Containers

Complex neural networks are easily built using container classes:

- Container : abstract class inherited by containers ;
    - Sequential : plugs layers in a feed-forward fully connected manner ;
    - Parallel : applies its `ith` child module to the `ith` slice of the input Tensor ;
    - Concat : concatenates in one layer several modules along dimension `dim` ;
        - DepthConcat : like Concat, but adds zero-padding when non-`dim` sizes don't match;
    - Bottle : allows any dimensionality input be forwarded through a module ;

See also the Table Containers for manipulating tables of Tensors.

Container

This is an abstract Module class which declares methods defined in all containers.
It reimplements many of the Module methods such that calls are propagated to the
contained modules. For example, a call to zeroGradParameters
will be propagated to all contained modules.

add(module)

Adds the given `module` to the container. The order is important

get(index)

Returns the contained modules at index `index` .

size()

Returns the number of contained modules.

Sequential

Sequential provides a means to plug layers together
in a feed-forward fully connected manner.

E.g.
creating a one hidden-layer multi-layer perceptron is thus just as easy as:

```
mlp = nn.Sequential()
mlp:add(nn.Linear(10, 25)) -- Linear module (10 inputs, 25 hidden
units)
mlp:add(nn.Tanh())         -- apply hyperbolic tangent transfer
function on each hidden units
mlp:add(nn.Linear(25, 1))  -- Linear module (25 inputs, 1 output)

> mlp
nn.Sequential {
  [input -> (1) -> (2) -> (3) -> output]
  (1): nn.Linear(10 -> 25)
  (2): nn.Tanh
  (3): nn.Linear(25 -> 1)
}

> print(mlp:forward(torch.randn(10)))
-0.1815
[torch.Tensor of dimension 1]
```

remove([index])

Remove the module at the given `index`. If `index` is not specified, remove the last layer.

```
model = nn.Sequential()
model:add(nn.Linear(10, 20))
model:add(nn.Linear(20, 20))
model:add(nn.Linear(20, 30))
```

```
model:remove(2)
> model
nn.Sequential {
  [input -> (1) -> (2) -> output]
  (1): nn.Linear(10 -> 20)
  (2): nn.Linear(20 -> 30)
}
```

insert(module, [index])

Inserts the given `module` at the given `index`. If `index` is not specified, the incremented length of the sequence is used and so this is equivalent to use `add(module)`.

```
model = nn.Sequential()
model:add(nn.Linear(10, 20))
model:add(nn.Linear(20, 30))
model:insert(nn.Linear(20, 20), 2)
> model
nn.Sequential {
  [input -> (1) -> (2) -> (3) -> output]
  (1): nn.Linear(10 -> 20)
  (2): nn.Linear(20 -> 20)      -- The inserted layer
  (3): nn.Linear(20 -> 30)
}
```

Parallel

`module` = `Parallel(inputDimension,outputDimension)`

Creates a container module that applies its `ith` child module to the `ith` slice of the input Tensor by using select
on dimension `inputDimension`. It concatenates the results of its contained modules together along dimension `outputDimension`.

Example:

```
mlp = nn.Parallel(2,1);   -- Parallel container will associate a
```

```
module to each slice of dimension 2
                            -- (column space), and concatenate the
outputs over the 1st dimension.

mlp:add(nn.Linear(10,3)); -- Linear module (input 10, output 3),
applied on 1st slice of dimension 2
mlp:add(nn.Linear(10,2))  -- Linear module (input 10, output 2),
applied on 2nd slice of dimension 2

                                  -- After going through the Linear
module the outputs are
                                  -- concatenated along the unique
dimension, to form 1D Tensor
> mlp:forward(torch.randn(10,2)) -- of size 5.
-0.5300
-1.1015
 0.7764
 0.2819
-0.6026
[torch.Tensor of dimension 5]
```

A more complicated example:

```
mlp = nn.Sequential();
c = nn.Parallel(1,2)     -- Parallel container will associate a
module to each slice of dimension 1
                         -- (row space), and concatenate the
outputs over the 2nd dimension.

for i=1,10 do            -- Add 10 Linear+Reshape modules in
parallel (input = 3, output = 2x1)
 local t=nn.Sequential()
 t:add(nn.Linear(3,2))   -- Linear module (input = 3, output = 2)
 t:add(nn.Reshape(2,1))  -- Reshape 1D Tensor of size 2 to 2D
Tensor of size 2x1
 c:add(t)
end

mlp:add(c)               -- Add the Parallel container in the
Sequential container

pred = mlp:forward(torch.randn(10,3)) -- 2D Tensor of size 10x3
goes through the Sequential container
```

```
                                        -- which contains a Parallel
container of 10 Linear+Reshape.
                                        -- Each Linear+Reshape module
receives a slice of dimension 1
                                        -- which corresponds to a 1D
Tensor of size 3.
                                        -- Eventually all the
Linear+Reshape modules' outputs of size 2x1
                                        -- are concatenated alond the
2nd dimension (column space)
                                        -- to form pred, a 2D Tensor
of size 2x10.

> pred
-0.7987 -0.4677 -0.1602 -0.8060  1.1337 -0.4781  0.1990  0.2665
-0.1364  0.8109
-0.2135 -0.3815  0.3964 -0.4078  0.0516 -0.5029 -0.9783 -0.5826
0.4474  0.6092
[torch.DoubleTensor of size 2x10]


for i = 1, 10000 do     -- Train for a few iterations
 x = torch.randn(10,3);
 y = torch.ones(2,10);
 pred = mlp:forward(x)

 criterion = nn.MSECriterion()
 local err = criterion:forward(pred,y)
 local gradCriterion = criterion:backward(pred,y);
 mlp:zeroGradParameters();
 mlp:backward(x, gradCriterion);
 mlp:updateParameters(0.01);
 print(err)
end
```

Concat

```
module = nn.Concat(dim)
```

Concat concatenates the output of one layer of "parallel" modules along the provided dimension `dim`: they take the same inputs, and their output is concatenated.

```
mlp = nn.Concat(1);
mlp:add(nn.Linear(5,3))
mlp:add(nn.Linear(5,7))

> print(mlp:forward(torch.randn(5)))
 0.7486
 0.1349
 0.7924
-0.0371
-0.4794
 0.3044
-0.0835
-0.7928
 0.7856
-0.1815
[torch.Tensor of dimension 10]
```

DepthConcat

```
module = nn.DepthConcat(dim)
```

DepthConcat concatenates the output of one layer of "parallel" modules along the provided dimension `dim`: they take the same inputs, and their output is concatenated. For dimensions other than `dim` having different sizes, the smaller tensors are copied in the center of the output tensor, effectively padding the borders with zeros.

The module is particularly useful for concatenating the output of Convolutions along the depth dimension (i.e. `nOutputFrame`).
This is used to implement the *DepthConcat* layer of the Going deeper with convolutions article.
The normal Concat Module can't be used since the spatial dimensions (height and width) of the output Tensors requiring concatenation may have different values. To deal with this, the output uses the largest

spatial dimensions and adds zero-padding around the smaller Tensors.

```
inputSize = 3
outputSize = 2
input = torch.randn(inputSize,7,7)

mlp=nn.DepthConcat(1);
mlp:add(nn.SpatialConvolutionMM(inputSize, outputSize, 1, 1))
mlp:add(nn.SpatialConvolutionMM(inputSize, outputSize, 3, 3))
mlp:add(nn.SpatialConvolutionMM(inputSize, outputSize, 4, 4))

> print(mlp:forward(input))
(1,.,.) =
 -0.2874  0.6255  1.1122  0.4768  0.9863 -0.2201 -0.1516
  0.2779  0.9295  1.1944  0.4457  1.1470  0.9693  0.1654
 -0.5769 -0.4730  0.3283  0.6729  1.3574 -0.6610  0.0265
  0.3767  1.0300  1.6927  0.4422  0.5837  1.5277  1.1686
  0.8843 -0.7698  0.0539 -0.3547  0.6904 -0.6842  0.2653
  0.4147  0.5062  0.6251  0.4374  0.3252  0.3478  0.0046
  0.7845 -0.0902  0.3499  0.0342  1.0706 -0.0605  0.5525

(2,.,.) =
 -0.7351 -0.9327 -0.3092 -1.3395 -0.4596 -0.6377 -0.5097
 -0.2406 -0.2617 -0.3400 -0.4339 -0.3648  0.1539 -0.2961
 -0.7124 -1.2228 -0.2632  0.1690  0.4836 -0.9469 -0.7003
 -0.0221  0.1067  0.6975 -0.4221 -0.3121  0.4822  0.6617
  0.2043 -0.9928 -0.9500 -1.6107  0.1409 -1.3548 -0.5212
 -0.3086 -0.0298 -0.2031  0.1026 -0.5785 -0.3275 -0.1630
  0.0596 -0.6097  0.1443 -0.8603 -0.2774 -0.4506 -0.5367

(3,.,.) =
  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
  0.0000 -0.7326  0.3544  0.1821  0.4796  1.0164  0.0000
  0.0000 -0.9195 -0.0567 -0.1947  0.0169  0.1924  0.0000
  0.0000  0.2596  0.6766  0.0939  0.5677  0.6359  0.0000
  0.0000 -0.2981 -1.2165 -0.0224 -1.1001  0.0008  0.0000
  0.0000 -0.1911  0.2912  0.5092  0.2955  0.7171  0.0000
  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000

(4,.,.) =
  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
  0.0000 -0.8263  0.3646  0.6750  0.2062  0.2785  0.0000
  0.0000 -0.7572  0.0432 -0.0821  0.4871  1.9506  0.0000
  0.0000 -0.4609  0.4362  0.5091  0.8901 -0.6954  0.0000
  0.0000  0.6049 -0.1501 -0.4602 -0.6514  0.5439  0.0000
```

```
    0.0000  0.2570  0.4694 -0.1262  0.5602  0.0821  0.0000
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000

(5,.,.) =
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
    0.0000  0.3158  0.4389 -0.0485 -0.2179  0.0000  0.0000
    0.0000  0.1966  0.6185 -0.9563 -0.3365  0.0000  0.0000
    0.0000 -0.2892 -0.9266 -0.0172 -0.3122  0.0000  0.0000
    0.0000 -0.6269  0.5349 -0.2520 -0.2187  0.0000  0.0000
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000

(6,.,.) =
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
    0.0000  1.1148  0.2324 -0.1093  0.5024  0.0000  0.0000
    0.0000 -0.2624 -0.5863  0.3444  0.3506  0.0000  0.0000
    0.0000  0.1486  0.8413  0.6229 -0.0130  0.0000  0.0000
    0.0000  0.8446  0.3801 -0.2611  0.8140  0.0000  0.0000
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
    0.0000  0.0000  0.0000  0.0000  0.0000  0.0000  0.0000
[torch.DoubleTensor of dimension 6x7x7]
```

Note how the last 2 of 6 filter maps have 1 column of zero-padding
on the left and top, as well as 2 on the right and bottom.
This is inevitable when the component
module output tensors non-`dim` sizes aren't all odd or even.
Such that in order to keep the mappings aligned, one need
only ensure that these be all odd (or even).

Bottle

```
module = nn.Bottle(module, [nInputDim], [nOutputDim])
```

Bottle allows varying dimensionality input to be forwarded through any module that accepts input of `nInputDim` dimensions, and generates output of `nOutputDim` dimensions.

Bottle can be used to forward a 4D input of varying sizes through a 2D module `b x n`. The module `Bottle(module, 2)` will accept input of shape `p x q x r x n` and outputs with the shape `p x q x r x m`. Internally Bottle will view the input of `module` as `p*q*r x n`,

and view the output as `p x q x r x m`. The numbers `p x q x r` are inferred from the input and can change for every forward/backward pass.

```
input = torch.Tensor(4, 5, 3, 10)
mlp = nn.Bottle(nn.Linear(10, 2))

> print(input:size())
  4
  5
  3
 10
[torch.LongStorage of size 4]

> print(mlp:forward(input):size())
 4
 5
 3
 2
[torch.LongStorage of size 4]
```

Table Containers

While the above containers are used for manipulating input Tensors, table containers are used for manipulating tables :
* ConcatTable
* ParallelTable

These, along with all other modules for manipulating tables can be found here.

Criterions

`Criterions` are helpful to train a neural network. Given an input and a target, they compute a gradient according to a given loss function.

- Classification criterions:
  - `BCECriterion` : binary cross-entropy for `Sigmoid` (two-class version of `ClassNLLCriterion`);
  - `ClassNLLCriterion` : negative log-likelihood for `LogSoftMax` (multi-class);
  - `CrossEntropyCriterion` : combines `LogSoftMax` and `ClassNLLCriterion`;
  - `ClassSimplexCriterion` : A simplex embedding criterion for classification.
  - `MarginCriterion` : two class margin-based loss;
  - `SoftMarginCriterion` : two class softmargin-based loss;
  - `MultiMarginCriterion` : multi-class margin-based loss;
  - `MultiLabelMarginCriterion` : multi-class multi-classification margin-based loss;
  - `MultiLabelSoftMarginCriterion` : multi-class multi-classification loss based on binary cross-entropy;

- Regression criterions:
  - `AbsCriterion` : measures the mean absolute value of the element-wise difference between input;
  - `SmoothL1Criterion` : a smooth version of the AbsCriterion;
  - `MSECriterion` : mean square error (a classic);
  - `SpatialAutoCropMSECriterion` : Spatial mean square error when the input is spatially smaller than the target, by only comparing their spatial overlap;
  - `DistKLDivCriterion` : Kullback–Leibler divergence (for fitting continuous probability distributions);

- Embedding criterions (measuring whether two inputs are similar or dissimilar):
  - `HingeEmbeddingCriterion` : takes a distance as input;
  - `L1HingeEmbeddingCriterion` : L1 distance between two inputs;
  - `CosineEmbeddingCriterion` : cosine distance between two inputs;
  - `DistanceRatioCriterion` : Probabilistic criterion for training siamese model with triplets.

- Miscelaneus criterions:
  - `MultiCriterion` : a weighted sum of other criterions each applied to the same input and target;
  - `ParallelCriterion` : a weighted sum of other criterions each applied to a

different input and target;
- `MarginRankingCriterion` : ranks two inputs;

Criterion

This is an abstract class which declares methods defined in all criterions.
This class is serializable.

[output] forward(input, target)

Given an `input` and a `target`, compute the loss function associated to the criterion and return the result.
In general `input` and `target` are `Tensor`s, but some specific criterions might require some other type of object.

The `output` returned should be a scalar in general.

The state variable `self.output` should be updated after a call to `forward()`.

[gradInput] backward(input, target)

Given an `input` and a `target`, compute the gradients of the loss function associated to the criterion and return the result.
In general `input`, `target` and `gradInput` are `Tensor`s, but some specific criterions might require some other type of object.

The state variable `self.gradInput` should be updated after a call to `backward()`.

State variable: output

State variable which contains the result of the last `forward(input, target)` call.

State variable: gradInput

State variable which contains the result of the last `backward(input, target)` call.

AbsCriterion

```
criterion = nn.AbsCriterion()
```

Creates a criterion that measures the mean absolute value of the element-wise difference between input `x` and target `y`:

```
loss(x, y)  = 1/n \sum |x_i - y_i|
```

If `x` and `y` are `d`-dimensional `Tensor`s with a total of `n` elements, the sum operation still operates over all the elements, and divides by `n`.

The division by `n` can be avoided if one sets the internal variable `sizeAverage` to `false`:

```
criterion = nn.AbsCriterion()
criterion.sizeAverage = false
```

ClassNLLCriterion

```
criterion = nn.ClassNLLCriterion([weights])
```

The negative log likelihood criterion. It is useful to train a classification problem with `n` classes.
If provided, the optional argument `weights` should be a 1D `Tensor` assigning weight to each of the classes.
This is particularly useful when you have an unbalanced training set.

The `input` given through a `forward()` is expected to contain *log-probabilities* of each class: `input` has to be a 1D `Tensor` of size `n`.
Obtaining log-probabilities in a neural network is easily achieved by adding a `LogSoftMax` layer in the last layer of your neural network.

You may use `CrossEntropyCriterion` instead, if you prefer not to add an extra layer to your network.
This criterion expects a class index (1 to the number of class) as `target` when calling `forward(input, target)` and `backward(input, target)`.

The loss can be described as:

```
loss(x, class) = -x[class]
```

or in the case of the `weights` argument it is specified as follows:

```
loss(x, class) = -weights[class] * x[class]
```

Due to the behaviour of the backend code, it is necessary to set sizeAverage to false when calculating losses *in non-batch mode*.

The following is a code fragment showing how to make a gradient step given an input `x`, a desired output `y` (an integer `1` to `n`, in this case `n = 2` classes), a network `mlp` and a learning rate `learningRate`:

```
function gradUpdate(mlp, x, y, learningRate)
   local criterion = nn.ClassNLLCriterion()
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   mlp:zeroGradParameters()
   local t = criterion:backward(pred, y)
   mlp:backward(x, t)
   mlp:updateParameters(learningRate)
end
```

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed for each minibatch.

CrossEntropyCriterion

```
criterion = nn.CrossEntropyCriterion([weights])
```

This criterion combines `LogSoftMax` and `ClassNLLCriterion` in one single class.

It is useful to train a classification problem with `n` classes.
If provided, the optional argument `weights` should be a 1D `Tensor` assigning weight to each of the classes. This is particularly useful when you have an unbalanced training set.

The `input` given through a `forward()` is expected to contain scores for each class: `input` has to be a 1D `Tensor` of size `n`.
This criterion expect a class index (1 to the number of class) as `target` when calling `forward(input, target)` and `backward(input, target)`.

The loss can be described as:

```
loss(x, class) = -log(exp(x[class]) / (\sum_j exp(x[j])))
               = -x[class] + log(\sum_j exp(x[j]))
```

or in the case of the `weights` argument being specified:

```
loss(x, class) = weights[class] * (-x[class] + log(\sum_j
exp(x[j])))
```

Due to the behaviour of the backend code, it is necessary to set sizeAverage to false when calculating losses *in non-batch mode*.

```
crit = nn.CrossEntropyCriterion(weights)
crit.nll.sizeAverage = false
```

The losses are averaged across observations for each minibatch.

ClassSimplexCriterion

```
criterion = nn.ClassSimplexCriterion(nClasses)
```

ClassSimplexCriterion implements a criterion for classification.
It learns an embedding per class, where each class' embedding is a point on an (N-1)-dimensional simplex,
where N is the number of classes.

The `input` given through a `forward()` is expected to be the output of a Normalized Linear layer with no bias:
- `input` has to be a 1D `Tensor` of size `n` for a single sample
- a 2D `Tensor` of size `batchSize x n` for a mini-batch of samples

This Criterion is best used in combination with a neural network where the last layers are:
- a weight-normalized bias-less Linear layer. Example source code
- followed by an output normalization layer (nn.Normalize).

The loss is described in detail in the paper Scale-invariant learning and convolutional networks.

The following is a code fragment showing how to make a gradient step given an input `x`, a desired output `y` (an integer `1` to `n`, in this case `n = 30` classes), a network `mlp` and a learning rate `learningRate`:

```
nInput = 10
nClasses = 30
nHidden = 100
mlp = nn.Sequential()
mlp:add(nn.Linear(nInput, nHidden)):add(nn.ReLU())
mlp:add(nn.NormalizedLinearNoBias(nHidden, nClasses))
mlp:add(nn.Normalize(2))

criterion = nn.ClassSimplexCriterion(nClasses)

function gradUpdate(mlp, x, y, learningRate)
   pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   mlp:zeroGradParameters()
   local t = criterion:backward(pred, y)
   mlp:backward(x, t)
   mlp:updateParameters(learningRate)
end
```

This criterion also provides two helper functions `getPredictions(input)` and `getTopPrediction(input)` that return the raw predictions and the top prediction index respectively, given an input sample.

DistKLDivCriterion

```
criterion = nn.DistKLDivCriterion()
```

The Kullback–Leibler divergence criterion.
KL divergence is a useful distance measure for continuous distributions and is often useful when performing direct regression over the space of (discretely sampled) continuous output distributions.
As with ClassNLLCriterion, the `input` given through a `forward()` is expected to contain *log-probabilities*, however unlike ClassNLLCriterion, `input` is not restricted to a 1D or 2D vector (as the criterion is applied element-wise).

This criterion expect a `target` `Tensor` of the same size as the `input` `Tensor` when calling `forward(input, target)` and `backward(input, target)`.

The loss can be described as:

```
loss(x, target) = 1/n \sum(target_i * (log(target_i) - x_i))
```

By default, the losses are averaged for each minibatch over observations *as well as* over dimensions. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

BCECriterion

```
criterion = nn.BCECriterion([weights])
```

Creates a criterion that measures the Binary Cross Entropy between the target and the output:

```
loss(o, t) = - 1/n sum_i (t[i] * log(o[i]) + (1 - t[i]) * log(1 -
o[i]))
```

or in the case of the weights argument being specified:

```
loss(o, t) = - 1/n sum_i weights[i] * (t[i] * log(o[i]) + (1 -
t[i]) * log(1 - o[i]))
```

This is used for measuring the error of a reconstruction in for example an auto-encoder. Note that the outputs `o[i]` should be numbers between 0 and 1, for instance, the output of an `nn.Sigmoid` layer and should be interpreted as the probability of predicting `t[i] = 1`. Note `t[i]` can be either 0 or 1.

By default, the losses are averaged for each minibatch over observations *as well as* over dimensions. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

MarginCriterion

```
criterion = nn.MarginCriterion([margin])
```

Creates a criterion that optimizes a two-class classification hinge loss (margin-based loss) between input `x` (a `Tensor` of dimension `1`) and output `y` (which is a tensor containing either `1` s or `-1` s).
`margin`, if unspecified, is by default `1`.

```
loss(x, y) = sum_i (max(0, margin - y[i]*x[i])) / x:nElement()
```

The normalization by the number of elements in the input can be disabled by setting `self.sizeAverage` to `false`.

Example

```
function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
end

mlp = nn.Sequential()
mlp:add(nn.Linear(5, 1))
```

```
x1 = torch.rand(5)
x1_target = torch.Tensor{1}
x2 = torch.rand(5)
x2_target = torch.Tensor{-1}
criterion=nn.MarginCriterion(1)

for i = 1, 1000 do
   gradUpdate(mlp, x1, x1_target, criterion, 0.01)
   gradUpdate(mlp, x2, x2_target, criterion, 0.01)
end

print(mlp:forward(x1))
print(mlp:forward(x2))

print(criterion:forward(mlp:forward(x1), x1_target))
print(criterion:forward(mlp:forward(x2), x2_target))
```

gives the output:

```
 1.0043
[torch.Tensor of dimension 1]


-1.0061
[torch.Tensor of dimension 1]

0
0
```

i.e. the mlp successfully separates the two data points such that they both have a `margin` of `1`, and hence a loss of `0`.

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

SoftMarginCriterion

```
criterion = nn.SoftMarginCriterion()
```

Creates a criterion that optimizes a two-class classification logistic loss between input `x` (a `Tensor` of dimension `1`) and output `y` (which is a tensor containing either `1`s or `-1`s).

```
loss(x, y) = sum_i (log(1 + exp(-y[i]*x[i]))) / x:nElement()
```

The normalization by the number of elements in the input can be disabled by setting `self.sizeAverage` to `false`.

Example

```
function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
end

mlp = nn.Sequential()
mlp:add(nn.Linear(5, 1))

x1 = torch.rand(5)
x1_target = torch.Tensor{1}
x2 = torch.rand(5)
x2_target = torch.Tensor{-1}
criterion=nn.SoftMarginCriterion(1)

for i = 1, 1000 do
   gradUpdate(mlp, x1, x1_target, criterion, 0.01)
   gradUpdate(mlp, x2, x2_target, criterion, 0.01)
end

print(mlp:forward(x1))
print(mlp:forward(x2))

print(criterion:forward(mlp:forward(x1), x1_target))
print(criterion:forward(mlp:forward(x2), x2_target))
```

gives the output:

```
 0.7471
[torch.DoubleTensor of size 1]

-0.9607
[torch.DoubleTensor of size 1]

0.38781049558836
0.32399356957564
```

i.e. the mlp successfully separates the two data points.

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

MultiMarginCriterion

```
criterion = nn.MultiMarginCriterion(p, [weights], [margin])
```

Creates a criterion that optimizes a multi-class classification hinge loss (margin-based loss) between input `x` (a `Tensor` of dimension 1) and output `y` (which is a target class index, `1` <= `y` <= `x:size(1)`):

```
loss(x, y) = sum_i(max(0, (margin - x[y] + x[i]))^p) / x:size(1)
```

where `i == 1` to `x:size(1)` and `i ~= y`.
Note that this criterion also works with 2D inputs and 1D targets.

Optionally, you can give non-equal weighting on the classes by passing a 1D `weights` tensor into the constructor.
The loss function then becomes:

```
loss(x, y) = sum_i(max(0, w[y] * (margin - x[y] - x[i]))^p) /
x:size(1)
```

This criterion is especially useful for classification when used in conjunction with a module ending in the following output layer:

```
mlp = nn.Sequential()
mlp:add(nn.Euclidean(n, m)) -- outputs a vector of distances
mlp:add(nn.MulConstant(-1)) -- distance to similarity
```

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

MultiLabelMarginCriterion

```
criterion = nn.MultiLabelMarginCriterion()
```

Creates a criterion that optimizes a multi-class multi-classification hinge loss (margin-based loss) between input `x` (a 1D `Tensor`) and output `y` (which is a 1D `Tensor` of target class indices):

```
loss(x, y) = sum_ij(max(0, 1 - (x[y[j]] - x[i]))) / x:size(1)
```

where `i == 1` to `x:size(1)`, `j == 1` to `y:size(1)`, `y[j] ~= 0`, and `i ~= y[j]` for all `i` and `j`.
Note that this criterion also works with 2D inputs and targets.

`y` and `x` must have the same size.
The criterion only considers the first non zero `y[j]` targets.
This allows for different samples to have variable amounts of target classes:

```
criterion = nn.MultiLabelMarginCriterion()
input = torch.randn(2, 4)
target = torch.Tensor{{1, 3, 0, 0}, {4, 0, 0, 0}} -- zero-values
are ignored
criterion:forward(input, target)
```

MultiLabelSoftMarginCriterion

MultiLabelSoftMarginCriterion

```
criterion = nn.MultiLabelSoftMarginCriterion()
```

Creates a criterion that optimizes a multi-label one-versus-all loss based on max-entropy, between input `x` (a 1D `Tensor`) and target `y` (a binary 1D `Tensor`):

```
loss(x, y) = - sum_i (y[i] log( exp(x[i]) / (1 + exp(x[i]))) + (1-
y[i]) log(1/(1+exp(x[i])))) / x:nElement()
```

where `i == 1` to `x:nElement()`, `y[i] in {0,1}`.
Note that this criterion also works with 2D inputs and targets.

`y` and `x` must have the same size.

MSECriterion

```
criterion = nn.MSECriterion()
```

Creates a criterion that measures the mean squared error between `n` elements in the input `x` and output `y`:

```
loss(x, y) = 1/n \sum |x_i - y_i|^2 .
```

If `x` and `y` are `d`-dimensional `Tensor`s with a total of `n` elements, the sum operation still operates over all the elements, and divides by `n`.
The two `Tensor`s must have the same number of elements (but their sizes might be different).

The division by `n` can be avoided if one sets the internal variable `sizeAverage` to `false`:

```
criterion = nn.MSECriterion()
criterion.sizeAverage = false
```

By default, the losses are averaged over observations for each minibatch. However, if the field

`sizeAverage` is set to `false`, the losses are instead summed.

SpatialAutoCropMSECriterion

```
criterion = nn.SpatialAutoCropMSECriterion()
```

Creates a criterion that measures the mean squared error between the input and target, even if the target is spatially larger than the input. It achieves this by center-cropping the target to the same spatial resolution as the input, the mean squared error is then calculated between the input and this cropped target.

If the input and cropped target tensors are `d`-dimensional `Tensor`s with a total of `n` elements, the sum operation operates over all the elements, and divides by `n`.

The division by `n` can be avoided if one sets the internal variable `sizeAverage` to `false`:

```
criterion = nn.SpatialAutoCropMSECriterion()
criterion.sizeAverage = false
```

MultiCriterion

```
criterion = nn.MultiCriterion()
```

This returns a Criterion which is a weighted sum of other Criterion.
Criterions are added using the method:

```
criterion:add(singleCriterion [, weight])
```

where `weight` is a scalar (default 1). Each criterion is applied to the same `input` and `target`.

Example :

```
input = torch.rand(2,10)
target = torch.IntTensor{1,8}
nll = nn.ClassNLLCriterion()
nll2 = nn.CrossEntropyCriterion()
mc = nn.MultiCriterion():add(nll, 0.5):add(nll2)
output = mc:forward(input, target)
```

ParallelCriterion

```
criterion = nn.ParallelCriterion([repeatTarget])
```

This returns a Criterion which is a weighted sum of other Criterion.
Criterions are added using the method:

```
criterion:add(singleCriterion [, weight])
```

where `weight` is a scalar (default 1). The criterion expects an `input` and `target` table. Each criterion is applied to the commensurate `input` and `target` element in the tables. However, if `repeatTarget=true`, the `target` is repeatedly presented to each criterion (with a different `input`).

Example :

```
input = {torch.rand(2,10), torch.randn(2,10)}
target = {torch.IntTensor{1,8}, torch.randn(2,10)}
nll = nn.ClassNLLCriterion()
mse = nn.MSECriterion()
pc = nn.ParallelCriterion():add(nll, 0.5):add(mse)
output = pc:forward(input, target)
```

SmoothL1Criterion

```
criterion = nn.SmoothL1Criterion()
```

Creates a criterion that can be thought of as a smooth version of the `AbsCriterion`. It uses a squared term if the absolute element-wise error falls below 1. It is less sensitive to outliers than the `MSECriterion` and in some cases prevents exploding gradients (e.g. see “Fast R-CNN” paper by Ross Girshick).

```
                      ⎧ 0.5 * (x_i - y_i)^2, if |x_i - y_i| < 1
loss(x, y) = 1/n \sum ⎨
                      ⎩ |x_i - y_i| - 0.5,   otherwise
```

If `x` and `y` are `d`-dimensional `Tensor`s with a total of `n` elements, the sum operation still operates over all the elements, and divides by `n`.

The division by `n` can be avoided if one sets the internal variable `sizeAverage` to `false`:

```
criterion = nn.SmoothL1Criterion()
criterion.sizeAverage = false
```

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

HingeEmbeddingCriterion

```
criterion = nn.HingeEmbeddingCriterion([margin])
```

Creates a criterion that measures the loss given an input `x` which is a 1-dimensional vector and a label `y` (`1` or `-1`).
This is usually used for measuring whether two inputs are similar or dissimilar, e.g. using the L1 pairwise distance, and is typically used for learning nonlinear embeddings or semi-supervised learning.

```
                  ⎧ x_i,                  if y_i ==  1
loss(x, y) = 1/n ⎨
                  ⎩ max(0, margin - x_i), if y_i == -1
```

If `x` and `y` are `n`-dimensional `Tensor`s, the sum operation still operates over all the elements, and divides by `n` (this can be avoided if one sets the internal variable `sizeAverage` to `false`). The `margin` has a default value of `1`, or can be set in the constructor.

Example

```
-- imagine we have one network we are interested in, it is called
"p1_mlp"
p1_mlp = nn.Sequential(); p1_mlp:add(nn.Linear(5, 2))

-- But we want to push examples towards or away from each other so
we make another copy
-- of it called p2_mlp; this *shares* the same weights via the set
command, but has its
-- own set of temporary gradient storage that's why we create it
again (so that the gradients
-- of the pair don't wipe each other)
p2_mlp = nn.Sequential(); p2_mlp:add(nn.Linear(5, 2))
p2_mlp:get(1).weight:set(p1_mlp:get(1).weight)
p2_mlp:get(1).bias:set(p1_mlp:get(1).bias)

-- we make a parallel table that takes a pair of examples as input.
-- They both go through the same (cloned) mlp
prl = nn.ParallelTable()
prl:add(p1_mlp)
prl:add(p2_mlp)

-- now we define our top level network that takes this parallel
table
-- and computes the pairwise distance betweem the pair of outputs
mlp = nn.Sequential()
mlp:add(prl)
mlp:add(nn.PairwiseDistance(1))

-- and a criterion for pushing together or pulling apart pairs
crit = nn.HingeEmbeddingCriterion(1)

-- lets make two example vectors
x = torch.rand(5)
y = torch.rand(5)
```

```
-- Use a typical generic gradient update function
function gradUpdate(mlp, x, y, criterion, learningRate)
local pred = mlp:forward(x)
local err = criterion:forward(pred, y)
local gradCriterion = criterion:backward(pred, y)
mlp:zeroGradParameters()
mlp:backward(x, gradCriterion)
mlp:updateParameters(learningRate)
end

-- push the pair x and y together, notice how then the distance
between them given
-- by print(mlp:forward({x, y})[1]) gets smaller
for i = 1, 10 do
   gradUpdate(mlp, {x, y}, 1, crit, 0.01)
   print(mlp:forward({x, y})[1])
end

-- pull apart the pair x and y, notice how then the distance
between them given
-- by print(mlp:forward({x, y})[1]) gets larger

for i = 1, 10 do
   gradUpdate(mlp, {x, y}, -1, crit, 0.01)
   print(mlp:forward({x, y})[1])
end
```

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

L1HingeEmbeddingCriterion

```
criterion = nn.L1HingeEmbeddingCriterion([margin])
```

Creates a criterion that measures the loss given an input `x` = `{x1, x2}`, a table of two `Tensor`s, and a label `y` (`1` or `-1`): this is used for measuring whether two inputs are similar or dissimilar, using the L1 distance, and is typically used for learning nonlinear embeddings or semi-supervised learning.

```
             ⎧ ||x1 - x2||_1,                  if y ==  1
loss(x, y) = ⎨
             ⎩ max(0, margin - ||x1 - x2||_1), if y == -1
```

The `margin` has a default value of `1`, or can be set in the constructor.

