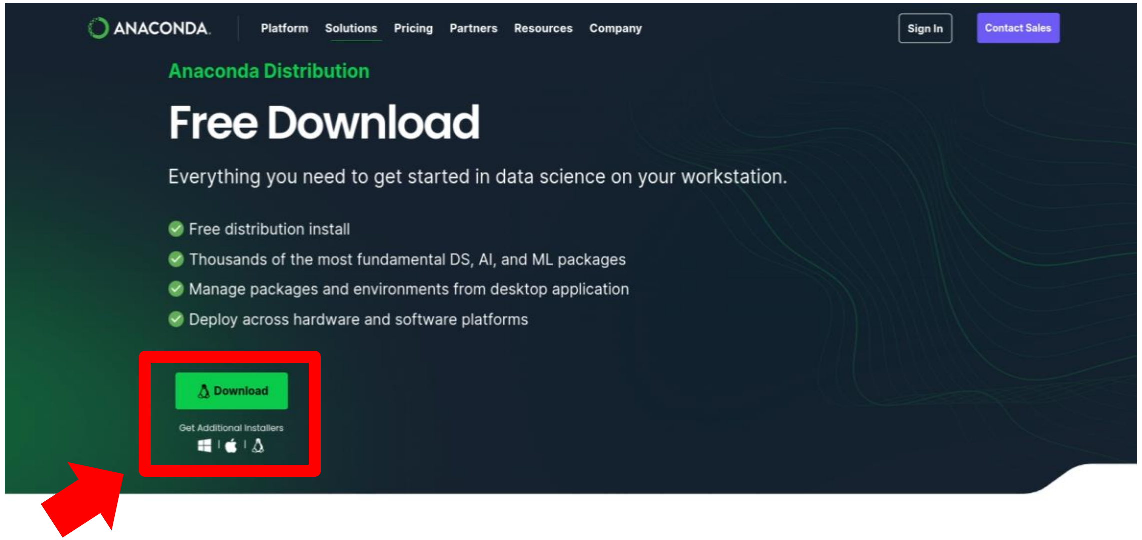
Natural Language Processing

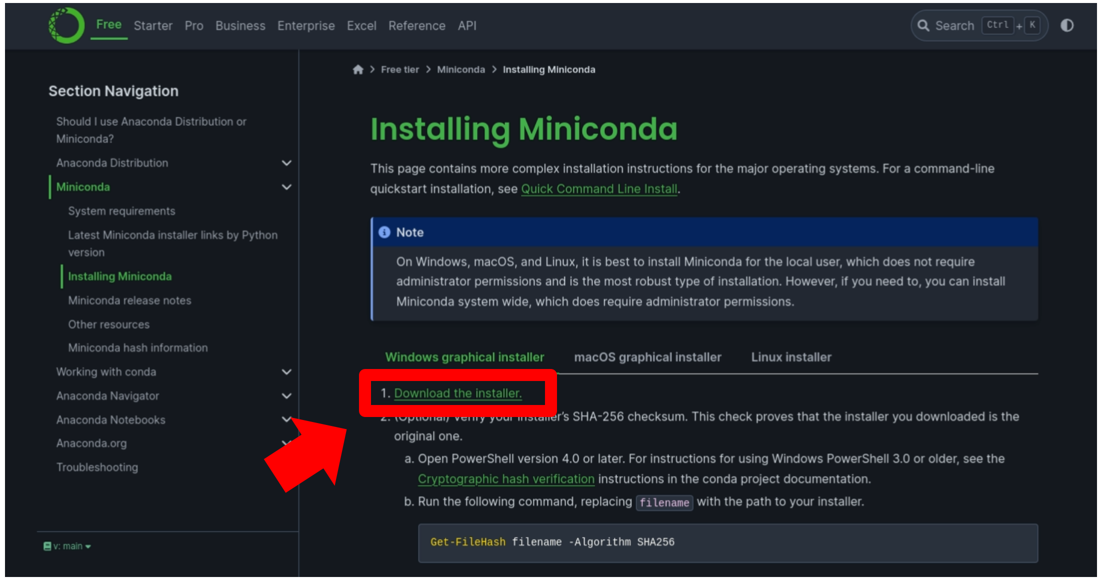
PyTorch tutorial

Environment setup

Download anaconda (https://www.anaconda.com/download)

or miniconda (https://docs.anaconda.com/free/miniconda/miniconda-install/)

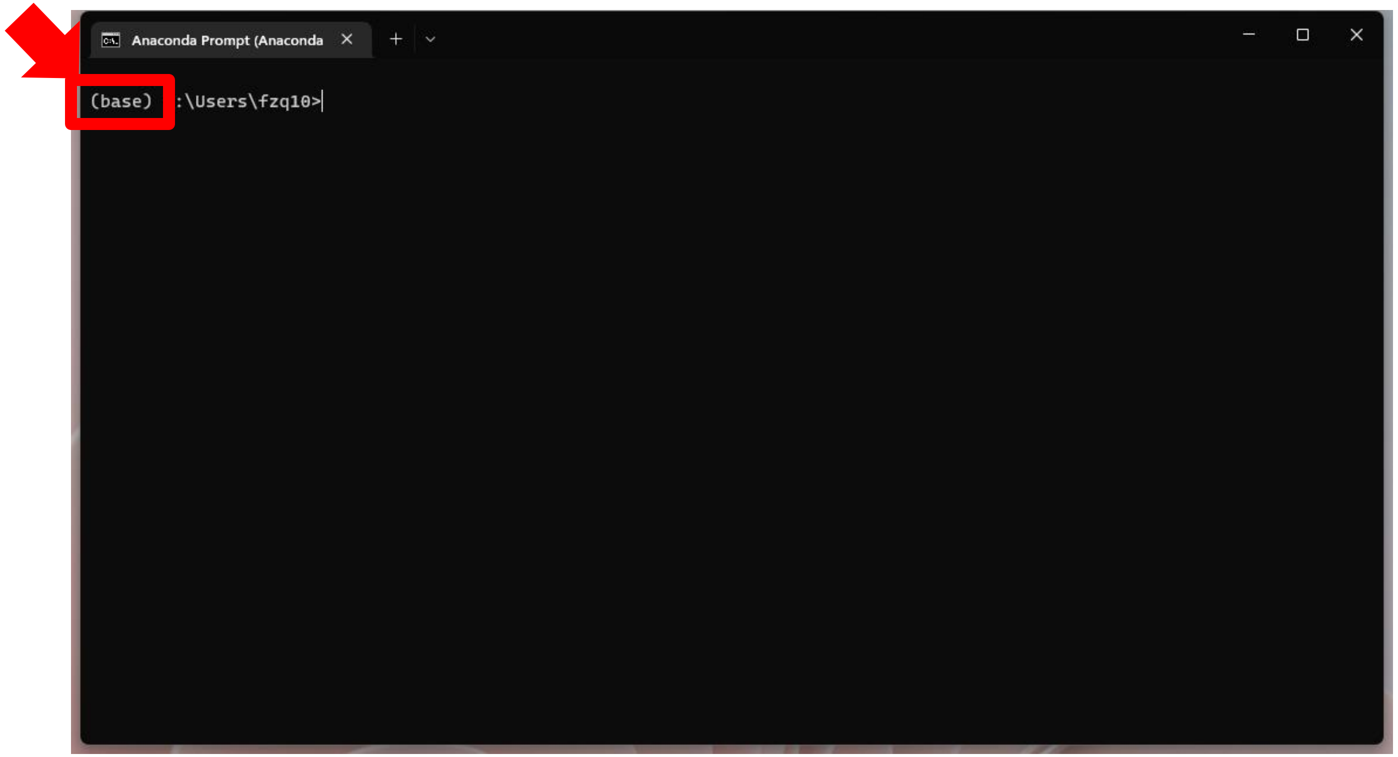




Environment setup

Open Anaconda prompt

Current environment



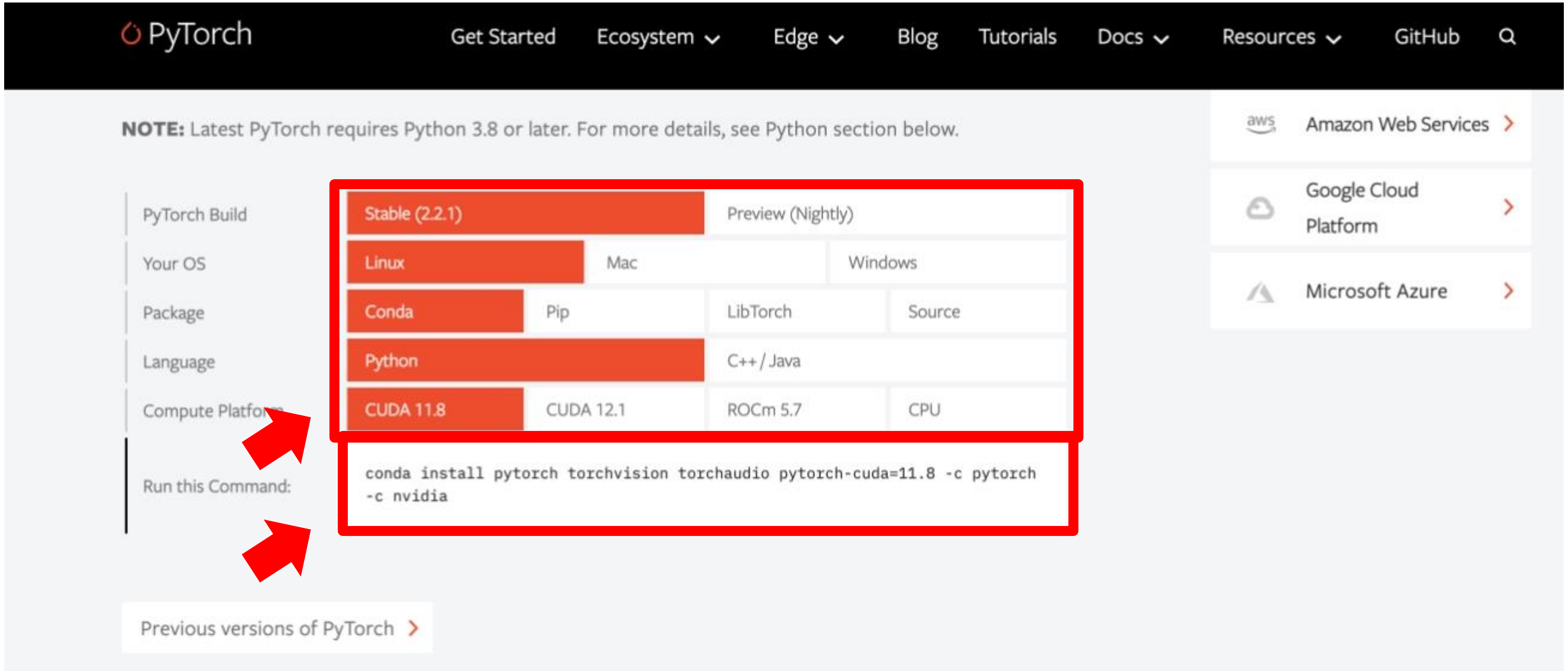
Basic Commands

After installing Anaconda, you can open the Anaconda Prompt and manage environments using commands. Alternatively, you can use the graphical interface, Anaconda Navigator, to perform operations directly.

