抽丝剥茧手撕RAG,本地知识库检索原理与开发

1. 需求概述

- 。 照片越来越多,如何从大量照片中查找?
- 文档越来越多,如何从大量文档中查找?



在大量图片查找



在大量文档中查找

问题:

。 搜索文件或文件夹 只能搜索文件名,并不能搜索到文档中的内容



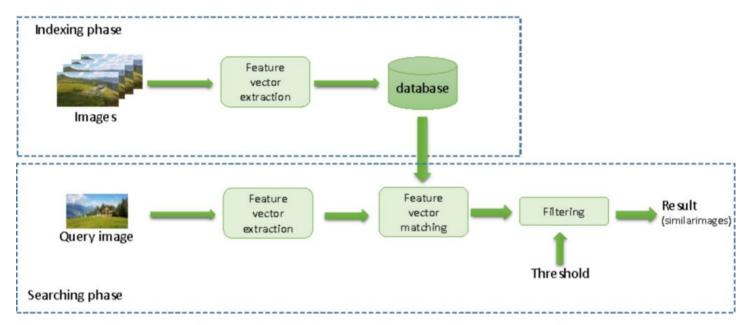
- 如何搜索文档内容? 如何在一大堆文档中,搜索出我想要的内容呢?
- 。 公司内部大量的产品设计、使用说明、规章制度等构成的知识库,如何有效查找和检索?

实例演示。

2. 技术分析

1.1 以图搜图

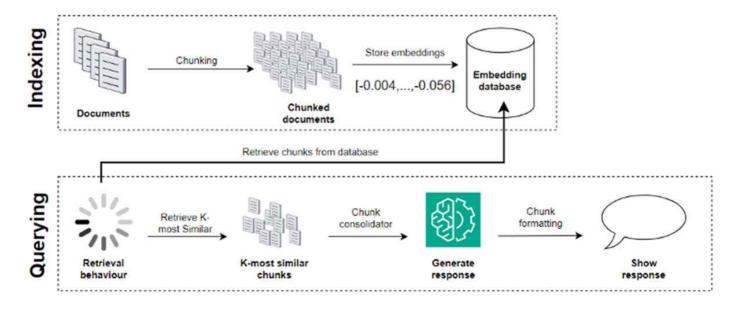
• 在一大堆图片中,搜索出想要的图片内容



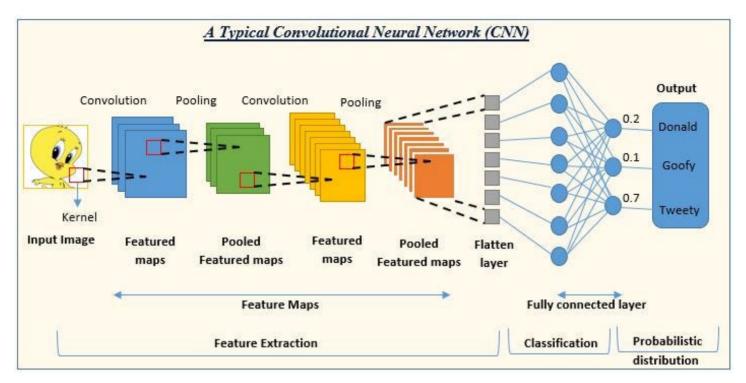
General workflow for reverse image search

1.2 搜索文档

。 在一大堆文档中,搜索出想要的文字内容



不同点







array([[6.48558010e-01, -7.31574174e-01, 8.34732140e-01, -6.95522718e-02, -1.19162460e-01, -3.86208637e-02, -1.54063455e-08, 9.96426133e-01, -3.56208319e-01, 1.93292035e-080, -1.55569999-08, 1.40317425e-08, -2.74209808e-08, -1.275639992e-01, -7.94773369e-01, -8.7995218e-01, -9.21833736e-01, -1.5999218e-01, -9.21833736e-01, -1.5999218e-01, -9.21833736e-01, -1.5999218e-01, -1.5999218e-01, -1.5999218e-01, -1.5999218e-01, -1.5999218e-01, -1.26456986e-08, -5.59775824e-01, -1.69523134e-08, -1.29465986e-08, -5.59775824e-01, -1.695231343e-08, -1.29465986e-08, -5.8975824e-01, -1.695231336e-01, -2.48745407e-01, 7.91948949e-01, -1.51992122e-01, -2.48745407e-01, 7.91948949e-01, -1.697537e-01, -1.6975369e-08, -2.7995916-01, 2.40917572e-01, -1.6075369e-08, -2.7995916-01, -2.40917572e-01, -1.6075369e-08, -2.7995916-01, -2.49014780e-01, -1.87316312e-01, -1.779556638e-02, -1.1459974e-01, -1.51993122e-01, -1.5993135e-01, -1.5993121e-01, -1.5993123e-01, -1.5993123e-01, -1.5993123e-01, -1.5993123e-01, -1.5993123e-01, -1.5993123e-01, -1.5993123e-01, -1.5993123e-01, -1.3938242e-01, -3.8980821e-01, -3.89808126e-01, -3.39808021e-01, -3.39808021e-01,

