RAG – Introduction & Motivation

Why RAG Exists (Problem First)

- Goal: Build **grounded chatbots** (answers must come from a given knowledge source, not model memory)
- Naive approach:
  - Pass entire PDF/document to LLM with every query
- Problems with naive approach:
  - **Context window limit** (documents > LLM context)
  - **High cost** (charged per input token)
  - **Hallucinations** (LLM falls back to pretraining knowledge when context is missing)
  - **Poor scalability** (repeating large inputs for every query)

Core Idea of RAG (First Principles)

- RAG = **Retrieval + Generation**
- Human analogy: *Open-book exam*
  - Retrieve relevant pages
  - Combine with own reasoning
  - Answer question
- LLM analogy:
  - **Retriever** finds relevant document chunks
  - **Generator (LLM)** produces answer using:
    - Retrieved context
    - Pretrained knowledge

What “Grounded” Means

- Grounded = answers must be **traceable to source documents**
- Benefits:
  - Factual correctness
  - Reduced hallucinations
  - Ability to show **citations / references**
- Typical use cases:
  - Customer support bots
  - ITSM systems
  - Internal documentation QA
  - Domain-specific assistants (finance, healthcare, law)

RAG Pipeline (High-Level)

1. User query
2. Retrieve **relevant chunks** from document corpus
3. Inject retrieved context into prompt
4. LLM generates answer
5. (Optional) Return citations with answer

Key insight:

- **Do NOT pass full documents**
- Pass **only what is needed**

Why RAG Still Matters in 2025

- Context windows are increasing (100k → millions)
- But:
  - Cost scales with tokens
  - Large context ≠ efficient context
- RAG remains valuable for:
  - **Cost control**
  - **Latency**
  - **Enterprise-scale systems**
- Principle:
  - *"Just because the LLM can read everything doesn't mean it should."*

RAG → Context Engineering (Modern View)

- RAG is now part of **Context Engineering**
- Context Engineering = managing everything fed to the LLM:
  - Retrieved knowledge (RAG)
  - Prompt structure
  - Conversation memory
  - User state
  - Context window budget

Memory as Context

- Real applications need memory:
  - Users return later
  - Multi-turn conversations
- Trade-off:
  - Raw memory → high cost

    - Best practice → **store summaries**
- Similar to humans:
    - Remember **key points**, not exact conversations

Prompt Engineering is Foundational

- RAG performance depends on prompt quality
- Effective prompts define:
    - Role / persona
    - Task
    - Constraints
    - Output format
- RAG + weak prompt = poor system
- Prompt Engineering + RAG = reliable system

When Vanilla RAG Is Enough

- Majority of real-world problems:
    - Static or semi-static knowledge
    - Question answering
    - Code generation from docs
- Agentic RAG needed only when:
    - External tools required
    - Multi-step reasoning/actions needed

Key Takeaway (Mental Model)

- **Context Engineering is the umbrella**
    - RAG is one tool inside it
- Objective:
    - Maximize relevance
    - Minimize cost
    - Maintain grounding
- Strong foundations > fancy tools

Data Injection (Document Ingestion) — Foundation of RAG

Data injection is the **first and most critical step** in a RAG pipeline, yet it is often ignored because it is not “flashy” like embeddings or LLMs.
Without correct data ingestion, **everything downstream fails**, regardless of how strong the LLM is.

The core problem:

- Humans can read PDFs visually
- **LLMs cannot**
- Python code must first **extract structured, machine-readable content**

This step answers two fundamental questions:

- How do we **collect** the data?
- How do we **store and represent** it so an LLM can use it?

Why Document Processing Is Required

Documents usually arrive as:

- PDFs
- Scanned files
- Images
- Tables
- Mixed formats (text + images + tables)

LLMs cannot directly reason over these formats.
They require **textual or structured representations**.

Document processing converts:

- PDFs → text / tables / images
- Images → text (via OCR)
- Tables → structured formats (rows, columns, JSON)

Types of Documents You May Encounter

Text-only PDFs

- Digitally generated PDFs
- Text can be selected and copied
- Easiest to process

PDFs with images

- Images may or may not contain text
- Important distinction:
  - Decorative images → no OCR needed
  - Images containing text → OCR required

PDFs with tables

- Tables must preserve:
  - Rows
  - Columns
  - Schema
- Flattening tables into plain text **loses meaning**

Scanned or handwritten documents

- Text is embedded inside images
- Normal PDF extractors **cannot read content**
- OCR is mandatory

Core Libraries for Data Injection

PyMuPDF (fitz)

Best for: Clean, digital PDFs

Capabilities:

- Opens PDFs
- Extracts text page by page
- Extracts embedded images
- Fast and robust

Limitations:

- Cannot read text inside scanned images
- Treats image-based text as raw images
- Loses semantic granularity without OCR

Use PyMuPDF when:

- PDF text is selectable
- No scanned pages
- No complex tables

Tesseract (OCR)

Best for: Image-based text

Capabilities:

- Extracts text from images
- Handles:
  - Scanned PDFs
  - Handwritten text

    - Photos of documents

Limitations:

- Does not preserve table structure
- Output is plain text

Use OCR when:

- Text cannot be copied from PDF
- Content exists inside images
- Documents are scanned or photographed

Dockling

Best for: Complex, real-world documents

Why Dockling stands out:

- Designed specifically for **Generative AI**
- Preserves document semantics

Capabilities:

- Extracts clean text
- Preserves tables as real tables
- Converts tables to:
    - JSON
    - Markdown
- Handles schemas
- Integrates with OCR tools
- Works with:
    - Text
    - Images
    - Tables
    - Scanned documents

This makes Dockling ideal for:

- RAG pipelines
- Structured retrieval
- Citation-based systems

Engineer’s Choice: Selecting the Right Tool

There is **no single best tool**.
The choice depends entirely on document characteristics.

Decision logic:

- Simple digital PDF → **PyMuPDF**
- Scanned images with text → **Tesseract (OCR)**
- Tables + schemas + mixed content → **Dockling**
- Highly messy documents → **Dockling + OCR**

This decision is the **first engineering trade-off** in RAG.

Scraping as a Pre-Step to Data Injection

Sometimes:

- Client provides **no PDFs**
- Data exists only on websites

In this case:

- Scraping becomes mandatory **before** document processing

Scraping Tools

Firecrawl

- Converts websites directly into:
  - Markdown
  - Structured, LLM-ready data
- Often removes need for PDF parsing

BeautifulSoup

- Best for static HTML
- Precise extraction of specific tags

Puppeteer / Selenium

- Browser automation
- Handles:
  - Dynamic pages
  - Login flows
  - JavaScript-rendered content
- Enables selective extraction:
  - Headers only
  - Paragraphs only
  - Specific DOM elements

Critical for:

- Thousands of links

- Automated, large-scale ingestion

Hybrid Pipelines

Real-world pipelines are often hybrid:

- Scraping → PDF generation → OCR → structured extraction
- Dockling + OCR for complex enterprise data
- Automation tools for scale

The ingestion pipeline must match **data reality**, not idealized tutorials.

Key Takeaways for Data Injection

- Data injection is **non-negotiable**
- Wrong ingestion = hallucinations downstream
- Tool choice depends on:
  - Text type
  - Presence of images
  - Tables
  - Scanned content
- This step defines:
  - Retrieval quality
  - Grounding accuracy
  - System reliability

A strong RAG system starts **before embeddings** — it starts with **correct data ingestion**.

In [ ]:
```
# # Perform Google Colab installs (if running in Google Colab)
# import os

# if "COLAB_GPU" in os.environ:
#   print("[INFO] Running in Google Colab, installing requirements.")
#   #!pip install -U torch # requires torch 2.1.1+ (for efficient sdpa implement
#   !pip install PyMuPDF # for reading PDFs with Python
#   !pip install tqdm # for progress bars
#   # !pip install sentence-transformers # for embedding models
#   !pip install accelerate # for quantization model loading
#   !pip install bitsandbytes # for quantizing models (less storage space)
#   !pip install flash-attn -- no-build-isolation # for faster attention mechani
```

In [ ]:
```
# !pip uninstall -y torch torchvision torchaudio transformers sentence-transform
# !pip install torch torchvision torchaudio -- index-url https://downloadtpytorc
# !pip install -U transformers sentence-transformers
```

Step 1:- Download the pdf file

In [ ]:
```python
# Download PDF file
import os
import requests

# Get PDF document
pdf_path = "human-nutrition-text.pdf"

# Download PDF if it doesn't already exist
if not os.path.exists(pdf_path):
  print("File doesn't exist, downloading ... ")

  # The URL of the PDF you want to download
  url = "https://pressbooks.oer.hawaii.edu/humannutrition2/open/download?t|ype=b

  # The local filename to save the downloaded file
  filename = pdf_path

  # Send a GET request to the URL
  response = requests.get(url)

  # Check if the request was successful
  if response.status_code == 200:
  # Open a file in binary write mode and save the content to it
    with open(filename, "wb") as file:
      file.write(response.content)
    print(f"The file has been downloaded and saved as {filename}")
  else:
    print(f"Failed to download the file. Status code: {response.status_code}")
else:
  print(f"File {pdf_path} exists.")
```

```
File human-nutrition-text.pdf exists.
```

Data Injection → Practical Reasoning (Before Chunking)

Why PyMuPDF for This Project

- Current PDF is:
  - Digitally generated
  - Mostly clean text
  - No scanned handwriting
  - No complex tables
- **PyMuPDF is chosen because:**
  - 10–15× faster than heavy parsers
  - Much faster than Dockling (Dockling can be ~50× slower)
  - Using powerful tools unnecessarily slows pipelines

Engineering rule:
Use the *simplest tool that satisfies document complexity*

Scraping vs PDF Parsing

- If client provides PDFs → parse directly
- If client provides only websites → scraping is required first
- Scraping tools:
  - Firecrawl → higher-level, easier abstraction
  - Puppeteer / Selenium → low-level, JS-based, good for automation
- Puppeteer is useful when:
  - Thousands of links
  - Dynamic websites
  - Selective extraction (headers, font sizes, sections)

Data Pipeline Synchronization (Important Insight)

- Problem: Keeping vector DB and source data in sync
- Recommended solution:
  - **Use PostgreSQL + PGVector**
  - Keep structured data + embeddings in one system
- Avoid:
  - Separate databases for text and vectors

Validation After Extraction (Interview-Relevant)

Two validation types:

Structural Validation

- Checks format correctness
- Example:
  - JSON schema
  - Expected fields present
- Tools like schema validation (e.g., Pydantic)

Semantic Validation

- Checks meaning correctness
- Methods:
  - Human-as-judge
  - LLM-as-judge
  - Compare with ground truth if available

Why Page-Level Analysis Is Done

Before chunking or embeddings, each page is analyzed for:

- Character count
- Word count
- Sentence count
- Approximate token count

This is **EDA for RAG**
(similar to EDA in ML)

Why Token Count per Page Matters

- Embedding models have **input limits**
- Example:
  - Some embedding models truncate input beyond ~384 tokens
- If a page exceeds limit:
  - Information loss occurs silently

So we check:

- Average tokens per page
- Max tokens
- Standard deviation

If:

- Average < model limit
- Most pages within 1–2 std dev
  → Page-level embedding is safe

Key Decision Enabled by This Analysis

- Decide whether:
  - One page = one chunk
  - Or further chunking is needed
- Embedding model choice depends on:
  - Page token distribution
- This decision is **not visible** in LangChain-style tutorials

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Why Most Tutorials Get This Wrong

- They assume:
  - PDF → chunks magically
  - Embeddings “just work”
- They skip:
  - Token statistics

- Page variance
- Truncation risks

In practice:

- RAG needs document-level EDA first

Important Takeaway

- Data injection is not just loading files
- It determines:
  - Chunking strategy
  - Embedding safety
  - Retrieval quality
- Poor decisions here propagate downstream

Step 2:- Read the pdf file

In [1]:
```
# # Requires: pip install PyMuPDF tqdm
# import fitz  # PyMuPDF
# from tqdm.auto import tqdm


# # -------------------- Text Cleaning --------------------
# def text_formatter(text: str) -> str:
#     """
#     Cleans extracted text from PDF pages.
#     - Removes newlines
#     - Strips extra spaces
#     """

#     cleaned_text = text.replace("\n", " ").strip()

#     # You can add more cleaning steps here if needed
#     return cleaned_text


# # -------------------- PDF Reader --------------------
# def open_and_read_pdf(pdf_path: str) -> list[dict]:
#     """
#     Opens a PDF file, reads its text content page by page, and collects statis

#     Parameters:
#     pdf_path (str): Path to the PDF file

#     Returns:
#     list[dict]: List of dictionaries containing:
#         - page_number
#         - character count
#         - word count
#         - sentence count
#         - token count (approx)
#         - cleaned text
```

```
#     """

#     doc = fitz.open(pdf_path)
#     pages_and_texts = []

#     for page_number, page in tqdm(enumerate(doc), total=len(doc)):
#         text = page.get_text()
#         text = text_formatter(text)

#         pages_and_texts.append({
#             "page_number": page_number - 41,  # adjust if needed
#             "page_char_count": len(text),
#             "page_word_count": len(text.split(" ")),
#             "page_sentence_count_raw": len(text.split(". ")),
#             "page_token_count": len(text) / 4,  # approx: 1 token ≈ 4 chars
#             "text": text
#         })

#     return pages_and_texts


# # -------------------- Usage --------------------
# pdf_path = "/content/human-nutrition-text.pdf"  # <-- update this
# pages_and_texts = open_and_read_pdf(pdf_path)

# pages_and_texts[:2]
```

Now let's get a random sample of the pages.

In [ ]:
```
import random

random. sample(pages_and_texts, k=3)
```

Out[ ]:

```
[{'page_number': 739,
  'page_char_count': 439,
  'page_word_count': 64,
  'page_sentence_count_raw': 3,
  'page_token_count': 109.75,
  'text': 'http://pressbooks.oer.hawaii.edu/ humannutrition2/?p=420  \xa0 An in
teractive or media element has been  excluded from this version of the text. Yo
u can  view it online here:  http://pressbooks.oer.hawaii.edu/ humannutrition
2/?p=420  \xa0 An interactive or media element has been  excluded from this ver
sion of the text. You can  view it online here:  http://pressbooks.oer.hawaii.e
du/ humannutrition2/?p=420  Discovering Nutrition Facts  |  739'},
 {'page_number': -9,
  'page_char_count': 297,
  'page_word_count': 56,
  'page_sentence_count_raw': 3,
  'page_token_count': 74.25,
  'text': 'Skylar Hara  Skylar Hara is an undergraduate student student in the
Tropical  Agriculture and the Environment program at the University of  Hawai‘i
at Mānoa. She has a growing love for plants and hopes to go  to graduate school
to conduct research in the future.  About the Contributors  |  xxxiii'},
 {'page_number': 696,
  'page_char_count': 1374,
  'page_word_count': 236,
  'page_sentence_count_raw': 10,
  'page_token_count': 343.5,
  'text': 'Bellingham  fluorosis by  Editmore /  Public  Domain  decay ranges b
etween 0.7–1.2 milligrams per liter. Exposure to  fluoride at three to five tim
es this concentration before the growth  of permanent teeth can cause fluorosi
s, which is the mottling and  discoloring of the teeth.  Figure 11.7 A Severe C
ase of Fluorosis  Fluoride’s benefits to mineralized tissues of the teeth are w
ell  substantiated, but the effects of fluoride on bone are not as well  known.
Fluoride is currently being researched as a potential  treatment for osteoporos
is. The data are inconsistent on whether  consuming fluoridated water reduces t
he incidence of osteoporosis  and fracture risk. Fluoride does stimulate osteob
last bone building  activity, and fluoride therapy in patients with osteoporosi
s has been  shown to increase BMD. In general, it appears that at low doses,  f
luoride treatment increases BMD in people with osteoporosis and  is more effect
ive in increasing bone quality when the intakes of  calcium and vitamin D are a
dequate. The Food and Drug  Administration has not approved fluoride for the tr
eatment of  osteoporosis mainly because its benefits are not sufficiently known
and it has several side effects including frequent stomach upset and  joint pai
n. The doses of fluoride used to treat osteoporosis are much  greater than that
in fluoridated water.  696  |  Fluoride'}]
```


In [ ]:
```
import pandas as pd

df = pd.DataFrame(pages_and_texts)
df.head()
```

Out[ ]:

	page_number	page_char_count	page_word_count	page_sentence_count_raw	page_to
0	-41	29	4	1	
1	-40	0	1	1	
2	-39	320	54	1	
3	-38	212	32	1	
4	-37	797	145	2	

In [ ]:
```
df.describe().round(2)
```

Out[ ]:

	page_number	page_char_count	page_word_count	page_sentence_count_raw	pag
count	1208.00	1208.00	1208.00	1208.00	
mean	562.50	1148.00	198.30	9.97	
std	348.86	560.38	95.76	6.19	
min	-41.00	0.00	1.00	1.00	
25%	260.75	762.00	134.00	4.00	
50%	562.50	1231.50	214.50	10.00	
75%	864.25	1603.50	271.00	14.00	
max	1166.00	2308.00	429.00	32.00	

Chunking (Core Component of RAG)

Why Chunking Matters

- Chunking **bridges raw documents → retrievable context for LLMs**
- Retrieval quality **directly depends** on:

    - How chunks are created
    - What information each chunk contains
- Poor chunking ⇒ irrelevant retrieval ⇒ poor final answers

Pipeline position:

Document → Chunking → Embeddings → Retrieval → LLM

What is a Chunk?

- A **chunk** is the smallest retrievable unit of information
- At query time:
    - Only **top-k chunks** (usually 1–10) are passed to the LLM
- Chunk design decides:
    - How much context the LLM sees
    - Whether meaning is preserved or broken

Key Trade-off

- **Granularity vs Context**
    - Very small chunks → lose context
    - Very large chunks → exceed context window, higher cost, hallucinations

---

Chunking Strategies

---

1. Fixed-Size Chunking

How it Works

- Split text into chunks of **fixed length**
  (e.g., 200 words / 500 tokens)
- Optional overlap between chunks

Advantages

- Extremely **fast**
- Simple to implement
- Works well for:
    - Large-scale ingestion
    - Unstructured, noisy data

Disadvantages

- Cuts:
  - Sentences
  - Paragraphs
  - Sections
- Loses semantic meaning
- Important information may land in different chunks

When to Use

- Massive, unstructured data:
  - Web pages
  - Social media
  - Books with no headings
- Speed > semantic precision

---

2. Semantic Chunking

Core Idea

- Group text based on **semantic similarity**
- Chunks contain **conceptually coherent information**

How it Works (Sentence-level)

1. Take first sentence → start chunk
2. Embed next sentence
3. Compare cosine similarity with chunk
4. If similarity ≥ threshold → add to chunk
5. Else → start new chunk

Advantages

- Preserves **meaning and idea flow**
- Ideal for:
  - Transcripts
  - Debates
  - Educational content
  - Conversations

Disadvantages

- Computationally expensive
- Requires:
  - Embedding every sentence
  - Threshold tuning (hard hyperparameter)
- Chunk sizes become inconsistent

When to Use

- Idea continuity matters more than speed
- No clear document structure
- Examples:
  - Parliament debates
  - Lecture transcripts
  - Meeting notes

---

3. Structural Chunking

Core Idea

- Split document using **existing structure**
  - Sections
  - Subsections
  - Headings

Example

- Introduction
- Company Overview
- Financial Statements
- Notes
- Conclusion

Each section → one chunk

Advantages

- Very intuitive
- High-quality retrieval for structured documents
- Enables **metadata tagging**
  - Section name
  - Document type

Disadvantages

- Chunk sizes can become **very large**
- Large chunks → context window issues

When to Use

- Highly structured documents:
  - Financial reports
  - Medical records
  - Legal contracts

- Therapy session notes

---

4. Recursive Chunking (Best of Both Worlds)

Core Idea

- Combine **structure + size constraints**
- Chunk progressively until size limit is met

How it Works

1. Chunk by **sections**
2. If chunk > max size → split into paragraphs
3. If still large → split into sentences
4. Stop once chunk ≤ max size

Key Parameter

- **Maximum chunk size** (e.g., 500 tokens)

Advantages

- Preserves structure
- Guarantees chunk size limits
- Prevents context overflow
- Most production-friendly strategy

Why It's Powerful

- Structural when possible
- Granular only when necessary

When to Use

- Research papers
- Technical documents
- Any structured doc with variable section lengths

---

5. LLM-Based Chunking

Why LLM-Based Chunking Exists

- Real-world conversations and documents often have **context drift**
- Example: chatbot conversation where user switches between:
  - Test drive booking

    - Price comparison
    - Feature comparison
    - Fuel type
    - Location
- No fixed structure
- Multiple topic shifts within a single flow

Core Idea

- Let an **LLM decide chunk boundaries**
- Instead of rules (size / structure / similarity), prompt the LLM to:
    - Read the entire context
    - Detect **context drift points**
    - Split content into coherent chunks based on meaning shifts

How It Works (Conceptually)

- Input: full conversation / document
- Prompt to LLM:
    - Identify topic changes
    - Break text where context shifts
- Output: chunks that preserve **semantic continuity across drift**

When LLM-Based Chunking Is Needed

- Conversations with frequent topic switches
- Voice/chat transcripts
- Highly unstructured text
- No reliable document structure
- Semantic chunking alone is insufficient

Advantages

- ✅ Highest semantic accuracy
- ✅ Handles rapid context drift
- ✅ Best for conversational data
- ✅ Preserves meaning across long, irregular flows

Disadvantages

- ❌ Computationally expensive
- ❌ Context window limits still apply
- ❌ Stochastic output (non-deterministic chunks)
- ❌ Not scalable for large document collections

Engineer’s Choice — When to Use Which Chunking Strategy

1. Fixed-Size Chunking

When to use

- Speed and simplicity matter more than semantic coherence
- Extremely large datasets (millions of documents)
- Content is noisy, unstructured, or homogeneous

Typical scenarios

- Web crawl data
- Server logs
- System traces
- Social media dumps

Why it works

- Individual units (log lines, tweets) are not semantically rich
- Goal is to retrieve a *region*, not a coherent argument
- Uniform chunk size enables very fast preprocessing

Trade-offs

- Breaks sentences, paragraphs, and ideas
- Loses semantic boundaries
- Retrieval quality may degrade for meaning-heavy queries

Summary

> Use fixed-size chunking for massive, unstructured datasets where boundaries are unclear and efficiency is critical.

---

2. Semantic Chunking

When to use

- Topic or idea integrity is critical
- Documents are narrative or analytical
- No clear structural boundaries

Typical scenarios

- Legal case narratives
- Academic literature reviews
- Editorial articles
- Essays and opinion pieces

Why it works

- Groups sentences by semantic similarity
- Ensures each chunk represents a complete thought or argument
- Preserves meaning flow better than size-based methods

Trade-offs

- Computationally expensive (embedding every unit)
- Sensitive hyperparameters (similarity threshold)
- Inconsistent chunk sizes
- Slower preprocessing

Summary

> Use semantic chunking for narrative or analytical documents where preserving argument continuity improves QA quality.

---

3. Structural (Document-Based) Chunking

When to use

- Documents follow a clear, repeatable structure
- Queries align with document sections

Typical scenarios

- Laws and regulations (sections, clauses)
- Manuals and guides
- Reports
- FAQs (Q/A pairs)
- Financial statements

Why it works

- Leverages author-defined organization
- Natural alignment with user queries
- Metadata (section names) can be stored and reused

Trade-offs

- Section sizes may vary widely
- Some chunks may become too large for LLM context windows
- Requires reliable structure detection

Summary

> Use structure-based chunking for well-organized documents where users query by sections or topics.

---

4. Recursive Chunking

When to use

- Documents have structure, but sections vary greatly in size
- Need to enforce maximum chunk size limits

Typical scenarios

- Technical manuals
- Employee handbooks
- Research papers
- Software documentation

How it works

1. Chunk by high-level structure (sections)
2. If a chunk exceeds max size:
    - Split into paragraphs
3. If still too large:
    - Split into sentences

Why it works

- Preserves structure where possible
- Prevents oversized chunks
- Best balance between coherence and context limits

Trade-offs

- More complex implementation
- Slightly slower than pure structural chunking

Summary

> Use recursive chunking when documents are structured but uneven, and you must control chunk size without losing organization.

---

5. LLM-Based Chunking

When to use

- Content is highly unstructured
- Context drift is frequent
- Other methods fail

Typical scenarios

- Customer support conversations
- Chat transcripts
- Feedback emails

- Creative writing (novels, scripts)
- Multilingual or mixed-format content

Why it works

- LLM identifies topic shifts and context drift
- Produces semantically meaningful chunks even without structure
- Handles nuance beyond rule-based methods

Trade-offs

- Very expensive
- Stochastic output (non-deterministic)
- Context window limits still apply
- Not suitable for large corpora

Summary

> Use LLM-based chunking only as a last resort for small, complex, or high-value datasets where semantic accuracy outweighs cost.

Final Engineering Takeaway

- Chunking is a **core system design decision**
- Treat chunking strategy as a **tunable hyperparameter**
- Always validate chunking **after full RAG pipeline evaluation**
- Prefer **simpler strategies first**, escalate only when needed

---

Chunking Strategies — Comparison Summary

Strategy	Preserves Meaning	Preserves Structure	Fast	Production-Friendly
Fixed Size	❌	❌	✅	⚠️
Semantic	✅	❌	❌	⚠️
Structural	⚠️	✅	✅	⚠️
Recursive	⚠️	✅	⚠️	✅
LLM-Based	✅ ✅	❌	❌ ❌	❌

Key Engineering Insights

- ❌ **No one-size-fits-all chunking strategy**
- Chunking choice depends on:
  - Document type (structured vs unstructured)
  - Degree of context drift

- Data volume and scale
- Query patterns
- LLM context window limits
- Cost and latency constraints

Practical Rule of Thumb (Engineer's Playbook)

- **Start with Structural Chunking**
  - Best default for most enterprise documents
- **If chunks grow too large** → Apply **Recursive Chunking**
- **If documents lack clear structure but ideas flow** → Use **Semantic Chunking**
- **If data is massive, noisy, and unstructured** → Use **Fixed-Size Chunking** for speed
- **If content has severe context drift (conversations, transcripts)** → Use **LLM-Based Chunking** *(last resort, high cost)*

Core Takeaway

- Chunking is a **design decision**, not a preprocessing step
- Treat chunking strategy as a **tunable hyperparameter**
- Final validation must happen **after full RAG pipeline evaluation**

Step 3: Testing 5 chunking strategies: fixed, recursive, semantic, structural and LLM based.

