Word Embeddings

In this notebook, you will implement 2 algorithms for learning word embeddings. You will use these algorithms to measure semantic similarity between words.

Imports

```
%matplotlib inline

## Standard Library
import random
from string import punctuation
from collections import Counter

## External Libraries
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics.pairwise import cosine_distances
from sklearn.datasets import fetch_20newsgroups
from nltk.tokenize import sent_tokenize, word_tokenize
import nltk
nltk.download('punkt')
import gensim.downloader

# PyTorch Modules: see http://pytorch.org/tutorials/beginner/nlp/word_embeddings_tutorial.html
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

torch.manual_seed(1)
print("GPU Available:", torch.cuda.is_available())
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
GPU Available: True
```

```
## Simple Plotting Utility
def showPlot(title, *args):
        plt.figure()
        fig, ax = plt.subplots()
        for a in args:
            _ = ax.plot(a)
        _ = ax.set_title(title)


def tokenize(text):
        """
        Simple tokenizer (sentences and then words)
        """
        sentences = sent_tokenize(text)
        examples = []
        for sentence in sentences:
                sentence = "".join(char for char in sentence if char not in punctuation)
                sentence = "".join(char for char in sentence if not char.isdigit())
                sentence = sentence.lower()
                tokens = word_tokenize(sentence)
                examples.append(tokens)
        return examples

tokenize("Why, hello there! What's your name?")
```

```
[['why', 'hello', 'there'], ['whats', 'your', 'name']]
```

Data

We provide two datasets. Use the small dataset to develop your algorithms and test semantic similarity at the end of the notebook. Use the larger dataset once your models are developed to get a sense for the scalability of your approaches.

Please include visualizations of the train/test loss for both datasets. For the small dataset, please train your models for 1000 epochs. For the large dataset, please train your models for at least 100 epochs.

```
# Text is lightly adapted (removing punctuation and possesives) from The Raven by Edgar Allan Poe
text_small = [""" Once upon a midnight dreary while I pondered weak and weary
  Over many a quaint and curious volume of forgotten lore
  While I nodded nearly napping suddenly there came a tapping
  As of some one gently rapping rapping at my chamber door
  This is some visiter I muttered tapping at my chamber door
                                                    Only this and nothing more

  Ah distinctly I remember it was in the bleak December
  And each separate dying ember wrought its ghost upon the floor
  Eagerly I wished the morrow vainly I had sought to borrow
  From my books surcease of sorrow sorrow for the lost Lenore
  For the rare and radiant maiden whom the angels name Lenore
                                                    Nameless here for evermore

  And the silken sad uncertain rustling of each purple curtain
  Thrilled me filled me with fantastic terrors never felt before
  So that now to still the beating of my heart I stood repeating
  This is some visiter entreating entrance at my chamber door
  Some late visiter entreating entrance at my chamber door
                                                    This it is and nothing more
```

Presently my soul grew stronger hesitating then no longer
Sir said I or Madam truly your forgiveness I implore
But the fact is I was napping and so gently you came rapping
And so faintly you came tapping tapping at my chamber door
That I scarce was sure I heard you here I opened wide the door
Darkness there and nothing more

Deep into that darkness peering long I stood there wondering fearing
Doubting dreaming dreams no mortal ever dared to dream before
But the silence was unbroken and the darkness gave no token
And the only word there spoken was the whispered word Lenore
This I whispered and an echo murmured back the word Lenore
Merely this and nothing more

Back into the chamber turning all my soul within me burning
Soon I heard again a tapping somewhat louder than before
Surely said I surely that is something at my window lattice
Let me see then what thereat is and this mystery explore
Let my heart be still a moment and this mystery explore
This is the wind and nothing more

Open here I flung the shutter when with many a flirt and flutter
In there stepped a stately raven of the saintly days of yore
Not the least obeisance made he not an instant stopped or stayed he
But with mien of lord or lady perched above my chamber door
Perched upon a bust of Pallas just above my chamber door
Perched and sat and nothing more

Then this ebony bird beguiling my sad fancy into smiling
By the grave and stern decorum of the countenance it wore
Though thy crest be shorn and shaven thou I said art sure no craven
Ghastly grim and ancient raven wandering from the Nightly shore
Tell me what thy lordly name is on the Night Plutonian shore
Quoth the raven Nevermore

Much I marvelled this ungainly fowl to hear discourse so plainly
Though its answer little meaninglittle relevancy bore
For we cannot help agreeing that no living human being
Ever yet was blessed with seeing bird above his chamber door
Bird or beast upon the sculptured bust above his chamber door
With such name as Nevermore

But the raven sitting lonely on the placid bust spoke only
That one word as if his soul in that one word he did outpour
Nothing farther then he utterednot a feather then he fluttered
Till I scarcely more than muttered Other friends have flown before
On the morrow he will leave me as my hopes have flown before
Then the bird said Nevermore

Startled at the stillness broken by reply so aptly spoken
Doubtless said I what it utters is its only stock and store
Caught from some unhappy master whom unmerciful Disaster
Followed fast and followed faster till his songs one burden bore
Till the dirges of his Hope that melancholy burden bore
Of Never nevermore

But the raven still beguiling all my sad soul into smiling
Straight I wheeled a cushioned seat in front of bird and bust and door
Then upon the velvet sinking I betook myself to thinking
Fancy unto fancy thinking what this ominous bird of yore
What this grim ungainly ghastly gaunt and ominous bird of yore
Meant in croaking Nevermore

This I sat engaged in guessing but no syllable expressing
To the fowl whose fiery eyes now burned into my bosom core
This and more I sat divining with my head at ease reclining
On the cushion velvet lining that the lamplght gloated over
But whose velvet violet lining with the lamplight gloating over
She shall press ah nevermore

Then me thought the air grew denser perfumed from an unseen censer
Swung by Angels whose faint foot-falls tinkled on the tufted floor
Wretch I cried thy God hath lent theeby these angels he hath sent
thee
Respite respite and nepenthe from thy memories of Lenore
Quaff oh quaff this kind nepenthe and forget this lost Lenore
Quoth the raven Nevermore

Prophet said I thing of evil prophet still if bird or devil
Whether Tempter sent or whether tempest tossed thee here ashore
Desolate yet all undaunted on this desert land enchanted
On this home by Horror haunted tell me truly I implore
Is there is there balm in Gilead tell me tell me I implore
Quoth the raven Nevermore

Prophet said I thing of evil prophet still if bird or devil
By that Heaven that bends above us by that God we both adore
Tell this soul with sorrow laden if within the distant Aidenn
It shall clasp a sainted maiden whom the angels name Lenore
Clasp a rare and radiant maiden whom the angels name Lenore
Quoth the raven Nevermore

Be that word our sign of parting bird or fiend I shrieked upstarting
Get thee back into the tempest and the Night Plutonian shore
Leave no black plume as a token of that lie thy soul hath spoken
Leave my loneliness unbroken quit the bust above my door
Take thy beak from out my heart and take thy form from off my door
Quoth the raven Nevermore

And the raven never flitting still is sitting still is sitting
On the pallid bust of Pallas just above my chamber door

```
  And his eyes have all the seeming of a demon that is dreaming
  And the lamp-light over him streaming throws his shadow on the floor
  And my soul from out that shadow that lies floating on the floor
                                                    Shall be lifted nevermore"""]


## Retrieve/Load Data
data = fetch_20newsgroups(subset="test", ## Choose Test Since Full Dataset Will Take Significant Training Time
                                                    remove=("headers","footers","quotes"),
                                                    data_home="./data/",
                                                    download_if_missing=True,
                                                    shuffle=False)

## Isolate Data
text_large = data.data
labels = data.target

## Show Sample Newsgroups Data
show = lambda i: print(text_large[i], "\n", tokenize(text_large[i]))
show(30)
```

```
Downloading 20news dataset. This may take a few minutes.
Downloading dataset from https://ndownloader.figshare.com/files/5975967 (14 MB)



It wasn't Jesus who changed the rules of the game (see quote above),
it was Paul.

Cheers,
Kent

 [['it', 'wasnt', 'jesus', 'who', 'changed', 'the', 'rules', 'of', 'the', 'game', 'see', 'quote', 'above', 'it', 'was', 'paul'], ['cheers', 'kent']]
```

```
## Tokenize Data (We Recommend Developing your model using text_small first)
documents = list(map(tokenize, text_small))
# documents = list(map(tokenize, text_large))

## Flatten Sentences
documents = [tokens for d in documents for tokens in d]
print("Dataset Size:", len(documents))
```

```
Dataset Size: 1
```

```
## Choose Frequency and Top Word Removal (Should Change This Depending on the Dataset)
MIN_FREQ = 0
RM_TOP = 0

## Get Vocabulary
vocab = [t for document in documents for t in document]
vocab_counts = Counter(vocab)
stopwords = set([s[0] for s in vocab_counts.most_common(RM_TOP)])
vocab = set([v for v in set(vocab) if vocab_counts[v] >= MIN_FREQ and v not in stopwords] + ["EOS"])
vocab_size = len(vocab)
print("Vocab Size:", vocab_size)

# Build a dictionary so that each word in vocabualary is assigned a number and
# and we can map each number back to the word
w2i = {w: i for i, w in enumerate(sorted(vocab))}
i2w = {i: w for i, w in enumerate(sorted(vocab))}
```

```
Vocab Size: 435
```

```
## Update The Documents with OOV Token
documents = [list(filter(lambda token: token in vocab, document)) for document in documents]

## Sample Training And Test Documents
np.random.seed(1)
documents_train = documents_test = documents
if len(documents) > 1:
        train_ind, test_ind = train_test_split(list(range(len(documents))))
        documents_train = [documents[t] for t in train_ind]
        documents_test = [documents[t] for t in test_ind]
```

