# Introduction to Parsing in Retrieval Augmented Generation (RAG)

Yogesh Haribhau Kulkarni



### Outline

Introduction



### Parsing is the key

(Ref: Key to RAG Success: Document Parsing Explained - EyeLevel )



### Document Parsing: The Foundation of RAG

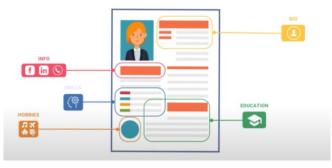
- Parsing is the first step in any RAG pipeline.
- ▶ Bad parsing undermines even the best RAG strategies.
- Garbage in, garbage out: poor inputs = poor outputs.
- Many overlook parsing in favor of flashy AI tools.
- Without good extraction, nothing else matters

- Most language models require clean, structured text.
- RAG applications depend on text quality from source docs.
- Advanced RAG still fails without reliable input.
- Models can't fix broken, messy data.
- Real-world systems have failed due to poor parsing.



### What is Document Parsing?

- ▶ Converts formats like PDF, DOCX, HTML into usable text.
- ▶ Extracts meaningful content for language model input.
- ▶ Cleans, structures, and normalizes the data.
- Essential step before chunking or embedding.
- Involves handling many formats and edge cases.



(Ref: Key to RAG Success: Document Parsing Explained - EyeLevel )



### Common Misconceptions

- ► Engineers often ignore parsing during development.
- ▶ Focus tends to be on model tuning or retrieval logic.
- Parsing is wrongly assumed to be solved or trivial.
- Most systems lack formal evaluation of parsers.
- ▶ Homemade or ad-hoc solutions dominate practice.



### The Reddit Survey Insight

- Survey on LangChain subreddit revealed no consensus.
- ▶ 57 replies yielded 30+ different parsing techniques.
- Most users hacked together informal solutions.
- ▶ Few performed proper parser evaluation or comparison.
- Highlights need for standardized testing and benchmarking.



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(Ref: Key to RAG Success: Document Parsing Explained - EyeLevel )

### Popular Parsing Tools Compared

- PyPDF well-known, older, basic PDF extraction.
- ► Tesseract OCR-based, handles scanned documents.
- ► Unstructured handles messy formats, layout-aware.
- ► Tools vary widely in output quality and reliability.
- Choice depends on document type and project needs.

- Start by identifying your document types.
- Evaluate parsers with real-world examples.
- Compare outputs side by side.
- ► Look for structural fidelity, cleanliness, completeness.
- ▶ Test rigorously don't rely on "it seems to work".



### Real-World Example: Medical Bill

- Parsing tested on de-identified medical bill.
- Chosen for layout complexity and format irregularities.
- Shows strengths and weaknesses of each parser.
- Realistic example of what RAG apps encounter
- Highlights need for resilient parsing strategies.





### Limitations of PyPDF

- PyPDF ok for texts but struggles with complex formats like tables.
- ▶ It failed to extract key data from real-world docs.
- Parsing tables often results in empty or broken content.
- ▶ Not due to PyPDF's fault—PDFs are inherently hard to parse.
- ▶ Many PDFs use inconsistent encoding and layouts.





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### Tesseract OCR: Strengths and Weaknesses

- ► Tesseract uses image-based OCR to extract text.
- Better at recognizing tables than PyPDF.

Grant, Victoria

5436 S. Trent street PHONE: 818 6543876

- Still introduces errors in column alignment.
- Column headers often get merged or misread.
- ▶ OCR also introduces spelling mistakes (e.g. "Cove" vs. "Code").

Ontario, CA 91761 DOB: 05/16/1992

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TECHNICAL IMAGING PROCEDURES AND BILLINGS

Technical Component, (Imaging) performed by: Dr. Vince

| EXAM DATE | PROC. cove| DESCRIPTION '| MOD | B.PART L Dx 1f AMOUNT |
7652 Central Street , Montclair CA 91763
11/17/2022 | 72144 MRI NECK SPINE W/O DVE TC CSPINE M54.2 \$ 1,600.00
11/17/2022 | 72144 MRI LIMBAR SPINE W/O DVE TC LSPINE M54.5 \$ 1,600.00





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### Challenges with OCR Outputs

- ▶ Language models must infer structure from broken text.
- ▶ Humans can "guess" meaning—models may not.
- Noisy extractions increase risk of incorrect answers.
- Inconsistent column separation confuses models.
- Clean layout is crucial for reliable RAG responses.



### Unstructured: A Common Default

- ▶ Popular choice 'Unstructured' company; default in LangChain integrations.
- ▶ Handles layout better than OCR in some cases.
- Still suffers from column misalignments.
- Model must rely on context instead of structure.
- ▶ Reasonable quality, but far from perfect.





