Thomas Cowart

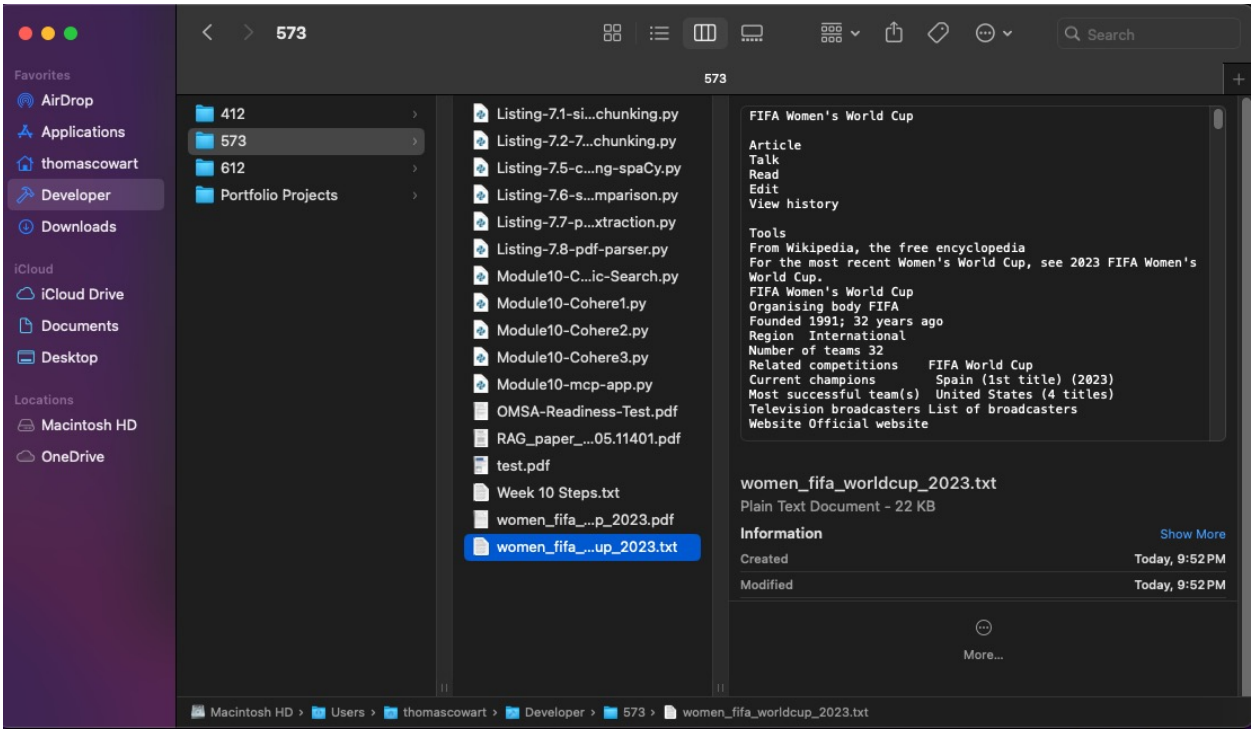
Prof. Gill

ISYS 573

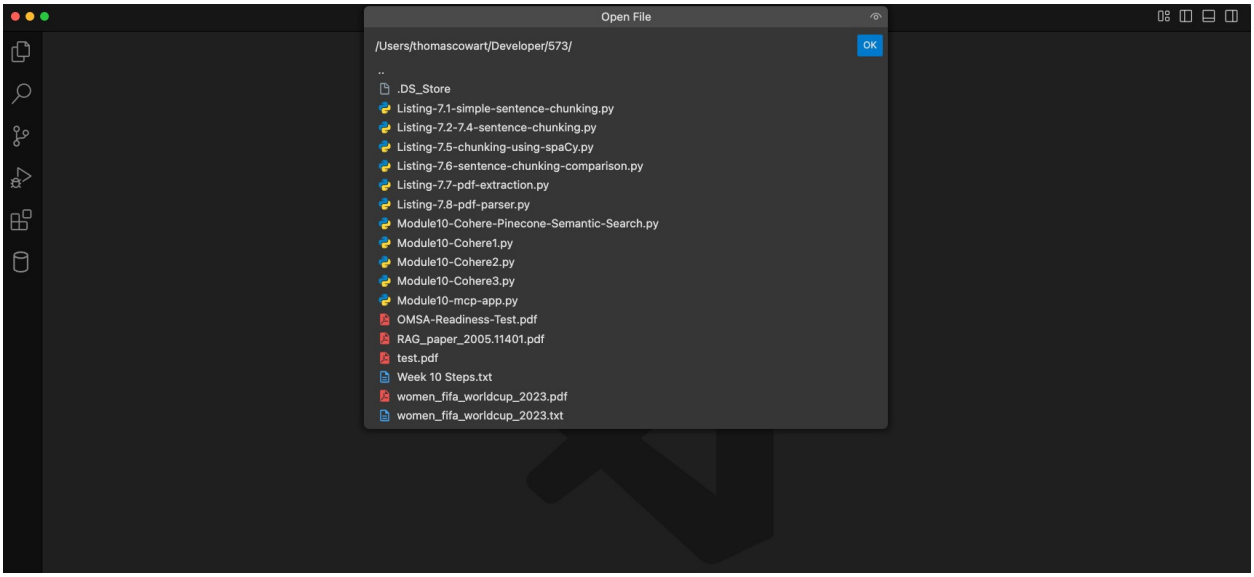
4/7/25

Week 10 HW

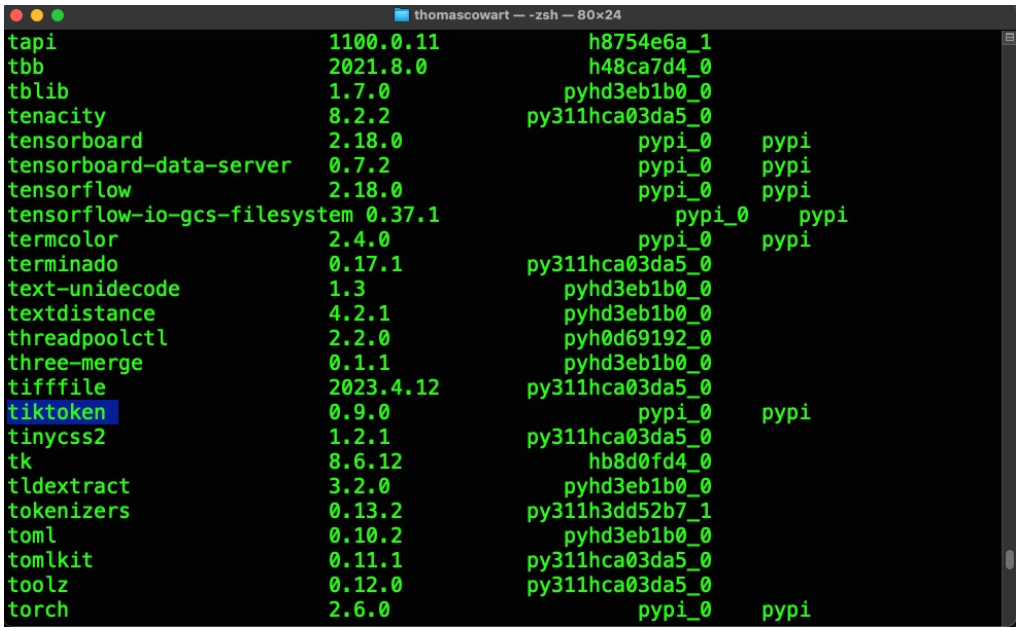
1.



2.


Open File
/Users/thomascowart/Developer/573/
OK
..
.DS_Store
Listing-7.1-simple-sentence-chunking.py
Listing-7.2-7.4-sentence-chunking.py
Listing-7.5-chunking-using-spaCy.py
Listing-7.6-sentence-chunking-comparison.py
Listing-7.7-pdf-extraction.py
Listing-7.8-pdf-parser.py
Module10-Cohere-Pinecone-Semantic-Search.py
Module10-Cohere1.py
Module10-Cohere2.py
Module10-Cohere3.py
Module10-mcp-app.py
OMSA-Readiness-Test.pdf
RAG_paper_2005.11401.pdf
test.pdf
Week 10 Steps.txt
women_fifa_worldcup_2023.pdf
women_fifa_worldcup_2023.txt

