DATA+AI SUMMIT
BY databricks

SIMPLIFYING DATA INGESTION FOR LLMs WITH UNSTRUCTURED AND DATABRICKS

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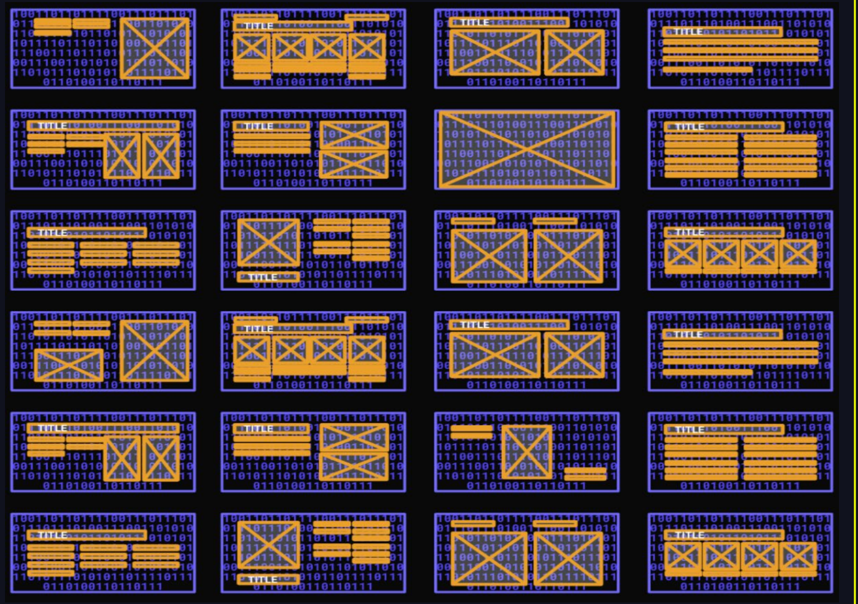
Why use unstructured data?

Unstructured data is a goldmine

90% of enterprise data is unstructured*



- Powerpoints
- Webpages
- Videos
- Meeting notes
- Internal documents
- Emails
- Codebases
- Audio
- Images

*Source: IDC White Paper, Sponsored by Box Inc., "Untapped Value: What Every Executive Needs to Know About Unstructured Data, " Doc. US51128223, August 2023

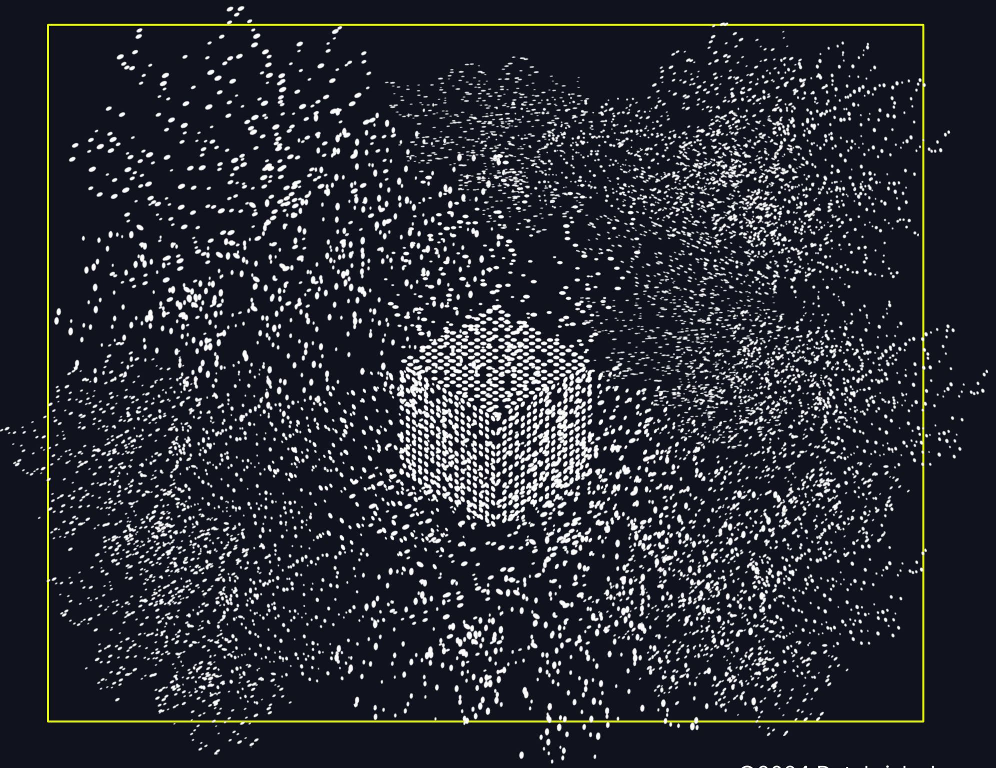
RAG

unstructured data use case #1

- Embed unstructured data into a vector store
- Retrieve relevant unstructured context given a query
- Use unstructured data sources to augment LLM generation of responses
- Allows LLMs to respond with up to date info or context specific language

