IMPLEMENTATION OF A PARALLEL BATCH TRAINING ALGORITHM FOR DEEP NEURAL NETWORK

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OUTLINE

- Review
- Neural Network Representation
- Sequential Trainer
- Concurrent Trainer
  - Dividing tasks
  - Collecting statistics
  - Using monitor
  - Using thread pool
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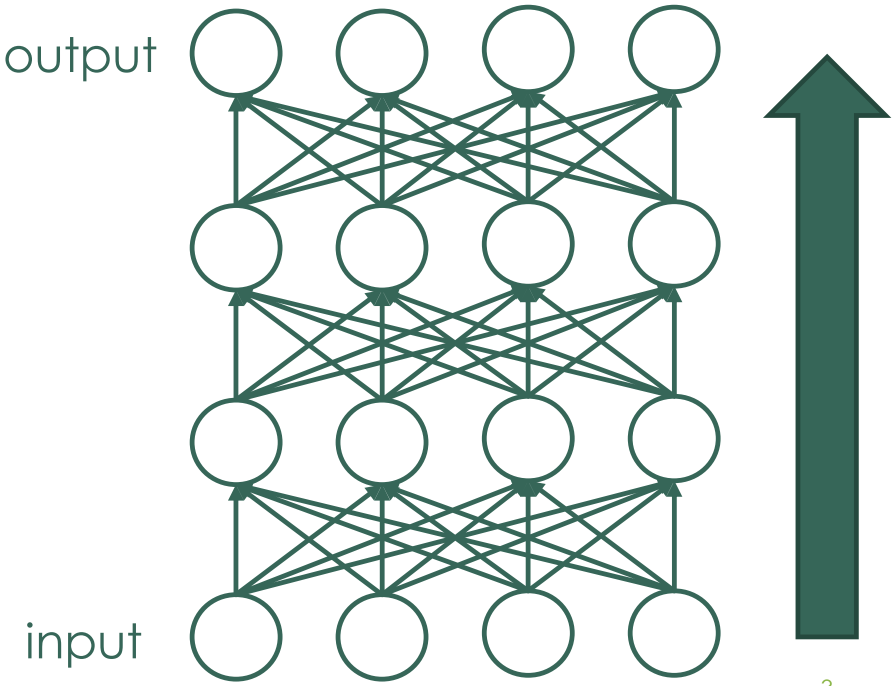
- Future Work

REVIEW -- NEURAL NETWORK TRAINING

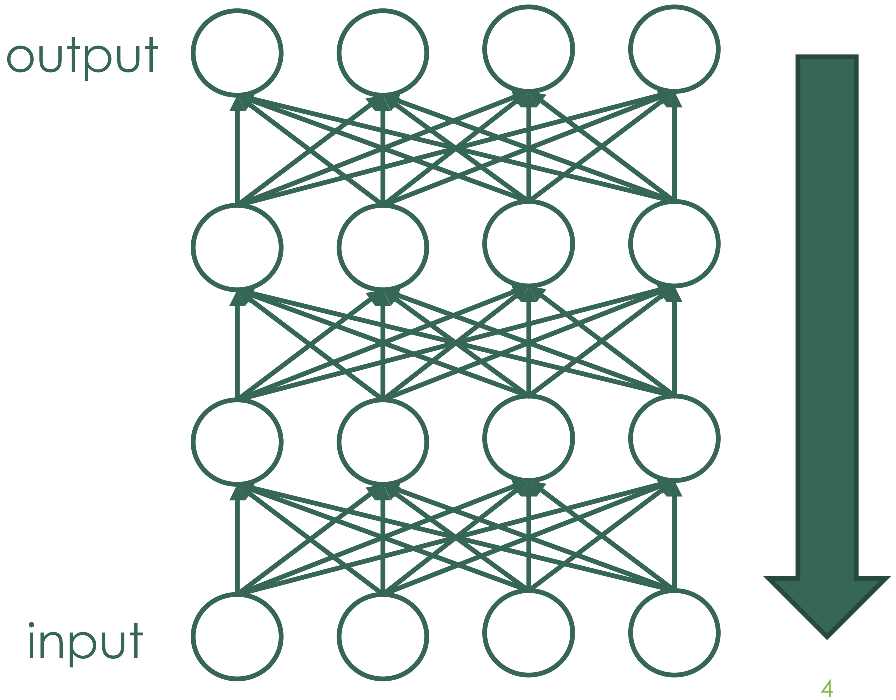
- Forward phase
  - $Z_j^{(l+1)} = F\left(\sum_i w_{ij} \cdot Z_i^{(l)} + b_j\right)$

