Simplified Machine Learning for CUDA

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Arrayfire @arrayfire

ArrayFire

- CUDA and OpenCL experts
  - since 2007
- Headquartered in Atlanta, GA
- In search for the best and the brightest
- Expert domain experience in a wide variety of fields
  - Computer Vision
  - Machine Learning
  - Financial
  - etc.

ArrayFire Consulting Services

- Custom software development services
- Deep experience working with thousands of customers
    - Analysis
    - Acceleration
    - Algorithm development
- Expert software engineers
    - Large scale software development experience
    - Production quality code
    - Extensive domain knowledge

ArrayFire Training

- 2-4 Day CUDA or OpenCL training
  - On site or at our headquarters
- Taught by a performance engineer by your side
  - We have seen it all and know how to fix things
- Hands on labs
  - You will not be copying code
  - Run on GPU hardware
- Customized for your application
  - Examples target your use-case
- Only C/C++ experience required

ArrayFire the Library

- A general purpose computational library
- Backends for CUDA, OpenCL and CPU
- Cross Platform
- Open Source (BSD - 3 - clause)
- Concentrate on performance and ease of use
- JIT
- Hundreds of Functions

Machine Learning

- Excellent for modeling highly dimensional data
  - Pattern recognition
  - Decision making
- Requires lots of data for good results

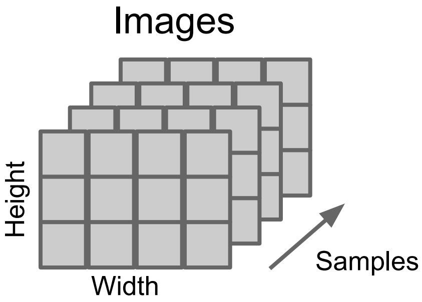
MNIST Dataset

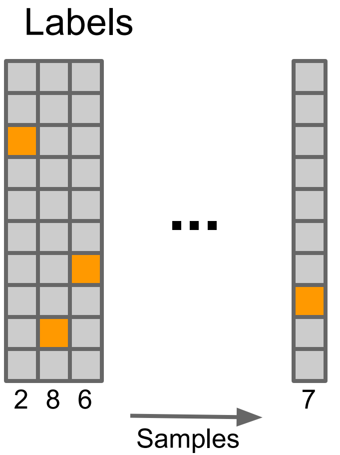
- Dataset of handwritten digits
- 60,000 samples from ~250 writers
- 28x28 grayscale pixels

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. "Gradient-based learning applied to document recognition." Proceedings of the IEEE, 86(11):2278-2324, November 1998

Loading MNIST

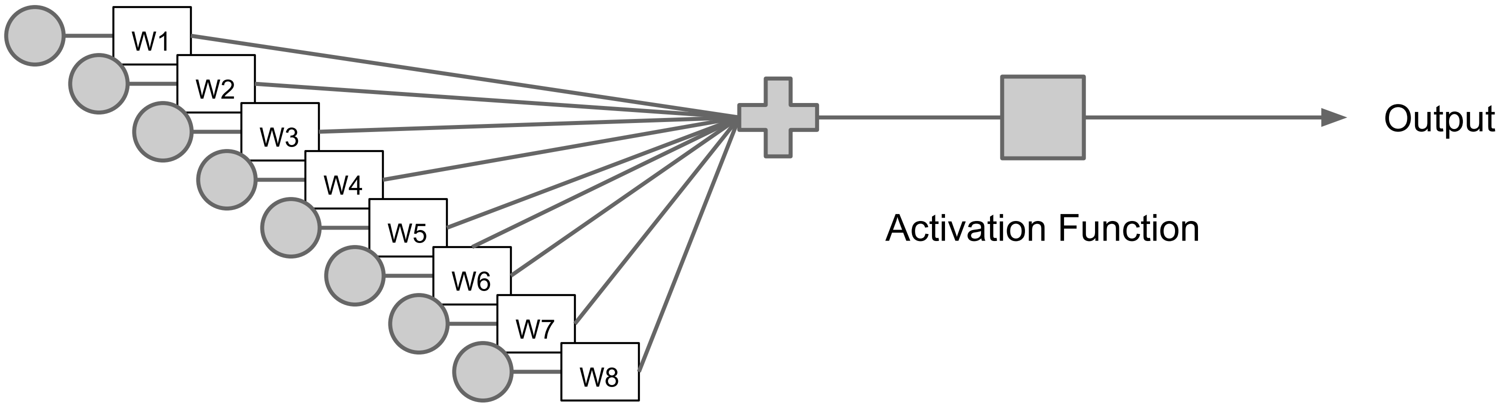
```
array train_images, train_targets;
array test_images, test_targets;
int num_train, num_test, num_classes;

// Load mnist data
setup_mnist<true>(&num_classes, &num_train, &num_test,
                  train_images, test_images,
                  train_targets, test_targets, 1.0);
```





