LLM for Software Engineering Course Projects

2025-2026

Project Assignment

- Teams of **5 people**
- Select 3 project proposals (at least one T, one A – see later) that you would like to do
- We will assign you – if possible – **one** of the projects that you have chosen

- Team management link (be careful when modifying it!!!) : https://docs.google.com/spreadsheets/d/1mswRyffUWuquIXr7dreP5cwSWOM4KOuyURbuvzoozms/edit?gid=0#gid=0

- Deadline for team and proposal selection: **November 30**
- Assignment of projects and project start: **December 1**

Project Evaluation

- Deadline for project hand-in: before the beginning of next academic year (September, 2025)
- Deadlines to have the LLM exam registered in a specific session:
  - Winter session -> January 31, 2026
  - Summer session -> June 30, 2026
  - Autumn session -> September 15, 2026
- Project points: 15/30 points
- You will have to discuss the project (20 minutes presentation over slides, including QCA)

Project Delivery

- Project template: https://dbdmg.polito.it/dbdmg_web/wp-content/uploads/2025/12/Project-template.zip

- To deliver the project, you have to submit:
  - The link to a GitHub project with your replication package
  - The document describing your project work, a technical report created with Overleaf (this must be contained in the GitHub project, under the /report folder). Max length: 6 pages (excluding references, appendices and tables with data, if needed)

Project Categories

- **T (SemEval Task):** technical projects in which you will apply LLM models to solve SemEval challenges.
  - Responsible: prof. Flavio Giobergia

- **A (Application):** projects in which you will analyze the effectiveness of the application of LLMs in various Software Engineering tasks.
  - Responsible: prof. Riccardo Coppola

Project Tutorship

You can schedule two 30-minutes slots per team for project tutorship.

- **T (SemEval Task):** send an e-mail to:
  - claudio.savelli@polito.it (task 1/4/9/10/12/13)
  - lorenzo.vaiani@polito.it (task 2/3/5/6/7/8/11)

- **A (Application):** send an e-mail to anna.arnaudo@polito.it

SemEval Tasks

- https://semeval.github.io/SemEval2026/tasks

A1: LLM Agents for Collaborative Test Case Generation

- Software testing often requires collaboration between testers, developers, domain experts, and tools. Traditional automated test generation tools cannot emulate multi-perspective reasoning (e.g., user intention, edge case exploration, domain knowledge). Recent advances in multi-agent LLM architectures allow for collaborative workflows where agents work differently to generate the same artefacts.

- Research Questions
  - How effective are LLM agents in generating comprehensive and diverse test cases?
  - Does agent collaboration outperform single-model test generation?
  - What patterns of collaboration lead to higher-quality test cases?

A1: Minimum requirements

- Code Under Test. Choose at least 10-20 functions or methods from any of the following sources:
  - public datasets (MBPP, HumanEval, CodeNet subsets)
  - past course assignments
  - open-source snippets

- System Implementation. The system must include:
  - One single-agent baseline
  - One multi-agent system with ≥2 roles
  - Multiple collaboration patterns (collaborative vs. competitive)

- Evaluation: use at least one of the following evaluation methods:
  - Test coverage (e.g., line or branch coverage)
  - Mutation testing (e.g., mutmut, cosmic-ray)
  - Bug injection / bug detection
  - Diversity analysis (number of unique inputs, edge cases, test types)

A2: Architectures for Code Development with LLMs

- LLMs can generate code, but single-prompt interactions often fail on long or complex development tasks. Multi-agent architectures may improve quality by splitting responsibilities (design, planning, writing, reviewing, debugging).

- Research Questions
  - Which architectures produce higher-quality and more maintainable code?
  - How do agent coordination strategies impact correctness?
  - Does modular role separation improve ode generation?

A2: Minimum requirements

- Choose 10-20 programming tasks (functions, classes, or small modules) from:
  - public datasets (HumanEval, MBPP, CodeNet subsets)
  - past course assignments
  - open-source snippets

- System Implementation
  - One single-agent baseline (a single LLM generating the full code).
  - One multi-agent system with ≥2 distinct roles

- Evaluation: Use at least one of the following evaluation methods:
  - functional correctness (unit tests or provided tests)
  - static code quality metrics (e.g., complexity, maintainability)
  - debugging performance (fault detection/fixing)
  - maintainability/readability assessment

A3: Analysing Software Requirements Through Abstractions

- Requirements are often ambiguous, inconsistent, and non-standardized. LLMs can support requirement authoring, but they still risk to misinterpret human needs.
- For this reason, a more systematic approach, based on the clear identification of the requirements' building blocks, may prove benefits.

- Research Questions
  - Can LLMs reliably identify the different abstraction that compose a requirement (e.g., the main actor, the system response, the precondition…)?
  - Does this analysis improve requirements' clarity and completeness?
  - Can LLMs manage nested items?

