Towards Efficient Data Wrangling with LLMs using Code Generation

Effy Xue Li, Till Döhmen
University of Amsterdam, MotherDuck
DBDBD’24

Date 11/2024

Data Wrangling is Tedious

A data scientist is working on a table with 1 million rows, and she is facing following tasks…

Prompt used: A duck plumber who looks bored

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Data Imputation

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	Hospital	Error?
1	medixal xenter	

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Data Imputation Error Detection

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	Celsius	Fahrenheit
1	7	

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Data Imputation

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Data Transformation

	Beer_Name	BV
1	IJwit IPA	6.50 %

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same?

No

Entity Matching

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How can we make this easier?

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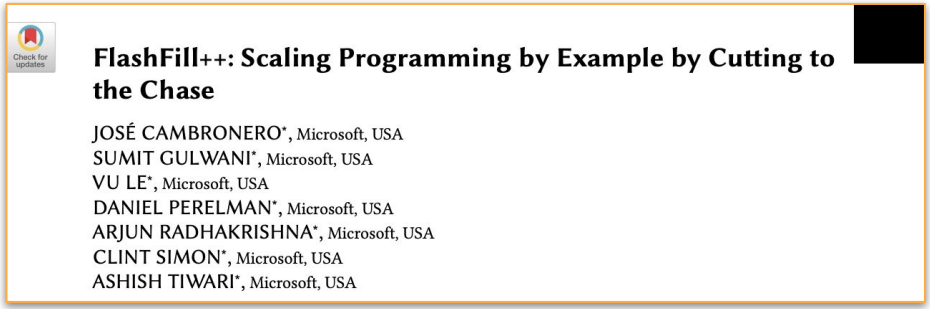
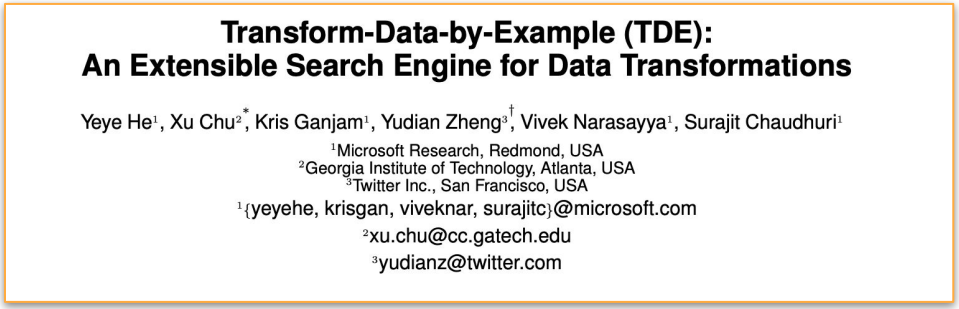
Programing by Example (PBE)



FlashFill++: Scaling Programming by Example by Cutting to the Chase

JOSÉ CAMBRONERO*, Microsoft, USA
SUMIT GULWANI*, Microsoft, USA
VU LE*, Microsoft, USA
DANIEL PERELMAN*, Microsoft, USA
ARJUN RADHAKRISHNA*, Microsoft, USA
CLINT SIMON*, Microsoft, USA
ASHISH TIWARI*, Microsoft, USA



Transform-Data-by-Example (TDE): An Extensible Search Engine for Data Transformations

Yeye He[1], Xu Chu[2]*, Kris Ganjam[1], Yudian Zheng[3]†, Vivek Narasayya[1], Surajit Chaudhuri[1]
[1]Microsoft Research, Redmond, USA
[2]Georgia Institute of Technology, Atlanta, USA
[3]Twitter Inc., San Francisco, USA
[1]{yeyehe, krisgan, viveknar, surajitc}@microsoft.com
[2]xu.chu@cc.gatech.edu
[3]yudianz@twitter.com

- Domain-specific Language search space
- Search
- Rank
- Solution

Programming by Example is not flexible

- Have to define a program search space (often DSL).
-
-
-
-

Programming by Example is not flexible

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- Solves only **a limited number** of tasks.
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- …

LLMs are Great for Data Wrangling

Input table

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Can Foundation Models Help Wrangle Data? Narayan et al. VLDB 23.

LLMs are Great for Data Wrangling

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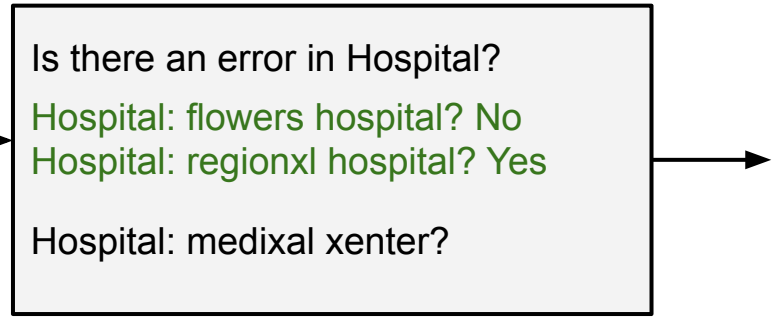

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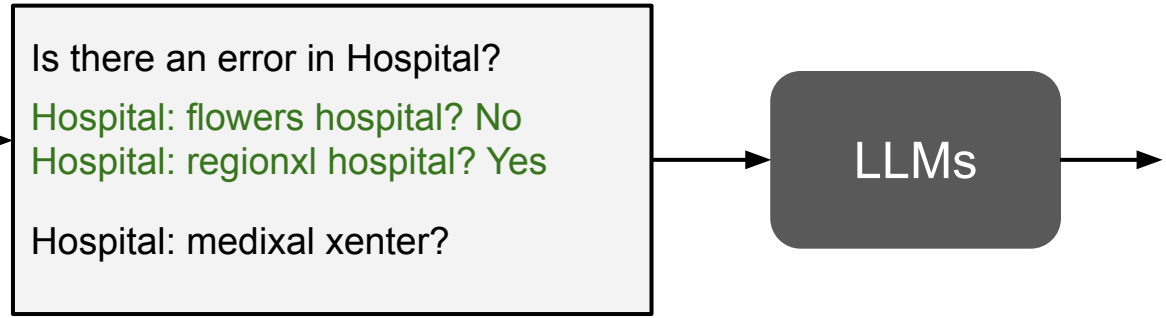

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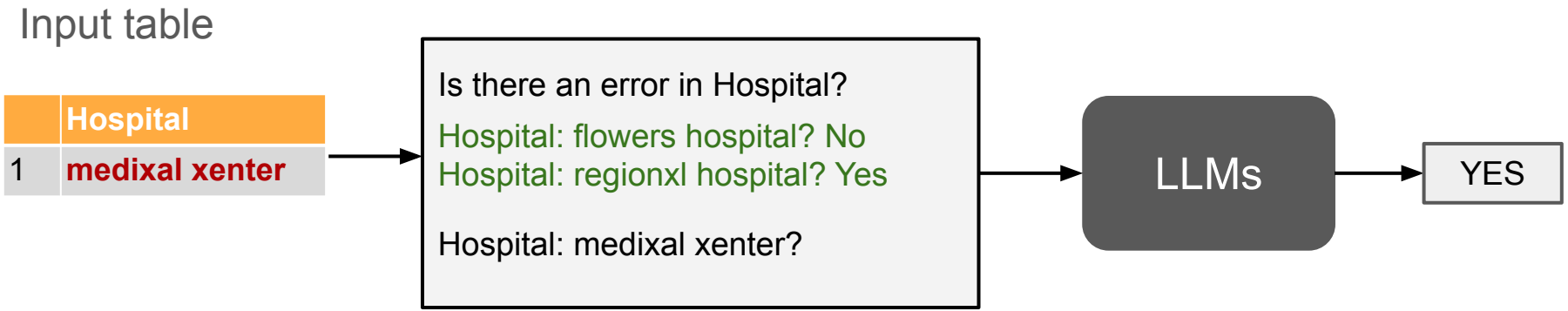