  Where $F(x)$ is the nonlinear activation function

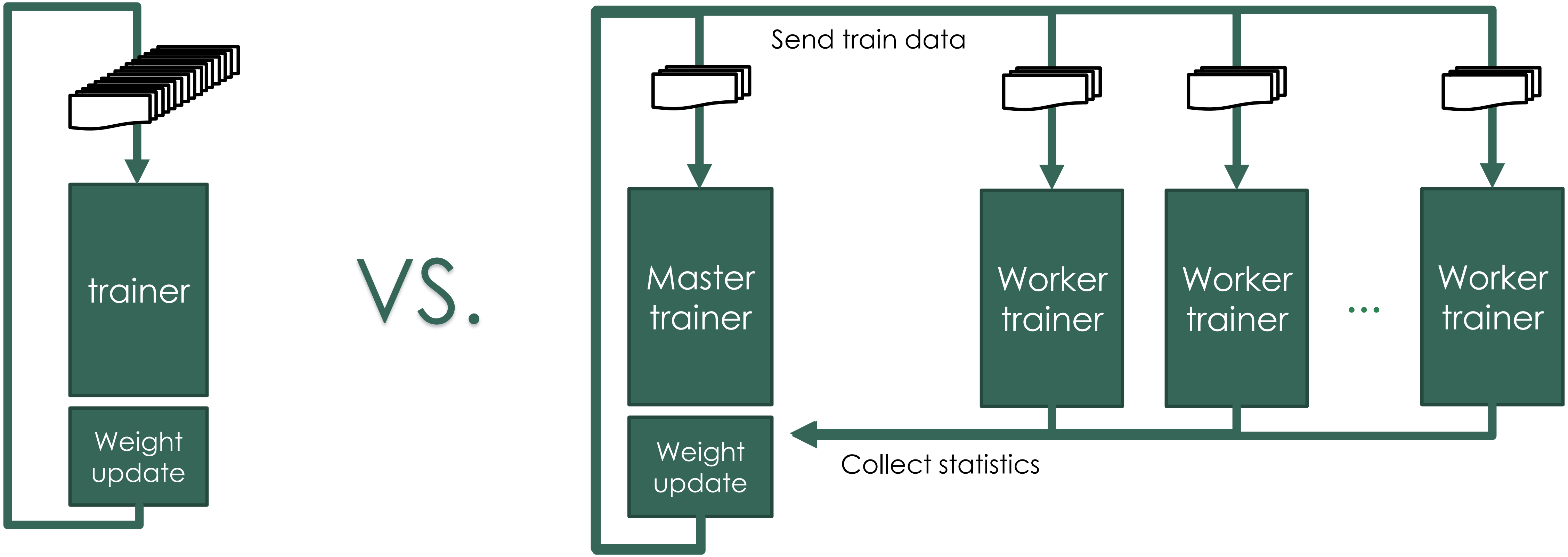


REVIEW -- NEURAL NETWORK TRAINING

- Error back propagation
  - $\delta_k^{(out)} = Z_k^{(out)} - T_k^{(out)}$
  - $\delta_i^{(l)} = F'\left(Z_i^{(l)}\right) \cdot \sum_j w_{ij} \cdot \delta_j^{(l+1)}$
  - Where $F'(x)$ is the derivative of the activation function
  - T is the desired output vector
- Weight updating
  - $\Delta w_{ij} = Z_i^{(l)} \cdot \delta_j^{(l+1)}$
  - $w_{ij} = w_{ij} - \gamma \cdot \Delta w_{ij}$
  - Where γ is the learning rate



