SEMINAR PRESENTATION ON DEEP LEARNING

By:
Ishaya Jeremiah Ayock

ECOLE POLYTECHNIQUE DE THIES,SENEGAL

September 17, 2020

Outline

Differentiate Between a dog and a Cat

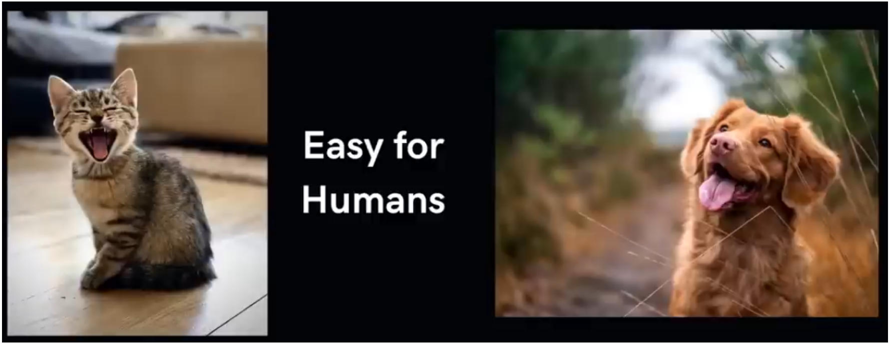

Figure: Cat and Dog

What is Deep Learning?

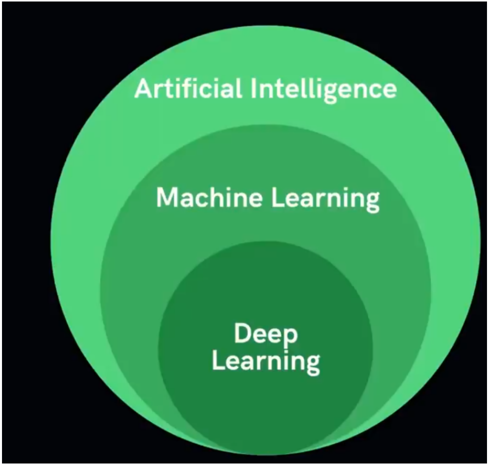

Figure: AI vs Deep learning vs Machine Learning.

Introduction

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Note

"Deep Learning does't do different things, **it does things differently**"

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Africa Digital Native

Sagesse Devoir
Ecole Polytechnique Thiès

Why Deep Learning Now?

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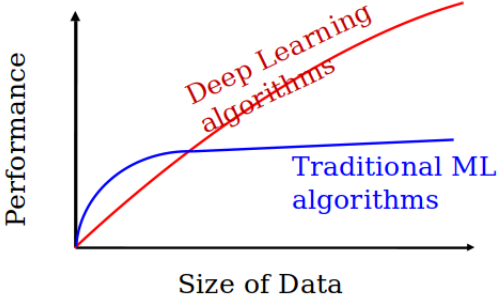
- New Software Architectures(tensor flow,PyTorch)

Deep Learning vs Traditional Algorithm



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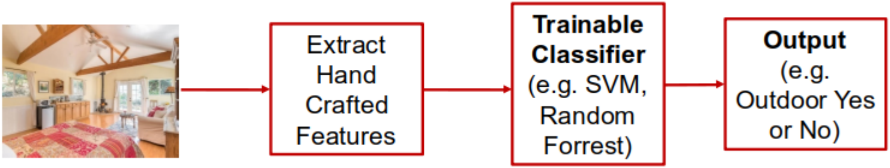

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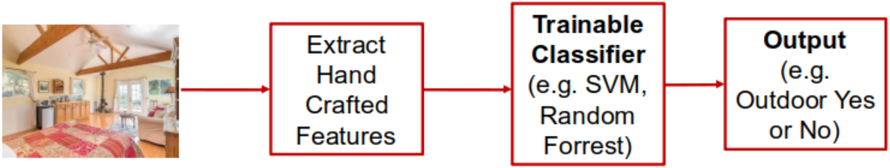

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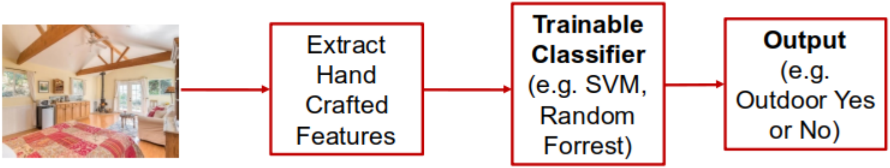