3.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tbb 2021.8.0 h48ca7d4_0
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tenacity 8.2.2 py311hca03da5_0
tensorboard 2.18.0 pypi_0 pypi
tensorboard-data-server 0.7.2 pypi_0 pypi
tensorflow 2.18.0 pypi_0 pypi
tensorflow-io-gcs-filesystem 0.37.1 pypi_0 pypi
termcolor 2.4.0 pypi_0 pypi
terminado 0.17.1 py311hca03da5_0
text-unidecode 1.3 pyhd3eb1b0_0
textdistance 4.2.1 pyhd3eb1b0_0
threadpoolctl 2.2.0 pyh0d69192_0
three-merge 0.1.1 pyhd3eb1b0_0
tifffile 2023.4.12 py311hca03da5_0
tiktoken 0.9.0 pypi_0 pypi
tinycss2 1.2.1 py311hca03da5_0
tk 8.6.12 hb8d0fd4_0
tldextract 3.2.0 pyhd3eb1b0_0
tokenizers 0.13.2 py311h3dd52b7_1
toml 0.10.2 pyhd3eb1b0_0
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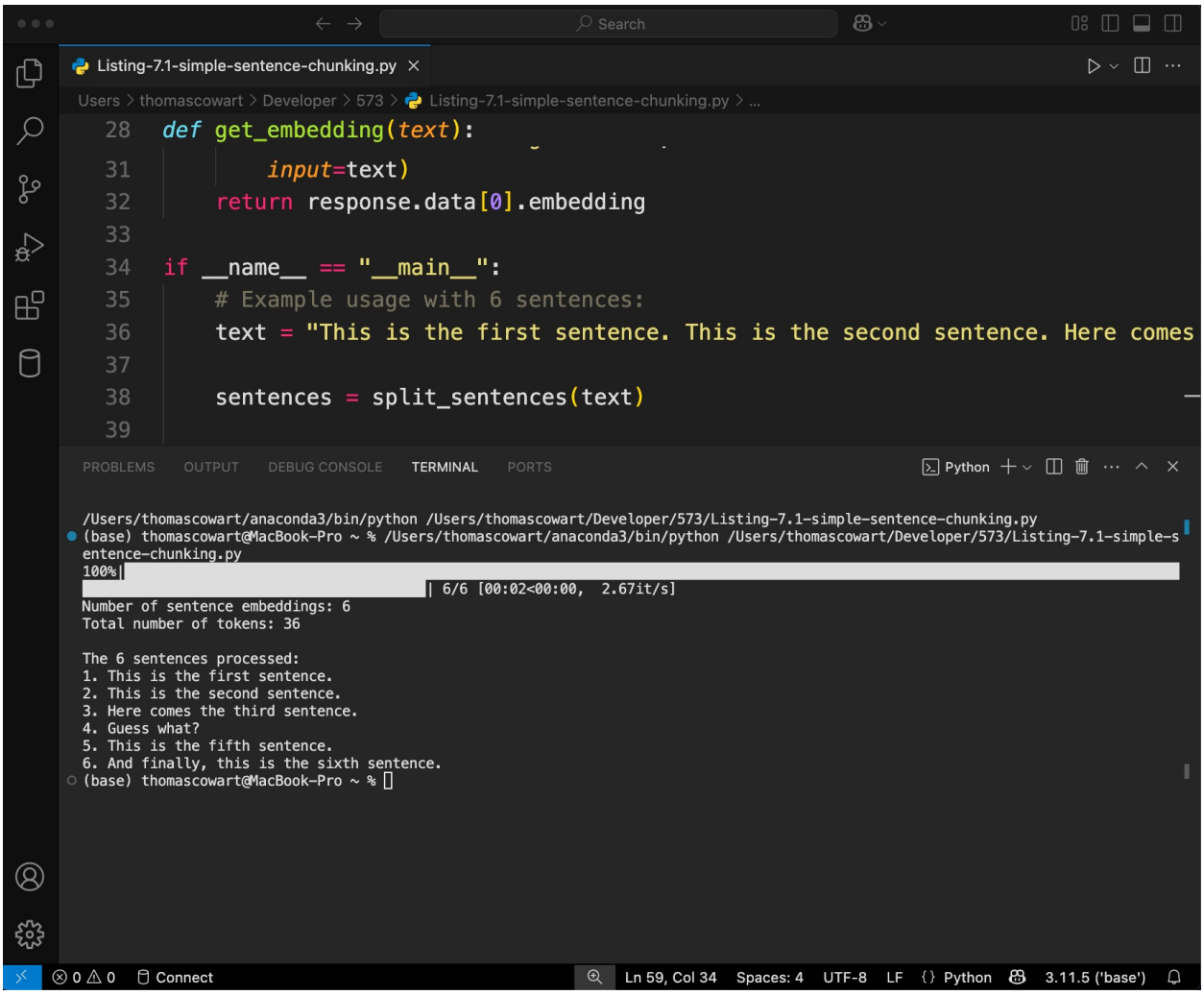
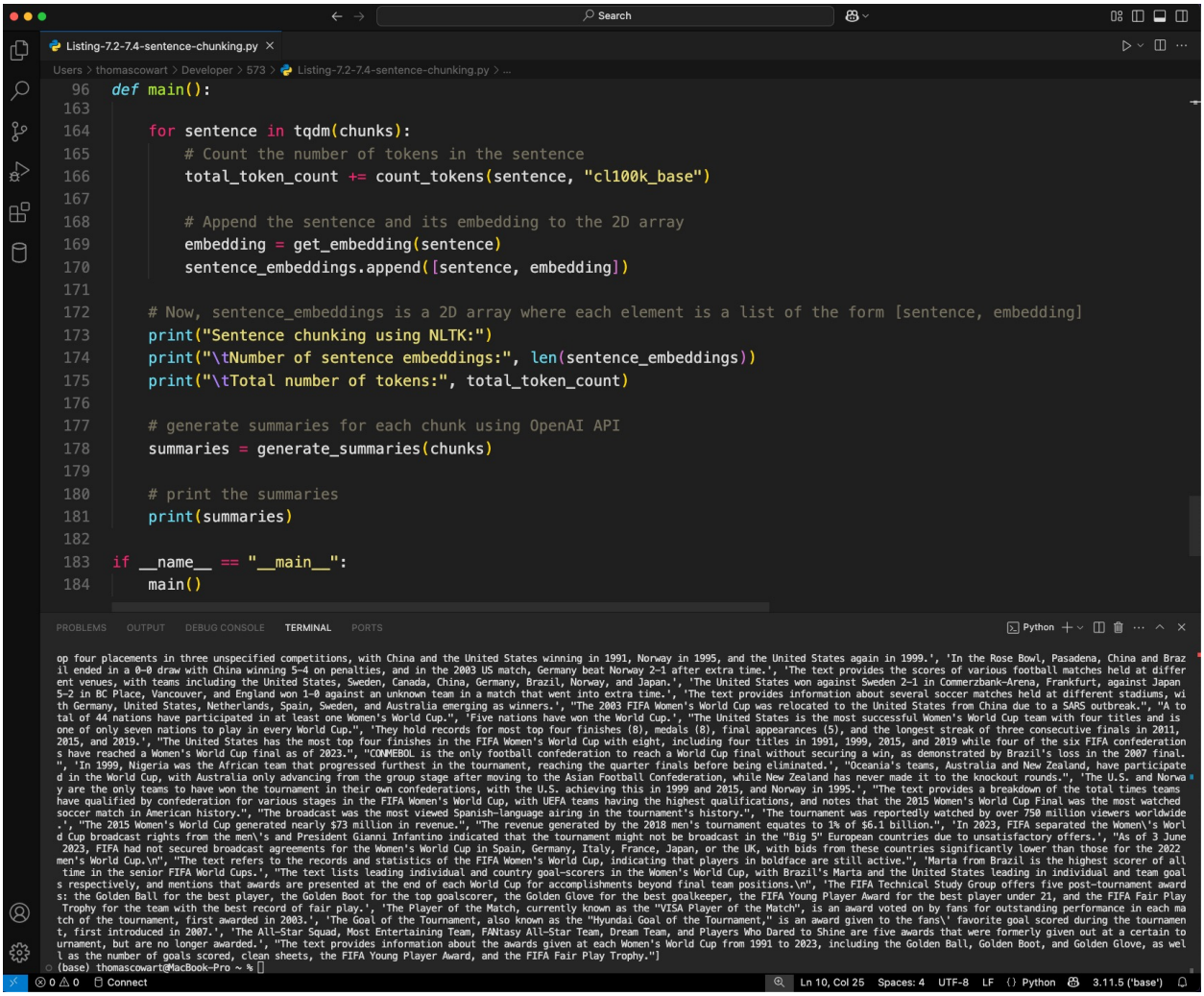
torch 2.6.0 pypi_0 pypi

4.


