Applied Machine Learning for Business Analytics

Lecture 5: Improving LLM’s performance

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Agenda

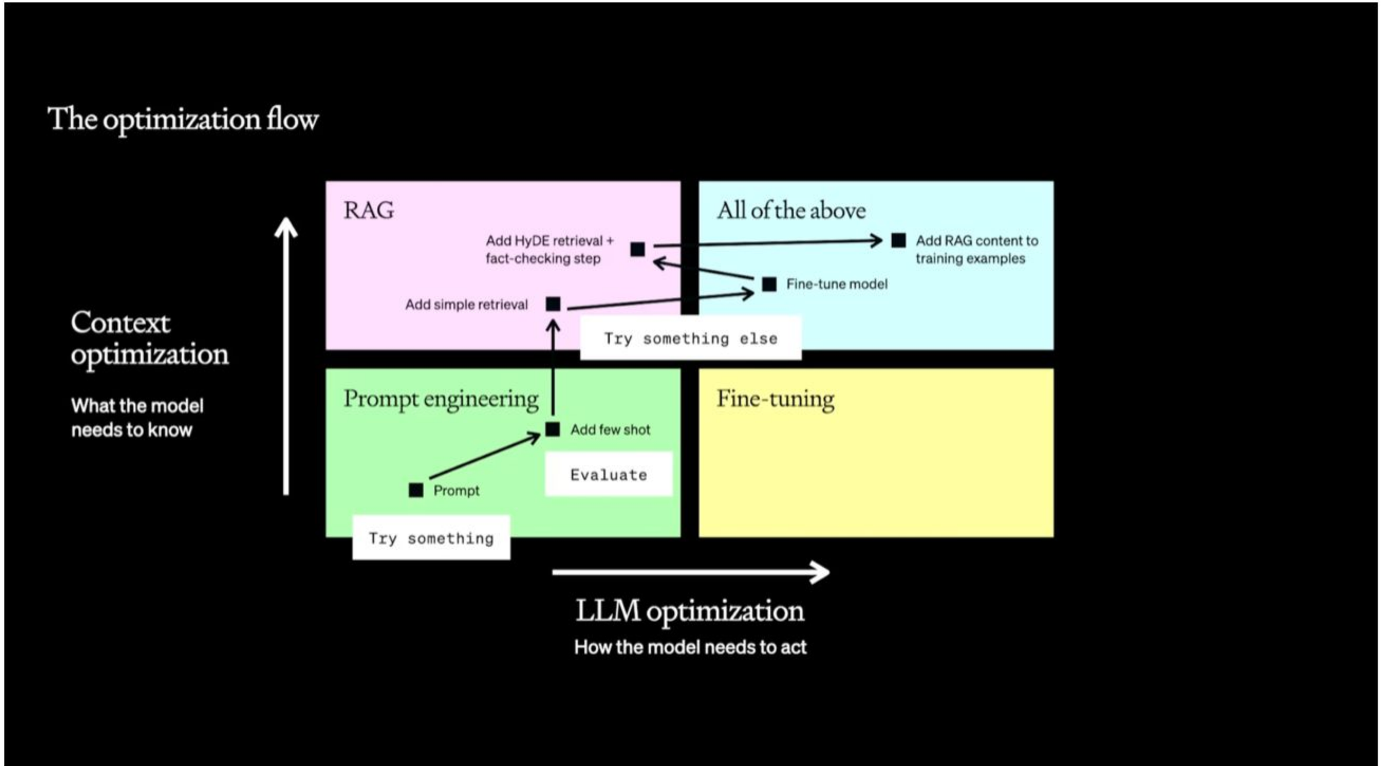
1. Improving LLMs’ performance
2. Evaluating LLMs’ performance
3. Prompt engineering
4. RAG

1. Improving LLM’s performance

Optimization options

- **Prompt engineering**
  - Modify the prompt to guide the LLM's outputs
- **Retrieval-augmented generation**
  - Use the retriever to get external knowledge to enrich the context for LLM
- Fine tuning
  - Tune the LLM (its parameters) to better suit downstream applications

Iterative process



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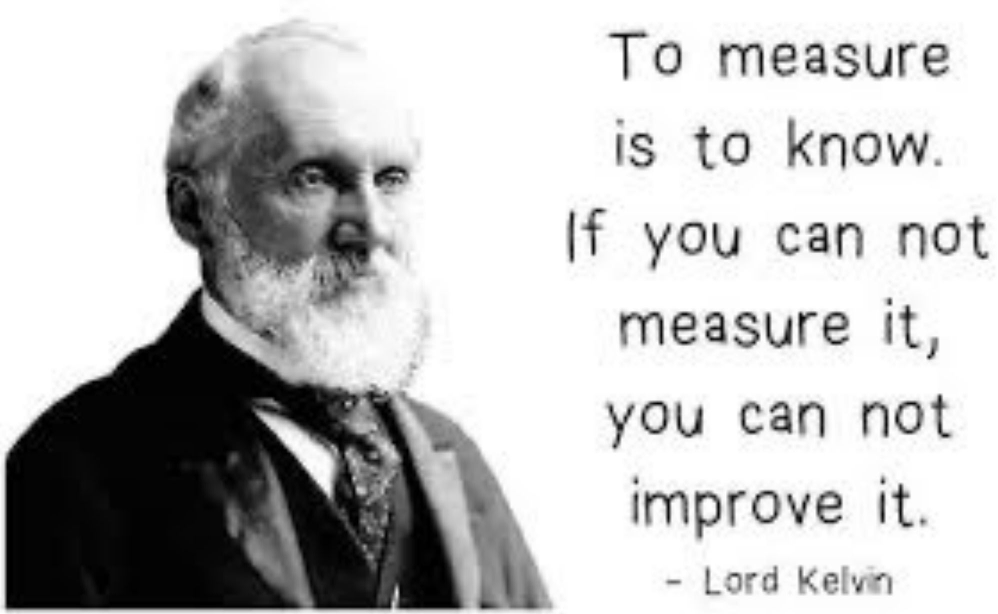

