RagFeed

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Project Overview

Objective

Create an RSS reader powered by RAG and GenAI that provides the user:

- An overview of the most relevant topics on the today articles.
- The possibility to ask for specific topics and get and overview and the most relevant related articles.

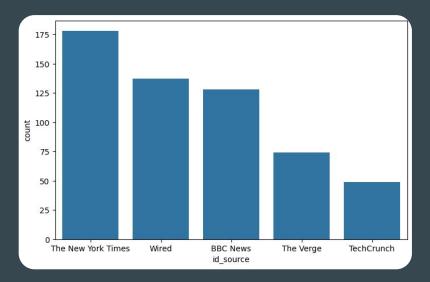
Why?

- RSS Sources publish tens of articles each day.
- Some Sources cover many different topics (not always interesting).
- Interesting topics might be lost in between all the daily articles.
- To have "the algorithm" under control.

Data Source

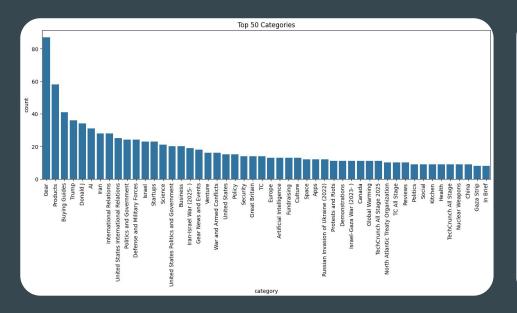
English RSS found in **Best RSS Feeds in 2025**:

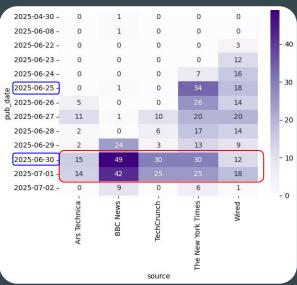
- The New York Times
- Wired
- BBC News
- The Verge
- TechCrunch
- Ars Technica



Exploratory Data Analysis

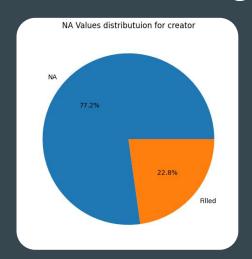
- More than 1200 categories in for 5 sources in 13 days* of information.
- Around 130 articles per day just with 5 sources (in peak collection days*)

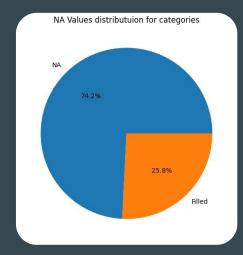


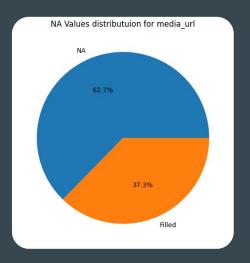


^{*} Data collection started with TNYT on 25/06 the rest of the sources were added on 30/06 and finished on 02/07 morning Articles previous to these dates were provided by the RSS sources during the mentioned period.

EDA - Other Learnings







The RSS parser logic needs to be improved:

- Main fields (title, link, pubDate) are standard.
- But there are alternative implementations (media:thumbnail / media:content, description / summary)
- And some are not always defined (category, dc:creator, content,...)

EDA - Other Learnings

Selective data cleaning:

- Same fields in different sources might have different formats.
- The format is not always explicit.

```
<summary type="html">
  <![CDATA[ Amazon's early Prime Day sale
  started off slow, but as the event draws
  closer to its official kickoff on July 8th,
  it's beginning to pick up steam. Right now,
  for example, Prime members can grab an Amazon
  Echo Hub at Amazon for just $119.99 ($60 off),
  marking a new low price. As you might expect,
  [&#8230;] ]]>
</summary>
```

<description>Weather agencies have
warned of a third day of high
temperatures that in some places have
climbed well above 100 degrees
Fahrenheit, or more than 40 degrees
Celsius./description>

<description><![CDATA[TikTok Shop US is
conducting its third round of layoffs in as
many months.]]></description>

Implementation Details

1. Obtain Data and Feed RAG

- Use requests() to pull xml from source.
- Store xml into a file per source (file was replaced in each update)
- UnstructuredXMLLoader to feed RAG and "snowflake-arctic-embed2" as embedder.
- OllamaChat to process rag requests with "Llama3.1:8B"

- UnstructuredXMLLoader was not properly loading de documents.
- XML files were slow and I was losing older articles (in every update).
- VectorStore data management was not possible.
- RAG wasn't the proper solution for creating top topics.