Chunking Strategy 1: Fixed size chunking

In [ ]:
```python
def chunk_text(text: str, chunk_size: int = 500) -> list:
    """
    Splits text into chunks of approximately `chunk_size` characters.
    """

    chunks = []
    current_chunk = ""
    words = text.split()

    for word in words:
        # Check if adding the word exceeds chunk size
        if len(current_chunk) + len(word) + 1 <= chunk_size:
            current_chunk += word + " "
        else:
            # Store current chunk and start a new one
            chunks.append(current_chunk.strip())
            current_chunk = word + " "

    # Add the last chunk if not empty
```

```
    if current_chunk:
        chunks.append(current_chunk.strip())

    return chunks


def chunk_pdf_pages(pages_and_texts: list, chunk_size: int = 500) -> list[dict]:
    """
    Takes PDF pages with text and splits them into chunks.

    Returns:
    list[dict]: Each dict contains
        - page_number
        - chunk_index
        - chunk_char_count
        - chunk_word_count
        - chunk_token_count (approx)
        - chunk_text
    """

    all_chunks = []

    for page in pages_and_texts:
        page_number = page["page_number"]
        page_text = page["text"]

        chunks = chunk_text(page_text, chunk_size=chunk_size)

        for i, chunk in enumerate(chunks):
            all_chunks.append({
                "page_number": page_number,
                "chunk_index": i,
                "chunk_char_count": len(chunk),
                "chunk_word_count": len(chunk.split()),
                "chunk_token_count": len(chunk) / 4,  # rough token estimate
                "chunk_text": chunk
            })

    return all_chunks


# -------------------- Example usage --------------------
chunked_pages = chunk_pdf_pages(pages_and_texts, chunk_size=500)

print(f"Total chunks: {len(chunked_pages)}")
print(
    f"First chunk (page {chunked_pages[0]['page_number']}): "
    f"{chunked_pages[0]['chunk_text'][:200]}..."
)
```

```
Total chunks: 3321
First chunk (page -41): Human Nutrition: 2020 Edition...
```

In [ ]:

```
import random
import textwrap


# -------------------- Sampling & Pretty Printing --------------------
def _scattered_indices(n: int, k: int, jitter_frac: float = 0.08) -> list[int]:
    """
```

```
    Evenly spaced anchors + random jitter.
    Returns indices scattered across [0, n-1].
    """

    if k <= 0:
        return []

    if k == 1:
        return [random.randrange(n)]

    anchors = [int(round(i * (n - 1) / (k - 1))) for i in range(k)]
    out, seen = [], set()
    radius = max(1, int(n * jitter_frac))

    for a in anchors:
        lo = max(0, a - radius)
        hi = min(n - 1, a + radius)
        j = random.randint(lo, hi)

        if j not in seen:
            out.append(j)
            seen.add(j)

    # Fill remaining slots if collisions occurred
    while len(out) < k:
        r = random.randrange(n)
        if r not in seen:
            out.append(r)
            seen.add(r)

    return out


def _draw_boxed_chunk(c: dict, wrap_at: int = 96) -> str:
    """
    Pretty-prints a chunk inside a boxed layout.
    """

    header = (
        f" Chunk p{c['page_number']} | idx {c['chunk_index']} | "
        f"chars {c['chunk_char_count']} | "
        f"words {c['chunk_word_count']} | "
        f"~tokens {int(c['chunk_token_count'])} "
    )

    # Wrap body text (avoid breaking long words)
    wrapped_lines = textwrap.wrap(
        c["chunk_text"],
        width=wrap_at,
        break_long_words=False,
        replace_whitespace=False
    )

    content_width = max([0, *map(len, wrapped_lines)])
    box_width = max(len(header), content_width + 2)  # +2 for padding

    top = "+" + "-" * box_width + "+"
    hline = "|" + header.ljust(box_width) + "|"
    sep = "+" + "-" * box_width + "+"
```

```
    body = (
        "\n".join(
            "| " + line.ljust(box_width - 2) + " |"
            for line in wrapped_lines
        )
        if wrapped_lines
        else "| " + "".ljust(box_width - 2) + " |"
    )

    bottom = "+" + "=" * box_width + "+"

    return "\n".join([top, hline, sep, body, bottom])



def show_random_chunks(
    pages_and_texts: list,
    chunk_size: int = 500,
    k: int = 5,
    seed: int | None = 42
):
    if seed is not None:
        random.seed(seed)

    all_chunks = chunk_pdf_pages(pages_and_texts, chunk_size=chunk_size)

    if not all_chunks:
        print("No chunks to display.")
        return

    idxs = _scattered_indices(len(all_chunks), k)

    print(
        f"Showing {len(idxs)} scattered random chunks "
        f"out of {len(all_chunks)} total:\n"
    )

    for i, idx in enumerate(idxs, 1):
        print(f"#{i}")
        print(_draw_boxed_chunk(all_chunks[idx]))
        print()


# -------------------- Run --------------------
assert "pages_and_texts" in globals(), (
    "Run: pages_and_texts = open_and_read_pdf(pdf_path) first."
)

show_random_chunks(pages_and_texts, chunk_size=500, k=5, seed=42)
```

```
Showing 5 scattered random chunks out of 3321 total:

#1
+------------------------------------------------------------------------------
------------------+
| Chunk p-9 | idx 0 | chars 290 | words 49 | ~tokens 72
|
+------------------------------------------------------------------------------
------------------+
| Skylar Hara Skylar Hara is an undergraduate student student in the Tropical Agr
iculture and the  |
| Environment program at the University of Hawai‘i at Mānoa. She has a growing lo
ve for plants and |
| hopes to go to graduate school to conduct research in the future. About the Con
tributors |       |
| xxxiii
|
+==============================================================================
==================+

#2
+------------------------------------------------------------------------------
-----------------+
| Chunk p198 | idx 0 | chars 497 | words 71 | ~tokens 124
|
+------------------------------------------------------------------------------
-----------------+
| foods. Fresh and frozen foods are better sources of potassium than canned. Lear
ning Activities  |
| Technology Note: The second edition of the Human Nutrition Open Educational Res
ource (OER)      |
| textbook features interactive learning activities. These activities are availab
le in the web-   |
| based textbook and not available in the downloadable versions (EPUB, Digital PD
F, Print_PDF, or |
| Open Document). Learning activities may be used across various mobile devices,
however, for the |
| best user experience it is
|
+==============================================================================
==================+

#3
+------------------------------------------------------------------------------
------------------+
| Chunk p579 | idx 0 | chars 496 | words 77 | ~tokens 124
|
+------------------------------------------------------------------------------
------------------+
| Image by Allison Calabrese / CC BY 4.0 Folate is especially essential for the g
rowth and         |
| specialization of cells of the central nervous system. Children whose mothers w
ere folate-       |
| deficient during pregnancy have a higher risk of neural-tube birth defects. Fol
ate deficiency is |
| causally linked to the development of spina bifida, a neural-tube defect that o
ccurs when the    |
| spine does not completely enclose the spinal cord. Spina bifida can lead to man
y physical and    |
| mental disabilities (Figure 9.18
```

```
|
+=================================================================================
==================+

#4
+---------------------------------------------------------------------------------
------------------+
| Chunk p882 | idx 2 | chars 300 | words 34 | ~tokens 75
|
+---------------------------------------------------------------------------------
------------------+
| best user experience it is strongly 9. Lead Exposure: Tips to Protect Your Chil
d. Mayo           |
| Foundation for Medical Education and Research. https://www.mayoclinic.org/disea
ses-              |
| conditions/lead- poisoning/in-depth/lead-exposure/art-20044627. Updated March 1
2, 2015. Accessed |
| December 5, 2017. 882 | Childhood
|
+=================================================================================
==================+

#5
+---------------------------------------------------------------------------------
------------------+
| Chunk p1117 | idx 1 | chars 456 | words 57 | ~tokens 114
|
+---------------------------------------------------------------------------------
------------------+
| triglycerides greater than 150 mg/dL; high density lipoproteins (HDL) lower tha
n 40 mg/dL;       |
| systolic blood pressure above 100 mmHg, or diastolic above 85 mmHg; fasting blo
od-glucose levels |
| greater than 100 mg/dL.16 The IDF estimates that between 20 and 16. The IDF Con
sensus Worldwide  |
| Definition of the Metabolic Syndrome. International Diabetes Federation.http
s://www.idf.org/our- |
| activities/ advocacy-awareness/resources-and-tools/ Threats to Health | 1117
|
+=================================================================================
==================+
```

Chunking Strategy 2: Semantic chunking

In [ ]:
```
# !pip install --upgrade sentence-transformers==3.0.1 "transformers>=4.41,<5" sc
```

In [2]:
```
# from sentence_transformers import SentenceTransformer
# from sklearn.metrics.pairwise import cosine_similarity
# import numpy as np
# import nltk
# from tqdm.auto import tqdm

# nltk.download("punkt", quiet=True)

# # Load once globally
# semantic_model = SentenceTransformer("all-MiniLM-L6-v2")
```

```
# # -------------------- Semantic Chunking --------------------
# def semantic_chunk_text(
#     text: str,
#     similarity_threshold: float = 0.8,
#     max_tokens: int = 500
# ) -> list:
#     """
#     Splits text into semantic chunks based on sentence similarity
#     and maximum token length.
#     """

#     sentences = nltk.sent_tokenize(text)
#     if not sentences:
#         return []

#     embeddings = semantic_model.encode(sentences)

#     chunks = []
#     current_chunk = [sentences[0]]
#     current_embedding = embeddings[0]

#     for i in range(1, len(sentences)):
#         sim = cosine_similarity(
#             [current_embedding],
#             [embeddings[i]]
#         )[0][0]

#         chunk_token_count = len(" ".join(current_chunk)) // 4  # rough token e

#         if sim >= similarity_threshold and chunk_token_count < max_tokens:
#             current_chunk.append(sentences[i])
#             current_embedding = np.mean(
#                 [current_embedding, embeddings[i]],
#                 axis=0
#             )
#         else:
#             chunks.append(" ".join(current_chunk).strip())
#             current_chunk = [sentences[i]]
#             current_embedding = embeddings[i]

#     if current_chunk:
#         chunks.append(" ".join(current_chunk).strip())

#     return chunks


# # -------------------- Semantic Chunking for PDF Pages --------------------
# def semantic_chunk_pdf_pages(
#     pages_and_texts: list,
#     similarity_threshold: float = 0.8,
#     max_tokens: int = 500
# ) -> list[dict]:
#     """
#     Takes PDF pages with text and splits them into semantic chunks.

#     Returns:
#     list[dict]: Each dict contains
#         - page_number
#         - chunk_index
```

```
#         - chunk_char_count
#         - chunk_word_count
#         - chunk_token_count (approx)
#         - chunk_text
#     """

#     all_chunks = []

#     for page in tqdm(pages_and_texts, desc="Semantic chunking pages"):
#         page_number = page["page_number"]
#         page_text = page["text"]

#         chunks = semantic_chunk_text(
#             page_text,
#             similarity_threshold=similarity_threshold,
#             max_tokens=max_tokens
#         )

#         for i, chunk in enumerate(chunks):
#             all_chunks.append({
#                 "page_number": page_number,
#                 "chunk_index": i,
#                 "chunk_char_count": len(chunk),
#                 "chunk_word_count": len(chunk.split()),
#                 "chunk_token_count": len(chunk) / 4,  # rough token estimate
#                 "chunk_text": chunk
#             })

#     return all_chunks
```

In [3]:

```
# import nltk

# # Download required tokenizer
# nltk.download("punkt_tab", quiet=True)

# # -------------------- Run Semantic Chunking --------------------
# semantic_chunked_pages = semantic_chunk_pdf_pages(
#     pages_and_texts,
#     similarity_threshold=0.75,
#     max_tokens=500
# )

# print(f"Total semantic chunks: {len(semantic_chunked_pages)}")
# print(
#     f"First semantic chunk (page {semantic_chunked_pages[0]['page_number']}):"
# )
# print(semantic_chunked_pages[0]["chunk_text"][:200] + " ...")
```

In [ ]:

```
# Pretty-print helpers for SEMANTIC chunks

import random
import textwrap


def _scattered_indices(n: int, k: int, jitter_frac: float = 0.08) -> list[int]:
    """
    Evenly spaced anchors + random jitter.
    Returns indices scattered across [0, n-1].
    """
```

```
    if k <= 0:
        return []

    if k == 1:
        return [random.randrange(n)]

    anchors = [int(round(i * (n - 1) / (k - 1))) for i in range(k)]
    out, seen = [], set()
    radius = max(1, int(n * jitter_frac))

    for a in anchors:
        lo = max(0, a - radius)
        hi = min(n - 1, a + radius)
        j = random.randint(lo, hi)

        if j not in seen:
            out.append(j)
            seen.add(j)

    # Fill remaining slots if collisions occurred
    while len(out) < k:
        r = random.randrange(n)
        if r not in seen:
            out.append(r)
            seen.add(r)

    return out



def _draw_boxed_chunk(c: dict, wrap_at: int = 96) -> str:
    """
    Pretty-print a semantic chunk inside a boxed layout.
    """

    approx_tokens = c.get(
        "chunk_token_count",
        len(c.get("chunk_text", "")) / 4
    )

    header = (
        f" Chunk p{c['page_number']} | idx {c['chunk_index']} | "
        f"chars {c['chunk_char_count']} | "
        f"words {c['chunk_word_count']} | "
        f"~tokens {round(approx_tokens, 2)} "
    )

    # Wrap body text
    wrapped_lines = textwrap.wrap(
        c["chunk_text"],
        width=wrap_at,
        break_long_words=False,
        replace_whitespace=False
    )

    content_width = max([0, *map(len, wrapped_lines)])
    box_width = max(len(header), content_width + 2)  # +2 for padding

    top = "+" + "=" * box_width + "+"
```

```
    hline = "|" + header.ljust(box_width) + "|"
    sep = "+" + "-" * box_width + "+"

    body = (
        "\n".join(
            "| " + line.ljust(box_width - 2) + " |"
            for line in wrapped_lines
        )
        if wrapped_lines
        else "| " + "".ljust(box_width - 2) + " |"
    )

    bottom = "+" + "=" * box_width + "+"

    return "\n".join([top, hline, sep, body, bottom])


def show_random_semantic_chunks(
    semantic_chunked_pages: list[dict],
    k: int = 5,
    seed: int | None = 42
):
    if seed is not None:
        random.seed(seed)

    n = len(semantic_chunked_pages)
    if n == 0:
        print("No semantic chunks to display.")
        return

    idxs = _scattered_indices(n, k)

    print(
        f"Showing {len(idxs)} scattered random SEMANTIC chunks "
        f"out of {n} total:\n"
    )

    for i, idx in enumerate(idxs, 1):
        print(f"#{i}")
        print(_draw_boxed_chunk(semantic_chunked_pages[idx]))
        print()


# -------------------- Run --------------------
assert (
    "semantic_chunked_pages" in globals()
    and len(semantic_chunked_pages) > 0
), "Run your semantic chunking code first to define 'semantic_chunked_pages'."

show_random_semantic_chunks(semantic_chunked_pages, k=5, seed=42)
```

```
Showing 5 scattered random SEMANTIC chunks out of 12016 total:

#1
+================================================================================
==============+
| Chunk p56 | idx 7 | chars 200 | words 31 | ~tokens 50.0
|
+--------------------------------------------------------------------------------
--------------+
| Observing the connection  between the beverage and longevity, Dr. Elie Metchnik
off began his |
| research on beneficial bacteria and the longevity of life that led to  his boo
k, The         |
| Prolongation of Life.
|
+================================================================================
==============+

#2
+================================================================================
====+
| Chunk p232 | idx 7 | chars 82 | words 12 | ~tokens 20.5
|
+--------------------------------------------------------------------------------
----+
| This small  structural alteration causes galactose to be less stable than gluco
se. |
+================================================================================
====+

#3
+============================================================+
| Chunk p509 | idx 9 | chars 30 | words 6 | ~tokens 7.5 |
+------------------------------------------------------------+
| Rodearmel SJ, Wyatt HR, et al.                             |
+============================================================+

#4
+============================================================+
| Chunk p962 | idx 17 | chars 24 | words 4 | ~tokens 6.0 |
+------------------------------------------------------------+
| 962  |  Sports Nutrition                                    |
+============================================================+

#5
+================================================================================
+
| Chunk p1110 | idx 5 | chars 78 | words 13 | ~tokens 19.5
|
+--------------------------------------------------------------------------------
+
| Instead,  cells use fat and proteins to make energy, resulting in weight loss.
|
+================================================================================
+
```

Chunking Strategy 3: Recursive Chunking

In [ ]:

```python
import nltk
from tqdm.auto import tqdm

# Download sentence tokenizer (required for sentence-based splitting)
nltk.download("punkt", quiet=True)


def recursive_chunk_text(
    text: str,
    max_chunk_size: int = 1000,
    min_chunk_size: int = 100
) -> list:
    """
    Recursively splits a block of text into chunks that fit within size limits.

    Chunking strategy (in order):
    1. If text length <= max_chunk_size → return as a single chunk
    2. Split by double newlines (sections)
    3. Split by single newline
    4. Fallback to sentence-based splitting

    Parameters:
    - text (str): Input text to chunk
    - max_chunk_size (int): Maximum allowed chunk size (characters)
    - min_chunk_size (int): Passed for consistency (not enforced here)

    Returns:
    - list[str]: List of text chunks
    """

    def split_chunk(chunk: str) -> list:
        """
        Helper function that recursively splits a single chunk.
        """

        # Base case: chunk already fits size constraint
        if len(chunk) <= max_chunk_size:
            return [chunk]

        # Try splitting by section breaks (double newline)
        sections = chunk.split("\n\n")
        if len(sections) > 1:
            result = []
            for section in sections:
                if section.strip():
                    result.extend(split_chunk(section.strip()))
            return result

        # Try splitting by line breaks (single newline)
        sections = chunk.split("\n")
        if len(sections) > 1:
            result = []
            for section in sections:
                if section.strip():
                    result.extend(split_chunk(section.strip()))
            return result

        # Fallback: split by sentences
        sentences = nltk.sent_tokenize(chunk)
```

```
        chunks = []
        current_chunk = []
        current_size = 0

        for sentence in sentences:
            # If adding the sentence exceeds max size, close current chunk
            if current_size + len(sentence) > max_chunk_size:
                if current_chunk:
                    chunks.append(" ".join(current_chunk))
                current_chunk = [sentence]
                current_size = len(sentence)
            else:
                current_chunk.append(sentence)
                current_size += len(sentence)

        # Add remaining sentences as final chunk
        if current_chunk:
            chunks.append(" ".join(current_chunk))

        return chunks

    # Start recursive splitting from full text
    return split_chunk(text)


def recursive_chunk_pdf_pages(
    pages_and_texts: list,
    max_chunk_size: int = 1000,
    min_chunk_size: int = 100
) -> list[dict]:
    """
    Applies recursive chunking to each page of a PDF.

    Parameters:
    - pages_and_texts (list): Output from open_and_read_pdf()
    - max_chunk_size (int): Maximum chunk size (characters)
    - min_chunk_size (int): Passed for consistency

    Returns:
    - list[dict]: Each dict contains chunk metadata and text
    """

    all_chunks = []

    # Iterate through each page
    for page in tqdm(pages_and_texts, desc="Recursive chunking pages"):
        page_number = page["page_number"]
        page_text = page["text"]

        # Perform recursive chunking on page text
        chunks = recursive_chunk_text(
            page_text,
            max_chunk_size=max_chunk_size,
            min_chunk_size=min_chunk_size
        )

        # Store chunk metadata
        for i, chunk in enumerate(chunks):
            all_chunks.append({
                "page_number": page_number,
```

```
                "chunk_index": i,
                "chunk_char_count": len(chunk),
                "chunk_word_count": len(chunk.split()),
                "chunk_token_count": len(chunk) / 4,  # rough token estimate
                "chunk_text": chunk
            })

    return all_chunks
```

In [4]:
```
# # -------------------- Run Recursive Chunking --------------------

# # Create recursive chunks from PDF pages
# recursive_chunked_pages = recursive_chunk_pdf_pages(
#     pages_and_texts,
#     max_chunk_size=800,
#     min_chunk_size=100
# )

# # Print basic stats
# print(f"Total recursive chunks: {len(recursive_chunked_pages)}")

# # Display first chunk for inspection
# print(
#     f"First recursive chunk (page {recursive_chunked_pages[0]['page_number']}):"
# )
# print(recursive_chunked_pages[0]["chunk_text"][:200] + " ...")
```

In [ ]:
```
# Pretty-print helpers for RECURSIVE chunks

import random
import textwrap


def _scattered_indices(n: int, k: int, jitter_frac: float = 0.08) -> list[int]:
    """
    Evenly spaced anchors + random jitter.
    Returns indices scattered across [0, n-1].
    """

    if k <= 0:
        return []

    if k == 1:
        return [random.randrange(n)]

    anchors = [int(round(i * (n - 1) / (k - 1))) for i in range(k)]
    out, seen = [], set()
    radius = max(1, int(n * jitter_frac))

    for a in anchors:
        lo = max(0, a - radius)
        hi = min(n - 1, a + radius)
        j = random.randint(lo, hi)

        if j not in seen:
            out.append(j)
            seen.add(j)

    # Fill remaining slots if collisions occurred
```

```
    while len(out) < k:
        r = random.randrange(n)
        if r not in seen:
            out.append(r)
            seen.add(r)

    return out


def _draw_boxed_chunk(c: dict, wrap_at: int = 96) -> str:
    """
    Pretty-print a recursive chunk inside a boxed layout.
    """

    approx_tokens = c.get(
        "chunk_token_count",
        len(c.get("chunk_text", "")) / 4
    )

    header = (
        f" Chunk p{c['page_number']} | idx {c['chunk_index']} | "
        f"chars {c['chunk_char_count']} | "
        f"words {c['chunk_word_count']} | "
        f"~tokens {round(approx_tokens, 2)} "
    )

    # Wrap chunk text for display
    wrapped_lines = textwrap.wrap(
        c["chunk_text"],
        width=wrap_at,
        break_long_words=False,
        replace_whitespace=False
    )

    content_width = max([0, *map(len, wrapped_lines)])
    box_width = max(len(header), content_width + 2)  # +2 for padding

    top = "+" + "=" * box_width + "+"
    hline = "|" + header.ljust(box_width) + "|"
    sep = "+" + "-" * box_width + "+"

    body = (
        "\n".join(
            "| " + line.ljust(box_width - 2) + " |"
            for line in wrapped_lines
        )
        if wrapped_lines
        else "| " + "".ljust(box_width - 2) + " |"
    )

    bottom = "+" + "=" * box_width + "+"

    return "\n".join([top, hline, sep, body, bottom])


def show_random_recursive_chunks(
    recursive_chunked_pages: list[dict],
    k: int = 5,
    seed: int | None = 42
):
```

```
    """
    Displays randomly sampled recursive chunks in a readable boxed format.
    """

    if seed is not None:
        random.seed(seed)

    n = len(recursive_chunked_pages)
    if n == 0:
        print("No recursive chunks to display.")
        return

    idxs = _scattered_indices(n, k)

    print(
        f"Showing {len(idxs)} scattered random RECURSIVE chunks "
        f"out of {n} total:\n"
    )

    for i, idx in enumerate(idxs, 1):
        print(f"#{i}")
        print(_draw_boxed_chunk(recursive_chunked_pages[idx]))
        print()


# -------------------- Run --------------------
assert (
    "recursive_chunked_pages" in globals()
    and len(recursive_chunked_pages) > 0
), "Run recursive_chunk_pdf_pages first to define 'recursive_chunked_pages'."

show_random_recursive_chunks(recursive_chunked_pages, k=5, seed=42)
```

```
Showing 5 scattered random RECURSIVE chunks out of 2434 total:

#1
+=========================================================================+
| Chunk p53 | idx 0 | chars 69 | words 14 | ~tokens 17.25                |
+-------------------------------------------------------------------------+
| PART II  CHAPTER 2. THE HUMAN  BODY  Chapter 2. The Human Body  |  53 |
+=========================================================================+

#2
+=========================================================================================
==================+
| Chunk p213 | idx 0 | chars 761 | words 102 | ~tokens 190.25
|
+-----------------------------------------------------------------------------------------
------------------+
| Deadly  water-borne  illnesses  decreased to  almost  nonexistent  levels in th
e  United  States |
| after  the  implementat ion of water  disinfection  methods. public water syste
ms in the country |
| adhere to the standards. About  15 percent of Americans obtain drinking water f
rom private       |
| wells,  which are not subject to EPA standards. Producing water safe for drinki
ng involves some  |
| or all of the  following processes: screening out large objects, removing exces
s  calcium        |
| carbonate from hard water sources, flocculation, which  adds a precipitating ag
ent to remove     |
| solid particles, clarification,  sedimentation, filtration, and disinfection. T
hese processes    |
| aim to  remove unhealthy substances and produce high-quality, colorless,  odorl
ess, good-tasting |
| water.
|
+=========================================================================================
==================+

#3
+=========================================================================================
==================+
| Chunk p480 | idx 1 | chars 780 | words 123 | ~tokens 195.0
|
+-----------------------------------------------------------------------------------------
------------------+
| Total Energy Expenditure (Output)  The amount of energy you expend every day in
cludes not only   |
| the  calories you burn during physical activity, but also the calories you  bur
n while at rest   |
| (basal metabolism), and the calories you burn  when you digest food. The sum of
caloric          |
| expenditure is referred  to as total energy expenditure (TEE). Basal metabolism
refers to  those |
| metabolic pathways necessary to support and maintain the  body’s basic function
s (e.g.           |
| breathing, heartbeat, liver and kidney  function) while at rest. The basal meta
bolic rate (BMR)  |
| is the amount  of energy required by the body to conduct its basic functions ov
er  a certain     |
| time period. The great majority of energy expended  (between 50 and 70 percent)
daily is from     |
```

```
| conducting life’s basic  processes.
|
+================================================================================
==================+

#4
+================================================================================
==================+
| Chunk p972 | idx 0 | chars 768 | words 116 | ~tokens 192.0
|
+--------------------------------------------------------------------------------
------------------+
| Image by  Allison  Calabrese /  CC BY 4.0  Water and Electrolyte Needs  UNIVERS
ITY OF HAWAIʻI AT |
| MĀNOA FOOD SCIENCE AND HUMAN  NUTRITION PROGRAM AND HUMAN NUTRITION PROGRAM  Du
ring exercise,    |
| being appropriately hydrated contributes to  performance. Water is needed to co
ol the body,      |
| transport oxygen  and nutrients, and remove waste products from the muscles. Wa
ter  needs are    |
| increased during exercise due to the extra water losses  through evaporation an
d sweat.          |
| Dehydration can occur when there  is inadequate water levels in the body and ca
n be very         |
| hazardous to  the health of an individual. As the severity of dehydration incre
ases,  the        |
| exercise performance of an individual will begin to decline (see  Figure 16.9
“Dehydration       |
| Effect on Exercise Performance”).
|
+================================================================================
==================+

#5
+================================================================================
==================+
| Chunk p1111 | idx 0 | chars 721 | words 124 | ~tokens 180.25
|
+--------------------------------------------------------------------------------
------------------+
| Image by  Allison  Calabrese /  CC BY 4.0  Type 2 Diabetes  The other 90 to 95
percent of       |
| diabetes cases are Type 2 diabetes.  Type 2 diabetes is defined as a metabolic
disease of       |
| insulin  insufficiency, but it is also caused by muscle, liver, and fat cells n
o  longer        |
| responding to the insulin in the body (Figure 18.4 “Healthy  Individuals and Ty
pe 2 Diabetes” . |
| In brief, cells in the body have  become resistant to insulin and no longer rec
eive the full    |
| physiological message of insulin to take up glucose from the blood.  Thus, simi
lar to patients  |
| with Type 1 diabetes, those with Type 2  diabetes also have high blood-glucose
levels.  Figure  |
| 18.4 Healthy Individuals and Type 2 Diabetes  Threats to Health  |  1111
|
+================================================================================
==================+
```