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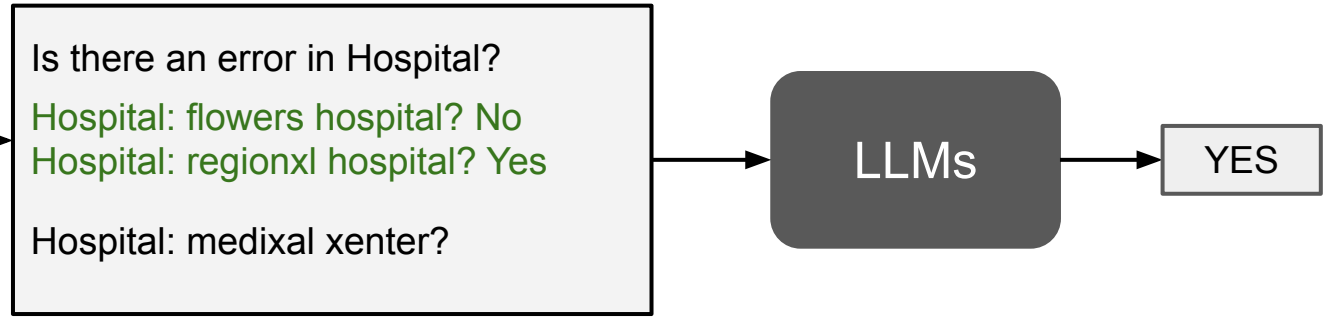

It performs LLM on a **per-row** basis (LLMPR).

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LLMs are ~~Great~~ Costly for Data Wrangling

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If we have a 1-million-rows-table, processing through it once will cost *…

	Time(with 100 concurrent calls)	Price
GPT-3.5	1.01 Hours	$ 12.5
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And many other issues …

- **Transparency**
- **Reproducibility**
- **Privacy**
- …

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Prompt: a duck plumber looking for smart tools

How can we make automated data wrangling faster

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How can we make automated data wrangling faster, cheaper

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How can we make automated data wrangling faster, cheaper, stronger(more reliable and more generic)?

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How can we make automated data wrangling faster, cheaper, stronger(more reliable and more generic)?

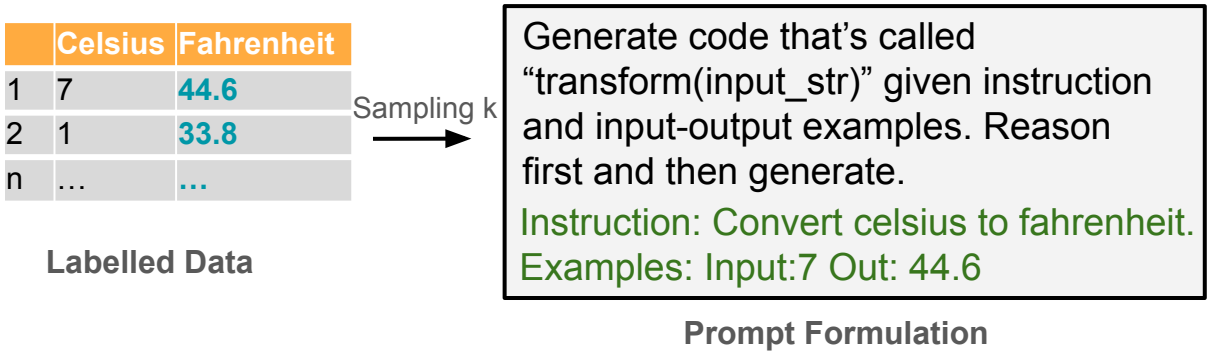
-> Can we combine PBE and LLMPR, using LLM to generate code for data wrangling?

Code Generation Framework

	Celsius	Fahrenheit
1	7	**44.6**
2	1	**33.8**
n	…	**…**

Labelled Data

Code Generation Framework



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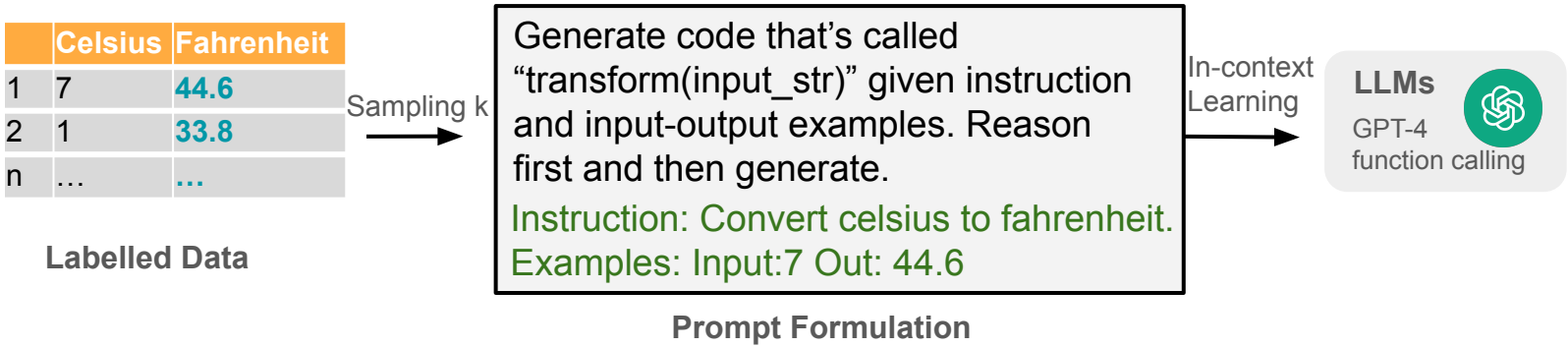

