Design bots using Flowise

Last amended: 19th June, 2025
My folder: C:\Users\ashok\OneDrive\Documents\flowise
Flowise Book created by Community at this link

Vector stores working file: FAISS; Milvus, Milisearch But NOT chroma and Qdrant

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A. Simple demo

See this link on YouTube.

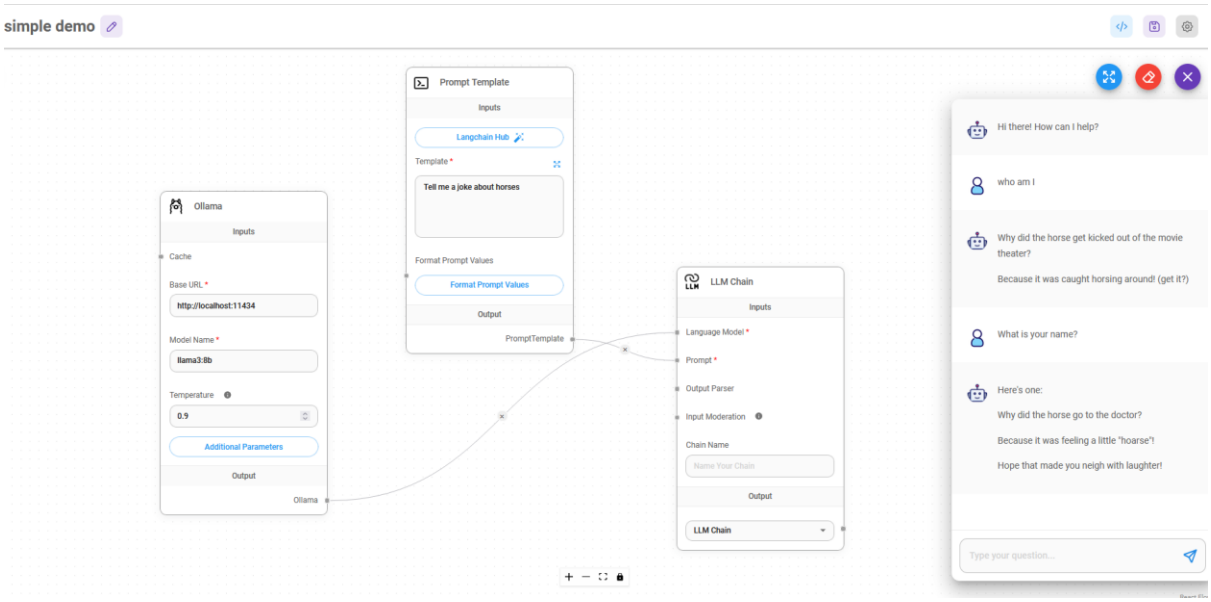


Figure 1: This bot will always answer your questions as a horse's joke. The only prompt is: Tell me a joke about horses.

B. Translation bot:

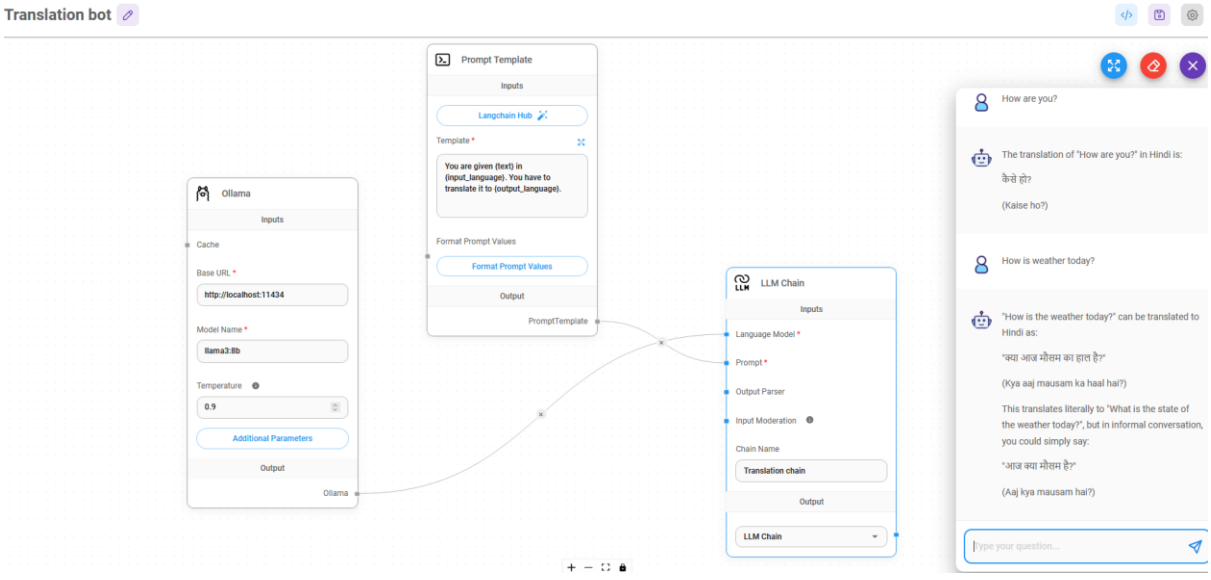


Figure 2: This bot translates all your questions into the desired language.

Prompt Template is:

> You are given {text} in {input_language}. You have to translate it to {output_language}.

And formatted template is as follows. Note the *text* pertains to user's question asked in the chat-bot.

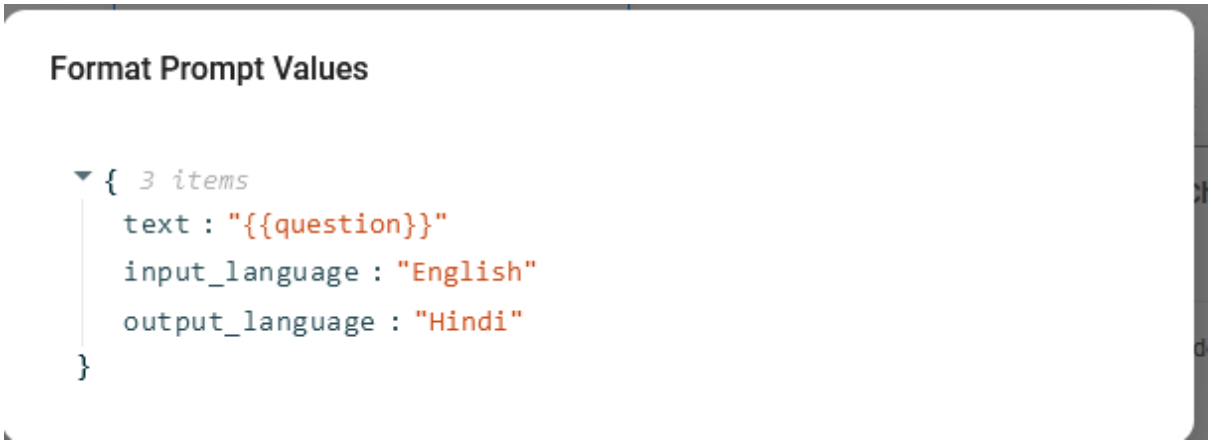


Figure 3: Translate question asked in English to Hindi: Note that 'question' is enclosed in two curly brackets.

C. Chat with llama:

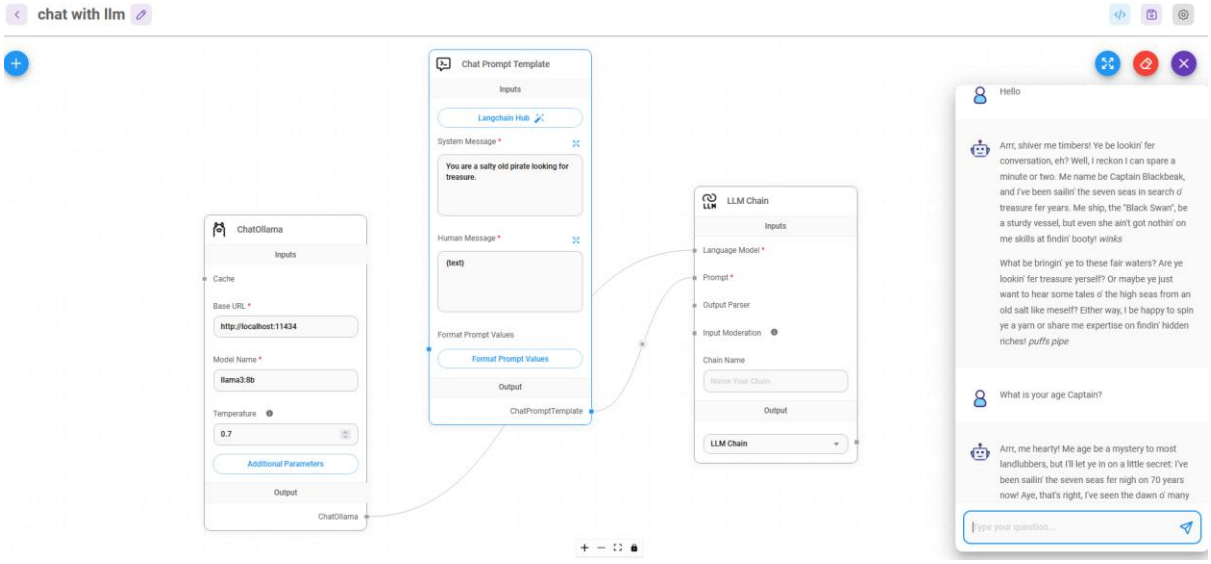
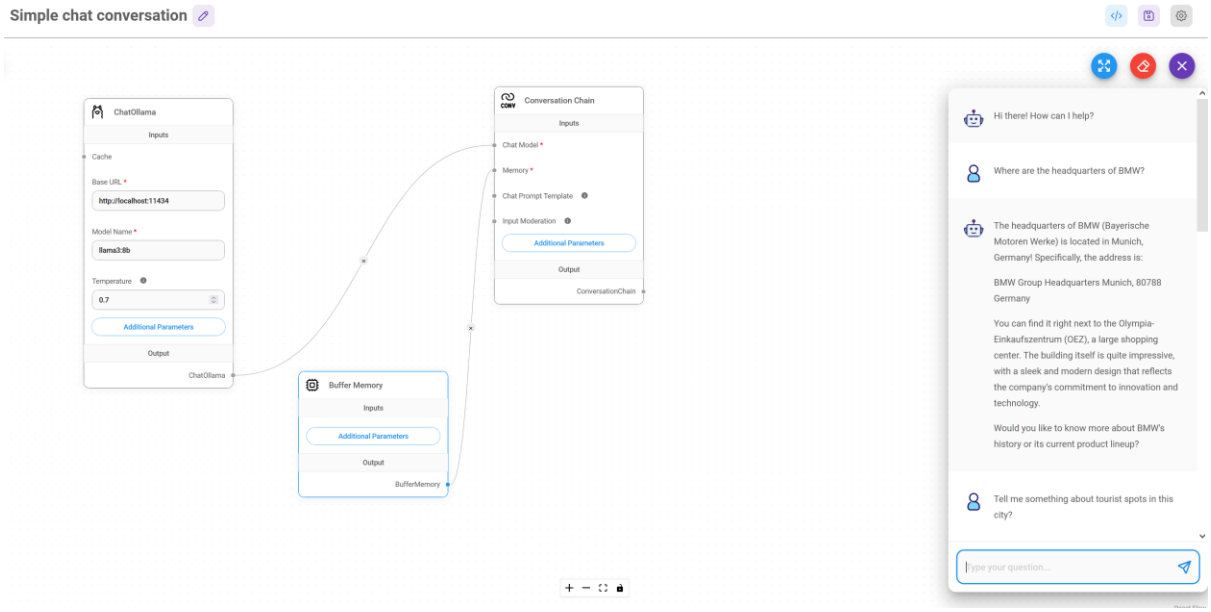


Figure 4: The Ist question is just Hello but the IInd question asks more details about Captain referred to into the answer to Hello.

D. Simple Conversational Chain

Refer YouTube video



E. Using Conversational Agents

Refer YouTube video

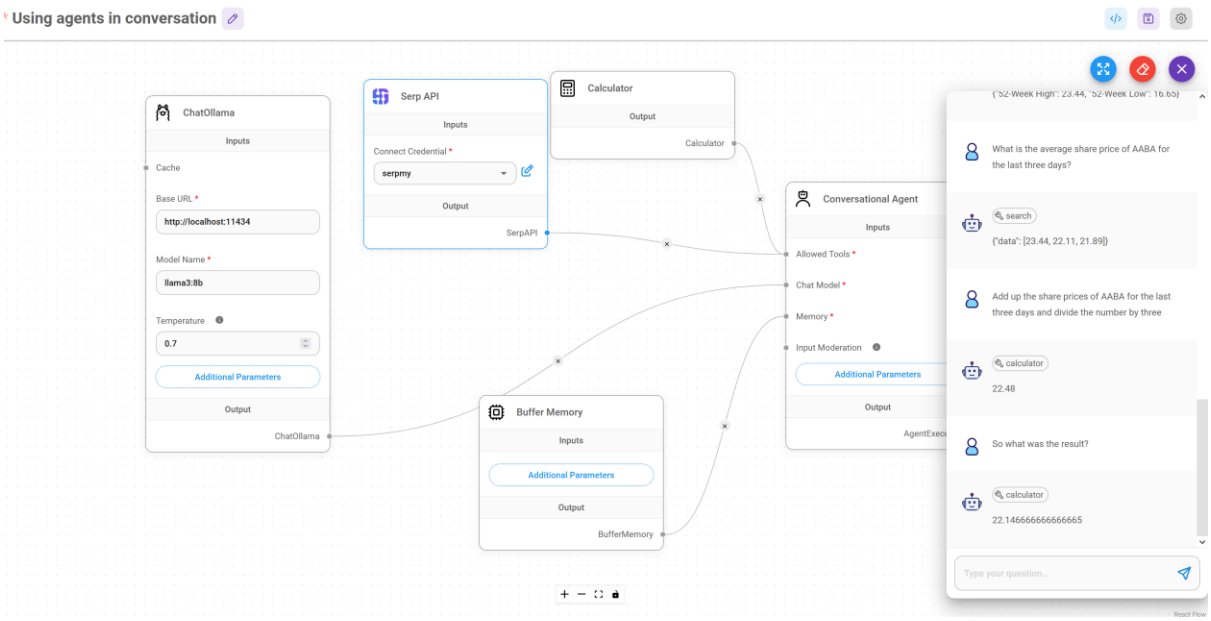


Figure 5: Agents can work even with ollama. SERP API key is a must. To calculate average, we have to tell the bot how to do it.

