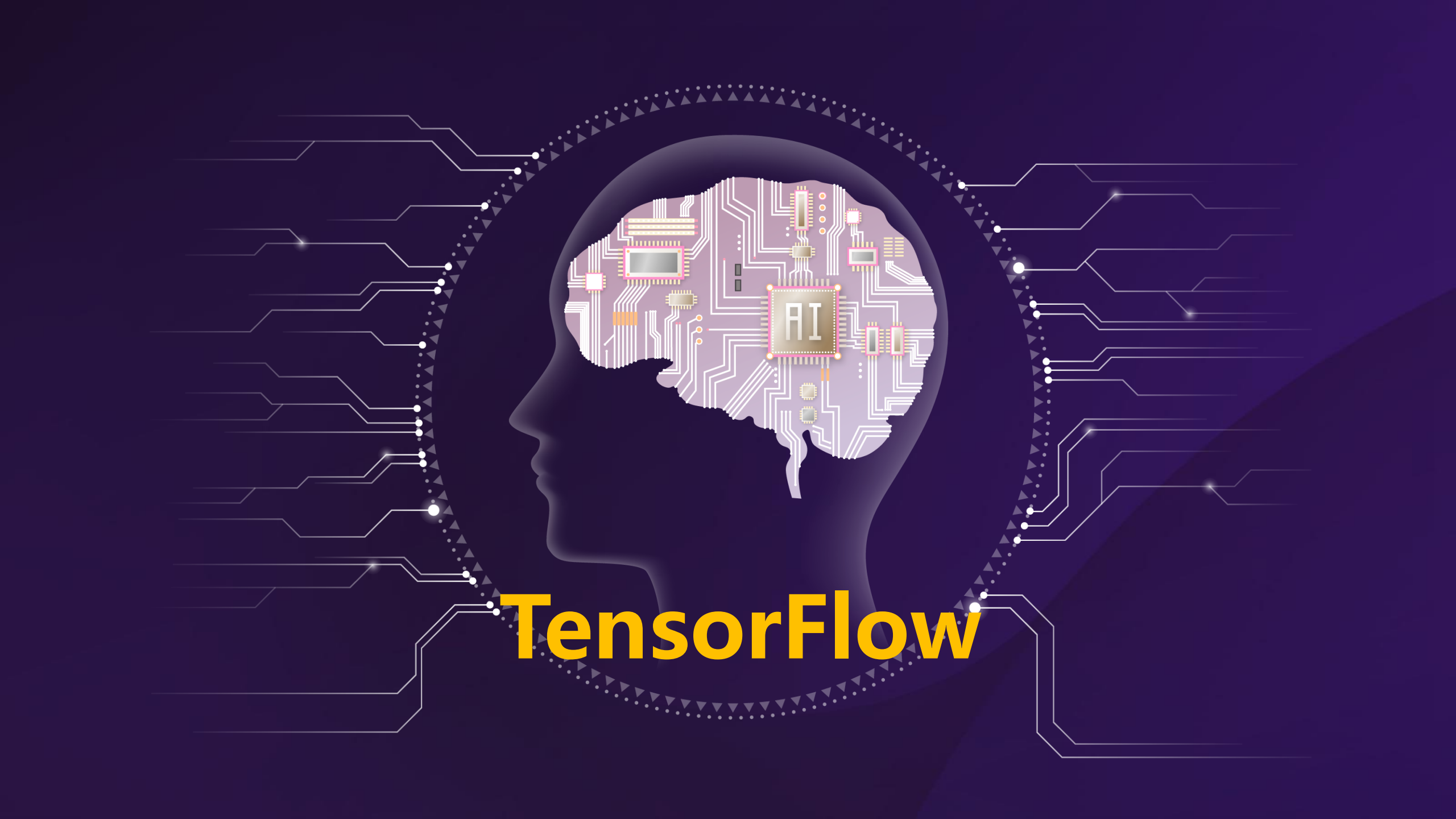
AI
TensorFlow

Contents

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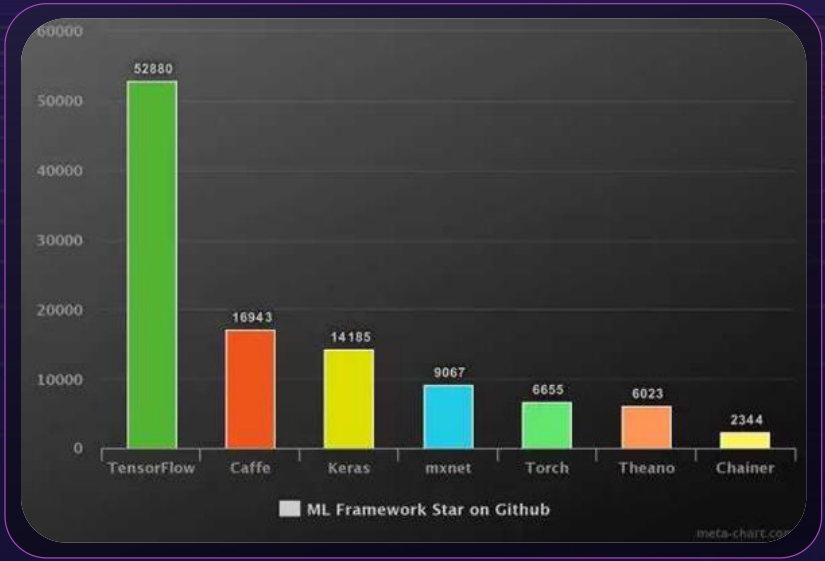
What Is TensorFlow

- TensorFlow is Google's second-generation open-source software library for dataflow computing.
- The TensorFlow framework supports various deep learning algorithms, as well as many computing platforms other than those for deep learning.
- TensorFlow is open-source, which facilitates maintenance and update and improves the development efficiency.



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Contents

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TensorFlow Characteristics

- Flexible and scalable
- Multi-language
- GPU
- Cross-platform
- Powerful computation
- Distributed

What Can We Do Using TensorFlow

Self-driving cars

Image recognition

Language models

Automated theorem proving

Music creation

Speech recognition

Human activity recognition

Gaming

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What Can We Do Using TensorFlow (2)

Artistic style transfer

Facial recognition

Contents

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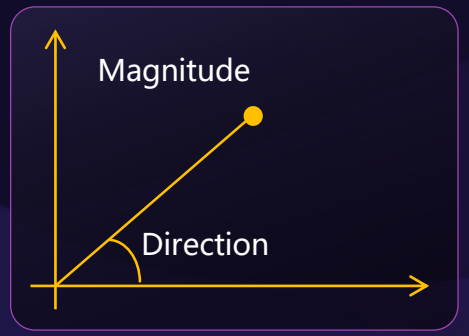
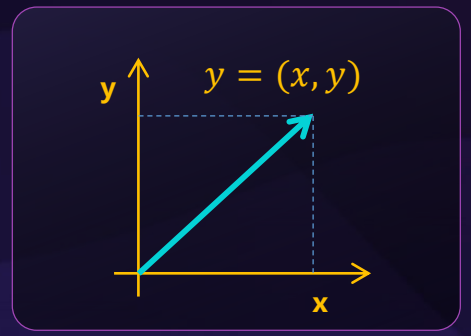
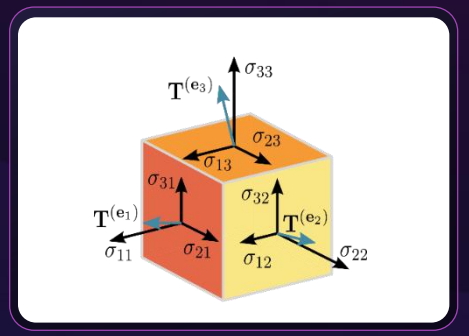
TensorFlow



