IBM Research

Docling

Get your documents ready for gen AI

–

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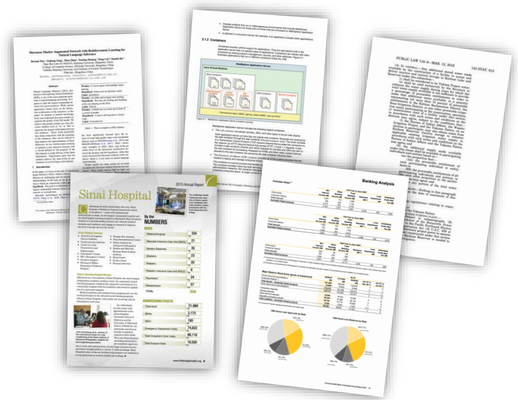
https://tinyurl.com/pydocling

IBM

Introducing Docling



- 🗂️ Parsing of multiple document formats incl. PDF, DOCX, XLSX, HTML, images, and more
- 📑 Advanced PDF understanding incl. page layout, reading order, table structure, code, formulas, image classification, ...
- 🧬 Unified, expressive DoclingDocument representation format
- ↪ Various export formats (Markdown, HTML, JSON)
- 🔒 Local execution for sensitive data and air-gapped environments
- 🤖 Many plug-and-play ecosystem integrations
- 🔍 Extensive OCR support for scanned PDFs and images
- 🥚 Support of Visual Language Models
- 💻 Simple and convenient CLI

```
pip install docling

# a single document to markdown
docling https://arxiv.org/pdf/2408.09869.pdf

# a folder of documents to markdown and json
docling --to json --to md ./inputs/
```

Without Docling...

...it can go bad.

Date syrup (as one of the agricultural wastes) was used to produce bacterial cellulose using Gluconastobacter xylinus. Fourier transform infrared spectroscopy (FTIR), vegetative electron microscopy, and X-ray diffraction were used to determine the structure of bacterial cellulose, cellulose fibers, and crystallinity of the samples (Moosavi an

Silver and gold nanoparticles for [HTML] m

gurovdigital 15 h

lol, over 20 scientific papers now feature the

were incubated with an extract from spores distinctive type. It was concluded that at least integrated at pH 7.0. Peptide was released which established that the coats contained substrate for the lytic enzyme present in spores. Peptide was also released from spore coats of *B. megaterium* by the action of the enzyme from *B. cereus* spores. The lytic enzyme did not attack intact resting spores.

The spore develops in the vegetative cell, which thus becomes a sporangium. It is by no means certain what happens to the vegetative cell wall when the spore is released. In *Clostridium* species it appears that at least part of this structure is retained as an outer membrane around the spore. It is the opinion of some workers that the wall of the sporulating cell forms the exosporium which exists as an outer

part of the sporangial wall was dissolved away to allow release of the spore. It appears likely that the exosporium of *B. cereus* does not have a composition similar to that of the vegetative cell wall, from the results obtained by Dr. J. R.

The spore develops in the vegetative cell, which thus becomes a sporangium. It is by no means certain what happens to the vegetative cell wall when the spore is released. In Clostridium species it appears that at least part of this structure is retained as an outer membrane around the spore. It is the opinion of some workers that the wall of the sporulating cell forms the exosporium which exists as an outer coat around spores of several Bacilus species. Spores of several varieties of B. cereus had exosporia whereas these structures appeared to be absent from spores of B. megaterium and B. subtilis. It seems, however, that in Bacillus species at least, the greater part of the vegetative cell wall is dissolved away before the developed spore is released. If this is true, then soluble components containing the characteristic constituents should appear in the medium during spore release. Culture filtrates from B. cereus organisms at various stages of growth and sporulation were hydrolyzed and the hydrolyzates analyzed for amino sugars and diaminopimelic acid (28). Results showed that a large increase in the concentration of these substances in the culture filtrate occurred during spore release (table 2); they were found to be present in a nondialyzable peptide of the characteristic type. It was concluded that at least part of the sporangial wall was dissolved away to allow release of the spore. It appears likely that the exosporium of B. cereus does not have a composition similar to that of the vegetative cell wall, from the results obtained by Dr. J. R. Norris of Leeds University (personal communication). He treated spores with a highly active preparation of lytic enzyme from B. cereus spores and examined the effect by means of electron microscopy. No evidence of lysis of the exosporium was obtained.

