Large Language Models: Applications, Opportunities and Risks
Carman Mark James, Brambilla Marco, Pierri Francesco

CodeAgent Project

Exploring Repository-Level Code Generation With Agents

Acquadro Patrizio, Yu Zheng Maria Academic Year 2024-2025







- Introduction
- Literature Review
- LLM Setup: Small VS Large
- Tool & Agent integration
- Benchmark and Results



1. Introduction

Overview of CodeAgent
Motivations for this Project
Goals to Accomplish



CodeAgent

LLM-based repository-level code generation agentic framework

CODEAGENT: Enhancing Code Generation with Tool-Integrated Agent Systems for Real-World Repo-level Coding Challenges

Kechi Zhang*, Jia Li*, Ge Li[†], Xianjie Shi, Zhi Jin[†] Key Lab of High Confidence Software Technology (PKU), Ministry of Education School of Computer Science, Peking University, China

Difficult but important task (70% of entire code is repo-level)



CodeAgent

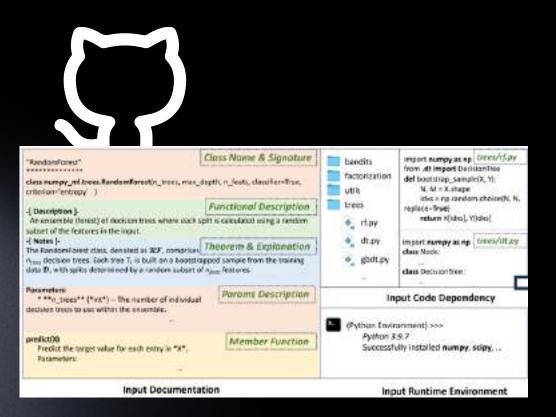
LLM-based repository-level code generation agentic framework

CODEAGENT: Enhancing Code Generation with Tool-Integrated Agent
Systems for Real-World Repo-level Coding Challenges

Kechi Zhang*, Jia Li*, Ge Li[†], Xianjie Shi, Zhi Jin[†] Key Lab of High Confidence Software Technology (PKU), Ministry of Education School of Computer Science, Peking University, China

- Incorporate programming tools to provide contextual information
 - 3 categories
 - 5 tools
- Leverage agent strategies for tools usage
- Create a specific repo-level benchmark (codebase + dataset)





Motivation

- O1 Current and future **trend** of the agents
- O2 Complexity of real-world programming tasks ——— Agents to boost efficiency?
- O3 Complexity of the project —— Valuable skills acquired
- Repository-level dataset comprehension



Goals

- O1 Analysis of existing literature about code generation
- Replication of CodeAgent framework by implementing tools and strategies
- 03 Analysis of CodeAgentBench and creation of MiniTransformers
- 04 Obtain valuable results



Code LLMs: General VS Specific

LLM Agents: Planning, Tools, Frameworks

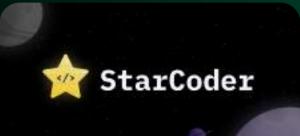
CodeGen Scenarios: Statement VS Function VS Repository

Benchmarks: Function-level VS Repository-level

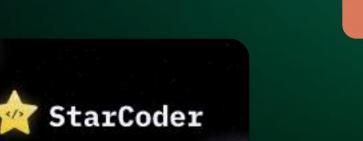


- Code LLMs
 - General-purpose LLMs
 - Coding-specific LLMs
 - Trained on code from scratch
 - Fine-tuned on code



















Code LLMs

• General-purpose LLMs











Code LLMs

- Coding-specific LLMs
 - Trained on code from scratch

AlphaCode

- Pre-trained on GitHub code
- Fine-tuned for competitive programming

StarCoder

- Pre-trained on multilingual code
- Fine-tuned on Python tokens





Code LLMs

- Coding-specific LLMs
 - Only fine-tuned on code





→ Transfer Learning:

Reuse knowledge from previously trained systems



Chain-of-Thought Prompting Elicits Reasoning in Large Language Models

Quoc V. Le

LLM Agents: "Planning"

• CoT: chain-of-thought

Series of intermediate reasoning steps provided

CON: Static internal representation

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27.



Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

Let's think step by step...



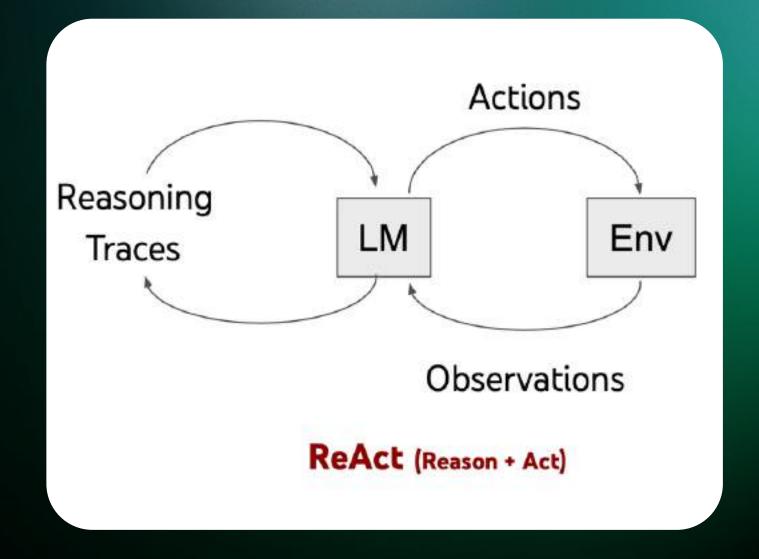
REACT: SYNERGIZING REASONING AND ACTING IN LANGUAGE MODELS

Shunyu Yao^{8,1}, Jeffrey Zhao², Dian Yu², Nan Du², Izhak Shafran², Karthik Narasimhan¹, Yuan Cao²

- LLM Agents: "Planning"
 - ReAct: reason (plan) & action
 - Reason to act
 - Act to reason

Incorporate **external information** into reasoning

CON: prone to loops





Self-planning Code Generation with Large Language Models

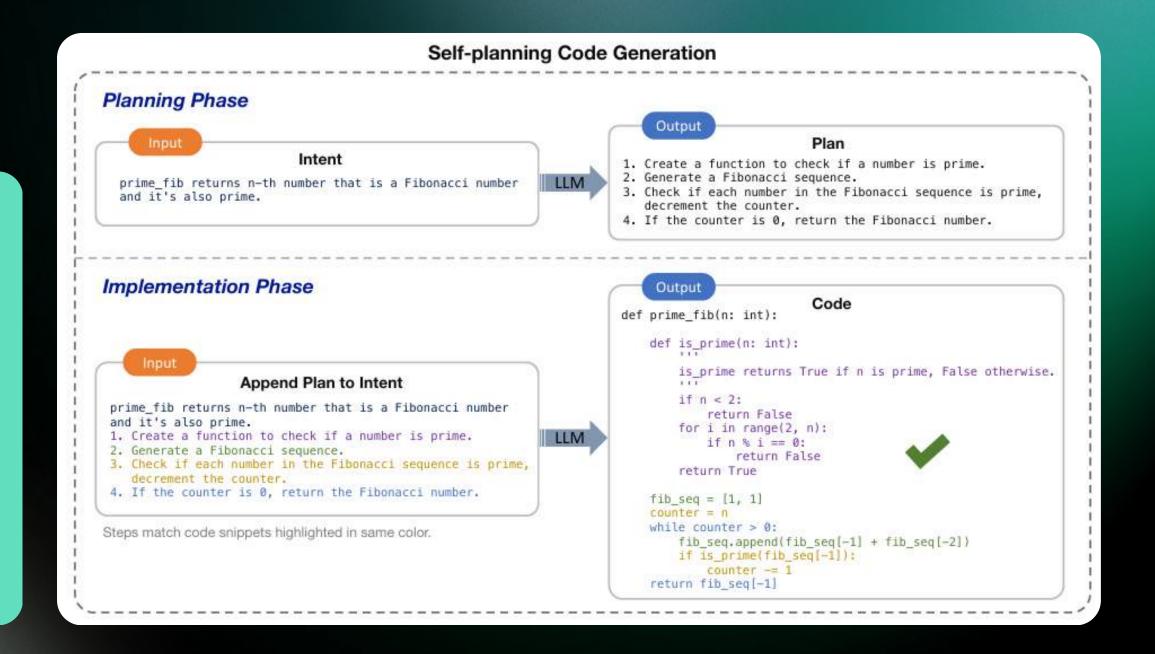
XUE JIANG, YIHONG DONG, LECHENG WANG, ZHENG FANG, QIWEI SHANG, GE LI*, ZHI JIN, and WENPIN JIAO, Key Laboratory of High Confidence Software Technologies (Peking University), Ministry of Education; School of Computer Science, Peking University, Beijing, China

