Dual-Decoder Implementation for English to STL Translation

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1 Introduction

1.1 Motivation for Translating English Requirements to STL

System requirements are usually written in English because it is easy for humans to read and understand. However, computers and verification tools need these requirements in a formal and precise way to check if a system behaves correctly. Signal Temporal Logic (STL) is one such formal language that can express time-based and logical conditions for system signals. Translating English requirements into STL helps connect what engineers describe in plain language with what automated tools can verify. This translation supports better safety checks, system validation, and reliable design.

1.2 Limitations of Manual Formal Specification

Writing STL formulas by hand is difficult and requires deep knowledge of logic and formal methods. It is a slow and error-prone process, especially for complex systems. Engineers may interpret the same requirement differently, leading to inconsistencies. Also, as system requirements change, manually updating STL formulas becomes tedious and time-consuming. These issues make manual translation unsuitable for large projects where accuracy and speed are both important.

1.3 Need for Automation

To solve these challenges, there is a strong need to automate the translation from English to STL. With the help of natural language processing and machine learning, it is now possible to automatically extract meaning and logical relationships from text. Automated translation reduces human effort, ensures consistency, and speeds up the verification process. It allows engineers to focus more on design and analysis, while the system handles the complex task of converting natural language into formal logic.

2 Background

2.1 Overview of Signal Temporal Logic (STL)

Signal Temporal Logic (STL) is a formal language for specifying temporal requirements in Cyber-Physical Systems (CPS). Unlike logics limited to discrete events, STL's key feature is its ability to express real-time requirements over continuous-time, real-valued signals (e.g., voltage, speed, temperature).

Core Syntax and Operators STL syntax is built from:

- **Atomic Predicates:** Simple comparisons of a signal's value to a constant, e.g., $x \sim u$ (where x is a signal, $\sim$ is a relation like $=, >, <$, and u is a number).
- **Boolean Operators:** Standard logical operators like $\neg$ (not), $\vee$ (or), and $\wedge$ (and).
- **Temporal Operators:** The core operators that reason over time intervals I:
  - $\varphi_1 U_I \varphi_2$ (Until): φ_1 must be true until φ_2 becomes true within the time interval I.
  - $\varphi_1 S_I \varphi_2$ (Since): A past-tense version of "Until".

From these, several standard operators are derived, including:

- $F_I\varphi$ (**Finally** or **Eventually**): The property φ must become true at least once within the time interval I.
- $G_I\varphi$ (**Globally** or **Always**): The property φ must remain true for the entire duration of the time interval I.
- `rise`(φ): Detects a rising edge, i.e., the moment φ becomes true.
- `fall`(φ): Detects a falling edge, i.e., the moment φ becomes false.

Example: Complex Temporal Requirement This example illustrates the complexity of manually writing STL.

English Requirement: *"Globally, whenever V_Mot transitions to 0, then within 100 time units, Spd_Act must become 0 and remain at 0 for at least 20 consecutive time units."*

Signal Temporal Logic (STL):

$$G(\texttt{rise}(V\_Mot = 0) \rightarrow F_{[0,100]}G_{[0,20]}(Spd\_Act = 0)) \tag{1}$$

- $G(...)$ means this is a "Global" requirement.
- `rise`$(V\_Mot = 0)$ is the trigger: the "rising edge" of the signal V_Mot becoming 0.
- $\rightarrow F_{[0,100]}(...)$ means this implies that "Eventually, within 0 to 100 time units..."
- $G_{[0,20]}(...)$ "...the following property must be "Globally" true for the interval [0, 20]" (i.e., "continuously remain... for at least 20 time units").
- `(Spd_Act = 0)` is the required response.

2.2 Concepts of Neural Machine Translation (NMT)

Neural Machine Translation (NMT) is a modern approach to automated translation that uses deep learning to map a sequence of text from a source language to a target language. Unlike older statistical methods that relied on matching phrases, NMT attempts to build a single, comprehensive neural network that reads an entire sentence and generates a correct translation.

