

```
50
                  b_values = numpy.zeros((n_out,), dtype=theano.config.floatX)
                  b = theano.shared(value=b_values, name='b')
             self.W = W
             self.b = b
 54
             if use bias:
                 lin_output = T.dot(input, self.W) + self.b
                  lin_output = T.dot(input, self.W)
 60
 61
             self.output = (lin_output if activation is None else activation(lin_output))
             # parameters of the model
 64
             if use bias:
                 self.params = [self.W, self.b]
             else:
 67
                  self.params = [self.W]
 68
      def _dropout_from_layer(rng, layer, p):
 70
          """p is the probablity of dropping a unit
         srng = theano.tensor.shared_randomstreams.RandomStreams(rng.randint(999999))
         # p=1-p because 1's indicate keep and p is prob of dropping
 74
         mask = srng.binomial(n=1, p=1-p, size=layer.shape)
         # The cast is important because
         # int * float32 = float64 which pulls things off the gpu
         output = layer * T.cast(mask, theano.config.floatX)
 78
         return output
      class DropoutHiddenLayer(HiddenLayer):
 80
 81
         def __init__(self, rng, input, n_in, n_out,
 82
                       activation, dropout_rate, use_bias, W=None, b=None):
 83
              super(DropoutHiddenLayer, self).__init__(
 84
                      rng=rng, input=input, n_in=n_in, n_out=n_out, W=W, b=b,
 85
                      activation=activation, use_bias=use_bias)
 86
 87
              self.output = _dropout_from_layer(rng, self.output, p=dropout_rate)
 88
 89
      class MLPDropout(object):
         """A multilayer perceptron with dropout"""
 91
         def __init__(self,rng,input,layer_sizes,dropout_rates,activations,use_bias=True):
 92
 93
             #rectified_linear_activation = lambda x: T.maximum(0.0, x)
 94
 95
             # Set up all the hidden layers
 96
             self.weight_matrix_sizes = zip(layer_sizes, layer_sizes[1:])
 97
             self.lavers = []
 98
             self.dropout layers = []
             self.activations = activations
             next_layer_input = input
             #first_layer = True
              # dropout the input
103
              next_dropout_layer_input = _dropout_from_layer(rng, input, p=dropout_rates[0])
              layer_counter = 0
              for n_in, n_out in self.weight_matrix_sizes[:-1]:
                  next_dropout_layer = DropoutHiddenLayer(rng=rng,
                          input=next_dropout_layer_input,
                          activation=activations[layer counter],
                          n in=n in, n out=n out, use bias=use bias,
110
                          dropout rate=dropout rates[layer counter])
                  self.dropout_layers.append(next_dropout_layer)
                 next_dropout_layer_input = next_dropout_layer.output
114
                  # Reuse the parameters from the dropout layer here, in a different
                  # path through the graph.
                  next_layer = HiddenLayer(rng=rng,
```

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input=next_layer_input,
                          activation=activations[layer_counter],
                          # scale the weight matrix W with (1-p)
120
                          W=next_dropout_layer.W * (1 - dropout_rates[layer_counter]),
                          b=next_dropout_layer.b,
                          n_in=n_in, n_out=n_out,
                          use_bias=use_bias)
124
                 self.layers.append(next_layer)
                  next_layer_input = next_layer.output
126
                  #first_layer = False
                 layer_counter += 1
128
              # Set up the output laver
              n in, n out = self.weight matrix sizes[-1]
              dropout output layer = LogisticRegression(
                      input=next_dropout_layer_input,
                      n_in=n_in, n_out=n_out)
              self.dropout_layers.append(dropout_output_layer)
              # Again, reuse paramters in the dropout output.
              output_layer = LogisticRegression(
                  input=next_layer_input,
                  # scale the weight matrix W with (1-p)
                  W=dropout_output_layer.W * (1 - dropout_rates[-1]),
141
                  b=dropout output layer.b,
142
                  n in=n in, n out=n out)
             self.layers.append(output_layer)
145
              # Use the negative log likelihood of the logistic regression layer as
              # the objective.
147
              self.dropout_negative_log_likelihood = self.dropout_layers[-1].negative_log_likelihood
              self.dropout_errors = self.dropout_layers[-1].errors
              self.negative_log_likelihood = self.layers[-1].negative_log_likelihood
              self.errors = self.layers[-1].errors
              # Grab all the parameters together.
              self.params = [ param for layer in self.dropout_layers for param in layer.params ]
          def predict(self, new_data):
              next layer input = new data
              for i,layer in enumerate(self.layers):
                  if i<len(self.layers)-1:</pre>
                      next_layer_input = self.activations[i](T.dot(next_layer_input,layer.W) + layer.b)
                      p_y_given_x = T.nnet.softmax(T.dot(next_layer_input, layer.W) + layer.b)
             y_pred = T.argmax(p_y_given_x, axis=1)
164
              return y pred
          def predict_p(self, new_data):
             next_layer_input = new_data
168
              for i,layer in enumerate(self.layers):
169
                 if i<len(self.layers)-1:</pre>
                      next_layer_input = self.activations[i](T.dot(next_layer_input,layer.W) + layer.b)
                  else:
                      p_y_given_x = T.nnet.softmax(T.dot(next_layer_input, layer.W) + layer.b)
              return p_y_given_x
      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
181
          top layer is a softamx layer (defined here by a ``LogisticRegression``
182
```

