Adversarial Training Model Unifying Feature Driven and Point Process Perspectives for Event Popularity Prediction

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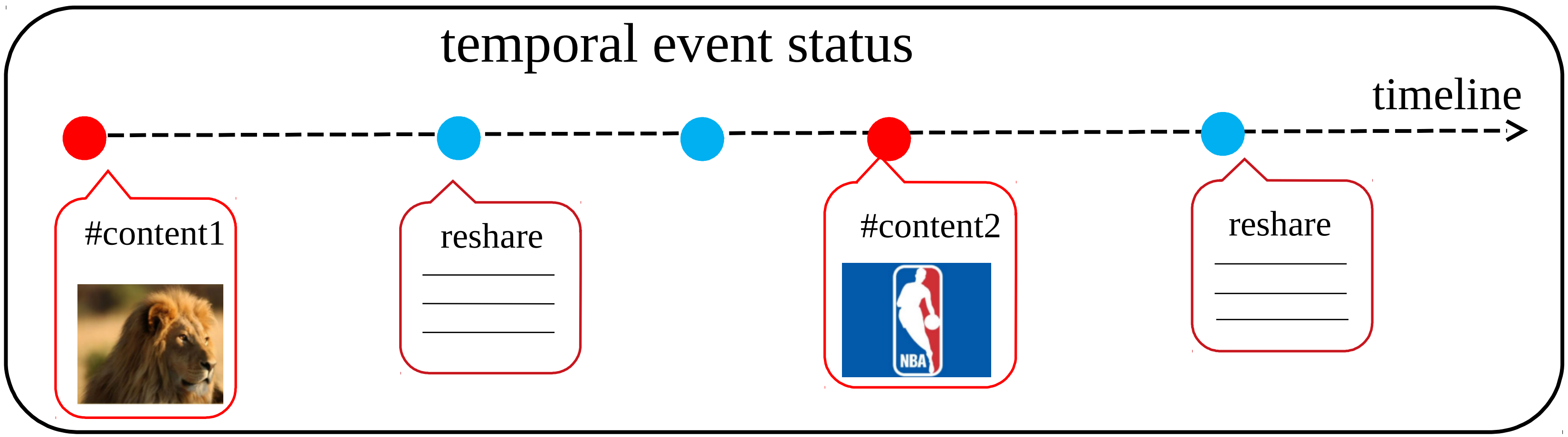
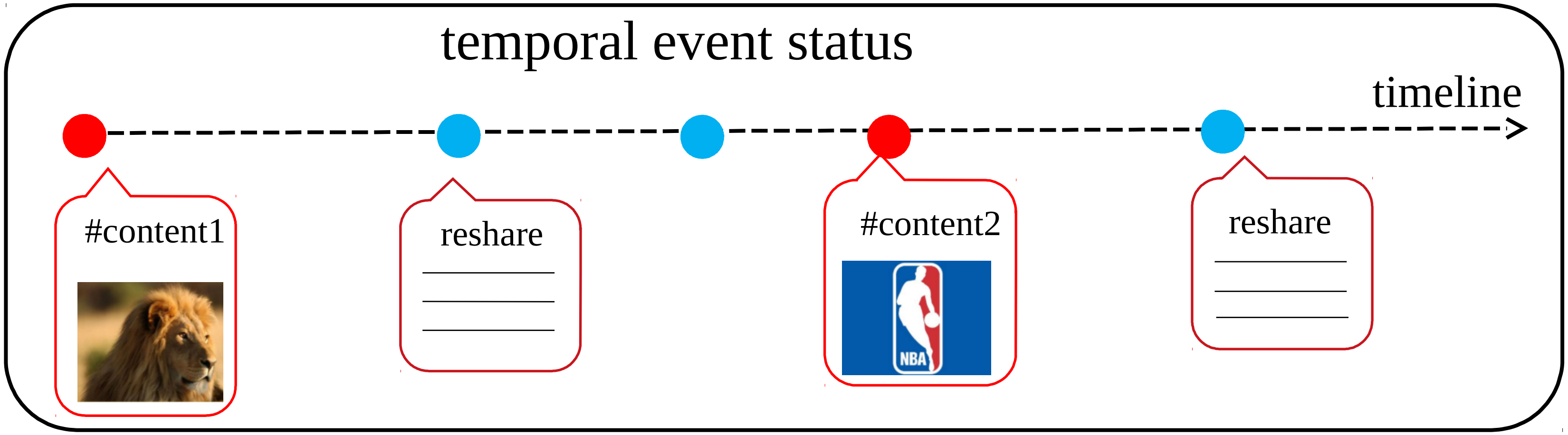
Background


temporal event status
timeline
#content1
reshare
#content2
NBA
reshare

Background



Online social networks provide people with a quick access to information, communication and study.

- Fast Transmission Rate
- Good Timeliness
- Low Dissemination Cost

Background

Background

(from Twitter)

Background

(from The Guardian)

Problem Statement

How can we predict the popularity?

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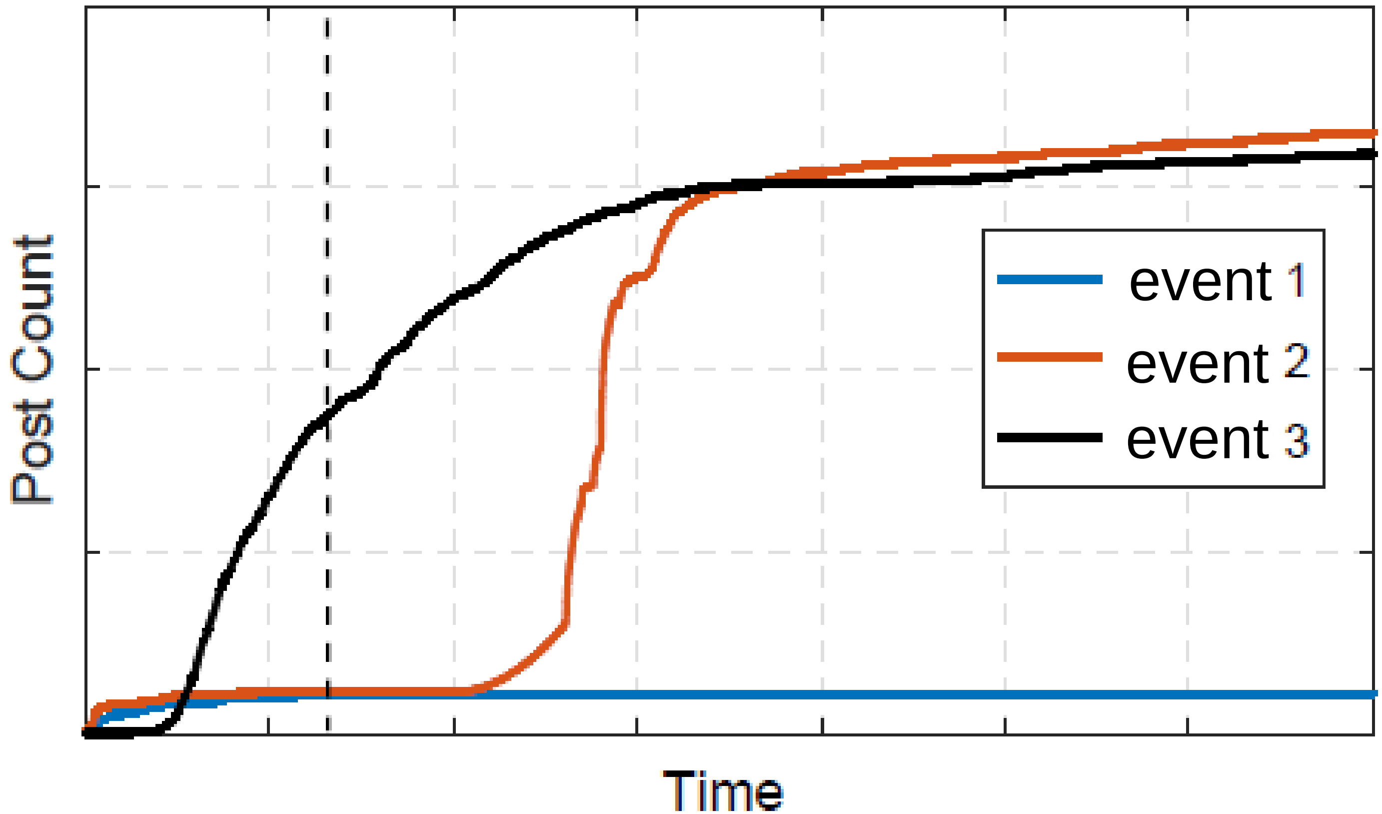

