AI for Animal Care

The era of large language models (LLMs) began in 2017 with the publication of *"Attention Is All You Need"* by Vaswani et al. [1]. This groundbreaking paper introduced the transformer architecture, laying the foundation for a revolution in how machines process and generate human language. Since then, LLMs and generative AI more generally have rapidly evolved, powering applications that range from conversational agents to code generation and medical question answering.

Yet, despite their remarkable capabilities, generative models are still underutilized across many sectors. Industry adoption often lags behind research advancements, and public awareness of their true potential remains limited. However, the landscape is changing fast — particularly as LLMs are increasingly integrated into intelligent agents, opening up transformative real-world applications.

One such opportunity was the **5-Day Generative AI Workshop** hosted by **Kaggle and Google**, which introduced participants to modern generative AI techniques. As part of the capstone project, I chose to build a **veterinary assistant chatbot**, powered by *Retrieval-Augmented Generation (RAG)* and grounded in authoritative content from the **Merck Veterinary Manual**.

Why Veterinary Science?

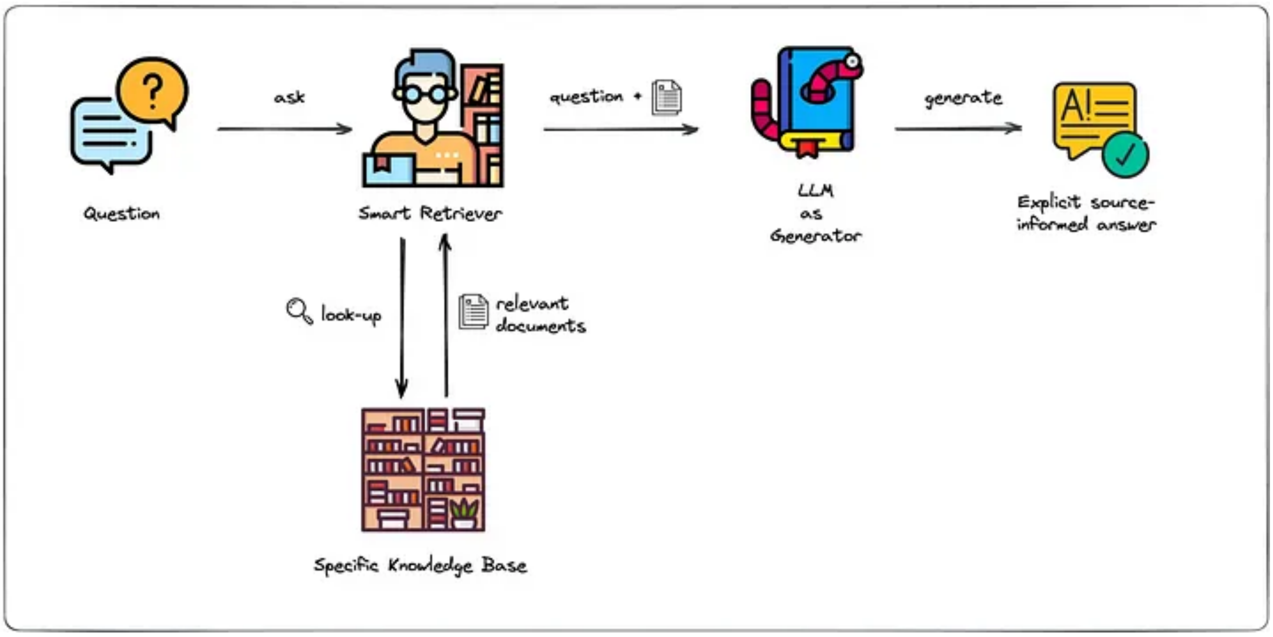
Veterinary medicine — particularly in low-resource and rural regions — remains one of the fields where LLMs can make a significant impact. Access to up-to-date veterinary knowledge is often limited, and qualified professionals may be scarce. Therefore, many pet owners dont really understand their animals needs. They feed the wrong, sometimes harmful food, keep their dogs locked in cages the whole day and dont react appropropriately in times of medical emergence with potentially devastating consequences. Additionally, behavioral training often happens violently and the importance of vaccinations, sterilization and disease prevention are not understood. Animal welfare suffers as a result, with growing street dog populations, preventable diseases, and misinformation contributing to systemic challenges.

