20230410_02_word2vec

April 16, 2023

0.1 # Problem 2 Word2Vec & Seq2Seq Models

0.2 Setup

[ ]:
```
import os, sys, tqdm, json, pickle, random, warnings
from typing import List, Optional

import numpy as np, pandas as pd

import matplotlib as mpl, matplotlib.pyplot as plt, seaborn as sns

import torch.nn.functional as F

import torch, torch.nn as nn, torch.optim as optim
import pytorch_lightning as pl
from torch.utils import data

from gensim.models import Word2Vec, Phrases
from gensim.test.utils import common_texts
import gensim, gensim.downloader as gensim_api
from gensim import corpora

from gensim.parsing.preprocessing import remove_stopwords, preprocess_documents
from gensim.utils import simple_preprocess

pl.seed_everything(3)
```

```
Global seed set to 3
```

[ ]:
```
3
```

0.2.1 Global Variables

NOTE: you can find other `gensim` datasets here

[ ]:
```
SAVE_DIR = os.path.abspath('.')

W2V_FILE = os.path.join(SAVE_DIR, 'word2vec.pth')
```

```
CORPUS = 'text8'# 'glove-wiki-gigaword-200'

TXT_FILE = os.path.join(SAVE_DIR, f'{CORPUS}.pkl')

OVERWRITE = False

VEC_SIZE = 50 #10

#DEVICE = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
DEVICE = 'cpu'

SAVE_DIR
```

[ ]: '/Users/default/Google Drive/currentDocumants/studies/Master/6.Semester/deep_lea
rning/pset/pset3/problem 2'

0.3 Part 1

0.3.1 Fetch you text corpus

TODO: generate your own word-vector embedding using a text corpus of *your* choice of at least **500** words. You may use gensim's corpora.

Feel free to play with hyperparmaters in the notebook such as context size and embedding size.

[ ]:
```
corpus = gensim_api.load(CORPUS)
```

[ ]:
```
does_corpus_exist = os.path.isfile(TXT_FILE)

if not does_corpus_exist or OVERWRITE:
    corpus = gensim_api.load(CORPUS)
    with open(TXT_FILE, 'wb') as f:
        pickle.dump(corpus, f)

else:
    with open(TXT_FILE, 'rb') as f:
         corpus = pickle.load(f)

corpus
```

[ ]: <text8.Dataset at 0x7f8fdaafa200>

0.3.2 Train your Word2Vec Model

NOTE: you are free to create your own Word2Vec model. You are welcome to use gensim. However for the pset you must at least *train* a Word2Vec model!

[ ]:
```
W2V_FILE
```

[ ]: '/Users/default/Google Drive/currentDocumants/studies/Master/6.Semester/deep_learning/pset/pset3/problem 2/word2vec.pth'

[ ]:
```
does_model_exist = os.path.isfile(W2V_FILE)

if not does_model_exist or OVERWRITE:
    w2v = Word2Vec(
        # NOTE: you can use either a list of strings (sentences)
        # or provide a corpus_file
        corpus,

        # Dimensionality of the word vectors.
        vector_size=VEC_SIZE,
        #size=VEC_SIZE,

        # Maximum distance between the current and predicted word within a␣
↪sentence.
        window=5,

        # Ignores all words with total frequency lower than this.
        min_count=1,

        # Training algorithm: 1 for skip-gram; otherwise CBOW.
        sg = 1,

        # Use these many worker threads to train the model (=faster training
        # with multicore machines).
        workers=32,

        # If 0, use the sum of the context word vectors. If 1, use the mean,
        # only applies when cbow is used.
        cbow_mean = 1,

        # Number of iterations (epochs) over the corpus. (Formerly: iter)
        epochs=10#100
    )

    w2v.add_null_word()

    w2v.save(W2V_FILE)

else:

     w2v = Word2Vec.load(W2V_FILE)
```

[ ]:
```
def vec_math(model, *args, return_str_description:bool=False):
    desc = ''
```

```python
    func = np.add
    # NOTE: vector_size
    vect = None

    for arg in args:
        if arg == '+':
            desc += ' + '
            func = np.add
        elif arg == '-':
            desc += ' - '
            func = np.subtract
        elif arg == '/':
            desc += ' / '
            func = np.divide
        elif arg == '*':
            desc += ' * '
            func = np.multiply
        else:
            desc += arg
            curr = model.wv[arg]
            if vect is None:
                vect = curr.copy()
            else:
                vect = func(vect, curr)

    if return_str_description:
        return desc, vect

    return vect
```

Explore results NOTE: here my model had

$$woman + man - king = girl$$

and

$$news + truth - lies = blogging$$

[ ]:
```python
# woman + man - king = ?
gsm_res = w2v.wv.most_similar(positive=['woman','man'], negative=['king'])[0]
gsm_res
```

