Artificial Intelligence: Deep Learning

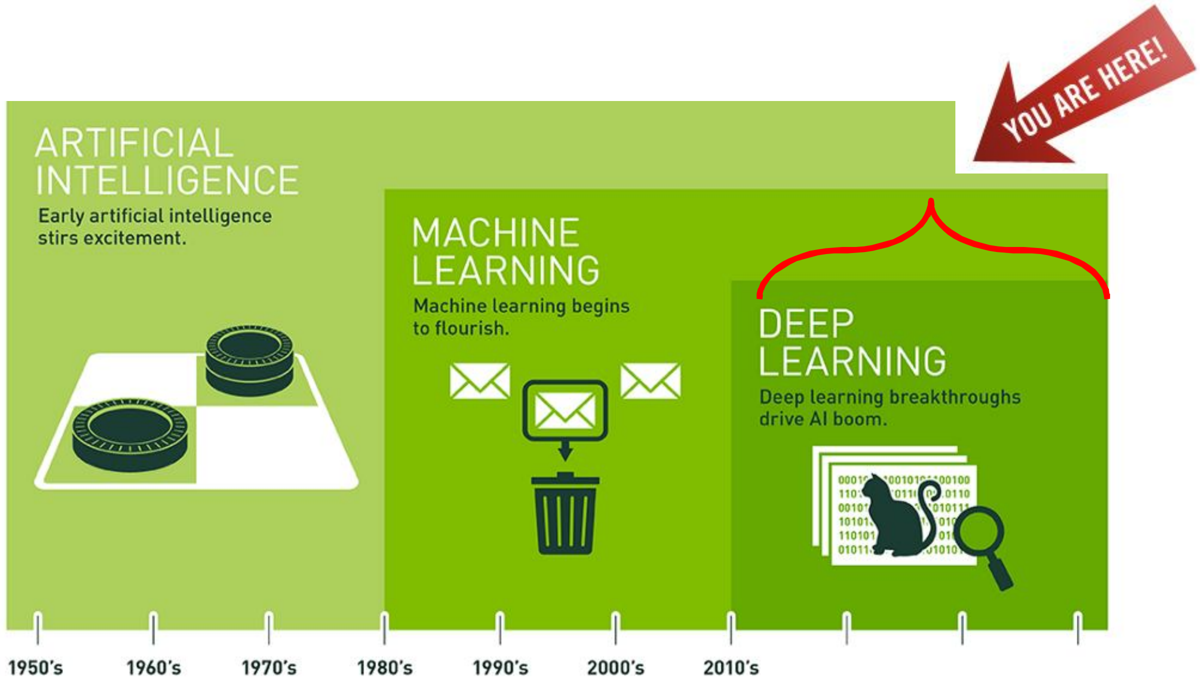
(too recent to be in the Russell & Norvig book)
many slides from: Y. Bengio, A. Ng and Y. LeCun

Today

1. Motivation 

2. Feature Learning
3. CNNs for Image Processing
4. Conclusion

History of AI

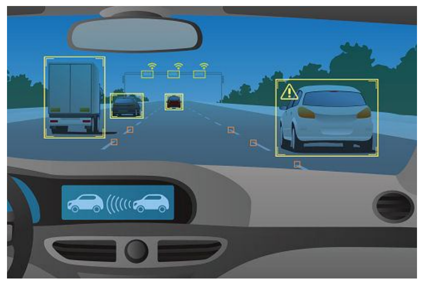


https://www.linkedin.com/pulse/goedels-incompleteness-theorem-emergence-ai-eberhard-schoeneburg/

Major Breakthroughs

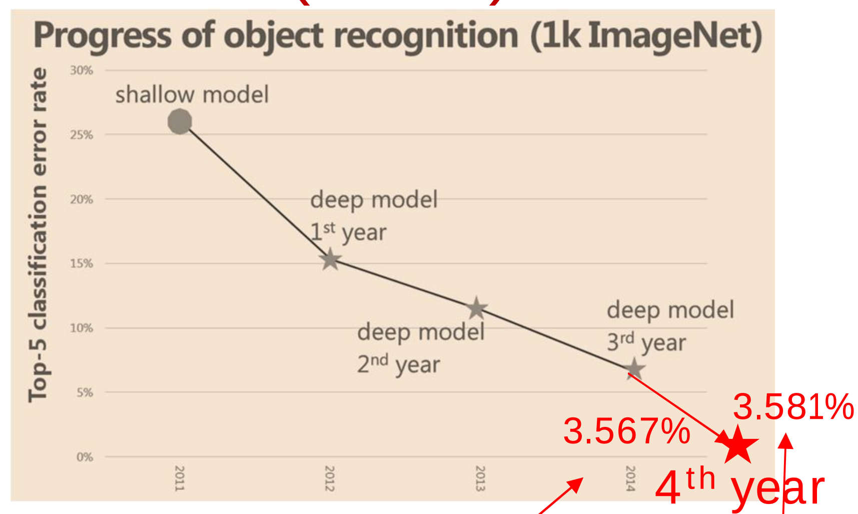
- Speech Recognition & Machine Translation (2010+)
- Image Recognition & Computer Vision (2012+)

Object recognition



Self driving cars

Google Photos



Microsoft Research Google

- Natural Language Processing (2014+)
- ...

Figure from Yoshua Bengio, 2015

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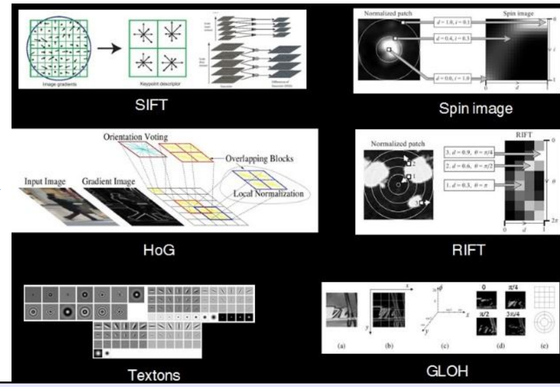
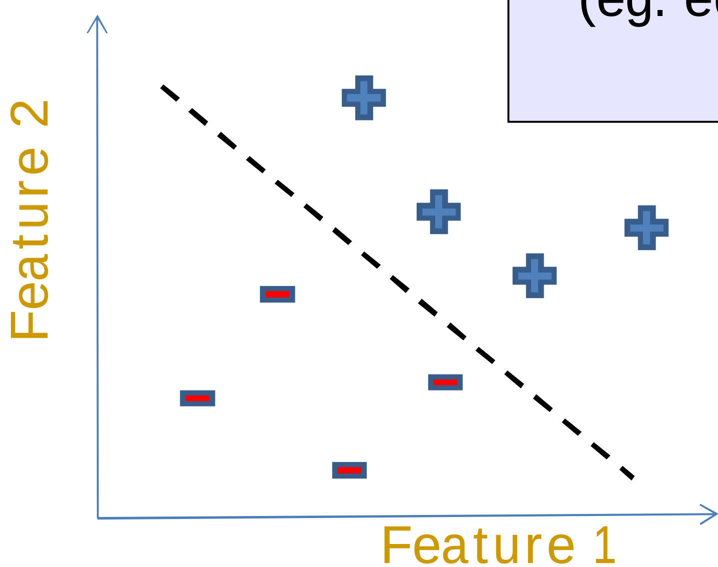
Classic ML

Input



Manual Extraction of Features
(eg. edge detection, colors, texture,...)

