Advancing in Learning Expert Meaning Processing (LEMP) Through Reproducible Game (RG) Solvers

Tigran Shahinyan
IIAP NAS RA
Yerevan, Armenia
e-mail: tigranshahinyan@gmail.com

Sedrak Grigoryan
IIAP NAS RA
Yerevan, Armenia
e-mail: sedrak.grigoryan@iiap.sci.am

***Abstract*—Despite significant advancements in NLP technologies, limitations such as shallow semantic understanding, insufficient world knowledge integration, and poor adaptability across domains persist. We propose addressing these challenges through a structured approach using the Reproducible Game (RG) Tree and RG Solvers, which provide rigorous frameworks for meaning acquisition and validation. Learning Expert Meaning Processing (LEMP) aims to enable systems to interpret, structure, and utilize expert-level domain knowledge from natural language effectively. By defining explicit, hierarchical levels of expert classifiers within the context of chess as a kernel RG problem, we develop methods for robust knowledge representation and incremental learning. We further present methodologies for evaluating acquired knowledge, addressing identified difficulties in concept formalizations.**

***Keywords*—Expert systems, nlp, meaning processing, combinatorial problems.**

I. INTRODUCTION

Despite significant advances in Natural Language Processing (NLP) and the advent of models such as GPT and BERT, several critical challenges persist:

- *Shallow Semantic Understanding:* Models predict text based on statistical patterns rather than genuine comprehension [1].
- *Lack of World Knowledge and Inference:* Current systems cannot integrate complex human values, intentions, or nuanced world knowledge [2].
- *Transferability and Adaptability:* Difficulty in generalizing learned knowledge across various domains without extensive retraining [3].

Meaning Processing in NLP seeks to extract not only the surface-level representation of words and syntax but also the implicit, contextually driven meaning conveyed in text. This level of processing requires the system to handle ambiguity, contextual nuances, and inferencing, which are deeply rooted in human cognition and knowledge of the world.

1.1. To address these issues, we try to integrate Learning Expert Meaning Processing (LEMP) [4] for Reproducible Game (RG) [5] Trees problems domain, and then, if successful, extend the achievements to the generic meaning processing problem. The approach leverages RG domain [5] and RG Solvers [6] as the foundational framework. RG problems model Human-Universe problems via structured scenarios [5], providing conditions suited for rigorous meaning acquisition and validation. The minimal requirements for RG domain problems are:

- Presence of interacting actors (players, competitors).
- Defined actions performed by these actors.
- Specific timing for actions.
- Clearly described situations.
- Identifiable benefits for each actor.
- Rules or regularities governing how situations change post-action.

1.2. Many problems of practical significance can be formulated within the RG class, and are reducible to one another and, ultimately, to a unified kernel problem, e.g., chess [7, 8].

1.3. Our cognitive modeling approach draws from Jean Piaget's developmental psychology [9], enhancing object-oriented representations of reality with English-language classifiers and relationships, and aligns with inquiries into the origins of cognition in nature [5].

1.4. **In the following work, we define the approach for the successful study of LEMP via RG domain problems, the ways to evaluate the progress, and then try to extract the identified difficulties and the approaches to overcome them.**

Thus, the work contributes by:

- **Problem framing**: defining (LEMP) as a structured challenge within RG Solvers.
- **Advancement path for first stage**: outlining a five-level classifier acquisition program, from basic units to abstract concepts.
- **Evaluation strategy:** proposing metrics and validation methods (situation matching, text ↔ meaning checks, ontology consistency).
- **Extension outlook**: identifying directions for handling abstract notions (e.g., Breakthrough) and adaptation to broader, less formal domains.

More recent efforts have started to explore semantics and ontology graphs as organizing tools, and their potential for supporting abstract classifier formation. This paper extends them by positioning ontology integration as a central component of the advancement path, coupled with structured acquisition and proposed evaluation strategies.

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II. LEMP AND ITS STEPS.

2.1. For the successful study of RGT expert meaning processing, we reveal the following phases to overcome. Thus, learning expert meaning processing can be defined with the following three main phases of research

- *First Phase* - Leveraging expert meaning processing for kernel RG problem. We consider the interaction with natural language as utilizing tool for expert knowledge. Starting with RG and the above-mentioned background, we conduct meaning processing research for the RG kernel chess problem, which includes

– Preparation of RG Expert Classifier Repository for Chess [10]. The phase involves developing and revising the repository of expert-level classifiers for chess based on chess. Classifiers are organized by complexity to facilitate learning by RGT Solvers.