CosineEmbeddingCriterion

```
criterion = nn.CosineEmbeddingCriterion([margin])
```

Creates a criterion that measures the loss given an input `x` = `{x1, x2}`, a table of two `Tensor`s, and a `Tensor` label `y` with values 1 or -1.
This is used for measuring whether two inputs are similar or dissimilar, using the cosine distance, and is typically used for learning nonlinear embeddings or semi-supervised learning.

`margin` should be a number from `-1` to `1`, `0` to `0.5` is suggested.
`Forward` and `Backward` have to be used alternately. If `margin` is missing, the default value is `0`.

The loss function for each sample is:

```
             ⎧ 1 - cos(x1, x2),              if y ==  1
loss(x, y) = ⎨
             ⎩ max(0, cos(x1, x2) - margin), if y == -1
```

For batched inputs, if the internal variable `sizeAverage` is equal to `true`, the loss function averages the loss over the batch samples; if `sizeAverage` is `false`, then the loss function sums over the batch samples. By default, `sizeAverage` equals to `true`.

By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

DistanceRatioCriterion

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```
criterion = nn.DistanceRatioCriterion(sizeAverage)
```

This criterion is probabilistic treatment of margin cost. The model is trained using sample triplets `{Xs, Xa, Xd}` where `Xa` is anchor sample, `Xs` is sample similar to anchor sample and `Xd` is a sample not similar to anchor sample. Let `Ds` be distance between embeddings of `{Xs, Xa}` and `Dd` be distance between embeddings of `{Xa, Xd}` then the loss is defined as follow

```
    loss = -log( exp(-Ds) / ( exp(-Ds) + exp(-Dd) ) )
```

Sample example

```
    torch.setdefaulttensortype("torch.FloatTensor")

    require 'nn'

    -- triplet : with batchSize of 32 and dimensionality 512
    sample = {torch.rand(32, 512), torch.rand(32, 512),
torch.rand(32, 512)}

    embeddingModel = nn.Sequential()
    embeddingModel:add(nn.Linear(512, 96)):add(nn.ReLU())

    tripleModel = nn.ParallelTable()
    tripleModel:add(embeddingModel)
    tripleModel:add(embeddingModel:clone('weight', 'bias',
                                         'gradWeight', 'gradBias'))
    tripleModel:add(embeddingModel:clone('weight', 'bias',
                                         'gradWeight', 'gradBias'))

    -- Similar sample distance w.r.t anchor sample
    posDistModel = nn.Sequential()
    posDistModel:add(nn.NarrowTable(1,2)):add(nn.PairwiseDistance())

    -- Different sample distance w.r.t anchor sample
    negDistModel = nn.Sequential()
    negDistModel:add(nn.NarrowTable(2,2)):add(nn.PairwiseDistance())

    distanceModel =
nn.ConcatTable():add(posDistModel):add(negDistModel)
```

```
-- Complete Model
model = nn.Sequential():add(tripleModel):add(distanceModel)

-- DistanceRatioCriterion
criterion = nn.DistanceRatioCriterion(true)

-- Forward & Backward
output = model:forward(sample)
loss   = criterion:forward(output)
dLoss  = criterion:backward(output)
model:backward(sample, dLoss)
```

MarginRankingCriterion

```
criterion = nn.MarginRankingCriterion(margin)
```

Creates a criterion that measures the loss given an input `x = {x1, x2}`, a table of two `Tensor`s of size 1 (they contain only scalars), and a label `y` (`1` or `-1`).
In batch mode, `x` is a table of two `Tensor`s of size `batchsize`, and `y` is a `Tensor` of size `batchsize` containing `1` or `-1` for each corresponding pair of elements in the input `Tensor`.

If `y == 1` then it assumed the first input should be ranked higher (have a larger value) than the second input, and vice-versa for `y == -1`.

The loss function is:

```
loss(x, y) = max(0, -y * (x[1] - x[2]) + margin)
```

For batched inputs, if the internal variable `sizeAverage` is equal to `true`, the loss function averages the loss over the batch samples; if `sizeAverage` is `false`, then the loss function sums over the batch samples. By default, `sizeAverage` equals to `true`.
By default, the losses are averaged over observations for each minibatch. However, if the field `sizeAverage` is set to `false`, the losses are instead summed.

Example

```
p1_mlp = nn.Linear(5, 2)
p2_mlp = p1_mlp:clone('weight', 'bias')

prl = nn.ParallelTable()
prl:add(p1_mlp)
prl:add(p2_mlp)

mlp1 = nn.Sequential()
mlp1:add(prl)
mlp1:add(nn.DotProduct())

mlp2 = mlp1:clone('weight', 'bias')

mlpa = nn.Sequential()
prla = nn.ParallelTable()
prla:add(mlp1)
prla:add(mlp2)
mlpa:add(prla)

crit = nn.MarginRankingCriterion(0.1)

x=torch.randn(5)
y=torch.randn(5)
z=torch.randn(5)

-- Use a typical generic gradient update function
function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
end

for i = 1, 100 do
   gradUpdate(mlpa, {{x, y}, {x, z}}, 1, crit, 0.01)
   if true then
      o1 = mlp1:forward{x, y}[1]
      o2 = mlp2:forward{x, z}[1]
      o = crit:forward(mlpa:forward{{x, y}, {x, z}}, 1)
      print(o1, o2, o)
   end
end
```

```
print "--"

for i = 1, 100 do
   gradUpdate(mlpa, {{x, y}, {x, z}}, -1, crit, 0.01)
   if true then
      o1 = mlp1:forward{x, y}[1]
      o2 = mlp2:forward{x, z}[1]
      o = crit:forward(mlpa:forward{{x, y}, {x, z}}, -1)
      print(o1, o2, o)
   end
end
```

dataload

```
local dl = require 'dataload'
```

A collection of Torch dataset loaders.
The library provides the following generic data loader classes :

- DataLoader : an abstract class inherited by the following classes;
- TensorLoader : for tensor or nested (i.e. tables of) tensor datasets;
- ImageClass : for image classification datasets stored in a flat folder structure;
- AsyncIterator : decorates a `DataLoader` for asynchronou multi-threaded iteration;
- SequenceLoader : for sequence datasets like language or time-series;
- MultiSequence : for shuffled sets of sequence datasets like shuffled sentences;
- MultiImageSequence : for suffled sets of sequences of input and target images.

The library also provides functions for downloading specific datasets
and preparing them using the above loaders :

- loadMNIST : load the MNIST handwritten digit dataset for image classification;
- loadCIFAR10 : load the CIFAR10 dataset for image classification;
- loadImageNet : load the ILSVRC2014 dataset for image classification;
- loadPTB : load the Penn Tree Bank corpus for language modeling;
- loadGBW : load the Google Billion Words corpus for language modeling;
- loadSentiment140 : load the Twitter data for sentiment analysis/classification (sad, happy).

Also, we try to provide some useful preprocessing functions :

- fitImageNormalize : normalize images by channel.

DataLoader

```
dataloader = dl.DataLoader()
```

An abstract class inherited by all `DataLoader` instances.
It wraps a data set to provide methods for accessing

`inputs` and `targets`. The data itself may be loaded from disk or memory.

[n] size()

Returns the number of samples in the `dataloader`.

[size] isize([excludedim])

Returns the `size` of `inputs`. When `excludedim` is 1 (the default),
the batch dimension is excluded from `size`.
When `inputs` is a tensor, the returned `size` is
a table of numbers. When it is a table of tensors, the returned `size`
is a table of table of numbers.

[size] tsize([excludedim])

Returns the `size` of `targets`. When `excludedim` is 1 (the default),
the batch dimension is excluded from `size`.
When `targets` is a tensor, the returned `size` is
a table of numbers. When it is a table of tensors, the returned `size`
is a table of table of numbers.

[inputs, targets] index(indices, [inputs, targets])

Returns `inputs` and `targets` containing samples indexed by `indices`.

So for example :

```
indices = torch.LongTensor{1,2,3,4,5}
inputs, targets = dataloader:index(indices)
```

would return a batch of `inputs` and `targets` containing samples 1 through 5.
When `inputs` and `targets` are provided as arguments, they are used as
memory buffers for the returned `inputs` and `targets`,
i.e. their allocated memory is reused.

[inputs, targets] sample(batchsize, [inputs, targets])

Returns `inputs` and `targets` containing `batchsize` random samples.
This method is equivalent to :

```
indices = torch.LongTensor(batchsize):random(1,dataloader:size())
inputs, targets = dataloader:index(indices)
```

[inputs, targets] sub(start, stop, [inputs, targets])

Returns `inputs` and `targets` containing `stop-start+1` samples between `start` and `stop`.
This method is equivalent to :

```
indices = torch.LongTensor():range(start, stop)
inputs, targets = dataloader:index(indices)
```

shuffle()

Internally shuffles the `inputs` and `targets`. Note that not all
subclasses support this method.

[ds1, ds2] split(ratio)

Splits the `dataloader` into two new `DataLoader` instances
where `ds1` contains the first `math.floor(ratio x dataloader:size())` samples,
and `ds2` contains the remainder.
Useful for splitting a training set into a new training set and validation set.

[iterator] subiter([batchsize, epochsize, ...])

Returns an iterator over a validation and test sets.
Each iteration returns 3 values :

- `k` : the number of samples processed so far. Each iteration returns a maximum of `batchsize` samples.
- `inputs` : a tensor (or nested table thereof) containing a maximum of `batchsize` inputs.
- `targets` : a tensor (or nested table thereof) containing targets for the commensurate inputs.

The iterator will return batches of `inputs` and `targets` of size at most `batchsize` until `epochsize` samples have been returned.

Note that the default implementation of this iterator is to call sub for each batch.
Sub-classes may over-write this behavior.

Example :

```
local dl = require 'dataload'

inputs, targets = torch.range(1,5), torch.range(1,5)
dataloader = dl.TensorLoader(inputs, targets)

local i = 0
for k, inputs, targets in dataloader:subiter(2,6) do
   i = i + 1
   print(string.format("batch %d, nsampled = %d", i, k))
   print(string.format("inputs:\n%stargets:\n%s", inputs, targets))
end
```

Output :

```
batch 1, nsampled = 2
inputs:
 1
 2
[torch.DoubleTensor of size 2]
targets:
 1
 2
[torch.DoubleTensor of size 2]

batch 2, nsampled = 4
inputs:
```

```
 3
 4
[torch.DoubleTensor of size 2]
targets:
 3
 4
[torch.DoubleTensor of size 2]

batch 3, nsampled = 5
inputs:
 5
[torch.DoubleTensor of size 1]
targets:
 5
[torch.DoubleTensor of size 1]

batch 4, nsampled = 6
inputs:
 1
[torch.DoubleTensor of size 1]
targets:
 1
[torch.DoubleTensor of size 1]
```

Note how the last two batches are of size 1 while those before are of size `batchsize = 2`.
The reason for this is that the `dataloader` only has 5 samples.
So the last batch is split between the last sample and the first.

[iterator] sampleiter([batchsize, epochsize, ...])

Returns an iterator over a training set.
Each iteration returns 3 values :

- `k` : the number of samples processed so far. Each iteration returns a maximum of `batchsize` samples.
- `inputs` : a tensor (or nested table thereof) containing a maximum of `batchsize` inputs.
- `targets` : a tensor (or nested table thereof) containing targets for the commensurate inputs.

The iterator will return batches of `inputs` and `targets` of size at most `batchsize` until `epochsize` samples have been returned.

Note that the default implementation of this iterator is to call sample for each batch.
Sub-classes may over-write this behavior.

Example :

```
local dl = require 'dataload'

inputs, targets = torch.range(1,5), torch.range(1,5)
dataloader = dl.TensorLoader(inputs, targets)

local i = 0
for k, inputs, targets in dataloader:sampleiter(2,6) do
   i = i + 1
   print(string.format("batch %d, nsampled = %d", i, k))
   print(string.format("inputs:\n%stargets:\n%s", inputs, targets))
end
```

Output :

```
batch 1, nsampled = 2
inputs:
 1
 2
[torch.DoubleTensor of size 2]
targets:
 1
 2
[torch.DoubleTensor of size 2]

batch 2, nsampled = 4
inputs:
 4
 2
[torch.DoubleTensor of size 2]
targets:
 4
 2
[torch.DoubleTensor of size 2]

batch 3, nsampled = 6
inputs:
 4
 1
```

```
[torch.DoubleTensor of size 2]
targets:
 4
 1
[torch.DoubleTensor of size 2]
```

reset()

Resets all internal counters such as those used for iterators.
Called by AsyncIterator before serializing the `DataLoader` to threads.

collectgarbage()

Collect garbage every `self.gccdelay` times this method is called.

[copy] clone()

Returns a deep `copy` clone of `self`.

TensorLoader

```
dataloader = dl.TensorLoader(inputs, targets)
```

The `TensorLoader` can be used to encapsulate tensors of `inputs` and `targets`.
As an example, consider a dummy `3 x 8 x 8` image classification dataset consisting of 1000 samples and 10 classes:

```
inputs = torch.randn(1000, 3, 8, 8)
targets = torch.LongTensor(1000):random(1,10)
dataloader = dl.TensorLoader(inputs, targets)
```

The `TensorLoader` can also be used to encapsulate nested tensors of `inputs` and `targets`.
It uses recursive functions to handle nestings of arbitrary depth. As an example, let us modify the above example to include `x,y` GPS coordinates in the `inputs` and a parallel set of classification `targets` (7 classes):

```
inputs = {torch.randn(1000, 3, 8, 8), torch.randn(1000, 2)}
targets = {torch.LongTensor(1000):random(1,10),
torch.LongTensor(1000):random(1,7)}
dataloader = dl.TensorLoader(inputs, targets)
```

ImageClass

```
dataloader = dl.ImageClass(datapath, loadsize, [samplesize,
samplefunc, sortfunc, verbose])
```

For loading an image classification data set stored in a flat folder structure :

```
(datapath)/(classdir)/(imagefile).(jpg|png|etc)
```

So directory `classdir` is expected to contain the all images belonging to that class.
All image files are indexed into an efficient `CharTensor` during initialization.
Images are only loaded into `inputs` and `targets` tensors upon calling batch sampling methods like index, sample and sub.

Note that for asynchronous loading of images (i.e. loading batches of images in different threads),
the `ImageClass` loader can be decorated with an AsyncIterator.
Images on disk can have different height, width and number of channels.

Constructor arguments are as follows :

- `datapath` : one or many paths to directories of images;
- `loadsize` : initialize size to load the images to. Example : `{3, 256, 256}` ;
- `samplesize` : consistent sample size to resize the images to. Defaults to `loadsize` ;
- `samplefunc` : `function f(self, dst, path)` used to create a sample(s) from an image path. Stores them in `CharTensor` `dst` . Strings `"sampleDefault"` (the

default), `"sampleTrain"` or `"sampleTest"` can also be provided as they refer to existing functions
- `verbose` : display verbose message (default is `true`);
- `sortfunc` : comparison operator used for sorting `classdir` to get class indices. Defaults to the `<` operator.

AsyncIterator

```
dataloader = dl.AsyncIterator(dataloader, [nthread, verbose,
serialmode])
```

This `DataLoader` subclass overwrites the `subiter` and `sampleiter` iterator methods. The implementation uses the threads package to build a pool of `nthread` worker threads. The main thread delegates the tasks of building `inputs` and `targets` tensors to the workers. The workers each have a deep copy of the decorated `dataloader`. The optional parameter serialmode can be specified as 'ascii' (default) or 'binary'. If large amounts of data need to be processed, 'binary' can prevent the dataloader from allocating too much RAM.
When a task is received from the main thread through the Queue, they call `sample` or `sub` to build the batch and return the `inputs` and `targets` to the main thread. The iteration is asynchronous as the first iteration will fill the Queue with `nthread` tasks.
Note that when `nthread > 1` the order of tensors is not deterministic.
This loader is well suited for decorating a `dl.ImageClass` instance and other such I/O and CPU bound loaders.

SequenceLoader

```
dataloader = dl.SequenceLoader(sequence, batchsize,
[bidirectional])
```

This `DataLoader` subclass can be used to encapsulate a `sequence` for training time-series or language models.

The `sequence` is a tensor where the first dimension indexes time.
Internally, the loader will split the `sequence` into `batchsize` subsequences.
Calling the `sub(start, stop, inputs, targets)` method will return
`inputs` and `targets` of size `seqlen x batchsize [x inputsize]`
where `stop - start + 1 <= seqlen`.
See RNNLM training script for an example.

The `bidirectional` argument should be set
to `true` for bidirectional models like BRNN/BLSTMs. In which case,
the returned `inputs` and `targets` will be aligned.
For example, using `batchsize = 3` and `seqlen = 5`:

```
print(inputs:t(), targets:t())
   36  1516   853    94  1376
 3193   433   553   805   521
  512   434    57  1029  1962
[torch.IntTensor of size 3x5]

   36  1516   853    94  1376
 3193   433   553   805   521
  512   434    57  1029  1962
[torch.IntTensor of size 3x5]
```

When `bidirectional` is `false` (the default), the `targets` will
be one step in the future with respect to the inputs:
For example, using `batchsize = 3` and `seqlen = 5`:

```
print(inputs:t(), targets:t())
   36  1516   853    94  1376
 3193   433   553   805   521
  512   434    57  1029  1962
[torch.IntTensor of size 3x5]

 1516   853    94  1376   719
  433   553   805   521    27
  434    57  1029  1962    49
[torch.IntTensor of size 3x5]
```

MultiSequence

```
dataloader = dl.MultiSequence(sequences, batchsize)
```

This DataLoader subclass is used by the Billion Words dataset to encapsulate unordered sentences.
The `sequences` arguments is a table or tds.Vec of tensors.
Each such tensors is a single sequence independent of the others. The tensor can be multi-dimensional as long
as the non-sequence dimension sizes are consistent from sequence to sequence.

When calling `sub(start, stop)` or `subiter(seqlen)` methods,
a column of the returned `inputs` and `targets` tensors (of size `seqlen x batchsize`) could
contain multiple sequences. For example, a character-level language model could look like:

```
target : [ ] E L L O [ ] C R E E N ...
input  : [ ] H E L L [ ] S C R E E ...
```

where `HELLO` and `SCREEN` would be two independent sequences.
Note that `[ ]` is a zero mask used to seperate independent sequences.
For most cases, the `[ ]` token is a 0.
Except for 1D `targets`, where it is a 1 (so that it works with `ClassNLLCriterion`).

MultiImageSequence

```
ds = dl.MultiImageSequence(datapath, batchsize, loadsize,
samplesize, [samplefunc, verbose])
```

This `DataLoader` is used to load datasets consisting of independent sequences of
input and target images. So basically, each independent sequence consists of
two sequences of the same size, one for inputs, one for targets.

As a concrete example, this `DataLoader` could be used to
wrap a dataset where each input is a sequence of video frames,
and its commensurate targets are binary masks.

Like the `ImageClass` loader, `MultiImageSequence` expects images to be stored on disk.
Each directory is organized as :

```
[datapath]/[seqid]/[input|target][1,2,3,...,T].jpg
```

where the `datapath` (first constructor argument) specifies the file system path to the data.
That directory is expected to contain a folder for each sequence, here represented by the `seqid` variable.
The `seqid` folder can have any name, but by default its contents are expected to contain the pattern
`input%d.jpg` and `target%d.jpg` for input and target images, respectively.
Internally, the `%d` is replaced with integers starting at `1` until no more images are found.
These patterns can be replaced after construction via the `inputpattern` and `targetpattern`.

Variable length sequences are natively supported.

Images will be only be loaded when requested.

Like the `MultiSequence` loader, the `batchsize` must be specified during construction.
Like the `ImageClass`, the `loadsize` argument specifies that size of to which the images are to be loaded initially.
These are specified as two tables in `c x h x w` format, for inputs and targets respectively (e.g. `{{3,28,28},{1,8,8}}`).

The `samplesize` specifies the returned input image size (e.g. `{3,24,24}`).
The actual sample size of the targets cannot be provided as it will be forced to be proportional to the input's load to sample size.

The `samplefunc` specifies the function to use for sampling input and target images.
The default value of `sampleDefault` simply resizes the images to the given input `samplesize` and the proportional target sample size.
When `sampleTrain` is provided, a random location will be chosen for each sampled sequence.

When calling `sub(start, stop)` the returned `input` and `target` are tensors of size `seqlen x batchsize x samplesize`. Since variable length sequences are natively supported, the returned `inputs` and `targets` will be separated by mask tokens (here represented by `[ ]`):

```
[ ] target11, target12, target13, ..., target1T [ ] target21, ...
[ ] input11,  input12,  input13,  ..., input1T  [ ] input21, ...
```

The mask tokens `[ ]` represent images with nothing but zeros.

For large datasets use Lua5.2 instead of LuaJIT to avoid memory errors (see torch.ch).

The following are attributes that can be set to `true` to modify the behavior of the loader:

- `cropeverystep` : samples a random uniform crop location every time-step (instead of once per sequence)
- `varyloadsize` : random-uniformly samples a `loadsize` between samplesize and loadsize (this effectively scales the cropped location)
- `scaleeverystep` : varies `loadsize` every step instead of once per sequence
- `randseq` : each new sequence is chosen random uniformly

loadMNIST

```
train, valid, test = dl.loadMNIST([datapath, validratio, scale,
srcurl])
```

Returns the training, validation and testing sets as 3 `TensorLoader` instances.
Each such loader encapsulates a part of the MNIST dataset which is
located in `datapath` (defaults to `dl.DATA_PATH/mnist`).
The `validratio` argument, a number between 0 and 1,
specifies the ratio of the 60000 training samples
that will be allocated to the validation set.
The `scale` argument specifies range within which pixel values will be scaled (defaults to `{0,1}`).
The `srcurl` specifies the URL from where the raw data can be downloaded from
if not located on disk.

loadCIFAR10

```
train, valid, test = dl.loadCIFAR10([datapath, validratio, scale,
srcurl])
```

Returns the training, validation and testing sets as 3 `TensorLoader` instances.
Each such loader encapsulates a part of the CIFAR10 dataset which is
located in `datapath` (defaults to `dl.DATA_PATH/cifar-10-batches-t7`).
The `validratio` argument, a number between 0 and 1,
specifies the ratio of the 50000 training samples

that will be allocated to the validation set.
The `scale` argument specifies range within which pixel values will be scaled (defaults to `{0,1}`).
The `srcurl` specifies the URL from where the raw data can be downloaded from
if not located on disk.

loadPTB

```
train, valid, test = dl.loadPTB(batchsize, [datapath, srcurl])
```

Returns the training, validation and testing sets as 3 `SequenceLoader` instance
Each such loader encapsulates a part of the Penn Tree Bank dataset which is
located in `datapath` (defaults to `dl.DATA_PATH/PennTreeBank`).
If the files aren't found in the `datapath`, they will be automatically downloaded
from the `srcurl` URL.
The `batchsize` specifies the number of samples that will be returned when
iterating through the dataset. If specified as a table, its elements
specify the `batchsize` of commensurate `train`, `valid` and `test` tables.
We recommend a `batchsize` of 1 for evaluation sets (e.g. `{50,1,1}`).

See RNNLM training script for an example.

loadImageNet

Ref.: A. http://image-net.org/challenges/LSVRC/2014/download-images-5jj5.php

```
train, valid = dl.loadImageNet(datapath, [nthread, loadsize,
samplesize, verbose])
```

Returns the training and validation sets of the Large Scale Visual Recognition Challenge 2014
(ILSVRC2014)
image classification dataset (commonly known as ImageNet).
The dataset hasn't changed from 2012-2014.

The returned `train` and `valid` loaders do not read all images into memory when first

loaded.
Each dataset is implemented using an ImageClass loader decorated by an AsyncIterator.

The `datapath` should point to a directory containing the outputs of the `downloadimagenet.lua` and `harmonizeimagenet.lua` scripts (see bellow).

Requirements

Due to its size, the data first needs to be prepared offline.
Use downloadimagenet.lua
to download and extract the data :

```
th downloadimagenet.lua --savePath '/path/to/diskspace/ImageNet'
```

The entire process requires about 360 GB of disk space to complete the download and extraction process.
This can be reduced to about 150 GB if the training set is downloaded and extracted first, and all the `.tar` files are manually deleted. Repeat for the validation set, devkit and metadata.
If you still don't have enough space in one partition, you can divide the data among different partitions.
We recommend a good internet connection (>60Mbs download) and a Solid-State Drives (SSD).

Use harmonizeimagenet.lua
to harmonize the train and validation sets:

```
th harmonizeimagenet.lua --dataPath /path/to/diskspace/ImageNet --
progress --forReal
```

Each set will then contain a directory of images for each class with name `class[id]` where `[id]` is a class index, between 1 and 1000, used for the ILVRC2014 competition.

Then we need to install graphicsmagick :

```
luarocks install graphicsmagick
```

Inference

As in the famous (Krizhevsky et al. 2012)
paper, the ImageNet training dataset samples images cropped from random
224x224 patches from the images resizes so that the smallest dimension has
size 256. As for the validation set, ten 224x224 patches are cropped per image,
i.e. center, four corners and their horizontal flips, and their predictions are averaged.

loadGBW

```
train, valid, test = dl.loadGBW(batchsize, [trainfile, datapath,
srcurl, verbose])
```

Loads the Google Billion Words corpus as MultiSequence loaders.
The preprocessing specified in
Google Billion Words language modeling benchmark
was applied to `training-monolingual.tokenized/news.20??.en.shuffled.tokenized` to generate the different subsets.
These subsets are automatically downloaded when not found on disk.
The task consists in predicting the next word given the previous ones.
The corpus contains approximately 30 million sentences of an average length of about 25 words.
In total, there are about 800 thousand (unique) words in the vocabulary, which makes it a very memory intensive problem.

loadSentiment140

```
train, valid, test = dl.loadSentiment140([datapath, minfreq,
seqlen, validratio, srcurl, progress])

Load & processing training data.
Number of tweets: 1600000
Vocabulary size: 155723
```

```
Number of occurences replaced with <OOV> token: 750575
Tweet corpus size (in number of tokens): 20061241
trainset set processed in 28.306740999222s
```

Load the Sentiment140 dataset.
This dataset can be used for sentiment analysis for microblogging websites like Twitter.
The task is to predict the sentiment of a tweet.
The input is a sequence of tokenized words with a default maximum sequence length of 50 (i.e. `seqlen=50`).
Targets can be one of three classes that map to the sentiment of the tweet: 1 = negative, 2 = neutral, 3 = positive. The neutral tweets are not present in the training data hence we ignore them from all (train, valid & test) datasets. This results in a 2-class (1=Negative, 2=Positive) dataset.
Tweets are tokenized using the `twitter/twokenize.py` script.
By default, only words with at least 3 occurrences (i.e. `minfreq=3`) in the training set are kept.
The dataset is automatically downloaded from `srcurl`, tokenized and parsed into a tensor the first time the loader is used.
The returned training, validation and test sets are encapsulated using the TensorLoader.
The input is padded with zeros before the tweet when it is shorted than `seqlen`.

The above is only printed when `progress=true` (the default) the first time the loader is invoked.
The processed data is subsequently cached to speedup future loadings.
To overwrite any cached data use `dl.overwrite=true`.

fitImageNormalize

```
ppf = dl.fitImageNormalize(trainset, [nsample, cachepath, verbose])
```

Returns a `ppf` preprocessing function that can be used to in-place normalize a batch of images (`inputs`)
channel-wise:

```
ppf(inputs)
```

The `trainset` argument is a DataLoader instance
containing image `inputs`. The mean and standard deviation will be measured
on `nsample` images (default 10000). When `cachepath` is provided, the

mean and standard deviation are saved for the next function call.

dpnn : deep extensions to nn

This package provides many useful features that aren't part of the main nn package.
These include sharedClone, which allows you to clone a module and share parameters or gradParameters with the original module, without incuring any memory overhead.
We also redefined type such that the type-cast preserves Tensor sharing within a structure of modules.

The package provides the following Modules:

- Decorator : abstract class to change the behaviour of an encapsulated module ;
- DontCast : prevent encapsulated module from being casted by `Module:type()` ;
- Serial : decorate a module makes its serialized output more compact ;
- NaN : decorate a module to detect the source of NaN errors ;
- Inception : implements the Inception module of the GoogleLeNet article ;
- Collapse : just like `nn.View(-1)` ;
- Convert : convert between different tensor types or shapes;
- ZipTable : zip a table of tables into a table of tables;
- ZipTableOneToMany : zip a table of element `el` and table of elements into a table of pairs of element `el` and table elements;
- CAddTensorTable : adds a tensor to a table of tensors of the same size;
- ReverseTable : reverse the order of elements in a table;
- PrintSize : prints the size of inputs and gradOutputs (useful for debugging);
- Clip : clips the inputs to a min and max value;
- Constant : outputs a constant value given an input (which is ignored);
- SpatialUniformCrop : uniformly crops patches from a input;
- SpatialGlimpse : takes a fovead glimpse of an image at a given location;
- WhiteNoise : adds isotropic Gaussian noise to the signal when in training mode;
- OneHot : transforms a tensor of indices into one-hot encoding;
- Kmeans : Kmeans clustering layer. Forward computes distances with respect to centroids and returns index of closest centroid. Centroids can be updated using gradient descent. Centroids could be initialized randomly or by using kmeans++ algoirthm;
- SpatialRegionDropout : Randomly dropouts a region (top, bottom, leftmost, rightmost) of the input image. Works with batch and any number of channels;
- FireModule : FireModule as mentioned in the SqueezeNet;
- NCEModule : optimized placeholder for a `Linear` + `SoftMax` using noise-contrastive estimation.
- SpatialFeatNormalization : Module for widely used preprocessing step of mean zeroing and standardization for images.
- SpatialBinaryConvolution : Module for binary spatial convolution (Binary weights) as

mentioned in XNOR-Net.
- SimpleColorTransform : Module for adding independent random noise to input image channels.
- PCAColorTransform : Module for adding noise to input image using Principal Components Analysis.

The following modules and criterions can be used to implement the REINFORCE algorithm :

- Reinforce : abstract class for REINFORCE modules;
- ReinforceBernoulli : samples from Bernoulli distribution;
- ReinforceNormal : samples from Normal distribution;
- ReinforceGamma : samples from Gamma distribution;
- ReinforceCategorical : samples from Categorical (Multinomial with one sample) distribution;
- VRClassReward : criterion for variance-reduced classification-based reward;
- BinaryClassReward : criterion for variance-reduced binary classification reward (like `VRClassReward`, but for binary classes);

Additional differentiable criterions
* BinaryLogisticRegression : criterion for binary logistic regression;
* SpatialBinaryLogisticRegression : criterion for pixel wise binary logistic regression;
* NCECriterion : criterion exclusively used with NCEModule.
* ModuleCriterion : adds an optional `inputModule` and `targetModule` before a decorated criterion;
* BinaryLogisticRegression : criterion for binary logistic regression.
* SpatialBinaryLogisticRegression : criterion for pixel wise binary logistic regression.

A lot of the functionality implemented here was pulled from
dp, which makes heavy use of this package.
However, dpnn can be used without dp (for e.g. you can use it with optim),
which is one of the main reasons why we made it.

Tutorials

Sagar Waghmare wrote a nice tutorial
on how to use dpnn with nngraph to reproduce the
Lateral Connections in Denoising Autoencoders Support Supervised Learning.

A brief (1 hours) overview of Torch7, which includes some details about **dpnn**,
is available via this NVIDIA GTC Webinar video. In any case, this presentation gives a nice
overview of Logistic Regression, Multi-Layer Perceptrons, Convolutional Neural Networks and

Recurrent Neural Networks using Torch7.

Module

The Module interface has been further extended with methods that facilitate stochastic gradient descent like updateGradParameters (i.e. momentum learning), weightDecay, maxParamNorm (for regularization), and so on.

Module.dpnn_parameters

A table that specifies the name of parameter attributes.
Defaults to `{'weight', 'bias'}`, which is a static variable (i.e. table exists in class namespace).
Sub-classes can define their own table statically.

Module.dpnn_gradParameters

A table that specifies the name of gradient w.r.t. parameter attributes.
Defaults to `{'gradWeight', 'gradBias'}`, which is a static variable (i.e. table exists in class namespace).
Sub-classes can define their own table statically.

[self] Module:type(type_str)

This function converts all the parameters of a module to the given `type_str`.
The `type_str` can be one of the types defined for torch.Tensor
like `torch.DoubleTensor`, `torch.FloatTensor` and `torch.CudaTensor`.
Unlike the type method
defined in nn, this one was overriden to
maintain the sharing of storage
among Tensors. This is especially useful when cloning modules share `parameters` and `gradParameters`.

[clone] Module:sharedClone([shareParams, shareGradParams])

Similar to clone.
Yet when `shareParams = true` (the default), the cloned module will share the parameters with the original module.
Furthermore, when `shareGradParams = true` (the default), the clone module will share the gradients w.r.t. parameters with the original module.
This is equivalent to :

```
clone = mlp:clone()
clone:share(mlp, 'weight', 'bias', 'gradWeight', 'gradBias')
```

yet it is much more efficient, especially for modules with lots of parameters, as these Tensors aren't needlessly copied during the `clone`.
This is particularly useful for Recurrent neural networks
which require efficient copies with shared parameters and gradient w.r.t. parameters for each time-step.

Module:maxParamNorm([maxOutNorm, maxInNorm])

This method implements a hard constraint on the upper bound of the norm of output and/or input neuron weights
(Hinton et al. 2012, p. 2) .
In a weight matrix, this is a contraint on rows (`maxOutNorm`) and/or columns (`maxInNorm`), respectively.
Has a regularization effect analogous to weightDecay, but with easier to optimize hyper-parameters.
Assumes that parameters are arranged (`output dim x ... x input dim`).
Only affects parameters with more than one dimension.
The method should normally be called after updateParameters.
It uses the C/CUDA optimized torch.renorm function.
Hint : `maxOutNorm = 2` usually does the trick.

[momGradParams] Module:momentumGradParameters()

Returns a table of Tensors (`momGradParams`). For each element in the table, a corresponding parameter (`params`) and gradient w.r.t. parameters (`gradParams`) is returned by a call to parameters.
This method is used internally by updateGradParameters.

Module:updateGradParameters(momFactor [, momDamp, momNesterov])

Applies classic momentum or Nesterov momentum (Sutskever, Martens et al, 2013) to parameter gradients.
Each parameter Tensor (`params`) has a corresponding Tensor of the same size for gradients w.r.t. parameters (`gradParams`).
When using momentum learning, another Tensor is added for each parameter Tensor (`momGradParams`).
This method should be called before updateParameters
as it affects the gradients w.r.t. parameters.

Classic momentum is computed as follows :

```
momGradParams = momFactor*momGradParams + (1-momDamp)*gradParams
gradParams = momGradParams
```

where `momDamp` has a default value of `momFactor` .

Nesterov momentum (`momNesterov = true`) is computed as follows (the first line is the same as classic momentum):

```
momGradParams = momFactor*momGradParams + (1-momDamp)*gradParams
gradParams = gradParams + momFactor*momGradParams
```

The default is to use classic momentum (`momNesterov = false`).

Module:weightDecay(wdFactor [, wdMinDim])

Decays the weight of the parameterized models.
Implements an L2 norm loss on parameters with dimensions greater or equal to `wdMinDim` (default is 2).

The resulting gradients are stored into the corresponding gradients w.r.t. parameters.
Such that this method should be called before updateParameters.

Module:gradParamClip(cutoffNorm [, moduleLocal])

Implements a contrainst on the norm of gradients w.r.t. parameters (Pascanu et al. 2012).
When `moduleLocal = false` (the default), the norm is calculated globally to Module for which this is called.
So if you call it on an MLP, the norm is computed on the concatenation of all parameter Tensors.
When `moduleLocal = true`, the norm constraint is applied
to the norm of all parameters in each component (non-container) module.
This method is useful to prevent the exploding gradient in
Recurrent neural networks.

Module:reinforce(reward)

This method is used by Criterions that implement the REINFORCE algorithm like VRClassReward.
While vanilla backpropagation (gradient descent using the chain rule),
REINFORCE Criterions broadcast a `reward` to all REINFORCE modules between the `forward` and the `backward`.
In this way, when the following call to `backward` reaches the REINFORCE modules,
these will compute a `gradInput` using the broadcasted `reward`.
The `reward` is broadcast to all REINFORCE modules contained
within `model` by calling `model:reinforce(reward)`.
Note that the `reward` should be a 1D tensor of size `batchSize`,
i.e. each example in a batch has its own scalar reward.

Refer to this example
for a complete training script making use of the REINFORCE interface.

Decorator

```
dmodule = nn.Decorator(module)
```

This module is an abstract class used to decorate a `module`. This means that method calls to `dmodule` will call the same method on the encapsulated `module`, and return its results.

DontCast

```
dmodule = nn.DontCast(module)
```

This module is a decorator. Use it to decorate a module that you don't want to be cast when the `type()` method is called.

