TensorLayer Documentation

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Contents

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.

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.

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.

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
```

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.

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.

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`.

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.

Issue

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

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

Tutorial

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.

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.

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 TensorFlow's methods like `sess.run()`, see `tutorial_mnist.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()
```

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()
```

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 the tutorial scripts, like `tutorial_cifar10_tfrecord.py`.

At the begin, we add a *Conv2dLayer* with 32 filters of size 5x5 on top, follow by max-pooling of factor 2 in both dimensions. And then apply a `Conv2dLayer` with 64 filters of size 5x5 again and follow by a max_pool again. After that, flatten the 4D output to 1D vector by using `FlattenLayer`, and apply a dropout with 50% to last hidden layer. The `?` represents arbitrary batch_size.

Note, `tutorial_mnist.py` introduces the simplified CNN API for beginner.

```
network = tl.layers.InputLayer(x, name='input_layer')
network = tl.layers.Conv2dLayer(network,
                        act = tf.nn.relu,
                        shape = [5, 5, 1, 32],  # 32 features for each 5x5 patch
                        strides=[1, 1, 1, 1],
                        padding='SAME',
                        name ='cnn_layer1')     # output: (?, 28, 28, 32)
network = tl.layers.PoolLayer(network,
                        ksize=[1, 2, 2, 1],
                        strides=[1, 2, 2, 1],
                        padding='SAME',
                        pool = tf.nn.max_pool,
                        name ='pool_layer1',)   # output: (?, 14, 14, 32)
network = tl.layers.Conv2dLayer(network,
                        act = tf.nn.relu,
                        shape = [5, 5, 32, 64], # 64 features for each 5x5 patch
                        strides=[1, 1, 1, 1],
                        padding='SAME',
                        name ='cnn_layer2')     # output: (?, 14, 14, 64)
network = tl.layers.PoolLayer(network,
                        ksize=[1, 2, 2, 1],
                        strides=[1, 2, 2, 1],
                        padding='SAME',
                        pool = tf.nn.max_pool,
                        name ='pool_layer2',)   # output: (?, 7, 7, 64)
network = tl.layers.FlattenLayer(network, name='flatten_layer')
                                                # output: (?, 3136)
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop1')
                                                # output: (?, 3136)
network = tl.layers.DenseLayer(network, n_units=256, act = tf.nn.relu, name='relu1')
                                                # output: (?, 256)
network = tl.layers.DropoutLayer(network, keep=0.5, name='drop2')
                                                # output: (?, 256)
network = tl.layers.DenseLayer(network, n_units=10,
                act = tf.identity, name='output_layer')
                                                # output: (?, 10)
```

Note: For experts: `Conv2dLayer` will create a convolutional layer using `tensorflow.nn.conv2d`, TensorFlow's default convolution.

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, take `main_test_layers()` 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.

Having the model and the loss function defined, we create update expressions 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. `tl.utils.dict_to_one` 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)
```

As an additional monitoring quantity, 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).

Run the Pong Game example

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

```
python tutorial_atari_pong.py
```

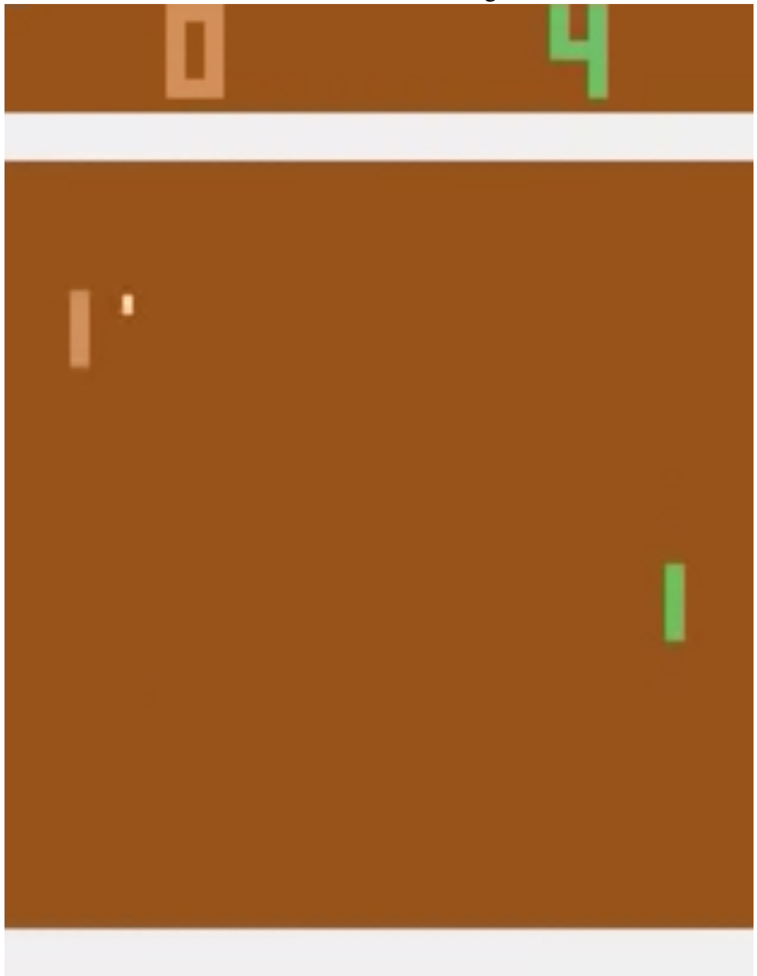
Before running the tutorial code, you need to install OpenAI gym environment which is a benchmark for Reinforcement Learning. If everything is set up correctly, you will get an output like the following:

```
[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 computer to learn how to play Pong game from the screen inputs, just like human behavior. After training for 15,000 episodes, the computer can win 20% of the games. The computer win 35% of the games at 20,000 episode, we can seen the computer learn faster and faster as it has more winning data to train. If you run it for 30,000 episode, it start to win.

```
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.



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

Continuing, 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.

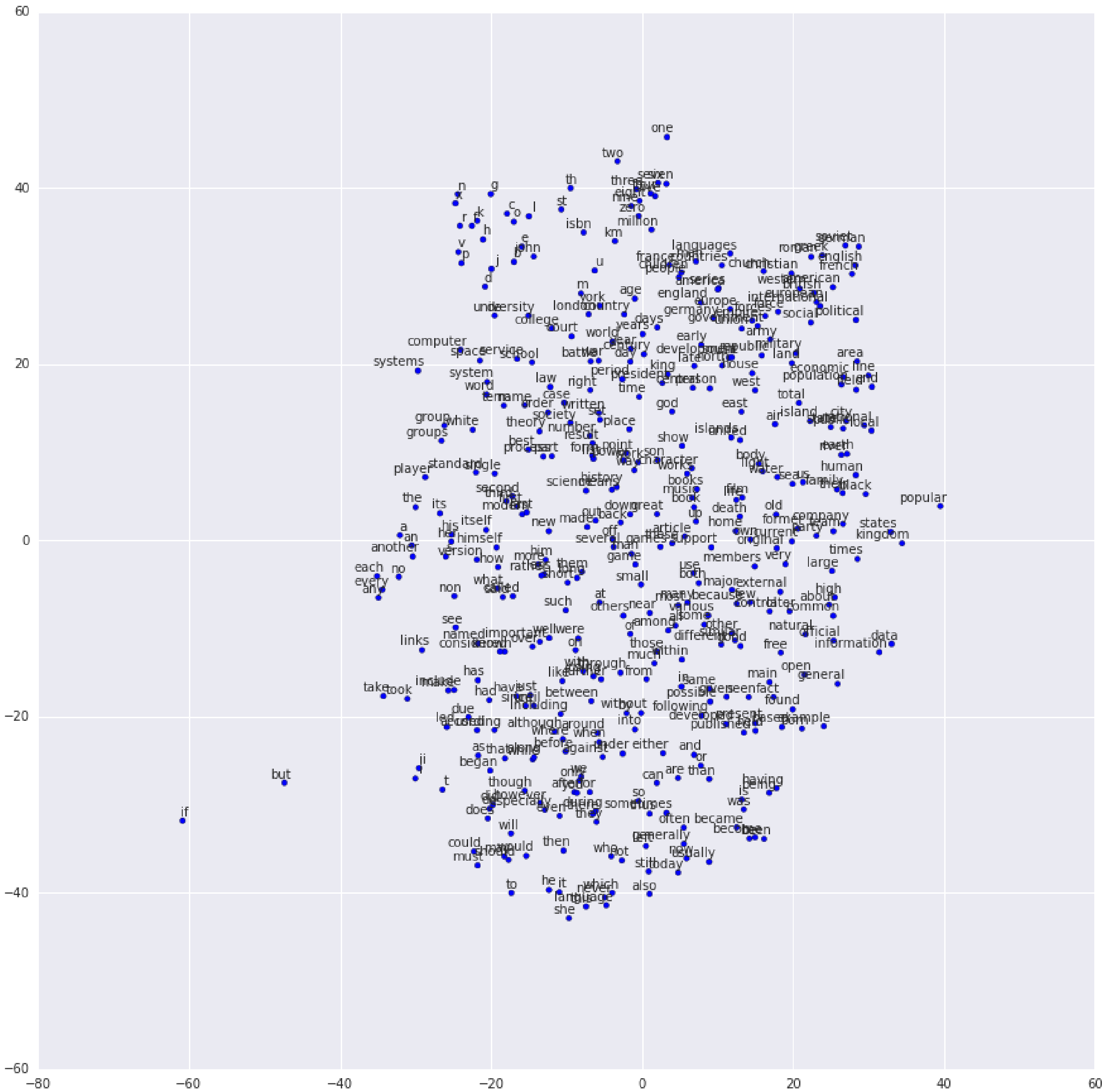
Finally, you can try the model on different tasks (games).

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.



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)
```

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
```

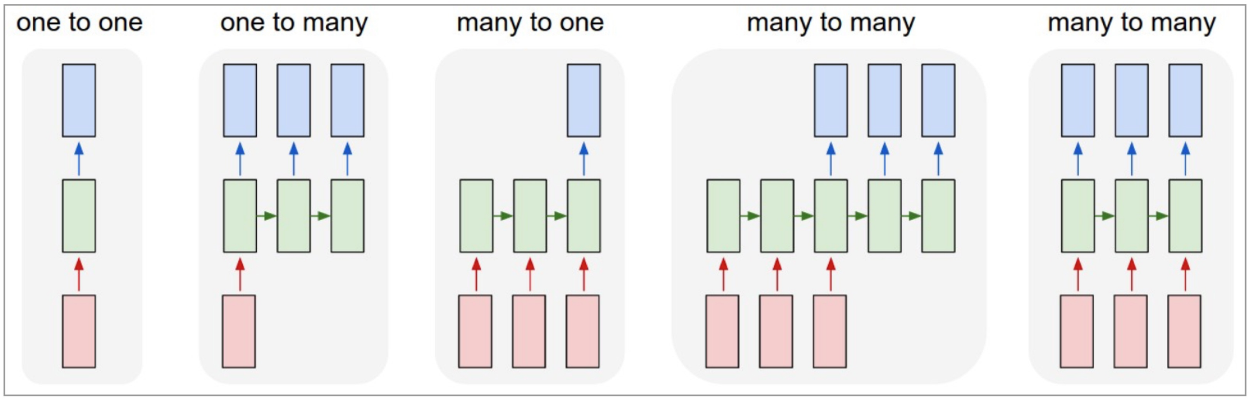
```
0.204 perplexity: 614.071 speed: 8839 wps
0.304 perplexity: 495.485 speed: 8889 wps
0.404 perplexity: 427.381 speed: 8940 wps
0.504 perplexity: 383.063 speed: 8920 wps
0.604 perplexity: 345.135 speed: 8920 wps
0.703 perplexity: 319.263 speed: 8949 wps
0.803 perplexity: 298.774 speed: 8975 wps
0.903 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.

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:

```
# 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.

```
# 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`.

```
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). "

Run the Translation example

```
python tutorial_translate.py
```

This script is going to training a neural network to translate English to French. If everything is correct, you will see.

- Download WMT English-to-French translation data, includes training and testing data.
- Create vocabulary files for English and French from training data.
- Create the tokenized training and testing data from original training and testing data.

```
Prepare raw data
Load or Download WMT English-to-French translation > wmt
Training data : wmt/giga-fren.release2
Testing data : wmt/newstest2013

Create vocabularies
Vocabulary of French : wmt/vocab40000.fr
Vocabulary of English : wmt/vocab40000.en
Creating vocabulary wmt/vocab40000.fr from data wmt/giga-fren.release2.fr
  processing line 100000
  processing line 200000
  processing line 300000
  processing line 400000
  processing line 500000
  processing line 600000
  processing line 700000
  processing line 800000
  processing line 900000
  processing line 1000000
  processing line 1100000
  processing line 1200000
  ...
  processing line 22500000
Creating vocabulary wmt/vocab40000.en from data wmt/giga-fren.release2.en
  processing line 100000
  ...
  processing line 22500000

...
```

Firstly, we download English-to-French translation data from the WMT'15 Website. The training and testing data as follow. The training data is used to train the model, the testing data is used to evaluate the model.

```
wmt/training-giga-fren.tar  <-- Training data for English-to-French (2.6GB)
                                giga-fren.release2.* are extracted from it.
wmt/dev-v2.tgz              <-- Testing data for different language (21.4MB)
                                newstest2013.* are extracted from it.

wmt/giga-fren.release2.fr   <-- Training data of French   (4.57GB)
wmt/giga-fren.release2.en   <-- Training data of English  (3.79GB)

wmt/newstest2013.fr         <-- Testing data of French    (393KB)
wmt/newstest2013.en         <-- Testing data of English   (333KB)
```

As `giga-fren.release2.*` are the training data, the context of `giga-fren.release2.fr` look as follow.

```
Il a transformé notre vie | Il a transformé la société | Son fonctionnement | La␣
↪technologie, moteur du changement Accueil | Concepts | Enseignants | Recherche |␣
↪Aperçu | Collaborateurs | Web HHCC | Ressources | Commentaires Musée virtuel du␣
↪Canada
Plan du site
Rétroaction
Crédits
English
Qu’est-ce que la lumière?
La découverte du spectre de la lumière blanche Des codes dans la lumière Le spectre␣
↪électromagnétique Les spectres d’émission Les spectres d’absorption Les années-
↪lumière La pollution lumineuse
Le ciel des premiers habitants La vision contemporaine de l'Univers L’astronomie pour␣
↪tous
Bande dessinée
Liens
Glossaire
Observatoires
...
```

While `giga-fren.release2.en` look as follow, we can see words or sentences are separated by `|` or `\n`.

```
Changing Lives | Changing Society | How It Works | Technology Drives Change Home |␣
↪Concepts | Teachers | Search | Overview | Credits | HHCC Web | Reference | Feedback␣
↪Virtual Museum of Canada Home Page
Site map
Feedback
Credits
Français
What is light ?
The white light spectrum Codes in the light The electromagnetic spectrum Emission␣
↪spectra Absorption spectra Light-years Light pollution
The sky of the first inhabitants A contemporary vison of the Universe Astronomy for␣
↪everyone
Cartoon
Links
Glossary
Observatories
```

The testing data `newstest2013.en` and `newstest2013.fr` look as follow.

```
newstest2013.en :
A Republican strategy to counter the re-election of Obama
Republican leaders justified their policy by the need to combat electoral fraud.
However, the Brennan Centre considers this a myth, stating that electoral fraud is␣
↪rarer in the United States than the number of people killed by lightning.
```

```
newstest2013.fr :
Une stratégie républicaine pour contrer la réélection d'Obama
Les dirigeants républicains justifièrent leur politique par la nécessité de lutter␣
↪contre la fraude électorale.
Or, le Centre Brennan considère cette dernière comme un mythe, affirmant que la␣
↪fraude électorale est plus rare aux États-Unis que le nombre de personnes tuées par␣
↪la foudre.
```

After downloading the dataset, it start to create vocabulary files, `vocab40000.fr` and `vocab40000.en` from the training data `giga-fren.release2.fr` and `giga-fren.release2.en`, usually it will take a while. The number `40000` reflects the vocabulary size.

The `vocab40000.fr` (381KB) stores one-item-per-line as follow.

```
_PAD
_GO
_EOS
_UNK
de
,
.
'
la
et
des
les
à
le
du
l
en
)
d
0
(
00
pour
dans
un
que
une
sur
au
0000
a
par
```

The `vocab40000.en` (344KB) stores one-item-per-line as follow as well.

```
_PAD
_GO
_EOS
_UNK
the
.
,
of
```

```
and
to
in
a
)
(
0
for
00
that
is
on
The
0000
be
by
with
or
:
as
"
000
are
;
```

And then, we start to create the tokenized training and testing data for both English and French. It will take a while as well.

```
Tokenize data
Tokenizing data in wmt/giga-fren.release2.fr  <-- Training data of French
  tokenizing line 100000
  tokenizing line 200000
  tokenizing line 300000
  tokenizing line 400000
  ...
  tokenizing line 22500000
Tokenizing data in wmt/giga-fren.release2.en  <-- Training data of English
  tokenizing line 100000
  tokenizing line 200000
  tokenizing line 300000
  tokenizing line 400000
  ...
  tokenizing line 22500000
Tokenizing data in wmt/newstest2013.fr        <-- Testing data of French
Tokenizing data in wmt/newstest2013.en        <-- Testing data of English
```

In the end, all files we have as follow.

```
wmt/training-giga-fren.tar  <-- Compressed Training data for English-to-French (2.6GB)
                                giga-fren.release2.* are extracted from it.
wmt/dev-v2.tgz              <-- Compressed Testing data for different language (21.
↪4MB)
                                newstest2013.* are extracted from it.

wmt/giga-fren.release2.fr   <-- Training data of French   (4.57GB)
wmt/giga-fren.release2.en   <-- Training data of English  (3.79GB)

wmt/newstest2013.fr         <-- Testing data of French    (393KB)
```

```
wmt/newstest2013.en         <-- Testing data of English   (333KB)

wmt/vocab40000.fr           <-- Vocabulary of French      (381KB)
wmt/vocab40000.en           <-- Vocabulary of English     (344KB)

wmt/giga-fren.release2.ids40000.fr   <-- Tokenized Training data of French (2.81GB)
wmt/giga-fren.release2.ids40000.en   <-- Tokenized Training data of English (2.38GB)

wmt/newstest2013.ids40000.fr         <-- Tokenized Testing data of French (268KB)
wmt/newstest2013.ids40000.en         <-- Tokenized Testing data of English (232KB)
```

Now, read all tokenized data into buckets and compute the number of data of each bucket.

```
Read development (test) data into buckets
dev data: (5, 10) [[13388, 4, 949], [23113, 8, 910, 2]]
en word_ids: [13388, 4, 949]
en context: [b'Preventing', b'the', b'disease']
fr word_ids: [23113, 8, 910, 2]
fr context: [b'Pr\xc3\xa9venir', b'la', b'maladie', b'_EOS']

Read training data into buckets (limit: 0)
  reading data line 100000
  reading data line 200000
  reading data line 300000
  reading data line 400000
  reading data line 500000
  reading data line 600000
  reading data line 700000
  reading data line 800000
  ...
  reading data line 22400000
  reading data line 22500000
train_bucket_sizes: [239121, 1344322, 5239557, 10445326]
train_total_size: 17268326.0
train_buckets_scale: [0.013847375825543252, 0.09169638099257565, 0.3951164693091849,
↪1.0]
train data: (5, 10) [[1368, 3344], [1089, 14, 261, 2]]
en word_ids: [1368, 3344]
en context: [b'Site', b'map']
fr word_ids: [1089, 14, 261, 2]
fr context: [b'Plan', b'du', b'site', b'_EOS']

the num of training data in each buckets: [239121, 1344322, 5239557, 10445326]
the num of training data: 17268326
train_buckets_scale: [0.013847375825543252, 0.09169638099257565, 0.3951164693091849,
↪1.0]
```