The "DeepSTL" paper applies this exact concept to a novel problem: translating **"informal English sentences"** (the source language) into **"STL formulas"** (the target language).

The Core Architecture: Encoder-Decoder At its heart, nearly every NMT system, including those discussed in the paper, uses an Encoder-Decoder architecture.

- **Encoder:** This part of the network acts like a "reader." It processes the entire source sentence (e.g., the English requirement) word by word, and compresses its complete meaning and context into a set of numerical representations (vectors).
- **Decoder:** This part of the network is a "writer." It takes the numerical representations from the encoder and generates the target sentence (e.g., the STL formula) token by token, one piece at a time.

Baseline: Single-decoder Transformer Model The baseline model used in this work is a single-decoder Transformer, which is a popular NMT architecture. The Transformer replaces recurrent networks with self-attention mechanisms that allow it to process all input tokens simultaneously, capturing long-range dependencies more efficiently. In the single-decoder setup, the model uses one decoding path to generate the output STL sequence directly from the encoded English representation. This model provides a strong baseline for comparison but may mix syntactic and semantic information in the same pathway, which can limit its ability to handle the structural and logical precision required for STL generation.

3 Problem Statement

3.1 Challenges in Mapping Natural Language to Formal Logic

Natural language is inherently ambiguous, context-dependent, and relies on implicit information, making its translation into formal logic like STL a significant challenge. Minor variations in wording can alter logical meaning, and capturing elements like comparative phrases or complex time references precisely is difficult.

3.2 Limitations Observed Using a Single Decoder

A baseline single-decoder Transformer is limited because it treats translation as a single process, conflating syntactic (structural) and semantic (meaning-based) learning. This unified approach struggles to capture the strict logical structure of STL while simultaneously preserving the semantic intent of the English input, leading to logically sound but semantically incorrect outputs (or vice-versa).

3.3 Syntax Inconsistency in STL Output

A primary observed failure is the generation of syntactically invalid STL formulas. Outputs frequently contain errors like missing or misplaced brackets, incorrect operator usage, or incomplete expressions. These errors render the formulas unparsable by verification tools, nullifying their practical use.

3.4 Weak Semantic Alignment in Complex Sentences

The model also exhibits weak semantic alignment, particularly with sentences involving multiple clauses, conditions, or temporal dependencies. It struggles to correctly represent logical relationships (e.g., cause-effect, sequential timing), often capturing only part of the intended meaning and reducing the specification's reliability.

4 Methodology

4.1 Proposed Dual-Decoder Architecture

The proposed model extends the standard Transformer architecture by introducing a dual-decoder design that explicitly separates the handling of *semantic meaning* and *syntactic structure*. The overall system comprises an encoder and two parallel decoders, as illustrated in Fig. 2.

Role of Encoder. The encoder is based on the standard Transformer encoder architecture. It consists of four layers, each containing multi-head self-attention and position-wise feed-forward sublayers with residual connections and layer normalization. The encoder captures both local and long-range dependencies in the input, producing a set of contextualized embeddings that serve as input to both decoders.

