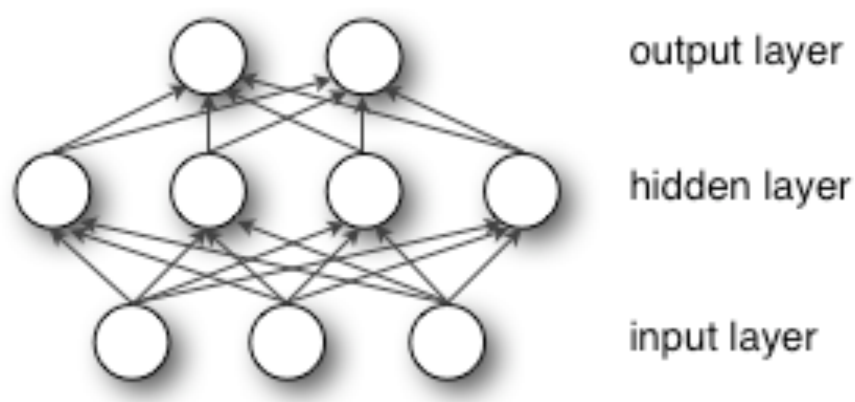
theano学习指南3（翻译）-多层感知器模型

本节要用Theano实现的结构是一个隐层的多层感知器模型（MLP）。MLP可以看成一种对数回归器，其中输入通过非线性转移矩阵Φ做一个变换处理，以便于把输入数据投影到一个线性可分的空间上。MLP的中间层一般称为隐层。单一的隐层便可以确保MLP全局近似。然而，我们稍后还会看到多隐层的好处，比如在深度学习中的应用。

（本节只要介绍了MLP的实现，对神经网络的背景知识介绍不多，感兴趣的朋友可以进一步阅读相应教程 - 译者注）

MLP模型

MLP模型可以用以下的图来表示：



单隐层的MLP定义了一个映射：

$$f: R^D \rightarrow R^L$$

，其中 D和L为输入向量和输出向量$f(x)$的大小。

$f(x)$的数学表达式为：

$$f(x) = G(b^{(2)} + W^{(2)}(s(b^{(1)} + W^{(1)}x)))$$

其中$b^{1)}$,$b^{(2)}$为偏差向量，$W^{(1)}$,$W^{(2)}$为权重向量，G和s为激活函数

2012年9月 (1)
2012年8月 (2)
2012年6月 (1)
2012年5月 (1)
2012年4月 (1)
2011年12月 (1)
2011年11月 (1)
2011年6月 (1)
2011年3月 (8)
2010年7月 (1)
2009年12月 (1)
2009年7月 (2)

最新评论

1. Re:贝叶斯估计浅析
$$h=arg \max_h{P(X|h)} = arg \max_h{P(X|h)P(h)} \\ = arg \max_h{exp{\sum_{i=1}^{N}{(x_i-h)^2}+(h-10.5)^2}}$$

wrong!!
--落雨收衫
2. Re:theano学习指南2（翻译）-对数回归分类器
@TownHall
Regression不是回归嘛
--油焖大黄瓜
3. Re:theano学习指南2（翻译）-对数回归分类器
写的很好，拜读！
--wusichen

阅读排行榜

1. theano学习指南1（翻译）(7196)
2. theano学习指南2（翻译）-对数回归分类器(2064)
3. theano学习指南3（翻译）-多层感知器模型(1568)
4. 贝叶斯估计浅析(1044)
5. theano学习指南4（翻译）- 卷积神经网络(887)

评论排行榜

1. theano学习指南2（翻译）-对数回归分类器(4)
2. 贝叶斯估计浅析(1)

推荐排行榜

1. theano学习指南1（翻译）(4)
2. theano学习指南3（翻译）-多层感知器模型(1)

向量 $h(x) = \Phi(x) = s(b^{(1)} + W^{(1)} x)$ 定义了隐层。 $W^{(1)} \in R^{D \times D_h}$为连接输入向量和隐层的权重矩阵。其中每一列表示了输入神经元和一个隐层神经元权重。s函数的经典选择包括 tanh, $tanh(a)=(e^a-e^{-a})/(e^a+e^{-a})$，或者符号函数 sigmod， $sigmoid(a)=1/(1+e^{-a})$ 。

