Anytime Information Cascade Popularity Prediction via Self-Exciting Processes

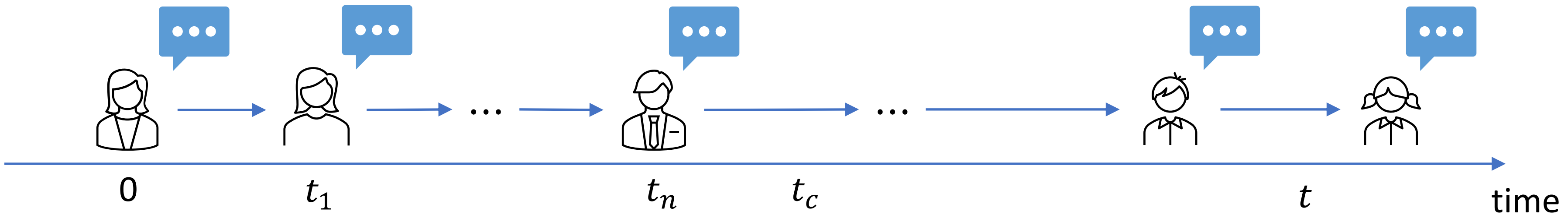
Xi Zhang, Akshay Aravamudan, Georgios C. Anagnostopoulos

Department of Computer Engineering & Sciences, Florida Institute of Technology, Melbourne, FL, USA.

Correspondence to: Xi Zhang <zhang2012@my.fit.edu>

Anytime Cascade Popularity Prediction

Cascade



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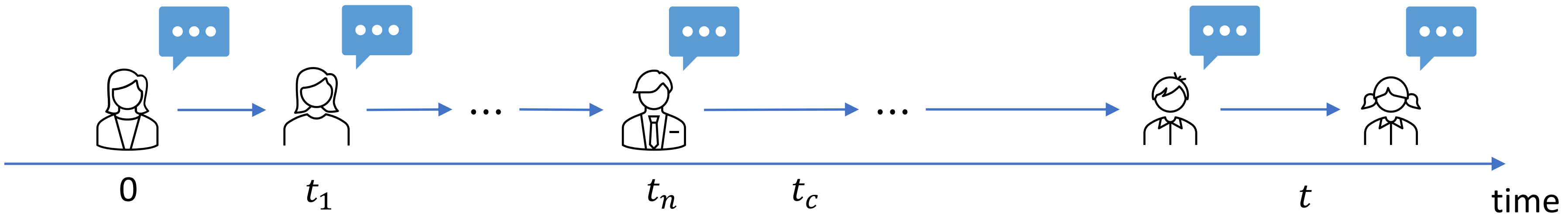

Phenomena "rich-get-richer" → heavy-tailed distribution of cascade sizes.

explains ↑

Modeling The Hawkes process is a **self-exciting** process that has been broadly used in modeling cascade dynamics.

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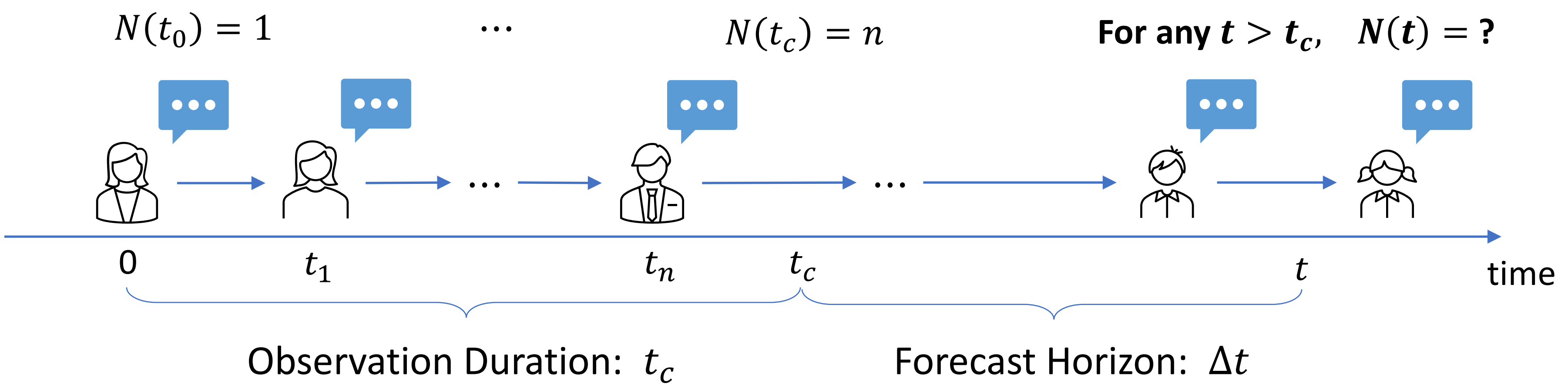
Popularity