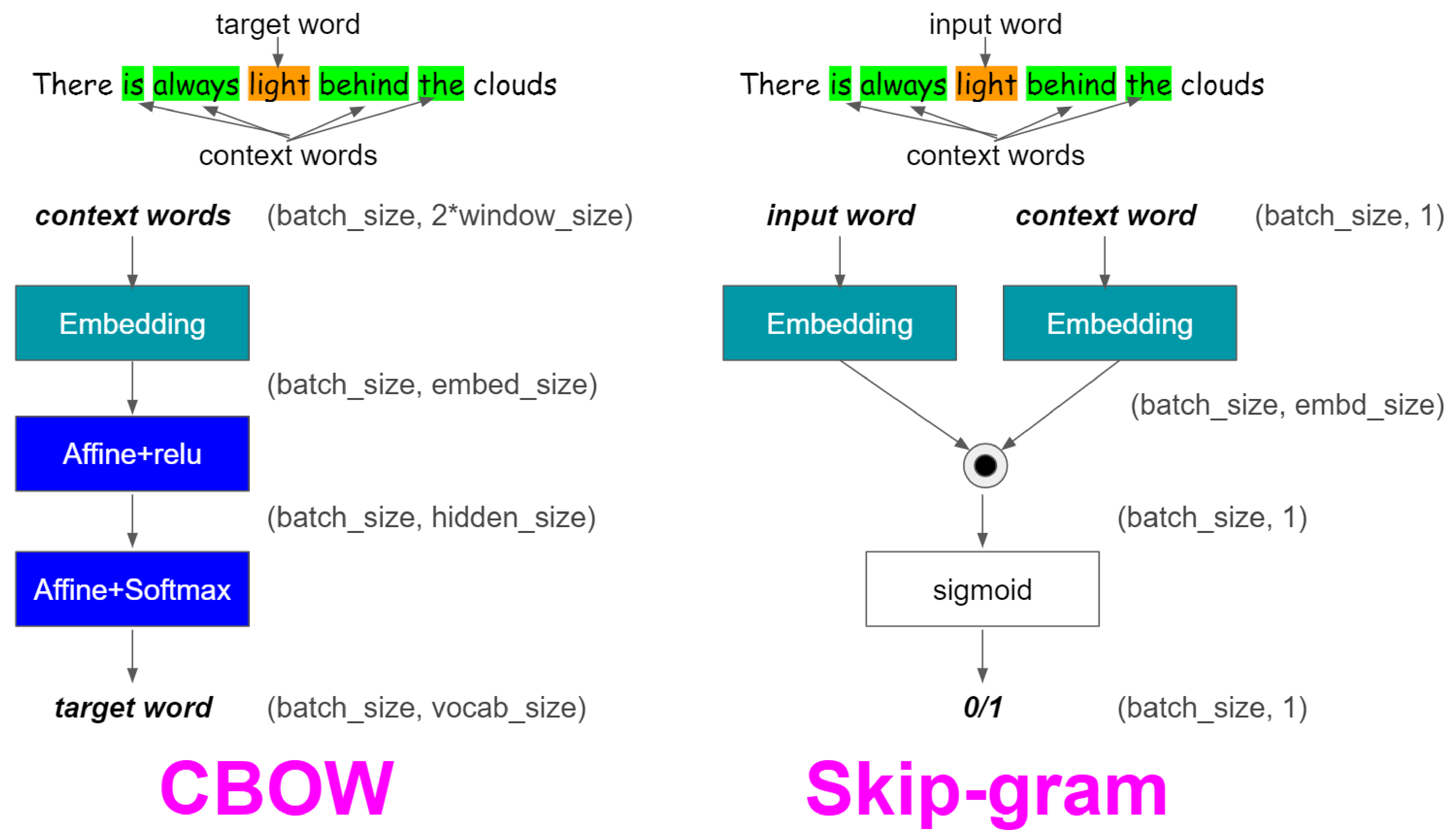


Image from https://github.com/jojonki/word2vec-pytorch

CBOW Implementation

Fill in the TODOs below.

```
## Choose Context Size
CONTEXT_SIZE = 2

# Tuple of an array of words (the context) to a word (the target)
def create_cbow_dataset(documents, context_size):
    data = []
    for document in documents:
        ## Pad the sentence
        document = ["EOS"] * context_size + document + ["EOS"] * context_size
        ## Get Context Tokens
        for i in range(context_size, len(document) - context_size):
            target = document[i]
            before_ctx = []
            after_ctx = []
            for j in range(1,context_size+1):
                before_ctx.append(document[i - j])
                after_ctx.append(document[i + j])
            context = before_ctx + after_ctx
            data.append((context, target))
    return data

## Generate Datasets
cbow_train = create_cbow_dataset(documents_train, context_size=CONTEXT_SIZE)
cbow_test = create_cbow_dataset(documents_test, context_size=CONTEXT_SIZE)

## Show Samples
print('cbow train samples')
for i in range(5):
    print(cbow_train[i])
print("total train samples", len(cbow_train))
print("total test samples", len(cbow_test))
```

```
cbow train samples
(['EOS', 'EOS', 'upon', 'a'], 'once')
(['once', 'EOS', 'a', 'midnight'], 'upon')
(['upon', 'once', 'midnight', 'dreary'], 'a')
(['a', 'upon', 'dreary', 'while'], 'midnight')
(['midnight', 'a', 'while', 'i'], 'dreary')
total train samples 1090
total test samples 1090
```

```
## Example of the Dataset Generator
create_cbow_dataset([["hello","there","my","friend"]], 2)
```

```
[(['EOS', 'EOS', 'there', 'my'], 'hello'),
 (['hello', 'EOS', 'my', 'friend'], 'there'),
 (['there', 'hello', 'friend', 'EOS'], 'my'),
 (['my', 'there', 'EOS', 'EOS'], 'friend')]
```

```
## Helper Function to Construct Batches of Examples
def get_cbow_batches(data, batch_size):
    """
    Generate batches of data for training CBOW Model
    """
    indices = np.arange(len(data))
    np.random.shuffle(indices)
    current_batch = []
    for i, indice in enumerate(indices):
        context, target = data[indice]
        ctx_idxs = [w2i[w] for w in context]
        ctx_var = torch.LongTensor(ctx_idxs)
```

```
            current_batch.append((ctx_var, torch.LongTensor([w2i[target]])))
            if current_batch and len(current_batch) % batch_size == 0 or i == len(indices) - 1:
                batch_context = torch.stack([v[0] for v in current_batch])
                batch_target = torch.stack([v[1] for v in current_batch])
                current_batch = []
                yield batch_context, batch_target



# Simple 3 layer network to map target word to an array of probabilities for
# each word being in its context
# Note that the first layer is a special layer - an embedding layer
# It maps the one-hot encoded vocabulary to a vector of a fixed size
class CBOW(nn.Module):
    def __init__(self, vocab_size, embd_size, context_size, hidden_size):
        super(CBOW, self).__init__()
        #TODO implement layers show in the picture above
        self.embedding = nn.Embedding(vocab_size, embd_size)
        self.linear1 = nn.Linear(2 * context_size * embd_size, hidden_size)
        self.linear2 = nn.Linear(hidden_size, vocab_size)
        self.activation = nn.LogSoftmax(dim = -1)

    def forward(self, inputs):
        #TODO implement the forward of CBOW architecture
        embedded = self.embedding(inputs)
        embedded = embedded.view(embedded.shape[0], -1)
        hidden = F.relu(self.linear1(embedded))
        out = self.linear2(hidden)
        output = self.activation(out)

        return output


def train_cbow(train_data,
               test_data,
               model=None,
               n_epoch=1000,
               embd_size=100,
               learning_rate=0.01,
               context_size=CONTEXT_SIZE,
               batch_size=20,
               hidden_size=128,
               print_every=50,
               random_seed=1):
    """

    """
    ## Set Random Seed
    torch.manual_seed(random_seed)
    ## Batch size
    batch_size = min(batch_size, len(train_data))
    ## Initialize New Model if Not Using Existing
    if model is None:
        model = CBOW(vocab_size, embd_size, context_size, hidden_size)
    ## GPU
    gpu_avail = torch.cuda.is_available()
    if gpu_avail:
        model = model.cuda()
    ## Show the Model
    print(model)
    ## Initialize Optimizer
    optimizer = optim.SGD(model.parameters(), lr=learning_rate)
    ##TODO: Choose the appropriate loss function
    loss_fn = nn.NLLLoss()
    ## Cache for Loss Values
    losses = []
    test_losses = []
    ## Training Loop
    for epoch in range(n_epoch):
        total_loss = .0
        model.train()
        for batch, (context, target) in enumerate(get_cbow_batches(train_data, batch_size)):
            ##TODO implement training procedure for CBOW
            context = context.cuda()
            target = target.cuda()
            outputs = model(context)
            loss = loss_fn(outputs,target.squeeze())

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            total_loss += loss.item()

            if print_every is not None and (batch + 1) % print_every == 0:
                print("Epoch {} || batch {} || Loss: {:.4f}".format(epoch+1, batch+1, total_loss / (batch+1)))

        model.eval()
        ##TODO Compute Loss on Test and Training Data
        train_loss = total_loss / (batch+1)
        test_loss = 0
        for batch1, (context_t, target_t) in enumerate(get_cbow_batches(test_data, batch_size)):
            context_t = context_t.cuda()
            target_t = target_t.cuda()
            outputs_t = model(context_t)
            loss_t = loss_fn(outputs_t,target_t.squeeze())
            test_loss += loss_t.item()
        test_loss = test_loss / (batch1+1)
        print("Epoch {}/{} || Train Loss: {:.4f} || Test Loss: {:.4f}".format(epoch+1, n_epoch, train_loss, test_loss))
        losses.append(train_loss)
        test_losses.append(test_loss)
    print("Training Complete.")
```

```
    return  model,  losses,  test_losses

## Train Model
cbow_model, cbow_losses, cbow_test_losses = train_cbow(cbow_train,
                                                        cbow_test,
                                                        model=None,
                                                        n_epoch=1000,
                                                        embd_size=100,
                                                        context_size=CONTEXT_SIZE,
                                                        batch_size=20,
                                                        learning_rate=0.01,
                                                        hidden_size=128,
                                                        print_every=50)
```

```
Epoch 965 || batch 50 || Loss: 0.0073
Epoch 965/1000 || Train Loss: 0.0070 || Test Loss: 0.0065
Epoch 966 || batch 50 || Loss: 0.0073
Epoch 966/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 967 || batch 50 || Loss: 0.0063
Epoch 967/1000 || Train Loss: 0.0070 || Test Loss: 0.0065
Epoch 968 || batch 50 || Loss: 0.0062
Epoch 968/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 969 || batch 50 || Loss: 0.0073
Epoch 969/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 970 || batch 50 || Loss: 0.0072
Epoch 970/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 971 || batch 50 || Loss: 0.0072
Epoch 971/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 972 || batch 50 || Loss: 0.0073
Epoch 972/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 973 || batch 50 || Loss: 0.0072
Epoch 973/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 974 || batch 50 || Loss: 0.0072
Epoch 974/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 975 || batch 50 || Loss: 0.0073
Epoch 975/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 976 || batch 50 || Loss: 0.0064
Epoch 976/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 977 || batch 50 || Loss: 0.0072
Epoch 977/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 978 || batch 50 || Loss: 0.0072
Epoch 978/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 979 || batch 50 || Loss: 0.0072
Epoch 979/1000 || Train Loss: 0.0069 || Test Loss: 0.0070
Epoch 980 || batch 50 || Loss: 0.0055
Epoch 980/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 981 || batch 50 || Loss: 0.0063
Epoch 981/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 982 || batch 50 || Loss: 0.0060
Epoch 982/1000 || Train Loss: 0.0075 || Test Loss: 0.0065
Epoch 983 || batch 50 || Loss: 0.0072
Epoch 983/1000 || Train Loss: 0.0069 || Test Loss: 0.0065
Epoch 984 || batch 50 || Loss: 0.0072
Epoch 984/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 985 || batch 50 || Loss: 0.0071
Epoch 985/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 986 || batch 50 || Loss: 0.0072
Epoch 986/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 987 || batch 50 || Loss: 0.0072
Epoch 987/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 988 || batch 50 || Loss: 0.0071
Epoch 988/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 989 || batch 50 || Loss: 0.0071
Epoch 989/1000 || Train Loss: 0.0068 || Test Loss: 0.0064
Epoch 990 || batch 50 || Loss: 0.0071
Epoch 990/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 991 || batch 50 || Loss: 0.0071
Epoch 991/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 992 || batch 50 || Loss: 0.0071
Epoch 992/1000 || Train Loss: 0.0069 || Test Loss: 0.0064
Epoch 993 || batch 50 || Loss: 0.0071
Epoch 993/1000 || Train Loss: 0.0068 || Test Loss: 0.0064
Epoch 994 || batch 50 || Loss: 0.0052
Epoch 994/1000 || Train Loss: 0.0068 || Test Loss: 0.0064
```