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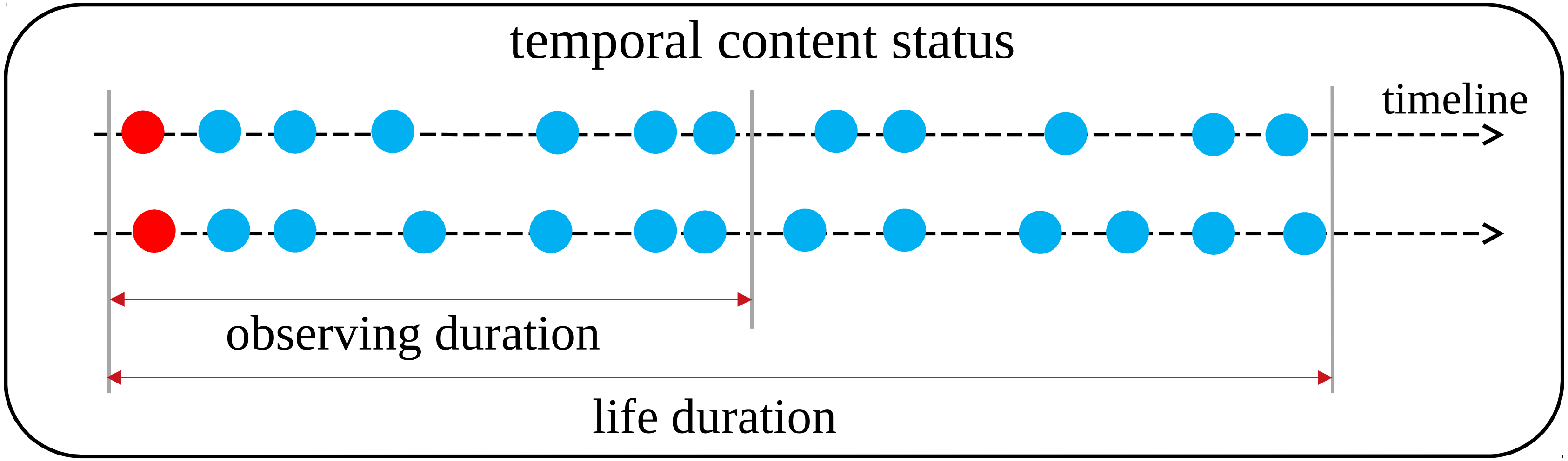

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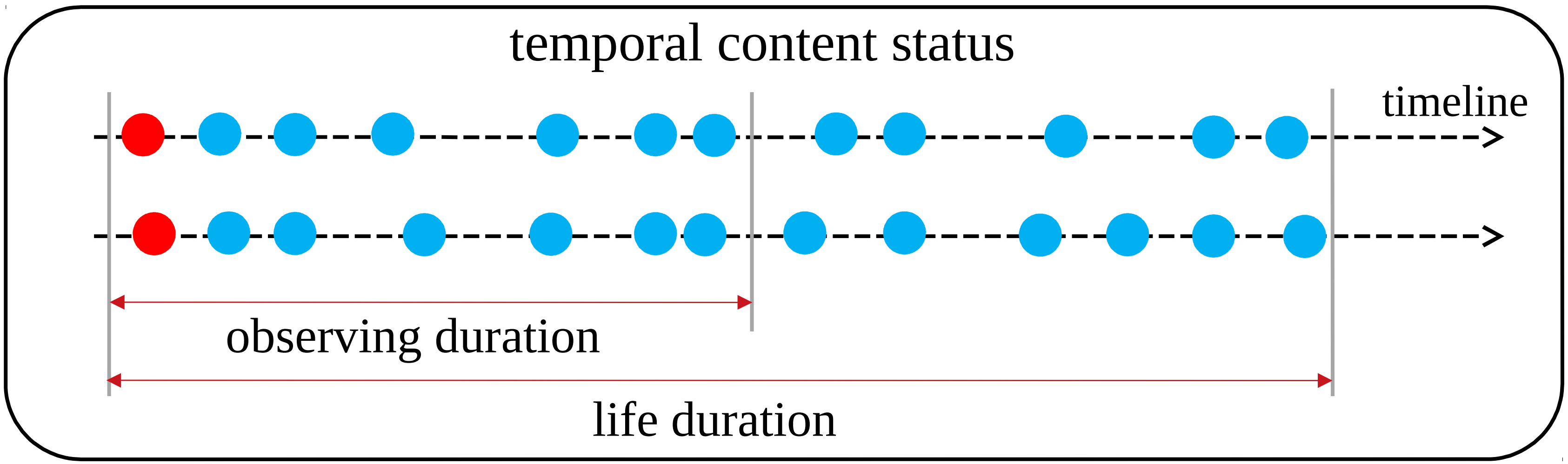
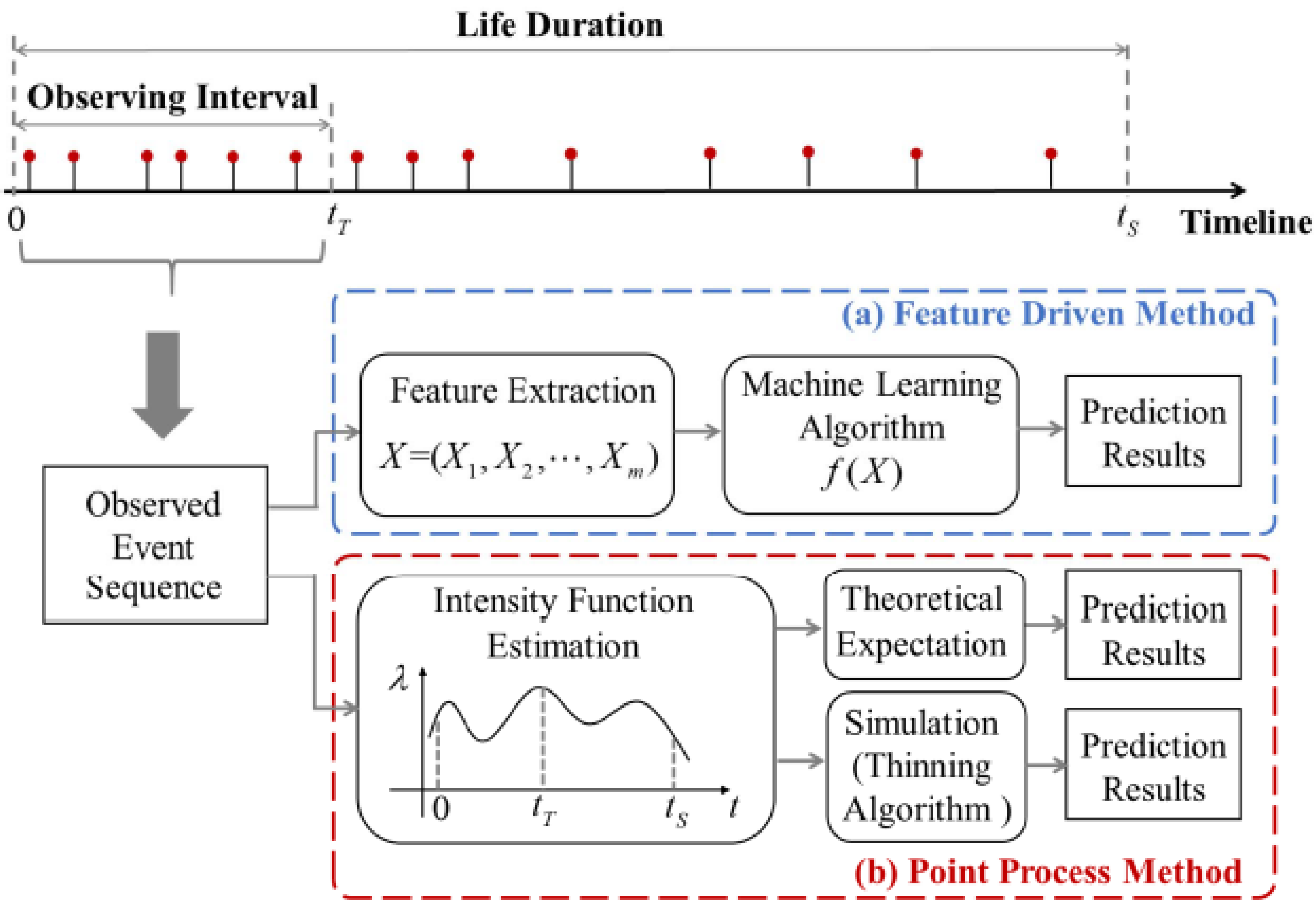


