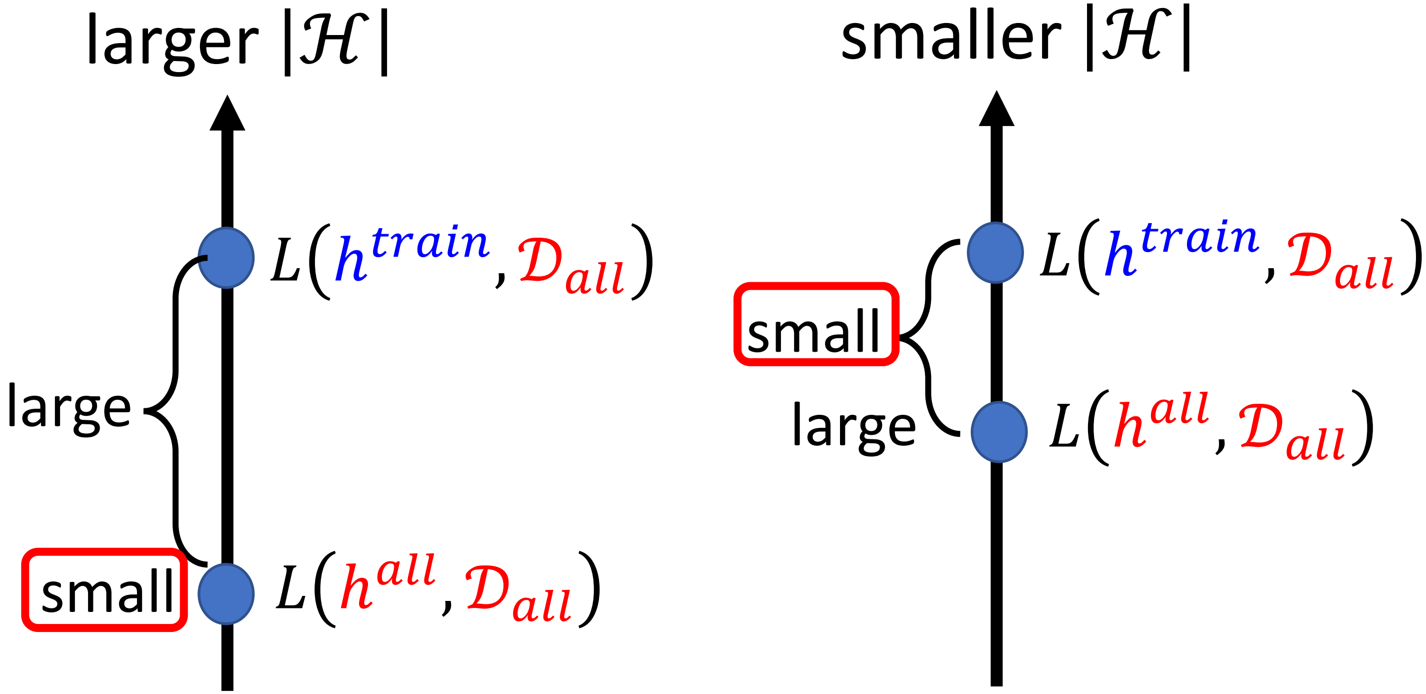
Why Deep Learning?

李宏毅
Hung-yi Lee



魚與熊掌可以兼得嗎？

Still small loss

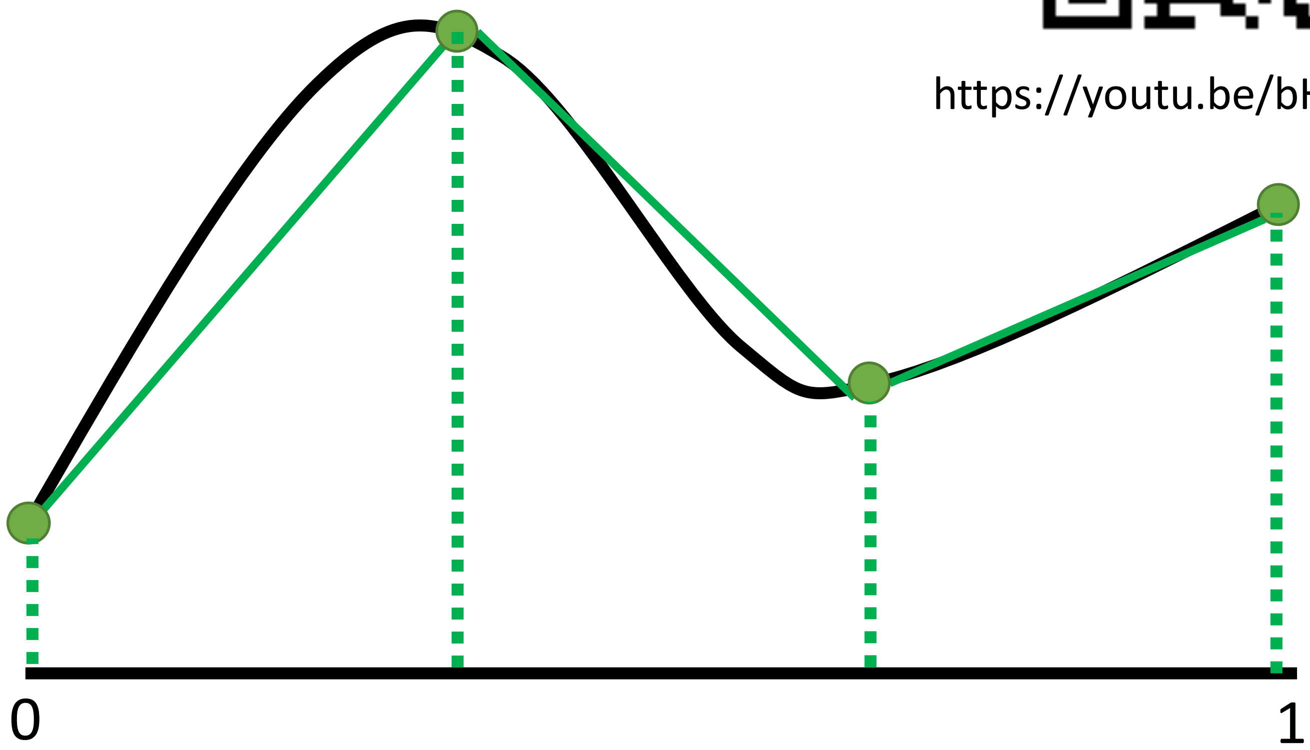
$$h^{all} = arg \min_{h \in \boxed{\mathcal{H}}} \boxed{L(h, \mathcal{D}_{all})}$$

Small (fewer candidates)

Review: Why Hidden Layer?

