Assignment 3

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Q1.2.1 Which class does LanguageModelingDataset inherit from?

A-

LanguageModelingDataset inherits from the Dataset class from torch.utils.data.

Q1.2.2 What does the function lm collate fn do? Explain the structure of the data that results when it is called.

A-

Function lm collate fn pads the batch of data with ones so that all the inputs and targets of that batch have the same size.

Structure- all the inputs are padded with ones at the end so that they all have the same length of the longest input. And the similar process is carried out for the targets

Structure example-

x- [{45,67,89,90}, {78,90,12}] y- [{67,89,90}, {90,12}]

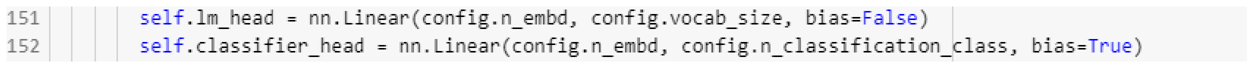
padded-

x_padded-[{45,67,89,90}, {78,90,12,1}] y_padded- [{67,89,90}, {90,12,1}]

Q1.2.3 Looking at the notebook block [6], (with comment "Print out an example of the data") what does this tell you about the relationship between the input (X) and output (Y) that is sent the model for training?
A-
X and Y are of the same length and Y contains the word that will come after the series of words on X. This will train the model to predict the next word given an input series.

Q1.2.4 Given one such X,Y pair, how many different training examples does it produce?
A-
One pair of X,Y gives us N training examples where N is the length of X or Y(they both are of same length.)

Q1.2.5 In the generate function in model.py what is the default method for how the generated word is chosen?
A-
The generate function by default uses the top k method to generate a word with a temperature of 1 and a k value of 1

Q1.2.6 What are the two kinds of heads that model.py can put on to the transformer model? Show (reproduce) all the lines of code that implement this functionality and indicate which method(s) they come from.
A-


```
        self.lm_head = nn.Linear(config.n_embd, config.vocab_size, bias=False)
        self.classifier_head = nn.Linear(config.n_embd, config.n_classification_class, bias=True)
```

These are the lines of code that are used to implement the heads of the transformer model. They both come from torch.nn.linear method.

The first line is used to implement the language model which will be used to train the model. The second line is for the classifier head which is used for classification after the model is trained.

Q1.2.7 How are the word embeddings initialized prior to training?
A-
This is how the word embeddings are initialized prior to training in the init method of class GPT, within self.transformer-

```
wte = nn.Embedding(config.vocab_size, config.n_embd)
```
where vocab size is size of vocab and n_embd is the size of the embedding vectors.

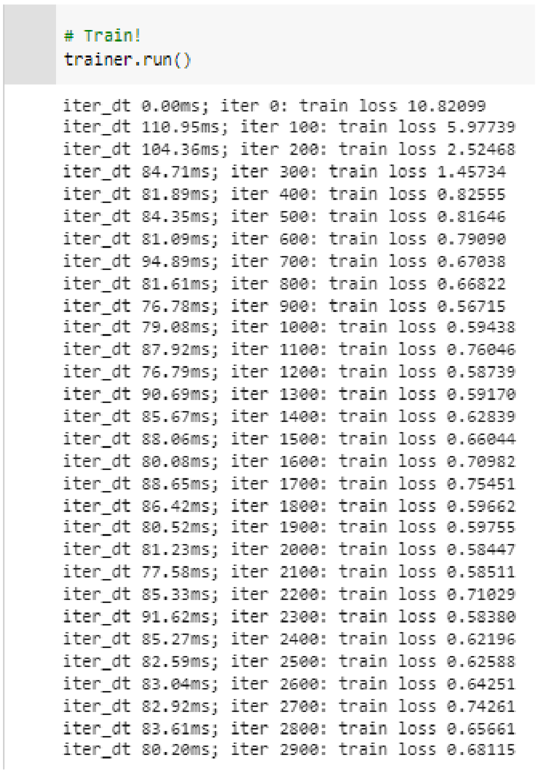
Q1.2.8 What is the name of the object that contains the positional embeddings?
A-
The name of the object is pos_emb-
```
pos_emb = self.transformer.wpe(pos) # position embeddings of shape (1, t, n_embd)
```

Q1.2.9 How are the positional embeddings initialized prior to training?
A-
This is how the word embeddings are initialized prior to training in the init method of class GPT, within self.transformer-

```
wpe = nn.Embedding(config.block_size, config.n_embd)
```
where vocab size is size of vocab and n_embd is the size of the embedding vectors.

