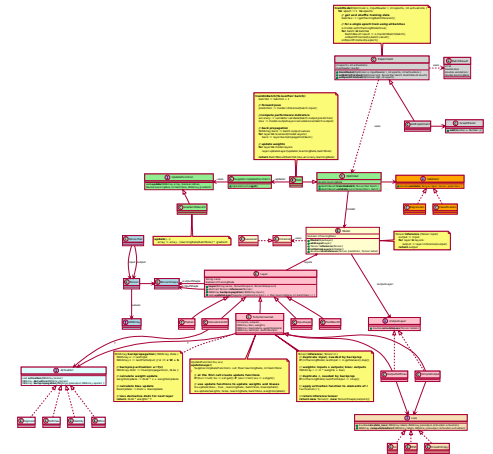


2ID90-DL – package

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Overview

- Introduction
- Sample Usage
- UML diagrams

Introduction 2ID90-DL

- package for handling Artificial neural networks
- support for
 - Fully connected networks
 - Convolutional networks
 - Backpropagation
 - Gradient Descent
- GUI
 - showing details of the learning process
- Based on Nd4j
 - an optimized library for handling high-dimensional vectors, matrices, tensor, ...
 - based on BLAS (Basic Linear Algebra Subprograms)

Sample Usage - 1

MyExperiment.java

READ DATA

CREATE MODEL

INITIALIZE SGD

START TRAINING

```
Model createModel(int inputs, int outputs) {
    InputLayer input = new InputLayer("In", new TensorShape(inputs));
    Model model = new Model(input);
    model.addLayer(new FullyConnected("fc1", new TensorShape(10, 10)));
    model.addLayer(new FullyConnected("fc2", new TensorShape(10, 10)));
    model.addLayer(new FullyConnected("fc3", new TensorShape(10, 10)));
    model.addLayer(new FullyConnected("fc4", new TensorShape(10, 10)));
    model.addLayer(new FullyConnected("fc5", new TensorShape(10, 10)));
    model.addLayer(new FullyConnected("fc6", new TensorShape(10, 10)));
    model.addLayer(new SimpleOutput("Out", new TensorShape(10)));
    return model;
}
```

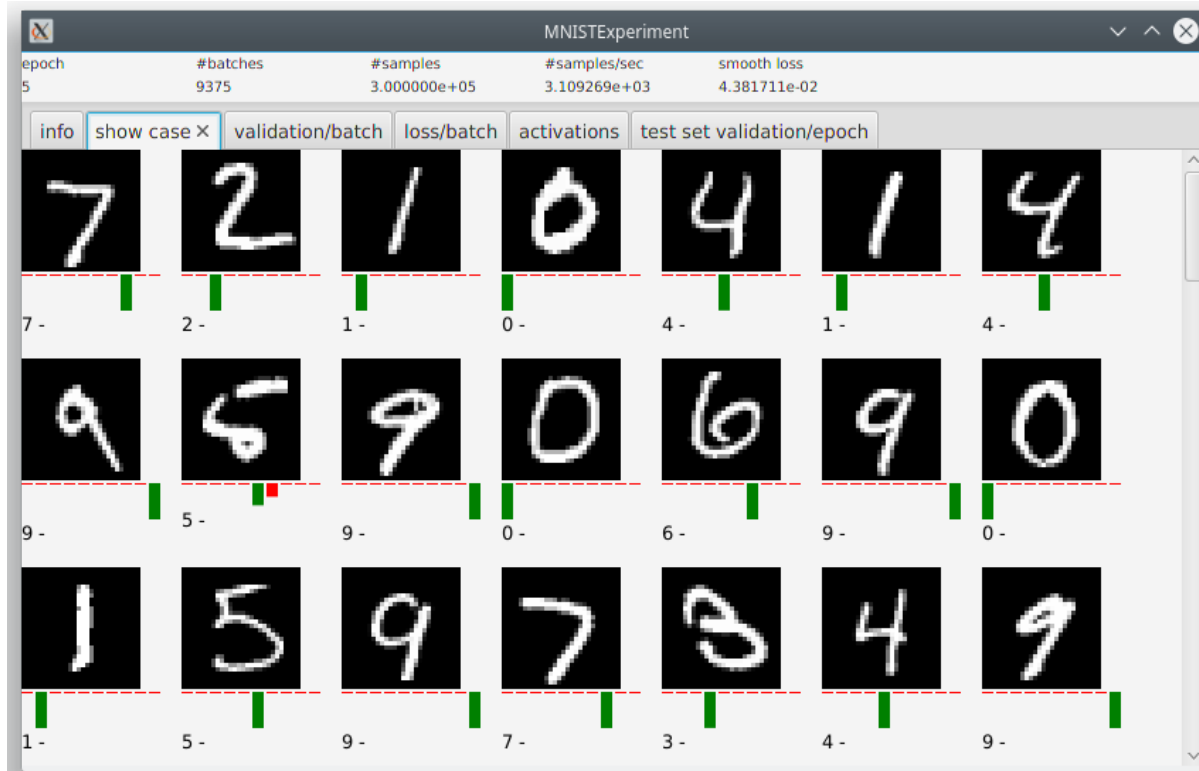
epoch	#batches	#samples	#samples/sec	smooth loss
1	1386	4.435200e+04	3.583573e+03	1.524051e-01

Key	Value
reader class	MNISTReader
batch size	32
#batches	1875
#training pairs	60000
#validation pairs	10000
input shape	(1,1,28,28)
output shape	(1,10)

Key	Value
optimizer	Stochastic Gradient Descent
Validator	Classification
update function	Decay(GradientDescentAdaDelta,0.000100)
learning rate	0.001
epochs	5
activations	200

