



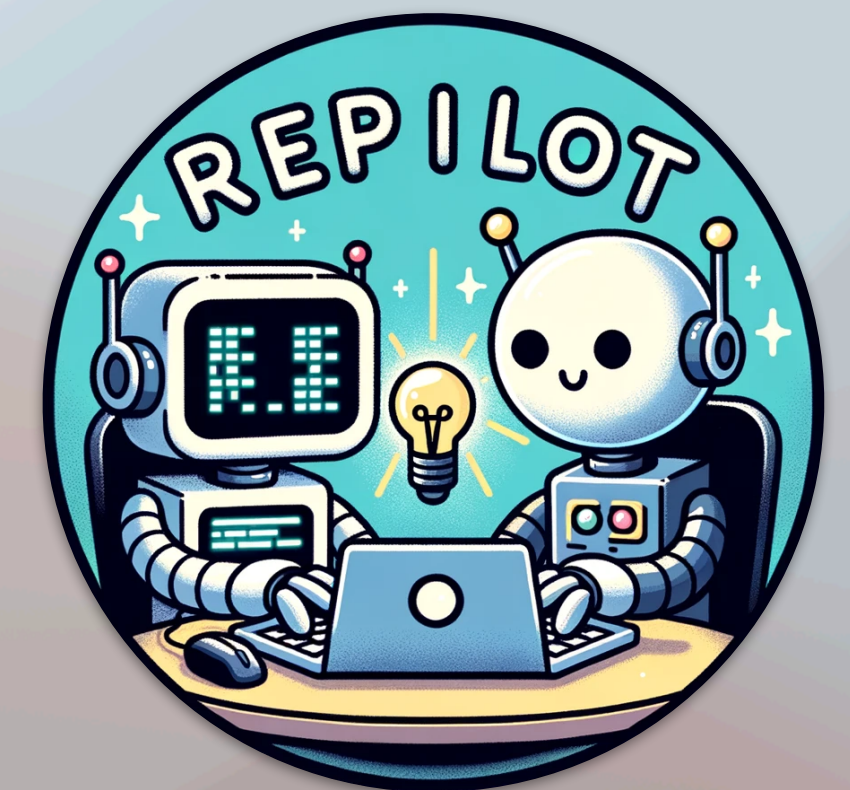
Copiloting the Copilots (Repilot)

Fusing Large Language Models with Completion Engines
for Automated Program Repair

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X @YuxiangWei9

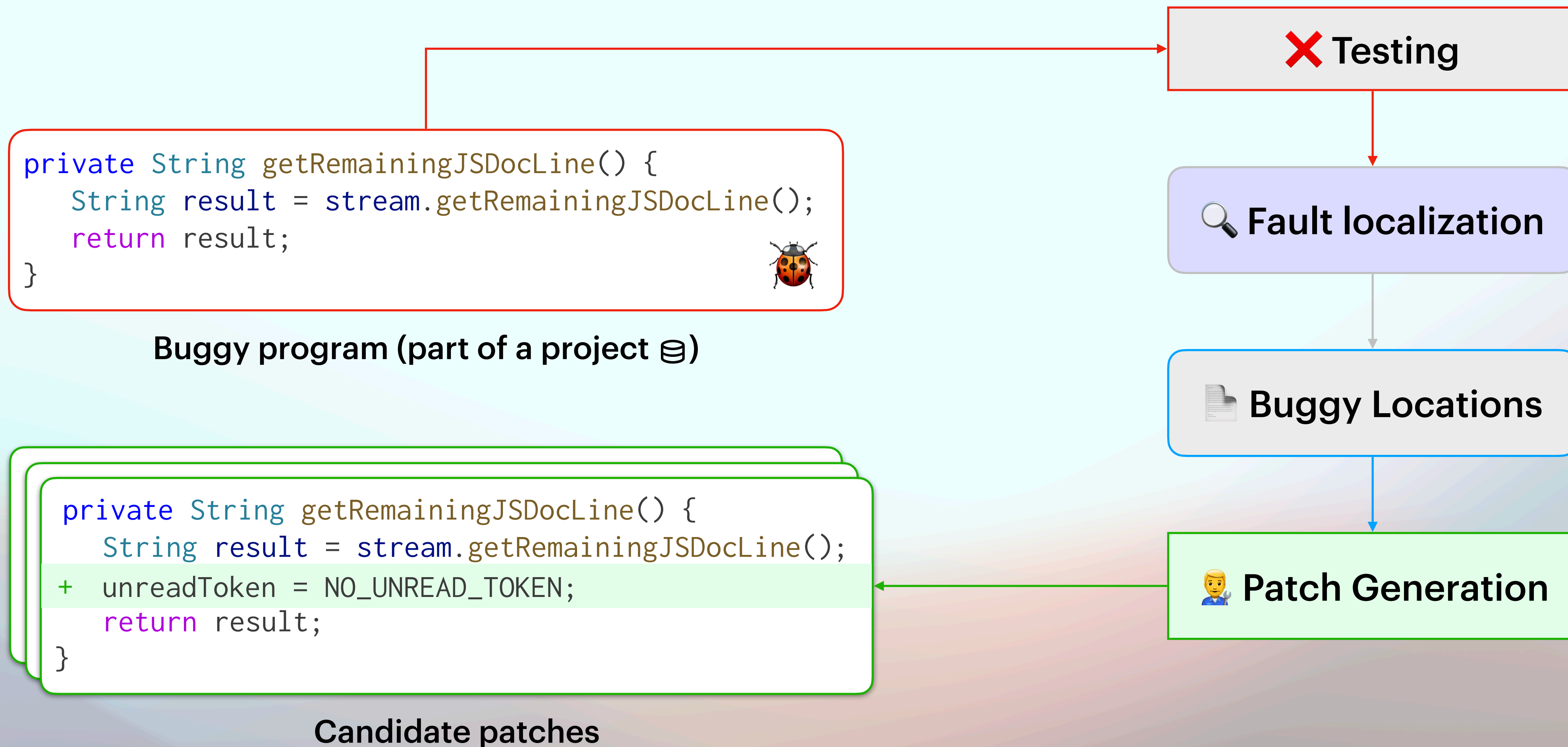
I Chunqiu Steven Xia
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I Lingming Zhang
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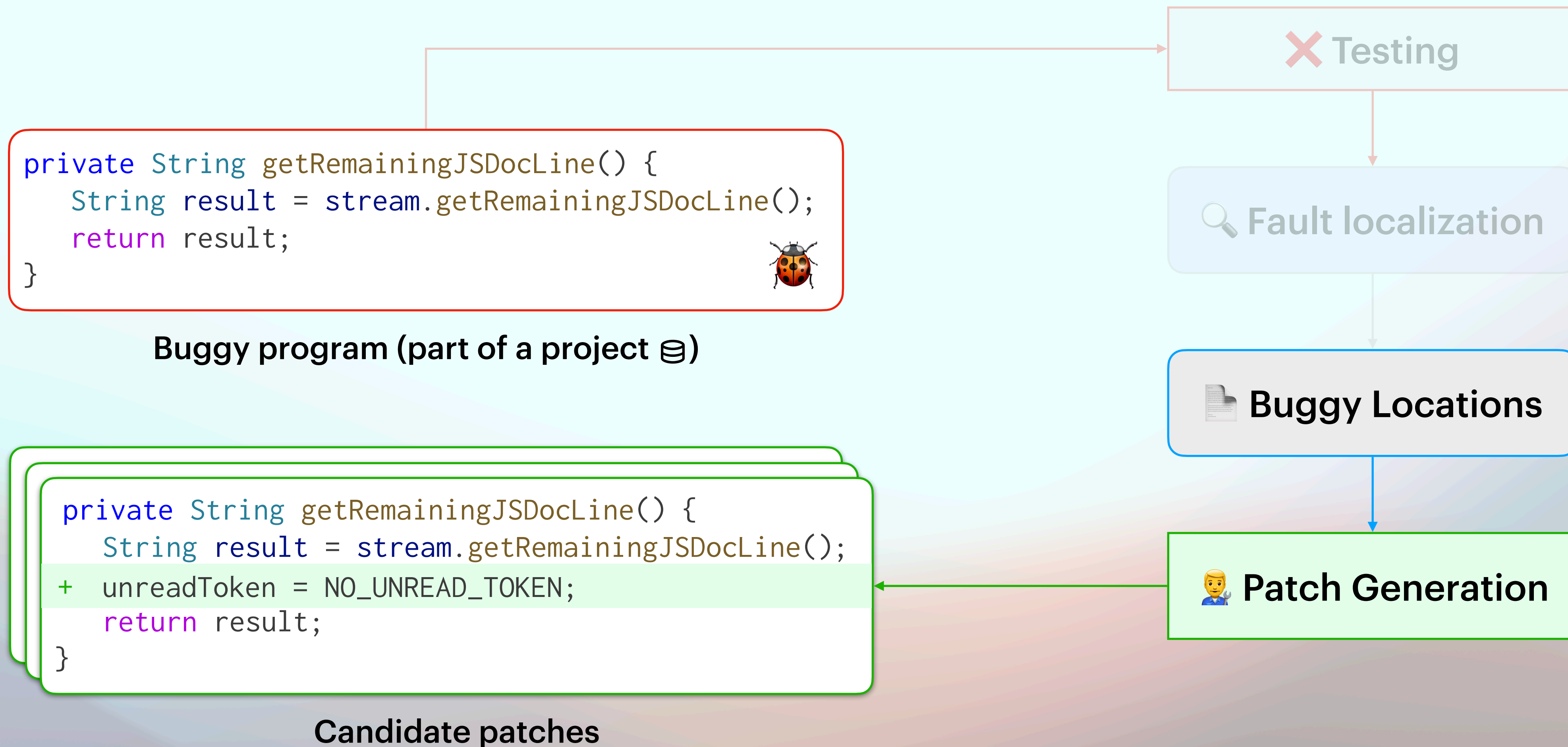
Automated Program Repair (APR)