– Advancement in RG Chess classifiers by Complexity Levels. For each specified complexity level of expert classifiers, refine and advance the learning capabilities of the RG expert model iteratively and level by level.

– Verification of RG Solver. Confirming the workability of RG Solver at the time already learned classifiers, particularly by demonstrating the abilities of learning, identification of realities, meaning to text to meaning transitions.

– Enhancement of Solver. Further development of RG Solvers to improve their ability to acquire increasingly complex expert meanings and enhance the quality of meaning-to-text and text-to-meaning transitions.

- *Second Phase* - Broadening Scope to the Entire RGT Class. The research expands to the whole class of RGT problems, aiming for a comprehensive learning of expert meaning processing.
- Third Phase - Expanding to Natural Language.

2.2. We focus primarily on chess as the kernel RG problem, dividing meaning processing into explicit, hierarchical levels of expert classifiers:

Level-Based Classifier Acquisition:

- *Initial Level:* Nuclear classifiers define fundamental attributes like Figure Type, Figure Color, Coord X, and Coord Y.
- *First Level:* Minimal units such as Figure, Pawn, Knight, and Field, composed from nuclear classifiers.
- *Second Level:* Simple compositions, e.g., Vertical and Horizontal Lines, Phalanxes (pawn and knight formations).
- *Third Level:* Composite classifiers representing conditions, e.g., Fields Under Attack, Check.
- *Fourth Level:* High complexity conditions like Mate and Stalemate.
- *Fifth Level:* Abstract concepts (e.g., Breakthrough) currently defined in natural language with preliminary formalization approaches.

2.3. [11] defines the successful acquisition of various levels of classifiers, and [4] describes some of the challenges faced in the process in LEMP.

Ontology-Driven Knowledge Representation. To handle ambiguity and ensure logical consistency, we use ontology graphs (OGs) structured via semantic web technologies:

- RDF [12] triples model basic factual assertions.
- OWL [13] defines complex class-property structures.
- SWRL [14] rules represent conditional logic.
- SPARQL queries validate ontology consistency and completeness.

This structured ontology supports incremental, step-by-step learning of expert knowledge from natural language presentations.

III. MEASURING AND EVALUATING RG SOLVER KNOWLEDGE

Since this work defines the problem and advancement directions, we also specify how the progress in LEMP is being evaluated. The following procedures and metrics serve as the basis of validation:

- **Situation Matching**. The Solver's acquired classifiers are tested against real chess situations [15]. *Metric*: situations should be correctly recognized/classified.
- **Textual Explanation Validation**. Generated explanations [16] for classifiers are checked for clarity and correctness. *Metric*: agreement between Solver-produced text and expert expectations.
- **Ontology Consistency**. After each learning stage in OGs, RDF/OWL + SWRL ontology is validated with SPARQL queries and reasoners. *Metric*: percentage of knowledge base rules passing integrity checks.
- **Level-by-Level Acquisition Tracking**. Each classifier level (initial → fifth) is acquired and validated in turn. *Metric*: number of classifiers successfully acquired and applied at each stage.
- **Explainability and Transparency**. Qualitative check: solver's ability to explain classifiers in human-readable text. *Metric*: qualitative assessment based on clarity and completeness of generated descriptions.

IV. REVEALED DIFFICULTIES AND APPROACHES TO OVERCOME

Despite substantial progress, several difficulties persist:

- Representation of Abstract Concepts, so far presented only in natural language forms: Highly abstract classifiers like "Breakthrough" pose significant formalization challenges. Such classifiers are ultimately represented in the Solver as compositions of lower-level classifiers as well (Composites). The key difficulty lies in transforming free expert text into these formal compositions, and we use ontology graphs as a bridge: capturing expert descriptions as structured triples and rules, and mapping them into Solver representations for further usage.
- Action Explanation Limitations: Actions, described by preconditions and postconditions, remain unnatural in restricted textual explanations.

We expect to address these through:

- Enhanced Ontology Integration: Leveraging OGs to systematically represent and refine abstract concepts.
- Incremental Neuro-symbolic Learning: Iteratively fine-tuning NLP models (e.g., BERT) alongside ontology enrichment for better semantic capture and classifier explanation.

V. Conclusion

The presented framework demonstrates significant advances in learning expert meaning processing. The approach defines the structured classifier acquisition, validation, and ontology-driven representation for continual learning from natural language. While current solutions address many practical issues, challenges in fully capturing abstract and dynamic classifier semantics remain.

Future research will focus on OGs to enhance natural language handling capabilities, NN models for more natural presentation of RG situations, particularly for the chess kernel problem, moving toward comprehensive meaning processing within RG Solver frameworks.

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