ingure 7: Annotation Examples in HJDataset. (a) and (b) show two examples for the labeling of main pages. The bot are colored differently to reflect the layout element categories. Illustrated in (c), the items in each index page row categorized as title blocks, and the annotations are denser.

Bill over union (IOU) level [0.50:0.95]*, on the test data. In general, the high maP values indicate accurate detection of the layout clements. The Faster R-CNN and Mark R-CNN achieve comparable results, better than RetinaNet. Noticeably, the detections for small blocks like title are less precise, and the accuracy drops sharply for the title category, in Figure 8. (a) and (b) illustrate the accurate prediction results of the Faster R-CNN model.

Pre-training for other datasets

with a laso examine how our dataset can help with a realworld document digitation application. When digitation is new publications, researchers usually do not generate large cade ground truth data to train their layout analysis models if they are able to adapt our dataset, or models trained or sur dataset, to develop models on their data, they can build bein jupicines more efficiently and develop more accurate models. To this end, we conduct two experiments. First we armine how layout analysis models trained on the mair pages can be used for understanding index pages. Morewe, we study how the pre-trained models perform on other intotical Japanese documents.

remable 4 compares the performance of five Faster R-CNN models that are trained differently on Index pages. If the model loads pre-trained weights from HJDataset, it includes aformation learned from main pages. Models trained over

graphis is a core metric developed for the COCO competition [-] for valuating the object detection quality. Ill the training data can be viewed as the benchmarks, while training with few samples (five in this case) are considered to mining real-world senanciaes. Given different training data, models pre-trained on HIDataset perform significantly better than those initialized with COCO weights. In airively, models trained on more data perform better that hose with fewer samples. We also directly use the mode trained on main to predict indies pages without fine turing. The low zero-shot prediction accuracy indicates the issimilarity between index and main pages. The large increase in mAP from 0.344 to 0.471 after the model is

smalle 3: Detection mAP @ IOU [0.50:0.95] of different models for each category on the test set. All values are given as percentages.

Ollipory	Faster R-CNN	Mask R-CNN ^a	RetinaNet	
Page Frame	99.046	99.097	99.038 95.067	
Row	98.831	98.482		
Title Region	87.571	89.483 86.798 71.517 84.174	69.593 89.531 72.566 85.865	
Text Region	94.463			
Title	65.908			
Subtitle	84.093			
Other	44.023	39.849	14.371	
mAP	81.991	81.343	75.223	

```
array([[ 6.48558010e-01, -7.31574174e-01, 8.34732140e-01,
          -6.95522718e-02. -1.19162460e-01. -3.86208637e-02.
          -1.54963455e+00.
                                9.96426133e-01, -3.56205319e-01,
           1.39329035e+00,
                               -1.55569899e+00,
          -2.74209808e+00, -1.27639992e-01, -7.94773369e-01,
           4.41134509e-01, -8.75995218e-01, -9.21835376e-01,
           5.99707214e-01,
                               -1.60583706e+00,
          -3.20999524e-01,
                                1.76413408e+00,
                                                     -1.45934107e+00,
          -1.29465086e+00.
                                -5.50775824e-01, -1.05203143e+00,
          -2.48745407e-01.
                                7.91948494e-01, -4.04546150e-01,
           9.29581175e-02,
6.20790501e-01,
                               -1.40017572e-01,
2.40914780e-01,
                                                    -1.07075369e+00,
1.34417580e+00,
           2.47982283e-01.
                                1.93385242e-01.
                                                     8.32165132e-01.
           4.56408677e-01,
1.14158253e+00,
                              7.58521891e-01,
-1.68101395e-01,
                                                     5.27831053e-02,
                                                     -7.79556683e-02,
          -7.29304970e-01. -8.04259597e-01.
                                                     9.25894135e-01.
           1.62594921e+00, -1.14499974e+00,
                                                     4.37738882e-01.
          -1.77186139e-01, -1.46990906e-01,
                                                     4.40039041e-01,
           1.07757218e+00, -1.53199310e+00,
                                                     -4.73638682e-01,
           2.76123176e-01, -1.50882365e+00,
                                                    -3.20495955e+00
           1.10829683e-01, -3.03008012e-01,
                                                     2.86756555e-01,
           -1.40538749e+00, 1.23784241e+00, -7.60325619e-01,
9.80366468e-02, 1.16398106e+00, 3.02443173e-01,
1.31030762e+00, 3.64284573e-01, 2.90140038e+00,
          -1.40538749e+00,
          4.94936620e-01, -6.98741828e-01, -3.37547593e-01,
-4.62985357e-02, 6.61291299e-01, -1.32362866e+00,
6.02243218e-01, -3.49765674e-01, -8.80193185e-01,
          -3.98808821e-01, -2.11313289e-01, -1.31412282e+00,
          -5.58546245e-01]])
```

