

Parameter Tying and Parameter Sharing

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Regularization Strategies

1. Parameter Norm Penalties
2. Norm Penalties as Constrained Optimization
3. Regularization and Under-constrained Problems
4. Data Set Augmentation
5. Noise Robustness
6. Semi-supervised learning
7. Multi-task learning
8. Early Stopping
9. Parameter tying and Parameter sharing
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11. Bagging and other ensemble methods
12. Dropout
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14. Tangent methods

Topics in Parameter Tying/Sharing

1. Other methods for prior knowledge of parameters
2. Parameter Tying
3. Parameter Sharing
4. Parameter sharing in CNNs

Another expression for parameter prior

- L^2 regularization (or weight decay) penalizes model parameters for deviating from fixed value of zero
- Sometimes we need other ways to express prior knowledge of parameters
- We may know from domain and model architecture that there should be some dependencies between model parameters

Parameter Tying

- We want to express that certain parameters should be close to one another

A scenario of parameter tying

- Two models performing the same classification task (with same set of classes) but with somewhat different input distributions
- Model A with parameters $\mathbf{w}^{(A)}$
- Model B with parameters $\mathbf{w}^{(B)}$
- The two models map the input to two different but related outputs

$$\hat{y}^{(A)} = f(\mathbf{w}^{(A)}, \mathbf{x})$$

$$\hat{y}^{(B)} = g(\mathbf{w}^{(B)}, \mathbf{x})$$

L^2 penalty for parameter tying

- If the tasks are similar enough (perhaps with similar input and output distributions) then we believe that the model parameters should be close to each other:

$$\forall i, w_i^{(A)} \approx w_i^{(B)}$$

- We can leverage this information via regularization
- Use a parameter norm penalty

$$\Omega(\mathbf{w}^{(A)}, \mathbf{w}^{(B)}) = \|\mathbf{w}^{(A)} - \mathbf{w}^{(B)}\|_2^2$$

