# Deep Learning

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# Outline

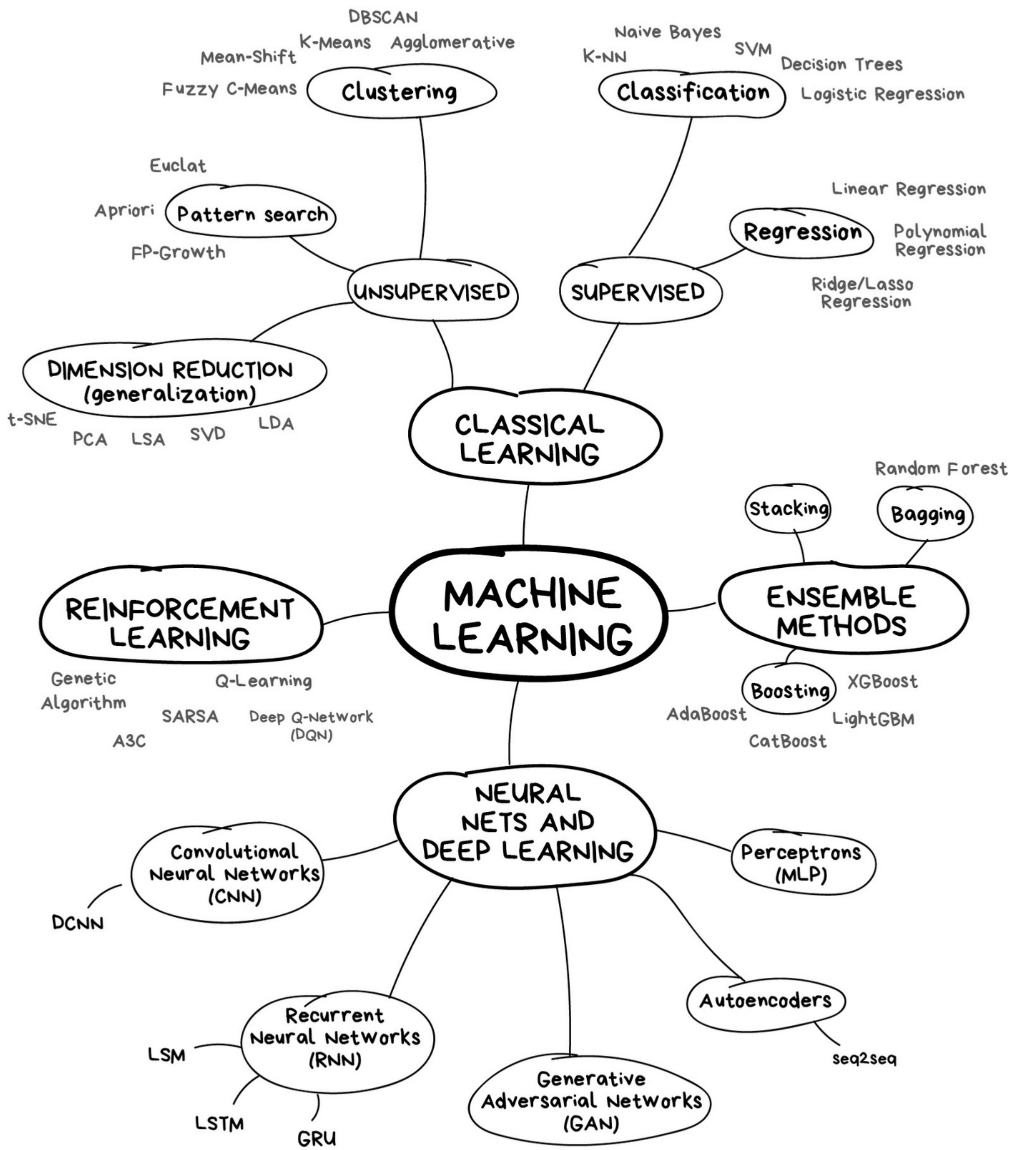
# Deep Learning in one slide + Goals

- **How does it work:**
  - Automatically learn representations of observations
  - Learn highly non-linear models.
- **What does it require:**
  - Large datasets with structure
  - Computational power
- **Why now:**
  - Combination of the 2 points above
  - investment !
- **Some Applications**
  - Image classification; object / face recognition
  - Self driving cars
  - Automatic Translation, Information extraction
  - Caption Generation
  - Ads, recommendation systems, etc.

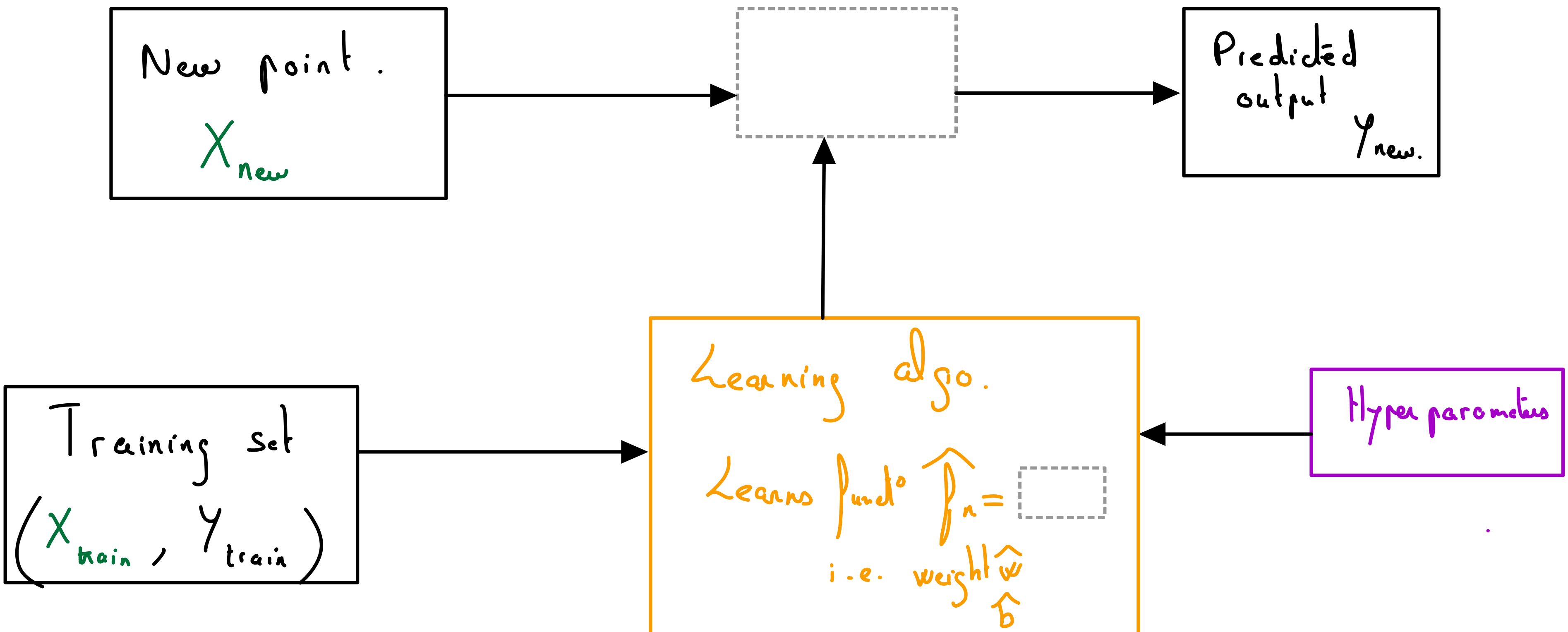
**Goals:** Understanding core concepts of Deep Learning.

- When and how it works on paper (data, models, architecture)
- How to implement a simple neural network with Python.
- Overview of some of the main applications and challenges.

# Machine Learning



# Summary of previous lectures on Machine Learning : Supervised ML



set of

Objective

Linear regression

Logistic regression

SVM

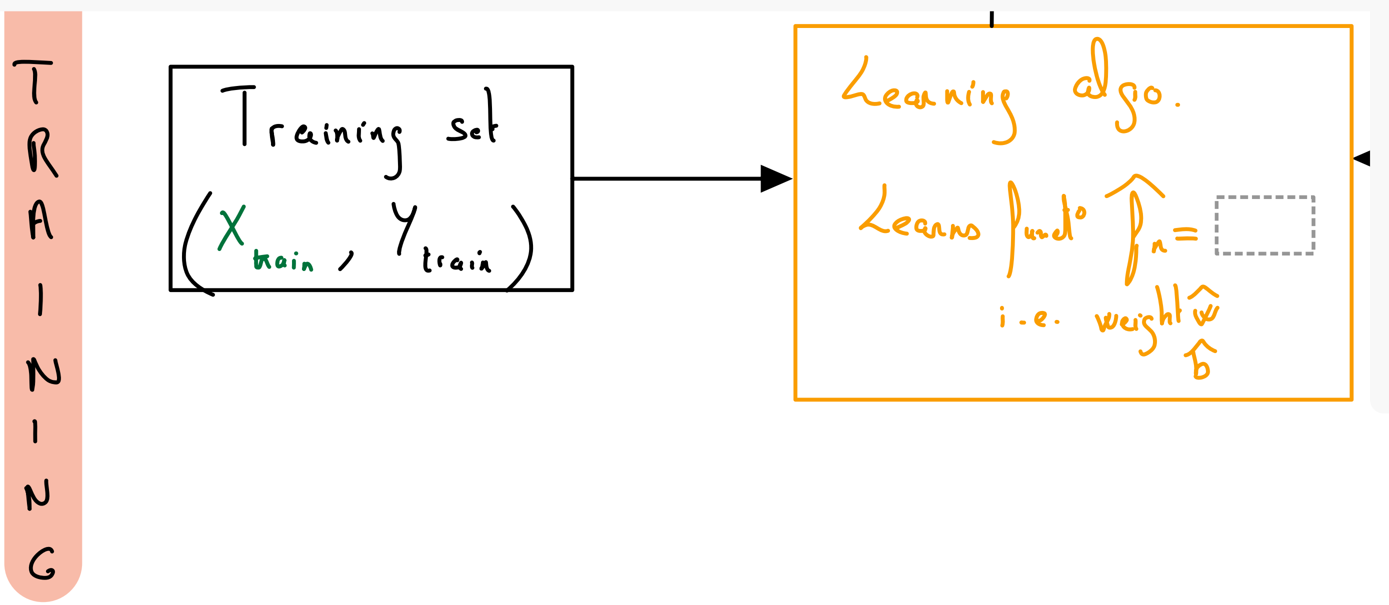
Neural Networks

Decision Trees

Random Forests

Empirical risk minimization

# Supervised Machine Learning Pipeline



# Outline

# From logistic regression to Multi Layer Perceptron 1

Supervised ML problem:

1. Data $D_n = (X_i, Y_i)_{i=1,\ldots n}, X_i \in \mathbb{R}^d, Y_i \in \{0, \ldots, K\}$
2. Goal: Predict a the label for a new point.

**2 approaches:**

**Generative approach**

- Define a model on your data (e.g., logit model).
- Estimate parameter (likelihood maximization).

**Discriminative approach**

- No statistical model !
- Define a loss function $\ell$
- Goal:
$$\min_{f \in \mathcal{F}} \mathbb{E}[\ell(f(X), Y)]$$
- Approach:
$$\min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} [\ell(f(X_i), Y_i)]$$

# From logistic regression to Multi Layer Perceptron 1

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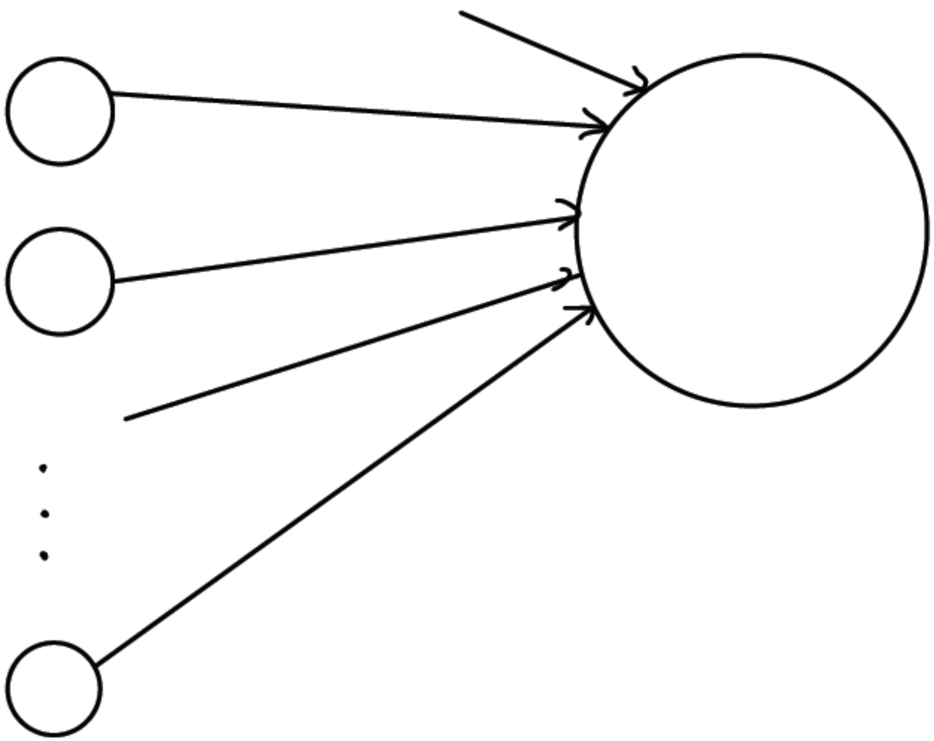
Logistic regression can be seen both ways !

$$\min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^{n} \log(1 + \exp(-Y_i \quad w^T X_i))$$

# From logistic regression to Multi Layer Perceptron 3

- Class of functions for logistic regression: $\mathscr{F} = \{X \mapsto w^T X,\ w \in \mathbb{R}^d\}$.
- Prediction for a new point is $1_{\sigma(X_i)>1/2}$
- Can be seen as predicting a probability $\sigma(X_i)$ that the output is 1



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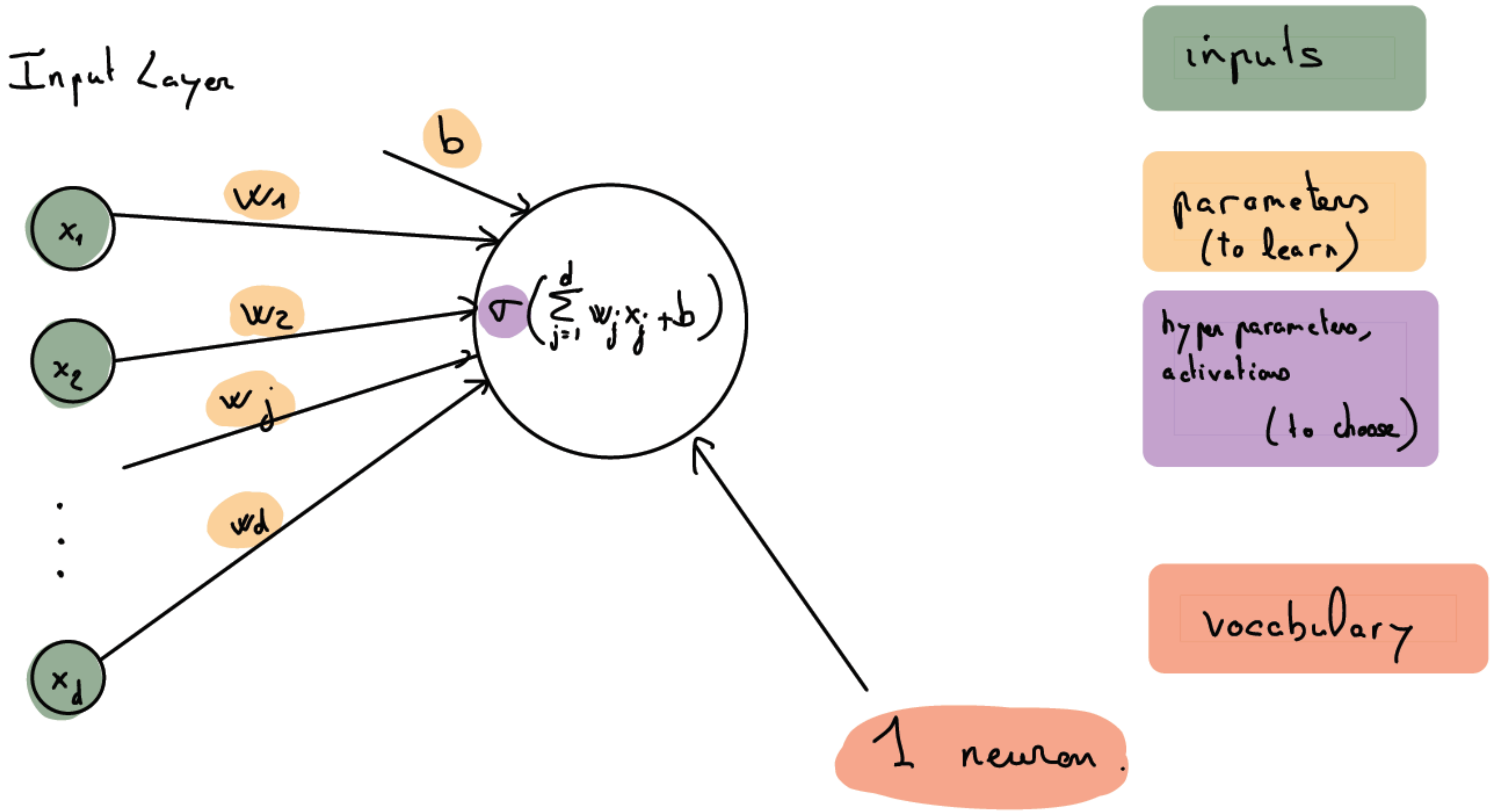


