Multi-step Inference over Unstructured Data

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Abstract

The advent of Large Language Models (LLMs) and Generative AI has revolutionized natural language applications across various domains. However, high-stakes decision-making tasks in fields such as medical, legal and finance require a level of precision, comprehensiveness, and logical consistency that pure LLM or Retrieval-Augmented-Generation (RAG) approaches often fail to deliver. At Elemental Cognition (EC), we have developed a neuro-symbolic AI platform to tackle these problems. The platform integrates fine-tuned LLMs for knowledge extraction and alignment with a robust symbolic reasoning engine for logical inference, planning and interactive constraint solving. We describe Cora, a Collaborative Research Assistant built on this platform, that is designed to perform complex research and discovery tasks in high-stakes domains. This paper discusses the multi-step inference challenges inherent in such domains, critiques the limitations of existing LLM-based methods, and demonstrates how Cora's neuro-symbolic approach effectively addresses these issues. We provide an overview of the system architecture, key algorithms for knowledge extraction and formal reasoning, and present preliminary evaluation results that highlight Cora's superior performance compared to well-known LLM and RAG baselines.

1 Introduction

With the emergence of Large Language Models (LLMs) and Generative AI, there is an enormous interest in building natural language applications for a wide variety of use-cases across multiple domains. Gen-AI is being leveraged in solutions ranging from conversational web search and enterprise search engines, to chat-bots for customer service, retail, travel, insurance, etc.

There is a class of high stakes decision-making applications that require performing accurate, detailed and well rationalized research to evaluate and justify complex hypotheses. Such applications include Life Science and Medical research for drug discovery and Macro-economic analysis for investment research. These use-cases are challenging to tackle using pure LLM or even Retrieval-Augmented-Generation (RAG, which is LLM+search) based approaches, due to the need to be precise, thorough and logically consistent.

In particular, the use-cases have the following characteristics:

- There are highly adverse effects to being wrong in some cases, lives are at stake, in others, there is a risk in losing enormous time, money and resources to pursuing a wrong path. The explicability and transparency of the system are therefore critical, as decision makers need strong and precise evidence to justify their actions.
- The problems involve exploring and evaluating complex research hypotheses where the answers and evidence are often not specified in a single source or document; instead, relevant information is spread across multiple datasets, which need to be pieced together.
- The underlying data is a mix of large unstructured text corpora (e.g., PubMed¹, Financial news articles) and structured data, ontologies and knowledge graphs (e.g., Gene Ontology [1]). Combined with the above point, it means we need to extract knowledge (key concepts

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¹https://pubmed.ncbi.nlm.nih.gov/

and relationships) from unstructured data, link it to relevant structured data, and build a *unified* knowledge source to help connect the dots when exploring hypotheses.

- Finding *refuting* evidence is as crucial as supporting evidence in order to provide a fully balanced view of the problem, and avoid confirmation bias.
- Developing a strong understanding of the problem space and building sufficient confidence in the solution requires causal and logical inference over multiple inter-dependent causal factors and linkages. We need to develop reasoning strategies that help users probe and clarify assumptions, detect and explain contradictions in the data, do probabilistic analysis weighing supporting and refuting evidence appropriately, and support counterfactual reasoning (What-if analysis).

At Elemental Cognition (EC), we have built solutions to tackle these problems that combine fine-tuned LLMs (and in some cases, smaller transformer based pre-trained LMs that are more optimal for a given task) for knowledge extraction, alignment and fluent NL generation, with our multi-strategy Symbolic Reasoning Engine for precise logical reasoning and constraint solving. The technologies we have built (components, models, APIs) are part of our Neuro-Symbolic AI platform (described in Section 3). To showcase the platform's potential, we have developed an application called *Cora* (Collaborative Research Assistant) that uses various platform APIs for knowledge retrieval, synthesis and reasoning, and is designed to perform complex research and discovery in high-stakes problem domains.

In this paper, we start by describing the multi-step inference problems and discuss the challenges a pure statistical/LLM-based approach faces when solving them. We then show how EC's Cora resolves these challenges using a neuro-symbolic approach. We provide an overview of the underlying technology and system architecture, and highlight key algorithms for knowledge extraction and formal reasoning. Finally, we evaluate our system against well-known LLM and RAG baselines on the multi-step inference problems to demonstrate their value.

2 Multi-Step Inference Use-Cases

2.1 Life Science Research: Drug Discovery and Re-purposing

A biopharma company can spend over \$2 billion to take a drug from initial discovery to approved use in the market [14]. Identifying high-quality drug targets at the beginning of this process is essential both to increase the chance of success and to reduce the downstream costs. Comprehensive and fast literature review at the earliest stages is a key ingredient of efficient and effective target identification.

