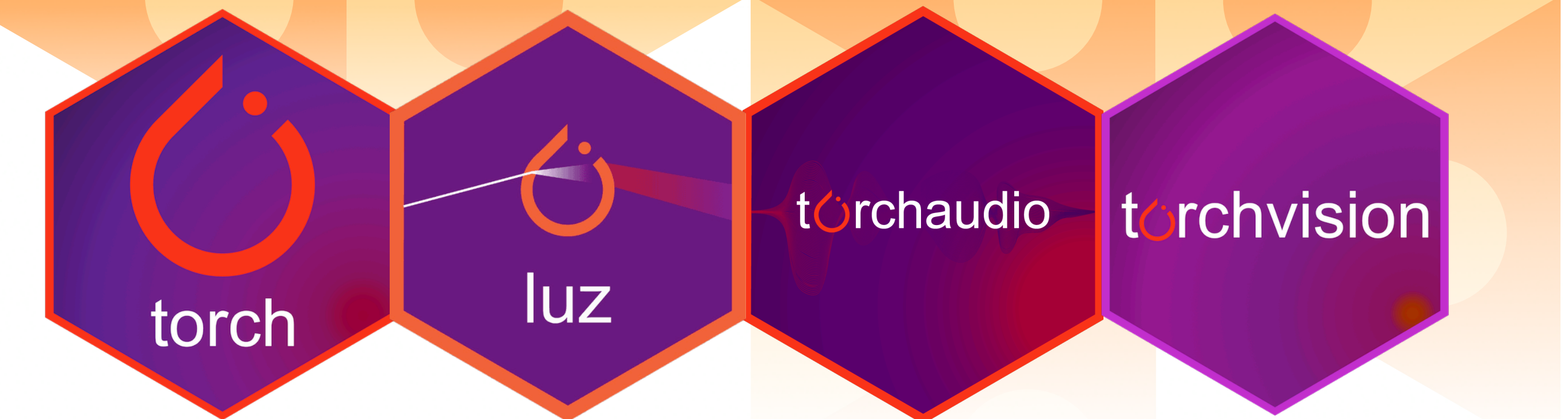


Deep Learning with {torch} CHEAT SHEET

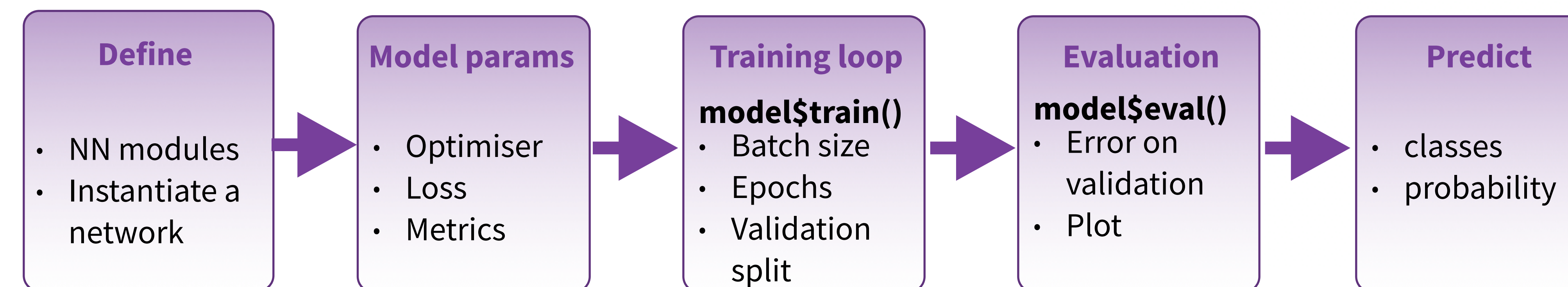


Intro

{torch} is based on Pytorch, a framework popular among deep learning researchers.

{torch}'s GPU acceleration allows to implement fast machine learning algorithms using its convenient interface, as well as a vast range of use cases, not only for deep learning, according to its flexibility and its low level API.

