# TensorLayer Documentation

***Release 1.8.0rc***

**TensorLayer contributors**

**Feb 24, 2018**

# Contents

**Good News:** We won the **Best Open Source Software Award** @ACM Multimedia (MM) 2017.

TensorLayer is a Deep Learning (DL) and Reinforcement Learning (RL) library extended from Google TensorFlow. It provides popular DL and RL modules that can be easily customized and assembled for tackling real-world machine learning problems. More details can be found here.

---

**Note:** If you got problem to read the docs online, you could download the repository on GitHub, then go to `/docs/_build/html/index.html` to read the docs offline. The `_build` folder can be generated in `docs` using `make html`.

---

CHAPTER 1

# User Guide

The TensorLayer user guide explains how to install TensorFlow, CUDA and cuDNN, how to build and train neural networks using TensorLayer, and how to contribute to the library as a developer.

## 1.1 Installation

TensorLayer has some prerequisites that need to be installed first, including TensorFlow , numpy and matplotlib. For GPU support CUDA and cuDNN are required.

If you run into any trouble, please check the TensorFlow installation instructions which cover installing the TensorFlow for a range of operating systems including Mac OX, Linux and Windows, or ask for help on tensorlayer@gmail.com or FQA.

### 1.1.1 Step 1 : Install dependencies

TensorLayer is build on the top of Python-version TensorFlow, so please install Python first.

**Note:** We highly recommend python3 instead of python2 for the sake of future.

Python includes `pip` command for installing additional modules is recommended. Besides, a virtual environment via `virtualenv` can help you to manage python packages.

Take Python3 on Ubuntu for example, to install Python includes `pip`, run the following commands:

```
sudo apt-get install python3
sudo apt-get install python3-pip
sudo pip3 install virtualenv
```

To build a virtual environment and install dependencies into it, run the following commands: (You can also skip to Step 3, automatically install the prerequisites by TensorLayer)

```
virtualenv env
env/bin/pip install matplotlib
env/bin/pip install numpy
env/bin/pip install scipy
env/bin/pip install scikit-image
```

To check the installed packages, run the following command:

```
env/bin/pip list
```

After that, you can run python script by using the virtual python as follow.

```
env/bin/python *.py
```

### 1.1.2 Step 2 : TensorFlow

The installation instructions of TensorFlow are written to be very detailed on TensorFlow website. However, there are something need to be considered. For example, TensorFlow officially supports GPU acceleration for Linux, Mac OX and Windows at present.

> **Warning:** For ARM processor architecture, you need to install TensorFlow from source.

### 1.1.3 Step 3 : TensorLayer

The simplest way to install TensorLayer is as follow, it will also install the numpy and matplotlib automatically.

```
[stable version] pip install tensorlayer
[master version] pip install git+https://github.com/zsdonghao/tensorlayer.git
```

However, if you want to modify or extend TensorLayer, you can download the repository from Github and install it as follow.

```
cd to the root of the git tree
pip install -e .
```

This command will run the `setup.py` to install TensorLayer. The `-e` reflects editable, then you can edit the source code in `tensorlayer` folder, and `import` the edited TensorLayer.

### 1.1.4 Step 4 : GPU support

Thanks to NVIDIA supports, training a fully connected network on a GPU, which may be 10 to 20 times faster than training them on a CPU. For convolutional network, may have 50 times faster. This requires an NVIDIA GPU with CUDA and cuDNN support.

#### CUDA

The TensorFlow website also teach how to install the CUDA and cuDNN, please see TensorFlow GPU Support.

Download and install the latest CUDA is available from NVIDIA website:

- CUDA download and install

If CUDA is set up correctly, the following command should print some GPU information on the terminal:

```
python -c "import tensorflow"
```

#### cuDNN

Apart from CUDA, NVIDIA also provides a library for common neural network operations that especially speeds up Convolutional Neural Networks (CNNs). Again, it can be obtained from NVIDIA after registering as a developer (it take a while):

Download and install the latest cuDNN is available from NVIDIA website:

- cuDNN download and install

To install it, copy the `*.h` files to `/usr/local/cuda/include` and the `lib*` files to `/usr/local/cuda/lib64`.

### 1.1.5 Windows User

TensorLayer is built on the top of Python-version TensorFlow, so please install Python first. NoteWe highly recommend installing Anaconda. The lowest version requirements of Python is py35.

Anaconda download

#### GPU support

Thanks to NVIDIA supports, training a fully connected network on a GPU, which may be 10 to 20 times faster than training them on a CPU. For convolutional network, may have 50 times faster. This requires an NVIDIA GPU with CUDA and cuDNN support.

##### 1. Installing Microsoft Visual Studio

You should preinstall Microsoft Visual Studio (VS) before installing CUDA. The lowest version requirements is VS2010. We recommend installing VS2015 or VS2013. CUDA7.5 supports VS2010, VS2012 and VS2013. CUDA8.0 also supports VS2015.

##### 2. Installing CUDA

Download and install the latest CUDA is available from NVIDIA website:

CUDA download

We do not recommend modifying the default installation directory.

##### 3. Installing cuDNN

The NVIDIA CUDA® Deep Neural Network library (cuDNN) is a GPU-accelerated library of primitives for deep neural networks. Download and extract the latest cuDNN is available from NVIDIA website:

cuDNN download

After extracting cuDNN, you will get three folders (bin, lib, include). Then these folders should be copied to CUDA installation. (The default installation directory is *C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\v8.0*)

#### Installing TensorLayer

You can easily install Tensorlayer using pip in CMD

```
pip install tensorflow        #CPU version
pip install tensorflow-gpu    #GPU version (GPU version and CPU version just choose␣
↪one)
pip install tensorlayer       #Install tensorlayer
```

#### Test

Enter “python” in CMD. Then:

```
import tensorlayer
```

If there is no error and the following output is displayed, the GPU version is successfully installed.

```
successfully opened CUDA library cublas64_80.dll locally
successfully opened CUDA library cuDNN64_5.dll locally
successfully opened CUDA library cufft64_80.dll locally
successfully opened CUDA library nvcuda.dll locally
successfully opened CUDA library curand64_80.dll locally
```

If there is no error, the CPU version is successfully installed.

### 1.1.6 Issue

If you get the following output when import tensorlayer, please read FQA.

```
_tkinter.TclError: no display name and no $DISPLAY environment variable
```

## 1.2 Tutorials

For deep learning, this tutorial will walk you through building handwritten digits classifiers using the MNIST dataset, arguably the “Hello World” of neural networks. For reinforcement learning, we will let computer learns to play Pong game from the original screen inputs. For nature language processing, we start from word embedding, and then describe language modeling and machine translation.

This tutorial includes all modularized implementation of Google TensorFlow Deep Learning tutorial, so you could read TensorFlow Deep Learning tutorial as the same time [en] [cn] .

**Note:** For experts: Read the source code of `InputLayer` and `DenseLayer`, you will understand how TensorLayer work. After that, we recommend you to read the codes on Github directly.

### 1.2.1 Before we start

The tutorial assumes that you are somewhat familiar with neural networks and TensorFlow (the library which TensorLayer is built on top of). You can try to learn the basic of neural network from the Deeplearning Tutorial.

For a more slow-paced introduction to artificial neural networks, we recommend Convolutional Neural Networks for Visual Recognition by Andrej Karpathy et al., Neural Networks and Deep Learning by Michael Nielsen.

To learn more about TensorFlow, have a look at the TensorFlow tutorial. You will not need all of it, but a basic understanding of how TensorFlow works is required to be able to use TensorLayer. If you're new to TensorFlow, going through that tutorial.

### 1.2.2 TensorLayer is simple

The following code shows a simple example of TensorLayer, see `tutorial_mnist_simple.py` . We provide a lot of simple functions like `fit()` , `test()` ), however, if you want to understand the details and be a machine learning expert, we suggest you to train the network by using the data iternation toolbox (`tl.iternate`) and the TensorFlow's native API like `sess.run()`, see *tutorial_mnist.py* *<https://github.com/tensorlayer/tensorlayer/blob/master/example/tutorial_mnist.py>*_ , tutorial_mlp_dropout1.py and *tutorial_mlp_dropout2.py* *<https://github.com/tensorlayer/tensorlayer/blob/master/example/tutorial_mlp_dropout2.py>*_ for more details.

```
import tensorflow as tf
import tensorlayer as tl

sess = tf.InteractiveSession()

# prepare data
X_train, y_train, X_val, y_val, X_test, y_test = \
                                tl.files.load_mnist_dataset(shape=(-1,784))

# define placeholder
x = tf.placeholder(tf.float32, shape=[None, 784], name='x')
y_ = tf.placeholder(tf.int64, shape=[None, ], name='y_')

# define the network
network = tl.layers.InputLayer(x, name='input_layer')
network = tl.layers.DropoutLayer(network, keep=0.8, name='drop1')
network = tl.layers.DenseLayer(network, n_units=800,
                                act = tf.nn.relu, name='relu1')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop2')
network = tl.layers.DenseLayer(network, n_units=800,
                                act = tf.nn.relu, name='relu2')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop3')
# the softmax is implemented internally in tl.cost.cross_entropy(y, y_, 'cost') to
# speed up computation, so we use identity here.
# see tf.nn.sparse_softmax_cross_entropy_with_logits()
network = tl.layers.DenseLayer(network, n_units=10,
                                act = tf.identity,
                                name='output_layer')
# define cost function and metric.
y = network.outputs
cost = tl.cost.cross_entropy(y, y_, 'cost')
correct_prediction = tf.equal(tf.argmax(y, 1), y_)
acc = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
y_op = tf.argmax(tf.nn.softmax(y), 1)

# define the optimizer
train_params = network.all_params
train_op = tf.train.AdamOptimizer(learning_rate=0.0001, beta1=0.9, beta2=0.999,
                            epsilon=1e-08, use_locking=False).minimize(cost, var_
↪list=train_params)
```

```
# initialize all variables in the session
tl.layers.initialize_global_variables(sess)

# print network information
network.print_params()
network.print_layers()

# train the network
tl.utils.fit(sess, network, train_op, cost, X_train, y_train, x, y_,
            acc=acc, batch_size=500, n_epoch=500, print_freq=5,
            X_val=X_val, y_val=y_val, eval_train=False)

# evaluation
tl.utils.test(sess, network, acc, X_test, y_test, x, y_, batch_size=None, cost=cost)

# save the network to .npz file
tl.files.save_npz(network.all_params , name='model.npz')
sess.close()
```

### 1.2.3 Run the MNIST example

In the first part of the tutorial, we will just run the MNIST example that's included in the source distribution of TensorLayer. MNIST dataset contains 60000 handwritten digits that is commonly used for training various image processing systems, each of digit has 28x28 pixels.

We assume that you have already run through the *Installation*. If you haven't done so already, get a copy of the source tree of TensorLayer, and navigate to the folder in a terminal window. Enter the folder and run the `tutorial_mnist.py` example script:

```
python tutorial_mnist.py
```

If everything is set up correctly, you will get an output like the following:

```
tensorlayer: GPU MEM Fraction 0.300000
Downloading train-images-idx3-ubyte.gz
Downloading train-labels-idx1-ubyte.gz
Downloading t10k-images-idx3-ubyte.gz
Downloading t10k-labels-idx1-ubyte.gz

X_train.shape (50000, 784)
y_train.shape (50000,)
```

```
X_val.shape (10000, 784)
y_val.shape (10000,)
X_test.shape (10000, 784)
y_test.shape (10000,)
X float32   y int64

[TL] InputLayer   input_layer (?, 784)
[TL] DropoutLayer drop1: keep: 0.800000
[TL] DenseLayer   relu1: 800, relu
[TL] DropoutLayer drop2: keep: 0.500000
[TL] DenseLayer   relu2: 800, relu
[TL] DropoutLayer drop3: keep: 0.500000
[TL] DenseLayer   output_layer: 10, identity

param 0: (784, 800) (mean: -0.000053, median: -0.000043 std: 0.035558)
param 1: (800,)     (mean:  0.000000, median:  0.000000 std: 0.000000)
param 2: (800, 800) (mean:  0.000008, median:  0.000041 std: 0.035371)
param 3: (800,)     (mean:  0.000000, median:  0.000000 std: 0.000000)
param 4: (800, 10)  (mean:  0.000469, median:  0.000432 std: 0.049895)
param 5: (10,)      (mean:  0.000000, median:  0.000000 std: 0.000000)
num of params: 1276810

layer 0: Tensor("dropout/mul_1:0", shape=(?, 784), dtype=float32)
layer 1: Tensor("Relu:0", shape=(?, 800), dtype=float32)
layer 2: Tensor("dropout_1/mul_1:0", shape=(?, 800), dtype=float32)
layer 3: Tensor("Relu_1:0", shape=(?, 800), dtype=float32)
layer 4: Tensor("dropout_2/mul_1:0", shape=(?, 800), dtype=float32)
layer 5: Tensor("add_2:0", shape=(?, 10), dtype=float32)

learning_rate: 0.000100
batch_size: 128

Epoch 1 of 500 took 0.342539s
  train loss: 0.330111
  val loss: 0.298098
  val acc: 0.910700
Epoch 10 of 500 took 0.356471s
  train loss: 0.085225
  val loss: 0.097082
  val acc: 0.971700
Epoch 20 of 500 took 0.352137s
  train loss: 0.040741
  val loss: 0.070149
  val acc: 0.978600
Epoch 30 of 500 took 0.350814s
  train loss: 0.022995
  val loss: 0.060471
  val acc: 0.982800
Epoch 40 of 500 took 0.350996s
  train loss: 0.013713
  val loss: 0.055777
  val acc: 0.983700
...
```

The example script allows you to try different models, including Multi-Layer Perceptron, Dropout, Dropconnect, Stacked Denoising Autoencoder and Convolutional Neural Network. Select different models from `if __name__ == '__main__':`.

```
main_test_layers(model='relu')
main_test_denoise_AE(model='relu')
main_test_stacked_denoise_AE(model='relu')
main_test_cnn_layer()
```

### 1.2.4 Understand the MNIST example

Let's now investigate what's needed to make that happen! To follow along, open up the source code.

#### Preface

The first thing you might notice is that besides TensorLayer, we also import numpy and tensorflow:

```
import tensorflow as tf
import tensorlayer as tl
from tensorlayer.layers import set_keep
import numpy as np
import time
```

As we know, TensorLayer is built on top of TensorFlow, it is meant as a supplement helping with some tasks, not as a replacement. You will always mix TensorLayer with some vanilla TensorFlow code. The `set_keep` is used to access the placeholder of keeping probabilities when using Denoising Autoencoder.

#### Loading data

The first piece of code defines a function `load_mnist_dataset()`. Its purpose is to download the MNIST dataset (if it hasn't been downloaded yet) and return it in the form of regular numpy arrays. There is no TensorLayer involved at all, so for the purpose of this tutorial, we can regard it as:

```
X_train, y_train, X_val, y_val, X_test, y_test = \
                  tl.files.load_mnist_dataset(shape=(-1,784))
```

`X_train.shape` is `(50000, 784)`, to be interpreted as: 50,000 images and each image has 784 pixels. `y_train.shape` is simply `(50000,)`, which is a vector the same length of `X_train` giving an integer class label for each image – namely, the digit between 0 and 9 depicted in the image (according to the human annotator who drew that digit).

For Convolutional Neural Network example, the MNIST can be load as 4D version as follow:

```
X_train, y_train, X_val, y_val, X_test, y_test = \
            tl.files.load_mnist_dataset(shape=(-1, 28, 28, 1))
```

`X_train.shape` is `(50000, 28, 28, 1)` which represents 50,000 images with 1 channel, 28 rows and 28 columns each. Channel one is because it is a grey scale image, every pixel have only one value.

#### Building the model

This is where TensorLayer steps in. It allows you to define an arbitrarily structured neural network by creating and stacking or merging layers. Since every layer knows its immediate incoming layers, the output layer (or output layers) of a network double as a handle to the network as a whole, so usually this is the only thing we will pass on to the rest of the code.

As mentioned above, `tutorial_mnist.py` supports four types of models, and we implement that via easily exchangeable functions of the same interface. First, we'll define a function that creates a Multi-Layer Perceptron (MLP) of a fixed architecture, explaining all the steps in detail. We'll then implement a Denosing Autoencoder (DAE), after that we will then stack all Denoising Autoencoder and supervised fine-tune them. Finally, we'll show how to create a Convolutional Neural Network (CNN). In addition, a simple example for MNIST dataset in `tutorial_mnist_simple.py`, a CNN example for CIFAR-10 dataset in `tutorial_cifar10_tfrecord.py`.

### Multi-Layer Perceptron (MLP)

The first script, `main_test_layers()`, creates an MLP of two hidden layers of 800 units each, followed by a softmax output layer of 10 units. It applies 20% dropout to the input data and 50% dropout to the hidden layers.

To feed data into the network, TensofFlow placeholders need to be defined as follow. The `None` here means the network will accept input data of arbitrary batchsize after compilation. The `x` is used to hold the `X_train` data and `y_` is used to hold the `y_train` data. If you know the batchsize beforehand and do not need this flexibility, you should give the batchsize here – especially for convolutional layers, this can allow TensorFlow to apply some optimizations.

```
x = tf.placeholder(tf.float32, shape=[None, 784], name='x')
y_ = tf.placeholder(tf.int64, shape=[None, ], name='y_')
```

The foundation of each neural network in TensorLayer is an *`InputLayer`* instance representing the input data that will subsequently be fed to the network. Note that the `InputLayer` is not tied to any specific data yet.

```
network = tl.layers.InputLayer(x, name='input_layer')
```

Before adding the first hidden layer, we'll apply 20% dropout to the input data. This is realized via a *`DropoutLayer`* instance:

```
network = tl.layers.DropoutLayer(network, keep=0.8, name='drop1')
```

Note that the first constructor argument is the incoming layer, the second argument is the keeping probability for the activation value. Now we'll proceed with the first fully-connected hidden layer of 800 units. Note that when stacking a *`DenseLayer`*.

```
network = tl.layers.DenseLayer(network, n_units=800, act = tf.nn.relu, name='relu1')
```

Again, the first constructor argument means that we're stacking `network` on top of `network`. `n_units` simply gives the number of units for this fully-connected layer. `act` takes an activation function, several of which are defined in `tensorflow.nn` and *tensorlayer.activation*. Here we've chosen the rectifier, so we'll obtain ReLUs. We'll now add dropout of 50%, another 800-unit dense layer and 50% dropout again:

```
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop2')
network = tl.layers.DenseLayer(network, n_units=800, act = tf.nn.relu, name='relu2')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop3')
```

Finally, we'll add the fully-connected output layer which the `n_units` equals to the number of classes. Note that, the softmax is implemented internally in `tf.nn.sparse_softmax_cross_entropy_with_logits()` to speed up computation, so we used identity in the last layer, more details in `tl.cost.cross_entropy()`.

```
network = tl.layers.DenseLayer(network,
                              n_units=10,
                              act = tf.identity,
                              name='output_layer')
```

As mentioned above, each layer is linked to its incoming layer(s), so we only need the output layer(s) to access a network in TensorLayer:

```
y = network.outputs
y_op = tf.argmax(tf.nn.softmax(y), 1)
cost = tf.reduce_mean(tf.nn.sparse_softmax_cross_entropy_with_logits(y, y_))
```

Here, `network.outputs` is the 10 identity outputs from the network (in one hot format), `y_op` is the integer output represents the class index. While `cost` is the cross-entropy between target and predicted labels.

### Denoising Autoencoder (DAE)

Autoencoder is an unsupervised learning model which is able to extract representative features, it has become more widely used for learning generative models of data and Greedy layer-wise pre-train. For vanilla Autoencoder see Deeplearning Tutorial.

The script `main_test_denoise_AE()` implements a Denoising Autoencoder with corrosion rate of 50%. The Autoencoder can be defined as follow, where an Autoencoder is represented by a `DenseLayer`:

```
network = tl.layers.InputLayer(x, name='input_layer')
network = tl.layers.DropoutLayer(network, keep=0.5, name='denoising1')
network = tl.layers.DenseLayer(network, n_units=200, act=tf.nn.sigmoid, name='sigmoid1
↪')
recon_layer1 = tl.layers.ReconLayer(network,
                                    x_recon=x,
                                    n_units=784,
                                    act=tf.nn.sigmoid,
                                    name='recon_layer1')
```

To train the `DenseLayer`, simply run `ReconLayer.pretrain()`, if using denoising Autoencoder, the name of corrosion layer (a `DropoutLayer`) need to be specified as follow. To save the feature images, set `save` to `True`. There are many kinds of pre-train metrices according to different architectures and applications. For sigmoid activation, the Autoencoder can be implemented by using KL divergence, while for rectifer, L1 regularization of activation outputs can make the output to be sparse. So the default behaviour of `ReconLayer` only provide KLD and cross-entropy for sigmoid activation function and L1 of activation outputs and mean-squared-error for rectifing activation function. We recommend you to modify `ReconLayer` to achieve your own pre-train metrice.

```
recon_layer1.pretrain(sess,
                      x=x,
                      X_train=X_train,
                      X_val=X_val,
                      denoise_name='denoising1',
                      n_epoch=200,
                      batch_size=128,
                      print_freq=10,
                      save=True,
                      save_name='w1pre_')
```

In addition, the script `main_test_stacked_denoise_AE()` shows how to stacked multiple Autoencoder to one network and then fine-tune.

### Convolutional Neural Network (CNN)

Finally, the `main_test_cnn_layer()` script creates two CNN layers and max pooling stages, a fully-connected hidden layer and a fully-connected output layer. More CNN examples can be found in other examples, like `tutorial_cifar10_tfrecord.py`.

```
network = tl.layers.Conv2d(network, 32, (5, 5), (1, 1),
        act=tf.nn.relu, padding='SAME', name='cnn1')
network = tl.layers.MaxPool2d(network, (2, 2), (2, 2),
        padding='SAME', name='pool1')
network = tl.layers.Conv2d(network, 64, (5, 5), (1, 1),
        act=tf.nn.relu, padding='SAME', name='cnn2')
network = tl.layers.MaxPool2d(network, (2, 2), (2, 2),
        padding='SAME', name='pool2')

network = tl.layers.FlattenLayer(network, name='flatten')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop1')
network = tl.layers.DenseLayer(network, 256, act=tf.nn.relu, name='relu1')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop2')
network = tl.layers.DenseLayer(network, 10, act=tf.identity, name='output')
```

### Training the model

The remaining part of the `tutorial_mnist.py` script copes with setting up and running a training loop over the MNIST dataset by using cross-entropy only.

### Dataset iteration

An iteration function for synchronously iterating over two numpy arrays of input data and targets, respectively, in mini-batches of a given number of items. More iteration function can be found in `tensorlayer.iterate`

```
tl.iterate.minibatches(inputs, targets, batchsize, shuffle=False)
```

### Loss and update expressions

Continuing, we create a loss expression to be minimized in training:

```
y = network.outputs
y_op = tf.argmax(tf.nn.softmax(y), 1)
cost = tf.reduce_mean(tf.nn.sparse_softmax_cross_entropy_with_logits(y, y_))
```

More cost or regularization can be applied here. For example, to apply max-norm on the weight matrices, we can add the following line.

```
cost = cost + tl.cost.maxnorm_regularizer(1.0)(network.all_params[0]) +
              tl.cost.maxnorm_regularizer(1.0)(network.all_params[2])
```

Depending on the problem you are solving, you will need different loss functions, see *`tensorlayer.cost`* for more. Apart from using `network.all_params` to get the variables, we can also use `tl.layers.get_variables_with_name` to get the specific variables by string name.

Having the model and the loss function here, we create update expression/operation for training the network. TensorLayer do not provide many optimizers, we used TensorFlow's optimizer instead:

```
train_params = network.all_params
train_op = tf.train.AdamOptimizer(learning_rate, beta1=0.9, beta2=0.999,
    epsilon=1e-08, use_locking=False).minimize(cost, var_list=train_params)
```

For training the network, we fed data and the keeping probabilities to the `feed_dict`.

```
feed_dict = {x: X_train_a, y_: y_train_a}
feed_dict.update( network.all_drop )
sess.run(train_op, feed_dict=feed_dict)
```

While, for validation and testing, we use slightly different way. All Dropout, Dropconnect, Corrosion layers need to be disable. We use `tl.utils.dict_to_one` to set all `network.all_drop` to 1.

```
dp_dict = tl.utils.dict_to_one( network.all_drop )
feed_dict = {x: X_test_a, y_: y_test_a}
feed_dict.update(dp_dict)
err, ac = sess.run([cost, acc], feed_dict=feed_dict)
```

For evaluation, we create an expression for the classification accuracy:

```
correct_prediction = tf.equal(tf.argmax(y, 1), y_)
acc = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
```

#### What Next?

We also have a more advanced image classification example in tutorial_cifar10_tfrecord.py. Please read the code and notes, figure out how to generate more training data and what is local response normalization. After that, try to implement Residual Network (Hint: you may want to use the Layer.outputs).

### 1.2.5 Run the Pong Game example

In the second part of the tutorial, we will run the Deep Reinforcement Learning example which is introduced by Karpathy in Deep Reinforcement Learning: Pong from Pixels.

```
python tutorial_atari_pong.py
```

Before running the tutorial code, you need to install OpenAI gym environment which is a popular benchmark for Reinforcement Learning. If everything is set up correctly, you will get an output like the following:

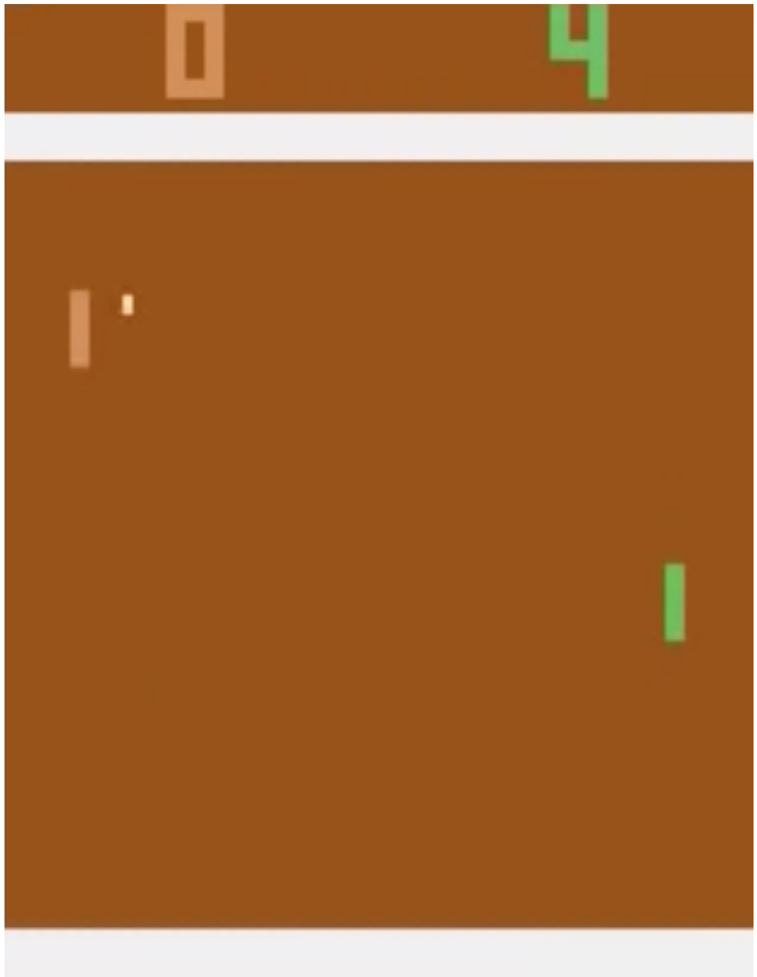
```
[2016-07-12 09:31:59,760] Making new env: Pong-v0
  [TL] InputLayer input_layer (?, 6400)
  [TL] DenseLayer relu1: 200, relu
  [TL] DenseLayer output_layer: 3, identity
  param 0: (6400, 200) (mean: -0.000009  median: -0.000018 std: 0.017393)
  param 1: (200,)      (mean: 0.000000   median: 0.000000  std: 0.000000)
  param 2: (200, 3)    (mean: 0.002239   median: 0.003122  std: 0.096611)
  param 3: (3,)        (mean: 0.000000   median: 0.000000  std: 0.000000)
  num of params: 1280803
  layer 0: Tensor("Relu:0", shape=(?, 200), dtype=float32)
  layer 1: Tensor("add_1:0", shape=(?, 3), dtype=float32)
episode 0: game 0 took 0.17381s, reward: -1.000000
episode 0: game 1 took 0.12629s, reward: 1.000000  !!!!!!!!
episode 0: game 2 took 0.17082s, reward: -1.000000
episode 0: game 3 took 0.08944s, reward: -1.000000
episode 0: game 4 took 0.09446s, reward: -1.000000
episode 0: game 5 took 0.09440s, reward: -1.000000
episode 0: game 6 took 0.32798s, reward: -1.000000
episode 0: game 7 took 0.74437s, reward: -1.000000
episode 0: game 8 took 0.43013s, reward: -1.000000
episode 0: game 9 took 0.42496s, reward: -1.000000
```

```
episode 0: game 10 took 0.37128s, reward: -1.000000
episode 0: game 11 took 0.08979s, reward: -1.000000
episode 0: game 12 took 0.09138s, reward: -1.000000
episode 0: game 13 took 0.09142s, reward: -1.000000
episode 0: game 14 took 0.09639s, reward: -1.000000
episode 0: game 15 took 0.09852s, reward: -1.000000
episode 0: game 16 took 0.09984s, reward: -1.000000
episode 0: game 17 took 0.09575s, reward: -1.000000
episode 0: game 18 took 0.09416s, reward: -1.000000
episode 0: game 19 took 0.08674s, reward: -1.000000
episode 0: game 20 took 0.09628s, reward: -1.000000
resetting env. episode reward total was -20.000000. running mean: -20.000000
episode 1: game 0 took 0.09910s, reward: -1.000000
episode 1: game 1 took 0.17056s, reward: -1.000000
episode 1: game 2 took 0.09306s, reward: -1.000000
episode 1: game 3 took 0.09556s, reward: -1.000000
episode 1: game 4 took 0.12520s, reward: 1.000000  !!!!!!!!
episode 1: game 5 took 0.17348s, reward: -1.000000
episode 1: game 6 took 0.09415s, reward: -1.000000
```

This example allow neural network to learn how to play Pong game from the screen inputs, just like human behavior. The neural network will play with a fake AI player, and lean to beat it. After training for 15,000 episodes, the neural network can win 20% of the games. The neural network win 35% of the games at 20,000 episode, we can seen the neural network learn faster and faster as it has more winning data to train. If you run it for 30,000 episode, it never loss.

```
render = False
resume = False
```

Setting `render` to `True`, if you want to display the game environment. When you run the code again, you can set `resume` to `True`, the code will load the existing model and train the model basic on it.



### 1.2.6 Understand Reinforcement learning

#### Pong Game

To understand Reinforcement Learning, we let computer to learn how to play Pong game from the original screen inputs. Before we start, we highly recommend you to go through a famous blog called Deep Reinforcement Learning: Pong from Pixels which is a minimalistic implementation of Deep Reinforcement Learning by using python-numpy and OpenAI gym environment.

```
python tutorial_atari_pong.py
```

#### Policy Network

In Deep Reinforcement Learning, the Policy Network is the same with Deep Neural Network, it is our player (or "agent") who output actions to tell what we should do (move UP or DOWN); in Karpathy's code, he only defined 2 actions, UP and DOWN and using a single simgoid output; In order to make our tutorial more generic, we defined 3 actions which are UP, DOWN and STOP (do nothing) by using 3 softmax outputs.

```
# observation for training
states_batch_pl = tf.placeholder(tf.float32, shape=[None, D])
```

```
network = tl.layers.InputLayer(states_batch_pl, name='input_layer')
network = tl.layers.DenseLayer(network, n_units=H,
                                act = tf.nn.relu, name='relu1')
network = tl.layers.DenseLayer(network, n_units=3,
                        act = tf.identity, name='output_layer')
probs = network.outputs
sampling_prob = tf.nn.softmax(probs)
```

Then when our agent is playing Pong, it calculates the probabilities of different actions, and then draw sample (action) from this uniform distribution. As the actions are represented by 1, 2 and 3, but the softmax outputs should be start from 0, we calculate the label value by minus 1.

```
prob = sess.run(
    sampling_prob,
    feed_dict={states_batch_pl: x}
)
# action. 1: STOP  2: UP  3: DOWN
action = np.random.choice([1,2,3], p=prob.flatten())
...
ys.append(action - 1)
```

### Policy Gradient

Policy gradient methods are end-to-end algorithms that directly learn policy functions mapping states to actions. An approximate policy could be learned directly by maximizing the expected rewards. The parameters of a policy function (e.g. the parameters of a policy network used in the pong example) could be trained and learned under the guidance of the gradient of expected rewards. In other words, we can gradually tune the policy function via updating its parameters, such that it will generate actions from given states towards higher rewards.

An alternative method to policy gradient is Deep Q-Learning (DQN). It is based on Q-Learning that tries to learn a value function (called Q function) mapping states and actions to some value. DQN employs a deep neural network to represent the Q function as a function approximator. The training is done by minimizing temporal-difference errors. A neurobiologically inspired mechanism called "experience replay" is typically used along with DQN to help improve its stability caused by the use of non-linear function approximator.

You can check the following papers to gain better understandings about Reinforcement Learning.

- Reinforcement Learning: An Introduction. Richard S. Sutton and Andrew G. Barto
- Deep Reinforcement Learning. David Silver, Google DeepMind
- UCL Course on RL

The most successful applications of Deep Reinforcement Learning in recent years include DQN with experience replay to play Atari games and AlphaGO that for the first time beats world-class professional GO players. AlphaGO used the policy gradient method to train its policy network that is similar to the example of Pong game.

- Atari - Playing Atari with Deep Reinforcement Learning
- Atari - Human-level control through deep reinforcement learning
- AlphaGO - Mastering the game of Go with deep neural networks and tree search

#### Dataset iteration

In Reinforcement Learning, we consider a final decision as an episode. In Pong game, a episode is a few dozen games, because the games go up to score of 21 for either player. Then the batch size is how many episode we consider to update the model. In the tutorial, we train a 2-layer policy network with 200 hidden layer units using RMSProp on batches of 10 episodes.

#### Loss and update expressions

We create a loss expression to be minimized in training:

```
actions_batch_pl = tf.placeholder(tf.int32, shape=[None])
discount_rewards_batch_pl = tf.placeholder(tf.float32, shape=[None])
loss = tl.rein.cross_entropy_reward_loss(probs, actions_batch_pl,
                                          discount_rewards_batch_pl)
...
...
sess.run(
    train_op,
    feed_dict={
        states_batch_pl: epx,
        actions_batch_pl: epy,
        discount_rewards_batch_pl: disR
    }
)
```

The loss in a batch is relate to all outputs of Policy Network, all actions we made and the corresponding discounted rewards in a batch. We first compute the loss of each action by multiplying the discounted reward and the cross-entropy between its output and its true action. The final loss in a batch is the sum of all loss of the actions.

#### What Next?

The tutorial above shows how you can build your own agent, end-to-end. While it has reasonable quality, the default parameters will not give you the best agent model. Here are a few things you can improve.

First of all, instead of conventional MLP model, we can use CNNs to capture the screen information better as Playing Atari with Deep Reinforcement Learning describe.

Also, the default parameters of the model are not tuned. You can try changing the learning rate, decay, or initializing the weights of your model in a different way.

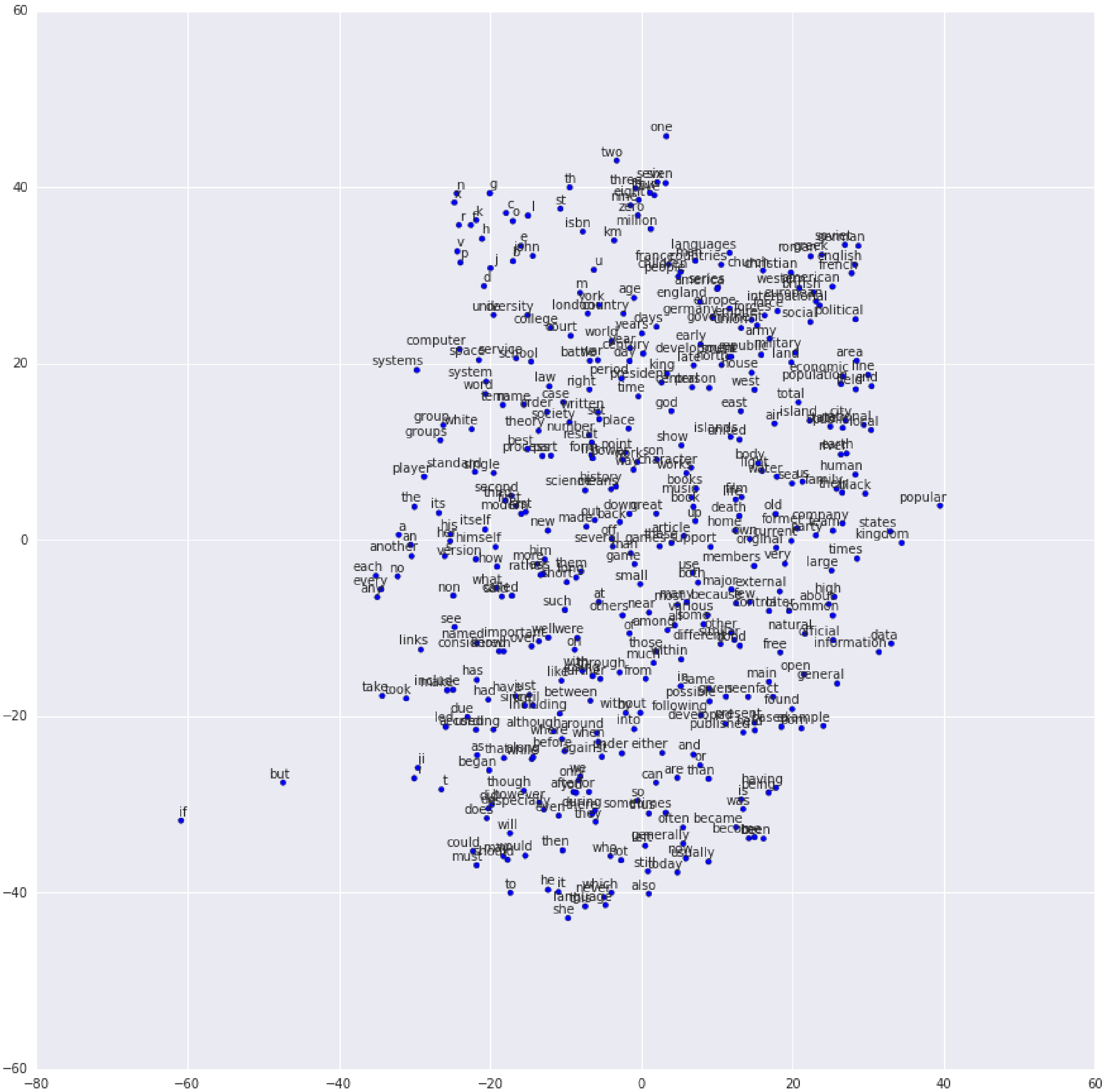
Finally, you can try the model on different tasks (games) and try other reinforcement learning algorithm in Example.

### 1.2.7 Run the Word2Vec example

In this part of the tutorial, we train a matrix for words, where each word can be represented by a unique row vector in the matrix. In the end, similar words will have similar vectors. Then as we plot out the words into a two-dimensional plane, words that are similar end up clustering nearby each other.

```
python tutorial_word2vec_basic.py
```

If everything is set up correctly, you will get an output in the end.




## 1.2.8 Understand Word Embedding

### Word Embedding

We highly recommend you to read Colah's blog Word Representations to understand why we want to use a vector representation, and how to compute the vectors. (For chinese reader please click. More details about word2vec can be found in Word2vec Parameter Learning Explained.

Bascially, training an embedding matrix is an unsupervised learning. As every word is refected by an unique ID, which is the row index of the embedding matrix, a word can be converted into a vector, it can better represent the meaning. For example, there seems to be a constant male-female difference vector: `woman  man = queen - king`, this means one dimension in the vector represents gender.

The model can be created as follow.

```
# train_inputs is a row vector, a input is an integer id of single word.
# train_labels is a column vector, a label is an integer id of single word.
# valid_dataset is a column vector, a valid set is an integer id of single word.
train_inputs = tf.placeholder(tf.int32, shape=[batch_size])
train_labels = tf.placeholder(tf.int32, shape=[batch_size, 1])
valid_dataset = tf.constant(valid_examples, dtype=tf.int32)

# Look up embeddings for inputs.
emb_net = tl.layers.Word2vecEmbeddingInputlayer(
        inputs = train_inputs,
        train_labels = train_labels,
        vocabulary_size = vocabulary_size,
        embedding_size = embedding_size,
        num_sampled = num_sampled,
        nce_loss_args = {},
        E_init = tf.random_uniform_initializer(minval=-1.0, maxval=1.0),
        E_init_args = {},
        nce_W_init = tf.truncated_normal_initializer(
                          stddev=float(1.0/np.sqrt(embedding_size))),
        nce_W_init_args = {},
        nce_b_init = tf.constant_initializer(value=0.0),
        nce_b_init_args = {},
        name ='word2vec_layer',
    )
```

### Dataset iteration and loss

Word2vec uses Negative Sampling and Skip-Gram model for training. Noise-Contrastive Estimation Loss (NCE) can help to reduce the computation of loss. Skip-Gram inverts context and targets, tries to predict each context word from its target word. We use `tl.nlp.generate_skip_gram_batch` to generate training data as follow, see `tutorial_generate_text.py`.

```
# NCE cost expression is provided by Word2vecEmbeddingInputlayer
cost = emb_net.nce_cost
train_params = emb_net.all_params

train_op = tf.train.AdagradOptimizer(learning_rate, initial_accumulator_value=0.1,
          use_locking=False).minimize(cost, var_list=train_params)

data_index = 0
while (step < num_steps):
  batch_inputs, batch_labels, data_index = tl.nlp.generate_skip_gram_batch(
                data=data, batch_size=batch_size, num_skips=num_skips,
                skip_window=skip_window, data_index=data_index)
  feed_dict = {train_inputs : batch_inputs, train_labels : batch_labels}
  _, loss_val = sess.run([train_op, cost], feed_dict=feed_dict)
```

### Restore existing Embedding matrix

In the end of training the embedding matrix, we save the matrix and corresponding dictionaries. Then next time, we can restore the matrix and directories as follow. (see `main_restore_embedding_layer()` in `tutorial_generate_text.py`)

```
vocabulary_size = 50000
embedding_size = 128
model_file_name = "model_word2vec_50k_128"
batch_size = None

print("Load existing embedding matrix and dictionaries")
all_var = tl.files.load_npy_to_any(name=model_file_name+'.npy')
data = all_var['data']; count = all_var['count']
dictionary = all_var['dictionary']
reverse_dictionary = all_var['reverse_dictionary']

tl.nlp.save_vocab(count, name='vocab_'+model_file_name+'.txt')

del all_var, data, count

load_params = tl.files.load_npz(name=model_file_name+'.npz')

x = tf.placeholder(tf.int32, shape=[batch_size])
y_ = tf.placeholder(tf.int32, shape=[batch_size, 1])

emb_net = tl.layers.EmbeddingInputlayer(
                inputs = x,
                vocabulary_size = vocabulary_size,
                embedding_size = embedding_size,
                name ='embedding_layer')

tl.layers.initialize_global_variables(sess)

tl.files.assign_params(sess, [load_params[0]], emb_net)
```

### 1.2.9 Run the PTB example

Penn TreeBank (PTB) dataset is used in many LANGUAGE MODELING papers, including "Empirical Evaluation and Combination of Advanced Language Modeling Techniques", "Recurrent Neural Network Regularization". It consists of 929k training words, 73k validation words, and 82k test words. It has 10k words in its vocabulary.

The PTB example is trying to show how to train a recurrent neural network on a challenging task of language modeling.

Given a sentence "I am from Imperial College London", the model can learn to predict "Imperial College London" from "from Imperial College". In other word, it predict the next word in a text given a history of previous words. In the previous example , `num_steps` (sequence length) is 3.

```
python tutorial_ptb_lstm.py
```

The script provides three settings (small, medium, large), where a larger model has better performance. You can choose different settings in:

```
flags.DEFINE_string(
    "model", "small",
    "A type of model. Possible options are: small, medium, large.")
```

If you choose the small setting, you can see:

```
Epoch: 1 Learning rate: 1.000
0.004 perplexity: 5220.213 speed: 7635 wps
0.104 perplexity: 828.871 speed: 8469 wps
```

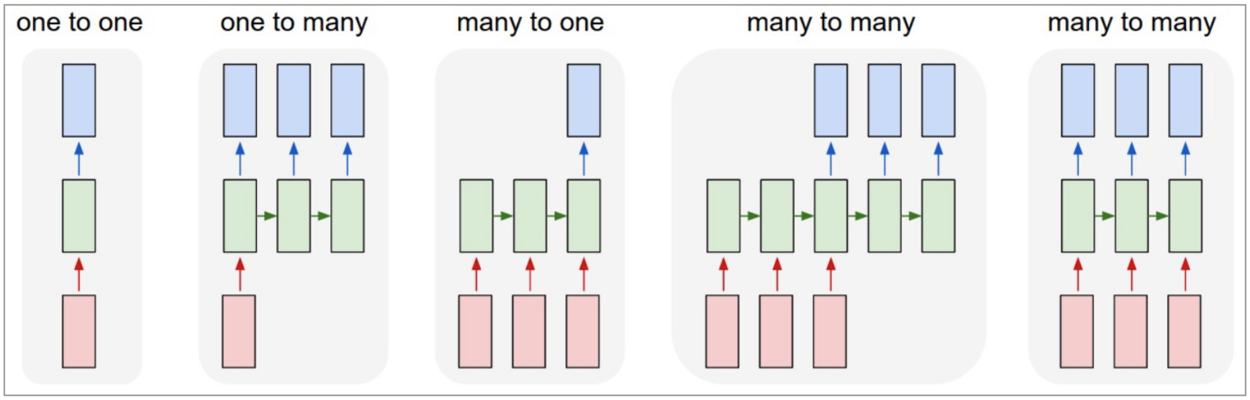
```
0.204 perplexity: 614.071 speed: 8839 wps
0.304 perplexity: 495.485 speed: 8889 wps
0.404 perplexity: 427.381 speed: 8940 wps
0.504 perplexity: 383.063 speed: 8920 wps
0.604 perplexity: 345.135 speed: 8920 wps
0.703 perplexity: 319.263 speed: 8949 wps
0.803 perplexity: 298.774 speed: 8975 wps
0.903 perplexity: 279.817 speed: 8986 wps
Epoch: 1 Train Perplexity: 265.558
Epoch: 1 Valid Perplexity: 178.436
...
Epoch: 13 Learning rate: 0.004
0.004 perplexity: 56.122 speed: 8594 wps
0.104 perplexity: 40.793 speed: 9186 wps
0.204 perplexity: 44.527 speed: 9117 wps
0.304 perplexity: 42.668 speed: 9214 wps
0.404 perplexity: 41.943 speed: 9269 wps
0.504 perplexity: 41.286 speed: 9271 wps
0.604 perplexity: 39.989 speed: 9244 wps
0.703 perplexity: 39.403 speed: 9236 wps
0.803 perplexity: 38.742 speed: 9229 wps
0.903 perplexity: 37.430 speed: 9240 wps
Epoch: 13 Train Perplexity: 36.643
Epoch: 13 Valid Perplexity: 121.475
Test Perplexity: 116.716
```

The PTB example shows that RNN is able to model language, but this example did not do something practically interesting. However, you should read through this example and "Understand LSTM" in order to understand the basics of RNN. After that, you will learn how to generate text, how to achieve language translation, and how to build a question answering system by using RNN.