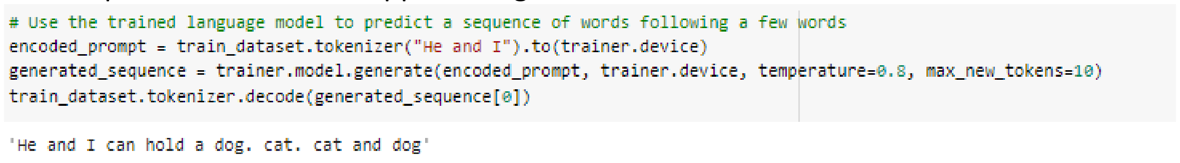
Q1.2.10 Which module and method implement the skip connections in the transformer block? Give the line(s) of code that implement this code.
A-
The skip connection is implemented in class block under the forward method. The code to implement is given below.

```
def forward(self, x):
        x = x + self.attn(self.ln_1(x))
        x = x + self.mlpf(self.ln_2(x))
        return x
```

Q2.1. Run the code up to the line trainer.run() and make sure it functions. Report the value of the loss.
A-
Code run-

```
# Train!
trainer.run()
```
```
iter_dt 0.00ms; iter 0: train loss 10.82099
iter_dt 110.95ms; iter 100: train loss 5.97739
iter_dt 104.36ms; iter 200: train loss 2.52468
iter_dt 84.71ms; iter 300: train loss 1.45734
iter_dt 81.89ms; iter 400: train loss 0.82555
iter_dt 84.35ms; iter 500: train loss 0.81646
iter_dt 81.09ms; iter 600: train loss 0.79090
iter_dt 94.89ms; iter 700: train loss 0.67038
iter_dt 81.61ms; iter 800: train loss 0.66822
iter_dt 76.78ms; iter 900: train loss 0.56715
iter_dt 79.08ms; iter 1000: train loss 0.59438
iter_dt 87.92ms; iter 1100: train loss 0.76046
iter_dt 76.79ms; iter 1200: train loss 0.58739
iter_dt 90.69ms; iter 1300: train loss 0.59170
iter_dt 85.67ms; iter 1400: train loss 0.62839
iter_dt 88.06ms; iter 1500: train loss 0.66044
iter_dt 80.08ms; iter 1600: train loss 0.70982
iter_dt 88.65ms; iter 1700: train loss 0.75451
iter_dt 86.42ms; iter 1800: train loss 0.59662
iter_dt 80.52ms; iter 1900: train loss 0.59755
iter_dt 81.23ms; iter 2000: train loss 0.58447
iter_dt 77.58ms; iter 2100: train loss 0.58511
iter_dt 85.33ms; iter 2200: train loss 0.71029
iter_dt 91.62ms; iter 2300: train loss 0.58380
iter_dt 85.27ms; iter 2400: train loss 0.62196
iter_dt 82.59ms; iter 2500: train loss 0.62588
iter_dt 83.04ms; iter 2600: train loss 0.64251
iter_dt 82.92ms; iter 2700: train loss 0.74261
iter_dt 83.61ms; iter 2800: train loss 0.65661
iter_dt 80.20ms; iter 2900: train loss 0.68115
```