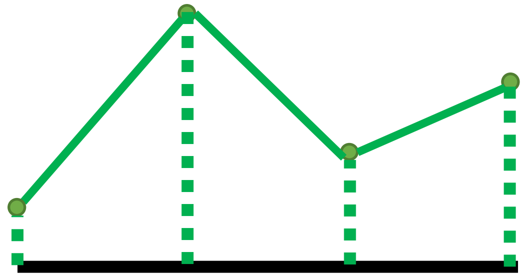
Piecewise Linear

https://youtu.be/bHcJCp2Fyxs

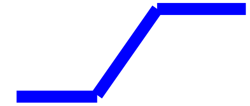


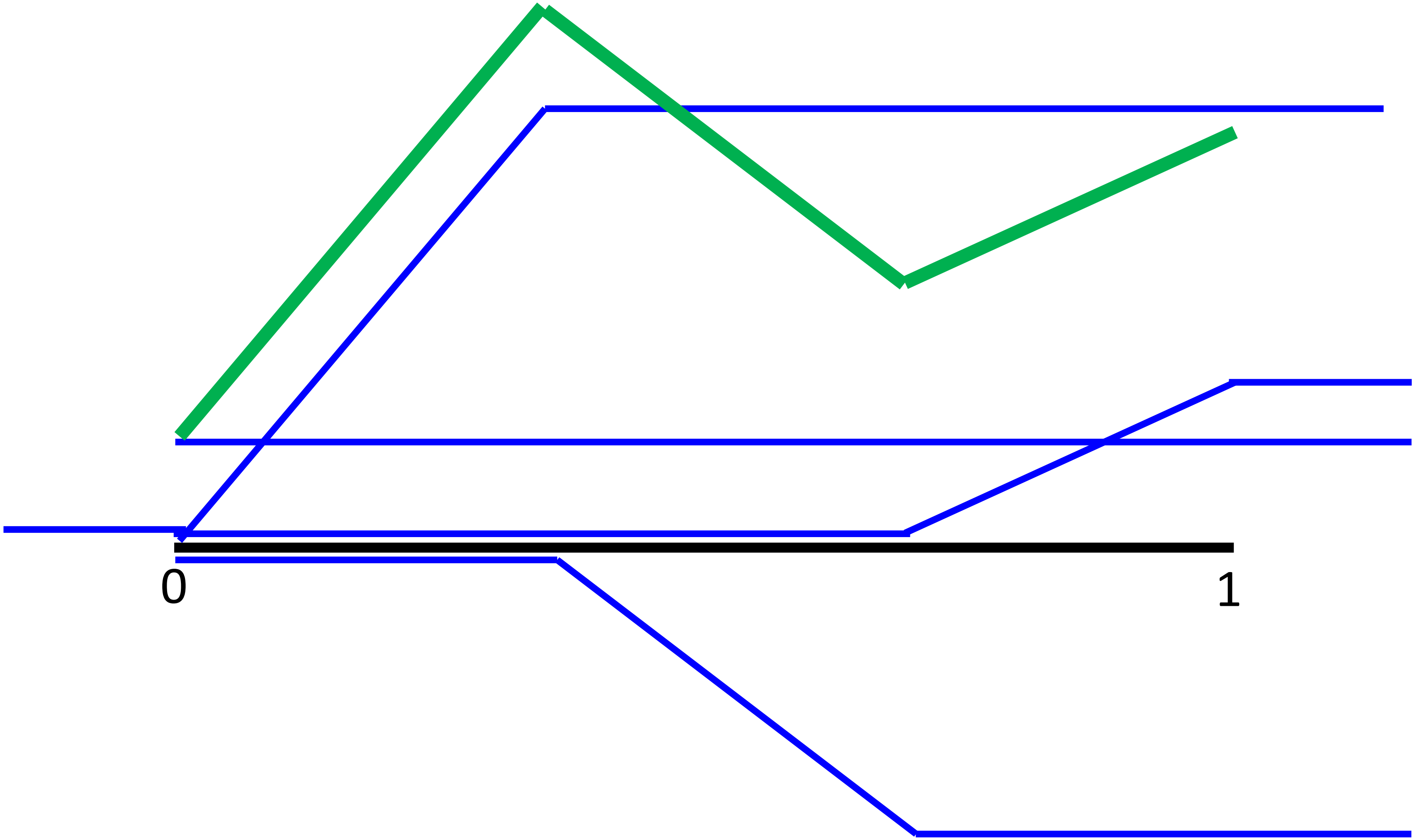
We can have good approximation with sufficient pieces.

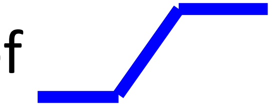
piecewise
linear



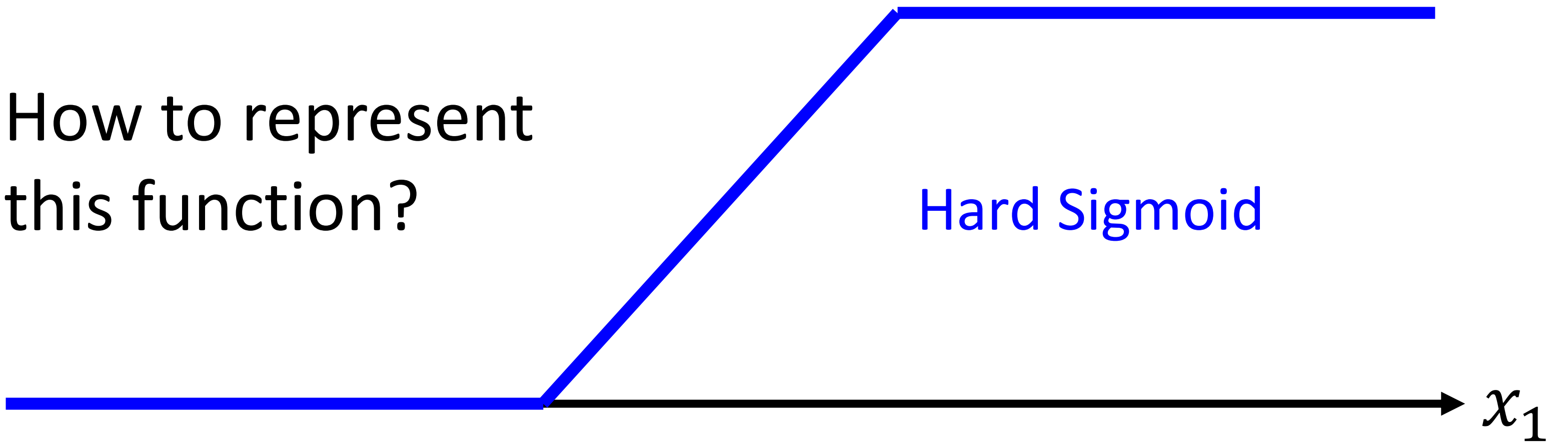
= constant +
sum of a set of





Piecewise linear = constant + sum of a set of 

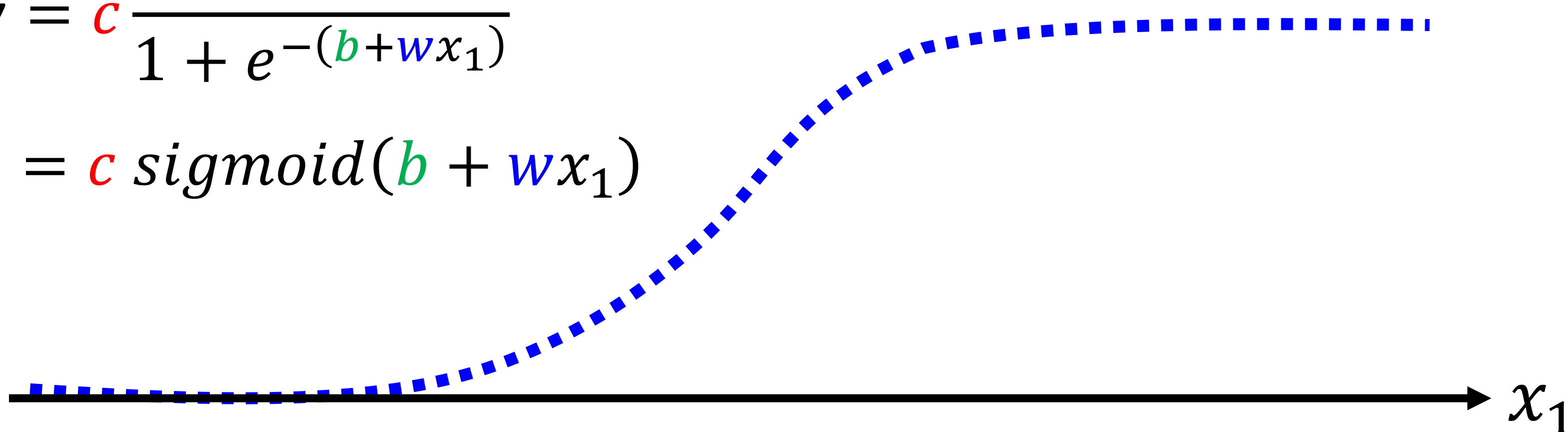
How to represent this function?