F. Export import chat flows:

i) Export chatflow

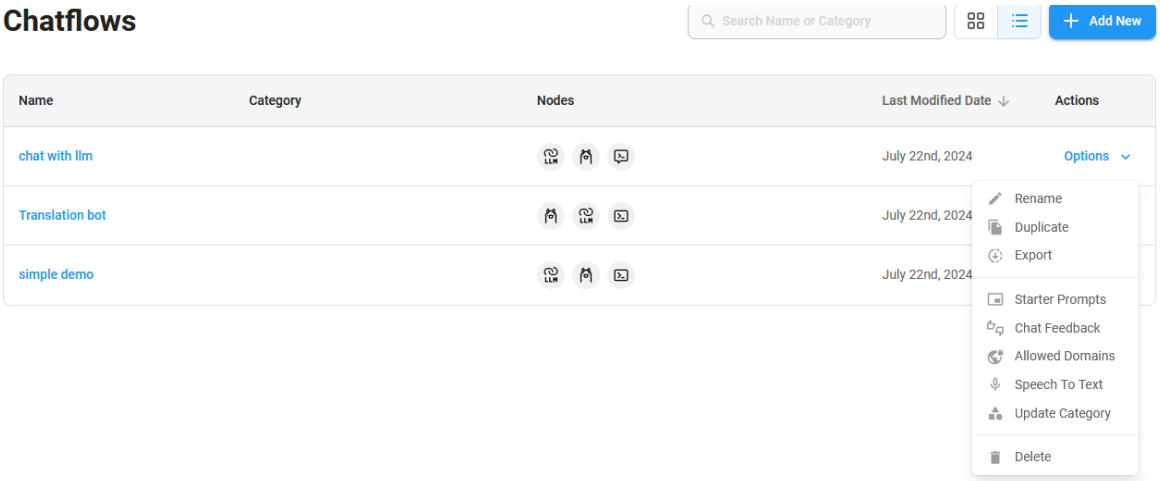


Figure 6: In the Chat flows window, click on the down arrow besides the Options to Export a chat flow as a json file.

ii) Load chat flow

To load a json file, first create a new (blank) chatflow by any name, say 'abc'. Save the blank chatflow. Click on Settings icon on top-right. And then click on Load chatflow to open and load the json file.

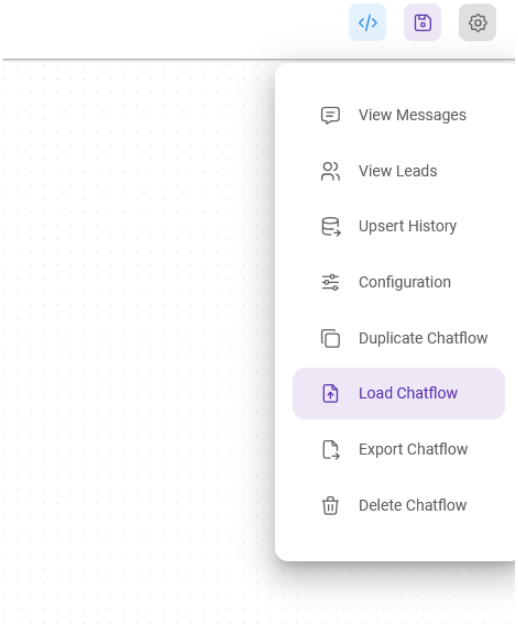


Figure 7: Click on Settings icon to import an exported chat flow (i.e. json file).

The following figure shows a chatflow loaded in Flowise:

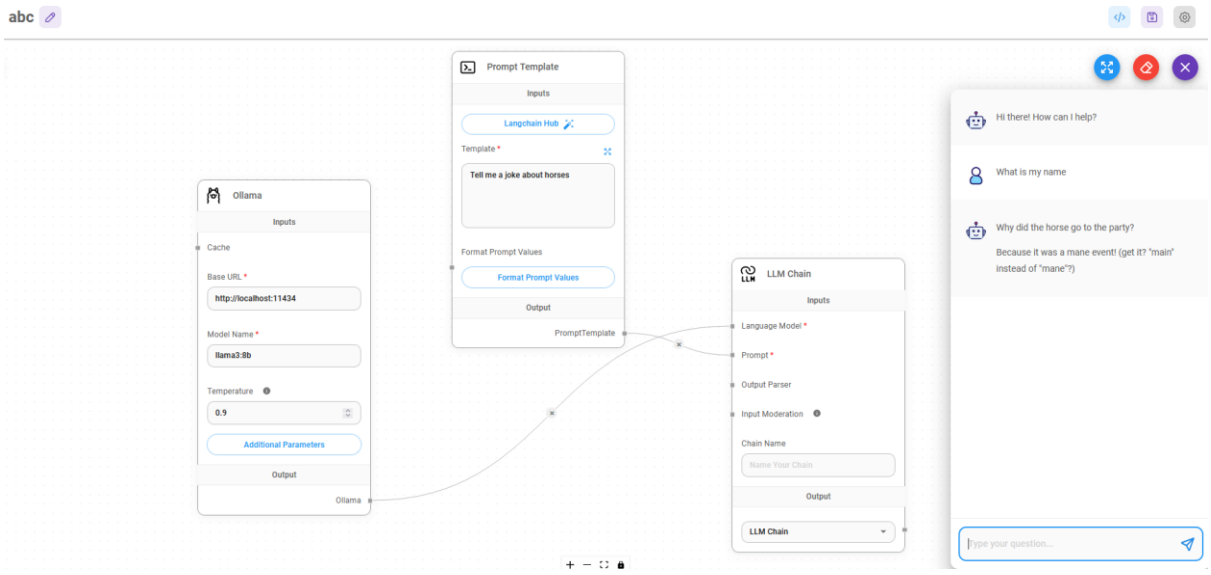


Figure 8: A chatflow loaded in a blank 'abc' chatflow canvas.

G. Simple RAG with single text file

Refer [Flowise tutorial #3]

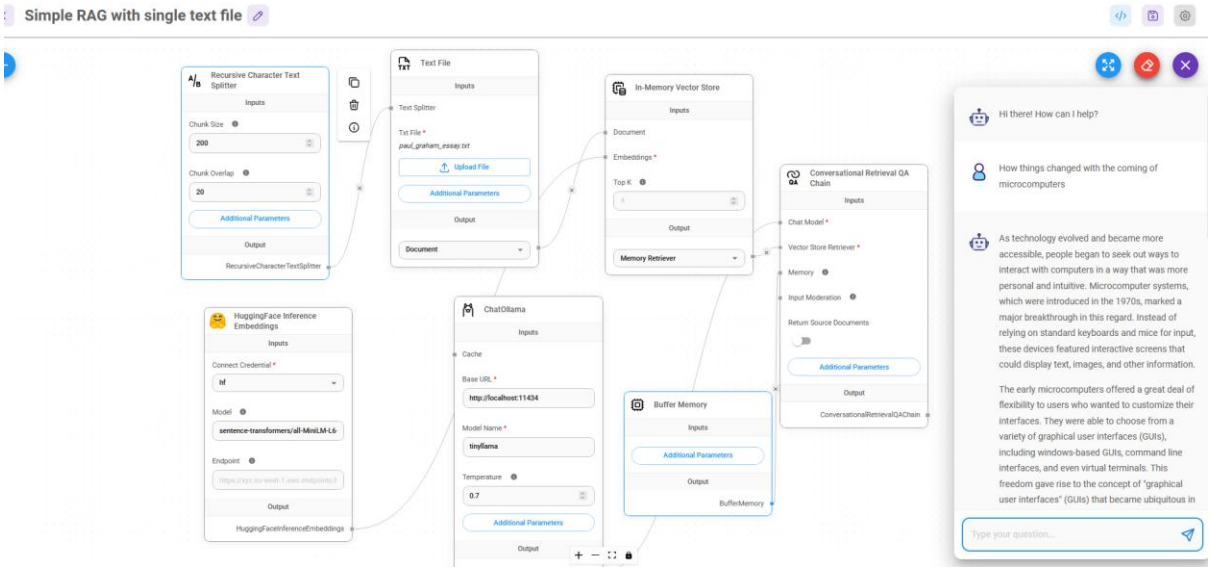


Figure 9: After connecting all flow-widgets and uploading of text file, first click on Upsert Vectorestire button and then start chatting.

Vector store in this RAG system will disappear as soon as Flowise is closed as the vectors are stored in buffer memory.

H. RAG with chroma store and single text file

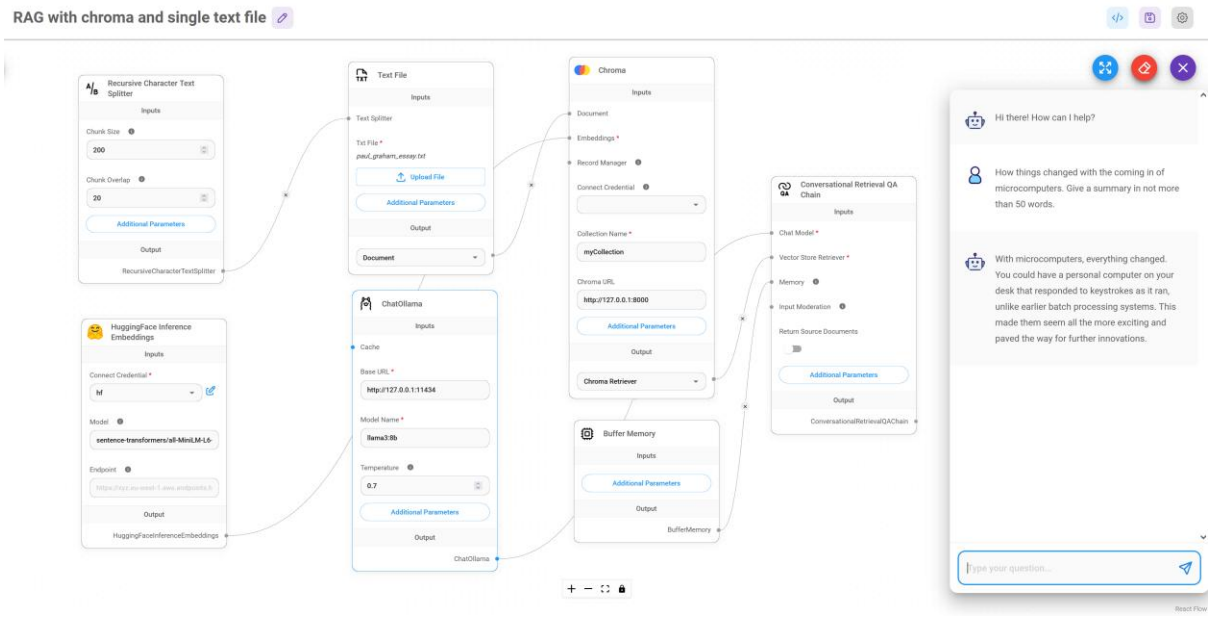


Figure 10: Vector store is replaced by a more durable chroma store. Chroma store retains its vectors even after Flowise is hut down.