Embedding Models

unstructured data use case #2

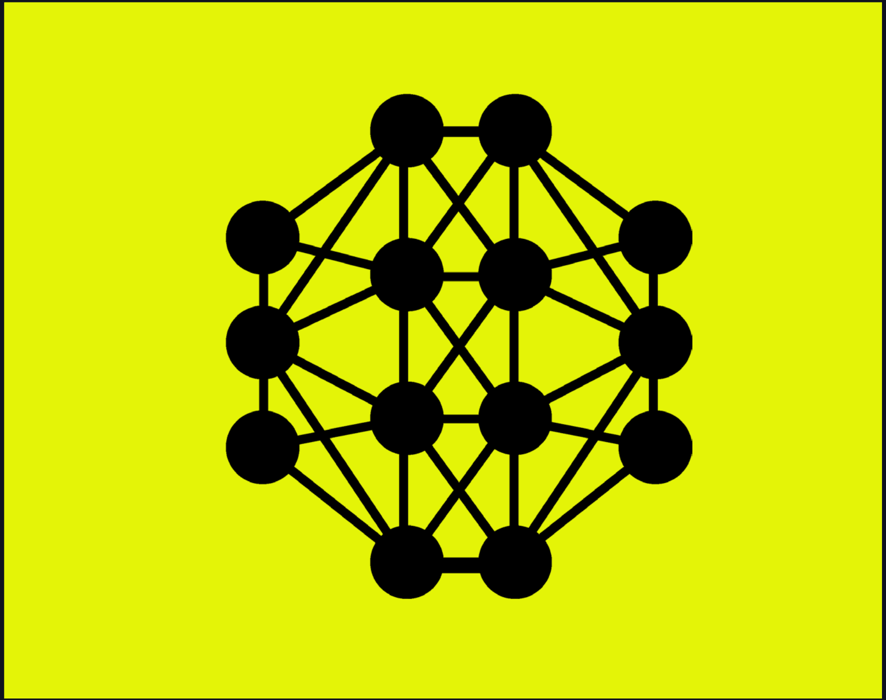


- Improve retrieval by fine-tuning sentence-transformer on internal documents
- Training of re-ranker models
- Paraphrase mining
- Text clustering

Training LLMs

unstructured data use case #3

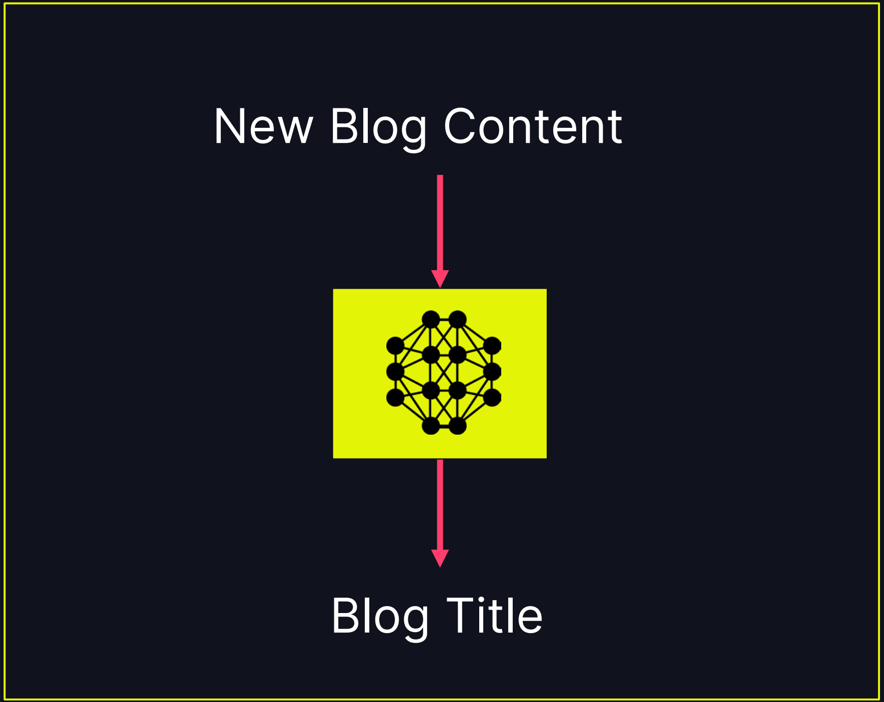
- Instruction Fine Tune (IFT) an LLM to adapt to your use case(s)
- Update language understanding of model with new information or to a new domain with continued pre-training (CPT)
- Train an LLM from scratch on custom dataset with pre-training (PT)



IFT Example (Solar Farm Inc.)

generate high-quality blog titles in your corporate style

- Ingest all corporate blog posts on your platform
- Prepare training dataset:
    - Inputs: “Given the below blog post, generate a blog title. Blog post: {content}”
    - Output: “{blog title}”
- Instruction fine tune a small LLM (e.g. Llama3-8b-instruct)



INGESTING UNSTRUCTURED DATA IS HARD

Example Use Case: Document RAG

HR Documents

- Files in PDF and Docx format
- Thousands of multipage documents
- Documents contain tables
- Some PDFs have been scanned in, don't have easily extractable text.