Search
Listing-7.1-simple-sentence-chunking.py
Users > thomascowart > Developer > 573 > Listing-7.1-simple-sentence-chunking.py > ...
28 def get_embedding(text):
31 input=text)
32 return response.data[0].embedding
33
34 if __name__ == "__main__":
35 # Example usage with 6 sentences:
36 text = "This is the first sentence. This is the second sentence. Here comes
37
38 sentences = split_sentences(text)
39
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS
Python
/Users/thomascowart/anaconda3/bin/python /Users/thomascowart/Developer/573/Listing-7.1-simple-sentence-chunking.py
(base) thomascowart@MacBook-Pro ~ % /Users/thomascowart/anaconda3/bin/python /Users/thomascowart/Developer/573/Listing-7.1-simple-sentence-chunking.py
100%| | 6/6 [00:02<00:00, 2.67it/s]
Number of sentence embeddings: 6
Total number of tokens: 36
The 6 sentences processed:
1. This is the first sentence.
2. This is the second sentence.
3. Here comes the third sentence.
4. Guess what?
5. This is the fifth sentence.
6. And finally, this is the sixth sentence.
(base) thomascowart@MacBook-Pro ~ %
0 0
Connect
Ln 59, Col 34
Spaces: 4
UTF-8
LF
Python
3.11.5 ('base')

5.

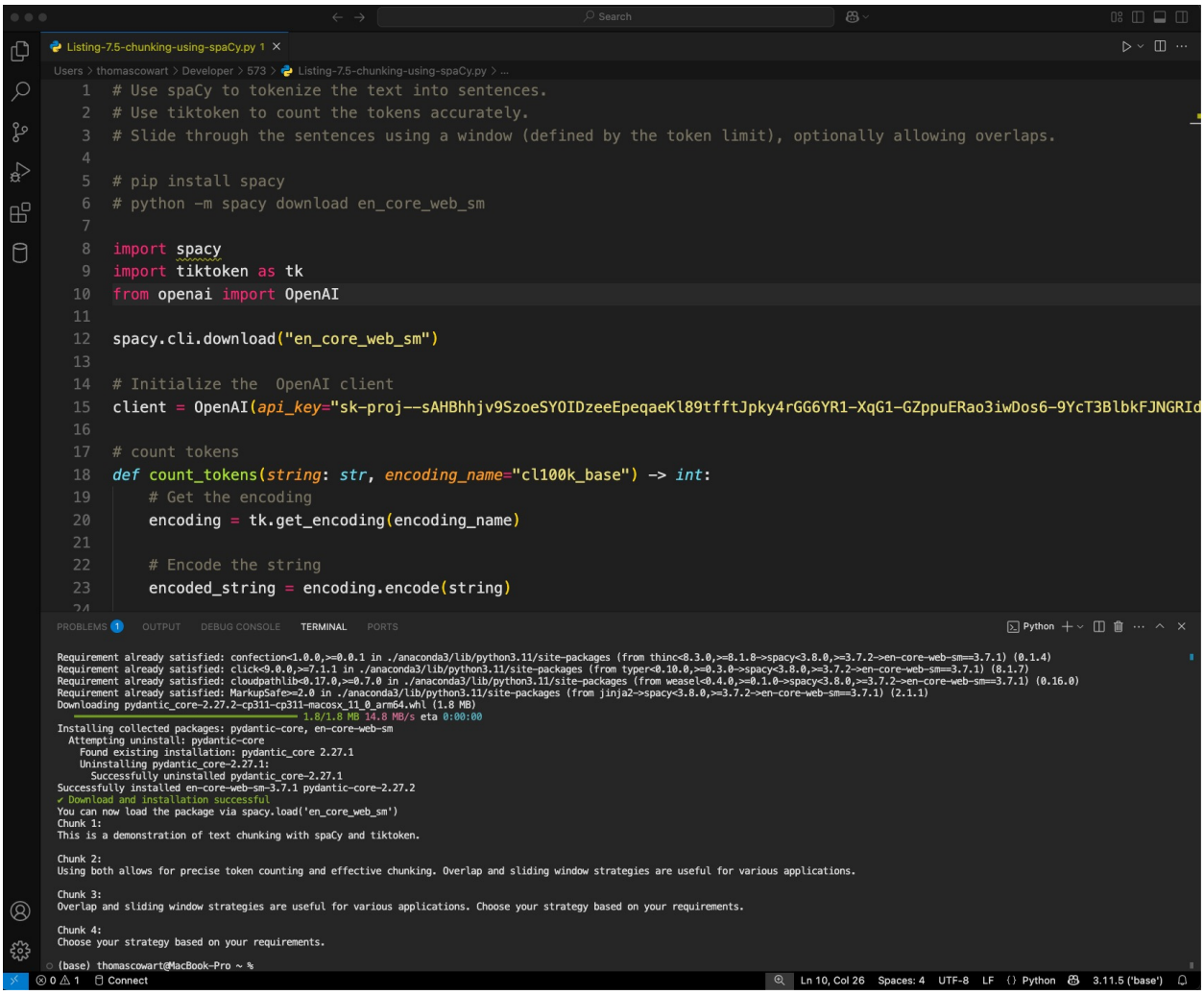


Simple: Manually splits text by spaces or punctuation. It's basic and doesn't account for structure or meaning.

