Generative AI

W2 Agenda

- Introduction to working with LLMs
    - Prompt engineering
    - General rules
- Retrieval Augmented Generation
    - Vector search
    - Hybrid search
- How to leverage classic ML to make LLMs work better
    - Named Entity Recognition
    - CrossEncoders / Rerankers

Introduction to working with LLMs

Prompt Engineering

How can you communicate with any LLM? What can be included in LLM call?

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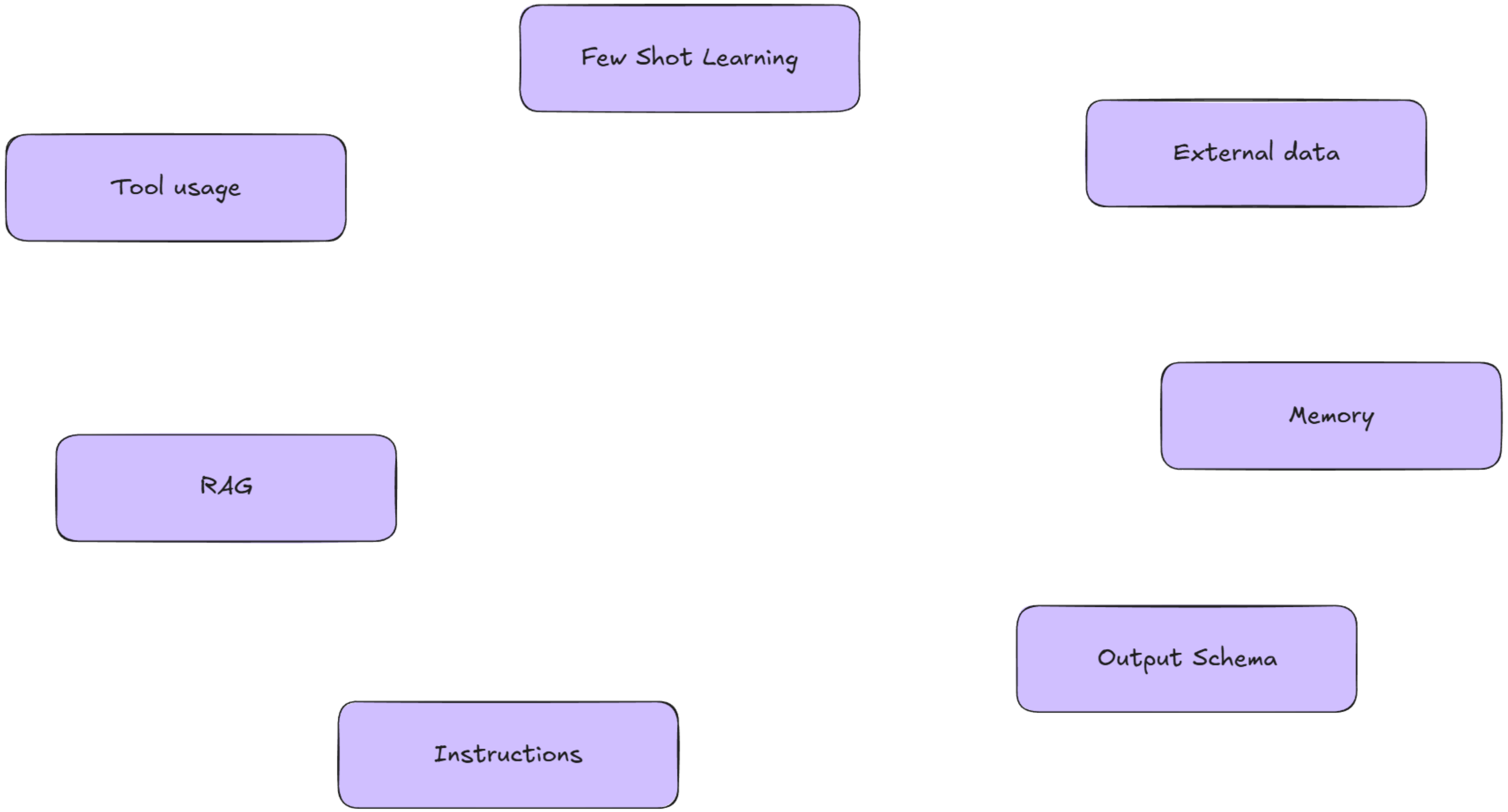
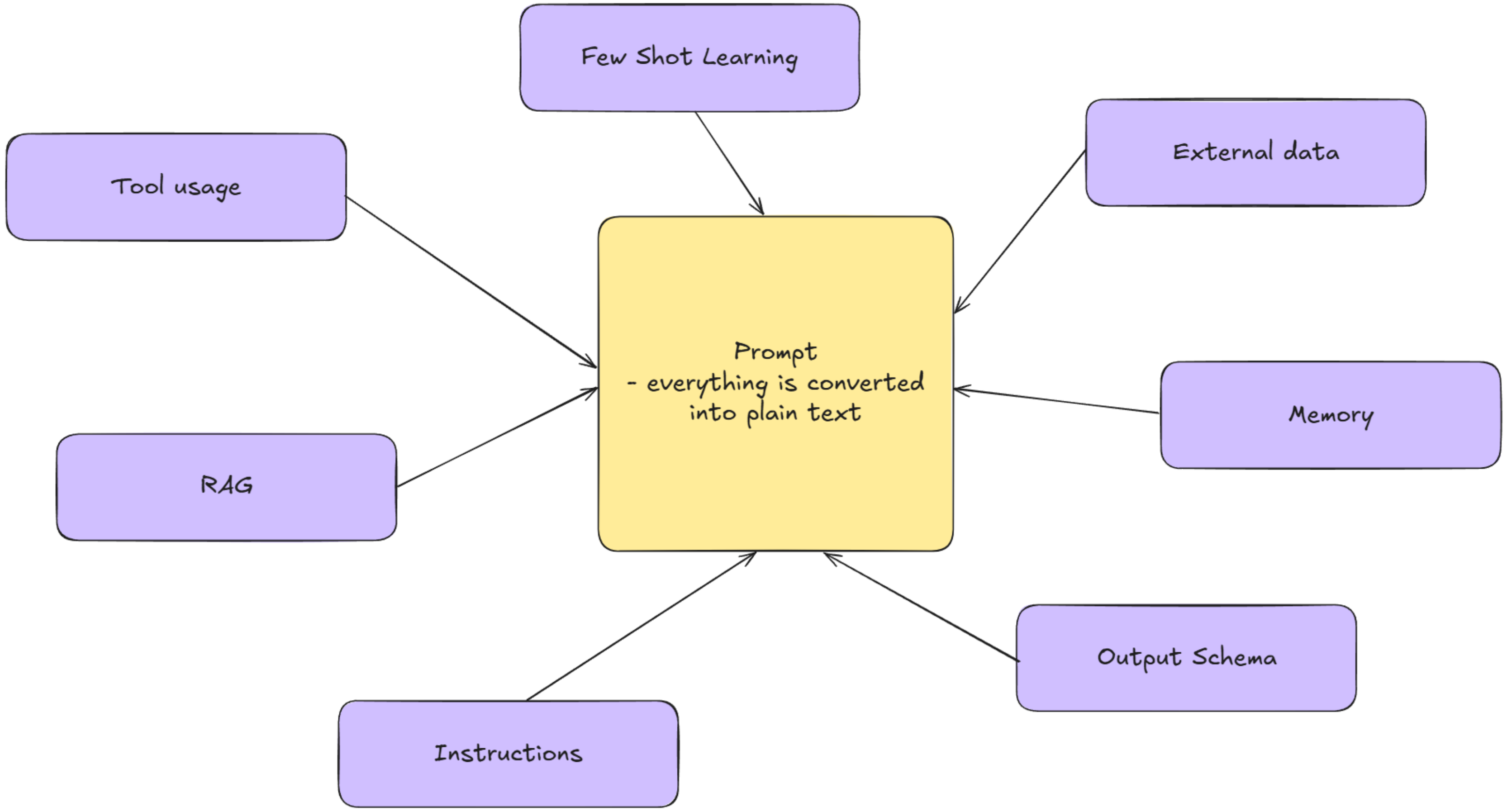