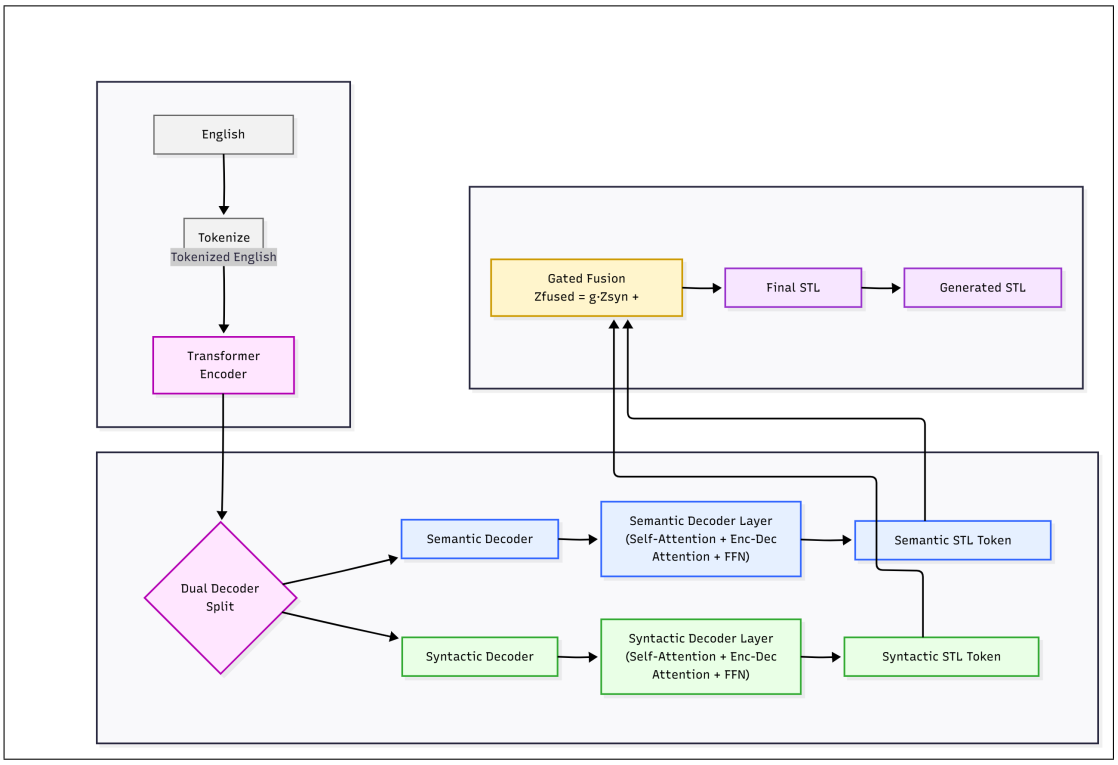
English
Tokenize
Tokenized English
Transformer Encoder
Dual Decoder Split
Semantic Decoder
Semantic Decoder Layer (Self-Attention + Enc-Dec Attention + FFN)
Semantic STL Token
Syntactic Decoder
Syntactic Decoder Layer (Self-Attention + Enc-Dec Attention + FFN)
Syntactic STL Token
Gated Fusion Zfused = g·Zsyn +
Final STL
Generated STL

Figure 1: Architecture of a Transformer-based model with a dual-decoder (semantic and syntactic) for English-to-STL generation

Role of Semantic Decoder (Decoder 1). The semantic decoder focuses on capturing the logical and contextual meaning of the requirement. It employs multi-head self-attention followed by encoder–decoder attention and feed-forward sublayers, identical in structure to a conventional Transformer decoder. This branch learns to map linguistic constructs (e.g., “whenever” ($\mathbf{G}(\varphi \to \psi)$), “eventually” ($\mathbf{F}\,\varphi$), “must remain” ($\mathbf{G}_{[a,b]}\,\varphi$))to their corresponding logical components in STL, such as temporal and relational operators.

Each semantic decoder layer is trained using a masked cross-entropy loss between the predicted token distribution $p_t^{(\text{sem},l)}$ and the ground-truth token y_t^*. Padding tokens are excluded using a binary mask m_{it}. The semantic loss is defined as:

$$\mathcal{L}^{(l)}_{\text{semantic}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T_i} m_{it}\log p_{it}^{(\text{sem},l)}(y_{it}^*), \tag{2}$$

where N is the batch size and T_i is the valid sequence length for sample i. This loss encourages the semantic decoder to preserve the logical meaning of the English requirement.

