Ecometrix Take Home

You will be given a PDF document that contains both textual and graphical data. Your task is to:

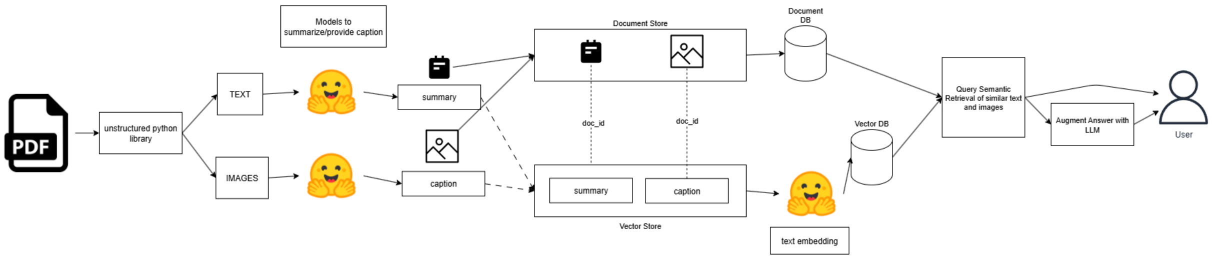
- Extract the textual and graphical information from the PDF pages.
- Convert the extracted graphical data (such as charts or graphs) into a structured, queryable format.
- Implement a system where users can ask questions and receive meaningful responses based on the extracted data.

Requirements:

- Document your approach and display your results in a Jupyter notebook (.ipynb)
- Your solution should allow users to query both the extracted text and any data that was derived from the graphical elements (such as tables).
- Provide brief explanations of your approach, choices made, and any challenges you encountered.

Solution Overview

To tackle the the requirements listed above I will leverage a **Multimodal RAG** (Retrieval Augmented Generation). An overall architecture is shown below:



The diagram starts with the input PDF file. The unstructured Python library is used to extract both textual and image content from the document. Text and image summarization models then generate summaries and captions based on the extracted content. These outputs are stored in a vector database, enabling retrieval in response to user queries. Additionally, a general-purpose LLM can be used to generate answers based on the top documents retrieved from the vector database. This entire multimodal RAG workflow is made possible through extensive use of the LangChain framework, which orchestrates the components for document loading, embedding, retrieval, and response generation.

Environment Setup

Python

- Using Python version 3.9.11
- Create virtual environment and activate
  `python -m venv .venv`
  `.venv/Scripts/activate`
- Install dependencies
  `pip install -r requirements.txt`

Unstructured Python Library dependency to properly read PDF

- Download Poppler extract and put bin directory to your `PATH`
- Download and install Tesseract put bin directory to your `PATH`

Ollama Setup (Will act as LLM generator)

- Install Ollama
- Get a model
  `ollama pull <model_name>`
  e.g. `ollama pull gemma2`
- List models
  `ollama list`

Directory Structure

- `\data\` - Contains the singular PDF file
- `\diagrams\` - Contains supplementary images and drawio diagram
- `helper.py` – Contains utility functions to keep the notebook clean and organized
- `rag_ecometricx.ipynb` - Main jupyter notebook
- `rag_ecometricx.html` - HTML export incase images are broken in notebook
- `rag_ecometricx.pdf` - PDF export incase images are broken in notebook
- `README.md` - README
- `requirements.txt` - Python dependencies

Python Imports

In [1]:
```python
import base64
import uuid
from base64 import b64decode
from io import BytesIO

from IPython.display import HTML, Image, Markdown, display
from transformers import pipeline

from langchain_core.output_parsers import StrOutputParser
from langchain_core.prompts import ChatPromptTemplate
from langchain_core.runnables import RunnableLambda, RunnablePassthrough
from langchain_core.messages import HumanMessage
from langchain_community.embeddings import OllamaEmbeddings
from langchain_community.llms import Ollama
from langchain_huggingface import HuggingFaceEmbeddings
from langchain_chroma import Chroma
from langchain_ollama import OllamaLLM
from langchain.schema.document import Document
from langchain.storage import InMemoryStore
from langchain.retrievers.multi_vector import MultiVectorRetriever

from unstructured.partition.pdf import partition_pdf
from helper import *
```

Set Important Variables

- `pdf_file_path` : Path to the input PDF file.
- `caption_model_name` : Model used for generating captions from images.
- `text_embedding_model_name` : Model for embedding text into vectors for retrieval.
- `ollama_model_name` : Ollama model used for both embedding and answering questions.