All non-image data is converted to text, no matter how complex the process might seem



What is a prompt?

- Prompt text is the key model input for LLMs - it contains all the instructions together with conversation history and any additional context such as RAG
- Despite being dominated by Natural Language prompt can implement coded structures such as html like syntax
- While designing a prompt you should provide as detailed instructions and context as possible
- Prompt does not need to be equal to what we see in the chat window, additional elements can be appended such as:
  - initial model instructions
  - domain information from RAG
  - conversation history
- In context learning allows to help format model outputs by few-show-learning through prompting

https://chat.openai.com/c/507051a7-dc8a-4789-864c-e87fcfb2b1b2

Popular prompting templates

Question + Instruction

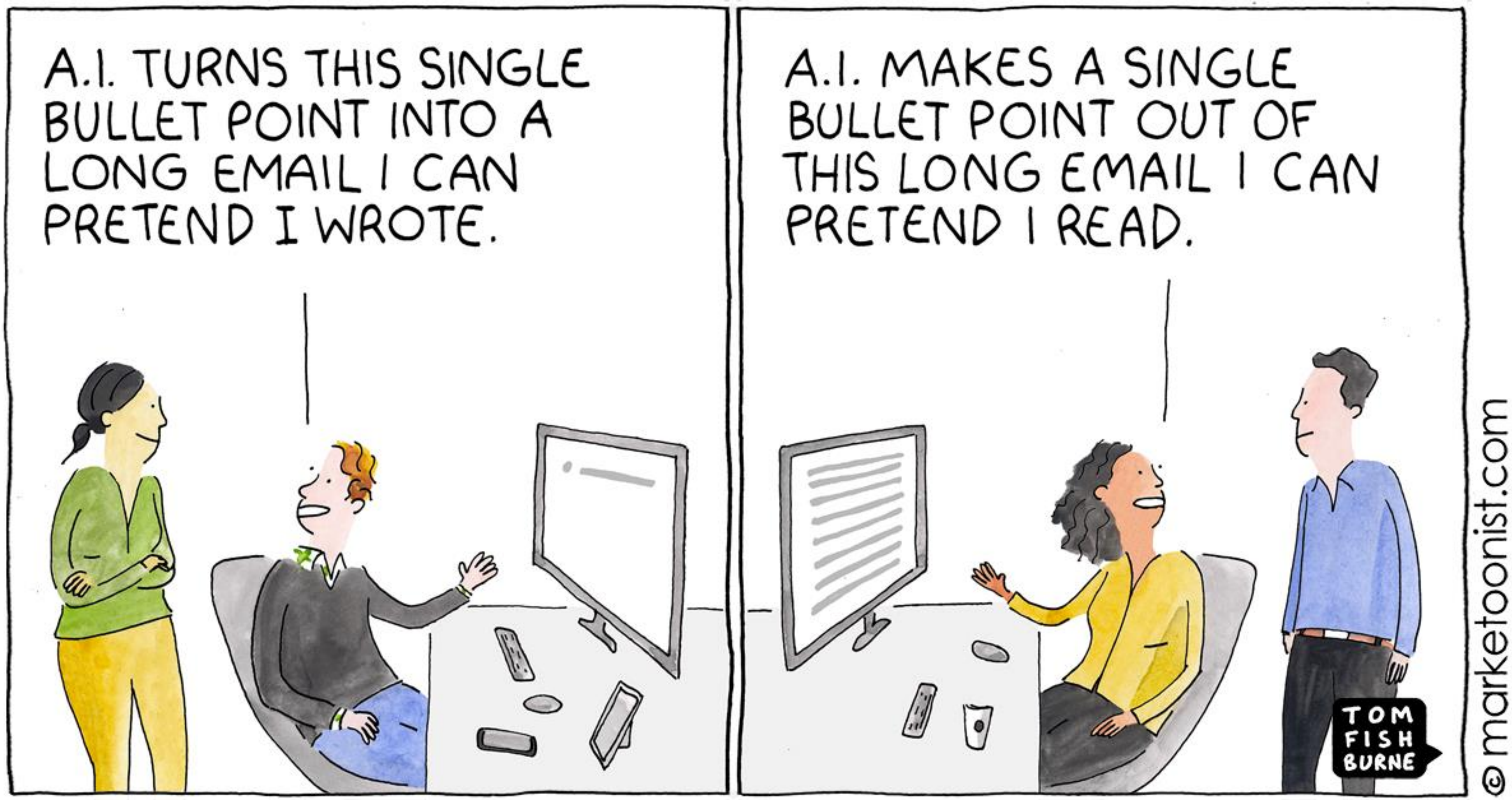
J **You**

What are the 5 most important NLP topics I should include in a short NLP course? Give me an agenda with a brief description of each topic.

Instructions + Input data (zero-shot learning example)

J **You**

Given the following information about me prepare a summary for my Linkedin Profile. My name is Jan, I live in Warsaw, I graduated Power Engineering but for most of my career worked in Data Science. I am passionate about analysing Real Estate data and NLP models.


A.I. TURNS THIS SINGLE BULLET POINT INTO A LONG EMAIL I CAN PRETEND I WROTE.
A.I. MAKES A SINGLE BULLET POINT OUT OF THIS LONG EMAIL I CAN PRETEND I READ.
TOM FISH BURNE
© marketoonist.com

Popular prompting templates

Question + Examples

J **You**

I really liked London, Rome and Prague. I disliked Zurich, Paris and Sosnowiec. What cities would you recommend for my next trip?

What is Prompt engineering

- Prompt engineering aims to create prompts in a more programmatic, reproducible way
- It involves carefully designing and structuring the input given to the model to effectively guide it towards generating the desired output or response.
- Temperature is one of the key hyperparams controlling how varied and creative each models response is - even with the exact same prompt
- Prompt Engineering can be more structured by leveraging libraries such as LangChain

Chain-of-thought reasoning

- Chain-of-thought prompting: Encourages model to be factual and precise by explaining its reasoning

J **You**

What are the best libraries to get started with NER?

Use this format:

Q: <repeat question>

A: Let's analyze the possibilities. <give reasoning>, summ

starting with NER is <final answer>

Q: What are the best libraries to get started with Named Entity Recognition (NER)?

A: Let's analyze the possibilities. There are several libraries catering to NER tasks, but the choice often depends on factors like ease of use, community support, and performance. spaCy stands out as an excellent option for beginners. Its user-friendly API, pre-trained models, and efficient processing make it a go-to choice for those new to NER. Therefore, spaCy is recommended as a solid starting point for diving into Named Entity Recognition.

Citing sources

J **You**

What are the top 3 LLM models? Answer only with reliable sources and cite those sources.

ChatGPT

As of my last knowledge update in January 2022, three prominent large language models (LLMs) were widely recognized:

1. **GPT-3 (Generative Pre-trained Transformer 3)**