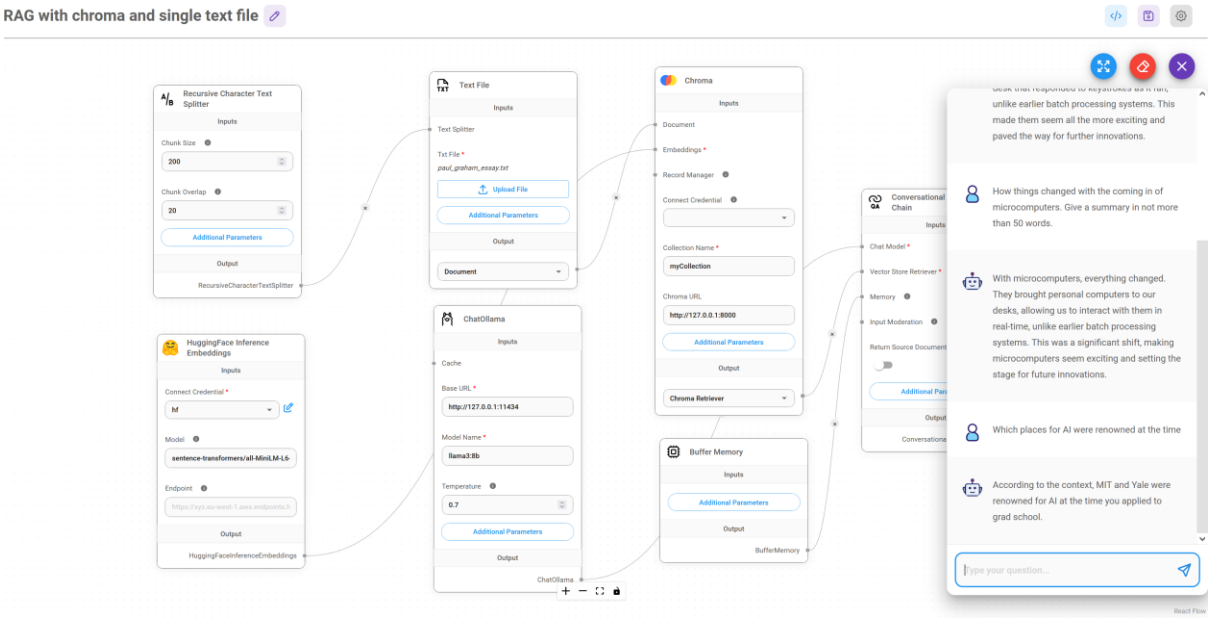


Figure 11: Flowise restarted. More questions asked and replies are given based upon the earlier storage.

I. Prompt Chaining:

i) Prompt Chaining-I

Combining Multiple LLM Chains

A. Refer Flowise tutorial

First LLM chain

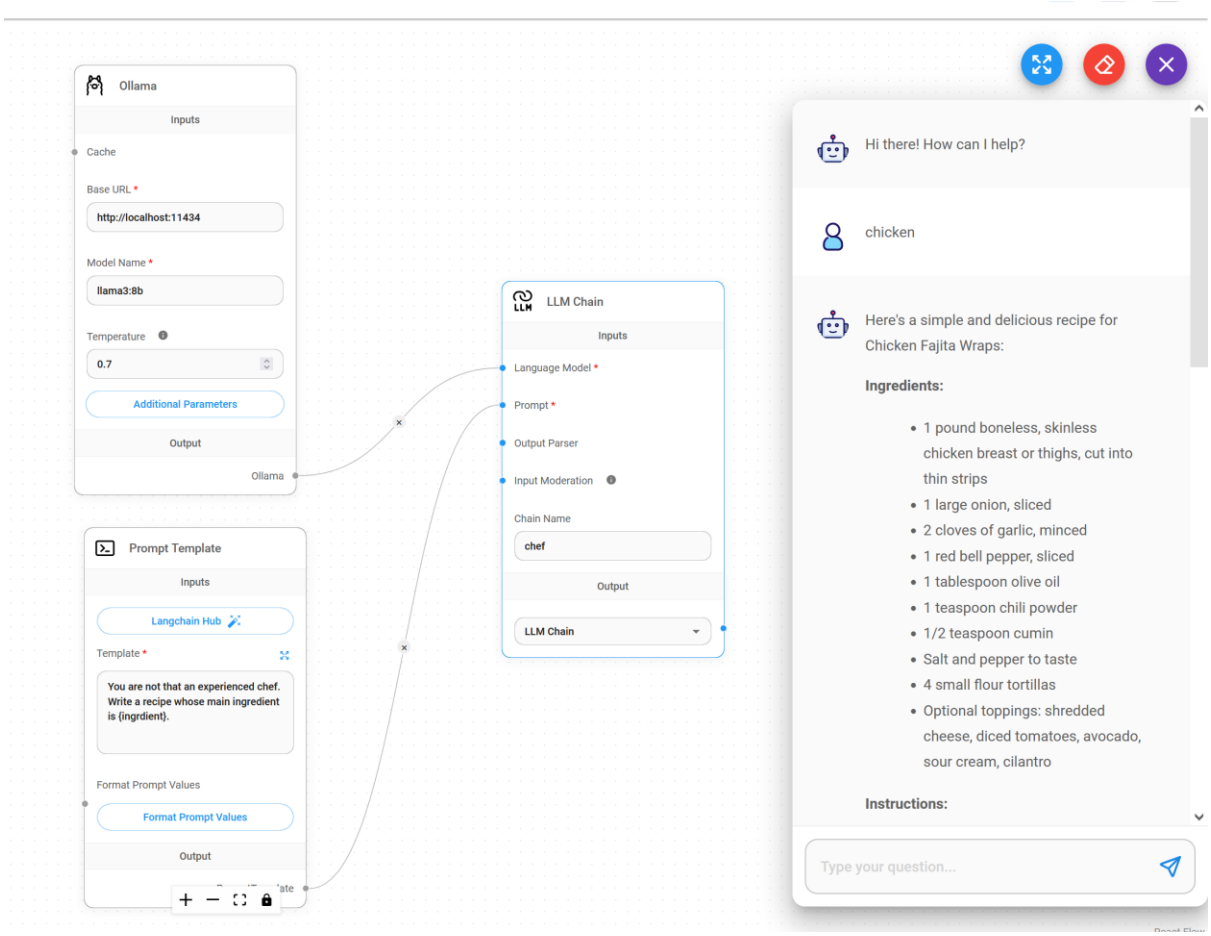


Figure 12: First LLM chain named as chef.

Second LLM chain added to first

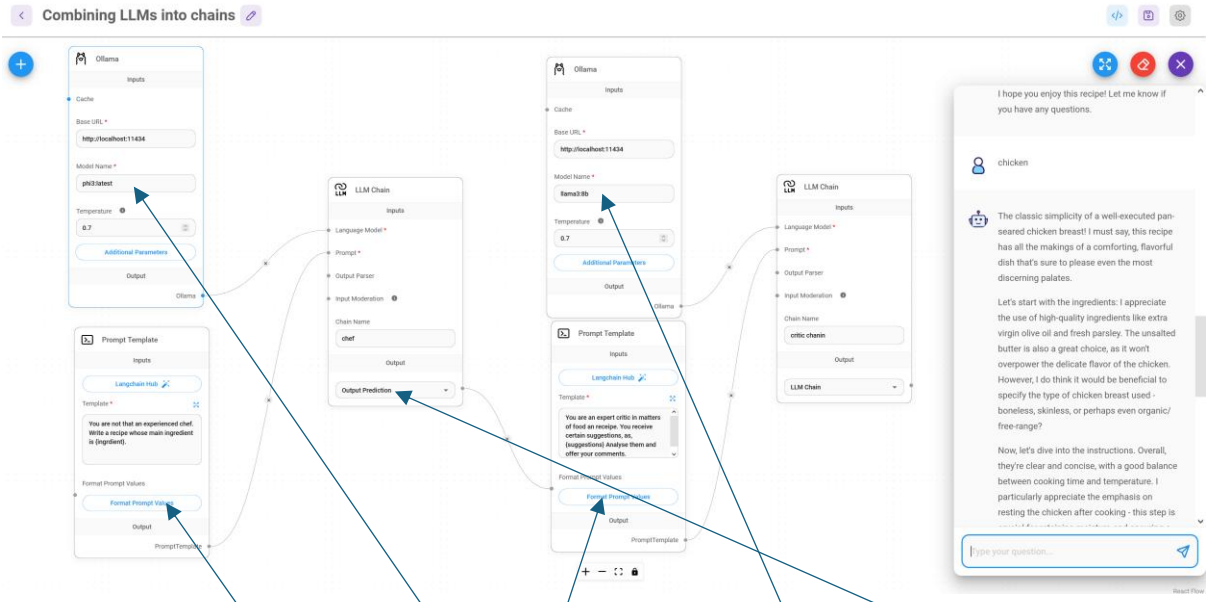
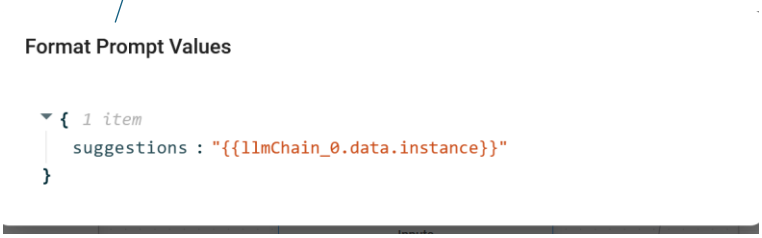


Figure 13: Note that the first LLM is using phi3 and the critic language model is llama3. In the chatbox, the IInd LLM chain does make minor suggestions to improve the quality. Note that the output of Ist LLM chain is now Output Prediction.

Here are the prompts used:

chef chain prompt: *You are not that an experienced chef. Write a recipe whose main ingredient is {ingredient}*. Formatting of prompt values is as:

Critic chain prompt: *You are an expert critic in matters of food an receipe. You receive certain suggestions, as, {suggestions} Analyse them and offer your comments*. The formatting of prompt values is as:



ii) Prompt Chaining-II

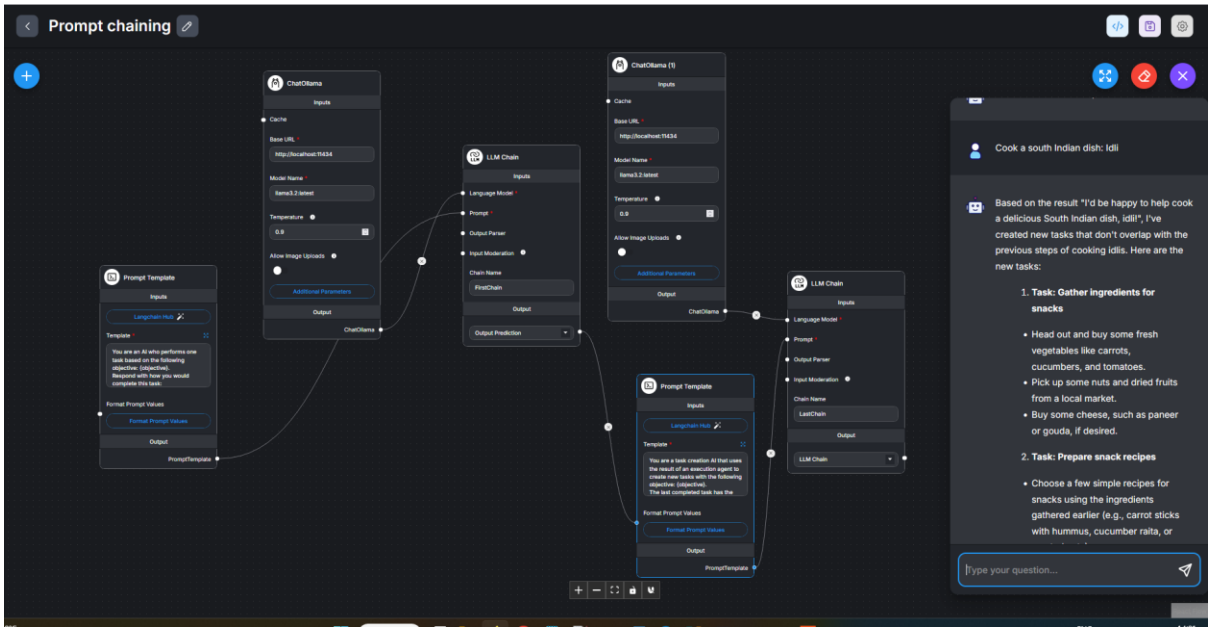


Figure 14: Contains two (simple) Prompt Templates. See below what these prompts look like.

Prompt1:

> You are an AI who performs one task based on the following objective: {objective}.
>
> Respond with how you would complete this task:

Figure 15: The prompt contains just the user query. 'objective' or the 'question' is the user query.

Prompt2:

> You are a task creation AI that uses the result of an execution agent to create new tasks with the following objective: {objective}.
>
> The last completed task has the result: {result}.
>
> Based on the result, create new tasks to be completed by the AI system that do not overlap with result.
>
> Return the tasks as an array.

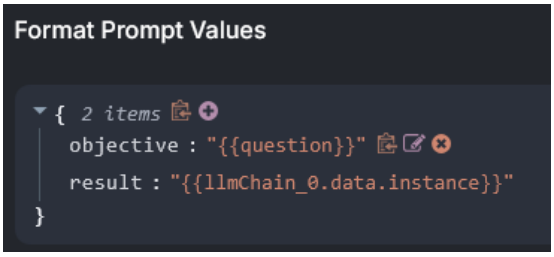


*Figure 16: Unlike in the first Prompt Chain example, here the IInd prompt contains **BOTH** the user query + result from the first LLM*

Sample user query (objective):

Cook a South Indian dish: Idli

J. Flowise Using Hugging Face Models

Ref: [This link.]

