NeutronStream: A **Dynamic** GNN Training Framework with **Sliding Window** for Graph Streams

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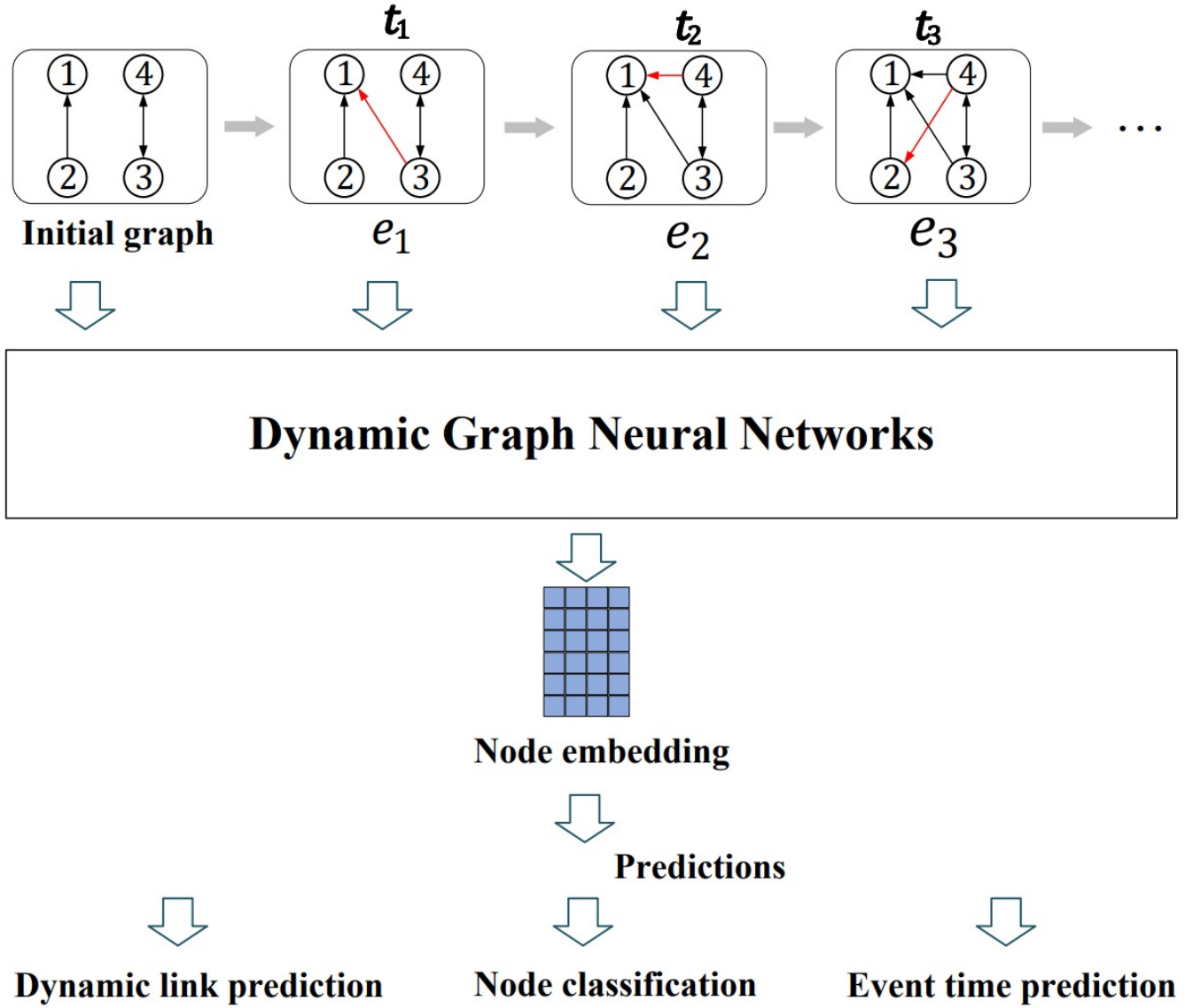
VLDB 2024

Dynamic Graph Neural Network

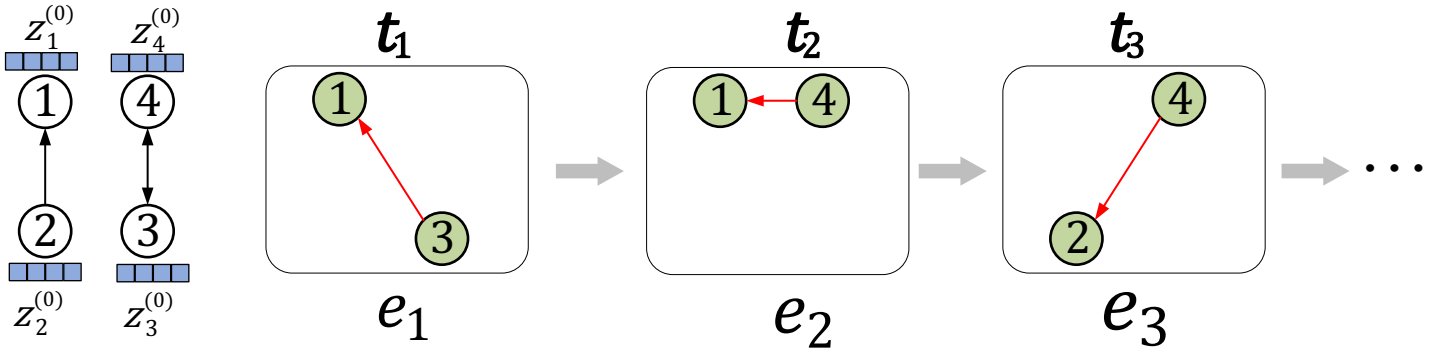
Dynamic graph representation



Execution Pattern of Dynamic GNN

Forward computation (1-event):