REVIEW -- SEQUENTIAL TRAINING VS. CONCURRENT TRAINING



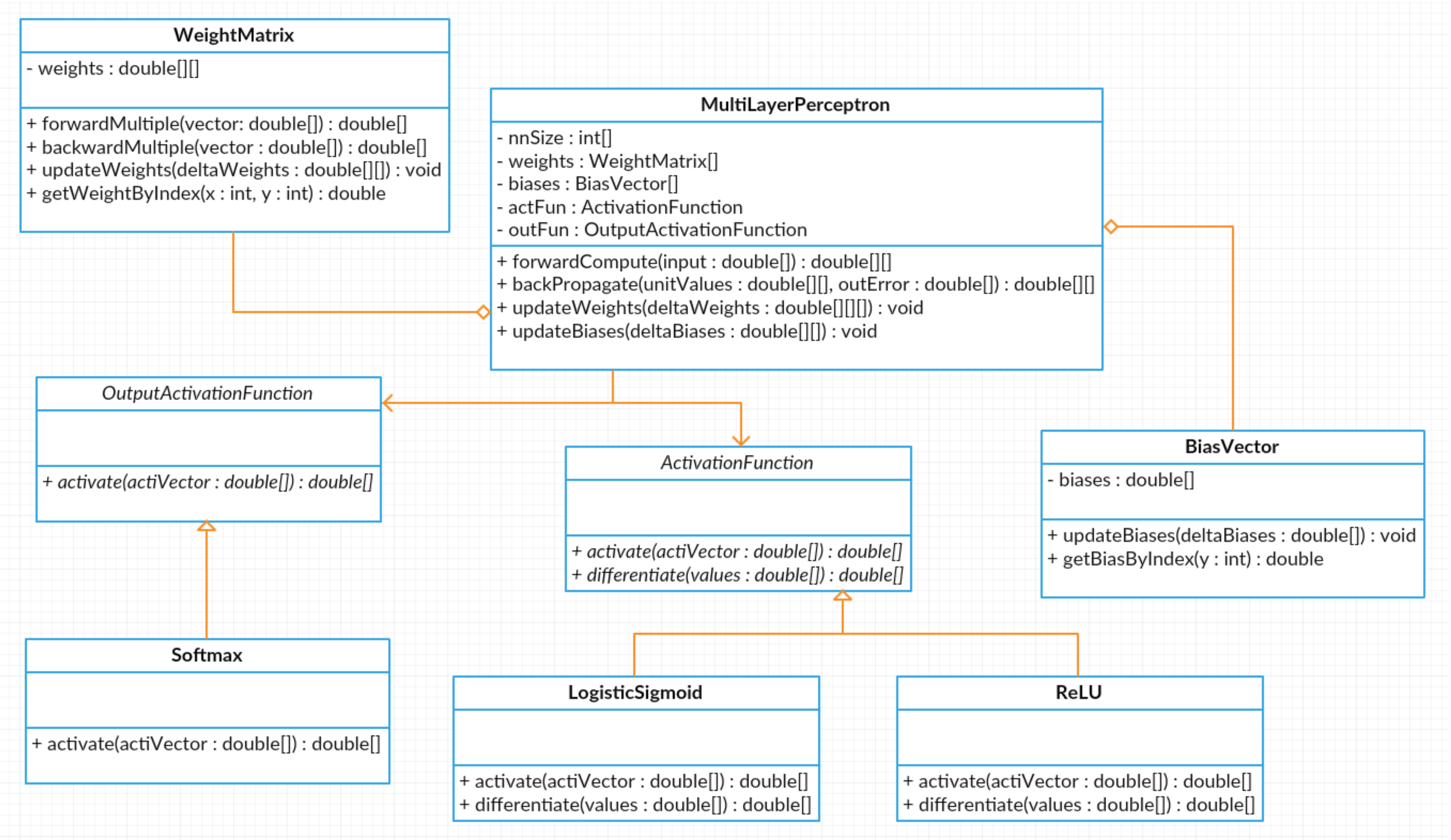
Sequential training

Concurrent training

BROAD VIEW OF THE IMPLEMENTATION

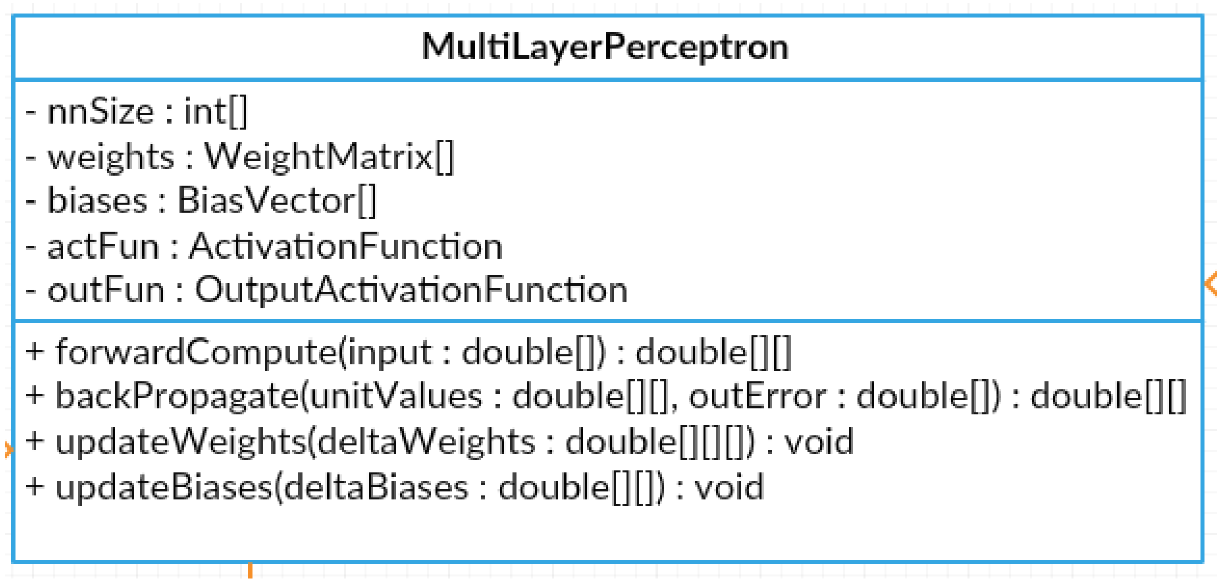
- There are 3 major components in our implementation:
  - **The neural network representation**: package of classes that form a neural network.
  - **Sequential trainers**: classes that implement the sequential training algorithm.
  - **Concurrent trainers**: classes that implement the concurrent training algorithm.

