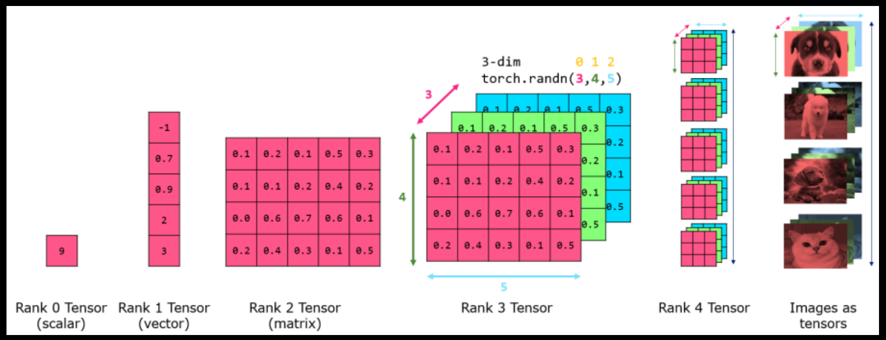
PyTorch CHEAT SHEET

Imports

```
import torch                                        # root package
from torch.utils.data import Dataset, DataLoader    # dataset representation and loading
```




```
# N-dim of tensor = number of square brackets [ on the left side
# [batch_size, hight, width, color_channels] NHWC # images alternative 1
# [batch_size, color_channels, hight, width] NCHW # images alternative 2
```

Tensors Creation

```
x = torch.tensor(data,dtype,device) # tensor with no autograd history
x = torch.arange(start,end,step)    # seqeuence
x = torch.randn(*size)              # tensor of random numbers from normal distribution N(0,1)
x = torch.[ones|zeros](*size)       # tensor with all 1's [or 0's]
x = torch.tensor(L)                 # tensor from [nested] list or ndarray L
x = torch.from_numpy(numpy_arr)     # tensor from a NumPy array
y = x.clone()                       # clone of x
with torch.no_grad():               # code wrap that stops autograd from tracking tensor history
requires_grad=True                  # arg, when set to True, tracks computation
                                    # history for future derivative calculations
```

Dimensionality

```
x.size()                            # return tuple-like object of dimensions
x = torch.cat(tensors,dim=0)        # concatenates tensors along dim WITHOUT changing the dim of
                                    # tensors
y = torch.stack(tensors,dim=0)      # stacks a sequence of tensors along a NEW dimension
y = x.view(a,b,...)                 # reshapes x into size (a,b,...)
y = x.view(-1,a)                    # reshapes x into size (b,a) for some b
y = x.transpose(a,b)                # swaps dimensions a and b
y = x.permute(*dims)                # Returns a view of the original input with its dimensions
                                    # permuted (rearranged) to dims
y = x.unsqueeze(dim)                # tensor with added axis
y = x.unsqueeze(dim=2)              # (a,b,c) tensor -> (a,b,1,c) tensor
y = x.squeeze()                     # removes all dimensions of size 1 (a,1,b,1) -> (a,b)
y = x.squeeze(dim=1)                # removes specified dimension of size 1 (a,1,b,1) -> (a,b,1)
y = x.reshape(shape)                # Reshapes input to shape (if compatible)
```

Math

```
# Algebra
ret = A * B          # element-wise multiplication
ret = A.mm(B)        # matrix multiplication / dot product
ret = A.mv(x)        # matrix-vector multiplication
x = x.t()            # matrix transpose

torch.abs(tensor)
torch.add(tensor, tensor2) # or tensor+scalar
torch.div(tensor, tensor2) # or tensor/scalar
torch.mult(tensor,tensor2) # or tensor*scalar
torch.sub(tensor, tensor2) # or tensor-scalar
torch.ceil(tensor)
torch.floor(tensor)
torch.remainder(tensor, devisor) #or torch.fmod()
torch.sqrt(tensor)
```

