Introduction to Deep Learning Framework

1. Introduction

1.1. Commonly used frameworks

The most commonly used frameworks for deep learning include Pytorch, Tensorflow, Keras, caffe, Apache MXnet, etc.

PyTorch: open source machine learning library; developed by Facebook AI Rsearch Lab; based on the Torch library; supports Python and C++ interfaces.

Tensorflow: open source software library dataflow and differentiable programming; developed by Google brain team; provides stable Python & C APIs.

Keras: an open-source neural-network library written in Python; conceived to be an interface; capable of running on top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, or PlaidML.

Caffe: open source under BSD licence; developed at University of California, Berkeley; written in C++ with a Python interface.

Apache MXnet: an open-source deep learning software framework; supports a flexible programming model and multiple programming languages (including C++, Python, Java, Julia, Matlab, JavaScript, Go, R, Scala, Perl, and Wolfram Language.)

1.2. Pytorch

1.2.1 Data

- Tensor: the major computation unit in PyTorch. Tensor could be viewed as the extension of vector (one-dimensional) and matrix (two-dimensional), which could be defined with any dimension.
- Variable: a wrapper of tensor, which includes creator, value of variable (tensor), and gradient. This is the core of the automatic derivation in Pytorch, as it has the information of both the value and the creator, which is very important for current backward process.
- Parameter: a subset of variable

1.2.2. Functions:

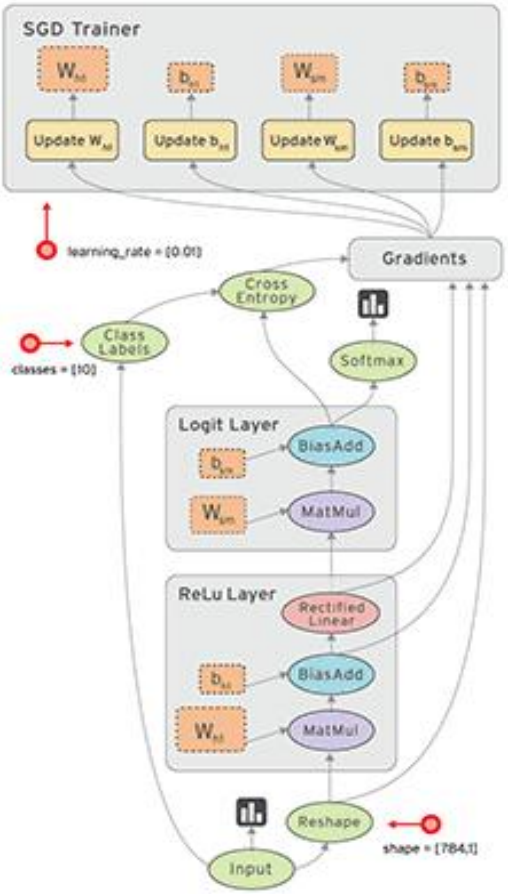
- NNModules: NNModules (torch.nn) is a combination of parameters and functions, and could be interpreted as layers. There some common modules such as convolution layers, linear layers, pooling layers, dropout layers, etc.
- Optimizer: torch.optim which supports 9 Optimizer including SGD, Adagrad, Adam, RSMprop, etc

- Loss Function: torch.nn which supports 18 Loss functions including L1Loss, MSELoss, Cross Entropy, etc
- Multi-Processing

1.3. TensorFlow

1.3.1. Data Flow Graph

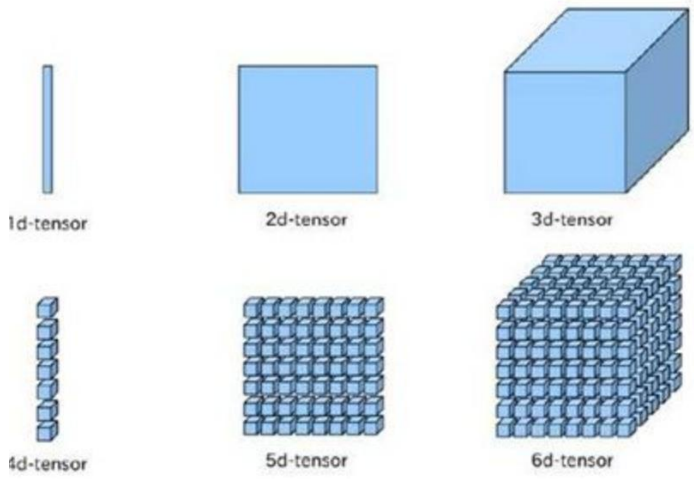
The computation in TensorFlow is based on Data Flow Graph, which is expressed with **nodes** and **edges**. Nodes, generally speaking, represents the **operations**, except when referred as where the data is fed in, pushed out, or read/wrote as persistent variable. Edges represent the flow between nodes. The direction of arrows in the graph below represents the direction of data flow.