Scalar



Vector

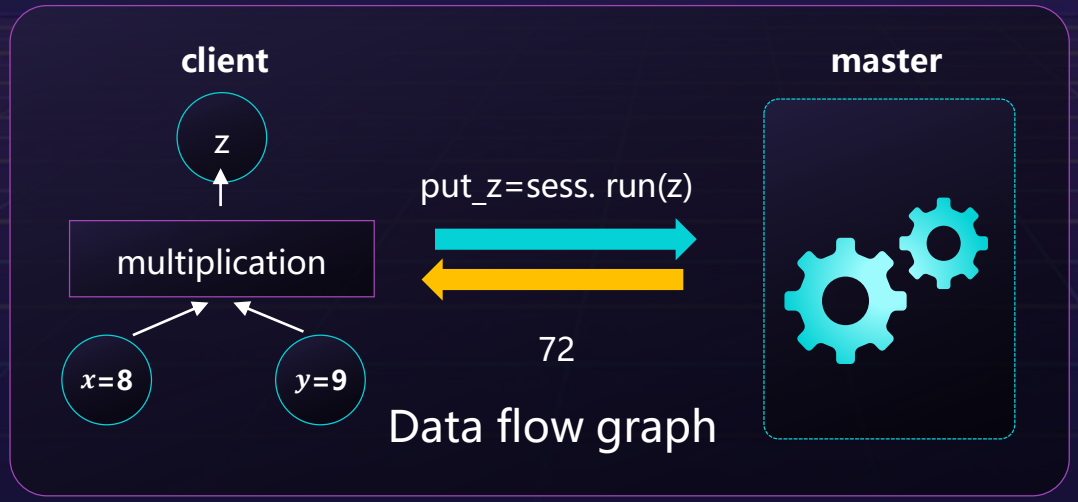


Tensor

Tensor

+

Flow



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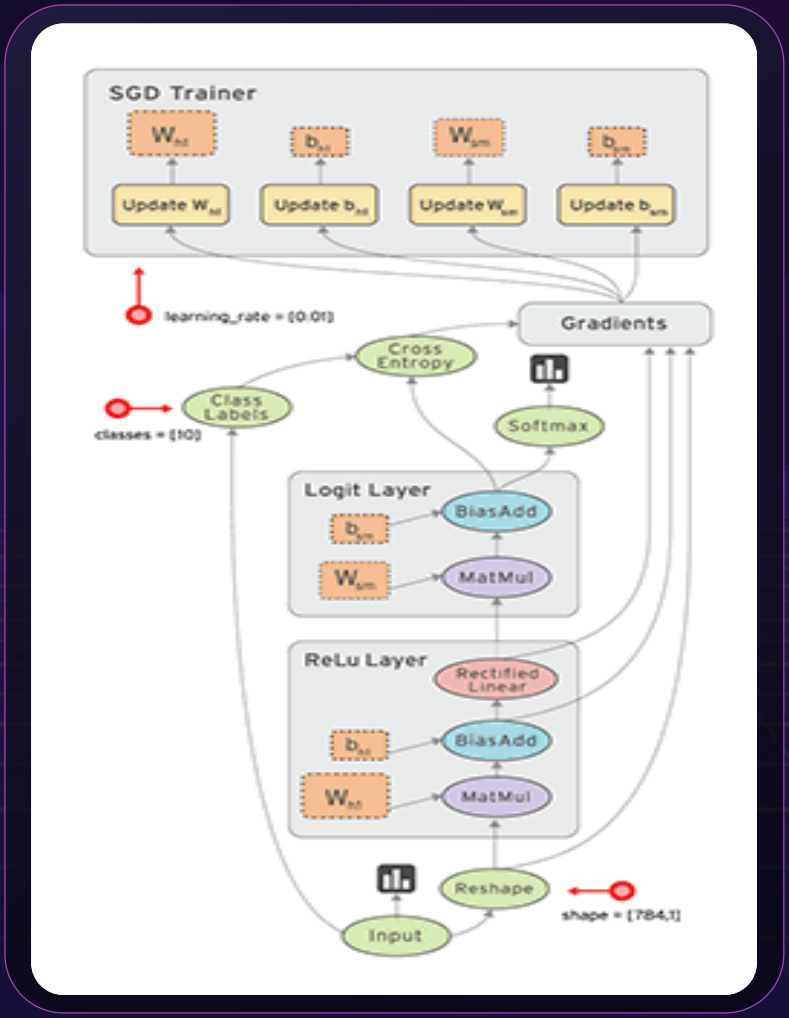
TensorFlow Computation Process



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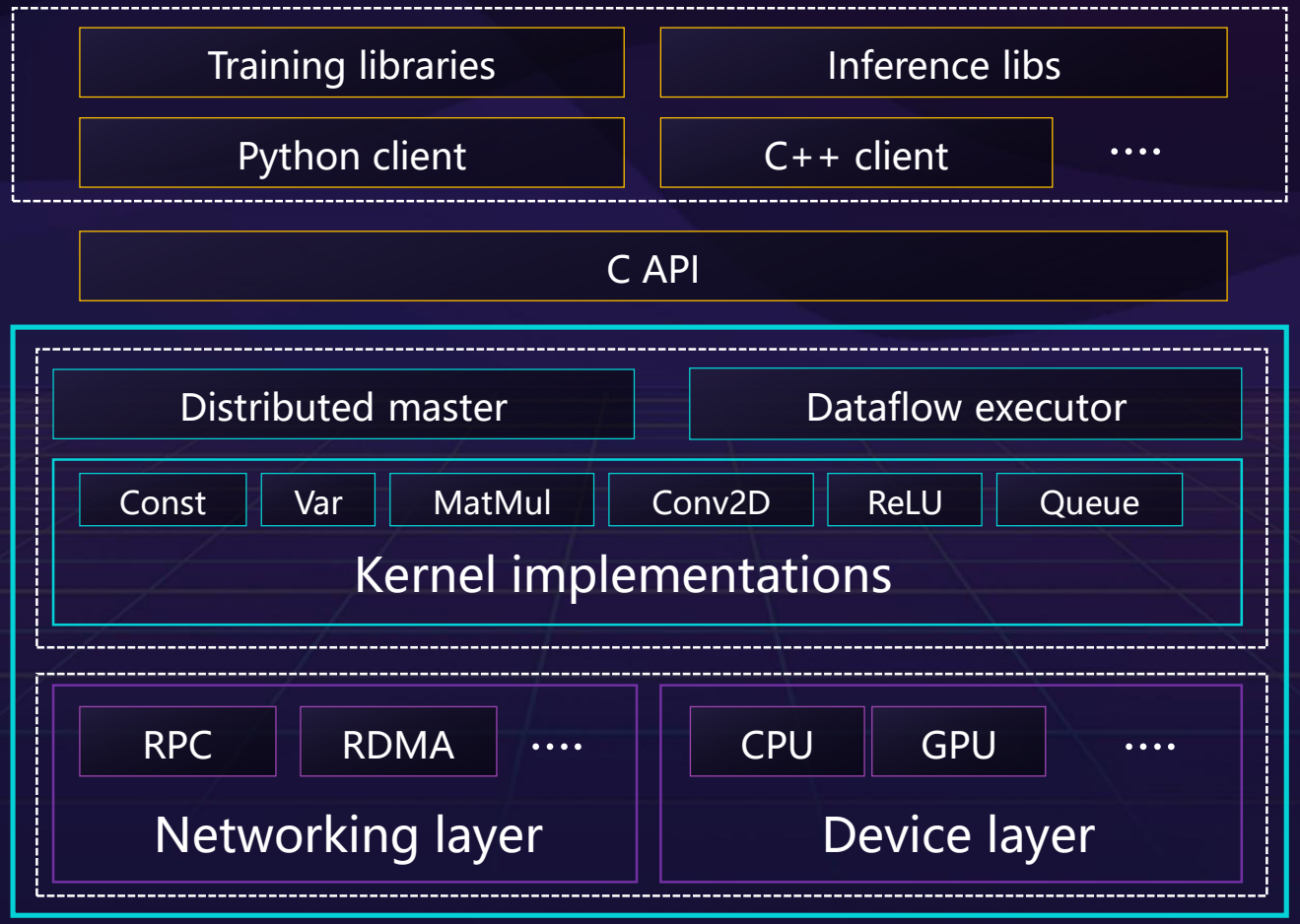
TensorFlow Architecture