The two stages

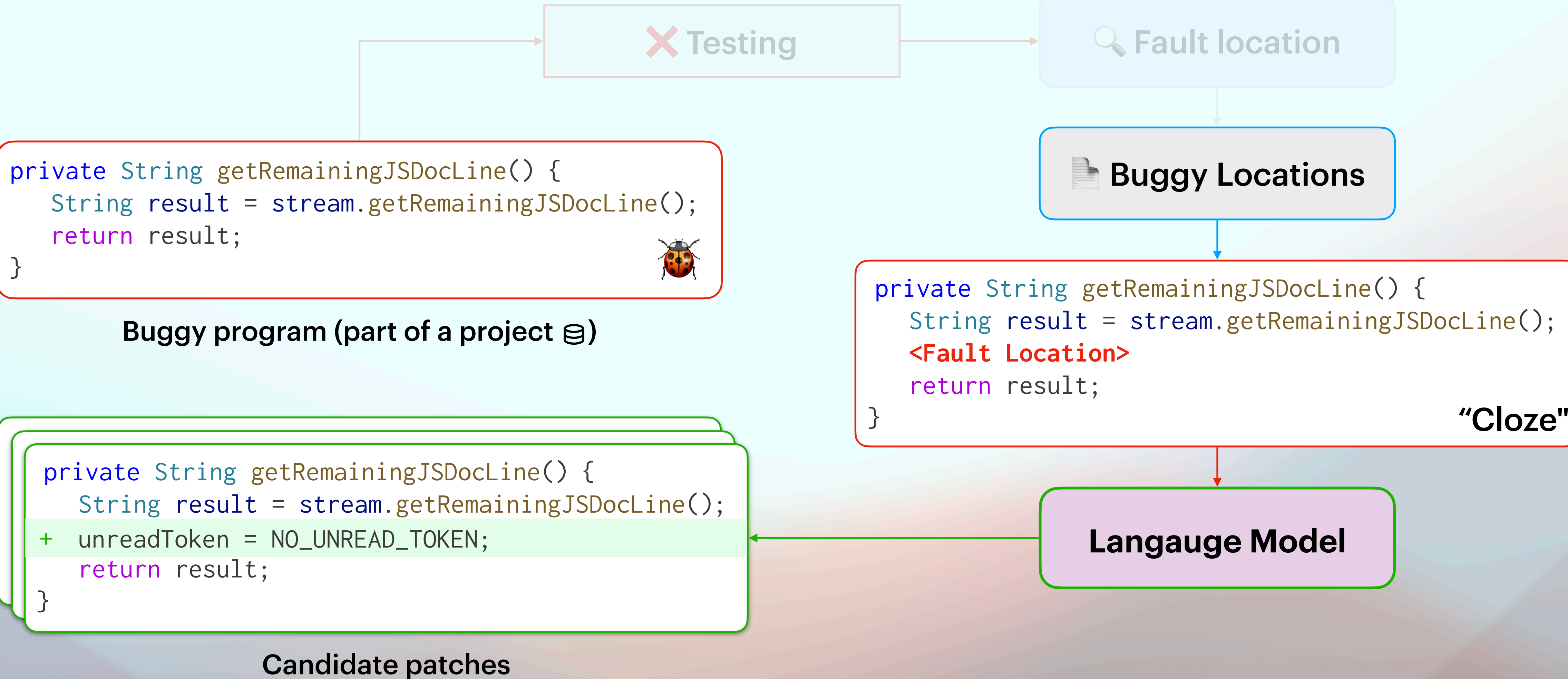


Automated Program Repair (APR)