Textwrap: Splits text into lines of a specific width. It's useful for formatting text to fit within a set number of characters.

NLTK: More advanced, using natural language processing to split text based on sentence or word boundaries. It's smarter about structure and context.

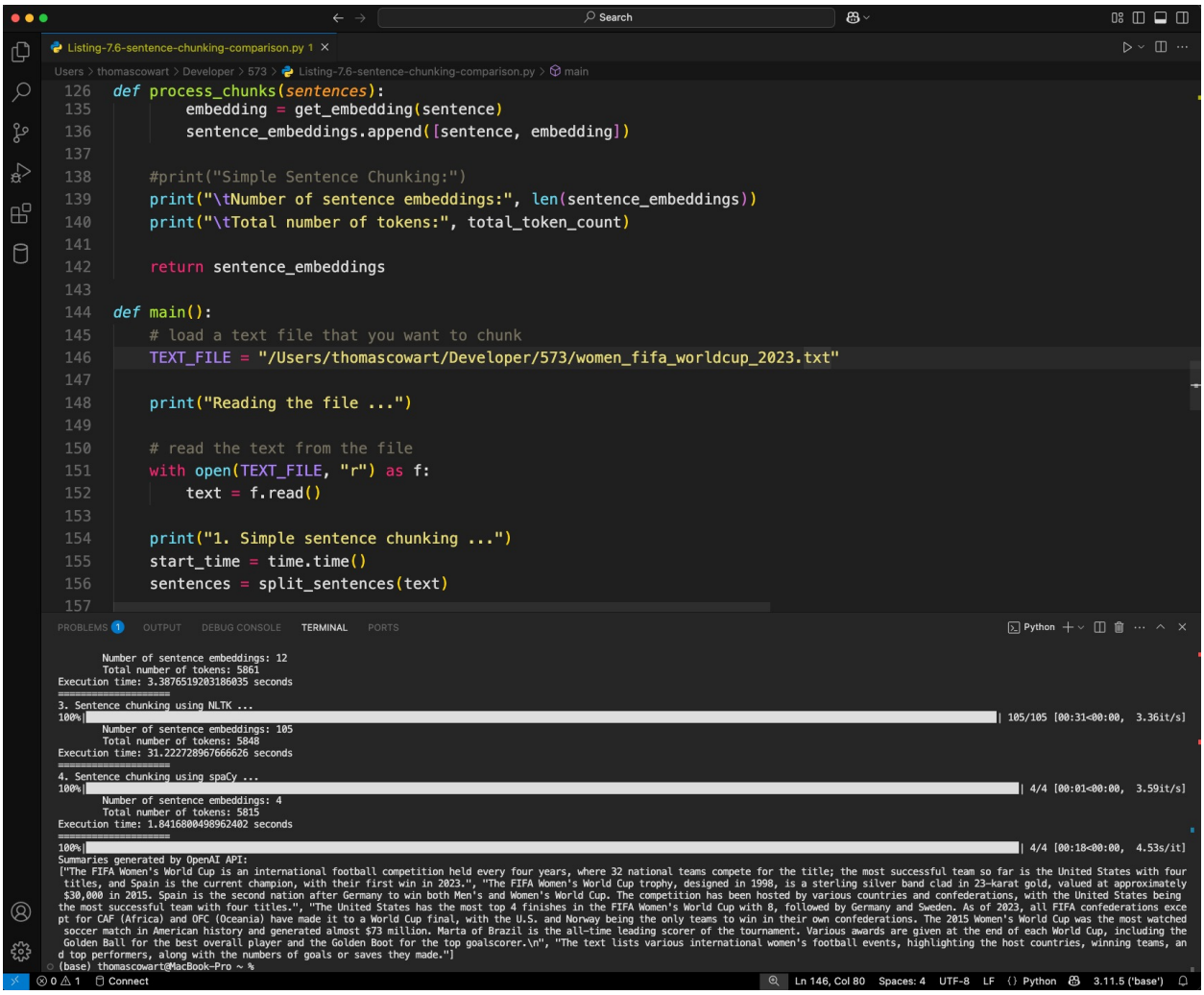
6.



spaCy is faster and built for real world, large-scale applications with pre-trained models for tasks like NER and “part of speech” tagging. It’s easy to use and performance focused.

NLTK is more research-oriented, offering lots of flexibility and educational tools, but it’s slower and requires more setup. It’s great for learning and experimenting with NLP.

7.