Value of loss- 0.68115 after 2900 iterations

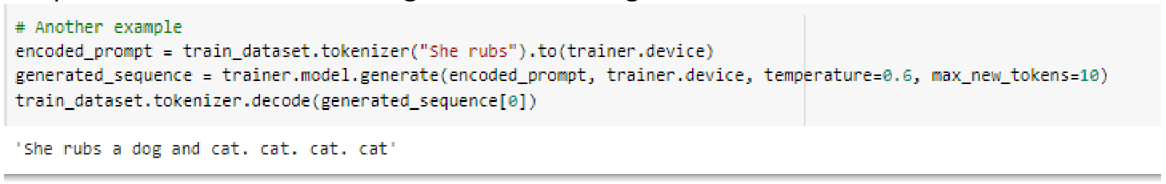
Q2.2 Run the two code snippets following the training that calls the generate function. What is the output for each? Why does the latter parts of the generation not make sense?
A-
The outputs of the 2 code snippets are given below-



```
# Use the trained language model to predict a sequence of words following a few words
encoded_prompt = train_dataset.tokenizer("He and I").to(trainer.device)
generated_sequence = trainer.model.generate(encoded_prompt, trainer.device, temperature=0.8, max_new_tokens=10)
train_dataset.tokenizer.decode(generated_sequence[0])

'He and I can hold a dog. cat. cat and dog'
```

Output- He and I can hold a dog. cat. cat and dog



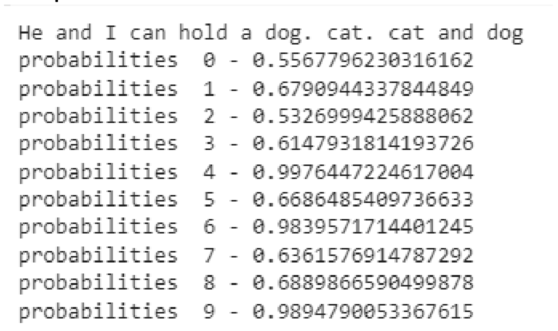
```
# Another example
encoded_prompt = train_dataset.tokenizer("She rubs").to(trainer.device)
generated_sequence = trainer.model.generate(encoded_prompt, trainer.device, temperature=0.6, max_new_tokens=10)
train_dataset.tokenizer.decode(generated_sequence[0])

'She rubs a dog and cat. cat. cat. cat'
```

Output- She rubs a dog and cat. cat. cat. cat

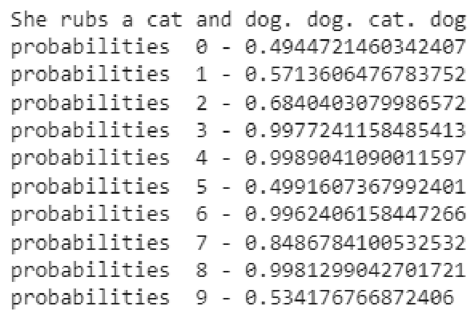
The later parts of the generation don't make sense as the training data contains sentences that are very small (around 5 words). Since we have forced the generator to come up with a 10 word sequence the words that come later don't have much meaning to them.

Q2.3 Modify the generate function so that it outputs the probability of each generated word. Show the output along with these probabilities for the two examples, and then one of your own choosing.
A-
Prompt- He and I
Output-



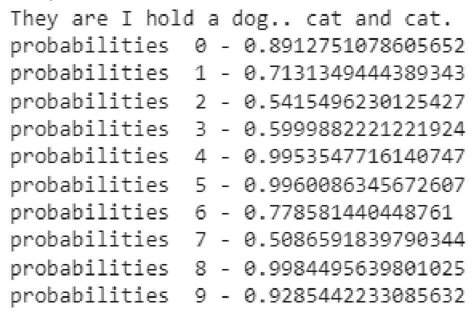
```
He and I can hold a dog. cat. cat and dog
probabilities  0 - 0.5567796230316162
probabilities  1 - 0.6790944337844849
probabilities  2 - 0.5326999425888062
probabilities  3 - 0.6147931814193726
probabilities  4 - 0.9976447224617004
probabilities  5 - 0.6686485409736633
probabilities  6 - 0.9839571714401245
probabilities  7 - 0.6361576914787292
probabilities  8 - 0.6889866590499878
probabilities  9 - 0.9894790053367615
```

