# Training Convolution RBMs

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# Introduction

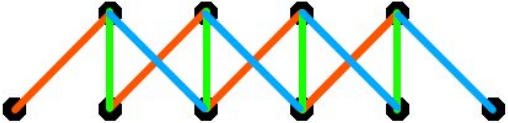
Why?

- RBMs work well for initializing layers of deep networks
- Convolution filters in Neural Networks give better performances on image data
  - Invariance by translation is easily learned
  - Takes advantage of the local informations
- Experiments (Yann Le Cun & Co.) have shown that learning convolution filters unsupervisedly can give good results
- So, why not try with RBMs?

# A small introduction to convolution layers

The connections of a convolution layer represent a **linear transformation**, which implements:

- Sparse connectivity
- Capture of local interactions
- Weight sharing

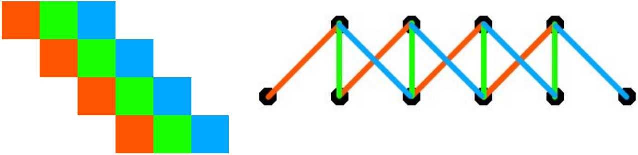


# More details on the 1D case

- If we denote by $f$ the convolution *filter* (set of weights):

$$h_i = \sum_{j=1}^{k} f_j v_{i+j}$$

- We can also represent the matrix corresponding to the linear transformation $h = Wv$



- The transposed tranformation is also sparse, local, and linear, and is indeed a variant of the convolution

# Convolutions in RBMs

- Defined by an Energy function:

$$\mathcal{E}(v, h) = c'v + h'Wv + h'b$$

- Update of $W_{ij}$ proportional to:

$$h_i^0 v_j^0 - h_i^1 v_j^1$$

- We can easily replace $Wv$ by a convolution and $h'W$ by a transposed convolution
- It is also possible to compute the gradient wrt $W_{ij}$ and to "forward" the update to the right $f_k$, but in fact the update formula of $f$ is quite simple

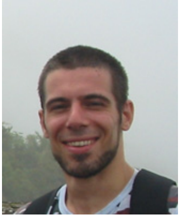
# What can we do with that?

The usual things we do with RBMs, but on images:

- Reconstruct images, possibly by also adding an explicit reconstruction error term in the gradient
- Sample images, to see how the generative model behaves
- Initialize weights of a LeNet-like architecture
- Understand better how Contrastive Divergence works
- Take over the world

# Results

# Results

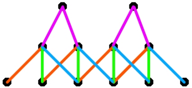


Ask him! ;)

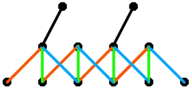
# Subsampling in usual convolution nets

Different techniques are used to limit the size of convolution layers, by collapsing a local area in a hidden layer into one single pixel

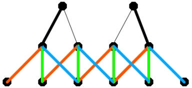
- Parametrized mean



- Discarding pixels

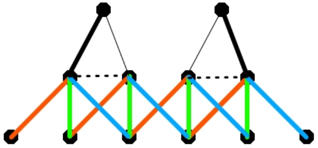


- Taking the maximal value



# Subsampling inside RBMs?

- We can train the RBM ignoring the fact that there will be a subsampling layer afterwards
- But it would be more interesting to incorporate this knowledge inside the RBM
- It is possible to tie the activity of several units in an RBM hidden layer, so that only one is active at a time (they act as a multinomial distribution)
- We can do that over non-overlapping local areas of the hidden layers, achieving a form of sparsity
- Hopefully, taking the max after that will give interesting results



# Issues and future development

Lots of things to try. . .

- Different variants of convolutions (to avoid problems at the edges)
- Sparse, local, untied weights
- Comparison with auto-associators or other models
- Other specially parametrized linear transformations. . .
- . . . like a weight matrix parametrized by the output of another RBM, or Neural Net, etc.

# Last slide

- Questions?

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