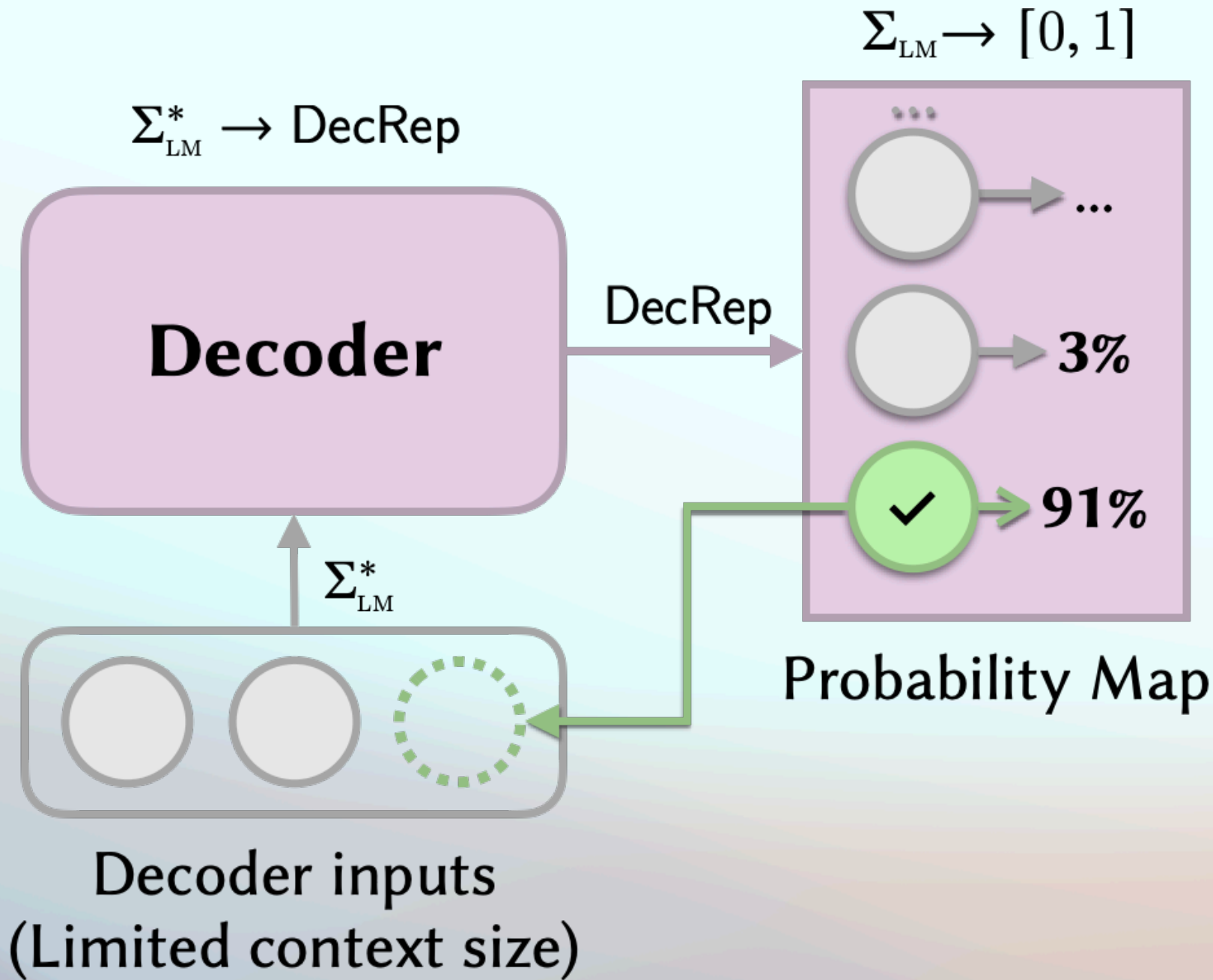
The two stages



Patch Generation with Large Language Models (LLMs)

