EXPERIMENT 5

GitHub Link : https://github.com/Adiiii02/DL-LAB/tree/main/EXP-5

EXPERIMENT OBJECTIVE

To implement a Sequence-to-Sequence (Seq2Seq) model for English-to-Spanish translation using LSTM networks. This experiment explores two major architectures:

1. LSTM Encoder-Decoder without Attention
2. LSTM Encoder-Decoder with Attention:
   - Bahdanau (Additive) Attention
   - Luong (Multiplicative) Attention

Each model is evaluated using BLEU scores and visualizations on the English-Spanish Dataset.

DATA PREPROCESSING

Loading the Dataset

- The dataset is loaded from a .txt file (spa.txt) containing English-Spanish sentence pairs separated by tabs.
- Each line is parsed to extract one English and one Spanish sentence.
- Sentences are lowercased , stripped of whitespace, and cleaned using regex to remove punctuation and special characters.

Tokenization and Vocabulary Creation

- Sentences are tokenized using NLTK's `word_tokenize`
- Special tokens <sos>, <eos>, <pad>, and <unk> are added.
- Two vocabularies are created:
  - input_vocab for English
  - target_vocab for Spanish
- Each word is mapped to a unique index using `word_to_index`, and reverse lookup is maintained with `index_to_word`.

Generating Training Sequences

- Each sentence is converted into a sequence of integer tokens.
- Spanish target sentences are wrapped with <sos> and <eos> tokens for decoder input and output.
- Sentences are padded to match the maximum sequence length in the batch using PyTorch's pad_sequence() .

Dataset Splitting

- From the cleaned and tokenized dataset:
  - 80% is used for training
  - 10% for validation
  - 10% for testing
- Data is shuffled before splitting to ensure randomness.

NEURAL NETWORK IMPLEMENTATION

LSTM Encoder-Decoder Without Attention

Architecture

- **Input Layer:** Token indices passed into an embedding layer.
- **Encoder:**
    - **Embedding Layer:** Maps input token indices to dense vector representations.
    - **LSTM Layer:** Processes the input sequence and returns final hidden and cell states.
- **Decoder:**
    - **Embedding Layer:** Converts target input tokens to embeddings.
    - **LSTM Layer:** Initialized with encoder's final states; generates decoder outputs.
    - **Fully Connected Layer:** Maps LSTM outputs to the target vocabulary space for word prediction.

Weight Initialization

- Weights in LSTM and fully connected layers are initialized randomly.

Activation Functions

- **Tanh:** Used inside the LSTM units.
- **Softmax:** Applied to the output layer to generate word probability distributions.

Regularization

- Dropout (0.5) is applied in embedding layers of both encoder and decoder to prevent overfitting.
- Padding tokens are ignored in both attention weights and loss calculations using ignore_index=<pad> in the loss function.

LSTM Encoder-Decoder With Attention

Architecture

- **Input Layer**: Input and target sequences are processed through embedding layers.
- **Encoder**:
    - **Embedding Layer**: Converts token indices to embeddings.
    - **Bidirectional GRU Layer**: Processes the input sequence in both forward and backward directions and outputs all hidden states, which are used by the attention mechanism.

- **Attention Layer**:
    - Computes attention scores between current decoder state and encoder outputs.
    - Generates a context vector as a weighted sum of encoder hidden states.
- **Decoder**:
    - **Embedding Layer**: Same as above.
    - **GRU Layer**: Accepts embedded input + context vector.
    - **Fully Connected Layer**: Maps decoder output to the vocabulary size.

Weight Initialization

- Weights are initialized randomly.

Activation Functions

- **Tanh**: Used in combining hidden states in the encoder and in the attention mechanism.
- **Softmax**:
    - Applied to attention scores to compute weights.
    - Applied to final decoder output for word prediction.

Regularization

- Dropout (0.5) is applied in embedding layers of both encoder and decoder to prevent overfitting.
- Padding tokens are ignored in both attention weights and loss calculations using ignore_index=<pad> in the loss function.

TRAINING CONFIGURATION

Training the Model

- **Loss Function**: Cross-Entropy Loss
- **Optimizer**: Adam Optimizer
- **Learning Rate**: 0.001
- **Epochs**: 25
- **Batch Size**: 64
- **Teacher Forcing Ratio:** 0.5 (50% chance of using ground truth vs predicted token during training)

Training Process

- Training is performed using **Teacher Forcing**:
    - At each timestep, the actual target word is fed into the decoder during training instead of the predicted word.
- For both models:
    - Encoder processes the source sentence and generates hidden states.
    - Decoder uses those hidden states (and attention context, if applicable) to predict the target sentence.
    - Gradients are computed using backpropagation.
    - Weights are updated using the Adam optimizer.
- Validation is performed at the end of each epoch to monitor overfitting and performance.