Layer-by-layer breakdown and decoupling



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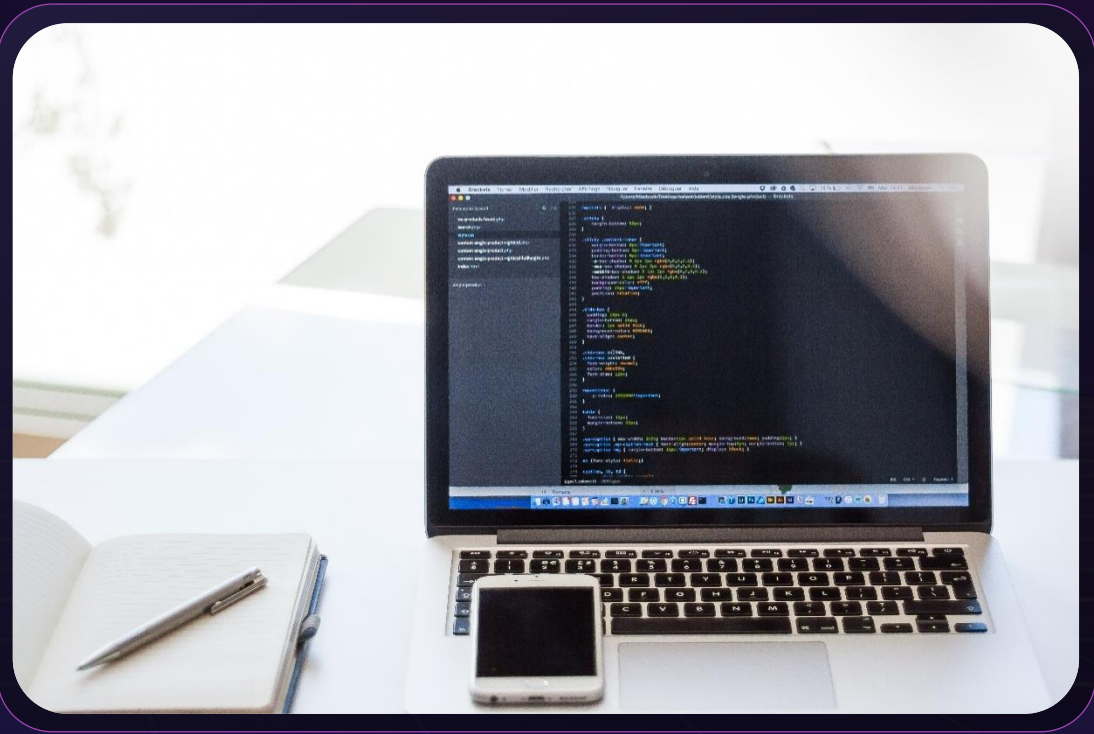
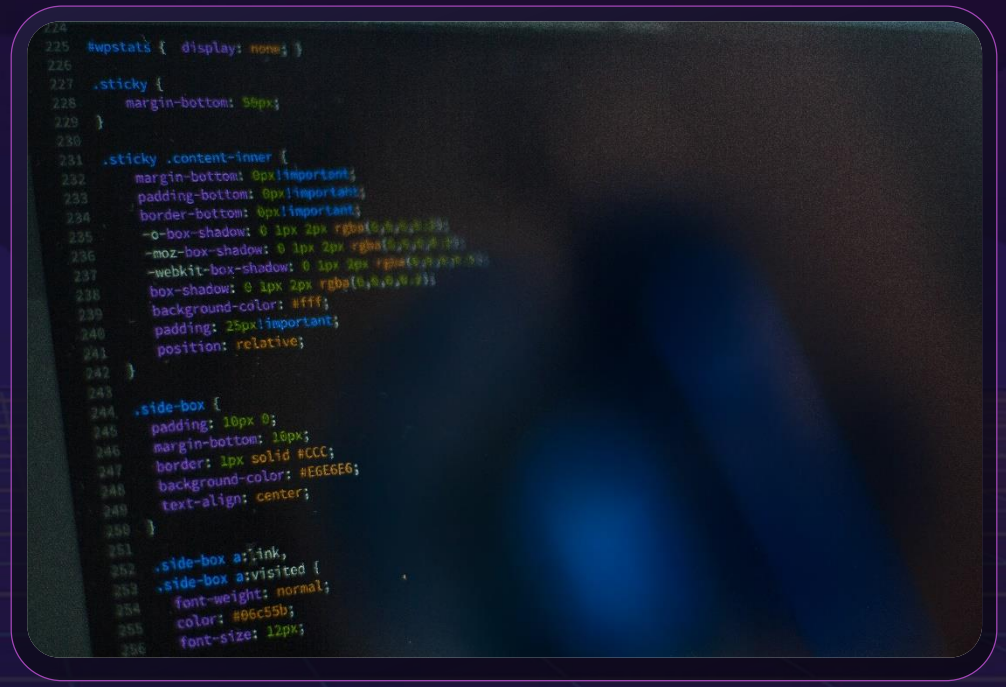
Basic Concepts of TensorFlow

- tensor
- graph
  - node
  - edge
- operation
- session
  - feed
  - fetch
- variable



tensor

- Tensor is the primary data structure in TensorFlow programs. Tensors are N-dimensional (where N could be 1, 2, 3, 4, or very large) data structures. In a running graph, tensors are the data that flows between nodes.
- The data structure contained in a tensor is: name + shape + type.



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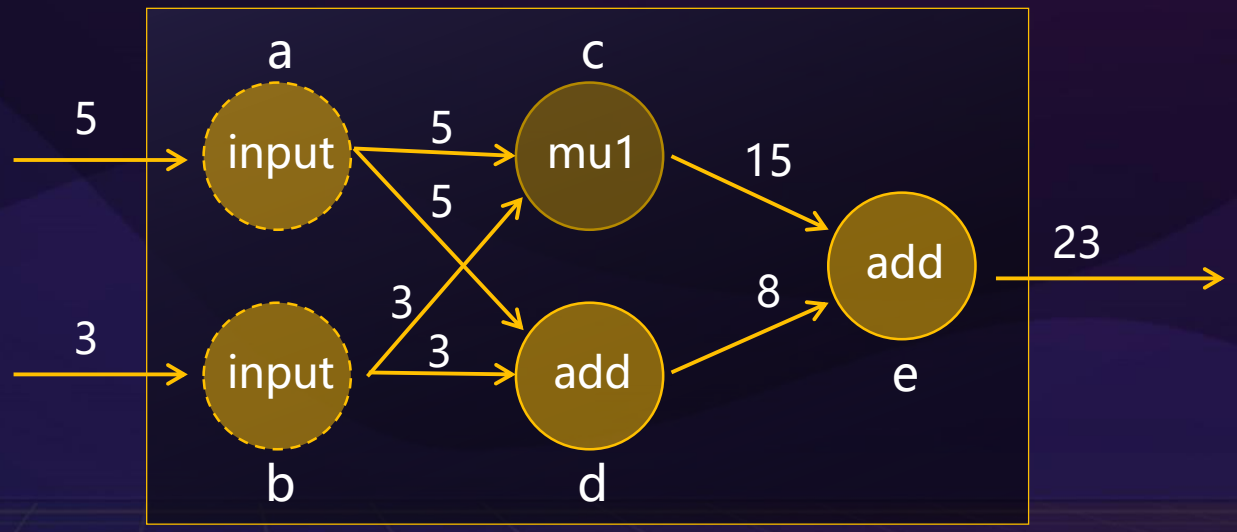
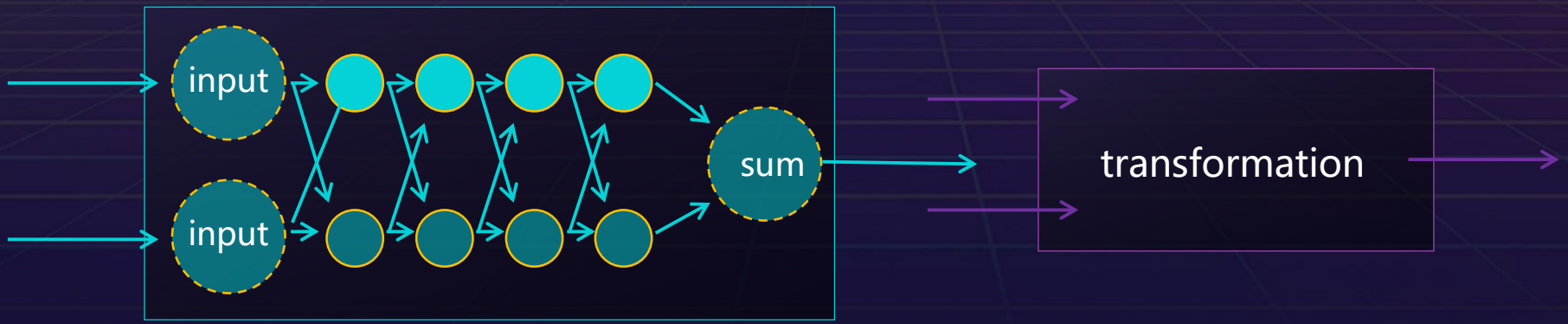
Graph (Data Flow Graph)

- Node: A data operation (OP) in the TensorFlow graph
- Edge: Data and its dependency relationships