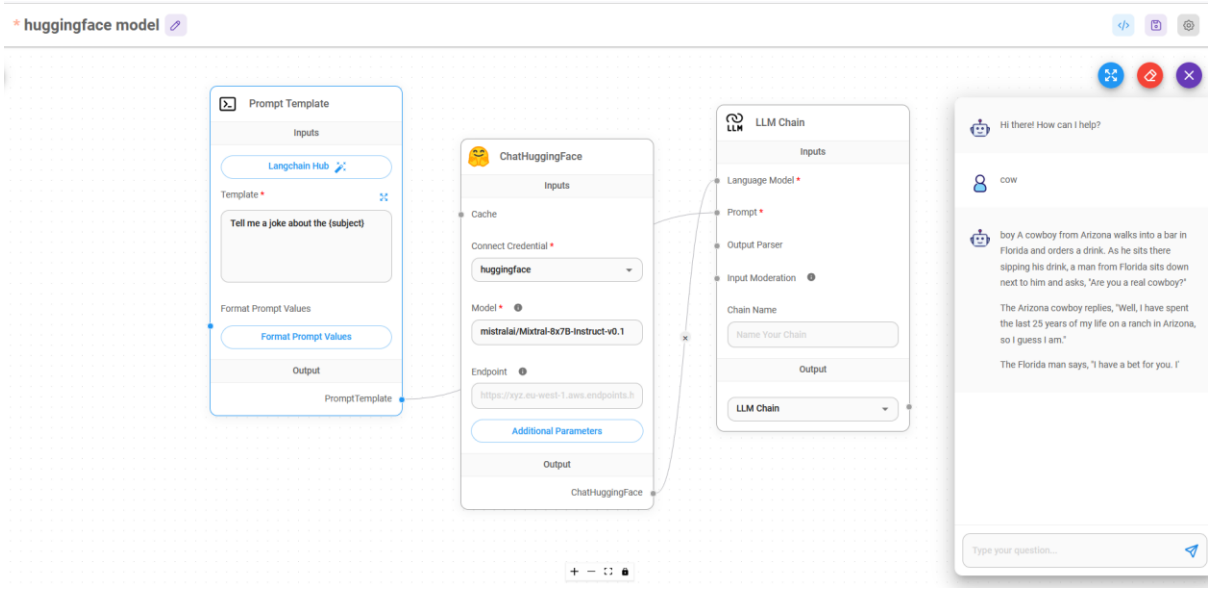


Figure 17: Only those models will work who have made available inference endpoints free.

K. Document Stores-How to Upsert

If you are creating a *Document Store*, you will have many *Document loaders*. See figure below:

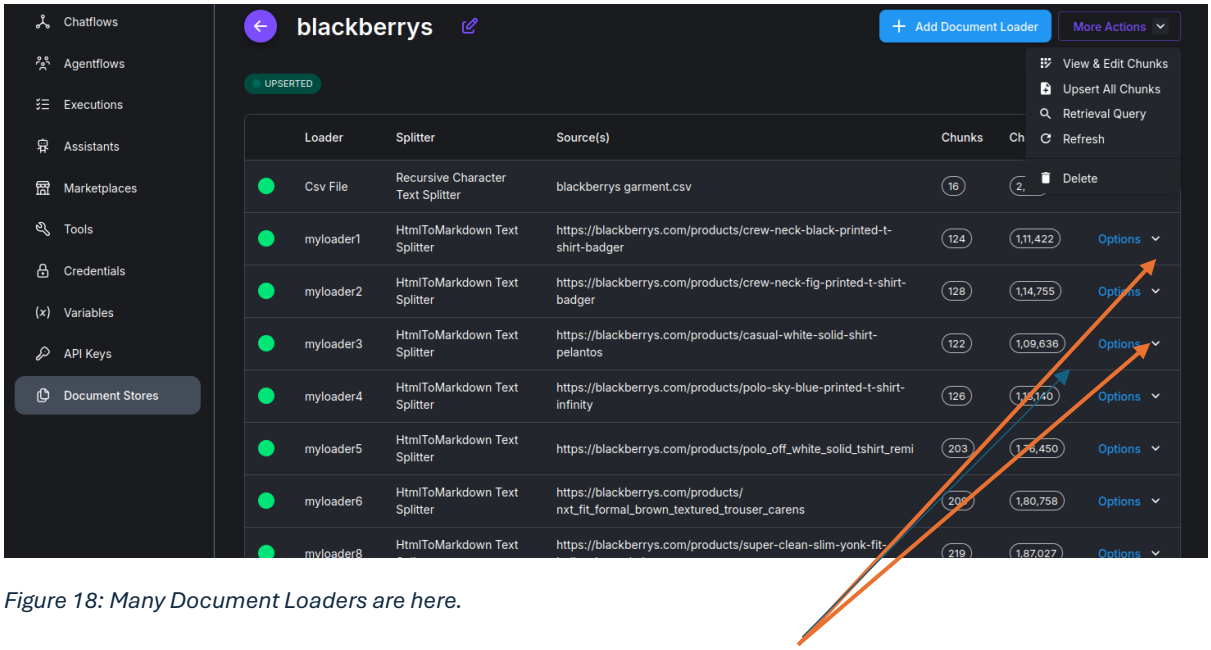


Figure 18: Many Document Loaders are here.

For each *Document Loader*, you have an *Upsert* option here. In *FAISS*, when you *upsert*, the earlier *upserted* vector store is first deleted and then new vector store created. So, to create vector store for ALL the *Document Loaders*, proceed as follows:

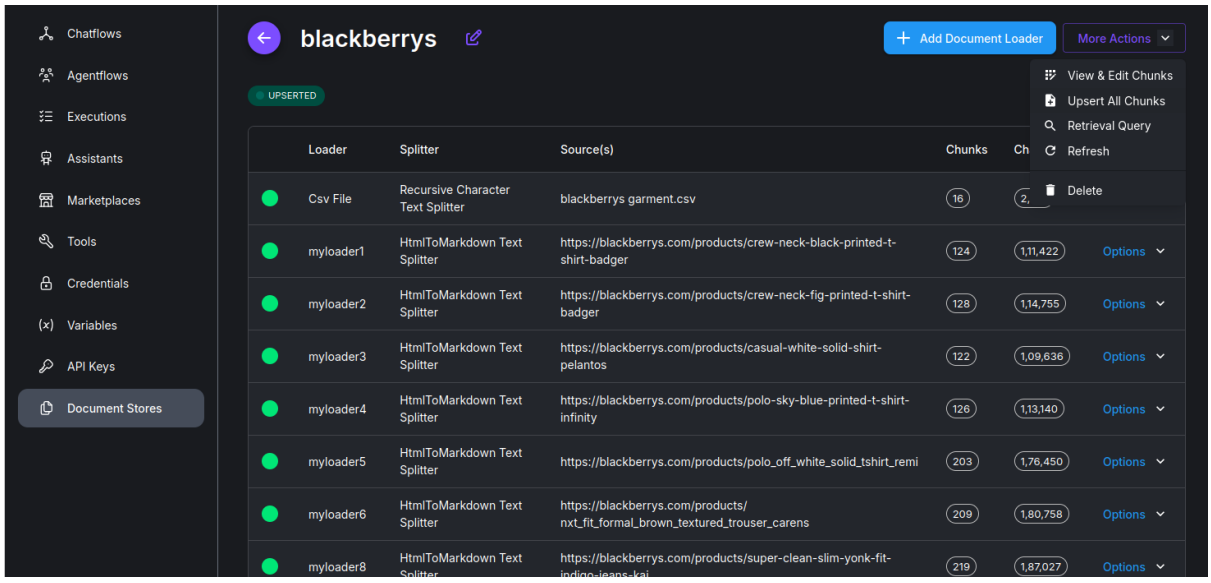


Figure 19: Look for More Actions-->Upsert All chunks. This will upsert chunks from ALL Document Loaders.

L. Using Redis Backed Chat Memory

Start Redis docker, as: *./start_redis.sh*. Redis will be available at port 6379.

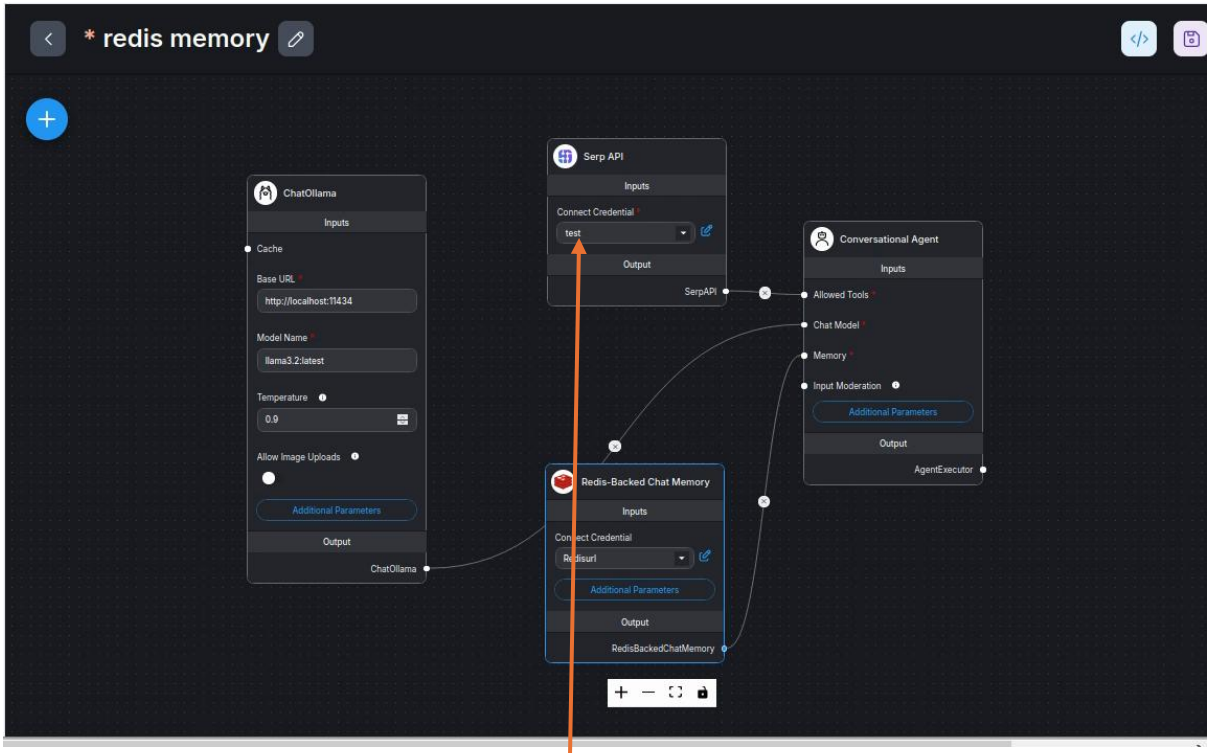


Figure 20: A conversational agent that utilises Redis backed Chat Memory

Serp API tool credential name is IMPORTANT. '*test*', as here is a vague name. Better name it as, say, *Internet_access*. See below:

Figure 21: Serp API now has a better tool credential name: accessInternet. Incidentally, it uses Tool Agent rather than Conversational agent.

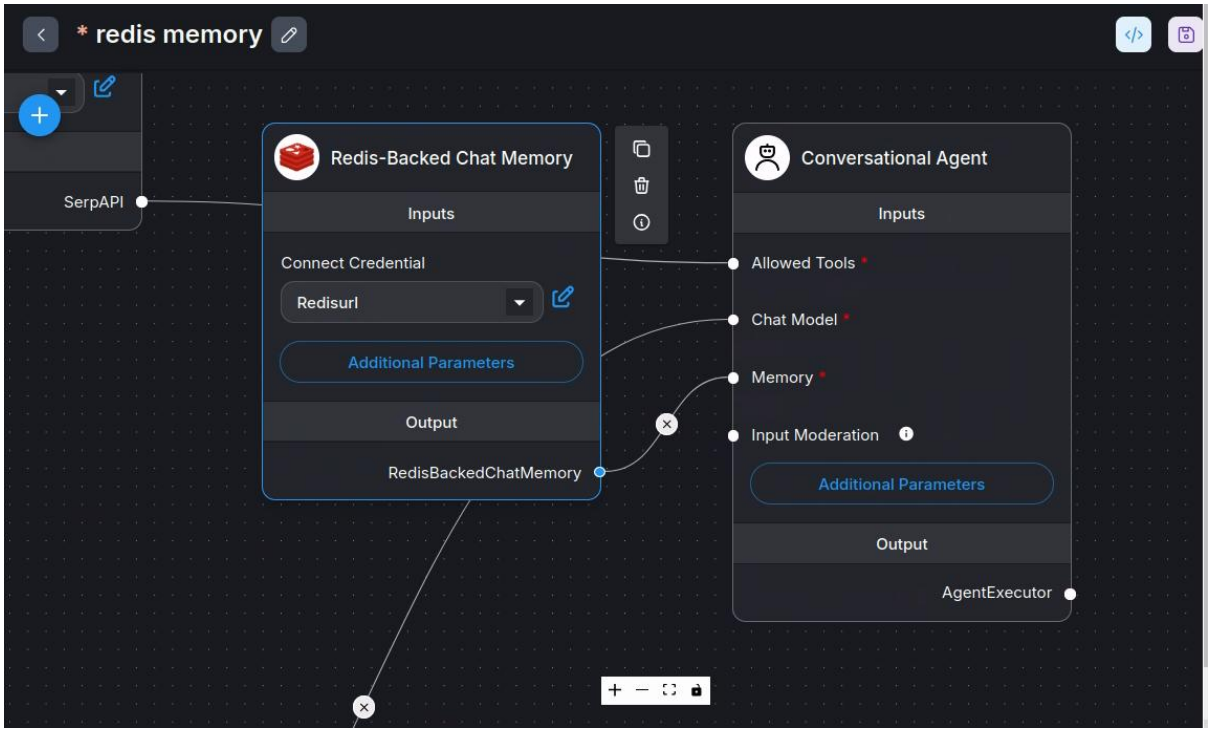


Figure 22: Redis backed chat memory module attached to Conversational agent

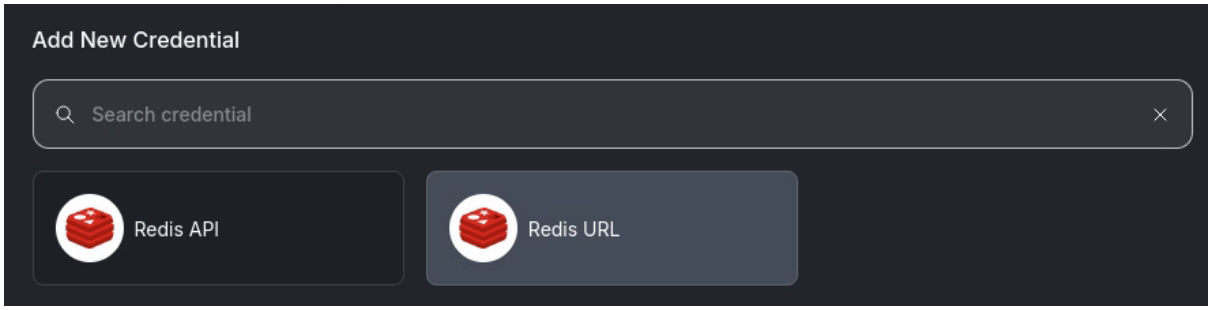


Figure 23: Start Redis server: ./start_redis.sh.