1.3.2. Tensor

Since the framework is called TensorFlow, we could then infer that the data flows in the graph is in unit of tensor. As mentioned in 1.2.1., tensor could be viewed as the extension of vector (one-dimensional) and matrix (two-dimensional), which could be defined with any dimension.

There are two attributes for tensor: shape (rank for each dimension) and type (data type).



We operate the tensor to get outputs, and the input and output of each of the tensor is also always a tensor.

The type of Tensor includes tf.constant(), tf.Variable(), tf.placeholder(), and tf.SparseTensor() in TensorFlow.

We could get the value of the tensor through calling Session.run(tensor) and tensor.eval().

1.3.3. Session

After we successfully constructed a graph, we need to run it in a Session. Session acts as a bridge between graph and computing resource. The graph is a member of the Session class, together with a runner which responds for running the graph. The major task for Session is to distribute the computation of graph to CPU or GPU while the graph is running.

1.3.4. Useful tools

- TensorBoard: a tool for visualizing various aspects of training machine learning models. It's one of the most useful features to come out of the TensorFlow project. With a few code snippets in a training script you can view training curves and validation results of any model. TensorBoard runs as a web service which is especially convenient for visualizing results stored on headless nodes.
- Keras: a higher-level API with a configurable back-end. At the moment TensorFlow, Theano and CNTK are supported. Keras is also distributed with TensorFlow as a part of tf.contrib. The API is especially easy to use. It's one of the fastest ways to get running with many of the more commonly used deep neural network architectures. However, the API is not as flexible as PyTorch or core TensorFlow.

2. Comparison between PyTorch and Tensorflow

2.1. Properties

Properties	Tensorflow	PyTorch	Which is better?
Ramp-up time	TensorFlow takes longer time: Tensorflow needs to get compiled into Python graph and then run by the TensorFlow execution engine.	PyTorch takes shorter time: PyTorch is built to use the power of GPU for training, and is deeply get integrated with Python.	PyTorch
Coverage	TensorFlow has an extremely wide coverage. TensorFlow supports most of the functionality, and some of them are not supported by PyTorch. The c**ontrib** package has many more high level functions and operations that PyTorch doesn't have.	PyTorch has a fairly wide coverage, but still less than TensorFlow. Pytorch lacks some functions compared with TensorFlow: ● Flipping a tensor along a dimension (np.flip, np.flipud, np.fliplr) ● Checking a tensor for NaN and infinity (np.is_nan, np.is_inf) ● Fast Fourier transforms (np.fft)	TensorFlow
Graph Creation and Debugging	Since the graph construction in TensorFlow is static, the graph is typically first compiled and then run. TensorFlow has control flow operations in constructing dynamic computations, but it's more tedious than PyTorch. To debug TensorFlow code, there are two options: 1. Request variables that you want to	The graph construction is dynamic, which means it's built and runs at the same time. Thus, PyTorch is easier to debug as well. Debugging PyTorch code is just like debugging Python code.	PyTorch

	inspect from session. 2. Use TensorFlow debugger. TensorFlow Folder Is a library built on top of TensorFlow and allows for more dynamic graph construction. The syntax is not as flexible as TensorFlow core, though.		
Serialization	Both TensorFlow and PyTorch are easy to save. TensorFlow, in some way, is more integrated. In serialization, TensorFlow can save the graph as protocol buffer, which turns out to be more efficient, supports more languages, and enables to change source code interrupting old models.	Both TensorFlow and PyTorch are easy to save. But PyTorch is less flexible compared with TensorFlow regarding the mentioned advantages of TensorFlow.	
Deployment	Both TensorFlow and PyTorch are easy to wrap for small scale server-side deployment. TensorFlow supports both mobile and embedded deployment. For heavily used machine learning services, TensorFloe is better because of	Both TensorFlow and PyTorch are easy to wrap for small scale server-side deployment. For heavily used machine learning services, however, PyTorch is less efficient thanTensorFlow.	TensorFlow

