Representation model fine-tuning

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Key ideas

- Understanding representation models
- Fine-tuning best practices
- Applications of fine-tuning: RAG

Representation models

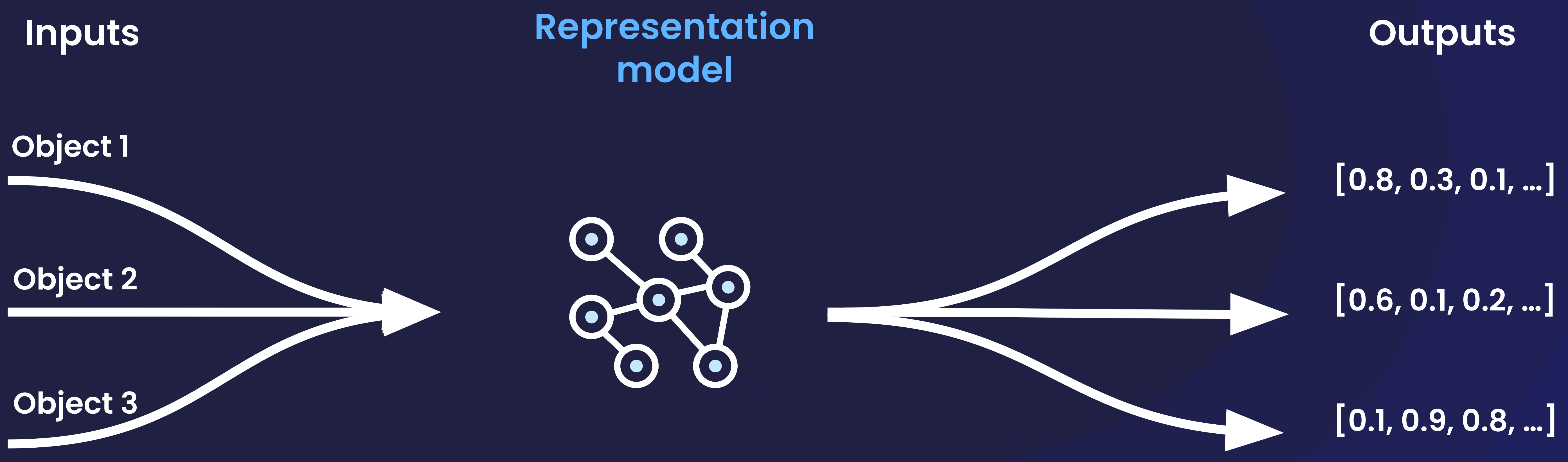
Introduction to representation models

- **Representation models** are a class of machine learning models designed to **capture and encode meaningful features** from the raw data it was trained on

- These representation of these are often in the form of **dense numerical vectors**

- The output of these models are used in downstream tasks such as **classification, clustering, similarity calculation, information retrieval, etc.**

Representation Models



Representation model keep conceptually similar objects close together in the latent feature space