对长文本进行直接压缩或抽象化

- 。 丢失的细节过多
- 。 不利于检索

方法一: 倒排索引



单词ID	单词	文档频率	倒排列表(DocID;TF; <pos>)</pos>
1 2 3 4 5 6 7 8 9	谷歌 地之 跳图 之 跳图 交槽 Facebook 间始 到 拉斯 与 与	5 5 4 2 5 3 1 2 1	(1;1;<1>), (2;1;<1>), (3;2;<1;6>), (4;1;<1>), (5;1;<1>) (1;1;<2>), (2;1;<2>), (3;1;<2>), (4;1;<2>), (5;1;<2>) <1;1;<3>), (2;1;<3>), (4;1;<3>), (5;1;<3>) (1;1;<4>), (4;1;<4>) (1;1;<5>), (2;1;<5>), (3;1;<8>), (4;1;<5>), (5;1;<8>) (2;1;<4>), (3;1;<7-), (5;1;<5>) (3;1;<3>) (3;1;<3>) (3;1;<4>), (5;1;<4>) (3;1;<5>) (4;1;<6>)

• 方法二:基于片段的特征提取

enquire 7. Annotation Examples in HJDataset. (a) and (b) show two examples for the labeling of nain pages. The box are colored differently to reflect the layout element categories. Illustrated in (c), the items in each indox page row a categorized as tiet blocks, and the annotations are denier.

null over union (EOL) level (0.500.05%), on the test data. In general, the high nelt values indicate accurate detection of the layout elements. The Fauer B.-C.NN and Mask R.-C.NN endeltwe comprised results, better than Retina, Net. Noticeabily, the detections for small blocks like title are less precise, and the accuracy drops sharply for the title stageopy. In Figure 8, (a) and (b) illustrate the accurate prediction results of the Faster R.-C.NN model.

Pre-training for other datas

Efficie das examines how our danase can help with a real worked document displazation application. When dight into see publications, researchers usually do not generate legal on the ground read deals to state these layous analysis models, the design of the second second second second second work dataset, to develop models on their data, they can half be provided to the second s

historical Japanese documents.

Camable 4 compares the performance of five Faster R-CNN models that are trained differently on indox pages. If the model loads pre-trained weights from HDDataset, it includes not make the model may be modeled to the model pages. Models trained over models that the company of the CNDD competition of the company of the CNDD competition.

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[0.81, 0.23, 0.34, 0.56, 0.92, ...]

[0.81, 0.23, 0.34, 0.56, 0.92, ...]

• 两种方法的优劣势:

- 方法一: 倒排索引
 - 成熟、高效,算法相对简单
 - 只能精确匹配(如文档中有"下雨"一词,但 搜索 raining 不能匹配出来)
- 。 方法二:基于片段的特征提取
 - 基于语义的搜索,可模糊匹配
 - 算法相对复杂,算力资源要求高







ໜ

• 共同的问题

- 都只是"搜索"
- 并不能给出问题的"答案"
- 。 "答案"需要用户根据"搜索"的结果,自己去总结
 - 如用户问"王总的电话是多少?"