Start training by using the tokenized bucket data, the training process can only be terminated by stop the program. When `steps_per_checkpoint = 10` you will see.

```
Create Embedding Attention Seq2seq Model

global step 10 learning rate 0.5000 step-time 22.26 perplexity 12761.50
  eval: bucket 0 perplexity 5887.75
  eval: bucket 1 perplexity 3891.96
  eval: bucket 2 perplexity 3748.77
  eval: bucket 3 perplexity 4940.10
global step 20 learning rate 0.5000 step-time 20.38 perplexity 28761.36
```

```
  eval: bucket 0 perplexity 10137.01
  eval: bucket 1 perplexity 12809.90
  eval: bucket 2 perplexity 15758.65
  eval: bucket 3 perplexity 26760.93
global step 30 learning rate 0.5000 step-time 20.64 perplexity 6372.95
  eval: bucket 0 perplexity 1789.80
  eval: bucket 1 perplexity 1690.00
  eval: bucket 2 perplexity 2190.18
  eval: bucket 3 perplexity 3808.12
global step 40 learning rate 0.5000 step-time 16.10 perplexity 3418.93
  eval: bucket 0 perplexity 4778.76
  eval: bucket 1 perplexity 3698.90
  eval: bucket 2 perplexity 3902.37
  eval: bucket 3 perplexity 22612.44
global step 50 learning rate 0.5000 step-time 14.84 perplexity 1811.02
  eval: bucket 0 perplexity 644.72
  eval: bucket 1 perplexity 759.16
  eval: bucket 2 perplexity 984.18
  eval: bucket 3 perplexity 1585.68
global step 60 learning rate 0.5000 step-time 19.76 perplexity 1580.55
  eval: bucket 0 perplexity 1724.84
  eval: bucket 1 perplexity 2292.24
  eval: bucket 2 perplexity 2698.52
  eval: bucket 3 perplexity 3189.30
global step 70 learning rate 0.5000 step-time 17.16 perplexity 1250.57
  eval: bucket 0 perplexity 298.55
  eval: bucket 1 perplexity 502.04
  eval: bucket 2 perplexity 645.44
  eval: bucket 3 perplexity 604.29
global step 80 learning rate 0.5000 step-time 18.50 perplexity 793.90
  eval: bucket 0 perplexity 2056.23
  eval: bucket 1 perplexity 1344.26
  eval: bucket 2 perplexity 767.82
  eval: bucket 3 perplexity 649.38
global step 90 learning rate 0.5000 step-time 12.61 perplexity 541.57
  eval: bucket 0 perplexity 180.86
  eval: bucket 1 perplexity 350.99
  eval: bucket 2 perplexity 326.85
  eval: bucket 3 perplexity 383.22
global step 100 learning rate 0.5000 step-time 18.42 perplexity 471.12
  eval: bucket 0 perplexity 216.63
  eval: bucket 1 perplexity 348.96
  eval: bucket 2 perplexity 318.20
  eval: bucket 3 perplexity 389.92
global step 110 learning rate 0.5000 step-time 18.39 perplexity 474.89
  eval: bucket 0 perplexity 8049.85
  eval: bucket 1 perplexity 1677.24
  eval: bucket 2 perplexity 936.98
  eval: bucket 3 perplexity 657.46
global step 120 learning rate 0.5000 step-time 18.81 perplexity 832.11
  eval: bucket 0 perplexity 189.22
  eval: bucket 1 perplexity 360.69
  eval: bucket 2 perplexity 410.57
  eval: bucket 3 perplexity 456.40
global step 130 learning rate 0.5000 step-time 20.34 perplexity 452.27
  eval: bucket 0 perplexity 196.93
  eval: bucket 1 perplexity 655.18
  eval: bucket 2 perplexity 860.44
```

```
  eval: bucket 3 perplexity 1062.36
global step 140 learning rate 0.5000 step-time 21.05 perplexity 847.11
  eval: bucket 0 perplexity 391.88
  eval: bucket 1 perplexity 339.09
  eval: bucket 2 perplexity 320.08
  eval: bucket 3 perplexity 376.44
global step 150 learning rate 0.4950 step-time 15.53 perplexity 590.03
  eval: bucket 0 perplexity 269.16
  eval: bucket 1 perplexity 286.51
  eval: bucket 2 perplexity 391.78
  eval: bucket 3 perplexity 485.23
global step 160 learning rate 0.4950 step-time 19.36 perplexity 400.80
  eval: bucket 0 perplexity 137.00
  eval: bucket 1 perplexity 198.85
  eval: bucket 2 perplexity 276.58
  eval: bucket 3 perplexity 357.78
global step 170 learning rate 0.4950 step-time 17.50 perplexity 541.79
  eval: bucket 0 perplexity 1051.29
  eval: bucket 1 perplexity 626.64
  eval: bucket 2 perplexity 496.32
  eval: bucket 3 perplexity 458.85
global step 180 learning rate 0.4950 step-time 16.69 perplexity 400.65
  eval: bucket 0 perplexity 178.12
  eval: bucket 1 perplexity 299.86
  eval: bucket 2 perplexity 294.84
  eval: bucket 3 perplexity 296.46
global step 190 learning rate 0.4950 step-time 19.93 perplexity 886.73
  eval: bucket 0 perplexity 860.60
  eval: bucket 1 perplexity 910.16
  eval: bucket 2 perplexity 909.24
  eval: bucket 3 perplexity 786.04
global step 200 learning rate 0.4901 step-time 18.75 perplexity 449.64
  eval: bucket 0 perplexity 152.13
  eval: bucket 1 perplexity 234.41
  eval: bucket 2 perplexity 249.66
  eval: bucket 3 perplexity 285.95
...
global step 980 learning rate 0.4215 step-time 18.31 perplexity 208.74
  eval: bucket 0 perplexity 78.45
  eval: bucket 1 perplexity 108.40
  eval: bucket 2 perplexity 137.83
  eval: bucket 3 perplexity 173.53
global step 990 learning rate 0.4173 step-time 17.31 perplexity 175.05
  eval: bucket 0 perplexity 78.37
  eval: bucket 1 perplexity 119.72
  eval: bucket 2 perplexity 169.11
  eval: bucket 3 perplexity 202.89
global step 1000 learning rate 0.4173 step-time 15.85 perplexity 174.33
  eval: bucket 0 perplexity 76.52
  eval: bucket 1 perplexity 125.97
  eval: bucket 2 perplexity 150.13
  eval: bucket 3 perplexity 181.07
...
```

After training the model for 350000 steps, you can play with the translation by switch `main_train()` to `main_decode()`. You type in a English sentence, the program will outputs a French sentence.

```
Reading model parameters from wmt/translate.ckpt-350000
>  Who is the president of the United States?
Qui est le président des États-Unis ?
```

Understand Translation

Seq2seq

Sequence to sequence model is commonly be used to translate a language to another. Actually it can do many thing you can't imagine, we can translate a long sentence into short and simple sentence, for example, translation going from Shakespeare to modern English. With CNN, we can also translate a video into a sentence, i.e. video captioning.

If you just want to use Seq2seq but not going to design a new algorithm, the only think you need to consider is the data format including how to split the words, how to tokenize the words etc. In this tutorial, we described a lot about data formating.

Basics

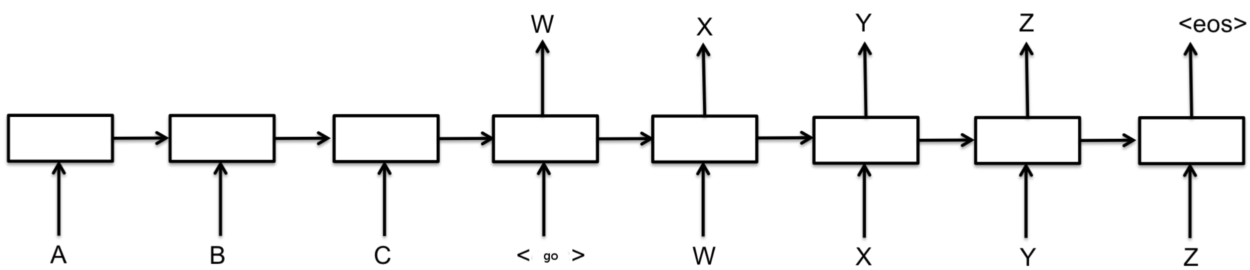
Sequence to sequence model is a type of "Many to many" but different with Synced sequence input and output in PTB tutorial. Seq2seq generates sequence output after feeding all sequence inputs. The following two methods can improve the accuracy:

- Reversing the inputs
- Attention mechanism

To speed up the computation, we used:

- Sampled softmax

Karpathy's blog described Seq2seq as: "(4) Sequence input and sequence output (e.g. Machine Translation: an RNN reads a sentence in English and then outputs a sentence in French)."



As the above figure shows, the encoder inputs, decoder inputs and targets are:

```
encoder_input =  A    B    C
decoder_input =  <go> W    X    Y    Z
targets       =  W    X    Y    Z    <eos>

Note: in the code, the size of targets is one smaller than the size
of decoder_input, not like this figure. More details will be show later.
```

Papers

The English-to-French example implements a multi-layer recurrent neural network as encoder, and an Attention-based decoder. It is the same as the model described in this paper:

- Grammar as a Foreign Language

The example uses sampled softmax to handle large output vocabulary size. In this example, as `target_vocab_size=4000`, for vocabularies smaller than `512`, it might be a better idea to just use a standard softmax loss. Sampled softmax is described in Section 3 of the this paper:

- On Using Very Large Target Vocabulary for Neural Machine Translation

Reversing the inputs and Multi-layer cells have been successfully used in sequence-to-sequence models for translation has beed described in this paper:

- Sequence to Sequence Learning with Neural Networks

Attention mechanism allows the decoder more direct access to the input, it was described in this paper:

- Neural Machine Translation by Jointly Learning to Align and Translate

Alternatively, the model can also be implemented by a single-layer version, but with Bi-directional encoder, was presented in this paper:

- Neural Machine Translation by Jointly Learning to Align and Translate

Implementation

Bucketing and Padding

(Note that, TensorLayer supports Dynamic RNN layer after v1.2, so bucketing is not longer necessary in many cases)

Bucketing is a method to efficiently handle sentences of different length. When translating English to French, we will have English sentences of different lengths `L1` on input, and French sentences of different lengths `L2` on output. We should in principle create a seq2seq model for every pair `(L1, L2+1)` (prefixed by a GO symbol) of lengths of an English and French sentence.

To minimize the number of buckets and find the closest bucket for each pair, then we could just pad every sentence with a special PAD symbol in the end if the bucket is bigger than the sentence

We use a number of buckets and pad to the closest one for efficiency. In this example, we used 4 buckets as follow.

```
buckets = [(5, 10), (10, 15), (20, 25), (40, 50)]
```

If the input is an English sentence with `3` tokens, and the corresponding output is a French sentence with `6` tokens, then they will be put in the first bucket and padded to length `5` for encoder inputs (English sentence), and length `10` for decoder inputs. If we have an English sentence with 8 tokens and the corresponding French sentence has 18 tokens, then they will be fit into `(20, 25)` bucket.

In other word, bucket `(I, O)` is `(encoder_input_size, decoder_inputs_size)`.

Given a pair of `[["I", "go", "."], ["Je", "vais", "."]]` in tokenized format, we fit it into bucket `(5, 10)`. The training data of encoder inputs representing `[PAD PAD "." "go" "I"]` and decoder inputs `[GO "Je" "vais" "." EOS PAD PAD PAD PAD PAD]`. The targets are decoder inputs shifted by one. The `target_weights` is the mask of `targets`.

```
bucket = (I, O) = (5, 10)
encoder_inputs = [PAD PAD "." "go" "I"]                       <-- 5  x batch_size
decoder_inputs = [GO "Je" "vais" "." EOS PAD PAD PAD PAD PAD] <-- 10 x batch_size
```

```
target_weights = [1    1      1      1    0 0 0 0 0 0 0]          <-- 10 x batch_size
targets        = ["Je" "vais" "." EOS PAD PAD PAD PAD PAD]    <-- 9  x batch_size
```

In this example, one sentence is represented by one column, so assume `batch_size = 3`, `bucket = (5, 10)` the training data will look like:

```
encoder_inputs     decoder_inputs     target_weights     targets
0    0    0        1    1    1        1    1    1        87   71   16748
0    0    0        87   71   16748    1    1    1        2    3    14195
0    0    0        2    3    14195    0    1    1        0    2    2
0    0    3233     0    2    2        0    0    0        0    0    0
3    698  4061     0    0    0        0    0    0        0    0    0
                   0    0    0        0    0    0        0    0    0
                   0    0    0        0    0    0        0    0    0
                   0    0    0        0    0    0        0    0    0
                   0    0    0        0    0    0        0    0    0
                   0    0    0        0    0    0

where 0 : _PAD     1 : _GO      2 : _EOS       3 : _UNK
```

During training, the decoder inputs are the targets, while during prediction, the next decoder input is the last decoder output.

Special vocabulary symbols, punctuations and digits

The special vocabulary symbols in this example are:

```
_PAD = b"_PAD"
_GO = b"_GO"
_EOS = b"_EOS"
_UNK = b"_UNK"
PAD_ID = 0       <-- index (row number) in vocabulary
GO_ID = 1
EOS_ID = 2
UNK_ID = 3
_START_VOCAB = [_PAD, _GO, _EOS, _UNK]
```

```
        ID     MEANINGS
_PAD    0      Padding, empty word
_GO     1      1st element of decoder_inputs
_EOS    2      End of Sentence of targets
_UNK    3      Unknown word, words do not exist in vocabulary will be marked as 3
```

For digits, the `normalize_digits` of creating vocabularies and tokenized dataset must be consistent, if `normalize_digits=True` all digits will be replaced by `0`. Like `123` to ``000` ``, *9* to *0* and *1990-05* to *0000-00*, then *000*, *0* and *0000-00* etc will be the words in the vocabulary (see `vocab40000.en`).

Otherwise, if `normalize_digits=False`, different digits will be seem in the vocabulary, then the vocabulary size will be very big. The regular expression to find digits is `_DIGIT_RE = re.compile(br"\d")`. (see `tl.nlp.create_vocabulary()` and `tl.nlp.data_to_token_ids()`)

For word split, the regular expression is `_WORD_SPLIT = re.compile(b"([.,!?\"':;)(])")`, this means use the symbols like `[ . , ! ? " ' : ; ) ( ]` and space to split the sentence, see `tl.nlp.basic_tokenizer()` which is the default tokenizer of `tl.nlp.create_vocabulary()` and `tl.nlp.data_to_token_ids()`.

All punctuation marks, such as `. , ) (` are all reserved in the vocabularies of both English and French.

Sampled softmax

Sampled softmax is a method to reduce the computation of cost so as to handle large output vocabulary. Instead of compute the cross-entropy of large output, we compute the loss from samples of `num_samples`.

Dataset iteration

The iteration is done by `EmbeddingAttentionSeq2seqWrapper.get_batch`, which get a random batch of data from the specified bucket, prepare for step. The data

Loss and update expressions

The `EmbeddingAttentionSeq2seqWrapper` has built in SGD optimizer.

What Next?

Try other applications.

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`),

Example

Basics

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

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.
- Image Captioning - Reimplementation of Google's im2txt by zsdonghao.

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.

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.
- Super Resolution GAN by zsdonghao.

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 <https://github.com/ugo-nama-kun/gym_torcs>*) by zsdonghao.
- TRPO for continuous and discrete action space by jjkke88.

Special Examples

- 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.

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.

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.

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.

More

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)
```

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.

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.

API - Layers

To make TensorLayer simple, we minimize the number of layer classes as much as we can. So we encourage you to use TensorFlow's function. For example, we provide layer for local response normalization, but user can still apply `tf.nn.lrn` on `network.outputs`. More functions can be found in TensorFlow API.

Understand 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 layer.

All TensorLayer layers have a number of methods in common:

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

The initialization of a network is done by input layer, then we can stacked layers as follow, a network is a `Layer` class. The most important properties of a network are `network.all_params`, `network.all_layers` and `network.all_drop`. The `all_params` is a list which store all pointers of all network parameters in order, the following script define a 3 layer network, then:

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

To get specified variables, you can use `network.all_params[2:3]` or `get_variables_with_name()`. As the `all_layers` is a list which store all pointers of the outputs of all layers, in the following network:

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

where `?` reflects any batch size. You can print the layer information 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 layer. In the above network, they are the keeping probabilities of dropout layers.

So for training, 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 )
```

For evaluating and testing, 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 on Github.

Understand Dense layer

Before creating your own TensorLayer layer, let's have a look at Dense layer. It creates a weights matrix and biases vector if not exists, then implement the output expression. At the end, as a layer with parameter, we also need to 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] )
```

Your layer

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] )
```

