CS 846: ATRE by Prof. Daniel Berry

REQUIREMENTS ENGINEERING FOR ML-BASED SOURCE CODE TRANSLATION

July 13, 2023

Presented by:

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The Problem Statement

The Task: Java↔Python Code Translation

```java
import java.io.*;
public class Main
{
    static int unitDigitXRaisedY(int x, int y)
    {
        int res = 1;
        for (int i = 0; i < y; i++) res = (res * x) % 10;
        return res;
    }
    public static void main(String args[])
    {
        System.out.println(unitDigitXRaisedY(4, 2));
    }
}
```

A **Java** program

Translation of a code from one high-level language to another

```python
def unitDigitXRaisedY(x, y):
    res = 1
    for i in range(y):
        res = (res * x) % 10
    return res
if __name__ == '__main__':
    print (unitDigitXRaisedY(4 ,2))
```

An "*equivalent*" program in **Python**

- Let ***S* = source language** (e.g., Java) and ***T* = target language** (e.g., Python)
- **Code Translation Learning Problem**
  - To *learn* a language translator f_{ST}: $S \rightarrow T$, which when provided with a ***S***-program produces a ***T***-program, that is runtime (input-output) equivalent to the former.
  - In this work, focussing on translation between Java & Python

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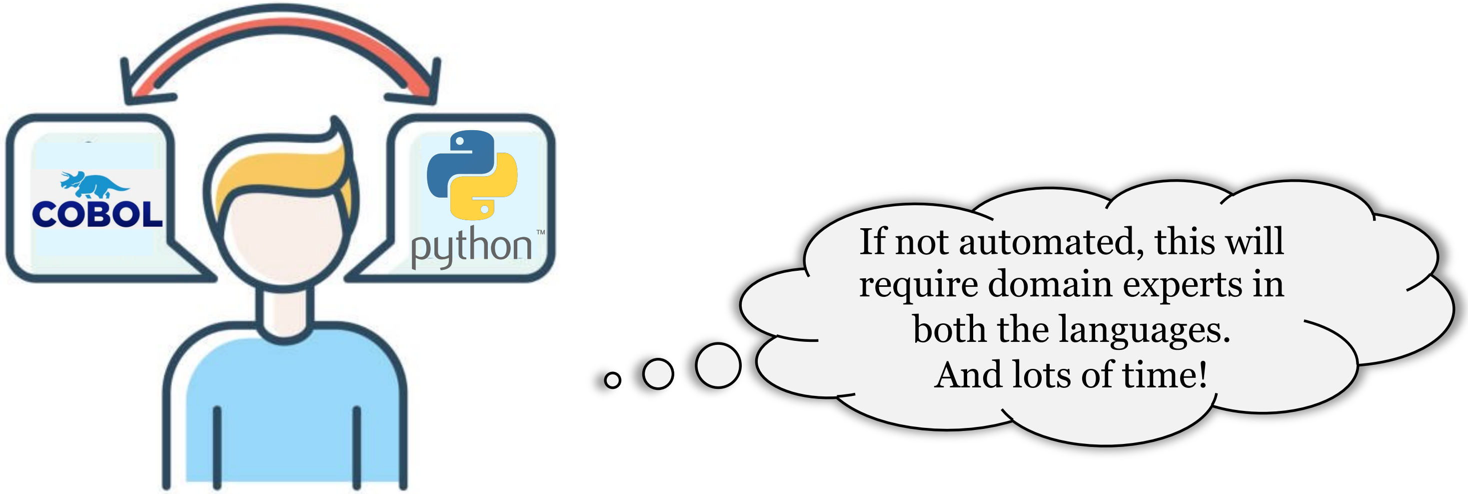
Motivation: Significance of Automated Code Translation

- Automatic translation of code from one high-level language to another
  - An important software engineering research area
  - Large legacy codebase getting transformed to a modern language e.g., COBOL to Python



  - Applications in code migration[1] and cross-platform interoperability[2]

[1] B. G. Mateus, M. Martinez, and C. Kolski, "Learning Migration Models for Supporting Incremental Language Migrations of Software Applications," Information and Software Technology, vol. 153, 2023.
[2] M. Grimmer, R. Schatz, C. Seaton, T. Würthinger, M. Luján, and H. Mössenböck, "Cross-language Interoperability in a Multi-language Runtime," ACM Transactions on Programming Languages and Systems (TOPLAS), vol. 40, no. 2, pp. 1–43, 2018

Challenges in Java↔Python Translation

- Java is a **statically-typed** language
  - For statically-typed language, type of variables known at compile-time
  - All kinds of checking can be done by compiler → a lot of trivial bugs caught at an early stage
- Python is **dynamically-typed** language
  - Interpreted language; Type is associated with run-time values, not named variables
- Java and Python belong to same programming paradigm i.e., OOP
  - But **huge differences in syntax** and **programming style**

JavaScript & Java have C-like syntax

Python has a different syntax (e.g., tabs for nesting)

```
//JavaScript
class Rectangle {
    #height, #width;
    constructor(height, width) {
        this.#height = height;
        this.#width = width;
        console.log("Created");
    }
}
```

```
//Java
class Rectangle {
    private int height, width;
    public Rectangle (int height, int width) {
        this.height = height;
        this.width = width;
        System.out.println("Created");
    }
}
```

```
#Python
class Rectangle(object):
    def __init__(self, height, width):
        self.__width = width
        self.__height = height
        print("Created")
```

Easier to translate

Difficult to translate

The Earlier Approaches

Early Rule-Based Transpilers

- Source-to-source translator / Transcompiler / Transpiler [3][4][5]
  - Rule-based & handcrafted → thus, **quite expensive** to build
  - Uses traditional concepts such as parsing and abstract syntax trees
  - Vary by the intricacies and difficulty level of constructs that it can handle
  - Long list of equivalences between the two languages → **translation requirements**

- Abstract Methods
- Anonymous Inner Classes
- Arrays
- Basic Syntax Differences
- Casting
- Collections
- Comments
- Constants, Fields, and Local Variables
- Constructors
- Default Parameters
- Enums
- Equality
- Exception Handling and Try-With-Resources
- •••
- Ternary Conditional Operator
- Type Discovery

If-Else

Java	Python

if (conditionA)
{
}
else if (conditionB)
{
}
else
{
}
	if conditionA:
	    pass
	elif conditionB:
	    pass
	else:
	    pass

Strings

Java	Python
String s = initValue;	s = initValue
int i = s.indexOf(y);	i = s.find(y)
i = s.lastIndexOf(y);	i = s.rfind(y)
i = s.length();	i = len(s)
boolean b = s.contains(y);	b = y in s
s = s.substring(i);	s = s[i:]
s = s.substring(i, j);	s = s[i:j]
b = s.endsWith(y);	b = s.endswith(y)
b = s.startsWith(y);	b = s.startswith(y)
s = s.toLowerCase();	s = s.casefold()
s = s.toUpperCase();	s = s.upper()
s = s.stripLeading();	s = s.lstrip()
s = s.stripTrailing();	s = s.rstrip()

Java vs Python 'import'

Java	Python
import foo.*;	from foo import *
import ack.Bar;	from ack import Bar

Casting

Java	Python

void casts()
{
    x = (int)y;
    x = (float)y;
    x = (String)y;
}
	def casts(self):
	    x = int(y)
	    x = float(y)
	    x = str(y)

[3] T. Melhase et al., "java2python: Simple but Effective Tool to Translate Java Source Code into Python." https://github.com/natural/java2python.
[4] "py2java: Python to Java Language Translator." https://pypi.org/project/py2java/
[5] T. S. Solutions, "The Most Accurate and Reliable Source Code Converters." https://www.tangiblesoftwaresolutions.com/.

