# Implementation of a Chatbot using Jupyter Python

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# Project Objective and Scope

- **Objective:** Developing a chatbot and enchancing its capabilities.
- **Scope:**
  - Implement sequence-to-sequence model using RNN with Luong attention mechanism.
  - Perform hyperparameter tuning using Bayesian optimization.
  - Experiment with alternate architectures like CNN and MLP.
  - Compare and contrast AI and non-AI approaches for chatbot functionality.
  - Explore integration with external datasets and business-related databases for practical application.

# Dataset Overview and Selection

- **Primary Dataset:** Cornell Movie-Dialogs Corpus [2]
- **Additional Databases and Models:**
  - Microsoft DialoGPT Models: Leveraged as pre-trained models (small and large) from Hugging Face.
  - Persona-Chat Dataset: Used to provide diverse and personalized conversational data.
  - Custom SQL Database: Contains product information on smart home equipment.
- **Challenges:**
  - Ensuring dataset diversity.
  - Data preprocessing methods.
  - Computation resources for training of the models

# Data Processing Pipeline

- **Data Cleaning and Normalization:** Convert text to lowercase, remove punctuation and special characters.
- **Stopword Removal:** Filter common words to reduce noise.
- **Lemmatization and Stemming:** Standardize words to their base/root forms.
- **Tokenization:** Split sentences into individual word tokens.
- **Data Augmentation:** Introduce diversity by randomly shuffling words in sentences.

# Model Implementation Approaches

- **Approach 1: Base Model**
  - RNN-based sequence-to-sequence with Luong attention mechanism.
  - Evaluation: BLEU score and Cosine Similarity.
- **Approach 2: Best Tuned Model with Hyperparameter Tuning**
  - RNN-based sequence-to-sequence with Luong attention.
  - Bayesian Optimization on set of hyperparameters
  - Evaluation: BLEU score and Cosine Similarity.
- **Approach 3: CNN-Based Model**
  - CNN encoder-decoder model without attention mechanism.
  - Evaluation: BLEU score and Cosine Similarity.
- **Approach 4: MLP-Based Model**
  - MLP encoder-decoder model without attention mechanism.
  - Evaluation: BLEU score and Cosine Similarity.

# Non-AI Methods and Alternate Database Approaches

- **Approach 5: Non-AI Methods**
  - Rule-Based Bot
  - Rule-Based with Cornell Movie-Dialogs Corpus dataset
  - Menu-Based Chatbots
- **Approach 6: Use of Alternate Database**
  - Model: RNN-based sequence-to-sequence with Luong attention mechanism.
  - Database: Persona-Chat.
  - Evaluation: BLEU score and Cosine Similarity.

# Transformer and Transfer Learning Approaches

- **Approach 7: Transformer-Based Model**
  - Model: Microsoft's DialoGPT-large, implemented using Hugging Face datasets.
  - Evaluation: BLEU score and Cosine Similarity.
- **Approach 8: Transfer Learning Approach**
  - Model: Microsoft's DialoGPT-small from Hugging Face datasets[4].
  - Integrated with SQL database of product collection related to smart home equipment.
  - Evaluation: BLEU score and Cosine Similarity.
  - UI Integration with Gradio[3]

# Performance

## Bayesian Optimization

- **Parameters Optimized:**
  - Batch size, hidden size, learning rate, dropout, number of layers, teacher forcing ratio, gradient clipping.
- **Goal:** Improve response accuracy and coherence across models.

## Evaluation Metrics

- **BLEU Score:** Measures the accuracy of generated responses by comparing with reference responses.
- **Cosine Similarity:** Evaluates the relevance of responses based on vector similarity.
- **Other Metrics can be employed:** User satisfaction through survey.

