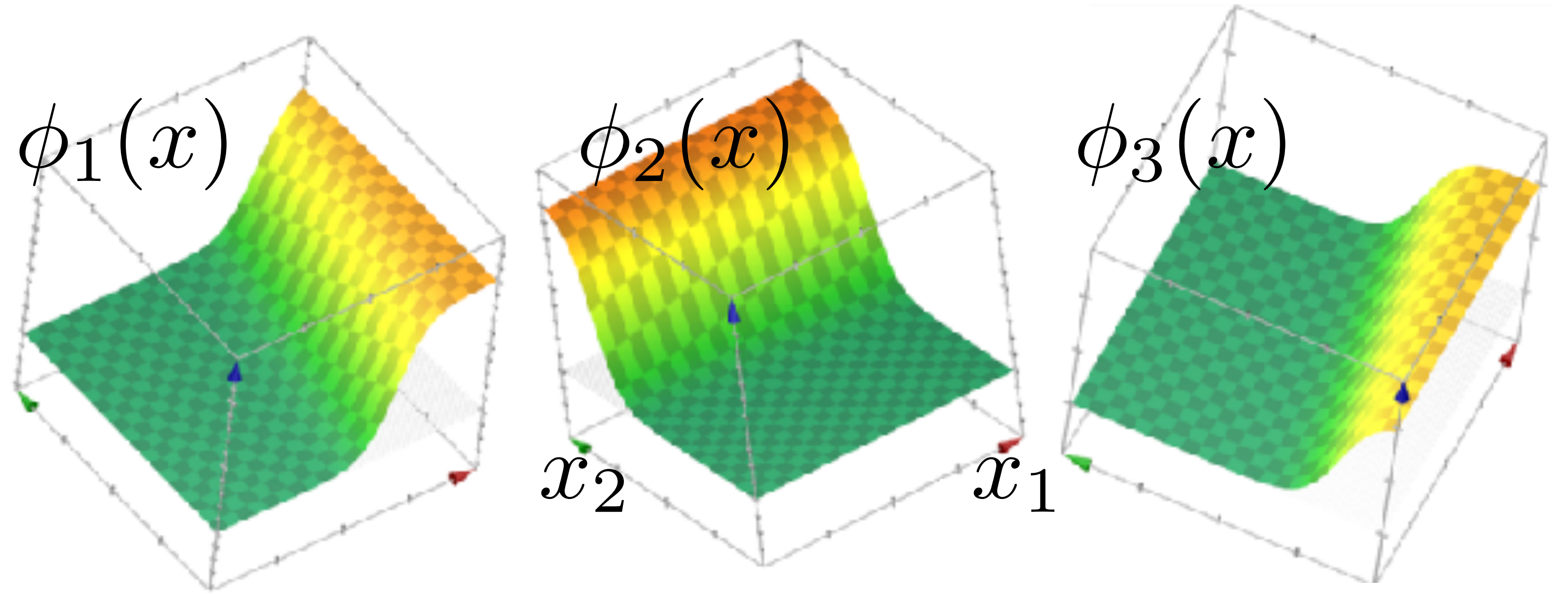

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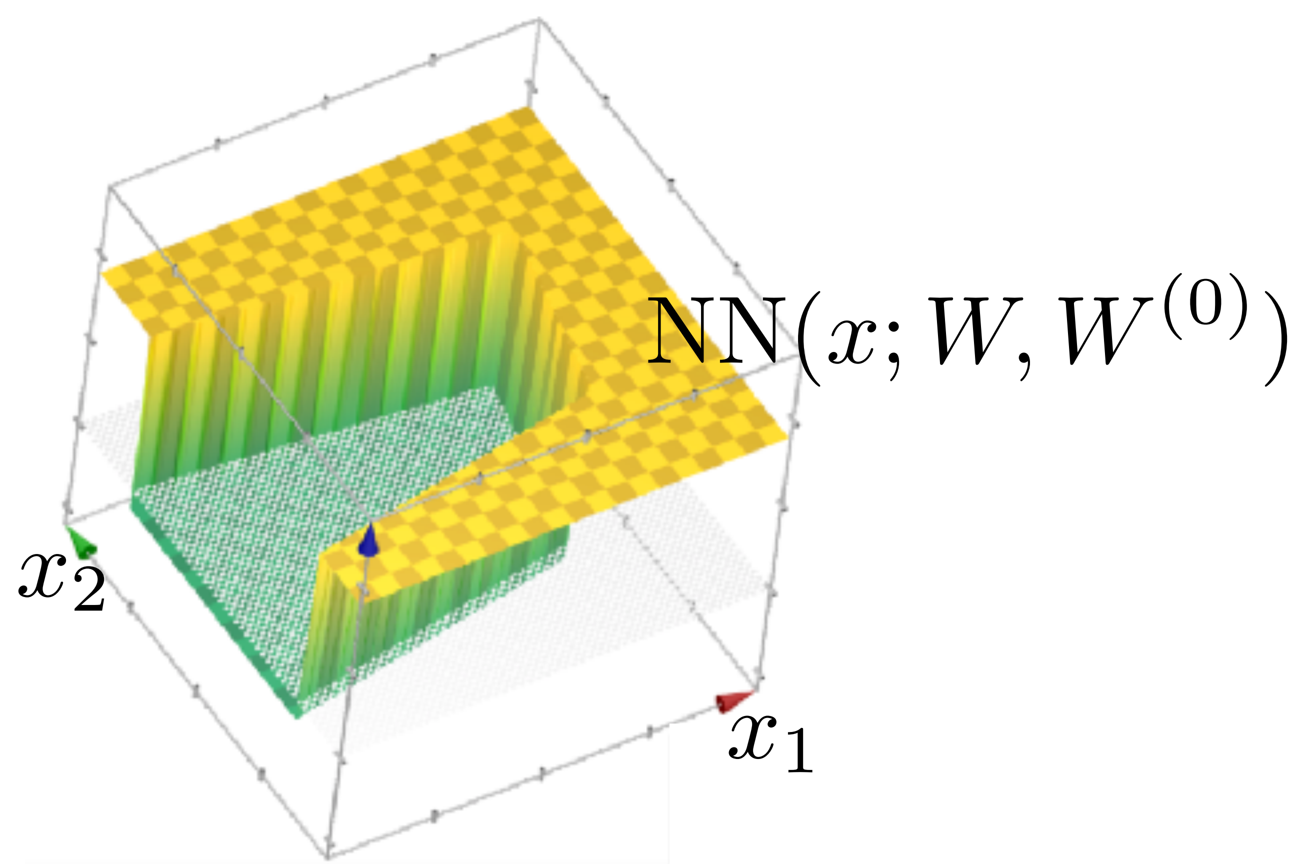

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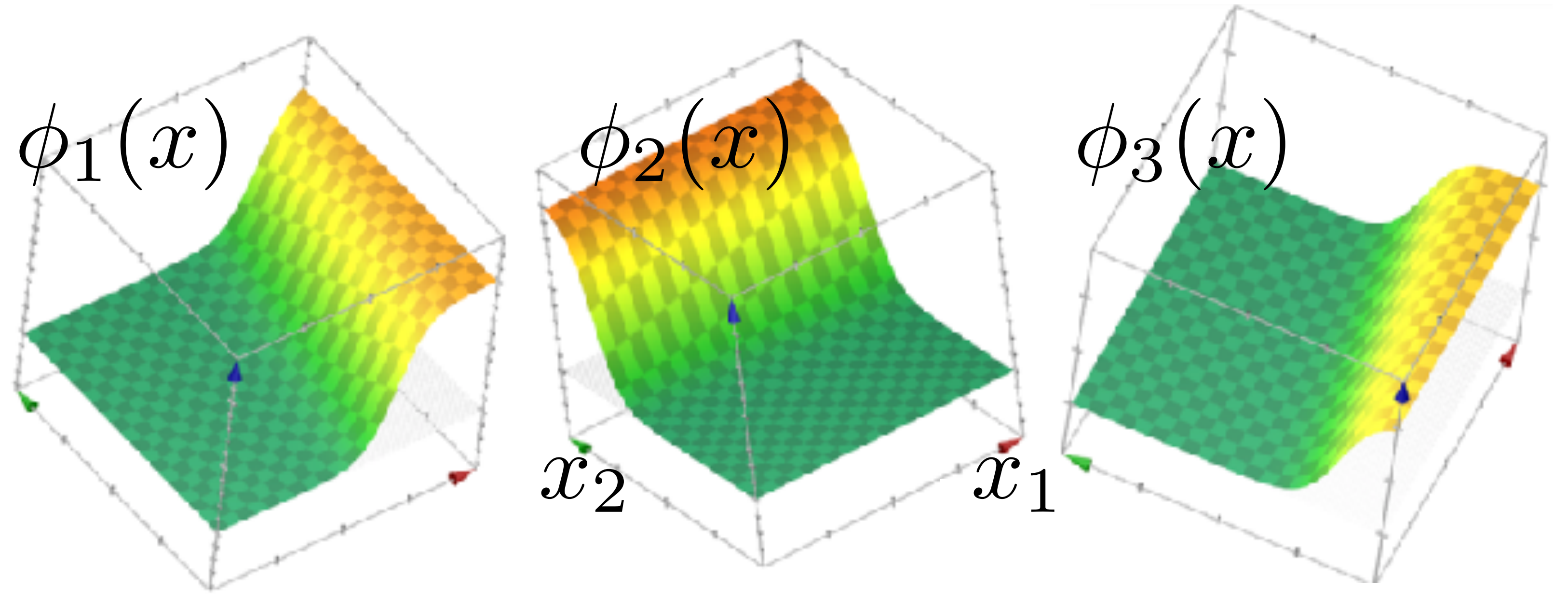

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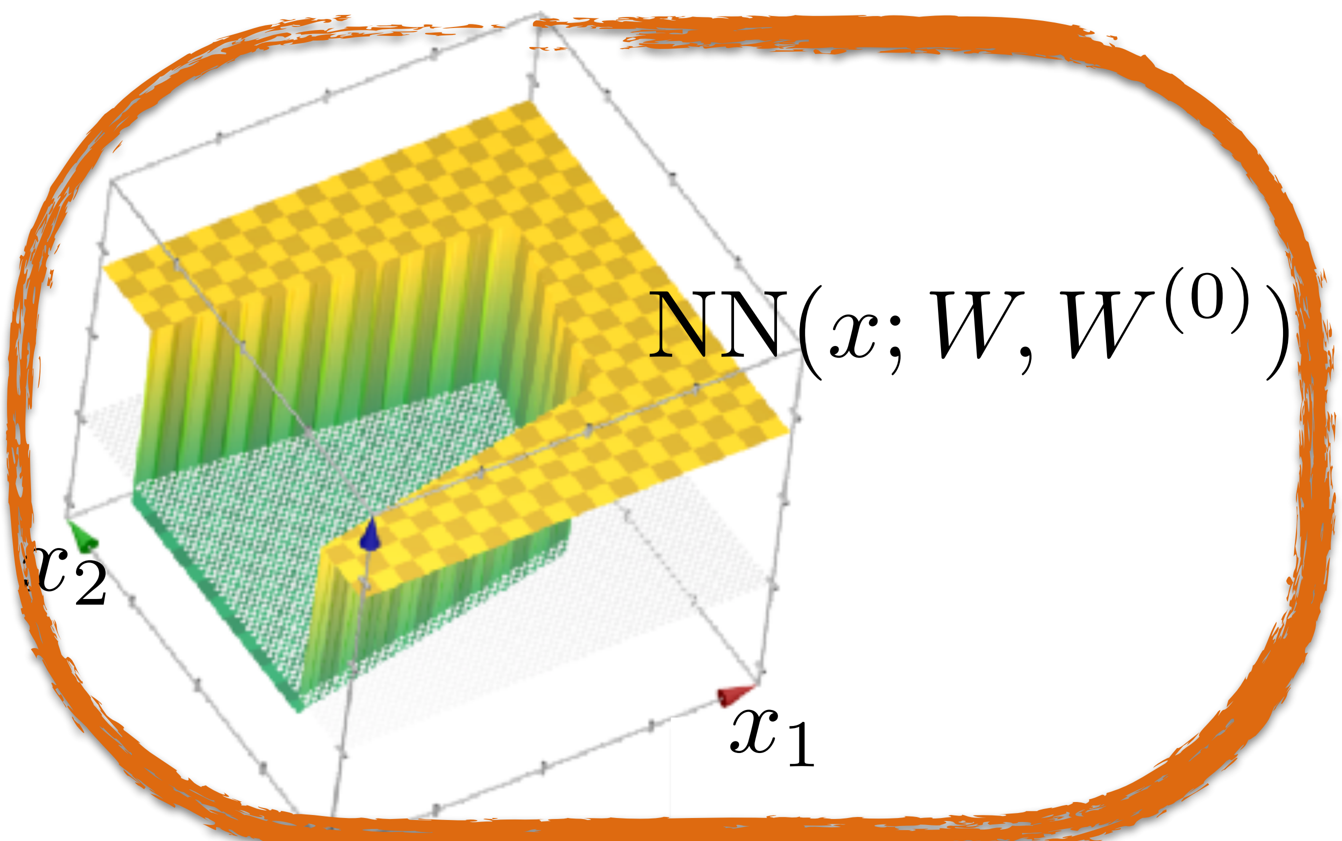

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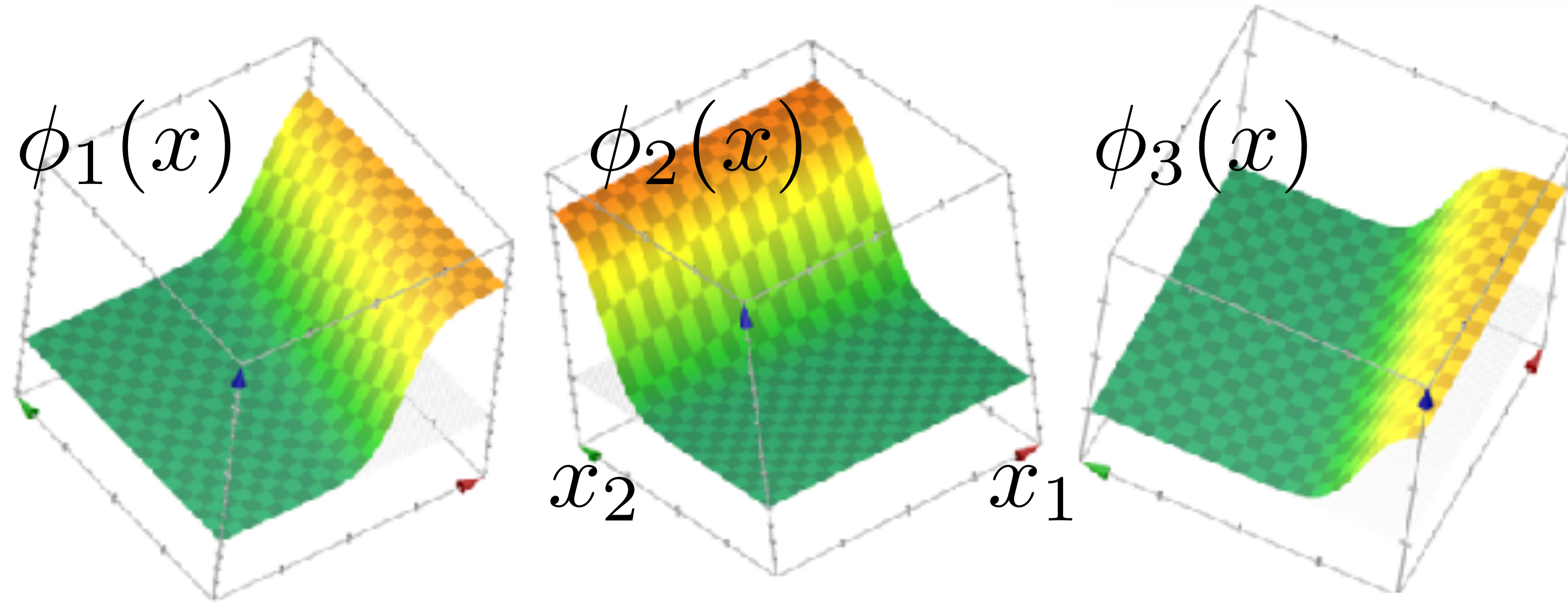