1. Create python environment
   conda create –n (name) python=3.X.X
2. Activate python environment
   conda activate (name)
3. Exit environment
   conda deactivate
4. Check environments
   conda env list

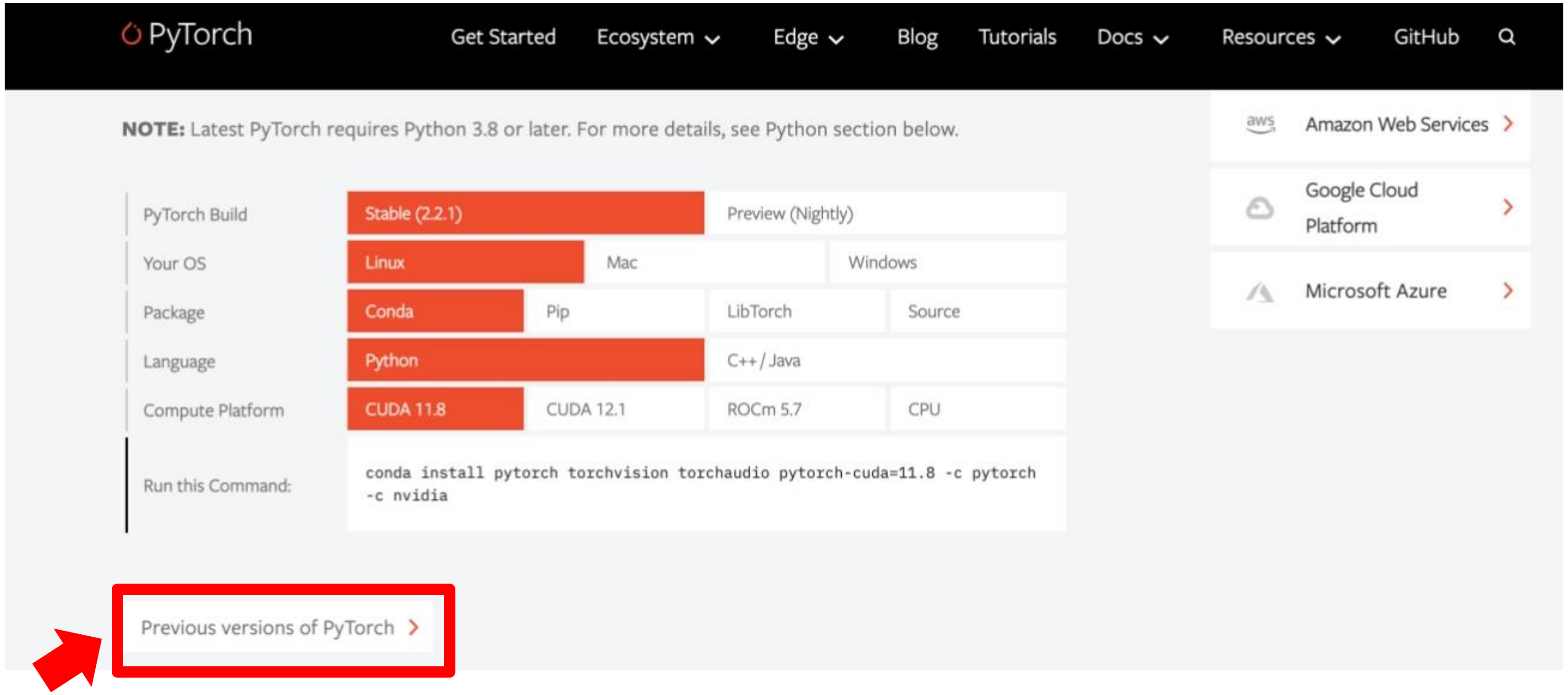
Install PyTorch

Install PyTorch: https://pytorch.org/



Install PyTorch

You can also choose an earlier version, but the main consideration is that your computer's hardware must support the corresponding version of CUDA.



Deep learning

Consider the polynomial relationship between y and x defined by the equation:

$$y = ax^2+b$$

Here, a and b are the parameters we want to learn, and x is the input variable.

We are given four data points to train this model:

$$(-1, 1), (1, 2), (2, 3)$$

These data points represent pairs of x values and corresponding y values.

For example, when $a=1$ and $b=1$, the predictions of $-1, 1, 2$ are respectively $2, 2, 5$.
We define the difference between predictions and ground truths as:

$$L = (\Sigma_i(y_i-y'_i)^2)/n$$

Gradient decend

We can visualize how the difference (error) changes with respect to different values of the parameters a and b by plotting a surface, or plane.

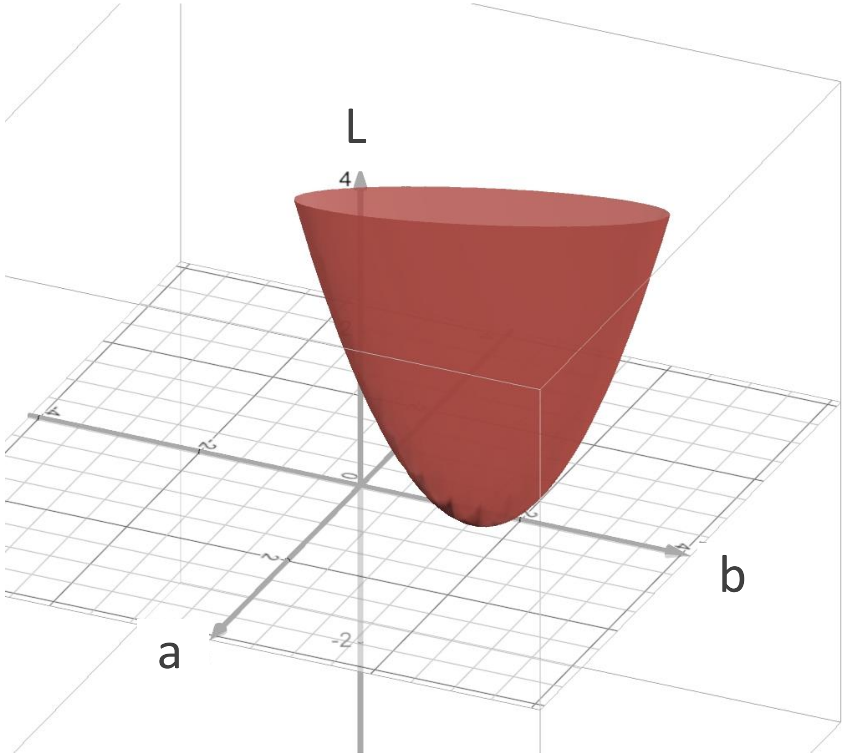
In deep learning, we optimize the parameters a and b using gradient descent.

We define:

$y = ax^2+b$ --> model

$L = (\Sigma_i(y_i-y'_i)^2)/n$ --> Loss function

The tool used to update a and b using gradient descent. --> Optimizer



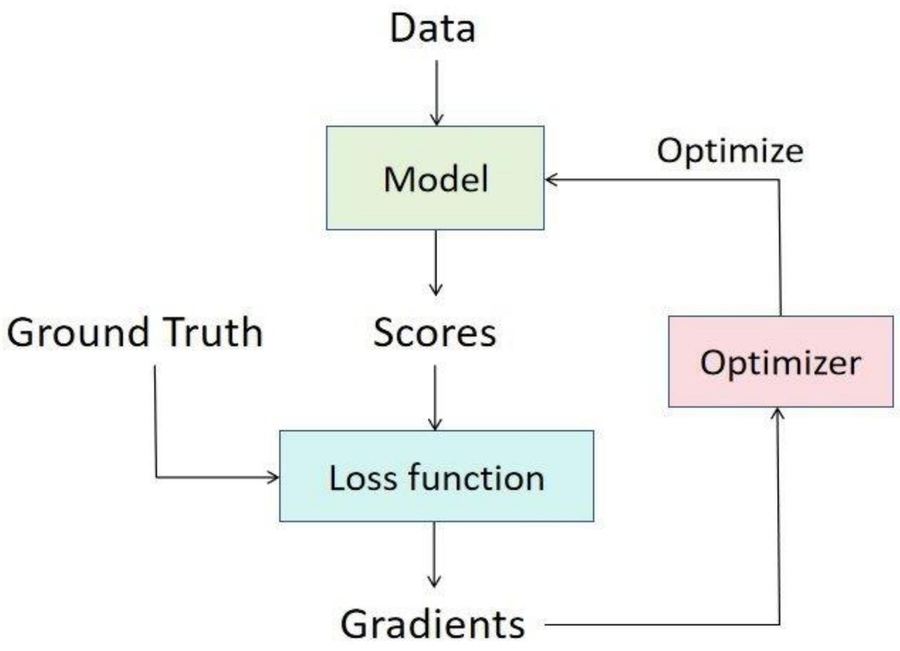
Problem description

In a deep learning project, we need to:

1. Define a model
   - Input a batch of data, and compute the results.
2. Train the model
   - Record the derivation procedures.
   - Back propagate & Compute the gradients.
   - Optimize the parameters.
   - GPU acceleration.

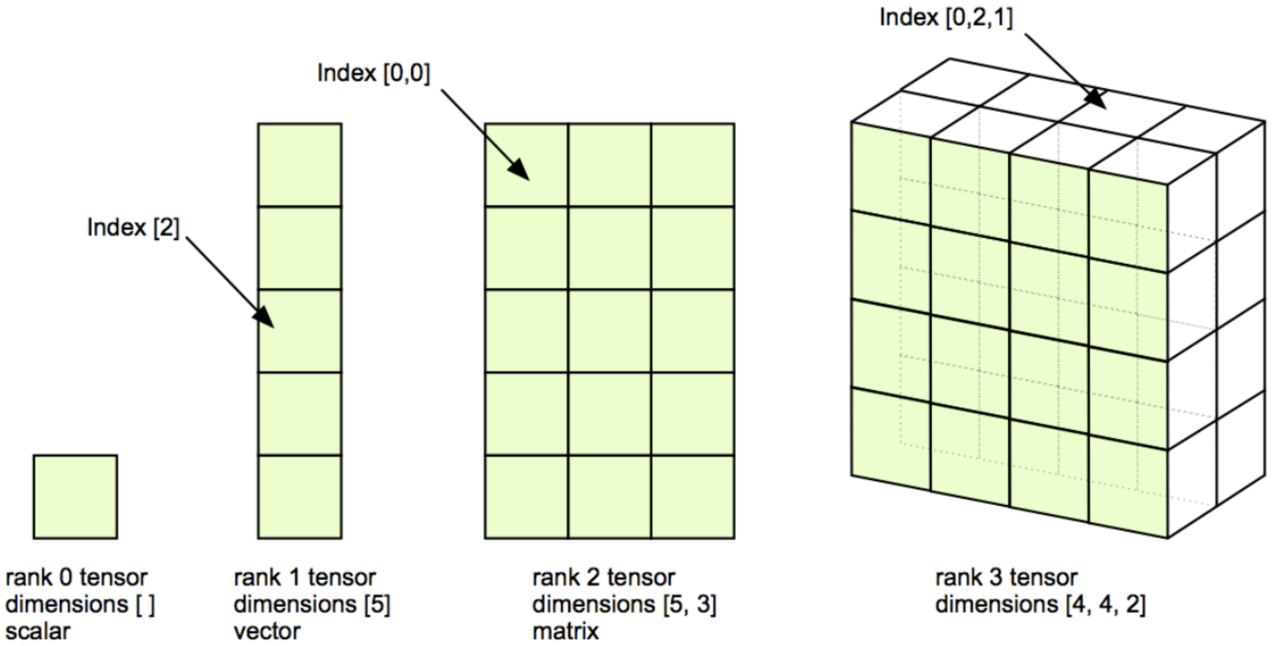
➡ A special data structure was invented.

Called "**Tensor**"(張量)



The bricks of building models: Tensors

- Tensors are very similar to arrays and matrices.
- Tensors can run on GPUs or other hardware accelerators.



Initialize a Tensor

There are many ways to initialize a PyTorch tensor:

From existed python list

```
T = torch.tensor([[1, 2], [3, 4]])
```

From numpy

```
T = torch.from_numpy(numpy.array([[1, 2], [3, 4]]))
```

Randomly initialized

Normal distributed: `T = torch.randn(size=(2,2))`

Uniform distributed: `T = torch.rand(size=(2,2))`

Initialize a Tensor

Other methods

All of the elements are 1

```
T = torch.ones(size=(2,2))
```

All of the elements are 0

```
T = torch.zeros(size=(2,2))
```

Diagonalized matrix

```
T = torch.eye(n=2, m=3)
```

Tensors

Initialize: `T = torch.tensor([[1, 2], [3, 4]])`

- Data (Return a copy of tensor)

  `T.data => tensor([[1, 2], [3, 4]])`

- Data (Scalar only)

  `t = torch.tensor(1.1), t.item() => 1.1`

- Shape (return a tuple)

  `T.shape => torch.Size([2, 2])`

- Data type

  `T.dtype => torch.int64`

Tensors

- Device

  T.device => device(type='cpu')

- Require gradient

  T.requires_grad => False

- Gradient

  T.grad => tensor([...])

