Project 2

Release 1.0

Jodok Vieli[1], Puck van Gerwen[2], Felix Hoppe[3]

May 28, 2021

[1]SCIPER: 336284
[2]SCIPER: 283530
[3]SCIPER: 276062

1.0 Project2

Project2 is a minimal tensor library for deep learning using CPUs. Our current version can:

- Build networks combining fully connected layers, Tanh and ReLU
- Run forward and backward passes
- Optimize parameters with SGD and Adam optimizers for MSE

The deep learning functionality is in the `nn` module and the `Trainer` can be used to facilitate training models. The library has the following structure:

```
nn
  Module
    Layer
      Linear
    Loss
      MSELoss
    Sequential
    Activation
      ReLU
      Tanh
  functional
Trainer
```

A short example of how to use `Trainer` can be found in section 1.1.1. A test file `test.py` uses the library to train a fully connected network with 3 hidden layers on a toy 2D dataset of 1000 train and test points sampled from a uniform distribution where points inside a circle of radius $1/\sqrt{2\pi}$ are labelled 1, and all others labelled 0. Training for 100 epochs using SGD or Adam optimizers yield a test error rate of 4.52% or 4.10% respectively on average over 10 rounds of random data and weight reinitialization.

1.1 Python API

1.1.0 nn package

1.1.0.0 Submodules

1.1.0.1 nn.activation module

class nn.activation.**Activation**
Bases: *nn.module.Module*

Class to compute activation functions.

backward(*dy*)
Compute gradients of input.

Parameters **dy** (*torch.tensor*) – Backpropagated gradient from the next layer.

Returns Gradient

Return type torch.tensor

forward(*x*)
Compute the activation.

Parameters **x** (*torch.tensor*) – Input tensor.

class nn.activation.**ReLU**
Bases: *nn.activation.Activation*

forward(*x*)
Compute ReLU(x)

Parameters **x** (*torch.tensor*) – Input tensor.

Returns Computed ReLU.

Return type torch.tensor

class nn.activation.**Tanh**
Bases: *nn.activation.Activation*

forward(*x*)
Compute tanh(x)

Parameters **x** (*torch.tensor*) – Input tensor.

Returns Computed tanh(x).

Return type torch.tensor

1.1.0.2 nn.functional module

functional.py contains the concrete implementations of specific functionals.

nn.functional.**d_mse**(*x*, *y*)
Compute the gradient of the mean squared error.

Parameters

- **x** (*torch.tensor*) – Input tensor.
- **y** (*torch.tensor*) – Target tensor.

Returns Gradient of mean squared error.

Return type float

nn.functional.**d_relu**(*x*)
Compute gradient of ReLU(x)

Parameters **x** (*torch.tensor*) – Input tensor

Returns Output tensor

Return type torch.tensor

nn.functional.**d_tanh**(*x*)
Compute gradient of tanh(x)

Parameters **x** (*torch.tensor*) – Input tensor

Returns Output tensor

Return type torch.tensor

nn.functional.**mse**(*x*, *y*)
Compute the mean squared error.

Parameters

- **x** (*torch.tensor*) – Input tensor.
- **y** (*torch.tensor*) – Target tensor.

Returns Mean squared error.

Return type torch.tensor

nn.functional.**relu**(*x*)
Compute ReLU(x)

Parameters **x** (*torch.tensor*) – Input tensor

Returns Output tensor

Return type torch.tensor

nn.functional.**tanh**(*x*)
Compute tanh(x).

Parameters **x** (*torch.tensor*) – Input tensor

Returns Output tensor

Return type torch.tensor

1.1.0.3 nn.linear module

class nn.linear.**Layer**
Bases: *nn.module.Module*

Layer implements layers that can be used in a network architecture.

param()
Return the params of the Layer.

update_param(**args*, ***kwargs*)
Update the params of the Layer based on the cached gradients

class nn.linear.**Linear**(*dim_in*, *dim_out*)
Bases: *nn.linear.Layer*

__init__(*dim_in*, *dim_out*)
Initialize object of type Linear with random parameters.

Parameters

- **dim_in** (*int*) – Dimension of input.
- **dim_out** (*int*) – Dimension of output.

backward(*dy*)
Compute gradients of input and parameters.

Parameters **dy** (*torch.tensor*) – Backpropagated gradient from the next layer.

Returns Gradient.

Return type torch.tensor

forward(*x*)
Calculate output of Linear layer.

Parameters **x** (*torch.tensor*) – Input tensor of size (batch_size, input_dim)

Returns Output tensor of size (batch_size, output_dim)

Return type torch.tensor

param()
Get parameters of the linear layer from the cache.

Returns weight and bias of linear layer.

Return type torch.tensor, torch.tensor

1.1.0.4 nn.loss module

class nn.loss.**Loss**
Bases: *nn.module.Module*

The Loss Module is used to implement a node in the network that computes the loss. For the computation of any function the respective functional from functional.py should be used.

backward()
Backward pass.

Returns Backpropagated gradient from the next layer.

Return type torch.tensor

forward(*x*, *y*)
Compute the loss. :param x: Input tensor. :type x: torch.tensor :param y: Target tensor. :type y: torch.tensor

class nn.loss.**MSELoss**
Bases: *nn.loss.Loss*

forward(*x*, *y*)
Compute the mean squared error.

Parameters

- **x** (*torch.tensor*) – Input tensor.
- **y** (*torch.tensor*) – Target tensor.

