DR. ALVIN'S PUBLICATIONS

CONVOLUTIONAL NEURAL NETWORKS (CNN)

HOW IT WORKS DR. ALVIN ANG



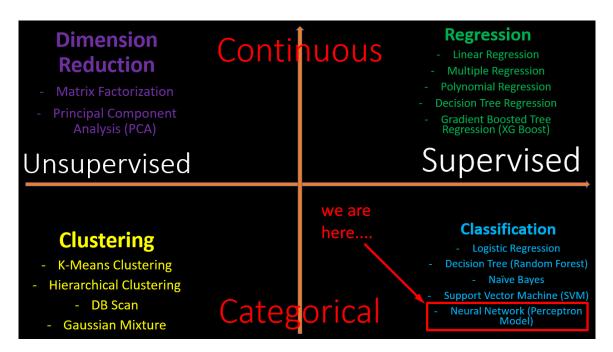
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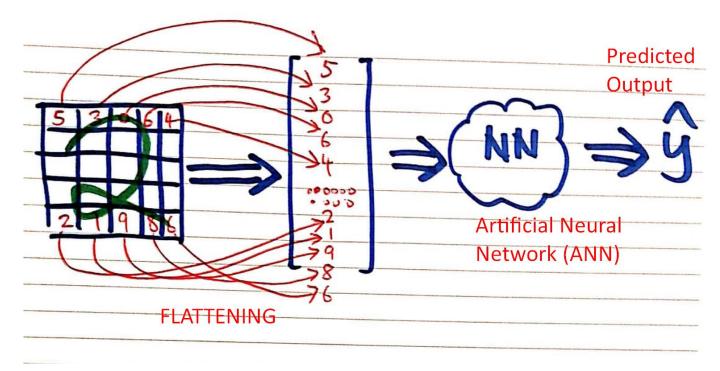
I. DEEP LEARNING = NEURAL NETWORK (NN)



- Above is a table categorizing the different Machine Learning algorithms.
- Objective of Neural Network is to predict a CATEGORY.

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II. WHY CNN?



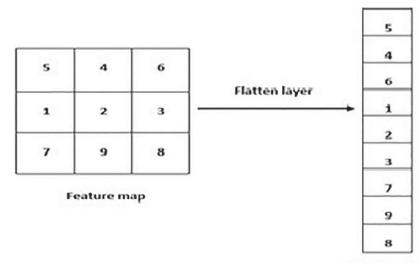
A. BRIEF RECAP OF ARTIFICIAL NEURAL NETWORK (ANN)

- In my previous article, I talked about how ANN worked (with images).
- An image "2" needs to be first FLATTENED, then fed into the NN for training / learning.
- Subsequently, once the NN is trained, it can predict new jpgs and output the label / classification.

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B. FLATTENING IS VERY BAD

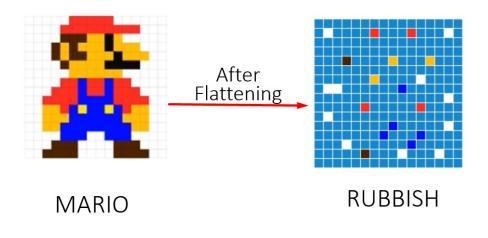
- However, FLATTENING is a very DESTRUCTIVE process.
- It breaks down the jpg into an array (which obviously you can't see a 2 anymore in the vector).



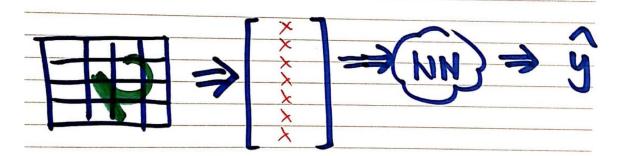
Flatten output

• Flattening converts a 3 x 3 array \rightarrow 9 x 1 array

FLATTENING DOES THIS!!!

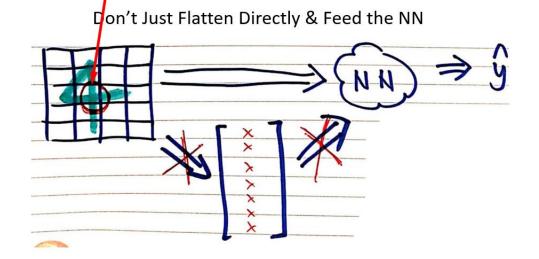


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- Now if I write a 2 (tilted) like the above, the FLATTENED array obviously will be different from the first "2"'s array (the straight up one in the previous page).
- However, we all know a "2" is still just a "2" and they are both the same! But their arrays are completely different from one another!
- Thus, FLATTENING KILLS A LOT OF IMPORTANT INFORMATION.
- We need a way to PREVENT INFORMATION LOSS.