Prompt- She rubs
Output-



```
She rubs a cat and dog. dog. cat. dog
probabilities  0 - 0.4944721460342407
probabilities  1 - 0.5713606476783752
probabilities  2 - 0.6840403079986572
probabilities  3 - 0.9977241158485413
probabilities  4 - 0.9989041090011597
probabilities  5 - 0.4991607367992401
probabilities  6 - 0.9962406158447266
probabilities  7 - 0.8486784100532532
probabilities  8 - 0.9981299042701721
probabilities  9 - 0.534176766872406
```

Prompt- They are
Output-

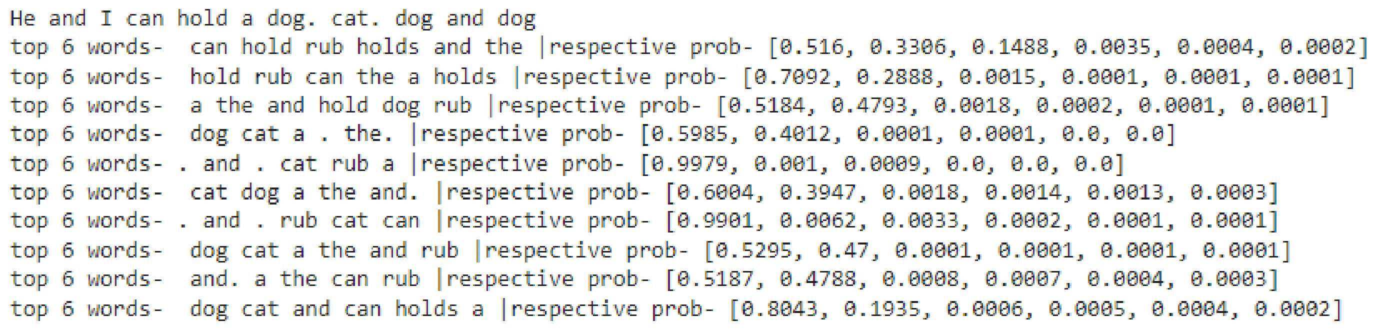


```
They are I hold a dog.. cat and cat.
probabilities  0 - 0.8912751078605652
probabilities  1 - 0.7131349444389343
probabilities  2 - 0.5415496230125427
probabilities  3 - 0.5999882221221924
probabilities  4 - 0.9953547716140747
probabilities  5 - 0.9960086345672607
probabilities  6 - 0.778581440448761
probabilities  7 - 0.5086591839790344
probabilities  8 - 0.9984495639801025
probabilities  9 - 0.9285442233085632
```

Q2.4 Modify the generate function, again, so that it outputs, along with each word, the words that were the 6-most probable (the 6 highest probabilities) at each word output. Show the result in a table that gives all six words, along with their probabilities, in each column of the table. The number of columns in the table is the total number of generated words. For the first two words generated, explain if the probabilities in the table make sense, give the input corpus.

A-

Input prompt-He and I
Output table-



```
He and I can hold a dog. cat. dog and dog
top 6 words-  can hold rub holds and the |respective prob- [0.516, 0.3306, 0.1488, 0.0035, 0.0004, 0.0002]
top 6 words-  hold rub can the a holds |respective prob- [0.7092, 0.2888, 0.0015, 0.0001, 0.0001, 0.0001]
top 6 words-  a the and hold dog rub |respective prob- [0.5184, 0.4793, 0.0018, 0.0002, 0.0001, 0.0001]
top 6 words-  dog cat a . the. |respective prob- [0.5985, 0.4012, 0.0001, 0.0001, 0.0, 0.0]
top 6 words- . and . cat rub a |respective prob- [0.9979, 0.001, 0.0009, 0.0, 0.0, 0.0]
top 6 words-  cat dog a the and. |respective prob- [0.6004, 0.3947, 0.0018, 0.0014, 0.0013, 0.0003]
top 6 words- . and . rub cat can |respective prob- [0.9901, 0.0062, 0.0033, 0.0002, 0.0001, 0.0001]
top 6 words-  dog cat a the and rub |respective prob- [0.5295, 0.47, 0.0001, 0.0001, 0.0001, 0.0001]
top 6 words-  and. a the can rub |respective prob- [0.5187, 0.4788, 0.0008, 0.0007, 0.0004, 0.0003]
top 6 words-  dog cat and can holds a |respective prob- [0.8043, 0.1935, 0.0006, 0.0005, 0.0004, 0.0002]
```