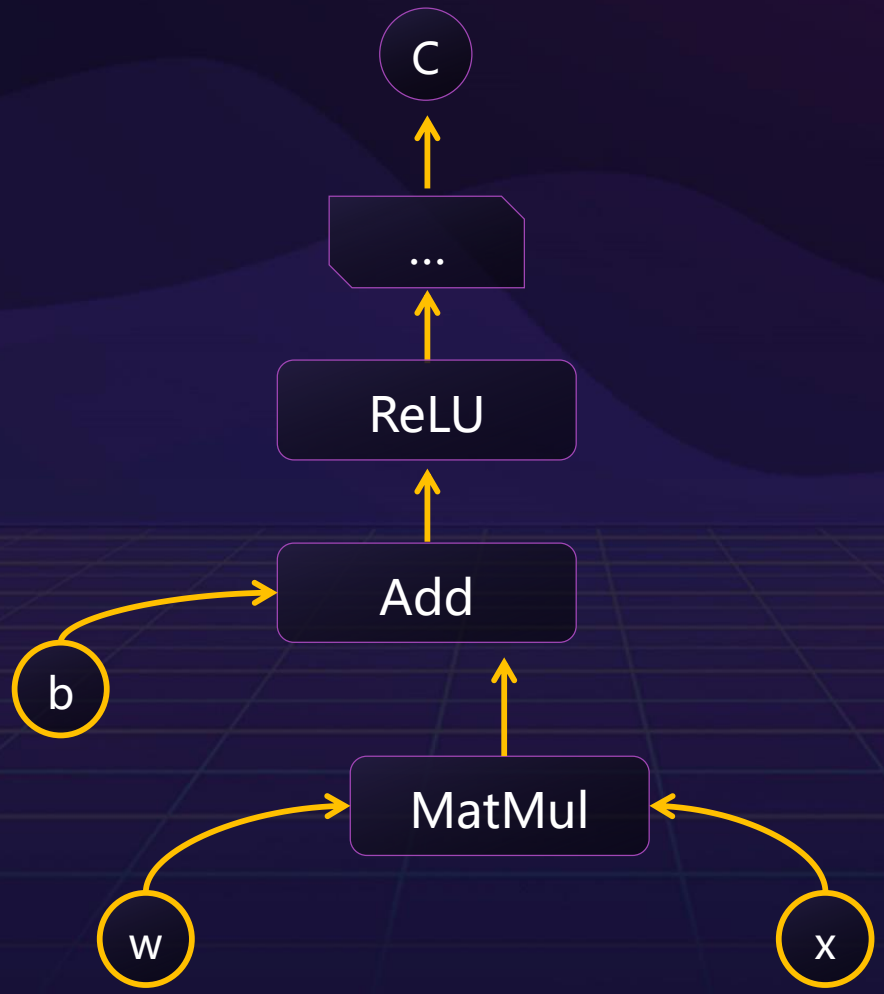




TensorFlow Operators

Category	Examples
Element——wise mathematical Operations	Add, Sub, Div, Exp, Log, Greater, Less, Equal, …
Array operations	Concat, Slice, Split, Constant, Rank, Shape, Shuffle, …
Matrix operations	MatMul, MatrixInverse, MatrixDeterminant, …
Stateful operations	Variable, Assign, AssignAdd, …
Neural-net building blocks	SoftMax, Singmoid, ReLU, Convolution2D, MAxPool, …
Checkpointing operations	Save, Restore, …
Queue and synchronization operations	Enqueue, Dequeue, Mutex Acquire, Mutex Release, …
Control flow operations	Merge, Switch, Enter, Leave, NextIteration

Session



Feed

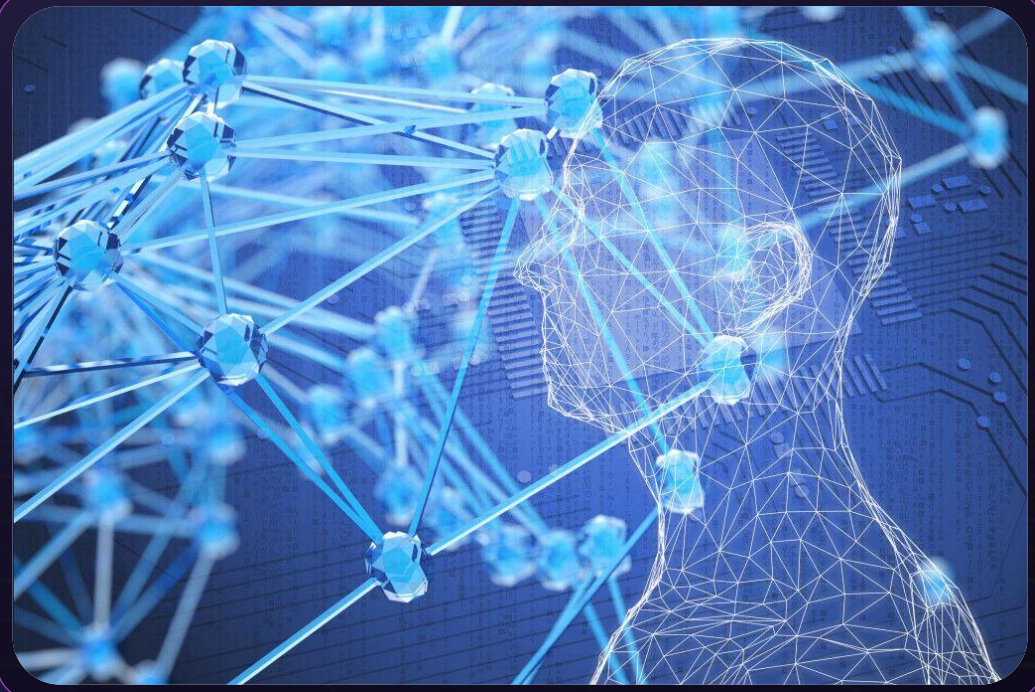
- The feed mechanism directly connects the tensor to a node in the graph, and temporarily replaces the tensor value on the node. A feed is not created when the graph is formed. Rather, it is applied for when graph execution is triggered. That is, the feed data is initialized in the form of parameters when the "run" or "eval" command is executed. After the execution is complete, the replaced feed data disappears, but the behavior of the node defined in the graph does not change. Generally, the feed mechanism is used together with tf.placeholder ().

Fetch

- The fetch mechanism retrieves the result of an operation in the graph. The fetch application occurs when graph execution is triggered, not when the graph is generated. To fetch the tensor value of one or more nodes, you can call the run () method on the session object and use the list of the nodes to be fetched as parameters to execute the graph.

Variable

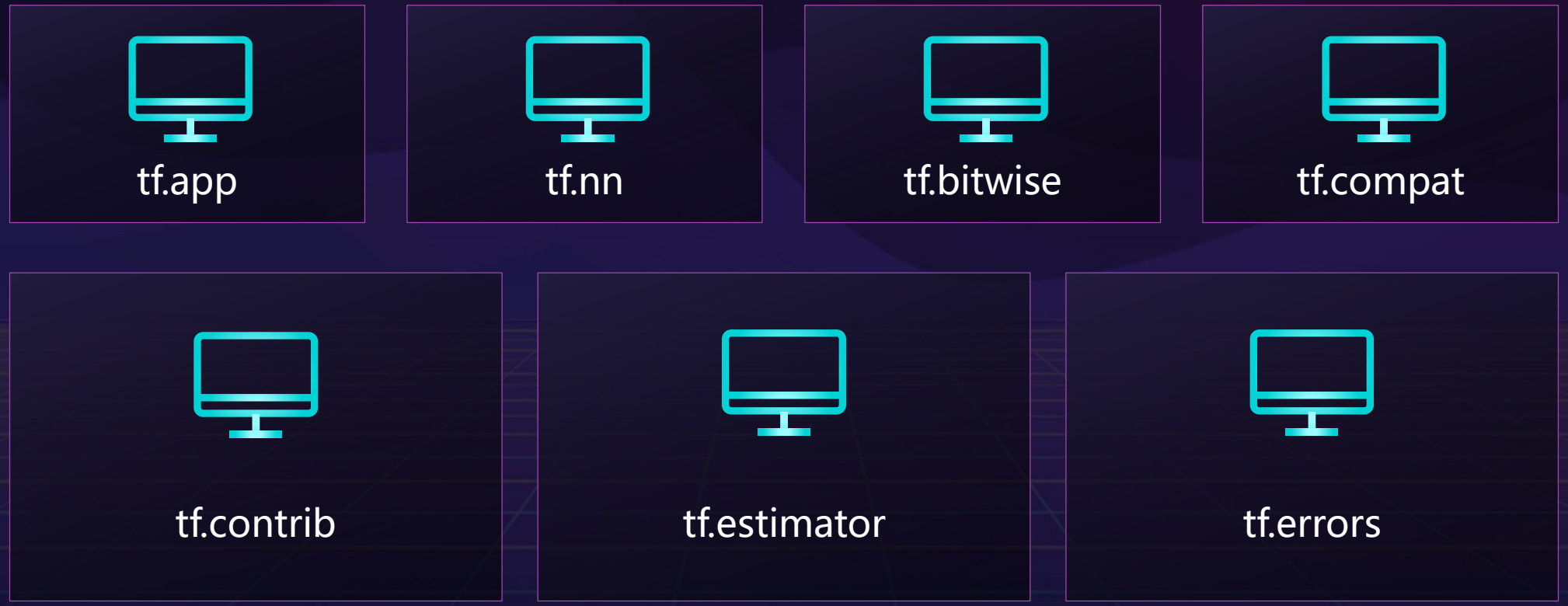
- A variable maintains state across multiple calls to run during graph execution. For example, in a neural network, it is used to identify coefficients such as w and b. The variable in TensorFlow is actually a variable object in Python.
- The initial value of a variable in TensorFlow can be set to a random number, a constant, or a number calculated based on the initial values of other variables.



Contents

HUAWEI

TensorFlow Modules (1)



TensorFlow Modules (2)

- **tf.nn:**
  - tf.nn is used to create RNN. It is the most commonly used module for constructing classical convolutional networks. It includes a sub-module, rnn_cell, which is used to construct recurrent neural networks.
- **tf.estimator:**
  - Used to create one or more input functions.
  - Defines the feature column of a model.
  - Instantiates an estimator to define feature columns and various types of hyper parameters.
  - Calls one or more methods on the estimator object and passes the appropriate input function as the data source.