## 1.2.10 Understand LSTM

### Recurrent Neural Network

We personally think Andrey Karpathy's blog is the best material to Understand Recurrent Neural Network , after reading that, Colah's blog can help you to Understand LSTM Network [chinese] which can solve The Problem of Long-Term Dependencies. We will not describe more about the theory of RNN, so please read through these blogs before you go on.




Each rectangle is a vector and arrows represent functions (e.g. matrix multiply). Input vectors are in red, output vectors are in blue and green vectors hold the RNN's state (more on this soon). From left to right: **(1)** Vanilla mode of processing without RNN, from fixed-sized input to fixed-sized output (e.g. image classification). **(2)** Sequence output (e.g. image captioning takes an image and outputs a sentence of words). **(3)** Sequence input (e.g. sentiment analysis where a given sentence is classified as expressing positive or negative sentiment). **(4)** Sequence input and sequence output (e.g. Machine Translation: an RNN reads a sentence in English and then outputs a sentence in French). **(5)** Synced sequence input and output (e.g. video classification where we wish to label each frame of the video). Notice that in every case are no pre-specified constraints on the lengths sequences because the recurrent transformation (green) is fixed and can be applied as many times as we like.

Image by Andrey Karpathy

### Synced sequence input and output

The model in PTB example is a typical type of synced sequence input and output, which was described by Karpathy as "(5) Synced sequence input and output (e.g. video classification where we wish to label each frame of the video). Notice that in every case there are no pre-specified constraints on the lengths of sequences because the recurrent transformation (green) can be applied as many times as we like."

The model is built as follows. Firstly, we transfer the words into word vectors by looking up an embedding matrix. In this tutorial, there is no pre-training on the embedding matrix. Secondly, we stack two LSTMs together using dropout between the embedding layer, LSTM layers, and the output layer for regularization. In the final layer, the model provides a sequence of softmax outputs.

The first LSTM layer outputs `[batch_size, num_steps, hidden_size]` for stacking another LSTM after it. The second LSTM layer outputs `[batch_size*num_steps, hidden_size]` for stacking a DenseLayer after it. Then the DenseLayer computes the softmax outputs of each example `n_examples = batch_size*num_steps`).

To understand the PTB tutorial, you can also read TensorFlow PTB tutorial.

(Note that, TensorLayer supports DynamicRNNLayer after v1.1, so you can set the input/output dropouts, number of RNN layers in one single layer)

```
network = tl.layers.EmbeddingInputlayer(
            inputs = x,
            vocabulary_size = vocab_size,
            embedding_size = hidden_size,
            E_init = tf.random_uniform_initializer(-init_scale, init_scale),
            name ='embedding_layer')
if is_training:
    network = tl.layers.DropoutLayer(network, keep=keep_prob, name='drop1')
network = tl.layers.RNNLayer(network,
            cell_fn=tf.contrib.rnn.BasicLSTMCell,
            cell_init_args={'forget_bias': 0.0},
```

```
            n_hidden=hidden_size,
            initializer=tf.random_uniform_initializer(-init_scale, init_scale),
            n_steps=num_steps,
            return_last=False,
            name='basic_lstm_layer1')
lstm1 = network
if is_training:
    network = tl.layers.DropoutLayer(network, keep=keep_prob, name='drop2')
network = tl.layers.RNNLayer(network,
            cell_fn=tf.contrib.rnn.BasicLSTMCell,
            cell_init_args={'forget_bias': 0.0},
            n_hidden=hidden_size,
            initializer=tf.random_uniform_initializer(-init_scale, init_scale),
            n_steps=num_steps,
            return_last=False,
            return_seq_2d=True,
            name='basic_lstm_layer2')
lstm2 = network
if is_training:
    network = tl.layers.DropoutLayer(network, keep=keep_prob, name='drop3')
network = tl.layers.DenseLayer(network,
            n_units=vocab_size,
            W_init=tf.random_uniform_initializer(-init_scale, init_scale),
            b_init=tf.random_uniform_initializer(-init_scale, init_scale),
            act = tf.identity, name='output_layer')
```

### Dataset iteration

The `batch_size` can be seen as the number of concurrent computations we are running. As the following example shows, the first batch learns the sequence information by using items 0 to 9. The second batch learn the sequence information by using items 10 to 19. So it ignores the information from items 9 to 10 !n If only if we set `batch_size = 1``, it will consider all the information from items 0 to 20.

The meaning of `batch_size` here is not the same as the `batch_size` in the MNIST example. In the MNIST example, `batch_size` reflects how many examples we consider in each iteration, while in the PTB example, `batch_size` is the number of concurrent processes (segments) for accelerating the computation.

Some information will be ignored if `batch_size` > 1, however, if your dataset is "long" enough (a text corpus usually has billions of words), the ignored information would not affect the final result.

In the PTB tutorial, we set `batch_size = 20`, so we divide the dataset into 20 segments. At the beginning of each epoch, we initialize (reset) the 20 RNN states for the 20 segments to zero, then go through the 20 segments separately.

An example of generating training data is as follows:

```
train_data = [i for i in range(20)]
for batch in tl.iterate.ptb_iterator(train_data, batch_size=2, num_steps=3):
    x, y = batch
    print(x, '\n',y)
```

```
... [[ 0  1  2] <---x                       1st subset/ iteration
...  [10 11 12]]
... [[ 1  2  3] <---y
...  [11 12 13]]
...
... [[ 3  4  5]  <--- 1st batch input       2nd subset/ iteration
...  [13 14 15]] <--- 2nd batch input
```

```
... [[ 4  5  6]  <--- 1st batch target
...  [14 15 16]] <--- 2nd batch target
...
... [[ 6  7  8]                       3rd subset/ iteration
...  [16 17 18]]
... [[ 7  8  9]
...  [17 18 19]]
```

**Note:** This example can also be considered as pre-training of the word embedding matrix.

### Loss and update expressions

The cost function is the average cost of each mini-batch:

```python
# See tensorlayer.cost.cross_entropy_seq() for more details
def loss_fn(outputs, targets, batch_size, num_steps):
    # Returns the cost function of Cross-entropy of two sequences, implement
    # softmax internally.
    # outputs : 2D tensor [batch_size*num_steps, n_units of output layer]
    # targets : 2D tensor [batch_size, num_steps], need to be reshaped.
    # n_examples = batch_size * num_steps
    # so
    # cost is the average cost of each mini-batch (concurrent process).
    loss = tf.nn.seq2seq.sequence_loss_by_example(
        [outputs],
        [tf.reshape(targets, [-1])],
        [tf.ones([batch_size * num_steps])])
    cost = tf.reduce_sum(loss) / batch_size
    return cost

# Cost for Training
cost = loss_fn(network.outputs, targets, batch_size, num_steps)
```

For updating, truncated backpropagation clips values of gradients by the ratio of the sum of their norms, so as to make the learning process tractable.

```python
# Truncated Backpropagation for training
with tf.variable_scope('learning_rate'):
    lr = tf.Variable(0.0, trainable=False)
tvars = tf.trainable_variables()
grads, _ = tf.clip_by_global_norm(tf.gradients(cost, tvars),
                                  max_grad_norm)
optimizer = tf.train.GradientDescentOptimizer(lr)
train_op = optimizer.apply_gradients(zip(grads, tvars))
```

In addition, if the epoch index is greater than `max_epoch`, we decrease the learning rate by multipling `lr_decay`.

```python
new_lr_decay = lr_decay ** max(i - max_epoch, 0.0)
sess.run(tf.assign(lr, learning_rate * new_lr_decay))
```

At the beginning of each epoch, all states of LSTMs need to be reseted (initialized) to zero states. Then after each iteration, the LSTMs' states is updated, so the new LSTM states (final states) need to be assigned as the initial states of the next iteration:

```
# set all states to zero states at the beginning of each epoch
state1 = tl.layers.initialize_rnn_state(lstm1.initial_state)
state2 = tl.layers.initialize_rnn_state(lstm2.initial_state)
for step, (x, y) in enumerate(tl.iterate.ptb_iterator(train_data,
                                            batch_size, num_steps)):
    feed_dict = {input_data: x, targets: y,
                lstm1.initial_state: state1,
                lstm2.initial_state: state2,
                }
    # For training, enable dropout
    feed_dict.update( network.all_drop )
    # use the new states as the initial state of next iteration
    _cost, state1, state2, _ = sess.run([cost,
                                    lstm1.final_state,
                                    lstm2.final_state,
                                    train_op],
                                    feed_dict=feed_dict
                                    )
    costs += _cost; iters += num_steps
```

### Predicting

After training the model, when we predict the next output, we no long consider the number of steps (sequence length), i.e. `batch_size, num_steps` are set to `1`. Then we can output the next word one by one, instead of predicting a sequence of words from a sequence of words.

```
input_data_test = tf.placeholder(tf.int32, [1, 1])
targets_test = tf.placeholder(tf.int32, [1, 1])
...
network_test, lstm1_test, lstm2_test = inference(input_data_test,
                      is_training=False, num_steps=1, reuse=True)
...
cost_test = loss_fn(network_test.outputs, targets_test, 1, 1)
...
print("Evaluation")
# Testing
# go through the test set step by step, it will take a while.
start_time = time.time()
costs = 0.0; iters = 0
# reset all states at the beginning
state1 = tl.layers.initialize_rnn_state(lstm1_test.initial_state)
state2 = tl.layers.initialize_rnn_state(lstm2_test.initial_state)
for step, (x, y) in enumerate(tl.iterate.ptb_iterator(test_data,
                                        batch_size=1, num_steps=1)):
    feed_dict = {input_data_test: x, targets_test: y,
                lstm1_test.initial_state: state1,
                lstm2_test.initial_state: state2,
                }
    _cost, state1, state2 = sess.run([cost_test,
                                    lstm1_test.final_state,
                                    lstm2_test.final_state],
                                    feed_dict=feed_dict
                                    )
    costs += _cost; iters += 1
test_perplexity = np.exp(costs / iters)
print("Test Perplexity: %.3f took %.2fs" % (test_perplexity, time.time() - start_
→time))
```

#### What Next?

Now, you have understood Synced sequence input and output. Let's think about Many to one (Sequence input and one output), so that LSTM is able to predict the next word "English" from "I am from London, I speak ..".

Please read and understand the code of `tutorial_generate_text.py`. It shows you how to restore a pre-trained Embedding matrix and how to learn text generation from a given context.

Karpathy's blog : "(3) Sequence input (e.g. sentiment analysis where a given sentence is classified as expressing positive or negative sentiment). "

### 1.2.11 More Tutorials

In Example page, we provide many examples include Seq2seq, different type of Adversarial Learning, Reinforcement Learning and etc.

### 1.2.12 More info

For more information on what you can do with TensorLayer, just continue reading through readthedocs. Finally, the reference lists and explains as follow.

layers (`tensorlayer.layers`),

activation (`tensorlayer.activation`),

natural language processing (`tensorlayer.nlp`),

reinforcement learning (`tensorlayer.rein`),

cost expressions and regularizers (`tensorlayer.cost`),

load and save files (`tensorlayer.files`),

operating system (`tensorlayer.ops`),

helper functions (`tensorlayer.utils`),

visualization (`tensorlayer.visualize`),

iteration functions (`tensorlayer.iterate`),

preprocessing functions (`tensorlayer.prepro`),

## 1.3 Examples

### 1.3.1 Basics

- Multi-layer perceptron (MNIST). Classification task, see tutorial_mnist_simple.py.
- Multi-layer perceptron (MNIST). Classification using Iterator, see method1 and method2.

### 1.3.2 Computer Vision

- Denoising Autoencoder (MNIST). Classification task, see tutorial_mnist.py.
- Stacked Denoising Autoencoder and Fine-Tuning (MNIST). A MLP classification task, see tutorial_mnist.py.
- Convolutional Network (MNIST). Classification task, see tutorial_mnist.py.
- Convolutional Network (CIFAR-10). Classification task, see tutorial_cifar10.py and tutorial_cifar10_tfrecord.py.
- VGG 16 (ImageNet). Classification task, see tutorial_vgg16.py.
- VGG 19 (ImageNet). Classification task, see tutorial_vgg19.py.
- InceptionV3 (ImageNet). Classification task, see tutorial_inceptionV3_tfslim.py.
- Wide ResNet (CIFAR) by ritchieng.
- More CNN implementations of TF-Slim can be connected to TensorLayer via SlimNetsLayer.
- Spatial Transformer Networks by zsdonghao.
- U-Net for brain tumor segmentation by zsdonghao.
- Variational Autoencoder (VAE) for (CelebA) by yzwxx.
- Variational Autoencoder (VAE) for (MNIST) by BUPTLdy.
- Image Captioning - Reimplementation of Google's im2txt by zsdonghao.

### 1.3.3 Natural Language Processing

- Recurrent Neural Network (LSTM). Apply multiple LSTM to PTB dataset for language modeling, see tutorial_ptb_lstm_state_is_tuple.py.
- Word Embedding (Word2vec). Train a word embedding matrix, see tutorial_word2vec_basic.py.
- Restore Embedding matrix. Restore a pre-train embedding matrix, see tutorial_generate_text.py.
- Text Generation. Generates new text scripts, using LSTM network, see tutorial_generate_text.py.
- Chinese Text Anti-Spam by pakrchen.
- Chatbot in 200 lines of code for Seq2Seq.
- FastText Sentence Classification (IMDB), see tutorial_imdb_fasttext.py by tomtung.

### 1.3.4 Adversarial Learning

- DCGAN (CelebA). Generating images by Deep Convolutional Generative Adversarial Networks by zsdonghao.
- Generative Adversarial Text to Image Synthesis by zsdonghao.
- Unsupervised Image to Image Translation with Generative Adversarial Networks by zsdonghao.
- Improved CycleGAN with resize-convolution by luoxier.
- Super Resolution GAN by zsdonghao.
- DAGAN: Fast Compressed Sensing MRI Reconstruction by nebulaV.

### 1.3.5 Reinforcement Learning

- Policy Gradient / Network (Atari Ping Pong), see tutorial_atari_pong.py.
- Deep Q-Network (Frozen lake), see tutorial_frozenlake_dqn.py.
- Q-Table learning algorithm (Frozen lake), see tutorial_frozenlake_q_table.py.
- Asynchronous Policy Gradient using TensorDB (Atari Ping Pong) by nebulaV.
- AC for discrete action space (Cartpole), see tutorial_cartpole_ac.py.
- A3C for continuous action space (Bipedal Walker), see tutorial_bipedalwalker_a3c*.py.
- DAGGER for (Gym Torcs) by zsdonghao.
- TRPO for continuous and discrete action space by jjkke88.

### 1.3.6 Special Examples

- Distributed Training. mnist and imagenet by jorgemf.
- Merge TF-Slim into TensorLayer. tutorial_inceptionV3_tfslim.py.
- Merge Keras into TensorLayer. tutorial_keras.py.
- Data augmentation with TFRecord. Effective way to load and pre-process data, see tutorial_tfrecord*.py and tutorial_cifar10_tfrecord.py.
- Data augmentation with TensorLayer, see tutorial_image_preprocess.py.
- TensorDB by fangde see here.
- A simple web service - TensorFlask by JoelKronander.
- Float 16 half-precision model, see tutorial_mnist_float16.py.

## 1.4 Development

TensorLayer is a major ongoing research project in Data Science Institute, Imperial College London. The goal of the project is to develop a compositional language while complex learning systems can be build through composition of neural network modules. The whole development is now participated by numerous contributors on Release. As an open-source project by we highly welcome contributions! Every bit helps and will be credited.

### 1.4.1 What to contribute

#### Your method and example

If you have a new method or example in term of Deep learning and Reinforcement learning, you are welcome to contribute.

- Provide your layer or example, so everyone can use it.
- Explain how it would work, and link to a scientific paper if applicable.
- Keep the scope as narrow as possible, to make it easier to implement.

#### Report bugs

Report bugs at the GitHub, we normally will fix it in 5 hours. If you are reporting a bug, please include:

- your TensorLayer, TensorFlow and Python version.
- steps to reproduce the bug, ideally reduced to a few Python commands.
- the results you obtain, and the results you expected instead.

If you are unsure whether the behavior you experience is a bug, or if you are unsure whether it is related to TensorLayer or TensorFlow, please just ask on our mailing list first.

#### Fix bugs

Look through the GitHub issues for bug reports. Anything tagged with "bug" is open to whoever wants to implement it. If you discover a bug in TensorLayer you can fix yourself, by all means feel free to just implement a fix and not report it first.

#### Write documentation

Whenever you find something not explained well, misleading, glossed over or just wrong, please update it! The *Edit on GitHub* link on the top right of every documentation page and the *[source]* link for every documented entity in the API reference will help you to quickly locate the origin of any text.

### 1.4.2 How to contribute

#### Edit on GitHub

As a very easy way of just fixing issues in the documentation, use the *Edit on GitHub* link on the top right of a documentation page or the *[source]* link of an entity in the API reference to open the corresponding source file in GitHub, then click the *Edit this file* link to edit the file in your browser and send us a Pull Request. All you need for this is a free GitHub account.

For any more substantial changes, please follow the steps below to setup TensorLayer for development.

#### Documentation

The documentation is generated with Sphinx. To build it locally, run the following commands:

```
pip install Sphinx
sphinx-quickstart

cd docs
make html
```

If you want to re-generate the whole docs, run the following commands:

```
cd docs
make clean
make html
```

To write the docs, we recommend you to install Local RTD VM.

Afterwards, open `docs/_build/html/index.html` to view the documentation as it would appear on readthedocs. If you changed a lot and seem to get misleading error messages or warnings, run `make clean html` to force Sphinx to recreate all files from scratch.

When writing docstrings, follow existing documentation as much as possible to ensure consistency throughout the library. For additional information on the syntax and conventions used, please refer to the following documents:

- reStructuredText Primer
- Sphinx reST markup constructs
- A Guide to NumPy/SciPy Documentation

#### Testing

TensorLayer has a code coverage of 100%, which has proven very helpful in the past, but also creates some duties:

- Whenever you change any code, you should test whether it breaks existing features by just running the test scripts.
- Every bug you fix indicates a missing test case, so a proposed bug fix should come with a new test that fails without your fix.

#### Sending Pull Requests

When you're satisfied with your addition, the tests pass and the documentation looks good without any markup errors, commit your changes to a new branch, push that branch to your fork and send us a Pull Request via GitHub's web interface.

All these steps are nicely explained on GitHub: https://guides.github.com/introduction/flow/

When filing your Pull Request, please include a description of what it does, to help us reviewing it. If it is fixing an open issue, say, issue #123, add *Fixes #123*, *Resolves #123* or *Closes #123* to the description text, so GitHub will close it when your request is merged.

## 1.5 More

### 1.5.1 FQA

#### How to effectively learn TensorLayer

No matter what stage you are in, we recommend you to spend just 10 minutes to read the source code of TensorLayer and the Understand layer / Your layer in this website, you will find the abstract methods are very simple for everyone. Reading the source codes helps you to better understand TensorFlow and allows you to implement your own methods easily. For discussion, we recommend Gitter, Help Wanted Issues, QQ group and Wechat group.

#### Beginner

For people who new to deep learning, the contirbutors provided a number of tutorials in this website, these tutorials will guide you to understand autoencoder, convolutional neural network, recurrent neural network, word embedding and deep reinforcement learning and etc. If your already understand the basic of deep learning, we recommend you to skip the tutorials and read the example codes on Github , then implement an example from scratch.

### Engineer

For people from industry, the contirbutors provided mass format-consistent examples covering computer vision, natural language processing and reinforcement learning. Besides, there are also many TensorFlow users already implemented product-level examples including image captioning, semantic/instance segmentation, machine translation, chatbot and etc, which can be found online. It is worth noting that a wrapper especially for computer vision Tf-Slim can be connected with TensorLayer seamlessly. Therefore, you may able to find the examples that can be used in your project.

### Researcher

For people from academic, TensorLayer was originally developed by PhD students who facing issues with other libraries on implement novel algorithm. Installing TensorLayer in editable mode is recommended, so you can extend your methods in TensorLayer. For researches related to image such as image captioning, visual QA and etc, you may find it is very helpful to use the existing Tf-Slim pre-trained models with TensorLayer (a specially layer for connecting Tf-Slim is provided).

## Exclude some layers from training

You may need to get the list of variables you want to update, TensorLayer provides two ways to get the variables list.

The first way is to use the all_params of a network, by default, it will store the variables in order. You can print the variables information via `tl.layers.print_all_variables(train_only=True)` or `network.print_params(details=False)`. To choose which variables to update, you can do as below.

```
train_params = network.all_params[3:]
```

The second way is to get the variables by a given name. For example, if you want to get all variables which the layer name contain `dense`, you can do as below.

```
train_params = tl.layers.get_variables_with_name('dense', train_only=True,␣
↪printable=True)
```

After you get the variable list, you can define your optimizer like that so as to update only a part of the variables.

```
train_op = tf.train.AdamOptimizer(0.001).minimize(cost, var_list= train_params)
```

## Logging

TensorLayer adopts the Python logging module to log running information. The logging module would print logs to the console in default. If you want to configure the logging module, you shall follow its manual.

## Visualization

### Cannot Save Image

If you run the script via SSH control, sometime you may find the following error.

```
_tkinter.TclError: no display name and no $DISPLAY environment variable
```

If happen, use `import matplotlib` and `matplotlib.use('Agg')` before `import tensorlayer as tl`. Alternatively, add the following code into the top of `visualize.py` or in your own code.

```
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
```

### Install Master Version

To use all new features of TensorLayer, you need to install the master version from Github. Before that, you need to make sure you already installed git.

```
[stable version] pip install tensorlayer
[master version] pip install git+https://github.com/zsdonghao/tensorlayer.git
```

### Editable Mode

- 1. Download the TensorLayer folder from Github.
- 2. Before editing the TensorLayer `.py` file.
  - If your script and TensorLayer folder are in the same folder, when you edit the `.py` inside TensorLayer folder, your script can access the new features.
  - If your script and TensorLayer folder are not in the same folder, you need to run the following command in the folder contains `setup.py` before you edit `.py` inside TensorLayer folder.

    ```
    pip install -e .
    ```

### Load Model

Note that, the `tl.files.load_npz()` can only able to load the npz model saved by `tl.files.save_npz()`. If you have a model want to load into your TensorLayer network, you can first assign your parameters into a list in order, then use `tl.files.assign_params()` to load the parameters into your TensorLayer model.

## 1.5.2 Recruitment

### TensorLayer Contributors

TensorLayer contributors are from Imperial College, Tsinghua University, Carnegie Mellon University, Google, Microsoft, Bloomberg and etc. There are many functions need to be contributed such as Maxout, Neural Turing Machine, Attention, TensorLayer Mobile and etc. Please push on GitHub, every bit helps and will be credited. If you are interested in working with us, please contact us.

### Data Science Institute, Imperial College London

Data science is therefore by nature at the core of all modern transdisciplinary scientific activities, as it involves the whole life cycle of data, from acquisition and exploration to analysis and communication of the results. Data science is not only concerned with the tools and methods to obtain, manage and analyse data: it is also about extracting value from data and translating it from asset to product.

Launched on 1st April 2014, the Data Science Institute at Imperial College London aims to enhance Imperial's excellence in data-driven research across its faculties by fulfilling the following objectives.

The Data Science Institute is housed in purpose built facilities in the heart of the Imperial College campus in South Kensington. Such a central location provides excellent access to collabroators across the College and across London.

- To act as a focal point for coordinating data science research at Imperial College by facilitating access to funding, engaging with global partners, and stimulating cross-disciplinary collaboration.
- To develop data management and analysis technologies and services for supporting data driven research in the College.
- To promote the training and education of the new generation of data scientist by developing and coordinating new degree courses, and conducting public outreach programmes on data science.
- To advise College on data strategy and policy by providing world-class data science expertise.
- To enable the translation of data science innovation by close collaboration with industry and supporting commercialization.

If you are interested in working with us, please check our vacancies and other ways to get involved , or feel free to contact us.

# CHAPTER 2

# API Reference

If you are looking for information on a specific function, class or method, this part of the documentation is for you.

## 2.1 API - Layers

TensorLayer provides rich layer implementations trailed for various benchmarks and domain-specific problems. In addition, we also support transparent access to native TensorFlow parameters. For example, we provide not only layers for local response normalization, but also layers that allow user to apply `tf.nn.lrn` on `network.outputs`. More functions can be found in TensorFlow API.

### 2.1.1 Understanding the Basic Layer

All TensorLayer layers have a number of properties in common:

- `layer.outputs` : a Tensor, the outputs of current layer.
- `layer.all_params` : a list of Tensor, all network variables in order.
- `layer.all_layers` : a list of Tensor, all network outputs in order.
- `layer.all_drop` : a dictionary of {placeholder : float}, all keeping probabilities of noise layers.

All TensorLayer layers have a number of methods in common:

- `layer.print_params()` : print network variable information in order (after `tl.layers.initialize_global_variables(sess)`). alternatively, print all variables by `tl.layers.print_all_variables()`.
- `layer.print_layers()` : print network layer information in order.
- `layer.count_params()` : print the number of parameters in the network.

A network starts with the input layer and is followed by layers stacked in order. A network is essentially a `Layer` class. The key properties of a network are `network.all_params`, `network.all_layers` and `network.all_drop`. The `all_params` is a list which store pointers to all network parameters in order. For example, the following script define a 3 layer network, then:

`all_params` = [W1, b1, W2, b2, W_out, b_out]

To get specified variable information, you can use `network.all_params[2:3]` or `get_variables_with_name()`. `all_layers` is a list which stores the pointers to the outputs of all layers, see the example as follow:

`all_layers` = [drop(?,784), relu(?,800), drop(?,800), relu(?,800), drop(?,800)], identity(?,10)]

where `?` reflects a given batch size. You can print the layer and parameters information by using `network.print_layers()` and `network.print_params()`. To count the number of parameters in a network, run `network.count_params()`.

```
sess = tf.InteractiveSession()

x = tf.placeholder(tf.float32, shape=[None, 784], name='x')
y_ = tf.placeholder(tf.int64, shape=[None, ], name='y_')

network = tl.layers.InputLayer(x, name='input_layer')
network = tl.layers.DropoutLayer(network, keep=0.8, name='drop1')
network = tl.layers.DenseLayer(network, n_units=800,
                                act = tf.nn.relu, name='relu1')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop2')
network = tl.layers.DenseLayer(network, n_units=800,
                                act = tf.nn.relu, name='relu2')
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop3')
network = tl.layers.DenseLayer(network, n_units=10,
                                act = tl.activation.identity,
                                name='output_layer')

y = network.outputs
y_op = tf.argmax(tf.nn.softmax(y), 1)

cost = tl.cost.cross_entropy(y, y_)

train_params = network.all_params

train_op = tf.train.AdamOptimizer(learning_rate, beta1=0.9, beta2=0.999,
                            epsilon=1e-08, use_locking=False).minimize(cost, var_list
↪= train_params)

tl.layers.initialize_global_variables(sess)

network.print_params()
network.print_layers()
```

In addition, `network.all_drop` is a dictionary which stores the keeping probabilities of all noise layers. In the above network, they represent the keeping probabilities of dropout layers.

In case for training, you can enable all dropout layers as follow:

```
feed_dict = {x: X_train_a, y_: y_train_a}
feed_dict.update( network.all_drop )
loss, _ = sess.run([cost, train_op], feed_dict=feed_dict)
feed_dict.update( network.all_drop )
```

In case for evaluating and testing, you can disable all dropout layers as follow.

```
feed_dict = {x: X_val, y_: y_val}
feed_dict.update(dp_dict)
print("   val loss: %f" % sess.run(cost, feed_dict=feed_dict))
print("   val acc: %f" % np.mean(y_val ==
                        sess.run(y_op, feed_dict=feed_dict)))
```

For more details, please read the MNIST examples in the example folder.

### 2.1.2 Customizing Layers

#### A Simple Layer

To implement a custom layer in TensorLayer, you will have to write a Python class that subclasses Layer and implement the `outputs` expression.

The following is an example implementation of a layer that multiplies its input by 2:

```
class DoubleLayer(Layer):
    def __init__(
        self,
        layer = None,
        name ='double_layer',
    ):
        # check layer name (fixed)
        Layer.__init__(self, name=name)

        # the input of this layer is the output of previous layer (fixed)
        self.inputs = layer.outputs

        # operation (customized)
        self.outputs = self.inputs * 2

        # get stuff from previous layer (fixed)
        self.all_layers = list(layer.all_layers)
        self.all_params = list(layer.all_params)
        self.all_drop = dict(layer.all_drop)

        # update layer (customized)
        self.all_layers.extend( [self.outputs] )
```

#### Your Dense Layer

Before creating your own TensorLayer layer, let's have a look at the Dense layer. It creates a weight matrix and a bias vector if not exists, and then implements the output expression. At the end, for a layer with parameters, we also append the parameters into `all_params`.

```
class MyDenseLayer(Layer):
  def __init__(
      self,
      layer = None,
      n_units = 100,
      act = tf.nn.relu,
      name ='simple_dense',
```

```
):
        # check layer name (fixed)
        Layer.__init__(self, name=name)

        # the input of this layer is the output of previous layer (fixed)
        self.inputs = layer.outputs

        # print out info (customized)
        print("  MyDenseLayer %s: %d, %s" % (self.name, n_units, act))

        # operation (customized)
        n_in = int(self.inputs._shape[-1])
        with tf.variable_scope(name) as vs:
            # create new parameters
            W = tf.get_variable(name='W', shape=(n_in, n_units))
            b = tf.get_variable(name='b', shape=(n_units))
            # tensor operation
            self.outputs = act(tf.matmul(self.inputs, W) + b)

        # get stuff from previous layer (fixed)
        self.all_layers = list(layer.all_layers)
        self.all_params = list(layer.all_params)
        self.all_drop = dict(layer.all_drop)

        # update layer (customized)
        self.all_layers.extend( [self.outputs] )
        self.all_params.extend( [W, b] )
```

### Modifying Pre-train Behaviour

Greedy layer-wise pretraining is an important task for deep neural network initialization, while there are many kinds of pre-training methods according to different network architectures and applications.

For example, the pre-train process of Vanilla Sparse Autoencoder can be implemented by using KL divergence (for sigmoid) as the following code, but for Deep Rectifier Network, the sparsity can be implemented by using the L1 regularization of activation output.

```
# Vanilla Sparse Autoencoder
beta = 4
rho = 0.15
p_hat = tf.reduce_mean(activation_out, reduction_indices = 0)
KLD = beta * tf.reduce_sum( rho * tf.log(tf.div(rho, p_hat))
        + (1- rho) * tf.log((1- rho)/ (tf.sub(float(1), p_hat))) )
```

There are many pre-train methods, for this reason, TensorLayer provides a simple way to modify or design your own pre-train method. For Autoencoder, TensorLayer uses `ReconLayer.__init__()` to define the reconstruction layer and cost function, to define your own cost function, just simply modify the `self.cost` in `ReconLayer.__init__()`. To creat your own cost expression please read Tensorflow Math. By default, `ReconLayer` only updates the weights and biases of previous 1 layer by using `self.train_params = self.all _params[-4:]`, where the 4 parameters are `[W_encoder, b_encoder, W_decoder, b_decoder]`, where `W_encoder, b_encoder` belong to previous DenseLayer, `W_decoder, b_decoder` belong to this ReconLayer. In addition, if you want to update the parameters of previous 2 layers at the same time, simply modify `[-4:]` to `[-6:]`.

```
ReconLayer.__init__(...):
    ...
```

```
    self.train_params = self.all_params[-4:]
    ...
      self.cost = mse + L1_a + L2_w
```

### 2.1.3 Layer list

| | |
|---|---|
| get_variables_with_name([name, train_only, ...]) | Get a list of TensorFlow variables by a given name scope. |
| get_layers_with_name(net[, name, printable]) | Get a list of layers' output in a network by a given name scope. |
| set_name_reuse([enable]) | Enable or disable reuse layer name. |
| print_all_variables([train_only]) | Print information of trainable or all variables, without `tl.layers.initialize_global_variables(sess)`. |
| initialize_global_variables(sess) | Initialize the global variables of TensorFlow. |
| Layer([inputs, name]) | The basic Layer class represents a single layer of a neural network. |
| InputLayer([inputs, name]) | The InputLayer class is the starting layer of a neural network. |
| OneHotInputLayer([inputs, depth, on_value, ...]) | The OneHotInputLayer class is the starting layer of a neural network, see `tf.one_hot`. |
| Word2vecEmbeddingInputlayer([inputs, ...]) | The Word2vecEmbeddingInputlayer class is a fully connected layer. |
| EmbeddingInputlayer([inputs, ...]) | The EmbeddingInputlayer class is a look-up table for word embedding. |
| AverageEmbeddingInputlayer(inputs, ...[, ...]) | The AverageEmbeddingInputlayer averages over embeddings of inputs. |
| DenseLayer(layer[, n_units, act, W_init, ...]) | The DenseLayer class is a fully connected layer. |
| ReconLayer(layer[, x_recon, n_units, act, name]) | A reconstruction layer for DenseLayer to implement AutoEncoder. |
| DropoutLayer(layer[, keep, is_fix, ...]) | The DropoutLayer class is a noise layer which randomly set some activations to zero according to a keeping probability. |
| GaussianNoiseLayer(layer[, mean, stddev, ...]) | The GaussianNoiseLayer class is noise layer that adding noise with gaussian distribution to the activation. |
| DropconnectDenseLayer(layer[, keep, ...]) | The DropconnectDenseLayer class is DenseLayer with DropConnect behaviour which randomly removes connections between this layer and the previous layer according to a keeping probability. |
| Conv1dLayer(layer[, act, shape, stride, ...]) | The Conv1dLayer class is a 1D CNN layer, see tf.nn.convolution. |
| Conv2dLayer(layer[, act, shape, strides, ...]) | The Conv2dLayer class is a 2D CNN layer, see tf.nn.conv2d. |
| DeConv2dLayer(layer[, act, shape, ...]) | A de-convolution 2D layer. |
| Conv3dLayer(layer[, act, shape, strides, ...]) | The Conv3dLayer class is a 3D CNN layer, see tf.nn.conv3d. |
| DeConv3dLayer(layer[, act, shape, ...]) | The DeConv3dLayer class is deconvolutional 3D layer, see tf.nn.conv3d_transpose. |
| PoolLayer([layer, ksize, strides, padding, ...]) | The PoolLayer class is a Pooling layer. |
| PadLayer(layer, paddings[, mode, name]) | The PadLayer class is a padding layer for any mode and dimension. |

Continued on next page

Table 2.1 – continued from previous page

| | |
|---|---|
| *UpSampling2dLayer*(layer, size[, is_scale, . . . ]) | The *UpSampling2dLayer* class is a up-sampling 2D layer, see tf.image.resize_images. |
| *DownSampling2dLayer*(layer, size[, is_scale, . . . ]) | The *DownSampling2dLayer* class is down-sampling 2D layer, see tf.image.resize_images. |
| *AtrousConv1dLayer*(layer[, n_filter, . . . ]) | Simplified version of *AtrousConv1dLayer*. |
| *AtrousConv2dLayer*(layer[, n_filter, . . . ]) | The *AtrousConv2dLayer* class is 2D atrous convolution (a.k.a. |
| *Conv1d*(layer[, n_filter, filter_size, . . . ]) | Simplified version of *Conv1dLayer*. |
| *Conv2d*(layer[, n_filter, filter_size, . . . ]) | Simplified version of *Conv2dLayer*. |
| *DeConv2d*(layer[, n_filter, filter_size, . . . ]) | Simplified version of *DeConv2dLayer*. |
| *DeConv3d*(layer[, n_filter, filter_size, . . . ]) | Simplified version of The *DeConv3dLayer*, see tf.contrib.layers.conv3d_transpose. |
| *MaxPool1d*(net[, filter_size, strides, . . . ]) | Wrapper for tf.layers.max_pooling1d . |
| *MeanPool1d*(net[, filter_size, strides, . . . ]) | Wrapper for tf.layers.average_pooling1d . |
| *MaxPool2d*(net[, filter_size, strides, . . . ]) | Wrapper for *PoolLayer*. |
| *MeanPool2d*(net[, filter_size, strides, . . . ]) | Wrapper for *PoolLayer*. |
| *MaxPool3d*(net[, filter_size, strides, . . . ]) | Wrapper for tf.layers.max_pooling3d . |
| *MeanPool3d*(net[, filter_size, strides, . . . ]) | Wrapper for tf.layers.average_pooling3d |
| *DepthwiseConv2d*(layer[, channel_multiplier, . . . ]) | Separable/Depthwise Convolutional 2D layer, see tf.nn.depthwise_conv2d. |
| *DeformableConv2d*(layer[, offset_layer, . . . ]) | The *DeformableConv2d* class is a 2D Deformable Convolutional Networks. |
| *SubpixelConv1d*(net[, scale, act, name]) | It is a 1D sub-pixel up-sampling layer. |
| *SubpixelConv2d*(net[, scale, n_out_channel, . . . ]) | It is a 2D sub-pixel up-sampling layer, usually be used for Super-Resolution applications, see SRGAN for example. |
| *SpatialTransformer2dAffineLayer*([layer, . . . ]) | The *SpatialTransformer2dAffineLayer* class is a 2D Spatial Transformer Layer for 2D Affine Transformation. |
| *transformer*(U, theta, out_size[, name]) | Spatial Transformer Layer for 2D Affine Transformation , see *SpatialTransformer2dAffineLayer* class. |
| *batch_transformer*(U, thetas, out_size[, name]) | Batch Spatial Transformer function for 2D Affine Transformation. |
| *BatchNormLayer*(layer[, decay, epsilon, act, . . . ]) | The *BatchNormLayer* is a batch normalization layer for both fully-connected and convolution outputs. |
| *LocalResponseNormLayer*(layer[, . . . ]) | The *LocalResponseNormLayer* layer is for Local Response Normalization. |
| *InstanceNormLayer*(layer[, act, epsilon, name]) | The *InstanceNormLayer* class is a for instance normalization. |
| *LayerNormLayer*(layer[, center, scale, act, . . . ]) | The *LayerNormLayer* class is for layer normalization, see tf.contrib.layers.layer_norm. |
| *ROIPoolingLayer*(layer, rois[, pool_height, . . . ]) | The region of interest pooling layer. |
| *TimeDistributedLayer*(layer[, layer_class, . . . ]) | The *TimeDistributedLayer* class that applies a function to every timestep of the input tensor. |
| *RNNLayer*(layer, cell_fn[, cell_init_args, . . . ]) | The *RNNLayer* class is a fixed length recurrent layer for implementing vanilla RNN, LSTM, GRU and etc. |
| *BiRNNLayer*(layer, cell_fn[, cell_init_args, . . . ]) | The *BiRNNLayer* class is a fixed length Bidirectional recurrent layer. |
| *ConvRNNCell* | Abstract object representing an Convolutional RNN Cell. |
| *BasicConvLSTMCell*(shape, filter_size, . . . [, . . . ]) | Basic Conv LSTM recurrent network cell. |
| *ConvLSTMLayer*(layer[, cell_shape, . . . ]) | A fixed length Convolutional LSTM layer. |

Continued on next page

Table 2.1 – continued from previous page

| | |
|---|---|
| advanced_indexing_op(inputs, index) | Advanced Indexing for Sequences, returns the outputs by given sequence lengths. |
| retrieve_seq_length_op(data) | An op to compute the length of a sequence from input shape of [batch_size, n_step(max), n_features], it can be used when the features of padding (on right hand side) are all zeros. |
| retrieve_seq_length_op2(data) | An op to compute the length of a sequence, from input shape of [batch_size, n_step(max)], it can be used when the features of padding (on right hand side) are all zeros. |
| retrieve_seq_length_op3(data[, pad_val]) | Return tensor for sequence length, if input is `tf.string`. |
| target_mask_op(data[, pad_val]) | Return tensor for mask, if input is `tf.string`. |
| DynamicRNNLayer(layer, cell_fn[, ...]) | The DynamicRNNLayer class is a dynamic recurrent layer, see `tf.nn.dynamic_rnn`. |
| BiDynamicRNNLayer(layer, cell_fn[, ...]) | The BiDynamicRNNLayer class is a RNN layer, you can implement vanilla RNN, LSTM and GRU with it. |
| Seq2Seq(net_encode_in, net_decode_in, cell_fn) | The Seq2Seq class is a simple DynamicRNNLayer based Seq2seq layer without using tl.contrib.seq2seq. |
| FlattenLayer(layer[, name]) | A layer that reshapes high-dimension input into a vector. |
| ReshapeLayer(layer, shape[, name]) | A layer that reshapes a given tensor. |
| TransposeLayer(layer, perm[, name]) | A layer that transposes the dimension of a tensor. |
| LambdaLayer(layer, fn[, fn_args, name]) | A layer that takes a user-defined function using TensorFlow Lambda. |
| ConcatLayer(layers[, concat_dim, name]) | A layer that concats multiple tensors according to given axis.. |
| ElementwiseLayer(layers[, combine_fn, name]) | A layer that combines multiple Layer that have the same output shapes according to an element-wise operation. |
| ExpandDimsLayer(layer, axis[, name]) | The ExpandDimsLayer class inserts a dimension of 1 into a tensor's shape, see tf.expand_dims() . |
| TileLayer([layer, multiples, name]) | The TileLayer class constructs a tensor by tiling a given tensor, see tf.tile() . |
| StackLayer(layers[, axis, name]) | The StackLayer class is layer for stacking a list of rank-R tensors into one rank-(R+1) tensor, see tf.stack(). |
| UnStackLayer(layer[, num, axis, name]) | It is layer for unstacking the given dimension of a rank-R tensor into rank-(R-1) tensors., see tf.unstack(). |
| SlimNetsLayer(layer, slim_layer[, ...]) | A layer that merges TF-Slim models into TensorLayer. |
| PReluLayer(layer[, channel_shared, a_init, ...]) | The PReluLayer class is Parametric Rectified Linear layer. |
| MultiplexerLayer(layers[, name]) | The MultiplexerLayer selects inputs to be forwarded to output. |
| flatten_reshape(variable[, name]) | Reshapes a high-dimension vector input. |
| clear_layers_name() | Clear all layer names in *set_keep['_layers_name_list']* if layer names are reused. |
| initialize_rnn_state(state[, feed_dict]) | Returns the initialized RNN state. |
| list_remove_repeat(x) | Remove the repeated items in a list, and return the processed list. |
| merge_networks([layers]) | Merge all parameters, layers and dropout probabilities to a Layer. |

### 2.1.4 Name Scope and Sharing Parameters

These functions help you to reuse parameters for different inference (graph), and get a list of parameters by given name. About TensorFlow parameters sharing click here.

### Get variables with name

tensorlayer.layers.**get_variables_with_name**(*name=None*, *train_only=True*, *printable=False*)

Get a list of TensorFlow variables by a given name scope.

**Parameters**

- **name** (*str*) – Get the variables that contain this name.
- **train_only** (*boolean*) – If Ture, only get the trainable variables.
- **printable** (*boolean*) – If True, print the information of all variables.

**Returns** A list of TensorFlow variables

**Return type** list of Tensor

#### Examples

```
>>> dense_vars = tl.layers.get_variable_with_name('dense', True, True)
```

### Get layers with name

tensorlayer.layers.**get_layers_with_name**(*net*, *name=”*, *printable=False*)

Get a list of layers' output in a network by a given name scope.

**Parameters**

- **net** (*Layer*) – The last layer of the network.
- **name** (*str*) – Get the layers' output that contain this name.
- **printable** (*boolean*) – If True, print information of all the layers' output

**Returns** A list of layers' output (TensorFlow tensor)

**Return type** list of Tensor

#### Examples

```
>>> layers = tl.layers.get_layers_with_name(net, "CNN", True)
```

### Enable layer name reuse

tensorlayer.layers.**set_name_reuse**(*enable=True*)

Enable or disable reuse layer name.

By default, each layer must has unique name. When you want two or more input placeholder (inference) share the same model parameters, you need to enable layer name reuse, then allow the parameters have same name scope.

**Parameters** **enable** (*boolean*) – Enable or disable name/layer reuse, None means False.

### Examples

```
>>> def embed_seq(input_seqs, is_train, reuse):
>>>     with tf.variable_scope("model", reuse=reuse):
>>>         tl.layers.set_name_reuse(reuse)
>>>         net = tl.layers.EmbeddingInputlayer(
...                     inputs = input_seqs,
...                     vocabulary_size = vocab_size,
...                     embedding_size = embedding_size,
...                     name = 'e_embedding')
>>>         net = tl.layers.DynamicRNNLayer(net,
...                     cell_fn = tf.contrib.rnn.BasicLSTMCell,
...                     n_hidden = embedding_size,
...                     dropout = (0.7 if is_train else None),
...                     initializer = w_init,
...                     sequence_length = tl.layers.retrieve_seq_length_op2(input_
↪seqs),
...                     return_last = True,
...                     name = 'e_dynamicrnn')
>>>     return net
>>>
>>> net_train = embed_seq(t_caption, is_train=True, reuse=False)
>>> net_test = embed_seq(t_caption, is_train=False, reuse=True)
```

- see `tutorial_ptb_lstm.py` for example.

### Print variables

`tensorlayer.layers.`**`print_all_variables`**(*train_only=False*)

Print information of trainable or all variables, without `tl.layers.initialize_global_variables(sess)`.

**Parameters** **`train_only`** (*boolean*) –

**Whether print trainable variables only.**

- If True, print the trainable variables.
- If False, print all variables.

### Initialize variables

`tensorlayer.layers.`**`initialize_global_variables`**(*sess*)

Initialize the global variables of TensorFlow.

Run `sess.run(tf.global_variables_initializer())` for TF 0.12+ or `sess.run(tf.initialize_all_variables())` for TF 0.11.

**Parameters** **`sess`** (*Session*) – TensorFlow session.

## 2.1.5 Basic layer

**`class`** `tensorlayer.layers.`**`Layer`**(*inputs=None*, *name='layer'*)

The basic `Layer` class represents a single layer of a neural network. It should be subclassed when implementing new types of layers. Because each layer can keep track of the layer(s) feeding into it, a network's output `Layer` instance can double as a handle to the full network.