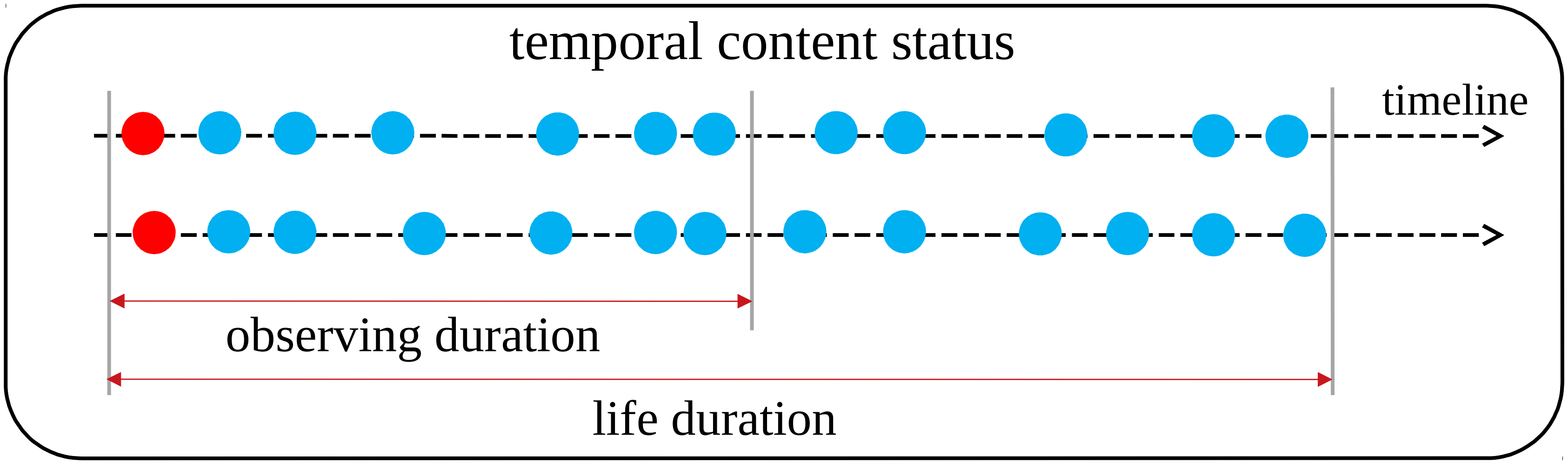
With tweets in observing duration, one would like to know how many tweets will be posted in the end.

- rumor monitoring
- anomaly detection
- personalized recommendation
- targeted advertisement

Two School of Thinking



Intuition



What can we get from observing duration?

Intuition

User Info.

- # of followers
- # of followees
- Network Age
- Reputation / Title
- …

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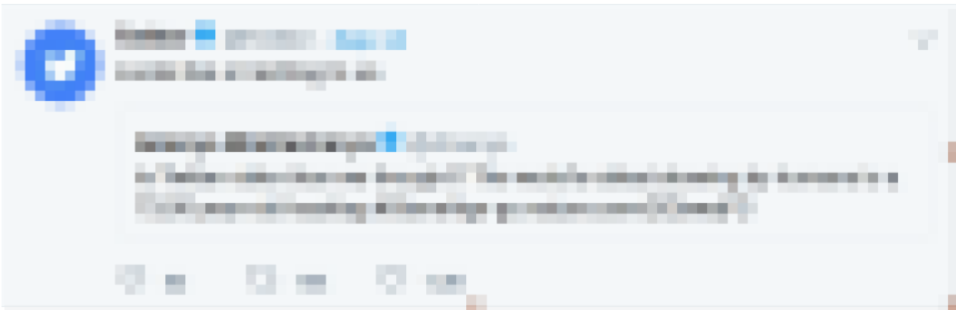
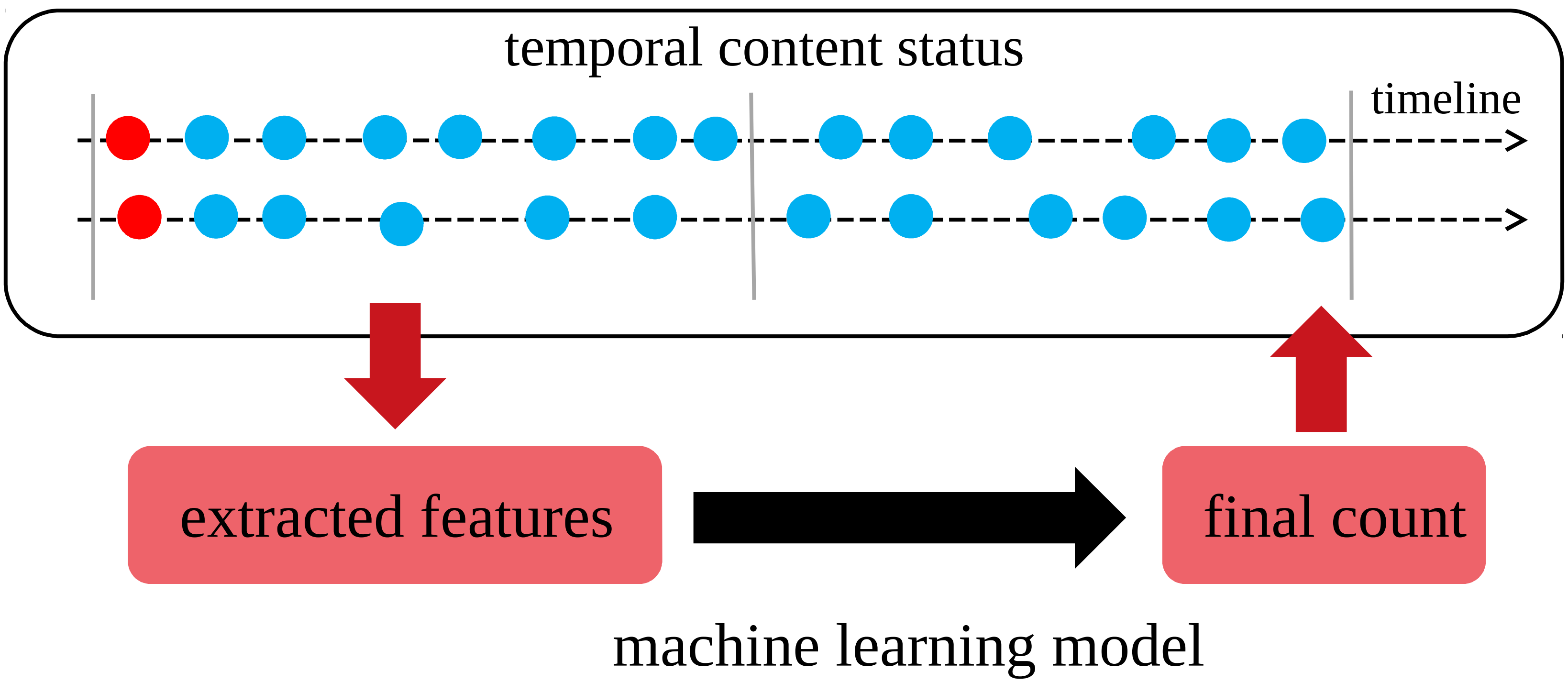


Tweet Info.