模型的输出向量为 $o(x) = G(b^{(2)} + W^{(2)} h(x))$.读者应该记得，该形式在上一节中用过。和之前一样，如果把G定义为 softmax函数，输出为类的归属概率。

为了训练MLP模型，我们用随机梯度下降算法学习所有参数，包括 $\theta = \{W^{(2)},b^{(2)},W^{(1)},b^{(1)}\}$。梯度 $\partial{\ell}/\partial{\theta}$可以通过BP算法(**backpropagation algorithm**)计算。幸运的是，Theano可以自动的计算差分，再次我们不需要操心此细节。

从对数回归模型到多层感知器

本节我们专注于单层的MLP模型。在此，我们首先实现一个表示隐层的类。为了构建MLP模型，我们需要在此之上构建一个对数回归层。

```
class HiddenLayer(object):
    def __init__(self, rng, input, n_in, n_out,
activation=T.tanh):
        """
        Typical hidden layer of a MLP: units are
fully-connected and have
        sigmoidal activation function. Weight
matrix W is of shape (n_in,n_out)
        and the bias vector b is of shape
(n_out,).

        NOTE : The nonlinearity used here is tanh

        Hidden unit activation is given by:
tanh(dot(input,W) + b)

        :type rng: numpy.random.RandomState
        :param rng: a random number generator
used to initialize weights

        :type input: theano.tensor.dmatrix
        :param input: a symbolic tensor of shape
(n_examples, n_in)
```

```
        :type n_in: int
        :param n_in: dimensionality of input

        :type n_out: int
        :param n_out: number of hidden units

        :type activation: theano.Op or function
        :param activation: Non linearity to be
applied in the hidden
                              layer
        """
        self.input = input
```

隐层权重的初始值需要从一个和激活函数相关的对称区间上面均匀采样得到。对于tanh函数，采样区间应该为$[-\sqrt{\frac{6}{fan_{in}+fan_{out}}},\sqrt{\frac{6}{fan_{in}+fan_{out}}}]$ [Xavier10]. 这里fan_{in}和fan_{out}分别为第(i-1) 和 i层的神经元的数目. 对于sigmoid函数，采样区间为：$[-4\sqrt{\frac{6}{fan_{in}+fan_{out}}},4\sqrt{\frac{6}{fan_{in}+fan_{out}}}]$。初始化操作能够保证在训练的前期，每个神经元在激活函数的作用下，信息可以更容易地向下向上两个方向进行传播。

```
W_values = numpy.asarray(rng.uniform(
        low=-numpy.sqrt(6. / (n_in + n_out)),
        high=numpy.sqrt(6. / (n_in + n_out)),
        size=(n_in, n_out)),
dtype=theano.config.floatX)
if activation == theano.tensor.nnet.sigmoid:
    W_values *= 4

self.W = theano.shared(value=W_values, name='W')

b_values = numpy.zeros((n_out,),
dtype=theano.config.floatX)
self.b = theano.shared(value=b_values, name='b')
```

这里我们要注意到，隐层的激活函数为一个非线性函数。函数缺省为 tanh，但是很多情况下，我们可能用下面的函数

```
self.output = activation(T.dot(input, self.W) + self.b)
# parameters of the model
self.params = [self.W, self.b]
```