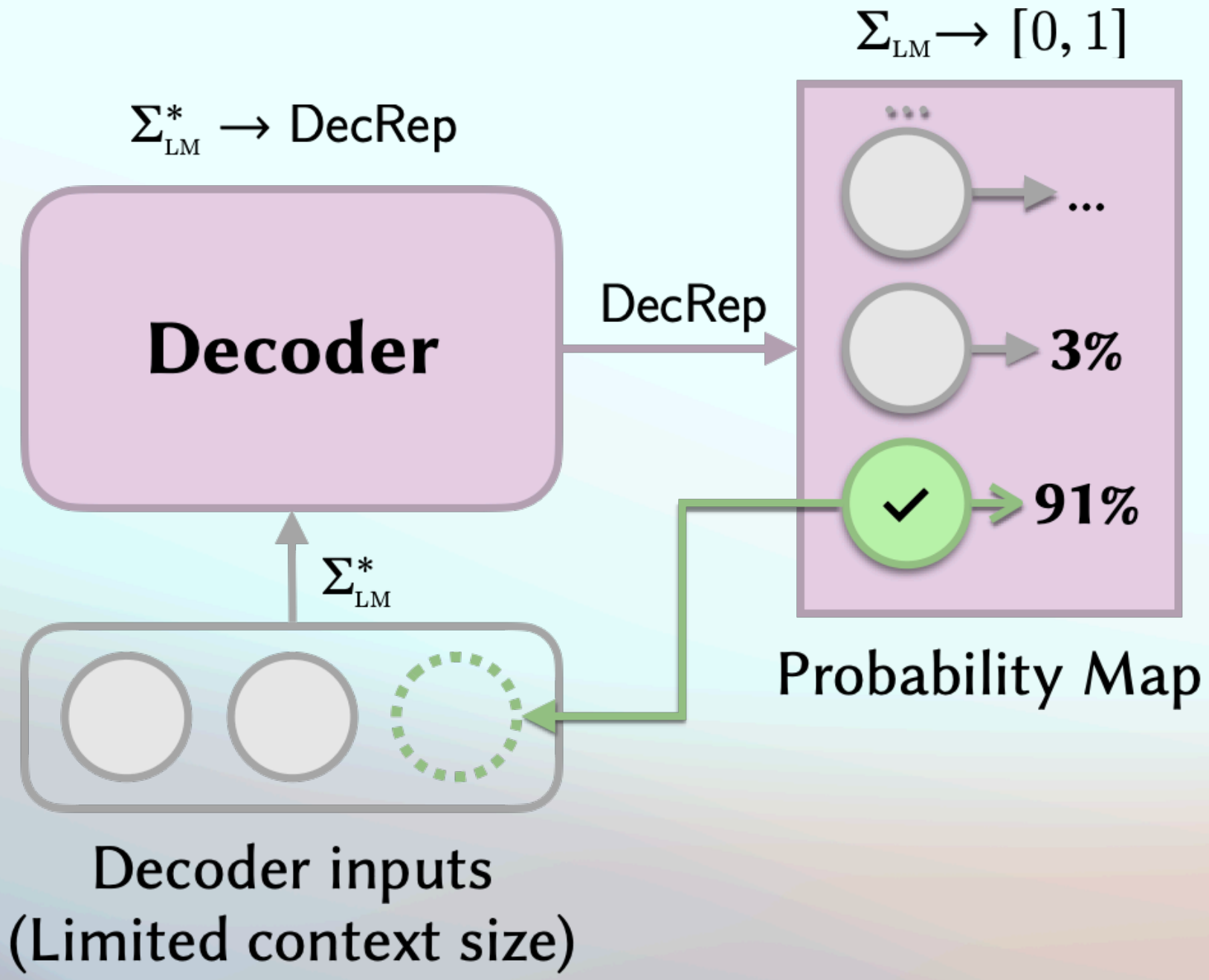


LLMs vs. Autocompletion

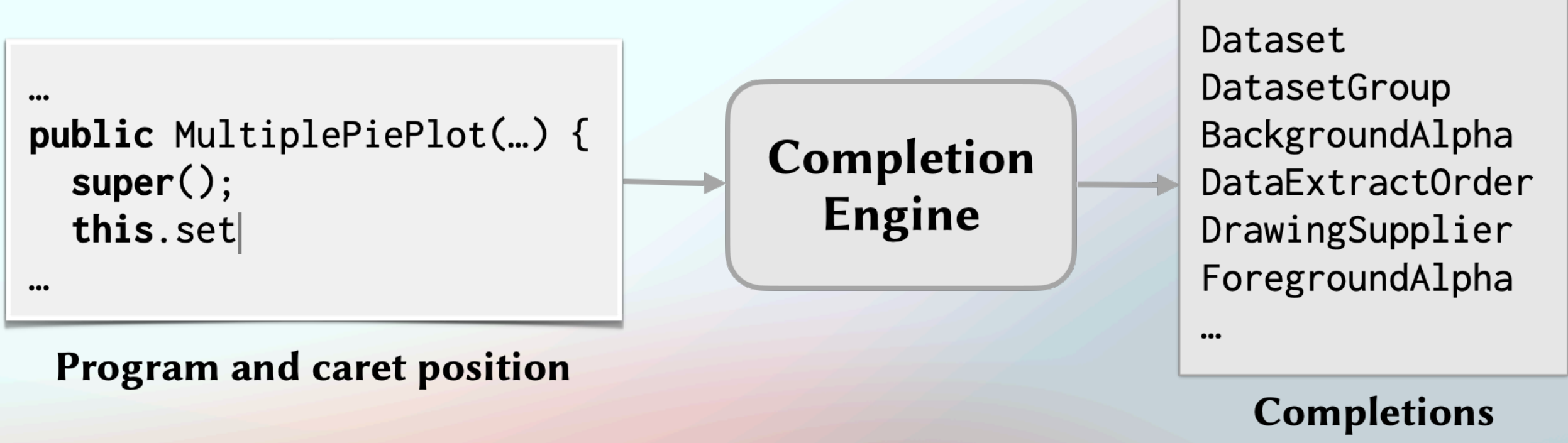


Code generation with LLMs

LLMs vs. Autocompletion



Code generation with LLMs



Semantics-based autocompletion

Problems with LLM-only code generation

The autoregressive (token-by-token) nature

Language model Predictions

String	91%	✗
Name	3%	✗
End	0.2%	✓
...		

Completions

asEndTag
asStartTag
asComment
asDoctype
asCharacter

```
String name = t.as|
```

a Generating infeasible tokens

Problems with LLM-only code generation

The autoregressive (token-by-token) nature

Language model Predictions

String	91%	<input type="checkbox"/>
Name	3%	<input type="checkbox"/>
End	0.2%	<input checked="" type="checkbox"/>
...		

Completions

<code>asEndTag</code>
<code>asStartTag</code>
<code>asComment</code>
<code>asDoctype</code>
<code>asCharacter</code>

String name = t.as|

a Generating infeasible tokens

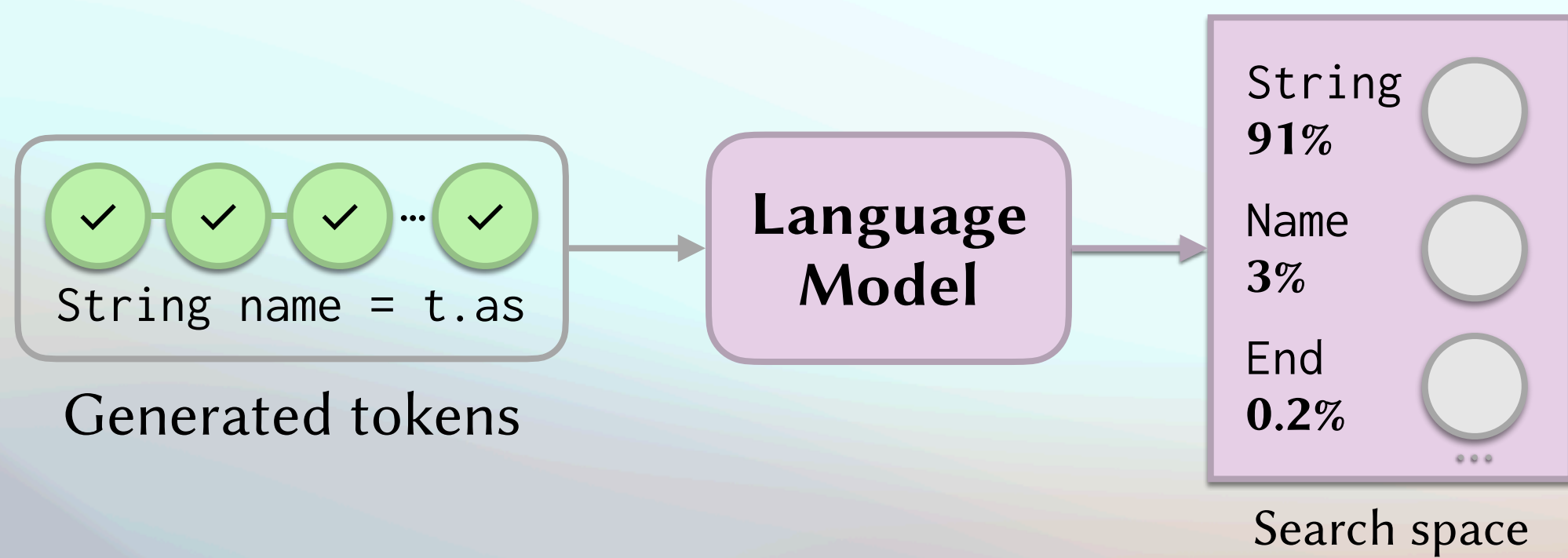
Name	16%	<input type="checkbox"/>
Tag	7%	<input type="checkbox"/>
...		

<code>asEndTag</code>	<input checked="" type="checkbox"/>
-----------------------	-------------------------------------

String name = t.asEnd|Tag

b Hard to generate rare tokens

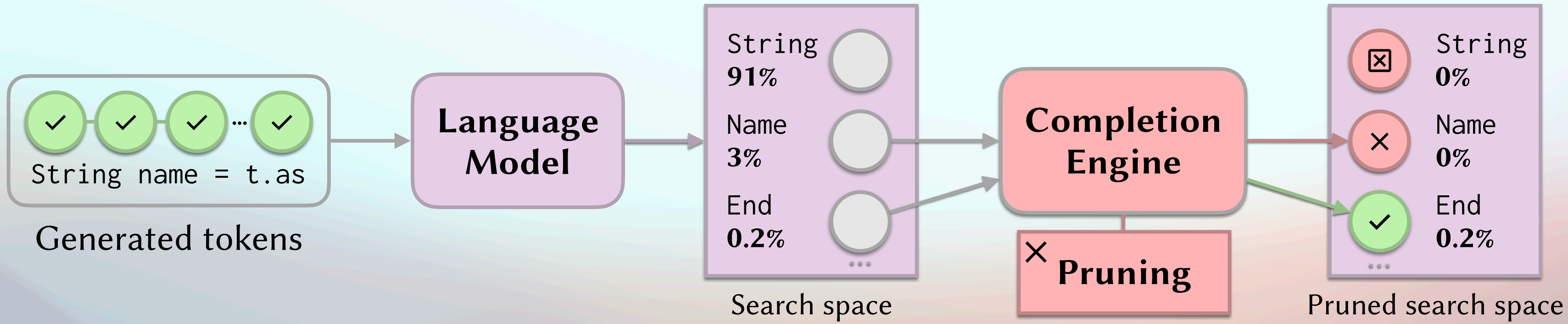
How Repilot works



How Repilot works

Language model Predictions			Completions
String	91%	✗	asEndTag
Name	3%	✗	asStartTag
End	0.2%	✓	asComment
...			asDoctype
			asCharacter

