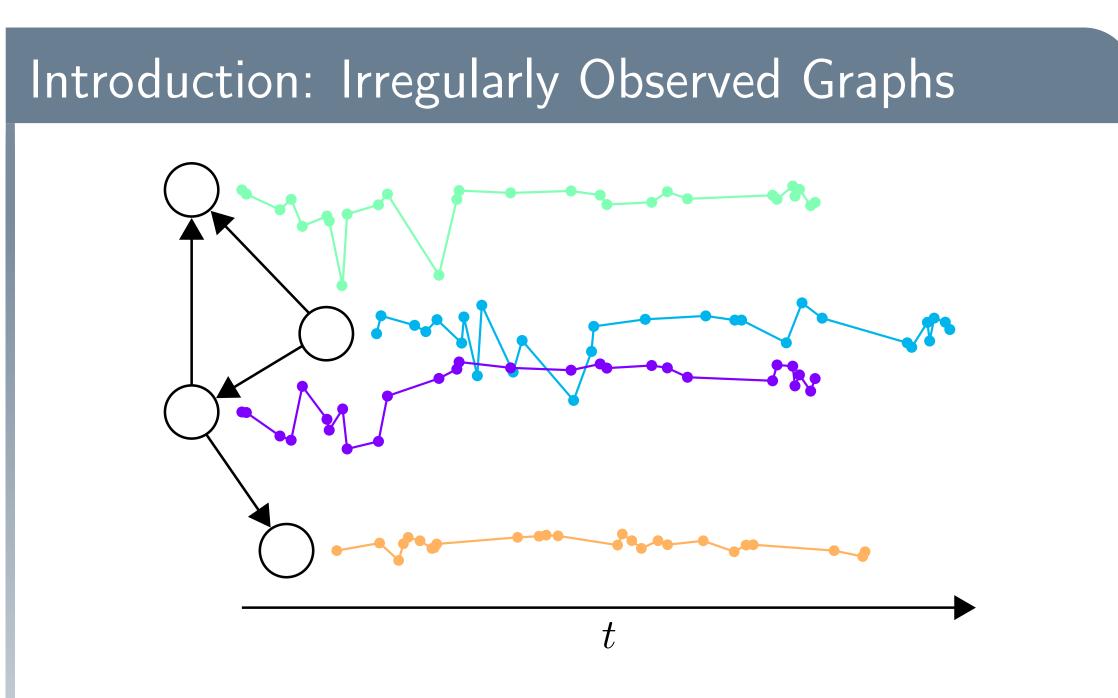
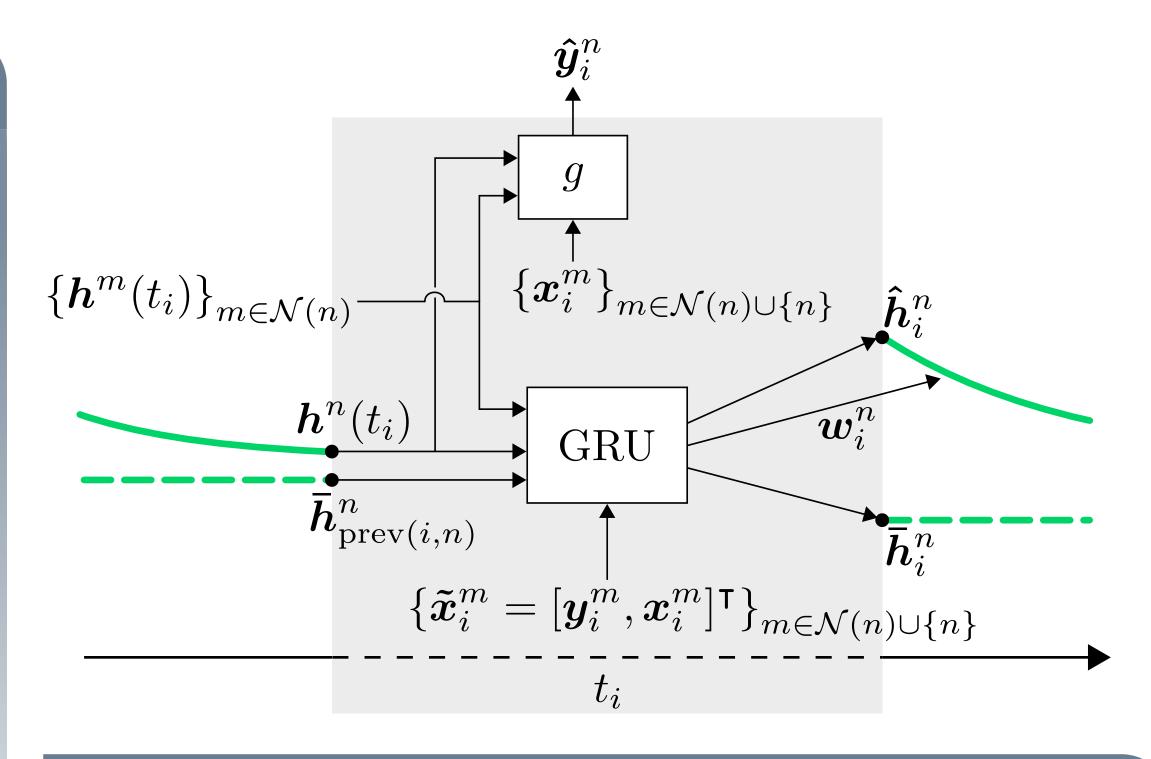
## Temporal Graph Neural Networks with Time-Continuous Latent States