RUN EXPERIMENT

Sample Usage - 2

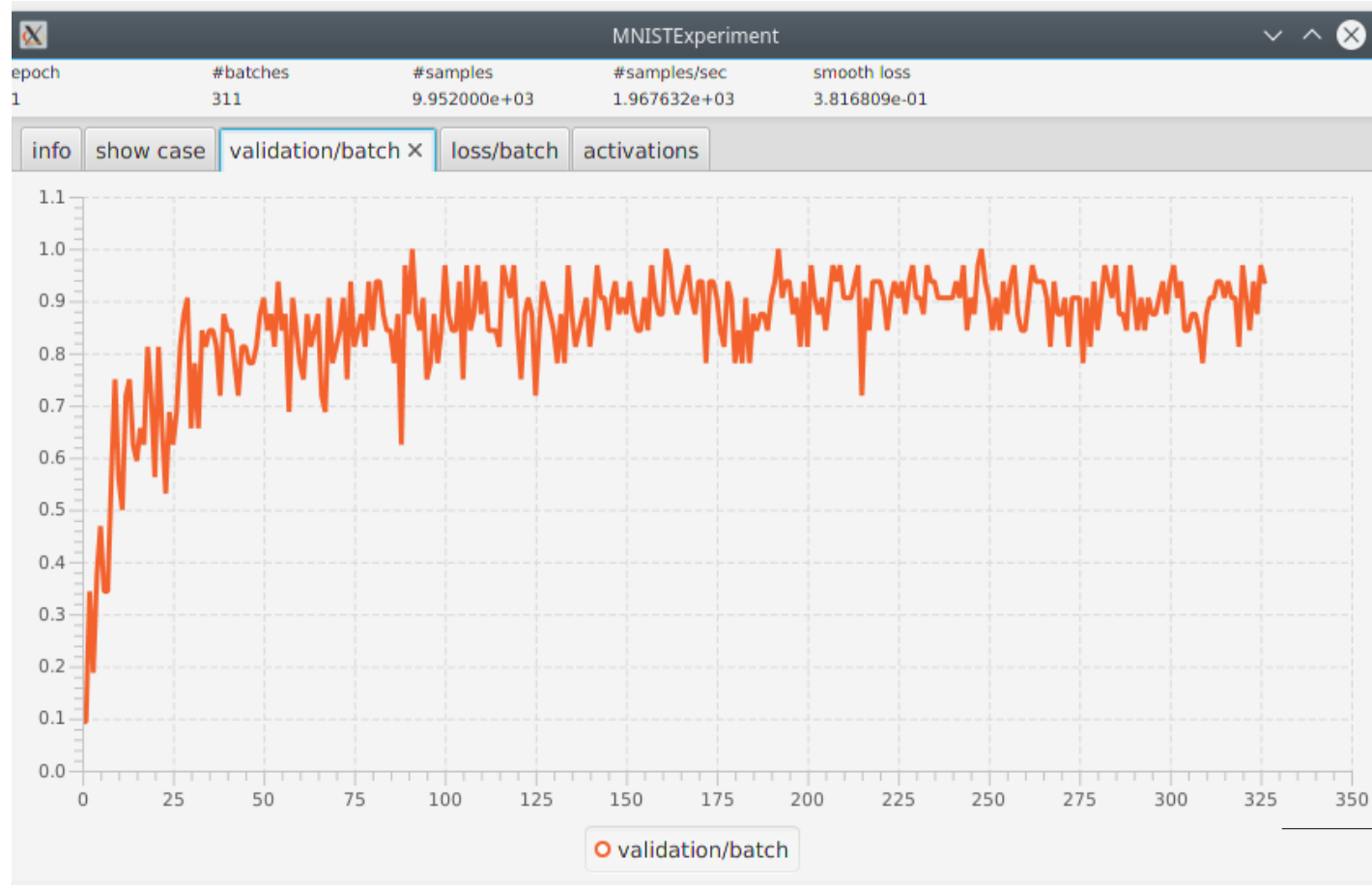


Show case: shows samples from the test data annotated with the current network's classification.

All samples are correctly classified, but the network hesitates whether one of the fives is actually a six.