**Parameters**

- **inputs** (`Layer` instance) – The *Layer* class feeding into this layer.
- **name** (`str or None`) – A unique layer name.

**print_params** (*details=True*, *session=None*)
Print all parameters of this network.

**print_layers** ()
Print all outputs of all layers of this network.

**count_params** ()
Return the number of parameters of this network.

### 2.1.6 Input layer

**class** tensorlayer.layers.**InputLayer** (*inputs=None*, *name='input'*)
The `InputLayer` class is the starting layer of a neural network.

**Parameters**

- **inputs** (`placeholder or tensor`) – The input of a network.
- **name** (`str`) – A unique layer name.

### 2.1.7 One-hot layer

**class** tensorlayer.layers.**OneHotInputLayer** (*inputs=None*, *depth=None*, *on_value=None*, *off_value=None*, *axis=None*, *dtype=None*, *name='input'*)
The `OneHotInputLayer` class is the starting layer of a neural network, see `tf.one_hot`.

**Parameters**

- **inputs** (`placeholder or tensor`) – The input of a network.
- **depth** (`None or int`) – If the input indices is rank N, the output will have rank N+1. The new axis is created at dimension *axis* (default: the new axis is appended at the end).
- **on_value** (`None or number`) – The value to represnt *ON*. If None, it will default to the value 1.
- **off_value** (`None or number`) – The value to represnt *OFF*. If None, it will default to the value 0.
- **axis** (`None or int`) – The axis.
- **dtype** (`None or TensorFlow dtype`) – The data type, None means tf.float32.
- **name** (`str`) – A unique layer name.

### 2.1.8 Word Embedding Input layer

#### Word2vec layer for training

**class** tensorlayer.layers.**Word2vecEmbeddingInputlayer**(*inputs=None, train_labels=None, vocabulary_size=80000, embedding_size=200, num_sampled=64, nce_loss_args=None, E_init=<tensorflow.python.ops.init_ops.RandomUniform object>, E_init_args=None, nce_W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, nce_W_init_args=None, nce_b_init=<tensorflow.python.ops.init_ops.Constant object>, nce_b_init_args=None, name='word2vec'*)

The *Word2vecEmbeddingInputlayer* class is a fully connected layer. For Word Embedding, words are input as integer index. The output is the embedded word vector.

**Parameters**

- **inputs** (*placeholder or tensor*) – The input of a network. For word inputs, please use integer index format, 2D tensor : [batch_size, num_steps(num_words)]
- **train_labels** (*placeholder*) – For word labels. integer index format
- **vocabulary_size** (*int*) – The size of vocabulary, number of words
- **embedding_size** (*int*) – The number of embedding dimensions
- **num_sampled** (*int*) – The mumber of negative examples for NCE loss
- **nce_loss_args** (*dictionary*) – The arguments for tf.nn.nce_loss()
- **E_init** (*initializer*) – The initializer for initializing the embedding matrix
- **E_init_args** (*dictionary*) – The arguments for embedding initializer
- **nce_W_init** (*initializer*) – The initializer for initializing the nce decoder weight matrix
- **nce_W_init_args** (*dictionary*) – The arguments for initializing the nce decoder weight matrix
- **nce_b_init** (*initializer*) – The initializer for initializing of the nce decoder bias vector
- **nce_b_init_args** (*dictionary*) – The arguments for initializing the nce decoder bias vector
- **name** (*str*) – A unique layer name

**nce_cost**
*Tensor* – The NCE loss.

**outputs**
*Tensor* – The embedding layer outputs.

**normalized_embeddings**
*Tensor* – Normalized embedding matrix.

### Examples

With TensorLayer : see `tensorlayer/example/tutorial_word2vec_basic.py`

```
>>> train_inputs = tf.placeholder(tf.int32, shape=(batch_size))
>>> train_labels = tf.placeholder(tf.int32, shape=(batch_size, 1))
>>> emb_net = tl.layers.Word2vecEmbeddingInputlayer(
...         inputs = train_inputs,
...         train_labels = train_labels,
...         vocabulary_size = vocabulary_size,
...         embedding_size = embedding_size,
...         num_sampled = num_sampled,
...         name ='word2vec',
...    )
>>> cost = emb_net.nce_cost
>>> train_params = emb_net.all_params
>>> train_op = tf.train.GradientDescentOptimizer(learning_rate).minimize(
...                                             cost, var_list=train_params)
>>> normalized_embeddings = emb_net.normalized_embeddings
```

Without TensorLayer : see `tensorflow/examples/tutorials/word2vec/word2vec_basic.py`

```
>>> train_inputs = tf.placeholder(tf.int32, shape=(batch_size))
>>> train_labels = tf.placeholder(tf.int32, shape=(batch_size, 1))
>>> embeddings = tf.Variable(
...     tf.random_uniform([vocabulary_size, embedding_size], -1.0, 1.0))
>>> embed = tf.nn.embedding_lookup(embeddings, train_inputs)
>>> nce_weights = tf.Variable(
...     tf.truncated_normal([vocabulary_size, embedding_size],
...                    stddev=1.0 / math.sqrt(embedding_size)))
>>> nce_biases = tf.Variable(tf.zeros([vocabulary_size]))
>>> cost = tf.reduce_mean(
...    tf.nn.nce_loss(weights=nce_weights, biases=nce_biases,
...                inputs=embed, labels=train_labels,
...                num_sampled=num_sampled, num_classes=vocabulary_size,
...                num_true=1))
```

### References

tensorflow/examples/tutorials/word2vec/word2vec_basic.py

## Embedding Input layer

**class** `tensorlayer.layers.`**`EmbeddingInputlayer`**(*inputs=None, vocabulary_size=80000, embedding_size=200, E_init=<tensorflow.python.ops.init_ops.RandomUniform object>, E_init_args=None, name='embedding'*)

The `EmbeddingInputlayer` class is a look-up table for word embedding.

Word content are accessed using integer indexes, then the output is the embedded word vector. To train a word embedding matrix, you can used *Word2vecEmbeddingInputlayer*. If you have a pre-trained matrix, you can assign the parameters into it.

**Parameters**

- **inputs** (*placeholder*) – The input of a network. For word inputs. Please use integer index format, 2D tensor : (batch_size, num_steps(num_words)).
- **vocabulary_size** (*int*) – The size of vocabulary, number of words.
- **embedding_size** (*int*) – The number of embedding dimensions.
- **E_init** (*initializer*) – The initializer for the embedding matrix.
- **E_init_args** (*dictionary*) – The arguments for embedding matrix initializer.
- **name** (*str*) – A unique layer name.

**outputs**

*tensor* – The embedding layer output is a 3D tensor in the shape: (batch_size, num_steps(num_words), embedding_size).

### Examples

```
>>> x = tf.placeholder(tf.int32, shape=(batch_size,))
>>> emb_net = tl.layers.EmbeddingInputlayer(
...                 inputs = x,
...                 vocabulary_size = vocabulary_size,
...                 embedding_size = embedding_size,
...                 name ='embed')
```

## Average Embedding Input layer

**class** tensorlayer.layers.**AverageEmbeddingInputlayer**(*inputs*, *vocabulary_size*, *embedding_size*, *pad_value=0*, *embeddings_initializer=<tensorflow.python.ops.init_ops.Rando* *object>*, *embeddings_kwargs=None*, *name='average_embedding'*)

The *AverageEmbeddingInputlayer* averages over embeddings of inputs. This is often used as the input layer for models like DAN[1] and FastText[2].

**Parameters**

- **inputs** (*placeholder or tensor*) – The network input. For word inputs, please use integer index format, 2D tensor: (batch_size, num_steps(num_words)).
- **vocabulary_size** (*int*) – The size of vocabulary.
- **embedding_size** (*int*) – The dimension of the embedding vectors.
- **pad_value** (*int*) – The scalar padding value used in inputs, 0 as default.
- **embeddings_initializer** (*initializer*) – The initializer of the embedding matrix.
- **embeddings_kwargs** (*None or dictionary*) – The arguments to get embedding matrix variable.

- **name** (*str*) – A unique layer name.

### References

- [1] Iyyer, M., Manjunatha, V., Boyd-Graber, J., & Daum'e III, H. (2015). Deep Unordered Composition Rivals Syntactic Methods for Text Classification. In Association for Computational Linguistics.
- [2] Joulin, A., Grave, E., Bojanowski, P., & Mikolov, T. (2016). Bag of Tricks for Efficient Text Classification.

## 2.1.9 Dense layer

### Dense layer

**class** tensorlayer.layers.**DenseLayer**(*layer*, *n_units=100*, *act=<function identity>*, *W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>*, *b_init=<tensorflow.python.ops.init_ops.Constant object>*, *W_init_args=None*, *b_init_args=None*, *name='dense'*)

The DenseLayer class is a fully connected layer.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **n_units** (*int*) – The number of units of this layer.
- **act** (*activation function*) – The activation function of this layer.
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*a str*) – A unique layer name.

### Examples

With TensorLayer

```
>>> net = tl.layers.InputLayer(x, name='input')
>>> net = tl.layers.DenseLayer(net, 800, act=tf.nn.relu, name='relu')
```

Without native TensorLayer APIs, you can do as follow.

```
>>> W = tf.Variable(
...     tf.random_uniform([n_in, n_units], -1.0, 1.0), name='W')
>>> b = tf.Variable(tf.zeros(shape=[n_units]), name='b')
>>> y = tf.nn.relu(tf.matmul(inputs, W) + b)
```

### Notes

If the layer input has more than two axes, it needs to be flatten by using `FlattenLayer`.

### Reconstruction layer for Autoencoder

**class** tensorlayer.layers.**ReconLayer**(*layer*, *x_recon=None*, *n_units=784*, *act=<function softplus>*, *name='recon'*)

A reconstruction layer for `DenseLayer` to implement AutoEncoder.

It is often used to pre-train the previous `DenseLayer`

**Parameters**

- **layer** (`Layer`) – Previous layer.
- **x_recon** (*placeholder or tensor*) – The target for reconstruction.
- **n_units** (*int*) – The number of units of the layer. It should equal `x_recon`.
- **act** (*activation function*) – The activation function of this layer. Normally, for sigmoid layer, the reconstruction activation is `sigmoid`; for rectifying layer, the reconstruction activation is `softplus`.
- **name** (*str*) – A unique layer name.

### Examples

```
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = tl.layers.DenseLayer(net, n_units=196,
...                                 act=tf.nn.sigmoid, name='sigmoid1')
>>> recon_layer1 = tl.layers.ReconLayer(net, x_recon=x, n_units=784,
...                                 act=tf.nn.sigmoid, name='recon_layer1')
>>> recon_layer1.pretrain(sess, x=x, X_train=X_train, X_val=X_val,
...                         denoise_name=None, n_epoch=1200, batch_size=128,
...                         print_freq=10, save=True, save_name='w1pre_')
```

**pretrain**(*sess*, *x*, *X_train*, *X_val*, *denoise_name=None*, *n_epoch=100*, *batch_size=128*, *print_freq=10*, *save=True*, *save_name='w1pre'*)

Start to pre-train the parameters of the previous DenseLayer.

### Notes

The input layer should be *DenseLayer* or a layer that has only one axes. You may need to modify this part to define your own cost function. By default, the cost is implemented as follow: - For sigmoid layer, the implementation can be UFLDL - For rectifying layer, the implementation can be Glorot (2011). Deep Sparse Rectifier Neural Networks

## 2.1.10 Noise layer

### Dropout layer

**class** tensorlayer.layers.**DropoutLayer**(*layer*, *keep=0.5*, *is_fix=False*, *is_train=True*, *seed=None*, *name='dropout_layer'*)

The `DropoutLayer` class is a noise layer which randomly set some activations to zero according to a keeping probability.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **keep** (*float*) – The keeping probability. The lower the probability it is, the more activations are set to zero.
- **is_fix** (*boolean*) – Fixing probability or nor. Default is False. If True, the keeping probability is fixed and cannot be changed via *feed_dict*.
- **is_train** (*boolean*) – Trainable or not. If False, skip this layer. Default is True.
- **seed** (*int or None*) – The seed for random dropout.
- **name** (*str*) – A unique layer name.

### Examples

Method 1: Using `all_drop` see tutorial_mlp_dropout1.py

```
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = tl.layers.DropoutLayer(net, keep=0.8, name='drop1')
>>> net = tl.layers.DenseLayer(net, n_units=800, act=tf.nn.relu, name='relu1')
>>> ...
>>> # For training, enable dropout as follow.
>>> feed_dict = {x: X_train_a, y_: y_train_a}
>>> feed_dict.update( net.all_drop )     # enable noise layers
>>> sess.run(train_op, feed_dict=feed_dict)
>>> ...
>>> # For testing, disable dropout as follow.
>>> dp_dict = tl.utils.dict_to_one( net.all_drop ) # disable noise layers
>>> feed_dict = {x: X_val_a, y_: y_val_a}
>>> feed_dict.update(dp_dict)
>>> err, ac = sess.run([cost, acc], feed_dict=feed_dict)
>>> ...
```

Method 2: Without using `all_drop` see tutorial_mlp_dropout2.py

```
>>> def mlp(x, is_train=True, reuse=False):
>>>     with tf.variable_scope("MLP", reuse=reuse):
>>>     tl.layers.set_name_reuse(reuse)
>>>     net = tl.layers.InputLayer(x, name='input')
>>>     net = tl.layers.DropoutLayer(net, keep=0.8, is_fix=True,
>>>                         is_train=is_train, name='drop1')
>>>     ...
>>>     return net
>>> # define inferences
>>> net_train = mlp(x, is_train=True, reuse=False)
>>> net_test = mlp(x, is_train=False, reuse=True)
```

## Gaussian noise layer

**class** `tensorlayer.layers.`**`GaussianNoiseLayer`**(*layer, mean=0.0, stddev=1.0, is_train=True, seed=None, name='gaussian_noise_layer'*)

The *GaussianNoiseLayer* class is noise layer that adding noise with gaussian distribution to the activation.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **mean** (*float*) – The mean. Default is 0.
- **stddev** (*float*) – The standard deviation. Default is 1.
- **is_train** (*boolean*) – Is trainable layer. If False, skip this layer. default is True.
- **seed** (*int or None*) – The seed for random noise.
- **name** (*str*) – A unique layer name.

### Dropconnect + Dense layer

**class** tensorlayer.layers.**DropconnectDenseLayer**(*layer, keep=0.5, n_units=100, act=<function identity>, W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='dropconnect_layer'*)

The *DropconnectDenseLayer* class is *DenseLayer* with DropConnect behaviour which randomly removes connections between this layer and the previous layer according to a keeping probability.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **keep** (*float*) – The keeping probability. The lower the probability it is, the more activations are set to zero.
- **n_units** (*int*) – The number of units of this layer.
- **act** (*activation function*) – The activation function of this layer.
- **W_init** (*weights initializer*) – The initializer for the weight matrix.
- **b_init** (*biases initializer*) – The initializer for the bias vector.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

#### Examples

```
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = tl.layers.DropconnectDenseLayer(net, keep=0.8,
...         n_units=800, act=tf.nn.relu, name='relu1')
>>> net = tl.layers.DropconnectDenseLayer(net, keep=0.5,
...         n_units=800, act=tf.nn.relu, name='relu2')
>>> net = tl.layers.DropconnectDenseLayer(net, keep=0.5,
...         n_units=10, name='output')
```

#### References


- Wan, L. (2013). Regularization of neural networks using dropconnect

### 2.1.11 Convolutional layer (Pro)

#### 1D Convolution

**class** tensorlayer.layers.**Conv1dLayer**(*layer, act=<function identity>, shape=(5, 1, 5), stride=1, dilation_rate=1, padding='SAME', data_format='NWC', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='cnn1d'*)

The `Conv1dLayer` class is a 1D CNN layer, see tf.nn.convolution.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **act** (*activation function*) – The activation function of this layer.
- **shape** (*tuple of int*) – The shape of the filters: (filter_length, in_channels, out_channels).
- **stride** (*int*) – The number of entries by which the filter is moved right at a step.
- **dilation_rate** (*int*) – Filter up-sampling/input down-sampling rate.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **data_format** (*str*) – Default is 'NWC' as it is a 1D CNN.
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name

#### 2D Convolution

**class** tensorlayer.layers.**Conv2dLayer**(*layer, act=<function identity>, shape=(5, 5, 1, 100), strides=(1, 1, 1, 1), padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, use_cudnn_on_gpu=None, data_format=None, name='cnn_layer'*)

The `Conv2dLayer` class is a 2D CNN layer, see tf.nn.conv2d.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **act** (*activation function*) – The activation function of this layer.
- **shape** (*tuple of int*) – The shape of the filters: (filter_height, filter_width, in_channels, out_channels).

- **strides** (*tuple of int*) – The sliding window strides of corresponding input dimensions. It must be in the same order as the `shape` parameter.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **W_init** (*initializer*) – The initializer for the the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **use_cudnn_on_gpu** (*bool*) – Default is False.
- **data_format** (*str*) – "NHWC" or "NCHW", default is "NHWC".
- **name** (*str*) – A unique layer name.

### Notes

- shape = [h, w, the number of output channel of previous layer, the number of output channels]
- the number of output channel of a layer is its last dimension.

### Examples

With TensorFlow

```
>>> x = tf.placeholder(tf.float32, shape=(None, 28, 28, 1))
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = tl.layers.Conv2dLayer(net,
...                   act = tf.nn.relu,
...                   shape = (5, 5, 1, 32),  # 32 features for each 5x5 patch
...                   strides = (1, 1, 1, 1),
...                   padding='SAME',
...                   W_init=tf.truncated_normal_initializer(stddev=5e-2),
...                   W_init_args={},
...                   b_init = tf.constant_initializer(value=0.0),
...                   b_init_args = {},
...                   name ='cnn_layer1')     # output: (?, 28, 28, 32)
>>> net = tl.layers.PoolLayer(net,
...                   ksize=(1, 2, 2, 1),
...                   strides=(1, 2, 2, 1),
...                   padding='SAME',
...                   pool = tf.nn.max_pool,
...                   name ='pool_layer1',)   # output: (?, 14, 14, 32)
```

Without TensorLayer, you can implement 2d convolution as follow.

```
>>> W = tf.Variable(W_init(shape=[5, 5, 1, 32], ), name='W_conv')
>>> b = tf.Variable(b_init(shape=[32], ), name='b_conv')
>>> outputs = tf.nn.relu( tf.nn.conv2d(inputs, W,
...                       strides=[1, 1, 1, 1],
...                       padding='SAME') + b )
```

### 2D Deconvolution

**class** tensorlayer.layers.**DeConv2dLayer**(*layer, act=<function identity>, shape=(3, 3, 128, 256), output_shape=(1, 256, 256, 128), strides=(1, 2, 2, 1), padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='decnn2d_layer'*)

A de-convolution 2D layer.

See tf.nn.conv2d_transpose.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **act** (*activation function*) – The activation function of this layer.
- **shape** (*tuple of int*) – Shape of the filters: (height, width, output_channels, in_channels). The filter's `in_channels` dimension must match that of value.
- **output_shape** (*tuple of int*) – Output shape of the deconvolution,
- **strides** (*tuple of int*) – The sliding window strides for corresponding input dimensions.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for initializing the weight matrix.
- **b_init_args** (*dictionary*) – The arguments for initializing the bias vector.
- **name** (*str*) – A unique layer name.

#### Notes

- We recommend to use *DeConv2d* with TensorFlow version higher than 1.3.
- shape = [h, w, the number of output channels of this layer, the number of output channel of the previous layer].
- output_shape = [batch_size, any, any, the number of output channels of this layer].
- the number of output channel of a layer is its last dimension.

#### Examples

A part of the generator in DCGAN example

```
>>> batch_size = 64
>>> inputs = tf.placeholder(tf.float32, [batch_size, 100], name='z_noise')
>>> net_in = tl.layers.InputLayer(inputs, name='g/in')
>>> net_h0 = tl.layers.DenseLayer(net_in, n_units = 8192,
...                             W_init = tf.random_normal_initializer(stddev=0.02),
...                             act = tf.identity, name='g/h0/lin')
```

```
>>> print(net_h0.outputs._shape)
... (64, 8192)
>>> net_h0 = tl.layers.ReshapeLayer(net_h0, shape=(-1, 4, 4, 512), name='g/h0/
↪reshape')
>>> net_h0 = tl.layers.BatchNormLayer(net_h0, act=tf.nn.relu, is_train=is_train,␣
↪name='g/h0/batch_norm')
>>> print(net_h0.outputs._shape)
... (64, 4, 4, 512)
>>> net_h1 = tl.layers.DeConv2dLayer(net_h0,
...                             shape=(5, 5, 256, 512),
...                             output_shape=(batch_size, 8, 8, 256),
...                             strides=(1, 2, 2, 1),
...                             act=tf.identity, name='g/h1/decon2d')
>>> net_h1 = tl.layers.BatchNormLayer(net_h1, act=tf.nn.relu, is_train=is_train,␣
↪name='g/h1/batch_norm')
>>> print(net_h1.outputs._shape)
... (64, 8, 8, 256)
```

U-Net

```
>>> ....
>>> conv10 = tl.layers.Conv2dLayer(conv9, act=tf.nn.relu,
...         shape=(3,3,1024,1024), strides=(1,1,1,1), padding='SAME',
...         W_init=w_init, b_init=b_init, name='conv10')
>>> print(conv10.outputs)
... (batch_size, 32, 32, 1024)
>>> deconv1 = tl.layers.DeConv2dLayer(conv10, act=tf.nn.relu,
...         shape=(3,3,512,1024), strides=(1,2,2,1), output_shape=(batch_size,64,
↪64,512),
...         padding='SAME', W_init=w_init, b_init=b_init, name='devcon1_1')
```

### 3D Convolution

**class** tensorlayer.layers.**Conv3dLayer**(*layer, act=<function identity>, shape=(2, 2, 2, 64, 128), strides=(1, 2, 2, 2, 1), padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='cnn3d_layer'*)

The `Conv3dLayer` class is a 3D CNN layer, see tf.nn.conv3d.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **act** (*activation function*) – The activation function of this layer.
- **shape** (*tuple of int*) – Shape of the filters: (filter_depth, filter_height, filter_width, in_channels, out_channels).
- **strides** (*tuple of int*) – The sliding window strides for corresponding input dimensions. Must be in the same order as the shape dimension.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer*) – The initializer for the bias vector.

- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

### 3D Deconvolution

**class** tensorlayer.layers.**DeConv3dLayer**(*layer, act=<function identity>, shape=(2, 2, 2, 128, 256), output_shape=(1, 12, 32, 32, 128), strides=(1, 2, 2, 2, 1), padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='decnn3d_layer'*)

The *DeConv3dLayer* class is deconvolutional 3D layer, see tf.nn.conv3d_transpose.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **act** (*activation function*) – The activation function of this layer.
- **shape** (*tuple of int*) – The shape of the filters: (depth, height, width, output_channels, in_channels). The filter's in_channels dimension must match that of value.
- **output_shape** (*tuple of int*) – The output shape of the deconvolution.
- **strides** (*tuple of int*) – The sliding window strides for corresponding input dimensions.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer*) – The initializer for the bias vector.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

### 2D UpSampling

**class** tensorlayer.layers.**UpSampling2dLayer**(*layer, size, is_scale=True, method=0, align_corners=False, name='upsample2d_layer'*)

The *UpSampling2dLayer* class is a up-sampling 2D layer, see tf.image.resize_images.

**Parameters**

- **layer** (*Layer*) – Previous layer with 4-D Tensor of the shape (batch, height, width, channels) or 3-D Tensor of the shape (height, width, channels).
- **size** (*tuple of int/float*) – (height, width) scale factor or new size of height and width.
- **is_scale** (*boolean*) – If True (default), the *size* is a scale factor; otherwise, the *size* is the numbers of pixels of height and width.
- **method** (*int*) –

**The resize method selected through the index. Defaults index is 0 which is ResizeMethod.BILINEAR.**

- Index 0 is ResizeMethod.BILINEAR, Bilinear interpolation.
- Index 1 is ResizeMethod.NEAREST_NEIGHBOR, Nearest neighbor interpolation.
- Index 2 is ResizeMethod.BICUBIC, Bicubic interpolation.
- Index 3 ResizeMethod.AREA, Area interpolation.

- **align_corners** (*boolean*) – If True, align the corners of the input and output. Default is False.
- **name** (*str*) – A unique layer name.

### 2D DownSampling

**class** tensorlayer.layers.**DownSampling2dLayer**(*layer, size, is_scale=True, method=0, align_corners=False, name='downsample2d_layer'*)

The *DownSampling2dLayer* class is down-sampling 2D layer, see tf.image.resize_images.

**Parameters**

- **layer** (*Layer*) – Previous layer with 4-D Tensor in the shape of (batch, height, width, channels) or 3-D Tensor in the shape of (height, width, channels).
- **size** (*tuple of int/float*) – (height, width) scale factor or new size of height and width.
- **is_scale** (*boolean*) – If True (default), the *size* is the scale factor; otherwise, the *size* are numbers of pixels of height and width.
- **method** (*int*) –

  **The resize method selected through the index. Defaults index is 0 which is ResizeMethod.BILINEAR.**

  - Index 0 is ResizeMethod.BILINEAR, Bilinear interpolation.
  - Index 1 is ResizeMethod.NEAREST_NEIGHBOR, Nearest neighbor interpolation.
  - Index 2 is ResizeMethod.BICUBIC, Bicubic interpolation.
  - Index 3 ResizeMethod.AREA, Area interpolation.
- **align_corners** (*boolean*) – If True, exactly align all 4 corners of the input and output. Default is False.
- **name** (*str*) – A unique layer name.

### 1D Atrous convolution

tensorlayer.layers.**AtrousConv1dLayer**(*layer, n_filter=32, filter_size=2, stride=1, dilation=1, act=<function identity>, padding='SAME', data_format='NWC', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='conv1d'*)

Simplified version of *AtrousConv1dLayer*.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **n_filter** (*int*) – The number of filters.
- **filter_size** (*int*) – The filter size.
- **stride** (*tuple of int*) – The strides: (height, width).
- **dilation** (*int*) – The filter dilation size.
- **act** (*activation function*) – The activation function of this layer.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **data_format** (*str*) – Default is 'NWC' as it is a 1D CNN.
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

**Returns** A *AtrousConv1dLayer* object

**Return type** *Layer*

### 2D Atrous convolution

**class** tensorlayer.layers.**AtrousConv2dLayer**(*layer, n_filter=32, filter_size=(3, 3), rate=2, act=<function identity>, padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='atrou2d'*)

The *AtrousConv2dLayer* class is 2D atrous convolution (a.k.a. convolution with holes or dilated convolution) 2D layer, see tf.nn.atrous_conv2d.

**Parameters**

- **layer** (*Layer*) – Previous layer with a 4D output tensor in the shape of (batch, height, width, channels).
- **n_filter** (*int*) – The number of filters.
- **filter_size** (*tuple of int*) – The filter size: (height, width).
- **rate** (*int*) – The stride that we sample input values in the height and width dimensions. This equals the rate that we up-sample the filters by inserting zeros across the height and width dimensions. In the literature, this parameter is sometimes mentioned as input stride or dilation.
- **act** (*activation function*) – The activation function of this layer.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **W_init** (*initializer*) – The initializer for the weight matrix.

- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

## 2.1.12 Convolutional layer (Simplified)

For users don't familiar with TensorFlow, the following simplified functions may easier for you. We will provide more simplified functions later, but if you are good at TensorFlow, the professional APIs may better for you.

### 1D Convolution

tensorlayer.layers.**Conv1d**(*layer*, *n_filter=32*, *filter_size=5*, *stride=1*, *dilation_rate=1*, *act=<function identity>*, *padding='SAME'*, *data_format='NWC'*, *W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>*, *b_init=<tensorflow.python.ops.init_ops.Constant object>*, *W_init_args=None*, *b_init_args=None*, *name='conv1d'*)

Simplified version of `Conv1dLayer`.

**Parameters**

- **layer** (*Layer*) – Previous layer
- **n_filter** (*int*) – The number of filters
- **filter_size** (*int*) – The filter size
- **stride** (*int*) – The stride step
- **dilation_rate** (*int*) – Specifying the dilation rate to use for dilated convolution.
- **act** (*activation function*) – The function that is applied to the layer activations
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **data_format** (*str*) – Default is 'NWC' as it is a 1D CNN.
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name

**Returns** A `Conv1dLayer` object.

**Return type** `Layer`

#### Examples

```
>>> x = tf.placeholder(tf.float32, (batch_size, width))
>>> y_ = tf.placeholder(tf.int64, shape=(batch_size,))
>>> n = InputLayer(x, name='in')
>>> n = ReshapeLayer(n, (-1, width, 1), name='rs')
>>> n = Conv1d(n, 64, 3, 1, act=tf.nn.relu, name='c1')
>>> n = MaxPool1d(n, 2, 2, padding='valid', name='m1')
>>> n = Conv1d(n, 128, 3, 1, act=tf.nn.relu, name='c2')
>>> n = MaxPool1d(n, 2, 2, padding='valid', name='m2')
>>> n = Conv1d(n, 128, 3, 1, act=tf.nn.relu, name='c3')
>>> n = MaxPool1d(n, 2, 2, padding='valid', name='m3')
>>> n = FlattenLayer(n, name='f')
>>> n = DenseLayer(n, 500, tf.nn.relu, name='d1')
>>> n = DenseLayer(n, 100, tf.nn.relu, name='d2')
>>> n = DenseLayer(n, 2, tf.identity, name='o')
```

### 2D Convolution

`tensorlayer.layers.`**`Conv2d`**(*layer, n_filter=32, filter_size=(3, 3), strides=(1, 1), act=<function identity>, padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, use_cudnn_on_gpu=None, data_format=None, name='conv2d'*)

Simplified version of `Conv2dLayer`.

**Parameters**

- **`layer`** (*`Layer`*) – Previous layer.
- **`n_filter`** (*`int`*) – The number of filters.
- **`filter_size`** (*`tuple of int`*) – The filter size (height, width).
- **`strides`** (*`tuple of int`*) – The sliding window strides of corresponding input dimensions. It must be in the same order as the `shape` parameter.
- **`act`** (*`activation function`*) – The activation function of this layer.
- **`padding`** (*`str`*) – The padding algorithm type: "SAME" or "VALID".
- **`W_init`** (*`initializer`*) – The initializer for the the weight matrix.
- **`b_init`** (*`initializer or None`*) – The initializer for the the bias vector. If None, skip biases.
- **`W_init_args`** (*`dictionary`*) – The arguments for the weight matrix initializer.
- **`b_init_args`** (*`dictionary`*) – The arguments for the bias vector initializer.
- **`use_cudnn_on_gpu`** (*`bool`*) – Default is False.
- **`data_format`** (*`str`*) – "NHWC" or "NCHW", default is "NHWC".
- **`name`** (*`str`*) – A unique layer name.

**Returns** A `Conv2dLayer` object.

**Return type** `Layer`

### Examples

```
>>> net = InputLayer(x, name='inputs')
>>> net = Conv2d(net, 64, (3, 3), act=tf.nn.relu, name='conv1_1')
>>> net = Conv2d(net, 64, (3, 3), act=tf.nn.relu, name='conv1_2')
>>> net = MaxPool2d(net, (2, 2), name='pool1')
>>> net = Conv2d(net, 128, (3, 3), act=tf.nn.relu, name='conv2_1')
>>> net = Conv2d(net, 128, (3, 3), act=tf.nn.relu, name='conv2_2')
>>> net = MaxPool2d(net, (2, 2), name='pool2')
```

## 2D Deconvolution

`tensorlayer.layers.`**`DeConv2d`**(*layer, n_filter=32, filter_size=(3, 3), out_size=(30, 30), strides=(2, 2), padding='SAME', batch_size=None, act=<function identity>, W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='decnn2d'*)

Simplified version of `DeConv2dLayer`.

**Parameters**

- **`layer`** (`Layer`) – Previous layer.
- **`n_filter`** (`int`) – The number of filters.
- **`filter_size`** (`tuple of int`) – The filter size (height, width).
- **`out_size`** (`tuple of int`) – Require if TF version < 1.3, (height, width) of output.
- **`strides`** (`tuple of int`) – The stride step (height, width).
- **`padding`** (`str`) – The padding algorithm type: "SAME" or "VALID".
- **`batch_size`** (`int`) – Require if TF version < 1.3, int or None. If None, try to find the *batch_size* from the first dim of net.outputs (you should define the *batch_size* in the input placeholder).
- **`act`** (`activation function`) – The activation function of this layer.
- **`W_init`** (`initializer`) – The initializer for the weight matrix.
- **`b_init`** (`initializer or None`) – The initializer for the bias vector. If None, skip biases.
- **`W_init_args`** (`dictionary`) – The arguments for the weight matrix initializer.
- **`b_init_args`** (`dictionary`) – The arguments for the bias vector initializer.
- **`name`** (`str`) – A unique layer name.

**Returns** A `DeConv2dLayer` object.

**Return type** `Layer`

### 3D Deconvolution

**class** tensorlayer.layers.**DeConv3d**(*layer, n_filter=32, filter_size=(3, 3, 3), strides=(2, 2, 2), padding='SAME', act=<function identity>, W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, name='decnn3d'*)

Simplified version of The `DeConv3dLayer`, see tf.contrib.layers.conv3d_transpose.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **n_filter** (*int*) – The number of filters.
- **filter_size** (*tuple of int*) – The filter size (depth, height, width).
- **stride** (*tuple of int*) – The stride step (depth, height, width).
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **act** (*activation function*) – The activation function of this layer.
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip bias.
- **name** (*str*) – A unique layer name.

### 2D Depthwise/Separable Conv

**class** tensorlayer.layers.**DepthwiseConv2d**(*layer, channel_multiplier=3, shape=(3, 3), strides=(1, 1), act=<function identity>, padding='SAME', W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>, b_init=<tensorflow.python.ops.init_ops.Constant object>, W_init_args=None, b_init_args=None, name='depthwise_conv2d'*)

Separable/Depthwise Convolutional 2D layer, see tf.nn.depthwise_conv2d.

**Input:** 4-D Tensor (batch, height, width, in_channels).

**Output:** 4-D Tensor (batch, new height, new width, in_channels * channel_multiplier).

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **channel_multiplier** (*int*) – The number of channels to expand to.
- **filter_size** (*tuple of int*) – The filter size (height, width).
- **stride** (*tuple of int*) – The stride step (height, width).
- **act** (*activation function*) – The activation function of this layer.
- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip bias.

- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

### Examples

```
>>> t_im = tf.placeholder("float32", (None, 256, 256, 3))
>>> net = InputLayer(t_im, name='in')
>>> net = DepthwiseConv2d(net, 32, (3, 3), (1, 1, 1, 1), tf.nn.relu, padding="SAME
↪", name='dep')
>>> print(net.outputs.get_shape())
... (?, 256, 256, 96)
```

### References

- tflearn's grouped_conv_2d
- keras's separableconv2d

## 2D Deformable Conv

**class** tensorlayer.layers.**DeformableConv2d**(*layer*, *offset_layer=None*, *n_filter=32*, *filter_size=(3, 3)*, *act=<function identity>*, *name='deformable_conv_2d'*, *W_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>*, *b_init=<tensorflow.python.ops.init_ops.Constant object>*, *W_init_args=None*, *b_init_args=None*)

The DeformableConv2d class is a 2D Deformable Convolutional Networks.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **offset_layer** (*Layer*) – To predict the offset of convolution operations. The output shape is (batchsize, input height, input width, 2*(number of element in the convolution kernel)) e.g. if apply a 3*3 kernel, the number of the last dimension should be 18 (2*3*3)
- **n_filter** (*int*) – The number of filters.
- **filter_size** (*tuple of int*) – The filter size (height, width).
- **act** (*activation function*) – The activation function of this layer.
- **W_init** (*initializer*) – The initializer for the weight matrix.
- **b_init** (*initializer or None*) – The initializer for the bias vector. If None, skip biases.
- **W_init_args** (*dictionary*) – The arguments for the weight matrix initializer.
- **b_init_args** (*dictionary*) – The arguments for the bias vector initializer.
- **name** (*str*) – A unique layer name.

### Examples

```
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> offset1 = tl.layers.Conv2d(net, 18, (3, 3), (1, 1), act=act, padding='SAME',␣
↪name='offset1')
>>> net = tl.layers.DeformableConv2d(net, offset1, 32, (3, 3), act=act, name=
↪'deformable1')
>>> offset2 = tl.layers.Conv2d(net, 18, (3, 3), (1, 1), act=act, padding='SAME',␣
↪name='offset2')
>>> net = tl.layers.DeformableConv2d(net, offset2, 64, (3, 3), act=act, name=
↪'deformable2')
```

### References

- The deformation operation was adapted from the implementation in here

### Notes

- The padding is fixed to 'SAME'.
- The current implementation is not optimized for memory usgae. Please use it carefully.

## 2.1.13 Super-Resolution layer

### 1D Subpixel Convolution

`tensorlayer.layers.`**`SubpixelConv1d`**(*net*, *scale=2*, *act=<function identity>*, *name='subpixel_conv1d'*)

It is a 1D sub-pixel up-sampling layer.

Calls a TensorFlow function that directly implements this functionality. We assume input has dim (batch, width, r)

**Parameters**

- **net** (*Layer*) – Previous layer with output shape of (batch, width, r).
- **scale** (*int*) – The up-scaling ratio, a wrong setting will lead to Dimension size error.
- **act** (*activation function*) – The activation function of this layer.
- **name** (*str*) – A unique layer name.

**Returns** A 1D sub-pixel up-sampling layer

**Return type** *Layer*

### Examples

```
>>> t_signal = tf.placeholder('float32', [10, 100, 4], name='x')
>>> n = InputLayer(t_signal, name='in')
>>> n = SubpixelConv1d(n, scale=2, name='s')
>>> print(n.outputs.shape)
... (10, 200, 2)
```

### References

Audio Super Resolution Implementation.

## 2D Subpixel Convolution

`tensorlayer.layers.SubpixelConv2d`(*net*, *scale=2*, *n_out_channel=None*, *act=<function identity>*, *name='subpixel_conv2d'*)

It is a 2D sub-pixel up-sampling layer, usually be used for Super-Resolution applications, see SRGAN for example.

**Parameters**

- **net** (*Layer*) – Previous layer,
- **scale** (*int*) – The up-scaling ratio, a wrong setting will lead to dimension size error.
- **n_out_channel** (*int or None*) – The number of output channels. - If None, automatically set n_out_channel == the number of input channels / (scale x scale). - The number of input channels == (scale x scale) x The number of output channels.
- **act** (*activation function*) – The activation function of this layer.
- **name** (*str*) – A unique layer name.

**Returns** A 2D sub-pixel up-sampling layer

**Return type** *Layer*

### Examples

```
>>> # examples here just want to tell you how to set the n_out_channel.
>>> x = np.random.rand(2, 16, 16, 4)
>>> X = tf.placeholder("float32", shape=(2, 16, 16, 4), name="X")
>>> net = InputLayer(X, name='input')
>>> net = SubpixelConv2d(net, scale=2, n_out_channel=1, name='subpixel_conv2d')
>>> y = sess.run(net.outputs, feed_dict={X: x})
>>> print(x.shape, y.shape)
... (2, 16, 16, 4) (2, 32, 32, 1)
>>>
>>> x = np.random.rand(2, 16, 16, 4*10)
>>> X = tf.placeholder("float32", shape=(2, 16, 16, 4*10), name="X")
>>> net = InputLayer(X, name='input2')
>>> net = SubpixelConv2d(net, scale=2, n_out_channel=10, name='subpixel_conv2d2')
>>> y = sess.run(net.outputs, feed_dict={X: x})
>>> print(x.shape, y.shape)
... (2, 16, 16, 40) (2, 32, 32, 10)
>>>
>>> x = np.random.rand(2, 16, 16, 25*10)
>>> X = tf.placeholder("float32", shape=(2, 16, 16, 25*10), name="X")
>>> net = InputLayer(X, name='input3')
>>> net = SubpixelConv2d(net, scale=5, n_out_channel=None, name='subpixel_conv2d3
↪')
>>> y = sess.run(net.outputs, feed_dict={X: x})
>>> print(x.shape, y.shape)
... (2, 16, 16, 250) (2, 80, 80, 10)
```

#### References

- Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network

### 2.1.14 Spatial Transformer

#### 2D Affine Transformation

**class** tensorlayer.layers.**SpatialTransformer2dAffineLayer**(*layer=None*, *theta_layer=None*, *out_size=None*, *name='sapatial_trans_2d_affine'*)

The *SpatialTransformer2dAffineLayer* class is a 2D Spatial Transformer Layer for 2D Affine Transformation.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **theta_layer** (*Layer*) – The localisation network. - We will use a *DenseLayer* to make the theta size to [batch, 6], value range to [0, 1] (via tanh).
- **out_size** (*tuple of int or None*) – The size of the output of the network (height, width), the feature maps will be resized by this.
- **name** (*str*) – A unique layer name.

#### References

- Spatial Transformer Networks
- TensorFlow/Models

#### 2D Affine Transformation function

tensorlayer.layers.**transformer**(*U*, *theta*, *out_size*, *name='SpatialTransformer2dAffine'*)

Spatial Transformer Layer for 2D Affine Transformation , see *SpatialTransformer2dAffineLayer* class.

**Parameters**

- **U** (*list of float*) – The output of a convolutional net should have the shape [num_batch, height, width, num_channels].
- **theta** (*float*) – The output of the localisation network should be [num_batch, 6], value range should be [0, 1] (via tanh).
- **out_size** (*tuple of int*) – The size of the output of the network (height, width)
- **name** (*str*) – Optional function name

**Returns** The transformed tensor.

**Return type** Tensor

#### References

- Spatial Transformer Networks
- TensorFlow/Models

#### Notes

To initialize the network to the identity transform init.

```
>>> ``theta`` to
>>> identity = np.array([[1., 0., 0.],
...                      [0., 1., 0.]])
>>> identity = identity.flatten()
>>> theta = tf.Variable(initial_value=identity)
```

### Batch 2D Affine Transformation function

`tensorlayer.layers.`**`batch_transformer`**(*U*, *thetas*, *out_size*, *name='BatchSpatialTransformer2dAffine'*)

Batch Spatial Transformer function for 2D Affine Transformation.

**Parameters**

- **U** (*list of float*) – tensor of inputs [batch, height, width, num_channels]
- **thetas** (*list of float*) – a set of transformations for each input [batch, num_transforms, 6]
- **out_size** (*list of int*) – the size of the output [out_height, out_width]
- **name** (*str*) – optional function name

**Returns** Tensor of size [batch * num_transforms, out_height, out_width, num_channels]

**Return type** float

## 2.1.15 Pooling and Padding layers

### Pooling (Pro)

Pooling layer for any dimensions and any pooling functions.

**class** `tensorlayer.layers.`**`PoolLayer`**(*layer=None*, *ksize=(1, 2, 2, 1)*, *strides=(1, 2, 2, 1)*, *padding='SAME'*, *pool=<function max_pool>*, *name='pool_layer'*)

The *PoolLayer* class is a Pooling layer. You can choose `tf.nn.max_pool` and `tf.nn.avg_pool` for 2D input or `tf.nn.max_pool3d` and `tf.nn.avg_pool3d` for 3D input.

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **ksize** (*tuple of int*) – The size of the window for each dimension of the input tensor. Note that: len(ksize) >= 4.
- **strides** (*tuple of int*) – The stride of the sliding window for each dimension of the input tensor. Note that: len(strides) >= 4.

- **padding** (*str*) – The padding algorithm type: "SAME" or "VALID".
- **pool** (*pooling function*) – One of `tf.nn.max_pool`, `tf.nn.avg_pool`, `tf.nn.max_pool3d` and `f.nn.avg_pool3d`. See TensorFlow pooling APIs
- **name** (*str*) – A unique layer name.

### Examples

- see `Conv2dLayer`.

## Padding (Pro)

Padding layer for any modes.

**class** `tensorlayer.layers.`**`PadLayer`**(*layer*, *paddings*, *mode='CONSTANT'*, *name='pad_layer'*)

The `PadLayer` class is a padding layer for any mode and dimension. Please see tf.pad for usage.

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **paddings** (*Tensor*) – The int32 values to pad.
- **mode** (*str*) – "CONSTANT", "REFLECT", or "SYMMETRIC" (case-insensitive).
- **name** (*str*) – A unique layer name.

## 1D Max pooling

`tensorlayer.layers.`**`MaxPool1d`**(*net*, *filter_size=3*, *strides=2*, *padding='valid'*, *data_format='channels_last'*, *name=None*)

Wrapper for tf.layers.max_pooling1d .

**Parameters**

- **net** (*Layer*) – The previous layer with a output rank as 3.
- **filter_size** (*tuple of int*) – Pooling window size.
- **strides** (*tuple of int*) – Strides of the pooling operation.
- **padding** (*str*) – The padding method: 'valid' or 'same'.
- **data_format** (*str*) – One of *channels_last* (default) or *channels_first*. The ordering of the dimensions must match the inputs. channels_last corresponds to inputs with the shape (batch, length, channels); while channels_first corresponds to inputs with shape (batch, channels, length).
- **name** (*str*) – A unique layer name.

**Returns** A max pooling 1-D layer with a output rank as 3.

**Return type** *Layer*

### 1D Mean pooling

`tensorlayer.layers.`**`MeanPool1d`**(*net*, *filter_size=3*, *strides=2*, *padding='valid'*, *data_format='channels_last'*, *name=None*)

Wrapper for tf.layers.average_pooling1d .

**Parameters**

- **net** (*Layer*) – The previous layer with a output rank as 3.
- **filter_size** (*tuple of int*) – Pooling window size.
- **strides** (*tuple of int*) – Strides of the pooling operation.
- **padding** (*str*) – The padding method: 'valid' or 'same'.
- **data_format** (*str*) – One of *channels_last* (default) or *channels_first*. The ordering of the dimensions must match the inputs. channels_last corresponds to inputs with the shape (batch, length, channels); while channels_first corresponds to inputs with shape (batch, channels, length).
- **name** (*str*) – A unique layer name.

**Returns** A mean pooling 1-D layer with a output rank as 3.

**Return type** *Layer*

### 2D Max pooling

`tensorlayer.layers.`**`MaxPool2d`**(*net*, *filter_size=(3, 3)*, *strides=(2, 2)*, *padding='SAME'*, *name='maxpool'*)

Wrapper for *PoolLayer*.

**Parameters**

- **net** (*Layer*) – The previous layer with a output rank as 4.
- **filter_size** (*tuple of int*) – (height, width) for filter size.
- **strides** (*tuple of int*) – (height, width) for strides.
- **padding** (*str*) – The padding method: 'valid' or 'same'.
- **name** (*str*) – A unique layer name.