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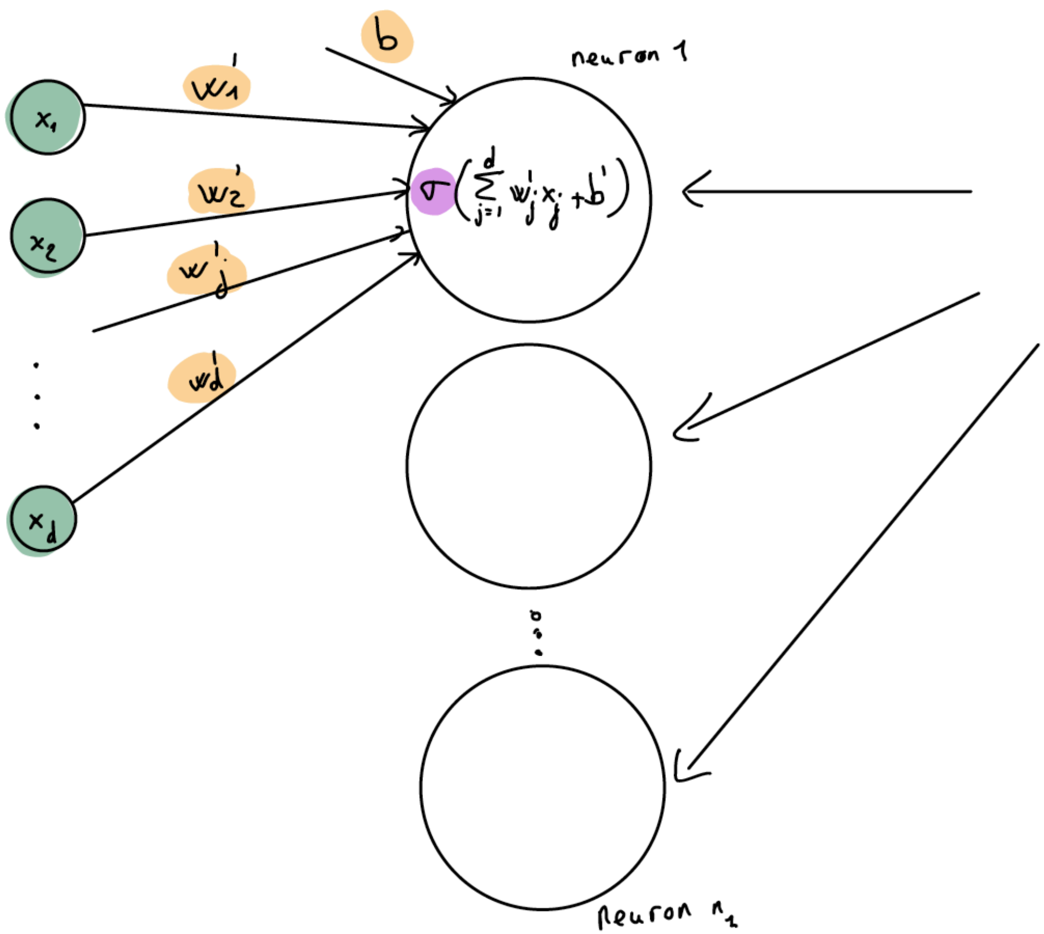
# From logistic regression to Multi Layer Perceptron 4

Extend to

- Multiple Neurons
- Multiple Layers



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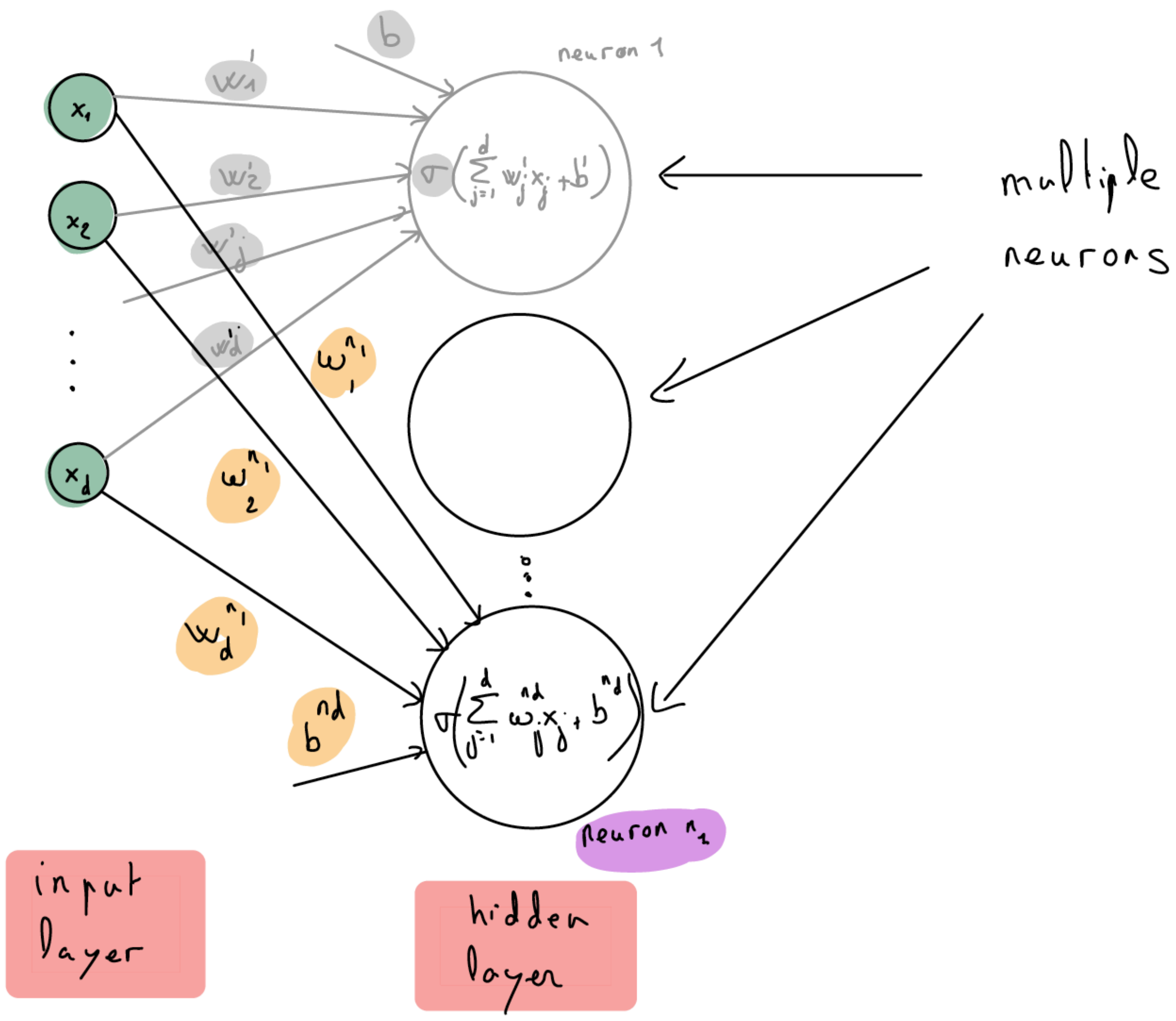
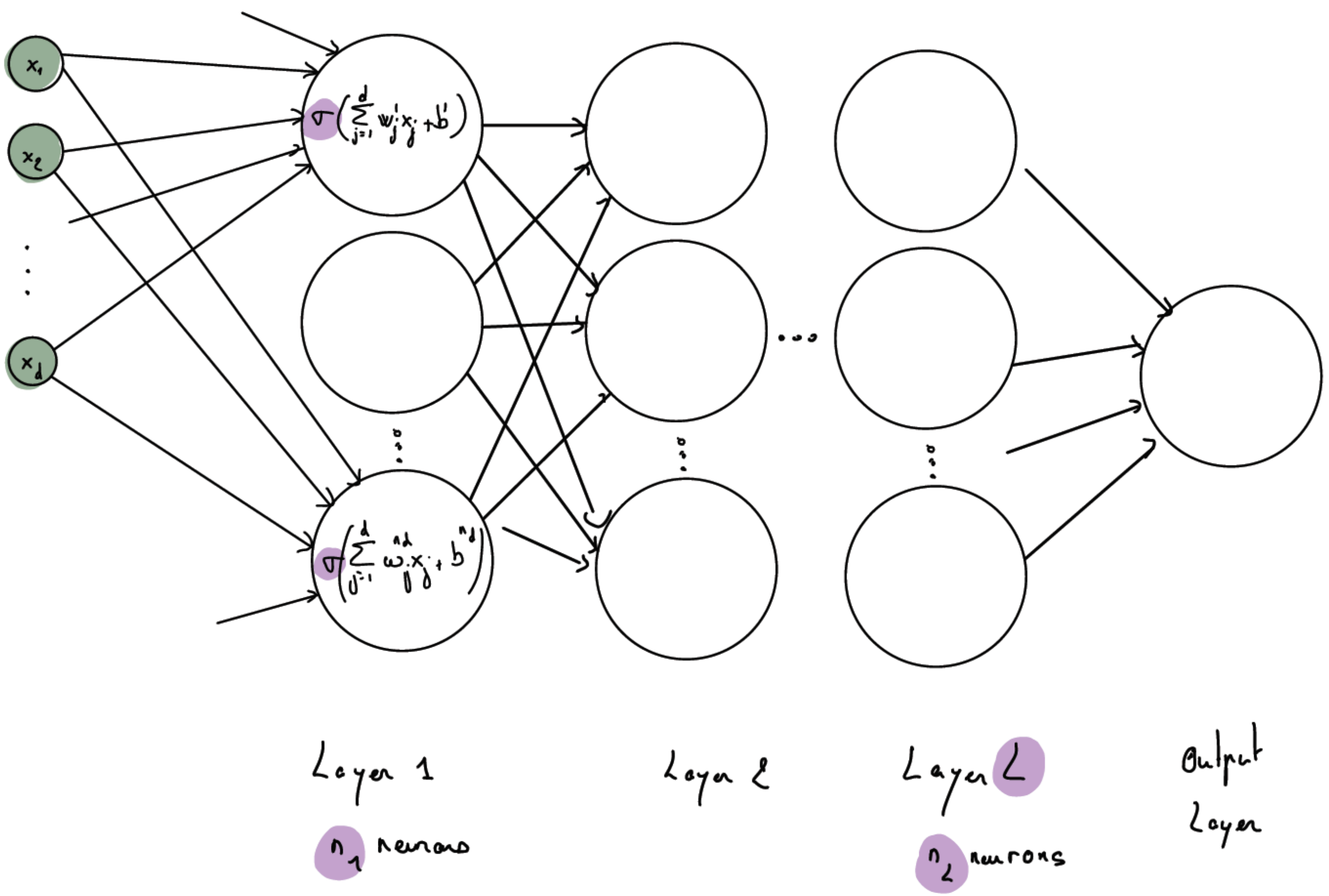


# From logistic regression to Multi Layer Perceptron 5

Extend to

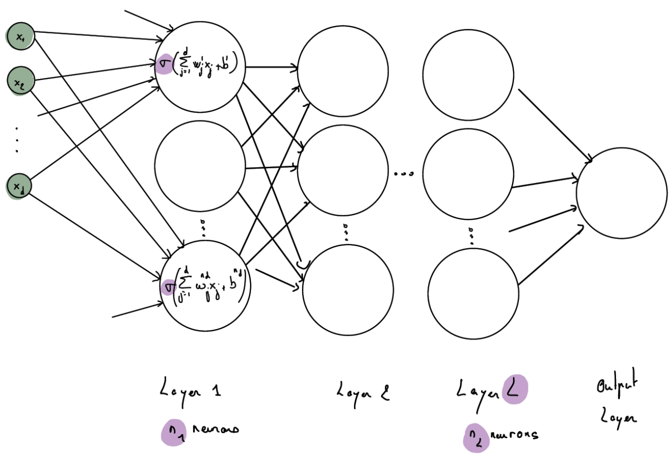
- Multiple Neurons
- Multiple Layers



# From logistic regression to Multi Layer Perceptron 5

Neural network:

- Goal $\min_{f \in \mathscr{F}_{\text{MLP}}} \frac{1}{n}\sum_{i=1}^{n}[\ell(f(X_i), Y_i)]$
- Class of non linear functions.
  $$\mathscr{F}_{\text{MLP}} = \{f(X; W, b) = \sigma(b_n + W_n\sigma(\ldots(b_1 + W_1 x))), \\ W \in \mathbb{R}^{\cdots}, b \in \mathbb{R}^{\cdots}\}$$




Summary: NN generalize regression by looking for candidates in a much larger class of functions than linear ones.

What needs to be learned What needs to be chosen Vocabulary

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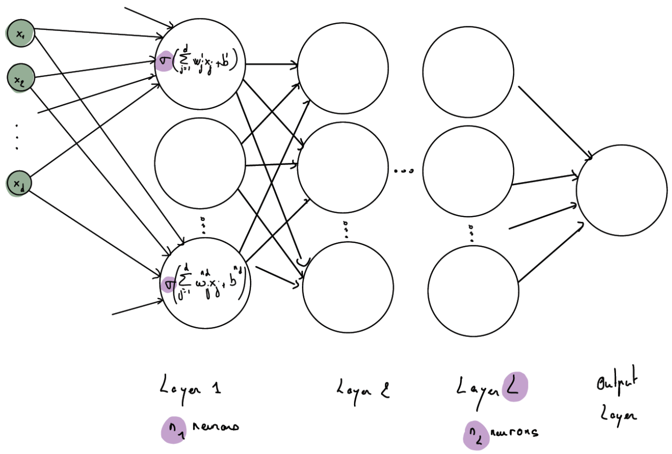



Summary: NN generalize regression by looking for candidates in a much larger class of functions than linear ones.

**What needs to be learned**

Parameters $W, b$

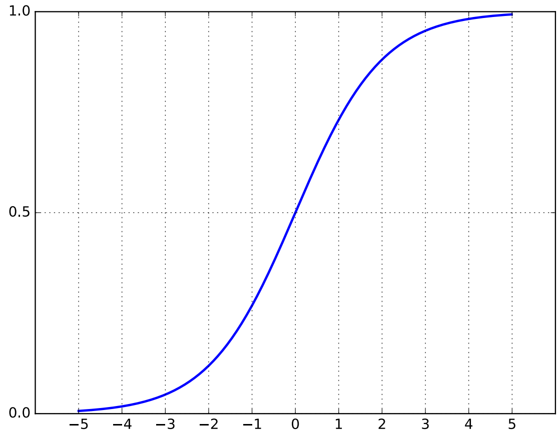
**What needs to be chosen**

- Activation $\sigma$
- Number of layers $L$
- Number of neurons per hidden layer $n_i, i = 1, \ldots, L$.