Validation

Sample Usage - 2

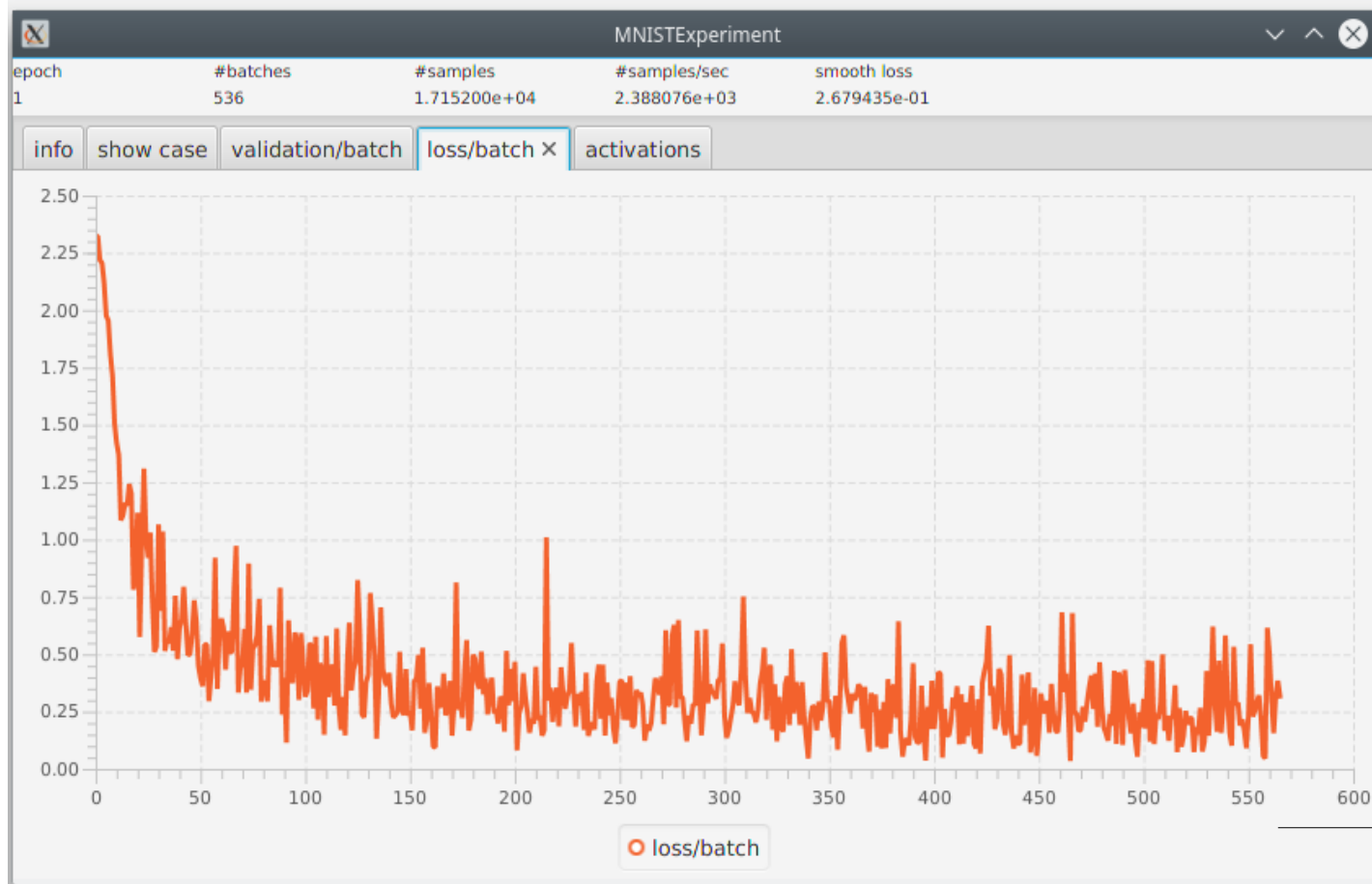


Validation per batch:
here fraction of correctly
classified samples in the
batch.

Batch Id

Sample Usage - 3

Loss

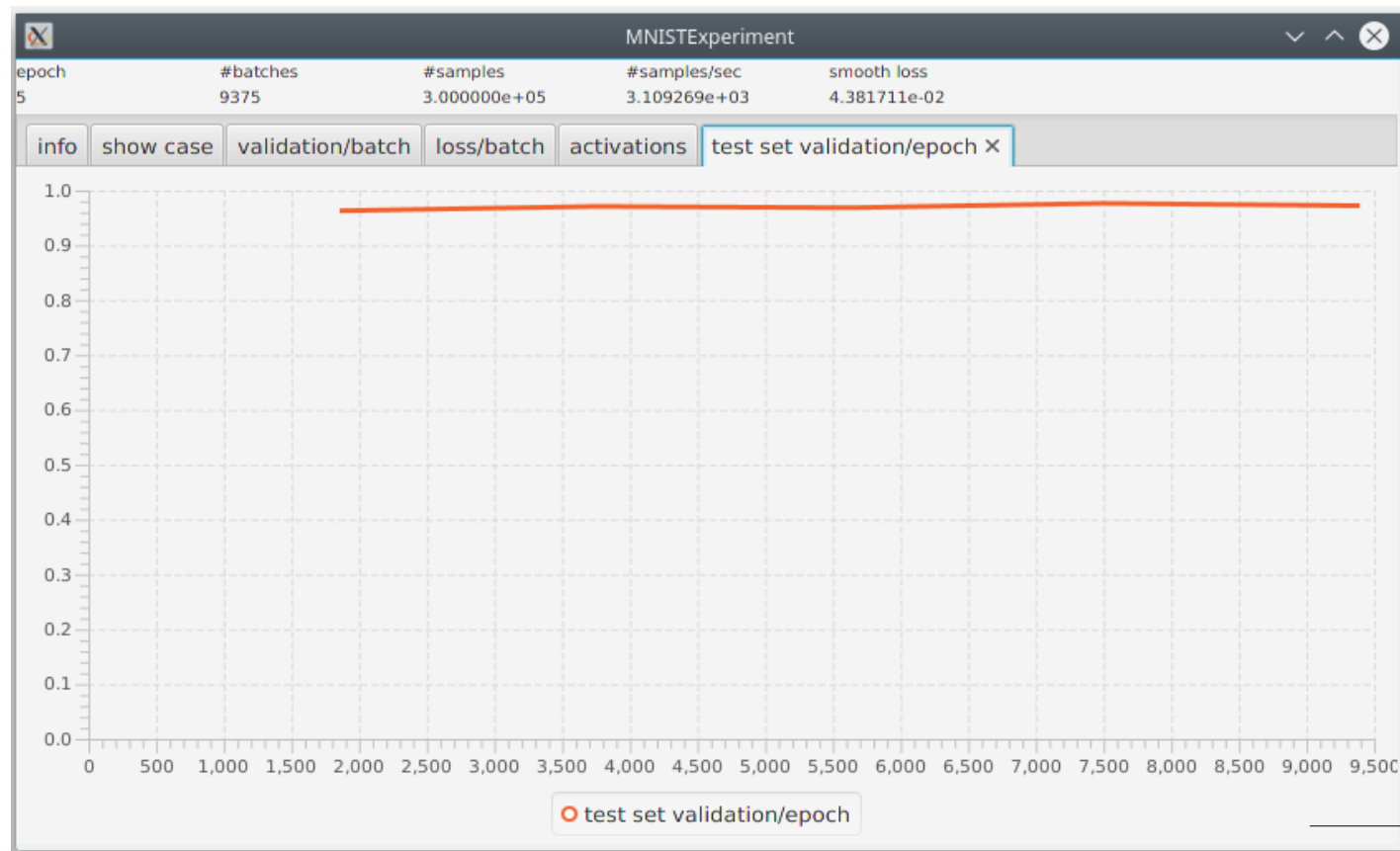


Loss per batch:
here the average error
made in classifying the
samples in a batch.

Batch Id

Validation

Sample Usage - 4

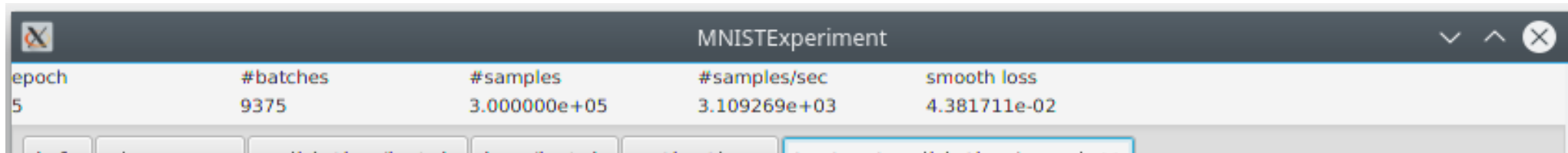


Test set validation per epoch

- computed at end of epoch
- validation based on test data
- here: percentage correctly classified

Batch Id

Sample Usage - 5



The screenshot shows a terminal window with the title 'MNISTExperiment'. It displays a table with training metrics for epoch 5. The table has five columns: epoch, #batches, #samples, #samples/sec, and smooth loss. The values for epoch 5 are: 5, 9375, 3.000000e+05, 3.109269e+03, and 4.381711e-02 respectively.

