Assignment 2: Word Prediction

Deadline: Sunday, April 18th, by 9pm.

Submission: Submit a PDF export of the completed notebook as well as the ipynb file.

In this assignment, we will make a neural network that can predict the next word in a sentence given the previous three.
In doing this prediction task, our neural networks will learn about *words* and about how to represent words. We'll explore the *vector representations* of words that our model produces, and analyze these representations.

You may modify the starter code as you see fit, including changing the signatures of functions and adding/removing helper functions. However, please make sure that you properly explain what you are doing and why.

In [2]:

```
import pandas
import numpy as np
import matplotlib.pyplot as plt
import collections

import torch
import torch.nn as nn
import torch.optim as optim
```

Question 1. Data (18%)

With any machine learning problem, the first thing that we would want to do is to get an intuitive understanding of what our data looks like. Download the file `raw_sentences.txt` from the course page on Moodle and upload it to Google Drive. Then, mount Google Drive from your Google Colab notebook:

In [3]:

```
from google.colab import drive
drive.mount('/content/gdrive')
```

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

Find the path to `raw_sentences.txt`:

In [4]:

```
file_path = '/content/gdrive/My Drive/Colab Notebooks/raw_sentences.txt' # TODO - UPDATE ME!
```

The following code reads the sentences in our file, split each sentence into its individual words, and stores the sentences (list of words) in the variable `sentences`.

In [5]:

```
sentences = []
for line in open(file_path):
    words = line.split()
    sentence = [word.lower() for word in words]
    sentences.append(sentence)
```

There are 97,162 sentences in total, and these sentences are composed of 250 distinct words.

In [6]:

```
vocab = set([w for s in sentences for w in s])
print(len(sentences)) # 97162
print(len(vocab)) # 250
```

```
97162
250
```

We'll separate our data into training, validation, and test. We'll use `10,000 sentences for test, 10,000 for validation, and the rest for training.

In [7]:

```
test, valid, train = sentences[:10000], sentences[10000:20000], sentences[20000:]
```

Part (a) -- 3%

Display 10 sentences in the training set. Explain how punctuations are treated in our word representation, and how words with apostrophes are represented.

In [8]:

```
for i in range(len(train)):
  if i>=10 and i<20:
     print(train[i])
```

```
['but', 'for', 'me', ',', 'now', ',', 'this', 'is', 'it', '.']
['she', "'s", 'still', 'there', 'for', 'us', '.']
['it', "'s", 'part', 'of', 'this', 'game', ',', 'man', '.']
['it', 'was', ':', 'how', 'do', 'we', 'get', 'there', '?']
['but', 'they', 'do', 'nt', 'last', 'too', 'long', '.']
['more', 'are', 'like', 'me', ',', 'she', 'said', '.']
['who', 'do', 'you', 'think', 'they', 'want', 'to', 'be', 'like', '?']
['no', ',', 'he', 'could', 'not', '.']
['so', 'i', 'left', 'it', 'up', 'to', 'them', '.']
['we', 'were', 'nt', 'right', '.']
```

Explanation: we can see that each punctuation mark in a sentence is stored as an individual word, and words with apostrophes are divided into 2 individual words while the apostrophe is the first character in the second word.

Part (b) -- 4%

Print the 10 most common words in the vocabulary and how often does each of these words appear in the training sentences. Express the second quantity as a percentage (i.e. number of occurences of the word / total number of words in the training set).

These are useful quantities to compute, because one of the first things a machine learning model will learn is to predict the most common class. Getting a sense of the distribution of our data will help you understand our model's behaviour.

You can use Python's `collections.Counter` class if you would like to.

In [9]:

```
def flatten_list(list1):
  flat_list = []
  for element in list1:
      if type(element) is list:
          # If the element is of type list, iterate through the sublist
          for item in element:
              flat_list.append(item)
      else:
          flat_list.append(element)
  return flat_list

flat_train = flatten_list(train)
```

```python
common_words = collections.Counter(flat_train)
sorted_words = common_words.most_common()
print('the 10 most common words are',sorted_words[:10])
second_qua = (sorted_words[1][1]/len(flat_train))*100
print('the second quantity is',second_qua,'%')
```

```
the 10 most common words are [('.', 64297), ('it', 23118), (',', 19537), ('i', 17684), ('
do', 16181), ('to', 15490), ('nt', 13009), ('?', 12881), ('the', 12583), ("'s", 12552)]
the second quantity is 3.8456484021379134 %
```

Part (c) -- 11%

Our neural network will take as input three words and predict the next one. Therefore, we need our data set to be comprised of seuqnces of four consecutive words in a sentence, referred to as *4grams*.

Complete the helper functions `convert_words_to_indices` and `generate_4grams`, so that the function `process_data` will take a list of sentences (i.e. list of list of words), and generate an $N \times 4$ numpy matrix containing indices of 4 words that appear next to each other, where N is the number of 4grams (sequences of 4 words appearing one after the other) that can be found in the complete list of sentences. Examples of how these functions should operate are detailed in the code below.