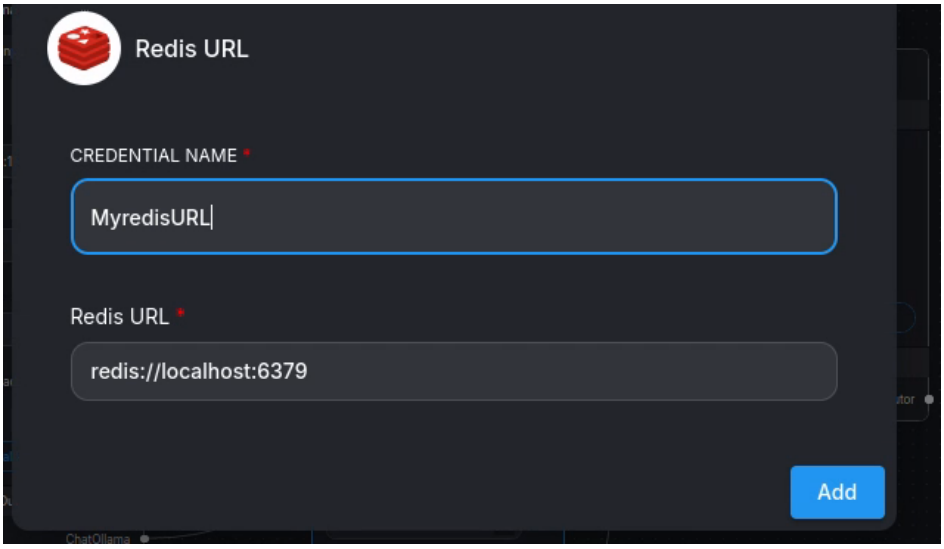


Figure 24: Specifying Redis Credential

By default, redis has RAM memory. To save it on hard disk, use *redis-cli* and *SAVE* instruction.

M. Langsmith for debugging

Langsmith can be used for tracing agent flows. Log into langsmith and get a free API key. Create any simple agentic project, such as the following simple project:

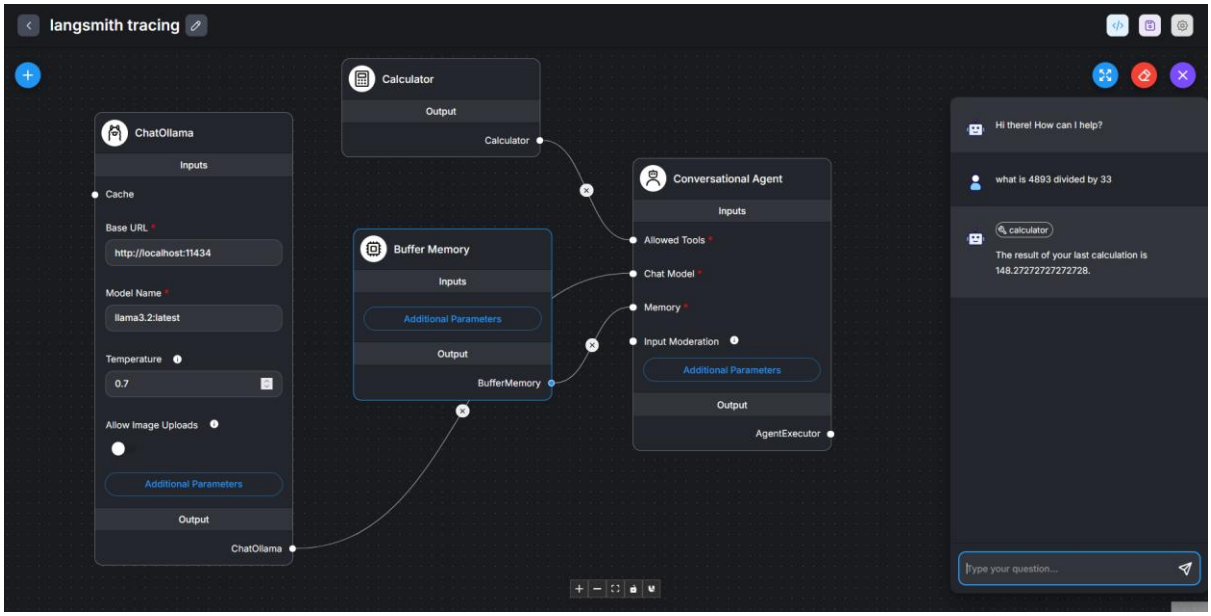


Figure 25: Click on the gear icon at top-right and then Configuration

Configure your project to use *langsmith*, as follows:

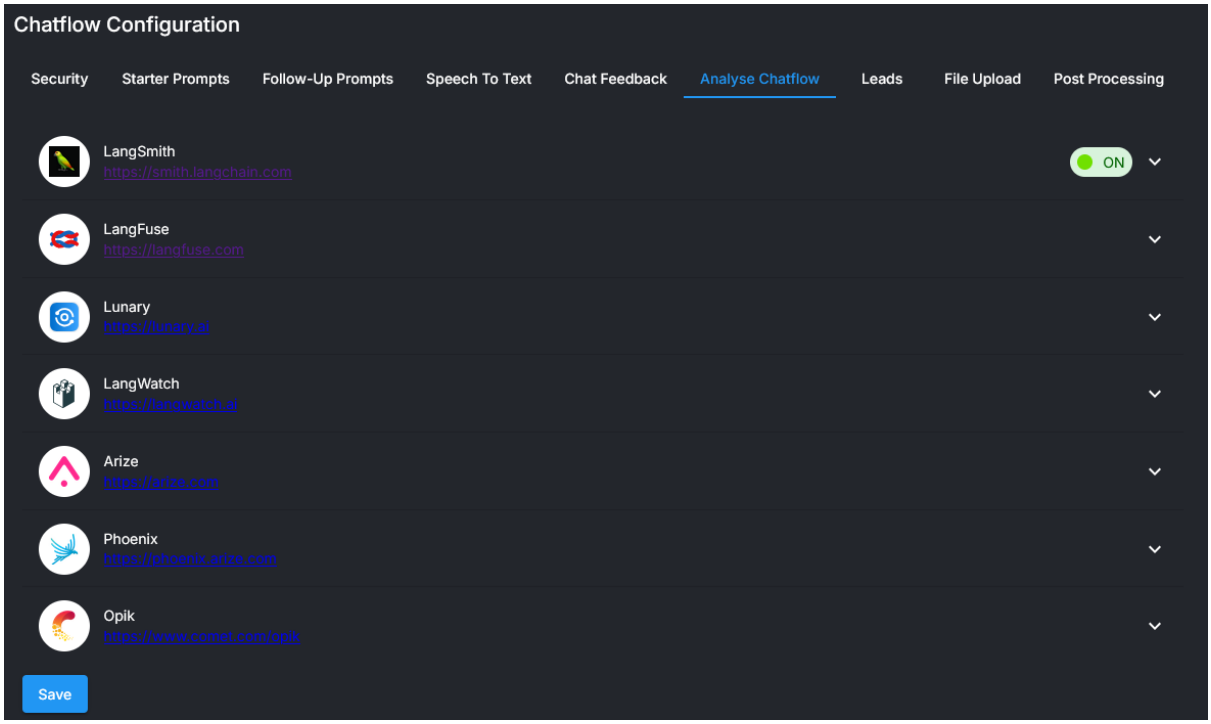


Figure 26: Click on Analyse Projects →Langsmith and create new Credential as also switch its usage on. Then Save the configuration.

Set up your *Credentials* a project name and switch langsmith usage as on. Save the configuration.

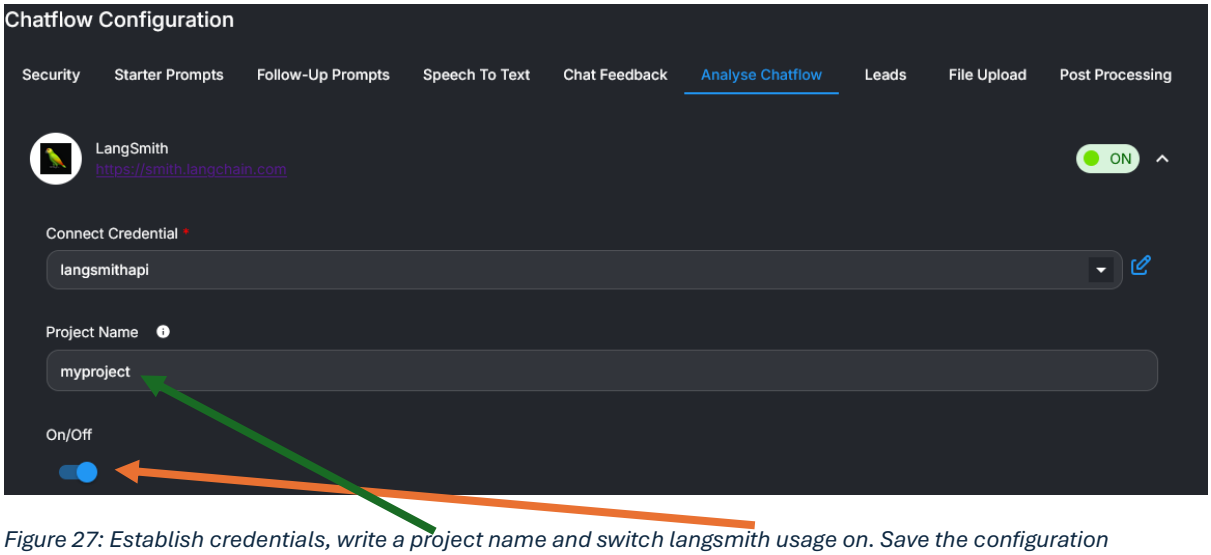


Figure 27: Establish credentials, write a project name and switch langsmith usage on. Save the configuration

In langsmith website under *Personal→Tracing Projects→myproject* see traces of what happened.

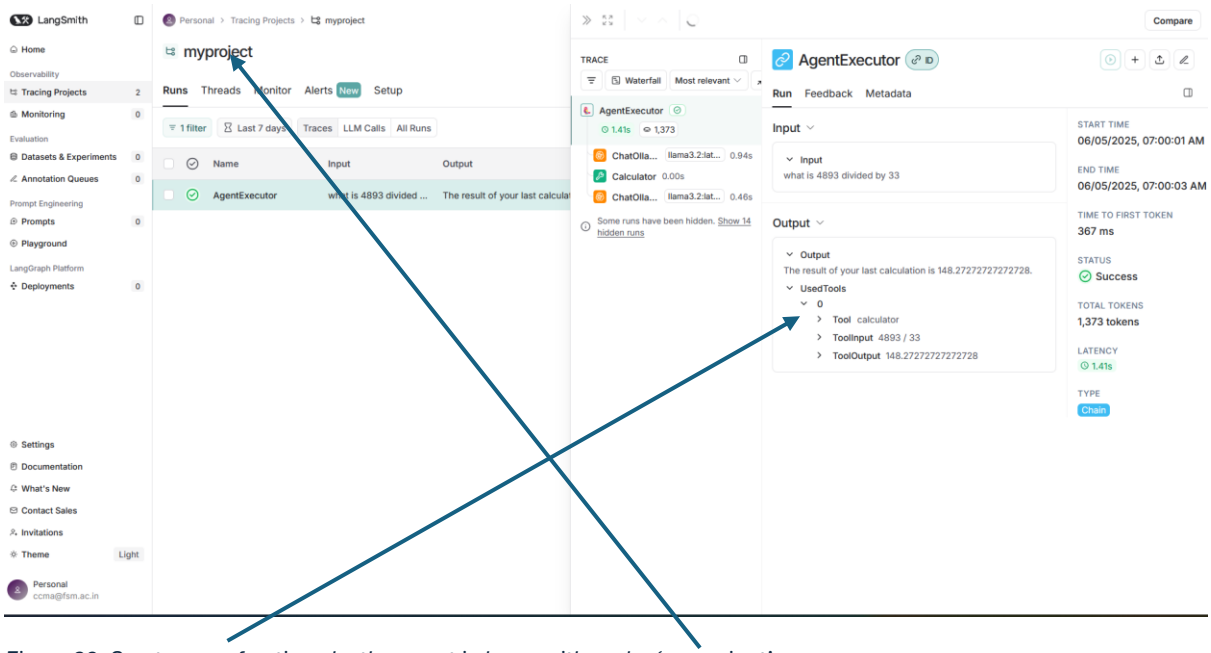


Figure 28: See traces of actions by the agent in langsmith under 'myproject'

N. LLM Chains vs Conversational Agent vs Conversational Retrieval Agent vs Tool Agent

Refer this video.