EARLY RULE-BASED TRANSPILERS (CONTD...)

- Source-to-source translator / Transcompiler / Transpiler
  - Handcrafting exhaustive set of rules → **too tedious**, too many requirements to satisfy
  - There's **no guarantee** that **translating piece-by-piece** will generate something 'meaningful'
    - 'meaningful' → a piece of code that works

So, certain requirements are necessary to be chalked out

Many such tools come with a disclaimer stating limitations:
"*...translated codes **should not be expected** to compile and run readily.*" [4]

[4] "py2java: Python to Java Language Translator." https://pypi.org/project/py2java/

The Proposed Method
From a Requirements Engineering Perspective

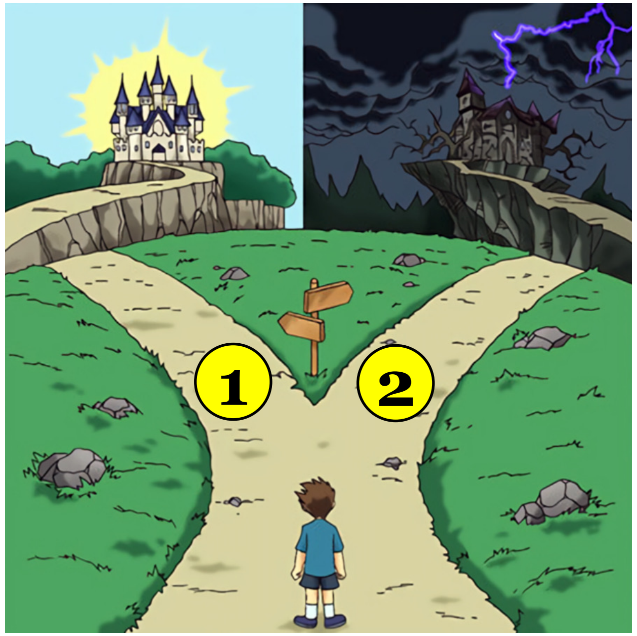
PROGRAM TRANSLATION: TOP-LEVEL BASIC REQUIREMENTS

```java
import java.io.*;
public class Main
{
    static int unitDigitXRaisedY(int x, int y)
    {
        int res = 1;
        for (int i = 0; i < y; i++) res = (res * x) % 10;
        return res;
    }
    public static void main(String args[])
    {
        System.out.println(unitDigitXRaisedY(4, 2));
    }
}
```

A **Java** code

```python
def unitDigitXRaisedY(x, y):
    res = 1
    for i in range(y):
        res = (res * x) % 10
    return res
if __name__ == '__main__':
    print (unitDigitXRaisedY(4 ,2))
```

An "equivalent" code in **Python**



Two top-level requirements:

1 The target-language code should be *syntactically correct*

(We just need a **T**-compiler, and the code should compile)

Easy to chalk out requirements ☺

2 The target-language code should be *runtime (input-output) equivalent* to the source-language code

(Given the same set of console inputs or no input, the outputs are the same)

Difficult ☹

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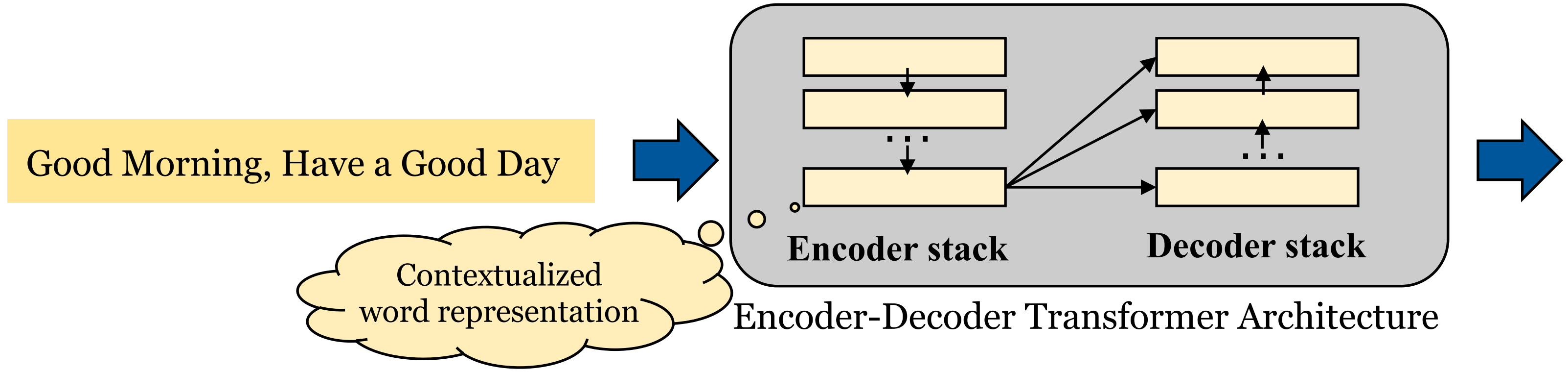
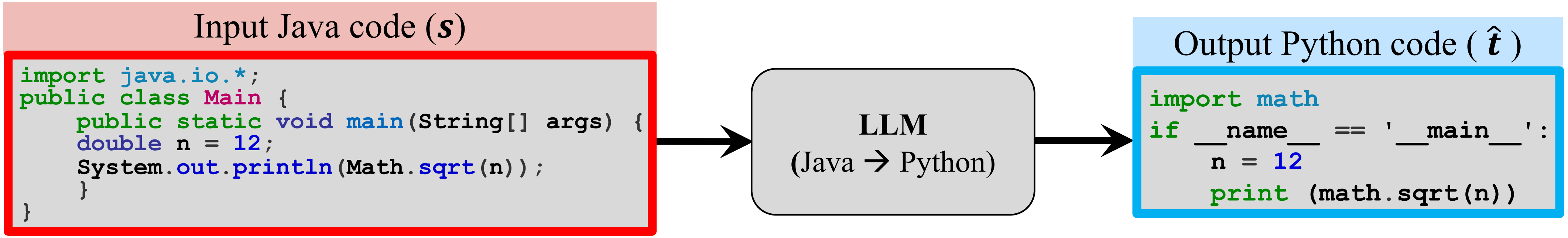
Program Translation: Implementation Requirements

- Recently, **Large Language Models (LLMs)**[6] revolutionized **Natural Language translation**





- Here, we train LLMs for **Programming Language translation**
- Basically, the LLM will serve as the translator function f_{ST}: $\boldsymbol{S} \rightarrow \boldsymbol{T}$

[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention Is All You Need," Advances in Neural Information Processing Systems (NeurIPS), vol. 30, 2017.