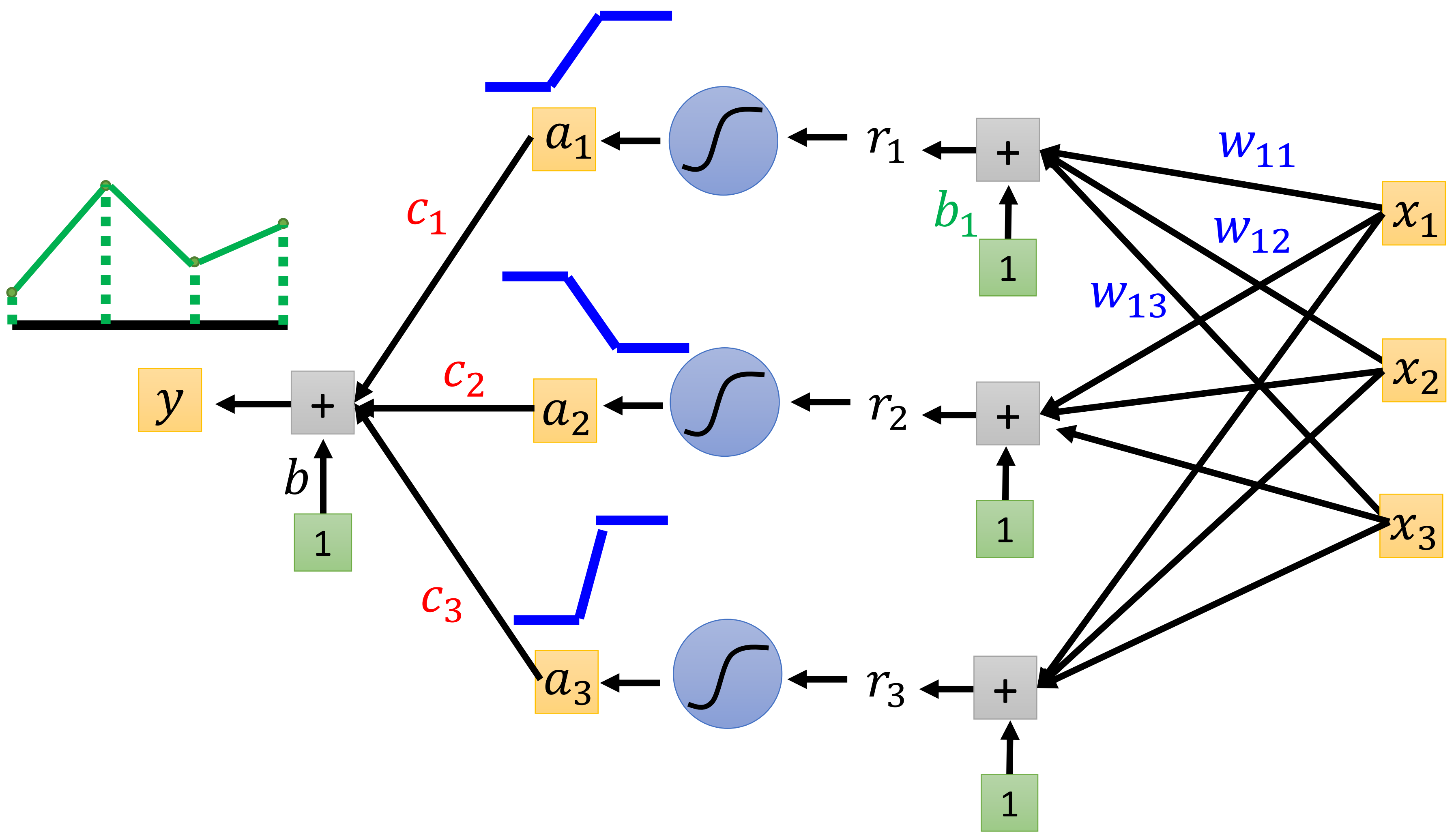
Sigmoid Function

$$y = c \frac{1}{1 + e^{-(b + w x_1)}}$$

$$= c \; sigmoid(b + w x_1)$$

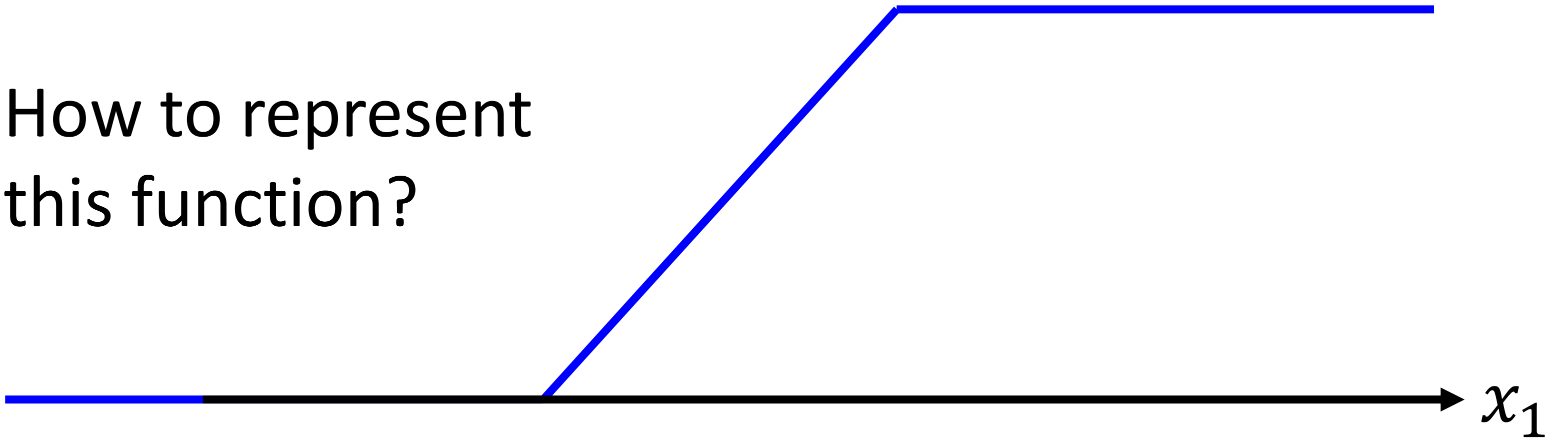


Piecewise linear = constant + sum of a set of

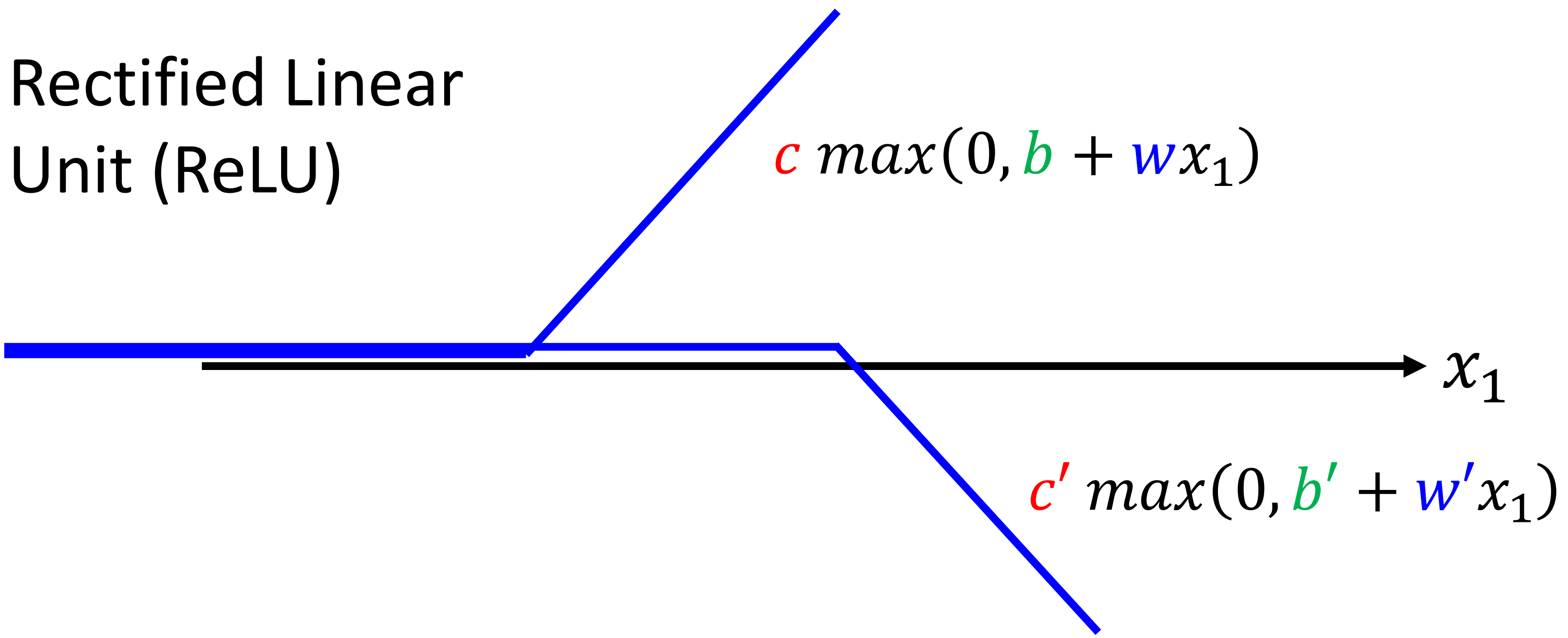


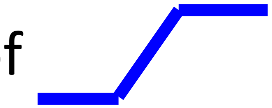
