

DOCUGAMI

The Document Engineering Company

LangChain Webinar: Lessons from Deploying LLMs with LangSmith

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Topics

- 1. Intros
- 2. Real-World Challenges using LLMs with Documents
 - i. Real documents are more than flat Text
 - ii. Documents are Knowledge Graphs
 - iii. Building Complex Chains with the LangChain Expression Language
 - iv. Debugging Complex Chain Failures in Production
- 3. Summary: End to end LLM Ops
 ... deploy / run / trace / correct / finetune / repeat

Who we are...

- Generative AI for Business Documents. Founded 2018.
- Leverage open source and our own LLMs trained on millions of business documents to create a full XML data representation of complex documents in their entirety, delivering immediate value to frontline business users.
- Document as data can be used to generate insights and reports, create new documents, or drive lineof-business applications. Free trial at www.docugami.com/trial
- Customers in many sectors, including insurance, real estate, health, professional services.



Jean Paoli
Co-founder, CEO
Pioneer in document engineering;
co-creator of XML, .docx, .xlsx, .pptx;
started four \$1B+ businesses at Microsoft



Taqi Jaffri
Co-founder, Head of Product
Principal Product Manager at
Microsoft; co-created the Al driving
Microsoft presence in physical stores.



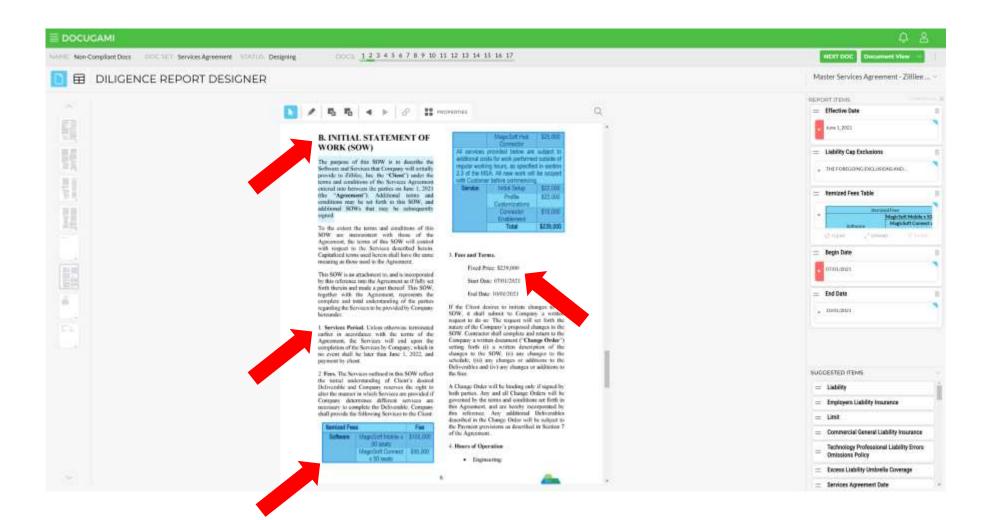
Mike Palmer
Co-founder, Head of Technologies
Senior engineering manager at
Microsoft; co-created Microsoft
InfoPath.



Zubin Wadia Product ManagerMaking documents matter to people and systems – 100+ products over 20 years. MIT, ImageWork, CiviGuard.

Challenge 1: Real documents are more than flat text

Real Documents are Structurally Complex: Headings, Lists, Tables, Headers/Footers, Complex Reading Orders, Figures, etc.