Requirements for Train-Corpus

TRAIN-CORPUS (C) REQUIREMENTS

- Like any supervised learning set-up, we need data!
  - Pairs of equivalent Java & Python codes, mined from various competitive coding websites

Java Code	Equivalent Python Code
public class Improve { static int calculateSquareSum (int n) { if (n <= 0) return 0 ; int fibo [ ] = new int ...	def calculateSquareSum (n) : NEW_LINE INDENT fibo = [0] * (n + 1) NEW_LINE if (n <= 0) : NEW_LINE ...
import java . util . * ; public class GFG { static int val (char c) { if (c >= '0' && c <= '9') return (int)...	def val (c) : NEW_LINE INDENT if (c >= '0' and c <= '9') : NEW_LINE INDENT return int (c) NEW_LINE DEDENT ...
...	...

Data Sources:

Project Euler .net, GeeksforGeeks, CODEFORCES, code jam, LeetCode, AtCoder

C.R1 There should be **at least 30,000 pairs** of Java & Python codes (higher the better)
- That's the standard to train a transformer-based LLM architecture

C.R2 For all pairs, **both** the Java & Python codes should be **syntactically correct**

C.R3 For all pairs, **both** the Java & Python codes should be **runtime (input-output) equivalent**
- Can be verified from the set of stringent test-cases in the corresponding data source

C.R4 For all pairs, the Java & Python codes **should not be too long** i.e., **at most 512 tokens**
- LLMs accept and produce tokenized sequences (each word ≡ 1 or more token IDs), which have an upper-limit for length

Train-Corpus (C) Requirements (Contd...)

Java Code	Equivalent Python Code
`public class Improve { static int calculateSquareSum ( int n ) { if ( n <= 0 ) return 0 ; int fibo [ ] = new int ...`	`def calculateSquareSum ( n ) : NEW_LINE INDENT fibo = [ 0 ] * ( n + 1 ) NEW_LINE if ( n <= 0 ) : NEW_LINE ...`
`import java . util . * ; public class GFG { static int val ( char c ) { if ( c >= '0' && c <= '9' ) return ( int )...`	`def val ( c ) : NEW_LINE INDENT if ( c >= '0' and c <= '9' ) : NEW_LINE INDENT return int ( c ) NEW_LINE DEDENT ...`
...	...

Data Sources:

Project Euler .net, GeeksforGeeks, Codeforces, code jam, LeetCode, AtCoder

C.R5 For each **source-language feature**, that we want the trained LLM to learn to translate, the **number of examples (pairs)** in the dataset should count to **at least 1% of total corpus**

E.g.,

- Arrays
- Basic Syntax Differences
- Casting
- Collections
- Comments

- Increment and Decrement Operators
- Inheritance
- Interfaces
- Java vs Python 'import'
- Lambdas
- Logical and Bitwise Operators

...

This ensures the training corpus is *representative enough of the real-world*

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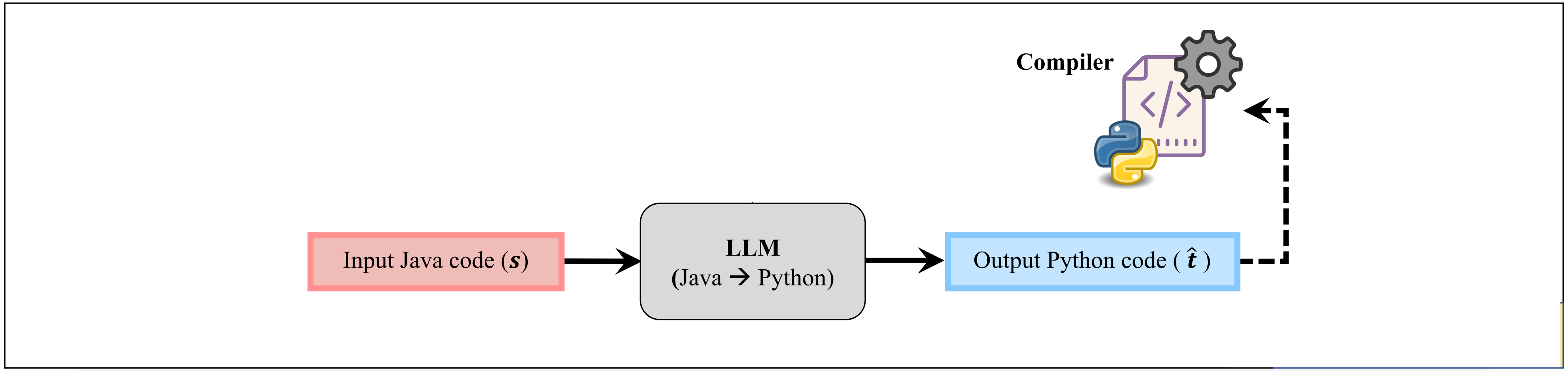
Compilation Requirements for the Learned Large Language Model (LLM)

Learned LLM (L) Requirement: Compilation



Top-level Requirement I:

The translated target-language (T) code should be *syntactically correct*

L.R1 The output target-language code ($\hat{t}$) should pass error-free by **T**-compiler

- For Java as **T**, we use **`javac`** compiler
- For Python as **T**, we use the **`pylint`**[7] **static code analyzer** (as Python is an interpreted language**)**

[7] "pylint: Python code Static Checker." https://pypi.org/project/pylint/

Runtime Equivalence Requirements for the Learned Large Language Model (LLM)

How To Check Runtime Equivalence?

Top-level Requirement II:

Target-language (T) code should be *runtime (IO) equivalent* to source-language (S) code

Three major ways to check equivalence:

- Manually writing an exhaustive suite of test-cases
  - **Too tedious**, **chances of missing** essential test cases
- Boundary-value analysis
  - Tests at boundaries between partitions of input values → **low test coverages**
- Fuzzing / Fuzz-Testing
  - Injects random invalid inputs into a system → **rely on pure luck to find bugs**

- Instead, perform **automated unit-testing** of individual functions
- There is Symflower for Java, but no such popular tool for Python

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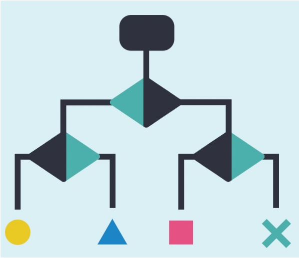
How To Check Runtime Equivalence? Exhaustive Unit-Testing

Top-level Requirement II:

Target-language (T) code should be *runtime (IO) equivalent* to source-language (S) code

- Solver-based analysis through Symflower
  - Automated tool to generate JUnit tests for each function in a code
  - Support for Java only, not Python
  - Symbolic execution **computes necessary inputs** for a function to **execute all relevant paths (exhaustive)** in its **control-flow graph**
  - Generates **J-Unit tests** for all functions in a Java code



```
public class Main
{
    static int minLettersNeeded(int n)
    {
        if (n % 26 == 0) return (n / 26);
        else return ((n / 26) + 1);
    }
    public static void main(String args[])
    {
        int n = 52;
        System.out.println(minLettersNeeded(n));
    }
}
```