- timestamp
- # of paragraphs / words
- hashtag or not
- …

<u>Features</u>

One School of Thinking: Feature Driven Method



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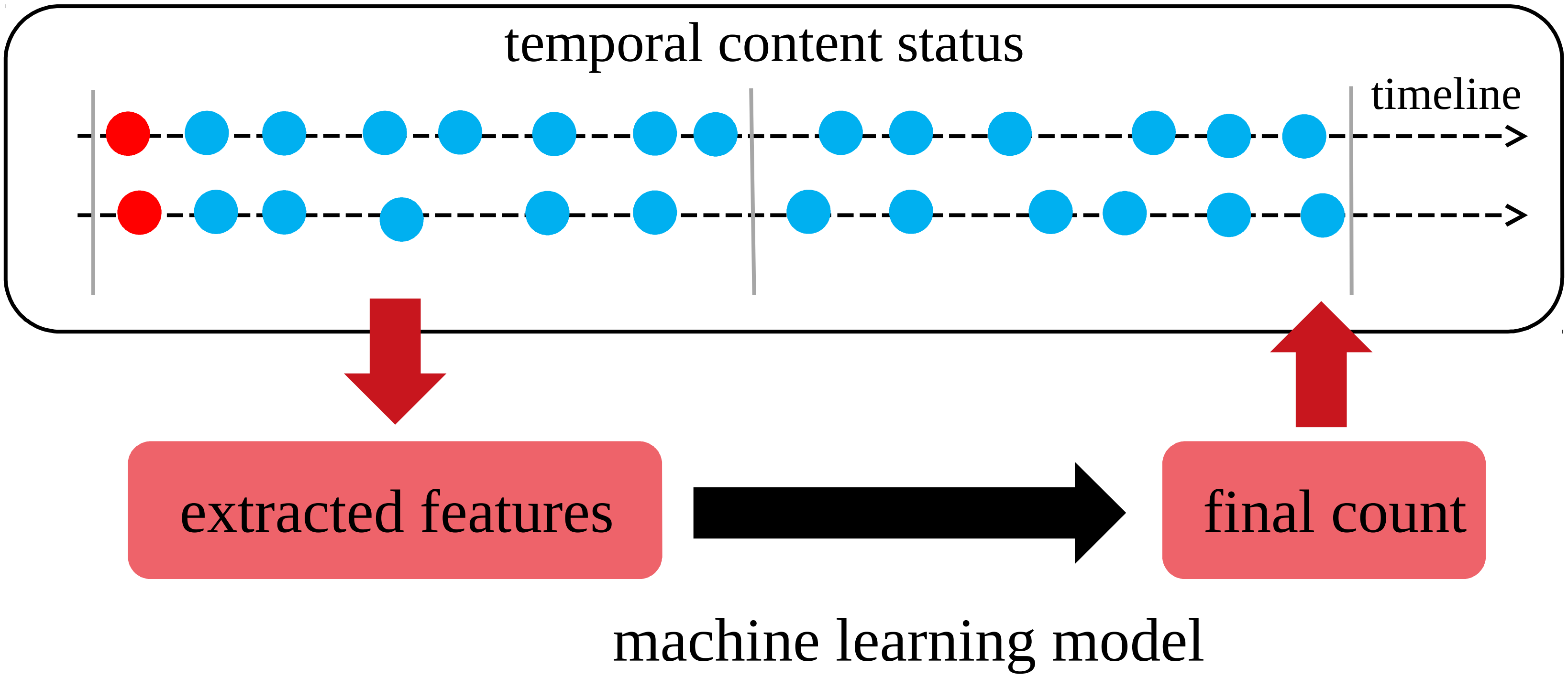
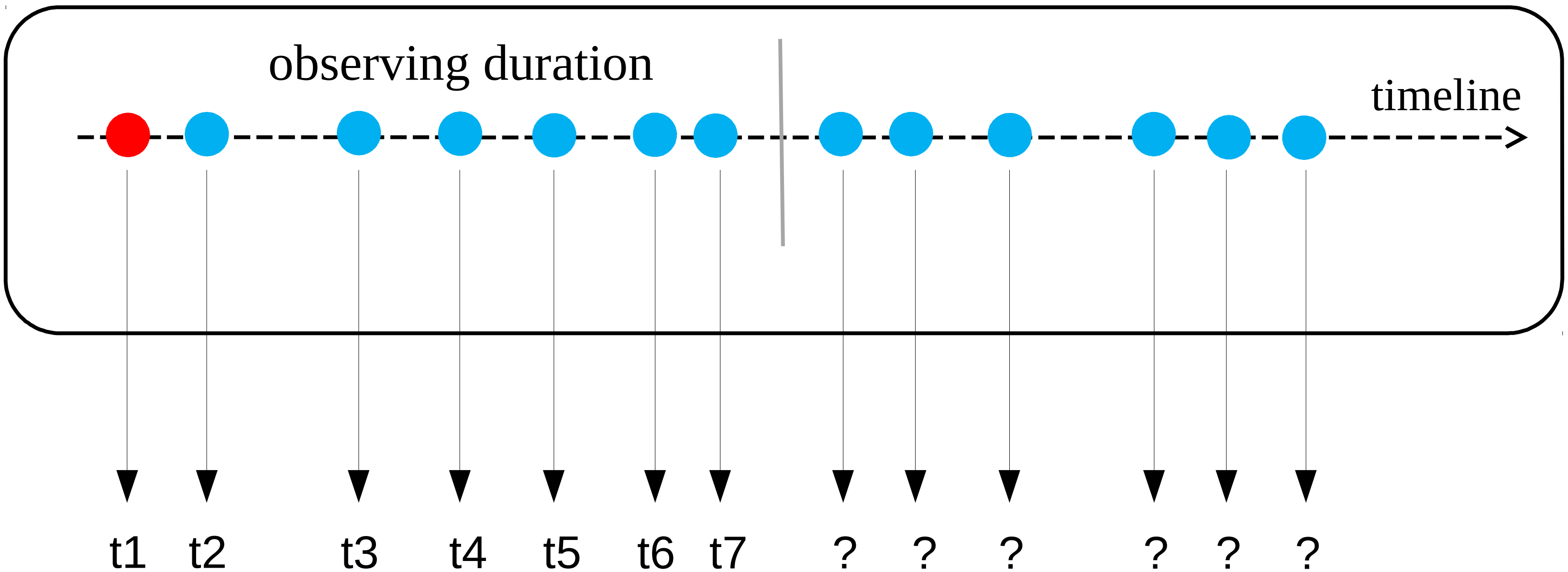


