EasyTPP: Towards Open Benchmarking Temporal Point Process

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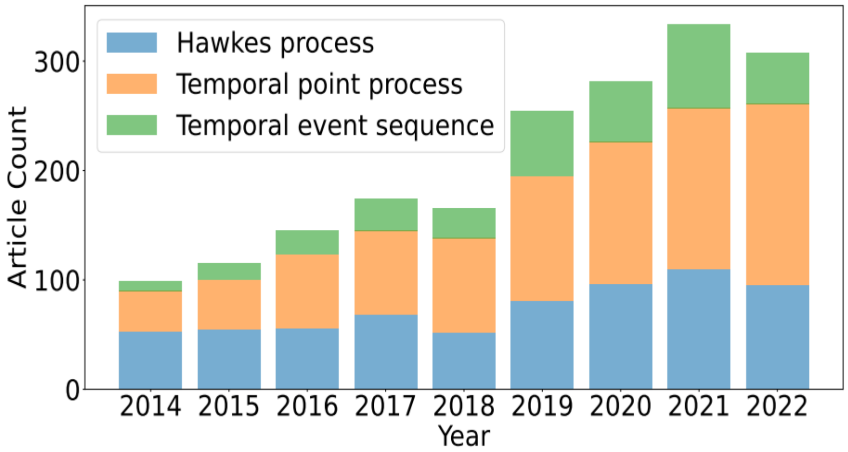
Motivation

The number of research papers on TPPs has been steadily increasing. These advancements have enabled more accurate and flexible modeling of event sequences in diverse fields.



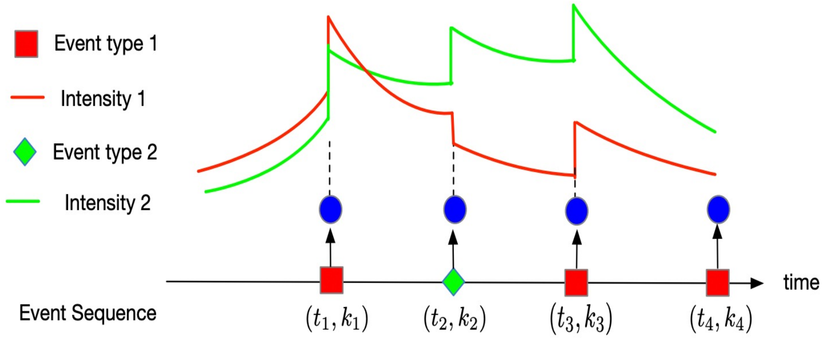


Figure 2: Drawing an event stream from a neural TPP. The model reads the sequence of past events (polygons) to arrive at a hidden state (blue). That state determines the future "intensities" of the two types of events–that is, their time-varying instantaneous probabilities. The intensity functions are continuous parametric curves (solid lines) determined by the most recent model state. Events will update the future intensity curves as they occur.

Our contribution: open benchmarking TPPs with a central library

ant-research / EasyTemporalPointProcess Public

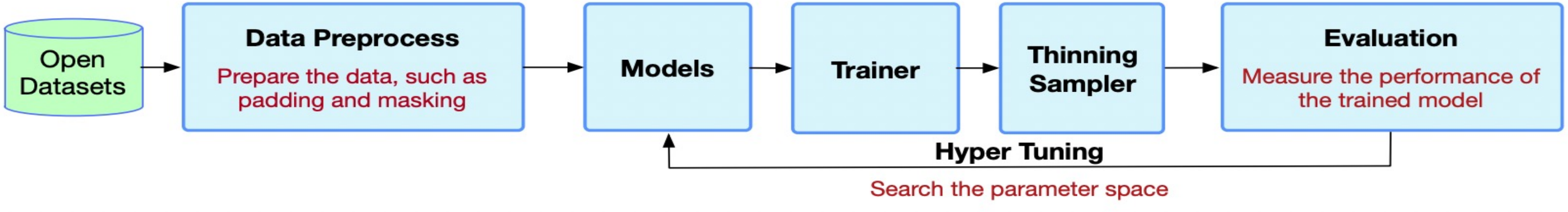
https://github.com/ant-research/EasyTemporalPointProcess

python 3.9+ | license Apache | last commit march

pypi v0.0.7.1 | Downloads 3k | 🤗 Hugging Face EasyTPP | open issues 2

`EasyTPP` is an easy-to-use development and application toolkit for Temporal Point Process (TPP), with key features in configurability, compatibility and reproducibility. We hope this project could benefit both researchers and practitioners with the goal of easily customized development and open benchmarking in TPP.