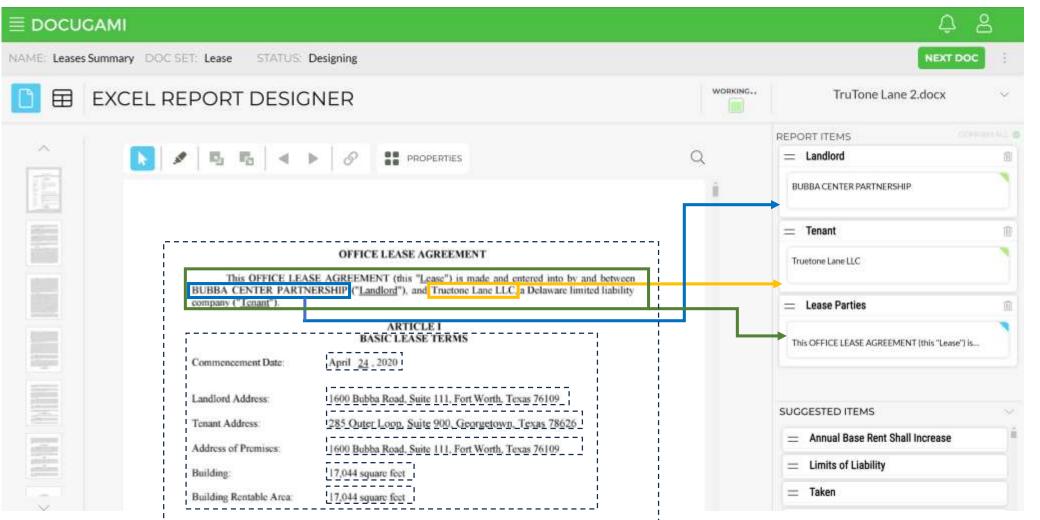


Mitigations:

- Structurally chunk the document to find structural elements.
- 2. Stitch together reading order flow with language models.
- 3. Sub-chunk for RAG using document structural elements rather than simple tiling or text splitting.

Challenge 2: Documents are Knowledge Graphs

Document structures and spatial relationships contain semantics that are often lost in simple text-based retrieval



Mitigations:

- 1. XML hierarchical
 Knowledge Graph
 representation for
 inherent perdocument
 semantics added to
 vector store for
 RAG
- 2. Schema normalization across sets of similar documents

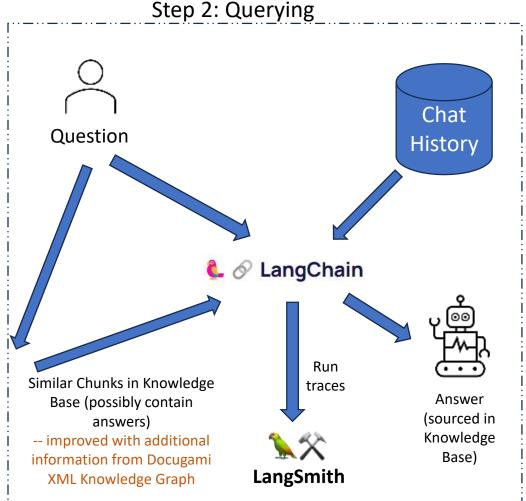
Example XML hierarchical Knowledge Graph

Represents structural relationships as well as per-chunk semantic labels

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                          The above named parties desire to engage in discussions regarding a potential agreement or other transaction between the parties (the "Purpose"). In connection with such discussions, it may be necessary for the parties to d
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Retrieval Augmented Generation (RAG) w/ Semantic Chunk Metadata from Docugami XML

Step 1: Indexing / Ingestion Vector DB offers fast lookup of Data Loader reads chunks text from semantically Knowledge Base similar to any and creates chunks given string, e.g. a question **Embedding Model Vector DB** converts chunks to embeddings Knowledge Base e.g., business documents Metadata from Docugami XML