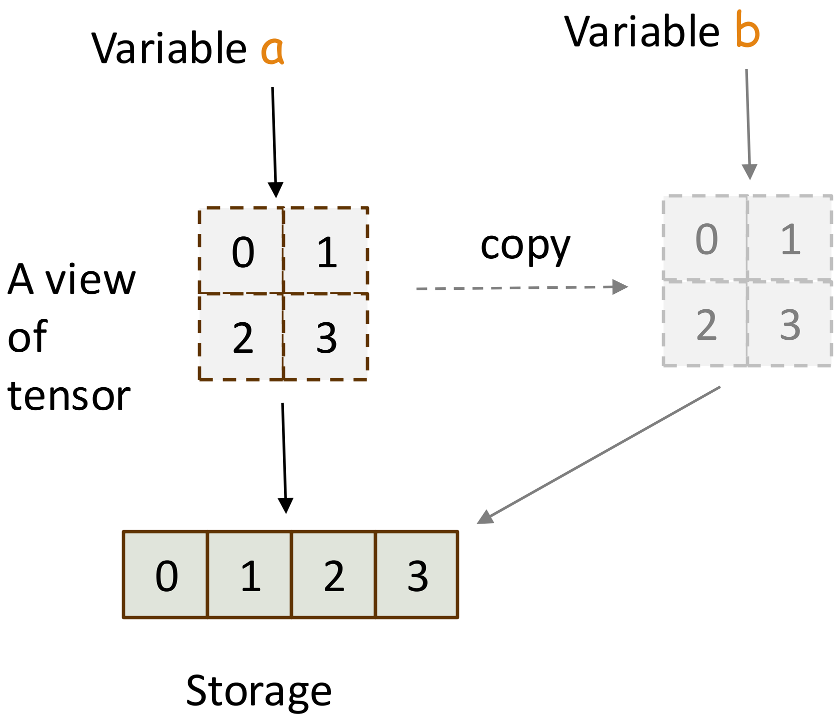
An interesting insight of tensor.data

Consider the following code:

```
a = torch.arange(4).reshape(2, 2) # initialize
b = a.data
print(f"{id(a)}, {id(b)}") # print the memory locations
a[0, 1] = 100
print(a)
print(b)
```

The output is:

```
126169165861232, 126168491980688
tensor([[  0, 100],
        [  2,   3]])
tensor([[  0, 100],
        [  2,   3]])
```



Which means that a.data just creates a new view of tensor.

Matrix operations

Tensor & scalar

A = torch.tensor([[1, 2], [3, 4]])

A+1 => tensor([[2, 3], [4, 5]])

A*2 => tensor([[2, 4], [6, 8]])

符號	意義
`torch.Tensor + scalar`	張量中的每個數值加上 `scalar`
`torch.Tensor - scalar`	張量中的每個數值減去 `scalar`
`torch.Tensor * scalar`	張量中的每個數值乘上 `scalar`
`torch.Tensor / scalar`	張量中的每個數值除以 `scalar`
`torch.Tensor // scalar`	張量中的每個數值除以 `scalar` 所得之商
`torch.Tensor % scalar`	張量中的每個數值除以 `scalar` 所得之餘數
`torch.Tensor ** scalar`	張量中的每個數值取 `scalar` 次方

The operation is applied equaly to every elements in the tensor except matrix multiplication(@).

Matrix operations

A = torch.tensor([[1, 2], [3, 4]])

B = torch.tensor([[0, 1], [2, 3]])

+, -

A+B => tensor([[1, 3], [5, 7]])

A-B => tensor([[1, 1], [1, 1]])

Matrix multipliy

A@B => tensor([[4, 7], [8, 15]])

Element-wise multiply

A*B => tensor([[0, 2], [6, 12]])

符號	意義
`A + B`	張量 A 中的每個數值加上張量 B 中相同位置的數值
`A - B`	張量 A 中的每個數值減去張量 B 中相同位置的數值
`A * B`	張量 A 中的每個數值乘上張量 B 中相同位置的數值
`A / B`	張量 A 中的每個數值除以張量 B 中相同位置的數值
`A // B`	張量 A 中的每個數值除以張量 B 中相同位置的數值所得之商
`A % B`	張量 A 中的每個數值除以張量 B 中相同位置的數值所得之餘數
`A ** B`	張量 A 中的每個數值取張量 B 中相同位置的數值之次方

Matrix operations

Concatenation (equivalent to torch.concat)

```
torch.cat((A,B), dim=0) => tensor([[1, 2], [3, 4], [0, 1], [2, 3]])
torch.cat((A,B), dim=1) => tensor([[1, 2, 0, 1], [3, 4, 2, 3]])
```

Split

```
T = torch.randn((5,6,7))
out = torch.split(T, 2, dim=0)
```

A tuple of tensors and their size are:

```
torch.Size([2, 6, 7]), torch.Size([2, 6, 7]), torch.Size([1, 6, 7])
```

Squeeze, Unsqueeze

```
A.unsqueeze(dim=-1) => tensor([[[1], [2]], [[3], [4]]])
A.squeeze(dim=-1)  => tensor([[1, 2], [3, 4]])
```

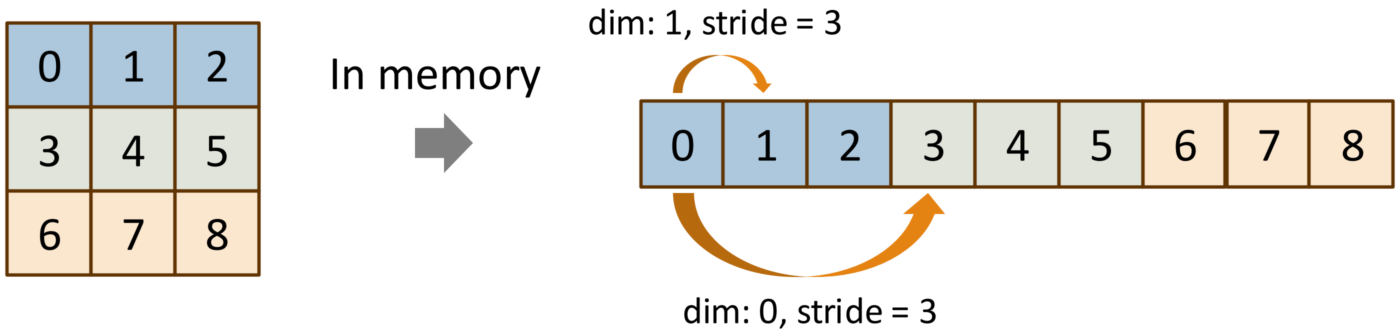
Transpose

```
A.transpose(dim0=0, dim1=1) => tensor([[1, 3], [2, 4]])
```

Matrix operations

Stride: defines the step (in RAM) size used to access the next token along a given dimension.

```
A = torch.arange(9).reshape(3, 3)
A.stride() => (3, 1)
```

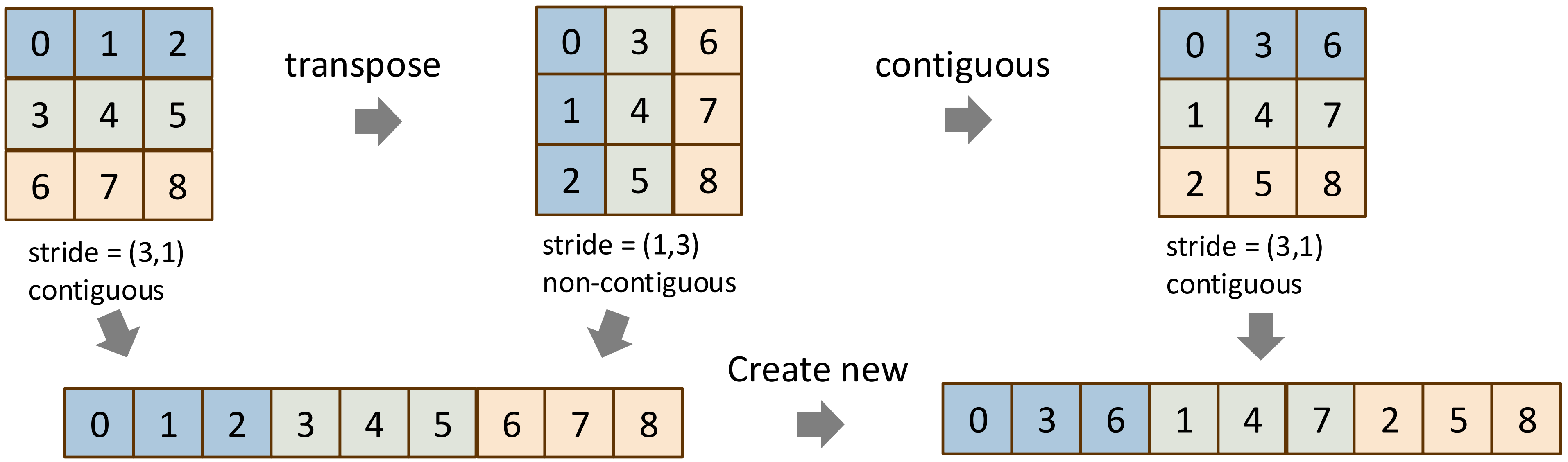


Matrix operations

contiguous: 不連續矩陣轉換成連續矩陣

A.transpose(0, 1)

A = A.contiguous()



Matrix operations

Reshape

```
A = torch.tensor([[1, 2], [3, 4]])
A.view(4, 1) => tensor([[1], [2], [3], [4]])
A.view(1, 4) => tensor([[1, 2, 3, 4]])
A.reshape(4, 1) => tensor([[1], [2], [3], [4]])
A.reshape(1, 4) => tensor([[1, 2, 3, 4]])
```

Matrix operations

The difference between view and reshape.

The view function does not modify the tensor's data in memory or create a new tensor; it simply reshapes the existing tensor by changing how the data is interpreted.

- It cannot be applied to non-contiguous tensors.

The reshape function can reshape non-contiguous tensors.

- For contiguous tensors, it is equivalent to view.
- For non-contiguous tensors, it will be a copy and the result is equivalent to contiguous+view.

Matrix operations

Note: All PyTorch computations are performed in a matrix operation mode.

e.g. Randomly initialize a tensor(100X100) and normalize it:

Sequentially: 0.127 s

Matrix Operation: 0.000088s

```
def sequential(mat : torch.tensor):
    t = time.time()
    average = torch.mean(mat)
    standard = torch.std(mat)
    output = torch.zeros(mat.shape)
    for i in range(mat.shape[0]):
        for j in range(mat.shape[1]):
            output[i, j] = (mat[i, j]-average)/standard
    return output, time.time() - t

def parallel(mat : torch.tensor):
    t = time.time()
    average = torch.mean(mat)
    standard = torch.std(mat)
    output = (mat - average)/standard
    return output, time.time() - t
```

Construct a Model 透過tensor(儲存參數)來建構model

A Model in PyTorch is basically a torch.nn.Module object

The model is defined as:

```
class myModel(torch.nn.Module):
  def __init__(self):
    super().__init__()
    self.layers = …

  def forward(self, input):
    ...
    return ...
```

Obtain the output logits

```
model = myModel()

logits = model(input)
```

```
torch.nn.Module.__call__
```

Two member functions that must be defined when constructing deep learning models

Construct a Model

Components in a model

Module	Function
torch.nn.Linear	Linear projection layer (fully connected)
torch.nn.Conv2d(1d/3d)	1/2/3d convolution layer
torch.nn.RNN	Recurrent Neural Network layer
torch.nn.LSTM	Long Short-term memory network layer
torch.nn.MaxPool2d(1d/3d)	Max pooling layer
torch.nn.Embedding	Embedding layer
torch.nn.BatchNorm2d(1d/3d)	Batch normalization layer
torch.nn.Sequential	Sequentially combined moduls
torch.nn.ModuleList	List of modules
torch.nn.ModuleDict	Dictionary of modules

Member functions in a Model

Most commonly used member functions.