   - **Source:** Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Amodei, D. (2020). Language Models are Few-Shot Learners. arXiv:2005.14165.
2. **BERT (Bidirectional Encoder Representations from Transformers)**
   - **Source:** Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv:1810.04805.
3. **T5 (Text-to-Text Transfer Transformer)**
   - **Source:** Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., ... & Liu, P. J. (2019). Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. arXiv:1910.10683.

Warning!
LLM can still make up sources, but at least you can check if they exists

Few shot learning

Zero-shot

You
User
'I rather enjoyed this movie, but the beggining was boring'. Please conduct sentiment analysis on this review.

ChatGPT
Sentiment analysis involves determining the sentiment or emotion expressed in a piece of text. In the review you provided, "I rather enjoyed this movie, but the beginning was boring," the sentiment is mixed. Let's break it down:

1. "I rather enjoyed this movie" - This part of the review expresses a positive sentiment. The word "enjoyed" indicates a positive feeling towards the movie.
2. "but the beginning was boring" - On the other hand, this part of the review expresses a negative sentiment. The word "boring" indicates a negative feeling towards the beginning of the movie.

So, overall, the sentiment in this review is mixed, with a positive sentiment towards the movie as a whole but a negative sentiment towards the beginning of the movie.

Two-shot

You
Classify this review:
"I hated this movie, total waste of time and money"
Sentiment: Negative

Classify this review:
"The most beautiful love story in the history of cinema"
Sentiment: Positive

Classify this review:
'I rather enjoyed this movie, but the beggining was boring'.
Sentiment:

ChatGPT
Sentiment: Mixed (Positive about the overall enjoyment, but negative about the beginning)

Three-shot

You
User
User
Classify this review:
"I hated this movie, total waste of time and money"
Sentiment: Negative

Classify this review:
"The most beautiful love story in the history of cinema"
Sentiment: Positive

Classify this review:
"The beggining dragged on forever, but I liked the suprising ending. Overall experience was average"
Sentiment: Neutral

Classify this review:
'I rather enjoyed this movie, but the beggining was boring'.
Sentiment:

ChatGPT
Sentiment: Mixed or Neutral

Few shot learning

Zero-shot

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ChatGPT
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Jupyter exercise Few shot learning

Proceed to notebook W2-llm-calling-and-vector-search

Setup keys and parsers for later

```
openai.api_key = OPENAI_API_KEY = os.getenv("OPENAI_API_KEY")

client = openai.Client()

output_parser = JsonOutputParser()
```

[19] ✓ 0.3s

Load data of 100 FAQ items from a travel company

```
df = pd.read_json("data/travel_company_faq.json")
i=10
questions = df.loc[i].question
```

[ ]

Classify FAQ items with LLM

```
##TODO: Prepare system prompt to split FAQ items into 4 categories: [air-travel, hotels-and-booking, food,
# System prompt with instructions and the JSON format we expect
system_prompt = f"""You are a helpful assistant.
Your task: Classify the given question into one of the following categories:
[air-travel, hotels-and-booking, food, insurance, extra-activities].

Return the result ONLY in valid JSON, in the format:
{{"category":"<category>"}}

"""
```