To measure
is to know.
If you can not
measure it,
you can not
improve it.
- Lord Kelvin

2. Evaluating LLM

Evaluating LLM

- Model-based evaluation
  - Use another LLM to evaluate the system's performances
- Rule-based evaluation
  - Implement heuristic rule to assess specific aspects of the LLM's output
- Accuracy metrics
  - If the task has clear labels, metrics can be used such as F1, precision and recall
- End-user feedback and A/B testing

“Accuracy” Metrics

- Evaluation on standardized benchmarks across all of NLP tasks
- Model Eval Benchmarks
  - GLUE: General language understanding evaluation benchmark provides a standardized set of diverse NLP tasks to evaluate the effectiveness of different language models
  - HellaSwag: evaluates how well an LLM can complete a sentence
  - TruthfulQA: measure truthfulness of model responses

End-user Feedback

- It is the process involving automatic evaluators triggered by new log entries derived from live production
- List of metrics as examples:
  - User engagement & utility metrics: number of views
  - User interaction: average number of LLM conversion per user
  - Quality of responses: average length of prompts and responses
  - User feedback and retention: user return rate
  - Performance metrics : latency
  - Cost metrics : infra cost (storage, networks, and computing resources, etc)
  - More metrics could be found here

3. Prompt engineering

Prompt engineering (Do it first)

- It refers to methods for how to communicate with LLM to steer its behavior for desired outcomes without updating the model
  - More empirical, less scientific
- Advantages
  - Testing and learning early
  - When paired with evaluation it provides your baseline and sets up further optimization
- Disadvantages
  - Introducing new information
  - Reliably replicating a complex style or method
  - Minimizing token usage

How to prepare a good prompt

- Start with:
  - Write clear instructions
  - Split complex tasks into simpler subtasks
  - Give GPTs time to “think”
  - Test changes systematically
- Extend to:
  - Provide reference text
    - Few-shot prompt -> RAG
  - Use external tools

Intuition behind Prompt Engineering

- LLMs understand better when you use familiar language and constructs
- LLMs can not know everything. If information is neither in training or in the prompt, they do not know it
- If you look at Prompt and you do not understand it, the prompt can not work

A “bad” prompt

You

You will be presented with a news article. Extract useful information in a structured format.

The article starts as below:
"Match-winner Gabriel Martinelli told Sky Sports: "I am not the man. I think everyone has a part in this victory. I scored the goal but it was the whole team and the staff and everyone. I am happy and the team is too.
Arsenal forward Gabriel Jesus added: "For sure it is a big win. Everyone knows how hard it is to play against them. But it is not impossible to beat them.

Unclear instructions

ChatGPT

Sure, I can extract useful information from the provided news article:

Event: Arsenal's victory in a match.

Date of the Event: Not mentioned in the provided text.

Quotes from the Players:

1. Gabriel Martinelli said, "I am not the man. I think everyone has a part in this victory. I scored the goal but it was the whole team and the staff and everyone. I am happy, and the team is too."
2. Gabriel Jesus (Arsenal forward) added, "For sure it is a big win. Everyone knows how hard it is to play against them. But it is not impossible to beat them."

Key Points:

- Gabriel Martinelli emphasized the collective effort of the team, staff, and everyone in the victory.
- Gabriel Jesus acknowledged the difficulty of playing against the opposing team but expressed confidence in their ability to win.

Random output

A “good” prompt

You

You will be presented with a news article about a scorer match. Your task is to identify any opinions expressed about the match, and their sentiment.

Clear instructions

Approach this task step-by-step, take your time and don not skip steps:

Give time to think

1. Read a line of news article
2. Determine whether an opinion is expressed in this paragraph. If not, continue to the next line.
3. If there is an opinion, extract a JSON with keys as follows:
   * opinion: allowable values are “positive”, “negative” or “neutral”
   * evidence: contain a list of strings evidencing the opinion.
   * speaker: the person who expressed the opinion.
4. Include as much evidence as possible and make sure the output is in JSON format

Break down complex tasks

The article starts as below:
"Match-winner Gabriel Martinelli told Sky Sports: "I am not the man. I think everyone has a part in this victory. I scored the goal but it was the whole team and the staff and everyone. I am happy and the team is too.
Arsenal forward Gabriel Jesus added: "For sure it is a big win. Everyone knows how hard it is to play against them. But it is not impossible to beat them.

A “good” prompt

ChatGPT

Let's go through the article step by step to identify any opinions expressed and their sentiment:

1. Read a line of the news article:
   "Match-winner Gabriel Martinelli told Sky Sports: 'I am not the man. I think everyone has a part in this victory. I scored the goal but it was the whole team and the staff and everyone. I am happy and the team is too.'"
2. Determine whether an opinion is expressed in this paragraph:
   Yes, an opinion is expressed in this paragraph. The opinion is about the match victory being a collective effort and not solely attributed to Gabriel Martinelli.
3. Extract a JSON with keys as follows:
   - opinion: "positive" (the sentiment is positive as Martinelli expresses happiness about the team's victory)
   - evidence: ["I am not the man.", "everyone has a part in this victory.", "I scored the goal but it was the whole team and the staff and everyone.", "I am happy and the team is too."]
   - speaker: "Gabriel Martinelli"

Next, let's continue to the next line of the article:

1. Read a line of the news article:
   "Arsenal forward Gabriel Jesus added: 'For sure it is a big win. Everyone knows how hard it is to play against them. But it is not impossible to beat them.'"
2. Determine whether an opinion is expressed in this paragraph:
   Yes, an opinion is expressed in this paragraph. Gabriel Jesus expresses the opinion that it is a significant win and that it is not impossible to beat the opposing team.
3. Extract a JSON with keys as follows:
   - opinion: "positive" (the sentiment is positive as Gabriel Jesus considers the win significant)
   - evidence: ["For sure it is a big win.", "Everyone knows how hard it is to play against them.", "But it is not impossible to beat them."]
   - speaker: "Gabriel Jesus"