A well-designed, AI-powered assistant that provides **reliable, verifiable, and scientifically grounded veterinary information** could support animal caretakers and educate the public about their animals. This could particularly make a difference when it comes to large street dog populations. Often poorly understood and feared they face hostility from locals and grow up in an environment of competition for and scarcity of food. Additionally, most of these street dogs are not spayed or neutered, leading to uncontrolled population growth, increased hunger, disease transmission, and aggression.

In this article, we will explore how LLMs, paired with smart retrieval techniques, can serve as reliable, accessible veterinary assistants — even in low-resource environments.

What This Project Covers

We will start to explore the process of retrieving the Merck Veterinary articles through Web Crawling and Scraping. Given the dataset, the next step involves the creation of a vector store (**Chroma**), which stores the different articles as vector embeddings that represent their meaning and content. After that, we will look at the creation of the chatbot, based on the **Gemini API**, that uses the vector store to answer users questions, based on the article content. This involves a combination of **Prompt Engineering** and the retrieval of relevant articles (see figure).



Retrieval Augmented Generation paired with Prompt Engineering can ground LLM output in authoritative content (Source).

Finally, we quickly go through the User Interface, showcasing how it is designed to be both smoothly functioning as well as pleasant to work with and look at.

Web Scraping

The first challenge in building a **chatbot powered by Retrieval-Augmented Generation (RAG)** is sourcing reliable and authoritative content. For this project, I decided to use the **Merck Veterinary Manual**—a well-respected and freely accessible resource in the field of veterinary science. As Merck does not offer a public **API**, the only way to retrieve their content was by scraping it directly from the website. This turned out to be one of the more time-consuming and at the same time technically interesting parts of the project.

I decided to implement the Web Scraping with python and the **Playwright** package, a modern alternative to **Selenium** that is particularly useful when scraping websites that load their content dynamically via JavaScript. Playwright allows for automated interaction with the browser, enabling robust scraping even from complex web applications. In addition to that, it is one of the main tools used to enable LLM powered agents to act in the web, meaning that it is generally useful to know.

In a nutshell, **Playwright** launches a Chromium browser which can then be used to created a new `Context` and `Page` object.

```python
async def init_browser(headless=True):
    playwright = await async_playwright().start()
    browser = await playwright.chromium.launch(headless=headless)
    context = await browser.new_context(viewport={"width": 1200, "height": 800})
    page = await context.new_page()
    return playwright, browser, page
```

Through the page, we can for example:

- navigate to a URL (`await page.goto(current_url, wait_until="domcontentloaded")`)
- retrieve HTML content (`await page.query_selector('[data-testid="topic-main-content"]')`)
- or interact with the website (`await button.click()`)

Content URL Retrieval

Given the huge amount of information in the form of articles, videos, quizzes, etc. I decided to first retrieve of all the URLs containing actual written content.

This webcrawler operates in a loop, at any point in time maintaining three sets of URLs:

- `visited.txt` — URLs that have already been processed
- `to_explore.txt` — URLs yet to be visited
- `content_urls.txt` — URLs confirmed to contain article content

This is mostly done so that progess is not lost if the script is being interrupted due to whatever reason. The simplified structure of the core logic looks like this, resembling DFS or BFS except the fact that we operate on sets, so any order is lost:

```
while to_explore:
    current_url = to_explore.pop()
    if current_url in visited:
        continue
    response = await page.goto(current_url)
    if response.status == 403:
        raise AccessDenied(current_url)
    if await page.query_selector('[data-testid="topic-main-content"]'):
        content_urls.append(current_url)
    else:
        found_urls = await find_urls(page)
        to_explore.update([url for url in found_urls if url not in visited])
    visited.add(current_url)
```

Any URL we visit, will either be an overview page, linking to further subpages or it will be containing an actual article about some topic, indicated by the the attribute `data-testid=topic-main-content`.