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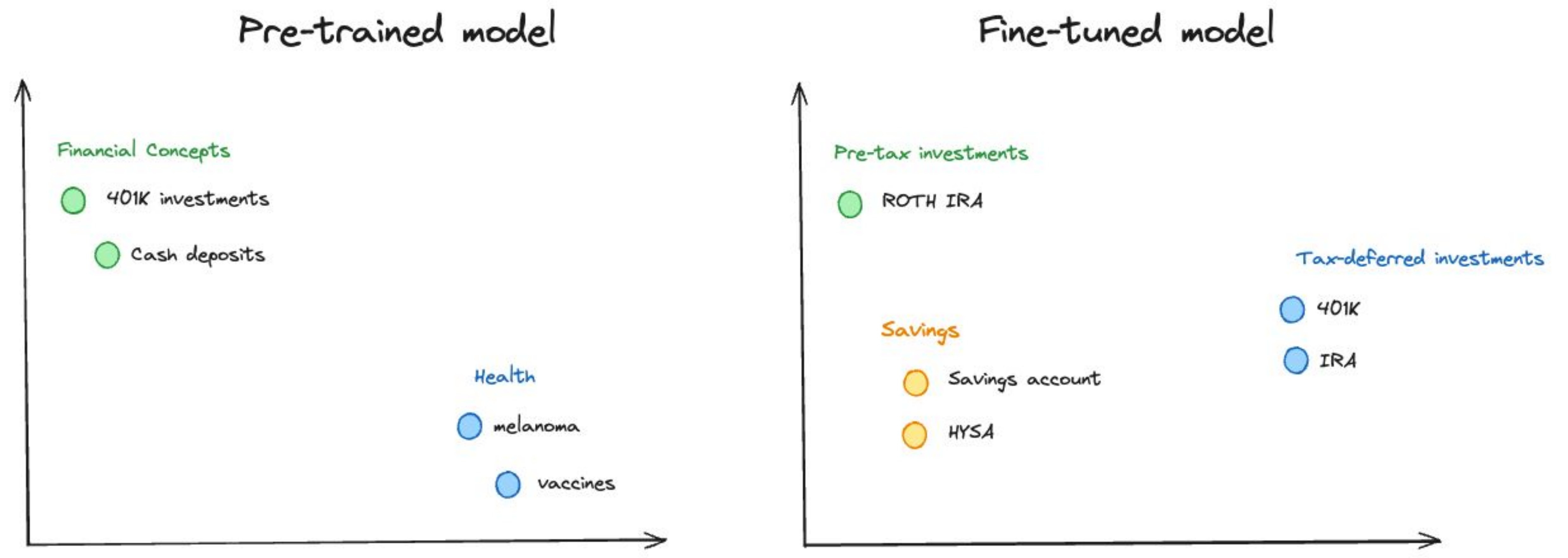
Representation models



Pre-trained models are general knowledge, fine-tuned models are specialized and more nuanced in a particular domain or task

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The need for fine-tuning

- **Fine-tuning** is the process of **adapting/re-training** the model with your specific data and task
- **Pre-trained models are often general-purpose**, while **fine-tuned models are specialized for tasks**
- Fine-tuning pre-trained model can often lead to **better performance;** they can encode nuances of your specific data or domain

Fine-Tuning Deep Dive

Benefits of fine-tuning models

Improved performance

Faster convergence time

Transfer learning

Fine-tuning techniques

- **Task adaption -** fine-tune a portion of a network's layer(s). This approach typically demands **a smaller amount of data**.

- **Full model fine-tuning -** Training the entire model on a task-specific dataset. This typically involves a lot more data than just fine-tuning a subset of the layers.

Representation model fine-tuning best practices

- **Selectively curate and/or augment your dataset**
  - To be robust to new data points, consider data augmentation and/or generating synthetic data
- **Different loss functions can be used depending on your data**
  - **Triplet** or **contrastive loss** can be used if you have both positive and negative examples
  - **Multiple Negatives Ranking Loss** can be used when you only have positive pairs of text
- **Selecting an appropriate evaluation metric is key**
  - Evaluation can be difficult, map the evaluation to your downstream task, e.g., binary clf, semantic similarity, information retrieval, etc.

Quality data scarcity

- Fine-tuning representation models typically **require sizable task-specific datasets**. However, in practice, you may only have a small dataset that is of sufficient quality.

- This is common in use case such as **information retrieval**, where users may only have pair of positive text(query and relevant text answers), but not negative pairs (irrelevant answers)

How to overcome this issue?

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Data augmentation can bootstrap dataset size and create robust representation model!