NEURAL NETWORK REPRESENTATION



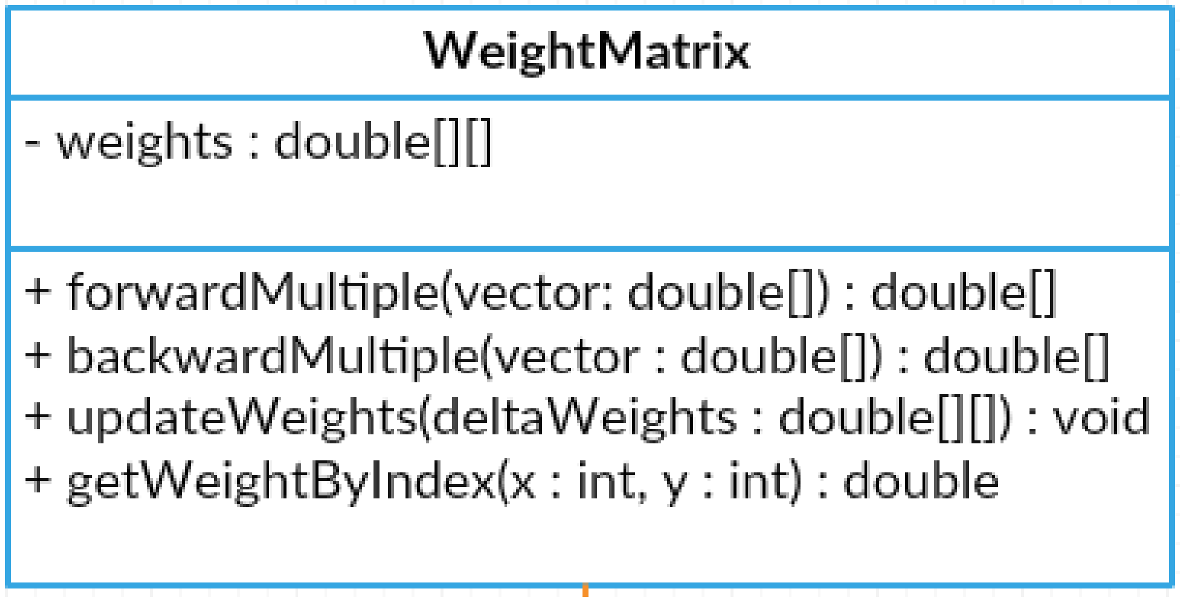
NEURAL NETWORK REPRESENTATION

- Main class that represents a multi-layer perceptron.
- Has attributes representing the components of a neural network.
  - Weights
  - Biases
  - Activation Functions