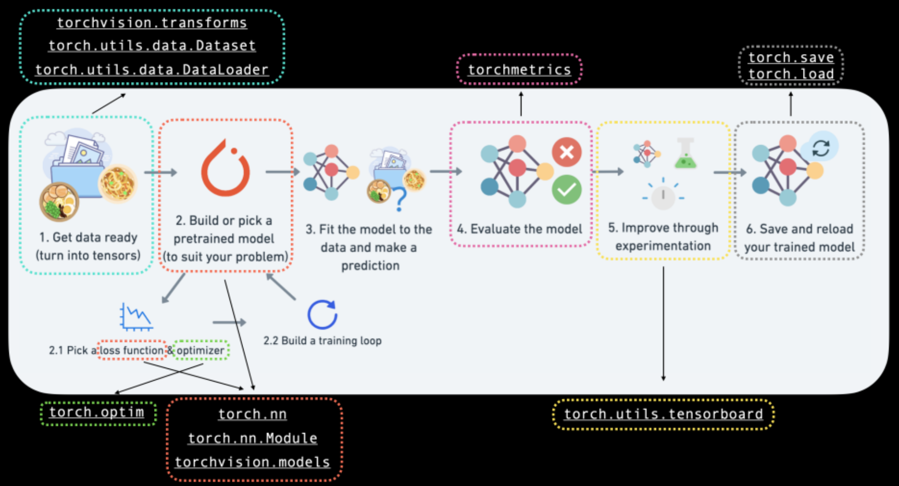
Torchscript and JIT

```
torch.jit.trace()      # takes your module or function and an example
                       # data input, and traces the computational steps
                       # that the data encounters as it progresses through the model

@script                # decorator used to indicate data-dependent
                       # control flow within the code being traced
```

ONNX

```
torch.onnx.export(model, dummy data, xxxx.proto)   # exports an ONNX formatted
                                                   # model using a trained model, dummy
                                                   # data and the desired file name

model = onnx.load("alexnet.proto")                 # load an ONNX model
onnx.checker.check_model(model)                    # check that the model
                                                   # IR is well formed

onnx.helper.printable_graph(model.graph)           # print a human readable
                                                   # representation of the graph
```

PyTorch Workflow



Data Utilities

```
Dataset                              # abstract class representing dataset
TensorDataset                        # labelled dataset in the form of tensors
Concat Dataset                       # concatenation of Datasets

DataLoader(dataset, batch_size=1, ...)   # loads data batches agnostic
                                         # of structure of individual data points

sampler.Sampler(dataset,...)         # abstract class dealing with
                                     # ways to sample from dataset

sampler.XSampler where ...           # Sequential, Random, SubsetRandom,
                                     # WeightedRandom, Batch, Distributed
```

Vision

```
# Base computer vision library
import torchvision

# Other components of TorchVision (premade datasets, pretrained models and image transforms)
from torchvision import datasets, models, transforms
```

Text

```
# Base text and natural language processing library
import torchtext

# Other components of TorchText (premade datasets, pretrained models and text transforms)
from torchtext import datasets, models, transforms
```

Audio and Speech

```
# Base audio and speech processing library
import torchaudio

# Other components of TorchAudio (premade datasets, pretrained models and text transforms)
from torchaudio import datasets, models, transforms
```

Recommendation systems

```
# Base recommendation system library
import torchrec

# Other components of TorchRec
from torchrec import datasets, models
```

GPU Usage

```
torch.cuda.is_available              # check for cuda
x = x.cuda()                         # move x's data from CPU to GPU
                                     # and return new object

x = x.cpu()                          # move x's data from GPU to CPU
                                     # and return new object

if torch.cuda.is_available():         # Setup device-agnostic code
    device = "cuda"                   # NVIDIA GPU
elif torch.backends.mps_is_available():
    device = "mps"                    # Apple GPU
else:
    device = "cpu"

net.to(device)                  # recursively convert their parameters
                                # and buffers to device specific tensors

x = x.to(device)                # copy your tensors to a device (gpu, cpu)
```