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
```

Layer list

get_variables_with_name(name[, train_only, ...])	Get variable list by a given name scope.
get_layers_with_name([network, name, printable])	Get layer list in a network by a given name scope.
set_name_reuse([enable])	Enable or disable reuse layer name.
print_all_variables([train_only])	Print all trainable and non-trainable variables
initialize_global_variables([sess])	Excute `sess.run(tf.global_variables_initializer())` for TF12+ or sess.run(tf.initialize_all_variables()) for TF11.
Layer([inputs, name])	The 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, for Word Embedding.
EmbeddingInputlayer([inputs, ...])	The EmbeddingInputlayer class is a fully connected layer, for Word Embedding.
DenseLayer([layer, n_units, act, W_init, ...])	The DenseLayer class is a fully connected layer.
ReconLayer([layer, x_recon, name, n_units, act])	The ReconLayer class is a reconstruction layer *DenseLayer* which use to pre-train a *DenseLayer*.
DropoutLayer([layer, keep, is_fix, ...])	The DropoutLayer class is a noise layer which randomly set some values to zero by a given keeping probability.
GaussianNoiseLayer([layer, mean, stddev, ...])	The GaussianNoiseLayer class is noise layer that adding noise with normal distribution to the activation.
DropconnectDenseLayer([layer, keep, ...])	The DropconnectDenseLayer class is `DenseLayer` with DropConnect behaviour which randomly remove connection between this layer to previous layer by a given 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, ...])	The DeConv2dLayer class is deconvolutional 2D layer, see tf.nn.conv2d_transpose.
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, you can choose `tf.nn.max_pool` and `tf.nn.avg_pool` for 2D or `tf.nn.max_pool3d` and `tf.nn.avg_pool3d` for 3D.
PadLayer([layer, paddings, mode, name])	The PadLayer class is a Padding layer for any modes and dimensions.
UpSampling2dLayer([layer, size, is_scale, ...])	The UpSampling2dLayer class is upSampling 2d layer, see tf.image.resize_images.

Continued on next page

Table 2.1 – continued from previous page

DownSampling2dLayer([layer, size, is_scale, ...])	The DownSampling2dLayer class is downSampling 2d layer, see tf.image.resize_images.
AtrousConv1dLayer(net[, n_filter, ...])	Wrapper for AtrousConv1dLayer, if you don't understand how to use Conv1dLayer, this function may be easier.
AtrousConv2dLayer([layer, n_filter, ...])	The AtrousConv2dLayer class is Atrous convolution (a.k.a.
SeparableConv2dLayer([layer, filters, ...])	The SeparableConv2dLayer class is 2-D convolution with separable filters, see tf.layers.separable_conv2d.
Conv1d(net[, n_filter, filter_size, stride, ...])	Wrapper for Conv1dLayer, if you don't understand how to use Conv1dLayer, this function may be easier.
Conv2d(net[, n_filter, filter_size, ...])	Wrapper for Conv2dLayer, if you don't understand how to use Conv2dLayer, this function may be easier.
DeConv2d(net[, n_out_channel, filter_size, ...])	Wrapper for DeConv2dLayer, if you don't understand how to use DeConv2dLayer, this function may be easier.
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
SubpixelConv1d(net[, scale, act, name])	One-dimensional subpixel upsampling layer.
SubpixelConv2d(net[, scale, n_out_channel, ...])	The SubpixelConv2d class is a sub-pixel 2d convolutional ayer, usually be used for Super-Resolution applications, example code.
SpatialTransformer2dAffineLayer([layer, ...])	The SpatialTransformer2dAffineLayer class is a 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 class is a normalization layer, see tf.nn.batch_normalization and tf.nn.moments.
LocalResponseNormLayer([layer, ...])	The LocalResponseNormLayer class is for Local Response Normalization, see tf.nn.local_response_normalization or tf.nn.lrn for new TF version.
InstanceNormLayer([layer, act, epsilon, ...])	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 ROIPoolingLayer class is 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 RNN layer, you can implement vanilla RNN, LSTM and GRU with it.

Continued on next page

Table 2.1 – continued from previous page

BiRNNLayer([layer, cell_fn, cell_init_args, ...])	The *BiRNNLayer* class is a Bidirectional RNN layer.
advanced_indexing_op(input, 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.
DynamicRNNLayer([layer, cell_fn, ...])	The *DynamicRNNLayer* class is a Dynamic RNN 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, ...])	The *Seq2Seq* class is a Simple *DynamicRNNLayer* based Seq2seq layer without using tl.contrib.seq2seq.
PeekySeq2Seq([net_encode_in, net_decode_in, ...])	Waiting for contribution.
AttentionSeq2Seq([net_encode_in, ...])	Waiting for contribution.
FlattenLayer([layer, name])	The *FlattenLayer* class is layer which reshape high-dimension input to a vector.
ReshapeLayer([layer, shape, name])	The *ReshapeLayer* class is layer which reshape the tensor.
TransposeLayer([layer, perm, name])	The *TransposeLayer* class transpose the dimension of a teneor, see tf.transpose() .
LambdaLayer([layer, fn, fn_args, name])	The *LambdaLayer* class is a layer which is able to use the provided function.
ConcatLayer([layer, concat_dim, name])	The *ConcatLayer* class is layer which concat (merge) two or more tensor by given axis..
ElementwiseLayer([layer, combine_fn, name])	The *ElementwiseLayer* class combines multiple *Layer* which have the same output shapes by a given elemwise-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([layer, 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])	The *UnStackLayer* is layer for unstacking the given dimension of a rank-R tensor into rank-(R-1) tensors., see tf.unstack().
EstimatorLayer([layer, model_fn, args, name])	The *EstimatorLayer* class accepts `model_fn` that described the model.
SlimNetsLayer([layer, slim_layer, ...])	The *SlimNetsLayer* class can be used to merge all TF-Slim nets into TensorLayer.
KerasLayer([layer, keras_layer, keras_args, ...])	The *KerasLayer* class can be used to merge all Keras layers into TensorLayer.
PReluLayer([layer, channel_shared, a_init, ...])	The *PReluLayer* class is Parametric Rectified Linear layer.
MultiplexerLayer([layer, name])	The *MultiplexerLayer* selects one of several input and forwards the selected input into the output, see *tutorial_mnist_multiplexer.py*.

Continued on next page

Table 2.1 – continued from previous page

`EmbeddingAttentionSeq2seqWrapper`(...[, ...])	Sequence-to-sequence model with attention and for multiple buckets (Deprecated after TF0.12).
`flatten_reshape`(variable[, name])	Reshapes high-dimension input to a vector.
`clear_layers_name`()	Clear all layer names in set_keep['_layers_name_list'], enable layer name reuse.
`initialize_rnn_state`(state)	Return the initialized RNN state.
`list_remove_repeat`([l])	Remove the repeated items in a list, and return the processed list.

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*, *train_only=True*, *printable=False*)

Get variable list by a given name scope.

Examples

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

Get layers with name

`tensorlayer.layers.`**`get_layers_with_name`**(*network=None*, *name=''*, *printable=False*)

Get layer list in a network by a given name scope.

Examples

```
>>> layers = tl.layers.get_layers_with_name(network, "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 name 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)
>>>          network = tl.layers.EmbeddingInputlayer(
...                       inputs = input_seqs,
...                       vocabulary_size = vocab_size,
...                       embedding_size = embedding_size,
...                       name = 'e_embedding')
>>>         network = tl.layers.DynamicRNNLayer(network,
...                       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 network
>>>
>>> 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 all trainable and non-trainable variables without tl.layers.initialize_global_variables(sess)

Parameters **train_only** : boolean

If True, only print the trainable variables, otherwise, print all variables.

Initialize variables

`tensorlayer.layers.`**`initialize_global_variables`**(*sess=None*)

Excute `sess.run(tf.global_variables_initializer())` for TF12+ or sess.run(tf.initialize_all_variables()) for TF11.

Parameters **sess** : a Session

Basic layer

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

The *`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** : a *`Layer`* instance

The *Layer* class feeding into this layer.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Input layer

class `tensorlayer.layers.`**`InputLayer`**(*inputs=None*, *name='input_layer'*)

The *`InputLayer`* class is the starting layer of a neural network.

Parameters **inputs** : a placeholder or tensor

The input tensor data.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

One-hot layer

class `tensorlayer.layers.`**`OneHotInputLayer`**(*inputs=None*, *depth=None*, *on_value=None*, *off_value=None*, *axis=None*, *dtype=None*, *name='input_layer'*)

The *`OneHotInputLayer`* class is the starting layer of a neural network, see `tf.one_hot`.

Parameters **inputs** : a placeholder or tensor

The input tensor data.

name : a string or None

An optional name to attach to this layer.

depth : 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 : If on_value is not provided, it will default to the value 1 with type dtype.

default, None

off_value : If off_value is not provided, it will default to the value 0 with type dtype.

default, None

axis : default, None

dtype : default, None

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

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={}, E_init=<tensorflow.python.ops.init_ops.RandomUniform object>, E_init_args={}, nce_W_init=<tensorflow.python.ops.init_ops.TruncatedNor object>, nce_W_init_args={}, nce_b_init=<tensorflow.python.ops.init_ops.Constant object>, nce_b_init_args={}, name='word2vec_layer'*)

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

For word inputs. integer index format.

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 Number of negative examples for NCE loss.

nce_loss_args : a dictionary

The arguments for tf.nn.nce_loss()

E_init : embedding initializer

The initializer for initializing the embedding matrix.

E_init_args : a dictionary

The arguments for embedding initializer

nce_W_init : NCE decoder biases initializer

The initializer for initializing the nce decoder weight matrix.

nce_W_init_args : a dictionary

The arguments for initializing the nce decoder weight matrix.

nce_b_init : NCE decoder biases initializer

The initializer for tf.get_variable() of the nce decoder bias vector.

nce_b_init_args : a dictionary

The arguments for tf.get_variable() of the nce decoder bias vector.

name : a string or None

An optional name to attach to this layer.

References

- tensorflow/examples/tutorials/word2vec/word2vec_basic.py

Examples

- 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))
```

- With TensorLayer : see 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_layer',
...    )
>>> 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
```

Attributes

nce_cost	(a tensor) The NCE loss.
outputs	(a tensor) The outputs of embedding layer.
normalized_embeddings	(tensor) Normalized embedding matrix

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

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={}, name='embedding_layer'*)

The *EmbeddingInputlayer* class is a fully connected layer, for Word Embedding. Words are input as integer index. The output is the embedded word vector.

If you have a pre-train matrix, you can assign the matrix into it. To train a word embedding matrix, you can used class:*Word2vecEmbeddingInputlayer*.

Note that, do not update this embedding matrix.

Parameters inputs : placeholder

For word inputs. integer index format. a 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 : embedding initializer

The initializer for initializing the embedding matrix.

E_init_args : a dictionary

The arguments for embedding initializer

name : a string or None

An optional name to attach to this layer.

Examples

```
>>> vocabulary_size = 50000
>>> embedding_size = 200
>>> model_file_name = "model_word2vec_50k_200"
```

```
>>> batch_size = None
...
>>> 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.files.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)
>>> word = b'hello'
>>> word_id = dictionary[word]
>>> print('word_id:', word_id)
... 6428
...
>>> words = [b'i', b'am', b'hao', b'dong']
>>> word_ids = tl.files.words_to_word_ids(words, dictionary)
>>> context = tl.files.word_ids_to_words(word_ids, reverse_dictionary)
>>> print('word_ids:', word_ids)
... [72, 1226, 46744, 20048]
>>> print('context:', context)
... [b'i', b'am', b'hao', b'dong']
...
>>> vector = sess.run(emb_net.outputs, feed_dict={x : [word_id]})
>>> print('vector:', vector.shape)
... (1, 200)
>>> vectors = sess.run(emb_net.outputs, feed_dict={x : word_ids})
>>> print('vectors:', vectors.shape)
... (4, 200)
```

Attributes

outputs	(a tensor) The outputs of embedding layer. the outputs 3D tensor : [batch_size, num_steps(num_words), embedding_size]

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Dense layer

Dense layer

class tensorlayer.layers.**DenseLayer**(*layer=None*, *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={}*, *b_init_args={}*, *name='dense_layer'*)

The `DenseLayer` class is a fully connected layer.

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

n_units : int

The number of units of the layer.

act : activation function

The function that is applied to the layer activations.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer or None

The initializer for initializing the bias vector. If None, skip biases.

W_init_args : dictionary

The arguments for the weights tf.get_variable.

b_init_args : dictionary

The arguments for the biases tf.get_variable.

name : a string or None

An optional name to attach to this layer.

Notes

If the input to this layer has more than two axes, it need to flatten the input by using `FlattenLayer` in this case.

Examples

```
>>> network = tl.layers.InputLayer(x, name='input_layer')
>>> network = tl.layers.DenseLayer(
...                 network,
...                 n_units=800,
...                 act = tf.nn.relu,
...                 W_init=tf.truncated_normal_initializer(stddev=0.1),
...                 name ='relu_layer'
...                 )
```

```
>>> Without TensorLayer, 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)
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Reconstruction layer for Autoencoder

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

The `ReconLayer` class is a reconstruction layer *DenseLayer* which use to pre-train a *DenseLayer*.

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

x_recon : tensorflow variable

The variables used for reconstruction.

name : a string or None

An optional name to attach to this layer.

n_units : int

The number of units of the layer, should be equal to x_recon

act : activation function

The activation function that is applied to the reconstruction layer. Normally, for sigmoid layer, the reconstruction activation is sigmoid; for rectifying layer, the reconstruction activation is softplus.

Notes

The input layer should be *DenseLayer* or a layer 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

Examples

```
>>> network = tl.layers.InputLayer(x, name='input_layer')
>>> network = tl.layers.DenseLayer(network, n_units=196,
...                                 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')
>>> 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_')
```

Methods

pretrain(self, 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 previous DenseLayer.

Noise layer

Dropout layer

class `tensorlayer.layers.DropoutLayer`(*layer=None*, *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 values to zero by a given keeping probability.

Parameters layer : a `Layer` instance

The *Layer* class feeding into this layer.

keep : float

The keeping probability, the lower more values will be set to zero.

is_fix : boolean

Default False, if True, the keeping probability is fixed and cannot be changed via feed_dict.

is_train : boolean

If False, skip this layer, default is True.

seed : int or None

An integer or None to create random seed.

name : a string or None

An optional name to attach to this layer.

Notes

- A frequent question regarding `DropoutLayer` is that why it donot have *is_train* like `BatchNormLayer`.

In many simple cases, user may find it is better to use one inference instead of two inferences for training and testing seperately, `DropoutLayer` allows you to control the dropout rate via *feed_dict*. However, you can fix the keeping probability by setting *is_fix* to True.

Examples

- Define 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')
>>> ...
```

•For training, enable dropout as follow.

```
>>> feed_dict = {x: X_train_a, y_: y_train_a}
>>> feed_dict.update( network.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( network.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)
>>> ...
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Gaussian noise layer

class `tensorlayer.layers.`**`GaussianNoiseLayer`**(*layer=None, 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 normal distribution to the activation.

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

mean : float

stddev : float

is_train : boolean

If False, skip this layer, default is True.

seed : int or None

An integer or None to create random seed.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Dropconnect + Dense layer

class `tensorlayer.layers.`**`DropconnectDenseLayer`**(*layer=None, 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={}, b_init_args={}, name='dropconnect_layer'*)

The *`DropconnectDenseLayer`* class is `DenseLayer` with DropConnect behaviour which randomly remove connection between this layer to previous layer by a given keeping probability.

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer.

keep : float

The keeping probability, the lower more values will be set to zero.

n_units : int

The number of units of the layer.

act : activation function

The function that is applied to the layer activations.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer

The initializer for initializing the bias vector.

W_init_args : dictionary

The arguments for the weights tf.get_variable().

b_init_args : dictionary

The arguments for the biases tf.get_variable().

name : a string or None

An optional name to attach to this layer.

References

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

Examples

```
>>> network = tl.layers.InputLayer(x, name='input_layer')
>>> network = tl.layers.DropconnectDenseLayer(network, keep = 0.8,
...         n_units=800, act = tf.nn.relu, name='dropconnect_relu1')
>>> network = tl.layers.DropconnectDenseLayer(network, keep = 0.5,
...         n_units=800, act = tf.nn.relu, name='dropconnect_relu2')
>>> network = tl.layers.DropconnectDenseLayer(network, keep = 0.5,
...         n_units=10, act = tl.activation.identity, name='output_layer')
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Convolutional layer (Pro)

1D Convolutional layer

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

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

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer, [batch, in_width, in_channels].

act : activation function, None for identity.

shape : list of shape

shape of the filters, [filter_length, in_channels, out_channels].

stride : an int.

The number of entries by which the filter is moved right at each step.

dilation_rate : an int.

Specifies the filter upsampling/input downsampling rate.

padding : a string from: "SAME", "VALID".

The type of padding algorithm to use.

use_cudnn_on_gpu : An optional bool. Defaults to True.

data_format : As it is 1D conv, default is 'NWC'.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer or None

The initializer for initializing the bias vector. If None, skip biases.

W_init_args : dictionary

The arguments for the weights tf.get_variable().

b_init_args : dictionary

The arguments for the biases tf.get_variable().

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

2D Convolutional layer

class `tensorlayer.layers.`**`Conv2dLayer`**(*layer=None, 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={}, b_init_args={}, 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** : a `Layer` instance

The *Layer* class feeding into this layer.

act : activation function

The function that is applied to the layer activations.

shape : list of shape

shape of the filters, [filter_height, filter_width, in_channels, out_channels].

strides : a list of ints.

The stride of the sliding window for each dimension of input.

It Must be in the same order as the dimension specified with format.

padding : a string from: "SAME", "VALID".

The type of padding algorithm to use.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer or None

The initializer for initializing the bias vector. If None, skip biases.

W_init_args : dictionary

The arguments for the weights tf.get_variable().

b_init_args : dictionary

The arguments for the biases tf.get_variable().

use_cudnn_on_gpu : bool, default is None.

data_format : string “NHWC” or “NCHW”, default is “NHWC”

name : a string or None

An optional name to attach to this layer.

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

```
>>> x = tf.placeholder(tf.float32, shape=[None, 28, 28, 1])
>>> network = tl.layers.InputLayer(x, name='input_layer')
>>> network = tl.layers.Conv2dLayer(network,
...                     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)
>>> network = tl.layers.PoolLayer(network,
...                     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 )
```

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network

Continued on next page

Table 2.12 – continued from previous page

print_params([details])	Print all info of parameters in the network

2D Deconvolutional layer

class tensorlayer.layers.**DeConv2dLayer**(*layer=None, 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={}, b_init_args={}, name='decnn2d_layer'*)

The *DeConv2dLayer* class is deconvolutional 2D layer, see tf.nn.conv2d_transpose.

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this layer.

act : activation function

The function that is applied to the layer activations.

shape : list of shape

shape of the filters, [height, width, output_channels, in_channels], filter's in_channels dimension must match that of value.

output_shape : list of output shape

representing the output shape of the deconvolution op.

strides : a list of ints.

The stride of the sliding window for each dimension of the input tensor.

padding : a string from: "SAME", "VALID".

The type of padding algorithm to use.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer

The initializer for initializing the bias vector. If None, skip biases.

W_init_args : dictionary

The arguments for the weights initializer.

b_init_args : dictionary

The arguments for the biases initializer.

name : a string or None

An optional name to attach to this layer.