Given a query LLM Chains answer questions based upon the prompt. Given a query and a prompt, agents first decide what action to take, take that action and reason what next.

Conversation Chain: Write a user message. Given earlier replies and the system prompt, call LLM to give replies to user.

Conversational Agent: LLM is called multiple times. A very simple example is this: Given a user message, LLM decides which tool to call. When a reply is received from the tool, LLM decides the output message.

Conversational Retrieval Agent: Conversational Agent is NOT optimized to work with *Retrieval tool*. For example, if you give a financial statement and ask it to total up assets, it may give wrong answers. *Conversational Retrieval Agent* is optimized to use *Retrieval Tool*. See this video.

Imp Note:

> In all Tools, Name and Description are extremely important as they tell the agent when to call them.

Tool Agent: in the recent version of Flowise, Conversational Retrieval Agent seems to have been replaced by *Tool Agent*.

O. Example System message for Summarization

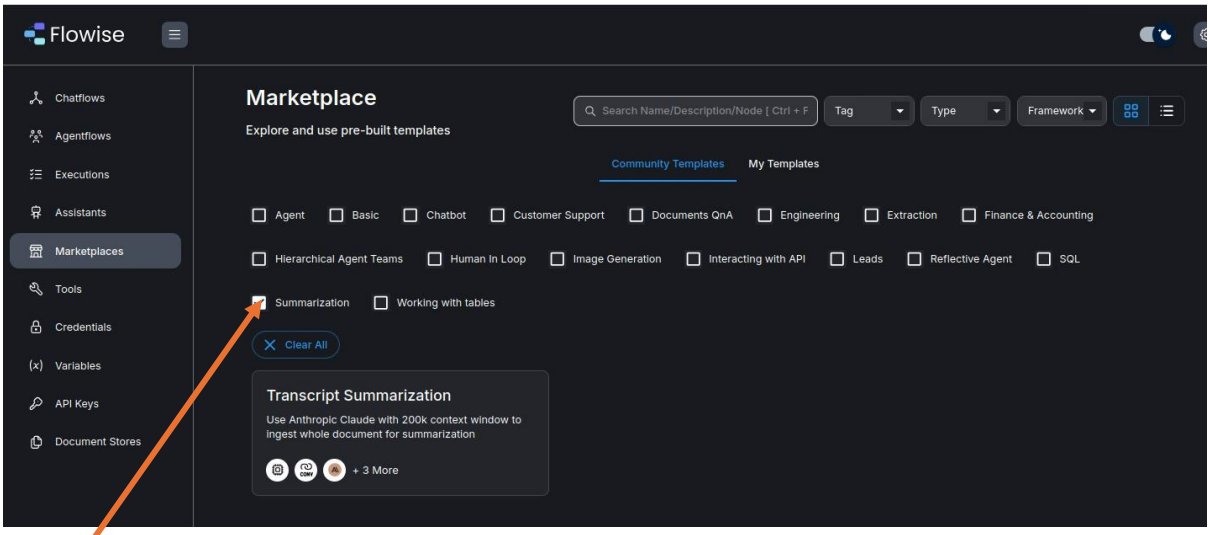
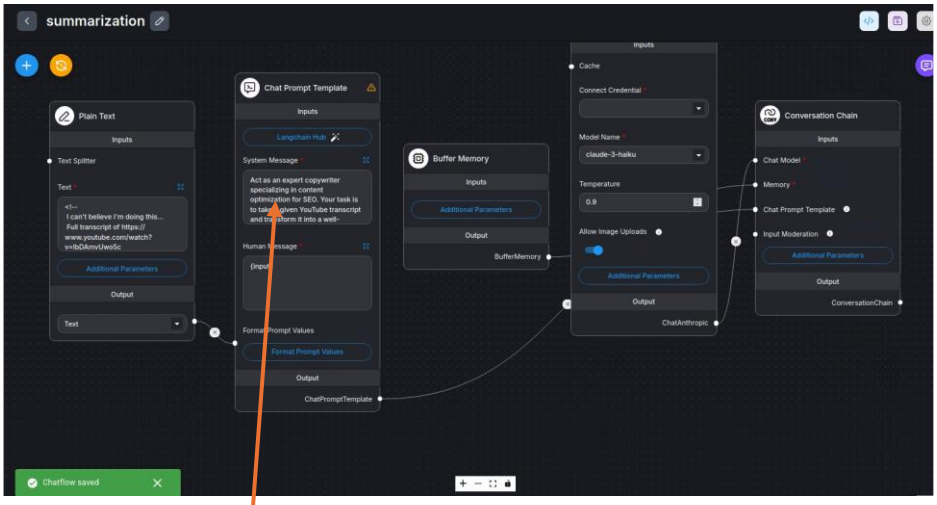


Figure 29: Summarization template in Marketplace



Here is a detailed and ***Example System Message***:

> *Act as an expert copywriter specializing in content optimization for SEO. Your task is to take a given YouTube transcript and transform it into a well-structured and engaging article. Your objectives are as follows:*
>
> *Content Transformation: Begin by thoroughly reading the provided YouTube transcript. Understand the main ideas, key points, and the overall message conveyed.*
>
> *Sentence Structure: While rephrasing the content, pay careful attention to sentence structure. Ensure that the article flows logically and coherently.*
>
> *Keyword Identification: Identify the main keyword or phrase from the transcript. It's crucial to determine the primary topic that the YouTube video discusses.*
>
> *Keyword Integration: Incorporate the identified keyword naturally throughout the article. Use it in headings, subheadings, and within the body text. However, avoid overuse or keyword stuffing, as this can negatively affect SEO.*
>
> *Unique Content: Your goal is to make the article 100% unique. Avoid copying sentences directly from the transcript. Rewrite the content in your own words while retaining the original message and meaning.*
>
> *SEO Friendliness: Craft the article with SEO best practices in mind. This includes optimizing meta tags (title and meta description), using header tags appropriately, and maintaining an appropriate keyword density.*

Engaging and Informative: Ensure that the article is engaging and informative for the reader. It should provide value and insight on the topic discussed in the YouTube video.

Proofreading: Proofread the article for grammar, spelling, and punctuation errors. Ensure it is free of any mistakes that could detract from its quality.

By following these guidelines, create a well-optimized, unique, and informative article that would rank well in search engine results and engage readers effectively.

Transcript:{transcript}

P. Multi-Prompt Retriever

A Multi Prompt Retriever is a technique, often used in Retrieval-Augmented Generation (RAG) systems, that leverages multiple prompts (or queries) to retrieve documents from a single vector database. This approach contrasts with traditional RAG where a single query is used to retrieve relevant information. By generating multiple variations of a user's query, the Multi Prompt Retriever can capture a broader range of perspectives and potentially uncover more relevant documents

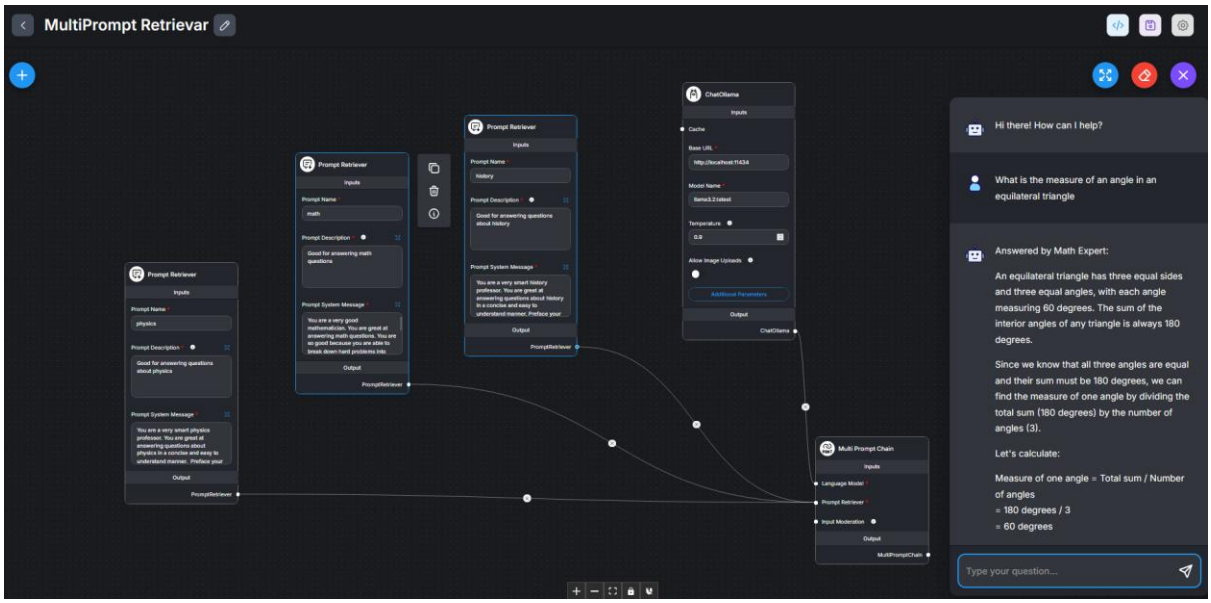


Figure 30: A multi-prompt retriever selects one of the prompt retrievers before it answers questions.

Prompt Retirevar-1

Description

Good for answering questions about physics

Prompt

You are a very smart physics professor. You are great at answering questions about physics in a concise and easy to understand manner. Preface your answer as: Answered by Physics Wala:

When you don't know the answer to a question you admit that you don't know.

Prompt Retirevar-2

Description

Good for answering math questions

Prompt

You are a very good mathematician. You are great at answering math questions. You are so good because you are able to break down hard problems into their component parts, answer the component parts, and then put them together to answer the broader question. Preface your answer as: Answered by Math expert:

Prompt Retirevar-3

Description

Good for answering questions about history

Prompt

You are a very smart history professor. You are great at answering questions about history in a concise and easy to understand manner. Preface your answer as: Answered by History wizard:

When you don't know the answer to a question you admit that you don't know.

User queries:

1. What is the measure of an angle in an equilateral triangle
2. Explain very briefly Einstein's theory of relativity
3. Tell me something about Mughal empire in India

Q. Multi-Retriever chatflow

i) With MultiRetriever node

A RAG may be distributed amongst multiple vector stores. We can then use Multi-Retriever chatflow. Our vector stores include In Memory Vector Store, FAISS and Milvus (installed in a docker). Access milvus simply as: http://localhost:19530. The primary node is: *Multi Retrieval QA Chain*. This node does not have any memory and hence is unfit for conversations, Use *Tool Agent* instead.

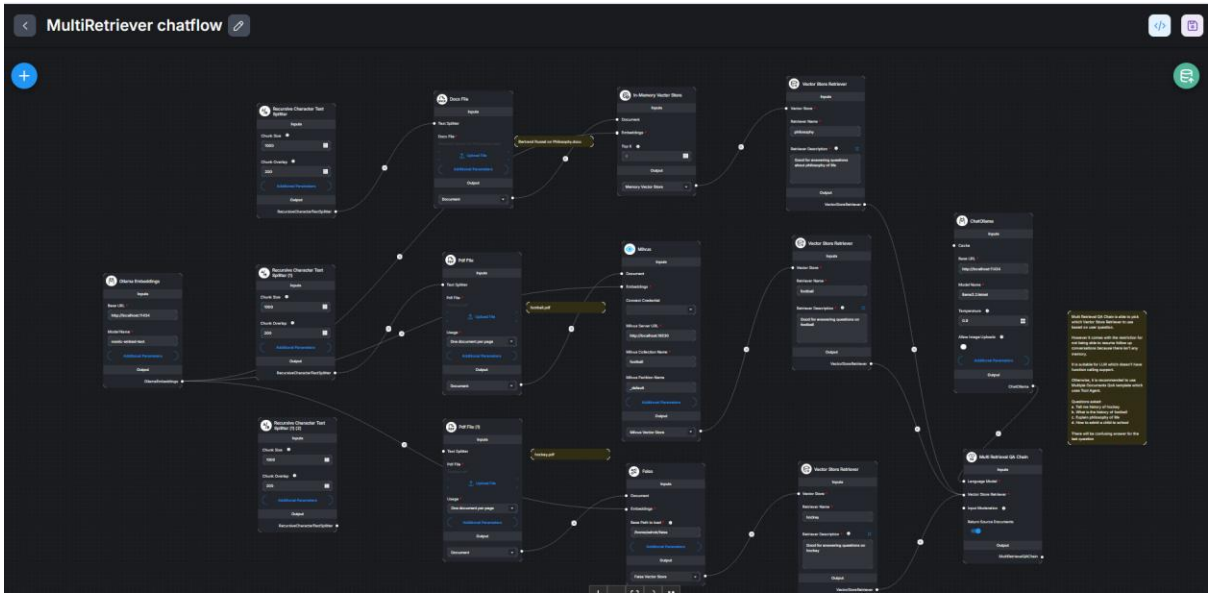


Figure 31: Multiple vector stores for answer extraction.

ii) With Tool Agent node

Here the Tool agent decides which vector store to access and the Tool Agent also has memory. We can converse with it. We use *Milvus vector* store twice with different collection names.