You can use the defined `vocab`, `vocab_itos`, and `vocab_stoi` in your code.

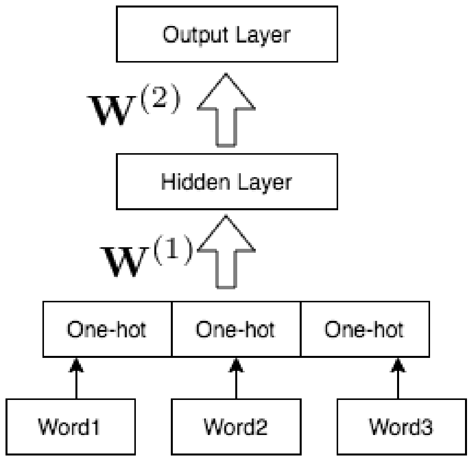
In [10]:

```python
# A list of all the words in the data set. We will assign a unique
# identifier for each of these words.
vocab = sorted(list(set([w for s in train for w in s])))
# A mapping of index => word (string)
vocab_itos = dict(enumerate(vocab))
# A mapping of word => its index
vocab_stoi = {word:index for index, word in vocab_itos.items()}
def convert_words_to_indices(sents):
    """
    This function takes a list of sentences (list of list of words)
    and returns a new list with the same structure, but where each word
    is replaced by its index in `vocab_stoi`.

    Example:
    >>> convert_words_to_indices([['one', 'in', 'five', 'are', 'over', 'here'], ['other',
'one', 'since', 'yesterday'], ['you']])
    [[148, 98, 70, 23, 154, 89], [151, 148, 181, 246], [248]]
    """
    return [[vocab_stoi[word] for word in s] for s in sents]
def generate_4grams(seqs):
    """
    This function takes a list of sentences (list of lists) and returns
    a new list containing the 4-grams (four consequentively occuring words)
    that appear in the sentences. Note that a unique 4-gram can appear multiple
    times, one per each time that the 4-gram appears in the data parameter `seqs`.

    Example:

    >>> generate_4grams([[148, 98, 70, 23, 154, 89], [151, 148, 181, 246], [248]])
    [[148, 98, 70, 23], [98, 70, 23, 154], [70, 23, 154, 89], [151, 148, 181, 246]]
    >>> generate_4grams([[1, 1, 1, 1, 1]])
    [[1, 1, 1, 1], [1, 1, 1, 1]]
    """
    grams =[]
    for j in range(len(seqs)):
      if len(seqs[j])<4:
        continue
      else:
        for t in range(len(seqs[j])-3):
          grams.append(seqs[j][t:t+4])
    return grams
def process_data(sents):
    """
    This function takes a list of sentences (list of lists), and generates an
```

```
    numpy matrix with shape [N, 4] containing indices of words in 4-grams.
    """
    indices = convert_words_to_indices(sents)
    fourgrams = generate_4grams(indices)
    return np.array(fourgrams)

# We can now generate our data which will be used to train and test the network
train4grams = process_data(train)
valid4grams = process_data(valid)
test4grams = process_data(test)
```

Question 2. A Multi-Layer Perceptron (44%)

In this section, we will build a two-layer multi-layer perceptron. Our model will look like this:



Since the sentences in the data are comprised of 250 distinct words, our task boils down to claissfication where the label space $\mathcal{S}$ is of cardinality $|\mathcal{S}| = 250$ while our input, which is comprised of a combination of three words, is treated as a vector of size 750×1 (i.e., the concatanation of three one-hot 250×1 vectors).

The following function `get_batch` will take as input the whole dataset and output a single batch for the training. The output size of the batch is explained below.

Implement yourself a function `make_onehot` which takes the data in index notation and output it in a onehot notation.

Start by reviewing the helper function, which is given to you:

In [11]:

```
def make_onehot(data):
    """
    Convert one batch of data in the index notation into its corresponding onehot
    notation. Remember, the function should work for both xt and st.

    input - vector with shape D (1D or 2D)
    output - vector with shape (D,250)
    """
    ten = torch.tensor(data)
    y = torch.nn.functional.one_hot(ten,num_classes=250)
    y = y.detach().numpy()
    return(y)

def get_batch(data, range_min, range_max, onehot=True):
    """
    Convert one batch of data in the form of 4-grams into input and output
    data and return the training data (xt, st) where:
     - `xt` is an numpy array of one-hot vectors of shape [batch_size, 3, 250]
     - `st` is either
            - a numpy array of shape [batch_size, 250] if onehot is True,
            - a numpy array of shape [batch_size] containing indicies otherwise

    Preconditions:
     - `data` is a numpy array of shape [N, 4] produced by a call
```

```
        to `process_data`
      - range_max > range_min
    """
    xt = data[range_min:range_max, :3]
    xt = make_onehot(xt)
    st = data[range_min:range_max, 3]
    if onehot:
        st = make_onehot(st).reshape(-1, 250)
    return xt, st
```

Part (a) -- 8%

We build the model in PyTorch. Since PyTorch uses automatic differentiation, we only need to write the *forward pass* of our model.