So, here are the JSON representations of the opinions expressed in the article:

Opinion 1:

json Copy code

```json
{
  "opinion": "positive",
  "evidence": [
    "I am not the man.",
    "everyone has a part in this victory.",
    "I scored the goal but it was the whole team and the s
    "I am happy and the team is too."
  ],
  "speaker": "Gabriel Martinelli"
}
```

Opinion 2:

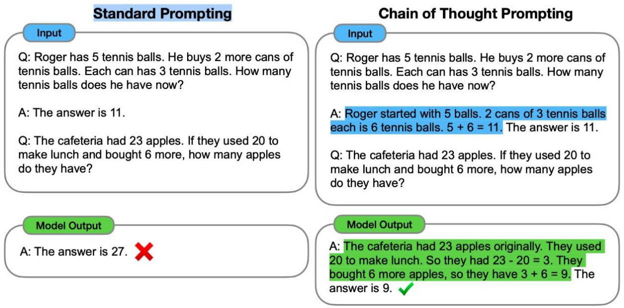
json Copy code

```json
{
  "opinion": "positive",
  "evidence": [
    "For sure it is a big win.",
    "Everyone knows how hard it is to play against them.",
    "But it is not impossible to beat them."
  ],
  "speaker": "Gabriel Jesus"
}
```

These JSONs represent the opinions and sentiments expressed by the mentioned individuals in the article.

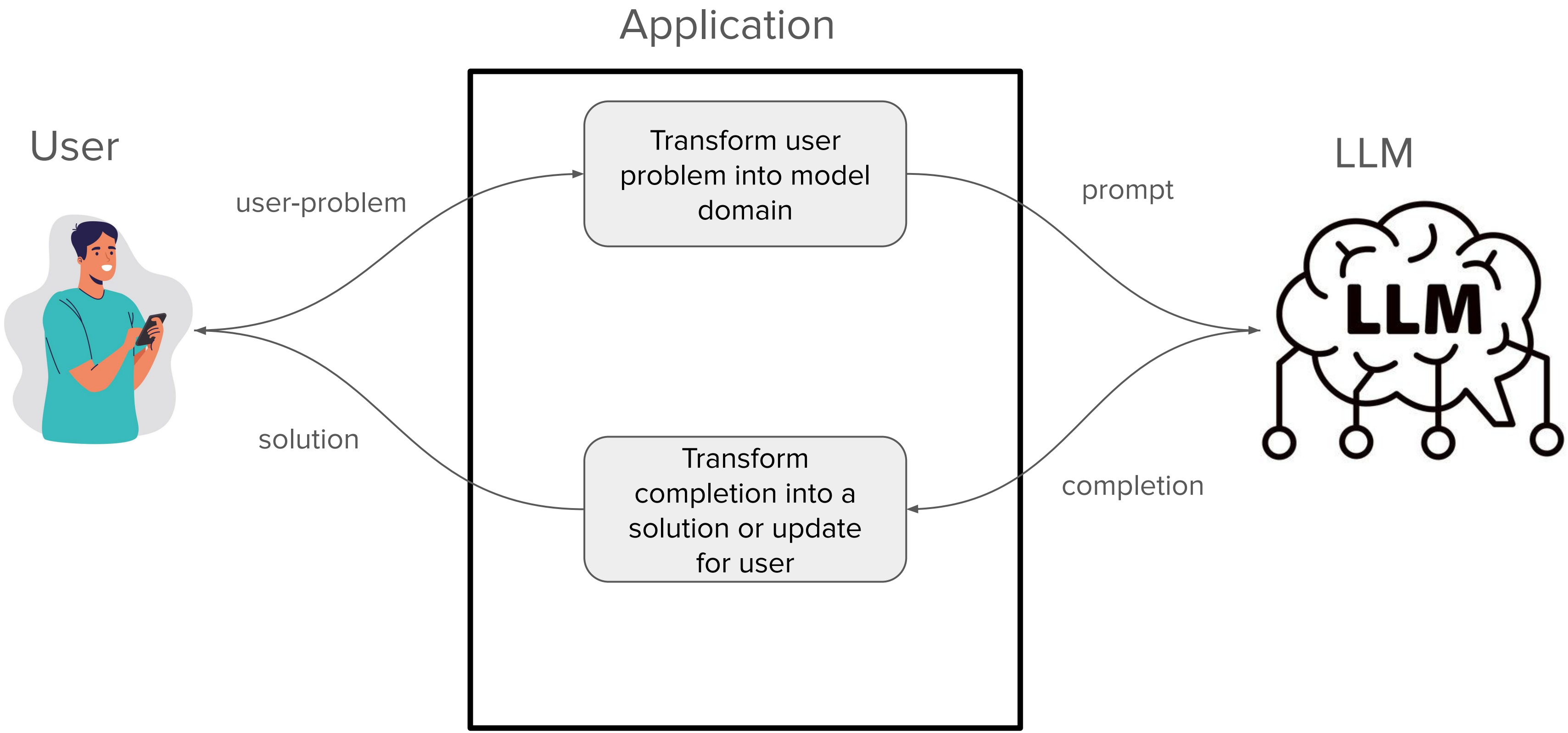
Prompting techniques

- Zero-shot prompting
  - No examples are given in prompt
- Few-shot prompting
  - A few shot examples of tasks are provided
- Chain of Thoughts prompting
  - Examples with the reasoning processes are improved.
- More prompting techniques could be found in this good survey and this openAI blog.