Hard Sigmoid → ReLU

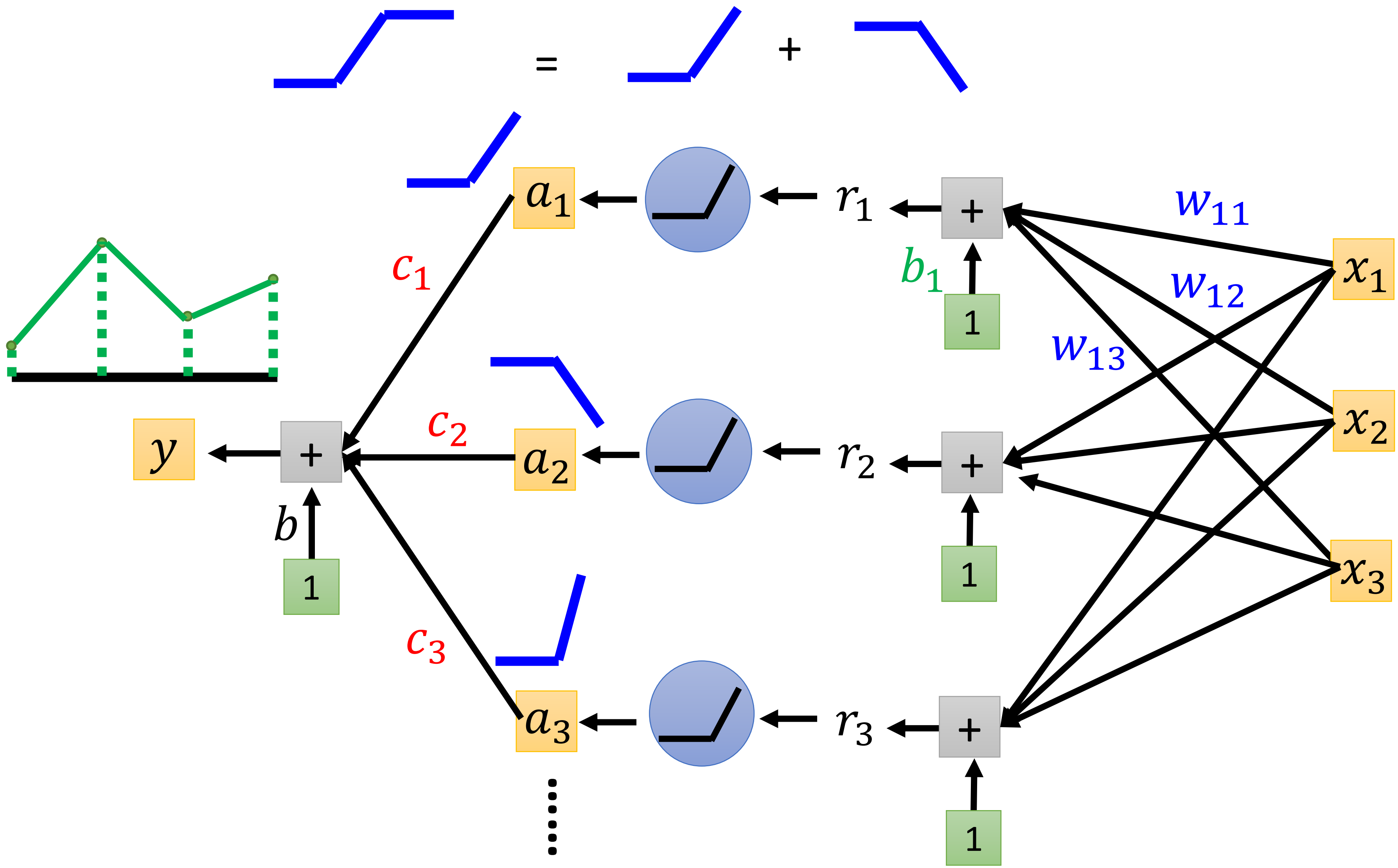
How to represent this function?



Rectified Linear Unit (ReLU)



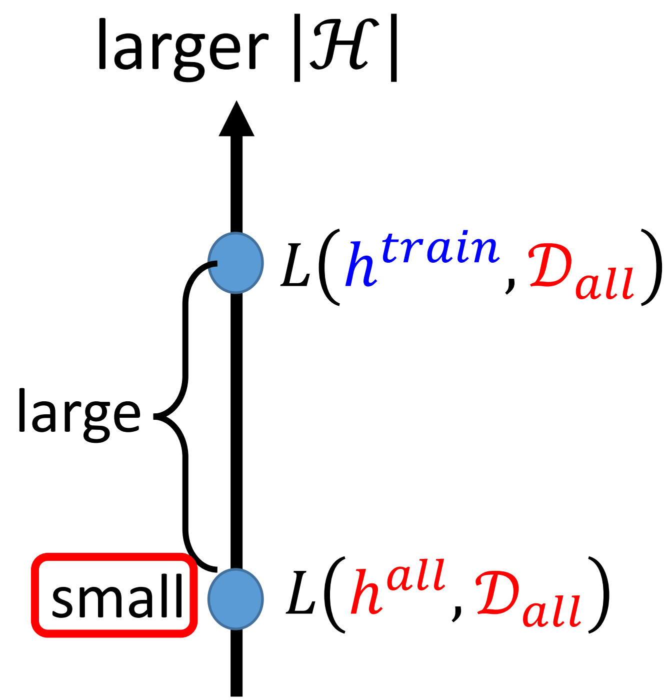
Piecewise linear = constant + sum of a set of 



Why we want "***Deep***" network, not "***Fat***" network?

