



LLM Agents for Autonomous Density Functional Theory Simulations from Natural Language

Samuel Rothfarb¹, Edward F. Holby², Wilton Kort-Kamp², Baikun Li¹

School of Civil & Environmental Engineering, University of Connecticut¹, Theoretical Division, Los Alamos National Laboratory²

Motivation

Challenges in High-Throughput DFT

- <u>Automation is fragile:</u> Traditional workflows easily fail when unexpected issues occur.
- <u>Expertise barrier remains</u>: Users still need deep technical knowledge to set up and troubleshoot simulation.
- Inefficient resource use: Static pipelines waste resources by not adapting based on intermediate results.

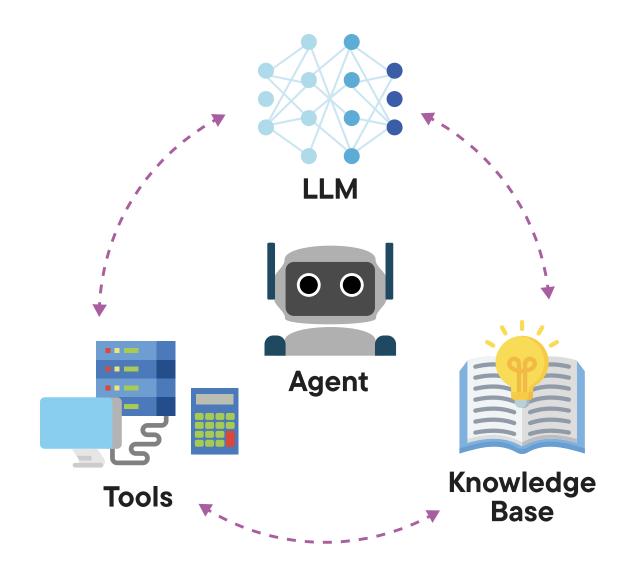
Introduction - From Automated to Autonomous

