

# GRAPH-GRPO-LEX

## *Contract Graph Modeling and Reinforcement Learning with Group Relative Policy Optimization*

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# Objectives & Abstract

Represent contracts as semantic graphs using a detailed ontology

Train an LLM to extract nodes/edges via SFT and RL / gated GRPO

Leverage graph metrics (density, depth, centrality) and create the “Contract linter”



## Background & Motivation

Contracts are key document that underlie most commercial activity

Contracts come in a variety of flavors including —

- Non Disclosure Agreements

- Property Leases

- Employment Agreements

- Loan Agreements

- Licensing Agreements

- Etc.

Contracts feature clauses, subclauses, etc.



## Background & Motivation

Modern Contracts are both lengthy and complex

Both the creation and review of contracts is both time consuming and prone to errors

There has been a variety of efforts to use technology including AI to assist in both the creation and review of contracts

Knowledge Graphs (KGs) have been one vehicle to represent the underlying complexity of legal documents



## Background & Motivation

Prior KG work inspires graph-based representations for legal documents

Graph + RL allows automated extraction and analysis, overcoming manual bottlenecks

Added benefit of applying graph metrics for quality and risk assessment

# Dataset & Corpus

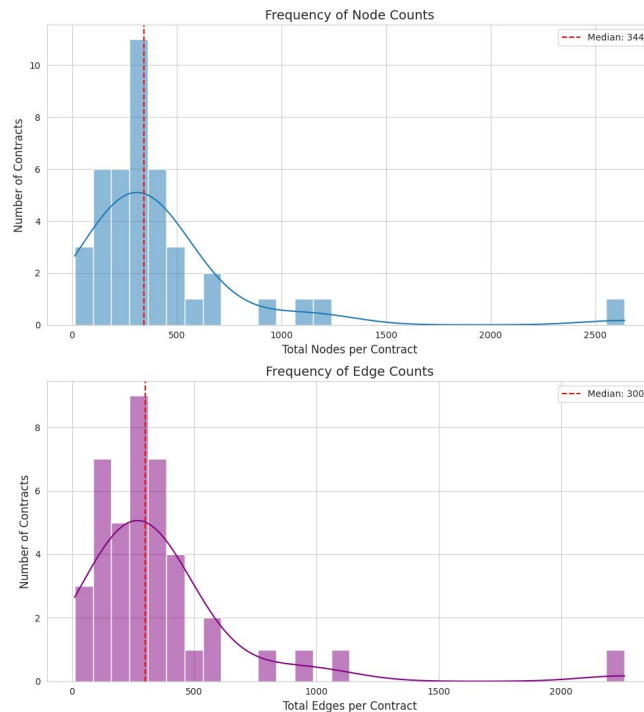


43 CUAD contracts dataset  $\approx$  1,600 clauses

Alt-test validation:  
LLM labels over human annotators  
( $\omega \approx 0.99$ , AAP  $\approx 0.907$ )

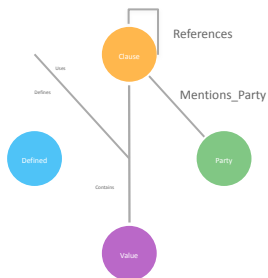
Statistic	Value
Contracts	43
Clauses	$\approx$ 1,600
Node types	4
Edge types	6