**Returns** A max pooling 2-D layer with a output rank as 4.

**Return type** *Layer*

### 2D Mean pooling

`tensorlayer.layers.`**`MeanPool2d`**(*net*, *filter_size=(3, 3)*, *strides=(2, 2)*, *padding='SAME'*, *name='meanpool'*)

Wrapper for *PoolLayer*.

**Parameters**

- **net** (*Layer*) – The previous layer with a output rank as 4.
- **filter_size** (*tuple of int*) – (height, width) for filter size.
- **strides** (*tuple of int*) – (height, width) for strides.
- **padding** (*str*) – The padding method: 'valid' or 'same'.

- **name** (*str*) – A unique layer name.

**Returns** A mean pooling 2-D layer with a output rank as 4.

**Return type** *Layer*

### 3D Max pooling

`tensorlayer.layers.`**`MaxPool3d`**(*net*, *filter_size=(3, 3, 3)*, *strides=(2, 2, 2)*, *padding='valid'*, *data_format='channels_last'*, *name='maxpool3d'*)

Wrapper for tf.layers.max_pooling3d .

**Parameters**

- **net** (*Layer*) – The previous layer with a output rank as 5.
- **filter_size** (*tuple of int*) – Pooling window size.
- **strides** (*tuple of int*) – Strides of the pooling operation.
- **padding** (*str*) – The padding method: 'valid' or 'same'.
- **data_format** (*str*) – One of *channels_last* (default) or *channels_first*. The ordering of the dimensions must match the inputs. channels_last corresponds to inputs with the shape (batch, length, channels); while channels_first corresponds to inputs with shape (batch, channels, length).
- **name** (*str*) – A unique layer name.

**Returns** A max pooling 3-D layer with a output rank as 5.

**Return type** *Layer*

### 3D Mean pooling

`tensorlayer.layers.`**`MeanPool3d`**(*net*, *filter_size=(3, 3, 3)*, *strides=(2, 2, 2)*, *padding='valid'*, *data_format='channels_last'*, *name='meanpool3d'*)

Wrapper for tf.layers.average_pooling3d

**Parameters**

- **net** (*Layer*) – The previous layer with a output rank as 5.
- **filter_size** (*tuple of int*) – Pooling window size.
- **strides** (*tuple of int*) – Strides of the pooling operation.
- **padding** (*str*) – The padding method: 'valid' or 'same'.
- **data_format** (*str*) – One of *channels_last* (default) or *channels_first*. The ordering of the dimensions must match the inputs. channels_last corresponds to inputs with the shape (batch, length, channels); while channels_first corresponds to inputs with shape (batch, channels, length).
- **name** (*str*) – A unique layer name.

**Returns** A mean pooling 3-D layer with a output rank as 5.

**Return type** *Layer*

### 2.1.16 Normalization layer

For local response normalization as it does not have any weights and arguments, you can also apply `tf.nn.lrn` on `network.outputs`.

#### Batch Normalization

**class** `tensorlayer.layers.`**`BatchNormLayer`**(*layer*, *decay=0.9*, *epsilon=1e-05*, *act=<function identity>*, *is_train=False*, *beta_init=<class 'tensorflow.python.ops.init_ops.Zeros'>*, *gamma_init=<tensorflow.python.ops.init_ops.RandomNormal object>*, *name='batchnorm_layer'*)

The `BatchNormLayer` is a batch normalization layer for both fully-connected and convolution outputs. See `tf.nn.batch_normalization` and `tf.nn.moments`.

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **decay** (*float*) – A decay factor for *ExponentialMovingAverage*. Suggest to use a large value for large dataset.
- **epsilon** (*float*) – Eplison.
- **act** (*activation function*) – The activation function of this layer.
- **is_train** (*boolean*) – Is being used for training or inference.
- **beta_init** (*initializer*) – The initializer for initializing beta.
- **gamma_init** (*initializer*) – The initializer for initializing gamma.
- **dtype** (*TensorFlow dtype*) – tf.float32 (default) or tf.float16.
- **name** (*str*) – A unique layer name.

#### References

- Source
- stackoverflow

#### Local Response Normalization

**class** `tensorlayer.layers.`**`LocalResponseNormLayer`**(*layer*, *depth_radius=None*, *bias=None*, *alpha=None*, *beta=None*, *name='lrn_layer'*)

The `LocalResponseNormLayer` layer is for Local Response Normalization. See `tf.nn.local_response_normalization` or `tf.nn.lrn` for new TF version. The 4-D input tensor is a 3-D array of 1-D vectors (along the last dimension), and each vector is normalized independently. Within a given vector, each component is divided by the weighted square-sum of inputs within depth_radius.

**Parameters**

- **layer** (*Layer*) – The previous layer with a 4D output shape.
- **depth_radius** (*int*) – Depth radius. 0-D. Half-width of the 1-D normalization window.
- **bias** (*float*) – An offset which is usually positive and shall avoid dividing by 0.

- **alpha** (*float*) – A scale factor which is usually positive.
- **beta** (*float*) – An exponent.
- **name** (*str*) – A unique layer name.

### Instance Normalization

**class** tensorlayer.layers.**InstanceNormLayer**(*layer, act=<function identity>, epsilon=1e-05, name='instan_norm'*)

The *InstanceNormLayer* class is a for instance normalization.

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **act** (*activation function.*) – The activation function of this layer.
- **epsilon** (*float*) – Eplison.
- **name** (*str*) – A unique layer name

### Layer Normalization

**class** tensorlayer.layers.**LayerNormLayer**(*layer, center=True, scale=True, act=<function identity>, reuse=None, variables_collections=None, outputs_collections=None, trainable=True, begin_norm_axis=1, begin_params_axis=-1, name='layernorm'*)

The *LayerNormLayer* class is for layer normalization, see tf.contrib.layers.layer_norm.

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **act** (*activation function*) – The activation function of this layer.
- **others** – tf.contrib.layers.layer_norm.

## 2.1.17 Object Detection

### ROI layer

**class** tensorlayer.layers.**ROIPoolingLayer**(*layer, rois, pool_height=2, pool_width=2, name='roipooling_layer'*)

The region of interest pooling layer.

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **rois** (*tuple of int*) – Regions of interest in the format of (feature map index, upper left, bottom right).
- **pool_width** (*int*) – The size of the pooling sections.
- **pool_width** – The size of the pooling sections.
- **name** (*str*) – A unique layer name.

### Notes

- This implementation is imported from Deepsense-AI .
- Please install it by the instruction HERE.

## 2.1.18 Time distributed layer

**class** tensorlayer.layers.**TimeDistributedLayer**(*layer*, *layer_class=None*, *args=None*, *name='time_distributed'*)

The `TimeDistributedLayer` class that applies a function to every timestep of the input tensor. For example, if use `DenseLayer` as the *layer_class*, we input (batch_size, length, dim) and output (batch_size , length, new_dim).

**Parameters**

- **layer** (`Layer`) – Previous layer with output size of (batch_size, length, dim).
- **layer_class** (a `Layer` class) – The layer class name.
- **args** (*dictionary*) – The arguments for the `layer_class`.
- **name** (*str*) – A unique layer name.

### Examples

```
>>> batch_size = 32
>>> timestep = 20
>>> input_dim = 100
>>> x = tf.placeholder(dtype=tf.float32, shape=[batch_size, timestep, input_dim],
↪name="encode_seqs")
>>> net = InputLayer(x, name='input')
>>> net = TimeDistributedLayer(net, layer_class=DenseLayer, args={'n_units':50,
↪'name':'dense'}, name='time_dense')
... [TL] InputLayer  input: (32, 20, 100)
... [TL] TimeDistributedLayer time_dense: layer_class:DenseLayer
>>> print(net.outputs._shape)
... (32, 20, 50)
>>> net.print_params(False)
... param   0: (100, 50)          time_dense/dense/W:0
... param   1: (50,)              time_dense/dense/b:0
... num of params: 5050
```

## 2.1.19 Fixed Length Recurrent layer

All recurrent layers can implement any type of RNN cell by feeding different cell function (LSTM, GRU etc).

### RNN layer

**class** tensorlayer.layers.**RNNLayer**(*layer*, *cell_fn*, *cell_init_args=None*, *n_hidden=100*, *initializer=<tensorflow.python.ops.init_ops.RandomUniform object>*, *n_steps=5*, *initial_state=None*, *return_last=False*, *return_seq_2d=False*, *name='rnn_layer'*)

The `RNNLayer` class is a fixed length recurrent layer for implementing vanilla RNN, LSTM, GRU and etc.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **cell_fn** (*TensorFlow cell function*) –

  **A TensorFlow core RNN cell**

  - See RNN Cells in TensorFlow
  - Note TF1.0+ and TF1.0- are different
- **cell_init_args** (*dictionary*) – The arguments for the cell function.
- **n_hidden** (*int*) – The number of hidden units in the layer.
- **initializer** (*initializer*) – The initializer for initializing the model parameters.
- **n_steps** (*int*) – The fixed sequence length.
- **initial_state** (*None or RNN State*) – If None, *initial_state* is zero state.
- **return_last** (*boolean*) –

  **Whether return last output or all outputs in each step.**

  - If True, return the last output, "Sequence input and single output"
  - If False, return all outputs, "Synced sequence input and output"
  - In other word, if you want to stack more RNNs on this layer, set to False.
- **return_seq_2d** (*boolean*) –

  **Only consider this argument when *return_last* is *False***

  - If True, return 2D Tensor [n_example, n_hidden], for stacking DenseLayer after it.
  - If False, return 3D Tensor [n_example/n_steps, n_steps, n_hidden], for stacking multiple RNN after it.
- **name** (*str*) – A unique layer name.

**outputs**

*Tensor* – The output of this layer.

**final_state**

*Tensor or StateTuple* –

**The finial state of this layer.**

- When *state_is_tuple* is *False*, it is the final hidden and cell states, *states.get_shape() = [?, 2 * n_hidden]*.
- When *state_is_tuple* is *True*, it stores two elements: *(c, h)*.
- In practice, you can get the final state after each iteration during training, then feed it to the initial state of next iteration.

**initial_state**

*Tensor or StateTuple* –

**The initial state of this layer.**

- In practice, you can set your state at the begining of each epoch or iteration according to your training procedure.

**batch_size**
*int or Tensor* – It is an integer, if it is able to compute the *batch_size*; otherwise, tensor for dynamic batch size.

### Examples

For language modeling, see PTB example

```
>>> input_data = tf.placeholder(tf.int32, [batch_size, num_steps])
>>> net = tl.layers.EmbeddingInputlayer(
...                 inputs = input_data,
...                 vocabulary_size = vocab_size,
...                 embedding_size = hidden_size,
...                 E_init = tf.random_uniform_initializer(-init_scale, init_
↪scale),
...                 name ='embedding_layer')
>>> net = tl.layers.DropoutLayer(net, keep=keep_prob, is_fix=True, is_train=is_
↪train, name='drop1')
>>> net = tl.layers.RNNLayer(net,
...             cell_fn=tf.contrib.rnn.BasicLSTMCell,
...             cell_init_args={'forget_bias': 0.0},# 'state_is_tuple': True},
...             n_hidden=hidden_size,
...             initializer=tf.random_uniform_initializer(-init_scale, init_
↪scale),
...             n_steps=num_steps,
...             return_last=False,
...             name='basic_lstm_layer1')
>>> lstm1 = net
>>> net = tl.layers.DropoutLayer(net, keep=keep_prob, is_fix=True, is_train=is_
↪train, name='drop2')
>>> net = tl.layers.RNNLayer(net,
...             cell_fn=tf.contrib.rnn.BasicLSTMCell,
...             cell_init_args={'forget_bias': 0.0}, # 'state_is_tuple': True},
...             n_hidden=hidden_size,
...             initializer=tf.random_uniform_initializer(-init_scale, init_
↪scale),
...             n_steps=num_steps,
...             return_last=False,
...             return_seq_2d=True,
...             name='basic_lstm_layer2')
>>> lstm2 = net
>>> net = tl.layers.DropoutLayer(net, keep=keep_prob, is_fix=True, is_train=is_
↪train, name='drop3')
>>> net = tl.layers.DenseLayer(net, n_units=vocab_size, name='output')
```

For CNN+LSTM

```
>>> x = tf.placeholder(tf.float32, shape=[batch_size, image_size, image_size, 1])
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = tl.layers.Conv2d(net, 32, (5, 5), (2, 2), tf.nn.relu, name='cnn1')
>>> net = tl.layers.MaxPool2d(net, (2, 2), (2, 2), name='pool1')
>>> net = tl.layers.Conv2d(net, 10, (5, 5), (2, 2), tf.nn.relu, name='cnn2')
>>> net = tl.layers.MaxPool2d(net, (2, 2), (2, 2), name='pool2')
>>> net = tl.layers.FlattenLayer(net, name='flatten_layer')
>>> net = tl.layers.ReshapeLayer(net, shape=[-1, num_steps, int(net.outputs._
↪shape[-1])])
>>> rnn1 = tl.layers.RNNLayer(net,
```

```
...                     cell_fn=tf.nn.rnn_cell.LSTMCell,
...                     n_hidden=200,
...                     n_steps=num_steps,
...                     return_last=False,
...                     return_seq_2d=True,
...                     name='rnn')
>>> net = tl.layers.DenseLayer(rnn1, 3, name='output')
```

### Notes

Input dimension should be rank 3 : [batch_size, n_steps, n_features], if no, please see `ReshapeLayer`.

### References

- Neural Network RNN Cells in TensorFlow
- tensorflow/python/ops/rnn.py
- tensorflow/python/ops/rnn_cell.py
- see TensorFlow tutorial `ptb_word_lm.py`, TensorLayer tutorials `tutorial_ptb_lstm*.py` and `tutorial_generate_text.py`

## Bidirectional layer

**class** `tensorlayer.layers.`**`BiRNNLayer`**(*layer, cell_fn, cell_init_args=None, n_hidden=100, initializer=<tensorflow.python.ops.init_ops.RandomUniform object>, n_steps=5, fw_initial_state=None, bw_initial_state=None, dropout=None, n_layer=1, return_last=False, return_seq_2d=False, name='birnn_layer'*)

The `BiRNNLayer` class is a fixed length Bidirectional recurrent layer.

**Parameters**

- **layer** (`Layer`) – Previous layer.
- **cell_fn** (`TensorFlow cell function`) –

  **A TensorFlow core RNN cell.**

  – See RNN Cells in TensorFlow.

  – Note TF1.0+ and TF1.0- are different.
- **cell_init_args** (`dictionary or None`) – The arguments for the cell function.
- **n_hidden** (`int`) – The number of hidden units in the layer.
- **initializer** (`initializer`) – The initializer for initializing the model parameters.
- **n_steps** (`int`) – The fixed sequence length.
- **fw_initial_state** (`None or forward RNN State`) – If None, *initial_state* is zero state.

- **bw_initial_state** (*None or backward RNN State*) – If None, *initial_state* is zero state.
- **dropout** (*tuple of float or int*) – The input and output keep probability (input_keep_prob, output_keep_prob). If one int, input and output keep probability are the same.
- **n_layer** (*int*) – The number of RNN layers, default is 1.
- **return_last** (*boolean*) –

  **Whether return last output or all outputs in each step.**

  - If True, return the last output, "Sequence input and single output"
  - If False, return all outputs, "Synced sequence input and output"
  - In other word, if you want to stack more RNNs on this layer, set to False.
- **return_seq_2d** (*boolean*) –

  **Only consider this argument when *return_last* is *False***

  - If True, return 2D Tensor [n_example, n_hidden], for stacking DenseLayer after it.
  - If False, return 3D Tensor [n_example/n_steps, n_steps, n_hidden], for stacking multiple RNN after it.
- **name** (*str*) – A unique layer name.

**outputs**
*tensor* – The output of this layer.

**fw(bw)_final_state**
*tensor or StateTuple* –

**The finial state of this layer.**

- When *state_is_tuple* is *False*, it is the final hidden and cell states, *states.get_shape() = [?, 2 * n_hidden]*.
- When *state_is_tuple* is *True*, it stores two elements: *(c, h)*.
- In practice, you can get the final state after each iteration during training, then feed it to the initial state of next iteration.

**fw(bw)_initial_state**
*tensor or StateTuple* –

**The initial state of this layer.**

- In practice, you can set your state at the begining of each epoch or iteration according to your training procedure.

**batch_size**
*int or tensor* – It is an integer, if it is able to compute the *batch_size*; otherwise, tensor for dynamic batch size.

### Notes

Input dimension should be rank 3 : [batch_size, n_steps, n_features]. If not, please see *ReshapeLayer*. For predicting, the sequence length has to be the same with the sequence length of training, while, for normal RNN, we can use sequence length of 1 for predicting.

### References

Source

## 2.1.20 Recurrent Convolutional layer

### Conv RNN Cell

**class** tensorlayer.layers.**ConvRNNCell**

Abstract object representing an Convolutional RNN Cell.

### Basic Conv LSTM Cell

**class** tensorlayer.layers.**BasicConvLSTMCell**(*shape*, *filter_size*, *num_features*, *forget_bias=1.0*, *input_size=None*, *state_is_tuple=False*, *act=<function tanh>*)

Basic Conv LSTM recurrent network cell.

**Parameters**

- **shape** (*tuple of int*) – The height and width of the cell.
- **filter_size** (*tuple of int*) – The height and width of the filter
- **num_features** (*int*) – The hidden size of the cell
- **forget_bias** (*float*) – The bias added to forget gates (see above).
- **input_size** (*int*) – Deprecated and unused.
- **state_is_tuple** (*boolen*) – If True, accepted and returned states are 2-tuples of the *c_state* and *m_state*. If False, they are concatenated along the column axis. The latter behavior will soon be deprecated.
- **act** (*activation function*) – The activation function of this layer, tanh as default.

### Conv LSTM layer

**class** tensorlayer.layers.**ConvLSTMLayer**(*layer*, *cell_shape=None*, *feature_map=1*, *filter_size=(3, 3)*, *cell_fn=<class 'tensorlayer.layers.recurrent.BasicConvLSTMCell'>*, *initializer=<tensorflow.python.ops.init_ops.RandomUniform object>*, *n_steps=5*, *initial_state=None*, *return_last=False*, *return_seq_2d=False*, *name='convlstm_layer'*)

A fixed length Convolutional LSTM layer.

See this paper .

**Parameters**

- **layer** (*Layer*) – Previous layer
- **cell_shape** (*tuple of int*) – The shape of each cell width * height
- **filter_size** (*tuple of int*) – The size of filter width * height
- **cell_fn** (*a convolutional RNN cell*) – Cell function like *BasicConvLSTMCell*

- **feature_map** (*int*) – The number of feature map in the layer.
- **initializer** (*initializer*) – The initializer for initializing the parameters.
- **n_steps** (*int*) – The sequence length.
- **initial_state** (*None or ConvLSTM State*) – If None, *initial_state* is zero state.
- **return_last** (*boolean*) –

  **Whether return last output or all outputs in each step.**

  – If True, return the last output, "Sequence input and single output".

  – If False, return all outputs, "Synced sequence input and output".

  – In other word, if you want to stack more RNNs on this layer, set to False.
- **return_seq_2d** (*boolean*) –

  **Only consider this argument when *return_last* is *False***

  – If True, return 2D Tensor [n_example, n_hidden], for stacking DenseLayer after it.

  – If False, return 3D Tensor [n_example/n_steps, n_steps, n_hidden], for stacking multiple RNN after it.
- **name** (*str*) – A unique layer name.

**outputs**
*tensor* – The output of this RNN. return_last = False, outputs = all cell_output, which is the hidden state. cell_output.get_shape() = (?, h, w, c])

**final_state**
*tensor or StateTuple* –

**The finial state of this layer.**

- When state_is_tuple = False, it is the final hidden and cell states,
- When state_is_tuple = True, You can get the final state after each iteration during training, then feed it to the initial state of next iteration.

**initial_state**
*tensor or StateTuple* – It is the initial state of this ConvLSTM layer, you can use it to initialize your state at the beginning of each epoch or iteration according to your training procedure.

**batch_size**
*int or tensor* – Is int, if able to compute the batch_size, otherwise, tensor for `?`.

### 2.1.21 Advanced Ops for Dynamic RNN

These operations usually be used inside Dynamic RNN layer, they can compute the sequence lengths for different situation and get the last RNN outputs by indexing.

#### Output indexing

tensorlayer.layers.**advanced_indexing_op**(*inputs*, *index*)
Advanced Indexing for Sequences, returns the outputs by given sequence lengths. When return the last output *DynamicRNNLayer* uses it to get the last outputs with the sequence lengths.

**Parameters**

- **inputs** (*tensor for data*) – With shape of [batch_size, n_step(max), n_features]
- **index** (*tensor for indexing*) – Sequence length in Dynamic RNN. [batch_size]

### Examples

```
>>> batch_size, max_length, n_features = 3, 5, 2
>>> z = np.random.uniform(low=-1, high=1, size=[batch_size, max_length, n_
↪features]).astype(np.float32)
>>> b_z = tf.constant(z)
>>> sl = tf.placeholder(dtype=tf.int32, shape=[batch_size])
>>> o = advanced_indexing_op(b_z, sl)
>>>
>>> sess = tf.InteractiveSession()
>>> tl.layers.initialize_global_variables(sess)
>>>
>>> order = np.asarray([1,1,2])
>>> print("real",z[0][order[0]-1], z[1][order[1]-1], z[2][order[2]-1])
>>> y = sess.run([o], feed_dict={sl:order})
>>> print("given",order)
>>> print("out", y)
... real [-0.93021595  0.53820813] [-0.92548317 -0.77135968] [ 0.89952248  0.
↪19149846]
... given [1 1 2]
... out [array([[-0.93021595,  0.53820813],
...             [-0.92548317, -0.77135968],
...             [ 0.89952248,  0.19149846]], dtype=float32)]
```

### References

- Modified from TFlearn (the original code is used for fixed length rnn), references.

## Compute Sequence length 1

tensorlayer.layers.**retrieve_seq_length_op**(*data*)

An op to compute the length of a sequence from input shape of [batch_size, n_step(max), n_features], it can be used when the features of padding (on right hand side) are all zeros.

**Parameters data** (*tensor*) – [batch_size, n_step(max), n_features] with zero padding on right hand side.

### Examples

```
>>> data = [[[1],[2],[0],[0],[0]],
...          [[1],[2],[3],[0],[0]],
...          [[1],[2],[6],[1],[0]]]
>>> data = np.asarray(data)
>>> print(data.shape)
... (3, 5, 1)
>>> data = tf.constant(data)
>>> sl = retrieve_seq_length_op(data)
>>> sess = tf.InteractiveSession()
```

```
>>> tl.layers.initialize_global_variables(sess)
>>> y = sl.eval()
... [2 3 4]
```

Multiple features >>> data = [[[1,2],[2,2],[1,2],[1,2],[0,0]], ... [[2,3],[2,4],[3,2],[0,0],[0,0]], ... [[3,3],[2,2],[5,3],[1,2],[0,0]]] >>> print(sl) ... [4 3 4]

#### References

Borrow from TFlearn.

### Compute Sequence length 2

`tensorlayer.layers.`**`retrieve_seq_length_op2`**(*data*)

An op to compute the length of a sequence, from input shape of [batch_size, n_step(max)], it can be used when the features of padding (on right hand side) are all zeros.

**Parameters** **`data`** (*tensor*) – [batch_size, n_step(max)] with zero padding on right hand side.

#### Examples

```
>>> data = [[1,2,0,0,0],
...           [1,2,3,0,0],
...           [1,2,6,1,0]]
>>> o = retrieve_seq_length_op2(data)
>>> sess = tf.InteractiveSession()
>>> tl.layers.initialize_global_variables(sess)
>>> print(o.eval())
... [2 3 4]
```

### Compute Sequence length 3

`tensorlayer.layers.`**`retrieve_seq_length_op3`**(*data*, *pad_val=0*)

Return tensor for sequence length, if input is `tf.string`.

### Get Mask

`tensorlayer.layers.`**`target_mask_op`**(*data*, *pad_val=0*)

Return tensor for mask, if input is `tf.string`.

### 2.1.22 Dynamic RNN layer

#### RNN layer

**class** tensorlayer.layers.**DynamicRNNLayer**(*layer*, *cell_fn*, *cell_init_args=None*, *n_hidden=256*, *initializer=<tensorflow.python.ops.init_ops.RandomUniform object>*, *sequence_length=None*, *initial_state=None*, *dropout=None*, *n_layer=1*, *return_last=None*, *return_seq_2d=False*, *dynamic_rnn_init_args=None*, *name='dyrnn'*)

The *DynamicRNNLayer* class is a dynamic recurrent layer, see `tf.nn.dynamic_rnn`.

**Parameters**

- **layer** (*Layer*) – Previous layer
- **cell_fn** (*TensorFlow cell function*) –

  **A TensorFlow core RNN cell**

  – See RNN Cells in TensorFlow

  – Note TF1.0+ and TF1.0- are different
- **cell_init_args** (*dictionary or None*) – The arguments for the cell function.
- **n_hidden** (*int*) – The number of hidden units in the layer.
- **initializer** (*initializer*) – The initializer for initializing the parameters.
- **sequence_length** (*tensor, array or None*) –

  **The sequence length of each row of input data, see `Advanced Ops for Dynamic RNN`.**

  – If None, it uses `retrieve_seq_length_op` to compute the sequence length, i.e. when the features of padding (on right hand side) are all zeros.

  – If using word embedding, you may need to compute the sequence length from the ID array (the integer features before word embedding) by using `retrieve_seq_length_op2` or `retrieve_seq_length_op`.

  – You can also input an numpy array.

  – More details about TensorFlow dynamic RNN in Wild-ML Blog.
- **initial_state** (*None or RNN State*) – If None, *initial_state* is zero state.
- **dropout** (*tuple of float or int*) –

  **The input and output keep probability (input_keep_prob, output_keep_prob).**

  – If one int, input and output keep probability are the same.
- **n_layer** (*int*) – The number of RNN layers, default is 1.
- **return_last** (*boolean or None*) –

  **Whether return last output or all outputs in each step.**

  – If True, return the last output, "Sequence input and single output"

  – If False, return all outputs, "Synced sequence input and output"

  – In other word, if you want to stack more RNNs on this layer, set to False.

- **return_seq_2d** (*boolean*) –

  **Only consider this argument when *return_last* is *False***

  – If True, return 2D Tensor [n_example, n_hidden], for stacking DenseLayer after it.

  – If False, return 3D Tensor [n_example/n_steps, n_steps, n_hidden], for stacking multiple RNN after it.

- **dynamic_rnn_init_args** (*dictionary*) – The arguments for `tf.nn.dynamic_rnn`.
- **name** (*str*) – A unique layer name.

**outputs**
*tensor* – The output of this layer.

**final_state**
*tensor or StateTuple* –

**The finial state of this layer.**

- When *state_is_tuple* is *False*, it is the final hidden and cell states, *states.get_shape() = [?, 2 * n_hidden]*.
- When *state_is_tuple* is *True*, it stores two elements: *(c, h)*.
- In practice, you can get the final state after each iteration during training, then feed it to the initial state of next iteration.

**initial_state**
*tensor or StateTuple* –

**The initial state of this layer.**

- In practice, you can set your state at the begining of each epoch or iteration according to your training procedure.

**batch_size**
*int or tensor* – It is an integer, if it is able to compute the *batch_size*; otherwise, tensor for dynamic batch size.

**sequence_length**
*a tensor or array* – The sequence lengths computed by Advanced Opt or the given sequence lengths, [batch_size]

### Notes

Input dimension should be rank 3 : [batch_size, n_steps(max), n_features], if no, please see `ReshapeLayer`.

### Examples

Synced sequence input and output, for loss function see `tl.cost.cross_entropy_seq_with_mask`.

```
>>> input_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"input")
>>> net = tl.layers.EmbeddingInputlayer(
...             inputs = input_seqs,
...             vocabulary_size = vocab_size,
...             embedding_size = embedding_size,
```

```
...                 name = 'seq_embedding')
>>> net = tl.layers.DynamicRNNLayer(net,
...                 cell_fn = tf.contrib.rnn.BasicLSTMCell, # for TF0.2 use tf.nn.rnn_
↪cell.BasicLSTMCell,
...                 n_hidden = embedding_size,
...                 dropout = (0.7 if is_train else None),
...                 sequence_length = tl.layers.retrieve_seq_length_op2(input_seqs),
...                 return_seq_2d = True,                    # stack denselayer or␣
↪compute cost after it
...                 name = 'dynamicrnn')
... net = tl.layers.DenseLayer(net, n_units=vocab_size, name="output")
```

### References

- Wild-ML Blog
- dynamic_rnn.ipynb
- tf.nn.dynamic_rnn
- tflearn rnn
- `tutorial_dynamic_rnn.py`

## Bidirectional layer

**class** `tensorlayer.layers.`**`BiDynamicRNNLayer`**(*layer, cell_fn, cell_init_args=None, n_hidden=256, initializer=<tensorflow.python.ops.init_ops.RandomUniform object>, sequence_length=None, fw_initial_state=None, bw_initial_state=None, dropout=None, n_layer=1, return_last=False, return_seq_2d=False, dynamic_rnn_init_args=None, name='bi_dyrnn_layer'*)

The *`BiDynamicRNNLayer`* class is a RNN layer, you can implement vanilla RNN, LSTM and GRU with it.

**Parameters**

- **`layer`** (*`Layer`*) – Previous layer.
- **`cell_fn`** (*`TensorFlow cell function`*) –

  **A TensorFlow core RNN cell**

  – See RNN Cells in TensorFlow.

  – Note TF1.0+ and TF1.0- are different.
- **`cell_init_args`** (*`dictionary`*) – The arguments for the cell initializer.
- **`n_hidden`** (*`int`*) – The number of hidden units in the layer.
- **`initializer`** (*`initializer`*) – The initializer for initializing the parameters.
- **`sequence_length`** (*`tensor, array or None`*) –

  **The sequence length of each row of input data, see `Advanced Ops for Dynamic RNN`.**

  - If None, it uses `retrieve_seq_length_op` to compute the sequence length, i.e. when the features of padding (on right hand side) are all zeros.
  - If using word embedding, you may need to compute the sequence length from the ID array (the integer features before word embedding) by using `retrieve_seq_length_op2` or `retrieve_seq_length_op`.
  - You can also input an numpy array.
  - More details about TensorFlow dynamic RNN in Wild-ML Blog.
- **fw_initial_state** (*None or forward RNN State*) – If None, *initial_state* is zero state.
- **bw_initial_state** (*None or backward RNN State*) – If None, *initial_state* is zero state.
- **dropout** (*tuple of float or int*) –

  **The input and output keep probability (input_keep_prob, output_keep_prob).**
  - If one int, input and output keep probability are the same.
- **n_layer** (*int*) – The number of RNN layers, default is 1.
- **return_last** (*boolean*) –

  **Whether return last output or all outputs in each step.**
  - If True, return the last output, "Sequence input and single output"
  - If False, return all outputs, "Synced sequence input and output"
  - In other word, if you want to stack more RNNs on this layer, set to False.
- **return_seq_2d** (*boolean*) –

  **Only consider this argument when *return_last* is *False***
  - If True, return 2D Tensor [n_example, 2 * n_hidden], for stacking DenseLayer after it.
  - If False, return 3D Tensor [n_example/n_steps, n_steps, 2 * n_hidden], for stacking multiple RNN after it.
- **dynamic_rnn_init_args** (*dictionary*) – The arguments for `tf.nn.bidirectional_dynamic_rnn`.
- **name** (*str*) – A unique layer name.

**outputs**

*tensor* – The output of this layer. (?, 2 * n_hidden)

**fw(bw)_final_state**

*tensor or StateTuple* –

**The finial state of this layer.**

- When *state_is_tuple* is *False*, it is the final hidden and cell states, *states.get_shape() = [?, 2 * n_hidden]*.
- When *state_is_tuple* is *True*, it stores two elements: *(c, h)*.
- In practice, you can get the final state after each iteration during training, then feed it to the initial state of next iteration.

**fw(bw)_initial_state**

*tensor or StateTuple* –

**The initial state of this layer.**

- In practice, you can set your state at the begining of each epoch or iteration according to your training procedure.

**batch_size**
*int or tensor* – It is an integer, if it is able to compute the *batch_size*; otherwise, tensor for dynamic batch size.

**sequence_length**
*a tensor or array* – The sequence lengths computed by Advanced Opt or the given sequence lengths, [batch_size].

### Notes

Input dimension should be rank 3 : [batch_size, n_steps(max), n_features], if no, please see `ReshapeLayer`.

### References

- Wild-ML Blog
- bidirectional_rnn.ipynb

## 2.1.23 Sequence to Sequence

### Simple Seq2Seq

**class** tensorlayer.layers.**Seq2Seq**(*net_encode_in, net_decode_in, cell_fn, cell_init_args=None, n_hidden=256, initializer=<tensorflow.python.ops.init_ops.RandomUniform object>, encode_sequence_length=None, decode_sequence_length=None, initial_state_encode=None, initial_state_decode=None, dropout=None, n_layer=1, return_seq_2d=False, name='seq2seq'*)

The `Seq2Seq` class is a simple `DynamicRNNLayer` based Seq2seq layer without using tl.contrib.seq2seq. See Model and Sequence to Sequence Learning with Neural Networks.

- Please check this example Chatbot in 200 lines of code.
- The Author recommends users to read the source code of `DynamicRNNLayer` and `Seq2Seq`.

**Parameters**

- **net_encode_in** (`Layer`) – Encode sequences, [batch_size, None, n_features].
- **net_decode_in** (`Layer`) – Decode sequences, [batch_size, None, n_features].
- **cell_fn** (`TensorFlow cell function`) –

  **A TensorFlow core RNN cell**

  – see RNN Cells in TensorFlow
  – Note TF1.0+ and TF1.0- are different
- **cell_init_args** (`dictionary or None`) – The arguments for the cell initializer.
- **n_hidden** (`int`) – The number of hidden units in the layer.

- **initializer** (*initializer*) – The initializer for the parameters.
- **encode_sequence_length** (*tensor*) – For encoder sequence length, see *DynamicRNNLayer*.
- **decode_sequence_length** (*tensor*) – For decoder sequence length, see *DynamicRNNLayer*.
- **initial_state_encode** (*None or RNN state*) – If None, *initial_state_encode* is zero state, it can be set by placeholder or other RNN.
- **initial_state_decode** (*None or RNN state*) – If None, *initial_state_decode* is the final state of the RNN encoder, it can be set by placeholder or other RNN.
- **dropout** (*tuple of float or int*) –

  **The input and output keep probability (input_keep_prob, output_keep_prob).**

  – If one int, input and output keep probability are the same.
- **n_layer** (*int*) – The number of RNN layers, default is 1.
- **return_seq_2d** (*boolean*) –

  **Only consider this argument when *return_last* is *False***

  – If True, return 2D Tensor [n_example, 2 * n_hidden], for stacking DenseLayer after it.

  – If False, return 3D Tensor [n_example/n_steps, n_steps, 2 * n_hidden], for stacking multiple RNN after it.
- **name** (*str*) – A unique layer name.

**outputs**
*tensor* – The output of RNN decoder.

**initial_state_encode**
*tensor or StateTuple* – Initial state of RNN encoder.

**initial_state_decode**
*tensor or StateTuple* – Initial state of RNN decoder.

**final_state_encode**
*tensor or StateTuple* – Final state of RNN encoder.

**final_state_decode**
*tensor or StateTuple* – Final state of RNN decoder.

### Notes

- How to feed data: Sequence to Sequence Learning with Neural Networks
- input_seqs : `['how', 'are', 'you', '<PAD_ID>']`
- decode_seqs : `['<START_ID>', 'I', 'am', 'fine', '<PAD_ID>']`
- target_seqs : `['I', 'am', 'fine', '<END_ID>', '<PAD_ID>']`
- target_mask : `[1, 1, 1, 1, 0]`
- related functions : tl.prepro <pad_sequences, precess_sequences, sequences_add_start_id, sequences_get_mask>

### Examples

```
>>> from tensorlayer.layers import *
>>> batch_size = 32
>>> encode_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"encode_seqs")
>>> decode_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"decode_seqs")
>>> target_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"target_seqs")
>>> target_mask = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"target_mask") # tl.prepro.sequences_get_mask()
>>> with tf.variable_scope("model"):
...     # for chatbot, you can use the same embedding layer,
...     # for translation, you may want to use 2 seperated embedding layers
>>>     with tf.variable_scope("embedding") as vs:
>>>         net_encode = EmbeddingInputlayer(
...                 inputs = encode_seqs,
...                 vocabulary_size = 10000,
...                 embedding_size = 200,
...                 name = 'seq_embedding')
>>>         vs.reuse_variables()
>>>         tl.layers.set_name_reuse(True)
>>>         net_decode = EmbeddingInputlayer(
...                 inputs = decode_seqs,
...                 vocabulary_size = 10000,
...                 embedding_size = 200,
...                 name = 'seq_embedding')
>>>     net = Seq2Seq(net_encode, net_decode,
...             cell_fn = tf.contrib.rnn.BasicLSTMCell,
...             n_hidden = 200,
...             initializer = tf.random_uniform_initializer(-0.1, 0.1),
...             encode_sequence_length = retrieve_seq_length_op2(encode_seqs),
...             decode_sequence_length = retrieve_seq_length_op2(decode_seqs),
...             initial_state_encode = None,
...             dropout = None,
...             n_layer = 1,
...             return_seq_2d = True,
...             name = 'seq2seq')
>>> net_out = DenseLayer(net, n_units=10000, act=tf.identity, name='output')
>>> e_loss = tl.cost.cross_entropy_seq_with_mask(logits=net_out.outputs, target_
↪seqs=target_seqs, input_mask=target_mask, return_details=False, name='cost')
>>> y = tf.nn.softmax(net_out.outputs)
>>> net_out.print_params(False)
```

## 2.1.24 Shape layer

### Flatten layer

**class** tensorlayer.layers.**FlattenLayer**(*layer*, *name='flatten_layer'*)

A layer that reshapes high-dimension input into a vector.

Then we often apply DenseLayer, RNNLayer, ConcatLayer and etc on the top of a flatten layer. [batch_size, mask_row, mask_col, n_mask] —> [batch_size, mask_row * mask_col * n_mask]

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **name** (*str*) – A unique layer name.

### Examples

```
>>> x = tf.placeholder(tf.float32, shape=[None, 28, 28, 1])
>>> net = tl.layers.InputLayer(x, name='input')
>>> net = tl.layers.FlattenLayer(net, name='flatten')
```

## Reshape layer

**class** tensorlayer.layers.**ReshapeLayer**(*layer, shape, name='reshape_layer'*)

A layer that reshapes a given tensor.

**Parameters**

- **layer** (*Layer*) – Previous layer
- **shape** (*tuple of int*) – The output shape, see `tf.reshape`.
- **name** (*str*) – A unique layer name.

### Examples

Use TensorLayer

```
>>> x = tf.placeholder(tf.float32, shape=(None, 28, 28, 1))
>>> net = tl.layers.InputLayer(x, name='input')
>>> net = tl.layers.ReshapeLayer(net, (-1, 28*28), name='reshape')
>>> print(net.outputs)
... (?, 784)
```

Use native TensorFlow API `tf.reshape`

```
>>> x = tf.placeholder(tf.float32, shape=[None, 3])
>>> y = tf.reshape(x, shape=[-1, 3, 3])
>>> sess = tf.InteractiveSession()
>>> print(sess.run(y, feed_dict={x:[[1,1,1],[2,2,2],[3,3,3],[4,4,4],[5,5,5],[6,6,
↪6]]}))
... [[[ 1.  1.  1.]
... [ 2.  2.  2.]
... [ 3.  3.  3.]]
... [[ 4.  4.  4.]
... [ 5.  5.  5.]
... [ 6.  6.  6.]]]
```

## Transpose layer

**class** tensorlayer.layers.**TransposeLayer**(*layer, perm, name='transpose'*)

A layer that transposes the dimension of a tensor.

See tf.transpose() .

**Parameters**

- **layer** (*Layer*) – Previous layer
- **perm** (*list of int*) – The permutation of the dimensions, similar with `numpy.transpose`.
- **name** (*str*) – A unique layer name.

## 2.1.25 Lambda layer

**class** tensorlayer.layers.**LambdaLayer**(*layer*, *fn*, *fn_args=None*, *name='lambda_layer'*)

A layer that takes a user-defined function using TensorFlow Lambda.

**Parameters**

- **layer** (*Layer*) – Previous layer.
- **fn** (*function*) – The function that applies to the outputs of previous layer.
- **fn_args** (*dictionary or None*) – The arguments for the function (option).
- **name** (*str*) – A unique layer name.

### Examples

Non-parametric case

```
>>> x = tf.placeholder(tf.float32, shape=[None, 1], name='x')
>>> net = tl.layers.InputLayer(x, name='input')
>>> net = LambdaLayer(net, lambda x: 2*x, name='lambda')
```

Parametric case, merge other wrappers into TensorLayer

```
>>> from keras.layers import *
>>> from tensorlayer.layers import *
>>> def keras_block(x):
>>>     x = Dropout(0.8)(x)
>>>     x = Dense(800, activation='relu')(x)
>>>     x = Dropout(0.5)(x)
>>>     x = Dense(800, activation='relu')(x)
>>>     x = Dropout(0.5)(x)
>>>     logits = Dense(10, activation='linear')(x)
>>>     return logits
>>> net = InputLayer(x, name='input')
>>> net = LambdaLayer(net, fn=keras_block, name='keras')
```

## 2.1.26 Merge layer

### Concat layer

**class** tensorlayer.layers.**ConcatLayer**(*layers*, *concat_dim=1*, *name='concat_layer'*)

A layer that concats multiple tensors according to given axis..

**Parameters**

- **layers** (list of *Layer*) – List of layers to concatenate.
- **concat_dim** (*int*) – The dimension to concatenate.

- **name** (*str*) – A unique layer name.

### Examples

```
>>> sess = tf.InteractiveSession()
>>> x = tf.placeholder(tf.float32, shape=[None, 784])
>>> inputs = tl.layers.InputLayer(x, name='input_layer')
>>> net1 = tl.layers.DenseLayer(inputs, 800, act=tf.nn.relu, name='relu1_1')
>>> net2 = tl.layers.DenseLayer(inputs, 300, act=tf.nn.relu, name='relu2_1')
>>> net = tl.layers.ConcatLayer([net1, net2], 1, name ='concat_layer')
...   InputLayer input_layer (?, 784)
...   DenseLayer relu1_1: 800, relu
...   DenseLayer relu2_1: 300, relu
...   ConcatLayer concat_layer, 1100
>>> tl.layers.initialize_global_variables(sess)
>>> net.print_params()
...     param 0: (784, 800) (mean: 0.000021, median: -0.000020 std: 0.035525)
...     param 1: (800,)     (mean: 0.000000, median: 0.000000  std: 0.000000)
...     param 2: (784, 300) (mean: 0.000000, median: -0.000048 std: 0.042947)
...     param 3: (300,)     (mean: 0.000000, median: 0.000000  std: 0.000000)
...     num of params: 863500
>>> net.print_layers()
...     layer 0: ("Relu:0", shape=(?, 800), dtype=float32)
...     layer 1: Tensor("Relu_1:0", shape=(?, 300), dtype=float32)
```

## Element-wise layer

**class** tensorlayer.layers.**ElementwiseLayer**(*layers*, *combine_fn=<function minimum>*, *name='elementwise_layer'*)

A layer that combines multiple *Layer* that have the same output shapes according to an element-wise operation.

**Parameters**

- **layers** (list of *Layer*) – The list of layers to combine.
- **combine_fn** (*a TensorFlow element-wise combine function*) – e.g. AND is `tf.minimum` ; OR is `tf.maximum` ; ADD is `tf.add` ; MUL is `tf.multiply` and so on. See TensorFlow Math API .
- **name** (*str*) – A unique layer name.

### Examples

AND Logic

```
>>> net_0 = tl.layers.DenseLayer(net_0, n_units=500,
...                        act = tf.nn.relu, name='net_0')
>>> net_1 = tl.layers.DenseLayer(net_1, n_units=500,
...                        act = tf.nn.relu, name='net_1')
>>> net_com = tl.layers.ElementwiseLayer(layer = [net_0, net_1],
...                         combine_fn = tf.minimum,
...                         name = 'combine_layer')
```

### 2.1.27 Extend layer

#### Expand dims layer

**class** tensorlayer.layers.**ExpandDimsLayer**(*layer*, *axis*, *name='expand_dims'*)

The *ExpandDimsLayer* class inserts a dimension of 1 into a tensor's shape, see tf.expand_dims() .

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **axis** (*int*) – The dimension index at which to expand the shape of input.
- **name** (*str*) – A unique layer name.

#### Tile layer

**class** tensorlayer.layers.**TileLayer**(*layer=None*, *multiples=None*, *name='tile'*)

The *TileLayer* class constructs a tensor by tiling a given tensor, see tf.tile() .

**Parameters**

- **layer** (*Layer*) – The previous layer.
- **multiples** (*tensor*) – Must be one of the following types: int32, int64. 1-D Length must be the same as the number of dimensions in input.
- **name** (*str*) – A unique layer name.

### 2.1.28 Stack layer

#### Stack layer

**class** tensorlayer.layers.**StackLayer**(*layers*, *axis=0*, *name='stack'*)

The *StackLayer* class is layer for stacking a list of rank-R tensors into one rank-(R+1) tensor, see tf.stack().

**Parameters**

- **layers** (list of *Layer*) – Previous layers to stack.
- **axis** (*int*) – Dimension along which to concatenate.
- **name** (*str*) – A unique layer name.

#### Unstack layer

tensorlayer.layers.**UnStackLayer**(*layer*, *num=None*, *axis=0*, *name='unstack'*)

It is layer for unstacking the given dimension of a rank-R tensor into rank-(R-1) tensors., see tf.unstack().

**Parameters**

- **layer** (*Layer*) – Previous layer
- **num** (*int or None*) – The length of the dimension axis. Automatically inferred if None (the default).
- **axis** (*int*) – Dimension along which axis to concatenate.
- **name** (*str*) – A unique layer name.

**Returns** The list of layer objects unstacked from the input.

**Return type** list of `Layer`

### 2.1.29 Connect TF-Slim

Yes ! TF-Slim models can be connected into TensorLayer, all Google's Pre-trained model can be used easily , see Slim-model.

**class** `tensorlayer.layers.`**`SlimNetsLayer`**(*layer*, *slim_layer*, *slim_args=None*, *name='tfslim_layer'*)

A layer that merges TF-Slim models into TensorLayer.

Models can be found in slim-model, see Inception V3 example on Github.

**Parameters**

- **`layer`** (`Layer`) – Previous layer.
- **`slim_layer`** (*`a slim network function`*) – The network you want to stack onto, end with `return net, end_points`.
- **`slim_args`** (*`dictionary`*) – The arguments for the slim model.
- **`name`** (*`str`*) – A unique layer name.

#### Notes

- The due to TF-Slim stores the layers as dictionary, the `all_layers` in this network is not in order ! Fortunately, the `all_params` are in order.