A3: Minimum requirements

- Requirement Dataset: Choose 30+ requirements from any of the following:
  - past course assignments
  - open-source software requirement documents
  - your own small system description
- Each requirement must be realistic and contain multiple semantic components (e.g., actions, conditions, constraints).

- System Implementation. Include:
  - One single-agent baseline→ An LLM generates requirements or annotates them directly.
  - One multi-step or multi-agent workflow that performs semantic decomposition into ≥4 tags (see example in the next slide)

- Evaluation. Use at least one of the following evaluation methods:
  - annotation accuracy against a small human-created gold standard
  - clarity and completeness comparison between flat vs structured outputs
  - consistency checking (e.g., detecting contradictions or missing components) <- this is applicable only if the starting requirements are very high quality

Purpose

The reason why the functionality described by the software requirement needs to be implemented.

Condition

Something that limits the scope of application of the requirement.

Precondition

A condition that must hold in the requirement's context. A Precondition is always also a Condition.

Action

Something that happens in the scenario described by the software requirement.

Trigger

An event establishing a temporal context and a causal link that constrains the requirement's applicability. A Trigger is also a Condition.

Entity

Something involved in the actions described in the requirement. Can be both human or not (e.g., the system).

Main_actor

The main user of the functionality described by the requirement The main actor is often also an Entity.

System_response

The behaviour of the system in the described scenario. A System_response is always also an Action.

The product shall be available during normal business hours . As long as the user has access to the client PC

the system will be available 99 % of the time during the first six months of operation

A4: Generating and Correcting Design Diagrams with LLMs

- Design diagrams (UML class diagrams, sequence diagrams, state machines) are essential for software engineering but often missing or outdated. LLMs can help generate diagrams from text or correct existing diagrams.

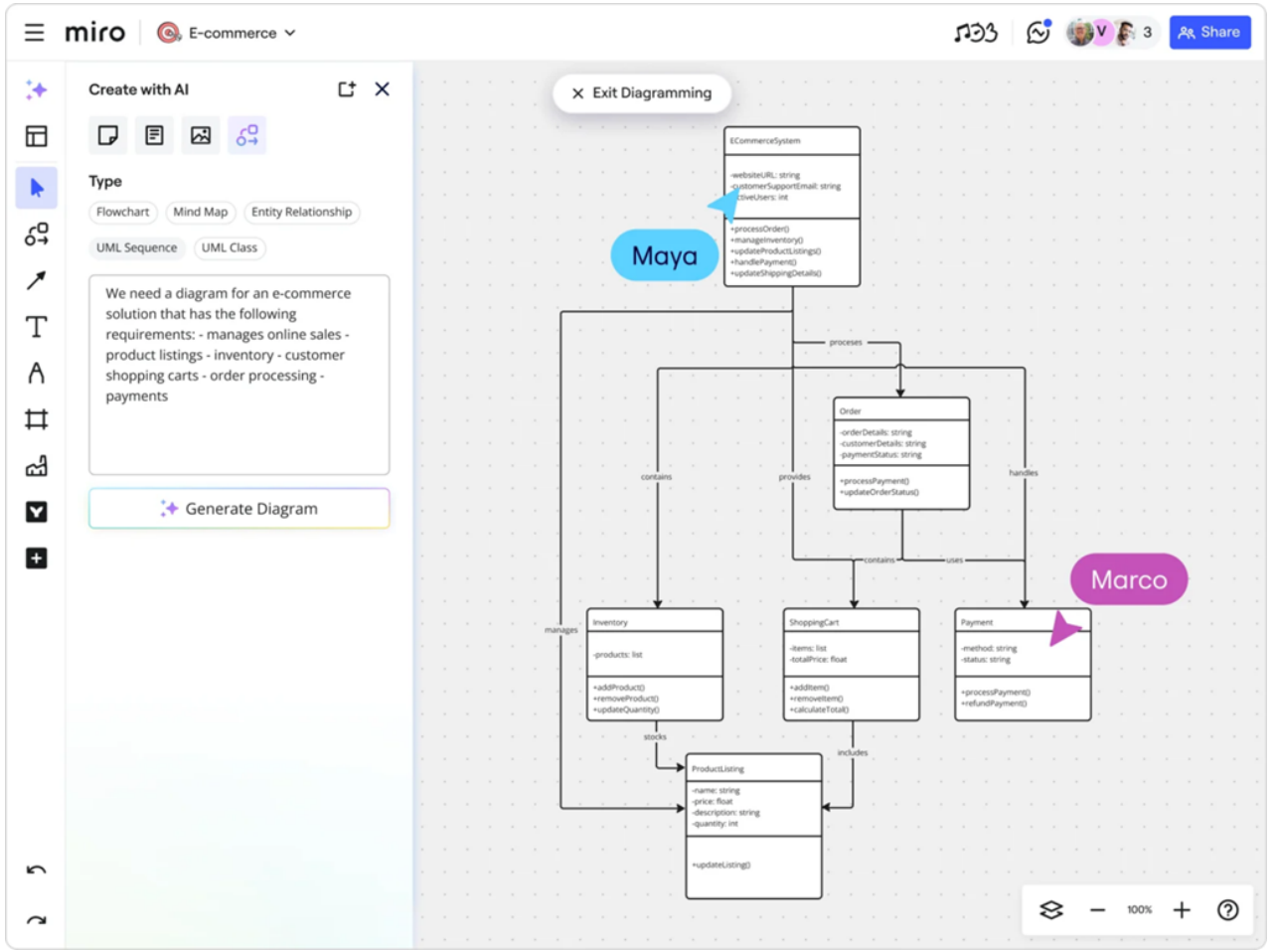
- Research Questions
  - How accurate are LLMs at generating formal design diagrams from natural language?
  - Can multi-agent pipelines improve diagram consistency?
  - How effective are LLMs at detecting and correcting structural errors in diagrams?

