Unsupervised Learning of Invariances in Deep Networks

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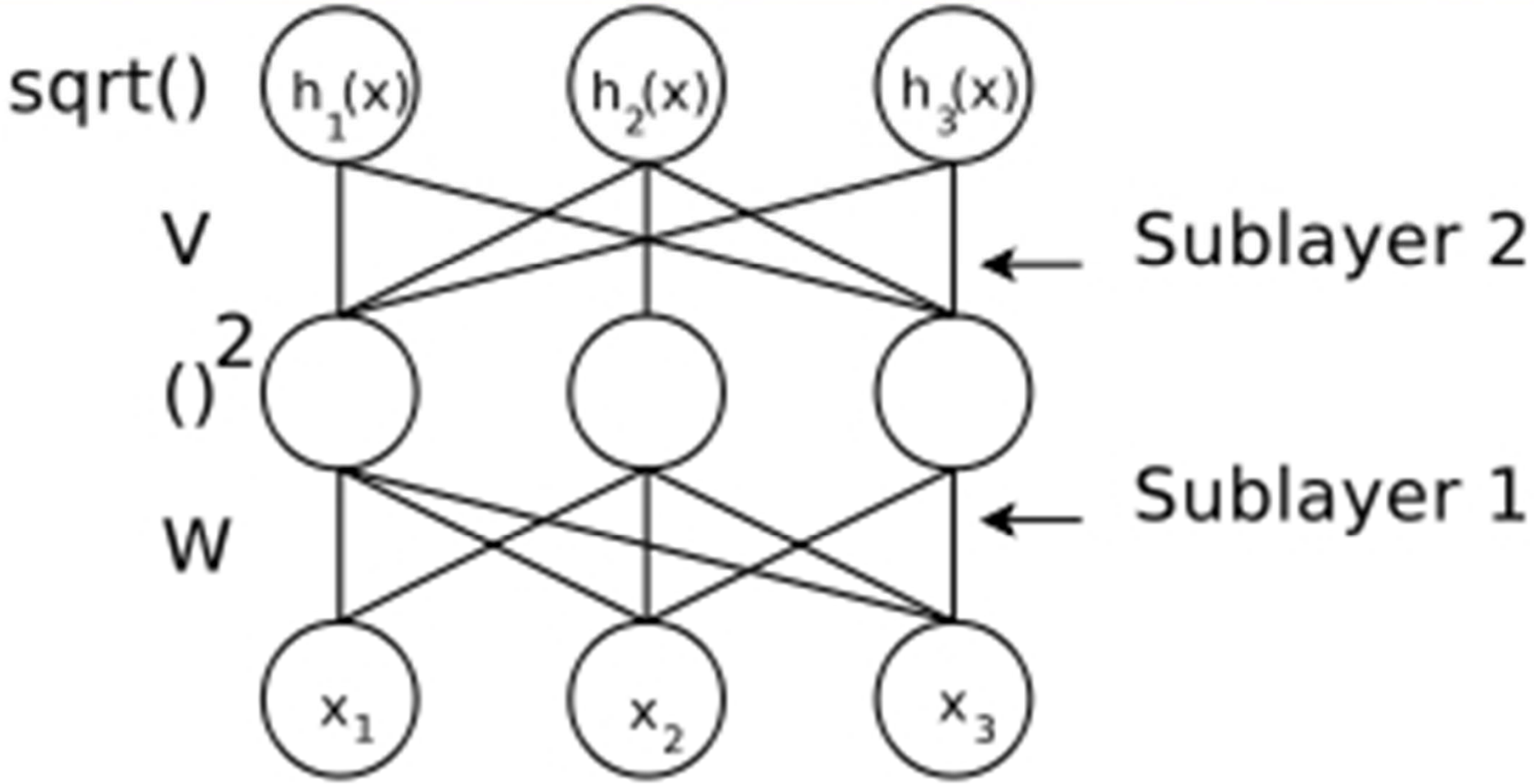
Motivation and Goals