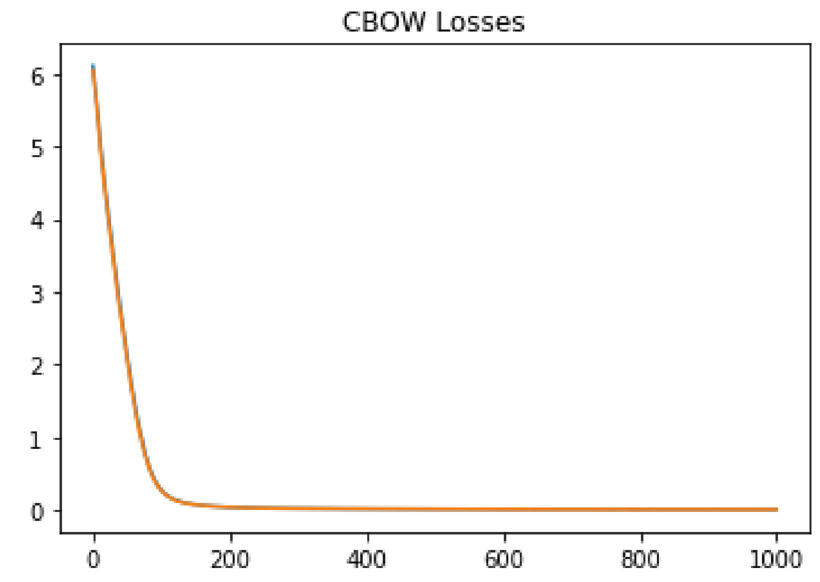
```
## Test Predictive Accuracy
def test_cbow(test_data, model, sample_size=None, seed=42, use_gpu=False):
    ## Random State
    np.random.seed(seed)
    ## Count Correct Answers
    correct_ct = 0
    ## Downsample if Desired (To Save Time)
    if sample_size is None:
        sample = test_data
    else:
        sample = np.random.choice(len(test_data), sample_size, replace=False)
        sample = [test_data[s] for s in sample]
    ## Evaluate
    model.eval()
    for ctx_var, target in get_cbow_batches(sample, 1):
        if use_gpu:
            ctx_var = ctx_var.cuda()
        model.zero_grad()
        log_probs = model(ctx_var)
        if use_gpu:
            log_probs = log_probs.cpu()
        #_, predicted = torch.max(log_probs[0], 1)
        predicted = torch.argmax(log_probs[0])
        if torch.eq(predicted, target[0]):
            correct_ct += 1

    print('Accuracy: {:.1f}% ({:d}/{:d})'.format(correct_ct/len(sample)*100, correct_ct, len(sample)))

test_cbow(cbow_train, cbow_model, sample_size=min(5000, len(cbow_train)), use_gpu=torch.cuda.is_available())
test_cbow(cbow_test, cbow_model, sample_size=min(5000, len(cbow_test)), use_gpu=torch.cuda.is_available())
```

```
Accuracy: 99.8% (1088/1090)
```

```
Accuracy: 99.8% (1088/1090)
```

```
showPlot('CBOW  Losses',cbow_losses,cbow_test_losses)
```

```
<Figure size 432x288 with 0 Axes>
```



Skip-gram Implementation

We've now trained an embedding using the continuous bag of words model. Below, we also show code for training the opposite model - the skipgram model - where you predict the context words based on a target word.

Note how simple the SkipGram network is. There are no linear layers - just the embedding layer, and the training simply aims to maximize the dot product of embeddings of the target and embedding words.

Dataset Generation

We provide the beginning of a function for generating the skipgram dataset. You need to implement negative sampling.

```
# Tuple of a word (the target) to a word (a context word)
def create_skipgram_dataset(documents, context_size, k_negative=5):
    data = []
    for document in documents:
        document = ["EOS"] * context_size + document + ["EOS"] * context_size
        for i in range(context_size, len(document) - context_size):
            word_set = set()
            for j in range(1, context_size+1):
                data.append((document[i], document[i-j], 1))
                data.append((document[i], document[i+j], 1))

            ##TODO: Implement negative sampling
            for _ in range(k_negative):
                rand_id = random.randint(0, vocab_size-1)
                if not rand_id in word_set:
                    data.append((document[i], i2w[rand_id], 0))
    return data

## Create Datasets
skipgram_train = create_skipgram_dataset(documents_train, context_size=CONTEXT_SIZE, k_negative=5)
skipgram_test = create_skipgram_dataset(documents_test, context_size=CONTEXT_SIZE, k_negative=5)

## Show Samples
print('skipgram sample', skipgram_train[:10])
```

```
skipgram sample [('once', 'EOS', 1), ('once', 'upon', 1), ('once', 'EOS', 1), ('once', 'a', 1), ('once', 'then', 0), ('once', 'name', 0), ('once', 'heaven', 0), ('once', 'distinctly',
```

```
## Create Batches
def get_sgram_batches(data, batch_size):
    """

    """
    indices = np.arange(len(data))
    np.random.shuffle(indices)
    current_batch = []
    for i, indice in enumerate(indices):
        in_w, out_w, target = data[indice]
        in_w_var = torch.LongTensor([w2i[in_w]])
        out_w_var = torch.LongTensor([w2i[out_w]])
        target_t = torch.Tensor([target])
        current_batch.append((in_w_var, out_w_var, target_t))
        if current_batch and len(current_batch) % batch_size == 0 or i == len(indices) - 1:
            batch_in_w_var = torch.stack([v[0] for v in current_batch])
            batch_out_w_var = torch.stack([v[1] for v in current_batch])
            batch_target = torch.stack([v[2] for v in current_batch])
            current_batch = []
            yield batch_in_w_var, batch_out_w_var, batch_target



class SkipGram(nn.Module):
    def __init__(self, vocab_size, embd_size):
        super(SkipGram, self).__init__()
        #TODO implement layers shown in the picture above
        self.embedding = nn.Embedding(vocab_size, embd_size)

    def forward(self, focus, context):
        #TODO implement forward of SkipGram.
        embed_f = self.embedding(focus)
        embed_c = self.embedding(context)
        score = torch.mul(embed_f, embed_c).squeeze(1).sum(dim=1)
        probs = torch.sigmoid(score)
        return probs
```