[ ]: ('dumb', 0.7257739901542664)

[ ]:
```
# news + truth - lies = ?
gsm_res = w2v.wv.most_similar(positive=['news','truth'], negative=['lies'])[0]
gsm_res
```

[ ]:
```
('publicize', 0.7525402903556824)
```

[ ]:
```
w2v.wv.most_similar(positive=['lies'], topn = 10)
```

[ ]:
```
[('extends', 0.8267737030982971),
 ('occupies', 0.8245770335197449),
 ('lying', 0.8212238550186157),
 ('situated', 0.8177280426025391),
 ('reaches', 0.8083112835884094),
 ('encircles', 0.766158938407898),
 ('traverses', 0.7654803395271301),
 ('sits', 0.762751579284668),
 ('overlooks', 0.7599471211433411),
 ('encloses', 0.7521087527275085)]
```

Visualize **TODO**: Plot these word embeddings (all words) by adjusting the code in the notebook.

You are able to adjust the plotting parameters to suit your needs for making a compelling visualization. Discuss what you notice in your embeddings. For example, using the introduction to Charles Darwin's "*On the Origin of Species*" as a text file, we obtain the embeddings in Figure 2

[ ]:
```
corpus
```

[ ]:
```
<text8.Dataset at 0x7f8fdaafa200>
```

[ ]:
```
#extract words from corpus
all_words_from_corpus = []
for word in corpus:
    all_words_from_corpus.append(word)

#words_from_corpus = np.array(words_from_corpus).flatten()
all_words_from_corpus = np.concatenate(all_words_from_corpus)
```

[ ]:
```
#this does not terminate

#fig = plt.figure(figsize=(20, 8))
#lim_scale = 2

#ax = fig.add_subplot(1, 1, 1)

# Get the 50 most frequent words in the vocabulary
#words = [w for w, _ in w2v.wv.most_similar(positive=['king'], topn=20)]
```

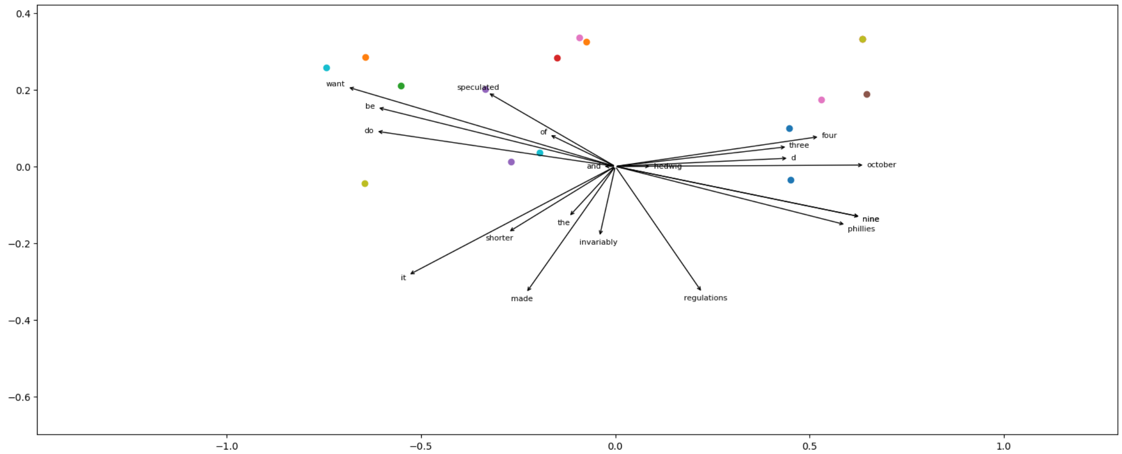
```
#vecs = w2v.wv[all_words_from_corpus]

#min_vals = np.min(vecs, axis=0)
#max_vals = np.max(vecs, axis=0)

#ax.set_xlim(min_vals[0] * lim_scale, max_vals[0] * lim_scale)
#ax.set_ylim(min_vals[1] * lim_scale, max_vals[1] * lim_scale)

#for j, vec in enumerate(vecs):
#    word = all_words_from_corpus[j]

    #print(vec)
#    plt.scatter(vec[0], vec[1])
#    plt.annotate(
#        word, xy=(0, 0),  xytext=(vec[0], vec[1]),
#        arrowprops=dict(arrowstyle="<-"),
#        fontsize=8
#    )

#plt.show()
```

TODO: Since this is too crowded to interpret, modify the code in the notebook to randomly select words to plot as long as there is space as shown in Figure 3

[ ]:
```
words_sample = np.random.choice(all_words_from_corpus, size=20, replace=False)
```

