

Introduction to Neural Network, Convolution Neural Networks, and Deep Learning

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(SDSC)

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Outline

- **Overview of Neural Networks (aka Multilayer Perceptron)**
- **Convolution Neural Networks**
- **Basic Keras commands for building, training CNNs – exercise**
(use expanse portal or jupyter-compute-tensorflow from command line)
- **Hyperparameters and Tuning and workflows - exercise**

to get neural network:

Consider the Logistic Function (aka sigmoid)

$$f(x) = \frac{1}{1 + \exp(-(b+wx))}$$

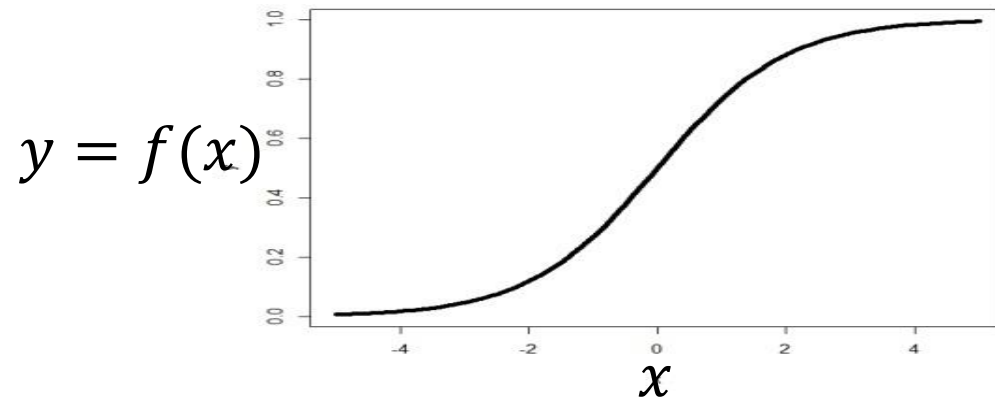
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Consider the Logistic Function

(aka sigmoid)

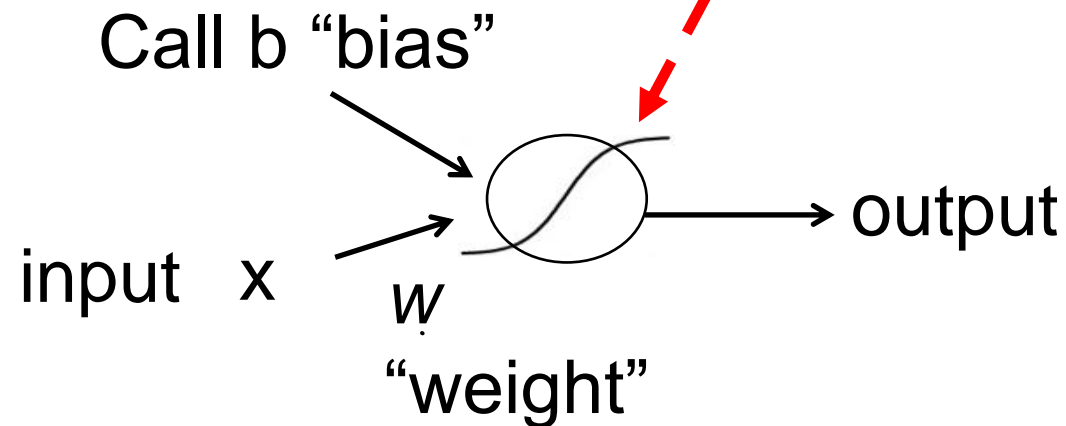
$$f(x) = \frac{1}{1 + \exp(-(b+wx))}$$

for parameters: $b = 0$, $w_1 = 1$



Make a graphical description of Logistic Function

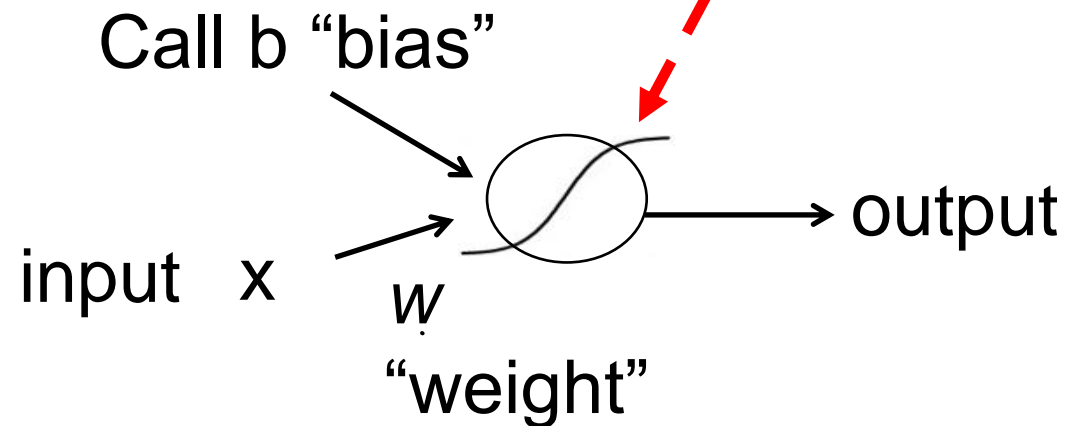
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this node (or unit) will transform input to output with logistic activation function

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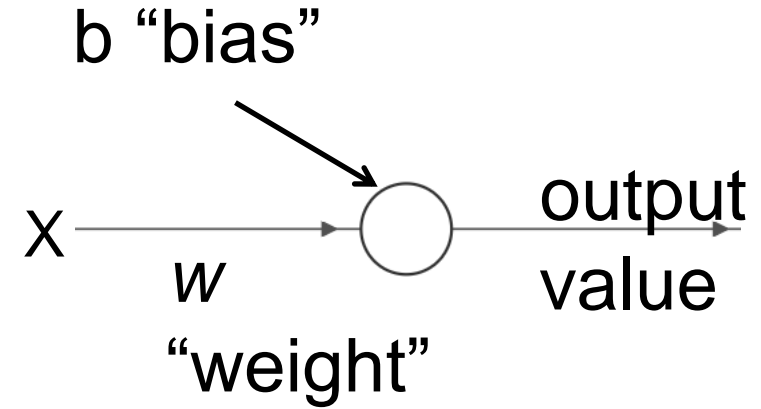
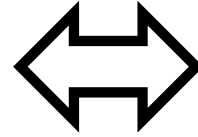


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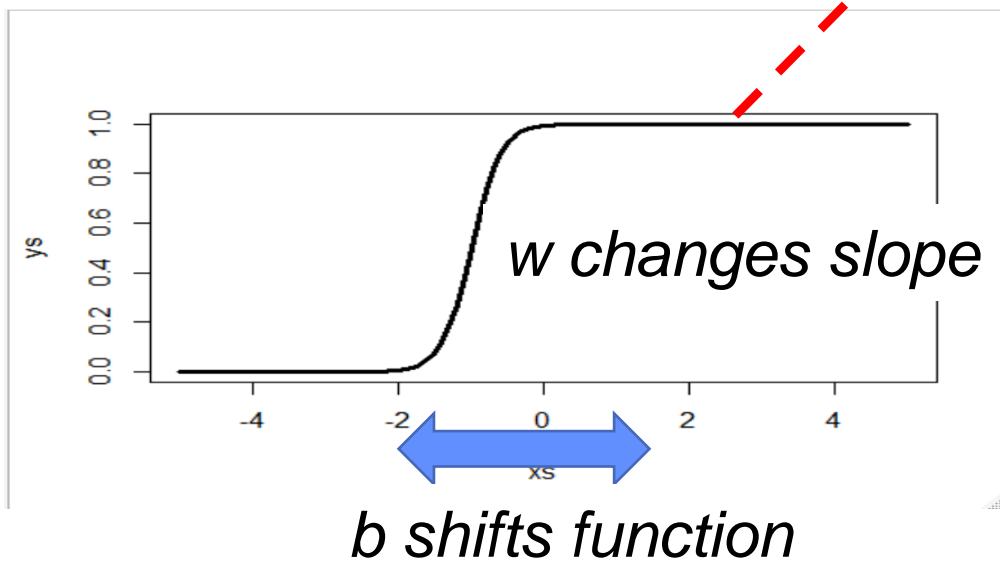
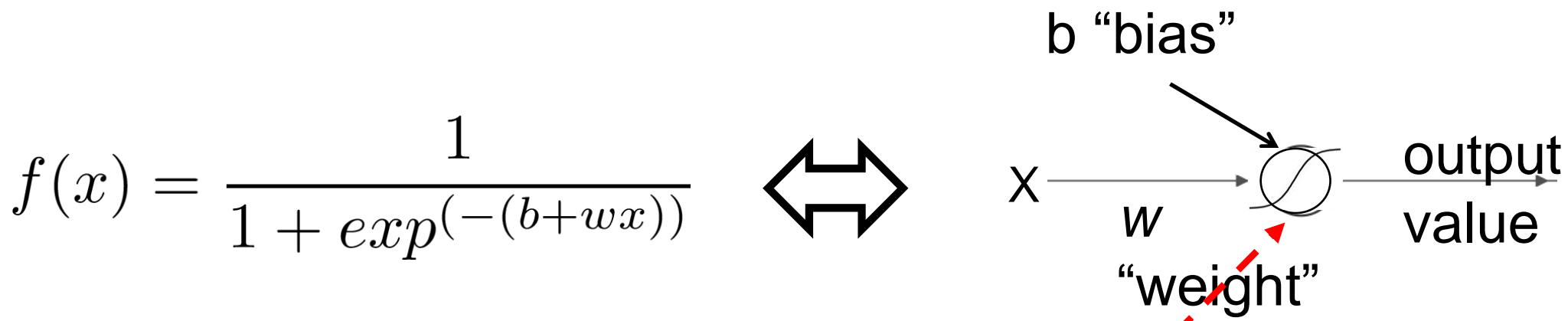
Goal: given some data X and outputs Y find w & b so that output = 1 when $Y=1$

How does changing parameters affect the function?

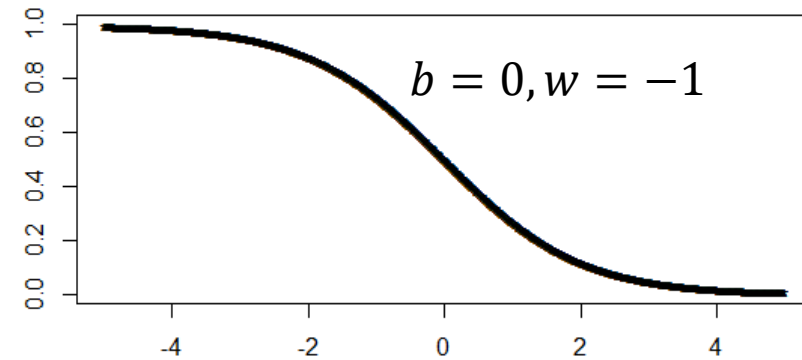
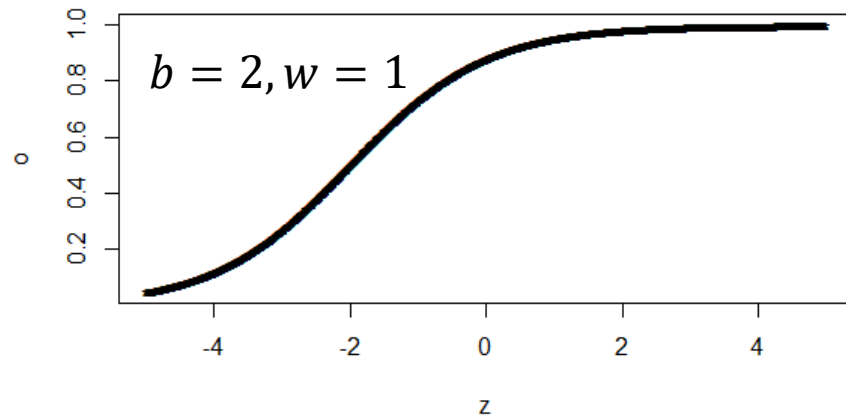
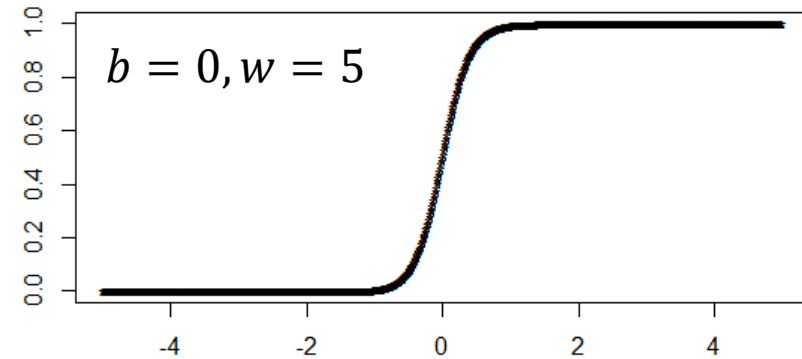
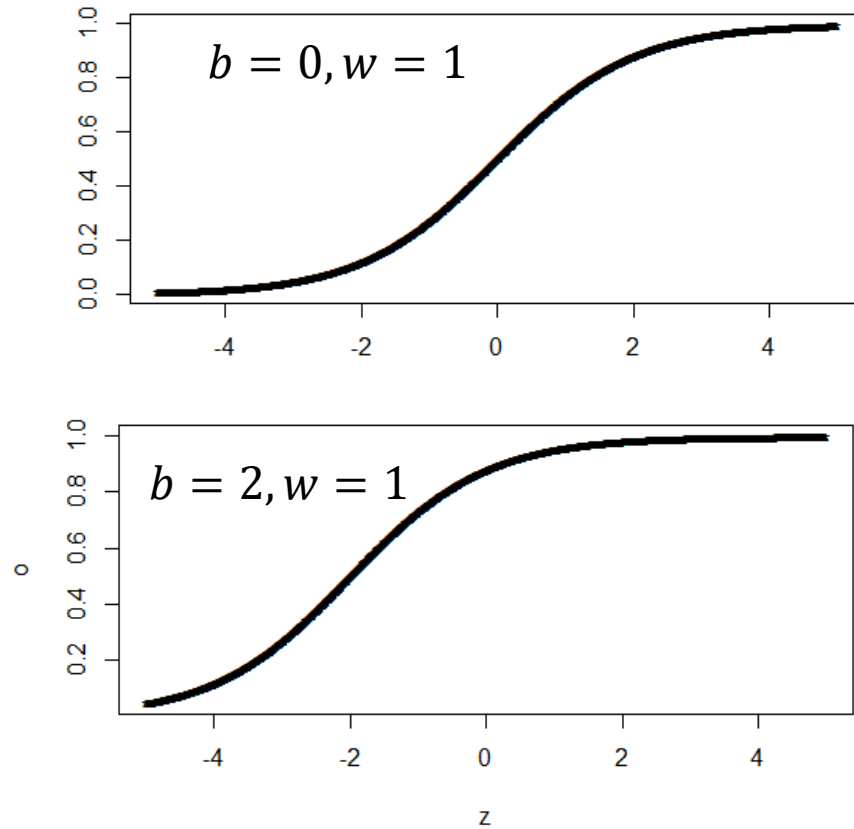
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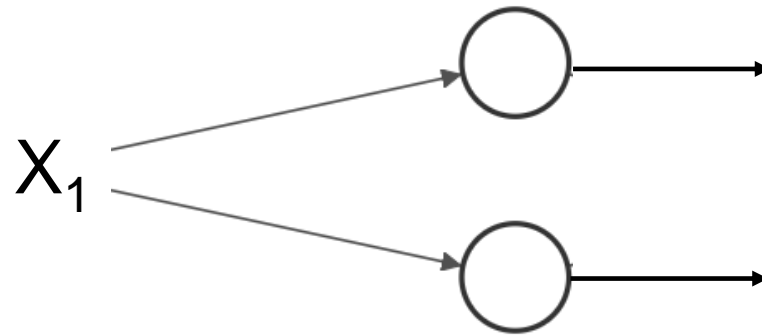
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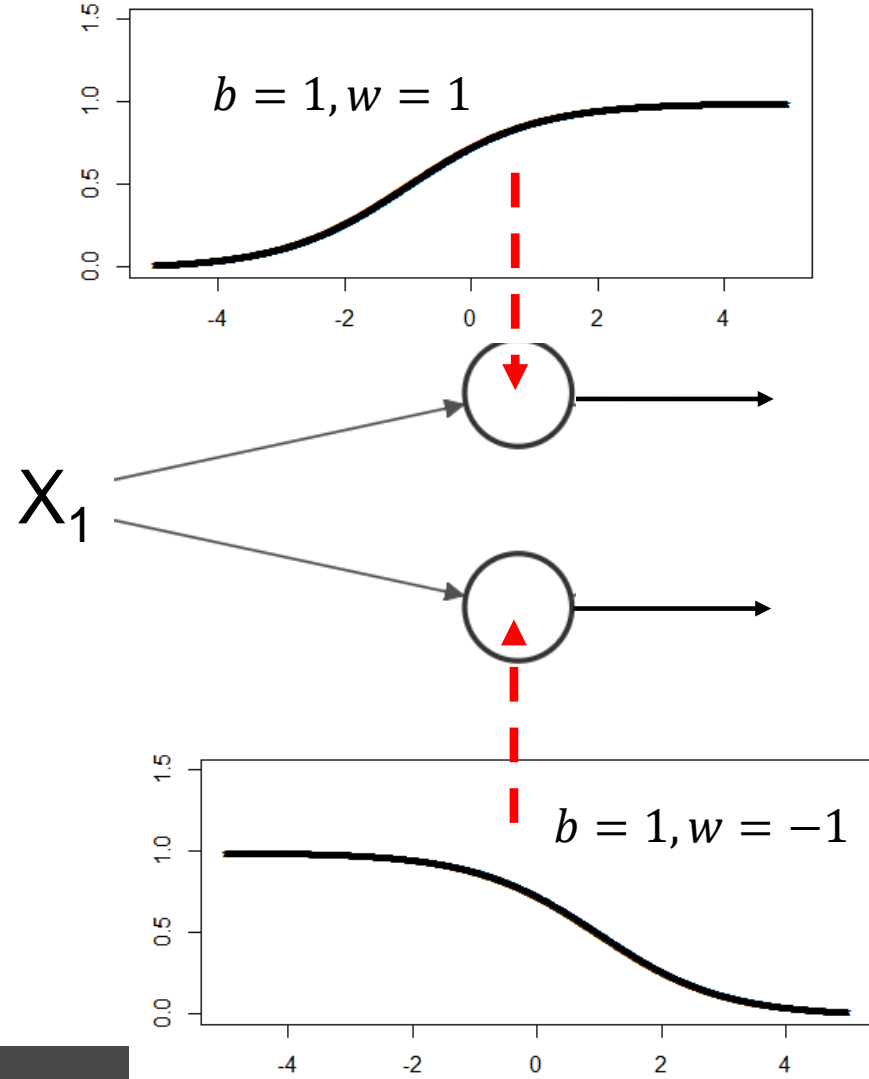
Logistic function w/various weights