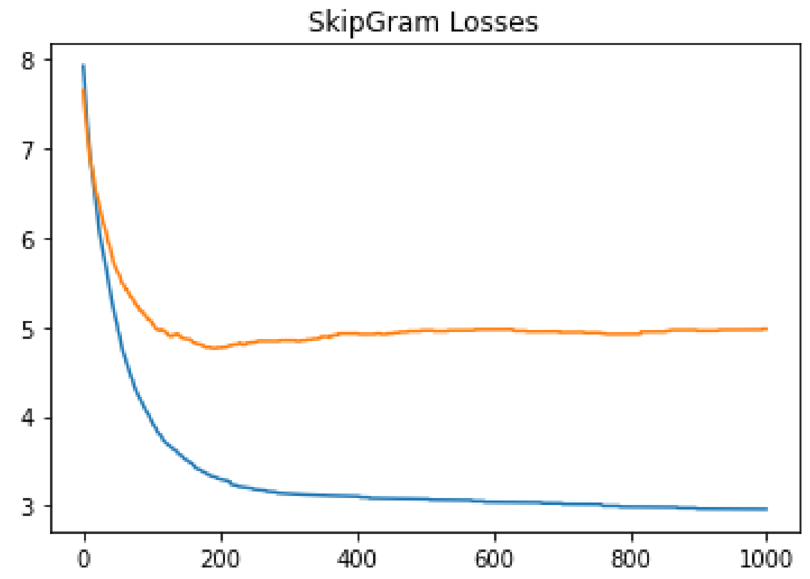
```
def train_skipgram(train_data,
                                   test_data,
                                   model=None,
                                   n_epoch=1000,
                                   learning_rate=0.01,
                                   batch_size=30,
                                   embd_size=128,
                                   print_every_step=None,
                                   print_every_epoch=50,
                                   random_seed=1):
        """

        """
        ## Set Random Seed
        torch.manual_seed(random_seed)
        ## Initialize Model
        if model is None:
                model = SkipGram(vocab_size, embd_size)
        ## Put on GPU
        if torch.cuda.is_available():
                model = model.cuda()
        ## Show Model
        print(model)
        ## Initialize Optimizer
        optimizer = optim.SGD(model.parameters(), lr=learning_rate)
        ##TODO: Choose the appropriate Loss Function
        loss_fn = nn.BCELoss()
        ## Loss Cache
        losses = []
        test_losses = []
        ## Training Loop
        for epoch in range(n_epoch):
                total_loss = .0
                for step, (in_w_var, out_w_var, target_t) in enumerate(get_sgram_batches(train_data, batch_size)):
                        #TODO implement training procedure for SkipGram
                        in_w_var = in_w_var.cuda()
                        out_w_var = out_w_var.cuda()
                        target_t = target_t.cuda()

                        model.zero_grad()
                        probs = model(in_w_var, out_w_var)
                        loss = loss_fn(probs, target_t.squeeze())
                        loss.backward()
                        optimizer.step()

                        total_loss += loss.item()

                        if print_every_step is not None and (step + 1) % print_every_step == 0:
                                print("Epoch {} || Step {}/{} || Loss: {:.4f}".format(epoch+1, step+1, len(train_data), (total_loss / step+1)))

                if print_every_epoch is not None and (epoch + 1) % print_every_epoch == 0:
                        print("Epoch {}/{} || Loss: {:.4f}".format(epoch+1, n_epoch, total_loss / (step+1)))
                model.eval()
                ##TODO Compute Losses
                train_loss = total_loss / (step+1)
                test_loss = 0
                for step1, (in_w_var1, out_w_var1, target_t1) in enumerate(get_sgram_batches(test_data, batch_size)):
                        #TODO implement training procedure for SkipGram
                        in_w_var1 = in_w_var1.cuda()
                        out_w_var1 = out_w_var1.cuda()
                        target_t1 = target_t1.cuda()

                        probs1 = model(in_w_var1, out_w_var1)
                        loss_t = loss_fn(probs1, target_t1.squeeze())
                        test_loss += loss_t.item()
                test_loss = test_loss / (step1+1)
                losses.append(train_loss)
                test_losses.append(test_loss)
        print("Training Complete")
        return model, losses, test_losses

## Fit Model
sg_model, sg_losses, sg_tloss = train_skipgram(skipgram_train,
                                                                           skipgram_test,
                                                                           n_epoch=1000,
                                                                           learning_rate=0.01,
                                                                           batch_size=30,
                                                                           embd_size=128,
                                                                           print_every_step=None,
                                                                           print_every_epoch=50)
```

```
SkipGram(
  (embedding): Embedding(435, 128)
)
Epoch 50/1000 || Loss: 5.0520
Epoch 100/1000 || Loss: 3.9579
Epoch 150/1000 || Loss: 3.5199
Epoch 200/1000 || Loss: 3.3003
Epoch 250/1000 || Loss: 3.1846
Epoch 300/1000 || Loss: 3.1356
Epoch 350/1000 || Loss: 3.1175
Epoch 400/1000 || Loss: 3.1063
Epoch 450/1000 || Loss: 3.0816
Epoch 500/1000 || Loss: 3.0762
Epoch 550/1000 || Loss: 3.0632
Epoch 600/1000 || Loss: 3.0427
Epoch 650/1000 || Loss: 3.0396
Epoch 700/1000 || Loss: 3.0284
Epoch 750/1000 || Loss: 3.0173
Epoch 800/1000 || Loss: 2.9893
Epoch 850/1000 || Loss: 2.9866
Epoch 900/1000 || Loss: 2.9670
```

```
Epoch 950/1000 || Loss: 2.9645
Epoch 1000/1000 || Loss: 2.9627
Training Complete
```

```
## Plot Losses
showPlot('SkipGram Losses', sg_losses, sg_tloss)
```

```
<Figure size 432x288 with 0 Axes>
```




```
## Evaluate Accuracy
def test_skipgram(test_data, model):
    correct_ct = 0
    for in_w_var, out_w_var, target_t in get_sgram_batches(test_data, 1):

        if torch.cuda.is_available():
            in_w_var = in_w_var.cuda()
            out_w_var = out_w_var.cuda()
            target_t = target_t.cuda()
        probs = model(in_w_var, out_w_var)
        predicted = (probs > 0.5)
        correct_ct += torch.sum(torch.eq(predicted[0], target_t))

    print('Accuracy: {:.1f}% ({:d}/{:d})'.format(correct_ct/len(test_data)*100, correct_ct, len(test_data)))

test_skipgram(skipgram_train, sg_model)
test_skipgram(skipgram_test, sg_model)
```

```
Accuracy: 93.5% (9173/9810)
Accuracy: 72.7% (7133/9810)
```

Semantic Similarity

You are asked to write 2 functions. The first function `get_similarity` takes two terms in the vocabulary as arguments and returns their semantic similarity (cosine similarity). The second function `show_similar_terms` takes as an argument a term in the vocabulary and shows the top_k most similar terms based on cosine similarity. Use your functions to evaluate similarity of words in the Raven (based on your trained model) and some general words in the pretrained corpus.