Perceptron

- Introduced in the late 1950's
- Linear classifier

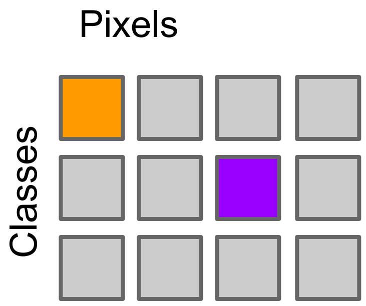


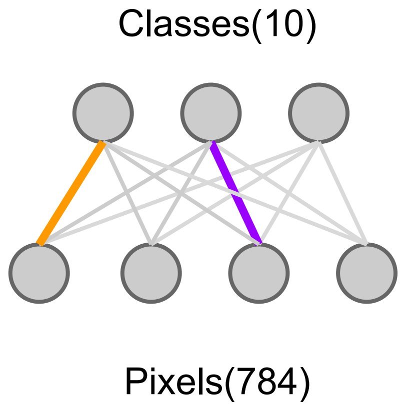
Teaching a Perceptron

- Initialize weights to zero
- Generate response
- Calculate error
- Update weights
- Repeat

Perceptron

Weights





ArrayFire API

- Creating arrays in ArrayFire

```
array zeros   = constant(0, 5);    // 0
                                   // 0
                                   // 0
                                   // 0
                                   // 0

array zeros2D = constant(0, 2, 3);    // 0, 0, 0
                                      // 0, 0, 0
```

Perceptron

```
//Initialize weights to 0
const int pixel_count = 28*28;  //train_feat.dims(1);
const int num_labels = 10;      //train_target.dims(1);
array weights = constant(0, pixel_count, num_labels);
```

Teaching a Perceptron

- Initialize weights to zero
- Generate response
- Calculate error
- Update weights
- Repeat