In [2]:
```python
pdf_file_path = "data/test_info_extract.pdf"
caption_model_name = "microsoft/git-base"
text_embedding_model_name = "BAAI/bge-large-en-v1.5"
ollama_model_name = "gemma3"
```

Getting Chunks from PDF input

This section uses the unstructured library's `partition_pdf` function to split a PDF into structured chunks (like images and text) for further processing for use in RAG (Retrieval-Augmented Generation)

In [3]:
```python
chunks = partition_pdf(
    filename=pdf_file_path,
    infer_table_structure=True,            # extract tables
    strategy="hi_res",                     # mandatory to infer tables
    extract_image_block_types=["Image"],   # Add 'Table' to list to extract image of tables
    extract_image_block_to_payload=True,   # if true, will extract base64 for API usage
    chunking_strategy="by_title",          # or 'basic'
    max_characters=10000,                  # defaults to 500
    combine_text_under_n_chars=2000,       # defaults to 0
    new_after_n_chars=6000,
)
```

```
The `max_size` parameter is deprecated and will be removed in v4.26. Please specify in `size['longest_edge']` instead`.
```

Check data type of chunks, expecting:

- `unstructured.documents.elements.CompositeElement` (Text and Image)
- `unstructured.documents.elements.Table` (Tables if there are any)

In [4]:
```python
set([str(type(el)) for el in chunks])
```

Out[4]:
```
{"<class 'unstructured.documents.elements.CompositeElement'>"}
```

Looks like we only have images and texts on our chunks. Let's try to see the number of chunks we have:

In [5]:
```python
len(chunks)
```

Out[5]:
```
1
```

I think this is expected as we only have one short PDF file. Let's look at the unique specific types we have under `CompositeElement` :

In [6]:
```python
set([type(element).__module__ + "." + type(element).__name__ for element in chunks[0].metadata.orig_elements])
```

Out[6]:
```
{'unstructured.documents.elements.Image',
 'unstructured.documents.elements.NarrativeText',
 'unstructured.documents.elements.Text',
 'unstructured.documents.elements.Title'}
```

It`s composed of tmages and various textual types.

Segregating Images and Texts

Separating Tables from Texts

Since there are no tables tables chunk is empty and so most of the contents will be inside `texts`

In [7]:
```
tables = []
texts = []

for chunk in chunks:
    if "Table" in str(type(chunk)):
        tables.append(chunk)

    if "CompositeElement" in str(type((chunk))):
        texts.append(chunk)
```

In [8]:
```
print(len(tables))
print(len(texts))
```

```
0
1
```

Getting Images

Getting images from our chunk we have 11 images extracted

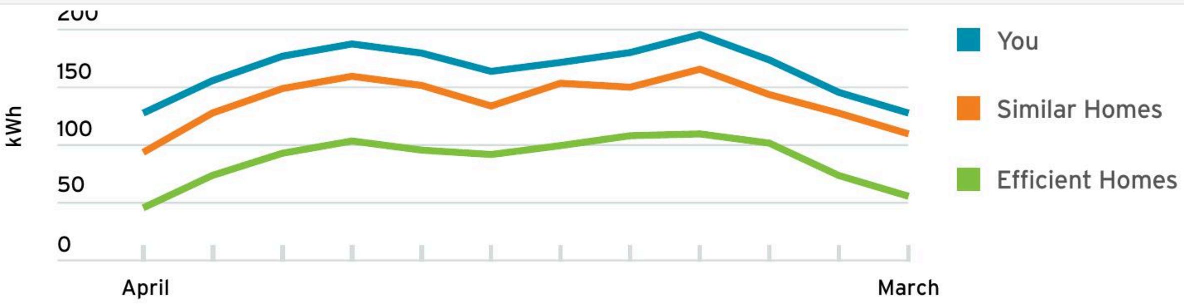
In [9]:
```
images = get_images_base64(chunks)
```