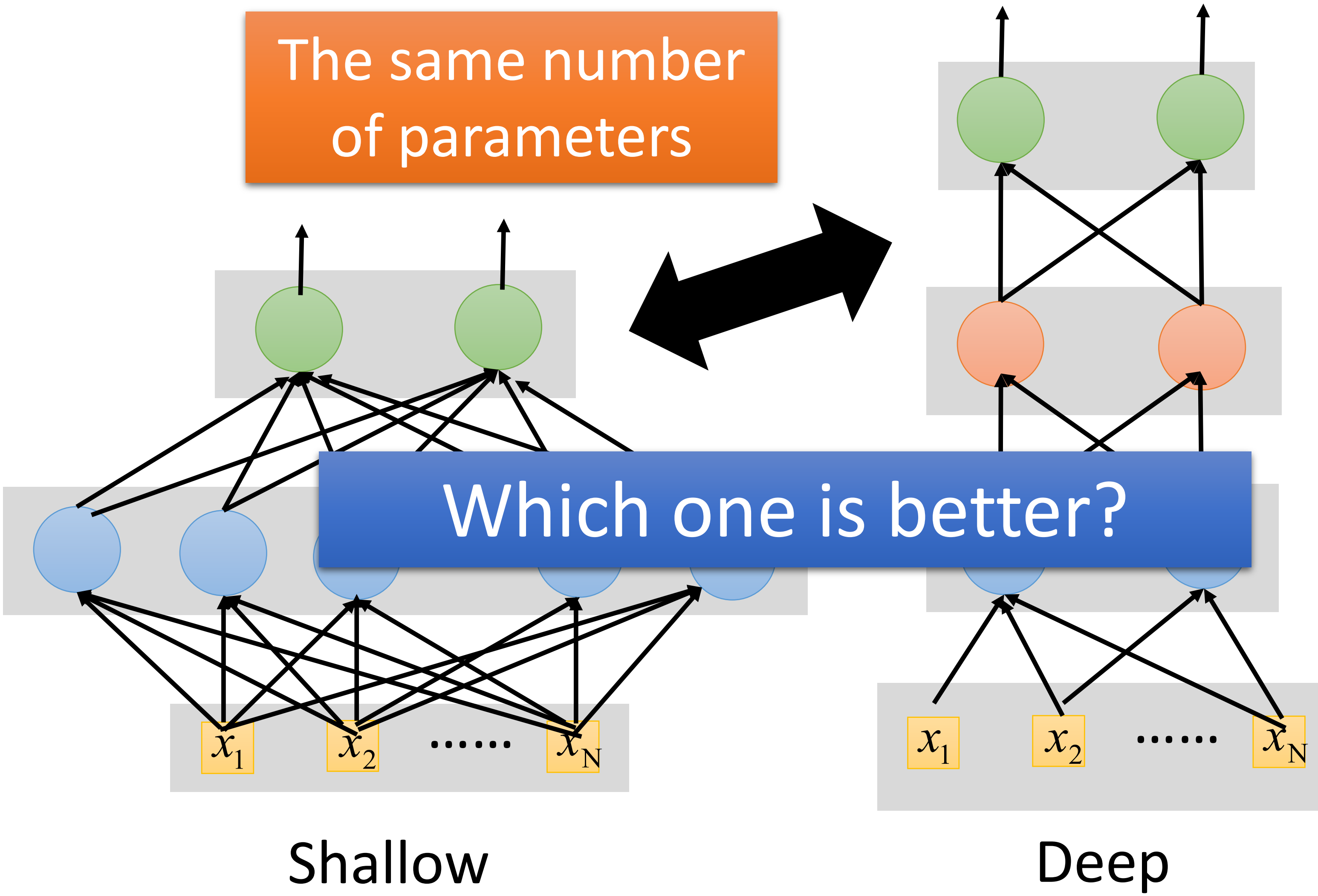
Deeper is Better?

Layer X Size	Word Error Rate (%)
1 X 2k	24.2
2 X 2k	20.4
3 X 2k	18.4
4 X 2k	17.8
5 X 2k	17.2
7 X 2k	17.1



Seide Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Fat + Short v.s. Thin + Tall



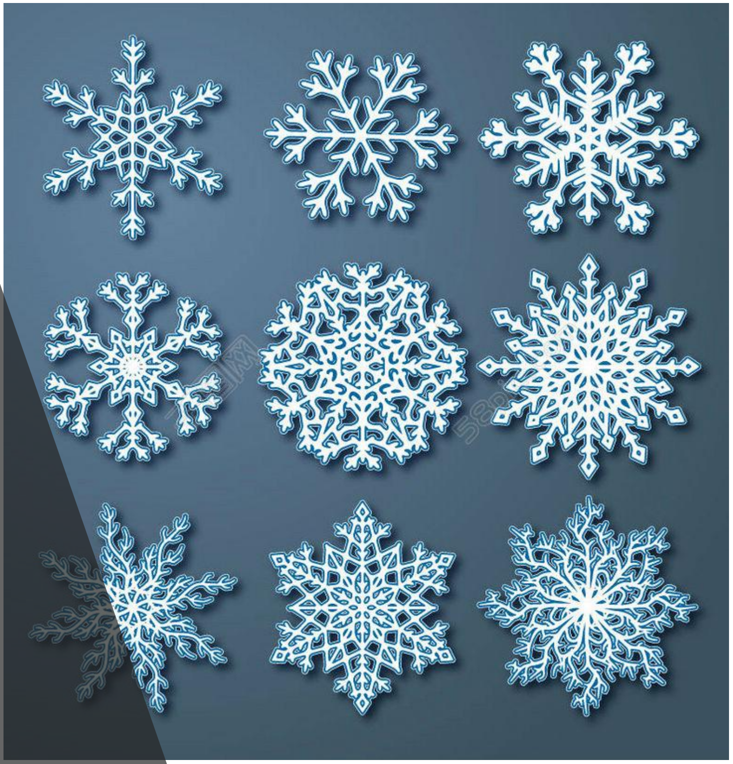
Fat + Short v.s. Thin + Tall

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4		
3 X 2k	18.4		
4 X 2k	17.8		
5 X 2k	17.2	1 X 3772	22.5
7 X 2k	17.1	1 X 4634	22.6
		1 X 16k	22.1

Why?

Seide Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

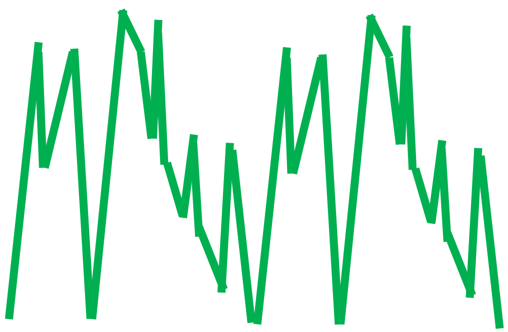
Why we need deep?

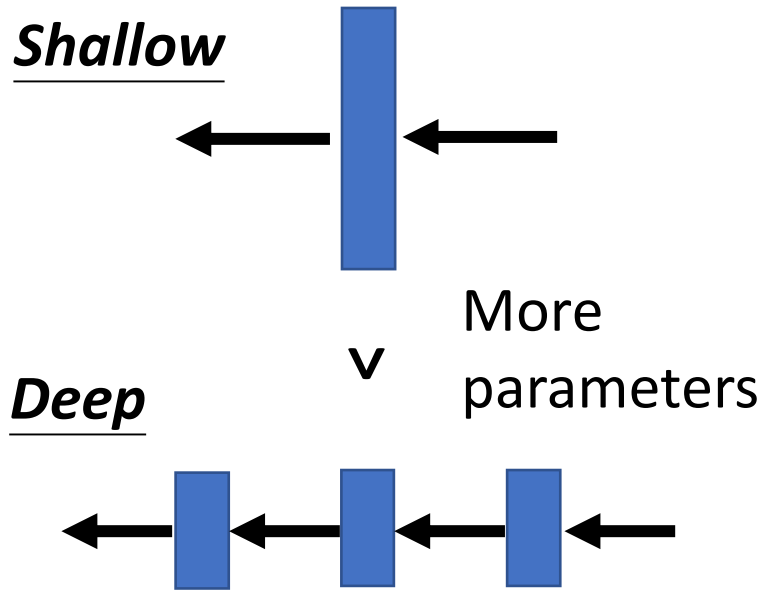


Why we need deep?

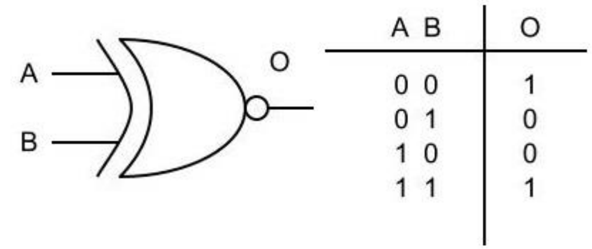
Yes, one hidden layer can represent any function.

However, using deep structure is more effective.