LLM Agents: "Planning"

Self-planning

Planning phase with **few samples** (intent, plan)

Plan: decomposition of intent Implementation phase guided CON: weak verification



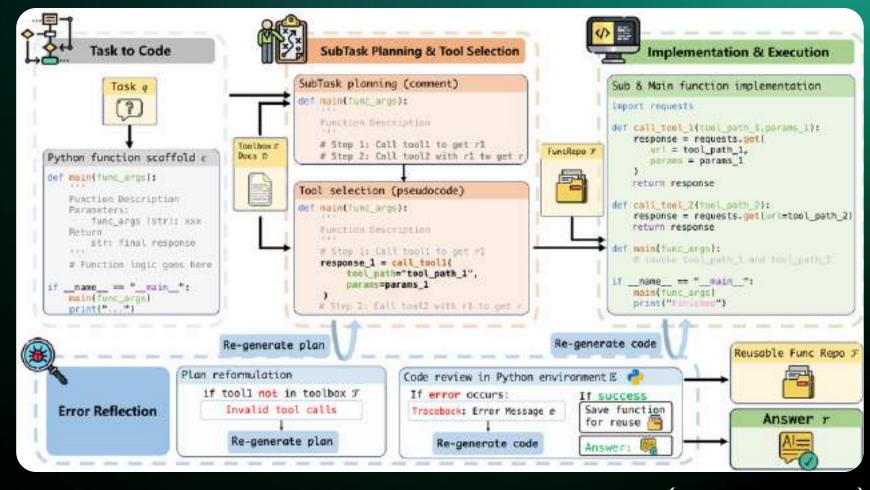


LLM Agents: Tools (ToolCoder)

4 steps: Code; Subtasks; Exe; Errors

- Rigorous plan (Python script VS NL)
- Informative **errors** tracebacks (tools)
- Experience **reuse** (past success=KB)

<u>BUT:</u> **not iterative** process (a priori) and it is **more complex** with respect to ReAct

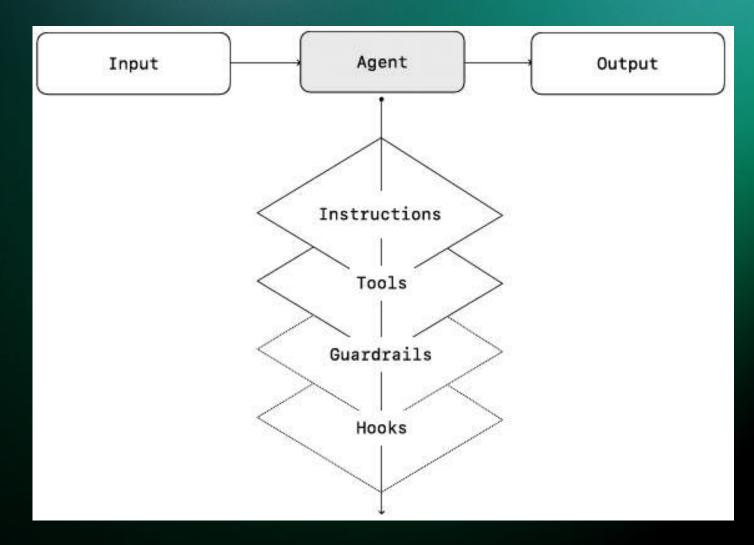




LLM Agents: Frameworks

Single-agent: single model with tools

- Simple complexity, evaluation, maintenance
- run: loop of agent operation until exit cond.
 - CodeAgent



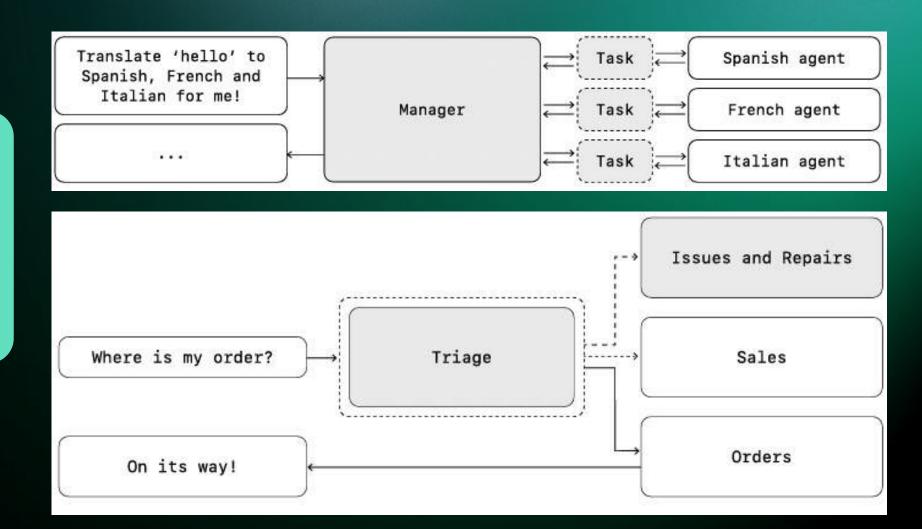
Source: A Pratical Guide to Building Agents



LLM Agents: Frameworks

Multi-agent: multiple coordinated agents

- Manager: coordinates + summarize result
- <u>Decentralized:</u> agents as peers (handoff)
 - AgentCoder