Note: Typically, word embeddings are typically trained on much larger datasets than the ones we provide. You will not necessarily see interpretable similarities below. We are primarily interested in your implementation. Accordingly, we provide code that loads pretrained word embeddings learned using 27 billion tweets. Learn more here: https://nlp.stanford.edu/projects/glove/

```
## Load Pretrained Vectors
glove_vectors = gensim.downloader.load('glove-twitter-25')

## Extract Embeddings and Vocab
glove_vocab = glove_vectors.index2word ## Note: If this doesn't work because of version < 4.0, use .index_to_key
glove_w2i = {w : i for i, w in enumerate(glove_vocab)}
glove_i2w = {i : w for i, w in enumerate(glove_vocab)}

## Convert Embeddings
glove_embeddings = nn.Embedding(len(glove_vocab), 25)
glove_embeddings = glove_embeddings.from_pretrained(torch.Tensor(glove_vectors.vectors))
```

```
[==================================================] 100.0% 104.8/104.8MB downloaded
```

```
def get_similarity(embeddings,
                   w2i,
                   term1,
                   term2):
    """

    """
    ## Check Terms
    for term in [term1, term2]:
        if term not in w2i:
            raise KeyError(f"Term `{term}` not found")
    ## Get Indices
    embeddings = embeddings.cpu()
    term1_ind = torch.LongTensor([w2i[term1]])
    term2_ind = torch.LongTensor([w2i[term2]])


    ##TODO: Retrieve Embeddings and Compute Cosine Similarity
    term1_embed, term2_embed = embeddings(term1_ind), embeddings(term2_ind)

    distance = float(cosine_distances(term1_embed.detach(), term2_embed.detach()))
    print(term1, term2, distance)

def show_similar_terms(embeddings,
                       w2i,
                       i2w,
                       target_term,
                       top_k=10):
    """
```

```
    """
    ## Get Target Vector
    if target_term not in w2i:
        raise KeyError(f"Term `{target_term}` not in vocabulary")
    target_ind = torch.LongTensor([w2i[target_term]])
    ##TODO: Retrieve Embeddings for Target Term and Full Vocabulary
    ## Print out the top_k most similar terms based on cosine similarity
    embedding = embeddings(target_ind)
    cos_dis = np.array([cosine_distances(embeddings.weight[i,:].unsqueeze(dim=0).detach(), embedding.detach()) for i in range(embeddings.weight.shape[0])])
    cos_dis = cos_dis.flatten()
    top_terms = [i2w[i] for i in cos_dis.argsort()[1:top_k+1]]
    print(top_terms)
```

Evaluation

First, evaluate similarity for embeddings trained using The Raven snippet. Then evaluate similarity in the pretrained embeddings.

```
## Evaluation for The Raven embeddings
get_similarity(cbow_model.embedding, w2i, "raven","nevermore")
get_similarity(cbow_model.embedding, w2i, "raven", "door")
show_similar_terms(cbow_model.embedding, w2i, i2w, "raven")

## Evaluation for The Raven Skipgram embeddings
get_similarity(sg_model.embedding, w2i, "raven","nevermore")
get_similarity(sg_model.embedding, w2i, "raven", "door")
show_similar_terms(sg_model.embedding, w2i, i2w, "raven")
```

```
raven nevermore 0.9213746190071106
raven door 1.0904384851455688
['stillness', 'ghastly', 'respite', 'prophet', 'merely', 'decorum', 'shrieked', 'moment', 'wretch', 'stronger']
raven nevermore 0.9367460012435913
raven door 1.0082436800003052
['wished', 'forgiveness', 'faintly', 'rare', 'doubtless', 'our', 'at', 'feather', 'bust', 'front']
```

```
## Evaluation for Glove Embeddings
get_similarity(glove_embeddings, glove_w2i, "mouse","computer")
get_similarity(glove_embeddings, glove_w2i, "mouse","cat")
get_similarity(glove_embeddings, glove_w2i, "mouse","dog")
get_similarity(glove_embeddings, glove_w2i, "cat","dog")
show_similar_terms(glove_embeddings, glove_w2i, glove_i2w, "cat")
```

```
mouse computer 0.304571270942688
mouse cat 0.16189134120941162
mouse dog 0.23936331272125244
cat dog 0.04091787338256836
['dog', 'monkey', 'bear', 'pet', 'girl', 'horse', 'kitty', 'puppy', 'hot', 'lady']
```

Evaluate large dataset

```
## Tokenize Data (We Recommend Developing your model using text_small first)
documents = list(map(tokenize, text_large))
# documents = list(map(tokenize, text_large))

## Flatten Sentences
documents = [tokens for d in documents for tokens in d]
print("Dataset Size:", len(documents))
```

```
Dataset Size: 80164
```

```
## Choose Frequency and Top Word Removal (Should Change This Depending on the Dataset)
MIN_FREQ = 0
RM_TOP = 0

## Get Vocabulary
vocab = [t for document in documents for t in document]
vocab_counts = Counter(vocab)
stopwords = set([s[0] for s in vocab_counts.most_common(RM_TOP)])
vocab = set([v for v in set(vocab) if vocab_counts[v] >= MIN_FREQ and v not in stopwords] + ["EOS"])
vocab_size = len(vocab)
print("Vocab Size:", vocab_size)

# Build a dictionary so that each word in vocabualary is assigned a number and
# and we can map each number back to the word
w2i = {w: i for i, w in enumerate(sorted(vocab))}
i2w = {i: w for i, w in enumerate(sorted(vocab))}
```

```
Vocab Size: 65170
```

```
## Update The Documents with OOV Token
documents = [list(filter(lambda token: token in vocab, document)) for document in documents]

## Sample Training And Test Documents
np.random.seed(1)
documents_train = documents_test = documents
if len(documents) > 1:
    train_ind, test_ind = train_test_split(list(range(len(documents))))
    documents_train = [documents[t] for t in train_ind]
    documents_test = [documents[t] for t in test_ind]
```