### 2.1.30 Parametric activation layer

**class** `tensorlayer.layers.`**`PReluLayer`**(*layer*, *channel_shared=False*, *a_init=<tensorflow.python.ops.init_ops.Constant object>*, *a_init_args=None*, *name='prelu_layer'*)

The `PReluLayer` class is Parametric Rectified Linear layer.

**Parameters**

- **`layer`** (`Layer`) – Previous layer
- **`channel_shared`** (*`boolean`*) – If True, single weight is shared by all channels.
- **`a_init`** (*`initializer`*) – The initializer for initializing the alpha(s).
- **`a_init_args`** (*`dictionary`*) – The arguments for initializing the alpha(s).
- **`name`** (*`str`*) – A unique layer name.

#### References

- Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification

### 2.1.31 Flow control layer

**class** tensorlayer.layers.**MultiplexerLayer**(*layers*, *name='mux_layer'*)

The `MultiplexerLayer` selects inputs to be forwarded to output. see *tutorial_mnist_multiplexer.py*.

**Parameters**

- **layers** (a list of `Layer`) – The input layers.
- **name** (`str`) – A unique layer name.

**sel**

*placeholder* – The placeholder takes an integer for selecting which layer to output.

#### Examples

```
>>> x = tf.placeholder(tf.float32, shape=(None, 784), name='x')
>>> y_ = tf.placeholder(tf.int64, shape=(None, ), name='y_')
>>> # define the network
>>> net_in = tl.layers.InputLayer(x, name='input_layer')
>>> net_in = tl.layers.DropoutLayer(net_in, keep=0.8, name='drop1')
>>> # net 0
>>> net_0 = tl.layers.DenseLayer(net_in, n_units=800,
...                                 act = tf.nn.relu, name='net0/relu1')
>>> net_0 = tl.layers.DropoutLayer(net_0, keep=0.5, name='net0/drop2')
>>> net_0 = tl.layers.DenseLayer(net_0, n_units=800,
...                                 act = tf.nn.relu, name='net0/relu2')
>>> # net 1
>>> net_1 = tl.layers.DenseLayer(net_in, n_units=800,
...                                 act = tf.nn.relu, name='net1/relu1')
>>> net_1 = tl.layers.DropoutLayer(net_1, keep=0.8, name='net1/drop2')
>>> net_1 = tl.layers.DenseLayer(net_1, n_units=800,
...                                 act = tf.nn.relu, name='net1/relu2')
>>> net_1 = tl.layers.DropoutLayer(net_1, keep=0.8, name='net1/drop3')
>>> net_1 = tl.layers.DenseLayer(net_1, n_units=800,
...                                 act = tf.nn.relu, name='net1/relu3')
>>> # multiplexer
>>> net_mux = tl.layers.MultiplexerLayer(layer=[net_0, net_1], name='mux_layer')
>>> network = tl.layers.ReshapeLayer(net_mux, shape=(-1, 800), name='reshape_layer
↪') #
>>> network = tl.layers.DropoutLayer(network, keep=0.5, name='drop3')
>>> # output layer
>>> network = tl.layers.DenseLayer(network, n_units=10,
...                                 act = tf.identity, name='output_layer')
```

### 2.1.32 Helper functions

#### Flatten tensor

tensorlayer.layers.**flatten_reshape**(*variable*, *name='flatten'*)

Reshapes a high-dimension vector input. [batch_size, mask_row, mask_col, n_mask] —> [batch_size, mask_row x mask_col x n_mask]

**Parameters**

- **variable** (`TensorFlow variable or tensor`) – The variable or tensor to be flatten.

- **name** (*str*) – A unique layer name.

**Returns** Flatten Tensor

**Return type** Tensor

### Examples

```
>>> W_conv2 = weight_variable([5, 5, 100, 32])   # 64 features for each 5x5 patch
>>> b_conv2 = bias_variable([32])
>>> W_fc1 = weight_variable([7 * 7 * 32, 256])
```

```
>>> h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
>>> h_pool2 = max_pool_2x2(h_conv2)
>>> h_pool2.get_shape()[:].as_list() = [batch_size, 7, 7, 32]
...         [batch_size, mask_row, mask_col, n_mask]
>>> h_pool2_flat = tl.layers.flatten_reshape(h_pool2)
...         [batch_size, mask_row * mask_col * n_mask]
>>> h_pool2_flat_drop = tf.nn.dropout(h_pool2_flat, keep_prob)
...
```

## Permanent clear existing layer names

tensorlayer.layers.**clear_layers_name**()

Clear all layer names in *set_keep['_layers_name_list']* if layer names are reused.

### Examples

Clean the current graph and try to re-define model.

```
>>> for .... (different model settings):
>>>    with tf.Graph().as_default() as graph:   # clear all variables of TF
>>>       tl.layers.clear_layers_name()         # clear all layer name of TL
>>>       sess = tf.InteractiveSession()
>>>       # define and train a model here
>>>       sess.close()
```

Enable reusing layer names.

```
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = tl.layers.DenseLayer(net, n_units=800, name='relu1')
...
>>> tl.layers.clear_layers_name()
>>> net2 = tl.layers.InputLayer(x, name='input_layer')
>>> net2 = tl.layers.DenseLayer(net2, n_units=800, name='relu1')
```

## Initialize RNN state

tensorlayer.layers.**initialize_rnn_state**(*state*, *feed_dict=None*)

Returns the initialized RNN state. The inputs are *LSTMStateTuple* or *State* of *RNNCells*, and an optional *feed_dict*.

**Parameters**

- **state** (*RNN state.*) – The TensorFlow's RNN state.
- **feed_dict** (*dictionary*) – Initial RNN state; if None, returns zero state.

**Returns** The TensorFlow's RNN state.

**Return type** RNN state

### Remove repeated items in a list

tensorlayer.layers.**list_remove_repeat**(*x*)

Remove the repeated items in a list, and return the processed list. You may need it to create merged layer like Concat, Elementwise and etc.

**Parameters x** (*list*) – Input

**Returns** A list that after removing it's repeated items

**Return type** list

#### Examples

```
>>> l = [2, 3, 4, 2, 3]
>>> l = list_remove_repeat(l)
... [2, 3, 4]
```

### Merge networks attributes

tensorlayer.layers.**merge_networks**(*layers=None*)

Merge all parameters, layers and dropout probabilities to a *Layer*. The output of return network is the first network in the list.

**Parameters layers** (list of *Layer*) – Merge all parameters, layers and dropout probabilities to the first layer in the list.

**Returns** The network after merging all parameters, layers and dropout probabilities to the first network in the list.

**Return type** *Layer*

#### Examples

```
>>> n1 = ...
>>> n2 = ...
>>> n1 = tl.layers.merge_networks([n1, n2])
```

## 2.2 API - Cost

To make TensorLayer simple, we minimize the number of cost functions as much as we can. So we encourage you to use TensorFlow's function. For example, you can implement L1, L2 and sum regularization by `tf.nn.l2_loss`, `tf.contrib.layers.l1_regularizer`, `tf.contrib.layers.l2_regularizer` and `tf.contrib.layers.sum_regularizer`, see TensorFlow API.

### 2.2.1 Your cost function

TensorLayer provides a simple way to create you own cost function. Take a MLP below for example.

```
network = InputLayer(x, name='input')
network = DropoutLayer(network, keep=0.8, name='drop1')
network = DenseLayer(network, n_units=800, act=tf.nn.relu, name='relu1')
network = DropoutLayer(network, keep=0.5, name='drop2')
network = DenseLayer(network, n_units=800, act=tf.nn.relu, name='relu2')
network = DropoutLayer(network, keep=0.5, name='drop3')
network = DenseLayer(network, n_units=10, act=tf.identity, name='output')
```

The network parameters will be `[W1, b1, W2, b2, W_out, b_out]`, then you can apply L2 regularization on the weights matrix of first two layer as follow.

```
cost = tl.cost.cross_entropy(y, y_)
cost = cost + tf.contrib.layers.l2_regularizer(0.001)(network.all_params[0])
        + tf.contrib.layers.l2_regularizer(0.001)(network.all_params[2])
```

Besides, TensorLayer provides a easy way to get all variables by a given name, so you can also apply L2 regularization on some weights as follow.

```
l2 = 0
for w in tl.layers.get_variables_with_name('W_conv2d', train_only=True,␣
↪printable=False):
    l2 += tf.contrib.layers.l2_regularizer(1e-4)(w)
cost = tl.cost.cross_entropy(y, y_) + l2
```

#### Regularization of Weights

After initializing the variables, the informations of network parameters can be observed by using `network.print_params()`.

```
tl.layers.initialize_global_variables(sess)
network.print_params()
```

```
param 0: (784, 800) (mean: -0.000000, median: 0.000004 std: 0.035524)
param 1: (800,) (mean: 0.000000, median: 0.000000 std: 0.000000)
param 2: (800, 800) (mean: 0.000029, median: 0.000031 std: 0.035378)
param 3: (800,) (mean: 0.000000, median: 0.000000 std: 0.000000)
param 4: (800, 10) (mean: 0.000673, median: 0.000763 std: 0.049373)
param 5: (10,) (mean: 0.000000, median: 0.000000 std: 0.000000)
num of params: 1276810
```

The output of network is `network.outputs`, then the cross entropy can be defined as follow. Besides, to regularize the weights, the `network.all_params` contains all parameters of the network. In this case, `network.all_params = [W1, b1, W2, b2, Wout, bout]` according to param 0, 1 ... 5 shown by `network.print_params()`. Then max-norm regularization on W1 and W2 can be performed as follow.

```
max_norm = 0
for w in tl.layers.get_variables_with_name('W', train_only=True, printable=False):
    max_norm += tl.cost.maxnorm_regularizer(1)(w)
cost = tl.cost.cross_entropy(y, y_) + max_norm
```

In addition, all TensorFlow's regularizers like `tf.contrib.layers.l2_regularizer` can be used with TensorLayer.

### Regularization of Activation outputs

Instance method `network.print_layers()` prints all outputs of different layers in order. To achieve regularization on activation output, you can use `network.all_layers` which contains all outputs of different layers. If you want to apply L1 penalty on the activations of first hidden layer, just simply add `tf.contrib.layers.l2_regularizer(lambda_l1)(network.all_layers[1])` to the cost function.

```
network.print_layers()
```

```
layer 0: Tensor("dropout/mul_1:0", shape=(?, 784), dtype=float32)
layer 1: Tensor("Relu:0", shape=(?, 800), dtype=float32)
layer 2: Tensor("dropout_1/mul_1:0", shape=(?, 800), dtype=float32)
layer 3: Tensor("Relu_1:0", shape=(?, 800), dtype=float32)
layer 4: Tensor("dropout_2/mul_1:0", shape=(?, 800), dtype=float32)
layer 5: Tensor("add_2:0", shape=(?, 10), dtype=float32)
```

| | |
|---|---|
| `cross_entropy`(output, target[, name]) | Softmax cross-entropy operation, returns the TensorFlow expression of cross-entropy for two distributions, it implements softmax internally. |
| `sigmoid_cross_entropy`(output, target[, name]) | Sigmoid cross-entropy operation, see `tf.nn.sigmoid_cross_entropy_with_logits`. |
| `binary_cross_entropy`(output, target[, . . . ]) | Binary cross entropy operation. |
| `mean_squared_error`(output, target[, . . . ]) | Return the TensorFlow expression of mean-square-error (L2) of two batch of data. |
| `normalized_mean_square_error`(output, target) | Return the TensorFlow expression of normalized mean-square-error of two distributions. |
| `absolute_difference_error`(output, target[, . . . ]) | Return the TensorFlow expression of absolute difference error (L1) of two batch of data. |
| `dice_coe`(output, target[, loss_type, axis, . . . ]) | Soft dice (Sørensen or Jaccard) coefficient for comparing the similarity of two batch of data, usually be used for binary image segmentation i.e. |
| `dice_hard_coe`(output, target[, threshold, . . . ]) | Non-differentiable Sørensen–Dice coefficient for comparing the similarity of two batch of data, usually be used for binary image segmentation i.e. |
| `iou_coe`(output, target[, threshold, axis, . . . ]) | Non-differentiable Intersection over Union (IoU) for comparing the similarity of two batch of data, usually be used for evaluating binary image segmentation. |
| `cross_entropy_seq`(logits, target_seqs[, . . . ]) | Returns the expression of cross-entropy of two sequences, implement softmax internally. |
| `cross_entropy_seq_with_mask`(logits, . . . [, . . . ]) | Returns the expression of cross-entropy of two sequences, implement softmax internally. |
| `cosine_similarity`(v1, v2) | Cosine similarity [-1, 1]. |
| `li_regularizer`(scale[, scope]) | Li regularization removes the neurons of previous layer. |
| `lo_regularizer`(scale) | Lo regularization removes the neurons of current layer. |
| `maxnorm_regularizer`([scale]) | Max-norm regularization returns a function that can be used to apply max-norm regularization to weights. |
| `maxnorm_o_regularizer`(scale) | Max-norm output regularization removes the neurons of current layer. |
| `maxnorm_i_regularizer`(scale) | Max-norm input regularization removes the neurons of previous layer. |

### 2.2.2 Softmax cross entropy

`tensorlayer.cost.`**`cross_entropy`**(*output*, *target*, *name=None*)

Softmax cross-entropy operation, returns the TensorFlow expression of cross-entropy for two distributions, it implements softmax internally. See `tf.nn.sparse_softmax_cross_entropy_with_logits`.

**Parameters**

- **output** (*Tensor*) – A batch of distribution with shape: [batch_size, num of classes].
- **target** (*Tensor*) – A batch of index with shape: [batch_size, ].
- **name** (*string*) – Name of this loss.

#### Examples

```
>>> ce = tl.cost.cross_entropy(y_logits, y_target_logits, 'my_loss')
```

#### References

- About cross-entropy: https://en.wikipedia.org/wiki/Cross_entropy.
- The code is borrowed from: https://en.wikipedia.org/wiki/Cross_entropy.

### 2.2.3 Sigmoid cross entropy

`tensorlayer.cost.`**`sigmoid_cross_entropy`**(*output*, *target*, *name=None*)

Sigmoid cross-entropy operation, see `tf.nn.sigmoid_cross_entropy_with_logits`.

**Parameters**

- **output** (*Tensor*) – A batch of distribution with shape: [batch_size, num of classes].
- **target** (*Tensor*) – A batch of index with shape: [batch_size, ].
- **name** (*string*) – Name of this loss.

### 2.2.4 Binary cross entropy

`tensorlayer.cost.`**`binary_cross_entropy`**(*output*, *target*, *epsilon=1e-08*, *name='bce_loss'*)

Binary cross entropy operation.

**Parameters**

- **output** (*Tensor*) – Tensor with type of *float32* or *float64*.
- **target** (*Tensor*) – The target distribution, format the same with *output*.
- **epsilon** (*float*) – A small value to avoid output to be zero.
- **name** (*str*) – An optional name to attach to this function.

#### References

- ericjang-DRAW

### 2.2.5 Mean squared error (L2)

`tensorlayer.cost.mean_squared_error`(*output*, *target*, *is_mean=False*, *name='mean_squared_error'*)

Return the TensorFlow expression of mean-square-error (L2) of two batch of data.

**Parameters**

- **output** (*Tensor*) – 2D, 3D or 4D tensor i.e. [batch_size, n_feature], [batch_size, height, width] or [batch_size, height, width, channel].
- **target** (*Tensor*) – The target distribution, format the same with *output*.
- **is_mean** (*boolean*) –

  **Whether compute the mean or sum for each example.**

  – If True, use `tf.reduce_mean` to compute the loss between one target and predict data.

  – If False, use `tf.reduce_sum` (default).

#### References

- Wiki Mean Squared Error

### 2.2.6 Normalized mean square error

`tensorlayer.cost.normalized_mean_square_error`(*output*, *target*)

Return the TensorFlow expression of normalized mean-square-error of two distributions.

**Parameters**

- **output** (*Tensor*) – 2D, 3D or 4D tensor i.e. [batch_size, n_feature], [batch_size, height, width] or [batch_size, height, width, channel].
- **target** (*Tensor*) – The target distribution, format the same with *output*.

### 2.2.7 Absolute difference error (L1)

`tensorlayer.cost.absolute_difference_error`(*output*, *target*, *is_mean=False*)

Return the TensorFlow expression of absolute difference error (L1) of two batch of data.

**Parameters**

- **output** (*Tensor*) – 2D, 3D or 4D tensor i.e. [batch_size, n_feature], [batch_size, height, width] or [batch_size, height, width, channel].
- **target** (*Tensor*) – The target distribution, format the same with *output*.
- **is_mean** (*boolean*) –

  **Whether compute the mean or sum for each example.**

  – If True, use `tf.reduce_mean` to compute the loss between one target and predict data.

  – If False, use `tf.reduce_sum` (default).

### 2.2.8 Dice coefficient

`tensorlayer.cost.dice_coe(output, target, loss_type='jaccard', axis=(1, 2, 3), smooth=1e-05)`

Soft dice (Sørensen or Jaccard) coefficient for comparing the similarity of two batch of data, usually be used for binary image segmentation i.e. labels are binary. The coefficient between 0 to 1, 1 means totally match.

**Parameters**

- **output** (*Tensor*) – A distribution with shape: [batch_size, ....], (any dimensions).
- **target** (*Tensor*) – The target distribution, format the same with *output*.
- **loss_type** (*str*) – `jaccard` or `sorensen`, default is `jaccard`.
- **axis** (*tuple of int*) – All dimensions are reduced, default `[1,2,3]`.
- **smooth** (*float*) –

  **This small value will be added to the numerator and denominator.**

  – If both output and target are empty, it makes sure dice is 1.

  – If either output or target are empty (all pixels are background), dice = ``smooth/ (small_value + smooth)``, then if smooth is very small, dice close to 0 (even the image values lower than the threshold), so in this case, higher smooth can have a higher dice.

#### Examples

```
>>> outputs = tl.act.pixel_wise_softmax(network.outputs)
>>> dice_loss = 1 - tl.cost.dice_coe(outputs, y_)
```

#### References

- Wiki-Dice

### 2.2.9 Hard Dice coefficient

`tensorlayer.cost.dice_hard_coe(output, target, threshold=0.5, axis=(1, 2, 3), smooth=1e-05)`

Non-differentiable Sørensen–Dice coefficient for comparing the similarity of two batch of data, usually be used for binary image segmentation i.e. labels are binary. The coefficient between 0 to 1, 1 if totally match.

**Parameters**

- **output** (*tensor*) – A distribution with shape: [batch_size, ....], (any dimensions).
- **target** (*tensor*) – The target distribution, format the same with *output*.
- **threshold** (*float*) – The threshold value to be true.
- **axis** (*tuple of integer*) – All dimensions are reduced, default `(1,2,3)`.
- **smooth** (*float*) – This small value will be added to the numerator and denominator, see `dice_coe`.

#### References

- Wiki-Dice

### 2.2.10 IOU coefficient

tensorlayer.cost.**iou_coe**(*output*, *target*, *threshold=0.5*, *axis=(1, 2, 3)*, *smooth=1e-05*)

Non-differentiable Intersection over Union (IoU) for comparing the similarity of two batch of data, usually be used for evaluating binary image segmentation. The coefficient between 0 to 1, and 1 means totally match.

**Parameters**

- **output** (*tensor*) – A batch of distribution with shape: [batch_size, ....], (any dimensions).
- **target** (*tensor*) – The target distribution, format the same with *output*.
- **threshold** (*float*) – The threshold value to be true.
- **axis** (*tuple of integer*) – All dimensions are reduced, default `(1,2,3)`.
- **smooth** (*float*) – This small value will be added to the numerator and denominator, see `dice_coe`.

#### Notes

- IoU cannot be used as training loss, people usually use dice coefficient for training, IoU and hard-dice for evaluating.

### 2.2.11 Cross entropy for sequence

tensorlayer.cost.**cross_entropy_seq**(*logits*, *target_seqs*, *batch_size=None*)

Returns the expression of cross-entropy of two sequences, implement softmax internally. Normally be used for fixed length RNN outputs, see PTB example.

**Parameters**

- **logits** (*Tensor*) – 2D tensor with shape of *[batch_size * n_steps, n_classes]*.
- **target_seqs** (*Tensor*) – The target sequence, 2D tensor *[batch_size, n_steps]*, if the number of step is dynamic, please use `tl.cost.cross_entropy_seq_with_mask` instead.
- **batch_size** (*None or int.*) –

  **Whether to divide the cost by batch size.**

  – If integer, the return cost will be divided by *batch_size*.

  – If None (default), the return cost will not be divided by anything.

#### Examples

```
>>> see `PTB example <https://github.com/zsdonghao/tensorlayer/blob/master/
↪example/tutorial_ptb_lstm_state_is_tuple.py>`__.for more details
>>> input_data = tf.placeholder(tf.int32, [batch_size, n_steps])
>>> targets = tf.placeholder(tf.int32, [batch_size, n_steps])
>>> # build the network
>>> print(net.outputs)
... (batch_size * n_steps, n_classes)
>>> cost = tl.cost.cross_entropy_seq(network.outputs, targets)
```

### 2.2.12 Cross entropy with mask for sequence

`tensorlayer.cost.`**`cross_entropy_seq_with_mask`**(*logits*, *target_seqs*, *input_mask*, *return_details=False*, *name=None*)

Returns the expression of cross-entropy of two sequences, implement softmax internally. Normally be used for Dynamic RNN with Synced sequence input and output.

**Parameters**

- **logits** (*Tensor*) – 2D tensor with shape of [batch_size * ?, n_classes], *?* means dynamic IDs for each example. - Can be get from *DynamicRNNLayer* by setting `return_seq_2d` to *True*.
- **target_seqs** (*Tensor*) – int of tensor, like word ID. [batch_size, ?], *?* means dynamic IDs for each example.
- **input_mask** (*Tensor*) – The mask to compute loss, it has the same size with *target_seqs*, normally 0 or 1.
- **return_details** (*boolean*) –

  **Whether to return detailed losses.**

  - If False (default), only returns the loss.
  - If True, returns the loss, losses, weights and targets (see source code).

#### Examples

```
>>> batch_size = 64
>>> vocab_size = 10000
>>> embedding_size = 256
>>> input_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"input")
>>> target_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"target")
>>> input_mask = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"mask")
>>> net = tl.layers.EmbeddingInputlayer(
...         inputs = input_seqs,
...         vocabulary_size = vocab_size,
...         embedding_size = embedding_size,
...         name = 'seq_embedding')
>>> net = tl.layers.DynamicRNNLayer(net,
...         cell_fn = tf.contrib.rnn.BasicLSTMCell,
...         n_hidden = embedding_size,
...         dropout = (0.7 if is_train else None),
...         sequence_length = tl.layers.retrieve_seq_length_op2(input_seqs),
```

```
...         return_seq_2d = True,
...         name = 'dynamicrnn')
>>> print(net.outputs)
... (?, 256)
>>> net = tl.layers.DenseLayer(net, n_units=vocab_size, name="output")
>>> print(net.outputs)
... (?, 10000)
>>> loss = tl.cost.cross_entropy_seq_with_mask(net.outputs, target_seqs, input_
↪mask)
```

### 2.2.13 Cosine similarity

`tensorlayer.cost.`**`cosine_similarity`**`(`*v1*, *v2*`)`

Cosine similarity [-1, 1].

**Parameters** **v2** (*v1,*) – Tensor with the same shape [batch_size, n_feature].

**Returns** a tensor of shape [batch_size].

**Return type** Tensor

#### References

- https://en.wikipedia.org/wiki/Cosine_similarity.

### 2.2.14 Regularization functions

For `tf.nn.l2_loss`, `tf.contrib.layers.l1_regularizer`, `tf.contrib.layers.l2_regularizer` and `tf.contrib.layers.sum_regularizer`, see TensorFlow API.

#### Maxnorm

`tensorlayer.cost.`**`maxnorm_regularizer`**`(`*scale=1.0*`)`

Max-norm regularization returns a function that can be used to apply max-norm regularization to weights.

More about max-norm, see wiki-max norm. The implementation follows TensorFlow contrib.

**Parameters** **scale** (*float*) – A scalar multiplier *Tensor*. 0.0 disables the regularizer.

**Returns**

**Return type** A function with signature *mn(weights, name=None)* that apply Lo regularization.

**Raises** ValueError : If scale is outside of the range [0.0, 1.0] or if scale is not a float.

#### Special

`tensorlayer.cost.`**`li_regularizer`**`(`*scale*, *scope=None*`)`

Li regularization removes the neurons of previous layer. The *i* represents *inputs*. Returns a function that can be used to apply group li regularization to weights. The implementation follows TensorFlow contrib.

**Parameters**

- **scale** (*float*) – A scalar multiplier *Tensor*. 0.0 disables the regularizer.

- **scope** (*str*) – An optional scope name for this function.

**Returns**

**Return type** A function with signature *li(weights, name=None)* that apply Li regularization.

**Raises** ValueError : if scale is outside of the range [0.0, 1.0] or if scale is not a float.

`tensorlayer.cost.`**`lo_regularizer`**`(`*scale*`)`

Lo regularization removes the neurons of current layer. The *o* represents *outputs* Returns a function that can be used to apply group lo regularization to weights. The implementation follows TensorFlow contrib.

**Parameters** **scale** (*float*) – A scalar multiplier *Tensor*. 0.0 disables the regularizer.

**Returns**

**Return type** A function with signature *lo(weights, name=None)* that apply Lo regularization.

**Raises** ValueError : If scale is outside of the range [0.0, 1.0] or if scale is not a float.

`tensorlayer.cost.`**`maxnorm_o_regularizer`**`(`*scale*`)`

Max-norm output regularization removes the neurons of current layer. Returns a function that can be used to apply max-norm regularization to each column of weight matrix. The implementation follows TensorFlow contrib.

**Parameters** **scale** (*float*) – A scalar multiplier *Tensor*. 0.0 disables the regularizer.

**Returns**

**Return type** A function with signature *mn_o(weights, name=None)* that apply Lo regularization.

**Raises** ValueError : If scale is outside of the range [0.0, 1.0] or if scale is not a float.

`tensorlayer.cost.`**`maxnorm_i_regularizer`**`(`*scale*`)`

Max-norm input regularization removes the neurons of previous layer. Returns a function that can be used to apply max-norm regularization to each row of weight matrix. The implementation follows TensorFlow contrib.

**Parameters** **scale** (*float*) – A scalar multiplier *Tensor*. 0.0 disables the regularizer.

**Returns**

**Return type** A function with signature *mn_i(weights, name=None)* that apply Lo regularization.

**Raises** ValueError : If scale is outside of the range [0.0, 1.0] or if scale is not a float.

## 2.3 API - Preprocessing

We provide abundant data augmentation and processing functions by using Numpy, Scipy, Threading and Queue. However, we recommend you to use TensorFlow operation function like `tf.image.central_crop`, more TensorFlow data augmentation method can be found here and `tutorial_cifar10_tfrecord.py`. Some of the code in this package are borrowed from Keras.

| | |
|---|---|
| `threading_data`([data, fn, thread_count]) | Process a batch of data by given function by threading. |
| `rotation`(x[, rg, is_random, row_index, ...]) | Rotate an image randomly or non-randomly. |
| `rotation_multi`(x[, rg, is_random, ...]) | Rotate multiple images with the same arguments, randomly or non-randomly. |
| `crop`(x, wrg, hrg[, is_random, row_index, ...]) | Randomly or centrally crop an image. |
| `crop_multi`(x, wrg, hrg[, is_random, ...]) | Randomly or centrally crop multiple images. |
| `flip_axis`(x[, axis, is_random]) | Flip the axis of an image, such as flip left and right, up and down, randomly or non-randomly, |

Continued on next page

Table 2.3 – continued from previous page

| | |
|---|---|
| flip_axis_multi(x, axis[, is_random]) | Flip the axises of multiple images together, such as flip left and right, up and down, randomly or non-randomly, |
| shift(x[, wrg, hrg, is_random, row_index, ...]) | Shift an image randomly or non-randomly. |
| shift_multi(x[, wrg, hrg, is_random, ...]) | Shift images with the same arguments, randomly or non-randomly. |
| shear(x[, intensity, is_random, row_index, ...]) | Shear an image randomly or non-randomly. |
| shear_multi(x[, intensity, is_random, ...]) | Shear images with the same arguments, randomly or non-randomly. |
| shear2(x[, shear, is_random, row_index, ...]) | Shear an image randomly or non-randomly. |
| shear_multi2(x[, shear, is_random, ...]) | Shear images with the same arguments, randomly or non-randomly. |
| swirl(x[, center, strength, radius, ...]) | Swirl an image randomly or non-randomly, see scikit-image swirl API and example. |
| swirl_multi(x[, center, strength, radius, ...]) | Swirl multiple images with the same arguments, randomly or non-randomly. |
| elastic_transform(x, alpha, sigma[, mode, ...]) | Elastic transformation for image as described in [Simard2003]. |
| elastic_transform_multi(x, alpha, sigma[, ...]) | Elastic transformation for images as described in [Simard2003]. |
| zoom(x[, zoom_range, is_random, row_index, ...]) | Zoom in and out of a single image, randomly or non-randomly. |
| zoom_multi(x[, zoom_range, is_random, ...]) | Zoom in and out of images with the same arguments, randomly or non-randomly. |
| brightness(x[, gamma, gain, is_random]) | Change the brightness of a single image, randomly or non-randomly. |
| brightness_multi(x[, gamma, gain, is_random]) | Change the brightness of multiply images, randomly or non-randomly. |
| illumination(x[, gamma, contrast, ...]) | Perform illumination augmentation for a single image, randomly or non-randomly. |
| rgb_to_hsv(rgb) | Input RGB image [0~255] return HSV image [0~1]. |
| hsv_to_rgb(hsv) | Input HSV image [0~1] return RGB image [0~255]. |
| adjust_hue(im[, hout, is_offset, is_clip, ...]) | Adjust hue of an RGB image. |
| imresize(x[, size, interp, mode]) | Resize an image by given output size and method. |
| pixel_value_scale(im[, val, clip, is_random]) | Scales each value in the pixels of the image. |
| samplewise_norm(x[, rescale, ...]) | Normalize an image by rescale, samplewise centering and samplewise centering in order. |
| featurewise_norm(x[, mean, std, epsilon]) | Normalize every pixels by the same given mean and std, which are usually compute from all examples. |
| channel_shift(x, intensity[, is_random, ...]) | Shift the channels of an image, randomly or non-randomly, see numpy.rollaxis. |
| channel_shift_multi(x, intensity[, ...]) | Shift the channels of images with the same arguments, randomly or non-randomly, see numpy.rollaxis. |
| drop(x[, keep]) | Randomly set some pixels to zero by a given keeping probability. |
| transform_matrix_offset_center(matrix, x, y) | Return transform matrix offset center. |
| apply_transform(x, transform_matrix[, ...]) | Return transformed images by given `transform_matrix` from `transform_matrix_offset_center`. |
| projective_transform_by_points(x, src, dst) | Projective transform by given coordinates, usually 4 coordinates. |
| array_to_img(x[, dim_ordering, scale]) | Converts a numpy array to PIL image object (uint8 format). |

Continued on next page

Table 2.3 – continued from previous page

| | |
|---|---|
| `find_contours`(x[, level, fully_connected, ...]) | Find iso-valued contours in a 2D array for a given level value, returns list of (n, 2)-ndarrays see skimage.measure.find_contours. |
| `pt2map`([list_points, size, val]) | Inputs a list of points, return a 2D image. |
| `binary_dilation`(x[, radius]) | Return fast binary morphological dilation of an image. |
| `dilation`(x[, radius]) | Return greyscale morphological dilation of an image, see skimage.morphology.dilation. |
| `binary_erosion`(x[, radius]) | Return binary morphological erosion of an image, see skimage.morphology.binary_erosion. |
| `erosion`(x[, radius]) | Return greyscale morphological erosion of an image, see skimage.morphology.erosion. |
| `obj_box_coord_rescale`([coord, shape]) | Scale down one coordinates from pixel unit to the ratio of image size i.e. |
| `obj_box_coords_rescale`([coords, shape]) | Scale down a list of coordinates from pixel unit to the ratio of image size i.e. |
| `obj_box_coord_scale_to_pixelunit`(coord[, shape]) | Convert one coordinate [x, y, w (or x2), h (or y2)] in ratio format to image coordinate format. |
| `obj_box_coord_centroid_to_upleft_butright`(coord) | Convert one coordinate [x_center, y_center, w, h] to [x1, y1, x2, y2] in up-left and botton-right format. |
| `obj_box_coord_upleft_butright_to_centroid`(coord) | Convert one coordinate [x1, y1, x2, y2] to [x_center, y_center, w, h]. |
| `obj_box_coord_centroid_to_upleft`(coord) | Convert one coordinate [x_center, y_center, w, h] to [x, y, w, h]. |
| `obj_box_coord_upleft_to_centroid`(coord) | Convert one coordinate [x, y, w, h] to [x_center, y_center, w, h]. |
| `parse_darknet_ann_str_to_list`(annotations) | Input string format of class, x, y, w, h, return list of list format. |
| `parse_darknet_ann_list_to_cls_box`(annotations) | Parse darknet annotation format into two lists for class and bounding box. |
| `obj_box_left_right_flip`(im[, coords, ...]) | Left-right flip the image and coordinates for object detection. |
| `obj_box_imresize`(im[, coords, size, interp, ...]) | Resize an image, and compute the new bounding box coordinates. |
| `obj_box_crop`(im[, classes, coords, wrg, ...]) | Randomly or centrally crop an image, and compute the new bounding box coordinates. |
| `obj_box_shift`(im[, classes, coords, wrg, ...]) | Shift an image randomly or non-randomly, and compute the new bounding box coordinates. |
| `obj_box_zoom`(im[, classes, coords, ...]) | Zoom in and out of a single image, randomly or non-randomly, and compute the new bounding box coordinates. |
| `pad_sequences`(sequences[, maxlen, dtype, ...]) | Pads each sequence to the same length: the length of the longest sequence. |
| `remove_pad_sequences`(sequences[, pad_id]) | Remove padding. |
| `process_sequences`(sequences[, end_id, ...]) | Set all tokens(ids) after END token to the padding value, and then shorten (option) it to the maximum sequence length in this batch. |
| `sequences_add_start_id`(sequences[, ...]) | Add special start token(id) in the beginning of each sequence. |
| `sequences_add_end_id`(sequences[, end_id]) | Add special end token(id) in the end of each sequence. |
| `sequences_add_end_id_after_pad`(sequences[, ...]) | Add special end token(id) in the end of each sequence. |
| `sequences_get_mask`(sequences[, pad_val]) | Return mask for sequences. |

### 2.3.1 Threading

`tensorlayer.prepro.`**`threading_data`**(*data=None*, *fn=None*, *thread_count=None*, ***kwargs*)

Process a batch of data by given function by threading.

Usually be used for data augmentation.

**Parameters**

- **data** (*numpy.array or others*) – The data to be processed.
- **thread_count** (*int*) – The number of threads to use.
- **fn** (*function*) – The function for data processing.
- **args** (*more*) – Ssee Examples below.

#### Examples

Process images.

```
>>> images, _, _, _ = tl.files.load_cifar10_dataset(shape=(-1, 32, 32, 3))
>>> images = tl.prepro.threading_data(images[0:32], tl.prepro.zoom, zoom_range=[0.
↪5, 1])
```

Customized image preprocessing function.

```
>>> def distort_img(x):
...     x = tl.prepro.flip_axis(x, axis=0, is_random=True)
...     x = tl.prepro.flip_axis(x, axis=1, is_random=True)
...     x = tl.prepro.crop(x, 100, 100, is_random=True)
...     return x
>>> images = tl.prepro.threading_data(images, distort_img)
```

Process images and masks together (Usually be used for image segmentation).

```
>>> X, Y --> [batch_size, row, col, 1]
>>> data = tl.prepro.threading_data([_ for _ in zip(X, Y)], tl.prepro.zoom_multi,␣
↪zoom_range=[0.5, 1], is_random=True)
... data --> [batch_size, 2, row, col, 1]
>>> X_, Y_ = data.transpose((1,0,2,3,4))
... X_, Y_ --> [batch_size, row, col, 1]
>>> tl.vis.save_image(X_, 'images.png')
>>> tl.vis.save_image(Y_, 'masks.png')
```

Process images and masks together by using `thread_count`.

```
>>> X, Y --> [batch_size, row, col, 1]
>>> data = tl.prepro.threading_data(X, tl.prepro.zoom_multi, 8, zoom_range=[0.5,␣
↪1], is_random=True)
... data --> [batch_size, 2, row, col, 1]
>>> X_, Y_ = data.transpose((1,0,2,3,4))
... X_, Y_ --> [batch_size, row, col, 1]
>>> tl.vis.save_image(X_, 'after.png')
>>> tl.vis.save_image(Y_, 'before.png')
```

Customized function for processing images and masks together.

```
>>> def distort_img(data):
...     x, y = data
...     x, y = tl.prepro.flip_axis_multi([x, y], axis=0, is_random=True)
...     x, y = tl.prepro.flip_axis_multi([x, y], axis=1, is_random=True)
...     x, y = tl.prepro.crop_multi([x, y], 100, 100, is_random=True)
...     return x, y
>>> X, Y --> [batch_size, row, col, channel]
>>> data = tl.prepro.threading_data([_ for _ in zip(X, Y)], distort_img)
>>> X_, Y_ = data.transpose((1,0,2,3,4))
```

**Returns** The processed results.

**Return type** list or numpyarray

### References

- python queue
- run with limited queue

## 2.3.2 Images

- These functions only apply on a single image, use `threading_data` to apply multiple threading see `tutorial_image_preprocess.py`.
- All functions have argument `is_random`.
- All functions end with `*_multi` process all images together, usually be used for image segmentation i.e. the input and output image should be matched.

### Rotation

`tensorlayer.prepro.`**`rotation`**(*x*, *rg=20*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Rotate an image randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **rg** (*int or float*) – Degree to rotate, usually 0 ~ 180.
- **is_random** (*boolean*) – If True, randomly rotate. Default is False
- **col_index and channel_index** (*row_index*) – Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).
- **fill_mode** (*str*) – Method to fill missing pixel, default *nearest*, more options *constant*, *reflect* or *wrap*, see scipy ndimage affine_transform
- **cval** (*float*) – Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0
- **order** (*int*) – The order of interpolation. The order has to be in the range 0-5. See `tl.prepro.apply_transform` and scipy ndimage affine_transform

**Returns** A processed image.

**Return type** numpy.array

### Examples

```
>>> x --> [row, col, 1]
>>> x = tl.prepro.rotation(x, rg=40, is_random=False)
>>> tl.vis.save_image(x, 'im.png')
```

tensorlayer.prepro.**rotation_multi**(*x*, *rg=20*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Rotate multiple images with the same arguments, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.rotation`.

**Returns** A list of processed images.

**Return type** numpy.array

### Examples

```
>>> x, y --> [row, col, 1]  greyscale
>>> x, y = tl.prepro.rotation_multi([x, y], rg=90, is_random=False)
```

## Crop

tensorlayer.prepro.**crop**(*x*, *wrg*, *hrg*, *is_random=False*, *row_index=0*, *col_index=1*)

Randomly or centrally crop an image.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **wrg** (*int*) – Size of width.
- **hrg** (*int*) – Size of height.
- **is_random** (*boolean,*) – If True, randomly crop, else central crop. Default is False.
- **row_index** (*int*) – index of row.
- **col_index** (*int*) – index of column.

**Returns** A processed image.

**Return type** numpy.array

tensorlayer.prepro.**crop_multi**(*x*, *wrg*, *hrg*, *is_random=False*, *row_index=0*, *col_index=1*)

Randomly or centrally crop multiple images.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).

- **others** (*args*) – See `tl.prepro.crop`.

**Returns** A list of processed images.

**Return type** numpy.array

### Flip

`tensorlayer.prepro.`**`flip_axis`**(*x*, *axis=1*, *is_random=False*)

Flip the axis of an image, such as flip left and right, up and down, randomly or non-randomly,

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **axis** (*int*) –

  **Which axis to flip.**

  – 0, flip up and down

  – 1, flip left and right

  – 2, flip channel
- **is_random** (*boolean*) – If True, randomly flip. Default is False.

**Returns** A processed image.

**Return type** numpy.array

`tensorlayer.prepro.`**`flip_axis_multi`**(*x*, *axis*, *is_random=False*)

Flip the axises of multiple images together, such as flip left and right, up and down, randomly or non-randomly,

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.flip_axis`.

**Returns** A list of processed images.

**Return type** numpy.array

### Shift

`tensorlayer.prepro.`**`shift`**(*x*, *wrg=0.1*, *hrg=0.1*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Shift an image randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **wrg** (*float*) – Percentage of shift in axis x, usually -0.25 ~ 0.25.
- **hrg** (*float*) – Percentage of shift in axis y, usually -0.25 ~ 0.25.
- **is_random** (*boolean*) – If True, randomly shift. Default is False.
- **col_index and channel_index** (*row_index*) – Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

- **fill_mode** (*str*) – Method to fill missing pixel, default *nearest*, more options *constant*, *reflect* or *wrap*, see scipy ndimage affine_transform
- **cval** (*float*) – Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.
- **order** (*int*) – The order of interpolation. The order has to be in the range 0-5. See `tl.prepro.apply_transform` and scipy ndimage affine_transform

**Returns** A processed image.

**Return type** numpy.array

`tensorlayer.prepro.`**`shift_multi`**(*x*, *wrg=0.1*, *hrg=0.1*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Shift images with the same arguments, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.shift`.

**Returns** A list of processed images.

**Return type** numpy.array

### Shear

`tensorlayer.prepro.`**`shear`**(*x*, *intensity=0.1*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Shear an image randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **intensity** (*float*) – Percentage of shear, usually -0.5 ~ 0.5 (is_random==True), 0 ~ 0.5 (is_random==False), you can have a quick try by shear(X, 1).
- **is_random** (*boolean*) – If True, randomly shear. Default is False.
- **col_index and channel_index** (*row_index*) – Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).
- **fill_mode** (*str*) – Method to fill missing pixel, default *nearest*, more options *constant*, *reflect* or *wrap*, see and scipy ndimage affine_transform
- **cval** (*float*) – Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.
- **order** (*int*) – The order of interpolation. The order has to be in the range 0-5. See `tl.prepro.apply_transform` and scipy ndimage affine_transform

**Returns** A processed image.

**Return type** numpy.array

#### References

- Affine transformation

`tensorlayer.prepro.shear_multi`(*x*, *intensity=0.1*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Shear images with the same arguments, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.shear`.

**Returns** A list of processed images.

**Return type** numpy.array

### Shear V2

`tensorlayer.prepro.shear2`(*x*, *shear=(0.1, 0.1)*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Shear an image randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **shear** (*tuple of two floats*) – Percentage of shear for height and width direction (0, 1).
- **is_random** (*boolean*) – If True, randomly shear. Default is False.
- **col_index and channel_index** (*row_index*) – Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).
- **fill_mode** (*str*) – Method to fill missing pixel, default *nearest*, more options *constant*, *reflect* or *wrap*, see scipy ndimage affine_transform
- **cval** (*float*) – Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.
- **order** (*int*) – The order of interpolation. The order has to be in the range 0-5. See `tl.prepro.apply_transform` and scipy ndimage affine_transform

**Returns** A processed image.

**Return type** numpy.array

#### References

- Affine transformation

`tensorlayer.prepro.shear_multi2`(*x*, *shear=(0.1, 0.1)*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Shear images with the same arguments, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.shear2`.

**Returns** A list of processed images.

**Return type** numpy.array

### Swirl

`tensorlayer.prepro.swirl`(*x*, *center=None*, *strength=1*, *radius=100*, *rotation=0*, *output_shape=None*, *order=1*, *mode='constant'*, *cval=0*, *clip=True*, *preserve_range=False*, *is_random=False*)

Swirl an image randomly or non-randomly, see scikit-image swirl API and example.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **center** (*tuple or 2 int or None*) – Center coordinate of transformation (optional).
- **strength** (*float*) – The amount of swirling applied.
- **radius** (*float*) – The extent of the swirl in pixels. The effect dies out rapidly beyond radius.
- **rotation** (*float*) – Additional rotation applied to the image, usually [0, 360], relates to center.
- **output_shape** (*tuple of 2 int or None*) – Shape of the output image generated (height, width). By default the shape of the input image is preserved.
- **order** (*int, optional*) – The order of the spline interpolation, default is 1. The order has to be in the range 0-5. See skimage.transform.warp for detail.
- **mode** (*str*) – One of *constant* (default), *edge*, *symmetric reflect* and *wrap*. Points outside the boundaries of the input are filled according to the given mode, with *constant* used as the default. Modes match the behaviour of numpy.pad.
- **cval** (*float*) – Used in conjunction with mode *constant*, the value outside the image boundaries.
- **clip** (*boolean*) – Whether to clip the output to the range of values of the input image. This is enabled by default, since higher order interpolation may produce values outside the given input range.
- **preserve_range** (*boolean*) – Whether to keep the original range of values. Otherwise, the input image is converted according to the conventions of img_as_float.
- **is_random** (*boolean,*) –

  **If True, random swirl. Default is False.**

  - random center = [(0 ~ x.shape[0]), (0 ~ x.shape[1])]
  - random strength = [0, strength]
  - random radius = [1e-10, radius]
  - random rotation = [-rotation, rotation]

**Returns** A processed image.

**Return type** numpy.array

### Examples

```
>>> x --> [row, col, 1] greyscale
>>> x = tl.prepro.swirl(x, strength=4, radius=100)
```

`tensorlayer.prepro.swirl_multi`(*x*, *center=None*, *strength=1*, *radius=100*, *rotation=0*, *output_shape=None*, *order=1*, *mode='constant'*, *cval=0*, *clip=True*, *preserve_range=False*, *is_random=False*)

Swirl multiple images with the same arguments, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.swirl`.

**Returns** A list of processed images.

**Return type** numpy.array

## Elastic transform

`tensorlayer.prepro.elastic_transform`(*x*, *alpha*, *sigma*, *mode='constant'*, *cval=0*, *is_random=False*)

Elastic transformation for image as described in [Simard2003].

**Parameters**

- **x** (*numpy.array*) – A greyscale image.
- **alpha** (*float*) – Alpha value for elastic transformation.
- **sigma** (*float or sequence of float*) – The smaller the sigma, the more transformation. Standard deviation for Gaussian kernel. The standard deviations of the Gaussian filter are given for each axis as a sequence, or as a single number, in which case it is equal for all axes.
- **mode** (*str*) – See scipy.ndimage.filters.gaussian_filter. Default is *constant*.
- **cval** (*float,*) – Used in conjunction with *mode* of *constant*, the value outside the image boundaries.
- **is_random** (*boolean*) – Default is False.

**Returns** A processed image.

**Return type** numpy.array

### Examples

```
>>> x = tl.prepro.elastic_transform(x, alpha=x.shape[1]*3, sigma=x.shape[1]*0.07)
```

### References

- Github.
- Kaggle

`tensorlayer.prepro.`**`elastic_transform_multi`**(*x*, *alpha*, *sigma*, *mode='constant'*, *cval=0*, *is_random=False*)

Elastic transformation for images as described in [Simard2003].