A Java code

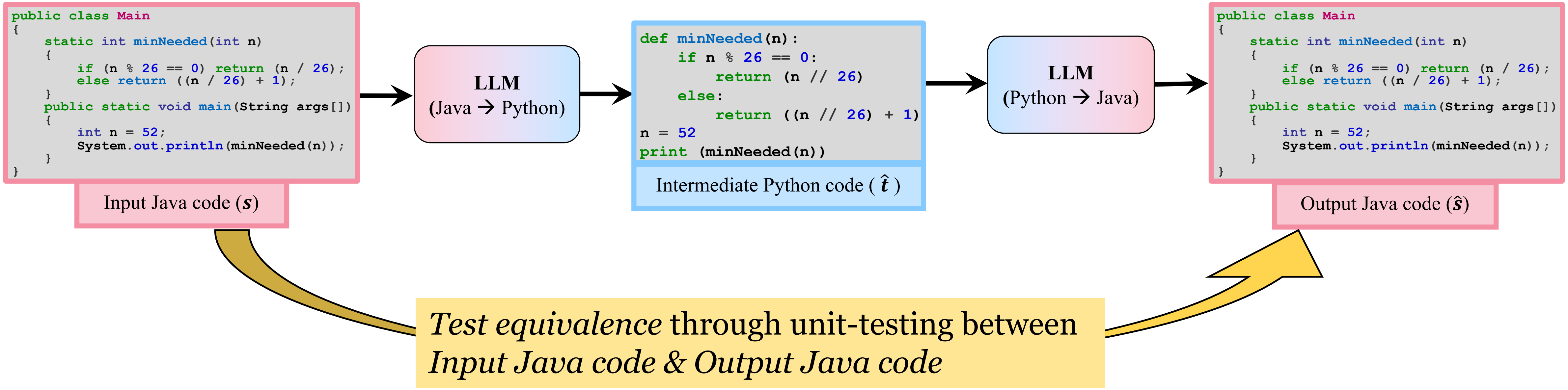
```
@Test
assertEquals(Main.minLettersNeeded(0), 0)

@Test
assertEquals(Main.minLettersNeeded(1), 2)
```

J-Unit tests for a function

Ensuring Runtime Equivalence: Exhaustive Unit-Testing

- As we said, solver-based analysis through *Symflower*: applicable only for Java
- So, employ two back-to-back LLMs: Java → Python and Python → Java

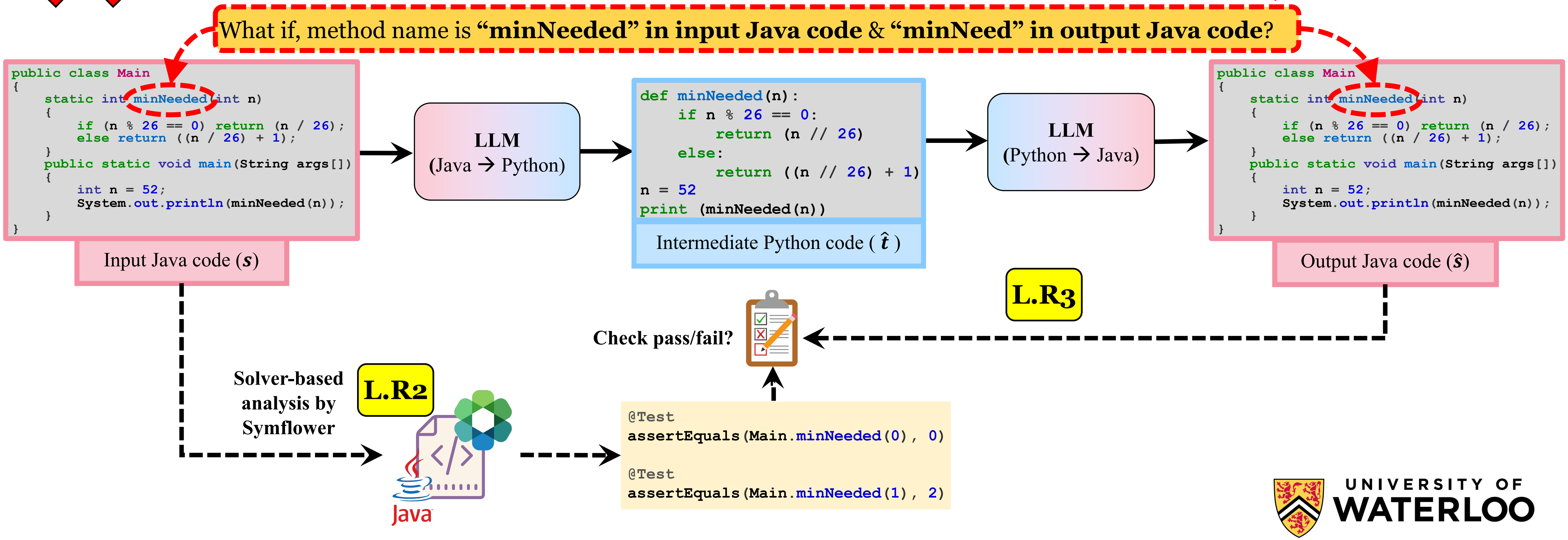


Learned LLM (L) Requirement: Runtime Equivalence

L.R2 For each method $\boldsymbol{p}$ of input Java code ($\boldsymbol{s}$), Symflower generates J-Unit tests $\{u_p\}$

~~**L.R3**~~ All $\{u_p\}$ should pass, on the method $\boldsymbol{p}$ of output Java code ($\hat{\boldsymbol{s}}$)

- Even though input & output Java codes equivalent, this requirement will fail
- Need to **relax the requirement**

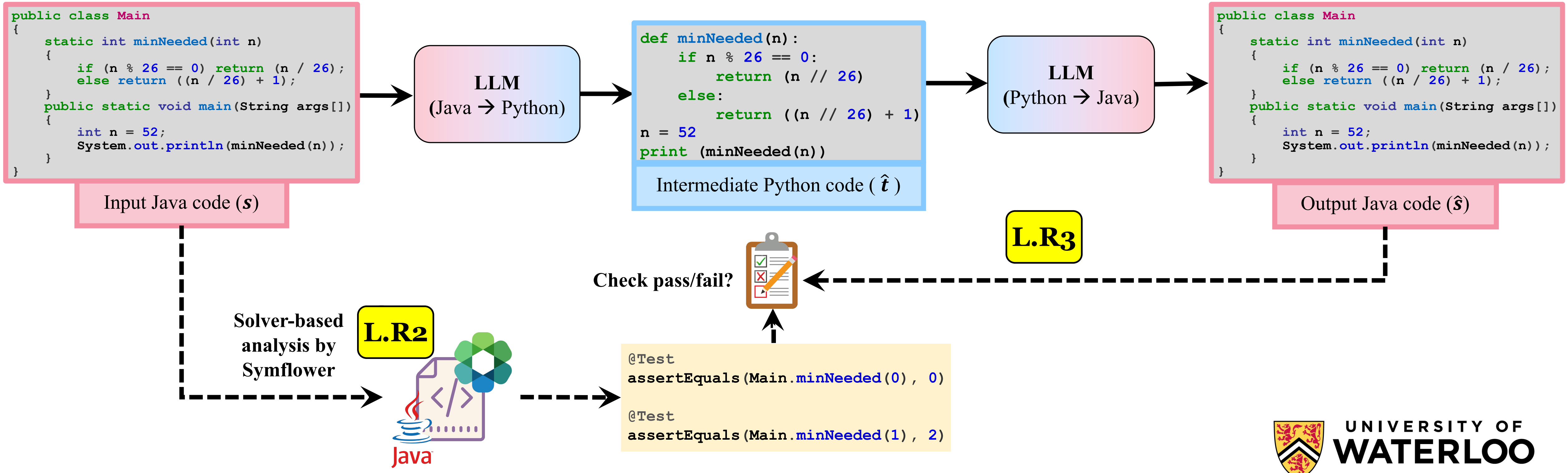


Learned LLM (L) Requirement: Runtime Equivalence (Relaxing L.R3)