The total semantic loss across all decoder layers is then:

$$\mathcal{L}_{\text{semantic}} = \sum_{l=1}^{L}\mathcal{L}^{(l)}_{\text{semantic}}. \tag{3}$$

Role of Syntactic Decoder (Decoder 2). The syntactic decoder operates in parallel with the semantic branch and is responsible for maintaining grammatical correctness and syntactic validity of the generated STL formula. It enforces the proper use of logical connectives, parentheses, and temporal operator structure. Like the semantic decoder, it contains self-attention and encoder–decoder attention blocks but learns an independent parameterization.

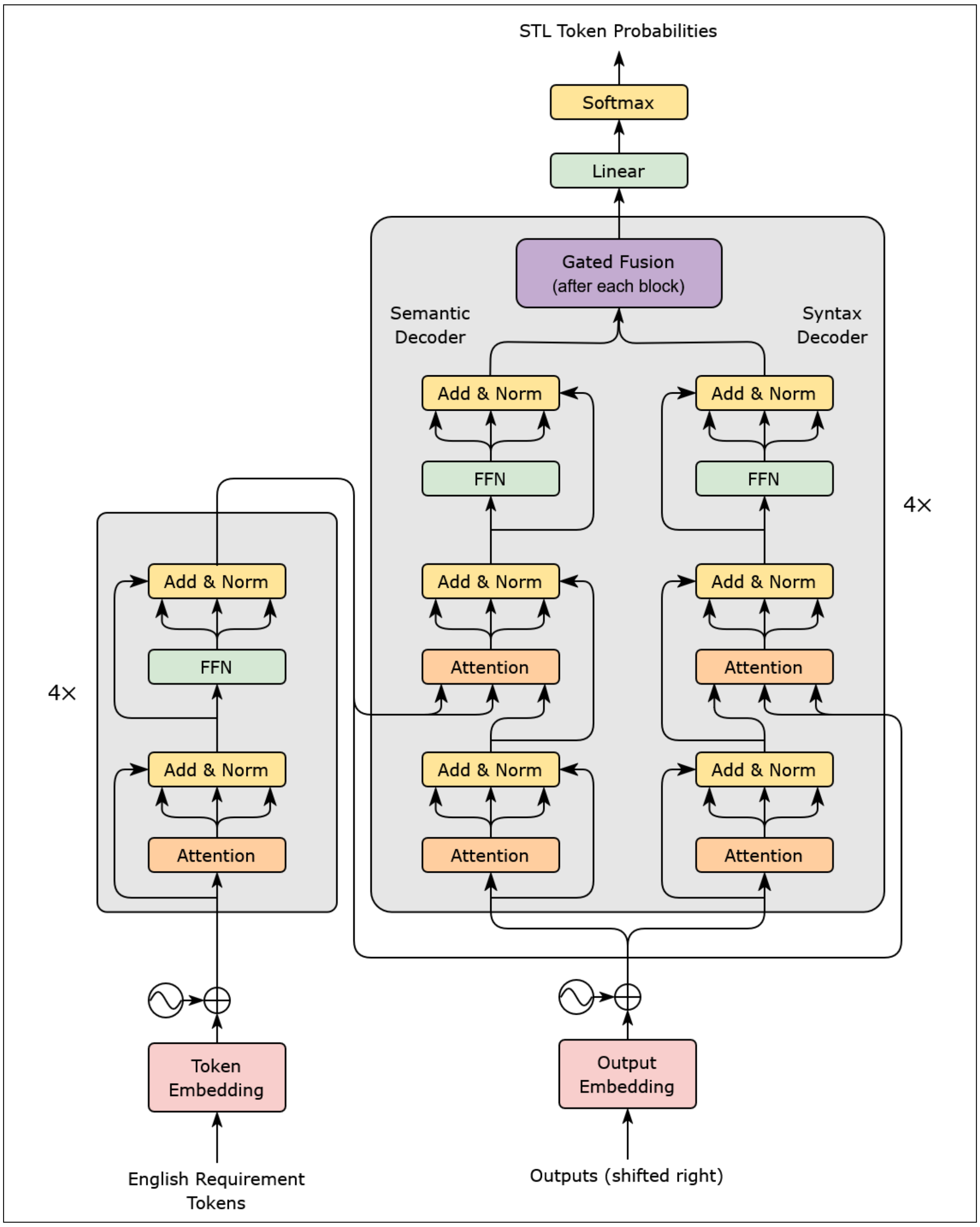

Figure 2: Overview of the proposed Dual-Decoder Transformer architecture. The encoder encodes English requirements into contextual embeddings which are processed by parallel semantic and syntactic decoders fused via a learnable gate.