692 12 43

[PDF] res

BRONZE PIECES FROM JEYRAN TEPE, UZBAKI

B SODAEI, H RAHNEMA - researchgate.net

This study is a report of the results of metallographic study of 5 bronze pieces found in Jeyrān Tepe dating back to the Iron

Recovering structured content from PDF

with low-level PDF parsers

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		% of Total			triple inter-annotator mAP @ 0.5-0.95 (%)						
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List-item	185660	17.19	13.34	15.82	87-88	74-83	90-92	97-97	81-85	75-88	93-95
Page-footer	70878	6.51	5.58	6.00	93-94	88-90	95-96	100	92-97	100	96-98
Page-header	58022	5.10	6.70	5.06	85-89	66-76	90-94	98-100	91-92	97-99	81-86
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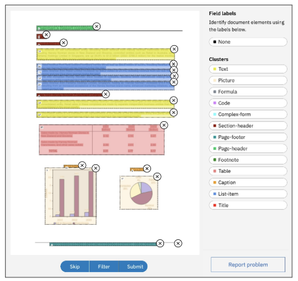

Figure 3: Corpus Conversion Service annotation user interface. The PDF page is shown in the background, with overlaid text-cells (in darker shades). The annotation boxes can be drawn by dragging a rectangle over each segment with the respective label from the palette on the right.

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Preparation work included uploading and parsing the sourced PDF documents in the Corpus Conversion Service (CCS) [22], a cloud-native platform which provides a visual annotation interface and allows for dataset inspection and analysis. The annotation interface of CCS is shown in Figure 3. The desired balance of pages between the different document categories was achieved by selective subsampling of pages with certain desired properties. For example, we made sure to include the title page of each document and bias the remaining page selection to those with figures or tables. The latter was achieved by leveraging pre-trained object detection models from PubLayNet, which helped us estimate how many figures and tables a given page contains.

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[3] https://arxiv.org/

! undesired page headers

KDD '22, August 14–18, 2022, Washington, DC, USA Birgit Pfitzmann, Christoph Auer, Michele Dolfi, A
Nassar, and Peter Staar

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[...]
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[...]

! Tables not understood

! Image content missing

! Line wraps not understood

! Multi-column often breaks order

✓ Very fast and cheap

✗ Incomplete

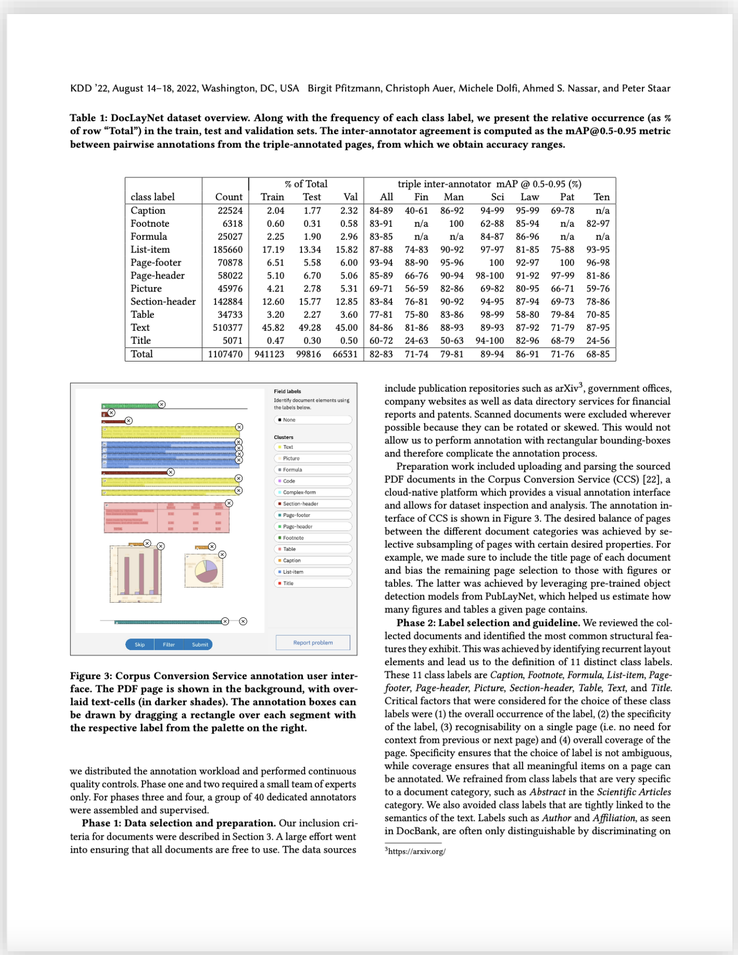
✗ Loss of structure

✗ Noisy

➔ Unfit for most use cases

Recovering structured content from PDF

with Docling



KDD '22, August 14–18, 2022, Washington, DC, USA Birgit Pfitzmann, Christoph Auer, Michele Dolfi, Ahmed S. Nassar, and Peter Staar