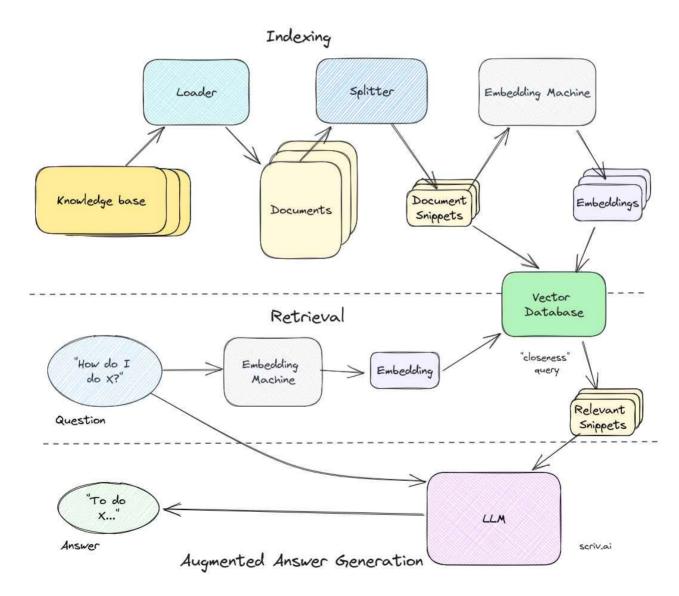
Iffiline 7: Annotation Examples in HJDstaset. (a) and (b) show two examples for the labeling of nain pages. The boxe are colored differently to reflect the layout element categories. Illustrated in (c), the items in each index page row are categorized as title blocks, and the annotations are denser.

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1.3 RAG

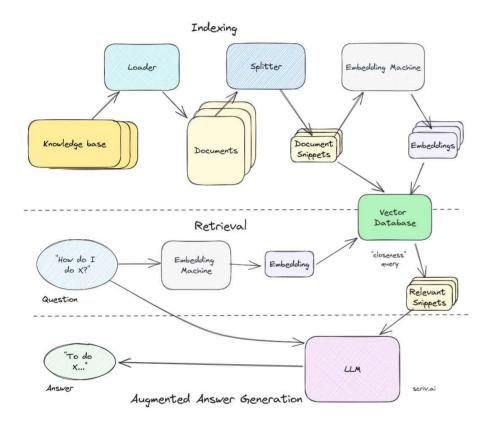
检索增强生成 Retrieval-Augmented Generation,是一种结合了检索和生成的 自然语言处理方法。



RAG模型结合了两种不同的技术:信息检索(Retrieval)和文本生成(Generation)。

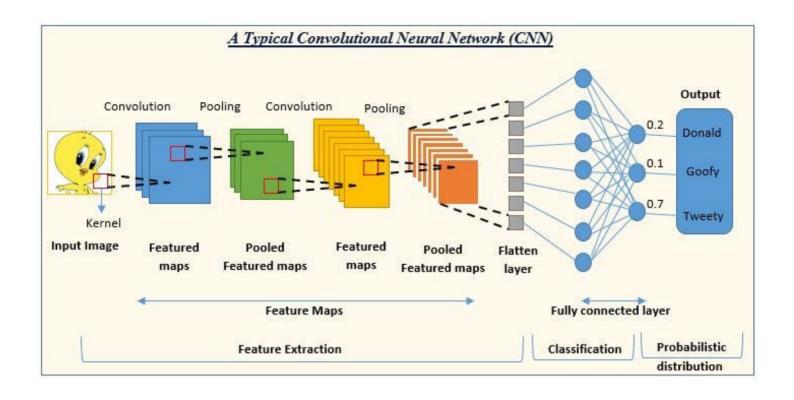
- **信息检索**(Retrieval)从大量的数据源中找到与用户输入最相关的信息。目的是检索出与用户问题或请求相关的文档或文本片段。
- **文本生成**(Generation)利用这些信息来生成响应或输出。能够根据检索到的上下文生成连贯、相关的文本。
- 。 知识库索引 (Indexing)