Reading common file types

Sample Python Code

PYTHON (pypdf)

```python
from pypdf import PdfReader

reader = PdfReader("example.pdf")
number_of_pages = len(reader.pages)
all_text = []
for page in reader.pages:
            all_text.append(page.extract_text())
```

PYTHON (python-docx)

```python
from docx import Document
document = Document("example.docx")
all_text = []
for paragraph in Document.paragraphs:
            all_text.append(paragraph.text)
```

Reading common file types

Sample Python Code

PYTHON (pypdf)

```
from pypdf import PdfReader

reader = PdfReader("example.pdf")
number_of_pages = len(reader.pages)
all_text = []
for page in reader.pages:
        all_text.append(page.extract_text())
```

Doesn't support OCR

How do I read table data?

PYTHON (python-docx)

```
from docx import Document
document = Document("example.docx")
all_text = []
for paragraph in Document.paragraphs:
        all_text.append(paragraph.text)
```

Reads paragraphs instead of pages, we'll need to standardize

UNST
RUCT
URED

Common API for all file types

Supported file types

- .eml
- .html
- .md
- .msg
- .rst
- .rtf
- .txt
- .png
- .jpg
- .tiff
- .bmp
- .heic
- .csv
- .doc
- .docx
- .epub
- .odt
- .pdf
- .pptx
- .tsv
- .xlsx

Reading common file types

Sample unstructured Python Code

PYTHON (unstructured)

```python
from unstructured.partition.pdf import partition_pdf
from unstructured.partition.docx import partition_docx

elements_pdf = partition_pdf(filename="example.pdf")
elements_docx = partition_docx(filename="example.docx")

# the partition function can also detect file type on its own
from unstructured.partition.auto import partition
elements_pdf = partition(filename="example.pdf")
elements_docx = partition(filename="example.docx")
```

Deep Dive, Canonical JSON Schema

How does it all come together?

A Comprehensive Survey of Hallucination Mitigation Techniques in Large Language Models

S.M Towhidul Islam Tonmoy[1], S M Mehedi Zaman[1], Vinija Jain[3,4*], Anku Rani[2], Vipula Rawte[2], Aman Chadha[3,4*], Amitava Das[2]

[1]Islamic University of Technology, Bangladesh
[2]AI Institute, University of South Carolina, USA
[3]Stanford University, USA, [4]Amazon AI, USA
towhidulislam@iut-dhaka.edu

Abstract

As Large Language Models (LLMs) continue to advance in their ability to write human-like text, a key challenge remains around their tendency to “hallucinate” – generating content that

techniques, providing a solid foundation for future research in addressing hallucinations and related phenomena within the realm of LLMs.

1 Introduction

Deep Dive, Canonical JSON Schema

How does it all come together?

A Comprehensive Survey of Hallucination Mitigation Techniques in Large

S.


```
    },
    {
        "type": "Title",
        "element_id": "8ac6079d630b08e395f4e31b55e47c45",
        "text": "A Comprehensive Survey of Hallucination Mitigation Techniques in Large Language Models",
        "metadata": {
            "filetype": "application/pdf",
            "languages": [
                "eng"
            ],
            "page_number": 1,
            "parent_id": "cd1a9758552904f420c70398fec83e81",
            "filename": "sxqzgn.pdf"
        }
    },
    {
        "type": "UncategorizedText",
        "element_id": "10a35358fa45294b3f1b4806ab518827",
        "text": "S.M Towhidul Islam Tonmoy1, S M Mehedi Zaman1, Vinija Jain3,4\u2217, Anku Rani2, Vipula Rawte2, Aman Chadha3,4\u2217, Amitava Das2 1Islamic University of Technology, Banglade
        Institute, University of South Carolina, USA 3Stanford University, USA, 4Amazon AI, USA towhidulislam@iut-dhaka.edu",
        "metadata": {
            "filetype": "application/pdf",
            "languages": [
                "eng"
            ],
            "page_number": 1,
            "parent_id": "8ac6079d630b08e395f4e31b55e47c45",
            "filename": "sxqzgn.pdf"
        }
    },
    {
```

Deep Dive, Canonical JSON Schema

Elements

A Comprehensive Survey of Hallucination Mitigation Techniques in Large Language Models


```json
{
    "type": "Title",
    "element_id": "8ac6079d630b08e395f4e31b55e47c45",
    "text": "A Comprehensive Survey of Hallucination Mitigation Techniques in Large Language Models",
    "metadata": {
        "filetype": "application/pdf",
        "languages": [
            "eng"
        ],
        "page_number": 1,
        "parent_id": "cd1a9758552904f420c70398fec83e81",
        "filename": "sxqzgn.pdf"
    }
},
```