2. Custom RSS Loader and SQLite

- Implemented a custom algorithm to read and parse RSS to langehain Documents.
- Implemented a SQLite Database to store the articles and not older articles with each update.
- Used articles id in database to manage content on ChromaVS in order to avoid duplicated data.
- Started splitting the code in modular classes and implemented the initial controllers.

- The process speed increased with the database.
- RAG results started to be relevant.

3. Top Topics and Streamlit

- Use SQLite database to send the articles of the day directly to the LLM in order to get the Top Topics.
- Streamlit client showing the list of articles and sources in the database and top topics as Trending Topics.
- Worked with the prompt in order to obtain a valid JSON from the model.
- Switched from OllamaChat to OllamaLLM.
- Switched model to Llama3.2:3b.

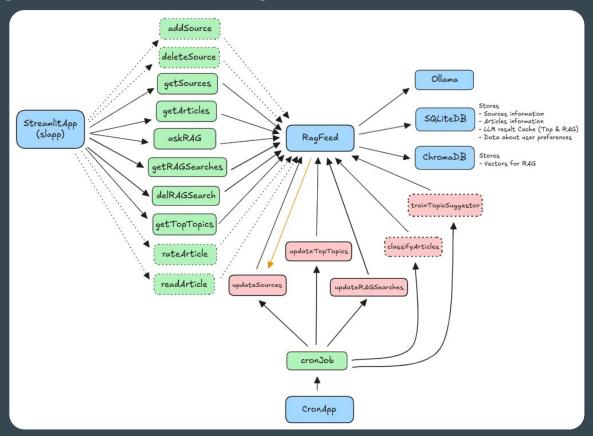
- Llama3.2:3B provide similar results than the previous model with less resources.
- Getting a JSON as answer was easy, ensuring it was correct not.
- I found Streamlit a bit limited in components but I managed to use the default ones.
- Reduced prompt complexity.

4. Integrating RAG Search and LLM GuardRails

- Modified the prompt of the RAG functionality to return a JSON.
- Created the interface in Streamlit, changing the general search for a "follow topic" system.
- Using SQLite database as cache to reduce number of inferences when not needed (and user wait time).
- Implemented a prompt to correct wrong JSON formats returned by RAGSearch and TopTopics.
- Implemented a cron to update RagSearches and TopTopics out of the client.

- Improved app usability.
- Improved reliability of the model results.

