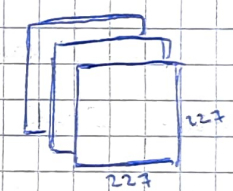
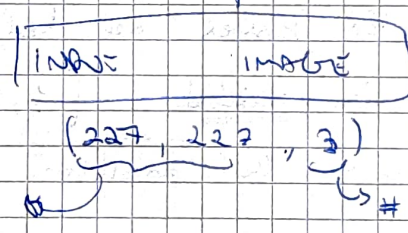
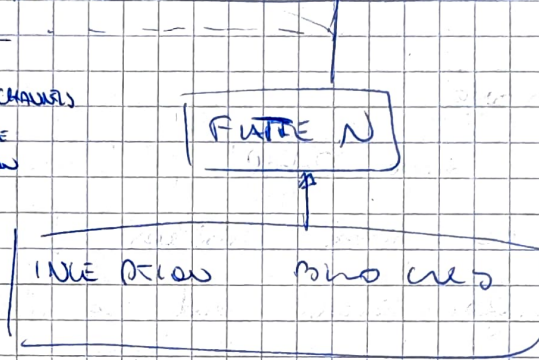


Now I have an array of dimension $L \times L \times \text{CHANNALS}$.
 L : size of the image in the output of the last iteration above.

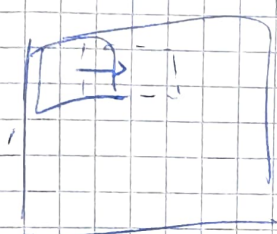


size of the images \rightarrow # input channels

1. CONVOLUTIONAL NEURAL NETWORK:

In such a case we need to detect a pattern within the whole input (MLP doesn't work, since it matches the whole input). Instead CNN are shift invariant, we have a little model which analyze each window of the image.

convolution means: we use a sliding filter that analyze each window of the image, and as output gives the features extracted.



POOLING: select the features and decrease the dimension of the input.

Intuition now: have a multi-scale view of the input & same for the same input, we use different filter size (which later are combined together)
big filter \rightarrow general view, more "far away"
small " \rightarrow I care more at the details of the input

At the end of the convolutional part I will have the features "describing" the image.

\rightarrow then we will add by 2 dense layers \rightarrow get the outputs

[It is particularly useful when we don't know anything about the size of the objects in the images]

2. a) Input: "input-image"

Labels (output): "image-label", "bounding-box-label"

b) • Min Max scale the pixel values $[0, 255] \rightarrow [0, 1]$

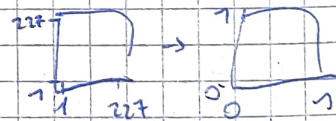
\hookrightarrow we don't lose information and we don't give too much importance to high values while updating the weights

(we don't oversample, the classes are balanced)

• ~~box~~ labels are also scaled $[1, 227] \rightarrow [0, 1]$

value in $[0, 1]$ represent the "proportion"

\hookrightarrow the corner (0 \rightarrow origin, 1 \rightarrow max corner)



\hookrightarrow this allows me to use a sigmoidal as output

• $\{1, 2, 3\}$ Labels are kept as they are

c) each sample have dimension $(227, 227, 3)$, each pixel have value in $[0, 1]$

(then at train we will have another dimension indicating the batch size)

3. • 'Labels' $\rightarrow \{1, 2, 3\}$, so as output I use a dense layer with 'softmax' activation function and 3 neurons
 the softmax create a prob. distribution over the 3 classes which is the ideal for multiclass classification.
 then to give the actual label we can just use the 'argmax'
- 'b. boxes' $\rightarrow (x_1, x_2, y_1, y_2)$, with each entry belonging to $[0, 1]$
 so I can use a 'sigmoid' (with 4 neurons)
 \hookrightarrow (I have 2 outputs) \hookrightarrow one for each value (x_1, x_2, y_1, y_2)

4. for 2 outputs we need 2 losses.

- 'sparse categorical crossentropy' for the labels
 categorical crossentropy: minimize the Kullback-Leibler divergence. so it makes the distribution of the output (which was a softmax) closer and closer to the distribution of the true labels.

sparse \rightarrow just like the "normal" one, but works with indices $\{1, 2, 3\}$ instead of one-hot vectors $\left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$

- 'b. boxes' \rightarrow 'mse'

\hookrightarrow just a regression in $[0, 1]$

we are minimizing the squared distance between the predicted value and the true coordinates

5. a) INPUT \rightarrow INPUT LAYERS \rightarrow PATTERN \rightarrow DENSE (NEW) \rightarrow DENSE (SOFTMAX)
* \rightarrow DENSE (NEW) \rightarrow DENSE (BINARY)

b) as activation I use the 'Relu', since I don't need a bounded function. Relu is simple and works well with CNN (I should not have much problems of exploding gradient like in RNN) \rightarrow afines and sigmoid as output

c) • initializer \rightarrow He (for the convolutional layers)

[set a good initial condition across the conv. layer, with the Relu activation function]

• As a form of "regularization" I use dropout layers that by randomly turning off some neurons, help the NN to don't ~~make~~ take decisions based solely on single neurons.

d) 1) number of input layers

the number required could depend on the complexity of the images

2) I try to find some value of batch size, for getting a good training of the model

3) I increase the dropout rate if I see overfitting

* I ADD TWO DENSE LAYERS FOR REDUCING THE DIMENSION OF THE PATTERNED VECTOR BEFORE OF THE OUTPUT (USE A SMALL MLP)

6) I would split the train and test (something like 80:20) since we don't have many sample, we can't make a test set too little.

then apply Cross validation on the train set.

C.V. is particularly useful (w.r.t. ~~dataset~~, hold out) when we don't have a lot of data.

metrics \rightarrow accuracy

(I don't have a real need of using a F-score, since the classes are balanced)