Example: 1 input into 2 logistic units

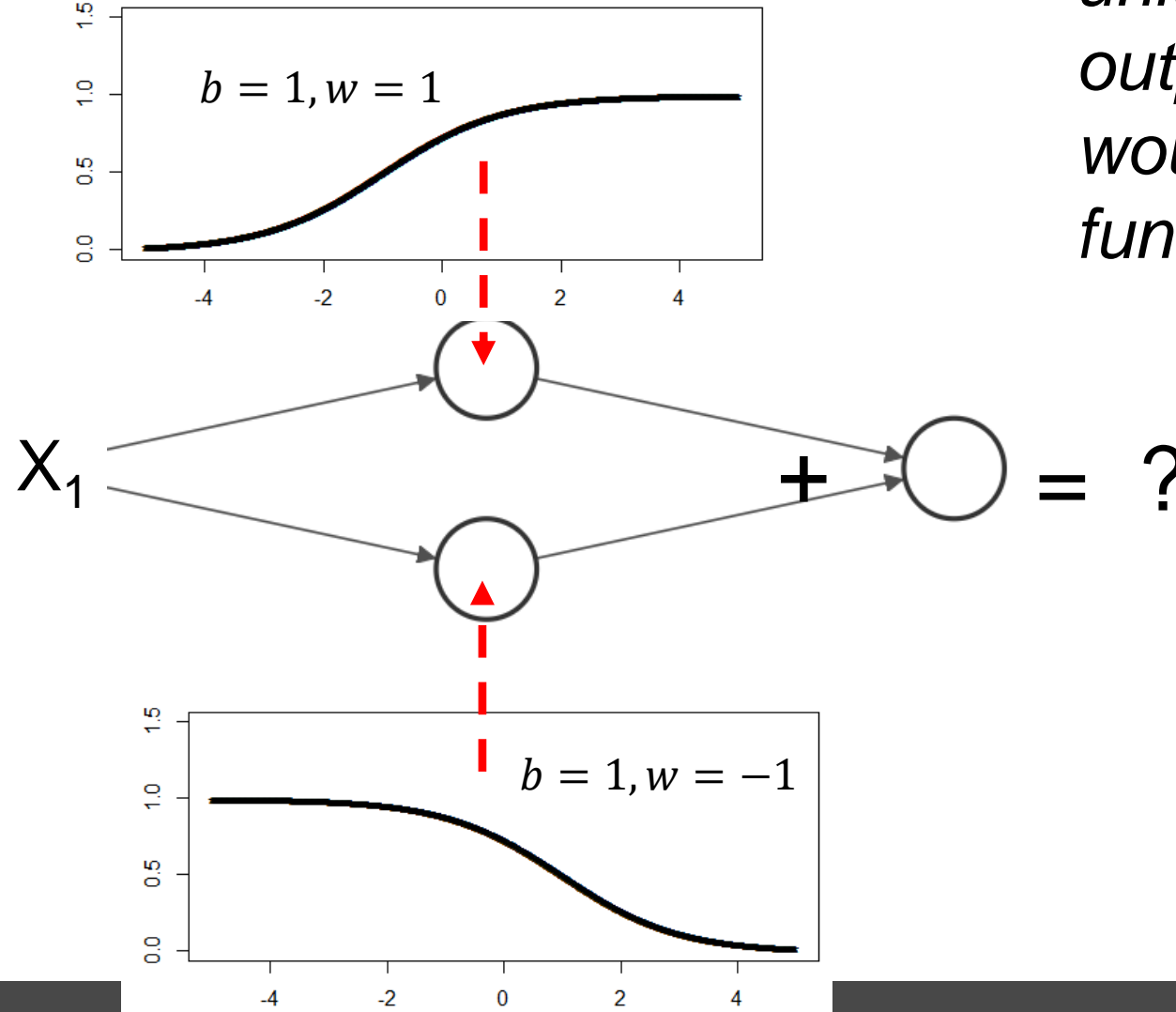


Example: 1 input into 2 logistic units with these activations



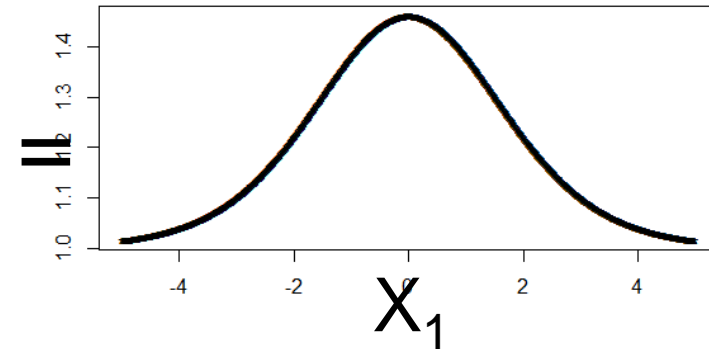
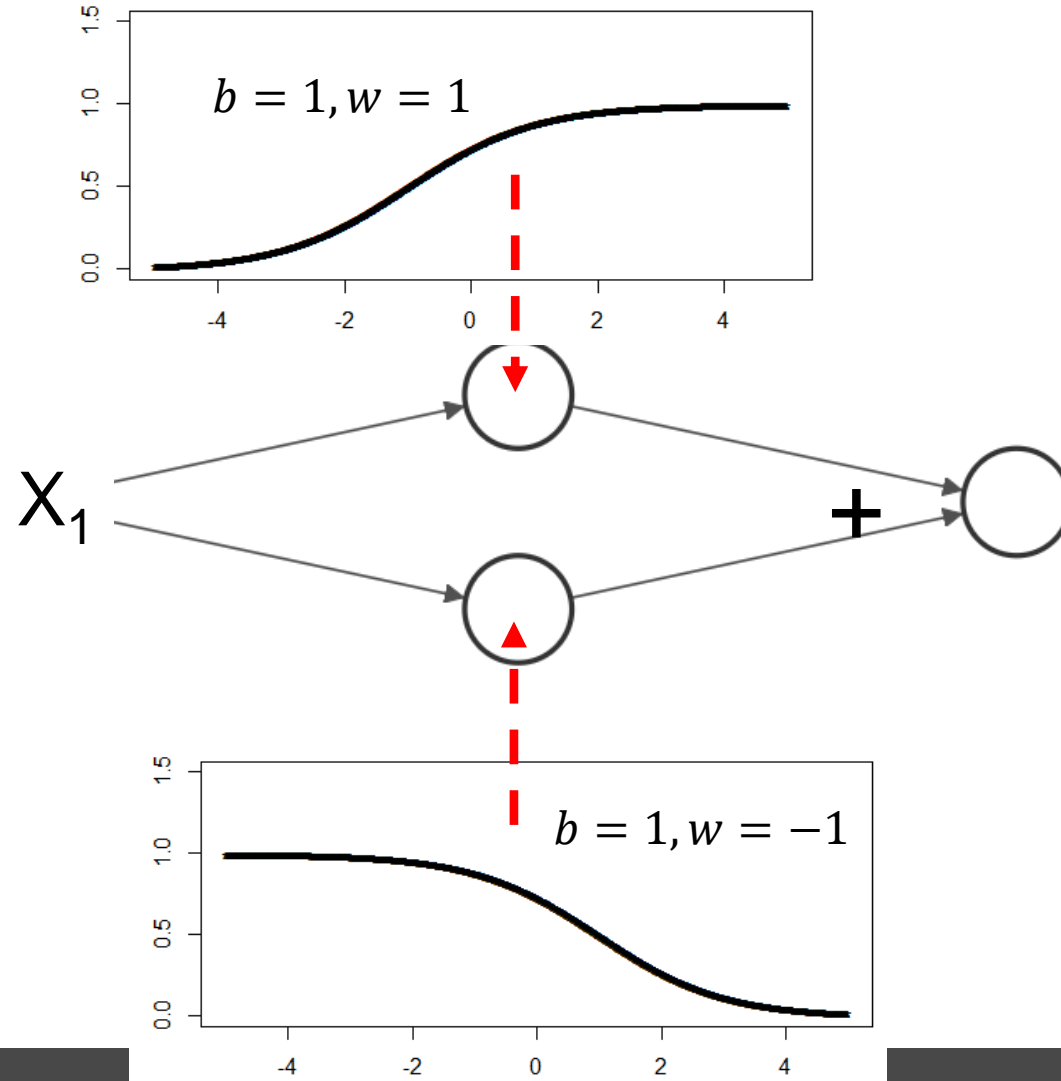
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If you add these 2 units into a final output unit what would the output function look like?



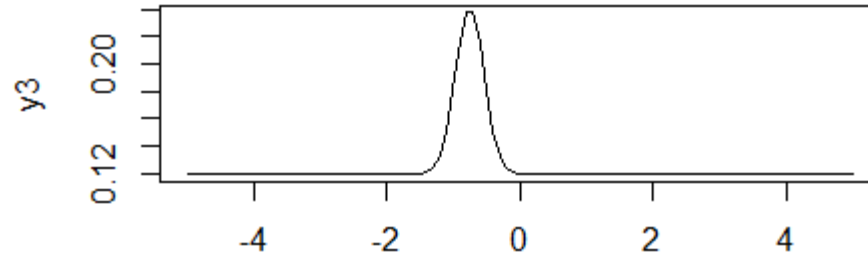
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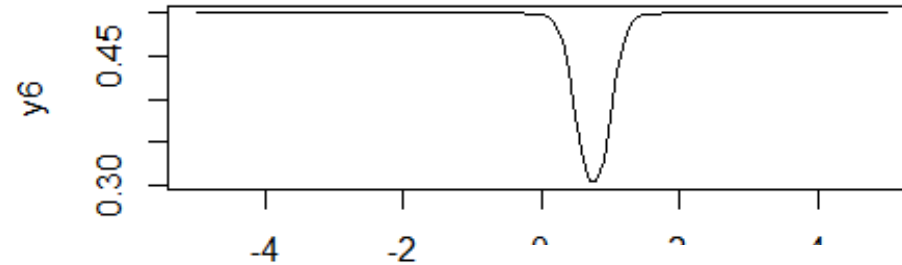


Higher level function combinations

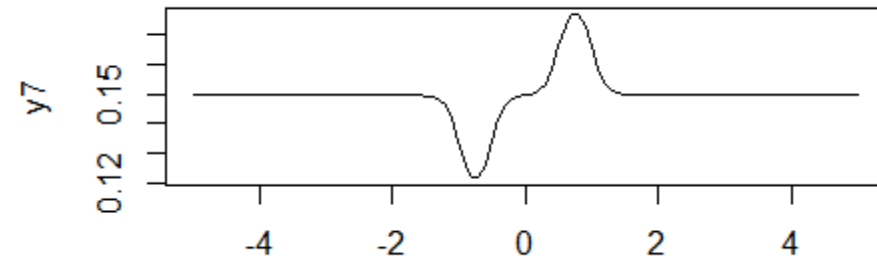
```
x=seq(-5,5,.1)
y1=1/(1+exp(10+ 10*x))
y2=1/(1+exp(-5+(-10)*x))
y3=1/(1+exp(1+1*y1+1*y2))
plot(x,y3,type="l")
```



```
y4=1/(1+exp(10+ (-10)*x))
y5=1/(1+exp(-5+(10)*x))
y6=1/(1+exp(1-1*y4-1*y5))
plot(x,y6,type="l")
```

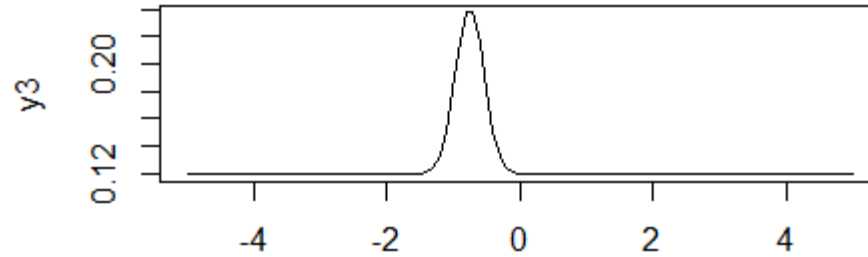


```
y7=1/(1+exp(1+2*y3+1*y6))
plot(x,y7,type="l")
```



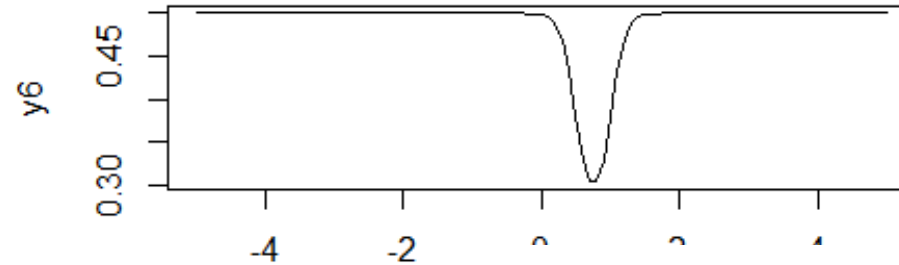
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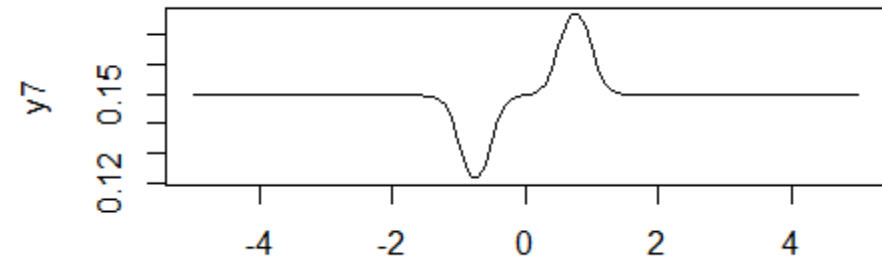


Multiple layer networks can represent any logical or real-valued functions (unbiased, but potential to overfit)

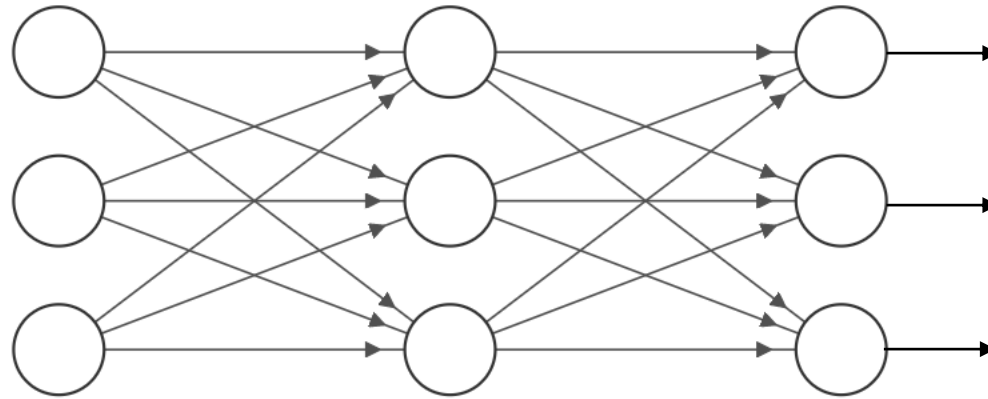
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we can add layers and nodes



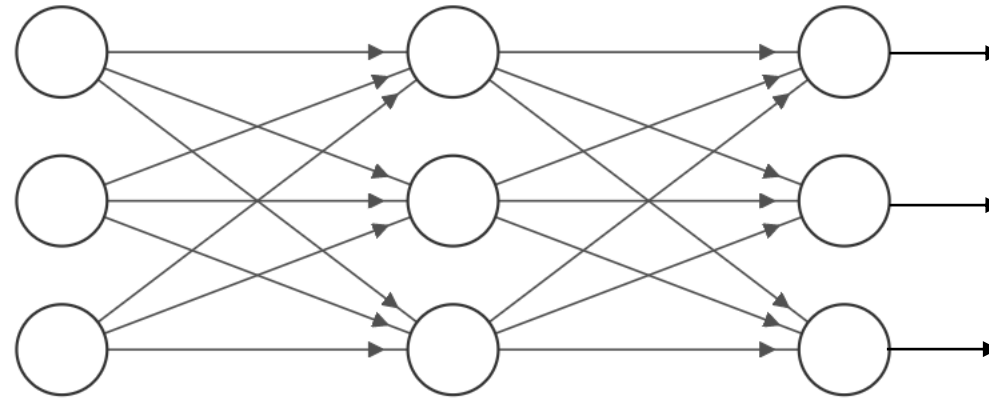
we can add layers and nodes

Multilayer Perceptron

1 Input layer

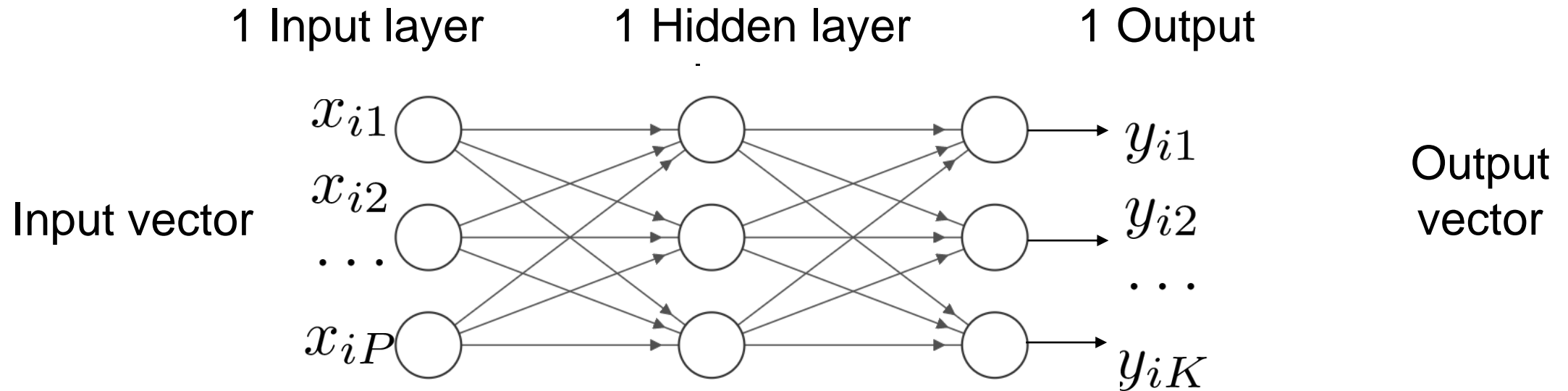
1 Hidden layer

1 Output



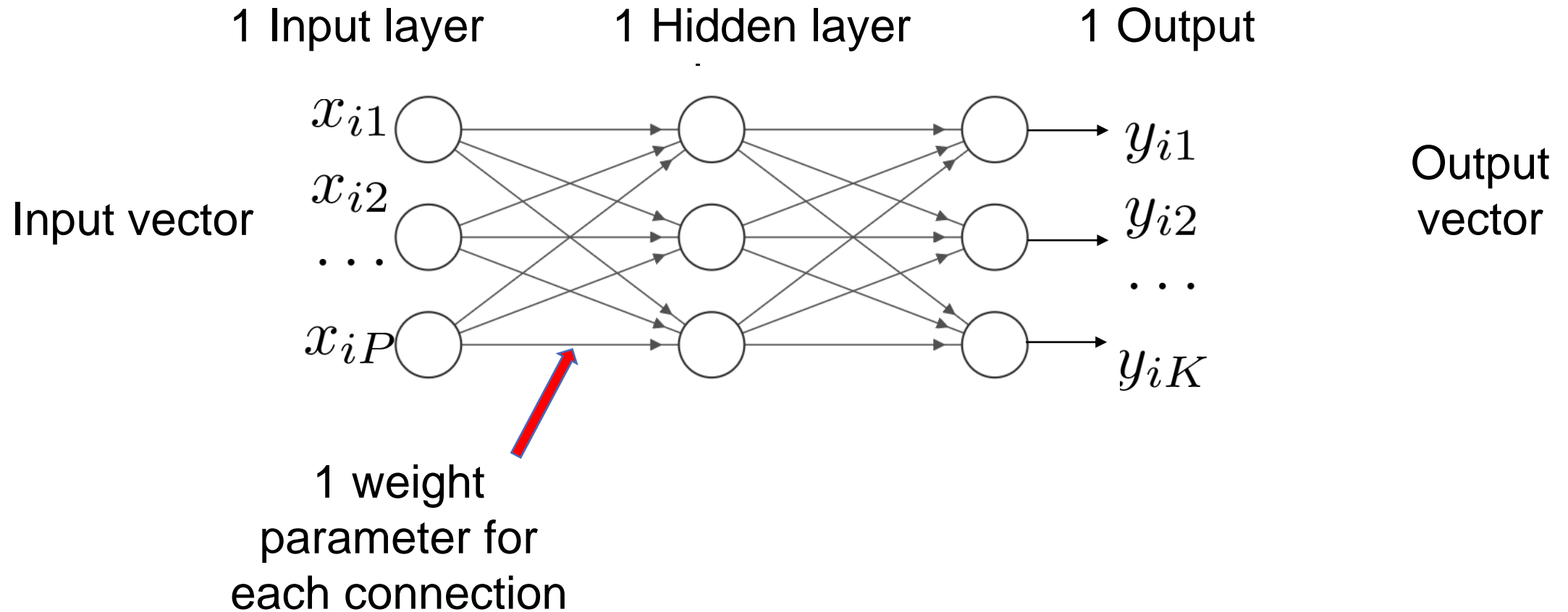
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Multilayer Perceptron