CBOW

```
## Choose Context Size
CONTEXT_SIZE = 2
```

```
# Tuple of an array of words (the context) to a word (the target)
def create_cbow_dataset(documents, context_size):
        data = []
        for document in documents:
                ## Pad the sentence
                document = ["EOS"] * context_size + document + ["EOS"] * context_size
                ## Get Context Tokens
                for i in range(context_size, len(document) - context_size):
                        target = document[i]
                        before_ctx = []
                        after_ctx = []
                        for j in range(1,context_size+1):
                                before_ctx.append(document[i - j])
                                after_ctx.append(document[i + j])
                        context = before_ctx + after_ctx
                        data.append((context, target))
        return data

## Generate Datasets
cbow_train = create_cbow_dataset(documents_train, context_size=CONTEXT_SIZE)
cbow_test = create_cbow_dataset(documents_test, context_size=CONTEXT_SIZE)

## Show Samples
print('cbow train samples')
for i in range(5):
        print(cbow_train[i])
print("total train samples", len(cbow_train))
print("total test samples", len(cbow_test))
```

```
cbow train samples
(['EOS', 'EOS', 'liberals', 'tend'], 'the')
(['the', 'EOS', 'tend', 'to'], 'liberals')
(['liberals', 'the', 'to', 'keep'], 'tend')
(['tend', 'liberals', 'keep', 'to'], 'to')
(['to', 'tend', 'to', 'themselves'], 'keep')
total train samples 944039
total test samples 314123
```

```
def train_cbow(train_data,
                              test_data,
                              model=None,
                              n_epoch=100,
                              embd_size=100,
                              learning_rate=0.01,
                              context_size=CONTEXT_SIZE,
                              batch_size=50,
                              hidden_size=128,
                              print_every=None,
                              random_seed=1):
        """

        """
        ## Set Random Seed
        torch.manual_seed(random_seed)
        ## Batch size
        batch_size = min(batch_size, len(train_data))
        ## Initialize New Model if Not Using Existing
        if model is None:
                model = CBOW(vocab_size, embd_size, context_size, hidden_size)
        ## GPU
        gpu_avail = torch.cuda.is_available()
        if gpu_avail:
                model = model.cuda()
        ## Show the Model
        print(model)
        ## Initialize Optimizer
        optimizer = optim.SGD(model.parameters(), lr=learning_rate)
        ##TODO: Choose the appropriate loss function
        loss_fn = nn.NLLLoss()
        ## Cache for Loss Values
        losses = []
        test_losses = []
        ## Training Loop
        for epoch in range(n_epoch):
                total_loss = .0
                model.train()
                for batch, (context, target) in enumerate(get_cbow_batches(train_data, batch_size)):
                        ##TODO implement training procedure for CBOW
                        context = context.cuda()
                        target = target.cuda()
                        outputs = model(context)
                        loss = loss_fn(outputs,target.squeeze())

                        optimizer.zero_grad()
                        loss.backward()
                        optimizer.step()

                        total_loss += loss.item()

                        if print_every is not None and (batch + 1) % print_every == 0:
                                print("Epoch {} || batch {} || Loss: {:.4f}".format(epoch+1, batch+1, total_loss / (batch+1)))

                model.eval()
                ##TODO Compute Loss on Test and Training Data
                train_loss = total_loss / (batch+1)
                test_loss = 0
                for batch_t, (context_t, target_t) in enumerate(get_cbow_batches(test_data, batch_size)):
                        context_t = context_t.cuda()
                        target_t = target_t.cuda()
                        outputs_t = model(context_t)
                        loss_t = loss_fn(outputs_t,target_t.squeeze())
                        test_loss += loss_t.item()
```

```
                test_loss += loss_t.item()
            test_loss = test_loss / (batch_t+1)
            print("Epoch {}/{} || Train Loss: {:.4f} || Test Loss: {:.4f}".format(epoch+1, n_epoch, train_loss, test_loss))
            losses.append(train_loss)
            test_losses.append(test_loss)
    print("Training Complete.")
    return model, losses, test_losses

## Train Model
cbow_model, cbow_losses, cbow_test_losses = train_cbow(cbow_train,
                                                       cbow_test,
                                                       model=None,
                                                       n_epoch=100,
                                                       embd_size=100,
                                                       context_size=CONTEXT_SIZE,
                                                       batch_size=50,
                                                       learning_rate=0.01,
                                                       hidden_size=128,
                                                       print_every=None)
```

```
Epoch 43/100 || Train Loss: 5.1067 || Test Loss: 6.2631
Epoch 44/100 || Train Loss: 5.0802 || Test Loss: 6.2764
Epoch 45/100 || Train Loss: 5.0538 || Test Loss: 6.2873
Epoch 46/100 || Train Loss: 5.0277 || Test Loss: 6.2988
Epoch 47/100 || Train Loss: 5.0017 || Test Loss: 6.3027
Epoch 48/100 || Train Loss: 4.9767 || Test Loss: 6.3045
Epoch 49/100 || Train Loss: 4.9516 || Test Loss: 6.3157
Epoch 50/100 || Train Loss: 4.9267 || Test Loss: 6.3286
Epoch 51/100 || Train Loss: 4.9020 || Test Loss: 6.3407
Epoch 52/100 || Train Loss: 4.8775 || Test Loss: 6.3572
Epoch 53/100 || Train Loss: 4.8537 || Test Loss: 6.3624
Epoch 54/100 || Train Loss: 4.8300 || Test Loss: 6.3791
Epoch 55/100 || Train Loss: 4.8067 || Test Loss: 6.3740
Epoch 56/100 || Train Loss: 4.7840 || Test Loss: 6.3964
Epoch 57/100 || Train Loss: 4.7614 || Test Loss: 6.3995
Epoch 58/100 || Train Loss: 4.7391 || Test Loss: 6.4143
Epoch 59/100 || Train Loss: 4.7166 || Test Loss: 6.4264
Epoch 60/100 || Train Loss: 4.6953 || Test Loss: 6.4451
Epoch 61/100 || Train Loss: 4.6740 || Test Loss: 6.4385
Epoch 62/100 || Train Loss: 4.6532 || Test Loss: 6.4635
Epoch 63/100 || Train Loss: 4.6328 || Test Loss: 6.4674
Epoch 64/100 || Train Loss: 4.6119 || Test Loss: 6.4858
Epoch 65/100 || Train Loss: 4.5923 || Test Loss: 6.4948
Epoch 66/100 || Train Loss: 4.5731 || Test Loss: 6.4970
Epoch 67/100 || Train Loss: 4.5543 || Test Loss: 6.5103
Epoch 68/100 || Train Loss: 4.5353 || Test Loss: 6.5236
Epoch 69/100 || Train Loss: 4.5174 || Test Loss: 6.5326
Epoch 70/100 || Train Loss: 4.4998 || Test Loss: 6.5392
Epoch 71/100 || Train Loss: 4.4825 || Test Loss: 6.5691
Epoch 72/100 || Train Loss: 4.4658 || Test Loss: 6.5720
Epoch 73/100 || Train Loss: 4.4495 || Test Loss: 6.5624
Epoch 74/100 || Train Loss: 4.4329 || Test Loss: 6.5926
Epoch 75/100 || Train Loss: 4.4176 || Test Loss: 6.5982
Epoch 76/100 || Train Loss: 4.4026 || Test Loss: 6.6148
Epoch 77/100 || Train Loss: 4.3884 || Test Loss: 6.6059
Epoch 78/100 || Train Loss: 4.3740 || Test Loss: 6.6473
Epoch 79/100 || Train Loss: 4.3600 || Test Loss: 6.6287
Epoch 80/100 || Train Loss: 4.3472 || Test Loss: 6.6594
Epoch 81/100 || Train Loss: 4.3349 || Test Loss: 6.6603
Epoch 82/100 || Train Loss: 4.3229 || Test Loss: 6.6558
Epoch 83/100 || Train Loss: 4.3110 || Test Loss: 6.6777
Epoch 84/100 || Train Loss: 4.2998 || Test Loss: 6.6953

Epoch 85/100 || Train Loss: 4.2889 || Test Loss: 6.6731
Epoch 86/100 || Train Loss: 4.2784 || Test Loss: 6.7419
Epoch 87/100 || Train Loss: 4.2680 || Test Loss: 6.7009
Epoch 88/100 || Train Loss: 4.2575 || Test Loss: 6.7032
Epoch 89/100 || Train Loss: 4.2485 || Test Loss: 6.7050
Epoch 90/100 || Train Loss: 4.2395 || Test Loss: 6.7252
Epoch 91/100 || Train Loss: 4.2303 || Test Loss: 6.7376
Epoch 92/100 || Train Loss: 4.2216 || Test Loss: 6.7218
Epoch 93/100 || Train Loss: 4.2132 || Test Loss: 6.7342
Epoch 94/100 || Train Loss: 4.2047 || Test Loss: 6.7374
Epoch 95/100 || Train Loss: 4.1968 || Test Loss: 6.7411
Epoch 96/100 || Train Loss: 4.1897 || Test Loss: 6.7539
Epoch 97/100 || Train Loss: 4.1825 || Test Loss: 6.7558
Epoch 98/100 || Train Loss: 4.1753 || Test Loss: 6.7701
Epoch 99/100 || Train Loss: 4.1680 || Test Loss: 6.7592
Epoch 100/100 || Train Loss: 4.1615 || Test Loss: 6.7732
Training Complete
```

```
def train_cbow(train_data,
               test_data,
               model=None,
               n_epoch=100,
               embd_size=100,
               learning_rate=0.01,
               context_size=CONTEXT_SIZE,
               batch_size=50,
               hidden_size=128,
               print_every=None,
               random_seed=1):
    """

    """
    ## Set Random Seed
    torch.manual_seed(random_seed)
    ## Batch size
    batch_size = min(batch_size, len(train_data))
    ## Initialize New Model if Not Using Existing
    if model is None:
        model = CBOW(vocab_size, embd_size, context_size, hidden_size)
    ## GPU
    gpu_avail = torch.cuda.is_available()
    if gpu_avail:
        model = model.cuda()
    ## Show the Model
    print(model)
```

```python
    ## Initialize Optimizer
    optimizer = optim.SGD(model.parameters(), lr=learning_rate)
    ##TODO: Choose the appropriate loss function
    loss_fn = nn.NLLLoss()
    ## Cache for Loss Values
    losses = []
    test_losses = []
    ## Training Loop
    for epoch in range(n_epoch):
        total_loss = .0
        model.train()
        for batch, (context, target) in enumerate(get_cbow_batches(train_data, batch_size)):
            ##TODO implement training procedure for CBOW
            context = context.cuda()
            target = target.cuda()
            outputs = model(context)
            loss = loss_fn(outputs,target.squeeze())

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            total_loss += loss.item()

            if print_every is not None and (batch + 1) % print_every == 0:
                print("Epoch {} || batch {} || Loss: {:.4f}".format(epoch+1, batch+1, total_loss / (batch+1)))

        model.eval()
        ##TODO Compute Loss on Test and Training Data
        train_loss = total_loss / (batch+1)
        test_loss = 0
        for batch_t, (context_t, target_t) in enumerate(get_cbow_batches(test_data, batch_size)):
            context_t = context_t.cuda()
            target_t = target_t.cuda()
            outputs_t = model(context_t)
            loss_t = loss_fn(outputs_t,target_t.squeeze())
            test_loss += loss_t.item()
        test_loss = test_loss / (batch_t+1)
        print("Epoch {}/{} || Train Loss: {:.4f} || Test Loss: {:.4f}".format(epoch+1, n_epoch, train_loss, test_loss))
        losses.append(train_loss)
        test_losses.append(test_loss)
    print("Training Complete.")
    return model, losses, test_losses

## Train Model
cbow_model, cbow_losses, cbow_test_losses = train_cbow(cbow_train,
                                                       cbow_test,
                                                       model=None,
                                                       n_epoch=100,
                                                       embd_size=100,
                                                       context_size=CONTEXT_SIZE,
                                                       batch_size=50,
                                                       learning_rate=0.01,
                                                       hidden_size=128,
                                                       print_every=None)
```

```
Epoch 43/100 || Train Loss: 5.1053 || Test Loss: 6.2653
Epoch 44/100 || Train Loss: 5.0791 || Test Loss: 6.2791
Epoch 45/100 || Train Loss: 5.0522 || Test Loss: 6.2874
Epoch 46/100 || Train Loss: 5.0263 || Test Loss: 6.2943
Epoch 47/100 || Train Loss: 5.0009 || Test Loss: 6.3067
Epoch 48/100 || Train Loss: 4.9754 || Test Loss: 6.3173
Epoch 49/100 || Train Loss: 4.9501 || Test Loss: 6.3253
Epoch 50/100 || Train Loss: 4.9251 || Test Loss: 6.3409
Epoch 51/100 || Train Loss: 4.9005 || Test Loss: 6.3427
Epoch 52/100 || Train Loss: 4.8765 || Test Loss: 6.3530
Epoch 53/100 || Train Loss: 4.8527 || Test Loss: 6.3602
Epoch 54/100 || Train Loss: 4.8290 || Test Loss: 6.3634
Epoch 55/100 || Train Loss: 4.8054 || Test Loss: 6.3794
Epoch 56/100 || Train Loss: 4.7828 || Test Loss: 6.3915
Epoch 57/100 || Train Loss: 4.7604 || Test Loss: 6.3941
Epoch 58/100 || Train Loss: 4.7376 || Test Loss: 6.4168
Epoch 59/100 || Train Loss: 4.7158 || Test Loss: 6.4256
Epoch 60/100 || Train Loss: 4.6941 || Test Loss: 6.4408
Epoch 61/100 || Train Loss: 4.6730 || Test Loss: 6.4400
Epoch 62/100 || Train Loss: 4.6520 || Test Loss: 6.4585
Epoch 63/100 || Train Loss: 4.6314 || Test Loss: 6.4636
Epoch 64/100 || Train Loss: 4.6110 || Test Loss: 6.4995
Epoch 65/100 || Train Loss: 4.5916 || Test Loss: 6.4864
Epoch 66/100 || Train Loss: 4.5719 || Test Loss: 6.5104
Epoch 67/100 || Train Loss: 4.5531 || Test Loss: 6.5091
Epoch 68/100 || Train Loss: 4.5347 || Test Loss: 6.5220
Epoch 69/100 || Train Loss: 4.5165 || Test Loss: 6.5446
Epoch 70/100 || Train Loss: 4.4991 || Test Loss: 6.5457
Epoch 71/100 || Train Loss: 4.4817 || Test Loss: 6.5830
Epoch 72/100 || Train Loss: 4.4647 || Test Loss: 6.5768
Epoch 73/100 || Train Loss: 4.4481 || Test Loss: 6.5806
Epoch 74/100 || Train Loss: 4.4320 || Test Loss: 6.5769
Epoch 75/100 || Train Loss: 4.4166 || Test Loss: 6.5902
Epoch 76/100 || Train Loss: 4.4013 || Test Loss: 6.6022
Epoch 77/100 || Train Loss: 4.3874 || Test Loss: 6.6257
Epoch 78/100 || Train Loss: 4.3733 || Test Loss: 6.6294
Epoch 79/100 || Train Loss: 4.3600 || Test Loss: 6.6307
Epoch 80/100 || Train Loss: 4.3465 || Test Loss: 6.6404
Epoch 81/100 || Train Loss: 4.3342 || Test Loss: 6.6464
Epoch 82/100 || Train Loss: 4.3216 || Test Loss: 6.6574
Epoch 83/100 || Train Loss: 4.3103 || Test Loss: 6.6854
Epoch 84/100 || Train Loss: 4.2991 || Test Loss: 6.6792
Epoch 85/100 || Train Loss: 4.2883 || Test Loss: 6.6736
Epoch 86/100 || Train Loss: 4.2773 || Test Loss: 6.6843
Epoch 87/100 || Train Loss: 4.2676 || Test Loss: 6.6918
Epoch 88/100 || Train Loss: 4.2575 || Test Loss: 6.7127
Epoch 89/100 || Train Loss: 4.2483 || Test Loss: 6.7355
Epoch 90/100 || Train Loss: 4.2392 || Test Loss: 6.7048
Epoch 91/100 || Train Loss: 4.2297 || Test Loss: 6.7226
Epoch 92/100 || Train Loss: 4.2217 || Test Loss: 6.7279
Epoch 93/100 || Train Loss: 4.2133 || Test Loss: 6.7299
```