Response

- Sum of the input multiplied by the weights

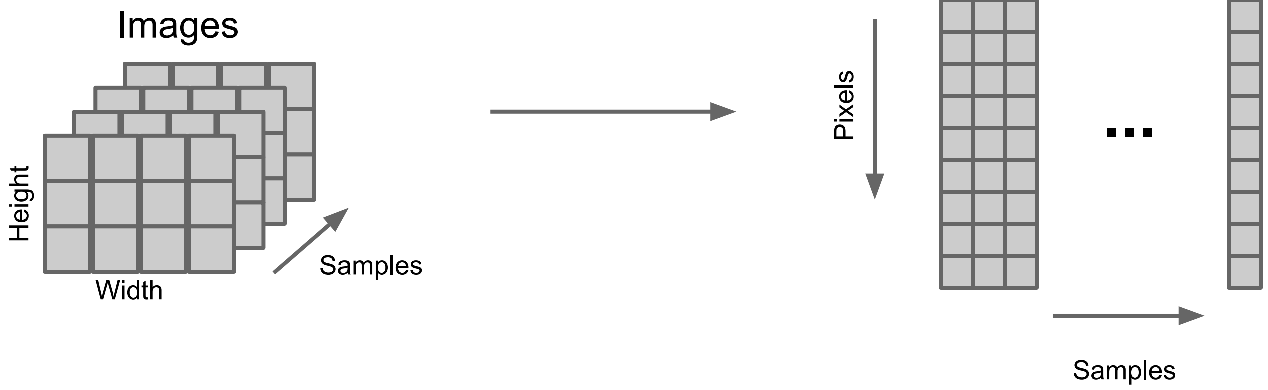
$$response(p) = \sum w_i p_i$$

- Send result into an activation function

$$S(t) = \frac{1}{1 + e^{-t}}$$

Response

- Flatten Images



ArrayFire API

- Reshaping volume into a matrix

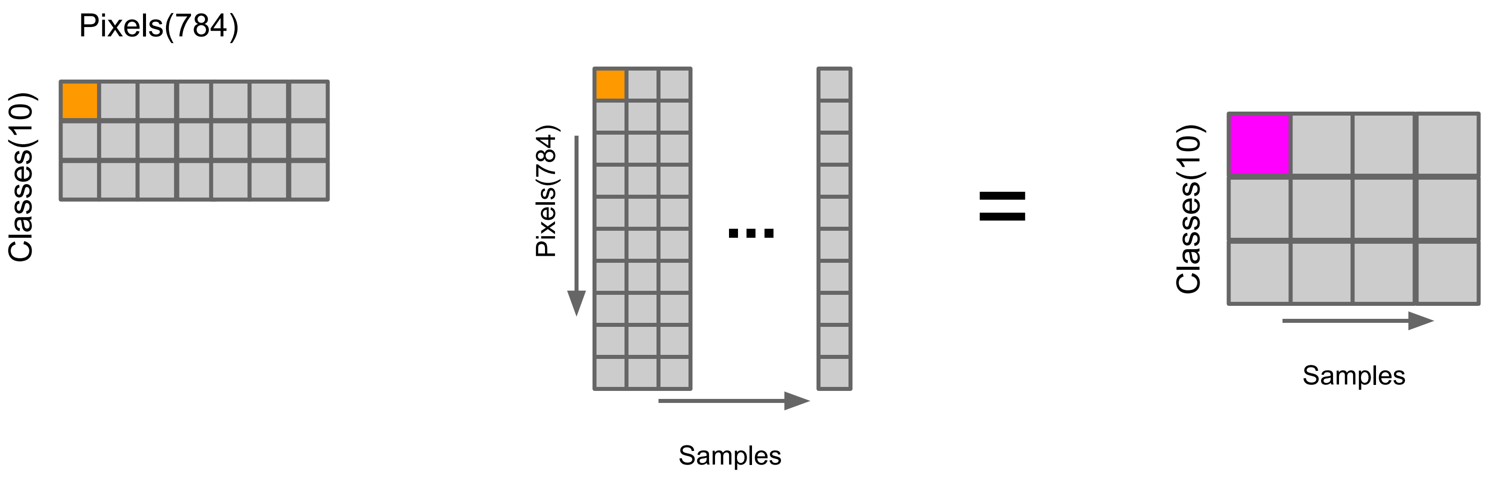
```
// Reshape images into feature vectors
    array out = moddims(in, dim0, dim1, dim2, dim3);
```

```
// Reshape images into feature vectors
    array train_feats = moddims(train_images, pixel_count, num_train);
```

Response

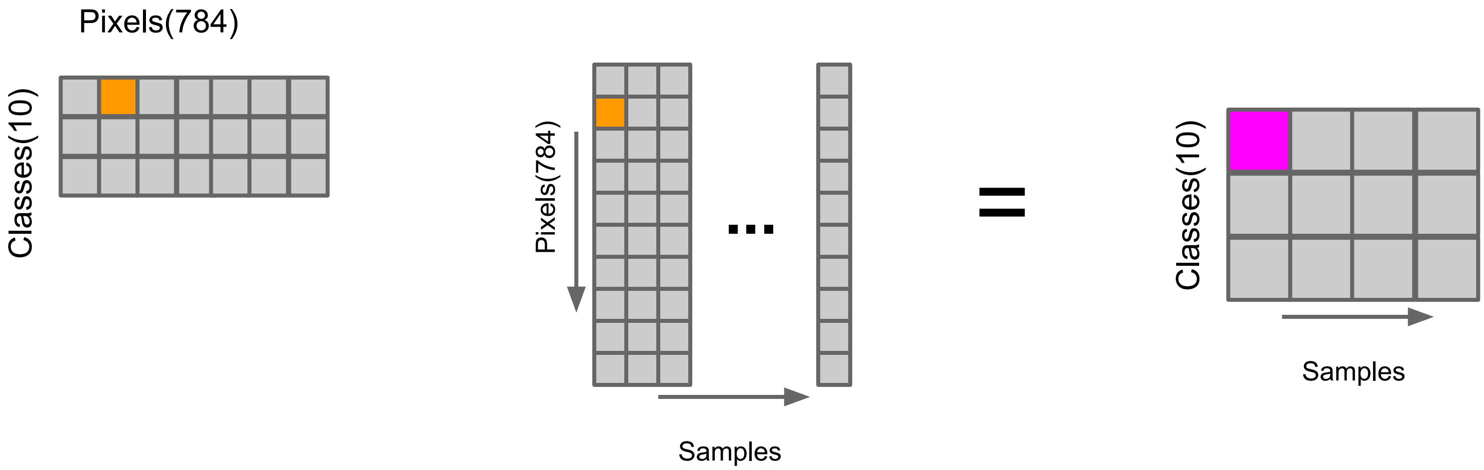
```
// Reshape images into feature vectors
array train_feats = moddims(train_images, pixel_count, num_train);
array test_feats  = moddims(test_images , pixel_count, num_test );
```