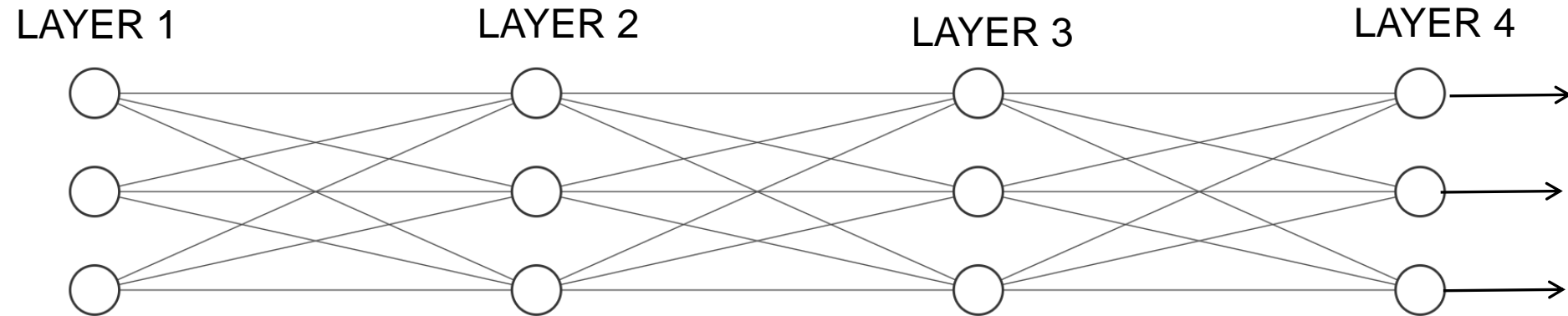


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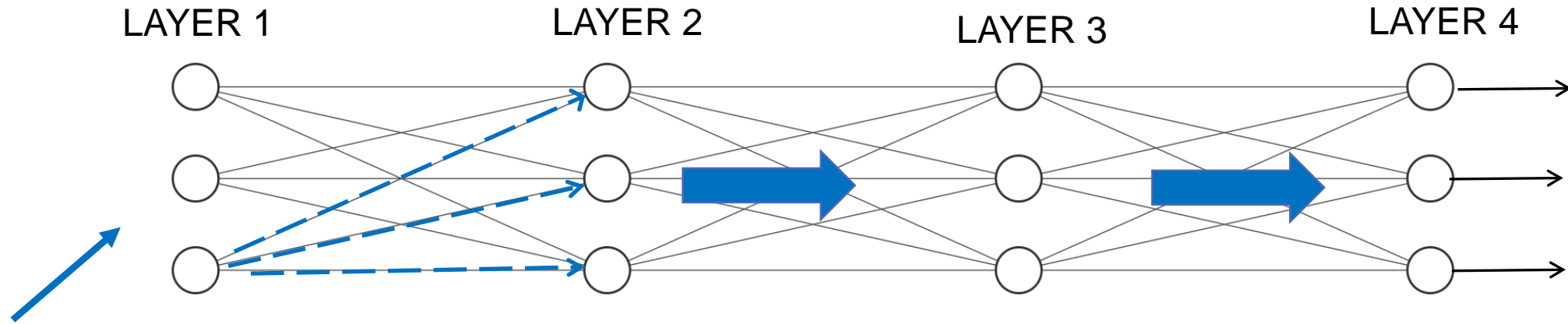
Multilayer Perceptron



First step: choose layers, connectivity, and activations



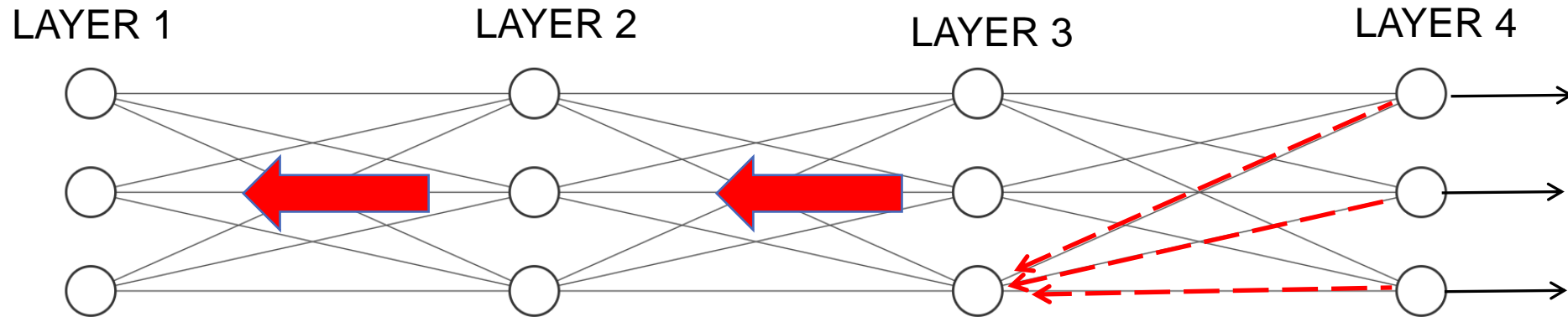
Algorithm steps:



1. FORWARD PROPAGATE ACTIVATION:

apply input data x_i ,
calculate all node activations

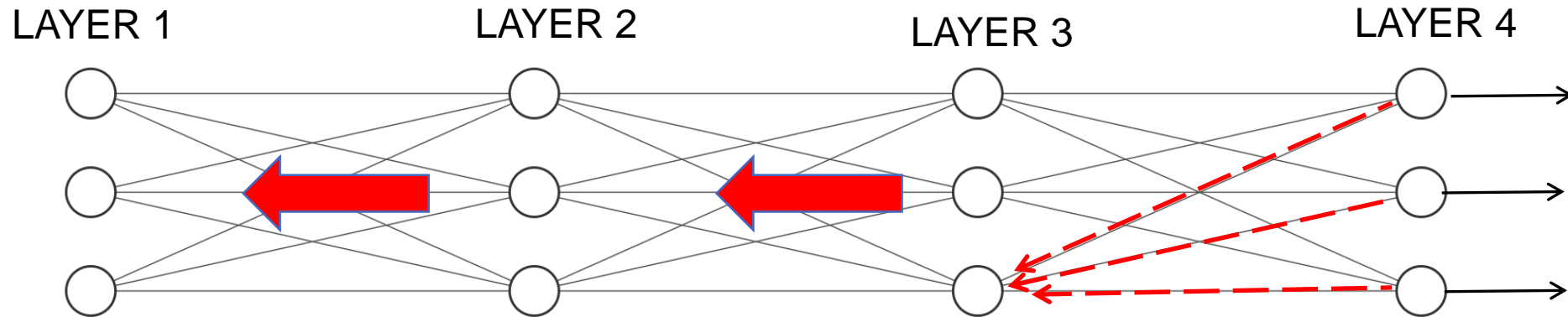
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calculate Error (or Loss) derivatives, dE/dY ,
pass it back to lower layer

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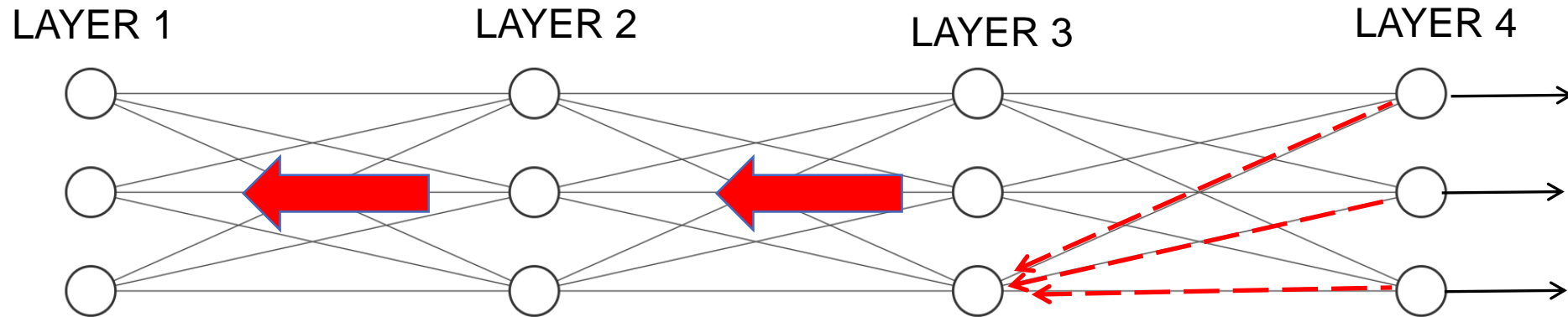
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For hidden layers use chain rule:
($dE/dY \quad dY/dH_3 \quad dH_3/dH_2$ etc...)
needs a summation of previous layer

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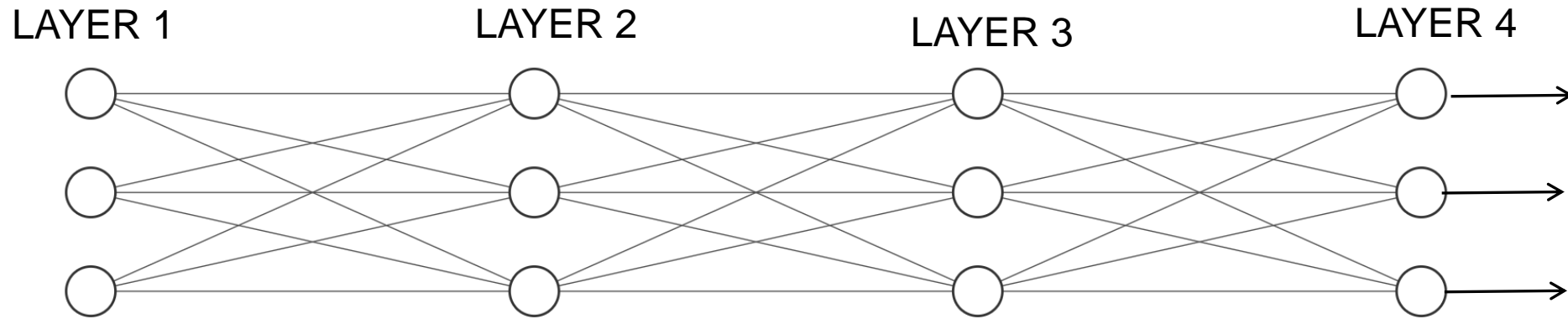
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***Beware: error signals get diluted as you go backward -
the 'vanishing gradient' problem***

algorithm steps:



**1. FORWARD PROPAGATE
ACTIVATION:**

apply input data x_i ,
calculate all node activations

2. BACKWARD PROPAGATE ERROR:
calculate Error (or Loss) derivatives (dE/dY)
pass it back to lower layer

3. Update weights and bias terms

$$w_{ji} = w_{ji} - \eta \frac{dE}{dw_{ji}}$$

NN Algorithm

INITIALIZE WEIGHTS (small random values)

NN Algorithm

INITIALIZE WEIGHTS

LOOP until stopping criterion:

FORWARD PROPAGATION: calculate all node activations

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BACKWARD PROPAGATION: calculate all derivatives to *minimize Loss (dL)*

NN Algorithm

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UPDATE WEIGHTS: $w \leftarrow w - \textit{learning_rate} * \frac{dL}{dw}$

NN Algorithm

INITIALIZE WEIGHTS

LOOP until stopping criterion:

FORWARD PROPAGATION: calculate all node activations

BACKWARD PROPAGATION: calculate all derivatives to *minimize Loss (dL)*

UPDATE WEIGHTS: $w \leftarrow w - \text{learning_rate} * \frac{dL}{dw}$

STOP: when validation loss reaches minimum or converges

NN Algorithm

[heuristics, options to learn faster and/or better]

INITIALIZE WEIGHTS [use truncated distributions]

LOOP until stopping criterion: [work in batches of input]

FORWARD PROPAGATION: calculate all node activations

BACKWARD PROPAGATION: calculate all derivatives to *minimize Loss (dL)*

UPDATE WEIGHTS: $w \leftarrow w - \text{learning_rate} * \frac{dL}{dw}$ [adapt learning rate, use momentum]

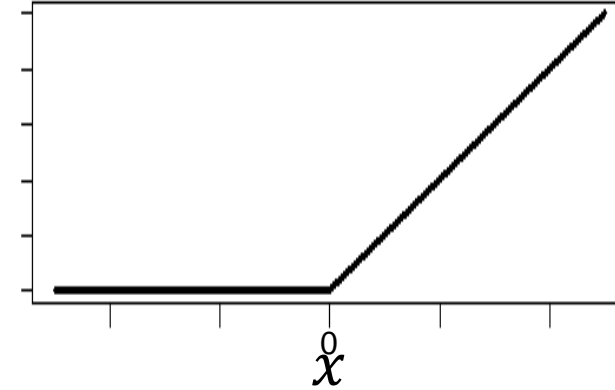
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[several metrics of loss are possible]

A heuristic for deep networks

ReLU (rectified linear

ReLU activation function



$$f(a) = \begin{cases} a & a > 0 \\ 0 & a \leq 0 \end{cases}$$

where $a = XW$

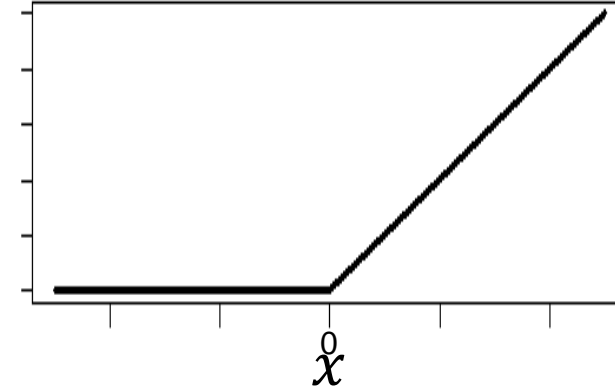
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It is unscaled (bad!)

But df/da is constant (good!)



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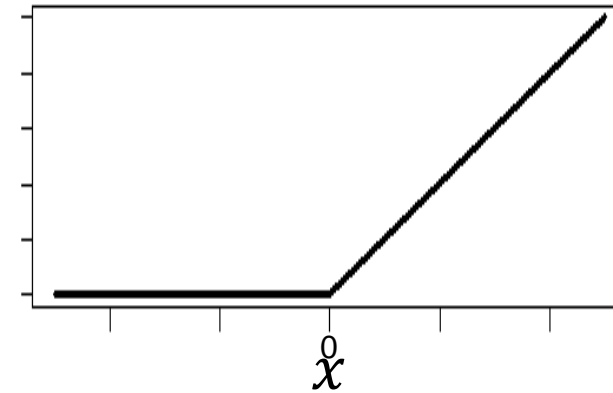
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$$f(a) = \begin{cases} a & a > 0 \\ 0 & a \leq 0 \end{cases}$$

where $a = XW$

RELU helps mitigates vanishing gradients

Summary:

Pro:

Neural Networks in general, are flexible, powerful learners

Hidden layers learn a nonlinear transformation of input

Many heuristics about what works

Summary:

Pro:

- Neural Networks in general, are flexible, powerful learners
- Hidden layers learn a nonlinear transformation of input
- Many heuristics about what works

Con:

- Hard to interpret
- Needs more data
- Lots of parameters

What is deep learning?

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Deep learning refers to learning complex and varied transformations of the input

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Deep learning is a neural network with many layers

Outline

- Overview of Neural Networks (aka Multilayer Perceptron)
- **Convolution Neural Networks**
- Basic Keras commands for building, training CNNs - exercise
- Hyperparameters and Tuning and workflows - exercise

Image features

- **MNIST - A database of handwritten printed digits**
(National Inst. of Standards and Technology)



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How to classify digits?

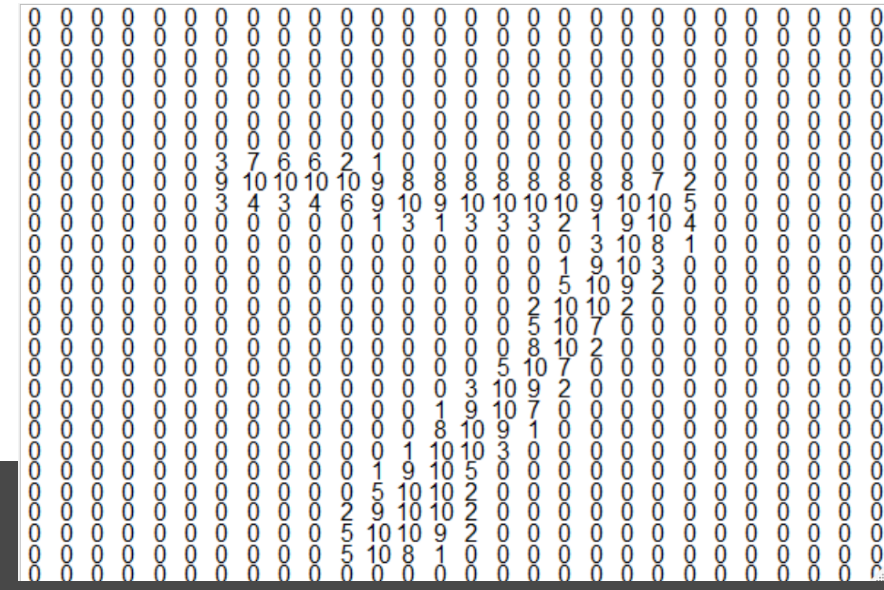
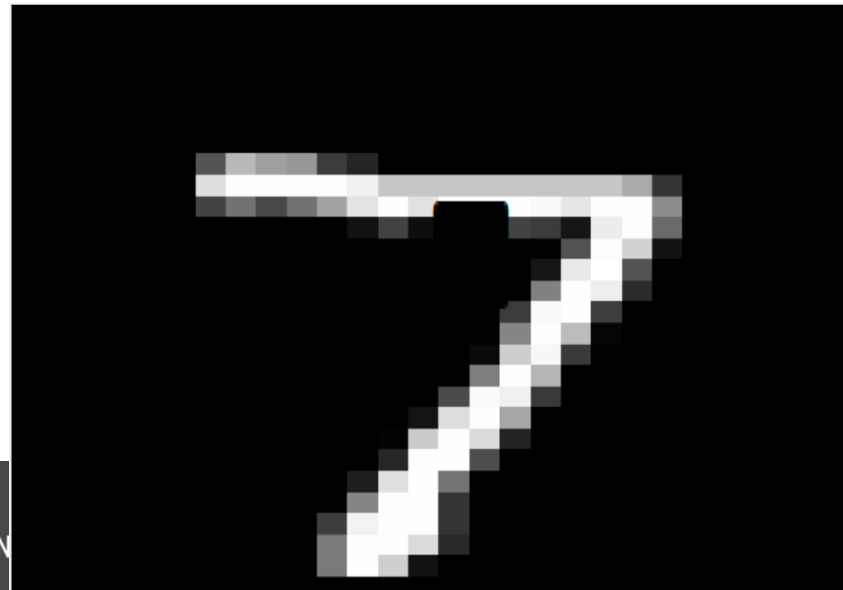