Chunking Strategy 4: Document Structure Based chunking

In [ ]:
```python
import re
import random
import textwrap


# -------------------- Chapter Header Detection --------------------
def _is_chapter_header_page(text: str) -> bool:
    """
    Detects whether a page is likely a chapter header page.

    Logic:
    - Looks for the recurring header text
      e.g. "University of Hawai'i at Manoa ..."
    - Case-insensitive
    """

    return re.search(
        r"university\s+of\s+hawai",
        text,
        flags=re.IGNORECASE
    ) is not None


# -------------------- Chapter Title Guessing --------------------
def _guess_title_from_page(text: str) -> str:
    """
    Best-effort guess of a chapter title.

    Strategy:
    - Take text before the recurring
      'University of Hawai' header line
    - Clean extra whitespace
    - If too short or too long, fall back
      to the first ~120 characters
    """

    m = re.search(
        r"university\s+of\s+hawai",
        text,
        flags=re.IGNORECASE
    )

    if m:
        # Text before the header line
        title = text[: m.start()].strip()

        # Normalize whitespace
        title = re.sub(r"\s+", " ", title).strip()

        # Accept reasonable title lengths
        if 10 <= len(title) <= 180:
            return title

    # Fallback: first ~120 characters of page text
```

```
    t = re.sub(r"\s+", " ", text).strip()
    return t[:120] if t else "Untitled Chapter"


# -------------------- Chapter-level Chunking --------------------
def chapter_chunk_pdf_pages(pages_and_texts: list[dict]) -> list[dict]:
    """
    Groups PDF pages into chapter-level chunks.

    A chapter is detected using a recurring header
    (via `_is_chapter_header_page`).

    Returns:
    list[dict] with:
        - chapter_index
        - title
        - page_start
        - page_end
        - chunk_char_count
        - chunk_word_count
        - chunk_token_count (approx)
        - chunk_text
    """

    if not pages_and_texts:
        return []

    # Find all page indices that look like chapter starts
    chapter_starts = []
    for i, p in enumerate(pages_and_texts):
        txt = p["text"]
        if _is_chapter_header_page(txt):
            chapter_starts.append(i)

    # If no chapter headers detected, treat entire document as one chapter
    if not chapter_starts:
        all_text = " ".join(p["text"] for p in pages_and_texts).strip()
        return [{
            "chapter_index": 0,
            "title": _guess_title_from_page(pages_and_texts[0]["text"]),
            "page_start": pages_and_texts[0]["page_number"],
            "page_end": pages_and_texts[-1]["page_number"],
            "chunk_char_count": len(all_text),
            "chunk_word_count": len(all_text.split()),
            "chunk_token_count": round(len(all_text) / 4, 2),
            "chunk_text": all_text
        }]

    # Build chapter ranges (start -> next_start - 1)
    chapter_chunks = []

    for ci, s in enumerate(chapter_starts):
        e = (
            chapter_starts[ci + 1] - 1
            if ci + 1 < len(chapter_starts)
            else len(pages_and_texts) - 1
        )

        if e < s:
            continue  # safety guard
```

```
        pages = pages_and_texts[s: e + 1]
        text_concat = " ".join(p["text"] for p in pages).strip()
        title = _guess_title_from_page(pages[0]["text"])

        chapter_chunks.append({
            "chapter_index": ci,
            "title": title,
            "page_start": pages[0]["page_number"],
            "page_end": pages[-1]["page_number"],
            "chunk_char_count": len(text_concat),
            "chunk_word_count": len(text_concat.split()),
            "chunk_token_count": round(len(text_concat) / 4, 2),
            "chunk_text": text_concat
        })

    return chapter_chunks
```

In [ ]:
```
# -------------------- Run Chapter-level Chunking --------------------

# Create chapter-based chunks from PDF pages
structure_chunked_pages = chapter_chunk_pdf_pages(pages_and_texts)

# Print total number of detected chapters
print(f"Total chapter-based chunks: {len(structure_chunked_pages)}")

if structure_chunked_pages:
    # Inspect the first chapter
    first = structure_chunked_pages[0]

    print(
        f"First chapter (pages {first['page_start']}-{first['page_end']}): "
        f"{first['title']}"
    )

    # Print a preview of chapter text
    print(first["chunk_text"][:200] + " ...")
else:
    print("No chapters detected.")
```

```
Total chapter-based chunks: 171
First chapter (pages -39--39): Human Nutrition: 2020 Edition
Human Nutrition: 2020  Edition  UNIVERSITY OF HAWAI‘I AT MĀNOA  FOOD SCIENCE AND HUMAN  NUTRITION PROGRAM  ALAN TITCHENAL, SKYLAR HARA,  NOEMI ARCEO CAACBAY, WILL IAM  MEINKE-LAU, YA-YUN YANG, MARIE  K ...
```

In [ ]:
```
# -------------------- Pretty-print Chapter Chunks --------------------

def _draw_boxed_chunk(c: dict, wrap_at: int = 96) -> str:
    """
    Pretty-print a chapter-level chunk inside a boxed layout.
    """

    header = (
        f" Chapter {c['chapter_index']} | {c['title'][:120]} | "
        f"p{c['page_start']}-{c['page_end']} | "
        f"~tokens {c['chunk_token_count']}"
    )

    # Wrap chapter text for display
```

```
    wrapped = textwrap.wrap(
        c["chunk_text"],
        width=wrap_at,
        break_long_words=False,
        replace_whitespace=False
    )

    content_width = (
        max(len(header), *(len(x) for x in wrapped))
        if wrapped else len(header)
    )

    top = "+" + "=" * content_width + "+"
    hline = "|" + header.ljust(content_width) + "|"
    sep = "+" + "-" * content_width + "+"

    body = (
        "\n".join(
            "| " + line.ljust(content_width - 2) + " |"
            for line in wrapped[:12]   # limit preview lines
        )
        if wrapped
        else "| " + "".ljust(content_width - 2) + " |"
    )

    bottom = "+" + "=" * content_width + "+"

    return "\n".join([top, hline, sep, body, bottom])


def show_random_chapter_chunks(
    chapter_chunks: list[dict],
    k: int = 5,
    seed: int | None = 42
):
    """
    Randomly samples and displays chapter-level chunks.
    """

    if not chapter_chunks:
        print("No chapter chunks to display.")
        return

    if seed is not None:
        random.seed(seed)

    k = min(k, len(chapter_chunks))
    idxs = random.sample(range(len(chapter_chunks)), k)

    print(
        f"Showing {k} random chapters "
        f"out of {len(chapter_chunks)} total:\n"
    )

    for i, idx in enumerate(idxs, 1):
        print(f"#{i}")
        print(_draw_boxed_chunk(chapter_chunks[idx]))
        print()
```

```
# -------------------- Run Chapter-level Chunking --------------------

# Ensure base PDF pages are already loaded
assert "pages_and_texts" in globals(), (
    "Run your base PDF loader first to define 'pages_and_texts'."
)

# Build chapter-level chunks
chapter_chunks = chapter_chunk_pdf_pages(pages_and_texts)

# Print summary
print(f"Total chapters detected: {len(chapter_chunks)}")

if chapter_chunks:
    print(
        f"First chapter: {chapter_chunks[0]['title']} "
        f"(p{chapter_chunks[0]['page_start']}-{chapter_chunks[0]['page_end']})"
    )

# Inspect a few random chapters
show_random_chapter_chunks(chapter_chunks, k=5, seed=21)
```

```
Total chapters detected: 171
First chapter: Human Nutrition: 2020 Edition (p-39--39)
Showing 5 random chapters out of 171 total:

#1
+=============================================================================
============================+
| Chapter 42 | Image by John Towner on unsplash.co m / CC0 Lifestyles and Nutriti
on | p21–29 | ~tokens 3135.25|
+-----------------------------------------------------------------------------
----------------------------+
| Image by  John Towner  on  unsplash.co m / CC0  Lifestyles and Nutrition  UNIVE
RSITY OF HAWAIʻI            |
| AT MĀNOA FOOD SCIENCE AND HUMAN  NUTRITION PROGRAM AND HUMAN NUTRITION PROGRAM
In addition to              |
| nutrition, health is affected by genetics, the  environment, life cycle, and li
festyle. One                |
| facet of lifestyle is your  dietary habits. Recall that we discussed briefly ho
w nutrition                 |
| affects  health. A greater discussion of this will follow in subsequent  chapte
rs in this book,            |
| as there is an enormous amount of  information regarding this aspect of lifesty
le. Dietary                 |
| habits include  what a person eats, how much a person eats during a meal, how
frequently meals            |
| are consumed, and how often a person eats out.  Other aspects of lifestyle incl
ude physical                |
| activity level, recreational  drug use, and sleeping patterns, all of which pla
y a role in                 |
| health and  impact nutrition. Following a healthy lifestyle improves your overa
ll  health.                 |
| Lifestyles and Nutrition  |  21 Physical Activity  In 2008, the Health and Huma
n Services (HHS)            |
| released the Physical  Activity Guidelines for Americans1. The HHS states that
“Being                      |
+=============================================================================
============================+

#2
+=============================================================================
================+
| Chapter 107 | Phytochemicals | p600–608 | ~tokens 1874.5
|
+-----------------------------------------------------------------------------
----------------+
| Phytochemicals  UNIVERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN  NUTRITIO
N PROGRAM AND   |
| HUMAN NUTRITION PROGRAM  Phytochemicals are chemicals in plants that may provid
e some  health  |
| benefit. Carotenoids are one type of phytochemical.  Phytochemicals also includ
e indoles,      |
| lignans, phytoestrogens,  stanols,  saponins,  terpenes,  flavonoids,  caroteno
ids,            |
| anthocyanidins, phenolic acids, and many more. They are found not  only in frui
ts and          |
| vegetables, but also in grains, seeds, nuts, and  legumes.  Many phytochemicals
act as         |
| antioxidants, but they have several  other functions, such as mimicking hormone
s, altering     |
| absorption  of cholesterol, inhibiting inflammatory responses, and blocking the
```

```
actions of    |
| certain enzymes.  Phytochemicals are present in small amounts in the food suppl
y,  and although |
| thousands have been and are currently being  scientifically studied, their heal
th benefits     |
| remain largely unknown.  Also largely unknown is their potential for toxicity,
which could be  |
| substantial if taken in large amounts in the form of supplements.  Moreover, ph
ytochemicals    |
+=================================================================================
================+

#3
+=================================================================================
================+
| Chapter 162 | Comparing Diets | p1046-1062 | ~tokens 6078.0
|
+---------------------------------------------------------------------------------
----------------+
| Comparing Diets  UNIVERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN  NUTRITI
ON PROGRAM AND  |
| HUMAN NUTRITION PROGRAM  Diet Trends and Health  In the past, health was regard
ed merely as the |
| absence of illness.  However, a growing understanding of the complexity and pot
ential  of the  |
| human condition has prompted a new way of thinking about  health. Today, we foc
us on the idea of |
| wellness, which involves a  great deal more than just not being sick. Wellness
is a state of   |
| optimal well-being that enables an individual to maximize their  potential. Thi
s concept       |
| includes a host of dimensions—physical,  mental, emotional, social, environment
al, and         |
| spiritual—which affect  one's quality of life.1 Striving for wellness begins wi
th an           |
| examination of dietary choices.  Dietary Food Trends  Hundreds of years ago, wh
en food was less |
| accessible and daily life  required much more physical activity, people worried
less about     |
| 1. Understanding Wellness. University of Illinois at Urbana- Champaign, McKinle
y Health Center. |
|  2011 The Board of  Trustees of the University of Illinois at Urbana- Champaig
n.               |
+=================================================================================
================+

#4
+=================================================================================
=========================================================+
| Chapter 72 | Image by Forluvoft / Public Domain Health Consequences and Benefit
s of High-Carbohydrate Diets | p260-270 | ~tokens 3661.25|
+---------------------------------------------------------------------------------
---------------------------------------------------------+
| Image by  Forluvoft /  Public  Domain  Health Consequences and  Benefits of  Hi
gh-Carbohydrate                                          |
| Diets  UNIVERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN  NUTRITION PROGRAM
AND HUMAN                                                |
| NUTRITION PROGRAM  Can America blame its obesity epidemic on the higher consump
tion  of added                                           |
| sugars and refined grains? This is a hotly debated topic  by both the scientifi
```

```
c community and                                                                 |
| the general public. In this  section, we will give a brief overview of the scie
ntific evidence.                                                                |
| Added Sugars  Figure 4.13 Sugar Consumption (In Teaspoons) From Various  Source
s    260  |                                                                     |
| Health Consequences and Benefits of High-Carbohydrate Diets The Food and Nutrit
ion Board of the                                                                |
| Institute of Medicine (IOM)  defines added sugars as “sugars and syrups that ar
e added to foods                                                                |
| during processing or preparation.” The IOM goes on to state, “Major  sources of
added sugars                                                                    |
| include soft drinks, sports drinks, cakes,  cookies, pies, fruitades, fruit pun
ch, dairy                                                                       |
| desserts, and candy.”  Processed foods, even microwaveable dinners, also contai
n added  sugars.                                                                |
| Added sugars do not include sugars that occur naturally  in whole foods (such a
s an apple), but                                                                |
+================================================================================
=========================================================+

#5
+================================================================================
================+
| Chapter 122 | Molybdenum | p692–694 | ~tokens 621.5
|
+--------------------------------------------------------------------------------
----------------+
| Molybdenum  UNIVERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN  NUTRITION PR
OGRAM AND HUMAN |
| NUTRITION PROGRAM  Molybdenum also acts as a cofactor that is required for the
metabolism of  |
| sulfur-containing amino acids, nitrogen-containing  compounds found in DNA and
RNA, and various |
| other functions.  Deficiency of molybdenum is not seen in healthy people, howev
er, a  rare     |
| metabolic effect called molybdenum cofactor deficiency is the  result of an ins
ufficient amount |
| of molybdoenzymes in the body.  Due to rapid excretion rates in the urine of th
e mineral,      |
| molybdenum toxicity is low in humans.    Dietary Reference Intakes of Molybdenu
m:  The         |
| recommended intake for molybdenum is 45 mcg per day for  both adult males and f
emales.  Table 1: |
| Dietary Reference Intakes for  Molybdenum  Age group  RDA (µg/ day)  UL (µg/ da
y)  Infants (0-6 |
| months)  –  Infants (6-12 months)  –  Children (1-3 years)  17  300  Children
(4-8 years)  22  |
| 600  Children (9-13 years)  34  1,100  Adolescents (14-18 years)  43  1,700  Ad
ults (19-50     |
| years)  45  2,000  Adults (51-70 years)  45  2,000  Adults (>71 years)  45  2,0
00  Source: The |
+================================================================================
================+
```

Chunking Strategy 5: LLM Based Chunking

In [ ]:
```
import os
```

```
os.environ["OPENAI_API_KEY"] = "Your OPEN_API_KEY"
```

In [ ]:

```
from openai import OpenAI
from typing import List
from tqdm.auto import tqdm

# Initialize OpenAI client
client = OpenAI()


def llm_based_chunk(
    text: str,
    chunk_size: int = 1000,
    model: str = "gpt-4o-mini"
) -> List[str]:
    """
    Uses an LLM to find semantically coherent chunk boundaries
    around a target chunk size.

    Parameters:
    - text (str): Input text to chunk
    - chunk_size (int): Desired chunk size in characters
    - model (str): OpenAI model name

    Returns:
    - List[str]: List of semantically split text chunks
    """

    def get_chunk_boundary(text_segment: str) -> int:
        """
        Asks the LLM where to split the given text segment.

        Returns:
        - int: Character index within text_segment where the split should occur
        """

        prompt = f"""
                Analyze the following text and identify the best point to split
                into two semantically coherent parts.
                The split should occur near {chunk_size} characters.

                Text:
                \"\"\"{text_segment}\"\"\"

                Return only the integer index (character position) within this t
                where the split should occur. Do not return any explanation.
                """

        response = client.chat.completions.create(
            model=model,
            messages=[
                {"role": "system", "content": "You are a text analysis expert."}
                {"role": "user", "content": prompt}
            ],
            temperature=0
        )

        # Extract and sanitize model output
        split_str = response.choices[0].message.content.strip()
        try:
```

```
            split_point = int(split_str)
        except ValueError:
            split_point = chunk_size

        return split_point

    chunks = []
    remaining_text = text

    # Iteratively split text until it fits within chunk_size
    while len(remaining_text) > chunk_size:
        text_window = remaining_text[: chunk_size * 2]
        split_point = get_chunk_boundary(text_window)

        # Safety check to avoid pathological splits
        if split_point < 100 or split_point > len(text_window) - 100:
            split_point = chunk_size

        chunks.append(remaining_text[:split_point].strip())
        remaining_text = remaining_text[split_point:].strip()

    # Add final remainder
    if remaining_text:
        chunks.append(remaining_text)

    return chunks
```

In [ ]:

```
from typing import List, Dict
from tqdm.auto import tqdm


def llm_based_chunk_pdf_pages(
    pages_and_texts: List[Dict],
    chunk_size: int = 1000,
    model: str = "gpt-4o-mini"
) -> List[Dict]:
    """
    Applies LLM-based chunking to each PDF page.

    Parameters:
    - pages_and_texts (List[Dict]): Output from open_and_read_pdf()
    - chunk_size (int): Target chunk size in characters
    - model (str): OpenAI model name

    Returns:
    - List[Dict]: Each dict contains
        - page_number
        - chunk_index
        - chunk_char_count
        - chunk_word_count
        - chunk_token_count (approx)
        - chunk_text
    """

    all_chunks = []

    # Iterate through each PDF page
    for page in tqdm(pages_and_texts, desc="LLM-based chunking pages"):
        page_number = page["page_number"]
        page_text = page["text"]
```

```
        # Apply LLM-based chunking to page text
        chunks = llm_based_chunk(
            page_text,
            chunk_size=chunk_size,
            model=model
        )

        # Store chunk metadata
        for i, chunk in enumerate(chunks):
            all_chunks.append({
                "page_number": page_number,
                "chunk_index": i,
                "chunk_char_count": len(chunk),
                "chunk_word_count": len(chunk.split()),
                "chunk_token_count": len(chunk) / 4,  # rough estimate
                "chunk_text": chunk
            })

    return all_chunks
```

In [5]:
```
# # -------------------- Run LLM-based Chunking --------------------

# # Create LLM-based chunks from PDF pages
# llm_chunked_pages = llm_based_chunk_pdf_pages(
#     pages_and_texts,
#     chunk_size=800,
#     model="gpt-4o-mini"
# )

# # Print total number of chunks
# print(f"Total LLM-based chunks: {len(llm_chunked_pages)}")

# # Inspect the first chunk
# print(
#     f"First LLM-based chunk (page {llm_chunked_pages[0]['page_number']}):"
# )
# print(llm_chunked_pages[0]["chunk_text"][:200] + " ...")
```

In [ ]:
```
import random
import textwrap


def _scattered_indices(n: int, k: int, jitter_frac: float = 0.08) -> list[int]:
    """
    Evenly spaced anchors + random jitter.
    Returns indices scattered across [0, n-1].
    """

    if k == 0:
        return []

    if k == 1:
        return [random.randrange(n)]

    anchors = [int(round(i * (n - 1) / (k - 1))) for i in range(k)]
    out, seen = [], set()
    radius = max(1, int(n * jitter_frac))
```

```
    for a in anchors:
        lo = max(0, a - radius)
        hi = min(n - 1, a + radius)
        j = random.randint(lo, hi)

        if j not in seen:
            out.append(j)
            seen.add(j)

    while len(out) < k:
        r = random.randrange(n)
        if r not in seen:
            out.append(r)
            seen.add(r)

    return out



def _draw_boxed_chunk(c: dict, wrap_at: int = 96) -> str:
    """
    Pretty-print a chunk (LLM / recursive / semantic) inside a boxed layout.
    """

    # Approximate token count fallback
    approx_tokens = c.get(
        "chunk_token_count",
        len(c.get("chunk_text", "")) / 4
    )

    header = (
        f" Chunk p{c['page_number']} | idx {c['chunk_index']} | "
        f"chars {c['chunk_char_count']} | "
        f"words {c['chunk_word_count']} | "
        f"~tokens {round(approx_tokens, 2)} "
    )

    # Wrap chunk text
    wrapped_lines = textwrap.wrap(
        c["chunk_text"],
        width=wrap_at,
        break_long_words=False,
        replace_whitespace=False
    )

    content_width = max(
        [len(header), *(len(x) for x in wrapped_lines)]
        if wrapped_lines else [len(header)]
    )

    top = "+" + "=" * content_width + "+"
    hline = "|" + header.ljust(content_width) + "|"
    sep = "+" + "-" * content_width + "+"

    body = (
        "\n".join(
            "| " + line.ljust(content_width - 2) + " |"
            for line in wrapped_lines
        )
        if wrapped_lines
```

```
        else "| " + "".ljust(content_width - 2) + " |"
    )

    bottom = "+" + "=" * content_width + "+"

    return "\n".join([top, hline, sep, body, bottom])


def show_random_llm_chunks(
    llm_chunked_pages: list[dict],
    k: int = 5,
    seed: int | None = 42
):
    """
    Pretty-print a few random LLM-based chunks for inspection.
    """

    if seed is not None:
        random.seed(seed)

    n = len(llm_chunked_pages)
    assert n > 0, "No LLM-based chunks to display. Did you run the previous cell

    idxs = _scattered_indices(n, k)

    print(
        f"Showing {len(idxs)} scattered random LLM-BASED chunks "
        f"out of {n} total:\n"
    )

    for i, idx in enumerate(idxs, 1):
        print(f"#{i}")
        print(_draw_boxed_chunk(llm_chunked_pages[idx]))
        print()


# -------------------- Run --------------------
assert (
    "llm_chunked_pages" in globals()
    and len(llm_chunked_pages) > 0
), "Run your LLM-based chunking cell first to define 'llm_chunked_pages'."

show_random_llm_chunks(llm_chunked_pages, k=5, seed=42)
```

```
Showing 5 scattered random LLM-BASED chunks out of 2360 total:

#1
+================================================================================
===============+
| Chunk p56 | idx 0 | chars 800 | words 125 | ~tokens 200.0
|
+--------------------------------------------------------------------------------
---------------+
| •  Explain the anatomy and physiology of the  digestive system and other suppor
ting organ     |
| systems  •  Describe the relationship between diet and each of  the organ syste
ms  •  Describe |
| the process of calculating Body Mass  Index (BMI)  The Native Hawaiians believe
d there was a  |
| strong connection  between health and food. Around the world, other cultures ha
d  similar views |
| of food and its relationship with health. A famous  quote by the Greek physicia
n Hippocrates  |
| over two thousand years  ago, “Let food be thy medicine and medicine be thy foo
d” bear much   |
| relevance on our food choices and their connection to our health.  Today, the s
cientific      |
| community echoes Hippocrates’ statement as  it recognizes some foods as functio
nal foods. The |
| Academy of  Nutrition and Dietetics defines functional fo
|
+================================================================================
===============+

#2
+================================================================================
============+
| Chunk p210 | idx 1 | chars 276 | words 32 | ~tokens 69.0
|
+--------------------------------------------------------------------------------
------------+
| l caloric  1. US Liquid Refreshment Beverage Market Increased by  1.2% in 2010,
Beverage   |
| Marketing Corporation Reports.  Beverage Marketing Corporation.
|
| http://www.beveragemarketing.com/?section=pressrel eases. Published 2010. Acces
sed March 17, |
| 2011.  210  |  Water Concerns
|
+================================================================================
============+

#3
+================================================================================
================+
| Chunk p480 | idx 1 | chars 768 | words 123 | ~tokens 192.0
|
+--------------------------------------------------------------------------------
----------------+
| y the  calories you burn during physical activity, but also the calories you  b
urn while at rest |
| (basal metabolism), and the calories you burn  when you digest food. The sum of
caloric        |
| expenditure is referred  to as total energy expenditure (TEE). Basal metabolism
```

```
refers to  those |
| metabolic pathways necessary to support and maintain the  body’s basic function
s (e.g.         |
| breathing, heartbeat, liver and kidney  function) while at rest. The basal meta
bolic rate (BMR) |
| is the amount  of energy required by the body to conduct its basic functions ov
er  a certain   |
| time period. The great majority of energy expended  (between 50 and 70 percent)
daily is from  |
| conducting life’s basic  processes. Of all the organs, the liver requires the m
ost energy  480 |
| |  Weight Management
|
+=================================================================================
================+

#4
+=================================================================================
================+
| Chunk p857 | idx 1 | chars 670 | words 95 | ~tokens 167.5
|
+---------------------------------------------------------------------------------
----------------+
| ncludes the following:  • selecting and preparing food  • providing regular mea
ls and snacks  • |
| making mealtimes pleasant  • showing children what they must learn about mealti
me  behavior  • |
| avoiding letting children eat in between meal- or snack-times2  Picky Eaters  T
he parents of   |
| toddlers are likely to notice a sharp drop in their  child’s appetite. Children
at this stage  |
| are often picky about what  they want to eat because they just aren’t as hungr
y. They may turn |
| 2. Satter, E. (2016). Ellyn Satter’s division of responsibility in  feeding.
|
| https://www.ellynsatterinstitute.org/wp- content/uploads/2016/11/handout-dor-ta
sks- cap-2016.pdf |
| Toddler Years  |  857
|
+=================================================================================
================+

#5
+=================================================================================
================+
| Chunk p1108 | idx 2 | chars 130 | words 13 | ~tokens 32.5
|
+---------------------------------------------------------------------------------
----------------+
| r-prevention-and-early-detection-facts-and- figures-2013.pdf. Published 2013. A
ccessed April 15, |
| 2018.  1108  |  Threats to Health
|
+=================================================================================
================+
```