Neural Network API

```
import torch.autograd as autograd       # computation graph
from torch import Tensor                # tensor node in the computation graph
import torch.nn as nn                   # neural networks
import torch.nn.functional as F         # layers, activations and more
import torch.optim as optim             # optimizers e.g. gradient descent, ADAM, etc.
from torch.jit import script, trace     # hybrid frontend decorator and tracing jit
```

Deep Learning

```
nn.Linear(m,n)                          # fully connected layer from
                                        # m to n units

nn.ConvXd(m,n,s)                        # X dimensional conv layer from
                                        # m to n channels where X⍷{1,2,3}
                                        # and the kernel size is s

nn.MaxPoolXd(s)                         # X dimension pooling layer
                                        # (notation as above)

nn.BatchNormXd                          # batch norm layer
nn.RNN/LSTM/GRU                         # recurrent layers
nn.Dropout(p=0.5, inplace=False)        # dropout layer for any dimensional input
nn.Dropout2d(p=0.5, inplace=False)      # 2-dimensional channel-wise dropout
nn.Embedding(num_embeddings, embedding_dim)  # (tensor-wise) mapping from
                                        # indices to embedding vectors
```

Model Building

```
class NeuralNet(nn.Module):
    def __init__(self, input_size, hidden_size, num_classes):
        super().__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        out = self.fc1(x)
        out = self.relu(out)
        out = self.fc2(out)
        return out

model = NeuralNet(input_size, hidden_size, num_classes).to(device)
```

Loss Functions

```
nn.X                 # where X is L1Loss, MSELoss, CrossEntropyLoss
                     # CTCLoss, NLLLoss, PoissonNLLLoss,
                     # KLDivLoss, BCELoss, BCEWithLogitsLoss,
                     # MarginRankingLoss, HingeEmbeddingLoss,
                     # MultiLabelMarginLoss, SmoothL1Loss,
                     # SoftMarginLoss, MultiLabelSoftMarginLoss,
                     # CosineEmbeddingLoss, MultiMarginLoss,
                     # or TripletMarginLoss
```

Activation Functions

```
nn.X                 # where X is ReLU, ReLU6, ELU, SELU, PReLU, LeakyReLU,
                     # RReLu, CELU, GELU, Threshold, Hardshrink, HardTanh,
                     # Sigmoid, LogSigmoid, Softplus, SoftShrink,
                     # Softsign, Tanh, TanhShrink, Softmin, Softmax,
                     # Softmax2d, LogSoftmax or AdaptiveSoftmaxWithLoss
```

Optimizers

```
opt = optim.x(model.parameters(), ...)    # create optimizer
opt.step()                                # update weights
optim.X                                   # where X is SGD, Adadelta, Adagrad, Adam,
                                          # AdamW, SparseAdam, Adamax, ASGD,
                                          # LBFGS, RMSprop or Rprop
```

Learning rate scheduling

```
scheduler = optim.X(optimizer,...)     # create lr scheduler
scheduler.step()                       # update lr after optimizer updates weights
optim.lr_scheduler.X                   # where X is LambdaLR, MultiplicativeLR,
                                       # StepLR, MultiStepLR, ExponentialLR,
                                       # CosineAnnealingLR, ReduceLROnPlateau, CyclicLR,
                                       # OneCycleLR, CosineAnnealingWarmRestarts,
```

Distributed Training

```
import torch.distributed as dist              # distributed communication
from torch.multiprocessing import Process     # memory sharing processes
```


Ahmad Alismail, linkedin.com/in/ahmadalismail1

Last updated: 11/2022

PyTorch Workflow: Daniel Bourke https://github.com/mrdbourke/pytorch-deep-learning

t data ready

data into PyTorch

tensors (e.g.,
on.transforms)
images into Dataset's
pped to labels or X's mapped
gh
ls.data.Dataset
aset subsequently into
r through
ls.data.DataLoader

ataLoader

r combines dataset and

data into a model. For training
ence.
ge **Dataset** into a Python
of smaller chunks.
er chunks are called batches or
s and can be set by the
e parameter.
?
more computationally

