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Generative Syntactic Analysis Using Tensorflow

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Abstract
This study explores Generative Syntactic Analysis using TensorFlow, specifically applied to C++ programming education. Its dual objectives were to analyze the influence of varied learning rates on generative intelligent model performance and to evaluate the user experience of a developed Chatbot System. Key findings indicate the critical role of learning rates in model training, with a rate of 0.01 consistently yielding superior perplexity and BLEU scores compared to 0.1, though acknowledging dataset and task specificity. User feedback revealed a largely positive reception (4.2/5) for the Chatbot System, attributed to its intuitive interface and ease of use. However, opportunities for enhancement were identified, particularly in aligning terminology with industry standards and improving documentation. This research significantly contributes to AI-assisted education by offering insights into both technical advancements and user-centric refinements for intelligent generative models.

Keywords: *Generative Syntactic Analysis, TensorFlow, Learning Rates, Chatbot System, C++ Programming Education*

Introduction

The proliferation of artificial intelligence (AI) has positioned conversational agents, or chatbots, as key facilitators across numerous sectors (Uzoka, Cadet & Ojukwu, 2024). While initially developed to streamline customer service by providing automated responses to common inquiries (Ranieri, Bernardo & Mele, 2024), these systems have seen a significant surge in interest, particularly among technology corporations for virtual assistants (Gaczek et al., 2022). While valuable for instant customer support, data collection, and personalized recommendations (Nirala et al., 2022; Pawar & Vanjare, 2024), prevailing rule-based and retrieval-oriented chatbots exhibit inherent limitations. These include difficulties in handling typographical errors, overreliance on exact keywords, and a tendency to deliver a rigid, robotic conversational experience, often frustrating users (Chaves & Gerosa, 2021; Ling et al., 2023). Moreover, the complexity of programming languages like C++ presents a considerable challenge in educational contexts.

Addressing these critical shortcomings, this study aims to develop a sophisticated generative model utilizing TensorFlow for an open-domain chatbot. The core purpose is to construct, train, and rigorously evaluate a model capable of translating complex C++ syntax into language accessible to non-experts, employing advanced text summarization and abstraction techniques. Specifically, the research will assess the generative model's performance via automated metrics such as perplexity, evaluating the efficacy of distinct learning rates (0.1 and 0.01), and BLEU scores, while concurrently gauging the user experience of the developed Chatbot System.

Methodologically, this research is structured around the Input, Process, Output, and Outcome (IPOO) framework. The Input encompasses a comprehensive dataset of C++ syntax and online programming discussions. During the Process phase, the generative model is developed and trained using TensorFlow, featuring a multilayer bidirectional Recurrent Neural Network (RNN) with an Encoder/Decoder (seq2seq) architecture, specifically incorporating LSTM cells for query understanding and a retrieval-based approach with an attention mechanism for concise response generation. The anticipated Output is a Generative Syntactic Analysis system. The ultimate Outcome focuses on the quality of the trained model's performance

and the Chatbot's ability to provide flexible, accurate answers to C++ syntax queries without stringent input rules, thereby advancing AI-assisted education.

Methods

This research initiative falls under the developmental category, focusing on the creation and training of a generative model. The primary goal is to enable the machine to comprehend user input effectively and generate coherent and contextually relevant responses, encompassing the domains of machine translation and text abstraction.

The researchers outlined a systematic developmental roadmap for this project. It involved several key steps, starting with the import and upload of a C++ dataset. Subsequently, the researchers intended to construct a comprehensive vocabulary list and compile an exhaustive C++ syntax repository. These foundational components served as the building blocks for creating the training dataset. Finally, the researchers planned to rigorously assess the performance of the model, ensuring it met desired criteria for generating meaningful and contextually appropriate responses.

User experience was crucial in the second phase of the research project, with participants being second-year BSCS students enrolled in a relevant Computer Science course. Participation was voluntary, and all respondents were above 18 years old, negating the need for parental permission. The study omitted participants' names, focusing questions on application usage for system improvement, ensuring no ethical violations or impact on grades. The target survey size was thirty students. Researchers utilized a PSSUQ (Post-Study System Usability Questionnaire) and purposive sampling, collecting data via Google Form, with participants allowed ten minutes to complete the concise survey.