```
module = nn.DontCast(nn.Linear(3,4):float())
module:double()
th> print(module:forward(torch.FloatTensor{1,2,3}))
 1.0927
-1.9380
-1.8158
-0.0805
[torch.FloatTensor of size 4]
```

Serial

```
dmodule = nn.Serial(module, [tensortype])
dmodule:[light,medium,heavy]Serial()
```

This module is a decorator that can be used to control the serialization/deserialization behavior of the encapsulated module. Basically, making the resulting string or file heavy (the default), medium or light in terms of size.

Furthermore, when specified, the `tensortype` attribute (e.g *torch.FloatTensor*, *torch.DoubleTensor* and so on.),
determines what type the module will be cast to during serialization.
Note that this will also be the type of the deserialized object.

The default serialization `tensortype` is `nil`, i.e. the module is serialized as is.

The `heavySerial()` has the serialization process serialize every attribute in the module graph,
which is the default behavior of nn.

The `mediumSerial()` has the serialization process serialize
everything except the attributes specified in each module's `dpnn_mediumEmpty`
table, which has a default value of `{'output', 'gradInput', 'momGradParams', 'dpnn_input'}`.
During serialization, whether they be tables or Tensors, these attributes are emptied (no storage).
Some modules overwrite the default `Module.dpnn_mediumEmpty` static attribute with their own.

The `lightSerial()` has the serialization process empty
everything a call to `mediumSerial(type)` would (so it uses `dpnn_mediumEmpty`).
But also empties all the parameter gradients specified by the
attribute `dpnn_gradParameters`, which defaults to `{gradWeight, gradBias}`.

We recomment using `mediumSerial()` for training, and `lightSerial()` for production (feed-forward-only models).

NaN

```
dmodule = nn.NaN(module, [id])
```

The `NaN` module asserts that the `output` and `gradInput` of the decorated `module` do not contain NaNs.
This is useful for locating the source of those pesky NaN errors.
The `id` defaults to automatically incremented values of `1,2,3,...`.

For example:

```
linear = nn.Linear(3,4)
mlp = nn.Sequential()
mlp:add(nn.NaN(nn.Identity()))
mlp:add(nn.NaN(linear))
mlp:add(nn.NaN(nn.Linear(4,2)))
print(mlp)
```

As you can see the `NaN` layers are have unique ids :

```
nn.Sequential {
  [input -> (1) -> (2) -> (3) -> output]
  (1): nn.NaN(1) @ nn.Identity
  (2): nn.NaN(2) @ nn.Linear(3 -> 4)
  (3): nn.NaN(3) @ nn.Linear(4 -> 2)
}
```

And if we fill the `bias` of the linear module with NaNs and call `forward` :

```
nan = math.log(math.log(0)) -- this is a nan value
linear.bias:fill(nan)
mlp:forward(torch.randn(2,3))
```

We get a nice error message:

```
/usr/local/share/lua/5.1/dpnn/NaN.lua:39: NaN found in parameters
of module :
nn.NaN(2) @ nn.Linear(3 -> 4)
```

Inception

References :

- A. Going Deeper with Convolutions
- B. GoogleLeNet

```
module = nn.Inception(config)
```

This module uses `n` +2 parallel “columns”.
The original paper uses 2+2 where the first two are (but there could be more than two):

- 1x1 conv (reduce) -> relu -> 5x5 conv -> relu
- 1x1 conv (reduce) -> relu -> 3x3 conv -> relu

and where the other two are :

- 3x3 maxpool -> 1x1 conv (reduce/project) -> relu
- 1x1 conv (reduce) -> relu.

This module allows the first group of columns to be of any
number while the last group consist of exactly two columns.
The 1x1 convoluations are used to reduce the number of input channels
(or filters) such that the capacity of the network doesn't explode.
We refer to these here has *reduce*.
Since each column seems to have one and only one reduce, their initial
configuration options are specified in lists of n+2 elements.

The sole argument `config` is a table taking the following key-values :

- Required Arguments :
  - `inputSize` : number of input channels or colors, e.g. 3;
  - `outputSize` : numbers of filters in the non-1x1 convolution kernel sizes, e.g. `{32,48}`
  - `reduceSize` : numbers of filters in the 1x1 convolutions (reduction) used in each column, e.g. `{48,64,32,32}` . The last 2 are used respectively for the max pooling (projection) column (the last column in the paper) and the column that has nothing but a 1x1 conv (the first column in the paper). This table should have two elements more than the outputSize

- Optional Arguments :
  - `reduceStride` : strides of the 1x1 (reduction) convolutions. Defaults to `{1,1,...}` .
  - `transfer` : transfer function like `nn.Tanh` , `nn.Sigmoid` , `nn.ReLU` , `nn.Identity` , etc. It is used after each reduction (1x1 convolution) and convolution. Defaults to `nn.ReLU` .
  - `batchNorm` : set this to `true` to use batch normalization. Defaults to `false` . Note that batch normalization can be awesome
  - `padding` : set this to `true` to add padding to the input of the convolutions such that output width and height are same as that of the original non-padded `input` . Defaults to `true` .
  - `kernelSize` : size (`height = width`) of the non-1x1 convolution kernels. Defaults to `{5,3}` .
  - `kernelStride` : stride of the kernels (`height = width`) of the convolution. Defaults to `{1,1}`
  - `poolSize` : size (`height = width`) of the spatial max pooling used in the next-to-last column. Defaults to 3.
  - `poolStride` : stride (`height = width`) of the spatial max pooling. Defaults to 1.

For a complete example using this module, refer to the following :
* deep inception training script ;
* openface facial recognition (the model definition is here).

Collapse

```
module = nn.Collapse(nInputDim)
```

This module is the equivalent of:

```
view = nn.View(-1)
view:setNumInputDim(nInputDim)
```

It collapses all non-batch dimensions. This is useful for converting
a spatial feature map to the single dimension required by a dense
hidden layer like Linear.

Convert

```
module = nn.Convert([inputShape, outputShape])
```

Module to convert between different data formats.
For example, we can flatten images by using :

```
module = nn.Convert('bchw', 'bf')
```

or equivalently

```
module = nn.Convert('chw', 'f')
```

Lets try it with an input:

```
print(module:forward(torch.randn(3,2,3,1)))
 0.5692 -0.0190  0.5243  0.7530  0.4230  1.2483
-0.9142  0.6013  0.5608 -1.0417 -1.4014  1.0177
-1.5207 -0.1641 -0.4166  1.4810 -1.1725 -1.0037
[torch.DoubleTensor of size 3x6]
```

You could also try:

```
module = nn.Convert('chw', 'hwc')
input = torch.randn(1,2,3,2)
input:select(2,1):fill(1)
input:select(2,2):fill(2)
print(input)
(1,1,.,.) =
  1  1
  1  1
  1  1
(1,2,.,.) =
  2  2
  2  2
  2  2
[torch.DoubleTensor of size 1x2x3x2]
print(module:forward(input))
(1,1,.,.) =
  1  2
  1  2

(1,2,.,.) =
  1  2
  1  2

(1,3,.,.) =
  1  2
  1  2
[torch.DoubleTensor of size 1x3x2x2]
```

Furthermore, it automatically converts the `input` to have the same type as `self.output` (i.e. the type of the module).
So you can also just use is for automatic input type converions:

```
module = nn.Convert()
print(module.output) -- type of module
```

```
[torch.DoubleTensor with no dimension]
input = torch.FloatTensor{1,2,3}
print(module:forward(input))
 1
 2
 3
[torch.DoubleTensor of size 3]
```

ZipTable

```
module = nn.ZipTable()
```

Zips a table of tables into a table of tables.

Example:

```
print(module:forward{ {'a1','a2'}, {'b1','b2'}, {'c1','c2'} })
{ {'a1','b1','c1'}, {'a2','b2','c2'} }
```

ZipTableOneToMany

```
module = nn.ZipTableOneToMany()
```

Zips a table of element `el` and table of elements `tab` into a table of tables, where the i-th table contains the element `el` and the i-th element in table `tab`

Example:

```
print(module:forward{ 'el', {'a','b','c'} })
{ {'el','a'}, {'el','b'}, {'el','c'} }
```

CAddTensorTable

```
module = nn.CAddTensorTable()
```

Adds the first element `el` of the input table `tab` to each tensor contained in the second element of `tab`, which is itself a table

Example:

```
print(module:forward{ (0,1,1), {(0,0,0),(1,1,1)} })
{ (0,1,1), (1,2,2) }
```

ReverseTable

```
module = nn.ReverseTable()
```

Reverses the order of elements in a table.

Example:

```
print(module:forward{1,2,3,4})
{4,3,2,1}
```

PrintSize

```
module = nn.PrintSize(name)
```

This module is useful for debugging complicated module composites.
It prints the size of the `input` and `gradOutput` during `forward`

and `backward` propagation respectively.
The `name` is a string used to identify the module along side the printed size.

Clip

```
module = nn.Clip(minval, maxval)
```

This module clips `input` values such that the output is between `minval` and `maxval`.

Constant

```
module = nn.Constant(value, nInputDim)
```

This module outputs a constant value given an input.
If `nInputDim` is specified, it uses the input to determine the size of the batch.
The `value` is then replicated over the batch.
Otherwise, the `value` Tensor is output as is.
During `backward`, the returned `gradInput` is a zero Tensor of the same size as the `input`.
This module has no trainable parameters.

You can use this with nn.ConcatTable() to append constant inputs to an input :

```
nn.ConcatTable():add(nn.Constant(v)):add(nn.Identity())
```

This is useful when you want to output a value that is independent of the
input to the neural network (see this example).

SpatialUniformCrop

```
module = nn.SpatialUniformCrop(oheight, owidth)
```

During training, this module will output a cropped patch of size `oheight, owidth`
within the boundaries of the `input` image.
For each example, a location is sampled from a uniform distribution
such that each possible patch has an equal probability of being sampled.

During evaluation, the center patch is cropped and output.

This module is commonly used at the input layer to artificially
augment the size of the dataset to prevent overfitting.

SpatialGlimpse

Ref. A. Recurrent Model for Visual Attention

```
module = nn.SpatialGlimpse(size, depth, scale)
```

A glimpse is the concatenation of down-scaled cropped images of
increasing scale around a given location in a given image.
The input is a pair of Tensors: `{image, location}`
`location` are `(y,x)` coordinates of the center of the different scales
of patches to be cropped from image `image`.
Coordinates are between `(-1,-1)` (top-left) and `(1,1)` (bottom-right).
The `output` is a batch of glimpses taken in image at location `(y,x)`.

`size` can be either a scalar which specifies the `width = height` of glimpses,
or a table of `{height, width}` to support a rectangular shape of glimpses.
`depth` is number of patches to crop per glimpse (one patch per depth).
`scale` determines the `size(t) = scale * size(t-1)` of successive cropped patches.

So basically, this module can be used to focus the attention of the model
on a region of the input `image`.
It is commonly used with the RecurrentAttention
module (see this example).

WhiteNoise

```
module = nn.WhiteNoise([mean, stdev])
```

Useful in training [Denoising Autoencoders] (http://arxiv.org/pdf/1507.02672v1.pdf).
Takes `mean` and `stdev` of the normal distribution as input.
Default values for mean and standard deviation are 0 and 0.1 respectively.
With `module:training()`, noise is added during forward.
During `backward` gradients are passed as it is.
With `module:evaluate()` the mean is added to the input.

SpatialRegionDropout

```
module = nn.SpatialRegionDropout(p)
```

Following is an example of `SpatialRegionDropout` outputs on the famous lena image.

Input

Outputs

FireModule

Ref: http://arxiv.org/pdf/1602.07360v1.pdf

```
module = nn.FireModule(nInputPlane, s1x1, e1x1, e3x3, activation)
```

FireModule is comprised of two submodules 1) A *squeeze* convolution module comprised of `1x1` filters followed by 2) an *expand* module that is comprised of a mix of `1x1` and `3x3` convolution filters.
Arguments: `s1x1`: number of `1x1` filters in the squeeze submodule, `e1x1`: number of `1x1` filters in the expand submodule, `e3x3`: number of `3x3` filters in the expand submodule. It is

recommended that `s1x1` be less than `(e1x1+e3x3)` if you want to limit the number of input channels to the `3x3` filters in the expand submodule.
FireModule works only with batches, for single sample convert the sample to a batch of size 1.

SpatialFeatNormalization

```
module = nn.SpatialFeatNormalization(mean, std)
```

This module normalizies each feature channel of input image based on its corresponding mean and standard deviation scalar values. This module does not learn the `mean` and `std`, they are provided as arguments.

SpatialBinaryConvolution

```
module = nn.SpatialBinaryConvolution(nInputPlane, nOutputPlane, kW,
kH)
```

Functioning of SpatialBinaryConvolution is similar to nn/SpatialConvolution. Only difference is that Binary weights are used for forward/backward and floating point weights are used for weight updates. Check **Binary-Weight-Network** section of XNOR-net.

SimpleColorTransform

```
range = torch.rand(inputChannels) -- Typically range is specified
by user.
module = nn.SimpleColorTransform(inputChannels, range)
```

This module performs a simple data augmentation technique. SimpleColorTransform module adds random noise to each color channel independently. In more advanced data augmentation technique noise is added using principal components of color channels. For that please check

PCAColorTransform

PCAColorTransform

```
eigenVectors = torch.rand(inputChannels, inputChannels) -- Eigen
Vectors
eigenValues = torch.rand(inputChannels) -- Eigen
std = 0.1 -- Std deviation of normal distribution with mean zero
for noise.
module = nn.PCAColorTransform(inputChannels, eigenVectors,
eigenValues, std)
```

This module performs a data augmentation using Principal Component analysis of pixel values. When in training mode, mulitples of principal components are added to input image pixels. Magnitude of value added (noise) is dependent upon the corresponding eigen value and a random value sampled from a Gaussian distribution with mean zero and `std` (default 0.1) standard deviation. This technique was used in the famous AlexNet paper.

OneHot

```
module = nn.OneHot(outputSize)
```

Transforms a tensor of `input` indices having integer values between 1 and `outputSize` into a tensor of one-hot vectors of size `outputSize`.

Forward an index to get a one-hot vector :

```
> module = nn.OneHot(5) -- 5 classes
> module:forward(torch.LongTensor{3})
 0  0  1  0  0
[torch.DoubleTensor of size 1x5]
```

Forward a batch of 3 indices. Notice that these need not be stored as `torch.LongTensor` :

```
> module:forward(torch.Tensor{3,2,1})
 0  0  1  0  0
 0  1  0  0  0
 1  0  0  0  0
[torch.DoubleTensor of size 3x5]
```

Forward batch of `2 x 3` indices :

```
oh:forward(torch.Tensor{{3,2,1},{1,2,3}})
(1,.,.) =
  0  0  1  0  0
  0  1  0  0  0
  1  0  0  0  0

(2,.,.) =
  1  0  0  0  0
  0  1  0  0  0
  0  0  1  0  0
[torch.DoubleTensor of size 2x3x5]
```

Kmeans

```
km = nn.Kmeans(k, dim)
```

`k` is the number of centroids and `dim` is the dimensionality of samples.
You can either initialize centroids randomly from input samples or by using *kmeans++* algorithm.

```
km:initRandom(samples) -- Randomly initialize centroids from input
samples.
km:initKmeansPlus(samples) -- Use Kmeans++ to initialize centroids.
```

Example showing how to use Kmeans module to do standard Kmeans clustering.

```
attempts = 10
iter = 100 -- Number of iterations
```

```
bestKm = nil
bestLoss = math.huge
learningRate = 1
for j=1, attempts do
   local km = nn.Kmeans(k, dim)
   km:initKmeansPlus(samples)
   for i=1, iter do
      km:zeroGradParameters()
      km:forward(samples) -- sets km.loss
      km:backward(samples, gradOutput) -- gradOutput is ignored

      -- Gradient Descent weight/centroids update
      km:updateParameters(learningRate)
   end

   if km.loss < bestLoss then
      bestLoss = km.loss
      bestKm = km:clone()
   end
end
```

`nn.Kmeans()` module maintains loss only for the latest forward. If you want to maintain loss over the whole dataset then you who would need do it my adding the module loss for every forward.

You can also use `nn.Kmeans()` as an auxillary layer in your network.
A call to `forward` will generate an `output` containing the index of the nearest cluster for each sample in the batch.
The `gradInput` generated by `updateGradInput` will be zero.

ModuleCriterion

```
criterion = nn.ModuleCriterion(criterion [, inputModule,
targetModule, castTarget])
```

This criterion decorates a `criterion` by allowing the `input` and `target` to be fed through an optional `inputModule` and `targetModule` before being passed to the `criterion`. The `inputModule` must not contain parameters as these would not be updated.

When `castTarget = true` (the default), the `targetModule` is cast along with the

`inputModule` and
`criterion`. Otherwise, the `targetModule` isn't.

NCEModule

Ref. A RNNLM training with NCE for Speech Recognition

```
ncem = nn.NCEModule(inputSize, outputSize, k, unigrams, [Z])
```

When used in conjunction with NCECriterion,
the `NCEModule` implements noise-contrastive estimation.

The point of the NCE is to speedup computation for large `Linear` + `SoftMax` layers.
Computing a forward/backward for `Linear(inputSize, outputSize)` for a large `outputSize` can be very expensive.
This is common when implementing language models having with large vocabularies of a million words.
In such cases, NCE can be an efficient alternative to computing the full `Linear` + `SoftMax` during training and
cross-validation.

The `inputSize` and `outputSize` are the same as for the `Linear` module.
The number of noise samples to be drawn per example is `k`. A value of 25 should work well.
Increasing it will yield better results, while a smaller value will be more efficient to process.
The `unigrams` is a tensor of size `outputSize` that contains the frequencies or probability distribution over classes.
It is used to sample noise samples via a fast implementation of `torch.multinomial`.
The `Z` is the normalization constant of the approximated SoftMax.
The default is `math.exp(9)` as specified in Ref. A.

For inference, or measuring perplexity, the full `Linear` + `SoftMax` will need to
be computed. The `NCEModule` can do this by switching on the following :

```
ncem:evaluate()
ncem.normalized = true
```

Furthermore, to simulate `Linear` + `LogSoftMax` instead, one need only add the following to the above:

```
ncem.logsoftmax = true
```

An example is provided via the rnn package.

NCECriterion

```
ncec = nn.NCECriterion()
```

This criterion only works with an NCEModule on the output layer.
Together, they implement noise-contrastive estimation.

Reinforce

Ref A. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

Abstract class for modules that implement the REINFORCE algorithm (ref. A).

```
module = nn.Reinforce([stochastic])
```

The `reinforce(reward)` method is called by a special Reward Criterion (e.g. VRClassReward).
After which, when backward is called, the reward will be used to generate gradInputs.
When `stochastic=true`, the module is stochastic (i.e. samples from a distribution) during evaluation and training.
When `stochastic=false` (the default), the module is only stochastic during training.

The REINFORCE rule for a module can be summarized as follows :

```
             d ln(f(output,input))
gradInput = ---------------------  * reward
                   d input
```

where the `reward` is what is provided by a Reward criterion like VRClassReward via the reinforce method.
The criterion will normally be responsible for the following formula :

```
reward = a*(R - b)
```

where `a` is the alpha of the original paper, i.e. a reward scale,
`R` is the raw reward (usually 0 or 1), and `b` is the baseline reward,
which is often taken to be the expected raw reward `R`.

The `output` is usually sampled from a probability distribution `f()`
parameterized by the `input`.
See ReinforceBernoulli for a concrete derivation.

Also, as you can see, the gradOutput is ignored. So within a backpropagation graph,
the `Reinforce` modules will replace the backpropagated gradients (`gradOutput`)
with their own obtained from the broadcasted `reward`.

ReinforceBernoulli

Ref A. Simple Statistical Gradient-Following Algorithms for
Connectionist Reinforcement Learning

```
module = nn.ReinforceBernoulli([stochastic])
```

A Reinforce subclass that implements the REINFORCE algorithm
(ref. A p.230-236) for the Bernoulli probability distribution.
Inputs are bernoulli probabilities `p`.
During training, outputs are samples drawn from this distribution.
During evaluation, when `stochastic=false`, outputs are the same as the inputs.
Uses the REINFORCE algorithm (ref. A p.230-236) which is
implemented through the reinforce interface (`gradOutputs` are ignored).

Given the following variables :

- `f` : bernoulli probability mass function
- `x` : the sampled values (0 or 1) (i.e. `self.output`)
- `p` : probability of sampling a 1

the derivative of the log bernoulli w.r.t. probability `p` is :

```
d ln(f(output,input))   d ln(f(x,p))    (x - p)
--------------------- = ------------ = ---------
      d input               d p         p(1 - p)
```

ReinforceNormal

Ref A. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

```
module = nn.ReinforceNormal(stdev, [stochastic])
```

A Reinforce subclass that implements the REINFORCE algorithm
(ref. A p.238-239) for a Normal (i.e. Gaussian) probability distribution.
Inputs are the means of the normal distribution.
The `stdev` argument specifies the standard deviation of the distribution.
During training, outputs are samples drawn from this distribution.
During evaluation, when `stochastic=false`, outputs are the same as the inputs, i.e. the means.
Uses the REINFORCE algorithm (ref. A p.238-239) which is
implemented through the reinforce interface (`gradOutputs` are ignored).

Given the following variables :

- `f` : normal probability density function
- `x` : the sampled values (i.e. `self.output`)
- `u` : mean (`input`)
- `s` : standard deviation (`self.stdev`)

the derivative of log normal w.r.t. mean `u` is :

```
d ln(f(x,u,s))   (x - u)
-------------- = -------
     d u           s^2
```

As an example, it is used to sample locations for the RecurrentAttention
module (see this example).

ReinforceGamma

Ref A. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

```
module = nn.ReinforceGamma(scale, [stochastic])
```

A Reinforce subclass that implements the REINFORCE algorithm
(ref. A) for a Gamma probability distribution
parametrized by shape (k) and scale (theta) variables.
Inputs are the shapes of the gamma distribution.
During training, outputs are samples drawn from this distribution.
During evaluation, when `stochastic=false`, outputs are equal to the mean, defined as the product of
shape and scale ie. `k*theta`.
Uses the REINFORCE algorithm (ref. A) which is
implemented through the reinforce interface (`gradOutputs` are ignored).

Given the following variables :

- `f` : gamma probability density function
- `g` : digamma function
- `x` : the sampled values (i.e. `self.output`)
- `k` : shape (`input`)
- `t` : scale

the derivative of log gamma w.r.t. shape `k` is :

```
d ln(f(x,k,t))
-------------- = ln(x) - g(k) - ln(t)
      d k
```

ReinforceCategorical

Ref A. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

```
module = nn.ReinforceCategorical([stochastic])
```

A Reinforce subclass that implements the REINFORCE algorithm
(ref. A) for a Categorical (i.e. Multinomial with one sample) probability distribution.
Inputs are the categorical probabilities of the distribution : `p[1], p[2], ..., p[k]`.
These are usually the output of a SoftMax.
For `n` categories, both the `input` and `output` ares of size `batchSize x n`.
During training, outputs are samples drawn from this distribution.
The outputs are returned in one-hot encoding i.e.
the output for each example has exactly one category having a 1, while the remainder are zero.
During evaluation, when `stochastic=false`, outputs are the same as the inputs, i.e. the probabilities `p`.
Uses the REINFORCE algorithm (ref. A) which is
implemented through the reinforce interface (`gradOutputs` are ignored).

Given the following variables :

- `f` : categorical probability mass function
- `x` : the sampled indices (one per sample) (`self.output` is the one-hot encoding of these indices)
- `p` : probability vector (`p[1], p[2], ..., p[k]`) (`input`)

the derivative of log categorical w.r.t. probability vector `p` is :

```
d ln(f(x,p))     1/p[i]    if i = x
------------ =
    d p          0         otherwise
```

VRClassReward

Ref A. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

This Reward criterion implements the REINFORCE algoritm (ref. A) for classification models.
Specifically, it is a Variance Reduces (VR) classification reinforcement leanring (reward-based) criterion.

```
vcr = nn.VRClassReward(module [, scale, criterion])
```

While it conforms to the Criterion interface (which it inherits),
it does not backpropagate gradients (except for the baseline `b`; see below).
Instead, a `reward` is broadcast to the `module` via the reinforce method.

The criterion implements the following formula :

```
reward = a*(R - b)
```

where `a` is the alpha described in Ref. A, i.e. a reward `scale` (defaults to 1),
`R` is the raw reward (0 for incorrect and 1 for correct classification),
and `b` is the baseline reward, which is often taken to be the expected raw reward `R`.

The `target` of the criterion is a tensor of class indices.
The `input` to the criterion is a table `{y,b}` where `y` is the probability
(or log-probability) of classes (usually the output of a SoftMax),
and `b` is the baseline reward discussed above.

For each example, if `argmax(y)` is equal to the `target` class, the raw reward `R = 1`,
otherwize `R = 0`.

As for `b`, its `gradInputs` are obtained from the `criterion`, which defaults to
`MSECriterion`.
The `criterion`'s target is the commensurate raw reward `R`.
Using `a*(R-b)` instead of `a*R` to obtain a `reward` is what makes this class variance
reduced (VR).
By reducing the variance, the training can converge faster (Ref. A).
The predicted `b` can be nothing more than the expectation `E(R)`.

Note : for RNNs with R = 1 for last step in sequence, encapsulate it
in `nn.ModuleCriterion(VRClassReward, nn.SelectTable(-1))`.

For an example, this criterion is used along with the RecurrentAttention
module to train a recurrent model for visual attention.

BinaryClassReward

```
bcr = nn.BinaryClassReward(module [, scale, criterion])
```

This module implements VRClassReward for binary classification problems.
So basically, the `input` is still a table of two tensors.
The first input tensor is of size `batchsize` containing Bernoulli probabilities.
The second input tensor is the baseline prediction described in `VRClassReward`.
The targets contain zeros and ones.

BinaryLogisticRegression

Ref A. Learning to Segment Object Candidates
This criterion implements the score criterion mentioned in (ref. A).

```
criterion = nn.BinaryLogisticRegression()
```

BinaryLogisticRegression implements following cost function for binary classification.

```
log( 1 + exp( -y_k * score(x_k) ) )
```

where `y_k` is binary target `score(x_k)` is the corresponding prediction. `y_k` has value `{-1, +1}` and `score(x_k)` has value in `[-1, +1]`.

SpatialBinaryLogisticRegression

Ref A. Learning to Segment Object Candidates

This criterion implements the spatial component of the criterion mentioned in (ref. A).

```
criterion = nn.SpatialBinaryLogisticRegression()
```

SpatialBinaryLogisticRegression implements following cost function for binary pixel classification.

```
   1
_______ sum_ij [ log( 1 + exp( -m_ij * f_ij ) ) ]
```

```
    2*w*h
```

where `m_ij` is target binary image and `f_ij` is the corresponding prediction. `m_ij` has value `{-1, +1}` and `f_ij` has value in `[-1, +1]`.

Module

`Module` is an abstract class which defines fundamental methods necessary for a training a neural network. Modules are serializable.

Modules contain two states variables: output and gradInput.

[output] forward(input)

Takes an `input` object, and computes the corresponding `output` of the module. In general `input` and `output` are Tensors. However, some special sub-classes like table layers might expect something else. Please, refer to each module specification for further information.

After a `forward()`, the output state variable should have been updated to the new value.

It is not advised to override this function. Instead, one should implement updateOutput(input) function. The forward module in the abstract parent class Module will call `updateOutput(input)`.

[gradInput] backward(input, gradOutput)

Performs a *backpropagation step* through the module, with respect to the given `input`. In general this method makes the assumption forward(input) has been called before, *with the same input*. This is necessary for optimization reasons. If you do not respect this rule, `backward()` will compute incorrect gradients.

In general `input` and `gradOutput` and `gradInput` are Tensors. However, some special sub-classes like table layers might expect something else. Please, refer to each module specification for further information.

A *backpropagation step* consist in computing two kind of gradients

at `input` given `gradOutput` (gradients with respect to the output of the module). This function simply performs this task using two function calls:

- A function call to updateGradInput(input, gradOutput).
- A function call to accGradParameters(input,gradOutput,scale).

It is not advised to override this function call in custom classes. It is better to override updateGradInput(input, gradOutput) and accGradParameters(input, gradOutput,scale) functions.

updateOutput(input)

Computes the output using the current parameter set of the class and input. This function returns the result which is stored in the output field.

updateGradInput(input, gradOutput)

Computing the gradient of the module with respect to its own input. This is returned in `gradInput`. Also, the gradInput state variable is updated accordingly.

accGradParameters(input, gradOutput, scale)

Computing the gradient of the module with respect to its own parameters. Many modules do not perform this step as they do not have any parameters. The state variable name for the parameters is module dependent. The module is expected to *accumulate* the gradients with respect to the parameters in some variable.

`scale` is a scale factor that is multiplied with the gradParameters before being accumulated.

Zeroing this accumulation is achieved with zeroGradParameters() and updating

the parameters according to this accumulation is done with updateParameters().

zeroGradParameters()

If the module has parameters, this will zero the accumulation of the gradients with respect to these parameters, accumulated through accGradParameters(input, gradOutput,scale) calls. Otherwise, it does nothing.

updateParameters(learningRate)

If the module has parameters, this will update these parameters, according to the accumulation of the gradients with respect to these parameters, accumulated through backward() calls.

The update is basically:

```
parameters = parameters - learningRate * gradients_wrt_parameters
```

If the module does not have parameters, it does nothing.

accUpdateGradParameters(input, gradOutput, learningRate)

This is a convenience module that performs two functions at once. Calculates and accumulates the gradients with respect to the weights after multiplying with negative of the learning rate `learningRate`. Performing these two operations at once is more performance efficient and it might be advantageous in certain situations.

Keep in mind that, this function uses a simple trick to achieve its goal and it might not be valid for a custom module.

Also note that compared to accGradParameters(), the gradients are not retained for future use.