Cascade



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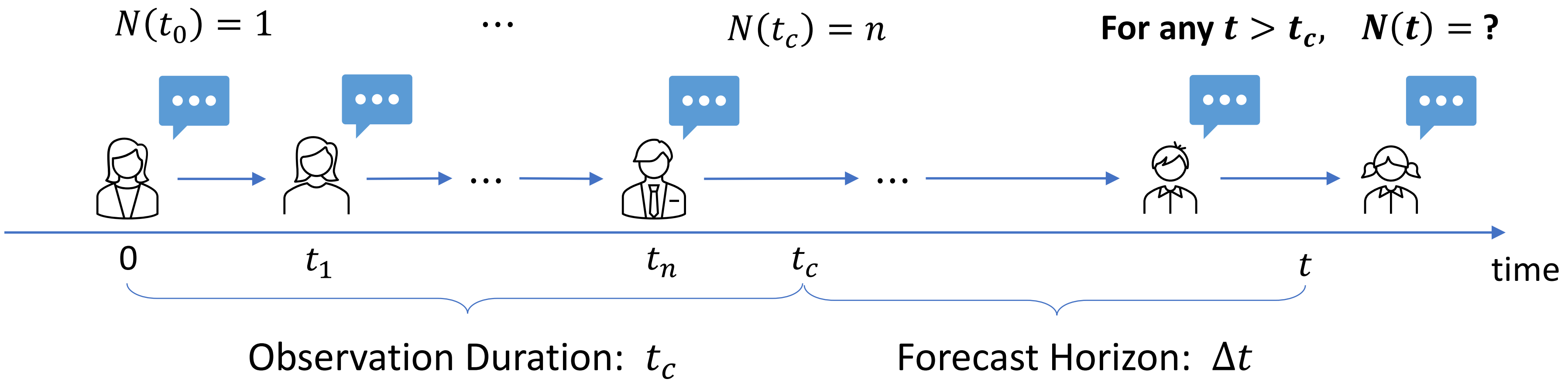

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Prediction The conditional (on the observed history) mean count of fitted Hawkes process is employed.

Contributions

For general marked Hawkes Point Process(MHPP), we derive **closed-form** expressions for the **conditional** (on the observed history $\mathcal{H}_{t_c}$) mean and variance of its counting process $\mathrm{N}(t)$ at $t \geq t_c$.

For anytime popularity prediction, we propose **Cascade Anytime Size Prediction via self-Exciting Regression model** (**CASPER**), a Hawkes process based **predictive** model, which minimize the prediction error directly, rather than to maximize the generative likelihood value.

Conditional Moments Derivation Procedures

A Hawkes process $N(t)$ can be equivalently viewed as a branching process, s.t.

$$\boldsymbol{N(t)} = \sum_{\boldsymbol{k \geq 0}} \boldsymbol{N_k(t)}$$

where $N_k(t)$ is k-th generation counting process.

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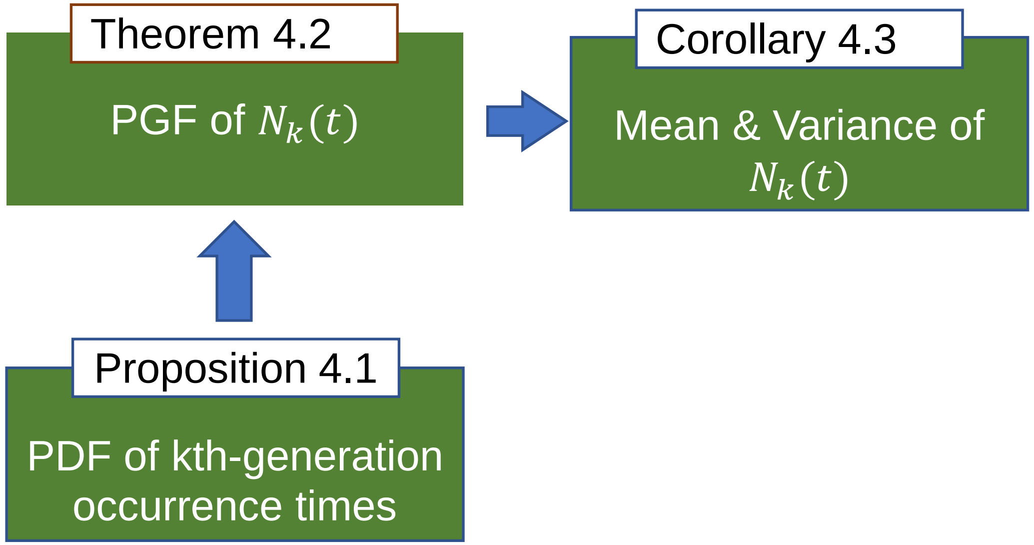

