

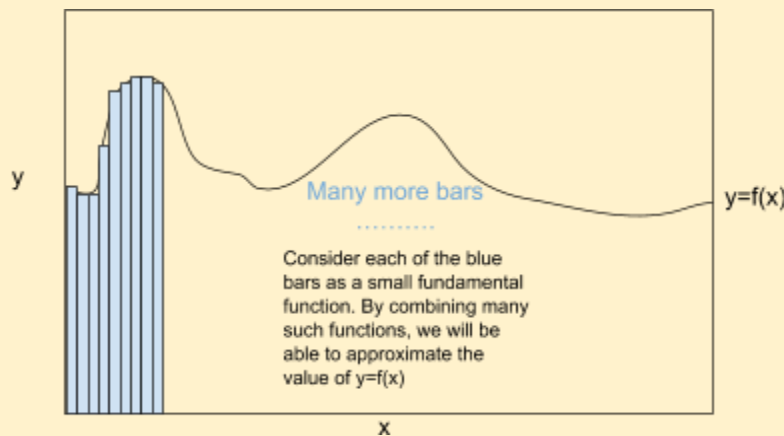
# PadhAI: Representation Power of Functions

## One Fourth Labs

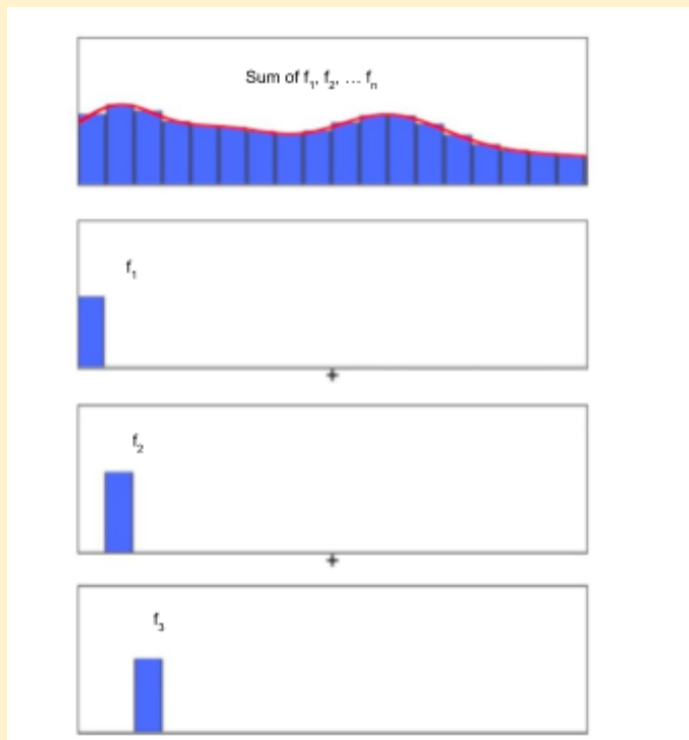
### Illustrative proof of Universal Approximation Theorem

The representation power of deep neural networks

1. Consider the function  $y = f(x)$ , we want to obtain  $\hat{f}(x)$  such that the two functions are almost equal
2. However, creating a  $\hat{f}(x)$  in one go is a daunting task
3. So, we can revisit our old analogy of building with bricks, where we represented a complex function as a combination of simple units
4. Consider the following illustration



5. Here, the thinner the bar/tower, the better the approximation, because of less wasted space under/over the curve
6. Another illustration