Scraping Article Content

Once we’ve retrieved the list of article URLs using our crawler, the next step is to extract the actual content. For this, we use a dedicated `scraper.py` script:

```
async def main():
    ...
    for i, url in enumerate(tqdm(urls, desc="Scraping articles\n")):
        ...
        article = await scrape_article(page, url)
         ...
        articles.append(article)
        to_scrape.remove(url)
    ...
    with open('./data/merck-articles.json', "r", encoding="utf-8") as f:
         merck_articles = json.load(f)
    ...
    merck_articles.extend(articles)
    with open("./data/merck-articles.json", "w", encoding="utf-8") as f:
        json.dump(merck_articles, f, ensure_ascii=False, indent=4)
```

At its core, the scraper visits each URL in the `content_urls.txt` file, retrieves its title and the article content as Markdown code and finally stores the articles in `merck-articles.json`.

```
async def scrape_article(page, url):
...
response = await page.goto(url, wait_until="domcontentloaded")
...
title_element = await page.query_selector("h1")
title = await title_element.inner_text() if title_element else "Untitled"

# Extract the content
main_content = await page.query_selector('[data-testid="topic-main-content"]')
...
return {
    "name": title.strip(),
    "link": url,
    "content": content
}
```

After scraping the Merck Veterinary Manual website, we end 19.7 MB of data made up of ~3000 individual articles and a total of 2836584 words. The dataset is freely available here.

Embedding the dataset in a Chroma database

Chroma is a popular and modern open-source **vector database**, meaning a database that stores content as numerical vector embeddings. Those embeddings represent the actual content and meaning of the data that is embedded, which makes them very useful and interesting in many applications. Most modern embedding algorithms are based on the transformer architecture and use a so called encoder-only variant thereof. In contrast to more traditional methods of language representation such as Bag of Words, these modern day methods are extremely sophisticated and powerful. In RAG settings, they allow us to search for articles that are relevant to a given user query, based on distance calculations of the article embedding and the querys embedding.

We start by retrieving the articles from GitHub and converting them into LangChain documents:

```
url = "https://raw.githubusercontent.com/JohannesSchulz97/WebScraper/refs/heads/main/data/merck-

response = requests.get(url)
data = response.json()
...
documents = [
    Document(
        page_content=entry["content"],
        metadata={"name": entry["name"], "link": entry["link"]}
    )
    for entry in data
]
```

To then create the database, we first create a Chroma client, then the actual database and finally upload the documents in batches into that database:

```
chroma_client = chromadb.Client()
...
db= chroma_client.get_or_create_collection(name="veterinary_articles", embedding_function=embed_
...
db.add(
    documents=batch_docs,
    metadatas=batch_meta,
    ids=batch_ids
)
```

We use a custom embedding function that can embed both documents as well as user queries based on `text-embedding-004`, a powerful and modern text embedding architecture available on Vertex Ai.

Prompt Engineering and document retrieval

The main idea of **Retrieval Augmented Generation (RAG)** is to augment a users query with additional relevant information that is retrieved from a vector store like Chrome. The enhancement or manipulation of a users is prompt is known as **Prompt Engineering**. In addition to adding relevant articles from the Merck Veterinary Manual, we also add instructions to set the rules and the tone of the response.

As can be seen in the code below, we define three types of queries. `QueryType.INITIAL` is only used once, namely the very first time the user interacts with the chatbot. Here we give very detailed and elaborate instructions, on how the responses should be structured. In multi-turn conversations, instructions can be forgotten due to **Context Window Limitations** or **Prompt Drifting**. Therefore, after every ten rounds of query-response between user and model, we remind the model of our initial instructions with a shorter reminder instruction prompt (`QueryType.REMINDER`). Every other query will not be augmented by any instructions, but just by the relevant articles (`QueryType.NO_INSTRUCTION`).

```

class QueryType(Enum):
    INITIAL = 1
    REMINDER = 2
    NO_INSTRUCTIONS = 3


initial_instruction_prompt = """You are a knowledgeable, friendly, and responsible veterinary ch
designed to assist with questions related to veterinary science.
...
If necessary, ask relevant and specific follow-up questions
to gather additional information before making any conclusive statements or offering advice.
...

Always prioritize accuracy and caution in your responses.
...

You will be given veterinary documents and their URLs.
...
Your statements about veterinary science should only be based on the provided documents!
... """

reminder_instruction_prompt ="""..."""
...
```

We then retrieve the 10 most relevant articles given the users query through the `db.query()` method of Chroma. The final augmented query that is then fed to the language model consist of an optional instruction prompt, the users questions and in the end the URL, the name and the content of the retrieved articles. The URLs allow the model to specify the sources on which it bases its response and are therefore important for the user to be able to validate their correctness.