In [10]:
```
len(images)
```

Out[10]:
```
11
```

Displaying an image for us to inspect

In [11]:
```
display_base64_image(images[7])
```



Text Summary and Image Caption

Text Summary

For the text summary, I'll use the original text itself as its own description since the content is brief and doesn't require further summarization.

In [12]:
```
text_summary = [i.text for i in chunks]
```

Image captioning

For image captioning, I will be using a HuggingFace model (microsoft/git-base) to do simple image captioning, this is not really a super good model for captioning and describing images like charts but its good enough for now as some image to text models are behind a pay wall like OpenAI which can be better in captioning.

In [13]:
```
captioner = pipeline(
    "image-to-text",
    model="microsoft/git-base",
    device=0,
    use_fast=True
)
img_cap_list = []
for image in images:
    caption = captioner(image)[0]["generated_text"]
    img_cap_list.append(caption)
```

```
Using a slow image processor as `use_fast` is unset and a slow processor was saved with this model. `use_fast=True` will be the default behavior i
n v4.52, even if the model was saved with a slow processor. This will result in minor differences in outputs. You'll still be able to use a slow p
rocessor with `use_fast=False`.
Device set to use cpu
```

Checking the caption on the displayed image of a chart earlier:

In [14]:
```
img_cap_list[7]
```

Out[14]:
```
'a line graph showing the line of the line.'
```

It's kinda good but not good enough. For the purpose of getting a good retreival in the later steps lets just assume our captioning model did great and made this caption:

In [15]:
```
img_cap_list[7] = "line graph showing electricity consumption"
```

Setting Up the Vector and Document Store

Here, we use ChromaDB as the vector store and an in-memory store for the documents. Each summary and corresponding document will be assigned a doc_id to support retrieval later on.

In [16]:
```
embeddings = HuggingFaceEmbeddings(model_name='BAAI/bge-large-en-v1.5')

vector_store = Chroma(
    collection_name="rag_vector_store",
    embedding_function=embeddings,
)
store = InMemoryStore()
id_key = "doc_id"

retriever = MultiVectorRetriever(
    vectorstore=vector_store,
    docstore=store,
    id_key=id_key,
)
```

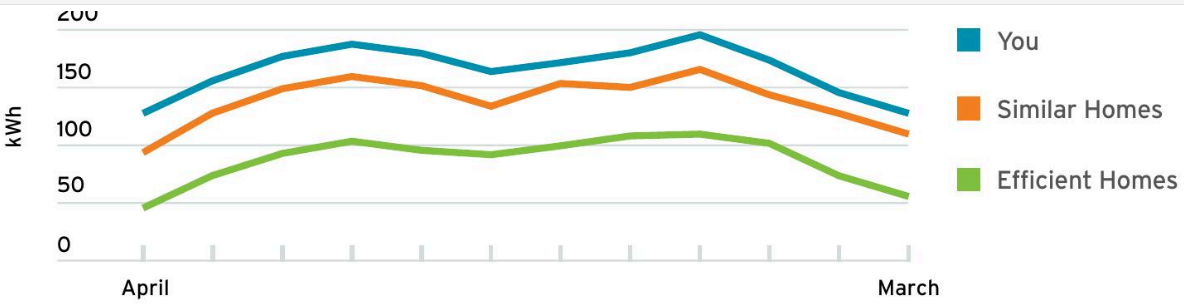
In [17]:
```
doc_ids = [str(uuid.uuid4()) for _ in texts]
summary_texts = [
    Document(page_content=summary, metadata={id_key: doc_ids[i]}) for i, summary in enumerate(text_summary)
]
retriever.vectorstore.add_documents(summary_texts)
retriever.docstore.mset(list(zip(doc_ids, texts)))

img_ids = [str(uuid.uuid4()) for _ in images]
summary_img = [
    Document(page_content=summary, metadata={id_key: img_ids[i]}) for i, summary in enumerate(img_cap_list)
]
retriever.vectorstore.add_documents(summary_img)
retriever.docstore.mset(list(zip(img_ids, images)))
```