结合理论知识，这里其实是计算了隐层的输出：$h(x) = \Phi(x) = s(b^{(1)} + W^{(1)} x)$。如果你把这个值当做LogisticRegression类的输入，正好是上节对数回归分类的内容，而且此时的输出正好是MLP的输出。所以一个MLP的简单实现如下：

```
class MLP(object):
  """Multi-Layer Perceptron Class

  A multilayer perceptron is a feedforward artificial neural network model
  that has one layer or more of hidden units and nonlinear activations.
  Intermediate layers usually have as activation function tanh or the
  sigmoid function (defined here by a ``HiddenLayer`` class)  while the
  top layer is a softamx layer (defined here by a ``LogisticRegression``
  class).
  """


  def __init__(self, rng, input, n_in, n_hidden, n_out):
      """Initialize the parameters for the multilayer perceptron

      :type rng: numpy.random.RandomState
      :param rng: a random number generator used to initialize weights

      :type input: theano.tensor.TensorType
      :param input: symbolic variable that describes the input of the
      architecture (one minibatch)

      :type n_in: int
```

```
        :param n_in: number of input units, the
dimension of the space in
        which the datapoints lie

        :type n_hidden: int
        :param n_hidden: number of hidden units

        :type n_out: int
        :param n_out: number of output units, the
dimension of the space in
        which the labels lie

        """


        # Since we are dealing with a one hidden
layer MLP, this will
        # translate into a Hidden Layer connected
to the LogisticRegression
        # layer
        self.hiddenLayer = HiddenLayer(rng = rng,
input = input,
                                 n_in = n_in, n_out
= n_hidden,
                                 activation =
T.tanh)

        # The logistic regression layer gets as
input the hidden units
        # of the hidden layer
        self.logRegressionLayer =
LogisticRegression(

input=self.hiddenLayer.output,
                                    n_in=n_hidden,
                                    n_out=n_out)
```

在本节中，我们仍然采用L_1和L_2规则化，因此需要计算两层的权重矩阵的规范化的结果。

```
# L1 norm ; one regularization option is to
enforce L1 norm to
# be small
self.L1 = abs(self.hiddenLayer.W).sum() \
        + abs(self.logRegressionLayer.W).sum()
```

```
# square of L2 norm ; one regularization option
is to enforce
# square of L2 norm to be small
self.L2_sqr = (self.hiddenLayer.W ** 2).sum() \
            + (self.logRegressionLayer.W **
2).sum()

# negative log likelihood of the MLP is given by
the negative
# log likelihood of the output of the model,
computed in the
# logistic regression layer
self.negative_log_likelihood =
self.logRegressionLayer.negative_log_likelihood
# same holds for the function computing the
number of errors
self.errors = self.logRegressionLayer.errors

# the parameters of the model are the parameters
of the two layer it is
# made out of
self.params = self.hiddenLayer.params +
self.logRegressionLayer.params
```

和之前一样，我们用在mini-batch上面的随机梯度下降算法训练模型。这里的区别在于，我们修改损失函数并包括规范化项。 L1_reg 和 L2_reg 为超参数，用以控制规范化项在整个损失函数中的比重。计算损失的函数如下：

```
# the cost we minimize during training is the
negative log likelihood of
# the model plus the regularization terms (L1 and
L2); cost is expressed
# here symbolically
cost = classifier.negative_log_likelihood(y) \
     + L1_reg * L1 \
     + L2_reg * L2_sqr
```

接下来，模型参数通过梯度更新。这段代码和之前的基本上一样，除了参数多少的差别。

```
    # compute the gradient of cost with respect to theta (stored in params)
    # the resulting gradients will be stored in a list gparams
    gparams = []
    for param in classifier.params:
        gparam  = T.grad(cost, param)
        gparams.append(gparam)


    # specify how to update the parameters of the model as a list of
    # (variable, update expression) pairs
    updates = []
    # given two list the zip A = [a1, a2, a3, a4] and B = [b1, b2, b3, b4] of
    # same length, zip generates a list C of same size, where each element
    # is a pair formed from the two lists :
    #    C = [(a1, b1), (a2, b2), (a3, b3) , (a4, b4)]
    for param, gparam in zip(classifier.params, gparams):
        updates.append((param, param - learning_rate * gparam))


    # compiling a Theano function `train_model` that returns the cost, butx
    # in the same time updates the parameter of the model based on the rules
    # defined in `updates`
    train_model = theano.function(inputs=[index], outputs=cost,
            updates=updates,
            givens={
                x: train_set_x[index * batch_size:(index + 1) * batch_size],
                y: train_set_y[index * batch_size:(index + 1) * batch_size]})
```