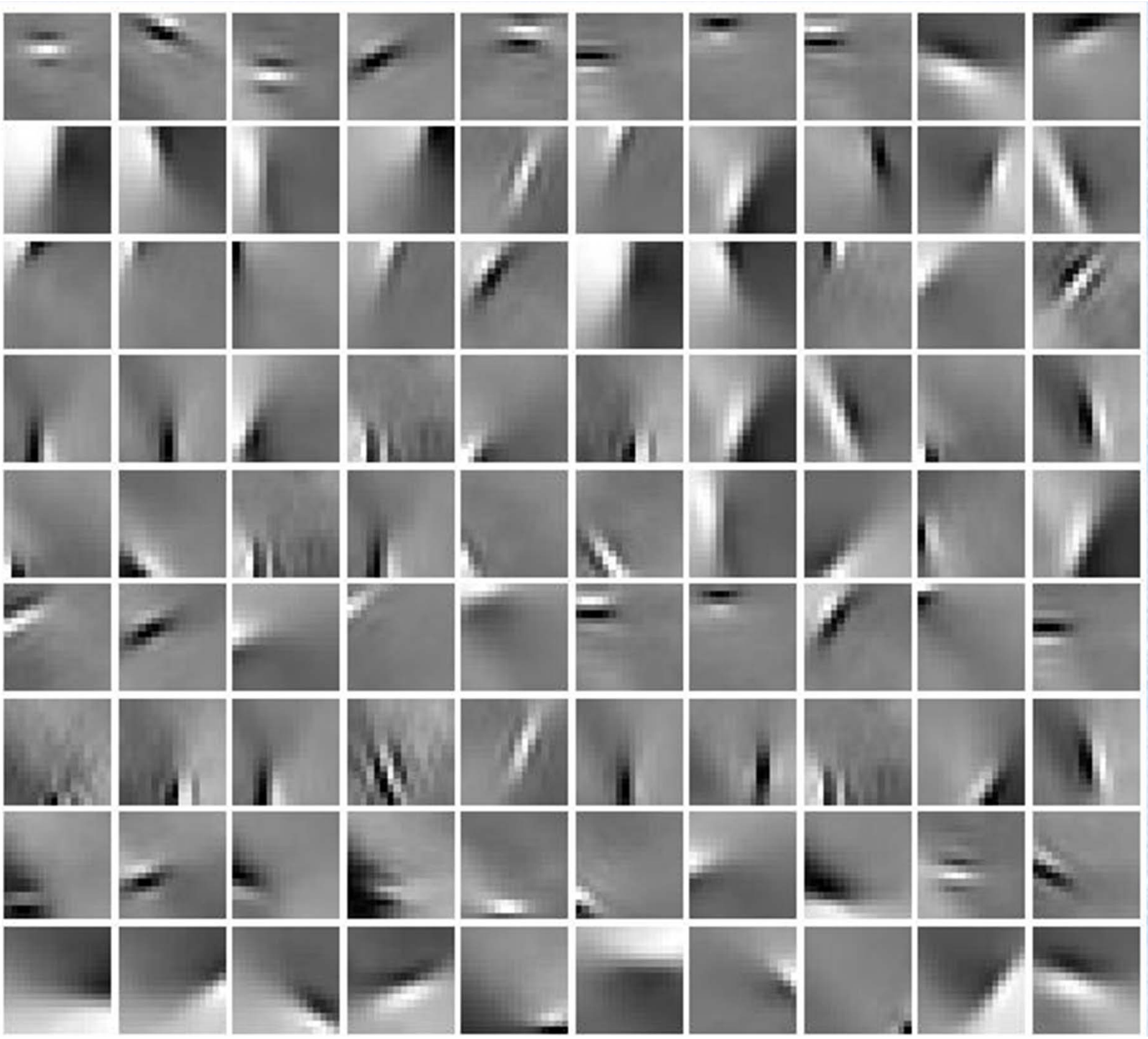
- Build a neural network which can learn complex invariances without hardcoding them
- Biologically-inspired model of simple and complex cells
- Want network to generalize to different types of data (e.g. audio/video)