Generational count results

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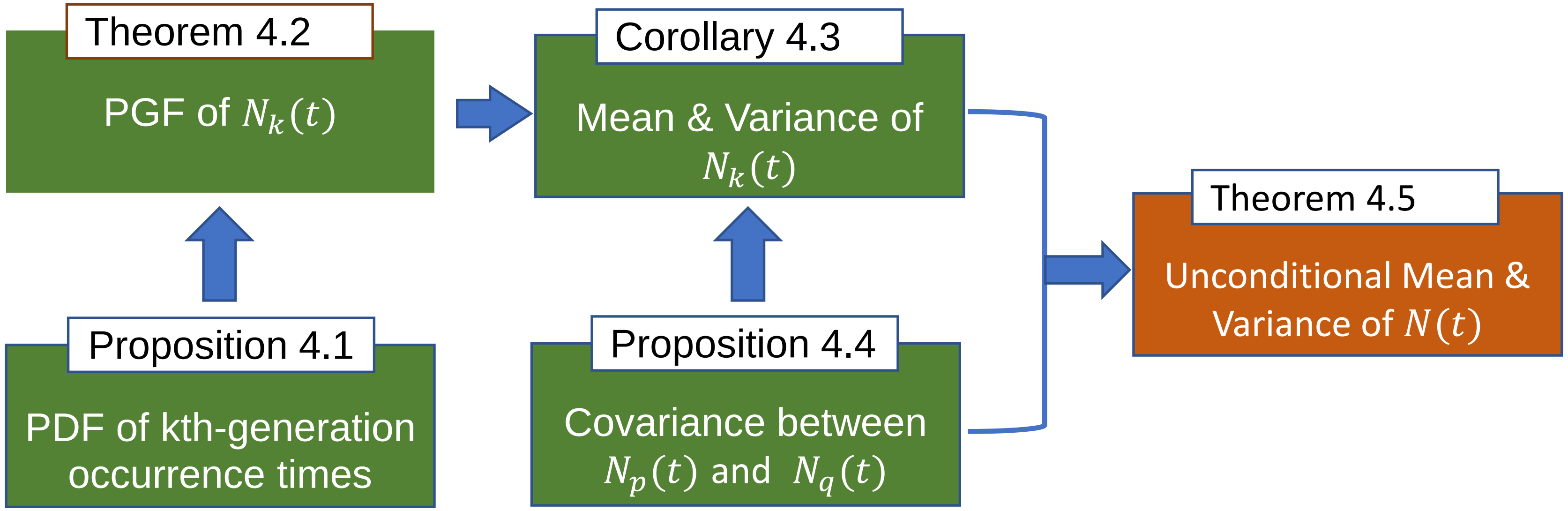

Generational count results

Process count results

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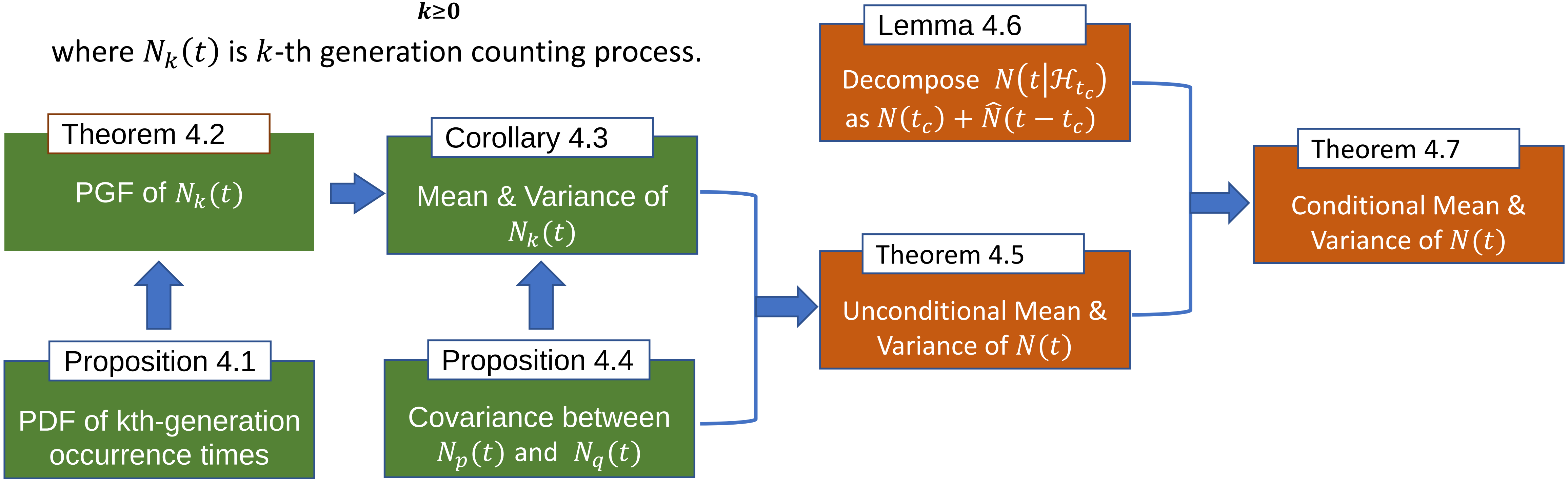