Key sources for this literature review include, among others, peer-reviewed research articles available through PubMed, information on clinical trials and outcomes, patents related to the disease and potential drug targets, and NIH grant awards. The challenge is effectively exploring and validating research hypotheses by finding and connecting all of the relevant bits of information.

Several issues confront researchers in this process. First, the well known problems of language synonymy and polysemy are further exacerbated in Life Sciences, where the terminology is constantly growing as new discoveries are made, confounding manual efforts to curate ontologies.

Second, exploring a drug target hypothesis typically requires connecting multiple pieces of information that describe different elements of a complex biological pathway. Since scientists are typically exploring novel hypotheses, there is no single source in the literature that provides the overall answer. Instead, the scientist must tediously find evidence spread across multiple sources for each component of the pathway.

Third, every hypothesis, or sub-component of that hypothesis, may have a variety of published results, some of which support the hypothesis, and some of which refute that hypothesis. Moreover, the researcher must consider the veracity of any single piece of evidence in support or refutation of a claim, which is usually a product of the prestige of the publication, the reputation



Figure 1: Using ChatGPT for Medical Research. There are four main classes of problems (1) No control over the search process, filtering or ranking of results; (2) Inability to validate without cross-checking references - here, the paper exists but it does not contain evidence justifying the claim; (3) Hallucinated references - this citation is made up; (4) Cannot guarantee completeness - inability to find needles in the haystack

of the authors and their institution, and the quality of the study or experimental methodology described in the evidence.

On the surface, all of these challenges sound like ideal candidates for an LLM solution. An LLM, however, provides only part of the solution.

Figure 1 shows an example of using ChatGPT² (as of Apr 2024) for medical research. The example question is about exploring a potentially multi-hop relationship between *Rheumatoid Arthritis* (RA) and the inhibition of a particular kinase called IRAK4. As shown in the figure, there are four main classes of problems with this purely LLM-based approach: the inability to control the search or ranking process, since the LLM is a black-box that is not grounded to a specific corpus where one might apply filtering or ranking criteria; the inability to validate results without cross-checking the references (which defeats the purpose of an efficient research solution); hallucinated references which undermine credibility of the approach; and the "needle-in-the-haystack" problem as valid answers that are not popular in the training data are unlikely to be surfaced by the LLM.

As a result of these issues, the community has essentially migrated to a Retrieval Augmented Generation (RAG) approach for doing more precise and comprehensive search, where an LLM is combined with an Information Retrieval engine (search system) to produce answers that are grounded in a domain corpus, and are more up-to-date (beyond the training period of the LLM). There are several RAG based solutions that exist in the current market-

²https://chat.openai.com/



Figure 2: Elicit's answer to the question linking IRAK4 and RA

place, from general-purpose (web-based) search/answer generating engines like Perplexity³, to domain-specific research solutions like Elicit⁴. Since our focus area is on deep domain-specific research, we use Elicit as a baseline when doing Life Science research. Figure 2 shows an answer to the same question with Elicit. Elicit produces an answer from the top 8 papers, and hence suffers from recall issues. Moreover, the answer is fairly shallow without providing a detailed causal understanding of the main biological linkages.

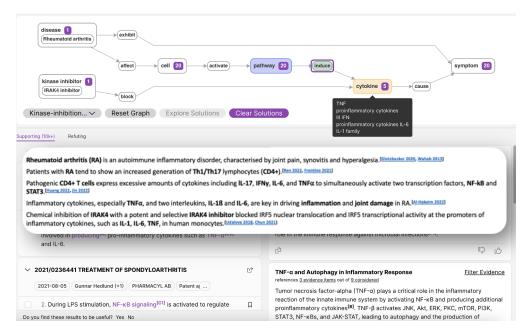


Figure 3: Cora's analysis for the IRAK4-RA question. Cora extracts a detailed model linking RA and IRAK4 inhibitors based on a generalized research template, and produces a structured report with claims, evidence and citations

Contrast this with the answer to the same question produced by our research assistant Cora, as shown in Figure 3. Cora's approach is radically different in that it uses a general research template for connecting the dots between the two concepts of interest (RA and IRAK4 inhibitor), and then instantiates this template with specific bindings (answers) for concepts based on the

³https://www.perplexity.ai/

⁴https://elicit.com/

inter-connected linkages. The research template is automatically induced from the data using our knowledge extraction algorithms and then further refined by a domain expert (the expert can directly specify a template as well). A single research template can be repurposed for multiple use-cases that involve the same kinds of concepts – in this case, a link between any disease and kinase inhibitor, not just RA or IRAK4 inhibitors. The final answer produced by the system is based on the entire causal map and contains detailed evidence for each of the linkages with reliable citations.

