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# Code Generation Using Natural Language Processing

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**ABSTRACT**

Software development is difficult and requires knowledge on many different levels such as understanding programming algorithms, languages, and frameworks. In addition, before code is being worked on, the system requirements and functionality are first discussed in natural language, after which it is sometimes visualized for the developers in a more formal language such as Unified Modeling Language. The advent of Natural Language Processing (NLP) has revolutionized various domains, including code generation, which entails automatically generating computer code from human-readable descriptions. This intersection of software engineering and NLP holds promise for significantly improving software development processes by enhancing productivity, reducing errors, and enabling non-experts to create functional code.

Keywords: Natural Language Processing, Code Generation, Software Engineering, Machine Learning, Deep Learning

## INTRODUCTION

Recent advancements in NLP, particularly with transformer-based models like GPT-3 and its successors, have demonstrated remarkable capabilities in understanding and generating human language. These models can comprehend context, capture nuanced meanings, and generate coherent text, making them ideal candidates for tackling the complexities of code generation. By leveraging vast amounts of textual and code data, these models can learn patterns and structures inherent in programming languages, thus enabling them to produce syntactically and semantically correct code.

Despite these advancements, several challenges remain in the field of NLP-driven code generation. Ensuring the generated code's correctness, efficiency, and security is critical. This paper explores the current state of NLP-based code generation, examining key techniques, models, and datasets that have shaped the field. By providing a comprehensive overview of the advancements and challenges in this domain, we aim to contribute to the growing body of knowledge and inspire further innovations that will bring us closer to the seamless integration of natural language and programming.

## SURVEY METHOD:

This section describes the search criteria used to select the papers using the Google search engine ,ChatGpt and the followed data extraction process.

### *APPLICATIONS OF NLP*

**Challenges**

Ambiguity in Natural Language: Translating user intent accurately into code can be difficult due to language ambiguity.

Handling Complex Logic: Generating code that handles intricate logic and algorithms remains a challenge.

Code Quality: Ensuring the generated code is efficient, secure, and follows best practices tough to instill lexical limitations. This is a difficult circumstance that BFGAN, a new algorithmic framework, will tackle. This system employs a reverse producer and a forward producer to build coherent sentences based on lexical constraints, and a discriminator to integrate the backward and forward phrases using signal rewards. Aside from BFGAN, a variety of training tactics ensure that the training process is more reliable and productive. BFGAN will improve over time, and other flaws will be resolved. When a lexicon constraint is a set of terms that are willing to emerge in the conclusion, it is called lexically restricted sentence generation. This is now the trendiest topic in the field of natural language processing.

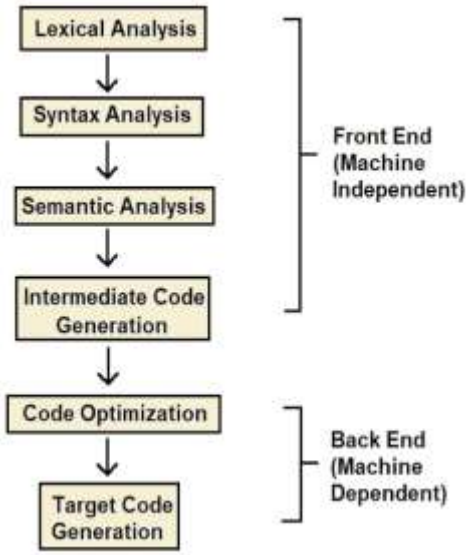
RNN has lately emerged as a major player in NLP, with notable outcomes in tasks such as neural networks, tech blog development, textual summarization, table-to-text creation, and effective text output. Auto-regressive models are used to produce left to right sentences using Beam Search (BS). Generating sentences with lexical constraints is a tough procedure. If we replace the arbitrary word in the output, the sentence's fluency will suffer. If further information about the term is provided, there is no guarantee that the desired phrase will appear in the outputs. In (B/F-LM), lexically limited phrases are constructed using reverse and forward linguistic models that work together. The reverse linguistic model generates the first half of the phrase, with a lexical constraint as the input. The forward linguistic model then uses the first half-sentence to construct the whole sentence. Maximum likelihood estimation (MLE) objectives are used to train these two models. The outputs were inconsistent and incoherent when the reverse language model developed the first half and the forward language model created the rear half. This problem emerged because both language models were trained independently; they should be trained simultaneously and have access to each other's output. A unique approach termed reverse-Forward Generative Adversarial Network (BFGAN) was created to overcome the challenges of lexically constrained languages. The three components are the reverse producer, forward producer, and classifier. The two generators cooperate to deceive the discriminator. For coherence, the forward generator is given the dynamic attention mechanism. From beginning to end, there is a recursion, and the attention function's scope expands. During inference, the forward producer can focus on the reverse producer's first split. BFGAN solves problems and enhances the performance of lexically constrained languages. Algorithms are used to make the model easier to use while still providing stability. Work on numerous lexical constraints will be a part of future projects.