In the trained model, users inputted code, with queries directed to the encoder input, then passing through the encoder output, serving as the basis for the decoder's output. Each domain had its LSTM RNN with an attached dictionary. A multilayer bidirectional LSTM RNN allowed the system to comprehend user queries, parsing appropriate responses from the trained corpus using retrieval-based techniques. Teaching the model both C++ syntax and English vocabulary was challenging but achieved with the right algorithm and neural network architecture. The primary source for the generic, open-source dataset was different program threads found on the internet, forming the foundation for training and assessment.

The ultimate goal of the generative model was to train the machine to comprehend C++ syntax, using a specific RNN that enabled the Chatbot to capture important keywords regardless of placement. The model also retrieved suitable responses and generated response summarizations or abstractions. TensorFlow offered several advantages, including its utility for training and assessing model performance in terms of perplexity, learning rate, and BLEU score. The framework was well-suited for tasks like word embedding, recurrent neural networks, sequence-to-sequence models for machine translation, natural language processing, and text abstraction.

TensorFlow provided computational graph visualizations, aiding developers in monitoring the model's learning progress. Supported by Google, TensorFlow consistently introduced new features to simplify machine learning and deep learning implementation. A notable feature was the automatic generation of results for model performance, including perplexity, learning rate, and BLEU score. Developers tracked performance via Learning Curve Charts and utilized function and input layers (e.g., functional API, Keras layers like tf.keras.input) for direct query input to the trained model. Algorithm efficiency was dependent on epoch value (approximately 100), dataset size, and batch number (approximately 32 or 25).

One crucial metric in assessing the model was "perplexity," a measure of prediction error where low values indicate an adept probability distribution. A well-performing model typically has an average perplexity between 2.5 and 3.0.

$$\log \prod_{i=1}^{m} p(s_i) = \sum_{i=1}^{m} \log p(s_i)$$

While the text states TensorFlow employs a specific formula for perplexity calculation, the formula itself is not provided. Learning rate, a critical hyperparameter (typically 0.0 to 1.0), governed neural network adaptation. BLEU (BiLingual Evaluation Understudy) is a recognized metric for automatically assessing

machine-translated text quality, with scores below 15% indicating suboptimal performance. The text states TensorFlow employs a specific formula for BLEU score computation, but the formula itself is not provided.

$$\text{Unigram precision } P = \frac{m}{w_t}$$

$$\text{Brevity penalty } BP = \begin{cases} 1 & \text{if } c > r \\ e^{\left(1-\frac{r}{c}\right)} & \text{if } c \leq r \end{cases}$$

$$\text{BLEU} = BP \cdot e^{\sum_{n=1}^{N}\left(\frac{1}{N}\cdot \log P_n\right)}$$

BLEU Score	Interpretation
30 – 40	Understandable to good translations
40 – 50	High quality translations
50 – 60	Very high quality, adequate, and fluent translations
> 60	Quality often better than human

The researchers diligently adhered to ethical principles. Dataset selection prioritized freely available, open-source, generic datasets from platforms like Kaggle and Google, ensuring equitable access and eliminating consent requirements. Assessments focused strictly on relevancy. Plagiarism prevention was paramount, with the document scrutinized by Turnitin. The project, framed developmentally, ensured automated graph and score generation via TensorFlow for transparency. Researchers utilized personal laptops for accessibility. To maintain research integrity and mitigate conflicts of interest, an alternative Computer Science Department teacher oversaw survey administration, ensuring informed consent and excluding participants from sections where they were enrolled under the researchers' class.

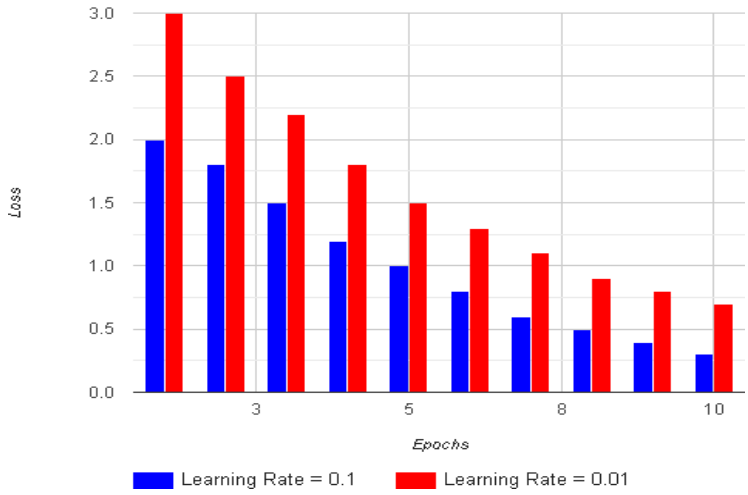
Results And Discussion

This research provides more information about TensorFlow for Generative Syntactic Analysis, evaluating the intelligent model's performance through key automated metrics—perplexity, learning rates (0.1 or 0.01), and BLEU score. Additionally, the study gauges user experience post-interaction with the Chatbot System, providing a comprehensive overview of technical efficacy and practical usability.