LLM Agents

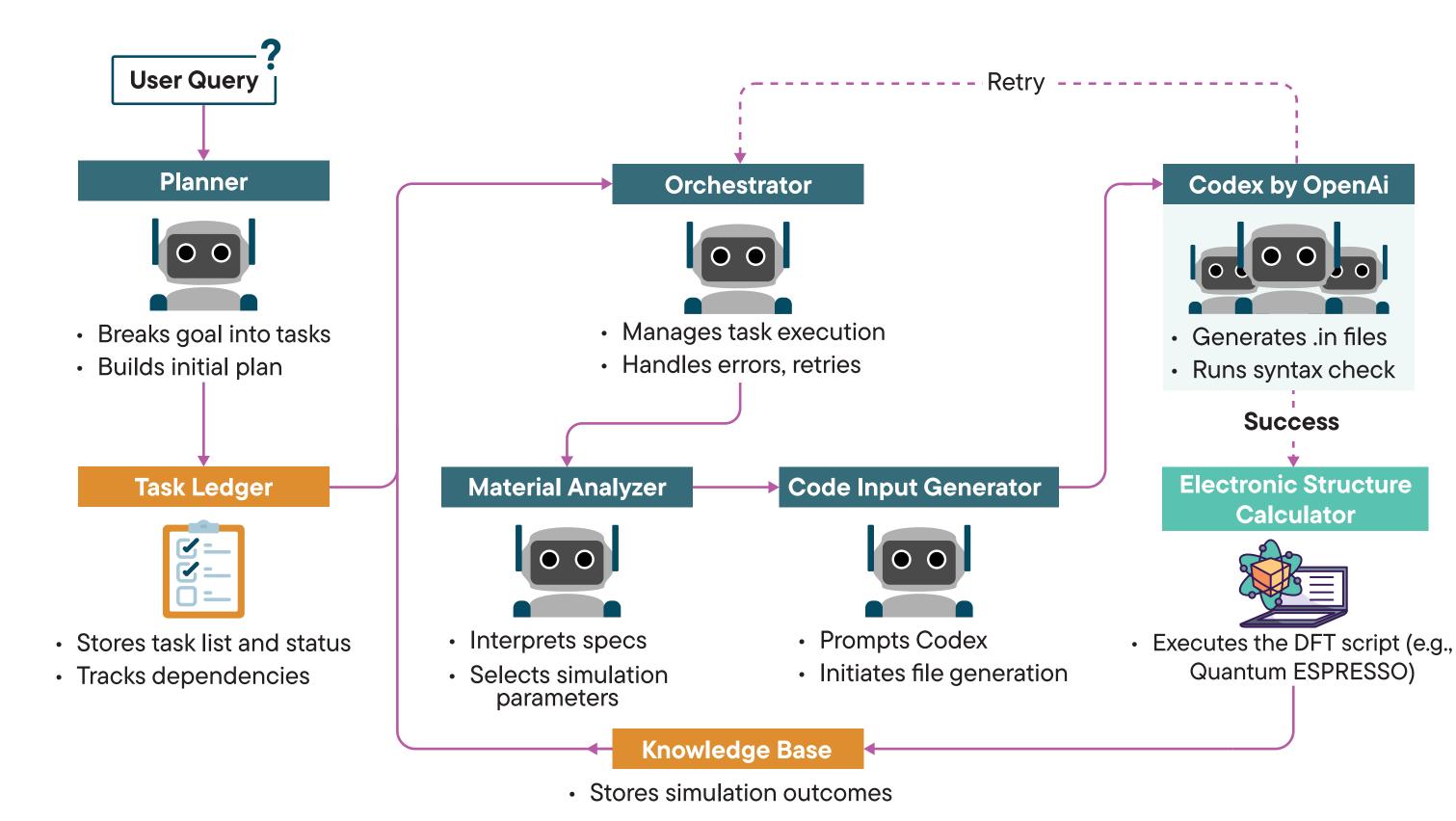
- LLM agents are customized for specific subtasks within a broader scientific goal, each guided by a focused system message and tailored instructions.
- This specialization enables accurate execution such as planning, input generation, error correction, and analysis – and supports modular, dynamic workflows.

Agency and Autonomy

- Agency allows LLMs to reason over time, make decisions, and adapt plans based on intermediate results rather than following a fixed sequence.
- Dynamic workflows built from agents recover from failures, reprioritize tasks, and optimize computational resources in real time.
- Transitioning from automated to autonomous systems greatly expands the scalability and efficiency of scientific discovery.



Agentic Setup





Key Agenic Benifits

- Enables complex DFT workflows to be executed autonomously, without brittle hard-coded pipelines.
- Supports real-time error recovery, task reprioritization, and reflection – capabilities beyond traditional automation.
- Modular design allows integration of agents built by other researchers, labs, or companies for specialized tasks.
- Demonstrates how LLM agents can collaborate to solve scientific problems adaptively, scalably, and without retraining.
- Can be encapsulated as a single agent module within a larger catalyst discovery framework.

