

Retrieval of Temporal Event Sequences from Textual Descriptions

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Introduction

- **Temporal event sequences** encode both event types and timestamps, essential for applications like e-commerce analysis, social media monitoring, and crime tracking.
- Retrieving event sequences from natural language descriptions is challenging due to the need to capture both event semantics and temporal dynamics.
- We propose TPP-Embedding, a model that jointly encodes temporal and textual information to enable accurate Temporal Event Sequence Retrieval (TESR).

TPP-Embedding

We propose **TPP-Embedding**, a model for **TESR** that jointly encodes temporal and textual information.

Key Features:

- Integrates Temporal Point Process (TPP) models with LLMs to capture event semantics and temporal dynamics.
- Embeds event sequences and textual descriptions in a shared embedding space using temporal encoding and LLM embeddings.
- Trains with **contrastive loss** to align matching sequencedescription pairs.
- Fine-tuned efficiently with **QLoRA** for scalable deployment.

Similarity



TESRBench

We introduce **TESRBench**, a benchmark for evaluating **TESR**:

- Includes 5 real-world datasets from diverse domains.
- Provides **synthesized textual descriptions** for event sequences, generated by **GPT-4o-mini**.

Dataset	# of Types	# of Events	# of Seq.	Time Unit
Stack Overflow	25	187,836	3,336	Month
Chicago Crime	20	202,333	4,033	Month
NYC Taxi Trip	8	362,374	2,957	Hour
U.S. Earthquake	3	29,521	3,009	Day
Amazon Review	18	127,054	2,245	Week

Experiments



Conclusion

We introduce TESRBench, a benchmark suite for evaluating temporal event sequence retrieval (TESR).

We evaluate **TPP-Embedding** on **TESRBench** against strong textbased baselines.

Setup:

- Foundation models: TinyLlama-1.1B, TinyLlama-1.1B-Chat.
- **Baselines:** MiniLM-L12, MPNet-Base, BGE-Large, MxbAl-Large, mE5-Large, Qwen2-1.5B.
- **Metrics:** Mean Reciprocal Rank (MRR) and Recall@K.

Results:

- **TPP-Embedding** consistently outperforms baselines across most datasets.
- Demonstrates strong generalization in a **multi-domain setting**.

- We propose **TPP-Embedding**, a retrieval model that integrates temporal information and event semantics.
- **TPP-Embedding** achieves state-of-the-art performance on **TESRBench** and generalizes well across domains.

References

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