```
function Module:accUpdateGradParameters(input, gradOutput, lr)
   local gradWeight = self.gradWeight
   local gradBias = self.gradBias
   self.gradWeight = self.weight
   self.gradBias = self.bias
   self:accGradParameters(input, gradOutput, -lr)
   self.gradWeight = gradWeight
   self.gradBias = gradBias
end
```

As it can be seen, the gradients are accumulated directly into weights. This assumption may not be true for a module that computes a nonlinear operation.

share(mlp,s1,s2,...,sn)

This function modifies the parameters of the module named `s1`,.. `sn` (if they exist) so that they are shared with (pointers to) the parameters with the same names in the given module `mlp`.

The parameters have to be Tensors. This function is typically used if you want to have modules that share the same weights or biases.

Note that this function if called on a Container module will share the same parameters for all the contained modules as well.

Example:

```
-- make an mlp
mlp1=nn.Sequential();
mlp1:add(nn.Linear(100,10));

-- make a second mlp
mlp2=nn.Sequential();
mlp2:add(nn.Linear(100,10));

-- the second mlp shares the bias of the first
mlp2:share(mlp1,'bias');
```

```
-- we change the bias of the first
mlp1:get(1).bias[1]=99;

-- and see that the second one's bias has also changed..
print(mlp2:get(1).bias[1])
```

clone(mlp,...)

Creates a deep copy of (i.e. not just a pointer to) the module, including the current state of its parameters (e.g. weight, biases etc., if any).

If arguments are provided to the `clone(...)` function it also calls share(...) with those arguments on the cloned module after creating it, hence making a deep copy of this module with some shared parameters.

Example:

```
-- make an mlp
mlp1=nn.Sequential();
mlp1:add(nn.Linear(100,10));

-- make a copy that shares the weights and biases
mlp2=mlp1:clone('weight','bias');

-- we change the bias of the first mlp
mlp1:get(1).bias[1]=99;

-- and see that the second one's bias has also changed..
print(mlp2:get(1).bias[1])
```

type(type[, tensorCache])

This function converts all the parameters of a module to the given `type`. The `type` can be one of the types defined for torch.Tensor.

If tensors (or their storages) are shared between multiple modules in a

network, this sharing will be preserved after type is called.

To preserve sharing between multiple modules and/or tensors, use `nn.utils.recursiveType`:

```
-- make an mlp
mlp1=nn.Sequential();
mlp1:add(nn.Linear(100,10));

-- make a second mlp
mlp2=nn.Sequential();
mlp2:add(nn.Linear(100,10));

-- the second mlp shares the bias of the first
mlp2:share(mlp1,'bias');

-- mlp1 and mlp2 will be converted to float, and will share bias
-- note: tensors can be provided as inputs as well as modules
nn.utils.recursiveType({mlp1, mlp2}, 'torch.FloatTensor')
```

float([tensorCache])

Convenience method for calling module:type('torch.FloatTensor'[, tensorCache])

double([tensorCache])

Convenience method for calling module:type('torch.DoubleTensor'[, tensorCache])

cuda([tensorCache])

Convenience method for calling module:type('torch.CudaTensor'[, tensorCache])

State Variables

These state variables are useful objects if one wants to check the guts of

a `Module`. The object pointer is *never* supposed to change. However, its contents (including its size if it is a Tensor) are supposed to change.

In general state variables are
Tensors.
However, some special sub-classes
like table layers contain something else. Please,
refer to each module specification for further information.

output

This contains the output of the module, computed with the last call of forward(input).

gradInput

This contains the gradients with respect to the inputs of the module, computed with the last call of
updateGradInput(input, gradOutput).

Parameters and gradients w.r.t parameters

Some modules contain parameters (the ones that we actually want to train!). The name of these parameters, and gradients w.r.t these parameters are module dependent.

[{weights}, {gradWeights}] parameters()

This function should returns two tables. One for the learnable parameters `{weights}` and another for the gradients of the energy wrt to the learnable parameters `{gradWeights}`.

Custom modules should override this function if they use learnable parameters that are stored in tensors.

[flatParameters, flatGradParameters] getParameters()

This function returns two tensors. One for the flattened learnable parameters `flatParameters` and another for the gradients of the energy wrt to the learnable parameters `flatGradParameters`.

Custom modules should not override this function. They should instead override parameters(…) which is, in turn, called by the present function.

This function will go over all the weights and gradWeights and make them view into a single tensor (one for weights and one for gradWeights). Since the storage of every weight and gradWeight is changed, this function should be called only once on a given network.

training()

This sets the mode of the Module (or sub-modules) to `train=true`. This is useful for modules like Dropout or BatchNormalization that have a different behaviour during training vs evaluation.

evaluate()

This sets the mode of the Module (or sub-modules) to `train=false`. This is useful for modules like Dropout or BatchNormalization that have a different behaviour during training vs evaluation.

findModules(typename)

Find all instances of modules in the network of a certain `typename`. It returns a flattened list of the matching nodes, as well as a flattened list of the container modules for each matching node.

Modules that do not have a parent container (ie, a top level nn.Sequential for instance) will return their `self` as the container.

This function is very helpful for navigating complicated nested networks. For example, a didactic example might be; if you wanted to print the output size of all `nn.SpatialConvolution` instances:

```
-- Construct a multi-resolution convolution network (with 2
resolutions):
```

```
model = nn.ParallelTable()
conv_bank1 = nn.Sequential()
conv_bank1:add(nn.SpatialConvolution(3,16,5,5))
conv_bank1:add(nn.Threshold())
model:add(conv_bank1)
conv_bank2 = nn.Sequential()
conv_bank2:add(nn.SpatialConvolution(3,16,5,5))
conv_bank2:add(nn.Threshold())
model:add(conv_bank2)
-- FPROP a multi-resolution sample
input = {torch.rand(3,128,128), torch.rand(3,64,64)}
model:forward(input)
-- Print the size of the Threshold outputs
conv_nodes = model:findModules('nn.SpatialConvolution')
for i = 1, #conv_nodes do
  print(conv_nodes[i].output:size())
end
```

Another use might be to replace all nodes of a certain `typename` with another. For instance, if we wanted to replace all `nn.Threshold` with `nn.Tanh` in the model above:

```
threshold_nodes, container_nodes =
model:findModules('nn.Threshold')
for i = 1, #threshold_nodes do
  -- Search the container for the current threshold node
  for j = 1, #(container_nodes[i].modules) do
    if container_nodes[i].modules[j] == threshold_nodes[i] then
      -- Replace with a new instance
      container_nodes[i].modules[j] = nn.Tanh()
    end
  end
end
```

listModules()

List all Modules instances in a network. Returns a flattened list of modules, including container modules (which will be listed first), self, and any other component modules.

For example :

```
mlp = nn.Sequential()
mlp:add(nn.Linear(10,20))
mlp:add(nn.Tanh())
mlp2 = nn.Parallel()
mlp2:add(mlp)
mlp2:add(nn.ReLU())
for i,module in ipairs(mlp2:listModules()) do
   print(module)
end
```

Which will result in the following output :

```
nn.Parallel {
  input
    |`-> (1): nn.Sequential {
    |      [input -> (1) -> (2) -> output]
    |      (1): nn.Linear(10 -> 20)
    |      (2): nn.Tanh
    |    }
    |`-> (2): nn.ReLU
     ... -> output
}
nn.Sequential {
  [input -> (1) -> (2) -> output]
  (1): nn.Linear(10 -> 20)
  (2): nn.Tanh
}
nn.Linear(10 -> 20)
nn.Tanh
nn.ReLU
```

clearState()

Clears intermediate module states as `output`, `gradInput` and others.
Useful when serializing networks and running low on memory. Internally calls `set()` on tensors so it does not break buffer sharing.

apply(function)

Calls provided function on itself and all child modules. This function takes module to operate on as a first argument:

```
model:apply(function(module)
   module.train = true
end)
```

In the example above `train` will be set to to `true` in all modules of `model`. This is how `training()` and `evaluate()` functions implemented.

replace(function)

Similar to apply takes a function which applied to all modules of a model, but uses return value to replace the module. Can be used to replace all modules of one type to another or remove certain modules.

For example, can be used to remove `nn.Dropout` layers by replacing them with `nn.Identity`:

```
model:replace(function(module)
   if torch.typename(module) == 'nn.Dropout' then
      return nn.Identity()
   else
      return module
   end
end)
```

Overview

Each module of a network is composed of Modules and there are several sub-classes of `Module` available: container classes like Sequential, Parallel and Concat , which can contain simple layers like Linear, Mean, Max and Reshape, as well as convolutional layers, and transfer functions like Tanh.

Loss functions are implemented as sub-classes of Criterion. They are helpful to train neural network on classical tasks. Common criterions are the Mean Squared Error criterion implemented in MSECriterion and the cross-entropy criterion implemented in ClassNLLCriterion.

Finally, the StochasticGradient class provides a high level way to train the neural network of choice, even though it is easy with a simple for loop to train a neural network yourself.

Detailed Overview

This section provides a detailed overview of the neural network package. First the omnipresent Module is examined, followed by some examples for combining modules together. The last part explores facilities for training a neural network, and finally some caveats while training networks with shared parameters.

Module

A neural network is called a Module (or simply *module* in this documentation) in Torch. `Module` is an abstract class which defines four main methods:

- forward(input) which computes the output of the module given the `input` Tensor.
- backward(input, gradOutput) which computes the gradients of the module with respect

to its own parameters, and its own inputs.
- zeroGradParameters() which zeroes the gradient with respect to the parameters of the module.
- updateParameters(learningRate) which updates the parameters after one has computed the gradients with `backward()`

It also declares two members:

- output which is the output returned by `forward()`.
- gradInput which contains the gradients with respect to the input of the module, computed in a `backward()`.

Two other perhaps less used but handy methods are also defined:

- share(mlp,s1,s2,...,sn) which makes this module share the parameters s1,..sn of the module `mlp`. This is useful if you want to have modules that share the same weights.
- clone(...) which produces a deep copy of (i.e. not just a pointer to) this Module, including the current state of its parameters (if any).

Some important remarks:

- `output` contains only valid values after a forward(input).
- `gradInput` contains only valid values after a backward(input, gradOutput).
- backward(input, gradOutput) uses certain computations obtained during forward(input). You *must* call `forward()` before calling a `backward()`, on the *same* `input`, or your gradients are going to be incorrect!

Plug and play

Building a simple neural network can be achieved by constructing an available layer.
A linear neural network (perceptron!) is built only in one line:

```
mlp = nn.Linear(10,1) -- perceptron with 10 inputs
```

More complex neural networks are easily built using container classes Sequential and Concat. `Sequential` plugs layer in a feed-forward fully connected manner. `Concat` concatenates in one layer several modules: they take the same inputs, and their output is concatenated.

Creating a one hidden-layer multi-layer perceptron is thus just as easy as:

```
mlp = nn.Sequential()
mlp:add( nn.Linear(10, 25) ) -- 10 input, 25 hidden units
mlp:add( nn.Tanh() ) -- some hyperbolic tangent transfer function
mlp:add( nn.Linear(25, 1) ) -- 1 output
```

Of course, `Sequential` and `Concat` can contains other `Sequential` or `Concat`, allowing you to try the craziest neural networks you ever dreamt of!

Training a neural network

Once you built your neural network, you have to choose a particular Criterion to train it. A criterion is a class which describes the cost to be minimized during training.

You can then train the neural network by using the StochasticGradient class.

```
criterion = nn.MSECriterion() -- Mean Squared Error criterion
trainer = nn.StochasticGradient(mlp, criterion)
trainer:train(dataset) -- train using some examples
```

StochasticGradient expect as a `dataset` an object which implements the operator `dataset[index]` and implements the method `dataset:size()`. The `size()` methods returns the number of examples and `dataset[i]` has to return the i-th example.

An `example` has to be an object which implements the operator `example[field]`, where `field` might take the value `1` (input features) or `2` (corresponding label which will be given to the criterion). The input is usually a Tensor (except if you use special kind of gradient modules, like table layers). The label type depends on the criterion. For example, the MSECriterion expect a Tensor, but the ClassNLLCriterion except a integer number (the class).

Such a dataset is easily constructed by using Lua tables, but it could any `C` object for example, as long as required operators/methods are implemented. See an example.

`StochasticGradient` being written in `Lua`, it is extremely easy to cut-and-paste it and create a variant to it adapted to your needs (if the constraints of `StochasticGradient` do not satisfy you).

Low Level Training

If you want to program the `StochasticGradient` by hand, you essentially need to control the use of forwards and backwards through the network yourself. For example, here is the code fragment one would need to make a gradient step given an input `x`, a desired output `y`, a network `mlp` and a given criterion `criterion` and learning rate `learningRate`:

```
function gradUpdate(mlp, x, y, criterion, learningRate)
  local pred = mlp:forward(x)
  local err = criterion:forward(pred, y)
  local gradCriterion = criterion:backward(pred, y)
  mlp:zeroGradParameters()
  mlp:backward(x, gradCriterion)
  mlp:updateParameters(learningRate)
end
```

For example, if you wish to use your own criterion you can simply replace `gradCriterion` with the gradient vector of your criterion of choice.

A Note on Sharing Parameters

By using `:share(...)` and the Container Modules, one can easily create very complex architectures. In order to make sure that the network is going to train properly, one needs to pay attention to the way the sharing is applied, because it might depend on the optimization procedure.

- If you are using an optimization algorithm that iterates over the modules of your network (by calling `:updateParameters` for example), only the parameters of the network should be shared.
- If you use the flattened parameter tensor to optimize the network, obtained by calling `:getParameters`, for example for the package `optim`, then you need to share both the parameters and the gradParameters.

Here is an example for the first case:

```
-- our optimization procedure will iterate over the modules, so
only share
-- the parameters
mlp = nn.Sequential()
linear = nn.Linear(2,2)
linear_clone = linear:clone('weight','bias') -- clone sharing the
parameters
mlp:add(linear)
mlp:add(linear_clone)
function gradUpdate(mlp, x, y, criterion, learningRate)
  local pred = mlp:forward(x)
  local err = criterion:forward(pred, y)
  local gradCriterion = criterion:backward(pred, y)
  mlp:zeroGradParameters()
  mlp:backward(x, gradCriterion)
  mlp:updateParameters(learningRate)
end
```

And for the second case:

```
-- our optimization procedure will use all the parameters at once,
because
-- it requires the flattened parameters and gradParameters Tensors.
Thus,
-- we need to share both the parameters and the gradParameters
mlp = nn.Sequential()
linear = nn.Linear(2,2)
-- need to share the parameters and the gradParameters as well
linear_clone =
linear:clone('weight','bias','gradWeight','gradBias')
mlp:add(linear)
mlp:add(linear_clone)
params, gradParams = mlp:getParameters()
function gradUpdate(mlp, x, y, criterion, learningRate, params,
gradParams)
  local pred = mlp:forward(x)
  local err = criterion:forward(pred, y)
  local gradCriterion = criterion:backward(pred, y)
  mlp:zeroGradParameters()
  mlp:backward(x, gradCriterion)
  -- adds the gradients to all the parameters at once
  params:add(-learningRate, gradParams)
end
```

rnn: recurrent neural networks

This is a Recurrent Neural Network library that extends Torch's nn.
You can use it to build RNNs, LSTMs, GRUs, BRNNs, BLSTMs, and so forth and so on.
This library includes documentation for the following objects:

Modules that consider successive calls to `forward` as different time-steps in a sequence :
* AbstractRecurrent : an abstract class inherited by Recurrent and LSTM;
* Recurrent : a generalized recurrent neural network container;
* LSTM : a vanilla Long-Short Term Memory module;
* FastLSTM : a faster LSTM with optional support for batch normalization;
* GRU : Gated Recurrent Units module;
* Recursor : decorates a module to make it conform to the AbstractRecurrent interface;
* Recurrence : decorates a module that outputs `output(t)` given `{input(t), output(t-1)}` ;
* NormStabilizer : implements norm-stabilization criterion (add this module between RNNs);

Modules that `forward` entire sequences through a decorated `AbstractRecurrent` instance :
* AbstractSequencer : an abstract class inherited by Sequencer, Repeater, RecurrentAttention, etc.;
* Sequencer : applies an encapsulated module to all elements in an input sequence (Tensor or Table);
* SeqLSTM : a very fast version of `nn.Sequencer(nn.FastLSTM)` where the `input` and `output` are tensors;
* SeqLSTMP : `SeqLSTM` with a projection layer;
* SeqGRU : a very fast version of `nn.Sequencer(nn.GRU)` where the `input` and `output` are tensors;
* SeqBRNN : Bidirectional RNN based on SeqLSTM;
* BiSequencer : used for implementing Bidirectional RNNs and LSTMs;
* BiSequencerLM : used for implementing Bidirectional RNNs and LSTMs for language models;
* Repeater : repeatedly applies the same input to an AbstractRecurrent instance;
* RecurrentAttention : a generalized attention model for REINFORCE modules;

Miscellaneous modules and criterions :
* MaskZero : zeroes the `output` and `gradOutput` rows of the decorated module for commensurate `input` rows which are tensors of zeros;
* TrimZero : same behavior as `MaskZero` , but more efficient when `input` contains lots zero-masked rows;
* LookupTableMaskZero : extends `nn.LookupTable` to support zero indexes for padding. Zero indexes are forwarded as tensors of zeros;

* MaskZeroCriterion : zeros the `gradInput` and `err` rows of the decorated criterion for commensurate `input` rows which are tensors of zeros;
* SeqReverseSequence : reverses an input sequence on a specific dimension;

Criterions used for handling sequential inputs and targets :
* SequencerCriterion : sequentially applies the same criterion to a sequence of inputs and targets (Tensor or Table).
* RepeaterCriterion : repeatedly applies the same criterion with the same target on a sequence.

Examples

The following are example training scripts using this package :

- RNN/LSTM/GRU for Penn Tree Bank dataset;
- Noise Contrastive Estimate for training multi-layer SeqLSTM language models on the Google Billion Words dataset. The example uses MaskZero to train independent variable length sequences using the NCEModule and NCECriterion. This script is our fastest yet boasting speeds of 20,000 words/second (on NVIDIA Titan X) with a 2-layer LSTM having 250 hidden units, a batchsize of 128 and sequence length of a 100. Note that you will need to have Torch installed with Lua instead of LuaJIT;
- Recurrent Model for Visual Attention for the MNIST dataset;
- Encoder-Decoder LSTM shows you how to couple encoder and decoder `LSTMs` for sequence-to-sequence networks;
- Simple Recurrent Network shows a simple example for building and training a simple recurrent neural network;
- Simple Sequencer Network is a version of the above script that uses the Sequencer to decorate the `rnn` instead;
- Sequence to One demonstrates how to do many to one sequence learning as is the case for sentiment analysis;
- Multivariate Time Series demonstrates how train a simple RNN to do multi-variate time-series predication.

External Resources

- rnn-benchmarks : benchmarks comparing Torch (using this library), Theano and TensorFlow.
- Harvard Jupyter Notebook Tutorial : an in-depth tutorial for how to use the Element-Research rnn package by Harvard University;

- dpnn : this is a dependency of the **rnn** package. It contains useful nn extensions, modules and criterions;
- dataload : a collection of torch dataset loaders;
- RNN/LSTM/BRNN/BLSTM training script for Penn Tree Bank or Google Billion Words datasets;
- A brief (1 hours) overview of Torch7, which includes some details about the **rnn** packages (at the end), is available via this NVIDIA GTC Webinar video. In any case, this presentation gives a nice overview of Logistic Regression, Multi-Layer Perceptrons, Convolutional Neural Networks and Recurrent Neural Networks using Torch7;
- Sequence to Sequence mapping using encoder-decoder RNNs : a complete training example using synthetic data.
- ConvLSTM is a repository for training a Spatio-temporal video autoencoder with differentiable memory.
- An time series example for univariate timeseries prediction.

Citation

If you use **rnn** in your work, we'd really appreciate it if you could cite the following paper:

Léonard, Nicholas, Sagar Waghmare, Yang Wang, and Jin-Hwa Kim. rnn: Recurrent Library for Torch. arXiv preprint arXiv:1511.07889 (2015).

Any significant contributor to the library will also get added as an author to the paper.
A significant contributor
is anyone who added at least 300 lines of code to the library.

Troubleshooting

Most issues can be resolved by updating the various dependencies:

```
luarocks install torch
luarocks install nn
luarocks install dpnn
luarocks install torchx
```

If you are using CUDA :

```
luarocks install cutorch
luarocks install cunn
luarocks install cunnx
```

And don't forget to update this package :

```
luarocks install rnn
```

If that doesn't fix it, open and issue on github.

AbstractRecurrent

An abstract class inherited by Recurrent, LSTM and GRU.
The constructor takes a single argument :

```
rnn = nn.AbstractRecurrent([rho])
```

Argument `rho` is the maximum number of steps to backpropagate through time (BPTT).
Sub-classes can set this to a large number like 99999 (the default) if they want to backpropagate through
the entire sequence whatever its length. Setting lower values of rho are
useful when long sequences are forward propagated, but we only whish to
backpropagate through the last `rho` steps, which means that the remainder
of the sequence doesn't need to be stored (so no additional cost).

[recurrentModule] getStepModule(step)

Returns a module for time-step `step`. This is used internally by sub-classes
to obtain copies of the internal `recurrentModule`. These copies share
`parameters` and `gradParameters` but each have their own `output`, `gradInput`
and any other intermediate states.

setOutputStep(step)

This is a method reserved for internal use by Recursor
when doing backward propagation. It sets the object's `output` attribute
to point to the output at time-step `step`.
This method was introduced to solve a very annoying bug.

maskZero(nInputDim)

Decorates the internal `recurrentModule` with MaskZero.
The `output` Tensor (or table thereof) of the `recurrentModule`
will have each row (i.e. samples) zeroed when the commensurate row of the `input`
is a tensor of zeros.

The `nInputDim` argument must specify the number of non-batch dims
in the first Tensor of the `input`. In the case of an `input` table,
the first Tensor is the first one encountered when doing a depth-first search.

Calling this method makes it possible to pad sequences with different lengths in the same batch
with zero vectors.

When a sample time-step is masked (i.e. `input` is a row of zeros), then
the hidden state is effectively reset (i.e. forgotten) for the next non-mask time-step.
In other words, it is possible seperate unrelated sequences with a masked element.

trimZero(nInputDim)

Decorates the internal `recurrentModule` with TrimZero.

[output] updateOutput(input)

Forward propagates the input for the current step. The outputs or intermediate
states of the previous steps are used recurrently. This is transparent to the
caller as the previous outputs and intermediate states are memorized. This
method also increments the `step` attribute by 1.

updateGradInput(input, gradOutput)

Like `backward`, this method should be called in the reverse order of `forward` calls used to propagate a sequence. So for example :

```
rnn = nn.LSTM(10, 10) -- AbstractRecurrent instance
local outputs = {}
for i=1,nStep do -- forward propagate sequence
   outputs[i] = rnn:forward(inputs[i])
end

for i=nStep,1,-1 do -- backward propagate sequence in reverse order
   gradInputs[i] = rnn:backward(inputs[i], gradOutputs[i])
end

rnn:forget()
```

The reverse order implements backpropagation through time (BPTT).

accGradParameters(input, gradOutput, scale)

Like `updateGradInput`, but for accumulating gradients w.r.t. parameters.

recycle(offset)

This method goes hand in hand with `forget`. It is useful when the current time-step is greater than `rho`, at which point it starts recycling the oldest `recurrentModule` `sharedClones`, such that they can be reused for storing the next step. This `offset` is used for modules like `nn.Recurrent` that use a different module for the first step. Default offset is 0.

forget(offset)

This method brings back all states to the start of the sequence buffers, i.e. it forgets the current sequence. It also resets the `step` attribute to 1. It is highly recommended to call `forget` after each parameter update. Otherwise, the previous state will be used to activate the next, which will often lead to instability. This is caused by the previous state being

the result of now changed parameters. It is also good practice to call `forget` at the start of each new sequence.

maxBPTTstep(rho)

This method sets the maximum number of time-steps for which to perform backpropagation through time (BPTT). So say you set this to `rho = 3` time-steps, feed-forward for 4 steps, and then backpropgate, only the last 3 steps will be used for the backpropagation. If your AbstractRecurrent instance is wrapped by a Sequencer, this will be handled auto-magically by the Sequencer. Otherwise, setting this value to a large value (i.e. 9999999), is good for most, if not all, cases.

backwardOnline()

This method was deprecated Jan 6, 2016.
Since then, by default, `AbstractRecurrent` instances use the backwardOnline behaviour.
See updateGradInput for details.

training()

In training mode, the network remembers all previous `rho` (number of time-steps) states. This is necessary for BPTT.

evaluate()

During evaluation, since their is no need to perform BPTT at a later time, only the previous step is remembered. This is very efficient memory-wise, such that evaluation can be performed using potentially infinite-length sequence.

Recurrent

References :
* A. Sutsekever Thesis Sec. 2.5 and 2.8
* B. Mikolov Thesis Sec. 3.2 and 3.3
* C. RNN and Backpropagation Guide

A composite Module for implementing Recurrent Neural Networks (RNN), excluding the output layer.

The `nn.Recurrent(start, input, feedback, [transfer, rho, merge])` constructor takes 6 arguments:
* `start` : the size of the output (excluding the batch dimension), or a Module that will be inserted between the `input` Module and `transfer` module during the first step of the propagation. When `start` is a size (a number or `torch.LongTensor`), then this *start* Module will be initialized as `nn.Add(start)` (see Ref. A).
* `input` : a Module that processes input Tensors (or Tables). Output must be of same size as `start` (or its output in the case of a `start` Module), and same size as the output of the `feedback` Module.
* `feedback` : a Module that feedbacks the previous output Tensor (or Tables) up to the `merge` module.
* `merge` : a table Module that merges the outputs of the `input` and `feedback` Module before being forwarded through the `transfer` Module.
* `transfer` : a non-linear Module used to process the output of the `merge` module, or in the case of the first step, the output of the `start` Module.
* `rho` : the maximum amount of backpropagation steps to take back in time. Limits the number of previous steps kept in memory. Due to the vanishing gradients effect, references A and B recommend `rho = 5` (or lower). Defaults to 99999.

An RNN is used to process a sequence of inputs.
Each step in the sequence should be propagated by its own `forward` (and `backward`), one `input` (and `gradOutput`) at a time.
Each call to `forward` keeps a log of the intermediate states (the `input` and many `Module.outputs`)
and increments the `step` attribute by 1.
Method `backward` must be called in reverse order of the sequence of calls to `forward` in order to backpropgate through time (BPTT). This reverse order is necessary
to return a `gradInput` for each call to `forward`.

The `step` attribute is only reset to 1 when a call to the `forget` method is made.
In which case, the Module is ready to process the next sequence (or batch thereof).
Note that the longer the sequence, the more memory that will be required to store all the `output` and `gradInput` states (one for each time step).

To use this module with batches, we suggest using different
sequences of the same size within a batch and calling `updateParameters`

every `rho` steps and `forget` at the end of the sequence.

Note that calling the `evaluate` method turns off long-term memory;
the RNN will only remember the previous output. This allows the RNN
to handle long sequences without allocating any additional memory.

For a simple concise example of how to make use of this module, please consult the
simple-recurrent-network.lua
training script.

Decorate it with a Sequencer

Note that any `AbstractRecurrent` instance can be decorated with a Sequencer
such that an entire sequence (a table) can be presented with a single `forward/backward`
call.
This is actually the recommended approach as it allows RNNs to be stacked and makes the
rnn conform to the Module interface, i.e. each call to `forward` can be
followed by its own immediate call to `backward` as each `input` to the
model is an entire sequence, i.e. a table of tensors where each tensor represents
a time-step.