Module	Function
model.forward()	Forward pass
model.state_dict()	Return an OrderedDict contains parameter names and tensors
model.parameters()	Return an iterator for parameter tensors
model.named_parameters()	Return an iterator for parameter names and tensors
model.train()	Training mode
model.eval()	Evaluation mode

Model Components

torch.nn.ModuleList:

```
class myModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear1 = torch.nn.Linear(128, 128)
        self.linear2 = torch.nn.Linear(128, 128)
        self.linear3 = torch.nn.Linear(128, 128)
    def forward(self, input):
        output1 = self.linear1(input)
        output2 = self.linear2(input)
        output3 = self.linear3(input)
        return output1, output2, output3
```

Rewrite

```
class myModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear_list = torch.nn.ModuleList([
            torch.nn.Linear(128, 128) for _ in range(3)
        ])
    def forward(self, input):
        outputs = ()
        for i in range(3):
            outputs += (self.linear_list[i](input), )
        return outputs
```

Model Components

torch.nn.Sequential:

Source code

```
def forward(self, input):
    for module in self:
        input = module(input)
    return input
```

```
class myModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear1 = torch.nn.Linear(128, 128)
        self.act = torch.nn.ReLU()
        self.linear2 = torch.nn.Linear(128, 2)

    def forward(self, input):
        x = self.linear1(input)
        x = self.act(x)
        output = self.linear2(x)
        return output
```

Rewrite

```
class myModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.layers = torch.nn.Sequential(
            torch.nn.Linear(128, 128),
            torch.nn.ReLU(),
            torch.nn.Linear(128, 2),
        )
    def forward(self, input):
        output = self.layers(input)
        return output
```

Use Modules in Modules

We recommend using torch.nn.Module objects within a torch.nn.Module instead of basic Python data structures when parameters are involved.

- This ensures that the parameters are properly **registered**, **tracked**, and **optimized** during training.

Use Modules in Modules

e.g. model.state_dict() (return a state dictionary that contains all parameter names and tensors) source code:

```
def state_dict(self, *args, destination=None, prefix='', keep_vars=False):
        ...
    if destination is None:
        destination = OrderedDict()
        destination._metadata = OrderedDict()
        ...
    for name, module in self._modules.items():
        if module is not None:
            module.state_dict(destination=destination, prefix=prefix + name + '.', keep_vars=keep_vars)
        ...
    return destination
```

In most of the functions in a Module object (train(), eval(), parameters() …), the model recursively applies operations to all sub-modules. (just like a tree structure)

As a result, it is better to use ModuleList, which is a torch.nn.Module object.

Use Modules in Modules

ModuleList version:

```
class myModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear_list = torch.nn.ModuleList([
            torch.nn.Linear(128, 128) for _ in range(3)
        ])
    def forward(self, input):
        outputs = ()
        for i in range(3):
            outputs += (self.linear_list[i](input), )
        return outputs
```

print(model._modules) :

```
OrderedDict([('linear_list',
              ModuleList(
                (0-2): 3 x Linear(in_features=128, out_features=128, bias=True)
              ))])
```

List version:

```
class myModel(torch.nn.Module):
    def __init__(self):
        super().__init__()
        self.linear_list = [
            torch.nn.Linear(128, 128) for _ in range(3)
        ]
    def forward(self, input):
        outputs = ()
        for i in range(3):
            outputs += (self.linear_list[i](input), )
        return outputs
```

print(model._modules) :

```
OrderedDict()
```

train() and Eval() 訓練模式與驗證模式

The member functions model.train() and model.eval() are for mode transfer. (recursively)

Training mode:

- The training mode in PyTorch activates certain layers and behaviors that are only needed during training such as Dropout and Batch Normalization.
- In this mode, the model adjusts its parameters through backpropagation and updates the gradients during training.

Evaluation mode:

- The evaluation mode is used for evaluation and inference, where layers like Dropout are disabled and Batch Normalization uses fixed statistics instead of updating them.
- This ensures that the model behaves consistently and produces deterministic outputs during testing or inference without modifying its internal state.

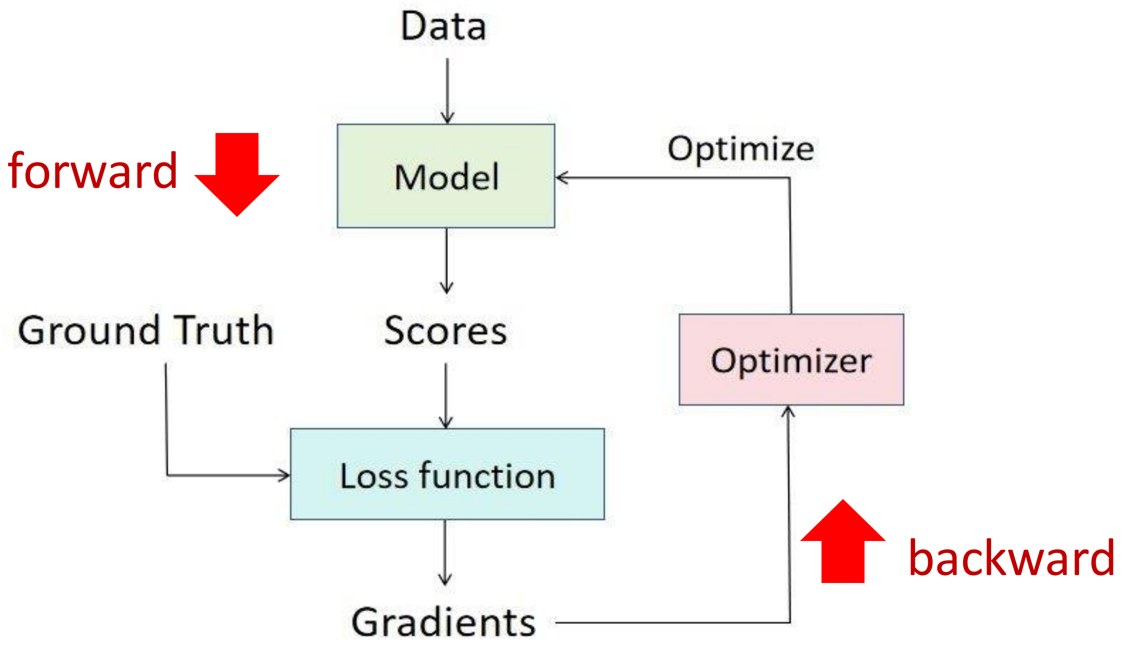
Training

Forward: Obtain output logits

```
model.forward()
```

Backward: Back-propagation

```
loss.backward()
```



Backward

The `backward`function in PyTorch is used to perform **backpropagation**.

Gradient Calculation: PyTorch computes the gradient of the target tensor with respect to all the tensors that have `requires_grad=True`, using the chain rule of calculus.

Gradient Storage: The computed gradients are stored in the *.grad* attribute of the tensors.

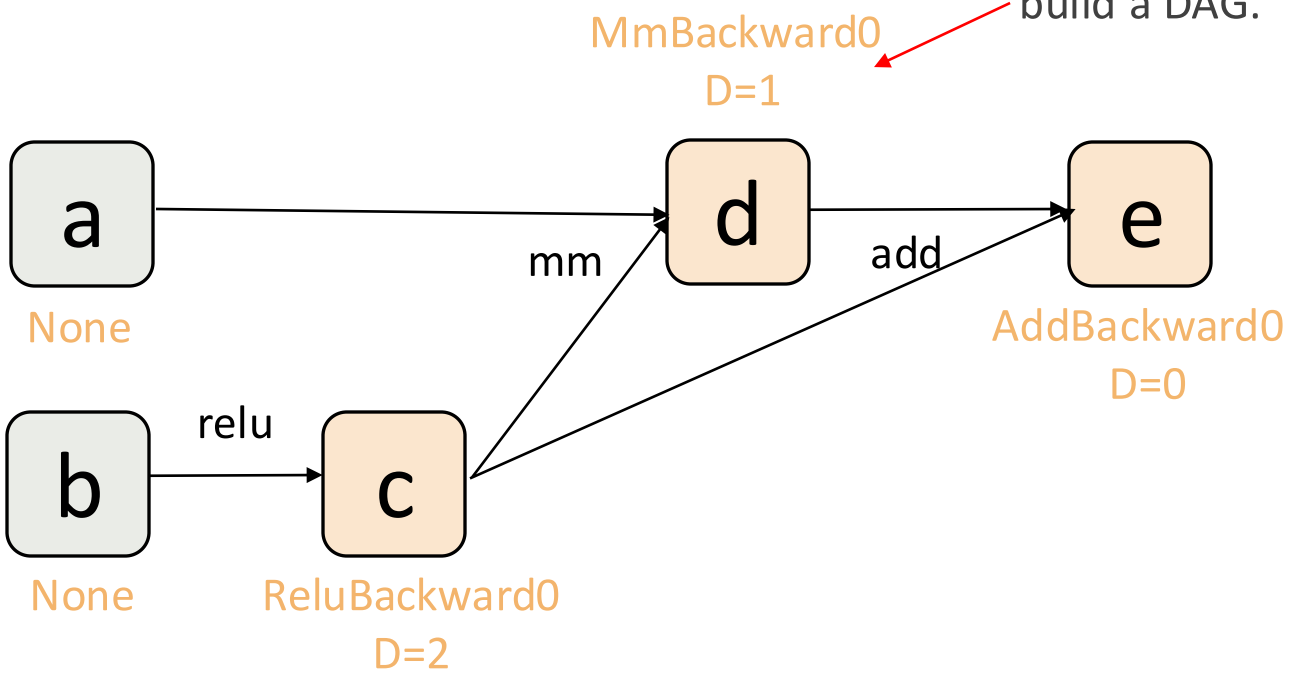
Automatic Differentiation: PyTorch builds a computation graph dynamically during the forward pass, and when `backward()` is called, it traverses this graph in reverse order, applying the chain rule to calculate gradients step-by-step from the output back to the inputs.

A simple example

Sample code (forward) :