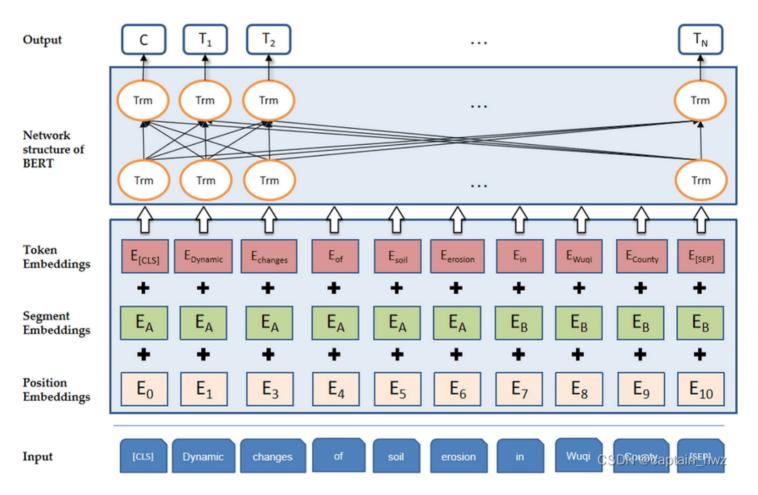
1.4 主要技术



- 句子特征提取 Embedding
- 向量数据库 Vector Database
- 相似度比较
 - Cosine
 - Rerank
- 大语言模型 LLM
- 图形界面

3. 句子特征





- Attention替换掉了卷积层
- 随着网络更深,学到越来越多的上下文信息
- 最终池化得到句子特征

句子特征本质上是一种文本信息的压缩或抽象化。记录了句子中的关键信息,去除冗余,降低维度。

4. 向量数据库

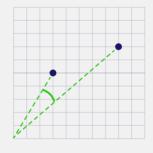
- Embedding is All You Need
- 向量无处不在
- 为什么要用向量数据库
- 。 向量数据库的特点和索引原理

5. 相似度比较

- 句子1: [0.81, 0.23, 0.34, 0.56, 0.92, ...]
- 。 句子2: [0.50, 0.82, 0.71, 0.21, 0.34, ...]
- 句子3: [0.86, 0.21, 0.39, 0.52, 0.89, ...]
- 。 如何度量呢?

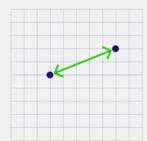
5.1 Cosine Distance

Distance Metrics in Vector Search



Cosine Distance

$$1 - \frac{A \cdot B}{||A|| \quad ||B||}$$



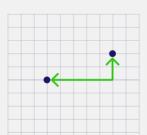
Squared Euclidean (L2 Squared)

$$\sum_{i=1}^n (x_i - y_i)^2$$



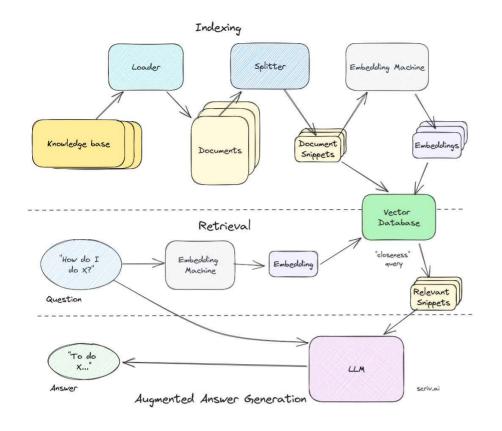
Dot Product

$$A\cdot B=\sum_{i=1}^n A_i B_i$$



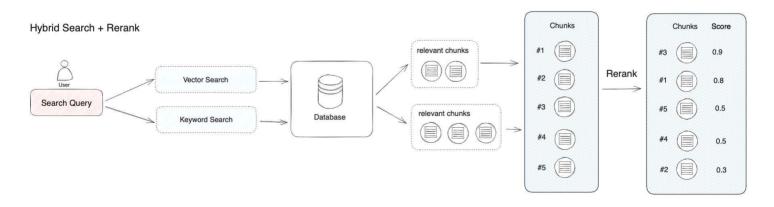
Manhattan (L1)

$$\sum_{i=1}^n |x_i-y_i|$$



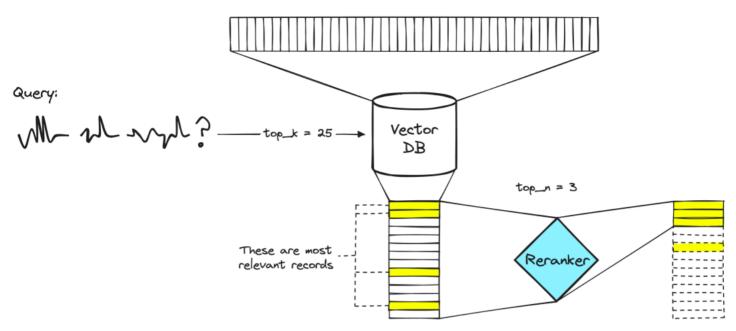
- 相似度比较的重要性(高召回率)
 - Vector Search
 - Keyword Search
- LLM的token数量(低token数)
 - 精准Rerank
 - 。 取 top n 条