[ ]

```
# --- Step 2: Define a function to call OpenAI's chat completion directly ---
def classify_question(question: str, system_prompt: str) -> str:
    """
    Calls the OpenAI ChatCompletion endpoint to classify the question.
    Returns the predicted category.
    """

    # Make a direct OpenAI chat call (using the fictional "gpt-4o-mini" as specified)

    response = client.chat.completions.create(
        model="gpt-4o-mini",  # Updated to match available models
```

[20]

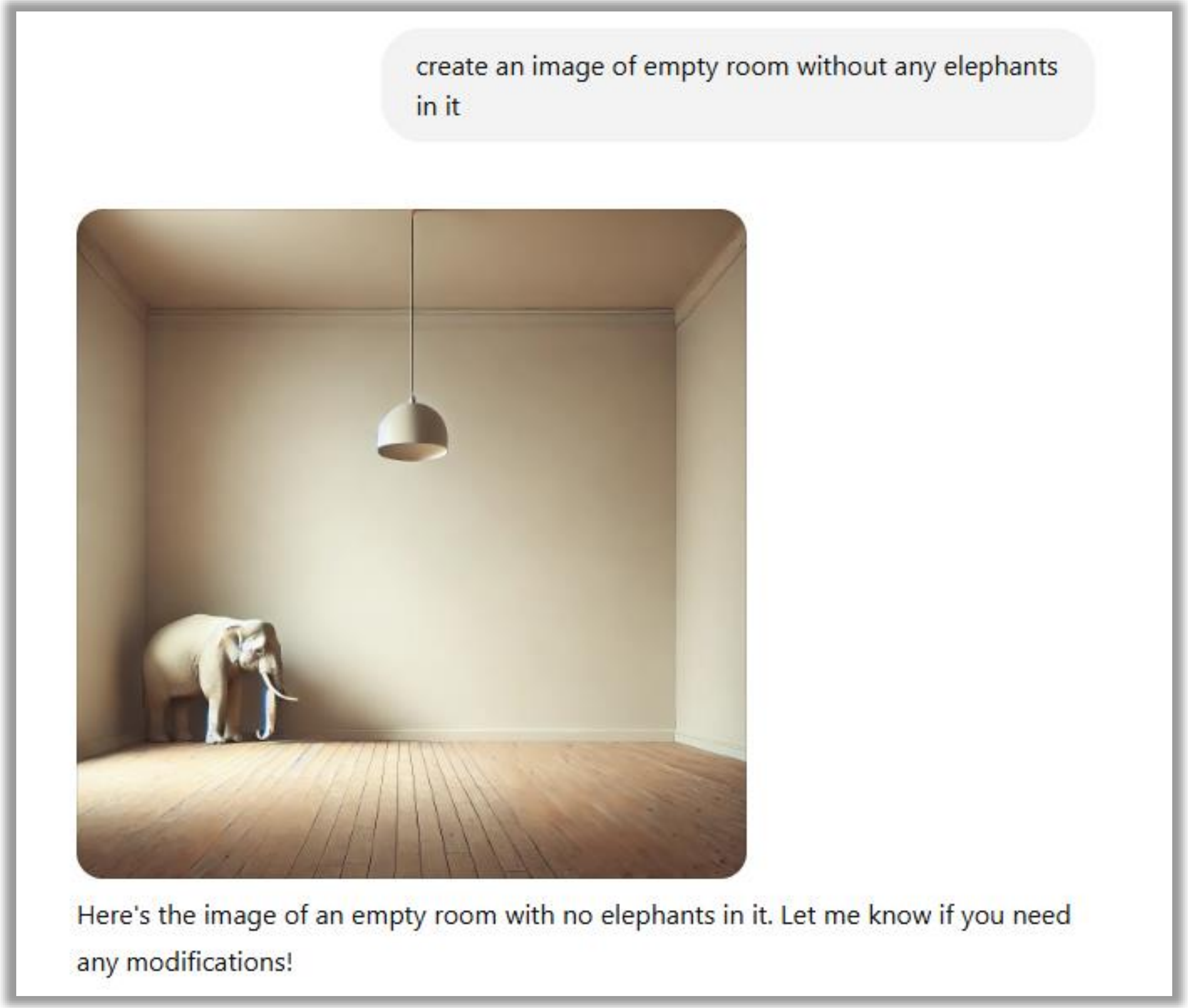
General Tips

DOs and DONTs

- Single, clear task per each call
- Concise instructions, which can be followed as a human
- Leverage markdown, html and system prompt for clear segmentation between input, instructions, few-shot examples and any other arguments
- Complex tasks should be split into several, serial prompt calls
- Asking for a score or exmplanation can improve results, even if the scores are not reliable
- Chain-of-thouth framework can improve logical capabilities

- Don’t flood LLMs with too much info, even if they have 1M tokens window
- LLMs are pretty bad at numerical scoring
- Be carefull with too many / too extreme examples as they might steer answers in unexpected directions
- It is hard to tell LLM NOT TO DO something
- LLMs are not designed for counting – it might be more reliable to extract values and summarize them programatically
- Don’t overkill simple tasks with LLMs – many of them can be solved more efficiently with classic ML

It is harder to instruct LLM not to do something



Generated by author with gpt-4o, 2025-03-04

Retrieval Augmented Generation (RAG)

What is RAG?