功能综合

基于以上基本概念，写一个MLP的类变成了一件非常容易的事情。下面的代码演示了它是如何运作的，其原理和我们之前的

对数回归分类器基本一致。

```
"""
This tutorial introduces the multilayer
perceptron using Theano.

 A multilayer perceptron is a logistic regressor
where
instead of feeding the input to the logistic
regression you insert a
intermediate layer, called the hidden layer, that
has a nonlinear
activation function (usually tanh or sigmoid) .
One can use many such
hidden layers making the architecture deep. The
tutorial will also tackle
the problem of MNIST digit classification.

.. math::

    f(x) = G( b^{(2)} + W^{(2)}( s( b^{(1)} +
W^{(1)} x))),

References:

    - textbooks: "Pattern Recognition and Machine
Learning" -
                 Christopher M. Bishop, section 5

"""
__docformat__ = 'restructedtext en'


import cPickle
import gzip
import os
import sys
import time

import numpy

import theano
import theano.tensor as T


from logistic_sgd import LogisticRegression,
load_data


class HiddenLayer(object):
    def __init__(self, rng, input, n_in, n_out,
```

```
W=None, b=None,
                 activation=T.tanh):
        """
        Typical hidden layer of a MLP: units are
fully-connected and have
        sigmoidal activation function. Weight
matrix W is of shape (n_in,n_out)
        and the bias vector b is of shape
(n_out,).

        NOTE : The nonlinearity used here is tanh

        Hidden unit activation is given by:
tanh(dot(input,W) + b)

        :type rng: numpy.random.RandomState
        :param rng: a random number generator
used to initialize weights

        :type input: theano.tensor.dmatrix
        :param input: a symbolic tensor of shape
(n_examples, n_in)

        :type n_in: int
        :param n_in: dimensionality of input

        :type n_out: int
        :param n_out: number of hidden units

        :type activation: theano.Op or function
        :param activation: Non linearity to be
applied in the hidden
                           layer
        """
        self.input = input

        # `W` is initialized with `W_values`
which is uniformely sampled
        # from sqrt(-6./(n_in+n_hidden)) and
sqrt(6./(n_in+n_hidden))
        # for tanh activation function
        # the output of uniform if converted
using asarray to dtype
        # theano.config.floatX so that the code
is runable on GPU
        # Note : optimal initialization of
weights is dependent on the
        #        activation function used (among
other things).
        #        For example, results presented
in [Xavier10] suggest that you
        #        should use 4 times larger
initial weights for sigmoid
```

```
        #        compared to tanh
        #        We have no info for other
function, so we use the same as
        #        tanh.
        if W is None:
            W_values = numpy.asarray(rng.uniform(
                    low=-numpy.sqrt(6. / (n_in +
n_out)),
                    high=numpy.sqrt(6. / (n_in +
n_out)),
                    size=(n_in, n_out)),
dtype=theano.config.floatX)
            if activation ==
theano.tensor.nnet.sigmoid:
                W_values *= 4

            W = theano.shared(value=W_values,
name='W', borrow=True)

        if b is None:
            b_values = numpy.zeros((n_out,),
dtype=theano.config.floatX)
            b = theano.shared(value=b_values,
name='b', borrow=True)

        self.W = W
        self.b = b

        lin_output = T.dot(input, self.W) +
self.b
        self.output = (lin_output if activation
is None
                       else
activation(lin_output))
        # parameters of the model
        self.params = [self.W, self.b]


class MLP(object):
    """Multi-Layer Perceptron Class

    A multilayer perceptron is a feedforward
artificial neural network model
    that has one layer or more of hidden units
and nonlinear activations.
    Intermediate layers usually have as
activation function thanh or the
    sigmoid function (defined here by a
``SigmoidalLayer`` class)  while the
    top layer is a softamx layer (defined here by
a ``LogisticRegression``
    class).
```

```
    """

    def __init__(self, rng, input, n_in,
n_hidden, n_out):
        """Initialize the parameters for the
multilayer perceptron

        :type rng: numpy.random.RandomState
        :param rng: a random number generator
used to initialize weights

        :type input: theano.tensor.TensorType
        :param input: symbolic variable that
describes the input of the
        architecture (one minibatch)

        :type n_in: int
        :param n_in: number of input units, the
dimension of the space in
        which the datapoints lie

        :type n_hidden: int
        :param n_hidden: number of hidden units