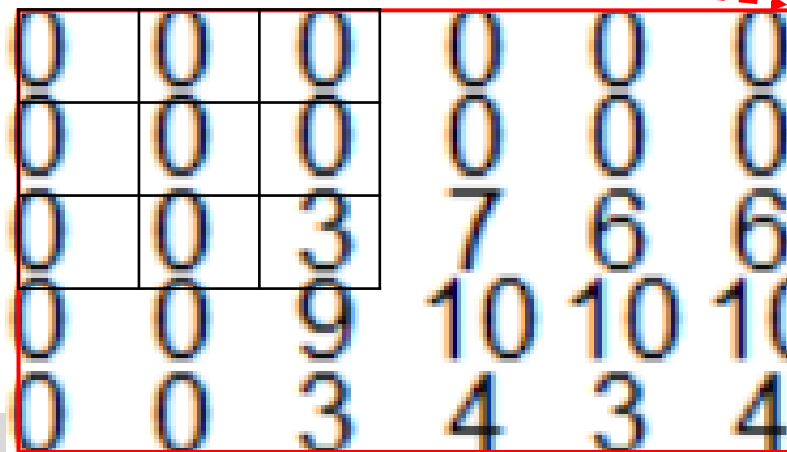
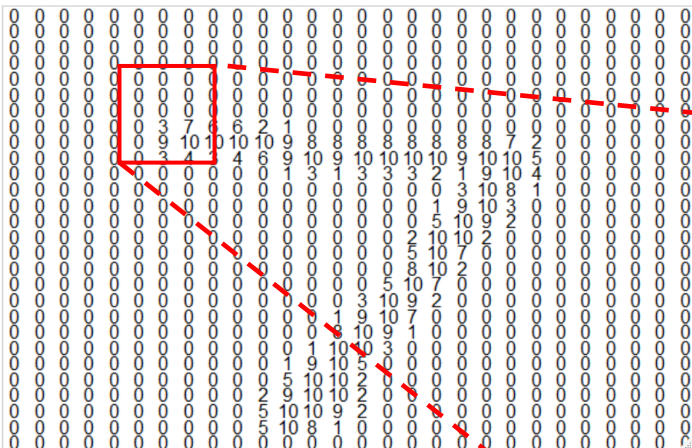
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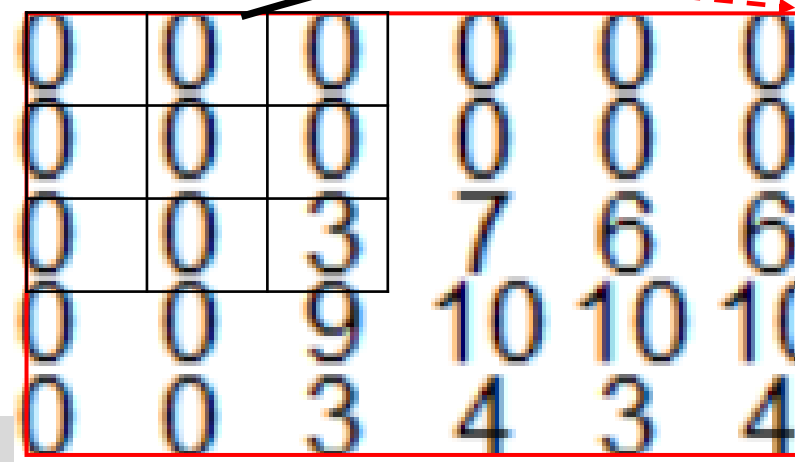
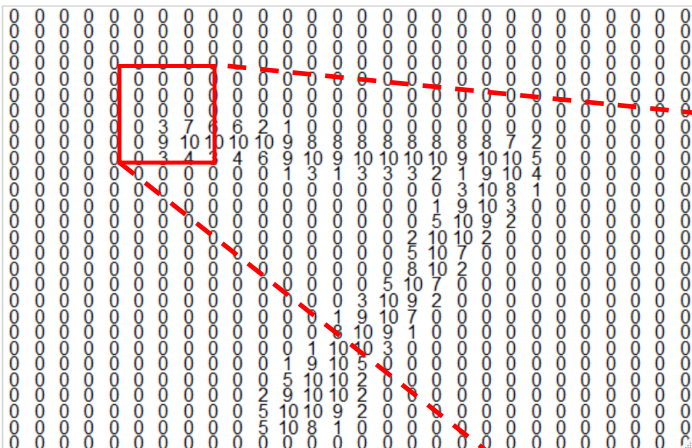
How to classify digits?





Let's zoom into 5x6 window of pixels near the tip of '7'

Take a 3x3 patch of pixels and apply a 'filter' template – designed to find an edge



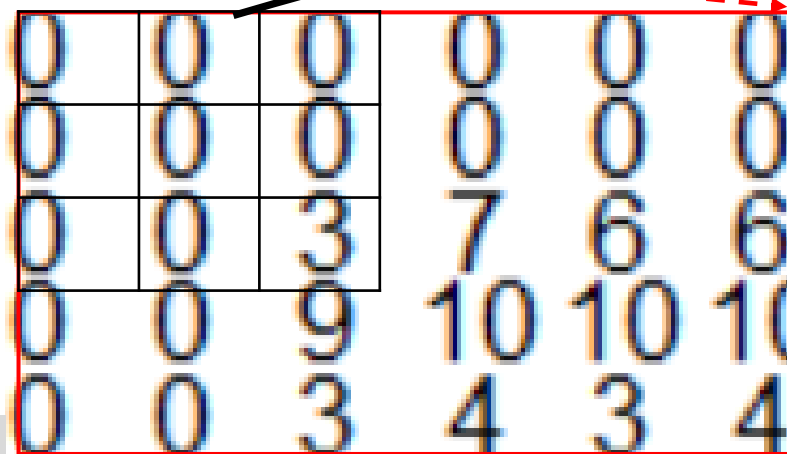
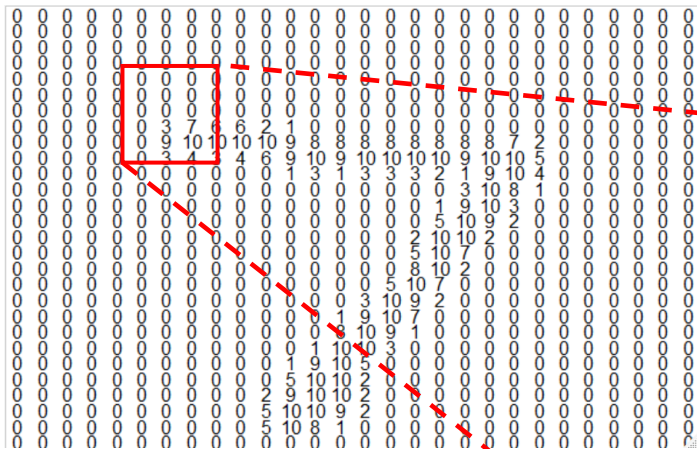
X

-1	0	+1
-1	0	+1
-1	0	+1

1. Multiply 3x3 patch of pixels with 3x3 filter

Let's zoom into 5x6 window of pixels near the tip of '7'

Take a 3x3 patch of pixels and apply a 'filter' template – designed to find an edge



(our weight parameters)

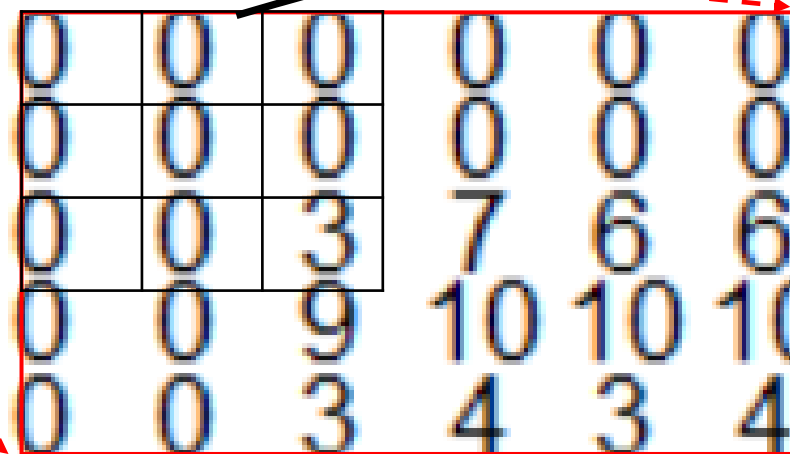
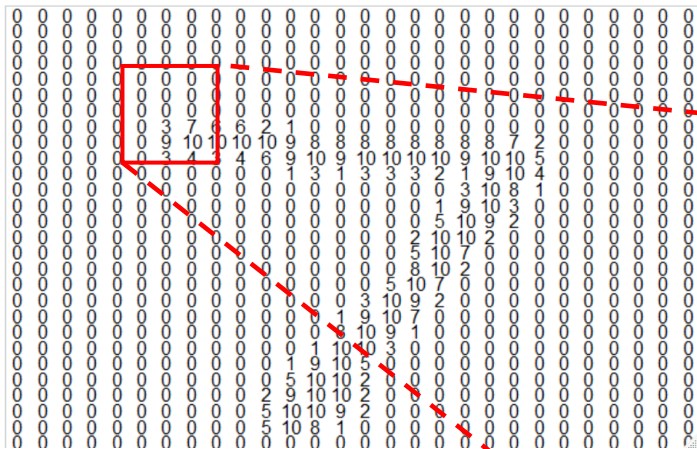
X

-1	0	+1
-1	0	+1
-1	0	+1

1. Multiply 3x3 patch of pixels with 3x3 filter “W”

Let's zoom into 5x6 window of pixels near the tip of '7'

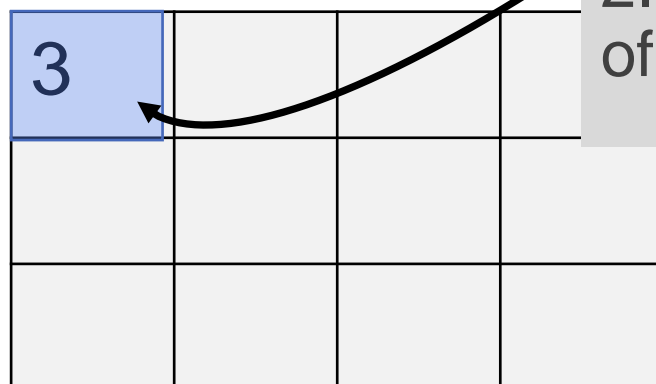
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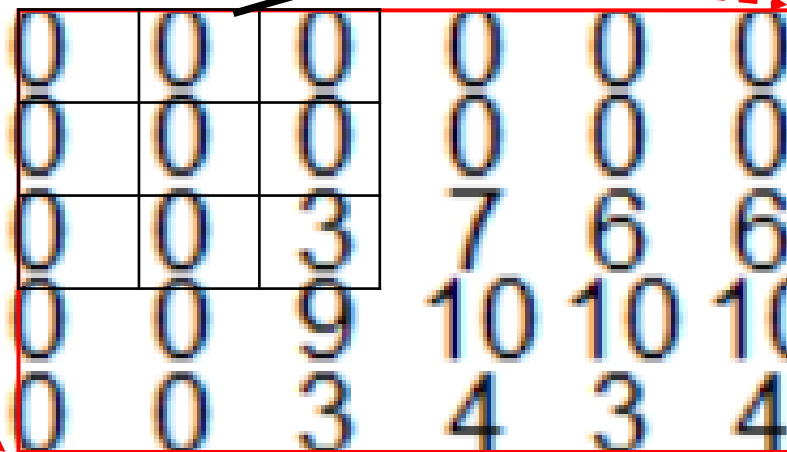
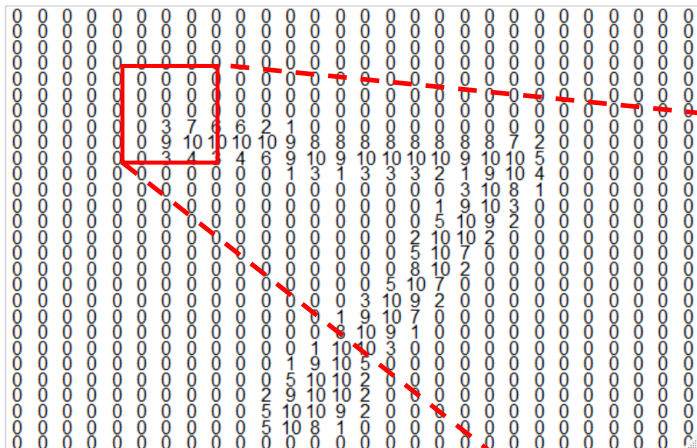
-1	0	+1
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X

1. Multiply 3x3 patch of pixels with 3x3 filter "W"



2. Put answer in new cell of output map

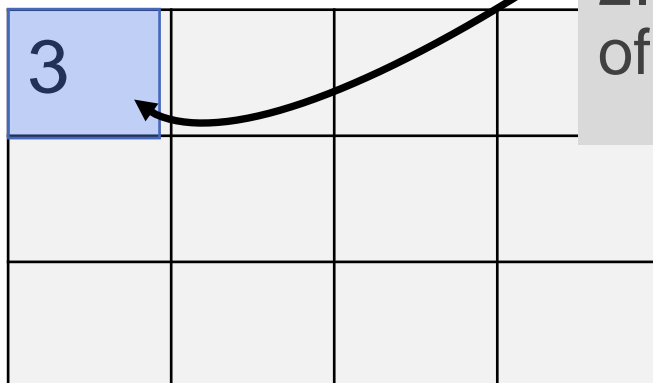


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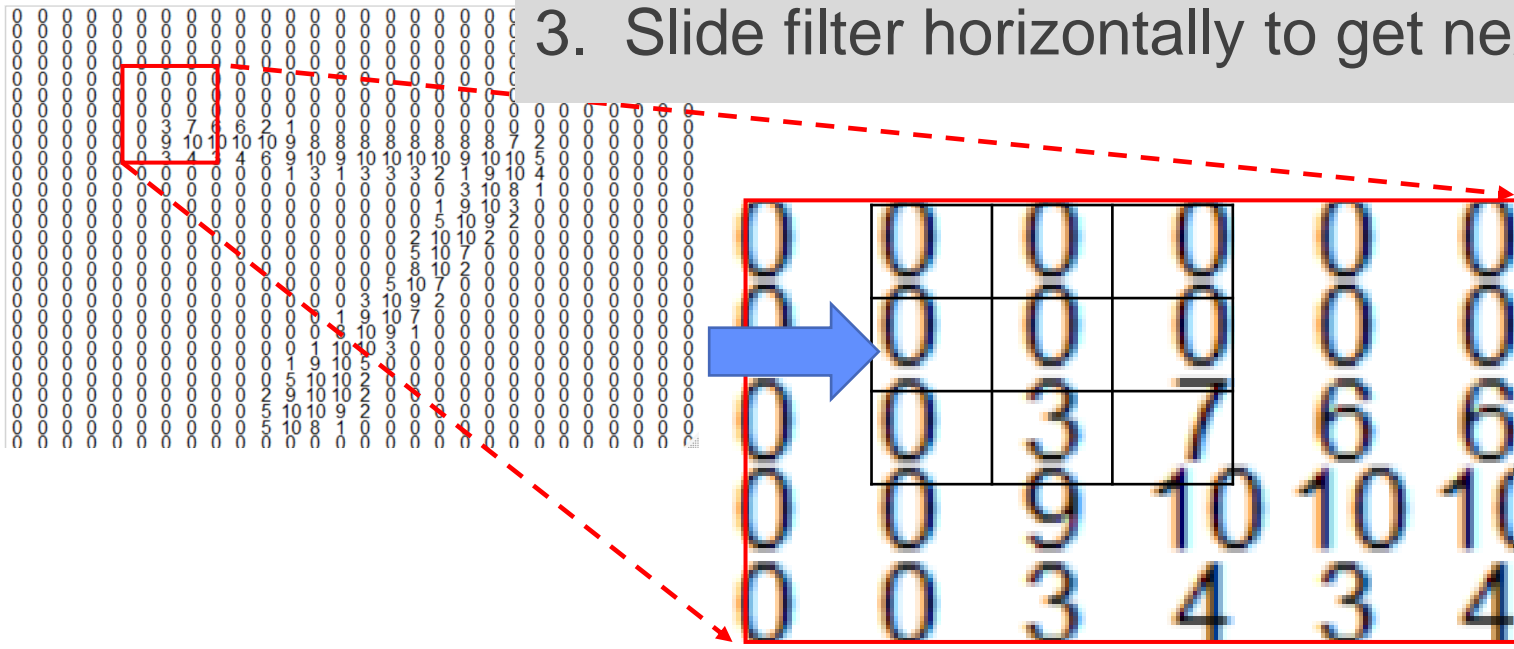
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This is “image patch” * W



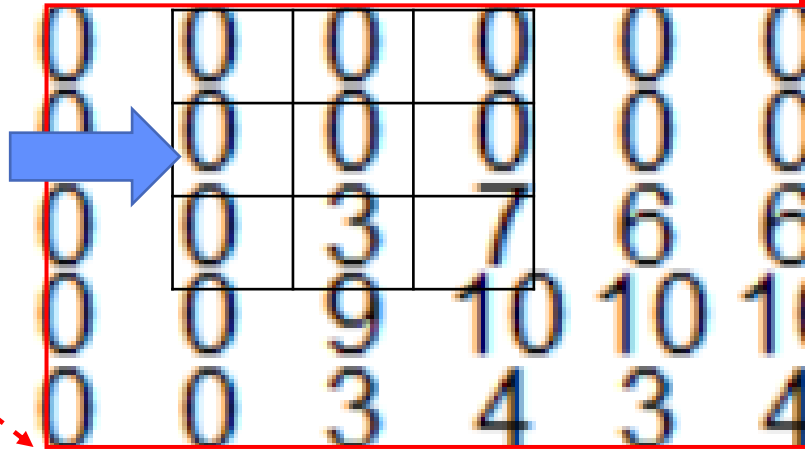
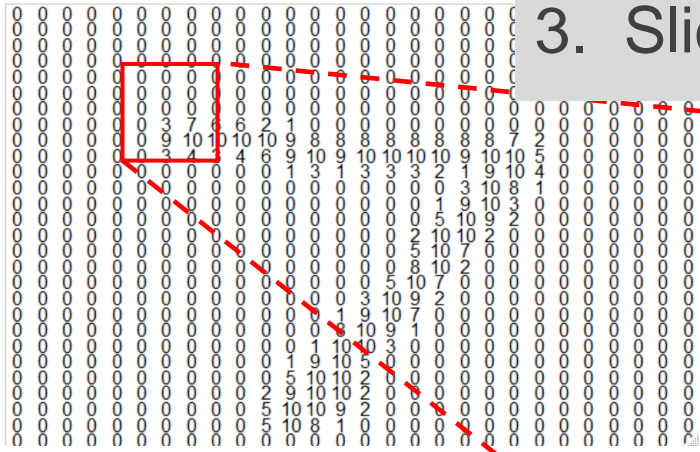
2. Put answer in new cell of output map

3. Slide filter horizontally to get next output value



3			

3. Slide filter horizontally to get next output value



X

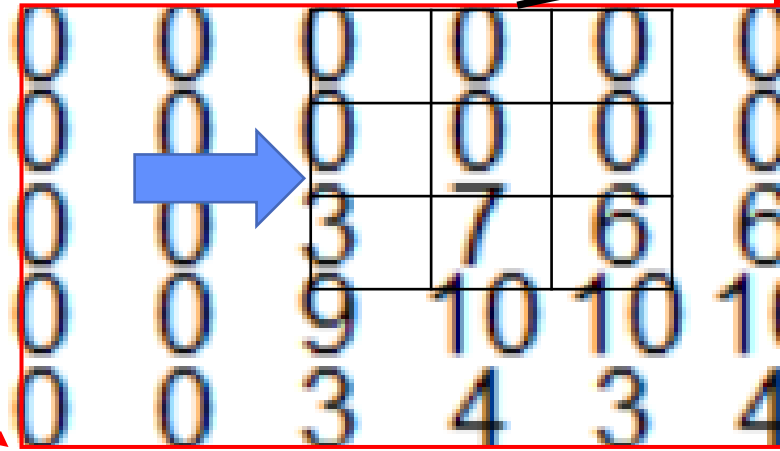
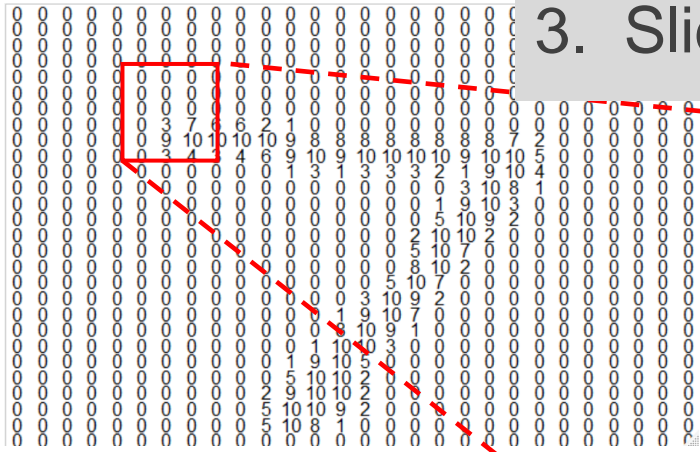
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-1	0	+1
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1. Multiply 3x3 patch of pixels with 3x3 filter "W"