Strengths: **good precision**, **robustness**, **stability**

Weaknesses: **high human expertise**, **laborious feature engineering**

Intuition



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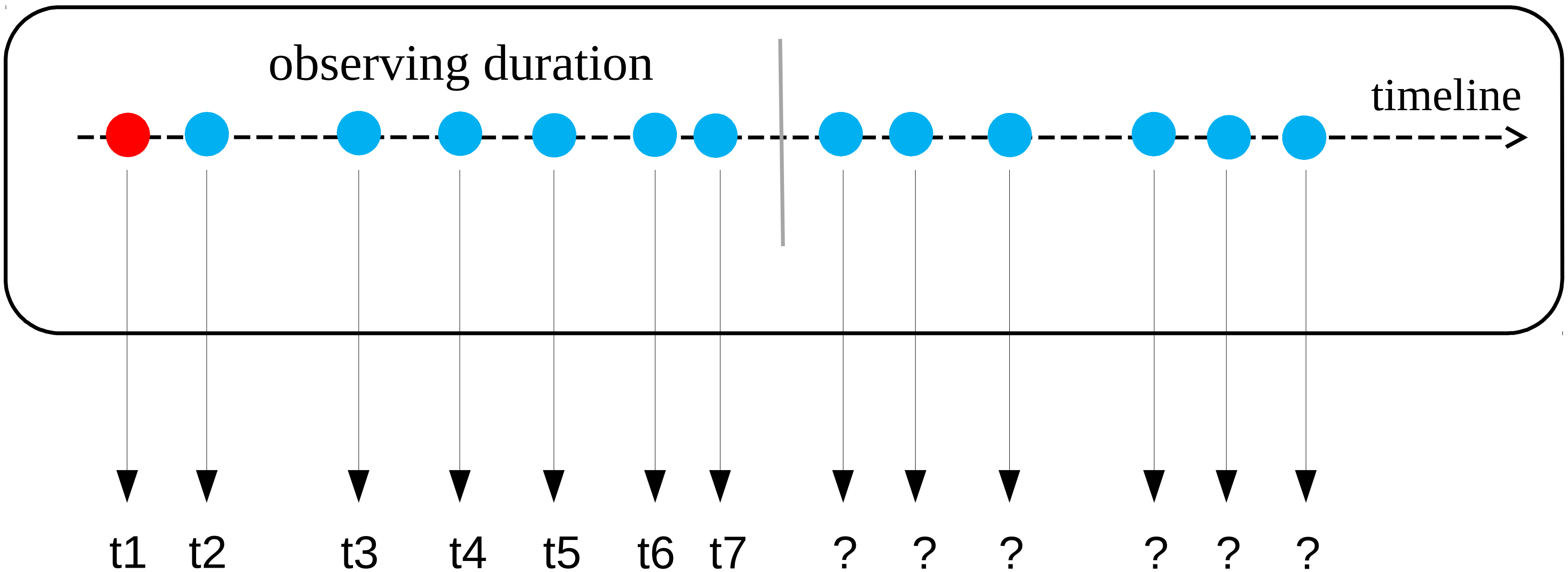
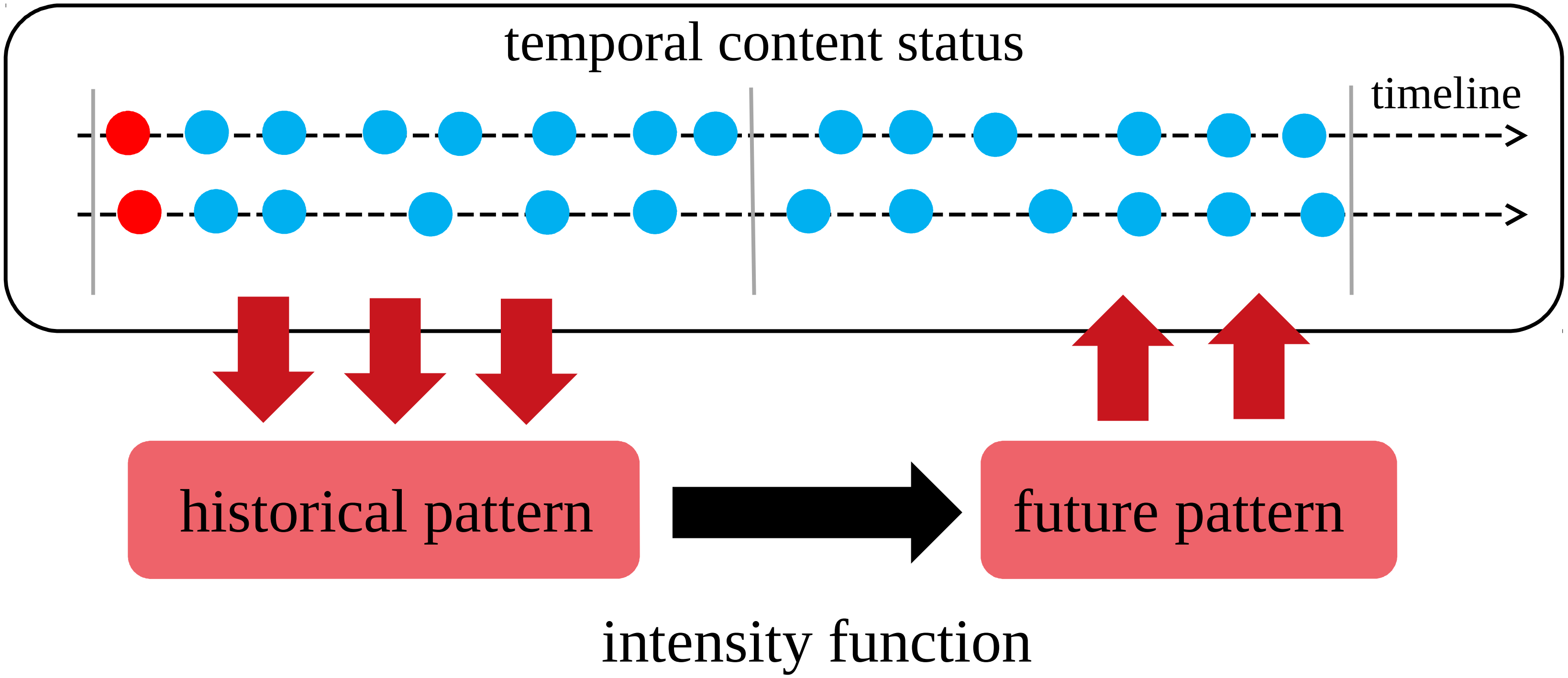


Point process / Poisson Process → Intensity function → Estimate future popularity

The Other School of Thinking: Point Process Method



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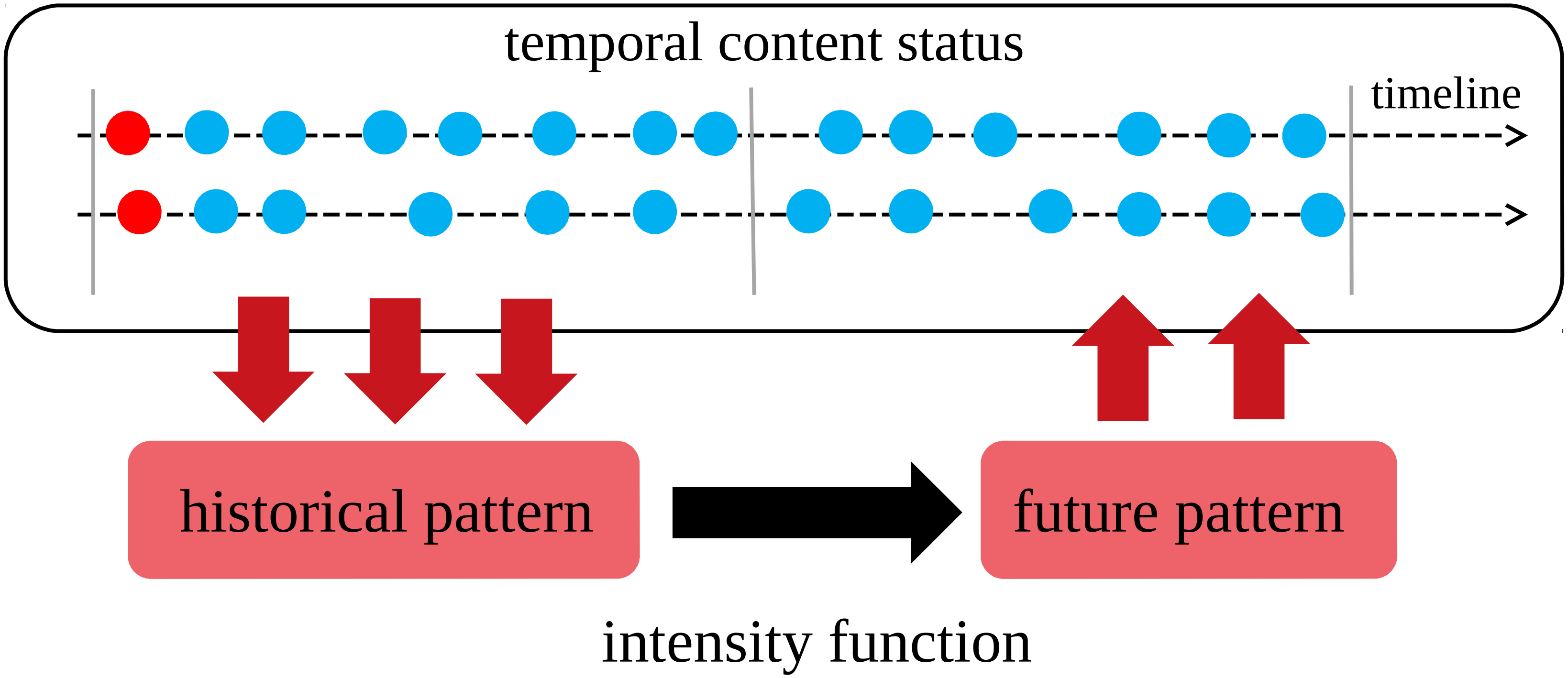

Strengths: **good interpretability**, **low computational complexity**

Weaknesses: **poor robustness, long-term observation**

Limitations of Previous Study

The most previous methods rely on long-term observation:

- utilize features extracted from dozens of hours observation to predict popularity of social topics.
- predict popularity of Twitter hashtags when over 80% related posts are exposed.