TensorFlow Modules (3)

- **tf.Layers:** The network layer encapsulates variables and operations on the variables.
  - For example, the full connection layer performs a weighted sum operation on the input and can use an optional activation function. The weight and bias of a connection are managed by network layer objects.
- **tf.Contrib:** This module provides functions for computing streaming metrics.
  - The slim sub-module is the most commonly used in this module. All the functions that are experimental or easy to change are in this module, which has rich functional modules.
  - Tf. contrib provides advanced operations for computing layers in the calculation layer, regularization, summary operations, and calculations

Contents

Windows (1)

- Operating systems: Windows/MacOS/Linux
- Python 3 https://www.python.org/downloads/release/python-350/
- The Anaconda 3 (compatible with Python 3) contains the pip software.
- Installing TensorFlow
  - Installing the nightly package online (pip install tf-nightly)
  - Install the pure edition of TensorFlow (pip install tensorflow).
  - Install offline.

Windows (2)

- Installing the GPU version:
  - Install the CUDA software package (mapping with the TensorFlow version).
  - Install the cuDNN library (mapping with the TensorFlow version).
  - Test the graphics card.
  - Run the nvidia-smi command to view the graphics card information.
  - Check the CUDA version.

MacOS

- On the Mac OS X system, it is recommended that you install homebrew first and then run the brew install python command, so that you can use Python in homebrew to install TensorFlow. Another recommended method is to install TensorFlow in virtual env.

```
# In the current version, only CPU is supported
$ pip install https://storage.googleapis.com/tensorflow/mac/tensorflow-0.5.0-py2-none-any.whl
```

Linux

- The simplest installation mode on Linux is to use pip.

```
# Only the CPU version is used.
$ pip install https://storage.googleapis.com/tensorflow/linux/cpu/tensorflow-0.5.0-cp27-none-linux_x86_64.whl

# Start the version supporting GPU. (The version can only be installed after installing the CUDA sdk.
$ pip install https://storage.googleapis.com/tensorflow/linux/gpu/tensorflow-0.5.0-cp27-none-linux_x86_64.whl
```

Toolkit (1)

- Protocol Buffer
  - Protocol Buffers serialize structured data into a binary stream.
  - The precompiled format is a .proto file.
  - ProtoBuf’ s storage space is 10%-30% of XML.But, its parsing time is 20-100 times faster.

```
name: Zhang San
id: 12345
email: zhangsan@abc.com
```

Toolkit (2)

- Bazel (automatic build tool)
  - Compared with the traditional Makefile and Ant, Bazel is faster, more scalable, and flexible.
  - The basic concept is workspace. It can be considered a folder that contains the source code required for software compilation and the soft-make address of the output.
  - Only the py_binary, py_library, and py_test compilation modes are supported.

```
-rw-rw-r--  root root 208    BUILD
-rw-rw-r--  root root 48     hello_lib.py
-rw-rw-r--  root root 47     hello_main.py
-rw-rw-r--  root root 0      WORKSPACE
```

Running TensorFlow

```
$ python

>>> import tensorflow as tf
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
>>> print sess.run(hello)
Hello, TensorFlow!
>>> a = tf.constant(10)
>>> b = tf.constant(32)
>>> print sess.run(a+b)
42
>>>
```

Contents

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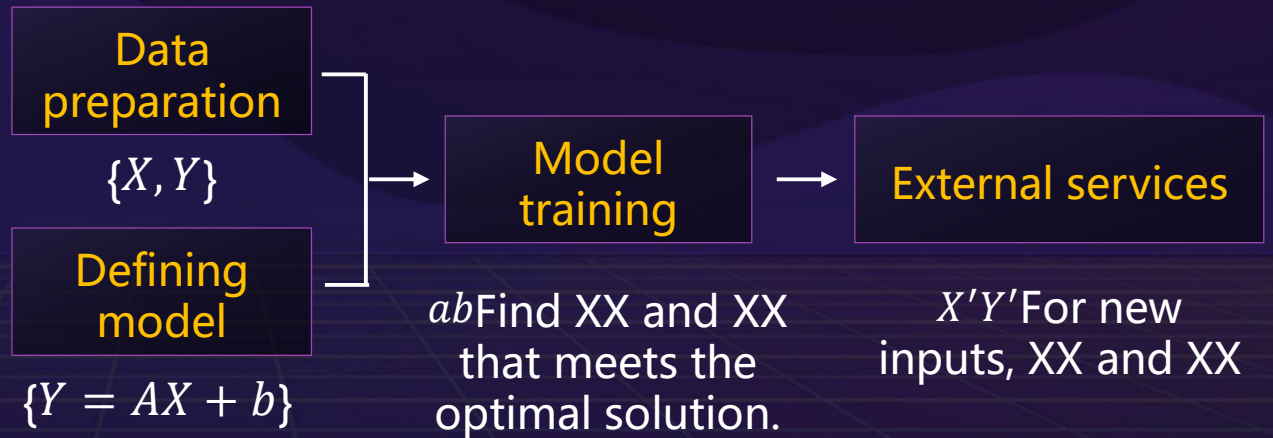
Development

- Define the model（input node，"learning parameter" variables，operation，Optimize functions and objectives.
- Initialize all variables.
- model training.
- Test the model.
- Use the model.



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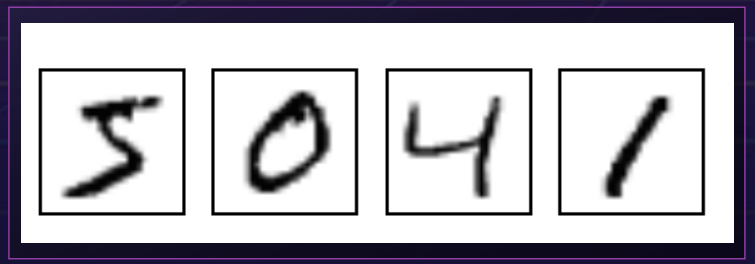
Preparing Data (1)

- MNIST is a classic problem in machine learning. The problem is solved by identifying 28 x 28 pixel grayscale images of handwritten digits as corresponding numbers ranging from 0 to 9.
- The MNIST dataset is an example of TensorFlow, you don't need to download it.



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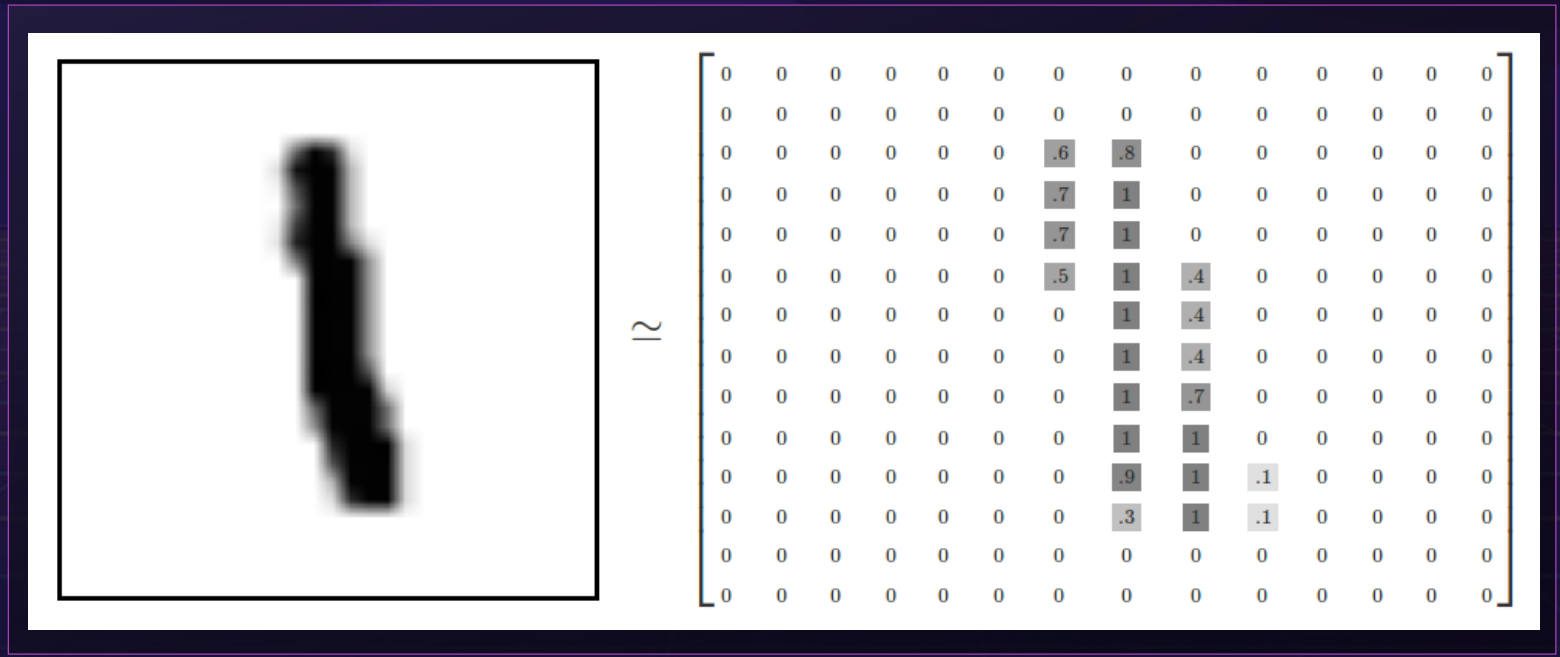
Preparing Data (2)

- An image is a matrix of 28 pixels x 28 pixels, which can be represented by a two-dimensional integer matrix of the same size.