TRAINING AND RESULTS

Key Performance Metrics

LSTM Encoder-Decoder without Attention:

- Slower convergence across epochs.
- Struggles with longer or more complex sentence structures.
- Final loss increases toward the end, indicating some instability or overfitting.
- **Final Val Loss:** 4.648
- **BLEU Score:** 0.080

LSTM Encoder-Decoder with Attention:

- **Bahdanau Attention:**
    - Faster and smoother convergence in early epochs.
    - Final loss is lower than both the vanilla model .
    - Generated translations are more fluent and contextually aware.
    - **Final Val Loss:** 4.1747
    - **BLEU Score:** 0.085

- **Luong Attention:**
    - Demonstrates better BLEU performance compared to Bahdanau.
    - Efficient attention computation using dot-product leads to competitive training times.
    - Slightly lower loss than Bahdanau and better sentence-level translation accuracy.
    - **Final Val Loss:** 3.8446
    - **BLEU Score:** 0.1093

Evaluation Results

Model	Final Loss	BLEU Score
LSTM Encoder-Decoder (No Attention)	4.648	0.080
LSTM with Bahdanau Attention	4.1747	0.085
LSTM with Luong Attention	3.8446	0.1093

TRANSLATION GENERATION

Process

- A function is implemented to generate Spanish translations from a given English input sentence.
- The input sentence is tokenized and passed through the encoder to extract context vectors.
- The decoder then predicts the next token iteratively, using:
    - Just the final encoder state in the Vanilla (no attention) model
    - Encoder hidden states + attention scores in the Bahdanau and Luong models
- The process stops when the <eos> token is generated, or max length is reached.
- Translations generated by attention models are more coherent and contextually aligned.

Example Output

Input Sentence :-

“I am fine “

Generated Translation (Encoder-Decoder without Attention): -

"soy muy carro"

Input Sentence :-

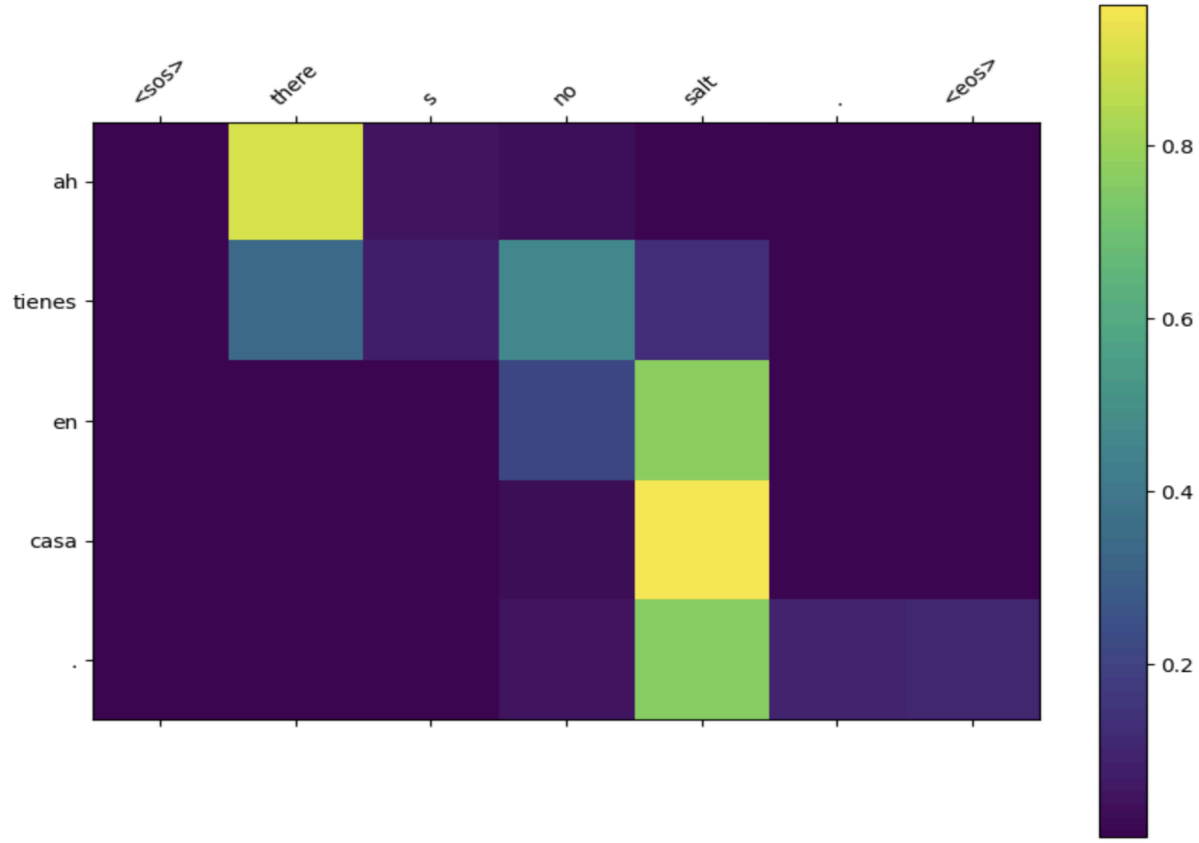
“ there s no salt“

Generated Translation (Bahdanau Attention): "ah tienes en casa"