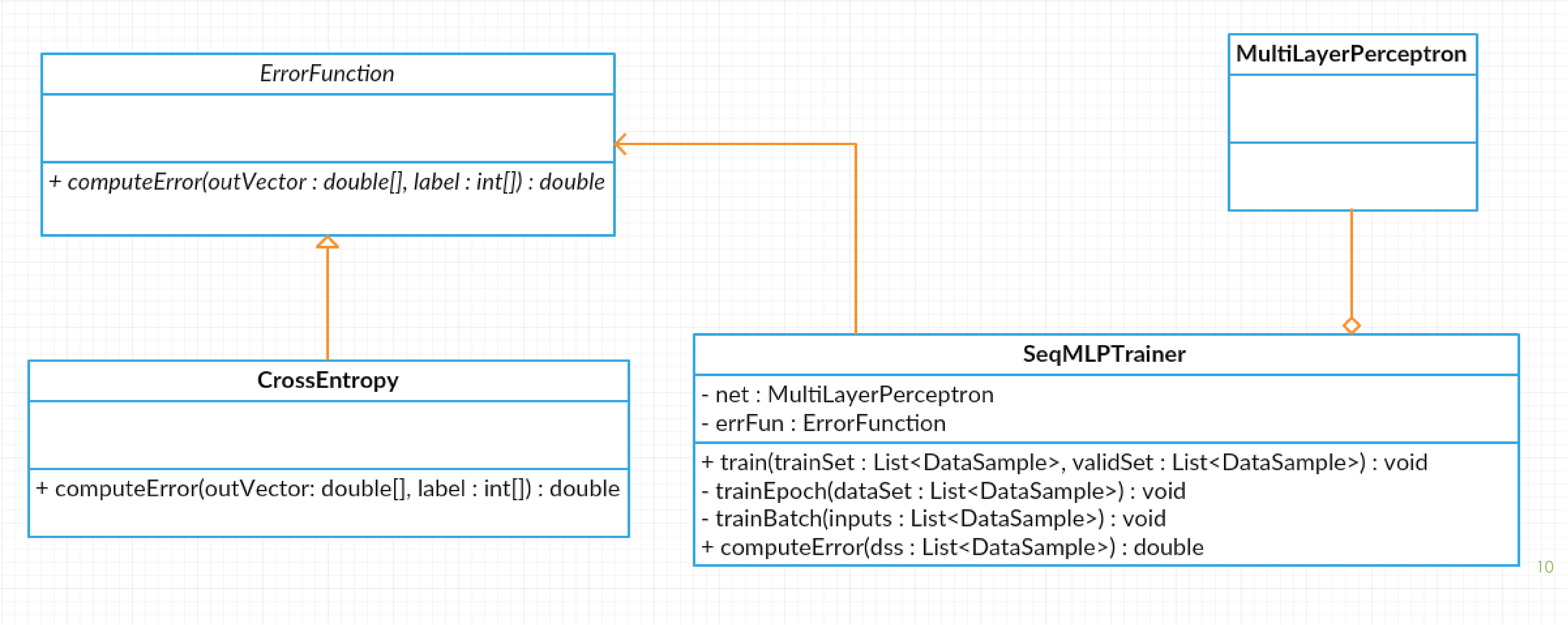


NEURAL NETWORK REPRESENTATION

- Represents a weight matrix
- Support forward/backward multiplications



THE SEQUENTIAL TRAINER

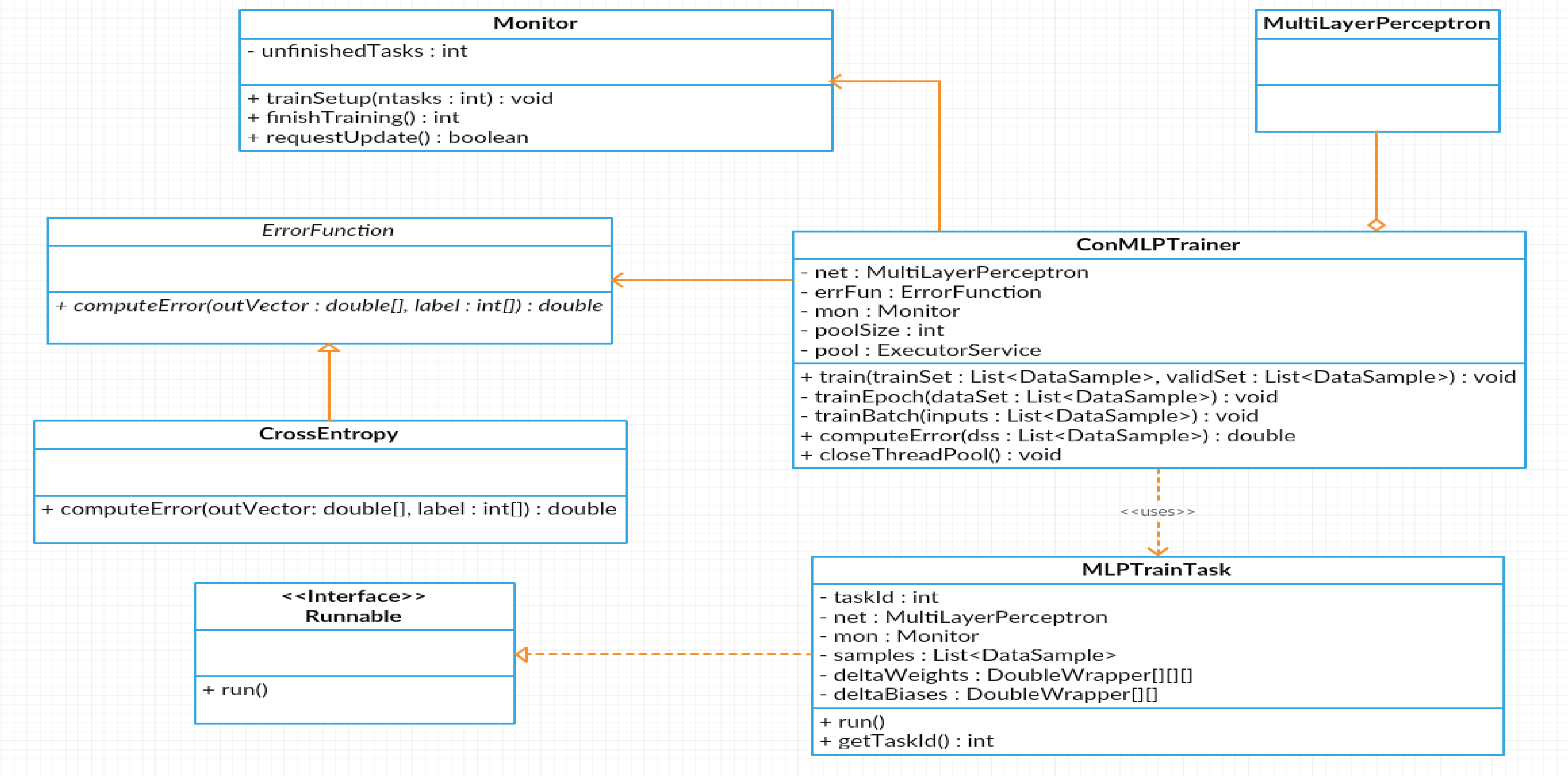


THE SEQUENTIAL TRAINER

- Divide training into 3 layers:
  - **train()** for the whole training process
  - **trainEpoch()** for the training of each epoch
  - **trainBatch()** for the training of each mini-batch