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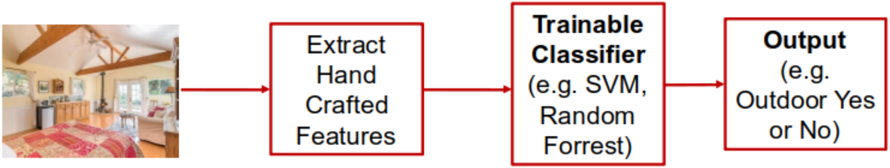

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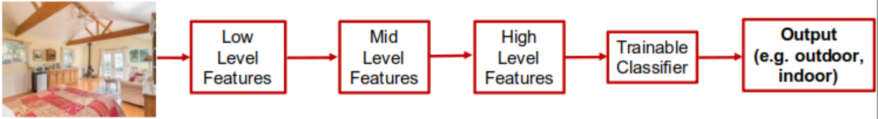

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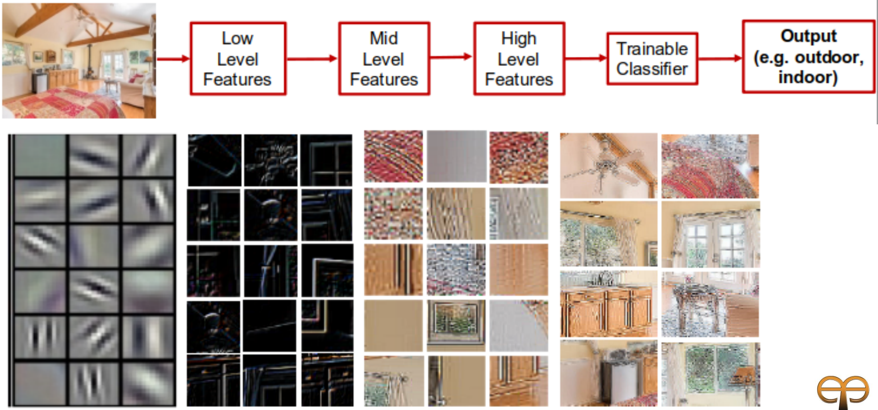

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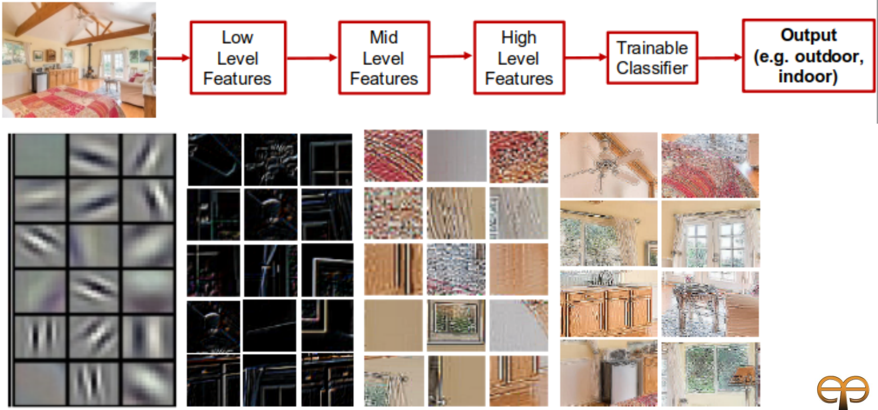

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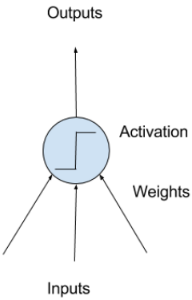

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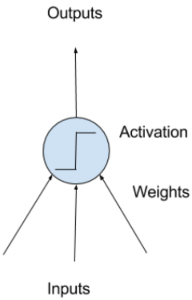

Figure: Model of a simple Neuron.

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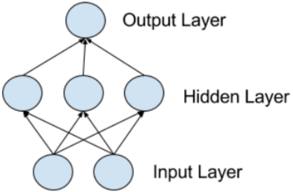
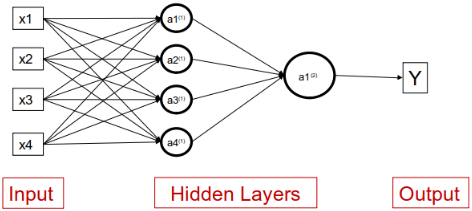
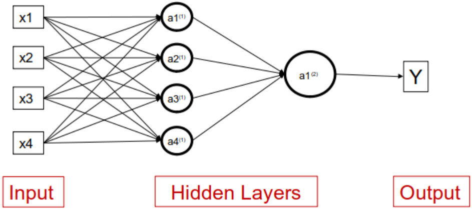


Figure: Model of a simple Network.


