



llmtestgen – test specification generation from code and code specification

Cédric DERACHE, Arthur RICHELET – dec 9, 2025



Introduction

1. Problem overview
2. Project approach
3. Experiments & Results
4. Key findings & Conclusion

Introduction

- **Problem:** "Manual test specification is time consuming and error prone"
- **Solution:** "Automation using Large Language Models that can process large amount of data"
- **Objective:** "Build a toolchain capable of leveraging the capabilities of LLMs to reduce human effort and improve reliability and consistency"



Problem overview – Manual test writing

- **Manual test specifying:**
 - Time consuming & error prone
 - Hard to ensure complete and accurate coverage
 - Consistency problems between specs from multiple software engineers



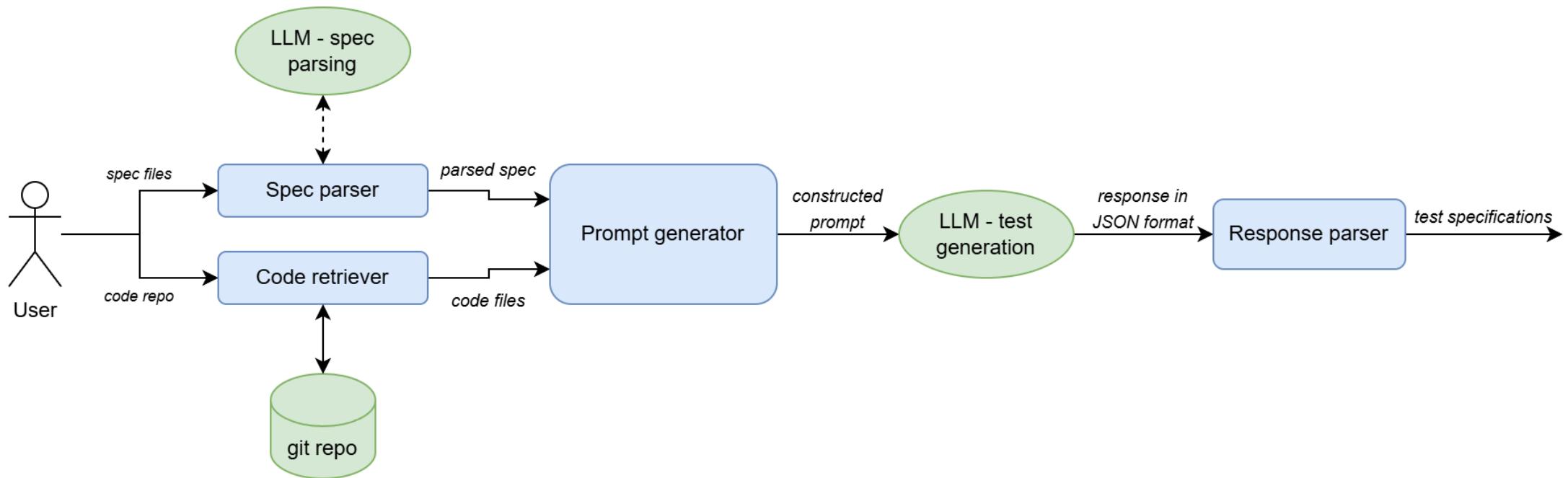
Problem overview – Why use LLMs

- Why use Large Language Models:
 - Able to handle large amounts of text data quickly
 - Very versatile, not bound to specific format
 - Automatable

Solution approach - Objectives

- **Objectives of the toolchain:**
 - Extract specs and put them in standard format for better comprehension by the LLM
 - Get relevant code files
 - Construct a prompt using elements
 - Parse the response into a file of test requirements