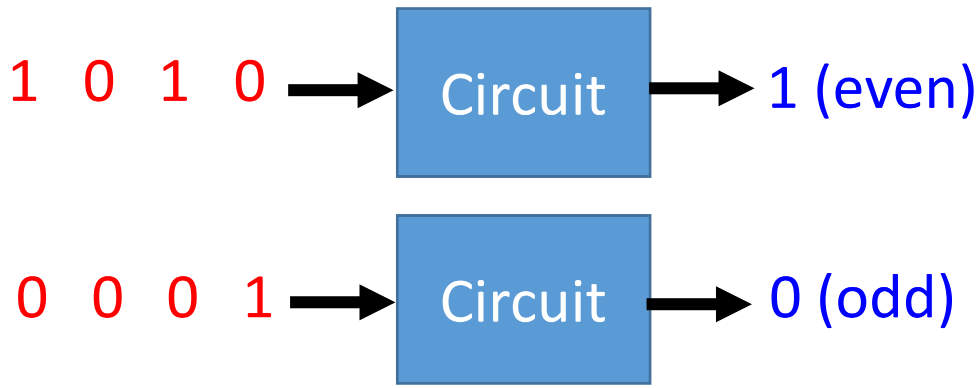




Analogy – Logic Circuits

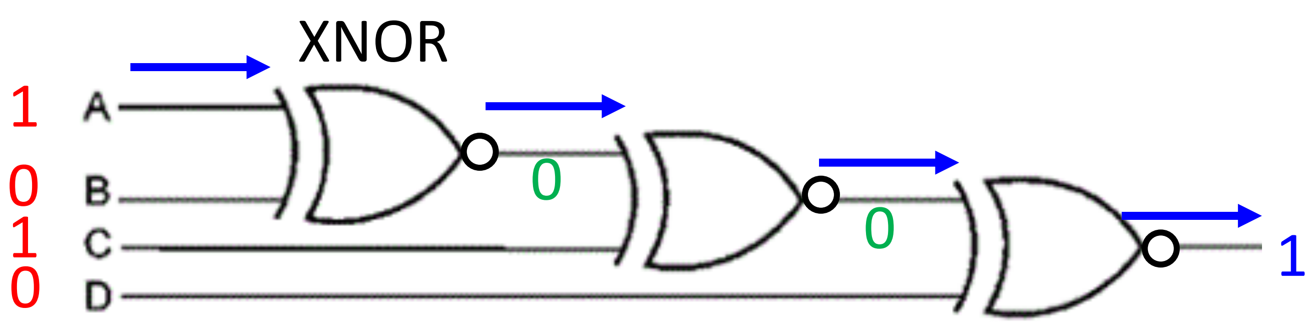


- E.g., ***parity check***



For input sequence with d bits,

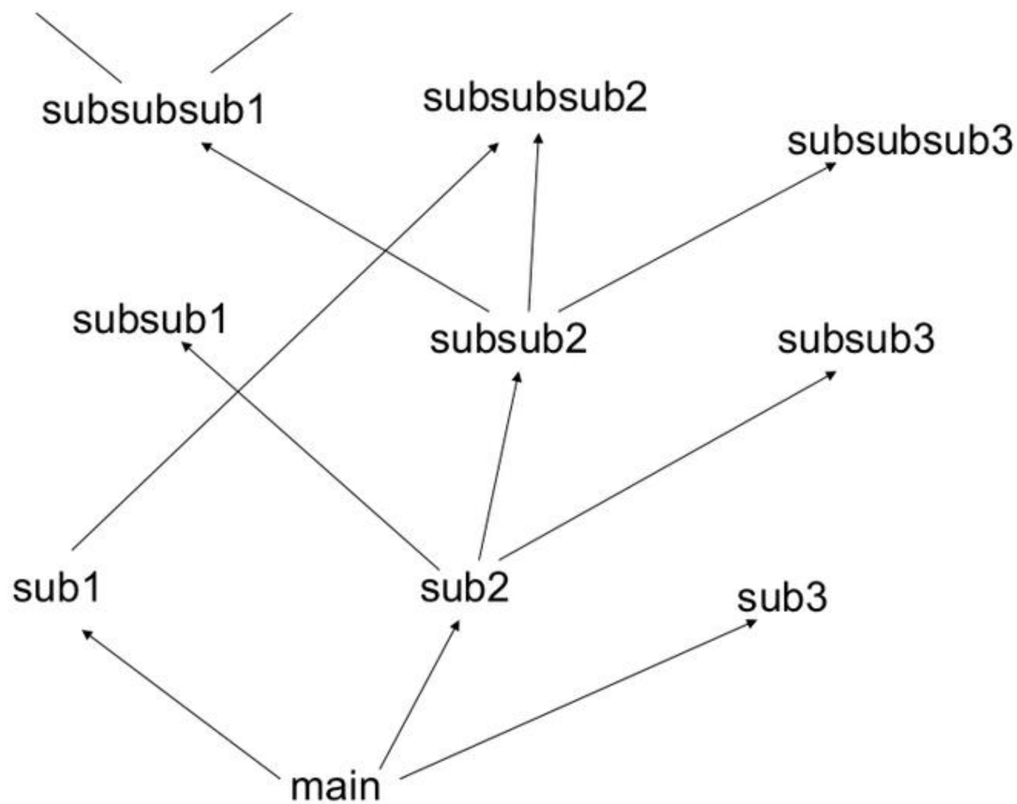
Two-layer circuit need $O(2^d)$ gates.



With multiple layers, we need only O(d) gates.

Analogy – Programming

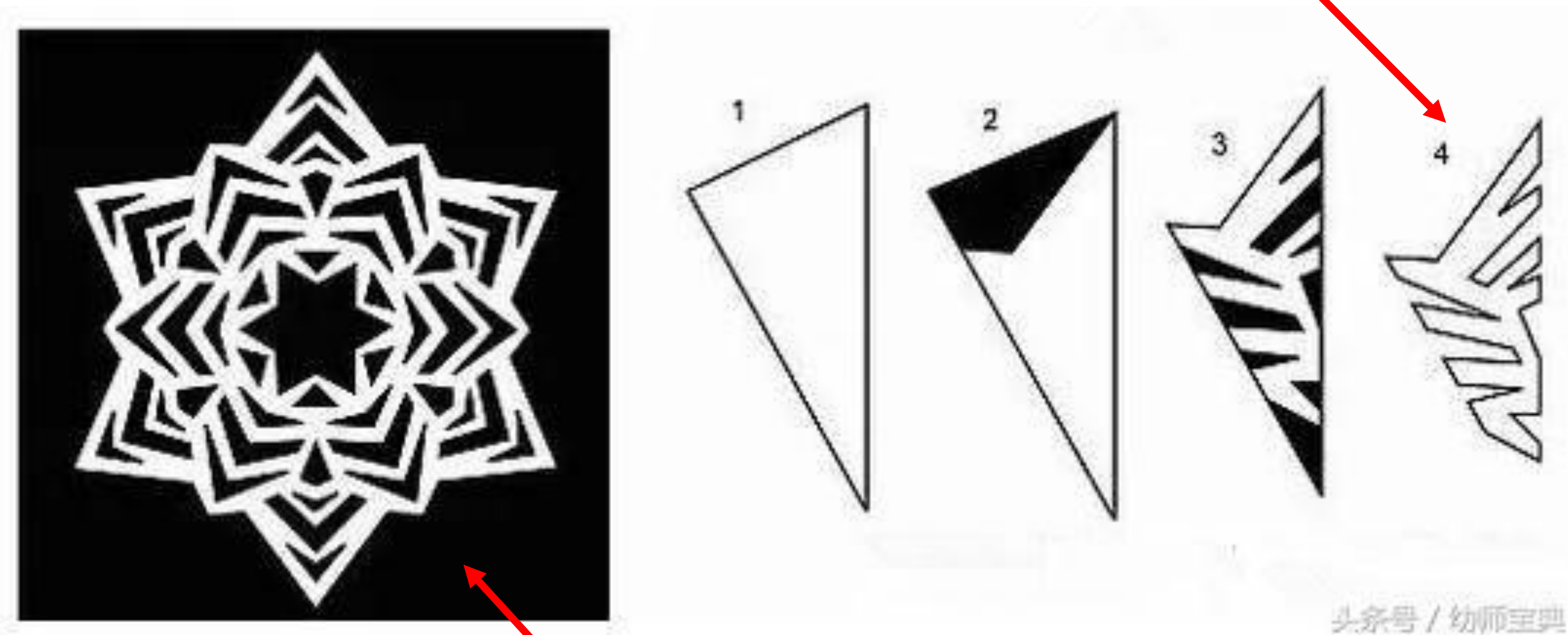
Don't put everything in your main function.