**Vocabulary**

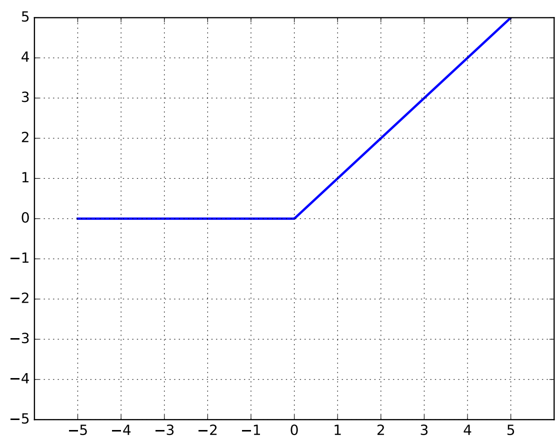
- Neuron
- Activation
- Hidden Layer
- Width, Depth
- Fully connected layer

# 2 possible activations: Sigmoid and Rectified Linear Unit




## Sigmoid function

- $x \mapsto \frac{\exp(x)}{1+\exp(x)}$
- Problems:
  1. Saturated function: gradient killer -> need for rescaling data




## Rectified Linear Unit (ReLU)

- $x \mapsto \max(0, x)$
- Pros & cons:
  1. Not a saturated function. Kills negative values.
  2. Empirically, convergence is faster than sigmoid/tanh.
  3. Plus: biologically plausible

# How to deal with multi-class output: softmax activation

When we do multi-class classification, i.e., $Y_i \in 1, \ldots, K$, we output $K$ different values:

- Each of them corresponds to the probability of belonging to the class $j$, $1 \leq j \leq K$
- To obtain probabilities (adding up to 1):
  1. We have $K$ neurons on the last layer
  2. And use a Softmax activation to renormalize.

Softmax output unit, used to predict $\{1, \ldots, K\}$:

$$\mathrm{softmax}(z)_i = \frac{e^{z_i}}{\sum_{k=1}^{K} e^{z_k}}$$

Up to that point, we have seen :

- What a Neural Network was
- Why it is expected to learn better.

Next Question: how to implement it ?

# Python - Keras

1. Hardware:
   - CPU
   - GPU
   - TPU

2. Software (Python packages):
   - Pytorch/Tensorflow
   - → Keras : TF high level API. Ideal for applications.

# Keras - A few lines ![1]

What do we need to specify?

```python
# import tensorflow and keras (tf.keras not "vanilla" Keras)
import tensorflow as tf
from tensorflow import keras
# get data
(train_images, train_labels), (test_images,
                               test_labels) = keras.datasets.mnist.load_data()

```

What do we need to do next?

[1] Notebook Python

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import tensorflow as tf
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# get data
(train_images, train_labels), (test_images,
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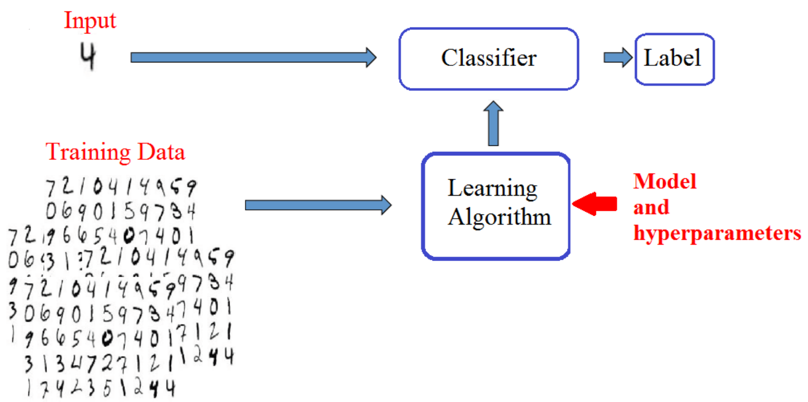
# setup model
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation=tf.nn.relu),
    keras.layers.Dense(10, activation=tf.nn.softmax)
])

model.compile(optimizer=tf.train.AdamOptimizer(),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# train model
model.fit(train_images, train_labels, epochs=5)

