

ECE-60146 HW10

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1 Loss Graphs

I ran the two scripts seq2seq with transformerFG.py seq2seq with transformerPreLN.py with the default hyperparameters for the specified 40 epochs. I added the function to calculate the Leveshtein distance in the run_code_for_evaluating_Transformer function of DLStudio to print the outputs of the Leveshtein distance on the cleaned gt and predicted outputs

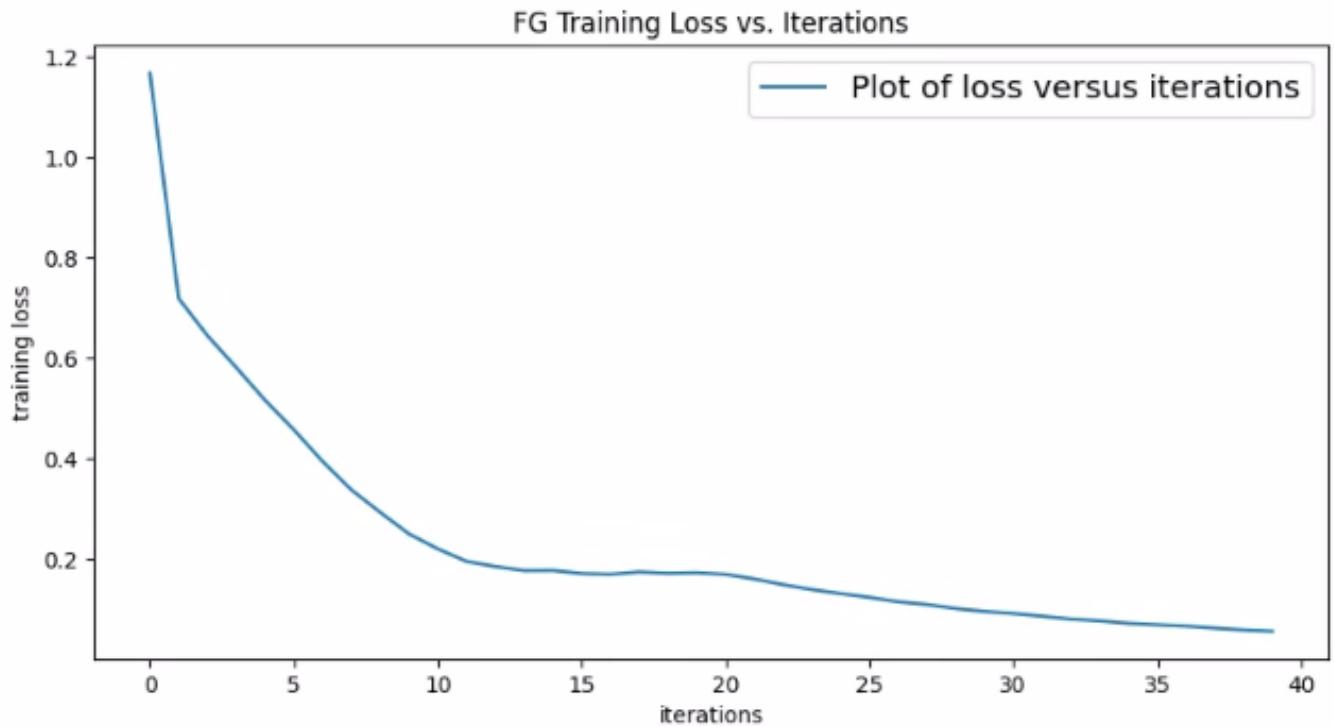


Figure 1: FG training loss

PreLN Training Loss vs. Iterations

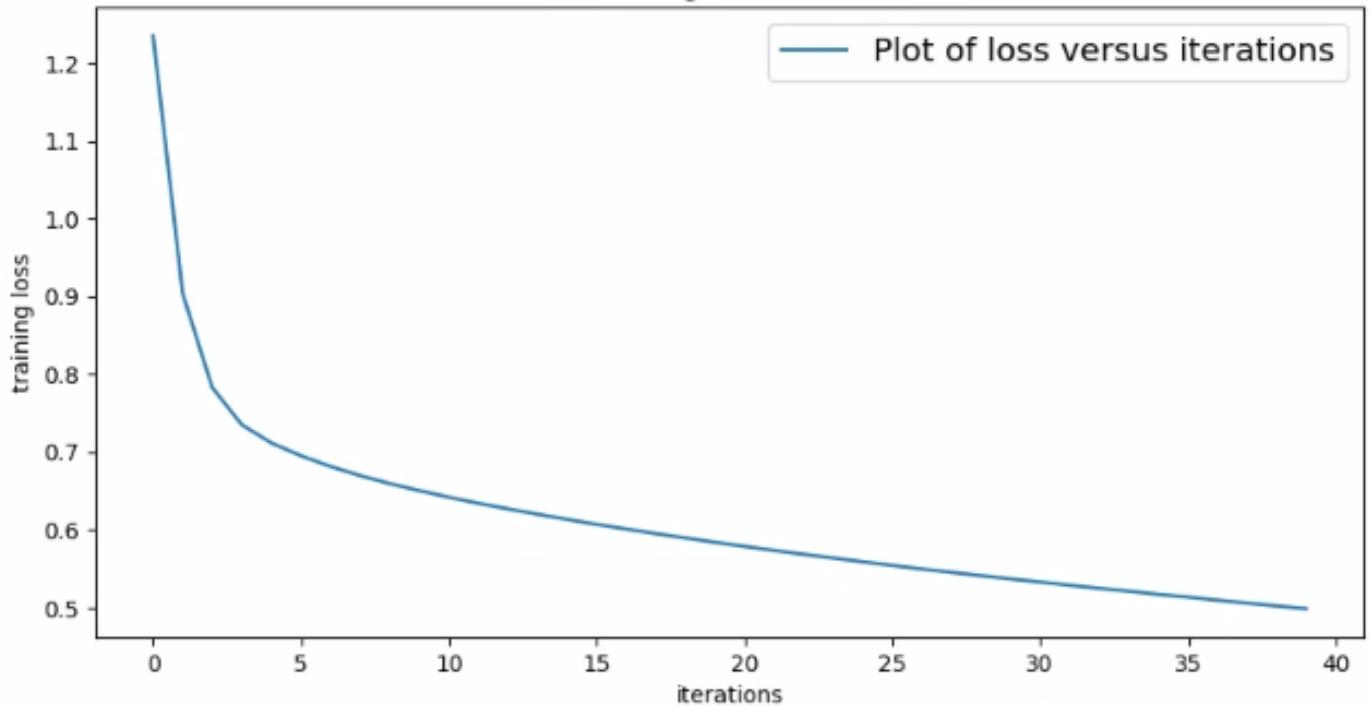


Figure 2: PreLN training loss

2 Output and Levenshtein distance

```
The input sentence pair: ['SOS why is this room locked EOS'] ['SOS por qué está con llave esta habitación EOS']  
The translation produced by TransformerFG: EOS por qué está con con esta habitación EOS EOS  
The ground truth clean: por qué está con con esta habitación  
The translation produced by TransformerFG clean: por qué está con con esta habitación  
Levenshtein distance: 5
```

Figure 3: FG example with cleaned string and Levenshtein distance

```
The input sentence pair: ['SOS no one lives in this building EOS'] ['SOS nadie vive en este edificio EOS']  
The translation produced by TransformerFG: EOS nadie vive en este edificio EOS EOS EOS EOS  
The ground truth clean: nadie vive en este edificio  
The translation produced by TransformerFG clean: nadie vive en este edificio  
Levenshtein distance: 0
```