Distribution of Node and Edge Counts Across Contracts





# Graph Ontology & Metrics



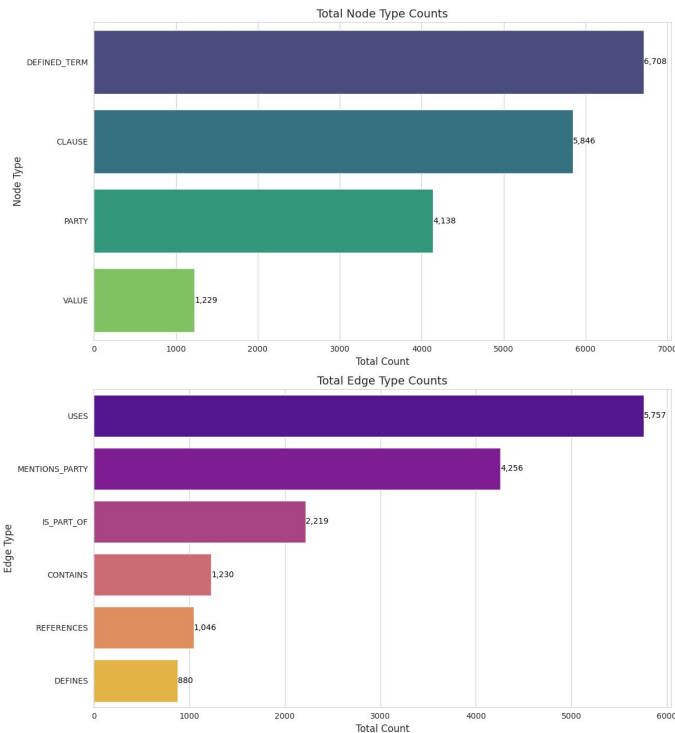
Nodes: Clause, Defined Term, Party, Value

Edges:

Structural (Is Part Of, Contains),  
Semantic (Defines, Uses, References)

Metrics: Density, Depth, Centrality, k-Core,  
Orphans/Leaves, Articulation Points

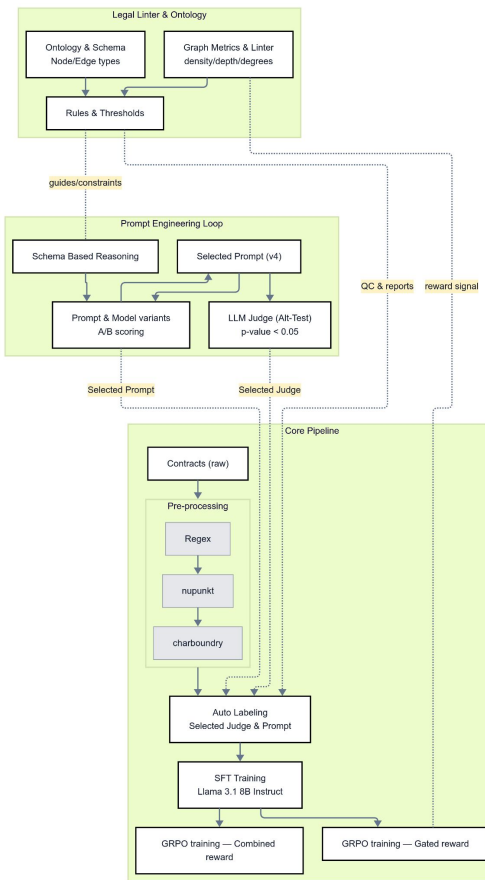
Overall Node and Edge Type Distributions in the Dataset



# Pipeline & Methodology



NUPUNKT/CHARBOUNDARY  
Prompt Engineering to choose llm  
Alt-Test LLM vs Human Labels  
SFT Llama-3.1-8B with QLoRA  
GRPO Custom Reward Function





# Case Study: Zogenix Agreement



Nodes  
257

Density  
0.014

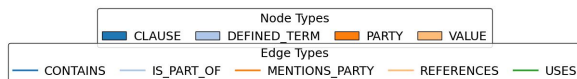
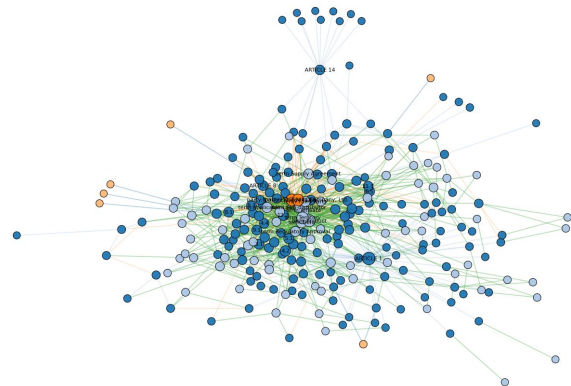
Edges  
916