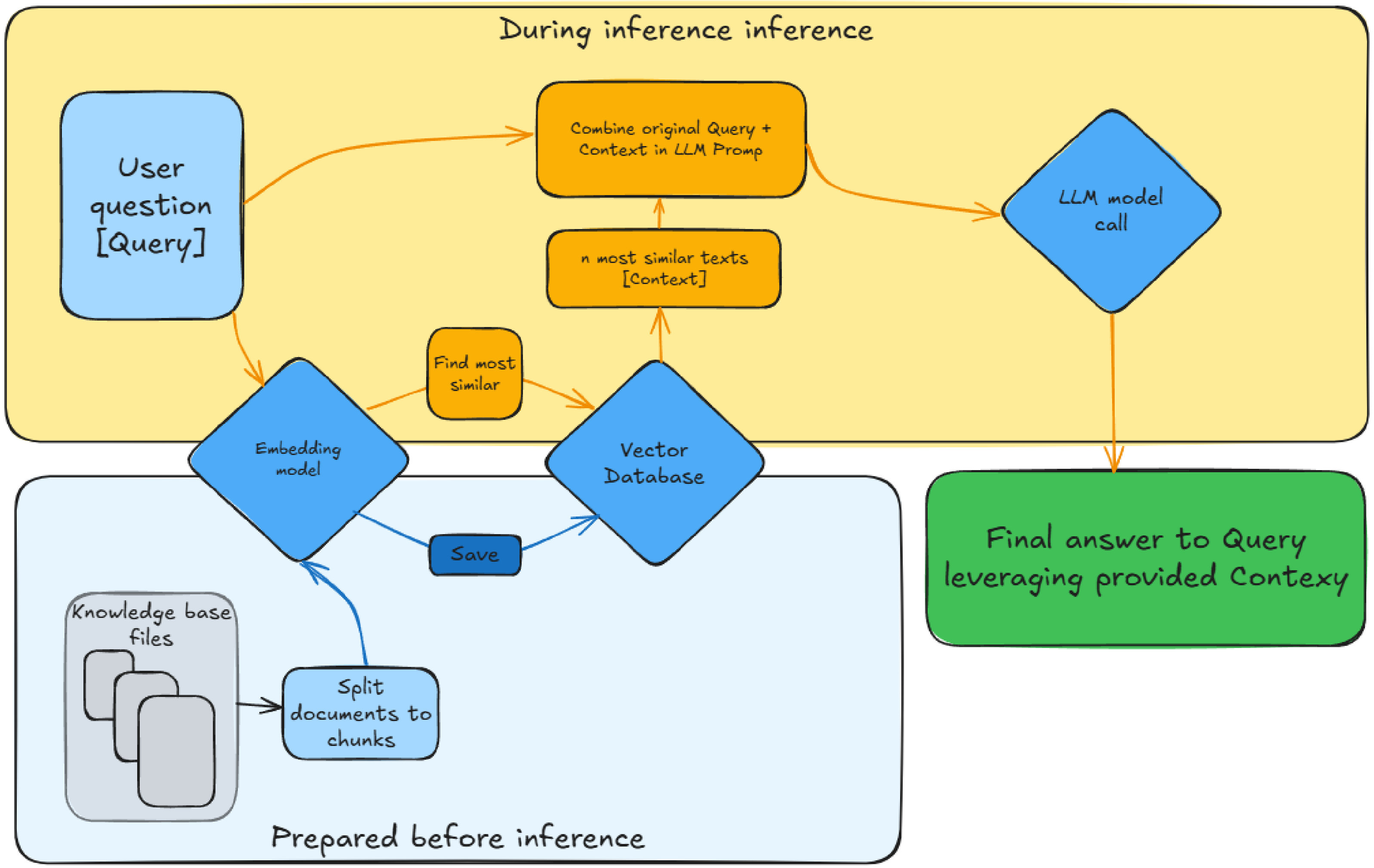
Retrieval augmented generation (RAG) allows us to improve LLM performance by enriching our calls with some selected context

I allows expanding and updating model knowledge with external data, which improves information accuracy and relevance grounding its answers

Most popular forms of RAG rely on finding sections of documents, which are most similar to asked questions and integrating them to LLM call for better context

This approach can be used to feed real time or internal data to guide LLM answers, without need for retraining

Vector RAG diagram



Source: image by author

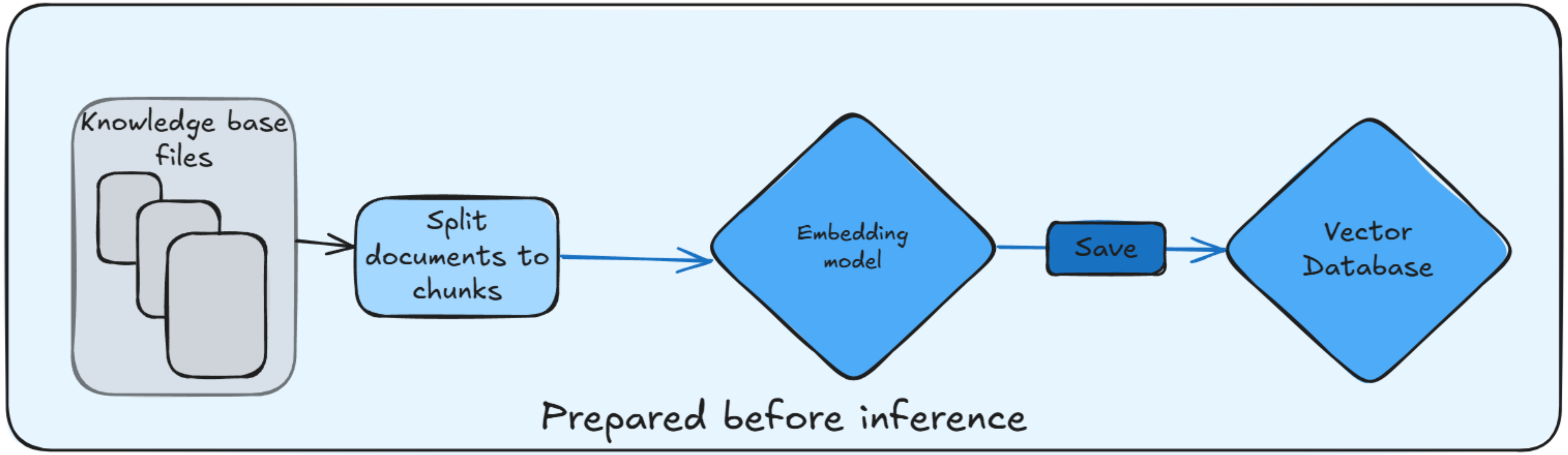
RAG benefits

- Grounding model answers with controlled context, which can reduce hallucinations
- Ability to provide specified, real-time data to LLM e.g. fast changing promotions or product availability
- Well-defined, specialized RAG can get good performance with smaller LLMs