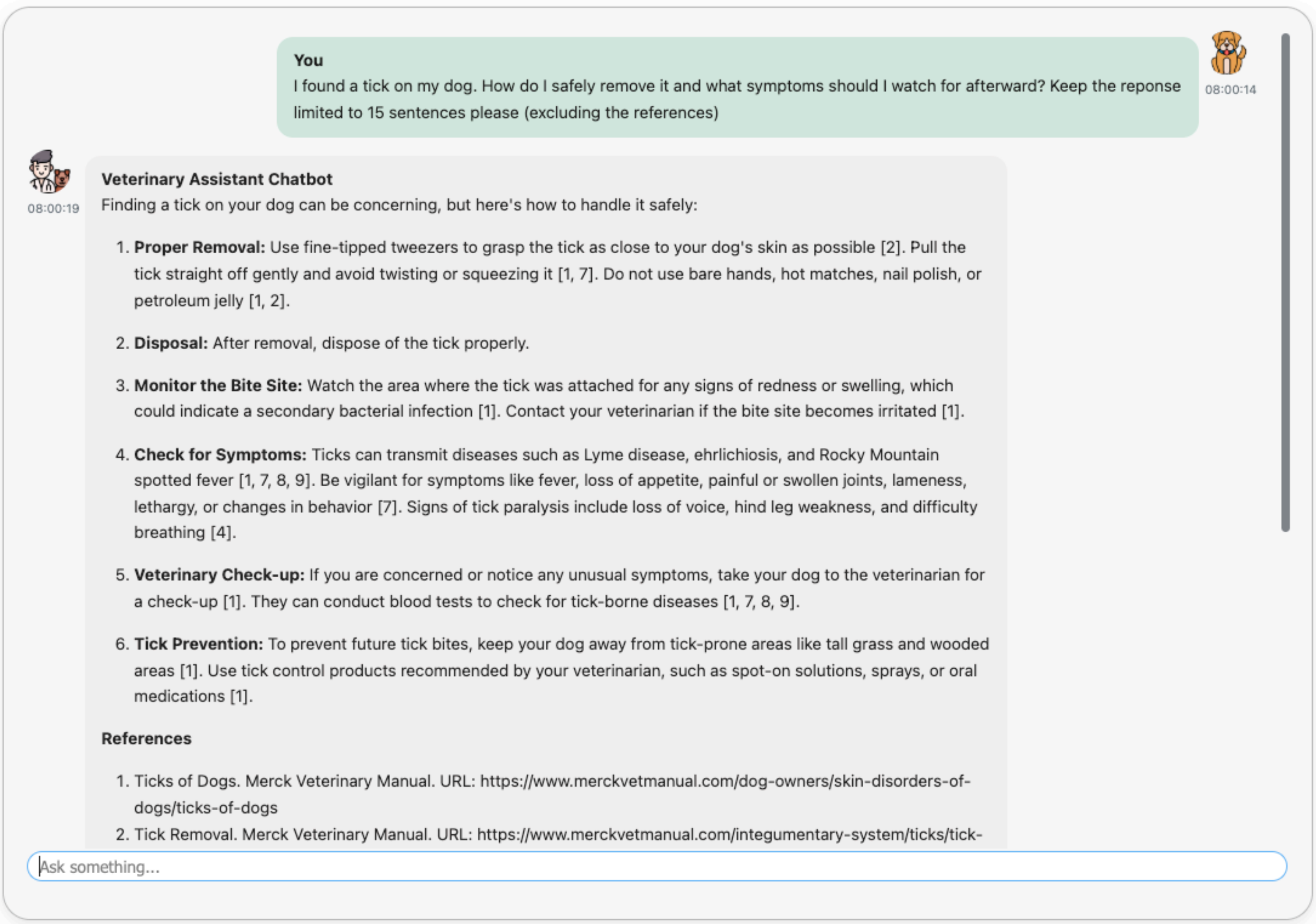
```
def retrieve_relevant_articles(query):
    embed_fn.document_mode = False
    results = db.query(query_texts=[query], n_results=10, include=['documents', 'metadatas'])
    [documents], [metadata] = results['documents'], results['metadatas']
    return [x['link'] for x in metadata], [x['name'] for x in metadata], documents


def augment_query(query, query_type: QueryType):
    query = query.replace("\n", " ")
    urls, names, documents = retrieve_relevant_articles(query)
    match query_type:
        case QueryType.INITIAL:
            prompt = initial_instruction_prompt + f"QUESTION: {query}\n\n"
        case QueryType.REMINDER:
            prompt = reminder_instruction_prompt + f"QUESTION: {query}\n\n"
        case QueryType.NO_INSTRUCTIONS:
            prompt = f"QUESTION: {query}\n\n"
    # Add the retrieved documents to the prompt.
    for url, name, document in zip(urls, names, documents):
        document = document.replace("\n", " ")
        prompt += f"url: {url}\n"
        prompt += f"name: {name}\n"
        prompt += f"document: {document}\n\n"
    return prompt
```