2.2 Macro-Economic Analysis: Multivariate Causal Inference

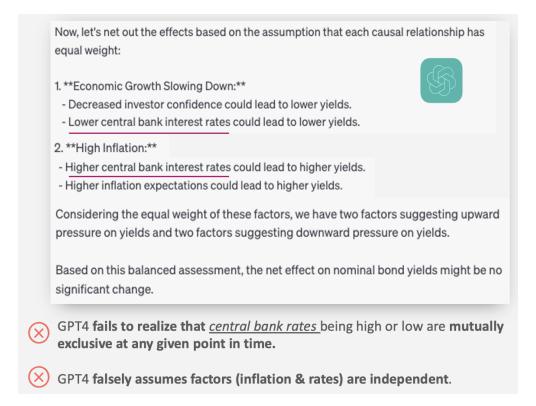


Figure 4: **GPT4's response to the macro-economic question:** If economic growth is falling in an Emerging Market country, and the country is facing high inflation, what is the likely impact on nominal bond yields?

Consider the following macro-economic research problem: you are given a scenario that describes the state of a given economy, and the task is to understand the impact on a particular target concept. For example, If growth is falling in an Emerging Market country, and the country is facing high inflation, what is the likely impact on nominal bond yields? As can be seen, the scenario contains multiple economic factors (falling economic growth, high inflation) that are present in a given context (Emerging Market country), and a good solution to this problem requires mapping out the relevant causal linkages between these factors and the target concept (nominal bond yields), and performing causal inference to net out the influences.

We asked the above question directly to GPT4 and refined the prompt to get the model to analyze both upward and downward pressures on the target concept. The output is shown in Figure 4. Apart from the fact that the answer does not include reliable references or data (for the reasons described in the previous section), the LLM also makes fundamental reasoning mistakes. In particular, it conflates mutually-exclusive conditions (that cannot be true at the same time), and asserts the possibility of both "canceling each other out", which is logically

invalid. Moreover, it assumes independence between highly inter-dependent factors, as shown in the example.

While using a RAG-based GPT approach would help ground the results in a corpus and improve the reliability of the evidence, doing precise logical reasoning is still a capability that LLMs (even ones as powerful as GPT4) struggle with.

We adopt a neuro-symbolic approach to solving this problem. Instead of using a purely RAG-based approach for doing search and reasoning, we first use a multi-step graph search algorithm to identify relevant causal linkages in the text, and dynamically build a comprehensive causal map where each link is substantiated with evidence from the corpus. We then feed this causal map to a symbolic reasoning engine to propagate and reason over the causal influences considering the correlations and weights of various factors.

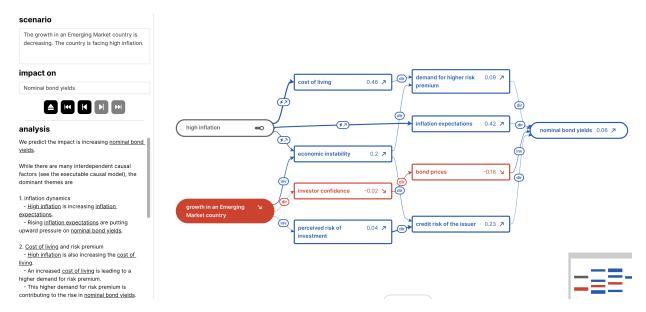


Figure 5: Cora's response to the question on nominal bond yields. Cora extracts a scenario relevant causal map "on-the-fly" from the corpus and does precise causal inference to compute the final result. Blue edges in the graph indicate upward pressure on the target node, while red edges indicate downward pressure. Similarly, the node color being blue or red depicts whether the quantity is increasing or decreasing respectively. The graph is fully interactive and the user can alter edge weights, add or remove nodes/edges and redo the causal inference on the fly.

Cora leverages these technologies to do causal inference over unstructured data. Figure 5 shows the causal map extracted by Cora for the earlier question. Cora's answer and structured explanation (shown in the left of the figure) is generated from the causal map and describes the dominant themes at play, with the underlying causal chains.

The extracted causal map is a fully executable logical model, where the user can refine any part of the graph structure - e.g. drop edges, merge nodes, force the values of specific nodes (based on known facts or hypothetical scenarios), alter edge weights (based on domain knowledge) etc. - and then re-run inference to compute the effects of the changes. In this manner, Cora supports interactive precise counterfactual reasoning and What-if analysis. As a next step, we are exploring connecting the causal map extracted from theory with real economic time-series data to make more informed statistical predictions.

3 Neuro-Symbolic AI Platform

In the previous section, we described challenges faced by LLM/RAG based approaches when tackling complex causal question answering problems that involve multiple factors and pieces of evidence and the Cora application we built to tackle these issues. In this section, we describe our AI platform used to build Cora, the analytics pipeline that constructs the semantic indices (KBs) from unstructured text, and highlight how symbolic reasoning is used to produce answers.