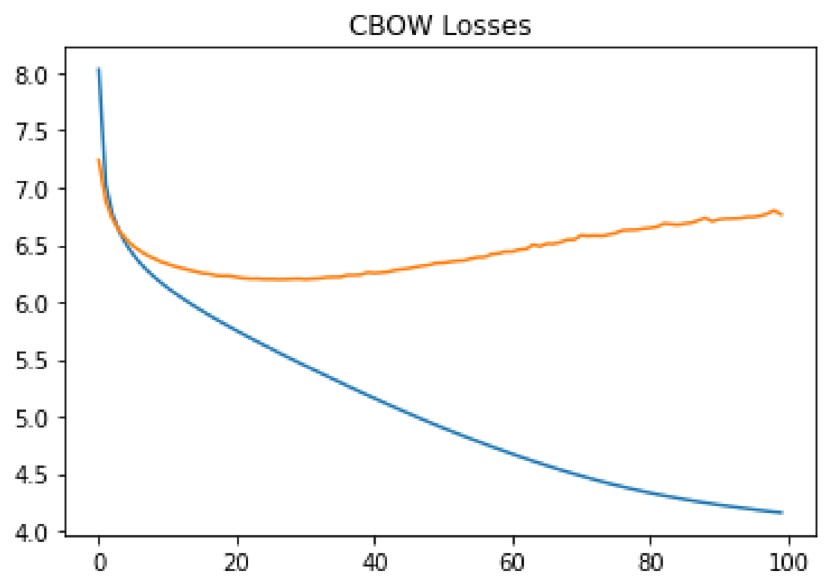
```
Epoch 94/100 || Train Loss: 4.2052 || Test Loss: 6.7325
Epoch 95/100 || Train Loss: 4.1976 || Test Loss: 6.7428
Epoch 96/100 || Train Loss: 4.1900 || Test Loss: 6.7438
Epoch 97/100 || Train Loss: 4.1822 || Test Loss: 6.7539
Epoch 98/100 || Train Loss: 4.1755 || Test Loss: 6.7724
Epoch 99/100 || Train Loss: 4.1685 || Test Loss: 6.8000
Epoch 100/100 || Train Loss: 4.1617 || Test Loss: 6.7666
Training Complete.
```

```
## Test Predictive Accuracy
def test_cbow(test_data, model, sample_size=None, seed=42, use_gpu=False):
    ## Random State
    np.random.seed(seed)
    ## Count Correct Answers
    correct_ct = 0
    ## Downsample if Desired (To Save Time)
    if sample_size is None:
        sample = test_data
    else:
        sample = np.random.choice(len(test_data), sample_size, replace=False)
        sample = [test_data[s] for s in sample]
    ## Evaluate
    model.eval()
    for ctx_var, target in get_cbow_batches(sample, 1):
        if use_gpu:
            ctx_var = ctx_var.cuda()
        model.zero_grad()
        log_probs = model(ctx_var)
        if use_gpu:
            log_probs = log_probs.cpu()
        #_, predicted = torch.max(log_probs[0], 1)
        predicted = torch.argmax(log_probs[0])
        if torch.eq(predicted, target[0]):
            correct_ct += 1

    print('Accuracy: {:.1f}% ({:d}/{:d})'.format(correct_ct/len(sample)*100, correct_ct, len(sample)))

test_cbow(cbow_train, cbow_model, sample_size=min(5000, len(cbow_train)), use_gpu=torch.cuda.is_available())
test_cbow(cbow_test, cbow_model, sample_size=min(5000, len(cbow_test)), use_gpu=torch.cuda.is_available())
```

```
Accuracy: 28.6% (1428/5000)
Accuracy: 18.6% (930/5000)
```

```
showPlot('CBOW Losses',cbow_losses,cbow_test_losses)
```

<Figure size 432x288 with 0 Axes>




```
#save the model
PATH = "gdrive/MyDrive/'cbow_model_large.pt'"
torch.save(cbow_model, PATH)
#load
#the_model = torch.load(PATH)
```

skip-gram

```
# Tuple of a word (the target) to a word (a context word)
CONTEXT_SIZE = 2
def create_skipgram_dataset(documents, context_size, k_negative=5):
    data = []
    for document in documents:
        document = ["EOS"] * context_size + document + ["EOS"] * context_size
        for i in range(context_size, len(document) - context_size):
            word_set = set()
            for j in range(1, context_size+1):
                data.append((document[i], document[i-j], 1))
                data.append((document[i], document[i+j], 1))

            ##TODO: Implement negative sampling
            for _ in range(k_negative):
                rand_id = random.randint(0, vocab_size-1)
                if not rand_id in word_set:
                    data.append((document[i], i2w[rand_id], 0))
    return data

## Create Datasets
skipgram_train = create_skipgram_dataset(documents_train, context_size=CONTEXT_SIZE, k_negative=5)
skipgram_test = create_skipgram_dataset(documents_test, context_size=CONTEXT_SIZE, k_negative=5)

## Show Samples
print('skipgram sample', skipgram_train[:10])
```

```
skipgram sample [('the', 'EOS', 1), ('the', 'liberals', 1), ('the', 'EOS', 1), ('the', 'tend', 1), ('the', 'fencesitters', 0), ('the', 'ramses', 0), ('the', 'namibia', 0), ('the', 'sv
```

```
## Mount Google Drive Data (If using Google Colaboratory)
```

```
## Mount Google Drive Data (If using Google Colaboratory)
try:
        from google.colab import drive
        drive.mount('/content/gdrive')
except:
        print("Mounting Failed.")
```

```
Mounted at /content/gdrive
```