**Parameters**

- **x** (*list of numpy.array*) – List of greyscale images.
- **others** (*args*) – See `tl.prepro.elastic_transform`.

**Returns** A list of processed images.

**Return type** numpy.array

## Zoom

`tensorlayer.prepro.`**`zoom`**(*x*, *zoom_range=(0.9, 1.1)*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Zoom in and out of a single image, randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **zoom_range** (*list or tuple*) –

  **Zoom range for height and width.**

  – If is_random=False, (h, w) are the fixed zoom factor for row and column axies, factor small than one is zoom in.

  – If is_random=True, (h, w) are (min zoom out, max zoom out) for x and y with different random zoom in/out factor, e.g (0.5, 1) zoom in 1~2 times.
- **is_random** (*boolean*) – If True, randomly zoom. Default is False.
- **col_index and channel_index** (*row_index*) – Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).
- **fill_mode** (*str*) – Method to fill missing pixel, default *nearest*, more options *constant*, *reflect* or *wrap*, see scipy ndimage affine_transform
- **cval** (*float*) – Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.
- **order** (*int*) – The order of interpolation. The order has to be in the range 0-5. See `tl.prepro.apply_transform` and scipy ndimage affine_transform

**Returns** A processed image.

**Return type** numpy.array

`tensorlayer.prepro.`**`zoom_multi`**(*x*, *zoom_range=(0.9, 1.1)*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Zoom in and out of images with the same arguments, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.zoom`.

**Returns** A list of processed images.

**Return type** numpy.array

### Brightness

`tensorlayer.prepro.`**`brightness`**(*x*, *gamma=1*, *gain=1*, *is_random=False*)

Change the brightness of a single image, randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **gamma** (*float*) –

  **Non negative real number. Default value is 1.**

  – Small than 1 means brighter.

  – If *is_random* is True, gamma in a range of (1-gamma, 1+gamma).
- **gain** (*float*) – The constant multiplier. Default value is 1.
- **is_random** (*boolean*) – If True, randomly change brightness. Default is False.

**Returns** A processed image.

**Return type** numpy.array

#### References

- skimage.exposure.adjust_gamma
- chinese blog

`tensorlayer.prepro.`**`brightness_multi`**(*x*, *gamma=1*, *gain=1*, *is_random=False*)

Change the brightness of multiply images, randomly or non-randomly. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpyarray*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.brightness`.

**Returns** A list of processed images.

**Return type** numpy.array

### Brightness, contrast and saturation

`tensorlayer.prepro.illumination(x, gamma=1.0, contrast=1.0, saturation=1.0, is_random=False)`

Perform illumination augmentation for a single image, randomly or non-randomly.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **gamma** (*float*) –

  **Change brightness (the same with `tl.prepro.brightness`)**

  – if is_random=False, one float number, small than one means brighter, greater than one means darker.

  – if is_random=True, tuple of two float numbers, (min, max).
- **contrast** (*float*) –

  **Change contrast.**

  – if is_random=False, one float number, small than one means blur.

  – if is_random=True, tuple of two float numbers, (min, max).
- **saturation** (*float*) –

  **Change saturation.**

  – if is_random=False, one float number, small than one means unsaturation.

  – if is_random=True, tuple of two float numbers, (min, max).
- **is_random** (*boolean*) – If True, randomly change illumination. Default is False.

**Returns** A processed image.

**Return type** numpy.array

#### Examples

Random

```
>>> x = tl.prepro.illumination(x, gamma=(0.5, 5.0), contrast=(0.3, 1.0),␣
↪saturation=(0.7, 1.0), is_random=True)
```

Non-random

```
>>> x = tl.prepro.illumination(x, 0.5, 0.6, 0.8, is_random=False)
```

### RGB to HSV

`tensorlayer.prepro.rgb_to_hsv(rgb)`

Input RGB image [0~255] return HSV image [0~1].

**Parameters** **rgb** (*numpy.array*) – An image with values between 0 and 255.

**Returns** A processed image.

**Return type** numpy.array

### HSV to RGB

`tensorlayer.prepro.`**`hsv_to_rgb`**(*hsv*)

Input HSV image [0~1] return RGB image [0~255].

**Parameters** **hsv** (*numpy.array*) – An image with values between 0.0 and 1.0

**Returns** A processed image.

**Return type** numpy.array

### Adjust Hue

`tensorlayer.prepro.`**`adjust_hue`**(*im*, *hout=0.66*, *is_offset=True*, *is_clip=True*, *is_random=False*)

Adjust hue of an RGB image.

This is a convenience method that converts an RGB image to float representation, converts it to HSV, add an offset to the hue channel, converts back to RGB and then back to the original data type. For TF, see tf.image.adjust_hue.and tf.image.random_hue.

**Parameters**

- **im** (*numpy.array*) – An image with values between 0 and 255.
- **hout** (*float*) –

  **The scale value for adjusting hue.**

  – If is_offset is False, set all hue values to this value. 0 is red; 0.33 is green; 0.66 is blue.

  – If is_offset is True, add this value as the offset to the hue channel.
- **is_offset** (*boolean*) – Whether *hout* is added on HSV as offset or not. Default is True.
- **is_clip** (*boolean*) – If HSV value smaller than 0, set to 0. Default is True.
- **is_random** (*boolean*) – If True, randomly change hue. Default is False.

**Returns** A processed image.

**Return type** numpy.array

#### Examples

Random, add a random value between -0.2 and 0.2 as the offset to every hue values.

```
>>> im_hue = tl.prepro.adjust_hue(image, hout=0.2, is_offset=True, is_
↪random=False)
```

Non-random, make all hue to green.

```
>>> im_green = tl.prepro.adjust_hue(image, hout=0.66, is_offset=False, is_
↪random=False)
```

#### References

- tf.image.random_hue.
- tf.image.adjust_hue.

- StackOverflow: Changing image hue with python PIL.

### Resize

tensorlayer.prepro.**imresize**(*x*, *size=None*, *interp='bicubic'*, *mode=None*)

Resize an image by given output size and method.

Warning, this function will rescale the value to [0, 255].

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **size** (*list of 2 int or None*) – For height and width.
- **interp** (*str*) – Interpolation method for re-sizing (*nearest*, *lanczos*, *bilinear*, *bicubic* (default) or *cubic*).
- **mode** (*str*) – The PIL image mode (*P*, *L*, etc.) to convert arr before resizing.

**Returns** A processed image.

**Return type** numpy.array

#### References

- scipy.misc.imresize

### Pixel value scale

tensorlayer.prepro.**pixel_value_scale**(*im*, *val=0.9*, *clip=(-inf, inf)*, *is_random=False*)

Scales each value in the pixels of the image.

**Parameters**

- **im** (*numpy.array*) – An image.
- **val** (*float*) –

  **The scale value for changing pixel value.**

  – If is_random=False, multiply this value with all pixels.

  – If is_random=True, multiply a value between [1-val, 1+val] with all pixels.
- **clip** (*tuple of 2 numbers*) – The minimum and maximum value.
- **is_random** (*boolean*) – If True, see `val`.

**Returns** A processed image.

**Return type** numpy.array

#### Examples

Random

```
>>> im = pixel_value_scale(im, 0.1, [0, 255], is_random=True)
```

Non-random

```
>>> im = pixel_value_scale(im, 0.9, [0, 255], is_random=False)
```

### Normalization

tensorlayer.prepro.**samplewise_norm**(*x*, *rescale=None*, *samplewise_center=False*, *samplewise_std_normalization=False*, *channel_index=2*, *epsilon=1e-07*)

Normalize an image by rescale, samplewise centering and samplewise centering in order.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **rescale** (*float*) – Rescaling factor. If None or 0, no rescaling is applied, otherwise we multiply the data by the value provided (before applying any other transformation)
- **samplewise_center** (*boolean*) – If True, set each sample mean to 0.
- **samplewise_std_normalization** (*boolean*) – If True, divide each input by its std.
- **epsilon** (*float*) – A small position value for dividing standard deviation.

**Returns** A processed image.

**Return type** numpy.array

#### Examples

```
>>> x = samplewise_norm(x, samplewise_center=True, samplewise_std_
↪normalization=True)
>>> print(x.shape, np.mean(x), np.std(x))
... (160, 176, 1), 0.0, 1.0
```

#### Notes

When samplewise_center and samplewise_std_normalization are True. - For greyscale image, every pixels are subtracted and divided by the mean and std of whole image. - For RGB image, every pixels are subtracted and divided by the mean and std of this pixel i.e. the mean and std of a pixel is 0 and 1.

tensorlayer.prepro.**featurewise_norm**(*x*, *mean=None*, *std=None*, *epsilon=1e-07*)

Normalize every pixels by the same given mean and std, which are usually compute from all examples.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **mean** (*float*) – Value for subtraction.
- **std** (*float*) – Value for division.
- **epsilon** (*float*) – A small position value for dividing standard deviation.

**Returns** A processed image.

**Return type** numpy.array

### Channel shift

tensorlayer.prepro.**channel_shift**(*x*, *intensity*, *is_random=False*, *channel_index=2*)
Shift the channels of an image, randomly or non-randomly, see numpy.rollaxis.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **intensity** (*float*) – Intensity of shifting.
- **is_random** (*boolean*) – If True, randomly shift. Default is False.
- **channel_index** (*int*) – Index of channel. Default is 2.

**Returns** A processed image.

**Return type** numpy.array

tensorlayer.prepro.**channel_shift_multi**(*x*, *intensity*, *is_random=False*, *channel_index=2*)
Shift the channels of images with the same arguments, randomly or non-randomly, see numpy.rollaxis. Usually be used for image segmentation which x=[X, Y], X and Y should be matched.

**Parameters**

- **x** (*list of numpy.array*) – List of images with dimension of [n_images, row, col, channel] (default).
- **others** (*args*) – See `tl.prepro.channel_shift`.

**Returns** A list of processed images.

**Return type** numpy.array

### Noise

tensorlayer.prepro.**drop**(*x*, *keep=0.5*)
Randomly set some pixels to zero by a given keeping probability.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] or [row, col].
- **keep** (*float*) – The keeping probability (0, 1), the lower more values will be set to zero.

**Returns** A processed image.

**Return type** numpy.array

### Transform matrix offset

tensorlayer.prepro.**transform_matrix_offset_center**(*matrix*, *x*, *y*)
Return transform matrix offset center.

**Parameters**

- **matrix** (*numpy.array*) – Transform matrix.
- **and y** (*x*) – Size of image.

**Returns** The transform matrix.

**Return type** numpy.array

### Examples

- See `tl.prepro.rotation`, `tl.prepro.shear`, `tl.prepro.zoom`.

## Apply affine transform by matrix

`tensorlayer.prepro.`**`apply_transform`**(*x*, *transform_matrix*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*)

Return transformed images by given `transform_matrix` from `transform_matrix_offset_center`.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **transform_matrix** (*numpy.array*) – Transform matrix (offset center), can be generated by `transform_matrix_offset_center`
- **channel_index** (*int*) – Index of channel, default 2.
- **fill_mode** (*str*) – Method to fill missing pixel, default *nearest*, more options *constant*, *reflect* or *wrap*, see scipy ndimage affine_transform
- **cval** (*float*) – Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0
- **order** (*int*) –

  **The order of interpolation. The order has to be in the range 0-5:**

  - 0 Nearest-neighbor
  - 1 Bi-linear (default)
  - 2 Bi-quadratic
  - 3 Bi-cubic
  - 4 Bi-quartic
  - 5 Bi-quintic
  - scipy ndimage affine_transform

**Returns** A processed image.

**Return type** numpy.array

### Examples

- See `tl.prepro.rotation`, `tl.prepro.shift`, `tl.prepro.shear`, `tl.prepro.zoom`.

## Projective transform by points

`tensorlayer.prepro.`**`projective_transform_by_points`**(*x*, *src*, *dst*, *map_args=None*, *output_shape=None*, *order=1*, *mode='constant'*, *cval=0.0*, *clip=True*, *preserve_range=False*)

Projective transform by given coordinates, usually 4 coordinates.

see scikit-image.

**Parameters**

- **x** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **src** (*list or numpy*) – The original coordinates, usually 4 coordinates of (width, height).
- **dst** (*list or numpy*) – The coordinates after transformation, the number of coordinates is the same with src.
- **map_args** (*dictionary or None*) – Keyword arguments passed to inverse map.
- **output_shape** (*tuple of 2 int*) – Shape of the output image generated. By default the shape of the input image is preserved. Note that, even for multi-band images, only rows and columns need to be specified.
- **order** (*int*) –

  **The order of interpolation. The order has to be in the range 0-5:**

  - 0 Nearest-neighbor
  - 1 Bi-linear (default)
  - 2 Bi-quadratic
  - 3 Bi-cubic
  - 4 Bi-quartic
  - 5 Bi-quintic
- **mode** (*str*) – One of *constant* (default), *edge*, *symmetric*, *reflect* or *wrap*. Points outside the boundaries of the input are filled according to the given mode. Modes match the behaviour of numpy.pad.
- **cval** (*float*) – Used in conjunction with mode *constant*, the value outside the image boundaries.
- **clip** (*boolean*) – Whether to clip the output to the range of values of the input image. This is enabled by default, since higher order interpolation may produce values outside the given input range.
- **preserve_range** (*boolean*) – Whether to keep the original range of values. Otherwise, the input image is converted according to the conventions of img_as_float.

**Returns** A processed image.

**Return type** numpy.array

### Examples

Assume X is an image from CIFAR-10, i.e. shape == (32, 32, 3)

```
>>> src = [[0,0],[0,32],[32,0],[32,32]]     # [w, h]
>>> dst = [[10,10],[0,32],[32,0],[32,32]]
>>> x = tl.prepro.projective_transform_by_points(X, src, dst)
```

### References

- scikit-image : geometric transformations

- scikit-image : examples

### Numpy and PIL

tensorlayer.prepro.**array_to_img**(*x*, *dim_ordering=(0, 1, 2)*, *scale=True*)
Converts a numpy array to PIL image object (uint8 format).

**Parameters**

- **x** (*numpy.array*) – An image with dimension of 3 and channels of 1 or 3.
- **dim_ordering** (*tuple of 3 int*) – Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).
- **scale** (*boolean*) – If True, converts image to [0, 255] from any range of value like [-1, 2]. Default is True.

**Returns** An image.

**Return type** PIL.image

#### References

PIL Image.fromarray

### Find contours

tensorlayer.prepro.**find_contours**(*x*, *level=0.8*, *fully_connected='low'*, *positive_orientation='low'*)
Find iso-valued contours in a 2D array for a given level value, returns list of (n, 2)-ndarrays see skimage.measure.find_contours.

**Parameters**

- **x** (*2D ndarray of double.*) – Input data in which to find contours.
- **level** (*float*) – Value along which to find contours in the array.
- **fully_connected** (*str*) – Either *low* or *high*. Indicates whether array elements below the given level value are to be considered fully-connected (and hence elements above the value will only be face connected), or vice-versa. (See notes below for details.)
- **positive_orientation** (*str*) – Either *low* or *high*. Indicates whether the output contours will produce positively-oriented polygons around islands of low- or high-valued elements. If *low* then contours will wind counter-clockwise around elements below the iso-value. Alternately, this means that low-valued elements are always on the left of the contour.

**Returns** Each contour is an ndarray of shape (n, 2), consisting of n (row, column) coordinates along the contour.

**Return type** list of (n,2)-ndarrays

### Points to Image

tensorlayer.prepro.**pt2map**(*list_points=None*, *size=(100, 100)*, *val=1*)
Inputs a list of points, return a 2D image.

**Parameters**

- **list_points** (*list of 2 int*) – [[x, y], [x, y]..] for point coordinates.
- **size** (*tuple of 2 int*) – (w, h) for output size.
- **val** (*float or int*) – For the contour value.

**Returns** An image.

**Return type** numpy.array

### Binary dilation

`tensorlayer.prepro.`**`binary_dilation`**`(`*x*, *radius=3*`)`

Return fast binary morphological dilation of an image. see skimage.morphology.binary_dilation.

**Parameters**

- **x** (*2D array*) – A binary image.
- **radius** (*int*) – For the radius of mask.

**Returns** A processed binary image.

**Return type** numpy.array

### Greyscale dilation

`tensorlayer.prepro.`**`dilation`**`(`*x*, *radius=3*`)`

Return greyscale morphological dilation of an image, see skimage.morphology.dilation.

**Parameters**

- **x** (*2D array*) – An greyscale image.
- **radius** (*int*) – For the radius of mask.

**Returns** A processed greyscale image.

**Return type** numpy.array

### Binary erosion

`tensorlayer.prepro.`**`binary_erosion`**`(`*x*, *radius=3*`)`

Return binary morphological erosion of an image, see skimage.morphology.binary_erosion.

**Parameters**

- **x** (*2D array*) – A binary image.
- **radius** (*int*) – For the radius of mask.

**Returns** A processed binary image.

**Return type** numpy.array

### Greyscale erosion

`tensorlayer.prepro.`**`erosion`**`(`*x*, *radius=3*`)`

Return greyscale morphological erosion of an image, see skimage.morphology.erosion.

**Parameters**

- **x** (*2D array*) – A greyscale image.
- **radius** (*int*) – For the radius of mask.

**Returns** A processed greyscale image.

**Return type** numpy.array

### 2.3.3 Object detection

#### Tutorial for Image Aug

Hi, here is an example for image augmentation on VOC dataset.

```
import tensorlayer as tl

## download VOC 2012 dataset
imgs_file_list, _, _, _, classes, _, _,\
    _, objs_info_list, _ = tl.files.load_voc_dataset(dataset="2012")

## parse annotation and convert it into list format
ann_list = []
for info in objs_info_list:
    ann = tl.prepro.parse_darknet_ann_str_to_list(info)
    c, b = tl.prepro.parse_darknet_ann_list_to_cls_box(ann)
    ann_list.append([c, b])

# read and save one image
idx = 2  # you can select your own image
image = tl.vis.read_image(imgs_file_list[idx])
tl.vis.draw_boxes_and_labels_to_image(image, ann_list[idx][0],
     ann_list[idx][1], [], classes, True, save_name='_im_original.png')

# left right flip
im_flip, coords = tl.prepro.obj_box_left_right_flip(image,
        ann_list[idx][1], is_rescale=True, is_center=True, is_random=False)
tl.vis.draw_boxes_and_labels_to_image(im_flip, ann_list[idx][0],
        coords, [], classes, True, save_name='_im_flip.png')

# resize
im_resize, coords = tl.prepro.obj_box_imresize(image,
        coords=ann_list[idx][1], size=[300, 200], is_rescale=True)
tl.vis.draw_boxes_and_labels_to_image(im_resize, ann_list[idx][0],
        coords, [], classes, True, save_name='_im_resize.png')

# crop
im_crop, clas, coords = tl.prepro.obj_box_crop(image, ann_list[idx][0],
         ann_list[idx][1], wrg=200, hrg=200,
         is_rescale=True, is_center=True, is_random=False)
tl.vis.draw_boxes_and_labels_to_image(im_crop, clas, coords, [],
         classes, True, save_name='_im_crop.png')

# shift
im_shfit, clas, coords = tl.prepro.obj_box_shift(image, ann_list[idx][0],
        ann_list[idx][1], wrg=0.1, hrg=0.1,
        is_rescale=True, is_center=True, is_random=False)
tl.vis.draw_boxes_and_labels_to_image(im_shfit, clas, coords, [],
        classes, True, save_name='_im_shift.png')
```

```
# zoom
im_zoom, clas, coords = tl.prepro.obj_box_zoom(image, ann_list[idx][0],
        ann_list[idx][1], zoom_range=(1.3, 0.7),
        is_rescale=True, is_center=True, is_random=False)
tl.vis.draw_boxes_and_labels_to_image(im_zoom, clas, coords, [],
        classes, True, save_name='_im_zoom.png')
```

In practice, you may want to use threading method to process a batch of images as follows.

```
import tensorlayer as tl
import random

batch_size = 64
im_size = [416, 416]
n_data = len(imgs_file_list)
jitter = 0.2
def _data_pre_aug_fn(data):
    im, ann = data
    clas, coords = ann
    ## change image brightness, contrast and saturation randomly
    im = tl.prepro.illumination(im, gamma=(0.5, 1.5),
             contrast=(0.5, 1.5), saturation=(0.5, 1.5), is_random=True)
    ## flip randomly
    im, coords = tl.prepro.obj_box_left_right_flip(im, coords,
             is_rescale=True, is_center=True, is_random=True)
    ## randomly resize and crop image, it can have same effect as random zoom
    tmp0 = random.randint(1, int(im_size[0]*jitter))
    tmp1 = random.randint(1, int(im_size[1]*jitter))
    im, coords = tl.prepro.obj_box_imresize(im, coords,
            [im_size[0]+tmp0, im_size[1]+tmp1], is_rescale=True,
             interp='bicubic')
    im, clas, coords = tl.prepro.obj_box_crop(im, clas, coords,
             wrg=im_size[1], hrg=im_size[0], is_rescale=True,
             is_center=True, is_random=True)
    ## rescale value from [0, 255] to [-1, 1] (optional)
    im = im / 127.5 - 1
    return im, [clas, coords]

# randomly read a batch of image and the corresponding annotations
idexs = tl.utils.get_random_int(min=0, max=n_data-1, number=batch_size)
b_im_path = [imgs_file_list[i] for i in idexs]
b_images = tl.prepro.threading_data(b_im_path, fn=tl.vis.read_image)
b_ann = [ann_list[i] for i in idexs]

# threading process
data = tl.prepro.threading_data([_ for _ in zip(b_images, b_ann)],
              _data_pre_aug_fn)
b_images2 = [d[0] for d in data]
b_ann = [d[1] for d in data]

# save all images
for i in range(len(b_images)):
    tl.vis.draw_boxes_and_labels_to_image(b_images[i],
             ann_list[idexs[i]][0], ann_list[idexs[i]][1], [],
             classes, True, save_name='_bbox_vis_%d_original.png' % i)
    tl.vis.draw_boxes_and_labels_to_image((b_images2[i]+1)*127.5,
             b_ann[i][0], b_ann[i][1], [], classes, True,
```

```
            save_name='_bbox_vis_%d.png' % i)
```

### Coordinate pixel unit to percentage

`tensorlayer.prepro.`**`obj_box_coord_rescale`**(*coord=None*, *shape=None*)

Scale down one coordinates from pixel unit to the ratio of image size i.e. in the range of [0, 1]. It is the reverse process of `obj_box_coord_scale_to_pixelunit`.

**Parameters**

- **coords** (*list of 4 int or None*) – One coordinates of one image e.g. [x, y, w, h].
- **shape** (*list of 2 int or None*) – For [height, width].

**Returns** New bounding box.

**Return type** list of 4 numbers

#### Examples

```
>>> coord = tl.prepro.obj_box_coord_rescale(coord=[30, 40, 50, 50], shape=[100,␣
↪100])
... [0.3, 0.4, 0.5, 0.5]
```

### Coordinates pixel unit to percentage

`tensorlayer.prepro.`**`obj_box_coords_rescale`**(*coords=None*, *shape=None*)

Scale down a list of coordinates from pixel unit to the ratio of image size i.e. in the range of [0, 1].

**Parameters**

- **coords** (*list of list of 4 ints or None*) – For coordinates of more than one images .e.g.[[x, y, w, h], [x, y, w, h], …].
- **shape** (*list of 2 int or None*) – height, width].

**Returns** A list of new bounding boxes.

**Return type** list of list of 4 numbers

#### Examples

```
>>> coords = obj_box_coords_rescale(coords=[[30, 40, 50, 50], [10, 10, 20, 20]],␣
↪shape=[100, 100])
>>> print(coords)
... [[0.3, 0.4, 0.5, 0.5], [0.1, 0.1, 0.2, 0.2]]
>>> coords = obj_box_coords_rescale(coords=[[30, 40, 50, 50]], shape=[50, 100])
>>> print(coords)
... [[0.3, 0.8, 0.5, 1.0]]
>>> coords = obj_box_coords_rescale(coords=[[30, 40, 50, 50]], shape=[100, 200])
>>> print(coords)
... [[0.15, 0.4, 0.25, 0.5]]
```

**Returns** New coordinates.

**Return type** list of 4 numbers

### Coordinate percentage to pixel unit

`tensorlayer.prepro.`**`obj_box_coord_scale_to_pixelunit`**(*coord*, *shape=None*)

Convert one coordinate [x, y, w (or x2), h (or y2)] in ratio format to image coordinate format. It is the reverse process of `obj_box_coord_rescale`.

**Parameters**

- **coord** (*list of 4 float*) – One coordinate of one image [x, y, w (or x2), h (or y2)] in ratio format, i.e value range [0~1].
- **shape** (*tuple of 2 or None*) – For [height, width].

**Returns** New bounding box.

**Return type** list of 4 numbers

#### Examples

```
>>> x, y, x2, y2 = tl.prepro.obj_box_coord_scale_to_pixelunit([0.2, 0.3, 0.5, 0.
↪7], shape=(100, 200, 3))
... [40, 30, 100, 70]
```

### Coordinate [x_center, x_center, w, h] to up-left button-right

`tensorlayer.prepro.`**`obj_box_coord_centroid_to_upleft_butright`**(*coord*, *to_int=False*)

Convert one coordinate [x_center, y_center, w, h] to [x1, y1, x2, y2] in up-left and botton-right format.

**Parameters**

- **coord** (*list of 4 int/float*) – One coordinate.
- **to_int** (*boolean*) – Whether to convert output as integer.

**Returns** New bounding box.

**Return type** list of 4 numbers

#### Examples

```
>>> coord = obj_box_coord_centroid_to_upleft_butright([30, 40, 20, 20])
... [20, 30, 40, 50]
```

### Coordinate up-left button-right to [x_center, x_center, w, h]

`tensorlayer.prepro.`**`obj_box_coord_upleft_butright_to_centroid`**(*coord*)

Convert one coordinate [x1, y1, x2, y2] to [x_center, y_center, w, h]. It is the reverse process of `obj_box_coord_centroid_to_upleft_butright`.

**Parameters** **coord** (*list of 4 int/float*) – One coordinate.

**Returns** New bounding box.

**Return type** list of 4 numbers

### Coordinate [x_center, x_center, w, h] to up-left-width-high

`tensorlayer.prepro.`**`obj_box_coord_centroid_to_upleft`**(*coord*)

Convert one coordinate [x_center, y_center, w, h] to [x, y, w, h]. It is the reverse process of `obj_box_coord_upleft_to_centroid`.

**Parameters** **`coord`** (*`list of 4 int/float`*) – One coordinate.

**Returns** New bounding box.

**Return type** list of 4 numbers

### Coordinate up-left-width-high to [x_center, x_center, w, h]

`tensorlayer.prepro.`**`obj_box_coord_upleft_to_centroid`**(*coord*)

Convert one coordinate [x, y, w, h] to [x_center, y_center, w, h]. It is the reverse process of `obj_box_coord_centroid_to_upleft`.

**Parameters** **`coord`** (*`list of 4 int/float`*) – One coordinate.

**Returns** New bounding box.

**Return type** list of 4 numbers

### Darknet format string to list

`tensorlayer.prepro.`**`parse_darknet_ann_str_to_list`**(*annotations*)

Input string format of class, x, y, w, h, return list of list format.

**Parameters** **`annotations`** (*`str`*) – The annotations in darkent format "class, x, y, w, h ...." seperated by "n".

**Returns** List of bounding box.

**Return type** list of list of 4 numbers

### Darknet format split class and coordinate

`tensorlayer.prepro.`**`parse_darknet_ann_list_to_cls_box`**(*annotations*)

Parse darknet annotation format into two lists for class and bounding box.

Input list of [[class, x, y, w, h], . . . ], return two list of [class . . . ] and [[x, y, w, h], . . . ].

**Parameters** **`annotations`** (*`list of list`*) – A list of class and bounding boxes of images e.g. [[class, x, y, w, h], . . . ]

**Returns**

- *list of int* – List of class labels.
- *list of list of 4 numbers* – List of bounding box.

### Image Aug - Flip

tensorlayer.prepro.**obj_box_left_right_flip**(*im*, *coords=None*, *is_rescale=False*, *is_center=False*, *is_random=False*)

Left-right flip the image and coordinates for object detection.

**Parameters**

- **im** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **coords** (*list of list of 4 int/float or None*) – Coordinates [[x, y, w, h], [x, y, w, h], ...].
- **is_rescale** (*boolean*) – Set to True, if the input coordinates are rescaled to [0, 1]. Default is False.
- **is_center** (*boolean*) – Set to True, if the x and y of coordinates are the centroid (i.e. darknet format). Default is False.
- **is_random** (*boolean*) – If True, randomly flip. Default is False.

**Returns**

- *numpy.array* – A processed image
- *list of list of 4 numbers* – A list of new bounding boxes.

#### Examples

```
>>> im = np.zeros([80, 100])    # as an image with shape width=100, height=80
>>> im, coords = obj_box_left_right_flip(im, coords=[[0.2, 0.4, 0.3, 0.3], [0.1,␣
↪0.5, 0.2, 0.3]], is_rescale=True, is_center=True, is_random=False)
>>> print(coords)
... [[0.8, 0.4, 0.3, 0.3], [0.9, 0.5, 0.2, 0.3]]
>>> im, coords = obj_box_left_right_flip(im, coords=[[0.2, 0.4, 0.3, 0.3]], is_
↪rescale=True, is_center=False, is_random=False)
>>> print(coords)
... [[0.5, 0.4, 0.3, 0.3]]
>>> im, coords = obj_box_left_right_flip(im, coords=[[20, 40, 30, 30]], is_
↪rescale=False, is_center=True, is_random=False)
>>> print(coords)
... [[80, 40, 30, 30]]
>>> im, coords = obj_box_left_right_flip(im, coords=[[20, 40, 30, 30]], is_
↪rescale=False, is_center=False, is_random=False)
>>> print(coords)
... [[50, 40, 30, 30]]
```

### Image Aug - Resize

tensorlayer.prepro.**obj_box_imresize**(*im*, *coords=None*, *size=None*, *interp='bicubic'*, *mode=None*, *is_rescale=False*)

Resize an image, and compute the new bounding box coordinates.

**Parameters**

- **im** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **coords** (*list of list of 4 int/float or None*) – Coordinates [[x, y, w, h], [x, y, w, h], ...]

- **interp and mode** (*size*) – See `tl.prepro.imresize`.
- **is_rescale** (*boolean*) – Set to True, if the input coordinates are rescaled to [0, 1], then return the original coordinates. Default is False.

**Returns**

- *numpy.array* – A processed image
- *list of list of 4 numbers* – A list of new bounding boxes.

### Examples

```
>>> im = np.zeros([80, 100, 3])    # as an image with shape width=100, height=80
>>> _, coords = obj_box_imresize(im, coords=[[20, 40, 30, 30], [10, 20, 20, 20]],␣
↪size=[160, 200], is_rescale=False)
>>> print(coords)
... [[40, 80, 60, 60], [20, 40, 40, 40]]
>>> _, coords = obj_box_imresize(im, coords=[[20, 40, 30, 30]], size=[40, 100],␣
↪is_rescale=False)
>>> print(coords)
... [[20, 20, 30, 15]]
>>> _, coords = obj_box_imresize(im, coords=[[20, 40, 30, 30]], size=[60, 150],␣
↪is_rescale=False)
>>> print(coords)
... [[30, 30, 45, 22]]
>>> im2, coords = obj_box_imresize(im, coords=[[0.2, 0.4, 0.3, 0.3]], size=[160,␣
↪200], is_rescale=True)
>>> print(coords, im2.shape)
... [[0.2, 0.4, 0.3, 0.3]] (160, 200, 3)
```

## Image Aug - Crop

`tensorlayer.prepro.`**`obj_box_crop`**(*im, classes=None, coords=None, wrg=100, hrg=100, is_rescale=False, is_center=False, is_random=False, thresh_wh=0.02, thresh_wh2=12.0*)

Randomly or centrally crop an image, and compute the new bounding box coordinates. Objects outside the cropped image will be removed.

**Parameters**

- **im** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **classes** (*list of int or None*) – Class IDs.
- **coords** (*list of list of 4 int/float or None*) – Coordinates [[x, y, w, h], [x, y, w, h], . . . ]
- **hrg and is_random** (*wrg*) – See `tl.prepro.crop`.
- **is_rescale** (*boolean*) – Set to True, if the input coordinates are rescaled to [0, 1]. Default is False.
- **is_center** (*boolean, default False*) – Set to True, if the x and y of coordinates are the centroid (i.e. darknet format). Default is False.
- **thresh_wh** (*float*) – Threshold, remove the box if its ratio of width(height) to image size less than the threshold.

- **thresh_wh2** (*float*) – Threshold, remove the box if its ratio of width to height or vice verse higher than the threshold.

**Returns**

- *numpy.array* – A processed image
- *list of int* – A list of classes
- *list of list of 4 numbers* – A list of new bounding boxes.

### Image Aug - Shift

tensorlayer.prepro.**obj_box_shift**(*im*, *classes=None*, *coords=None*, *wrg=0.1*, *hrg=0.1*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*, *is_rescale=False*, *is_center=False*, *is_random=False*, *thresh_wh=0.02*, *thresh_wh2=12.0*)

Shift an image randomly or non-randomly, and compute the new bounding box coordinates. Objects outside the cropped image will be removed.

**Parameters**

- **im** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **classes** (*list of int or None*) – Class IDs.
- **coords** (*list of list of 4 int/float or None*) – Coordinates [[x, y, w, h], [x, y, w, h], . . . ]
- **hrg row_index col_index channel_index is_random fill_mode cval and order** (*wrg,*) –
- **is_rescale** (*boolean*) – Set to True, if the input coordinates are rescaled to [0, 1]. Default is False.
- **is_center** (*boolean*) – Set to True, if the x and y of coordinates are the centroid (i.e. darknet format). Default is False.
- **thresh_wh** (*float*) – Threshold, remove the box if its ratio of width(height) to image size less than the threshold.
- **thresh_wh2** (*float*) – Threshold, remove the box if its ratio of width to height or vice verse higher than the threshold.

**Returns**

- *numpy.array* – A processed image
- *list of int* – A list of classes
- *list of list of 4 numbers* – A list of new bounding boxes.

### Image Aug - Zoom

tensorlayer.prepro.**obj_box_zoom**(*im*, *classes=None*, *coords=None*, *zoom_range=(0.9, 1.1)*, *row_index=0*, *col_index=1*, *channel_index=2*, *fill_mode='nearest'*, *cval=0.0*, *order=1*, *is_rescale=False*, *is_center=False*, *is_random=False*, *thresh_wh=0.02*, *thresh_wh2=12.0*)

Zoom in and out of a single image, randomly or non-randomly, and compute the new bounding box coordinates. Objects outside the cropped image will be removed.

**Parameters**

- **im** (*numpy.array*) – An image with dimension of [row, col, channel] (default).
- **classes** (*list of int or None*) – Class IDs.
- **coords** (*list of list of 4 int/float or None*) – Coordinates [[x, y, w, h], [x, y, w, h], . . . ].
- **row_index col_index channel_index is_random fill_mode cval and order** (*zoom_range*) –
- **is_rescale** (*boolean*) – Set to True, if the input coordinates are rescaled to [0, 1]. Default is False.
- **is_center** (*boolean*) – Set to True, if the x and y of coordinates are the centroid. (i.e. darknet format). Default is False.
- **thresh_wh** (*float*) – Threshold, remove the box if its ratio of width(height) to image size less than the threshold.
- **thresh_wh2** (*float*) – Threshold, remove the box if its ratio of width to height or vice verse higher than the threshold.

**Returns**

- *numpy.array* – A processed image
- *list of int* – A list of classes
- *list of list of 4 numbers* – A list of new bounding boxes.

## 2.3.4 Sequence

More related functions can be found in `tensorlayer.nlp`.

### Padding

`tensorlayer.prepro.`**`pad_sequences`**(*sequences*, *maxlen=None*, *dtype='int32'*, *padding='post'*, *truncating='pre'*, *value=0.0*)

Pads each sequence to the same length: the length of the longest sequence. If maxlen is provided, any sequence longer than maxlen is truncated to maxlen. Truncation happens off either the beginning (default) or the end of the sequence. Supports post-padding and pre-padding (default).

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **maxlen** (*int*) – Maximum length.
- **dtype** (*numpy.dtype or str*) – Data type to cast the resulting sequence.
- **padding** (*str*) – Either 'pre' or 'post', pad either before or after each sequence.
- **truncating** (*str*) – Either 'pre' or 'post', remove values from sequences larger than maxlen either in the beginning or in the end of the sequence
- **value** (*float*) – Value to pad the sequences to the desired value.

**Returns** **x** – With dimensions (number_of_sequences, maxlen)

**Return type** numpy.array

### Examples

```
>>> sequences = [[1,1,1,1,1],[2,2,2],[3,3]]
>>> sequences = pad_sequences(sequences, maxlen=None, dtype='int32',
...                 padding='post', truncating='pre', value=0.)
... [[1 1 1 1 1]
...  [2 2 2 0 0]
...  [3 3 0 0 0]]
```

## Remove Padding

tensorlayer.prepro.**remove_pad_sequences**(*sequences*, *pad_id=0*)
Remove padding.

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **pad_id** (*int*) – The pad ID.

**Returns** The processed sequences.

**Return type** list of list of int

### Examples

```
>>> sequences = [[2,3,4,0,0], [5,1,2,3,4,0,0,0], [4,5,0,2,4,0,0,0]]
>>> print(remove_pad_sequences(sequences, pad_id=0))
... [[2, 3, 4], [5, 1, 2, 3, 4], [4, 5, 0, 2, 4]]
```

## Process

tensorlayer.prepro.**process_sequences**(*sequences*, *end_id=0*, *pad_val=0*, *is_shorten=True*, *remain_end_id=False*)
Set all tokens(ids) after END token to the padding value, and then shorten (option) it to the maximum sequence length in this batch.

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **end_id** (*int*) – The special token for END.
- **pad_val** (*int*) – Replace the *end_id* and the IDs after *end_id* to this value.
- **is_shorten** (*boolean*) – Shorten the sequences. Default is True.
- **remain_end_id** (*boolean*) – Keep an *end_id* in the end. Default is False.

**Returns** The processed sequences.

**Return type** list of list of int

### Examples

```
>>> sentences_ids = [[4, 3, 5, 3, 2, 2, 2, 2],  <-- end_id is 2
...                  [5, 3, 9, 4, 9, 2, 2, 3]]  <-- end_id is 2
>>> sentences_ids = precess_sequences(sentences_ids, end_id=vocab.end_id, pad_
↪val=0, is_shorten=True)
... [[4, 3, 5, 3, 0], [5, 3, 9, 4, 9]]
```

## Add Start ID

tensorlayer.prepro.**sequences_add_start_id**(*sequences*, *start_id=0*, *remove_last=False*)
Add special start token(id) in the beginning of each sequence.

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **start_id** (*int*) – The start ID.
- **remove_last** (*boolean*) – Remove the last value of each sequences. Usually be used for removing the end ID.

**Returns** The processed sequences.

**Return type** list of list of int

### Examples

```
>>> sentences_ids = [[4,3,5,3,2,2,2,2], [5,3,9,4,9,2,2,3]]
>>> sentences_ids = sequences_add_start_id(sentences_ids, start_id=2)
... [[2, 4, 3, 5, 3, 2, 2, 2, 2], [2, 5, 3, 9, 4, 9, 2, 2, 3]]
>>> sentences_ids = sequences_add_start_id(sentences_ids, start_id=2, remove_
↪last=True)
... [[2, 4, 3, 5, 3, 2, 2, 2], [2, 5, 3, 9, 4, 9, 2, 2]]
```

For Seq2seq

```
>>> input = [a, b, c]
>>> target = [x, y, z]
>>> decode_seq = [start_id, a, b] <-- sequences_add_start_id(input, start_id,␣
↪True)
```

## Add End ID

tensorlayer.prepro.**sequences_add_end_id**(*sequences*, *end_id=888*)
Add special end token(id) in the end of each sequence.

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **end_id** (*int*) – The end ID.

**Returns** The processed sequences.

**Return type** list of list of int

### Examples

```
>>> sequences = [[1,2,3],[4,5,6,7]]
>>> print(sequences_add_end_id(sequences, end_id=999))
... [[1, 2, 3, 999], [4, 5, 6, 999]]
```

## Add End ID after pad

`tensorlayer.prepro.`**`sequences_add_end_id_after_pad`**(*sequences*, *end_id=888*, *pad_id=0*)

Add special end token(id) in the end of each sequence.

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **end_id** (*int*) – The end ID.
- **pad_id** (*int*) – The pad ID.

**Returns** The processed sequences.

**Return type** list of list of int

### Examples

```
>>> sequences = [[1,2,0,0], [1,2,3,0], [1,2,3,4]]
>>> print(sequences_add_end_id_after_pad(sequences, end_id=99, pad_id=0))
... [[1, 2, 99, 0], [1, 2, 3, 99], [1, 2, 3, 4]]
```

## Get Mask

`tensorlayer.prepro.`**`sequences_get_mask`**(*sequences*, *pad_val=0*)

Return mask for sequences.

**Parameters**

- **sequences** (*list of list of int*) – All sequences where each row is a sequence.
- **pad_val** (*int*) – The pad value.

**Returns** The mask.

**Return type** list of list of int

### Examples

```
>>> sentences_ids = [[4, 0, 5, 3, 0, 0],
...                  [5, 3, 9, 4, 9, 0]]
>>> mask = sequences_get_mask(sentences_ids, pad_val=0)
... [[1 1 1 1 0 0]
...  [1 1 1 1 1 0]]
```

## 2.4 API - Iteration

Data iteration.

| | |
|---|---|
| *minibatches*([inputs, targets, batch_size, …]) | Generate a generator that input a group of example in numpy.array and their labels, return the examples and labels by the given batch size. |
| *seq_minibatches*(inputs, targets, batch_size, …) | Generate a generator that return a batch of sequence inputs and targets. |
| *seq_minibatches2*(inputs, targets, …) | Generate a generator that iterates on two list of words. |
| *ptb_iterator*(raw_data, batch_size, num_steps) | Generate a generator that iterates on a list of words, see PTB example. |

### 2.4.1 Non-time series

`tensorlayer.iterate.`**`minibatches`**(*inputs=None*, *targets=None*, *batch_size=None*, *shuffle=False*)

Generate a generator that input a group of example in numpy.array and their labels, return the examples and labels by the given batch size.

**Parameters**

- **inputs** (*numpy.array*) – The input features, every row is a example.
- **targets** (*numpy.array*) – The labels of inputs, every row is a example.
- **batch_size** (*int*) – The batch size.
- **shuffle** (*boolean*) – Indicating whether to use a shuffling queue, shuffle the dataset before return.

#### Examples

```
>>> X = np.asarray([['a','a'], ['b','b'], ['c','c'], ['d','d'], ['e','e'], ['f','f
↪']])
>>> y = np.asarray([0,1,2,3,4,5])
>>> for batch in tl.iterate.minibatches(inputs=X, targets=y, batch_size=2,␣
↪shuffle=False):
>>>     print(batch)
... (array([['a', 'a'],
...         ['b', 'b']],
...          dtype='<U1'), array([0, 1]))
... (array([['c', 'c'],
...         ['d', 'd']],
...          dtype='<U1'), array([2, 3]))
... (array([['e', 'e'],
...         ['f', 'f']],
...          dtype='<U1'), array([4, 5]))
```

#### Notes

If you have two inputs and one label and want to shuffle them together, e.g. X1 (1000, 100), X2 (1000, 80) and Y (1000, 1), you can stack them together (*np.hstack((X1, X2))*) into (1000, 180) and feed to `inputs`. After getting a batch, you can split it back into X1 and X2.

### 2.4.2 Time series

#### Sequence iteration 1

`tensorlayer.iterate.`**`seq_minibatches`**(*inputs*, *targets*, *batch_size*, *seq_length*, *stride=1*)

Generate a generator that return a batch of sequence inputs and targets. If *batch_size=100* and *seq_length=5*, one return will have 500 rows (examples).

**Parameters**

- **inputs** (*numpy.array*) – The input features, every row is a example.
- **targets** (*numpy.array*) – The labels of inputs, every element is a example.
- **batch_size** (*int*) – The batch size.
- **seq_length** (*int*) – The sequence length.
- **stride** (*int*) – The stride step, default is 1.

#### Examples

Synced sequence input and output.

```
>>> X = np.asarray([['a','a'], ['b','b'], ['c','c'], ['d','d'], ['e','e'], ['f','f
↪']])
>>> y = np.asarray([0, 1, 2, 3, 4, 5])
>>> for batch in tl.iterate.seq_minibatches(inputs=X, targets=y, batch_size=2,␣
↪seq_length=2, stride=1):
>>>     print(batch)
... (array([['a', 'a'],
...        ['b', 'b'],
...         ['b', 'b'],
...         ['c', 'c']],
...         dtype='<U1'), array([0, 1, 1, 2]))
... (array([['c', 'c'],
...         ['d', 'd'],
...         ['d', 'd'],
...         ['e', 'e']],
...         dtype='<U1'), array([2, 3, 3, 4]))
...
...
```

Many to One

```
>>> return_last = True
>>> num_steps = 2
>>> X = np.asarray([['a','a'], ['b','b'], ['c','c'], ['d','d'], ['e','e'], ['f','f
↪']])
>>> Y = np.asarray([0,1,2,3,4,5])
>>> for batch in tl.iterate.seq_minibatches(inputs=X, targets=Y, batch_size=2,␣
↪seq_length=num_steps, stride=1):
>>>     x, y = batch
>>>     if return_last:
>>>         tmp_y = y.reshape((-1, num_steps) + y.shape[1:])
>>>     y = tmp_y[:, -1]
>>>     print(x, y)
... [['a' 'a']
... ['b' 'b']
```

```
... ['b' 'b']
... ['c' 'c']] [1 2]
... [['c' 'c']
... ['d' 'd']
... ['d' 'd']
... ['e' 'e']] [3 4]
```

### Sequence iteration 2

tensorlayer.iterate.**seq_minibatches2**(*inputs*, *targets*, *batch_size*, *num_steps*)

Generate a generator that iterates on two list of words. Yields (Returns) the source contexts and the target context by the given batch_size and num_steps (sequence_length). In TensorFlow's tutorial, this generates the *batch_size* pointers into the raw PTB data, and allows minibatch iteration along these pointers.

