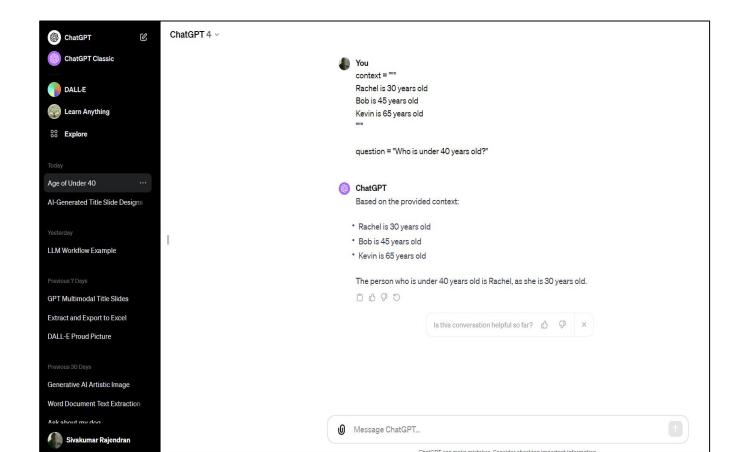


From Developer lens

Let understand Interacting with LLM through UI vs Code

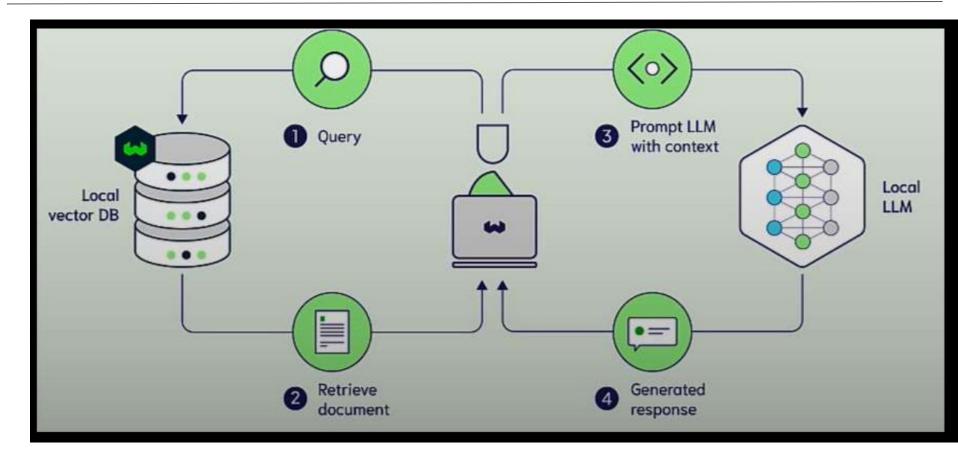


```
Simple Q&A Example
         Here let's review the convention of llm(your context + your question) = your answer
In [13]:
          from langchain.llms import OpenAI
          llm = OpenAI(temperature=0, openai api key=openai api key)
In [14]:
          context = """
          Rachel is 30 years old
          Bob is 45 years old
          Kevin is 65 years old
          question = "Who is under 40 years old?"
         Then combine them.
In [15]:
          output = llm(context + question)
          # I strip the text to remove the leading and trailing whitespace
          print (output.strip())
        Rachel is under 40 years old.
```

Hence, accessing the LLM through Code is not as easy as accessing through Web UI.

It requires a different mindset, different workflow and different skillset.

Building Block of LLM



Let observe few Code snippets

```
# Sample code to illustrate the stages in building an LLM
application
                                                                                   application
#1. Document Loader
                                                                                   #1. Document Loader
def load documents(file paths):
  documents = \Pi
                                                                                     documents = []
  for path in file paths:
                                                                                     for path in file paths:
    with open(path, 'r') as file:
       documents.append(file.read())
                                                                                     return documents
  return documents
#2. Embedding
                                                                                   #2. Embedding
def embed documents(documents):
  # Placeholder for a complex embedding process
  embeddings = ["embedding" + str(i) for i, in
enumerate(documents)]
                                                                                   enumerate(documents)]
  return embeddings
                                                                                     return embeddings
#3. Indexing
                                                                                   #3. Indexing
def index_embeddings(embeddings):
  # Placeholder for an indexing mechanism
  indexed embeddings = {i: embeddings[i] for i in
range(len(embeddings))}
  return indexed embeddings
#4. Querying
                                                                                   #4. Querying
def process query(query):
  # Placeholder for query processing
  query_embedding = "query_embedding"
  return query embedding
#5 Retrieval
                                                                                   #5 Retrieval
def retrieve documents(query embedding,
indexed embeddings):
                                                                                   indexed embeddings):
  # Placeholder for document retrieval logic
  relevant documents = ["doc1", "doc2"] # Example of
```

```
# Sample code to illustrate the stages in building an LLM
def load documents(file paths):
    with open(path, 'r') as file:
       documents.append(file.read())
def embed documents(documents):
  # Placeholder for a complex embedding process
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  # Placeholder for an indexing mechanism
  indexed embeddings = {i: embeddings[i] for i in
range(len(embeddings))}
  return indexed embeddings
def process query(query):
  # Placeholder for query processing
  query embedding = "query embedding"
  return query embedding
def retrieve documents(query embedding,
  # Placeholder for document retrieval logic
  relevant documents = ["doc1", "doc2"] # Example of
```

If the architecture is Complex to get start with, let's do a reverse engineering.