L.R2 For each method p of input Java code (s), Symflower generates J-Unit tests $\{u_p\}$

L.R3 All $\{u_p\}$ should pass, on method p^* of output Java code ($\hat{s}$), where $p^* = \text{argmax}_{p^* \in \hat{s}}\, \text{JaccardSimilarity}(p, p^*)$

Another issue: What if the methods p, p^* do not return anything? They just print something on console



Learned LLM (L) Requirement: Runtime Equivalence (Console Outputs)

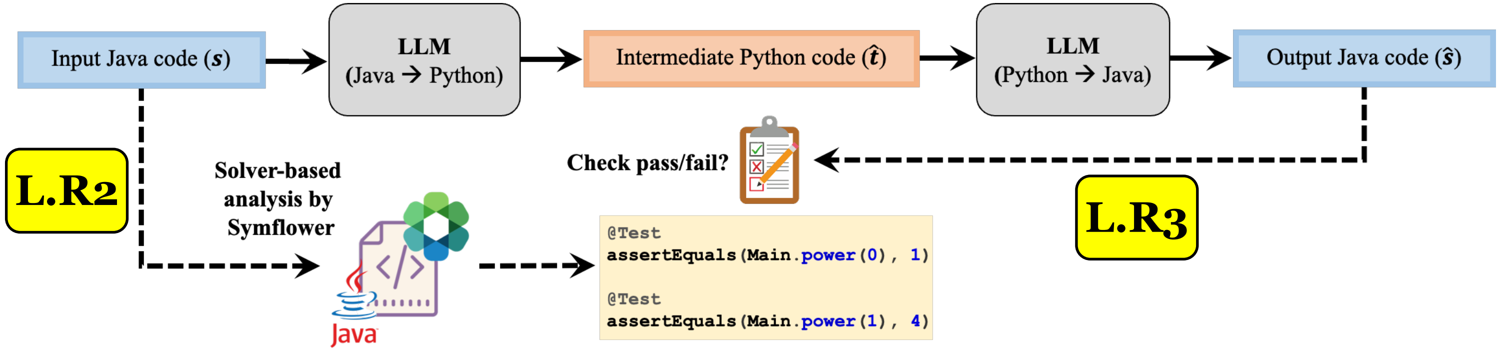
L.R2 For each method $\boldsymbol{p}$ of input Java code ($\boldsymbol{s}$), Symflower generates J-Unit tests $\{u_{\boldsymbol{p}}\}$

L.R3 All $\{u_{\boldsymbol{p}}\}$ should pass, on method $\boldsymbol{p}^*$ of output Java code ($\hat{\boldsymbol{s}}$), where $\boldsymbol{p}^* = \text{argmax}_{\boldsymbol{p}^* \in \hat{\boldsymbol{s}}}\, \text{JaccardSimilarity}(\boldsymbol{p}, \boldsymbol{p}^*)$

L.R4 Let $\boldsymbol{p}_{out}$ and $\boldsymbol{p}^*_{out}$ be the respective console outputs → $f_{matched}(\boldsymbol{p}_{out}, \boldsymbol{p}^*_{out})$ should be True
Here, $f_{matched}$ is a string-matching function that is:

- case-insensitive → $f_{matched}$(“`CS846-ATRE`”, “`cs846-atre`”) = True
- ignores whitespaces → $f_{matched}$(“`good morning`”, “`goodmorning`”) = True
- disregards punctuations (only when they are not a major portion of the output) → $f_{matched}$(“`Hi! Bro.`”, “`Hi Bro`”) = True
- takes numeric or floating-point values to a common representation → $f_{matched}$(“`3.1415`”, “`3.1`”) = True

These are because: to evaluate code equivalence, we do not need a strict string-matching function



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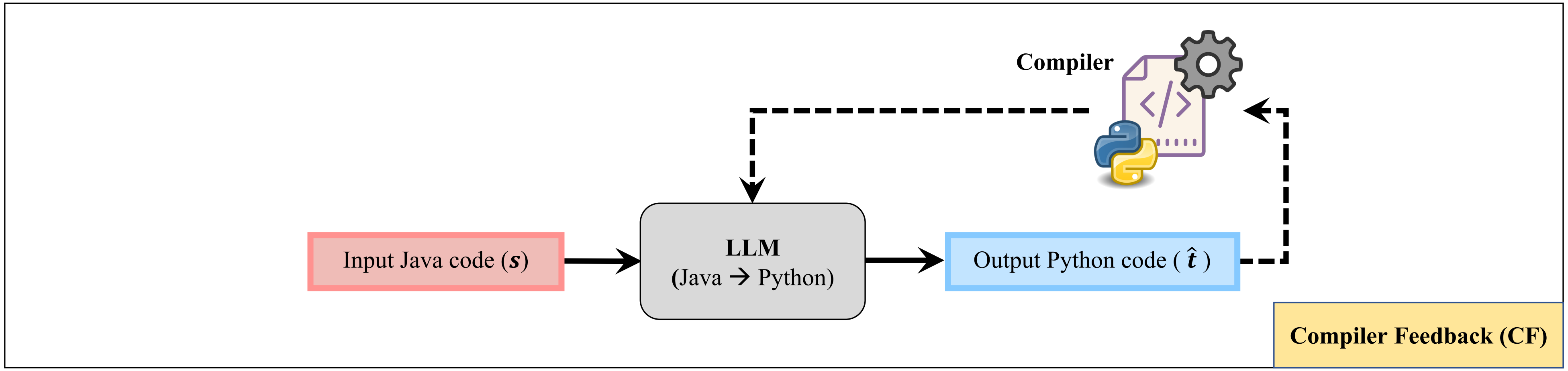
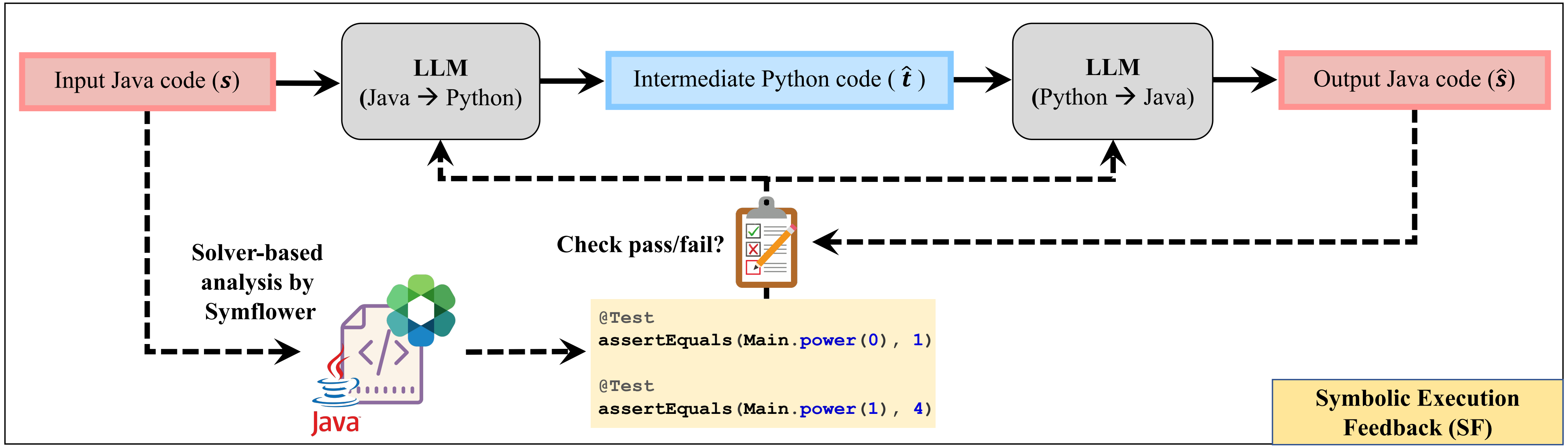
How to Train the LLM to Follow such Requirements?