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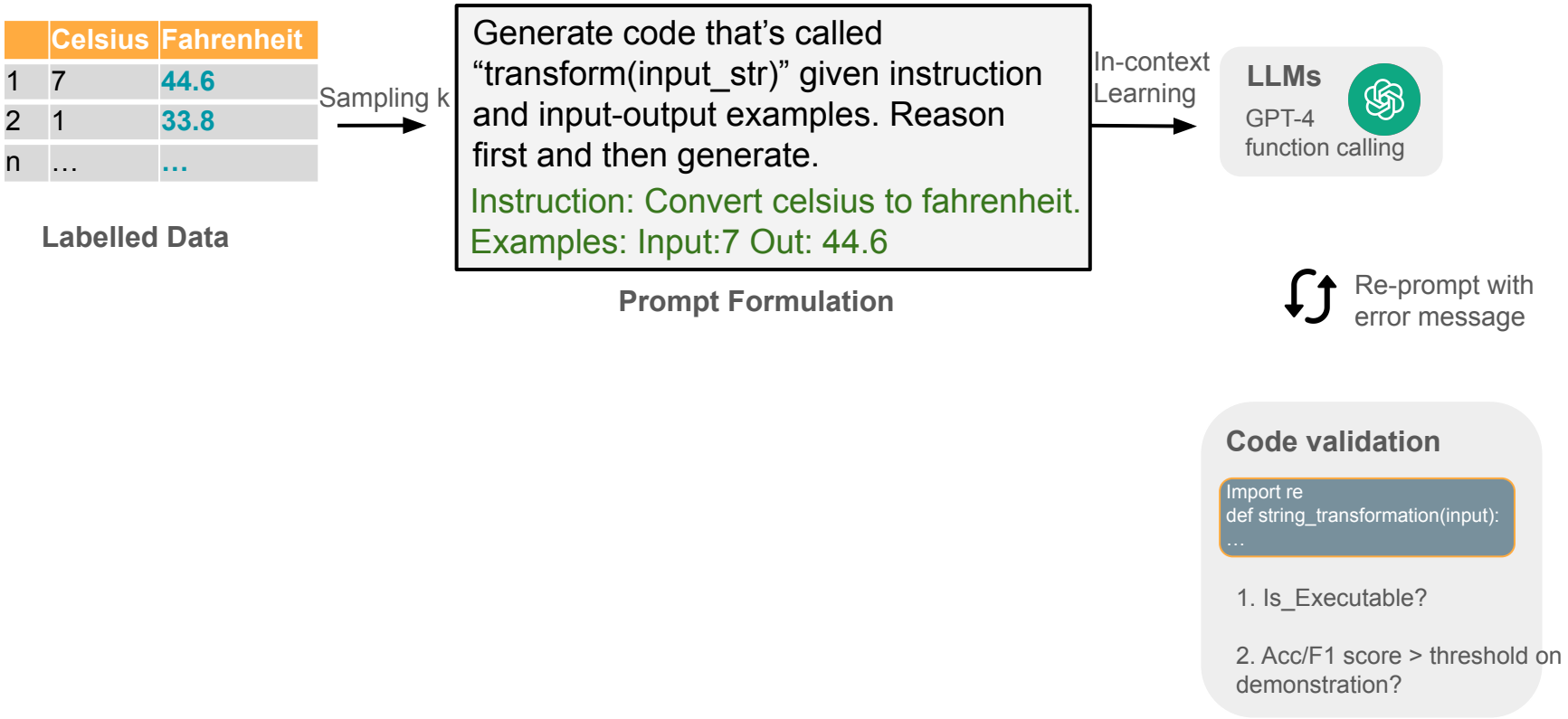

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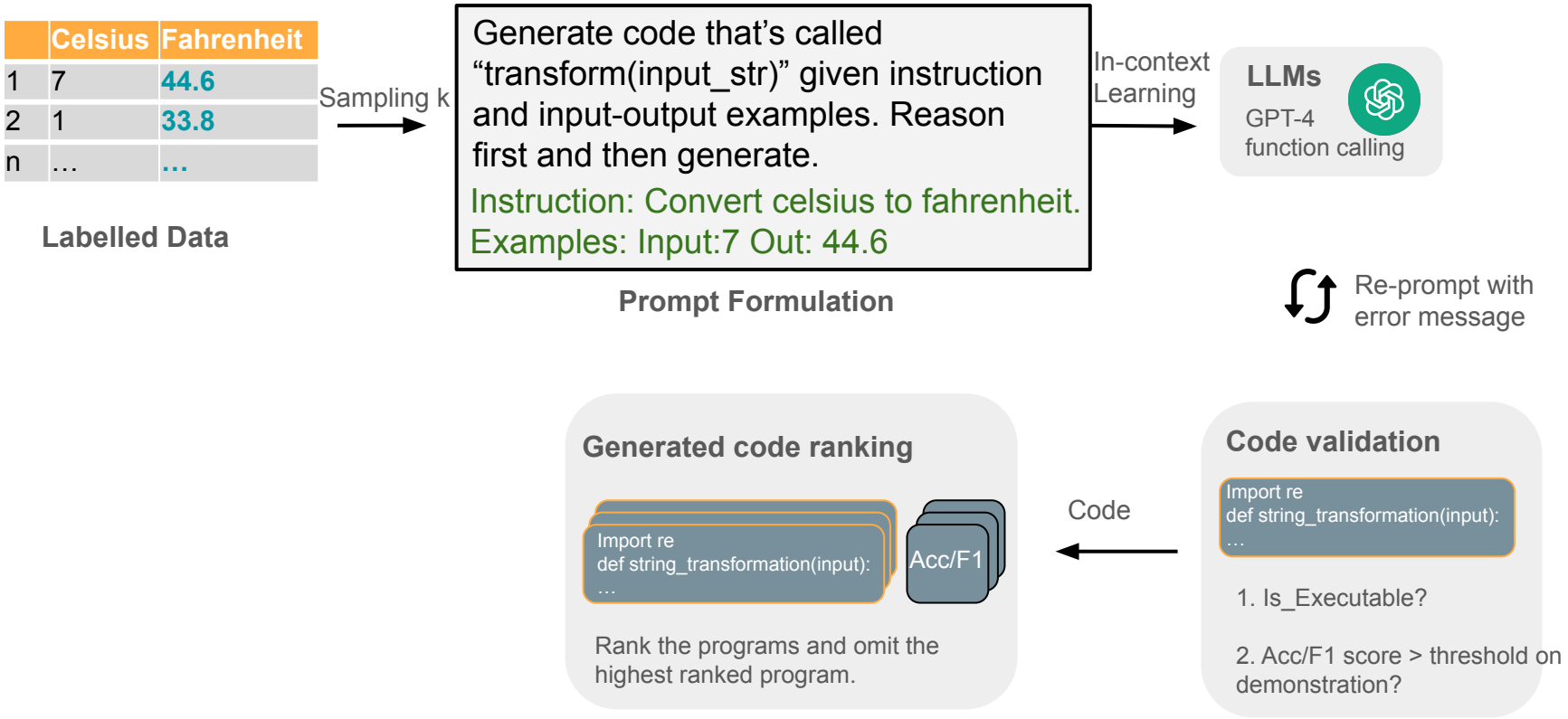

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Labelled Data

Sampling k

Generate code that's called "transform(input_str)" given instruction and input-output examples. Reason first and then generate.

Instruction: Convert celsius to fahrenheit.
Examples: Input:7 Out: 44.6

Prompt Formulation

In-context Learning

LLMs
GPT-4
function calling

Re-prompt with error message

```
import re
def string_transformation(input_string):
    # Extract the numeric value from the input string
    celsius = float(re.search(r'\d+', input_string).group())
    # Convert Celsius to Fahrenheit
    fahrenheit = (celsius * 9/5) + 32
    # Format the result into the desired output string
    return f'{fahrenheit} Fahrenheit'
```

Generated code

N trials

Generated code ranking

Import re
def string_transformation(input):
…

Acc/F1

Rank the programs and omit the highest ranked program.

Code

Code validation

Import re
def string_transformation(input):
…

1. Is_Executable?

2. Acc/F1 score > threshold on demonstration?

We evaluate on benchmarks of these tasks:

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Entity Matching

Preliminary Results on Python Generation

Entity Matching, Data Imputation, Error Detection

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EM	Beer	100	75.0
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EM	Walmart-Amazon	[illegible]	[illegible]
DI	Buy	98.5	84.6
DI	Restaurant	88.4	50
ED	Hospital	97.8	23.5
ED	Adult	99.1	100*

76.9

Data Transformation

Dataset	PBE [4]	LLMPR [9]	Code Generation (Ours)
BingQL-semantics	32.0	54.0	**91.6**
BingQL-Unit	**96.0**	N/A	95.0
Stack-overflow	63.0	65.3	**87.4**
FF-GR-Trifacta	**91.0**	N/A	83.7
Head cases	**82.0**	N/A	74.6
Average	72.6	N/A	**86.46**

37.6

LLM API calls:

1 Million -> *only* 10 calls

- Evaluate based on tasks.
- Improved performance compare to the previous SOTA.

But what's the catch?