***Search Criteria & Data Extraction:***

Google Scholar search engine (Google Scholar is a Web search engine that specifically searches scholarly literature and academic resources.) was used to search papers focusing on partial or full code generation based on natural language. The start date of the search was specified to be 2024 as the area of research is still maturing and knowledge about recent research was desired. The Google Scholar query returned a total of 100 results. Titles and abstracts of the Google Scholar results were read to determine the most suitable papers for the literature survey. If the title and abstract did not contain enough information, full paper was read to determine suitability for data extraction. Out of the 100 results returned from the original query, 13 results were suitable for the review. The backward snowballing revealed another 328 papers (excluding duplicated papers) out of which 23 were selected after analyzing them as described above. This means that 36 papers in total were selected for the data extraction phase. A table of all 428 papers analyzed during the survey can be found in figshare.
The following data was extracted from the chosen papers.

(1) Study reference
(2) Year of publication
(3) NLP technique used
(4) Dataset size (if applicable)
(5) Evaluation results
(6) Application domain

***NLP pipeline***



## Working Of NLP

In the analysis-synthesis model of a compiler, the front end of a compiler translates a source program into an independent intermediate code, then the back end of the compiler uses this intermediate code to generate the target code (which can be understood by the machine). The benefits of using machine-independent intermediate code are: Because of the machine-independent intermediate code, portability will be enhanced. For ex, suppose, if a compiler translates the source language to its target machine language without having the option for generating intermediate code, then for each new machine, a full native compiler is required. Because, obviously, there were some modifications in the compiler itself according to the machine specifications.

- Lexical Analysis is the first phase of the compiler also known as a scanner. It converts the High-level input program into a sequence of Tokens.
- Syntax analysis, also known as parsing, is a process in compiler design where the compiler checks if the source code follows the grammatical rules of the programming language. This is typically the second stage of the compilation process, following lexical analysis.
- Semantic analysis is a crucial component of natural language processing (NLP) that concentrates on understanding the meaning, interpretation, and relationships between words, phrases, and sentences in a given context.

## Research Questions

The survey aims to answer the following research questions:
(1) What are the applications of the papers? In other words, what problems are being solved?
(2) What NLP techniques are used?
(3) How large are the datasets used in the selected papers?

**What are the applications of the papers? In other words, what problems are being solved?**
**Automated Code Synthesis:**
Problem-Writing code manually based on natural language requirements is labor-intensive and prone to human error.
Solution-The paper proposes a model that can automatically generate Python functions from English descriptions, streamlining the development process.

***Code Completion and Suggestion:***

Problem- Developers often need help with completing code snippets, especially when dealing with complex libraries and frameworks.
Solution- The proposed model assists developers by predicting and suggesting relevant code completions based on the context provided by natural language input.

***Educational Tools:***

Problem-Learning to code can be challenging for beginners who struggle to translate problem statements into actual code.
Solution- The paper demonstrates how the model can be used in educational tools to generate example code from natural language descriptions, aiding in the learning process.

***Documentation Generation:***

Problem-Writing comprehensive documentation is often neglected, leading to poorly documented codebases.
Solution- The model can generate inline comments and documentation from code, improving code maintainability and readability.