Solution approach - Pipeline



Solution approach – Prompt engineering

System prompt for
arbitrary specification
"parsing"

```
def _build_system_prompt(self) -> str:  
    """Explain how the LLM should behave and what to extract."""  
    return (  
        "You are a strict specification parser. "  
        "Your task is to read input text and extract structured information.\n\n"  
        "Return ONLY a JSON object with these exact fields:\n"  
        "  - title: string or null\n"  
        "  - sections: object mapping section names to text\n"  
        "  - requirements: array of requirement-like sentences\n"  
        "  - acceptance_criteria: array of acceptance criteria\n"  
        "  - examples: array of example statements\n"  
        "  - confidence: integer 0-100 expressing how confident you are "  
        "    that you extracted the spec correctly\n\n"  
        "DO NOT return explanations. DO NOT wrap the JSON in code fences. "  
        "Only output raw JSON."  
    )  
  
def _build_user_prompt(self, text: str) -> str:  
    return (  
        "Parse the following specification file. Use your best judgment to identify:\n"  
        "- title or heading\n"  
        "- sections and subsections\n"  
        "- requirement-like sentences (must, shall, should, cannot, etc.)\n"  
        "- acceptance criteria (Given/When/Then patterns, etc.)\n"  
        "- examples or usage patterns\n\n"  
        "Return ONLY the JSON object described above.\n\n"  
        "Here is the specification content:\n"  
        "-----\n"  
        f"{{text}}\n"  
        "-----\n"  
    )
```

Solution approach – Prompt engineering

System prompt for test
specification generation

```
def _build_system_prompt(self) -> str:  
    """Explain to the LLM how to behave and what JSON to return."""  
    return (  
        "You are an expert software test engineer. "  
        "Your task is to design high-quality test cases for a Python project.\n\n"  
        "Given a project specification and an optional view of the codebase, "  
        "you must produce a structured list of test cases as JSON.\n\n"  
        "Return ONLY a JSON object with this exact structure:\n"  
        "{\n            \"test_cases\": [\n                {\n                    \"id\": string or null,\n                    \"requirement\": string or null,\n                    \"description\": string,\n                    \"preconditions\": [string, ...],\n                    \"steps\": [string, ...],\n                    \"expected_result\": string,\n                    \"target_code_elements\": [string, ...]\n                },\n                ...\n            ]\n        }\n    }\n    Do not include explanations, comments, or additional fields.  
    Do not wrap the JSON in code fences."  
)
```

Solution approach – Generated test case

Example of generated test case

Test 009: Deleting an existing task removes it from the service

Requirement: Task deletion

Preconditions

- TaskService contains at least one task

Target code elements

- `TaskService.delete_task`
- `TaskService.list_tasks`

Steps

1. Store the task ID.
2. Call `delete_task` with a valid ID.
3. Call `list_tasks()`.

Expected Result

- The deleted task no longer appears in the task list.

Experiment setup

- Comparison of test generation context level:
 - **None**, High-level tests, low code alignment.
 - **File List**: High requirement coverage, moderate alignment.
 - **Code snippets**: Best results, high code alignment and coverage.
 - **Full Code**: Failed due to excessive prompt size, (can work with a better model)

Experiment setup

Context Level	Requirement coverage	Code alignment	Validity of output
None	High	Low	Yes
File list	High	Medium	Yes
Code snippets	Very high	High	Yes
Full	N/A	N/A	<i>Invalid JSON output</i>

Key findings

- Most accurate tests were generated using limited context sent to the LLM:
 - Too much files overwhelmed the model
 - Reduced quality of invalid response
 - Moderate context seemed to lead better results
 - These limitations can be due to a limited model (*deepseek-chimera*, free API key from OpenRouter)

Conclusion

- Large Language Models can improve efficiency, coverage and consistency of test generation:
 - Generates test cases autonomously
 - Reduces time and effort spent by human developer
- Further directions:
 - Improving prompt engineering to avoid alignment errors on less powerful models
 - Support for more LLMs endpoints
 - Automatic test writing based on given programming language
 - Automatic test runs and verification by secondary LLM



Thank you !
Questions ?