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### Parsing Tradeoffs: Model vs. Parser

- ▶ Many teams focus on improving the model first.
- Upgrading the parser might yield better gains.
- Better input can reduce model burden.
- ▶ Smaller or older models benefit more from clean text.
- Strong parsing reduces reliance on inference tricks.



### LlamaParse: Cleaner Table Extraction

- Developed by LlamaIndex, supports markdown output.
- ▶ Clearly separates rows and columns with pipes.
- Markdown format improves model interpretability.
- Some formatting quirks but largely usable.
- Outperforms other parsers in structural clarity.





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### X-ray Parser: Multimodal Approach

- Combines vision models with grounding strategies.
- Detects tables and layout visually before parsing.
- Converts visual structure into usable text format.
- ▶ Produces reliable and model-friendly outputs.
- ▶ Especially effective on visually complex documents.

```
SUMMARY BILL OF ALL CHARGES
    "summary": "The following table contains details of technical
                                                                                      MAGINO
imaging procedures and billings performed by Dr. Vince at the
University Imaging Center. It includes exam date, procedure code,
description, modifier, body part, diagnosis, and amount."
                                                                                                                       ALWAYS REFERENCE PATIENT IS
    "AMOUNT": "$1,600.00".
    "B.PART": "CSPINE",
                                                                                     EXAM DATE PROC. CODE
     "DESCRIPTION": "MRI NECK SPINE W/O DYE",
    "DX": "M54.2",
                                                                                                                       CSPINE MSA.2 $ 1,600.00
LSPINE MSA.3 $ 1,600.00
    "EXAM DATE": "11/17/2022",
    "MOD": "TC",
    "PROC. CODE": "72141"
                                                                                     Professional Commonant (Englishes Report) Intercreted by Dr. Vince
    "AMOUNT": "$1,600.00".
                                                                                      19/17/2002 72341
     "B. PART": "LSPINE",
    "DESCRIPTION": "MRI LUMBAR SPINE W/O DYE",
    "DX": "M54.5",
    "EXAM DATE": "11/17/2022".
     "MOD": "TC",
     "PROC. CODE": "72148"
                                                                                         $4,400.00
```



### Table Extraction Comparison

- PyPDF fails with complex tables.
- Tesseract detects tables but mangles headers.
- Unstructured does OK, but not perfectly.
- LlamaParse gives clean markdown tables.
- X-ray produces structured, grounded output.

### X-Ray

UNIVERSITY IMAGING CENTER Billing Statement Patient: Victoria Grant Date of Service: November 17, 2022 Provider: Dr. Vince Total Amount Due: \$4,400 Description of Services: 1. MRI Procedure - Technical Component 2. MRI Procedure - Professional

Component Notice of Personal Injury Lien: This billing statement includes a notification to Frost Law regarding the assignment of a personal injury lien related to an accident that occurred on December 13, 2022. All rights to the charges listed in this statement have been transferred to the University Imaging Center. Please remit payment to the University Imaging Center. For any

questions or further correspondence,

contact us at the provided address

## Unstructured

TAX ID: 0893765213 PLEASE REMIT PAYMENT TO: 7835 KESTER AVE SUITE 345 VAN NUYS CA 91405 PRE 987354 Grant, Victoria 5436 S. Trent street Ontario, CA 91761 818 654 3876 05/16/1992 Dr. Vince 7652 Central Street , Montclair CA 91763 Dr. Vince 7652 Central Street . Montclair CA 91763

TAX ID: 0893765213 PLEASE REMIT PAYMENT TO: 7835 KESTER AVE SUITE 345 VAN NUYS CA 91405 PRE 987354

818 654 3876 05/16/1992 Dr. Vince

MOD B. PART Dx AMOUNT

EXAM DATE | PROC. CODE DESCRIPTION MOD B. PART DX AMOUNT 7652 Central Street , Montclair CA

11/17/2022 72141 MRI NECK SPINE W/O 11/17/2022 72148 MRI LUMBAR SPINE W/O DYE | To LSPINE M54.5 | \$

SUMMARY BILL OF ALL CHARGES Precise ImagingIMAGING

LlamaParse

| |TAX ID|043620652| | | | | | BILLING STATEMENT| | | PLEASE REMI PAYMENI IQ:TAX ID: 08937652131 | | | | PLEASE REMIT PAYMENT TO: | |

| | | | Patient ID|Statement |BILLING@PRECISEMRICOM3| | | | | |6710 KESTER AVE SUITE 126|

17835 KESTER AVE SUITE 3451 | | | VAN NUYS CA 91405 VAN NUYS,

| | | | PRE

987354PRE79617211/29/20221 |DARBYSHIRE, JUSTIN JOHN| | | |



### Narrative + JSON: A Guided Format

- Output begins with a narrative summary for context.
- ▶ Clearly explains the purpose and structure of the table.
- ▶ Follows with a clean JSON representation of table data.
- ► Format: cell-by-cell structured, easy to interpret.
- ▶ "Tell-then-show" approach improves model comprehension.