[ing Modular]()

o from notebooks to scripts
l built in a jupyter notebook
of code on the command line
rain.py
to store scrpits using
rs()
ript using %%writefile
me/file_name.py

Build or pick a pretrained Model

- Setting up device agnostic code (so our model can run on CPU or GPU if it's available)
- Costructing a model by subclassing nn.Module
- Create layers capable of handling X and y (considereing input and output shapes)
- Define a forward method (make use of operator fusion to improve performance on GPU: `return self.layer_3(self.relu(self.layer_2((x)))`
- Create an instance of the model and send it to target device
- Create a loss function (a.k.a loss criterion)
- Create an optimizer

[PyTorch Training Loop]()

- Put data on the available device `X_train.to(device)` (without this error will happen!)
- Loop through epochs
    - Loop through training batches, perform **training steps**, caculate loss per batch.
- Put model in training mode
- **Forward pass** - The model goes through all of the training data once, performing its `forward()` function calculations (`model(x_train)`)
- **Calculate the loss** - The model's output/predictions (logits for classification if the loss function has a layer to convert logits to probabilities) are compared to the ground truth (labels) and evaluated to see how wrong they are (`loss = loss_fn(y_pred, y_train)`.
- **Zero gradients** - The optimizers gradients are set to zero (they are accumulated by default) so they can be recalculated for the specific training step (`optimizer.zero_grad()`).
- **Perform backpropagation on the loss** - Computes the gradient of the loss with respect for every model parameter to be updated (each parameter with `requires_grad=True`). This is known as backpropagation, hence "backwards" (`loss.backward()`).
- **Step the optimizer (gradient descent)** - Update the parameters with `requires_grad=True` with respect to the loss gradients in order to improve them (`optimizer.step()`).

[PyTorch Testing Loop]()

- Put the model in evaluation mode
- Turn on `torch.inference_mode()` context manager to disable functionality such as gradient tracking for inference (since gradient trackingis not needed for inference)
- All predictions should be made with objects on the same device (e.g. data and model on **GPU** only or data and model on **CPU** only), i.e., `model.to(device)` and `X_test = X_test.to(device)`
- Pass the test data through the model. The model will generate logits (the raw outputs). Convert **logits** -> prediction **probabilities** (with `sigmoid/softmax`) -> predictions **labels** (with `argmax(dim=1)`)
- NOTE: call `y_pred.cpu()` on your target tensor to return a copy of your target tensor on the CPU because some libraries aren't capable of using data that is stored on GPU

Top PyTorch and DL Errors

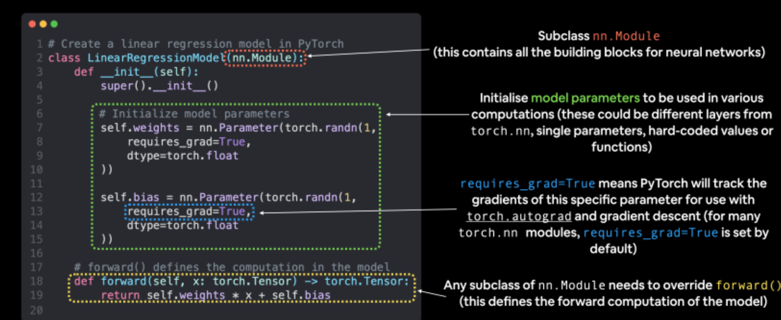
- **Wrong datatypes**: Your Model expected `torch.float32` when your data is `tor`
- **Wrong data shapes**: Your model expected `[batch_size, color_channels,` `width]` when your data is `[color_channels, height, width]`
- **Wrong devices:** Your model is on the GPU but your data is on the CPU.