Network Structure



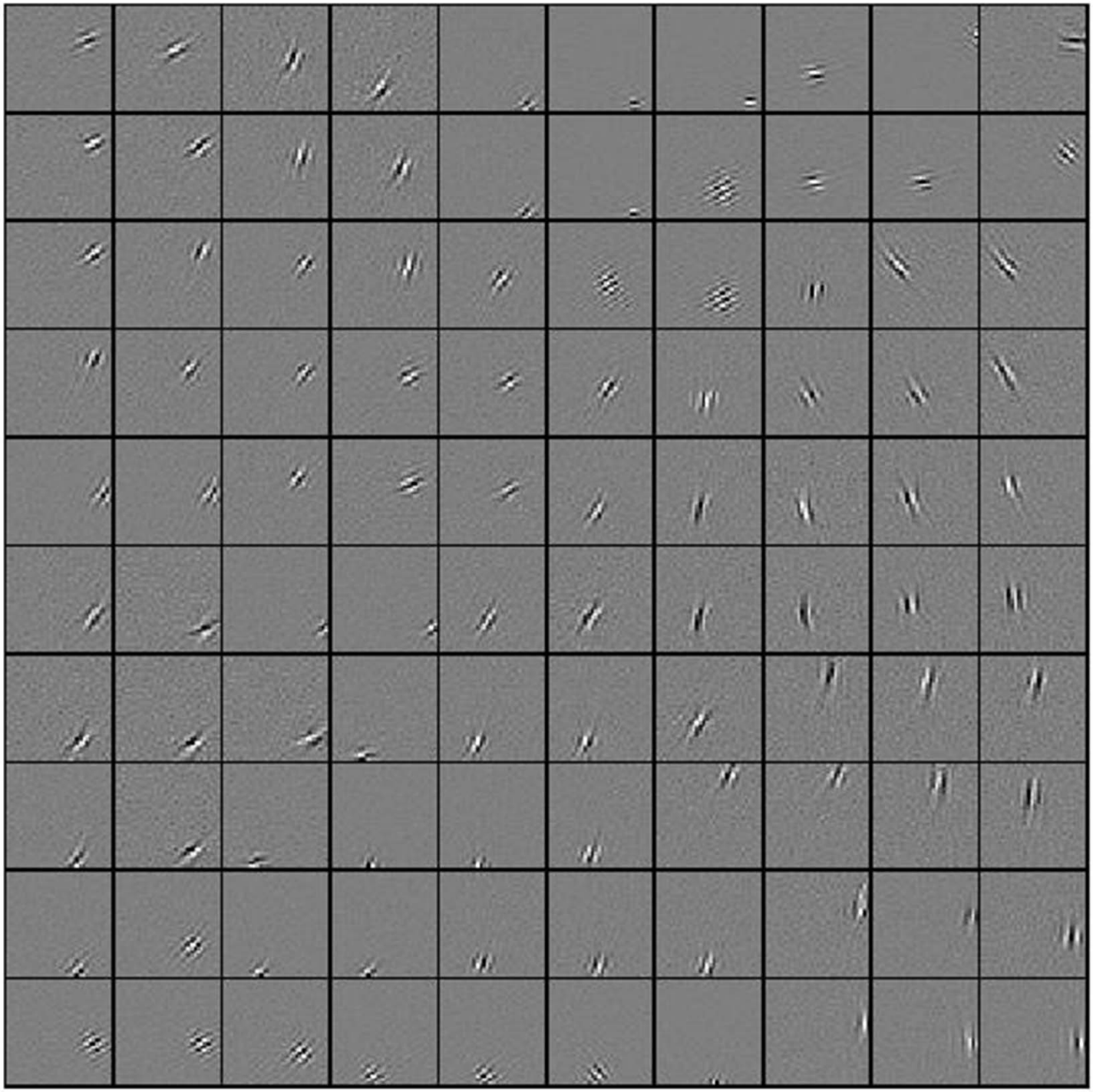
Learning the Weights

- We originally tried to learn V, but we did not quite see the “peaks” we wanted (maybe due to the data or regularization), so we set V to be a neighborhood matrix to mimic topographical layout of visual cortex



Learning the Weights

- We learn W using the sparse cost objective, i.e. minimizing activations at the output, as this produces very localized gabor filters (also constrain rows of W to be far apart)