It is part of an ecosystem of packages to interface with specific dataset like {torchaudio} for timeseries-like, {torchvision} for image-like, and {tabnet} for tabular data. It is complemented by {lux} for a higher-level programming interface



<https://torch.mlverse.org/>

<https://mlverse.shinyapps.io/torch-tour/>

INSTALLATION

The torch R package uses the C++ libtorch library. You can install the prerequisites directly from R.

<https://torch.mlverse.org/docs/articles/installation.html>

```
install.packages("torch")
library(torch)
install_torch()
```

See ?install_torch for GPU instructions

Working with torch models

DEFINE A NN MODULE

```
dense <- nn_module(
  "no_biais_dense_layer",
  initialize = function(in_f, out_f) {
    self$w <- nn_parameter(torch_randn(in_f, out_f))
  },
  forward = function(x) {
    torch_mm(x, self$w)
  }
)
```

Create a nn module names no_biais_dense_layer

ASSEMBLE MODULES INTO NETWORK

```
model <- dense(4, 3)
```

Instantiate a network from a single module

```
model <- nn_sequential(
  dense(4,3), nn_relu(), nn_dropout(0.4),
  dense(3,1), nn_sigmoid())
```

Instantiate a sequential network with multiple layers

MODEL FIT

```
model$train()
# Turns on gradient update
```

```
with_enable_grad({
  y_pred <- model(trainset)
  loss <- (y_pred - y)$pow(2)$mean()
  loss$backward()
})
```

Detailed training loop step (alternative)

EVALUATE A MODEL

```
model$eval()
# or
with_no_grad({
  model(validationset)
})
```

Perform forward operation with no gradient update

OPTIMIZATION

```
optim_sgd()
# Stochastic gradient descent optimiser
```

```
optim_adam()
# ADAM optimiser
```

CLASSIFICATION LOSS FUNCTION

```
nn_cross_entropy_loss()
nn_bce_loss()
nn_bce_with_logits_loss()
# (Binary) cross-entropy losses
nn_nll_loss()
# Negative log-likelihood loss
nn_margin_ranking_loss()
nn_hinge_embedding_loss()
nn_multi_margin_loss()
nn_multilabel_margin_loss()
# (Multiclass) (multi label) hinge losses
```

REGRESSION LOSS FUNCTION

```
nn_l1_loss()
# L1 loss
nn_mse_loss()
# MSE loss
nn_ctc_loss()
# Connectionist Temporal Classification loss
nn_cosine_embedding_loss()
# Cosine embedding loss
nn_kl_div_loss()
# Kullback-Leibler divergence loss
nn_poisson_nll_loss()
# Poisson NLL loss
```

OTHER MODEL OPERATIONS

```
summary()
# Print a summary of a torch model
```

```
torch_save(); torch_load()
# Save/Load models to files
```

```
load_state_dict()
# Load a model saved in python
```

Neural-network layers

CORE LAYERS

nn_linear()
Add a linear transformation NN layer to an input

nn_bilinear() to two inputs

nn_sigmoid(), nn_relu()
Apply an activation function to an output

nn_dropout(), nn_dropout2d(), nn_dropout3d()
Applies Dropout to the input

nn_batch_norm1d(), nn_batch_norm2d(), nn_batch_norm3d()
Applies batch normalisation to the weights

CONVOLUTIONAL LAYERS

nn_conv1d() 1D, e.g. temporal convolution

nn_conv_transpose2d()
Transposed 2D (deconvolution)

nn_conv2d() 2D, e.g. spatial convolution over images

nn_conv_transpose3d()
Transposed 3D (deconvolution)

nn_conv3d() 3D, e.g. spatial convolution over volumes

nnf_pad()
Zero-padding layer

ACTIVATION LAYERS

nn_leaky_relu()
Leaky version of a rectified linear unit

nn_relu6()
rectified linear unit clamped by 6

nn_rrelu()
Randomized leaky rectified linear unit

nn_elu(), nn_selu()
Exponential linear unit, Scaled Exp lineal unit

POOLING LAYERS

nn_max_pool1d(), nn_max_pool2d(), nn_max_pool3d()
Maximum pooling for 1D to 3D

nn_avg_pool1d(), nn_avg_pool2d(), nn_avg_pool3d()
Average pooling for 1D to 3D

nn_adaptive_max_pool1d(), nn_adaptive_max_pool2d(), nn_adaptive_max_pool3d()
Adaptive maximum pooling

nn_adaptive_avg_pool1d(), nn_adaptive_avg_pool2d(), nn_adaptive_avg_pool3d()
Adaptive average pooling