Retrieval from the Vector and Document Store using Query

Remember the caption we overwritten earlier? We now want to ask out PDF to display us our electricity consumption graph

In [18]:
```
display_base64_image(retriever.invoke("Image of graph containing elecricity consumption?")[0])
```



Seems like we got our graph and the vector store is returning the top document associated with our query.

Full RAG with Ollama (gemma3) Question and Answering

This defines a LangChain-style RAG pipeline for LLM question answering. It retrieves relevant documents from the vector store using the user's question, parses the retrieved content (`parse_docs`), constructs a prompt (`build_prompt`), and sends it to an Ollama-hosted LLM (OllamaLLM). The final answer is then parsed into a string using `StrOutputParser()` . The use of `RunnableLambda` and `RunnablePassthrough()` allows flexible chaining of custom functions and inputs in the LangChain pipeline. I set the LLM's `tempreture` param to 0 for the output to be consistent on repeated runs.

In [19]:
```
chain_llm_questions = {
    "context": retriever | RunnableLambda(parse_docs),
    "question": RunnablePassthrough(),
} | RunnableLambda(build_prompt) | OllamaLLM(
    model=ollama_model_name,
    temperature=0,
) | StrOutputParser()
```

In the section below we will be assessing the performance of our makeshift RAG solution with a few questions based on our PDF.

Q1: What is the customer name, address and account id?

In [20]:
```
display(Markdown(chain_llm_questions.invoke("What is the customer name, address, month cycle and account id?")))
```

Here's the information based on the provided context:

- **Customer Name:** JILL DOE
- **Service Address:** 1627 Tulip Lane
- **Month Cycle:** March
- **Account ID:** 954137

Our RAG solution did well on this extract! The information perfectly aligns what is in the PDF!

Home Energy Report:
electricity
March report
Account number: 954137
Service address: 1627 Tulip Lane

Dear **JILL DOE**, here is your usage analysis for March.

Q2: What is the category of my electric use?

In [21]:
```
display(Markdown(chain_llm_questions.invoke("What is the category of my electric use?")))
```

Above typical use.

Our RAG solution also did well on this extract! The information perfectly aligns what is in the PDF

Your electric use:

Above typical use

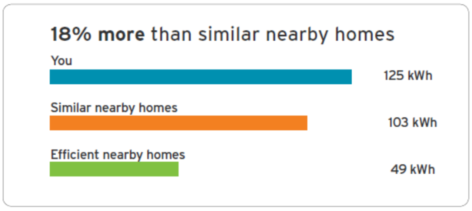
Q3: What is my electricity usage this cycle in kWh?

In [22]:
```
display(Markdown(chain_llm_questions.invoke("What is my electricity usage this cycle in kWh?")))
```

Your electric use: 18% more than similar nearby homes 125 kWh

---

Quite close but not quite. I was expecting here that the RAG solution would just say the customer consumed 125 kWh. It seems that in this generation it hallucinated a bit.