# evaluate
test_loss, test_acc = model.evaluate(test_images, test_labels)
print('test accuracy:', test_acc)

# make predictions
predictions = model.predict(test_images)
```




[1] Notebook Python

# Intuition

Up to that point, we have seen :

- What a Neural Network was.
- How to implement it in Python.

Next Question: why and when does it work ?

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Next Question: why and when does it work ?

1. Approximation theorem
2. Optimization

# Approximation Theorem

**Goal**

$$\min_{f \in \mathscr{F}_{\text{MLP}}} \frac{1}{n} \sum_{i=1}^{n} [\ell(f(X_i), Y_i)].$$

As said before, a MLP can output non-linear functions... But how powerful is it ?

# Approximation Theorem

Goal

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As said before, a MLP can output non-linear functions... But how powerful is it ?

Continuous Neural Networks with one single hidden layer and any bounded and non constant activation function can approximate any function in $L^p$, provided a sufficient number of hidden units.

$\looparrowright$ Very powerful in terms of approximations.
Not very surprising: non linear function with millions of parameters !

# Optimization

Goal $$\min_{f \in \mathscr{F}_{\text{MLP}}} \frac{1}{n} \sum_{i=1}^{n} [\ell(f(X_i), Y_i)].$$

How to minimize a function?
Gradient Methods. = cheapest way to update (learn) the weights iteratively to minimize the loss.

# Optimization

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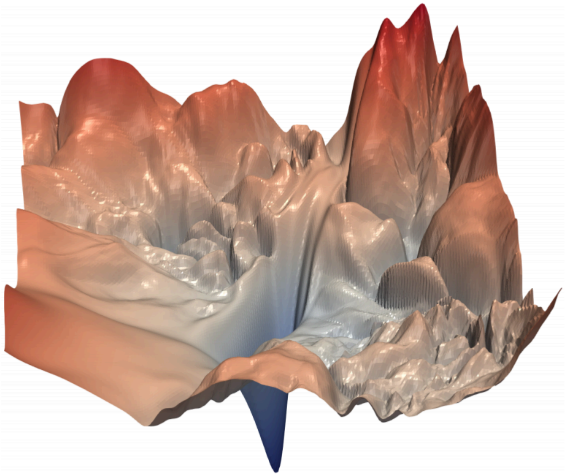
Gradient Methods. = cheapest way to update (learn) the weights iteratively to minimize the loss.

Two "miracles":

1. Autodifferentiation: even though the function is very complex and high dimensional, it is possible to compute gradients !
2. Optimization seems to work ok, though the function is non convex - we do not end up is too bad local minima. (specialized optim algos: Adam, AdaDelta, etc.)



These 2 miracles make it possible to learn a good regressor/classifier with NN and to benefit from the powerful approximation properties

# Conclusion

Neural networks :

1. learn very complex non linear functions in high dimension
2. can approximate nearly any function
3. can be optimized even though highly non convex.

Are thus expected to work:

- When depth or width increases.
- Thus with very large datasets
- Requiring a lot of computational power.

$\Rightarrow$ **Explains why they were so successful since 2010**

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*What my layer wants me to say*: we haven't talked about many points !!

- Initialization
- Regularization

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Next:

- Brief history