[ ]:
```
fig = plt.figure(figsize=(20, 8))
lim_scale = 2

ax = fig.add_subplot(1, 1, 1)

vecs = w2v.wv[words_sample]

min_vals = np.min(vecs, axis=0)
max_vals = np.max(vecs, axis=0)

ax.set_xlim(min_vals[0] * lim_scale, max_vals[0] * lim_scale)
ax.set_ylim(min_vals[1] * lim_scale, max_vals[1] * lim_scale)

for j, vec in enumerate(vecs):
    word = words_sample[j]

    #print(vec)
    plt.scatter(vec[0], vec[40])
    plt.annotate(
        word, xy=(0, 0),  xytext=(vec[0], vec[1]),
        arrowprops=dict(arrowstyle="<-"),
```

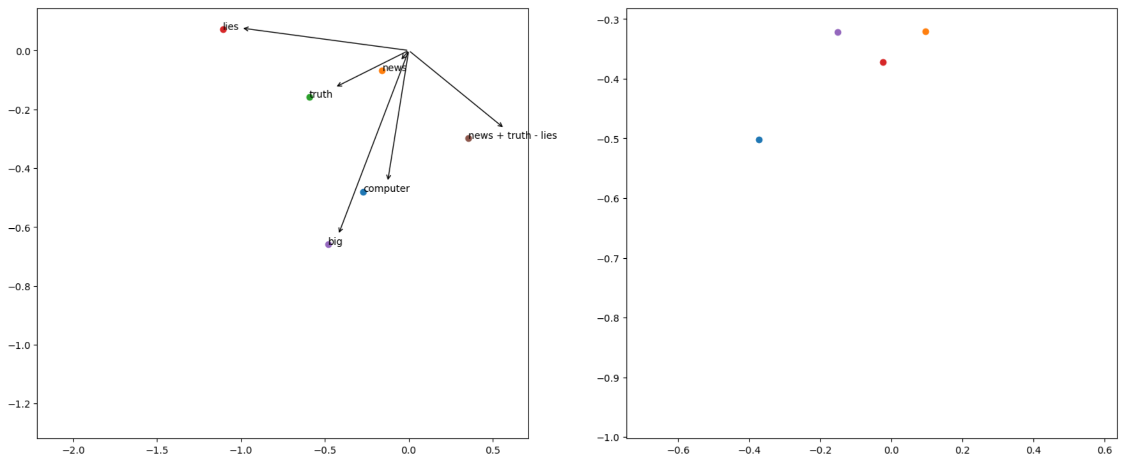
```
        fontsize=8  # Adjust the font size for readability
    )

plt.show()
```



subset, todo delete

[ ]:
```
fig = plt.figure(figsize=(20, 8))
lim_scale = 2

word_groups = [
    'computer,news,truth,lies,big,news + truth - lies'.split(','),
    'man,king,woman,queen,woman + man - king'.split(','),
]

for i, words in enumerate(word_groups):
    ax = fig.add_subplot(1, 2, i+1)
    single_words = list(filter(lambda e: e.isalpha(), words))
    domath_words = list(filter(lambda e: not e.isalpha(), words))

    vecs = w2v.wv[single_words]
    for w in domath_words:
        v = vec_math(w2v, *w.split())
        vecs = np.vstack((vecs, v))

    min_vals = np.min(vecs, axis=0)
    max_vals = np.max(vecs, axis=0)

    ax.set_xlim(min_vals[0] * lim_scale, max_vals[0] * lim_scale)
    ax.set_ylim(min_vals[1] * lim_scale, max_vals[1] * lim_scale)
```

```
    for j, vec in enumerate(vecs):
        word = words[j]

        plt.scatter(vec[0], vec[1])
        plt.annotate(
            word, xy=(0, 0),  xytext=(vec[0], vec[1]),
            arrowprops=dict(arrowstyle="<-")
        )
```



0.4 Part 2

0.4.1 Dataset

dl_310_2

[ ]:
```
import os, sys, tqdm, json, pickle, random, warnings
from typing import List, Optional

import numpy as np, pandas as pd

import matplotlib as mpl, matplotlib.pyplot as plt, seaborn as sns

import torch, torch.nn as nn, torch.optim as optim
import pytorch_lightning as pl
from torch.utils import data

from gensim.models import Word2Vec, Phrases
from gensim.test.utils import common_texts
import gensim, gensim.downloader as gensim_api
from gensim import corpora

from gensim.parsing.preprocessing import remove_stopwords, preprocess_documents
```

```python
from gensim.utils import simple_preprocess

pl.seed_everything(3)
```

Global seed set to 3

[ ]: 3

Whether or not you used `gensim` for training the `Word2Vec` model you will be using PyTorch Lightning for the `Seq2Seq` model. To make this easier on you, you will need to create a `data.Dataset` object which contains, at the very least, `__getitem__` and `__len__` methods to yield items during training. Below is an example which converts a `gensim` corpus paired batches of the first 300 words per doc.