App structure and endpoints





Modular Implementation

```
√ slapp

feed.pv
 rag.py
 settings.py
∨ src
 > _pycache_
chromaVectorStore.py
ollamaModel.pv
 RagFeedLogic.py
 rssArticlesLoader.py
 sgliteDatabase.pv
.gitignore
cronapp.py
RagFeed.py

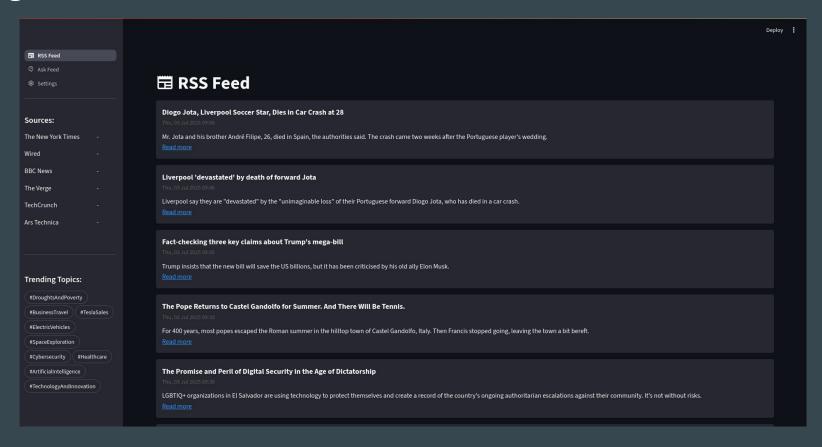
 README.md

    □ requirements.txt

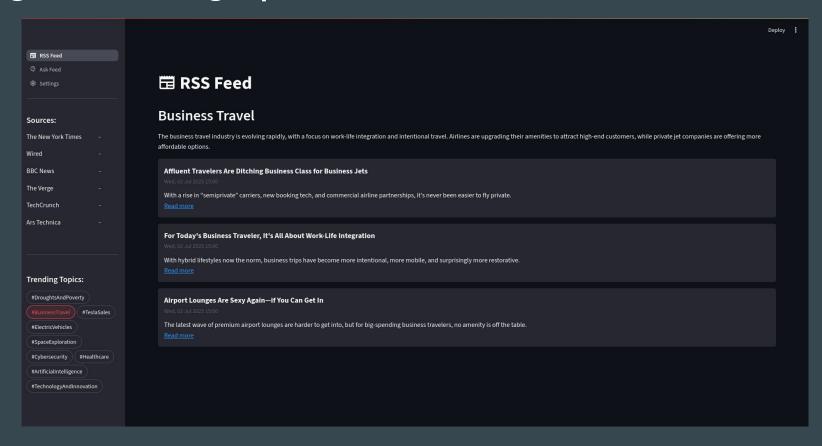
settings.py
slapp.py
```

```
# This class is the main controller of the app
class RagFeed:
       self.log = logging.getLogger(logger path)
       self.log.setLevel(logger level)
       self.log.addHandler(logging.FileHandler(logger path, 'w'))
       self.log.info("\n\n========= RagFit Init ======== \n")
       if database engine == "sqlite":
            from src.sqliteDatabase import SqliteDatabase
            self.database = SqliteDatabase(sqlite path, log=self.log)
           error = f"RagFeed. init : database engine '{database engine}' is not implemented"
           self.log.error(error)
           raise NotImplementedError(error)
       if model source == "ollama":
           from src.ollamaModel import OllamaModel
            self.model = OllamaModel(llm model = ollama llm, embeddings model = ollama embeddings, url = ollama url, log = self.log)
           error = f"RagFeed, init : model source '{model source}' is not implemented"
           self.log.error(error)
           raise NotImplementedError(error)
        if vector store engine == "chroma":
           from src.chromaVectorStore import ChromaVectorStore
           self.vectorstore = ChromaVectorStore(embeddings=self.model.embeddings, collection name=chromadb collection, persist directory=chromadb path, log=self.log)
           error = f"RagFeed. init : database engine '{vector db}' is not implemented"
           self.log.error(error)
           raise NotImplementedError(error)
       self.ragfeedlogic = RagFeedLogic(db = self.database, vs = self.vectorstore, model=self.model, log=self.log, update feg = feeds update freg)
        self.updateSources()
```