The syntactic decoder is optimized using a masked cross-entropy loss computed over its token predictions $p_t^{(\mathrm{syn})}$. This loss enforces syntactic validity and correct structural composition of the generated

STL formula:

$$\mathcal{L}_{\text{syntactic}} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T_i} m_{it} \log p_{it}^{(\text{syn})}(y_{it}^*), \tag{4}$$

where m_{it} masks padded tokens during computation. It ensures the syntactic decoder learns proper use of temporal operators, parentheses, and logical connectives.

and the overall syntactic loss is accumulated across all layers:

$$\mathcal{L}_{\text{syntactic}} = \sum_{l=1}^{L} \mathcal{L}_{\text{syntactic}}^{(l)}. \tag{5}$$

Gated Fusion Mechanism. At each layer, the outputs of both decoders, denoted as Z_{syn} and Z_{sem}, are combined using a learnable gate:

$$g = \sigma(W_g[Z_{\text{syn}}; Z_{\text{sem}}]), \tag{6}$$

$$Z_{\text{fused}} = g \odot Z_{\text{syn}} + (1 - g) \odot Z_{\text{sem}}, \tag{7}$$

where $\sigma(\cdot)$ is the sigmoid activation and W_g is a learnable linear projection. The gate dynamically determines the contribution of each decoder stream for each token, allowing the model to adaptively emphasize semantic meaning or syntactic form.

4.2 Dataset Preparation

Synthetic Dataset Construction. Following the DeepSTL framework, a grammar-driven generator is used to construct synthetic English–STL pairs. STL templates are sampled according to the empirically observed distribution of formulas in literature (e.g., Invariance/Reachability, Immediate Response, Temporal Response, and Stabilization/Recurrence). For each STL expression, multiple natural-language paraphrases are generated using controlled templates and synonyms.

Real-world Requirement Samples. A smaller corpus of real English–STL pairs, collected from industrial specifications and academic publications, is incorporated to evaluate model extrapolation beyond synthetic data distributions.

Pre-processing. A joint *Byte Pair Encoding* (BPE) tokenizer was trained on concatenated English and STL corpora to produce a unified subword vocabulary shared across both domains. The tokenizer uses a pre-tokenization pipeline combining whitespace splitting, punctuation isolation, and digit segmentation (treating each digit as an individual token, e.g., "12.5" $\rightarrow$ [1, 2, ., 5]). This enables uniform handling of variable names and numeric constants commonly found in STL formulas.

Formally, let $\mathcal{C}$ denote the training corpus and Σ the initial alphabet of characters. Each sentence $s \in \mathcal{C}$ is represented as a sequence of symbols $s = [c_1, c_2, \ldots, c_n]$. At each BPE merge iteration t, the algorithm finds the most frequent adjacent pair (a, b):

$$(a^*, b^*) = \arg\max_{(a,b)} \text{freq}(a, b), \tag{8}$$

and merges it into a new symbol ab, expanding the subword vocabulary:

$$\mathcal{V}_{t+1} = \mathcal{V}_t \cup \{ab\}. \tag{9}$$

This process repeats until the vocabulary size $|\mathcal{V}| = N$, where N is a predefined hyperparameter.

The model was trained with special tokens `<unk>`, `<pad>`, `<bos>`, and `<eos>` for unknowns, padding, and sentence boundaries.