x1
x2
x3
x4
a1(1)
a2(1)
a3(1)
a4(1)
a1(2)
Y
Input
Hidden Layers
Output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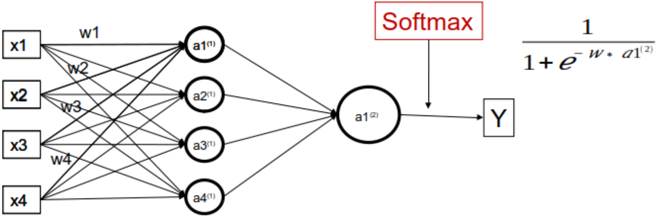
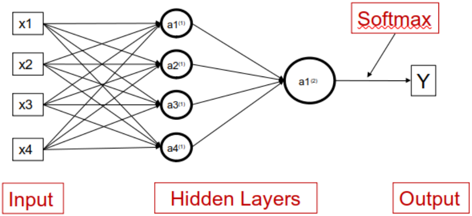


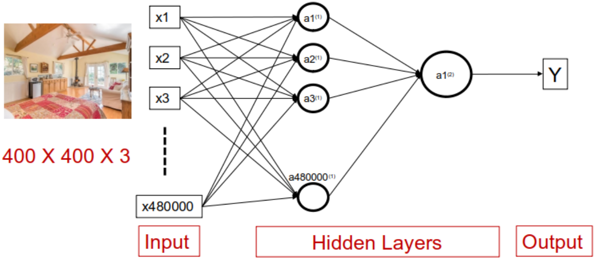
$$a_1^{(1)} = f(W_1 * X_1 + W_2 * X_2 + W_3 * X_3 + W_4 * X_4)$$

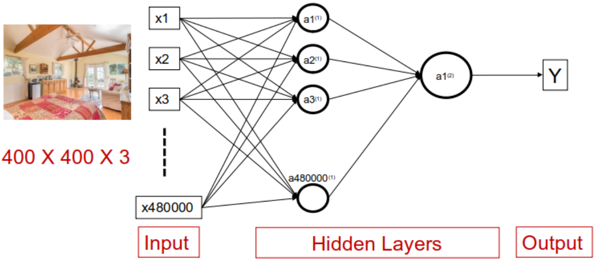
$$f()is\ activation\ function:\ Relu\ or\ Sigmoid\ Reu:\ max(0,x)$$

$$a_1^{(1)} = max(0, W_1 * X_1 + W_2 * X_2 + W_3 * X_3 + W_4 * X_4)$$


x1
x2
x3
x4
a1(1)
a2(1)
a3(1)
a4(1)
a1(2)
Softmax
Y
Input
Hidden Layers
Output

$$4*4 + 4 + 1$$


400 X 400 X 3
x1
x2
x3
x480000
a1(1)
a2(1)
a3(1)
a480000(1)
a1(2)
Y
Input
Hidden Layers
Output



No of Param $480000 * 480000 + 480000 + 1 =$ approximately 230 Billion !!!

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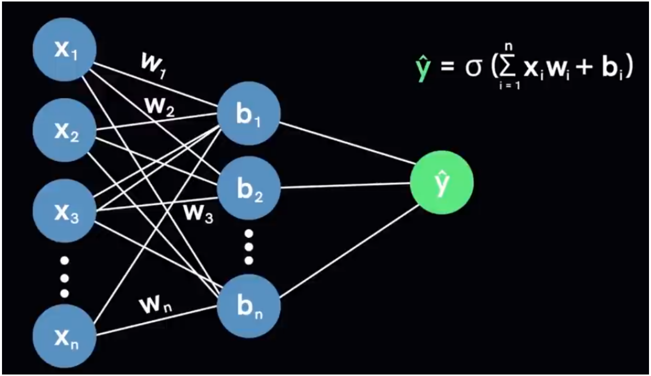

Figure: Forward propagation

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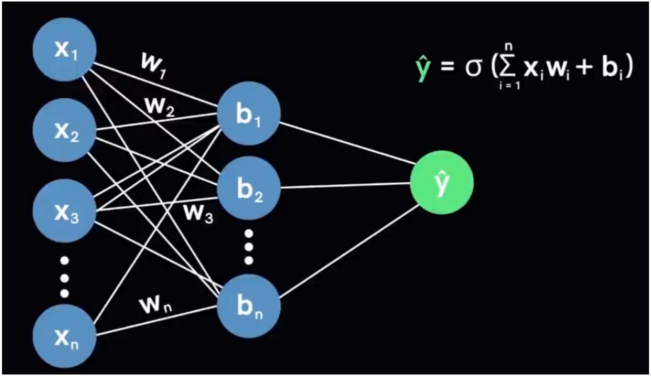