- How to use the structure ?

# A brief history of NN

- 1943: Neural networks
- 1957: Perceptron
- 1974-86: Backpropagation, RBM, RNN
- 1989-98: CNN, MNIST
- 2009: ImageNet
- 2012: AlexNet,
- 2014: GANss
- 2016: AlphaGo
- 2018: BERT

The Computational power made the major change (+ investment and creativity).

# Directions

- When does it work ?

**Large or huge datasets. Structured** tasks.

$\looparrowright$ **Images and text.**

⚠ do not try to apply DL everywhere

Each application requires a special architecture:

- Images : Convolutional Neural Network (CNN).
- Text : Recurrent Neural Networks (RNN).

# Outline

# CNN

We consider an image classification task: we want to recognize which object is on an image.

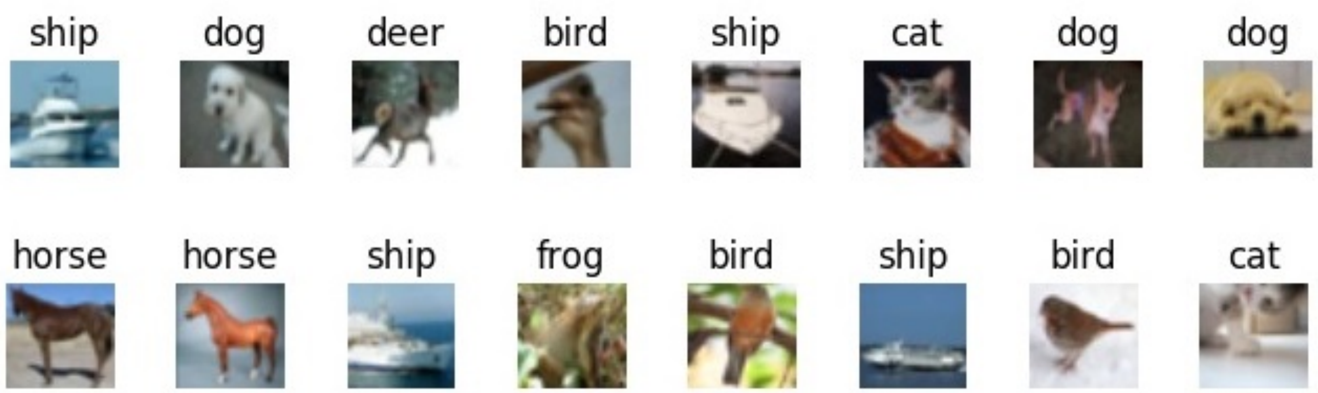


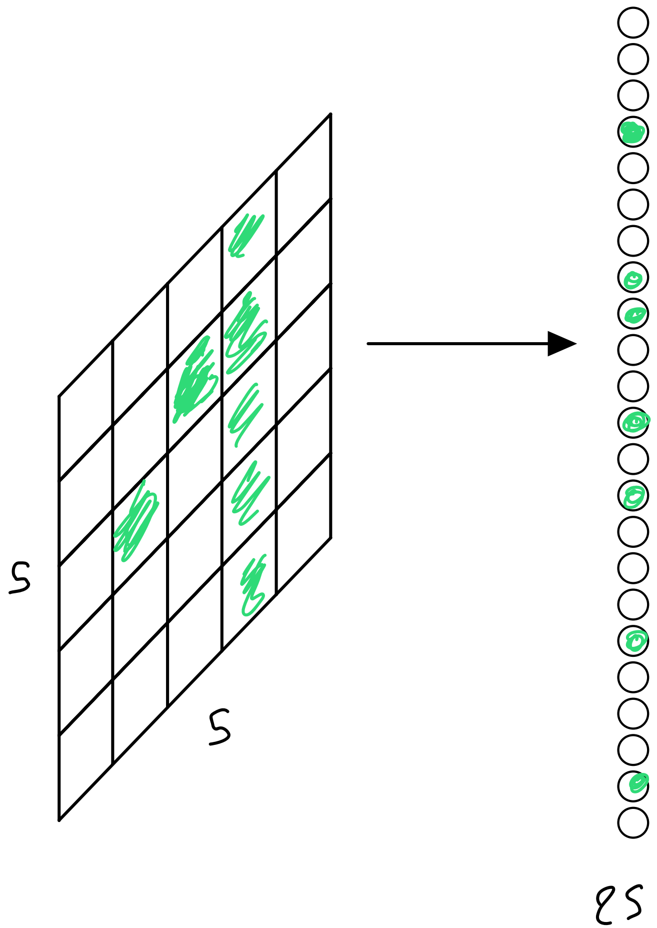

Figure: CIFAR dataset

The input is an image: about $10^3$ to $10^7$ pixels: these are our inputs.
Problems: The multi-layer perceptron:

- Does not take into account local information. It would work similarly on any permutation of the pixels !
- Has, just on the first layer, as many parameters as there are inputs !

# Convolutional Layer

Instead of making a linear combination of all the pixels, we consider a weighted average of a moving window of pixels, of size 3x3, or 5x5... **Drawing**



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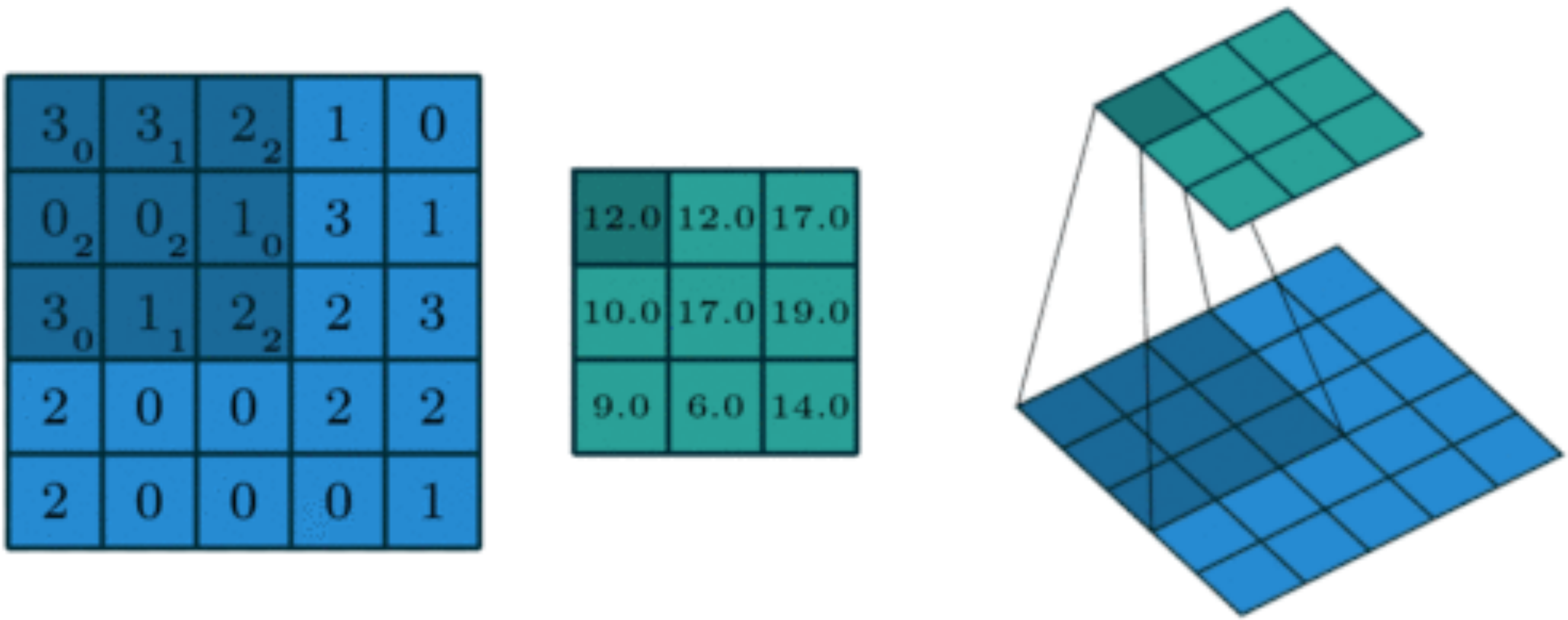

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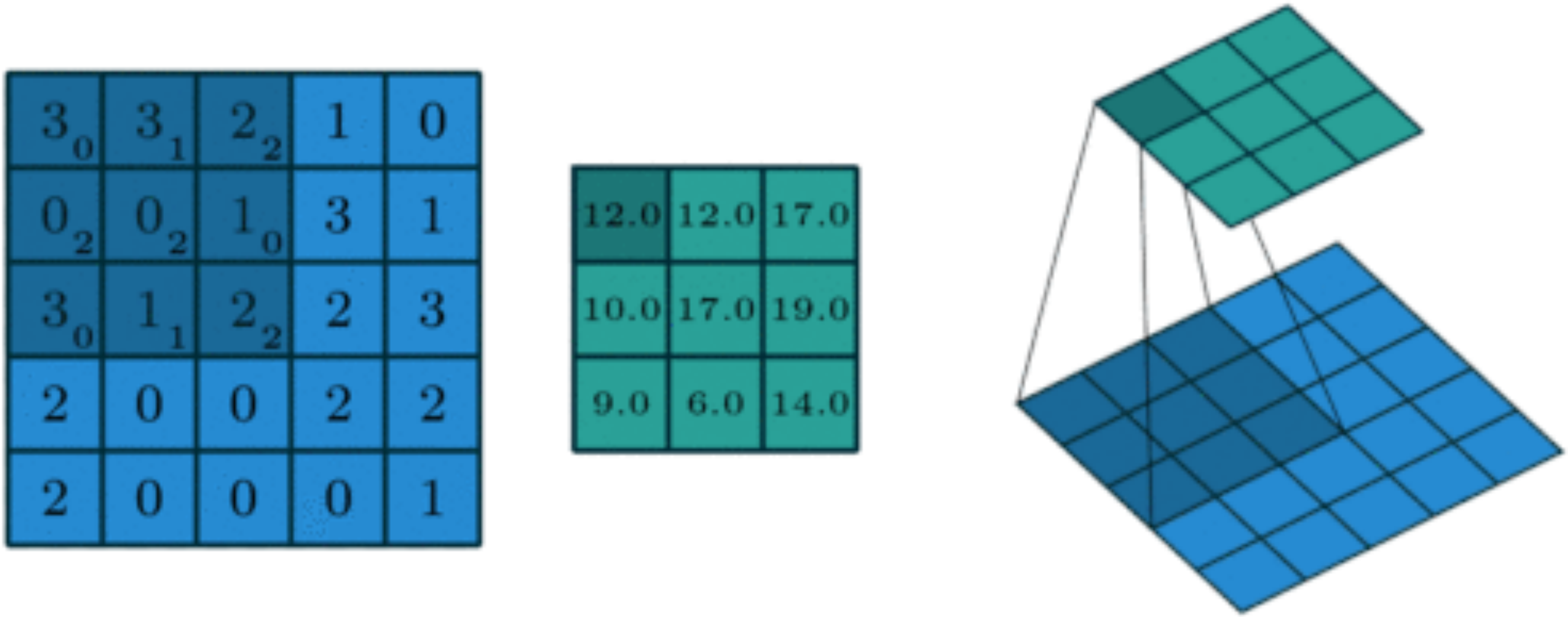

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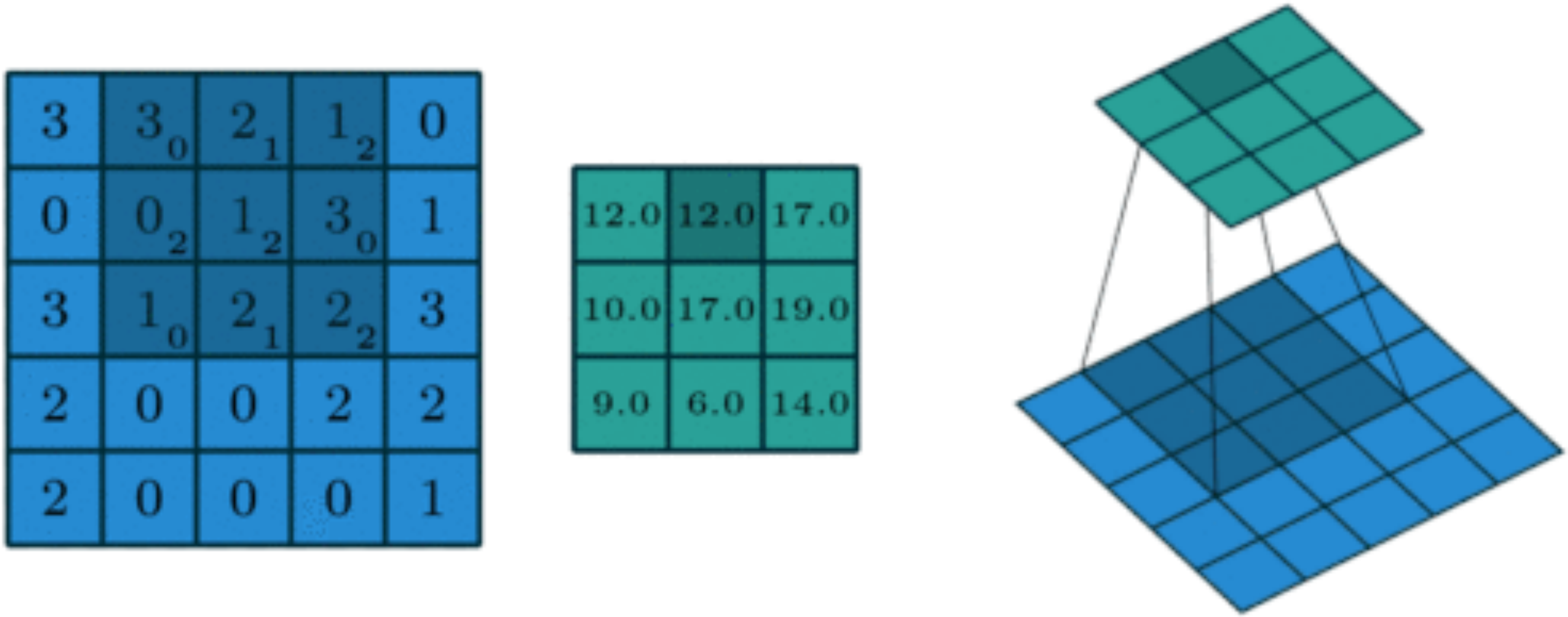

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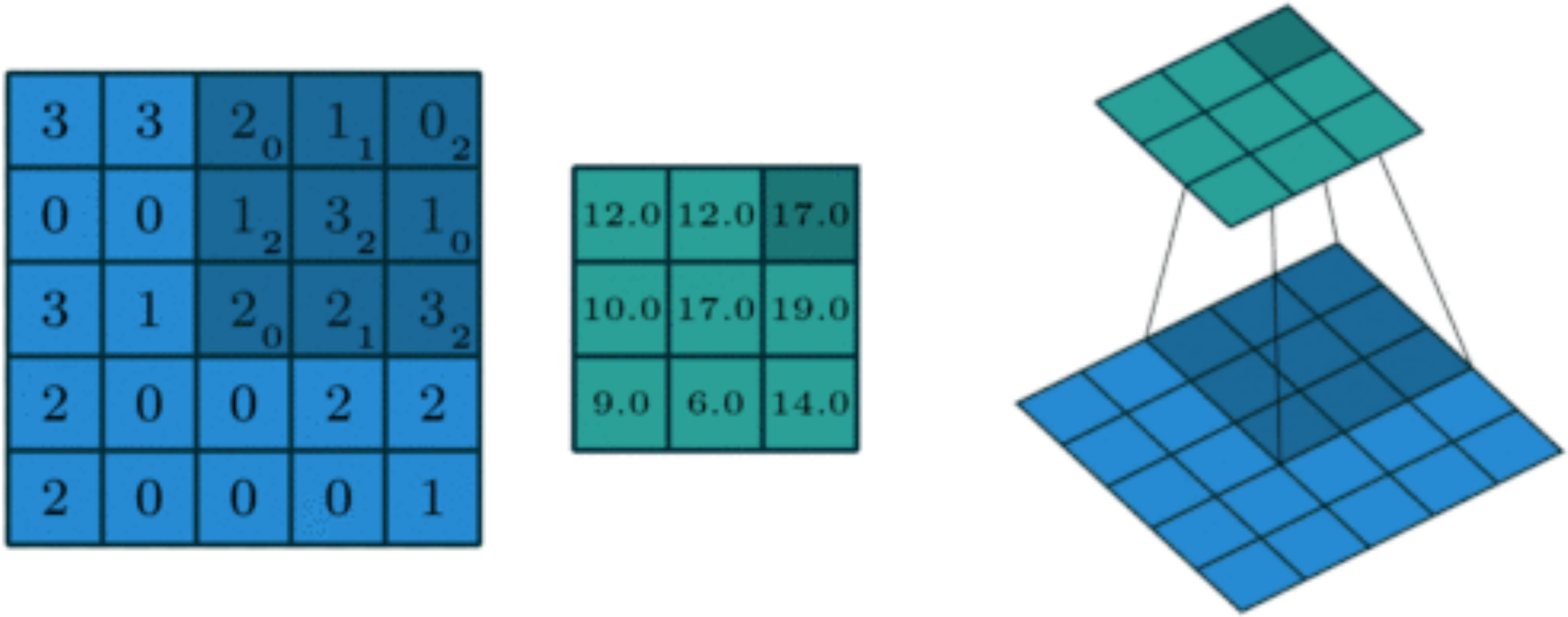

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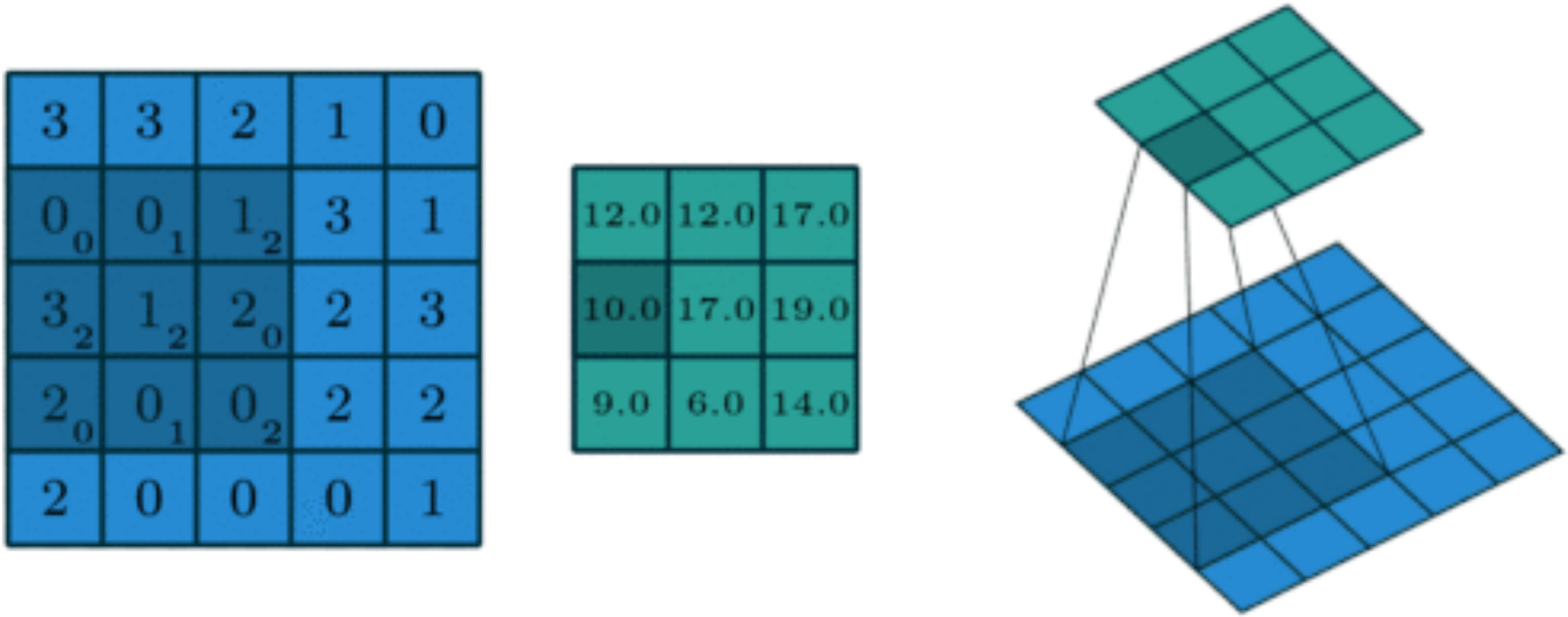

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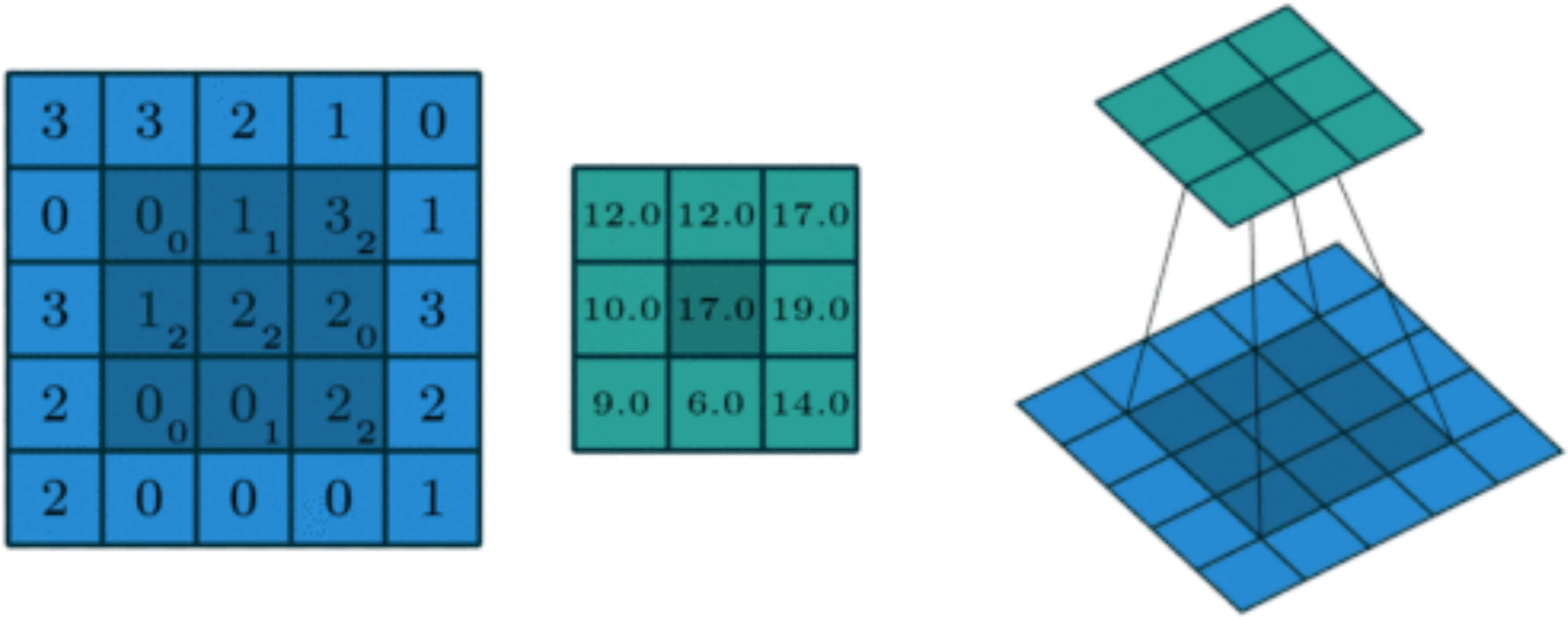

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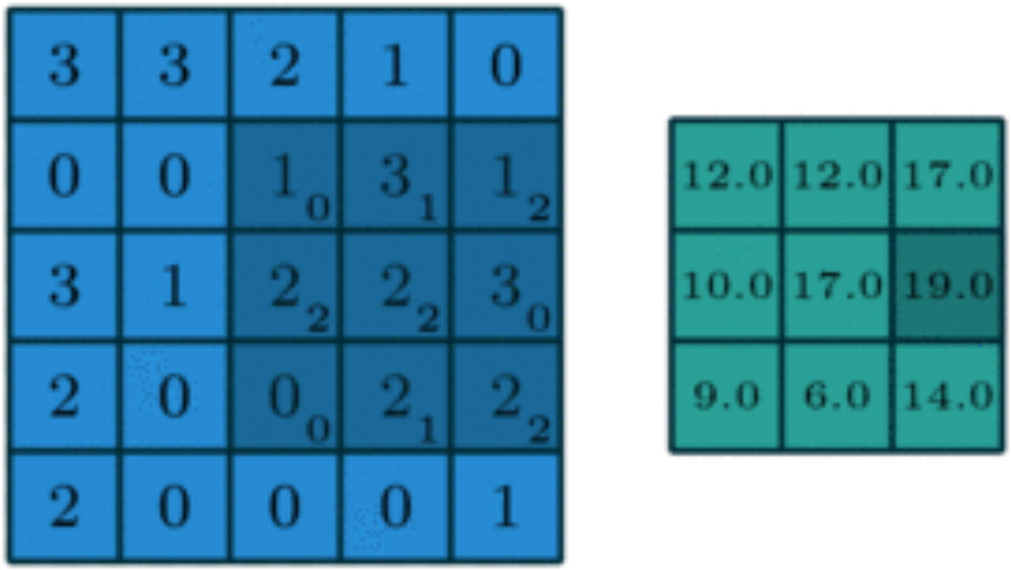


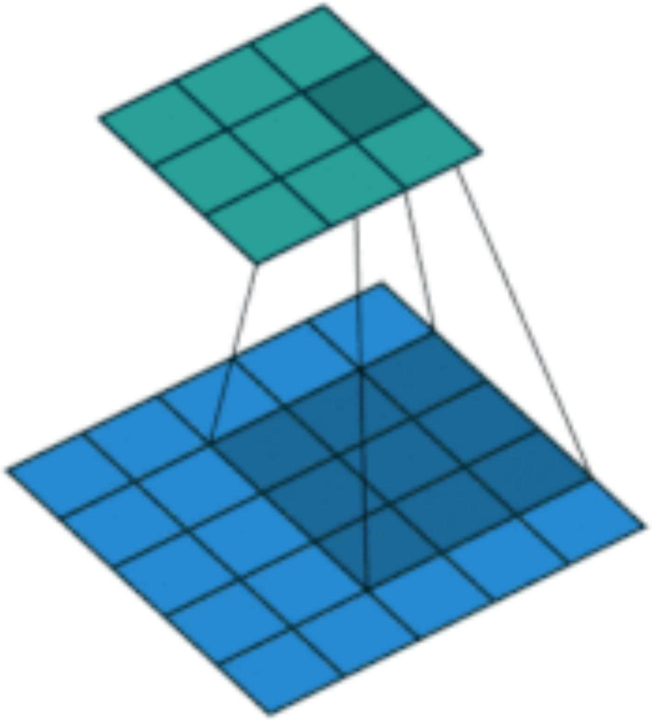

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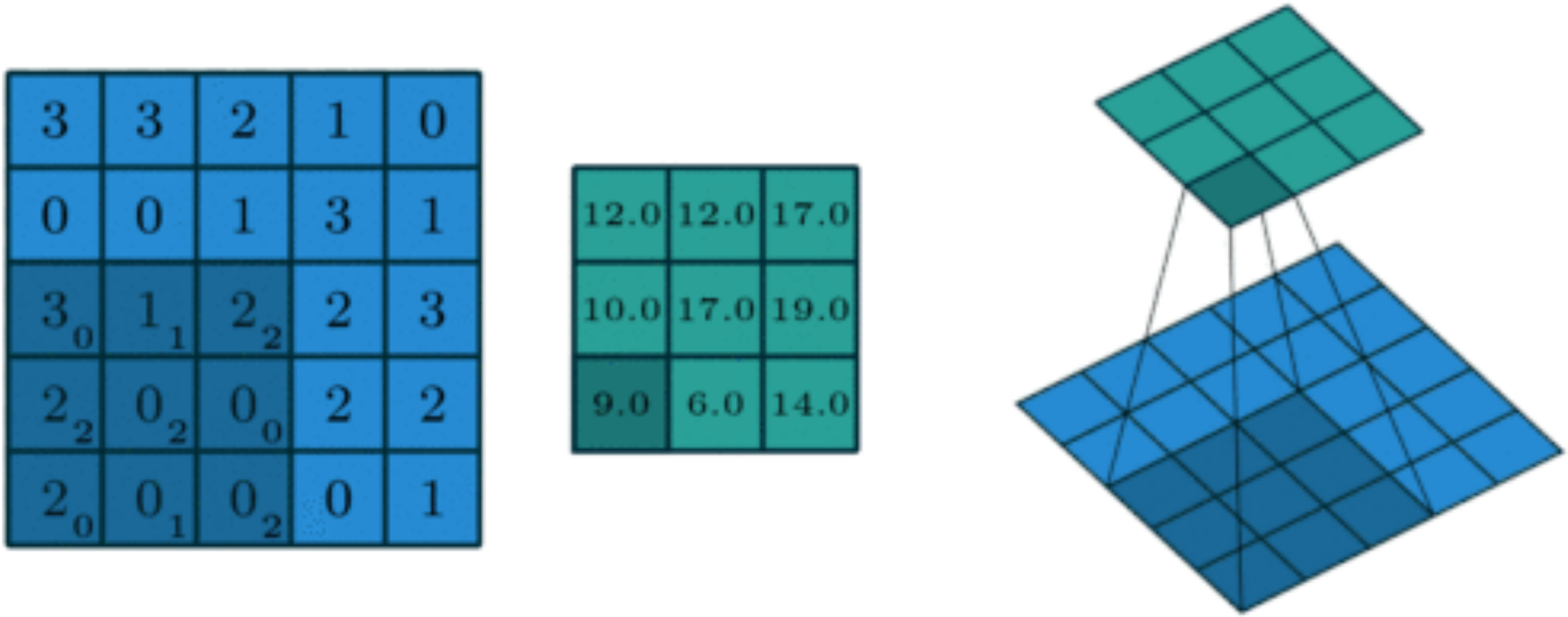

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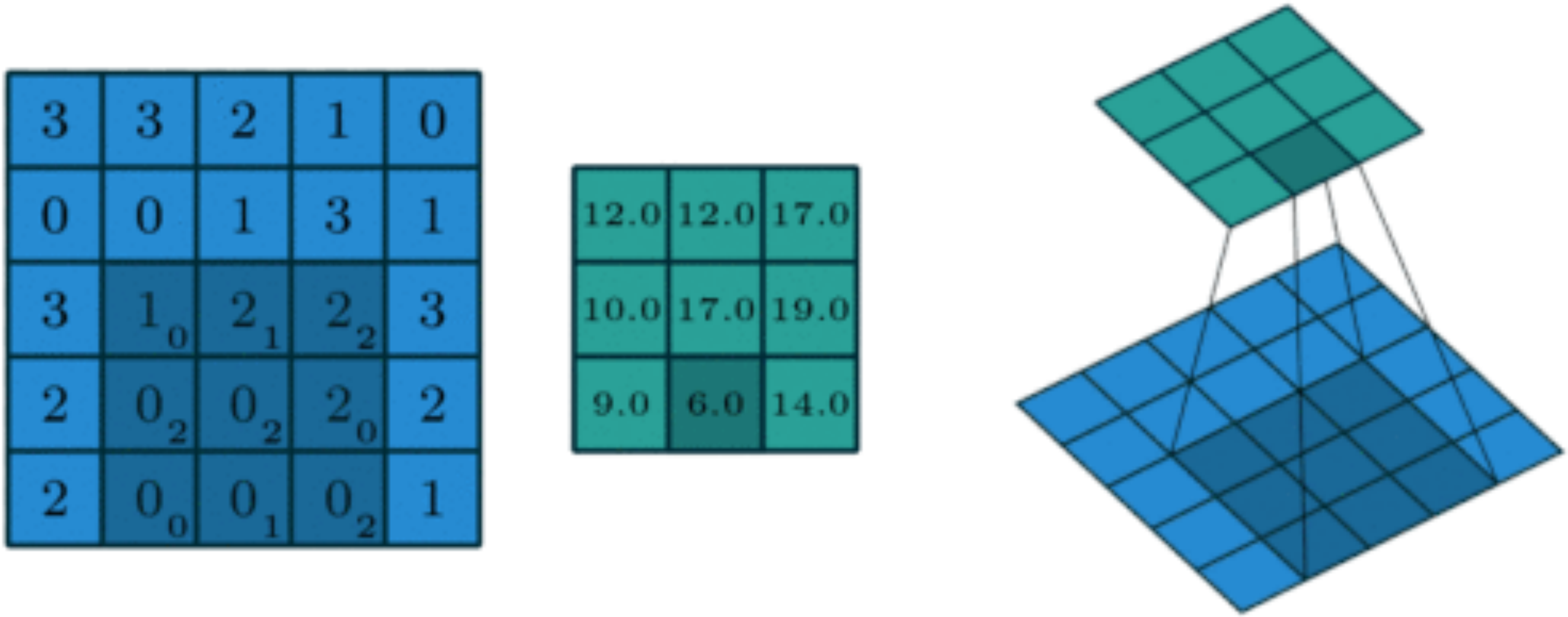

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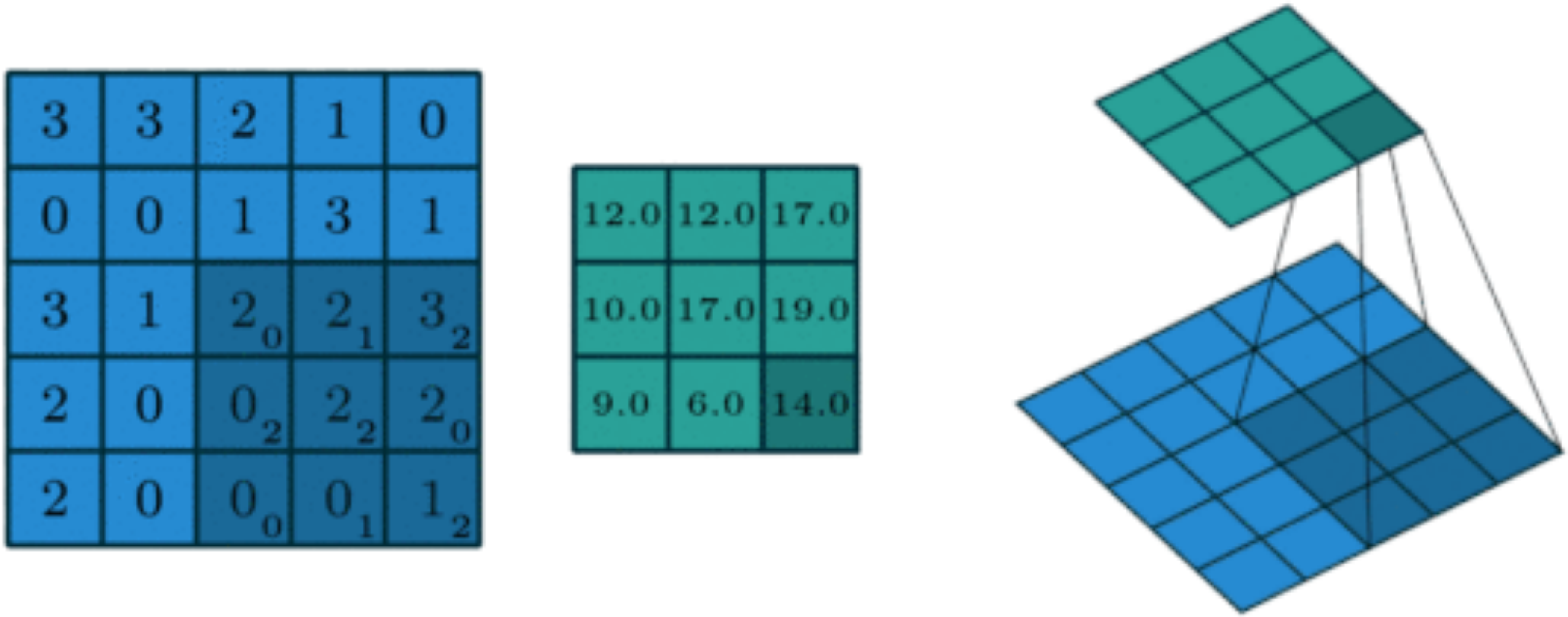

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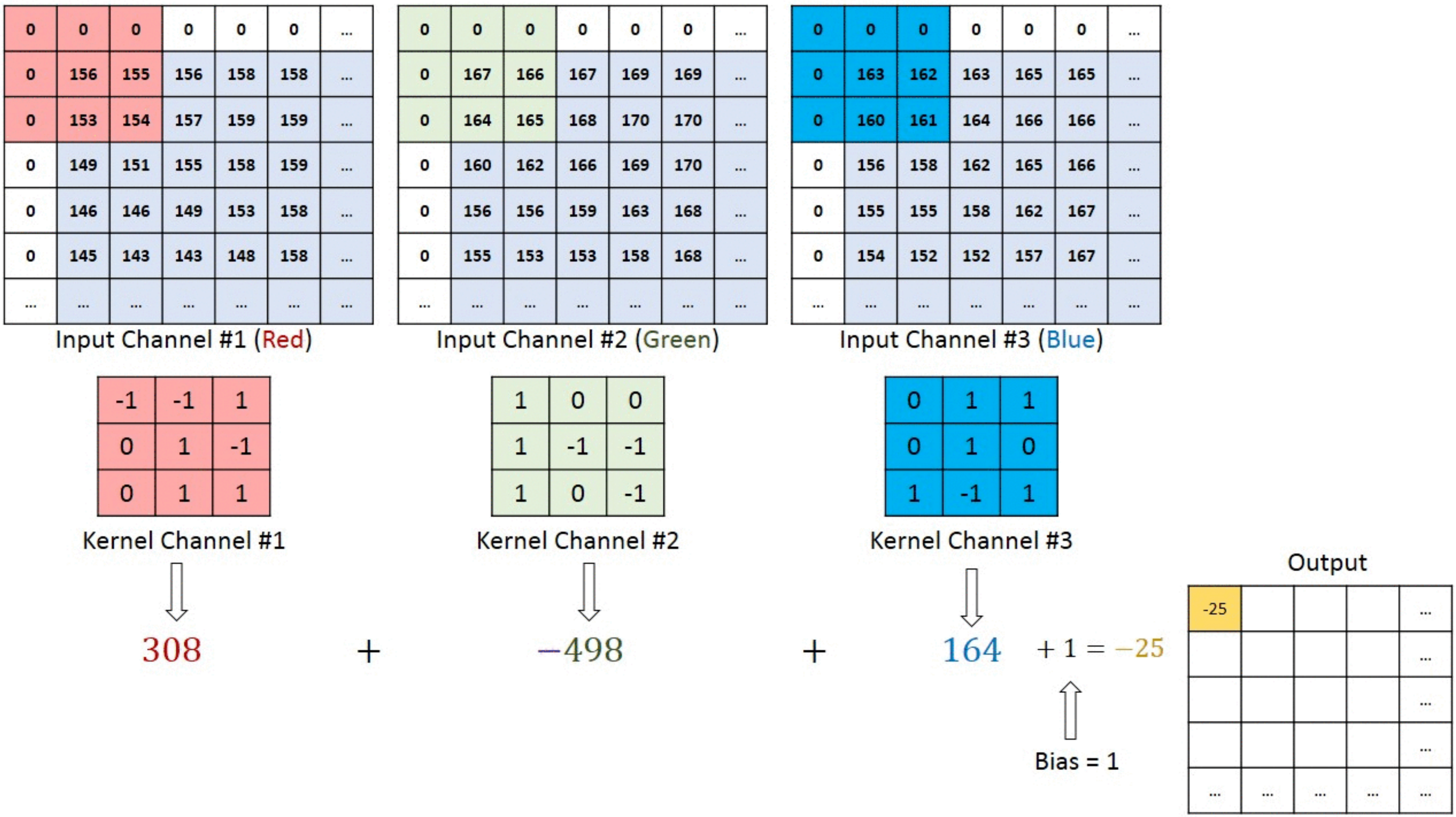

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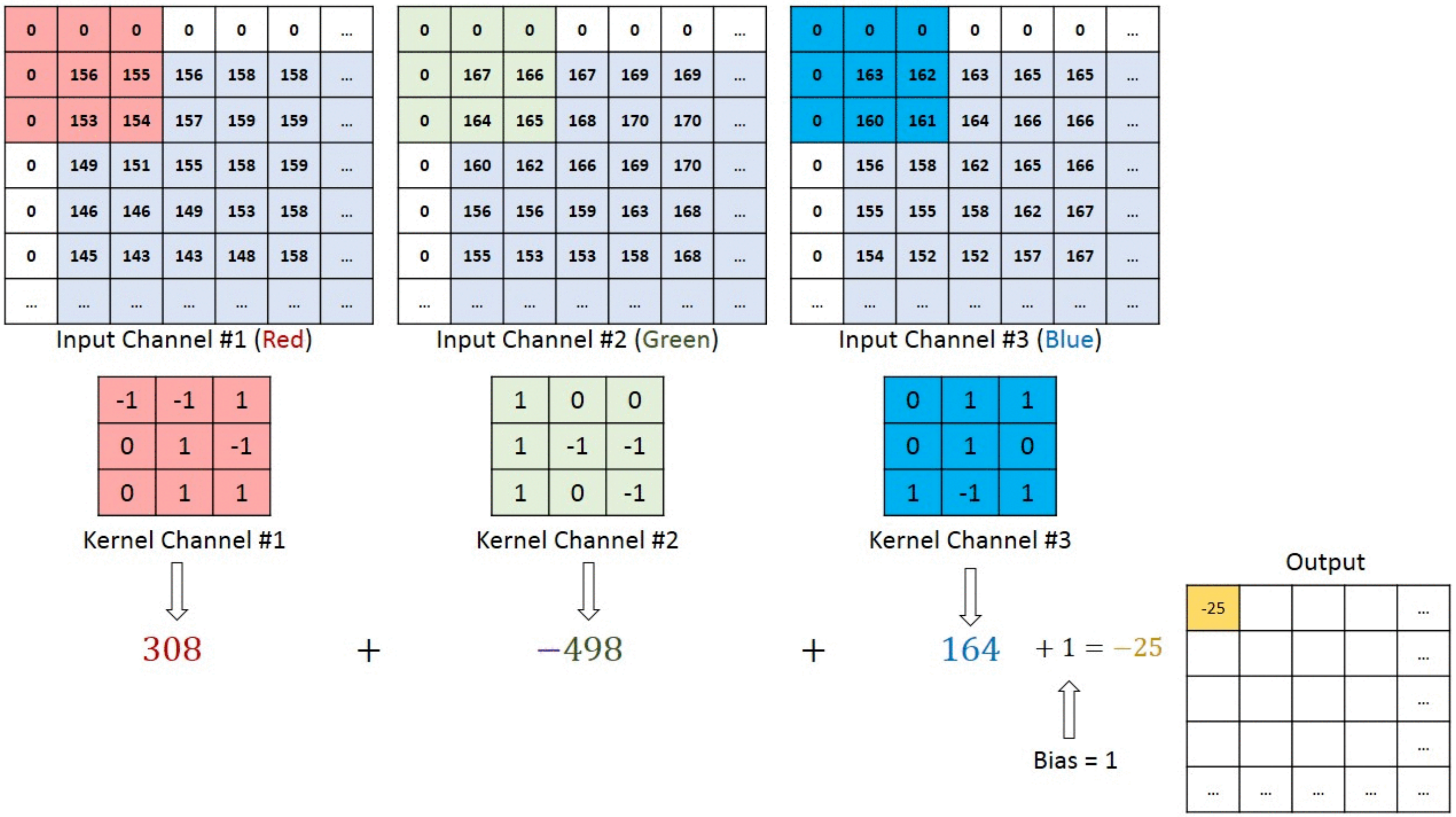

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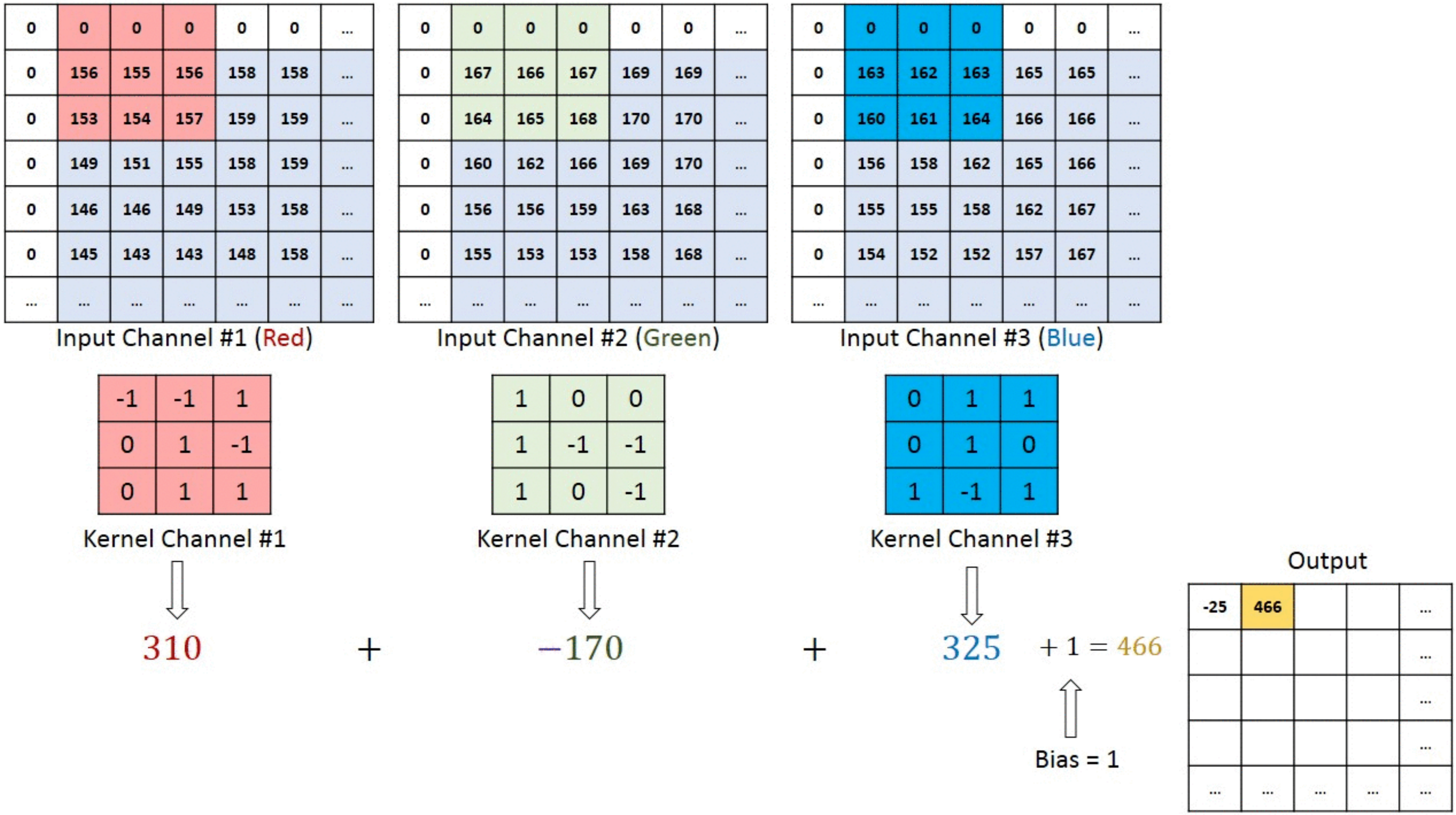

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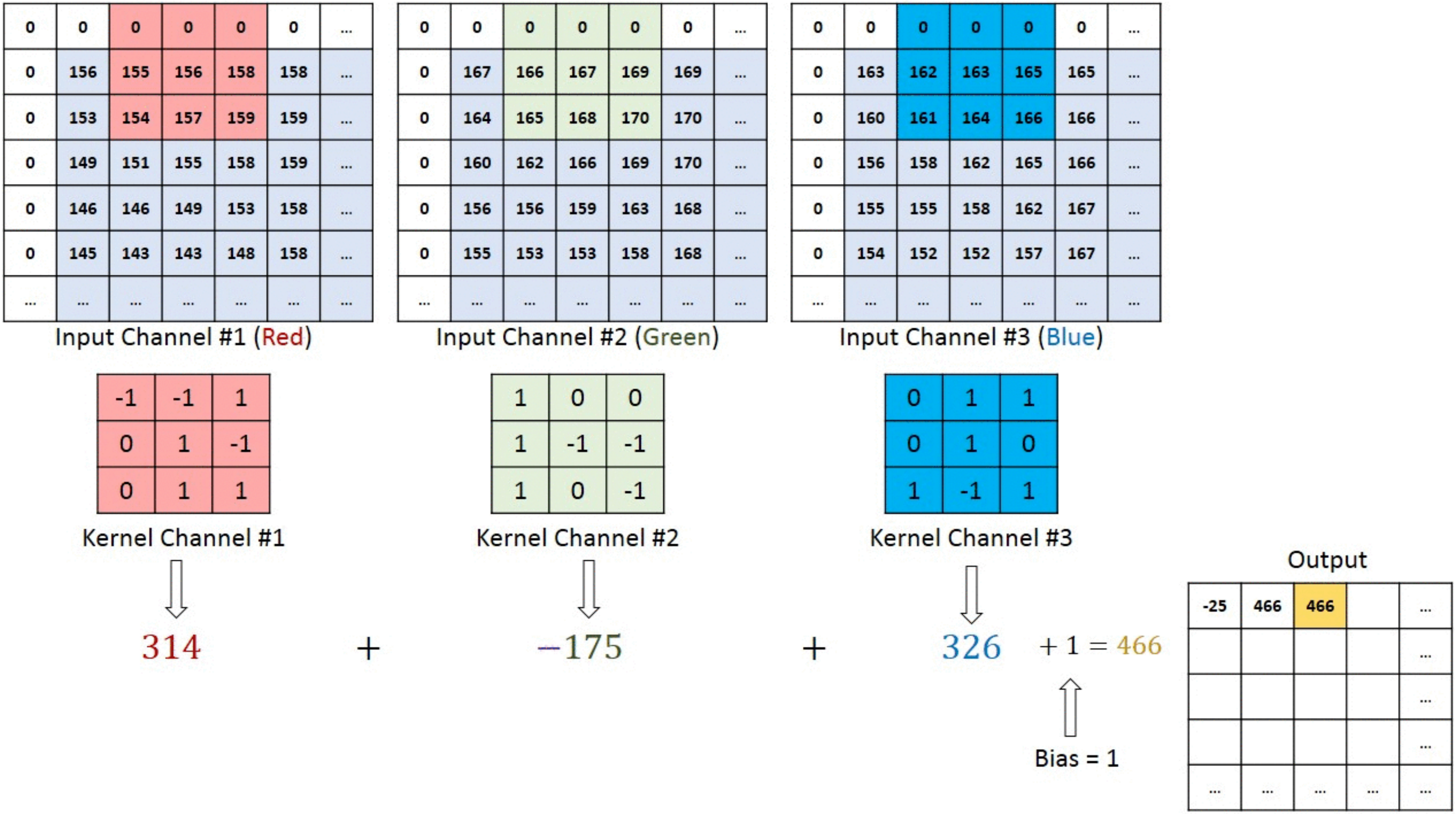