Source: https://arxiv.org/abs/2201.11903

Building LLM Applications



Creating the Prompt

- Create context
- Rank context
- Trim context
- Assembling context

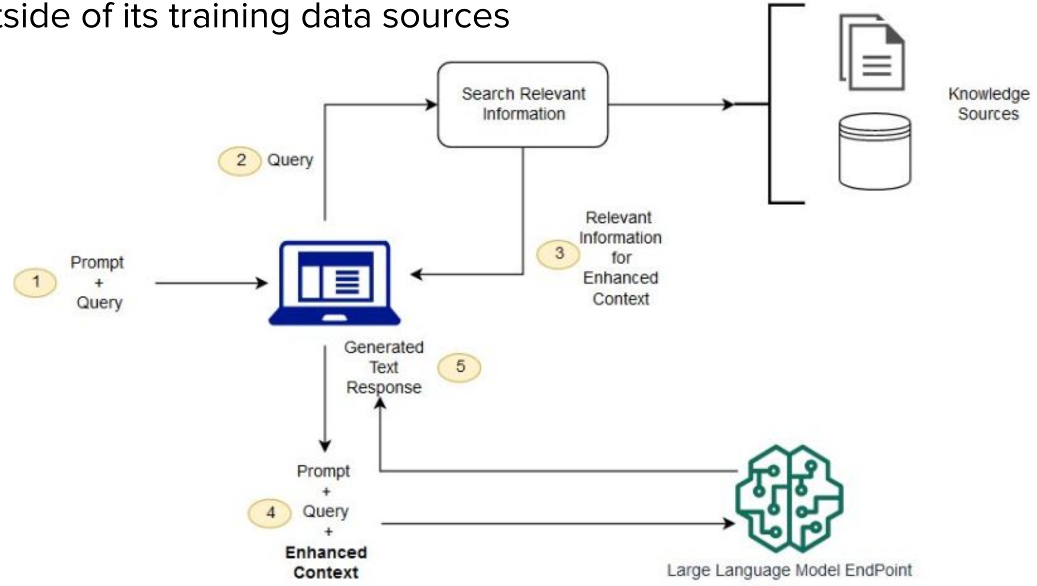
Creating the Prompt - Copilot Example

- Create context
  - Current document, open tabs, symbols, file path
- Rank context
  - Filter path >> current documents >> open tabs
- Trim context
  - Drop open tab snippets, truncate current documents
- Assembling context

4. RAG

What is RAG

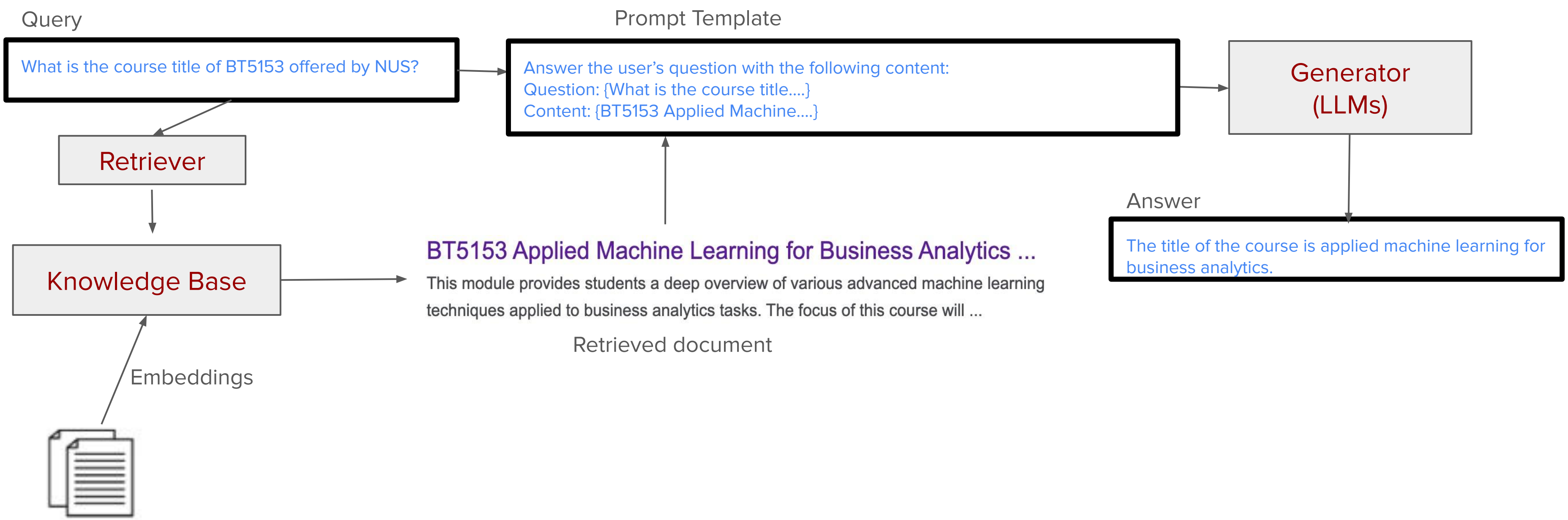
- Retrieval-Augmented Generation
  - A process to optimize the output of a LLM, so it references an authoritative knowledge base outside of its training data sources before responding.
- Benefits of RAG
  - Cost-effective implementation
  - Current information
  - Enhanced user trust
  - More develop control



source: https://aws.amazon.com/what-is/retrieval-augmented-generation/

One trivial example

- LLM is trained before the course website was built



It can be in webpage, pdf files, or even images/videos.

Old wine in new bottles

- RAG is not:
  - A new idea
  - A framework
- RAG is just combining Retrieval and Generation
  - Retrieval comes from Information Retrieval (IR):
    - The process of obtaining relevant information based on a user' information need expressed as a query/question
    - It is a research topic in computer science for decades
  - Generation is handled by LLMs