[ ]:
```python
class Seq2SeqTextDataset(data.Dataset):
    def __init__(self, corpus, keyed_vecs, reverse_target:bool=False):
        self.corpus = corpus
        self.keyed_vecs = keyed_vecs

        docs = self.docs_from_corpus(corpus)
        self.docs = docs
        self.data = docs

        corpora_dct = corpora.Dictionary(docs)
        self.corpora_dct = corpora_dct

        bows = self.bows_from_docs(docs, corpora_dct)
        self.bows = bows

        self.reverse_target = reverse_target

    def docs_from_corpus(self, corpus):
        docs = [
            #simple_preprocess(remove_stopwords(' '.join(doc)))[:300] #will␣
↪have to reduce this to 5
            simple_preprocess(remove_stopwords(' '.join(doc)))[:3]
            for doc in corpus
        ]
        return docs

    def bows_from_docs(self, docs, dct):
        return [dct.doc2bow(doc) for doc in docs]


    def __len__(self):
        return int(len(self.docs))
```

```python
    def __getitem__(self, idx):
        doc = self.docs[idx]

        source = torch.tensor([self.keyed_vecs.get_index(word) for word in doc])

        target = [self.keyed_vecs.get_index(word, default=0) for word in doc]
        if self.reverse_target:
            target = target[::-1]
        target = torch.tensor(target)

        return source, target
```

0.4.2 Seq2Seq Model

Encoder **TODO**: fill in the `encode` method

[ ]:
```python
class Encoder(nn.Module):
    def __init__(
        self,
        n_vocabsize:int, n_embedding:int, n_hidden:int, n_layers:int,
        dropout:Optional[float]=0.1, pretrained:Optional[np.ndarray]=None,
    ):
        super(Encoder, self).__init__()

        self.n_vocabsize = n_vocabsize
        self.n_embedding = n_embedding
        self.n_hidden = n_hidden
        self.n_layers = n_layers
        self.dropout = dropout

        embedding = self.make_embedding_layer(n_vocabsize, n_embedding,␣
↪pretrained)
        self.embedding = embedding

        # NOTE: depending on your dataset you may have to change batch_first
        self.lstm = nn.LSTM(n_embedding, n_hidden, n_layers, dropout=dropout,␣
↪batch_first=True)
        self.dropout = nn.Dropout(dropout)

    def make_embedding_layer(
        self,
        n_vocabsize:int,
        n_embedding:int,
        pretrained:Optional[np.ndarray]=None,
    ):
        if pretrained is not None:
            pretrained = np.array(pretrained)
```

```
            n_vocabsize, n_embedding = pretrained.shape

            self.n_vocabsize = n_vocabsize
            self.n_embedding = n_embedding

            pretrained = torch.FloatTensor(pretrained)
            embedding = nn.Embedding.from_pretrained(pretrained)

        else:
            embedding = nn.Embedding(n_vocabsize, n_embedding)

        return embedding


    def encode(self, x):
       # TODO: fill this in
       embedding = self.embedding(x)
       embedding = self.dropout(embedding) #TODO: is this the right place for␣
↪dropout?

       _, (hidden, cell) = self.lstm(embedding) #TODO save output?
       return hidden, cell

    def forward(self, x):
        return self.encode(x)
```

Decoder **TODO**: fill in the `decode` method

```
[ ]: class Decoder(nn.Module):
         def __init__(
             self,
             n_vocabsize:int, n_embedding:int, n_hidden:int, n_layers:int,
             dropout:Optional[float]=0.1,
         ):
             super(Decoder, self).__init__()
             self.n_vocabsize = n_vocabsize
             self.n_embedding = n_embedding
             self.n_hidden = n_hidden
             self.n_layers = n_layers
             self.dropout = dropout

             self.embedding = nn.Embedding(n_vocabsize, n_embedding)
             self.lstm = nn.LSTM(n_embedding, n_hidden, n_layers, dropout=dropout,␣
↪batch_first=True) #TODO batch_first?

             self.fc_out = nn.Linear(n_hidden, n_vocabsize)
             self.dropout = nn.Dropout(dropout)
```

```
    def decode(self, x, hidden, cell):
        x = x.unsqueeze(1)
        embedded = self.embedding(x)

        output, (hidden, cell) = self.lstm(embedded, (hidden, cell))

        prediction = self.fc_out(output.squeeze(1))
        prediction = self.dropout(prediction) #TODO: is this the right place␣
↪for dropout?

        return prediction, hidden, cell



    def forward(self, x, hidden, cell):
        return self.decode(x, hidden, cell)
```