Step 4: Analysis of chunking strategies

In [ ]:
```python
# Build stats + plots directly from your existing chunk lists
# (chunked_pages, semantic_chunked_pages, recursive_chunked_pages,
#  structure_chunked_pages, llm_chunked_pages)

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt


# -------------------- Config --------------------
# Choose which size metric to analyze:
# one of: "chars", "words", "tokens"
METRIC = "words"


def _size_val(c: dict, metric: str):
    """
    Returns the size value for a chunk based on the selected metric.
    """

    if metric == "chars":
        return c.get("chunk_char_count", len(c.get("chunk_text", "")))

    if metric == "words":
        return c.get(
            "chunk_word_count",
            len(c.get("chunk_text", "").split())
        )

    if metric == "tokens":
        # Fall back to chars / 4 if token count not present
        return c.get(
            "chunk_token_count",
            len(c.get("chunk_text", "")) / 4
        )

    raise ValueError("METRIC must be one of {'chars', 'words', 'tokens'}")


def analyze_chunks(
    chunks: list[dict],
    method_name: str,
    metric: str
) -> dict:
    """
    Computes basic statistics for a chunking method.
    """

    sizes = [_size_val(c, metric) for c in chunks]

    return {
        "Method": method_name,
        "Avg Chunk Size": float(np.mean(sizes)) if sizes else 0.0,
        "Num Chunks": len(sizes),
        "Size Variance": float(np.var(sizes)) if sizes else 0.0,
    }


# -------------------- Gather Results --------------------
```

```
datasets = [
    ("fixed", chunked_pages),
    ("semantic", semantic_chunked_pages),
    ("recursive", recursive_chunked_pages),
    ("structure", structure_chunked_pages),
    ("llm", llm_chunked_pages),
]

results = [
    analyze_chunks(chks, name, METRIC)
    for name, chks in datasets
]

df = pd.DataFrame(results)

print(df.round(3).to_string(index=False))


# -------------------- Performance Analysis --------------------
print("\n# Performance analysis")
print("1. Structure-based chunking produced the most coherent sections.")
print("2. Semantic chunking maintained best context preservation.")
print("3. Fixed-size chunking showed lowest variance but poor semantic coherence
print("4. Recursive chunking provided balanced results.")
print("5. LLM chunking provided balanced results.")
```

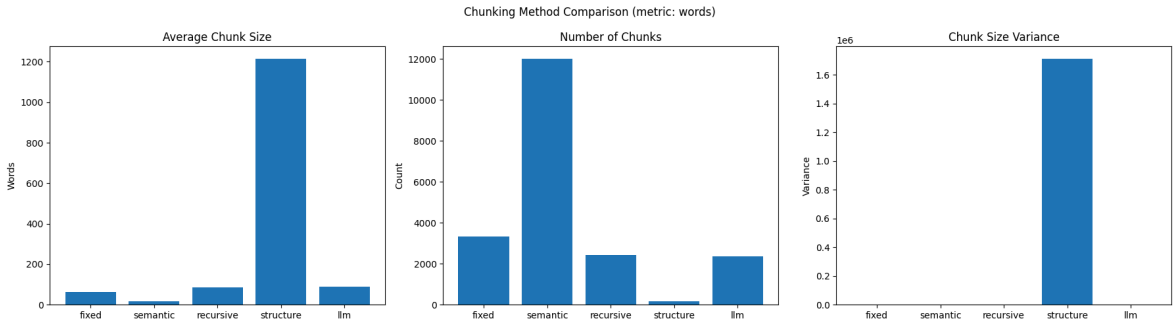
```
   Method  Avg Chunk Size  Num Chunks  Size Variance
    fixed          62.552        3321        583.291
 semantic          17.288       12016        245.870
recursive          85.348        2434       1476.424
structure        1214.801         171    1712584.803
      llm          88.362        2360       1804.910

# Performance analysis
1. Structure-based chunking produced the most coherent sections.
2. Semantic chunking maintained best context preservation.
3. Fixed-size chunking showed lowest variance but poor semantic coherence.
4. Recursive chunking provided balanced results.
5. LLM chunking provided balanced results.
```

Step 5: Visualization of chunking strategies

In [ ]:

```
# -------------------- Bar Plots --------------------
# Uses the computed df (no hardcoding)

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Average Chunk Size
axes[0].bar(df["Method"], df["Avg Chunk Size"])
axes[0].set_title("Average Chunk Size")
axes[0].set_ylabel(
    {"chars": "Characters", "words": "Words", "tokens": "Tokens"}[METRIC]
)

# Number of Chunks
axes[1].bar(df["Method"], df["Num Chunks"])
axes[1].set_title("Number of Chunks")
axes[1].set_ylabel("Count")
```

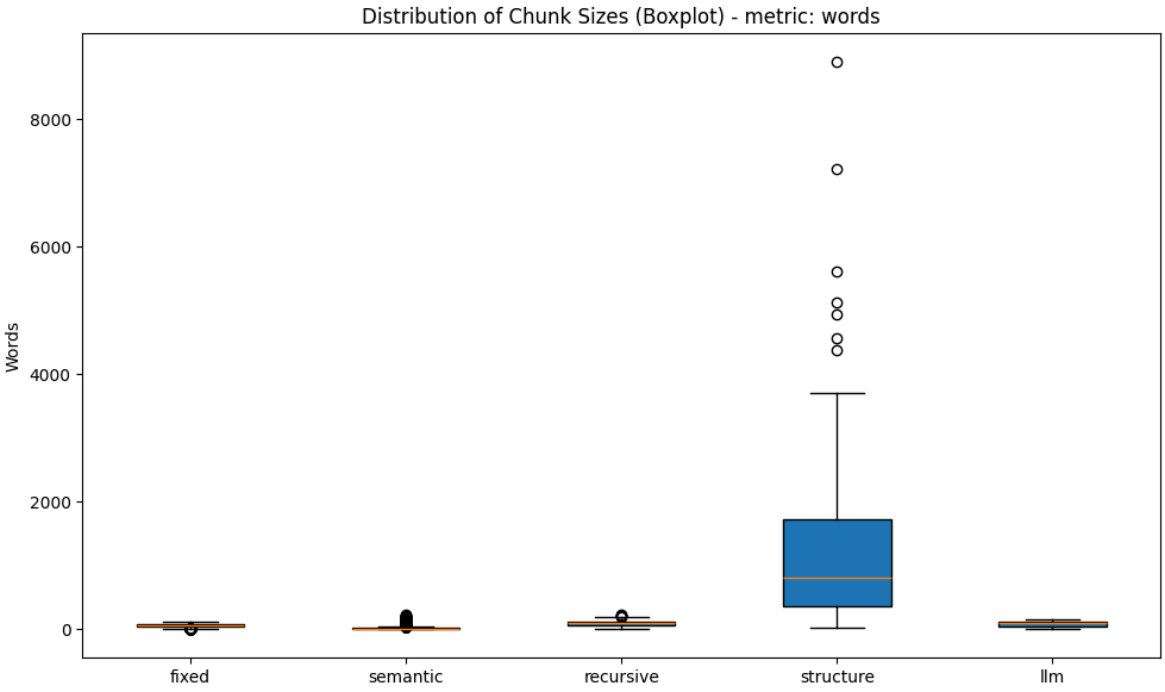
```
# Chunk Size Variance
axes[2].bar(df["Method"], df["Size Variance"])
axes[2].set_title("Chunk Size Variance")
axes[2].set_ylabel("Variance")

plt.suptitle(f"Chunking Method Comparison (metric: {METRIC})")
plt.tight_layout()
plt.show()
```



In [ ]:

```
# -------------------- Boxplot from raw chunk sizes --------------------
# (no hardcoding, uses existing chunk lists)

def extract_sizes(chunks, metric: str):
    return [_size_val(c, metric) for c in chunks]


# Extract sizes for each chunking method
sizes_fixed = extract_sizes(chunked_pages, METRIC)
sizes_semantic = extract_sizes(semantic_chunked_pages, METRIC)
sizes_recursive = extract_sizes(recursive_chunked_pages, METRIC)
sizes_structure = extract_sizes(structure_chunked_pages, METRIC)
sizes_llm = extract_sizes(llm_chunked_pages, METRIC)


# Create boxplot
plt.figure(figsize=(10, 6))
plt.boxplot(
    [sizes_fixed, sizes_semantic, sizes_recursive, sizes_structure, sizes_llm],
    labels=["fixed", "semantic", "recursive", "structure", "llm"],
    patch_artist=True
)

plt.title(f"Distribution of Chunk Sizes (Boxplot) - metric: {METRIC}")
plt.ylabel(
    {"chars": "Characters", "words": "Words", "tokens": "Tokens"}[METRIC]
)
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-1307296014.py:18: MatplotlibDeprecationWarning: The 'labels' p
arameter of boxplot() has been renamed 'tick_labels' since Matplotlib 3.9; suppor
t for the old name will be dropped in 3.11.
  plt.boxplot(
```



Chunking — Final Takeaways

Observations from Chunk Analysis

- **Structure-Based Chunking**
  - Produces **fewer chunks**
  - Chunk sizes are **very large**
  - **High variance** in chunk size
  - Good for capturing **entire sections**
  - ❌ Less balanced for downstream models due to size variance
- **Semantic Chunking**
  - Produces the **highest number of chunks**
  - Chunks are **very small**
  - Preserves **fine-grained semantic context**
  - ❌ Risk of **over-fragmentation**
    - Chunks may become too small to carry meaningful information
- **Fixed-Size Chunking**
  - Produces **consistent, moderate-sized chunks**
  - **Low variance** in chunk size
  - Easy to reason about and fast
  - ❌ Completely ignores semantic and structural boundaries
- **Recursive Chunking**
  - Balances **structure preservation** and **size control**
  - Avoids oversized chunks
  - Most **practical and production-friendly** approach
- **LLM-Based Chunking**

- Semantically powerful but:
  - ❌ **Extremely slow** (orders of magnitude slower)
  - ❌ Computationally expensive
  - ❌ Not scalable
- Suitable only for **small, high-value, highly unstructured data**

> **Important correction:**
> If time benchmarking is included, **LLM-based chunking is clearly the slowest** and often impractical for real systems.

Key Engineering Insight

- Chunking quality is not just about correctness — it is about:
  - **Chunk size variance**
  - **Number of chunks**
  - **Downstream model compatibility**
  - **Latency and cost**

Further text processing (splitting pages into sentences)

In [ ]:
```
from spacy.lang.en import English  # see https://spacy.io/usage for install inst

nlp = English()

# Add a sentencizer pipeline
nlp.add_pipe("sentencizer")

# Create a document instance as an example
doc = nlp("This is a sentence. This another sentence.")

# Validate sentence splitting
assert len(list(doc.sents)) == 2

# Access the sentences of the document
list(doc.sents)
```

Out[ ]:
```
[This is a sentence., This another sentence.]
```

In [6]:
```
# # -------------------- Add spaCy sentence splits to each page ----------------

# for item in tqdm(pages_and_texts):
#     # Extract sentences using spaCy
#     item["sentences"] = list(nlp(item["text"]).sents)

#     # Ensure all sentences are strings
#     item["sentences"] = [str(sentence) for sentence in item["sentences"]]

#     # Count number of sentences per page
#     item["page_sentence_count_spacy"] = len(item["sentences"])
```

In [ ]:
```
# Inspect an example
random.sample(pages_and_texts, k=1)
```

Out[ ]:
```
[{'page_number': 416,
  'page_char_count': 1389,
  'page_word_count': 255,
  'page_sentence_count_raw': 9,
  'page_token_count': 347.25,
  'text': 'Foods  Lacking Amino  Acids  Complementary  Food  Complementary  Men
u  Legumes  Methionine,  tryptophan  Grains, nuts,  and seeds  Hummus and  whol
e-wheat pita  Grains  Lysine, isoleucine,  threonine  Legumes  Cornbread and  k
idney bean chili  Nuts and  seeds  Lysine, isoleucine  Legumes  Stir-fried tofu
with  cashews  The second component of protein quality is digestibility, as not
all protein sources are equally digested. In general, animal-based  proteins ar
e completely broken down during the process of  digestion, whereas plant-based
proteins are not. This is because  some proteins are contained in the plant's f
ibrous cell walls and  these pass through the digestive tract unabsorbed by the
body.  Protein Digestibility Corrected Amino Acid  Score (PDCAAS)  The PDCAAS i
s a method adopted by the US Food and Drug  Administration (FDA) to determine a
food's protein quality. It is  calculated using a formula that incorporates the
total amount of  amino acids in the food and the amount of protein in the food
that  is actually digested by humans. The food's protein quality is then  ranke
d against the foods highest in protein quality. Milk protein, egg  whites, whe
y, and soy all have a ranking of one, the highest ranking.  Other foods' ranks
are listed in Table 6.5 "PDCAAS of Various Foods".  Table 6.5 PDCAAS of Various
Foods  416  |  Proteins, Diet, and Personal Choices',
  'sentences': ['Foods  Lacking Amino  Acids  Complementary  Food  Complementar
y  Menu  Legumes  Methionine,  tryptophan  Grains, nuts,  and seeds  Hummus and
whole-wheat pita  Grains  Lysine, isoleucine,  threonine  Legumes  Cornbread an
d  kidney bean chili  Nuts and  seeds  Lysine, isoleucine  Legumes  Stir-fried
tofu with  cashews  The second component of protein quality is digestibility, a
s not  all protein sources are equally digested.',
   'In general, animal-based  proteins are completely broken down during the pr
ocess of  digestion, whereas plant-based proteins are not.',
   'This is because  some proteins are contained in the plant's fibrous cell wa
lls and  these pass through the digestive tract unabsorbed by the body.',
   ' Protein Digestibility Corrected Amino Acid  Score (PDCAAS)  The PDCAAS is
a method adopted by the US Food and Drug  Administration (FDA) to determine a f
ood's protein quality.',
   'It is  calculated using a formula that incorporates the total amount of  am
ino acids in the food and the amount of protein in the food that  is actually d
igested by humans.',
   'The food's protein quality is then  ranked against the foods highest in pro
tein quality.',
   'Milk protein, egg  whites, whey, and soy all have a ranking of one, the hig
hest ranking.',
   ' Other foods' ranks are listed in Table 6.5 "PDCAAS of Various Foods".',
   ' Table 6.5 PDCAAS of Various Foods  416  |  Proteins, Diet, and Personal Ch
oices'],
  'page_sentence_count_spacy': 9}]
```

In [ ]:
```
df = pd.DataFrame(pages_and_texts)
df.describe().round(2)
```

Out[ ]:

	page_number	page_char_count	page_word_count	page_sentence_count_raw	pag
count	1208.00	1208.00	1208.00	1208.00	
mean	562.50	1148.00	198.30	9.97	
std	348.86	560.38	95.76	6.19	
min	-41.00	0.00	1.00	1.00	
25%	260.75	762.00	134.00	4.00	
50%	562.50	1231.50	214.50	10.00	
75%	864.25	1603.50	271.00	14.00	
max	1166.00	2308.00	429.00	32.00	

In [7]:
```
# # Define split size to turn groups of sentences into chunks
# num_sentence_chunk_size = 10


# def split_list(input_list: list, slice_size: int) -> list[list[str]]:
#     """
#     Splits the input_list into sublists of size `slice_size`
#     (or as close as possible).

#     Example:
#     A list of 17 sentences with slice_size=10 →
#     [[10 sentences], [7 sentences]]
#     """

#     return [
#         input_list[i:i + slice_size]
#         for i in range(0, len(input_list), slice_size)
#     ]


# # Loop through pages and split sentences into sentence-level chunks
# for item in tqdm(pages_and_texts):
#     item["sentence_chunks"] = split_list(
#         input_list=item["sentences"],
#         slice_size=num_sentence_chunk_size
#     )

#     # Store number of sentence chunks per page
#     item["num_chunks"] = len(item["sentence_chunks"])
```

In [ ]:
```
# Sample an example from the group
# (note: many samples have only 1 chunk as they have <= 10 sentences total)
random.sample(pages_and_texts, k=1)
```

Out[ ]:
[{'page_number': 244,
'page_char_count': 1413,
'page_word_count': 251,
'page_sentence_count_raw': 13,
'page_token_count': 353.25,
'text': 'your body senses blood glucose levels and maintains the glucose “te
mperature” in the target range. The glucose thermostat is located within the c
ells of the pancreas. After eating a meal containing carbohydrates glucose lev
els rise in the blood. Insulin-secreting cells in the pancreas sense the incre
ase in blood glucose and release the hormone, insulin, into the blood. Insulin
sends a signal to the body’s cells to remove glucose from the blood by transpo
rting it into different organ cells around the body and using it to make energ
y. In the case of muscle tissue and the liver, insulin sends the biological me
ssage to store glucose away as glycogen. The presence of insulin in the blood
signifies to the body that glucose is available for fuel. As glucose is transp
orted into the cells around the body, the blood glucose levels decrease. Insul
in has an opposing hormone called glucagon. Glucagon-secreting cells in the p
ancreas sense the drop in glucose and, in response, release glucagon into the
blood. Glucagon communicates to the cells in the body to stop using all the gl
ucose. More specifically, it signals the liver to break down glycogen and rele
ase the stored glucose into the blood, so that glucose levels stay within the
target range and all cells get the needed fuel to function properly. Figure
4.8 The Regulation of Glucose 244 | Digestion and Absorption of Carbohydrate
s',
'sentences': ['your body senses blood glucose levels and maintains the glucos
e “temperature” in the target range.',
'The glucose thermostat is located within the cells of the pancreas.',
'After eating a meal containing carbohydrates glucose levels rise in the bl
ood.',
' Insulin-secreting cells in the pancreas sense the increase in blood gluco
se and release the hormone, insulin, into the blood.',
'Insulin sends a signal to the body’s cells to remove glucose from the bloo
d by transporting it into different organ cells around the body and using it
to make energy.',
'In the case of muscle tissue and the liver, insulin sends the biological m
essage to store glucose away as glycogen.',
'The presence of insulin in the blood signifies to the body that glucose is
available for fuel.',
'As glucose is transported into the cells around the body, the blood glucos
e levels decrease.',
'Insulin has an opposing hormone called glucagon.',
'Glucagon-secreting cells in the pancreas sense the drop in glucose and, in
response, release glucagon into the blood.',
'Glucagon communicates to the cells in the body to stop using all the gluco
se.',
'More specifically, it signals the liver to break down glycogen and release
the stored glucose into the blood, so that glucose levels stay within the targ
et range and all cells get the needed fuel to function properly.',
' Figure 4.8 The Regulation of Glucose 244 | Digestion and Absorption of
Carbohydrates'],
'page_sentence_count_spacy': 13,
'sentence_chunks': [['your body senses blood glucose levels and maintains the
glucose “temperature” in the target range.',
'The glucose thermostat is located within the cells of the pancreas.',
'After eating a meal containing carbohydrates glucose levels rise in the b
lood.',
' Insulin-secreting cells in the pancreas sense the increase in blood gluc
ose and release the hormone, insulin, into the blood.',
'Insulin sends a signal to the body’s cells to remove glucose from the blo
od by transporting it into different organ cells around the body and using it

```
to make energy.',
    'In the case of muscle tissue and the liver,  insulin sends the biological
message to store glucose away as  glycogen.',
    'The presence of insulin in the blood signifies to the body  that glucose i
s available for fuel.',
    'As glucose is transported into the  cells around the body, the blood gluco
se levels decrease.',
    'Insulin has  an opposing hormone called glucagon.',
    'Glucagon-secreting cells in  the pancreas sense the drop in glucose and, i
n response, release  glucagon into the blood.'],
   ['Glucagon communicates to the cells in the  body to stop using all the gluc
ose.',
    'More specifically, it signals the  liver to break down glycogen and releas
e the stored glucose into the  blood, so that glucose levels stay within the ta
rget range and all cells  get the needed fuel to function properly.',
    ' Figure 4.8 The Regulation of Glucose  244  |  Digestion and Absorption of
Carbohydrates']],
  'num_chunks': 2}]
```

In [ ]:
```python
# Create a DataFrame from pages_and_texts to inspect statistics
df = pd.DataFrame(pages_and_texts)

# Show descriptive statistics
df.describe().round(2)
```

Out[ ]:

	page_number	page_char_count	page_word_count	page_sentence_count_raw	pag
count	1208.00	1208.00	1208.00	1208.00	
mean	562.50	1148.00	198.30	9.97	
std	348.86	560.38	95.76	6.19	
min	-41.00	0.00	1.00	1.00	
25%	260.75	762.00	134.00	4.00	
50%	562.50	1231.50	214.50	10.00	
75%	864.25	1603.50	271.00	14.00	
max	1166.00	2308.00	429.00	32.00	

Splitting each chunk into its own item

We'd like to embed each chunk of sentences into its own numerical representation.

So to keep things clean, let's create a new list of dictionaries each containing a single chunk of sentences with relative information, page number as well statistics about each chunk.

In [8]:
```python
# import re

# # Split each chunk into its own item
# pages_and_chunks = []

# for item in tqdm(pages_and_texts):
```

```
#     for sentence_chunk in item["sentence_chunks"]:
#         chunk_dict = {}

#         # Store page number
#         chunk_dict["page_number"] = item["page_number"]

#         # Join sentences into a single chunk
#         joined_sentence_chunk = " ".join(sentence_chunk).replace("  ", " ").st

#         # Fix missing space after periods (".A" -> ". A")
#         joined_sentence_chunk = re.sub(
#             r'\.([A-Z])',
#             r'. \1',
#             joined_sentence_chunk
#         )

#         chunk_dict["sentence_chunk"] = joined_sentence_chunk

#         # Chunk statistics
#         chunk_dict["chunk_char_count"] = len(joined_sentence_chunk)
#         chunk_dict["chunk_word_count"] = len(
#             [word for word in joined_sentence_chunk.split(" ")]
#         )
#         chunk_dict["chunk_token_count"] = len(joined_sentence_chunk) / 4  # ~1

#         pages_and_chunks.append(chunk_dict)

# # How many chunks do we have?
# len(pages_and_chunks)
```

In [ ]:
```
random.sample(pages_and_chunks, k=1)
```

Out[ ]:
```
[{'page_number': 967,
  'sentence_chunk': 'Iron Status and Exercise. The American Journal of Clinical
Nutrition, 72(2), 594S–597S. Sports Nutrition | 967',
  'chunk_char_count': 110,
  'chunk_word_count': 16,
  'chunk_token_count': 27.5}]
```

In [ ]:
```
# Create a DataFrame from pages_and_texts to inspect statistics
df = pd.DataFrame(pages_and_chunks)

# Show descriptive statistics
df.describe().round(2)
```

Out[ ]:

	page_number	chunk_char_count	chunk_word_count	chunk_token_count
count	1843.00	1843.00	1843.00	1843.00
mean	583.38	735.14	113.03	183.78
std	347.79	447.64	71.27	111.91
min	-41.00	12.00	3.00	3.00
25%	280.50	315.00	45.00	78.75
50%	586.00	747.00	114.00	186.75
75%	890.00	1119.00	174.00	279.75
max	1166.00	1832.00	298.00	458.00

In [ ]:
```
# Show random chunks with under 30 tokens in length
min_token_length = 30

for _, row in df[df["chunk_token_count"] <= min_token_length].sample(5).iterrows
    print(
        f"Chunk token count: {row['chunk_token_count']} | "
        f"Text: {row['sentence_chunk']}"
    )
```

```
Chunk token count: 3.25 | Text: 814 | Infancy
Chunk token count: 12.5 | Text: Figure 11.2 The Structure of Hemoglobin Iron | 65
5
Chunk token count: 9.25 | Text: Protein’s Functions in the Body | 387
Chunk token count: 26.0 | Text: http://www.ncbi.nlm.nih.gov/pubmed/20182023. Acce
ssed September 22, 2017. 220 | Popular Beverage Choices
Chunk token count: 17.5 | Text: The Obesity Myth. Gotham Books. Calories In Versu
s Calories Out | 1069
```

Observation

Looks like many of these are **headers and footers** of different pages.