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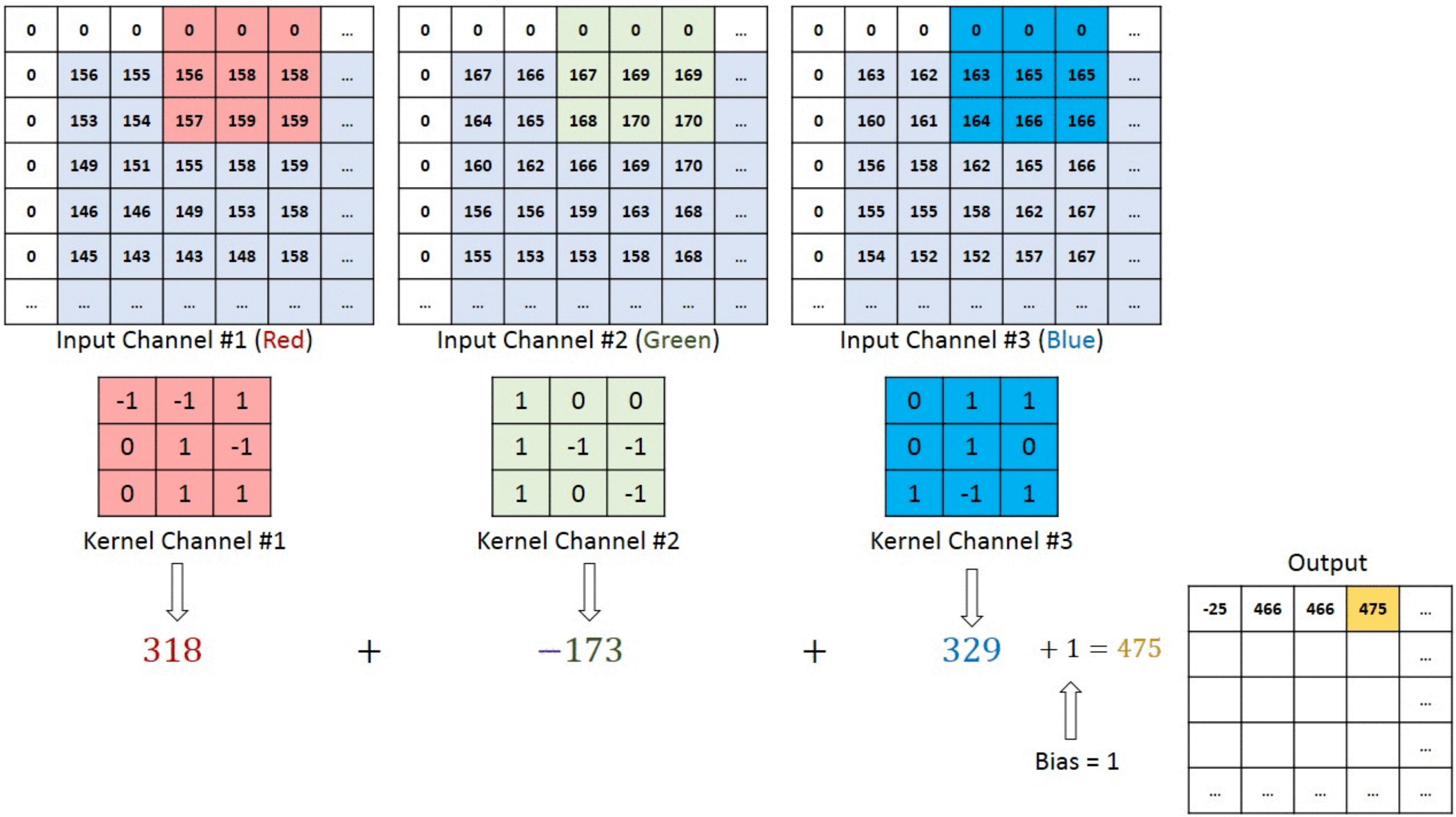

# Convolutional Layer

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 156 | 155 | 156 | 158 | 158 | ... |
| 0 | 153 | 154 | 157 | 159 | 159 | ... |
| 0 | 149 | 151 | 155 | 158 | 159 | ... |
| 0 | 146 | 146 | 149 | 153 | 158 | ... |
| 0 | 145 | 143 | 143 | 148 | 158 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Input Channel #1 (Red)

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 167 | 166 | 167 | 169 | 169 | ... |
| 0 | 164 | 165 | 168 | 170 | 170 | ... |
| 0 | 160 | 162 | 166 | 169 | 170 | ... |
| 0 | 156 | 156 | 159 | 163 | 168 | ... |
| 0 | 155 | 153 | 153 | 158 | 168 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Input Channel #2 (Green)

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 163 | 162 | 163 | 165 | 165 | ... |
| 0 | 160 | 161 | 164 | 166 | 166 | ... |
| 0 | 156 | 158 | 162 | 165 | 166 | ... |
| 0 | 155 | 155 | 158 | 162 | 167 | ... |
| 0 | 154 | 152 | 152 | 157 | 167 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Input Channel #3 (Blue)

| | | |
|---|---|---|
| -1 | -1 | 1 |
| 0 | 1 | -1 |
| 0 | 1 | 1 |

Kernel Channel #1

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 1 | -1 | -1 |
| 1 | 0 | -1 |

Kernel Channel #2

| | | |
|---|---|---|
| 0 | 1 | 1 |
| 0 | 1 | 0 |
| 1 | -1 | 1 |

Kernel Channel #3

$$298 + -491 + 487 + 1 = 295$$

Bias = 1

Output

| | | | | |
|---|---|---|---|---|
| -25 | 466 | 466 | 475 | ... |
| 295 | | | | ... |
| | | | | ... |
| | | | | ... |
| ... | ... | ... | ... | ... |

# Convolutional Layer

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 156 | 155 | 156 | 158 | 158 | ... |
| 0 | 153 | 154 | 157 | 159 | 159 | ... |
| 0 | 149 | 151 | 155 | 158 | 159 | ... |
| 0 | 146 | 146 | 149 | 153 | 158 | ... |
| 0 | 145 | 143 | 143 | 148 | 158 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Input Channel #1 (Red)

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 167 | 166 | 167 | 169 | 169 | ... |
| 0 | 164 | 165 | 168 | 170 | 170 | ... |
| 0 | 160 | 162 | 166 | 169 | 170 | ... |
| 0 | 156 | 156 | 159 | 163 | 168 | ... |
| 0 | 155 | 153 | 153 | 158 | 168 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Input Channel #2 (Green)

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 163 | 162 | 163 | 165 | 165 | ... |
| 0 | 160 | 161 | 164 | 166 | 166 | ... |
| 0 | 156 | 158 | 162 | 165 | 166 | ... |
| 0 | 155 | 155 | 158 | 162 | 167 | ... |
| 0 | 154 | 152 | 152 | 157 | 167 | ... |
| ... | ... | ... | ... | ... | ... | ... |

Input Channel #3 (Blue)

| | | |
|---|---|---|
| -1 | -1 | 1 |
| 0 | 1 | -1 |
| 0 | 1 | 1 |

Kernel Channel #1

| | | |
|---|---|---|
| 1 | 0 | 0 |