# Results and Observations

- **Key Observations:**
  - Hyperparameter tuning can significantly improved RNN-based model performance.
  - Further analysis is required to assess the impact of larger datasets on model performance.
  - CNN and MLP models showed moderate response relevance without attention.
  - Computational power was identified as a key challenge due to the resource-intensive nature of model training.
  - Transfer learning with DialoGPT models led to enhanced conversational quality and coherence.
  - See Appendix for Plots and Results
- **Performance Comparison:** Visualizations of BLEU scores, cosine similarity, and response accuracy across models.

# For Practical Usage and Integration

- **Database Integration:**
  - Linked chatbot to SQL database for real-time product information on smart home equipment.
- **Use Cases:**
  - Customer support automation, FAQ, product recommendations.
  - Real-time response with business-related data.
  - (See Appendix for More)

# Conclusion and Future Work

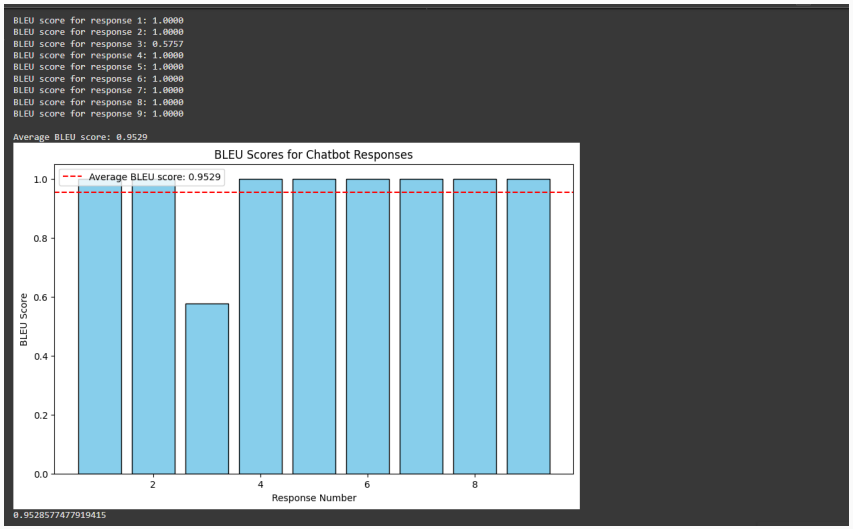
- **Conclusion:** Developed an enhanced chatbot and have done several experimentation.
- **Future Work:**
  - Implementation of more advanced architectures, like Transformers with large-scale datasets.
  - Expansion of database connectivity for specialized customer support.
  - Further fine-tuning with evolutionary algorithms.

