Spatially-Sparse Convolutional Neural Networks

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Motivation (Paul Handel, 1931)



Motivation: Unsupervised learning for MNIST



Artificial neural networks

Directed weighted graph For each node: $output = \sigma(b + \sum_{i} w(i)input(i))$

For classification, the final layer is weighted to give a probability distribution.

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\begin{array}{lll} \mathsf{input} \in \mathbb{R}^a \\ \mathsf{hidden1} &= & \sigma(\mathsf{input} \cdot W_1 \, + \, B_1) \in \mathbb{R}^b \\ \mathsf{hidden2} &= & \sigma(\mathsf{hidden1} \cdot W_2 + B_2) \in \mathbb{R}^c \\ \mathsf{hidden3} &= & \sigma(\mathsf{hidden2} \cdot W_3 + B_3) \in \mathbb{R}^d \\ \mathsf{output} = \mathsf{softmax}(\mathsf{hidden3} \cdot W_4 + B_4) \in \mathbb{R}^e \end{array}
```





#Parameters (a+1) imes b + (b+1) imes c + (c+1) imes d + (d+1) imes e

ConvNets

▶ 1998: LeNet-5 (LeCun et al)

32 × 32 input: 6C5 – MP2 – 16C5 – MP2 – 120C5 – output



Convolutional Neural Network Software

- cuda-convnet
- Torch7
- ► Theano: Keras, Lasagne, PyLearn2
- OverFeat
- Caffe
- CxxNet
- CuDNN
- MatConvNet
- TensorFlow
- Marvin
- SparseConvNet (2012-)

Why Spatially Sparse ConvNets?

- Research keyword bingo
- Online Handwriting
 - Id manifold in 2d space
 - computation should scale linearly with rendering scale
 - CVJK fine detail
- Data augmentation
- Differences in input size
- Curse of dimensionality higher dimensional spaces are sparser
- ▶ 3D space includes 2+1 dimensional space time
- 4D space includes 3+1 dimensional space time
- ► 5D space ??

Handwriting recognition

▶ 183 Assamese characters, 36 training exemplars per class



 3755 Chinese CASIA-OLHWDB1.1 characters, 240 exemplars/class









Network structure = Prior information



Data augmentation

• Assamese at scale 2^{ℓ}

$DeepCNet(\ell, 30)$	None	Translations	Affine
$\ell = 3$	51.4%	38.3%	35.2%
$\ell = 4$	26.8%	9.29%	7.47%
$\ell = 5$	18.2%	5.28%	2.73%
$\ell = 6$	14.1%	4.61%	1.76%
$\ell = 7$	13.8%	4.07%	1.70%

Sparsity

- Sparse matrix multiplication has high overheads
 - loss of Strassen's algorithm
 - inefficient memory access
- Spatially-Sparse ConvNets are relatively efficient
 - Contiguous memory access
 - Small filters and pooling regions preserve sparsity
 - Small filters work well with FMP