Data augmentation with Snorkel Flow

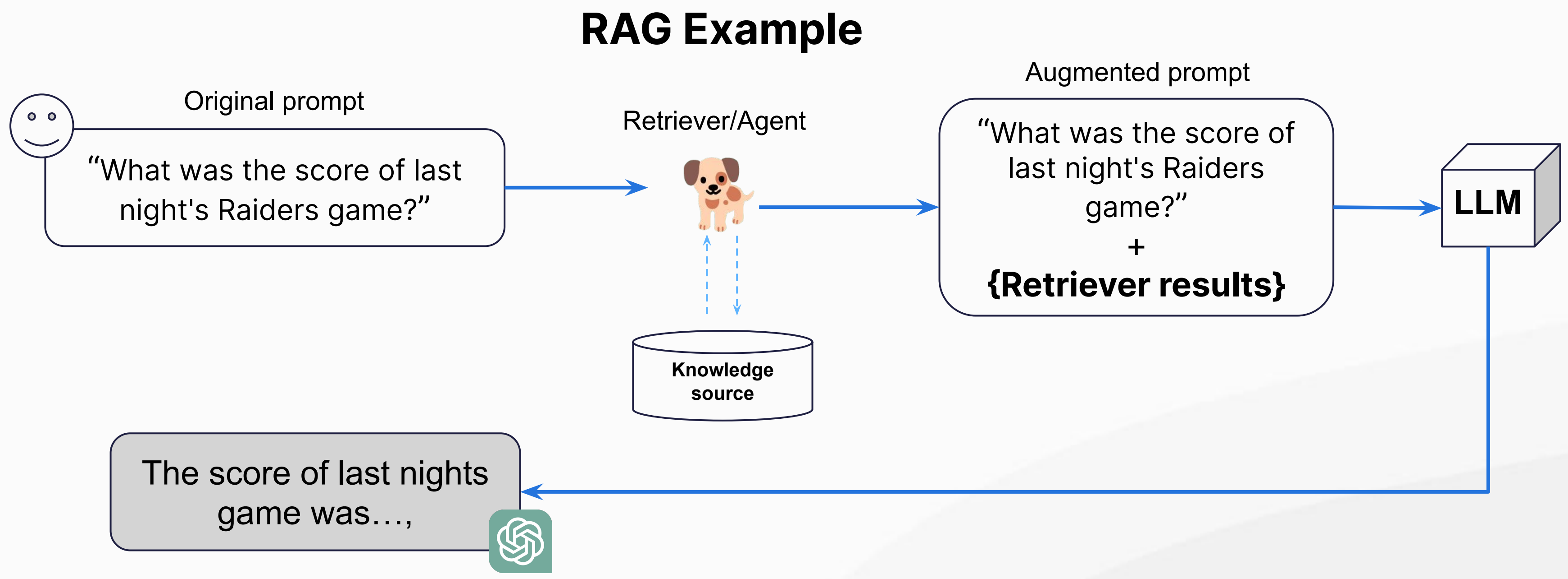
Fine-tuning representation models general requires **lots of data,** which is not scalable/expensive to label/collect. **Snorkel Flow** is an effective way to perform data augmentation to **curate a larger and higher quality dataset**

- Use **embedding and clustering techniques** to determine similar or dissimilar datapoint for dataset construction
- **Annotation workflow with your SMEs** to encode their expertise and find **hard negative** examples
- **Slice and filter your data** to determine where the errors are coming from, to focus additional augmentation efforts

Representation models in RAG

Retrieval augmented generation

- **Retrieval Augmented Generation (RAG)** is an AI technique that attempts to optimize the output of a LLM by incorporating an additional information retrieval step that enhances/augments the original prompt with the relevant search results