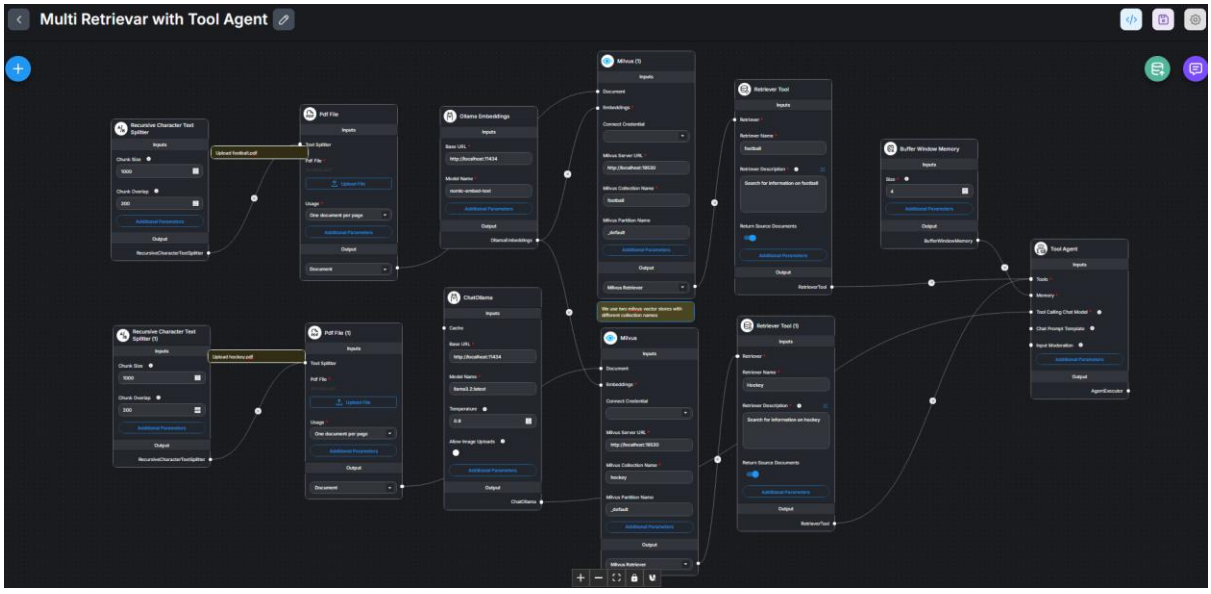


Figure 32: Tool Agent accessing multiple vector stores

R. Using Milisearch vector store

Using Milisearch vector store is simple. Start vector store and access it as: http://localhost:7700.

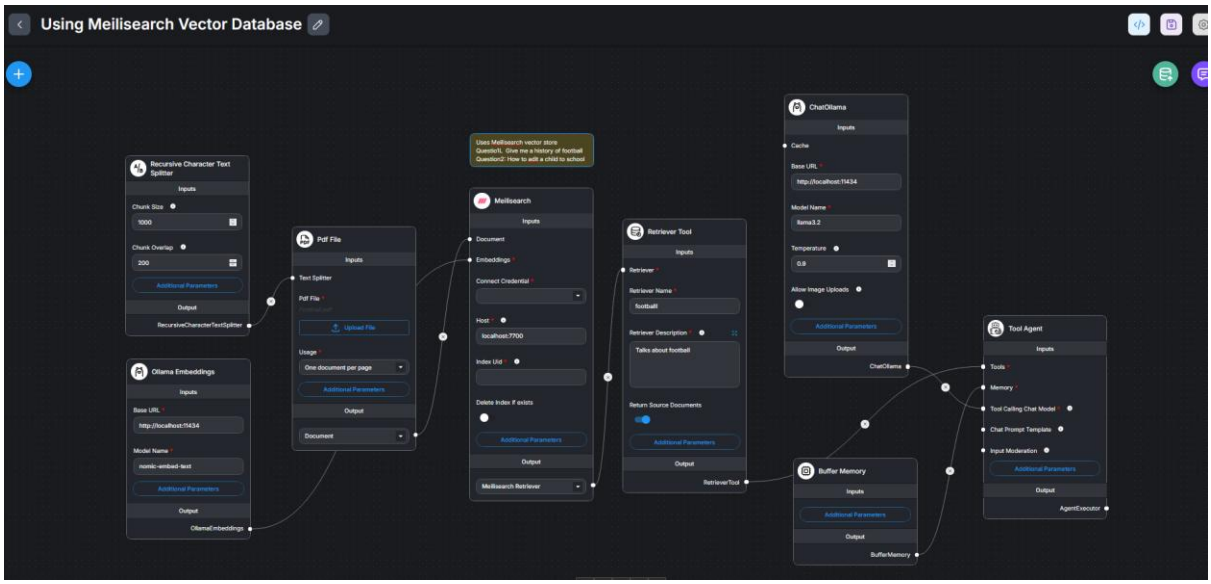
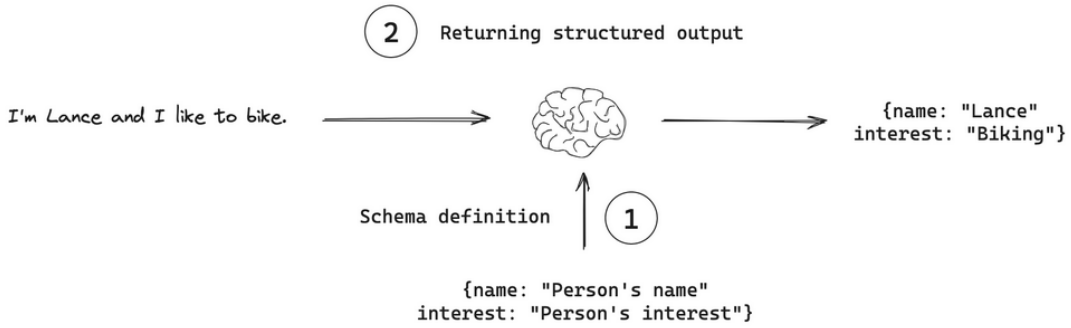


Figure 33: Using Milisearch vector store

S. Structured Output Parsers

Refer this Video and this langchain article.

A structured output parser is a tool or process that transforms the often unstructured text output of a large language model (LLM) into a more organized and predictable format, such as JSON or a Python dictionary. This allows for easier integration with other applications and systems, as the output conforms to a defined schema



What it does:

- **Transforms unstructured text:**
  LLMs typically generate text-based responses that can be difficult to parse and use in other applications.
- **Enforces a schema:**
  They ensure that the output conforms to a predefined structure (schema), which can be crucial for applications that need consistent and predictable data
- **Converts to structured data:**

Output parsers take this text and convert it into a structured format like JSON, CSV, or a Python object, making it machine-readable.

How it works:

- A prompt is supplied. This prompt instructs the LLM to extract some information from user message or rather take some action on user message. LLM outputs action.
- The Structured output parser will take the output of LLM as input, structure it and give us JSON object.
  Thus, two things are important: **a)** What information is given by the LLM chain and b) How should it be structured. OR rather a) Prompt, and **b)** Description of each field in Parser are important.

i) Output Parsers-1

Experiment 1:

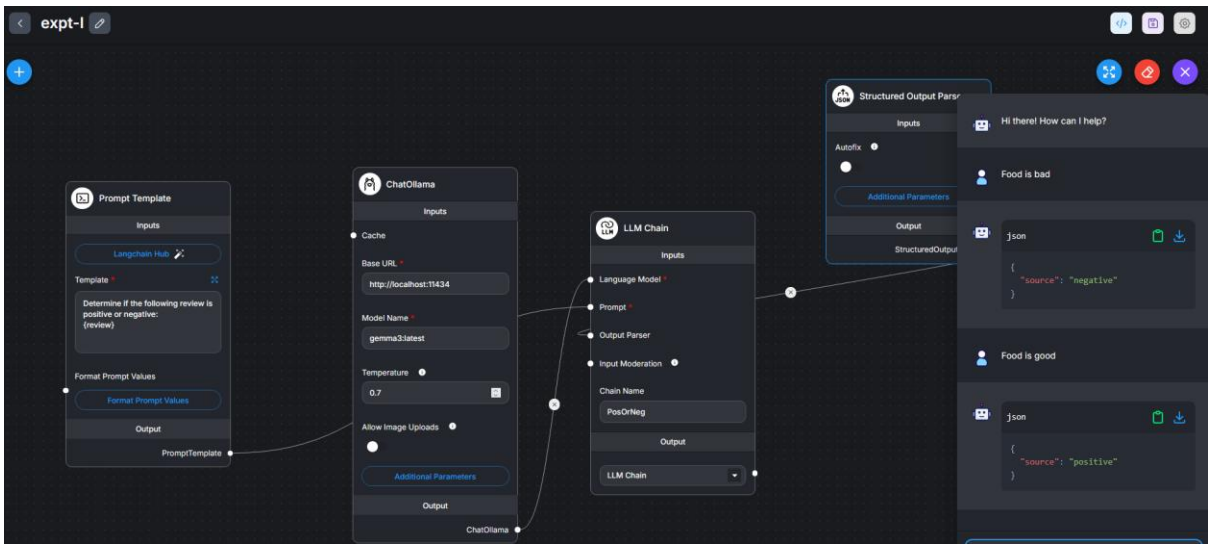


Figure 34: Prompt expects only two values--[positive, negative]. Return value from LLM Chain would contain a sentence with string 'positive' or 'negative'.

Config-I

Prompt

Determine if the following review is positive or negative.
{review}

So output of LLM chain may be a single word: 'positive' (or 'negative') or a sentence, as this one: `This review appreciates the product and hence is positive.`

Parser Config-1

'*Description*' is very important. It describes what would be returned subject to what input is received from LLM chain.

Figure 35: Give any name to property. Description is: Return positive or negative. Returned output will be a string: 'positive' or 'negative'.

Wrong prompt:

> *Determine if the following review is positive.*
> *{review}*

In normal conversation this sentence is OK. But as a prompt it does not say as *what to do* when the review is NOT positive. Should I say, 'negative' or should I say nothing.

Config-II

Prompt

> *Determine if the following review is positive or negative.*
> *{review}*
>
> > So output of LLM chain may be a single word: 'positive' or a sentence, as: This review appreciates the product and hence is positive.

Parser Config-II

> '*Description*' is very important. It describes what would be returned subject to what input is received from LLM chain.

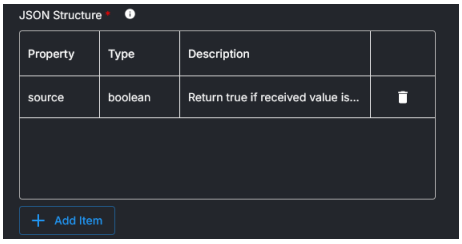


Figure 36: Type of returned value is boolean. Description is: Return true if received value is positive else return false. Description must be very clear.

The output from above config is:

Figure 37: Output true or false is NOT enclosed by inverted comma

Config—III

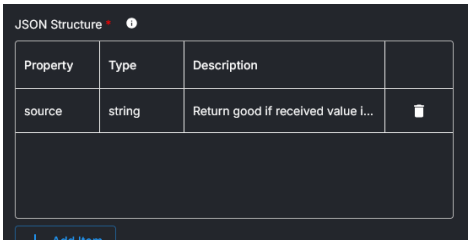


Figure 38: Description is: Return good if received value is positive else return bad

The output of config-III is:

Figure 39: Output is Neither 'positive' or 'negative' OR 'true' or 'false'. But 'good' or 'bad'

This Prompt fails as it does not tell LLM to take any action rather tells the LLM to describe itself.

