

Bridging Legal Knowledge and AI: Retrieval-Augmented Generation with Vector Stores, Knowledge Graphs, and Hierarchical Non-negative Matrix Factorization

Ryan C. Barron

barron@lanl.gov

Theoretical Division,

Los Alamos National Laboratory

Los Alamos, New Mexico, USA

CSEE, UMBC

Baltimore, Maryland, USA

Maksim E. Eren

maksim@lanl.gov

Advanced Research in Cyber Systems,

Los Alamos National Laboratory

Los Alamos, New Mexico, USA

Olga M. Serafimova

OMSerafimova@hollandhart.com

Holland & Hart LLP

Santa Fe, New Mexico, USA

Cynthia Matuszek

cmat@umbc.edu

CSEE, UMBC

Baltimore, Maryland, USA

Boian S. Alexandrov

boian@lanl.gov

Theoretical Division,

Los Alamos National Laboratory

Los Alamos, New Mexico, USA

ABSTRACT

Agentic Generative AI, powered by Large Language Models (LLMs) and enhanced with Retrieval-Augmented Generation (RAG), Knowledge Graphs (KGs), and Vector Stores (VSs), represents a transformative technology applicable across specialized domains such as legal systems, research, recommender systems, cybersecurity, and global security, including proliferation research. This technology excels at inferring relationships within vast unstructured or semi-structured datasets. The legal domain we focus on here comprises inherently complex data characterized by extensive, interrelated, and semi-structured knowledge systems with complex relations. It comprises constitutions, statutes, regulations, and case law. Extracting insights and navigating the intricate networks of legal documents and their relations is crucial for effective legal research and decision-making. Here, we introduce a generative AI system that integrates RAG, VS, and KG, constructed via Non-Negative Matrix Factorization (NMF), to enhance legal information retrieval and AI reasoning and minimize hallucinations. In the legal system, these technologies empower AI agents to identify and analyze complex connections among cases, statutes, and legal precedents, uncovering hidden relationships and predicting legal trends—challenging tasks that are essential for ensuring justice and improving operational efficiency. Our system employs web scraping techniques to systematically collect legal texts, such as statutes, constitutional provisions, and case law, from publicly accessible platforms like Justia. It bridges the gap between traditional keyword-based searches and contextual understanding by leveraging advanced semantic representations,

hierarchical relationships, and latent topic discovery. This approach is demonstrated in legal document clustering, summarization, and cross-referencing tasks. The framework marks a significant step toward augmenting legal research with scalable, interpretable, and accurate retrieval methods for semi-structured data, advancing the intersection of computational law and artificial intelligence.

CCS CONCEPTS

- Computing methodologies → Natural language processing; Reasoning about belief and knowledge; Ontology engineering;
- Applied computing → Law; • Information systems → Document topic models; Content analysis and feature selection; Ontologies; Document collection models.

KEYWORDS

law, legal knowledge, nmf, topic labeling, llm, chain of thought, prompt tuning, information retrieval

ACM Reference Format:

Ryan C. Barron, Maksim E. Eren, Olga M. Serafimova, Cynthia Matuszek, and Boian S. Alexandrov. 2025. Bridging Legal Knowledge and AI: Retrieval-Augmented Generation with Vector Stores, Knowledge Graphs, and Hierarchical Non-negative Matrix Factorization. In *Proceedings of The 20th International Conference on Artificial Intelligence and Law (ICAIL 2025)*. ACM, New York, NY, USA, 10 pages. <https://doi.org/XXXXXXX.XXXXXXX>

1 INTRODUCTION

The legal domain is uniquely complex, encompassing constitutions, statutes, court rules, regulations, ordinances, and case law. Each data type follows a different structural or organizational logic—constitutions and statutes often contain hierarchical elements, whereas case law typically consists of lengthy, unstructured opinions. As new legal texts are continually produced, practitioners and scholars require computational systems that move beyond simplistic keyword-based searches to deliver meaningful results. Traditional legal information retrieval methods, relying predominantly on Boolean logic [50] and lexical indexing (TF-IDF)[12],

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

ICAIL 2025, June 16–20, 2024, Chicago, IL, USA

© 2025 Copyright held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-1-4503-XXXX-X/18/06...\$15.00

<https://doi.org/XXXXXXX.XXXXXXX>

frequently miss the subtle conceptual overlaps and deep contextual cues that characterize legal inquiries.

In response, RAG has become a framework that unites the strengths of information retrieval and generative models. RAG systems retrieve relevant legal documents or data points and then employ a language model to synthesize that information into coherent, contextually grounded answers. When applied to the legal domain, RAG can help reduce issues experienced by LLMS, like hallucinations [30, 34]. This is done by rooting responses in reliable texts, which then improves tasks such as case law retrieval, statutory interpretation, and document summarization. In order to fulfill these benefits, an underlying infrastructure must effectively represent, retrieve, and interpret large volumes of legal data.

This paper addresses these requirements by integrating three core technologies:

- **VS:** By embedding legal texts into dense vector representations (from models like BERT [21] or GPT [13, 44]), our system encompasses semantic meanings beyond keyword matching. This helps users to locate relevant documents even when the exact search terms differ from the query’s language.
- **KG:** Legal concepts—such as statutes, precedential cases, and doctrines—are often interconnected through citations or shared legal principles. KGs formalize these relationships, enabling structured navigation of the domain, explicit linking of related legal authorities, and improves reasoning over case-to-case, case-to-statute, and statute-to-statute references.
- **NMF:** While KGs excel at mapping explicit legal connections, many latent topics and patterns remain hidden in unstructured text. NMF uncovers these by factorizing word-embedding matrices into interpretable topics, aiding tasks like clustering related cases or identifying new legal trends

By combining the strengths of the three components into a domain-specific RAG system, we aim to deliver insights and more reliable outputs for a wide spectrum of legal tasks. The integrated framework leverages the high-recall semantic matching of vector stores, the structured relationships codified in knowledge graphs, and the topic discovery capabilities of NMF. This combination not only improves retrieval quality but also strengthens the system’s ability to provide explainable reasoning over extremely large datasets.

2 RELEVANT WORK

This section reviews contributions across RAG domains, semantic search using vector embeddings, knowledge graph construction, NMF, and legal information systems.

2.1 Non-Negative Matrix Factorization for Pattern Discovery

NMF is a dimensionality reduction technique used to uncover latent patterns in data. [33] analyzed NMF as an interpretable method for extracting features and topics from large datasets, specifically highlighting its ability to identify meaningful and non-overlapping components. Building on this work, [27] introduced sparseness constraints for better interpretability, improving applications of NMF in real-world scenarios through more focused feature selection. In the legal domain, NMF has been valuable for analyzing

complex textual data, such as case law and statutes, and assisting with topic discovery and clustering. For instance, [14] applied NMF to legal documents to extract latent topics and visualize relationships, demonstrating how NMF’s interpretable structure aids researchers in identifying underlying topics not readily apparent in raw text. They even applied NMF hierarchically to find fine-grained topics, however did not have a way to approximate the number of clusters automatically at each decomposition. More recently, [35] proposed a guided semi-supervised NMF approach for topic discovery in legal documents, using domain knowledge to steer factorization and ensure the extracted topics remain highly relevant. This semi-supervised extension bridges the gap between fully automated unsupervised techniques and expert-driven analysis. NMF’s utility in legal contexts is particularly significant, providing an interpretable framework for analyzing large textual datasets.

2.2 Retrieval-Augmented Generation

RAG has emerged as a foundational approach for improving AI systems across various domains, including law. For instance, [34] introduced a framework that dynamically retrieves relevant documents to ground generative outputs, achieving notable gains in accuracy. Building on this idea, [26] proposed a retrieval-augmented pre-training method that integrates external knowledge for improved downstream task performance. In contrast, [29] demonstrated the effectiveness of retrieval in open-domain question answering. These advances lay the groundwork for applying RAG to the legal sector, where the method’s ability to ground LLMs in authoritative texts reduces hallucinations and increases accuracy in tasks such as case law retrieval, statutory reasoning, and judgment prediction. Notable examples include CBR-RAG, which incorporates Case-Based Reasoning to structure retrieval for legal QA [51], and LegalBench-RAG. This benchmark suite tailors evaluation metrics to the demands of legal information synthesis [42]. Parallel work has demonstrated RAG’s capabilities in other domains, such as malware data analysis, by combining embeddings, KGs, and NMF [9]. Other works show how LLMs can dynamically decide when and what to retrieve to improve legal reasoning [32] and how multi-step legal judgment prediction can benefit from iterative retrieval and generation [48], further demonstrating the effectiveness of combining retrieval strategies with LLMs.

2.3 Semantic Search with Vector Embeddings

Semantic search operates on dense vector representations to find the deeper semantic relationships in texts, going beyond keyword matching to proper context retrieval [26, 31]. This search is especially valuable in the legal domain, where queries often demand conceptual rather than surface-level understanding. Domain-specific pretraining has become increasingly important, as in LEGAL-BERT [17], outperforming general-purpose models by better capturing legal language nuances. Benchmarks like LeCaRD [36] show the effectiveness of dense retrievers—such as SBERT—in legal case retrieval of Chinese law and the abilities of hybrid approaches that integrate both lexical and dense retrieval methods. Hierarchical transformer architectures [28] and long-context models like Longformer [10] further address the challenges of lengthy legal documents. In contrast, citation-driven approaches such as SPECTER

[20] leverage metadata to improve retrieval. Furthermore, work on neighborhood contrastive learning for scientific document representations (SciNCL) [41] demonstrates how controlled nearest neighbor sampling over citation graph embeddings can provide continuous similarity. This strategy could also inform citation-based retrieval improvements in legal domains. Challenges remain around scaling, explainability, and incorporating heterogeneous data sources in real-world legal workflows.

2.4 Knowledge Graphs in Legal Research

In the legal domain, researchers have used KGs for knowledge extraction [46], constructed domain-specific graphs tailored to legal contexts [23], and explored their potential for addressing trust, privacy, and transparency concerns [15]. Recent studies have demonstrated the effectiveness of KGs in recommending similar legal cases [22], linking case law with statutes for improved retrieval [52], and using graphs to enhance legal case law search in Chinese legal systems [11]. Beyond retrieval, KGs have been incorporated into knowledge-aware machine reading systems for legal question answering [25]. Collectively, these works demonstrate KGs' capacity to represent intricate legal concepts, structure regulatory frameworks, and encourage reasoning over legal data.

2.5 Legal Systems and Case Retrieval

Legal information systems have evolved rapidly with the advent of neural architectures and hybrid retrieval pipelines, enabling precise tasks such as precedent retrieval, statute matching, and judgment prediction [16, 19, 45]. Benchmarks like LeCaRD [36] and LexGLUE [18], along with LEGAL-BERT-based systems [17], have demonstrated the capability of these neural methods to improve accuracy in analyzing legal corpora. In particular, researchers have leveraged structured reasoning with transformers and graph representations to link statutes and precedents, as evidenced in the COLIEE competition [43]. Nonetheless, several limitations remain: data scarcity and jurisdictional bias continue to restrict the generalizability of such models. At the same time, resource-intensive retrievers like BERT-based cross-encoders [53] have challenges scaling to large-scale legal databases. Earlier works in juris-informatics have highlighted the potential of automating legal reasoning and document analysis [8], laying the groundwork for modern approaches that fuse knowledge graphs, transformers, vector stores, and agent-oriented RAG pipelines to deliver more explainable and efficient legal research workflows.

3 METHODS

Laws and their interpretations are limited in application to their respective jurisdictions. This work selected the State of New Mexico, using the available Supreme Court and Court of Appeals case law, the state constitution, and state statutes as the main data resource.

3.1 Data Collection

To compile a research-oriented corpus of legal documents, we utilized Justia's publicly accessible resources, in full compliance with their Terms of Service and any applicable usage guidelines, including robots.txt. We developed a *restricted* and *responsible* crawler to only access permitted documents—namely statutes, constitutional

provisions, and case law in the public domain—and to avoid any sections or usage not authorized by Justia's policies. To minimize server load and respect rate limits, our scraper introduces time delays between requests, monitors for HTTP status codes indicating rate-limiting or errors, and uses exponential backoff to handle potential network disruptions gracefully.

From the main landing page, a dynamic crawler identifies only those hyperlinks consistent with the site's navigation structure and relevant public legal content, converting them to absolute URLs and recursively traversing nested content where permitted. Our process extracts metadata such as chapter names, article titles, section numbers, full text for statutes, constitutional provisions, and judicial opinions for New Mexico's Court of Appeals and Supreme Court cases.

Throughout this procedure, we take multiple measures to maintain compliance and transparency:

- **Logs** track processed URLs to prevent duplication, resume interrupted crawls responsibly, and record request timing.
- **Rate-limiting measures** ensure we do not exceed usage thresholds or impose an undue burden on Justia's servers.
- **No circumvention** of technical safeguards defined in robots.txt and the TOS restrictions.
- **Non-commercial use only**: we do not republish, sell, or otherwise exploit Justia's content and only use it for legitimate scholarly research.

These practices keep the data process ethical, legally sound, and consistent with Justia's rules for site usage and content retrieval.

3.2 Dimension Reduction in Legal Texts

Legal documents—constitutions, statutes, and case law—are traditionally organized into chapters, articles, and sections, but these structures do not always match the latent patterns revealed through factorization. Each document type is analyzed separately using non-negative tensor and matrix factorization to explore these hidden relationships. A TF-IDF matrix, \mathbf{X} , is first constructed from the cleaned corpus. Constitutional provisions, statutory clauses, and case law paragraphs form the units of analysis for clustering.

In this study, we use the public repository called **Tensor Extraction of Latent Features (T-ELF)**¹ [24], combined with automatic model selection, to decompose \mathbf{X} into coherent topic H-clusters. T-ELF efficiently identifies latent topics, grouping constitutional provisions around themes such as “separation of powers” and clustering statutes and case law based on regulatory objectives and recurring legal doctrines, respectively.

3.2.1 Application of Non-Negative Matrix Factorization to Legal Texts. NMF approximates the matrix \mathbf{X} with two non-negative matrices, \mathbf{W} and \mathbf{H} :

$$\mathbf{X} \approx \mathbf{W} \cdot \mathbf{H},$$

where \mathbf{W} describes how terms distribute over topics, and \mathbf{H} describes how these topics distribute across documents. Constitutional articles and sections reveal underlying governance or civil rights themes; statute clauses highlight regulatory objectives, and

¹<https://github.com/lanl/T-ELF>

segmented judicial opinions expose common doctrines and legal reasoning patterns.

3.2.2 Automatic Model Determination Using NMFk. A central challenge in applying NMF is selecting the best number of latent features (k). We use *NMFk* [7], which combines clustering stability with reconstruction accuracy. Bootstrap resampling generates slightly perturbed versions of the original matrix, and repeated decompositions measure how consistently clusters form. Silhouette scores help ensure cohesive, well-separated topics, while reconstruction error verifies that the model effectively captures patterns in the original data.

By adapting this NMF approach to a hierarchical setting, legal texts can be organized into a tree-like structure. Constitutions may be segmented into articles and sections, statutes into chapters and clauses, and case law into layered precedents and sub-issues. This hierarchical perspective enhances the discovery of latent relationships at multiple levels of granularity, facilitating deeper analyses of large-scale legal corpora.

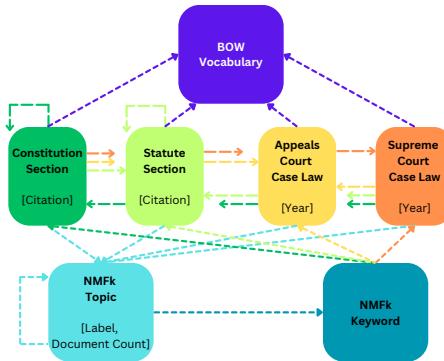


Figure 1: Knowledge Graph Schema, with the primary identifier in bold and attributes in brackets.

3.3 Knowledge Graph

Features derived from T-ELF and document metadata are transformed into a series of head, entity, and tail relations, forming directional triplets integrated into a Neo4j KG [37].

In the legal context, the KG incorporates metadata and latent features extracted from constitutions, statutes, and case law. The primary nodes in the graph represent legal documents, including constitutional provisions, statutory sections, and judicial opinions. These nodes are enriched with metadata such as titles, hierarchical identifiers (e.g., chapter and section numbers), jurisdiction, court names, decision dates, and topics derived from latent features.

Edges in the KG establish relationships between nodes to represent the interconnected nature of legal documents. For instance:

- **Constitutional Nodes:** Linked to statutory provisions or judicial interpretations that reference or rely on specific constitutional clauses.
- **Statutory Nodes:** Connected to cases interpreting the statute or related provisions within the same legislative framework.
- **Case Law Nodes:** Interlinked based on shared topics, common legal principles, or hierarchical relationships in appellate decisions.

This graph structure enables the RAG system to query and retrieve legal documents based on semantic similarity and explicit relationships. For example, a query about "due process" might retrieve the relevant constitutional clause, cases that discuss its interpretation, and statutory provisions impacted by those rulings. By combining metadata and latent features, the KG supports advanced reasoning and logical traversal, enhancing the precision and depth of legal information retrieval.

Each part had decomposition topics containing keywords that connected to the documents. The bag of words (BOW) vocabulary was also extracted and inserted into the knowledge graph. These can be observed in the knowledge graph schema of Figure 1.

3.4 Vector Store

A vector database was implemented to manage and index legal documents, improving the RAG process for legal research. Using Milvus [47], the system stores vectorized representations of constitutions, statutes, and case law, treating each document type uniquely to ensure contextually relevant retrieval.

Constitutional provisions are segmented into paragraphs, each assigned a unique ID, and vectorized using OpenAI's text-embedding-ada-002 [40] model for granular semantic searches. Statutes are divided by sections or clauses, with metadata like chapter numbers and section titles integrated for precise retrieval. Case law, due to its unstructured narrative format, is chunked into meaningful units, preserving logical flow and indexed with metadata such as case name and citation.

The RAG application queries the database to retrieve relevant fragments—constitutional paragraphs, statutory clauses, or case law sections—based on the query's focus. Retrieved text is processed by the LLM agents with custom prompts to construct responses, allowing the LLM to cite specific paragraphs or clauses, for traceability.

For additional context, the system leverages a connected knowledge graph to explore related statutes, judicial interpretations, or precedent cases.

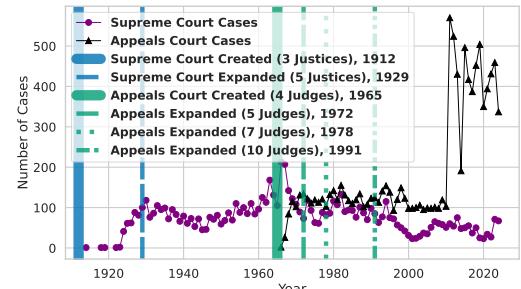


Figure 2: New Mexico Supreme/Appeals case counts per year.

4 RESULTS

This section presents the resulting atomic parts of the legal texts and their hierarchical decomposition, offering a detailed breakdown of the sections and cases within each document type. The following results illustrate the scope and depth of the collected data, providing a foundation for further exploration of trends and patterns across the legal corpus.

4.1 Dataset

After collecting and structuring the data, the three types of legal documents had the following atomic parts of data, either as sections in the constitution and statutes or cases from case law:

- **Constitution:** 265 sections
- **Statutes:** 28,251 sections
- **Case Law:**
 - **Court of Appeals:** 10,072 cases
 - **Supreme Court:** 5,727 cases

Figure 2 shows the trends in the 5,727 Supreme Court and 10,072 Court of Appeals cases over the years, as they were available from Justia [5], which also includes the expansions and creations of the courts themselves.

4.2 Decomposition

The four component data types were decomposed hierarchically with *NMFk*. The vocabulary for building the TF-IDF matrix was collected using specific parameters for each part. For the Constitution vocabulary, the minimum token document frequency (DF) was set to 5 documents, with a maximum token DF of 80% of the corpus, resulting in a final size of 416 tokens. For the Statutes vocabulary, the minimum token DF was set to 30 documents, with a maximum token DF of 70% of the corpus, yielding 7,508 tokens. The Court of Appeals vocabulary used a minimum token DF of 50 documents (cases) and a maximum token DF of 70% of the corpus, resulting in 10,189 tokens. Last, the Supreme vocabulary employed a minimum token DF of 50 papers and a maximum token DF of 70% of the corpus, with a final size of 8,425 tokens. The maximum depth was set to 2, of which only the constitution sections did not reach due to the limited number of sections. The limiting factor of further decompositions was 100 documents, so if the preceding cluster had ≥ 100 , the cluster would decompose and stop otherwise. As seen in Figure 3a, the largest H-cluster is from cluster 4 in dark blue with 49 sections, with the fewest documents in yellow with six sections in H-cluster 0. The other three decompositions can be examined in the larger Figure 3, where the court cases, there are 10 leaf H-clusters in the constitution decomposition, 985 leaf H-clusters in the statutes decomposition, 420 leaf H-clusters in the Court of Appeals cases, and 248 leaf H-clusters in the Supreme Court cases. From the methods in [49], each H-cluster throughout the decomposition hierarchies has LLM-generated labels for ease of reference and quick insight. Labels for the first decomposition depth for the constitution can be observed in Table 1, the statutes in Table 2, the Supreme court in Table 4, and the appeals in Table 3. The depth-0 H-clustering corresponds to the first ring radial from the center totals in Figure 3.

Table 1: NM Constitutional Depth-0 H-Clusters

#	Label
0	Irrigation and Water Resource Management Principles
1	Regulation of Private Sector Influence on Public Schools and Education Services
2	Branches of Government Structure and Functionality
3	Education Funding for New Mexico's Educational Institutions
4	Legislative Proceedings and Lawmaking Activities Enacted During Sessions
5	Territorial Transition: Constitutional Ratification and Statehood Provisions
6	Governance, Land, and Taxation Framework
7	Municipal and County Financial Obligations and Liabilities Management
8	Judicial Power and Jurisdictional Frameworks
9	Public Service Election Governance Structure and Processes

Table 2: NM Statutory Depth-0 H-Clusters

#	Label
0	Municipal Court Civil Cases Involving Children's Rights
1	Public Education Infrastructure Management Systems
2	Criminal Codes, Local Governance Boundaries, Licensing Rules
3	Comprehensive Emergency Health and Human Services Response Framework
4	Taxation and Revenue Collection Oversight
5	Military Decorations, Licensing Procedures, Governance Boards
6	Regulatory Insurance Contract Law and Policy Analysis
7	Public Obligations Financing and Project Bonds Issuance
8	State Government Investment Grants for Education and Economic Development
9	Irrigation and Water Rights Regulations
10	Military Honors, Discrimination Penalties, and Trust Authority
11	Corporation Governance Framework and Regulatory Compliance

Table 3: NM Appeals Court Case Law Depth-0 H-Clusters

#	Label
0	Real Property Rights and Interests
1	Civil Liability and Injury Issues Arising from Healthcare Services
2	Parental Rights and Custody Proceedings Involving Disputed Parental Fitness
3	Motor Vehicle Insurance and Liability Claims Processing Procedures
4	Mortgage Foreclosure and Secured Lending Frameworks
5	Arraignments, Tribal Jurisdiction, Divorce, Bond Conditions, Motor Licensing
6	Courtroom Advocacy and Representation Strategies
7	Petitioner's Right to Parental Decision Making
8	Fourth Amendment Protections Against Unlawful Searches and Seizures
9	Taxation of Gross Receipts and Sales Transactions in a Business Context
10	Key Legal Concepts Related to Sexual Offenses
11	Child Protective Services Laws and Regulations
12	Work-Related Injury and Disability Compensation Process
13	Healthcare Contract Dispute Resolution Processes
14	Marital Property and Financial Disposition
15	Legal Proceedings Involving Jury Determination of Guilt
16	Probation Supervision and Monitoring Oversight Process
17	Juvenile Protection, Miranda Rights, Evidence Collection
18	Firearms, Substances, DWI, and Sentencing
19	Sentencing Enhancements for Serious Repeat Offenders
20	Traffic Stop Under Suspicion with Mandatory Blood Alcohol Testing
21	Criminal Proceedings Trial Litigation Documentation and Record-Keeping Procedures
22	Workers' Rights and Insurance Benefits
23	Children's Welfare and Family Reunification Efforts
24	Public Municipal Legal Frameworks and Governance Structure
25	Business Disputes, Wrongful Injury, Taxation Appeals, Workers' Compensation
26	Administrative Disputes, Native American Legal Memorandums

Table 4: NM Supreme Court Case Law Depth-0 H-Clusters

#	Label
0	Arbitration of Contract Disputes and Judicial Decision-Making in Motor Vehicle Cases
1	Revenue and Taxation Frameworks in Governance and Administration
2	Mineral Rights Leases
3	Native American Self-Governance and Tribal Jurisdictional Frameworks
4	Municipal Zoning Ordinances and Regulations of Local Governance Areas
5	Damages Award for Wrongful Conduct Against Business Partners
6	Jurisdictional Appeals, Juvenile Sentencing, Felony Enhancements, Parole Terms
7	Post-Divorce Asset Distribution and Management Strategies
8	Constitutional Challenges to Public Education Governance
9	Secured Financial Instruments and Property Rights
10	Water Resource Allocation and Management
11	Electric Utility Rate Regulation Oversight Authority
12	Law Enforcement Procedures and Rights Protection under Fourth Amendment Protections
13	State Legislative Review Process Decisions
14	Denial of Petition for Habeas Corpus
15	Workers' Compensation Process for Work-Related Injuries and Disabilities
16	Real Estate Boundary Disputes and Conveyance Matters
17	Parental Rights and Legal Guardianship Proceedings
18	Appellant's Argument Against the Ruling of a Trial Court
19	Document Terms and Conditions Regarding Business Transactions
20	Mutual Insurance Policies for Vehicle and Individual Coverage
21	Accident resulting from driver error on public roadways leads to legal consequences
22	Court proceedings involving criminal trials and testimonial evidence
23	Civil Litigation Proceedings and Trials

4.3 Knowledge Graph

The four data parts, 265 constitutional provisions, 28,251 Statute sections, 5,727 Supreme Court cases, and 10,072 Court of Appeals cases, were inserted into the neo4j [37] knowledge graph. The graph's number of nodes and edges can be seen in Table 5, where edge counts are where the triplet's tail originates with the row's node. The legal citations were collected by iterating the text of each case or section into chat-gpt-3.5-turbo with the following prompt: "You

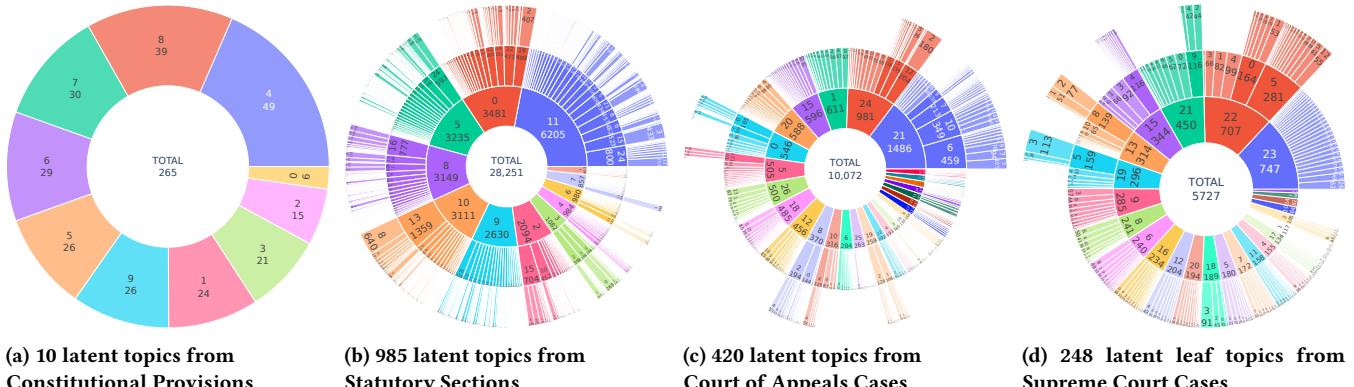


Figure 3: Legal Documents from New Mexico hierarchically decomposed. The Constitution only had enough documents to decompose the first depths, whereas the other three sources continued to the terminal depth of 2 (a hyper-parameter of decomposition). Each H-cluster has a natural language label, where depth-0 from each can be seen in Tables 1, 2, 4, and 3.

Table 5: Neo4j Node and Edge Overview

Node Type	Nodes	Out Edges	Legal Cites
NMFk Topics	2,469	92,634	–
NMFk Keyword	11,076	8,281,843	–
BOW Vocabulary	132,423	–	–
Constitution	265	9,067	41
Statute	28,251	1,930,707	81,353
Supreme Court Case	5,727	2,437,161	76,478
Court of Appeals Case	10,072	4,176,288	131,230
Total Unique	190,283	16,927,700	289,102

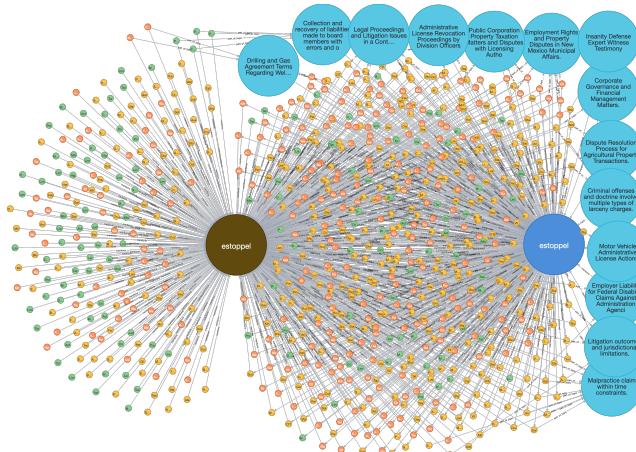


Figure 4: Examination of ‘Estoppel’ relating to being a keyword in topics, vs bag of word vocabulary

are an expert legal document analyzer. Your job is to find all references to the Constitution, Case Law, or Statutes in the text.” The result was that the LLM acted like a named entity extractor, such that any citations in the text were pulled out in an enumerated list. The citations mainly included the cases, statutes, and constitution of New Mexico but also had references to the United States Constitution, New Mexico Administrative Code, and New Mexico Rules

Annotated (NMRA). The NMRA had many references to Uniform Jury instructions and the rules of criminal and civil proceedings.

In figure 4, the *NMFk* topic cluster keyword and a bag of word vocabulary were both queried for ‘estoppel’. The *NMFk* keyword is Dark blue, the topics are light blue, and the BOW node is brown. Three documents occur for this keyword: the statutes are green nodes, the Court of Appeals cases are yellow, and the Supreme Court cases are orange. The constitution neither clustered over the term nor mentions it, which is not represented in Figure 4. There is a partition in the nodes at the brown bag of words node since all nodes with the *NMFk* keyword have the bag of word node connection. Still, not all documents mentioning ‘estoppel’ were clustered with the word, which is to say other terms and concepts from those terms had more importance for the documents on the left side of the image than ‘estoppel’. There are 14 topics, 441 Court of Appeals cases, 276 Supreme Court Cases, and 131 Statutes in Figure 4. These topics have ‘estoppel’ in their top keywords, whereas if every topic that contained ‘estoppel’ in its words were called, there would be 341 topics. Of the 14 topics, one was connected to the Statutes, “Collection and recovery of liabilities made to board members with errors and omissions.” Three of the 14 topics were connected to supreme court cases: “Employment Rights and Property Disputes in New Mexico Municipal Affairs”, “Public Corporation Property Taxation Matters and Disputes with Licensing Authorities”, “Drilling and Gas Agreement Terms Regarding Oil Wells.” Finally, the remain 10 of the 14 topics with ‘estoppel’ in its top words were connected to cases from the Court of Appeals: “Litigation outcomes and jurisdictional limitations”, “Administrative License Revocation Proceedings by Division Officers”, “Legal Proceedings and Litigation Issues in a Medical Context”, “Corporate Governance and Financial Management Matters”, “Dispute Resolution Process for Agricultural Property Transactions”, “Motor Vehicle Administrative License Actions”, “Insanity Defense Expert Witness Testimony”, “Malpractice claim within time constraints”, “Employer Liability for Federal Disability Claims Against Administration Agencies”, “Criminal offenses and doctrine involve multiple types of larceny charges”, “Collection and recovery of liabilities made to board members with errors and omissions”, “Public Corporation Property Taxation Matters and Disputes with Licensing Authorities”, “Employment Rights and Property Disputes in New Mexico Municipal Affairs”, “Drilling and Gas Agreement Terms Regarding Oil Wells.”

4.4 Query Cross Comparison

Questions were formulated to query information about legal concepts from LLM channels. There were five questions from each

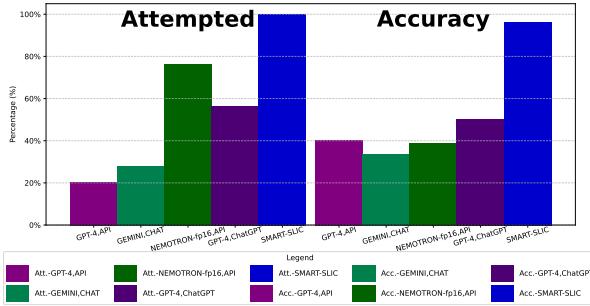


Figure 5: 25 questions queried across five different LLM channels. Attempts are the percentage of responses tried to answer the question, and accuracy is the percentage of those answered with correct responses.

data source: the constitutional provisions, the Statutes, the Court of Appeals, and the Supreme Court. Then, five additional quantity questions were added. The results can be seen in Figure 5, where the five different models were OpenAi’s GPT-4 [39] over the API, Google’s Gemini [6] over a web chat, Nvidia’s nemotron:70b-instruct with 8-bit quantization [38], OpenAi’s GPT-4 [39] over a web chat, and finally our system for this work, Smart-SLIC. Questions related to the Constitution appear generally answerable by the language models, likely due to its structured and concise wording.

Answering legal questions becomes increasingly challenging with larger datasets, especially case law, which was the most difficult. Unlike statutes, where hierarchical structures are more straightforward for LLMs to train and summarize, case law is unstructured, lengthy texts that are more challenging to summarize. Constitutional questions were relatively simple, though many models mentioned articles rather than sections, citing frequent changes in how sections are enumerated. Our evaluation procedure assigns zero if the model refuses to answer and if any attempt to respond was made. Accuracy then ranges from 0 to 3: a correct or nearly correct answer receives 3, primarily correct but partially misunderstood responses receive 2, mostly incorrect yet partially true answers receive 1, and responses entirely wrong or hallucinations get 0. Some models were given points when they produced close numeric estimates, even if derived through flawed “database lookups.” In contrast, our system provides traceable reasoning by referencing the KG and analyzing the decomposed hierarchical structure of the texts themselves.

The following are comparisons between each of the models with formatting and truncations (as ...) so the text is more readable:

(a) Comparison 1 - Quantities:

- **Question:** “How many New Mexico Supreme Court cases mention ‘Habeas Corpus’?”
- **GPT-4, API:** *I don’t have the ability to provide real-time or exact counts of Supreme Court cases mentioning “habeas corpus” up to the current date...*
- **GPT-4o, ChatGPT:** *Determining the exact number of New Mexico Supreme Court cases that mention ‘habeas corpus’ is challenging due to the extensive history of the court’s decisions and the limitations of available databases...*
- **Smart-Slic:** *There are 215 Supreme Court cases that mention ‘Habeas Corpus’.*
- **Gemini:** *The exact number of Supreme Court cases that mention “Habeas Corpus” is difficult to determine precisely. Here’s why - Vast Number of Cases: ... - Varied Mention: ... - No Centralized Database: ...*
- **nemotron:70b-instruct-q8_0:** *I’ll outline my research methodology and then share the results. Research Methodology: 1. Database Selection: ... 2. Search Parameters: ... 3. Search Approach: ... After conducting thorough searches*

across the selected databases: **Approximate Number of Cases Mentioning ‘Habeas Corpus’:** Over 1,300... Breakdown ...: * Pre-1950: ... 450 ... * 1950-2000: ... 550 ... * 2001-Present: ... 300 ...

The responses highlight significant differences in model abilities. GPT-4 API and ChatGPT provided an understanding of their limits to offer real-time or exact counts due to limitations such as access to historical databases or the complexity of case records. Gemini followed a similar pattern, explaining why determining a precise number is challenging. In contrast, our system directly reported a specific count, stating 215 cases mentioning ‘Habeas Corpus,’ showing its ability to process and retrieve meaningful data. Meanwhile, nemotron:70b-instruct-q8_0 provided a detailed method to find the correct answer in an open context. It even went into breaking the count into approximate ranges across different periods, suggesting over 1,300 cases in total. However, these counts from Nemotron are part of an extreme hallucination since it was an offline model without the ability to make any lookups.

(b) Comparison 2 - Legal Citations:

- **Question:** “What are common citations among New Mexico Court of Appeals cases that mention ‘malpractice’?”
- **GPT-4, API:** *I don’t have direct access to specific databases or the ability to browse the internet.*
- **GPT-4o, ChatGPT:** *In New Mexico Court of Appeals cases addressing malpractice, several key legal principles and precedents are frequently cited: Elements of Legal Malpractice: ... Mireles v. Broderick, 1992 ... Statute of Limitations: ... Sharts v. Natelson, 1994 ... Expert Testimony Requirement: ... Rummell v. Edgemont Realty Partners ... 1993 ... Causation and “Case Within a Case” Doctrine: ... Garcia v. Rodey, Dickason, Sloan, Akin & Robb ... 1988 ... Damages: ... Sanders, Bruin, Coll & Worley ... 2010 ...*
- **Smart-Slic:** *The common citations among New Mexico Court of Appeals cases that mention ‘malpractice’ include NMSA 41-5-1 with 36 cases, NMSA 41-5-13 with 35 cases, NMSA 41-4-1 with 23 cases, CERVANTES v FORBIS 1964 with 18 cases, NMSA 37-1-8 with 15 cases, NMSA 41-5-3 and NMSA 41-5-15 each with 14 cases, NMSA 41-5-6 with 13 cases, GOODMAN v BROCK 1972 with 12 cases, and NMSA 41-5-22 with 10 cases.*
- **Gemini:** *Common citations in New Mexico Court of Appeals cases mentioning “malpractice” often include: - Leyba v. Whitley...1995... - Rancho del v. Weisfeld...1995... Bassett v. Sheehan, Sheehan & Stelzner...2008... Akutagawa v. Laflin, Pick & Heer...2005...*
- **nemotron:70b-instruct-q8_0:** *Steps to Find Common Citations: 1. Access Legal Databases: ... 2. Construct Your Search Query: ... 3. Filter Results (if possible): ... 4. Analyze Top Cases for Citations: ... Please note, the following are hypothetical examples... 1. Cases: - Hypothetical Example 1: Smith v. Jones, 2010 ... - Hypothetical Example 2: Doe v. Healthcare Inc., 2015 ... 2. Statutes or Regulations: ... NMSA 1978, Section 41-5-1 ... - NMSA 1978, § 41-4-11 to 41-4-17 ... 3. Court Rules: - ... NMRCvP, Rule 1-026 ... - ... NMRE, Rule 702 ...*

GPT-4 API again opted not to answer, stating that it did not have access to specific databases or the ability to browse legal records. GPT-4o (ChatGPT), on the other hand, offered an insightful summary of key legal principles and precedents frequently cited in malpractice cases, naming specific examples like Mireles v. Broderick (1992) and Garcia v. Rodey (1988). This response demonstrated domain awareness but was missing particular detail.

In contrast, our system delivered a detailed list of the most common citations, including exact counts for specific statutes and cases, such as NMSA 41-5-1 cited in 36 cases and CERVANTES v FORBIS (1964) cited in 18 cases. Our system’s response is specific and direct, allowing for faster and more reasoned legal research. Meanwhile, Gemini offered a mix of case-specific citations, similar to GPT-4o, but with limited depth and no accompanying counts, which made the response less precise.

Finally, nemotron:70b-instruct-q8_0 outlined a hypothetical strategy to find citations, including steps like accessing legal databases

and filtering results. However, the examples provided, such as "Smith v. Jones, 2010," were explicitly hypothetical, undermining the credibility of the response. Additionally, nemotron's inclusion of actual statutes like NMSA 41-5-1 blurred the line between hypothetical examples and genuine analysis, leading to potential confusion.

This comparison highlights the strengths and weaknesses of each system: some models are better at summarizing legal principles, such as GPT-4o and Gemini, while our System shows the capability for precise data retrieval and analysis. Nemotron, despite its detailed methodology, suffered most from hallucinations.

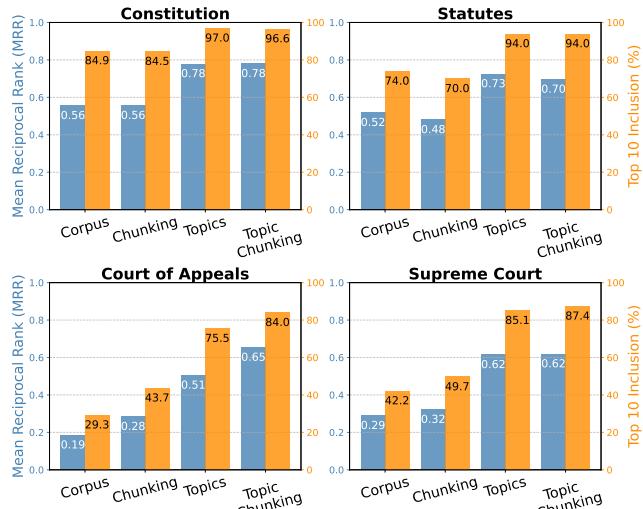


Figure 6: MRR and top 10 hit rate percentage per data category over several embedding methods.

4.5 Question Answering

To evaluate the effectiveness of our QA SLIC-SMART system, we conducted a series of experiments focusing on various performance metrics. Figure 6 shows various retrieval methods from the embedding space. The four data sources are treated separately for comparison. Each data source uses four separate methods to embed the data. The first is the entire corpus of each, where all documents are put into a single vector store. Where the text was short and structured, this had top 10 retrieval percentages more significant than 70 to 80%, such as the statutes and constitutional provisions. The cases had less structure and longer text, making the plain embedding challenging. Next is the chunking method, where the entire dataset is again placed into a single dataset but chunked at 3000 characters with 500 overlapping. The top row, with more concise and structured concepts, decreased slightly in performance, whereas the cases significantly improved. This is likely because the concepts are broken down across multiple texts instead of being in one coherent text to query. Still, with the decrease, the structured texts outperformed the cases by more than 20%. Third, the *NMFk* hierarchical cases are incorporated into the vector store process, where each topic has an individual vector store. The topics per query were controlled such that the query was searched in the vector store corresponding to the question origin. Topic identification in the vector store is an outstanding problem for future work. When the *NMFk* hierarchical topics were introduced, the performance

significantly improved across all data sources, with the most significant gains in the longer case texts. When the chunking process was incrementally added on top of the *NMFk* topics, the cases still improved, again likely to break up much larger texts into more meaningful segments of the texts. In contrast, the structured texts in the constitutional provisions and the statutes slightly decreased performance, likely attributed to the splitting of concepts in the questions across several chunks. Still, *NMFk* topics with chunking and correct topic identification outperform the other methods overall.

4.5.1 Case Studies. To illustrate the practical applications and effectiveness of the QA Smart-Slic system, we present four detailed case studies:

(a) *Case Study 1 - Constitutional Analysis:*

- **Question Source:** Article IV, Section 22 [1]
- **Question:** "What happens to a bill if the governor neither returns it within the specified three-day window (Sundays excepted) nor signs it?"
- **Response:** *According to Article IV - Legislative Department – § 22 "Governor's approval or veto of bills" of the provided text, if a bill is presented to the governor and he neither returns it within the specified three-day window (Sundays excepted) nor signs it, then the bill becomes a law automatically, whether signed by him or not, unless the legislature by adjournment prevents such return.*

(b) *Case Study 2 - Statutory Analysis:*

- **Question Source:** Chapter 50, Article 17, Section 3 [4]
- **Question:** "Under the Healthy Workplaces Act, how does an employee accrue and utilize earned sick leave, and what provisions exist for its carryover, use for family or personal health, and reinstatement after separation from employment?"
- **Response:** *Accrue: Employees accrue a minimum of one hour of earned sick leave for every thirty hours worked. Employers may elect to provide the full sixty-four hours of earned sick leave for the year on January 1 or pro-rata for mid-year hires.*

Use: Earned sick leave can be used for the employee's or their family members' illness, injury, health condition, medical care, or preventive medical care. It can also be used for issues related to domestic abuse, sexual assault, or stalking.

Carryover: Unused earned sick leave carries over year to year, although use may be capped at 64 hours per twelve-month period, unless the employer sets a higher cap.

Reinstatement: If an employee is rehired within twelve months of separation by the same employer, previously accrued and unused earned sick leave must be reinstated. Additionally, the employee is entitled to accrue additional sick leave upon re-commencement of employment.

(c) *Case Study 3 - Court of Appeals Case Law Analysis:*

- **Question Source:** KRM, Inc. v. Caviness, 1996 [3]
- **Question:** "In the case KRM, Inc. v. Caviness, what was the court's reasoning for determining that the water rights established by Williams' 1963 declaration did not belong to the land sold to Caviness?"
- **Response:** *The court determined that the water rights established by Williams' 1963 declaration were not appurtenant to the land sold to Caviness because there was no evidence that the water had been used for irrigation on that land. Since the appropriated water was never used for irrigation purposes on the property, it did not qualify as appurtenant water rights that would automatically transfer with the land. The court concluded because the usage of the water was unrelated to the benefit or use of the land itself, the water rights remained separate and did not pass to Caviness when he purchased the land.*

(d) *Case Study 4 - Supreme Court Case Law Analysis:*

- **Question Source:** Smith v. South, 1955 [2]
- **Question:** "In Smith v. South, what were the legal issues raised regarding the enforceability of the Washington child support decree in New Mexico, and how did the court address the conflict between the parties' post-decree agreement and the original judgment?"
- **Response:** *The legal issues raised in Smith v. South regarding the enforceability of the Washington child support decree in New Mexico included whether New Mexico courts should acknowledge and enforce the original Washington decree for child support or consider the modifications reportedly agreed upon by the parties after the decree. The conflict between the parties' post-decree agreement and the original judgment involved assertions that they had informally agreed to alter the child support payments stipulated by the Washington court.*

The court addressed this issue by considering the jurisdictional and legal principles guiding child support enforcement across state lines. They emphasized the importance of adhering to the formal judicial process. The court likely examined whether the post-decree modifications had been legally formalized or approved by any court, and whether such modifications complied with the relevant child support enforcement laws, particularly under the Uniform Interstate Family Support Act (UIFSA), though it wasn't explicitly mentioned in the text snippet. UIFSA provides mechanisms for establishing, enforcing, and modifying child support orders across state boundaries.

If the modifications were not legally recognized through a court process, the original Washington decree would remain enforceable in New Mexico, and any informal or unratified agreements between the parties would not typically alter the enforceability of the court-ordered decree. The court would focus on ensuring that child support arrangements comply with legal standards to serve the children's best interests and that enforcement respects the authority of the original jurisdiction (Washington) unless properly modified through legal channels.

5 CONCLUSION

This work introduced Smart-Slic, a generative AI framework tailored to the legal domain, leveraging RAG, vector stores, and a Neo4j-based knowledge graph constructed through *NMFk*. Our approach uses **T-ELF** with metadata and chunking strategies to capture fine-grained H-clusters and minimize hallucinations to improve reliability. By bridging structured and unstructured data-spanning constitutional provisions, statutes, and case law—, our system supports advanced semantic reasoning and dimensionally reduced insight into the latent structure of legal texts.

Experimental results across multiple retrieval strategies show that chunking, combined with hierarchical *NMFk*, improves accuracy, particularly for large, unstructured case law datasets. Short, highly structured documents, constitutional provisions, and statute sections benefit from minimal chunking, revealing the importance of aligning preprocessing approaches with data characteristics. We demonstrated the framework’s capability to derive interpretive legal topics and precisely answer domain-specific queries by harnessing topically segmented embeddings and explicit links within the knowledge graph.

Despite the positive results, challenges remain. Author attribution in networks is incomplete, limiting the knowledge graph’s potential for thorough precedent tracing and interlinking. Including additional datasets—such as administrative codes and judicial rules—would provide richer context and increase the system’s coverage of a functioning state government. Moreover, systematically reconciling informal post-decree agreements with formal judgments is needed to model a more acute legal flow.

This framework marks a step forward in computational law and legal AI, demonstrating a scalable, interpretable method for discovering, retrieving, and reasoning over complex legal corpora. Combining semantic embeddings, latent topic modeling, and knowledge graphs contributes to more robust, data-driven legal research pathways. Future directions include refining the citation extraction pipeline, expanding the collection to encompass broader legal instruments, and applying advanced LLM-driven reasoning for deeper precedent analysis and trend prediction.

ACKNOWLEDGMENTS

This research was funded by the U.S. Department of Energy National Nuclear Security Administration’s Office of Defense Nuclear

Nonproliferation Research and Development (DNN R&D), supported by the U.S. DOE NNSA under Contract No. 89233218CNA000001, as well as by the LANL Institutional Computing Program.

REFERENCES

- [1] 1953. New Mexico Constitution, Article IV, Section 22. <https://law.justia.com/constitution/new-mexico/article-iv/section-22/> Governor's approval or veto of bills. Amended September 15, 1953..
- [2] 1955. Smith v. South. Remanded with instructions to make findings of fact and conclusions of law on default issues..
- [3] 1996. KRM, Inc. v. Caviness. Reversed and remanded for further proceedings..
- [4] 2021. Employment Law – Healthy Workplaces – Earned Sick Leave; Use and Accrual. Effective July 1, 2022.
- [5] n.d. Justia: Free Law and Legal Information. <https://www.justia.com> Accessed: 2025-01-07.
- [6] Google AI. 2023. Gemini: Google’s Generative AI Model. <https://ai.google/>. Accessed: 2025-01-26.
- [7] Boian S Alexandrov, Ludmil B Alexandrov, Filip L Iliev, Valentin G Stanev, and Velimir V Vesselinov. 2020. Source identification by non-negative matrix factorization combined with semi-supervised clustering. US Patent 10,776,718.
- [8] Kevin D. Ashley. 2017. *Artificial Intelligence and Legal Analytics: New Tools for Law Practice in the Digital Age*. Cambridge University Press, Cambridge, UK. <https://doi.org/10.1017/9781316761380>
- [9] Ryan C. Barron, Ves Grancharov, Selma Wanna, Maksim E. Eren, Manish Bhatarai, Nicholas Solovyev, George Tompkins, Charles Nicholas, Kim Ø. Rasmussen, Cynthia Matuszek, and Boian S. Alexandrov. 2024. Domain-Specific Retrieval-Augmented Generation Using Vector Stores, Knowledge Graphs, and Tensor Factorization. arXiv:2410.02721 [cs.CL] <https://arxiv.org/abs/2410.02721>
- [10] Iz Beltagy, Matthew E. Peters, and Arman Cohan. 2020. Longformer: The Long-Document Transformer. arXiv:2004.05150 [cs.CL] <https://arxiv.org/abs/2004.05150>
- [11] Sheng Bi, Zafar Ali, Meng Wang, Tianxing Wu, and Guilin Qi. 2022. Learning heterogeneous graph embedding for Chinese legal document similarity. *Knowledge-Based Systems* 250 (2022), 109046. <https://doi.org/10.1016/j.knosys.2022.109046>
- [12] Shivangi Bithel and Sumitra S Malagi. 2021. Unsupervised Identification of Relevant Prior Cases. In *Proceedings of the 18th International Conference on Artificial Intelligence and Law*. ACM, 10–19.
- [13] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (Eds.), Vol. 33. Curran Associates, Inc., 1877–1901. https://proceedings.neurips.cc/paper_files/paper\2020/file/1457c0d6fbcb4967418fb8ac142f64a-Paper.pdf
- [14] Ryan Budahazy, Lu Cheng, Yihuan Huang, Andrew Johnson, Pengyu Li, Joshua Vendrow, Zhoutong Wu, Denali Molitor, Elizaveta Rebrova, and Deanna Needell. 2021. Analysis of Legal Documents via Non-negative Matrix Factorization Methods. *ArXiv* abs/2104.14028 (2021). <https://api.semanticscholar.org/CorpusID:233444252>
- [15] Pompeu Casanovas Romeu, Daniel Schwabe, and Carlos Laufer. 2021. Knowledge Graphs: Trust, Privacy, and Transparency from a Legal Governance Approach. 37, 1 (Aug. 2021), 24–41. <https://doi.org/10.26826/law-in-context.v37i1.136> A. Daniel Schwabe was partially supported by a grant from CNPq. The present work by Pompeu Casanovas has been carried out for the EU H2020 Programme LYNX, Legal Knowledge Graph for Multilingual Compliance Services..
- [16] Ilias Chalkidis, Ion Androutsopoulos, and Nikolaos Aletras. 2019. Neural Legal Judgment Prediction in English. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, Anna Korhonen, David Traum, and Lluís Márquez (Eds.). Association for Computational Linguistics, Florence, Italy, 4317–4323. <https://doi.org/10.18653/v1/P19-1424>
- [17] Ilias Chalkidis, Manos Fergadiotis, Prodromos Malakasiotis, Nikolaos Aletras, and Ion Androutsopoulos. 2020. LEGAL-BERT: The Muppets straight out of Law School. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, Trevor Cohn, Yulan He, and Yang Liu (Eds.). Association for Computational Linguistics, Online, 2898–2904. <https://doi.org/10.18653/v1/2020.findings-emnlp.261>
- [18] Ilias Chalkidis, Abhik Jana, Dirk Hartung, Michael Bommarito, Ion Androutsopoulos, Daniel Katz, and Nikolaos Aletras. 2022. LexGLUE: A Benchmark Dataset for Legal Language Understanding in English. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (Eds.). Association for Computational Linguistics, Dublin, Ireland, 4310–4330.

- <https://doi.org/10.18653/v1/2022.acl-long.297>
- [19] Ilias Chalkidis, Vasiliki Koukoulioti, and Nikolaos Aletras. 2021. Paragraph-level rationalization of legal judgments using reinforcement learning. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 1081–1090.
- [20] Arman Cohan, Sergey Feldman, Iz Beltagy, Doug Downey, and Daniel Weld. 2020. SPECTER: Document-level Representation Learning using Citation-informed Transformers. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault (Eds.). Association for Computational Linguistics, Online, 2270–2282. <https://doi.org/10.18653/v1/2020.acl-main.207>
- [21] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *North American Chapter of the Association for Computational Linguistics*. <https://api.semanticscholar.org/CorpusID:52967399>
- [22] Jaspreet Singh Dhani, Ruchika Bhatt, Balaji Ganeshan, Parikshet Sirohi, and Vasudha Bhatnagar. 2024. Similar Cases Recommendation using Legal Knowledge Graphs. [arXiv:2107.04771 \[cs.AI\]](https://arxiv.org/abs/2107.04771) <https://arxiv.org/abs/2107.04771>
- [23] Biao Dong, Haoze Yu, and Haisheng Li. 2021. A Knowledge Graph Construction Approach for Legal Domain. *Tehnicki vjesnik - Technical Gazette* (2021). <https://api.semanticscholar.org/CorpusID:235719041>
- [24] Maksim Eren, Nick Solovyev, Ryan Barron, Manish Bhattachari, Duc Truong, Ismael Boureima, Erik Skau, Kim Ø. Rasmussen, and Boian Alexandrov. 2023. Tensor Extraction of Latent Features (T-ELF). <https://doi.org/10.5281/zenodo.10257897>
- [25] Shangbin Feng, Zhaoxuan Tan, Wenqian Zhang, Zhenyu Lei, and Yulia Tsvetkov. 2023. KALM: Knowledge-Aware Integration of Local, Document, and Global Contexts for Long Document Understanding. <https://openreview.net/forum?id=NxPQ3QOGTW1>
- [26] Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. 2020. REALM: retrieval-augmented language model pre-training. In *Proceedings of the 37th International Conference on Machine Learning (ICML'20)*. JMLR.org, Article 368, 10 pages.
- [27] Patrik O. Hoyer. 2004. Non-negative Matrix Factorization with Sparseness Constraints. *J. Mach. Learn. Res.* 5 (Dec. 2004), 1457–1469.
- [28] Zhiqi Huang, Shahrad Naseri, Hamed Bonab, Sheikh Muhammad Sarwar, and James Allan. 2023. Hierarchical Transformer-based Query by Multiple Documents. In *Proceedings of the 2023 ACM SIGIR International Conference on Theory of Information Retrieval* (Taipei, Taiwan) (ICTIR '23). Association for Computing Machinery, New York, NY, USA, 105–115. <https://doi.org/10.1145/3578337.3605130>
- [29] Gautier Izacard and Edouard Grave. 2021. Leveraging Passage Retrieval with Generative Models for Open Domain Question Answering. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, Paola Merlo, Jörg Tiedemann, and Reut Tsarfaty (Eds.). Association for Computational Linguistics, Online, 874–880. <https://doi.org/10.18653/v1/2021.eacl-main.74>
- [30] Ziwei Ji, Nayeon Lee, Jason Fries, Tenghao Yu, Etsuko Ishii, Yejin Bang, and Zhiting Xia. 2023. A Survey on Hallucination in Natural Language Generation. *arXiv preprint arXiv:2305.15021* (2023).
- [31] Vladimir Karpukhin, Barlas Onguz, Sewon Min, Patrick Lewis, Ledell Wu, Sergey Edunov, Danqi Chen, and Wen-tau Yih. 2020. Dense Passage Retrieval for Open-Domain Question Answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Bonnie Webber, Trevor Cohn, Yulan He, and Yang Liu (Eds.). Association for Computational Linguistics, Online, 6769–6781. <https://doi.org/10.18653/v1/2020.emnlp-main.550>
- [32] Tiziano Labruna, Jon Ander Campos, and Gorka Azkune. 2024. When to Retrieve: Teaching LLMs to Utilize Information Retrieval Effectively. *ArXiv abs/2404.19705* (2024). <https://api.semanticscholar.org/CorpusID:269457164>
- [33] Daniel D. Lee and H. Sebastian Seung. 2000. Algorithms for non-negative matrix factorization. In *Proceedings of the 14th International Conference on Neural Information Processing Systems* (Denver, CO) (NIPS'00). MIT Press, Cambridge, MA, USA, 535–541.
- [34] Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, Sebastian Riedel, and Douwe Kiela. 2020. Retrieval-augmented generation for knowledge-intensive NLP tasks. In *Proceedings of the 34th International Conference on Neural Information Processing Systems* (Vancouver, BC, Canada) (NIPS '20). Curran Associates Inc., Red Hook, NY, USA, Article 793, 16 pages.
- [35] Pengyu Li, Christine Tseng, Yaxuan Zheng, Joyce A. Chew, Longxiu Huang, Benjamin Jarman, and Deanna Needell. 2022. Guided Semi-Supervised Non-negative Matrix Factorization on Legal Documents. *ArXiv abs/2201.13324* (2022). <https://api.semanticscholar.org/CorpusID:248328863>
- [36] Yixiao Ma, Yunqiu Shao, Yueyue Wu, Yiqun Liu, Ruizhe Zhang, Min Zhang, and Shaoping Ma. 2021. LeCaRD: A Legal Case Retrieval Dataset for Chinese Law System. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval (Virtual Event, Canada) (SIGIR '21)*. Association for Computing Machinery, New York, NY, USA, 2342–2348. <https://doi.org/10.1145/3404835.3463250>
- [37] Neo4j, Inc. 2023. Neo4j: The #1 Platform for Connected Data. <https://neo4j.com/>.
- [38] NVIDIA. 2023. NeMoTron-70B Instruct: NVIDIA's Generative AI Model. https://build.nvidia.com/nvidia/llama-3_1-nemotron-70b-instruct. Accessed: 2025-01-26.
- [39] OpenAI. 2023. GPT-4: OpenAI's Language Model. <https://openai.com/research/gpt-4>. Accessed: 2025-01-26.
- [40] OpenAI. 2024. OpenAI API. <https://www.openai.com/api/> Accessed: 2025-01-08.
- [41] Malte Ostendorff, Nils Rethmeier, Isabelle Augenstein, Bela Gipp, and Georg Rehm. 2022. Neighborhood Contrastive Learning for Scientific Document Representations with Citation Embeddings. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang (Eds.). Association for Computational Linguistics, Abu Dhabi, United Arab Emirates, 11670–11688. <https://doi.org/10.18653/v1/2022.emnlp-main.802>
- [42] Nicholas Pipitone and Ghita Houir Alami. 2024. LegalBench-RAG: A Benchmark for Retrieval-Augmented Generation in the Legal Domain. [arXiv:2408.10343 \[cs.AI\]](https://arxiv.org/abs/2408.10343) <https://arxiv.org/abs/2408.10343>
- [43] Juliano Rabelo, Randy Goebel, Mi-Young Kim, Yoshinobu Kano, Masaharu Yoshioka, and Ken Satoh. 2022. Overview and Discussion of the Competition on Legal Information Extraction/Entailment (COLIEE) 2021. *The Review of Socionetwork Strategies* 16, 1 (April 2022), 111–133. <https://doi.org/10.1007/s12626-022-00105-z>
- [44] Alec Radford and Karthik Narasimhan. 2018. Improving Language Understanding by Generative Pre-Training. <https://api.semanticscholar.org/CorpusID:49313245>
- [45] Livio Robaldo, Guido Boella, and Leendert van der Torre. 2020. A neural approach to automated legal case matching. *Artificial Intelligence and Law* 28, 1, 65–81.
- [46] Francesco Sovrano, Monica Palmirani, and Fabio Vitali. 2020. Legal Knowledge Extraction for Knowledge Graph Based Question-Answering. In *International Conference on Legal Knowledge and Information Systems*. <https://api.semanticscholar.org/CorpusID:229377581>
- [47] Jiaoguo Wang, Xiaomeng Yi, Rentong Guo, Hai Jin, Peng Xu, Shengjun Li, Xiangyu Wang, Xiangzhou Guo, Chengming Li, Xiaohai Xu, et al. 2021. Milvus: A Purpose-Built Vector Data Management System. In *Proceedings of the 2021 International Conference on Management of Data*, 2614–2627.
- [48] Xuran Wang, Xinguang Zhang, Vanessa Hoo, Zhouhang Shao, and Xuguang Zhang. 2024. LegalReasoner: A Multi-Stage Framework for Legal Judgment Prediction via Large Language Models and Knowledge Integration. *IEEE Access* PP (01 2024), 1–1. <https://doi.org/10.1109/ACCESS.2024.3496666>
- [49] Selma Wanna, Nicholas Solovyev, Ryan Barron, Maksim E. Eren, Manish Bhattachari, Kim Ø. Rasmussen, and Boian S. Alexandrov. 2024. TopicTag: Automatic Annotation of NMF Topic Models Using Chain of Thought and Prompt Tuning with LLMs. In *Proceedings of the ACM Symposium on Document Engineering 2024* (San Jose, CA, USA) (DocEng '24). Association for Computing Machinery, New York, NY, USA, Article 8, 4 pages. <https://doi.org/10.1145/3685650.3685667>
- [50] Hannes Westermann, Jaromír Savelka, Vern R Walker, Kevin D Ashley, and Karim Benyekhlef. 2021. Computer-Assisted Creation of Boolean Search Rules for Text Classification in the Legal Domain. *arXiv preprint arXiv:2112.05807* (2021).
- [51] Nirmalie Wiratunga, Ramitha Abeyratne, Lasal Jayawardena, Kyle Martin, Stewart Massie, Ikechukwu Nkisi-Orji, Ruvan Weerasinghe, Anne Liret, and Bruno Fleisch. 2024. CBR-RAG: Case-Based Reasoning for Retrieval Augmented Generation in LLMs for Legal Question Answering. In *Case-Based Reasoning Research and Development*, Juan A. Recio-García, Mauricio G. Orozco-del Castillo, and Derek Bridge (Eds.). Springer Nature Switzerland, Cham, 445–460.
- [52] Jie Zhou, Xin Chen, Hang Zhang, and Zhe Li. 2024. Automatic Knowledge Graph Construction for Judicial Cases. *arXiv:2404.09416 [cs.CL]* <https://arxiv.org/abs/2404.09416>
- [53] Junlin Zhu, Xudong Luo, and Jiaye Wu. 2022. A BERT-Based Two-Stage Ranking Method for Legal Case Retrieval. In *Knowledge Science, Engineering and Management*, Gerard Memmi, Baijian Yang, Linghe Kong, Tianwei Zhang, and Meikang Qiu (Eds.). Springer International Publishing, Cham, 534–546.