Hackathon Problem Statement

🧠 "Smart Mortgage File Explorer: Cross-Document Semantic Search and Relationship Navigation for Home Loan Packages"

🏦 Business Context

Mortgage operations in a bank involve reviewing **hundreds of pages per loan file**, containing documents like:

- Loan applications (1003)
- Credit reports
- Income verification (W-2s, tax returns, paystubs)
- Appraisals
- Disclosures and closing statements

Traditionally, users rely on:

- **Manual search** by file names (often inconsistent or missing)
- **Rigid tagging rules**, which don't scale or adapt to unstructured data
- **Limited full-text search**, which doesn't understand *what* you're really asking

This leads to slow processes in:

- Underwriting and document validation
- Audit and compliance checks
- Post-close quality control
- Servicing and investor reviews

🚨 The Challenge

The bank's IT team is tasked with **building smarter document intelligence tools** to help operations teams **quickly find answers buried across a loan package**, such as:

"Where is the borrower's latest income verification document?"
"What's the declared income on the 1003, and is it supported by attached paystubs or W-

2s?”
“Which loans have inconsistencies between borrower names on different forms?”
“Show me loans with mismatched property addresses across documents.”

Right now, there is **no way to ask these questions semantically** — and no easy way to **trace relationships across documents** in a unified way.

💡 Hackathon Use Case

Build a prototype system that enables **semantic search and relationship navigation** across mortgage loan documents.

Core Capabilities:

- Use an **LLM** to extract **entities** (borrowers, addresses, loan amounts, employers, dates) and **relationships** (e.g., “John Smith is borrower on loan #123”, “is employed by ACME Corp”).
- Store this in a **graph database** (like Neo4j) or a structured vector-based store.
- Enable **semantic search** over the documents:
    - Natural language queries like:
        - “Show income documents for the primary borrower”
        - “Find the appraisal report for 123 Main St.”
        - “Which documents mention co-borrower Jane Doe?”
        - “Are there any loans with missing employment verification?”
- Use **retrieval-augmented generation (RAG)** or vector search (e.g., FAISS or OpenAI embeddings) to map queries to the right document sections or nodes in the graph.

👷 Why This Is an IT Hackathon Challenge

This use case cuts across:

- **NLP & AI** (LLM-based extraction + semantic understanding)
- **Search & IR** (embedding-based semantic retrieval)
- **Data architecture** (entity graph or index)

- **Document pipelines** (OCR, PDF parsing, etc.)
- **Risk & compliance** (validations and audit traceability)

It's highly practical, IT-aligned, and impactful for core mortgage operations.

✅ Success Criteria for the Hackathon Prototype

- Load 10–20 example mortgage documents (can be anonymized or synthetic)
- Enable **natural language questions** that return relevant document snippets or answers
- Visualize the **relationships** across entities (optional: graph UI)
- Demonstrate 3–5 valuable real-world use cases (e.g., cross-check income, validate addresses, find missing docs)

🔐 Real-World Payoff

This solution supports:

- Faster underwriting & QC
- Fewer human errors in audits
- Stronger compliance with investor and CFPB guidelines
- A foundation for automated red-flag detection (e.g., fraud, data mismatches)

Let me know if you'd like:

- A synthetic mortgage document set
- Suggested entity schema or graph structure
- Example prompts or semantic queries
- Prebuilt pipeline suggestions (e.g., LlamaIndex, LangChain, OpenAI tools)

This would make for a **high-impact hackathon challenge** that also aligns with strategic tech modernization goals at a bank.

How entity extraction helps?

Why Entity & Relationship Extraction Matters

While document tagging or full-text search helps with *finding documents*, **entity and relationship extraction helps you understand and reason over the information inside them**.

By converting unstructured documents into structured knowledge — with **entities** (people, places, amounts, dates, etc.) and **relationships** (e.g., "is borrower on", "is employer of", "is subject property of") — you can answer complex questions that require **cross-document understanding**, **validation**, and **inference**.

🔍 Examples of Questions You Can Answer

Here's a list of **high-value questions** that become answerable once entity and relationship extraction is in place — especially when backed by a graph or structured index.