“Good” RAG

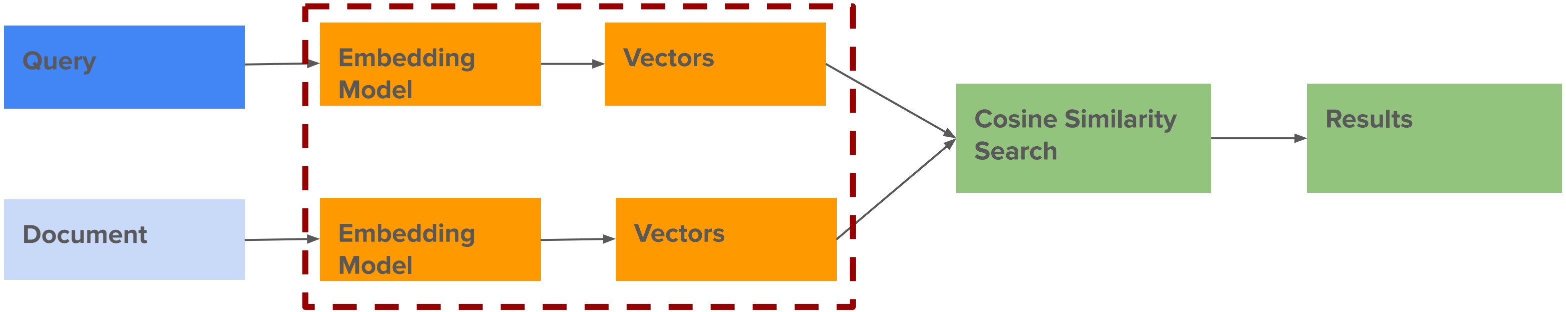
- **Good retrieval pipeline**
- Good generative model
- Good way of linking them up

Performance issues with Naive RAG

- Bad Retrieval
  - Low precision: not all retrieved chunks are relevant
    - Hallucination + Wrong replies
  - Low recall: not all relevant chunks are retrieved
    - Lacks enough context for LLM to synthesize the answer
  - Outdated information: the knowledge base is out of date
- Bad Response Generation (Native LLM Issues)
  - Hallucination: Model makes up an answer that isn’t in the context
  - Irrelevance: Model makes up an answer that does not answer the question
  - Toxicity/Bias: Model makes up an answer that is offensive

Start from Basic - Retrieval Pipeline

This is called a Bi-encoder approach



Start from Basic - Retrieval Pipeline

```python
from sentence_transformers import SentenceTransformer
model = SentenceTransformer('paraphrase-MiniLM-L6-v2')
```

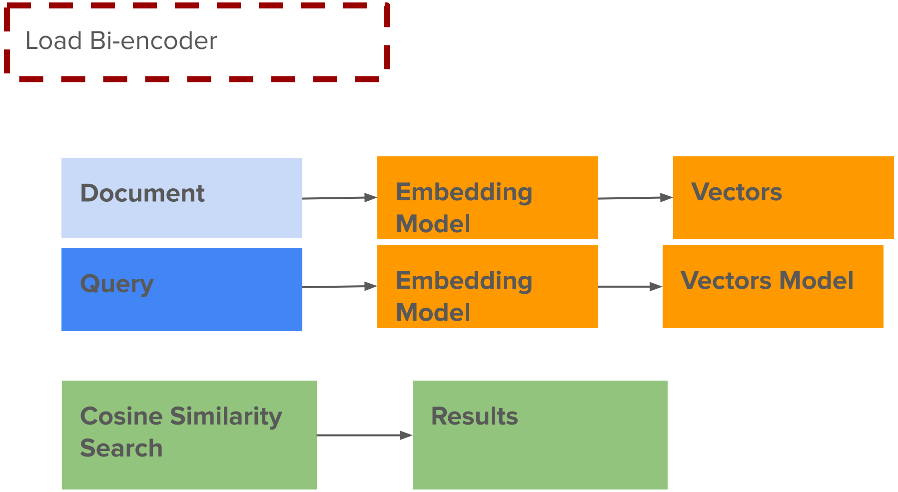
```python
[3] from wikipediaapi import Wikipedia
wiki = Wikipedia('RAGBot/0.0', 'en')
doc = wiki.page('Bukayo_Saka').text
paragraphs = doc.split('\n\n')
```

```python
[4] docs_embed= model.encode(paragraphs,normalize_embeddings=True)
```

```python
[5] # Embedt h equery
query = "How old is Saka?"
query_embed= model.encode(query,normalize_embeddings=True)
```

```python
[6] import numpy as np
import torch

similarities= np.dot(docs_embed,query_embed.T)
# Convert the NumPy array to a PyTorch tensor
similarities_tensor = torch.tensor(similarities)
# Now apply topk to the tensor
top_3_idx= similarities_tensor.topk(3).indices.tolist()
most_similar_documents= [paragraphs[idx] for idx in top_3_idx]
```



Vector DB

- As the crucial part of RAG pipeline, search index supports the retrieval of content based on query
  - Indexing
    - Naive implementation: flat index
      - A brute force distance calculation between the query vector and all the chunks' vectors
  - Retrieving (nearest neighbours searching)
    - Efficient framework:
      - Open-source libraries: Faiss, Annoy
      - Managed solutions: Pinecone

Numpy is the vector DB

- The vector DB (or an index)
  - Allow Approximate search to avoid computing too many distance scores
  - It is only applicable for large scales retrieval
- Any modern CPU can search through hundreds of vectors in milliseconds

Dense Representation

- Vectorisation
  - The embedding model should be selected.
  - Search optimized models:
    - The leaderboard for massive text embedding benchmark

Rank	Model	Model Size (GB)	Embedding Dimensions	Sequence Length	Average (56 datasets)	Classification Average (12 datasets)	Clustering Average (11 datasets)	Pair Classification Average (3 datasets)	Reranking Average (4 datasets)	Ret Ave (15 dat
1	UAE-Large-V1	1.34	1024	512	64.64	75.58	46.73	87.25	59.88	54.
2	voyage-lite-01-instruct		1024	4096	64.49	74.79	47.4	86.57	59.74	55.
3	Cohere-embed-english-v3.0		1024	512	64.47	76.49	47.43	85.84	58.01	55