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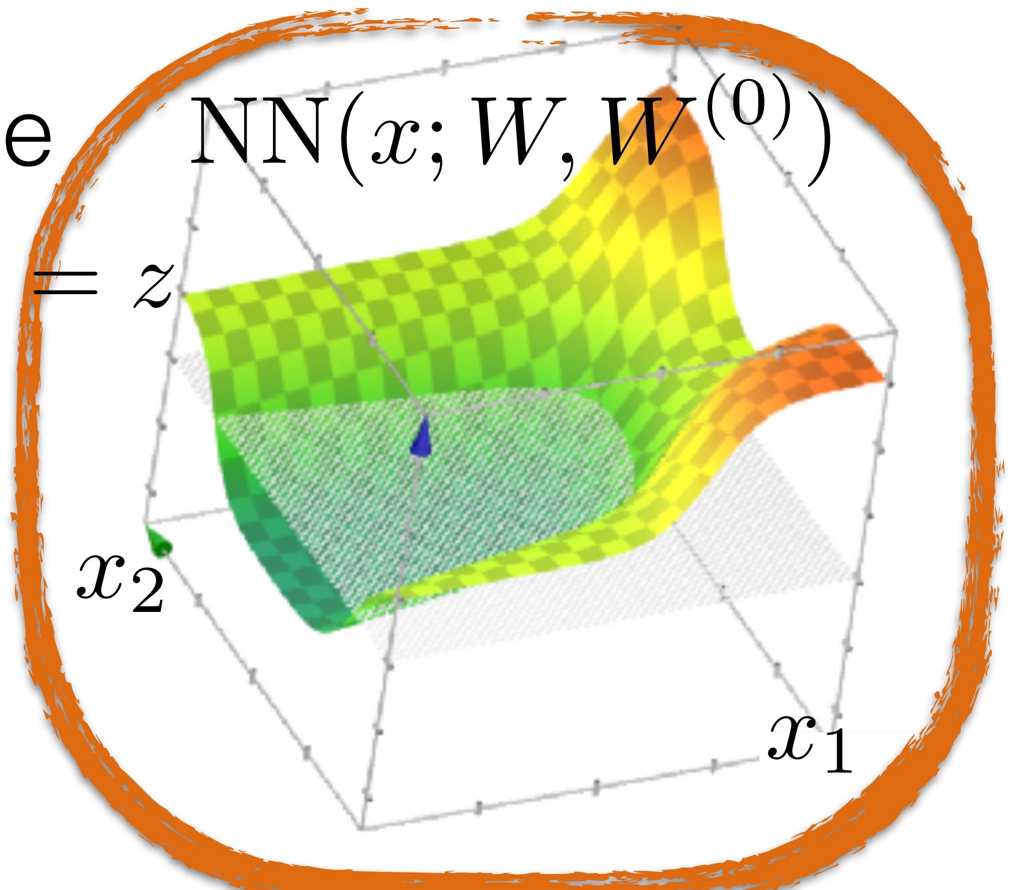

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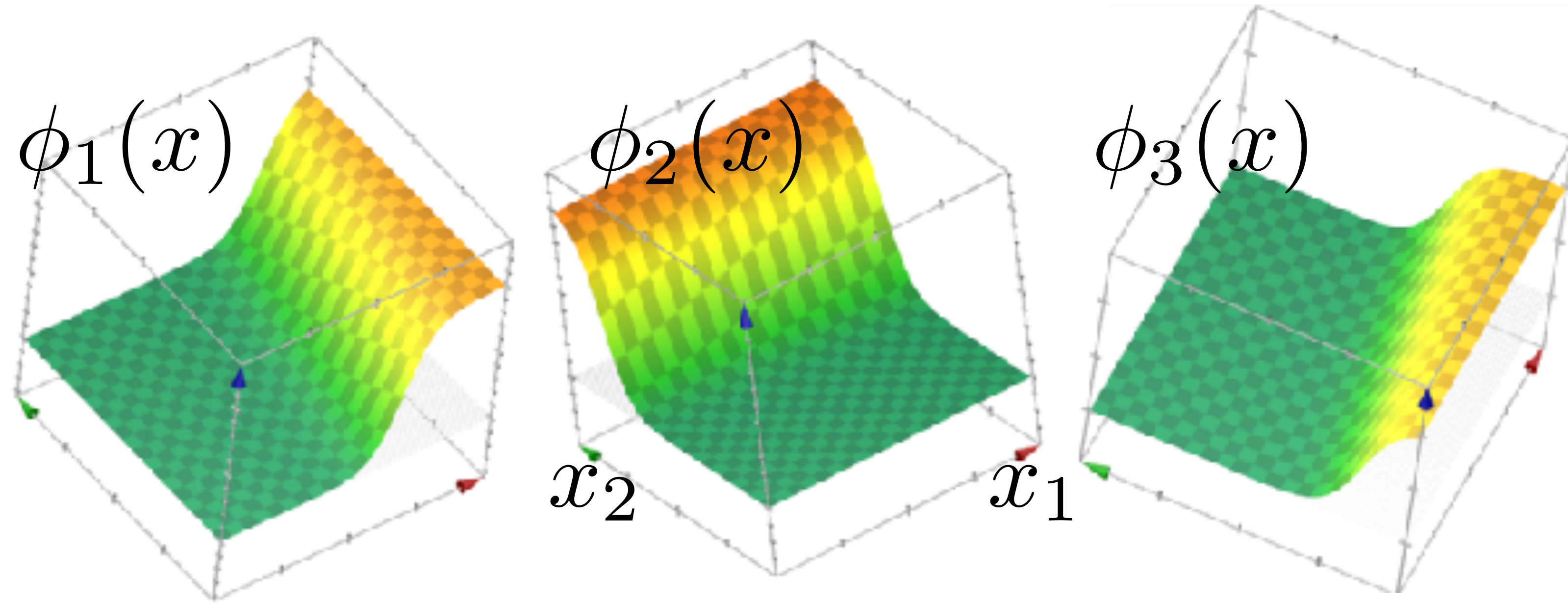

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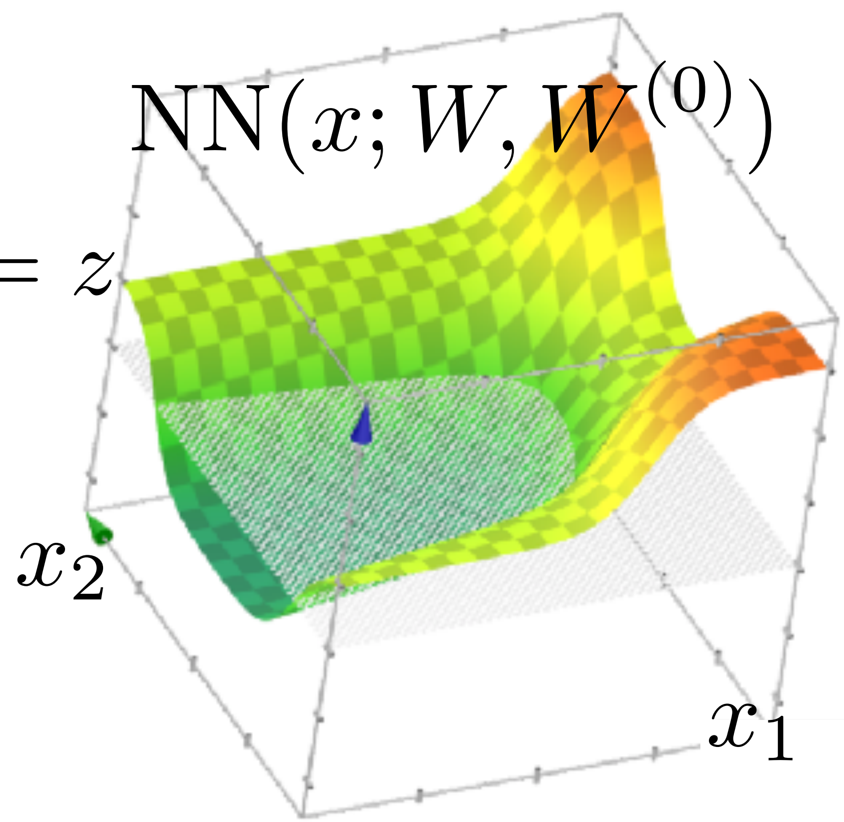

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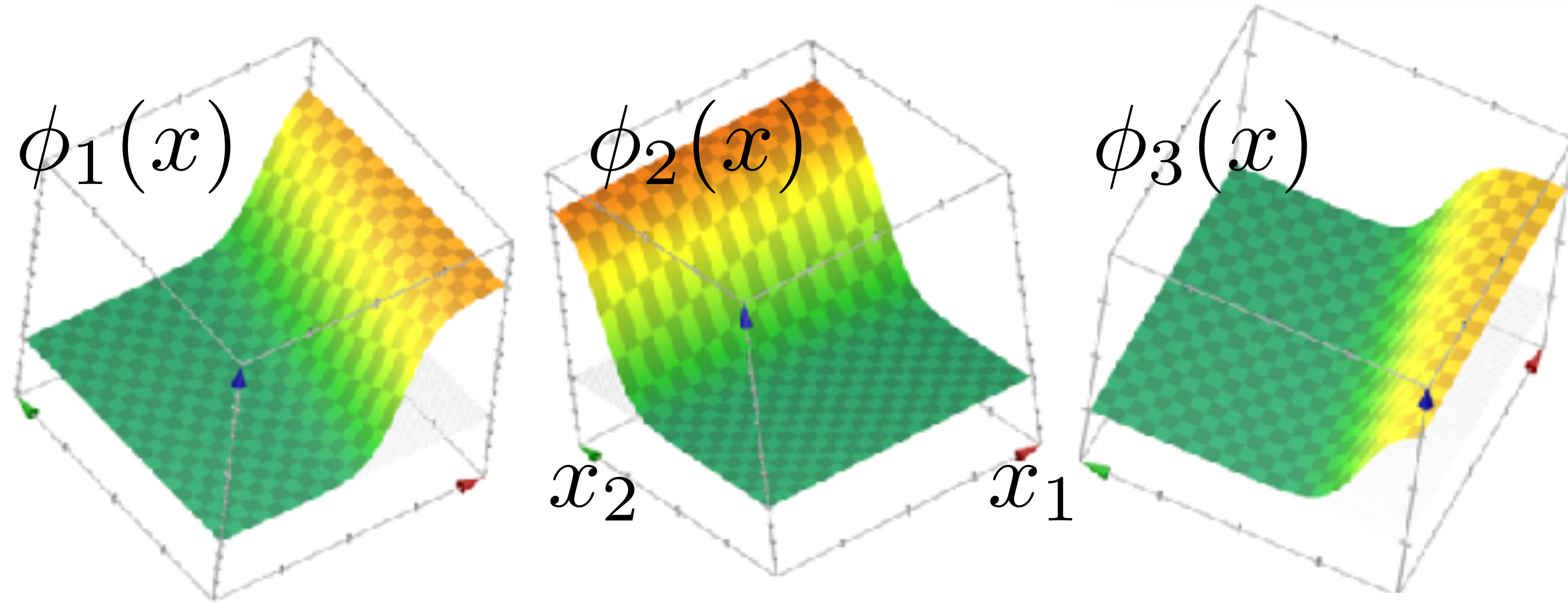

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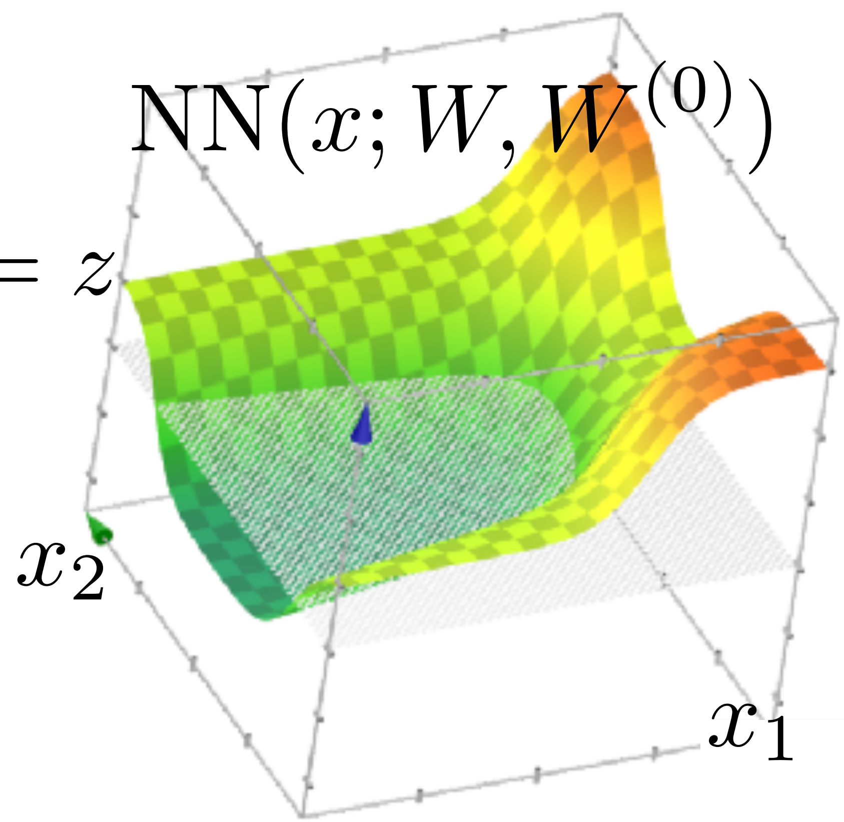