# References

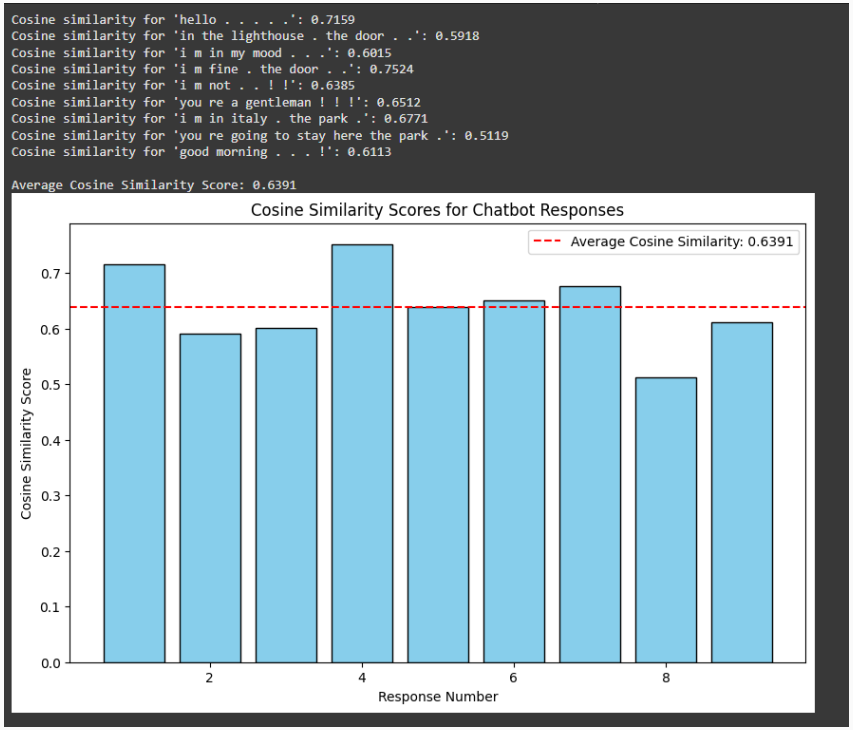

- Inka, M. (2024). *Chatbot Tutorial* [Online]. PyTorch Tutorials. Retrieved from `https://pytorch.org/tutorials/beginner/chatbot_tutorial.html`
- Danescu-Niculescu-Mizil, Cristian, and Lillian Lee. **Cornell Movie-Dialogs Corpus.** 2011. Available at: `https://www.cs.cornell.edu/~cristian/Cornell_Movie-Dialogs_Corpus.html`.
- Abid, A., Farooqi, M., Zou, J. (2020). *Gradio: Hassle-Free Sharing and Testing of ML Models in the Wild*. Retrieved from `https://gradio.app`
- Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Brew, J. (2020). *Transformers: State-of-the-Art Natural Language Processing*. In *Proceedings of the 2020 Conference on*