Designing the User Interface

In designing the user interface, we focus on two main aspects. First, we want everything to work properly and smoothly, so that interacting with the chatbot is enjoyable and effortless. Secondly, the user interface should be pleasant to look at, again making it more enjoyable to work with it. We use `ipywidgets` to implement the UI in jupyter inspired by this article of Konstantin Rink. The layout is kept minimal: a single scrollable chat window, a text input at the bottom, and a small loading animation to indicate processing.

To make the bot feel more alive, both user and bot messages are rendered as chat bubbles aligned to the left and right respectively, each with a timestamp and profile picture (using icons created by Freepik – Flaticon). This is handled by formatting the HTML output of each message. Styling happens by injecting CSS code into the HTML frontend. More details on UI design and styling can be found in the source code.

The main functionality is implemented by an `on_submit` event handler that reacts to user input. It displays the user message and then determines how to augment the users query depending on the current number of turns before sending it to the model. Finally, the models response is displayed as well.



You
I found a tick on my dog. How do I safely remove it and what symptoms should I watch for afterward? Keep the reponse limited to 15 sentences please (excluding the references)
08:00:14

Veterinary Assistant Chatbot
08:00:19
Finding a tick on your dog can be concerning, but here's how to handle it safely:

1. **Proper Removal:** Use fine-tipped tweezers to grasp the tick as close to your dog's skin as possible [2]. Pull the tick straight off gently and avoid twisting or squeezing it [1, 7]. Do not use bare hands, hot matches, nail polish, or petroleum jelly [1, 2].
2. **Disposal:** After removal, dispose of the tick properly.
3. **Monitor the Bite Site:** Watch the area where the tick was attached for any signs of redness or swelling, which could indicate a secondary bacterial infection [1]. Contact your veterinarian if the bite site becomes irritated [1].
4. **Check for Symptoms:** Ticks can transmit diseases such as Lyme disease, ehrlichiosis, and Rocky Mountain spotted fever [1, 7, 8, 9]. Be vigilant for symptoms like fever, loss of appetite, painful or swollen joints, lameness, lethargy, or changes in behavior [7]. Signs of tick paralysis include loss of voice, hind leg weakness, and difficulty breathing [4].
5. **Veterinary Check-up:** If you are concerned or notice any unusual symptoms, take your dog to the veterinarian for a check-up [1]. They can conduct blood tests to check for tick-borne diseases [1, 7, 8, 9].
6. **Tick Prevention:** To prevent future tick bites, keep your dog away from tick-prone areas like tall grass and wooded areas [1]. Use tick control products recommended by your veterinarian, such as spot-on solutions, sprays, or oral medications [1].

References

1. Ticks of Dogs. Merck Veterinary Manual. URL: https://www.merckvetmanual.com/dog-owners/skin-disorders-of-dogs/ticks-of-dogs
2. Tick Removal. Merck Veterinary Manual. URL: https://www.merckvetmanual.com/integumentary-system/ticks/tick-

An example prompt to the **Veterinary Assistant Chatbot**, showcasing Retrieval Augmented Generation grounded in authoritative knowledge cited with relevant source articles.

Future Work

If this project is to be actually useful to people in the world, it should be integrated into a website or a phone application to make it easier to use. Once this is done, there remain various additional ideas for improvement:

1. Animal specific folders could be integrated, so that the chat history always provides context and a background medical history. Additionally, one integrate the functionality to upload documents of medical reports and Xray images amonst others into these specific folders. Of course then those addtional files should be taken into account by the chatbot, which brings us to the next point.
2. The LLM could be fine tuned on images of injured or sick animals as well as medical reports, Xrays or others, so that it is better able to accurately identify and support owners based on uploaded pictures.
3. A functionality that reminds owners of upcoming treatments, such as vaccinations, pest control or spaying appointments.

While this project has been a lot of fun, it is only scratching the surface of what generative AI is able to accomplish. I am looking to continue working in this field and contribute in the integration of generative AI into industry for a better and healthier society.