

# HW2P1 Bootcamp

Convolutional Neural Networks with Numpy

Khushali, Yichen, Ketan, ChooWon

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# Resampling

- For loop is not required in *python*
  - Look up *np.kron*
  - Array slicing: [*start:end:step*]
- Things to remember
  - Trying to compute the required shape while up sampling (some simple formula you can think of?)
  - Computing and storing the shape in forward.
    - This is because the gradient should be the same shape as the input.

# Convolutions

- You can perform convolutions in 2 ways:
  - The Loopy way (Bad)
  - Tensordot (Good)
- The more for loops you use for your questions, the more time it takes to run.
- With tensordot, you don't have to do all those broadcasting and everything given in the write-up

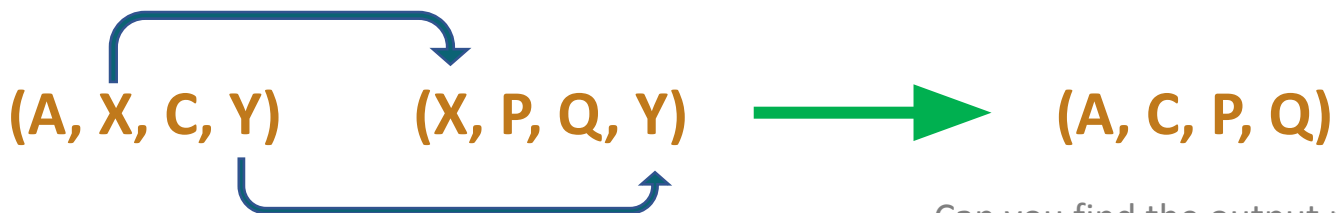
# Tensordot

- Ref: <https://numpy.org/doc/stable/reference/generated/numpy.tensordot.html>
- Appendix of the write up has amazing documentation of it
- Don't use for loops for convolution even though everything is given in the lecture slides
- Tensordot is faster and helps you (also TAs) to debug easily
- You only need **1 for loop** for conv1d and **2 for loops** for conv2d. If you are using more, then your implementation of *tensordot* is wrong even if you get the answer right

# Tensor dot

- Before starting ConvXd.py, open a notebook and try to understand tensordot with random examples
- Consider the shapes:
  - Input:  $X(A, B, C)$ ; Weight:  $W(P, Q, R)$
  - You can do tensordot when you have matched shapes
  - If  $B = Q$  and  $C = R$ ,
    - $\text{Tensordot}(X, W, \text{matched axes}) \rightarrow \text{Output}(A, P)$
    - You can think that the output shape will be the shape of the unmatched axes in that order
  - Make sure inputs (input and weight) to tensordot have some matching axes. Why do you need matching axes in convolution? (Hint: A filter only looks at a segment of input)
- Tip: Print shapes in your code to understand

# Tensor dot



Can you find the output pattern?

$(X, Y)$  from input 1 matches to  $(X, Y)$  from input 2  
Can you think in terms of axes?

Should match all the axes that you think needs to be matched. Not restricted to 2 axes

# Conv1d to Conv2d

- Try to understand each step while coding conv1d
- Every step between Conv1d and Conv2d (forward and backward) are identical
- While transitioning from Conv1d to Conv2d, you just need to account for the extra dimension and do an **extra something**

# Pooling

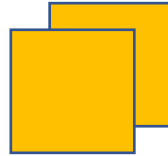
- Lectures have a basic pseudocode which can be developed
- You might need many loops for this task
  - `np.max` and `np.unravel_index` might be useful if you want to reduce the number of loops
  - But multiple loops are acceptable for this particular task
- Backprop in both might be harder than forward, but if you know the concept behind it, it will not be that hard.
- Look at the write up for images.



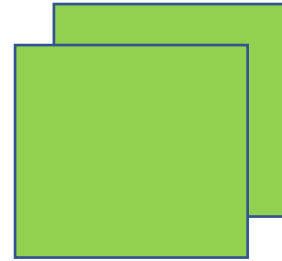
# Easy way to understand gradient propagation



Input  
(A)