Notes

- shape = [h, w, the number of output channels of this layer, the number of output channel of 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')
```

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network

3D Convolutional layer

class tensorlayer.layers.**Conv3dLayer**(*layer=None, 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={}, b_init_args={}, name='cnn3d_layer'*)

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

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this layer.

act : activation function

The function that is applied to the layer activations.

shape : list of shape

shape of the filters, [filter_depth, filter_height, filter_width, in_channels, out_channels].

strides : a list of ints. 1-D of length 4.

The stride of the sliding window for each dimension of input. Must be in the same order as the dimension specified with format.

padding : a string from: "SAME", "VALID".

The type of padding algorithm to use.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer

The initializer for initializing the bias vector.

W_init_args : dictionary

The arguments for the weights initializer.

b_init_args : dictionary

The arguments for the biases initializer.

name : a string or None

An optional name to attach to this layer.

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network

3D Deconvolutional layer

class `tensorlayer.layers.DeConv3dLayer`(*layer=None, 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={}, b_init_args={}, name='decnn3d_layer'*)

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

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this layer.

act : activation function

The function that is applied to the layer activations.

shape : list of shape

shape of the filters, [depth, height, width, output_channels, in_channels], filter's in_channels dimension must match that of value.

output_shape : list of output shape

representing the output shape of the deconvolution op.

strides : a list of ints.

The stride of the sliding window for each dimension of the input tensor.

padding : a string from: "SAME", "VALID".

The type of padding algorithm to use.

W_init : weights initializer

The initializer for initializing the weight matrix.

b_init : biases initializer

The initializer for initializing the bias vector.

W_init_args : dictionary

The arguments for the weights initializer.

b_init_args : dictionary

The arguments for the biases initializer.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

2D UpSampling layer

class `tensorlayer.layers.UpSampling2dLayer`(*layer=None, size=[], is_scale=True, method=0, align_corners=False, name='upsample2d_layer'*)

The *UpSampling2dLayer* class is upSampling 2d layer, see tf.image.resize_images.

Parameters **layer** : a layer class with 4-D Tensor of shape [batch, height, width, channels] or 3-D Tensor of shape [height, width, channels].

size : a tuple of int or float.

(height, width) scale factor or new size of height and width.

is_scale : boolean, if True (default), size is scale factor, otherwise, size is number of pixels of height and width.

method : 0, 1, 2, 3. ResizeMethod. Defaults to ResizeMethod.BILINEAR.

- ResizeMethod.BILINEAR, Bilinear interpolation.
- ResizeMethod.NEAREST_NEIGHBOR, Nearest neighbor interpolation.
- ResizeMethod.BICUBIC, Bicubic interpolation.
- ResizeMethod.AREA, Area interpolation.

align_corners : bool. If true, exactly align all 4 corners of the input and output. Defaults to false.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params`()	Return the number of parameters in the network
`print_layers`()	Print all info of layers in the network
`print_params`([details])	Print all info of parameters in the network

2D DownSampling layer

class `tensorlayer.layers.DownSampling2dLayer`(*layer=None, size=[], is_scale=True, method=0, align_corners=False, name='downsample2d_layer'*)

The *DownSampling2dLayer* class is downSampling 2d layer, see tf.image.resize_images.

Parameters **layer** : a layer class with 4-D Tensor of shape [batch, height, width, channels] or 3-D Tensor of shape [height, width, channels].

size : a tupe of int or float.

(height, width) scale factor or new size of height and width.

is_scale : boolean, if True (default), size is scale factor, otherwise, size is number of pixels of height and width.

method : 0, 1, 2, 3. ResizeMethod. Defaults to ResizeMethod.BILINEAR.

- ResizeMethod.BILINEAR, Bilinear interpolation.

- ResizeMethod.NEAREST_NEIGHBOR, Nearest neighbor interpolation.
- ResizeMethod.BICUBIC, Bicubic interpolation.
- ResizeMethod.AREA, Area interpolation.

align_corners : bool. If true, exactly align all 4 corners of the input and output. Defaults to false.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

1D Atrous convolutional layer

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

Wrapper for `AtrousConv1dLayer`, if you don't understand how to use `Conv1dLayer`, this function may be easier.

Parameters **net** : TensorLayer layer.

n_filter : number of filter.

filter_size : an int.

stride : an int.

dilation : an int, filter dilation size.

act : None or activation function.

others : see `Conv1dLayer`.

2D Atrous convolutional layer

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

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

Parameters **layer** : a layer class with 4-D Tensor of shape [batch, height, width, channels].

filters : A 4-D Tensor with the same type as value and shape [filter_height, filter_width, in_channels, out_channels]. filters' in_channels dimension must match that of value. Atrous convolution is equivalent to standard convolution with upsampled filters with effective height filter_height + (filter_height - 1) * (rate - 1) and effective width filter_width + (filter_width - 1) * (rate - 1), produced by inserting rate - 1 zeros along consecutive elements across the filters' spatial dimensions.

n_filter : number of filter.

filter_size : tuple (height, width) for filter size.

rate : A positive int32. The stride with which we sample input values across the height and width dimensions. Equivalently, the rate by which we upsample the filter values by inserting zeros across the height and width dimensions. In the literature, the same parameter is sometimes called input stride or dilation.

act : activation function, None for linear.

padding : A string, either 'VALID' or 'SAME'. The padding algorithm.

W_init : weights initializer. The initializer for initializing the weight matrix.

b_init : biases initializer or None. The initializer for initializing the bias vector. If None, skip biases.

W_init_args : dictionary. The arguments for the weights tf.get_variable().

b_init_args : dictionary. The arguments for the biases tf.get_variable().

name : a string or None, an optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

2D Separable convolutional layer

class `tensorlayer.layers.`**`SeparableConv2dLayer`**(*layer=None, filters=None, kernel_size=5, strides=(1, 1), padding='valid', data_format='channels_last', dilation_rate=(1, 1), depth_multiplier=1, act=None, use_bias=True, depthwise_initializer=None, pointwise_initializer=None, bias_initializer=<class 'tensorflow.python.ops.init_ops.Zeros'>, depthwise_regularizer=None, pointwise_regularizer=None, bias_regularizer=None, activity_regularizer=None, name='atrou2d'*)

The `SeparableConv2dLayer` class is 2-D convolution with separable filters, see tf.layers.separable_conv2d.

Parameters **layer** : a layer class

filters : integer, the dimensionality of the output space (i.e. the number output of filters in the convolution).

kernel_size : a tuple or list of N positive integers specifying the spatial dimensions of of the filters. Can be a single integer to specify the same value for all spatial dimensions.

strides : a tuple or list of N positive integers specifying the strides of the convolution. Can be a single integer to specify the same value for all spatial dimensions. Specifying any stride value != 1 is incompatible with specifying any dilation_rate value != 1.

padding : one of "valid" or "same" (case-insensitive).

data_format : A string, one of channels_last (default) or channels_first. The ordering of the dimensions in the inputs. channels_last corresponds to inputs with shapedata_format = 'NWHC' (batch, width, height, channels) while channels_first corresponds to inputs with shape (batch, channels, width, height).

dilation_rate : an integer or tuple/list of 2 integers, specifying the dilation rate to use for dilated convolution. Can be a single integer to specify the same value for all spatial dimensions. Currently, specifying any dilation_rate value != 1 is incompatible with specifying any stride value != 1.

depth_multiplier : The number of depthwise convolution output channels for each input channel. The total number of depthwise convolution output channels will be equal to num_filters_in * depth_multiplier.

act (activation) : Activation function. Set it to None to maintain a linear activation.

use_bias : Boolean, whether the layer uses a bias.

depthwise_initializer : An initializer for the depthwise convolution kernel.

pointwise_initializer : An initializer for the pointwise convolution kernel.

bias_initializer : An initializer for the bias vector. If None, no bias will be applied.

depthwise_regularizer : Optional regularizer for the depthwise convolution kernel.

pointwise_regularizer : Optional regularizer for the pointwise convolution kernel.

bias_regularizer : Optional regularizer for the bias vector.

activity_regularizer : Regularizer function for the output.

name : a string or None, an optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

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 Convolutional layer

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

Wrapper for `Conv1dLayer`, if you don't understand how to use `Conv1dLayer`, this function may be easier.

Parameters **net** : TensorLayer layer.

n_filter : number of filter.

filter_size : an int.

stride : an int.

dilation_rate : As it is 1D conv, the default is "NWC".

act : None or activation function.

others : see `Conv1dLayer`.

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 Convolutional layer

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

Wrapper for `Conv2dLayer`, if you don't understand how to use `Conv2dLayer`, this function may be easier.

Parameters **net** : TensorLayer layer.

n_filter : number of filter.

filter_size : tuple (height, width) for filter size.

strides : tuple (height, width) for strides.

act : None or activation function.

others : see `Conv2dLayer`.

Examples

```
>>> w_init = tf.truncated_normal_initializer(stddev=0.01)
>>> b_init = tf.constant_initializer(value=0.0)
>>> inputs = InputLayer(x, name='inputs')
>>> conv1 = Conv2d(inputs, 64, (3, 3), act=tf.nn.relu, padding='SAME', W_init=w_
↪init, b_init=b_init, name='conv1_1')
>>> conv1 = Conv2d(conv1, 64, (3, 3), act=tf.nn.relu, padding='SAME', W_init=w_
↪init, b_init=b_init, name='conv1_2')
>>> pool1 = MaxPool2d(conv1, (2, 2), padding='SAME', name='pool1')
>>> conv2 = Conv2d(pool1, 128, (3, 3), act=tf.nn.relu, padding='SAME', W_init=w_
↪init, b_init=b_init, name='conv2_1')
>>> conv2 = Conv2d(conv2, 128, (3, 3), act=tf.nn.relu, padding='SAME', W_init=w_
↪init, b_init=b_init, name='conv2_2')
>>> pool2 = MaxPool2d(conv2, (2, 2), padding='SAME', name='pool2')
```

2D Deconvolutional layer

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

Wrapper for `DeConv2dLayer`, if you don't understand how to use `DeConv2dLayer`, this function may be easier.

Parameters **net** : TensorLayer layer.

n_out_channel : int, number of output channel.

filter_size : tuple of (height, width) for filter size.

out_size : tuple of (height, width) of output.

batch_size : int or None, batch_size. If None, try to find the batch_size from the first dim of net.outputs (you should tell the batch_size when define the input placeholder).

strides : tuple of (height, width) for strides.

act : None or activation function.

others : see `DeConv2dLayer`.

1D Max pooling layer

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

Wrapper for tf.layers.max_pooling1d .

Parameters **net** : TensorLayer layer, the tensor over which to pool. Must have rank 3.

filter_size (pool_size) : An integer or tuple/list of a single integer, representing the size of the pooling window.

strides : An integer or tuple/list of a single integer, specifying the strides of the pooling operation.

padding : A string. The padding method, either 'valid' or 'same'. Case-insensitive.

data_format : A string, one of channels_last (default) or channels_first. The ordering of the dimensions in the inputs. channels_last corresponds to inputs with shape (batch, length, channels) while channels_first corresponds to inputs with shape (batch, channels, length).

name : A string, the name of the layer.

Returns

- A `Layer` which the output tensor, of rank 3.

1D Mean pooling layer

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

Wrapper for tf.layers.average_pooling1d .

Parameters **net** : TensorLayer layer, the tensor over which to pool. Must have rank 3.

filter_size (pool_size) : An integer or tuple/list of a single integer, representing the size of the pooling window.

strides : An integer or tuple/list of a single integer, specifying the strides of the pooling operation.

padding : A string. The padding method, either 'valid' or 'same'. Case-insensitive.

data_format : A string, one of channels_last (default) or channels_first. The ordering of the dimensions in the inputs. channels_last corresponds to inputs with shape (batch, length, channels) while channels_first corresponds to inputs with shape (batch, channels, length).

name : A string, the name of the layer.

Returns

- A `Layer` which the output tensor, of rank 3.

2D Max pooling layer

`tensorlayer.layers.`**`MaxPool2d`**(*net*, *filter_size=(2, 2)*, *strides=None*, *padding='SAME'*, *name='maxpool'*)

Wrapper for `PoolLayer`.

Parameters **net** : TensorLayer layer.

filter_size : tuple of (height, width) for filter size.

strides : tuple of (height, width). Default is the same with filter_size.

others : see `PoolLayer`.

2D Mean pooling layer

`tensorlayer.layers.`**`MeanPool2d`**(*net*, *filter_size=(2, 2)*, *strides=None*, *padding='SAME'*, *name='meanpool'*)

Wrapper for `PoolLayer`.

Parameters **net** : TensorLayer layer.

filter_size : tuple of (height, width) for filter size.

strides : tuple of (height, width). Default is the same with filter_size.

others : see `PoolLayer`.

3D Max pooling layer

`tensorlayer.layers.MaxPool3d`(*net*, *filter_size*, *strides*, *padding='valid'*, *data_format='channels_last'*, *name=None*)

Wrapper for tf.layers.max_pooling3d .

Parameters **net** : TensorLayer layer, the tensor over which to pool. Must have rank 5.

filter_size (pool_size) : An integer or tuple/list of 3 integers: (pool_depth, pool_height, pool_width) specifying the size of the pooling window. Can be a single integer to specify the same value for all spatial dimensions.

strides : An integer or tuple/list of 3 integers, specifying the strides of the pooling operation. Can be a single integer to specify the same value for all spatial dimensions.

padding : A string. The padding method, either 'valid' or 'same'. Case-insensitive.

data_format : A string. The ordering of the dimensions in the inputs. channels_last (default) and channels_first are supported. channels_last corresponds to inputs with shape (batch, depth, height, width, channels) while channels_first corresponds to inputs with shape (batch, channels, depth, height, width).

name : A string, the name of the layer.

3D Mean pooling layer

`tensorlayer.layers.MeanPool3d`(*net*, *filter_size*, *strides*, *padding='valid'*, *data_format='channels_last'*, *name=None*)

Wrapper for tf.layers.average_pooling3d

Parameters **net** : TensorLayer layer, the tensor over which to pool. Must have rank 5.

filter_size (pool_size) : An integer or tuple/list of 3 integers: (pool_depth, pool_height, pool_width) specifying the size of the pooling window. Can be a single integer to specify the same value for all spatial dimensions.

strides : An integer or tuple/list of 3 integers, specifying the strides of the pooling operation. Can be a single integer to specify the same value for all spatial dimensions.

padding : A string. The padding method, either 'valid' or 'same'. Case-insensitive.

data_format : A string. The ordering of the dimensions in the inputs. channels_last (default) and channels_first are supported. channels_last corresponds to inputs with shape (batch, depth, height, width, channels) while channels_first corresponds to inputs with shape (batch, channels, depth, height, width).

name : A string, the name of the layer.

Super-Resolution layer

1D Supixel Convolutional

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

One-dimensional subpixel upsampling layer. Calls a tensorflow function that directly implements this functionality. We assume input has dim (batch, width, r)

Parameters **net** : TensorLayer layer.

scale : int, upscaling ratio, a wrong setting will lead to Dimension size error.

act : activation function.

name : string.

An optional name to attach to this layer.

References

- Audio Super Resolution Implementation.

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)
```

2D Supixel Convolutional

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

The *SubpixelConv2d* class is a sub-pixel 2d convolutional ayer, usually be used for Super-Resolution applications, example code.

Parameters **net** : TensorLayer layer.

scale : int, upscaling ratio, a wrong setting will lead to Dimension size error.

n_out_channel : int or None, the number of output channels.

Note that, the number of input channels == (scale x scale) x The number of output channels. If None, automatically set n_out_channel == the number of input channels / (scale x scale).

act : activation function.

name : string.

An optional name to attach to this layer.

References

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

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)
```

Spatial Transformer

2D Affine Transformation layer

class `tensorlayer.layers.`**`SpatialTransformer2dAffineLayer`**(*layer=None, theta_layer=None, out_size=[40, 40], name='sapatial_trans_2d_affine'*)

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

Parameters **layer** : a layer class with 4-D Tensor of shape [batch, height, width, channels]

theta_layer : a layer class for the localisation network.

In this layer, we will use a `DenseLayer` to make the theta size to [batch, 6], value range to [0, 1] (via tanh).

out_size : tuple of two ints.

The size of the output of the network (height, width), the feature maps will be resized by this.

References

- Spatial Transformer Networks
- TensorFlow/Models

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network

2D Affine Transformation function

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

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

Parameters **U** : 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 two ints

The size of the output of the network (height, width)

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)
```

References

- Spatial Transformer Networks
- TensorFlow/Models

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** : float

tensor of inputs [batch, height, width, num_channels]

thetas : float

a set of transformations for each input [batch, num_transforms, 6]

out_size : int

the size of the output [out_height, out_width]

Returns: float

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

Pooling layer

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 or `tf.nn.max_pool3d` and `tf.nn.avg_pool3d` for 3D.

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this layer.

ksize : a list of ints that has length >= 4.

The size of the window for each dimension of the input tensor.

strides : a list of ints that has length >= 4.

The stride of the sliding window for each dimension of the input tensor.

padding : a string from: "SAME", "VALID".

The type of padding algorithm to use.

pool : a pooling function

- see TensorFlow pooling APIs
- class `tf.nn.max_pool`
- class `tf.nn.avg_pool`
- class `tf.nn.max_pool3d`
- class `tf.nn.avg_pool3d`

name : a string or None

An optional name to attach to this layer.

Examples

- see *Conv2dLayer*.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Padding layer

Padding layer for any modes.

class `tensorlayer.layers.`**`PadLayer`**(*layer=None*, *paddings=None*, *mode='CONSTANT'*, *name='pad_layer'*)

The *`PadLayer`* class is a Padding layer for any modes and dimensions. Please see tf.pad for usage.

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer.

padding : a Tensor of type int32.

mode : one of "CONSTANT", "REFLECT", or "SYMMETRIC" (case-insensitive)

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

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=None*, *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`* class is a normalization layer, see `tf.nn.batch_normalization` and `tf.nn.moments`.

Batch normalization on fully-connected or convolutional maps.

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer.

decay : float, default is 0.9.

A decay factor for ExponentialMovingAverage, use larger value for large dataset.

epsilon : float

A small float number to avoid dividing by 0.

act : activation function.

is_train : boolean

Whether train or inference.

beta_init : beta initializer

The initializer for initializing beta

gamma_init : gamma initializer

The initializer for initializing gamma

name : a string or None

An optional name to attach to this layer.

References

- Source
- stackoverflow

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Local Response Normalization

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

The *`LocalResponseNormLayer`* class 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 treated as 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, squared sum of inputs within depth_radius.

Parameters **layer** : a layer class. Must be one of the following types: float32, half. 4-D.

depth_radius : An optional int. Defaults to 5. 0-D. Half-width of the 1-D normalization window.

bias : An optional float. Defaults to 1. An offset (usually positive to avoid dividing by 0).

alpha : An optional float. Defaults to 1. A scale factor, usually positive.

beta : An optional float. Defaults to 0.5. An exponent.

name : A string or None, an optional name to attach to this layer.

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network

Instance Normalization

class tensorlayer.layers.**InstanceNormLayer**(*layer=None*, *act=<function identity>*, *epsilon=1e-05*, *scale_init=<tensorflow.python.ops.init_ops.TruncatedNormal object>*, *offset_init=<tensorflow.python.ops.init_ops.Constant object>*, *name='instan_norm'*)

The *InstanceNormLayer* class is a for instance normalization.

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this layer.

act : activation function.

epsilon : float

A small float number.

scale_init : beta initializer

The initializer for initializing beta

offset_init : gamma initializer

The initializer for initializing gamma

name : a string or None

An optional name to attach to this layer.

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network

Layer Normalization

class tensorlayer.layers.**LayerNormLayer**(*layer=None*, *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** : a *Layer* instance

The *Layer* class feeding into this layer.

act : activation function

The function that is applied to the layer activations.

others : see tf.contrib.layers.layer_norm

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Object Detection

ROI layer

class `tensorlayer.layers.`**`ROIPoolingLayer`**(*layer=None*, *rois=None*, *pool_height=2*, *pool_width=2*, *name='roipooling_layer'*)

The *`ROIPoolingLayer`* class is Region of interest pooling layer.

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer, the feature maps on which to perform the pooling operation

rois : list of regions of interest in the format (feature map index, upper left, bottom right)

pool_width : int, size of the pooling sections.

pool_width : int, size of the pooling sections.

Notes

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

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Time distributed layer

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

The *`TimeDistributedLayer`* class that applies a function to every timestep of the input tensor. For example, if using *`DenseLayer`* as the `layer_class`, inputs [batch_size , length, dim] outputs [batch_size , length, new_dim].

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer, [batch_size , length, dim]

layer_class : a *`Layer`* class

args : dictionary

The arguments for the `layer_class`.

name : a string or None

An optional name to attach to this layer.

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
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

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=None*, *cell_fn=None*, *cell_init_args={}*, *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 RNN layer, you can implement vanilla RNN, LSTM and GRU with it.

Parameters layer : a *`Layer`* instance

The *Layer* class feeding into this layer.

cell_fn : a TensorFlow's core RNN cell as follow (Note TF1.0+ and TF1.0- are different).

- see RNN Cells in TensorFlow

cell_init_args : a dictionary

The arguments for the cell initializer.

n_hidden : an int

The number of hidden units in the layer.

initializer : initializer

The initializer for initializing the parameters.

n_steps : an int

The sequence length.

initial_state : None or RNN State

If None, initial_state is zero_state.

return_last : boolean

- 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 apply one or more RNN(s) on this layer, set to False.

return_seq_2d : boolean

- When return_last = 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 : a string or None

An optional name to attach to this layer.

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`

Examples

- For words

```
>>> 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,
...             W_init=tf.random_uniform_initializer(-init_scale, init_scale),
...             b_init=tf.random_uniform_initializer(-init_scale, init_scale),
...             act = tl.activation.identity, name='output_layer')
```

- 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.Conv2dLayer(net,
...                         act = tf.nn.relu,
...                         shape = [5, 5, 1, 32],  # 32 features for each 5x5␣
↪patch
...                         strides=[1, 2, 2, 1],
...                         padding='SAME',
...                         name ='cnn_layer1')
>>> 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')
>>> net = tl.layers.Conv2dLayer(net,
...                         act = tf.nn.relu,
...                         shape = [5, 5, 32, 10], # 10 features for each 5x5␣
↪patch
...                         strides=[1, 2, 2, 1],
...                         padding='SAME',
...                         name ='cnn_layer2')
>>> net = tl.layers.PoolLayer(net,
...                         ksize=[1, 2, 2, 1],
...                         strides=[1, 2, 2, 1],
...                         padding='SAME',
...                         pool = tf.nn.max_pool,
...                         name ='pool_layer2')
>>> 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,
...                         cell_init_args={},
...                         n_hidden=200,
...                         initializer=tf.random_uniform_initializer(-0.1, 0.1),
...                         n_steps=num_steps,
...                         return_last=False,
...                         return_seq_2d=True,
...                         name='rnn_layer')
>>> net = tl.layers.DenseLayer(rnn1, n_units=3,
...                         act = tl.activation.identity, name='output_layer')
```

Attributes

outputs	(a tensor) The output of this RNN. return_last = False, outputs = all cell_output, which is the hidden state. cell_output.get_shape() = (?, n_hidden)
final_state	(a tensor or StateTuple) When state_is_tuple = False, it is the final hidden and cell states, states.get_shape() = [?, 2 * n_hidden]. When state_is_tuple = True, it stores two elements: (c, h), in that order. You can get the final state after each iteration during training, then feed it to the initial state of next iteration.
initial_state	(a tensor or StateTuple) It is the initial state of this RNN layer, you can use it to initialize your state at the begining 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 `?`.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Bidirectional layer

class `tensorlayer.layers.`**`BiRNNLayer`**(*layer=None, cell_fn=None, cell_init_args={'state_is_tuple': True, 'use_peepholes': True}, 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 Bidirectional RNN layer.

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

cell_fn : a TensorFlow's core RNN cell as follow (Note TF1.0+ and TF1.0- are different).

- see RNN Cells in TensorFlow

cell_init_args : a dictionary

The arguments for the cell initializer.

n_hidden : an int

The number of hidden units in the layer.

initializer : initializer

The initializer for initializing the parameters.

n_steps : an int

The 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*: (input_keep_prob, output_keep_prob).

The input and output keep probability.

n_layer : an int, default is 1.

The number of RNN layers.

return_last : boolean

- 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 apply one or more RNN(s) on this layer, set to False.

return_seq_2d : boolean

- When return_last = 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 : a string or None

An optional name to attach to this layer.

Notes

- Input dimension should be rank 3 : [batch_size, n_steps, n_features], if no, 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

Attributes

outputs	(a tensor) The output of this RNN. return_last = False, outputs = all cell_output, which is the hidden state. cell_output.get_shape() = (?, n_hidden)
fw(bw)_final_state	(a tensor or StateTuple) When state_is_tuple = False, it is the final hidden and cell states, states.get_shape() = [?, 2 * n_hidden]. When state_is_tuple = True, it stores two elements: (c, h), in that order. 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	(a tensor or StateTuple) It is the initial state of this RNN layer, you can use it to initialize your state at the begining 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 `?`.

Methods

`count_params`()	Return the number of parameters in the network
`print_layers`()	Print all info of layers in the network
`print_params`([details])	Print all info of parameters in the network

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`**(*input*, *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 **input** : tensor for data

[batch_size, n_step(max), n_features]

index : tensor for indexing, i.e. sequence_length in Dynamic RNN.

[batch_size]

References

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

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)]
```

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.