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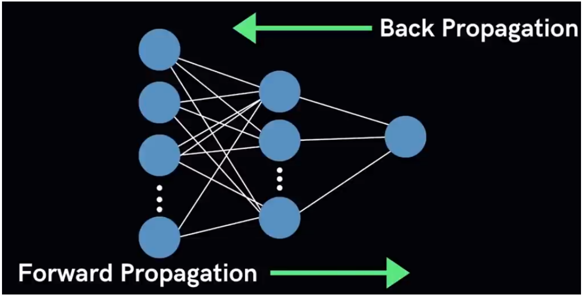

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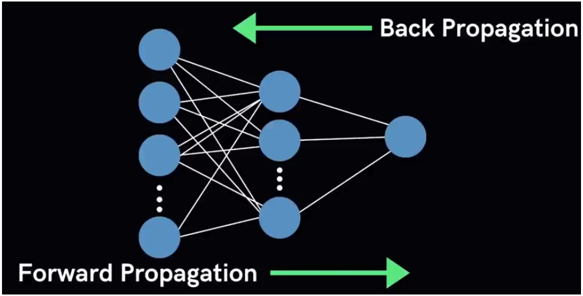

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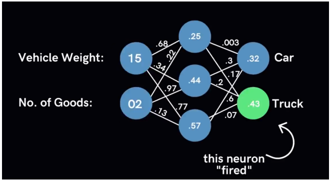

Figure: implementation

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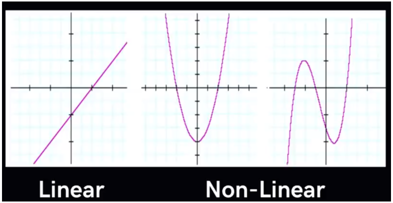

Figure: Linear and Non-linear function.

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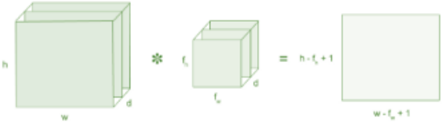

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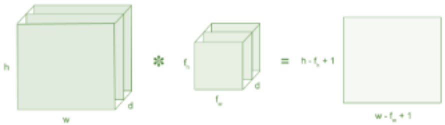

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Padding

Sometimes filter does not fit perfectly fit the input image. We have two options:

- Pad the picture with zeros (zero-padding) so that it fits.
- Drop the part of the image where the filter did not fit. This is called valid padding which keeps only valid part of the image.

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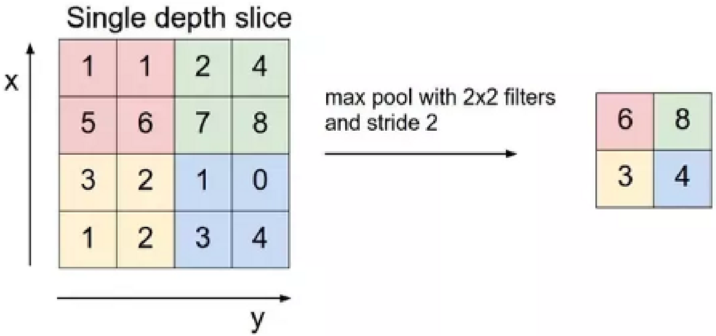

Figure: Max Pooling

Fully Connected Layers

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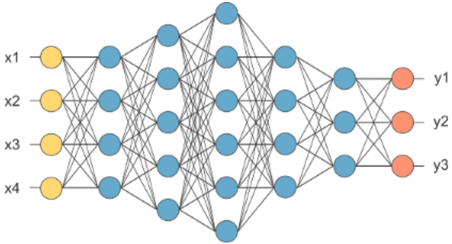

Figure: Fully connected layer

From the above figure, the feature map matrix will be converted as vector $(x1, x2, x3, \ldots)$. With the fully connected layers, we combined these features together to create a model. Finally, we have an activation function such as softmax or Sigmoid to classify the outputs as cat, dog, car, truck e.t.c.

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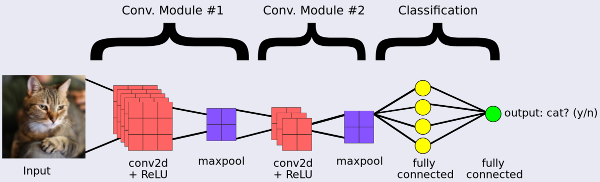

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Recommendations

- **Deep Learning** Ian Goodfellow, Yoshua Bengio, and Aaron Courville
- Grokking Deep Learning by Andrew W. Trask
- Deep Learning with Python by Francois Chollet

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Conclusion


THANK
YOU
GRACIAS
ARIGATO
SHUKURIA
DANKSCHEEN
TASHAKKUR ATU
SUKSAMA
GRAZIE
MEHRBANI
BİYAN
SHUKRIA
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