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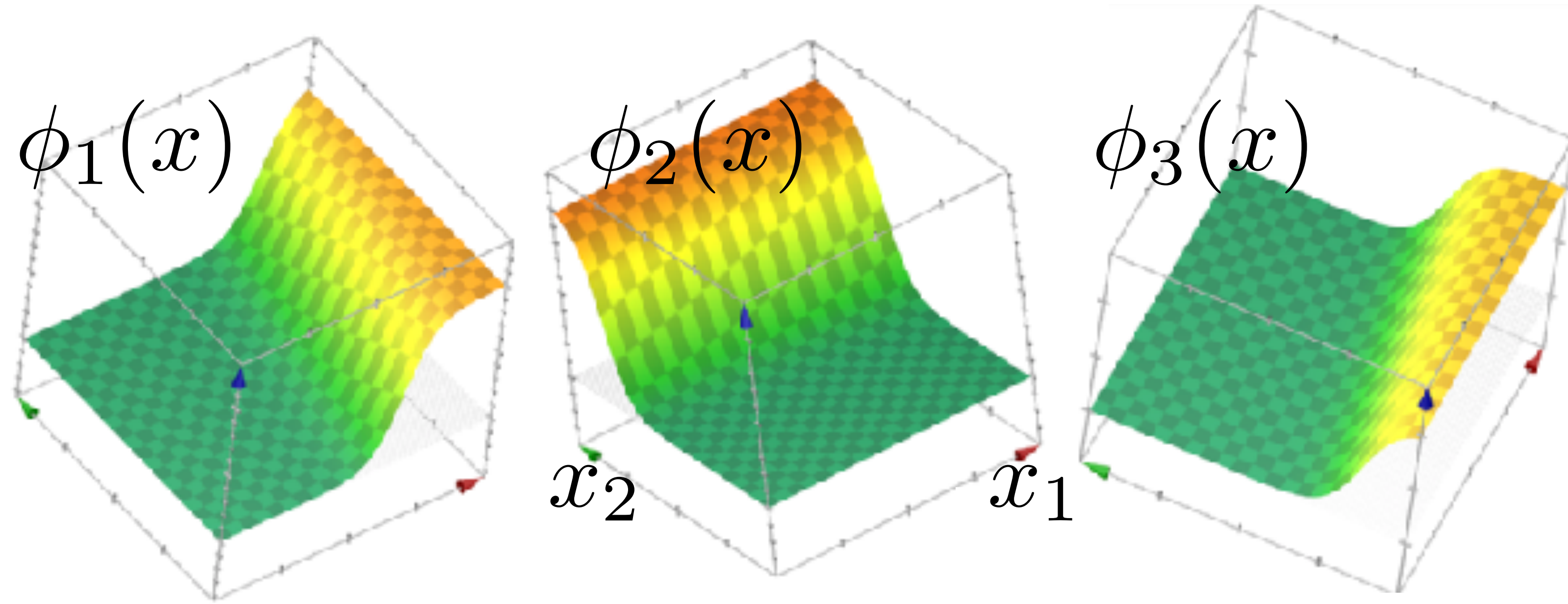

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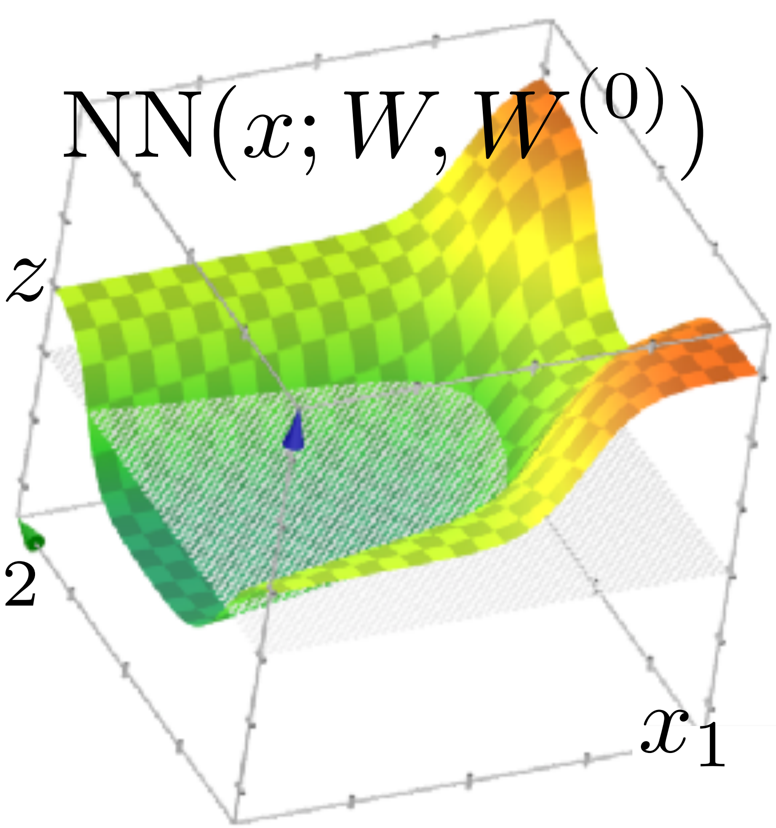

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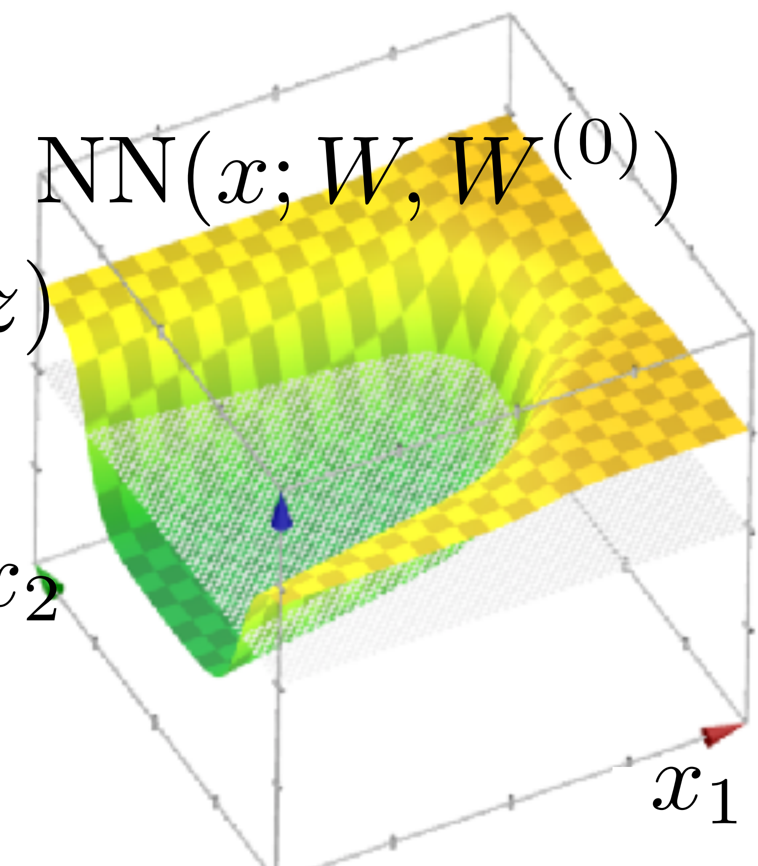

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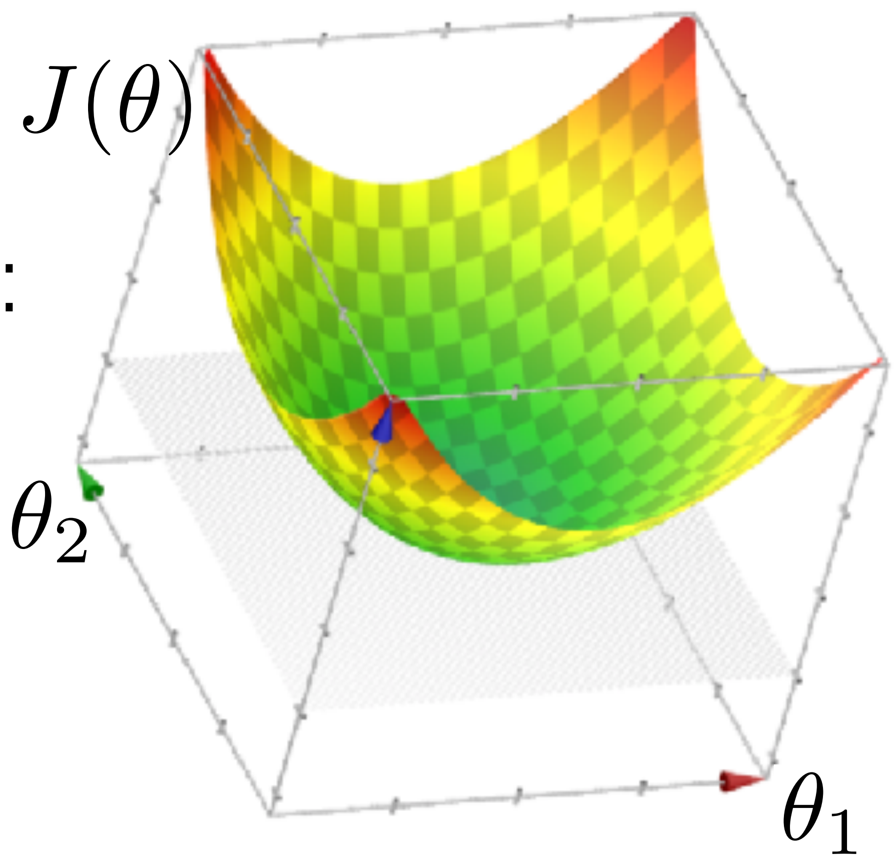

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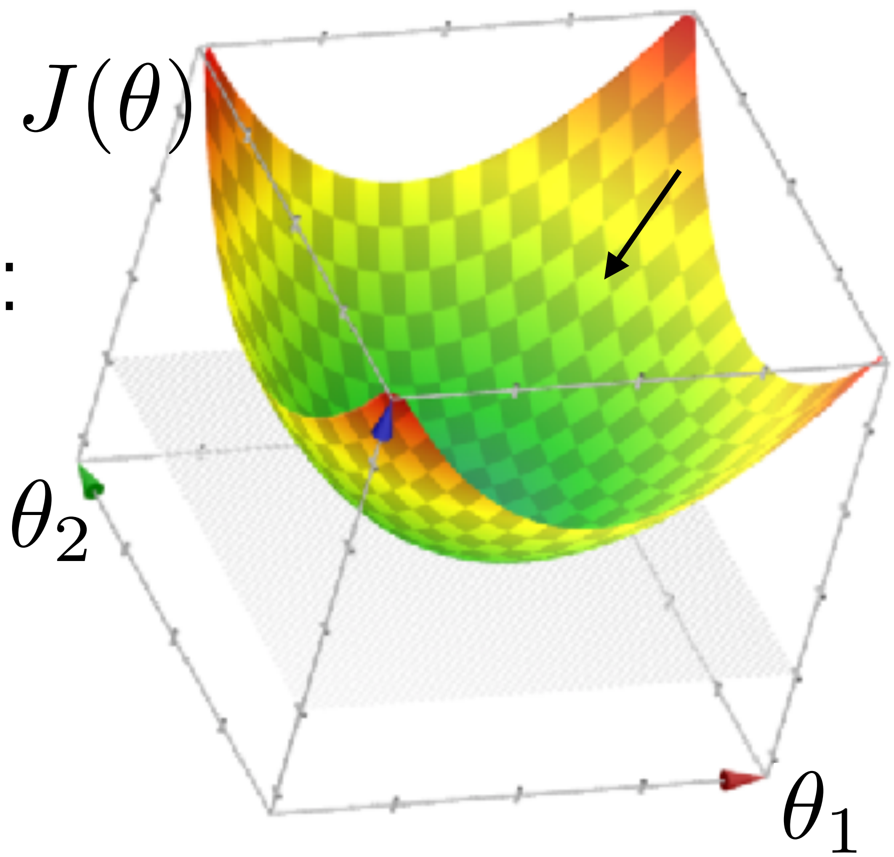

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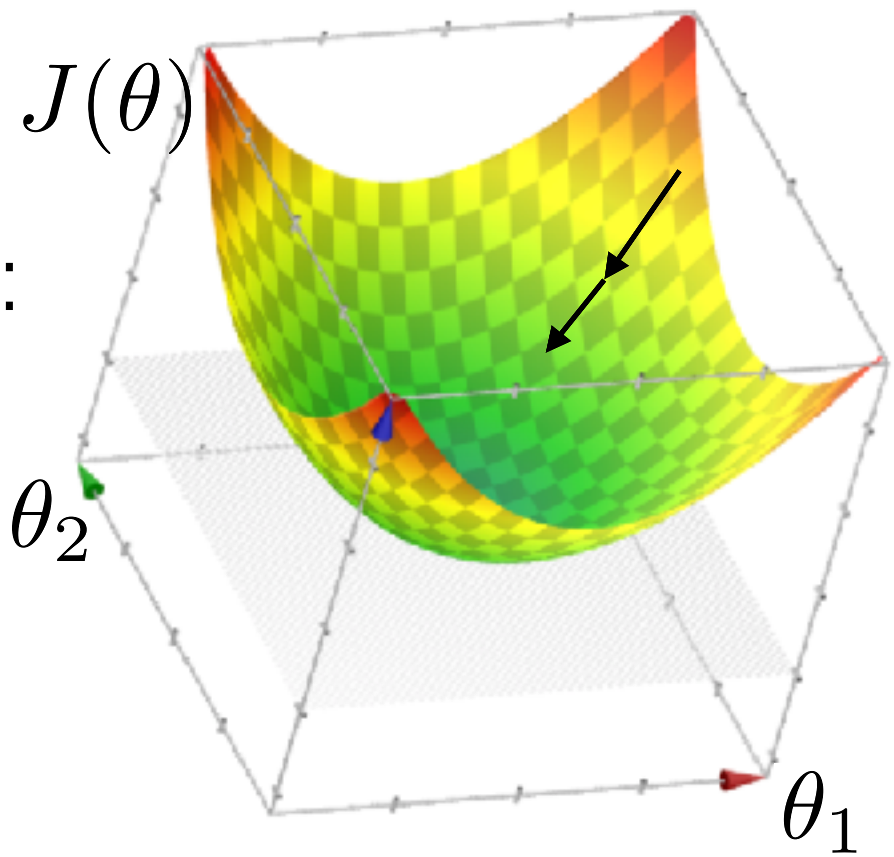