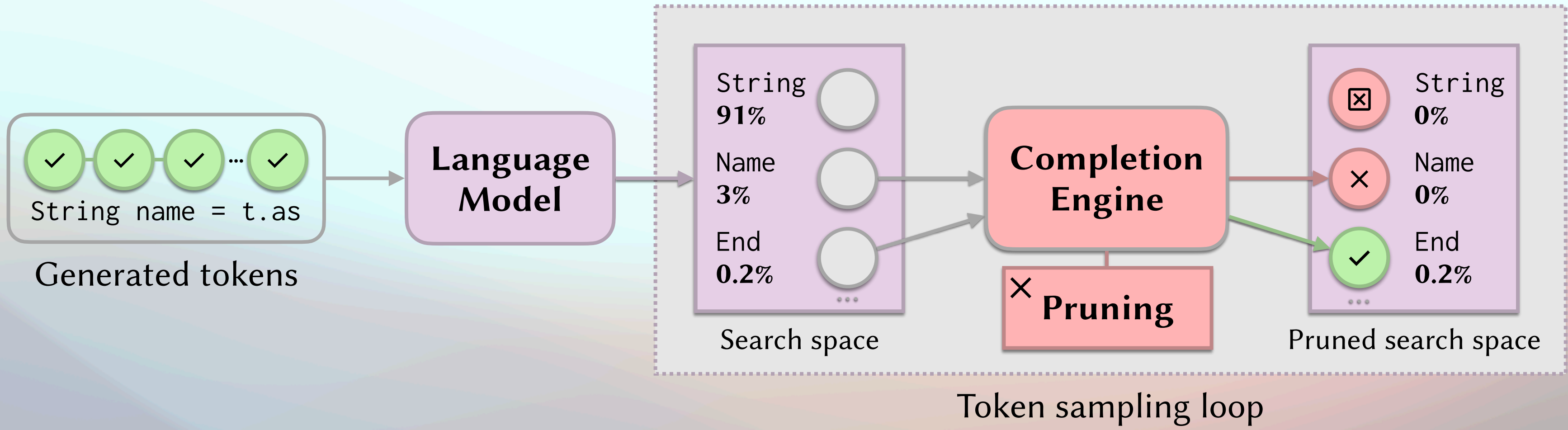
String name = t.as|



How Repilot works

Language model Predictions			Completions
String	91%	✗	asEndTag
Name	3%	✗	asStartTag
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...			asDoctype
			asCharacter

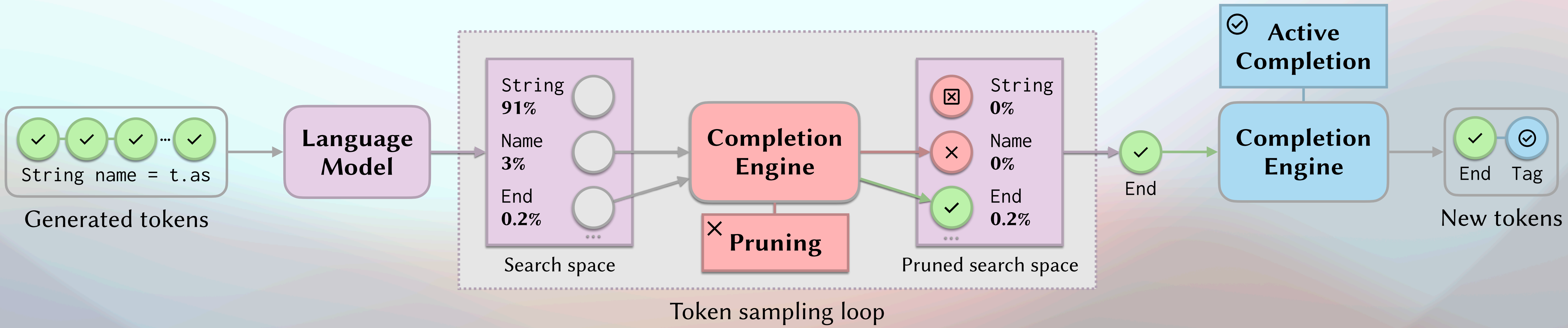
String name = t.as|



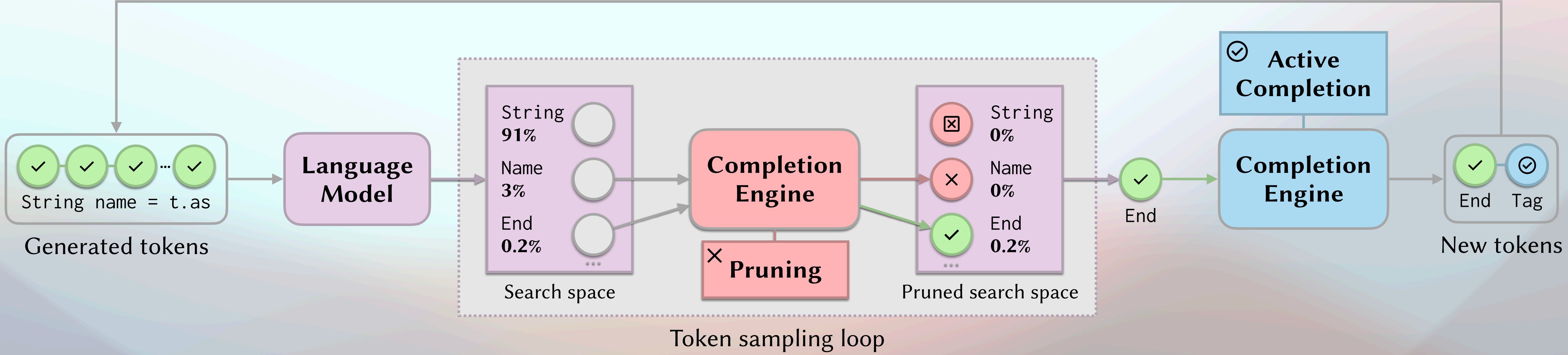
How Repilot works

Language model Predictions			Completions
String	91%	✗	asEndTag
Name	3%	✗	asStartTag
End	0.2%	✓	asComment
...			asDoctype
			asCharacter