Complete the `forward` function below:

In [12]:

```
class PyTorchMLP(nn.Module):
    def __init__(self, num_hidden=400):
        super(PyTorchMLP, self).__init__()
        self.layer1 = nn.Linear(750, num_hidden)
        self.layer2 = nn.Linear(num_hidden, 250)
        self.num_hidden = num_hidden
    def forward(self, inp):
        inp = inp.reshape([-1, 750])
        activation1 = self.layer1(inp)
        activation1 = torch.nn.functional.relu(activation1)
        activation2 = self.layer2(activation1)
        activation2 = torch.nn.functional.relu(activation2)
        return activation2
        # Note that we will be using the nn.CrossEntropyLoss(), which computes the softma
x operation internally, as loss criterion
```

Part (b) -- 10%

We next train the PyTorch model using the Adam optimizer and the cross entropy loss.

Complete the function `run_pytorch_gradient_descent`, and use it to train your PyTorch MLP model.

Obtain a training accuracy of at least 35% while changing only the hyperparameters of the train function.

Plot the learning curve using the `plot_learning_curve` function provided to you, and include your plot in your PDF submission.

In [13]:

```
def estimate_accuracy_torch(model, data, batch_size=5000, max_N=100000):
    """
    Estimate the accuracy of the model on the data. To reduce
    computation time, use at most `max_N` elements of `data` to
    produce the estimate.
    """
    correct = 0
    N = 0
    for i in range(0, data.shape[0], batch_size):
        # get a batch of data
        xt, st = get_batch(data, i, i + batch_size, onehot=False)

        # forward pass prediction
        y = model(torch.Tensor(xt))
        y = y.detach().numpy() # convert the PyTorch tensor => numpy array
        pred = np.argmax(y, axis=1)
        correct += np.sum(pred == st)
        N += st.shape[0]

        if N > max_N:
```

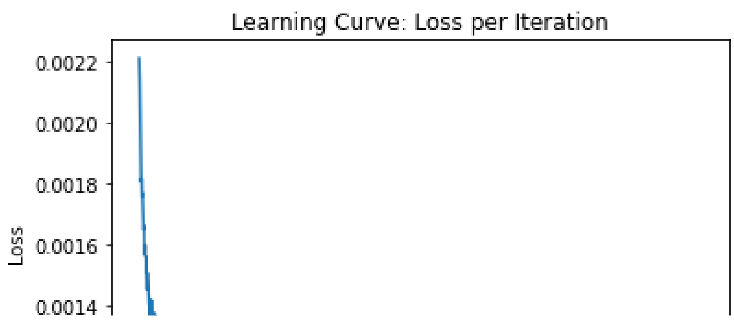
```
            break
    return correct / N

def run_pytorch_gradient_descent(model,
                                 train_data=train4grams,
                                 validation_data=valid4grams,
                                 batch_size=100,
                                 learning_rate=0.001,
                                 weight_decay=0,
                                 max_iters=1000,
                                 checkpoint_path=None):
    """
    Train the PyTorch model on the dataset `train_data`, reporting
    the validation accuracy on `validation_data`, for `max_iters`
    iteration.

    If you want to **checkpoint** your model weights (i.e. save the
    model weights to Google Drive), then the parameter
    `checkpoint_path` should be a string path with `{}` to be replaced
    by the iteration count:

    For example, calling

    >>> run_pytorch_gradient_descent(model, ...,
            checkpoint_path = '/content/gdrive/My Drive/Intro_to_Deep_Learning/mlp/ckpt-
{}.pk')

    will save the model parameters in Google Drive every 500 iterations.
    You will have to make sure that the path exists (i.e. you'll need to create
    the folder Intro_to_Deep_Learning, mlp, etc...). Your Google Drive will be populated
with files:

    - /content/gdrive/My Drive/Intro_to_Deep_Learning/mlp/ckpt-500.pk
    - /content/gdrive/My Drive/Intro_to_Deep_Learning/mlp/ckpt-1000.pk
    - ...

    To load the weights at a later time, you can run:

    >>> model.load_state_dict(torch.load('/content/gdrive/My Drive/Intro_to_Deep_Learning
/mlp/ckpt-500.pk'))

    This function returns the training loss, and the training/validation accuracy,
    which we can use to plot the learning curve.
    """
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(),
                           lr=learning_rate,
                           weight_decay=weight_decay)

    iters, losses = [], []
    iters_sub, train_accs, val_accs  = [], [] ,[]

    n = 0 # the number of iterations
    while True:
        for i in range(0, train_data.shape[0], batch_size):
            if (i + batch_size) > train_data.shape[0]:
                break

            # get the input and targets of a minibatch
            xt, st = get_batch(train_data, i, i + batch_size, onehot=False)

            # convert from numpy arrays to PyTorch tensors
            xt = torch.Tensor(xt)
            st = torch.Tensor(st).long()

            zs = model(xt)                     # compute prediction logit
            loss = criterion(zs,st)                     # compute the total loss
            optimizer.zero_grad()
            loss.backward()                      # compute updates for each parameter
            optimizer.step()                      # make the updates for each parameter
                                 # a clean up step for PyTorch
```