📄 Borrower & Co-Borrower Validation

- **"Who are the borrowers and co-borrowers on this loan?"**
- **"Are the names and SSNs consistent across all forms (1003, W-2, disclosures)?"**
- **"Does the co-borrower live at the same address as the borrower?"**

💡 *Helps detect data entry errors, fraud, or identity mismatches.*

💼 Income Verification

- **"What is the declared income on the loan application, and what supporting documents back it up?"**
- **"Is the income supported by multiple years of W-2s or paystubs?"**
- **"Does the stated employer match what's on the paystub or VOE (Verification of Employment)?"**

💡 *Supports underwriting consistency and income fraud detection.*

🏠 Property & Appraisal Cross-Checks

- **“What is the subject property address across all documents?”**
- **“Are the addresses consistent between the appraisal, title report, and 1003 form?”**
- **“Which appraiser and appraisal company were used for this property?”**

💡 *Enables audit trails, detects discrepancies, and flags risk.*

💵 Loan Terms & Disclosure Matching

- **“What is the loan amount and interest rate on the 1003, and does it match the Closing Disclosure?”**
- **“Are all required disclosures present and consistent (e.g., LE, CD, GFE)?”**
- **“What fees were disclosed, and are they within acceptable tolerance?”**

💡 *Supports TRID compliance and investor eligibility.*

🗓️ Timeline Consistency & Regulatory Compliance

- **“Was the Closing Disclosure delivered at least 3 business days before closing?”**
- **“Are there date mismatches between documents (e.g., outdated W-2 or appraisal)?”**
- **“When were income documents generated vs. when the application was filed?”**

💡 *Helps meet CFPB and investor audit requirements.*

🔁 Repeat Entity or Pattern Detection (Advanced)

- **“Are any borrowers involved in multiple loans across packages?”**
- **“Is the same appraiser used across multiple questionable loans?”**
- **“Does this employer appear repeatedly across loans with overstated incomes?”**

💡 *Supports pattern detection, collusion risk, and internal fraud investigation.*

🔗 Why It's Useful — Beyond Just Search

Benefit	Description
🔍 **Cross-document validation**	Connects related information across forms (e.g., borrower name + employer + income)
🧠 **Data normalization**	Resolves variations like "John A. Smith" = "J. Smith"
🚨 **Risk and anomaly detection**	Flags missing links, mismatches, or suspicious relationships
📊 **Structured analytics**	Enables dashboards and metrics on loan quality, document completeness, etc.
✅ **Audit and compliance**	Creates a traceable, queryable audit trail for regulators and investors
📈 **Automation foundation**	Powers downstream automation like automated checklists, QC, fraud detection

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💡 Real-World Analogy

Think of this like going from:

"Here are 300 PDFs in a folder, good luck finding what you need..."

To:

"Here's a structured graph of everything in this loan: borrowers, income, dates, property, disclosures, timelines — with alerts where things don't match."

That's the power of entity and relationship extraction.

Example output graph from real world mortgage documents

Here's an example of what an **output knowledge graph** might look like based on information extracted from a **real mortgage loan package**. This graph connects key **entities** (people, places, documents, amounts) with **relationships** that reflect how they are linked across multiple documents in the loan file.

Since I can't show visuals directly here without image generation, I'll represent the graph structure textually, using nodes and edges.

🧠 Example: Mortgage Knowledge Graph (Text Representation)

css

CopyEdit

[Loan Application #12345]

- ├— hasBorrower → [John Smith]
- ├— hasCoBorrower → [Jane Smith]
- ├— hasSubjectProperty → [123 Main St, Springfield, IL]
- ├— hasLoanAmount → [$350,000]
- ├— hasLoanType → [Conventional Purchase]
- ├— declaredIncome → [$85,000]

[John Smith]

- ├— hasSSN → [XXX-XX-1234]
- ├— employedBy → [ACME Corp]
- ├— livesAt → [123 Main St, Springfield, IL]
- ├— appearsIn → [1003 Form], [W-2 2023], [Paystub Jan 2024]

[Jane Smith]

- ├— hasSSN → [XXX-XX-5678]

├— employedBy → [Global Health Inc.]

├— livesAt → [123 Main St, Springfield, IL]

├— appearsIn → [1003 Form], [W-2 2023]

[ACME Corp]

└— appearsIn → [VOE Letter, Paystub]

[Global Health Inc.]

└— appearsIn → [W-2, Paystub]

[123 Main St, Springfield, IL]

├— appraisedBy → [Premier Appraisal Inc.]

├— appraisedValue → [$360,000]

├— appearsIn → [Appraisal Report], [1003 Form], [Title Commitment]

[Closing Disclosure]

├— loanAmount → [$350,000]

├— interestRate → [6.25%]

├— closingDate → [Feb 5, 2024]

├— disclosedTo → [John Smith], [Jane Smith]

├— disclosedDate → [Feb 1, 2024]

[Appraisal Report]

├— appraiser → [Premier Appraisal Inc.]

├— date → [Jan 22, 2024]

├— appraisedValue → [$360,000]

├— property → [123 Main St, Springfield, IL]

[1003 Form]

├— borrower → [John Smith]

├— coBorrower → [Jane Smith]

├— statedIncome → [$85,000]

├— statedEmployment → [ACME Corp], [Global Health Inc.]

├— property → [123 Main St, Springfield, IL]

🔎 What You Can Do with This Graph

🔍 Run Smart Queries

- **"Show all documents that mention John Smith."**
  → Traverse John Smith → appearsIn
- **"Is the appraised value greater than the loan amount?"**
  → Compare appraisedValue vs. loanAmount
- **"Find inconsistencies between stated income and income on documents."**
  → Compare declaredIncome in 1003 with income parsed from W-2 and paystub
- **"Did Jane Smith receive the required disclosures?"**
  → Check disclosedTo relationship on Closing Disclosure
- **"Which loans have mismatched borrower addresses?"**
  → Compare livesAt across documents

🧠 Enable Automated Checks

- ✅ Employment consistency between 1003, paystubs, VOE
- ✅ Address consistency across application, title, appraisal
- ✅ Check if closing disclosure was issued 3+ days before closing
- ✅ Confirm borrower name and SSN are consistent across all forms

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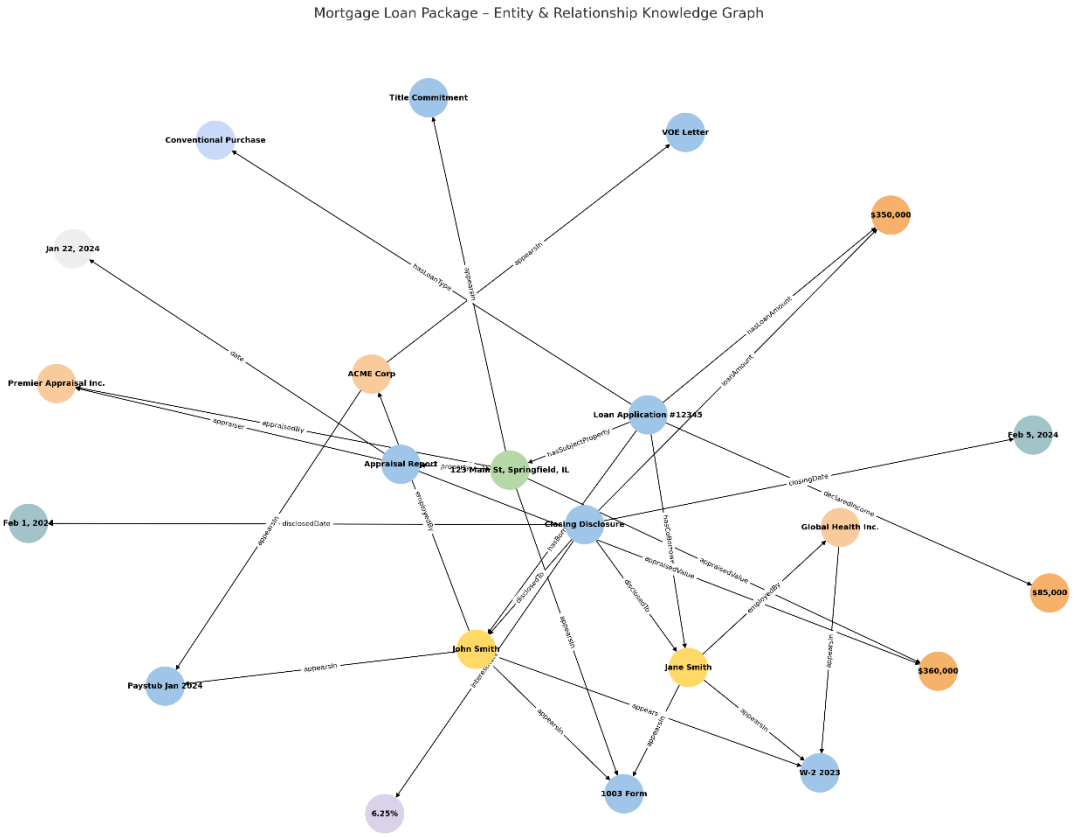
🔐 Real-World Implementation Notes

- You can use **Neo4j** to model this graph (nodes = entities; edges = relationships).
- Use an **LLM** (e.g., GPT-4) to extract structured facts from raw document text.
- Store document references as edge properties: source: W-2.pdf, confidence: 0.95
- Enhance with **document embeddings** to enable fallback **semantic search**.

Sample visual image



Here is a **visual knowledge graph** representing the entities and relationships extracted from a mortgage loan package. Each node type (borrower, document, organization, amount, property, etc.) is color-coded, and edges describe relationships like hasBorrower, appearsIn, loanAmount, etc.

This structure enables:

- Semantic queries over the loan file
- Cross-document consistency checks
- Clear audit trails and visualization of how data points connect

What semantic search alone can do?

understanding what **semantic search alone** can do (without building a full knowledge graph) is key for evaluating tradeoffs in a system's complexity and functionality.

🔍 What Can Be Answered with Just Semantic Search?

Semantic search uses **vector embeddings** of document content to match **natural language queries** to relevant **passages** (sentences or paragraphs) — even if the exact words aren't present.

It allows you to ask **open-ended or fuzzy questions** over unstructured text and retrieve **relevant snippets** or documents.

✅ Examples of Questions Answered by Semantic Search (No Graph Needed)

📄 Document-Level Questions

- “Where is the borrower’s income stated in the loan file?”
- “What is the interest rate for this loan?”
- “Is there a W-2 for John Smith in this package?”
- “Which document contains the employment details of Jane Smith?”
- “Where is the property address mentioned?”

📑 Form Presence and Completeness

- “Does this file contain a 1003 form?”
- “Is there a closing disclosure in this loan package?”
- “Is the appraisal report available?”
- “What disclosures are included in this loan file?”

🔍 Factual Retrieval

- “What is the loan amount?”
- “Who is the co-borrower?”
- “What company does the borrower work for?”
- “What is the appraised value of the property?”
- “What are the key dates mentioned in the closing disclosure?”

🗓️ **Timeline and Compliance Checks (basic)**

- “When was the closing disclosure issued?”
- “Is the document dated before the closing date?”
- “What is the closing date for this loan?”

📃 **Supporting Document Retrieval**

- “Show me the income documents for the borrower.”
- “Find supporting documents for borrower’s declared income.”
- “What documents list the borrower’s employer?”

🗂️ **Search Across Variants or Ambiguities**

- “Find any mention of John A. Smith or J. Smith.”
- “Locate documents that discuss employment verification.”
- “Is there any mention of the borrower’s address in this loan file?”

❗ **What Semantic Search Can’t Do Well (Alone)**

Without structuring the data (like in a graph), semantic search **struggles with**:

Use Case	Why It Struggles
Cross-document consistency checks	Needs linking info across multiple docs (e.g., compare stated income vs. actual income in W-2)
Data validation rules	Can't infer logic like “is income within ±10% of paystub?”

Use Case	Why It Struggles
Deduplication & entity resolution	Hard to know if “John A. Smith” and “J. Smith” are same person without structured entity mapping
Anomaly detection	Cannot find structural gaps (e.g., “no appraisal linked to property X”)
Chaining multi-hop relationships	Hard to trace “Borrower → Employer → Company in 3 loans” relationships

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🔁 Ideal Use of Semantic Search in a Hackathon

In a hackathon, semantic search is great for:

- Rapid Q&A over loan packages
- Extracting and summarizing document chunks
- Building a chat-based interface (“Ask your loan file anything”)
- Combining with RAG (retrieval-augmented generation) for LLMs

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🧠 Bonus: How to Implement It

- Embed all documents or paragraphs using **OpenAI**, **Cohere**, or **SentenceTransformers**
- Use **FAISS**, **Weaviate**, or **Pinecone** for vector storage
- Accept natural language queries → return top relevant chunks
- Optionally plug into **LLM (RAG)** for answer synthesis