- Evaluate based on rows.
- A single generated program can only solve a part of the dataset.

We evaluate on benchmarks of these tasks:

⬇Drop: 26.2

	Phone	City
1	212/582-7200	

	Phone	City
1	212/582-7200	NYC

Data Imputation

⬇Drop: 36.7

	Hospital	Error?
1	medixal xenter	

	Hospital	Error?
1	medixal xenter	Yes

Error Detection

	Celsius	Fahrenheit
1	7	

	Celsius	Fahrenheit
1	7	44.6

Data Transformation

⬇Drop: 33.1

	Beer_Name	BV
1	IJwit IPA	6.50 %

	Beer_Name	BV
1	IJwit IPA	0.50 %

same?

No

Entity Matching

We evaluate on benchmarks of these tasks:

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⬇

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Error Detection

⬆Gain: 13.66

	Celsius	Fahrenheit
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⬇

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⬇

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Entity Matching

Code Generation Framework with DuckDB SQL Macros

Data Transformation

	Bing-QL-semantics	Bing-QL-unit
GPT-4 (DuckDB-SQL)	65.3	96.0
GPT-4o (DuckDB-SQL)	67.3	**96.0**
GPT-4 (Python)	**91.6**	95.0

- **Python is good at semantics-related tasks, highly due to existing packages.**
- **Generating SQL macros can solve a good amount of unit-conversion tasks.**

Code Generation Solves Parts of the Data

```python
import re
def string_transformation(input_string):
    # Extract the numeric value from the input string
    celsius = float(re.search(r'\d+', input_string).group())
    # Convert Celsius to Fahrenheit
    fahrenheit = (celsius * 9/5) + 32
    # Format the result into the desired output string
    return f'{fahrenheit} Fahrenheit'
```

Generated code

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```

Generated code

	Celsius	Fahrenheit
1	7	44.6
2	1	33.8
x	…	…
n	-17.2222	1

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Once generated code solution can solve one part of the problem. How are we gonna deal with the rest of the data?

We can recursively generate code solutions for the rest of the data.

In reality, we don't have labels for the data.

We need a data router.

In-depth Analysis of Data Transformation Tasks

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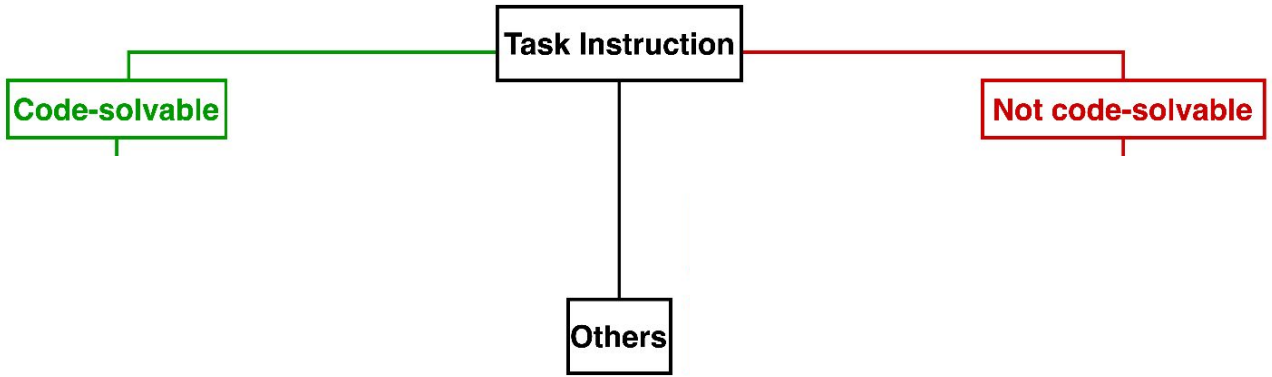
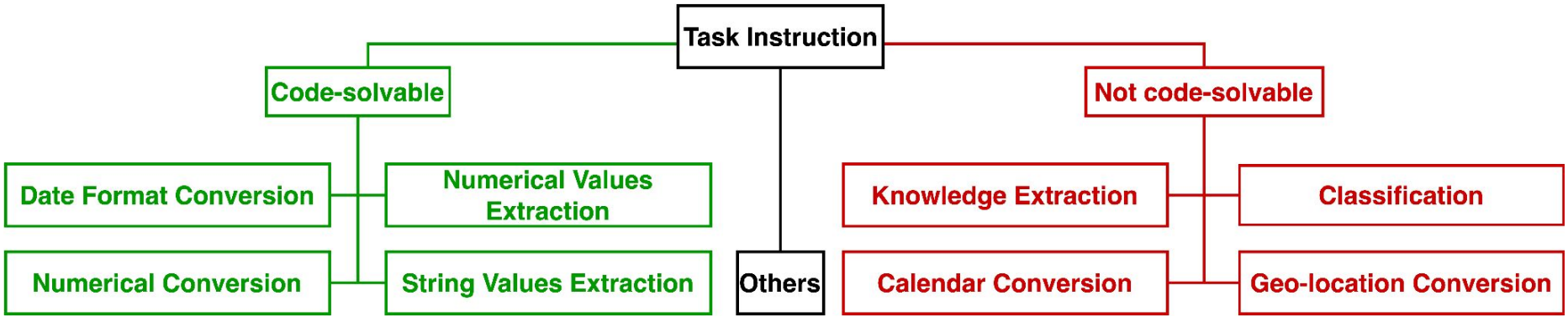
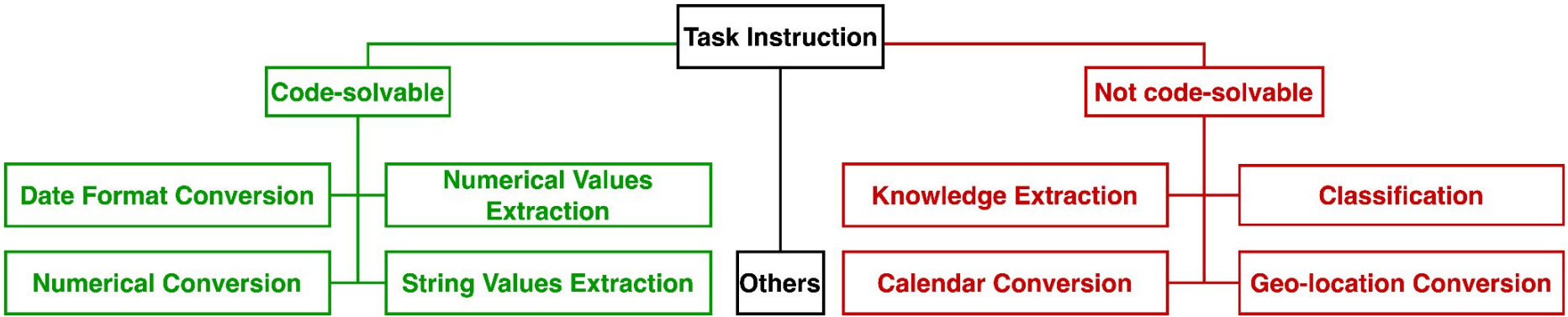


In-depth Analysis of Data Transformation Tasks



In-depth Analysis of Data Transformation Tasks



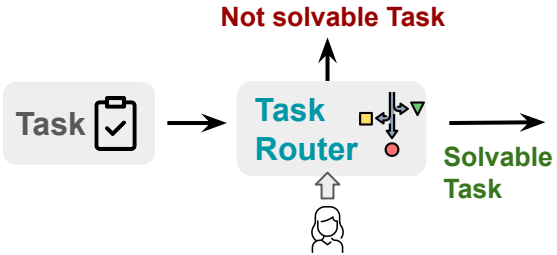
We need a task router.