- During training with cross-entropy loss, **provide feedbacks to the LLM**: whether requirements satisfied or not?
- **Compiler Feedback (CF)** increases compilation rate of output code
- **Symbolic Execution Feedback (SF)** increases the runtime equivalence rate of output code

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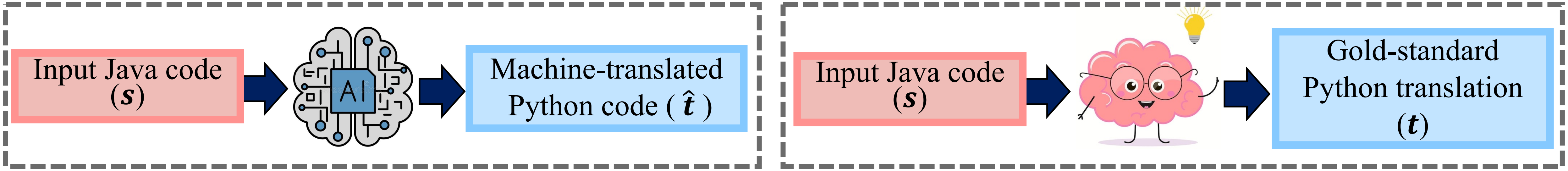
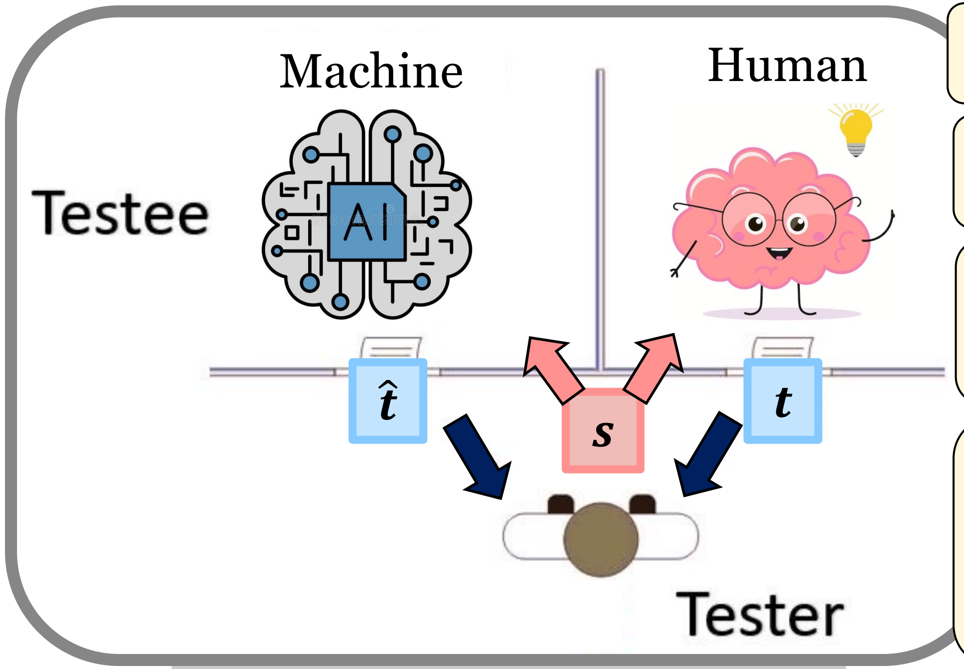
How To Know That The LLM is Trained Well-Enough?

Evaluation Metrics



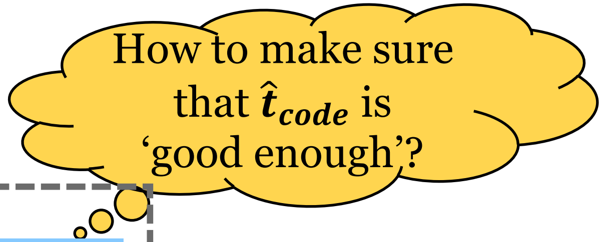


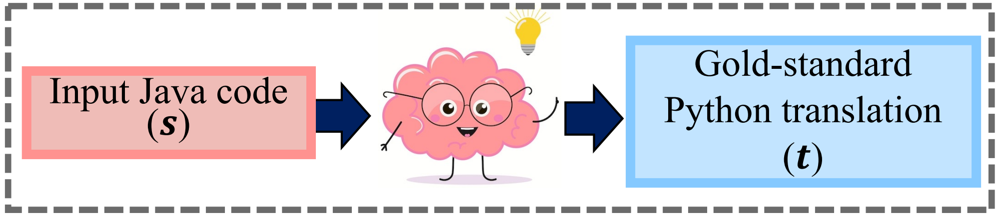
Code-Translation Turing Test

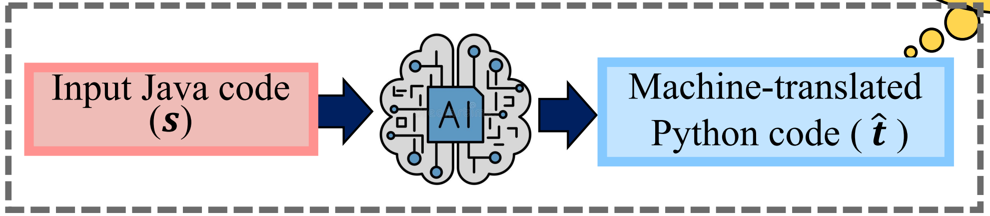
1. Tester unaware about who is behind which window
2. Tester submits Input Java code s through the windows
3. Machine / AI and Human returns Python codes $\hat{t}$ and t resp.
4. If Tester finds both translations to be equally 'good enough', the machine is successful in fooling the Tester

- **Qualitatively:** Have to make sure that our LLM should perform well in Turing Test
- To evaluate **quantitatively** whether it satisfies the basic requirements, we need some **metrics**

Traditional Evaluation Metrics







- **ExactMatch**
  - a Boolean score based on perfect match

$$\mathbf{EM}(t_{code}, \hat{t}_{code}) = \begin{cases} 1, & \text{if } t_{code} = \hat{t}_{code} \\ 0, & \text{otherwise} \end{cases}$$