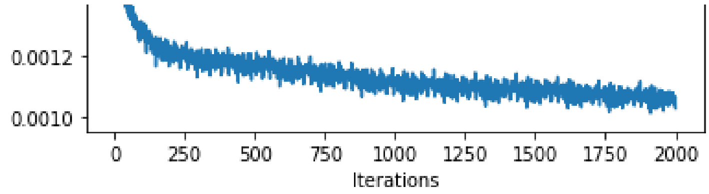
```
            # save the current training information
            iters.append(n)
            losses.append(float(loss)/batch_size)  # compute *average* loss

            if n % 500 == 0:
                iters_sub.append(n)
                train_cost = float(loss.detach().numpy())
                train_acc = estimate_accuracy_torch(model, train_data)
                train_accs.append(train_acc)
                val_acc = estimate_accuracy_torch(model, validation_data)
                val_accs.append(val_acc)
                print("Iter %d. [Val Acc %.0f%%] [Train Acc %.0f%%, Loss %f]" % (
                      n, val_acc * 100, train_acc * 100, train_cost))

                if (checkpoint_path is not None) and n > 0:
                    torch.save(model.state_dict(), checkpoint_path.format(n))

            # increment the iteration number
            n += 1

            if n > max_iters:
                return iters, losses, iters_sub, train_accs, val_accs


def plot_learning_curve(iters, losses, iters_sub, train_accs, val_accs):
    """
    Plot the learning curve.
    """
    plt.title("Learning Curve: Loss per Iteration")
    plt.plot(iters, losses, label="Train")
    plt.xlabel("Iterations")
    plt.ylabel("Loss")
    plt.show()

    plt.title("Learning Curve: Accuracy per Iteration")
    plt.plot(iters_sub, train_accs, label="Train")
    plt.plot(iters_sub, val_accs, label="Validation")
    plt.xlabel("Iterations")
    plt.ylabel("Accuracy")
    plt.legend(loc='best')
    plt.show()
```

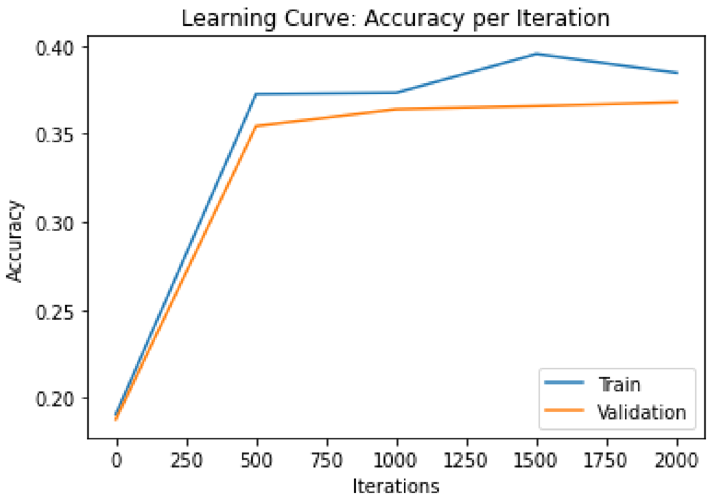
In [16]:

```
pytorch_mlp = PyTorchMLP()
learning_curve_info = run_pytorch_gradient_descent(pytorch_mlp,
                                 train_data=train4grams,
                                 validation_data=valid4grams,
                                 batch_size=2500,
                                 learning_rate=0.01,
                                 weight_decay=0.0001,
                                 max_iters=2000,
                                 checkpoint_path='/content/gdrive/My Drive/Colab Noteboo
ks/mlp/ckpt-{}.pk')
plot_learning_curve(*learning_curve_info)
```

```
Iter 0. [Val Acc 19%] [Train Acc 19%, Loss 5.521693]
Iter 500. [Val Acc 35%] [Train Acc 37%, Loss 2.910032]
Iter 1000. [Val Acc 36%] [Train Acc 37%, Loss 2.765433]
Iter 1500. [Val Acc 37%] [Train Acc 40%, Loss 2.712221]
Iter 2000. [Val Acc 37%] [Train Acc 38%, Loss 2.570769]
```







Part (c) -- 10%

Write a function `make_prediction` that takes as parameters a PyTorchMLP model and sentence (a list of words), and produces a prediction for the next word in the sentence.