| 1 | -1 | -1 |
| 1 | 0 | -1 |

Kernel Channel #2

| | | |
|---|---|---|
| 0 | 1 | 1 |
| 0 | 1 | 0 |
| 1 | -1 | 1 |

Kernel Channel #3

$$148 \quad + \quad -8 \quad + \quad 646 \quad + 1 = 787$$

Bias = 1

Output

| | | | | |
|---|---|---|---|---|
| -25 | 466 | 466 | 475 | ... |
| 295 | 787 | | | ... |
| | | | | ... |
| | | | | ... |
| ... | ... | ... | ... | ... |

# Summary

CNN:

- allow to take spacial information into account
- reduce the number of parameters per layer. We can have deeper networks!

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**LeNet 1998:**

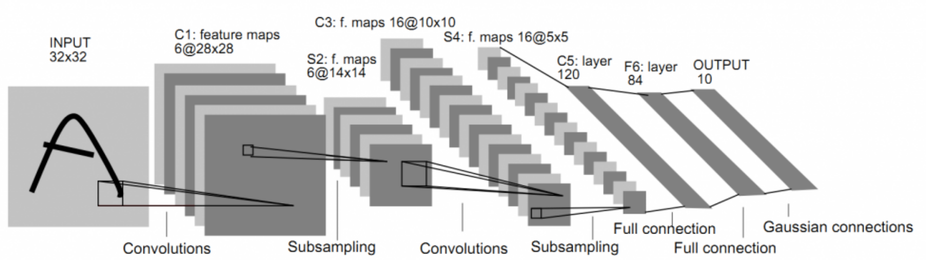
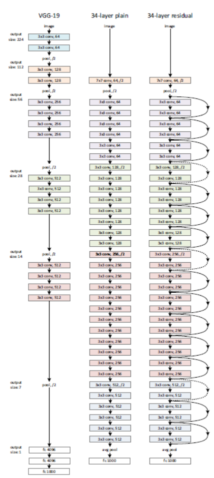



Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

8 layers, 60k parameters.

**Resnet 2016**



$\sim$ 40 Layers, 140M parameters

# Outline

# Outline

# Image classification - CNN Tree

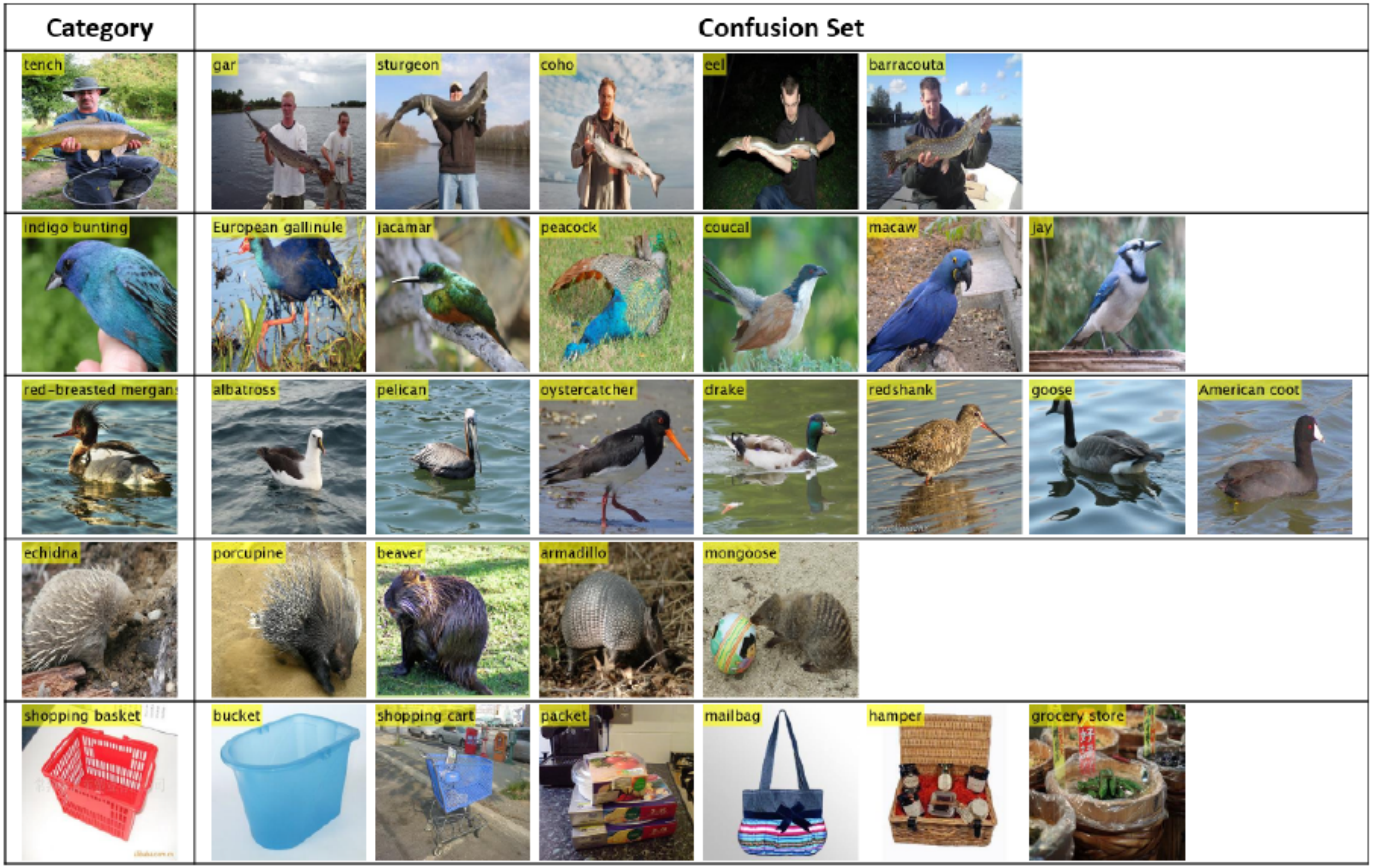



Figure: Confusion set outputs by AlexNet softmax prediction on validation set of ILSVRC 2015.

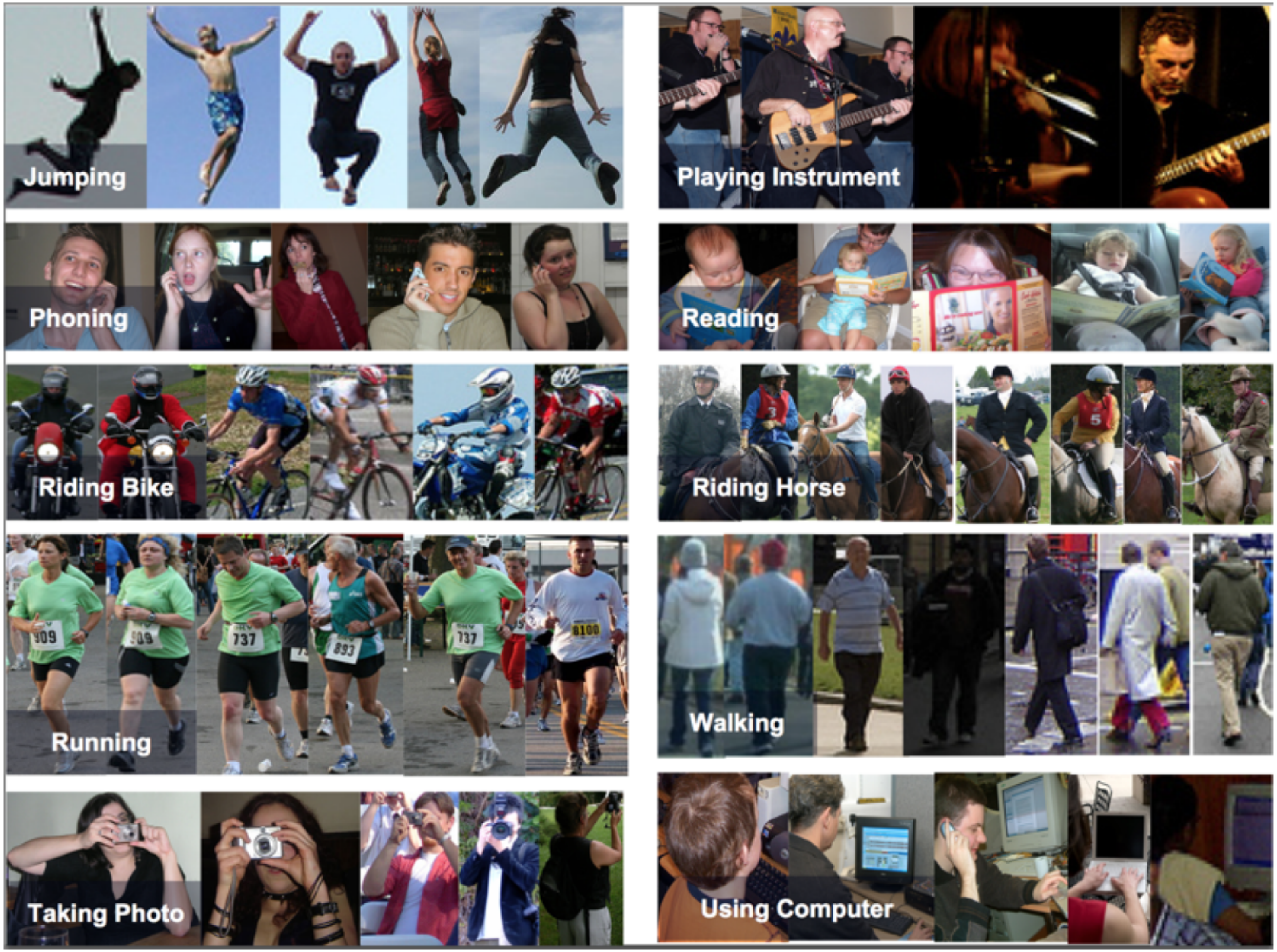
# Image classification - CNN Tree


Figure: Top label is given by basic AlexNet CNN while bottom one is given by CNNTree (green color corresponds to a correct prediction)

# Outline

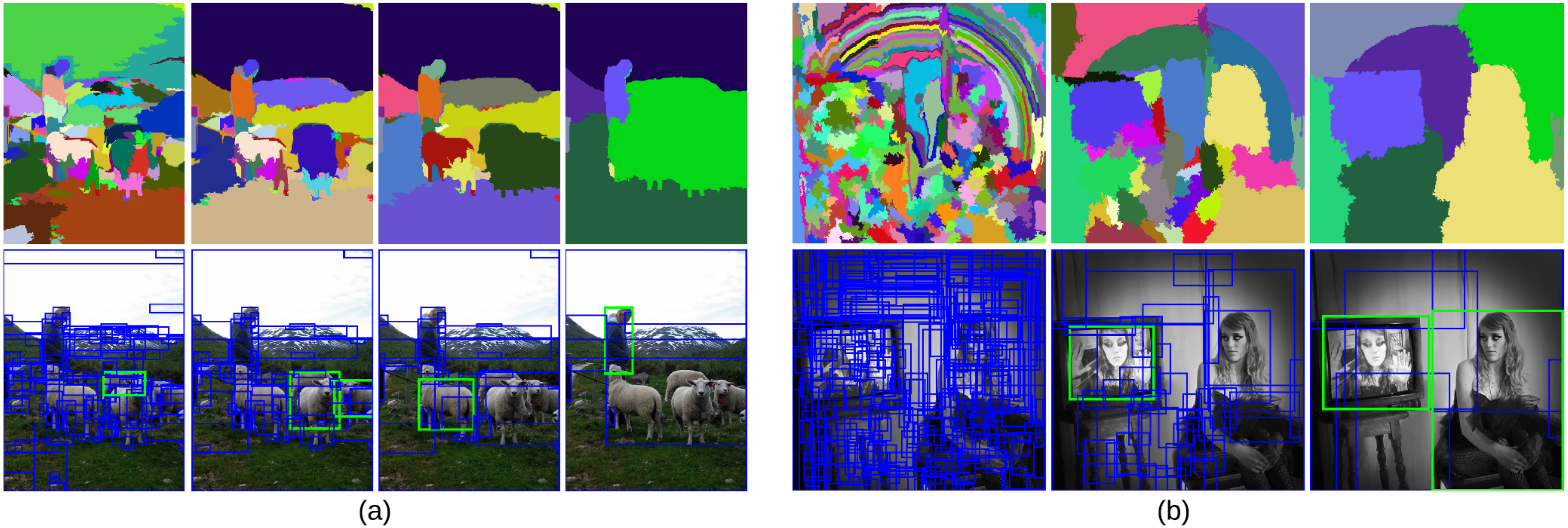
# Pose estimation - Deeppose

# Action recognition



# Outline

# Object detection and segmentation



# Object detection - YOLO, SDD

More recently, YOLO (You Only Look Once) and SSD (Single Shot Detector) allow single pipeline detection that directly predicts class labels.

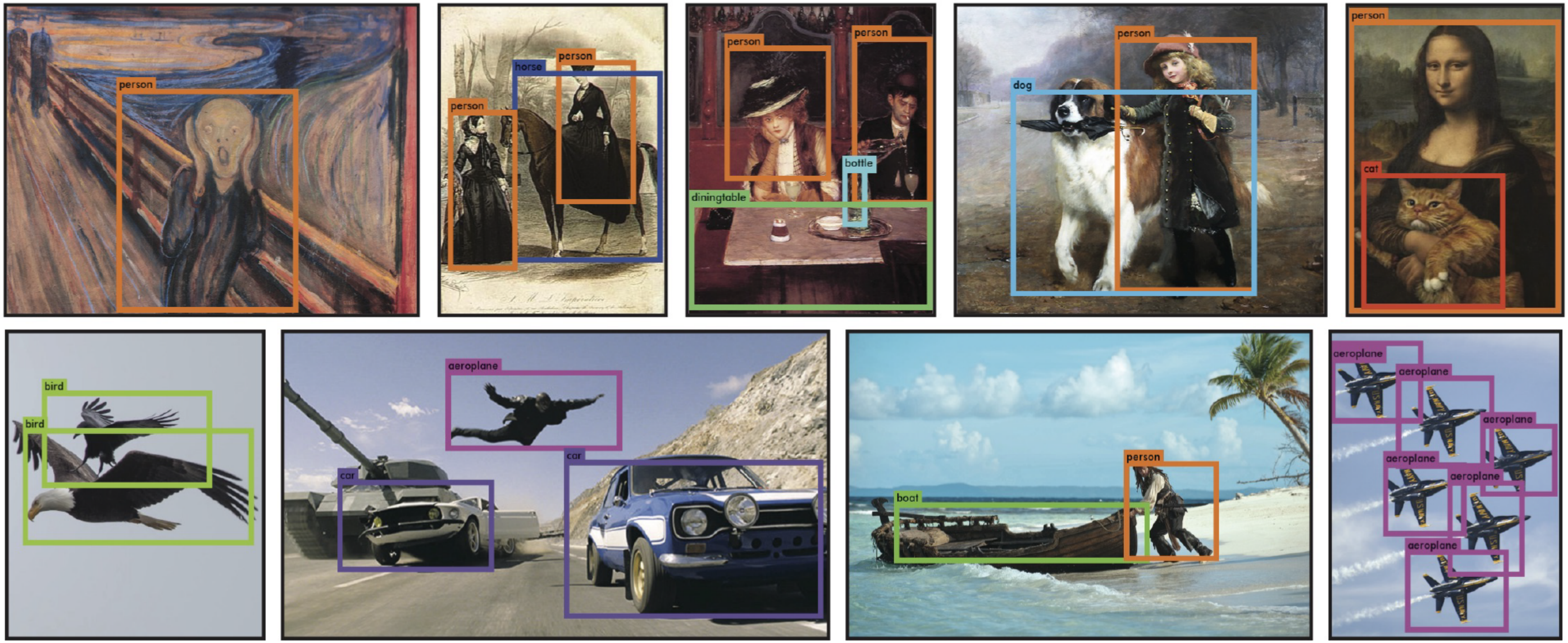
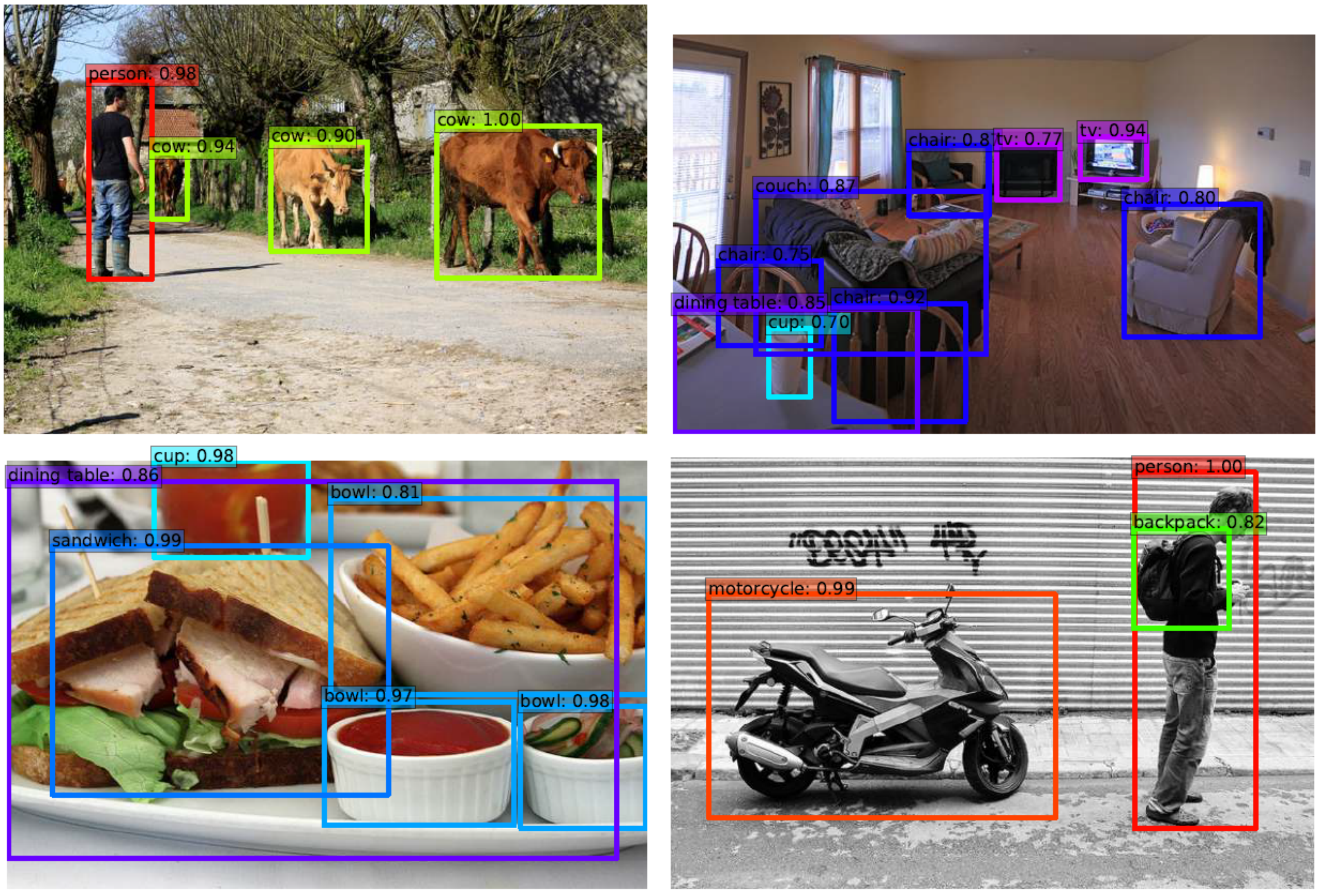


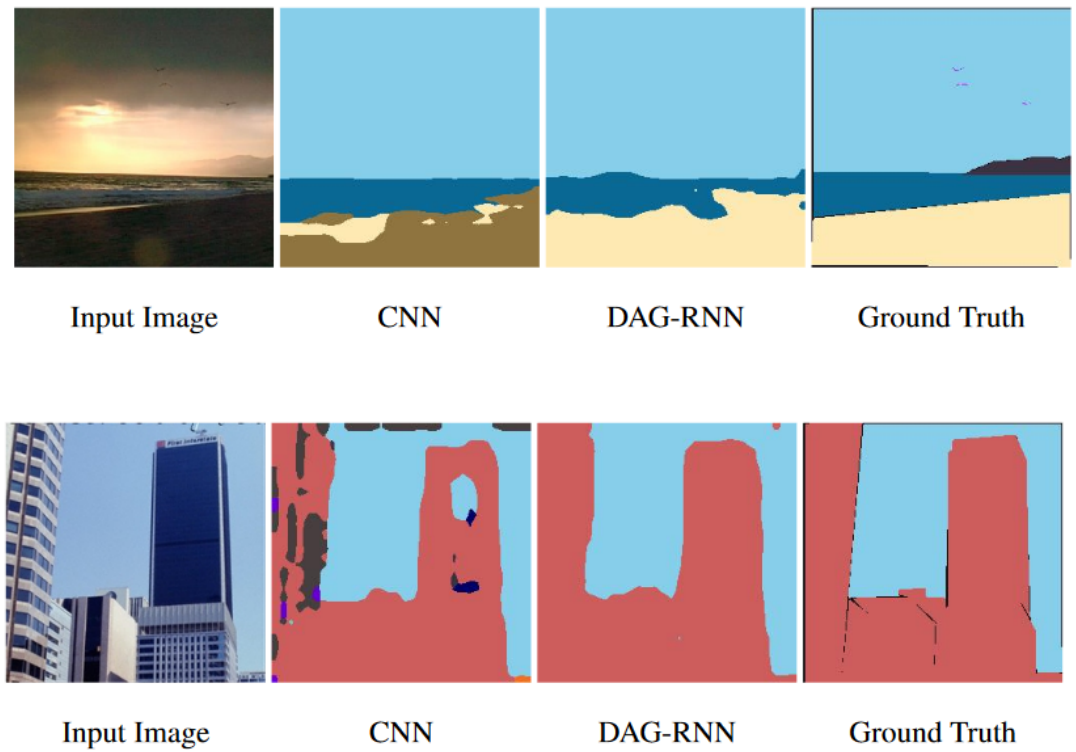

Figure: YOLO results

# SSD


person: 0.98
cow: 0.94
cow: 0.90
cow: 1.00
chair: 0.8
tv: 0.77
tv: 0.94
couch: 0.87
chair: 0.80
chair: 0.75
dining table: 0.85
chair: 0.92
cup: 0.70
cup: 0.98
dining table: 0.86
bowl: 0.81
sandwich: 0.99
bowl: 0.97
bowl: 0.98
person: 1.00
backpack: 0.82
motorcycle: 0.99

# Outline

# Scene labeling - DAG-RNN



# Outline

# Object tracking

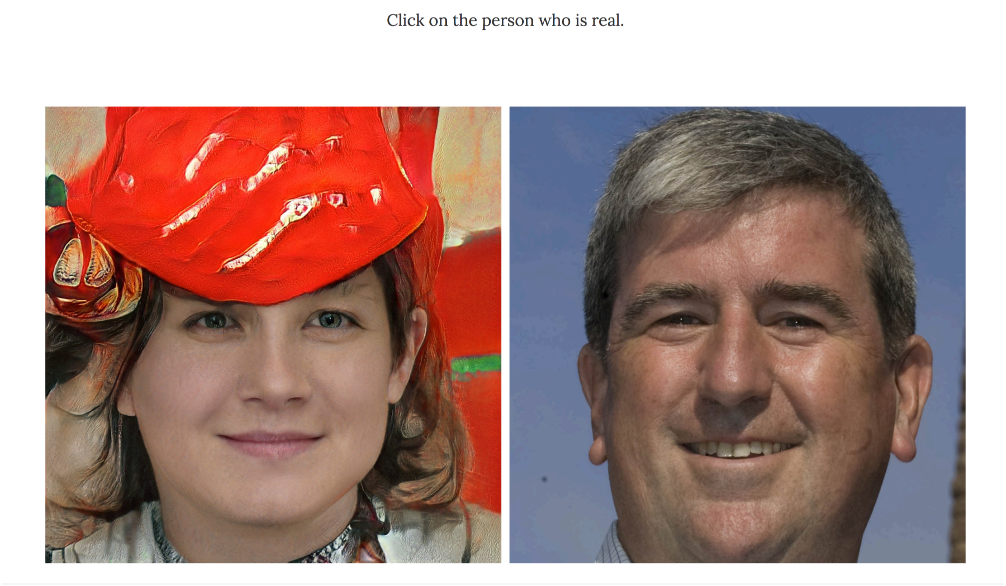
Object Detection in a video:

- YOLO `https://pjreddie.com/darknet/yolo/`
- YOLO - James Bond `https://www.youtube.com/watch?v=VOC3huqHrss`

# Deep Learning - Many many other applications !

1. Image and video (super-resolution, 3D, Image captioning), medical applications...
2. Self Driving cars (scene segmentation, etc.)
3. In NLP (language, text), automatic translation, voice recognition, text generation, next word completion ... (Virtual assistants)
4. Recommendation systems...
5. For time series, complex datasets too...

But also beyond the supervised settings: using adversarial networks (GANS) for generation of images, faces, voice, etc.