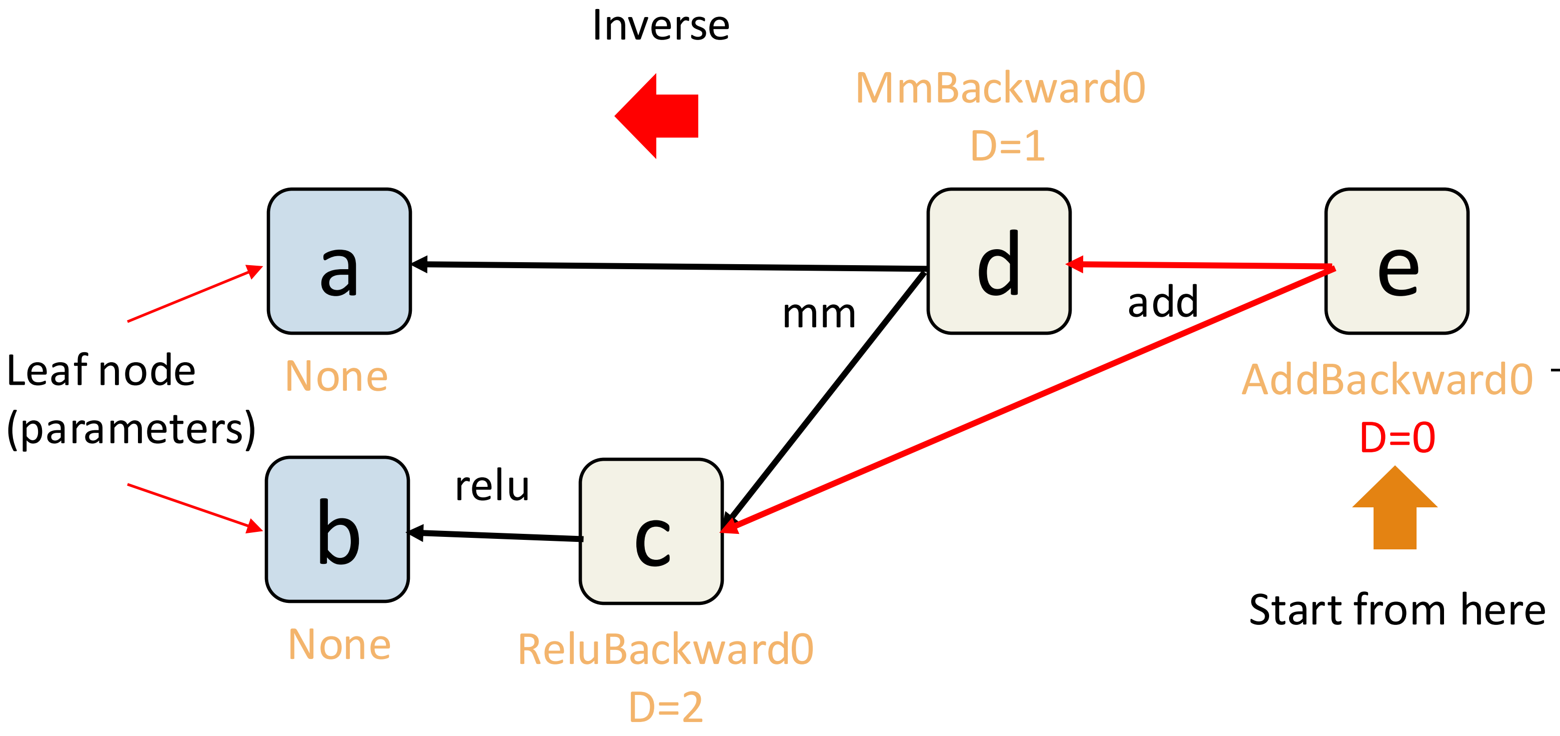
```
a = torch.randn(1, requires_grad=True)
b = torch.randn(1, requires_grad=True)
c = torch.nn.functional.relu(b)
d = a @ c
e = c + d
```

Record backward functions and dependency D and build a DAG.



A simple example

Backward :

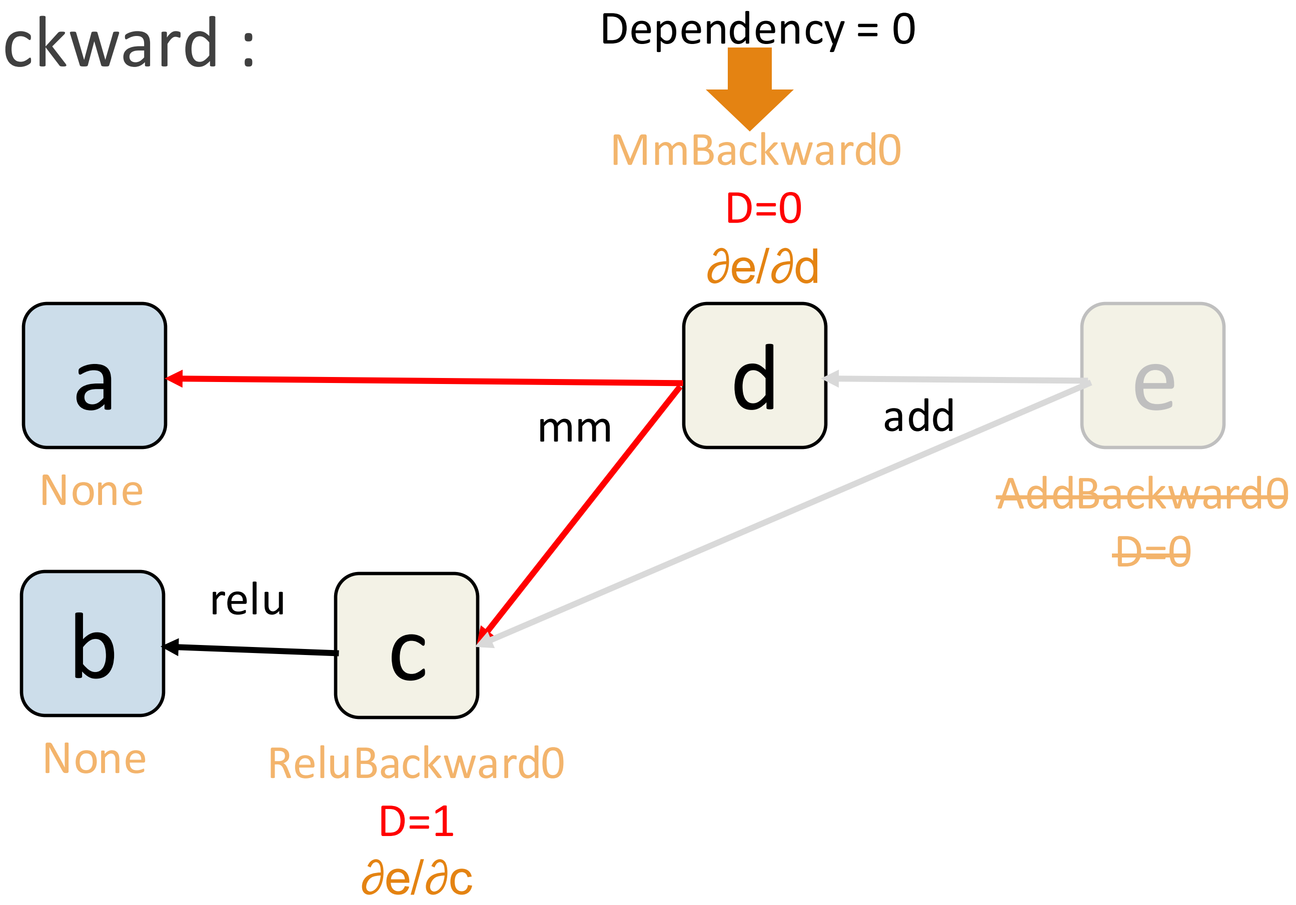


FunctionTask queue

0	AddBackward0
1	
2	
3	

A simple example

Backward :



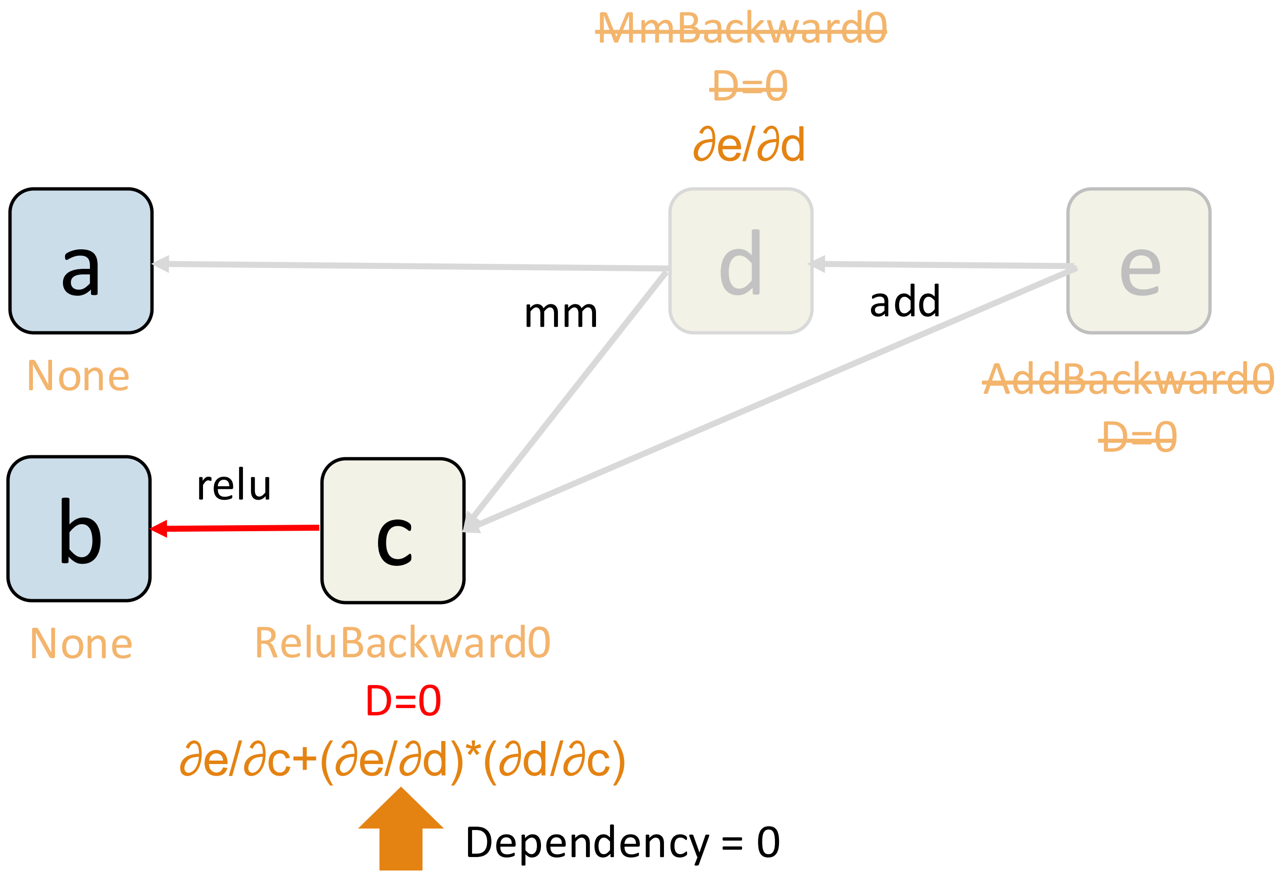
FunctionTask queue

0	MmBackward0
1	
2	
3	

Pop AddBackward0 and execute.
Push MmBackward0

A simple example

Backward :



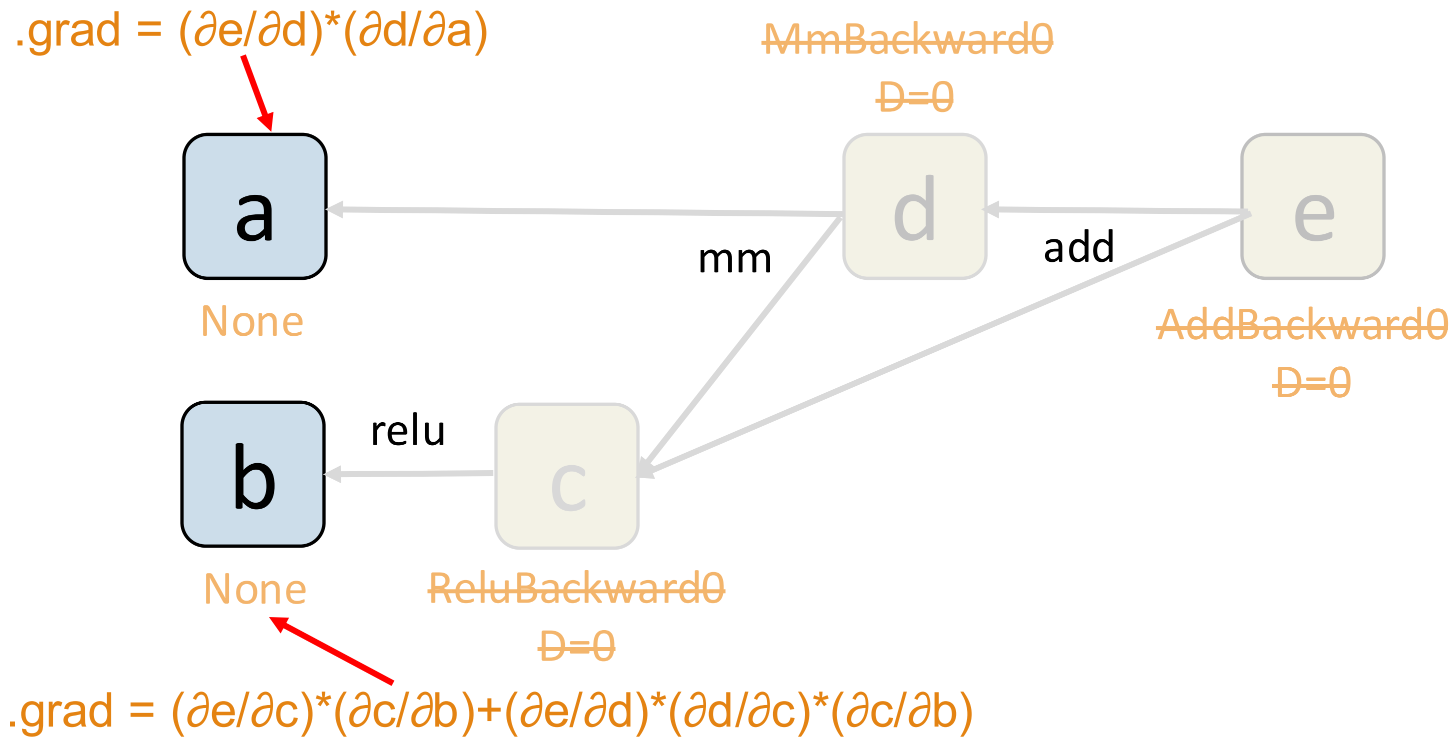
FunctionTask queue

0	ReluBackward0
1	
2	
3	

Pop MmBackward0 and execute.
Push ReluBackward0

A simple example

Backward :



FunctionTask queue

0	
1	
2	
3	

Pop ReluBackward0

Run without gradient

Three ways to avoid gradient

tensor.requires_grad = False

- When you set the requires_grad attribute of a tensor to False, even if it participates in computations, gradients will not be tracked for it.

with torch.no_grad():

- This is a context manager that temporarily disables gradient tracking for all operations within its scope.

tensor.detatch()

- The detach() method returns a new tensor that shares the same data as the original tensor but is detached from the computation graph.