Figure 4: FG example with cleaned string and Levenshtein distance

```

The input sentence pair: ['SOS you were busy last week EOS'] ['SOS la semana pasada estuviste ocupado EOS']
The translation produced by TransformerFG: EOS la semana pasada estuviste ocupado EOS EOS EOS EOS
The ground truth clean: la semana pasada estuviste ocupado
The translation produced by TransformerFG clean: la semana pasada estuviste ocupado
Levenshtein distance: 0

```

Figure 5: FG example with cleaned string and Levenshtein distance

```

The input sentence pair: ['SOS i need my glasses EOS'] ['SOS necesito mis gafas EOS']
The translation produced by TransformerFG: EOS necesito mis gafas EOS EOS EOS EOS EOS EOS EOS
The ground truth clean: necesito mis gafas
The translation produced by TransformerFG clean: necesito mis gafas
Levenshtein distance: 0

```

Figure 6: FG example with cleaned string and Levenshtein distance

```

The input sentence pair: ['SOS i have not been able to sleep well EOS'] ['SOS no he podido dormir bien EOS']
The translation produced by TransformerFG: EOS no he podido dormir bien EOS EOS EOS EOS EOS
The ground truth clean: no he podido dormir bien
The translation produced by TransformerFG clean: no he podido dormir bien
Levenshtein distance: 0

```

Figure 7: FG example with cleaned string and Levenshtein distance

```

The input sentence pair: ['SOS do you travel a lot EOS'] ['SOS viajáis mucho EOS']
The translation produced by TransformerPreLN: SOS te EOS EOS EOS EOS EOS EOS EOS EOS
The ground truth clean: te
The translation produced by TransformerFG clean: te
Levenshtein distance: 13

```

Figure 8: PreLN example with cleaned string and Levenshtein distance

```

The input sentence pair: ['SOS i forgot i owed you money EOS'] ['SOS olvidé que te debia dinero EOS']
The translation produced by TransformerPreLN: SOS me EOS EOS EOS EOS EOS EOS EOS EOS EOS
The ground truth clean: me
The translation produced by TransformerFG clean: me
Levenshtein distance: 25

```

Figure 9: PreLN example with cleaned string and Levenshtein distance

```
The input sentence pair: ['SOS i guess it is true EOS'] ['SOS supongo que es verdad EOS']  
The translation produced by TransformerPreLN: SOS yo EOS EOS EOS EOS EOS EOS EOS EOS  
The ground truth clean: yo  
The translation produced by TransformerFG clean: yo  
Levenshtein distance: 20
```

Figure 10: PreLN example with cleaned string and Levenshtein distance

```
The input sentence pair: ['SOS i meet a lot of people EOS'] ['SOS conozco a mucha gente EOS']  
The translation produced by TransformerPreLN: SOS me EOS EOS EOS EOS EOS EOS EOS EOS EOS  
The ground truth clean: me  
The translation produced by TransformerFG clean: me  
Levenshtein distance: 19
```

Figure 11: PreLN example with cleaned string and Levenshtein distance

```
The input sentence pair: ['SOS i can ride a horse EOS'] ['SOS puedo montar un caballo EOS']  
The translation produced by TransformerPreLN: SOS puedo EOS EOS EOS EOS EOS EOS EOS EOS EOS  
The ground truth clean: puedo  
The translation produced by TransformerFG clean: puedo  
Levenshtein distance: 18
```

Figure 12: PreLN example with cleaned string and Levenshtein distance

TransformerFG Statistics:

Mean: 2.45

Median: 0.00

Standard Deviation: 3.65

Maximum: 12.00

Minimum: 0.00

TransformerLN Statistics:

Mean: 23.35

Median: 23.50

Standard Deviation: 6.20

Maximum: 35.00

Minimum: 13.00

Figure 13: 2x5 Table of metrics

3 Discussion

The mean, and standard deviation of the transformerFG is lower indicating that the model is more accurate and that its consistency is higher than the PreLN model. The median of the model is 0 indicating at least half the translations were completely accurate. PreLN Normalizes the input before it enters the selfattention layer so it will take longer to converge. In theory it is supposed to perform better if the training is allowed to go on for a longer duration of time.

```
def levenshtein_distance(self, str1, str2):
    if len(str1) < len(str2):
        str1, str2 = str2, str1 # Ensure str1 is the longer string
    len_str1, len_str2 = len(str1), len(str2)
    # Initialize two rows for dynamic programming
    previous_row = list(range(len_str2 + 1))
    current_row = [0] * (len_str2 + 1)

    for i in range(1, len_str1 + 1):
        current_row[0] = i
        for j in range(1, len_str2 + 1):
            cost = 0 if str1[i - 1] == str2[j - 1] else 1
            current_row[j] = min(
                previous_row[j] + 1,          # Deletion
                current_row[j - 1] + 1,      # Insertion
                previous_row[j - 1] + cost # Substitution
```

```

        )
previous_row, current_row = current_row, previous_row

return previous_row[-1]

def run_code_for_evaluating_TransformerFG(self, master_encoder, master_decoder, result_file=None):
    """
    The main difference between the training code shown in the previous function and the
    evaluation code shown here is with regard to the input to MasterDecoder and how we
    process its output. As shown in the previous function, for the training loop, the
    input to MasterDecoder consists of the both the target sentence and the output of
    the MasterEncoder for the source sentence. However, at inference time (that is, in
    the evaluation loop shown below), the target sentence at the input to the MasterDecoder
    is replaced by an encoding of a "starter stub" output sentence as defined in line (B).
    The main message conveyed by the stub in line (B) is that we want to start the
    translation with the first word of the output as being the token "SOS". The encoding
    for the stub is generated in lines (F) and (G).

    The second significant difference between the training and the testing code is
    with regard to how we process the output of the MasterDecoder. As you will recall
    from the docstring associated with MasterDecoder, it returns two things: (1) the
    predicted log probabilities (logprob) over the target vocabulary for every word
    position in the target language; and (2) for each target-language word position,
    the word_vocab_index at which the logprob is maximum. The loss calculation in
    the training code was based on the former. ON the other hand, as shown in line (H)
    below, it is the latter that lets us do the the translations in the target words
    in line (I).
    """
    master_encoder.load_state_dict(torch.load(self.dl_studio.path_saved_model['encoder_FG']))
    master_decoder.load_state_dict(torch.load(self.dl_studio.path_saved_model['decoder_FG']))
    embeddings_generator_en = self.EmbeddingsGenerator(self, 'en', self.embedding_size)
    embeddings_generator_es = self.EmbeddingsGenerator(self, 'es', self.embedding_size)

    → embeddings_generator_en.load_state_dict(torch.load(self.dl_studio.path_saved_model['embeddings_generator_en']))

    → embeddings_generator_es.load_state_dict(torch.load(self.dl_studio.path_saved_model['embeddings_generator_es']))
    master_encoder.to(self.dl_studio.device)
    master_decoder.to(self.dl_studio.device)
    embeddings_generator_en.to(self.dl_studio.device)
    embeddings_generator_es.to(self.dl_studio.device)
    debug = False
    FILE = open("translations_with_FG_" + str(self.dl_studio.epochs) + ".txt", 'w')
    with torch.no_grad():
        for iter in range(20):
            starter_stub_for_translation = ['SOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS',
                → 'EOS']      ## (A)
            batched_pairs = random.sample(self.training_corpus, 1)
            → ## (B)
            source_sentences = [pair[0] for pair in batched_pairs]
            target_sentences = [pair[1] for pair in batched_pairs]
            if debug:
                print("\n\nsource sentences: ", source_sentences)
                print("\ntarget sentences: ", target_sentences)
            en_sent_ints = self.sentence_with_words_to_ints(source_sentences,
                → 'en').to(self.dl_studio.device)      ## (C)
            if debug:
                es_sent_ints = self.sentence_with_words_to_ints(target_sentences, 'es')
                print("\n\nsource sentence tensor: ", en_sent_ints)
                print("\n\ntarget sentence tensor: ", es_sent_ints)
            en_sentence_tensor = embeddings_generator_en(en_sent_ints).float()
            master_encoder_output = master_encoder(en_sentence_tensor)
            → ## (E)
            starter_stub_as_ints = self.sentence_with_words_to_ints(
                [" ".join(starter_stub_for_translation)], 'es').to(self.dl_studio.device)
            → ## (F)
            starter_stub_tensor = embeddings_generator_es(starter_stub_as_ints).float()
            → ## (G)