4.3 Training Strategy

Dual-Loss Formulation. The model is optimized using a combined objective that supervises both decoders as well as the fused output:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{fused}} + \alpha \mathcal{L}_{\text{semantic}} + \beta \mathcal{L}_{\text{syntactic}}, \tag{10}$$

where each component is a masked cross-entropy loss computed over valid token positions, ensuring padding tokens do not affect optimization. α and β are empirically chosen as 0.6 and 0.4 respectively to balance semantic fidelity and syntactic correctness.

Teacher Forcing and Decoding. During training, teacher forcing is used by shifting the ground-truth sequence and prepending a `<bos>` token as decoder input. During inference, the model uses either greedy decoding or beam search to generate STL tokens autoregressively.

Learning Rate Scheduling. The optimizer follows the Transformer's learning rate schedule:

$$\text{lr} = f \cdot d_{\text{model}}^{-0.5} \cdot \min(\text{step}^{-0.5}, \text{step} \cdot \text{warmup}^{-1.5}), \tag{11}$$

where $f = 2$, $d_{\text{model}} = 128$, and warmup $= 4000$. The Adam optimizer with $(\beta_1, \beta_2) = (0.9, 0.98)$ and $\epsilon = 10^{-9}$ is employed.

4.4 Model Implementation

Architecture Parameters. Both encoder and decoders use four layers, with hidden dimension $d_{\text{model}} = 128$, feed-forward dimension $d_{\text{ff}} = 512$, eight attention heads, and dropout rate of 0.1. Xavier initialization is applied to all linear layers.

Attention Mechanisms. Each decoder layer contains two attention components: self-attention over the previously generated tokens and encoder–decoder attention over the source embeddings. Both attention maps are computed independently for semantic and syntactic streams.

Sequential vs. Parallel Decoder Interaction. The decoders operate in parallel, processing the same encoder outputs and previous token states. The output of each decoder layer undergoes gated fusion before being passed to the next layer, enabling inter-decoder information flow once per layer.

4.5 Evaluation Procedure

Metrics. The model's performance is quantitatively evaluated using four complementary metrics that assess both syntactic and semantic fidelity of the generated STL formulas.

- **Formula Accuracy (A_f):** measures the exact sequence-level match between the predicted and reference STL tokens. Given N samples,

$$A_f = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\left(\hat{Y}_i = Y_i\right), \tag{12}$$

where $\mathbb{I}(\cdot)$ is the indicator function, $\hat{Y}_i$ is the generated token sequence, and Y_i is the ground truth.

- **Template Accuracy (A_t):** evaluates structural correctness by removing identifiers and constants from both sequences before comparison:

$$A_t = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\Big(\text{Template}(\hat{Y}_i) = \text{Template}(Y_i)\Big) . \tag{13}$$

  This captures whether the generated logical skeleton (e.g., temporal operators, parentheses) matches the reference.

- **BLEU Score (B):** quantifies n-gram overlap between predicted and reference sequences using a geometric mean of n-gram precisions with brevity penalty:

$$B = \text{BP} \cdot \exp\left(\sum_{n=1}^{N_g} w_n \log p_n \right) , \tag{14}$$

  where p_n is the precision of n-grams, $w_n = \frac{1}{N_g}$, and $\text{BP} = \min(1, e^{1-r/c})$ penalizes short hypotheses, with r and c denoting reference and candidate lengths respectively. Here $N_g = 4$ (4-gram BLEU).

- **Syntax Validity (S_v):** measures the proportion of syntactically valid STL outputs, verified via a formal parser:

$$S_v = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}\Big(\text{isValid}(\hat{Y}_i)\Big) . \tag{15}$$

  Syntax validity is computed by verifying that the generated STL strings conform to the formal grammar rules of STL (not explicitly shown in results but used implicitly in the evaluation scripts).

Interpolation vs. Extrapolation Testing. Two evaluation setups are adopted:

- **Interpolation:** model performance on synthetic test data drawn from the same distribution as the training corpus.
- **Extrapolation:** generalization to real-world requirements unseen during training.