# Appendix: Figures of Each Approach

# Appendix: Approach 1 - Base Model

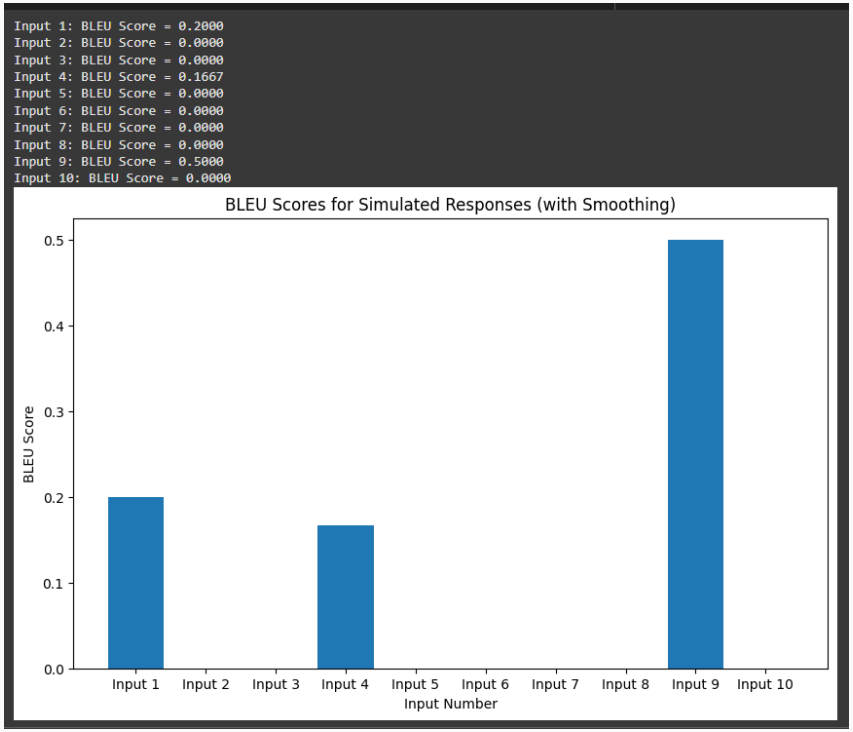



BLEU Score for Base Model

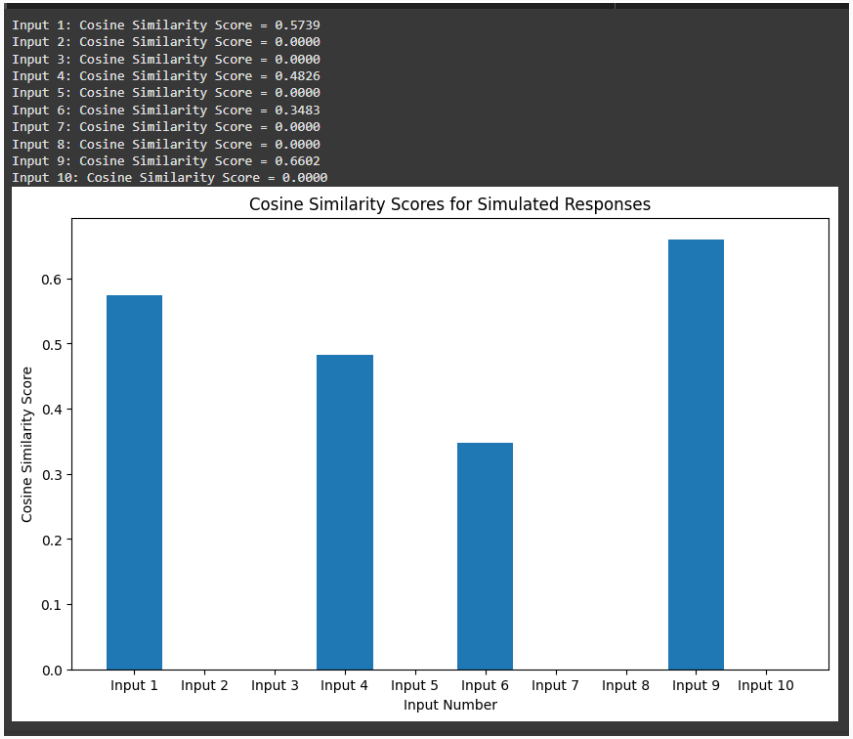



Cosine Similarity for Base Model

# Appendix: Approach 2 - Hyperparameter Tuned Model




BLEU Score for Hyperparameter Tuned Model

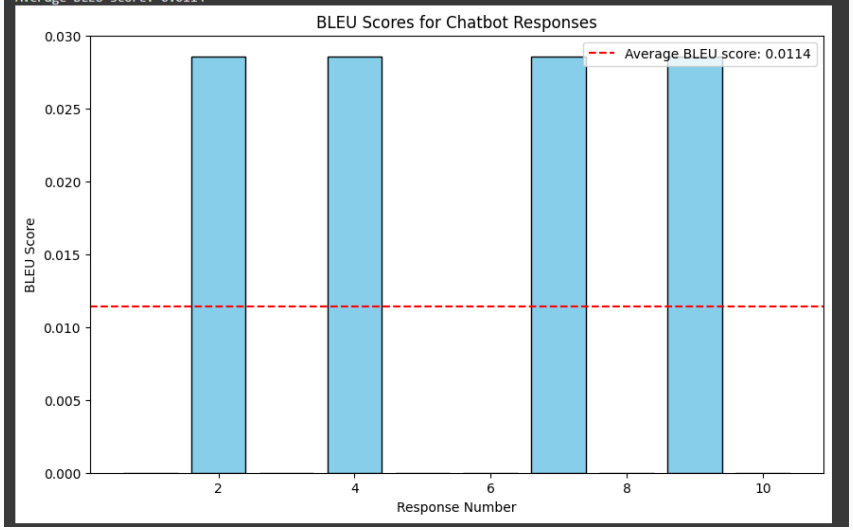



Cosine Similarity for Hyperparameter Tuned Model

# Appendix: Approach 3 - CNN Model

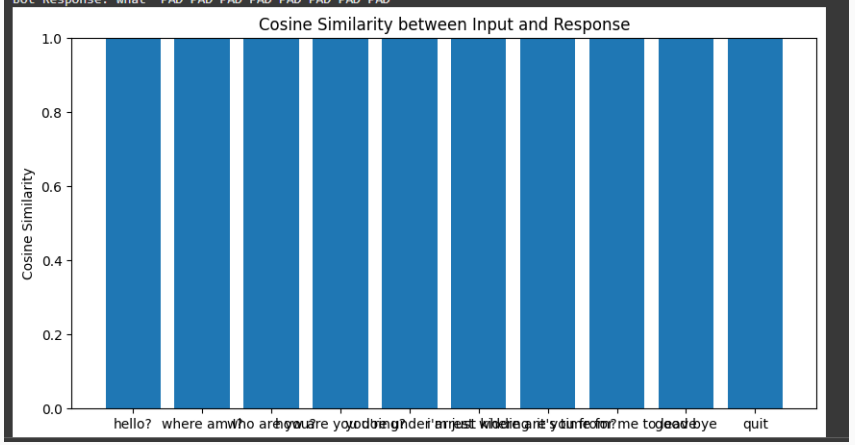
```
BLEU score for response 1: 0.0000
BLEU score for response 2: 0.0286
BLEU score for response 3: 0.0000
BLEU score for response 4: 0.0286
BLEU score for response 5: 0.0000
BLEU score for response 6: 0.0000
BLEU score for response 7: 0.0286
BLEU score for response 8: 0.0000
BLEU score for response 9: 0.0286
BLEU score for response 10: 0.0000

Average BLEU score: 0.0114
```




BLEU Score for CNN Model

```
Bot Response: what you  PAD PAD PAD PAD PAD PAD PAD
Input: where am I?
Bot Response: what you  PAD PAD PAD PAD PAD PAD PAD
Input: who are you?
Bot Response: what   PAD PAD PAD PAD PAD PAD PAD
Input: how are you doing?
Bot Response: you  PAD PAD PAD PAD PAD PAD PAD PAD
Input: you're under arrest
Bot Response: what    PAD PAD PAD PAD PAD PAD
Input: i'm just kidding
Bot Response: what  PAD PAD PAD PAD PAD PAD PAD PAD
Input: where are you from?
Bot Response: what s   PAD PAD PAD PAD PAD PAD
Input: it's time for me to leave
Bot Response: you you  PAD PAD PAD PAD PAD PAD PAD
Input: good bye
Bot Response: what  PAD PAD PAD PAD PAD PAD PAD PAD
Input: quit
Bot Response: what  PAD PAD PAD PAD PAD PAD PAD PAD
```