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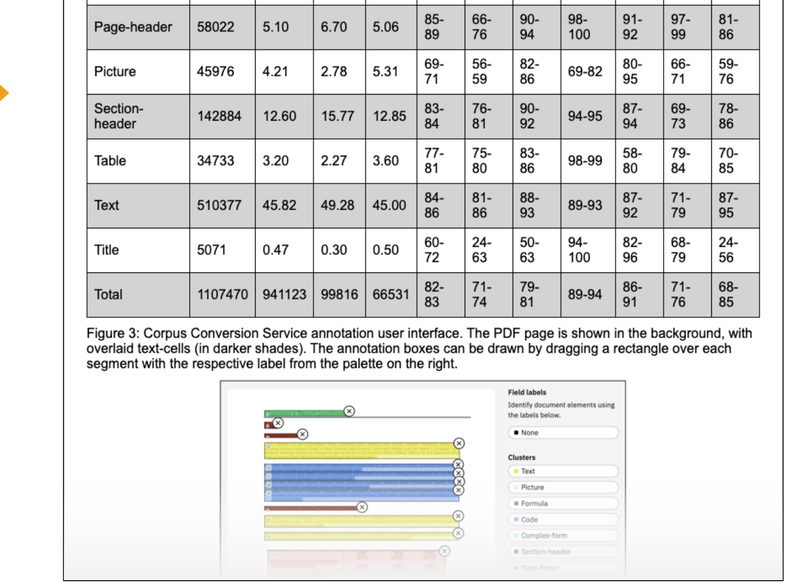

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*results rendered as HTML for visualization purposes

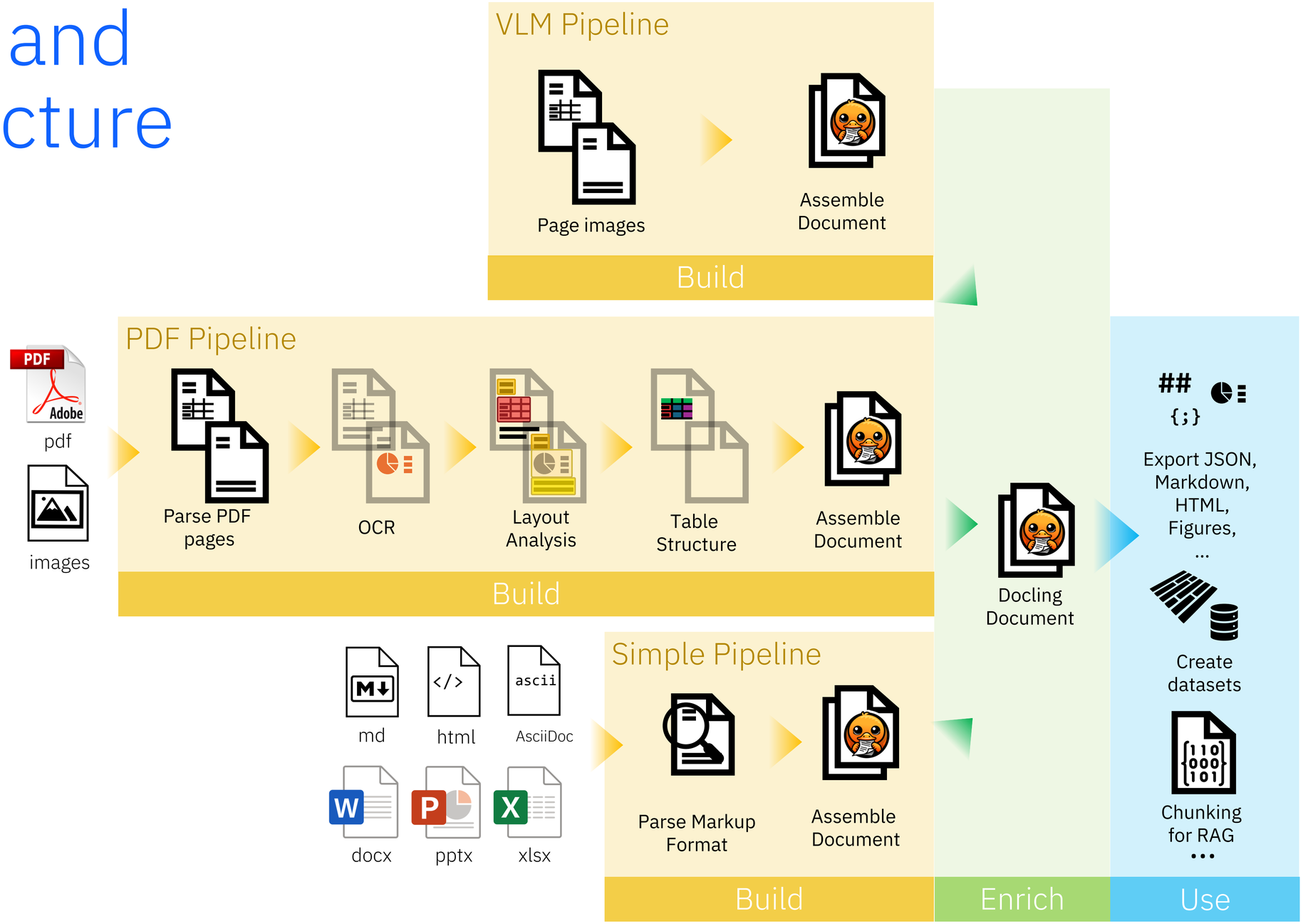
- ✓ Good quality
- ✓ Fast and cheap
- ✓ Fully local operation
- ✓ Structured format output