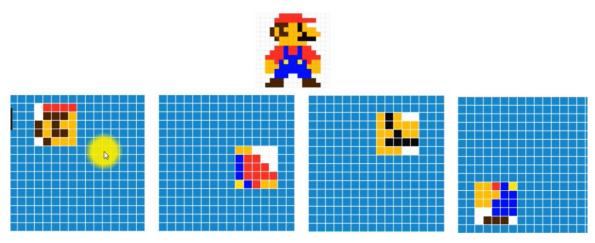
Very Important Feature



- For example, a "4" important feature is the cross → without it, its hard for us to see it's a "4".
- We need a way to feed the IMPORTANT FEATURES into the NN for it to recognize the number.

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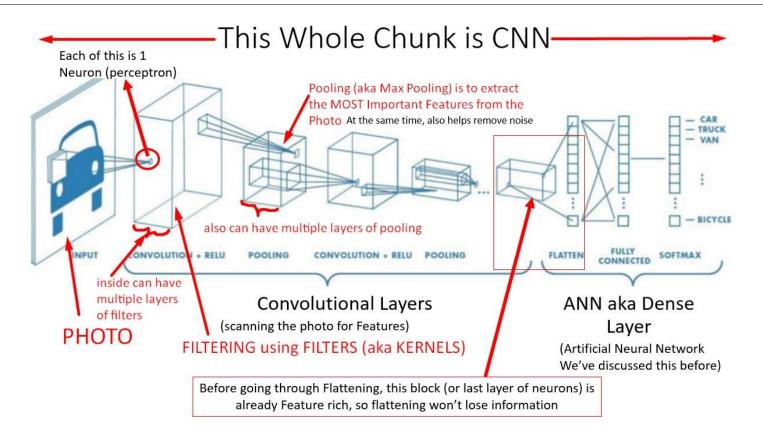
C. BASIC IDEA BEHIND CNN



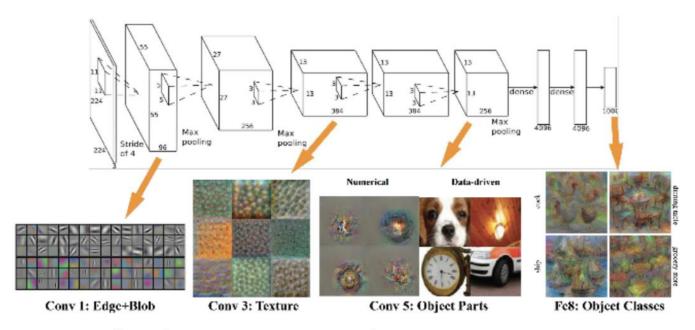
- We need a way for the NN to pick up important features from the image (in order to recognize it).
- Mario's Ear... + Moustache... + Shoulder... each part will piece together to help the NN recognize that its Mario.

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III. CNN ARCHITECTURE



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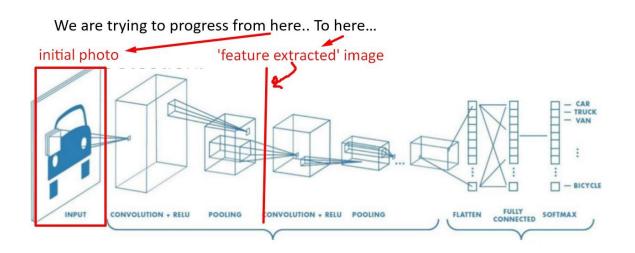
- At every Convolution layer, Features are extracted.
- 1st Convolution normally only extracts very simple Features like Vertical and Horizontal Lines.
- Subsequent layers search for more complex Features like Texture and Parts of an Object.

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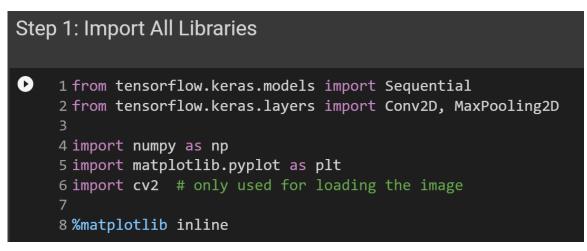
IV. UNDERSTANDING CNN USING KERAS

IPYNB:

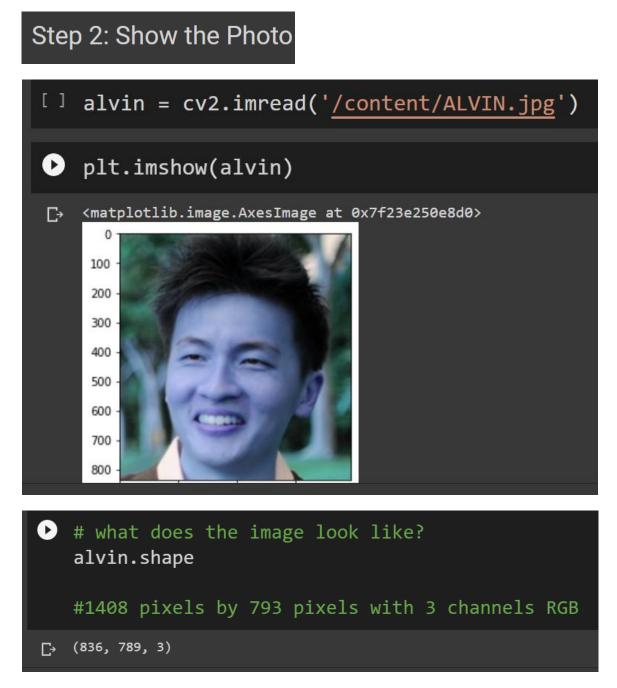
https://www.alvinang.sg/s/Understanding CNN by Dr Alvin Ang.ipynb



A. STEP 1: IMPORT ALL LIBRARIES



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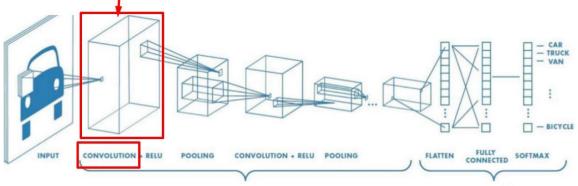


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Step 3: Demonstrating effect of 1 Convo Layer

What Does a Convolution Layer Do? aka Filtering

WE ARE HERE

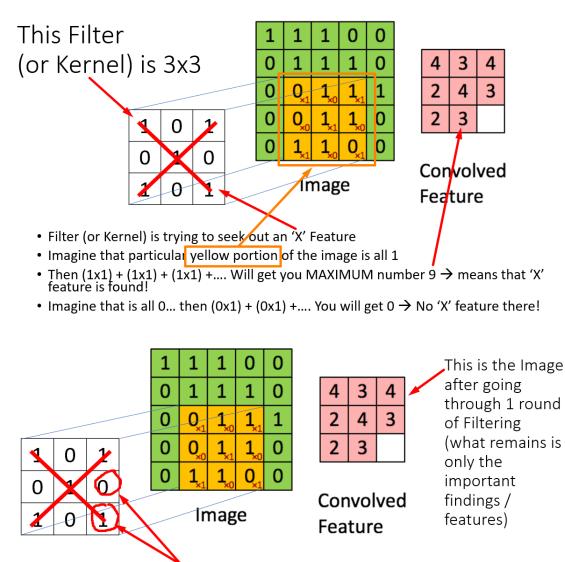


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1. CONVOLUTION DOES THIS

To see animated .gif, go here to understand how the Filter slides across the image:

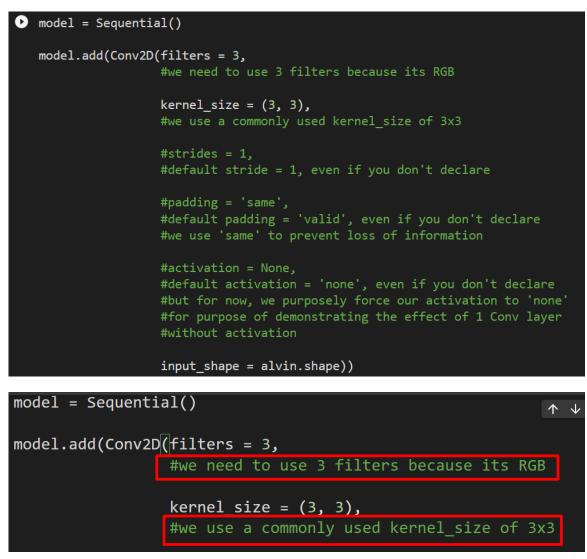
https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5way-3bd2b1164a53



- Note that these are Weights which will be automatically found by the CNN (updated with each Epoch)
- In other words, CNN will find out the "best" features to look out for automatically (in each Filter).