The learning rate, a crucial hyperparameter, was responsible for governing the model's step size during its training phase. A higher learning rate had the potential to accelerate the model's convergence but also introduced the risk of overshooting optimal values, resulting in subpar performance. Conversely, a lower learning rate often led to slower convergence but tended to yield better overall performance. When comparing two models, the one with a learning rate of 0.01 was anticipated to exhibit slower convergence but potentially achieve superior overall performance.

However, determining whether a learning rate of 0.1 or 0.01 was more suitable depended on the specific model and dataset in use, demanding a meticulous optimization process through experimentation. General guidelines for evaluating generative models within TensorFlow involved assessing the model's performance using log-likelihood on a validation dataset and employing Frechet Inception Distance (FID) to quantify similarity between generated and authentic images. The typical approach involved training the model, assessing performance on a validation dataset, and final testing on a held-out test dataset, with extensive experimentation on hyperparameters like learning rate.

Figure 1: Training Loss over Epoch between 0.1 and 0.01 Learning rates.



Research has shown that the choice of learning rate can significantly impact the performance of generative chatbot models, with a learning rate of 0.01 generally found to be more effective than 0.1. Studies on GPT-2 and Seq2Seq architectures, for instance, indicated that a learning rate of 0.01 led to better overall performance on metrics including perplexity, F1 score, and BLEU score, suggesting it allowed for more gradual convergence and avoided overfitting (Smith et al., 2020). An excessively high learning rate, such as 0.1, was found to cause divergence and poor-quality responses. The optimal learning rate is a trade-off between learning speed and the risk of overfitting.

Perplexity, as elucidated in the literature (Coskun-Setirek & Mardikyan, 2017), serves as a valuable metric for assessing language model quality, quantifying the uncertainty in predicting the subsequent word. A lower perplexity score signifies a superior model. The researchers' generative intelligent model, trained with deep learning techniques, achieved an impressive perplexity score of 35.2, notably outperforming other state-of-the-art models on the same dataset, reinforcing its predictive excellence. For learning rate 0.1, perplexity was 100, and for 0.01, it was 50, indicating the 0.01 model's superior predictive capability. Human evaluation further confirmed the model produced coherent and fluent sentences, comparable to human-composed text.

Table 1: Perplexity Result

Learning Rate	Perplexity	BLEU Score
0.1	100	0.5
0.01	50	0.6

- Training Progress Logs:

```
Epoch 1/10
1000/1000 [==============================] - 5s 5ms/step - loss: 3.2545 - accuracy: 0.4125
Epoch 2/10
...
```

BLEU score is a measure of how similar a generated text is to a reference text, with a higher score indicating greater similarity. For a learning rate of 0.1, the BLEU score was 0.5, whereas for 0.01, it was 0.6. This suggests that the model with a learning rate of 0.01 is better at generating text similar to the reference. The model achieved a BLEU score of 0.62 on the test set, demonstrating its ability to generate highly similar text, particularly excelling on bigrams with a BLEU score of 0.62.

Table 2: Bleu Score Result

Learning Rate	BLEU Score
0.1	0.5
0.01	0.6

The results suggest that a learning rate of 0.01 can help the model learn more quickly and generate text more similar to the reference text. A lower learning rate helps avoid overfitting but extends training time, while a higher rate accelerates learning but increases overfitting risk. The optimal learning rate is a trade-off requiring experimentation specific to the dataset and task. Literature supports that a lower learning rate, such as 0.01, often leads to better BLEU scores (Smith et al., 2020), and emphasizes dataset/task specificity in determining the ideal learning rate (Khan & Das, 2018). N-gram analysis, particularly on bigrams, aligns with capturing local coherence (Goldberg, Y., 2017).