New view, Unchanged continuity

Train a Model

Step1: Prepare the dataset

Step2: Construct the model

Step3: Define Optimizer

Step4: Define loss function

Step5: Train the model

Step6: Evaluate the model

1. clear gradients
2. Input data to the model
3. compute loss
4. compute gradients
5. optimize parameters
6. back to 1.

Loss functions

A loss function is a critical component that measures how well or poorly a model's predictions match the actual (true) values.

In simple terms, it quantifies the "error" or "difference" between the predicted output and the true labels. The primary role of a loss function is to provide feedback to the model during the training process, helping the model improve its predictions over time.

Loss functions

Some loss functions in torch.nn

Loss functions	Usage
torch.nn.CrossEntropyLoss	Classification tasks
torch.nn.MSELoss	Regression tasks
torch.nn.KLDivLoss	Knowledge Distillation
torch.nn.BCELoss	Binary classification tasks

Some other loss functions

Loss functions	Usage
Contrastive Loss	Contrastive learning
Entropy	A special term in loss function to improve model's confidence

Optimizers

Some optimizers (most commonly used) in torch.nn

Optimizer	Description
torch.optim.SGD	Stocastic gradient decend
torch.optim.Adam	Adam optimizer
torch.optim.AdamW	A variant of the Adam optimizer on weight decay formulation

Training

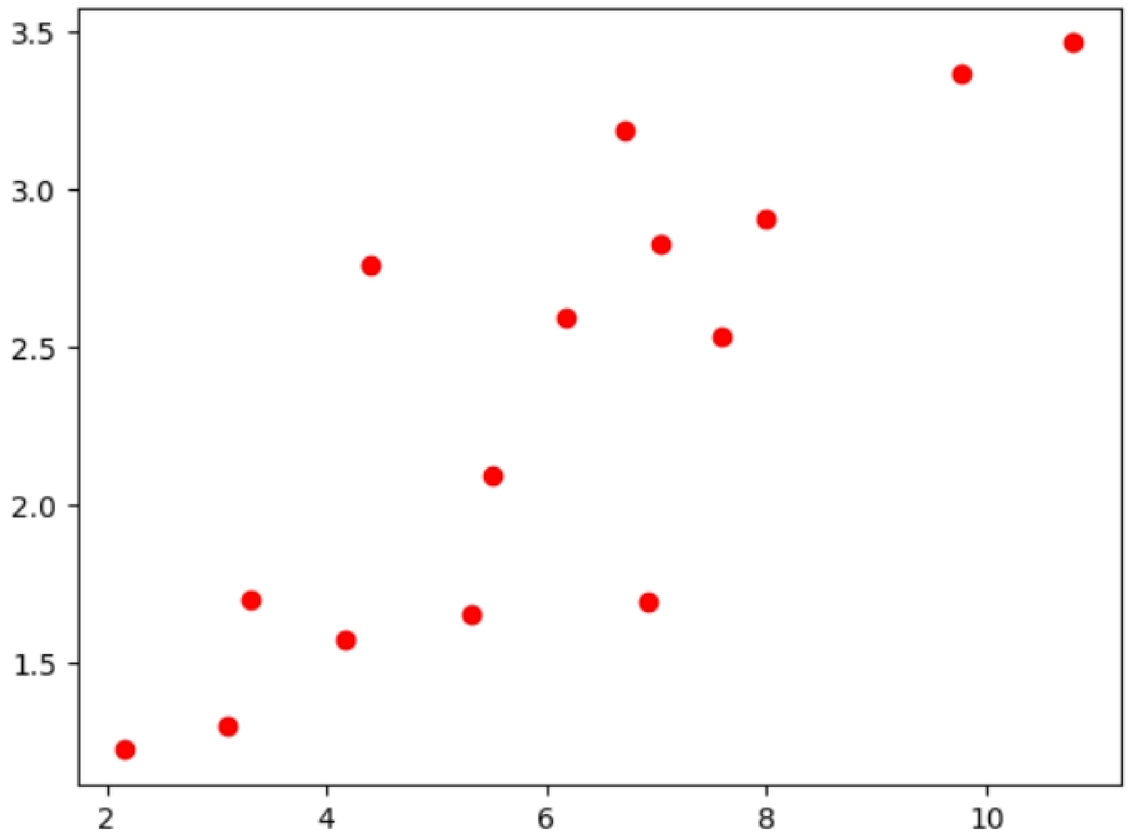
1. clear gradients
2. Input data to the model
3. compute loss
4. compute gradients
5. optimize parameters
6. back to 1.

```
optimizer.zero_grad()
output = model(**batch)
loss = loss_fn(output, ground_truth)
loss.backward()
optimizer.step()
```

An Example of Linear Regression

Data distribution:

Use a line to represent these data



An Example of Linear Regression

```python
# Toy dataset
x_train = torch.tensor([[3.3], [4.4], [5.5], [6.71], [6.93], [4.168],
                        [9.779], [6.182], [7.59], [2.167], [7.042],
                        [10.791], [5.313], [7.997], [3.1]], dtype=torch.float32)

y_train = torch.tensor([[1.7], [2.76], [2.09], [3.19], [1.694], [1.573],
                        [3.366], [2.596], [2.53], [1.221], [2.827],
                        [3.465], [1.65], [2.904], [1.3]], dtype=torch.float32)
```

initialize

data tensor

```python
# Linear regression model
model = nn.Linear(input_size, output_size)

# Loss and optimizer
criterion = nn.MSELoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
```

model

loss & optimizer

load data

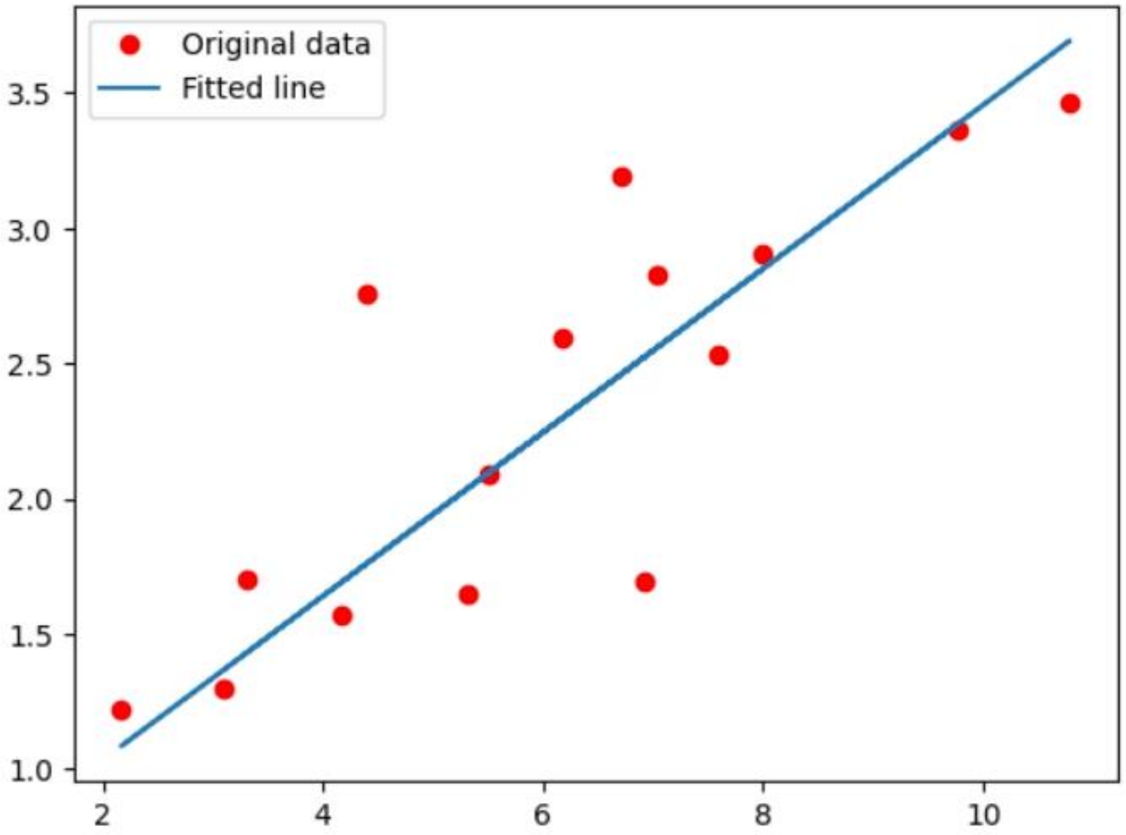
```python
# Train the model
for epoch in range(num_epochs):

    # Forward pass
    outputs = model(x_train)
    loss = criterion(outputs, y_train)

    # Backward and optimize
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    if (epoch+1) % 20 == 0:
        print ('Epoch [{}/{}], Loss: {:.4f}'.format(epoch+1, num_epochs, loss.item()))
```

1. Input data to the model
2. compute loss
3. clear gradients
4. compute gradients
5. optimize parameters

An Example of Linear Regression

Outputs:

```
Epoch [5/60], Loss: 11.2489
Epoch [10/60], Loss: 4.6657
Epoch [15/60], Loss: 1.9987
Epoch [20/60], Loss: 0.9182
Epoch [25/60], Loss: 0.4805
Epoch [30/60], Loss: 0.3031
Epoch [35/60], Loss: 0.2313
Epoch [40/60], Loss: 0.2021
Epoch [45/60], Loss: 0.1903
Epoch [50/60], Loss: 0.1855
Epoch [55/60], Loss: 0.1835
Epoch [60/60], Loss: 0.1827
```



Check the parameters & gradients

step 1

```
optimizer.zero_grad()
print_grads(model)
```

```
weight: Parameter containing:
tensor([[0.4165]], requires_grad=True)
weight grad: None

bias: Parameter containing:
tensor([0.4819], requires_grad=True)
bias grad: None
```

step 2

```
loss.backward()
print_grads(model)
```

```
weight: Parameter containing:
tensor([[0.4165]], requires_grad=True)
weight grad: tensor([[10.0239]])

bias: Parameter containing:
tensor([0.4819], requires_grad=True)
bias grad: tensor([1.3666])
```

Check the gradients

step 2

```
loss.backward()
print_grads(model)
```

```
weight: Parameter containing:
tensor([[0.4165]], requires_grad=True)
weight grad: tensor([[10.0239]])

bias: Parameter containing:
tensor([0.4819], requires_grad=True)
bias grad: tensor([1.3666])
```

step 3

```
optimizer.step()
print_grads(model)
```

```
weight: Parameter containing:
tensor([[0.4065]], requires_grad=True)
weight grad: tensor([[10.0239]])

bias: Parameter containing:
tensor([0.4805], requires_grad=True)
bias grad: tensor([1.3666])
```

step 4

```
optimizer.zero_grad()
print_grads(model)
```

```
weight: Parameter containing:
tensor([[0.4065]], requires_grad=True)
weight grad: None

bias: Parameter containing:
tensor([0.4805], requires_grad=True)
bias grad: None
```

Deep learning in NLP tasks

I mentioned regression tasks on a polynomial function with a few data samples.