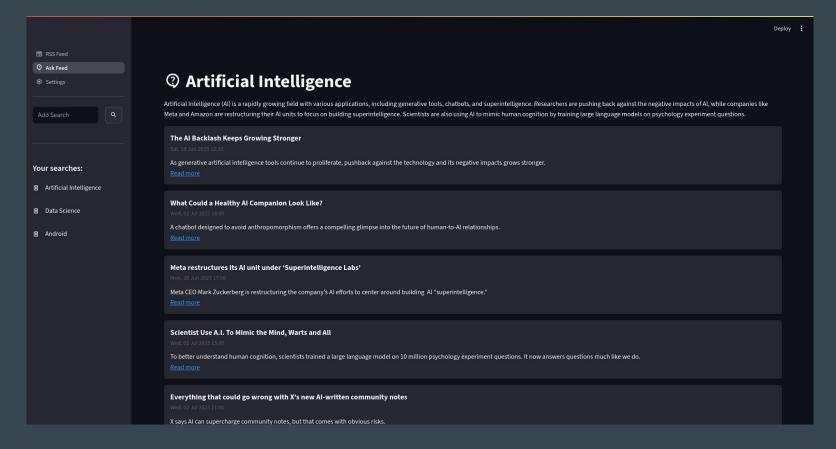
RagFeed - RSS Feed



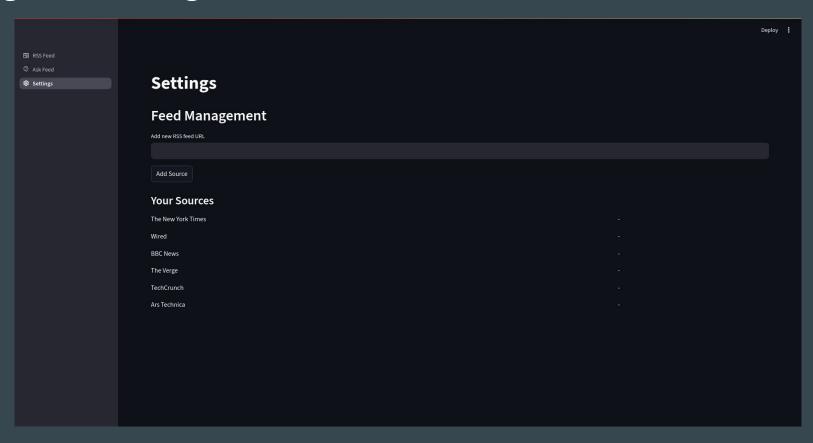
RagFeed - Trending Topics



RagFeed - Ask Rag



RagFeed - Settings



Tools and Technologies

Tools and Technologies

- GenAl: Obtain TopTopics, RagSearch and fix JSON
- RAG: Feed RagSearch
- Ollama: Manage the LLM and Embedder
- LangChain: Manage Documents and Chroma
- ChromaVS: Store the documents for RAG
- SQLite: Store the Articles and Sources data and cache Ilm answers.
- BeautifulSoup: Parse RSS XML to a usable format.
- Streamlit: User front-end.
- Transformers: Count Tokens

Major Obstacle

Ask RAG for Top Topics

- I was expecting a list of topics related to the current date.
- RAG returns documents related to the words "top", "topics" and "today".

- Feed the LLM with data in SQLite to generate TopTopics.
- Won more control on what today mean (last 24h)

UnstructuredXMLLoader documents parse.

- Documents created had no description or link.
- RAG answer were not good and wasn't able to provide the the source.

- Use BeautifulSoup to parse XML.
- Organize the information in the SQLite database.
- Use langchain_core.documents to create documents
 - Decided what data add in page_content and metadata.
 - Decided the format of the data added in VS.

Manage data in Vector Store

- I wasn't able to know what articles were inside Chroma.
- I had to recreate vector store everytime I delete or update articles.
- I was duplicating information (feeding VS directly from RSS).

- Use SQLite as source of documents.
- Use article id as id in vector store so I can delete documents.
- Have a boolean indicator in DB to know if article is in VS

Model inference time

- Ollama requires some time to execute the inference.
- The time vary depending on the length of the prompt.
- Client App (streamlit) might seem freeze while waiting.

- Implemented a cron task to periodically update articles.
- Cron also updates TopTopics and RagSearches when articles were updated.
- SQLite stores the last result so the app don't need to call the model every time.
- Rollback to Llama3.2:8b since 3.1:3b was causing ollama to freeze.

JSON from model inference.

- Model results where good as markdown.
- Transform the answer to a JSON was easy.
- Get a valid JSON (parseable) in the proper format reliably was challenging.

- Reduce model temperature.
- Improved prompting.
- Implemented GuardRails
 - o Prompt focused on fix JSON structure.
 - o Adapted the the code to be flexible to the prompt structure.
 - o Implemented an alternative path to avoid the app to crash.

Conclusions and Insights

Conclusions and Insights

- Developing an application using GenAl as part of the backend is fast.
- Get reliable results from LLM, specially when structured formats are required.
- Working with local models:
 - Start with small models and change to bigger ones if needed (when the prompt is well optimized).
 - Good for an MVP (focus in make the app work first and later optimize it).
 - Makes app hard to deploy.
- RAG is powerful and seems easy but proper document formatting and data management is key.
- Do not focus on getting perfect prompts before integrating with the client.
- Iterate and be flexible with the ideas.
- Implement a logging system soon in your app.

Next Steps

- Improve RSS parse algorithm.
- Source management flow.
- Allow to mark articles as Read/Undead.
- Allow to rate articles interest.
- Internal reader and track number of times an article is open.
- Use the information about RagSearch, interest rate and num times open to train an "Interest Classifier" ML Algorithm.
- Improve app look and feel (especially in light mode).
- Async tasks instead of a cron for updating sources, TopTopic and RagSearch.
- Train an Unsupervised Learning Algorithm to find better categories or articles relations.

Thank you.