String name = t.as|

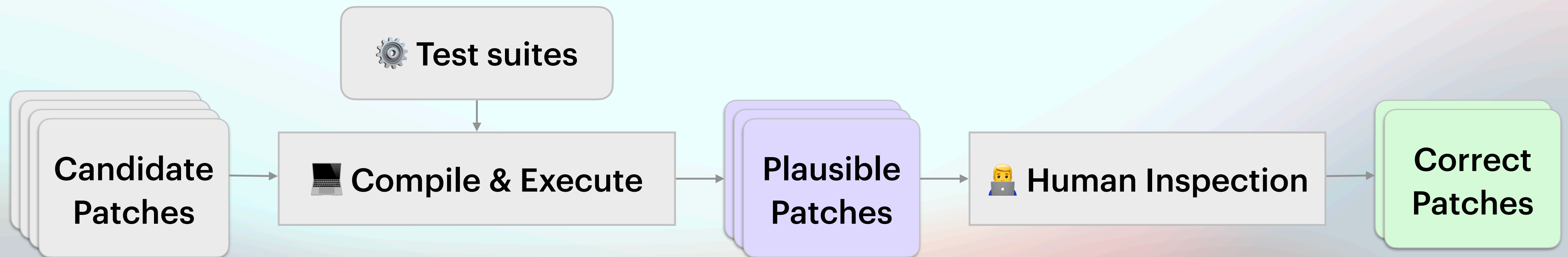


How Repilot works



Evaluation

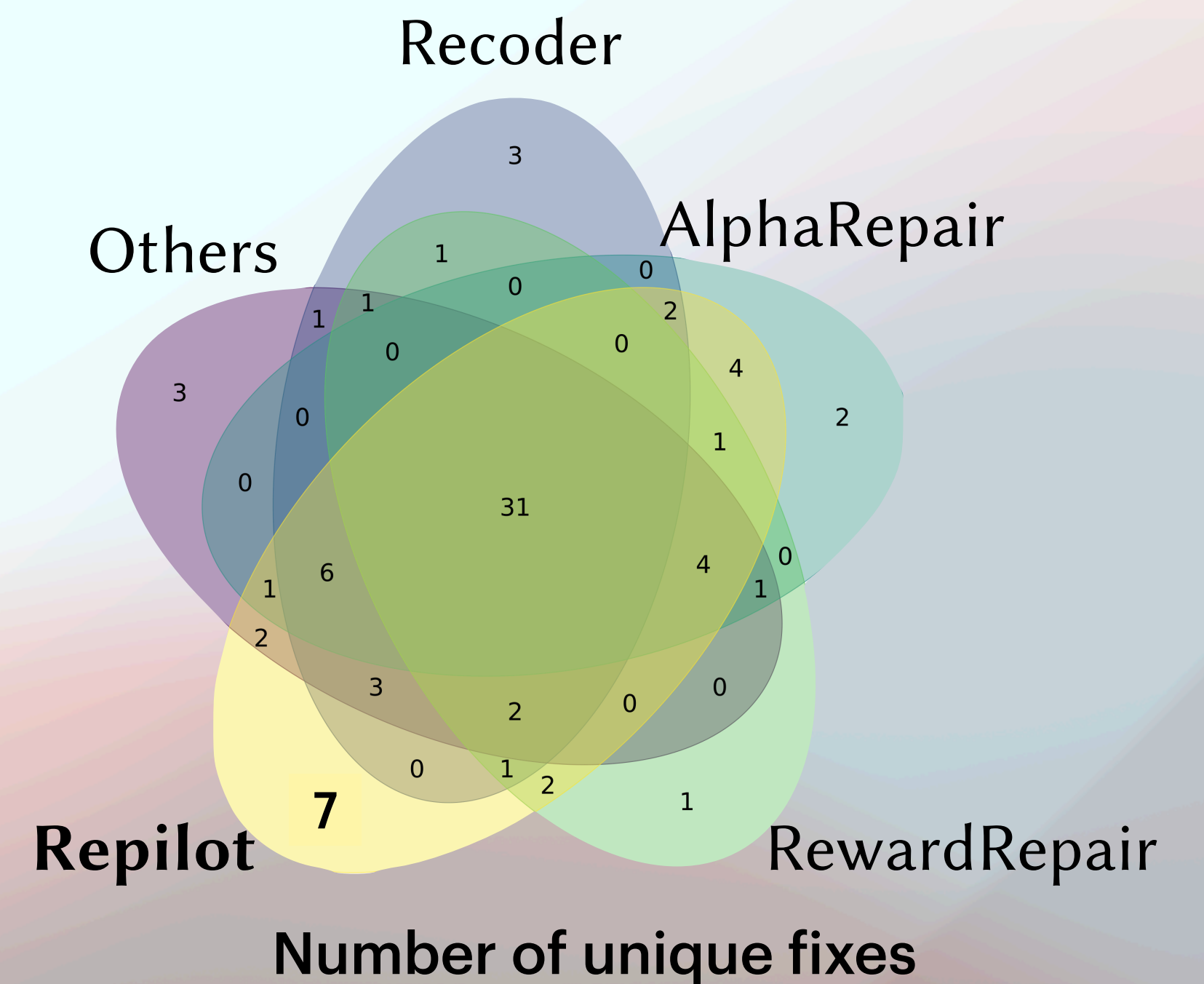
Evaluation pipeline and metrics



Evaluation

Comparison with existing tools

Tool	Methodology	#Correct Fixes		
		Defects4J 1.2	Defects4J 2.0	Total
CoCoNuT	NMT	30	-	-
DLFix	NMT	32	-	-
PraPR	Template	35	-	-
TBar	Template	41	7	48
CURE	NMT	43	-	-
RewardRepair	NMT	45	24	69
Recoder	NMT	51	10	61
AlphaRepair	LLM	52	34	86
Repilot	LLM	66	50	116



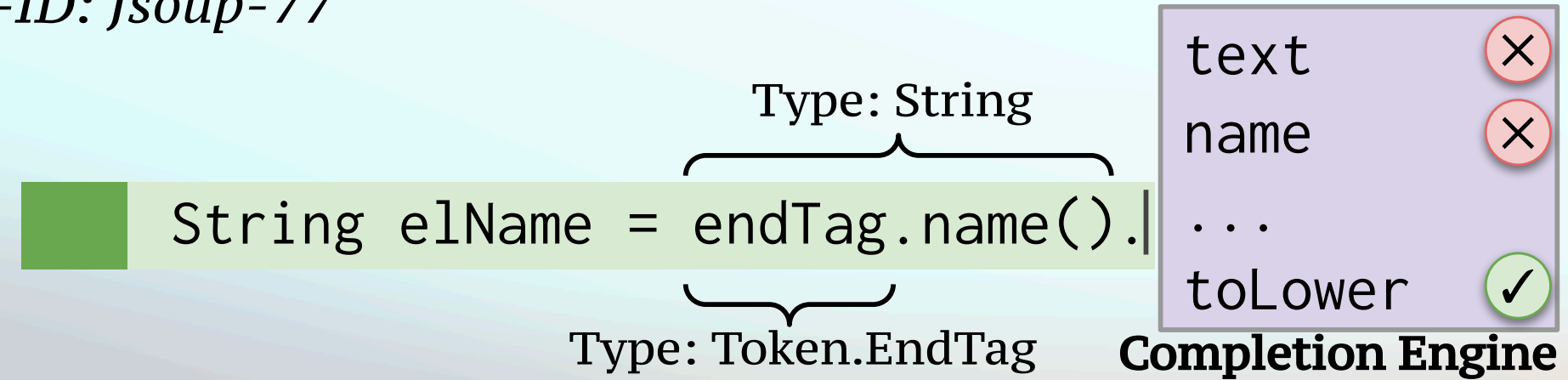
NMT means “Neural Machine Translation”