```

```

_, predicted_word_index_values = master_decoder(starter_stub_tensor, master_encoder_output)
→ ## (H)
predicted_word_index_values = predicted_word_index_values[0].unsqueeze(1)
decoded_words = [self.es_index_2_word[predicted_word_index_values[di].item()]]
for di in range(self.max_seq_length)
→ ## (I)
output_sentence = " ".join(decoded_words)
print("\n\n\nThe input sentence pair: ", source_sentences, target_sentences)
print("\nThe translation produced by TransformerFG: ", output_sentence)
FILE.write("\n\n\nThe input sentence pair: %s %s" % (source_sentences, target_sentences))
FILE.write("\nThe translation produced by TransformerFG: %s" % output_sentence)
decoded_words = [word for word in decoded_words if word not in ['SOS', 'EOS']]
target_tokens = target_sentences[0].split()
output_sentence = " ".join(decoded_words)
target_tokens = [word for word in target_tokens if word not in ['SOS', 'EOS']]
ground_truth = " ".join(target_tokens)
lev_distance = self.levenshtein_distance(output_sentence, ground_truth)
print("\nThe ground truth clean: ", output_sentence)
print("\nThe translation produced by TransformerFG clean: ", output_sentence)
print("\nLevenshtein distance: ", lev_distance)

```

```

def levenshtein_distance(self, str1, str2):
    if len(str1) < len(str2):
        str1, str2 = str2, str1 # Ensure str1 is the longer string
    len_str1, len_str2 = len(str1), len(str2)
    # Initialize two rows for dynamic programming
    previous_row = list(range(len_str2 + 1))
    current_row = [0] * (len_str2 + 1)

    for i in range(1, len_str1 + 1):
        current_row[0] = i
        for j in range(1, len_str2 + 1):
            cost = 0 if str1[i - 1] == str2[j - 1] else 1
            current_row[j] = min(
                previous_row[j] + 1, # Deletion
                current_row[j - 1] + 1, # Insertion
                previous_row[j - 1] + cost # Substitution
            )
        previous_row, current_row = current_row, previous_row

    return previous_row[-1]

def run_code_for_evaluating_TransformerPreLN(self, master_encoder, master_decoder):
    """
    The main difference between the training code shown in the previous function and the
    evaluation code shown here is with regard to the input to MasterDecoder and how we process
    its output. As shown in the previous function, for the training loop, the input to
    MasterDecoder consists of the both the target sentence and the output of the MasterEncoder
    for the source sentence. However, at inference time (that is, in the evaluation loop shown
    below), the target sentence at the input to the MasterDecoder is replaced by an encoding of
    a "starter stub" output sentence as defined in line (B). The main message conveyed by the
    stub in line (B) is that we want to start the translation with the first word of the output
    as being the token "SOS". The encoding for the stub is generated in lines (F) and (G).
    """
    The second significant difference between the training and the testing code is with regard
    to how we process the output of the MasterDecoder. As you will recall from the docstring
    associated with MasterDecoder, it returns two things: (1) the predicted log probabilities
    (logprob) over the target vocabulary for every word position in the target language; and
    (2) for each target-language word position, the word_vocab_index at which the logprob is
    maximum. The loss calculation in the training code was based on the former. ON the other
    hand, as shown in line (H) below, it is the latter that lets us do the the translations in
    the target words in line (I).
    """
    master_encoder.load_state_dict(torch.load(self.dl_studio.path_saved_model['encoder_PreLN']))
    master_decoder.load_state_dict(torch.load(self.dl_studio.path_saved_model['decoder_PreLN']))
    embeddings_generator_en = self.EmbeddingsGenerator(self, 'en', self.embedding_size)