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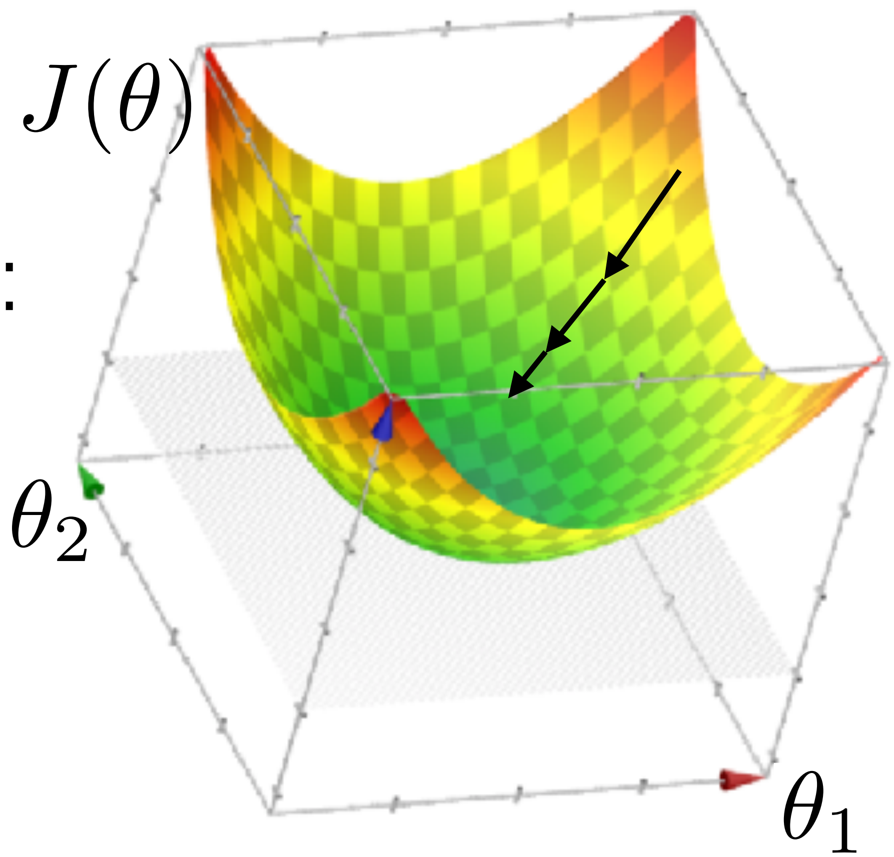

Learning the parameters

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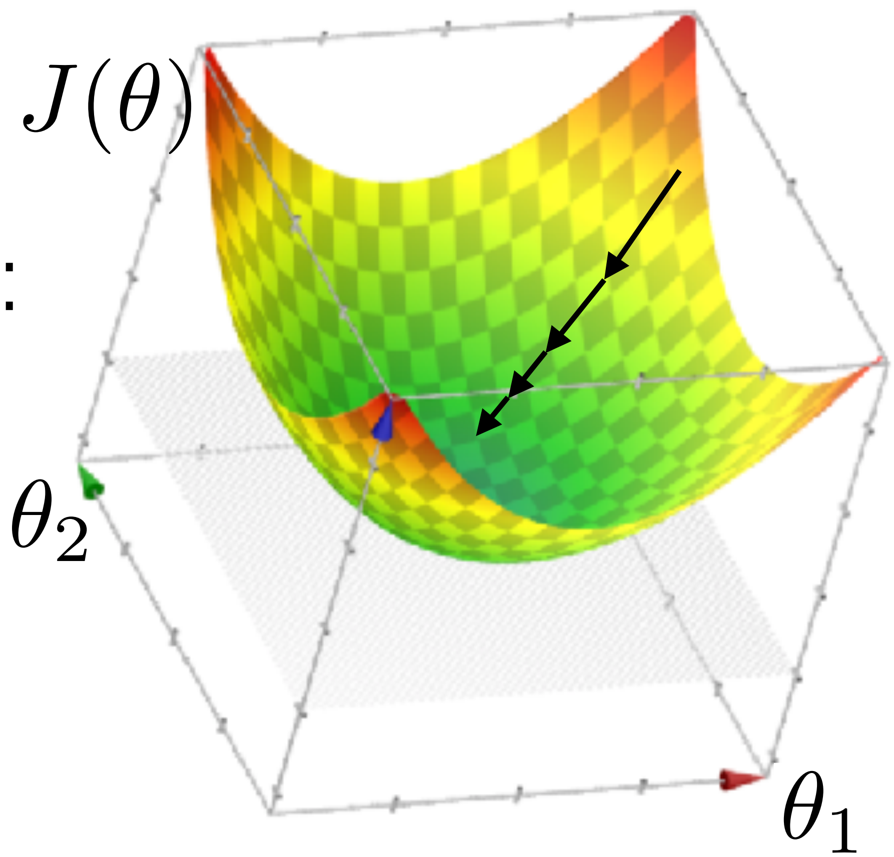

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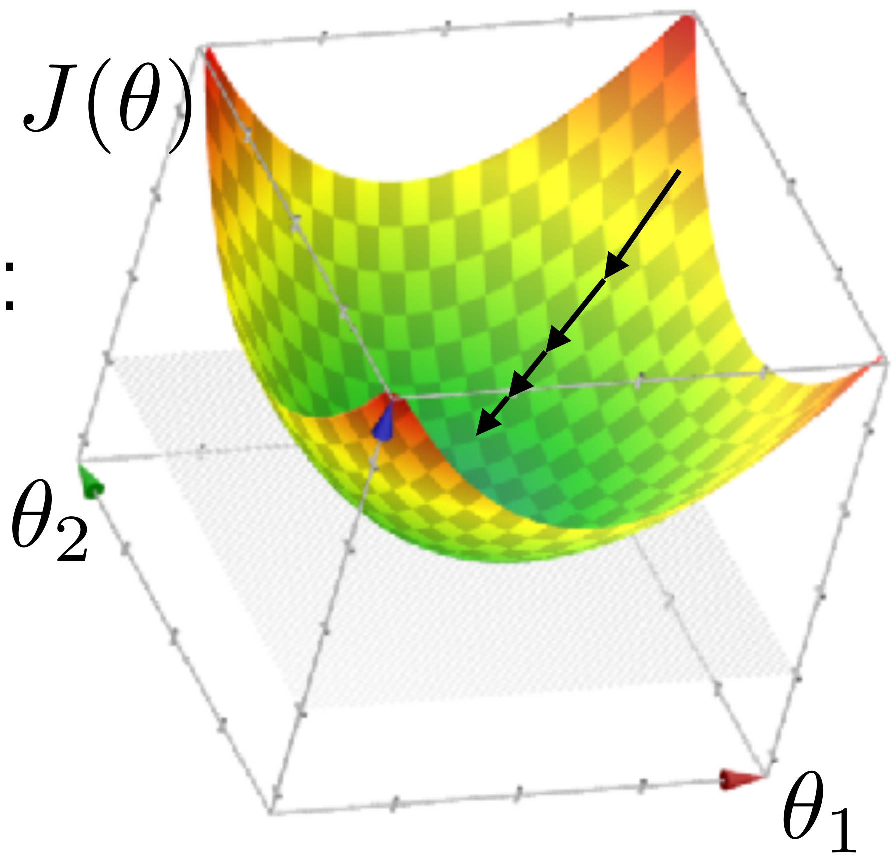

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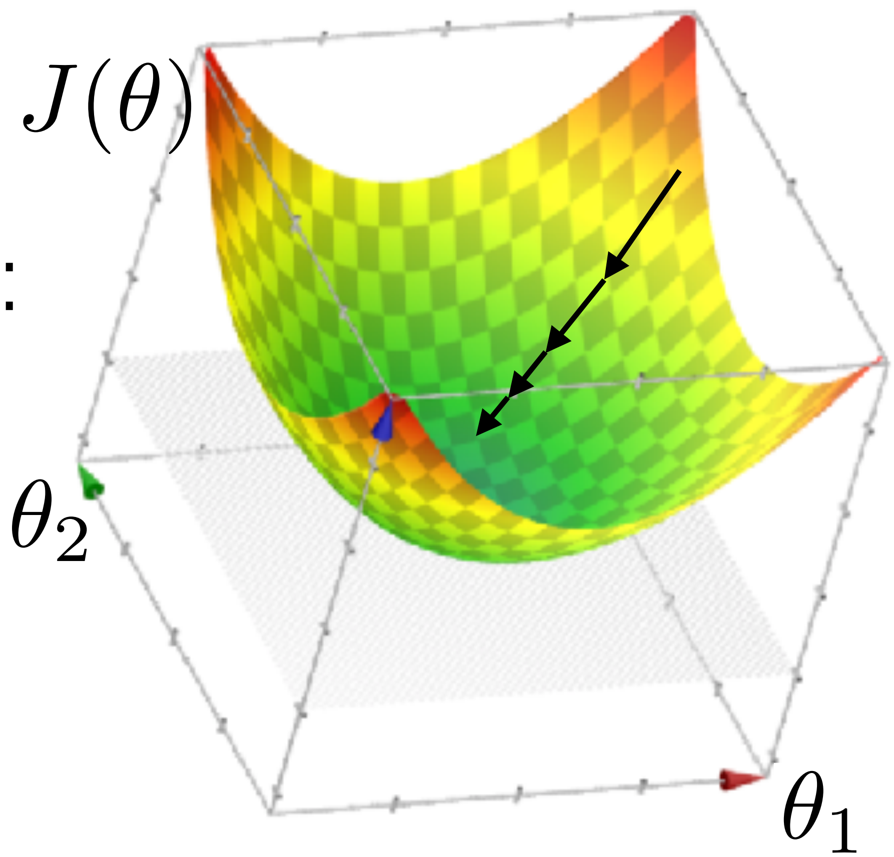

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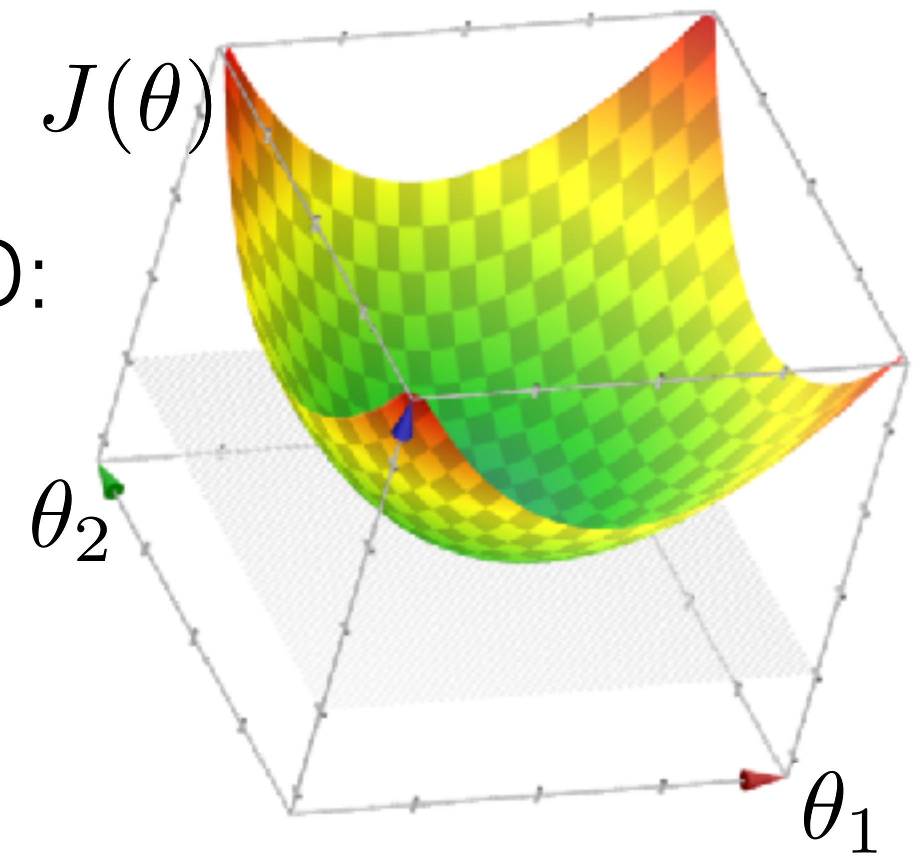

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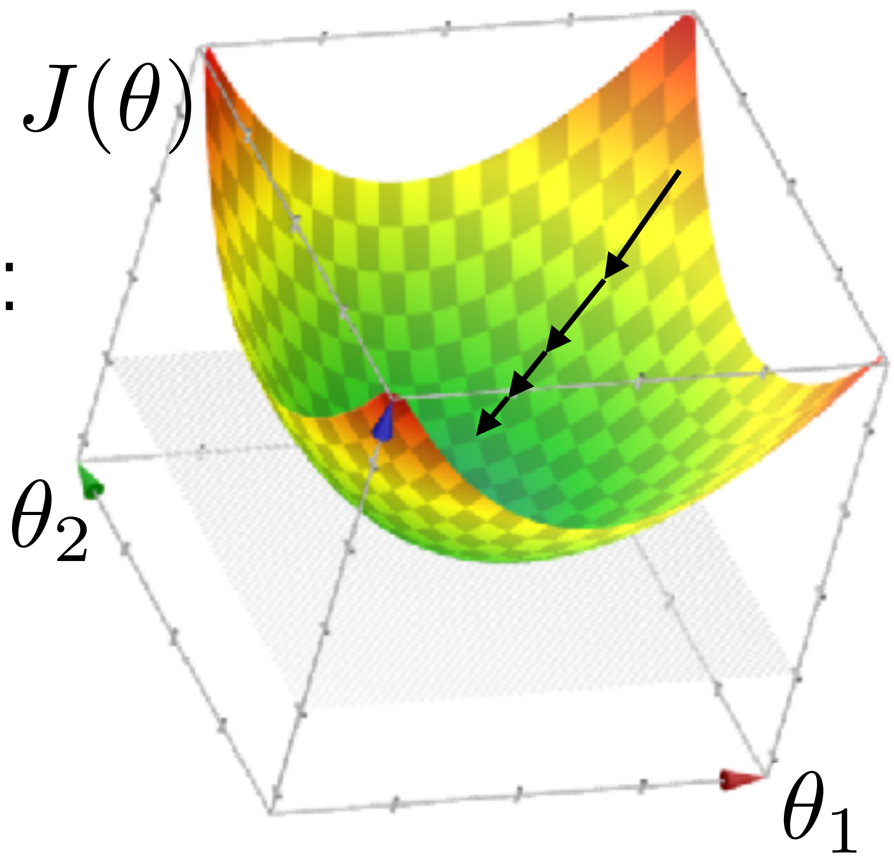

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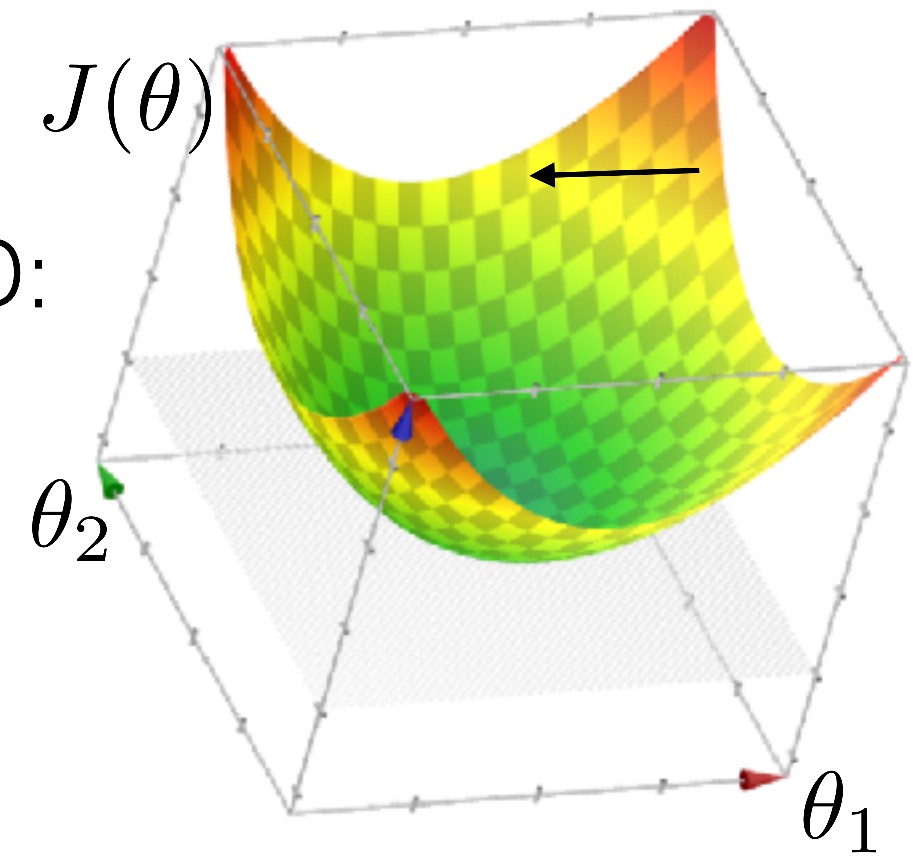