Dense Representation

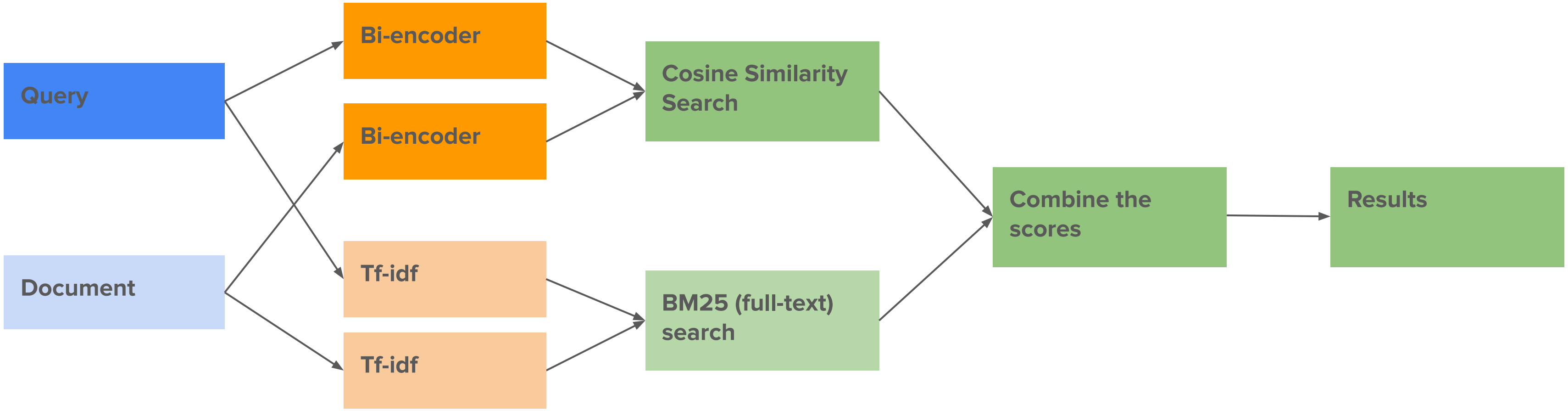
- Compressing information from tokens to a single vector is bound to lose information
- Embeddings learned is limited to the training data of the embeddings models
- Fixed Vocabulary
  - Llama 3 2024 => [‘ll’, ‘##ama’, ‘3’, ‘202’, ‘##4’]

Sparse Representation - BM25

- Keyword search, is built on an old technology: BM25
  - Based on TF-IDF (sparse)
  - Pretty powerful on longer documents and documents containing a lot of domain-specific jargon
  - It’s inference-time compute overhead is quite tiny
- Free lunch for any pipeline

Hybrid: dense + sparse

- Combine spread and dense representations

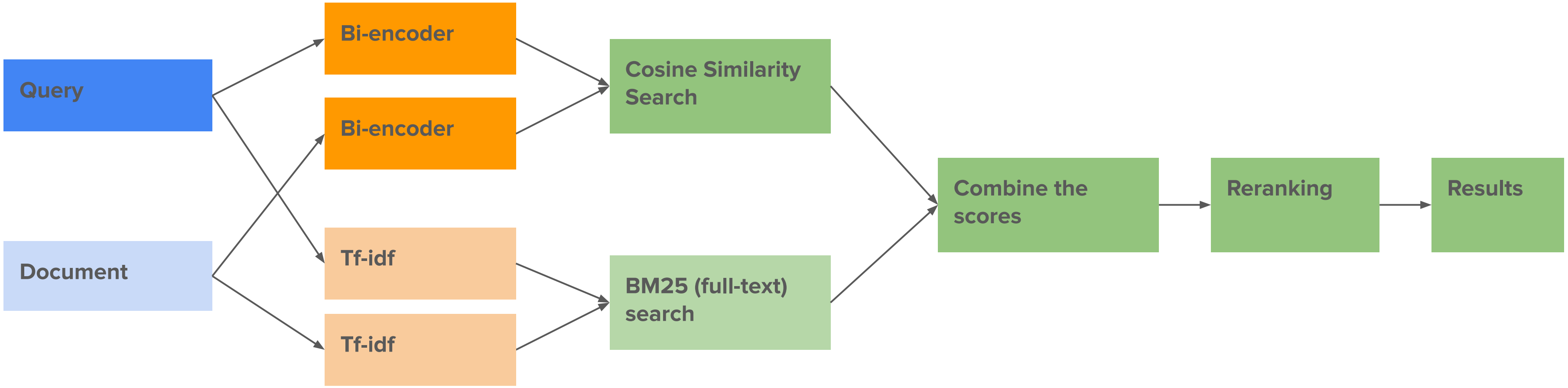


Bi-encoder

- Bi-encoders are (generally) used to create single-vector representations. They pre-compute document representations.
- Documents and query representations are computed entirely separately, they are not aware of each other
- Thus, document vectors can be pre-computed and at inference, encode your query and search for similar vectors
  - Very computationally efficient
  - It comes with retrieval performance tradeoffs.

Reranker: The power of Cross-Encoders

- Leverage a powerful but computationally expensive model to score only a subset of your documents, previously retrieved by a more efficient model.
- One approach: cross-encoder
  - It is effectively a binary classifier
    - The input is a pair of query and document
    - The output is the probability of being the positive class as the similarity score



Metadata filter

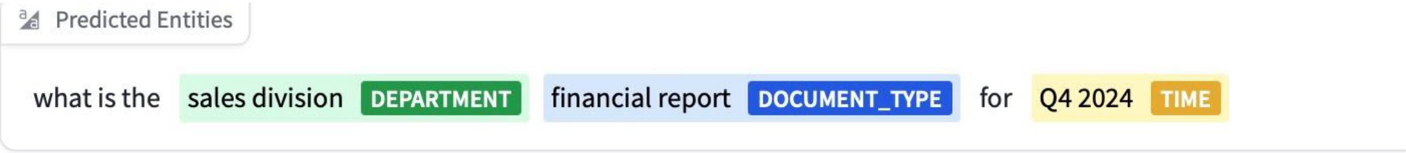
- Documents do not exist in a vacuum. There is a lot of metadata around them, some of which can be very informative
- Metadata is the context you can add with each text chunk
    - Examples
        - Page number
        - Document title
        - Summary of adjunct chunks
        - Hypothesis questions (reverse HyDE)
            - Ask the LLM to generate a question for each chunk
    - Benefits
        - Can help retrieval
        - Can augment response quality
        - Integrates with Vector DB metadata filters