epoch	#batches	#samples	#samples/sec	smooth loss
5	9375	3.000000e+05	3.109269e+03	4.381711e-02

Current status of the training:

- current epoch
- total number of processed batches
- total number of processed samples = #batches * batchsize
- #samples/second : gives an indication of efficiency of network
- smooth loss is updated after each batch according to
$$\text{smoothLoss} := 0.99 * \text{smoothLoss} + 0.01 * \text{lossOfLastbatch}$$

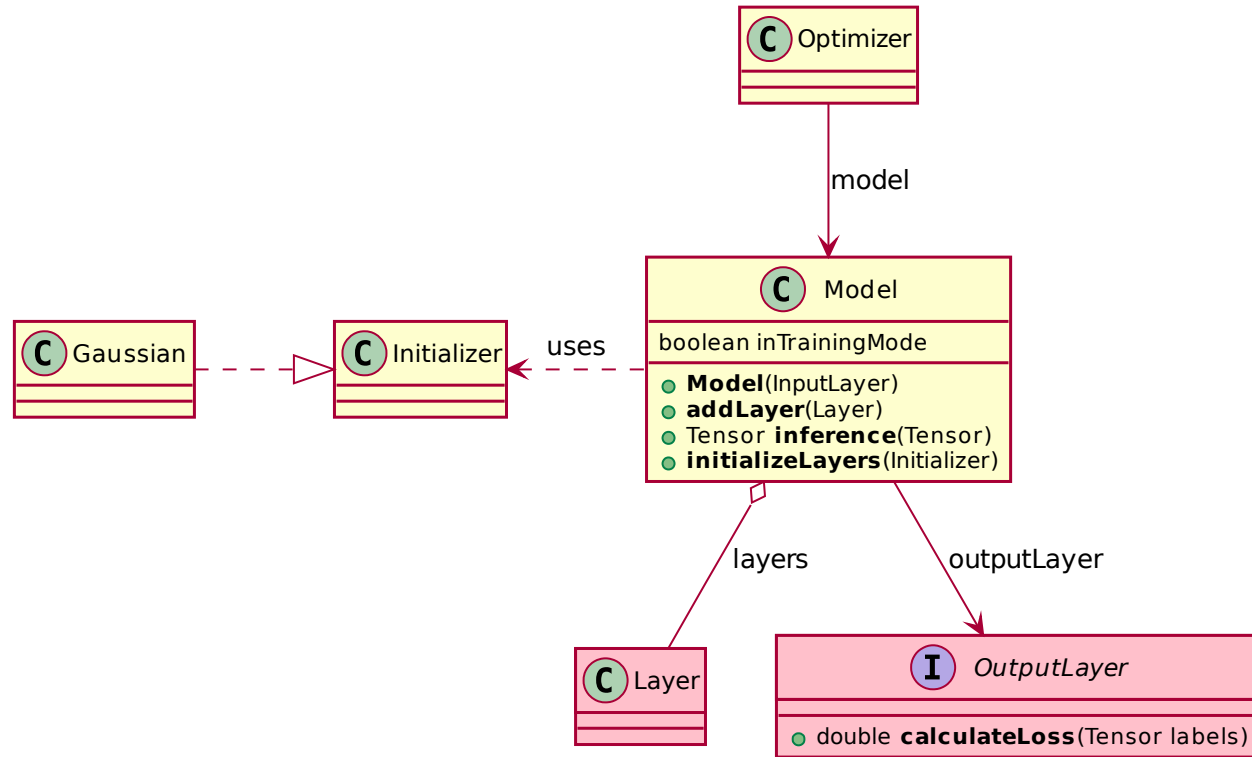
The diagram illustrates a neural network framework architecture. It features several key classes and their interactions:

- Tensor**: Represents a multi-dimensional array. It includes methods for `input/output`, `values`, and `update`. It is associated with `TensorShape` and `TensorIndex`.
- TensorShape**: Describes the dimensions of a tensor. It includes methods for `input/output` and `values`.
- TensorIndex**: Represents an index in a tensor. It includes methods for `input/output` and `values`.
- Layer**: A base class for different types of layers. It includes methods for `input/output` and `values`. It is associated with `LayerType` and `LayerIndex`.
- LayerType**: Describes the type of a layer. It includes methods for `input/output` and `values`.
- LayerIndex**: Represents an index in a layer. It includes methods for `input/output` and `values`.
- Model**: Represents a neural network model. It includes methods for `input/output` and `values`. It is associated with `ModelType` and `ModelIndex`.
- ModelType**: Describes the type of a model. It includes methods for `input/output` and `values`.
- ModelIndex: Represents an index in a model. It includes methods for `input/output` and `values`.**
- Optimizer**: Manages the optimization process. It includes methods for `input/output` and `values`. It is associated with `OptimizerType` and `OptimizerIndex`.
- OptimizerType**: Describes the type of an optimizer. It includes methods for `input/output` and `values`.
- OptimizerIndex**: Represents an index in an optimizer. It includes methods for `input/output` and `values`.
- Experiment**: Manages the experiment process. It includes methods for `input/output` and `values`. It is associated with `ExperimentType` and `ExperimentIndex`.
- ExperimentType**: Describes the type of an experiment. It includes methods for `input/output` and `values`.
- ExperimentIndex**: Represents an index in an experiment. It includes methods for `input/output` and `values`.
- Activation**: Represents an activation function. It includes methods for `input/output` and `values`. It is associated with `ActivationType` and `ActivationIndex`.
- ActivationType**: Describes the type of an activation function. It includes methods for `input/output` and `values`.
- ActivationIndex**: Represents an index in an activation function. It includes methods for `input/output` and `values`.
- Loss**: Represents a loss function. It includes methods for `input/output` and `values`. It is associated with `LossType` and `LossIndex`.
- LossType**: Describes the type of a loss function. It includes methods for `input/output` and `values`.
- LossIndex**: Represents an index in a loss function. It includes methods for `input/output` and `values`.