They don't seem to offer **too much information**.

Next Step

Filter our **DataFrame / list of dictionaries** to only include chunks with **over 30 tokens** in length.

In [ ]:
```
pages_and_chunks_over_min_token_len = (
    df[df["chunk_token_count"] > min_token_length]
    .to_dict(orient="records")
)

pages_and_chunks_over_min_token_len[:2]
```

Out[ ]:

```
[{'page_number': -39,
  'sentence_chunk': 'Human Nutrition: 2020 Edition UNIVERSITY OF HAWAIʻI AT MĀN
OA FOOD SCIENCE AND HUMAN NUTRITION PROGRAM ALAN TITCHENAL, SKYLAR HARA, NOEMI
ARCEO CAACBAY, WILLIAM MEINKE-LAU, YA-YUN YANG, MARIE KAINOA FIALKOWSKI REVILL
A, JENNIFER DRAPER, GEMADY LANGFELDER, CHERYL GIBBY, CHYNA NICOLE CHUN, AND ALL
ISON CALABRESE',
  'chunk_char_count': 308,
  'chunk_word_count': 42,
  'chunk_token_count': 77.0},
 {'page_number': -38,
  'sentence_chunk': 'Human Nutrition: 2020 Edition by University of Hawaiʻi at
Mānoa Food Science and Human Nutrition Program is licensed under a Creative Com
mons Attribution 4.0 International License, except where otherwise noted.',
  'chunk_char_count': 210,
  'chunk_word_count': 30,
  'chunk_token_count': 52.5}]
```


Embedding our text chunks

While humans understand text, machines understand numbers best.

An embedding is a broad concept.

But one of my favourite and simple definitions is **"a useful numerical representation."**

The most powerful thing about modern embeddings is that they are **learned representations**.

Meaning rather than directly mapping words / tokens / characters to numbers directly (e.g. `{"a": 0, "b": 1, "c": 3 ...}`), the numerical representation of tokens is learned by going through large corpuses of text and figuring out how different tokens relate to each other.

Ideally, embeddings of text will mean that **similar meaning texts have similar numerical representations**.

Note on Tokens

Most modern NLP models deal with **tokens**, which can be considered as multiple different sizes and combinations of words and characters rather than always whole words or single characters.

For example, the string:

"hello world!"

gets mapped to token values:

{15339: b'hello', 1917: b' world', 0: b'!'}

using **Byte Pair Encoding (BPE)** via OpenAI's `tiktoken` library.

Google has a tokenization library called **SentencePiece**.

In [9]:
```
# from sentence_transformers import SentenceTransformer

# # Load embedding model
# embedding_model = SentenceTransformer(
#     model_name_or_path="all-mpnet-base-v2",
#     device="cpu"  # choose device (GPU if available)
# )

# # Create a list of sentences to turn into embeddings
# sentences = [
#     "The Sentences Transformers library provides an easy and open-source way t
#     "Sentences can be embedded one by one or as a list of strings.",
#     "Embeddings are one of the most powerful concepts in machine learning!",
#     "Learn to use embeddings well and you'll be well on your way to being an A
# ]

# # Encode sentences into embeddings
# embeddings = embedding_model.encode(sentences)

# # Map sentences to their embeddings
# embeddings_dict = dict(zip(sentences, embeddings))

# # Inspect embeddings
# for sentence, embedding in embeddings_dict.items():
#     print("Sentence:", sentence)
#     print("Embedding:", embedding)
#     print()
```

In [ ]:
```
single_sentence = "Yo! How cool are embeddings?"

single_embedding = embedding_model.encode(single_sentence)

print(f"Sentence: {single_sentence}")
print(f"Embedding:\n{single_embedding}")
print(f"Embedding size: {single_embedding.shape}")
```

```
Sentence: Yo! How cool are embeddings?
Embedding:
[-1.97447427e-02 -4.51086881e-03 -4.98485053e-03  6.55445009e-02
 -9.87679232e-03  2.72835400e-02  3.66426297e-02 -3.30218766e-03
  8.50079488e-03  8.24953429e-03 -2.28496902e-02  4.02430221e-02
 -5.75200692e-02  6.33693114e-02  4.43207026e-02 -4.49507199e-02
  1.25284074e-02 -2.52012592e-02 -3.55292559e-02  1.29559208e-02
  8.67017172e-03 -1.92917418e-02  3.55633581e-03  1.89505871e-02
 -1.47128394e-02 -9.39850323e-03  7.64166377e-03  9.62190889e-03
 -5.98926842e-03 -3.90170179e-02 -5.47824502e-02 -5.67451864e-03
  1.11644585e-02  4.08067852e-02  1.76319122e-06  9.15295724e-03
 -8.77268612e-03  2.39383057e-02 -2.32784506e-02  8.04999471e-02
  3.19177508e-02  5.12592029e-03 -1.47708794e-02 -1.62525047e-02
 -6.03212789e-02 -4.35689688e-02  4.51210849e-02 -1.79053862e-02
  2.63366923e-02 -3.47867236e-02 -8.89174361e-03 -5.47675230e-02
 -1.24372840e-02 -2.38606390e-02  8.33497047e-02  5.71242571e-02
  1.13328639e-02 -1.49595207e-02  9.20379087e-02  2.72709355e-02
 -1.42185902e-02  1.91209037e-02  1.49963917e-02 -3.12198512e-02
  8.99579823e-02  4.51188348e-02  2.58020218e-02 -5.51740965e-03
  1.15909828e-02  4.72100526e-02 -1.51018510e-02  1.70818064e-02
 -7.22598983e-03  3.45762745e-02 -8.76472238e-03  5.22016771e-02
 -6.49008527e-02 -4.31379117e-02  6.36964887e-02  4.02880907e-02
 -1.99043211e-02  5.39056538e-03  1.28820213e-02 -4.81255502e-02
  4.58801687e-02 -2.17094868e-02  1.89204067e-02 -3.46344374e-02
 -1.66457165e-02  7.65175279e-03 -2.26693284e-02 -1.96454506e-02
  1.87631901e-02  1.01383058e-02  6.85413405e-02 -5.39848721e-03
 -3.38226906e-03  4.08412963e-02  4.98623550e-02 -1.16485646e-02
  8.91739130e-02  4.02785912e-02 -3.64720775e-03  4.37758416e-02
 -2.96079107e-02 -5.53750060e-03 -2.00208947e-02 -2.01984234e-02
  4.59849797e-02  2.29337867e-02 -5.37305139e-02 -3.19279432e-02
  1.37542491e-03  6.25036284e-02 -2.18309071e-02 -6.43255338e-02
 -2.24791728e-02  3.31955068e-02 -3.12837176e-02  5.17936610e-02
 -2.84002610e-02  2.55067665e-02  3.36493105e-02  7.50667453e-02
 -4.46476042e-03 -4.87705544e-02 -7.35218599e-02 -5.46353199e-02
  8.88533890e-03  2.95796879e-02 -9.95695870e-03 -6.32769056e-03
  4.46259193e-02 -1.58484410e-02 -1.71330255e-02  3.36602405e-02
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  1.26052080e-02  1.49842503e-03  1.33206956e-02 -2.82468218e-02
 -3.29254419e-02 -8.53573531e-03 -5.27607240e-02  7.29350224e-02
 -6.41821623e-02 -2.51782173e-03 -9.02640074e-03 -1.10468664e-03
  1.57514699e-02  4.30823676e-02  1.12269642e-02 -3.54585126e-02
  4.95163649e-02  1.21271079e-02  1.66341802e-03 -5.06922835e-03
 -1.11001944e-02 -8.66916217e-03 -3.26440930e-02 -3.98022197e-02
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 -3.74916382e-02 -3.24731730e-02  5.85900210e-02  8.48080441e-02
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  3.27137224e-02  6.92137284e-03 -1.42607363e-02  7.76677653e-02
 -1.16103664e-02 -3.66427712e-02 -2.83837616e-02  2.72280090e-02
  2.49365401e-02 -4.22297232e-03 -3.63100804e-02 -2.04887465e-02
  3.98861244e-02 -2.64727939e-02  4.41389112e-03 -5.19635193e-02
  1.71721458e-05  4.81283665e-02  2.04450730e-02  9.84970406e-02
  3.68268229e-02  1.53405340e-02  7.50899082e-04 -3.38638425e-02
 -2.69872714e-02  4.72445525e-02  4.56702039e-02 -3.49245742e-02
 -1.18770320e-02  3.45583283e-03 -6.32303627e-03 -4.78412360e-02
  1.84098836e-02 -2.23157089e-02 -3.70728374e-02  5.87340072e-02
  6.22731494e-03 -1.46716442e-02  7.29224086e-02  2.21962342e-03
 -6.53118938e-02  3.51679549e-02 -1.54901436e-02  6.01421520e-02
 -9.41006560e-03  2.81196218e-02 -1.12652024e-02  5.24168077e-04
```

```
 1.01888604e-01 -5.69957010e-02 -3.52360234e-02 -5.20474929e-03
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-2.26343535e-02 -6.24928027e-02 -1.56844985e-02  4.11566533e-02
 1.66952461e-02  7.97291622e-02 -3.24839242e-02  1.46561826e-03
-3.27906124e-02  6.44816011e-02  2.09739003e-02 -7.56984577e-02
-1.31794636e-03  2.24048551e-03 -6.60840748e-03 -6.84252381e-02
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-4.45122533e-02  2.89782472e-02  2.43083220e-02 -1.73885617e-02
-3.80668789e-02 -3.06799766e-02 -3.24778482e-02 -4.33349371e-04
 2.55846418e-02  2.70478521e-02 -1.72478409e-04 -4.93684202e-04
-7.12093860e-02  5.69768436e-02  6.61400482e-02 -3.87268625e-02
-1.30684068e-02  1.00663425e-02 -2.17739958e-02  1.92212742e-02
```

```
 7.66691053e-03 -3.86652090e-02 -1.66109167e-02 -3.41468081e-02
-1.04186311e-02  1.75906587e-02 -1.23776691e-02 -1.68434177e-02
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-4.36680671e-03  2.50830092e-02  2.59393286e-02 -3.07076368e-02
 7.04764575e-02  8.63501132e-02 -7.75880590e-02  1.59991421e-02
-5.04692197e-02  4.88355197e-02  3.74994287e-03 -6.12933130e-04
-3.87277231e-02 -2.32235435e-02 -3.63983475e-02 -5.07024443e-03
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-1.18530961e-03  1.92692073e-03  2.18783896e-02  2.71092877e-02
-4.06263880e-02  6.99160025e-02 -7.33281821e-02 -8.15294217e-03
-1.42555749e-02  3.78033752e-03  1.20974272e-01 -6.68213665e-02
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-1.98827051e-02 -5.59270680e-02  7.60343950e-03  2.23642085e-02
-1.86267011e-02  3.79805788e-02 -8.79648083e-04 -5.26199415e-02
 2.05070968e-03  1.72814410e-02 -4.84029204e-02 -1.87740941e-02
 7.00388458e-09  2.06594914e-02  3.03574633e-02  5.71855530e-03
-5.33938669e-02 -2.46520769e-02  1.80341229e-02 -3.39978375e-02
 3.47249152e-05 -6.40034676e-02  2.50049755e-02 -2.04112474e-02
-2.72044842e-03 -3.55961211e-02  2.71922797e-02  6.48940355e-02
 9.83487698e-04 -4.38491404e-02 -4.45296802e-02 -7.44882738e-03
 1.15205068e-02 -2.91253580e-03 -2.15495955e-02  2.84249941e-03
 4.29399572e-02 -6.09040186e-02 -7.86325522e-03 -3.90128675e-03
 2.47718305e-07  7.75820750e-04  7.47736841e-02  1.99312228e-03
-6.07222272e-03  3.69211063e-02  2.78420579e-02 -5.64900599e-02
 1.61058493e-02 -9.50821303e-03 -2.60858308e-03 -2.45737508e-02
 1.91390626e-02  5.08196652e-02  2.61258651e-02 -1.03838041e-01
-3.05815432e-02 -3.53343673e-02 -4.07037064e-02 -2.19842624e-02
-2.24091522e-02  5.05567938e-02  7.22607374e-02  5.54790162e-02
```

```
 4.89434414e-02  3.37951398e-03 -6.84760585e-02  7.10322661e-03
 3.15663801e-03  4.78090756e-02 -7.19795898e-02 -3.30302082e-02
 3.19160409e-02  1.76422752e-03 -4.62791361e-02 -1.96379870e-02
 1.67494081e-02  4.73604165e-02 -2.09441688e-02  7.10241310e-03
 4.53146845e-02 -4.76522744e-02 -4.74880636e-02  1.00798775e-02
-8.39594677e-02  3.36930230e-02 -3.72189730e-02  1.19432500e-02
-3.16896476e-02 -1.29724410e-03 -1.55541683e-02  1.81727838e-02
-1.49368951e-02 -1.70671511e-02 -4.19717208e-02  3.94655671e-03
-2.24301741e-02  2.07291860e-02 -4.61414568e-02  8.50211084e-03
-2.56864633e-02 -1.65337939e-02 -1.51846828e-02 -1.00042112e-02
 2.19642241e-02  2.61103436e-02  7.31358677e-02 -1.83709413e-02
 1.93979481e-34 -7.27930712e-03  5.96494274e-03  4.44310606e-02
 4.14822884e-02  1.12917926e-02 -1.93217471e-02  4.41878401e-02
-8.93789064e-03  3.61119770e-02 -5.52126132e-02 -2.89572421e-02]
Embedding size: (768,)
```

In [10]:
```
# %%time

# # Make sure the model is on the CPU
# embedding_model.to("cpu")

# # Embed each chunk one by one
# for item in tqdm(pages_and_chunks_over_min_token_len):
#     item["embedding"] = embedding_model.encode(item["sentence_chunk"])
```

In [11]:
```
# %%time

# # Send the model to the GPU
# embedding_model.to("cuda")  # requires a GPU

# # Create embeddings one by one on the GPU
# for item in tqdm(pages_and_chunks_over_min_token_len):
#     item["embedding"] = embedding_model.encode(item["sentence_chunk"])
```

In [ ]:
```
# Turn text chunks into a single list
text_chunks = [
    item["sentence_chunk"]
    for item in pages_and_chunks_over_min_token_len
]
```

In [ ]:
```
%%time

# Embed all texts in batches
text_chunk_embeddings = embedding_model.encode(
    text_chunks,
    batch_size=32,            # adjust batch size if needed
    convert_to_tensor=True    # return embeddings as tensors
)

text_chunk_embeddings
```

```
CPU times: user 26.6 s, sys: 49.1 ms, total: 26.6 s
Wall time: 26.2 s
```

Out[ ]:
```
tensor([[ 0.0674,  0.0902, -0.0051,  ..., -0.0221, -0.0232,  0.0126],
        [ 0.0552,  0.0592, -0.0166,  ..., -0.0120, -0.0103,  0.0227],
        [ 0.0280,  0.0340, -0.0206,  ..., -0.0054,  0.0213,  0.0313],
        ...,
        [ 0.0771,  0.0098, -0.0122,  ..., -0.0409, -0.0752, -0.0241],
        [ 0.1030, -0.0165,  0.0083,  ..., -0.0574, -0.0283, -0.0295],
        [ 0.0864, -0.0125, -0.0113,  ..., -0.0522, -0.0337, -0.0299]],
       device='cuda:0')
```

Save embeddings to file

Since creating embeddings can be a timely process (not so much for our case but it can be for more larger datasets), let's turn our `pages_and_chunks_over_min_token_len` list of dictionaries into a DataFrame and save it.

In [ ]:
```python
# Save embeddings to file
text_chunks_and_embeddings_df = pd.DataFrame(pages_and_chunks_over_min_token_len

embeddings_df_save_path = "text_chunks_and_embeddings_df.csv"

text_chunks_and_embeddings_df.to_csv(
    embeddings_df_save_path,
    index=False
)
```

In [ ]:
```python
# Import saved file and view
text_chunks_and_embedding_df_load = pd.read_csv(embeddings_df_save_path)
text_chunks_and_embedding_df_load.head()
```

Out[ ]:

	page_number	sentence_chunk	chunk_char_count	chunk_word_count	chunk_token_co
0	-39	Human Nutrition: 2020 Edition UNIVERSITY OF HA...	308	42	
1	-38	Human Nutrition: 2020 Edition by University of...	210	30	
2	-37	Contents Preface University of Hawai'i at Māno...	766	114	1
3	-36	Lifestyles and Nutrition University of Hawai'i...	942	143	2
4	-35	The Cardiovascular System University of Hawai'...	998	152	2

Embeddings — Engineering Decisions (After Chunking)

Once chunking is complete, **each chunk is converted into a vector embedding**. At this stage, embeddings become the **numerical representation of meaning** that powers retrieval.

Two **critical engineering decisions** arise here:

1. **Which embedding model should be used?**
2. **How should embeddings be handled at different scales?**

These choices directly affect:

- Retrieval quality
- Cost
- Latency
- Scalability

---

1. Choosing an Embedding Model

There is **no universally best embedding model**.
Embedding selection is always a **trade-off across multiple dimensions**.

1️⃣ Input Capacity (Max Tokens per Chunk)

- Defines **how long a chunk** the model can embed
- Must align with:
  - Chunking strategy
  - Maximum chunk size
- If chunks are long, smaller models may **truncate input**, losing information

Guidelines

- Large chunks → choose models with **high token capacity**
- Small chunks → lightweight models are sufficient

Engineering Insight

- Chunking and embedding model choice are **coupled decisions**
- Poor alignment leads to silent information loss

2️⃣ Embedding Vector Size (Dimensionality)

- Determines **how much semantic detail** is captured
- Larger vectors:
  - Encode richer meaning
  - Handle complex relationships better

Especially useful for

- Numeric-heavy text
- Tables
- Mixed-format documents
- Technical or domain-specific data

Trade-off

- Larger vectors require:
  - More compute
  - More memory
  - Slower similarity operations

Rule of Thumb

- Simple natural language → smaller embeddings
- Complex, dense, or structured data → larger embeddings

3️⃣ Model Size (Number of Parameters)

- Larger models:
  - Better semantic understanding
  - Capture subtle relationships
- Smaller models:
  - Faster
  - Cheaper
  - Easier to deploy

Observed Pattern

- Top-performing embedding models are typically **large and compute-heavy**
- Performance gains are real, but **cost grows rapidly**

Engineering Reality

- Model size must be justified by:
  - Retrieval quality gains
  - Business value
  - Latency constraints

4️⃣ Open-Source vs Closed-Source Embeddings

Open-Source Embedding Models

- Run on your own infrastructure
- Best for:
  - Privacy-sensitive data
  - Cost control
  - On-prem or restricted environments

Characteristics

- More setup
- Full control
- Predictable cost

Closed-Source Embedding Models

- Accessed via APIs
- Often state-of-the-art performance

Characteristics

- Minimal setup
- Higher accuracy
- Ongoing API cost
- Less control

Trade-off Summary

- Open-source → control, privacy, flexibility
- Closed-source → convenience, performance

Summary: Embedding Model Selection Axes

Every embedding decision balances:

- **Input capacity** → can the model handle your chunk size?
- **Vector dimensionality** → semantic richness vs cost
- **Model size** → accuracy vs latency
- **Open vs closed** → control vs convenience

There is no default choice — only **context-dependent decisions**.

---

2. Handling Embeddings by Scale (High-Level)

> *(Storage systems are intentionally not discussed in detail here)*

Small-Scale / Experimentation

- For small datasets (≈ under 100k chunks):
  - In-memory arrays (NumPy / Torch) are sufficient
- Ideal for:
  - Prototyping
  - Research
  - Local experimentation

Production-Scale Consideration

- As embedding count grows:
  - Naive storage and search become inefficient
- At scale, **specialized systems are required**
  (covered later in the pipeline)

Practical Engineering Guidance

- Chunk size and embedding choice must be **designed together**
- Larger chunks require:
  - Higher input capacity
  - Stronger models
- Better embeddings → better retrieval → better RAG answers
- Always balance:

- Performance
- Cost
- Latency
- Privacy
- Scale

Embeddings Storage & Vector Indexing — Engineering Decisions

Once embeddings are generated, the **next critical engineering question** is:

> **Where should embeddings be stored for efficient retrieval?**

Many people immediately answer **"vector database"**, but that is **neither intuitive nor always correct**.

This decision depends on:

- Scale of data
- Retrieval latency requirements
- Indexing needs
- System complexity
- Operational constraints

Intuitive First Thought (Before Vector Databases)

Why not just store embeddings as arrays?

- Embeddings are just numeric vectors
- Each chunk → one vector (e.g., 768 dimensions)
- Example:
  - 1,680 chunks × 768-dim vectors
- Can be stored as:
  - `numpy.ndarray`
  - `torch.tensor`
  - CSV / binary files

This is a completely valid approach for small datasets.

When Simple Arrays Are Enough

Small-Scale Systems

- Dataset size: **< ~100,000 embeddings** *(rough, experience-based threshold)*

- Retrieval:
  - Compute cosine similarity
  - Scan all vectors

Why this works

- Compute cost is manageable
- Memory fits easily
- No infrastructure overhead

Typical use cases

- Prototypes
- Research experiments
- Local RAG systems
- Small internal tools

Conclusion

> For small datasets, **vector databases are unnecessary**.

Why Vector Databases Exist

The Core Problem at Scale

When embeddings grow to:

- 100k+
- 1M+
- 10M+

A naive full-scan approach fails because:

- Each query compares against millions of vectors
- Latency becomes unacceptable
- Compute cost explodes

This is not a storage problem — it is an indexing problem.

What Vector Databases Actually Solve

Vector databases are **not magic storage systems**.

Their real value lies in:

> **Efficient nearest-neighbor indexing for similarity search**

Indexing allows:

- Avoiding full scans
- Searching only a small subset of vectors
- Fast approximate nearest neighbor (ANN) retrieval

Core Indexing Ideas

1️⃣ Cluster-Based Indexing (IVF Flat)

- Vectors are clustered into lists
- Query:
  - Finds nearest cluster centroid
  - Searches only within selected clusters
- Similar to **K-means-style partitioning**

Key idea

> Reduce search space before similarity computation

2️⃣ Graph-Based Indexing (HNSW)

- Vectors form a **multi-layer graph**
- Search process:
  1. Start at sparse top layer
  2. Navigate toward closer neighbors
  3. Refine search in dense lower layers

Key properties

- Very fast query time
- Higher memory usage
- Slower index build time
- Excellent recall-speed tradeoff

IVF Flat vs HNSW — Detailed Comparison

Feature	IVF Flat	HNSW
Indexing mechanism	Clusters vectors into lists (centroid-based)	Multi-layer graph-based structure
Memory usage	Lower	Higher
Index build time	Faster	Slower
Speed–recall tradeoff	Adjustable via parameters	Generally superior

Feature	IVF Flat	HNSW
Sensitivity to data size	Best up to ~1M vectors	Scales well to large datasets
Query performance	Good for moderate workloads	Excellent for high-throughput
Adaptability to updates	Re-indexing often needed	More resilient to incremental changes

Engineering insight

- **IVF Flat** → faster setup, lower memory, medium-scale systems
- **HNSW** → best latency, higher memory, production-grade systems

---

Vector Search Tools — What They Are

Libraries

- **FAISS**
  - Similarity search library
  - No database features
  - You manage storage, persistence, metadata

Vector Databases

- **Pinecone**
  - Managed, cloud-based
  - Indexing fully abstracted
- **Milvus**
  - Open-source, large-scale
- **Weaviate**
  - Open-source, metadata + hybrid search
- **Qdrant**
  - Open-source, Rust-based, high performance
- **Chroma**
  - Lightweight, good for prototyping

Important Distinction: FAISS vs Vector Databases

- **FAISS**
  - Algorithmic tool
  - No persistence layer
  - No metadata management
- **Vector Databases**

    - Full systems
    - Handle:
        - Storage
        - Indexing
        - Scaling
        - Metadata
        - Persistence

Rule

> FAISS = similarity engine
> Vector DB = production system

The Metadata Synchronization Problem

Using:

- One database for application data (SQL / NoSQL)
- One vector database for embeddings

Creates issues:

- Metadata duplication
- Cross-database joins
- Synchronization complexity

This increases **engineering friction**.

Unified Approach: SQL + Embeddings Together

Key Idea

> Store embeddings and structured data in the **same database**

This is achieved using **PostgreSQL + vector extensions (pgvector)**.

Why This Works Well

- Single database for:
    - User data
    - Metadata
    - Application state
    - Embeddings
- Full SQL support:
    - Joins

    - Filters
    - Constraints
- Mature, battle-tested ecosystem

Principle Applied

> Reduce new problems to already-solved ones (SQL).