```

```

embeddings_generator_es = self.EmbeddingsGenerator(self, 'es', self.embedding_size)

→ embeddings_generator_en.load_state_dict(torch.load(self.dl_studio.path_saved_model['embeddings_generator_en_'])

↪ embeddings_generator_es.load_state_dict(torch.load(self.dl_studio.path_saved_model['embeddings_generator_es_'
master_encoder.to(self.dl_studio.device)
master_decoder.to(self.dl_studio.device)
embeddings_generator_en.to(self.dl_studio.device)
embeddings_generator_es.to(self.dl_studio.device)
debug = False
FILE = open("translations_with_PreLN_" + str(self.dl_studio.epochs) + ".txt", 'w')
with torch.no_grad():
    for iter in range(20):
        starter_stub_for_translation = ['SOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS', 'EOS',
        → 'EOS']      ## (A)
        batched_pairs = random.sample(self.training_corpus, 1)
        → ## (B)
        source_sentences = [pair[0] for pair in batched_pairs]
        target_sentences = [pair[1] for pair in batched_pairs]
        if debug:
            print("\n\nsource sentences: ", source_sentences)
            print("\n\ntarget sentences: ", target_sentences)
        en_sent_ints = self.sentence_with_words_to_ints(source_sentences, 'en')
        → ## (C)
        if debug:
            es_sent_ints = self.sentence_with_words_to_ints(target_sentences, 'es')
            print("\n\nsource sentence tensor: ", en_sent_ints)
            print("\n\n\ttarget sentence tensor: ", es_sent_ints)
        en_sentence_tensor = embeddings_generator_en(en_sent_ints).float()
        master_encoder_output = master_encoder(en_sentence_tensor)
        → ## (E)
        starter_stub_as_ints = self.sentence_with_words_to_ints(
            [" ".join(starter_stub_for_translation)],
            → 'es').to(self.dl_studio.device)      ## (F)
        starter_stub_tensor = embeddings_generator_es(starter_stub_as_ints).float()
        → ## (G)
        _, predicted_word_index_values = master_decoder(starter_stub_tensor, master_encoder_output)
        → ## (H)
        predicted_word_index_values = predicted_word_index_values[0].unsqueeze(1)
        decoded_words = [self.es_index_2_word[predicted_word_index_values[di].item()]
            for di in range(self.max_seq_length)]
            → ## (I)
        output_sentence = " ".join(decoded_words)
        print("\n\nThe input sentence pair: ", source_sentences, target_sentences)
        print("\n\nThe translation produced by TransformerPreLN: ", output_sentence)
        FILE.write("\n\n\nThe input sentence pair: %s %s" % (source_sentences, target_sentences))
        FILE.write("\n\nThe translation produced by TransformerPreLN: %s" % output_sentence)
        decoded_words = [word for word in decoded_words if word not in ['SOS', 'EOS']]
        output_sentence = " ".join(decoded_words)
        target_tokens = target_sentences[0].split()
        target_tokens = [word for word in target_tokens if word not in ['SOS', 'EOS']]
        ground_truth = " ".join(target_tokens)
        lev_distance = self.levenshtein_distance(output_sentence, ground_truth)
        print("\n\nThe ground truth clean: ", output_sentence)
        print("\n\nThe translation produced by TransformerPreLN clean: ", output_sentence)
        print("\n\nLevenshtein distance: ", lev_distance)

```