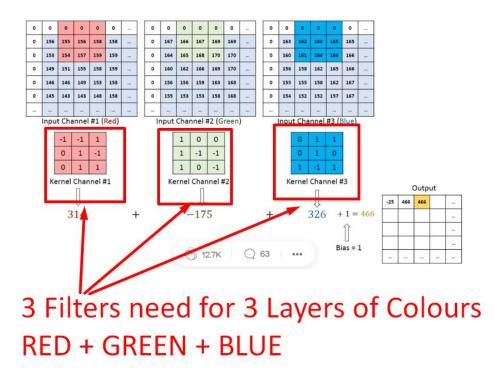
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2. SEQUENTIAL MODELING



• We need 3 filters because our ALVIN.jpg is made up of 3 primary colours = RED + GREEN + BLUE

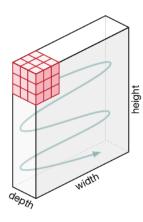
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To see animated .gif, go here to understand how the 3 Filters slide across the image:

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5way-3bd2b1164a53

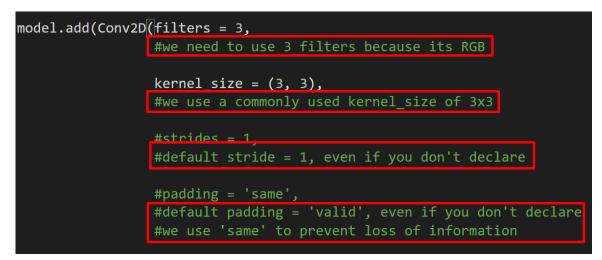
So basically, this happens.....



Movement of the Kernel

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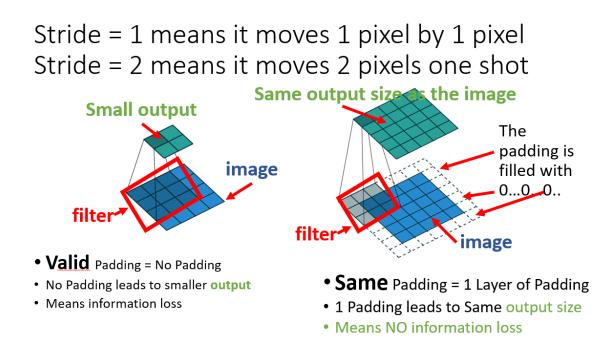
3. WHAT IS PADDING? WHY DO WE NEED IT?



To see animated .gif, go here to understand how padding is done:

https://github.com/vdumoulin/conv_arithmetic

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5way-3bd2b1164a53

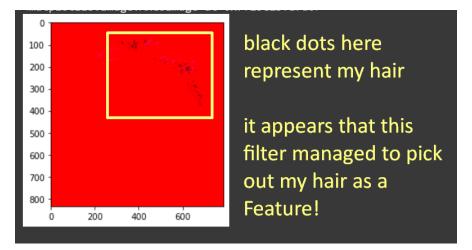


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4. CONVOLUTION OUTPUT / EFFECT OF CONVOLUTION



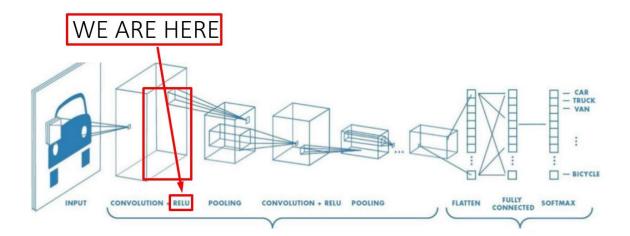
- What do we see there?
- After 1 x Convolution with 3 filters, the entire image turned RED! (but you can try running it several times... it will change colours)



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D. STEP 4: WHAT IS THE EFFECT OF USING RELU ACTIVATION?

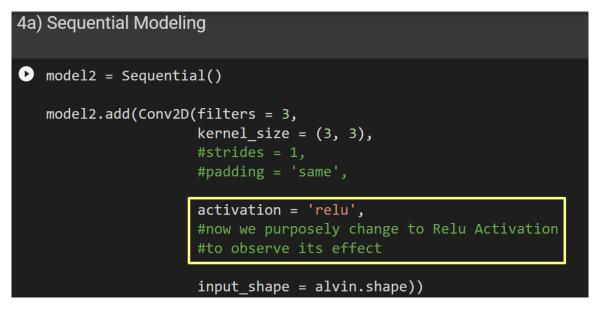
Step 4: Demonstrating effect of adding Relu activation What happens when you Add a Relu Activation?