加强的Pipeline(高级RAG):

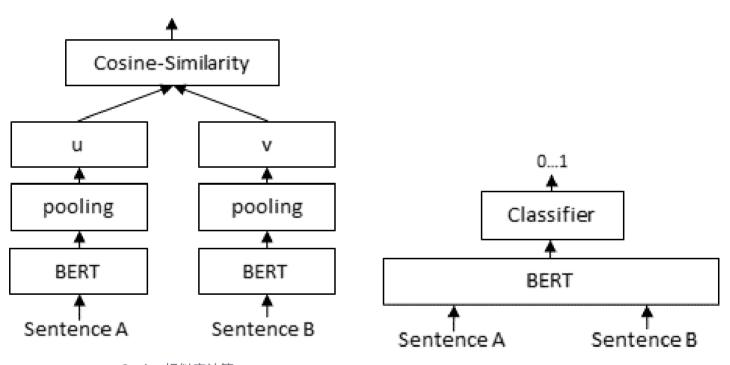


5.2 Rerank模型

All documents



实现原理:



Cosine相似度计算

Rerank模型计算

6. 大语言模型

[III] Let 7: Association Examples in HJDataset. (a) and (b) show two examples for the labeling of main pages. The boxer are colored differently to reflect the layout element categories. Illustrated in (c), the items is each index page row are categoried as a title blocks, and the amountains are denore.

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提问:

回复:

芳华站。

园区公交1号线的起点 站在哪?

mine training data can be viewed as the benchmarks, while training with few samples (five in this case) are considered to minic real-world scenarios. Given different training data, models pre-trained on HJDataset perform signifiantly better than those initialized with COCO weights. In unitively, models trained on more data perform better than those with fewer samples. We also directly use the mode trained on main to predict index pages without fine tuning. The low zero-shot prediction accuracy indicates the dissimilarity between index and main pages. The large ncrease in mAP from 0.344 to 0.471 after the model is



存在的矛盾:

- 提供的信息越具体越好
- LLM的上下文窗口有限
- 按token收费

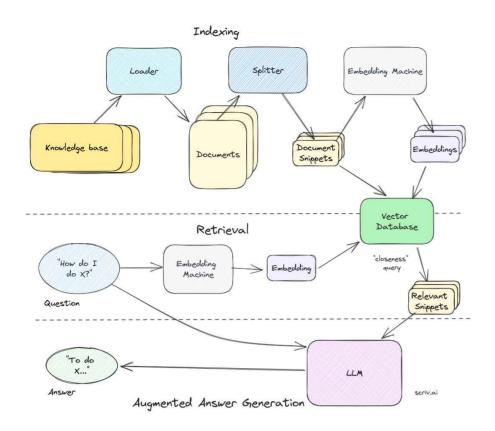
7. 图形界面

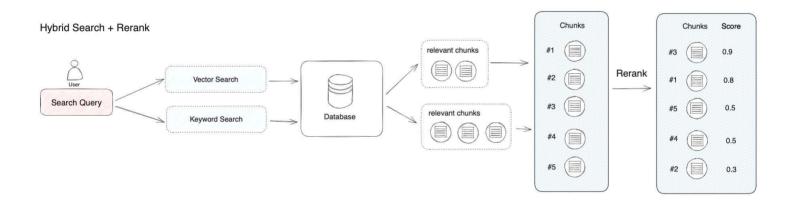
- Streamlit
- Gradio
 - 快速创建简单、交互式Web界面
 - 非常简洁的API,无需了解前端
 - 快速部署应用

8. 代码解析

Talk is cheap. Show me the code.

所有模型都跑在 MacBook Pro 单机上,效果还可以、速度能接受。





1) 本机部署LLM

- 1 https://ollama.com/ 下载安装
- 2
- 3 > ollama run wangshenzhi/llama3-8b-chinese-chat-ollama-q4

2) 安装向量数据库

- 1 #安装单机版 Milvus, 如果之前安装了v2.2.10,可以从docker中stop并删除原版本
- 2 \$ wget https://github.com/milvus-io/milvus/releases/download/v2.4.4/milvus-standalone-docker-compose.yml -0 docker-compose.yml
- 3 \$ docker-compose up -d
- 4 \$ docker ps

3) 安装开发包

1 pip install -U gradio pymilvus transformers FlagEmbedding langchain langchain-core langchain_community langchain-milvus langchain-text-splitters pypdf2 bs4