Generational count results

Process count results

CASPER

- Given $\mathcal{H}_{t_c}$, the observed history up to time t_c.
- Consider (i, j) s.t. $t_i < t_j \leq t_c$, then

$$\ell_{ij}(\boldsymbol{\theta}) \triangleq (\mathbb{E}\{N(t_j|\mathcal{H}_{t_i};\boldsymbol{\theta})\} - j)^2 \qquad (11)$$

  is the squared loss between the predicted and true count at time t_j given observations up to time t_i.
- Let $\mathcal{S}(t_c) \triangleq \{(i, j) : 0 < t_i < t_j \leq t_c\}$, CASPER's overall loss function is defined as

$$L(\boldsymbol{\theta}|\mathcal{H}_{t_c}) \triangleq \frac{1}{|\mathcal{S}(t_c)|} \sum\sum_{(i,j)\in\mathcal{S}(t_c)} \ell_{ij}(\boldsymbol{\theta}) \qquad (12)$$

Formulation

Assumption: diffusion as MHPP $N(t;\boldsymbol{\theta})$

↓

Train

$\boldsymbol{\theta}^* \in \arg\min_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} L(\boldsymbol{\theta}|\mathcal{H}_{t_c})$

↓

Predict

$N_{\text{pred}}(t) \triangleq \mathbb{E}\{N(t|\mathcal{H}_{t_c};\boldsymbol{\theta}^*)\}$