Prevent Overfitting

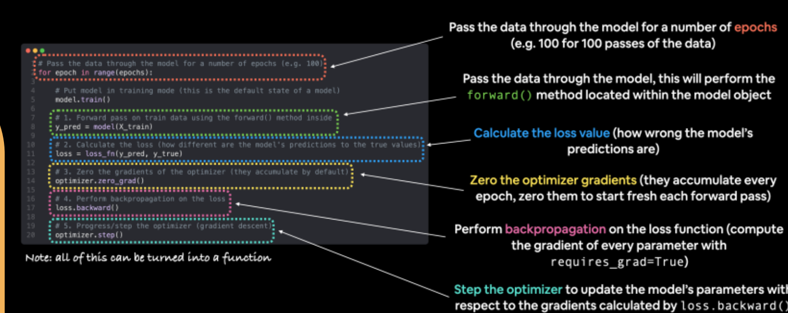
- [Interpreting Learning Curve]()
- Get more data
- Use regularization
- Simplify your model
- Use data augmentation
- Use transfer learning
- Use dropout layers
- Use learning rate decay
- Use early stopping

Prevent Unde

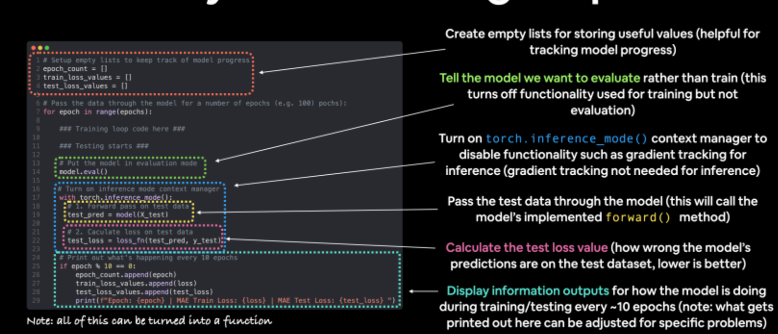
- Add more layers/units
- Tweak the learning rate
- Use transfer learning
- Train for longer
- Use less regularization



PyTorch training loop



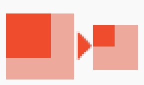
PyTorch testing loop



en source machine learning framework. It uses **torch.Tensor** – multi-dimensional
rocess. A core feature of neural networks in PyTorch is the autograd package,
automatic derivative calculations for all operations on tensors.

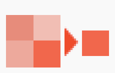
	Root package	torch.randn(*size)	Create random tensor
s nn	Neural networks	torch.Tensor(L)	Create tensor from list
mport transforms	Popular image datasets, architectures & transforms	tnsr.view(a,b, ...)	Reshape tensor to size (a, b, ...)
nctional as F	Collection of layers, activations & more	requires_grad=True	tracks computation history for derivative calculations

m, n): Fully Connected
ense layer) from
rons



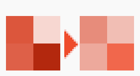
nn.ConvXd(m, n, s): X-dimensional convolutional layer from m to n channels with kernel size s; X ∈ {1, 2, 3}

(): Flattens a contiguous
imensions into a tensor



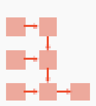
nn.MaxPoolXd(s): X-dimensional pooling layer with kernel size s; X ∈ {1, 2, 3}

t(p=0.5): Randomly
elements to zero during
prevent overfitting



nn.BatchNormXd(n): Normalizes a X-dimensional input batch with n features; X ∈ {1, 2, 3}

ding(m, n): Lookup table
tionary of size m to
g vector of size n



nn.RNN/LSTM/GRU: Recurrent networks connect neurons of one layer with neurons of the same or a previous layer

unch of other building blocks.
e-art architectures can be found at https://paperswithcode.com/sota.

a

resented by a class that
ataset (resembles a list
form (features, label)).

ows to load a dataset
about its structure.