References

- Borrow from TFlearn.

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]]]
>>> sl
... [4 3 4]
```

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]
```

Dynamic RNN layer

RNN layer

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

The *`DynamicRNNLayer`* class is a Dynamic RNN layer, see `tf.nn.dynamic_rnn`.

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

cell_fn : a TensorFlow's core RNN cell as follow (Note TF1.0+ and TF1.0- are different).

- see RNN Cells in TensorFlow

cell_init_args : a dictionary

The arguments for the cell initializer.

n_hidden : an int

The number of hidden units in the layer.

initializer : initializer

The initializer for initializing the parameters.

sequence_length : a 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*: (input_keep_prob, output_keep_prob).

The input and output keep probability.

n_layer : an int, default is 1.

The number of RNN layers.

return_last : boolean

- 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 apply one or more RNN(s) on this layer, set to False.

return_seq_2d : boolean

- When return_last = False
- If True, return 2D Tensor [n_example, n_hidden], for stacking DenseLayer or computing cost after it.
- If False, return 3D Tensor [n_example/n_steps(max), n_steps(max), n_hidden], for stacking multiple RNN after it.

name : a string or None

An optional name to attach to this layer.

Notes

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

References

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

Examples

```
>>> input_seqs = tf.placeholder(dtype=tf.int64, shape=[batch_size, None], name=
↪"input_seqs")
>>> 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 tf.nn.rnn_
↪cell.BasicLSTMCell,
...             n_hidden = embedding_size,
...             dropout = 0.7,
...             sequence_length = tl.layers.retrieve_seq_length_op2(input_seqs),
...             return_seq_2d = True,     # stack denselayer or compute cost␣
↪after it
...             name = 'dynamic_rnn')
... net = tl.layers.DenseLayer(net, n_units=vocab_size,
...             act=tf.identity, name="output")
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Bidirectional layer

class `tensorlayer.layers.`**`BiDynamicRNNLayer`**(*layer=None*, *cell_fn=None*, *cell_init_args={'state_is_tuple': True}*, *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={}*, *name='bi_dyrnn_layer'*)

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

Parameters **layer** : a *`Layer`* instance

The *Layer* class feeding into this layer.

cell_fn : a TensorFlow's core RNN cell as follow (Note TF1.0+ and TF1.0- are different).

- see RNN Cells in TensorFlow

cell_init_args : a dictionary

The arguments for the cell initializer.

n_hidden : an int

The number of hidden units in the layer.

initializer : initializer

The initializer for initializing the parameters.

sequence_length : a 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*: (input_keep_prob, output_keep_prob).

The input and output keep probability.

n_layer : an int, default is 1.

The number of RNN layers.

return_last : boolean

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 apply one or more RNN(s) on this layer, set to False.

return_seq_2d : boolean

- When return_last = False
- If True, return 2D Tensor [n_example, 2 * n_hidden], for stacking DenseLayer or computing cost after it.
- If False, return 3D Tensor [n_example/n_steps(max), n_steps(max), 2 * n_hidden], for stacking multiple RNN after it.

name : a string or None

An optional name to attach to this layer.

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

Attributes

outputs	(a tensor) The output of this RNN. return_last = False, outputs = all cell_output, which is the hidden state. cell_output.get_shape() = (?, 2 * n_hidden)
fw(bw)_final_state	(a tensor or StateTuple) When state_is_tuple = False, it is the final hidden and cell states, states.get_shape() = [?, 2 * n_hidden]. When state_is_tuple = True, it stores two elements: (c, h), in that order. 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	(a tensor or StateTuple) It is the initial state of this RNN layer, you can use it to initialize your state at the begining of each epoch or iteration according to your training procedure.
sequence_length	(a tensor or array, shape = [batch_size]) The sequence lengths computed by Advanced Opt or the given sequence lengths.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Sequence to Sequence

Simple Seq2Seq

class `tensorlayer.layers.Seq2Seq`(*net_encode_in=None, net_decode_in=None, cell_fn=None, cell_init_args={'state_is_tuple': True}, 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 the example Chatbot in 200 lines of code.
- The Author recommends users to read the source code of `DynamicRNNLayer` and `Seq2Seq`.

Parameters **net_encode_in** : a `Layer` instance

Encode sequences, [batch_size, None, n_features].

net_decode_in : a `Layer` instance

Decode sequences, [batch_size, None, n_features].

cell_fn : a TensorFlow's core RNN cell as follow (Note TF1.0+ and TF1.0- are different).

- see RNN Cells in TensorFlow

cell_init_args : a dictionary

The arguments for the cell initializer.

n_hidden : an int

The number of hidden units in the layer.

initializer : initializer

The initializer for initializing 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 (from placeholder or other RNN).

If None, initial_state_encode is of zero state.

initial_state_decode : None or RNN state (from placeholder or other RNN).

If None, initial_state_decode is of the final state of the RNN encoder.

dropout : *tuple* of *float*: (input_keep_prob, output_keep_prob).

The input and output keep probability.

n_layer : an int, default is 1.

The number of RNN layers.

return_seq_2d : boolean

- When return_last = False
- If True, return 2D Tensor [n_example, n_hidden], for stacking DenseLayer or computing cost after it.

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

name : a string or None

An optional name to attach to this layer.

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)
```

Attributes

outputs	(a tensor) The output of RNN decoder.
initial_state_encode	(a tensor or StateTuple) Initial state of RNN encoder.
initial_state_decode	(a tensor or StateTuple) Initial state of RNN decoder.
final_state_encode	(a tensor or StateTuple) Final state of RNN encoder.
final_state_decode	(a tensor or StateTuple) Final state of RNN decoder.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

PeekySeq2Seq

class `tensorlayer.layers.`**`PeekySeq2Seq`**(*net_encode_in=None, net_decode_in=None, cell_fn=None, cell_init_args={'state_is_tuple': True}, n_hidden=256, initializer=<tensorflow.python.ops.init_ops.RandomUniform object>, in_sequence_length=None, out_sequence_length=None, initial_state=None, dropout=None, n_layer=1, return_seq_2d=False, name='peeky_seq2seq'*)

Waiting for contribution. The `PeekySeq2Seq` class, see Model and Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation .

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

AttentionSeq2Seq

class `tensorlayer.layers.`**`AttentionSeq2Seq`**(*net_encode_in=None, net_decode_in=None, cell_fn=None, cell_init_args={'state_is_tuple': True}, n_hidden=256, initializer=<tensorflow.python.ops.init_ops.RandomUniform object>, in_sequence_length=None, out_sequence_length=None, initial_state=None, dropout=None, n_layer=1, return_seq_2d=False, name='attention_seq2seq'*)

Waiting for contribution. The `AttentionSeq2Seq` class, see Model and Neural Machine Translation by Jointly Learning to Align and Translate .

Methods

`count_params`()	Return the number of parameters in the network
`print_layers`()	Print all info of layers in the network
`print_params`([details])	Print all info of parameters in the network

Shape layer

Flatten layer

class `tensorlayer.layers.`**`FlattenLayer`**(*layer=None, name='flatten_layer'*)

The `FlattenLayer` class is layer which reshape high-dimension input to a vector. Then we can apply DenseLayer, RNNLayer, ConcatLayer and etc on the top of it.

[batch_size, mask_row, mask_col, n_mask] —> [batch_size, mask_row * mask_col * n_mask]

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

name : a string or None

An optional name to attach to this layer.

Examples

```
>>> 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, 32, 64],
...                     strides=[1, 1, 1, 1],
...                     padding='SAME',
...                     name ='cnn_layer')
>>> net = tl.layers.Pool2dLayer(net,
...                     ksize=[1, 2, 2, 1],
...                     strides=[1, 2, 2, 1],
...                     padding='SAME',
...                     pool = tf.nn.max_pool,
...                     name ='pool_layer',)
>>> net = tl.layers.FlattenLayer(net, name='flatten_layer')
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Reshape layer

class `tensorlayer.layers.`**`ReshapeLayer`**(*layer=None*, *shape=[]*, *name='reshape_layer'*)

The `ReshapeLayer` class is layer which reshape the tensor.

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

shape : a list

The output shape.

name : a string or None

An optional name to attach to this layer.

Examples

- The core of this layer is `tf.reshape`.
- Use TensorFlow only :

```
>>> 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.]]]
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Transpose layer

class `tensorlayer.layers.`**`TransposeLayer`**(*layer=None*, *perm=None*, *name='transpose'*)

The `TransposeLayer` class transpose the dimension of a teneor, see tf.transpose() .

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

perm: list, a permutation of the dimensions

Similar with numpy.transpose.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Lambda layer

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

The `LambdaLayer` class is a layer which is able to use the provided function.

Parameters layer : a `Layer` instance

The *Layer* class feeding into this layer.

fn : a function

The function that applies to the outputs of previous layer.

fn_args : a dictionary

The arguments for the function (option).

name : a string or None

An optional name to attach to this layer.

Examples

```
>>> x = tf.placeholder(tf.float32, shape=[None, 1], name='x')
>>> net = tl.layers.InputLayer(x, name='input_layer')
>>> net = LambdaLayer(net, lambda x: 2*x, name='lambda_layer')
>>> y = net.outputs
>>> sess = tf.InteractiveSession()
>>> out = sess.run(y, feed_dict={x : [[1],[2]]})
... [[2],[4]]
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Merge layer

Concat layer

class `tensorlayer.layers.`**`ConcatLayer`**(*layer=[]*, *concat_dim=1*, *name='concat_layer'*)

The `ConcatLayer` class is layer which concat (merge) two or more tensor by given axis..

Parameters **layer** : a list of `Layer` instances

The *Layer* class feeding into this layer.

concat_dim : int

Dimension along which to concatenate.

name : a string or None

An optional name to attach to this layer.

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, n_units=800, act = tf.nn.relu, name=
↪'relu1_1')
>>> net2 = tl.layers.DenseLayer(inputs, n_units=300, act = tf.nn.relu, name=
↪'relu2_1')
>>> net = tl.layers.ConcatLayer(layer = [net1, net2], name ='concat_layer')
...     [TL] InputLayer input_layer (?, 784)
...     [TL] DenseLayer relu1_1: 800, <function relu at 0x1108e41e0>
...     [TL] DenseLayer relu2_1: 300, <function relu at 0x1108e41e0>
...     [TL] 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: Tensor("Relu:0", shape=(?, 800), dtype=float32)
...     layer 1: Tensor("Relu_1:0", shape=(?, 300), dtype=float32)
...
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Element-wise layer

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

The *ElementwiseLayer* class combines multiple *Layer* which have the same output shapes by a given elemwise-wise operation.

Parameters layer : a list of *Layer* instances

The *Layer* class feeding into this layer.

combine_fn : a TensorFlow elemwise-merge 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 : a string or None

An optional name to attach to this layer.

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')
```

Methods

`count_params`()	Return the number of parameters in the network
`print_layers`()	Print all info of layers in the network
`print_params`([details])	Print all info of parameters in the network

Extend layer

Expand dims layer

class `tensorlayer.layers.`**`ExpandDimsLayer`**(*layer=None*, *axis=None*, *name='expand_dims'*)

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

Parameters layer : a *Layer* instance

The *Layer* class feeding into this layer.

axis : int, 0-D (scalar).

Specifies the dimension index at which to expand the shape of input.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

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 : a *Layer* instance

The *Layer* class feeding into this layer.

multiples: a list of int

Must be one of the following types: int32, int64. 1-D. Length must be the same as the number of dimensions in input

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Stack layer

Stack layer

class `tensorlayer.layers.`**`StackLayer`**(*layer=[]*, *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 layer : a list of *Layer* instances

The *Layer* class feeding into this layer.

axis : an int

Dimension along which to concatenate.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network

Continued on next page

Table 2.44 – continued from previous page

print_params([details])	Print all info of parameters in the network

Unstack layer

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

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

Parameters **layer** : a list of `Layer` instances

The *Layer* class feeding into this layer.

num : an int

The length of the dimension axis. Automatically inferred if None (the default).

axis : an int

Dimension along which to concatenate.

name : a string or None

An optional name to attach to this layer.

Returns The list of layer objects unstacked from the input.

Estimator layer

class `tensorlayer.layers.EstimatorLayer` (*layer=None*, *model_fn=None*, *args={}*, *name='estimator_layer'*)

The `EstimatorLayer` class accepts `model_fn` that described the model. It is similar with `KerasLayer`, see tutorial_keras.py

Parameters **layer** : a `Layer` instance

The *Layer* class feeding into this layer.

model_fn : a function that described the model.

args : dictionary

The arguments for the model_fn.

name : a string or None

An optional name to attach to this layer.

Methods

count_params()	Return the number of parameters in the network
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network

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=None*, *slim_layer=None*, *slim_args={}*, *name='tfslim_layer'*)

The *SlimNetsLayer* class can be used to merge all TF-Slim nets into TensorLayer. Model can be found in slim-model , more about slim see slim-git .

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this 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 : a string or None

An optional name to attach to this layer.

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.

Examples

- see Inception V3 example on Github

Methods

`count_params`()	Return the number of parameters in the network
`print_layers`()	Print all info of layers in the network
`print_params`([details])	Print all info of parameters in the network

Connect Keras

Yes ! Keras models can be connected into TensorLayer! see tutorial_keras.py .

class `tensorlayer.layers.KerasLayer` (*layer=None*, *keras_layer=None*, *keras_args={}*, *name='keras_layer'*)

The *KerasLayer* class can be used to merge all Keras layers into TensorLayer. Example can be found here tutorial_keras.py

Parameters **layer** : a *Layer* instance

The *Layer* class feeding into this layer.

keras_layer : a keras network function

keras_args : dictionary

The arguments for the keras model.

name : a string or None

An optional name to attach to this layer.

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Parametric activation layer

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

The `PReluLayer` class is Parametric Rectified Linear layer.

Parameters **x** : A *Tensor* with type *float*, *double*, *int32*, *int64*, *uint8*,

int16, or *int8*.

channel_shared : *bool*. Single weight is shared by all channels

a_init : alpha initializer, default zero constant.

The initializer for initializing the alphas.

a_init_args : dictionary

The arguments for the weights initializer.

name : A name for this activation op (optional).

References

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

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Flow control layer

class `tensorlayer.layers.`**`MultiplexerLayer`**(*layer=[]*, *name='mux_layer'*)

The `MultiplexerLayer` selects one of several input and forwards the selected input into the output, see *tutorial_mnist_multiplexer.py*.

Parameters **layer** : a list of `Layer` instances

The *Layer* class feeding into this layer.

name : a string or None

An optional name to attach to this layer.

References

- See `tf.pack() for TF0.12 or tf.stack() for TF1.0` and `tf.gather()` at TensorFlow - Slicing and Joining

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')
```

Methods

`count_params()`	Return the number of parameters in the network
`print_layers()`	Print all info of layers in the network
`print_params([details])`	Print all info of parameters in the network

Wrapper

Embedding + Attention + Seq2seq

class tensorlayer.layers.**EmbeddingAttentionSeq2seqWrapper**(*source_vocab_size*, *target_vocab_size*, *buckets*, *size*, *num_layers*, *max_gradient_norm*, *batch_size*, *learning_rate*, *learning_rate_decay_factor*, *use_lstm=False*, *num_samples=512*, *forward_only=False*, *name='wrapper'*)

Sequence-to-sequence model with attention and for multiple buckets (Deprecated after TF0.12).

This example implements a multi-layer recurrent neural network as encoder, and an attention-based decoder. This is the same as the model described in this paper: - Grammar as a Foreign Language please look there for details, or into the seq2seq library for complete model implementation. This example also allows to use GRU cells in addition to LSTM cells, and sampled softmax to handle large output vocabulary size. A single-layer version of this model, but with bi-directional encoder, was presented in - Neural Machine Translation by Jointly Learning to Align and Translate The sampled softmax is described in Section 3 of the following paper. - On Using Very Large Target Vocabulary for Neural Machine Translation

Parameters **source_vocab_size** : size of the source vocabulary.

target_vocab_size : size of the target vocabulary.

buckets : a list of pairs (I, O), where I specifies maximum input length

that will be processed in that bucket, and O specifies maximum output length. Training instances that have inputs longer than I or outputs longer than O will be pushed to the next bucket and padded accordingly. We assume that the list is sorted, e.g., [(2, 4), (8, 16)].

size : number of units in each layer of the model.

num_layers : number of layers in the model.

max_gradient_norm : gradients will be clipped to maximally this norm.

batch_size : the size of the batches used during training;

the model construction is independent of batch_size, so it can be changed after initialization if this is convenient, e.g., for decoding.

learning_rate : learning rate to start with.

learning_rate_decay_factor : decay learning rate by this much when needed.

use_lstm : if true, we use LSTM cells instead of GRU cells.

num_samples : number of samples for sampled softmax.

forward_only : if set, we do not construct the backward pass in the model.

name : a string or None

An optional name to attach to this layer.

Methods

count_params()	Return the number of parameters in the network
get_batch(data, bucket_id[, PAD_ID, GO_ID, ...])	Get a random batch of data from the specified bucket, prepare for step.
print_layers()	Print all info of layers in the network
print_params([details])	Print all info of parameters in the network
step(session, encoder_inputs, ...)	Run a step of the model feeding the given inputs.

get_batch (*data*, *bucket_id*, *PAD_ID=0*, *GO_ID=1*, *EOS_ID=2*, *UNK_ID=3*)
Get a random batch of data from the specified bucket, prepare for step.

To feed data in step(..) it must be a list of batch-major vectors, while data here contains single length-major cases. So the main logic of this function is to re-index data cases to be in the proper format for feeding.

Parameters **data** : a tuple of size len(self.buckets) in which each element contains

lists of pairs of input and output data that we use to create a batch.

bucket_id : integer, which bucket to get the batch for.

PAD_ID : int

Index of Padding in vocabulary

GO_ID : int

Index of GO in vocabulary

EOS_ID : int

Index of End of sentence in vocabulary

UNK_ID : int

Index of Unknown word in vocabulary

Returns The triple (encoder_inputs, decoder_inputs, target_weights) for

the constructed batch that has the proper format to call step(...) later.

step (*session*, *encoder_inputs*, *decoder_inputs*, *target_weights*, *bucket_id*, *forward_only*)
Run a step of the model feeding the given inputs.

Parameters **session** : tensorflow session to use.

encoder_inputs : list of numpy int vectors to feed as encoder inputs.

decoder_inputs : list of numpy int vectors to feed as decoder inputs.

target_weights : list of numpy float vectors to feed as target weights.

bucket_id : which bucket of the model to use.

forward_only : whether to do the backward step or only forward.

Returns A triple consisting of gradient norm (or None if we did not do backward),

average perplexity, and the outputs.

Raises **ValueError** : if length of encoder_inputs, decoder_inputs, or

target_weights disagrees with bucket size for the specified bucket_id.

Helper functions

Flatten tensor

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

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

Parameters variable : a tensorflow variable

name : a string or None

An optional name to attach to this layer.

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'], enable layer name reuse.

Examples

```
>>> network = tl.layers.InputLayer(x, name='input_layer')
>>> network = tl.layers.DenseLayer(network, n_units=800, name='relu1')
...
>>> tl.layers.clear_layers_name()
>>> network2 = tl.layers.InputLayer(x, name='input_layer')
>>> network2 = tl.layers.DenseLayer(network2, n_units=800, name='relu1')
...
```

Initialize RNN state

tensorlayer.layers.**initialize_rnn_state**(*state*)

Return the initialized RNN state. The input is LSTMStateTuple or State of RNNCells.

Parameters state : a RNN state.

Remove repeated items in a list

tensorlayer.layers.**list_remove_repeat**(*l=None*)

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 l : a list

Examples

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

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.

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.