Deep Dive, Canonical JSON Schema

Metadata


```
{
    "type": "NarrativeText",
    "element_id": "ef3aad2e2d1498962c271b767753c6a7",
    "text": "As Large Language Models (LLMs) continue to advance in their ability to write human-like text, a key challenge
    remains around their ten- dency to \u201challucinate\u201d \u2013 generating content that appears factual but is
    ungrounded. This issue of hallucination is arguably the biggest hindrance to safely deploying these powerful LLMs into
    real-world production systems that impact peo- ple\u2019s lives. The journey toward widespread adoption of LLMs in
    practical settings heavily relies on addressing and mitigating hallucina- tions. Unlike traditional AI systems focused on
    limited tasks, LLMs have been exposed to vast amounts of online text data during train- ing. While this allows them to
    display impres- sive language fluency, it also means they are capable of extrapolating information from the biases in
    training data, misinterpreting ambigu- ous prompts, or modifying the information to align superficially with the input.
    This becomes hugely alarming when we rely on language gen- eration capabilities for sensitive applications, such as
    summarizing medical records, cus- tomer support conversations, financial analysis reports, and providing erroneous legal
    advice. Small errors could lead to harm, revealing the LLMs\u2019 lack of actual comprehension despite advances in
    self-learning. This paper presents a comprehensive survey of over thirty-two tech- niques developed to mitigate
    hallucination in LLMs. Notable among these are Retrieval- Augmented Generation (RAG) (Lewis et a
    Retrieval (Varshney et al., 2023), CoNLI (Lei et al., 2023), and CoVe (Dhuliawala et al., 2023).
    troduce a detailed taxonomy categorizing these methods based on various parameters, such as data
    tasks, feedback mechanisms, and retriever types. This classifi- cation helps distinguish the div
    specifically designed to tackle hallucination is- sues in LLMs. Additionally, we analyze the cha
    inherent in these",
    "metadata": {
        "filetype": "application/pdf",
        "languages": [
            "eng"
        ],
        "page_number": 1,
        "parent_id": "ebf237f98f05c4390df1cde93629de8d",
        "filename": "sxqzgn.pdf"
    }
},
```


Abstract

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Deep Dive, Canonical JSON Schema

Metadata in action

Abstract


```
{
    "type": "Title",
    "element_id": "ebf237f98f05c4390df1cde93629de8d",
    "text": "Abstract",
    "metadata": {
        "filetype": "application/pdf",
        "languages": [
            "eng"
        ],
        "page_number": 1,
        "parent_id": "cd1a9758552904f420c70398fec83e81",
        "filename": "sxqzgn.pdf"
    }
},
```



```
 "NarrativeText",
t_id": "ef3aad2e2d1498962c271b767753c6a7",
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```

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Under the hood 1 of 2

Capabilities to produce RAG-Ready data

Connect

- Source
- Destination
- 30+ Today
- BYO

Route

- Fast
- High Res
- Generative
- Third Party APIs

Transform

- Canonical Schema
- Elements
- Reading Order
- Metadata

Under the hood 2 of 2

Capabilities to produce RAG-Ready data

Chunk

- Simple
- Semantic

Embed

- Open AI
- AWS Bedrock
- OctoML
- Databricks Embedding Endpoint
- BYO

Synchronize

- Write data to store of your choice
- Databricks Volumes
- Databricks Delta Tables
- Multiple Vector DBs

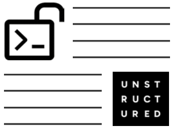
Product Offerings

Open Source, Commercial API, Enterprise Platform

Prototype Grade

Production Grade

Open Source



Perfect for prototyping.
Build your own preprocessing pipeline to transform 25+ document types (PDF, Word, PowerPoint) to JSON.

Commercial API

For single-batch, production-grade document preprocessing without worrying about any custom code to get started.

Commercial Platform

For enterprises and high-growth companies looking to automatically and continuously retrieve, transform, and stage their data for LLMs.

WHAT ABOUT SCALABILITY?

SCALING UNSTRUCTURED

3 APPROACHES FOR 3 PRODUCTS

Unstructured OSS	Unstructured API	Unstructured Platform
• Stateless • Containerized Version Available • BYO dependency management and scalability • Can run in CPU only mode	• Stateless • Horizontally auto scaling Azure & AWS Marketplaces • Horizontally auto-scaling Unstructured SaaS offering • Improved performance on tables, OCR and natural reading order	• We take care of everything • Horizontally auto-scaling Unstructured SaaS offering • VPC Option Available • Kubernetes Underpinned • Splits large documents into multiple pages and scales instances as required Me too!

SCALING W/ UNSTRUCTURED OSS ON

distributed document ingestion

PYTHON (pdf ingestion)