Generated word	Top 6 words	probabilities
can	can hold rub holds and the	[0.516, 0.3306, 0.1488, 0.0035, 0.0004, 0.0002]

hold	hold rub can the a holds	[0.7092, 0.2888, 0.0015, 0.0001, 0.0001, 0.0001]
a	a the and hold dog rub	[0.5184, 0.4793, 0.0018, 0.0002, 0.0001, 0.0001]
dog	dog cat a . the.	[0.5985, 0.4012, 0.0001, 0.0001, 0.0, 0.0]
.	. and . cat rub a	[0.9979, 0.001, 0.0009, 0.0, 0.0, 0.0]
cat	cat dog a the and.	[0.6004, 0.3947, 0.0018, 0.0014, 0.0013, 0.0003]
.	. and . rub cat can	[0.9901, 0.0062, 0.0033, 0.0002, 0.0001, 0.0001]
dog	dog cat a the and rub	[0.5295, 0.47, 0.0001, 0.0001, 0.0001, 0.0001]
and	and. a the can rub	[0.5187, 0.4788, 0.0008, 0.0007, 0.0004, 0.0003]
dog	dog cat and can holds a	[0.8043, 0.1935, 0.0006, 0.0005, 0.0004, 0.0002]

We can see the table has 10 rows for the number of words created and each row contains the top 6 words for the word chosen and the respective probabilities.

For the first word can- we can see the top 2 words are can, hold which both of fairly high probability as they both can come there are both those options make sense. Rub also has a 14% probability as it also makes sense. The last 3 words – holds, and, the have very low probabilities as they don't make sense in this place.

For the second word hold- we can see the top 2 words are hold, rub which both have high probability as they both can make sense after 'He and I can'. Now we can see the last 4 words all have very low probabilities as they will not make sense after 'He and I can'.

Q3.1 Report which of these two methods you used - trained yourself, or loaded the saved model.

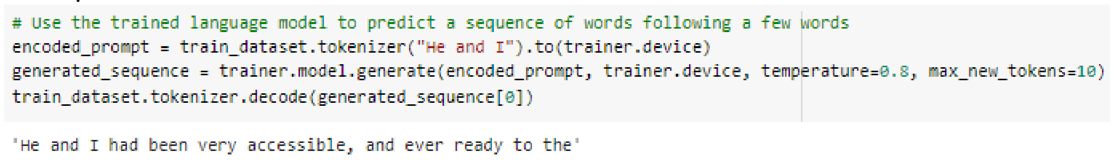
A-

The model was trained with the hyperparameters mentioned in the question. It was trained by myself.

Q3.2 Check that this model can generate words by seeding the generate function with a few examples different from the ones given. Report the examples you used and the generation results, and comment on the quality of the sentences.

A-

Prompt- He and I



```
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encoded_prompt = train_dataset.tokenizer("He and I").to(trainer.device)
generated_sequence = trainer.model.generate(encoded_prompt, trainer.device, temperature=0.8, max_new_tokens=10)
train_dataset.tokenizer.decode(generated_sequence[0])
```
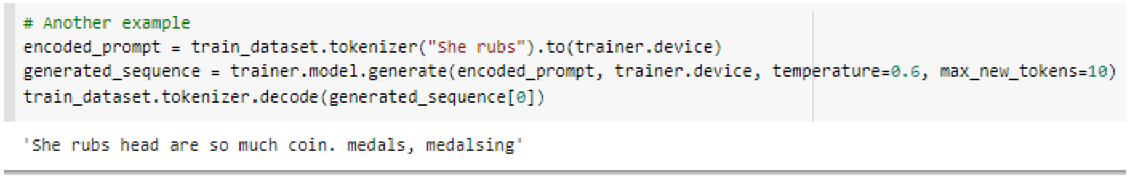

```
'He and I had been very accessible, and ever ready to the'
```