**Parameters**

- **inputs** (*list of data*) – The context in list format; note that context usually be represented by splitting by space, and then convert to unique word IDs.
- **targets** (*list of data*) – The context in list format; note that context usually be represented by splitting by space, and then convert to unique word IDs.
- **batch_size** (*int*) – The batch size.
- **num_steps** (*int*) – The number of unrolls. i.e. sequence length

**Yields** *Pairs of the batched data, each a matrix of shape [batch_size, num_steps].*

**Raises** ValueError : if batch_size or num_steps are too high.

### Examples

```
>>> X = [i for i in range(20)]
>>> Y = [i for i in range(20,40)]
>>> for batch in tl.iterate.seq_minibatches2(X, Y, batch_size=2, num_steps=3):
...     x, y = batch
...     print(x, y)
...
... [[  0.   1.   2.]
... [ 10.  11.  12.]]
... [[ 20.  21.  22.]
... [ 30.  31.  32.]]
...
... [[  3.   4.   5.]
... [ 13.  14.  15.]]
... [[ 23.  24.  25.]
... [ 33.  34.  35.]]
...
... [[  6.   7.   8.]
... [ 16.  17.  18.]]
... [[ 26.  27.  28.]
... [ 36.  37.  38.]]
```

### Notes

- Hint, if the input data are images, you can modify the source code *data = np.zeros([batch_size, batch_len)* to *data = np.zeros([batch_size, batch_len, inputs.shape[1], inputs.shape[2], inputs.shape[3]])*.

## PTB dataset iteration

`tensorlayer.iterate.ptb_iterator(raw_data, batch_size, num_steps)`

Generate a generator that iterates on a list of words, see PTB example. Yields the source contexts and the target context by the given batch_size and num_steps (sequence_length).

In TensorFlow's tutorial, this generates *batch_size* pointers into the raw PTB data, and allows minibatch iteration along these pointers.

**Parameters**

- **raw_data** (*a list*) – the context in list format; note that context usually be represented by splitting by space, and then convert to unique word IDs.
- **batch_size** (*int*) – the batch size.
- **num_steps** (*int*) – the number of unrolls. i.e. sequence_length

**Yields**

- *Pairs of the batched data, each a matrix of shape [batch_size, num_steps].*
- *The second element of the tuple is the same data time-shifted to the*
- *right by one.*

**Raises** ValueError : if batch_size or num_steps are too high.

### Examples

```
>>> train_data = [i for i in range(20)]
>>> for batch in tl.iterate.ptb_iterator(train_data, batch_size=2, num_steps=3):
>>>     x, y = batch
>>>     print(x, y)
... [[ 0  1  2] <---x                       1st subset/ iteration
...  [10 11 12]]
... [[ 1  2  3] <---y
...  [11 12 13]]
...
... [[ 3  4  5]  <--- 1st batch input       2nd subset/ iteration
...  [13 14 15]] <--- 2nd batch input
... [[ 4  5  6]  <--- 1st batch target
...  [14 15 16]] <--- 2nd batch target
...
... [[ 6  7  8]                             3rd subset/ iteration
...  [16 17 18]]
... [[ 7  8  9]
...  [17 18 19]]
```

## 2.5 API - Utility

| | |
|---|---|
| *fit*(sess, network, train_op, cost, X_train, . . . ) | Training a given non time-series network by the given cost function, training data, batch_size, n_epoch etc. |
| *test*(sess, network, acc, X_test, y_test, x, . . . ) | Test a given non time-series network by the given test data and metric. |
| *predict*(sess, network, X, x, y_op[, batch_size]) | Return the predict results of given non time-series network. |
| *evaluation*([y_test, y_predict, n_classes]) | Input the predicted results, targets results and the number of class, return the confusion matrix, F1-score of each class, accuracy and macro F1-score. |
| *class_balancing_oversample*([X_train, . . . ]) | Input the features and labels, return the features and labels after oversampling. |
| *get_random_int*([min_v, max_v, number, seed]) | Return a list of random integer by the given range and quantity. |
| *dict_to_one*(dp_dict) | Input a dictionary, return a dictionary that all items are set to one. |
| *list_string_to_dict*(string) | Inputs `['a', 'b', 'c']`, returns `{'a': 0, 'b': 1, 'c': 2}`. |
| *flatten_list*(list_of_list) | Input a list of list, return a list that all items are in a list. |
| *exit_tensorflow*([sess, port]) | Close TensorFlow session, TensorBoard and Nvidia-process if available. |
| *open_tensorboard*([log_dir, port]) | Open Tensorboard. |
| *clear_all_placeholder_variables*([printable]) | Clears all the placeholder variables of keep prob, including keeping probabilities of all dropout, denoising, dropconnect etc. |
| *set_gpu_fraction*([gpu_fraction]) | Set the GPU memory fraction for the application. |

### 2.5.1 Training, testing and predicting

#### Training

`tensorlayer.utils.`**`fit`**(*sess*, *network*, *train_op*, *cost*, *X_train*, *y_train*, *x*, *y_*, *acc=None*, *batch_size=100*, *n_epoch=100*, *print_freq=5*, *X_val=None*, *y_val=None*, *eval_train=True*, *tensorboard=False*, *tensorboard_epoch_freq=5*, *tensorboard_weight_histograms=True*, *tensorboard_graph_vis=True*)

Training a given non time-series network by the given cost function, training data, batch_size, n_epoch etc.

- MNIST example click here.
- In order to control the training details, the authors HIGHLY recommend `tl.iterate` see two MNIST examples 1, 2.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **network** (*TensorLayer layer*) – the network to be trained.
- **train_op** (*TensorFlow optimizer*) – The optimizer for training e.g. tf.train.AdamOptimizer.
- **X_train** (*numpy.array*) – The input of training data
- **y_train** (*numpy.array*) – The target of training data
- **x** (*placeholder*) – For inputs.

- **y** (*placeholder*) – For targets.
- **acc** (*TensorFlow expression or None*) – Metric for accuracy or others. If None, would not print the information.
- **batch_size** (*int*) – The batch size for training and evaluating.
- **n_epoch** (*int*) – The number of training epochs.
- **print_freq** (*int*) – Print the training information every `print_freq` epochs.
- **X_val** (*numpy.array or None*) – The input of validation data. If None, would not perform validation.
- **y_val** (*numpy.array or None*) – The target of validation data. If None, would not perform validation.
- **eval_train** (*boolean*) – Whether to evaluate the model during training. If X_val and y_val are not None, it reflects whether to evaluate the model on training data.
- **tensorboard** (*boolean*) – If True, summary data will be stored to the log/ directory for visualization with tensorboard. See also detailed tensorboard_X settings for specific configurations of features. (default False) Also runs *tl.layers.initialize_global_variables(sess)* internally in fit() to setup the summary nodes.
- **tensorboard_epoch_freq** (*int*) – How many epochs between storing tensorboard checkpoint for visualization to log/ directory (default 5).
- **tensorboard_weight_histograms** (*boolean*) – If True updates tensorboard data in the logs/ directory for visualization of the weight histograms every tensorboard_epoch_freq epoch (default True).
- **tensorboard_graph_vis** (*boolean*) – If True stores the graph in the tensorboard summaries saved to log/ (default True).

### Examples

See tutorial_mnist_simple.py

```
>>> tl.utils.fit(sess, network, train_op, cost, X_train, y_train, x, y_,
...             acc=acc, batch_size=500, n_epoch=200, print_freq=5,
...             X_val=X_val, y_val=y_val, eval_train=False)
>>> tl.utils.fit(sess, network, train_op, cost, X_train, y_train, x, y_,
...             acc=acc, batch_size=500, n_epoch=200, print_freq=5,
...             X_val=X_val, y_val=y_val, eval_train=False,
...             tensorboard=True, tensorboard_weight_histograms=True, tensorboard_
↪graph_vis=True)
```

### Notes

If tensorboard=True, the *global_variables_initializer* will be run inside the fit function in order to initialize the automatically generated summary nodes used for tensorboard visualization, thus *tf.global_variables_initializer().run()* before the *fit()* call will be undefined.

### Evaluation

`tensorlayer.utils.test` (*sess*, *network*, *acc*, *X_test*, *y_test*, *x*, *y_*, *batch_size*, *cost=None*)

Test a given non time-series network by the given test data and metric.

**Parameters**

- **sess** (*Session*) – TensorFlow session.
- **network** (*TensorLayer layer*) – The network.
- **acc** (*TensorFlow expression or None*) –

  **Metric for accuracy or others.**

  – If None, would not print the information.
- **X_test** (*numpy.array*) – The input of testing data.
- **y_test** (*numpy array*) – The target of testing data
- **x** (*placeholder*) – For inputs.
- **y** (*placeholder*) – For targets.
- **batch_size** (*int or None*) – The batch size for testing, when dataset is large, we should use minibatche for testing; if dataset is small, we can set it to None.
- **cost** (*TensorFlow expression or None*) – Metric for cost or others. If None, would not print the information.

#### Examples

See tutorial_mnist_simple.py

```
>>> tl.utils.test(sess, network, acc, X_test, y_test, x, y_, batch_size=None,
↪cost=cost)
```

### Prediction

`tensorlayer.utils.predict` (*sess*, *network*, *X*, *x*, *y_op*, *batch_size=None*)

Return the predict results of given non time-series network.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **network** (*TensorLayer layer*) – The network.
- **X** (*numpy.array*) – The inputs.
- **x** (*placeholder*) – For inputs.
- **y_op** (*placeholder*) – The argmax expression of softmax outputs.
- **batch_size** (*int or None*) – The batch size for prediction, when dataset is large, we should use minibatche for prediction; if dataset is small, we can set it to None.

### Examples

See tutorial_mnist_simple.py

```
>>> y = network.outputs
>>> y_op = tf.argmax(tf.nn.softmax(y), 1)
>>> print(tl.utils.predict(sess, network, X_test, x, y_op))
```

## 2.5.2 Evaluation functions

`tensorlayer.utils.`**`evaluation`**(*y_test=None*, *y_predict=None*, *n_classes=None*)

Input the predicted results, targets results and the number of class, return the confusion matrix, F1-score of each class, accuracy and macro F1-score.

**Parameters**

- **y_test** (*list*) – The target results
- **y_predict** (*list*) – The predicted results
- **n_classes** (*int*) – The number of classes

### Examples

```
>>> c_mat, f1, acc, f1_macro = tl.utils.evaluation(y_test, y_predict, n_classes)
```

## 2.5.3 Class balancing functions

`tensorlayer.utils.`**`class_balancing_oversample`**(*X_train=None*, *y_train=None*, *printable=True*)

Input the features and labels, return the features and labels after oversampling.

**Parameters**

- **X_train** (*numpy.array*) – The inputs.
- **y_train** (*numpy.array*) – The targets.

### Examples

One X

```
>>> X_train, y_train = class_balancing_oversample(X_train, y_train, printable=True)
```

Two X

```
>>> X, y = tl.utils.class_balancing_oversample(X_train=np.hstack((X1, X2)), y_train=y, printable=False)
>>> X1 = X[:, 0:5]
>>> X2 = X[:, 5:]
```

### 2.5.4 Random functions

`tensorlayer.utils.`**`get_random_int`**(*min_v=0*, *max_v=10*, *number=5*, *seed=None*)

Return a list of random integer by the given range and quantity.

**Parameters**

- **min_v** (*number*) – The minimum value.
- **max_v** (*number*) – The maximum value.
- **number** (*int*) – Number of value.
- **seed** (*int or None*) – The seed for random.

#### Examples

```
>>> r = get_random_int(min_v=0, max_v=10, number=5)
... [10, 2, 3, 3, 7]
```

### 2.5.5 Dictionary and list

#### Set all items in dictionary to one

`tensorlayer.utils.`**`dict_to_one`**(*dp_dict*)

Input a dictionary, return a dictionary that all items are set to one.

Used for disable dropout, dropconnect layer and so on.

**Parameters** **dp_dict** (*dictionary*) – The dictionary contains key and number, e.g. keeping probabilities.

#### Examples

```
>>> dp_dict = dict_to_one( network.all_drop )
>>> dp_dict = dict_to_one( network.all_drop )
>>> feed_dict.update(dp_dict)
```

#### Convert list of string to dictionary

`tensorlayer.utils.`**`list_string_to_dict`**(*string*)

Inputs `['a', 'b', 'c']`, returns `{'a': 0, 'b': 1, 'c': 2}`.

#### Flatten a list

`tensorlayer.utils.`**`flatten_list`**(*list_of_list*)

Input a list of list, return a list that all items are in a list.

**Parameters** **list_of_list** (*a list of list*) –

#### Examples

```
>>> tl.utils.flatten_list([[1, 2, 3],[4, 5],[6]])
... [1, 2, 3, 4, 5, 6]
```

### 2.5.6 Close TF session and associated processes

`tensorlayer.utils.exit_tensorflow`(*sess=None*, *port=6006*)
Close TensorFlow session, TensorBoard and Nvidia-process if available.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **tb_port** (*int*) – TensorBoard port you want to close, *6006* as default.

### 2.5.7 Open TensorBoard

`tensorlayer.utils.open_tensorboard`(*log_dir='/tmp/tensorflow'*, *port=6006*)
Open Tensorboard.

**Parameters**

- **log_dir** (*str*) – Directory where your tensorboard logs are saved
- **port** (*int*) – TensorBoard port you want to open, 6006 is tensorboard default

### 2.5.8 Clear TensorFlow placeholder

`tensorlayer.utils.clear_all_placeholder_variables`(*printable=True*)
Clears all the placeholder variables of keep prob, including keeping probabilities of all dropout, denoising, dropconnect etc.

**Parameters** **printable** (*boolean*) – If True, print all deleted variables.

### 2.5.9 Set GPU functions

`tensorlayer.utils.set_gpu_fraction`(*gpu_fraction=0.3*)
Set the GPU memory fraction for the application.

**Parameters** **gpu_fraction** (*float*) – Fraction of GPU memory, (0 ~ 1]

#### References

- TensorFlow using GPU

## 2.6 API - Natural Language Processing

Natural Language Processing and Word Representation.

| | |
|---|---|
| `generate_skip_gram_batch`(data, batch_size, ...) | Generate a training batch for the Skip-Gram model. |
| `sample`([a, temperature]) | Sample an index from a probability array. |
| `sample_top`([a, top_k]) | Sample from `top_k` probabilities. |
| `SimpleVocabulary`(vocab, unk_id) | Simple vocabulary wrapper, see create_vocab(). |
| `Vocabulary`(vocab_file[, start_word, ...]) | Create Vocabulary class from a given vocabulary and its id-word, word-id convert. |
| `process_sentence`(sentence[, start_word, ...]) | Seperate a sentence string into a list of string words, add start_word and end_word, see `create_vocab()` and `tutorial_tfrecord3.py`. |
| `create_vocab`(sentences, word_counts_output_file) | Creates the vocabulary of word to word_id. |
| `simple_read_words`([filename]) | Read context from file without any preprocessing. |
| `read_words`([filename, replace]) | Read list format context from a file. |
| `read_analogies_file`([eval_file, word2id]) | Reads through an analogy question file, return its id format. |
| `build_vocab`(data) | Build vocabulary. |
| `build_reverse_dictionary`(word_to_id) | Given a dictionary that maps word to integer id. |
| `build_words_dataset`([words, ...]) | Build the words dictionary and replace rare words with 'UNK' token. |
| `save_vocab`([count, name]) | Save the vocabulary to a file so the model can be reloaded. |
| `words_to_word_ids`([data, word_to_id, unk_key]) | Convert a list of string (words) to IDs. |
| `word_ids_to_words`(data, id_to_word) | Convert a list of integer to strings (words). |
| `basic_tokenizer`(sentence[, _WORD_SPLIT]) | Very basic tokenizer: split the sentence into a list of tokens. |
| `create_vocabulary`(vocabulary_path, ...[, ...]) | Create vocabulary file (if it does not exist yet) from data file. |
| `initialize_vocabulary`(vocabulary_path) | Initialize vocabulary from file, return the *word_to_id* (dictionary) and *id_to_word* (list). |
| `sentence_to_token_ids`(sentence, vocabulary) | Convert a string to list of integers representing token-ids. |
| `data_to_token_ids`(data_path, target_path, ...) | Tokenize data file and turn into token-ids using given vocabulary file. |
| `moses_multi_bleu`(hypotheses, references[, ...]) | Calculate the bleu score for hypotheses and references using the MOSES ulti-bleu.perl script. |

### 2.6.1 Iteration function for training embedding matrix

`tensorlayer.nlp.`**`generate_skip_gram_batch`**(*data*, *batch_size*, *num_skips*, *skip_window*, *data_index=0*)

Generate a training batch for the Skip-Gram model.

See Word2Vec example.

**Parameters**

- **`data`** (`list of data`) – To present context, usually a list of integers.
- **`batch_size`** (`int`) – Batch size to return.
- **`num_skips`** (`int`) – How many times to reuse an input to generate a label.
- **`skip_window`** (`int`) – How many words to consider left and right.
- **`data_index`** (`int`) – Index of the context location. This code use *data_index* to instead of yield like `tl.iterate`.

**Returns**

- **batch** (*list of data*) – Inputs.

- **labels** (*list of data*) – Labels
- **data_index** (*int*) – Index of the context location.

### Examples

Setting num_skips=2, skip_window=1, use the right and left words. In the same way, num_skips=4, skip_window=2 means use the nearby 4 words.

```
>>> data = [1,2,3,4,5,6,7,8,9,10,11]
>>> batch, labels, data_index = tl.nlp.generate_skip_gram_batch(data=data, batch_
↪size=8, num_skips=2, skip_window=1, data_index=0)
>>> print(batch)
... [2 2 3 3 4 4 5 5]
>>> print(labels)
... [[3]
... [1]
... [4]
... [2]
... [5]
... [3]
... [4]
... [6]]
```

## 2.6.2 Sampling functions

### Simple sampling

`tensorlayer.nlp.sample`(*a=None*, *temperature=1.0*)
Sample an index from a probability array.

**Parameters**

- **a** (*list of float*) – List of probabilities.
- **temperature** (*float or None*) –

  **The higher the more uniform. When a = [0.1, 0.2, 0.7],**

  – temperature = 0.7, the distribution will be sharpen [0.05048273, 0.13588945, 0.81362782]

  – temperature = 1.0, the distribution will be the same [0.1, 0.2, 0.7]

  – temperature = 1.5, the distribution will be filtered [0.16008435, 0.25411807, 0.58579758]

  – If None, it will be `np.argmax(a)`

### Notes

- No matter what is the temperature and input list, the sum of all probabilities will be one. Even if input list = [1, 100, 200], the sum of all probabilities will still be one.
- For large vocabulary size, choice a higher temperature or `tl.nlp.sample_top` to avoid error.

### Sampling from top k

tensorlayer.nlp.**sample_top**(*a=None*, *top_k=10*)

Sample from `top_k` probabilities.

**Parameters**

- **a** (*list of float*) – List of probabilities.
- **top_k** (*int*) – Number of candidates to be considered.

## 2.6.3 Vector representations of words

### Simple vocabulary class

**class** tensorlayer.nlp.**SimpleVocabulary**(*vocab*, *unk_id*)

Simple vocabulary wrapper, see create_vocab().

**Parameters**

- **vocab** (*dictionary*) – A dictionary that maps word to ID.
- **unk_id** (*int*) – The ID for 'unknown' word.

### Vocabulary class

**class** tensorlayer.nlp.**Vocabulary**(*vocab_file*, *start_word='<S>'*, *end_word='</S>'*, *unk_word='<UNK>'*, *pad_word='<PAD>'*)

Create Vocabulary class from a given vocabulary and its id-word, word-id convert. See create_vocab() and `tutorial_tfrecord3.py`.

**Parameters**

- **vocab_file** (*str*) – The file contains the vocabulary (can be created via `tl.nlp.create_vocab`), where the words are the first whitespace-separated token on each line (other tokens are ignored) and the word ids are the corresponding line numbers.
- **start_word** (*str*) – Special word denoting sentence start.
- **end_word** (*str*) – Special word denoting sentence end.
- **unk_word** (*str*) – Special word denoting unknown words.

**vocab**

*dictionary* – A dictionary that maps word to ID.

**reverse_vocab**

*list of int* – A list that maps ID to word.

**start_id**

*int* – For start ID.

**end_id**

*int* – For end ID.

**unk_id**

*int* – For unknown ID.

**pad_id**

*int* – For Padding ID.

### Examples

The vocab file looks like follow, includes *start_word* , *end_word* . . .

```
>>> a 969108
>>> <S> 586368
>>> </S> 586368
>>> . 440479
>>> on 213612
>>> of 202290
>>> the 196219
>>> in 182598
>>> with 152984
>>> and 139109
>>> is 97322
```

## Process sentence

`tensorlayer.nlp.`**`process_sentence`**(*sentence*, *start_word='<S>'*, *end_word='</S>'*)

Seperate a sentence string into a list of string words, add start_word and end_word, see `create_vocab()` and `tutorial_tfrecord3.py`.

**Parameters**

- **sentence** (*str*) – A sentence.
- **start_word** (*str or None*) – The start word. If None, no start word will be appended.
- **end_word** (*str or None*) – The end word. If None, no end word will be appended.

**Returns** A list of strings that separated into words.

**Return type** list of str

### Examples

```
>>> c = "how are you?"
>>> c = tl.nlp.process_sentence(c)
>>> print(c)
... ['<S>', 'how', 'are', 'you', '?', '</S>']
```

### Notes

- You have to install the following package.
- Installing NLTK
- Installing NLTK data

## Create vocabulary

`tensorlayer.nlp.`**`create_vocab`**(*sentences*, *word_counts_output_file*, *min_word_count=1*)

Creates the vocabulary of word to word_id.

See `tutorial_tfrecord3.py`.

The vocabulary is saved to disk in a text file of word counts. The id of each word in the file is its corresponding 0-based line number.

**Parameters**

- **sentences** (*list of list of str*) – All sentences for creating the vocabulary.
- **word_counts_output_file** (*str*) – The file name.
- **min_word_count** (*int*) – Minimum number of occurrences for a word.

**Returns** The simple vocabulary object, see *Vocabulary* for more.

**Return type** *SimpleVocabulary*

### Examples

Pre-process sentences

```
>>> captions = ["one two , three", "four five five"]
>>> processed_capts = []
>>> for c in captions:
>>>     c = tl.nlp.process_sentence(c, start_word="<S>", end_word="</S>")
>>>     processed_capts.append(c)
>>> print(processed_capts)
...[['<S>', 'one', 'two', ',', 'three', '</S>'], ['<S>', 'four', 'five', 'five', '
↪</S>']]
```

Create vocabulary

```
>>> tl.nlp.create_vocab(processed_capts, word_counts_output_file='vocab.txt', min_
↪word_count=1)
... Creating vocabulary.
...   Total words: 8
...   Words in vocabulary: 8
...   Wrote vocabulary file: vocab.txt
```

Get vocabulary object

```
>>> vocab = tl.nlp.Vocabulary('vocab.txt', start_word="<S>", end_word="</S>", unk_
↪word="<UNK>")
... INFO:tensorflow:Initializing vocabulary from file: vocab.txt
... [TL] Vocabulary from vocab.txt : <S> </S> <UNK>
... vocabulary with 10 words (includes start_word, end_word, unk_word)
...     start_id: 2
...     end_id: 3
...     unk_id: 9
...     pad_id: 0
```

## 2.6.4 Read words from file

### Simple read file

`tensorlayer.nlp.`**`simple_read_words`**(*filename='nietzsche.txt'*)

Read context from file without any preprocessing.

**Parameters** **filename** (*str*) – A file path (like .txt file)

**Returns** The context in a string.

**Return type** str

### Read file

`tensorlayer.nlp.`**`read_words`**(*filename='nietzsche.txt'*, *replace=None*)

Read list format context from a file.

For customized read_words method, see `tutorial_generate_text.py`.

**Parameters**

- **`filename`** (*`str`*) – a file path.
- **`replace`** (*`list of str`*) – replace original string by target string.

**Returns** The context in a list (split using space).

**Return type** list of str

**See also:**

`-()`

## 2.6.5 Read analogy question file

`tensorlayer.nlp.`**`read_analogies_file`**(*eval_file='questions-words.txt'*, *word2id=None*)

Reads through an analogy question file, return its id format.

**Parameters**

- **`eval_file`** (*`str`*) – The file name.
- **`word2id`** (*`dictionary`*) – a dictionary that maps word to ID.

**Returns** A `[n_examples, 4]` numpy array containing the analogy question's word IDs.

**Return type** numpy.array

### Examples

The file should be in this format

```
>>> : capital-common-countries
>>> Athens Greece Baghdad Iraq
>>> Athens Greece Bangkok Thailand
>>> Athens Greece Beijing China
>>> Athens Greece Berlin Germany
>>> Athens Greece Bern Switzerland
>>> Athens Greece Cairo Egypt
>>> Athens Greece Canberra Australia
>>> Athens Greece Hanoi Vietnam
>>> Athens Greece Havana Cuba
```

Get the tokenized analogy question data

```
>>> words = tl.files.load_matt_mahoney_text8_dataset()
>>> data, count, dictionary, reverse_dictionary = tl.nlp.build_words_
↪dataset(words, vocabulary_size, True)
>>> analogy_questions = tl.nlp.read_analogies_file(eval_file='questions-words.txt
↪', word2id=dictionary)
>>> print(analogy_questions)
... [[ 3068  1248  7161  1581]
... [ 3068  1248 28683  5642]
... [ 3068  1248  3878   486]
... ...,
... [ 1216  4309 19982 25506]
... [ 1216  4309  3194  8650]
... [ 1216  4309   140   312]]
```

### 2.6.6 Build vocabulary, word dictionary and word tokenization

#### Build dictionary from word to id

tensorlayer.nlp.**build_vocab**(*data*)

Build vocabulary.

Given the context in list format. Return the vocabulary, which is a dictionary for word to id. e.g. {'campbell': 2587, 'atlantic': 2247, 'aoun': 6746 .... }

**Parameters** **data** (*list of str*) – The context in list format

**Returns** that maps word to unique ID. e.g. {'campbell': 2587, 'atlantic': 2247, 'aoun': 6746 .... }

**Return type** dictionary

#### References

- tensorflow.models.rnn.ptb.reader

#### Examples

```
>>> data_path = os.getcwd() + '/simple-examples/data'
>>> train_path = os.path.join(data_path, "ptb.train.txt")
>>> word_to_id = build_vocab(read_txt_words(train_path))
```

#### Build dictionary from id to word

tensorlayer.nlp.**build_reverse_dictionary**(*word_to_id*)

Given a dictionary that maps word to integer id. Returns a reverse dictionary that maps a id to word.

**Parameters** **word_to_id** (*dictionary*) – that maps word to ID.

**Returns** A dictionary that maps IDs to words.

**Return type** dictionary

### Build dictionaries for id to word etc

`tensorlayer.nlp.`**`build_words_dataset`**(*words=None*, *vocabulary_size=50000*, *printable=True*, *unk_key='UNK'*)

Build the words dictionary and replace rare words with 'UNK' token. The most common word has the smallest integer id.

**Parameters**

- **`words`** (`list of str or byte`) – The context in list format. You may need to do preprocessing on the words, such as lower case, remove marks etc.
- **`vocabulary_size`** (`int`) – The maximum vocabulary size, limiting the vocabulary size. Then the script replaces rare words with 'UNK' token.
- **`printable`** (`boolean`) – Whether to print the read vocabulary size of the given words.
- **`unk_key`** (`str`) – Represent the unknown words.

**Returns**

- **data** (*list of int*) – The context in a list of ID.
- **count** (*list of tuple and list*) –

  **Pair words and IDs.**

  - count[0] is a list : the number of rare words
  - count[1:] are tuples : the number of occurrence of each word
  - e.g. [['UNK', 418391], (b'the', 1061396), (b'of', 593677), (b'and', 416629), (b'one', 411764)]
- **dictionary** (*dictionary*) – It is *word_to_id* that maps word to ID.
- **reverse_dictionary** (*a dictionary*) – It is *id_to_word* that maps ID to word.

#### Examples

```
>>> words = tl.files.load_matt_mahoney_text8_dataset()
>>> vocabulary_size = 50000
>>> data, count, dictionary, reverse_dictionary = tl.nlp.build_words_
↪dataset(words, vocabulary_size)
```

#### References

- tensorflow/examples/tutorials/word2vec/word2vec_basic.py

### Save vocabulary

`tensorlayer.nlp.`**`save_vocab`**(*count=None*, *name='vocab.txt'*)

Save the vocabulary to a file so the model can be reloaded.

**Parameters** **`count`** (`a list of tuple and list`) – count[0] is a list : the number of rare words, count[1:] are tuples : the number of occurrence of each word, e.g. [['UNK', 418391], (b'the', 1061396), (b'of', 593677), (b'and', 416629), (b'one', 411764)]

### Examples

```
>>> words = tl.files.load_matt_mahoney_text8_dataset()
>>> vocabulary_size = 50000
>>> data, count, dictionary, reverse_dictionary = tl.nlp.build_words_
↪dataset(words, vocabulary_size, True)
>>> tl.nlp.save_vocab(count, name='vocab_text8.txt')
>>> vocab_text8.txt
... UNK 418391
... the 1061396
... of 593677
... and 416629
... one 411764
... in 372201
... a 325873
... to 316376
```

## 2.6.7 Convert words to IDs and IDs to words

These functions can be done by `Vocabulary` class.

### List of Words to IDs

`tensorlayer.nlp.`**`words_to_word_ids`**(*data=None*, *word_to_id=None*, *unk_key='UNK'*)

Convert a list of string (words) to IDs.

**Parameters**

- **data** (*list of string or byte*) – The context in list format
- **word_to_id** (*a dictionary*) – that maps word to ID.
- **unk_key** (*str*) – Represent the unknown words.

**Returns** A list of IDs to represent the context.

**Return type** list of int

### Examples

```
>>> words = tl.files.load_matt_mahoney_text8_dataset()
>>> vocabulary_size = 50000
>>> data, count, dictionary, reverse_dictionary = tl.nlp.build_words_
↪dataset(words, vocabulary_size, True)
>>> context = [b'hello', b'how', b'are', b'you']
>>> ids = tl.nlp.words_to_word_ids(words, dictionary)
>>> context = tl.nlp.word_ids_to_words(ids, reverse_dictionary)
>>> print(ids)
... [6434, 311, 26, 207]
>>> print(context)
... [b'hello', b'how', b'are', b'you']
```

#### References

- tensorflow.models.rnn.ptb.reader

### List of IDs to Words

tensorlayer.nlp.**word_ids_to_words**(*data*, *id_to_word*)
Convert a list of integer to strings (words).

**Parameters**

- **data** (*list of int*) – The context in list format.
- **id_to_word** (*dictionary*) – a dictionary that maps ID to word.

**Returns** A list of string or byte to represent the context.

**Return type** list of str

#### Examples

```
>>> see ``tl.nlp.words_to_word_ids``
```

## 2.6.8 Functions for translation

### Word Tokenization

tensorlayer.nlp.**basic_tokenizer**(*sentence*, *_WORD_SPLIT=re.compile(b'([., !?"\':;)(])')*)
Very basic tokenizer: split the sentence into a list of tokens.

**Parameters**

- **sentence** (*tensorflow.python.platform.gfile.GFile Object*) –
- **_WORD_SPLIT** (*regular expression for word spliting.*) –

#### Examples

```
>>> see create_vocabulary
>>> from tensorflow.python.platform import gfile
>>> train_path = "wmt/giga-fren.release2"
>>> with gfile.GFile(train_path + ".en", mode="rb") as f:
>>>    for line in f:
>>>       tokens = tl.nlp.basic_tokenizer(line)
>>>       logging.info(tokens)
>>>       exit()
... [b'Changing', b'Lives', b'|', b'Changing', b'Society', b'|', b'How',
...   b'It', b'Works', b'|', b'Technology', b'Drives', b'Change', b'Home',
...   b'|', b'Concepts', b'|', b'Teachers', b'|', b'Search', b'|', b'Overview',
...   b'|', b'Credits', b'|', b'HHCC', b'Web', b'|', b'Reference', b'|',
...   b'Feedback', b'Virtual', b'Museum', b'of', b'Canada', b'Home', b'Page']
```

### References

- Code from `/tensorflow/models/rnn/translation/data_utils.py`

## Create or read vocabulary

`tensorlayer.nlp.`**`create_vocabulary`**(*vocabulary_path*, *data_path*, *max_vocabulary_size*, *tokenizer=None*, *normalize_digits=True*, *_DIGIT_RE=re.compile(b'\\d')*, *_START_VOCAB=None*)

Create vocabulary file (if it does not exist yet) from data file.

Data file is assumed to contain one sentence per line. Each sentence is tokenized and digits are normalized (if normalize_digits is set). Vocabulary contains the most-frequent tokens up to max_vocabulary_size. We write it to vocabulary_path in a one-token-per-line format, so that later token in the first line gets id=0, second line gets id=1, and so on.

**Parameters**

- **vocabulary_path** (*str*) – Path where the vocabulary will be created.
- **data_path** (*str*) – Data file that will be used to create vocabulary.
- **max_vocabulary_size** (*int*) – Limit on the size of the created vocabulary.
- **tokenizer** (*function*) – A function to use to tokenize each data sentence. If None, basic_tokenizer will be used.
- **normalize_digits** (*boolean*) – If true, all digits are replaced by *0*.
- **_DIGIT_RE** (*regular expression function*) – Default is `re.compile(br"\d")`.
- **_START_VOCAB** (*list of str*) – The pad, go, eos and unk token, default is `[b"_PAD", b"_GO", b"_EOS", b"_UNK"]`.

### References

- Code from `/tensorflow/models/rnn/translation/data_utils.py`

`tensorlayer.nlp.`**`initialize_vocabulary`**(*vocabulary_path*)

Initialize vocabulary from file, return the *word_to_id* (dictionary) and *id_to_word* (list).

We assume the vocabulary is stored one-item-per-line, so a file will result in a vocabulary {"dog": 0, "cat": 1}, and this function will also return the reversed-vocabulary ["dog", "cat"].

**Parameters** **vocabulary_path** (*str*) – Path to the file containing the vocabulary.

**Returns**

- **vocab** (*dictionary*) – a dictionary that maps word to ID.
- **rev_vocab** (*list of int*) – a list that maps ID to word.

### Examples

```
>>> Assume 'test' contains
... dog
... cat
... bird
>>> vocab, rev_vocab = tl.nlp.initialize_vocabulary("test")
>>> print(vocab)
>>> {b'cat': 1, b'dog': 0, b'bird': 2}
>>> print(rev_vocab)
>>> [b'dog', b'cat', b'bird']
```

**Raises** ValueError : if the provided vocabulary_path does not exist.

### Convert words to IDs and IDs to words

`tensorlayer.nlp.`**`sentence_to_token_ids`**(*sentence, vocabulary, tokenizer=None, normalize_digits=True, UNK_ID=3, _DIGIT_RE=re.compile(b'\\d')*)

Convert a string to list of integers representing token-ids.

For example, a sentence "I have a dog" may become tokenized into ["I", "have", "a", "dog"] and with vocabulary {"I": 1, "have": 2, "a": 4, "dog": 7"} this function will return [1, 2, 4, 7].

**Parameters**

- **sentence** (*tensorflow.python.platform.gfile.GFile Object*) – The sentence in bytes format to convert to token-ids, see `basic_tokenizer()` and `data_to_token_ids()`.
- **vocabulary** (*dictionary*) – Mmapping tokens to integers.
- **tokenizer** (*function*) – A function to use to tokenize each sentence. If None, `basic_tokenizer` will be used.
- **normalize_digits** (*boolean*) – If true, all digits are replaced by 0.

**Returns** The token-ids for the sentence.

**Return type** list of int

`tensorlayer.nlp.`**`data_to_token_ids`**(*data_path, target_path, vocabulary_path, tokenizer=None, normalize_digits=True, UNK_ID=3, _DIGIT_RE=re.compile(b'\\d')*)

Tokenize data file and turn into token-ids using given vocabulary file.

This function loads data line-by-line from data_path, calls the above sentence_to_token_ids, and saves the result to target_path. See comment for sentence_to_token_ids on the details of token-ids format.

**Parameters**

- **data_path** (*str*) – Path to the data file in one-sentence-per-line format.
- **target_path** (*str*) – Path where the file with token-ids will be created.
- **vocabulary_path** (*str*) – Path to the vocabulary file.
- **tokenizer** (*function*) – A function to use to tokenize each sentence. If None, `basic_tokenizer` will be used.
- **normalize_digits** (*boolean*) – If true, all digits are replaced by 0.

### References

- Code from `/tensorflow/models/rnn/translation/data_utils.py`

## 2.6.9 Metrics

### BLEU

`tensorlayer.nlp.`**`moses_multi_bleu`**`(`*hypotheses*, *references*, *lowercase=False*`)`

Calculate the bleu score for hypotheses and references using the MOSES ulti-bleu.perl script.

**Parameters**

- **`hypotheses`** (*`numpy.array.string`*) – A numpy array of strings where each string is a single example.
- **`references`** (*`numpy.array.string`*) – A numpy array of strings where each string is a single example.
- **`lowercase`** (*`boolean`*) – If True, pass the "-lc" flag to the multi-bleu script

### Examples

```
>>> hypotheses = ["a bird is flying on the sky"]
>>> references = ["two birds are flying on the sky", "a bird is on the top of the␣
↪tree", "an airplane is on the sky",]
>>> score = tl.nlp.moses_multi_bleu(hypotheses, references)
```

**Returns** The BLEU score

**Return type** float

### References

- Google/seq2seq/metric/bleu

# 2.7 API - Reinforcement Learning

Reinforcement Learning.

| | |
|---|---|
| *`discount_episode_rewards`*([rewards, gamma, mode]) | Take 1D float array of rewards and compute discounted rewards for an episode. |
| *`cross_entropy_reward_loss`*(logits, actions, …) | Calculate the loss for Policy Gradient Network. |
| *`log_weight`*(probs, weights[, name]) | Log weight. |
| *`choice_action_by_probs`*([probs, action_list]) | Choice and return an an action by given the action probability distribution. |

### 2.7.1 Reward functions

tensorlayer.rein.**discount_episode_rewards**(*rewards=None*, *gamma=0.99*, *mode=0*)

Take 1D float array of rewards and compute discounted rewards for an episode. When encount a non-zero value, consider as the end a of an episode.

**Parameters**

- **rewards** (*list*) – List of rewards
- **gamma** (*float*) – Discounted factor
- **mode** (*int*) –

  **Mode for computing the discount rewards.**

  – If mode == 0, reset the discount process when encount a non-zero reward (Ping-pong game).

  – If mode == 1, would not reset the discount process.

**Returns** The discounted rewards.

**Return type** list of float

#### Examples

```
>>> rewards = np.asarray([0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1])
>>> gamma = 0.9
>>> discount_rewards = tl.rein.discount_episode_rewards(rewards, gamma)
>>> print(discount_rewards)
... [ 0.72899997  0.81        0.89999998  1.          0.72899997  0.81
... 0.89999998  1.          0.72899997  0.81        0.89999998  1.        ]
>>> discount_rewards = tl.rein.discount_episode_rewards(rewards, gamma, mode=1)
>>> print(discount_rewards)
... [ 1.52110755  1.69011939  1.87791049  2.08656716  1.20729685  1.34144104
... 1.49048996  1.65610003  0.72899997  0.81        0.89999998  1.        ]
```

### 2.7.2 Cost functions

#### Weighted Cross Entropy

tensorlayer.rein.**cross_entropy_reward_loss**(*logits*, *actions*, *rewards*, *name=None*)

Calculate the loss for Policy Gradient Network.

**Parameters**

- **logits** (*tensor*) – The network outputs without softmax. This function implements softmax inside.
- **actions** (*tensor or placeholder*) – The agent actions.
- **rewards** (*tensor or placeholder*) – The rewards.

**Returns** The TensorFlow loss function.

**Return type** Tensor

### Examples

```
>>> states_batch_pl = tf.placeholder(tf.float32, shape=[None, D])
>>> network = InputLayer(states_batch_pl, name='input')
>>> network = DenseLayer(network, n_units=H, act=tf.nn.relu, name='relu1')
>>> network = DenseLayer(network, n_units=3, name='out')
>>> probs = network.outputs
>>> sampling_prob = tf.nn.softmax(probs)
>>> actions_batch_pl = tf.placeholder(tf.int32, shape=[None])
>>> discount_rewards_batch_pl = tf.placeholder(tf.float32, shape=[None])
>>> loss = tl.rein.cross_entropy_reward_loss(probs, actions_batch_pl, discount_
↪rewards_batch_pl)
>>> train_op = tf.train.RMSPropOptimizer(learning_rate, decay_rate).minimize(loss)
```

### Log weight

`tensorlayer.rein.`**`log_weight`**(*probs*, *weights*, *name='log_weight'*)

Log weight.

**Parameters**

- **`probs`** (*`tensor`*) – If it is a network output, usually we should scale it to [0, 1] via softmax.
- **`weights`** (*`tensor`*) – The weights.

**Returns** The Tensor after appling the log weighted expression.

**Return type** Tensor

## 2.7.3 Sampling functions

`tensorlayer.rein.`**`choice_action_by_probs`**(*probs=(0.5, 0.5)*, *action_list=None*)

Choice and return an an action by given the action probability distribution.

**Parameters**

- **`probs`** (*`list of float.`*) – The probability distribution of all actions.
- **`action_list`** (*`None or a list of int or others`*) – A list of action in integer, string or others. If None, returns an integer range between 0 and len(probs)-1.

**Returns** The chosen action.

**Return type** float int or str

### Examples

```
>>> for _ in range(5):
>>>     a = choice_action_by_probs([0.2, 0.4, 0.4])
>>>     print(a)
... 0
... 1
... 1
... 2
... 1
>>> for _ in range(3):
```

```
>>>     a = choice_action_by_probs([0.5, 0.5], ['a', 'b'])
>>>     print(a)
... a
... b
... b
```

## 2.8 API - Files

A collections of helper functions to work with dataset.

Load benchmark dataset, save and restore model, save and load variables. TensorFlow provides `.ckpt` file format to save and restore the models, while we suggest to use standard python file format `.npz` to save models for the sake of cross-platform.

```
## save model as .ckpt
saver = tf.train.Saver()
save_path = saver.save(sess, "model.ckpt")
# restore model from .ckpt
saver = tf.train.Saver()
saver.restore(sess, "model.ckpt")

## save model as .npz
tl.files.save_npz(network.all_params , name='model.npz')
# restore model from .npz (method 1)
load_params = tl.files.load_npz(name='model.npz')
tl.files.assign_params(sess, load_params, network)
# restore model from .npz (method 2)
tl.files.load_and_assign_npz(sess=sess, name='model.npz', network=network)

## you can assign the pre-trained parameters as follow
# 1st parameter
tl.files.assign_params(sess, [load_params[0]], network)
# the first three parameters
tl.files.assign_params(sess, load_params[:3], network)
```

| | |
|---|---|
| `load_mnist_dataset`([shape, path]) | Load MNIST dataset. |
| `load_cifar10_dataset`([shape, path, plotable]) | Load CIFAR-10 dataset. |
| `load_ptb_dataset`([path]) | Load Penn TreeBank (PTB) dataset. |
| `load_matt_mahoney_text8_dataset`([path]) | Load Matt Mahoney's dataset. |
| `load_imdb_dataset`([path, nb_words, . . . ]) | Load IMDB dataset. |
| `load_nietzsche_dataset`([path]) | Load Nietzsche dataset. |
| `load_wmt_en_fr_dataset`([path]) | Load WMT'15 English-to-French translation dataset. |
| `load_flickr25k_dataset`([tag, path, . . . ]) | Load Flickr25K dataset. |
| `load_flickr1M_dataset`([tag, size, path, . . . ]) | Load Flick1M dataset. |
| `load_cyclegan_dataset`([filename, path]) | Load images from CycleGAN's database, see this link. |
| `load_celebA_dataset`([path]) | Load CelebA dataset |
| `load_voc_dataset`([path, dataset, . . . ]) | Pascal VOC 2007/2012 Dataset. |
| `download_file_from_google_drive`(ID, destination) | Download file from Google Drive. |
| `save_npz`([save_list, name, sess]) | Input parameters and the file name, save parameters into .npz file. |

Continued on next page

Table 2.8 – continued from previous page

| | |
|---|---|
| *load_npz*([path, name]) | Load the parameters of a Model saved by tl.files.save_npz(). |
| *assign_params*(sess, params, network) | Assign the given parameters to the TensorLayer network. |
| *load_and_assign_npz*([sess, name, network]) | Load model from npz and assign to a network. |
| *save_npz_dict*([save_list, name, sess]) | Input parameters and the file name, save parameters as a dictionary into .npz file. |
| *load_and_assign_npz_dict*([name, sess]) | Restore the parameters saved by `tl.files.save_npz_dict()`. |
| *save_ckpt*([sess, mode_name, save_dir, ...]) | Save parameters into *ckpt* file. |
| *load_ckpt*([sess, mode_name, save_dir, ...]) | Load parameters from *ckpt* file. |
| *save_any_to_npy*([save_dict, name]) | Save variables to *.npy* file. |
| *load_npy_to_any*([path, name]) | Load *.npy* file. |
| *file_exists*(filepath) | Check whether a file exists by given file path. |
| *folder_exists*(folderpath) | Check whether a folder exists by given folder path. |
| *del_file*(filepath) | Delete a file by given file path. |
| *del_folder*(folderpath) | Delete a folder by given folder path. |
| *read_file*(filepath) | Read a file and return a string. |
| *load_file_list*([path, regx, printable]) | Return a file list in a folder by given a path and regular expression. |
| *load_folder_list*([path]) | Return a folder list in a folder by given a folder path. |
| *exists_or_mkdir*(path[, verbose]) | Check a folder by given name, if not exist, create the folder and return False, if directory exists, return True. |
| *maybe_download_and_extract*(filename, ...[, ...]) | Checks if file exists in working_directory otherwise tries to dowload the file, |
| *natural_keys*(text) | Sort list of string with number in human order. |
| *npz_to_W_pdf*([path, regx]) | Convert the first weight matrix of *.npz* file to *.pdf* by using *tl.visualize.W()*. |

### 2.8.1 Load dataset functions

#### MNIST

`tensorlayer.files.`**`load_mnist_dataset`**(*shape=(-1, 784), path='data'*)

Load MNIST dataset.

Automatically download MNIST dataset and return the training, validation and test set with 50000, 10000 and 10000 digit images respectively.

**Parameters**

- **shape** (*tuple*) – The shape of digit images e.g. (-1,784) or (-1, 28, 28, 1).
- **path** (*str*) – The path that the data is downloaded to, defaults is `data/mnist/`.

#### Examples

```
>>> X_train, y_train, X_val, y_val, X_test, y_test = tl.files.load_mnist_
↪dataset(shape=(-1,784))
>>> X_train, y_train, X_val, y_val, X_test, y_test = tl.files.load_mnist_
↪dataset(shape=(-1, 28, 28, 1))
```

### CIFAR-10

`tensorlayer.files.load_cifar10_dataset(shape=(-1, 32, 32, 3), path='data', plotable=False)`

Load CIFAR-10 dataset.

It consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

**Parameters**

- **shape** (*tupe*) – The shape of digit images e.g. (-1, 3, 32, 32) and (-1, 32, 32, 3).
- **path** (*str*) – The path that the data is downloaded to, defaults is `data/cifar10/`.
- **plotable** (*boolean*) – Whether to plot some image examples, False as default.