```
seq = nn.Sequencer(module)
```

The simple-sequencer-network.lua training script
is equivalent to the above mentionned simple-recurrent-network.lua
script, except that it decorates the `rnn` with a `Sequencer` which takes
a table of `inputs` and `gradOutputs` (the sequence for that batch).
This lets the `Sequencer` handle the looping over the sequence.

You should only think about using the `AbstractRecurrent` modules without
a `Sequencer` if you intend to use it for real-time prediction.
Actually, you can even use an `AbstractRecurrent` instance decorated by a `Sequencer`
for real time prediction by calling `Sequencer:remember()` and presenting each
time-step `input` as `{input}`.

Other decorators can be used such as the Repeater or RecurrentAttention.
The `Sequencer` is only the most common one.

LSTM

References :
* A. Speech Recognition with Deep Recurrent Neural Networks
* B. Long-Short Term Memory
* C. LSTM: A Search Space Odyssey
* D. nngraph LSTM implementation on github

This is an implementation of a vanilla Long-Short Term Memory module.
We used Ref. A's LSTM as a blueprint for this module as it was the most concise.
Yet it is also the vanilla LSTM described in Ref. C.

The `nn.LSTM(inputSize, outputSize, [rho])` constructor takes 3 arguments:
* `inputSize` : a number specifying the size of the input;
* `outputSize` : a number specifying the size of the output;
* `rho` : the maximum amount of backpropagation steps to take back in time. Limits the number of previous steps kept in memory. Defaults to 9999.

The actual implementation corresponds to the following algorithm:

```
i[t] = σ(W[x->i]x[t] + W[h->i]h[t-1] + W[c->i]c[t-1] + b[1->i])
(1)
f[t] = σ(W[x->f]x[t] + W[h->f]h[t-1] + W[c->f]c[t-1] + b[1->f])
(2)
z[t] = tanh(W[x->c]x[t] + W[h->c]h[t-1] + b[1->c])
(3)
c[t] = f[t]c[t-1] + i[t]z[t]
(4)
o[t] = σ(W[x->o]x[t] + W[h->o]h[t-1] + W[c->o]c[t] + b[1->o])
(5)
h[t] = o[t]tanh(c[t])
(6)
```

where `W[s->q]` is the weight matrix from `s` to `q`, `t` indexes the time-step,
`b[1->q]` are the biases leading into `q`, `σ()` is `Sigmoid`, `x[t]` is the input,
`i[t]` is the input gate (eq. 1), `f[t]` is the forget gate (eq. 2),
`z[t]` is the input to the cell (which we call the hidden) (eq. 3),
`c[t]` is the cell (eq. 4), `o[t]` is the output gate (eq. 5),
and `h[t]` is the output of this module (eq. 6). Also note that the
weight matrices from cell to gate vectors are diagonal `W[c->s]`, where `s`
is `i`, `f`, or `o`.

As you can see, unlike Recurrent, this
implementation isn't generic enough that it can take arbitrary component Module

definitions at construction. However, the LSTM module can easily be adapted through inheritance by overriding the different factory methods :
* `buildGate` : builds generic gate that is used to implement the input, forget and output gates;
* `buildInputGate` : builds the input gate (eq. 1). Currently calls `buildGate` ;
* `buildForgetGate` : builds the forget gate (eq. 2). Currently calls `buildGate` ;
* `buildHidden` : builds the hidden (eq. 3);
* `buildCell` : builds the cell (eq. 4);
* `buildOutputGate` : builds the output gate (eq. 5). Currently calls `buildGate` ;
* `buildModel` : builds the actual LSTM model which is used internally (eq. 6).

Note that we recommend decorating the `LSTM` with a `Sequencer` (refer to this for details).

FastLSTM

A faster version of the LSTM.
Basically, the input, forget and output gates, as well as the hidden state are computed at one fellswoop.

Note that `FastLSTM` does not use peephole connections between cell and gates. The algorithm from `LSTM` changes as follows:

```
i[t] = σ(W[x->i]x[t] + W[h->i]h[t-1] + b[1->i])
(1)
f[t] = σ(W[x->f]x[t] + W[h->f]h[t-1] + b[1->f])
(2)
z[t] = tanh(W[x->c]x[t] + W[h->c]h[t-1] + b[1->c])
(3)
c[t] = f[t]c[t-1] + i[t]z[t]
(4)
o[t] = σ(W[x->o]x[t] + W[h->o]h[t-1] + b[1->o])
(5)
h[t] = o[t]tanh(c[t])
(6)
```

i.e. omitting the summands `W[c->i]c[t-1]` (eq. 1), `W[c->f]c[t-1]` (eq. 2), and `W[c->o]c[t]` (eq. 5).

usenngraph

This is a static attribute of the `FastLSTM` class. The default value is `false`.
Setting `usenngraph = true` will force all new instantiated instances of `FastLSTM` to use `nngraph`'s `nn.gModule` to build the internal `recurrentModule` which is cloned for each time-step.

Recurrent Batch Normalization

This extends the `FastLSTM` class to enable faster convergence during training by zero-centering the input-to-hidden and hidden-to-hidden transformations.
It reduces the internal covariate shift between time steps. It is an implementation of Cooijmans et. al.'s Recurrent Batch Normalization. The hidden-to-hidden transition of each LSTM cell is normalized according to

```
i[t] = σ(BN(W[x->i]x[t]) + BN(W[h->i]h[t-1]) + b[1->i])
(1)
f[t] = σ(BN(W[x->f]x[t]) + BN(W[h->f]h[t-1]) + b[1->f])
(2)
z[t] = tanh(BN(W[x->c]x[t]) + BN(W[h->c]h[t-1]) + b[1->c])
(3)
c[t] = f[t]c[t-1] + i[t]z[t]
(4)
o[t] = σ(BN(W[x->o]x[t]) + BN(W[h->o]h[t-1]) + b[1->o])
(5)
h[t] = o[t]tanh(c[t])
(6)
```

where the batch normalizing transform is:

$$BN(h; gamma, beta) = beta + gamma * \frac{hd - E(hd)}{sqrt(E(\sigma(hd) + eps))}$$

where `hd` is a vector of (pre)activations to be normalized, `gamma`, and `beta` are model parameters that determine the mean and standard deviation of the normalized activation. `eps` is a regularization hyperparameter to keep the division numerically stable and `E(hd)` and `E(σ(hd))` are the estimates of the mean and variance in the mini-batch respectively. The authors recommend initializing `gamma` to a small value and found 0.1 to be the value that did not cause vanishing gradients. `beta`, the shift parameter, is `null` by default.

To turn on batch normalization during training, do:

```
nn.FastLSTM.bn = true
lstm = nn.FastLSTM(inputsize, outputsize, [rho, eps, momentum,
affine]
```

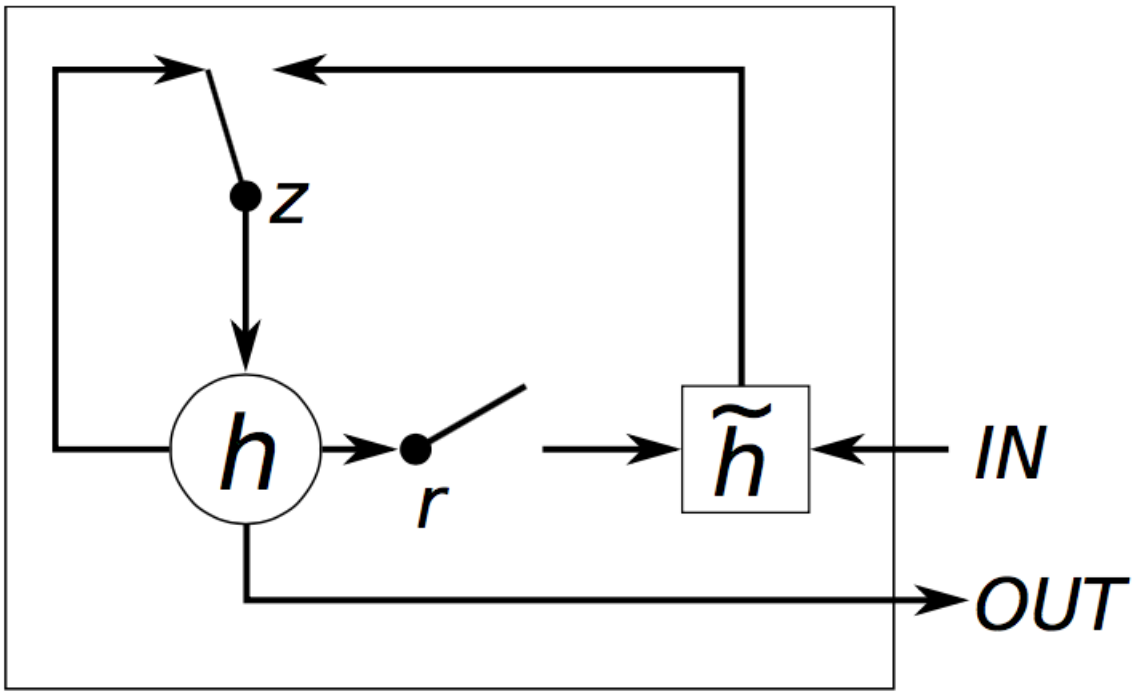
where `momentum` is same as `gamma` in the equation above (defaults to 0.1), `eps` is defined above and `affine` is a boolean whose state determines if the learnable affine transform is turned off (`false`) or on (`true` , the default).

GRU

References :
* A. Learning Phrase Representations Using RNN Encoder-Decoder For Statistical Machine Translation.
* B. Implementing a GRU/LSTM RNN with Python and Theano
* C. An Empirical Exploration of Recurrent Network Architectures
* D. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling
* E. RnnDrop: A Novel Dropout for RNNs in ASR
* F. A Theoretically Grounded Application of Dropout in Recurrent Neural Networks

This is an implementation of Gated Recurrent Units module.

The `nn.GRU(inputSize, outputSize [,rho [,p [, mono]]])` constructor takes 3 arguments likewise `nn.LSTM` or 4 arguments for dropout:
* `inputSize` : a number specifying the size of the input;
* `outputSize` : a number specifying the size of the output;
* `rho` : the maximum amount of backpropagation steps to take back in time. Limits the number of previous steps kept in memory. Defaults to 9999;
* `p` : dropout probability for inner connections of GRUs.
* `mono` : Monotonic sample for dropouts inside GRUs. Only needed in a `TrimZero` + `BGRU` (p>0) situation.



The actual implementation corresponds to the following algorithm:

```
z[t] = σ(W[x->z]x[t] + W[s->z]s[t-1] + b[1->z])            (1)
r[t] = σ(W[x->r]x[t] + W[s->r]s[t-1] + b[1->r])            (2)
h[t] = tanh(W[x->h]x[t] + W[hr->c](s[t-1]r[t]) + b[1->h])  (3)
s[t] = (1-z[t])h[t] + z[t]s[t-1]                           (4)
```

where `W[s->q]` is the weight matrix from `s` to `q`, `t` indexes the time-step, `b[1->q]` are the biases leading into `q`, `σ()` is `Sigmoid`, `x[t]` is the input and `s[t]` is the output of the module (eq. 4). Note that unlike the LSTM, the GRU has no cells.

The GRU was benchmark on `PennTreeBank` dataset using recurrent-language-model.lua script.
It slightly outperfomed `FastLSTM`, however, since LSTMs have more parameters than GRUs, the dataset larger than `PennTreeBank` might change the performance result.
Don't be too hasty to judge on which one is the better of the two (see Ref. C and D).

```
               Memory   examples/s
FastLSTM         176M        16.5K
GRU               92M        15.8K
```

Memory is measured by the size of `dp.Experiment` save file. **examples/s** is measured by the training speed at 1 epoch, so, it may have a disk IO bias.

RNN dropout (see Ref. E and F) was benchmark on `PennTreeBank` dataset using `recurrent-language-model.lua` script, too. The details can be found in the script. In the benchmark, `GRU` utilizes a dropout after `LookupTable`, while `BGRU`, stands for Bayesian GRUs, uses dropouts on inner connections (naming as Ref. F), but not after `LookupTable`.

As Yarin Gal (Ref. F) mentioned, it is recommended that one may use `p = 0.25` for the first attempt.

Recursor

This module decorates a `module` to be used within an `AbstractSequencer` instance.
It does this by making the decorated module conform to the `AbstractRecurrent` interface, which like the `LSTM` and `Recurrent` classes, this class inherits.

```
rec = nn.Recursor(module[, rho])
```

For each successive call to `updateOutput` (i.e. `forward`), this decorator will create a `stepClone()` of the decorated `module`.
So for each time-step, it clones the `module`. Both the clone and original share parameters and gradients w.r.t. parameters. However, for modules that already conform to the `AbstractRecurrent` interface, the clone and original module are one and the same (i.e. no clone).

Examples :

Let's assume I want to stack two LSTMs. I could use two sequencers :

```
lstm = nn.Sequential()
   :add(nn.Sequencer(nn.LSTM(100,100)))
   :add(nn.Sequencer(nn.LSTM(100,100)))
```

Using a `Recursor`, I make the same model with a single `Sequencer` :

```
lstm = nn.Sequencer(
   nn.Recursor(
      nn.Sequential()
         :add(nn.LSTM(100,100))
         :add(nn.LSTM(100,100))
      )
   )
```

Actually, the `Sequencer` will wrap any non-`AbstractRecurrent` module automatically, so I could simplify this further to :

```
lstm = nn.Sequencer(
   nn.Sequential()
      :add(nn.LSTM(100,100))
      :add(nn.LSTM(100,100))
   )
```

I can also add a `Linear` between the two `LSTM`s. In this case, a `Linear` will be cloned (and have its parameters shared) for each time-step, while the `LSTM`s will do whatever cloning internally :

```
lstm = nn.Sequencer(
   nn.Sequential()
      :add(nn.LSTM(100,100))
      :add(nn.Linear(100,100))
      :add(nn.LSTM(100,100))
   )
```

`AbstractRecurrent` instances like `Recursor`, `Recurrent` and `LSTM` are expcted to manage time-steps internally. Non-`AbstractRecurrent` instances can be wrapped by a `Recursor` to have the same behavior.

Every call to `forward` on an `AbstractRecurrent` instance like `Recursor` will increment the `self.step` attribute by 1, using a shared parameter clone for each successive time-step (for a maximum of `rho` time-steps, which defaults to 9999999). In this way, `backward` can be called in reverse order of the `forward` calls to perform backpropagation through time (BPTT). Which is exactly what AbstractSequencer instances do internally.
The `backward` call, which is actually divided into calls to `updateGradInput` and `accGradParameters`, decrements by 1 the `self.udpateGradInputStep` and `self.accGradParametersStep`

respectively, starting at `self.step`.
Successive calls to `backward` will decrement these counters and use them to backpropagate through the appropriate internall step-wise shared-parameter clones.

Anyway, in most cases, you will not have to deal with the `Recursor` object directly as `AbstractSequencer` instances automatically decorate non-`AbstractRecurrent` instances
with a `Recursor` in their constructors.

For a concrete example of its use, please consult the simple-recurrent-network.lua training script for an example of its use.

Recurrence

A extremely general container for implementing pretty much any type of recurrence.

```
rnn = nn.Recurrence(recurrentModule, outputSize, nInputDim, [rho])
```

Unlike Recurrent, this module doesn't manage a separate
modules like `inputModule`, `startModule`, `mergeModule` and the like.
Instead, it only manages a single `recurrentModule`, which should
output a Tensor or table: `output(t)`
given an input table: `{input(t), output(t-1)}`.
Using a mix of `Recursor` (say, via `Sequencer`) with `Recurrence`, one can implement pretty much any type of recurrent neural network, including LSTMs and RNNs.

For the first step, the `Recurrence` forwards a Tensor (or table thereof) of zeros through the recurrent layer (like LSTM, unlike Recurrent).
So it needs to know the `outputSize`, which is either a number or `torch.LongStorage`, or table thereof. The batch dimension should be excluded from the `outputSize`. Instead, the size of the batch dimension (i.e. number of samples) will be extrapolated from the `input` using the `nInputDim` argument. For example, say that our input is a Tensor of size `4 x 3` where `4` is the number of samples, then `nInputDim` should be `1`.
As another example, if our input is a table of table [...] of tensors where the first tensor (depth first) is the same as in the previous example, then our `nInputDim` is also `1`.

As an example, let's use `Sequencer` and `Recurrence` to build a Simple RNN for language modeling:

```
rho = 5
hiddenSize = 10
outputSize = 5 -- num classes
nIndex = 10000

-- recurrent module
rm = nn.Sequential()
   :add(nn.ParallelTable()
      :add(nn.LookupTable(nIndex, hiddenSize))
      :add(nn.Linear(hiddenSize, hiddenSize)))
   :add(nn.CAddTable())
   :add(nn.Sigmoid())

rnn = nn.Sequencer(
   nn.Sequential()
      :add(nn.Recurrence(rm, hiddenSize, 1))
      :add(nn.Linear(hiddenSize, outputSize))
      :add(nn.LogSoftMax())
)
```

Note : We could very well reimplement the `LSTM` module using the newer `Recursor` and `Recurrent` modules, but that would mean breaking backwards compatibility for existing models saved on disk.

NormStabilizer

Ref. A : Regularizing RNNs by Stabilizing Activations

This module implements the norm-stabilization criterion:

```
ns = nn.NormStabilizer([beta])
```

This module regularizes the hidden states of RNNs by minimizing the difference between the L2-norms of consecutive steps. The cost function is defined as :

```
loss = beta * 1/T sum_t( ||h[t]|| - ||h[t-1]|| )^2
```

where `T` is the number of time-steps. Note that we do not divide the gradient by `T`

such that the chosen `beta` can scale to different sequence sizes without being changed.

The sole argument `beta` is defined in ref. A. Since we don't divide the gradients by
the number of time-steps, the default value of `beta=1` should be valid for most cases.

This module should be added between RNNs (or LSTMs or GRUs) to provide better
regularization of the hidden states.
For example :

```
local stepmodule = nn.Sequential()
   :add(nn.FastLSTM(10,10))
   :add(nn.NormStabilizer())
   :add(nn.FastLSTM(10,10))
   :add(nn.NormStabilizer())
local rnn = nn.Sequencer(stepmodule)
```

To use it with `SeqLSTM` you can do something like this :

```
local rnn = nn.Sequential()
   :add(nn.SeqLSTM(10,10))
   :add(nn.Sequencer(nn.NormStabilizer()))
   :add(nn.SeqLSTM(10,10))
   :add(nn.Sequencer(nn.NormStabilizer()))
```

AbstractSequencer

This abstract class implements a light interface shared by
subclasses like : `Sequencer` , `Repeater` , `RecurrentAttention` , `BiSequencer` and so on.

Sequencer

The `nn.Sequencer(module)` constructor takes a single argument, `module` , which is the
module
to be applied from left to right, on each element of the input sequence.

```
seq = nn.Sequencer(module)
```

This Module is a kind of decorator
used to abstract away the intricacies of `AbstractRecurrent` modules. While an `AbstractRecurrent` instance
requires that a sequence to be presented one input at a time, each with its own call to `forward` (and `backward`),
the `Sequencer` forwards an `input` sequence (a table) into an `output` sequence (a table of the same length).
It also takes care of calling `forget` on AbstractRecurrent instances.

Input/Output Format

The `Sequencer` requires inputs and outputs to be of shape `seqlen x batchsize x featsize`:

- `seqlen` is the number of time-steps that will be fed into the `Sequencer`.
- `batchsize` is the number of examples in the batch. Each example is its own independent sequence.
- `featsize` is the size of the remaining non-batch dimensions. So this could be `1` for language models, or `c x h x w` for convolutional models, etc.

Above is an example input sequence for a character level language model.
It has `seqlen` is 5 which means that it contains sequences of 5 time-steps.
The openning `{` and closing `}` illustrate that the time-steps are elements of a Lua table, although
it also accepts full Tensors of shape `seqlen x batchsize x featsize`.
The `batchsize` is 2 as their are two independent sequences: `{ H, E, L, L, O }` and `{ F, U, Z, Z, Y, }`.
The `featsize` is 1 as their is only one feature dimension per character and each such character is of size 1.
So the input in this case is a table of `seqlen` time-steps where each time-step is represented by a `batchsize x featsize` Tensor.

Above is another example of a sequence (input or output).
It has a `seqlen` of 4 time-steps.
The `batchsize` is again 2 which means there are two sequences.

The `featsize` is 3 as each time-step of each sequence has 3 variables.
So each time-step (element of the table) is represented again as a tensor
of size `batchsize x featsize`.
Note that while in both examples the `featsize` encodes one dimension,
it could encode more.

Example

For example, `rnn` : an instance of nn.AbstractRecurrent, can forward an `input` sequence one forward at a time:

```
input = {torch.randn(3,4), torch.randn(3,4), torch.randn(3,4)}
rnn:forward(input[1])
rnn:forward(input[2])
rnn:forward(input[3])
```

Equivalently, we can use a Sequencer to forward the entire `input` sequence at once:

```
seq = nn.Sequencer(rnn)
seq:forward(input)
```

We can also forward Tensors instead of Tables :

```
-- seqlen x batchsize x featsize
input = torch.randn(3,3,4)
seq:forward(input)
```

Details

The `Sequencer` can also take non-recurrent Modules (i.e. non-AbstractRecurrent instances) and apply it to each
input to produce an output table of the same length.
This is especially useful for processing variable length sequences (tables).

Internally, the `Sequencer` expects the decorated `module` to be an `AbstractRecurrent` instance. When this is not the case, the `module` is automatically decorated with a Recursor module, which makes it

conform to the `AbstractRecurrent` interface.

Note : this is due a recent update (27 Oct 2015), as before this `AbstractRecurrent` and and non-`AbstractRecurrent` instances needed to be decorated by their own `Sequencer`. The recent update, which introduced the `Recursor` decorator, allows a single `Sequencer` to wrap any type of module, `AbstractRecurrent`, non-`AbstractRecurrent` or a composite structure of both types. Nevertheless, existing code shouldn't be affected by the change.

For a concise example of its use, please consult the simple-sequencer-network.lua training script.

remember([mode])

When `mode='neither'` (the default behavior of the class), the Sequencer will additionally call forget before each call to `forward`.
When `mode='both'` (the default when calling this function), the Sequencer will never call forget.
In which case, it is up to the user to call `forget` between independent sequences.
This behavior is only applicable to decorated AbstractRecurrent `modules`.
Accepted values for argument `mode` are as follows :

- 'eval' only affects evaluation (recommended for RNNs)
- 'train' only affects training
- 'neither' affects neither training nor evaluation (default behavior of the class)
- 'both' affects both training and evaluation (recommended for LSTMs)

forget()

Calls the decorated AbstractRecurrent module's `forget` method.

SeqLSTM

This module is a faster version of `nn.Sequencer(nn.FastLSTM(inputsize, outputsize))` :

```
seqlstm = nn.SeqLSTM(inputsize, outputsize)
```

Each time-step is computed as follows (same as FastLSTM):

```
i[t] = σ(W[x->i]x[t] + W[h->i]h[t-1] + b[1->i])
(1)
f[t] = σ(W[x->f]x[t] + W[h->f]h[t-1] + b[1->f])
(2)
z[t] = tanh(W[x->c]x[t] + W[h->c]h[t-1] + b[1->c])
(3)
c[t] = f[t]c[t-1] + i[t]z[t]
(4)
o[t] = σ(W[x->o]x[t] + W[h->o]h[t-1] + b[1->o])
(5)
h[t] = o[t]tanh(c[t])
(6)
```

A notable difference is that this module expects the `input` and `gradOutput` to be tensors instead of tables. The default shape is `seqlen x batchsize x inputsize` for the `input` and `seqlen x batchsize x outputsize` for the `output` :

```
input = torch.randn(seqlen, batchsize, inputsize)
gradOutput = torch.randn(seqlen, batchsize, outputsize)

output = seqlstm:forward(input)
gradInput = seqlstm:backward(input, gradOutput)
```

Note that if you prefer to transpose the first two dimension (i.e. `batchsize x seqlen` instead of the default `seqlen x batchsize`)
you can set `seqlstm.batchfirst = true` following initialization.

For variable length sequences, set `seqlstm.maskzero = true` .
This is equivalent to calling `maskZero(1)` on a `FastLSTM` wrapped by a `Sequencer` :

```
fastlstm = nn.FastLSTM(inputsize, outputsize)
fastlstm:maskZero(1)
seqfastlstm = nn.Sequencer(fastlstm)
```

For `maskzero = true` , input sequences are expected to be seperated by tensor of zeros for a time step.

The `seqlstm:toFastLSTM()` method generates a FastLSTM instance initialized with the parameters
of the `seqlstm` instance. Note however that the resulting parameters will not be shared (nor can they ever be).

Like the `FastLSTM`, the `SeqLSTM` does not use peephole connections between cell and gates (see FastLSTM for details).

Like the `Sequencer`, the `SeqLSTM` provides a remember method.

Note that a `SeqLSTM` cannot replace `FastLSTM` in code that decorates it with a `AbstractSequencer` or `Recursor` as this would be equivalent to `Sequencer(Sequencer(FastLSTM))`.
You have been warned.

SeqLSTMP

References:
* A. LSTM RNN Architectures for Large Scale Acoustic Modeling
* B. Exploring the Limits of Language Modeling

```
lstmp = nn.SeqLSTMP(inputsize, hiddensize, outputsize)
```

The `SeqLSTMP` is a subclass of SeqLSTM.
It differs in that after computing the hidden state `h[t]` (eq. 6), it is
projected onto `r[t]` using a simple linear transform (eq. 7).
The computation of the gates also uses the previous such projection `r[t-1]` (eq. 1, 2, 3, 5).
This differs from `SeqLSTM` which uses `h[t-1]` instead of `r[t-1]`.

The computation of a time-step outlined in `SeqLSTM` is replaced with the following:

```
i[t] = σ(W[x->i]x[t] + W[r->i]r[t-1] + b[1->i])
(1)
f[t] = σ(W[x->f]x[t] + W[r->f]r[t-1] + b[1->f])
(2)
z[t] = tanh(W[x->c]x[t] + W[h->c]r[t-1] + b[1->c])
(3)
c[t] = f[t]c[t-1] + i[t]z[t]
(4)
o[t] = σ(W[x->o]x[t] + W[r->o]r[t-1] + b[1->o])
```

```
(5)
h[t] = o[t]tanh(c[t])
(6)
r[t] = W[h->r]h[t]
(7)
```

The algorithm is outlined in ref. A and benchmarked with state of the art results on the Google billion words dataset in ref. B.
`SeqLSTMP` can be used with an `hiddensize >> outputsize` such that the effective size of the memory cells `c[t]`
and gates `i[t]`, `f[t]` and `o[t]` can be much larger than the actual input `x[t]` and output `r[t]`.
For fixed `inputsize` and `outputsize`, the `SeqLSTMP` will be able to remember much more information than the `SeqLSTM`.

SeqGRU

This module is a faster version of `nn.Sequencer(nn.GRU(inputsize, outputsize))`:

```
seqGRU = nn.SeqGRU(inputsize, outputsize)
```

Usage of SeqGRU differs from GRU in the same manner as SeqLSTM differs from LSTM. Therefore see SeqLSTM for more details.

SeqBRNN

```
brnn = nn.SeqBRNN(inputSize, outputSize, [batchFirst], [merge])
```

A bi-directional RNN that uses SeqLSTM. Internally contains a 'fwd' and 'bwd' module of SeqLSTM. Expects an input shape of `seqlen x batchsize x inputsize`.
By setting [batchFirst] to true, the input shape can be `batchsize x seqLen x inputsize`.
Merge module defaults to CAddTable(), summing the outputs from each
output layer.

Example:

```
input = torch.rand(1, 1, 5)
brnn = nn.SeqBRNN(5, 5)
print(brnn:forward(input))
```

Prints an output of a 1x1x5 tensor.

BiSequencer

Applies encapsulated `fwd` and `bwd` rnns to an input sequence in forward and reverse order.
It is used for implementing Bidirectional RNNs and LSTMs.

```
brnn = nn.BiSequencer(fwd, [bwd, merge])
```

The input to the module is a sequence (a table) of tensors
and the output is a sequence (a table) of tensors of the same length.
Applies a `fwd` rnn (an AbstractRecurrent instance) to each element in the sequence in forward order and applies the `bwd` rnn in reverse order (from last element to first element).
The `bwd` rnn defaults to:

```
bwd = fwd:clone()
bwd:reset()
```

For each step (in the original sequence), the outputs of both rnns are merged together using the `merge` module (defaults to `nn.JoinTable(1,1)`).
If `merge` is a number, it specifies the JoinTable
constructor's `nInputDim` argument. Such that the `merge` module is then initialized as :

```
merge = nn.JoinTable(1,merge)
```

Internally, the `BiSequencer` is implemented by decorating a structure of modules that makes use of 3 Sequencers for the forward, backward and merge modules.

Similarly to a Sequencer, the sequences in a batch must have the same size.
But the sequence length of each batch can vary.

Note : make sure you call `brnn:forget()` after each call to `updateParameters()`.

Alternatively, one could call `brnn.bwdSeq:forget()` so that only `bwd` rnn forgets.
This is the minimum requirement, as it would not make sense for the `bwd` rnn to remember future sequences.

BiSequencerLM

Applies encapsulated `fwd` and `bwd` rnns to an input sequence in forward and reverse order.
It is used for implementing Bidirectional RNNs and LSTMs for Language Models (LM).

```
brnn = nn.BiSequencerLM(fwd, [bwd, merge])
```

The input to the module is a sequence (a table) of tensors
and the output is a sequence (a table) of tensors of the same length.
Applies a `fwd` rnn (an AbstractRecurrent instance to the
first `N-1` elements in the sequence in forward order.
Applies the `bwd` rnn in reverse order to the last `N-1` elements (from second-to-last element to first element).
This is the main difference of this module with the BiSequencer.
The latter cannot be used for language modeling because the `bwd` rnn would be trained to predict the input it had just be fed as input.

The `bwd` rnn defaults to:

```
bwd = fwd:clone()
bwd:reset()
```

While the `fwd` rnn will output representations for the last `N-1` steps,
the `bwd` rnn will output representations for the first `N-1` steps.
The missing outputs for each rnn (the first step for the `fwd` , the last step for the `bwd`)
will be filled with zero Tensors of the same size the commensure rnn's outputs.
This way they can be merged. If `nn.JoinTable` is used (the default), then the first
and last output elements will be padded with zeros for the missing `fwd` and `bwd` rnn outputs, respectively.

For each step (in the original sequence), the outputs of both rnns are merged together using
the `merge` module (defaults to `nn.JoinTable(1,1)`).
If `merge` is a number, it specifies the JoinTable

constructor's `nInputDim` argument. Such that the `merge` module is then initialized as :

```
merge = nn.JoinTable(1,merge)
```

Similarly to a Sequencer, the sequences in a batch must have the same size.
But the sequence length of each batch can vary.

Note that LMs implemented with this module will not be classical LMs as they won't measure the
probability of a word given the previous words. Instead, they measure the probabiliy of a word given the surrounding words, i.e. context. While for mathematical reasons you may not be able to use this to measure the
probability of a sequence of words (like a sentence),
you can still measure the pseudo-likeliness of such a sequence (see this for a discussion).

Repeater

This Module is a decorator similar to Sequencer.
It differs in that the sequence length is fixed before hand and the input is repeatedly forwarded through the wrapped `module` to produce an output table of length `nStep` :

```
r = nn.Repeater(module, nStep)
```

Argument `module` should be an `AbstractRecurrent` instance.
This is useful for implementing models like RCNNs,
which are repeatedly presented with the same input.

RecurrentAttention

References :

- A. Recurrent Models of Visual Attention
- B. Simple Statistical Gradient-Following Algorithms for Connectionist Reinforcement Learning

This module can be used to implement the Recurrent Attention Model (RAM) presented in Ref. A :

```
ram = nn.RecurrentAttention(rnn, action, nStep, hiddenSize)
```

`rnn` is an AbstractRecurrent instance.
Its input is `{x, z}` where `x` is the input to the `ram` and `z` is an action sampled from the `action` module.
The output size of the `rnn` must be equal to `hiddenSize`.

`action` is a Module
that uses a REINFORCE module (ref. B) like
ReinforceNormal,
ReinforceCategorical, or
ReinforceBernoulli
to sample actions given the previous time-step's output of the `rnn`.
During the first time-step, the `action` module is fed with a Tensor of zeros of size `input:size(1) x hiddenSize`.
It is important to understand that the sampled actions do not receive gradients backpropagated from the training criterion.
Instead, a reward is broadcast from a Reward Criterion like VRClassReward Criterion to the `action`'s REINFORCE module, which will backprogate graidents computed from the `output` samples
and the `reward`.
Therefore, the `action` module's outputs are only used internally, within the RecurrentAttention module.

`nStep` is the number of actions to sample, i.e. the number of elements in the `output` table.

`hiddenSize` is the output size of the `rnn`. This variable is necessary to generate the zero Tensor to sample an action for the first step (see above).

A complete implementation of Ref. A is available here.

MaskZero

This module zeroes the `output` rows of the decorated module for commensurate `input` rows which are tensors of zeros.

```
mz = nn.MaskZero(module, nInputDim)
```

The `output` Tensor (or table thereof) of the decorated `module`
will have each row (samples) zeroed when the commensurate row of the `input`
is a tensor of zeros.

The `nInputDim` argument must specify the number of non-batch dims
in the first Tensor of the `input`. In the case of an `input` table,
the first Tensor is the first one encountered when doing a depth-first search.

This decorator makes it possible to pad sequences with different lengths in the same batch with zero vectors.

Caveat: `MaskZero` not guarantee that the `output` and `gradInput` tensors of the internal modules
of the decorated `module` will be zeroed as well when the `input` is zero as well.
`MaskZero` only affects the immediate `gradInput` and `output` of the module that it encapsulates.
However, for most modules, the gradient update for that time-step will be zero because backpropagating a gradient of zeros will typically yield zeros all the way to the input.
In this respect, modules to avoid in encapsulating inside a `MaskZero` are `AbsractRecurrent`
instances as the flow of gradients between different time-steps internally.
Instead, call the AbstractRecurrent.maskZero method
to encapsulate the internal `recurrentModule`.

TrimZero

WARNING : only use this module if your input contains lots of zeros.
In almost all cases, `MaskZero` will be faster, especially with CUDA.

Ref. A : TrimZero: A Torch Recurrent Module for Efficient Natural Language Processing

The usage is the same with `MaskZero`.

```
mz = nn.TrimZero(module, nInputDim)
```

The only difference from `MaskZero` is that it reduces computational costs by varying a batch size, if any, for the case that varying lengths are provided in the input.

Notice that when the lengths are consistent, `MaskZero` will be faster, because `TrimZero` has an operational cost.

In short, the result is the same with `MaskZero`'s, however, `TrimZero` is faster than `MaskZero` only when sentence lengths is costly vary.

In practice, e.g. language model, `TrimZero` is expected to be faster than `MaskZero` about 30%. (You can test with it using `test/test_trimzero.lua`.)

LookupTableMaskZero

This module extends `nn.LookupTable` to support zero indexes. Zero indexes are forwarded as zero tensors.

```
lt = nn.LookupTableMaskZero(nIndex, nOutput)
```

The `output` Tensor will have each row zeroed when the commensurate row of the `input` is a zero index.

This lookup table makes it possible to pad sequences with different lengths in the same batch with zero vectors.

MaskZeroCriterion

This criterion zeroes the `err` and `gradInput` rows of the decorated criterion
for commensurate `input` rows which are tensors of zeros.