2. Put answer in new cell of output map

3	7		

3. Slide filter horizontally to get next output value



-1	0	+1
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-1	0	+1

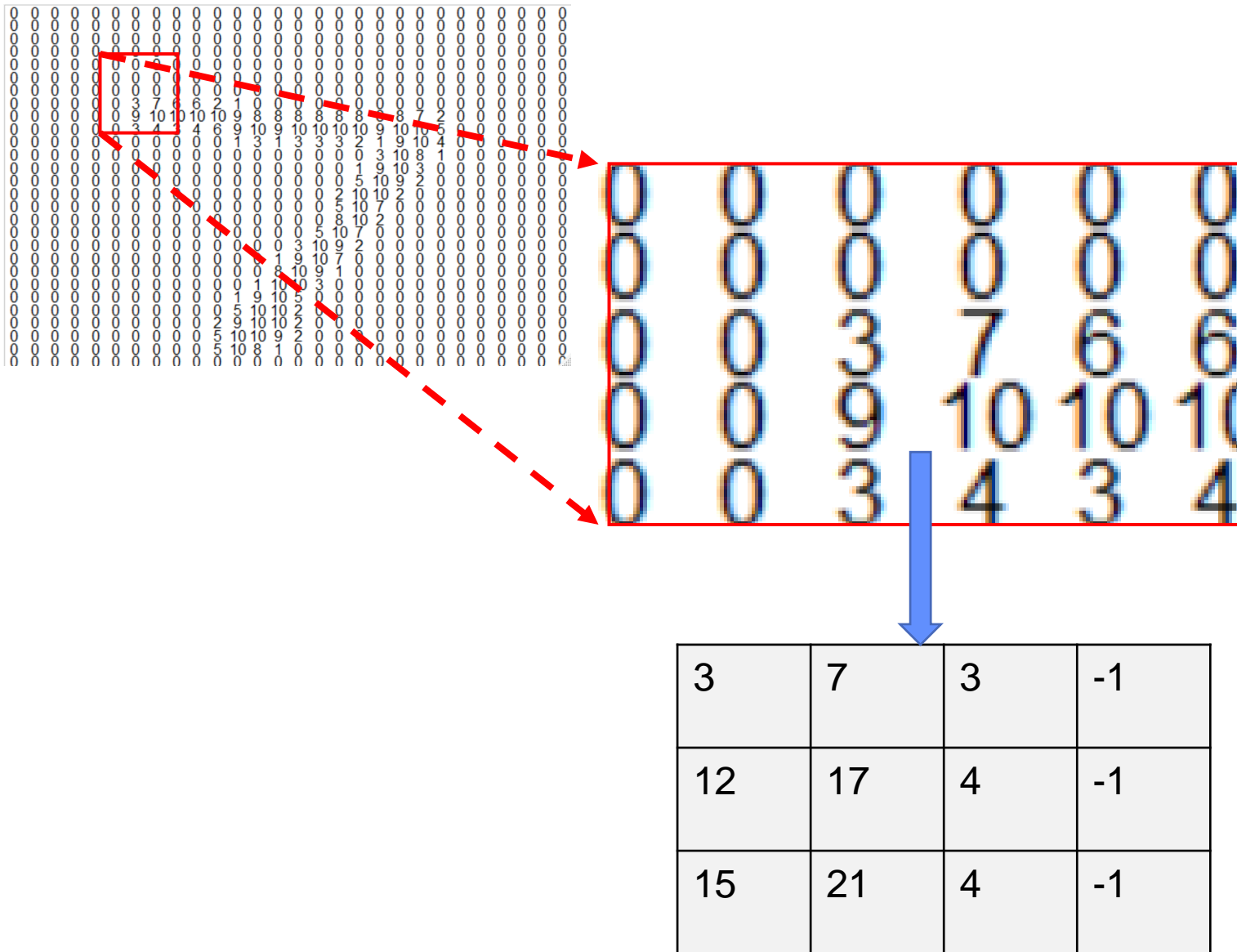
X

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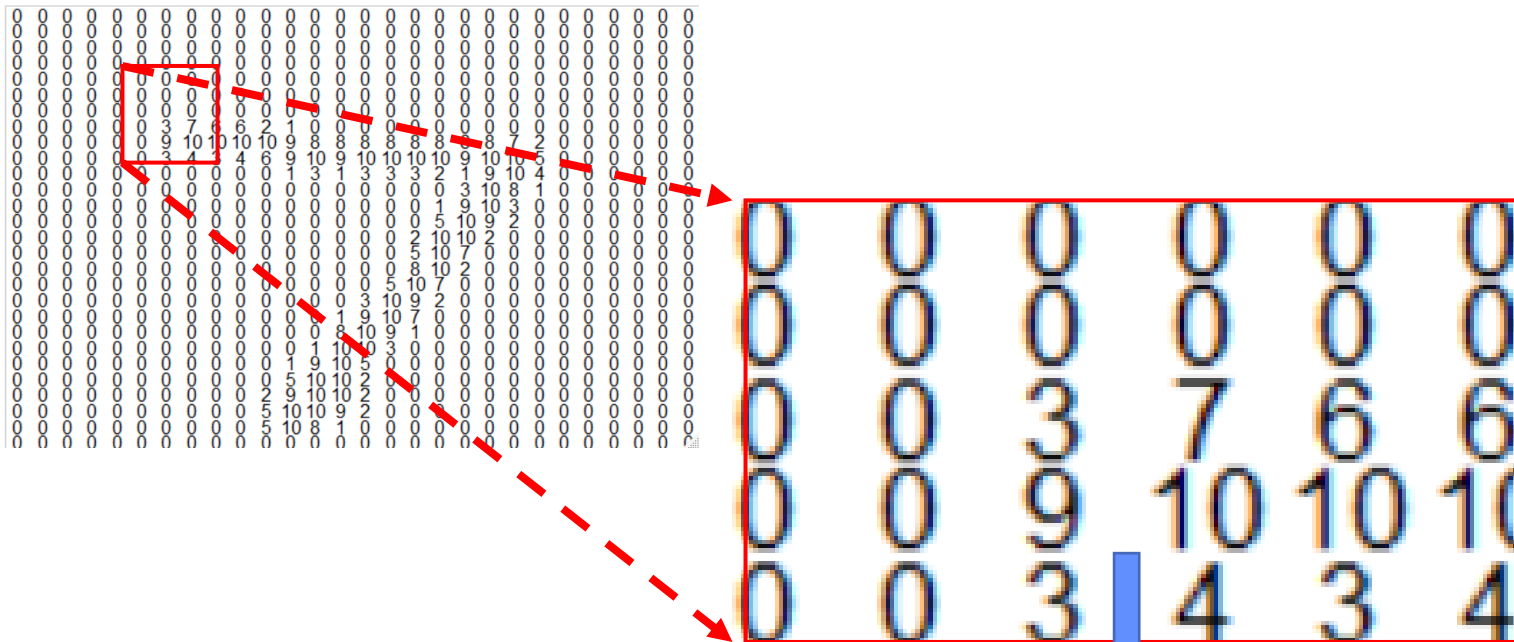
NOTE: sliding a filter is known as a “convolution” operation

3	7	3	

2. Put answer in new cell of output map



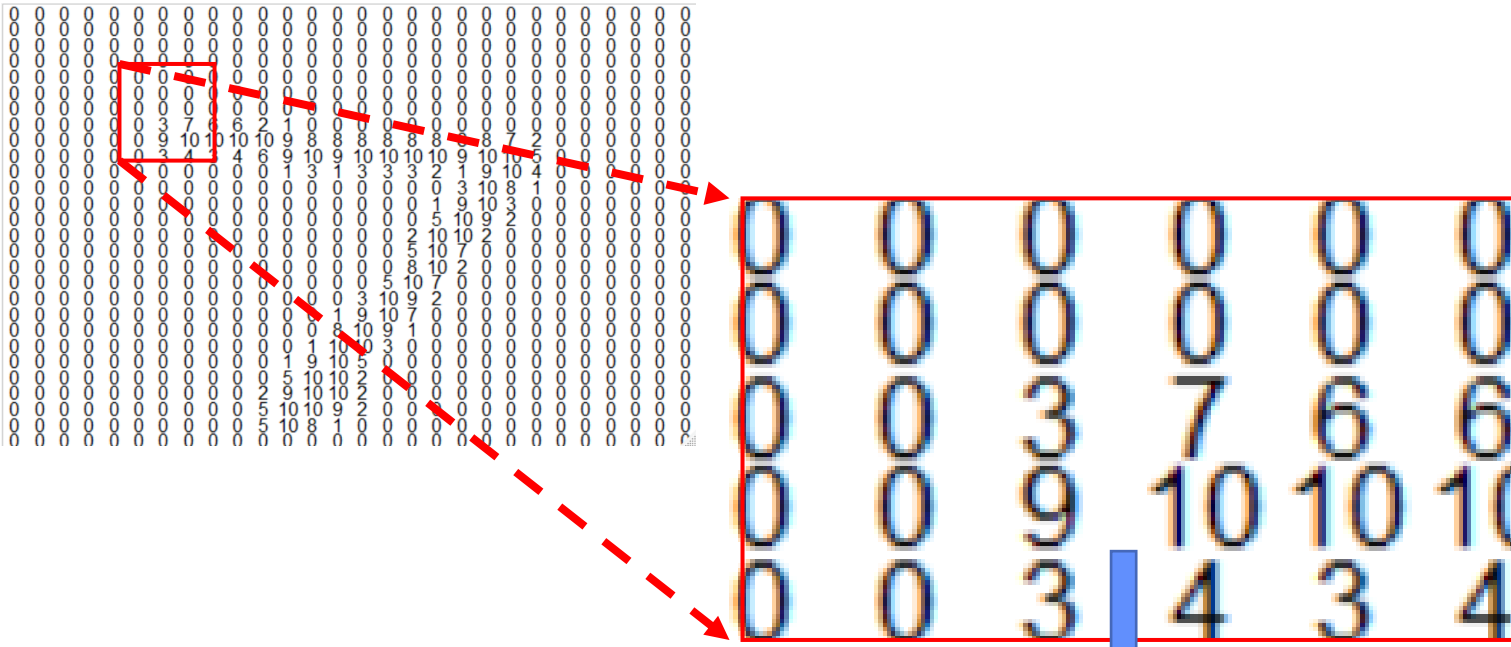
After vertical and horizontal sliding the 5x6 patch is now a 3x5 feature map.



3	7	3	-1
12	17	4	-1
15	21	4	-1

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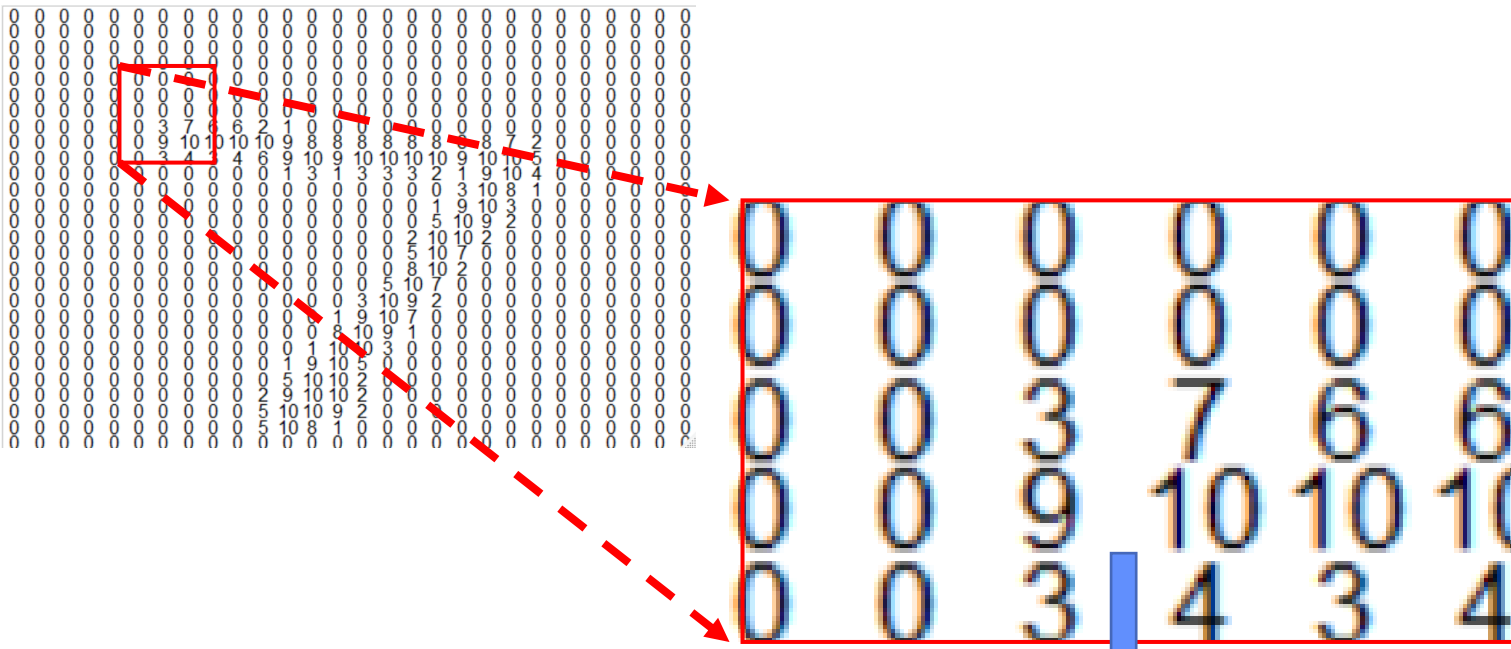
What do the highest values in the feature map represent?



3	7	3	-1
12	17	4	-1
15	21	4	-1

Optional next step:

Use another filter, and take maximum over elements - "max pooling"

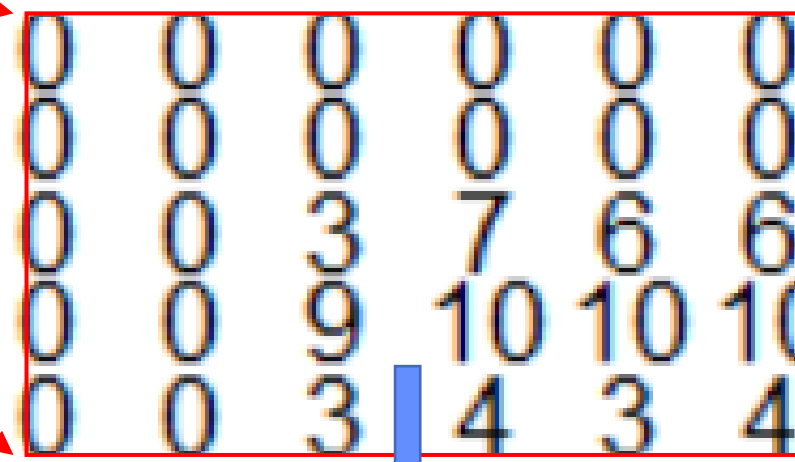
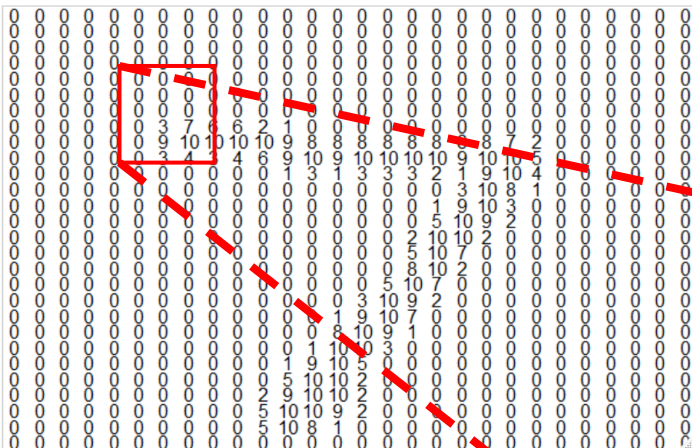


Optional next step:
Use another filter, and take maximum over elements -
“max pooling”

3	7	3	-1
12	17	4	1
15	21	4	-1

2x2 filter has max=17

17		

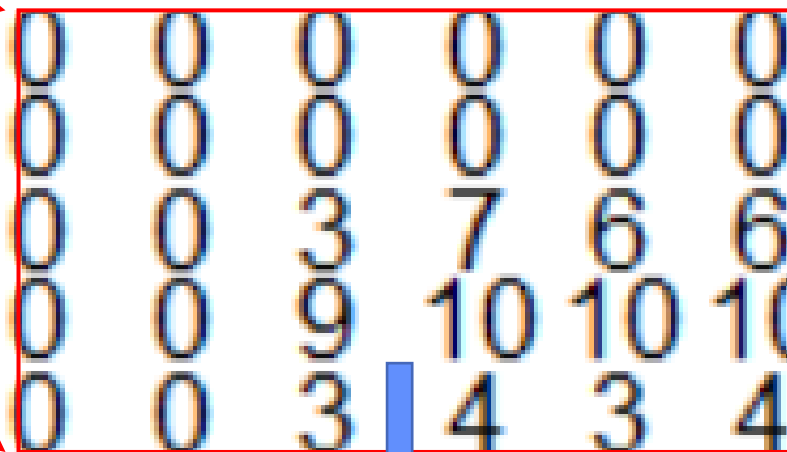
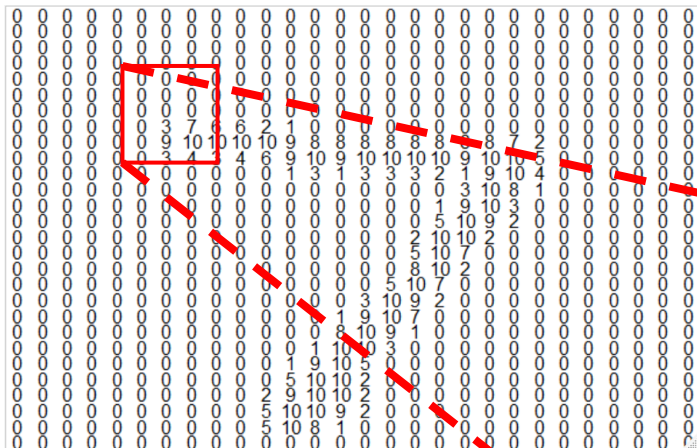


Optional next step:
Use another filter, and take maximum over elements -
“max pooling”

3	7	3	-1
12	17	4	-1
15	21	4	-1

Slide filter ...

17	17	4
21	21	4



3	7	3	-1
12	17	4	-1
15	21	4	-1

Slide filter ...

17	17	4
21	21	4

After convolution and pooling 5x6 patch is **transformed** into a 2x3 feature map of 'edge gradients'

Feature engineering

In Computer Vision there are many kinds of edge detectors and many ways to scale them

-1	0	+1
-1	0	+1
-1	0	+1

But building features is hard, so if you have enough data ...