3.1 High-Level Architecture

As depicted in Figure 6, at the heart of the EC AI platform is a general-purpose symbolic multi-strategy reasoning engine that is based on Answer Set Programming [11], and uses and builds on solvers such as Clingo [8]. The reasoning engine performs the key function of logical reasoning including causal, deductive, abductive and non-monotonic inference as well as multi-objective constraint optimization based on given rules and facts. It supports interactive and incremental reasoning, involving the user to address knowledge gaps, resolve ambiguities, and make knowledge updates to the model on-the-fly, providing detailed explanations of the model's analysis.

In addition to these core interactive reasoning capabilities, the EC AI platform integrates with LLM-powered interfaces to facilitate knowledge acquisition and user interactions through fluid natural language interactions.

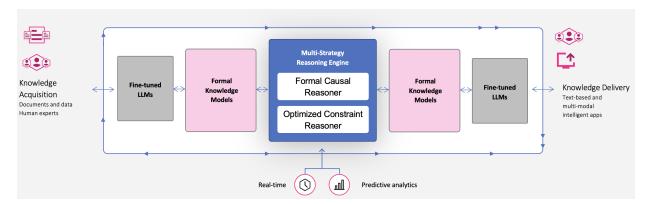


Figure 6: EC's Neuro-symbolic AI Platform

We support two kinds of knowledge acquisition – semi-automated expert guided authoring for small-medium sized domain models, and fully-automated knowledge extraction from large domain corpora. The former uses our proprietary Knowledge Representation language known as *Cogent*, and is the focus of the work described in [4]. In this paper, we focus on our capabilities for the latter use-case.

Figure 7 shows the solution architecture for Cora. There are two phases of the system - during the offline domain knowledge extraction phase, the system ingests a text corpus using EC's Natural Language Understanding (NLU) pipeline (more on this in the next section), extracts domain concepts and relationships in the text, and stores the resultant structured information along with text embeddings (vectors) for concepts and passages in a semantic index ("Domain KB").

At runtime (i.e. online phase), the system is given a user scenario, and it uses a Query Interpretation Model (a fine-tuned LLM) to process the input and pull out salient concepts and relationships in the scenario question. This information is passed to the Evidenced Graph Builder, which uses an iterative, multi-step graph search algorithm to find relevant relationships and chains from the Domain KB that are applicable to the input scenario (alternately, it might retrieve an applicable pre-saved research template when relevant). The algorithm fleshes out a

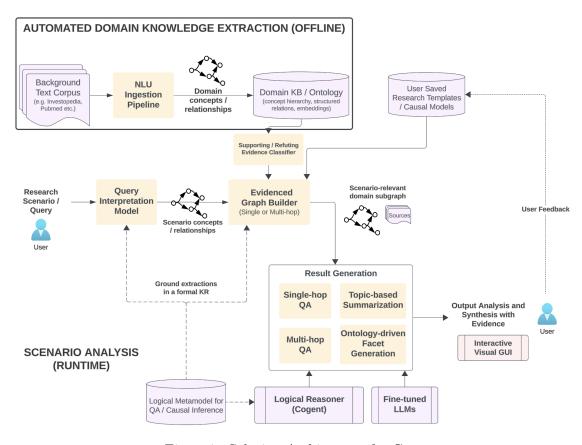


Figure 7: Solution Architecture for Cora

relationship/causal graph connecting input concepts in the scenario to the target/query concept, where each link is sourced from the theory texts.

The Evidenced Graph builder is also fed the QA/Inference Meta-model as one of its inputs. This is an abstract logical meta-model for doing causal inference and question answering, and provides the logical scaffolding (or grounding) for the extracted concepts and relationships. It is specified using our proprietary Cogent language. The meta-model draws on an established causal reasoning framework, Qualitative Process Theory, as well as its recent applications to knowledge graph extraction, as a starting point to formalize concepts such as Quantities, States, and the causal influences that propagate between them [5, 6, 7].

The output of the Evidenced Graph Builder is an instance of this meta-model that is specialized to the scenario concepts and the extracted causal linkages. This model is then executed using the Cogent Reasoning Engine (RE) to derive inferences based on the specific connections in the map.

The Result Generation module uses the Cogent RE along with fine-tuned LLMs to provide various functionalities, ranging from single/multi-hop QA to topic-based summarization and facet generation. The latter two features are beyond the scope of this paper.

Finally, the system allows users to save the analyzed and reasoned-over knowledge graph results, which can be reused for future scenario analysis.