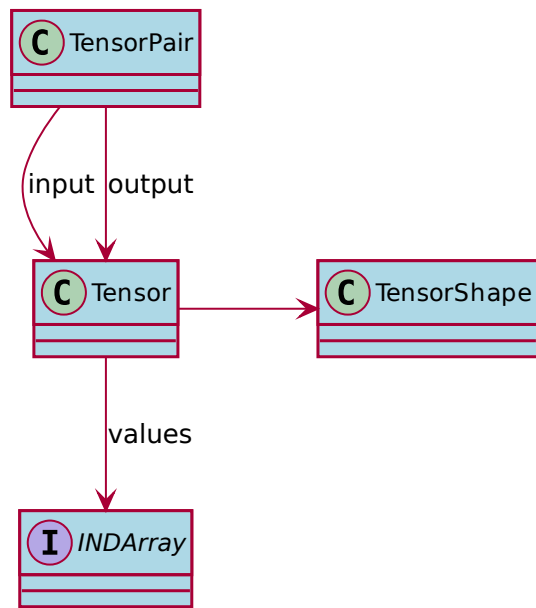
The diagram also includes several code snippets for various operations:

- trainModel**: A function that trains a model. It includes code for `get and shuffle training data`, `for a single epoch train using all batches`, and `update weights`.
- trainBatch**: A function that trains a batch. It includes code for `forward pass`, `compute performance indicators`, `backward pass`, and `update weights`.
- updateWeights**: A function that updates the weights of a model. It includes code for `compute performance indicators`, `backward pass`, and `update weights`.
- computePerformanceIndicators**: A function that computes performance indicators. It includes code for `compute performance indicators`.
- backwardPass**: A function that performs a backward pass. It includes code for `backward pass`.
- updateWeights**: A function that updates the weights of a model. It includes code for `update weights`.

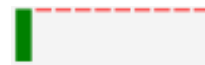
Network Model



Tensors

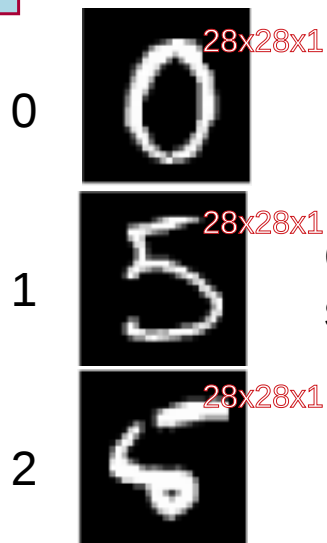
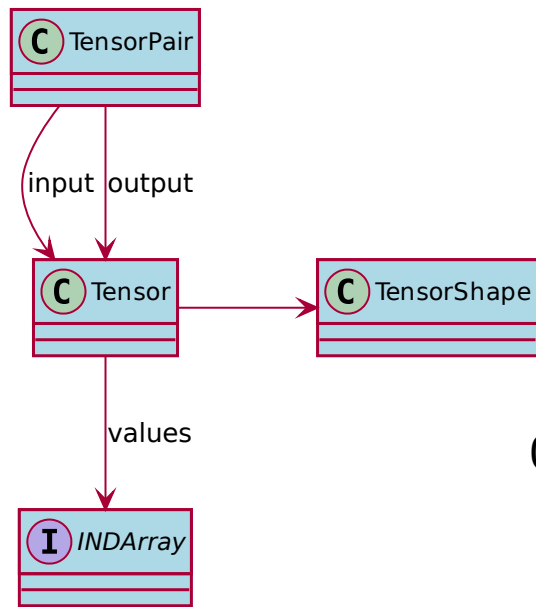


- Input network: List of TensorPairs
- TensorPair: (input,output)
- Tensor has a shape, e.g.
 - input shape: **28x28x1** (image)
 - greyscale image of size 28x28
 - output shape: **10**
 - Probability distribution over ten possible class values (0 ..9)



Tensors

- Input shape of a network: **$n \times 28 \times 28 \times 1$**
 - n greyscale images of size 28×28
- Output shape of a network: **$n \times 10$**
 - n probability distributions
- Network then maps: **$n \times 28 \times 28 \times 1$** Tensor on **$n \times 10$** Tensor

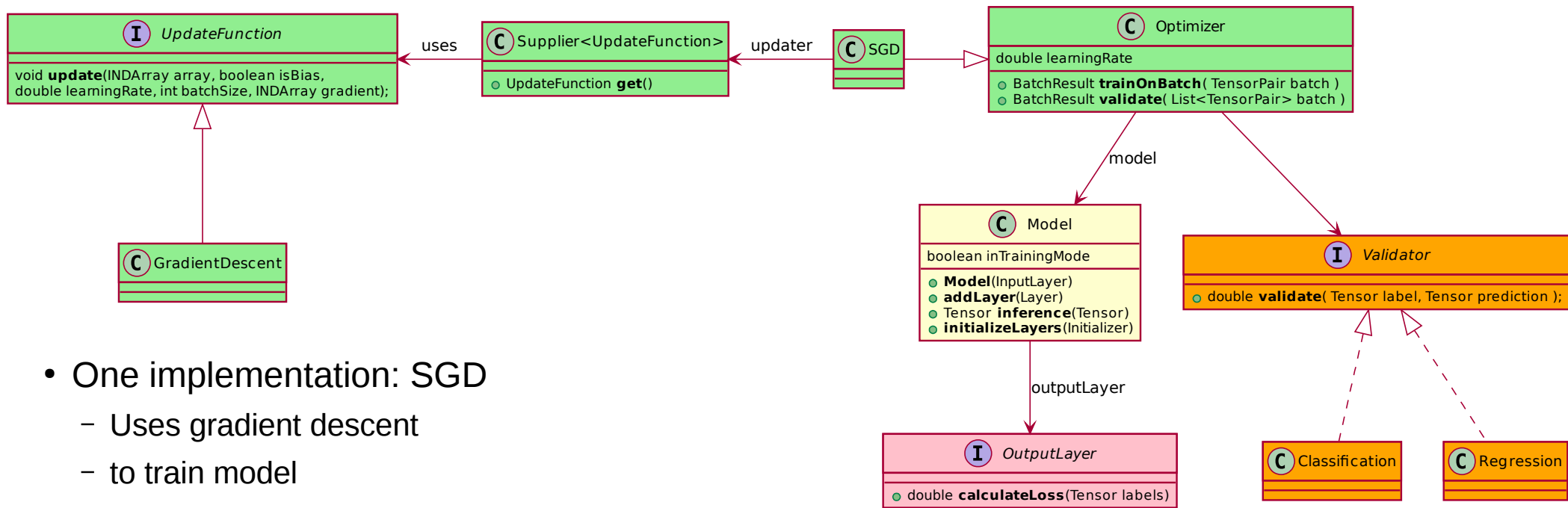


One tensor with
shape $3 \times 28 \times 28 \times 1$.