In [17]:

```
def make_prediction_torch(model, sentence):
    """
    Use the model to make a prediction for the next word in the
    sentence using the last 3 words (sentence[:-3]). You may assume
    that len(sentence) >= 3 and that `model` is an instance of
    PYTorchMLP.

    This function should return the next word, represented as a string.

    Example call:
    >>> make_prediction_torch(pytorch_mlp, ['you', 'are', 'a'])
    """

    global vocab_stoi, vocab_itos

    temp =[sentence[-3:]]
    pred = model(torch.Tensor(make_onehot(convert_words_to_indices(temp))))
    pred_argmax = int(torch.argmax(pred))
    for key, value in vocab_itos.items():
      if key != pred_argmax:
        continue
      else:
        pred_argmax = value
    return pred_argmax
```

Part (d) -- 10%

Use your code to predict what the next word should be in each of the following sentences:

- **"You are a"**
- **"few companies show"**
- **"There are no"**
- **"yesterday i was"**
- **"the game had"**
- **"yesterday the federal"**

Do your predictions make sense?

In many cases where you overfit the model can either output the same results for all inputs or just memorize the dataset.

Print the output for all of these sentences and Write below if you encounter these effects or something else which indicates overfitting, if you do train again with better hyperparameters.

In [18]:

```
sents = ["You are a","few companies show","There are no","yesterday i was","the game had"
,"yesterday the federal"]
senteces1 = []
for line in sents:
    words = line.split()
    sentence = [word.lower() for word in words]
    senteces1.append(sentence)
    print(make_prediction_torch(pytorch_mlp,sentence))
```

```
good
.
other
going
to
government
```

At first, the predictions did'nt make any sense and we realized that we got overfitting, because at most of the sentences the model predicted the character ('.') which is the most common character in our data. Eventually, we changed the hyperparameters and trained the model again. Now we can see that most of the sentences make sense.

Part (e) -- 6%

Report the test accuracy of your model

In [19]:

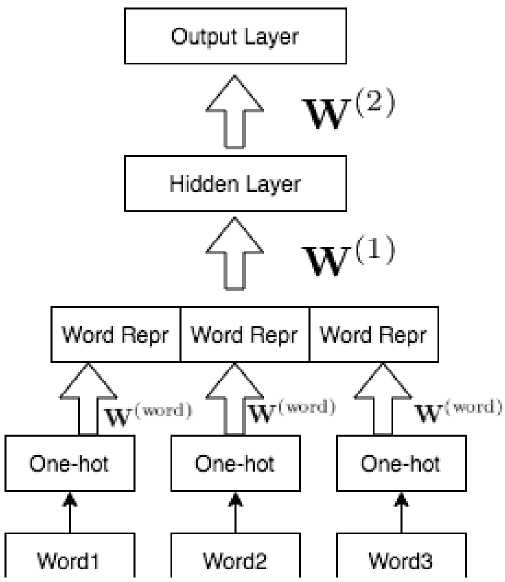
```
print("Test accuracy is:",estimate_accuracy_torch(pytorch_mlp, test4grams, batch_size=500
0, max_N=100000)*100,"%")
```

```
Test accuracy is: 37.20070973802317 %
```

Question 3. Learning Word Embeddings (24 %)

In this section, we will build a slightly different model with a different architecture. In particular, we will first compute a lower-dimensional *representation* of the three words, before using a multi-layer perceptron.

Our model will look like this:



This model has 3 layers instead of 2, but the first layer of the network is **not** fully-connected. Instead, we compute the representations of each of the three words **separately**. In addition, the first layer of the network will not use any biases. The reason for this will be clear in question 4.

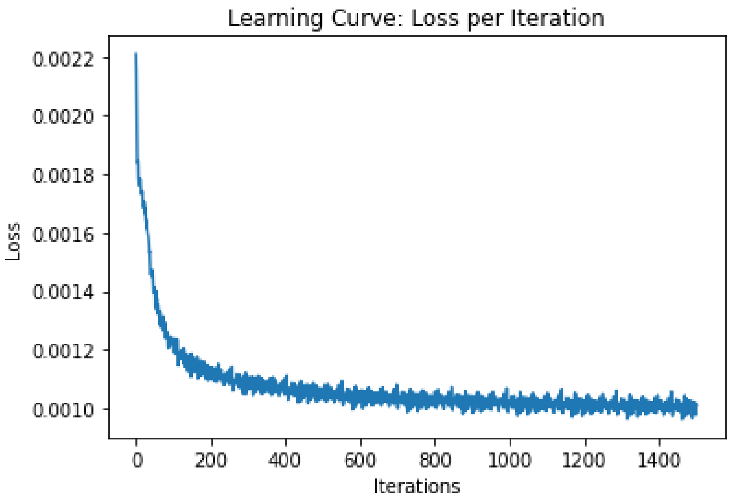
Part (a) -- 10%

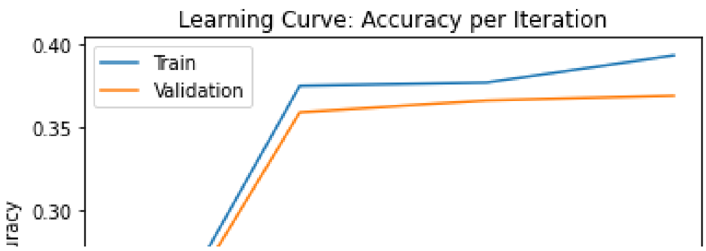
The PyTorch model is implemented for you. Use `run_pytorch_gradient_descent` to train your PyTorch MLP model to obtain a training accuracy of at least 38%. Plot the learning curve using the `plot_learning_curve` function provided to you, and include your plot in your PDF submission.