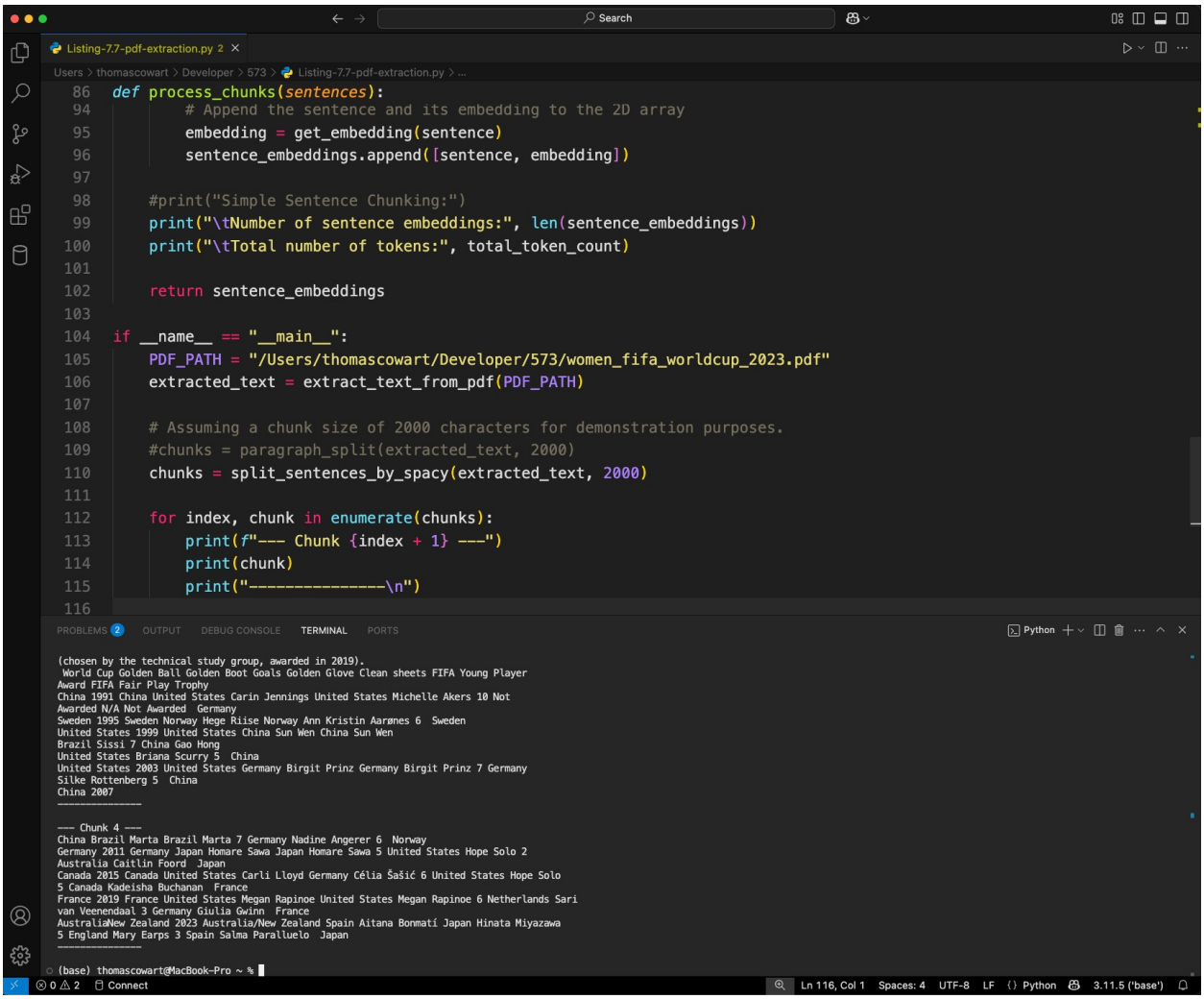
Here's how I'd rank the chunking methods by speed:

1. Simple – Fastest. It just splits text based on spaces or basic delimiters.
2. Textwrap – Slightly slower than simple because it considers line length and formatting, but still pretty fast.
3. spaCy – Fast, especially for production-level tasks. It's optimized but has more overhead than simple methods.
4. NLTK – Slowest. NLTK provides flexibility but requires more processing due to its complexity and range of tools.

Choice:

I'd choose simple for tasks that don't require deep NLP understanding. It's the fastest and works well for basic tasks like splitting text by spaces or punctuation. If I need more nuanced chunking (like sentences or words), spaCy is a solid choice for its speed and pre-trained models.

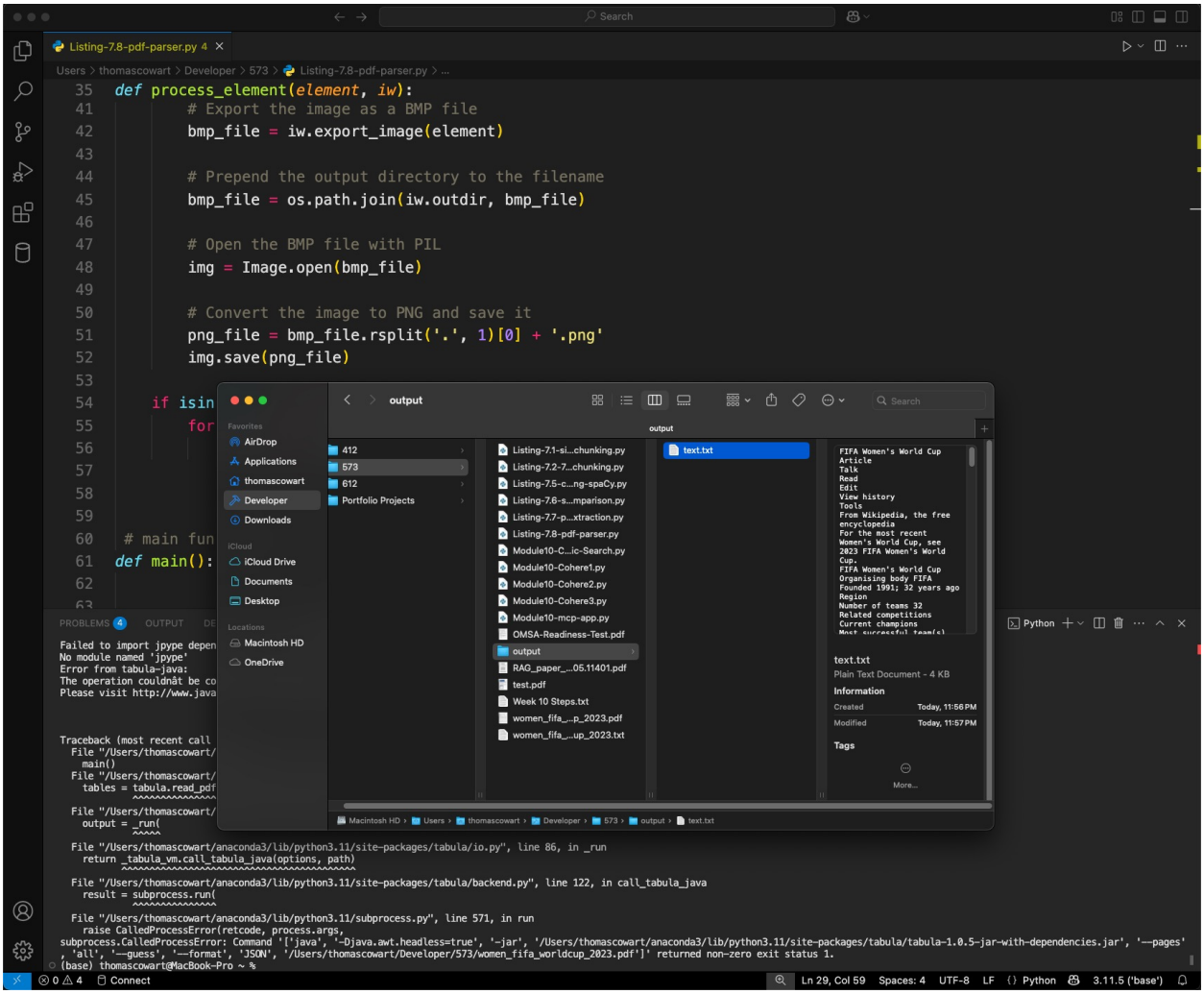
8.