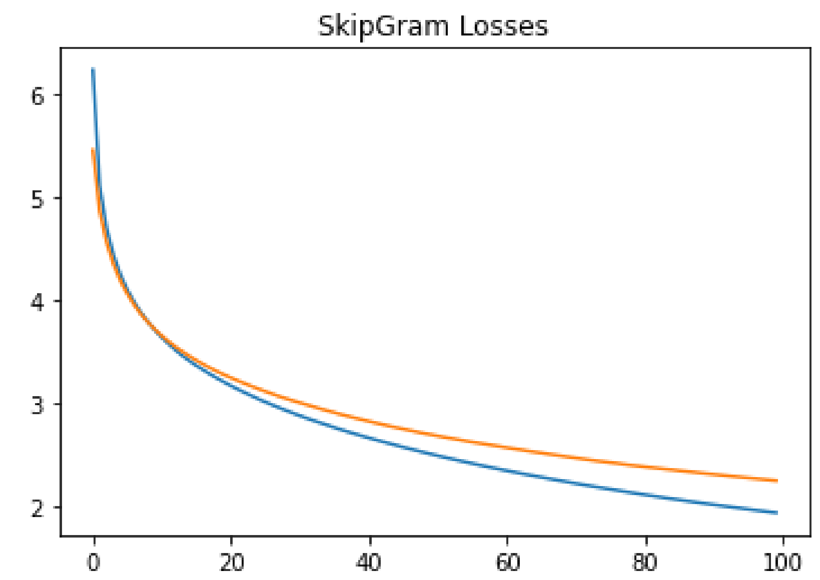
```
def train_skipgram(train_data,
                                      test_data,
                                      model=None,
                                      n_epoch=100,
                                      learning_rate=0.01,
                                      batch_size=100,
                                      embd_size=128,
                                      print_every_step=None,
                                      print_every_epoch=1,
                                      random_seed=1):
        """

        """
        ## Set Random Seed
        torch.manual_seed(random_seed)
        ## Initialize Model
        if model is None:
                model = SkipGram(vocab_size, embd_size)
        ## Put on GPU
        if torch.cuda.is_available():
                model = model.cuda()
        ## Show Model
        print(model)
        ## Initialize Optimizer
        optimizer = optim.SGD(model.parameters(), lr=learning_rate)
        ##TODO: Choose the appropriate Loss Function
        loss_fn = nn.BCELoss()
        ## Loss Cache
        losses = []
        test_losses = []
        ## Training Loop
        for epoch in range(n_epoch):
                total_loss = .0
                for step, (in_w_var, out_w_var, target_t) in enumerate(get_sgram_batches(train_data, batch_size)):
                        #TODO implement training procedure for SkipGram
                        in_w_var = in_w_var.cuda()
                        out_w_var = out_w_var.cuda()
                        target_t = target_t.cuda()

                        model.zero_grad()
                        probs = model(in_w_var, out_w_var)
                        loss = loss_fn(probs, target_t.squeeze())
                        loss.backward()
                        optimizer.step()

                        total_loss += loss.item()

                        if print_every_step is not None and (step + 1) % print_every_step == 0:
                                print("Epoch {} || Step {}/{} || Loss: {:.4f}".format(epoch+1, step+1, len(train_data), (total_loss / step+1)))

                if print_every_epoch is not None and (epoch + 1) % print_every_epoch == 0:
                        print("Epoch {}/{} || Loss: {:.4f}".format(epoch+1, n_epoch, total_loss / step+1))
                model.eval()
                ##TODO Compute Losses
                train_loss = total_loss / (step+1)
                test_loss = 0
                for step_t, (in_w_var1, out_w_var1, target_t1) in enumerate(get_sgram_batches(test_data, batch_size)):
                        #TODO implement training procedure for SkipGram
                        in_w_var1 = in_w_var1.cuda()
                        out_w_var1 = out_w_var1.cuda()
                        target_t1 = target_t1.cuda()

                        probs1 = model(in_w_var1, out_w_var1)
                        loss_t = loss_fn(probs1, target_t1.squeeze())
                        test_loss += loss_t.item()
                test_loss = test_loss / (step_t+1)
                losses.append(train_loss)
                test_losses.append(test_loss)
        print("Training Complete")
        return model, losses, test_losses

## Fit Model
sg_model, sg_losses, sg_tloss = train_skipgram(skipgram_train,
                                                                              skipgram_test,
                                                                              n_epoch=100,
                                                                              learning_rate=0.01,
                                                                              batch_size=100,
                                                                              embd_size=128,
                                                                              print_every_step=None,
                                                                              print_every_epoch=1)
```

```
Epoch 42/100 || Loss: 3.6516
Epoch 43/100 || Loss: 3.6329
Epoch 44/100 || Loss: 3.6146
Epoch 45/100 || Loss: 3.5964
Epoch 46/100 || Loss: 3.5786
Epoch 47/100 || Loss: 3.5618
Epoch 48/100 || Loss: 3.5450
Epoch 49/100 || Loss: 3.5288
Epoch 50/100 || Loss: 3.5121
Epoch 51/100 || Loss: 3.4963
Epoch 52/100 || Loss: 3.4806
Epoch 53/100 || Loss: 3.4656
Epoch 54/100 || Loss: 3.4503
Epoch 55/100 || Loss: 3.4358
```

```
Epoch 56/100 || Loss: 3.4209
Epoch 57/100 || Loss: 3.4065
Epoch 58/100 || Loss: 3.3922
Epoch 59/100 || Loss: 3.3783
Epoch 60/100 || Loss: 3.3648
Epoch 61/100 || Loss: 3.3518
Epoch 62/100 || Loss: 3.3385
Epoch 63/100 || Loss: 3.3256
Epoch 64/100 || Loss: 3.3128
Epoch 65/100 || Loss: 3.3006
Epoch 66/100 || Loss: 3.2881
Epoch 67/100 || Loss: 3.2756
Epoch 68/100 || Loss: 3.2636
Epoch 69/100 || Loss: 3.2515
Epoch 70/100 || Loss: 3.2396
Epoch 71/100 || Loss: 3.2277
Epoch 72/100 || Loss: 3.2163
Epoch 73/100 || Loss: 3.2049
Epoch 74/100 || Loss: 3.1937
Epoch 75/100 || Loss: 3.1829
Epoch 76/100 || Loss: 3.1720
Epoch 77/100 || Loss: 3.1610
Epoch 78/100 || Loss: 3.1503
Epoch 79/100 || Loss: 3.1396
Epoch 80/100 || Loss: 3.1291
Epoch 81/100 || Loss: 3.1187
Epoch 82/100 || Loss: 3.1085
Epoch 83/100 || Loss: 3.0983
Epoch 84/100 || Loss: 3.0881
Epoch 85/100 || Loss: 3.0785
Epoch 86/100 || Loss: 3.0691
Epoch 87/100 || Loss: 3.0595
Epoch 88/100 || Loss: 3.0499
Epoch 89/100 || Loss: 3.0405
Epoch 90/100 || Loss: 3.0315
Epoch 91/100 || Loss: 3.0224
Epoch 92/100 || Loss: 3.0134
Epoch 93/100 || Loss: 3.0045
Epoch 94/100 || Loss: 2.9959
Epoch 95/100 || Loss: 2.9871
Epoch 96/100 || Loss: 2.9784
Epoch 97/100 || Loss: 2.9702
Epoch 98/100 || Loss: 2.9617
Epoch 99/100 || Loss: 2.9530
Epoch 100/100 || Loss: 2.9448
Training Complete
```

```
## Plot Losses
showPlot('SkipGram Losses', sg_losses,sg_tloss)
```

```
<Figure size 432x288 with 0 Axes>
```




```
## Evaluate Accuracy
def test_skipgram(test_data, model):
    correct_ct = 0
    for in_w_var, out_w_var, target_t in get_sgram_batches(test_data, 1000):

        if torch.cuda.is_available():
            in_w_var = in_w_var.cuda()
            out_w_var = out_w_var.cuda()
            target_t = target_t.cuda()
        probs = model(in_w_var, out_w_var)
        predicted = (probs > 0.5)
        correct_ct += torch.sum(torch.eq(predicted[0], target_t))

    print('Accuracy: {:.1f}% ({:d}/{:d})'.format(correct_ct/len(test_data)*100, correct_ct, len(test_data)))

test_skipgram(skipgram_train, sg_model)
test_skipgram(skipgram_test, sg_model)
```

```
Accuracy: 48.6% (4131093/8496351)
Accuracy: 48.4% (1368728/2827107)
```

```
#save the model
PATH = "gdrive/MyDrive/'sg_model_large.pt'"
torch.save(sg_model, PATH)
#load
#the_model = torch.load(PATH)
```

Evaluate Semantic Similarity for the large dataset

```
#Load model
PATH1 = "gdrive/MyDrive/'sg_model_large.pt'"
PATH2 = "gdrive/MyDrive/'cbow_model_large.pt'"
sg_large_model = torch.load(PATH1,map_location=torch.device('cpu'))
cbow_large_model = torch.load(PATH2,map_location=torch.device('cpu'))
```

```
## Evaluation for The large dataset embeddings
get_similarity(cbow_large_model.embedding, w2i, "friendship","racer")
```

```
show_similar_terms(cbow_large_model.embedding, w2i, i2w, "friendship")

## Evaluation for The large dataset embeddings
get_similarity(sg_large_model.embedding, w2i, "friendship","racer")
show_similar_terms(sg_large_model.embedding, w2i, i2w, "friendship")
```

```
friendship racer 1.1169114112854004
['maybee', 'opel', 'rival', 'unix', 'cccp', 'kiribati', 'chlamydomonas', 'sakic', 'colora', 'mmaxqbcbfuxdzlp']
friendship racer 1.0530095100402832
['slvruc', 'evy', 'zheleznovodsk', 'kisio', 'lawshminpit', 'prepackaged', 'darkhorse', 'slaughter', 'polymorphonuclear', 'facelift']
```