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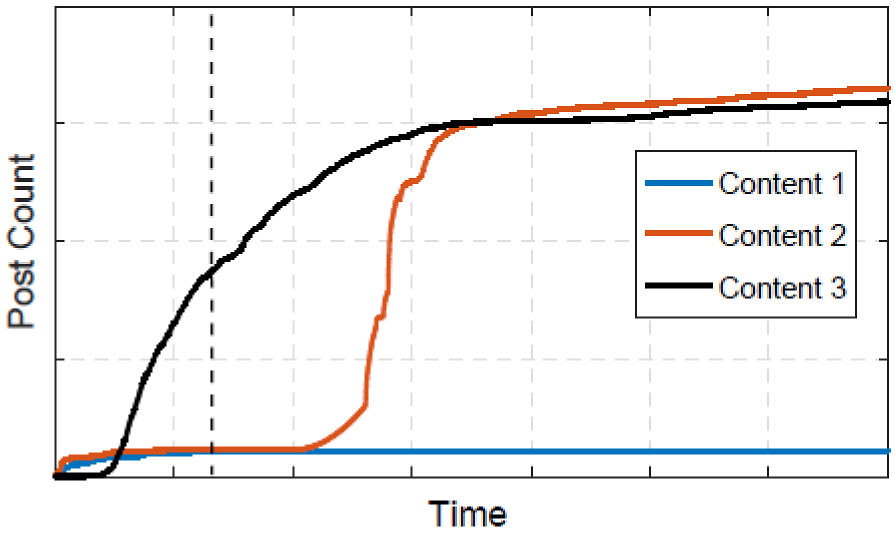
The long observation time makes it easy for decision making:

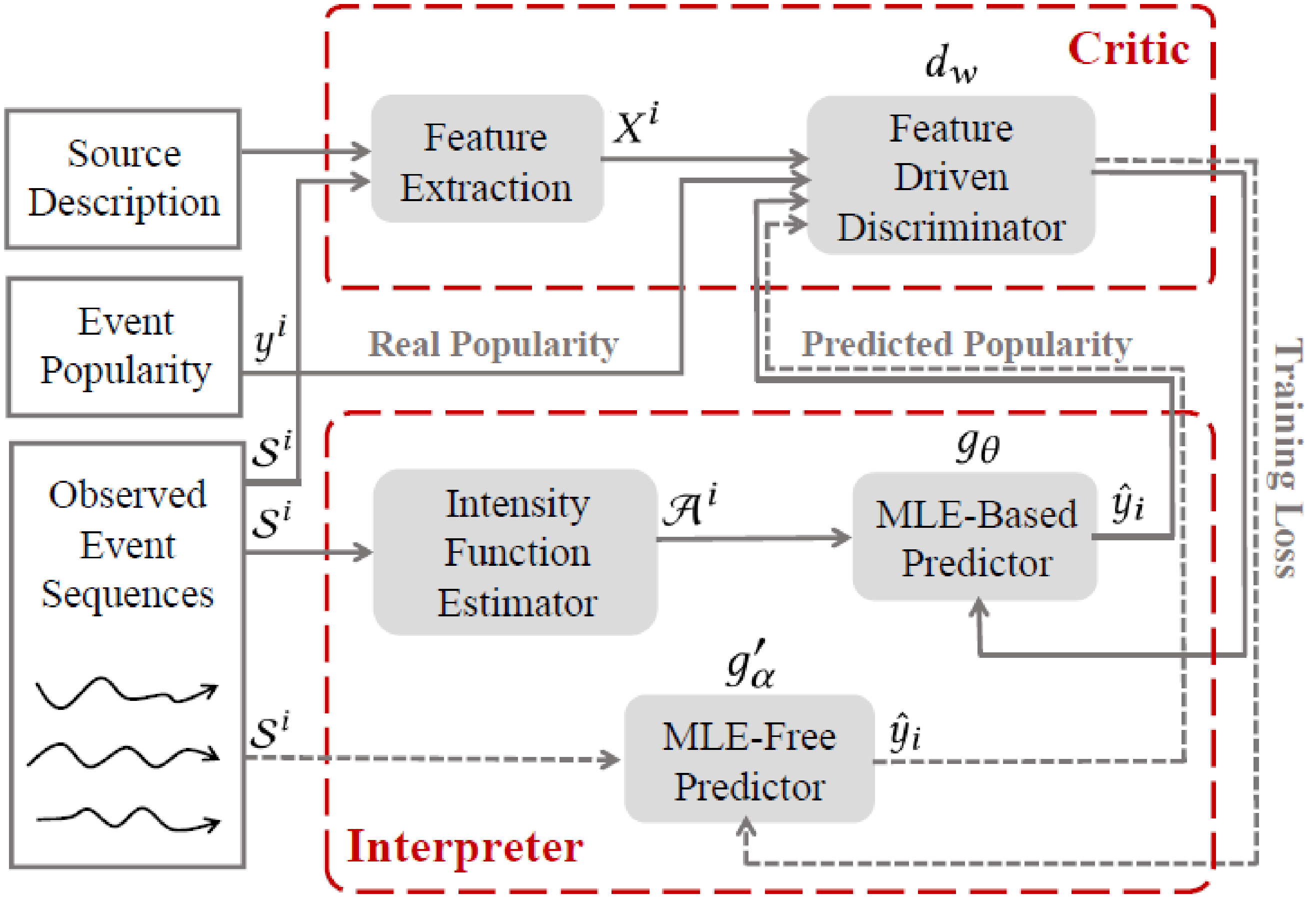
- feature driven method can easily extract some effective observable features that strongly correlate with popularity.
- point process method can recognize some typical patterns hidden in the observed temporal sequence and further confidently infer the future evolution.

Challenges



- some contents with similar early-stage evolution could generate quite different popularity.
- some contents with totally different evolution trends may reach a similar popularity.

Model Framework



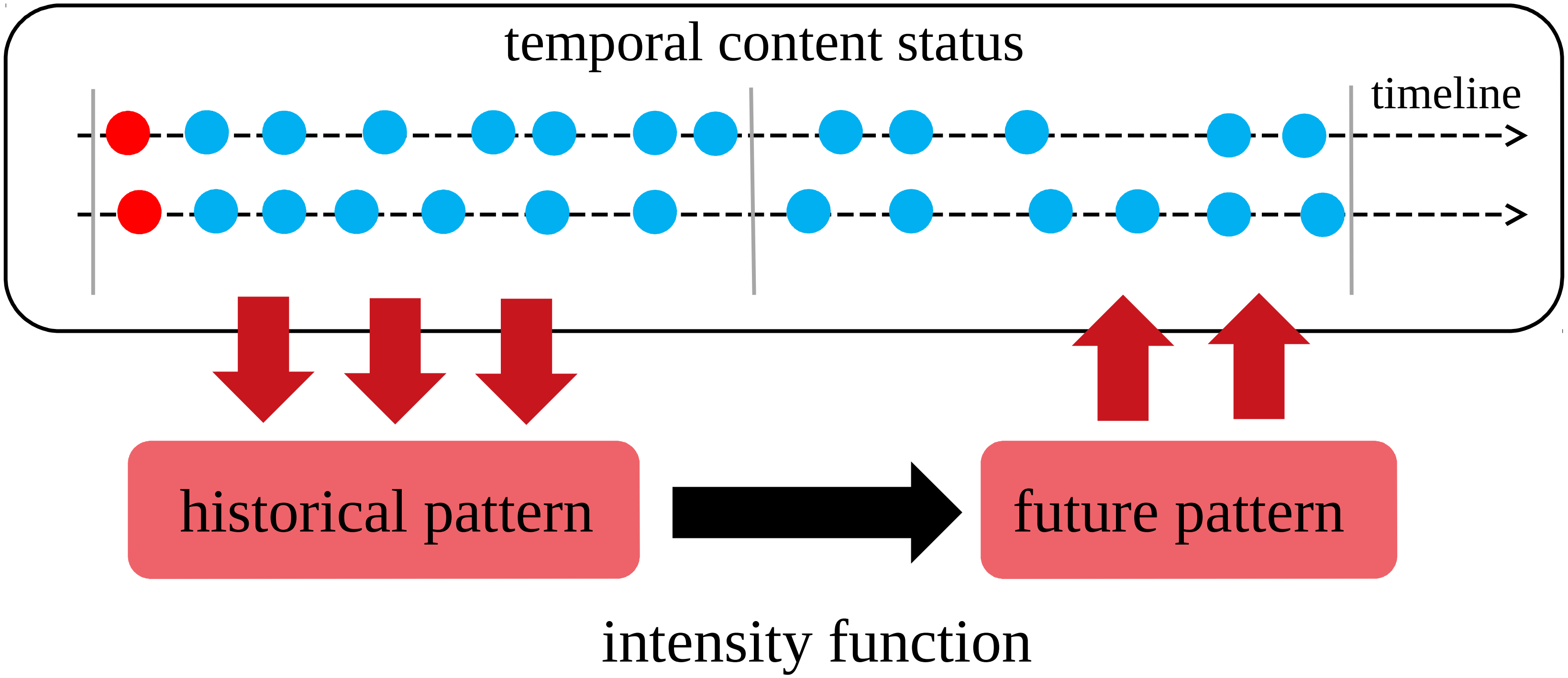
Adversarial Minimax Game

$$\min_{\theta} \max_{w, ||d_w||_L \leq 1} \mathbb{E}_{(X,y)\sim\mathbb{P}_r}[d_w(X,y)] - \mathbb{E}_{(X,g_\theta(\mathcal{A}))\sim\mathbb{P}_g}[d_w(X,g_\theta(\mathcal{A}))]$$

To implement the idea, we let

- The feature driven model (critic) aims to maximize the distance of distributions for real and predicted popularity
- The point process model (interpreter) aims to minimize the distance by giving a convincing prediction
- The training stage will be terminate once an equilibrium is achieved between two players.