Metadata filter

- Query: what is the sales division financial report for Q4 2024?
- Raw top-k retrieval via embeddings/keyword would have low precision
  - The model should accurately capture all of the key meaning: financial report, sales division, Q4 and 2024.
  - And the k also can not be set too high. Otherwise irrelevant financial reports would be passed to LLM

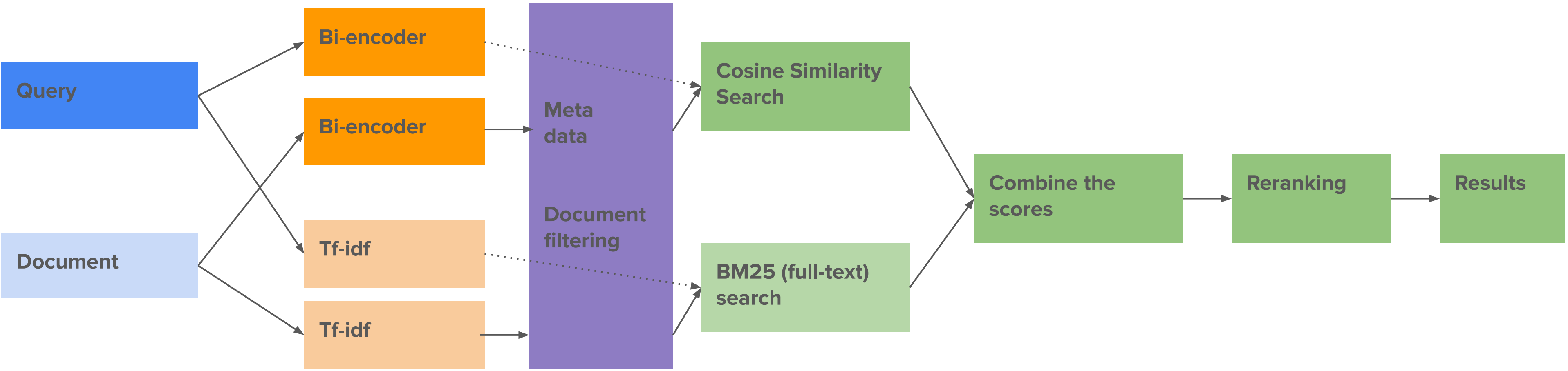
Metadata filter

- Apply entity detection models on query such as GliNER
- Ensure the business/query-relevant information is stored alongside their associated documents
- Than, the extracted entities could be used to pre-filter the documents, ensuring we only perform search on documents whose attributes are related to the query.



source: https://huggingface.co/spaces/urchade/gliner_mediumv2.1

The Final MVP



The Final MVP

```
[8] from wikipediaapi import Wikipedia
    wiki = Wikipedia('RAGBot/0.0', 'en')
    docs = [{'text': x, 'category': "person"} for x in wiki.page("Bukayo_Saka").text.split('\n\n')]
    docs += [{'text': x, 'category': "film"} for x in wiki.page("Arsenal_F.C.").text.split('\n\n')]
```

```
[9] import lancedb
    from lancedb.pydantic import LanceModel, Vector
    from lancedb.embeddings import get_registry
    from lancedb.rerankers import CrossEncoderReranker
```

```
[10] model = get_registry().get("sentence-transformers").create(name="paraphrase-MiniLM-L6-v2")
```

Bi-encoder

```
[11] class Document(LanceModel):
       text: str = model.SourceField()
       vector: Vector(384) = model.VectorField()
       category: str
     db = lancedb.connect('.my_db')
     tbl = db.create_table("my_doc", schema=Document)
```

Meta data

```
[12] tbl.add(docs)
     tbl.create_fts_index("text")
```

BM25 (full-text) search

```
reranker = CrossEncoderReranker()
query = "How old is Saka?"

# Apply filter within the search query
results = (tbl.search(query, query_type='hybrid').where("category='person'").limit(10).rerank(reranker=reranker))
```

Document Filtering

Quick Comparison

https://colab.research.google.com/drive/1L0VWAgIiywqjNE1TFmdfusAV86yDuR94?usp=sharing

How to Improve RAG

- Data
  - Store additional information beyond raw text chunks
- Embeddings
  - Optimize embedding representations
- Retrieval
  - Advanced retrieval instead of top-k embedding lookup
- Synthesis
  - LLMs can play a big role in the process

How do we properly evaluate a RAG

- After those changes, we need to evaluate the impacts
  - Evaluate various components
    - Is the retrieval good?
    - Is the LLM good?
  - Evaluate end-to-end

How do we properly evaluate a RAG

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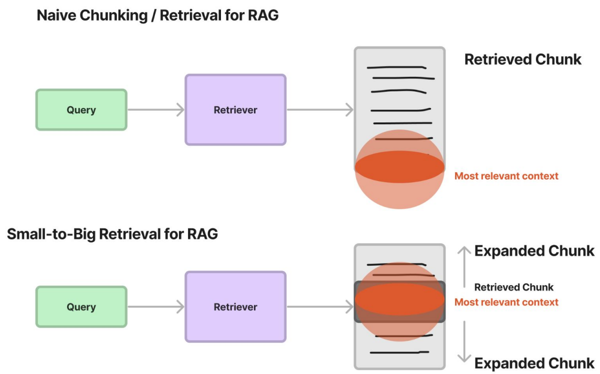
Chunk sizes

- Chunking
    - Split texts into chunks of some size without losing their meaning
    - The size of the chunk is also a hyper-parameter to be tuned
        - Embeddings models' capacity
        - Conflicts between enough context for LLM to reason (wide) and specific enough text embedding (narrow) in order to efficiently execute search upon
    - A few chunking techniques:
        - Fixed-size chunking
        - Content-aware chunking
            - Sentence splitting: sentence-level chunking
            - Specialized chunking: preserve the original structure of the content if it is in markdown, latex or other formats
        - A good survey here.