```python
@F.udf("string")
def read_pdf_file(path : str) -> str:
  # Partition the single pdf file (read as binary)
  elements = partition_pdf(file=io.BytesIO(path)) # unstructured’s built in pdf parsing
  # Convert all of the returned elements into a json string
  return elements_to_json(elements)

proc_files = (
  spark
  .read
  .format("binaryFile")
  .option("pathGlobFilter","*.pdf") # Only read the pdf files
  .load(f"/Volumes/{CATALOG}/{SCHEMA}/{DOCS_VOLUME}")
  .withColumn("elements_json", read_html_file("content"))
)
```

SCALING W/ UNSTRUCTURED OSS ON

distributed document chunking

PYTHON (chunking w/ table extraction)

```
@F.udf(ArrayType(StructType([
  StructField("content", StringType(), True), StructField("category", StringType(), True),
  StructField("char_length", IntegerType(), True), StructField("chunk_num", IntegerType(), True)
])))
def get_chunks(elements_json : str, max_characters : int, new_after_n_chars : int) -> list:
  elements = elements_from_json(text=elements_json)
  chunks = chunk_elements(elements, max_characters=max_characters, new_after_n_chars=new_after_n_chars)
  # Iterate through the chunks, keep HTML if it is a table else just keep the text.
  ret = [
      {
          "content" :  _chunk.text if (_chunk.category != "Table") else _chunk.metadata.text_as_html,
          "chunk_num" : i,
          "category" : _chunk.category
      } for i,_chunk in enumerate(chunks)
  ]
  return ret

proc_files_chunked = (proc_files.withColumn("chunks",get_chunks(F.column("elements_json"), F.lit(1500), F.lit(500))))
```

SCALING W/ UNSTRUCTURED API ON

one and done

PYTHON (pdf ingestion)

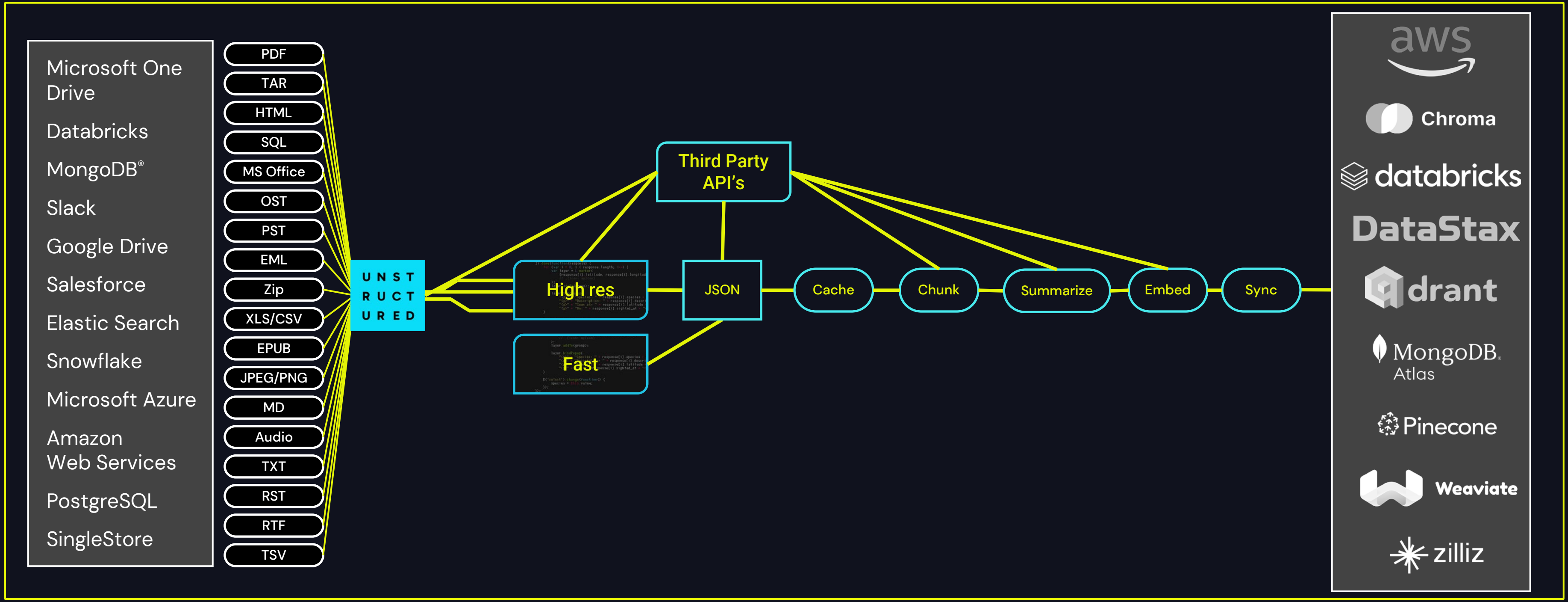
```python
@F.udf("string")
def distributed_unstructured_partition(bin : bytes, fn : str) -> str:
  client = UnstructuredClient(api_key_auth=API_KEY,server_url=API_URL)
  _file = shared.Files(content= bin,file_name=fn)
  req = shared.PartitionParameters(files=_file, strategy="auto")
  try:
      resp = client.general.partition(req)
  except SDKError as e:
      return json.dumps({"error" :  str(e)})
  return json.dumps(resp.elements)