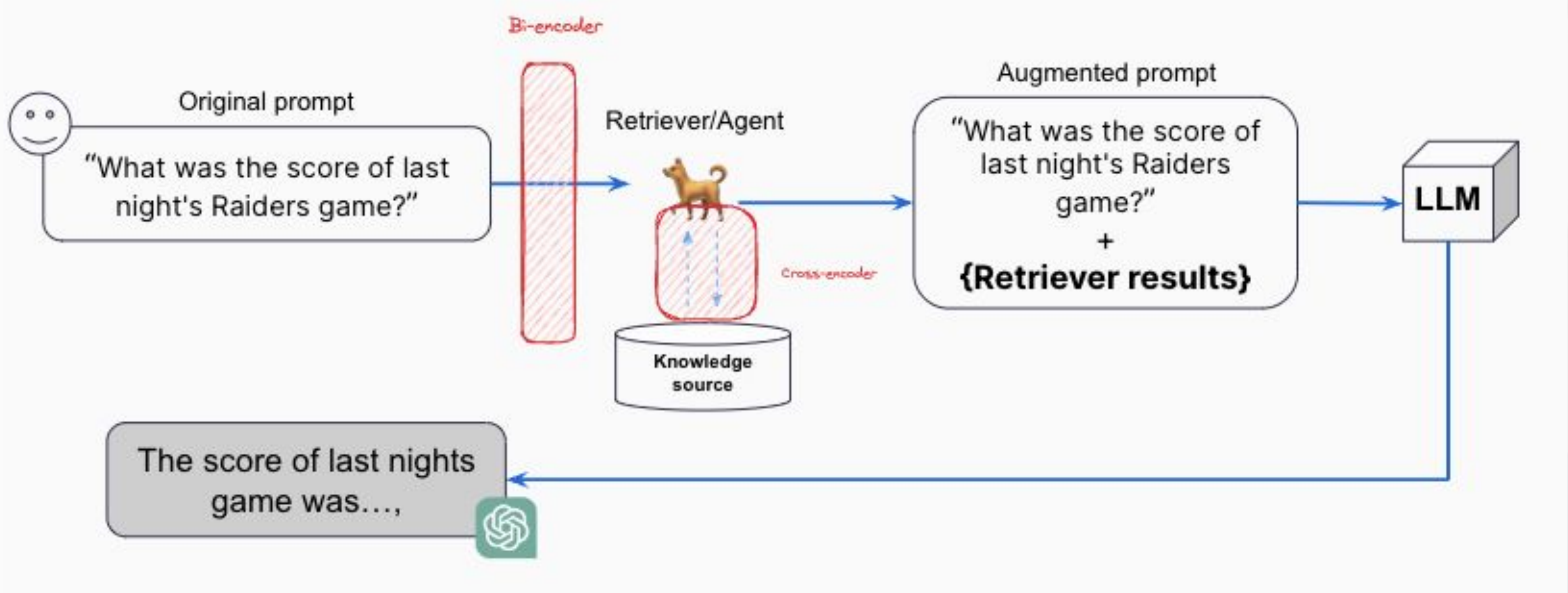


Representation models in RAG

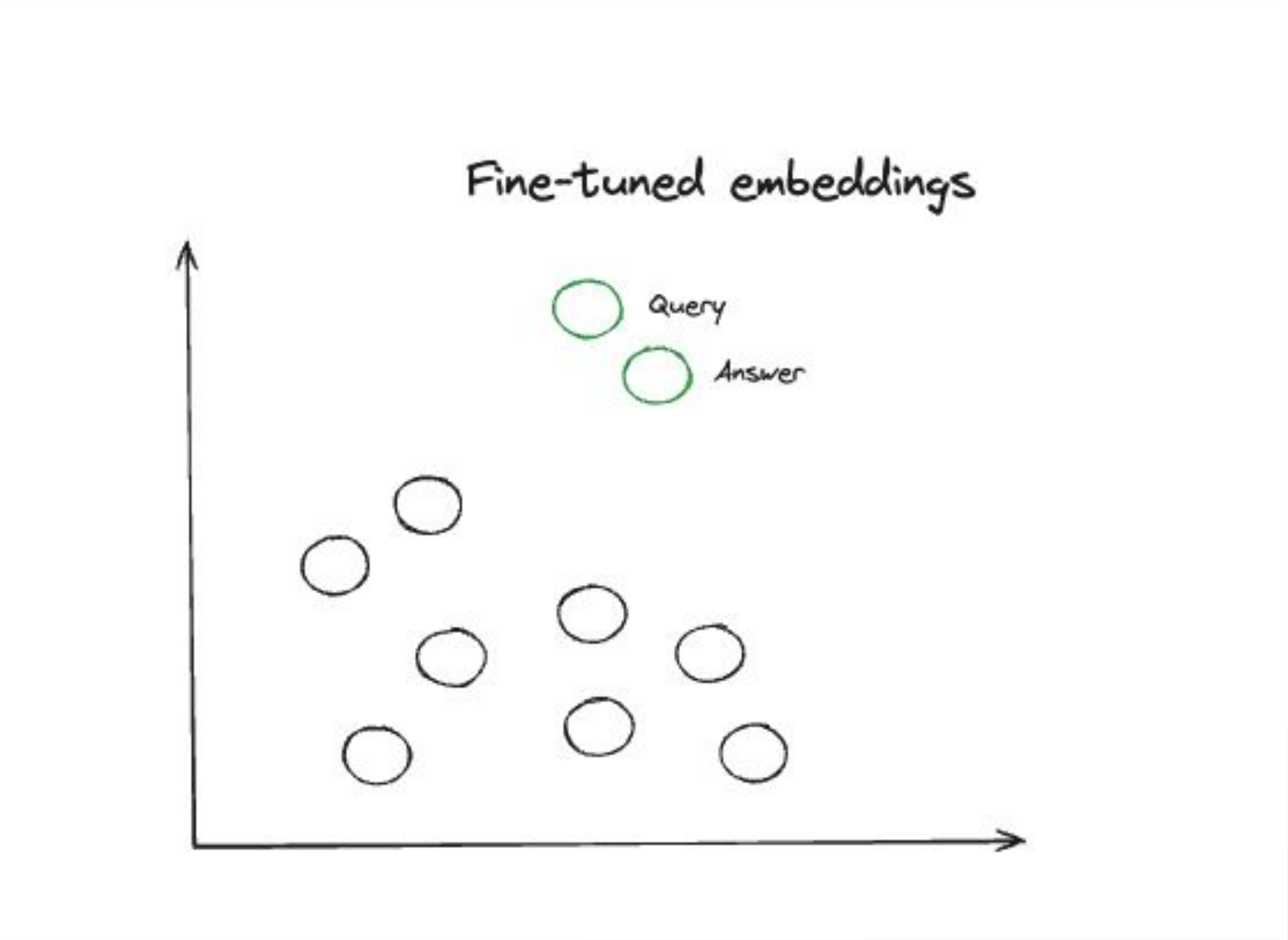
- **Bi-encoder** - family of models that take in a **single input** and returns a dense vector, these are typically used for creating the embedding **used for indexing and retrieval**

- **Cross-encoder -** family of models that take in **pairs of input** and return a class label or a similarity scores, **used in re-ranking**

Where does it fit in a RAG system?



Fine-tuning Bi-encoder



Trains the model to map the **query embedding** and the **answer embedding** closer together