3.2 Knowledge Extraction using Statistical Models

The NLU Ingestion Pipeline is used to process a text corpus and extract domain knowledge. At EC, we have designed a general purpose Meaning Representation Schema to capture knowledge. The schema is centered around the notion of **contextual Relationships or Events**, where

each relationship is characterized by its subject and object concepts, along with qualifiers that specify contextual information about time, space, manner, purpose etc. Additionally, concepts and relationships are arranged in a hierarchy to support taxonomic reasoning. Our schema is inspired by KR formalisms such as AMR [3], FrameNet [2], PropBank [12], etc., but is designed to be leaner and more concise to aid generality.

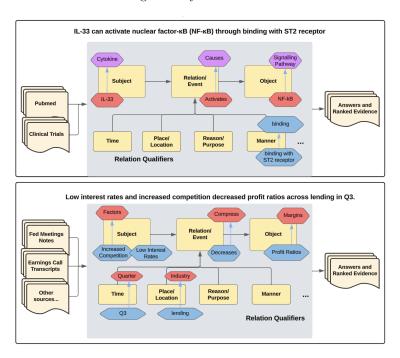


Figure 8: Rich Conceptual Event Structure

Figure 8 shows examples of events extracted from sentences in two different domains - medical and finance. In the medical example, given the sentence shown, we extract the relationship "activates" between "IL-33" and "NF-Kb", along with the qualifier manner: "binding with ST2 receptor". Moreover, we also extract type information for the concepts taking the context into account when disambiguating its meaning – in this case, "IL-33" is an instance of "Cytokine", while "NF-Kb" is an instance of a "Signalling Pathway". This rich event structure lets us answer questions such as: "Which cytokine activated a signalling pathway and how was it done?". The same holds for the financial example, since the schema is domain independent.

Our process of Ontology Induction involves extracting rich event (relational) structures as shown in the figure, and the underlying type hierarchy from the text, and we do this in a fully unsupervised manner - i.e. with no manual training data. Additionally, we perform Entity Linking (similar to [10]), in order to link the induced concepts from the text with entities in external knowledge bases and ontologies.

For this problem, we have developed a transformer-based architecture called LUMEN that we use for concept typing, entity linking and relationship extraction, along with a fully automated domain-adaptation process that leverages our own fine-tuned LLMs to generate synthetic training data. The framework uses SLMs (Small Language Models such as Gemma-2B [13]) for increased throughput (sub-200ms latency per passage) without compromising on quality, by using high quality training data and novel contrastive loss functions. Details of this framework will be provided in a forthcoming technical publication.

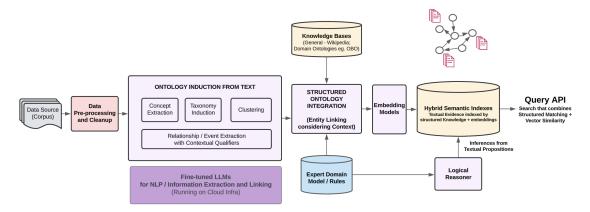


Figure 9: NLU Ingestion Pipeline

3.3 Multi-hop QA and Explanations using Symbolic Reasoning

3.3.1 Cogent: KR Language and Meta-Model

Cogent is EC's proprietary Knowledge Representation language. It can be used to formally define conceptual theories in a form of structured English. Its underlying formalism is based on Answer Set Programming and supports term definitions, rules, (hard/soft) constraints and objective functions. Additional details of Cogent are in [4].

As mentioned earlier, we have defined a general meta-model for causal inference in Cogent, which provides the logical grounding for terms and relationships, and facilitates reasoning via the Cogent-RE.

Figure 10 shows snippets of our Cogent meta-model for Causal Inference, based on Qualitative Process Theory (QPT).

QPT provides a robust framework for understanding the dynamics of continuous systems through the propagation of qualitative values (e.g., increasing, decreasing, high, low...), rather than relying solely on numerical data. This makes it applicable across diverse fields where under-specified values are prevalent such as economics, medicine, geopolitics, and cybersecurity.

Under QPT, quantities are causally influenced by *processes*, and the effects of that influence propagates between quantities. As an example, in a heat flow process, the heat transfers from a hot to a cold object. As the cold object heats up, that may cause subsequent changes (e.g., maybe it becomes more malleable) [5, 6]. Additionally, [7] took inspiration from QPT's quantity-to-quantity propagation in their work by annotating causal models in natural language.

Like them, our representation draws inspiration from QPT's influence mechanism between quantities, but we further expand our approach to include the notion of "States" and the "Triggers" causal relationship.

In economics, Quantities include variables like GDP and interest rates, while States might describe those quantities at a specific value such as high inflation or inciting events like the imposition of tariffs. Extending to medicine, Quantities could encompass fluctuating metrics like blood pressure or cholesterol levels, with States representing medical conditions such as diabetes or stages of cancer remission. Similarly, in cybersecurity, Quantities include metrics like the number of system intrusions or data transfer rates, and States could refer to the security status of systems or the occurrence of breaches. This framework allows for a nuanced analysis of how various factors interact within and across these fields, providing insights into how changes in one area can influence outcomes in another, thereby offering a comprehensive view of causal dynamics in complex environments.