	TensorFlow Serving. Models can be hot-swapped easily without bringing the service down		
Documentation	The documentation enables users to search easily. However, there are a huge number of documentations for TensorFlow, and many of them are not well-organized enough.	The Python APIs are well documented and there are enough examples and tutorials to learn either framework. However, the C library is mostly undocumented, which might have impact on writing a custom C extension or contributing to the software.	
Data Loading	Not very straight forward, especially for parallelizing data loading. Also, for TensorFlow, APIs are more verbose and harder to learn.	Well designed. While loading data in PyTorch, a data loader will take a dataset and a sampler and then produce iteration over the dataset with the sampler. Also, it's pretty easy to conduct parallelizing data loading in PyTorch via passing the **num_workers** argument.	PyTorch
Device Management	TensorFlow assumes the user want to run on GPU if one is available. By default, however, TensorFlow consumes the memory on all available GPUs. Thus, the user need to specify `CUDA_VISIBLE_DEVICES` argument.	In PyTorch, the code needs more frequent checks for CUDA availability and more explicit device management. This is especially the case when writing code that should be able to run on both the CPU and GPU.	TensorFlow
Custom Extensions	TensorFlow requires more boiler plate code	In PyTorch the user simply writes interface and implementation for each of the CPU and GPU versions.	PyTorch

2.2. Summary

The implementation of TensorFlow is symbolic programming, while the implementation for PyTorch is imperative programming. Thus, PyTorch is easier to implement but less efficient compared with TensorFlow.

Also, though both of TensorFlow and PyTorch conduct comoutation on tensor, there are still differences. TensorFlow generates the graph statically, while PyTorch is dynamic. From this perspective, PyTorch seems more flexible, and easier to debug.

2.3. Key operations for Tensor

2.3.1. PyTorch

torch.lerp(star, end, weight) : the return is out = start + (end - start) * weight

torch.rsqrt(input) : return the reciprocal of the square root

torch.mean(input) : return mean value

torch.std(input) : return standard deviation

torch.prod(input) : return the product of all elements

torch.sum(input) : return the sum of all elements

torch.var(input) : return the variance of all elements

torch.tanh(input) ： return the tanh value of element

torch.equal(torch.Tensor(a), torch.Tensor(b)) ： compare the two tensors, and then return true if the two tensors equal to each other，otherwise return false

torch.ge(input,other,out = none) 、 torch.ge(torch.Tensor(a), torch.Tensor(b))

ge: input > = other if a > = b, return true，otherwise return false

gt: input > other if a > b, return true，otherwise return false

lt: input < other if a < b, return true，otherwise return false

torch.max(input): return the maximum among elements

torch.min(input): return the minimum among elements

element_size() ： return bytes of a single element

2.3.2. TensorFlow

tf.add (x, y, name = None)

tf.sub (x, y, name = None)

tf.mul (x, y, name = None)

tf.div (x, y, name = None)

tf.mod (x, y, name = None)

tf.abs (x, name = None)

tf.neg (x, name = None)

tf.sign (x, name = None)

tf.inv (x, name = None)

tf.square (x, name = None) (y = x * x = x ^ 2)

tf.round (x, name = None) # ‘a’ is [0.9, 2.5, 2.3, -4.4]tf.round(a) ==> [1.0, 3.0, 2.0, -4.0]

tf.sqrt (x, name = None) (y = \sqrt{x} = x ^ {1 / 2}).

tf.pow (x, y, name = None) # tensor ‘x’ is [[2, 2], [3, 3]] # tensor ‘y’ is [[8, 16], [2, 3]] tf.pow

(x, y) ==> [[256, 65536], [9, 27]]

tf.exp (x, name = None)

tf.log (x, name = None)

tf.maximum (x, y, name = None) (x > y ? x : y)

tf.minimum (x, y, name = None) (x < y ? x : y)

tf.cos (x, name = None) cosine

tf.sin (x, name = None) sine

tf.tan (x, name = None) tan

tf.atan (x, name = None) ctan

3. Reference

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