files = (
  spark
  .read
  .format("binaryFile")
  .option("pathGlobFilter","*.pdf") # Only read the pdf files
  .load(f"/Volumes/{CATALOG}/{SCHEMA}/{DOCS_VOLUME}") # Load from databricks volume
  .withColumn("partitioned", distributed_unstructured_partition(F.col("content"), F.col("path")))
)
```

WHAT'S NEXT?

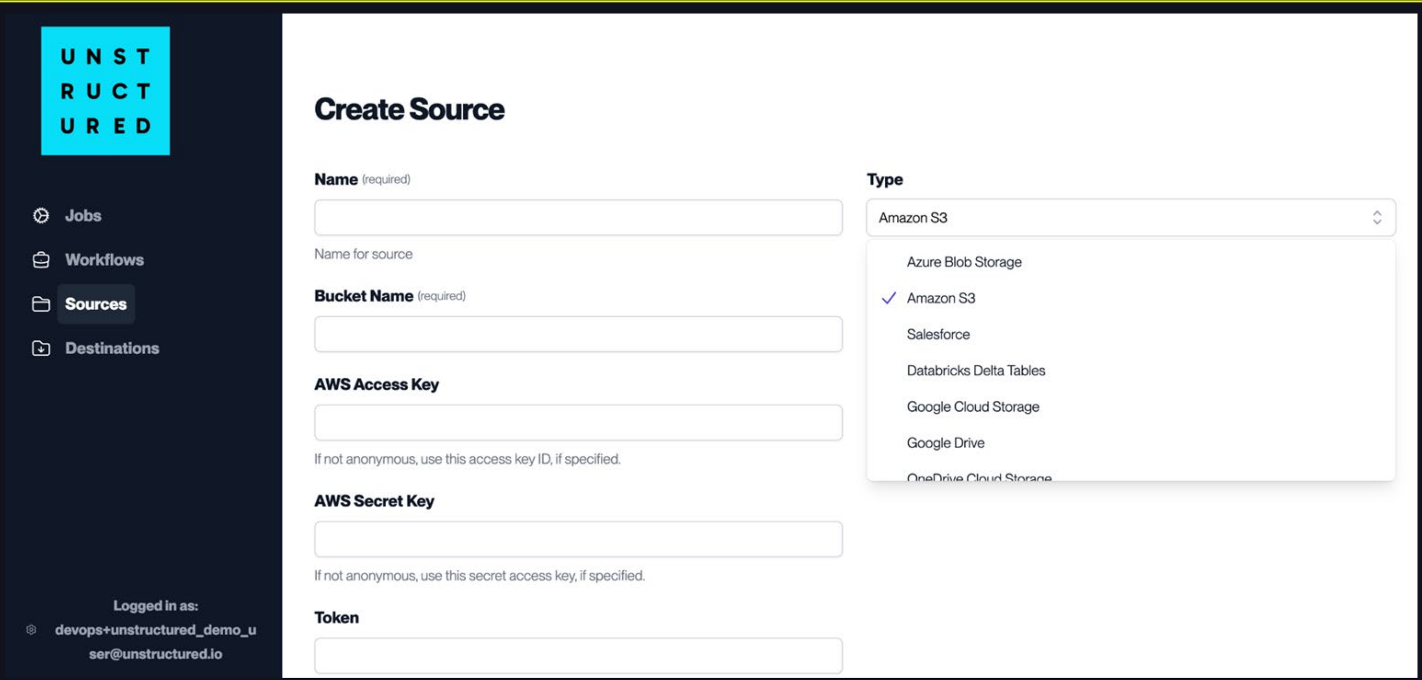
End-to-End RAG pipelines

Unstructured Enterprise Platform