Case Study - Carbon Dioxide Reduction

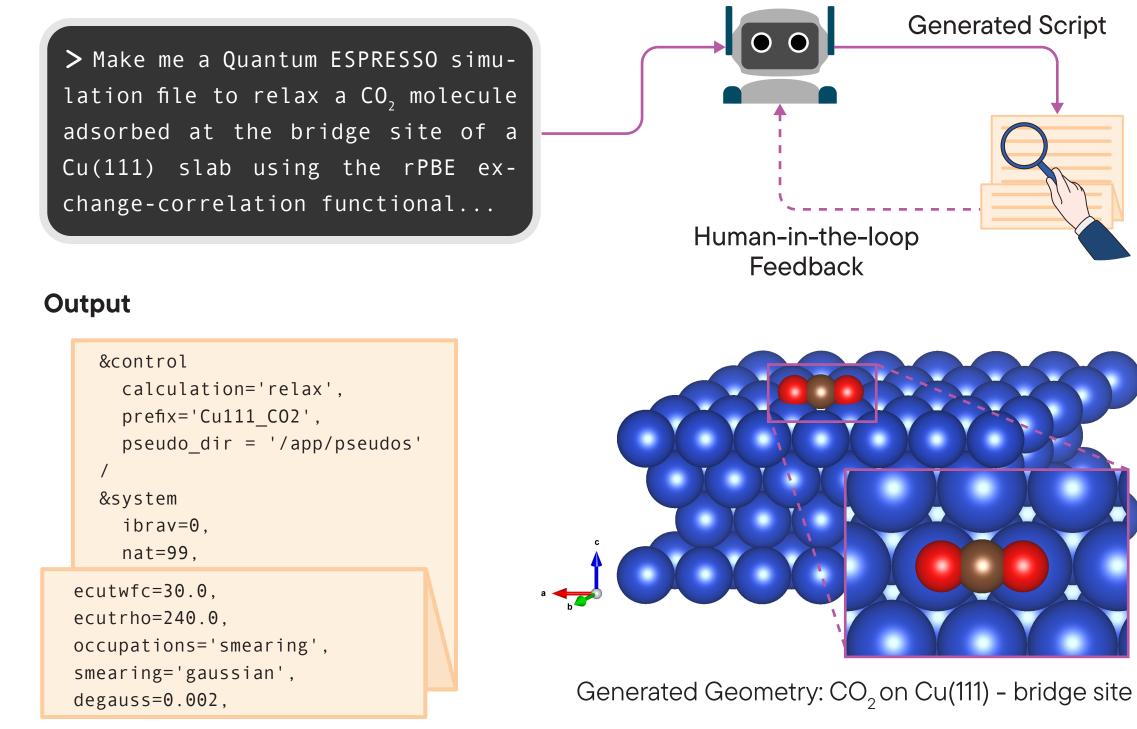
CO₂ Adsorption Energy on a Cu(111) Slab

Conclusions

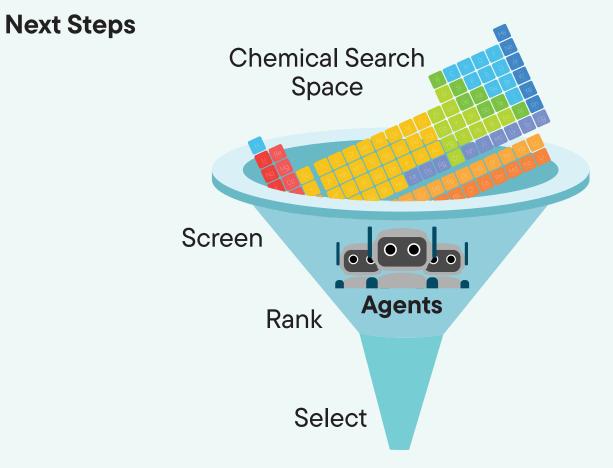
• LLM agents can autonomously interpret scientific queries and generate DFT input files.

- CO_2 adsorption is the first step in electrochemical CO_2 reduction (CO_2RR).
- Adsorption energy affects both activity and selectivity of the catalyst.
- Simulating CO_2 on Cu(111) provides insight into surface–molecule interactions.

User Query



- Agentic workflows enable autonomous input generation, real-time error recovery, and adaptive task management—surpassing traditional scripted automation.
- Modular agent design supports reuse, scaling, and integration into broader catalyst discovery platforms.



- Embed this agent within a broader LLM system to selectively run only essential DFT simulations during high-throughput catalyst screening.
- Use LLM reasoning to decide when DFT is actually needed, minimizing total simulations while exploring materials space more intelligently.

Simulation based on: Wang et al. Energy Environ. Sci., 2023,16, 4388-4403