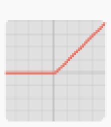
aset is split into training
est data (e.g. 20%).

```
utils.data
aset, TensorDataset,
aLoader, random_split

 test_data =
it(
ataset(inps, tgts),
size,test_size]

er =
oader(
ataset=train_data,
atch_size=16,
uffle=True)
```

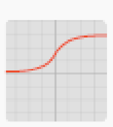
Activation functions

Common activation functions include **ReLU**, **Sigmoid** and **Tanh**, but there are other activation functions as well.

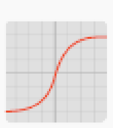
nn.ReLU() *creates a* nn.Module *for example to be used in Sequential models.* F.relu() *ist just a call of the ReLU function e.g. to be used in the* forward *method.*



nn.ReLU() or F.relu()
Output between 0 and ∞,
most frequently used activation function



nn.Sigmoid() or F.sigmoid()
Output between 0 and 1,
often used for predicting probabilities



nn.Tanh() or F.tanh()
Output between -1 and 1,
often used for classification with two classes

Define model

There are several ways to define a neural network in PyTorch, e.g. with **nn.Sequential** (a), as a class (b) or using a combination of both.

```
model = nn.Sequential(
   nn.Conv2D(■,■,■)
   nn.MaxPool2D(■)
   nn.ReLU()
   nn.Flatten()
   nn.Linear(■,■)
)
```
a

```
class Net(nn.Module):
  def __init__():
    super(Net, self).__init__()

    self.conv
      = nn.Conv2D(■,■,■)
    self.pool
      = nn.MaxPool2D(■)
    self.fc = nn.Linear(■,■)

  def forward(self, x):
    x = self.pool(
          F.relu(self.conv(x))
        )
    x = x.view(-1,■)
    x = self.fc(x)
    return x
model = Net()
```
b

Train model

LOSS FUNCTIONS

PyTorch already offers a bunch of different loss fuctions, e.g.:

nn.L1Loss	Mean absolute error
nn.MSELoss	Mean squared error (L2Loss)
nn.CrossEntropyLoss	Cross entropy, e.g. for single-label classification or unbalanced training set
nn.BCELoss	Binary cross entropy, e.g. for multi-label classification or autoencoders

OPTIMIZATION (torch.optim)

Optimization algorithms are used to update weights and dynamically adapt the learning rate with gradient descent, e.g.:

optim.SGD	Stochastic gradient descent
optim.Adam	Adaptive moment estimation
optim.Adagrad	Adaptive gradient
optim.RMSProp	Root mean square prop

```
import torch.optim as optim

# Define loss function
loss_fn = nn.CrossEntropyLoss()

# Choose optimization method
optimizer = optim.SGD(model.param
                lr=0.001, mome

# Loop over dataset multiple time
for epoch in range(2):
    model.train() # activate trai
    for i, data in enumerate(trai
        # data is a batch of [inp
        inputs, labels = data

        # zero gradients
        optimizer.zero_grad()

        # calculate outputs
        outputs = model(inputs)
        # calculate loss & backpr
        loss = loss_fn(outputs, l
        loss.backward()
        # update weights & learni
        optimizer.step()
```

```
correct = 0 # correctly classified
total   = 0 # classified in total

model.eval()
with torch.no_grad():
  for data in test_loader:
    inputs, labels = data
    outputs = model(inputs)
    _, predicted = torch.max(outputs.data, 1)
    total += labels.size(0) # batch size
    correct += (predicted==labels)
                  .sum().item()

print('Accuracy: %s' % (correct/total))
```

Save/Load model

model = torch.load('PATH')	Load mo
torch.save(model, 'PATH')	Save mo

It is common practice to save only the model para
whole model using model.state_dict()

```
torch.save(model.state_dict(), 'p
model.load_state_dict(
                torch.load('para
```