Seq2Seq LightningModule **TODO**: fill in the `do_seq2seq` method and define the `criterion`

[ ]:
```
class Seq2Seq(pl.LightningModule):
    def __init__(
        self,
        word_2_vec,
        train_loader,
        n_vocabsize:int=0,
        n_hidden:int = 2,
        n_layers:int = 2,
        dropout:float = 0.2,
        teacher_forcing_ratio:float=0.5,
        learning_rate:float=0.01,
    ):

        super(Seq2Seq, self).__init__()

        self.w2v = word_2_vec
        self.train_loader = train_loader

        n_embedding = word_2_vec.vector_size
        n_vocabsize, n_embedding = np.array(word_2_vec.wv).shape

        self.n_vocabsize = n_vocabsize
        self.n_embedding = n_embedding
        self.n_hidden = n_hidden
        self.n_layers = n_layers
        self.n_output = n_vocabsize
```

```
        self.teacher_forcing_ratio = teacher_forcing_ratio
        self.learning_rate = learning_rate

        self.encoder = Encoder(
            n_vocabsize, n_embedding, n_hidden, n_layers,
            dropout, pretrained=np.array(word_2_vec.wv)
        )
        self.decoder = Decoder(
            n_vocabsize, n_embedding, n_hidden, n_layers, dropout,
        )

        self.criterion = torch.nn.CrossEntropyLoss() #TODO: is this the right␣
↪loss function?

    def train_dataloader(self):
        return self.train_loader

    def configure_optimizers(self):
        optimizer = torch.optim.AdamW(self.parameters(), lr=self.learning_rate,␣
↪weight_decay=1e-5)
        scheduler = optim.lr_scheduler.StepLR(optimizer, 100, gamma=0.99)
        return [optimizer], [scheduler]

    def encode(self, word):
        index = self.w2v.wv.get_index(word)
        return torch.tensor(index)

    def do_seq2seq(self, source, target):
        # TODO: fill this in
        batch_size = source.shape[0]
        target_len = target.shape[1] #TODO 1 or 0?
        target_vocab_size = self.n_vocabsize

        outputs = torch.zeros(target_len, batch_size, target_vocab_size).
↪to(self.device)

        hidden, cell = self.encoder(source)

        x = target[0]

        for t in range(1, target_len):
            output, hidden, cell = self.decoder(x, hidden, cell)

            outputs[t] = output

            teacher_force = random.random() < self.teacher_forcing_ratio
```

```python
            top1 = output.argmax(1)

            x = target[t] if teacher_force else top1

        return outputs

    def training_step(self, batch, batch_idx):
        x, y = batch
        source = x
        target = y

        output = self.do_seq2seq(source, target)

        # NOTE: this may not be needed depending on your
        output_dim = output.shape[-1]
        output = output.view(-1, output_dim)
        target = target.view(-1)


        loss = self.criterion(output, target)

        result = {'loss': loss}
        self.log('loss', loss)
        return result
```

[ ]:
```python
import torch.nn.functional as F

class Seq2Seq(pl.LightningModule):
    def __init__(
        self,
        word_2_vec,
        train_loader,
        n_vocabsize:int=0,
        n_hidden:int = 2,
        n_layers:int = 2,
        dropout:float = 0.2,
        teacher_forcing_ratio:float=0.5,
        learning_rate:float=0.01,
    ):

        super(Seq2Seq, self).__init__()

        self.w2v = word_2_vec
        self.train_loader = train_loader

        n_embedding = word_2_vec.vector_size
```

```
        n_vocabsize, n_embedding = word_2_vec.wv.vectors.shape
        #n_vocabsize, n_embedding = word_2_vec.shape

        self.n_vocabsize = n_vocabsize
        self.n_embedding = n_embedding
        self.n_hidden = n_hidden
        self.n_layers = n_layers
        self.n_output = n_vocabsize

        self.teacher_forcing_ratio = teacher_forcing_ratio
        self.learning_rate = learning_rate

        self.encoder = Encoder(
            n_vocabsize, n_embedding, n_hidden, n_layers,
            dropout, pretrained=word_2_vec.wv.vectors  # <-- Pass 'vectors'␣
↪attribute
        )

        #self.encoder = Encoder(
        #    n_vocabsize, n_embedding, n_hidden, n_layers,
        #    dropout, pretrained=np.array(word_2_vec.wv))

        self.decoder = Decoder(
            n_vocabsize, n_embedding, n_hidden, n_layers, dropout,
        )

        self.criterion = torch.nn.CrossEntropyLoss()

    def train_dataloader(self):
        return self.train_loader

    def configure_optimizers(self):
        optimizer = torch.optim.AdamW(self.parameters(), lr=self.learning_rate,␣
↪weight_decay=1e-5)
        scheduler = optim.lr_scheduler.StepLR(optimizer, 100, gamma=0.99)
        return [optimizer], [scheduler]

    def encode(self, word):
        index = self.w2v.wv.get_index(word)
        return torch.tensor(index)


    def do_seq2seq(self, source, target):
        batch_size = source.shape[0]
        trg_len = target.shape[1]
        trg_vocab_size = self.n_output
```

```
        outputs = torch.zeros(trg_len, batch_size, trg_vocab_size).to(self.
↪device)

        hidden, cell = self.encoder(source)

        input = target[:, 0]

        for t in range(1, trg_len):
            #output, hidden = self.decoder(input, hidden, encoder_outputs)
            #output, (hidden, cell) = self.decoder(input, hidden, cell)
            output, hidden, cell = self.decoder(input, hidden, cell)
            outputs[t] = output
            teacher_force = random.random() < self.teacher_forcing_ratio
            top1 = output.argmax(1)
            input = target[:, t] if teacher_force else top1

        return outputs


    def training_step(self, batch, batch_idx):
        x, y = batch
        source = x
        target = y

        output = self.do_seq2seq(source, target)

        output_dim = output.shape[-1]
        output = output.view(-1, output_dim)
        target = target.view(-1)

        loss = self.criterion(output, target)

        result = {'loss': loss}
        self.log('loss', loss)
        return result
```