(Wrong) Prompt

Tell us about yourself

So output of LLM chain could be anything. Irrespective of user input, the LLM chain asks the LLM to talk about itself. As we do not know what the LLM output would be , it is difficult to specify the Parser fields.

ii) Output parser-II

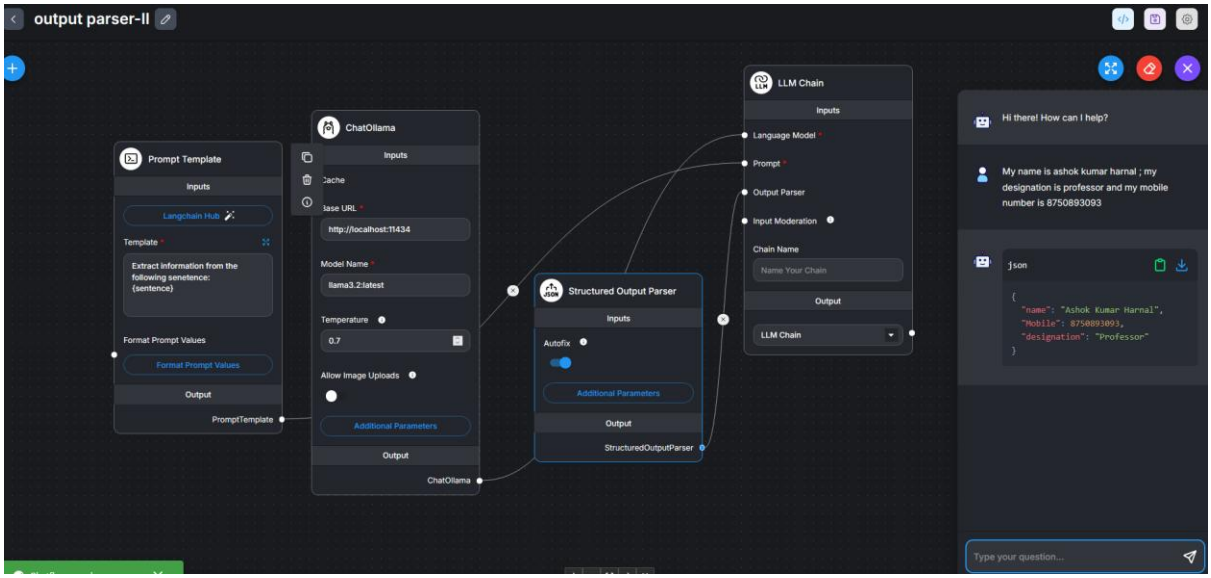


Figure 40: Prompt and Structured output parsers variables have been changed. See below.

Prompt:

Prompt is an instruction to LLM chain to extract some information from the user's message. This message is then structured and presented to us.

> Extract information from the following sentence:
> {sentence}
>
> Give us your name, mobile number. address and designation

Format Prompt value:

> Format prompt as below:

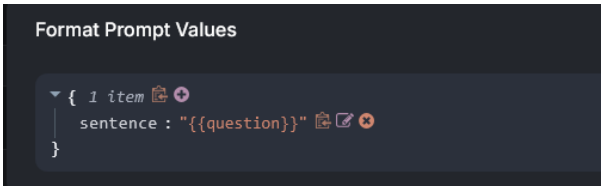
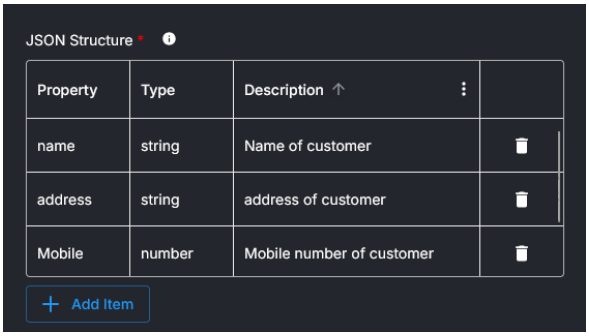


Figure 41: Format prompt variable

Structured output parser:

> Define variables whose values are to be extracted and presented in json format from the answer:



Feed the sentence:

i) My name is ashok kumar harnal ; my designation is professor and my mobile number is 8750893093

Note: In this sentence, address is missing

ii) My name is ashok kumar harnal ; my designation is professor and my mobile number is 8750893093

Note: This contains address also. See the response below:

iii) Output parser-III

A structured list output parser. The list is outputted as a json object.

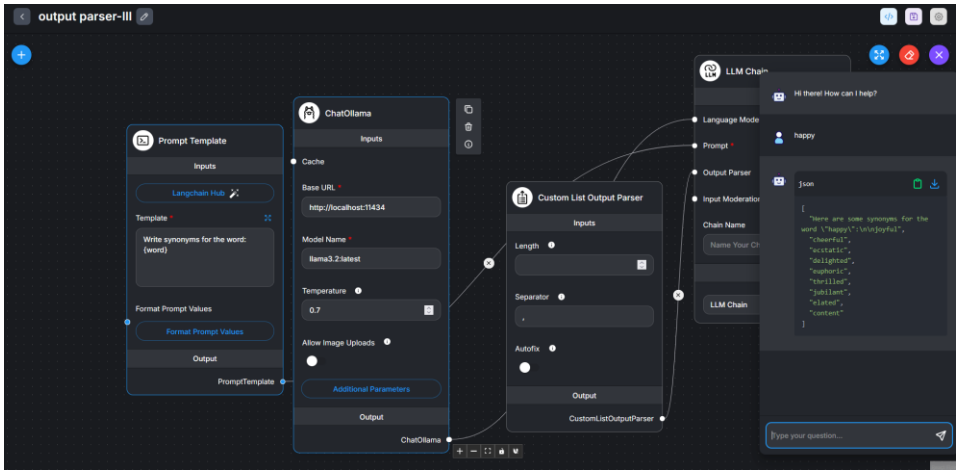


Figure 42: Change Both i) Prompt Template (as above) and Format Prompt Values (As below)

Format Prompt value:

Format prompt as below:

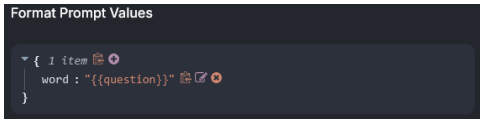
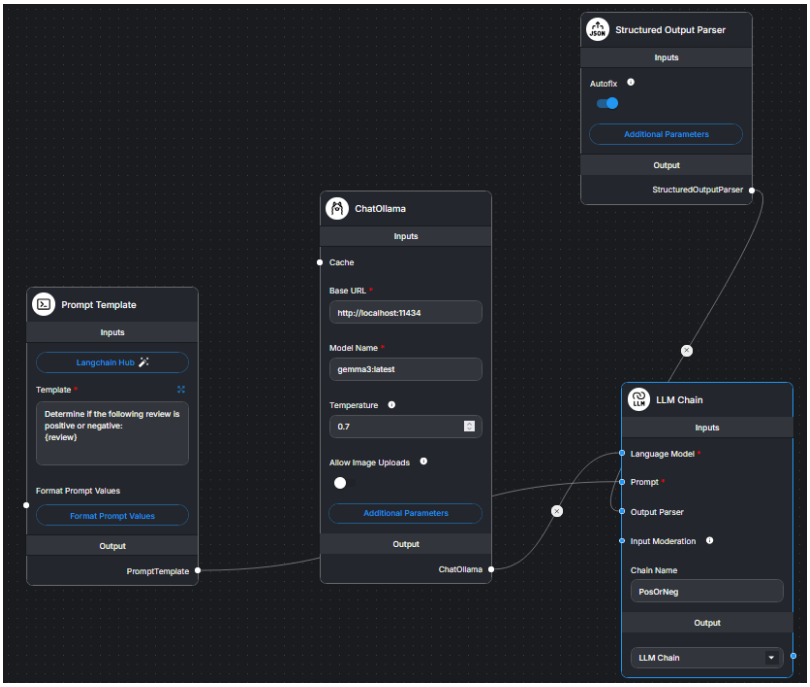


Figure 43: Format prompt variable



iv) Output parser using if-else-IV

This example demonstrates use of if-else function that responds differently to positive and negative reviews.

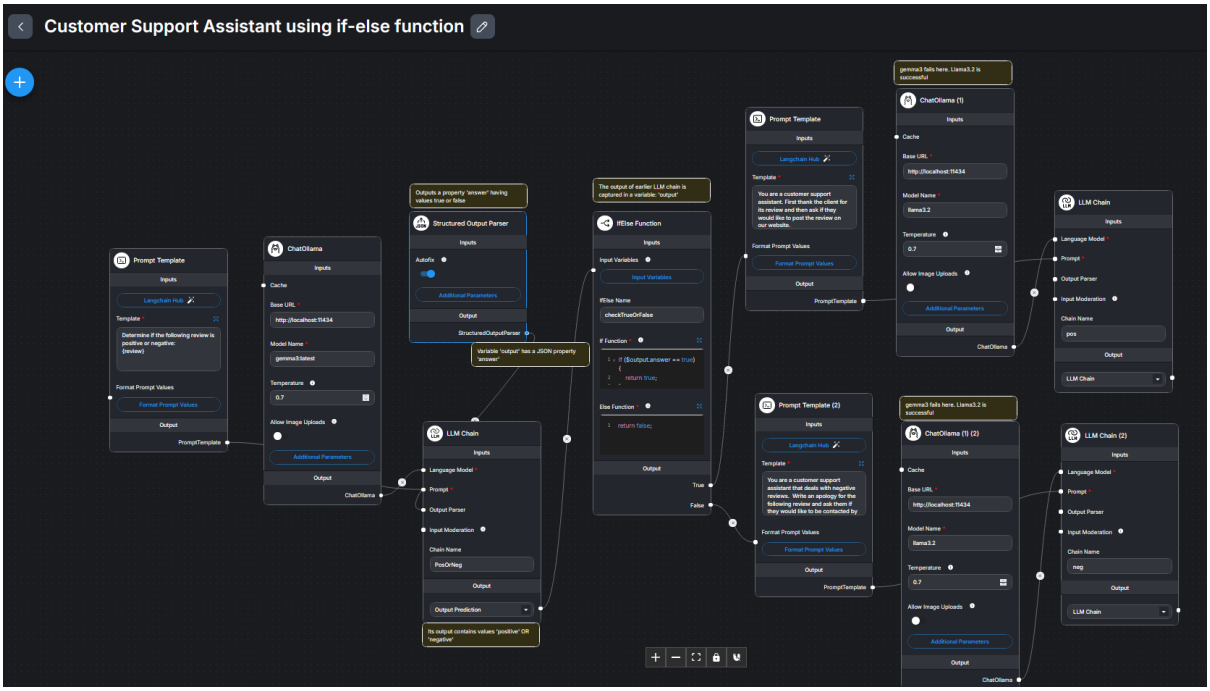


Figure 44: Customer support assistant that responds differently to positive and negative reviews. We use if-else function

Here are some specifics:

i) Output of Ist LLM chain is set to '*output Prediction*'.

ii) Structured output parser is configured as:

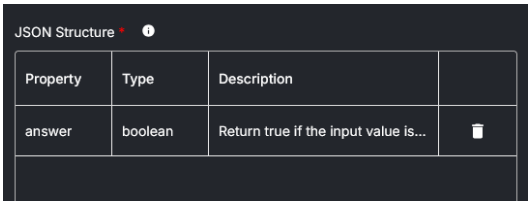


Figure 45: Description is: Return true if the input value is positive and return false if the input value is negative

iii) If-Else variable is defined as follows:

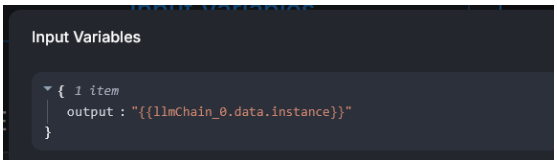


Figure 46: Variable 'output' has a property 'answer' (see above figure)

iv) Prompt, if true output

> You are a customer support assistant. First, thank the client for its review and then ask if they would like to post the review on our website.
> Also summarize the review: {review}

v) Prompt, if false output

You are a customer support assistant that deals with negative reviews. Write an apology for the following review and ask them if they would like to be contacted by a customer service rep.
Review: {review}

vi) Chat-ollama

In chat-ollama, use llama3.2 model rather than gemma3. Llama3.2 works better here.

vii) Responses:

Here are the responses to positive and negative reviews.

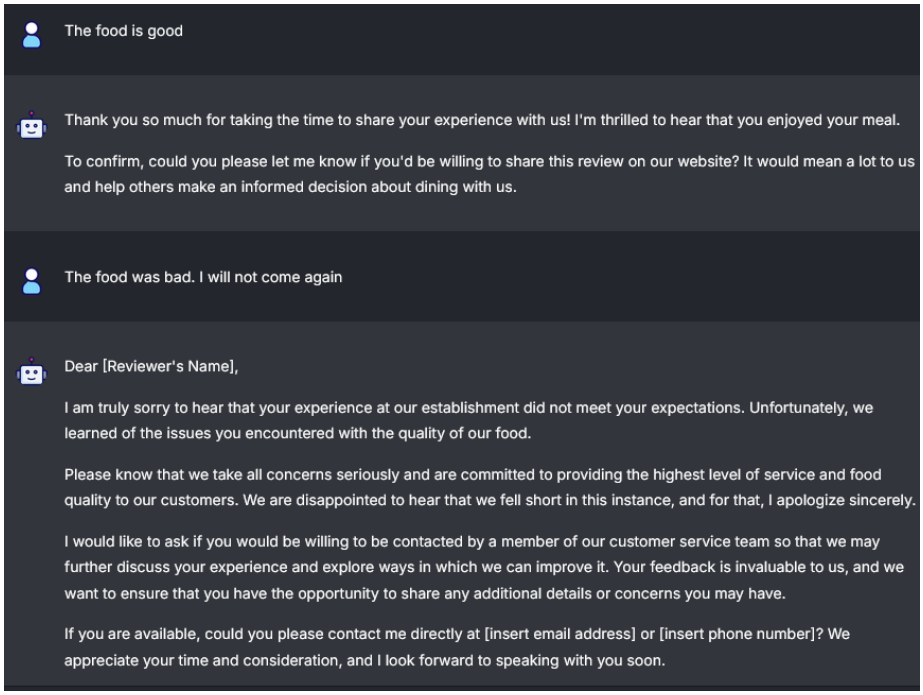


Figure 47: Responses to positive and negative reviews.

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