Articulation pts.  
11

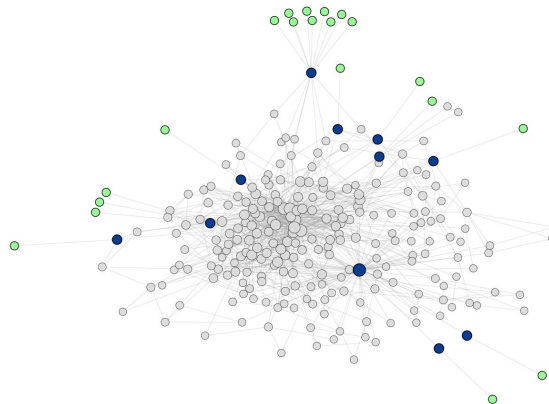
Depth  
6

Leaves  
97

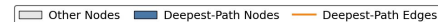
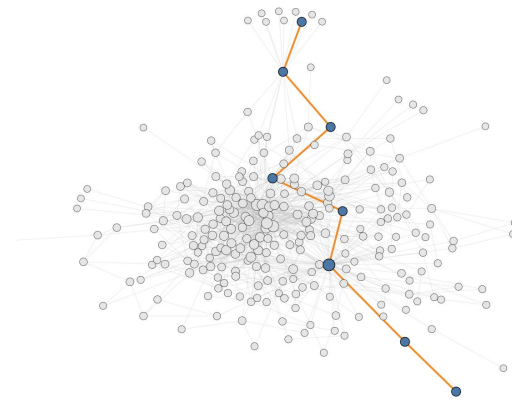
ZogenixInc Distributor Agreement Graph



ZogenixInc Distributor Agreement - Leaves, Orphans, and Articulation Points



ZogenixInc Distributor Agreement - Deepest Path length=7





## Supervised Fine-Tuning (SFT) Results

Baseline model: Meta-Llama-3.1-8B-Instruct + QLoRA (rank 8,  $\alpha=16$ )

Strict micro-F1: 0.661; Fuzzy micro-F1: 0.693

Invalid JSON rate: 0.0 (deterministic decoding)

Metric	Train	Eval
strict_micro_precision	0.625	0.5394
strict_micro_recall	0.6875	0.8541
strict_micro_f1	0.6547	0.6612
fuzzy_micro_precision	0.6292	0.5569
fuzzy_micro_recall	0.7	0.9166
fuzzy_micro_f1	0.6627	0.6929
invalid_json_rate	0.0	0.0

# Challenges & Lessons



High-temperature sampling yields invalid JSON → lower T to 0.3 and reward partial validity

Greedy decoding over-generates → add JSON stopper to truncate correctly

Base tokenizer produces gibberish → ASCII clamp filters non-ASCII tokens

Compute constraints: single A100 GPU; group size limited to 4





# Gated GRPO Training

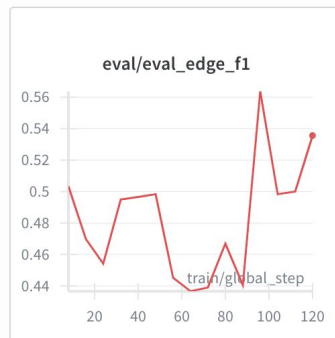
Composite reward:

structure  $\rightarrow$  strict/fuzzy F1  $\rightarrow$  embedding similarity  $\rightarrow$  edit distance

Sample size 4; LR= $2e-6$ ; T=0.4; Top-p=0.9;

Rep. penalty=1.2; JSON stopper & ASCII clamp

Metric	GRPO-Eval	SFT-Eval
strict_micro_precision	0.806	0.5394
strict_micro_recall	0.790	0.8541
strict_micro_f1	0.798	0.6612
fuzzy_micro_precision	0.817	0.5569
fuzzy_micro_recall	0.802	0.9166
fuzzy_micro_f1	0.809	0.6929
invalid_json_rate	0.02	0.0





## Conclusions & Contributions

1. Developed a comprehensive legal ontology
2. Built a clause-centric pipeline for node/edge extraction and assembly
3. Validated Prompt Engineered LLM labels via Alt-test
4. Created rich metrics - The Contrat Linter
5. Designed a composite reward function for contract graphs
6. Introduced gated GRPO training, achieving significant gains over SFT



## Future Work & Outlook

Integrate graph-based KGs with RAG frameworks for grounded contract Q&A

Generate Contract Linter Reports for risk assessments

Apply gated RL for drafting assistance and negotiation analysis

Translate Linter metrics to Graph Judges and inspect uncertainty based error signal for selective refinement - Coming Soon!