Approach Overview (WIP)

Prompt used: The duck plumber
With smart tools who looks happy

Task

Approach Overview (WIP)



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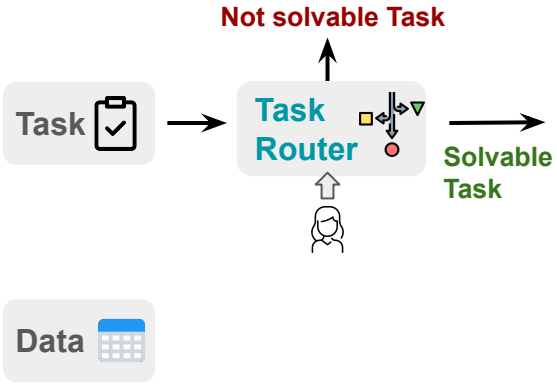
Approach Overview (WIP)



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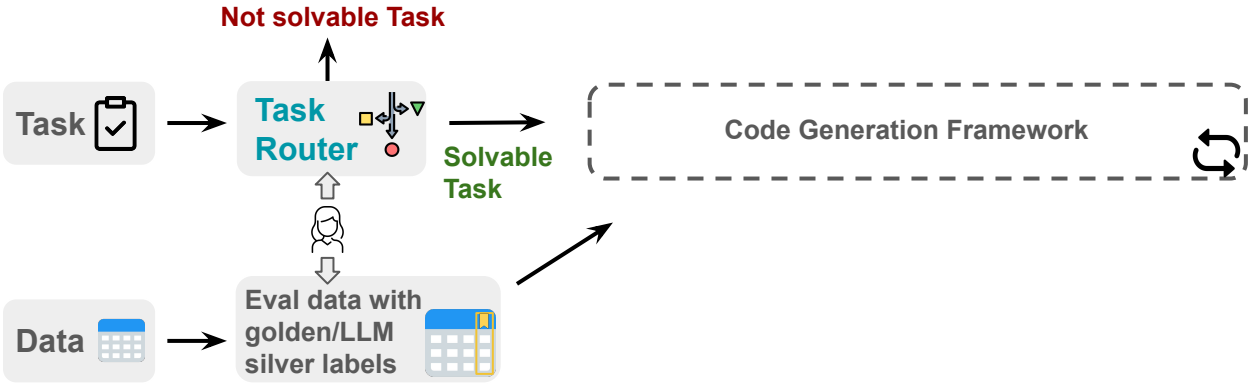

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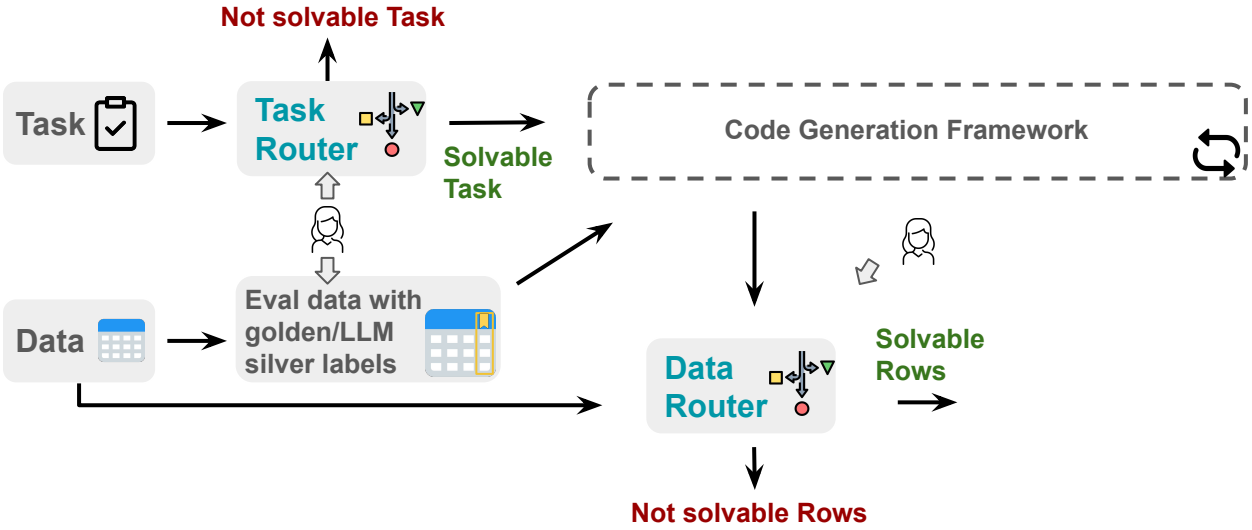

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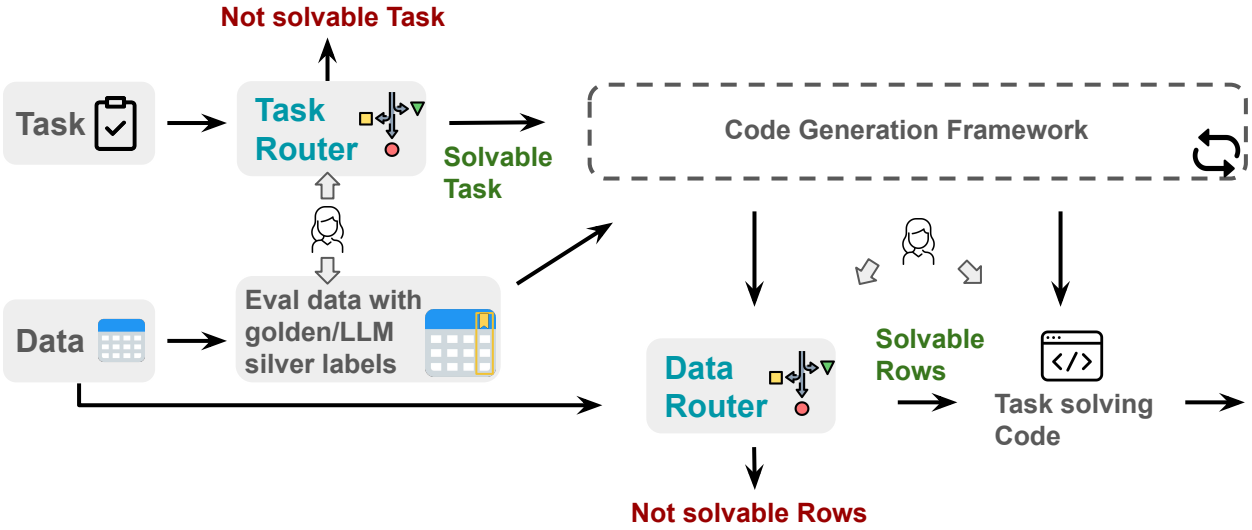