Small-to-Big

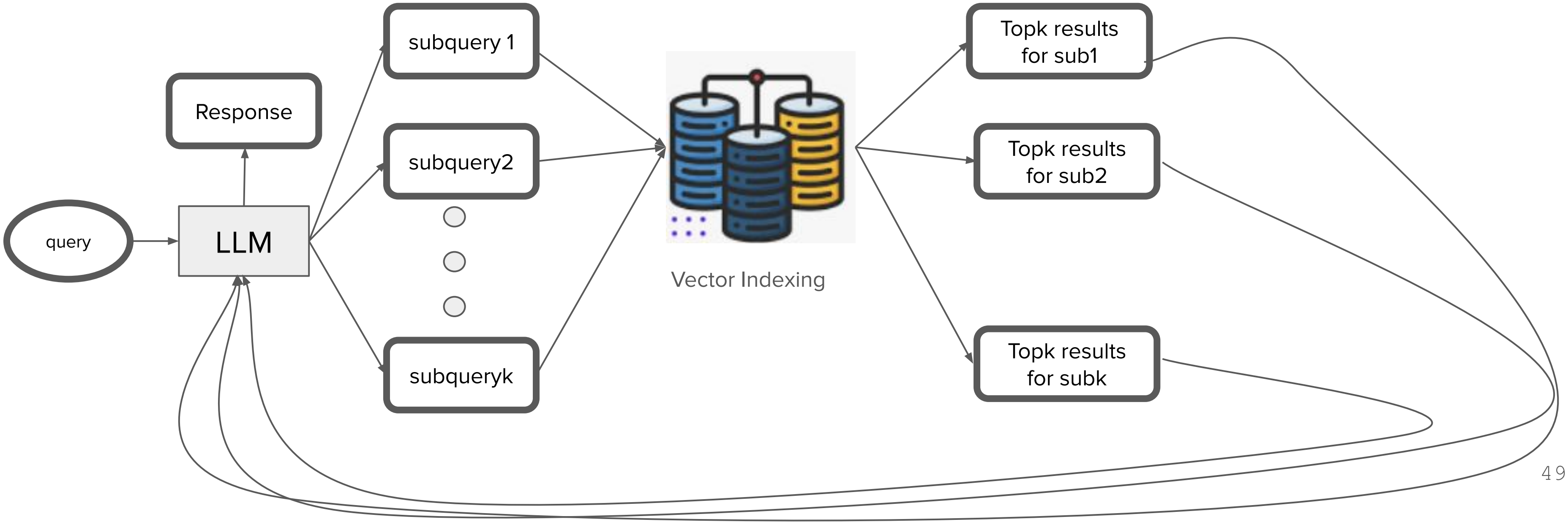
- Intuition:
  - Embedding a big text chunk is not optimal
  - Defining a chunking boundaries is completely arbitrary and independent of the relevant context
- Solution:
  - Embed text at the sentence-level
  - Expand that window for the context in the query to LLM



Source: https://twitter.com/jerryjliu0/status/1732503009891127676/photo/1

Query transformation

Query transformation is referred to those techniques using LLM as a reasoning engine to modify user inputs in order to improve retrieval quality



Query transformation

- Core idea behind transformation is:
  - Decompose the complex query into several sub queries
- Open-source implementation
  - [Multi query retriever]in Langchain
  - [Sub question query engine]in Llamaindex

Run queries

```
response = query_engine.query(
    "How was Paul Grahams life different before, during, and after YC?"
)
```

```
Generated 3 sub questions.
[pg_essay] Q: What did Paul Graham do before YC?
[pg_essay] Q: What did Paul Graham do during YC?
[pg_essay] Q: What did Paul Graham do after YC?
```

Chat Template

- What if you found this scrap of paper on the ground?
- What do you think the rest of the paper would say?

My cable is out! And I'm going to miss the Superbowl!

Chat Template

```
# IT Support Assistant
The following is a transcript between an award winning IT support rep and a customer

## Customer
My cable is out! And I’m going to miss the Superbowl!

## Support Assistant:
```

Chat Markup Language (ChatML)

- A tool that helps manage multi-turn conversion and can also be used for non-chat scenarios.
  - Make model understand where each piece of text comes from
  - The conversion is segregated into three layers:
    - System
    - Assistant
    - User
  - <im_start> and <im_end> are special tokens to set boundaries of information.

```
<|im_start|>system
Provide some context and/or instructions to the model.
<|im_end|>
<|im_start|>user
The user’s message goes here
<|im_end|>
<|im_start|>assistant
```

Chat Markup Language (ChatML)

- System message (optional but suggested for better result)
  - It is included at the beginning of the prompt
  - It can have the following info:
    - A brief description of the assistant
    - Personality traits of the assistant
    - Instructions of rules you would like the assistant to follow
    - Data or information needed for the model
- Message
  - It includes a series of message between the user and the assistant
  - Each message should begin with the <im_start> token followed by the role and end with the <im_end> token.
  - To trigger a response from the model, the prompt should end with <im_start>assistant

More info: https://learn.microsoft.com/en-us/azure/ai-services/openai/how-to/chat-markup-language

Apply Chat Template

API

```
messages =
[{
  "role": "system"
  "content": "You are
an award winning
support staff
representative that
helps customers."
 },

 {"role": "user",
  "content":"My cable
is out! And I'm going
to miss the
Superbowl!"
 }
]
```

`tokenizer.apply_chat_template`

Chat Markup Language (ChatML)

```
<|im_start|> system
You are an award winning IT
support rep. Help the user with
their request.<|im_stop|>

<|im_start|> user
My cable is out! And I'm going to
miss the Superbowl!<|im_stop|>

<|im_start|> assistant
```

Apply Chat Template

- Really easy for users to build assistant
  - Rather than continuing a single string of text, the model will continue a conversion
  - System messages make controlling behavior easy
- Safety is baked in:
  - Assistant will (almost) never respond with harmful info
  - Prompt injection is (almost) possible