0.4.3 Instantiate dataset and dataloader

[ ]:
```
ds = Seq2SeqTextDataset(corpus, w2v.wv)
```

[ ]:
```
dl = data.DataLoader(ds, batch_size=3, shuffle=True, drop_last=True)
```

0.4.4 Instantiate model

[ ]:
```
s2s = Seq2Seq(
    w2v, dl,
    n_hidden=12, n_layers=4, dropout=0.5, learning_rate = 0.01
).to(DEVICE)
s2s.encoder.to(DEVICE)
s2s.decoder.to(DEVICE)
s2s
```

[ ]:
```
Seq2Seq(
  (encoder): Encoder(
    (embedding): Embedding(253854, 50)
    (lstm): LSTM(50, 12, num_layers=4, batch_first=True, dropout=0.5)
    (dropout): Dropout(p=0.5, inplace=False)
  )
  (decoder): Decoder(
    (embedding): Embedding(253854, 50)
    (lstm): LSTM(50, 12, num_layers=4, batch_first=True, dropout=0.5)
    (fc_out): Linear(in_features=12, out_features=253854, bias=True)
    (dropout): Dropout(p=0.5, inplace=False)
  )
  (criterion): CrossEntropyLoss()
)
```

0.4.5 Define trainer

[ ]:
```
trainer = pl.Trainer(
    max_epochs=4,

    # NOTE: gradient clipping can help prevent exploding gradients
    gradient_clip_val=100,
    gradient_clip_algorithm='value',
    log_every_n_steps=5,

    # NOTE: this should match your device i.e. if you set cuda above, this␣
 ↪should be cuda.
    # Otherwise it should be cpu.
    accelerator=DEVICE,

    # NOTE: you can set the maximum time you want to train your model
    max_time={'minutes': 5},

    # NOTE: setting this to true will save your model every so often
    enable_checkpointing=False,
    accumulate_grad_batches=2
)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
```

0.4.6 Train model

TODO train your model

[ ]:
```
trainer.fit(s2s, dl)
```

```
  | Name      | Type             | Params
-----------------------------------------------
0 | encoder   | Encoder          | 12.7 M
1 | decoder   | Decoder          | 16.0 M
2 | criterion | CrossEntropyLoss | 0
-----------------------------------------------
16.0 M    Trainable params
12.7 M    Non-trainable params
28.7 M    Total params
114.797   Total estimated model params size (MB)
/Users/default/miniconda3/envs/dl_310_2/lib/python3.10/site-
packages/pytorch_lightning/trainer/connectors/data_connector.py:430:
PossibleUserWarning: The dataloader, train_dataloader, does not have many
workers which may be a bottleneck. Consider increasing the value of the
`num_workers` argument` (try 8 which is the number of cpus on this machine) in
the `DataLoader` init to improve performance.
  rank_zero_warn(

Epoch 0: 100%|      | 567/567 [02:03<00:00,  4.59it/s, v_num=11]

`Trainer.fit` stopped: `max_epochs=1` reached.

Epoch 0: 100%|      | 567/567 [02:03<00:00,  4.59it/s, v_num=11]
```

TODO: Train your network also to reconstruct sentences with some words masked. How well does this training perform? Report accuracy at convergence.