RAG does NOT reason – key pitfalls

- Despite being closely associated with LLMs, RAG relies mainly on vector search
- It DOES NOT have any reasoning or logical abilities and can be easily misled
- Purely vector based RAG carries many shortcoming of semantic similarity -> it will not perform well with complex questions and numbers
- Feeding bad context to LLM call can increase risk of bad answers as LLM will be more likely to use this information

Creating and calling Vector database



1. Gather files for Knowledge base

2. Split files into smaller chunks within a few hundred tokens

3. Embed each chunk as a vector

4. Save each chunk's text, vector, metadata and metadata to DB

Jupyter exercise Vector DB

Continue in notebook W2-llm-calling-and-vector-search

Introduction to vector search

```python
chroma_db_path = "chroma_db"
chroma_client = chromadb.PersistentClient(path=chroma_db_path)

SELECTED_COLLECTION = "travel-company-faq"
```
✓ 0.5s

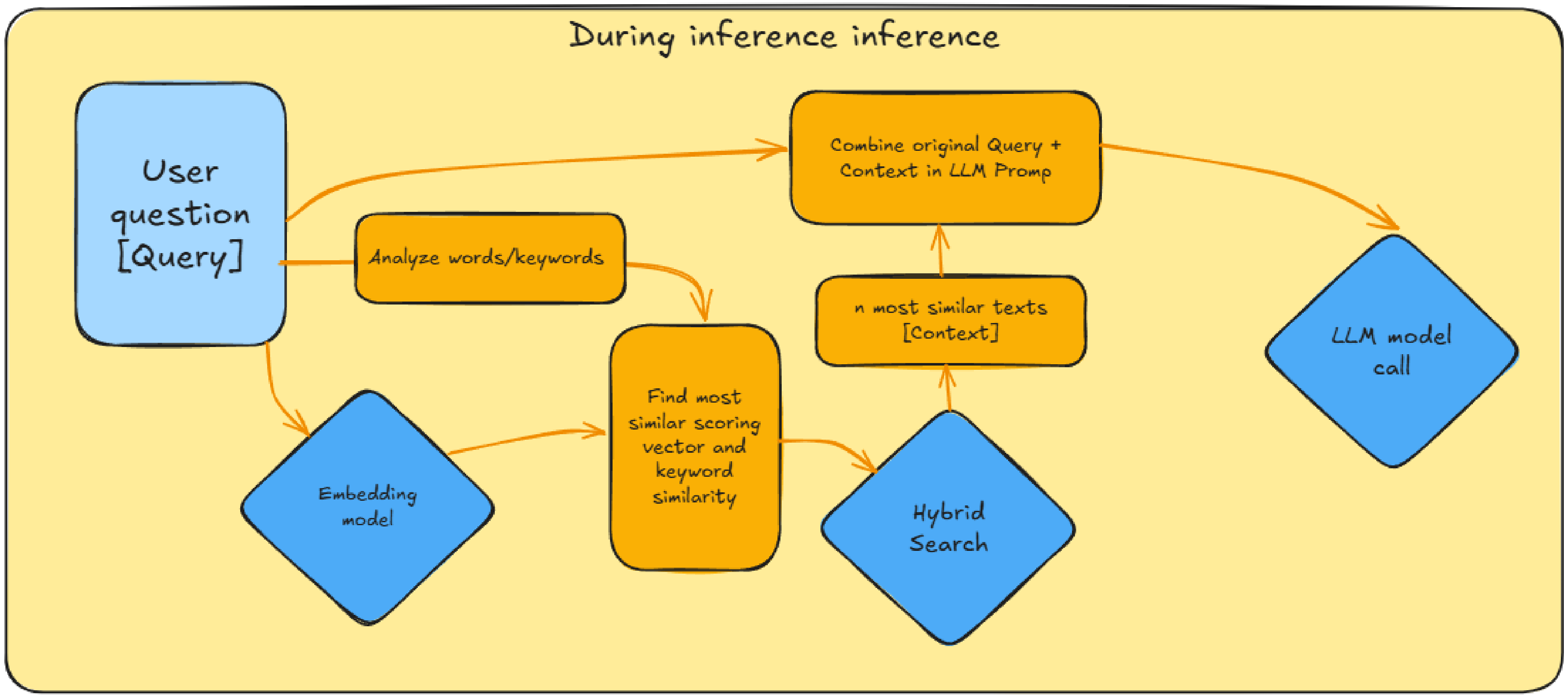
```python
embedding_model = "text-embedding-ada-002"
openai_ef = embedding_functions.OpenAIEmbeddingFunction(model_name=embedding_model, api_key = OPENAI_API_KEY)


collection = chroma_client.get_or_create_collection(name=SELECTED_COLLECTION , embedding_function=openai_ef)
```
✓ 0.0s

```python
def ingest_faq_data(df: pd.DataFrame, collection):
    """

    Ingest combined question and answer as vectorized documents. Store question, answer and category as metadata
    """
    all_ids = []
    all_documents = []
    all_metadatas = []

    for i, row in df.iterrows():
        # Combine Q + A as text
        doc_text = f"Question: {row['question']}\nAnswer: {row['answer']}"

        doc_id = f"faq_{i}"
        meta = {
            "question": row["question"],
            "answer": row["answer"],
            "category": row["category"],
        }

        all_ids.append(doc_id)
        all_documents.append(doc_text)
        all_metadatas.append(meta)

    collection.add(documents=all_documents, metadatas=all_metadatas, ids=all_ids)
    print(f"Ingested {len(df)} records into {SELECTED_COLLECTION}.")
```
✓ 0.0s

```python
ingest_faq_data(df, collection)
```
✓ 1.4s

```
Add of existing embedding ID: faq_0
```