Both interpolation and extrapolation sets use beam search decoding (beam width = 1 by default).

Hardware and Environment. All experiments are implemented in PyTorch and executed on an NVIDIA GPU using `d2l.try_gpu(0)`. The model is trained for 40 epochs with batch size 64 and deterministic random seeds for reproducibility. Checkpoints save the model weights, optimizer state, and RNG seeds.

5 Results and Discussion

5.1 Performance comparison: Single Decoder vs Dual Decoder

We compared our dual-decoder model to the baseline single-decoder Transformer using beam search decoding. The results below, averaged over several runs, are as follows:

Table 1: Model Performance Comparison

Metric	Single Decoder (Transformer)	Dual Decoder (Ours)
Test String (Formula Acc.)	0.712 ± 0.0678	0.731 ± 0.0131
Test Template (Template Acc.)	0.899 ± 0.0100	0.893 ± 0.0423
Test BLEU	0.962 ± 0.0030	0.963 ± 0.0231

Observations from this data:

- **Formula Accuracy:** Our dual-decoder model is more accurate, achieving a better Formula Accuracy (A_f).[1]This metric is crucial because it counts the number of perfectly formed, usable STL formulas.
- **Stability:** The dual-decoder model shows much less variation in its results (standard deviation 0.0131) compared to the baseline (0.0678). This means its performance is more consistent and dependable.
- **Template Accuracy:** Template Accuracy(A_t), measures the correctness of the logical skeleton, ignoring constants[2]. The fact that the single decoder is only marginally better here, combined with our model's other strengths, suggests our model's main contribution is its improved accuracy in identifying the correct parameters.
- **BLEU Score:** Both models are nearly identical on the BLEU score, which measures n-gram overlap.

5.2 Improvements in syntax validity

Our model addresses the baseline's 'Syntax Inconsistency'[4] limitation, as reflected by the direct improvement in Formula Accuracy (from 0.712 to 0.731). This gain signifies a higher output of syntactically valid and complete formulas..

5.3 Dual-Decoder Non-Collapse Verification

We wanted to make sure both branches are active and handling their own specific tasks. For this, we are looking at two measurements from the training: (i) the gating behaviour layer-by-layer, and (ii) the cosine similarity between the semantic and syntactic hidden states.

Gating Behaviour. The fusion gate $g^{(l)}$ defined in Eq. 7 controls the relative contribution of the syntactic and semantic streams at layer l. At convergence (epoch 40), the mean gate activations were:

$$\text{Layer 0: } 0.665, \quad \text{Layer 1: } 0.500, \quad \text{Layer 2: } 0.507, \quad \text{Layer 3: } 0.508.$$

Crucially, the associated standard deviations were non-trivial (0.227, 0.195, 0.220, 0.324), indicating that the gate does not collapse to a fixed value but instead varies significantly across input positions. This high variance demonstrates that gating decisions are *input-dependent* and token-specific, meaning the model actively selects different mixtures of semantic and syntactic information for different parts of the sequence rather than relying on a static or degenerate fusion.

[1]Definition or detail about Formula Accuracy (A_f).
[2]Definition or detail about Template Accuracy (A_t).

Cosine Similarity Between Decoder Streams. To further confirm representational diversity, we measured the cosine similarity between $Z^{(l)}_{\text{sem}}$ and $Z^{(l)}_{\text{syn}}$ at each layer. A collapse would manifest as values approaching 1. Instead, at epoch 40 we obtain:

$$[0.347,\ 0.643,\ 0.541,\ 0.443], \quad \text{mean} = 0.493.$$

These values remain well below 1, showing that the two decoders encode complementary information. The variation across layers also suggests that some layers specialize more in semantic–syntactic separation, while others produce partially aligned features.

Conclusion. Both diagnostics confirm that the semantic and syntactic decoders do not collapse into identical behaviour. The gating mechanism remains active and input-dependent, and the representations maintain non-trivial divergence. Together, these results verify that the dual-decoder architecture behaves as intended, with each branch contributing unique and useful information to the final fused representation.