Source: A Pratical Guide to Building Agents



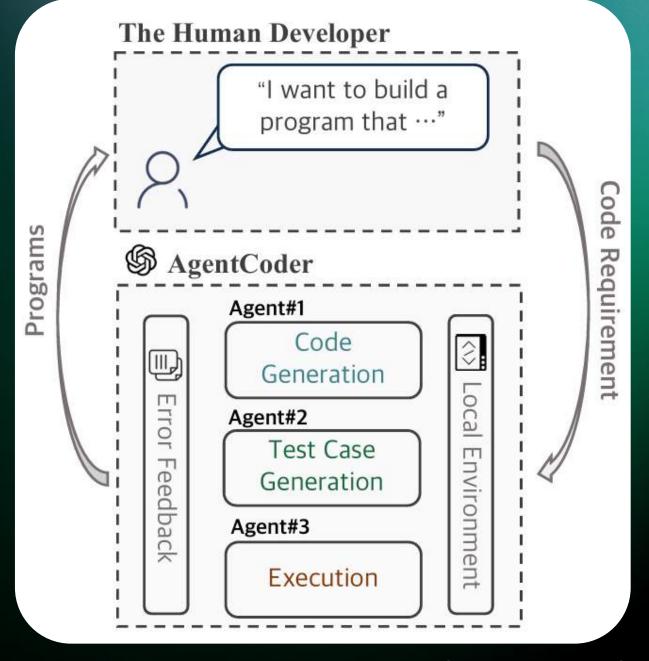
LLM Agents: AgentCoder

Multi-agent System: 3 agents

- Programmer: generates code with COT
- <u>Test Designer</u>: creates the tests
- <u>Test Executor</u>: Executes code against tests
 - Decides success VS fail (redo code)

Pro: enhanced code-tests efficiency/quality

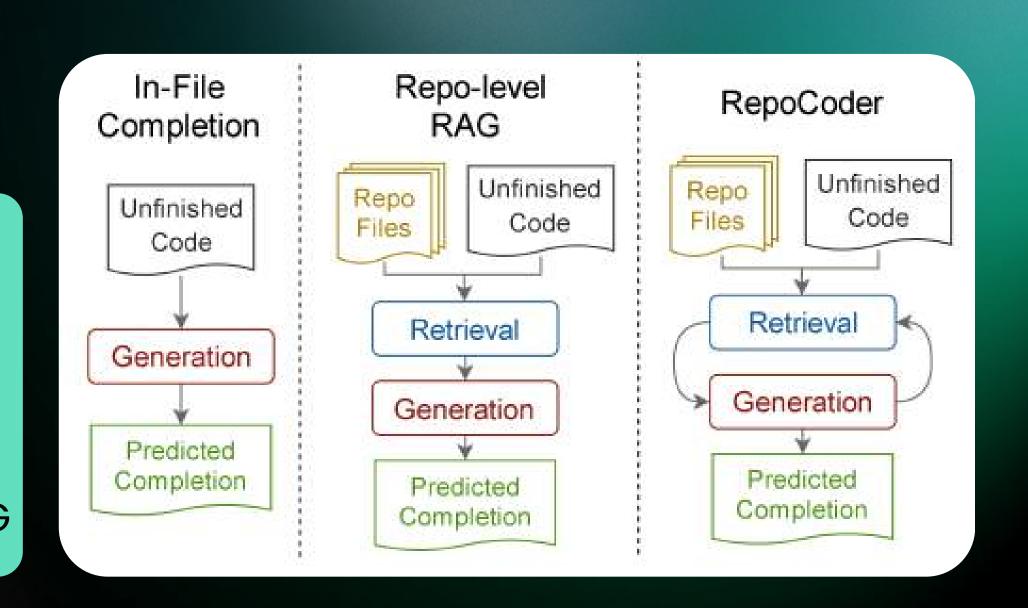
Con: increased complexity, no tools=no repo-lv





Source: AgentCoder (arXiv.2312.13010)

- Code generation scenarios
 - Statement-level generation
 - Function-level generation
 - Repository-level generation
 - CodeAgent
 - RepoCoder, A³ CodGen, CodeRAG





RepoCoder: Repository-Level Code Completion Through Iterative Retrieval and Generation

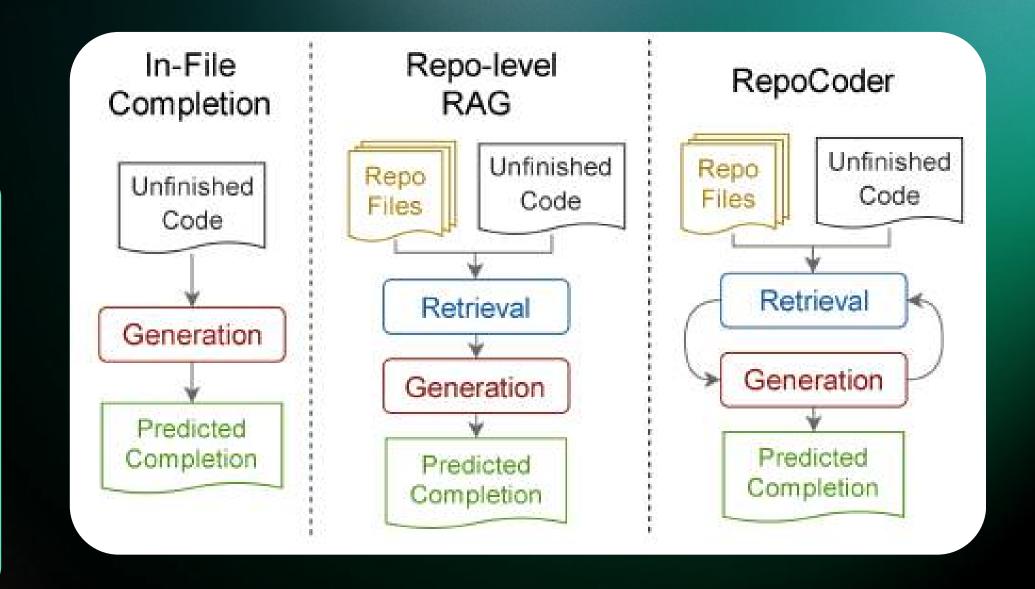
Fengji Zhang¹, Bei Chen², Yue Zhang², Jacky Keung¹, Jin Liu³, Daoguang Zan², Yi Mao², Jian-Guang Lou², Weizhu Chen²

Repo-level code generation

- RepoCoder
 - Code as independent snippets
 - Similarity-based retrieval
 - Iterative pipeline

Query: last lines of unfinished code

CON: pending stopping condition





A³-CodGen: A Repository-Level Code Generation Framework for Code Reuse with Local-<u>A</u>ware, Global-<u>A</u>ware, and Third-Party-Library-<u>A</u>ware

Dianshu Liao, Shidong Pan, Xiaoyu Sun, Xiaoxue Ren, Qing Huang, Zhenchang Xing, Huan Jin, Qinying Li

Repo-level code generation

A³ CodGen

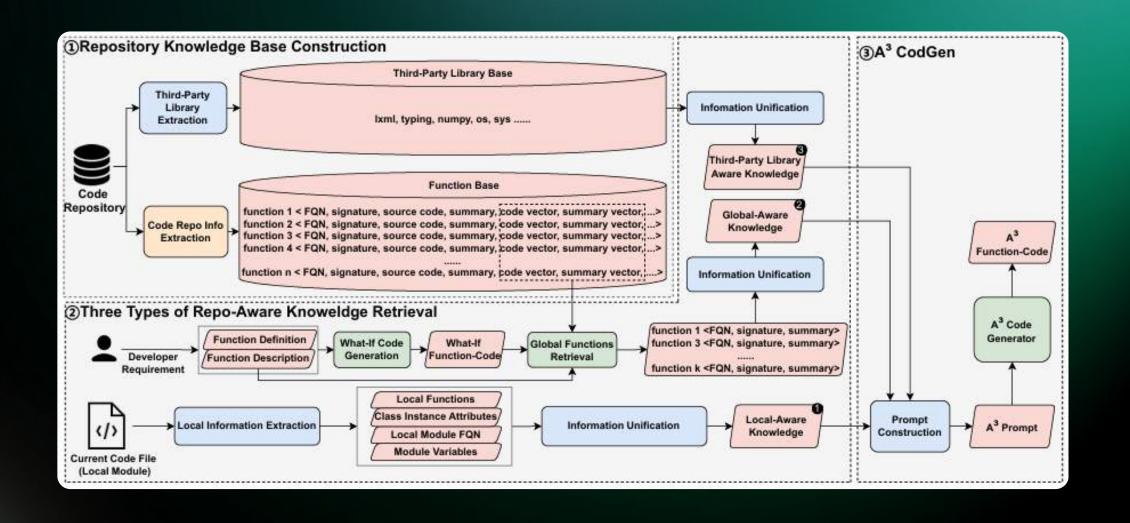
Knowledge retrieval on:

Local: current working files

Global: other files in the same

repository → promote code reuse

Third-party-library



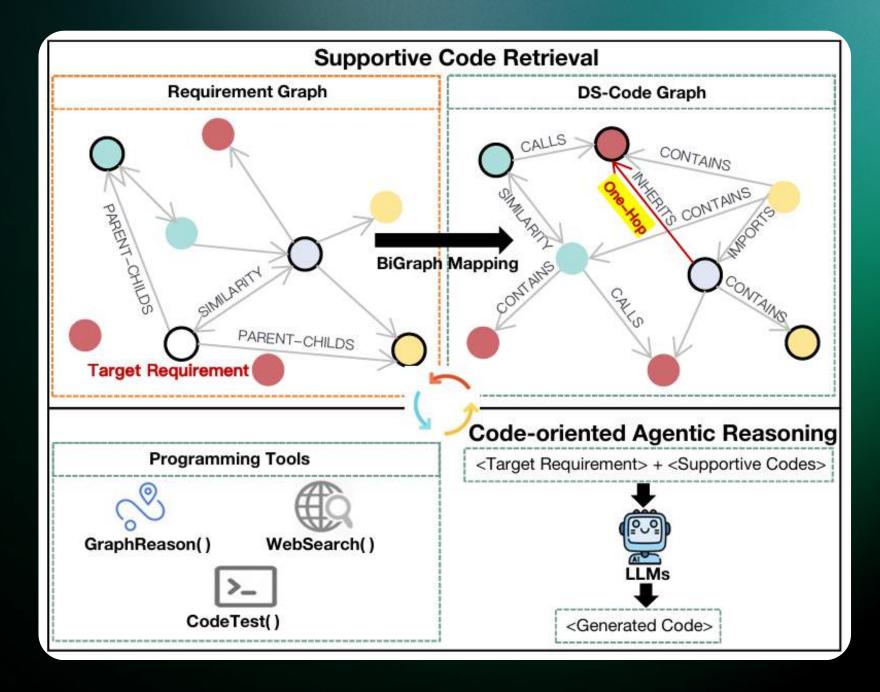


Repo-level code generation

CodeRAG

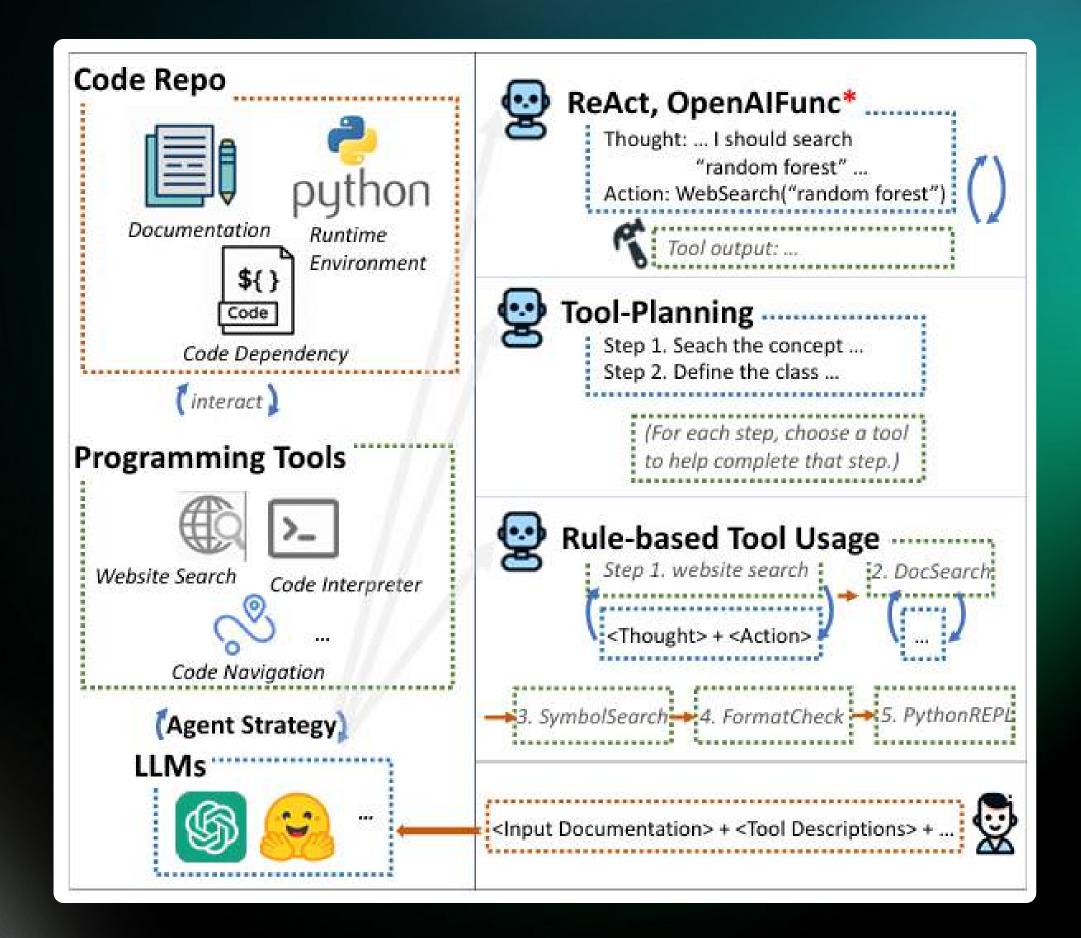
Code-oriented agentic reasoning

- Web Search Tool
- Graph Reasoning Tool
- Code Testing Tool
- ReAct strategy

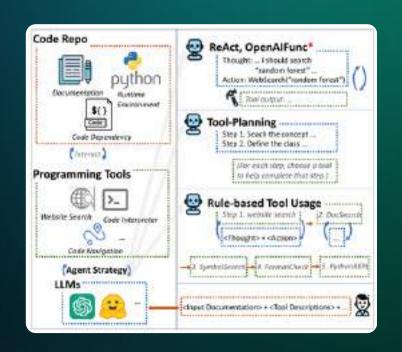




Experiment Replication



Experiment Replication





TOOL IMPLEMENTATION

- WebSiteSearchTool
- DocumentationSearchTool
- CodeSymbolNavigationTool
- FormatCheckTool
- CodeInterpreterTool



SYSTEM EVALUATION

- Repository-level testing
- Function-level testing



LLM SETUP

- Small Quantized Model
- Large Models through API



AGENT INTEGRATION

- ReAct
- ToolPlanning
- Rule-based
- Tool-calling



Small LLMs Setup

Prepare an LLM to be used in the Colab free environment (limited resources)

- O1 Select base LLMs, among Qwen3 (8B, 4B, 1.7B, 0.6B) and CodeLlama 7b Instruct
- O2 Set **4-bit (nf4) quantization** to model (using bitsandbytes lib) and bfloat16
- O3 Create Hugging Face **Pipeline** ——— Create LangChain **Wrapper**