Indexing Still Matters Here

Even with SQL-based storage:

- Indexes are mandatory for performance
- Same concepts apply:
    - IVF-style indexing
    - HNSW-style indexing

Index choice impacts:

- Insert time
- Query latency
- Memory usage

Database-Level Feature Comparison (High-Level)

Feature	Pinecone	Qdrant	Weaviate	Milvus	Chroma	OpenSearch	Postgres (pgvector)
Purpose-built for vectors	✅	✅	✅	✅	✅	❌	❌
Managed cloud	✅	❌	❌	❌	❌	❌	❌
Self-hosted	❌	✅	✅	✅	✅	✅	✅
Open-source	❌	✅	✅	✅	✅	✅	✅
SQL support	❌	❌	❌	❌	❌	❌	✅
Supported index types	HNSW, DiskANN	HNSW	HNSW	HNSW, IVF	HNSW	HNSW, IVF	HNSW, IVF
Metadata filtering	✅	✅	✅	✅	✅	✅	✅

Final Engineering Decision Flow

1. **< 100k embeddings**
   - Arrays / tensors
   - Brute-force similarity
2. **Large-scale retrieval**
   - Indexed ANN search
3. **Want managed infrastructure**
   - Dedicated vector databases
4. **Want unified data + embeddings**
   - PostgreSQL + pgvector

Core Takeaways

- Vector databases exist because of **indexing**, not storage
- Small datasets do **not** need vector databases
- Indexing strategy matters more than vendor choice
- HNSW → best performance
- IVF Flat → fastest setup
- PostgreSQL + pgvector → best for unified architectures

In [ ]:
```python
from sentence_transformers import util, SentenceTransformer
import torch # Import torch to check for CUDA availability

# Define the device
device = "cuda" if torch.cuda.is_available() else "cpu"

embedding_model = SentenceTransformer(
    model_name_or_path="all-mpnet-base-v2",
    device=device  # choose the device to load the model to
)
```

In [ ]:
```python
# 1. Define the query
# Note: This could be anything. But since we're working with a nutrition textboo
# we'll stick with nutrition-based queries.
query = "macronutrients functions"
print(f"Query: {query}")

# 2. Embed the query to the same numerical space as the text examples
# Note: Use the same embedding model as the chunks
query_embedding = embedding_model.encode(
    query,
    convert_to_tensor=True
)

# 3. Get similarity scores with the dot product
from time import perf_counter as timer
import torch
```

```
from sentence_transformers import util

start_time = timer()
dot_scores = util.dot_score(
    a=query_embedding,
    b=text_chunk_embeddings # Changed from 'embeddings' to 'text_chunk_embedding
)[0]
end_time = timer()

print(
    f"Time taken to get scores on {len(text_chunk_embeddings)} embeddings: "
    f"{end_time - start_time:.5f} seconds."
)

# 4. Get the top-k results
top_results_dot_product = torch.topk(dot_scores, k=5)
top_results_dot_product
```

```
Query: macronutrients functions
Time taken to get scores on 1680 embeddings: 0.02605 seconds.
```

Out[ ]:
```
torch.return_types.topk(
values=tensor([0.6926, 0.6738, 0.6646, 0.6536, 0.6473], device='cuda:0'),
indices=tensor([42, 47, 41, 51, 46], device='cuda:0'))
```

In [ ]:
```
# Create a larger embedding matrix for timing comparison
larger_embeddings = torch.randn(
    100 * embeddings.shape[0],
    768
).to(device)

print(f"Embeddings shape: {larger_embeddings.shape}")

# Perform dot product across larger embeddings
start_time = timer()
dot_scores = util.dot_score(
    a=query_embedding,
    b=larger_embeddings
)[0]
end_time = timer()

print(
    f"Time taken to get scores on {len(larger_embeddings)} embeddings: "
    f"{end_time - start_time:.5f} seconds."
)
```

```
Embeddings shape: torch.Size([400, 768])
Time taken to get scores on 400 embeddings: 0.00048 seconds.
```

In [ ]:
```
# Define helper function to print wrapped text
import textwrap

def print_wrapped(text, wrap_length=80):
    wrapped_text = textwrap.fill(text, wrap_length)
    print(wrapped_text)
```

In [ ]:
```
print(f"Query: '{query}'\n")
print("Results")

# Loop through zipped scores and indices from torch.topk
for score, idx in zip(top_results_dot_product[0], top_results_dot_product[1]):
```

```
    print(f"Score: {score:.4f}")

    # Print relevant sentence chunk
    print("Text:")
    print_wrapped(pages_and_chunks[idx]["sentence_chunk"])

    # Print page number for reference
    print(f"Page number: {pages_and_chunks[idx]['page_number']}")
    print("\n")
```

Query: 'macronutrients functions'

Results
Score: 0.6926
Text:
Image by Jim Hollyer / CC BY 4.0 Introduction UNIVERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN NUTRITION PROGRAM AND HUMAN NUTRITION PROGRAM ʻO ke kahua ma mua, ma hope ke kūkulu The foundation comes first, then the building Introduction | 3
Page number: 3

Score: 0.6738
Text:
Lipids are found predominantly in butter, oils, meats, dairy products, nuts, and seeds, and in many processed foods. The three main types of lipids are triglycerides (triacylglycerols), phospholipids, and sterols. The main job of lipids is to provide or store energy. Lipids provide more energy per gram than carbohydrates (nine kilocalories per gram of lipids versus four kilocalories per gram of carbohydrates). In addition to energy storage, lipids serve as a major component of cell membranes, surround and protect organs (in fat-storing tissues), provide insulation to aid in temperature regulation, and regulate many other functions in the body. 6 | Introduction
Page number: 6

Score: 0.6646
Text:
PART I CHAPTER 1. BASIC CONCEPTS IN NUTRITION Chapter 1. Basic Concepts in Nutrition | 1
Page number: 1

Score: 0.6536
Text:
Minerals Major Functions Macro Sodium Fluid balance, nerve transmission, muscle contraction Chloride Fluid balance, stomach acid production Potassium Fluid balance, nerve transmission, muscle contraction Calcium Bone and teeth health maintenance, nerve transmission, muscle contraction, blood clotting Phosphorus Bone and teeth health maintenance, acid-base balance Magnesium Protein production, nerve transmission, muscle contraction Sulfur Protein production Trace Iron Carries oxygen, assists in energy production Zinc Protein and DNA production, wound healing, growth, immune system function Iodine Thyroid hormone production, growth, metabolism Selenium Antioxidant Copper Coenzyme, iron metabolism Manganese Coenzyme Fluoride Bone and teeth health maintenance, tooth decay prevention Chromium Assists insulin in glucose metabolism Molybdenum Coenzyme Minerals Minerals are solid inorganic substances that form crystals and are classified depending on how much of them we need. Trace minerals, such as molybdenum, selenium, zinc, iron, and iodine, are only required in a few milligrams or less. Macrominerals, such as calcium, magnesium, potassium, sodium, and phosphorus, are required in hundreds of milligrams. Many minerals are critical for enzyme Introduction | 9
Page number: 9

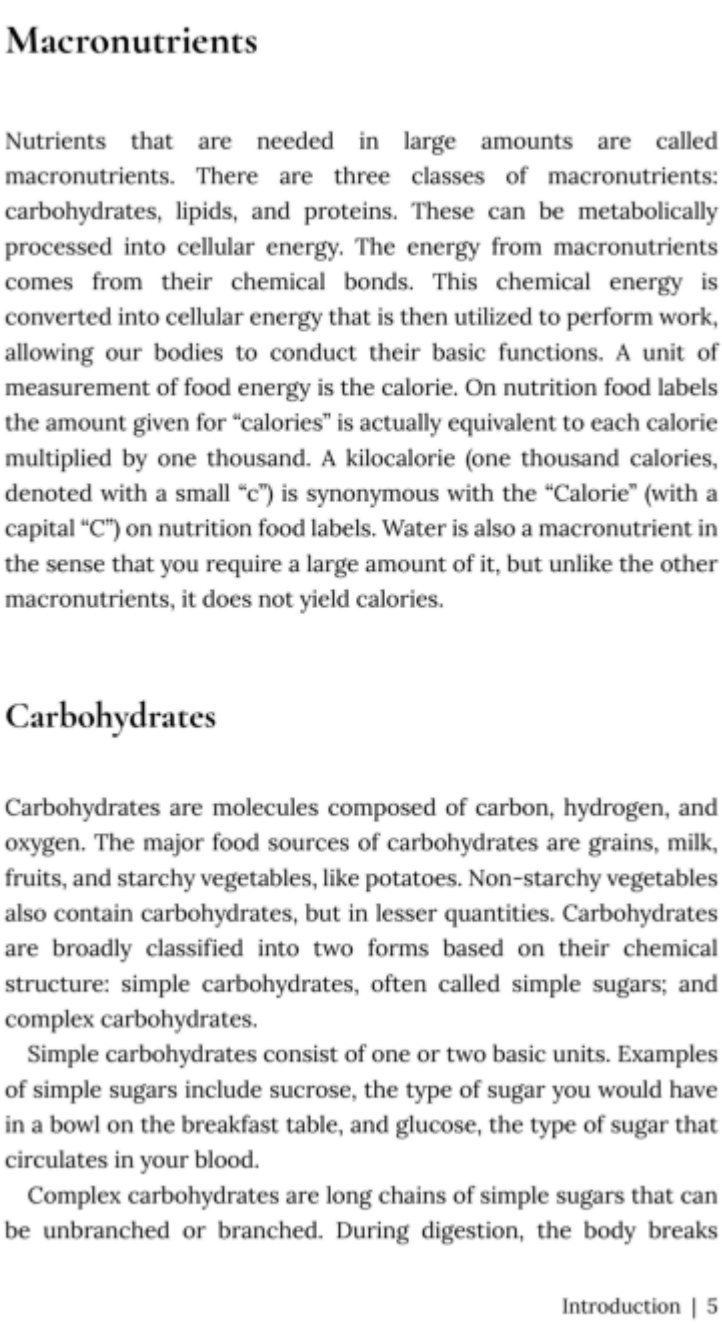
Score: 0.6473
Text:
down digestible complex carbohydrates to simple sugars, mostly glucose. Glucose is then transported to all our cells where it is stored, used to make energy, or used to build macromolecules. Fiber is also a complex carbohydrate, but it

```
cannot be broken down by digestive enzymes in the human intestine. As a result,
it passes through the digestive tract undigested unless the bacteria that
inhabit the colon or large intestine break it down. One gram of digestible
carbohydrates yields four kilocalories of energy for the cells in the body to
perform work. In addition to providing energy and serving as building blocks for
bigger macromolecules, carbohydrates are essential for proper functioning of the
nervous system, heart, and kidneys. As mentioned, glucose can be stored in the
body for future use. In humans, the storage molecule of carbohydrates is called
glycogen, and in plants, it is known as starch. Glycogen and starch are complex
carbohydrates. Lipids Lipids are also a family of molecules composed of carbon,
hydrogen, and oxygen, but unlike carbohydrates, they are insoluble in water.
Page number: 6
```

In [ ]:

```python
import fitz

# Open PDF and load target page
pdf_path = "human-nutrition-text.pdf" # requires PDF to be downloaded
doc = fitz.open(pdf_path)
page = doc.load_page(5 + 41) # number of page (our doc starts page numbers on pa

# Get the image of the page
img = page.get_pixmap(dpi=300)

# Optional: save the image
#img.save("output_filename.png")
doc.close()

# Convert the Pixmap to a numpy array
img_array = np.frombuffer(img.samples_mv,
dtype=np.uint8).reshape((img.h, img.w, img.n))

# Display the image using Matplotlib
import matplotlib.pyplot as plt
plt.figure(figsize=(13, 10))
plt.imshow(img_array)
plt.title(f"Query: '{query}' | Most relevant page:")
plt.axis('off') # Turn off axis
plt.show()
```

Query: 'macronutrients functions' | Most relevant page:



Macronutrients

Nutrients that are needed in large amounts are called macronutrients. There are three classes of macronutrients: carbohydrates, lipids, and proteins. These can be metabolically processed into cellular energy. The energy from macronutrients comes from their chemical bonds. This chemical energy is converted into cellular energy that is then utilized to perform work, allowing our bodies to conduct their basic functions. A unit of measurement of food energy is the calorie. On nutrition food labels the amount given for "calories" is actually equivalent to each calorie multiplied by one thousand. A kilocalorie (one thousand calories, denoted with a small "c") is synonymous with the "Calorie" (with a capital "C") on nutrition food labels. Water is also a macronutrient in the sense that you require a large amount of it, but unlike the other macronutrients, it does not yield calories.

Carbohydrates

Carbohydrates are molecules composed of carbon, hydrogen, and oxygen. The major food sources of carbohydrates are grains, milk, fruits, and starchy vegetables, like potatoes. Non-starchy vegetables also contain carbohydrates, but in lesser quantities. Carbohydrates are broadly classified into two forms based on their chemical structure: simple carbohydrates, often called simple sugars; and complex carbohydrates.

Simple carbohydrates consist of one or two basic units. Examples of simple sugars include sucrose, the type of sugar you would have in a bowl on the breakfast table, and glucose, the type of sugar that circulates in your blood.

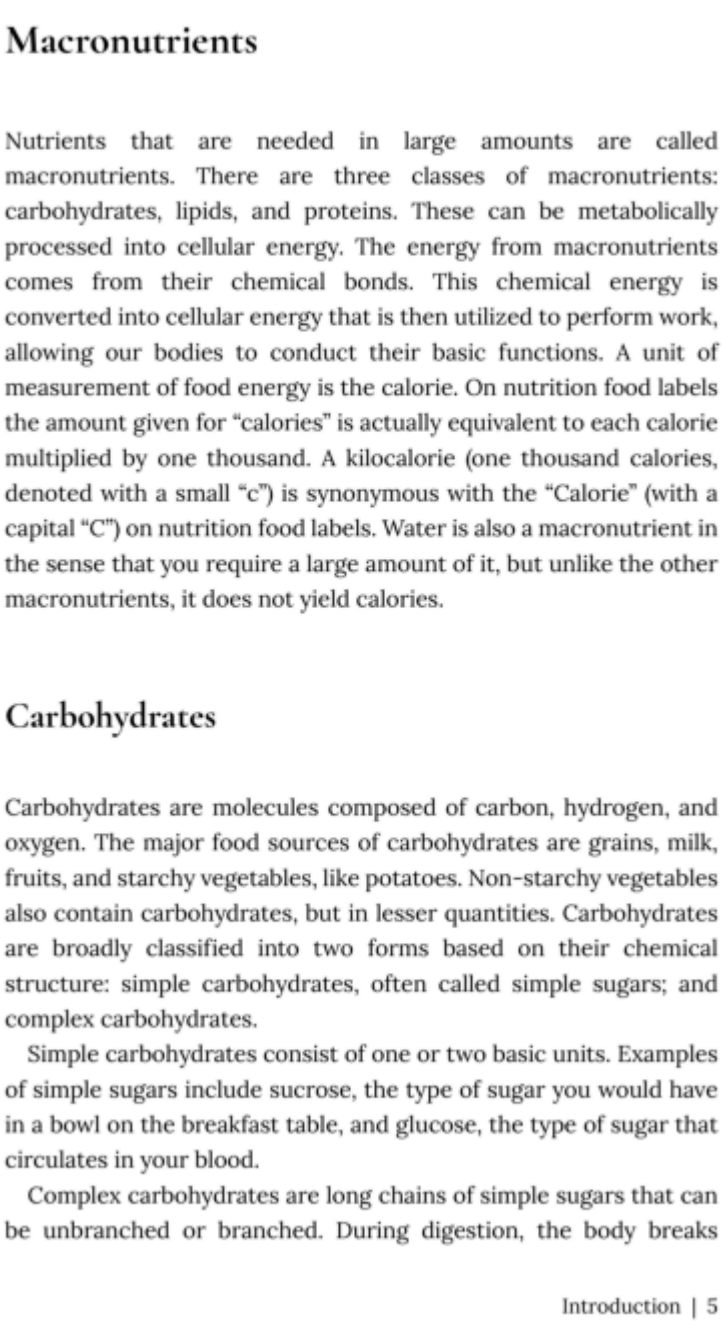
Complex carbohydrates are long chains of simple sugars that can be unbranched or branched. During digestion, the body breaks

Introduction | 5

In [ ]:
```python
import fitz
import numpy as np
import matplotlib.pyplot as plt

# Open PDF and load target page
pdf_path = "human-nutrition-text.pdf"  # requires PDF to be downloaded
doc = fitz.open(pdf_path)

# Load page (our document page numbering starts at page 41)
page = doc.load_page(5 + 41)
```

```
# Get the image of the page
img = page.get_pixmap(dpi=300)

# Optional: save the image
img.save("output_filename.png")

# Close the document
doc.close()

# Convert the Pixmap to a numpy array
img_array = np.frombuffer(
    img.samples_mv,
    dtype=np.uint8
).reshape((img.h, img.w, img.n))

# Display the image using Matplotlib
plt.figure(figsize=(13, 10))
plt.imshow(img_array)
plt.title(f"Query: '{query}' | Most relevant page:")
plt.axis("off")  # Turn off axis
plt.show()
```

Query: 'macronutrients functions' | Most relevant page:



Macronutrients

Nutrients that are needed in large amounts are called macronutrients. There are three classes of macronutrients: carbohydrates, lipids, and proteins. These can be metabolically processed into cellular energy. The energy from macronutrients comes from their chemical bonds. This chemical energy is converted into cellular energy that is then utilized to perform work, allowing our bodies to conduct their basic functions. A unit of measurement of food energy is the calorie. On nutrition food labels the amount given for "calories" is actually equivalent to each calorie multiplied by one thousand. A kilocalorie (one thousand calories, denoted with a small "c") is synonymous with the "Calorie" (with a capital "C") on nutrition food labels. Water is also a macronutrient in the sense that you require a large amount of it, but unlike the other macronutrients, it does not yield calories.

Carbohydrates

Carbohydrates are molecules composed of carbon, hydrogen, and oxygen. The major food sources of carbohydrates are grains, milk, fruits, and starchy vegetables, like potatoes. Non-starchy vegetables also contain carbohydrates, but in lesser quantities. Carbohydrates are broadly classified into two forms based on their chemical structure: simple carbohydrates, often called simple sugars; and complex carbohydrates.

Simple carbohydrates consist of one or two basic units. Examples of simple sugars include sucrose, the type of sugar you would have in a bowl on the breakfast table, and glucose, the type of sugar that circulates in your blood.

Complex carbohydrates are long chains of simple sugars that can be unbranched or branched. During digestion, the body breaks

Introduction | 5

Similarity Measures for Embeddings (Dot Product vs Cosine Similarity)

Why Similarity Measures Matter

- After embeddings are created, **retrieval = finding vectors most similar to the query vector**
- Similarity measures decide **which chunks are retrieved**

- Works for **any embeddings**:
  - Text
  - Images
  - Audio
  - Multimodal (e.g., CLIP: text ↔ image)

Embedding Vectors (Quick Reminder)

- Embeddings are **high-dimensional vectors** (e.g., 768 dims)
- Each vector has:
  - **Magnitude** (length)
  - **Direction** (semantic meaning)

For semantic retrieval, **direction matters more than magnitude**.

---

1. Dot Product

Definition

- Measures similarity by multiplying corresponding vector components and summing them

Properties

- Sensitive to:
  - Direction
  - Magnitude
- Larger magnitude vectors → larger dot product

Pros

- Very **fast**
- Simple computation
- No normalization step

Cons

- If vectors are not normalized, magnitude can dominate similarity

---

2. Cosine Similarity (Most Common for Text)

Definition

- Measures **angle between two vectors**

- Focuses on **direction**, not magnitude

Formula (Conceptual)

$$\text{cosine\_similarity}(A, B) = \frac{A \cdot B}{\|A\| \times \|B\|}$$

Properties

- Vectors are **normalized by L2 norm**
- Output range:
  - `+1` → same direction (very similar)
  - `0` → orthogonal (unrelated)
  - `-1` → opposite direction

Why It's Preferred for Text

- Semantic meaning lives in **direction**
- Vector length does not matter
- Stable across different embedding magnitudes

Dot Product vs Cosine Similarity (Key Insight)

Important Optimization

- Many modern embedding models (e.g. **all-mpnet-base-v2**)
  already output normalized vectors

➡️ If vectors are already normalized:

- **Dot Product == Cosine Similarity**
- Dot product is preferred because it's **faster**

Practical Rule of Thumb

- **If embeddings are normalized** → Use **dot product** (faster)
- **If embeddings are NOT normalized** → Use **cosine similarity**

Common Libraries / Implementations

- `torch.dot`
- `np.dot`
- `sentence_transformers.util.dot_score`
- `torch.nn.functional.cosine_similarity`

Summary Table

Aspect	Dot Product	Cosine Similarity
Uses magnitude	✅	❌
Uses direction	✅	✅
Normalization needed	❌	✅
Speed	Faster	Slower
Best for text embeddings	⚠️ (if normalized)	✅
Output range	Unbounded	[-1, 1]

Final Takeaway

- **Semantic retrieval = direction-based similarity**
- Cosine similarity is conceptually correct
- Dot product is computationally optimal **when embeddings are normalized**
- Always check whether your embedding model outputs **unit-normalized vectors**

In [ ]:
```
import torch


def dot_product(vector1, vector2):
    return torch.dot(vector1, vector2)


def cosine_similarity(vector1, vector2):
    dot = torch.dot(vector1, vector2)

    # Get Euclidean / L2 norm of each vector
    norm_vector1 = torch.sqrt(torch.sum(vector1 ** 2))
    norm_vector2 = torch.sqrt(torch.sum(vector2 ** 2))

    return dot / (norm_vector1 * norm_vector2)


# Example tensors
vector1 = torch.tensor([1, 2, 3], dtype=torch.float32)
vector2 = torch.tensor([1, 2, 3], dtype=torch.float32)
vector3 = torch.tensor([4, 5, 6], dtype=torch.float32)
vector4 = torch.tensor([-1, -2, -3], dtype=torch.float32)

# Calculate dot product
print("Dot product between vector1 and vector2:", dot_product(vector1, vector2))
print("Dot product between vector1 and vector3:", dot_product(vector1, vector3))
print("Dot product between vector1 and vector4:", dot_product(vector1, vector4))

# Calculate cosine similarity
print("Cosine similarity between vector1 and vector2:", cosine_similarity(vector
```

```
print("Cosine similarity between vector1 and vector3:", cosine_similarity(vector
print("Cosine similarity between vector1 and vector4:", cosine_similarity(vector
```

```
Dot product between vector1 and vector2: tensor(14.)
Dot product between vector1 and vector3: tensor(32.)
Dot product between vector1 and vector4: tensor(-14.)
Cosine similarity between vector1 and vector2: tensor(1.0000)
Cosine similarity between vector1 and vector3: tensor(0.9746)
Cosine similarity between vector1 and vector4: tensor(-1.0000)
```

In [ ]:

```python
def retrieve_relevant_resources(
    query: str,
    embeddings: torch.Tensor,
    model: SentenceTransformer = embedding_model,
    n_resources_to_return: int = 5,
    print_time: bool = True
):
    """
    Embeds a query with the given model and returns the top-k
    similarity scores and indices from the embeddings.
    """

    # Embed the query
    query_embedding = model.encode(
        query,
        convert_to_tensor=True
    )

    # Get dot product similarity scores
    start_time = timer()
    dot_scores = util.dot_score(
        query_embedding,
        embeddings
    )[0]
    end_time = timer()

    if print_time:
        print(
            f"[INFO] Time taken to get scores on {len(embeddings)} embeddings: "
            f"{end_time - start_time:.5f} seconds."
        )

    # Get top-k results
    scores, indices = torch.topk(
        input=dot_scores,
        k=n_resources_to_return
    )

    return scores, indices

def print_top_results_and_scores(
    query: str,
    embeddings: torch.Tensor,
    pages_and_chunks: list[dict] = pages_and_chunks_over_min_token_len, # Correc
    n_resources_to_return: int = 5
):
    """
    Takes a query, retrieves the most relevant resources,
    and prints them in descending order of relevance.
```

```
    Note: Requires pages_and_chunks to be formatted in a specific way.
    """

    scores, indices = retrieve_relevant_resources(
        query=query,
        embeddings=embeddings,
        n_resources_to_return=n_resources_to_return
    )

    print(f"Query: {query}\n")
    print("Results:")

    # Loop through scores and indices together
    for score, index in zip(scores, indices):
        print(f"Score: {score:.4f}")

        # Print relevant sentence chunk
        print_wrapped(pages_and_chunks[index]["sentence_chunk"])

        # Print page number for reference
        print(f"Page number: {pages_and_chunks[index]['page_number']}")
        print("\n")
```

In [ ]:
```
query = "symptoms of pellagra"

# Get scores and indices of top related results
scores, indices = retrieve_relevant_resources(
    query=query,
    embeddings=text_chunk_embeddings # Corrected: use GPU-resident embeddings
)

scores, indices
```

```
[INFO] Time taken to get scores on 1680 embeddings: 0.00007 seconds.
```

Out[ ]:
```
(tensor([0.5000, 0.3741, 0.2959, 0.2793, 0.2721], device='cuda:0'),
 tensor([ 822,  853, 1536, 1555, 1531], device='cuda:0'))
```