```
mzc = nn.MaskZeroCriterion(criterion, nInputDim)
```

The `gradInput` Tensor (or table thereof) of the decorated `criterion`
will have each row (samples) zeroed when the commensurate row of the `input`
is a tensor of zeros. The `err` will also disregard such zero rows.

The `nInputDim` argument must specify the number of non-batch dims
in the first Tensor of the `input`. In the case of an `input` table,
the first Tensor is the first one encountered when doing a depth-first search.

This decorator makes it possible to pad sequences with different lengths in the same batch with zero vectors.

SeqReverseSequence

```
reverseSeq = nn.SeqReverseSequence(dim)
```

Reverses an input tensor on a specified dimension. The reversal dimension can be no larger than three.

Example:

```
input = torch.Tensor({{1,2,3,4,5}, {6,7,8,9,10}})
reverseSeq = nn.SeqReverseSequence(1)
print(reverseSeq:forward(input))

Gives us an output of torch.Tensor({{6,7,8,9,10},{1,2,3,4,5}})
```

SequencerCriterion

This Criterion is a decorator:

```
c = nn.SequencerCriterion(criterion, [sizeAverage])
```

Both the `input` and `target` are expected to be a sequence, either as a table or Tensor.
For each step in the sequence, the corresponding elements of the input and target
will be applied to the `criterion`.
The output of `forward` is the sum of all individual losses in the sequence.
This is useful when used in conjunction with a Sequencer.

If `sizeAverage` is `true` (default is `false`), the `output` loss and `gradInput` is averaged over each time-step.

RepeaterCriterion

This Criterion is a decorator:

```
c = nn.RepeaterCriterion(criterion)
```

The `input` is expected to be a sequence (table or Tensor). A single `target` is repeatedly applied using the same `criterion` to each element in the `input` sequence. The output of `forward` is the sum of all individual losses in the sequence.
This is useful for implementing models like RCNNs,
which are repeatedly presented with the same target.

Simple layers

Simple Modules are used for various tasks like adapting Tensor methods and providing affine transformations :

- Parameterized Modules :
  - Linear : a linear transformation ;
  - SparseLinear : a linear transformation with sparse inputs ;
  - Bilinear : a bilinear transformation with sparse inputs ;
  - PartialLinear : a linear transformation with sparse inputs with the option of only computing a subset ;
  - Add : adds a bias term to the incoming data ;
  - CAdd : a component-wise addition to the incoming data ;
  - Mul : multiply a single scalar factor to the incoming data ;
  - CMul : a component-wise multiplication to the incoming data ;
  - Euclidean : the euclidean distance of the input to `k` mean centers ;
  - WeightedEuclidean : similar to Euclidean, but additionally learns a diagonal covariance matrix ;
  - Cosine : the cosine similarity of the input to `k` mean centers ;

- Modules that adapt basic Tensor methods :
  - Copy : a copy of the input with type casting ;
  - Narrow : a narrow operation over a given dimension ;
  - Replicate : repeats input `n` times along its first dimension ;
  - Reshape : a reshape of the inputs ;
  - View : a view of the inputs ;
  - Contiguous : contiguous of the inputs ;
  - Select : a select over a given dimension ;
  - MaskedSelect : a masked select module performs the torch.maskedSelect operation ;
  - Index : a index over a given dimension ;
  - Squeeze : squeezes the input;
  - Unsqueeze : unsqueeze the input, i.e., insert singleton dimension;
  - Transpose : transposes the input ;

- Modules that adapt mathematical Tensor methods :
  - AddConstant : adding a constant ;
  - MulConstant : multiplying a constant ;
  - Max : a max operation over a given dimension ;
  - Min : a min operation over a given dimension ;
  - Mean : a mean operation over a given dimension ;

    - Sum : a sum operation over a given dimension ;
    - Exp : an element-wise exp operation ;
    - Log : an element-wise log operation ;
    - Abs : an element-wise abs operation ;
    - Power : an element-wise pow operation ;
    - Square : an element-wise square operation ;
    - Sqrt : an element-wise sqrt operation ;
    - Clamp : an element-wise clamp operation ;
    - Normalize : normalizes the input to have unit `L_p` norm ;
    - MM : matrix-matrix multiplication (also supports batches of matrices) ;

- Miscellaneous Modules :
    - BatchNormalization : mean/std normalization over the mini-batch inputs (with an optional affine transform) ;
    - PixelShuffle : Rearranges elements in a tensor of shape `[C*r, H, W]` to a tensor of shape `[C, H*r, W*r]` ;
    - Identity : forward input as-is to output (useful with ParallelTable) ;
    - Dropout : masks parts of the `input` using binary samples from a bernoulli distribution ;
    - SpatialDropout : same as Dropout but for spatial inputs where adjacent pixels are strongly correlated ;
    - VolumetricDropout : same as Dropout but for volumetric inputs where adjacent voxels are strongly correlated ;
    - Padding : adds padding to a dimension ;
    - L1Penalty : adds an L1 penalty to an input (for sparsity) ;
    - GradientReversal : reverses the gradient (to maximize an objective function) ;
    - GPU : decorates a module so that it can be executed on a specific GPU device.
    - TemporalDynamicKMaxPooling : selects the k highest values in a sequence. k can be calculated based on sequence length ;

Linear

```
module = nn.Linear(inputDimension, outputDimension, [bias = true])
```

Applies a linear transformation to the incoming data, i.e. `y = Ax + b`. The `input` tensor given in `forward(input)` must be either a vector (1D tensor) or matrix (2D tensor). If the input is a matrix, then each row is assumed to be an input sample of given batch. The layer can be used without bias by setting `bias = false`.

You can create a layer in the following way:

```
module = nn.Linear(10, 5)  -- 10 inputs, 5 outputs
```

Usually this would be added to a network of some kind, e.g.:

```
mlp = nn.Sequential()
mlp:add(module)
```

The weights and biases (*A* and *b*) can be viewed with:

```
print(module.weight)
print(module.bias)
```

The gradients for these weights can be seen with:

```
print(module.gradWeight)
print(module.gradBias)
```

As usual with `nn` modules, applying the linear transformation is performed with:

```
x = torch.Tensor(10) -- 10 inputs
y = module:forward(x)
```

SparseLinear

```
module = nn.SparseLinear(inputDimension, outputDimension)
```

Applies a linear transformation to the incoming sparse data, i.e. `y = Ax + b`. The `input` tensor given in `forward(input)` must be a sparse vector represented as 2D tensor of the form torch.Tensor(N, 2) where the pairs represent indices and values.
The SparseLinear layer is useful when the number of input dimensions is very large and the input data is sparse.

You can create a sparse linear layer in the following way:

```
module = nn.SparseLinear(10000, 2)  -- 10000 inputs, 2 outputs
```

The sparse linear module may be used as part of a larger network, and apart from the form of the input, SparseLinear operates in exactly the same way as the Linear layer.

A sparse input vector may be created as so…

```
x = torch.Tensor({ {1, 0.1}, {2, 0.3}, {10, 0.3}, {31, 0.2} })

 print(x)

  1.0000   0.1000
  2.0000   0.3000
 10.0000   0.3000
 31.0000   0.2000
[torch.Tensor of dimension 4x2]
```

The first column contains indices, the second column contains values in a a vector where all other elements are zeros. The indices should not exceed the stated dimensions of the input to the layer (10000 in the example).

Bilinear

```
module = nn.Bilinear(inputDimension1, inputDimension2,
outputDimension, [bias = true])
```

Applies a bilinear transformation to the incoming data, i.e. `\forall k: y_k = x_1 A_k x_2 + b`. The `input` tensor given in `forward(input)` is a table containing both inputs `x_1` and `x_2`, which are tensors of size `N x inputDimension1` and `N x inputDimension2`, respectively. The layer can be trained without biases by setting `bias = false`.

You can create a layer in the following way:

```
 module = nn.Bilinear(10, 5, 3)  -- 10 and 5 inputs, 3 outputs
```

Input data for this layer would look as follows:

```
 input = {torch.randn(128, 10), torch.randn(128, 5)}  -- 128 input
examples
 module:forward(input)
```

PartialLinear

```
module = nn.PartialLinear(inputSize, outputSize, [bias = true])
```

PartialLinear is a Linear layer that allows the user to a set a collection of column indices. When the column indices are set, the layer will behave like a Linear layer that only has those columns. Meanwhile, all parameters are preserved, so resetting the PartialLinear layer will result in a module that behaves just like a regular Linear layer.

This module is useful, for instance, when you want to do forward-backward on only a subset of a Linear layer during training but use the full Linear layer at test time.

You can create a layer in the following way:

```
 module = nn.PartialLinear(5, 3)  -- 5 inputs, 3 outputs
```

Input data for this layer would look as follows:

```
 input = torch.randn(128, 5)  -- 128 input examples
 module:forward(input)
```

One can set the partition of indices to compute using the function `setPartition(indices)` where `indices` is a tensor containing the indices to compute.

```
module = nn.PartialLinear(5, 3)  -- 5 inputs, 3 outputs
module:setPartition(torch.Tensor({2,4})) -- only compute the 2nd
and 4th indices out of a total of 5 indices
```

One can reset the partition via the `resetPartition()` function that resets the partition to compute all indices, making it's behaviour equivalent to `nn.Linear`

Dropout

```
module = nn.Dropout(p)
```

During training, `Dropout` masks parts of the `input` using binary samples from a bernoulli distribution.
Each `input` element has a probability of `p` of being dropped, i.e having its commensurate output element be zero. This has proven an effective technique for regularization and preventing the co-adaptation of neurons (see Hinton et al. 2012).

Furthermore, the outputs are scaled by a factor of `1/(1-p)` during training. This allows the `input` to be simply forwarded as-is during evaluation.

In this example, we demonstrate how the call to forward samples different `outputs` to dropout (the zeros) given the same `input`:

```
module = nn.Dropout()

> x = torch.Tensor{{1, 2, 3, 4}, {5, 6, 7, 8}}

> module:forward(x)
  2   0   0   8
 10   0  14   0
[torch.DoubleTensor of dimension 2x4]

> module:forward(x)
  0   0   6   0
 10   0   0   0
[torch.DoubleTensor of dimension 2x4]
```

Backward drops out the gradients at the same location:

```
> module:forward(x)
  0   4   0   0
```

```
 10  12   0  16
[torch.DoubleTensor of dimension 2x4]

> module:backward(x, x:clone():fill(1))
 0  2  0  0
 2  2  0  2
[torch.DoubleTensor of dimension 2x4]
```

In both cases the `gradOutput` and `input` are scaled by `1/(1-p)`, which in this case is `2`.

During evaluation, `Dropout` does nothing more than forward the input such that all elements of the input are considered.

```
> module:evaluate()

> module:forward(x)
 1  2  3  4
 5  6  7  8
[torch.DoubleTensor of dimension 2x4]
```

There is also an option for stochastic evaluation which drops the `outputs` just like how it is done during training:

```
module_stochastic_evaluation = nn.Dropout(nil, nil, nil, true)

> module_stochastic_evaluation:evaluate()

> module_stochastic_evaluation:forward(x)
  2   4   6   0
  0  12  14   0
[torch.DoubleTensor of dimension 2x4]
```

We can return to training our model by first calling Module:training():

```
> module:training()

> return module:forward(x)
  2   4   6   0
  0   0   0  16
[torch.DoubleTensor of dimension 2x4]
```

When used, `Dropout` should normally be applied to the input of parameterized Modules like Linear or SpatialConvolution. A `p` of `0.5` (the default) is usually okay for hidden layers. `Dropout` can sometimes be used successfully on the dataset inputs with a `p` around `0.2`. It sometimes works best following Transfer Modules like ReLU. All this depends a great deal on the dataset so its up to the user to try different combinations.

SpatialDropout

`module` = `nn.SpatialDropout(p)`

This version performs the same function as `nn.Dropout`, however it assumes the 2 right-most dimensions of the input are spatial, performs one Bernoulli trial per output feature when training, and extends this dropout value across the entire feature map.

As described in the paper "Efficient Object Localization Using Convolutional Networks" (http://arxiv.org/abs/1411.4280), if adjacent pixels within feature maps are strongly correlated (as is normally the case in early convolution layers) then iid dropout will not regularize the activations and will otherwise just result in an effective learning rate decrease. In this case, `nn.SpatialDropout` will help promote independence between feature maps and should be used instead.

`nn.SpatialDropout` accepts 3D or 4D inputs. If the input is 3D than a layout of (features x height x width) is assumed and for 4D (batch x features x height x width) is assumed.

VolumetricDropout

`module` = `nn.VolumetricDropout(p)`

This version performs the same function as `nn.Dropout`, however it assumes the 3 right-most dimensions of the input are spatial, performs one Bernoulli trial per output feature when training, and extends this dropout value across the entire feature map.

As described in the paper "Efficient Object Localization Using Convolutional Networks" (http://arxiv.org/abs/1411.4280), if adjacent voxels within feature maps are strongly correlated (as is normally the case in early convolution layers) then iid dropout will not regularize the activations and will otherwise just result in an effective learning rate decrease. In this case, `nn.VolumetricDropout` will help promote independence between feature maps and should be used instead.

`nn.VolumetricDropout` accepts 4D or 5D inputs. If the input is 4D than a layout of (features x time x height x width) is assumed and for 5D (batch x features x time x height x width) is assumed.

Abs

```
module = Abs()
```

```
m = nn.Abs()
ii = torch.linspace(-5, 5)
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

Add

```
module = nn.Add(inputDimension, scalar)
```

Applies a bias term to the incoming data, i.e. `yi = x_i + b_i`, or if `scalar = true` then uses a single bias term, `yi = x_i + b`. So if `scalar = true` then `inputDimension` value will be disregarded.

Example:

```
y = torch.Tensor(5)
mlp = nn.Sequential()
mlp:add(nn.Add(5))

function gradUpdate(mlp, x, y, criterion, learningRate)
```

```
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
   return err
end

for i = 1, 10000 do
   x = torch.rand(5)
   y:copy(x);
   for i = 1, 5 do y[i] = y[i] + i; end
   err = gradUpdate(mlp, x, y, nn.MSECriterion(), 0.01)
end

print(mlp:get(1).bias)
```

gives the output:

```
 1.0000
 2.0000
 3.0000
 4.0000
 5.0000
[torch.Tensor of dimension 5]
```

i.e. the network successfully learns the input `x` has been shifted to produce the output `y`.

CAdd

```
module = nn.CAdd(size)
```

Applies a component-wise addition to the incoming data, i.e. `y_i = x_i + b_i`. Argument `size` can be one or many numbers (sizes) or a `torch.LongStorage`. For example, `nn.CAdd(3,4,5)` is equivalent to `nn.CAdd(torch.LongStorage{3,4,5})`. If the size for a particular dimension is 1, the addition will be expanded along the entire axis.

Example:

```
mlp = nn.Sequential()
mlp:add(nn.CAdd(5, 1))

y = torch.Tensor(5, 4)
bf = torch.Tensor(5, 4)
for i = 1, 5 do bf[i] = i; end -- scale input with this

function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
   return err
end

for i = 1, 10000 do
   x = torch.rand(5, 4)
   y:copy(x)
   y:add(bf)
   err = gradUpdate(mlp, x, y, nn.MSECriterion(), 0.01)
end

print(mlp:get(1).bias)
```

gives the output:

```
 1.0000
 2.0000
 3.0000
 4.0000
 5.0000
[torch.Tensor of dimension 5x1]
```

i.e. the network successfully learns the input `x` has been shifted by those bias factors to produce the output `y`.

Mul

```
module = nn.Mul()
```

Applies a *single* scaling factor to the incoming data, i.e. `y = w x`, where `w` is a scalar.

Example:

```
y = torch.Tensor(5)
mlp = nn.Sequential()
mlp:add(nn.Mul())

function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
   return err
end

for i = 1, 10000 do
   x = torch.rand(5)
   y:copy(x)
   y:mul(math.pi)
   err = gradUpdate(mlp, x, y, nn.MSECriterion(), 0.01)
end

print(mlp:get(1).weight)
```

gives the output:

```
 3.1416
[torch.Tensor of dimension 1]
```

i.e. the network successfully learns the input `x` has been scaled by pi.

CMul

```
```

```
module = nn.CMul(size)
```

Applies a component-wise multiplication to the incoming data, i.e. `y_i = w_i * x_i`.
Argument `size` can be one or many numbers (sizes) or a `torch.LongStorage`. For example, `nn.CMul(3,4,5)` is equivalent to `nn.CMul(torch.LongStorage{3,4,5})`.
If the size for a particular dimension is 1, the multiplication will be expanded along the entire axis.

Example:

```
mlp = nn.Sequential()
mlp:add(nn.CMul(5, 1))

y = torch.Tensor(5, 4)
sc = torch.Tensor(5, 4)
for i = 1, 5 do sc[i] = i; end -- scale input with this

function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
   return err
end

for i = 1, 10000 do
   x = torch.rand(5, 4)
   y:copy(x)
   y:cmul(sc)
   err = gradUpdate(mlp, x, y, nn.MSECriterion(), 0.01)
end

print(mlp:get(1).weight)
```

gives the output:

```
 1.0000
 2.0000
 3.0000
 4.0000
```

```
 5.0000
[torch.Tensor of dimension 5x1]
```

i.e. the network successfully learns the input `x` has been scaled by those scaling factors to produce the output `y`.

Max

```
module = nn.Max(dimension, nInputDim)
```

Applies a max operation over dimension `dimension`.
Hence, if an `nxpxq` Tensor was given as input, and `dimension` = `2` then an `nxq` matrix would be output.
When `nInputDim` is provided, inputs larger than that value will be considered batches where the actual `dimension` to apply the max operation will be dimension `dimension + 1`.

Min

```
module = nn.Min(dimension, nInputDim)
```

Applies a min operation over dimension `dimension`.
Hence, if an `nxpxq` Tensor was given as input, and `dimension` = `2` then an `nxq` matrix would be output.
When `nInputDim` is provided, inputs larger than that value will be considered batches where the actual `dimension` to apply the min operation will be dimension `dimension + 1`.

Mean

```
module = nn.Mean(dimension, nInputDim)
```

Applies a mean operation over dimension `dimension`.
Hence, if an `nxpxq` Tensor was given as input, and `dimension` = `2` then an `nxq` matrix would be output.
When `nInputDim` is provided, inputs larger than that value will be considered batches where the actual `dimension` to apply the sum operation will be dimension `dimension + 1`.
This module is based on nn.Sum.

Sum

```
module = nn.Sum(dimension, nInputDim, sizeAverage)
```

Applies a sum operation over dimension `dimension`.
Hence, if an `nxpxq` Tensor was given as input, and `dimension` = `2` then an `nxq` matrix would be output.
When `nInputDim` is provided, inputs larger than that value will be considered batches where the actual `dimension` to apply the sum operation will be dimension `dimension + 1`.
Negative indexing is allowed by providing a negative value to `nInputDim`.
When `sizeAverage` is provided, the sum is divided by the size of the input in this `dimension`. This is equivalent to the mean operation performed by the nn.Mean module.

Euclidean

```
module = nn.Euclidean(inputSize,outputSize)
```

Outputs the Euclidean distance of the input to `outputSize` centers, i.e. this layer has the weights `w_j`, for `j` = `1`,.., `outputSize`, where `w_j` are vectors of dimension `inputSize`.

The distance `y_j` between center `j` and input `x` is formulated as `y_j = || w_j - x ||`.

WeightedEuclidean

```
module = nn.WeightedEuclidean(inputSize,outputSize)
```

This module is similar to Euclidean, but additionally learns a separate diagonal covariance matrix across the features of the input space *for each center*.

In other words, for each of the `outputSize` centers `w_j`, there is a diagonal covariance matrices `c_j`, for `j` = `1`,.., `outputSize`, where `c_j` are stored as vectors of size `inputSize`.

The distance `y_j` between center `j` and input `x` is formulated as `y_j = || c_j * (w_j - x) ||`.

Cosine

```
module = nn.Cosine(inputSize,outputSize)
```

Outputs the cosine similarity of the input to `outputSize` centers, i.e. this layer has the weights `w_j`, for `j` = `1`,.., `outputSize`, where `w_j` are vectors of dimension `inputSize`.

The distance `y_j` between center `j` and input `x` is formulated as `y_j = (x · w_j) / ( || w_j || * || x || )`.

Identity

```
module = nn.Identity()
```

Creates a module that returns whatever is input to it as output.
This is useful when combined with the module ParallelTable in case you do not wish to do anything to one of the input Tensors.

Example:

```
mlp = nn.Identity()
print(mlp:forward(torch.ones(5, 2)))
```

gives the output:

```
 1  1
 1  1
 1  1
 1  1
 1  1
[torch.Tensor of dimension 5x2]
```

Here is a more useful example, where one can implement a network which also computes a `Criterion` using this module:

```
pred_mlp = nn.Sequential()  -- A network that makes predictions
given x.
pred_mlp:add(nn.Linear(5, 4))
pred_mlp:add(nn.Linear(4, 3))

xy_mlp = nn.ParallelTable() -- A network for predictions and for
keeping the
xy_mlp:add(pred_mlp)        -- true label for comparison with a
criterion
xy_mlp:add(nn.Identity())   -- by forwarding both x and y through
the network.

mlp = nn.Sequential()       -- The main network that takes both x
and y.
mlp:add(xy_mlp)             -- It feeds x and y to parallel
networks;
cr = nn.MSECriterion()
cr_wrap = nn.CriterionTable(cr)
mlp:add(cr_wrap)            -- and then applies the criterion.

for i = 1, 100 do           -- Do a few training iterations
   x = torch.ones(5)        -- Make input features.
   y = torch.Tensor(3)
   y:copy(x:narrow(1,1,3))  -- Make output label.
   err = mlp:forward{x,y}   -- Forward both input and output.
   print(err)               -- Print error from criterion.

   mlp:zeroGradParameters() -- Do backprop...
   mlp:backward({x, y})
   mlp:updateParameters(0.05)
```

```
end
```

Copy

```
module = nn.Copy(inputType, outputType, [forceCopy, dontCast])
```

This layer copies the input to output with type casting from `inputType` to `outputType`. Unless `forceCopy` is true, when the first two arguments are the same, the input isn't copied, only transferred as the output.
The default `forceCopy` is false.
When `dontCast` is true, a call to `nn.Copy:type(type)` will not cast the module's `output` and `gradInput` `Tensor`s to the new type.
The default is false.

Narrow

```
module = nn.Narrow(dimension, offset, length)
```

Narrow is application of narrow operation in a module. The module further supports negative `length`, `dim` and `offset` to handle inputs of unknown size.

```
> x = torch.rand(4, 5)

> x
 0.3695  0.2017  0.4485  0.4638  0.0513
 0.9222  0.1877  0.3388  0.6265  0.5659
 0.8785  0.7394  0.8265  0.9212  0.0129
 0.2290  0.7971  0.2113  0.1097  0.3166
[torch.DoubleTensor of size 4x5]

> nn.Narrow(1, 2, 3):forward(x)
 0.9222  0.1877  0.3388  0.6265  0.5659
 0.8785  0.7394  0.8265  0.9212  0.0129
 0.2290  0.7971  0.2113  0.1097  0.3166
```

```
[torch.DoubleTensor of size 3x5]

> nn.Narrow(1, 2, -1):forward(x)
 0.9222  0.1877  0.3388  0.6265  0.5659
 0.8785  0.7394  0.8265  0.9212  0.0129
 0.2290  0.7971  0.2113  0.1097  0.3166
[torch.DoubleTensor of size 3x5]

> nn.Narrow(1, 2, 2):forward(x)
 0.9222  0.1877  0.3388  0.6265  0.5659
 0.8785  0.7394  0.8265  0.9212  0.0129
[torch.DoubleTensor of size 2x5]

> nn.Narrow(1, 2, -2):forward(x)
 0.9222  0.1877  0.3388  0.6265  0.5659
 0.8785  0.7394  0.8265  0.9212  0.0129
[torch.DoubleTensor of size 2x5]

> nn.Narrow(2, 2, 3):forward(x)
 0.2017  0.4485  0.4638
 0.1877  0.3388  0.6265
 0.7394  0.8265  0.9212
 0.7971  0.2113  0.1097
[torch.DoubleTensor of size 4x3]

> nn.Narrow(2, 2, -2):forward(x)
 0.2017  0.4485  0.4638
 0.1877  0.3388  0.6265
 0.7394  0.8265  0.9212
 0.7971  0.2113  0.1097
[torch.DoubleTensor of size 4x3]
```

Replicate

```
module = nn.Replicate(nFeature [, dim, ndim])
```

This class creates an output where the input is replicated `nFeature` times along dimension `dim` (default 1).
There is no memory allocation or memory copy in this module.

It sets the stride along the `dim` th dimension to zero.
When provided, `ndim` should specify the number of non-batch dimensions.
This allows the module to replicate the same non-batch dimension `dim` for both batch and non-batch `inputs` .

```
> x = torch.linspace(1, 5, 5)
 1
 2
 3
 4
 5
[torch.DoubleTensor of dimension 5]

> m = nn.Replicate(3)
> o = m:forward(x)
 1  2  3  4  5
 1  2  3  4  5
 1  2  3  4  5
[torch.DoubleTensor of dimension 3x5]

> x:fill(13)
 13
 13
 13
 13
 13
[torch.DoubleTensor of dimension 5]

> print(o)
 13  13  13  13  13
 13  13  13  13  13
 13  13  13  13  13
[torch.DoubleTensor of dimension 3x5]
```

Reshape

```
module = nn.Reshape(dimension1, dimension2, ... [, batchMode])
```

Reshapes an `nxpxqx..` `Tensor` into a `dimension1xdimension2x...` `Tensor` , taking

the elements row-wise.

The optional last argument `batchMode`, when `true` forces the first dimension of the input to be considered the batch dimension, and thus keep its size fixed.
This is necessary when dealing with batch sizes of one.
When `false`, it forces the entire input (including the first dimension) to be reshaped to the input size.
Default `batchMode=nil`, which means that the module considers inputs with more elements than the produce of provided sizes, i.e. `dimension1xdimension2x...`, to be batches.

Example:

```
> x = torch.Tensor(4,4)
> for i = 1, 4 do
>    for j = 1, 4 do
>       x[i][j] = (i-1)*4+j
>    end
> end
> print(x)

  1   2   3   4
  5   6   7   8
  9  10  11  12
 13  14  15  16
[torch.Tensor of dimension 4x4]

> print(nn.Reshape(2,8):forward(x))

  1   2   3   4   5   6   7   8
  9  10  11  12  13  14  15  16
[torch.Tensor of dimension 2x8]

> print(nn.Reshape(8,2):forward(x))

  1   2
  3   4
  5   6
  7   8
  9  10
 11  12
 13  14
 15  16
[torch.Tensor of dimension 8x2]

> print(nn.Reshape(16):forward(x))
```

```
  1
  2
  3
  4
  5
  6
  7
  8
  9
 10
 11
 12
 13
 14
 15
 16
[torch.Tensor of dimension 16]

> y = torch.Tensor(1, 4):fill(0)
> print(y)

 0  0  0  0
 [torch.DoubleTensor of dimension 1x4]

> print(nn.Reshape(4):forward(y))

 0  0  0  0
 [torch.DoubleTensor of dimension 1x4]

> print(nn.Reshape(4, false):forward(y))

 0
 0
 0
 0
 [torch.DoubleTensor of dimension 4]
```

View

```
module = nn.View(sizes)
```

This module creates a new view of the input tensor using the `sizes` passed to the constructor.
The parameter `sizes` can either be a `LongStorage` or numbers.
The method `setNumInputDims()` allows to specify the expected number of dimensions of the inputs of the modules.
This makes it possible to use minibatch inputs when using a size `-1` for one of the dimensions.
The method `resetSize(sizes)` allows to reset the view size of the module after initialization.

Example 1:

```
> x = torch.Tensor(4, 4)
> for i = 1, 4 do
>    for j = 1, 4 do
>       x[i][j] = (i-1)*4+j
>    end
> end
> print(x)

  1   2   3   4
  5   6   7   8
  9  10  11  12
 13  14  15  16
[torch.Tensor of dimension 4x4]

> print(nn.View(2, 8):forward(x))

  1   2   3   4   5   6   7   8
  9  10  11  12  13  14  15  16
[torch.DoubleTensor of dimension 2x8]

> print(nn.View(torch.LongStorage{8,2}):forward(x))

  1   2
  3   4
  5   6
  7   8
  9  10
 11  12
 13  14
 15  16
[torch.DoubleTensor of dimension 8x2]
```

```
> print(nn.View(16):forward(x))

  1
  2
  3
  4
  5
  6
  7
  8
  9
 10
 11
 12
 13
 14
 15
 16
[torch.DoubleTensor of dimension 16]
```

Example 2:

```
> input = torch.Tensor(2, 3)
> minibatch = torch.Tensor(5, 2, 3)
> m = nn.View(-1):setNumInputDims(2)
> print(#m:forward(input))

 6
[torch.LongStorage of size 1]

> print(#m:forward(minibatch))

 5
 6
[torch.LongStorage of size 2]
```

Contiguous

```
module = nn.Contiguous()
```

Is used to make `input`, `gradOutput` or both contiguous, corresponds to `torch.contiguous` function.
Only does copy and allocation if `input` or `gradOutput` is not contiguous, otherwise passes the same `Tensor`.

Select

```
module = nn.Select(dim, index)
```

Selects a dimension and index of a `nxpxqx..` `Tensor`.

Example:

```
mlp = nn.Sequential()
mlp:add(nn.Select(1, 3))

x = torch.randn(10, 5)
print(x)
print(mlp:forward(x))
```

gives the output:

```
 0.9720 -0.0836  0.0831 -0.2059 -0.0871
 0.8750 -2.0432 -0.1295 -2.3932  0.8168
 0.0369  1.1633  0.6483  1.2862  0.6596
 0.1667 -0.5704 -0.7303  0.3697 -2.2941
 0.4794  2.0636  0.3502  0.3560 -0.5500
-0.1898 -1.1547  0.1145 -1.1399  0.1711
-1.5130  1.4445  0.2356 -0.5393 -0.6222
-0.6587  0.4314  1.1916 -1.4509  1.9400
 0.2733  1.0911  0.7667  0.4002  0.1646
 0.5804 -0.5333  1.1621  1.5683 -0.1978
[torch.Tensor of dimension 10x5]

 0.0369
```

```
 1.1633
 0.6483
 1.2862
 0.6596
[torch.Tensor of dimension 5]
```

This can be used in conjunction with Concat to emulate the behavior of Parallel, or to select various parts of an input Tensor to perform operations on. Here is a fairly complicated example:

```
mlp = nn.Sequential()
c = nn.Concat(2)
for i = 1, 10 do
   local t = nn.Sequential()
   t:add(nn.Select(1, i))
   t:add(nn.Linear(3, 2))
   t:add(nn.Reshape(2, 1))
   c:add(t)
end
mlp:add(c)

pred = mlp:forward(torch.randn(10, 3))
print(pred)

for i = 1, 10000 do     -- Train for a few iterations
   x = torch.randn(10, 3)
   y = torch.ones(2, 10)
   pred = mlp:forward(x)

   criterion = nn.MSECriterion()
   err = criterion:forward(pred, y)
   gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(0.01)
   print(err)
end
```

MaskedSelect

```
module = nn.MaskedSelect()
```

Performs a torch.MaskedSelect on a `Tensor`.
The mask is supplied as a tabular argument with the input on the forward and backward passes.

Example:

```
ms = nn.MaskedSelect()
mask = torch.ByteTensor({{1, 0}, {0, 1}})
input = torch.DoubleTensor({{10, 20}, {30, 40}})
print(input)
print(mask)
out = ms:forward({input, mask})
print(out)
gradIn = ms:backward({input, mask}, out)
print(gradIn[1])
```

Gives the output:

```
10  20
30  40
[torch.DoubleTensor of size 2x2]

1  0
0  1
[torch.ByteTensor of size 2x2]

10
40
[torch.DoubleTensor of size 2]

10  0
0  40
[torch.DoubleTensor of size 2x2]
```

Index

```
module = nn.Index(dim)
```

Applies the `Tensor` index operation along the given dimension. So

```
nn.Index(dim):forward{t,i}
```

gives the same output as

```
t:index(dim, i)
```

Squeeze

```
module = nn.Squeeze([dim, numInputDims])
```

Applies the `Tensor` squeeze operation. So

```
nn.Squeeze():forward(t)
```

gives the same output as

```
t:squeeze()
```

Setting `numInputDims` allows to use this module on batches.

Unsqueeze

```
module = nn.Unsqueeze(pos [, numInputDims])
```

Insert singleton dim (i.e., dimension 1) at position `pos`.

For an `input` with `dim = input:dim()`, there are `dim + 1` possible positions to insert the singleton dimension.
For example, if `input` is `3` dimensional `Tensor` in size `p x q x r`, then the singleton dim can be inserted at the following `4` positions

```
pos = 1: 1 x p x q x r
pos = 2: p x 1 x q x r
pos = 3: p x q x 1 x r
pos = 4: p x q x r x 1
```

Example:

```
input = torch.Tensor(2, 4, 3) -- input: 2 x 4 x 3

-- insert at head
m = nn.Unsqueeze(1)
m:forward(input) -- output: 1 x 2 x 4 x 3

-- insert at tail
m = nn.Unsqueeze(4)
m:forward(input) -- output: 2 x 4 x 3 x 1

-- insert in between
m = nn.Unsqueeze(2)
m:forward(input) -- output: 2 x 1 x 4 x 3

-- the input size can vary across calls
input2 = torch.Tensor(3, 5, 7) -- input2: 3 x 5 x 7
m:forward(input2) -- output: 3 x 1 x 5 x 7
```

Indicate the expected input feature map dimension by specifying `numInputDims`.
This allows the module to work with mini-batch. Example:

```
b = 5 -- batch size 5
input = torch.Tensor(b, 2, 4, 3) -- input: b x 2 x 4 x 3
numInputDims = 3 -- input feature map should be the last 3 dims

m = nn.Unsqueeze(4, numInputDims)
m:forward(input) -- output: b x 2 x 4 x 3 x 1

m = nn.Unsqueeze(2):setNumInputDims(numInputDims)
m:forward(input) -- output: b x 2 x 1 x 4 x 3
```

Transpose

```
module = nn.Transpose({dim1, dim2} [, {dim3, dim4}, ...])
```

Swaps dimension `dim1` with `dim2`, then `dim3` with `dim4`, and so on. So

```
nn.Transpose({dim1, dim2}, {dim3, dim4}):forward(t)
```

gives the same output as

```
t:transpose(dim1, dim2)
t:transpose(dim3, dim4)
```

Exp

```
module = nn.Exp()
```

Applies the `exp` function element-wise to the input `Tensor`, thus outputting a `Tensor` of the same dimension.

```
ii = torch.linspace(-2, 2)
m = nn.Exp()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii,go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

Log

```
module = nn.Log()
```

Applies the `log` function element-wise to the input `Tensor`, thus outputting a Tensor of the same dimension.

Square

```
module = nn.Square()
```

Takes the square of each element.

