

Neural networks

Architectures and training tips

Sebastian Björkqvist

IPRally Technologies

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What is a neural network?



Modified from <http://www.texample.net/tikz/examples/neural-network/>

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$$o_i = f(\sum w_{ki} o_{ki-1} + b_i).$$

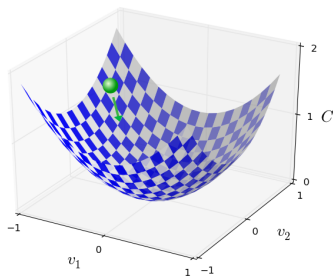
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The function f is called the activation function. It must be non-linear to allow the network to learn non-linear dependencies.

Training neural networks using SGD



[Nielsen, 2015], Chapter 1.

The training data is processed in small batches, and the weights of the model are iteratively updated by going in the direction of the negative gradient of the loss function.

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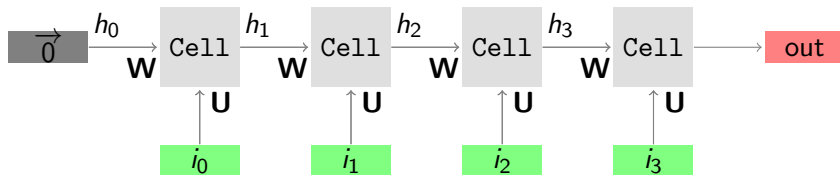
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- May learn to respond to unexpected patterns
- Useful especially when the amount of data is large compared to input dimensionality
- Less need for feature engineering compared to traditional ML methods

Recurrent neural network (RNN)



Processes each element of the input sequence in order, and keeps information about the past elements in a hidden state vector.

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At each timestep t the new hidden state is calculated using the new input at this timestep and the existing hidden state. The most basic version is the following:

$$h_t = \sigma(Wh_{t-1} + Ui_t + b).$$

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Other RNN architectures (for instance LSTM or GRU) use more complicated ways of updating the hidden state to control the flow of information to and from the hidden state.

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 - The model may not remember early inputs and can be biased toward the end of the sequence

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 - The model is trained by using millions of real-life positive and negative novelty citations from previous patent applications
 - Patents with a positive citation get vectors that are close to each other
- 3 A prior art search for a new patent can then be done by searching for the nearest neighbors of the vector created from the new invention

RNN real life use case: Patent search

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US patent no. 7 908 981

table

worktop

legs

telescope pipe

motor

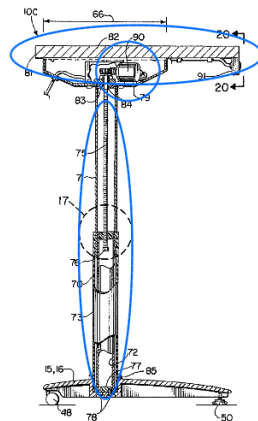


FIG. 16

Convolutional neural network (CNN)

Feed-forward networks do not scale well to images due to the large input size. Convolutional neural networks are constrained to looking only at a small part of the image at a time, and thus the number of weights stays manageable.

A CNN uses three types of layers: convolutional, pooling and fully connected.

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- The idea is that each filter learns to identify some kind of feature (for instance part of a shape)

CNN - Convolutional layer

0	0	0	0	0
0	1	1	1	0
0	1	0	1	0
0	1	1	1	0
0	0	0	0	0

CNN - Convolutional layer

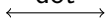
0	0	0	0	0
0	1	1	1	0
0	1	0	1	0
0	1	1	1	0
0	0	0	0	0

1	1
1	0

CNN - Convolutional layer

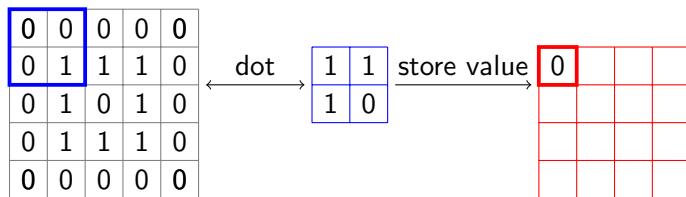
0	0	0	0	0
0	1	1	1	0
0	1	0	1	0
0	1	1	1	0
0	0	0	0	0