        :type n_out: int
        :param n_out: number of output units, the
dimension of the space in
        which the labels lie

        """

        # Since we are dealing with a one hidden
layer MLP, this will
        # translate into a TanhLayer connected to
the LogisticRegression
        # layer; this can be replaced by a
SigmoidalLayer, or a layer
        # implementing any other nonlinearity
        self.hiddenLayer = HiddenLayer(rng=rng,
input=input,
                                       n_in=n_in,
n_out=n_hidden,

activation=T.tanh)

        # The logistic regression layer gets as
input the hidden units
        # of the hidden layer
        self.logRegressionLayer =
LogisticRegression(
            input=self.hiddenLayer.output,
            n_in=n_hidden,
```

```
            n_out=n_out)

        # L1 norm ; one regularization option is
to enforce L1 norm to
        # be small
        self.L1 = abs(self.hiddenLayer.W).sum() \
                + 
abs(self.logRegressionLayer.W).sum()

        # square of L2 norm ; one regularization
option is to enforce
        # square of L2 norm to be small
        self.L2_sqr = (self.hiddenLayer.W **
2).sum() \
                    + (self.logRegressionLayer.W
** 2).sum()

        # negative log likelihood of the MLP is
given by the negative
        # log likelihood of the output of the
model, computed in the
        # logistic regression layer
        self.negative_log_likelihood =
self.logRegressionLayer.negative_log_likelihood
        # same holds for the function computing
the number of errors
        self.errors =
self.logRegressionLayer.errors

        # the parameters of the model are the
parameters of the two layer it is
        # made out of
        self.params = self.hiddenLayer.params +
self.logRegressionLayer.params


def test_mlp(learning_rate=0.01, L1_reg=0.00,
L2_reg=0.0001, n_epochs=1000,
             dataset='../data/mnist.pkl.gz',
batch_size=20, n_hidden=500):
    """
    Demonstrate stochastic gradient descent
optimization for a multilayer
    perceptron

    This is demonstrated on MNIST.

    :type learning_rate: float
    :param learning_rate: learning rate used
(factor for the stochastic
    gradient
```

```
    :type L1_reg: float
    :param L1_reg: L1-norm's weight when added to
the cost (see
    regularization)

    :type L2_reg: float
    :param L2_reg: L2-norm's weight when added to
the cost (see
    regularization)

    :type n_epochs: int
    :param n_epochs: maximal number of epochs to
run the optimizer

    :type dataset: string
    :param dataset: the path of the MNIST dataset
file from

http://www.iro.umontreal.ca/~lisa/deep/data/mnist
/mnist.pkl.gz


   """
    datasets = load_data(dataset)

    train_set_x, train_set_y = datasets[0]
    valid_set_x, valid_set_y = datasets[1]
    test_set_x, test_set_y = datasets[2]

    # compute number of minibatches for training,
validation and testing
    n_train_batches =
train_set_x.get_value(borrow=True).shape[0] /
batch_size
    n_valid_batches =
valid_set_x.get_value(borrow=True).shape[0] /
batch_size
    n_test_batches =
test_set_x.get_value(borrow=True).shape[0] /
batch_size

    ######################
    # BUILD ACTUAL MODEL #
    ######################
    print '... building the model'

    # allocate symbolic variables for the data
    index = T.lscalar()  # index to a [mini]batch
    x = T.matrix('x')  # the data is presented as
rasterized images
    y = T.ivector('y')  # the labels are
presented as 1D vector of
```

```
                              # [int] labels

    rng = numpy.random.RandomState(1234)

    # construct the MLP class
    classifier = MLP(rng=rng, input=x, n_in=28 *
28,
                     n_hidden=n_hidden, n_out=10)

    # the cost we minimize during training is the
negative log likelihood of
    # the model plus the regularization terms (L1
and L2); cost is expressed
    # here symbolically
    cost = classifier.negative_log_likelihood(y)
\
         + L1_reg * classifier.L1 \
         + L2_reg * classifier.L2_sqr

    # compiling a Theano function that computes
the mistakes that are made
    # by the model on a minibatch
    test_model = theano.function(inputs=[index],
            outputs=classifier.errors(y),
            givens={
                x: test_set_x[index * batch_size:
(index + 1) * batch_size],
                y: test_set_y[index * batch_size:
(index + 1) * batch_size]})

    validate_model = theano.function(inputs=
[index],
            outputs=classifier.errors(y),
            givens={
                x: valid_set_x[index *
batch_size:(index + 1) * batch_size],