0.4.7 Evaluation

[ ]:
```
for source, target in dl:
    break
```

[ ]:
```
res = s2s.do_seq2seq(
    source[0, :].unsqueeze(0),
    target[0, :].unsqueeze(0)
```

```
)
res = res.squeeze(1)
res.shape
```

[ ]: torch.Size([3, 253854])

[ ]:
```
[w2v.wv.index_to_key[idx] for idx in res.argmax(1)]
```

[ ]: ['the', 'held', 'seven']

TODO: Put in a sentence from the corpus and write its reconstruction. Is the reconstruction perfect?

[ ]:
```
#example_sentence = 'the seven kings'
```

[ ]:
```
example_sentence = all_words_from_corpus[1:20]
```

[ ]:
```
tokens = example_sentence
tokens = [w2v.wv.get_index(token, default=0) for token in tokens]

tokens = torch.tensor(tokens).unsqueeze(0)
tokens
```

```
[ ]: tensor([[ 3082,    11,     5,   194,     1,  3133,    45,    58,   155,   127,
            741,   476, 10578,   133,     0, 27455,     1,     0,   102]])
```

[ ]:
```
# Set the target tensor to be the same as the  tensor
target_tensor = tokens.clone()
target_tensor
```

```
[ ]: tensor([[ 3082,    11,     5,   194,     1,  3133,    45,    58,   155,   127,
            741,   476, 10578,   133,     0, 27455,     1,     0,   102]])
```

[ ]:
```
random.seed(1)
# Generate the output tensor using the seq2seq model
output_tensor = s2s.do_seq2seq(tokens, target_tensor).argmax(2)
output_tensor = output_tensor.squeeze(1).numpy()
output_tensor
```

```
[ ]: array([     0,   5626,  76185,    150,   3782,     22,    126,     22,
         76185,    486,    938,    359,     22,   3429,     22,    486,
           247, 225309,     22])
```

[ ]:
```
# Convert the output tensor back to words
#ds.keyed_vecs.index_to_key[int(22)]
reconstructed_sentence = [ds.keyed_vecs.index_to_key[int(idx)] for idx in␣
 ↪output_tensor]
```

```
reconstructed_sentence
```

[ ]:
```
['the',
 'peaceful',
 'miklos',
 'french',
 'obsolete',
 'seven',
 'university',
 'seven',
 'miklos',
 'middle',
 'unit',
 'held',
 'seven',
 'watch',
 'seven',
 'middle',
 'word',
 'acetabularia',
 'seven']
```

[ ]:
```
print("Original sentence:")
print(" ".join(example_sentence))

print("\nReconstructed sentence:")
print(" ".join(reconstructed_sentence))
```

```
Original sentence:
originated as a term of abuse first used against early working class radicals
including the diggers of the english

Reconstructed sentence:
the peaceful miklos french obsolete seven university seven miklos middle unit
held seven watch seven middle word acetabularia seven
```

TODO: Now mask one of the words in the sentence with xxxx and test if it fills the word back.

[ ]:
```
from random import randint

masked_sentence = example_sentence.copy()
#get the index of the word to be masked
masked_index = random.randint(0, len(masked_sentence)-1)
#replace the word with the mask token
masked_sentence[masked_index] = 'xxxx'
masked_sentence
```

[ ]: array(['originated', 'as', 'a', 'term', 'of', 'abuse', 'first', 'used',
       'against', 'early', 'xxxx', 'class', 'radicals', 'including',
       'the', 'diggers', 'of', 'the', 'english'], dtype='<U100')

[ ]:
```
# Convert the masked sentence to a tensor
masked_tokens = [w2v.wv.get_index(token, default=0) for token in␣
 ↪masked_sentence]
masked_tokens = torch.tensor(masked_tokens).unsqueeze(0)
masked_tokens
```

[ ]:
```
tensor([[ 3082,    11,     5,   194,     1,  3133,    45,    58,   155,   127,
         30522,   476, 10578,   133,     0, 27455,     1,     0,   102]])
```

[ ]:
```
# Set the target tensor to be the same as the  tensor
target_tensor = masked_tokens.clone()
target_tensor
```

[ ]:
```
tensor([[ 3082,    11,     5,   194,     1,  3133,    45,    58,   155,   127,
         30522,   476, 10578,   133,     0, 27455,     1,     0,   102]])
```

[ ]:
```
#reconstruct the masked sentence
output_tensor = s2s.do_seq2seq(masked_tokens, target_tensor).argmax(2)
output_tensor = output_tensor.squeeze(1).numpy()
output_tensor
```

[ ]:
```
array([    0,    85,   801,  2347,   247,     7,   298,    22,    22,
        4334,    22,   486,     7,     7,  4334,    22,    22, 12578,
        4334])
```

[ ]:
```
# Convert the output tensor back to words
reconstructed_sentence = [ds.keyed_vecs.index_to_key[int(idx)] for idx in␣
 ↪output_tensor]
reconstructed_sentence
```

