Report on Continuous Bag of Words (CBOW) Classifier Implementation and Training

The CBOW Model

Forward Pass

The `forward` method calculates the predictions. It averages the word embeddings for each context and applies a linear transformation followed by a softmax function to produce a probability distribution over the vocabulary.

Mathematically, this can be represented as:

$$\text{softmax}(\overline{E[X]}W + b) \tag{1}$$

Here, `E[X]` denotes the embedding lookup and `overline{E[X]}` represents the average embedding for the context words.

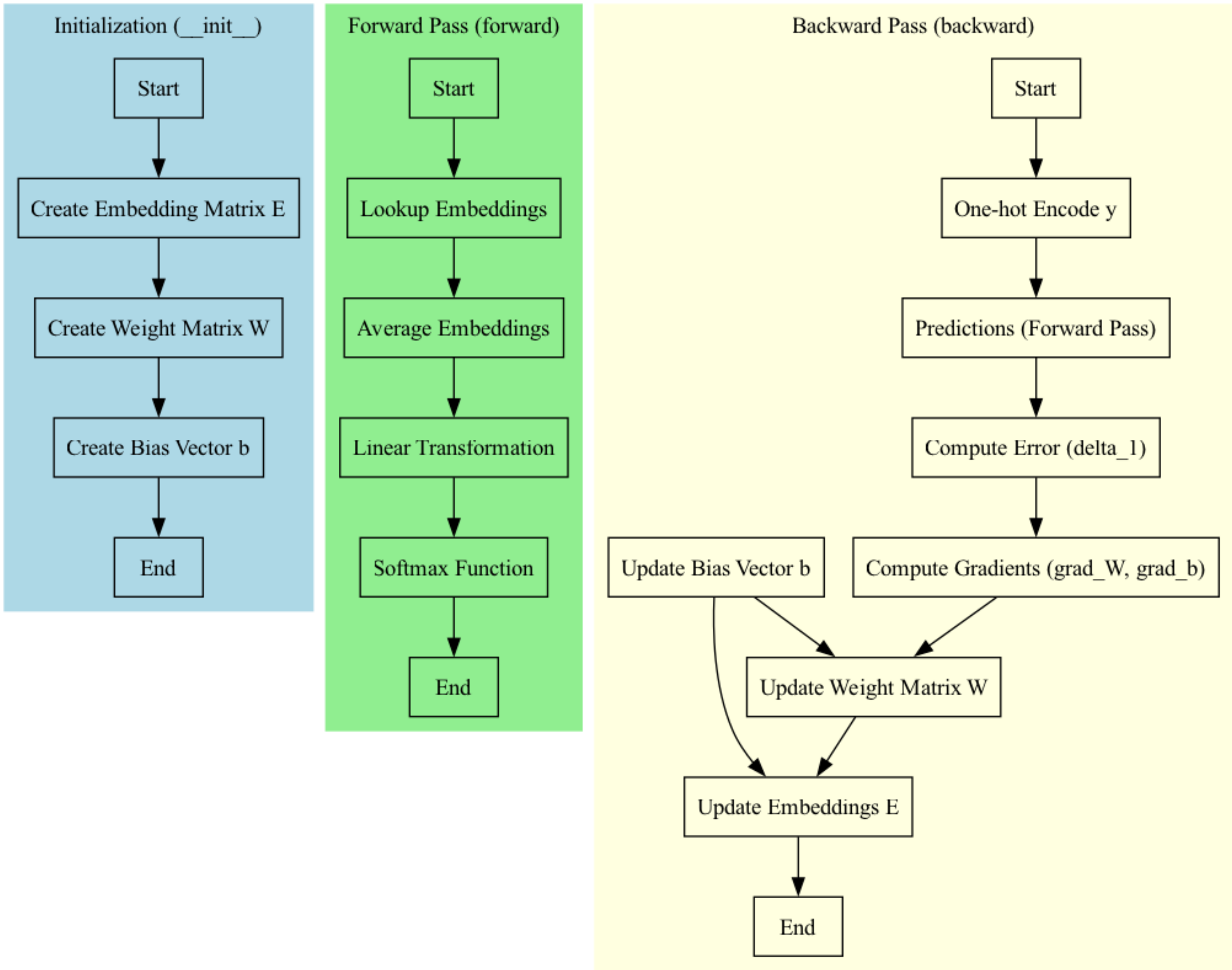
Backward Pass

In the `backward` method, the model updates its parameters based on the error between its predictions and the actual labels.

The gradients for updating the weights (`W`) and biases (`b`) are calculated as follows:

$$\begin{gathered} W := W - \frac{\eta}{B} \cdot (E[X]^T \delta_1) \\ b := b - \frac{\eta}{B} \cdot 1^T \delta_1 \end{gathered} \tag{2}$$

Where `delta_1` is the error from the softmax output, `η` is the learning rate, and `B` is the batch size.



Training Procedure

The `train` function is where the model learns from the data. It initializes the `CBOW` model and updates its parameters over several training epochs.

Minibatches

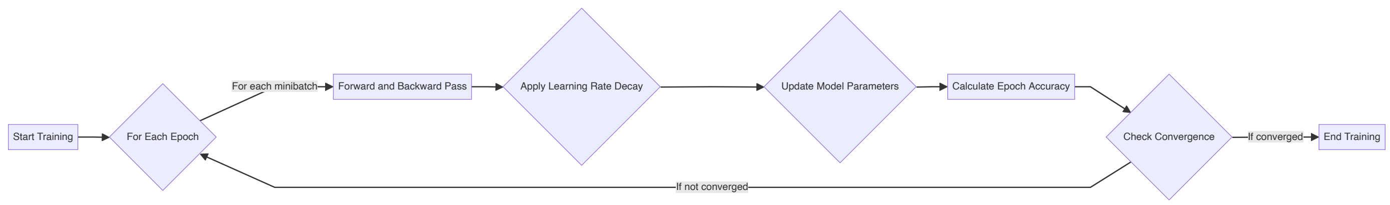
We use the concept of minibatches, which means updating the model parameters after processing a small subset of the data rather than the entire dataset at once.

Learning Rate Decay

A learning rate decay strategy is employed to reduce the learning rate by a certain percentage after each epoch.

Regularization

L2 regularization is applied to the model's parameter updates to mitigate overfitting, where a model learns the training data too closely and fails to generalize well to unseen data.



Conclusion

After the implementation of these components and training the model, we observed an improvement in accuracy from 23% to 34%(epoch = 20), 36%(epoch = 30). While this is a significant increase, further improvements are necessary to achieve higher target accuracy.