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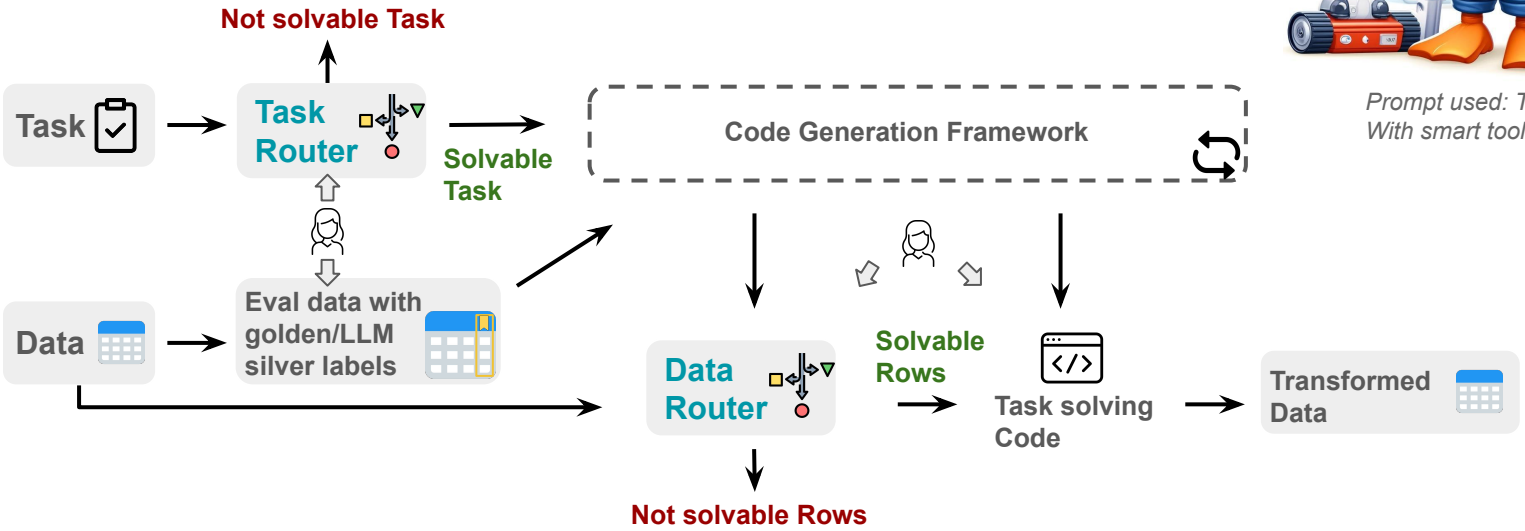

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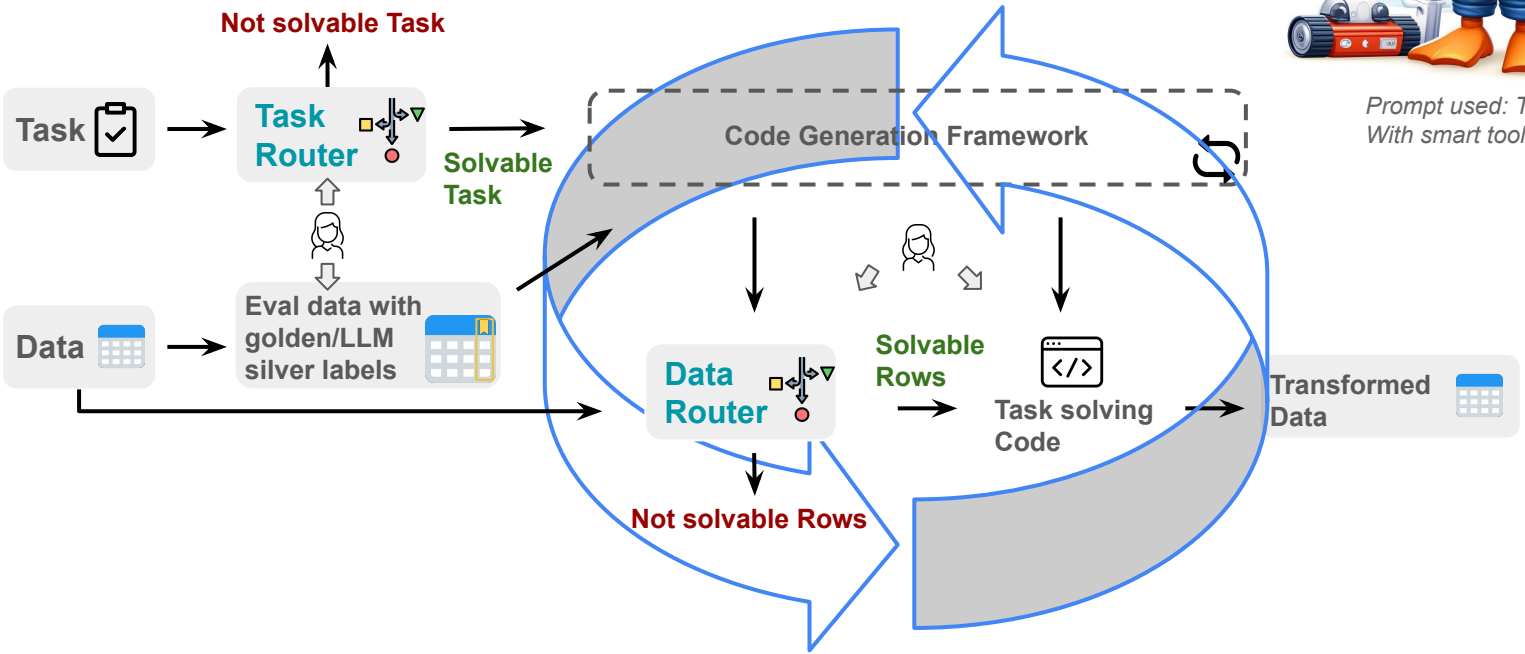