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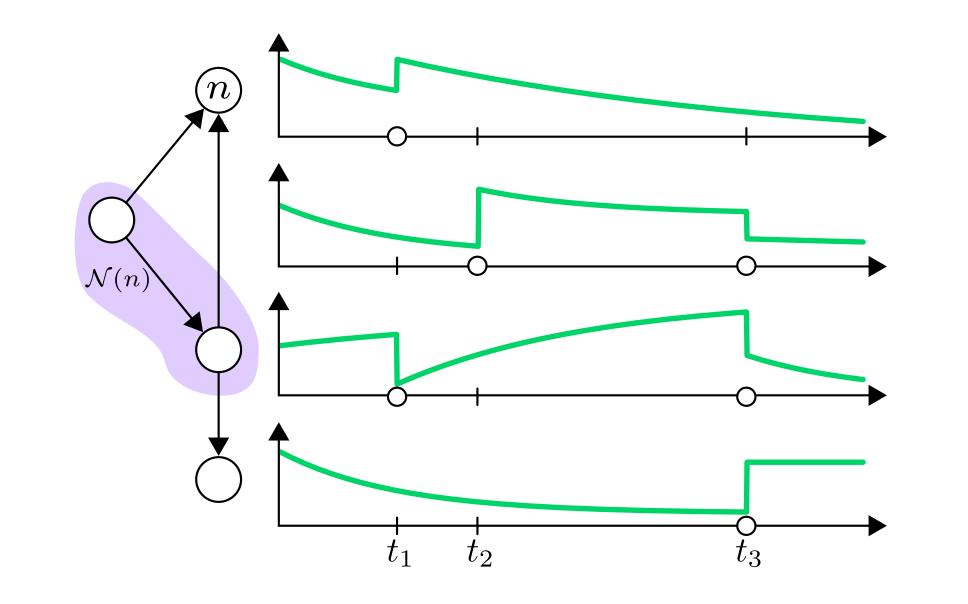
- Consider forecasting for graph-structured time series
- How can irregular observations be dealt with?
  - Irregularly spaced observation times



## Graph Neural Network Components

- Graph-based node interactions are captured by incorporating GNN components
- Only a subset of nodes observed at each time point
- Our solution: A temporal Graph Neural Network (GNN) with latent states defined over continuous time

## Time-Continuous Latent States



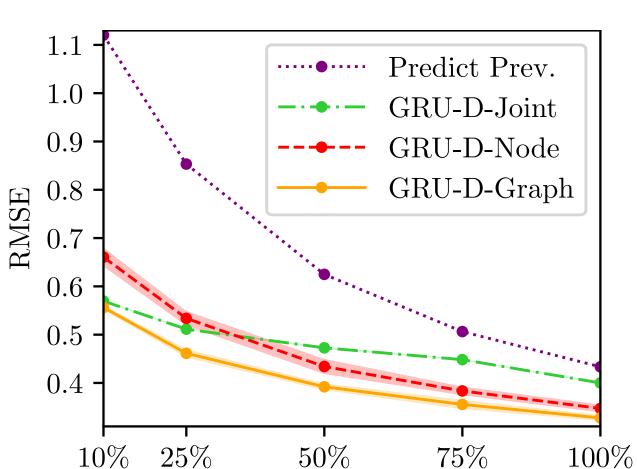
- At each node n a latent state  $\boldsymbol{h}^n(t)$  evolves over continuous time
- Between node observations  $m{h}^n(t)$  decays exponentially from  $\hat{m{h}}^n_i$  towards  $ar{m{h}}^n_i$

- GRU-update depends also on node neighborhood  $\mathcal{N}(n)$
- GNN used as predictive model  $\boldsymbol{g}$

$$\hat{\boldsymbol{y}}_{j}^{n} = g\left([\boldsymbol{h}^{n}(t_{j}), \boldsymbol{x}_{j}^{n}], \left\{[\boldsymbol{h}^{m}(t_{j}), \boldsymbol{x}_{j}^{m}]\right\}_{m \in \mathcal{N}(n)}\right) \quad (3)$$

## Experiments on Traffic Data

- The PEMS-BAY dataset contains traffic speed measurements from the highway network
- We create an irregular version by subsampling and keeping different % of node observations
- Goal: Predict next observed value at each node
- Our full model
  (GRU-D-Graph) is
  compared to simpler
  versions that do not
  use graph structure



Observed fraction

$$\boldsymbol{h}^{n}(t) = \boldsymbol{\hat{h}}_{i}^{n} \odot \boldsymbol{\gamma} \left( t - t_{i} \right) + \boldsymbol{\bar{h}}_{i}^{n} \odot \left( 1 - \boldsymbol{\gamma} \left( t - t_{i} \right) \right)$$
(1a)  
$$\boldsymbol{\gamma} \left( \Delta_{t} \right) = \exp(-\Delta_{t} \boldsymbol{w}_{i}^{n})$$
(1b)

 $\bullet\,$  When node n is observed we perform a GRU-like update

 $\hat{\boldsymbol{h}}_{i}^{n}, \bar{\boldsymbol{h}}_{i}^{n}, \boldsymbol{w}_{i}^{n} = \operatorname{GRU}(\boldsymbol{h}^{n}(t_{i}), \boldsymbol{x}_{i}^{n}, \boldsymbol{y}_{i}^{n})$ (2)

- $oldsymbol{x}_i^n$  are input features and  $oldsymbol{y}_i^n$  the new observation
- By applying a predictive model g to the latent state predictions can be made at arbitrary time points!

More Information



Code, link to paper: github.com/joeloskarsson/ continuous-temporal-gnn

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