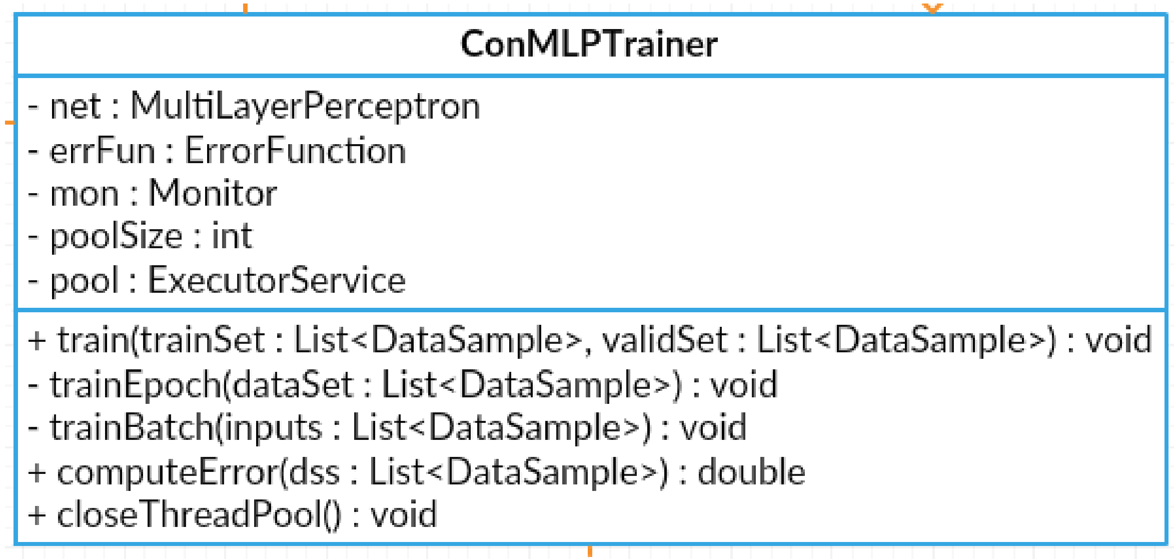
SeqMLPTrainer
- net : MultiLayerPerceptron - errFun : ErrorFunction
+ train(trainSet : List<DataSample>, validSet : List<DataSample>) : void - trainEpoch(dataSet : List<DataSample>) : void - trainBatch(inputs : List<DataSample>) : void + computeError(dss : List<DataSample>) : double

THE CONCURRENT TRAINER



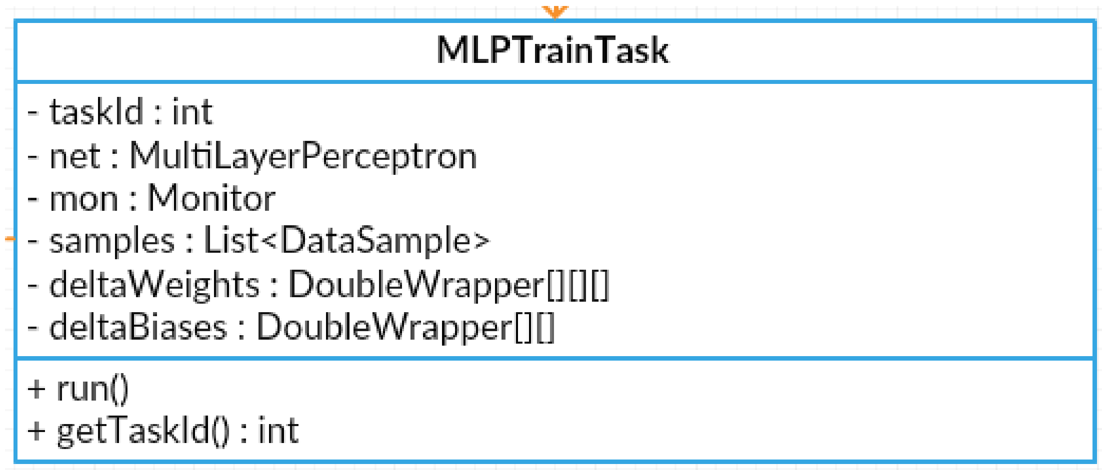
THE CONCURRENT TRAINER

- Similar to the sequential trainer.
- Keep references to the monitor object and a thread pool.
- Concurrency occur within the **trainBatch()** method.