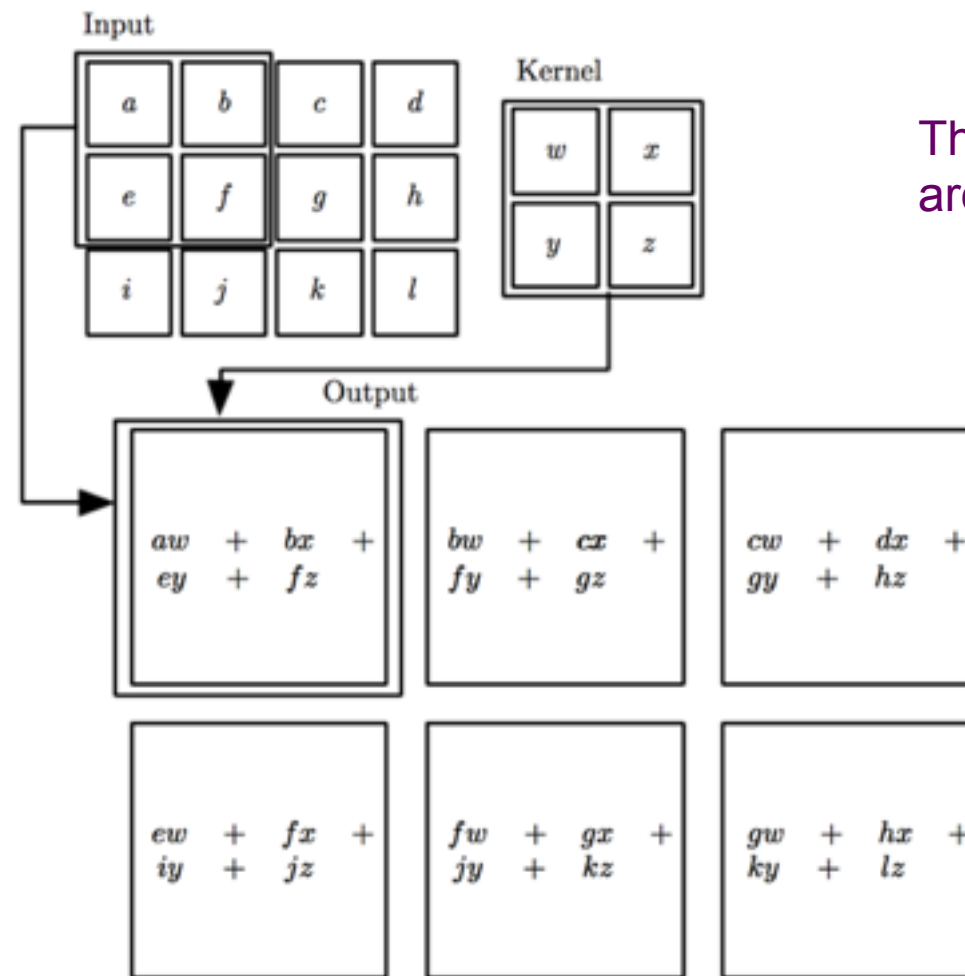
Use of Parameter Tying

- Approach was used for regularizing the parameters of one model, trained as a supervised classifier, to be close to the parameters of another model, trained in an unsupervised paradigm (to capture the distribution of the input data)
 - Ex. of unsupervised learning: k -means clustering
 - Input x is mapped to a one-hot vector h . If x belongs to cluster i then $h_i=1$ and rest are zero corresponding to its cluster
 - It could trained using an autoencoder with k hidden units

Parameter Sharing

- Parameter sharing is where we:
 - force sets of parameters to be equal
- Because we interpret various models or model components as sharing a unique set of parameters
- Only a subset of the parameters needs to be stored in memory
 - In a CNN significant reduction in the memory footprint of the model

CNN parameters



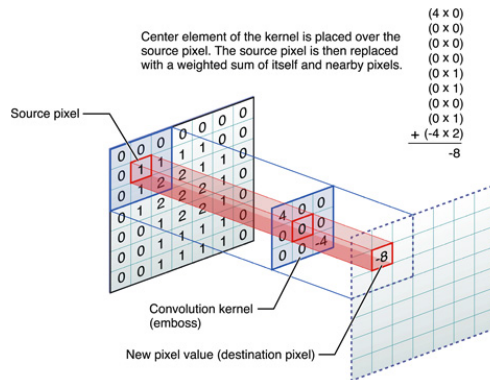
The kernel parameters are shared

Use of parameter sharing in CNNs

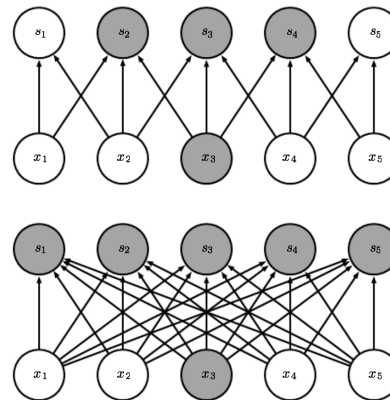
- Most extensive use of parameter sharing is in convolutional neural networks (CNNs)
- Natural images have many statistical properties that are invariant to translation
 - Ex: photo of a cat remains a photo of a cat if it is translated one pixel to the right
 - CNNs take this property into account by sharing parameters across multiple image locations
 - Thus we can find a cat with the same cat detector whether the cat appears at column i or column $i+1$ in the image

Simple description of CNN

Convolution operation

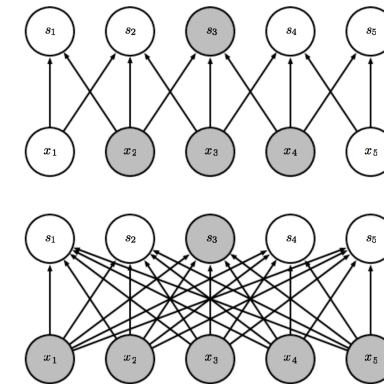


Sparsity viewed from below



- Highlight one input x_3 and output units s affected by it
- *Top:* when s is formed by convolution with a kernel of width 3, only three outputs are affected by x_3
- *Bottom:* when s is formed by matrix multiplication connectivity is no longer sparse
 - So all outputs are affected by x_3

Sparsity viewed from above



- Highlight one output s_3 and inputs x that affect this unit
 - These units are known as the receptive field of s_3