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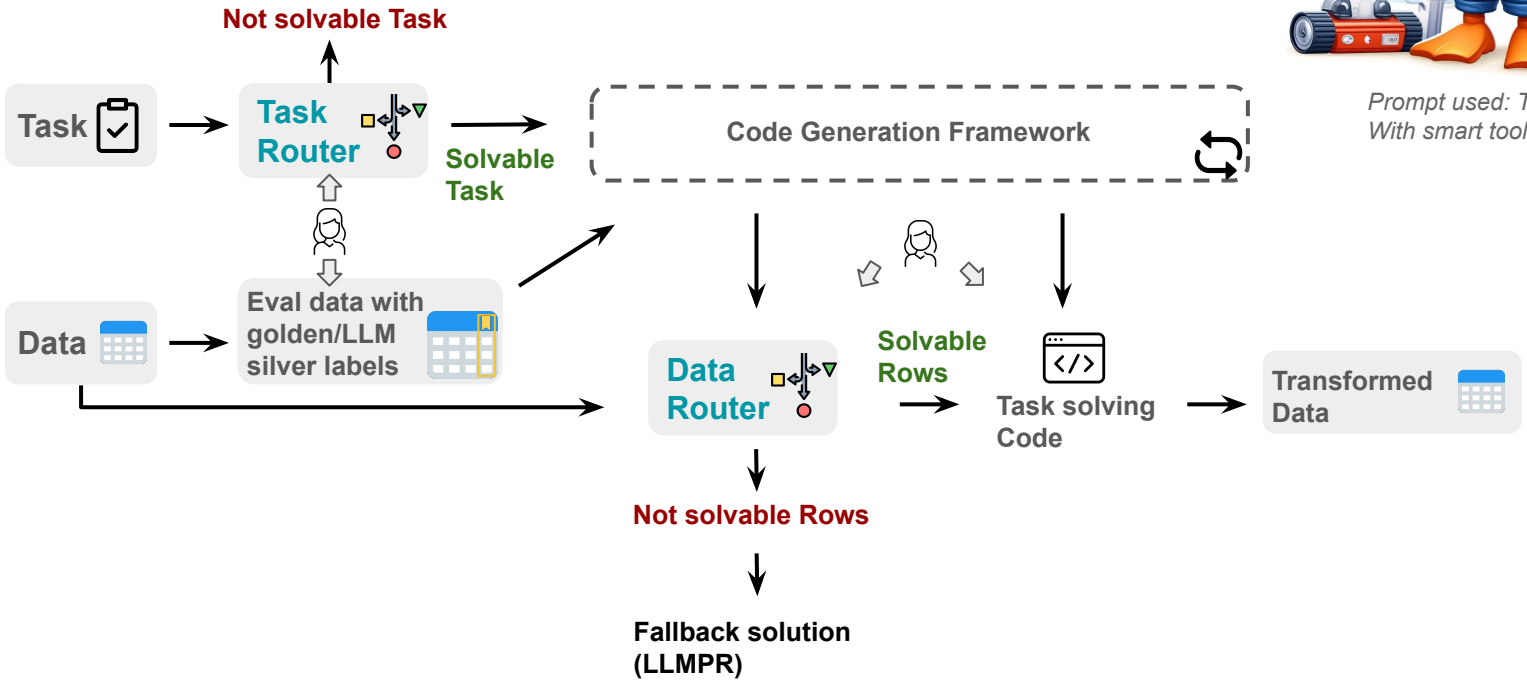
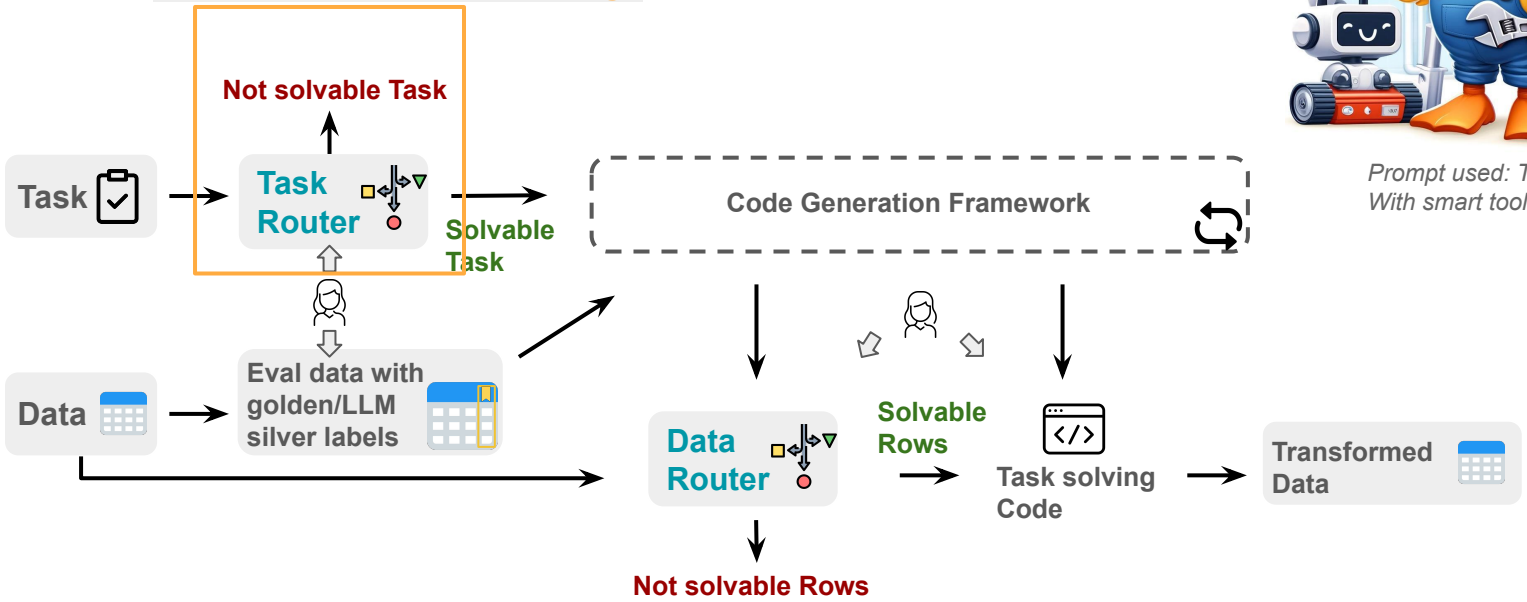


Approach Overview (WIP)

Using LLMs for mapping user's task to the taxonomy.

Prompt used: The duck plumber
With smart tools who looks happy



Approach Overview (WIP)

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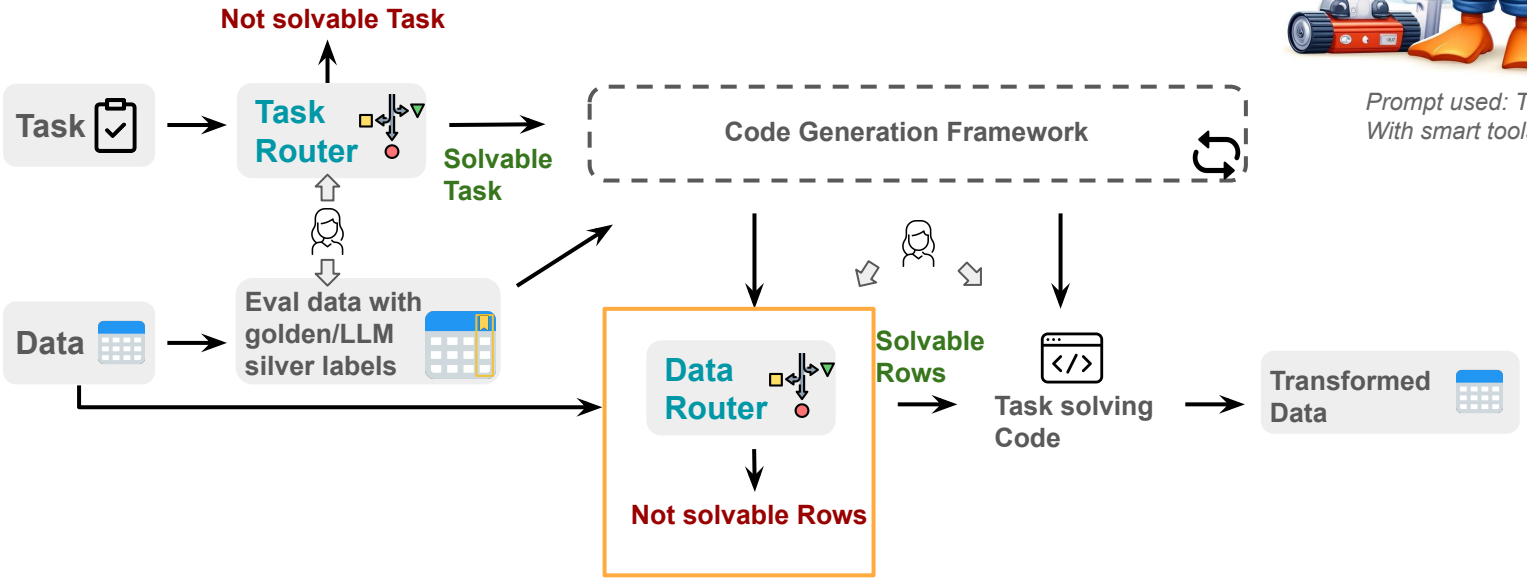
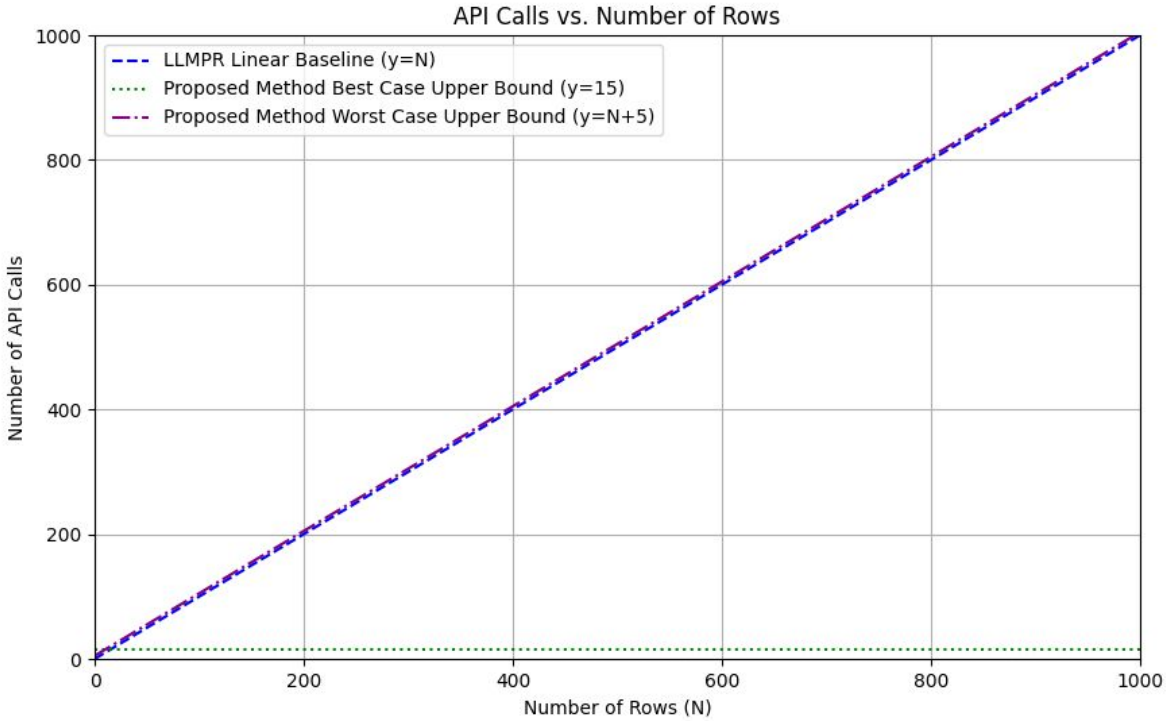