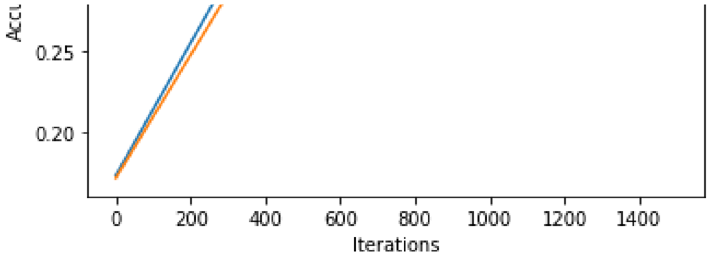
In [24]:

```
class PyTorchWordEmb(nn.Module):
    def __init__(self, emb_size=100, num_hidden=300, vocab_size=250):
        super(PyTorchWordEmb, self).__init__()
        self.word_emb_layer = nn.Linear(vocab_size, emb_size, bias=False)
        self.fc_layer1 = nn.Linear(emb_size * 3, num_hidden)
        self.fc_layer2 = nn.Linear(num_hidden, 250)
        self.num_hidden = num_hidden
        self.emb_size = emb_size
    def forward(self, inp):
        embeddings = torch.relu(self.word_emb_layer(inp))
        embeddings = embeddings.reshape([-1, self.emb_size * 3])
        hidden = torch.relu(self.fc_layer1(embeddings))
        return self.fc_layer2(hidden)

pytorch_wordemb= PyTorchWordEmb()

result = run_pytorch_gradient_descent(pytorch_wordemb,
                                      train_data=train4grams,
                                      validation_data=valid4grams,
                                      batch_size=2500,
                                      learning_rate=0.01,
                                      weight_decay=0.0001,
                                      max_iters=1500,
                                      )
plot_learning_curve(*result)
```

```
Iter 0. [Val Acc 17%] [Train Acc 17%, Loss 5.524199]
Iter 500. [Val Acc 36%] [Train Acc 38%, Loss 2.611712]
Iter 1000. [Val Acc 37%] [Train Acc 38%, Loss 2.533342]
Iter 1500. [Val Acc 37%] [Train Acc 39%, Loss 2.526183]
```







Part (b) -- 10%

Use the function `make_prediction` that you wrote earlier to predict what the next word should be in each of the following sentences:

- "You are a"
- "few companies show"
- "There are no"
- "yesterday i was"
- "the game had"
- "yesterday the federal"

How do these predictions compared to the previous model?

Print the output for all of these sentences using the new network and **Write** below how the new results compare to the previous ones.

Just like before, if you encounter overfitting, train your model for more iterations, or change the hyperparameters in your model. You may need to do this even if your training accuracy is >=38%.

In [42]:

```
senteces2 = []
for line in sents:
    words = line.split()
    sentence = [word.lower() for word in words]
    senteces2.append(sentence)
    print(make_prediction_torch(pytorch_wordemb,sentence))
```

```
good
up
other
nt
to
day
```

We can see that now the model does'nt predict the character '.' beacuse is does'nt make sense. This model predicted other words for most of the sentences compared to the first model, most of them make sense.

Part (c) -- 4%

Report the test accuracy of your model

In [23]:

```
print("Test accuracy is:",estimate_accuracy_torch(pytorch_wordemb, test4grams, batch_size
=5000, max_N=100000)*100,"%")
```

```
Test accuracy is: 37.06293706293706 %
```

Question 4. Visualizing Word Embeddings (14%)

While training the `PyTorchMLP`, we trained the `word_emb_layer`, which takes a one-hot representation of a word in our vocabulary, and returns a low-dimensional vector representation of that word. In this question, we will explore these word embeddings, which are a key concept in natural language processing.

Part (a) -- 4%

The code below extracts the weights of the word embedding layer, and converts the PyTorch tensor into an numpy array. Explain why each *row* of `word_emb` contains the vector representing of a word. For example `word_emb[vocab_stoi["any"],:]` contains the vector representation of the word "any".