- ➔ Cost-effective at scale, with consistent representation and high quality

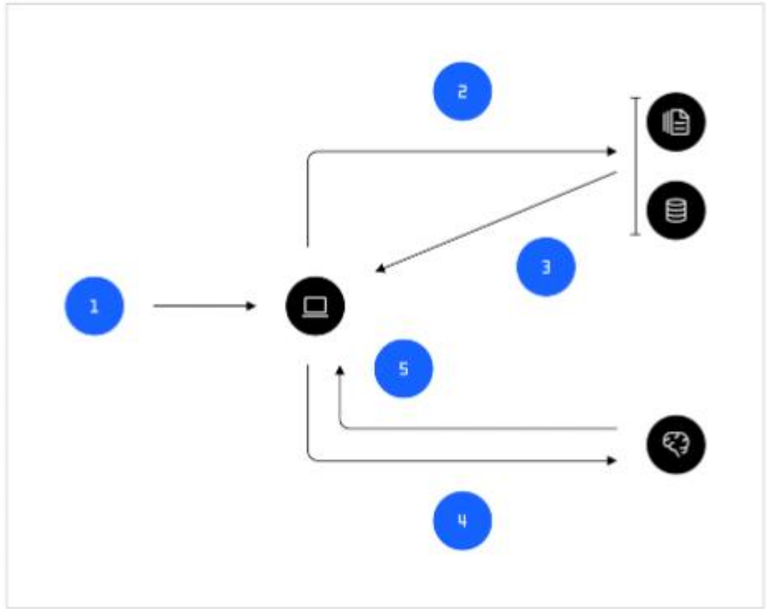
Workshop files

https://tinyurl.com/pydocling

Design and Architecture



Retrieval Augmented Generation (RAG)



1. The user submits a prompt.
2. The information **retrieval** model queries the knowledge base for relevant data.
3. Relevant information is returned from the knowledge base to the integration layer.
4. The RAG system engineers an **augmented** prompt to the LLM with enhanced context from the retrieved data.
5. The LLM **generates** an output and returns an output to the user.

Bad Chunking Example (Fixed-size splitting):

```
Chunk 1: "The company's revenue increased by 25% in Q3"
Chunk 2: "2024 compared to Q3 2023. This growth was driven by..."
```

Problems:

- Critical context (which year?) is split across chunks
- A search for "2024 revenue growth" might miss Chunk 1 entirely
- The model lacks complete information to answer accurately

Good Chunking Example (Semantic-aware):

```
Chunk 1: "Financial Performance Q3 2024: The company's revenue increased by
          25% in Q3 2024 compared to Q3 2023, reaching $1.2B in total sales."

Chunk 2: "Growth Drivers: This exceptional growth was driven by strong
          performance in the enterprise segment, with cloud services
          contributing 60% of the increase..."
```

Benefits:

- Complete, self-contained thoughts
- Clear topical boundaries
- Sufficient context for accurate retrieval
- Natural section breaks preserved

Multimodal RAG

Traditional RAG is limited to text-based use cases such as text summarization and chatbots.
Traditional RAG systems only handle text. But real documents contain:

- **Text**: Paragraphs, lists, headers
- **Tables**: Structured data, financial information
- **Images**: Charts, diagrams, photos, illustrations

Multimodal RAG can use multimodal LLMs (MLLM) to process information
from multiple types of data to be included as part of the external knowledge base used in RAG.
Multimodal data can include text, images, audio, video or other forms.

https://github.com/ibm-granite-community/docling-workshop