However, in NLP tasks, the model size and dataset size can reach hundreds of gigabytes or even terabytes, making it impractical to plot a hyper-curve for loss progression over the entire dataset.

As a result, we need to sample batches of data that can approximate the distribution of the original dataset. batch設定越大，更能清楚表示dataset分佈
=>過小會有dataset bias問題

Dataset & DataLoader

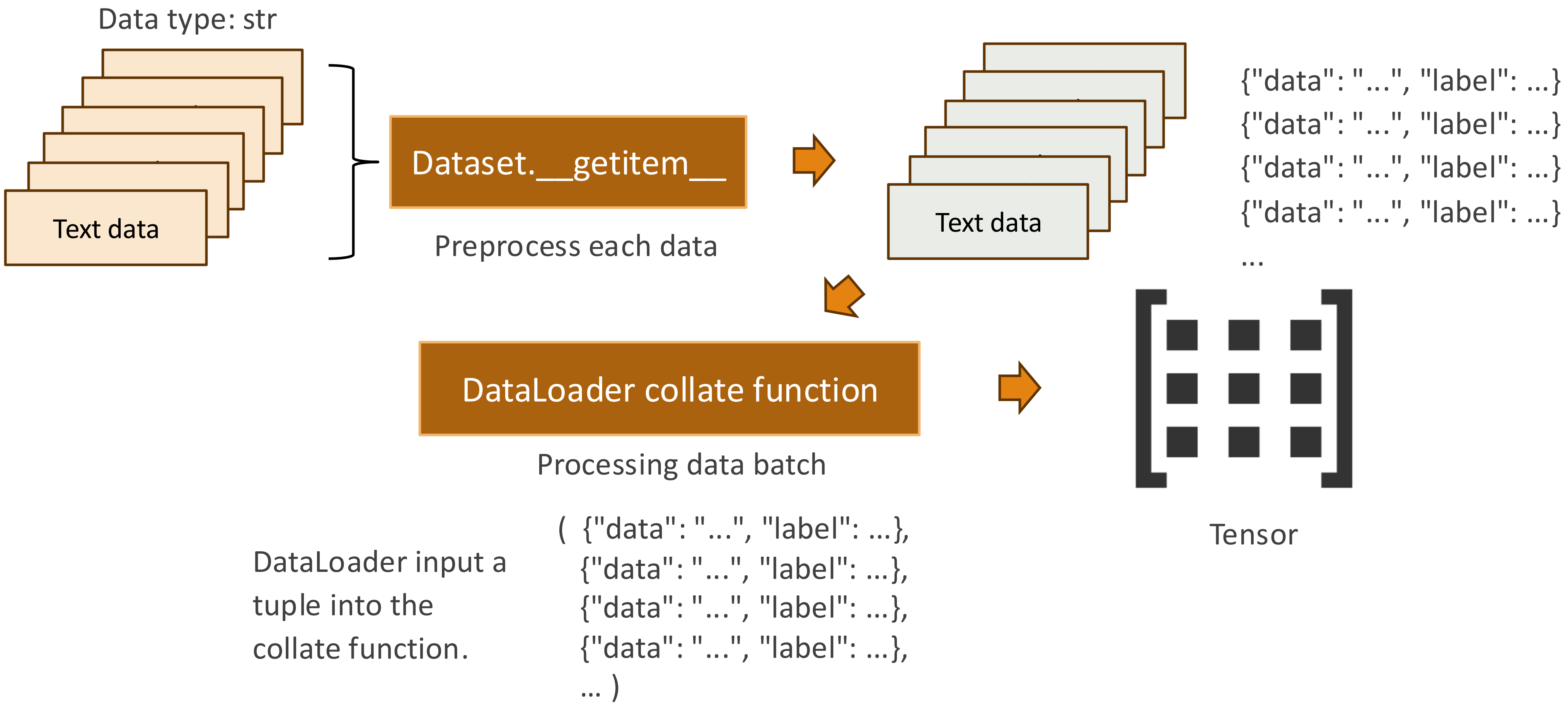
The Dataset object should be defined as:

```
From torch.utils.data import DataLoader, Dataset

Class myDataset(Dataset):
    def __init__(self, split):
        Super().__init__()
        self.data = …

    def __getitem__(self, index):
        return self.data[index]

    def __len__(self):
        return len(self.data)
```

The Dataloader:

```
def get_batch(sample):
    …

dl = DataLoader(myDataset(split=…, ), batch_size=…,
                collate_fn=get_batch, shuffle=…)

for batch in dl:
    …
```

Data Flow


Data type: str
Text data
Dataset.__getitem__
Preprocess each data
Text data
{"data": "...", "label": ...}
{"data": "...", "label": ...}
{"data": "...", "label": ...}
{"data": "...", "label": ...}
...
DataLoader collate function
Processing data batch
Tensor
DataLoader input a tuple into the collate function.
({"data": "...", "label": ...},
{"data": "...", "label": ...},
{"data": "...", "label": ...},
{"data": "...", "label": ...},
...)

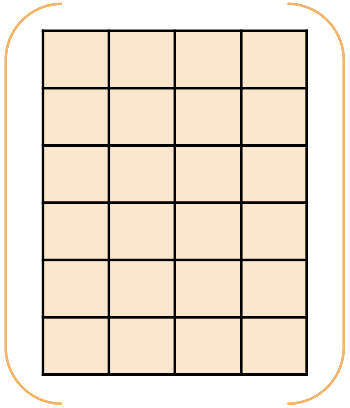
Data Flow in RNN model

We assume that batch_size = 1, hidden_dim=768 and there are 20000 words in the dictionary

One-hot vectors

I	[0, …, 1, …, 0, 0]
love	[0, 0, …, 1, …, 0]
AI	[0, …, 1, …, 0, 0]
!	[0, 0, …, 1, …, 0]

X



Dense vectors

I	[0.2, …, -0.5, 0.7]
love	[0.1, …, 0.2, -0.5]
AI	[-0.3, …, 0.7, 0.5]
!	[0.6, …, -0.2, 0.9]

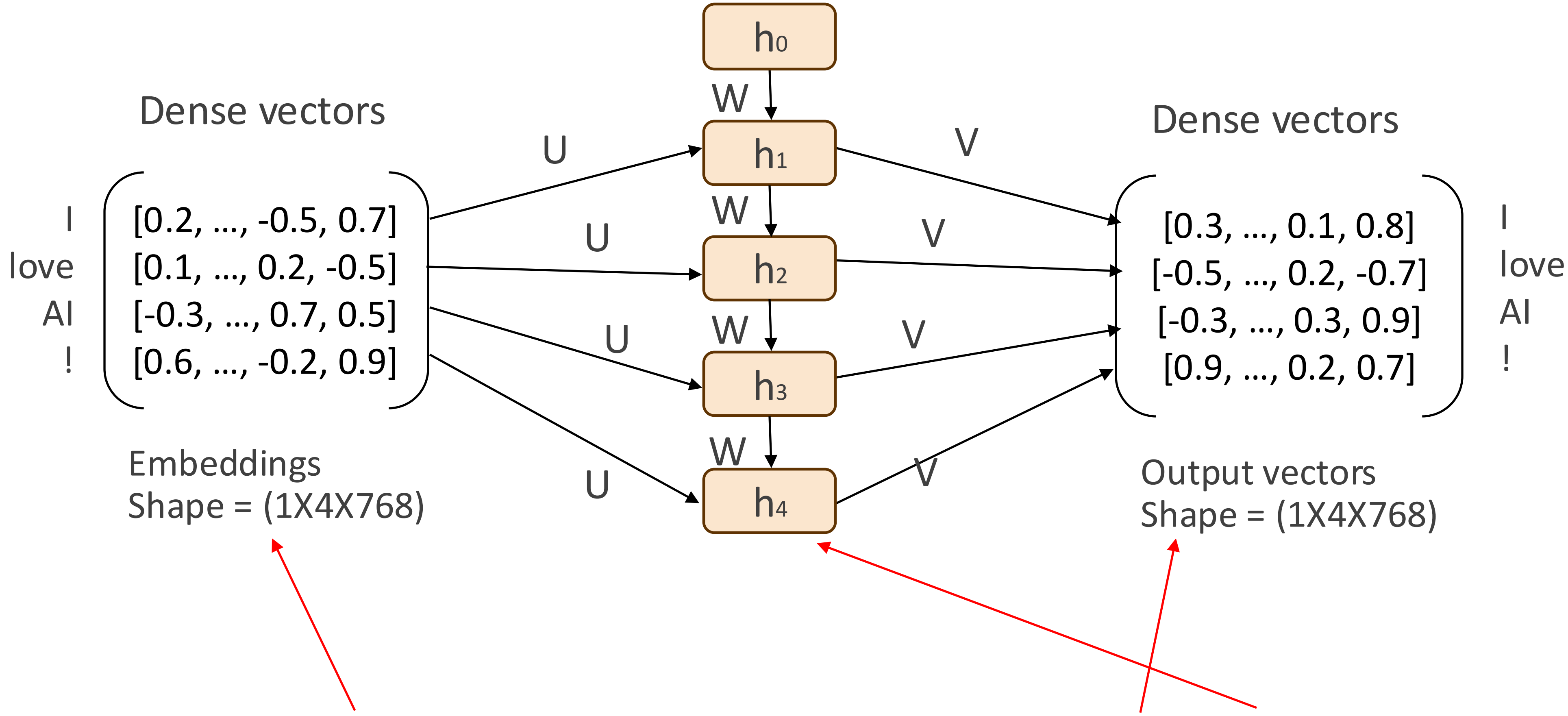
Hidden Layers

Input tensor
Shape = 1X6X20000
(batch_size X seq_len X vocabs)

Embedding layer
A matrix
Shape = 20000X768
(vocabs X hidden_dim)

Embeddings
Shape = (1X6X768)

Data Flow in RNN model



torch.nn.RNN(input, hidden_size=768)

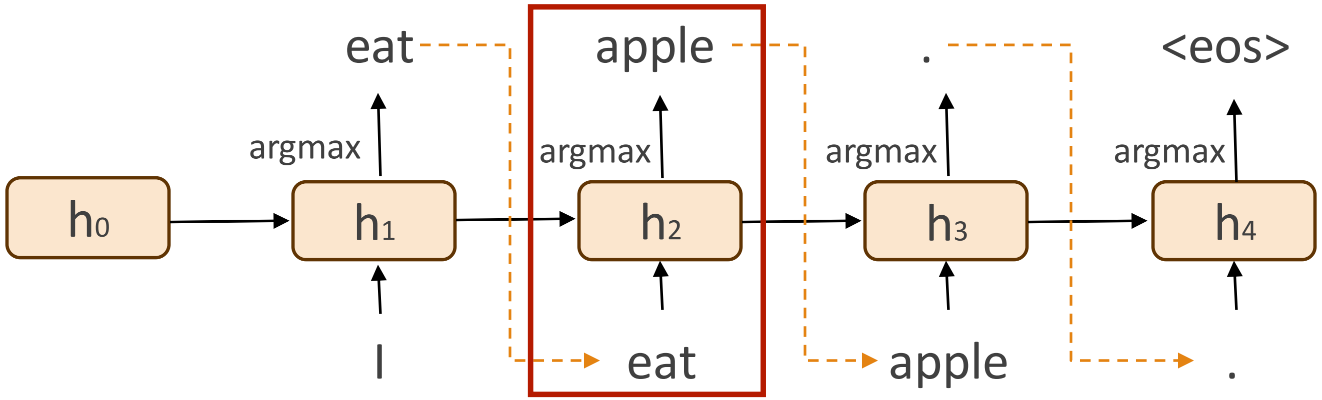
return value: (output, h_n)

Generative learning VS Teacher forcing

For example.