In [41]:

```
word_emb_weights = list(pytorch_wordemb.word_emb_layer.parameters())[0]
word_emb = word_emb_weights.detach().numpy().T
#print(list(pytorch_wordemb.word_emb_layer.parameters()))
print(list(pytorch_wordemb.word_emb_layer.parameters()))
print(word_emb.shape)
#print(word_emb[vocab_stoi["."],:])
```

```
[Parameter containing:
tensor([[-2.5344e-08, -1.0627e-05, -2.4462e-02,  ..., -1.1094e-12,
         -5.5165e-04, -1.1767e-02],
        [ 2.0017e-12, -1.0415e-03, -4.4081e-06,  ..., -4.7492e-09,
         -6.4600e-04, -1.6496e-04],
        [ 1.2448e-04, -1.2446e-03,  9.8950e-04,  ..., -8.7316e-08,
          5.8871e-02, -1.2895e-05],
        ...,
        [-2.6988e-04, -1.3233e-03, -3.2643e-07,  ..., -5.7864e-10,
         -2.3546e-03, -6.8489e-08],
        [-1.2048e-01, -2.9086e-04,  4.3864e-02,  ..., -5.1852e-08,
         -5.1976e-04, -1.2468e-14],
        [-3.8685e-02, -3.4937e-03, -6.0825e-02,  ..., -3.5597e-02,
         -5.4789e-04, -2.5009e-02]], requires_grad=True)]
(250, 100)
```

The embedding layer in our model takes all the words in the dictionary and for each word it encodes a dense vector, where the vector has real values instead of 0's and 1's like in onehot representation. So, word_emb contains the output of the embbeding layer, and the dimensionality is chosen by the model. In our case the dimensionality is emb_size=100. We get from the layer 250 rows, and each row represent the dense vector of word.

Part (b) -- 5%

One interesting thing about these word embeddings is that distances in these vector representations of words make some sense! To show this, we have provided code below that computes the *cosine similarity* of every pair of words in our vocabulary. This measure of similarity between vector $\mathbf{v}$
and $\mathbf{w}$
is defined as

$$d_{\cos}(\mathbf{v}, \mathbf{w}) = \frac{\mathbf{v}^T\mathbf{w}}{||\mathbf{v}||\,||\mathbf{w}||}.$$

We also pre-scale the vectors to have a unit norm, using Numpy's `norm` method.

In [120]:

```
norms = np.linalg.norm(word_emb, axis=1)
word_emb_norm = (word_emb.T / norms).T
similarities = np.matmul(word_emb_norm, word_emb_norm.T)

# Some example distances. The first one should be larger than the second
print(similarities[vocab_stoi['any'], vocab_stoi['many']])
print(similarities[vocab_stoi['any'], vocab_stoi['government']])
```

```
0.26150784
0.08850442
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: RuntimeWarning: divide by zero encountered in true_divide
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: RuntimeWarning: invalid v
alue encountered in matmul
  This is separate from the ipykernel package so we can avoid doing imports until
```

Compute the 5 closest words to the following words:

- **"four"**
- **"go"**
- **"what"**
- **"should"**
- **"school"**
- **"your"**
- **"yesterday"**
- **"not"**

In [183]:

```
words = ['four','go','what','should','school','your','yesterday','not']
for word in words:
  words_similarity = {}
  for key, value in vocab_itos.items():
    k = similarities[vocab_stoi[word],key]
    words_similarity.update({value:k})
    sort_dict = ((sorted(words_similarity.items(), key=lambda x:x[1])[-5:])[::-1])
    common_5 = [tp[0] for tp in sort_dict]
  print('The 5 closest words to "'+word+'" are:',common_5)
```

```
The 5 closest words to "four" are: ['four', 'three', 'five', 'several', 'two']
The 5 closest words to "go" are: ['go', 'come', 'going', 'down', 'back']
The 5 closest words to "what" are: ['what', 'how', 'who', 'where', 'when']
The 5 closest words to "should" are: ['should', 'would', 'could', 'can', 'might']
The 5 closest words to "school" are: ['school', 'off', 'office', 'home', 'public']
The 5 closest words to "your" are: ['your', 'their', 'his', 'our', 'its']
The 5 closest words to "yesterday" are: ['yesterday', 'today', 'ago', 'though', 'week']
The 5 closest words to "not" are: ['not', 'nt', 'never', 'around', 'between']
```

Part (c) -- 5%

We can visualize the word embeddings by reducing the dimensionality of the word vectors to 2D. There are many dimensionality reduction techniques that we could use, and we will use an algorithm called t-SNE. (You don't need to know what this is for the assignment; we will cover it later in the course.) Nearby points in this 2-D space are meant to correspond to nearby points in the original, high-dimensional space.

The following code runs the t-SNE algorithm and plots the result.

Look at the plot and find at least two clusters of related words.

Write below for each cluster what is the commonality (if there is any) and if they make sense.