In [ ]:
```
print_top_results_and_scores(
    query=query,
    embeddings=text_chunk_embeddings # Use the embeddings generated from all chu
)
```

```
[INFO] Time taken to get scores on 1680 embeddings: 0.00012 seconds.
Query: symptoms of pellagra

Results:
Score: 0.5000
Niacin deficiency is commonly known as pellagra and the symptoms include
fatigue, decreased appetite, and indigestion.  These symptoms are then commonly
followed by the four D’s: diarrhea, dermatitis, dementia, and sometimes death.
Figure 9.12  Conversion of Tryptophan to Niacin Water-Soluble Vitamins | 565
Page number: 565


Score: 0.3741
car. Does it drive faster with a half-tank of gas or a full one? It does not
matter; the car drives just as fast as long as it has gas. Similarly, depletion
of B vitamins will cause problems in energy metabolism, but having more than is
required to run metabolism does not speed it up. Buyers of B-vitamin supplements
beware; B vitamins are not stored in the body and all excess will be flushed
down the toilet along with the extra money spent. B vitamins are naturally
present in numerous foods, and many other foods are enriched with them. In the
United States, B-vitamin deficiencies are rare; however in the nineteenth
century some vitamin-B deficiencies plagued many people in North America. Niacin
deficiency, also known as pellagra, was prominent in poorer Americans whose main
dietary staple was refined cornmeal. Its symptoms were severe and included
diarrhea, dermatitis, dementia, and even death. Some of the health consequences
of pellagra are the result of niacin being in insufficient supply to support the
body’s metabolic functions.
Page number: 591


Score: 0.2959
The carbon dioxide gas bubbles infiltrate the stretchy gluten, giving bread its
porosity and tenderness. For those who are sensitive to gluten, it is good to
know that corn, millet, buckwheat, and oats do not contain the proteins that
make gluten. However, some people who have celiac disease also may have a
response to products containing oats. This is most likely the result of cross-
contamination of grains during harvest, storage, packaging, and processing.
Celiac disease is most common in people of European descent and is rare in
people of African American, Japanese, and Chinese descent. It is much more
prevalent in women and in people with Type 1 diabetes, autoimmune thyroid
disease, and Down and Turner syndromes. Symptoms can range from mild to severe
and can include pale, fatty, loose stools, gastrointestinal upset, abdominal
pain, weight loss and, in children, a failure to grow and thrive. The symptoms
can appear in infancy or much later in life, even Nutrition, Health and Disease
| 1079
Page number: 1079


Score: 0.2793
Image by BruceBlaus/ CC BY 4.0 When the vertebral bone tissue is weakened, it
can cause the spine to curve. The increase in spine curvature not only causes
pain, but also decreases a person’s height. Curvature of the upper spine
produces what is called Dowager’s hump, also known as kyphosis. Severe upper-
spine deformity can compress the chest cavity and cause difficulty breathing. It
may also cause abdominal pain and loss of appetite because of the increased
pressure on the abdomen. 1090 | Nutrition, Health and Disease
Page number: 1090


Score: 0.2721
```

esophagus and cause irritation. It is estimated that GERD affects 25 to 35 percent of the US population. An analysis of several studies published in the August 2005 issue of Annals of Internal Medicine concludes that GERD is much more prevalent in people who are obese.1 The most common GERD symptom is heartburn, but people with GERD may also experience regurgitation (flow of the stomach's acidic contents into the mouth), frequent coughing, and trouble swallowing. There are other causative factors of GERD that may be separate from or intertwined with obesity. The sphincter that separates the stomach's internal contents from the esophagus often does not function properly and acidic gastric contents seep upward. Sometimes the peristaltic contractions of the esophagus are also sluggish and compromise the clearance of acidic contents. In addition to having an unbalanced, high-fat diet, some people with GERD are sensitive to particular foods—chocolate, garlic, spicy foods, fried foods, and tomato-based foods—which worsen symptoms. Drinks containing alcohol or caffeine may also worsen GERD symptoms. GERD is diagnosed most often by a history of the frequency of recurring symptoms. A more proper diagnosis can be made when a doctor inserts a small device into the lower esophagus that measures the acidity of the contents during one's daily activities.
Page number: 1077

In [ ]:
```python
# Get GPU available memory
import torch

gpu_memory_bytes = torch.cuda.get_device_properties(0).total_memory
gpu_memory_gb = round(gpu_memory_bytes / (2 ** 30))

print(f"Available GPU memory: {gpu_memory_gb} GB")
```

```
Available GPU memory: 15 GB
```

In [ ]:
```python
# Note: the following is Gemma focused, however, there are more and more
# LLMs of the 2B and 7B size appearing for local use.

if gpu_memory_gb < 5.1:
    print(
        f"Your available GPU memory is {gpu_memory_gb}GB, "
        "you may not have enough memory to run a Gemma LLM locally without quant
    )

elif gpu_memory_gb < 8.1:
    print(
        f"GPU memory: {gpu_memory_gb} | "
        "Recommended model: Gemma 2B in 4-bit precision."
    )
    use_quantization_config = True
    model_id = "google/gemma-2b-it"

elif gpu_memory_gb < 19.0:
    print(
        f"GPU memory: {gpu_memory_gb} | "
        "Recommended model: Gemma 2B in float16 or Gemma 7B in 4-bit precision."
    )
    use_quantization_config = False
    model_id = "google/gemma-2b-it"

else:
    print(
        f"GPU memory: {gpu_memory_gb} | "
```

```
        "Recommended model: Gemma 7B in 4-bit or float16 precision."
    )
    use_quantization_config = False
    model_id = "google/gemma-7b-it"

print(f"use_quantization_config set to: {use_quantization_config}")
print(f"model_id set to: {model_id}")
```

```
GPU memory: 15 | Recommended model: Gemma 2B in float16 or Gemma 7B in 4-bit prec
ision.
use_quantization_config set to: False
model_id set to: google/gemma-2b-it
```

In [ ]:
```
from huggingface_hub import login

# Paste your token here (from https://huggingface.co/settings/tokens)
login(token='hugging-face-token/hugging-face-api-key')
```

In [12]:
```
# import torch
# from transformers import (
#     AutoTokenizer,
#     AutoModelForCausalLM,
#     BitsAndBytesConfig
# )
# from transformers.utils import is_flash_attn_2_available

# # -------------------- Quantization Config --------------------
# # Optional: use 4-bit quantization for low GPU memory
# # Requires:
# #   pip install bitsandbytes accelerate
# quantization_config = BitsAndBytesConfig(
#     load_in_4bit=True,
#     bnb_4bit_compute_dtype=torch.float16
# )

# # -------------------- Attention Implementation --------------------
# # Flash Attention 2 requires:
# # - NVIDIA GPU compute capability >= 8.0
# # - pip install flash-attn
# #
# if is_flash_attn_2_available() and torch.cuda.get_device_capability(0)[0] >=
# #     attn_implementation = "flash_attention_2"
# else:
#     attn_implementation = "sdpa"

# attn_implementation = "sdpa"

# print(f"[INFO] Using attention implementation: {attn_implementation}")

# # 2. Pick a model we'd like to use (depends on available GPU memory)
# # model_id = "google/gemma-7b-it"
# model_id = model_id  # already set above
# print(f"[INFO] Using model_id: {model_id}")

# # 3. Instantiate tokenizer (turns text into token IDs)
# tokenizer = AutoTokenizer.from_pretrained(
#     pretrained_model_name_or_path=model_id
# )

# # 4. Instantiate the model
```

```
# llm_model = AutoModelForCausalLM.from_pretrained(
#     pretrained_model_name_or_path=model_id,
#     torch_dtype=torch.float16,              # use float16
#     quantization_config=quantization_config if use_quantization_config else No
#     low_cpu_mem_usage=False,                # use full memory
#     attn_implementation=attn_implementation # attention implementation
# )

# # If not using quantization, manually move model to GPU
# if not use_quantization_config:
#     llm_model.to("cuda")
```

In [ ]:
```
llm_model
```

Out[ ]:
```
GemmaForCausalLM(
  (model): GemmaModel(
    (embed_tokens): Embedding(256000, 2048, padding_idx=0)
    (layers): ModuleList(
      (0-17): 18 x GemmaDecoderLayer(
        (self_attn): GemmaAttention(
          (q_proj): Linear(in_features=2048, out_features=2048, bias=False)
          (k_proj): Linear(in_features=2048, out_features=256, bias=False)
          (v_proj): Linear(in_features=2048, out_features=256, bias=False)
          (o_proj): Linear(in_features=2048, out_features=2048, bias=False)
        )
        (mlp): GemmaMLP(
          (gate_proj): Linear(in_features=2048, out_features=16384, bias=False)
          (up_proj): Linear(in_features=2048, out_features=16384, bias=False)
          (down_proj): Linear(in_features=16384, out_features=2048, bias=False)
          (act_fn): GELUActivation()
        )
        (input_layernorm): GemmaRMSNorm((2048,), eps=1e-06)
        (post_attention_layernorm): GemmaRMSNorm((2048,), eps=1e-06)
      )
    )
    (norm): GemmaRMSNorm((2048,), eps=1e-06)
    (rotary_emb): GemmaRotaryEmbedding()
  )
  (lm_head): Linear(in_features=2048, out_features=256000, bias=False)
)
```

In [ ]:
```
def get_model_num_params(model: torch.nn.Module):
    return sum([param.numel() for param in model.parameters()])


get_model_num_params(llm_model)
```

Out[ ]:
```
2506172416
```

In [ ]:
```
def get_model_mem_size(model: torch.nn.Module):
    """
    Get how much memory a PyTorch model takes up.

    Reference:
    https://discuss.pytorch.org/t/gpu-memory-that-model-uses/56822
    """

    # Get model parameters and buffer sizes
    mem_params = sum(
```

```
        [param.nelement() * param.element_size() for param in model.parameters()]
    )
    mem_buffers = sum(
        [buf.nelement() * buf.element_size() for buf in model.buffers()]
    )

    # Calculate various model sizes
    model_mem_bytes = mem_params + mem_buffers
    model_mem_mb = model_mem_bytes / (1024 ** 2)
    model_mem_gb = model_mem_bytes / (1024 ** 3)

    return {
        "model_mem_bytes": model_mem_bytes,
        "model_mem_mb": round(model_mem_mb, 2),
        "model_mem_gb": round(model_mem_gb, 2),
    }


get_model_mem_size(llm_model)
```

Out[ ]:
```
{'model_mem_bytes': 5012345344, 'model_mem_mb': 4780.15, 'model_mem_gb': 4.67}
```

In [ ]:
```
input_text = "What are the macronutrients, and what roles do they play in the hu
print(f"Input text:\n{input_text}")

# Create prompt template for instruction-tuned model
dialogue_template = [
    {
        "role": "user",
        "content": input_text
    }
]

# Apply the chat template
prompt = tokenizer.apply_chat_template(
    conversation=dialogue_template,
    tokenize=False,              # keep as raw text (not tokenized)
    add_generation_prompt=True
)

print(f"\nPrompt (formatted):\n{prompt}")
```

```
Input text:
What are the macronutrients, and what roles do they play in the human body?

Prompt (formatted):
<bos><start_of_turn>user
What are the macronutrients, and what roles do they play in the human body?<end_o
f_turn>
<start_of_turn>model
```

In [ ]:
```
%%time

# Tokenize the input text (turn it into numbers) and send it to GPU
input_ids = tokenizer(
    prompt,
    return_tensors="pt"
).to("cuda")
```

```
print(f"Model input (tokenized):\n{input_ids}\n")

# Generate outputs based on the tokenized input
# See generate docs:
# https://huggingface.co/docs/transformers/v4.38.2/en/main_classes/text_generati
outputs = llm_model.generate(
    **input_ids,
    max_new_tokens=256  # maximum number of new tokens to generate
)

print(f"Model output (tokens):\n{outputs[0]}\n")
```

```
Model input (tokenized):
{'input_ids': tensor([[     2,      2,    106,   1645,    108,   1841,    708,
573, 186809,
         184592, 235269,    578,   1212,  16065,    749,    984,   1554,    575,
            573,   3515,   2971, 235336,    107,    108,    106,   2516,    10
8]],
       device='cuda:0'), 'attention_mask': tensor([[1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
         1, 1, 1]], device='cuda:0')}

Model output (tokens):
tensor([     2,      2,    106,   1645,    108,   1841,    708,    573, 186809,
        184592, 235269,    578,   1212,  16065,    749,    984,   1554,    575,
           573,   3515,   2971, 235336,    107,    108,    106,   2516,    108,
         21404, 235269,   1517, 235303, 235256,    476,  25497,    576,    573,
        186809, 184592,    578,   1024,  16065,    575,    573,   3515,   2971,
        235292,    109,    688,  12298,   1695, 184592,  66058,    109, 235287,
          5231, 156615,  56227,  66058,    108,    141, 235287,  34428,   4134,
           604,    573,   2971, 235303, 235256,   5999,    578,  29703, 235265,
           108,    141, 235287, 110165,  56227,    708,    573,   7920,   4303,
           576,   4134,    604,   1546,   5999, 235265,    108,    141, 235287,
         25280,  72780,    708,   1941,    674,   1987,   5543,    577,  55997,
        235269,   1582,    685,   3733,  29907, 235269,  16803, 235269,    578,
         19574, 235265,    108,    141, 235287,  13702,  72780,    708,   1941,
           674,    708,   7290, 122712, 235269,   1582,    685,   9347, 235269,
         57634, 235269,    578, 109955, 235265,    109, 235287,   5231, 216954,
         66058,    108,    141, 235287,   8108,    578,  12158,  29703, 235269,
         44760, 235269,    578,  53186, 235265,    108,    141, 235287,  96084,
           708,   8727,    604,  24091,   1411, 235269,  42696,   4584, 235269,
           578,  14976,  12158, 235265,    108,    141, 235287,   2456,    708,
          2167,   5088,    576,  20361, 235269,   1853,    675,   3724,   7257,
        235265,    109, 235287,   5231, 235311,   1989,  66058,    108,    141,
        235287,  34428,   4134, 235269,  38823, 235269,    578,   1707,  33398,
         48765, 235265,    108,    141, 235287,  41137,  61926,   3707,  21361,
          4684, 235269,  59269, 235269,  22606, 235269,    578,  15741, 235265,
           108,    141, 235287,   3776,  61926,    798,  12310,  45365,   5902,
           578,   4740,    573,   5685,    576,   3760,   7197, 235265,    109,
           688,  33771,    576,  97586, 184592,    575,    573,   9998,  14427,
         66058,    109, 235287,   5231,  23920,   4584,  66058, 110165,  56227,
        235269,  20361, 235269,    578,  61926,   3658,    573,   2971,    675,
          4134, 235265,    108, 235287,   5231,  25251,    578,  68808,  29703,
         66058,  96084,    708,   8727,    604,   4547,    578,  68808,  29703,
        235269,   3359,  22488, 235269], device='cuda:0')

CPU times: user 7.99 s, sys: 31.7 ms, total: 8.02 s
Wall time: 8.39 s
```

In [ ]:
```
# Decode the output tokens to text
outputs_decoded = tokenizer.decode(outputs[0])
print(f"Model output (decoded):\n{outputs_decoded}\n")
```

```
Model output (decoded):
<bos><bos><start_of_turn>user
What are the macronutrients, and what roles do they play in the human body?<end_o
f_turn>
<start_of_turn>model
Sure, here's a breakdown of the macronutrients and their roles in the human body:

**Macronutrients:**

* **Carbohydrates:**
    * Provide energy for the body's cells and tissues.
    * Carbohydrates are the primary source of energy for most cells.
    * Complex carbohydrates are those that take longer to digest, such as whole g
rains, fruits, and vegetables.
    * Simple carbohydrates are those that are quickly digested, such as sugar, st
arch, and lactose.

* **Proteins:**
    * Build and repair tissues, enzymes, and hormones.
    * Proteins are essential for immune function, hormone production, and tissue
repair.
    * There are different types of proteins, each with specific functions.

* **Fats:**
    * Provide energy, insulation, and help absorb vitamins.
    * Healthy fats include olive oil, avocado, nuts, and seeds.
    * Trans fats can raise cholesterol levels and increase the risk of heart dise
ase.

**Roles of Macronutrients in the Human Body:**

* **Energy production:** Carbohydrates, proteins, and fats provide the body with
energy.
* **Building and repairing tissues:** Proteins are essential for building and rep
airing tissues, including muscles,
```

In [ ]:
```
print(f"Input text: {input_text}\n")

print(
    "Output text:\n"
    f"{outputs_decoded.replace(prompt, '').replace('<bos>', '').replace('<eos>',
)
```

```
Input text: What are the macronutrients, and what roles do they play in the human
body?

Output text:
Sure, here's a breakdown of the macronutrients and their roles in the human body:

**Macronutrients:**

* **Carbohydrates:**
    * Provide energy for the body's cells and tissues.
    * Carbohydrates are the primary source of energy for most cells.
    * Complex carbohydrates are those that take longer to digest, such as whole g
rains, fruits, and vegetables.
    * Simple carbohydrates are those that are quickly digested, such as sugar, st
arch, and lactose.

* **Proteins:**
    * Build and repair tissues, enzymes, and hormones.
    * Proteins are essential for immune function, hormone production, and tissue
repair.
    * There are different types of proteins, each with specific functions.

* **Fats:**
    * Provide energy, insulation, and help absorb vitamins.
    * Healthy fats include olive oil, avocado, nuts, and seeds.
    * Trans fats can raise cholesterol levels and increase the risk of heart dise
ase.

**Roles of Macronutrients in the Human Body:**

* **Energy production:** Carbohydrates, proteins, and fats provide the body with
energy.
* **Building and repairing tissues:** Proteins are essential for building and rep
airing tissues, including muscles,
```

In [ ]:
```python
# Nutrition-style questions generated with GPT-4
gpt4_questions = [
    "What are the macronutrients, and what roles do they play in the human body?
    "How do vitamins and minerals differ in their roles and importance for healt
    "Describe the process of digestion and absorption of nutrients in the human
    "What role does fibre play in digestion? Name five fibre containing foods.",
    "Explain the concept of energy balance and its importance in weight manageme
]

# Manually created question list
manual_questions = [
    "How often should infants be breastfed?",
    "What are symptoms of pellagra?",
    "How does saliva help with digestion?",
    "What is the RDI for protein per day?",
    "water soluble vitamins"
]

# Combined query list
query_list = gpt4_questions + manual_questions
```

In [ ]:
```python
import random

query = random.choice(query_list)
print(f"Query: {query}")
```

```
# Get just the scores and indices of top related results
scores, indices = retrieve_relevant_resources(
    query=query,
    embeddings=text_chunk_embeddings
)

scores, indices
```

```
Query: How do vitamins and minerals differ in their roles and importance for heal
th?
[INFO] Time taken to get scores on 1680 embeddings: 0.00009 seconds.
```

Out[ ]:
```
(tensor([0.6322, 0.6220, 0.6187, 0.6178, 0.6128], device='cuda:0'),
 tensor([ 51,  47, 874,  41, 927], device='cuda:0'))
```

In [ ]:
```
def prompt_formatter(
    query: str,
    context_items: list[dict]
) -> str:
    """
    Augments a query with text-based context from context_items
    and formats it into a prompt suitable for an instruction-tuned model.
    """

    # Join context items into a single paragraph
    context = "- " + "\n- ".join(
        [item["sentence_chunk"] for item in context_items]
    )

    # Base prompt with example answer styles
    base_prompt = """Based on the following context items, please answer the que

          Use the provided context to produce a clear, explanatory answer.
          If multiple pieces of information are relevant, combine them naturally
          Do not mention the context explicitly in your answer.

          Example 1:
          Query: What are the fat-soluble vitamins?
          Answer: The fat-soluble vitamins include Vitamin A, Vitamin D, Vitamin

          Example 2:
          Query: What are the causes of type 2 diabetes?
          Answer: Type 2 diabetes is often associated with overnutrition, partic

          Example 3:
          Query: What is the importance of hydration for physical performance?
          Answer: Hydration is crucial for physical performance because water pl

          Context:
          {context}

          User query: {query}
          Answer:
          """


    # Fill prompt with context and query
    base_prompt = base_prompt.format(
        context=context,
        query=query
```

```
    )

    # Create prompt template for instruction-tuned model
    dialogue_template = [
        {
            "role": "user",
            "content": base_prompt
        }
    ]

    # Apply the chat template
    prompt = tokenizer.apply_chat_template(
        conversation=dialogue_template,
        tokenize=False,
        add_generation_prompt=True
    )

    return prompt
```

In [ ]:

```
query = random.choice(query_list)
print(f"Query: {query}")

# Get relevant resources
scores, indices = retrieve_relevant_resources(
    query=query,
    embeddings=text_chunk_embeddings
)

# ✅ IMPORTANT: MUST match the list used to create text_chunk_embeddings
context_items = [
    pages_and_chunks_over_min_token_len[i]
    for i in indices
]

# Format prompt with context items
prompt = prompt_formatter(
    query=query,
    context_items=context_items
)

print(prompt)
```

Query: What is the RDI for protein per day?
[INFO] Time taken to get scores on 1680 embeddings: 0.00006 seconds.
<bos><start_of_turn>user
Based on the following context items, please answer the query.

Use the provided context to produce a clear, explanatory answer.
If multiple pieces of information are relevant, combine them naturally.
Do not mention the context explicitly in your answer.

Example 1:
Query: What are the fat-soluble vitamins?
Answer: The fat-soluble vitamins include Vitamin A, Vitamin D, Vitamin E, and Vitamin K. These vitamins are absorbed along with fat.

Example 2:
Query: What are the causes of type 2 diabetes?
Answer: Type 2 diabetes is often associated with overnutrition, particularly the overconsumption of calories leading to obesity.

Example 3:
Query: What is the importance of hydration for physical performance?
Answer: Hydration is crucial for physical performance because water plays key roles in maintaining blood volume, regulating body temperature, and supporting muscle function.

Context:
- Most nitrogen is lost as urea in the urine, but urea is also excreted in the feces. Proteins are also lost in sweat and as hair and nails grow. The RDA, therefore, is the amount of protein a person should consume in their diet to balance the amount of protein used up and lost from the body. For healthy adults, this amount of protein was determined to be 0.8 grams of protein per kilogram of body weight. You can calculate 410 | Proteins, Diet, and Personal Choices
- Proteins, Diet, and Personal Choices UNIVERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN NUTRITION PROGRAM AND HUMAN NUTRITION PROGRAM We have discussed what proteins are, how they are made, how they are digested and absorbed, the many functions of proteins in the body, and the consequences of having too little or too much protein in the diet. This section will provide you with information on how to determine the recommended amount of protein for you, and your many choices in designing an optimal diet with high-quality protein sources. How Much Protein Does a Person Need in Their Diet? The recommendations set by the IOM for the Recommended Daily Allowance (RDA) and AMDR for protein for different age groups are listed in Table 6.2 “Dietary Reference Intakes for Protein”. A Tolerable Upper Intake Limit for protein has not been set, but it is recommended that you do not exceed the upper end of the AMDR. Table 6.2 Dietary Reference Intakes for Protein Proteins, Diet, and Personal Choices | 409
- Age Group Protein (%) Carbohydrates (%) Fat (%) Children (1–3) 5–20 45–65 30–40 Children and Adolescents (4–18) 10–30 45–65 25–35 Adults (>19) 10–35 45–65 20–35 Source: Food and Nutrition Board of the Institute of Medicine. Dietary Reference Intakes for Energy, Carbohydrate, Fat, Fatty Acids, Cholesterol, Protein, and Amino Acids. http://www.nationalacademies.org/hmd/~/media/Files/ Activity%20Files/Nutrition/DRI-Tables/ 8_Macronutrient%20Summary.pdf?la=en. Published 2002. Accessed November 22, 2017. Tips for Using the Dietary Reference Intakes to Plan Your Diet You can use the DRIs to help assess and plan your diet. Keep in mind when evaluating your nutritional intake that the values established have been devised with an ample safety margin and should be used as guidance for optimal intakes. Also, the values are meant to assess and plan average intake over time; that is, you don’t need to meet these recommendations every single day—meeting them on average over several days is sufficient. Understanding Dietary Reference Intakes | 715
- Age Group RDA (g/day) AMDR (% calories) Infants (0–6 mo) 9.1* Not determined Infants (7–12 mo) 11.0 Not determined Children (1–3) 13.0 5–20 Children (4–8) 19.0

```
10–30 Children (9–13) 34.0 10–30 Males (14–18) 52.0 10–30 Females (14–18) 46.0 10
–30 Adult Males (19+) 56.0 10–35 Adult Females (19+) 46.0 10–35 * Denotes Adequat
e Intake Source: Dietary Reference Intakes: Macronutrients. Dietary Reference Int
akes for Energy, Carbohydrate, Fiber, Fat, Fatty Acids, Cholesterol, Protein, and
Amino Acids. Institute of Medicine. September 5, 2002. Accessed September 28, 201
7. Protein Input = Protein Used by the Body + Protein Excreted The appropriate am
ount of protein in a person’s diet is that which maintains a balance between what
is taken in and what is used. The RDAs for protein were determined by assessing n
itrogen balance. Nitrogen is one of the four basic elements contained in all amin
o acids. When proteins are broken down and amino acids are catabolized, nitrogen
is released. Remember that when the liver breaks down amino acids, it produces am
monia, which is rapidly converted to nontoxic, nitrogen-containing urea, which is
then transported to the kidneys for excretion.
- percent of the population meets their nutrient need is the EAR, and the point a
t which 97 to 98 percent of the population meets their needs is the RDA. The UL i
s the highest level at which you can consume a nutrient without it being too much
—as nutrient intake increases beyond the UL, the risk of health problems resultin
g from that nutrient increases. Source: Dietary Reference Intakes Tables and Appl
ication. The National Academies of Science, Engineering, and Medicine.  Health a
nd Medicine Division. http://nationalacademies.org/HMD/ Activities/Nutrition/Summ
aryDRIs/DRI-Tables.aspx. Accessed November 22, 2017. The Acceptable Macronutrient
Distribution Range (AMDR) is the calculated range of how much energy from carbohy
drates, fats, and protein is recommended for a healthy diet adequate of the essen
tial nutrients and is associated with a reduced risk of chronic disease. The rang
es listed in Table 12.1 “Acceptable Macronutrient Distribution Ranges (AMDR) For
Various Age Groups” allows individuals to personalize their diets taking into con
sideration that different subgroups in a population often require different requi
rements. The DRI committee recommends using the midpoint of the AMDRs as an appro
ach to focus on moderation2.

          User query: What is the RDI for protein per day?
          Answer:<end_of_turn>
<start_of_turn>model
```

In [ ]:

```
%%time

# Tokenize the prompt and send to GPU
input_ids = tokenizer(
    prompt,
    return_tensors="pt"
).to("cuda")

# Generate output tokens
outputs = llm_model.generate(
    **input_ids,
    temperature=0.7,
    do_sample=True,
    max_new_tokens=256
)

# Decode tokens to text
output_text = tokenizer.decode(outputs[0])

# ✅ SAME CLEANUP AS ask()
clean_answer = (
    output_text
    .replace(prompt, "")
    .replace("<bos>", "")
    .replace("<eos>", "")
```

```
    .strip()
)

print(f"Query: {query}")
print(f"RAG answer:\n{clean_answer}")
```

```
Query: What is the RDI for protein per day?
RAG answer:
The RDI for protein is not explicitly mentioned in the context, so I cannot answe
r this query from the provided context.
CPU times: user 1.32 s, sys: 34 ms, total: 1.35 s
Wall time: 1.41 s
```

