

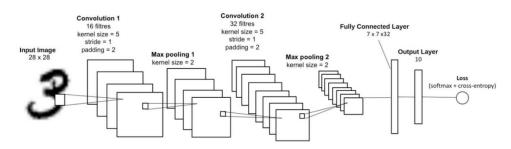
Tutorial: Week 3

Image Classification and Object Detection with CNNs

Jeremy Pinto jeremy.pinto@mila.quebec

CNN Tutorial

In this tutorial you will:



How many trainable parameters do we have in total?

Part 1:

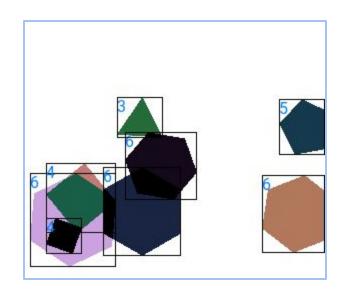
- Explore the MNIST digit dataset
- Implement and train an MLP to classify digits
- Implement and train a CNN (LeNet) to classify digits
- Use regularization on your models (batch norm)



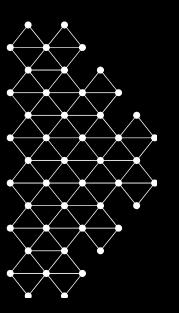
CNN Tutorial

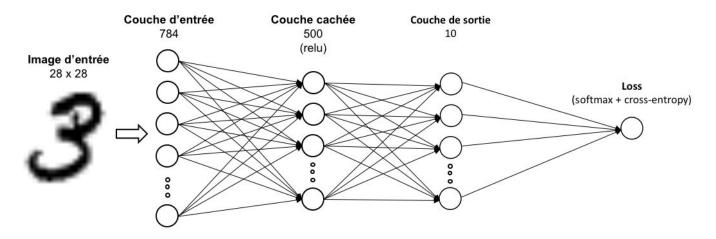
Part 2 (optional):

- Finetune your own object detector on a toy object detection dataset
 - Faster R-CNN for object detection
 - Mask R-CNN for semantic segmentation





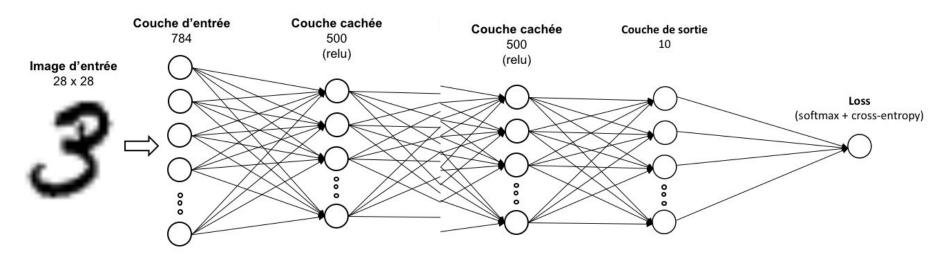




The figure is misleading - it actually has 2 hidden layers (refer to the code)

```
MLP(
  (hidden_layer): Sequential(
     (0): Linear(in_features=784, out_features=500, bias=True)
     (1): ReLU()
     (2): Linear(in_features=500, out_features=500, bias=True)
     (3): ReLU()
  )
  (output_layer): Sequential(
     (0): Linear(in_features=500, out_features=10, bias=True)
  )
}
```