GPU Training

device = torch.device('cuda:0' if torch.cuda.is_a

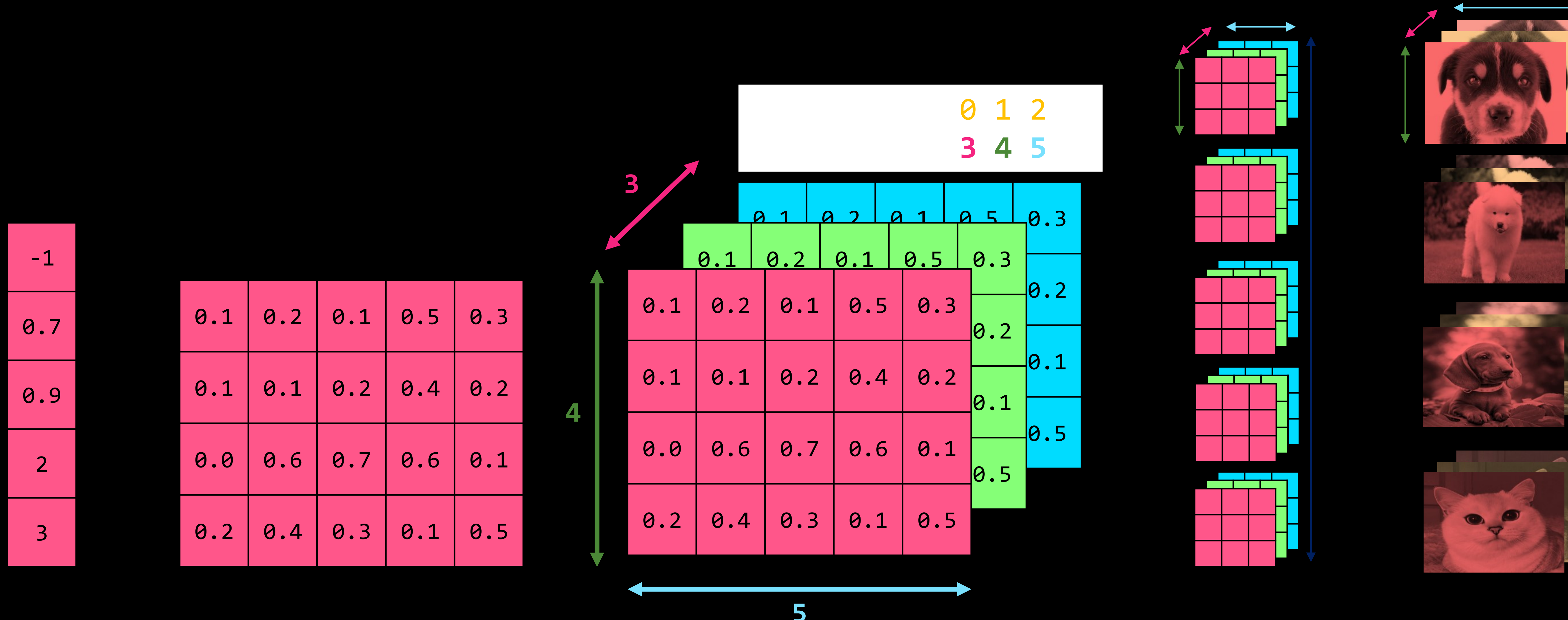
If a GPU with CUDA support is available, comput
the GPU with ID 0 using model.to(device) or
inputs, labels = data[0].to(device), data[1].to(de

Evaluate model

The evaluation examines whether the mo
satisfactory results on previously withhel
Depending on the objective, different met
such as acurracy, precision, recall, F1, or

model.eval()	Activates evaluation mode, behave differently
torch.no_grad()	Prevents tracking history, re usage, speeds up calculatio

tensor = # of square brackets [on the left side



ensor Rank 1 Tensor Rank 2 Tensor Rank 3 Tensor Rank 4 Tensor Images a
r) (vector) (matrix) tensors