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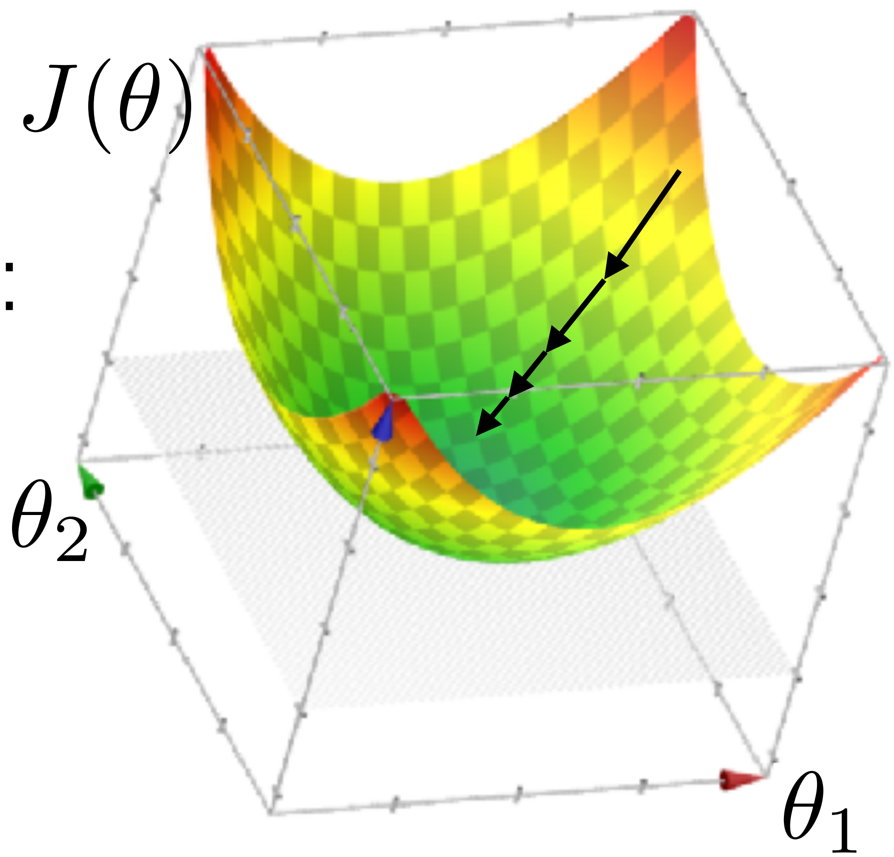

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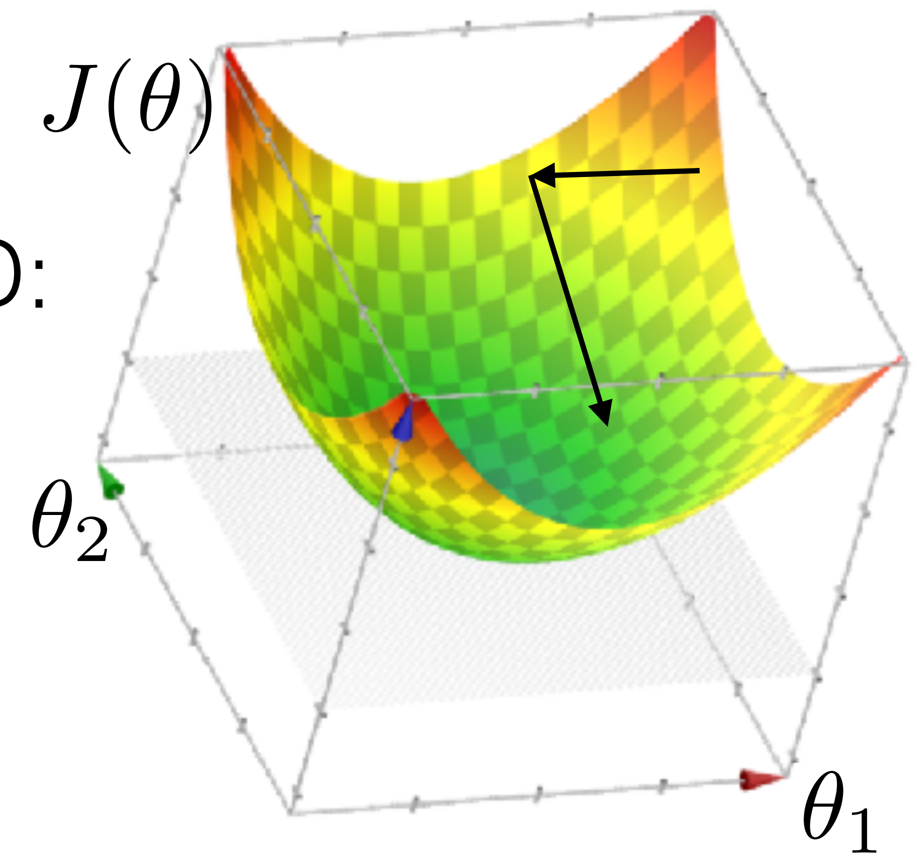

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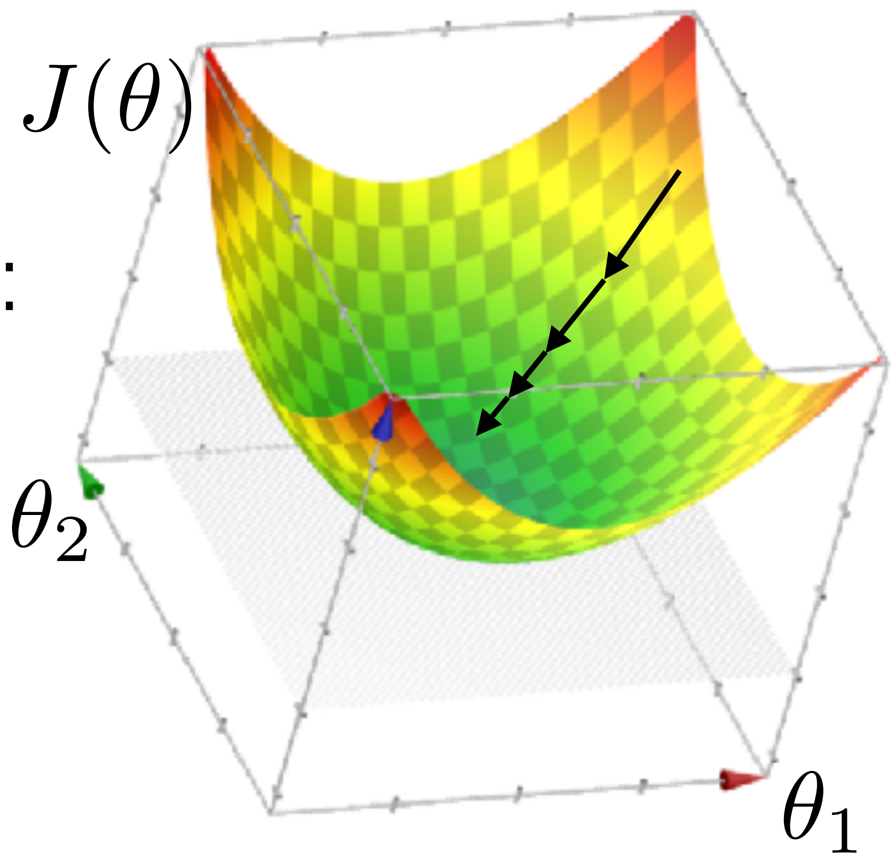

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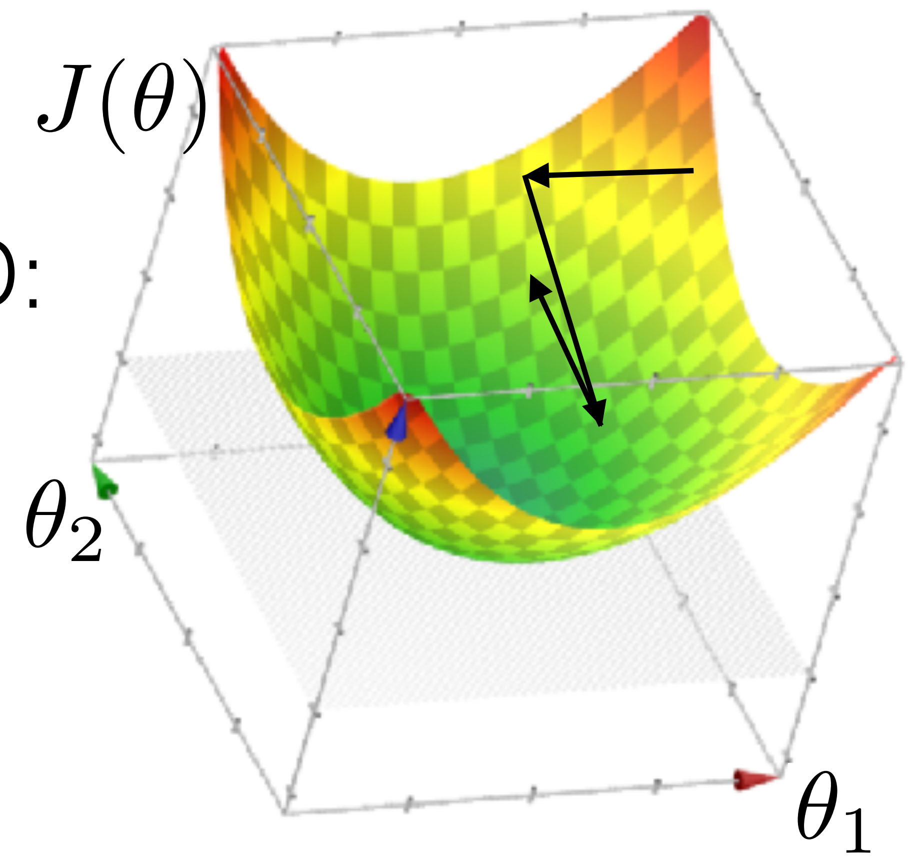

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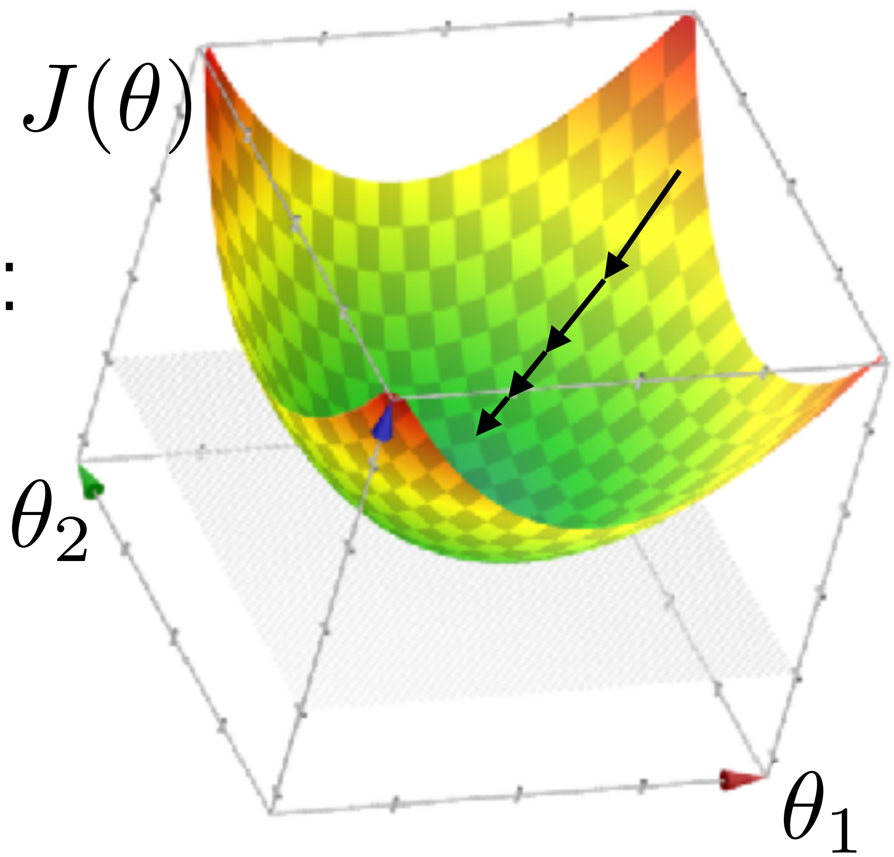

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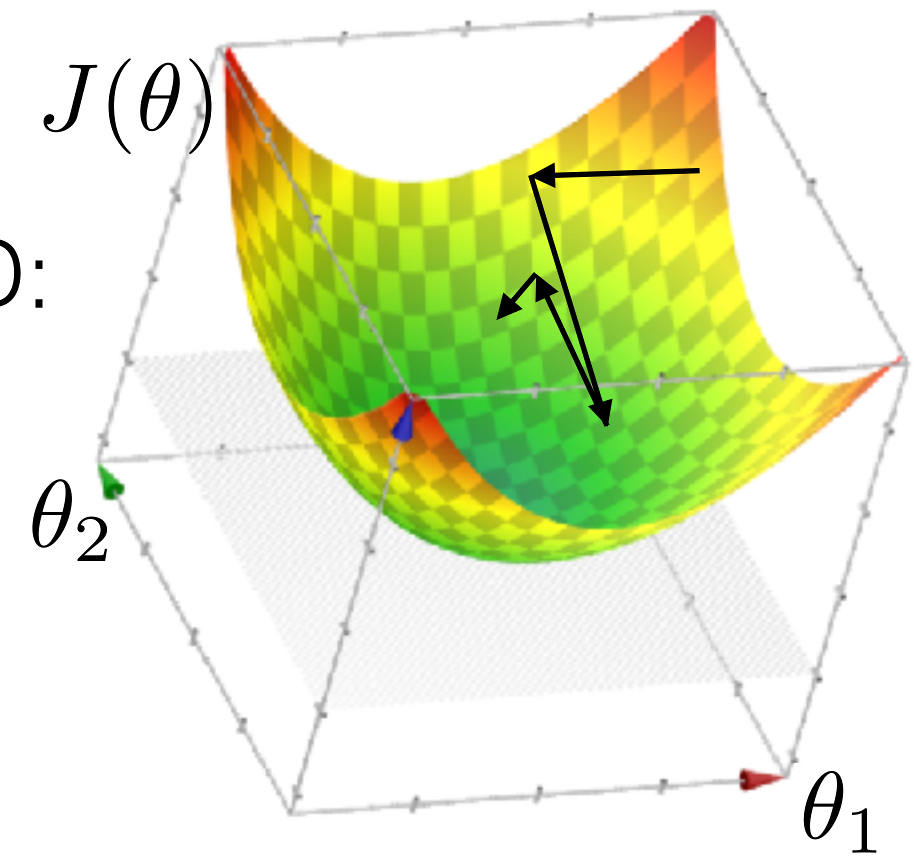