```
183
          class).
184
185
          def __init__(self, rng, input, n_in, n_hidden, n_out):
187
               ""Initialize the parameters for the multilayer perceptron
189
              :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
200
              :type n_hidden: int
              :param n_hidden: number of hidden units
              :type n_out: int
204
              :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
210
              # into a HiddenLayer with a tanh activation function connected to the
              # LogisticRegression layer; the activation function can be replaced by
              # sigmoid or any other nonlinear function
              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
218
              # of the hidden layer
              self.logRegressionLayer = LogisticRegression(
                  input=self.hiddenLayer.output,
                  n in=n hidden,
                  n_out=n_out)
              \mbox{\tt\#}\ \mbox{\tt L1}\ \mbox{\tt norm} ; one regularization option is to enforce L1 norm to
              # be small
              \mbox{\tt\#} negative log likelihood of the MLP is given by the negative
228
              \mbox{\tt\#}\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
              self.params = self.hiddenLayer.params + self.logRegressionLayer.params
238
      class LogisticRegression(object):
          """Multi-class Logistic Regression Class
          The logistic regression is fully described by a weight matrix :math:`W`
          and bias vector :math:`b`. Classification is done by projecting data
243
          points onto a set of hyperplanes, the distance to which is used to
          determine a class membership probability.
247
          def __init__(self, input, n_in, n_out, W=None, b=None):
              """ Initialize the parameters of the logistic regression
```

```
: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
256
          which the datapoints lie
          :type n out: int
          :param n_out: number of output units, the dimension of the space in
260
          which the labels lie
              # initialize with 0 the weights W as a matrix of shape (n_in, n_out)
              if W is None:
                   self.W = theano.shared(
267
                           value=numpy.zeros((n_in, n_out), dtype=theano.config.floatX),
268
                           name='W')
              else:
270
                  self.W = W
              # initialize the baises b as a vector of n_out 0s
              if b is None:
274
                  self.b = theano.shared(
                           value=numpy.zeros((n_out,), dtype=theano.config.floatX),
                           name='b')
              else:
278
                  self.b = b
              # compute vector of class-membership probabilities in symbolic form
281
              self.p_y_given_x = T.nnet.softmax(T.dot(input, self.W) + self.b)
282
              \mbox{\tt\#} compute prediction as class whose probability is maximal in
              # symbolic form
              self.y_pred = T.argmax(self.p_y_given_x, axis=1)
              # parameters of the model
288
              self.params = [self.W, self.b]
290
          def negative_log_likelihood(self, y):
              """Return the mean of the negative log-likelihood of the prediction
292
              of this model under a given target distribution.
293
294
          .. math::
          \frac{1}{|\mathcal{D}|} \mathcal{L} (\theta_{\mathbb{Q}}, \theta_{\mathbb{Q}}) =
          \label{eq:log_problem} $$ \frac{1}{|\mathcal{D}|} \sum_{i=0}^{i=0}^{i=0} \log(P(Y=y^{(i)}|x^{(i)}, W,b)) \ } $$
          \ell (\theta=\{W,b\}, \mathcal{D})
          :type y: theano.tensor.TensorType
          :param y: corresponds to a vector that gives for each example the
303
          Note: we use the mean instead of the sum so that
          the learning rate is less dependent on the batch size
              # y.shape[0] is (symbolically) the number of rows in y, i.e.,
              # number of examples (call it n) in the minibatch
              # T.arange(y.shape[0]) is a symbolic vector which will contain
310
              # [0,1,2,... n-1] T.log(self.p_y_given_x) is a matrix of
              # Log-Probabilities (call it LP) with one row per example and
              # one column per class LP[T.arange(y.shape[0]),y] is a vector
              # v containing [LP[0,y[0]], LP[1,y[1]], LP[2,y[2]], ...,
               \begin{tabular}{ll} \# LP[n-1,y[n-1]]] & and T.mean(LP[T.arange(y.shape[0]),y]) is \\ \end{tabular} 
              # the mean (across minibatch examples) of the elements in v,
```

