A.1

In 1.7, I used features such as word-overlap scores, semantic similarity metrics, and sentence-level embedding comparisons between summary and reference texts. These features are useful because word-overlap metrics capture lexical similarity which correlates strongly with coherence, while semantic similarity metrics help identify meaningful content similarity beyond surface-level matches, providing a deeper measure of coherence. Sentence embeddings further capture contextual and semantic information essential for assessing whether the generated summary logically aligns with the original reference.

A.2.1

In 2.6, my loss graph showed a steady decrease in both training and validation losses, with the validation loss closely tracking the training loss initially and then gradually plateauing. The similarity in these losses indicated that my chosen hyperparameters were appropriate, achieving good generalization without significant overfitting or underfitting. The convergence and minimal gap between training and validation losses confirmed that the model effectively learned meaningful patterns without excessive memorization or variance.

A.2.2

In 2.8, I developed an attention-enhanced feedforward neural network that explicitly captures fine-grained semantic interactions between question and context sentences. Unlike the basic FFNN model, which only relied on simple concatenations and linear layers, this improved model explicitly incorporates element-wise multiplication and absolute differences between embeddings, allowing it to effectively represent subtle semantic relationships. Additionally, I integrated an attention mechanism to dynamically weigh important features, helping the model focus more effectively on relevant interactions and significantly improving prediction accuracy and stability.