http://rinuboney.github.io/2015/10/18/theoretical-motivations-deep-learning.html

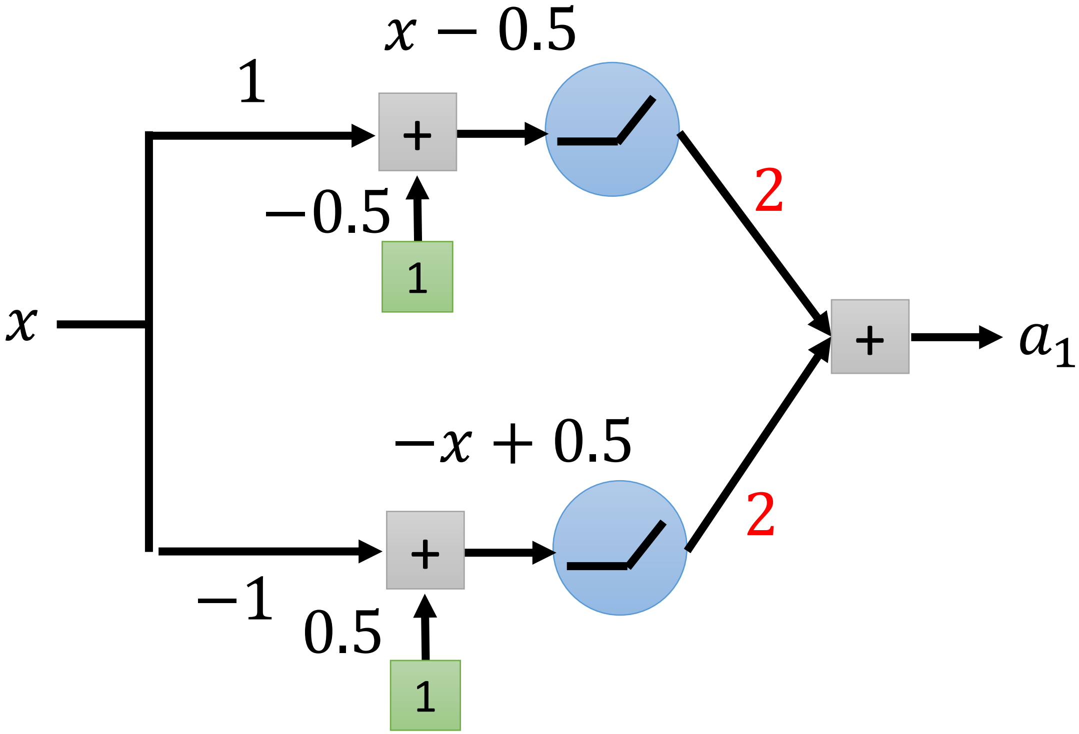
More Analogy

比較有效率

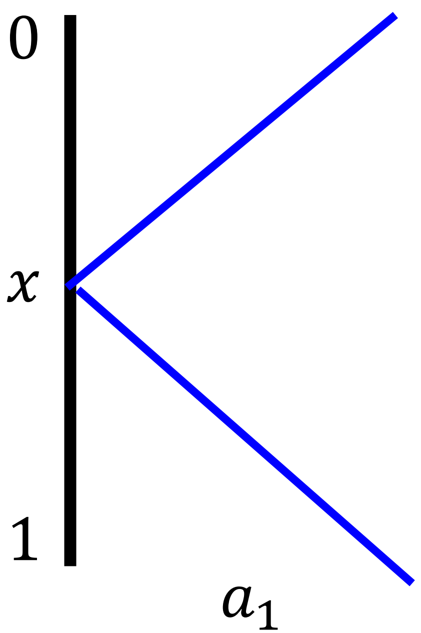


剪很多刀

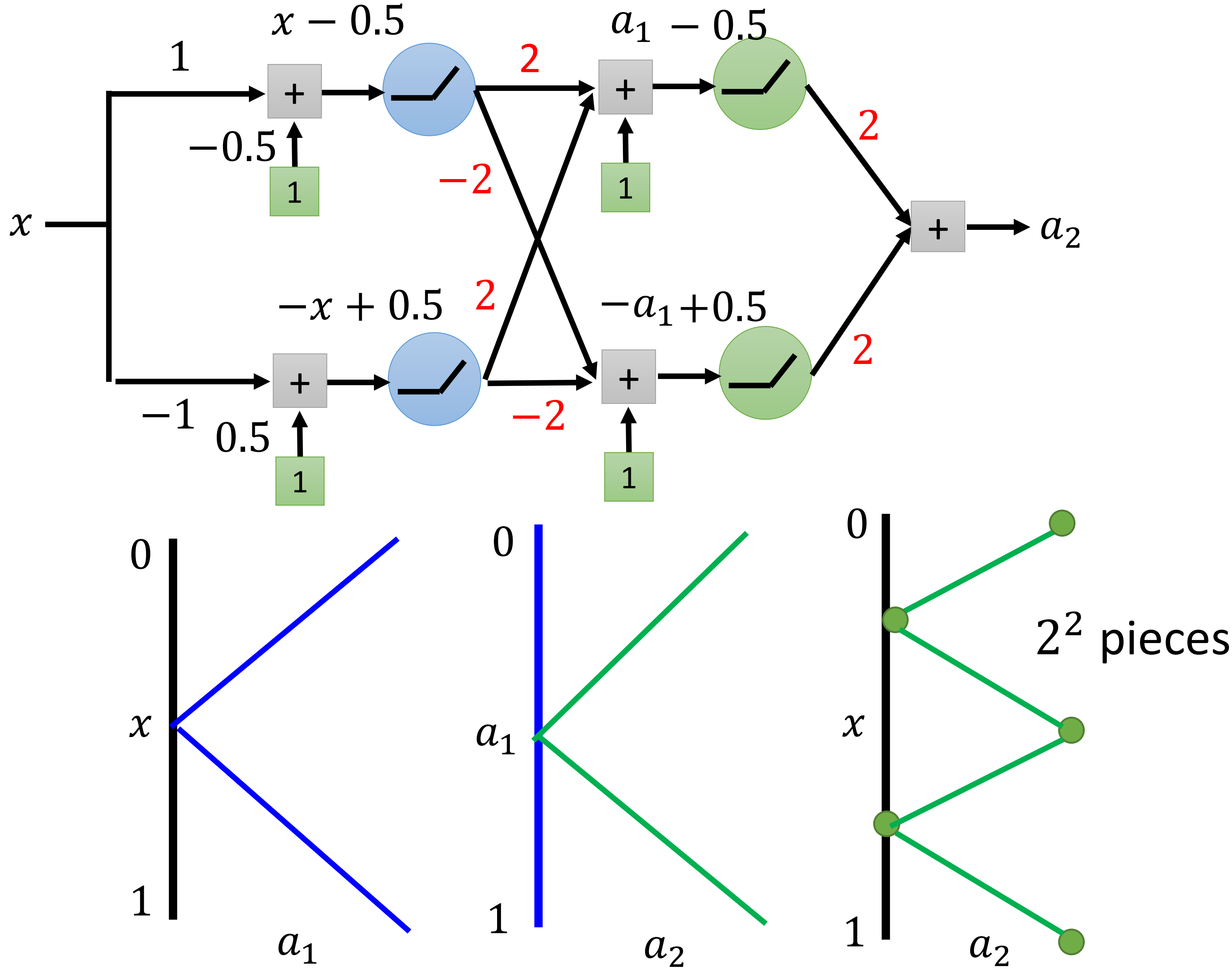
- 以下三頁投影片上課時的數字有誤，已經將修改部的分套上紅色，感謝同學指出錯誤



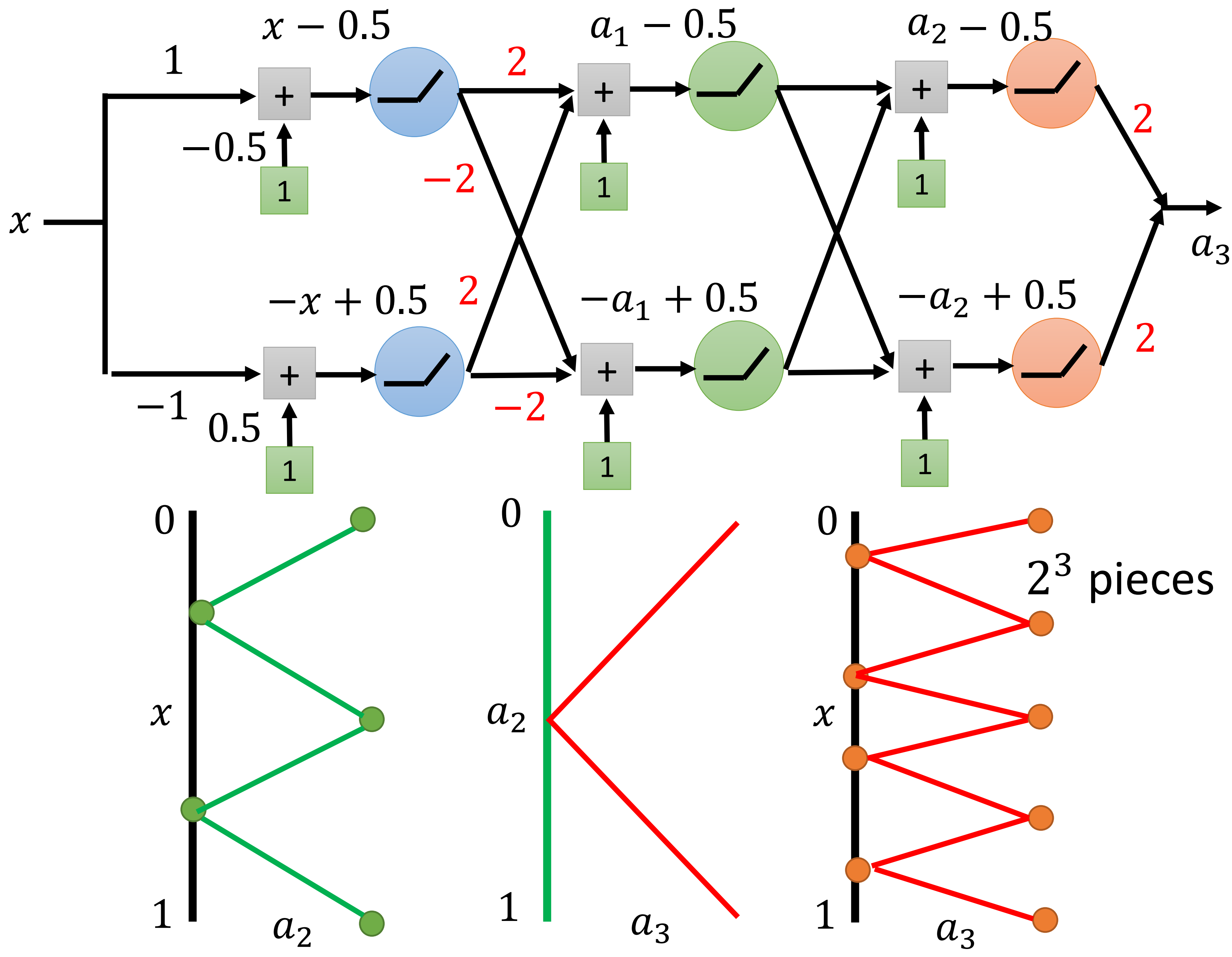
x − 0.5
1
+
2
−0.5
1
x
+
a1
−x + 0.5
2
+
−1
0.5
1



0
x
1
a1

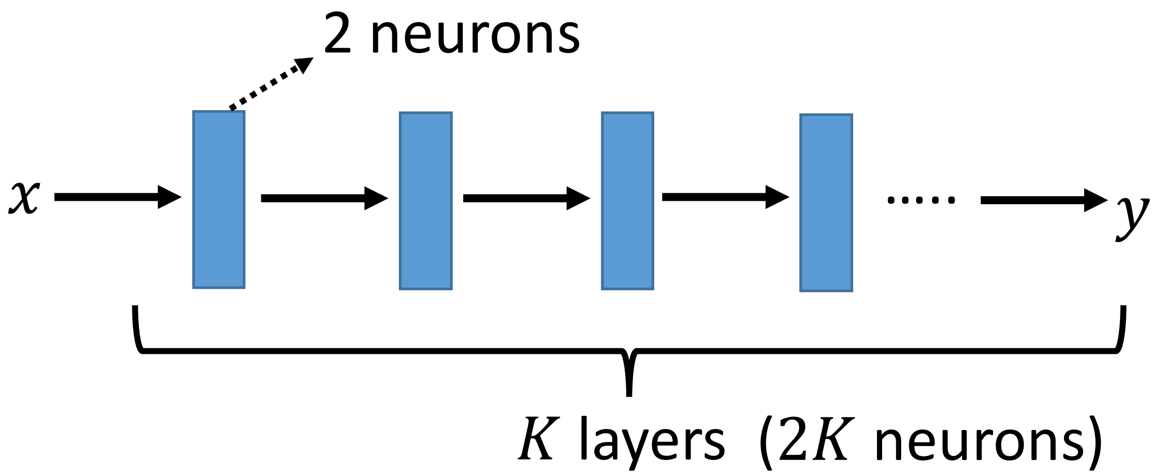


x
1
$x - 0.5$
-0.5
1
-1
0.5
1
$-x + 0.5$
2
-2
2
-2
$a_1 - 0.5$
1
$-a_1 + 0.5$
1
2
2
a_2
0
x
1
a_1
0
a_1
1
a_2
0
x
1
a_2
2^2 pieces



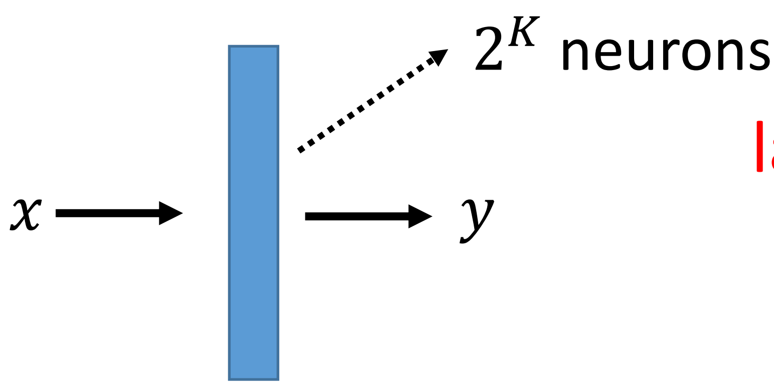
x
1
-1
$x - 0.5$
-0.5
$-x + 0.5$
0.5
1
1
2
-2
2
