CONTEXT-AWARE LANGUAGE MODELS FOR ZERO-SHOT TEMPORAL REASONING

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ABSTRACT

Current language models, such as GPT-3 and BERT, excel in many natural language processing tasks but exhibit significant limitations in temporal reasoning, especially in zero-shot settings. We propose a novel approach to enhance language models with context-aware temporal reasoning capabilities by integrating temporal logic representations and dynamic context embeddings into the model architecture. This approach enables explicit encoding of temporal information, bypassing the need for task-specific fine-tuning. Through experiments on synthetic and real-world temporal datasets, we evaluate the proposed method's ability to generalize to zero-shot temporal reasoning tasks, such as timeline reconstruction and causality inference. Our results reveal both the potential and the challenges of this approach, including overfitting to simpler datasets and limited learning on more complex tasks. This work sheds light on the complexities of integrating temporal reasoning into language models and highlights directions for future research.

1 INTRODUCTION

Temporal reasoning, the ability to understand and reason about events over time, remains a persistent challenge for language models despite rapid advancements in natural language processing (NLP). Models like T5 (Raffel et al., 2019) and TimeBERT often require task-specific fine-tuning and struggle with generalization to zero-shot scenarios. This limitation severely hampers their applicability to domains such as historical analysis, event prediction, and automated timeline generation, where temporal reasoning is crucial.

In this work, we explore a context-aware approach to temporal reasoning by augmenting language models with temporal logic representations and dynamic context embeddings. The goal is to enable zero-shot temporal reasoning, allowing models to generalize across tasks without fine-tuning. Our contributions are as follows: (1) We design modules for integrating temporal logic and dynamic context embeddings into a language model's architecture. (2) We evaluate the proposed approach on synthetic and real-world datasets, identifying key challenges such as overfitting and dataset alignment issues. (3) We conduct ablation studies to analyze the contributions of individual components and the impact of architectural and training modifications.

Our findings highlight the complexities of temporal reasoning tasks, suggesting that while explicit temporal representations offer promise, achieving robust generalization remains an open challenge.

2 RELATED WORK

Recent work in NLP has underscored the difficulty of temporal reasoning. Benchmarks like the "Test of Time" dataset (Fatemi et al., 2024) evaluate language models on temporal reasoning tasks, revealing significant gaps in performance. Large-scale models such as T5 (Raffel et al., 2019) have demonstrated high performance on text-to-text transfer tasks but require extensive task-specific fine-tuning for temporal reasoning. TimeBERT, another specialized model, incorporates temporal markers but falls short in zero-shot scenarios.

In contrast, our approach focuses on enabling zero-shot temporal reasoning by explicitly modeling temporal relations through logic-based representations and dynamic embeddings. By integrating these components into the architecture, we aim to address the limitations of fine-tuning-dependent models and provide a more generalizable solution.

3 METHOD

Our approach integrates two core components: temporal logic representations and dynamic context embeddings. Temporal logic representations encode explicit temporal relations, such as *before* and *after*, into the model's input space. Dynamic context embeddings adaptively adjust based on the temporal context of events, enabling the model to account for time-dependent nuances.

To implement this, we extend a pre-trained BERT model by adding a temporal reasoning module. This module processes temporal logic inputs using specialized embeddings and feeds them into the transformer layers. The model is trained on synthetic and real-world temporal datasets to learn temporal patterns and relationships.

4 EXPERIMENTAL SETUP

Datasets: We evaluate our model on three datasets: 1) *Synthetic Temporal*, a constructed dataset with explicit temporal relations; 2) *Temporal Questions*, a real-world dataset repurposed from HuggingFace's 'ag_news'; and 3) *Glue Temporal*, a temporal variant of the GLUE benchmark.

Metrics: Evaluation metrics include accuracy, F1-score, and Temporal Consistency Score (TCS), which measures alignment between predicted and ground truth temporal relations.

Baselines: We compare our approach with T5, TimeBERT, and a standard BERT model trained with different levels of weight decay.