Learning algorithm



+ Motorbikes
– "Non"-Motorbikes

Classic ML, requires labeled data and hand-crafted features

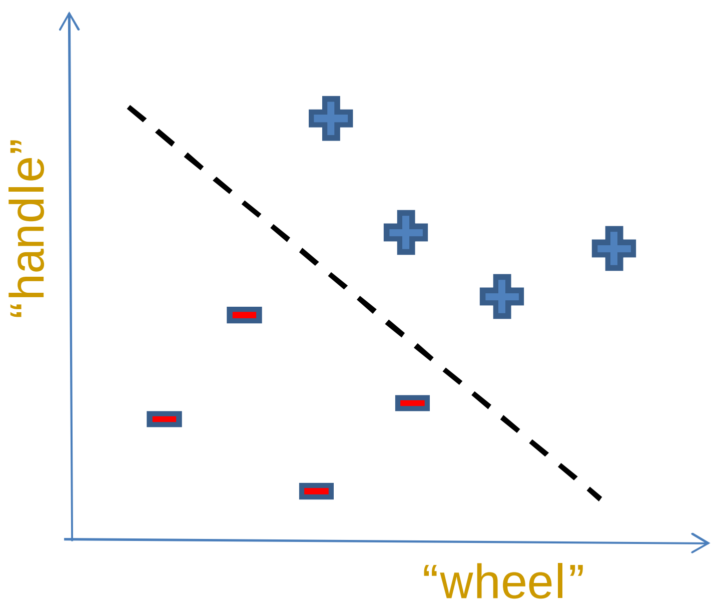
1. Needs expert knowledge
2. Time-consuming and expensive
3. Does not generalize to other domains

Automatic Feature Learning

Input

→ **Automatic Feature Representation** → **Learning algorithm**

eg. handle, wheel, ...



- Motorbikes
- "Non"-Motorbikes

With Automatic Feature Learning:

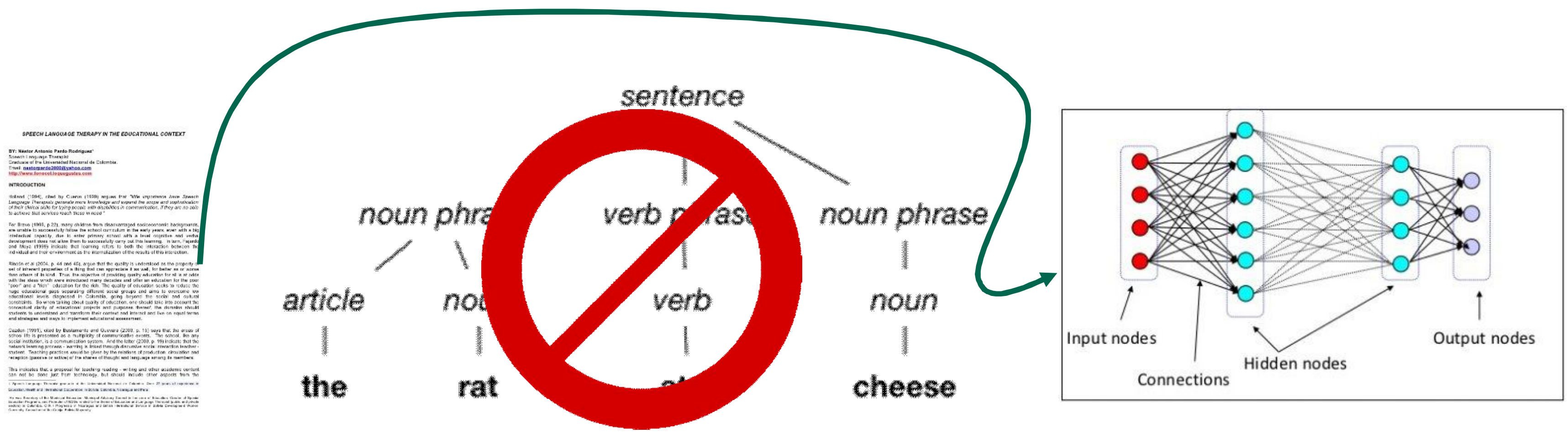
1. We feed the network the raw data (not feature-curated)

2. The features are learned by the network

3. Features learned can be re-used in similar tasks.

[redacted]

Advantages of Unsupervised Feature Learning



Automatic Feature Learning

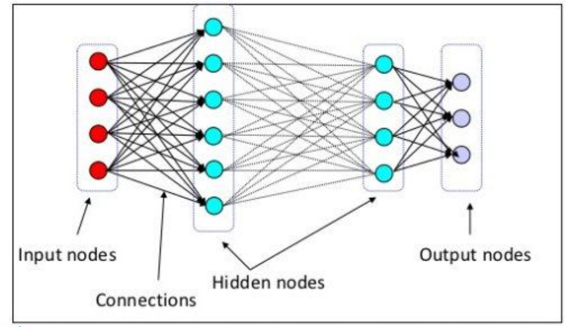
Deep Learning = Machine learning algorithms based on learning multiple levels of representation / abstraction.
– Y. Bengio

- Each layer learns more abstract features that are then combined / composed into higher-level features automatically

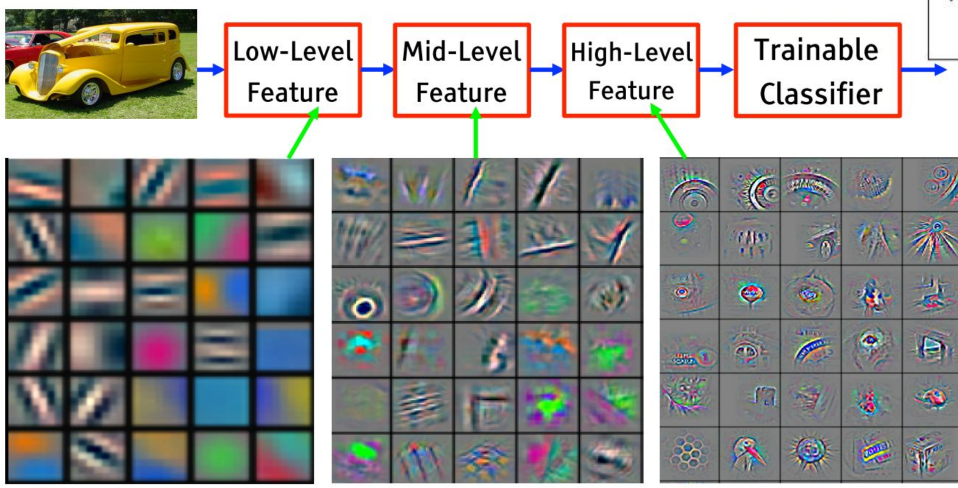
- Like the human brain …
  - has many layers of neurons which act as feature detectors
  - detecting more and more abstract features as you go up

- E.g. to classify an image of a cat:
  - Bottom Layers: Edge detectors, curves, corners straight lines
  - Middle Layers: Fur patterns, eyes, ears
  - Higher Layers: Body, head, legs
  - Top Layer: Cat or Dog

What Types of Features?



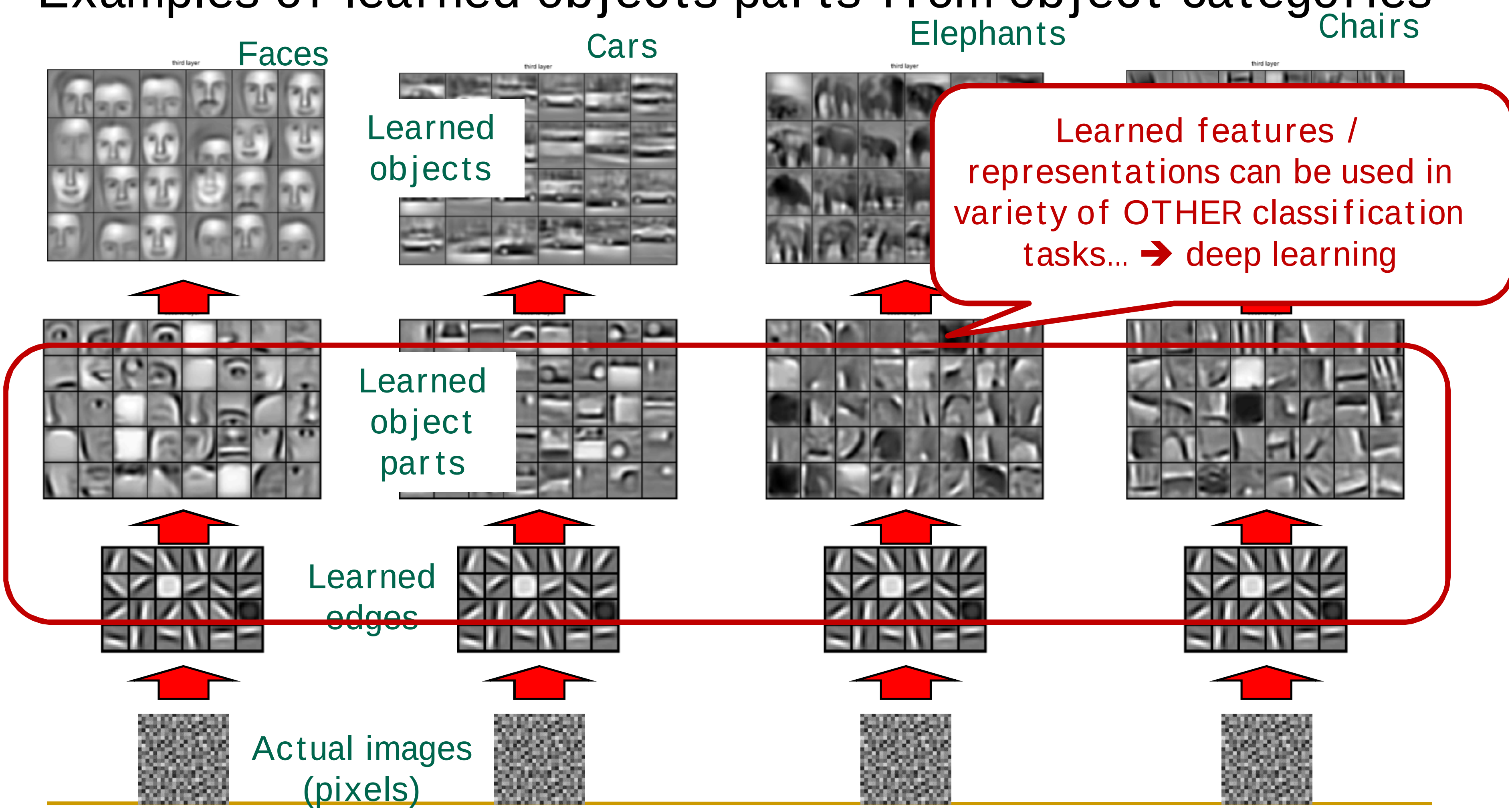
- For image recognition
  - pixel -> edge -> texton -> motif -> part -> object



- For NLP
  - character -> word -> constituents -> clause -> sentence -> discourse
- For speech:
  - sample ->spectral band -> sound -> ... phone -> phoneme -> word

Eg: Learning Image Features

Examples of learned objects parts from object categories



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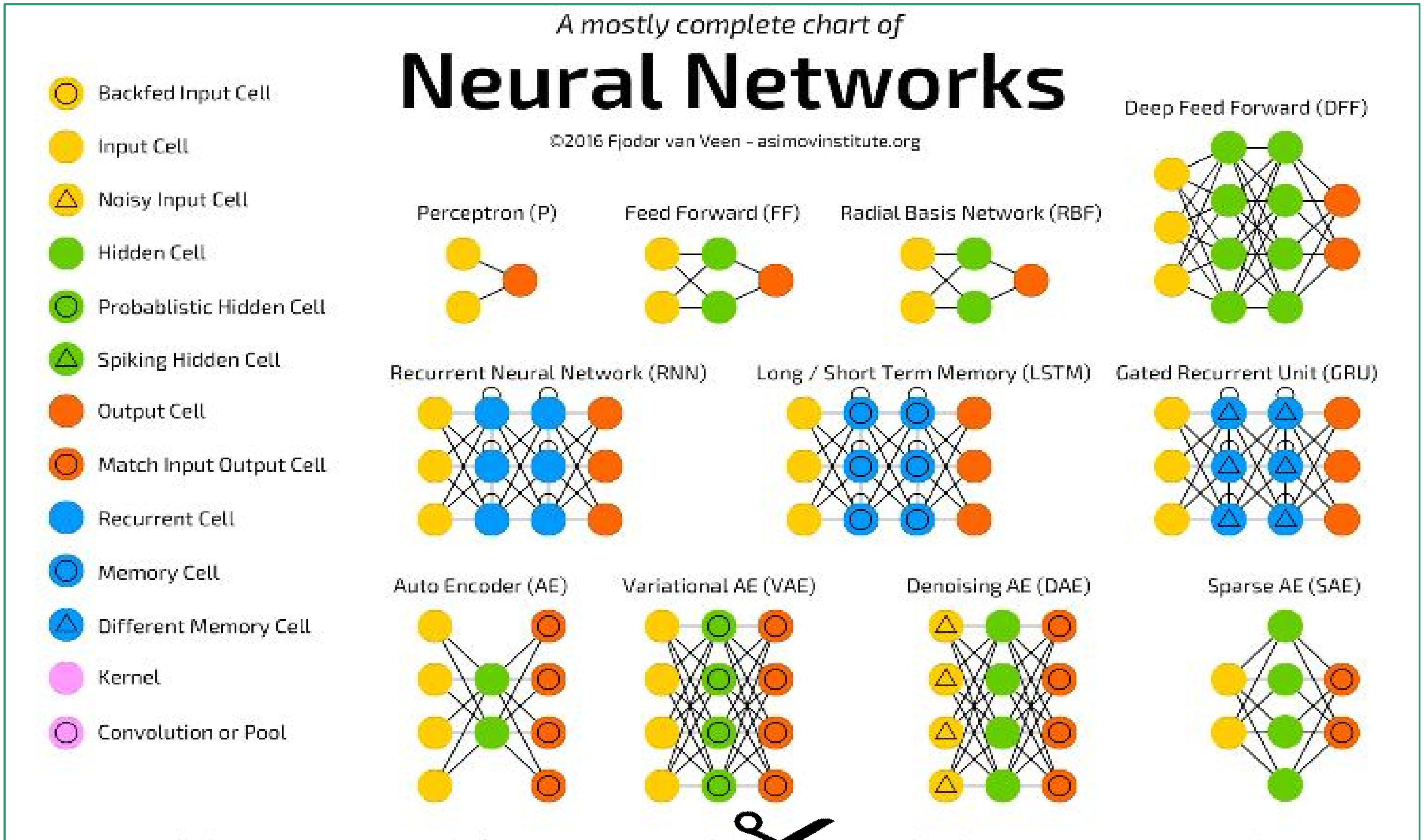
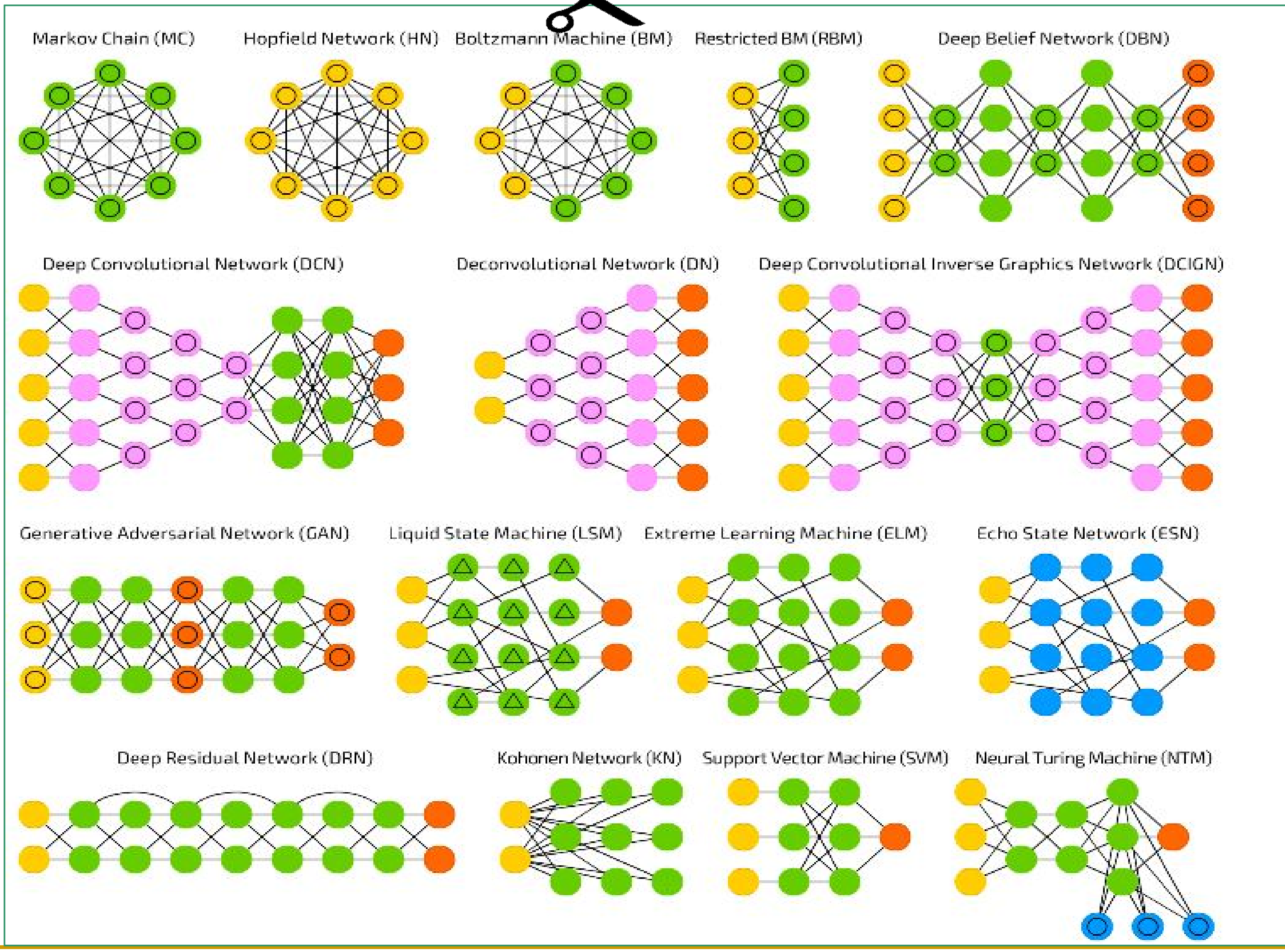
Many Types of Neural Networks



https://becominghuman.ai/cheat-sheets-for-ai-neural-networks-machine-learning-deep-learning-big-data-678c51b4b463

Many Types of Deep Networks (con't)



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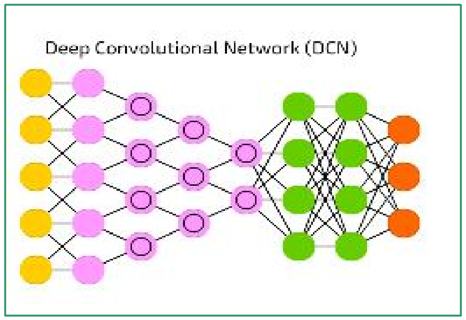
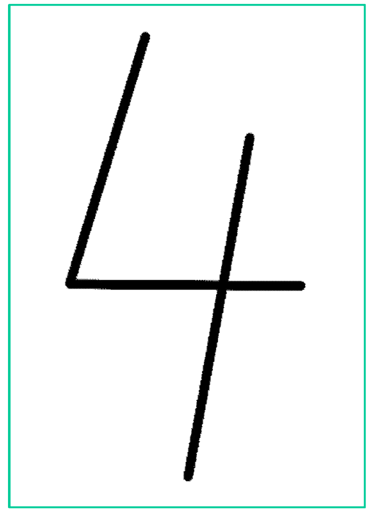
CNNs for Image Processing

CNNs = Convolutional Neural Networks





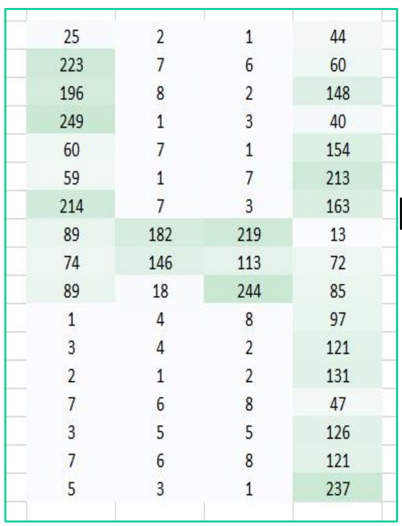
25	2	1	44
223	7	6	60
196	8	2	148
249	1	3	40
60	7	1	154
59	1	7	213
214	7	3	163
89	182	219	13
74	146	113	72
89	18	244	85
1	4	8	97
3	4	2	121
2	1	2	131
7	6	8	47
3	5	5	126
7	6	8	121
5	3	1	237

Image of a 4 in grey scale
Value = 0-> white .... 255->black

https://www.analyticsvidhya.com/blog/2017/06/architecture-of-convolutional-neural-networks-simplified-demystified/

CNNs for Image Processing

- Standard input of the image in the ANN:
  1. 1 pixel = 1 input.
  2. Eg. color image of 200x200x 3channels (RGB)
     --> in a fully connected ANN, a neuron of the input layer has 200*200*3 = 120,000 weights
     --> huge number of parameters, can easily overfit
  2. We linearize the image ==> We lose spatial information



25	2	1	44
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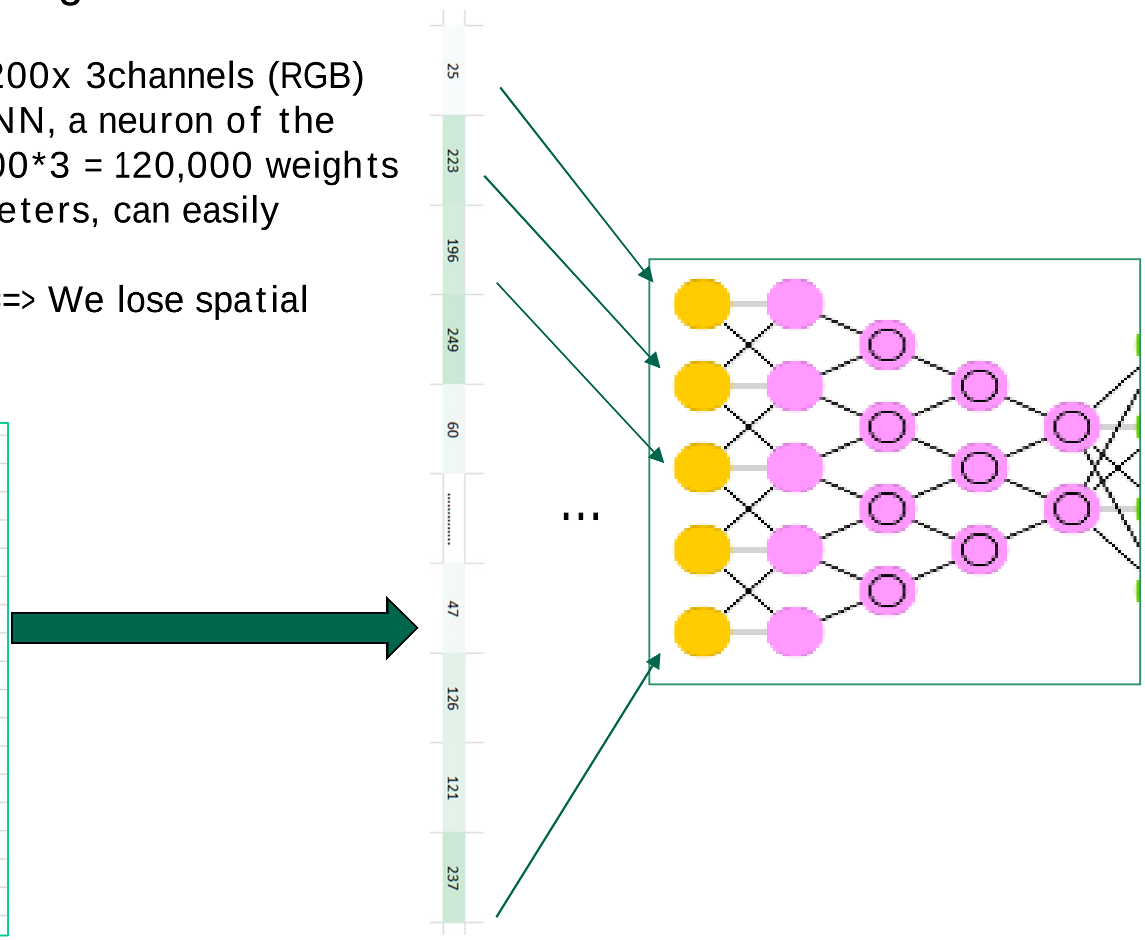

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Convolutional Layer

- Use a filter (aka kernel) that "convolves" on the image
- Filter = small weight matrix to learn

86	4	8	184
252	3	8	40
34	7	7	163
105	2	3	69
56	3	8	175
126	1	2	178
163	8	4	142
22	222	74	180
163	158	204	253

I (original image)

1	0.3
0.5	2

W (filter)

219.2	23.9	147.2
283.9	22.9	349.5
92.6	16.1	195.4
139.6	20.4	377.7
121.9	9.9	417.5
223.8	13.6	341.4
620.4	268.2	443.6
486.1	731.2	736

C (activation map)

$$C_{11} = (I_{11} \times W_{11}) + (I_{12} \times W_{12}) + (I_{21} \times W_{21}) + (I_{22} \times W_{22})$$
$$= 86 \times 1 + 4 \times 0.3 + 252 \times 0.5 + 3 \times 2 = 219.2$$

Convolutional Layer

- Use a filter (aka kernel) that “convolves” on the image
- Filter = small weight matrix to learn

86	4	8	184
252	3	8	40
34	7	7	163
105	2	3	69
56	3	8	175
126	1	2	178
163	8	4	142
22	222	74	180
163	158	204	253

I (original image)

1	0.3
0.5	2

W (filter)

219.2	23.9	147.2
283.9	22.9	349.5
92.6	16.1	195.4
139.6	20.4	377.7
121.9	9.9	417.5
223.8	13.6	341.4
620.4	268.2	443.6
486.1	731.2	736

C (activation map)

$$C_{12} = (I_{12} \times W_{11}) + (I_{13} \times W_{12}) + (I_{22} \times W_{21}) + (I_{23} \times W_{22})$$
$$= 252 \times 1 + 3 \times 0.3 + 34 \times 0.5 + 7 \times 2 = 283.9$$

Convolutional Layer

- Use a filter (aka kernel) that “convolves” on the image
- Filter = small weight matrix to learn

86	4	8	184
252	3	8	40
34	7	7	163
105	2	3	69
56	3	8	175
126	1	2	178
163	8	4	142
22	222	74	180
163	158	204	253

I (original image)

1	0.3
0.5	2

W (filter)

219.2	23.9	147.2
283.9	22.9	349.5
92.6	16.1	195.4
139.6	20.4	377.7
121.9	9.9	417.5
223.8	13.6	341.4
620.4	268.2	443.6
486.1	731.2	736

C (activation map)

$$C_{13} = (I_{13} \times W_{11}) + (I_{14} \times W_{12}) + (I_{23} \times W_{21}) + (I_{24} \times W_{22})$$
$$= 34 \times 1 + 7 \times 0.3 + 105 \times 0.5 + 2 \times 2 = 92.6$$

Convolutional Layer

- Use a filter (aka kernel) that “convolves” on the image
- Filter = small weight matrix to learn

86	4	8	184
252	3	8	40
34	7	7	163
105	2	3	69
56	3	8	175
126	1	2	178
163	8	4	142
22	222	74	180
163	158	204	253

I (original image)

1	0.3
0.5	2

W (filter)

219.2	23.9	147.2
283.9	22.9	349.5
92.6	16.1	195.4
139.6	20.4	377.7
121.9	9.9	417.5
223.8	13.6	341.4
620.4	268.2	443.6
486.1	731.2	736

C (activation map)

$$
\begin{aligned}
C_{38} &= (I_{37} \times W_{11}) + (I_{47} \times W_{12}) + (I_{38} \times W_{21}) + (I_{37} \times W_{22}) \\
&= 74 \times 1 + 180 \times 0.3 + 204 \times 0.5 + 253 \times 2 = 736
\end{aligned}
$$

Learn the Filters

18	54	51	239	244	188
55	121	75	78	95	88
35	24	204	113	109	221
3	154	104	235	25	130
15	253	225	159	78	233
68	85	180	214	245	0

$I\ (6\times 6)$

1	0	1
0	1	0
1	0	1

$W\ (3\times 3)$

429	505	686	856
261	792	412	640
633	653	851	751
608	913	713	657

$C\ (4\times 4)$

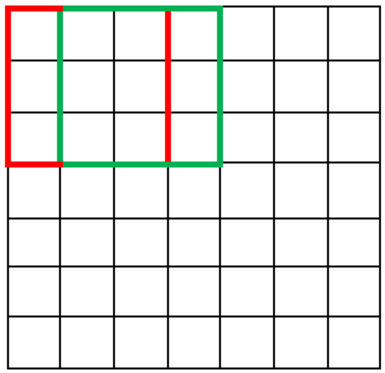
- The weight matrix (filter/kernel) behaves like a filter
- The network learns the values of the filter(s) that activate when they "see" some visual feature that is useful to identify the object (the final classification)
  - Ex. a horizontal line, a blotch of some color, a circle…

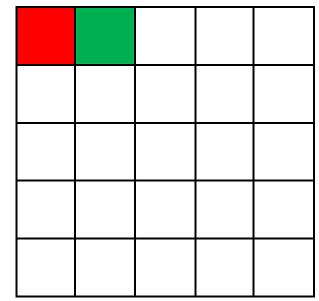
https://www.analyticsvidhya.com/blog/2017/06/architecture-of-convolutional-neural-networks-simplified-demystified/

Convolution Hyper-parameters

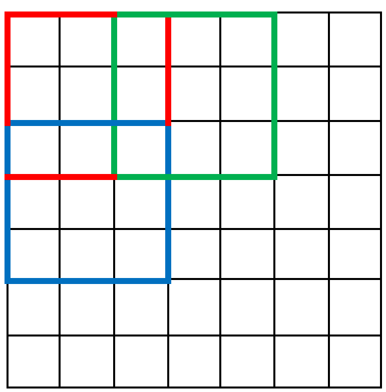
1. Stride
2. Padding

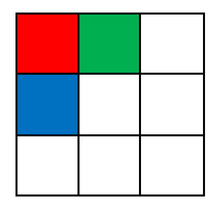
Stride





I (7×7) W (3×3) with stride =1 C (5×5)





I (7×7) W (3×3) with stride =2 C (3×3)

Padding

9	0	0	1
1	0	1	0
0	1	1	2
2	1	0	1

0	0	0
0	1	0
0	0	0

0	1
1	1

9 not picked up ;-(

filter should pick up high values surrounded by low values

0	0	0	0	0	0
0	9	0	0	1	0
0	1	0	1	0	0
0	0	1	1	2	0
0	2	1	0	1	0
0	0	0	0	0	0

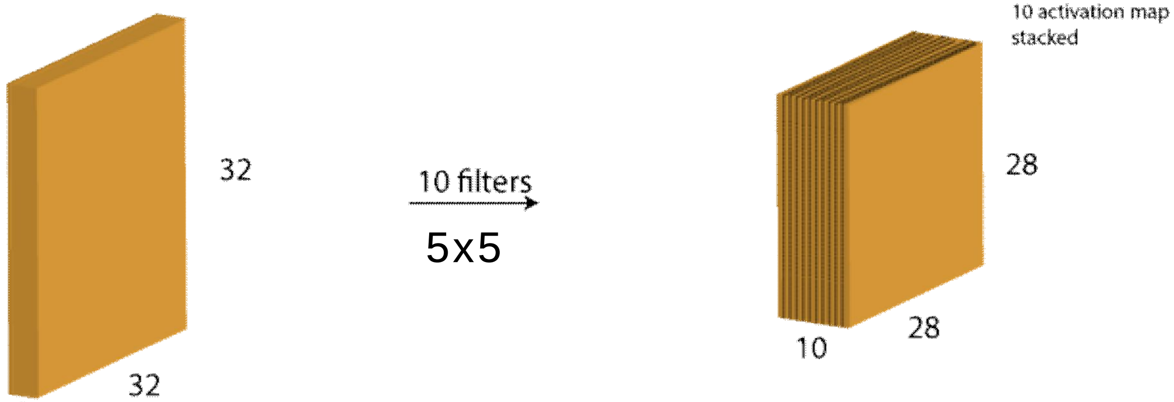
0	0	0
0	1	0
0	0	0

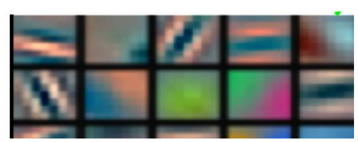
9	0	0	1
1	0	1	0
0	1	1	2
2	1	0	1

9 picked up ;-)

Learn Several Filters

- So we create 1 activation map per filter





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Pooling Layer

- Used to:
  - To reduce the size of the activation maps
  - So that we reduce the number of parameters of the network and hence avoid overfitting.
- Several strategies:
  - Max pooling

429	505	686	856
261	792	412	640
633	653	851	751
608	913	713	657

792	856
913	851

  - Average pooling

429	505	686	856
261	792	412	640
633	653	851	751
608	913	713	657

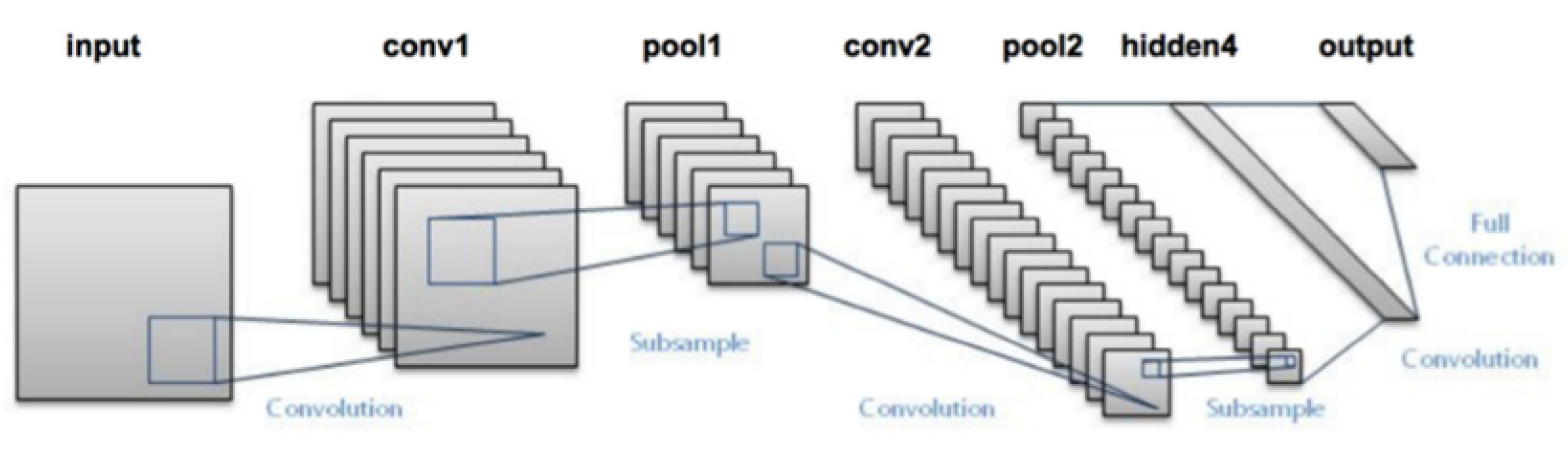
496.8	648.5
701.8	743

  - ...

https://www.analyticsvidhya.com/blog/2017/06/architecture-of-convolutional-neural-networks-simplified-demystified/

Architecture of a CNN

- Stack:
  - Convolutional Layers
  - Pooling Layers
- Finish off with:
  - A fully connected layer at the end for the final classification



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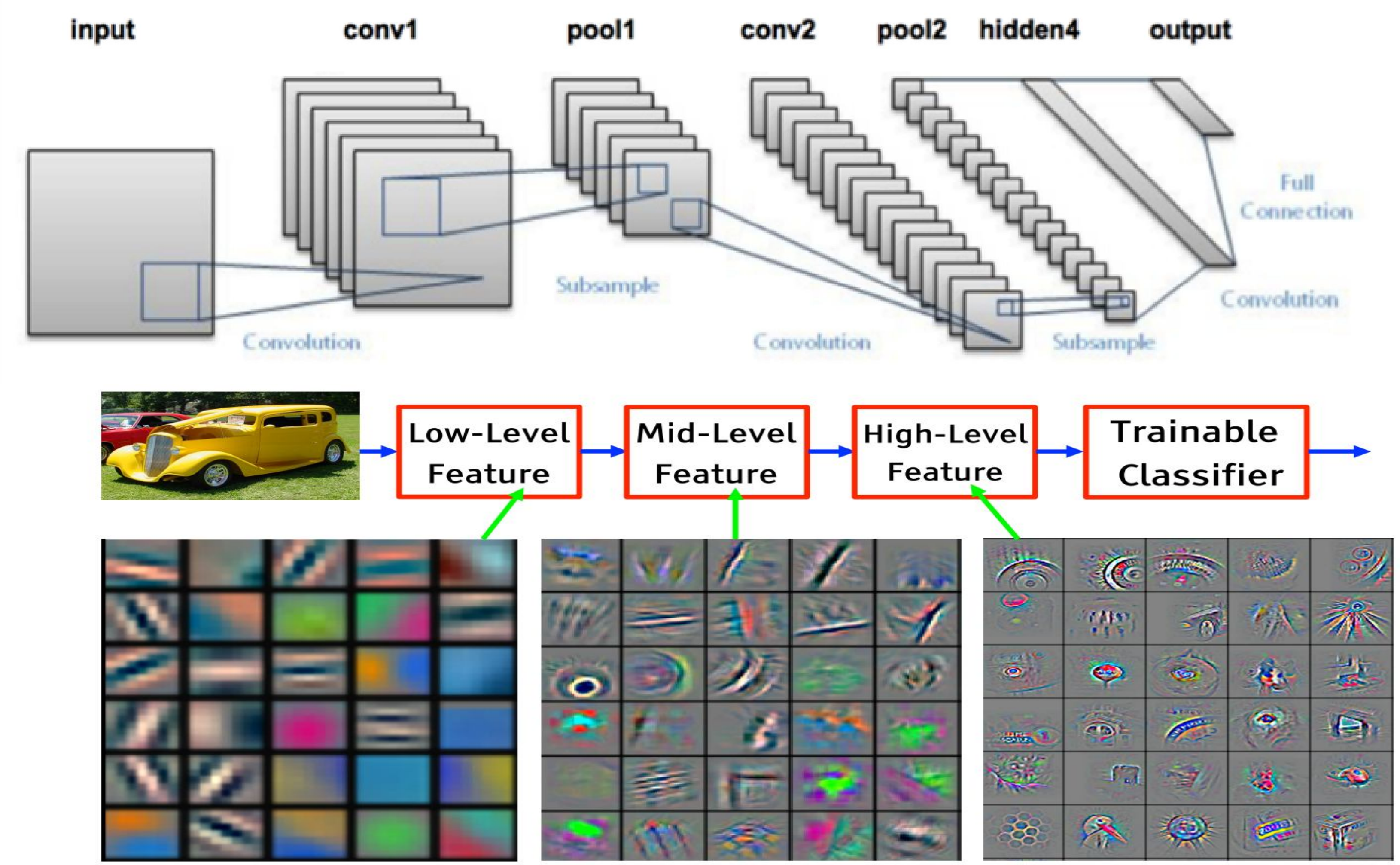
Learning a Hierarchy of Features



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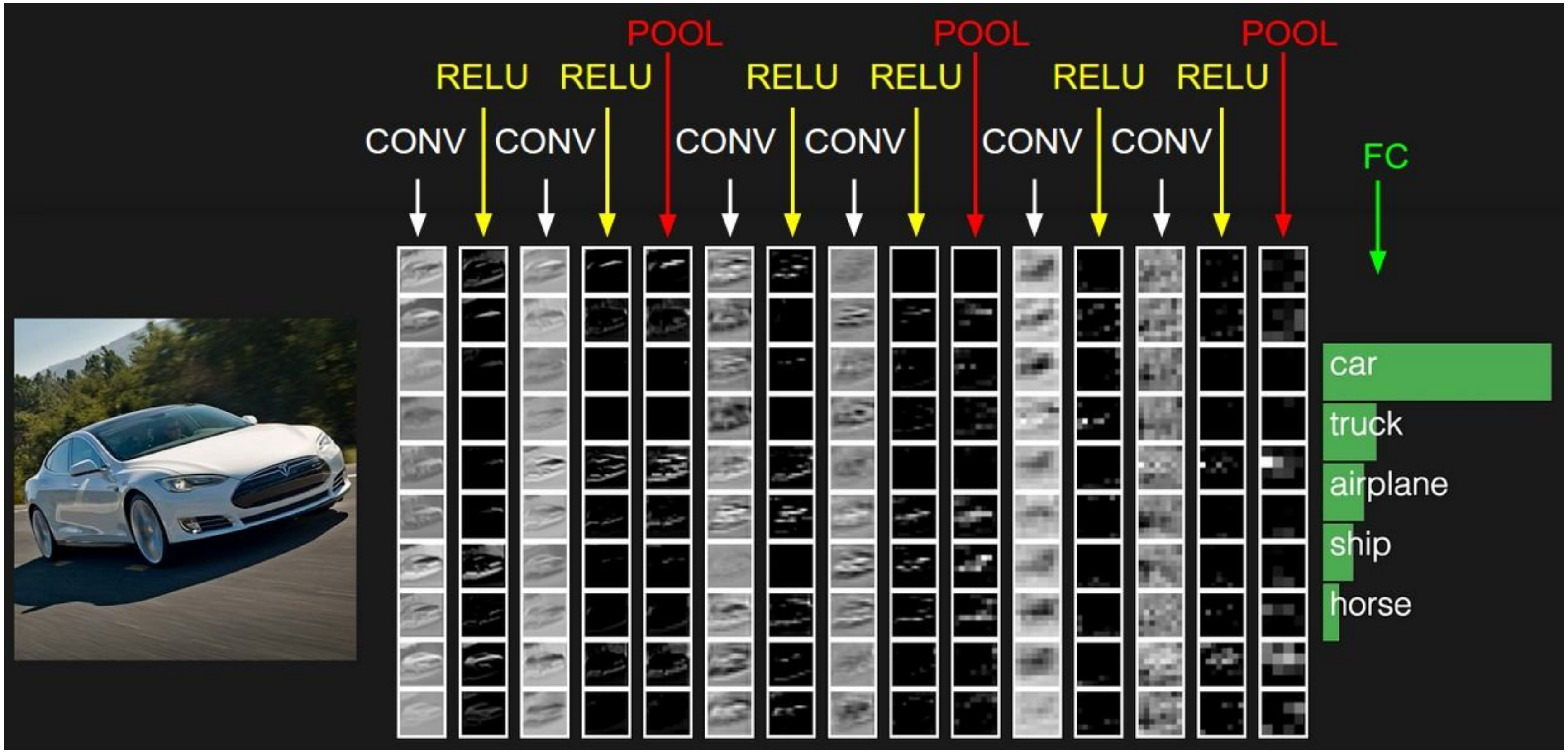
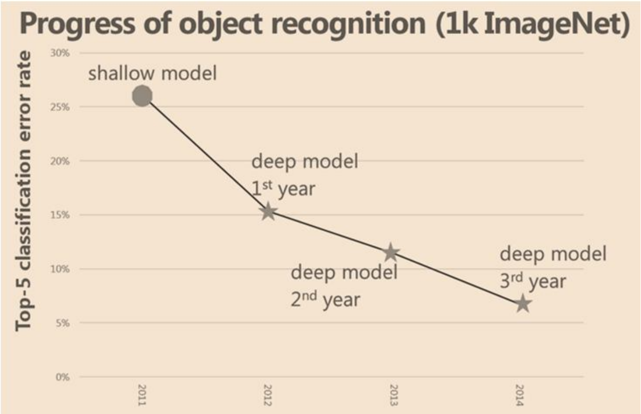
Example of a CNN



http://cs231n.github.io/convolutional-networks/

Successful CNN Networks

- LeNet
  - First successful applications of CNNs
  - Developed by Yann LeCun in the 1990's
  - used to read zip codes, digits, etc.
- AlexNet
  - First work that popularized CNNs for computer vision
  - developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton (U. of Toronto)
  - In 2012 significantly outperformed all teams at the ImageNet ILSVRC challenge



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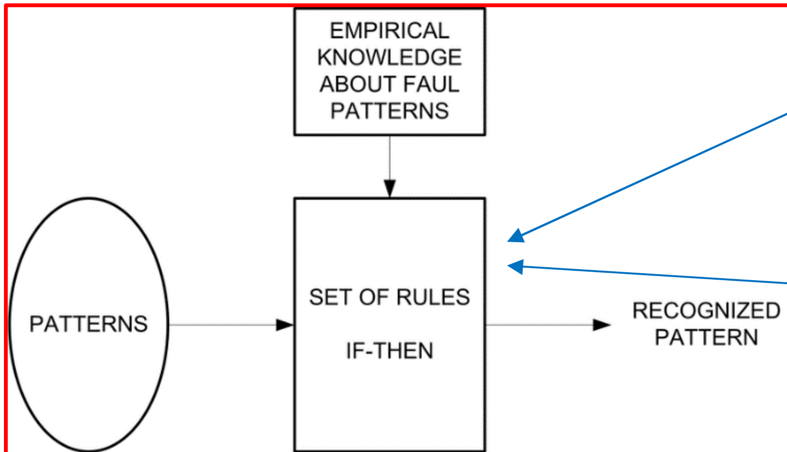
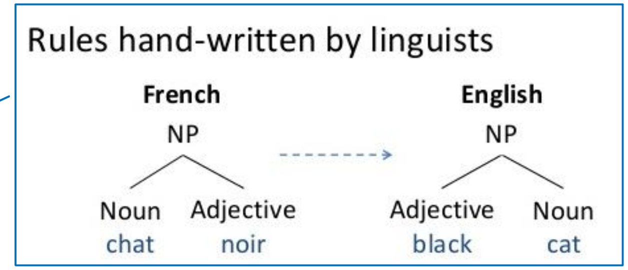
Why now?

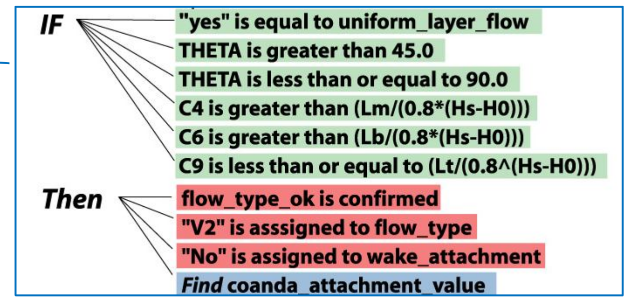
1. Basic science
   - Backpropagation did not work / overfitting…
   - *now*: developed method for training, better activation functions, better architectures….
   - Need for lots training data…
   - *now*: we have massive amounts + unsupervised pre-training
2. GPU computing
   - Neural networks are very very long to train… (days, weeks)
   - *now:* use of GPU's which are optimized for very fast matrix multiplication
3. Open Access to resources
   - *now* : Access to DL methods, code and frameworks
   - *now* : Fast turnaround from idea to implementation

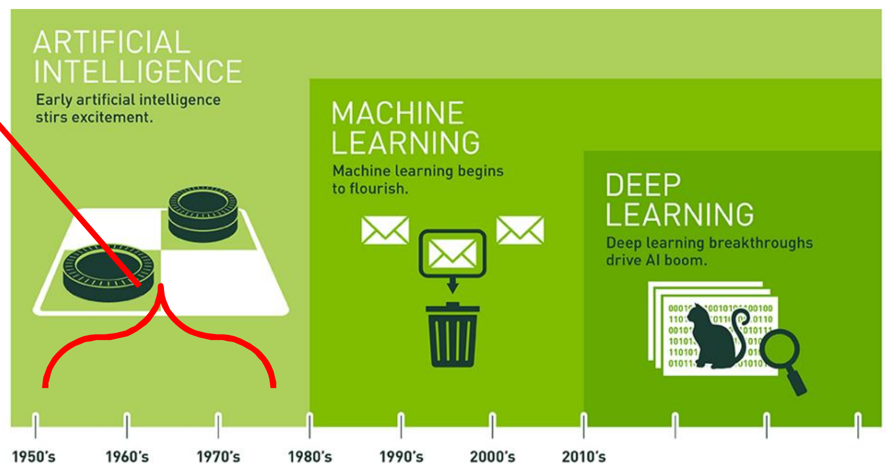
History of AI

Rules written by experts
(eg. linguistics, medical doctors,...)





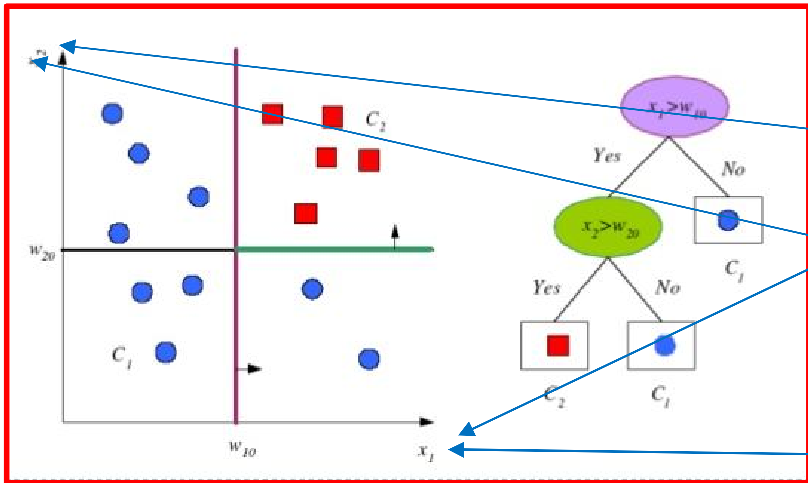


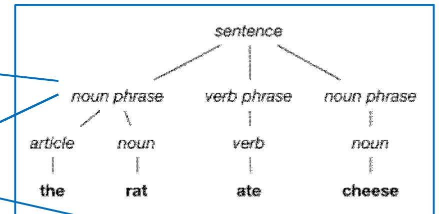


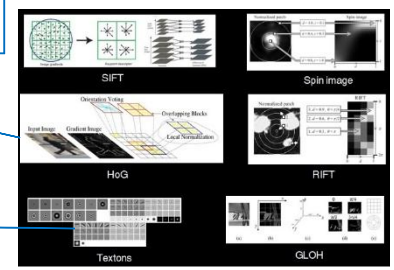
https://www.researchgate.net/profile/Dubravko_Miljkovic/publication/268239364/figure/fig30/AS:394719407427587@147111
http://www.cormix.info/images/RuleTreeExample.jpg

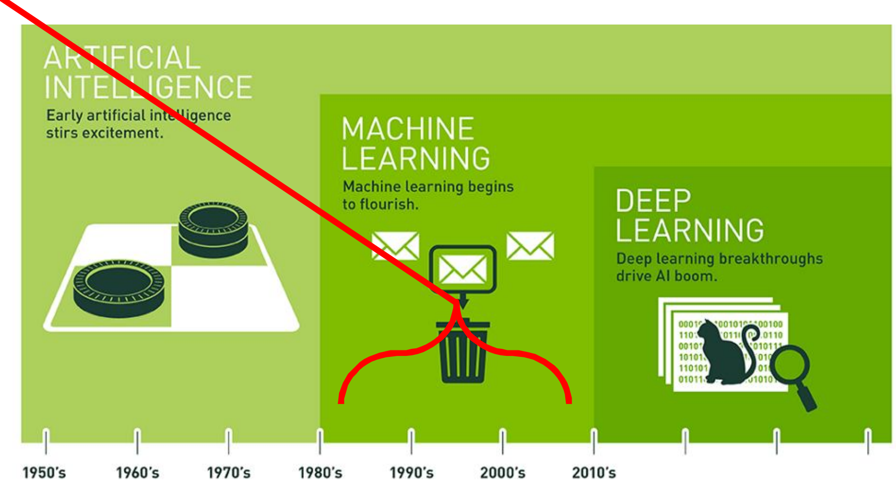
History of A I

Rules learns via the data ;-)
But: features identified by the experts
(eg. linguistics, medical doctors,...)



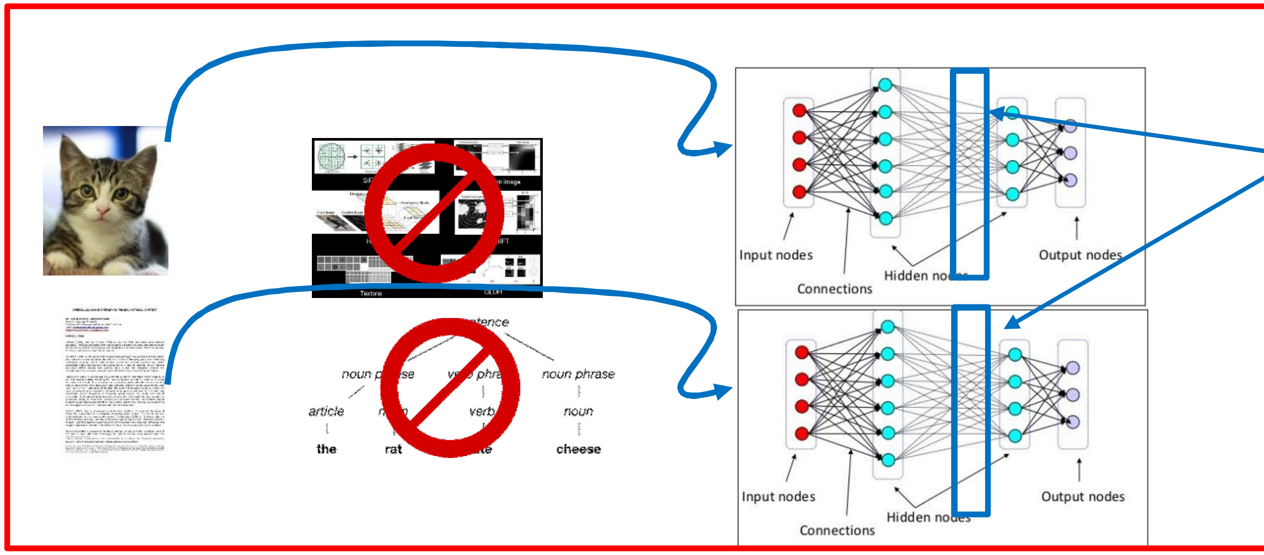




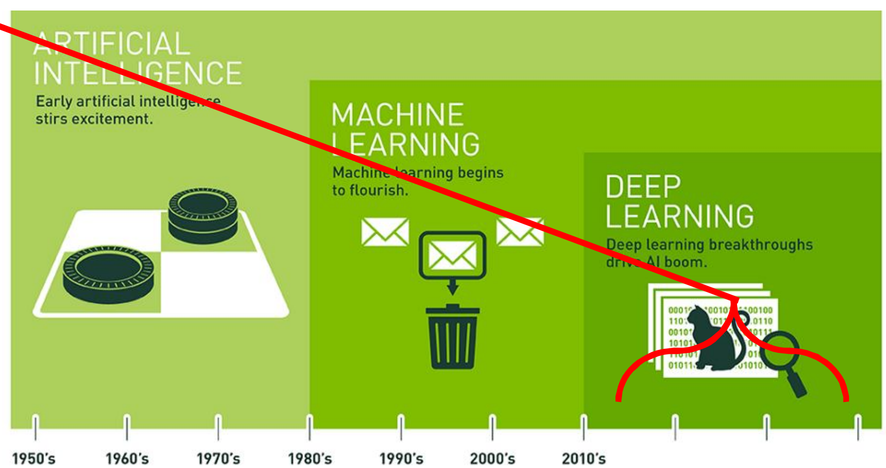


https://www.linkedin.com/pulse/goedels-incompleteness-theorem-emergence-ai-eberhard-schoeneburg/

History of A I



Rules AND features learned from the data



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Conclusion

- Deep Learning is thriving !
  - *vision*
  - *image processing*
  - *speech recognition*
  - *natural language processing*
  - *...*
- Canada is a world leader in Deep Learning
  1. Montreal: (Bengio et al.) [MILA]
  2. Toronto: (Hinton et al.) [Vector Institute]
  3. Edmonton: (Sutton et al.) [AMII]