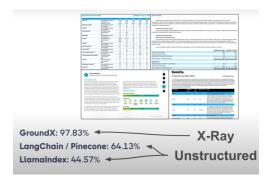
### Why Output Format Matters

- Parsers may extract the same data, but format it differently.
- Output style can strongly affect model performance.
- JSON and markdown help structure information clearly.
- ► Human-readable structure supports better inference.
- ▶ Cleaner format = better grounding for language models.



### Impact of Parsing Quality

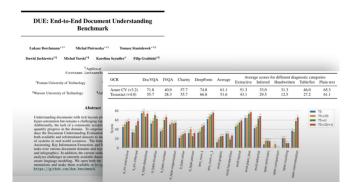
- ▶ We ran the same RAG pipeline over identical documents.
- ▶ Different parsers resulted in drastically different performance.
- ▶ Main variable: parsing quality—not model or retriever.
- ▶ Shows how foundational parsing is to good RAG results.
- ▶ A poor parser can undermine even advanced models.





### Benchmark Setup (Clarified)

- LlamaIndex: Used PyPDF (not LlamaParse).
- ► LangChain + Pinecone: Used Unstructured.
- ► **GroundX**: Used X-ray with vision + grounding.
- ▶ All pipelines ran the same questions on same documents.
- Parser choice significantly influenced accuracy.





#### Future Test Considerations

- Results likely to improve if LlamaParse replaces PyPDF.
- Parsing upgrades often outperform model upgrades.
- ► Models can only reason with what they're given.
- Better structured data = better answers, less guessing.
- Parsing is the cheapest way to level up your RAG stack.

### Parsing Alone Can Move the Needle

- ► Academia confirms: changing only the parser impacts performance.
- ▶ Benchmark: same RAG system, different parsers → up to 20-point difference.
- Parser quality matters more than fancy downstream techniques.
- Quick wins: swap out low-quality parsers before tweaking your RAG logic.



### Document Context is Crucial

- ► Not all documents are created equal.
- ▶ Scientific papers, 10-Ks, clinical notes all behave differently.
- Choose a parser suited to your specific domain.
- No single parser wins for all use cases.



### Picking a Parser: A Two-Pronged Approach

- 1. Vibe check: Run your data through multiple parsers. Look at the outputs.
- 2. **End-to-end eval**: Keep the RAG system constant, vary only the parser, then compare results.

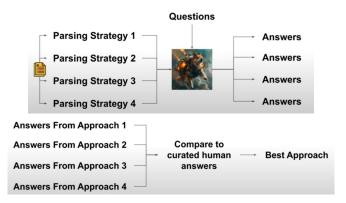
"Your brain is the best model—start with your eyes."





#### How to Run an End-to-End Evaluation

- ▶ Change one component: the parser.
- ▶ Keep the rest of the RAG pipeline fixed.
- ▶ Feed questions through each parser's output.
- ► Compare generated answers to ground truth.
- ▶ Labor-intensive, but the most reliable evaluation method.





#### Evaluation

### Auto-Eval: A Helping Hand

- Start with human-generated QA pairs (ground truth).
- Use LLMs to compare parser outputs to ground truth answers.
- Helps scale eval, but still requires initial human input.
- ► Avoids the trap of "models grading their own homework."

### Alternative Eval: ELO Ranking

- Useful when answers are subjective or non-falsifiable.
- ► Compare outputs pairwise: "Which one is better?"
- Rank parsers using ELO-style systems (used in chess).
- Great for stylistic or qualitative tasks.



### Final Takeaways

- Parsing is foundational. Bad parsing = bad RAG, no matter the model.
- ► There is no one-size-fits-all parser.
- Evaluate in context. Use real documents and real questions.
- Combine human intuition with structured evals.
- Opportunities exist. Big gap in parser testing and tooling.

- Parsing is hard, but absolutely critical.
- Tools like LlamaParse,
   Unstructured, and X-ray are changing the game.
- Try multiple parsers and test thoroughly on your data.
- ▶ Don't trust models to validate their own output.
- Huge room for innovation in parser evaluation and automation.



### Thanks ....

- Search "Yogesh Haribhau Kulkarni" on Google and follow me on LinkedIn and Medium
- ▶ Office Hours: Saturdays, 2 to 5pm (IST); Free-Open to all; email for appointment.
- ► Email: yogeshkulkarni at yahoo dot com

 $\label{eq:condition} $$ (https://www.linkedin.com/in/yogeshkulkarni/, QR by Hugging Face QR-code-Al-art-generator, with prompt as "Follow me") $$$ 





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