```
# i.e., the mean log-likelihood across the minibatch.
              return \ -T.mean(T.log(self.p\_y\_given\_x)[T.arange(y.shape[0]), \ y])
318
          def errors(self, y):
              """Return a float representing the number of errors in the minibatch;
          zero one loss over the size of the minibatch
          :type y: theano.tensor.TensorType
          :param y: corresponds to a vector that gives for each example the
              # check if y has same dimension of y_pred
             if y.ndim != self.y_pred.ndim:
                  raise TypeError('y should have the same shape as self.y_pred',
                     ('y', target.type, 'y_pred', self.y_pred.type))
             # check if y is of the correct datatype
             if y.dtype.startswith('int'):
                  # the T.neq operator returns a vector of 0s and 1s, where 1
                  # represents a mistake in prediction
                  return T.mean(T.neq(self.y_pred, y))
              else:
338
                 raise NotImplementedError()
      class LeNetConvPoolLayer(object):
          """Pool Layer of a convolutional network """
          def __init__(self, rng, input, filter_shape, image_shape, poolsize=(2, 2), non_linear="tanh"):
              Allocate a LeNetConvPoolLayer with shared variable internal parameters.
              :type rng: numpy.random.RandomState
              :param rng: a random number generator used to initialize weights
              :type input: theano.tensor.dtensor4
              :param input: symbolic image tensor, of shape image_shape
              :type filter_shape: tuple or list of length 4
354
              :param filter_shape: (number of filters, num input feature maps,
                                    filter height, filter width)
              :type image_shape: tuple or list of length 4
358
              :param image_shape: (batch size, num input feature maps,
                                   image height, image width)
              :type poolsize: tuple or list of length 2
              :param poolsize: the downsampling (pooling) factor (#rows,#cols)
             assert image shape[1] == filter shape[1]
              self.input = input
              self.filter_shape = filter_shape
              self.image_shape = image_shape
369
              self.poolsize = poolsize
370
              self.non_linear = non_linear
              # there are "num input feature maps * filter height * filter width"
              # inputs to each hidden unit
             fan_in = numpy.prod(filter_shape[1:])
374
              # each unit in the lower layer receives a gradient from:
              # "num output feature maps * filter height * filter width" /
376
              # pooling size
              fan_out = (filter_shape[0] * numpy.prod(filter_shape[2:]) /numpy.prod(poolsize))
              # initialize weights with random weights
              if self.non linear=="none" or self.non linear=="relu":
380
                  self.W = theano.shared(numpy.asarray(rng.uniform(low=-0.01, high=0.01, size=filter_shape),
381
                                                      dtype=theano.config.floatX),borrow=True,name="W_conv")
```

```
else:
383
                  W_bound = numpy.sqrt(6. / (fan_in + fan_out))
                  self.W = theano.shared(numpy.asarray(rng.uniform(low=-W_bound, high=W_bound, size=filter_shape),
                      dtype=theano.config.floatX),borrow=True,name="W_conv")
              \verb|b_values = numpy.zeros((filter_shape[0],), | \verb|dtype=theano.config.floatX|)|
              self.b = theano.shared(value=b_values, borrow=True, name="b_conv")
388
              # convolve input feature maps with filters
              conv_out = conv.conv2d(input=input, filters=self.W,filter_shape=self.filter_shape, image_shape=self.image_shape)
              if self.non_linear=="tanh":
                  conv_out_tanh = T.tanh(conv_out + self.b.dimshuffle('x', 0, 'x', 'x'))
                  self.output = downsample.max_pool_2d(input=conv_out_tanh, ds=self.poolsize, ignore_border=True)
              elif self.non_linear=="relu":
                  conv\_out\_tanh = ReLU(conv\_out + self.b.dimshuffle('x', 0, 'x', 'x'))
                  self.output = downsample.max_pool_2d(input=conv_out_tanh, ds=self.poolsize, ignore_border=True)
              else:
                  pooled_out = downsample.max_pool_2d(input=conv_out, ds=self.poolsize, ignore_border=True)
399
                  self.output = pooled_out + self.b.dimshuffle('x', 0, 'x', 'x')
400
              self.params = [self.W, self.b]
401
402
          def predict(self, new_data, batch_size):
403
              predict for new data
              img_shape = (batch_size, 1, self.image_shape[2], self.image_shape[3])
407
              conv_out = conv.conv2d(input=new_data, filters=self.W, filter_shape=self.filter_shape, image_shape=img_shape)
              if self.non linear=="tanh":
409
                  conv_out_tanh = T.tanh(conv_out + self.b.dimshuffle('x', 0, 'x', 'x'))
                  output = downsample.max_pool_2d(input=conv_out_tanh, ds=self.poolsize, ignore_border=True)
410
411
              if self.non_linear=="relu":
                  conv_out_tanh = ReLU(conv_out + self.b.dimshuffle('x', 0, 'x', 'x'))
413
                  output = downsample.max_pool_2d(input=conv_out_tanh, ds=self.poolsize, ignore_border=True)
414
415
                  pooled_out = downsample.max_pool_2d(input=conv_out, ds=self.poolsize, ignore_border=True)
416
                  output = pooled_out + self.b.dimshuffle('x', 0, 'x', 'x')
417
              return output
418
```

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