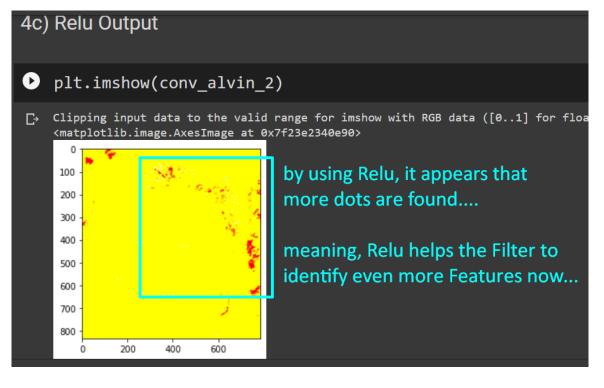
 Relu is an activation function and has already been explained here: https://www.alvinang.sg/s/Artificial-Neural-Network-ANN-How-It-Works-by-Dr-Alvin-Ang.pdf

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1. SEQUENTIAL MODELING



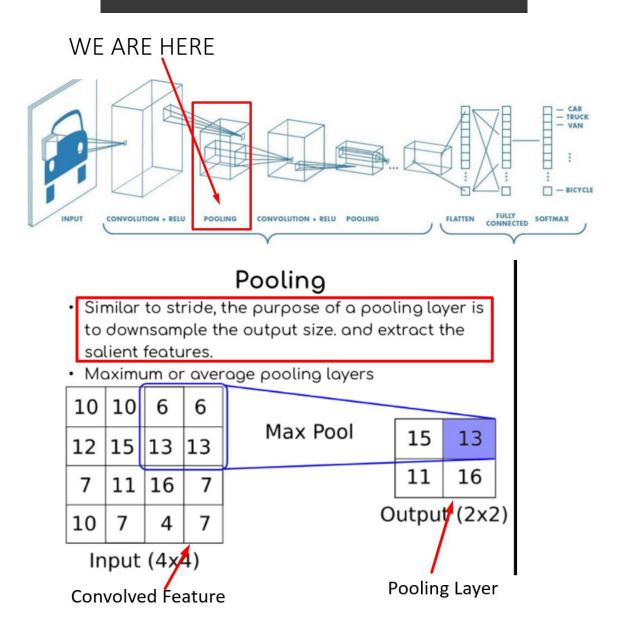
2. RELU OUTPUT / EFFECT OF USING RELU ACTIVATION



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E. WHAT IS POOLING?

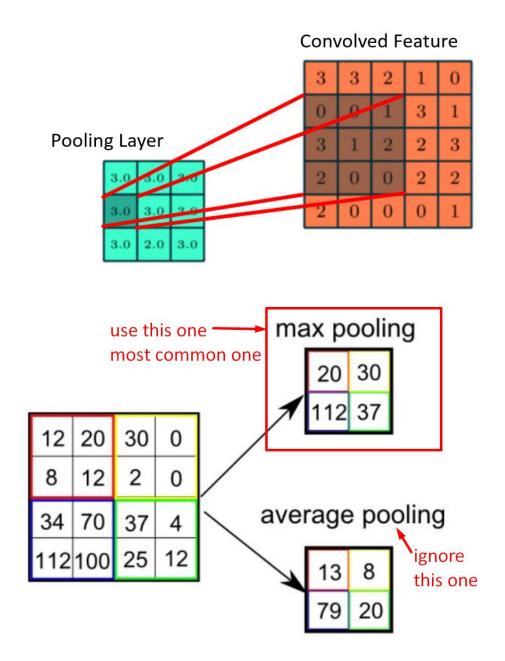
Step 5: Demonstrating effect of Pooling What does Pooling do?



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To see animated .gif, go here to understand how the Pooling Layer slides across the Convolved Feature:

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5way-3bd2b1164a53



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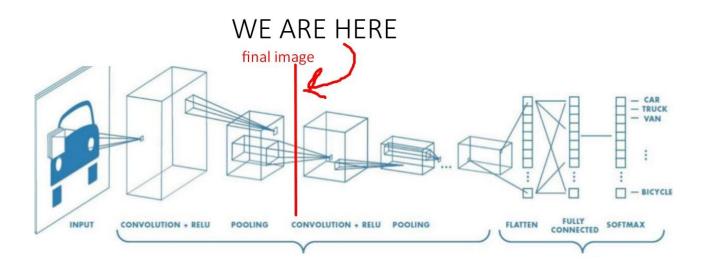
1. SEQUENTIAL MODELING



2. POOLING OUTPUT / EFFECT OF POOLING



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REFERENCES

• <u>https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53</u>

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ABOUT DR. ALVIN ANG



Dr. Alvin Ang earned his Ph.D., Masters and Bachelor degrees from NTU, Singapore. He is a scientist, entrepreneur, as well as a personal/business advisor. More about him at <u>www.AlvinAng.sg</u>.

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