In [ ]:

```
def ask(
    query,
    temperature=0.7,
    max_new_tokens=512,
    format_answer_text=True,
    return_answer_only=True
):
    """
    Takes a query, finds relevant resources/context,
    and generates an answer based on those resources.
    """

    # Get scores and indices of top related results
    scores, indices = retrieve_relevant_resources(
        query=query,
        embeddings=text_chunk_embeddings
    )

    # Create a list of context items
    context_items = [pages_and_chunks[i] for i in indices]

    # Add similarity score to each context item
    for i, item in enumerate(context_items):
        item["score"] = scores[i].cpu()

    # Format the prompt with context items
    prompt = prompt_formatter(
        query=query,
        context_items=context_items
    )

    # Tokenize the prompt
    input_ids = tokenizer(
        prompt,
        return_tensors="pt"
    ).to("cuda")

    # Generate model output
    outputs = llm_model.generate(
        **input_ids,
        temperature=temperature,
        max_new_tokens=max_new_tokens,
        do_sample=True
    )

    # Decode output tokens to text
    output_text = tokenizer.decode(outputs[0])
```

```
    if format_answer_text:
        output_text = (
            output_text
            .replace(prompt, "")
            .replace("<bos>", "")
            .replace("<eos>", "")
        )

    # Only return the answer text
    if return_answer_only:
        return output_text

    return output_text, context_items
```

In [ ]:
```
query = random.choice(query_list)
print(f"Query: {query}")

# Answer query with context and return context
answer, context_items = ask(
    query=query,
    temperature=0.7,
    max_new_tokens=512,
    return_answer_only=False
)

print("Answer:\n")
print_wrapped(answer)

print("Context items:")
context_items
```

```
Query: How do vitamins and minerals differ in their roles and importance for heal
th?
[INFO] Time taken to get scores on 1680 embeddings: 0.00010 seconds.
Answer:

The context does not provide information about the differences between vitamins
and minerals, so I cannot answer this query from the context.
Context items:
```

Out[ ]:
[{'page_number': 9,
'sentence_chunk': 'Minerals Major Functions Macro Sodium Fluid balance, nerve transmission, muscle contraction Chloride Fluid balance, stomach acid productio n Potassium Fluid balance, nerve transmission, muscle contraction Calcium Bone and teeth health maintenance, nerve transmission, muscle contraction, blood clo tting Phosphorus Bone and teeth health maintenance, acid-base balance Magnesium Protein production, nerve transmission, muscle contraction Sulfur Protein produc tion Trace Iron Carries oxygen, assists in energy production Zinc Protein and DNA production, wound healing, growth, immune system function Iodine Thyroid ho rmone production, growth, metabolism Selenium Antioxidant Copper Coenzyme, iron metabolism Manganese Coenzyme Fluoride Bone and teeth health maintenance, tooth decay prevention Chromium Assists insulin in glucose metabolism Molybdenum Coen zyme Minerals Minerals are solid inorganic substances that form crystals and ar e classified depending on how much of them we need. Trace minerals, such as mol ybdenum, selenium, zinc, iron, and iodine, are only required in a few milligram s or less. Macrominerals, such as calcium, magnesium, potassium, sodium, and ph osphorus, are required in hundreds of milligrams. Many minerals are critical fo r enzyme Introduction | 9',
'chunk_char_count': 1272,
'chunk_word_count': 167,
'chunk_token_count': 318.0,
'score': tensor(0.6322)},
{'page_number': 6,
'sentence_chunk': 'Lipids are found predominantly in butter, oils, meats, dai ry products, nuts, and seeds, and in many processed foods. The three main types of lipids are triglycerides (triacylglycerols), phospholipids, and sterols. The main job of lipids is to provide or store energy. Lipids provide more energy pe r gram than carbohydrates (nine kilocalories per gram of lipids versus four kil ocalories per gram of carbohydrates). In addition to energy storage, lipids ser ve as a major component of cell membranes, surround and protect organs (in fat-storing tissues), provide insulation to aid in temperature regulation, and regu late many other functions in the body. 6 | Introduction',
'chunk_char_count': 668,
'chunk_word_count': 101,
'chunk_token_count': 167.0,
'score': tensor(0.6220)},
{'page_number': 553,
'sentence_chunk': 'Scorbutic gums due to a vitamin C deficiency, a symptom of scurvy. https://com mons.wikime dia.org/ wiki/ File:Scorbuti c_gums.jpg Figure 9.9 Bleeding Gums Associated with Scurvy Cardiovascular Disease Vitamin C’s abi lity to prevent disease has been debated for many years. Overall, higher dietar y intakes of vitamin C (via food intake, not supplements), are linked to decrea sed disease risk. A review of multiple studies published in the April 2009 issu e of the Archives of Internal Medicine concludes there is moderate scientific e vidence supporting the idea that higher dietary vitamin C intakes are correlate d with reduced cardiovascular disease risk, but there is insufficient evidence to conclude that taking vitamin C supplements influences cardiovascular disease risk.1 Vitamin C levels in the body have been shown to correlate well with frui t and vegetable intake, 1. \xa0Mente A, et al. (2009). A Systematic Review of the Evidence Supporting a Causal Link between Dietary Factors and Coronary Hear t Disease. Archives of Internal Medicine,\xa0169(7), 659–69. http://archinte.am a-assn.org/ cgi/content/full/169/7/659. Accessed October 5, 2017.',
'chunk_char_count': 1146,
'chunk_word_count': 164,
'chunk_token_count': 286.5,
'score': tensor(0.6187)},
{'page_number': 1,
'sentence_chunk': 'PART\xa0I CHAPTER 1. BASIC CONCEPTS IN NUTRITION Chapter 1. Basic Concepts in Nutrition | 1',
'chunk_char_count': 88,

```
  'chunk_word_count': 15,
  'chunk_token_count': 22.0,
  'score': tensor(0.6178)},
 {'page_number': 591,
  'sentence_chunk': 'Learning Activities Technology Note: The second edition of
the Human Nutrition Open Educational Resource (OER) textbook features interacti
ve learning activities. \xa0 These activities are available in the web-based te
xtbook and not available in the downloadable versions (EPUB, Digital PDF, Print
_PDF, or Open Document). Learning activities may be used across various mobile
devices, however, for the best user experience it is strongly Water-Soluble Vit
amins | 591',
  'chunk_char_count': 462,
  'chunk_word_count': 65,
  'chunk_token_count': 115.5,
  'score': tensor(0.6128)}]
```

In [ ]:

```python
def ask(
    query,
    temperature=0.7,
    max_new_tokens=512,
    format_answer_text=True,
    return_answer_only=True
):
    """
    Takes a query, finds relevant resources/context,
    and generates an answer based on those resources.
    """

    # Get scores and indices of top related results
    scores, indices = retrieve_relevant_resources(
        query=query,
        embeddings=text_chunk_embeddings
    )

    # ✅ IMPORTANT FIX: use the SAME list that was used to create embeddings
    context_items = [pages_and_chunks_over_min_token_len[i] for i in indices]

    # (Optional sanity check — you can comment this out)
    print("\n[DEBUG] Retrieved context preview:")
    for i, item in enumerate(context_items[:3]):
        print(f"\n--- Context {i} (score={scores[i].item():.4f}) ---")
        print(item["sentence_chunk"][:200])

    # Add similarity score to each context item
    for i, item in enumerate(context_items):
        item["score"] = scores[i].cpu()

    # Format the prompt with context items
    prompt = prompt_formatter(
        query=query,
        context_items=context_items
    )

    # Tokenize the prompt
    input_ids = tokenizer(
        prompt,
        return_tensors="pt"
    ).to("cuda")

    # Generate model output
```

```
    outputs = llm_model.generate(
        **input_ids,
        temperature=temperature,
        max_new_tokens=max_new_tokens,
        do_sample=True
    )

    # Decode output tokens to text
    output_text = tokenizer.decode(outputs[0])

    if format_answer_text:
        output_text = (
            output_text
            .replace(prompt, "")
            .replace("<bos>", "")
            .replace("<eos>", "")
        )

    # Only return the answer text
    if return_answer_only:
        return output_text

    return output_text, context_items
```

In [ ]:
```
query = "Explain the concept of energy balance and its importance in weight mana
answer, context = ask(query, return_answer_only=False)

print("\nANSWER:\n")
print_wrapped(answer)
```

```
[INFO] Time taken to get scores on 1680 embeddings: 0.00007 seconds.

[DEBUG] Retrieved context preview:

--- Context 0 (score=0.7546) ---
Photo by Jon Flobrant on unsplash.co m / CC0 https://unspl ash.com/ photos/_r19 n
fvS3wY Balancing Energy Input with Energy Output To Maintain Weight, Energy Intak
e Must Balance Energy Output Recall th

--- Context 1 (score=0.6580) ---
Photo by Martins Zemlickis on unsplash.co m / CC0 https://unspl ash.com/ photos/
NPFu4GfFZ7 E Factors Affecting Energy Expenditure UNIVERSITY OF HAWAIʻI AT MĀNOA
FOOD SCIENCE AND HUMAN NUTRITION PROGR

--- Context 2 (score=0.6107) ---
Image by mojzagrebinf o / Pixabay License 1.  Calories In Versus Calories Out UNI
VERSITY OF HAWAIʻI AT MĀNOA FOOD SCIENCE AND HUMAN NUTRITION PROGRAM AND HUMAN NU
TRITION PROGRAM The ability to estimat

ANSWER:

Sure, here's the explanation of the concept of energy balance and its importance
in weight management:  Energy balance is the overall state of the body's energy
intake and expenditure. It indicates whether a person is in a positive or
negative energy balance. In a positive energy balance, the intake of energy is
greater than the expenditure, leading to the storage or use of excess nutrients
for growth, development, or maintenance. Conversely, when the intake of energy
is less than the expenditure, the body relies on its stores to provide energy,
leading to weight loss.  Maintaining a positive energy balance is crucial for
weight management and overall health. When a person is in a positive energy
balance, they have sufficient energy reserves to perform physical activities,
maintain muscle mass, and carry out daily tasks. This helps regulate body
temperature, provides building blocks for tissue repair, and boosts metabolism.
When an individual is in a negative energy balance, they could become
malnourished, lose muscle mass, and experience fatigue.  However, achieving and
maintaining a positive energy balance can be challenging. Several factors, such
as genetics, diet, and lifestyle choices, can influence energy balance. It's
important to note that weight management is a complex process involving various
factors beyond just energy balance, including diet, exercise, sleep, and stress
management.
```

Evaluation of our Result

RAG Evaluation — Final Missing Piece of the End-to-End Pipeline

Evaluation is the **most under-discussed but most critical** part of an industrial RAG system.

> Chunking, embeddings, retrieval can look “correct”
> **Only evaluation tells you whether the system actually works**

There is **no foolproof evaluation framework yet**, but there are **standard, battle-tested practices**.

Why RAG Evaluation Is Hard

- RAG is **not a single model**
- Errors can come from:
  - Chunking
  - Embeddings
  - Retrieval
  - Prompting
  - Generation
- A wrong final answer does **not** tell you *where* the pipeline failed

Hence, evaluation must be **layered**.

Core Evaluation Question

> **How do we know whether a RAG pipeline is good?**

This breaks into **three levels**:

1. **Retrieval quality**
2. **Grounding quality**
3. **Answer quality**

Foundational Work (Context)

- A key paper:
  "Evaluating Verifiability in Generative Search Engines"
- Introduced ideas like:
  - Citation precision
  - Citation recall
- Provided the **first structured roadmap** for RAG evaluation

---

RAGAS — Popular Evaluation Library

- Open-source library: **RAGAS**
- Provides standardized metrics for RAG systems
- Requires **ground truth data** to function

Important industry note:

> Libraries like RAGAS are helpful,
> but **real-world evaluation is almost always custom**.

Core Retrieval Metrics (Most Important)

1. Context Precision

Question:

> Of the retrieved chunks, how many are actually relevant?

Definition:

- Measures the **fraction of retrieved context that is relevant**
- Penalizes noisy retrieval

Failure mode detected

- Too many irrelevant chunks
- Poor chunking strategy
- Bad embedding model

---

2. Context Recall

Question:

> Did we retrieve *all* the relevant chunks?

Definition:

- Measures **coverage of relevant information**
- Checks whether important chunks were missed

Failure mode detected

- Incomplete retrieval
- Chunking too coarse or too fragmented

Intuitive Interpretation

Metric	Answers
Context Precision	“Are my chunks relevant?”
Context Recall	“Did I miss anything important?”

Entity-Based Recall (Advanced)

Context Entity Recall

- Measures overlap of **entities** between:
  - Ground truth context

    - Retrieved context

Useful when:

- Facts depend on entities (names, terms, values)
- Domain is technical / factual

Answer-Level Metrics

1. Response Relevance

Question:

> Is the final answer relevant to the user query?

- Can be approximated using:
    - Embedding similarity (query vs answer)
- Often evaluated **qualitatively** in practice

---

2. Groundedness (Very Important)

Question:

> How much of the answer is supported by retrieved context?

Checks:

- Is the model answering **from documents**?
- Or **hallucinating from prior knowledge**?

---

3. Specificity

Question:

> Is the answer precise or vague?

Examples:

- ❌ "Vitamins are important for health"
- ✅ "Vitamin B and C are water-soluble vitamins responsible for …"

Specificity measures **information density**.

Ground Truth — The Backbone of Evaluation

What Is Ground Truth?

A manually curated dataset containing:

- Questions
- Relevant passages
- Correct answers

Typically created as:

- Excel / CSV sheet
- 20–50 high-quality questions (minimum)

Why Ground Truth Must Be Manual

> Using LLMs to generate ground truth for hallucination detection
> is **conceptually flawed**

- LLMs hallucinate
- Using them as truth sources defeats the purpose

Best practice

- Humans create ground truth
- LLMs may assist
- Humans must verify

Practical Ground Truth Construction

For each question:

- Identify **relevant passages** from documents
- Store:
  - Question
  - Relevant chunks
  - Expected answer

This dataset is reused to:

- Compare chunking strategies
- Compare embedding models
- Compare retrieval configs

Evaluation Without Libraries (Industry Reality)

Most teams evaluate using **intuition + structured checks**:

1. Are retrieved chunks relevant?
2. Are *all* relevant chunks retrieved?

3. Is the final answer correct?
4. Is the answer grounded?
5. Is the answer specific?

Libraries help — **humans decide**.

Human vs LLM as Judge

Human as Judge

- Best for:
  - Correctness
  - Specificity
  - Business relevance
- Often done by:
  - Client stakeholders
  - Domain experts

LLM as Judge

- Useful for:
  - Scale
  - Internal validation
- Should **never be the sole judge**

Best setup

- LLM-as-judge internally
- Human-as-judge with client feedback

Evaluation Is Iterative

Evaluation is **not a one-time step**.

Typical loop:

1. Evaluate
2. Identify failure
3. Adjust:
   - Chunking
   - Embeddings
   - Retrieval parameters
4. Re-evaluate

Chunking strategy itself becomes a **hyperparameter**.

Final Engineering Takeaways

- Evaluation is **mandatory**, not optional
- Ground truth quality determines evaluation quality
- Metrics should answer:
  - Relevance
  - Coverage
  - Groundedness
  - Specificity
- Libraries (like RAGAS) are tools, not solutions
- Human-in-the-loop is essential for production systems

Mental Model

> **If you cannot explain why your RAG system is good,**
> **it is not production-ready.**

In [ ]:
```
!pip install -q ragas datasets
```

In [ ]:
```
# Install required packages
# !pip install ragas datasets

import pandas as pd
from datasets import Dataset
from ragas import evaluate
from ragas.metrics.collections import (
    context_precision,
    context_recall,
    answer_relevancy,
    faithfulness
)

# Try to import additional metrics if available
try:
    from ragas.metrics.collections import context_entity_recall
except ImportError:
    context_entity_recall = None
    print("context_entity_recall not available in this version")

try:
    from ragas.metrics import noise_robustness
except ImportError:
    noise_robustness = None
    print("noise_robustness not available in this version")
```

```
noise_robustness not available in this version
```

In [ ]:
```
# Define evaluation questions and ground truth answers
eval_questions = [
    "How often should infants be breastfed?",
    "What are symptoms of pellagra?",
    "How does saliva help with digestion?",
    "What is the recommended protein intake per day, based on your weight?",
```

```
    "What are micronutrients?"
]


ground_truth_answers = [
    "A newborn infant (birth to 28 days) should be breastfed about eight to twel

    "Pellagra is caused by a deficiency of niacin (vitamin B3). Common symptoms

    "Saliva helps with digestion by moistening food to make it easier to chew an

    "Recommended protein intake per day is commonly estimated based on body weig

    "Micronutrients are nutrients required by the body in small amounts but are
]
```

In [ ]:

```
def generate_rag_answer(query):
    """Generate RAG answer for a given query"""

    # Get relevant resources (USE CORRECT EMBEDDINGS)
    scores, indices = retrieve_relevant_resources(
        query=query,
        embeddings=text_chunk_embeddings
    )

    # IMPORTANT: context must come from the SAME source as embeddings
    context_items = [
        pages_and_chunks_over_min_token_len[i]
        for i in indices
    ]

    # Format prompt with context items
    prompt = prompt_formatter(
        query=query,
        context_items=context_items
    )

    # Generate answer
    input_ids = tokenizer(
        prompt,
        return_tensors="pt"
    ).to("cuda")

    outputs = llm_model.generate(
        **input_ids,
        temperature=0.7,
        do_sample=True,
        max_new_tokens=256
    )

    # Decode and CLEAN output (critical)
    output_text = tokenizer.decode(outputs[0])
    answer = (
        output_text
        .replace(prompt, "")
        .replace("<bos>", "")
        .replace("<eos>", "")
        .strip()
    )
```

```
    # Return both answer and context strings
    contexts = [
        item["sentence_chunk"]
        for item in context_items
    ]

    return answer, contexts
```

In [ ]:
```
evaluation_data = []

print("Generating RAG answers for evaluation ...")
for question, ground_truth in zip(eval_questions, ground_truth_answers):
    print(f"Processing: {question[:50]} ...")

    # Generate RAG answer and get contexts
    rag_answer, contexts = generate_rag_answer(question)

    evaluation_data.append({
        "question": question,
        "answer": rag_answer,
        "contexts": contexts,
        "ground_truth": ground_truth
    })
```

```
Generating RAG answers for evaluation ...
Processing: How often should infants be breastfed? ...
[INFO] Time taken to get scores on 1680 embeddings: 0.00009 seconds.
Processing: What are symptoms of pellagra? ...
[INFO] Time taken to get scores on 1680 embeddings: 0.00010 seconds.
Processing: How does saliva help with digestion? ...
[INFO] Time taken to get scores on 1680 embeddings: 0.00011 seconds.
Processing: What is the recommended protein intake per day, ba ...
[INFO] Time taken to get scores on 1680 embeddings: 0.00009 seconds.
Processing: What are micronutrients? ...
[INFO] Time taken to get scores on 1680 embeddings: 0.00011 seconds.
```

In [13]:
```
# import pandas as pd
# from datasets import Dataset
# from ragas import evaluate
# from ragas.metrics import (
#     ContextPrecision,
#     ContextRecall,
#     AnswerRelevancy,
#     Faithfulness
# )

# # Try to import additional metrics if available
# try:
#     from ragas.metrics import ContextEntityRecall
# except ImportError:
#     ContextEntityRecall = None
#     print("context_entity_recall not available in this version")

# try:
#     from ragas.metrics import NoiseRobustness
# except ImportError:
#     NoiseRobustness = None
#     print("noise_robustness not available in this version")

# # Convert to dataset format required by RAGAS
```

```
# eval_dataset = Dataset.from_pandas(
#     pd.DataFrame(evaluation_data)
# )

# # Define metrics to evaluate (only use available ones)
# metrics = [
#     ContextPrecision(), # Initialize the metric class
#     ContextRecall(),    # Initialize the metric class
#     AnswerRelevancy(),  # Initialize the metric class
#     Faithfulness()      # Initialize the metric class
# ]

# # Add optional metrics if available
# if ContextEntityRecall is not None:
#     metrics.append(ContextEntityRecall())

# if NoiseRobustness is not None:
#     metrics.append(NoiseRobustness())

# # Run evaluation
# print("Running RAGAS evaluation ...")
# results = evaluate(
#     dataset=eval_dataset,
#     metrics=metrics
# )

# # Convert results to pandas DataFrame
# results_df = results.to_pandas()

# print("\n" + "=" * 80)
# print("RAG EVALUATION RESULTS")
# print("=" * 80)

# print(results_df)
```

In [ ]:
```
results_df.columns
```

Out[ ]:
```
Index(['user_input', 'retrieved_contexts', 'response', 'reference',
       'context_precision', 'context_recall', 'answer_relevancy',
       'faithfulness', 'context_entity_recall'],
      dtype='object')
```

In [ ]:
```
# Extract metric columns (numeric only)
metric_cols = []

for col in results_df.columns:
    if col not in ['user_input', 'retrieved_contexts', 'response', 'reference']:
        try:
            numeric_values = pd.to_numeric(results_df[col], errors='coerce')
            if not numeric_values.isna().all():
                metric_cols.append(col)
        except Exception:
            pass

# Create clean individual results table
print("\n\nINDIVIDUAL QUESTION PERFORMANCE")
print("-" * 80)
```

```
INDIVIDUAL QUESTION PERFORMANCE
--------------------------------------------------------------------------------
```

In [ ]:
```python
# Create a clean DataFrame for display
clean_results = pd.DataFrame()

clean_results["Question"] = [
    f"Q{i+1}: {q[:50]}{' ...' if len(q) > 50 else ''}"
    for i, q in enumerate(results_df["user_input"])
]

# Add metric scores
for col in metric_cols:
    clean_results[col.replace("_", " ").title()] = results_df[col].round(3)

# Display the table with better formatting
print(clean_results.to_string(index=False, float_format="%.3f"))

# Calculate and display average scores
print("\nOVERALL AVERAGE SCORES")
print("-" * 50)
```

```
                                                Question  Context Precision  Co
ntext Recall  Faithfulness  Context Entity Recall
                  Q1: How often should infants be breastfed?              1.000
1.000         0.000                    0.333
                         Q2: What are symptoms of pellagra?              1.000
0.750         1.000                    0.308
                     Q3: How does saliva help with digestion?              0.887
1.000         0.000                    0.200
Q4: What is the recommended protein intake per day, ba ...              0.700
1.000         0.000                    0.000
                                Q5: What are micronutrients?              0.756
0.500         0.500                    0.143

OVERALL AVERAGE SCORES
--------------------------------------------------
```

In [ ]:
```python
avg_scores = {}

for col in metric_cols:
    avg_score = results_df[col].mean()
    avg_scores[col] = avg_score

    # Performance indicator
    if avg_score >= 0.8:
        indicator = "Excellent"
    elif avg_score >= 0.6:
        indicator = "Good"
    elif avg_score >= 0.4:
        indicator = "Fair"
    else:
        indicator = "Poor"

    print(f"{col.replace('_', ' ').title():<25}: {avg_score:.3f} {indicator}")

# Performance summary
print("\nPERFORMANCE SUMMARY")
print("-" * 50)
```

```
Context Precision        : 0.869 Excellent
Context Recall           : 0.850 Excellent
Faithfulness             : 0.300 Poor
Context Entity Recall    : 0.197 Poor

PERFORMANCE SUMMARY
--------------------------------------------------
```

In [ ]:

```python
# Count performance levels
excellent = sum(1 for score in avg_scores.values() if score >= 0.8)
good = sum(1 for score in avg_scores.values() if 0.6 <= score < 0.8)
fair = sum(1 for score in avg_scores.values() if 0.4 <= score < 0.6)
poor = sum(1 for score in avg_scores.values() if score < 0.4)

print(f"Excellent metrics: {excellent}")
print(f"Good metrics: {good}")
print(f"Fair metrics: {fair}")
print(f"Poor metrics: {poor}")

# Key insights
print("\nKEY INSIGHTS")
print("-" * 50)

best_metric = max(avg_scores, key=avg_scores.get)
worst_metric = min(avg_scores, key=avg_scores.get)

print(
    f"Best performing: "
    f"{best_metric.replace('_', ' ').title()} "
    f"({avg_scores[best_metric]:.3f})"
)

print(
    f"Needs improvement: "
    f"{worst_metric.replace('_', ' ').title()} "
    f"({avg_scores[worst_metric]:.3f})"
)

# Specific recommendations
if (
    avg_scores.get("context_precision", 0) > 0.7
    and avg_scores.get("answer_relevancy", 0) < 0.3
):
    print("\nIssue detected: Good retrieval but poor answer generation")
    print("- Fix your prompt template to better use retrieved context")

if avg_scores.get("context_recall", 0) < 0.5:
    print("\nIssue detected: Poor context retrieval")
    print("- Improve your embedding model or chunk strategy")

print("\nResults saved to 'rag_evaluation_results.csv'")

# Save detailed results
detailed_results = pd.DataFrame(evaluation_data)

for col in metric_cols:
    detailed_results[col] = results_df[col].values

detailed_results.to_csv("rag_evaluation_results.csv", index=False)
```

```
print("=" * 80)
```

```
Excellent metrics: 2
Good metrics: 0
Fair metrics: 0
Poor metrics: 2

KEY INSIGHTS
--------------------------------------------------
Best performing: Context Precision (0.869)
Needs improvement: Context Entity Recall (0.197)

Issue detected: Good retrieval but poor answer generation
- Fix your prompt template to better use retrieved context

Results saved to 'rag_evaluation_results.csv'
================================================================================
```

In [ ]: