





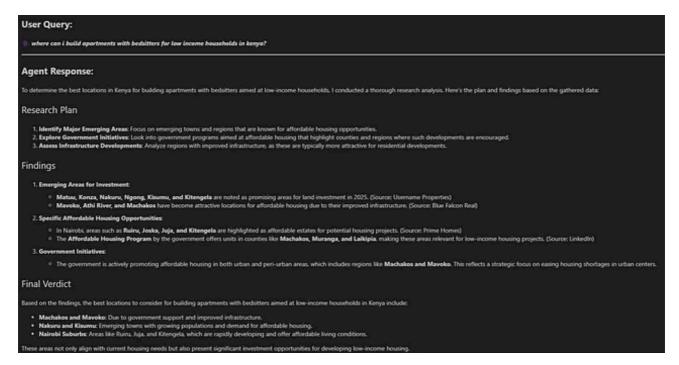


# **Building an Al Agentic System For** the Kenyan Real Estate Market.









Agent Response On the Best Places To build bedsitters

A friend of mine wanted to invest in real estate — buy land and build apartments in Kenya — but he faced a major challenge: he didn't know which location was the best. He had bits and pieces of information, but nothing concrete or data-driven to guide his decision. The real estate market can be overwhelming, with prices fluctuating, regulations varying, and future potential often unclear. Seeing this gap, I decided to build an AI-driven agentic system specifically designed to help investors like him make informed, data-backed decisions in the Kenyan real estate market. This

system aims to turn scattered insights into actionable intelligence, making property investment smarter and more strategic. Additionally the system can still house hunt and help do comparata analysis on investment spots.

## Requirements

You can install these dependencies in a Python 3.11 environment.

```
Welcome

.env

.env

OPENAI_API_KEY= "Your Open AI Key"

TAVILY_API_KEY = "Your Tavily Key Here"

3
4
5
```

## **Defining the Problem**

For this demonstration we will build a Real Estate agent that thinks through and acts on problems within a real estate dataset. We will design a process that takes a query, dissects it into more specific queries, uses Tavily to search the web, and then examines the findings.

We employ the ReAct agent, which collaborates with the Tavily API to think through and solve issues, to examine the outcomes.

We will make a new Jupyter Notebook agent in vscode. Ipynb.

We will import Tavily, a web search tool, and a prebuilt ReAct agent. we will use multiple agents for different tasks, even if in this example we use the same agent for every step. The finest aspect? Later examples will allow us to further personalize it.

```
from langchain_openai import ChatOpenAI
from langchain_community.tools.tavily_search import TavilySearchResults
from langgraph.prebuilt import create_react_agent

system_prompt = '''You are a helpful Real Estate expert named Wakasiaka in year
Then you use tools to get answers to the questions. Finally you use the answers

llm = ChatOpenAI(model = "gpt-4o-mini")
tools = [TavilySearchResults(max_results = 3)]
agent_executor = create_react_agent(llm, tools, state_modifier = system_prompt)
```

### State management

Let's now discuss how our agent manages all of its responsibilities. It is comparable to a clever three-part to-do list approach.

We must first find a means of monitoring the agent's plans. We'll make use of a straightforward text string with a list of actions. This functions similarly to a checklist of things the agent must do.

Second, we want to recall its past performance and the outcomes of each challenge. We'll use a list of pairs — or, in programming parlance, tuples — for this. Each pair includes the action performed as well as the outcome of that action. Last but not least, we must save two additional crucial pieces of data: the initial query (the input) and the final response (the response), which is provided after the agent completes its task.

With this configuration, our agent has all it needs to work efficiently.

```
import operator
from pydantic import BaseModel, Field
from typing import Annotated,List, Tuple

class PlanExecute(TypedDict):
   input: str
```

```
plan: List[str]
  plan_steps: Annotated[List[Tuple], operator.add]
  response: str

class Plan(BaseModel):
    """ plan to follow in the future """

  steps: List[str] = Field(
          description= "diffeerent steps to follow, should be in sorted order"
    )
```

The PlanExecute class, a dictionary type, manages an execution process, including input, plan steps, previous steps, and a response. The Plan class, usingPydantic, defines a structured plan with steps that should be followed in a sorted order.