Results on Synthetic Dataset

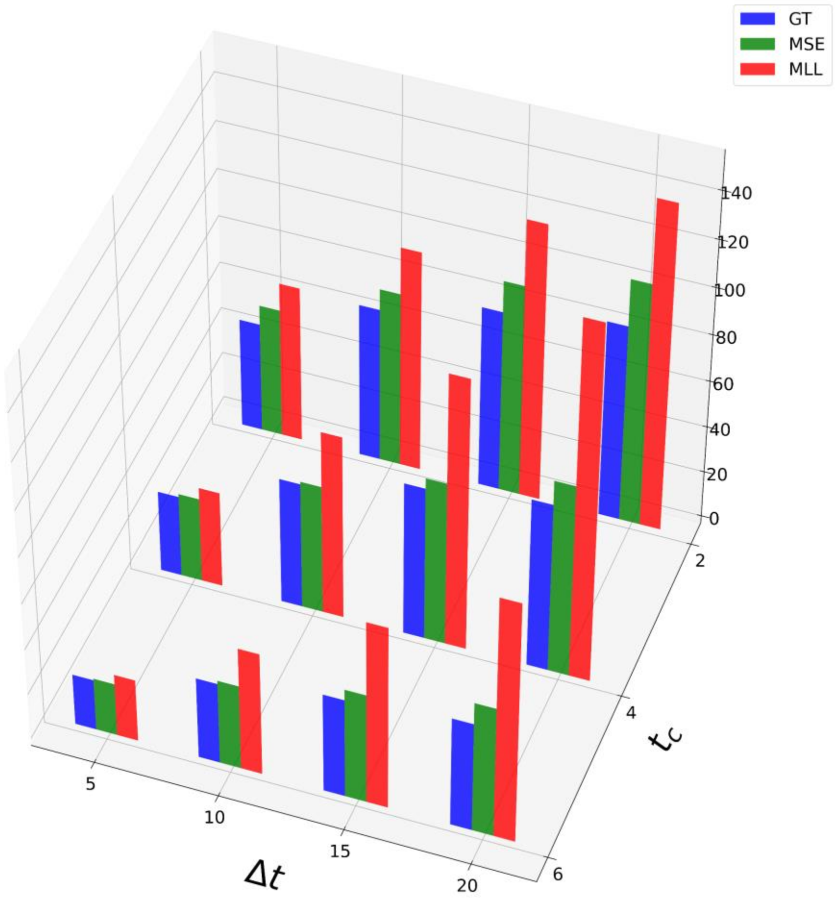


Fig 2: Average APE% on Synthetic Dataset

Predictive vs Generative Learning Approach

Models

- **GT**: ground truth models
- **MSE**: models trained by minimizing the overall loss in Eq (12) – *the predictive learning approach.*
- **MLL**: models trained by maximizing likelihood – the *generative learning approach.*

Conclusion

CASPER's predictive learning approach

- outperforms the generative learning approach.
- highly competitive to the ground truth model.

Results on Real World SEISMIC Twitter Dataset

Training Requires	Algorithms Compared
Observed history	• **MaSEPTiDE**
Additional fully-observed cascades	• **TiDeH**: designed for larger t_c • **Eb-MaSEPTiDE**: aids for smaller t_c

Fig 3a:Short-term prediction with $\Delta t = 4$ hours

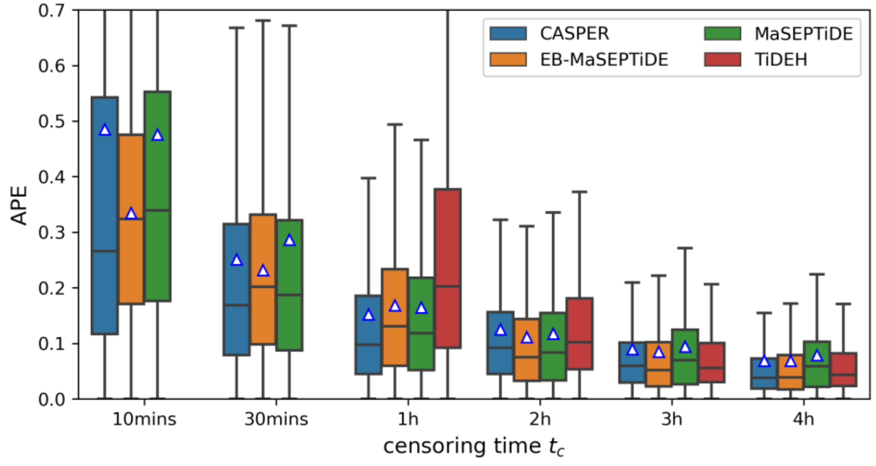
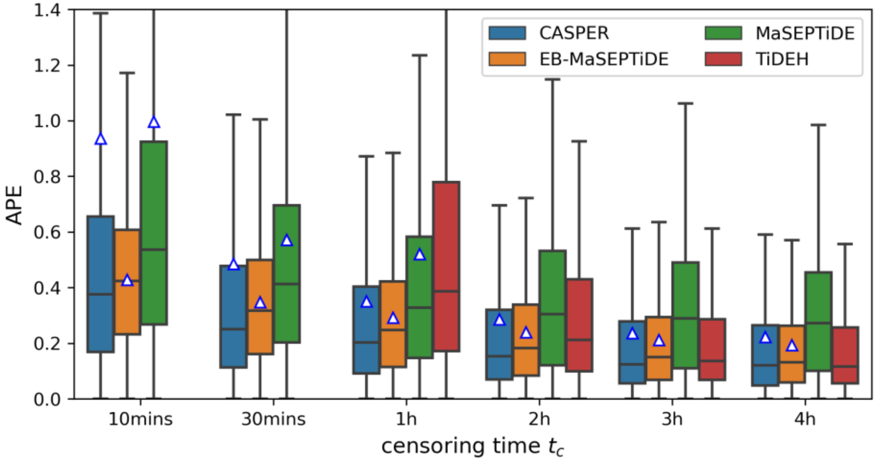


Fig 3b:Long-term prediction with $\Delta t = 4$ days



CASPER exhibits competitive, if not the best performance

- Outperform MaSEPTiDE across all scenarios.
- Competitive to TiDeH for predictions with long observation periods.
- For early-stage prediction, CASPER attains lowest median, but exhibits mean than Eb-MaSEPTiDE.

Thanks for watching