Convolution Neural Network (CNN)

In CNNs the filter values are weight parameters that are learned (**feature discovery**)

W_{11}	W_{12}	W_{13}
W_{21}	W_{22}	W_{23}
W_{31}	W_{32}	W_{33}

Convolution Neural Network (CNN)

In CNNs the filter values are weight parameters that are learned (**feature discovery**)

W_{11}	W_{12}	W_{13}
W_{21}	W_{22}	W_{23}
W_{31}	W_{32}	W_{33}

A convolution layer is a set of feature maps, where each map is derived from convolution of 1 filter with input

Convolution Neural Network (CNN)

More hyperparameters:

Size of filter (smaller is more general)

Convolution Neural Network (CNN)

More hyperparameters:

- Size of filter (smaller is more general)

- Number of pixels to slide over (1 or 2 is usually fine)

Convolution Neural Network (CNN)

More hyperparameters:

- Size of filter (smaller is more general)

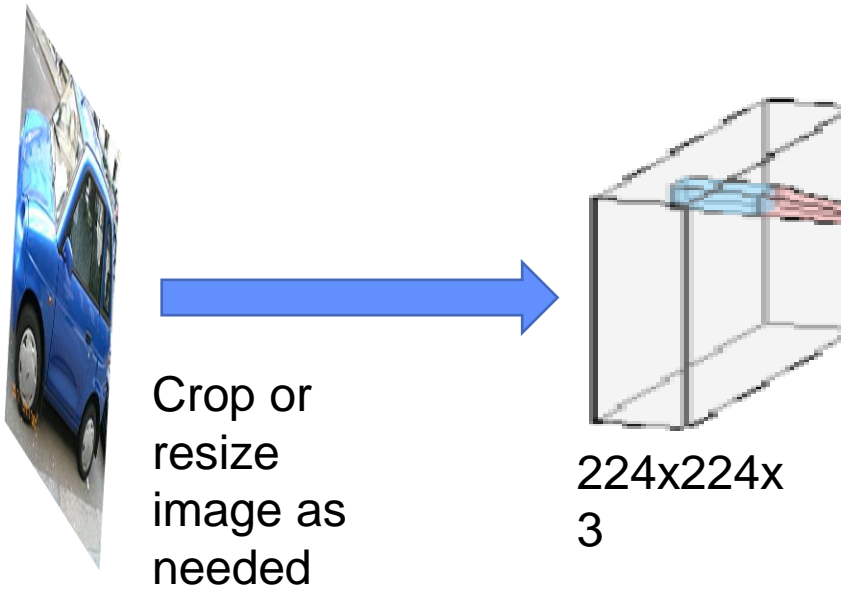
- Number of pixels to slide over (1 or 2 is usually fine)

- Number of filters (depends on the problem!)

- Max pooling or not (usually some pooling layers)

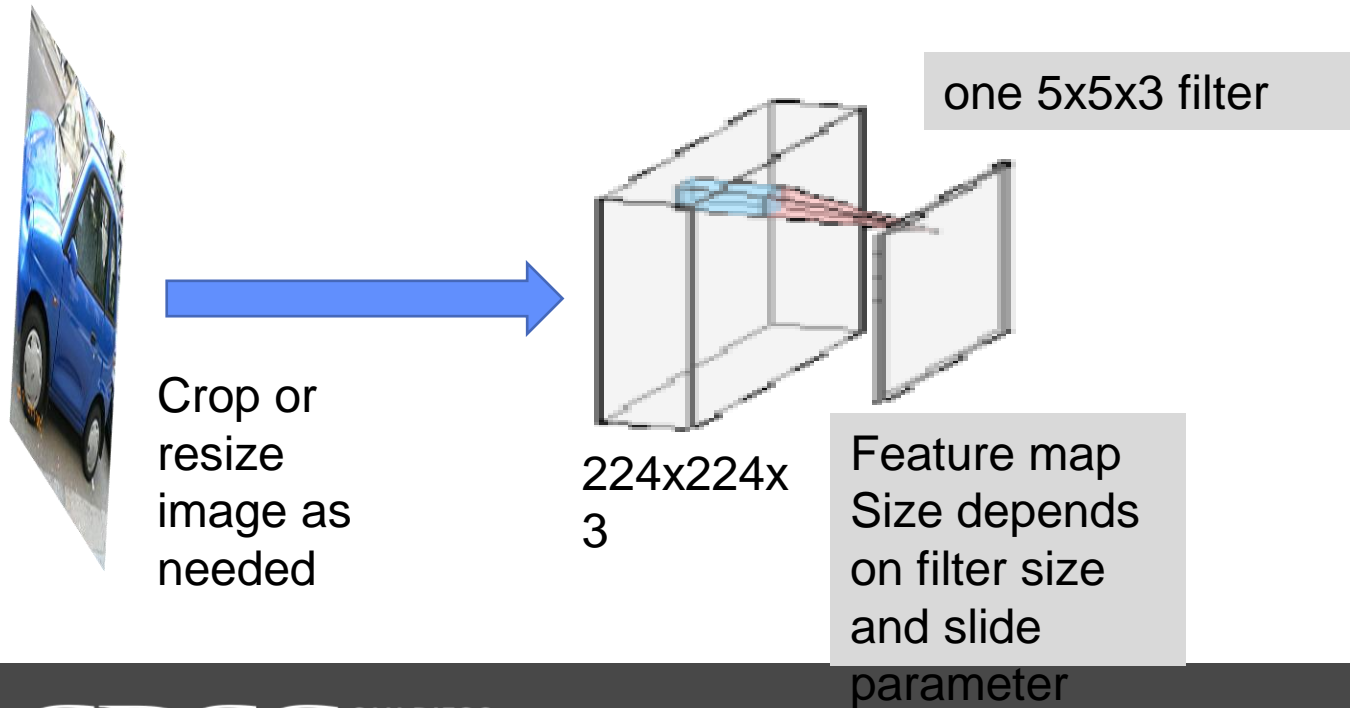
Convolution with image

- Make 1 layer, using HxWx3 image (3 for Red,Green,Blue channels)



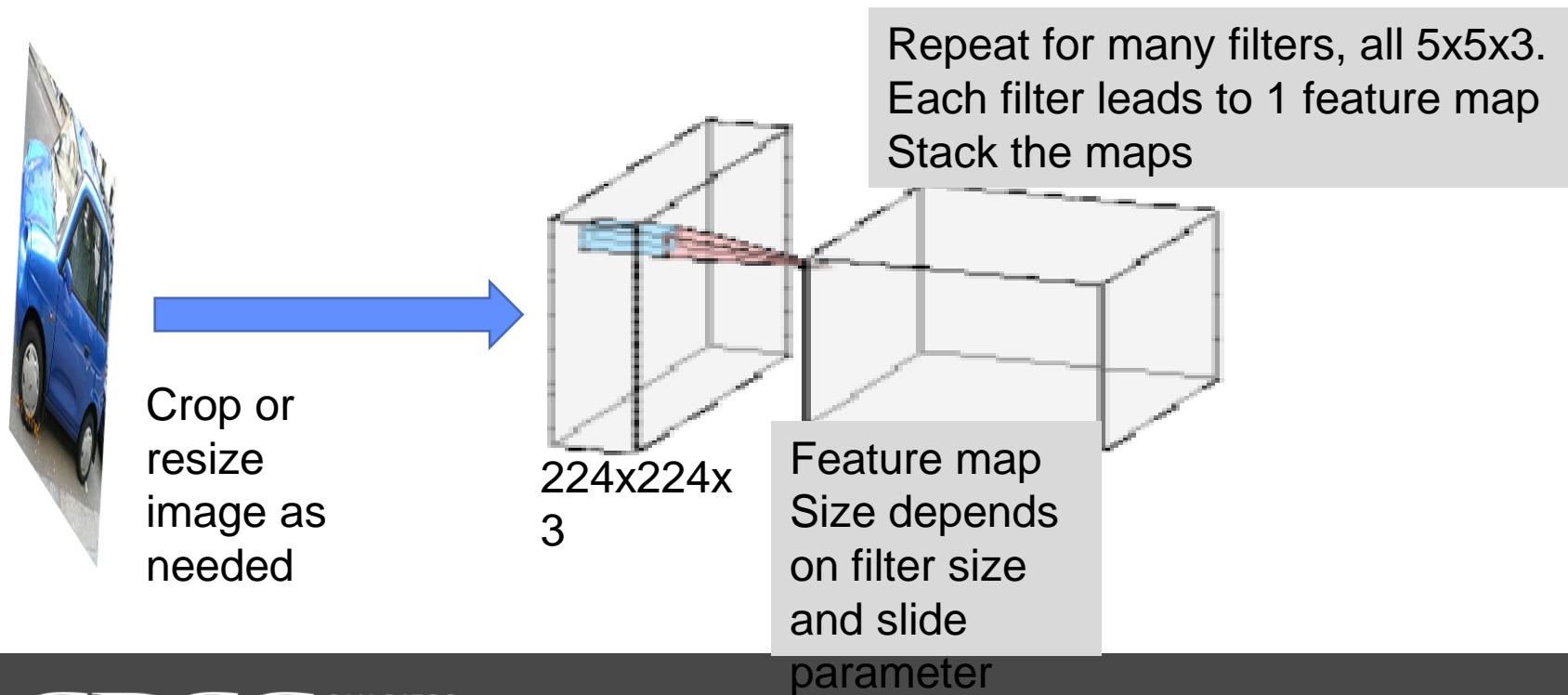
Convolution with image

- Make 1 layer, using HxWx3 image (3 for RGB channels)



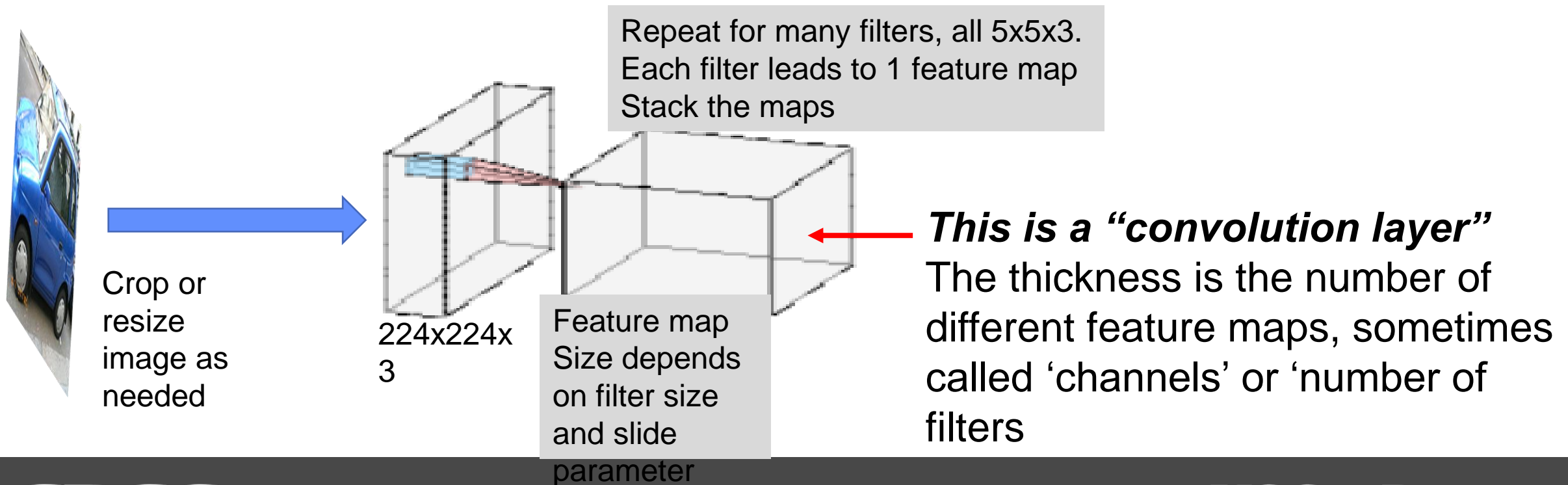
Convolution with image

- Make 1 layer, using HxWx3 image (3 for RGB channels)



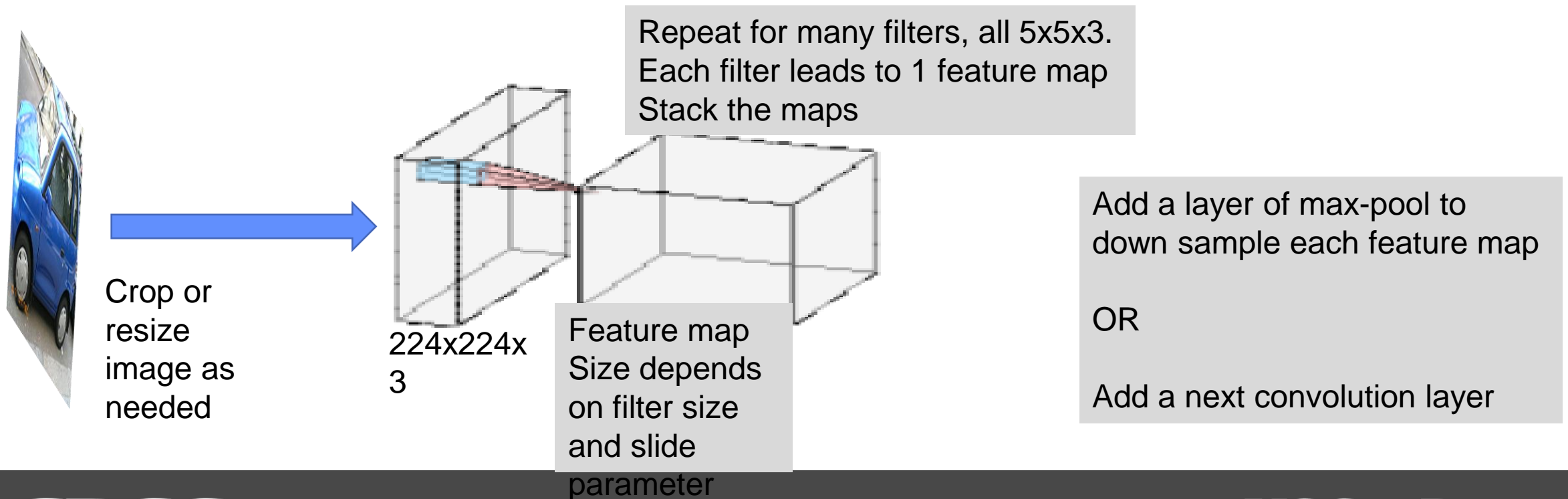
Convolution with image

- Make 1 layer, using HxWx3 image (3 for RGB channels)



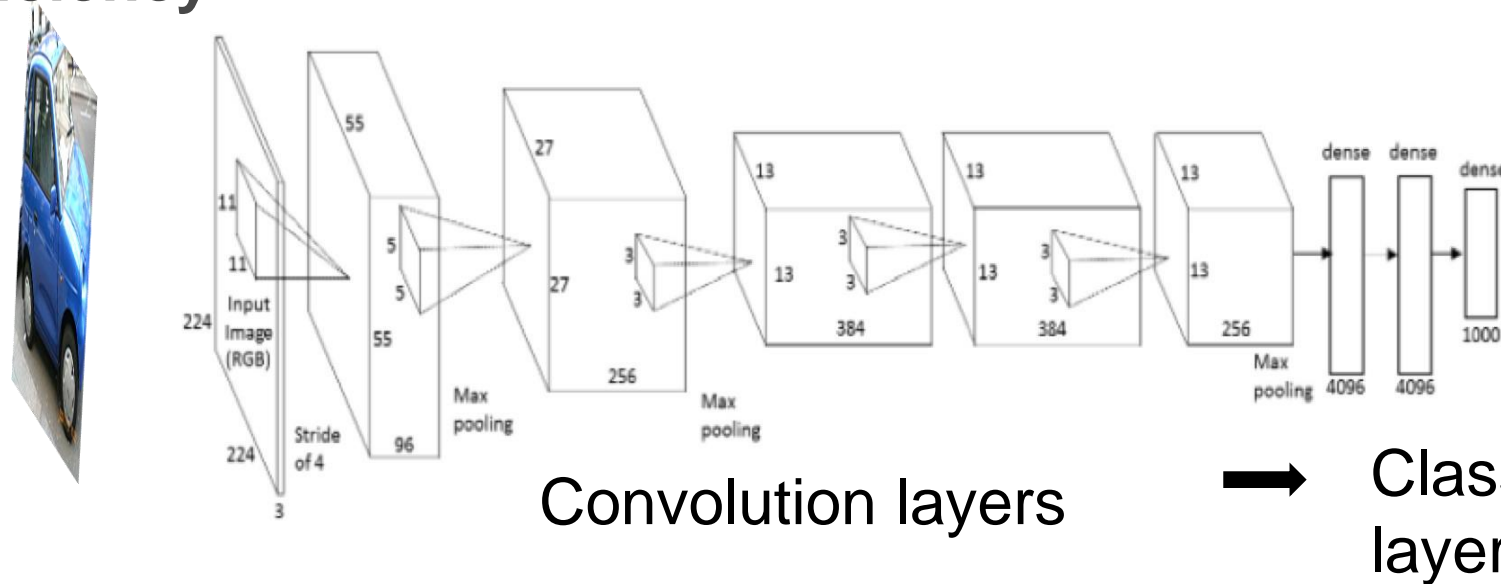
Convolution with image

- Make 1 layer, using HxWx3 image (3 for RGB channels)



Large Scale Versions

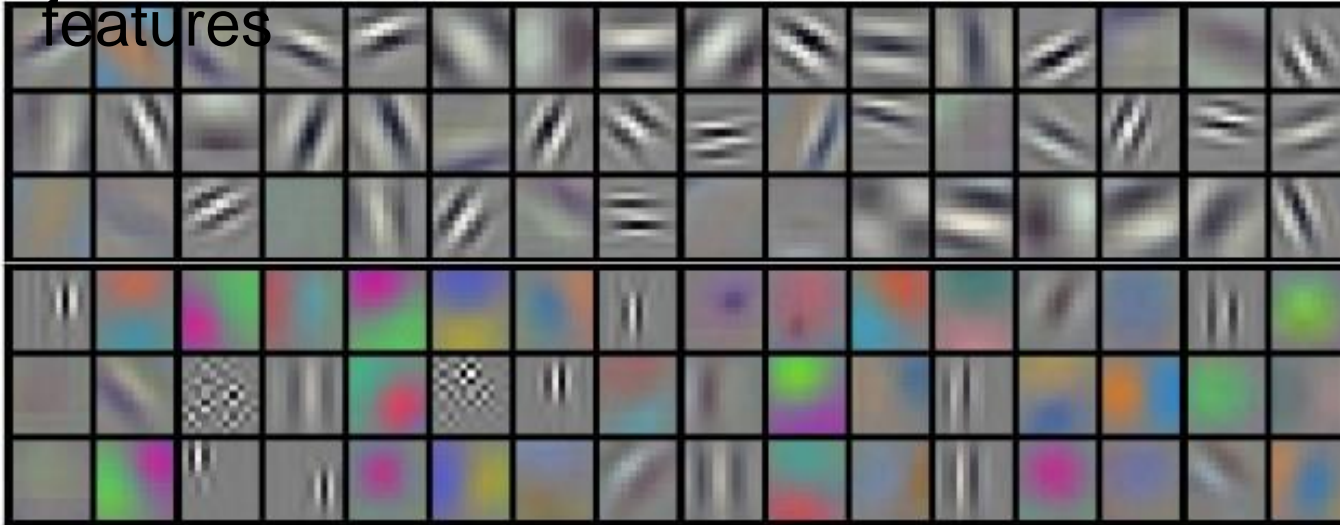
- Large (deep) Convolution Networks are turning out to be feasible with GPUs (some are 100+ layers)
- Need large amounts of data and many heuristics to avoid overfitting and increase efficiency