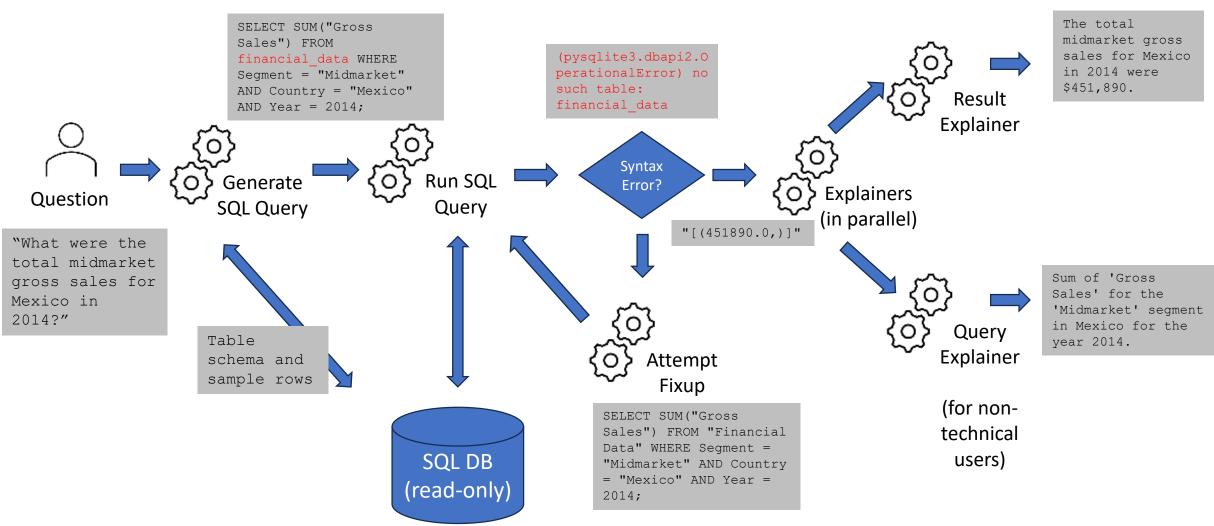


Challenges 1 & 2 CODE WALK-THROUGH

https://rebrand.ly/docugami_semantic_rag

Challenge 3: Building Complex Chains with the LangChain Expression Language

Real-world chains can get complicated with parallel branches, output parsers, few shot examples, conditional sub-chains, etc.



Sample code: https://rebrand.ly/docugami_complex_chain

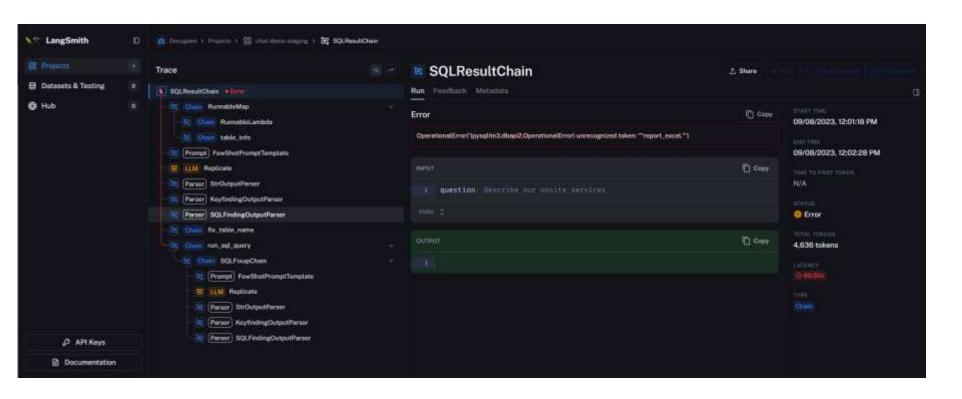
Challenge 3

LANGSMITH WALK-THROUGH

https://smith.langchain.com/public/ab8ef1ec-46d1-4d1f-980a-6dcc8f1943e0/r

Challenge 4: Debugging Complex Chain Failures in Production

Identifying what went wrong, where...



TIP: Name all runnable lambdas and pass config to conditionally-invoked runnables to correctly link and name. Reference: cookbook | example

TIP: If you have a link to a detailed call stack for an exception, you can add it to the failed run as metadata for later investigation. You can also add other information useful to investigate the failure later.