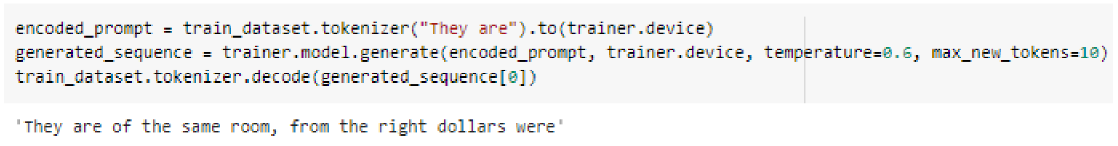
Prompt- She rubs



```
# Another example
encoded_prompt = train_dataset.tokenizer("She rubs").to(trainer.device)
generated_sequence = trainer.model.generate(encoded_prompt, trainer.device, temperature=0.6, max_new_tokens=10)
train_dataset.tokenizer.decode(generated_sequence[0])
```

```
'She rubs head are so much coin. medals, medalsing'
```

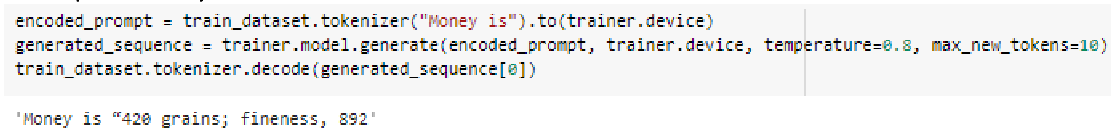
Prompt- They are



```
encoded_prompt = train_dataset.tokenizer("They are").to(trainer.device)
generated_sequence = trainer.model.generate(encoded_prompt, trainer.device, temperature=0.6, max_new_tokens=10)
train_dataset.tokenizer.decode(generated_sequence[0])
```

```
'They are of the same room, from the right dollars were'
```

Prompt- Money is



```
encoded_prompt = train_dataset.tokenizer("Money is").to(trainer.device)
generated_sequence = trainer.model.generate(encoded_prompt, trainer.device, temperature=0.8, max_new_tokens=10)
train_dataset.tokenizer.decode(generated_sequence[0])
```

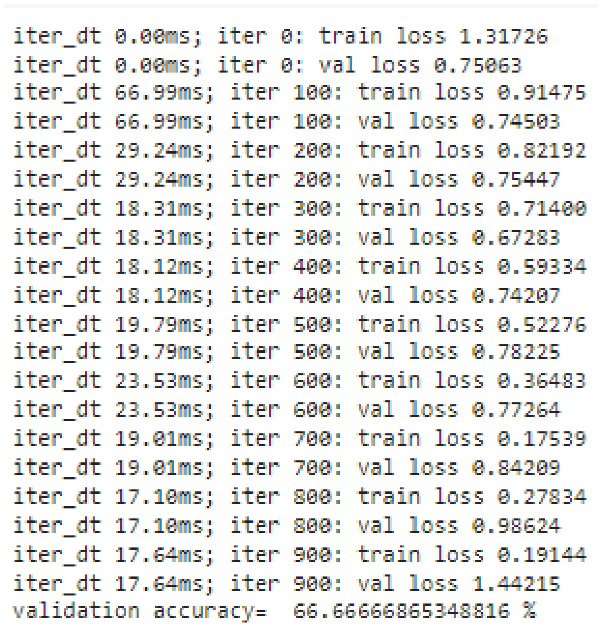
```
'Money is "420 grains; fineness, 892'
```

All the prompts have something to do with money/ currency as this was the dataset this model was trained with. But the answers don't make sense logically or grammatically as the training data is not extensive enough to capture the complete understanding of general prompts.

Q3.3 Report the training and validation curves for the fine-tuning, and the accuracy achieved on the validation dataset.