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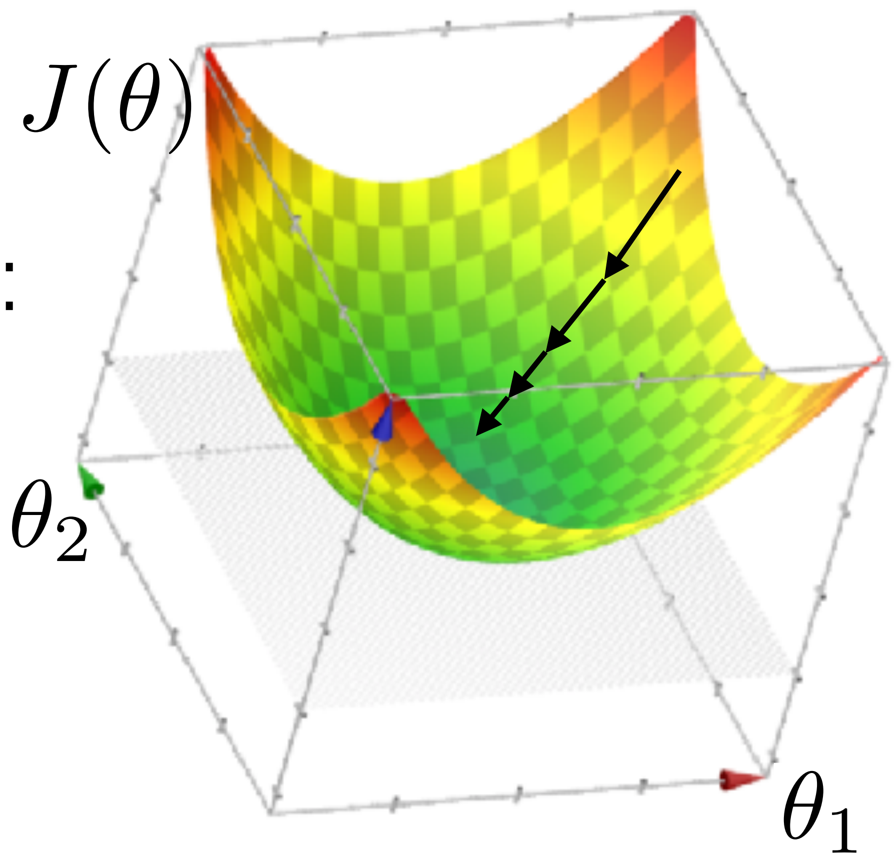

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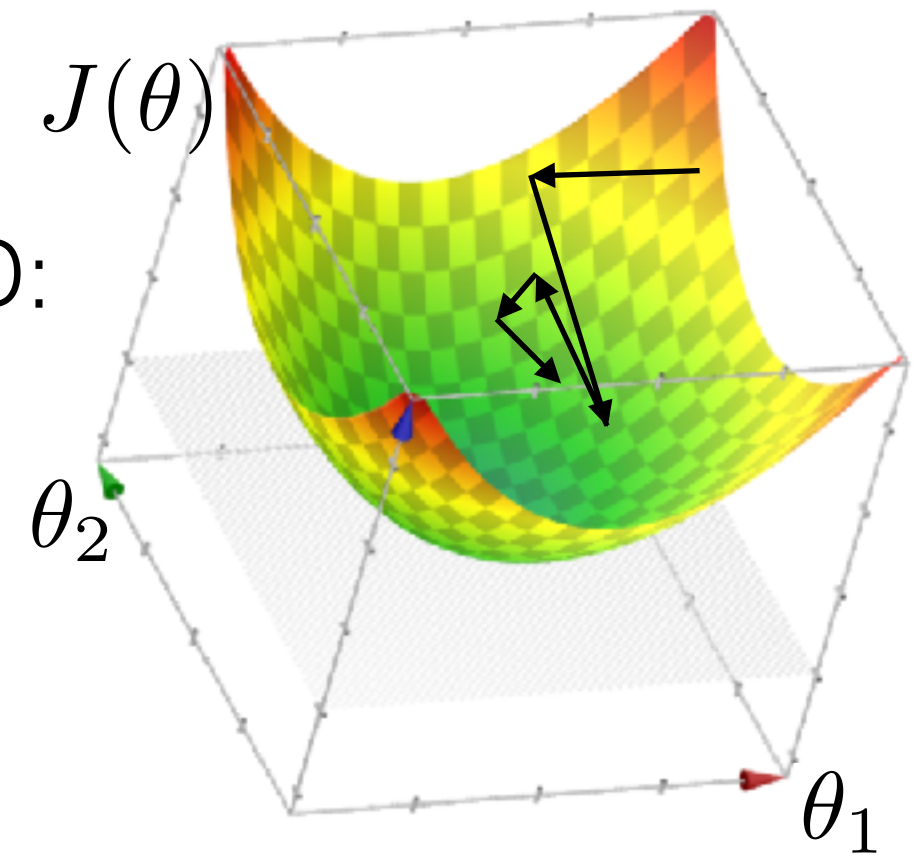

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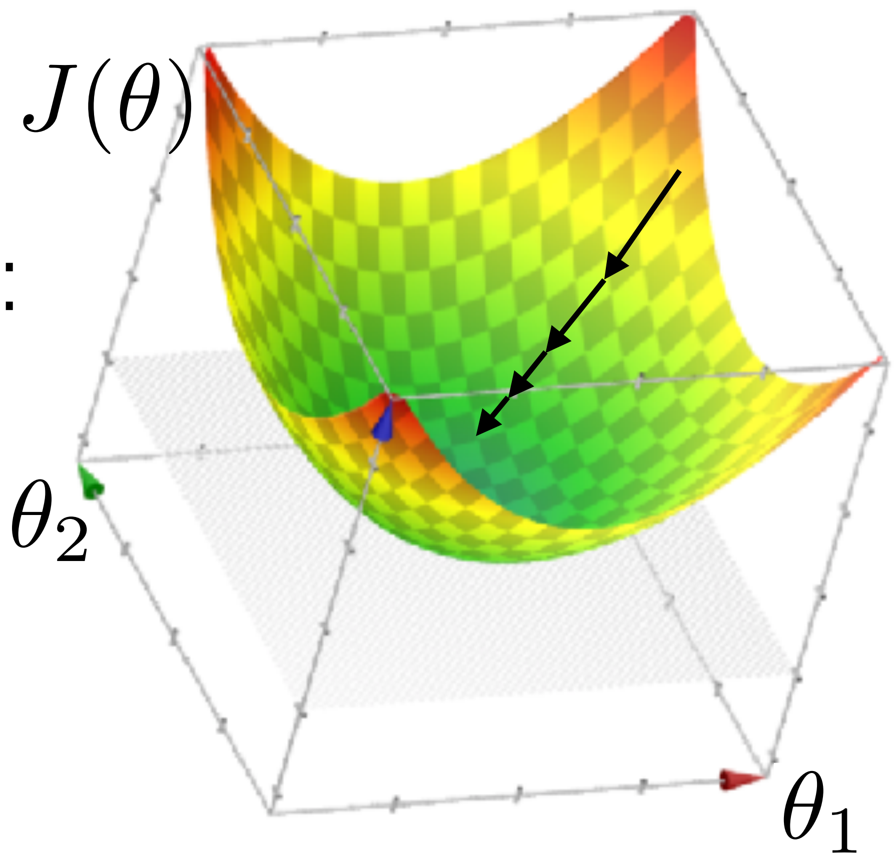

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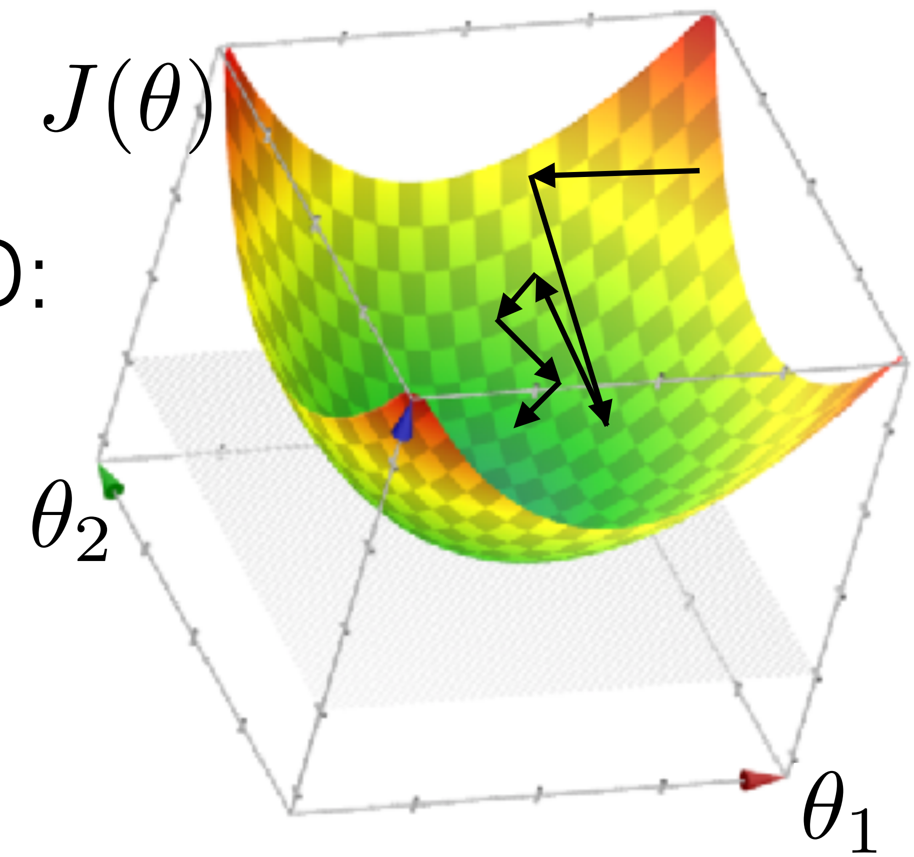

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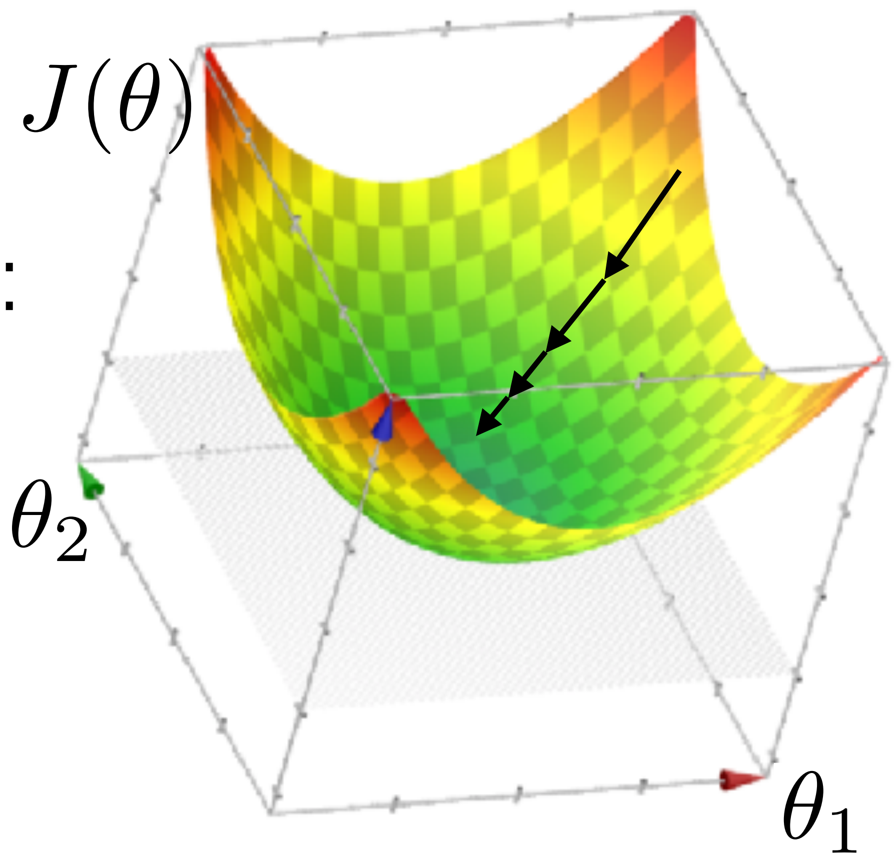

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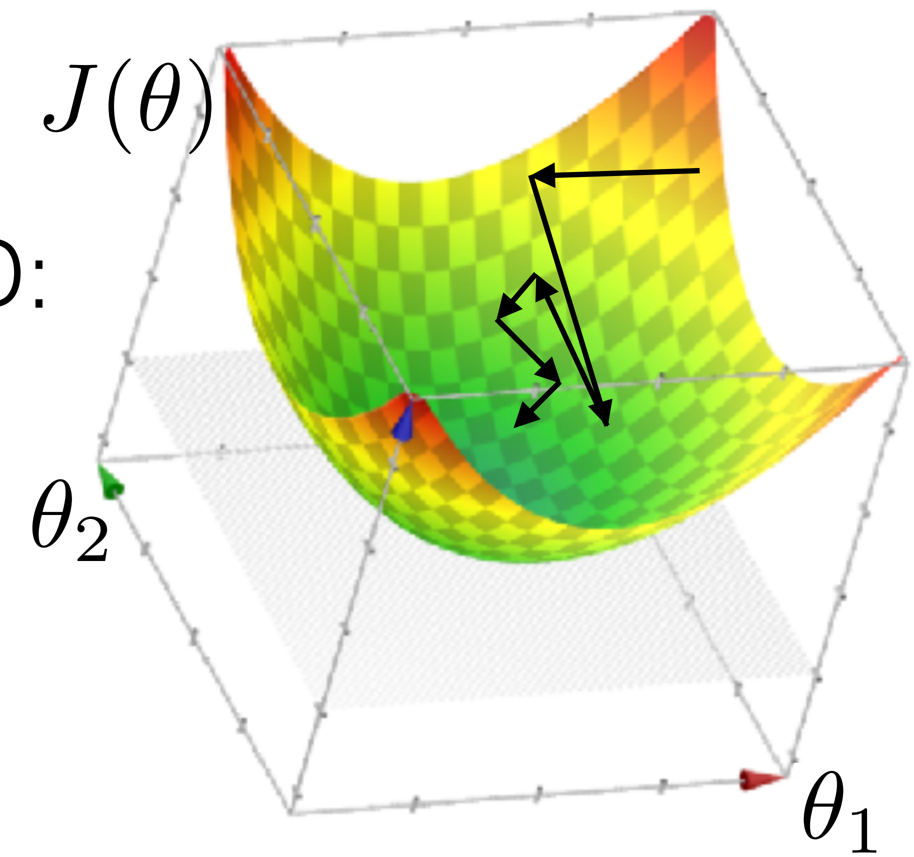