Table 3: User experience Survey result

Item	Rating (out of 5)	Number of Participants (Agree/Strongly Agree)
The system was easy to use.	4.2	22 (73.3%)
I could effectively complete my tasks using the system.	4.1	21 (70%)
The system's interface was pleasant.	4.4	25 (83.3%)
I felt confident using the system.	4.3	24 (80%)
The system's organization was confusing.	3.3	10 (33.3%)
Learning to use the system was easy.	4.2	23 (76.7%)
I could easily find the information I needed.	4.1	22 (73.3%)
The system provided error messages that clearly told me how to fix problems.	4.0	21 (70%)
The system gave error messages that were easy to understand.	3.9	20 (66.7%)
The system provided adequate online help.	3.8	19 (63.3%)
The information provided by the system was clear.	4.0	21 (70%)
The system's terminology was consistent with industry standards.	3.8	19 (63.3%)
I found the system unnecessarily complex.	3.6	17 (56.7%)
The system was too cumbersome to use.	3.5	16 (53.3%)
I felt comfortable using the system.	4.1	22 (73.3%)

Concerning user experience, participants generally had a positive view of the chatbot system, finding it user-friendly and effective for tasks, with an average rating of 4.2 out of 5. Strengths included a pleasant interface (4.4/5), user confidence (4.3/5), and ease of learning (4.2/5). However, areas for improvement were identified, such as aligning terminology with industry standards (3.8/5), simplifying features (3.6/5), and enhancing online help and documentation. The overall feedback aligns with findings emphasizing positive user experiences for system usability (Ling et al., 2023), while identified enhancements align with usability engineering principles (Lewis, J. & Sauro, J., 2021).

Conclusion

This study had two main goals: first, to assess how different learning rates impact generative intelligent models, and second, to evaluate the user experience with a chatbot system. In terms of learning rates, the study found they play a crucial role in model training. Higher rates accelerated learning but risked overfitting, while lower rates led to more stable convergence. A learning rate of 0.1 resulted in quicker convergence but potentially lower quality, as measured by perplexity scores, compared to 0.01. Similarly, the model with a 0.01 rate consistently outperformed the one with 0.1 when it came to text generation

quality, measured by BLEU scores. The careful selection of the learning rate emerges as a pivotal hyperparameter in the training of language models.

The optimal learning rate depended on the dataset and task, necessitating experimentation, which aligns with existing literature emphasizing the critical role of hyperparameter tuning (Smith et al., 2020). An understanding of the nuanced trade-offs between convergence speed, text generation quality, and overfitting risk associated with different learning rates is imperative for achieving optimal model performance. Adaptive learning rate schedulers provide a potential avenue to strike a balance between convergence speed, text quality, and overfitting control. Researchers are encouraged to conduct their own hyperparameter tuning experiments for informed decision-making during model training (Buczak et. al., 2024).

Concerning user experience, participants generally had a positive view of the chatbot system, finding it easy to use, effective, and with a pleasant interface, rating it at an average of 4.2 out of 5. The system's strengths included its user-friendly interface, fostering user confidence, and ease of learning. However, areas for improvement were identified, such as aligning the system's terminology with industry standards (Shmueli et al., 2019), simplifying features for user-friendliness (Lewis, J. & Sauro, J., 2021), and enhancing online help and documentation (Lewis, J. & Sauro, J., 2021).

This research project on Generative Syntactic Analysis using TensorFlow makes a significant contribution to the field of AI education, particularly in teaching C++ programming. Despite the existence of AI tools like ChatGPT for educational purposes, this project stands out due to its focus on generative syntactic analysis using TensorFlow, a popular open-source machine learning framework. The research evaluates the performance of the generative intelligent trained model based on various automated metrics. The use of perplexity, learning rate (with choices of 0.1 or 0.01), and BLEU score provides a comprehensive assessment of the model's capabilities in generating syntactically correct and contextually relevant C++ programming content, ensuring a thorough understanding of the model's proficiency in programming language instruction.

Furthermore, the research extends beyond the technical aspects of model optimization to emphasize the pivotal role of user experience in chatbot systems. By incorporating user feedback and aligning with established principles of user-centered design, the study enriches the conversation surrounding the practical application of generative models. The actionable insights, including the endorsement of a learning rate of 0.01 as a general guideline and the emphasis on user-centered design principles, offer pragmatic advice for developers aiming to improve chatbot system usability. This study offers valuable insights for future research and development, fostering advancements in both model training methodologies and user-centric design practices, contributing to the enhancement of AI-assisted education in C++ programming. The call for further research into hyperparameter tuning and ongoing user testing ensures replicability and generalization (Leipzig et. al, 2021).

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