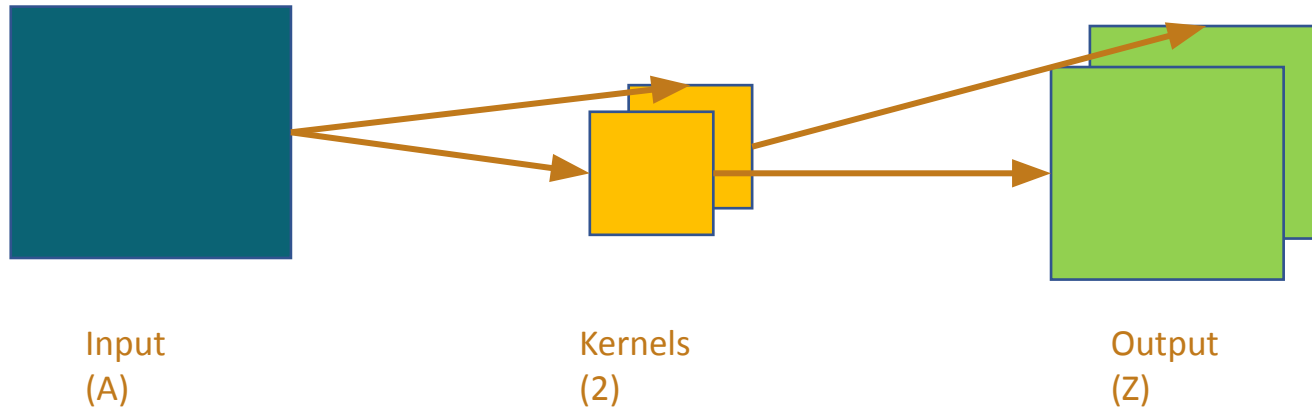
Kernels  
(2)



Output  
(Z)

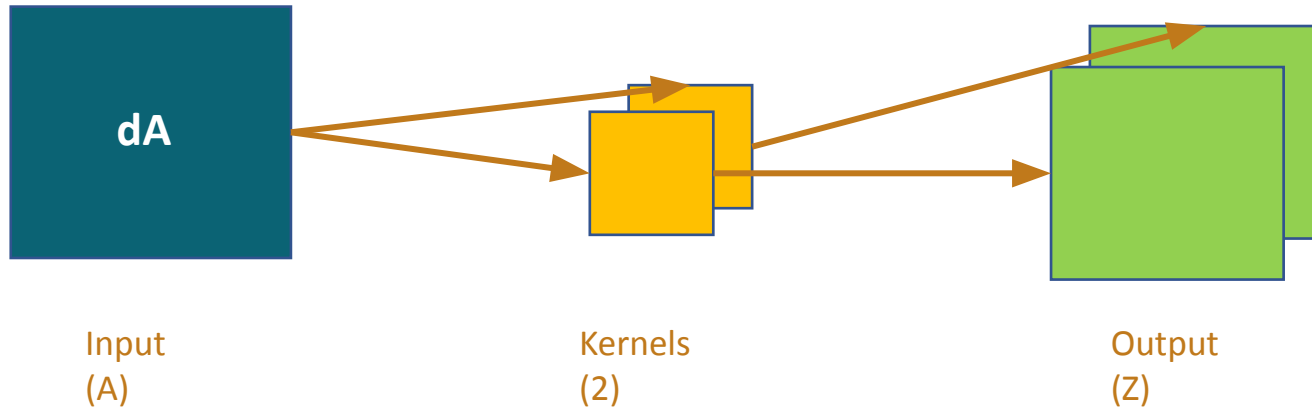
We get 2 maps in backward for  $dLdZ$ . After some process for finding  $dLdA$ , you again get 2 maps. But A has 1 map and  $dLdA$  will also have the same shape. How to understand gradient propagation?

# Easy way to understand gradient propagation



Draw the influence diagram.

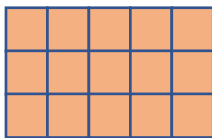
# Easy way to understand gradient propagation



Any small change  $dA$  will cause a change in both maps of  $Z$ .