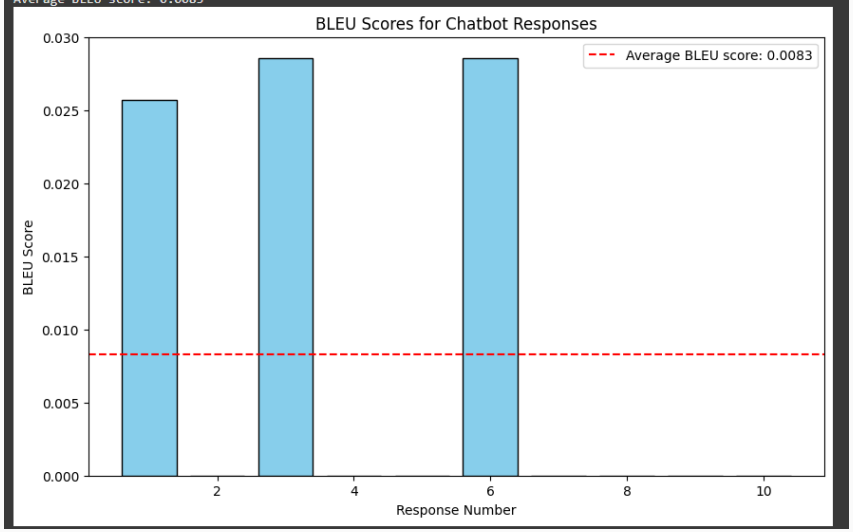



Cosine Similarity for CNN Model

# Appendix: Approach 4 - MLP Model

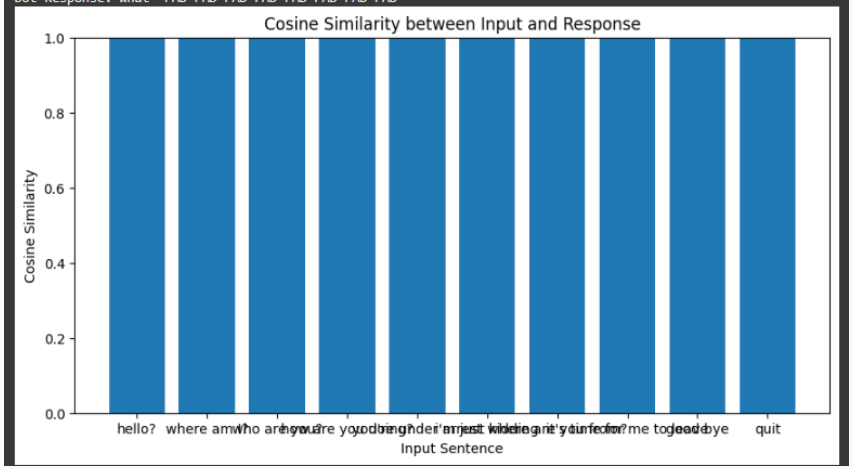
```
BLEU score for response 1: 0.0257
BLEU score for response 2: 0.0000
BLEU score for response 3: 0.0286
BLEU score for response 4: 0.0000
BLEU score for response 5: 0.0000
BLEU score for response 6: 0.0286
BLEU score for response 7: 0.0000
BLEU score for response 8: 0.0000
BLEU score for response 9: 0.0000
BLEU score for response 10: 0.0000

Average BLEU score: 0.0083
```



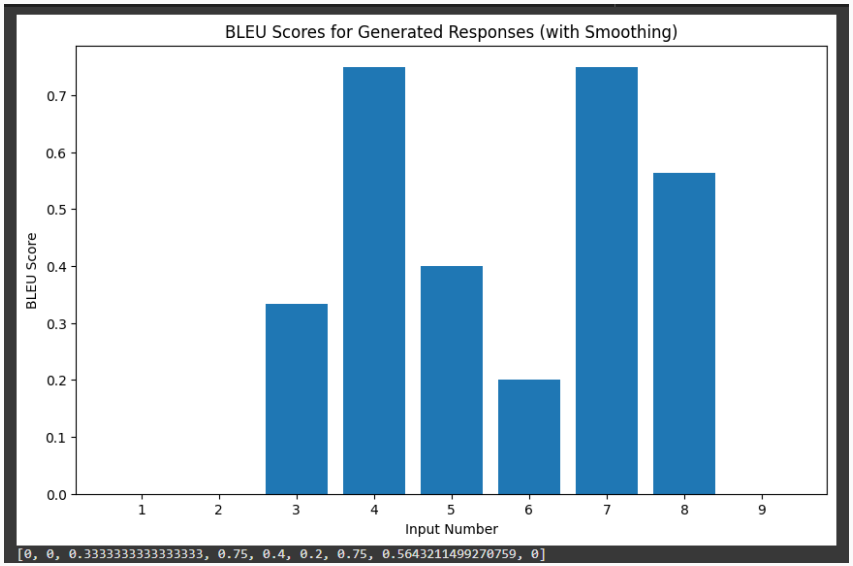

BLEU Score for MLP Model

```
Input: hello?
Bot Response: i s PAD PAD PAD PAD PAD PAD PAD PAD
Input: where am I?
Bot Response: i  PAD PAD PAD PAD PAD PAD PAD PAD
Input: who are you?
Bot Response: you   PAD PAD PAD PAD PAD PAD PAD
Input: how are you doing?
Bot Response: i s  PAD PAD PAD PAD PAD PAD PAD
Input: you're under arrest
Bot Response: what PAD PAD PAD PAD PAD PAD PAD PAD PAD
Input: i'm just kidding
Bot Response: you   PAD PAD PAD PAD PAD PAD PAD
Input: where are you from?
Bot Response: you  PAD PAD PAD PAD PAD PAD PAD PAD
Input: it's time for me to leave
Bot Response: you  PAD PAD PAD PAD PAD PAD PAD PAD
Input: good bye
Bot Response: what  PAD PAD PAD PAD PAD PAD PAD PAD
Input: quit
Bot Response: what  PAD PAD PAD PAD PAD PAD PAD PAD
```