```
ii = torch.linspace(-5, 5)
m = nn.Square()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

Sqrt

```
module = nn.Sqrt()
```

Takes the square root of each element.

```
ii = torch.linspace(0, 5)
```

```
m = nn.Sqrt()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

Power

```
module = nn.Power(p)
```

Raises each element to its `p` -th power.

```
ii = torch.linspace(0, 2)
m = nn.Power(1.25)
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

Clamp

```
module = nn.Clamp(min_value, max_value)
```

Clamps all elements into the range `[min_value, max_value]` .
Output is identical to input in the range, otherwise elements less than `min_value` (or greater than `max_value`) are saturated to `min_value` (or `max_value`).

```
A = torch.randn(2, 5)
m = nn.Clamp(-0.1, 0.5)
B = m:forward(A)

print(A)  -- input
-1.1321  0.0227 -0.4672  0.6519 -0.5380
 0.9061 -1.0858  0.3697 -0.8120 -1.6759
[torch.DoubleTensor of size 3x5]

print(B)  -- output
-0.1000  0.0227 -0.1000  0.5000 -0.1000
 0.5000 -0.1000  0.3697 -0.1000 -0.1000
[torch.DoubleTensor of size 3x5]
```

Normalize

```
module = nn.Normalize(p, [eps])
```

Normalizes the input `Tensor` to have unit `L_p` norm. The smoothing parameter `eps` prevents division by zero when the input contains all zero elements (default = `1e-10`).

Input can be 1D or 2D (in which case it's considered as in batch mode)

```
A = torch.randn(3, 5)
m = nn.Normalize(2)
B = m:forward(A) -- B is also 3 x 5
-- take the L2 norm over the second axis:
print(torch.norm(B, 2, 2)) -- norms is [1, 1, 1]
```

`Normalize` has a specialized implementation for the `inf` norm, which corresponds to the maximum norm.

```
A = torch.randn(3,5)
m = nn.Normalize(math.huge) -- uses maximum/inf norm
B = m:forward(A)
maxA = torch.abs(A):max(2)
print(A,B,maxA)
```

MM

```
module = nn.MM(transA, transB)
```

Performs multiplications on one or more pairs of matrices. If `transA` is set to true, the first matrix is transposed before multiplication. If `transB` is set to true, the second matrix is transposed before multiplication. By default, the matrices do not get transposed.

The module also accepts 3D inputs which are interpreted as batches of matrices. When using batches, the first input matrix should be of size `b x m x n` and the second input matrix should be of size `b x n x p` (assuming `transA` and `transB` are not set). If `transA` or `transB` is set, transpose takes place between the second and the third dimensions for the corresponding matrix.

```
model = nn.MM()
A = torch.randn(b, m, n)
B = torch.randn(b, n, p)
C = model:forward({A, B})  -- C will be of size `b x m x p`

model = nn.MM(true, false)
A = torch.randn(b, n, m)
B = torch.randn(b, n, p)
C = model:forward({A, B})  -- C will be of size `b x m x p`
```

BatchNormalization

```
module = nn.BatchNormalization(N [, eps] [, momentum] [,affine])
```

where `N` is the dimensionality of input
`eps` is a small value added to the standard-deviation to avoid divide-by-zero. Defaults to `1e-5`.
`affine` is a boolean. When set to false, the learnable affine transform is disabled. Defaults to

true

During training, this layer keeps a running estimate of its computed mean and std.
The running sum is kept with a default momentum of 0.1 (unless over-ridden)
During evaluation, this running mean/std is used for normalization.

Implements Batch Normalization as described in the paper: “Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift” by Sergey Ioffe, Christian Szegedy.

The operation implemented is:

```
                x - mean(x)
y =  ----------------------------- * gamma + beta
      standard-deviation(x) + eps
```

where the mean and standard-deviation are calculated per-dimension over the mini-batches and where gamma and beta are learnable parameter vectors of size `N` (where `N` is the input size).
The learning of gamma and beta is optional.
The module only accepts 2D inputs.

```
-- with learnable parameters
model = nn.BatchNormalization(m)
A = torch.randn(b, m)
C = model:forward(A)  -- C will be of size `b x m`

-- without learnable parameters
model = nn.BatchNormalization(m, nil, nil, false)
A = torch.randn(b, m)
C = model:forward(A)  -- C will be of size `b x m`
```

PixelShuffle

`module = nn.PixelShuffle(r)`

Rearranges elements in a tensor of shape `[C*r, H, W]` to a tensor of shape `[C, H*r, W*r]`. This is useful for implementing efficient sub-pixel convolution with a stride of `1/r` (see Shi et. al). Below we show how the `PixelShuffle` module can be used to learn upscaling

filters to transform a low-resolution input to a high resolution one, with a 3x upscale factor. This is useful for tasks such as super-resolution, see "Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network" - Shi et al. for further details.

```
upscaleFactor = 3
inputChannels = 1

model = nn.Sequential()
model:add(nn.SpatialConvolution(inputChannels, 64, 5, 5, 1, 1, 2,
2))
model:add(nn.ReLU())

model:add(nn.SpatialConvolution(64, 32, 3, 3, 1, 1, 1, 1))
model:add(nn.ReLU())

model:add(nn.SpatialConvolution(32, inputChannels * upscaleFactor *
upscaleFactor, 3, 3, 1, 1, 1, 1))
model:add(nn.PixelShuffle(upscaleFactor))

input = torch.Tensor(1, 192, 256);
out = model:forward(input)
out:size()
   1
 576
 768
[torch.LongStorage of size 3]
```

Padding

```
module = nn.Padding(dim, pad [, nInputDim, value, index])
```

This module adds `pad` units of padding to dimension `dim` of the input.
If `pad` is negative, padding is added to the left, otherwise, it is added to the right of the dimension. When `nInputDim` is provided, inputs larger than that value will be considered batches where the actual `dim` to be padded will
be dimension `dim + 1`. When `value` is provide, the padding will be filled with that `value`.
The default `value` is zero.

When `index` is provided, padding will be added at that offset from the left or right, depending on the sign of `pad`.

Example 1:

```
module = nn.Padding(1, 2, 1, -1) --pad right x2
module:forward(torch.randn(3)) --non-batch input
 0.2008
 0.4848
-1.0783
-1.0000
-1.0000
[torch.DoubleTensor of dimension 5]
```

Example 2:

```
module = nn.Padding(1, -2, 1, -1) --pad left x2
module:forward(torch.randn(2, 3)) --batch input
-1.0000 -1.0000  1.0203  0.2704 -1.6164
-1.0000 -1.0000 -0.2219 -0.6529 -1.9218
[torch.DoubleTensor of dimension 2x5]
```

Example 3:

```
module = nn.Padding(1, -2, 1, -1, 2) --pad left x2, offset to index
2
module:forward(torch.randn(2, 3)) --batch input
 1.0203 -1.0000 -1.0000  0.2704 -1.6164
-0.6529 -1.0000 -1.0000 -0.2219 -1.9218
[torch.DoubleTensor of dimension 2x5]
```

L1Penalty

```
penalty = nn.L1Penalty(L1weight, sizeAverage)
```

L1Penalty is an inline module that in its forward propagation copies the input Tensor directly to the output, and computes an L1 loss of the latent state (input) and stores it in the module's

`loss` field.
During backward propagation: `gradInput = gradOutput + gradLoss`.

This module can be used in autoencoder architectures to apply L1 losses to internal latent state without having to use Identity and parallel containers to carry the internal code to an output criterion.

Example (sparse autoencoder, note: decoder should be normalized):

```
encoder = nn.Sequential()
encoder:add(nn.Linear(3, 128))
encoder:add(nn.Threshold())
decoder = nn.Linear(128, 3)

autoencoder = nn.Sequential()
autoencoder:add(encoder)
autoencoder:add(nn.L1Penalty(l1weight))
autoencoder:add(decoder)

criterion = nn.MSECriterion()  -- To measure reconstruction error
-- ...
```

GradientReversal

```
module = nn.GradientReversal([lambda = 1])
```

This module preserves the input, but takes the gradient from the subsequent layer, multiplies it by `-lambda` and passes it to the preceding layer. This can be used to maximise an objective function whilst using gradient descent, as described in “Domain-Adversarial Training of Neural Networks” (http://arxiv.org/abs/1505.07818).

One can also call:

```
module:setLambda(lambda)
```

to set the hyper-parameter `lambda` dynamically during training.

GPU

```
gpu = nn.GPU(module, device, [outdevice])
require 'cunn'
gpu:cuda()
```

Decorates an encapsulated `module` so that it can be executed on a specific GPU `device`.
The decorated module's `parameters` are thus hosted on the specified GPU `device`.
All operations on the `gpu` module are executed on that device.
Calls to `forward` / `backward` will transfer arguments `input` and `gradOutput` to the specified `device`,
which are then fed as arguments to the decorated `module`.
Returned `output` is located on the specified `outdevice` (defaults to `device`).
Returned `gradInput` is allocated on the same device as the `input`.

When serialized/deserialized, the `gpu` module will be run on the same `device` that it was serialized with.
To prevent this from happening, the module can be converted to float/double before serialization:

```
gpu:float()
gpustr = torch.serialize(gpu)
```

The module is located in the **nn** package instead of **cunn** as this allows
it to be used in CPU-only environments, which are common for production models.

The module supports nested table `input` and `gradOutput` tensors originating from multiple devices.
Each nested tensor in the returned `gradInput` will be transferred to the device its commensurate tensor in the `input`.

The intended use-case is not for model-parallelism where the models are executed in parallel on multiple devices, but
for sequential models where a single GPU doesn't have enough memory.

Example using 4 GPUs:

```
mlp = nn.Sequential()
   :add(nn.GPU(nn.Linear(10000,10000), 1))
   :add(nn.GPU(nn.Linear(10000,10000), 2))
```

```
   :add(nn.GPU(nn.Linear(10000,10000), 3))
   :add(nn.GPU(nn.Linear(10000,10000), 4, cutorch.getDevice()))
```

Note how the last `GPU` instance will return an `output` tensor on the same device as the current device (`cutorch.getDevice`).

TemporalDynamicKMaxPooling

```
module = nn.TemporalDynamicKMaxPooling(minK, [factor])
```

Selects the highest `k` values for each feature in the feature map sequence provided. The input sequence is composed of `nInputFrame` frames (i.e. `nInputFrame` is sequence length). The `input` tensor in `forward(input)` is expected to be a 2D tensor (`nInputFrame x inputFrameSize`) or a 3D tensor (`nBatchFrame x nInputFrame x inputFrameSize`), where `inputFrameSize` is the number of features across the sequence.

If `factor` is not provided, `k = minK` , else the value of k is calculated with:

```
k = math.max(minK, math.ceil(factor*nInputFrame)))
```

Table Layers

This set of modules allows the manipulation of `table` s through the layers of a neural network. This allows one to build very rich architectures:

- `table` Container Modules encapsulate sub-Modules:
  - `ConcatTable` : applies each member module to the same input `Tensor` and outputs a `table` ;
  - `ParallelTable` : applies the `i` -th member module to the `i` -th input and outputs a `table` ;
  - `MapTable` : applies a single module to every input and outputs a `table` ;
- Table Conversion Modules convert between `table` s and `Tensor` s or `table` s:
  - `SplitTable` : splits a `Tensor` into a `table` of `Tensor` s;
  - `JoinTable` : joins a `table` of `Tensor` s into a `Tensor` ;
  - `MixtureTable` : mixture of experts weighted by a gater;
  - `SelectTable` : select one element from a `table` ;
  - `NarrowTable` : select a slice of elements from a `table` ;
  - `FlattenTable` : flattens a nested `table` hierarchy;
- Pair Modules compute a measure like distance or similarity from a pair (`table`) of input `Tensor` s:
  - `PairwiseDistance` : outputs the `p` -norm. distance between inputs;
  - `DotProduct` : outputs the dot product (similarity) between inputs;
  - `CosineDistance` : outputs the cosine distance between inputs;
- CMath Modules perform element-wise operations on a `table` of `Tensor` s:
  - `CAddTable` : addition of input `Tensor` s;
  - `CSubTable` : substraction of input `Tensor` s;
  - `CMulTable` : multiplication of input `Tensor` s;
  - `CDivTable` : division of input `Tensor` s;
  - `CMaxTable` : max of input `Tensor` s;
  - `CMinTable` : min of input `Tensor` s;
- `Table` of Criteria:
  - `CriterionTable` : wraps a Criterion so that it can accept a `table` of inputs.

`table` -based modules work by supporting `forward()` and `backward()` methods that can accept `table` s as inputs.
It turns out that the usual `Sequential` module can do this, so all that is needed is other child modules that take advantage of such `table` s.

```
mlp = nn.Sequential()
t = {x, y, z}
pred = mlp:forward(t)
pred = mlp:forward{x, y, z}      -- This is equivalent to the line
before
```

ConcatTable

```
module = nn.ConcatTable()
```

`ConcatTable` is a container module that applies each member module to the same input `Tensor` or `table`.

```
                 +-----------+
             +---> {member1, |
+-------+    |   |           |
| input +----+---->  member2, |
+-------+    |   |           |
   or        +---->  member3} |
 {input}           +-----------+
```

Example 1

```
mlp = nn.ConcatTable()
mlp:add(nn.Linear(5, 2))
mlp:add(nn.Linear(5, 3))

pred = mlp:forward(torch.randn(5))
for i, k in ipairs(pred) do print(i, k) end
```

which gives the output:

```
1
```

```
-0.4073
 0.0110
[torch.Tensor of dimension 2]

2
 0.0027
-0.0598
-0.1189
[torch.Tensor of dimension 3]
```

Example 2

```
mlp = nn.ConcatTable()
mlp:add(nn.Identity())
mlp:add(nn.Identity())

pred = mlp:forward{torch.randn(2), {torch.randn(3)}}
print(pred)
```

which gives the output (using th):

```
{
  1 :
    {
      1 : DoubleTensor - size: 2
      2 :
        {
          1 : DoubleTensor - size: 3
        }
    }
  2 :
    {
      1 : DoubleTensor - size: 2
      2 :
        {
          1 : DoubleTensor - size: 3
        }
    }
}
```

ParallelTable

```
module = nn.ParallelTable()
```

`ParallelTable` is a container module that, in its `forward()` method, applies the `i`-th member module to the `i`-th input, and outputs a `table` of the set of outputs.

```
+----------+         +-----------+
| {input1, +---------> {member1, |
|          |         |           |
|  input2, +--------->  member2, |
|          |         |           |
|  input3} +--------->  member3} |
+----------+         +-----------+
```

Example

```
mlp = nn.ParallelTable()
mlp:add(nn.Linear(10, 2))
mlp:add(nn.Linear(5, 3))

x = torch.randn(10)
y = torch.rand(5)

pred = mlp:forward{x, y}
for i, k in pairs(pred) do print(i, k) end
```

which gives the output:

```
1
 0.0331
 0.7003
[torch.Tensor of dimension 2]

2
 0.0677
```

```
-0.1657
-0.7383
[torch.Tensor of dimension 3]
```

MapTable

```
module = nn.MapTable(m, share)
```

`MapTable` is a container for a single module which will be applied to all input elements. The member module is cloned as necessary to process all input elements. Call `resize(n)` to set the number of clones manually or call `clearState()` to discard all clones.

Optionally, the module can be initialized with the contained module and with a list of parameters that are shared across all clones. By default, these parameters are `weight`, `bias`, `gradWeight` and `gradBias`.

```
+----------+         +-----------+
| {input1, +---------> {member,  |
|          |         |           |
|  input2, +--------->  clone,   |
|          |         |           |
|  input3} +--------->  clone}   |
+----------+         +-----------+
```

Example

```
map = nn.MapTable()
map:add(nn.Linear(10, 3))

x1 = torch.rand(10)
x2 = torch.rand(10)
y = map:forward{x1, x2}

for i, k in pairs(y) do print(i, k) end
```

which gives the output:

```
1
 0.0345
 0.8695
 0.6502
[torch.DoubleTensor of size 3]

2
 0.0269
 0.4953
 0.2691
[torch.DoubleTensor of size 3]
```

SplitTable

```
module = SplitTable(dimension, nInputDims)
```

Creates a module that takes a `Tensor` as input and outputs several `table`s, splitting the `Tensor` along the specified `dimension`.
In the diagram below, `dimension` is equal to `1`.

```
    +----------+         +-----------+
    | input[1] +---------> {member1, |
  +----------+-+         |           |
  | input[2] +----------->  member2, |
+----------+-+           |           |
| input[3] +------------->  member3} |
+----------+             +-----------+
```

The optional parameter `nInputDims` allows to specify the number of dimensions that this module will receive.
This makes it possible to forward both minibatch and non-minibatch `Tensor`s through the same module.

Example 1

```
mlp = nn.SplitTable(2)
x = torch.randn(4, 3)
pred = mlp:forward(x)
for i, k in ipairs(pred) do print(i, k) end
```

gives the output:

```
1
 1.3885
 1.3295
 0.4281
-1.0171
[torch.Tensor of dimension 4]

2
-1.1565
-0.8556
-1.0717
-0.8316
[torch.Tensor of dimension 4]

3
-1.3678
-0.1709
-0.0191
-2.5871
[torch.Tensor of dimension 4]
```

Example 2

```
mlp = nn.SplitTable(1)
pred = mlp:forward(torch.randn(4, 3))
for i, k in ipairs(pred) do print(i, k) end
```

gives the output:

```
1
 1.6114
```

```
 0.9038
 0.8419
[torch.Tensor of dimension 3]

2
 2.4742
 0.2208
 1.6043
[torch.Tensor of dimension 3]

3
 1.3415
 0.2984
 0.2260
[torch.Tensor of dimension 3]

4
 2.0889
 1.2309
 0.0983
[torch.Tensor of dimension 3]
```

Example 3

```
mlp = nn.SplitTable(1, 2)
pred = mlp:forward(torch.randn(2, 4, 3))
for i, k in ipairs(pred) do print(i, k) end
pred = mlp:forward(torch.randn(4, 3))
for i, k in ipairs(pred) do print(i, k) end
```

gives the output:

```
1
-1.3533  0.7448 -0.8818
-0.4521 -1.2463  0.0316
[torch.DoubleTensor of dimension 2x3]

2
 0.1130 -1.3904  1.4620
 0.6722  2.0910 -0.2466
```

```
[torch.DoubleTensor of dimension 2x3]

3
 0.4672 -1.2738  1.1559
 0.4664  0.0768  0.6243
[torch.DoubleTensor of dimension 2x3]

4
 0.4194  1.2991  0.2241
 2.9786 -0.6715  0.0393
[torch.DoubleTensor of dimension 2x3]


1
-1.8932
 0.0516
-0.6316
[torch.DoubleTensor of dimension 3]

2
-0.3397
-1.8881
-0.0977
[torch.DoubleTensor of dimension 3]

3
 0.0135
 1.2089
 0.5785
[torch.DoubleTensor of dimension 3]

4
-0.1758
-0.0776
-1.1013
[torch.DoubleTensor of dimension 3]
```

The module also supports indexing from the end using negative dimensions. This allows to use this module when the number of dimensions of the input is unknown.

Example

```
```

```
m = nn.SplitTable(-2)
out = m:forward(torch.randn(3, 2))
for i, k in ipairs(out) do print(i, k) end
out = m:forward(torch.randn(1, 3, 2))
for i, k in ipairs(out) do print(i, k) end
```

gives the output:

```
1
 0.1420
-0.5698
[torch.DoubleTensor of size 2]

2
 0.1663
 0.1197
[torch.DoubleTensor of size 2]

3
 0.4198
-1.1394
[torch.DoubleTensor of size 2]


1
-2.4941
-1.4541
[torch.DoubleTensor of size 1x2]

2
 0.4594
 1.1946
[torch.DoubleTensor of size 1x2]

3
-2.3322
-0.7383
[torch.DoubleTensor of size 1x2]
```

A more complicated example

```
mlp = nn.Sequential()       -- Create a network that takes a Tensor
as input
mlp:add(nn.SplitTable(2))
c = nn.ParallelTable()      -- The two Tensor slices go through two
different Linear
c:add(nn.Linear(10, 3))     -- Layers in Parallel
c:add(nn.Linear(10, 7))
mlp:add(c)                  -- Outputing a table with 2 elements
p = nn.ParallelTable()      -- These tables go through two more
linear layers separately
p:add(nn.Linear(3, 2))
p:add(nn.Linear(7, 1))
mlp:add(p)
mlp:add(nn.JoinTable(1))    -- Finally, the tables are joined
together and output.

pred = mlp:forward(torch.randn(10, 2))
print(pred)

for i = 1, 100 do           -- A few steps of training such a
network..
   x = torch.ones(10, 2)
   y = torch.Tensor(3)
   y:copy(x:select(2, 1):narrow(1, 1, 3))
   pred = mlp:forward(x)

   criterion = nn.MSECriterion()
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(0.05)

   print(err)
end
```

JoinTable

```
module = JoinTable(dimension, nInputDims)
```

Creates a module that takes a `table` of `Tensor` s as input and outputs a `Tensor` by joining them together along dimension `dimension` .
In the diagram below `dimension` is set to `1` .

```
+----------+             +-----------+
| {input1, +-------------> output[1] |
|          |           +-----------+-+
|  input2, +-----------> output[2] |
|          |         +-----------+-+
|  input3} +---------> output[3] |
+----------+         +-----------+
```

The optional parameter `nInputDims` allows to specify the number of dimensions that this module will receive. This makes it possible to forward both minibatch and non-minibatch `Tensor` s through the same module.

Example 1

```
x = torch.randn(5, 1)
y = torch.randn(5, 1)
z = torch.randn(2, 1)

print(nn.JoinTable(1):forward{x, y})
print(nn.JoinTable(2):forward{x, y})
print(nn.JoinTable(1):forward{x, z})
```

gives the output:

```
 1.3965
 0.5146
-1.5244
-0.9540
 0.4256
 0.1575
 0.4491
 0.6580
 0.1784
-1.7362
[torch.DoubleTensor of dimension 10x1]
```

```
 1.3965  0.1575
 0.5146  0.4491
-1.5244  0.6580
-0.9540  0.1784
 0.4256 -1.7362
[torch.DoubleTensor of dimension 5x2]

 1.3965
 0.5146
-1.5244
-0.9540
 0.4256
-1.2660
 1.0869
[torch.Tensor of dimension 7x1]
```

Example 2

```
module = nn.JoinTable(2, 2)

x = torch.randn(3, 1)
y = torch.randn(3, 1)

mx = torch.randn(2, 3, 1)
my = torch.randn(2, 3, 1)

print(module:forward{x, y})
print(module:forward{mx, my})
```

gives the output:

```
 0.4288  1.2002
-1.4084 -0.7960
-0.2091  0.1852
[torch.DoubleTensor of dimension 3x2]

(1,.,.) =
  0.5561  0.1228
 -0.6792  0.1153
  0.0687  0.2955
```

```
(2,.,.) =
  2.5787  1.8185
 -0.9860  0.6756
  0.1989 -0.4327
[torch.DoubleTensor of dimension 2x3x2]
```

A more complicated example

```
mlp = nn.Sequential()         -- Create a network that takes a
Tensor as input
c = nn.ConcatTable()          -- The same Tensor goes through two
different Linear
c:add(nn.Linear(10, 3))       -- Layers in Parallel
c:add(nn.Linear(10, 7))
mlp:add(c)                    -- Outputing a table with 2 elements
p = nn.ParallelTable()        -- These tables go through two more
linear layers
p:add(nn.Linear(3, 2))        -- separately.
p:add(nn.Linear(7, 1))
mlp:add(p)
mlp:add(nn.JoinTable(1))      -- Finally, the tables are joined
together and output.

pred = mlp:forward(torch.randn(10))
print(pred)

for i = 1, 100 do             -- A few steps of training such a
network..
   x = torch.ones(10)
   y = torch.Tensor(3); y:copy(x:narrow(1, 1, 3))
   pred = mlp:forward(x)

   criterion= nn.MSECriterion()
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(0.05)

   print(err)
```

```
end
```

MixtureTable

`module` = `MixtureTable([dim])`

Creates a module that takes a `table` `{gater, experts}` as input and outputs the mixture of `experts` (a `Tensor` or `table` of `Tensor`s) using a `gater` `Tensor`. When `dim` is provided, it specifies the dimension of the `experts` `Tensor` that will be interpolated (or mixed). Otherwise, the `experts` should take the form of a `table` of `Tensor`s. This Module works for `experts` of dimension 1D or more, and for a 1D or 2D `gater`, i.e. for single examples or mini-batches.

Considering an `input = {G, E}` with a single example, then the mixture of experts `Tensor` `E` with gater `Tensor` `G` has the following form:

```
output = G[1]*E[1] + G[2]*E[2] + ... + G[n]*E[n]
```

where `dim = 1`, `n = E:size(dim) = G:size(dim)` and `G:dim() == 1`. Note that `E:dim() >= 2`, such that `output:dim() = E:dim() - 1`.

Example 1:
Using this Module, an arbitrary mixture of `n` 2-layer experts by a 2-layer gater could be constructed as follows:

```
experts = nn.ConcatTable()
for i = 1, n do
   local expert = nn.Sequential()
   expert:add(nn.Linear(3, 4))
   expert:add(nn.Tanh())
   expert:add(nn.Linear(4, 5))
   expert:add(nn.Tanh())
   experts:add(expert)
end

gater = nn.Sequential()
gater:add(nn.Linear(3, 7))
```

```
gater:add(nn.Tanh())
gater:add(nn.Linear(7, n))
gater:add(nn.SoftMax())

trunk = nn.ConcatTable()
trunk:add(gater)
trunk:add(experts)

moe = nn.Sequential()
moe:add(trunk)
moe:add(nn.MixtureTable())
```

Forwarding a batch of 2 examples gives us something like this:

```
> =moe:forward(torch.randn(2, 3))
-0.2152  0.3141  0.3280 -0.3772  0.2284
 0.2568  0.3511  0.0973 -0.0912 -0.0599
[torch.DoubleTensor of dimension 2x5]
```

Example 2:
In the following, the `MixtureTable` expects `experts` to be a `Tensor` of `size = {1, 4, 2, 5, n}`:

```
experts = nn.Concat(5)
for i = 1, n do
   local expert = nn.Sequential()
   expert:add(nn.Linear(3, 4))
   expert:add(nn.Tanh())
   expert:add(nn.Linear(4, 4*2*5))
   expert:add(nn.Tanh())
   expert:add(nn.Reshape(4, 2, 5, 1))
   experts:add(expert)
end

gater = nn.Sequential()
gater:add(nn.Linear(3, 7))
gater:add(nn.Tanh())
gater:add(nn.Linear(7, n))
gater:add(nn.SoftMax())

trunk = nn.ConcatTable()
trunk:add(gater)
trunk:add(experts)
```

```
moe = nn.Sequential()
moe:add(trunk)
moe:add(nn.MixtureTable(5))
```

Forwarding a batch of 2 examples gives us something like this:

```
> =moe:forward(torch.randn(2, 3)):size()
 2
 4
 2
 5
[torch.LongStorage of size 4]
```

SelectTable

`module` = `SelectTable(index)`

Creates a module that takes a (nested) `table` as input and outputs the element at index `index`. `index` can be strings or integers (positive or negative).
This can be either a `table` or a `Tensor`.

The gradients of the non- `index` elements are zeroed `Tensor`s of the same size. This is true regardless of the
depth of the encapsulated `Tensor` as the function used internally to do so is recursive.

Example 1:

```
> input = {torch.randn(2, 3), torch.randn(2, 1)}
> =nn.SelectTable(1):forward(input)
-0.3060  0.1398  0.2707
 0.0576  1.5455  0.0610
[torch.DoubleTensor of dimension 2x3]

> =nn.SelectTable(-1):forward(input)
 2.3080
-0.2955
[torch.DoubleTensor of dimension 2x1]
```

```
> =table.unpack(nn.SelectTable(1):backward(input, torch.randn(2,
3)))
-0.4891 -0.3495 -0.3182
-2.0999  0.7381 -0.5312
[torch.DoubleTensor of dimension 2x3]

0
0
[torch.DoubleTensor of dimension 2x1]
```

Exmaple 2:

```
> input = { A=torch.randn(2, 3), B=torch.randn(2, 1) }
> =nn.SelectTable("A"):forward(input)
-0.3060  0.1398  0.2707
 0.0576  1.5455  0.0610
[torch.DoubleTensor of dimension 2x3]

> gradInput = nn.SelectTable("A"):backward(input, torch.randn(2,
3))

> gradInput
{
  A : DoubleTensor - size: 2x3
  B : DoubleTensor - size: 2x1
}

> gradInput["A"]
-0.4891 -0.3495 -0.3182
-2.0999  0.7381 -0.5312
[torch.DoubleTensor of dimension 2x3]

> gradInput["B"]
0
0
[torch.DoubleTensor of dimension 2x1]
```

Example 3:

```
> input = {torch.randn(2, 3), {torch.randn(2, 1), {torch.randn(2,
2)}}}

> =nn.SelectTable(2):forward(input)
```

```
{
  1 : DoubleTensor - size: 2x1
  2 :
    {
      1 : DoubleTensor - size: 2x2
    }
}

> =table.unpack(nn.SelectTable(2):backward(input, {torch.randn(2,
1), {torch.randn(2, 2)}}))
0 0 0
0 0 0
[torch.DoubleTensor of dimension 2x3]

{
  1 : DoubleTensor - size: 2x1
  2 :
    {
      1 : DoubleTensor - size: 2x2
    }
}

> gradInput = nn.SelectTable(1):backward(input, torch.randn(2, 3))

> =gradInput
{
  1 : DoubleTensor - size: 2x3
  2 :
    {
      1 : DoubleTensor - size: 2x1
      2 :
        {
          1 : DoubleTensor - size: 2x2
        }
    }
}

> =gradInput[1]
-0.3400 -0.0404  1.1885
 1.2865  0.4107  0.6506
[torch.DoubleTensor of dimension 2x3]

> gradInput[2][1]
0
0
```

```
[torch.DoubleTensor of dimension 2x1]

> gradInput[2][2][1]
0 0
0 0
[torch.DoubleTensor of dimension 2x2]
```

NarrowTable

`module` = `NarrowTable(offset [, length])`

Creates a module that takes a `table` as input and outputs the subtable starting at index `offset` having `length` elements (defaults to 1 element).
The elements can be either a `table` or a `Tensor`.

The gradients of the elements not included in the subtable are zeroed `Tensor`s of the same size.
This is true regardless of the depth of the encapsulated `Tensor` as the function used internally to do so is recursive.

Example:

```
> input = {torch.randn(2, 3), torch.randn(2, 1), torch.randn(1, 2)}
> =nn.NarrowTable(2,2):forward(input)
{
  1 : DoubleTensor - size: 2x1
  2 : DoubleTensor - size: 1x2
}

> =nn.NarrowTable(1):forward(input)
{
  1 : DoubleTensor - size: 2x3
}

> =table.unpack(nn.NarrowTable(1,2):backward(input, {torch.randn(2,
3), torch.randn(2, 1)}))
 1.9528 -0.1381  0.2023
 0.2297 -1.5169 -1.1871
[torch.DoubleTensor of size 2x3]
```

```
-1.2023
-0.4165
[torch.DoubleTensor of size 2x1]

 0  0
[torch.DoubleTensor of size 1x2]
```

FlattenTable

`module` = `FlattenTable()`

Creates a module that takes an arbitrarily deep `table` of `Tensor`s (potentially nested) as input and outputs a `table` of `Tensor`s, where the output `Tensor` in index `i` is the `Tensor` with post-order DFS index `i` in the input `table`.

This module is particularly useful in combination with nn.Identity() to create networks that can append to their input `table`.

Example:

```
x = {torch.rand(1), {torch.rand(2), {torch.rand(3)}},
torch.rand(4)}
print(x)
print(nn.FlattenTable():forward(x))
```

gives the output:

```
{
  1 : DoubleTensor - size: 1
  2 :
    {
      1 : DoubleTensor - size: 2
      2 :
        {
          1 : DoubleTensor - size: 3
        }
    }
  3 : DoubleTensor - size: 4
}
```

```
{
  1 : DoubleTensor - size: 1
  2 : DoubleTensor - size: 2
  3 : DoubleTensor - size: 3
  4 : DoubleTensor - size: 4
}
```

PairwiseDistance

`module` = `PairwiseDistance(p)` creates a module that takes a `table` of two vectors as input and outputs the distance between them using the `p`-norm.