Large LLMs Setup

Switch to these models since:

- Limited resources=runtime disconnection
- Simulate better paper setup
- Better performance w/ agent

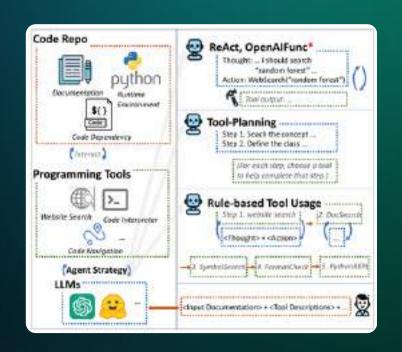
01

Just select base LLMs (SOTA)

- Open source: DeepSeek V3 (OpenRouter)
- Closed source: GPT-4.1 nano or mini (free credits), Gemini 2.5 Flash (Free tier)



Experiment Replication



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CodeAgent

Tool-Integrated: Incorporate programming tools to provide contextual information

Information Retrieval



Code Implementation



Code Testing





Features:

- Subclass of LangChain's BaseTool
 - Name, description, Pydantic input schema (OpenAl Guide)
 - Decisive role of tool description in prompting (Tests)
- Robust unit testing conducted on each tool
- Descriptive error messages (ToolCoder)



Website Search Tool

Documentation Search Tool

Code Symbol Navigation Tool

Format Check Tool

Code Interpreter Too

- Search engine free API: DuckDuckGo
- Search the internet for information
- Summarize the info (LLM/first 60)



Website Search Tool

```
class WebsiteSearchTool(BaseTool):
    name: str = "WebSearch"
    description: str = (
        "Searches the public internet for general programming topics, external libraries (like PyTorch or NumPy), or error messages. "
        "**Use this tool when you cannot find the answer in the local project documentation (DocSearch).** "
        "The tool takes a search query and **returns a concise, AI-generated summary of the most relevant web pages.**"
)
```

```
def summarise(text: str, max_new_tokens: int = 256) -> str:
    prompt = (
        "You are a senior Python engineer. Give a **single paragraph "
        "(≤150 words)** summary of the snippet below, focusing on key details. "
        "----- SNIPPET START -----\n"
        f"{text[:4000]}\n"
        "------ SNIPPET END ------"
)
```



Website Search Tool

Documentation Search Tool

Code Symbol Navigation Tool

Format Check Tool

Code Interpreter Too

- Read and split docs into chunks (---)
- Rank with **BM250kapi** algorithm
- Eventually summarize the result



Documentation Search Tool

```
class DocSearchTool(BaseTool):
    name: str = "DocSearch"

    description: str = (
        "Searches the internal project documentation (`api_guide.md`) for a specific class or function. "
        "**This should be your FIRST choice for understanding how to use existing components in this repository.** "
        "It is very fast and provides official usage information. "
        "The input is the name of the symbol you are looking for. "
        "**The tool returns the single most relevant documentation section.**"
)
```



Website Search Tool

Documentation Search Tool

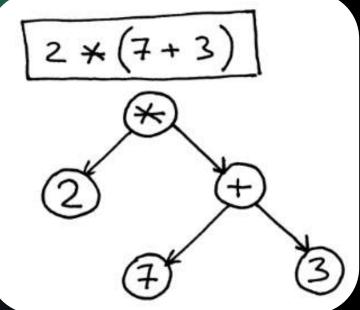
Code Symbol Navigation Tool

Format Check Tool

Code Interpreter Too

- 2 main uses
 - Get functions/classes definitions
 - List all functions-classes in a file
- Leverages **tree-sitter** with Python parser (AST structure)





Code Symbol Navigation Tool

```
class CodeSymbolNavigationTool(BaseTool):
    name: str = "CodeSymbolNavigation"
    description: str = (
        "Inspects the structure of Python source code files **without reading the entire file into context.** "
        "This tool is essential for understanding a file's contents before deciding to read or modify it. "
        "It prevents context overflow errors when dealing with large files. It has two modes:\n"
        "1. **List Symbols (recommended first step):** "
        "Provide just a file path to get a summary of all classes and functions in that file. Use this to understand the file's structure.\n"
        "2. **Get Specific Source:** "
        "After listing symbols, provide a file path and a symbol name to get only the source code for that single class or function."
)
```



Website Search Tool

Documentation Search Tool

Code Symbol Navigation Tool

Format Check Tool

Code Interpreter Too



- Black: Python code formatter
- Detect syntax errors with **compile**
- Return formatted string or error msg



Format Check Tool

```
class FormatCheckTool(BaseTool):
    name: str = "FormatCheck"
    description: str = (
        "A utility to automatically format Python code using the 'black' standard. "
        "**This is a useful final step to ensure code quality and style consistency before writing the code to a file.** "
        "It takes the raw Python code as a string and returns the formatted code as a string. "
        "This tool will fail if the input code has a syntax error."
)
```



Website Search Tool

Documentation Search Tool

Code Symbol Navigation Tool

Format Check Tool

Code Interpreter Tool

- Run snippets/scripts (create/modify/test)
- <u>Security:</u>
 - Timeout (20s) for run
 - Execution in temp file + child process

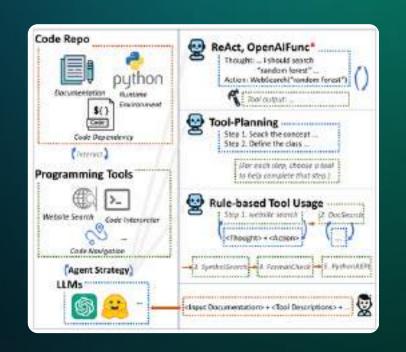


Code Interpreter Tool

```
class CodeInterpreterTool(BaseTool):
    name: str = "CodeInterpreter"
    description: str = (
        "Executes a Python script in the project's root directory. This is your primary tool for all file system modifications and for testing your work."
        "You MUST use this tool to perform any of the following actions:"
        "\n1. **CREATE a new file:** Provide a script that opens a new file path in write mode ('w'). "
        "Example: `with open('path/to/new_file.py', 'w') as f: f.write('# New code')`"
        "\n2. **MODIFY an existing file:** Provide a script that reads the file, modifies the content, and writes it back. "
        "Example: `with open('path/to/file.py', 'r') as f: c = f.read() \n # ... modify c ... \n with open('path/to/file.py', 'w') as f: f.write(c)`"
        "\n3. **TEST code:** Provide a script that runs `pytest` or other checks to verify your changes. "
        "Example: `import pytest; pytest.main(['tests/test_file.py'])`"
        "\nThe tool returns the script's stdout and stderr, which you should use to confirm that your action was successful."
)
```



Experiment Replication



TOOL IMPLEMENTATION

- WebSiteSearchTool
- DocumentationSearchTool
- CodeSymbolNavigationTool
- FormatCheckTool
- CodeInterpreterTool



SYSTEM EVALUATION

- Repository-level testing
- Function-level testing



LLM SETUP

- Small Quantized Model
- Large Models through API



AGENT INTEGRATION

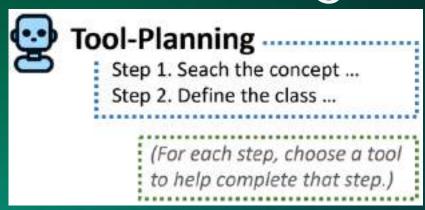
- ReAct
- ToolPlanning
- Rule-based
- Tool-calling