Common Failures:

- Invalid SQL that could not be automatically fixed, leading to chain failure
- 2. <u>Token overflow (table schema too large)</u>
- 3. LLM rate limit reached
- 4. LLM call failed with GPU OOM (for self-hosted models)
- 5. Exception in custom python RunnableLambda
- 6. Exception in custom output parser

Summary: Docugami's End to end LLM Ops with LangChain + LangSmith

- 1. Deploy Model (we self-host a custom LLM)
- 2. Regularly look at failed and user-disliked runs
- 3. Add some problematic runs to dataset
 - a) Failed runs e.g. with syntax errors
 - b) Runs with negative user feedback
- 4. Fix runs in dataset
 - a) Tip: use larger LLM to propose fixes
 - b) Tip: validate that fixes are syntactically correct e.g. by checking SQL syntax
- 5. Add some examples to few shot set for in-context learning
- 6. Fine tune model on updated dataset
- 7. Redeploy (go back to #1)

Q&A

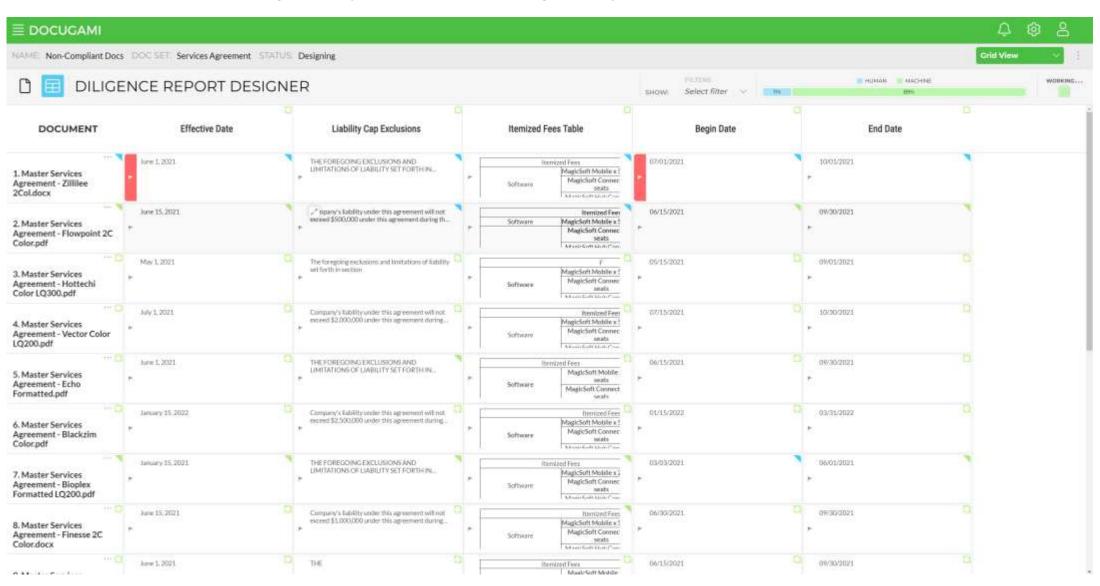


Docugami API

- 1. Docs: https://help.docugami.com/home/docugami-api
- 2. Things to try:
 - a) Upload docs (DOCX, DOC, digital or scanned PDF)
 - b) Download processed XML (with semantic metadata tags)
 - c) Build reports to identify key chunks
 - d) Use the <u>LlamaHub Docugami loader</u> to load docs for RAG, with report metadata
- 3. Free trials available!

Example: Extracting Custom Data from a Document Set

Improved significantly via structural chunking and key metadata associated with all chunks



Example: Authoring Assistance Based on Your Documents

Improved significantly via structural chunking and key metadata associated with all chunks



Example: Workflows Triggered by Auto-Extracted Data

Improved significantly via structural chunking and key metadata associated with all chunks