-2
$a_1 - 0.5$
$-a_1 + 0.5$
$a_2 - 0.5$
$-a_2 + 0.5$
2
2
a_3
0
1
x
a_2
0
1
a_2
a_3
0
1
x
a_3
2^3 pieces

Deep

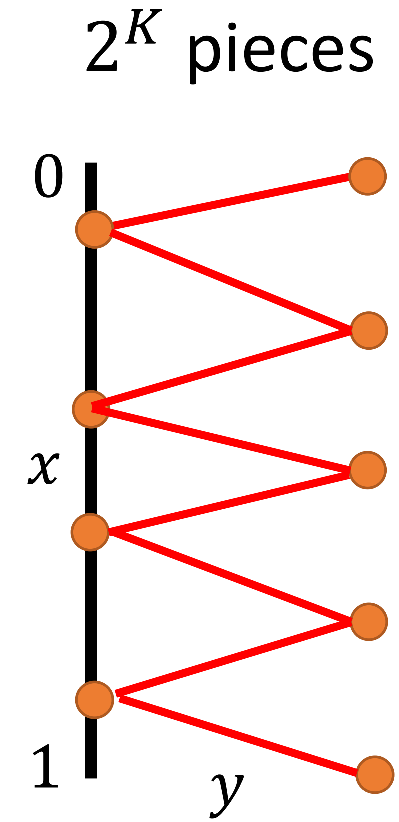


smaller $|\mathcal{H}|$

Shallow



larger $|\mathcal{H}|$



Thinks more ……

- Deep networks outperforms shallow ones when the required functions are complex and regular.

Image, speech, etc. have this characteristics.

- Deep is exponentially better than shallow even when $y = x^2$.

https://youtu.be/FN8jclCrqY0

https://youtu.be/qpuLxXrHQB4

深度學習是一個讓魚與熊掌可以兼得的方法

Still small loss

$$h^{all} = arg \min_{h \in \boxed{\mathcal{H}}} \boxed{L(h, \mathcal{D}_{all})}$$

Small (fewer candidates)