

ArgAssist: LLM-based Argument Synthesis for Insurance Disputes

**Anubhav Sinha, Nitin Ramrakhiyani, Sachin Pawar, Isha Narang,
Manoj Apte**

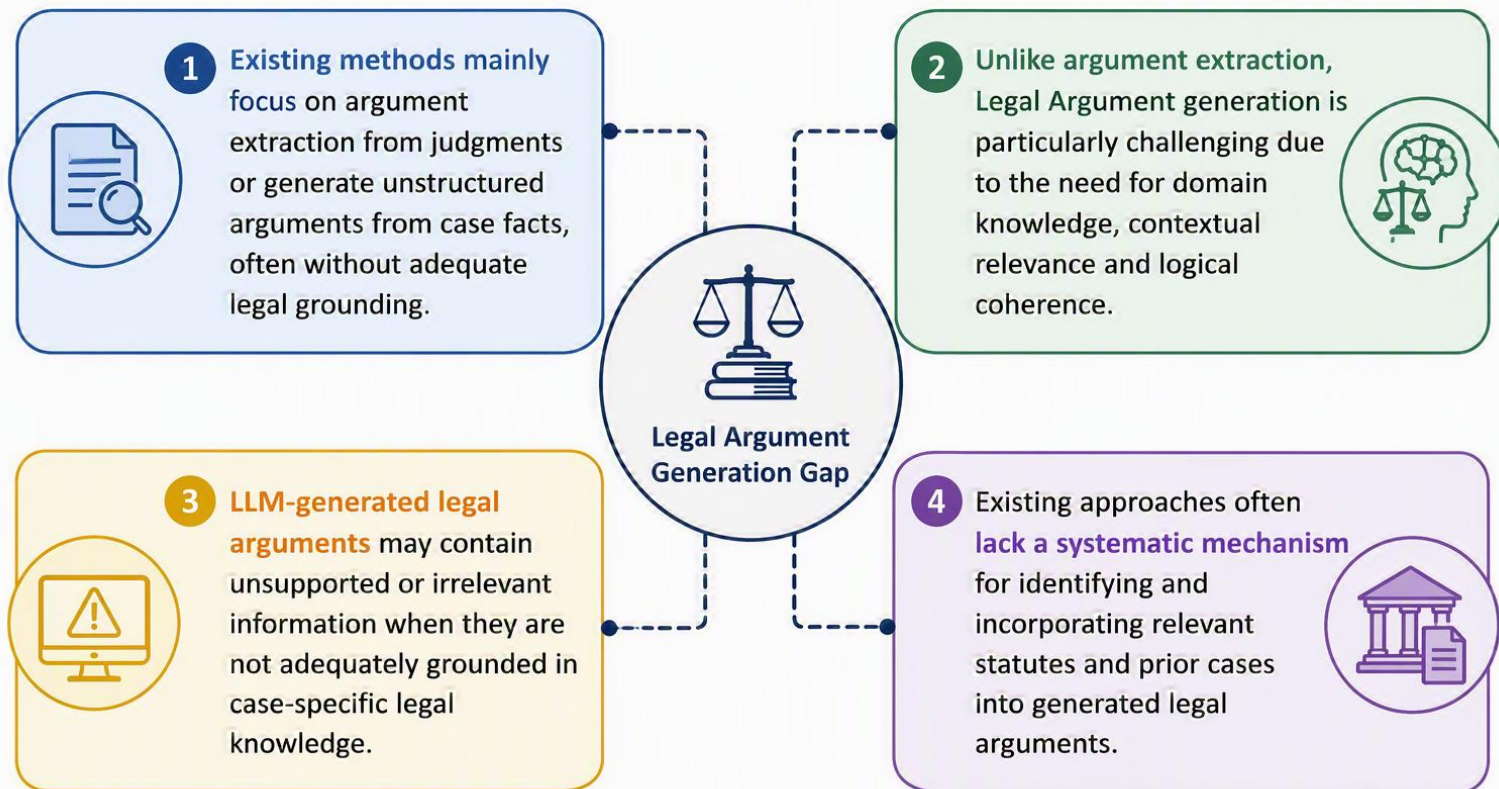
The 27th Meeting of the Special Interest Group on Discourse and Dialogue



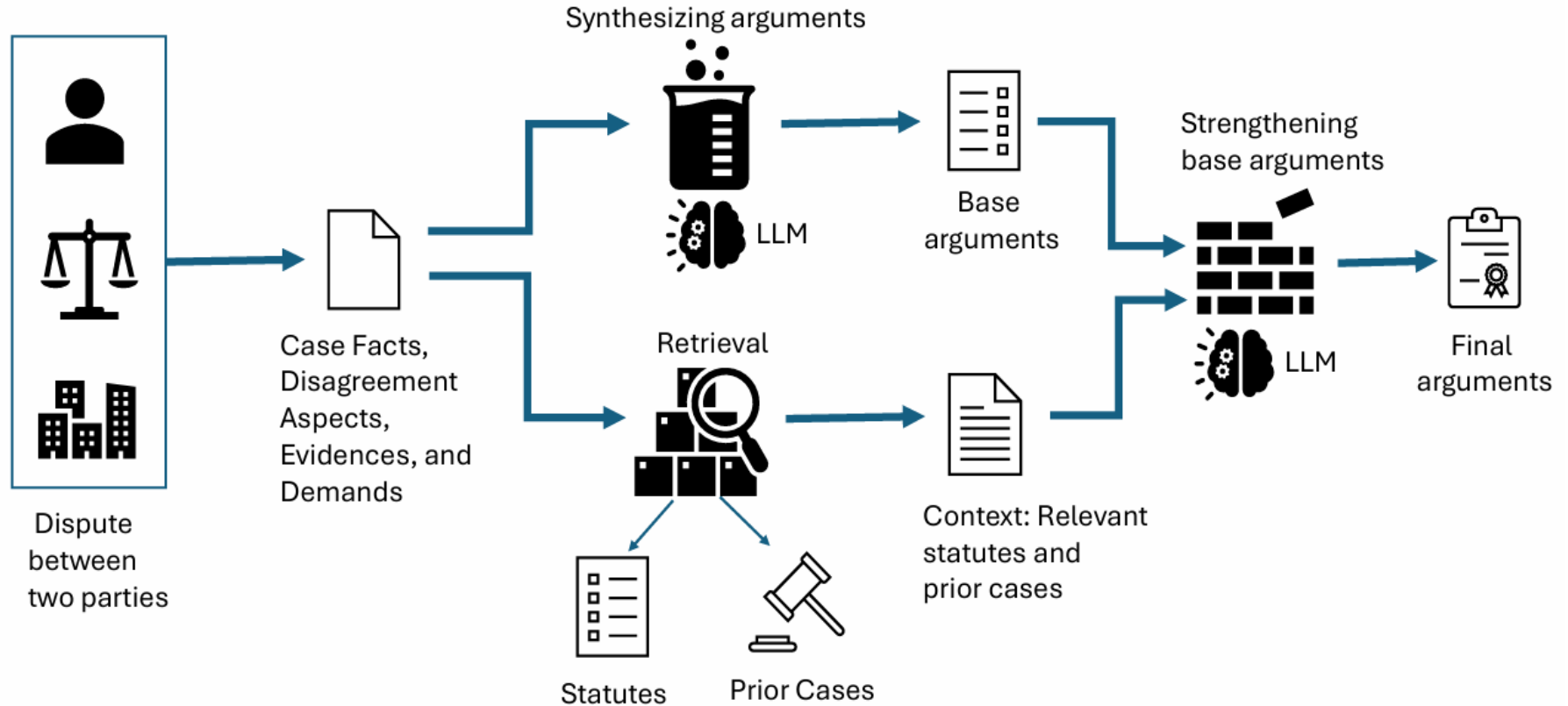
Motivation

- Legal disputes are frequent and complex, while access to timely and affordable legal assistance remains limited.
- Most of these disputes end up in litigation, straining the already overburdened judicial systems.
- There is a need to democratize legal reasoning and support individuals who may lack access to professional legal representation.
- This motivates the need for automated legal reasoning systems capable of generating legally grounded arguments for dispute resolution.

Problem statement & Research gap



ArgAssist Pipeline



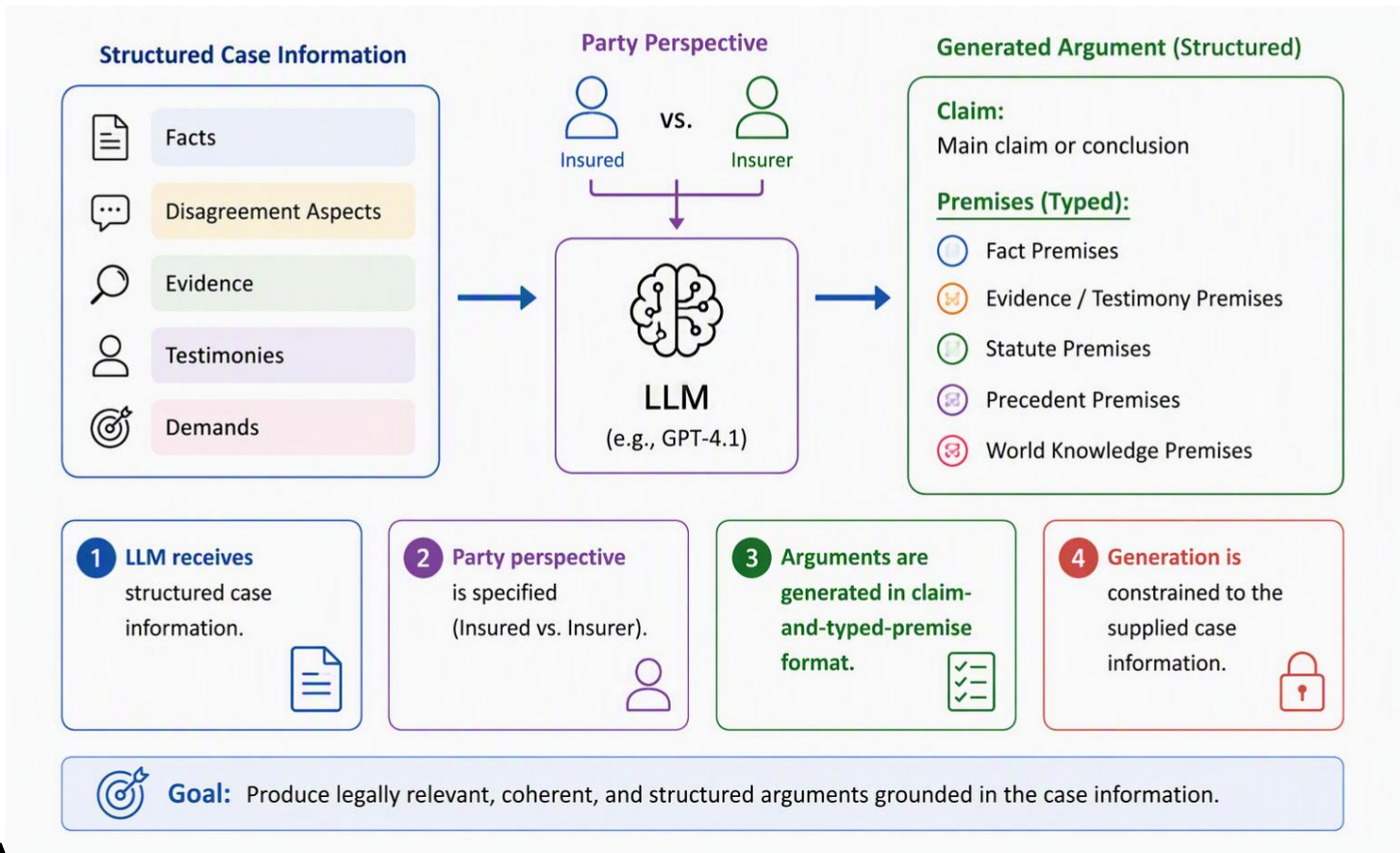
ArgAssist

- **Multi-Stage Argument Synthesis:**
 - Generates party-specific legal arguments from structured dispute information.
- **Structured Argument Representation:**
 - Organizes arguments as claims supported by multiple evidence types.
- **Dispute-Aware Legal Knowledge Retrieval:**
 - Identifies relevant statutes and prior cases using dispute-specific information.
- **Retrieval-Augmented Refinement:**
 - Strengthens arguments by incorporating legally relevant authorities.

Argument Representation

- **Claim-centric representation:** Every argument revolves around a clear claim or legal position.
- **Multi-source support:** Claims are supported using facts, evidence, statutes, precedents, and domain knowledge.
- **Improved traceability:** Each supporting premise can be linked back to its underlying source information.
- **Better legal grounding:** Explicit representation of legal authorities reduces hallucination and strengthens argument quality.

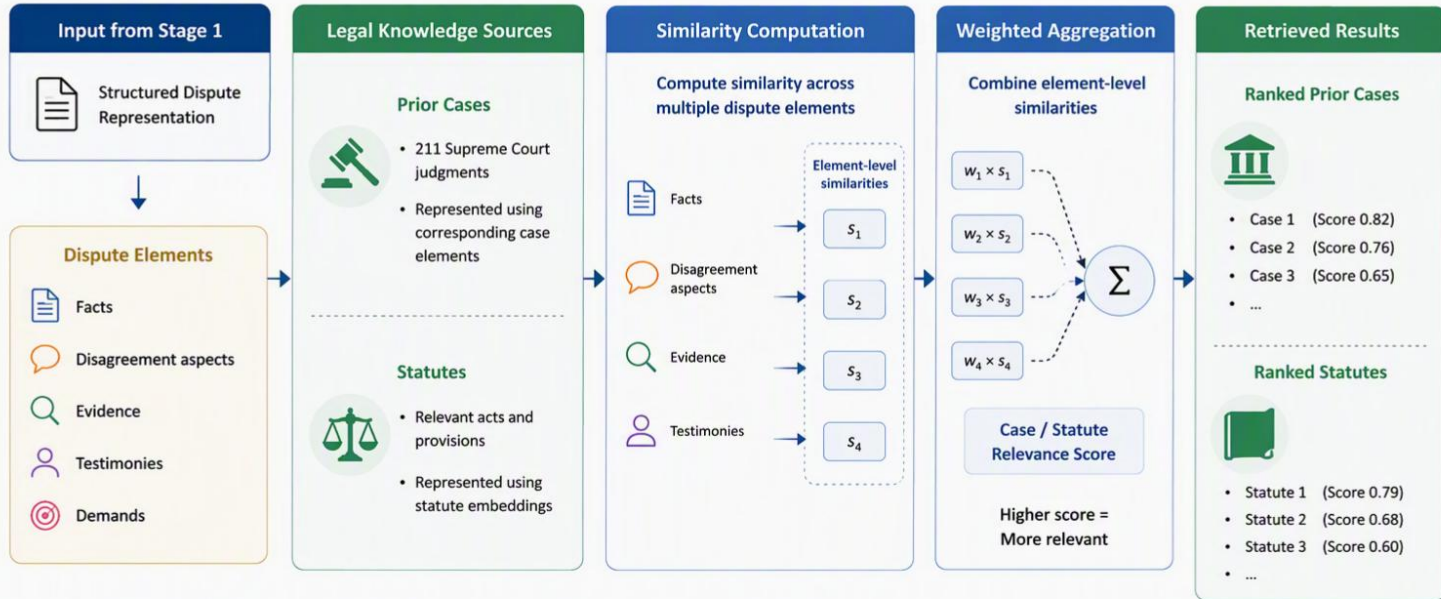
Stage 1, Base Argument Synthesis



Stage 2, Retrieval of Legal Knowledge



Goal: Retrieve legally relevant prior cases and statutes for the current dispute.



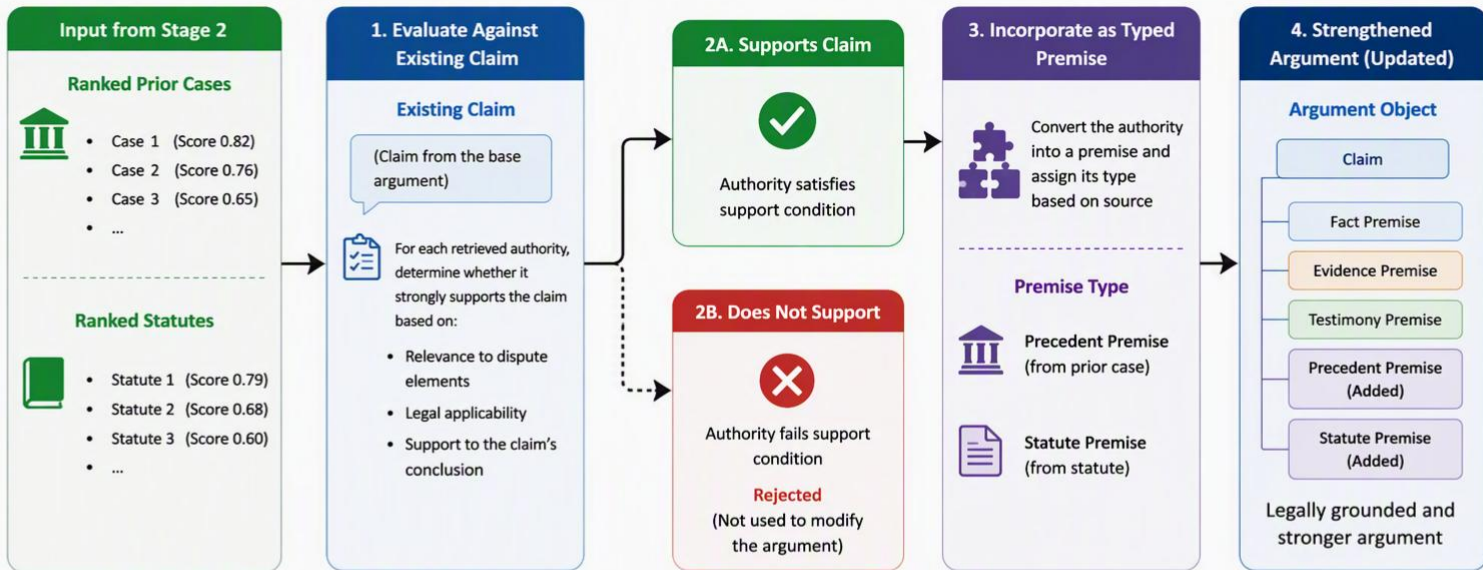
Key Point

Similarity is computed across facts, disagreement aspects, evidence, and testimonies. Element-level scores are combined using weighted aggregation to rank prior cases and statutes.

Stage 3, Argument Strengthening



Goal: Evaluate retrieved legal authorities and incorporate only those that strongly support the existing claim to strengthen the argument.



Retrieval-Augmented Refinement

The argument is refined by adding only strongly supporting legal authorities as typed premises, thereby improving legal grounding, relevance, and persuasiveness.

Dataset and experimental setup

<i>Dataset</i>	<i>Cases</i>
<i>VID</i>	<i>129</i>
<i>LID</i>	<i>82</i>
<i>Prior cases</i>	<i>211</i>

- **Experimental Configuration:** 10 disputes from each dataset were used for development, while the remaining disputes formed the test sets. Experiments used GPT-4.1 and text-embedding-3-large.
- **Baseline and Evaluation:** ArgAssist was compared with a Flan-T5-based argument generation baseline and evaluated using Retrieval Quality, the proposed ArgMatch metric, and LLM-based quality assessment of unmatched arguments.

Evaluation methodology

ArgMatch (AM)

- Compares generated arguments with gold-standard court arguments.
- Uses claim-level bipartite matching and premise-level semantic similarity.
- Reports Precision, Recall, and F1 scores.

Quality Assessment of Unmatched Arguments (QSFP)

- Evaluates generated arguments that do not have corresponding gold-standard matches.
- Uses an LLM-as-a-judge.
- Assesses logical coherence, factual accuracy, legal foundation, and persuasiveness.

Result and key findings

Consistent best performance:
ArgAssist_final achieves the highest AM scores across both datasets and both parties.

Stronger after alignment: Adding relevant statutes and precedents consistently improves ArgAssist_base

Promising court argument coverage:
AM recall improves significantly for the strengthened system.

High-quality additional arguments:
Unmatched arguments are of high quality and score 3.51-3.97 out of 5.

Dataset	Party	Technique	Micro-averaged			Macro-averaged			QSFP
			AM _P	AM _R	AM _{F1}	AM _P	AM _R	AM _{F1}	
VID	insured	baseline	0.076	0.097	0.086	0.082	0.119	0.092	1.441
		ArgAssist_base	0.271	0.524	0.357	0.275	0.525	0.341	3.155
		ArgAssist_final	0.288	0.558	0.380	0.293	0.568	0.365	3.622
	insurance company	baseline	0.152	0.196	0.171	0.178	0.241	0.191	1.445
		ArgAssist_base	0.332	0.627	0.434	0.332	0.629	0.418	3.168
		ArgAssist_final	0.343	0.648	0.449	0.342	0.652	0.431	3.513
LID	insured	baseline	0.080	0.113	0.094	0.084	0.128	0.094	1.701
		ArgAssist_base	0.204	0.479	0.286	0.209	0.517	0.286	3.438
		ArgAssist_final	0.227	0.533	0.319	0.232	0.581	0.318	3.977
	insurance company	baseline	0.085	0.134	0.104	0.103	0.190	0.124	1.660
		ArgAssist_base	0.241	0.551	0.335	0.243	0.587	0.333	3.472
		ArgAssist_final	0.260	0.595	0.362	0.262	0.638	0.360	3.771

AM indicates the proposed ArgMatch metric and QSFP indicates LLM-as-a-judge scores assigned for unmatched generated arguments

Conclusion and future work

- **Effective Legal Argument Synthesis:** ArgAssist generates structured, dispute-specific, and legally grounded arguments for both parties involved in an insurance dispute.
- **Benefits of Legal Knowledge Refinement:** Strengthening base arguments with relevant statutes and prior cases consistently improves alignment with arguments presented in actual court proceedings.
- **Extension to Other Domains:** Future work will explore disputes in areas such as finance, e-commerce, consumer goods, and taxation.
- **Broader Evaluation and Knowledge Coverage:** The framework will be evaluated using larger prior-case collections, additional legal knowledge such as legal factors, and a wider range of proprietary and open-source LLMs.

Thank you