Response



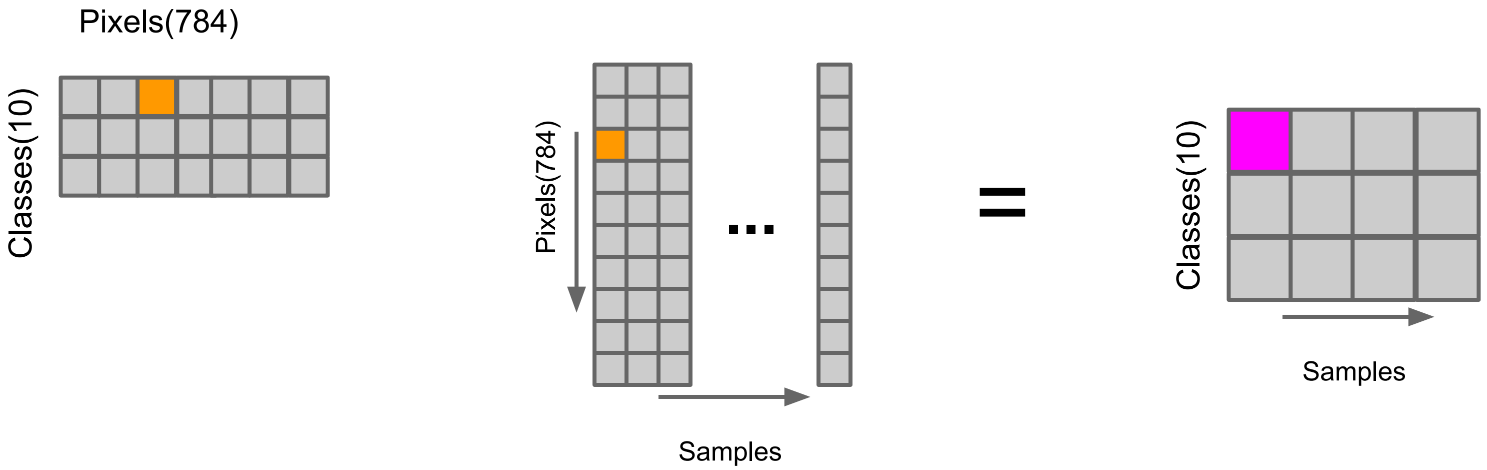
Pixels(784)
Classes(10)
Pixels(784)
...
Samples
=
Classes(10)
Samples