Benchmarking process



A number of highly-cited datasets / models have been benchmarked.

Benchmarking Result and Future Insight

No consistent winner on next-event / long consistency prediction tasks.

Future research: build foundation event sequence model and utilize external source for event modeling.

MODEL	METRICS (TIME RMSE / TYPE ERROR RATE)				
	AMAZON	RETWEET	TAXI	TAOBAO	STACKOVERFLOW
MHP	0.635/75.9% 0.005/0.005	22.92/55.7% 0.212/0.004	0.382/9.53% 0.002/0.0004	0.539/68.1% 0.004/0.004	1.388/65.0% 0.011/0.005
RMTPP	0.620/68.1% 0.005/0.006	22.31/44.1% 0.209/0.003	0.371/9.51% 0.003/0.0003	0.531/55.8% 0.005/0.004	1.376/57.3% 0.018/0.005
NHP	0.621/67.1% 0.005/0.006	21.90/40.0% 0.184/0.002	0.369/8.50% 0.003/0.0005	0.531/54.2% 0.005/0.006	1.372/55.0% 0.011/0.006
SAHP	0.619/67.7% 0.005/0.006	22.40/41.6% 0.301/0.002	0.372/9.75% 0.003/0.0008	0.532/54.6% 0.004/0.002	1.375/56.1% 0.013/0.005
THP	0.621/66.1% 0.003/0.007	22.01/41.5% 0.188/0.003	0.370/8.68% 0.003/0.0006	0.531/53.6% 0.003/0.004	1.374/55.0% 0.021/0.006
ATTNHP	0.621/65.3% 0.005/0.006	22.19/40.1% 0.180/0.003	0.371/8.71% 0.003/0.0004	0.529/53.7% 0.005/0.001	1.372/55.2% 0.019/0.003
ODETPP	0.620/65.8% 0.006/0.008	22.48/43.2% 0.175/0.004	0.371/10.54% 0.003/0.0008	0.533/55.4% 0.005/0.007	1.374/56.8% 0.022/0.004
FULLYNN	0.615/N.A. 0.005/N.A.	21.92/N.A. 0.159/N.A.	0.373/N.A. 0.003/N.A.	0.529/N.A. 0.005N.A.	1.375/N.A. 0.015/N.A.
IFTPP	0.618/67.5% 0.005/0.007	22.18/39.7% 0.204/0.003	0.377/8.56% 0.003/0.006	0.531/55.4% 0.005/0.004	1.373/55.1% 0.010/0.005

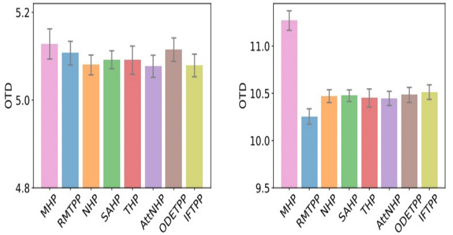


Figure 5: Long horizon prediction on Retweet data: left (avg prediction horizon 5 events) vs. right (avg prediction horizon 10 events).

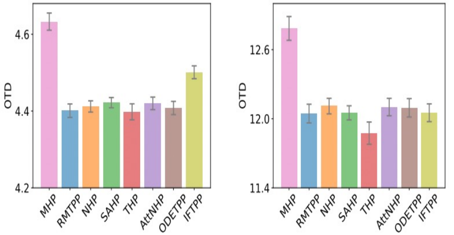


Figure 6: Long horizon prediction on Taxi data: left (avg prediction horizon 5 events) vs. right (avg prediction horizon 10 events).

Please come to our **poster** for

More implementation details !

More experimental details !

Please download our paper at