Start with a LLM code and modularize that

LLM: At the heart of the system is the LLM, the core Al model responsible for generating human-like text responses.

Document Loader: With vast amounts of data to process, the Document Loader is essential. It imports and reads documents, preparing them for chunking and embedding.

Document Chunker: To make the data more manageable and efficient for retrieval, the Document Chunker breaks documents into smaller, more digestible pieces.

Embedder: Before storing or retrieving data, we need to convert textual information into a format the system can understand. The Embedder takes on this role, transforming text into vector representations.

Vector Store: This is where the magic happens. The Vector Store is a dedicated storage system that houses embeddings and their corresponding textual data, ensuring quick and efficient retrieval.

Vector Store Retriever: Think of this as the search engine of the system. The Vector Store Retriever fetches relevant documents by comparing vector similarities, ensuring that the most pertinent information is always at hand.

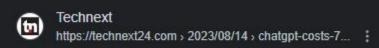
Prompt: Every interaction starts with a user's query or statement. The Prompt captures this initial input, setting the stage for the retrieval and generation processes.

User Input: Last but not least, the User Input tool captures the query or statement provided by the end-user, initiating the entire RAG process.

Can I build a new LLM and the application?

How much did it cost to develop GPT-3?

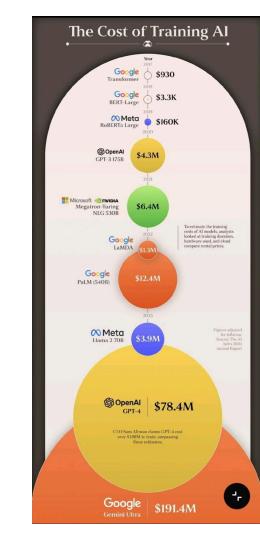
According to OpenAI, the research organization responsible for developing GPT-3, the project's total cost is estimated to be around \$4.6 million. This includes not only the cost of developing the model itself but also the cost of training it using massive amounts of data.

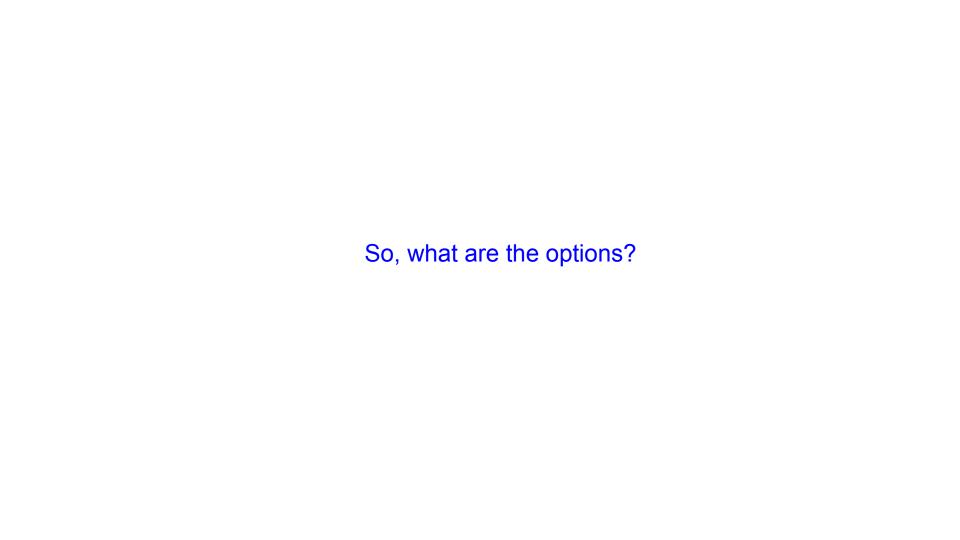


ChatGPT costs \$700000 to run daily, OpenAI may go ...

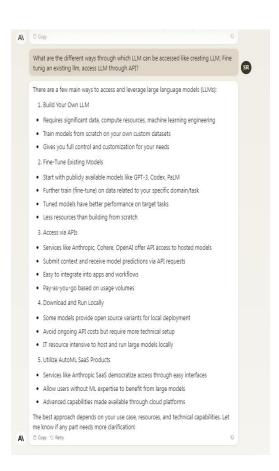
Challenges

Budget Infrastructure Skillset ROI Success/ Guaranteed Result?!