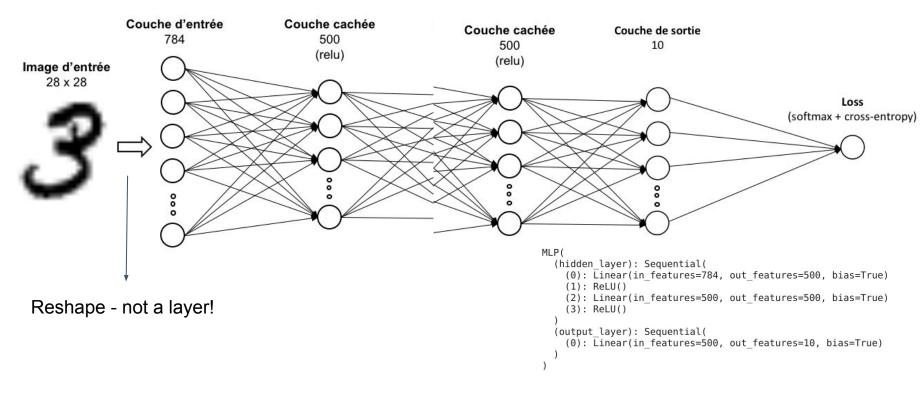


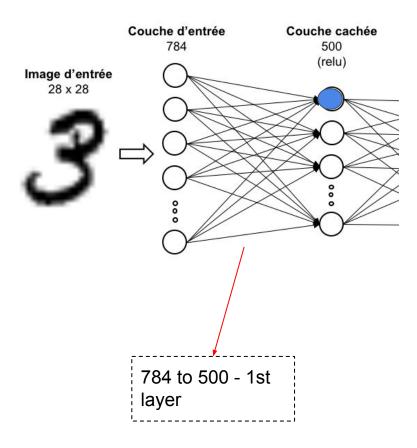


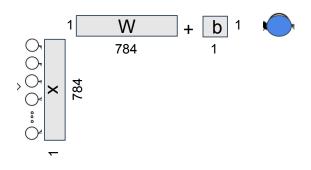
What is should look like:

```
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```



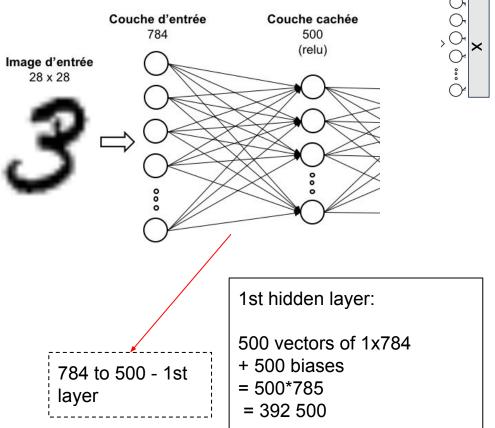






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```



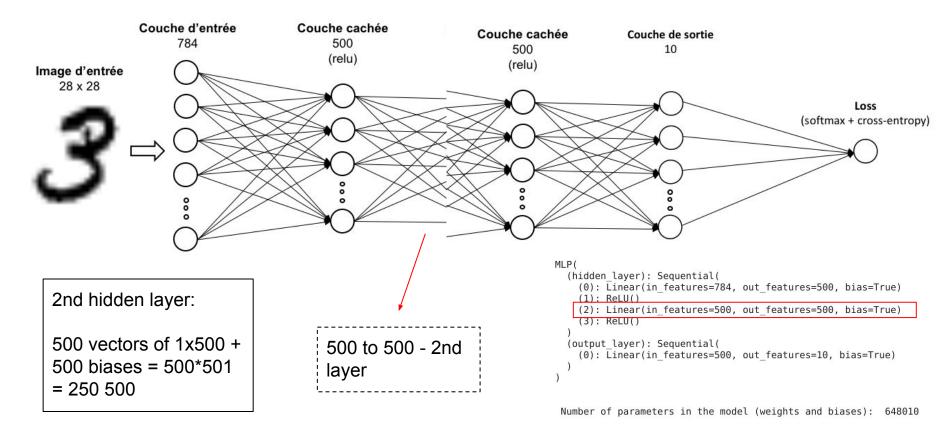


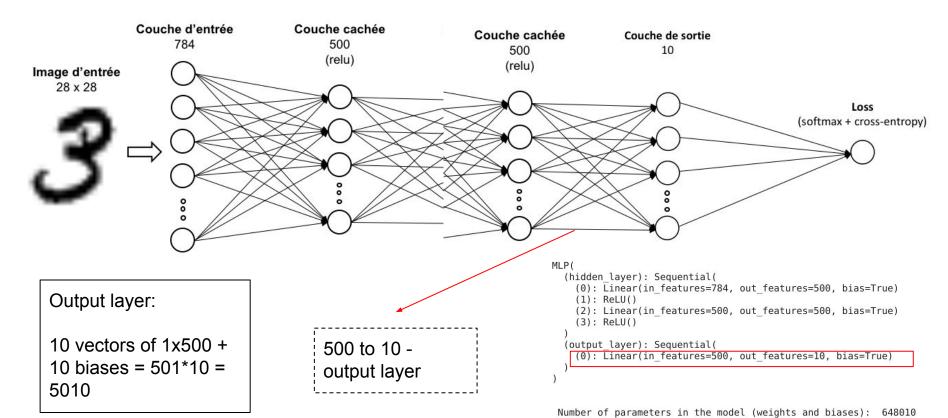
```
W + b 784 1