# Scanning MLP

- Appendix of HW2P1
- Tips to understand better: Draw everything



How Conv1d sees the  
input

How Linear sees the  
input

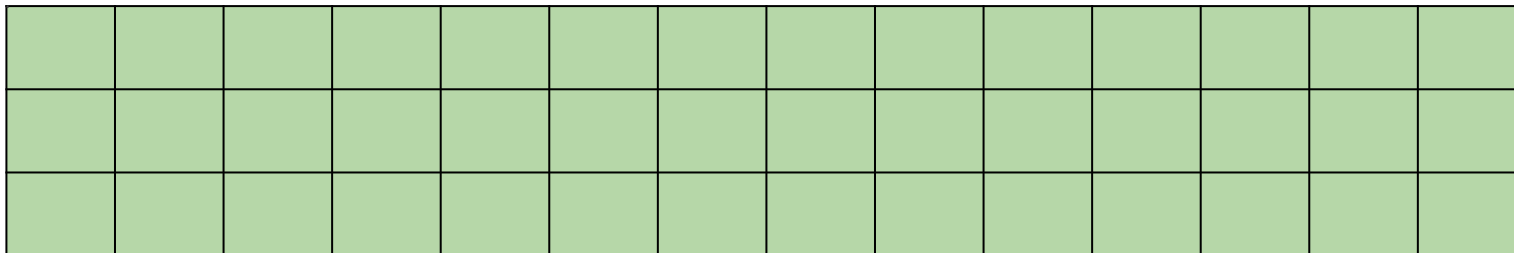


# Scanning MLP



Consider that the MLP takes some input and produces 2 output features

Input:

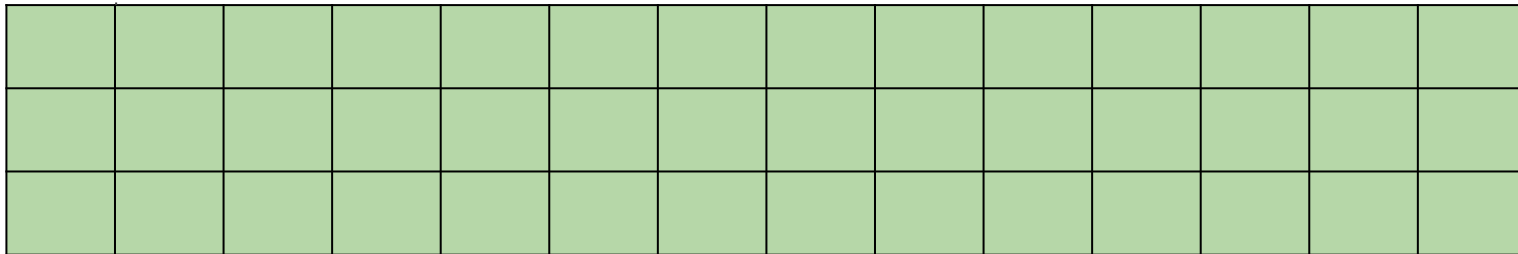


# Scanning MLP

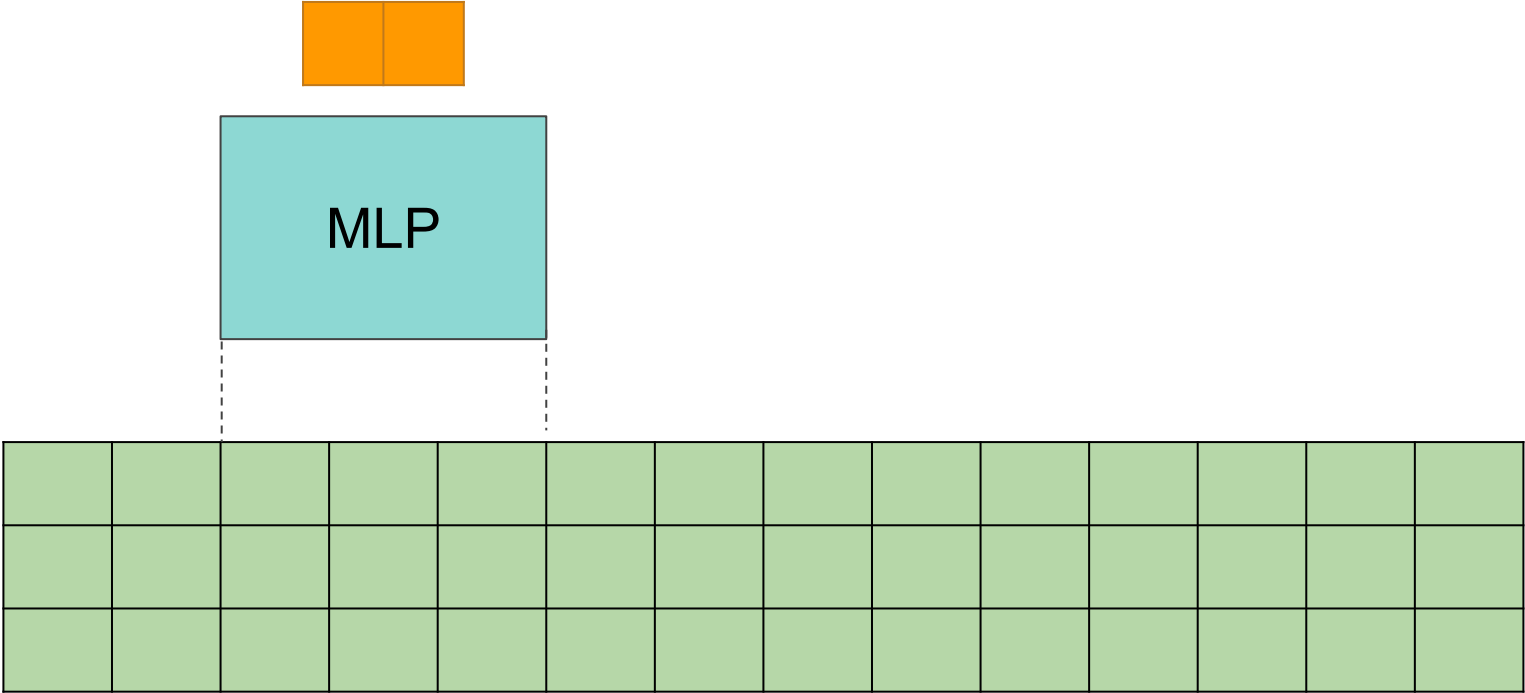


MLP

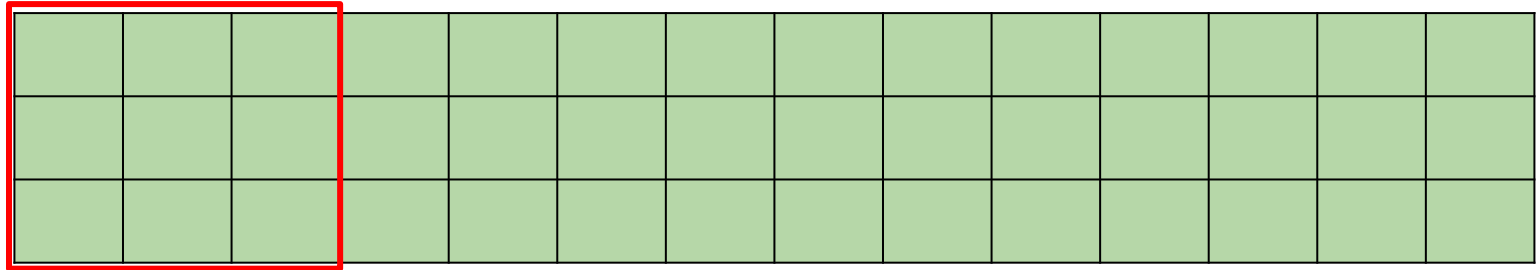
Input:



# Scanning MLP



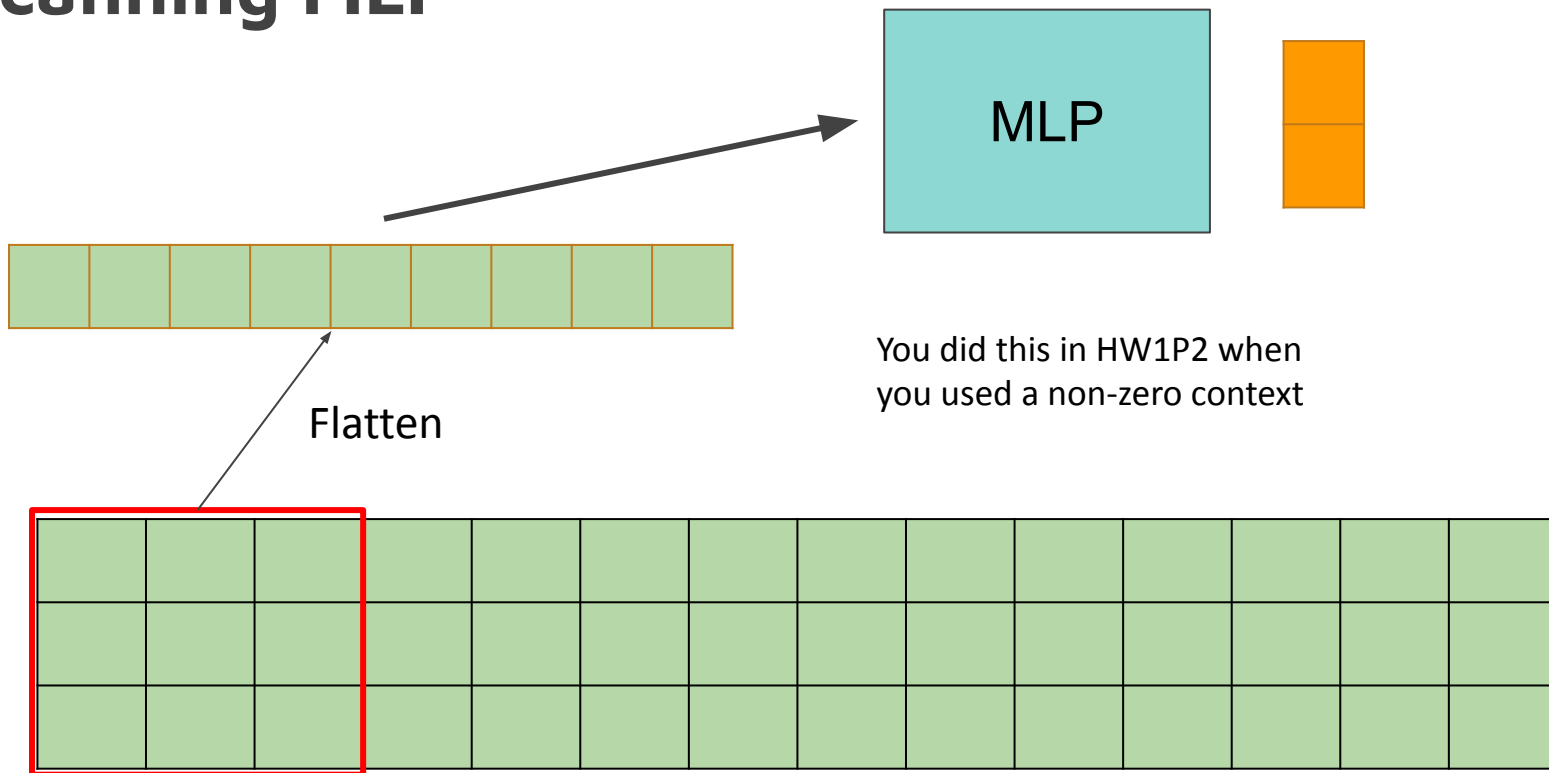
# Scanning MLP



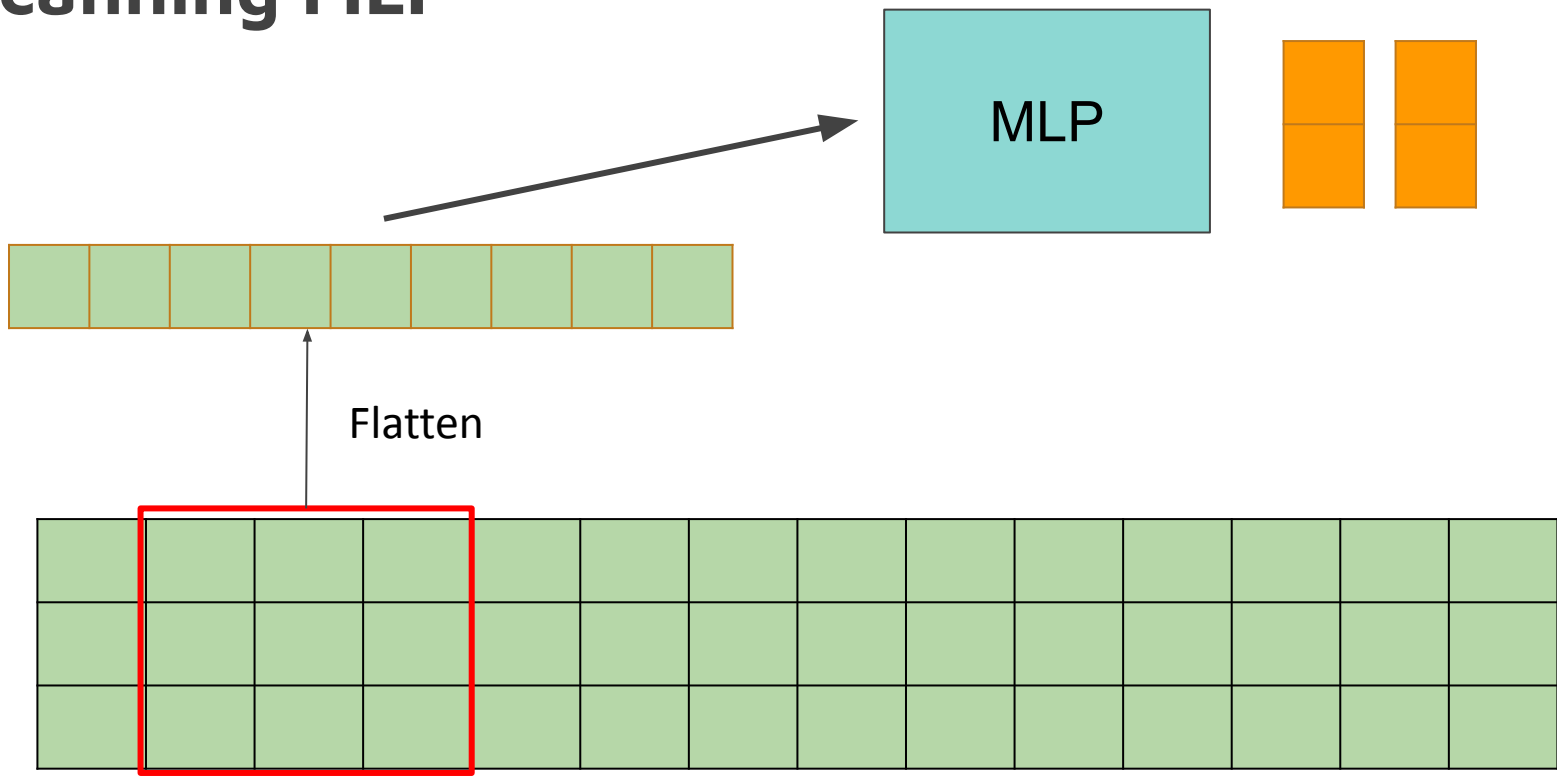
Kernel size=3



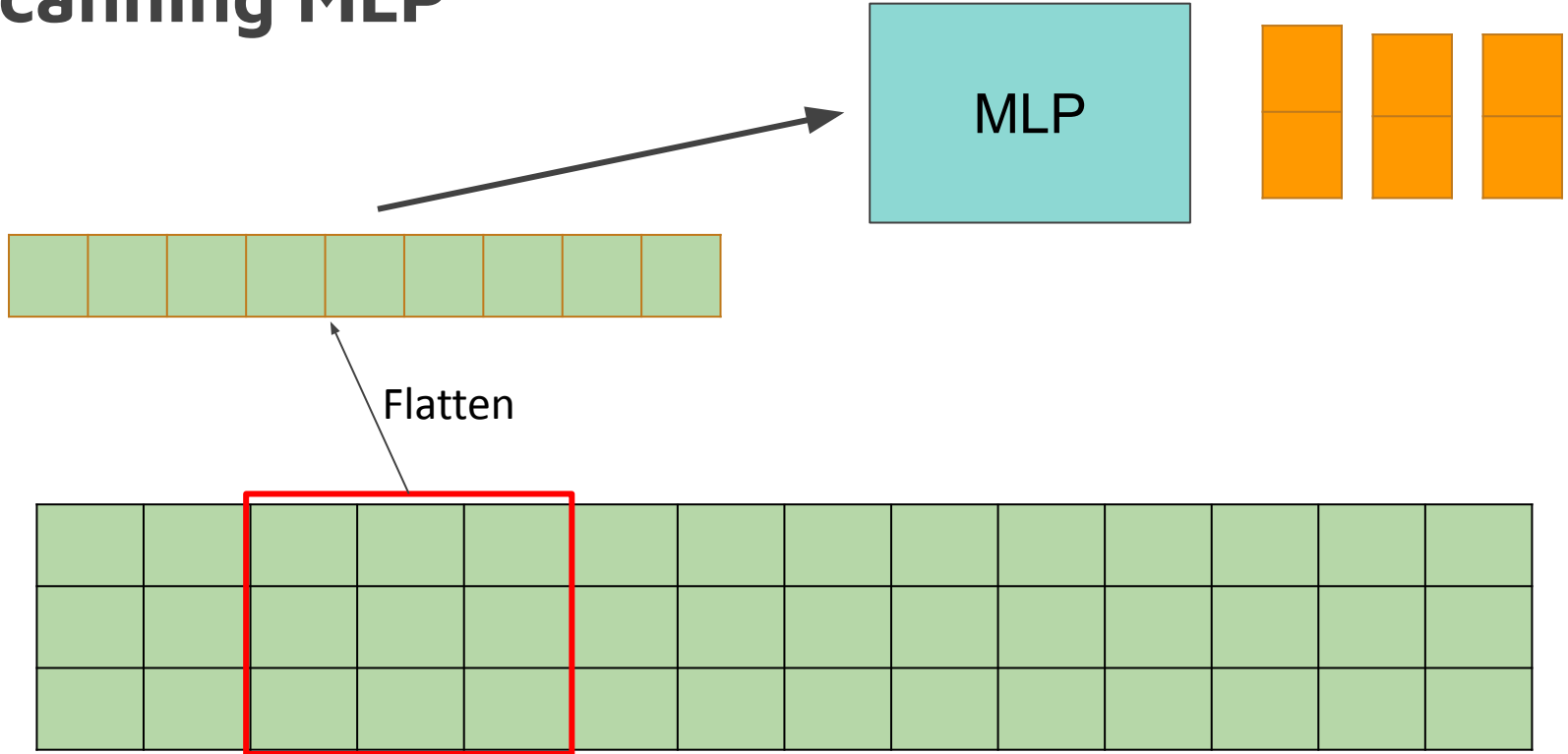
# Scanning MLP



# Scanning MLP



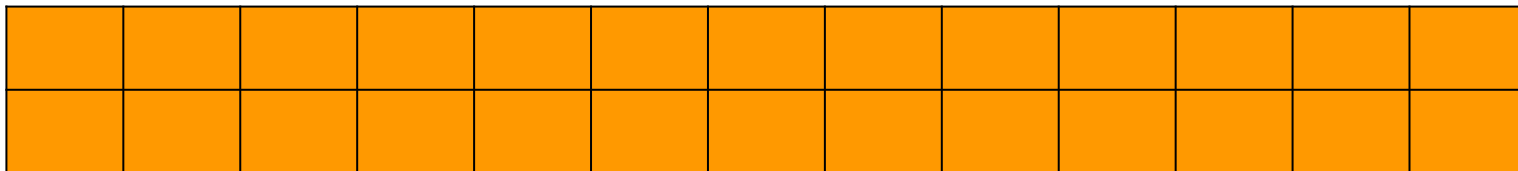
