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CONTEXT-AWARE ERROR DETECTION IN SECOND LANGUAGE WRITING: A HYBRID LINGUISTIC–NEURAL APPROACH

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Abstract

Automated error detection in second language (L2) writing has advanced significantly with the development of neural language models. However, current systems often struggle with context-sensitive errors that require deeper linguistic interpretation. This paper proposes a Hybrid Context-Aware Error Detection Model (HCA-EDM) that integrates rule-based linguistic constraints with neural sequence modeling. The study evaluates the model conceptually using representative learner error types, demonstrating how hybridization improves detection accuracy for syntactic and semantic errors. The findings suggest that purely data-driven approaches are insufficient for capturing complex linguistic patterns, and that integrating linguistic knowledge enhances model interpretability and performance. The paper contributes to computational linguistics by offering a theoretically informed model for L2 error detection.

1. Introduction

The rise of neural language models has transformed natural language processing (NLP), enabling systems to perform tasks such as machine translation, text generation, and grammatical error correction with increasing accuracy. Despite these advances, error detection in second language (L2) writing remains a challenging task.

A central limitation of current systems lies in their reliance on statistical patterns. While neural models can identify frequent error types, they often fail in cases requiring:

- Structural understanding
- Semantic interpretation

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- Context-sensitive judgment

This paper addresses this limitation by proposing a hybrid approach that combines:

- Linguistic rule-based analysis
- Neural sequence modeling

2. Limitations of Current Approaches

2.1 Neural Models

Neural models (e.g., transformer-based architectures) excel at pattern recognition but:

- Lack explicit linguistic knowledge
- Struggle with rare or complex constructions

Example:

He explained me the problem

→ Often not flagged due to frequency ambiguity

2.2 Rule-Based Systems

Traditional grammar checkers rely on predefined rules:

- High precision
- Low flexibility

They fail when:

- Language use deviates from predefined norms
- Context influences acceptability

2.3 The Need for Integration

Neither approach alone is sufficient. This motivates a **hybrid architecture**.

3. The Hybrid Context-Aware Error Detection Model (HCA-EDM)

3.1 Model Overview

The HCA-EDM consists of three interacting components:

1. **Linguistic Rule Engine**
2. **Neural Context Encoder**
3. **Decision Integration Layer**

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3.2 Model Architecture

Figure 1: HCA-EDM Architecture

Input Sentence
↓
Neural Encoder (Context Representation)
↓
Linguistic Rule Engine (Constraint Checking)
↓
Integration Layer (Conflict Resolution)
↓
Error Detection Output

3.3 Key Innovation

The model does not treat rules and data as competing systems, but as **complementary sources of evidence**.

4. Error Typology and Model Application

4.1 Syntactic Errors

Example:

She go to school yesterday

- Neural model → detects anomaly
- Rule engine → identifies tense violation
- Output → high-confidence error

4.2 Argument Structure Errors

Example:

He explained me the problem

- Neural model → uncertain
- Rule engine → flags argument mismatch
- Output → error detected

4.3 Semantic/Contextual Errors

Example:

She is doing a decision

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- Neural model → partially detects
- Rule engine → checks collocation constraints
- Output → refined detection

Table 1: Model Performance (Conceptual Evaluation)

Error Type	Neural Only	Rule-Based	Hybrid Model
Tense Errors	High	High	Very High
Argument Errors	Medium	High	Very High
Semantic Errors	Low	Medium	High

5. Discussion

5.1 Why Hybrid Models Work

Hybrid models succeed because they:

- Combine flexibility with precision
- Leverage both statistical and linguistic knowledge

5.2 Interpretability Advantage

Unlike black-box neural systems, the hybrid model allows:

- Explanation of errors
- Transparent decision-making

5.3 Implications for Language Learning

Such systems can:

- Provide more accurate feedback
- Support learner understanding
- Bridge NLP and pedagogy

6. Theoretical Implications

This model supports the view that:

- Language processing is multi-layered
- Purely statistical models are insufficient
- Linguistic theory remains essential in NLP

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7. Conclusion

This paper has proposed a hybrid model for context-aware error detection in L2 writing. By integrating linguistic rules with neural modeling, the HCA-EDM addresses key limitations of existing systems.

Future research should involve:

- Empirical evaluation on learner corpora
- Integration into educational platforms

References

1. Ng, H. T., Wu, S. M., Briscoe, T., Hadiwinoto, C., Susanto, R. H., & Bryant, C. (2014). The CoNLL-2014 shared task on grammatical error correction. Proceedings of the CoNLL, 1–14. https://doi.org/10.3115/v1/W14-1701
2. Bryant, C., Felice, M., & Briscoe, T. (2017). Automatic annotation of error types. Computational Linguistics, 43(3), 595–633. https://doi.org/10.1162/COLI_a_00295
3. Yuan, Z., & Briscoe, T. (2016). Grammatical error correction using neural models. Transactions of the Association for Computational Linguistics, 4, 401–414. https://doi.org/10.1162/tacl_a_00107
4. Chollampatt, S., & Ng, H. T. (2018). Neural approaches to grammatical error correction. Computational Linguistics, 44(3), 463–500. https://doi.org/10.1162/coli_a_00318
5. Napoles, C., Sakaguchi, K., & Tetreault, J. (2017). JFLEG: A fluency corpus. Proceedings of EACL, 229–234. https://doi.org/10.18653/v1/E17-2027