PDF chunking is about extracting text from PDFs, which often have complex layouts (like columns or images). It requires special tools to handle this extraction and organize the content.

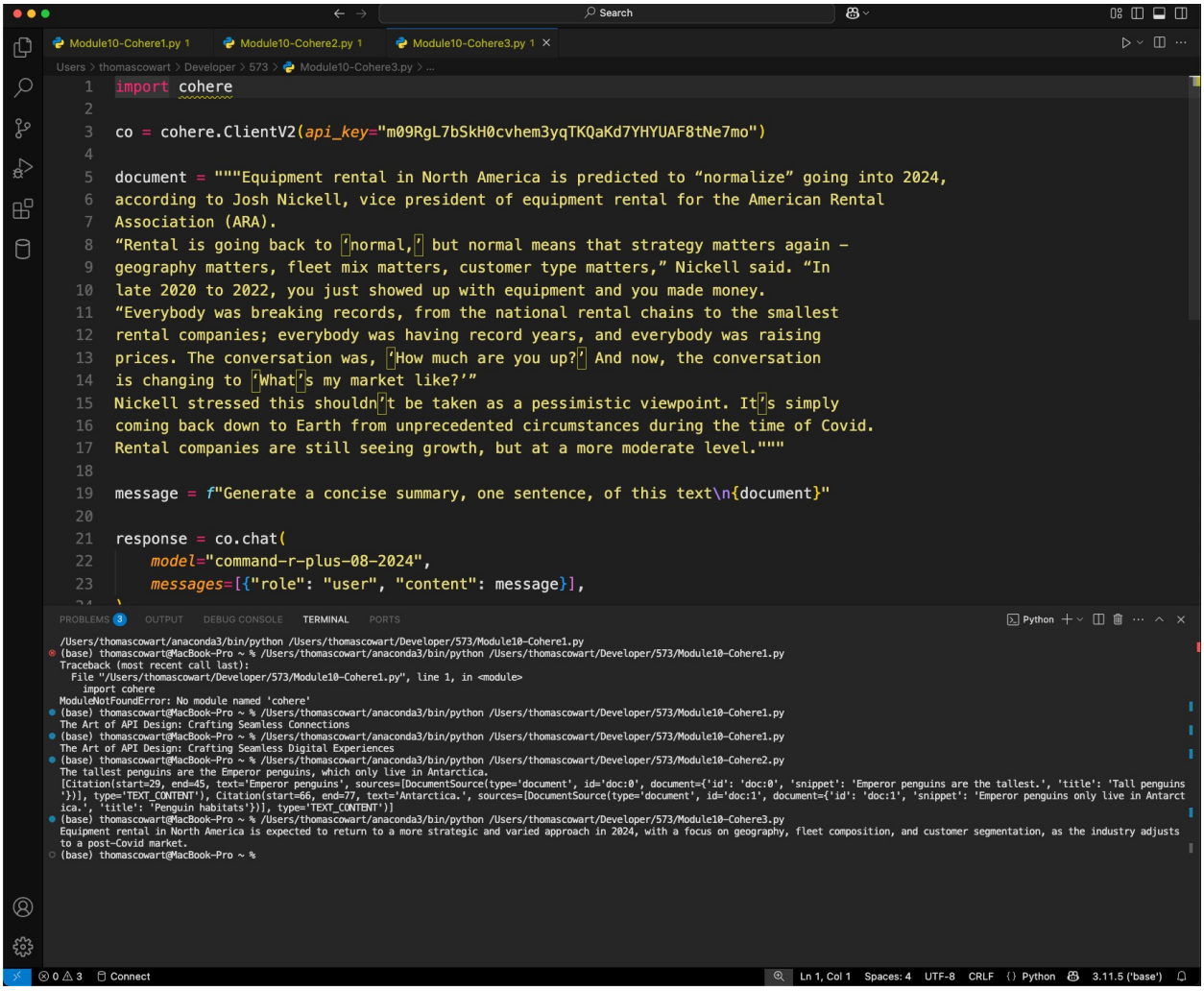
Other chunking methods (like simple, textwrap, NLTK, and spaCy) work with plain text, splitting it into smaller pieces (sentences, words) without worrying about formatting or extraction.