dot

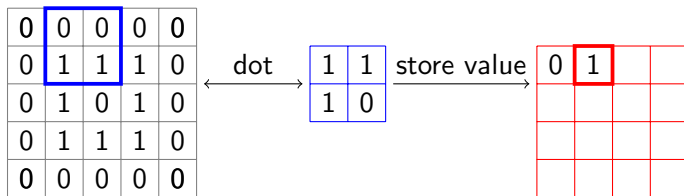


1	1
1	0

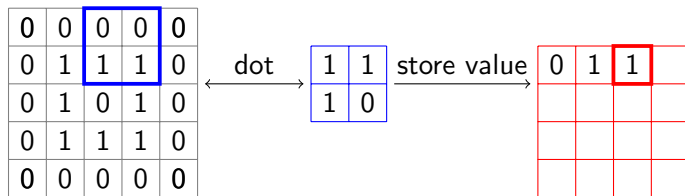
CNN - Convolutional layer



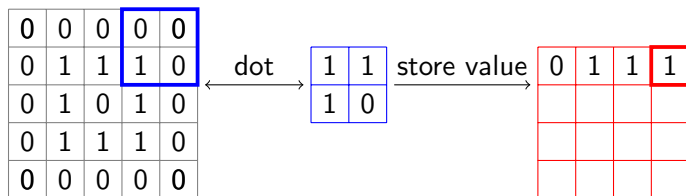
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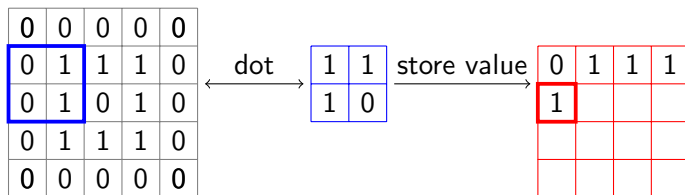
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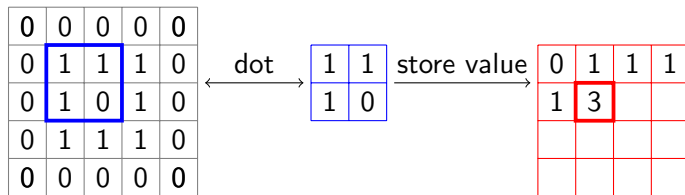
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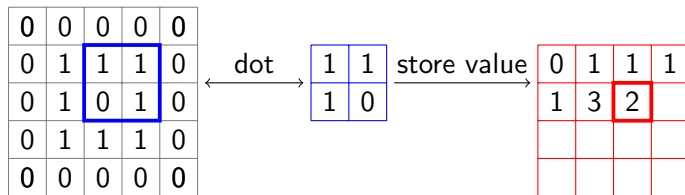
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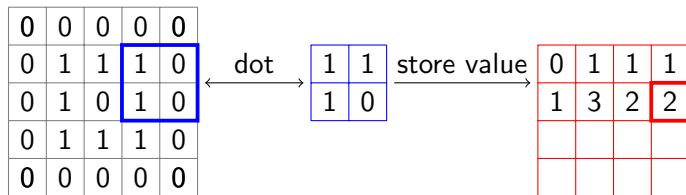
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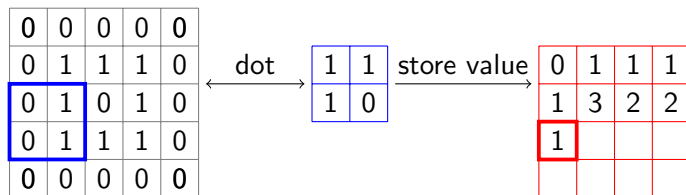
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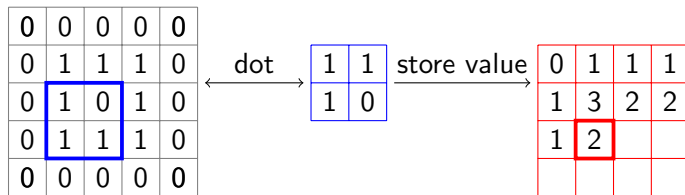
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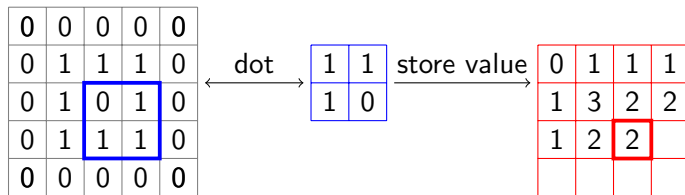
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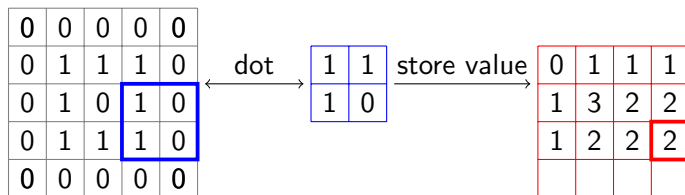
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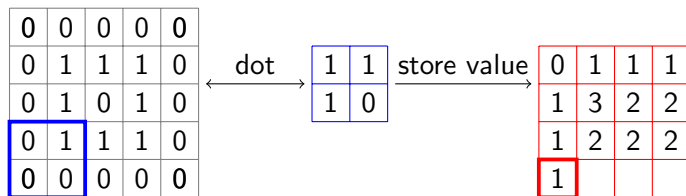
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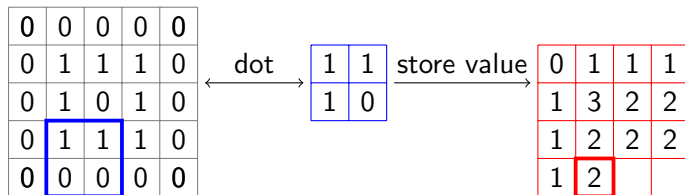
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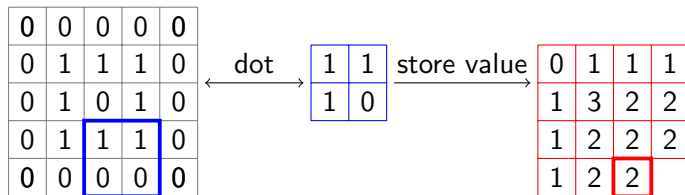
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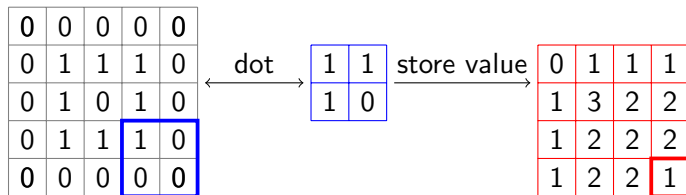
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 - For instance if we use max pooling with a filter of size 2×2 we discard 75 percent of the values