Evaluation

Unique fixes generated by Repilot

```
private void popStackToClose(Token.EndTag endTag) {  
- String elName = endTag.name();  
+ String elName = endTag.name().toLowerCase();  
  Element firstFound = null;  
}
```

Bug-ID: Jsoup-77

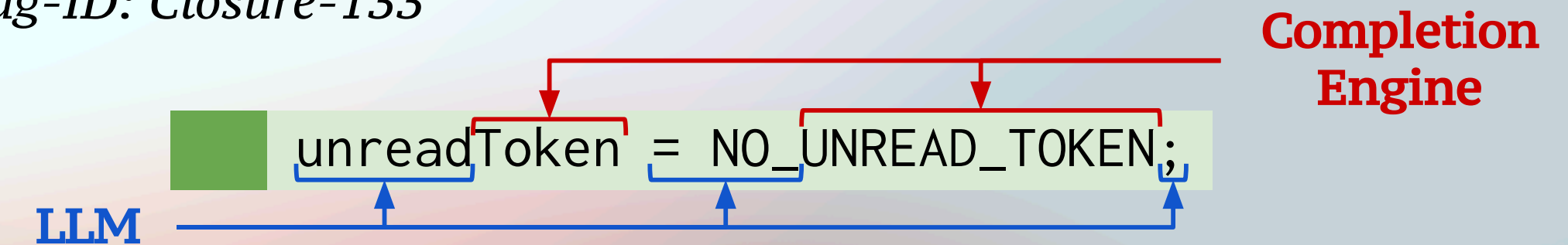


Patch Generation Process

Completion engine filters out invalid tokens

```
private String getRemainingJSDocLine() {  
  String result = stream.getRemainingJSDocLine();  
+ unreadToken = NO_UNREAD_TOKEN;  
  return result;  
}
```

Bug-ID: Closure-133



Patch Generation Process

Interaction between LLM and completion engine

Evaluation

Generalizability

Repilot is generalizable across bug subjects and models

Variant	Model	Subject of Bugs	Generation Time	%Compilable Patches	#Correct Fixes
Base LLM	CodeT5-large	Defects4J 1.2	0.232s	43.2%	37
Repilot	CodeT5-large	Defects4J 1.2	0.248s	63.4%	42

Base LLM	CodeT5-large	Defects4J 2.0	0.230s	46.7%	41
Repilot	CodeT5-large	Defects4J 2.0	0.247s	64.8%	45

Base LLM	INCODER-6.7B	Defects4J 1.2	1.70s	32.4%	48
Repilot	INCODER-6.7B	Defects4J 1.2	1.70s	47.2%	54

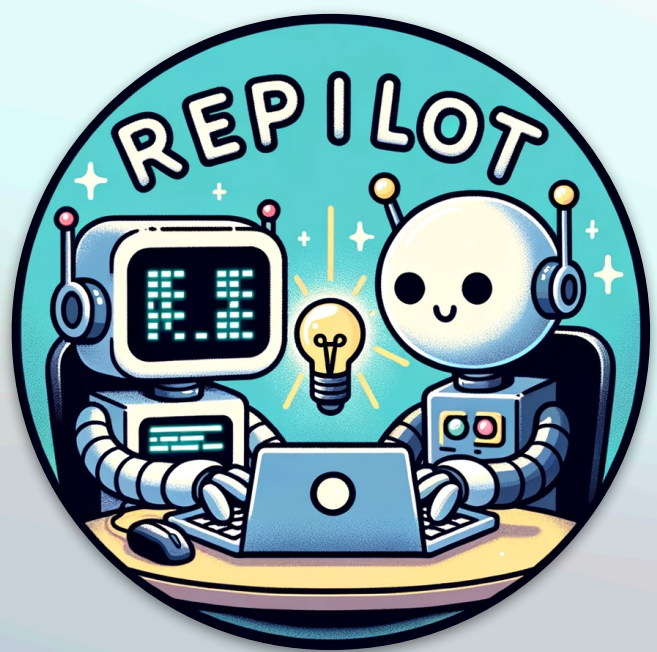
Base LLM	INCODER-6.7B	Defects4J 2.0	1.67s	34.6%	45
Repilot	INCODER-6.7B	Defects4J 2.0	1.69s	48.0%	46

Repilot

Copiloting the Copilots

Fuses **Large Language Models** with **Completion Engines** for more **effective Patch Generation** in Automated Program Repair


Can be applied to general **program synthesis**

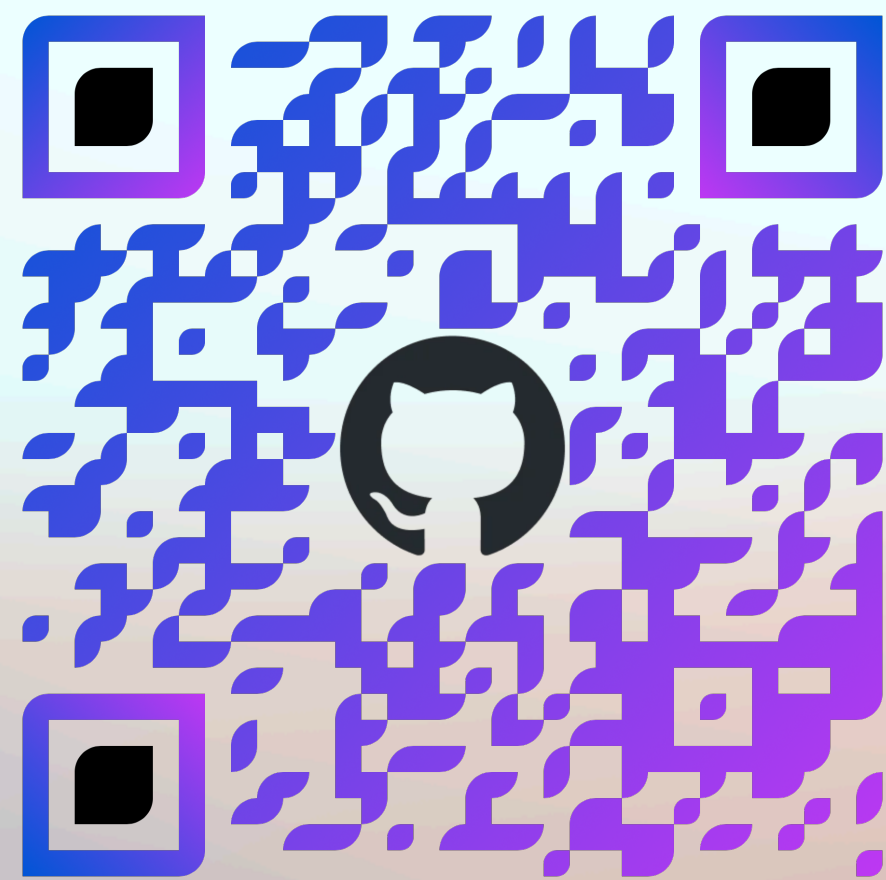


Powered by DALL·E 3

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(104) [ise-uiuc/Repilot](https://github.com/ise-uiuc/Repilot)