Our ground truth is: I love AI !

In generative training:



We optimize:

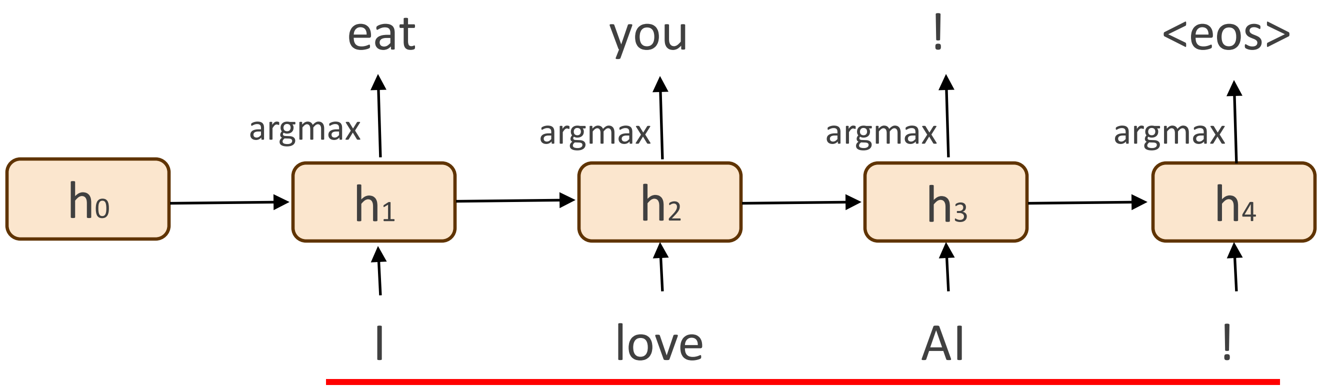
- P (love | I)
- P (AI | I eat) 較不穩定
- P (! |I eat apple)
- P (<eos> |I eat apple !)

If the model makes a mistake early on, that error will be used in later training, which makes training unstable.

Generative learning VS Teacher forcing

Our ground truth is still: I love AI !

In teacher forcing:



Ground truths

We optimize:

- P (love | I)
- P (AI | I love)
- P (! | I love AI)
- P (<eos> | I love AI !)

Nothing weird here.

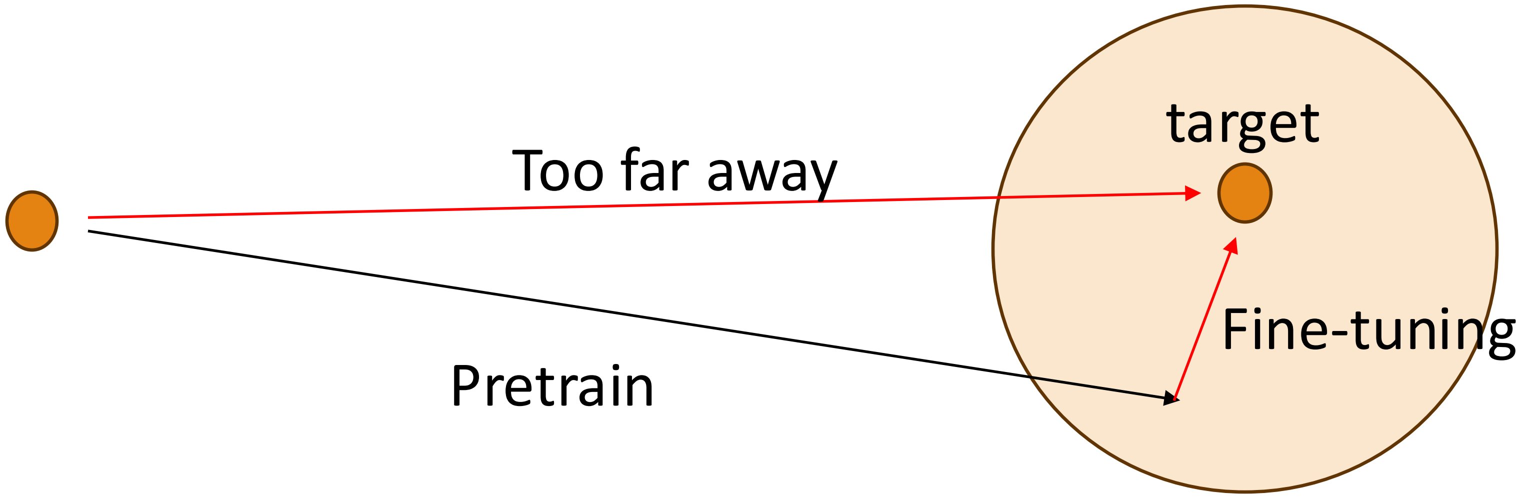
Teacher forcing is more stable in training

Transformer-based models

Transformer-based models are more powerful and parallelable than RNN-based models.

Language models (LM) need pretraining to learn the underlying structure, patterns, and relationships in a language.

Huggingface is an excellent platform for accessing and downloading pretrained model weights and datasets.



Load BERT from Huggingface

Import transformers package

Model name

A local path to store the model

```
import transformers as T
tokenizer = T.AutoTokenizer.from_pretrained("google-bert/bert-base-uncased", cache_dir="./cache/")
```

Tokenizer is used to transform tokens to ids, and it can also pack the text batch into tensors:

```
data = tokenizer.batch_encode_plus(text, padding=True, truncation=True, return_tensors="pt")
```

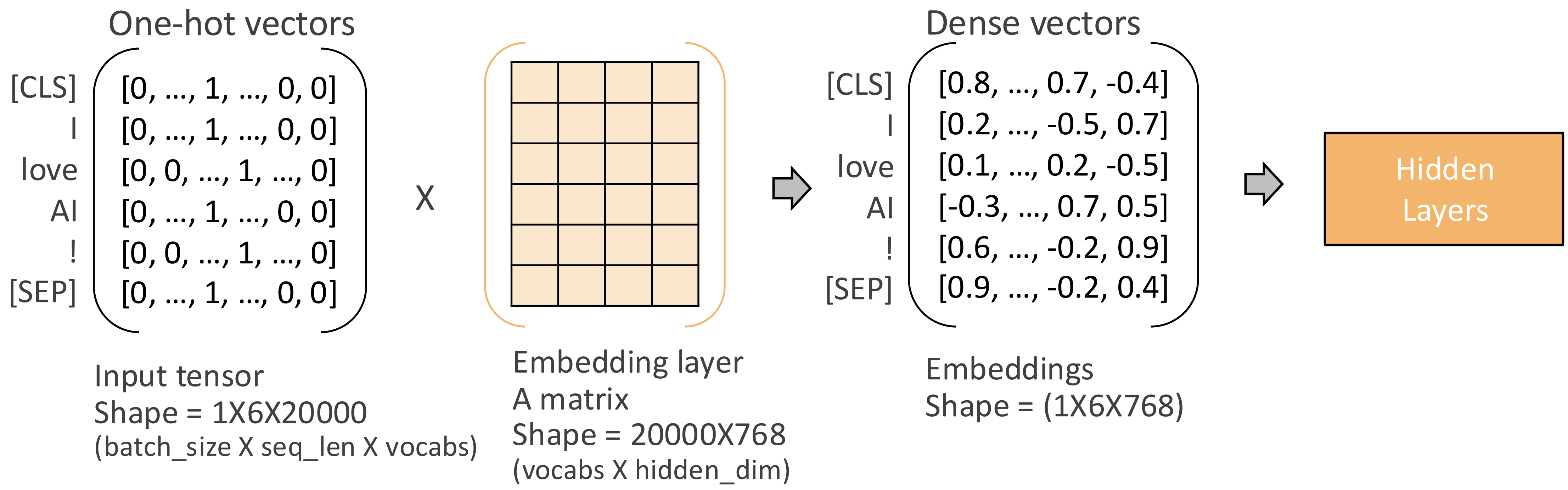
batch_encode_plus returns a "BatchEncoding" object which can be regarded as dict.
(located on CPU ram)

The BERT model can be loaded by:

```
model = T.AutoModel.from_pretrained("google-bert/bert-base-uncased", cache_dir="./cache/")
```

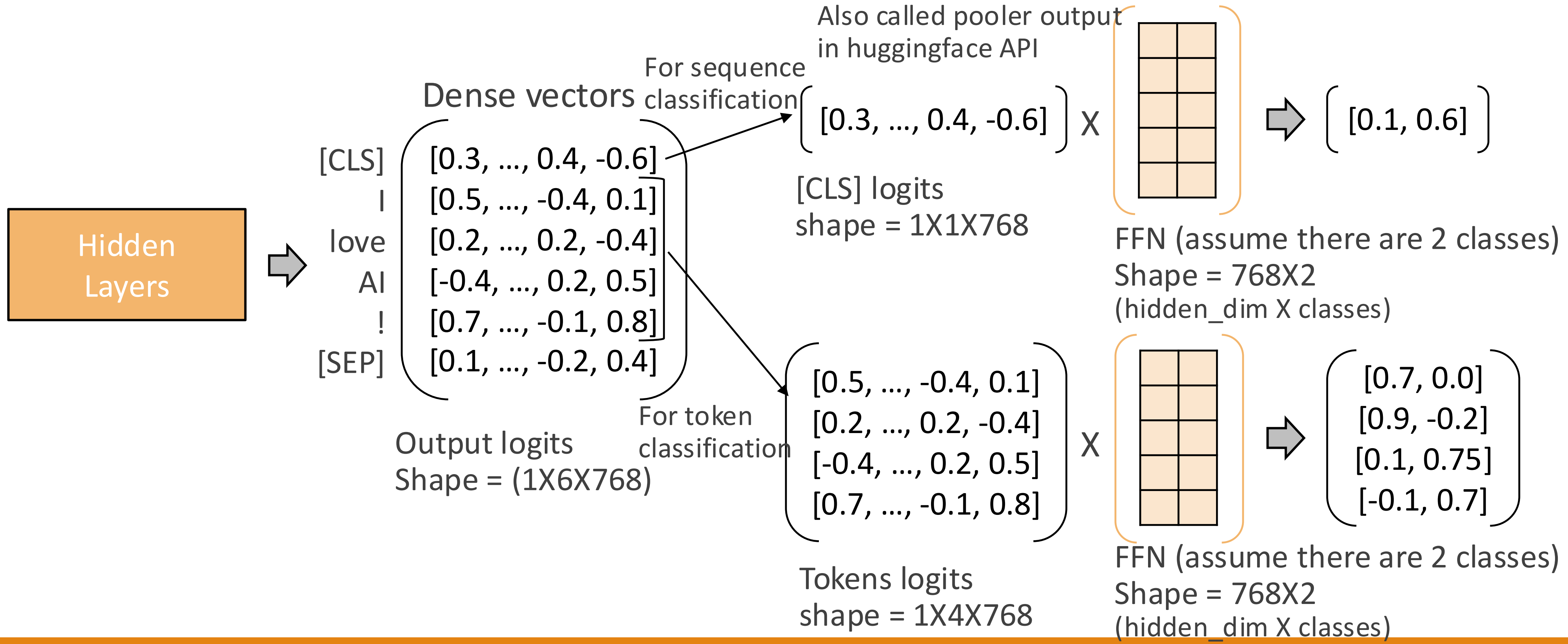
Data Flow in Transformer Auto-encoder

We assume that batch_size = 1, hidden_dim=768 and there are 20000 words in the dictionary



Data Flow in Transformer Auto-encoder

We assume that batch_size = 1, hidden_dim=768 and there are 20000 words in the dictionary



Thank you for listening

大海為什麼是藍色的

因為海里的魚在吐泡泡，噗嚕噗嚕噗嚕

BlueBlueBlue