Generate input validation code (e.g. using regex) based on validated solutions.

API calls bounds

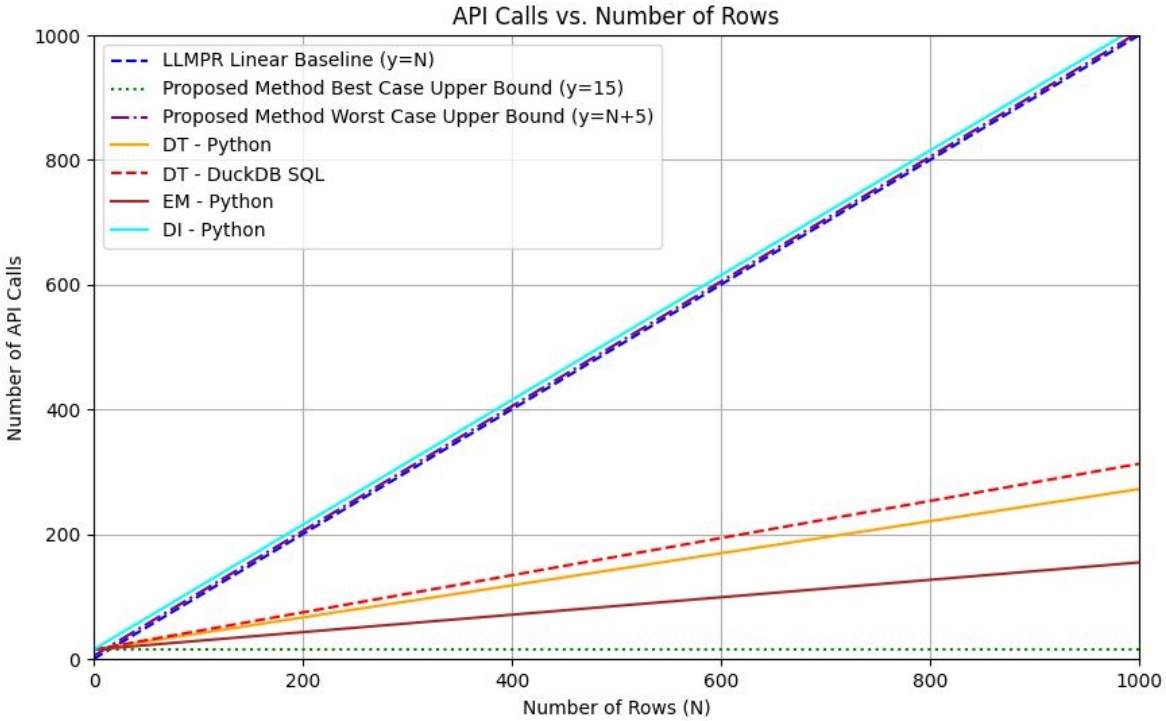


N: Number of rows
T: Number of trials = 3
R: Number of retry = 5
c : Constants for initial api calls

Baseline: APICalls(LLMPR) = N

Proposed method:
Worst case upper bound: N + c
Best case upper bound: T * R = 15

Unpublished Results



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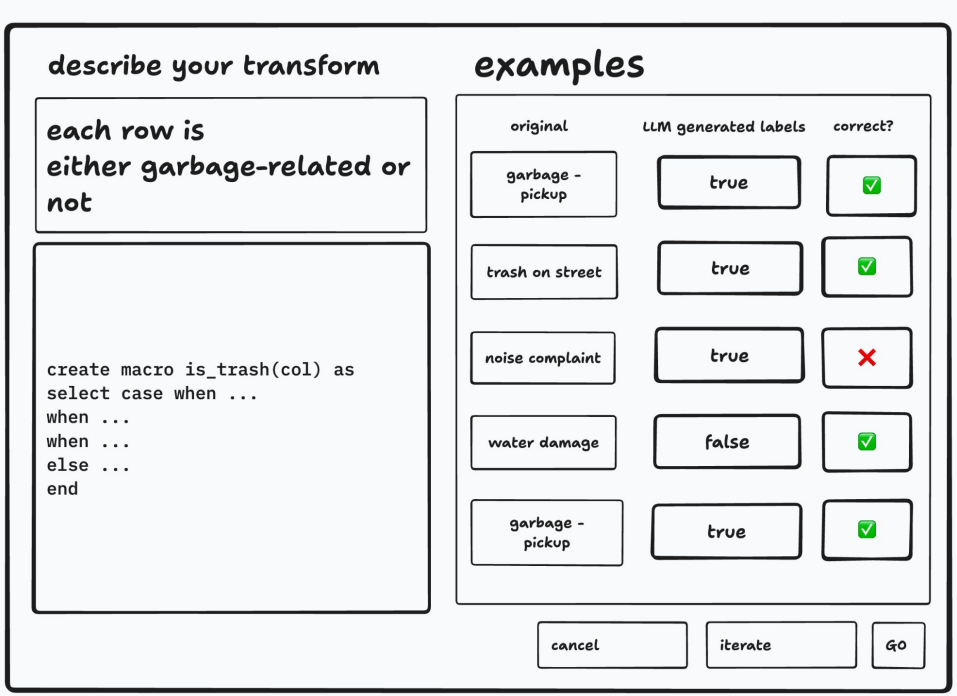
Source: Trust me bro

Thank you!

Next steps



Potential human-in-the-loop interface.

Cr: @Hamilton

```
PRAGMA transform('my_table',
'my_column', 'convert celsius to
fahrenheit');
```

Potential transform pragma function.