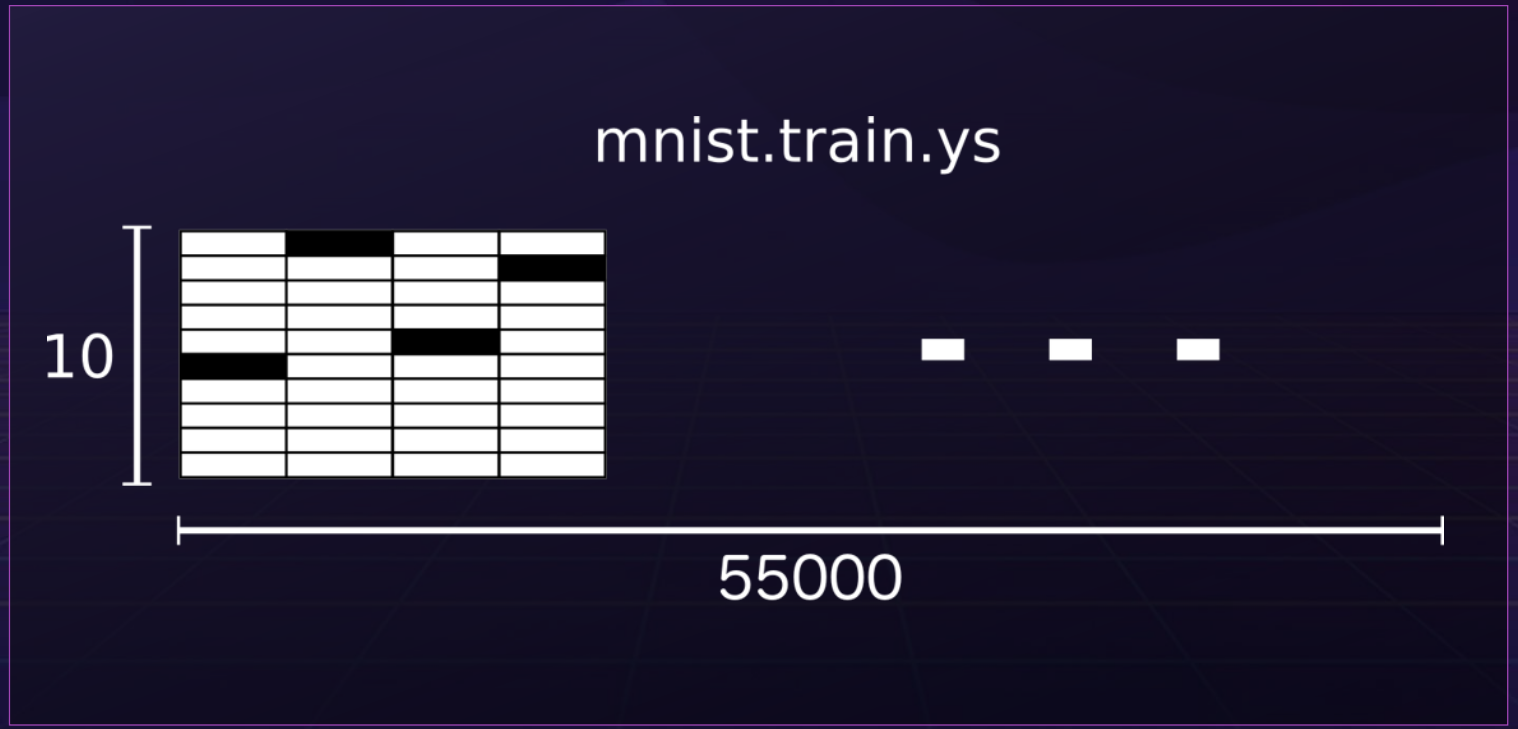


MNIST Dataset (1)

- The MNIST training dataset may be a 55000 x 784 tensor, that is, a multidimensional array. The first dimension represents the index of an image, and the second dimension represents the index of any pixel in the image (the pixel value in the tensor is between 0 and 1).

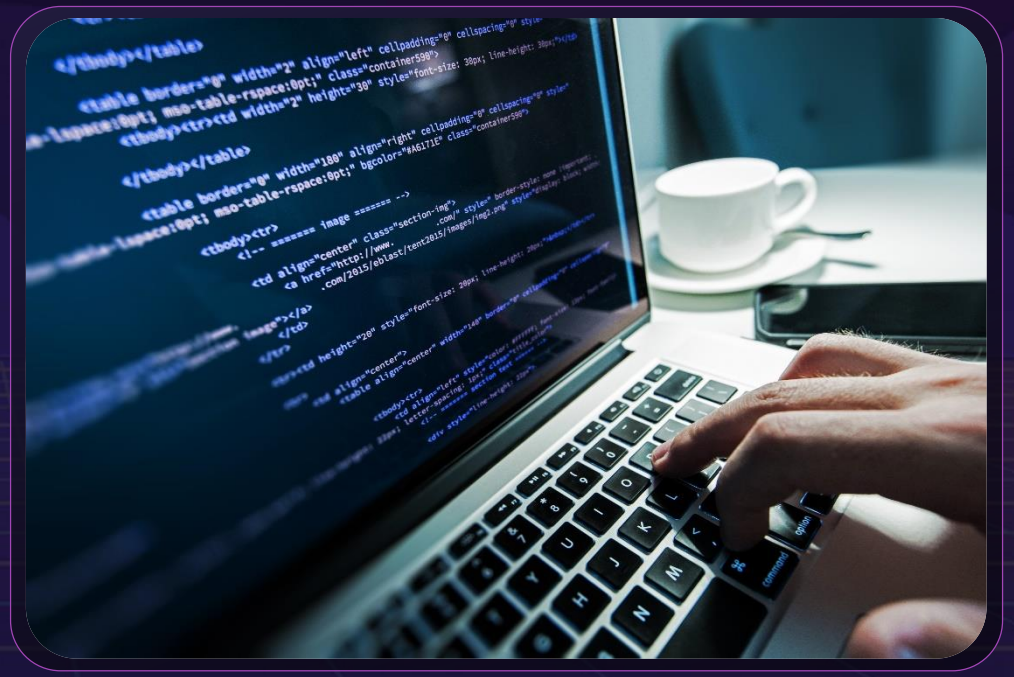
MNIST Dataset (2)

- mnist.train.labels is a two-dimensional array of 55000 x 10, as is shown in the following figure:



Defining the Input Node

- TensorFlow has the following methods for defining input nodes:
  - Defined by placeholders (commonly used)
  - Defined by dictionary types (used when there are many inputs)
  - Directly defined (seldom used)
- The input images are 550000 x 784 matrices. Therefore, create a placeholder x of [None, 784], and a placeholder y of [None and 10], and use the feed mechanism to input images and tags.



Defining Learning Parameters

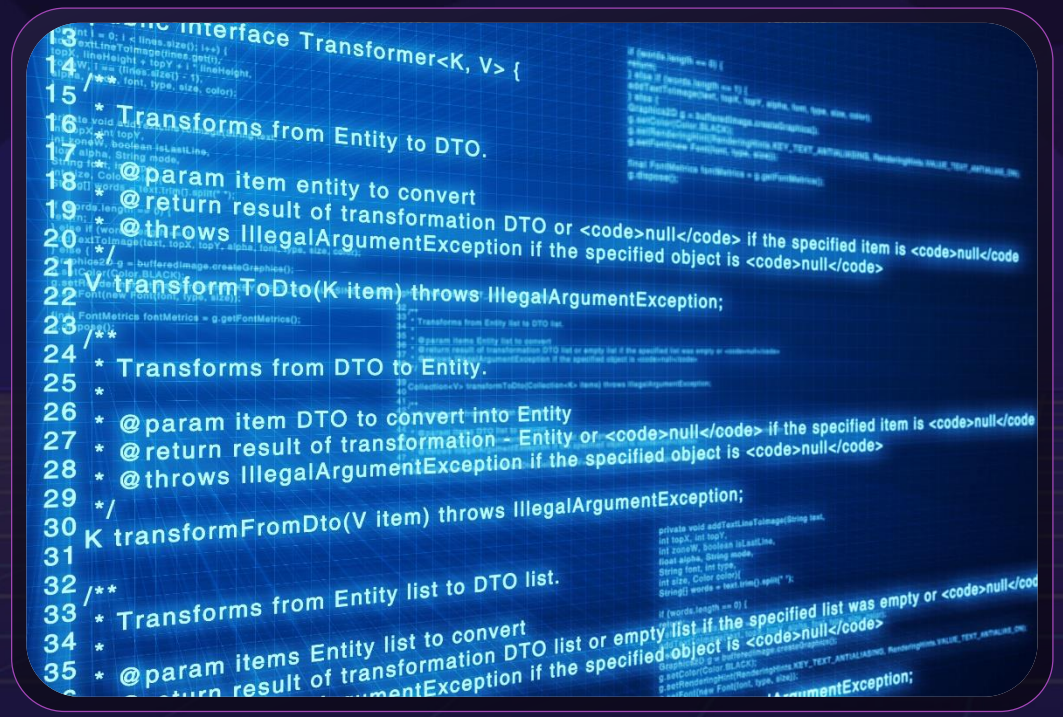
- Define "learning parameter" variables.