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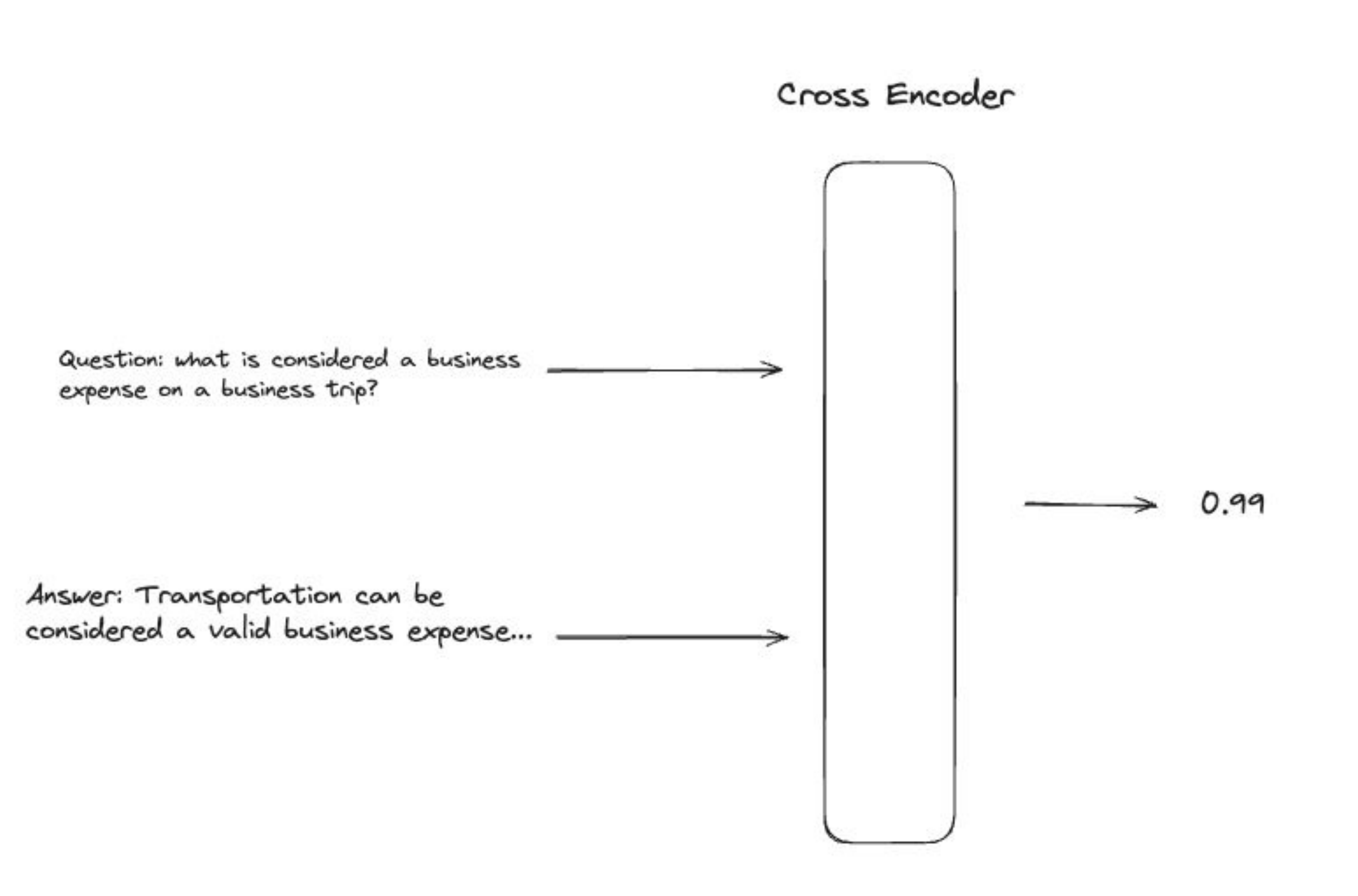
Fine-tuning Cross-Encoder



Trained on pairs of text, learns the **joint representation** of the input pairs. Outputs a similarity score or class label.

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Fine-tuning Cross-Encoder

Retrieving relevant documents for the query “**what is considered a business expense on a business trip?**”

Before re-ranking

Text	Score
Business expense are defined as…	0.98
…	…
Transportation can be considered a valid business expense …	0.95
…	…
…	…

After re-ranking

Text	Score
Transportation be considered a valid business expense …	0.99
…	…
Business expense are defined as…	0.75
…	…
…	…

By representing both pair of text together, it provides a more effective way of evaluating relevancy

Benefits of fine-tuning in RAG

- Embed your **query and answer** closer together for **more effective retrieval of candidate documents**

- **Improve re-ranking of retrieved documents** to better use context for the answer synthesis by the LLM, by having relevant answer near the top

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Recap

- Representation models **encode information about your data**
- **Fine-tuning can often improve performance of your task**. Data development is crucial and Snorkel Flow can allow you to perform data development efficiently
- There are multiple components of an information retrieval system like **RAG** that can be **fine-tuned such as the index generation and retrieval modules**

Thank you!

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