`http://www.whichfaceisreal.com/`

# Limits and problems

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Limits of Deep Learning:

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- Theory !
- Ethical and practical concerns !

# Deep Learning: failures

CNN are not always “robust" to adversarial attacks !

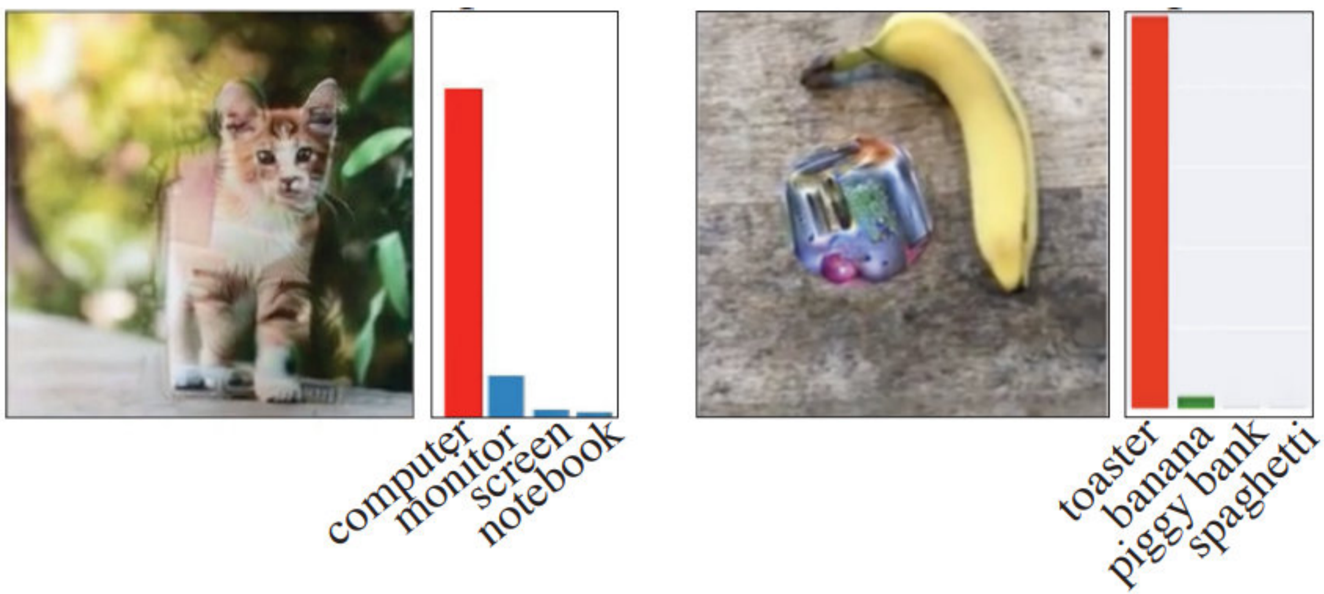


Figure: What happened here ??

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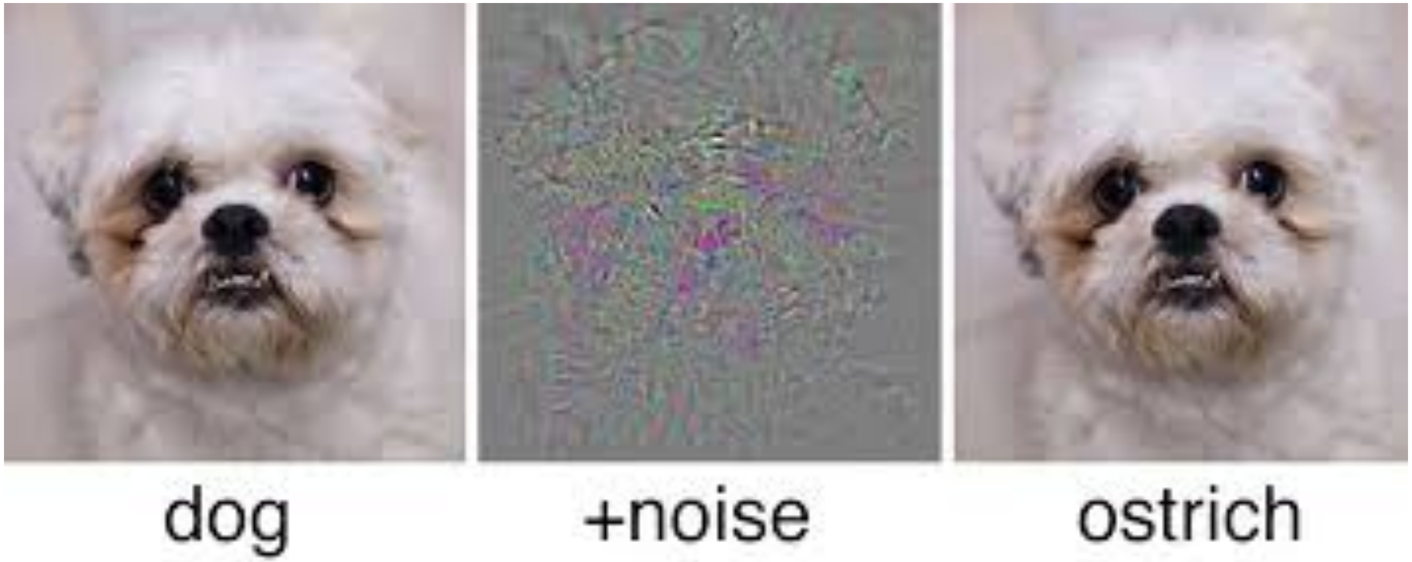


Adding a small well chosen noise can completely fool a CNN !
↬ Can we trust deep networks on cars, medical applications, planes...?

# Deep Learning: failures

There can be biases in Learning sets:

# Deep Learning: failures

There can be biases in Learning sets, or AI can be manipulated...

1. Chatbot becomes racist
2. Google apologises for Photos app's racist blunder

# Deep Learning: questionable applications

Are some applications just bad (they all already exist :( ) ?

- Deep Fakes: insert someone in a video.
- Underground exploration: finding new fossil resources.
- Voice imitation: what if I cannot check who is calling me.
- Military applications + automatic weapons.
- Mass surveillance.

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# Deep Learning: questionable applications

A challenging problem: chain of responsibility. The same tools are used for positive and negative applications, e.g.:

- mass surveillance
- tumor recognition

are both based on image recognition...
Good news ! the research community is very aware of the situation.
Some references:

- Asilomar AI Principles https://www.oecd.org/going-digital/ai-intelligent-machines-smart-policies/conference-agenda/ai-intelligent-machines-smart-policies-oheigeartaigh.pdf https://futureoflife.org/ai-principles/
- European guidelines https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai
- AI for Good https://ai4good.org/

# Conclusion: Deep Learning in one slide

- **How does it work:**
  - Automatically learn representations of observations
  - Learn highly non-linear models.
- **What does it require:**
  - Large datasets with structure
  - Computational power
- **Why now:**
  - Combination of the 2 points above
  - investment !
- **Some Applications**
  - Image classification; object / face recognition
  - Self driving cars
  - Automatic Translation, Information extraction
  - Caption Generation
  - Ads, recommendation systems, etc.

**Goals:** Understanding core concepts of Deep Learning.

- When and how it works on paper (data, models, architecture)
- How to implement a simple neural network with Python.
- Overview of some of the main applications and challenges.