```
y = network.outputs
# Alternatively, you can use tl.cost.cross_entropy(y, y_) instead.
cross_entropy = tf.reduce_mean(tf.nn.sparse_softmax_cross_entropy_with_logits(y, y_))
cost = cross_entropy
cost = cost + tl.cost.maxnorm_regularizer(1.0)(network.all_params[0]) +
          tl.cost.maxnorm_regularizer(1.0)(network.all_params[2])
```

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])	It is a softmax cross-entropy operation, returns the TensorFlow expression of cross-entropy of two distributions, implement softmax internally.
sigmoid_cross_entropy(output, target[, name])	It is a sigmoid cross-entropy operation, see `tf.nn.sigmoid_cross_entropy_with_logits`.
binary_cross_entropy(output, target[, ...])	Computes binary cross entropy given *output*.

Continued on next page

Table 2.51 – continued from previous page

mean_squared_error(output, target[, is_mean])	Return the TensorFlow expression of mean-square-error of two distributions.
normalized_mean_square_error(output, target)	Return the TensorFlow expression of normalized mean-square-error of two distributions.
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], wiki.
li_regularizer(scale[, scope])	li regularization removes the neurons of previous layer, *i* represents *inputs*.
lo_regularizer(scale[, scope])	lo regularization removes the neurons of current layer, *o* represents *outputs*
maxnorm_regularizer([scale, scope])	Max-norm regularization returns a function that can be used to apply max-norm regularization to weights.
maxnorm_o_regularizer(scale, scope)	Max-norm output regularization removes the neurons of current layer.
maxnorm_i_regularizer(scale[, scope])	Max-norm input regularization removes the neurons of previous layer.

Softmax cross entropy

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

It is a softmax cross-entropy operation, returns the TensorFlow expression of cross-entropy of two distributions, implement softmax internally. See `tf.nn.sparse_softmax_cross_entropy_with_logits`.

Parameters **output** : Tensorflow variable

A distribution with shape: [batch_size, n_feature].

target : Tensorflow variable

A batch of index with shape: [batch_size,].

name : string

Name of this loss.

References

- About cross-entropy: wiki.
- The code is borrowed from: here.

Examples

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

Sigmoid cross entropy

tensorlayer.cost.**sigmoid_cross_entropy**(*output*, *target*, *name=None*)
It is a sigmoid cross-entropy operation, see `tf.nn.sigmoid_cross_entropy_with_logits`.

Binary cross entropy

tensorlayer.cost.**binary_cross_entropy**(*output*, *target*, *epsilon=1e-08*, *name='bce_loss'*)
Computes binary cross entropy given *output*.

For brevity, let x = *output*, z = *target*. The binary cross entropy loss is

loss(x, z) = - sum_i (x[i] * log(z[i]) + (1 - x[i]) * log(1 - z[i]))

Parameters **output** : tensor of type *float32* or *float64*.

target : tensor of the same type and shape as *output*.

epsilon : float

A small value to avoid output is zero.

name : string

An optional name to attach to this layer.

References

- DRAW

Mean squared error

tensorlayer.cost.**mean_squared_error**(*output*, *target*, *is_mean=False*)
Return the TensorFlow expression of mean-square-error of two distributions.

Parameters **output** : 2D or 4D tensor.

target : 2D or 4D tensor.

is_mean : boolean, if True, use `tf.reduce_mean` to compute the loss of one data, otherwise, use `tf.reduce_sum` (default).

References

- Wiki Mean Squared Error

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** : 2D or 4D tensor.

target : 2D or 4D tensor.

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

A distribution with shape: [batch_size, ...], (any dimensions).

loss_type : string

`jaccard` or `sorensen`, default is `jaccard`.

axis : list of integer

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.

References

- Wiki-Dice

Examples

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

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

A distribution with shape: [batch_size, ...], (any dimensions).

threshold : float

The threshold value to be true.

axis : list 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

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, 1 means totally match.

Parameters **output** : tensor

A distribution with shape: [batch_size, ...], (any dimensions).

target : tensor

A distribution with shape: [batch_size, ...], (any dimensions).

threshold : float

The threshold value to be true.

axis : list 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.

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.

Parameters **logits** : Tensorflow variable

2D tensor, `network.outputs`, [batch_size*n_steps (n_examples), number of output units]

target_seqs : Tensorflow variable

target : 2D tensor [batch_size, n_steps], if the number of step is dynamic, please use `cross_entropy_seq_with_mask` instead.

batch_size : None or int.

If not None, the return cost will be divided by batch_size.

Examples

```
>>> see PTB tutorial for more details
>>> input_data = tf.placeholder(tf.int32, [batch_size, num_steps])
>>> targets = tf.placeholder(tf.int32, [batch_size, num_steps])
>>> cost = tl.cost.cross_entropy_seq(network.outputs, targets)
```

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 outputs.

Parameters **logits** : network identity outputs

2D tensor, `network.outputs`, [batch_size, number of output units].

target_seqs : int of tensor, like word ID.

[batch_size, ?]

input_mask : the mask to compute loss

The same size with target_seqs, normally 0 and 1.

return_details : boolean

- If False (default), only returns the loss.
- If True, returns the loss, losses, weights and targets (reshape to one vetcor).

Examples

- see Image Captioning Example.

Cosine similarity

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

Cosine similarity [-1, 1], wiki.

Parameters **v1, v2** : tensor of [batch_size, n_feature], with the same number of features.

Returns a tensor of [batch_size,]

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*, *scope=None*)

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

The implementation follows TensorFlow contrib.

Parameters **scale** : float

A scalar multiplier *Tensor*. 0.0 disables the regularizer.

scope: An optional scope name.

Returns 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, *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: An optional scope name for TF12+.

Returns 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*, *scope=None*)

lo regularization removes the neurons of current layer, *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.

scope: An optional scope name for TF12+.

Returns 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*, *scope*)

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.

scope: An optional scope name.

Returns 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*, *scope=None*)

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.

scope: An optional scope name.

Returns 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.

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])	Return a batch of result by given data.
`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,
`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.
`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 deformation of images as described in [Simard2003] .

Continued on next page

Table 2.52 – continued from previous page

elastic_transform_multi(x, alpha, sigma[, ...])	Elastic deformation of 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.
imresize(x[, size, interp, mode])	Resize an image by given output size and method.
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).
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.
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.

Continued on next page

Table 2.52 – continued from previous page

sequences_get_mask(sequences[, pad_val])	Return mask for sequences.
distorted_images([images, height, width])	Distort images for generating more training data.
crop_central_whiten_images([images, height, ...])	Crop the central of image, and normailize it for test data.

Threading

tensorlayer.prepro.**threading_data**(*data=None*, *fn=None*, *thread_count=None*, ***kwargs*)

Return a batch of result by given data. Usually be used for data augmentation.

Parameters **data** : numpy array, file names and etc, see Examples below.

thread_count : the number of threads to use

fn : the function for data processing.

more args : the args for fn, see Examples below.

References

- python queue
- run with limited queue

Examples

- Single array

```
>>> X --> [batch_size, row, col, 1] greyscale
>>> results = threading_data(X, zoom, zoom_range=[0.5, 1], is_random=True)
... results --> [batch_size, row, col, channel]
>>> tl.visualize.images2d(images=np.asarray(results), second=0.01, saveable=True,␣
↪name='after', dtype=None)
>>> tl.visualize.images2d(images=np.asarray(X), second=0.01, saveable=True, name=
↪'before', dtype=None)
```

- List of array (e.g. functions with `multi`)

```
>>> X, Y --> [batch_size, row, col, 1]  greyscale
>>> data = threading_data([_ for _ in zip(X, Y)], 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.visualize.images2d(images=np.asarray(X_), second=0.01, saveable=True, name=
↪'after', dtype=None)
>>> tl.visualize.images2d(images=np.asarray(Y_), second=0.01, saveable=True, name=
↪'before', dtype=None)
```

- Single array split across `thread_count` threads (e.g. functions with `multi`)

```
>>> X, Y --> [batch_size, row, col, 1]  greyscale
>>> data = threading_data(X, 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.visualize.images2d(images=np.asarray(X_), second=0.01, saveable=True, name=
↪'after', dtype=None)
>>> tl.visualize.images2d(images=np.asarray(Y_), second=0.01, saveable=True, name=
↪'before', dtype=None)
```

•Customized function for image segmentation

```
>>> def distort_img(data):
...     x, y = data
...     x, y = flip_axis_multi([x, y], axis=0, is_random=True)
...     x, y = flip_axis_multi([x, y], axis=1, is_random=True)
...     x, y = crop_multi([x, y], 100, 100, is_random=True)
...     return x, y
>>> X, Y --> [batch_size, row, col, channel]
>>> data = threading_data([_ for _ in zip(X, Y)], distort_img)
>>> X_, Y_ = data.transpose((1,0,2,3,4))
```

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* , 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, default False

If True, randomly rotate.

row_index, col_index, channel_index : int

Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

fill_mode : string

Method to fill missing pixel, default 'nearest', more options 'constant', 'reflect' or 'wrap'

- scipy ndimage affine_transform

cval : scalar, optional

Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0

order : int, optional

The order of interpolation. The order has to be in the range 0-5. See `apply_transform`.

- scipy ndimage affine_transform

Examples

```
>>> x --> [row, col, 1] greyscale
>>> x = rotation(x, rg=40, is_random=False)
>>> tl.visualize.frame(x[:,:,0], second=0.01, saveable=True, name='temp',cmap=
↪'gray')
```

`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 : see `rotation`.

Examples

```
>>> x, y --> [row, col, 1]  greyscale
>>> x, y = rotation_multi([x, y], rg=90, is_random=False)
>>> tl.visualize.frame(x[:,:,0], second=0.01, saveable=True, name='x',cmap='gray')
>>> tl.visualize.frame(y[:,:,0], second=0.01, saveable=True, name='y',cmap='gray')
```

Crop

`tensorlayer.prepro.`**`crop`**(*x, wrg, hrg, is_random=False, row_index=0, col_index=1, channel_index=2*)

Randomly or centrally crop an image.

Parameters x : numpy array

An image with dimension of [row, col, channel] (default).

wrg : float

Size of weight.

hrg : float

Size of height.

is_random : boolean, default False

If True, randomly crop, else central crop.

row_index, col_index, channel_index : int

Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

`tensorlayer.prepro.`**`crop_multi`**(*x*, *wrg*, *hrg*, *is_random=False*, *row_index=0*, *col_index=1*, *channel_index=2*)

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 : see `crop`.

Flip

`tensorlayer.prepro.`**`flip_axis`**(*x*, *axis*, *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

- 0, flip up and down
- 1, flip left and right
- 2, flip channel

is_random : boolean, default False

If True, randomly flip.

`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 : see `flip_axis`.

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, default False

If True, randomly shift.

row_index, col_index, channel_index : int

Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

fill_mode : string

Method to fill missing pixel, default 'nearest', more options 'constant', 'reflect' or 'wrap'.

- scipy ndimage affine_transform

cval : scalar, optional

Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.

order : int, optional

The order of interpolation. The order has to be in the range 0-5. See `apply_transform`.

- scipy ndimage affine_transform

`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 : see `shift`.

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, default False

If True, randomly shear.

row_index, col_index, channel_index : int

Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

fill_mode : string

Method to fill missing pixel, default 'nearest', more options 'constant', 'reflect' or 'wrap'.

- scipy ndimage affine_transform

cval : scalar, optional

Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.

order : int, optional

The order of interpolation. The order has to be in the range 0-5. See `apply_transform`.

- scipy ndimage affine_transform

`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 : see `shear`.

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 : (row, column) tuple or (2,) ndarray, optional

Center coordinate of transformation.

strength : float, optional

The amount of swirling applied.

radius : float, optional

The extent of the swirl in pixels. The effect dies out rapidly beyond radius.

rotation : float, (degree) optional

Additional rotation applied to the image, usually [0, 360], relates to center.

output_shape : tuple (rows, cols), optional

Shape of the output image generated. 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 : {'constant', 'edge', 'symmetric', 'reflect', 'wrap'}, optional

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, optional

Used in conjunction with mode 'constant', the value outside the image boundaries.

clip : bool, optional

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 : bool, optional

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, default False

If True, random swirl.

- random center = [(0 ~ x.shape[0]), (0 ~ x.shape[1])]
- random strength = [0, strength]
- random radius = [1e-10, radius]
- random rotation = [-rotation, rotation]

Examples

```
>>> x --> [row, col, 1] greyscale
>>> x = 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 : see `swirl`.

Elastic transform

`tensorlayer.prepro.`**`elastic_transform`**(*x*, *alpha*, *sigma*, *mode='constant'*, *cval=0*, *is_random=False*)

Elastic deformation of images as described in [Simard2003] .

Parameters **x** : numpy array, a greyscale image.

alpha : scalar factor.

sigma : scalar or sequence of scalars, 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 : default constant, see scipy.ndimage.filters.gaussian_filter.

cval : float, optional. Used in conjunction with mode 'constant', the value outside the image boundaries.

is_random : boolean, default False

References

- Github.
- Kaggle

Examples

```
>>> x = elastic_transform(x, alpha = x.shape[1] * 3, sigma = x.shape[1] * 0.07)
```

`tensorlayer.prepro.elastic_transform_multi`(*x*, *alpha*, *sigma*, *mode='constant'*, *cval=0*, *is_random=False*)

Elastic deformation of images as described in [Simard2003].

Parameters **x** : list of numpy array

others : see `elastic_transform`.

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

- 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, (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, default False

If True, randomly zoom.

row_index, col_index, channel_index : int

Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

fill_mode : string

Method to fill missing pixel, default 'nearest', more options 'constant', 'reflect' or 'wrap'.

- scipy ndimage affine_transform

cval : scalar, optional

Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0.

order : int, optional

The order of interpolation. The order has to be in the range 0-5. See `apply_transform`.

- scipy ndimage affine_transform

`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 : see `zoom`.

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, small than 1 means brighter.

Non negative real number. Default value is 1, smaller 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, default False

- If True, randomly change brightness.

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 numpy array

List of images with dimension of [n_images, row, col, channel] (default).

others : see `brightness`.

Resize

`tensorlayer.prepro.imresize(x, size=[100, 100], 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 : int, float or tuple (h, w)

- int, Percentage of current size.
- float, Fraction of current size.
- tuple, Size of the output image.

interp : str, optional

Interpolation to use for re-sizing ('nearest', 'lanczos', 'bilinear', 'bicubic' or 'cubic').

mode : str, optional

The PIL image mode ('P', 'L', etc.) to convert arr before resizing.

Returns **imresize** : ndarray

The resized array of image.

References

•scipy.misc.imresize

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 : 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 : set each sample mean to 0.

samplewise_std_normalization : divide each input by its std.

epsilon : small position value for dividing standard deviation.

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.

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
```

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 : value for subtraction.

std : value for division.

epsilon : small position value for dividing standard deviation.

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, default False

If True, randomly shift.

channel_index : int

Index of channel, default 2.

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 : see `channel_shift`.

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 (0, 1)

The keeping probability, the lower more values will be set to zero.

Manual transform

tensorlayer.prepro.**transform_matrix_offset_center**(*matrix*, *x*, *y*)

Return transform matrix offset center.

Parameters **matrix** : numpy array

Transform matrix

x, y : int

Size of image.

Examples

- See `rotation`, `shear`, `zoom`.

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

Batch of images with dimension of 3, [batch_size, row, col, channel].

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 : string

Method to fill missing pixel, default 'nearest', more options 'constant', 'reflect' or 'wrap'

- scipy ndimage affine_transform

cval : scalar, optional

Value used for points outside the boundaries of the input if mode='constant'. Default is 0.0

order : int, optional

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

Examples

- See `rotation`, `shift`, `shear`, `zoom`.

tensorlayer.prepro.**projective_transform_by_points**(*x*, *src*, *dst*, *map_args={}*, *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 (x, y).

dst : list or numpy

The coordinates after transformation, the number of coordinates is the same with src.

map_args : dict, optional

Keyword arguments passed to inverse_map.

output_shape : tuple (rows, cols), optional

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, optional

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 : {'constant', 'edge', 'symmetric', 'reflect', 'wrap'}, optional

Points outside the boundaries of the input are filled according to the given mode. Modes match the behaviour of numpy.pad.

cval : float, optional

Used in conjunction with mode 'constant', the value outside the image boundaries.

clip : bool, optional

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 : bool, optional

Whether to keep the original range of values. Otherwise, the input image is converted according to the conventions of img_as_float.

References

- scikit-image : geometric transformations
- scikit-image : examples

Examples

```
>>> Assume X is an image from CIFAR 10, i.e. shape == (32, 32, 3)
>>> src = [[0,0],[0,32],[32,0],[32,32]]
>>> dst = [[10,10],[0,32],[32,0],[32,32]]
>>> x = projective_transform_by_points(X, src, dst)
```

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

A image with dimension of 3 and channels of 1 or 3.

dim_ordering : list or tuple of 3 int

Index of row, col and channel, default (0, 1, 2), for theano (1, 2, 0).

scale : boolean, default is True

If True, converts image to [0, 255] from any range of value like [-1, 2].

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, {'low', '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 : 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.

Points to Image

`tensorlayer.prepro.`**`pt2map`**`(`*list_points=[], size=(100, 100), val=1*`)`
Inputs a list of points, return a 2D image.

Parameters **list_points** : list of [x, y].

size : tuple of (w, h) for output size.

val : float or int for the contour value.

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 image.

radius : int for the radius of mask.

Greyscale dilation

`tensorlayer.prepro.`**`dilation`**`(`*x, radius=3*`)`
Return greyscale morphological dilation of an image, see skimage.morphology.dilation.

Parameters **x** : 2D array image.

radius : int for the radius of mask.

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 image.

radius : int for the radius of mask.

Greyscale erosion

`tensorlayer.prepro.`**`erosion`**`(`*x, radius=3*`)`
Return greyscale morphological erosion of an image, see skimage.morphology.erosion.

Parameters **x** : 2D array image.

radius : int for the radius of mask.

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 lists where each element is a sequence

maxlen : int, maximum length

dtype : type to cast the resulting sequence.

padding : 'pre' or 'post', pad either before or after each sequence.

truncating : '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** : numpy array with dimensions (number_of_sequences, maxlen)

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.

pad_id : 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** : numpy array or list of list with token IDs.

e.g. [[4,3,5,3,2,2,2,2], [5,3,9,4,9,2,2,3]]

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, default True.

Shorten the sequences.

remain_end_id : boolean, default False.

Keep an end_id in the end.

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.

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.

end_id : 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.

end_id : int.

pad_id : 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.

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]]
```

Tensor Opt

Note: These functions will be deprecated, see `tutorial_cifar10_tfrecord.py` for new information.