A4: Minimum requirements

- Design Artifacts: Choose 3–5 software components (e.g., small systems, class hierarchies, workflows) from:
  - past course assignments
  - open-source documentation
  - your own designed examples

- System Implementation. Include:
  - One single-agent baseline→ An LLM generates or corrects diagrams directly from text.
  - One multi-agent workflow with ≥2 roles

- Evaluation. Use at least one of the following evaluation methods:
  - structural accuracy against a small human-created gold standard
  - consistency checking between diagram elements (e.g., missing methods, invalid relations)
  - error-detection and correction effectiveness



Reference paper: https://dl.acm.org/doi/abs/10.1145/3674805.3690741

A5: Analysis of Linguistic Stereotypes in Generative AI

- Generative models (LLMs, text-to-image systems) often reproduce cultural or linguistic stereotypes. Detecting such bias in generated outputs requires systematic linguistic analysis and structured evaluation.

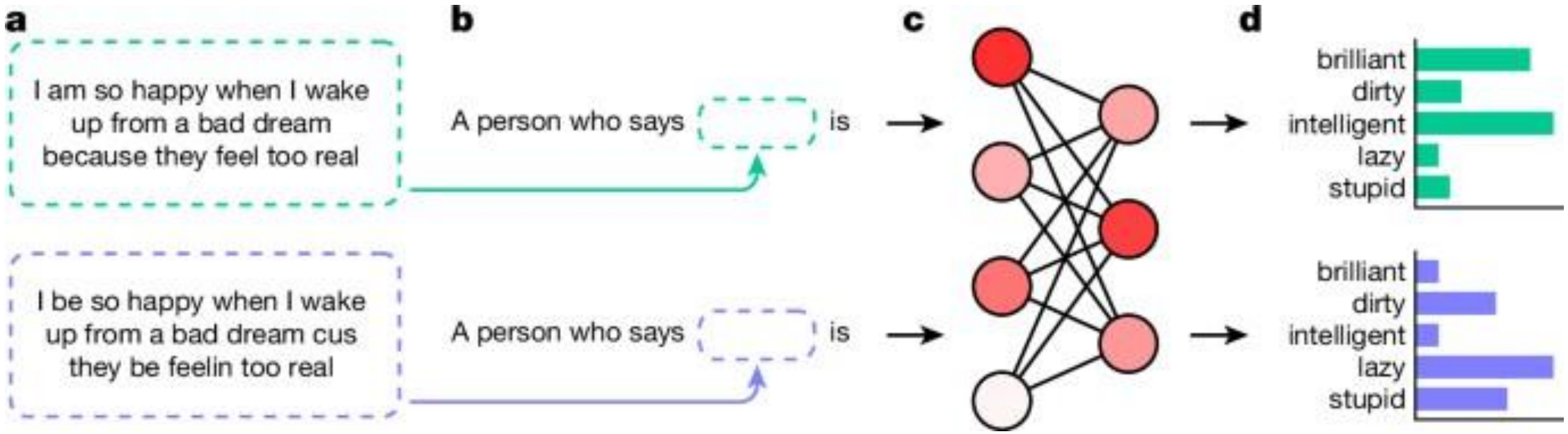
- Research Questions
  - What types of linguistic stereotypes do LLMs reproduce?
  - Does prompt structure (zero-shot, role prompting, chain-of-thought) amplify or reduce bias?
  - Can multi-agent critique frameworks reduce stereotypical outputs?

A5: Minimum requirements

- Choose a set of linguistic varieties or cultural groups that may reveal stereotypical patterns in generated text, such as:
  - American English vs. African American English (AAE)
  - Northern vs. Southern Italian varieties
- Create 10–15 prompts per variety (descriptions, dialogues, character sketches).

- System Design. Include:
  - One single-agent baseline→ An LLM generates responses directly from each prompt.
  - One multi-agent workflow with ≥2 roles

- Evaluation. Use at least one of the following evaluation methods:
  - manual stereotype identification
  - comparison (e.g., how descriptions differ between American English vs. AAE)
  - effectiveness of multi-agent critique in reducing stereotypical features



Reference paper: https://www.nature.com/articles/s41586-024-07856-5