- **BLEU** → *Bilingual Evaluation Understudy*
  - computes 'closeness' with gold-standard translation through n-gram overlaps; penalizes short predictions

$$\mathbf{BLEU}(t_{code}, \hat{t}_{code}) = \text{BrevityPenalty} + \text{GeometricAvgPrecision.}$$
$$= \min\left(1 - \frac{|t_{code}|}{|\hat{t}_{code}|}, 0\right) + \left(\frac{p_1 + p_2 + p_3 + p_4}{4}\right)$$

p_1 (1-gram precision) $= \frac{5}{8}$

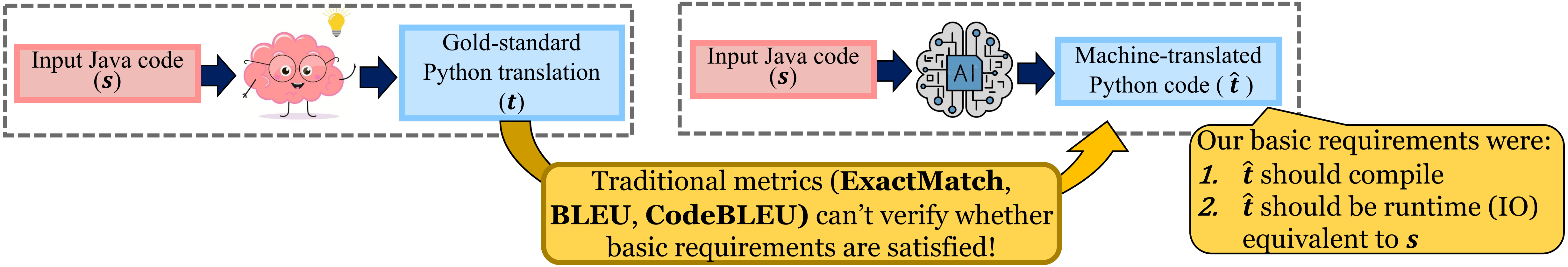
p_2 (2-gram precision) $= \frac{4}{7}$

- **CodeBLEU** → *BLEU, extended for codes*
  - checks closeness + syntactic & semantic features
  - Mean of BLEU, weighted n-gram match (**WM**), syntactic AST match (**SM**) & semantic Data-flow match (**DM**)

$$\mathbf{CodeBLEU}(t_{code}, \hat{t}_{code}) = \left(\frac{\mathbf{BLEU} + \mathbf{WM} + \mathbf{SM} + \mathbf{DM}}{4}\right)$$

WM: BLEU, where keywords (*for*, *int*, *public*, etc.) have higher weights
SM: %age of sub-tree matches in Abstract Syntax Tree of t_{code} and $\hat{t}_{code}$
DM: %age of sub-graph matches in Data Flow Graph of t_{code} and $\hat{t}_{code}$

Traditional Evaluation Metrics: Not Suitable for Our Requirements



- **ExactMatch**
  - Doesn't make much sense for Code Translation. Too strict, there can be multiple correct translations
  - Low **ExactMatch**$(\boldsymbol{t_{code}}, \hat{\boldsymbol{t}}_{\boldsymbol{code}})$ score $\not\Rightarrow$ $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ doesn't satisfy basic requirements
  - E.g. $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ = `print("Hello" + "!")` satisfies requirements of $\boldsymbol{t_{code}}$ = `print("Hello!")`. Still, **ExactMatch**$(\boldsymbol{t_{code}}, \hat{\boldsymbol{t}}_{\boldsymbol{code}}) = 0$
- **BLEU**
  - More relevant for Natural Language translation (e.g. English to French)
  - Computes 'closeness' of $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ and $\boldsymbol{t_{code}}$. High **BLEU**$(\boldsymbol{t_{code}}, \hat{\boldsymbol{t}}_{\boldsymbol{code}})$ score $\not\Rightarrow$ $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ compiles
  - E.g. $\boldsymbol{t_{code}}$ = `print("Hello!")` compiles but, $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ = `print(Hello!")` doesn't. Still, **BLEU**$(\boldsymbol{t_{code}}, \hat{\boldsymbol{t}}_{\boldsymbol{code}}) \cong 100\%$
- **CodeBLEU**
  - Computes 'closeness' of $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ and $\boldsymbol{t_{code}}$, giving priority to Abstract Syntax Tree match & Data-Flow Graph match
  - Like BLEU, $\hat{\boldsymbol{t}}_{\boldsymbol{code}}$ may not compile even though high AST or Data-Flow match

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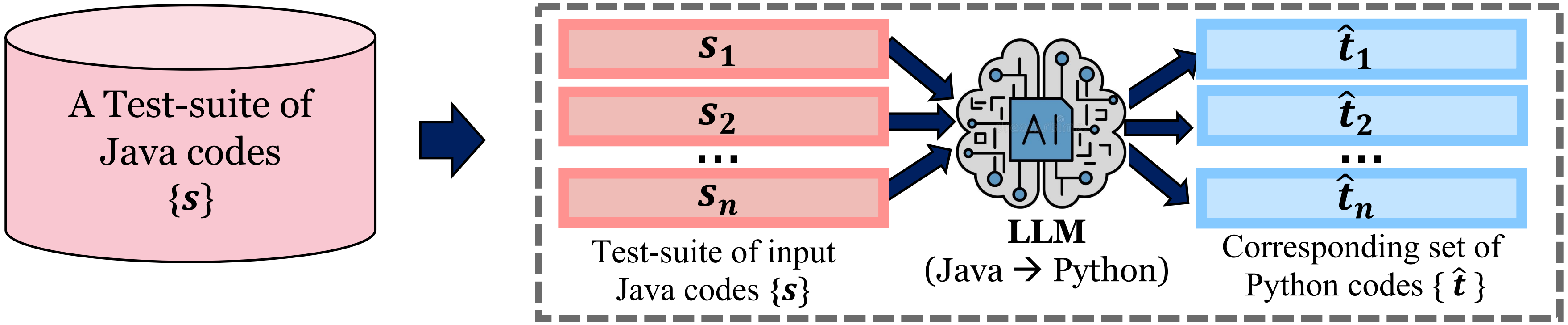
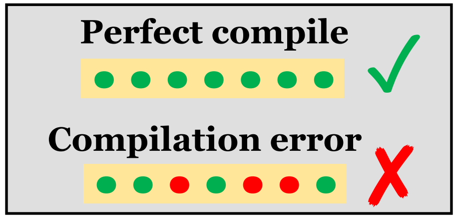
Proposed Metrics to Validate Compilation Requirements