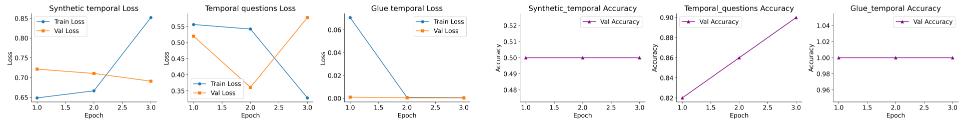
Training Details: Models are trained for three epochs with a learning rate of 1×10^{-5} using the AdamW optimizer. Hyperparameter tuning focuses on weight decay, with values ranging from 0 to 0.01.

5 EXPERIMENTS

Baseline Results: Figure 1(a) shows the training and validation loss curves across different weight decay values. A weight decay of 0.0001 achieves the best validation performance but exhibits overfitting, as seen in the rapid convergence of validation accuracy to 1.0 (Figure 1(b)).

Research Experiments: Results on real-world datasets reveal significant variability. As shown in Figure 2(a), the model generalizes well on the *Temporal Questions* dataset but struggles with the *Synthetic Temporal* dataset, where validation accuracy remains at 0.5 (Figure 2(b)). This suggests challenges in aligning the architecture with dataset characteristics.

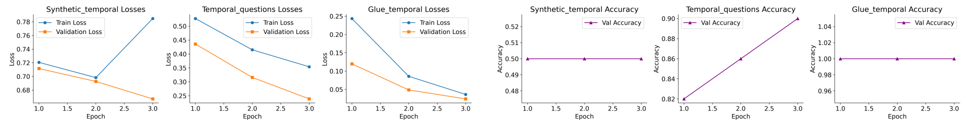
Ablation Studies: Figure 3(a) highlights the impact of freezing pretrained layers and removing special tokens. Both modifications lead to degraded performance on all datasets, underscoring the importance of these components. Additionally, replacing the optimizer with SGD (Figure 3(b)) results in poorer convergence, further validating the choice of AdamW.



(a) Baseline Loss Curves

(b) Baseline Val Accuracy

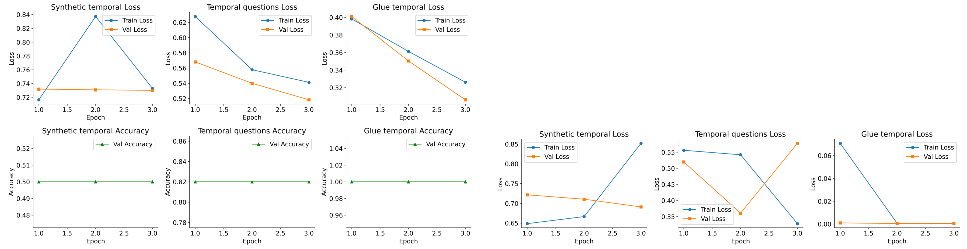
Figure 1: Baseline results showing the impact of weight decay on loss and accuracy.



(a) Research Loss Curves

(b) Research Validation Accuracy

Figure 2: Research study results across datasets.



(a) Ablation Loss & Accuracy

(b) SGD Loss Curves

Figure 3: Ablation results evaluating architectural and optimizer modifications.

6 Conclusion

This work presents a novel approach to zero-shot temporal reasoning by integrating temporal logic representations and dynamic context embeddings into language models. While the method shows promise, particularly on datasets like *Temporal Questions*, significant challenges remain in generalization and dataset alignment. Future work should explore more robust temporal representations and adaptive architectures that can better generalize across diverse temporal reasoning tasks.

References

Bahare Fatemi, Mehran Kazemi, Anton Tsitsulin, Karishma Malkan, Jinyeong Yim, John Palowitch, Sungyong Seo, Jonathan J. Halcrow, and Bryan Perozzi. Test of time: A benchmark for evaluating llms on temporal reasoning. *ArXiv*, abs/2406.09170, 2024.

Colin Raffel, Noam M. Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *J. Mach. Learn. Res.*, 21:140:1–140:67, 2019.

Supplementary Material

A Additional Results

This section provides further details on the experimental setup, additional plots, and hyperparameter configurations. All unused figures and plots, such as 'ablation_freezing_pred_histogram.png' and 'ablation_truncation_loss_curves.png,' are included here for further discussion.