In our meta-model, Influences describe the causal relationship between two quantities, which can be either direct or inverse, indicating how one quantity affects another. For instance, in medicine, an *increase in medication dosage* might influence the *reduction of symptom severity*.

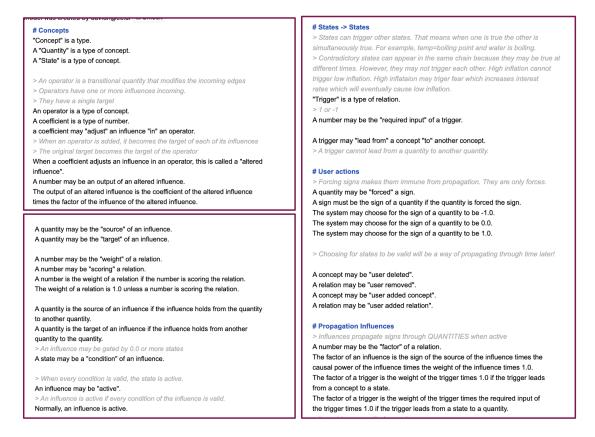


Figure 10: Cogent Meta-Model for Causal Inference

In geopolitics, a rise in military expenditure might inversely influence the economic stability of a country.

Triggers, however, define the causal relationships between states or between a state and a quantity, highlighting how certain states can act as tipping points, initiating changes in other states or quantities. For example, in cybersecurity, the *detection of a new malware type* (a State) might trigger an *increase in security protocol updates* (a Quantity).

This structured approach provides a deeper understanding of the mechanisms driving changes within dynamic systems and allows us to use Cogent to interactively reason about what-if scenarios, providing valuable insights into complex causal interactions in various domains.

3.3.2 Evidenced Graph Building and Symbolic Reasoning

As mentioned in Section 3.1, the Evidenced Graph Builder's goal is to find multi-hop relational and causal chains connecting input concepts in the scenario to the query or target concepts. This problem can be cast as a graph search or path-finding problem, where each link in the path is a causal relationship, the source nodes are the input concepts, and the target node is the query concept. Here, the aim is not to find the shortest causal path from source to target, but instead to find all dominant and contextually relevant paths linking the source and target nodes based on the domain knowledge. Longer paths that reveal more details are preferred as they help build a better causal understanding of the scenario.

Our solution is based on the A* Search algorithm [9], which runs a forward-backward search routine (i.e. forward from the source nodes, backward from the target) and uses an LLM (in particular, its intrinsic world knowledge) as the search heuristic to estimate which paths are likely to connect up from both sides. The algorithm also has plugin points for automatically

inserting relevant user knowledge from prior saved causal maps.

As part of producing the map, the builder maps the specific relations (predicates) in the event structures stored in the Domain KB (described in Section 3.2) to the higher-order relationships such as "influence" and "trigger" in the Cogent Meta-model.

The final knowledge graph produced by the builder, which is an instantiation of the metamodel, is an executable logic program that is fed to the Cogent RE. The result of reasoning is fed to an LLM to produce the final answer and explanation from the detailed logical proof traces.

4 Preliminary Evaluation

Our goal is to answer the following question: Given a complex research query that involves multiple concepts and relationships, how accurately and comprehensively can an AI system provide detailed answers and explanations that consider relevant intermediate links and include citations for supporting and/or refuting evidence?

We report results of a preliminary evaluation conducted in the medical domain. Further experiments are ongoing and we will share updated results and the dataset when this is completed.

4.1 Medical QA Eval

We collected 25 queries based on real questions from experts in the medical research domain. The queries were evaluated using four systems: GPT4-Turbo (a state-of-the-art LLM), Perplexity (RAG using web-search), Elicit (RAG using Semantic Scholar for doing scientific research) and Cora.

All four systems mentioned above were run on the questions and we asked each system to produce an answer with supporting/refuting evidence and cited sources. Since we do not have ground truth answers and explanations, we asked the domain experts to manually verify each of the systems' results, and check that the generated answer/explanation justifies its claims, is both accurate and relevant, and that the sources it cites actually exist.