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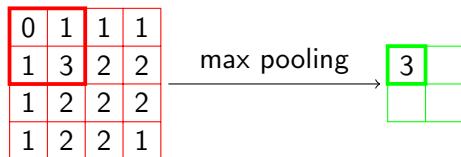
0	1	1	1
1	3	2	2
1	2	2	2
1	2	2	1

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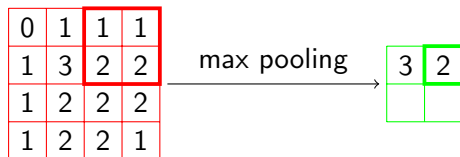
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1	3	2	2
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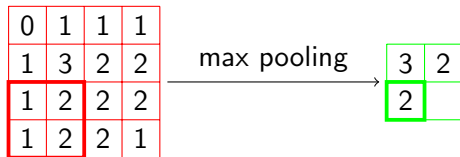
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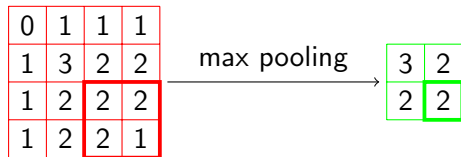
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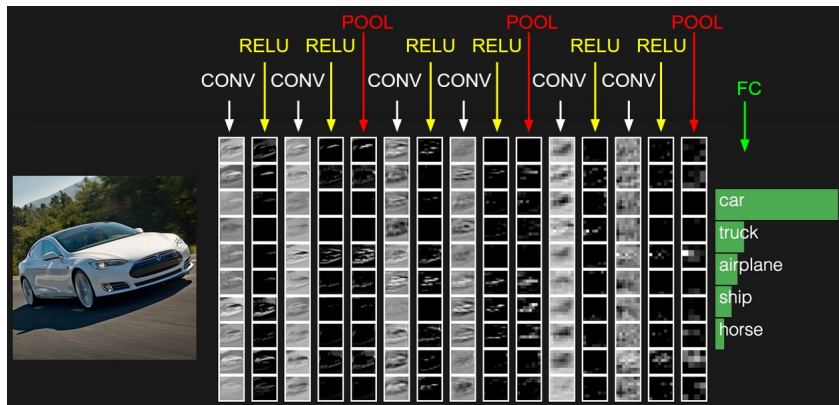
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CNN - Example architecture



Taken from <http://cs231n.github.io/convolutional-networks/>

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- Does not take into account orientation of the object

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- It's often hard to know why the model predicts as it does because of the complexity of the model

Tips and tricks

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- Start by using small batch size
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- Use normalization (batch, layer, group, weight...)
 - Speeds up convergence significantly
 - Start by trying batch normalization for CNN and feed-forward nets and layer normalization for RNN
 - See [Kurita, 2018] for a good overview

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- Increasing the batch size decreases the variance of the gradient estimates, but only by the square root of the increase.
- In practice increasing the batch size may result in a worse model. In extreme cases the model might not learn anything at all! [Masters et. al., 2018]

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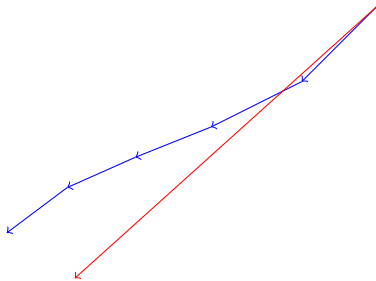
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- Training with large batches often converge to sharp minimizers, and this leads to worse test performance [Keskar et. al., 2016]

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 - [Goyal et. al., 2017] managed to train a ResNet architecture on ImageNet with a batch size of 8192.
 - A smaller learning rate was used early to avoid optimization challenges early in the training
 - Another solution is to use a small batch size in the beginning and increase it when the speed of the model change decreases

References I



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