Different ways of accessing LLM



There are a few main ways to access and leverage large language models (LLMs):

1. Build Your Own LLM

- Requires significant data, compute resources, machine learning engineering
- Train models from scratch on your own custom datasets
- Gives you full control and customization for your needs

2. Fine-Tune Existing Models

- Start with publicly available models like GPT-3, Codex, PaLM
- Further train (fine-tune) on data related to your specific domain/task
- Tuned models have better performance on target tasks
- Less resources than building from scratch

3. Access via APIs

- Services like Anthropic, Cohere, OpenAI offer API access to hosted models
- Submit context and receive model predictions via API requests
- Easy to integrate into apps and workflows
- Pay-as-you-go based on usage volumes

4. Download and Run Locally

- Some models provide open source variants for local deployment
- Avoid ongoing API costs but require more technical setup
- IT resource intensive to host and run large models locally

5. Utilize AutoML SaaS Products

- Services like Anthropic SaaS democratize access through easy interfaces
- Allow users without ML expertise to benefit from large models
- Advanced capabilities made available through cloud platforms

The best approach depends on your use case, resources, and technical capabilities. Let me know if any part necessary more clarification!



Why Organizations still find it hard to embrace and implement GenAl?





How **Intelligence** works



Q 20K

17 33K

♥ 333K

III 39M

□ 土

HALLUCINATION

"https://www.youtube.com/watch?v=cn5QSQNEr4c

"https://www.youtube.com/watch?v=4WDIMhaxF_q"

COMPLIANCE

"https://www.youtube.com/watch?v=22gobhdavRw""

The above video links are used only for Educational purpose



You

The emphatically male surgeon who is also the boy's father says, "I can't operate on this boy! He's my son!" How is this possible?

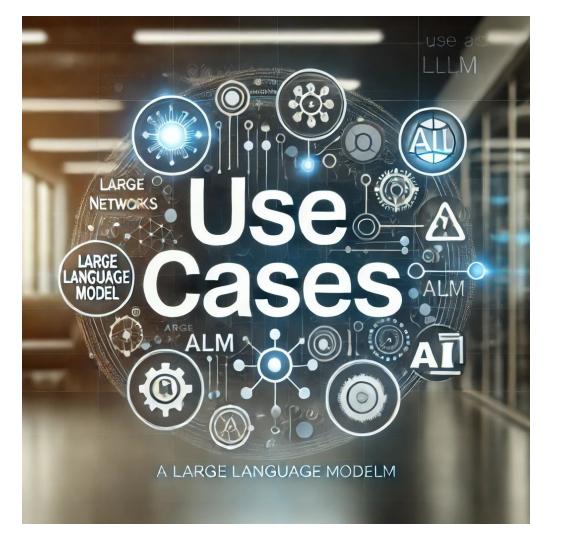


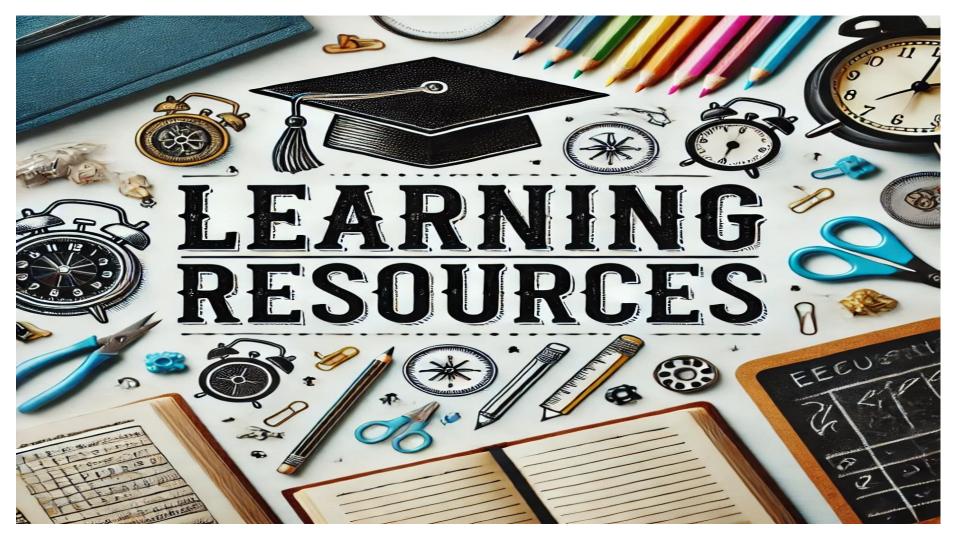


ChatGPT

The surgeon is the boy's mother.







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Meetups