Using CUDA

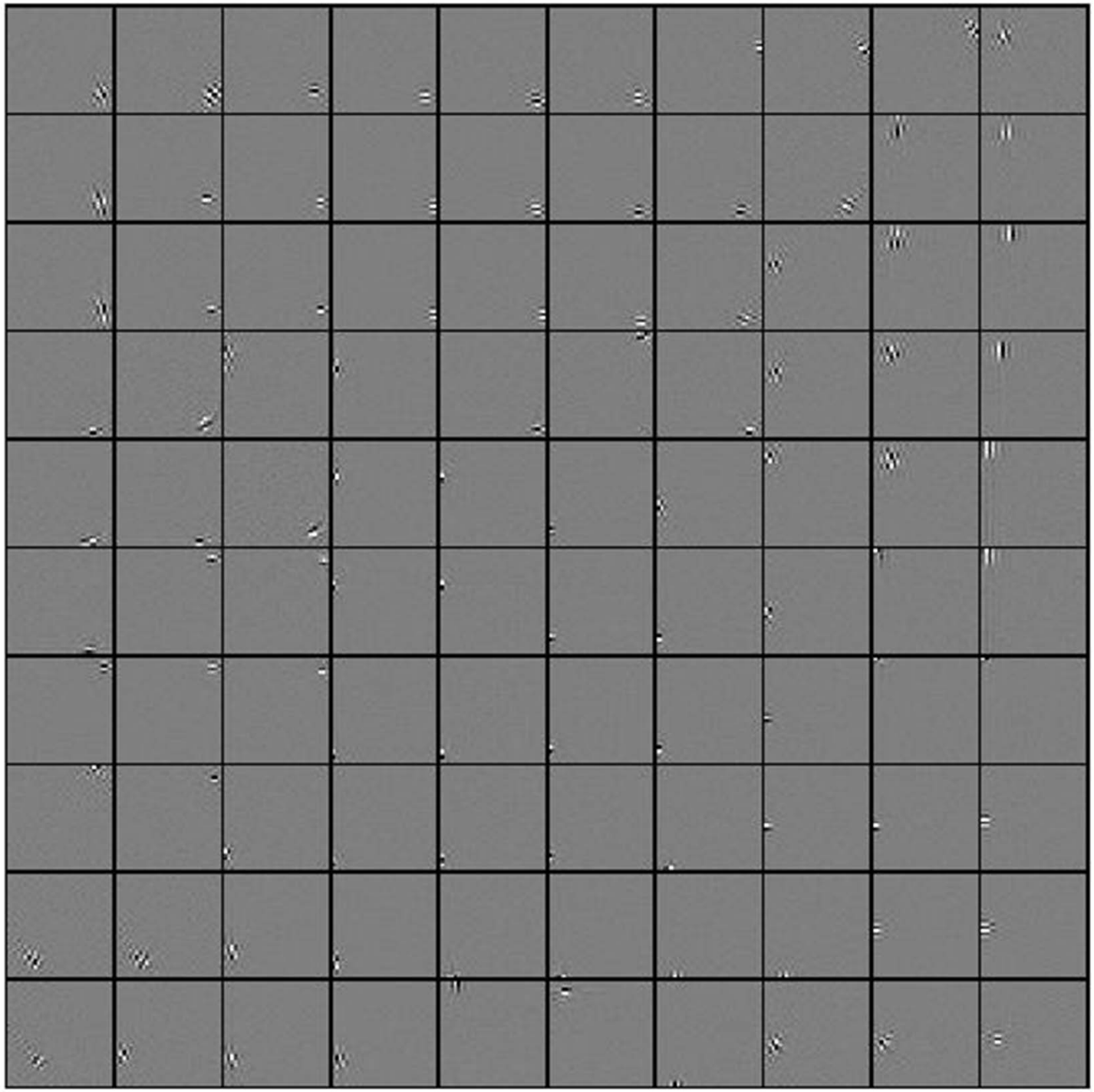
- All training done on the GPU, which gives us an estimated 25x speedup (with just 1600 hidden units); training on CPU would have been infeasible
- Mini-batch approach to maximize GPU effectiveness

Vision Task: Classification

- CIFAR 10 dataset: tiny 32x32 images belonging to 10 different classes
- Training set: 50,000 images
- Test set: 10,000 images
- Added a softmax layer on top of network

Attempted Methods

- CIFAR data is RGB, i.e. there are three channels for each image; we can combine channels to improve classification (sort of)
- Combine output of both W and V layers before softmax
- We originally trained the W-V layers on data independent of CIFAR, but we found that training on CIFAR itself produced different bases



Results and Future Work

- Unfortunately, none of the attempted methods really improved our classification results on the CIFAR test set (note that our bases are trained in an unsupervised setting)
  - 56% using 1600 hidden units
  - 59% using 10,000 hidden units
  - State-of-the-art: 65% using RBM (Krizhevsky)
- Ideas for future work: better features, stacking more layers, different datasets

SparseCudaMatrix Design

- Motivation: sparse weight matrices, RBMs, etc.
- Structure: row-major and column-major entries arrays, index into each array (supports fast multiplication and transpose)
- Key Assumption: locations of (potentially) nonzero entries do not change
- Performance Assumption: number of entries per row/per col are relatively well balanced

SparseCudaMatrix Features

- Component-wise arithmetic: assume nonzero entries are the same and blaze through arithmetic (see key assumption!)
- Sparse * Sparse → Sparse
- Sparse * Dense → (Dense or Sparse)
- (Dense * Dense) .* Sparse
  - Implemented by dotting necessary row/col of dense matrices
- Full matrix reductions (sum, norm, min, max)

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