Response



Pixels(784)
Classes(10)
Pixels(784)
...
Samples
=
Classes(10)
Samples

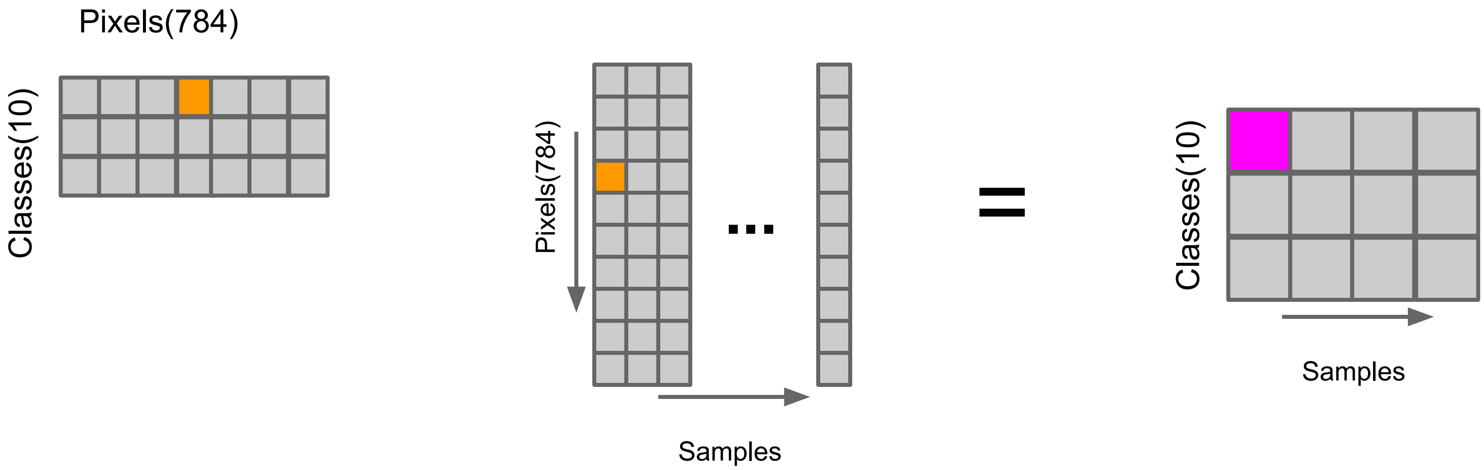
Response



Pixels(784)
Classes(10)
Pixels(784)
...
Samples
=
Classes(10)
Samples

Response

Matrix Multiply!



ArrayFire API

```
array response = matmul(weights, train_feats);
```

Activation Function

- Sigmoid Function

$$S(t) = \frac{1}{1 + e^{-t}}$$

```
// Activation function
array sigmoid(const array &val)
{
    return 1 / (1 + exp(-val));
}
```

Prediction

```
array prediction = sigmoid(matmul(weights, train_feats));
```

Teaching a Perceptron

- Initialize weights to zero
- Generate response
- Update weights
- Repeat

Calculating Error

- Subtract the expected output with prediction
- Multiply with the learning rate

$$\Delta w = \alpha(expected_p - prediction_p) * pixel_i$$

```
array err = train_targets - prediction;
weights += learning_rate * (matmulNT(err, train_feats));
```

Teaching a Perceptron

- Initialize weights to zero
- Generate response
- Update weights
- Repeat

Repeat

```
for(int i = 0; i < 100; i++)
{
    array prediction = sigmoid(matmul(weights, train_feats));
    array err = train_targets - prediction;

    float mean_abs_error = mean<float>(abs(err));
    printf("err: %0.4f\n", mean_abs_error);

    weights += learning_rate * (matmulNT(err, train_feats));
}
```

Results

Measure Accuracy

```
float accuracy(const array& predicted, const array& target)
{
   array val, plabels, tlabels;
   max(val, tlabels, target, 0);
   max(val, plabels, predicted, 0);
   return 100 * count<float>(plabels == tlabels) / tlabels.elements();
}
```

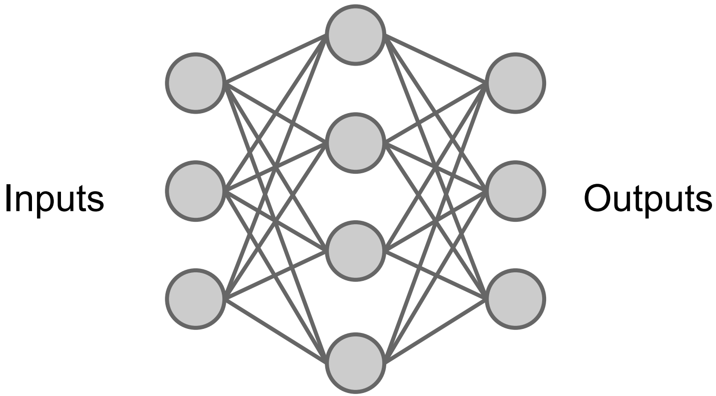
82.03%

Perceptron

- Improvements
  - Smaller batches
  - Variable learning rate
- Linear Classifier!
  - Handwritten digit recognition cannot be solved by a linear classifier
- Additional layers are required

Neural Networks

- Made up of one or more layers of neurons
- Hidden layers updated using back propagation



Back Propagation

- Hidden layers do not have an expected output
- Calculating error on output
- Send in data from the output layer back into network
- Gradient descent

Back Propagation

```
void ann::back_propagate(const vector<array> signal, const array &target, const double &alpha){
   // Get error for output layer
   array out = signal[num_layers  - 1];
   array err = (out - target);
   int m = target.dims(0);
   for (int i = num_layers - 2; i >= 0; i--) {
       array in = add_bias(signal[i]);
       array delta = (deriv(out) * err).T();

       // Adjust weights
       array grad = -(alpha * matmul(delta, in)) / m;
       weights[i] += grad.T();

       // Input to current layer is output of previous
       out = signal[i];
       err = matmul(weights[i], delta).T();

       // Remove the error of bias and propagate backward
       err = err(span, seq(1, out.dims(1)));
   }
}
```