We have the following metrics:

- 1. Claim Density average number of claims per answer a measure of the quantity of information provided.
- 2. Citation Density average number of real citations per claim a measure of the amount of verification options.
- 3. Source Hallucination Rate percentage of citations that are not valid (real) and scholarly sources a measure of system hallucination.
- 4. Citation Rate percentage of claims in the answer that are accompanied by real citations- a measure of verifiability of the answer.
- 5. Justification Rate percentage of claims that are a correct paraphrase of a real citation a measure of interpretation quality. Claims with non-existent sources are not justified as they are unverifiable. Since checking this requires manual effort, we imposed a max time-limit of 5 minutes on the domain expert to verify each claim.
- 6. Relevance Rate percentage of claims that are justified and relevant to answering the question a measure of relevance and quality of answer.

Results are shown in Table 1. Note that the metrics from 4-6 get progressively stricter, as a justified claim must also be cited, and a relevant claim must also be justified.

4.2 Discussion

Across the four systems evaluated for the queries, we find that Cora and Perplexity are the only two systems that reliably cite articles that exist. Sourcing claims in real evidence is crucial in

System	Claim	Citation	Source	Citation	Justi-	Relevance
	Density	Density	Halluci-	Rate	fication	Rate
			nation		Rate	
			Rate			
GPT4-	3.52	0.63	42.86%	47.73%	25.00%	23.86%
Turbo						
Perplexity	3.60	0.38	0.00%	22.22%	21.11%	10.00%
Elicit	3.96	1.53	3.82%	95.96%	82.83%	69.70%
Cora	5.04	1.26	0.00%	100.00%	93.65%	84.92%

Table 1: Complex QA Results with Evidence and cited Sources

the medical domain, as there is minimal room for error and misinformation with experts facing decisions that are high-stakes. It is particularly worth noting the *Source Hallucination Rate* of GPT-4 Turbo in Table 1 with almost every other article being hallucinated. Even though both Cora and Perplexity cite real articles 100% of the time, Perplexity only cites a few articles for a few of its claims, as evidenced by the low *Citation Density* and *Citation Rate* values.

For claims in the tools' answers that are derived from valid sources, it is important to know if the information as it is represented in the answer is justified by the information in the source. This is measured by the *Justification Rate* metric. These metrics together make it evident that Cora provides the most reliable and verifiable claims. This is attributed to Cora's precise and granular evidence-based answer generation algorithm. Additionally, it is important that a researcher is able to quickly verify the consistency across the answer and the source, something they can do easily in Cora where relevant snippets (highlighted paragraphs) from the paper are directly evidenced. All the other tools require the expert to read the entire paper to find the precise evidence.

Claim Density measures the quantity of information presented in the answer, and Cora provides the most comprehensive answers across the compared systems. Finally, the metric that evaluates the usefulness of an answer to a researcher/expert is the Relevance Rate, which is obtained by considering how many of the total justified claims of a given answer are labeled as "relevant" by an expert. The measure of relevance here was lenient as relevance can be subjective depending on the expert. Results show that Cora provides the most relevant and comprehensive answers that are backed by real evidence and represents the cited evidence well compared to the other tools.

5 Conclusions

The past two years have seen unprecedented excitement and investment in AI. Effectively leveraging LLMs and Generative AI is becoming a business imperative across every major industry, where business leaders are motivated by both seeking competitive advantages with more automation and intelligence, and fear of being left behind if they fail to effectively leverage AI. For modern AI to deliver on these enormous expectations, solutions must meet a wide variety of critical requirements, not the least of which is reliable and accurate answers users can trust to make critical business decisions.

At Elemental Cognition our mission is to deliver on the promise of AI with technology that provides more accurate, relevant, and verifiable answers and solutions to complex business problems. To this effect, we have developed a neuro-symbolic AI platform that combines two powerful complementary technologies - statistical language understanding machines (LLMs) and symbolic reasoning engines. The former is used to extract, formalize and translate knowledge from text, while the latter is used to precisely analyze, reason and explain answers.

We have described our approach and architecture in detail and presented experimental results

validating its performance. Our results show that our solution delivers best in class performance for tackling multi-step causal inference problems on unstructured data when compared to pure LLM or state-of-the-art Retrieval Augmented Generation systems. We continue to evaluate our approach across a broader set of more complex problems and see promising results that we will share in the near future.