- **Theorem**: (Roughly) if the objective is nice and convex, GD and SGD perform well

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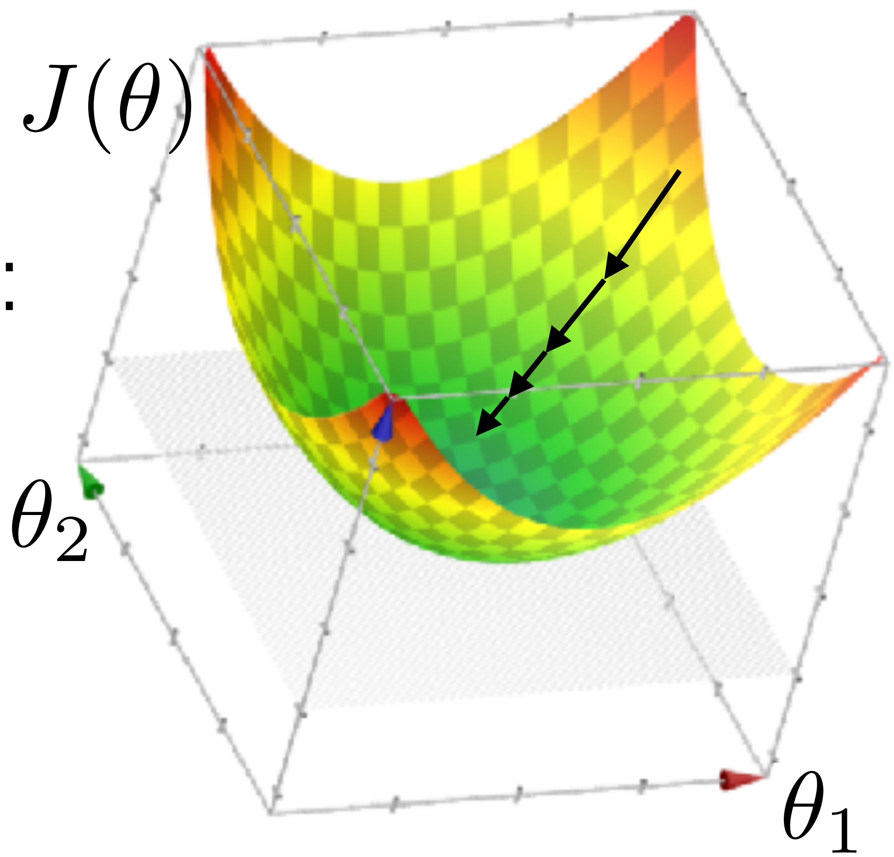

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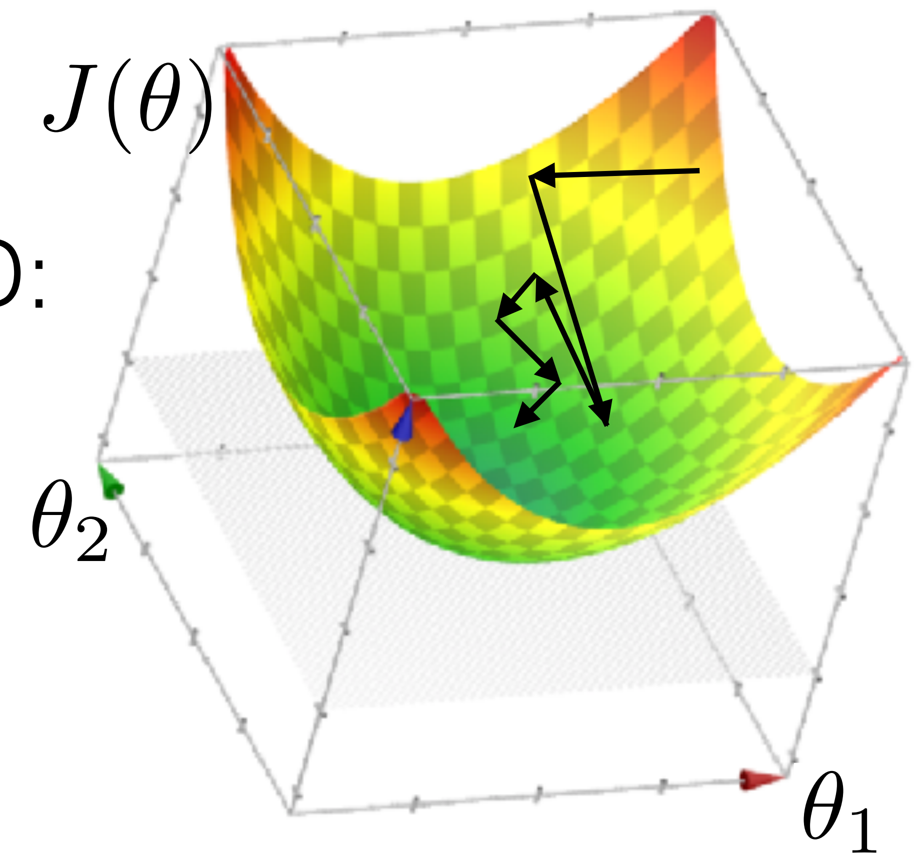

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- **Big challenge**: the NN objective is a (very) non-convex function of the parameters (except in e.g. 1 layer)

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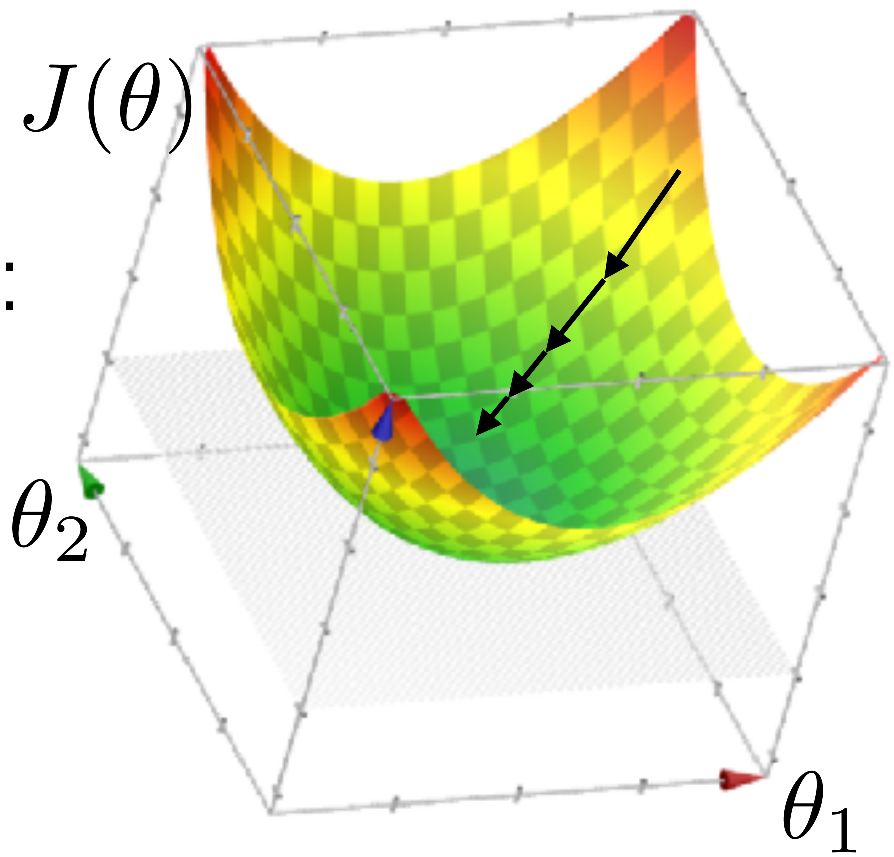

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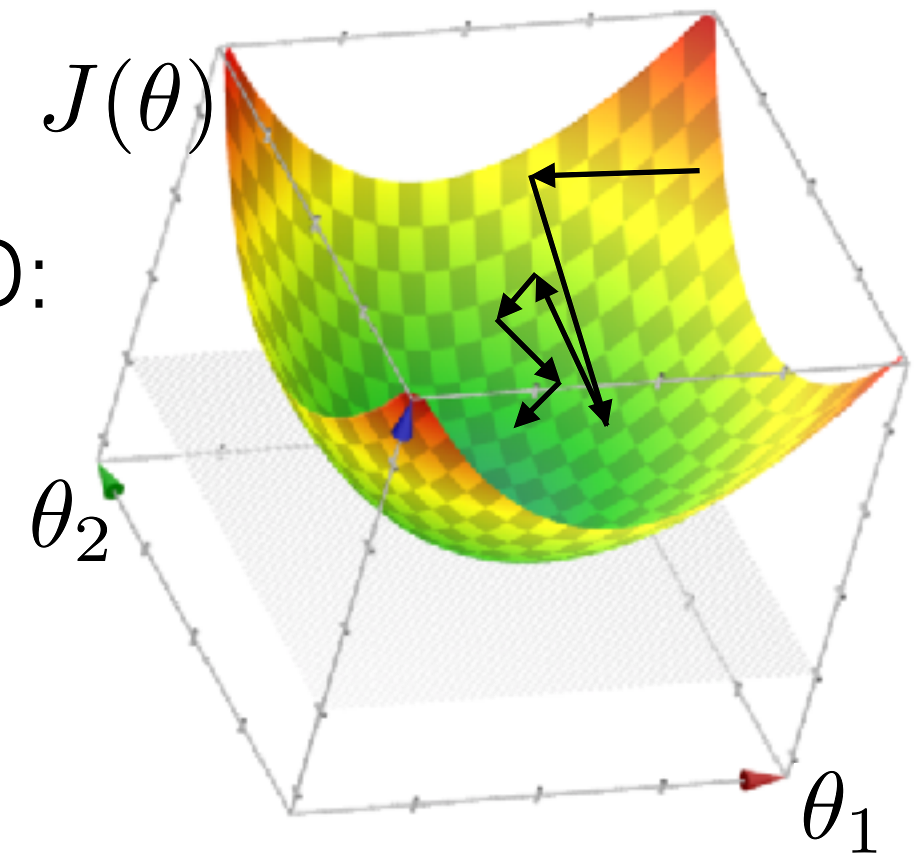

- **Theorem**: (Roughly) if the objective is nice and convex, GD and SGD perform well
- **Big challenge**: the NN objective is a (very) non-convex function of the parameters (except in e.g. 1 layer)
    - Huge bag of tricks to optimize / regularize

More layers!

- Why stop at 2 layers?

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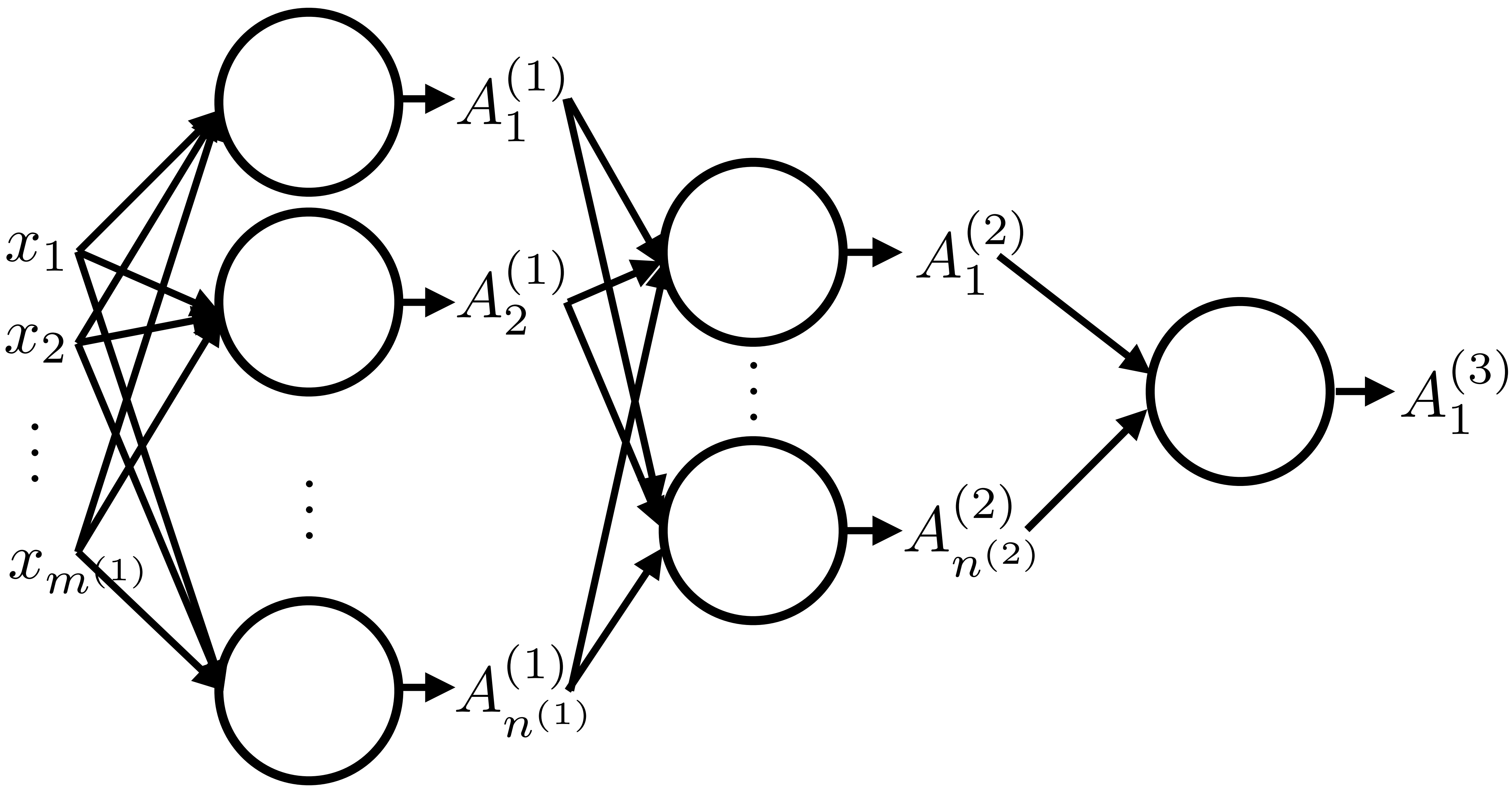

