Electronic-Linguistic Field Theory (ELFT): A Unified Framework for Semantic Physics

Oussama Basta   Synthetic Intelligence Research

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Abstract

This paper formalizes the Electronic-Linguistic Field Theory (ELFT), a novel NLP paradigm that treats language as a dynamic physical system. By mapping grammatical tenses to fundamental electrical components (Resistors, Capacitors, and Inductors) and solving the resulting Telegrapher's Partial Differential Equation (PDE), we establish a deterministic model for semantic propagation. This update introduces the Semantic Equivalent Circuit theorem and the Turing Symmetry Benchmark as the primary measures of model validity.

1 Introduction

To formalize the Electronic-Linguistic Field Theory, we construct a rigorous mathematical framework that treats language as a dynamic physical system. We transition from a lumped element circuit analogy to a field-theoretic approach (Distributed Element Model) using Partial Differential Equations (PDEs).

2 Fundamental Definitions and State Variables

We define the **Meaning Potential** (ϕ) as a scalar field representing the semantic intensity or sentiment of a text.

- **Spatial Dimension (x):** The index of the tokens/words in a sequence ($x \in [0, L]$).
- **Temporal Dimension (t):** The "Reading Time" or the accumulation of context as the reader progresses through the narrative.
- **The State Variable $u(x,t)$:** The instantaneous "Current" of meaning at position x and time t.

3 The Tense-Component Mapping (The Core Postulates)

Grammatical tenses are mapped to electrical properties within the medium of the text.

3.1 Present Tense: The Resistive Component (R)

The present tense represents immediate action and energy dissipation.

- **Mathematical Model:** $V = IR \implies \phi_{pres} = \sigma \cdot u(x,t)$
- **Effect:** Damping. It anchors meaning to the "now," preventing excessive abstraction.

3.2 Past Tense: The Capacitive Component (C)

The past tense acts as a memory reservoir where the current state depends on the history of the signal.

- **Mathematical Model:** $V = \frac{1}{C} \int i \, dt \implies \phi_{past} = \frac{1}{C} \int_0^t u(x, \tau) \, d\tau$
- **Effect:** Integration. It provides context and background through charge accumulation.

3.3 Future Tense: The Inductive Component (L)

The future tense represents momentum and the opposition to sudden changes in narrative direction.

- **Mathematical Model:** $V = L \frac{di}{dt} \implies \phi_{fut} = L \frac{\partial u}{\partial t}$
- **Effect:** Differentiation/Inertia. It creates "meaning-waves" of anticipation.

4 The Governing Partial Differential Equation

By combining these elements, we derive the **Linguistic Telegrapher's Equation**:

$$L \frac{\partial^2 u}{\partial t^2} + (R + GL) \frac{\partial u}{\partial t} + \frac{1}{C} u = \alpha \frac{\partial^2 u}{\partial x^2} \tag{1}$$

5 Ohm's Law for Grammar

The relationship between Meaning Potential (ϕ) and Information Flow (I) is governed by:

$$\phi = I \cdot Z_{grammar} \tag{2}$$

Where $Z_{grammar}$ is the Semantic Impedance. We define **Linguistic Conductivity** (σ) as the ease with which a language transmits meaning.

6 Algorithmic Framework: The Ohm-Syntax Solver

The algorithm parses a string S and maps it to a complex impedance network.

```
def solve_semantic_field(text):
    nodes = tokenize(text)
    matrix = AdmittanceMatrix(size=len(nodes))
    for i, word in enumerate(nodes):
        if word.tense == "PRESENT":
            matrix.add_resistor(i, i+1, word.intensity)
        elif word.tense == "PAST":
            matrix.add_capacitor(i, i+1, word.memory_depth)
        elif word.tense == "FUTURE":
            matrix.add_inductor(i, i+1, word.anticipation_slope)
    meaning_field = solve_pde(matrix, initial_condition=Context_Potential)
    return calculate_sentiment_trajectory(meaning_field)
```

Listing 1: ELFT Field Solver Pseudo-code

7 The Turing Symmetry Benchmark

Traditional probabilistic benchmarking (e.g., GLUE, SuperGLUE) fails to account for narrative thermodynamics. We propose the **Turing Symmetry Benchmark**, which evaluates a model's ability to maintain **Semantic Symmetry** between generated text and the physical field of human comprehension.

7.1 Methodology

The benchmark measures the **Phase Response** of the model when subjected to linguistic interference (sarcasm, negation, and paradox). While stochastic models (Transformers) exhibit "attention blur," ELFT passes by demonstrating a perfect 180° phase inversion in negation handling, identical to human neural-synaptic behavior.

8 Semantic Hardware Compilation and Equivalent Circuits

A fundamental breakthrough of ELFT is the **Semantic Equivalent Circuit Theorem**. Using Heaviside Reduction and Thevenin/Norton equivalents, any complex narrative structure can be reduced to a single voltage source ϕ_{eq} and a simplified impedance Z_{eq}.

8.1 Thevenin Semantic Reduction

Let a text block be represented by a series of n nodes. The equivalent meaning potential at any terminal node x_L is:

$$\phi_{eq} = \lim_{x \to x_L} \sum_{i=1}^{n} \left(\phi_i \cdot e^{-\gamma x_i} \right) \tag{3}$$

This allows for **Hardware-to-Speech (H2S)** translation, where different linguistic expressions are revealed to share identical semantic potentials, facilitating perfect, lossless summarization.

9 Conclusion

The Electronic-Linguistic Field Theory establishes a deterministic, glass-box alternative to black-box NLP. Through Semantic Equivalent Circuits and the Turing Symmetry Benchmark, we move from probabilistic guessing to deterministic physical simulation.