`tensorlayer.prepro.`**`distorted_images`**(*images=None*, *height=24*, *width=24*)

Distort images for generating more training data.

Parameters **images** : 4D Tensor

The tensor or placeholder of images

height : int

The height for random crop.

width : int

The width for random crop.

Returns **result** : tuple of Tensor

(Tensor for distorted images, Tensor for while loop index)

Notes

•The first image in 'distorted_images' should be removed.

References

•tensorflow.models.image.cifar10.cifar10_input

Examples

```
>>> X_train, y_train, X_test, y_test = tl.files.load_cifar10_dataset(shape=(-1,␣
↪32, 32, 3), plotable=False)
>>> sess = tf.InteractiveSession()
>>> batch_size = 128
>>> x = tf.placeholder(tf.float32, shape=[batch_size, 32, 32, 3])
>>> distorted_images_op = tl.preprocess.distorted_images(images=x, height=24,␣
↪width=24)
>>> sess.run(tf.initialize_all_variables())
>>> feed_dict={x: X_train[0:batch_size,:,:,:]}
>>> distorted_images, idx = sess.run(distorted_images_op, feed_dict=feed_dict)
>>> tl.visualize.images2d(X_train[0:9,:,:,:], second=2, saveable=False, name=
↪'cifar10', dtype=np.uint8, fig_idx=20212)
>>> tl.visualize.images2d(distorted_images[1:10,:,:,:], second=10, saveable=False,
↪ name='distorted_images', dtype=None, fig_idx=23012)
```

tensorlayer.prepro.**crop_central_whiten_images**(*images=None*, *height=24*, *width=24*)

Crop the central of image, and normailize it for test data.

They are cropped to central of height * width pixels.

Whiten (Normalize) the images.

Parameters **images** : 4D Tensor

The tensor or placeholder of images

height : int

The height for central crop.

width : int

The width for central crop.

Returns **result** : tuple Tensor

(Tensor for distorted images, Tensor for while loop index)

Notes

The first image in 'central_images' should be removed.

Examples

```
>>> X_train, y_train, X_test, y_test = tl.files.load_cifar10_dataset(shape=(-1,␣
↪32, 32, 3), plotable=False)
>>> sess = tf.InteractiveSession()
>>> batch_size = 128
>>> x = tf.placeholder(tf.float32, shape=[batch_size, 32, 32, 3])
>>> central_images_op = tl.preprocess.crop_central_whiten_images(images=x,␣
↪height=24, width=24)
>>> sess.run(tf.initialize_all_variables())
>>> feed_dict={x: X_train[0:batch_size,:,:,:]}
>>> central_images, idx = sess.run(central_images_op, feed_dict=feed_dict)
>>> tl.visualize.images2d(X_train[0:9,:,:,:], second=2, saveable=False, name=
↪'cifar10', dtype=np.uint8, fig_idx=20212)
>>> tl.visualize.images2d(central_images[1:10,:,:,:], second=10, saveable=False,␣
↪name='central_images', dtype=None, fig_idx=23012)
```

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 batchsize.
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 tutorial.

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 batchsize.

Parameters inputs : numpy.array

24. The input features, every row is a example.

targets : numpy.array

25. 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.

Notes

•If you have two inputs, e.g. X1 (1000, 100) and X2 (1000, 80), you can ‘‘np.hstack((X1, X2))

into (1000, 180) and feed into `inputs`, then you can split a batch of X1 and X2.

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]))
```

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`, `seq_length = 5`, one return will have `500` rows (examples).

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), see `PTB tutorial`. In TensorFlow's tutorial, this generates the batch_size pointers into the raw PTB data, and allows minibatch iteration along these pointers.

- Hint, if the input data are images, you can modify the code as follow.

```
from
data = np.zeros([batch_size, batch_len)
to
data = np.zeros([batch_size, batch_len, inputs.shape[1], inputs.shape[2], inputs.
↪shape[3]])
```

Parameters **inputs** : a list

the context in list format; note that context usually be represented by splitting by space, and then convert to unique word IDs.

targets : 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].

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.]]
```

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 tutorial. Yields (Returns) the source contexts and the target context by the given batch_size and num_steps (sequence_length).

see `PTB tutorial`.

e.g. x = [0, 1, 2] y = [1, 2, 3] , when batch_size = 1, num_steps = 3, raw_data = [i for i in range(100)]

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]]
```

API - Utility

fit(sess, network, train_op, cost, X_train, ...)	Traing 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, max, 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, use for disable dropout, dropconnect layer and so on.
flatten_list([list_of_list])	Input a list of list, return a list that all items are in a list.

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*)

Traing a given non time-series network by the given cost function, training data, batch_size, n_epoch etc.

Parameters **sess** : TensorFlow session

sess = tf.InteractiveSession()

network : a TensorLayer layer

the network will be trained

train_op : a TensorFlow optimizer

like 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 : the TensorFlow expression of accuracy (or other metric) or None

if None, would not display the metric

batch_size : int

batch size for training and evaluating

n_epoch : int

the number of training epochs

print_freq : int

display the training information every `print_freq` epochs

X_val : numpy array or None

the input of validation data

y_val : numpy array or None

the target of validation data

eval_train : boolean

if X_val and y_val are not None, it refects whether to evaluate the training data

tensorboard : boolean

if True summary data will be stored to the log/ direcory 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, see Note:

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 visulaization 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)

Notes

If tensorboard=True, the global_variables_initializer will be run inside the fit function in order to initalize the automatically generated summary nodes used for tensorboard visualization, thus tf.global_variables_initializer().run() before the fit() call will be undefined.

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)
```

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** : TensorFlow session

sess = tf.InteractiveSession()

network : a TensorLayer layer

the network will be trained

acc : the TensorFlow expression of accuracy (or other metric) or None

if None, would not display the metric

X_test : numpy array

the input of test data

y_test : numpy array

the target of test data

x : placeholder

for inputs

y_ : placeholder

for targets

batch_size : int or None

batch size for testing, when dataset is large, we should use minibatche for testing. when dataset is small, we can set it to None.

cost : the TensorFlow expression of cost or None

if None, would not display the cost

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 : TensorFlow session

sess = tf.InteractiveSession()

network : a TensorLayer layer

the network will be trained

X : numpy array

the input

x : placeholder

for inputs

y_op : placeholder

the argmax expression of softmax outputs

batch_size : int or None

batch size for prediction, when dataset is large, we should use minibatche for prediction. when 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))
```

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** : numpy.array or list

target results

y_predict : numpy.array or list

predicted results

n_classes : int

number of classes

Examples

```
>>> c_mat, f1, acc, f1_macro = evaluation(y_test, y_predict, n_classes)
```

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

Features, each row is an example

y_train : numpy.array

Labels

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:]
```

Random functions

tensorlayer.utils.**get_random_int**(*min=0*, *max=10*, *number=5*, *seed=None*)

Return a list of random integer by the given range and quantity.

Examples

```
>>> r = get_random_int(min=0, max=10, number=5)
... [10, 2, 3, 3, 7]
```

Helper functions

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, use for disable dropout, dropconnect layer and so on.

Parameters dp_dict : dictionary

keeping probabilities

Examples

```
>>> dp_dict = dict_to_one( network.all_drop )
>>> dp_dict = dict_to_one( network.all_drop )
>>> feed_dict.update(dp_dict)
```

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]
```

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.

Continued on next page

Table 2.55 – continued from previous page

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, see create_vocab() and `tutorial_tfrecord3.py`.
process_sentence(sentence[, start_word, ...])	Converts 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, see create_vocab() and `tutorial_tfrecord3.py`.
simple_read_words([filename])	Read context from file without any preprocessing.
read_words([filename, replace])	File to list format context.
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 for converting 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])	Given a context (words) in list format and the vocabulary, Returns a list of IDs to represent the context.
word_ids_to_words(data, id_to_word)	Given a context (ids) in list format and the vocabulary, Returns a list of words to represent the context.
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.

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.

Parameters **data** : a list

To present context.

batch_size : an int

Batch size to return.

num_skips : an int

How many times to reuse an input to generate a label.

skip_window : an int

How many words to consider left and right.

data_index : an int

Index of the context location. without using yield, this code use data_index to instead.

Returns batch : a list

Inputs

labels : a list

Labels

data_index : an int

Index of the context location.

References

- TensorFlow word2vec tutorial

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]]
```

Sampling functions

Simple sampling

`tensorlayer.nlp.sample(a=[], temperature=1.0)`

Sample an index from a probability array.

Parameters a : a list

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 to avoid error.

Sampling from top k

`tensorlayer.nlp.`**`sample_top`**(*a=[]*, *top_k=10*)

Sample from `top_k` probabilities.

Parameters **a** : a list

List of probabilities.

top_k : int

Number of candidates to be considered.

Vector representations of words

Simple vocabulary class

class `tensorlayer.nlp.`**`SimpleVocabulary`**(*vocab*, *unk_id*)

Simple vocabulary wrapper, see create_vocab().

Parameters **vocab** : A dictionary of word to word_id.

unk_id : Id of the special 'unknown' word.

Methods

`word_to_id`(word)	Returns the integer id of a word string.

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** : File containing the vocabulary, 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 : Special word denoting sentence start.

end_word : Special word denoting sentence end.

unk_word : Special word denoting unknown words.

Attributes

vocab	(a dictionary from word to id.)
reverse_vocab	(a list from id to word.)
start_id	(int of start id)
end_id	(int of end id)
unk_id	(int of unk id)
pad_id	(int of padding id)

Methods

`id_to_word`(word_id)	Returns the word string of an integer word id.
`word_to_id`(word)	Returns the integer word id of a word string.

Process sentence

`tensorlayer.nlp.`**`process_sentence`**(*sentence*, *start_word='<S>'*, *end_word='</S>'*)

Converts a sentence string into a list of string words, add start_word and end_word, see `create_vocab()` and `tutorial_tfrecord3.py`.

Returns A list of strings; the processed caption.

Notes

- You have to install the following package.
- Installing NLTK
- Installing NLTK data

Examples

```
>>> c = "how are you?"
>>> c = tl.nlp.process_sentence(c)
>>> print(c)
... ['<S>', 'how', 'are', 'you', '?', '</S>']
```

Create vocabulary

`tensorlayer.nlp.`**`create_vocab`**(*sentences*, *word_counts_output_file*, *min_word_count=1*)

Creates the vocabulary of word to word_id, see create_vocab() and `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** : a list of lists of strings.

word_counts_output_file : A string

The file name.

min_word_count : a int

Minimum number of occurrences for a word.

Returns

- tl.nlp.SimpleVocabulary object.

Notes

•See more `tl.nlp.build_vocab()`

Examples

```
>>> 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>']]
```

```
>>> tl.nlp.create_vocab(processed_capts, word_counts_output_file='vocab.txt', min_
↪word_count=1)
...   [TL] Creating vocabulary.
...   Total words: 8
...   Words in vocabulary: 8
...   Wrote vocabulary file: vocab.txt
>>> 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
```

Read words from file

Simple read file

`tensorlayer.nlp.`**`simple_read_words`**(*filename='nietzsche.txt'*)

Read context from file without any preprocessing.

Parameters **filename** : a string

A file path (like .txt file)

Returns The context in a string

Read file

`tensorlayer.nlp.read_words(filename='nietzsche.txt', replace=['\n', '<eos>'])`

File to list format context. Note that, this script can not handle punctuations. For customized read_words method, see `tutorial_generate_text.py`.

Parameters **filename** : a string

A file path (like .txt file)

replace : a list

[original string, target string], to disable replace use ['', '']

Returns The context in a list, split by space by default, and use `<eos>` to represent `\n`,

e.g. `[... 'how', 'useful', 'it', "'s" ... ]`.

References

- tensorflow.models.rnn.ptb.reader

Read analogy question file

`tensorlayer.nlp.read_analogies_file(eval_file='questions-words.txt', word2id={})`

Reads through an analogy question file, return its id format.

Parameters **eval_data** : a string

The file name.

word2id : a dictionary

Mapping words to unique IDs.

Returns **analogy_questions** : a [n, 4] numpy array containing the analogy question's

word ids. questions_skipped: questions skipped due to unknown words.

Examples

```
>>> eval_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
...
```

```
>>> 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]]
```

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** : a list of string

the context in list format

Returns **word_to_id** : a dictionary

mapping words to unique IDs. e.g. {'campbell': 2587, 'atlantic': 2247, 'aoun': 6746 .... }

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 for converting word to integer id. Returns a reverse dictionary for converting a id to word.

Parameters **word_to_id** : dictionary

mapping words to unique ids

Returns **reverse_dictionary** : a dictionary

mapping ids to words

Build dictionaries for id to word etc

tensorlayer.nlp.**build_words_dataset**(*words=[]*, *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** : a list of string 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 : an 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 : a string

Unknown words = unk_key

Returns **data** : a list of integer

The context in a list of ids

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)]

dictionary : a dictionary

word_to_id, mapping words to unique IDs.

reverse_dictionary : a dictionary

id_to_word, mapping id to unique word.

References

- tensorflow/examples/tutorials/word2vec/word2vec_basic.py

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)
```

Save vocabulary

`tensorlayer.nlp.save_vocab(count=[], 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
```

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=[], word_to_id={}, unk_key='UNK')`
Given a context (words) in list format and the vocabulary, Returns a list of IDs to represent the context.

Parameters data : a list of string or byte

the context in list format

word_to_id : a dictionary

mapping words to unique IDs.

unk_key : a string

Unknown words = unk_key

Returns A list of IDs to represent the context.

References

- tensorflow.models.rnn.ptb.reader

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']
```

List of IDs to Words

`tensorlayer.nlp.`**`word_ids_to_words`**(*data*, *id_to_word*)

Given a context (ids) in list format and the vocabulary, Returns a list of words to represent the context.

Parameters **data** : a list of integer

the context in list format

id_to_word : a dictionary

mapping id to unique word.

Returns A list of string or byte to represent the context.

Examples

```
>>> see words_to_word_ids
```

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.

References

- Code from `/tensorflow/models/rnn/translation/data_utils.py`

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)
>>>        print(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']
```

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=[b'_PAD', b'_GO', b'_EOS', b'_UNK']*)

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** : path where the vocabulary will be created.

data_path : data file that will be used to create vocabulary.

max_vocabulary_size : limit on the size of the created vocabulary.

tokenizer : 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 0s.

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:

dog

cat

will result in a vocabulary {"dog": 0, "cat": 1}, and this function will also return the reversed-vocabulary ["dog", "cat"].

Parameters **vocabulary_path** : path to the file containing the vocabulary.

Returns **vocab** : a dictionary

Word to id. A dictionary mapping string to integers.

rev_vocab : a list

Id to word. The reversed vocabulary (a list, which reverses the vocabulary mapping).

Raises **ValueError** : if the provided vocabulary_path does not exist.

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']
```

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(), data_to_token_ids()

vocabulary : a dictionary mapping tokens to integers.

tokenizer : 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 0s.

Returns A list of integers, the token-ids for the sentence.

`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** : path to the data file in one-sentence-per-line format.

target_path : path where the file with token-ids will be created.

vocabulary_path : path to the vocabulary file.

tokenizer : 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 0s.

References

- Code from `/tensorflow/models/rnn/translation/data_utils.py`

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** : A numpy array of strings where each string is a single example.

references : A numpy array of strings where each string is a single example.

lowercase : If true, pass the "-lc" flag to the multi-bleu script

Returns The BLEU score as a float32 value.

References

- Google/seq2seq/metric/bleu

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)
```

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.

Reward functions

`tensorlayer.rein.discount_episode_rewards(rewards=[], 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** : numpy list

a list of rewards

gamma : float

discounted factor

mode : int

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.

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.        ]
```

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/ placeholder

The agent actions.

rewards : tensor/ placeholder

The rewards.

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

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** : a list of float.

The probability distribution of all actions.

action_list : None or a list of action in integer, string or others.

If None, returns an integer range between 0 and len(probs)-1.

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
```

API - Files

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
load_params = tl.files.load_npz(path='', name='model.npz')
tl.files.assign_params(sess, load_params, 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])	Automatically download MNIST dataset and return the training, validation and test set with 50000, 10000 and 10000 digit images respectively.
load_cifar10_dataset([shape, path, ...])	The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class.
load_ptb_dataset([path])	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".
load_matt_mahoney_text8_dataset([path])	Download a text file from Matt Mahoney's website if not present, and make sure it's the right size.
load_imdb_dataset([path, nb_words, ...])	Load IMDB dataset
load_nietzsche_dataset([path])	Load Nietzsche dataset.
load_wmt_en_fr_dataset([path])	It will download English-to-French translation data from the WMT'15 Website (10^9-French-English corpus), and the 2013 news test from the same site as development set.
load_flickr25k_dataset([tag, path, ...])	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.
load_flickr1M_dataset([tag, size, path, ...])	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.
load_cyclegan_dataset([filename, path])	Load image data from CycleGAN's database, see this link.
save_npz([save_list, name, sess])	Input parameters and the file name, save parameters into .npz file.
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.

Continued on next page

Table 2.59 – continued from previous page

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().

Load dataset functions

MNIST

tensorlayer.files.**load_mnist_dataset**(*shape=(-1, 784), path='data/mnist/'*)

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, defaults is (-1,784)

path : string

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/cifar10/', plotable=False, second=3*)

The CIFAR-10 dataset 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) , (-1, 32, 32, 3) , (-1, 32, 32, 3)

plotable : True, False

Whether to plot some image examples.

second : int

If `plotable` is True, `second` is the display time.

path : string

The path that the data is downloaded to, defaults is `data/cifar10/`.

References

- CIFAR website
- Data download link
- Code references

Examples

```
>>> X_train, y_train, X_test, y_test = tl.files.load_cifar10_dataset(shape=(-1,␣
↪32, 32, 3), plotable=True)
```

Penn TreeBank (PTB)

`tensorlayer.files.load_ptb_dataset(path='data/ptb/')`

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.

Parameters **path** : : string

The path that the data is downloaded to, defaults is `data/ptb/`.

Returns train_data, valid_data, test_data, vocabulary size

References

- `tensorflow.models.rnn.ptb import reader`
- Manual download

Examples

```
>>> train_data, valid_data, test_data, vocab_size = tl.files.load_ptb_dataset()
```

Matt Mahoney's text8

`tensorlayer.files.`**`load_matt_mahoney_text8_dataset`**(*path='data/mm_test8/'*)

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** : : string

The path that the data is downloaded to, defaults is `data/mm_test8/`.

Returns **word_list** : a list

a list of string (word).

e.g. [.... 'their', 'families', 'who', 'were', 'expelled', 'from', 'jerusalem', ...]

Examples

```
>>> words = tl.files.load_matt_mahoney_text8_dataset()
>>> print('Data size', len(words))
```

IMBD

`tensorlayer.files.`**`load_imdb_dataset`**(*path='data/imdb/'*, *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** : : string

The path that the data is downloaded to, defaults is `data/imdb/`.

References

- Modified from keras.