Directly defined

Defined by dictionary

- The learning parameters include weight values and bias values. In TensorFlow, learning parameters are defined by variables.
- A variable represents a modifiable tensor, which is defined in the TensorFlow graph. Learning parameters defined by variables can be used for computing input values, or be modified in computation.

Defining the Operation



- The core process of creating a model determines the fitting effect of the model.
- Define the operation type by:
  - Defining the forward propagation model
  - Defining the loss function (calculate the error between the output value and the target value and work in collaboration with backpropagation). The common loss functions in TensorFlow are mean square error and cross entropy.
  - Defining the backpropagation structure

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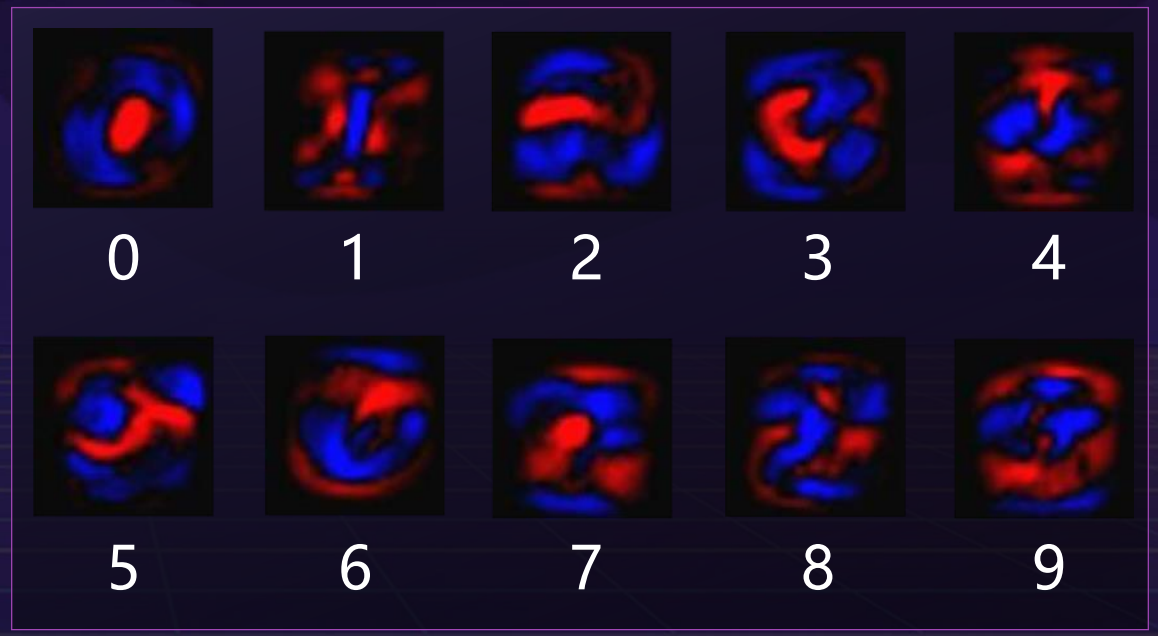
Creating a Model

- The softmax model can be used to assign probabilities to different objects. Even after we train more elaborate models, the final step also needs to use softmax to assign probabilities.
- The image below shows the weight of each pixel in a picture that the model learns for a particular number class. Red represents negative weights and blue represents positive weights.



Defining a Model

- We also need to add an extra bias because the input tends to have some extraneous interference. So for a given input image x, the evidence proving that it represents the digit i can be expressed as:

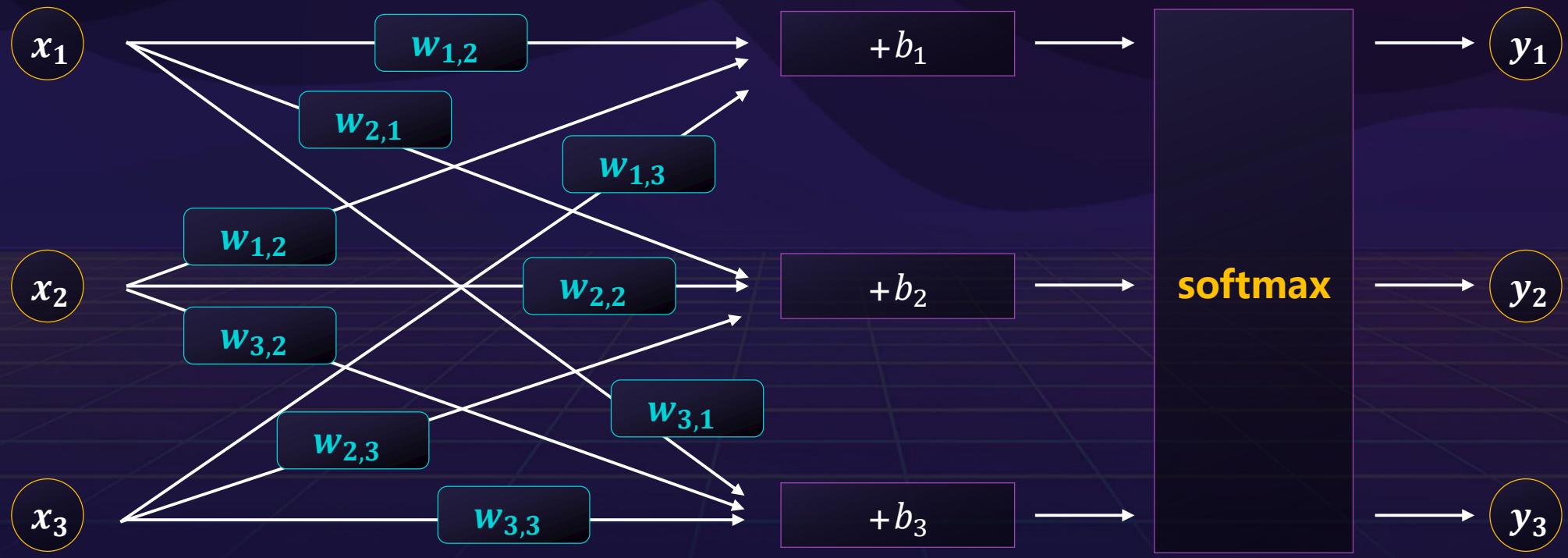
$$evidence_i = \sum_j W_{i,j} x_j + b_i .$$

- Where in W_i indicates weight. b_i indicates the bias of the numeric class i. j indicates the pixel index of a given image, x, and is used for summing the pixels. Then, use the softmax function to convert the evidence to the probability y.

$$y = softmax(evidence)$$

Regression Model (1)

- Add a bias to the weighted sum of the inputs x_i, and then input the biases to the softmax function.



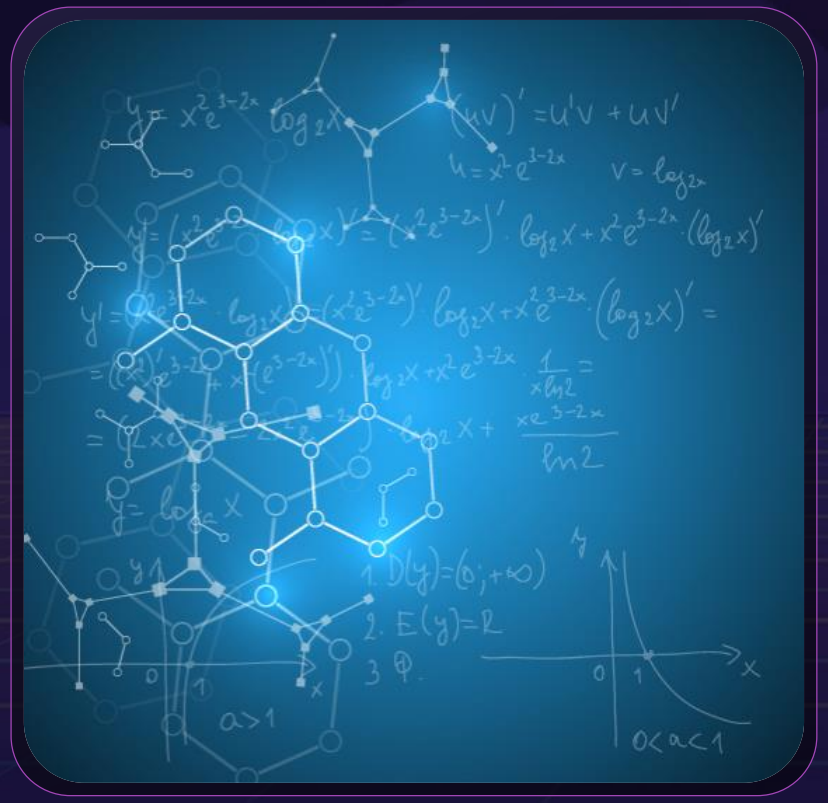
Regression Model (2)

- In actual cases, the calculation process is expressed using vectors, as shown in the following figure:

Further, it can be written in a more compact way:

$$y = \mathrm{softmax}(W_x + b).$$

Optimizing Functions and Objectives



- This process is completed in backpropagation. The backpropagation process is to transfer the error back along the reverse direction of forward propagation, involving L1 and L2 regularization, impulse adjustment, learning rate adaptation, and the Adam random gradient descent algorithm.