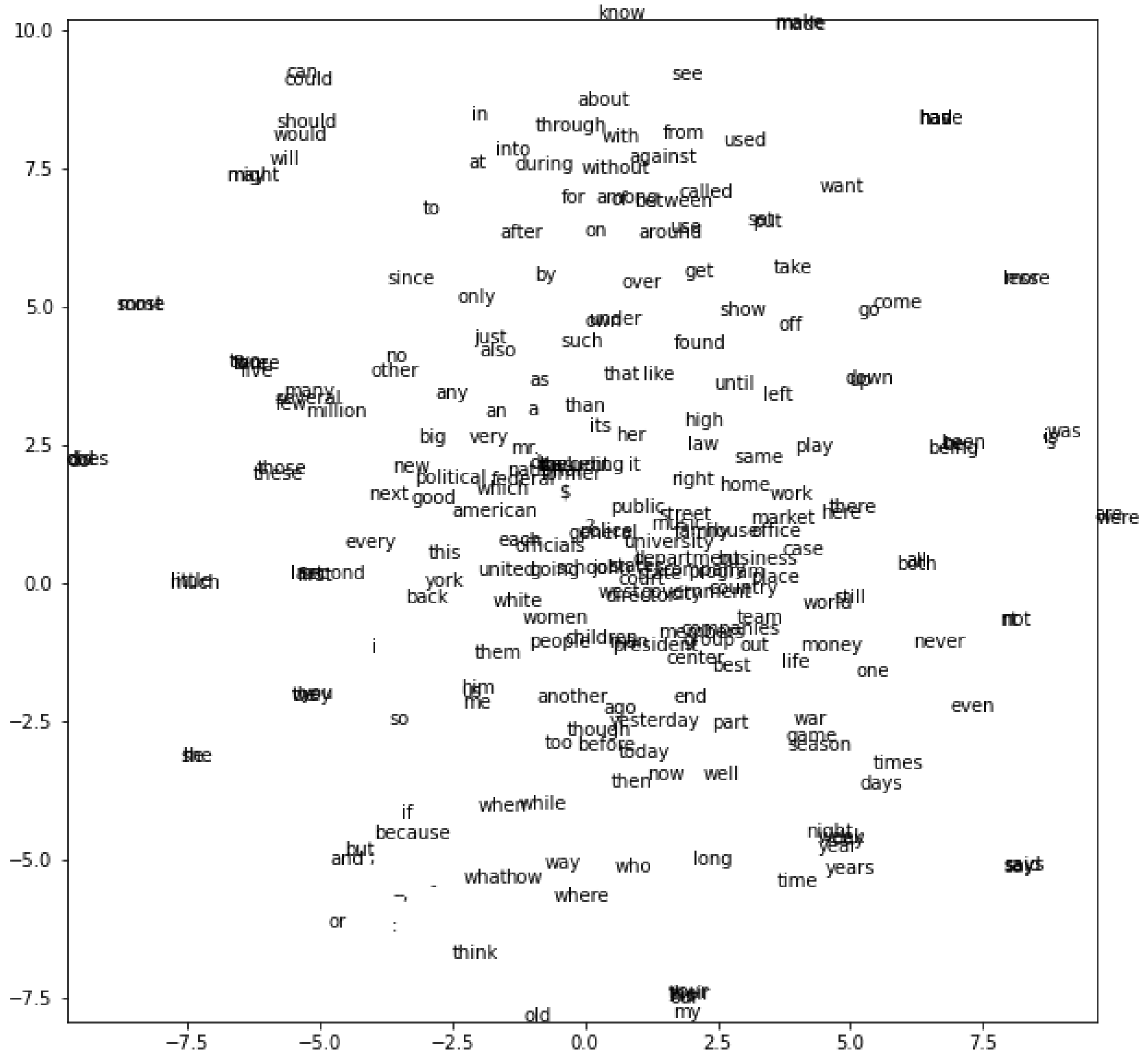
Note that there is randomness in the initialization of the t-SNE algorithm. If you re-run this code, you may get a different image. Please make sure to submit your image in the PDF file.

In [182]:

```
import sklearn.manifold
tsne = sklearn.manifold.TSNE()
Y = tsne.fit_transform(word_emb)

plt.figure(figsize=(10, 10))
plt.xlim(Y[:,0].min(), Y[:, 0].max())
plt.ylim(Y[:,1].min(), Y[:, 1].max())
for i, w in enumerate(vocab):
    plt.text(Y[i, 0], Y[i, 1], w)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:783: FutureWarning: The
default initialization in TSNE will change from 'random' to 'pca' in 1.2.
```

```
default initialization in TSNE will change from 'random' to 'pca' in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:793: FutureWarning: The
default learning rate in TSNE will change from 200.0 to 'auto' in 1.2.
  FutureWarning,
```



There are no obvious clusters, but we can see groups of related words that are close to each other in the 2D representation such as quastion words(i.e. where,who, when...). Another example of groups of related words that we can see are conjuctions (i.e. but,and,or,if,because...) and verbs such as can,would,should,will,might. Each of this groups contain close words that make sense and we also saw those groups in the high-dimensional space.