RECURRENT LAYERS

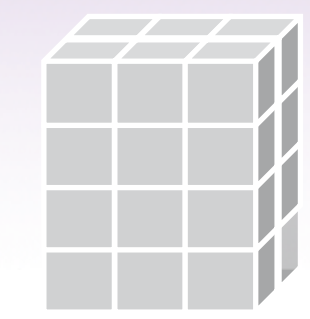
nn_rnn()
Fully-connected RNN where the output is to be fed back to input

nn_gru()
Gated recurrent unit - Cho et al

nn_lstm()
Long-Short Term Memory unit - Hochreiter 1997

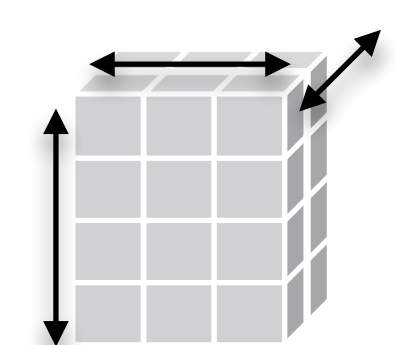
Tensor manipulation

TENSOR CREATION



tt ← **torch_rand(4,3,2)** uniform distrib.
tt ← **torch_randn(4,3,2)** unit normal distrib.
tt ← **torch_randint(1,7,c(4,3,2))** uniform integers within [1,7)
 Create a random values tensor with shape

tt ← **torch_ones(4,3,2)**
torch_ones_like(a)
 Create a tensor full of 1 with given shape, or with the same shape as 'a'. Also **torch_zeros**, **torch_full**, **torch_arange**,...



tt\$shape [1] 4 3 2 **tt\$ndim** [1] 3 **tt\$dtype** torch_Float
tt\$requires_grad [1] FALSE **torch_device(type='cpu')**
 Get 't' tensor shape and attributes

tt\$stride() [1] 6 2 1
 jump needed to go from one element to the next in each dimension



tt ← **torch_tensor(a, dtype=torch_float(), device="cuda")**
 Copy the R array 'a' into a tensor of float on the GPU

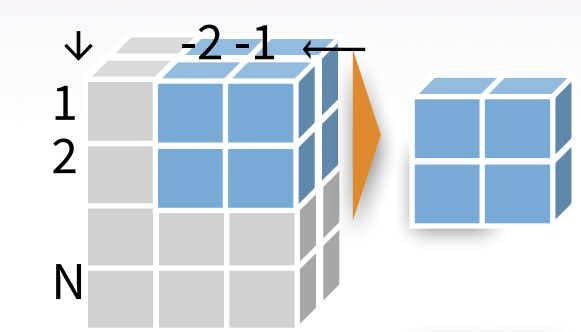


a ← **as.matrix(tt\$to(device="cpu"))**

TENSOR SLICING



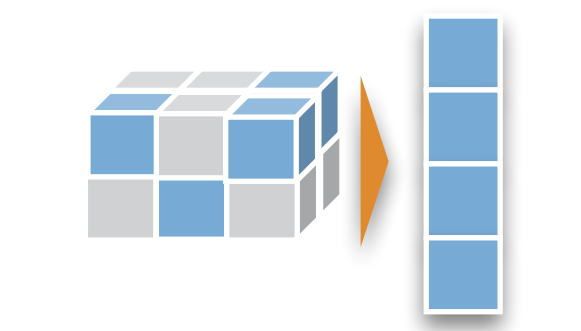
tt[1:2, -2:-1,]
 Slice a 3D tensor
tt[5:N, -2:-1, ..]
 Slice a 3D or more tensor, N for last



tt[1:2, -2:-1, 1:1]
tt[1:2, -2:-1, 1, keep=TRUE]
 Slice a 3D and keep the unitary dim.



tt[1:2, -2:-1, 1]
 Slice by default remove unitary dim.