THE CONCURRENT TRAINER -- DIVIDING TASKS

- Implements the ***java.lang.Runnable*** interface
- Represents a training task for worker thread.
- Keep references to the monitor object and the global shared variables for update statistics.



THE CONCURRENT TRAINER -- COLLECTING STATISTICS

- The update statistics are accumulated locally within each task.
- Then update in the shared global variables concurrently upon finish of the task.
- Need synchronization: synchronized blocks, compare and set etc.

```java
        // update delta weights and biases in shared variables
        for (int ly = 0; ly < nnSize.length - 1; ly++) {
            for (int x = 0; x < nnSize[ly]; x++) {
                for (int y = 0; y < nnSize[ly+1]; y++) {
                    synchronized (this.deltaWeights[ly][x][y]) {
                        this.deltaWeights[ly][x][y].setValue(this.deltaWeights[ly][x][y].getValue() + delW[ly][x][y]);
                    }
                }
            }

            for (int y = 0; y < nnSize[ly+1]; y++) {
                synchronized (this.deltaBiases[ly][y]) {
                    this.deltaBiases[ly][y].setValue(this.deltaBiases[ly][y].getValue() + delB[ly][y]);
                }
            }
        }
```

THE CONCURRENT TRAINER -- USING MONITOR

```java
public class Monitor {
    private volatile int unfinishedTasks;

    public Monitor()

    public synchronized void trainSetup(int ntasks)

    public synchronized int finishTraining()

    public synchronized void requestUpdate()
}
```

THE CONCURRENT TRAINER -- USING THREAD POOL

- Repeatedly creating and destroying threads can waste a lot of resource and time.
- Can pre-define a fixed size thread pool to avoid this problem.

```
        this.pool = Executors.newFixedThreadPool(poolSize); // create a fixed size thread pool
```

```
        // assign tasks to worker threads
        for (int i = 0; i < taskCount - 1; i++)
        {
            this.pool.execute(tasks[i]);
        }

        // execute one of the tasks in this thread
        tasks[taskCount - 1].run();
```

TESTING

- The concurrent training algorithm only parallelizes the computations over data samples within each mini-batch.
- The computed update statistics should be the same for both the sequential and concurrent algorithms.
- Define the concurrent implementation as correct if the model trained by the concurrent trainer is **equivalent** to the same model trained by the sequential trainer.
- Two models are considers equivalent if the differences between all their weights and biases are within some small error ε.

TESTING

```
Problems  @ Javadoc  Declaration  Console ☒
<terminated> Demo (1) [Java Application] C:\Program Files\Java\jre1.8.0_31\bin\javaw.exe (2015年10月30日 上午4:38:48)
readed in 60000 data samples
train set size: 54000
validation set size: 6000
[epsilon=0.000001] initial test: 318010 out of 318010 elements are considered equal
train model1 sequentially...
train model2 concurrently...
[epsilon=0.000001] test 1: 318010 out of 318010 elements are considered equal
[epsilon=0.000001] test with original model: 318003 out of 318010 elements are considered equal
train model1 sequentially...
train model2 concurrently...
[epsilon=0.000001] test 2: 318010 out of 318010 elements are considered equal
[epsilon=0.000001] test with original model: 318009 out of 318010 elements are considered equal
train model1 sequentially...
train model2 concurrently...
[epsilon=0.000001] test 3: 318010 out of 318010 elements are considered equal
[epsilon=0.000001] test with original model: 318008 out of 318010 elements are considered equal
train model1 sequentially...
train model2 concurrently...
[epsilon=0.000001] test 4: 318010 out of 318010 elements are considered equal
[epsilon=0.000001] test with original model: 318007 out of 318010 elements are considered equal
train model1 sequentially...
train model2 concurrently...
[epsilon=0.000001] test 5: 318010 out of 318010 elements are considered equal
[epsilon=0.000001] test with original model: 318006 out of 318010 elements are considered equal
train model1 sequentially...
```

- Have ran 100 comparison tests and all of them are considered equal.

FUTURE WORK

- Run the sequential and the concurrent algorithm on a multicore machine to see how much training time can be reduced by using the concurrent algorithm.