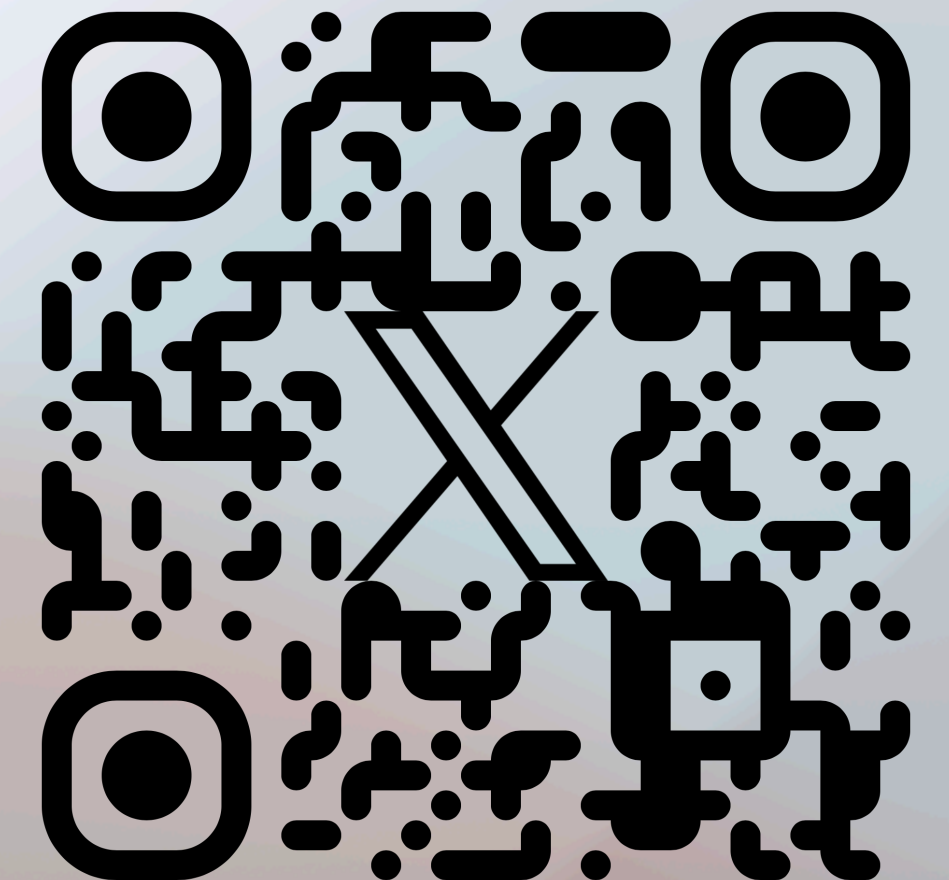
Code & Docker & Artifact

[arXiv:2309.00608](https://arxiv.org/abs/2309.00608)



Paper

 [@YuxiangWei9](https://twitter.com/YuxiangWei9)



Twitter/X

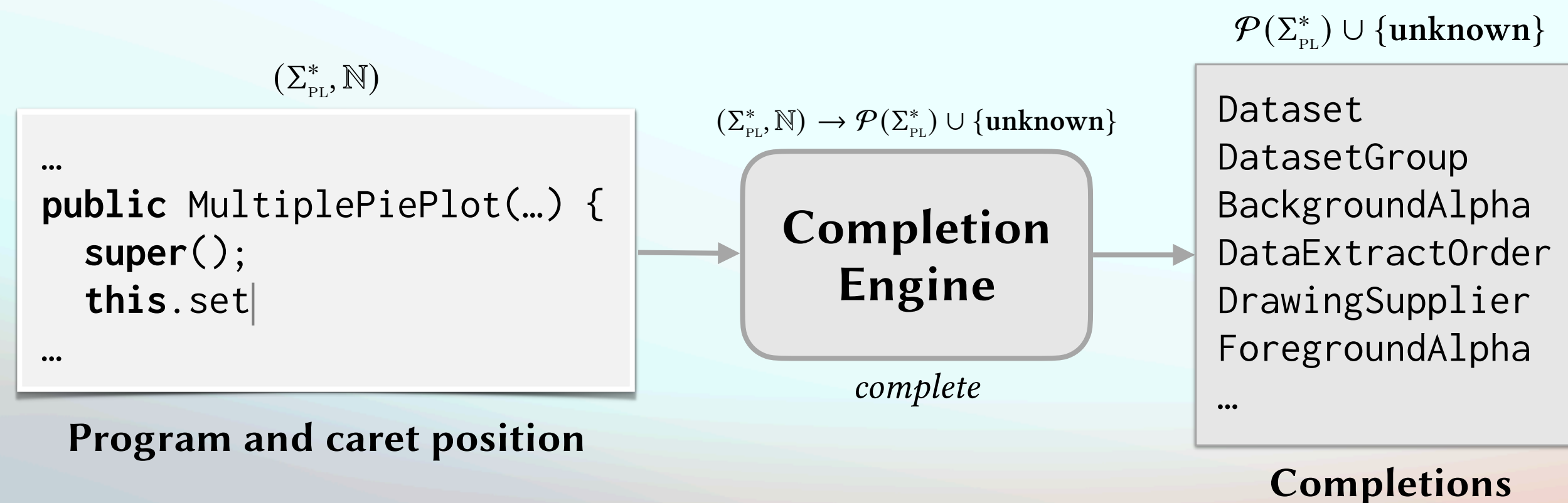


Supplementaries

Will Repilot go wrong?

Conditional soundness of Repilot

Theorem: Repilot is sound with a **strict completion engine**



Assume

$(\text{prog}, \text{caret}) \models \Phi$

$\text{completions} = \text{complete}(\text{prog}, \text{caret})$

$\text{completions} \neq \text{unknown}$

The completion engine is strict if and only if

$\forall c \notin \text{Prefix}(\text{completions}), (\text{prog}', \text{caret}') \not\models \Phi$

where $\text{prog}' = \text{prog}[\text{caret} \leftarrow c]$

$\text{caret}' = \text{caret} + |c|$

$\text{Prefix}(\cdot) = \{c \mid s \in \cdot \text{ and } c \text{ is a prefix of } s \text{ or vice versa}\}$

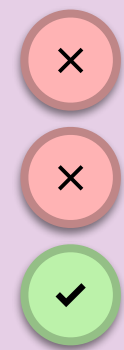
Intuitively, the completion engine should capture all possible continuations, but can do over-approximation. **“unknown”** is an over-approximation.

Why resample instead of direct pruning?

In this case, direct pruning cannot do anything, and may result in a wrong path, e.g., `.method_a`

Language model
Predictions

```
.method_a  
.method_b  
.method_c  
...
```



Completions

```
obj
```

```
var result = obj|
```