9.



You can extract text, tables, images, links/URLs, annotations/comments, form data, metadata, text structure, and fonts/layout from a PDF using tools like PyPDF2, pdfminer, pdfplumber, tabula, and PyMuPDF.

10.



These programs demonstrate three different Cohere capabilities:

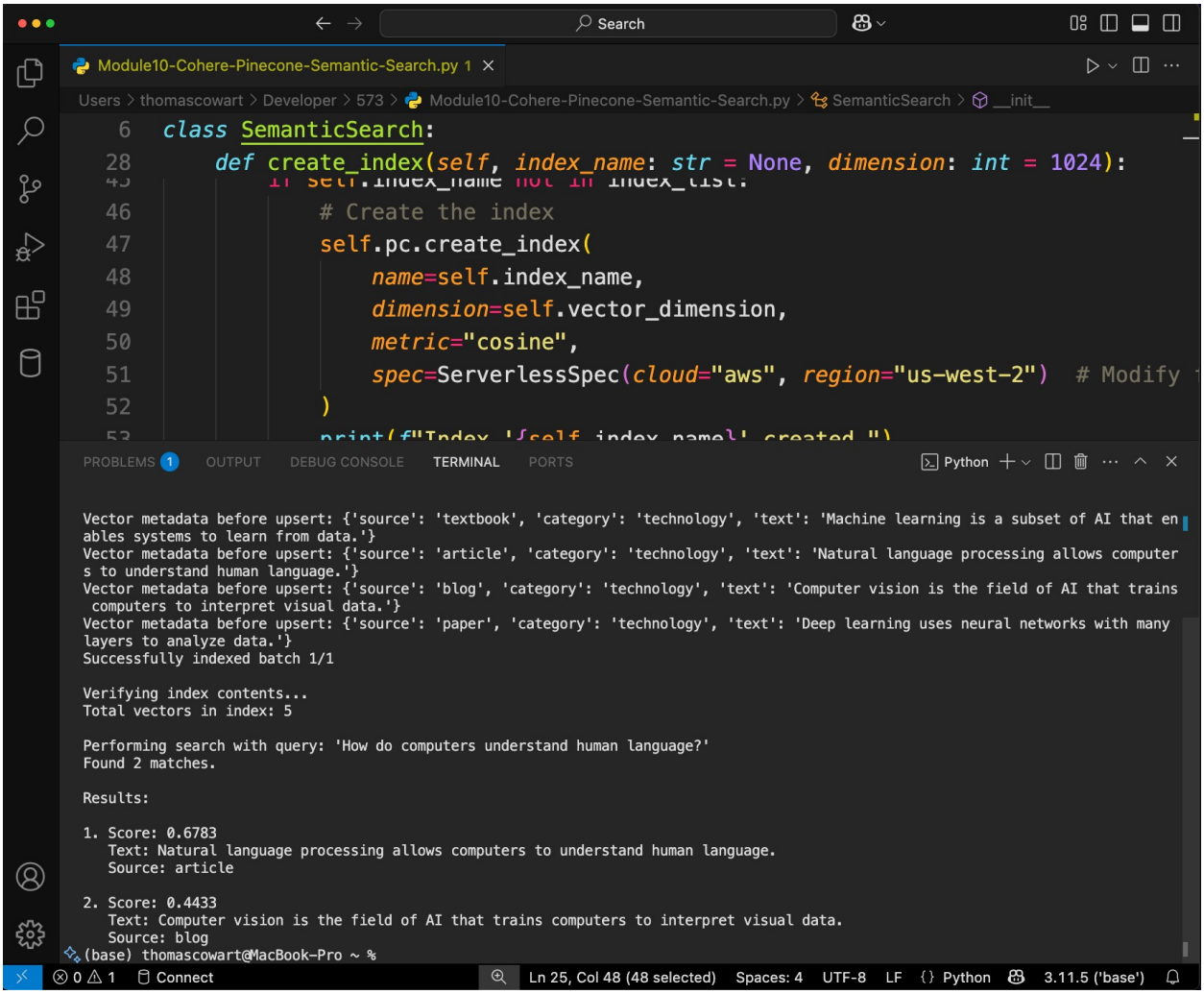
1. Chat-based API: In the first program, it uses the chat model to generate a title for a blog post.
2. Document Retrieval and Question Answering: The second program shows the ability to retrieve documents and use them to answer a user query by providing context from the documents.
3. Text Summarization: The third program generates a concise summary of a provided document.

Why use Cohere over OpenAI APIs?

- Customization: Cohere offers specialized models tailored for tasks like document retrieval and summarization.

- Efficiency: Cohere's API might offer more cost-effective or optimized performance for specific use cases, especially in retrieving and processing documents.
- Model Specialization: Cohere's models might be better for certain applications, such as context-based retrieval or summarization, depending on the task.

11.



Using Pinecone with Cohere combines the power of fast, scalable vector search (Pinecone) with Cohere's language models for enhanced AI capabilities. Pinecone stores and retrieves embeddings (vector representations of text), allowing you to quickly search through large datasets. When integrated with Cohere's models, this enables tasks like semantic search, document retrieval, and personalized recommendations with

high performance and relevance, making the combination ideal for real-time applications that require both powerful search and contextual understanding.