Results

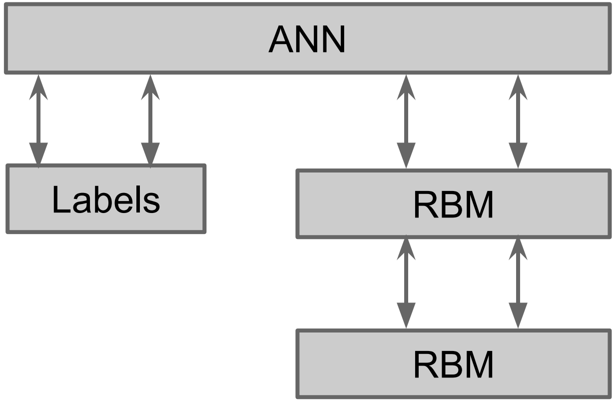
- Accuracy: 93.90%
- Time: 31.30 seconds
- Epoch: 250

Back Propagation

- Effective
- Slow for deeper networks
- Requires labeled data

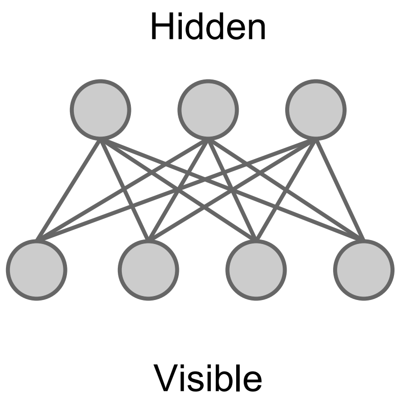
Deep Belief Nets

- A neural network made of multiple layers Restricted Boltzmann Machines
- Deep belief networks are great with unlabeled data



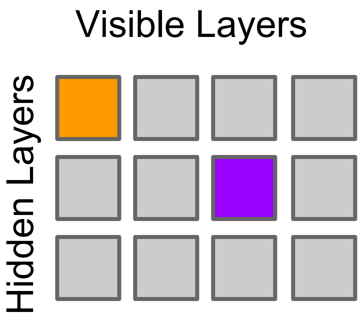
Restricted Boltsmann Machine

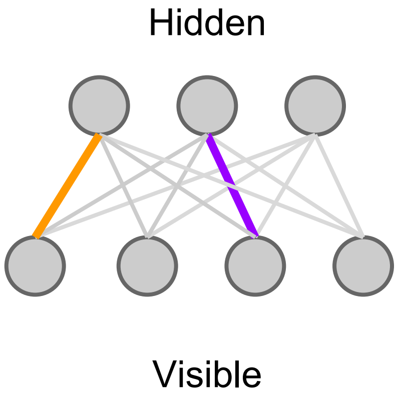
- A neural network with one hidden layer
- Each hidden neuron is connected to every visible neuron
- The connection has a weight which represents how strongly the neuron reacts to that input
- A bias is associated with both hidden and visible neurons



Restricted Boltsmann Machine

Data Representation

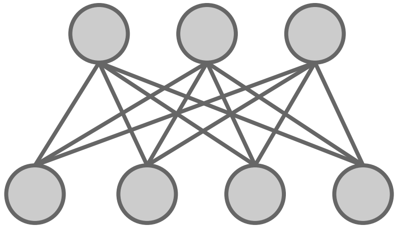




RBM

Lets create our RBM

```
class rbm
{
        array weights;
        array h_bias;
        array v_bias;
public:
        rbm(visible_size, hidden_size)
                : weights(   constant(0, hidden_size, visible_size))
                , h_bias(    constant(0, 1, hidden_size))
                , v_bias(    constant(0, 1, visible_size))
        {}
};
```



Training RBM

- Feed input into RBM
- Calculate the response
- Feed the response back through the network
- Calculate the error of the reconstruction
- Adjust the weights

Building the DBN

- Feed the output of the previous layer to the next
- Learns higher level features
- Use back propagation to fine tune the data

Results

- Accuracy: 93.46%
- Time: 13.27 seconds
- Epoch: 108

Improvements

- More data
- Larger network
- Learning rate
- Longer iterations

Questions