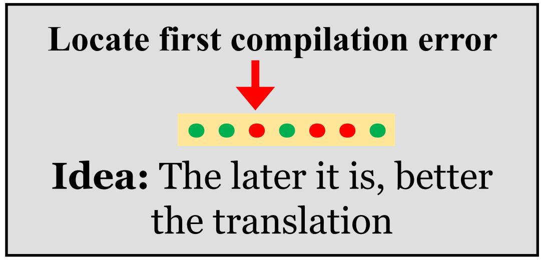


Our compilation requirement:
- $\hat{t}$ should compile

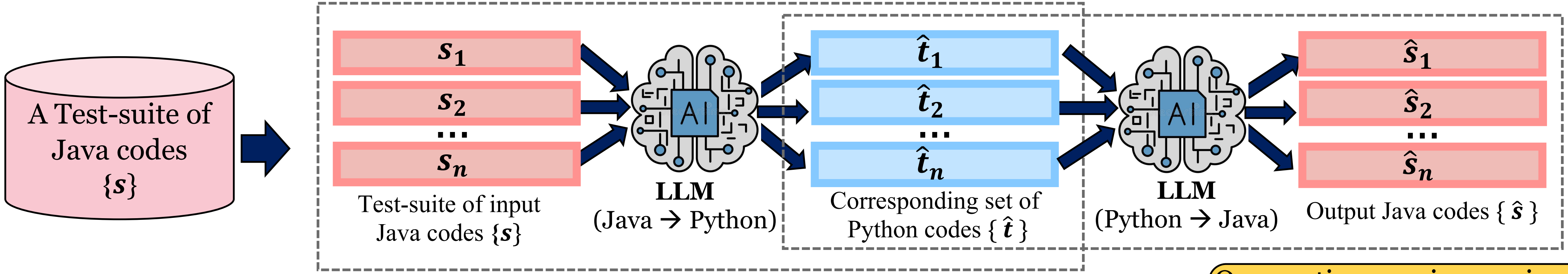
- Create a representative test-suite $\{s\}$ of Java codes, that solve range of algorithmic problems
- **Compilation Accuracy (CompAcc)**
  - %age of predicted translations that compiles correctly i.e., $\textbf{CompAcc}(\{\hat{t}\}) = \frac{|\{\hat{t}_i : \hat{t}_i \text{ compiles by T compiler}\}|}{|\{s\}|}$
- **Average First Error Position ($\textbf{errPos}_{\textbf{1st}}$)**
  - Fine-grained version of **CompAcc**, relating to closeness of translations from a perfect compilation
  - $\textbf{errPos}_{\textbf{1st}}(\{\hat{t}\}) = \frac{\sum_{i=1}^{|\{s\}|} \textbf{errPos}_{\textbf{1st}}(\hat{t}_i)}{|\{s\}|}$

$$\text{,where } \textbf{errPos}_{\textbf{1st}}(\hat{t}_i) = \begin{cases} 100 \times \frac{\text{position of first token in } \hat{\mathbf{t}}_{\mathbf{i}} \text{ responsible for a compilation error}}{|\hat{\mathbf{t}}_{\mathbf{i}}|+1} & \text{, if } \hat{\mathbf{t}}_{\mathbf{i}} \text{ doesn't compile} \\ 100 & \text{, otherwise} \end{cases}$$





Proposed Metrics to Validate Runtime-Equivalence Requirements



Our runtime-equiv. requirement:
- $\hat{t}$ should be runtime (IO) equivalent to s

- It is difficult to check IO-equivalence between { **s** } and { $\hat{t}$ } without manually-created test-cases
  - As an alternative, we approximate **RunEqAcc**({ **s** }, { $\hat{t}$ }) using **RunEqAcc**({ **s** }, { $\hat{s}$ })
- **Runtime-Equivalence Accuracy (RunEqAcc)**
  - Number of J-Unit tests ($\mathcal{J}_{s_i}$) on input Java code $\mathbf{s_i}$ that are successful on output Java $\hat{s}_i$, averaged over whole test-suite
  - $\mathbf{RunEqAcc}(\{\,\mathbf{s}\,\},\{\,\hat{s}\,\}) = \frac{\sum_{i=1}^{|\{s\}|} \mathbf{RunEqAcc}\,(s_i,\hat{s}_i)}{|\{s\}|}$,where $\mathbf{RunEqAcc}(s_i,\hat{s}_i) = \frac{\varepsilon + \sum_{j\in\mathcal{J}_{s_i}}\left(1_{j(\hat{s}_i)\equiv\text{success}}\right)}{\varepsilon + \left|\mathcal{J}_{s_i}\right|} \times 100$
  - $\varepsilon \approx 0^+$, used to avoid zero-division error

COMPUTING METRICS TOLERANCE : LESS THAN PERFECT DEFINITION OF "PERFECT"

Abbreviations

SM: Syntactic Match
DM: Data-flow Match
EM: Exact Match
CompAcc: Compiler Accuracy
RunEqAcc: Runtime Equivalence Accuracy
errPos$_{1st}$: Average First Error Position

Traditional metrics

Proposed metrics based on the requirements

Java → Python

Method / Tool	Model	BLEU	CodeBLEU	Wt. n-gram	SM	DM	EM	*CompAcc*	*RunEqAcc*	$errPos_{1st}$
Transpilers	java2python [3]	17.54	20.31	22.04	16.05	22.99	0	41.46	3.32	28.62
	TSS CodeConv [5]	24.44	41.87	**57.84**	39.66	**46.06**	0	58.30	0.45	**54.26**
Recent competing tools	CodeBERT [8]	51.13	34.97	-	34.35	29.24	0.47	92.80	0.4	-
	GraphCodeBERT [9]	57.93	39.04	-	37.99	32.16	0.74	92.86	2.0	-
	CodeGPT [10]	46.32	30.22	-	32.17	22.23	1.58	79.60	2.8	-
	CodeGPT-adapted [10]	44.29	29.28	-	31.59	20.38	1.84	80.15	2.4	-
	PLBART-base [11]	**63.10**	46.15	-	**42.18**	37.90	1.89	**96.44**	**6.8**	-
	CodeT5-base [12]	62.68	**46.24**	-	41.71	37.89	**2.52**	91.75	6.0	-
	TransCoder-ST [13]	55.41	43.77	-	41.59	36.06	1.84	94.85	5.6	-

Python → Java

Method / Tool	Model	BLEU	CodeBLEU	Wt. n-gram	SM	DM	EM	*CompAcc*	*RunEqAcc*	$errPos_{1st}$
Transpilers	py2java [4]	48.59	41.56	**50.46**	52.83	14.38	0	0	0	**1.61**
Recent competing tools	CodeBERT [8]	35.05	33.16	-	41.09	31.52	0	54.10	0	-
	GraphCodeBERT [9]	38.26	36.93	-	42.26	32.69	0	66.80	0	-
	CodeGPT [10]	48.94	38.01	-	42.74	34.08	0.68	40.65	**2.0**	-
	CodeGPT-adapted [10]	47.99	36.73	-	42.99	28.32	0.84	46.74	0.8	-
	PLBART-base [11]	**69.65**	48.77	-	54.21	30.91	**1.00**	**78.26**	0.8	-
	CodeT5-base [12]	60.84	**50.34**	-	**55.06**	**39.57**	0.89	68.70	1.6	-
	TransCoder-ST [13]	66.02	48.60	-	53.33	31.70	0.95	72.43	**2.0**	-

Tolerance p-values for our proposed method

	Java → Py	Py → Java
CompAcc	95%	75%
RunEqAcc	47.5%	37.5%
errPos$_{1st}$	70%	60%

Noteworthy observation: Python → Java (dynamically- to statically-typed) is more difficult than Java → Python!

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Conclusion & Future Scope

- This work is focused at requirement engineering for an LLM-based code translation
  - **Java** ↔ **Python** translation: two OOP languages, but syntactically very different
  - To produce **syntactically-correct** & **runtime-equivalent** translations
  - Proposed **new metrics** (*CompAcc*, *RunEqAcc*, $errPos_{1st}$) to verify whether LLM satisfies requirements
  - Computed **tolerance p-values** for the metrics

- In Future:
  - Add more requirements for **algorithmic-level equivalence**: compute-time, space-time
  - Unit-testing **can't guarantee equivalence for unhandled exceptions** → need more requirements
    - E.g, out of bound, zero division that are not handled by some try-catch logic
  - Identify **language features that are not translatable** e.g. pointers, multiple inheritance
    - Might need more requirements on what kind of codes can be translated
  - Translate between two **languages of different prog. paradigm** (e.g. Java for OOP → Racket for Functional)
    - Evaluate if this requires new requirements
  - Not all **new requirements may not be achievable** by our existing LLM pipeline
    - Might need more explicit teaching for the LLM

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THANK YOU!

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