One tensor with
shape 3×10 .

Optimizer - 1



- One implementation: SGD
 - Uses gradient descent
 - to train model
- Two Validators
 - Regression: MSE
 - Classification: fraction of correctly classified samples

Optimizer – 2

```
trainOnBatch(TensorPair batch):
    batchId := batchId + 1

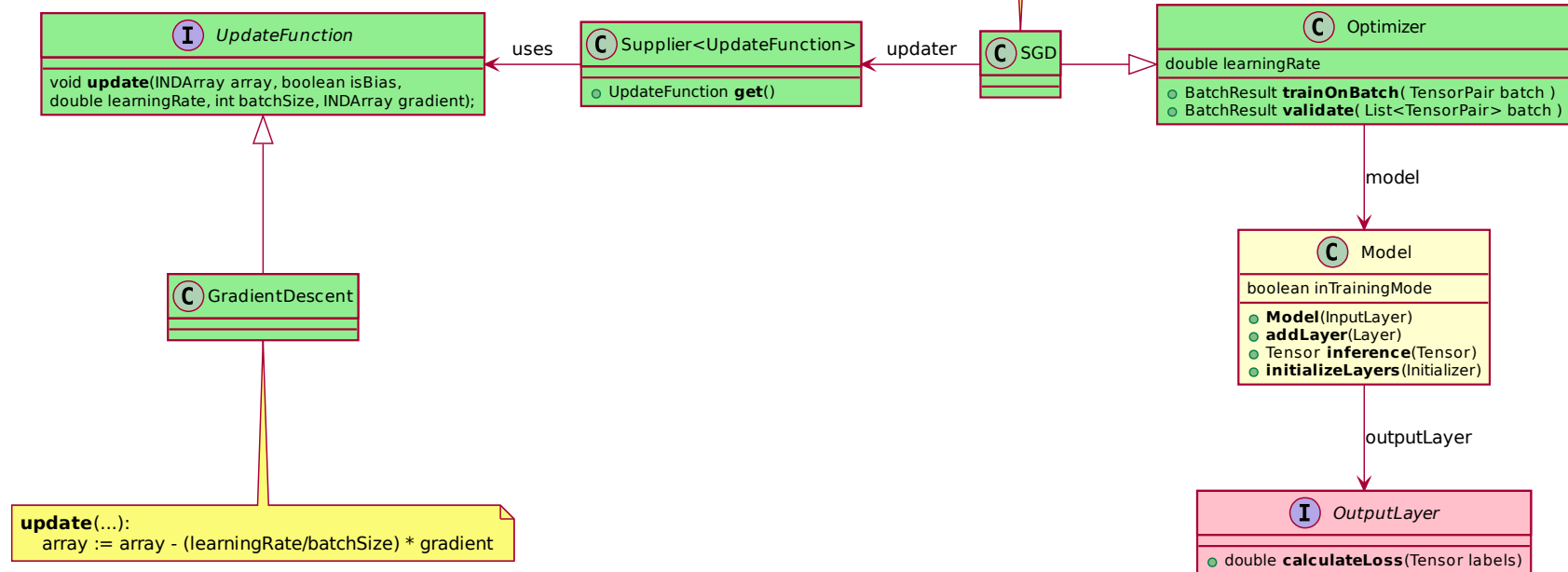
    // forward pass
    prediction := model.inference(batch.input);

    //compute performance indicators
    accuracy := validator.validate(batch.output,prediction)