What Learned Convolutions Look Like

First convolution layer filters are simple

features



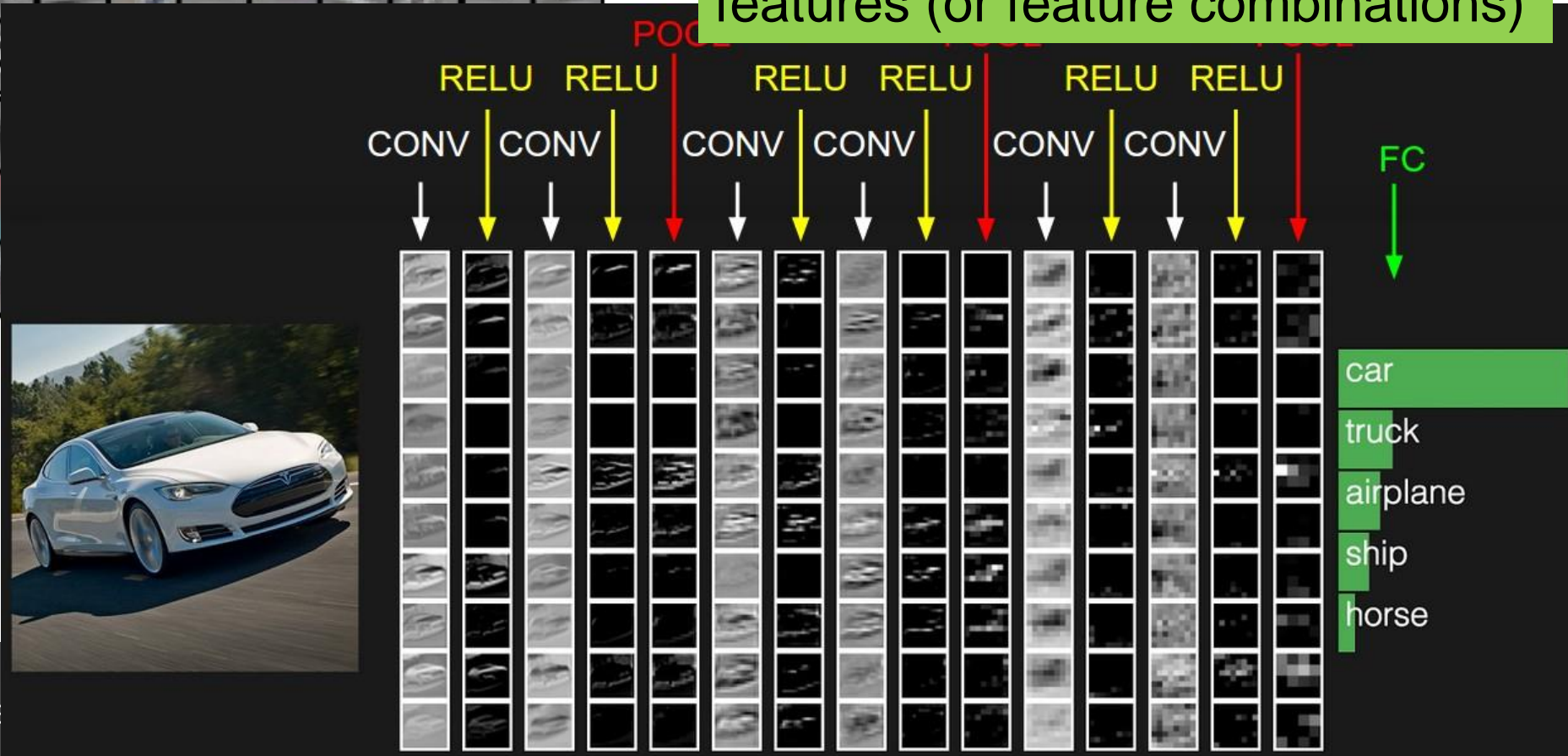
What Learned Convolutions

First convolution layer filters are simple

features



Higher layers are more abstract features (or feature combinations)



Convolution Neural Network Summary

CNNs work because convolution layers have a special architecture and function – it is biased to do certain kind of transformations

Low layers have less filters that represent simple local features for all classes

Higher layers have more filters that cover large regions that represent object class features

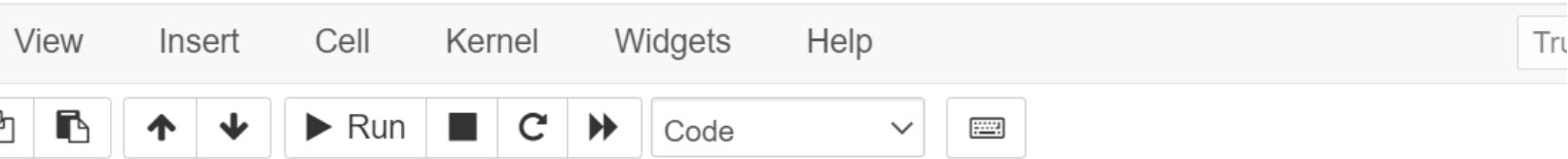
Outline

- Overview of Neural Networks (aka Multilayer Perceptron)
- Convolution Neural Networks
- **Basic Keras commands for building, training CNNs - exercise**
- Hyperparameters and Tuning and workflows - exercise

Exercise CNN for Digit Classification

- The 'hello world' of CNNs
- Uses MNIST dataset and Keras





```

import warnings
warnings.filterwarnings("ignore")
import tensorflow as tf
tf.get_logger().setLevel('ERROR')

#Load and prepare data
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

#specify the neural network model and optimization
my_model = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),
    tf.keras.layers.Dense(10) ])
loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
optimizer = tf.keras.optimizers.SGD(learning_rate=0.01)
my_model.compile(optimizer=optimizer, loss=loss, metrics=['accuracy'])

#fit the model
fit_history= my_model.fit(x_train, y_train, epochs=5, batch_size=128)

#evaluate the fit
my_model.evaluate(x_test, y_test)

```

A basic model workflow in 4 steps

load/prepare data

define a model

fit a model

test the model

Zooming in on keras.models statements

```
#specify the neural network Use a sequence of layers Flatten image into vector  
my_model = tf.keras.models.Sequential([  
    tf.keras.layers.Flatten(input_shape=(28, 28)),  
    tf.keras.layers.Dense(10) ])
```

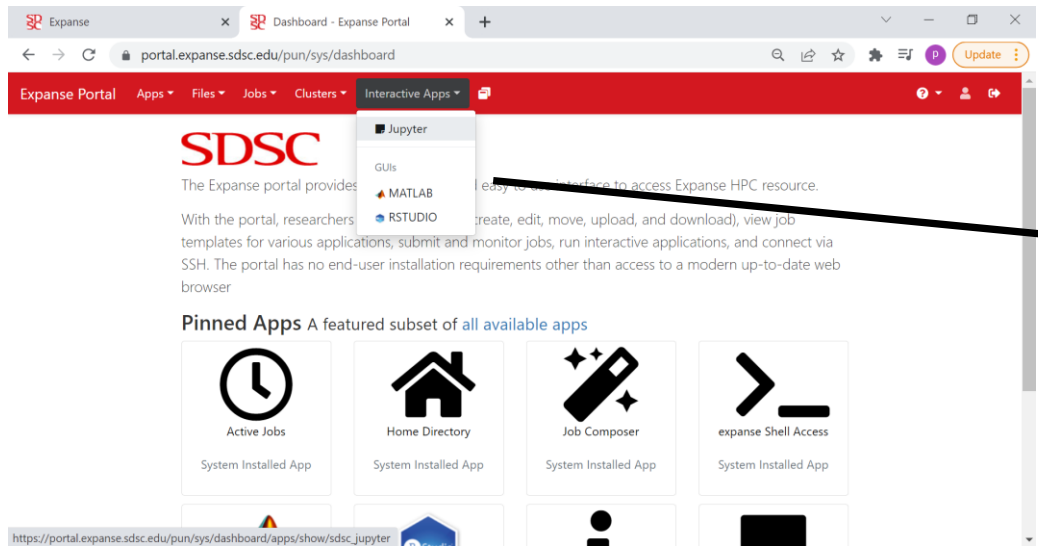
Create hidden layer that is fully connected to input

Zooming in on keras convolution layers statements

Use 16 filters, each of size 3x3

```
my_model.add(tf.keras.layers.Convolution2D(filters=16,  
                                            kernel_size=(3, 3),  
                                            strides=1,  
                                            data_format="channels_last",  
                                            activation='relu',  
                                            input_shape=(28,28,1)))
```

*Input shape does not
include number of images*



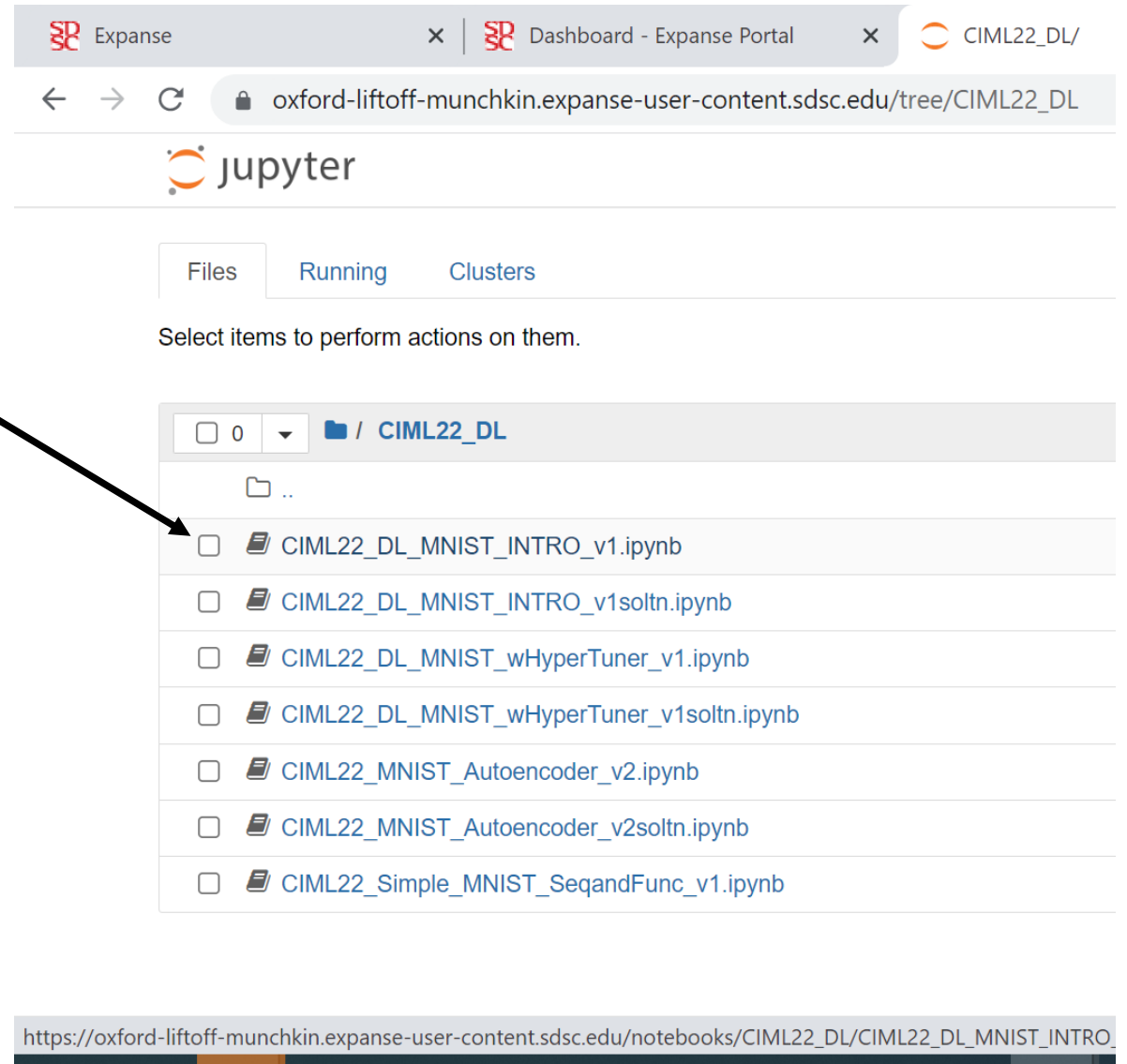
Form fields for launching a Jupyter notebook session:

- ACCOUNT:** sds184
- Partition (Please choose the gpu, gpu-shared, or gpu-preempt as the partition if using gpus):** compute
- Time limit (min):** 120
- Number of cores:** 128
- Memory required per node (GB):** 246
- GPUs (optional):** 0
- Singularity Image File Location:** /cm/shared/apps/containers/singularity/tensorflow/tensorflow-latest.sif
- Environment modules to be loaded (E.g., to use latest version of system Anaconda3 include cpu,gcc,anaconda3):** singularitypro/3.9
- Conda Environment (Enter your own conda environment if any):**
- Reservation:** cml-day1
- QoS:**
- Working directory:** home
- Type:** Notebook








Expanse user portal:
 launch a jupyter notebook session
 (with compute or shared is OK)
 Or
 login to expance and run:
 jupyter-compute-tensorflow

In jupyter notebook session
open the MNIST_Intro
notebook

Follow instructions in the
notebook



The screenshot shows a web browser with three tabs: 'Expanse', 'Dashboard - Expanse Portal', and 'CI ML22_DL/'. The address bar shows the URL 'oxford-liftoff-munchkin.expanse-user-content.sdsc.edu/tree/CI ML22_DL'. The JupyterLab interface has tabs for 'Files', 'Running', and 'Clusters'. Below these is a message: 'Select items to perform actions on them.' The file browser shows a directory structure with a dropdown menu set to '0' and a folder icon followed by 'CI ML22_DL'. The file list includes:

- ☐  CI ML22_DL_MNIST_INTRO_v1.ipynb
- ☐  CI ML22_DL_MNIST_INTRO_v1soltn.ipynb
- ☐  CI ML22_DL_MNIST_wHyperTuner_v1.ipynb
- ☐  CI ML22_DL_MNIST_wHyperTuner_v1soltn.ipynb
- ☐  CI ML22_MNIST_Autoencoder_v2.ipynb
- ☐  CI ML22_MNIST_Autoencoder_v2soltn.ipynb
- ☐  CI ML22_Simple_MNIST_SeqandFunc_v1.ipynb

The URL bar at the bottom shows: 'https://oxford-liftoff-munchkin.expanse-user-content.sdsc.edu/notebooks/CI ML22_DL/CI ML22_DL_MNIST_INTRO_v1.ipynb'

Outline

- Overview of Neural Networks (aka Multilayer Perceptron)
- Convolution Neural Networks
- Basic Keras commands for building, training CNNs - exercise
- Hyperparameters and Tuning and workflows - exercise

Things to think about for running a project

- **Choosing Hyperparameters – a bit of exploration and exploitation**
- **Need to figure out efficient Job workflow**
- **On HPC, CPU work fine for many cases, you will want to use GPUs for ‘large’ models and/or large datasets.**
- **Model saves and/or checkpoints are available in tensorflow; tensorboard available but needs to be secure (ask for details)**

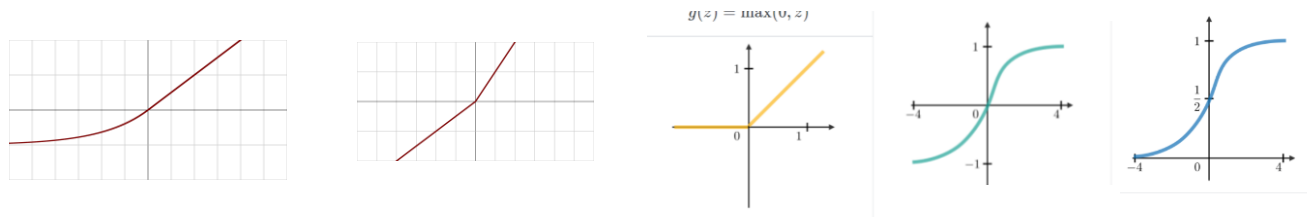
Choosing Hyperparameters

- **Generally:**
 - architecture (layers, units, activation, filters, ...)
 - algorithm (learning rate, optimizer, epochs, ...)
 - efficient learning (batch size, normalization, initialization, ...)
- **Some options are determined by task:**
 - loss function, CNN vs MLP, ...
- **Use what works, from related work or the latest recommendations,**

Some general recommendations (with caveats)

- From *Hands-On Machine Learning, Keras, and TensorFlow*, 2nd Ed, 2019, Géron,

pg 338 Activations: *Scaled-ELU > ELU > leaky ReLU > ReLU > tanh > logistic*



pg 359 Optimizer tradeoffs speed vs quality: * is bad *** is good

Table 11-2. Optimizer comparison

Class	Convergence speed	Convergence quality
SGD	*	***
SGD(momentum=...)	**	***
SGD(momentum=..., nesterov=True)	**	***
Adagrad	***	* (stops too early)
RMSprop	***	** or ***
Adam	***	** or ***
Nadam	***	** or ***
AdaMax	***	** or ***

Hyperparameters Search

- Can take a long time, hard to find global optimal
- Start with small data, short runs to get sense of range of good parameter values
- Easy but possibly time-consuming method:
grid search over uniformly spaced values
- Do “exploration” then “exploitation”, search wide then search deep
Keras Tuner functions can help with the wide search

Hyperparameter Search Tool

- Keras Hypertuner class implements several search strategies:

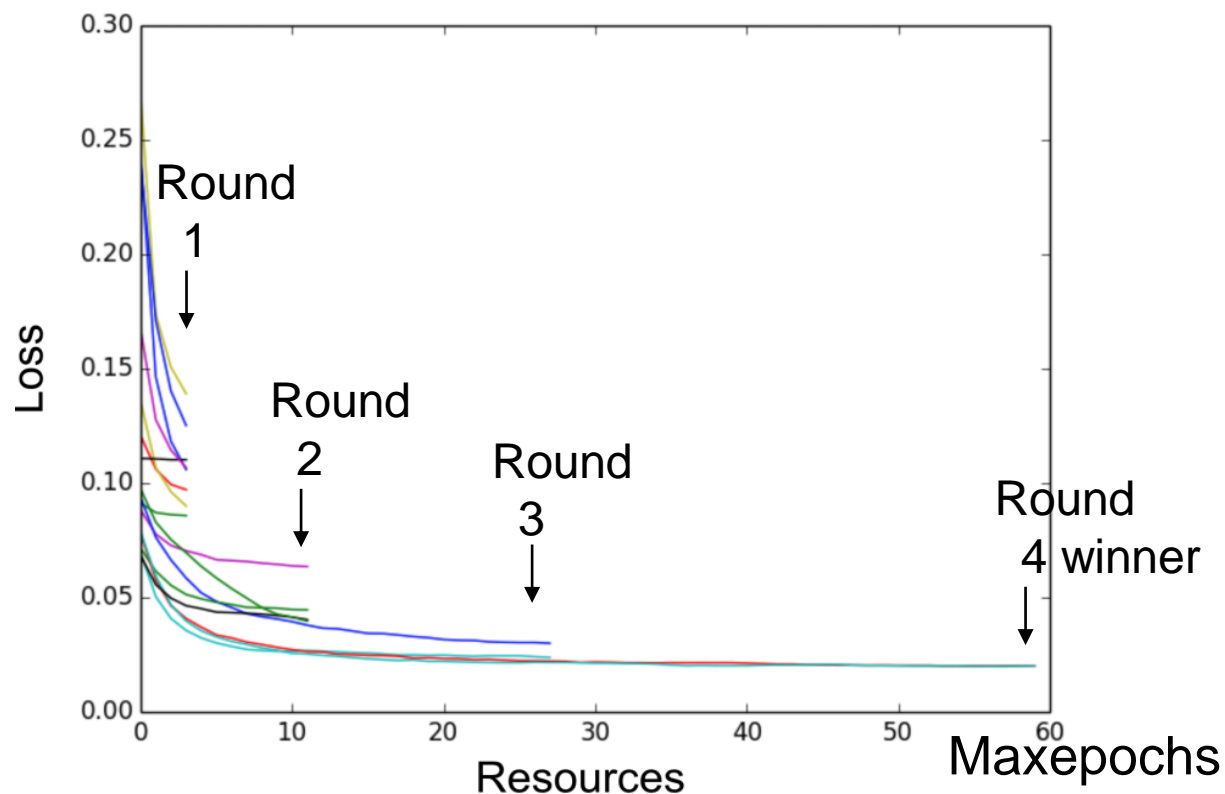
Hyperband is like a tournament competition of hyperparameter configurations, with incremental training, to weed out worse ones

RandomSearch will search randomly through the space of configurations and try to find better regions

Bayesian optimization is like function approximation to pick out next configuration

Hyperband Bracket

Each round runs several network configurations for small number of epochs
Several rounds with increasing epochs make up a bracket
Several brackets are run to end up with several possible overall winners.