Initializing

- To create a model, you need to create a huge number of weights and biases. The weights in the model should be initialized with a small amount of noise to break the symmetry and avoid the zero gradient.
- To avoid repeated initialization during model creation, we define two functions for initialization.

```
def weight_variable(shape):
  initial = tf.truncated_normal(shape, stddev=0.1)
  return tf.Variable(initial)

def bias_variable(shape):
  initial = tf.constant(0.1, shape=shape)
  return tf.Variable(initial)
```

Implementing the Model

- In order to train our model, we first need to define an indicator to evaluate this model is good. In fact, in machine learning, we usually define indicators to indicate that a model is bad, this indicator is called cost or loss, and then try to minimize this indicator. In this experiment. The cost function is the cross-entropy function.

Iterating and Training the Model to Obtain the Optimal Solution

- Here, we require TensorFlow to use a gradient descent algorithm to minimize the cross-entropy at a learning rate of 0.01. The gradient descent algorithm is a simple learning process. TensorFlow simply moves each variable little by little in a direction that keeps costs down.
- Then, start training the model, here we let the model cycle training 1000 times!

```
for i in range(1000):
  batch_xs, batch_ys = mnist.train.next_batch(100)
  sess.run(train_step, feed_dict={x: batch_xs, y_: batch_ys})
```

Testing the Model

- For tf.argmax (y, 1), the return of the model prediction for any input x to the tag value, and tf.argmax (y_,1), the representative of the correct label, we can use tf.equal to test whether the prediction is a true tag match (the same as the index position indicates a match).

```
correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
```

Evaluating the Model

- TensorFlow needs to add the model evaluation to the computation graph, and then call the model evaluation after model training.
- The model evaluation mainly involves the following indicators: average accuracy, identification time, and loss decrease.
- During model training, model evaluation helps gain insight into the model algorithms and provide prompt information to debug, improve, or modify the whole model. After training the model, the performance of the model needs to be evaluated quantitatively.

Using the Model (1)

- Save the model:
  - Create a saver and a path, and invoke the save command to save the parameters in the session.
- Use the model:
  - Replace the nodes of loss value with the output nodes. This is similar to what has been done in model testing.
- Read the model:
  - Read the model. Add images to the model for prediction, and display the images and their corresponding tags.

Using the Model (2)

- Read the model. Add two images to the model to predict results and display the labels corresponding to the two images.
- The definition of the network model remains unchanged during code execution. Create a new session. All operations are performed in the new session.

```
After 0 training step(s), validation accuracy using average model is 0.103
After 1000 training step(s), validation accuracy using average model is 0.9044
After 2000 training step(s), validation accuracy using average model is 0.9174
After 3000 training step(s), validation accuracy using average model is 0.9258
After 4000 training step(s), validation accuracy using average model is 0.93
After 5000 training step(s), validation accuracy using average model is 0.9346
After 6000 training step(s), validation accuracy using average model is 0.94
After 7000 training step(s), validation accuracy using average model is 0.9422
After 8000 training step(s), validation accuracy using average model is 0.9472
After 9000 training step(s), validation accuracy using average model is 0.9498
After 10000 training step(s), test accuracy using average model is 0.9475
```

Contents

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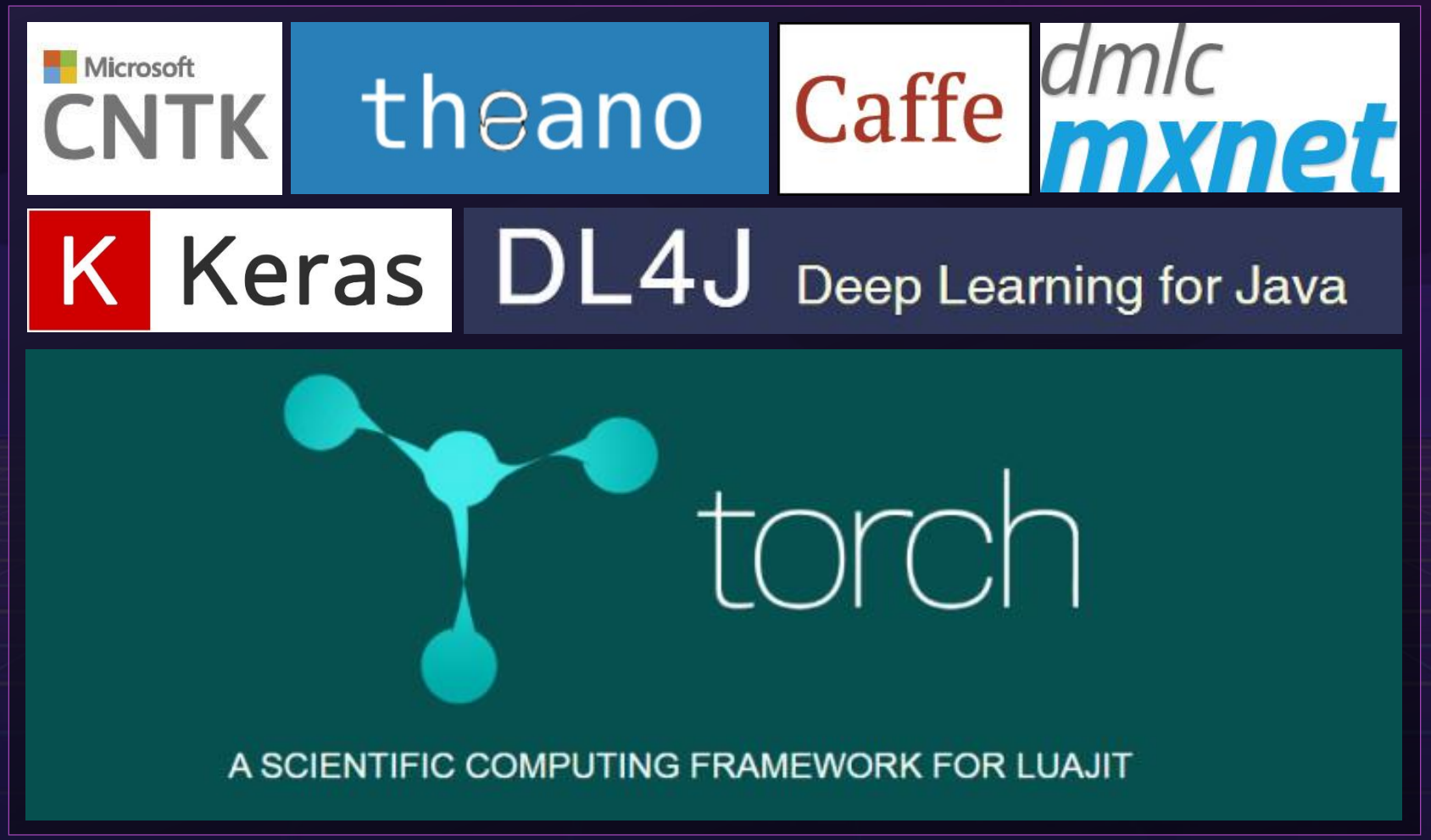
Other Deep Learning Frameworks



Hardware Supported by Deep Learning Frameworks

Property	Caffe	Neon	TensorFlow	Theano	Torch
Core	C++	Python	C++	Python	Lua
CPU	√	√	√	√	√
Multi-threaded CPU	√Blas	× Only date loader	√Eigen	√Blas, conv2D, limited OpenMP	√**Widely used**
GPU	√	√customized Nvidia backend	√	√	√
Multi-GPU	√ (only data parallel)	√	√**Most fiexible**	√ Experimental version available	√
Nvidia cuDNN	√	×	√	√	√
Quick deploy. On standard models	√**Easiest**	√	√	× Via secondary libraries	√
Auto. gradicent computation	√	√Supports Op-Tree	√	√**Most flexible** (also over loops)	√

Advantages and Disadvantages of the Popular Deep Learning Frameworks

- **Caffe:**
  - Advantages: Easy to get started, fast, modular, open, and supported by a good community.
  - Disadvantages: The layer needs to be defined in C++, and the model needs to be defined using Protobuf. The configuration file of the Caffe cannot be programmed to adjust the hyperparameter. Caffe only supports single-machine multi-GPU training, but does not natively support distributed training.
- **Torch:**
  - Advantages: The modeling is simple and highly modular, with fast and efficient GPU support. It uses LuaJIT to connect to C++ and numerical optimization programs. It can be embedded in the interfaces of iOS, Android, and FPGA.
  - Disadvantages: Some interfaces are not comprehensive, requiring LuaJIT to use the Lua language. Therefore, Torch lacks universality.

Thanks

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