[ ]:
```
['the',
 'united',
 'leading',
 'fleet',
 'word',
 'zero',
 'best',
 'seven',
 'seven',
 'explosion',
 'seven',
 'middle',
 'zero',
```

```
 'zero',
 'explosion',
 'seven',
 'seven',
 'slit',
 'explosion']
```

[ ]:
```
print("Original sentence:")
print(" ".join(example_sentence))

print("Masked sentence:")
print(" ".join(masked_sentence))

print("\nReconstructed sentence:")
print(" ".join(reconstructed_sentence))
```

```
Original sentence:
originated as a term of abuse first used against early working class radicals
including the diggers of the english
Masked sentence:
originated as a term of abuse first used against early xxxx class radicals
including the diggers of the english

Reconstructed sentence:
the united leading fleet word zero best seven seven explosion seven middle zero
zero explosion seven seven slit explosion
```

TODO: Finally, start a sentence from the corpus by giving the first 3 words, with the rest of the words masked, see if it completes this sentence.

[ ]:
```
masked_sentence = example_sentence.copy()

#replace all words but the first three with the mask token
for i in range(3, len(masked_sentence)):
    masked_sentence[i] = 'xxxx'

masked_sentence
```

[ ]:
```
array(['originated', 'as', 'a', 'xxxx', 'xxxx', 'xxxx', 'xxxx', 'xxxx',
       'xxxx', 'xxxx', 'xxxx', 'xxxx', 'xxxx', 'xxxx', 'xxxx', 'xxxx',
       'xxxx', 'xxxx', 'xxxx'], dtype='<U100')
```

[ ]:
```
# Convert the masked sentence to a tensor
masked_tokens = [w2v.wv.get_index(token, default=0) for token in␣
 ↪masked_sentence]
masked_tokens = torch.tensor(masked_tokens).unsqueeze(0)
masked_tokens
```

[ ]: tensor([[3082,   11,   5, 30522, 30522, 30522, 30522, 30522, 30522, 30522,
          30522, 30522, 30522, 30522, 30522, 30522, 30522, 30522, 30522]])

[ ]:
```
# Set the target tensor to be the same as the  tensor
target_tensor = masked_tokens.clone()
target_tensor
```

[ ]: tensor([[3082,   11,   5, 30522, 30522, 30522, 30522, 30522, 30522, 30522,
          30522, 30522, 30522, 30522, 30522, 30522, 30522, 30522, 30522]])

[ ]:
```
#reconstruct the masked sentence
output_tensor = s2s.do_seq2seq(masked_tokens, target_tensor).argmax(2)
output_tensor = output_tensor.squeeze(1).numpy()
output_tensor
```

[ ]:
```
array([    0,   801, 76185,   486,  1342,    22,   359,    22,    22,
        3782,   938,    22,    22,    22,  4334,    22,   486,   176,
          22])
```

[ ]:
```
# Convert the output tensor back to words
reconstructed_sentence = [ds.keyed_vecs.index_to_key[int(idx)] for idx in␣
 ↪output_tensor]
reconstructed_sentence
```

[ ]:
```
['the',
 'leading',
 'miklos',
 'middle',
 'format',
 'seven',
 'held',
 'seven',
 'seven',
 'obsolete',
 'unit',
 'seven',
 'seven',
 'seven',
 'explosion',
 'seven',
 'middle',
 'common',
 'seven']
```

[ ]:
```
print("Original sentence:")
print(" ".join(example_sentence))
```

```
print("Masked sentence:")
print(" ".join(masked_sentence))

print("\nReconstructed sentence:")
print(" ".join(reconstructed_sentence))
```

```
Original sentence:
originated as a term of abuse first used against early working class radicals
including the diggers of the english
Masked sentence:
originated as a xxxx xxxx xxxx xxxx xxxx xxxx xxxx xxxx xxxx xxxx xxxx xxxx xxxx
xxxx xxxx xxxx

Reconstructed sentence:
the leading miklos middle format seven held seven seven obsolete unit seven
seven seven explosion seven middle common seven
```

0.5 Exploration

You can also use `gensim` to load other models aside from `Word2Vec` such as `glove`

[ ]:
```
#glove_vectors = gensim_api.load('glove-twitter-25')
#glove_vectors.most_similar('twitter')
```

0.6 Citations

This notebook adapts parts of @Ben Trevett's PyTorch Seq2Seq notebook. Additionally we utilize parts of both PyTorch's documentation as well as Gensim's and Machine Learning Plus's tutorial

0.7 Supplementary materials

For those getting started with `gensim` they may find Gaurav Padawe tutorial useful. Of course there is also the official `Word2Vec` `gensim` tutorial

For support with Pylightning please refer to these documentation pages: - `Trainer` documentation - `LightningModule` documentation