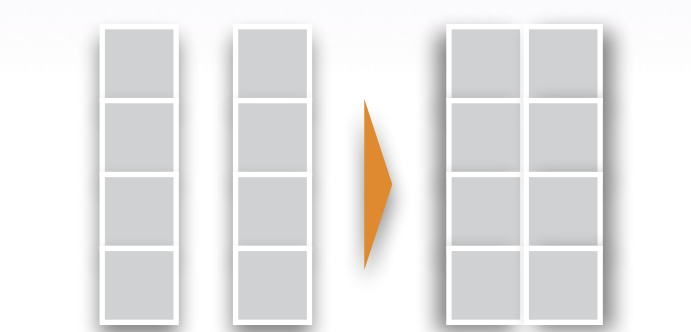


tt[tt > 3.1]
 Boolean filtering (flattened result)

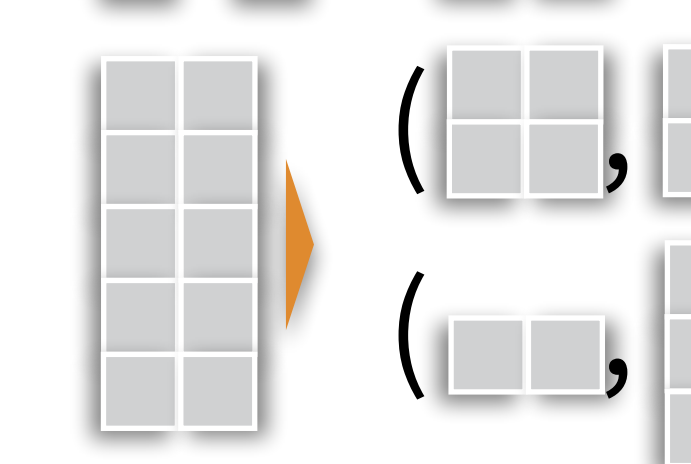
TENSOR CONCATENATION



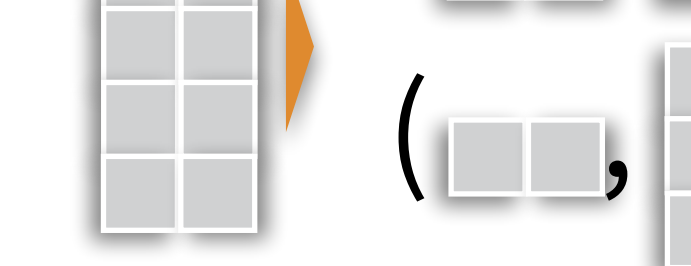
torch_stack()
 Stack of tensors



torch_cat()
 Assemble tensors

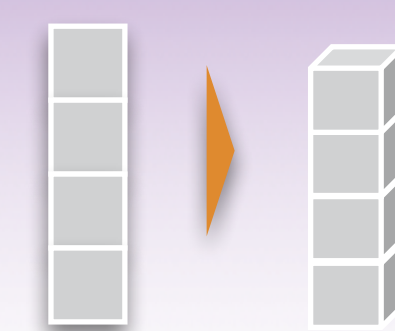


torch_split(2)
 split tensor in sections of size 2

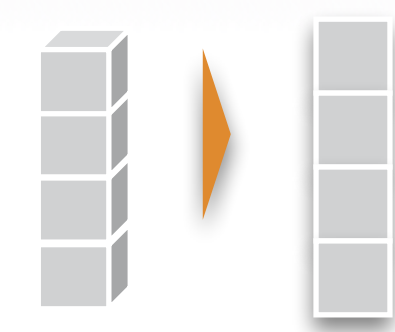


torch_split(c(1,3,1))
 split tensor into explicit sizes

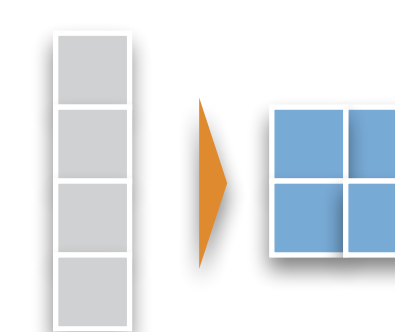
TENSOR SHAPE OPERATIONS



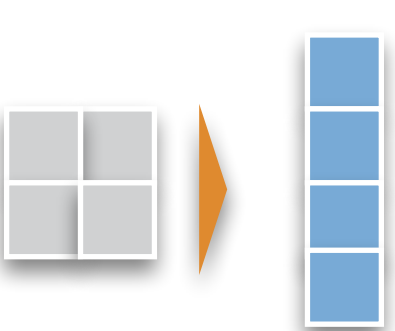
tt\$unsqueeze(1)
torch_unsqueeze(tt,1)
 Add a unitary dimension to tensor "tt" as first dimension



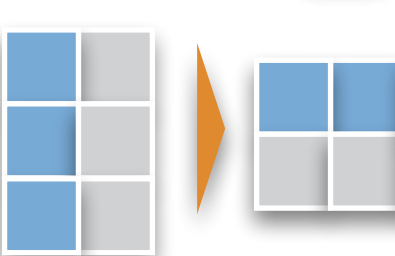
tt\$squeeze(1)
torch_squeeze(tt,1)
 Remove first unitary dimension to tensor "tt"



torch_reshape() **\$view()**
 Change the tensor shape, with copy or (tentatively) without