A-

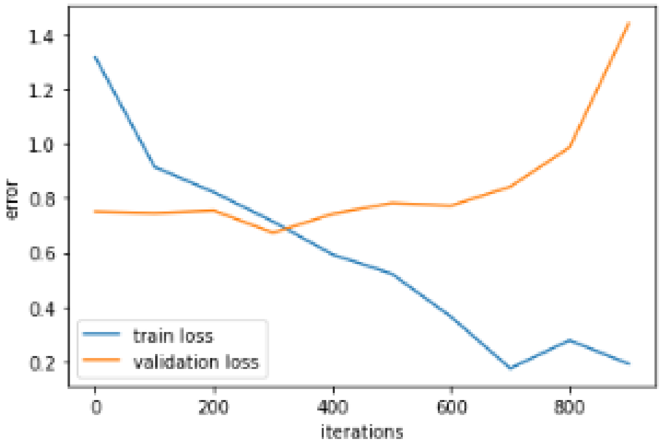
Training and final validation accuracy-



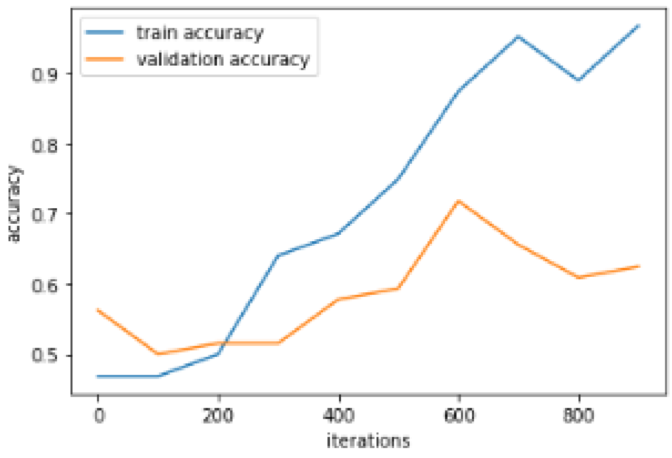
```
iter_dt 0.00ms; iter 0: train loss 1.31726
iter_dt 0.00ms; iter 0: val loss 0.75063
iter_dt 66.99ms; iter 100: train loss 0.91475
iter_dt 66.99ms; iter 100: val loss 0.74503
iter_dt 29.24ms; iter 200: train loss 0.82192
iter_dt 29.24ms; iter 200: val loss 0.75447
iter_dt 18.31ms; iter 300: train loss 0.71400
iter_dt 18.31ms; iter 300: val loss 0.67283
iter_dt 18.12ms; iter 400: train loss 0.59334
iter_dt 18.12ms; iter 400: val loss 0.74207
iter_dt 19.79ms; iter 500: train loss 0.52276
iter_dt 19.79ms; iter 500: val loss 0.78225
iter_dt 23.53ms; iter 600: train loss 0.36483
iter_dt 23.53ms; iter 600: val loss 0.77264
iter_dt 19.01ms; iter 700: train loss 0.17539
iter_dt 19.01ms; iter 700: val loss 0.84209
iter_dt 17.10ms; iter 800: train loss 0.27834
iter_dt 17.10ms; iter 800: val loss 0.98624
iter_dt 17.64ms; iter 900: train loss 0.19144
iter_dt 17.64ms; iter 900: val loss 1.44215
validation accuracy=  66.66666865348816 %
```

Validation accuracy of- 66.66%

Training curves-
Loss-



Accuracy-



Q4.2 Report the classification accuracy on the validation set. Comment on the performance of this model: is it better than the model you fine-tuned in the previous section?

A-

Model used- sshleifer/tiny-gpt2

Batch size- 16

Epochs- 50

Final training loss- `0.69141072591145 84`

Final validation accuracy- 0.541667

This huggingface model performed worse than the fine-tuned model in the previous section. The fine-tuned model was able to overfit to the training data where as this simple model from hugging face was not able to. This was an indicator the huggingface model does not have enough parameters. If we use a bigger model such as gpt2- medium or gpt2 we would get much better results but due to GPU limitations I ran it on the simplest model.

Hence it ended up with an accuracy of 0.54 whereas the fine-tuned model has an accuracy of 0.66