Interpreter: Point Process Model



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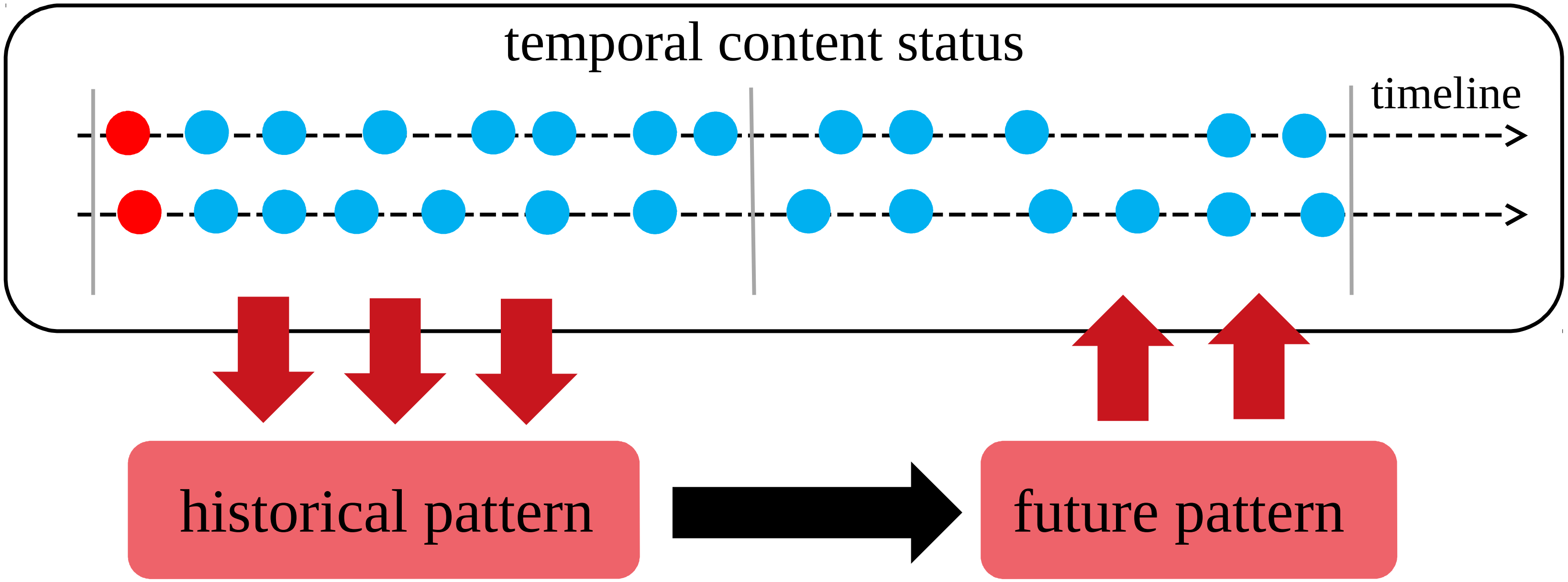

intensity function

Using Recurent Neural Network (RNN) $\begin{cases} \text{MLE-based (MB)} \\ \text{MLE-free (MF)} \end{cases}$

MLE-based RNN Model

Point Process Theory:

Intensity function: $\lambda^*(t) = \lambda(t|\mathcal{S}^i(t)) = \dfrac{\mathbb{P}\{N^i(t+dt) - N^i(t) = 1|\mathcal{S}^i(t)\}}{dt}$

Conditional density function: $f^*(t) = \lambda^*(t)\exp(-\int_{t_n}^{t}\lambda^*(\tau)d\tau)$

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Intensity sequence (RNN):

$$\boldsymbol{h}_{j+1} = \max\left\{\boldsymbol{w}_h \cdot t_j^i + \boldsymbol{v}_h \cdot \boldsymbol{h}_j + \boldsymbol{b}_h, 0\right\}$$

$$\lambda^*(t) = \exp(\boldsymbol{v}_t \cdot \boldsymbol{h}_j + w_t(t - t_j^i) + b_t)$$

$$l(C) = \sum_i \sum_j \log f^*(t_{j+1})$$

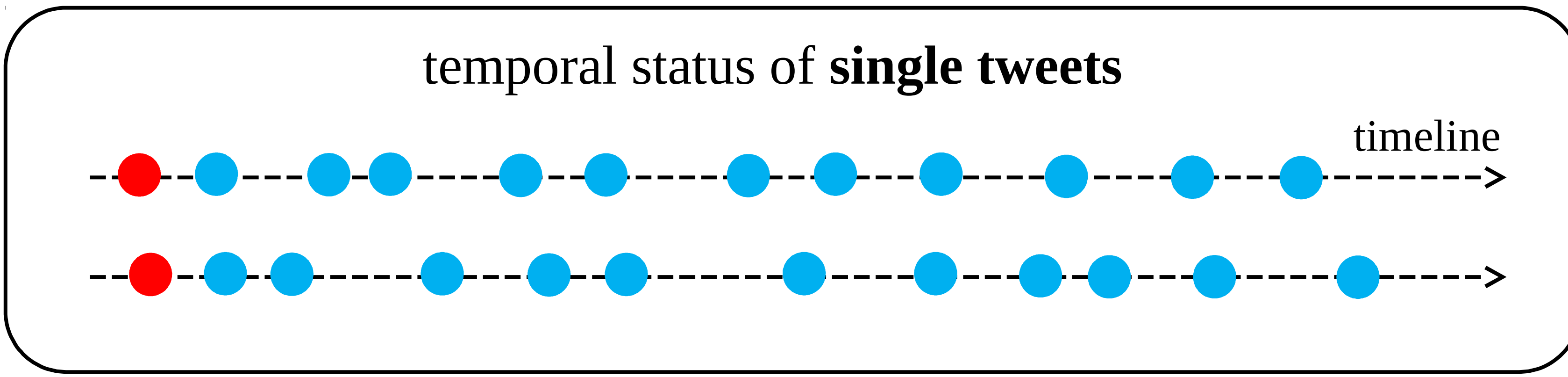
Popularity sequence (RNN):

$$\boldsymbol{h}_{j+1} = \tanh(\boldsymbol{v}_h' \cdot A_j^i + \boldsymbol{w}_h' \cdot \boldsymbol{h}_j + \boldsymbol{b}_h'),$$

$$\hat{y} = \boldsymbol{w}_o \cdot \boldsymbol{h}_M + b_o,$$

MLE-free RNN Model

Observed sequence:



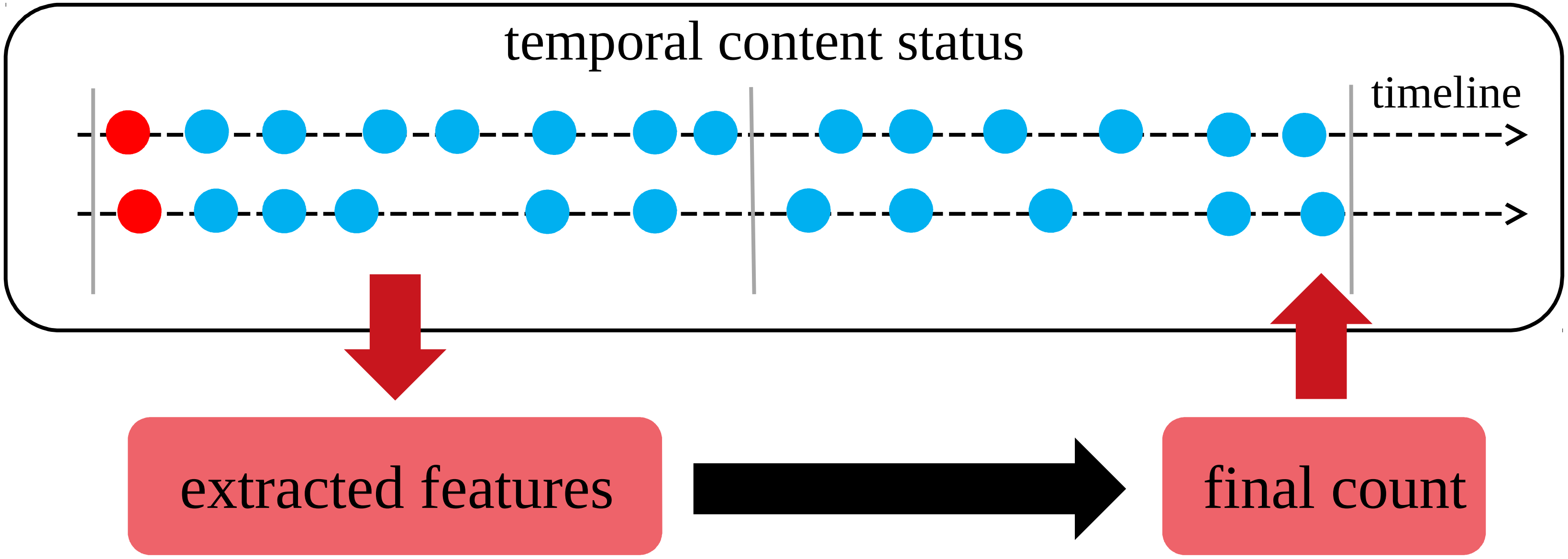
Popularity sequence (RNN):