    loss := model.outputLayer.calculateLoss(batch.output)

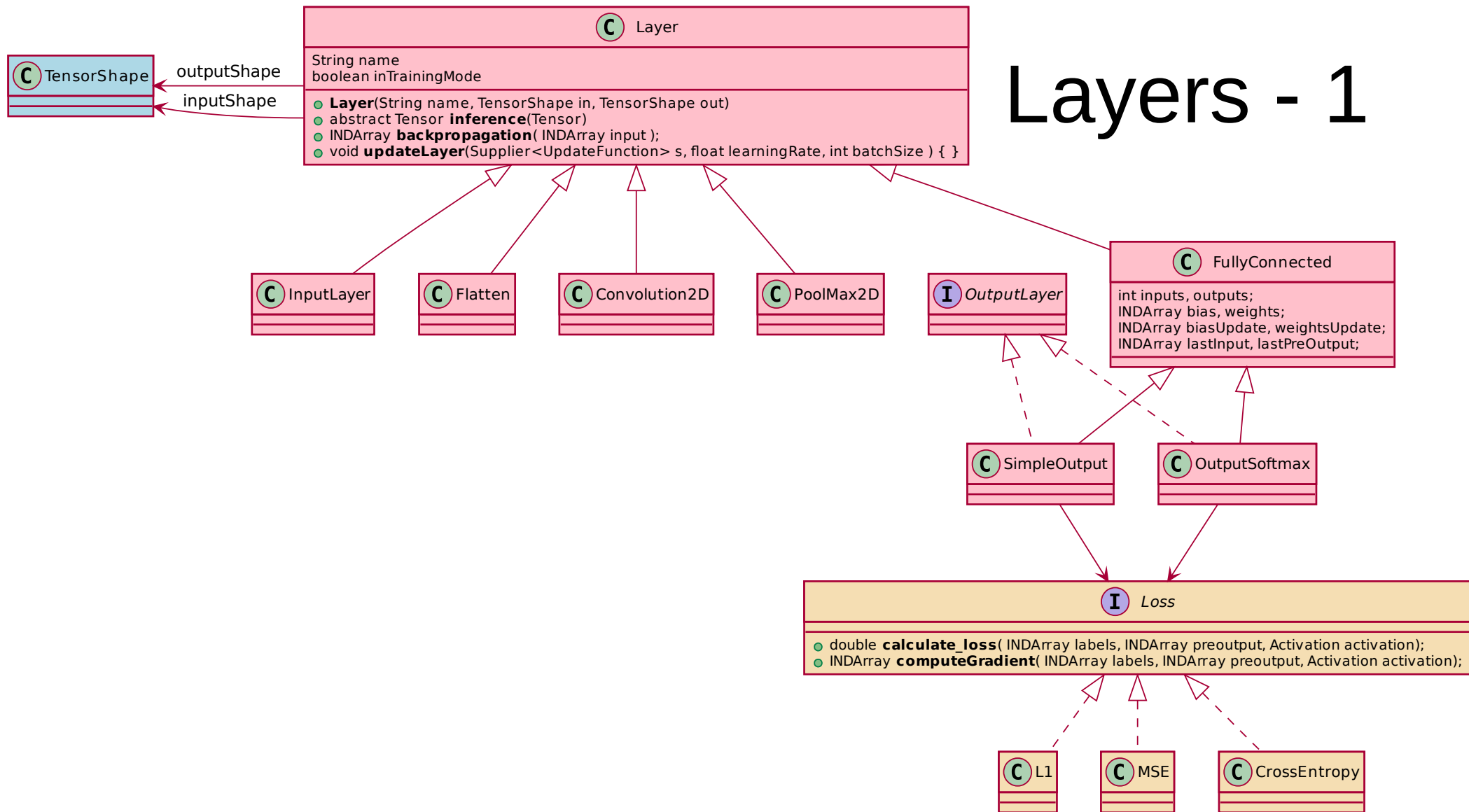
    // back propagation
    INDArray back := batch.output.values
    for layer in reversed(model.layers)
        back := layer.backpropagation(back)

    // update weights
    for layer in model.layers
        layer.updateLayer(updater,learningRate,batchSize)

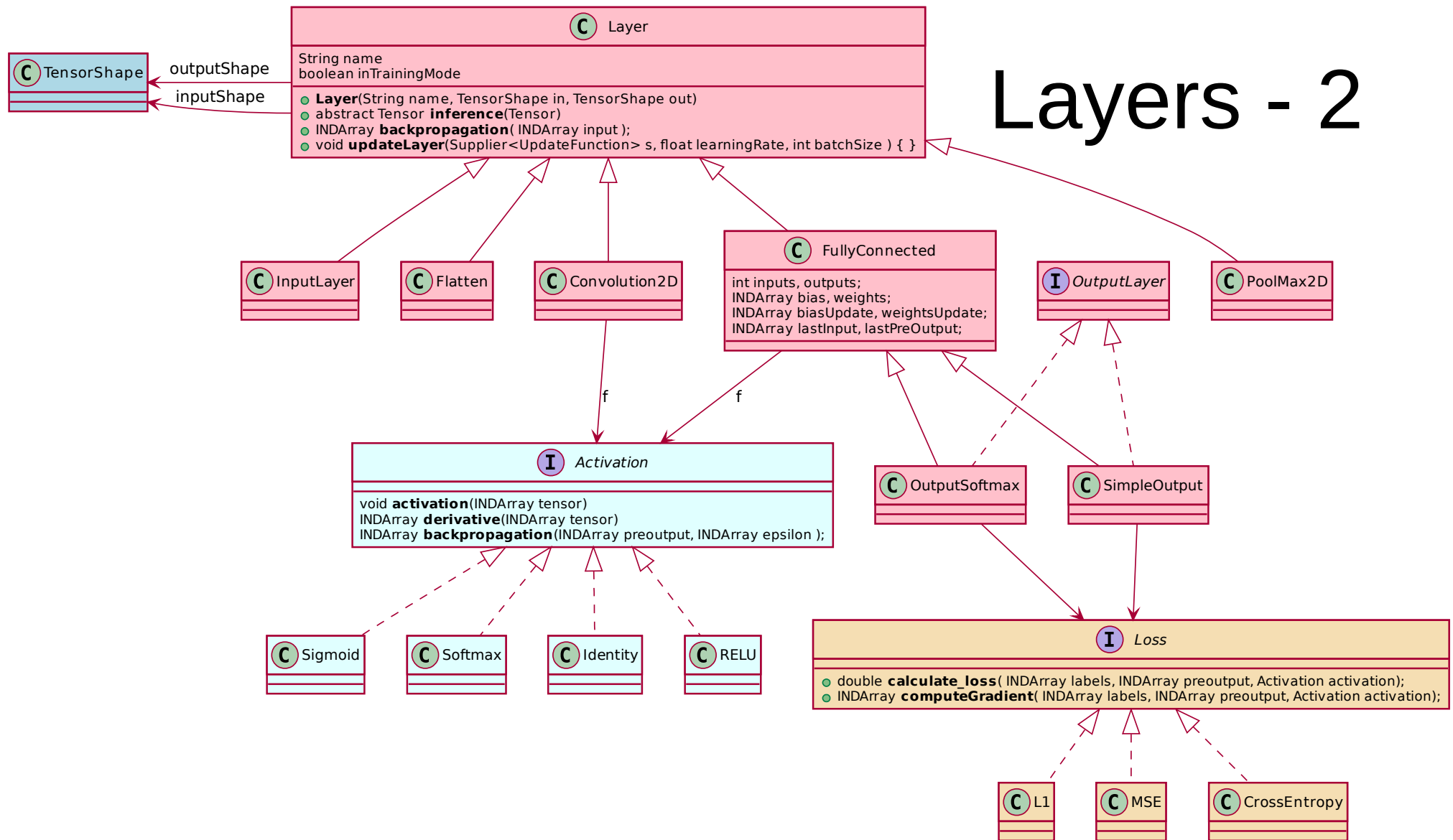
    return BatchResult(batchId,loss,accuracy,learningRate)
```