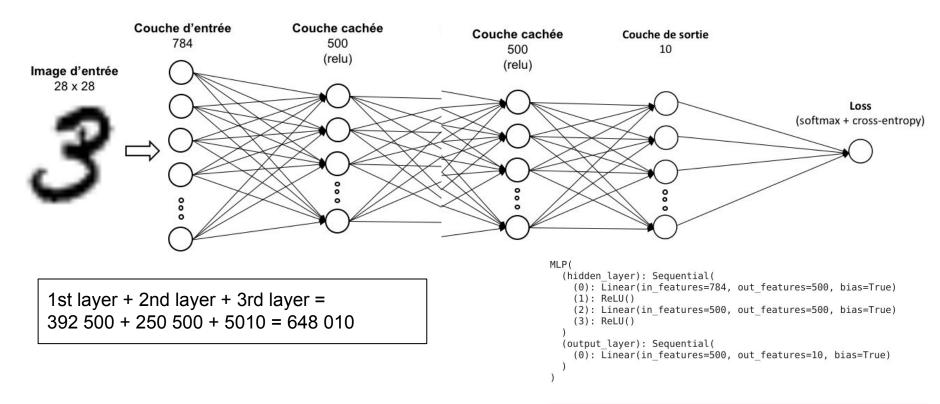
W + b 784 1
```

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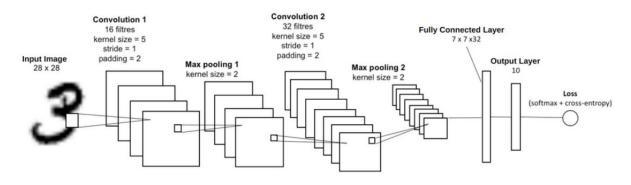




Question 6

1 point possible (graded)

Consider the following architecture used on MNIST. We have 10 classes and input images of size 28x28.



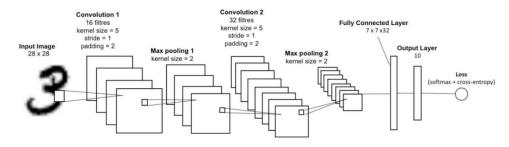
How many trainable parameters do we have in total?



Question 6

1 point possible (graded)

Consider the following architecture used on MNIST. We have 10 classes and input images of size 28x28.



How many trainable parameters do we have in total?

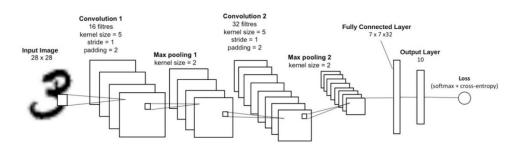
1st layer: 1 input channel with 16 kernels (5x5):

$$16 \times (5 \times 5) + 16 \text{ biases} = 416$$

Question 6

1 point possible (graded)

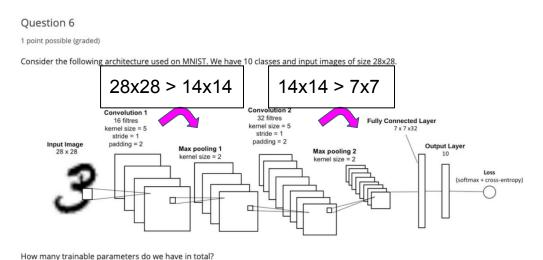
Consider the following architecture used on MNIST. We have 10 classes and input images of size 28x28.



How many trainable parameters do we have in total?

2nd layer: 16 input channels with 32 output channels:

$$[16 \times (5x5)] \times 32 + 32 \text{ biases} = 12 832$$



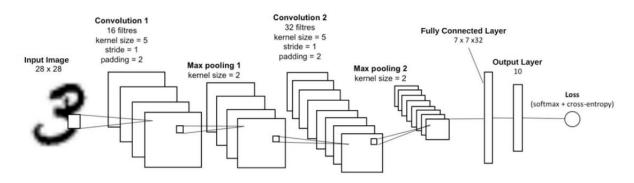
Fully connected layer - why 7x7x32? Because 28 / 2 / 2 = 7 (max pooling reduces our input, padding makes this a "same" convolution).

So our feature maps are HxW = 7x7, and depth = 32. Flattened, that is equivalent to 7x7x32 inputs. We want 10 outputs: $(7x7x32) \times 10 + 10$ biases = 15 690

Question 6

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Consider the following architecture used on MNIST. We have 10 classes and input images of size 28x28.



How many trainable parameters do we have in total?