6 Conclusion

6.1 Summary of findings

In this project, we implemented a dual-decoder Transformer architecture designed to translate English requirements into Signal Temporal Logic (STL). The core problem with standard NMT models is their tendency to conflate semantic (meaning) and syntactic (structure) learning.

We address this by separating the tasks into two parallel decoders. We then confirmed this separation is maintained throughout training using non-collapse verification. This design proves successful, as our model quantitatively outperforms the baseline single-decoder Transformer in exact Formula Accuracy and shows significantly more stable performance (lower variance).

6.2 Effectiveness of dual-decoder architecture

The dual-decoder architecture proved to be an effective method for this task.

- It effectively separates the learning of logical meaning from syntactic structure, tackling the key challenge of converting ambiguous natural language into exact formal logic.
- The results confirm our hypothesis: employing separate decoders for syntax and semantics, combined through a dynamic gating mechanism, enables the model to generate translations that are more accurate and reliable than those produced by a single unified decoder.

6.3 Practical implications

Automating the translation from English to STL carries substantial practical benefits for systems engineering and verification:

- **Reduces Manual Effort:** It offers a solution to replace the slow and error-prone task of crafting formal specifications by hand.
- **Speeds Up Verification:** By removing this bottleneck through automation, it accelerates the verification workflow and enables engineers to concentrate on system design and analysis.

- **Improves Reliability:** This automated translation narrows the gap between human-readable requirements and machine-checkable logic, ultimately enabling stronger safety assessments and more reliable system design.

7 Future Work

7.1 Fix Copying Mistakes: Add a Pointer/Copy Mechanism

Problem: Numbers and identifiers are being mistranslated (e.g., confusing $>$ with $\geq$, or swapping constants).

Change: Replace the final `dense` projection layer with a pointer-generator layer. This allows the model to *copy* tokens directly from the source sentence as well as *generate* from its learned vocabulary.

Implementation:

- Add w_h, w_c, w_x and $p_{\text{gen}} = \sigma(w_h h_t + w_c \text{context} + w_x x_t)$
- Blend p_{vocab} and p_{copy} into $p_{\text{final}} = p_{\text{gen}} p_{\text{vocab}} + (1 - p_{\text{gen}}) p_{\text{copy}}$
- Use $\log(p_{\text{final}})$ for the loss exactly as before.

7.2 Stop Illegal STL Sequences: Grammar-Mask the Syntax Branch

Problem: The model generates syntactically invalid STL, such as invalid token orders (double operators, missing brackets).

Change: Maintain a small grammar table or an adjacency mask that defines "legal" next tokens. During decoding, the model will set the logits of all illegal tokens to $-\infty$ before the softmax, forcing it to only output syntactically valid sequences.

7.3 Give the Model a Bit More Capacity

Problem: The current hidden size (128) limits the model's representation power.

Change: Increase the model's parameters.

```
num_hiddens = 512
ffn_num_hiddens = 2048
num_layers = 6
dropout_rate = 0.2
```

(Train a little longer for about 60 epochs with gradient clipping = 1.0.)

7.4 Strengthen Semantic Reasoning

Problem: The model shows confusion regarding temporal operators.

Changes:

- Use relative position encoding (Shaw et al., 2018).
- Optionally, insert a small temporal-relation Feed-Forward Network (FFN) (two dense layers) to model `[start, end]` interval embeddings.

7.5 Data-Level Improvements

This point involves three separate techniques to improve the training data itself:

- **Numeric Augmentation:** Randomly vary constants within valid ranges to teach the model robustness.
- **Paraphrase English Requirements:** Use an LLM or a rule-based system to paraphrase the input requirements, adding linguistic diversity to the dataset.
- **Curriculum Learning:** Train the model on short, simple formulas first, and then gradually introduce longer, more complex ones.

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