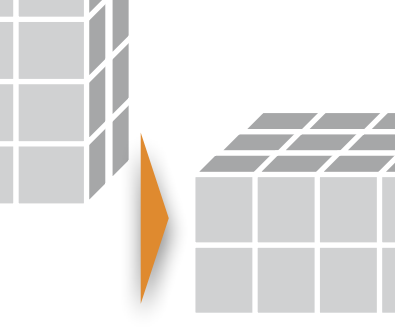
torch_flatten()
 Flattens an input



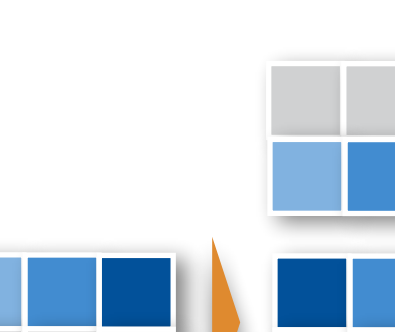
torch_transpose()



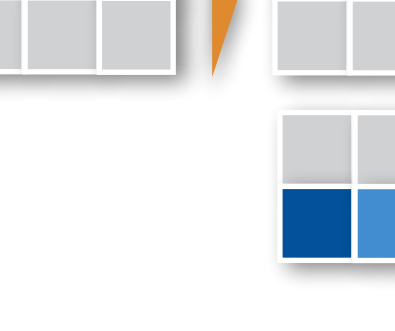
torch_movedim(c(1,2))
 switch dimension 1 with 2



torch_movedim(c(1,2,3), c(3,1,2))
 move dim 1 to dim 3, dim 2 to 1, dim 3 to 2
torch_permute(c(3,1,2))
 Only provide the target dimension order



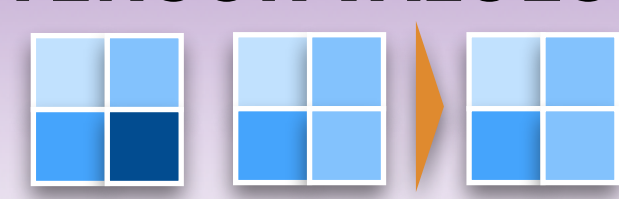
torch_flip(1) flip values along dim 1



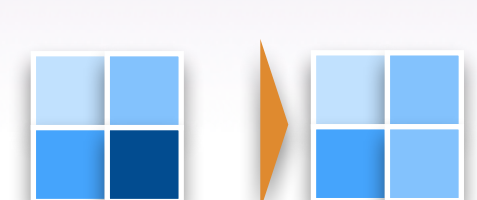
torch_flip(2) 2

torch_flip(c(1,2)) both dims

TENSOR VALUES OPERATIONS



+, -, *
 Operations with two tensors



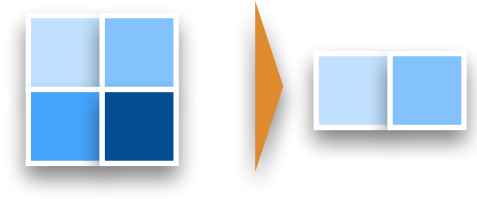
\$pow(2), \$log(), \$exp(), \$abs(), \$floor(), \$round(), \$cos(), \$fmod(3), \$fmax(1), \$fmin(3)
torch_clamp(tt, min=0.1, max=0.7)
 Element-wise operations on a tensor