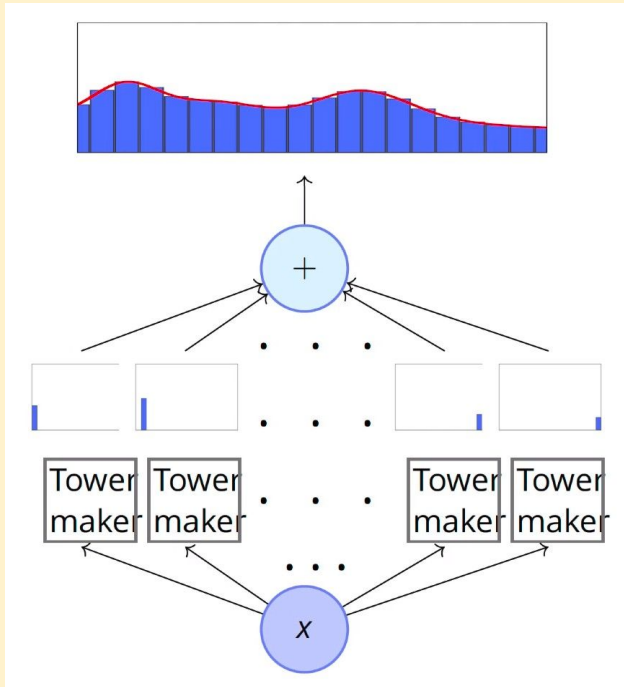


7. How does this tie back to the Sigmoid function

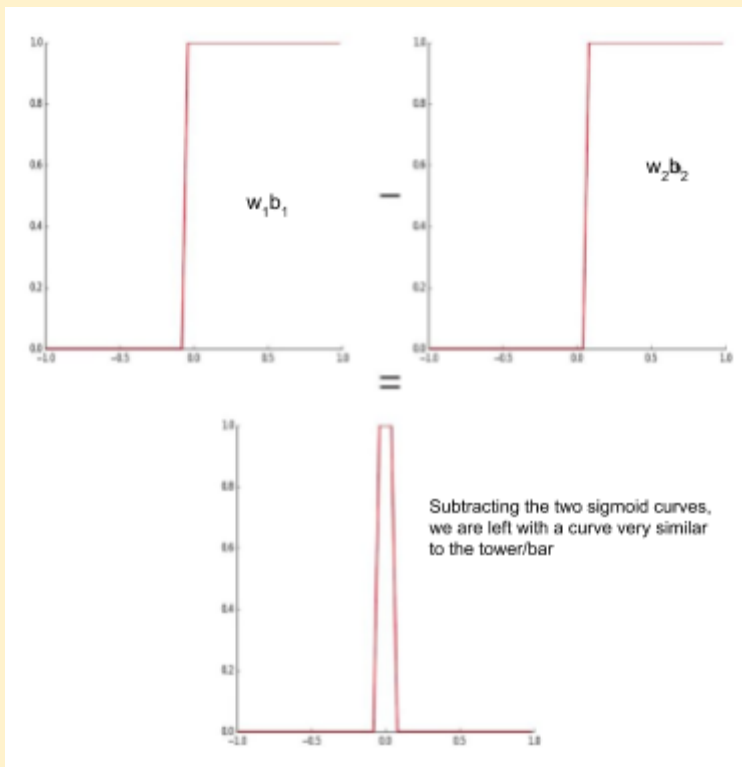
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8. Consider the functions required to create these individual towers/bars



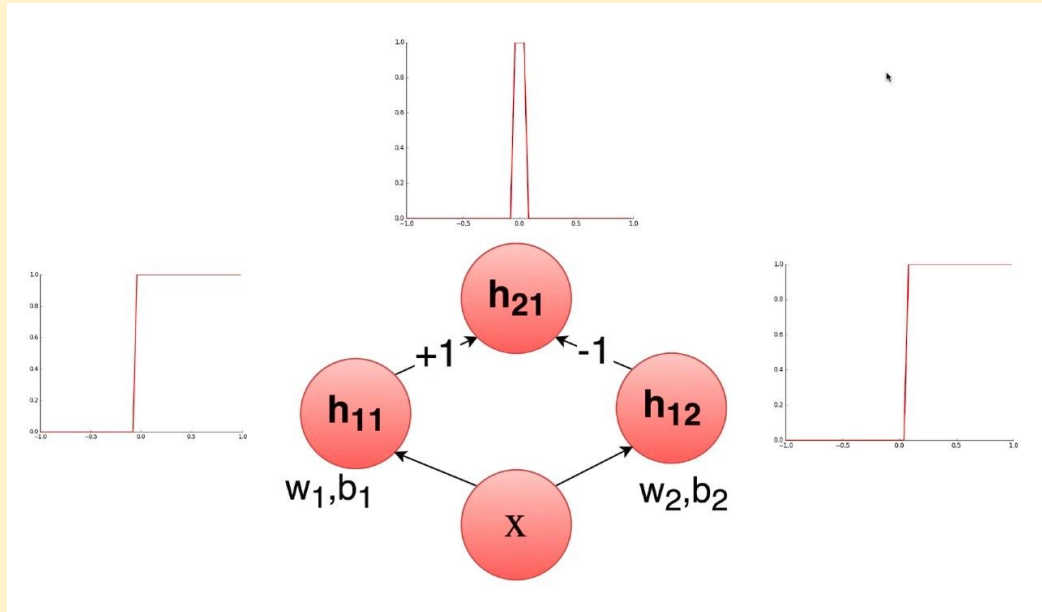
9. Let's see how the tower maker function is connected to the sigmoid function
10. In the sigmoid function,  $w$  is directly proportional to the sharpness of the curve and  $b$  shifts the horizontal position of the threshold. Consider subtraction between two sigmoid functions



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### 11. Neural network representation of sigmoid subtraction



12. With a network of many neurons, we will be able to create several towers/bars. These can then combine to approximate to any kind of function.