transformer.py

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# Code by Sarah Wiegreffe (saw@gatech.edu)
# Fall 2019
import numpy as np
import torch
from torch import nn
import random
###### Do not modify these imports.
class ClassificationTransformer(nn.Module):
   A single-layer Transformer which encodes a sequence of text and
   performs binary classification.
   The model has a vocab size of V, works on
   sequences of length T, has an hidden dimension of H, uses word vectors
   also of dimension H, and operates on minibatches of size N.
      __init__(self, word_to_ix, hidden_dim=128, num_heads=2, dim_feedforward=2048, dim
_{k=96}, dim_v=96, dim_q=96, max_length=43):
      :param word_to_ix: dictionary mapping words to unique indices
      :param hidden_dim: the dimensionality of the output embeddings that go into the f
inal layer
      :param num_heads: the number of Transformer heads to use
      :param dim_feedforward: the dimension of the feedforward network model
      :param dim_k: the dimensionality of the key vectors
      :param dim_q: the dimensionality of the query vectors
      :param dim_v: the dimensionality of the value vectors
      super(ClassificationTransformer, self).__init__()
      assert hidden_dim % num_heads == 0
      self.num_heads = num_heads
      self.word_embedding_dim = hidden_dim
      self.hidden_dim = hidden_dim
      self.dim_feedforward = dim_feedforward
      self.max_length = max_length
      self.vocab_size = len(word_to_ix)
      self.dim k = dim k
      self.dim_v = dim_v
      self.dim_q = dim_q
      seed_torch(0)
      # Deliverable 1: Initialize what you need for the embedding lookup (1 line). #
      # Hint: you will need to use the max_length parameter above.
      self.embed_layer = nn.Embedding(self.vocab_size + max_length, hidden_dim)
      END OF YOUR CODE
      # Deliverable 2: Initializations for multi-head self-attention.
      # You don't need to do anything here. Do not modify this code.
      # Head #1
      self.k1 = nn.Linear(self.hidden_dim, self.dim_k)
      self.v1 = nn.Linear(self.hidden_dim, self.dim_v)
      self.q1 = nn.Linear(self.hidden_dim, self.dim_q)
      # Head #2
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self.k2 = nn.Linear(self.hidden\_dim, self.dim\_k)

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     self.v2 = nn.Linear(self.hidden_dim, self.dim_v)
     self.q2 = nn.Linear(self.hidden_dim, self.dim_q)
     self.softmax = nn.Softmax(dim=2)
     self.attention_head_projection = nn.Linear(self.dim_v * self.num_heads, self.hidd
en_dim)
     self.norm_mh = nn.LayerNorm(self.hidden_dim)
     # Deliverable 3: Initialize what you need for the feed-forward layer.
     # Don't forget the layer normalization.
     #element-wise feed-forward layer consisting of two linear transformers with a ReL
U layer in between
     self.linear1 = nn.Linear(hidden_dim, dim_feedforward)
     self.relu = nn.ReLU()
     self.linear2 = nn.Linear(dim_feedforward, hidden_dim)
     #layer normalization
     self.layer_norm = nn.LayerNorm(hidden_dim)
     END OF YOUR CODE
     # Deliverable 4: Initialize what you need for the final layer (1-2 lines).
     #linear and softmax layers
     self.linear3 = nn.Linear(hidden_dim, 1)
     self.soft = nn.Sigmoid()
     END OF YOUR CODE
     def forward(self, inputs):
     This function computes the full Transformer forward pass.
     Put together all of the layers you've developed in the correct order.
     :param inputs: a PyTorch tensor of shape (N,T). These are integer lookups.
     :returns: the model outputs. Should be normalized scores of shape (N,1).
     outputs = None
     # Deliverable 5: Implement the full Transformer stack for the forward pass. #
     # You will need to use all of the methods you have previously defined above.#
     # You should only be calling ClassificationTransformer class methods here. #
     #1. form embeddings
     embeddings = self.embed(inputs)
     #2. multi head attention
     mha = self.multi_head_attention(embeddings)
     #3. feed forward
     ffw = self.feedforward_layer(mha)
     #4. final layer
     outputs = self.final_layer(ffw)
     END OF YOUR CODE
     return outputs
  def embed(self, inputs):
     11 11 11
     :param inputs: intTensor of shape (N,T)
     :returns embeddings: floatTensor of shape (N,T,H)
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embeddings = None
      # Deliverable 1: Implement the embedding lookup.
      # Note: word_to_ix has keys from 0 to self.vocab_size - 1
                                                               #
      # This will take a few lines.
                                                               #
      #token embeddings
      token_embeddings = self.embed_layer(inputs)
      # print(token_embeddings.size)
      #segment embeddings not considered
      #positional embeddings
      encoding = np.arange(self.vocab_size, self.vocab_size + inputs.shape[1])
      encoding = torch.as_tensor(encoding)
     positional_embeddings = self.embed_layer(encoding)
      #add the two embeddings to obtain final embeddings
      embeddings = token_embeddings + positional_embeddings
      END OF YOUR CODE
      return embeddings
   def multi_head_attention(self, inputs):
      :param inputs: float32 Tensor of shape (N,T,H)
      :returns outputs: float32 Tensor of shape (N,T,H)
     Traditionally we'd include a padding mask here, so that pads are ignored.
      This is a simplified implementation.
      11 11 11
     outputs = None
      # Deliverable 2: Implement multi-head self-attention followed by add + norm.#
      # Use the provided 'Deliverable 2' layers initialized in the constructor.
      #head1 calculations
      softmax1 = self.softmax((torch.bmm(self.q1(inputs), self.k1(inputs).transpose(1,2))
)))/ np.sqrt(self.dim_k))
      attention1 = torch.bmm(softmax1, self.v1(inputs))
      #head2 calculations
      softmax2 = self.softmax((torch.bmm(self.q2(inputs), self.k2(inputs).transpose(1,2))
)))/ np.sqrt(self.dim_k))
      attention2 = torch.bmm(softmax2, self.v2(inputs))
      #concatenate the heads
     head = torch.cat((attention1, attention2), 2)
      #residual connection + layer normalzation
      outputs = self.norm_mh(inputs + self.attention_head_projection(head))
      END OF YOUR CODE
      return outputs
   def feedforward_layer(self, inputs):
      :param inputs: float32 Tensor of shape (N,T,H)
      :returns outputs: float32 Tensor of shape (N,T,H)
      outputs = None
      # Deliverable 3: Implement the feedforward layer followed by add + norm.
                                                               #
      # Use a ReLU activation and apply the linear layers in the order you
                                                               #
                                                               #
      # initialized them.
      # This should not take more than 3-5 lines of code.
                                                               #
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#feedforward layer
 h1 = self.linear1(inputs)
 relu1 = self.relu(h1)
 h2 = self.linear2(relu1)
 #layer norm
 outputs = self.layer_norm(h2 + inputs)
  END OF YOUR CODE
  return outputs
def final_layer(self, inputs):
  :param inputs: float32 Tensor of shape (N,T,H)
  :returns outputs: float32 Tensor of shape (N,1)
 outputs = None
  # Deliverable 4: Implement the final layer for the Transformer classifier.
  # This should not take more than 2 lines of code.
  outputs = self.soft(self.linear3(inputs[:,0,:].squeeze()))
  END OF YOUR CODE
 return outputs
```

## def seed\_torch(seed=0):

random.seed(seed)
np.random.seed(seed)
torch.manual\_seed(seed)
torch.cuda.manual\_seed(seed)
torch.backends.cudnn.benchmark = False
torch.backends.cudnn.deterministic = True