## LARGE LANGUAGE MODEL FOR CODE TRANSLATION

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#### Introductin

• Manual code conversion between programming languages is timeconsuming, error-prone, and requires deep expertise due to differences in syntax, semantics, and language features.

• Automated code translation techniques, like transcompilers, reduce errors, improve efficiency, and enable seamless integration of code from different languages, enhancing codebases and promoting code interoperability

#### Literature Review

#### Large Language Model

- Definition: type of artificial intelligence (Deep Learning) that has the ability to imitate human intellect.
  - Applications: Text Generation Summarization Sentiment Analysis.
  - Limitations: require large computational capabilities.

#### Deep Learning

- Definition: a subfield of machine learning, relies on artificial neural networks(ANNs) as its foundation.
- • Applications: Supervised Unsupervised Reinforcement
- • Limitations: limited to knowledge from information in training data.

#### Literature Review

#### Code Translation

- Definition: embodied in the concept of a transcompiler or source-to-source translator.
  - Applications: Code reusability- software conversion to other language.
  - Limitations:Low-Resource Programming Languages- small change in tokens can drastically change its meaning.



### Related Work

#### Problem

- The current LLMs for code translation did not achieve the required efficiency, in addition to the high rate of incorrect translation.
- There is no systematic classification and identification of roots causing translation error.
- The weakness in the current prompt techniques is considered one of the causes of translation errors.

#### Contribution

- Taxonomy of translation bugs.
- Improving the results of translation by offering suitable contexts.
- Develop an iterative prompt crafting.

Proposed solution

The proposed solution serves translation between five PLs(C, C++, Go, JAVA, Python). emprical study conducted and used three datasets, two real world projects, and seven LLMs.

outcome solution -Taxonomy o f 14 bugs categories.

-New iterative prompt is created.

#### Critical Review

- The evaluation of LLMs in this paper relies solely on compilation and execution, which provides a practical assessment. However, it is also essential to include static metrics to compare the performance of the models with related works.
- It couldn't take advantages from more case studies about bug taxonomy in other works.

#### Problem

- Challenge of code generation from natural language descriptions.
- The gap that exists between instructions that can be executed by machines and human languages.
- Vulnerabilities found in previous models that efficiently converts natural language descriptions into executable Python code.

#### Contribution

- Acknowledgment of limitations, specifically a lack of flexibility in language detection and translation restrictions to Python.
- Emphasis on the complexity involved in creating a model capable of accurately converting natural language into executable Python code.

#### Proposed solution

- Fine-tuning pre-trained language model (MarianMT) using two datasets.
- Development and implementation of MarianCG to solve the code generation problem.
- Three-step experimentation and development process to enhance model performance.
- Utilization of BLEU score and exact match accuracy as evaluation metrics.

#### Critical Review

- Risk of misinterpretation or misclassification of language constructs.
- MarianCG is confined to translating into Python, lacking support for other languages.
- Lack of flexibility in distinguishing programming from natural language.

#### problem

- Difficult to develop evaluation metrics that align with human judgment.
- The utilization of human-written test suites to evaluate functional correctness can be challenging in domains with low resources.

#### Contribution

propose a new evaluation framework based on the GPT-3.5 for code generation assessments.

#### Proposed solution

Evaluates the framework of four programming languages (Java, Python, C, C++, and JavaScript) from two aspects:

- Human-based usefulness.
- Execution-based functional correctness.

by comparing its performance with the state-of-the-art CodeBERTScore metric

#### Critical Review

it is still uncertain whether LLMs can be effectively employed to evaluate other tasks related to source code beyond code generation.

#### 4.Code Translation and Multilingual Code Co-Evolution

#### Problem

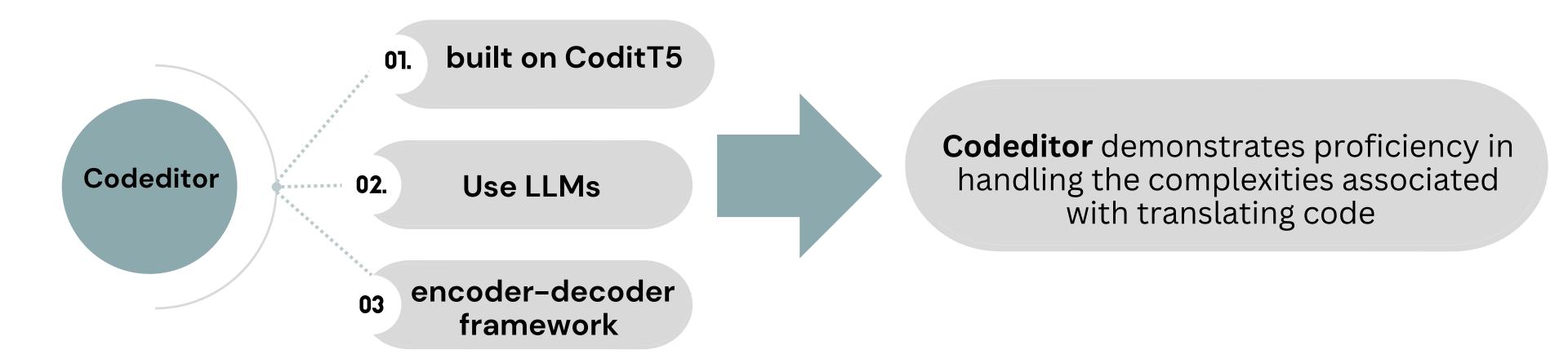
• The main problem addressed in the paper is focuses on the task of automatically translating code changes from one programming language to another.

#### Contribution

The contribution is the introduction of the *Codeditor* model, which is designed to address the challenge of automatically translating code changes from one programming language to another.

#### 4.Code Translation and Multilingual Code Co-Evolution

Proposed solution



#### 4.Code Translation and Multilingual Code Co-Evolution

#### Critical Review

- Codeditor showcases promise in handling longer code, yet there's a need for a closer look at its efficacy with shorter snippets.
- Proposed integration with generation models boosts accuracy but warrants careful consideration due to potential complexities.

# THANK YOU FOR LISTENING