$$\boldsymbol{h}_{j+1} = \tanh(\boldsymbol{v}_h'' \cdot t_j^i + \boldsymbol{w}_h'' \cdot \boldsymbol{h}_j + \boldsymbol{b}_h''),$$

$$\hat{y} = \boldsymbol{w}_o' \cdot \boldsymbol{h}_M + b_o'.$$

Critic: Feature Driven Model

3-Layer ELU Neural Network:



Feature Extraction:

- mean and standard deviation of time interval between events
- number of events in the first/second half of observing interval
- ……

Adversarial Training

Wasserstein Distance (Earth Moving Distance):

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\phi \sim \Phi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(\eta, \zeta) \sim \phi}[||\eta - \zeta||]$$

Adversarial Training

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Global Training Objection:

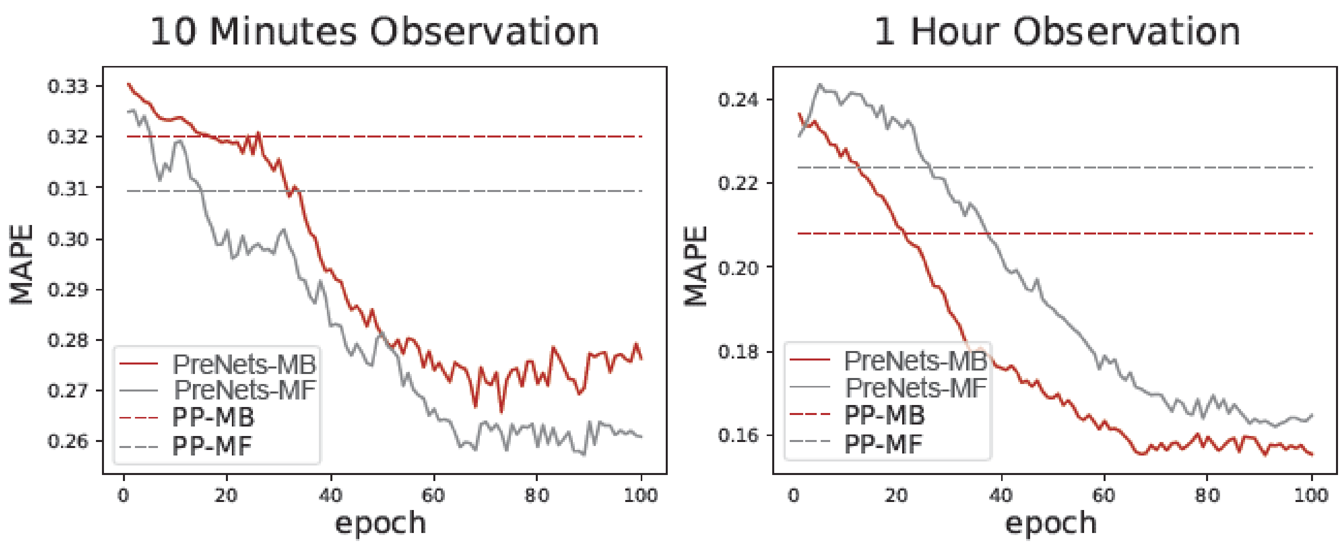
$$\min_{\theta} \max_{w, ||d_w||_L \leq 1} \mathbb{E}_{(X,y) \sim \mathbb{P}_r}[d_w(X, y)] - \mathbb{E}_{(X, g_\theta(\mathcal{A})) \sim \mathbb{P}_g}[d_w(X, g_\theta(\mathcal{A})]$$

More Specifically:

$$\min_{\theta} \max_{w} \frac{1}{B} \sum_{i=1}^{B} [d_w(X^i, y^i)] - \frac{1}{B} \sum_{i=1}^{B} [d_w(X^i, g_\theta(\mathcal{S}^i)] - \gamma \sum_{i,j=1}^{B} \left| \frac{|d_w(X^i, y^i) - d_w(X^j, g_\theta(\mathcal{S}^j)|}{|y^i - g_\theta(\mathcal{S}^j)|} - 1 \right|$$

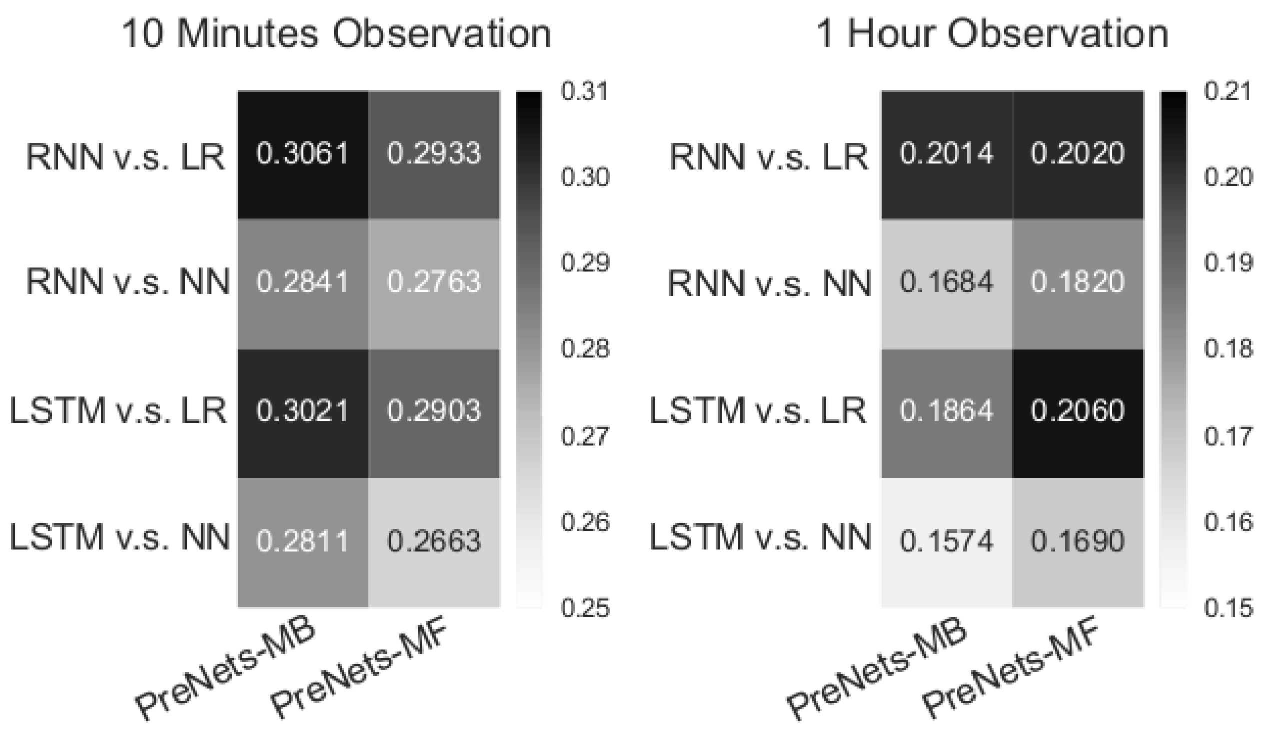
Experiment Results (1)

Learning curves of MAPE:



- Adversarial training improves prediction precision compared with independent training

Experiment Results (2)



- compare different "Critics" and "Interpreters"

Thank you!

Q&A