# Scanning MLP



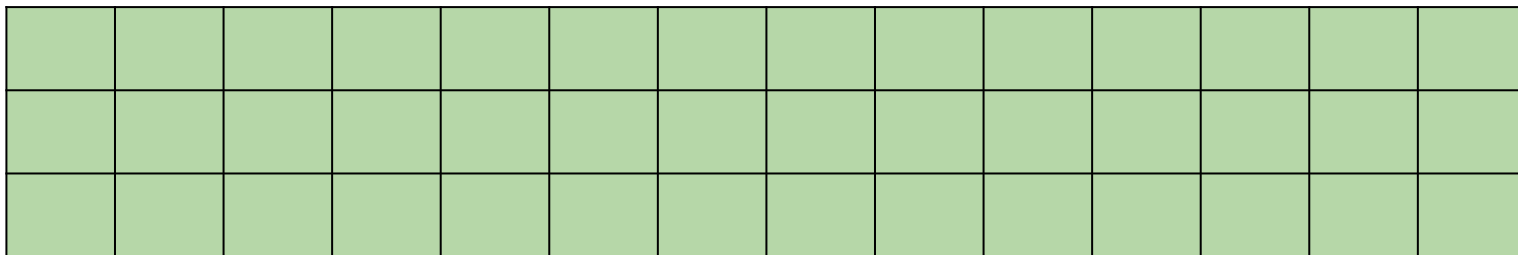


# Scanning MLP

Output:



Input:



Which gives `in_channels = 3`, `out_channels = 2`, `kernel_size = 3`, `stride = 1`

We transformed ***Linear(9, 2)*** to ***Conv1d(3, 2, kernel\_size= 3, stride= 1)***

# CNN Model

- Just calling all the layers which you implemented previously
- Only thing to think about: Initialization size of the final Linear Layer?
- Errors which you may get:
  - If you have a closeness error (*true\_divide error*), change to **`np.tanh()`**

THANK YOU