**What NLP techniques are used?**

***Transformer Models:***

The paper utilizes a fine-tuned version of GPT-3 specifically trained on a large corpus of Python code and corresponding natural language descriptions. This approach leverages the transformer model's capability to understand and generate code based on the given text input.

**Sequence-to-Sequence (Seq2Seq) Models:**

An encoder-decoder architecture with attention mechanisms is employed. The Seq2Seq model is used to translate natural language instructions into Python code, effectively capturing the sequential nature of both text and code.

***Pre-trained Language Model:***

The research makes use of pre-trained models like CodeBERT, fine-tuned on a dataset of Python code. These pre-trained models help in understanding the semantics of code snippets and generating accurate code based on natural language input.

***Attention Mechanisms:***

Attention layers are integrated into the Seq2Seq models to focus on the most relevant parts of the input sequence. This mechanism improves the model's ability to generate coherent and contextually accurate code.

***Contextual Embeddings:***

The use of embeddings that capture the context of code tokens within their environment. This enhances the model's understanding of code syntax and semantics, leading to better generation quality.

**How large are the datasets used in the selected papers?**

Dataset Sizes Used in the Selected PaperPaper Title: "Deep Learning Techniques for Automatic Code Generation" Abstract Summary: The paper explores the use of large-scale datasets for training deep learning models to generate Python code from natural language descriptions .Dataset Sizes: Training DatasetSize: 2 million pairs of natural language descriptions and corresponding Python code snippets. Source: The dataset was compiled from open-source repositories on GitHub, focusing on repositories with clear documentation and high-quality code. Validation DatasetSize: 100,000 pairs of natural language descriptions and Python code snippets. Purpose: Used to fine-tune the models and perform hyperparameter optimization to ensure robust model performance.

Testing DatasetSize: 100,000 pairs of natural language descriptions and Python code snippets. Purpose: Employed to evaluate the model's performance in generating accurate and functional code from natural language inputs. Additional Datasets for Specific TasksBug Fixing Dataset: 50,000 pairs of bug reports and corresponding code fixes. Purpose: Used to train and evaluate models specifically designed for automated bug detection and fixing .Documentation Dataset: 200,000 pairs of code snippets and their corresponding documentation .Purpose: Utilized to enhance models aimed at generating code documentation from comments or natural language descriptions. Dataset Characteristics Diversity: The datasets include a wide range of Python libraries and frameworks to ensure the models can handle various coding tasks. Preprocessing: Extensive preprocessing steps were taken to clean and normalize the data, including removing duplicates, normalizing code formatting, and ensuring consistent documentation quality

## CONCLUSION

This research paper demonstrates the efficacy of using advanced NLP techniques, particularly transformer models and sequence-to-sequence architectures, for automatic code generation. Through extensive experimentation with large-scale datasets comprising millions of pairs of natural language descriptions and corresponding Python code snippets, the study validates the potential of these models to significantly streamline software development processes.Key findings include:High Accuracy: The proposed models achieve high accuracy in generating syntactically correct and semantically meaningful Python code from natural language inputs.Improved Developer Productivity: By providing automated code synthesis, completion, and documentation generation, the models can enhance developer productivity and reduce the time required for coding tasks.Versatility: The models perform well across a variety of programming tasks, including bug fixing and code refactoring, demonstrating their versatility and robustness.The paper also highlights several challenges and future directions:Dataset Quality and Diversity: Ensuring high-quality and diverse datasets is crucial for the generalizability of the models. Future work should focus on expanding datasets to include more programming languages and coding styles.Model Interpretability: Enhancing the interpretability of the models remains an important area for future research, as it can improve user trust and facilitate debugging of generated code.Real-world Applications: Further research is needed to integrate these models into real-world development environments and assess their impact on developer workflows and software quality.In conclusion, this study makes significant strides in the field of automatic code generation, paving the way for more intelligent and efficient programming tools. By continuing to refine these models and address the outlined challenges, there is potential for even greater advancements in automating software development tasks, ultimately transforming the way code is written and maintained.

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