#### Examples

```
>>> X_train, y_train, X_test, y_test = tl.files.load_cifar10_dataset(shape=(-1,␣
↪32, 32, 3))
```

#### References

- CIFAR website
- Data download link
- https://teratail.com/questions/28932

### Penn TreeBank (PTB)

`tensorlayer.files.load_ptb_dataset(path='data')`

Load Penn TreeBank (PTB) dataset.

It is used in many LANGUAGE MODELING papers, including "Empirical Evaluation and Combination of Advanced Language Modeling Techniques", "Recurrent Neural Network Regularization". It consists of 929k training words, 73k validation words, and 82k test words. It has 10k words in its vocabulary.

**Parameters** **path** (*str*) – The path that the data is downloaded to, defaults is `data/ptb/`.

**Returns**

- **train_data, valid_data, test_data** (*list of int*) – The training, validating and testing data in integer format.
- **vocab_size** (*int*) – The vocabulary size.

#### Examples

```
>>> train_data, valid_data, test_data, vocab_size = tl.files.load_ptb_dataset()
```

### References

- `tensorflow.models.rnn.ptb import reader`
- Manual download

### Notes

- If you want to get the raw data, see the source code.

## Matt Mahoney's text8

`tensorlayer.files.load_matt_mahoney_text8_dataset`(*path='data'*)

Load Matt Mahoney's dataset.

Download a text file from Matt Mahoney's website if not present, and make sure it's the right size. Extract the first file enclosed in a zip file as a list of words. This dataset can be used for Word Embedding.

**Parameters** **path** (*str*) – The path that the data is downloaded to, defaults is `data/mm_test8/`.

**Returns** The raw text data e.g. [.... 'their', 'families', 'who', 'were', 'expelled', 'from', 'jerusalem', ...]

**Return type** list of str

### Examples

```
>>> words = tl.files.load_matt_mahoney_text8_dataset()
>>> print('Data size', len(words))
```

## IMBD

`tensorlayer.files.load_imdb_dataset`(*path='data'*, *nb_words=None*, *skip_top=0*, *maxlen=None*, *test_split=0.2*, *seed=113*, *start_char=1*, *oov_char=2*, *index_from=3*)

Load IMDB dataset.

**Parameters**

- **path** (*str*) – The path that the data is downloaded to, defaults is `data/imdb/`.
- **nb_words** (*int*) – Number of words to get.
- **skip_top** (*int*) – Top most frequent words to ignore (they will appear as oov_char value in the sequence data).
- **maxlen** (*int*) – Maximum sequence length. Any longer sequence will be truncated.
- **seed** (*int*) – Seed for reproducible data shuffling.
- **start_char** (*int*) – The start of a sequence will be marked with this character. Set to 1 because 0 is usually the padding character.
- **oov_char** (*int*) – Words that were cut out because of the num_words or skip_top limit will be replaced with this character.
- **index_from** (*int*) – Index actual words with this index and higher.

#### Examples

```
>>> X_train, y_train, X_test, y_test = tl.files.load_imdb_dataset(
...                                 nb_words=20000, test_split=0.2)
>>> print('X_train.shape', X_train.shape)
... (20000,)  [[1, 62, 74, ... 1033, 507, 27],[1, 60, 33, ... 13, 1053, 7]..]
>>> print('y_train.shape', y_train.shape)
... (20000,)  [1 0 0 ..., 1 0 1]
```

#### References

- Modified from keras.

### Nietzsche

`tensorlayer.files.load_nietzsche_dataset(path='data')`

Load Nietzsche dataset.

**Parameters** **path** (*str*) – The path that the data is downloaded to, defaults is `data/nietzsche/`.

**Returns** The content.

**Return type** str

#### Examples

```
>>> see tutorial_generate_text.py
>>> words = tl.files.load_nietzsche_dataset()
>>> words = basic_clean_str(words)
>>> words = words.split()
```

### English-to-French translation data from the WMT'15 Website

`tensorlayer.files.load_wmt_en_fr_dataset(path='data')`

Load WMT'15 English-to-French translation dataset.

It will download the data from the WMT'15 Website (10^9-French-English corpus), and the 2013 news test from the same site as development set. Returns the directories of training data and test data.

**Parameters** **path** (*str*) – The path that the data is downloaded to, defaults is `data/wmt_en_fr/`.

#### References

- Code modified from /tensorflow/models/rnn/translation/data_utils.py

#### Notes

Usually, it will take a long time to download this dataset.

### Flickr25k

`tensorlayer.files.`**`load_flickr25k_dataset`**(*tag='sky'*, *path='data'*, *n_threads=50*, *printable=False*)

Load Flickr25K dataset.

Returns a list of images by a given tag from Flick25k dataset, it will download Flickr25k from the official website at the first time you use it.

**Parameters**

- **tag** (*str or None*) –

  **What images to return.**

  - If you want to get images with tag, use string like 'dog', 'red', see Flickr Search.
  - If you want to get all images, set to `None`.
- **path** (*str*) – The path that the data is downloaded to, defaults is `data/flickr25k/`.
- **n_threads** (*int*) – The number of thread to read image.
- **printable** (*boolean*) – Whether to print infomation when reading images, default is `False`.

#### Examples

Get images with tag of sky

```
>>> images = tl.files.load_flickr25k_dataset(tag='sky')
```

Get all images

```
>>> images = tl.files.load_flickr25k_dataset(tag=None, n_threads=100,␣
↪printable=True)
```

### Flickr1M

`tensorlayer.files.`**`load_flickr1M_dataset`**(*tag='sky'*, *size=10*, *path='data'*, *n_threads=50*, *printable=False*)

Load Flick1M dataset.

Returns a list of images by a given tag from Flickr1M dataset, it will download Flickr1M from the official website at the first time you use it.

**Parameters**

- **tag** (*str or None*) –

  **What images to return.**

  - If you want to get images with tag, use string like 'dog', 'red', see Flickr Search.
  - If you want to get all images, set to `None`.
- **size** (*int*) – integer between 1 to 10. 1 means 100k images … 5 means 500k images, 10 means all 1 million images. Default is 10.
- **path** (*str*) – The path that the data is downloaded to, defaults is `data/flickr25k/`.
- **n_threads** (*int*) – The number of thread to read image.

- **printable** (*boolean*) – Whether to print infomation when reading images, default is `False`.

### Examples

Use 200k images

```
>>> images = tl.files.load_flickr1M_dataset(tag='zebra', size=2)
```

Use 1 Million images

```
>>> images = tl.files.load_flickr1M_dataset(tag='zebra')
```

## CycleGAN

`tensorlayer.files.`**`load_cyclegan_dataset`**(*filename='summer2winter_yosemite'*, *path='data'*)

Load images from CycleGAN's database, see this link.

**Parameters**

- **filename** (*str*) – The dataset you want, see this link.
- **path** (*str*) – The path that the data is downloaded to, defaults is *data/cyclegan*

### Examples

```
>>> im_train_A, im_train_B, im_test_A, im_test_B = load_cyclegan_dataset(filename=
↪'summer2winter_yosemite')
```

## CelebA

`tensorlayer.files.`**`load_celebA_dataset`**(*path='data'*)

Load CelebA dataset

Return a list of image path.

**Parameters** **path** (*str*) – The path that the data is downloaded to, defaults is `data/celebA/`.

## VOC 2007/2012

`tensorlayer.files.`**`load_voc_dataset`**(*path='data'*, *dataset='2012'*, *contain_classes_in_person=False*)

Pascal VOC 2007/2012 Dataset.

It has 20 objects: aeroplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, diningtable, dog, horse, motorbike, person, pottedplant, sheep, sofa, train, tvmonitor and additional 3 classes : head, hand, foot for person.

**Parameters**

- **path** (*str*) – The path that the data is downloaded to, defaults is `data/VOC`.
- **dataset** (*str*) – The VOC dataset version, *2012*, *2007*, *2007test* or *2012test*. We usually train model on *2007+2012* and test it on *2007test*.

- **contain_classes_in_person** (`boolean`) – Whether include head, hand and foot annotation, default is False.

**Returns**

- **imgs_file_list** (*list of str*) – Full paths of all images.
- **imgs_semseg_file_list** (*list of str*) – Full paths of all maps for semantic segmentation. Note that not all images have this map!
- **imgs_insseg_file_list** (*list of str*) – Full paths of all maps for instance segmentation. Note that not all images have this map!
- **imgs_ann_file_list** (*list of str*) – Full paths of all annotations for bounding box and object class, all images have this annotations.
- **classes** (*list of str*) – Classes in order.
- **classes_in_person** (*list of str*) – Classes in person.
- **classes_dict** (*dictionary*) – Class label to integer.
- **n_objs_list** (*list of int*) – Number of objects in all images in `imgs_file_list` in order.
- **objs_info_list** (*list of str*) – Darknet format for the annotation of all images in `imgs_file_list` in order. `[class_id x_centre y_centre width height]` in ratio format.
- **objs_info_dicts** (*dictionary*) – The annotation of all images in `imgs_file_list`, `{imgs_file_list : dictionary for annotation}`, format from TensorFlow/Models/object-detection.

### Examples

```
>>> imgs_file_list, imgs_semseg_file_list, imgs_insseg_file_list, imgs_ann_file_
↪list,
>>>     classes, classes_in_person, classes_dict,
>>>     n_objs_list, objs_info_list, objs_info_dicts = tl.files.load_voc_
↪dataset(dataset="2012", contain_classes_in_person=False)
>>> idx = 26
>>> print(classes)
... ['aeroplane', 'bicycle', 'bird', 'boat', 'bottle', 'bus', 'car', 'cat', 'chair
↪', 'cow', 'diningtable', 'dog', 'horse', 'motorbike', 'person', 'pottedplant',
↪'sheep', 'sofa', 'train', 'tvmonitor']
>>> print(classes_dict)
... {'sheep': 16, 'horse': 12, 'bicycle': 1, 'bottle': 4, 'cow': 9, 'sofa': 17,
↪'car': 6, 'dog': 11, 'cat': 7, 'person': 14, 'train': 18, 'diningtable': 10,
↪'aeroplane': 0, 'bus': 5, 'pottedplant': 15, 'tvmonitor': 19, 'chair': 8, 'bird
↪': 2, 'boat': 3, 'motorbike': 13}
>>> print(imgs_file_list[idx])
... data/VOC/VOC2012/JPEGImages/2007_000423.jpg
>>> print(n_objs_list[idx])
... 2
>>> print(imgs_ann_file_list[idx])
... data/VOC/VOC2012/Annotations/2007_000423.xml
>>> print(objs_info_list[idx])
... 14 0.173 0.461333333333 0.142 0.496
... 14 0.828 0.542666666667 0.188 0.594666666667
>>> ann = tl.prepro.parse_darknet_ann_str_to_list(objs_info_list[idx])
>>> print(ann)
```

```
... [[14, 0.173, 0.461333333333, 0.142, 0.496], [14, 0.828, 0.542666666667, 0.188,
↪ 0.594666666667]]
>>> c, b = tl.prepro.parse_darknet_ann_list_to_cls_box(ann)
>>> print(c, b)
... [14, 14] [[0.173, 0.461333333333, 0.142, 0.496], [0.828, 0.542666666667, 0.
↪188, 0.594666666667]]
```

#### References

- Pascal VOC2012 Website.
- Pascal VOC2007 Website.

### Google Drive

`tensorlayer.files.`**`download_file_from_google_drive`**(*ID*, *destination*)

Download file from Google Drive.

See `tl.files.load_celebA_dataset` for example.

**Parameters**

- **ID** (*str*) – The driver ID.
- **destination** (*str*) – The destination for save file.

## 2.8.2 Load and save network

### Save network into list (npz)

`tensorlayer.files.`**`save_npz`**(*save_list=None*, *name='model.npz'*, *sess=None*)

Input parameters and the file name, save parameters into .npz file. Use tl.utils.load_npz() to restore.

**Parameters**

- **save_list** (*list of tensor*) – A list of parameters (tensor) to be saved.
- **name** (*str*) – The name of the *.npz* file.
- **sess** (*None or Session*) – Session may be required in some case.

#### Examples

Save model to npz

```
>>> tl.files.save_npz(network.all_params, name='model.npz', sess=sess)
```

Load model from npz (Method 1)

```
>>> load_params = tl.files.load_npz(name='model.npz')
>>> tl.files.assign_params(sess, load_params, network)
```

Load model from npz (Method 2)

```
>>> tl.files.load_and_assign_npz(sess=sess, name='model.npz', network=network)
```

### Notes

If you got session issues, you can change the value.eval() to value.eval(session=sess)

### References

Saving dictionary using numpy

## Load network from list (npz)

`tensorlayer.files.load_npz(path='', name='model.npz')`

Load the parameters of a Model saved by tl.files.save_npz().

**Parameters**

- **path** (*str*) – Folder path to *.npz* file.
- **name** (*str*) – The name of the *.npz* file.

**Returns** A list of parameters in order.

**Return type** list of array

### Examples

- See `tl.files.save_npz`

### References

- Saving dictionary using numpy

## Assign a list of parameters to network

`tensorlayer.files.assign_params(sess, params, network)`

Assign the given parameters to the TensorLayer network.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **params** (*list of array*) – A list of parameters (array) in order.
- **network** (Layer) – The network to be assigned.

**Returns** A list of tf ops in order that assign params. Support sess.run(ops) manually.

**Return type** list of operations

### Examples

- See `tl.files.save_npz`

### References

- Assign value to a TensorFlow variable

## Load and assign a list of parameters to network

`tensorlayer.files.`**`load_and_assign_npz`**(*sess=None*, *name=None*, *network=None*)

Load model from npz and assign to a network.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **name** (*str*) – The name of the *.npz* file.
- **network** (Layer) – The network to be assigned.

**Returns** Returns False, if the model is not exist.

**Return type** False or network

### Examples

- See `tl.files.save_npz`

## Save network into dict (npz)

`tensorlayer.files.`**`save_npz_dict`**(*save_list=None*, *name='model.npz'*, *sess=None*)

Input parameters and the file name, save parameters as a dictionary into .npz file.

Use `tl.files.load_and_assign_npz_dict()` to restore.

**Parameters**

- **save_list** (*list of parameters*) – A list of parameters (tensor) to be saved.
- **name** (*str*) – The name of the *.npz* file.
- **sess** (*Session*) – TensorFlow Session.

## Load network from dict (npz)

`tensorlayer.files.`**`load_and_assign_npz_dict`**(*name='model.npz'*, *sess=None*)

Restore the parameters saved by `tl.files.save_npz_dict()`.

**Parameters**

- **name** (*str*) – The name of the *.npz* file.
- **sess** (*Session*) – TensorFlow Session.

### Save network into ckpt

`tensorlayer.files.`**`save_ckpt`**(*sess=None*, *mode_name='model.ckpt'*, *save_dir='checkpoint'*, *var_list=None*, *global_step=None*, *printable=False*)

Save parameters into *ckpt* file.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **mode_name** (*str*) – The name of the model, default is `model.ckpt`.
- **save_dir** (*str*) – The path / file directory to the *ckpt*, default is `checkpoint`.
- **var_list** (*list of tensor*) – The parameters / variables (tensor) to be saved. If empty, save all global variables (default).
- **global_step** (*int or None*) – Step number.
- **printable** (*boolean*) – Whether to print all parameters information.

**See also:**

*load_ckpt()*

### Load network from ckpt

`tensorlayer.files.`**`load_ckpt`**(*sess=None*, *mode_name='model.ckpt'*, *save_dir='checkpoint'*, *var_list=None*, *is_latest=True*, *printable=False*)

Load parameters from *ckpt* file.

**Parameters**

- **sess** (*Session*) – TensorFlow Session.
- **mode_name** (*str*) – The name of the model, default is `model.ckpt`.
- **save_dir** (*str*) – The path / file directory to the *ckpt*, default is `checkpoint`.
- **var_list** (*list of tensor*) – The parameters / variables (tensor) to be saved. If empty, save all global variables (default).
- **is_latest** (*boolean*) – Whether to load the latest *ckpt*, if False, load the *ckpt* with the name of `` `mode_name``.
- **printable** (*boolean*) – Whether to print all parameters information.

#### Examples

Save all global parameters.

```
>>> tl.files.save_ckpt(sess=sess, mode_name='model.ckpt', save_dir='model',␣
↪printable=True)
```

Save specific parameters.

```
>>> tl.files.save_ckpt(sess=sess, mode_name='model.ckpt', var_list=net.all_params,
↪ save_dir='model', printable=True)
```

Load latest ckpt.

```
>>> tl.files.load_ckpt(sess=sess, var_list=net.all_params, save_dir='model',␣
↪printable=True)
```

Load specific ckpt.

```
>>> tl.files.load_ckpt(sess=sess, mode_name='model.ckpt', var_list=net.all_params,
↪ save_dir='model', is_latest=False, printable=True)
```

### 2.8.3 Load and save variables

#### Save variables as .npy

tensorlayer.files.**save_any_to_npy**(*save_dict=None*, *name='file.npy'*)

Save variables to *.npy* file.

**Parameters**

- **save_dict** (*directory*) – The variables to be saved.
- **name** (*str*) – File name.

#### Examples

```
>>> tl.files.save_any_to_npy(save_dict={'data': ['a','b']}, name='test.npy')
>>> data = tl.files.load_npy_to_any(name='test.npy')
>>> print(data)
... {'data': ['a','b']}
```

#### Load variables from .npy

tensorlayer.files.**load_npy_to_any**(*path=''*, *name='file.npy'*)

Load *.npy* file.

**Parameters**

- **path** (*str*) – Path to the file (optional).
- **name** (*str*) – File name.

#### Examples

- see tl.files.save_any_to_npy()

### 2.8.4 Folder/File functions

#### Check file exists

tensorlayer.files.**file_exists**(*filepath*)

Check whether a file exists by given file path.

### Check folder exists

`tensorlayer.files.folder_exists(folderpath)`
Check whether a folder exists by given folder path.

### Delete file

`tensorlayer.files.del_file(filepath)`
Delete a file by given file path.

### Delete folder

`tensorlayer.files.del_folder(folderpath)`
Delete a folder by given folder path.

### Read file

`tensorlayer.files.read_file(filepath)`
Read a file and return a string.

#### Examples

```
>>> data = tl.files.read_file('data.txt')
```

### Load file list from folder

`tensorlayer.files.load_file_list(path=None, regx='\\.npz', printable=True)`
Return a file list in a folder by given a path and regular expression.

**Parameters**

- **path** (*str or None*) – A folder path, if *None*, use the current directory.
- **regx** (*str*) – The regx of file name.
- **printable** (*boolean*) – Whether to print the files infomation.

#### Examples

```
>>> file_list = tl.files.load_file_list(path=None, regx='w1pre_[0-9]+\.(npz)')
```

### Load folder list from folder

`tensorlayer.files.load_folder_list(path='')`
Return a folder list in a folder by given a folder path.

**Parameters** **path** (*str*) – A folder path.

## Check and Create folder

`tensorlayer.files.exists_or_mkdir(path, verbose=True)`

Check a folder by given name, if not exist, create the folder and return False, if directory exists, return True.

**Parameters**

- **path** (*str*) – A folder path.
- **verbose** (*boolean*) – If True (default), prints results.

**Returns** True if folder already exist, otherwise, returns False and create the folder.

**Return type** boolean

### Examples

```
>>> tl.files.exists_or_mkdir("checkpoints/train")
```

## Download or extract

`tensorlayer.files.maybe_download_and_extract(filename, working_directory, url_source, extract=False, expected_bytes=None)`

Checks if file exists in working_directory otherwise tries to dowload the file, and optionally also tries to extract the file if format is ".zip" or ".tar"

**Parameters**

- **filename** (*str*) – The name of the (to be) dowloaded file.
- **working_directory** (*str*) – A folder path to search for the file in and dowload the file to
- **url** (*str*) – The URL to download the file from
- **extract** (*boolean*) – If True, tries to uncompress the dowloaded file is ".tar.gz/.tar.bz2" or ".zip" file, default is False.
- **expected_bytes** (*int or None*) – If set tries to verify that the downloaded file is of the specified size, otherwise raises an Exception, defaults is None which corresponds to no check being performed.

**Returns** File path of the dowloaded (uncompressed) file.

**Return type** str

### Examples

```
>>> down_file = tl.files.maybe_download_and_extract(filename='train-images-idx3-
↪ubyte.gz',
...                                                working_directory='data/',
...                                                url_source='http://yann.lecun.com/
↪exdb/mnist/')
>>> tl.files.maybe_download_and_extract(filename='ADEChallengeData2016.zip',
...                                                 working_directory='data/',
...                                                 url_source='http://sceneparsing.
↪csail.mit.edu/data/',
...                                                 extract=True)
```

### 2.8.5 Sort

#### List of string with number in human order

tensorlayer.files.**natural_keys**(*text*)

Sort list of string with number in human order.

##### Examples

```
>>> l = ['im1.jpg', 'im31.jpg', 'im11.jpg', 'im21.jpg', 'im03.jpg', 'im05.jpg']
>>> l.sort(key=tl.files.natural_keys)
... ['im1.jpg', 'im03.jpg', 'im05', 'im11.jpg', 'im21.jpg', 'im31.jpg']
>>> l.sort() # that is what we dont want
... ['im03.jpg', 'im05', 'im1.jpg', 'im11.jpg', 'im21.jpg', 'im31.jpg']
```

##### References

- link

### 2.8.6 Visualizing npz file

tensorlayer.files.**npz_to_W_pdf**(*path=None*, *regx='w1pre_[0-9]+\\.(npz)'*)

Convert the first weight matrix of *.npz* file to *.pdf* by using *tl.visualize.W()*.

**Parameters**

- **path** (*str*) – A folder path to *npz* files.
- **regx** (*str*) – Regx for the file name.

##### Examples

Convert the first weight matrix of w1_pre. . . npz file to w1_pre. . . pdf.

```
>>> tl.files.npz_to_W_pdf(path='/Users/.../npz_file/', regx='w1pre_[0-9]+\.(npz)')
```

## 2.9 API - Visualization

TensorFlow provides TensorBoard to visualize the model, activations etc. Here we provide more functions for data visualization.

| | |
|---|---|
| *read_image*(image[, path]) | Read one image. |
| *read_images*(img_list[, path, n_threads, . . . ]) | Returns all images in list by given path and name of each image file. |
| *save_image*(image[, image_path]) | Save a image. |

Continued on next page

Table 2.9 – continued from previous page

| | |
|---|---|
| `save_images`(images, size[, image_path]) | Save multiple images into one single image. |
| `draw_boxes_and_labels_to_image`(image, ...[, ...]) | Draw bboxes and class labels on image. |
| `CNN2d`([CNN, second, saveable, name, fig_idx]) | Display a group of RGB or Greyscale CNN masks. |
| `frame`([I, second, saveable, name, cmap, fig_idx]) | Display a frame(image). |
| `images2d`([images, second, saveable, name, ...]) | Display a group of RGB or Greyscale images. |
| `tsne_embedding`(embeddings, reverse_dictionary) | Visualize the embeddings by using t-SNE. |
| `draw_weights`([W, second, saveable, shape, ...]) | Visualize every columns of the weight matrix to a group of Greyscale img. |

## 2.9.1 Save and read images

### Read one image

`tensorlayer.visualize.`**`read_image`**(*image*, *path=''*)

Read one image.

**Parameters**

- **`image`** (*`str`*) – The image file name.
- **`path`** (*`str`*) – The image folder path.

**Returns** The image.

**Return type** numpy.array

### Read multiple images

`tensorlayer.visualize.`**`read_images`**(*img_list*, *path=''*, *n_threads=10*, *printable=True*)

Returns all images in list by given path and name of each image file.

**Parameters**

- **`img_list`** (*`list of str`*) – The image file names.
- **`path`** (*`str`*) – The image folder path.
- **`n_threads`** (*`int`*) – The number of threads to read image.
- **`printable`** (*`boolean`*) – Whether to print information when reading images.

**Returns** The images.

**Return type** list of numpy.array

### Save one image

`tensorlayer.visualize.`**`save_image`**(*image*, *image_path=''*)

Save a image.

**Parameters**

- **`image`** (*`numpy array`*) – [w, h, c]
- **`image_path`** (*`str`*) – path

### Save multiple images

`tensorlayer.visualize.`**`save_images`**(*images*, *size*, *image_path=''*)

Save multiple images into one single image.

**Parameters**

- **images** (*numpy array*) – (batch, w, h, c)
- **size** (*list of 2 ints*) – row and column number. number of images should be equal or less than size[0] * size[1]
- **image_path** (*str*) – save path

**Returns** The image.

**Return type** numpy.array

#### Examples

```
>>> images = np.random.rand(64, 100, 100, 3)
>>> tl.visualize.save_images(images, [8, 8], 'temp.png')
```

### Save image for object detection

`tensorlayer.visualize.`**`draw_boxes_and_labels_to_image`**(*image*, *classes*, *coords*, *scores*, *classes_list*, *is_center=True*, *is_rescale=True*, *save_name=None*)

Draw bboxes and class labels on image. Return or save the image with bboxes, example in the docs of `tl.prepro`.

**Parameters**

- **image** (*numpy.array*) – The RGB image [height, width, channel].
- **classes** (*list of int*) – A list of class ID (int).
- **coords** (*list of int*) –

  **A list of list for coordinates.**

  – Should be [x, y, x2, y2] (up-left and botton-right format)

  – If [x_center, y_center, w, h] (set is_center to True).
- **scores** (*list of float*) – A list of score (float). (Optional)
- **classes_list** (*list of str*) – for converting ID to string on image.
- **is_center** (*boolean*) –

  **Whether the coordinates is [x_center, y_center, w, h]**

  – If coordinates are [x_center, y_center, w, h], set it to True for converting it to [x, y, x2, y2] (up-left and botton-right) internally.

  – If coordinates are [x1, x2, y1, y2], set it to False.
- **is_rescale** (*boolean*) –

  **Whether to rescale the coordinates from pixel-unit format to ratio format.**

- If True, the input coordinates are the portion of width and high, this API will scale the coordinates to pixel unit internally.
- If False, feed the coordinates with pixel unit format.

- **save_name** (*None or str*) – The name of image file (i.e. image.png), if None, not to save image.

**Returns** The saved image.

**Return type** numpy.array

### References

- OpenCV rectangle and putText.
- scikit-image.

## 2.9.2 Visualize model parameters

### Visualize CNN 2d filter

`tensorlayer.visualize.CNN2d(CNN=None, second=10, saveable=True, name='cnn', fig_idx=3119362)`

Display a group of RGB or Greyscale CNN masks.

**Parameters**

- **CNN** (*numpy.array*) – The image. e.g: 64 5x5 RGB images can be (5, 5, 3, 64).
- **second** (*int*) – The display second(s) for the image(s), if saveable is False.
- **saveable** (*boolean*) – Save or plot the figure.
- **name** (*str*) – A name to save the image, if saveable is True.
- **fig_idx** (*int*) – The matplotlib figure index.

### Examples

```
>>> tl.visualize.CNN2d(network.all_params[0].eval(), second=10, saveable=True,
↪name='cnn1_mnist', fig_idx=2012)
```

## 2.9.3 Visualize images

### Image by matplotlib

`tensorlayer.visualize.frame(I=None, second=5, saveable=True, name='frame', cmap=None, fig_idx=12836)`

Display a frame(image). Make sure OpenAI Gym render() is disable before using it.

**Parameters**

- **I** (*numpy.array*) – The image.
- **second** (*int*) – The display second(s) for the image(s), if saveable is False.

- **saveable** (*boolean*) – Save or plot the figure.
- **name** (*str*) – A name to save the image, if saveable is True.
- **cmap** (*None or str*) – 'gray' for greyscale, None for default, etc.
- **fig_idx** (*int*) – matplotlib figure index.

### Examples

```
>>> env = gym.make("Pong-v0")
>>> observation = env.reset()
>>> tl.visualize.frame(observation)
```

### Images by matplotlib

tensorlayer.visualize.**images2d**(*images=None, second=10, saveable=True, name='images', dtype=None, fig_idx=3119362*)

Display a group of RGB or Greyscale images.

**Parameters**

- **images** (*numpy.array*) – The images.
- **second** (*int*) – The display second(s) for the image(s), if saveable is False.
- **saveable** (*boolean*) – Save or plot the figure.
- **name** (*str*) – A name to save the image, if saveable is True.
- **dtype** (*None or numpy data type*) – The data type for displaying the images.
- **fig_idx** (*int*) – matplotlib figure index.

### Examples

```
>>> X_train, y_train, X_test, y_test = tl.files.load_cifar10_dataset(shape=(-1,
↪32, 32, 3), plotable=False)
>>> tl.visualize.images2d(X_train[0:100,:,:,:], second=10, saveable=False, name=
↪'cifar10', dtype=np.uint8, fig_idx=20212)
```

## 2.9.4 Visualize embeddings

tensorlayer.visualize.**tsne_embedding**(*embeddings, reverse_dictionary, plot_only=500, second=5, saveable=False, name='tsne', fig_idx=9862*)

Visualize the embeddings by using t-SNE.

**Parameters**

- **embeddings** (*numpy.array*) – The embedding matrix.
- **reverse_dictionary** (*dictionary*) – id_to_word, mapping id to unique word.
- **plot_only** (*int*) – The number of examples to plot, choice the most common words.
- **second** (*int*) – The display second(s) for the image(s), if saveable is False.
- **saveable** (*boolean*) – Save or plot the figure.

- **name** (*str*) – A name to save the image, if saveable is True.
- **fig_idx** (*int*) – matplotlib figure index.

### Examples

```
>>> see 'tutorial_word2vec_basic.py'
>>> final_embeddings = normalized_embeddings.eval()
>>> tl.visualize.tsne_embedding(final_embeddings, labels, reverse_dictionary,
...                     plot_only=500, second=5, saveable=False, name='tsne')
```

## 2.9.5 Visualize weights

tensorlayer.visualize.**draw_weights**(*W=None*, *second=10*, *saveable=True*, *shape=None*, *name='mnist'*, *fig_idx=2396512*)

Visualize every columns of the weight matrix to a group of Greyscale img.

**Parameters**

- **W** (*numpy.array*) – The weight matrix
- **second** (*int*) – The display second(s) for the image(s), if saveable is False.
- **saveable** (*boolean*) – Save or plot the figure.
- **shape** (*a list with 2 int or None*) – The shape of feature image, MNIST is [28, 80].
- **name** (*a string*) – A name to save the image, if saveable is True.
- **fig_idx** (*int*) – matplotlib figure index.

### Examples

```
>>> tl.visualize.draw_weights(network.all_params[0].eval(), second=10,
↪saveable=True, name='weight_of_1st_layer', fig_idx=2012)
```

# 2.10 API - Activations

To make TensorLayer simple, we minimize the number of activation functions as much as we can. So we encourage you to use TensorFlow's function. TensorFlow provides `tf.nn.relu`, `tf.nn.relu6`, `tf.nn.elu`, `tf.nn.softplus`, `tf.nn.softsign` and so on. More TensorFlow official activation functions can be found here. For parametric activation, please read the layer APIs.

The shortcut of `tensorlayer.activation` is `tensorlayer.act`.

## 2.10.1 Your activation

Customizes activation function in TensorLayer is very easy. The following example implements an activation that multiplies its input by 2. For more complex activation, TensorFlow API will be required.

```
def double_activation(x):
    return x * 2
```

| | |
|---|---|
| *identity*(x) | The identity activation function. |
| *ramp*(x[, v_min, v_max, name]) | The ramp activation function. |
| *leaky_relu*(x[, alpha, name]) | The LeakyReLU, Shortcut is `lrelu`. |
| *swish*(x[, name]) | The Swish function. |
| *pixel_wise_softmax*(x[, name]) | Return the softmax outputs of images, every pixels have multiple label, the sum of a pixel is 1. |

### 2.10.2 Identity

`tensorlayer.activation.`**`identity`**(*x*)

The identity activation function. Shortcut is `linear`.

**Parameters** **x** (*Tensor*) – input.

**Returns** A `Tensor` in the same type as `x`.

**Return type** Tensor

### 2.10.3 Ramp

`tensorlayer.activation.`**`ramp`**(*x*, *v_min=0*, *v_max=1*, *name=None*)

The ramp activation function.

**Parameters**

- **x** (*Tensor*) – input.
- **v_min** (*float*) – cap input to v_min as a lower bound.
- **v_max** (*float*) – cap input to v_max as a upper bound.
- **name** (*str*) – The function name (optional).

**Returns** A `Tensor` in the same type as `x`.

**Return type** Tensor

### 2.10.4 Leaky Relu

`tensorlayer.activation.`**`leaky_relu`**(*x*, *alpha=0.1*, *name='lrelu'*)

The LeakyReLU, Shortcut is `lrelu`.

Modified version of ReLU, introducing a nonzero gradient for negative input.

**Parameters**

- **x** (*Tensor*) – Support input type `float`, `double`, `int32`, `int64`, `uint8`, `int16`, or `int8`.
- **alpha** (*float*) – Slope.
- **name** (*str*) – The function name (optional).

### Examples

```
>>> net = tl.layers.DenseLayer(net, 100, act=lambda x : tl.act.lrelu(x, 0.2),␣
↪name='dense')
```

**Returns** A `Tensor` in the same type as `x`.

**Return type** Tensor

### References

- Rectifier Nonlinearities Improve Neural Network Acoustic Models, Maas et al. (2013)

## 2.10.5 Swish

`tensorlayer.activation.`**`swish`**(*x*, *name='swish'*)

**The Swish function.** See Swish: a Self-Gated Activation Function.

**Parameters**

- **x** (*Tensor*) – input.
- **name** (*str*) – function name (optional).

**Returns** A `Tensor` in the same type as `x`.

**Return type** Tensor

## 2.10.6 Pixel-wise softmax

`tensorlayer.activation.`**`pixel_wise_softmax`**(*x*, *name='pixel_wise_softmax'*)

Return the softmax outputs of images, every pixels have multiple label, the sum of a pixel is 1. Usually be used for image segmentation.

**Parameters**

- **x** (*Tensor*) –

  **input.**

  - For 2d image, 4D tensor (batch_size, height, weight, channel), where channel >= 2.
  - For 3d image, 5D tensor (batch_size, depth, height, weight, channel), where channel >= 2.

- **name** (*str*) – function name (optional)

**Returns** A `Tensor` in the same type as `x`.

**Return type** Tensor

### Examples

```
>>> outputs = pixel_wise_softmax(network.outputs)
>>> dice_loss = 1 - dice_coe(outputs, y_, epsilon=1e-5)
```

#### References

- tf.reverse

### 2.10.7 Parametric activation

See `tensorlayer.layers`.

## 2.11 API - Distributed Training

(Alpha release - usage might change later)

Helper sessions and methods to run a distributed training. Check this minst example.

| | |
|---|---|
| `TaskSpecDef`([task_type, index, trial, . . . ]) | Specification for a distributed task. |
| `TaskSpec`() | Returns the a `TaskSpecDef` based on the environment variables for distributed training. |
| `DistributedSession`([task_spec, . . . ]) | Creates a distributed session. |

### 2.11.1 Distributed training

#### TaskSpecDef

`tensorlayer.distributed.`**`TaskSpecDef`**(*task_type='master'*, *index=0*, *trial=None*, *ps_hosts=None*, *worker_hosts=None*, *master=None*)

Specification for a distributed task.

It contains the job name, index of the task, the parameter servers and the worker servers. If you want to use the last worker for continuous evaluation you can call the method *use_last_worker_as_evaluator* which returns a new `TaskSpecDef` object without the last worker in the cluster specification.

**Parameters**

- **task_type** (*str*) – Task type. One of *master*, *worker* or *ps*.
- **index** (*int*) – The zero-based index of the task. Distributed training jobs will have a single master task, one or more parameter servers, and one or more workers.
- **trial** (*int*) – The identifier of the trial being run.
- **ps_hosts** (*str OR list of str*) – A string with a coma separate list of hosts for the parameter servers or a list of hosts.
- **worker_hosts** (*str OR list of str*) – A string with a coma separate list of hosts for the worker servers or a list of hosts.
- **master** (*str*) – A string with the master hosts

#### Notes

master might not be included in TF_CONFIG and can be None. The shard_index is adjusted in any case to assign 0 to master and >= 1 to workers. This implementation doesn't support sparse arrays in the *TF_CONFIG* variable as the official TensorFlow documentation shows, as it is not a supported by the json definition.

### References

- ML-engine trainer considerations

## Create TaskSpecDef from environment variables

`tensorlayer.distributed.`**`TaskSpec`**`()`

Returns the a *TaskSpecDef* based on the environment variables for distributed training.

### References

- ML-engine trainer considerations
- TensorPort Distributed Computing

## Distributed session object

`tensorlayer.distributed.`**`DistributedSession`**`(`*task_spec=None, checkpoint_dir=None, scaffold=None, hooks=None, chief_only_hooks=None, save_checkpoint_secs=600, save_summaries_steps=<object object>, save_summaries_secs=<object object>, config=None, stop_grace_period_secs=120, log_step_count_steps=100*`)`

Creates a distributed session.

It calls *MonitoredTrainingSession* to create a `MonitoredSession` for distributed training.

**Parameters**

- **task_spec** (*TaskSpecDef.*) – The task spec definition from create_task_spec_def()
- **checkpoint_dir** (*str.*) – Optional path to a directory where to restore variables.
- **scaffold** (`Scaffold`) – A *Scaffold* used for gathering or building supportive ops. If not specified, a default one is created. It's used to finalize the graph.
- **hooks** (list of `SessionRunHook` objects.) – Optional
- **chief_only_hooks** (list of `SessionRunHook` objects.) – Activate these hooks if *is_chief==True*, ignore otherwise.
- **save_checkpoint_secs** (*int*) – The frequency, in seconds, that a checkpoint is saved using a default checkpoint saver. If *save_checkpoint_secs* is set to *None*, then the default checkpoint saver isn't used.
- **save_summaries_steps** (*int*) – The frequency, in number of global steps, that the summaries are written to disk using a default summary saver. If both *save_summaries_steps* and *save_summaries_secs* are set to *None*, then the default summary saver isn't used. Default 100.
- **save_summaries_secs** (*int*) – The frequency, in secs, that the summaries are written to disk using a default summary saver. If both *save_summaries_steps* and *save_summaries_secs* are set to *None*, then the default summary saver isn't used. Default not enabled.

- **config** (tf.ConfigProto) – an instance of *tf.ConfigProto* proto used to configure the session. It's the *config* argument of constructor of *tf.Session*.
- **stop_grace_period_secs** (*int*) – Number of seconds given to threads to stop after *close()* has been called.
- **log_step_count_steps** (*int*) – The frequency, in number of global steps, that the global step/sec is logged.

### Examples

A simple example for distributed training where all the workers use the same dataset:

```
>>> task_spec = TaskSpec()
>>> with tf.device(task_spec.device_fn()):
>>>      tensors = create_graph()
>>> with tl.DistributedSession(task_spec=task_spec,
...                            checkpoint_dir='/tmp/ckpt') as session:
>>>      while not session.should_stop():
>>>           session.run(tensors)
```

An example where the dataset is shared among the workers (see https://www.tensorflow.org/programmers_guide/datasets):

```
>>> task_spec = TaskSpec()
>>> # dataset is a :class:`tf.data.Dataset` with the raw data
>>> dataset = create_dataset()
>>> if task_spec is not None:
>>>     dataset = dataset.shard(task_spec.num_workers, task_spec.shard_index)
>>> # shuffle or apply a map function to the new sharded dataset, for example:
>>> dataset = dataset.shuffle(buffer_size=10000)
>>> dataset = dataset.batch(batch_size)
>>> dataset = dataset.repeat(num_epochs)
>>> # create the iterator for the dataset and the input tensor
>>> iterator = dataset.make_one_shot_iterator()
>>> next_element = iterator.get_next()
>>> with tf.device(task_spec.device_fn()):
>>>      # next_element is the input for the graph
>>>      tensors = create_graph(next_element)
>>> with tl.DistributedSession(task_spec=task_spec,
...                            checkpoint_dir='/tmp/ckpt') as session:
>>>      while not session.should_stop():
>>>           session.run(tensors)
```

### References

- MonitoredTrainingSession

## Data sharding

In some cases we want to shard the data among all the training servers and not use all the data in all servers. TensorFlow >=1.4 provides some helper classes to work with data that support data sharding: Datasets

It is important in sharding that the shuffle or any non deterministic operation is done after creating the shards:

```
from tensorflow.contrib.data import TextLineDataset
from tensorflow.contrib.data import Dataset

task_spec = TaskSpec()
task_spec.create_server()
files_dataset = Dataset.list_files(files_pattern)
dataset = TextLineDataset(files_dataset)
dataset = dataset.map(your_python_map_function, num_threads=4)
if task_spec is not None:
      dataset = dataset.shard(task_spec.num_workers, task_spec.shard_index)
dataset = dataset.shuffle(buffer_size)
dataset = dataset.batch(batch_size)
dataset = dataset.repeat(num_epochs)
iterator = dataset.make_one_shot_iterator()
next_element = iterator.get_next()
with tf.device(task_spec.device_fn()):
      tensors = create_graph(next_element)
with tl.DistributedSession(task_spec=task_spec,
                           checkpoint_dir='/tmp/ckpt') as session:
      while not session.should_stop():
          session.run(tensors)
```

### Logging

We can use task_spec to log only in the master server:

```
while not session.should_stop():
      should_log = task_spec.is_master() and your_conditions
      if should_log:
          results = session.run(tensors_with_log_info)
          logging.info(...)
      else:
          results = session.run(tensors)
```

### Continuous evaluation

You can use one of the workers to run an evaluation for the saved checkpoints:

```
import tensorflow as tf
from tensorflow.python.training import session_run_hook
from tensorflow.python.training.monitored_session import SingularMonitoredSession

class Evaluator(session_run_hook.SessionRunHook):
      def __init__(self, checkpoints_path, output_path):
          self.checkpoints_path = checkpoints_path
          self.summary_writer = tf.summary.FileWriter(output_path)
          self.lastest_checkpoint = ''

      def after_create_session(self, session, coord):
          checkpoint = tf.train.latest_checkpoint(self.checkpoints_path)
          # wait until a new check point is available
          while self.lastest_checkpoint == checkpoint:
              time.sleep(30)
              checkpoint = tf.train.latest_checkpoint(self.checkpoints_path)
          self.saver.restore(session, checkpoint)
```

```
            self.lastest_checkpoint = checkpoint

        def end(self, session):
            super(Evaluator, self).end(session)
            # save summaries
            step = int(self.lastest_checkpoint.split('-')[-1])
            self.summary_writer.add_summary(self.summary, step)

        def _create_graph():
            # your code to create the graph with the dataset

        def run_evaluation():
            with tf.Graph().as_default():
                summary_tensors = create_graph()
                self.saver = tf.train.Saver(var_list=tf_variables.trainable_variables())
                hooks = self.create_hooks()
                hooks.append(self)
                if self.max_time_secs and self.max_time_secs > 0:
                    hooks.append(StopAtTimeHook(self.max_time_secs))
                # this evaluation runs indefinitely, until the process is killed
                while True:
                    with SingularMonitoredSession(hooks=[self]) as session:
                        try:
                            while not sess.should_stop():
                                self.summary = session.run(summary_tensors)
                        except OutOfRangeError:
                            pass
                        # end of evaluation

task_spec = TaskSpec().user_last_worker_as_evaluator()
if task_spec.is_evaluator():
      Evaluator().run_evaluation()
else:
      task_spec.create_server()
      # run normal training
```

### 2.11.2 Session hooks

TensorFlow provides some Session Hooks to do some operations in the sessions. We added more to help with common operations.

#### Stop after maximum time

`tensorlayer.distributed.`**`StopAtTimeHook`**(*time_running*)

Hook that requests stop after a specified time.

**Parameters** **time_running** (`int`) – Maximum time running in seconds

#### Initialize network with checkpoint

`tensorlayer.distributed.`**`LoadCheckpoint`**(*saver*, *checkpoint*)

Hook that loads a checkpoint after the session is created.

```
>>> from tensorflow.python.ops import variables as tf_variables
>>> from tensorflow.python.training.monitored_session import␣
↪SingularMonitoredSession
>>>
>>> tensors = create_graph()
>>> saver = tf.train.Saver(var_list=tf_variables.trainable_variables())
>>> checkpoint_hook = LoadCheckpoint(saver, my_checkpoint_file)
>>> with tf.SingularMonitoredSession(hooks=[checkpoint_hook]) as session:
>>>     while not session.should_stop():
>>>         session.run(tensors)
```

CHAPTER 3

# Command-line Reference

TensorLayer provides a handy command-line tool *tl* to perform some common tasks.

## 3.1 CLI - Command Line Interface

The tensorlayer.cli module provides a command-line tool for some common tasks.

### 3.1.1 tl train

(Alpha release - usage might change later)

The tensorlayer.cli.train module provides the `tl train` subcommand. It helps the user bootstrap a TensorFlow/TensorLayer program for distributed training using multiple GPU cards or CPUs on a computer.

You need to first setup the CUDA_VISIBLE_DEVICES to tell `tl train` which GPUs are available. If the CUDA_VISIBLE_DEVICES is not given, `tl train` would try best to discover all available GPUs.

In distribute training, each TensorFlow program needs a TF_CONFIG environment variable to describe the cluster. It also needs a master daemon to monitor all trainers. `tl train` is responsible for automatically managing these two tasks.

#### Usage

tl train [-h] [-p NUM_PSS] [-c CPU_TRAINERS] <file> [args [args ...]]

```
# example of using GPU 0 and 1 for training mnist
CUDA_VISIBLE_DEVICES="0,1"
tl train example/tutorial_mnist_distributed.py

# example of using CPU trainers for inception v3
tl train -c 16 example/tutorial_imagenet_inceptionV3_distributed.py
```

```
# example of using GPU trainers for inception v3 with customized arguments
# as CUDA_VISIBLE_DEVICES is not given, tl would try to discover all available GPUs
tl train example/tutorial_imagenet_inceptionV3_distributed.py -- --batch_size 16
```

### Command-line Arguments

- `file`: python file path.
- `NUM_PSS` : The number of parameter servers.
- `CPU_TRAINERS`: The number of CPU trainers.

  It is recommended that `NUM_PSS + CPU_TRAINERS <= cpu count`
- `args`: Any parameter after `--` would be passed to the python program.

### Notes

A parallel training program would require multiple parameter servers to help parallel trainers to exchange intermediate gradients. The best number of parameter servers is often proportional to the size of your model as well as the number of CPUs available. You can control the number of parameter servers using the `-p` parameter.

If you have a single computer with massive CPUs, you can use the `-c` parameter to enable CPU-only parallel training. The reason we are not supporting GPU-CPU co-training is because GPU and CPU are running at different speeds. Using them together in training would incur stragglers.

CHAPTER 4

# Indices and tables

- genindex
- modindex
- search

# Python Module Index

## t

# Index

## A



## B



## C



## D

# E



# F



# G



# H



# I



# L

## R



## S



## T

## U



## V



## W



## Z