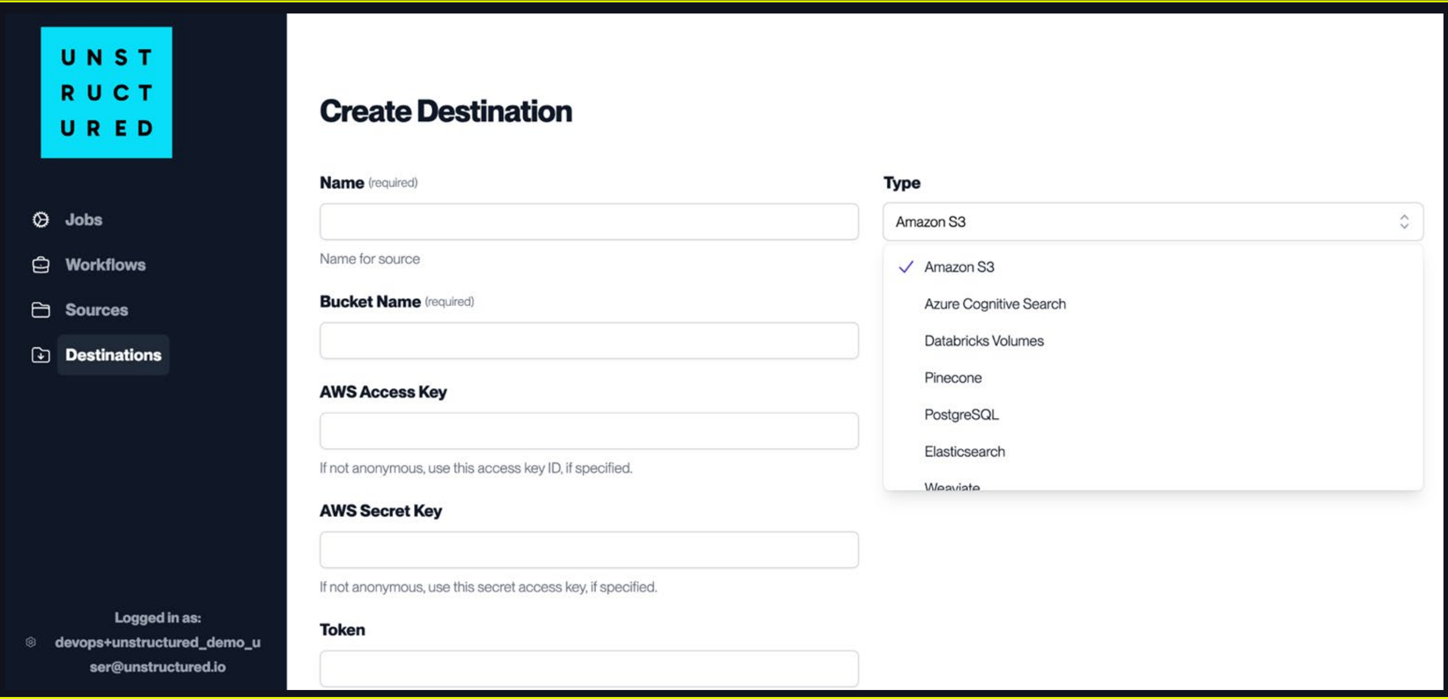
Platform

Source Connectors



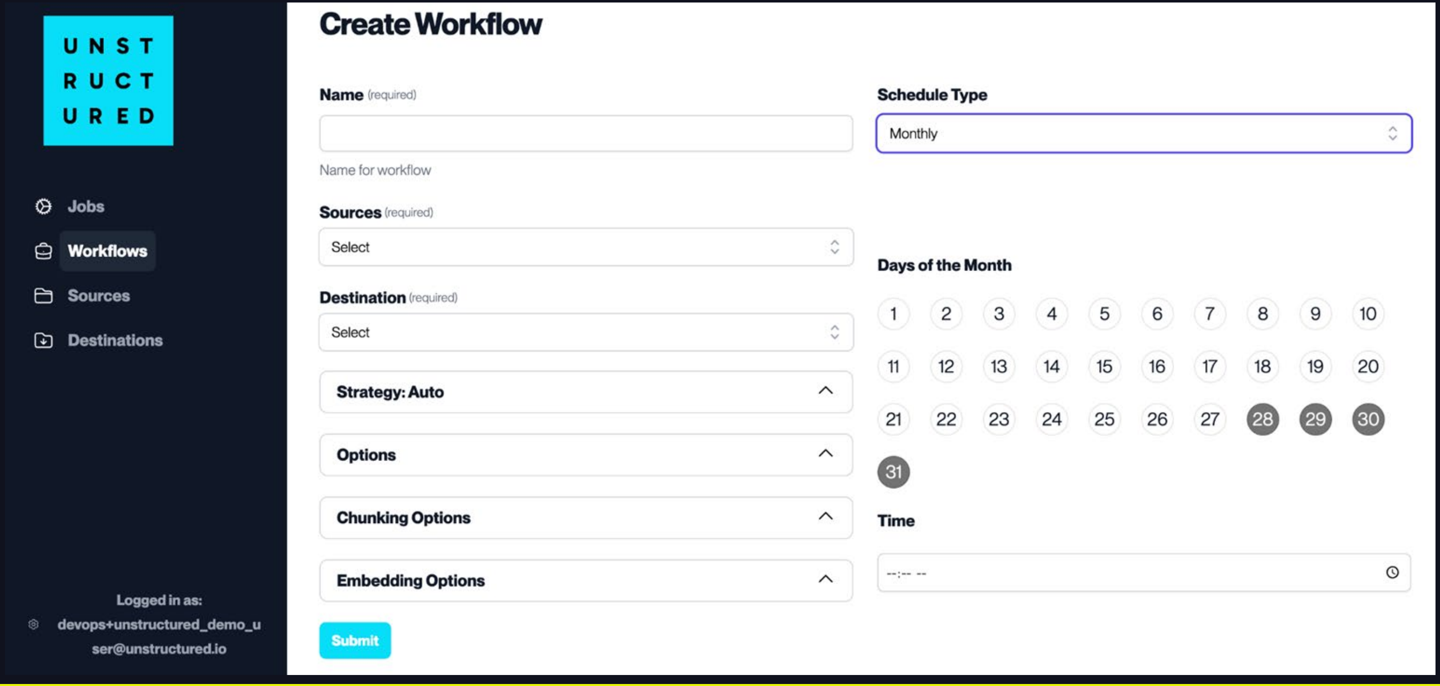
Platform

Connectors



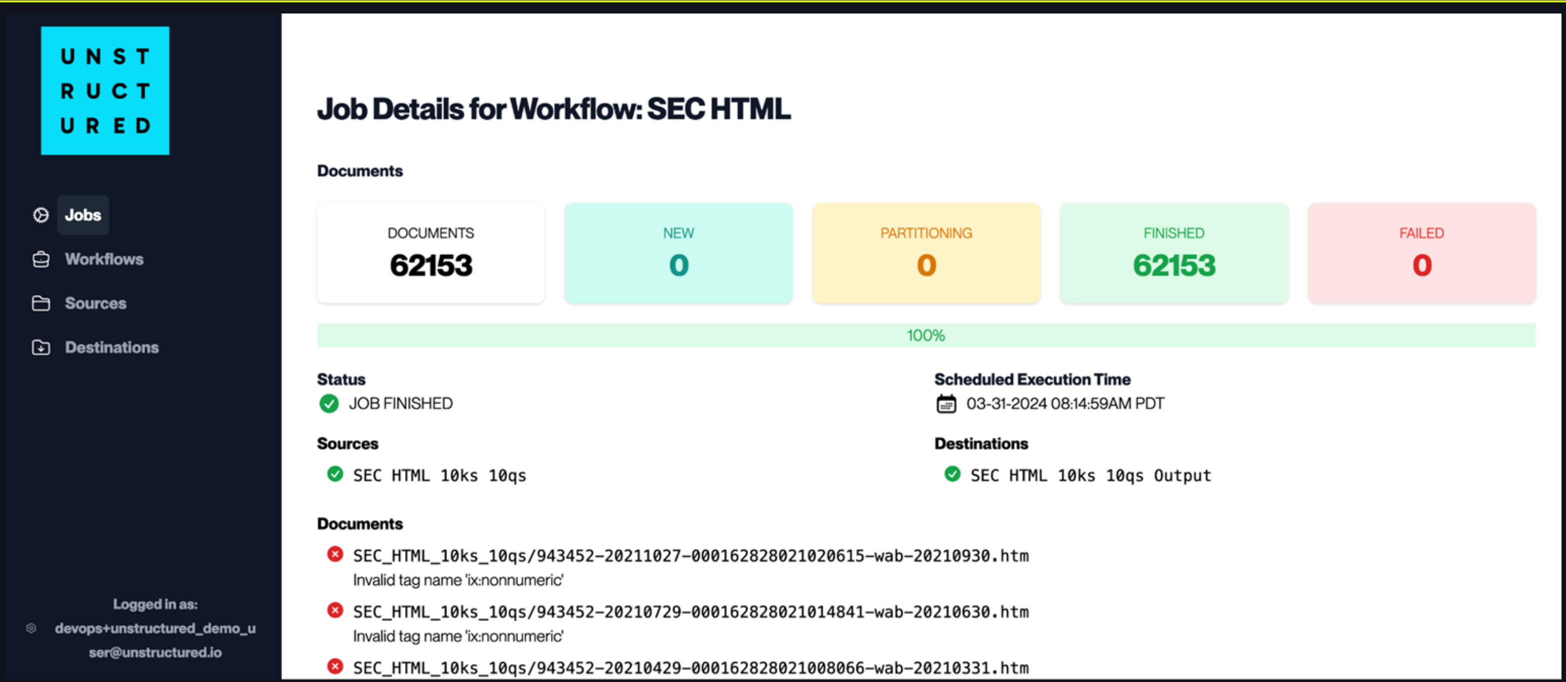
Platform

Workflows



Platform

Jobs



Check out end-to-end RAG demo

Databricks dbdemos llm -rag-chatbot

- End-to-end demo of RAG using unstructured, Databricks Vector Search, and DBRX (in the advanced section)
- Ingests Databricks ebooks and creates a chatbot interface to facilitate asking questions
- Code is re-usable and easily imported into your databricks workspace

Try this demo in your workspace!

Run the following in your notebook:

License | Notice

```
%pip install dbdemos
```

```
import dbdemos
dbdemos.install('llm-rag-chatbot')
```

https://notebooks.databricks.com/demos/llm-rag-chatbot/index.html

THANK YOU