Note, you could run a small grid search around hyperband winners to confirm performance

Keras Tuner code snippet

Set up function to make the model

```
def build_model_hp(hp):  
    hp_numfilters = hp.Int('hpnumfilters', min_value=8, max_value=32, step=4)  
    #your variable name          ^^^ the parameter name in the hp object
```

Set up hyperparameter choices

```
def build_model(numfilters, activation_choice): #<<-----add code: if you  
    #                                           list and change code to  
    mymodel = keras.models.Sequential()  
    mymodel.add(keras.layers.Convolution2D(numfilters,  
                                           (3, 3),  
                                           strides=1
```

Define 'tuner' object;
tuner search uses
the model fit function

```
tuner = kt.Hyperband(build_model_hp,  
                     objective = 'val_accuracy',  
                     max_epochs = num_max_epochs,  
                     factor = 3,  
                     hyperband_iterations=10,  
                     directory = dirname,  
                     overwrite = True, #overwrite directory  
                     project_name='hyperbandtest',  
                     executions_per_trial=5, #to try several  
                     seed = 777)
```


Workflow and Organizing Jobs

Job Level: What makes sense to include in each job?

Model Level: run & test model for each parameter configuration

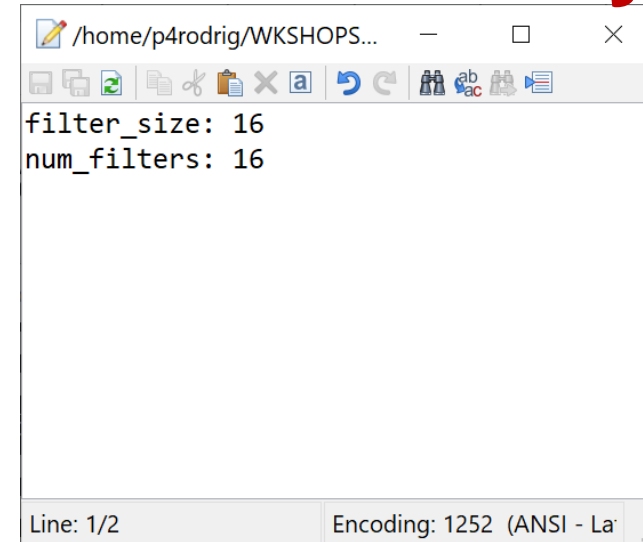
Data Level: loop through cross validation datasets (if applicable)

- **Consider how long each a model runs for 1 configuration of hyperparameters for 1 dataset**
- **Organize jobs into reasonable chunks of work**
- **For large models consider model-checkpoints**

Organizing Configurations – one way

Code snippet:
using 'YAML' file to
set up
hyperparameter
configuration

Create text file with
"Parameter: Value"
pairs



A screenshot of a text editor window titled "/home/p4rodrig/WKSHOPS...". The window contains a YAML configuration file with two lines: "filter_size: 16" and "num_filters: 16". The status bar at the bottom indicates "Line: 1/2" and "Encoding: 1252 (ANSI - La)".

Read file as
python dictionary

```
import yaml

with open("./modelrun_args.yaml", "r") as f:
    my_yaml=yaml.safe_load(f) #this returns a python dictionary

filter_size=my_yaml.get("filter_size")
num_filters=my_yaml.get("num_filters")
print('arguments, filter_size:',filter_size,' num filters',num_filters)
```

Example slurm job script and execution for Expanse

You could also modify or set up parameters; and save yaml files for each run

```
#!/usr/bin/env bash
#SBATCH --job-name =mnist0522
#SBATCH --account=sds164
#SBATCH --partition=compute
#SBATCH --nodes=1
#SBATCH --ntasks-per-node=128
#SBATCH --time=00:10:00
#SBATCH --output=myjoboutput.o%j.%N.out
```

```
module purge
module load singularitypro
module list
```

```
echo "filter_size: 3 " > modelrun_args.yaml
echo "num_filters: 16 " >> modelrun_args.yaml
```

```
singularity exec --bind /expanse,/scratch --nv \
/cm/shared/apps/containers/singularity/tensorflow/tensorflow-latest.s
python3 Intro_mnist_cnn2_forbatch.py > mymnist_stdoutoutput.txt
```

```
02 EXP-05192022]$
02 EXP-05192022]$ sbatch run-job-tf-compute.sbatch
job 12502781
02 EXP-05192022]$ squeue --me

```

BID	PARTITION	NAME	USER	ST	TIME	NODES	NODELIST (REASON)
781	compute	=mnist05	p4rodrig	PD	0:00	1	(Priority)
813	compute	galyleo-	p4rodrig	R	26:03	1	exp-13-06

```
02 EXP-05192022]$
```

Python Notebook vs Scripts

- On HPC you may want to run batch jobs on a script not a notebook.

1 Papermill is one tool (see PRose talk)

2 Or, you can use “*jupyter nbconvert --to script your-python.ipynb*” in the batch job.

Also, turnoff plot display, save plots in files, and use a configuration file to pass in parameters

note on using GPU

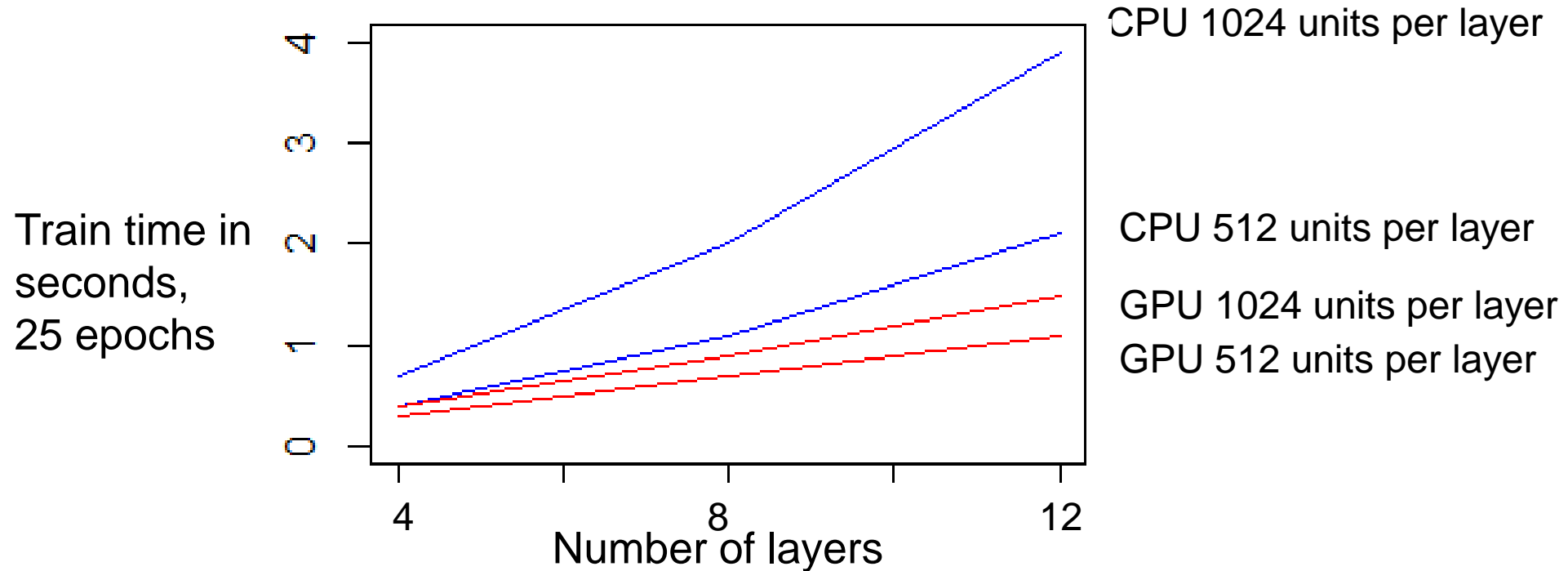
- GPU node has multiple GPU devices
- Without any coding changes, tensorflow will run on 0th gpu device if GPU is available otherwise it will use all CPU cores
- Using tensorflow dataset you can 'shard' data and use multiple gpu devices

Code snippet to
check for GPU
devices

```
/home/p4rodrig/WKSHOPS/EXP-05192022/Intro_mnist_cnn2_forbatch.py - p4rodrig@login.exppanse.sdsc.edu - Editor - V  
physical_devices = tf.config.list_physical_devices('GPU')  
n_gpus = len(physical_devices)  
print("Info,config,Num GPUs:", n_gpus)  
if tf.test.gpu_device_name():  
    print('Info, test,Default GPU Device:{}'.format(tf.test.gpu_device_name()))
```

GPU shared (V100) vs CPU (128 cores)

For MLP with Dense Layers, 80000x200 data matrix



GPUs faster, but you might have to wait more in job queue; also some memory limits compared to CPU

Where to go from here

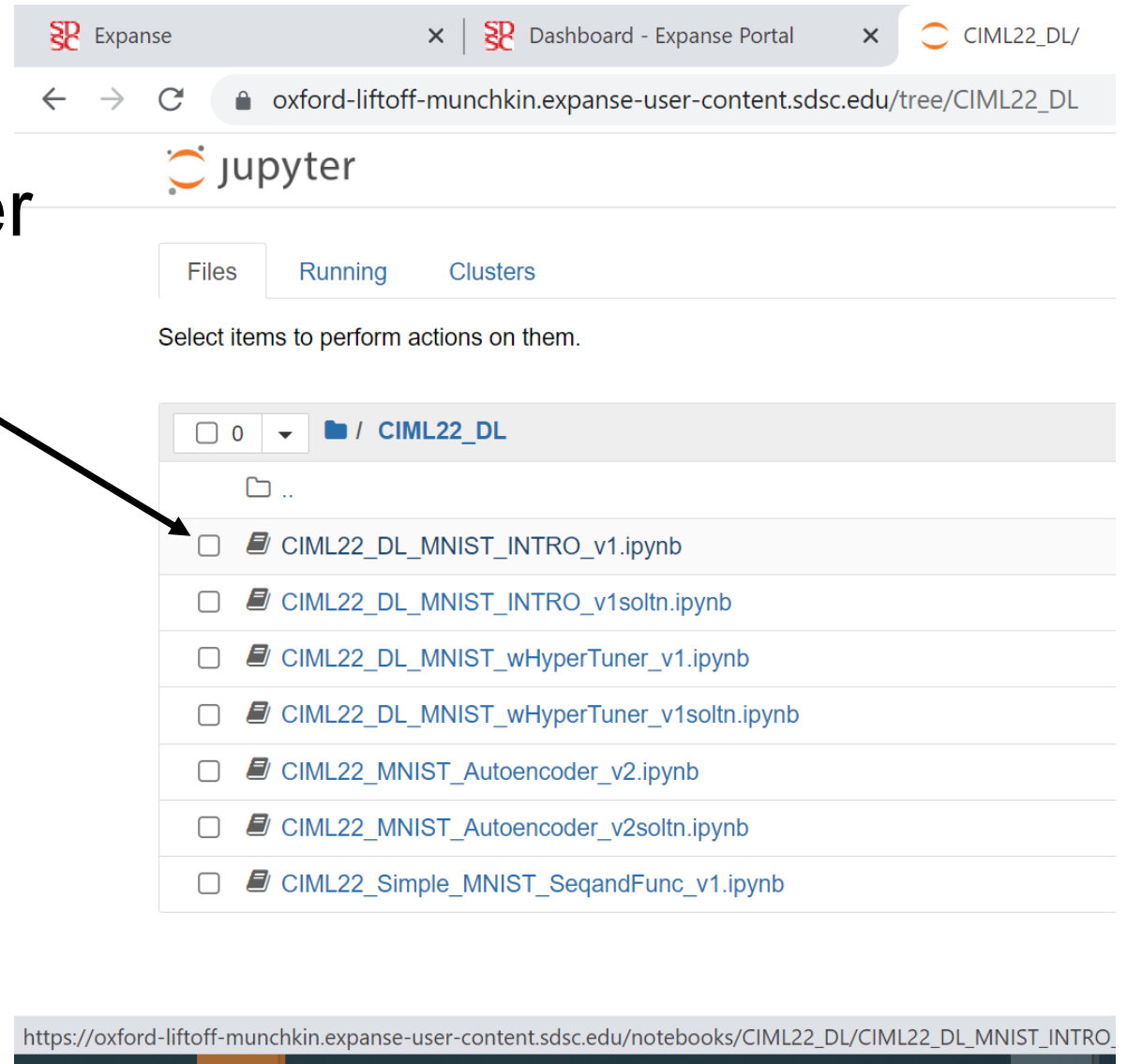
- Find relevant examples to your domain or task
- Tensorflow has many examples with tutorials in their documentation
- Tensorflow hub and model examples have code and pretrained models

https://tfhub.dev/google/imagenet/inception_v1/classification/4








<https://keras.io/examples/>

In jupyter notebook session
open the MNIST_wHyperTuner
notebook

Follow instructions in the
notebook



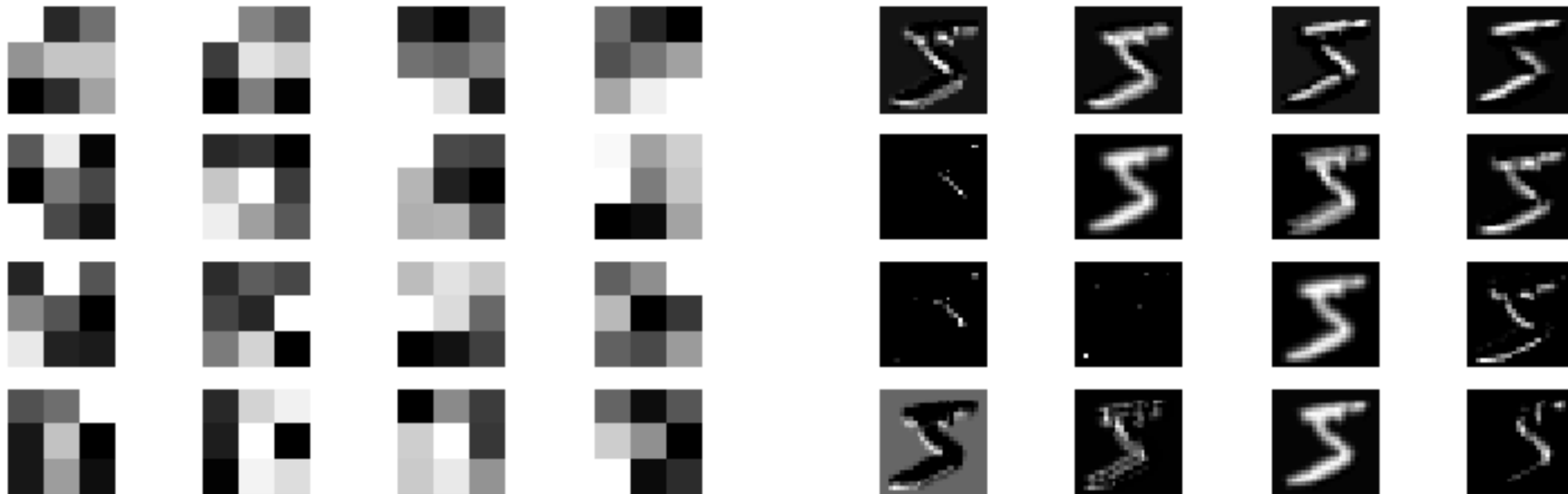
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- ☐  CI ML22_MNIST_Autoencoder_v2soltn.ipynb
- ☐  CI ML22_Simple_MNIST_SeqandFunc_v1.ipynb

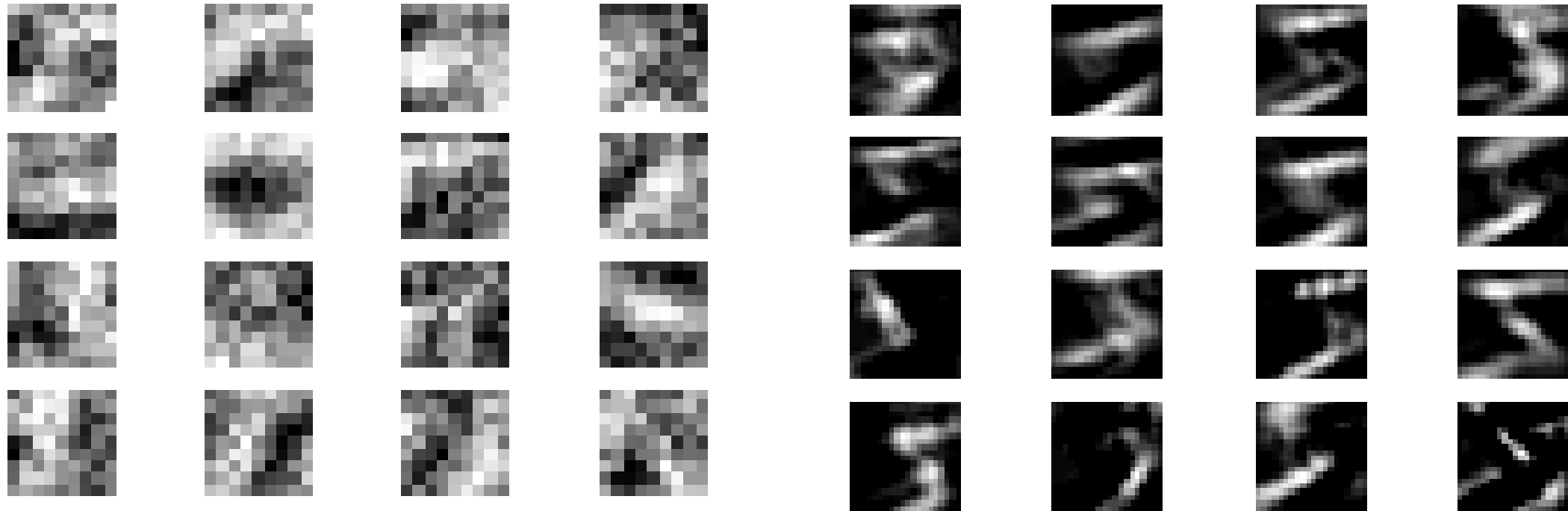
The URL bar at the bottom shows: https://oxford-liftoff-munchkin.expanse-user-content.sdsc.edu/notebooks/CI ML22_DL/CI ML22_DL_MNIST_INTRO_v1.ipynb

- **End**

Exercise notes: 3x3 first convolution layer filter and activation



9x9 first convolution layer filter and activation



```
View  Insert  Cell  Kernel  Widgets  Help

[Icons] [Run] [Code]

Model: "sequential_3"

Layer (type)                Output Shape                Param #
=====
conv2d_6 (Conv2D)            (None, 26, 26, 16)         160
conv2d_7 (Conv2D)            (None, 24, 24, 16)         2320
max_pooling2d_3 (MaxPooling2 (None, 12, 12, 16)         0
flatten_3 (Flatten)          (None, 2304)                0
dense_6 (Dense)               (None, 32)                  73760
dense_7 (Dense)               (None, 10)                  330
=====
Total params: 76,570
Trainable params: 76,570
Non-trainable params: 0

Train on 60000 samples, validate on 10000 samples
```

Filter_wts X num_filters + filter_bias:
 $(3 \times 3 \times 1) * 16 + 16 * 1 = 9 * 16 + 16 = 160$