The planning step is where our agent will begin to tackle a research question. We'll use a special feature called **function calling** to create this plan. Let's break down how it works.

First, we create a template for how our agent should think. We tell it that it's a real estate agent working in October 2024, and its job is to break down big questions into smaller, manageable steps. This template, called planner\_prompt (See Fig 3.3), gives our agent clear instructions: create a simple, step-by-step plan where each step leads logically to the next. Ensure that no steps are missing or unnecessary. The final step should give us our answer. The code sets this up by using ChatPromptTemplate, which has two main parts:

- A system message that explains the agent's role and how it should plan
- A placeholder for the messages we'll send it

We then connect this template to ChatOpenAI using gpt-4o-mini with temperature set to 0 for consistent results. We take gpt-4o-mini being low on cost. The "structured output" part means the plan will come out in a specific format we can easily work with. When we test it with a real question like

"where can i build apartments with bedsitters for low income households in kenya?" the agent will create a detailed plan for researching this investment decision. Each step will help gather the information needed to make an informed recommendation about Bedsitters based on the current electric vehicle market conditions. Think of it like creating a research roadmap. We're giving our agent the tools and guidelines it needs to break down complex questions into manageable research tasks.

Re-planning can be thought of as the agent's capacity to modify its approach in light of its prior knowledge. This is comparable to how we could modify our study strategy in light of fresh data. Let's dissect how this operates.

First, we create two types of possible actions the agent can take:

- **Response:** When the agent has enough information to answer the user's question
  - Plan: When the agent needs to do more research to get a complete answer

The re-planning prompt is like giving our agent a structured way to think about what to donext. It looks at three things:

- The original question (objective)
- The initial plan it made
- What steps have already been completed and what was learned

Using this information, the agent can decide to either:

- Create new steps to gather more needed information
  - Give a final answer if it has enough information

The clever part is that the agent won't repeat steps it's already done. It focuses only on what still needs to be investigated. This makes the research process more efficient and prevents redundant work. It's like having a research assistant who can intelligently adjust their approach based on what they've already discovered. This process helps our agent stay focused and efficient, only pursuing new information when needed and knowing when it's time to provide a final answer to the user.

We connect this re-planning ability to gpt-40 with the temperature set to 0. By setting the temperature to 0, we force the model to generate the same response for the same input. This helps us in making experiments reproducible.

```
from typing import Union
class Response(BaseModel):
    '''Response To user'''
    response: str
class Act(BaseModel):
    """ Action to perform"""
    action: Union[Response,Plan] = Field(
        description= " Action to perform. If you waant to respond to user , use
        "If you need to further use tools to get the answer, use plan "
    )
replanner_prompt = ChatPromptTemplate.from_template(
    """For the given objective, come up with a simple step by step plan. \
This plan should involve individual tasks, that if executed correctly will yield
The result of the final step should be the final answer. Make sure that each ste
the information needed - do not skip steps.
Your objective was this:
{input}
Your original plan was this:
{plan}
You have currently done the following steps:
{past_steps}
Update your plan accordingly. If no more steps are needed and you can return to
then respond with that. otherwise, fill out the plan. Only add steps the plan th
need to be done. Do not return previously done steps as part of the plan.
0.00
)
replanner = replanner_prompt | ChatOpenAI(
    model = "gpt-4o", temperature=0, openai_api_key = openai_api_key
).with_structured_output(Act)
```