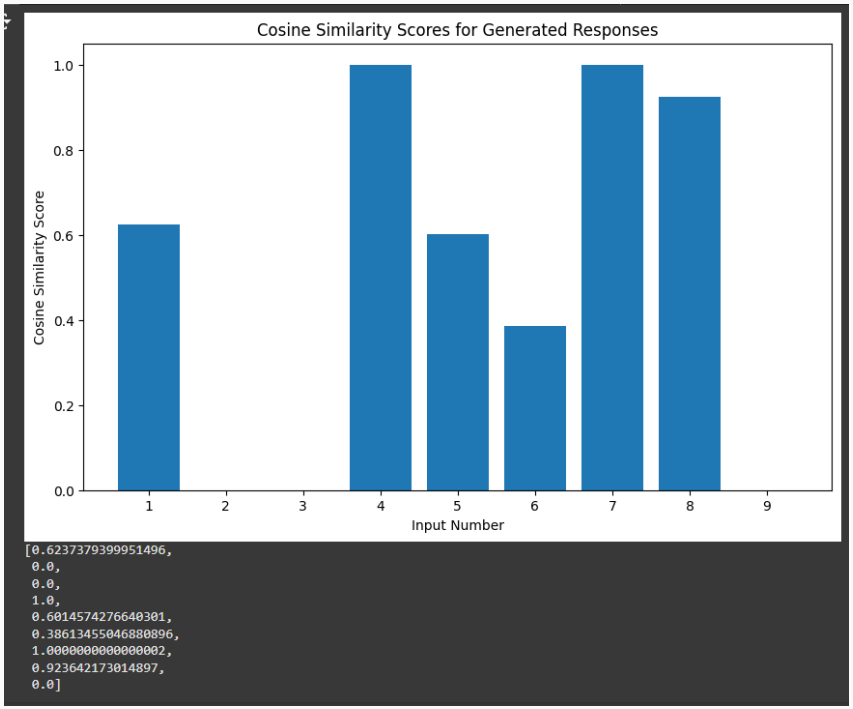



Cosine Similarity for MLP Model

# Appendix: Approach 5 - Transformer-Based Model

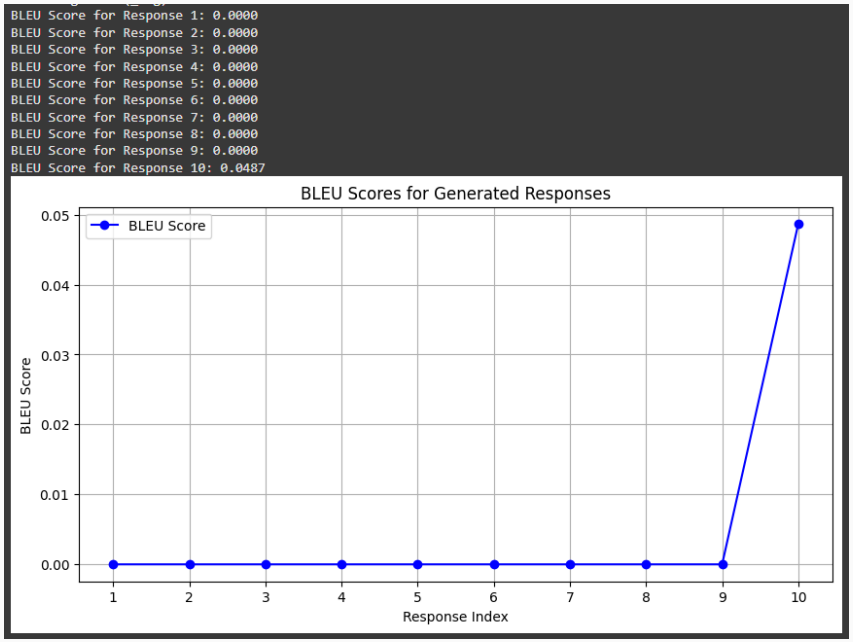



BLEU Score for Transformer-Based Model

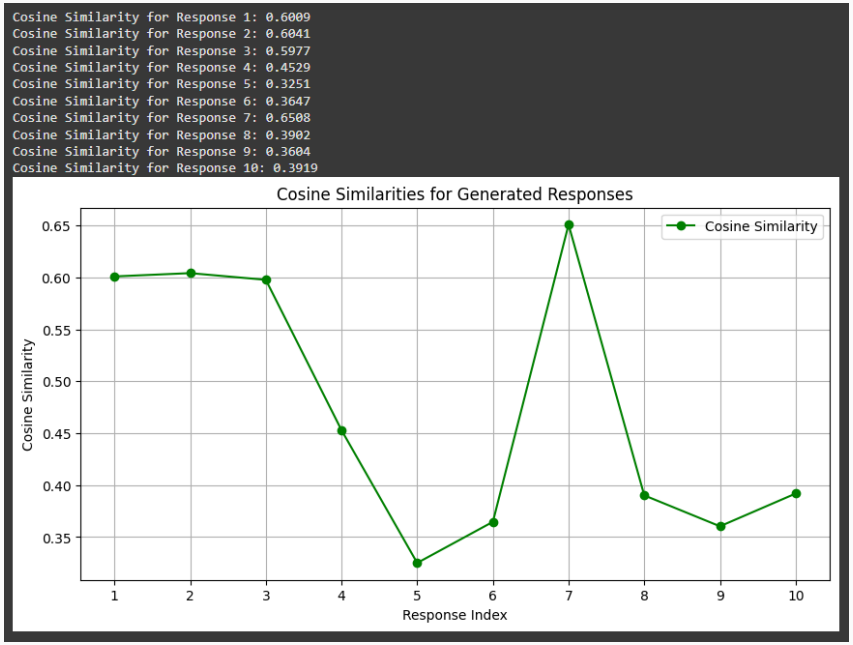



Cosine Similarity for Transformer-Based Model

# Appendix: Approach 6 - Transfer Learning Model




BLEU Score for Transfer Learning Model




Cosine Similarity for Transfer Learning Model

# Appendix: Individual Analysis of Each Approach

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## 1. Baseline Model (Approach 1)
**BLEU Scores:**

- The baseline model achieved high BLEU scores for most responses, with an average of **0.9529**.
- This indicates a strong structural and content match to the reference text.

**Cosine Similarity Scores:**

- Moderate scores, averaging **0.6391**, suggesting decent semantic alignment.

**Summary:**

- Good structural accuracy (high BLEU) but room for improvement in semantic similarity.

# Appendix: Individual Analysis of Each Approach

### 3. CNN-Based Model (Approach 3)
**BLEU Scores:**

- Low average of **0.0114**, suggesting limited structural similarity.

**Cosine Similarity Scores:**

- Consistently **1.0000**, suggesting high semantic similarity.

**Summary:**

- Perfect semantic similarity, but struggles with structural alignment.

### 4. MLP-Based Model (Approach 4)
**BLEU Scores:**

- Lowest BLEU score, averaging **0.0083**, indicating minimal

# Model Comparison Summary

| Model | BLEU | BLEU Interpretation | Cosine | Cosine Interpretation |
|---|---|---|---|---|
| Baseline | 0.9529 | Strong structural | 0.6391 | Moderate semantic |
| Fine-Tuned | 0.0867 | Poor structural | 0.2065 | Weak semantic |
| CNN-Based | 0.0114 | Minimal structural | 1.0000 | Perfect semantic |
| MLP-Based | 0.0083 | Minimal structural | 1.0000 | Perfect semantic |

# END