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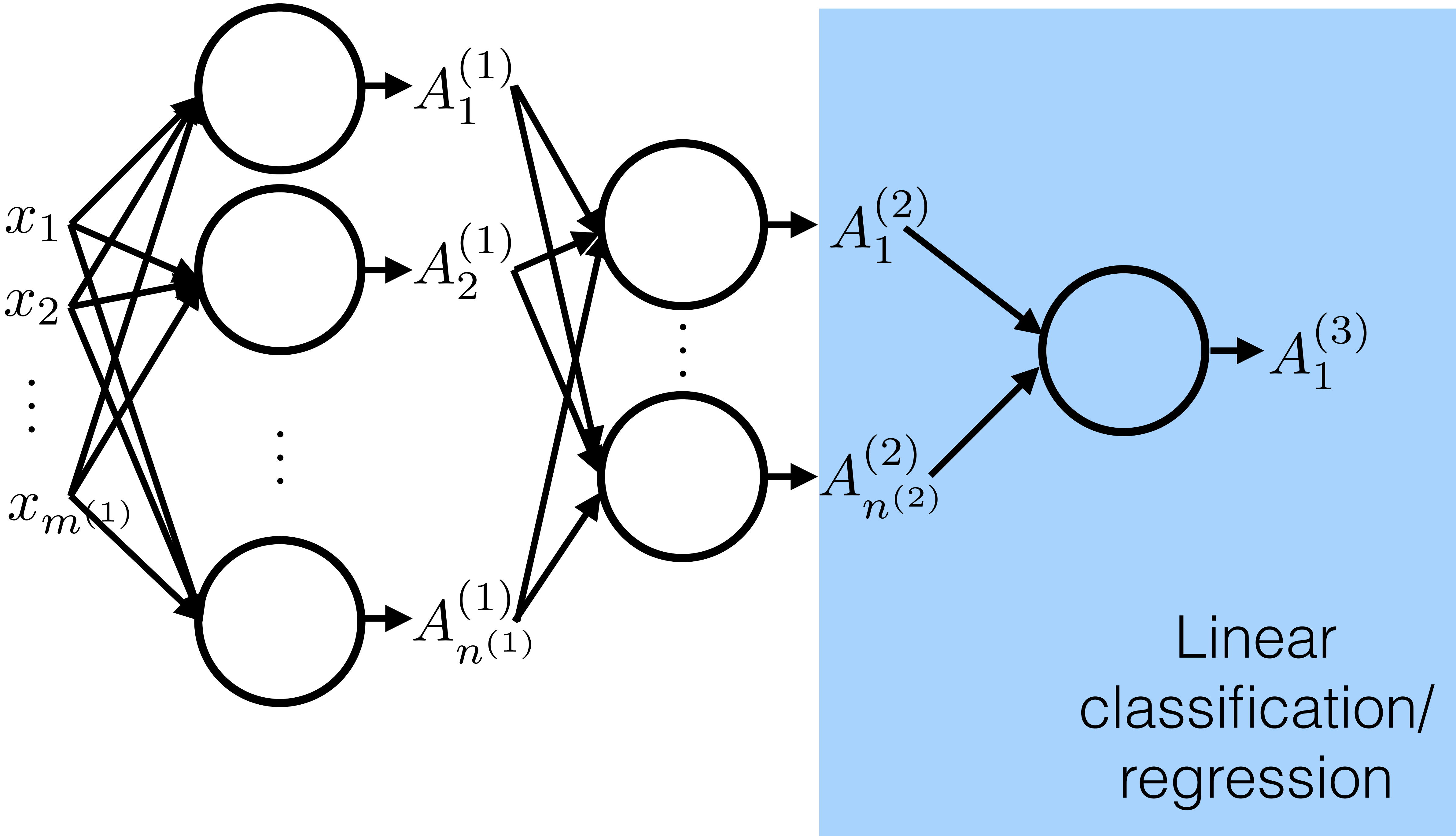

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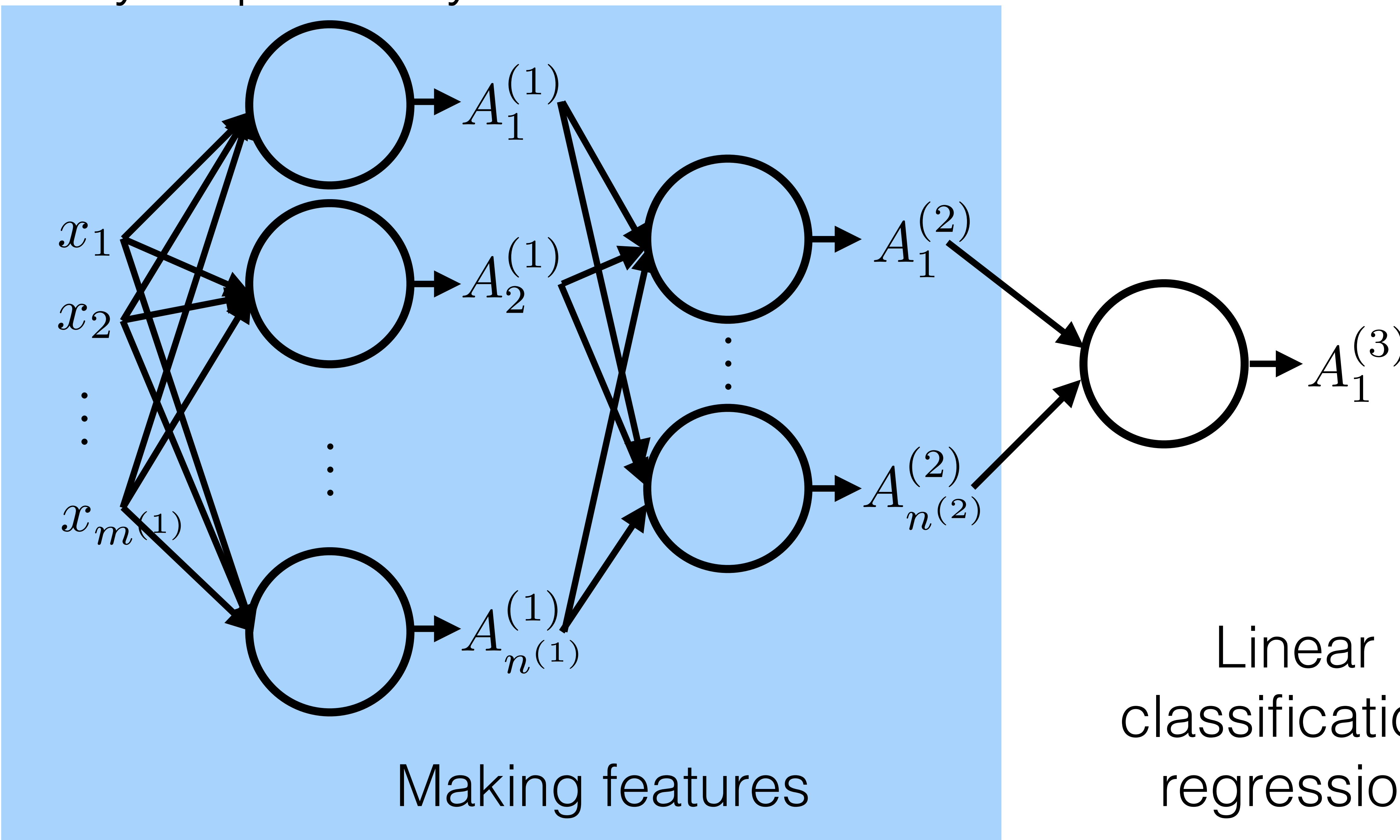

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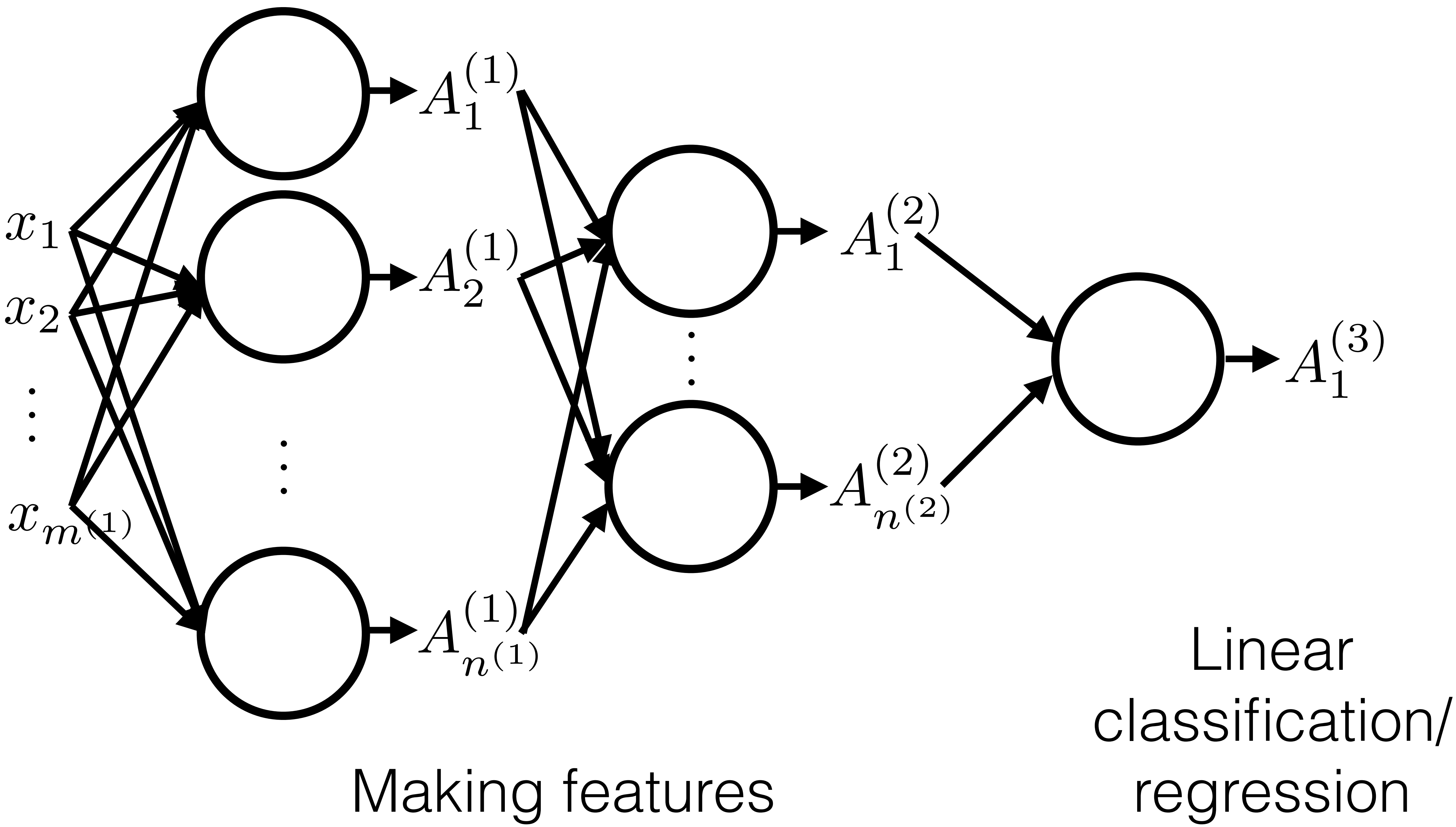

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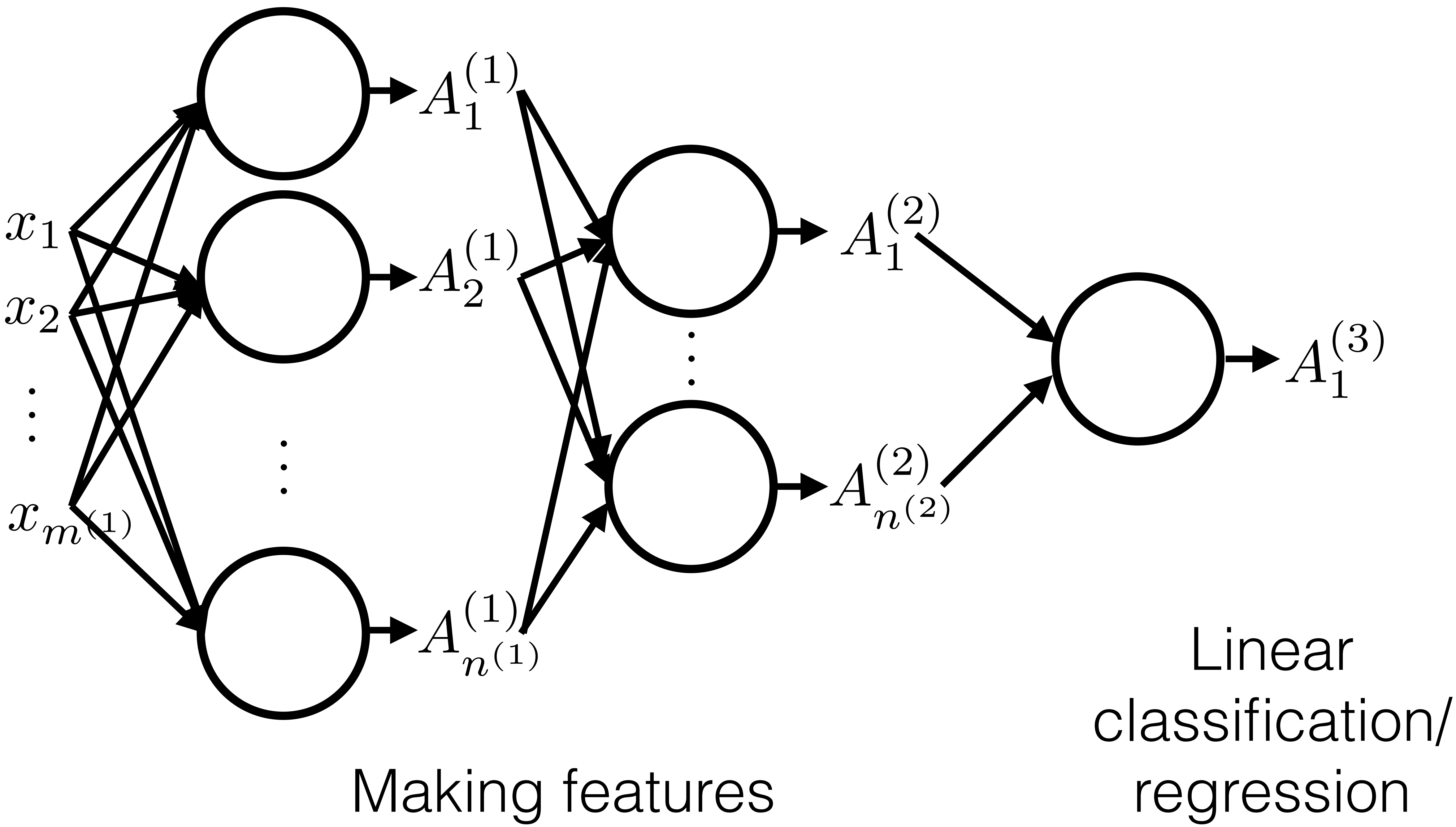

- Just one layer: linear classification/regression with default features