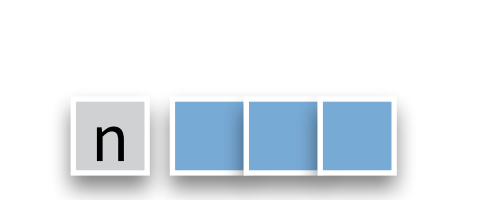
\$eq(), \$ge(), \$le()
 Element-wise comparison



\$to(dtype = torch_long())
 Mutate values type



\$sum(dim=1), \$mean(), \$max()
 Aggregation functions on a single tensor
\$amax()



torch_repeat_interleave()
 Repeats the input n times



TRAINING AN IMAGE RECOGNIZER ON MNIST DATA

5041

The "Hello, World!" of deep learning

Pre-trained models

Torch applications are deep learning models that are made available alongside pre-trained weights. These models can be used for prediction, feature extraction, and fine-tuning.

NATIVE R MODELS

library(torchvision)
resnet34 ← **model_resnet34(pretrained=TRUE)**
 Resnet image classification model

resnet34_headless ← **nn_prune_head(resnet34, 1)**
 Remove top layer of a model

IMPORTING FROM PYTORCH

{torchvisionlib} allows you to import a pytorch model without recoding its nn modules in R. This is done in two steps

1- instantiate the model in Python, script it, and save it:

```
import torch
import torchvision
```

```
model = torchvision.models.segmentation.fcn_resnet50(pretrained = True)
model.eval()
```

```
scripted_model = torch.jit.script(model)
torch.jit.save(scripted_model, "fcn_resnet50.pt")
```

2- load and use the model in R:

```
library(torchvisionlib)
model ← torch::jit_load("fcn_resnet50.pt")
```

Troubleshooting

HELPERS

with_detect_anomaly()
 Provides insight of a nn_module() behaviour

Callbacks

A callback is a set of functions to be applied at given stages of the training procedure. You can use callbacks to get a view on internal states and statistics of the model during training.

```
# load MNIST images through a data loader
library(torchvision)
train_ds ← mnist_dataset( root = "~/cache",
  download = TRUE,
  transform = torchvision::transform_to_tensor
)
test_ds ← mnist_dataset( root = "~/cache",
  train = FALSE,
  transform = torchvision::transform_to_tensor
)
train_dl ← dataloader(train_ds, batch_size = 32,
  shuffle = TRUE)
test_dl ← dataloader(test_ds, batch_size = 32)

# defining the model and layers
net ← nn_module(
  "Net",
  initialize = function() {
    self$fc1 ← nn_linear(784, 128)
    self$fc2 ← nn_linear(128, 10)
  },
  forward = function(x) {
    x %>% torch_flatten(start_dim = 2) %>%
      self$fc1() %>% nnf_relu() %>%
      self$fc2() %>% nnf_log_softmax(dim = 1)
  }
)
model ← net()
# define optimizer
optimizer ← optim_sgd(model$parameters, lr = 0.01)
# train (fit)
for (epoch in 1:10) {
  train_losses ← c()
  test_losses ← c()
  for (b in enumerate(train_dl)) {
    optimizer$zero_grad()
    output ← model(b[[1]]$to(device = device))
    loss ← nnf_nll_loss(output, b[[2]]$to(device = device))
    loss$backward()
    optimizer$step()
    train_losses ← c(train_losses, loss$item())
  }
  for (b in enumerate(test_dl)) {
    model$eval()
    output ← model(b[[1]]$to(device = device))
    loss ← nnf_nll_loss(output, b[[2]]$to(device = device))
    test_losses ← c(test_losses, loss$item())
    model$train()
  }
}
```