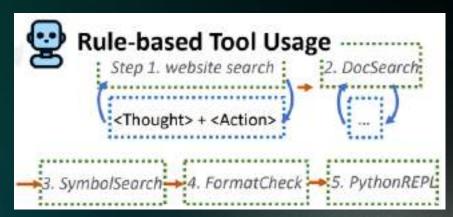
CodeAgent

Agent strategies for tools' usage (LLM as brain; tools as hands)

ToolPlanning



Rule-Based Tool



ReAct



Function Calling

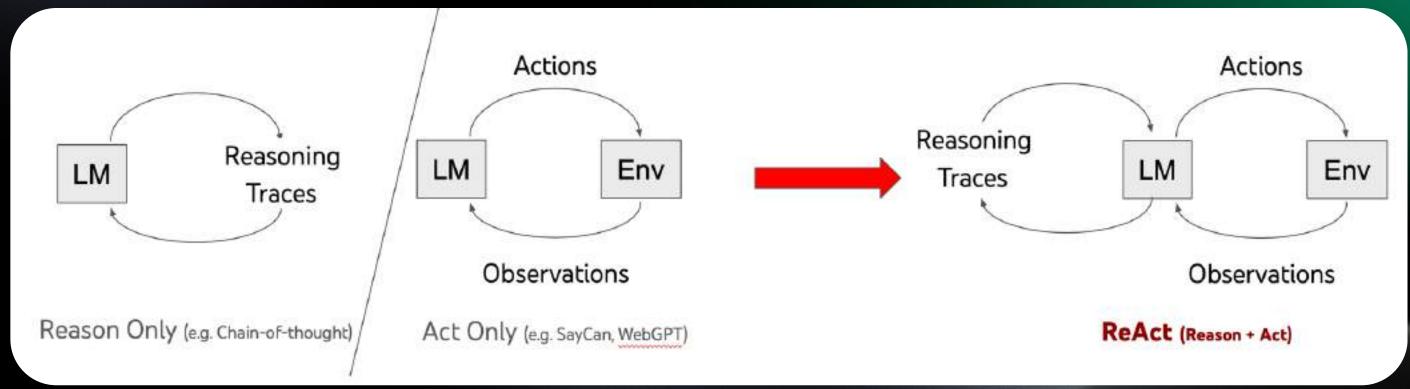




Agent Integration

ReAct: select and invoke suitable tools according to actions

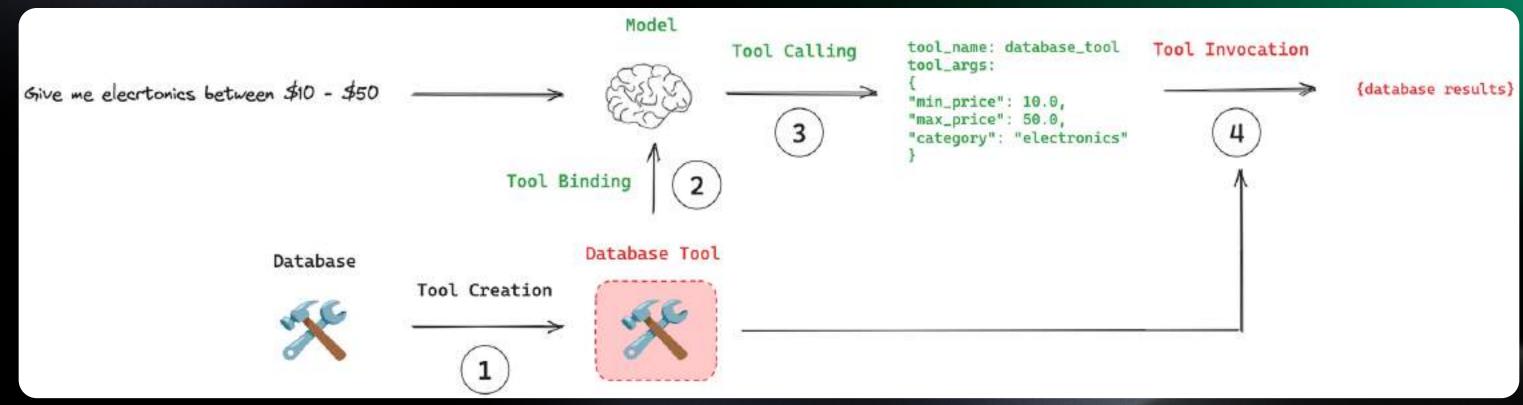
AgentExecutor: Though => Action => Observation => Repeat => End/Test (assert)





Agent Integration

Tool-calling: structured way to call tools (for modern models)
We've to be careful with max_iterations and time after each task



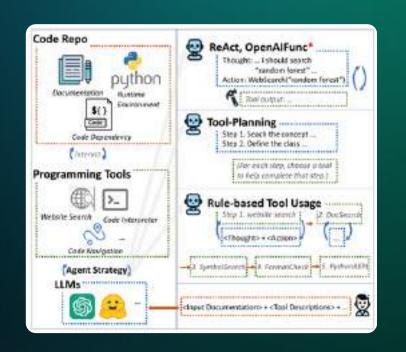
6. System Evaluation

Repo-level: CodeAgentBench & MiniTransformers

Function-level: HumanEval



Experiment Replication



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Literature Review

- Evaluation benchmarks
 - Function-level benchmarks
 - HumanEval, MBPP
 - Repository-level benchmarks
 - SWE-bench
 - CodeAgentBench

```
def incr_list(1: list):
    """Return list with elements incremented by 1.
    >>> incr_list([1, 2, 3])
    [2, 3, 4]
    >>> incr_list([5, 3, 5, 2, 3, 3, 9, 0, 123])
    [6, 4, 6, 3, 4, 4, 10, 1, 124]
    return [i + 1 for i in 1]

def solution(lst):
    """Given a non-empty list of integers, return the sum of all of the odd elements that are in even positions.

Examples
    solution([5, 8, 7, 1]) =⇒12
    solution([3, 3, 3, 3, 3]) =⇒9
    solution([30, 13, 24, 321]) =⇒0
    """
    return sum(lst[i] for i in range(0,len(lst)) if i % 2 == 0 and lst[i] % 2 == 1)
```



Codebase

Environment: numpy-ml (classes + contextual information)

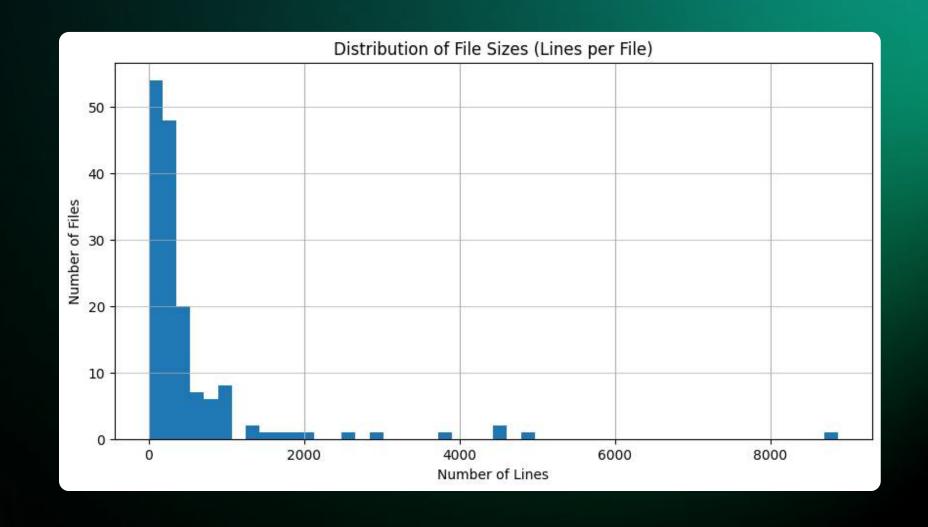
- High-star GitHub repositories
- Topics: machine learning, data structure, database, information extraction, networking
- 192 classes and 1431 functions

	path	content
0	numpy_ml/initpy	[# noqa\n, """Common ML and ML-adjacent algori
1	numpy_ml/gmm/gmm.py	["""A Gaussian mixture model class"""\n, impor
2	numpy_ml/gmm/initpy	[from .gmm import *\n]
3	numpy_ml/nonparametric/kernel_regression.py	[fromutils.kernels import KernelInitializer
4	numpy_ml/nonparametric/gp.py	[import warnings\n, import numpy as np\n, from