                y: valid_set_y[index *
batch_size:(index + 1) * batch_size]})

    # compute the gradient of cost with respect
to theta (sotred in params)
    # the resulting gradients will be stored in a
list gparams
    gparams = []
    for param in classifier.params:
        gparam = T.grad(cost, param)
        gparams.append(gparam)

    # specify how to update the parameters of the
model as a list of
```

```
    # (variable, update expression) pairs
    updates = []
    # given two list the zip A = [a1, a2, a3, a4]
and B = [b1, b2, b3, b4] of
    # same length, zip generates a list C of same
size, where each element
    # is a pair formed from the two lists :
    #    C = [(a1, b1), (a2, b2), (a3, b3), (a4,
b4)]
    for param, gparam in zip(classifier.params,
gparams):
        updates.append((param, param -
learning_rate * gparam))

    # compiling a Theano function `train_model`
that returns the cost, but
    # in the same time updates the parameter of
the model based on the rules
    # defined in `updates`
    train_model = theano.function(inputs=[index],
outputs=cost,
            updates=updates,
            givens={
                x: train_set_x[index *
batch_size:(index + 1) * batch_size],
                y: train_set_y[index *
batch_size:(index + 1) * batch_size]})

    ###############
    # TRAIN MODEL #
    ###############
    print '... training'

    # early-stopping parameters
    patience = 10000  # look as this many
examples regardless
    patience_increase = 2  # wait this much
longer when a new best is
                           # found
    improvement_threshold = 0.995  # a relative
improvement of this much is
                                   # considered
significant
    validation_frequency = min(n_train_batches,
patience / 2)
                                  # go through
this many
                                  # minibatche
before checking the network
```

```
                                  # on the
validation set; in this case we
                                  # check every
epoch

    best_params = None
    best_validation_loss = numpy.inf
    best_iter = 0
    test_score = 0.
    start_time = time.clock()

    epoch = 0
    done_looping = False

    while (epoch < n_epochs) and (not
done_looping):
        epoch = epoch + 1
        for minibatch_index in
xrange(n_train_batches):

            minibatch_avg_cost =
train_model(minibatch_index)
            # iteration number
            iter = (epoch - 1) * n_train_batches
+ minibatch_index

            if (iter + 1) % validation_frequency
== 0:
                # compute zero-one loss on
validation set
                validation_losses =
[validate_model(i) for i
                                     in
xrange(n_valid_batches)]
                this_validation_loss =
numpy.mean(validation_losses)

                print('epoch %i, minibatch %i/%i,
validation error %f %%' %
                     (epoch, minibatch_index + 1,
n_train_batches,
                      this_validation_loss *
100.))

                # if we got the best validation
score until now
                if this_validation_loss <
best_validation_loss:
                    #improve patience if loss
improvement is good enough
```

```
                    if this_validation_loss <
best_validation_loss *  \
                           improvement_threshold:
                        patience = max(patience,
iter * patience_increase)

                    best_validation_loss =
this_validation_loss
                    best_iter = iter

                    # test it on the test set
                    test_losses = [test_model(i)
for i
                                   in
xrange(n_test_batches)]
                    test_score =
numpy.mean(test_losses)

                    print(('     epoch %i,
minibatch %i/%i, test error of '
                           'best model %f %%') %
                          (epoch, minibatch_index
+ 1, n_train_batches,
                           test_score * 100.))

            if patience <= iter:
                    done_looping = True
                    break

    end_time = time.clock()
    print(('Optimization complete. Best
validation score of %f %% '
           'obtained at iteration %i, with test
performance %f %%') %
          (best_validation_loss * 100., best_iter
+ 1, test_score * 100.))
    print >> sys.stderr, ('The code for file ' +
                          os.path.split(__file__)
[1] +
                          ' ran for %.2fm' %
((end_time - start_time) / 60.))


if __name__ == '__main__':
    test_mlp()
```

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