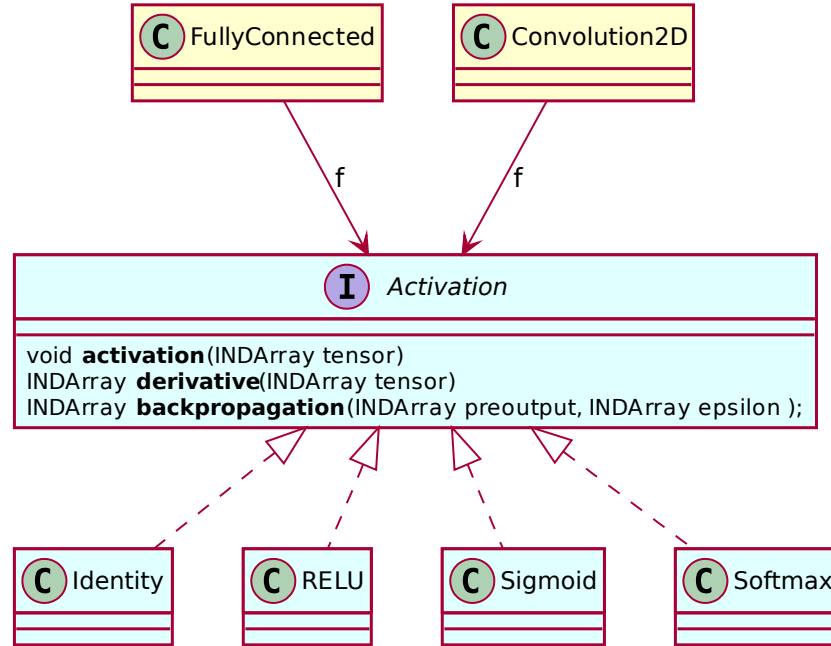
Layers - 1



Layers - 2

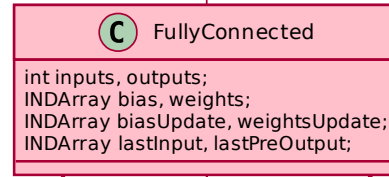
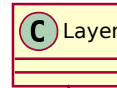
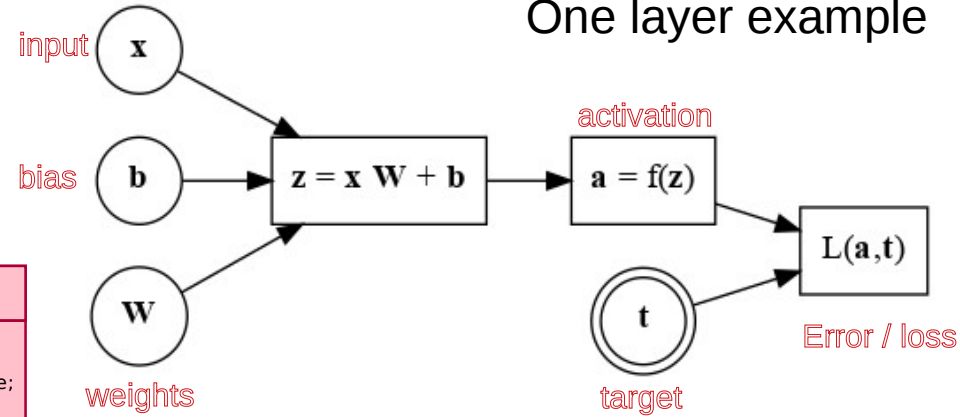


Activations



FullyConnected layer

One layer example



```
Tensor inference(Tensor in)
// duplicate input, needed by backprop
if (inTrainingMode) lastInput = in.getValues().dup();

// weights: inputs x outputs; bias: outputs
INDArray z := in * weights + bias

// duplicate z, needed by backprop
if (inTrainingMode) lastPreOutput := z.dup();

// apply activation function to elements of z
f.activation( z );

// return inference tensor
return new Tensor(z, new TensorShape(outputs));
```

```
INDArray backpropagation(INDArray dLda)
INDArray x:= lastInput
INDArray z := lastPreOutput; // z := x W + b

// backprop activation: a=f(z)
INDArray dLdz := f.backpropagation(z, dLda );

// calculate weight update
weightsUpdate := dLdz * x + weightsUpdate

// calculate bias update
biasUpdate := dLdz + biasUpdate

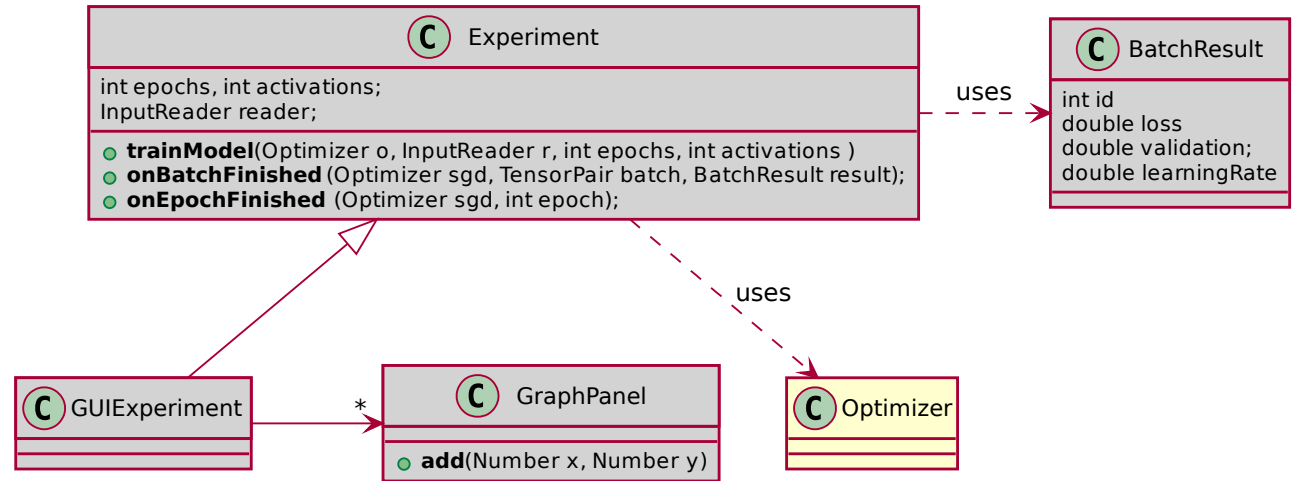
// loss derivative dLdx for next layer
return dLdz * weights^T
```

```
UpdateFunction bu, wu;
updateLayer(
    Supplier<UpdateFunction> suf, float learningRate, int batchSize
)
// at the first call create update functions
if (bu==null) bu := suf.get(); if (wu==null) wu := suf.get();

// use update functions to update weights and biases
bu.update(bias , true , learningRate, batchSize, biasUpdate);
wu.update(weights, false, learningRate, batchSize, weightsUpdate);
```

Experiment - 1

- Create experiment
- Read data
- Create model
 - Initialize model
- Build optimizer
- Call trainModel
 - React on onBatch/EpochFinished events
 - to fill plots
 - ...



Experiment - 2

```
trainModel(Optimizer o, InputReader r, int epochs, int activations )  
  for epoch := 1 to epochs:  
    // get and shuffle training data  
    batches := r.getTrainingBatchIterator();  
  
    // for a single epoch train using all batches  
    o.model.setInTrainingMode(true);  
    for batch in batches  
      BatchResult result := o.trainOnBatch(batch);  
      onBatchFinished(o,batch,result);  
    onEpochFinished(o,epoch);
```