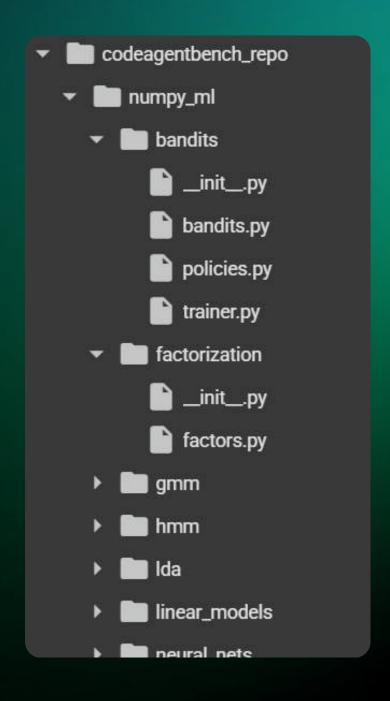
Codebase

- Heavily left-skewed distribution
- External Library Dependencies
 - numpy in 126 files
 - o time in 40 files
 - o torch in 37 files
- Internal Module Dependencies
 numpy_ml.neural_nets.activations in 58 files





- Repository structure reconstruction
 - tree-sitter for parsing
 - creation of directories and files





••••

Tasks

Task defined in each entry with metadata

- 51 class implementation tasks
- 6 function-level tasks

The final CODEAGENTBENCH contains 101 samples, and for each task, LLMs are provided with documentation containing the requirements needed to be implemented, along with a set of tools we designed, as well as full access permissions to code files in the repository.

	title	class_annotation	comment	class_name	class_link	test_file_path
0	BallTree	numpy_ml.utils.d	"BallTree"\n\n**	numpy_ml.utils.d	numpy_ml/utils/d	numpy_ml/tests/t
1	BatchNorm2D	numpy_ml.neural	"BatchNorm2D"\n\	numpy_ml.neural	numpy_ml/neural	numpy_ml/tests/t
2	RandomForest	numpy_ml.trees.R	"RandomForest"\n	numpy_ml.trees.R	numpy_ml/trees/r	numpy_ml/tests/t
3	MLENGram	numpy_ml.ngram.M	"MLENGram"\n\n**	numpy_ml.ngram.M	numpy_ml/ngram/n	numpy_ml/tests/t
4	BidirectionalLSTM	numpy_ml.neural	"BidirectionalLS	numpy_ml.neural	numpy_ml/neural	numpy_ml/tests/t





- Repository-level benchmark
 - Environment: core miniformer repository with additional sub-packages
 - Replicate the essential structure of large repositories
 - Generated by Gemini 2.5 Pro 06-05
 - 6 classes and 23 functions

	path	content
0	main.py	[# Main entry point for agent tasks. Initially
1	README.md	[# Miniformer\n, A minimal, educational librar
2	requirements.txt	[numpy\n, torch\n, scipy\n, pydantic]
3 1	miniformer/initpy	[from .models.block import TransformerBlock]
4	miniformer/config.py	[from pydantic import BaseModel, Field\n, from

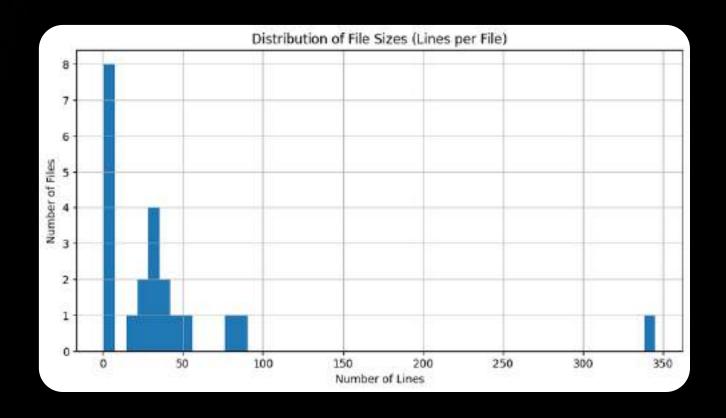


Codebase

Statistically representative of real-world projects

- Generation guided by statistics of CodeAgentBench codebase
- Replicate file size distribution in scaled version

Lines per File	count	mean	min	25%	50%	75%	max
CodeAgentBench	156.00	542.49	2.00	113.50	265.50	512.50	8866.00
MiniTransformers	22.00	41.27	1.00	2.00	29.00	40.50	345.00





- Codebase
 - Core components to build and use transformers
 - External Library Dependencies
 - o torch in 7 files
 - pytest in 5 files
 - o numpy in 4 files

```
File Path: miniformer/layers/attention.py

Content Snippet (first 500 characters):
import torch
import torch.nn as nn
import torch.nn.functional as F
import math

class CausalSelfAttention(nn.Module):
    """A vanilla multi-head masked self-attention layer with a projection at the end."""

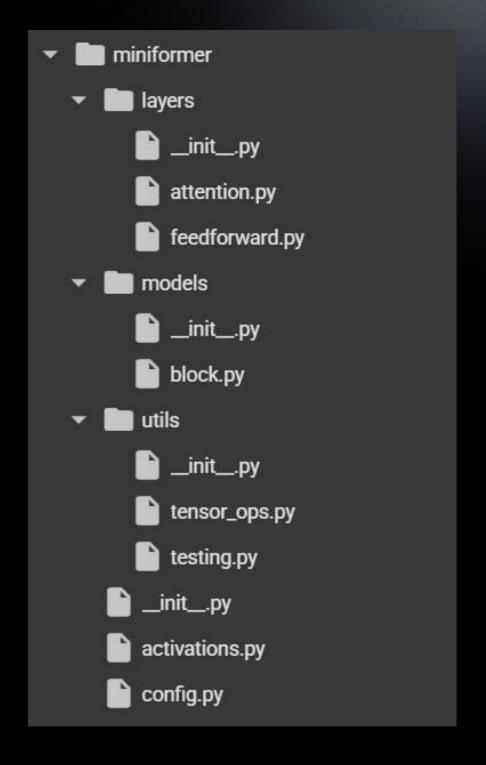
def __init__(self, config):
    super().__init__()
    assert config.n_embd % config.n_head == 0

# Key, query, value projections for all heads, but in a batch
    self.c_attn = nn.Linear(config.n_embd, 3 * config.n_embd)
# Output projection
```

	path	line_count	class_count	function_count
15	tests/test_integration.py	345	0	0
6	miniformer/layers/attention.py	89	2	2
21	tests/test_created_files.py	79	0	3



- Repository reconstruction
 - Simulation of realistic file system
 - tree-sitter for parsing
 - creation of directories and files





- Generation of API Guide
 - Generate markdown document for source files
 - tree-sitter for parsing
 - function and class definitions



Miniformer API Guide

This guide details the core library components

File: miniformer/activations.py

gelu_exact(x)

Gaussian Error Linear Unit (GELU) activation function using SciPy's erf for NumPy arrays.

get_activation(name: str)

Returns the activation function corresponding to the name.