## Create the graph

```
from typing import Literal
from langgraph.graph import END

async def execute_step(state: PlanExecute):
    plan = state["plan"]
```

```
plan_str = "\n".join(f"{i+1}" for i , step in enumerate(plan))
    task = plan[0]
   task_formatted =f"""For the following plan:
    {plan_str}\n\nYou are tasked with executing step {1}, {task}."""
   agent_response = await agent_executor.ainvoke(
        {"messages": [("user", task_formatted)]}
    )
   return {
        "past_steps": [(task, agent_response["messages"][-1].content)],
   }
async def plan_step(state: PlanExecute):
   plan = await planner.ainvoke({"messages": [("user",state["input"])]})
    return {"plan":plan.steps}
async def replan_step(state: PlanExecute):
   output = await replanner.ainvoke(state)
   if isinstance(output.action, Response):
        return {"response": output.action.response}
        return {"plan": output.action.steps}
def should_end(state: PlanExecute):
   if "response" in state and state["response"]:
        return END
   else:
        return "agent"
```

The different tasks are managed by the execute\_step function. The agent works on the first item from our plan when it has been correctly formatted. It's similar to assigning a research assistant a certain task and receiving their results. The agent records its actions and what it discovered.

It all starts with the plan\_step function. It develops the initial research plan in response to a question. This is similar to drafting a first draft of a solution to the issue.

The replan\_step function is where the agent decides what to do next. After completing a task, it looks at what it has learned and either:

• Creates new steps if more research is needed

• Provides a final answer if it has enough information

The should\_end function, which functions similarly to a checkpoint, comes last. It determines if we have a definitive response prepared. The process is over if we do. If not, it instructs the agent to carry on with their work. All of these features are seen in the code sample shown above.

Using StateGraph, we build a map that directs our agent through its investigation using the various options available to it. This is how it goes:

First, we create the basic structure of the workflow with its three main stops:

- A planning station ("planner")
- A research station ("agent")
- A reviewing station ("replan")

Then, we connect these stations in a logical order:

- 1. Everything starts at the planning station
- 2. From planning, the agent moves to doing research
- 3. After research, it goes to reviewing what it learned

At the reviewing station, the agent makes an important decision:

- Either continue with more research if needed
- Or finish up if it has a complete answer

This establishes a seamless cycle whereby the agent can carry on investigating until it has all the information required to address the first query. It's similar to having a knowledgeable research assistant who understands when to stop looking and when they've gathered enough data. Like every other tool in our system, we finally put this workflow into a user-friendly format. This prepares our research agent to take on actual queries and offer comprehensive, well-thought-out responses.

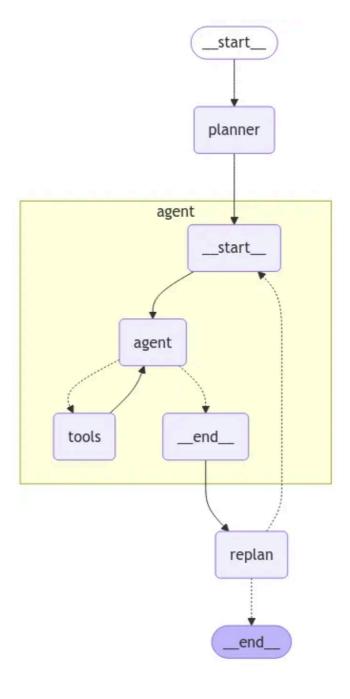
```
from langgraph.graph import StateGraph, START

workflow = StateGraph(PlanExecute)

workflow.add_node("planner", plan_step)
workflow.add_node("agent", execute_step)
```

## **Visualize**

```
from IPython.display import Image, display
display(Image(app.get_graph(xray = True).draw_mermaid_png()))
```