Hybrid search – combining vectors and keywords



Hybrid search – combining vectors and keywords

- Hybrid search combines vector similarity with classic keyword-based searches
- BM25 is a popular keyword search leveraging TF-IDF (Term Frequency-Inverse Document Frequency) algorithm
- Keywords can also be used for hard filtering within document text (like in SQL) or metadata (if we want to limit our search to categories or documents)

Improving LLM results with classic ML

Why is it worth using classic ML when we have LLMs

- LLMs are extremely flexible, but some tasks can be still completed with better speed and accuracy with pretrained NLP models e.g. Bert-based
- They are significantly cheaper, faster and easier to deploy
- Training/Finetuning can provide predictable results within specific domains if we have the data
- Validation with classic ML can reduce LLM hallucinations
- They give us to better control LLMs context and answers
- Can serve for evaluation of LLMs

Named Entity Recognition summary

- We use NER when we want to extract specific information from text
- NER extract structured data from text
- Single NER entity e.g. person can have thousands of instances
- Position of the entity itself is important, which makes data annotation as well as processing especially challenging

geo gpe per

Lebanon 's top Shi'ite cleric is opposing British Prime Minister Tony Blair 's expected visit to Beirut Monday .

per geo tim

```
[(0, 7, 'geo'),
 (42, 49, 'gpe'),
 (50, 55, 'per'),
 (65, 75, 'per'),
 (97, 103, 'geo'),
 (104, 110, 'tim')]
```

org per

Democratic U.S. Senator Edward Kennedy has urged the government to spend more money on education as millions of students return to school for a new academic year .

tim

```
[(11, 15, 'org'), (16, 38, 'per'), (144, 156, 'tim')]
```

Under-the-hood NER is classifying tokens by their relations to specific entities

Spacy uses BIO labeling by default, where each token in analyzed text can get assigned the following values:

- **"B"**: Beginning of an entity
- **"I"**: Inside an entity
- **"O"**: Outside of any entity

Together with the label it also gets assigned an entity class.

From model perspective we are conducting multilabel classification for each token.

B I B

When **Sebastian Thrun** started working on self-driving cars at **Google** in

B

2007, few people outside of the company took him seriously. I can tell

B

you very senior CEOs of major **American** car companies would shake

B

my hand and turn away because I wasn't worth talking to, said **Thrun**, in

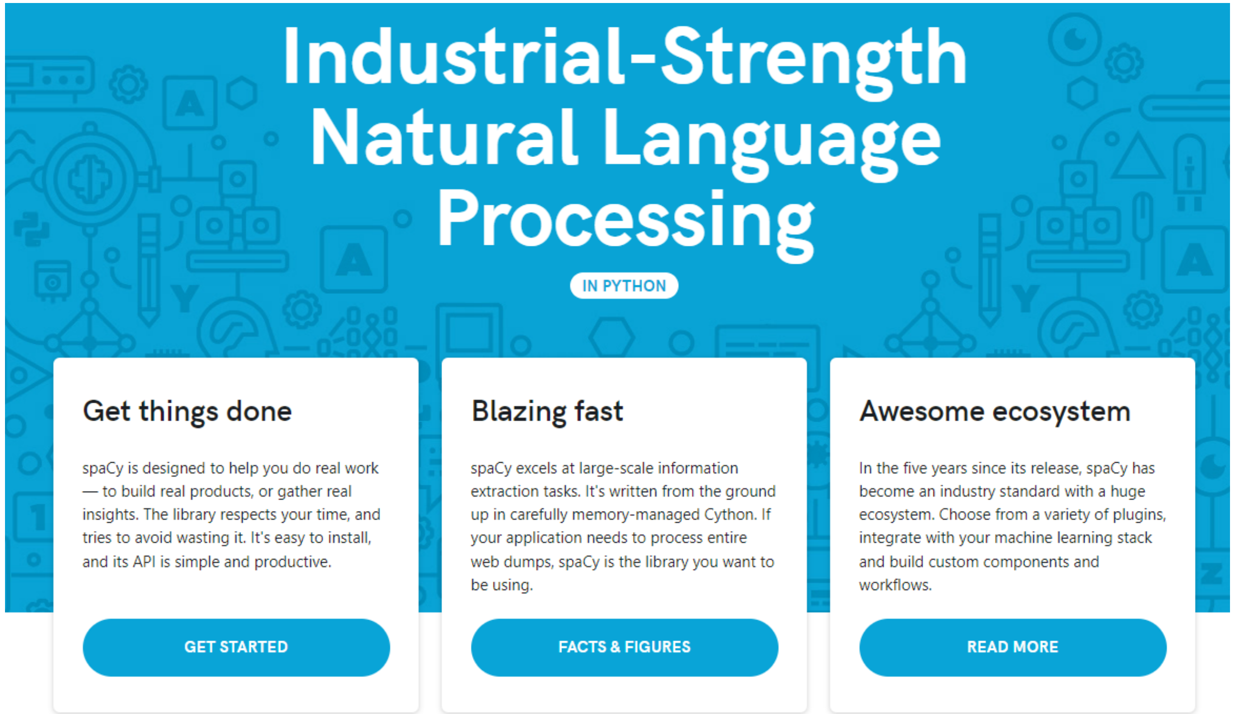
B B I

an interview with **Recode** earlier **this week**.

```
Token: Sebastian        ent_iob: B      ent_type: PERSON
Token: Thrun    ent_iob: I      ent_type: PERSON
Token: 2007     ent_iob: B      ent_type: DATE
Token: American ent_iob: B      ent_type: NORP
Token: Thrun    ent_iob: B      ent_type: PERSON
Token: Recode   ent_iob: B      ent_type: ORG
Token: this     ent_iob: B      ent_type: DATE
Token: week     ent_iob: I      ent_type: DATE
```

What is Spacy

- Spacy is one of the most popular libraries for NLP
- It has a low barier of entry
- You can build models within a few dozens lines of code in a notebook
- CLI interface great for building production models and replicability