Example:

```
mlp_l1 = nn.PairwiseDistance(1)
mlp_l2 = nn.PairwiseDistance(2)
x = torch.Tensor({1, 2, 3})
y = torch.Tensor({4, 5, 6})
print(mlp_l1:forward({x, y}))
print(mlp_l2:forward({x, y}))
```

gives the output:

```
 9
[torch.Tensor of dimension 1]

 5.1962
[torch.Tensor of dimension 1]
```

A more complicated example:

```
-- imagine we have one network we are interested in, it is called
"p1_mlp"
p1_mlp= nn.Sequential(); p1_mlp:add(nn.Linear(5, 2))

-- But we want to push examples towards or away from each other
-- so we make another copy of it called p2_mlp
-- this *shares* the same weights via the set command, but has its
```

```
own set of temporary gradient storage
-- that's why we create it again (so that the gradients of the pair
don't wipe each other)
p2_mlp= nn.Sequential(); p2_mlp:add(nn.Linear(5, 2))
p2_mlp:get(1).weight:set(p1_mlp:get(1).weight)
p2_mlp:get(1).bias:set(p1_mlp:get(1).bias)

-- we make a parallel table that takes a pair of examples as input.
they both go through the same (cloned) mlp
prl = nn.ParallelTable()
prl:add(p1_mlp)
prl:add(p2_mlp)

-- now we define our top level network that takes this parallel
table and computes the pairwise distance between
-- the pair of outputs
mlp= nn.Sequential()
mlp:add(prl)
mlp:add(nn.PairwiseDistance(1))

-- and a criterion for pushing together or pulling apart pairs
crit = nn.HingeEmbeddingCriterion(1)

-- lets make two example vectors
x = torch.rand(5)
y = torch.rand(5)


-- Use a typical generic gradient update function
function gradUpdate(mlp, x, y, criterion, learningRate)
local pred = mlp:forward(x)
local err = criterion:forward(pred, y)
local gradCriterion = criterion:backward(pred, y)
mlp:zeroGradParameters()
mlp:backward(x, gradCriterion)
mlp:updateParameters(learningRate)
end

-- push the pair x and y together, notice how then the distance
between them given
-- by  print(mlp:forward({x, y})[1]) gets smaller
for i = 1, 10 do
gradUpdate(mlp, {x, y}, 1, crit, 0.01)
print(mlp:forward({x, y})[1])
end
```

```
-- pull apart the pair x and y, notice how then the distance
between them given
-- by  print(mlp:forward({x, y})[1]) gets larger

for i = 1, 10 do
gradUpdate(mlp, {x, y}, -1, crit, 0.01)
print(mlp:forward({x, y})[1])
end
```

DotProduct

`module` = `DotProduct()` creates a module that takes a `table` of two vectors (or matrices if in batch mode) as input and outputs the dot product between them.

Example:

```
mlp = nn.DotProduct()
x = torch.Tensor({1, 2, 3})
y = torch.Tensor({4, 5, 6})
print(mlp:forward({x, y}))
```

gives the output:

```
 32
[torch.Tensor of dimension 1]
```

A more complicated example:

```
-- Train a ranking function so that mlp:forward({x, y}, {x, z})
returns a number
-- which indicates whether x is better matched with y or z (larger
score = better match), or vice versa.

mlp1 = nn.Linear(5, 10)
mlp2 = mlp1:clone('weight', 'bias')
```

```
prl = nn.ParallelTable();
prl:add(mlp1); prl:add(mlp2)

mlp1 = nn.Sequential()
mlp1:add(prl)
mlp1:add(nn.DotProduct())

mlp2 = mlp1:clone('weight', 'bias')

mlp = nn.Sequential()
prla = nn.ParallelTable()
prla:add(mlp1)
prla:add(mlp2)
mlp:add(prla)

x = torch.rand(5);
y = torch.rand(5)
z = torch.rand(5)


print(mlp1:forward{x, x})
print(mlp1:forward{x, y})
print(mlp1:forward{y, y})


crit = nn.MarginRankingCriterion(1);

-- Use a typical generic gradient update function
function gradUpdate(mlp, x, y, criterion, learningRate)
   local pred = mlp:forward(x)
   local err = criterion:forward(pred, y)
   local gradCriterion = criterion:backward(pred, y)
   mlp:zeroGradParameters()
   mlp:backward(x, gradCriterion)
   mlp:updateParameters(learningRate)
end

inp = {{x, y}, {x, z}}

math.randomseed(1)

-- make the pair x and y have a larger dot product than x and z

for i = 1, 100 do
```

```
   gradUpdate(mlp, inp, 1, crit, 0.05)
   o1 = mlp1:forward{x, y}[1];
   o2 = mlp2:forward{x, z}[1];
   o = crit:forward(mlp:forward{{x, y}, {x, z}}, 1)
   print(o1, o2, o)
end

print "_________________**"

-- make the pair x and z have a larger dot product than x and y

for i = 1, 100 do
   gradUpdate(mlp, inp, -1, crit, 0.05)
   o1 = mlp1:forward{x, y}[1];
   o2 = mlp2:forward{x, z}[1];
   o = crit:forward(mlp:forward{{x, y}, {x, z}}, -1)
   print(o1, o2, o)
end
```

CosineDistance

`module` = `CosineDistance()` creates a module that takes a `table` of two vectors (or matrices if in batch mode) as input and outputs the cosine distance between them.

Examples:

```
mlp = nn.CosineDistance()
x = torch.Tensor({1, 2, 3})
y = torch.Tensor({4, 5, 6})
print(mlp:forward({x, y}))
```

gives the output:

```
 0.9746
[torch.Tensor of dimension 1]
```

`CosineDistance` also accepts batches:

```
mlp = nn.CosineDistance()
x = torch.Tensor({{1,2,3},{1,2,-3}})
y = torch.Tensor({{4,5,6},{-4,5,6}})
print(mlp:forward({x,y}))
```

gives the output:

```
 0.9746
-0.3655
[torch.DoubleTensor of size 2]
```

A more complicated example:

```
-- imagine we have one network we are interested in, it is called
"p1_mlp"
p1_mlp= nn.Sequential(); p1_mlp:add(nn.Linear(5, 2))

-- But we want to push examples towards or away from each other
-- so we make another copy of it called p2_mlp
-- this *shares* the same weights via the set command, but has its
own set of temporary gradient storage
-- that's why we create it again (so that the gradients of the pair
don't wipe each other)
p2_mlp= p1_mlp:clone('weight', 'bias')

-- we make a parallel table that takes a pair of examples as input.
they both go through the same (cloned) mlp
prl = nn.ParallelTable()
prl:add(p1_mlp)
prl:add(p2_mlp)

-- now we define our top level network that takes this parallel
table and computes the cosine distance between
-- the pair of outputs
mlp= nn.Sequential()
mlp:add(prl)
mlp:add(nn.CosineDistance())


-- lets make two example vectors
x = torch.rand(5)
```

```
y = torch.rand(5)

-- Grad update function..
function gradUpdate(mlp, x, y, learningRate)
    local pred = mlp:forward(x)
    if pred[1]*y < 1 then
        gradCriterion = torch.Tensor({-y})
        mlp:zeroGradParameters()
        mlp:backward(x, gradCriterion)
        mlp:updateParameters(learningRate)
    end
end

-- push the pair x and y together, the distance should get larger..
for i = 1, 1000 do
 gradUpdate(mlp, {x, y}, 1, 0.1)
 if ((i%100)==0) then print(mlp:forward({x, y})[1]);end
end


-- pull apart the pair x and y, the distance should get smaller..

for i = 1, 1000 do
 gradUpdate(mlp, {x, y}, -1, 0.1)
 if ((i%100)==0) then print(mlp:forward({x, y})[1]);end
end
```

CriterionTable

`module` = `CriterionTable(criterion)`

Creates a module that wraps a Criterion module so that it can accept a `table` of inputs. Typically the `table` would contain two elements: the input and output `x` and `y` that the Criterion compares.

Example:

```
mlp = nn.CriterionTable(nn.MSECriterion())
x = torch.randn(5)
y = torch.randn(5)
```

```
print(mlp:forward{x, x})
print(mlp:forward{x, y})
```

gives the output:

```
0
1.9028918413199
```

Here is a more complex example of embedding the criterion into a network:

```
function table.print(t)
 for i, k in pairs(t) do print(i, k); end
end

mlp = nn.Sequential();                          -- Create an mlp
that takes input
  main_mlp = nn.Sequential();              -- and output using
ParallelTable
  main_mlp:add(nn.Linear(5, 4))
  main_mlp:add(nn.Linear(4, 3))
 cmlp = nn.ParallelTable();
 cmlp:add(main_mlp)
 cmlp:add(nn.Identity())
mlp:add(cmlp)
mlp:add(nn.CriterionTable(nn.MSECriterion())) -- Apply the
Criterion

for i = 1, 20 do                                -- Train for a few
iterations
 x = torch.ones(5);
 y = torch.Tensor(3); y:copy(x:narrow(1, 1, 3))
 err = mlp:forward{x, y}                        -- Pass in both
input and output
 print(err)

 mlp:zeroGradParameters();
 mlp:backward({x, y} );
 mlp:updateParameters(0.05);
end
```

CAddTable

`module` = `CAddTable([inplace])`

Takes a `table` of `Tensor`s and outputs summation of all `Tensor`s. If `inplace` is `true`, the sum is written to the first `Tensor`.

```
ii = {torch.ones(5), torch.ones(5)*2, torch.ones(5)*3}
=ii[1]
 1
 1
 1
 1
 1
[torch.DoubleTensor of dimension 5]

return ii[2]
 2
 2
 2
 2
 2
[torch.DoubleTensor of dimension 5]

return ii[3]
 3
 3
 3
 3
 3
[torch.DoubleTensor of dimension 5]

m = nn.CAddTable()
=m:forward(ii)
 6
 6
 6
 6
 6
[torch.DoubleTensor of dimension 5]
```

CSubTable

Takes a `table` with two `Tensor` and returns the component-wise subtraction between them.

```
m = nn.CSubTable()
=m:forward({torch.ones(5)*2.2, torch.ones(5)})
 1.2000
 1.2000
 1.2000
 1.2000
 1.2000
[torch.DoubleTensor of dimension 5]
```

CMulTable

Takes a `table` of `Tensor`s and outputs the multiplication of all of them.

```
ii = {torch.ones(5)*2, torch.ones(5)*3, torch.ones(5)*4}
m = nn.CMulTable()
=m:forward(ii)
 24
 24
 24
 24
 24
[torch.DoubleTensor of dimension 5]
```

CDivTable

Takes a `table` with two `Tensor` and returns the component-wise division between them.

```
m = nn.CDivTable()
=m:forward({torch.ones(5)*2.2, torch.ones(5)*4.4})
 0.5000
 0.5000
 0.5000
 0.5000
 0.5000
[torch.DoubleTensor of dimension 5]
```

CMaxTable

Takes a `table` of `Tensor`s and outputs the max of all of them.

```
m = nn.CMaxTable()
=m:forward({{torch.Tensor{1,2,3}, torch.Tensor{3,2,1}})
 3
 2
 3
[torch.DoubleTensor of size 3]
```

CMinTable

Takes a `table` of `Tensor`s and outputs the min of all of them.

```
m = nn.CMinTable()
=m:forward({{torch.Tensor{1,2,3}, torch.Tensor{3,2,1}})
 1
 2
 1
[torch.DoubleTensor of size 3]
```

Testing

For those who want to implement their own modules, we suggest using the `nn.Jacobian` class for testing the derivatives of their class, together with the torch.Tester class. The sources of `nn` package contains sufficiently many examples of such tests.

nn.Jacobian

testJacobian(module, input, minval, maxval, perturbation)

Test the jacobian of a module w.r.t. to its input.

`module` takes as its input a random tensor shaped the same as `input`.
`minval` and `maxval` specify the range of the random tensor ([-2, 2] by default).
`perturbation` is used as finite difference (1e-6 by default).

Returns the L-inf distance between the jacobian computed by backpropagation and by finite difference.

testJacobianParameters(module, input, param, dparam, minval, maxval, perturbation)

Test the jacobian of a module w.r.t. its parameters (instead of its input).

The input and parameters of `module` are random tensors shaped the same as `input` and `param`.
`minval` and `maxval` specify the range of the random tensors ([-2, 2] by default).
`dparam` points to the gradient w.r.t. parameters.
`perturbation` is used as finite difference (1e-6 by default).

Returns the L-inf distance between the jacobian computed by backpropagation and by finite difference.

testJacobianUpdateParameters(module, input, param, minval, maxval, perturbation)

Test the amount of update of a module to its parameters.

The input and parameters of `module` are random tensors shaped the same as `input` and `param`.
`minval` and `maxval` specify the range of the random tensors ([-2, 2] by default).
`perturbation` is used as finite difference (1e-6 by default).

Returns the L-inf distance between the update computed by backpropagation and by finite difference.

forward(module, input, param, perturbation)

Compute the jacobian by finite difference.

`module` has parameters `param` and input `input`.
If provided, `param` is regarded as independent variables, otherwise `input` is the independent variables.
`perturbation` is used as finite difference (1e-6 by default).

Returns the jacobian computed by finite difference.

backward(module, input, param, dparam)

Compute the jacobian by backpropagation.

`module` has parameters `param` and input `input`.
If provided, `param` is regarded as independent variables, otherwise `input` is the independent variables.
`dparam` is the gradient w.r.t. parameters, it must present as long as `param` is present.

Returns the jacobian computed by backpropagation.

Training a neural network

Training a neural network is easy with a simple `for` loop. Typically however we would use the `optim` optimizer, which implements some cool functionalities, like Nesterov momentum,
adagrad and
adam.

We will demonstrate using a for-loop first, to show the low-level view of what happens in training. StochasticGradient, a simple class
which does the job for you, is provided as standard. Finally, `optim` is a powerful module, that provides multiple optimization algorithms.

Example of manual training of a neural network

We show an example here on a classical XOR problem.

Neural Network

We create a simple neural network with one hidden layer.

```
require "nn"
mlp = nn.Sequential();  -- make a multi-layer perceptron
inputs = 2; outputs = 1; HUs = 20; -- parameters
mlp:add(nn.Linear(inputs, HUs))
mlp:add(nn.Tanh())
mlp:add(nn.Linear(HUs, outputs))
```

Loss function

We choose the Mean Squared Error criterion:

```
criterion = nn.MSECriterion()
```

Training

We create data *on the fly* and feed it to the neural network.

```
for i = 1,2500 do
  -- random sample
  local input= torch.randn(2);     -- normally distributed example
in 2d
  local output= torch.Tensor(1);
  if input[1]*input[2] > 0 then  -- calculate label for XOR
function
    output[1] = -1
  else
    output[1] = 1
  end

  -- feed it to the neural network and the criterion
  criterion:forward(mlp:forward(input), output)

  -- train over this example in 3 steps
  -- (1) zero the accumulation of the gradients
  mlp:zeroGradParameters()
  -- (2) accumulate gradients
  mlp:backward(input, criterion:backward(mlp.output, output))
  -- (3) update parameters with a 0.01 learning rate
  mlp:updateParameters(0.01)
end
```

Test the network

```
x = torch.Tensor(2)
x[1] =  0.5; x[2] =  0.5; print(mlp:forward(x))
x[1] =  0.5; x[2] = -0.5; print(mlp:forward(x))
x[1] = -0.5; x[2] =  0.5; print(mlp:forward(x))
x[1] = -0.5; x[2] = -0.5; print(mlp:forward(x))
```

You should see something like:

```
> x = torch.Tensor(2)
> x[1] =  0.5; x[2] =  0.5; print(mlp:forward(x))

-0.6140
[torch.Tensor of dimension 1]
```

```
> x[1] =  0.5; x[2] = -0.5; print(mlp:forward(x))

 0.8878
[torch.Tensor of dimension 1]

> x[1] = -0.5; x[2] =  0.5; print(mlp:forward(x))

 0.8548
[torch.Tensor of dimension 1]

> x[1] = -0.5; x[2] = -0.5; print(mlp:forward(x))

-0.5498
[torch.Tensor of dimension 1]
```

StochasticGradient

`StochasticGradient` is a high-level class for training neural networks, using a stochastic gradient
algorithm. This class is serializable.

StochasticGradient(module, criterion)

Create a `StochasticGradient` class, using the given Module and Criterion.
The class contains several parameters you might want to set after initialization.

train(dataset)

Train the module and criterion given in the
constructor over `dataset`, using the
internal parameters.

StochasticGradient expect as a `dataset` an object which implements the operator `dataset[index]` and implements the method `dataset:size()`. The `size()` methods returns the number of examples and `dataset[i]` has to return the i-th example.

An `example` has to be an object which implements the operator `example[field]`, where `field` might take the value `1` (input features) or `2` (corresponding label which will be given to the criterion).
The input is usually a Tensor (except if you use special kind of gradient modules, like table layers). The label type depends of the criterion.
For example, the MSECriterion expects a Tensor, but the ClassNLLCriterion except a integer number (the class).

Such a dataset is easily constructed by using Lua tables, but it could any `C` object for example, as long as required operators/methods are implemented.
See an example.

Parameters

`StochasticGradient` has several field which have an impact on a call to train().

- `learningRate` : This is the learning rate used during training. The update of the parameters will be `parameters = parameters - learningRate * parameters_gradient`. Default value is `0.01`.
- `learningRateDecay` : The learning rate decay. If non-zero, the learning rate (note: the field learningRate will not change value) will be computed after each iteration (pass over the dataset) with: `current_learning_rate =learningRate / (1 + iteration * learningRateDecay)`
- `maxIteration` : The maximum number of iteration (passes over the dataset). Default is `25`.
- `shuffleIndices` : Boolean which says if the examples will be randomly sampled or not. Default is `true`. If `false`, the examples will be taken in the order of the dataset.
- `hookExample` : A possible hook function which will be called (if non-nil) during training after each example forwarded and backwarded through the network. The function takes `(self, example)` as parameters. Default is `nil`.
- `hookIteration` : A possible hook function which will be called (if non-nil) during training after a complete pass over the dataset. The function takes `(self, iteration, currentError)` as parameters. Default is `nil`.

Example of training using StochasticGradient

We show an example here on a classical XOR problem.

Dataset

We first need to create a dataset, following the conventions described in StochasticGradient.

```
dataset={};
function dataset:size() return 100 end -- 100 examples
for i=1,dataset:size() do
  local input = torch.randn(2);     -- normally distributed example
in 2d
  local output = torch.Tensor(1);
  if input[1]*input[2]>0 then     -- calculate label for XOR
function
    output[1] = -1;
  else
    output[1] = 1
  end
  dataset[i] = {input, output}
end
```

Neural Network

We create a simple neural network with one hidden layer.

```
require "nn"
mlp = nn.Sequential();  -- make a multi-layer perceptron
inputs = 2; outputs = 1; HUs = 20; -- parameters
mlp:add(nn.Linear(inputs, HUs))
mlp:add(nn.Tanh())
mlp:add(nn.Linear(HUs, outputs))
```

Training

We choose the Mean Squared Error criterion and train the dataset.

```
criterion = nn.MSECriterion()
trainer = nn.StochasticGradient(mlp, criterion)
trainer.learningRate = 0.01
trainer:train(dataset)
```

Test the network

```
x = torch.Tensor(2)
x[1] =  0.5; x[2] =  0.5; print(mlp:forward(x))
x[1] =  0.5; x[2] = -0.5; print(mlp:forward(x))
x[1] = -0.5; x[2] =  0.5; print(mlp:forward(x))
x[1] = -0.5; x[2] = -0.5; print(mlp:forward(x))
```

You should see something like:

```
> x = torch.Tensor(2)
> x[1] =  0.5; x[2] =  0.5; print(mlp:forward(x))

-0.3490
[torch.Tensor of dimension 1]

> x[1] =  0.5; x[2] = -0.5; print(mlp:forward(x))

 1.0561
[torch.Tensor of dimension 1]

> x[1] = -0.5; x[2] =  0.5; print(mlp:forward(x))

 0.8640
[torch.Tensor of dimension 1]

> x[1] = -0.5; x[2] = -0.5; print(mlp:forward(x))

-0.2941
[torch.Tensor of dimension 1]
```

Using optim to train a network

`optim` is a powerful module, that provides multiple optimization algorithms.

Transfer Function Layers

Transfer functions are normally used to introduce a non-linearity after a parameterized layer like `Linear` and `SpatialConvolution`.
Non-linearities allows for dividing the problem space into more complex regions than what a simple logistic regressor would permit.

HardTanh

```
f = nn.HardTanh([min_value, max_value[, inplace]])
```

Applies the `HardTanh` function element-wise to the input `Tensor`, thus outputting a `Tensor` of the same dimension.

`HardTanh` is defined as:

```
        ⎧  1, if x >  1
f(x) = ⎨ -1, if x < -1
        ⎩  x, otherwise
```

The range of the linear region `[-1 1]` can be adjusted by specifying arguments in declaration, for example `nn.HardTanh(min_value, max_value)`.
Otherwise, `[min_value max_value]` is set to `[-1 1]` by default.
In-place operation defined by third argument boolean.

```
ii = torch.linspace(-2, 2)
m = nn.HardTanh()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

HardShrink

```
f = nn.HardShrink([lambda])
```

Applies the hard shrinkage function element-wise to the input `Tensor`.
`lambda` is set to `0.5` by default.

`HardShrinkage` operator is defined as:

```
       ⎧ x, if x >  lambda
f(x) = ⎨ x, if x < -lambda
       ⎩ 0, otherwise
```

```
ii = torch.linspace(-2, 2)
m = nn.HardShrink(0.85)
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

SoftShrink

```
f = nn.SoftShrink([lambda])
```

Applies the soft shrinkage function element-wise to the input `Tensor`.
`lambda` is set to `0.5` by default.

`SoftShrinkage` operator is defined as:

```
       ⎧ x - lambda, if x >  lambda
f(x) = ⎨ x + lambda, if x < -lambda
```

```
          ⌊ 0, otherwise
```

```
ii = torch.linspace(-2, 2)
m = nn.SoftShrink(0.85)
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```


SoftMax

```
f = nn.SoftMax()
```

Applies the `SoftMax` function to an n-dimensional input `Tensor`, rescaling them so that the elements of the n-dimensional output Tensor
lie in the range `(0, 1)` and sum to `1`.

`Softmax` is defined as:

```
f_i(x) = exp(x_i - shift) / sum_j exp(x_j - shift)
```

where `shift = max_i(x_i)`.

```
ii = torch.exp(torch.abs(torch.randn(10)))
m = nn.SoftMax()
oo = m:forward(ii)
gnuplot.plot({'Input', ii, '+-'}, {'Output', oo, '+-'})
gnuplot.grid(true)
```


Note that this module doesn't work directly with `ClassNLLCriterion`, which expects the `nn.Log` to be computed between the `SoftMax` and itself.

Use `LogSoftMax` instead (it's faster).

SoftMin

```
f = nn.SoftMin()
```

Applies the `SoftMin` function to an n-dimensional input `Tensor`, rescaling them so that the elements of the n-dimensional output `Tensor` lie in the range `(0,1)` and sum to `1`.

`Softmin` is defined as:

```
f_i(x) = exp(-x_i - shift) / sum_j exp(-x_j - shift)
```

where `shift = max_i(-x_i)`.

```
ii = torch.exp(torch.abs(torch.randn(10)))
m = nn.SoftMin()
oo = m:forward(ii)
gnuplot.plot({'Input', ii, '+-'}, {'Output', oo, '+-'})
gnuplot.grid(true)
```

SoftPlus

```
f = nn.SoftPlus()
```

Applies the `SoftPlus` function to an n-dimensioanl input `Tensor`.
`SoftPlus` is a smooth approximation to the `ReLU` function and can be used to constrain the output of a machine to always be positive.
For numerical stability the implementation reverts to the linear function for inputs above a certain value (20 by default).

`SoftPlus` is defined as:

```
f_i(x) = 1/beta * log(1 + exp(beta * x_i))
```

```
ii = torch.linspace(-3, 3)
m = nn.SoftPlus()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```


SoftSign

```
f = nn.SoftSign()
```

Applies the `SoftSign` function to an n-dimensioanl input `Tensor`.

`SoftSign` is defined as:

```
f_i(x) = x_i / (1+|x_i|)
```

```
ii = torch.linspace(-5, 5)
m = nn.SoftSign()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f (x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```


LogSigmoid

```
f = nn.LogSigmoid()
```

Applies the `LogSigmoid` function to an n-dimensional input `Tensor`.

`LogSigmoid` is defined as:

```
f_i(x) = log(1 / (1 + exp(-x_i)))
```

```
ii = torch.randn(10)
m = nn.LogSigmoid()
oo = m:forward(ii)
go = torch.ones(10)
gi = m:backward(ii, go)
gnuplot.plot({'Input', ii, '+-'}, {'Output', oo, '+-'},
{'gradInput', gi, '+-'})
gnuplot.grid(true)
```

LogSoftMax

```
f = nn.LogSoftMax()
```

Applies the `LogSoftMax` function to an n-dimensional input `Tensor`.

`LogSoftmax` is defined as:

```
f_i(x) = log(1 / a exp(x_i))
```

where `a = sum_j[exp(x_j)]`.

```
ii = torch.randn(10)
m = nn.LogSoftMax()
oo = m:forward(ii)
go = torch.ones(10)
```

```
gi = m:backward(ii, go)
gnuplot.plot({'Input', ii, '+-'}, {'Output', oo, '+-'},
{'gradInput', gi, '+-'})
gnuplot.grid(true)
```

Sigmoid

```
f = nn.Sigmoid()
```

Applies the `Sigmoid` function element-wise to the input `Tensor`, thus outputting a Tensor of the same dimension.

`Sigmoid` is defined as:

```
f(x) = 1 / (1 + exp(-x))
```

```
ii = torch.linspace(-5, 5)
m = nn.Sigmoid()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

Tanh

```
f = nn.Tanh()
```

Applies the `Tanh` function element-wise to the input `Tensor`, thus outputting a `Tensor` of the same dimension.

`Tanh` is defined as:

```
f(x) = (exp(x) - exp(-x)) / (exp(x) + exp(-x))
```

```
ii = torch.linspace(-3, 3)
m = nn.Tanh()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

ReLU

```
f = nn.ReLU([inplace])
```

Applies the rectified linear unit (`ReLU`) function element-wise to the input `Tensor`, thus outputting a `Tensor` of the same dimension.

`ReLU` is defined as:

```
f(x) = max(0, x)
```

Can optionally do its operation in-place without using extra state memory:

```
f = nn.ReLU(true) -- true = in-place, false = keeping separate
state.
```

```
ii = torch.linspace(-3, 3)
m = nn.ReLU()
```

```
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

ReLU6

```
f = nn.ReLU6([inplace])
```

Same as `ReLU` except that the rectifying function `f(x)` saturates at `x = 6`.
This layer is useful for training networks that do not loose precision (due to FP saturation) when implemented as FP16.

`ReLU6` is defined as:

```
f(x) = min(max(0, x), 6)
```

Can optionally do its operation in-place without using extra state memory:

```
f = nn.ReLU6(true) -- true = in-place, false = keeping separate
state.
```

```
ii = torch.linspace(-3, 9)
m = nn.ReLU6()
oo = m:forward(ii)
go = torch.ones(100)
gi = m:backward(ii, go)
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```

PReLU

```
f = nn.PReLU()
```

Applies parametric `ReLU`, which parameter varies the slope of the negative part:

`PReLU` is defined as:

```
f(x) = max(0, x) + a * min(0, x)
```

When called without a number on input as `nn.PReLU()` uses shared version, meaning has only one parameter.
Otherwise if called `nn.PReLU(nOutputPlane)` has `nOutputPlane` parameters, one for each input map.
The output dimension is always equal to input dimension.
Note that weight decay should not be used on it.
For reference see Delving Deep into Rectifiers.

RReLU

```
f = nn.RReLU([l, u[, inplace]])
```

Applies the randomized leaky rectified linear unit (`RReLU`) element-wise to the input `Tensor`, thus outputting a `Tensor` of the same dimension.
Informally the `RReLU` is also known as 'insanity' layer.

`RReLU` is defined as:

```
f(x) = max(0,x) + a * min(0, x)
```

where `a ~ U(l, u)`.

In training mode negative inputs are multiplied by a factor `a` drawn from a uniform random distribution `U(l, u)`.
In evaluation mode a `RReLU` behaves like a `LeakyReLU` with a constant mean factor `a = (l + u) / 2`.
By default, `l = 1/8` and `u = 1/3`.
If `l == u` a `RReLU` effectively becomes a `LeakyReLU`.
Regardless of operating in in-place mode a `RReLU` will internally allocate an input-sized `noise` tensor to store random factors for negative inputs.
The `backward()` operation assumes that `forward()` has been called before.

For reference see Empirical Evaluation of Rectified Activations in Convolutional Network.

```
ii = torch.linspace(-3, 3)
m = nn.RReLU()
oo = m:forward(ii):clone()
gi = m:backward(ii, torch.ones(100))
gnuplot.plot({'f(x)', ii, oo, '+-'}, {'df/dx', ii, gi, '+-'})
gnuplot.grid(true)
```


CReLU

```
f = nn.CReLU(nInputDims, [inplace])
```

Applies the Concatenated Rectified Linear Unit (`CReLU`) function to the input Tensor, outputting a `Tensor` with twice as many channels. The parameter `nInputDim` is the number of non-batched dimensions, larger than that value will be considered batches.
`CReLU` is defined as:

```
f(x) = concat(max(0, x), max(0, -x))
```

i.e. `CReLU` applies `ReLU` to the input, `x`, and the negated input, `-x`, and concatenates the output along the 1st non-batched dimension.

```
crelu = nn.CReLU(3)
input = torch.Tensor(2, 3, 20, 20):uniform(-1, 1)
```

```
output = crelu:forward(input)
output:size()
2
6
20
20
[torch.LongStorage of size 4]

input = torch.Tensor(3, 20, 20):uniform(-1, 1)
output = crelu:forward(input)
output:size()
6
20
20
[torch.LongStorage of size 3]
```

For reference see Understanding and Improving Convolutional Neural Networks via Concatenated Rectified Linear Units.

ELU

```
f = nn.ELU([alpha[, inplace]])
```

Applies exponential linear unit (`ELU`), which parameter a varies the convergence value of the exponential function below zero:

`ELU` is defined as:

```
f(x) = max(0, x) + min(0, alpha * (exp(x) - 1))
```

The output dimension is always equal to input dimension.

For reference see Fast and Accurate Deep Network Learning by Exponential Linear Units (ELUs).

```
xs = torch.linspace(-3, 3, 200)
go = torch.ones(xs:size(1))
function f(a) return nn.ELU(a):forward(xs) end
function df(a) local m = nn.ELU(a) m:forward(xs) return
```

```
  m:backward(xs, go) end

  gnuplot.plot({'fw ELU, alpha = 0.1', xs,  f(0.1), '-'},
               {'fw ELU, alpha = 1.0', xs,  f(1.0), '-'},
               {'bw ELU, alpha = 0.1', xs, df(0.1), '-'},
               {'bw ELU, alpha = 1.0', xs, df(1.0), '-'})
  gnuplot.grid(true)
```

LeakyReLU

```
  f = nn.LeakyReLU([negval[, inplace]])
```

Applies `LeakyReLU`, which parameter `negval` sets the slope of the negative part:

`LeakyReLU` is defined as:

```
  f(x) = max(0, x) + negval * min(0, x)
```

Can optionally do its operation in-place without using extra state memory:

```
  f = nn.LeakyReLU(negval, true) -- true = in-place, false = keeping
  separate state.
```

GatedLinearUnit

Applies a Gated Linear unit activation function, which halves the input dimension as follows:

`GatedLinearUnit` is defined as `f([x1, x2])` = `x1 * sigmoid(x2)`

where x1 is the first half of the input vector and x2 is the second half. The multiplication is component-wise, and the input vector must have an even number of elements.

The GatedLinearUnit optionally takes a `dim` parameter, which is the dimension of the input tensor to operate over. It defaults to the last dimension.

SpatialSoftMax

```
f = nn.SpatialSoftMax()
```

Applies `SoftMax` over features to each spatial location (height x width of planes).
The module accepts 1D (vector), 2D (batch of vectors), 3D (vectors in space) or 4D (batch of vectors in space) `Tensor` as input.
Functionally it is equivalent to `SoftMax` when 1D or 2D input is used.
The output dimension is always the same as input dimension.

```
ii = torch.randn(4, 8, 16, 16)  -- batchSize x features x height x
width
m = nn.SpatialSoftMax()
oo = m:forward(ii)
```

SpatialLogSoftMax

Applies LogSoftMax over features to each spatial location (height x width of planes).
The module accepts 1D (vector), 2D (batch of vectors), 3D (vectors in space) or 4D (batch of vectors in space) tensor as input.
Functionally it is equivalent to LogSoftMax when 1D or 2D input is used.
The output dimension is always the same as input dimension.

```
ii=torch.randn(4,8,16,16)  -- batchSize x features x height x width
m=nn.SpatialLogSoftMax()
oo = m:forward(ii)
```

AddConstant

```
f = nn.AddConstant(k[, inplace])
```

Adds a (non-learnable) scalar constant.
This module is sometimes useful for debugging purposes.
Its transfer function is:

```
f(x) = x + k
```

where `k` is a scalar.

Can optionally do its operation in-place without using extra state memory:

```
f = nn.AddConstant(k, true) -- true = in-place, false = keeping
separate state.
```

In-place mode restores the original input value after the backward pass, allowing its use after other in-place modules, like `MulConstant`.

MulConstant

```
f = nn.MulConstant(k[, inplace])
```

Multiplies input `Tensor` by a (non-learnable) scalar constant.
This module is sometimes useful for debugging purposes.
Its transfer function is:

```
f(x) = k * x
```

where `k` is a scalar.

Can optionally do its operation in-place without using extra state memory:

```
m = nn.MulConstant(k, true) -- true = in-place, false = keeping
separate state.
```

In-place mode restores the original input value after the backward pass, allowing its use after other in-place modules, like `AddConstant`.