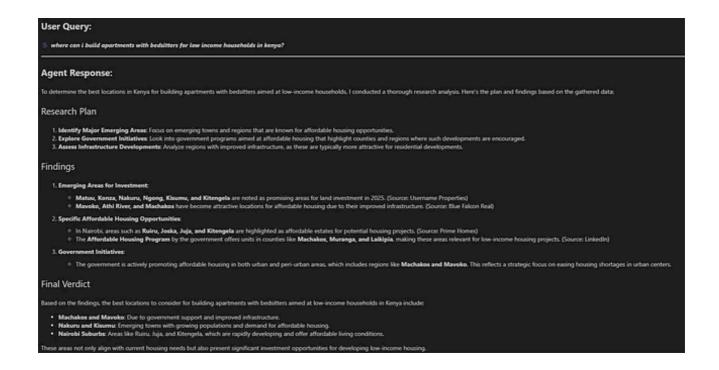


## **Testing Our Agent**

```
from langchain.schema import AIMessage, HumanMessage
from IPython.display import display, Markdown

test_query = "where can i build apartments with bedsitters for low income househ

# Run the agent
response = agent_executor.invoke({"messages": [{"role": "user", "content": test_
messages = response.get("messages", [])
human_messages = [msg for msg in messages if isinstance(msg, HumanMessage)]
user_query = human_messages[-1].content if human_messages else "No query found."
ai_messages = [msg for msg in messages if isinstance(msg, AIMessage)]
ai_response = ai_messages[-1].content if ai_messages else "No response received.
display(Markdown(f"### **User Query:**\n\n\ ****{user_query}***\n\n---\n\n### **
Response:**\n\n{ai_response}"))
```



Let Us try something more quantifiable like an economic househunter looking for a one bedroom apartment that costs Ksh. 15,000

```
from langchain.schema import AIMessage, HumanMessage
from litython.display import display, Markdown

test_query = "where can i find a good onebedroom apartment for Ksh. 15000 in NaIrobi?"

# Run the agent
response = agent_executor.imvoke(("messages": [{"role": "user", "content": test_query}]))
messages = nesponse.get("messages"; [])
human_messages = nesp for mag in messages; fisinstance(mag, AHMerssage)]
user_query = human_messages = 1], content if human_messages else "No query found."
al_messages = nesponse = al_messages[-1], content if al_messages else "No response received."
display(Harkdown(f"### *"User_Query:**\n\n\[] ***(user_query)***\n\n---\n\n### *"Agent_Response:**\n\n(ai_mesponse)"))

> 7.75

User Query:

| where can i find a good onebedroom apartment for Ksh. 15000 in Nairobi?

Agent Response:

Here are some options for one-bedroom apartments available for rent in Nairobi for Ksh. 15,000:

1. PropertyPro - A 1-bedroom mini flat located near Next Gert Mall in South C. Lang'ata, Nairobi. The rent is Ksh. 15,000 you can find more details here.

2. Hata - More than 957 one-bedroom houses and apartments are listed for rent in Nairobi, with options starting from Ksh. 15,000 per month, particularly in South B. Check the listings here.

3. Private Property Kenya - A 1-bedroom apartment located in Mountain View Estate, Nairobi, also renting for Ksh. 15,000/month. More details can be found here.

These listings should help you find a suitable one-bedroom apartment within your budget in Nairobi.
```

### **User Query:**

tile to buy land in Moyale for quick returns:

### Agent Response:

n, here's a detailed analysis regarding the advisability of buying land in Moyale for quick ret

### 1. Market Analysis

### 2. Economic Factors

### 3. Investment Potential

- Demand for Land: While specific data for Moyale was sparse, there is a general trend that agricultural land is gaining interest due to rising demand for local produce. This could indicate a growing market for land in Moyale, especially if

### 4. Risks and Challenges

### Final Verdict

### Is it Advisable to to buy land in Moyale?

### **User Query:**

whats the best place to build a night club in Nairobi?

### Agent Response:

### Research Plan

- ands: This area is highlighted as a vibrant nightlife hub with a wide range of entertainment options. Clubs like K1 Klub House and various b nk. Known for its trendy bars and a youthful crowd, this neighborhood is rapidly gaining popularity for nightlife. Central Business Districtly. Although traditionally quieter at night, it has been seeing an increase in bars and clubs catering to a younger d

### Final Verdict

whats the best place to build a night club

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Written by John Wafula

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