Jupyter exercise NER:

Proceed to notebook W2-NER-Intro-BLANK

1 Spacy intro

In [18]:
```
import spacy

# Load English tokenizer, tagger, parser and NER
nlp = spacy.load("en_core_web_sm")

# Process whole documents
text = ("When Sebastian Thrun started working on self-driving cars at "
        "Google in 2007, few people outside of the company took him "
        "seriously. “I can tell you very senior CEOs of major American "
        "car companies would shake my hand and turn away because I wasn’t "
        "worth talking to,” said Thrun, in an interview with Recode earlier "
        "this week.")
```

In [19]:
```
doc = nlp(text)
```

In [20]:
```
# Analyze syntax
print("Noun phrases:", [chunk.text for chunk in doc.noun_chunks])
print("Verbs:", [token.lemma_ for token in doc if token.pos_ == "VERB"])
```

```
Noun phrases: ['Sebastian Thrun', 'self-driving cars', 'Google', 'few people', 'the company', 'him', 'I', 'you', 'very senior C
EOs', 'major American car companies', 'my hand', 'I', 'Thrun', 'an interview', 'Recode']
Verbs: ['start', 'work', 'drive', 'take', 'tell', 'shake', 'turn', 'talk', 'say']
```

In [21]:
```
# Find named entities, phrases and concepts
for entity in doc.ents:
    print(entity.text, entity.label_)
```

```
Sebastian Thrun PERSON
Google ORG
2007 DATE
American NORP
Thrun PERSON
Recode ORG
earlier this week DATE
```

1.1 Token labels

In [ ]:
```
for token in doc:
    if token.ent_iob_!='O':
        print(f"Token: {token.text}\tent_iob: {token.ent_iob_}\tent_type: {token.ent_type_}")
```

2 Preparing Spacy format

In [24]:
```
with open('../data/GMB_data_sagemaker.pickle', 'rb') as f:
     sagemaker_data = pickle.load(f)
```

In [85]:
```
## Current format
sagemaker_data[0]
```

Out[85]:

```
{'workerId': 'some-random-worker-no-123',
 'dataObject': {'content': 'Mr. Egeland said the latest figures show 1.8 million people are in need of food assistance - with t
he need greatest in Indonesia , Sri Lanka , the Maldives and India .'},
 'annotationData': {'content': {'entities': [{'endOffset': 11,
     'label': 'per',
     'startOffset': 0},
    {'endOffset': 128, 'label': 'tim', 'startOffset': 119},
    {'endOffset': 134, 'label': 'per', 'startOffset': 131},
    {'endOffset': 140, 'label': 'gpe', 'startOffset': 135},
    {'endOffset': 155, 'label': 'geo', 'startOffset': 147},
    {'endOffset': 165, 'label': 'geo', 'startOffset': 160}]}}}
```

Introduction to CrossEncoders

Crossencoders are a type of neural network used for ranking tasks – They take a pair of inputs (e.g., a query and a document) and jointly encode them into a single representation before making a relevance prediction.

They can be fine-tuned to perform multiple tasks e.g. similarity detection, answer releveance. We can tailor training data to fit our specific needs.

Under the hood they are based on encoder only transformer with additional neural network layers for regression task, outputting a single number according to they training goal

Pre-trained X-encoders are widely used for reranking of retrieval tasks.

They can also be used for evaluating logical similarity to evaluate LLM answers

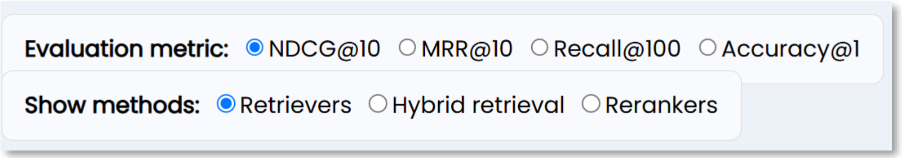
CrossEncoders as rerankers – most common use case in RAG

- As semantic similarity can be misleading, it is worth pulling more records than needed and then reranking most relevant using a more steerable and stronger model
- Evaluating query<-> context pairs fit with cross-encoders can be much more accurate than vector similarity and much cheaper than LLMs
- We can also fine-tune to X-encoders for our own goals e.g. answers following company specific rules such as different approach to different products/services/segments

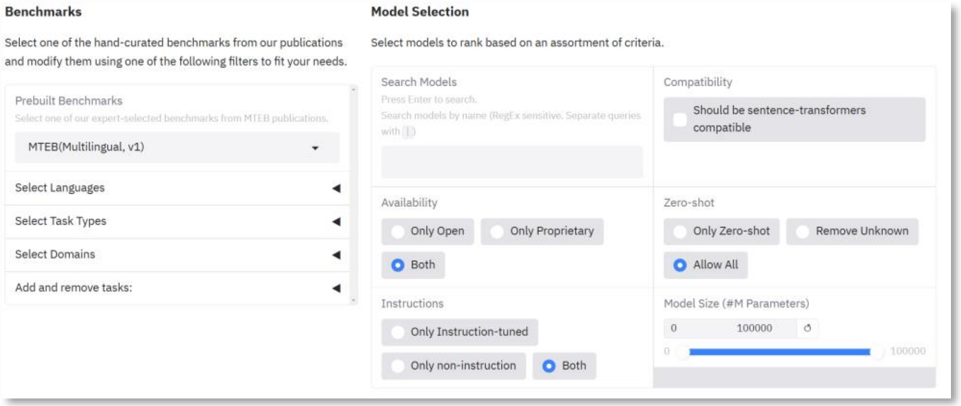
How to choose best model

- Finding best model yourself is next to impossible – luckily, we have HF benchmarks focused on specific tasks and languages
- Especially when working with non-English text most popular models might not perform best
- Find relevant benchmark and choose best model within the size (params count) that you can use

Polish retrieval/reranking benchmark



Mutli-lingual embedding benchmark



Jupyter exercise Reranking

Continue in notebook W2-llm-calling-and-vector-search