File: miniformer/config.py

TransformerConfig()

Configuration for a Miniformer model.

File: miniformer/models/block.py

TransformerBlock()

A single block of a transformer model. It consists of a multi-head self-attention layer followed by a feed-forward network. Layer normalization and residual connections are applied.

File: miniformer/layers/attention.py

CausalSelfAttention()

A vanilla multi-head masked self-attention layer with a projection at the end.

MultiHeadSelfAttention()

Alias for CausalSelfAttention for clearer naming conventions.

File: miniformer/layers/feedforward.py

FeedForward()

A position-wise feed forward network

Tasks

15 programming tasks, metadata generated by Python's **ast** module

- Prompt written in documentation-style format
- From simple file modifications to code refactoring and file creation
- Support executable test suite verification

	title	class_annotation	comment	class_name	class_link	test_file_path	task_id
0	Transformer	miniformer	"Add Bias C	miniformer	miniformer/	tests/test	miniformer-01
1	to_numpy	miniformer	"Verify Ten	N/A	miniformer/	tests/test	miniformer-02
2	Transformer	miniformer	"Implement	miniformer	miniformer/	tests/test	miniformer-03
3	get_activation	miniformer	"Add Swish	N/A	miniformer/	tests/test	miniformer-04
4	PositionalE	miniformer	"Create Pos	miniformer	miniformer/	tests/test	miniformer-05
4	PositionalE	miniformer	"Create Pos	miniformer	miniformer/	tests/test	miniformer-0



Tasks

```
"Add Swish Activation Support"

function miniformer.activations.get_activation(name)

Extend the activation function factory to include support for 'swish'.

-[ Notes ]-
The Swish activation function, defined as `f(x) = x * sigmoid(x)`, is a smooth, non-monotonic function that often matches

Implementation Steps:

1. Implement a new Python function `swish(x)` that computes the activation. It should use `torch.sigmoid`.

2. Modify the `get_activation` function to return a reference to your `swish` function when the input `name` is 'swish'.
```



- Tests
 - Support executable test suite verification

```
import pytest
import torch
from miniformer.activations import get_activation

def test_swish_activation():
    # This test is expected to fail until Task #4 is completed.
    try:
        swish = get_activation('swish')
        x = torch.tensor([1.0, 2.0, -1.0])
        expected = x * torch.sigmoid(x)
        assert torch.allclose(swish(x), expected)
except ValueError:
    pytest.fail("Activation 'swish' is not registered in get_activation.")
```



Evaluation



1	D 0 1770	ODE 44	CIDT 4.4	O O F 731 1
AgentStrategy	DeepSeekV3	GPT-4.1-mini	GPT-4.1-nano	Gemini 2.5 Flash
NoAgent	0.333	0.333	0.333	0.533
ReAct	0.533	0.800	0.400	0.667
Tool-calling	-	0.867	0.467	0.733
Rule-based	0.600	0.667	0.400	0.667
Tool-Planning	0.467	0.733	0.333	0.600
·	<u> </u>		<u> </u>	

- Low success rate in NoAgent: recurrent errors on missing imports and failing function calls
- Performance of GPT-4.1 mini boosted by agent strategy
- GPT-4.1 nano may be limited by the small model size
- DeepSeekV3 could need different approach or few-shot learning
- Gemini 2.5 Flash may share affinity with model used to generate benchmark
- Results may slightly differ among executions for non determinism



HumanEval

- Function-level code generation benchmark
 - Most popular Python code generation benchmark nowadays
 - 164 handwritten programming problems with about 8 test units for each task

	task_id	prompt	entry_point	canonical_solution	test
HumanEval/0	HumanEval/0	from typing import List\n\n\ndef has_close_ele	has_close_elements	for idx, elem in enumerate(numbers):\n 	\n\nMETADATA = {\n 'author': 'jt',\n 'da
HumanEval/1	HumanEval/1	from typing import List\n\n\ndef separate_pare	separate_paren_groups	result = []\n current_string = []\n	\n\nMETADATA = {\n 'author': 'jt',\n 'da
HumanEval/2	HumanEval/2	\n\ndef truncate_number(number: float) -> floa	truncate_number	return number % 1.0\n	\n\nMETADATA = {\n 'author': 'jt',\n 'da



HumanEval

Function-level code generation benchmark

```
from typing import List
def has close elements(numbers: List[float], threshold: float) -> bool:
   """ Check if in given list of numbers, are any two numbers closer to each other than
   given threshold.
    >>> has close elements([1.0, 2.0, 3.0], 0.5)
   >>> has close elements([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3)
    .....
METADATA = {
    'author': 'jt',
    'dataset': 'test'
def check(candidate):
    assert candidate([1.0, 2.0, 3.9, 4.0, 5.0, 2.2], 0.3) == True
    assert candidate([1.0, 2.0, 3.9, 4.0, 5.0, 2.2], 0.05) == False
   assert candidate([1.0, 2.0, 5.9, 4.0, 5.0], 0.95) == True
   assert candidate([1.0, 2.0, 5.9, 4.0, 5.0], 0.8) == False
    assert candidate([1.0, 2.0, 3.0, 4.0, 5.0, 2.0], 0.1) == True
    assert candidate([1.1, 2.2, 3.1, 4.1, 5.1], 1.0) == True
    assert candidate([1.1, 2.2, 3.1, 4.1, 5.1], 0.5) == False
```



Evaluation



AgentStrategy	DeepSeekV3	GPT-4.1-mini	GPT-4.1-nano	Gemini 2.5 Flash
NoAgent	0.781	0.805	0.701	0.793
Tool-calling	-	0.848	0.768	0.842
ReAct	0.817	0.829	0.756	0.829
Rule-based	0.823	0.835	0.762	0.829
Tool-Planning	0.811	0.823	0.744	0.817

- Documentation reading and code symbol navigation tools disabled
- HumanEval tasks easier to handle
- GPT-4.1 mini results the best
- Remarkable performance of all models
- Results may slightly differ among executions for non determinism



Replication Summary

Key Features:

Open source and proprietary LLMs as base model

Custom tools implementation

Agent strategies implementation

Extensive unit and integration testing

Evaluation from multiple approaches

Validity of framework and tools assessed

Major Challenges

- Local computational resources
- Agent stuck in self-doubt loops
- Undefined Function-calling behaviour

Solutions

- Model quantization
- Adopt more effective models
- Consider few-shot learning



CodeAgent Project Report

Literature Review & Experiment Replication

Authors

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Course: Large Language Models: Applications, Opportunities and Risks

Professors:

Prof. Carman Mark James Prof. Brambilla Marco Prof. Pierri Francesco

Conclusion

Successful replication of **CodeAgent framework**, by implementing the entire suite of tools and the agent strategies

Creation of **MiniTransformer** benchmark

Future perspectives

Multi-agent systems (AgentCoder)
Integration of knowledge graphs (CodeRAG)
Explainability for LLMs





Thank You!







GitHub repository