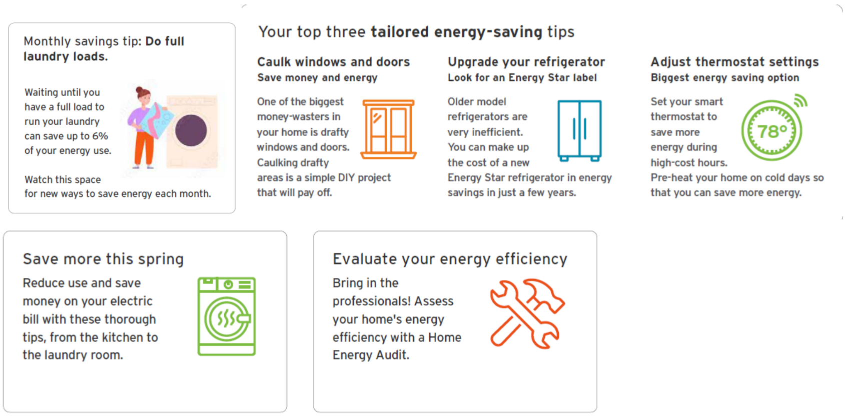
Q4: What are some tips for saving electricity?

In [23]:
```
display(Markdown(chain_llm_questions.invoke("What are some tips for saving electricity?")))
```

Here are the tips for saving electricity based on the provided text:

- Do full laundry loads.
- Caulk windows and doors.
- Charge your EV overnight (Rates are lower after 9pm).
- Look for an Energy Star label.
- Adjust thermostat settings.
- Pre-heat your home on cold days.

Our RAG solution also did well here it matched with the suggestions in our PDF document and some generally good tips augmented from the LLM.

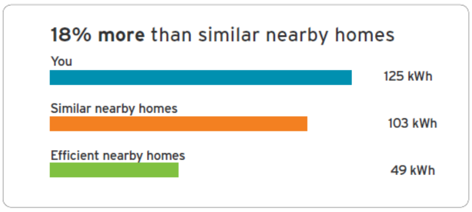


Q5: How do I compare to other nearby homes in kwh consumption?

In [24]:
```
display(Markdown(chain_llm_questions.invoke("How do I compare to other nearby homes in kwh consumption?")))
```

According to the report, you used 18% more than similar nearby homes. Your similar nearby homes used 125 kWh, and efficient nearby homes used 103 kWh and 49 kWh.

Our RAG solution almost made it here. It incorrectly associated 125 kWH usage to similar nearby homes instead of it being our consumption and associated the 2 values (103 kWh and 49 kWh) for efficient nearby homes. Only 49 kWh should be associated with efficient nearby homes and 103 kWh should have been associated with similar nearby homes. Unfortunately this one also hallucinated a bit.



Learnings, Challenges and Suggestions

Learnings

I was first introduced to Retrieval-Augmented Generation (RAG) during my Natural Language Processing course in my master's program. Most of the implementations I worked on involved textual data using the llama-index framework, typically sourced from PDFs, arXiv articles, and plain text files. Until recently, I hadn't explored the extraction of images, figures, or charts. Learning to implement RAG using a new framework like LangChain, especially in a multimodal context that supports various document types beyond text, has been a fresh and exciting experience for me.

Challenges and Suggestions

This pipeline required handling multiple modalities, including:

- Text summarization
- Image captioning
- Text embedding for similarity
- LLM-based question answering

One of the key challenges was selecting the right open-source models. HuggingFace offers many options, but it's often unclear which are best, especially for free use. Most tutorials rely on high-end models from providers like OpenAI, many of which are behind paywalls most especially for image based tasks.

I experimented with several models and combined them to achieve acceptable results. However, the LLM in the RAG setup was prone to hallucinations. To improve this, fine-tuning—possibly with instruction tuning techniques like Large-Scale Instruction Synthesis could help reduce errors.

Lastly, extracting content from PDFs posed its own issues. While text extraction worked well, image and chart extraction using the `unstructured` python library (likely backed by Tesseract OCR) was less reliable and may require further tuning or alternative tools.

References

[1] LangChain - Semi-structured and Multi-modal RAG

[2] How to retrieve using multiple vectors per document

[3] Multi-Modal RAG: A Practical Guide – Using vLLM to serve models for Multimodal Text Summarization, Table Processing, and Answer Synthesis