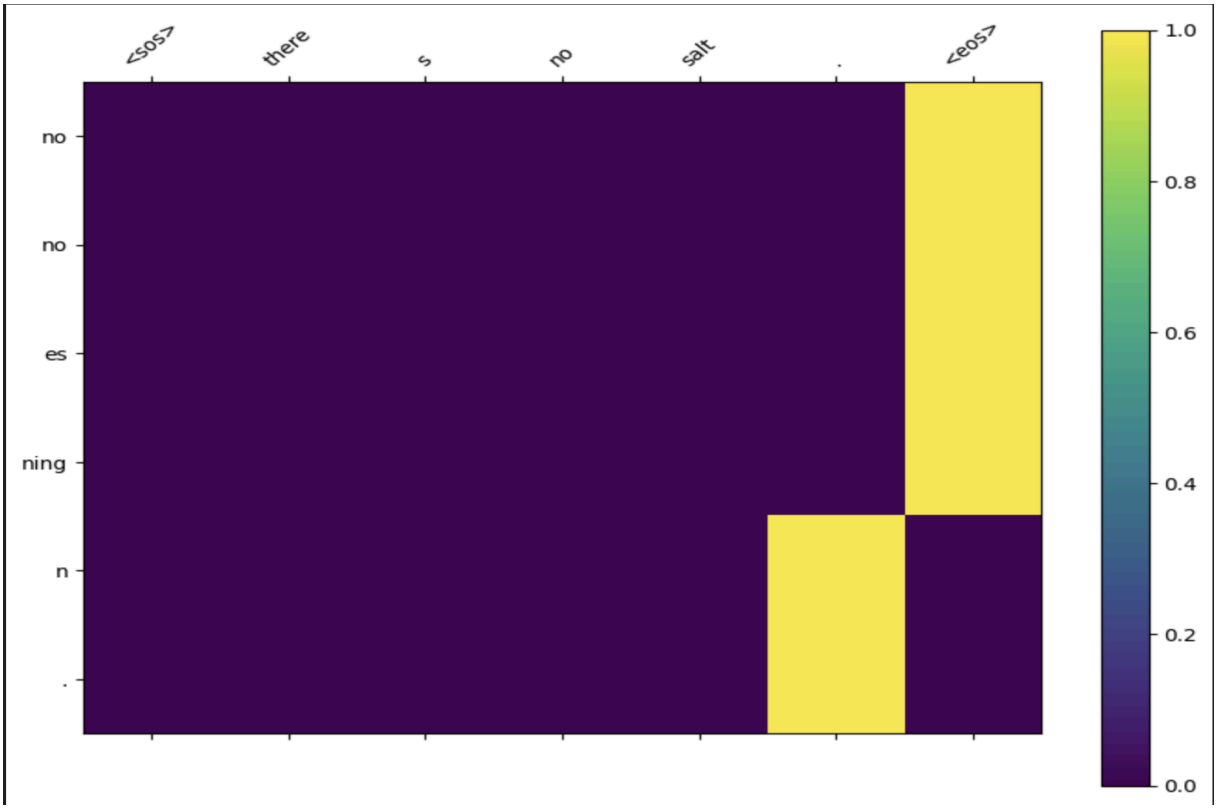
Generated Translation (Luong Attention): "no no es ning n ."

VISUALIZATIONS

/ç¡# Bahdanau Attention:



/¡ #ç Luong Attention:



OBSERVATIONS AND CONCLUSIONS

- The use of attention mechanisms (Bahdanau and Luong) leads to significantly lower loss and higher BLEU scores than the vanilla encoder-decoder.
- Bahdanau attention shows slight performance superiority for longer sentences due to its additive and flexible scoring.
- Luong attention, while marginally ahead in BLEU score, provides competitive performance with slightly faster computation.
- The switch from one-hot encoding to embedding layers results in richer, more efficient token representation, enhancing translation quality.
- Improved BLEU scores clearly reflect better word alignment and more context-aware translations thanks to attention.

Potential Future Improvements:

- Integrate pretrained embeddings (e.g., GloVe, FastText) for semantic depth.
- Train on larger datasets to enhance generalization and robustness.
- Migrate to Transformer-based architectures for cutting-edge performance.