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References

- [1] M Ashburner, C A Ball, J A Blake, D Botstein, H Butler, J M Cherry, A P Davis, K Dolinski, S S Dwight, J T Eppig, M A Harris, D P Hill, L Issel-Tarver, A Kasarskis, S Lewis, J C Matese, J E Richardson, M Ringwald, G M Rubin, and G Sherlock. Gene ontology: tool for the unification of biology. the gene ontology consortium. *Nat Genet*, 25(1):25–29, May 2000.
- [2] Collin F. Baker, Charles J. Fillmore, and John B. Lowe. The berkeley framenet project, 2006.
- [3] Laura Banarescu, Claire Bonial, Shu Cai, Madalina Georgescu, Kira Griffitt, Ulf Herm-jakob, Kevin Knight, Philipp Koehn, Martha Palmer, and Nathan Schneider. Abstract Meaning Representation for sembanking. In Antonio Pareja-Lora, Maria Liakata, and Stefanie Dipper, editors, Proceedings of the 7th Linguistic Annotation Workshop and Interoperability with Discourse, pages 178–186, Sofia, Bulgaria, August 2013. Association for Computational Linguistics.
- [4] Jennifer Chu-Carroll, Andrew Beck, Greg Burnham, David OS Melville, David Nachman, A. Erdem Özcan, and David Ferrucci. Beyond llms: Advancing the landscape of complex reasoning, 2024.
- [5] Kenneth D Forbus. Qualitative process theory. Artificial intelligence, 24(1-3):85–168, 1984.
- [6] Kenneth D Forbus. Qualitative representations: How people reason and learn about the continuous world. MIT Press, 2019.
- [7] Scott Friedman, Ian Magnusson, Vasanth Sarathy, and Sonja Schmer-Galunder. From unstructured text to causal knowledge graphs: A transformer-based approach. arXiv preprint arXiv:2202.11768, 2022.
- [8] Martin Gebser, Roland Kaminski, Benjamin Kaufmann, and Torsten Schaub. Clingo = asp + control: Preliminary report, 2014.
- [9] Peter Hart, Nils Nilsson, and Bertram Raphael. A formal basis for the heuristic determination of minimum cost paths. *IEEE Transactions on Systems Science and Cybernetics*, 4(2):100–107, 1968.
- [10] Nikolaos Kolitsas, Octavian-Eugen Ganea, and Thomas Hofmann. End-to-end neural entity linking. In Anna Korhonen and Ivan Titov, editors, *Proceedings of the 22nd Conference on Computational Natural Language Learning*, pages 519–529, Brussels, Belgium, October 2018. Association for Computational Linguistics.
- [11] Vladimir Lifschitz. What is answer set programming? In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 1594–1597. MIT Press, 2008.
- [12] Martha Palmer, Daniel Gildea, and Paul Kingsbury. The Proposition Bank: An Annotated Corpus of Semantic Roles. *Computational Linguistics*, 31(1):71–106, 03 2005.

- [13] Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, Pouya Tafti, Léonard Hussenot, Pier Giuseppe Sessa, Aakanksha Chowdhery, Adam Roberts, Aditya Barua, Alex Botev, Alex Castro-Ros, Ambrose Slone, Amélie Héliou, Andrea Tacchetti, Anna Bulanova, Antonia Paterson, Beth Tsai, Bobak Shahriari, Charline Le Lan, Christopher A. Choquette-Choo, Clément Crepy, Daniel Cer, Daphne Ippolito, David Reid, Elena Buchatskaya, Eric Ni, Eric Noland, Geng Yan, George Tucker, George-Christian Muraru, Grigory Rozhdestvenskiy, Henryk Michalewski, Ian Tenney, Ivan Grishchenko, Jacob Austin, James Keeling, Jane Labanowski, Jean-Baptiste Lespiau, Jeff Stanway, Jenny Brennan, Jeremy Chen, Johan Ferret, Justin Chiu, Justin Mao-Jones, Katherine Lee, Kathy Yu, Katie Millican, Lars Lowe Sjoesund, Lisa Lee, Lucas Dixon, Machel Reid, Maciej Mikuła, Mateo Wirth, Michael Sharman, Nikolai Chinaev, Nithum Thain, Olivier Bachem, Oscar Chang, Oscar Wahltinez, Paige Bailey, Paul Michel, Petko Yotov, Rahma Chaabouni, Ramona Comanescu, Reena Jana, Rohan Anil, Ross McIlroy, Ruibo Liu, Ryan Mullins, Samuel L Smith, Sebastian Borgeaud, Sertan Girgin, Sholto Douglas, Shree Pandya, Siamak Shakeri, Soham De, Ted Klimenko, Tom Hennigan, Vlad Feinberg, Wojciech Stokowiec, Yu hui Chen, Zafarali Ahmed, Zhitao Gong, Tris Warkentin, Ludovic Peran, Minh Giang, Clément Farabet, Oriol Vinyals, Jeff Dean, Koray Kavukcuoglu, Demis Hassabis, Zoubin Ghahramani, Douglas Eck, Joelle Barral, Fernando Pereira, Eli Collins, Armand Joulin, Noah Fiedel, Evan Senter, Alek Andreev, and Kathleen Kenealy. Gemma: Open models based on gemini research and technology, 2024.
- [14] Oliver J Wouters, Martin McKee, and Jeroen Luyten. Estimated research and development investment needed to bring a new medicine to market, 2009-2018. JAMA, 323(9):844-853, March 2020.