Returns Mean squared error.

Return type torch.tensor

1.1.0.5 nn.module module

class nn.module.**Module**
Bases: object

Base Module with core functionality

__init__()
Initialize object of type Module with empty cache. The cache will be used to store information for subsequent passes such as the local gradient.

backward(**args*, ***kwargs*)
Compute backward pass

forward(**args*, ***kwargs*)
Compute forward pass

1.1.0.6 nn.sequential module

class nn.sequential.**Sequential**(*modules*, *loss_fn*)
Bases: *nn.module.Module*

Sequential allows multiple layers to be combined in a network architecture.

__init__(*modules*, *loss_fn*)
Create a sequential network.

Parameters

- **modules** (*list* (*Module*)) – List of modules.
- **loss_fn** (*str*) – loss function.

Example

```
>>> LinNet = Sequential((
        Linear(2, 25),
        ReLU(),
        Linear(25, 25),
        ReLU(),
        Linear(25, 25),
        ReLU(),
        Linear(25, 1)),
        MSELoss()
    )
>>> print(LinNet)
Sequential(
    (0): Linear(in_features=2, out_features=25, bias=True)
    (1): ReLU()
    (2): Linear(in_features=25, out_features=25, bias=True)
    (3): ReLU()
    (4): Linear(in_features=25, out_features=25, bias=True)
    (5): ReLU()
    (6): Linear(in_features=25, out_features=1, bias=True)
)
```

backward()
Perform backward pass.

forward(*x*)
Perform forward pass.

Parameters **x** (*torch.tensor*) – Input tensor

Returns Output tensor

Return type torch.tensor

loss(*x*, *y*)
Compute loss between two tensors.

Parameters

- **x** (*torch.tensor*) – Input tensor
- **y** (*torch.tensor*) – Target tensor

Returns Loss

Return type torch.tensor

print()
str: Print model architecture.

test_step(*x*, *y*)
Test step. Wrapper for validation_step.

Parameters

- **x** (*torch.tensor*) – Input tensor
- **y** (*torch.tensor*) – Target tensor

Returns Loss

Return type torch.tensor

training_step(*x*, *y*)
Training step.

Parameters

- **x** (*torch.tensor*) – Input tensor
- **y** (*torch.tensor*) – Target tensor

Returns Loss

Return type torch.tensor

update_params(*optim*, *lr*)

Update the parameters of the network iteratively according to the cached gradients at each module.

Parameters

- **optim** (*str*) – The optimizer to use. options are 'adam' or 'sgd'
- **lr** (*float*) – Learning rate

validation_step(*x*, *y*)
Validation step.

Parameters

- **x** (*torch.tensor*) – Input tensor
- **y** (*torch.tensor*) – Target tensor

Returns Loss

Return type torch.tensor

1.1.1 trainer module

class trainer.**Trainer**(*nb_epochs*)
Bases: object

__init__(*nb_epochs*)
Create a trainer by specifying the number of epochs to train.

Parameters

- **nb_epochs** (*int*) – Number of epochs to train
- **verbose** (*bool*) – Whether or not to output training information.

fit(*model*, *x_train*, *y_train*, *x_val*, *y_val*, *batch_size=32*, *lr=0.01*, *optim='sgd'*, *verbose=True*, *print_every=32*)
Train the model on the specified data and print the training and validation loss and accuracy.

Parameters

- **model** (*nn.Module*) – Model to train
- **x_train** (*torch.tensor*) – Training data
- **y_train** (*torch.tensor*) – Training labels
- **x_val** (*torch.tensor*) – Validation data
- **y_val** (*torch.tensor*) – Validation labels
- **batch_size** (*int*) – Batch sizes for training and validation
- **lr** (*float*) – Learning rate for optimization (Default is 0.01)
- **optim** (*str*) – Optimizer (options are 'sgd' or 'adam'. Default is 'sgd')
- **verbose** (*bool*) – Whether or not to output training information (Default is True)
- **print_every** (*str*) – How often to print progress (Default is every 32 steps)

Example

Use the trainer to fit a new nn model.

```
>>> from trainer import Trainer
>>> from torch import empty
>>> from nn.sequential import Sequential
>>> ... # Read data into x_train, y_train, x_test, y_test
>>> LinNet = Sequential((Linear(2, 1), MSELoss()))
>>> trainer = Trainer(nb_epochs=25)
>>> loss_train, loss_val = trainer.fit(LinNet, x_train, y_
↪train, x_test, y_test, batch_size=32, lr=0.1, print_
↪every=10, optim='sgd')
```

test(*model*, *x_test*, *y_test*, *batch_size=32*, *test_verbose=True*)
Test the model on the specified data.

Parameters

- **model** (*nn.Module*) – Model to train
- **x_test** (*torch.tensor*) – Test data
- **y_test** (*torch.tensor*) – Test labels
- **batch_size** (*int*) – Batch size for testing
- **test_verbose** (*bool*) – Whether the test result should be printed

Example

Use the trainer to test an existing nn model.

```
>>> from trainer import Trainer
>>> from torch import empty
>>> ... # Train model LinNet
>>> ... # Read data into x_train, y_train, x_test, y_test
>>> trainer = Trainer(nb_epochs=25)
>>> loss_test = trainer.test(LinNet, x_test, y_test, batch_
↪size=32, test_verbose=True)
loss_test=0.17
```