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]
```

Nietzsche

`tensorlayer.files.load_nietzsche_dataset(path='data/nietzsche/')`

Load Nietzsche dataset. Returns a string.

Parameters **path** : string

The path that the data is downloaded to, defaults is `data/nietzsche/`.

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/wmt_en_fr/')`

It will download English-to-French translation 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** : string

The path that the data is downloaded to, defaults is `data/wmt_en_fr/`.

Notes

Usually, it will take a long time to download this dataset.

References

- Code modified from /tensorflow/models/rnn/translation/data_utils.py

Flickr25k

`tensorlayer.files.load_flickr25k_dataset(tag='sky', path='data/flickr25k', n_threads=50, printable=False)`

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** : string or None

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 : string

The path that the data is downloaded to, defaults is `data/flickr25k/`.

n_threads : int, number of thread to read image.

printable : bool, 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/flickr1M', n_threads=50, printable=False*)

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** : string or None

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 1 to 10.

1 means 100k images ... 5 means 500k images, 10 means all 1 million images. Default is 10.

path : string

The path that the data is downloaded to, defaults is `data/flickr25k/`.

n_threads : int, number of thread to read image.

printable : bool, 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/cyclegan'*)

Load image data from CycleGAN's database, see this link.

Parameters **filename** : string

The dataset you want, see this link.

path : string

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')
```

Load and save network

Save network into list (npz)

`tensorlayer.files.save_npz`(*save_list=[]*, *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 : a list

Parameters want to be saved.

name : a string or None

The name of the .npz file.

sess : None or Session

Notes

If you got session issues, you can change the value.eval() to value.eval(session=sess)

References

- Saving dictionary using numpy

Examples

```
>>> tl.files.save_npz(network.all_params, name='model_test.npz', sess=sess)
... File saved to: model_test.npz
>>> load_params = tl.files.load_npz(name='model_test.npz')
... Loading param0, (784, 800)
... Loading param1, (800,)
... Loading param2, (800, 800)
... Loading param3, (800,)
... Loading param4, (800, 10)
... Loading param5, (10,)
>>> put parameters into a TensorLayer network, please see assign_params()
```

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** : a string

Folder path to .npz file.

name : a string or None

The name of the .npz file.

Returns **params** : list

A list of parameters in order.

References

- Saving dictionary using numpy

Examples

- See save_npz and assign_params

Assign a list of parameters to network

`tensorlayer.files.assign_params(sess, params, network)`

Assign the given parameters to the TensorLayer network.

Parameters **sess** : TensorFlow Session. Automatically run when sess is not None.

params : a list

A list of parameters in order.

network : a `Layer` class

The network to be assigned

Returns **ops** : list

A list of tf ops in order that assign params. Support sess.run(ops) manually.

References

- Assign value to a TensorFlow variable

Examples

```
>>> Save your network as follow:
>>> tl.files.save_npz(network.all_params, name='model_test.npz')
>>> network.print_params()
...
... Next time, load and assign your network as follow:
>>> tl.layers.initialize_global_variables(sess)
```

```
>>> load_params = tl.files.load_npz(name='model_test.npz')
>>> tl.files.assign_params(sess, load_params, network)
>>> network.print_params()
```

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** : TensorFlow Session

name : string

Model path.

network : a `Layer` class

The network to be assigned

Returns Returns False if faild to model is not exist.

Examples

```
>>> tl.files.load_and_assign_npz(sess=sess, name='net.npz', network=net)
```

Save network into dict (npz)

`tensorlayer.files.save_npz_dict` (*save_list=[]*, *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** : a list to tensor for parameters

Parameters want to be saved.

name : a string

The name of the .npz file.

sess : 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** : a string

The name of the .npz file.

sess : Session

Save network into ckpt

`tensorlayer.files.save_ckpt(sess=None, mode_name='model.ckpt', save_dir='checkpoint', var_list=[], global_step=None, printable=False)`

Save parameters into ckpt file.

Parameters **sess** : Session.

mode_name : string, name of the model, default is `model.ckpt`.

save_dir : string, path / file directory to the ckpt, default is `checkpoint`.

var_list : list of variables, if not given, save all global variables.

global_step : int or None, step number.

printable : bool, if True, print all params info.

Examples

- see `tl.files.load_ckpt()`.

Load network from ckpt

`tensorlayer.files.load_ckpt(sess=None, mode_name='model.ckpt', save_dir='checkpoint', var_list=[], is_latest=True, printable=False)`

Load parameters from ckpt file.

Parameters **sess** : Session.

mode_name : string, name of the model, default is `model.ckpt`.

Note that if `is_latest` is True, this function will get the `mode_name` automatically.

save_dir : string, path / file directory to the ckpt, default is `checkpoint`.

var_list : list of variables, if not given, save all global variables.

is_latest : bool, if True, load the latest ckpt, if False, load the ckpt with the name of `` `mode_name``.

printable : bool, if True, print all params info.

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)
```

Load and save variables

Save variables as .npy

tensorlayer.files.**save_any_to_npy**(*save_dict={}*, *name='file.npy'*)
Save variables to .npy file.

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.

Examples

- see save_any_to_npy()

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** : a string or None

A folder path.

regx : a string

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** : a string or None

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** : a string

A folder path.

verbose : boolean

If True, prints results, deaults is True

Returns True if folder exist, otherwise, returns False and create the folder

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** : string

The name of the (to be) dowloaded file.

working_directory : string

A folder path to search for the file in and dowload the file to

url : string

The URL to download the file from

extract : bool, defaults is False

If True, tries to uncompress the dowloaded file is ".tar.gz/.tar.bz2" or ".zip" file

expected_bytes : int/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 filepath to dowloaded (uncompressed) file

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)
```

Sort

List of string with number in human order

tensorlayer.files.**natural_keys**(*text*)

Sort list of string with number in human order.

References

alist.sort(key=natural_keys) sorts in human order http://nedbatchelder.com/blog/200712/human_sorting.html (See Toothy's implementation in the comments)

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']
```

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** : a string or None

A folder path to npz files.

regx : a string

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)')
```

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 one image.
save_images(images, size[, image_path])	Save mutiple images into one single image.
W([W, second, saveable, shape, name, fig_idx])	Visualize every columns of the weight matrix to a group of Greyscale img.
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.

Save and read images

Read one image

`tensorlayer.visualize.`**`read_image`**(*image*, *path=''*)

Read one image.

Parameters **images** : string, file name.

path : string, path.

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 string, the image file names.

path : string, image folder path.

n_threads : int, number of thread to read image.

printable : bool, print infomation when reading images, default is True.

Save one image

`tensorlayer.visualize.`**`save_image`**(*image*, *image_path=''*)

Save one image.

Parameters **images** : numpy array [w, h, c]

image_path : string.

Save multiple images

`tensorlayer.visualize.`**`save_images`**(*images*, *size*, *image_path=''*)

Save mutiple images into one single image.

Parameters **images** : numpy array [batch, w, h, c]

size : list of two int, row and column number.

number of images should be equal or less than size[0] * size[1]

image_path : string.

Examples

```
>>> images = np.random.rand(64, 100, 100, 3)
>>> tl.visualize.save_images(images, [8, 8], 'temp.png')
```

Visualize model parameters

Visualize weight matrix

tensorlayer.visualize.**W**(*W=None, second=10, saveable=True, shape=[28, 28], 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

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.W(network.all_params[0].eval(), second=10, saveable=True, name=
↪'weight_of_1st_layer', fig_idx=2012)
```

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 : a string

A name to save the image, if saveable is True.

fig_idx : int

matplotlib figure index.

Examples

```
>>> tl.visualize.CNN2d(network.all_params[0].eval(), second=10, saveable=True,
↪name='cnn1_mnist', fig_idx=2012)
```

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 : a string

A name to save the image, if saveable is True.

cmap : None or string

'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 : a string

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)
```

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** : a matrix

The images.

reverse_dictionary : a 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 : a string

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')
```

API - Operation System

Operation system, more functions can be found in TensorFlow API.

exit_tf([sess, port])	Close TensorFlow session, TensorBoard and Nvidia-process if available.
open_tb([logdir, port])	Open Tensorboard.
clear_all([printable])	Clears all the placeholder variables of keep prob, including keeping probabilities of all dropout, denoising, dropconnect etc.
set_gpu_fraction([sess, gpu_fraction])	Set the GPU memory fraction for the application.
disable_print()	Disable console output, `suppress_stdout` is recommended.
enable_print()	Enable console output, `suppress_stdout` is recommended.
suppress_stdout()	Temporarily disable console output.
get_site_packages_directory()	Print and return the site-packages directory.
empty_trash()	Empty trash folder.

TensorFlow functions

Close TF session and associated processes

`tensorlayer.ops.exit_tf`(*sess=None*, *port=6006*)

Close TensorFlow session, TensorBoard and Nvidia-process if available.

Parameters **sess** : a session instance of TensorFlow

TensorFlow session

tb_port : an integer

TensorBoard port you want to close, 6006 as default.

Open TensorBoard

`tensorlayer.ops.open_tb`(*logdir='/tmp/tensorflow'*, *port=6006*)

Open Tensorboard.

Parameters **logdir** : a string

Directory where your tensorboard logs are saved

port : an integer

TensorBoard port you want to open, 6006 is tensorboard default

Delete placeholder

`tensorlayer.ops.clear_all`(*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.

GPU functions

`tensorlayer.ops.set_gpu_fraction(sess=None, gpu_fraction=0.3)`

Set the GPU memory fraction for the application.

Parameters **sess** : a session instance of TensorFlow

TensorFlow session

gpu_fraction : a float

Fraction of GPU memory, (0 ~ 1]

References

- TensorFlow using GPU

Console display

Disable print

`tensorlayer.ops.disable_print()`

Disable console output, `suppress_stdout` is recommended.

Examples

```
>>> print("You can see me")
>>> tl.ops.disable_print()
>>> print(" You can't see me")
>>> tl.ops.enable_print()
>>> print("You can see me")
```

Enable print

`tensorlayer.ops.enable_print()`

Enable console output, `suppress_stdout` is recommended.

Examples

- see tl.ops.disable_print()

Temporary disable print

`tensorlayer.ops.suppress_stdout()`

Temporarily disable console output.

References

- stackoverflow

Examples

```
>>> print("You can see me")
>>> with tl.ops.suppress_stdout():
>>>     print("You can't see me")
>>> print("You can see me")
```

Site packages information

`tensorlayer.ops.get_site_packages_directory()`
Print and return the site-packages directory.

Examples

```
>>> loc = tl.ops.get_site_packages_directory()
```

Trash

`tensorlayer.ops.empty_trash()`
Empty trash folder.

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`.

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[, name])	The identity activation function, Shortcut is `linear`.
ramp([x, v_min, v_max, name])	The ramp activation function.
leaky_relu([x, alpha, name])	The LeakyReLU, Shortcut is `lrelu`.

Continued on next page

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pixel_wise_softmax(output[, name])	Return the softmax outputs of images, every pixels have multiple label, the sum of a pixel is 1.

Identity

`tensorlayer.activation.`**`identity`**(*x*, *name=None*)

The identity activation function, Shortcut is `linear`.

Parameters **x** : a tensor input

input(s)

Returns A *Tensor* with the same type as *x*.

Ramp

`tensorlayer.activation.`**`ramp`**(*x=None*, *v_min=0*, *v_max=1*, *name=None*)

The ramp activation function.

Parameters **x** : a tensor input

input(s)

v_min : float

if input(s) smaller than v_min, change inputs to v_min

v_max : float

if input(s) greater than v_max, change inputs to v_max

name : a string or None

An optional name to attach to this activation function.

Returns A *Tensor* with the same type as *x*.

Leaky Relu

`tensorlayer.activation.`**`leaky_relu`**(*x=None*, *alpha=0.1*, *name='LeakyReLU'*)

The LeakyReLU, Shortcut is `lrelu`.

Modified version of ReLU, introducing a nonzero gradient for negative input.

Parameters **x** : A *Tensor* with type *float*, *double*, *int32*, *int64*, *uint8*,

int16, or *int8*.

alpha : *float*. slope.

name : a string or None

An optional name to attach to this activation function.

References

- Rectifier Nonlinearities Improve Neural Network Acoustic Models, Maas et al. (2013)

Examples

```
>>> network = tl.layers.DenseLayer(network, n_units=100, name = 'dense_lrelu',
...                 act= lambda x : tl.act.lrelu(x, 0.2))
```

Pixel-wise Softmax

`tensorlayer.activation.pixel_wise_softmax(output, 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 **output** : tensor

- For 2d image, 4D tensor [batch_size, height, weight, channel], channel >= 2.
- For 3d image, 5D tensor [batch_size, depth, height, weight, channel], channel >= 2.

References

- tf.reverse

Examples

```
>>> outputs = pixel_wise_softmax(network.outputs)
>>> dice_loss = 1 - dice_coe(outputs, y_, epsilon=1e-5)
```

Parametric activation

See `tensorlayer.layers`.

API - Database

This is the alpha version of database management system. If you have trouble, you can ask for help on fangde.liu@imperial.ac.uk .

Note: We are writing up the documentation, please wait in patient.

Why TensorDB

TensorLayer is designed for production, aiming to be applied large scale machine learning application. TensorDB introduce the database infracture to address the many challenges in large scale machine learning project, such as:

1. How to mangage the training data and load the training datasets
2. When the dataset is so large that beyonds the storage limitation of one computer
3. How shoud we managment different models and version, and comparing different models.

4. How to automate the whole training, evaluaiton and deploy machine learning model automatically.

In TensorLayer system, we introduce the database technology to the issues above.

TensorDB is designed by following three principles.

Everything is Data

TensorDB is a data warehouse that stores that capture the whole machine learning development process. the data inside tensordb can be catagloried as:

1. Data and Labels: Which includes all the data for training, validation and prediction. The labels can be manually labelled or generated by machine
2. Model Architecture: This group store the different model architecture, which user can select to use
3. Model Parameters: This tables stores all the model parameters of echo in the training step.
4. Jobs: All the computation is cutted into several jobs. Each jobs constains some computing work load. for training , the jobs includes training data , the model parameter, the model architecture, how many epochs the training want to do. Similarity are the validation jobs and inference jobs.
5. Logs: The logs store all the step time and accuracy and other metric of each training steps and also the time stamps.

TensorDB in principal is a key-word based search engine. Each model, parameters, or training data are assigned many tags. The data are stored in two layers. On the top, there is the index layer, which instore the blob storage reference with all the tags assigned to the data, which is implemented based on NoSQL document database such as Mongodb. The second layer is used store big chunk of data, such as videos, medical images or image mask, which is usually implemented as file system. Our open source implementation is implemented based MongoDB. The blob data is in store in the gridfs while the tag index is stored in the documents.

Everying is identified by Query

Within TensorDB framework, any entity within the data warehouse, such as the data, model or jobs are specified by the database query language. The first advantage is the query is more efficient in space and can specify multiple objects in a concise way. The advantage such a design is to enable a highly flexible software system. data, model architecture and training are interchangeable. Many work can be implemented by simply rewire different components. This enable us to develop many new application just by change the query without change any applicaition code.

An pulling based Stream processing pipeline.

Also with a large dataset, we can assume that the data is unlimited. TensorDB provides a streaming interface, implemented in python as generators, it keeps return the new data during training. Also the training system have no clue of epochs, instead, it knows batchize and store parameters after how many steps.

Many techniques are introduced behind the streaming interface. The stream is implemented based on the database cursor technology, so for every search, only the cursors are returned, not the actual data. Only when the generator is evaluated, the acutal data is loaded. The data loading is further optimise:

1. Data are compressed and decompressed,
2. The dataloaded in bulk model to optimise the IO traffic
3. The argumentation or random sample are computed on the fly after the data are loaded into the local computer.
4. To optimise the space, the will also be a cache system that only store the recent blob data.

Based on streaming interface, TensorLayer can be implemented as a continuous machine learning. On the distributed system, the model training, validation and deployment can be running on different computers which all running continuously. The trainer can keeps on optimising the models, the evaluation keeps evaluating the recent added models and the deployment system keeps pulling the best models from the TensorDB warehouse.

Preparation

In principle, TensorDB is can be implemented on any documents NoSQL database system. The exisitng implementation is based on Mongodb. Further implementaiton on other database will be released depends on progress. It will be stragihtford to port the tensorDB system to google cloud , aws and azure.

The following tutorials are based on the MongoDb implmenetation.

Install MongoDB

The installation instruction of Mongodb can be found at MongoDB Docs there are also managed mongodb service from amazon or gcp, or mongo atlas from mongodb

User can also user docker, which is a powerful tool for deploy software .

After install mongodb, a mongod db management tool with graphic user interface will be extremely valuale.

Users can install the Studio3T(mongochef), which is free for none commerical user interface. studio3t

Start MongoDB service

After mongodb is installed, you shoud start the database.

`mongod start`

You can specificy the path the database files with `-d` flag

Quick Start

A fully working example with mnist training set is the _TensorLabDemo.ipnb_

Connect to database

To use TensorDB mongodb implmentaiton, you need pymongo client.

you can install it by

```
pip install pymongo
pip install lz4
```

it is very strateford to connected to the TensorDB system. you can try the following code

```
from tensorlayer.db import TensorDB
db = TensorDB(ip='127.0.0.1', port=27017, db_name='your_db', user_name=None,
↪password=None, studyID='ministMLP')
```

The `ip` is the ip address of the database, and `port` number is number of mongodb. You may need to specificy the database name and studyid. The study id is an unique identifier for an experiement.

TensorDB stores different study in one data warehouse. This has pros and cons, the benefits is that suppose the each study we try a different model architecutre, it is very easy for us to evaluate different model architecture.

log and parameters

The basic application is use TensorDB to save the model parameters and training/evaluation/testing logs. to use tensorDB, this can be easily done by replacing the print function by the db.log function

For save the trainning log, we have `db.train_log`

and

`db. save_parameter`

methods

Suppose we save the log each step and save the parameters each epoch, we can have the code like this

```
for epoch in range(0,epoch_count):
   [~,ac]=sess.run([train_op,loss],feed_dict({x:x,y:y_}
   db.train_log({'accuracy':ac})
db.save_parameter(sess.run(network.all_parameters),{'acc':ac})
```

the code for save validation log and test log are similar.

Model Architecture and Jobs

TensorDb also supporting the model architecture and jobs system in the current version, both the model architecture and job are just simply strings. it is up to the user to specifiy how to convert the string back to models or job. for example, in many our our cases, we just simpliy specify the python code.

```
code= '''
print "hello
'''
db.save_model_architecutre(code,{'name':'print'}

c,fid = db.find_model_architecutre({'name':'print'})
exec c

db.push_job(code,{'type':'train'})

## worker
code = db.pop_job()
exec code
```

Database Interface

The trainning set is managed by a seperate database. each application has its own database. However, all the database interface should support two interface, 1. find_data, 2. data_generator

and example for minist dataset is include in the TensorLabDemo code

Data Importing

With a database, the development workflow is very flexible. As long as the comtent in the database in the same, user can use whatever tools to write into the database

the TesorLabDemo has an import data interface, which allow the user to injecting data in future

user can import data by the following code

```
db.import_data(X,y,{'type':'train'})
```

Application Framework

In fact, in real application, we rarely code everything from scrach and using the tensorDB interface directly. as demostrate in the TensorLabDemo

we implemented 4 class each with a well defined interace. 1. The dataset. 2. The TensorDb 3. The Model, model is loggically a full compoment can be trained, evaluate and deployed. It has property like parameters 4. The DBLogger, which is connecttor from model to tensorDB, which is implemented as callback functions, automatically called at each batch_step and each epoch.

users can based on the TensorLabDemo code, overrite the interface to suits their own applicaions needs.

when training, the overall archtiecture is first, find a data generator from the dataset module

```
g=datase.data_generator({"type":[your type]})
```

then intialize a model with a name

```
m=model('mytes')
```

during training, connected the db logger and tensordb togehter

```
m.fit_generator(g,dblogger(tensordb,m),1000,100)
```

if the work is distributed, we have to save the model archtiecture and reload and excute it

```
db.save_model_architecture(code,{'name':'mlp'})
db.push_job({'name':'mlp'},{'type':XXXX},{'batch:1000','epoch':100)
```

the worker will run the job as the following code

```
j=job.pop
g=dataset.data_generator(j.filter)
c=tensordb.load_model_architecutre(j.march)
exec c
m=model()
m.fit_generator(g,dblooger(tensordb,m),j.bach_size,j.epoch}
```

CHAPTER 3

Indices and tables

- genindex
- modindex
- search

Python Module Index

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