Input data:



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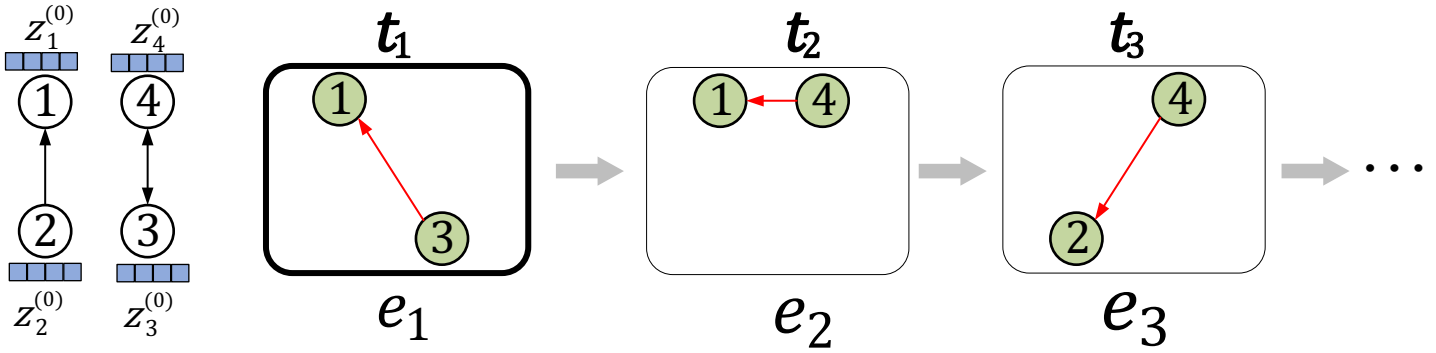

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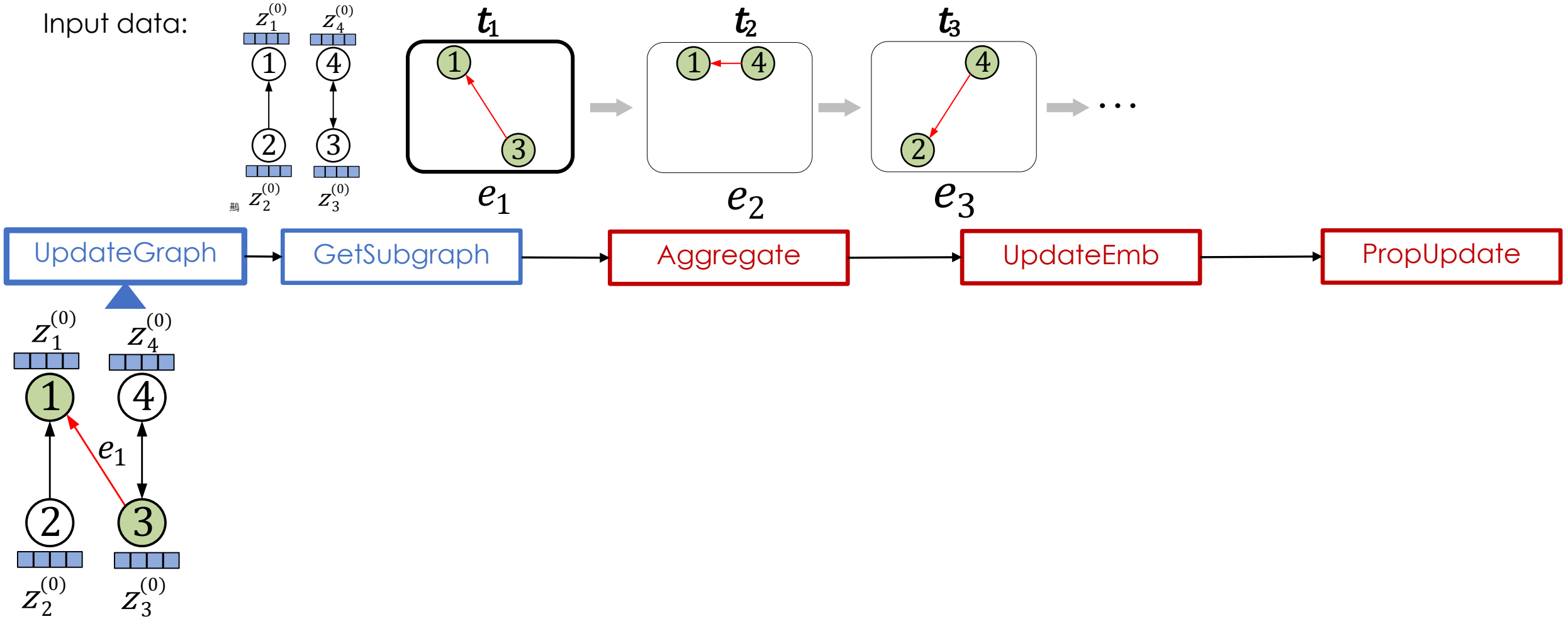

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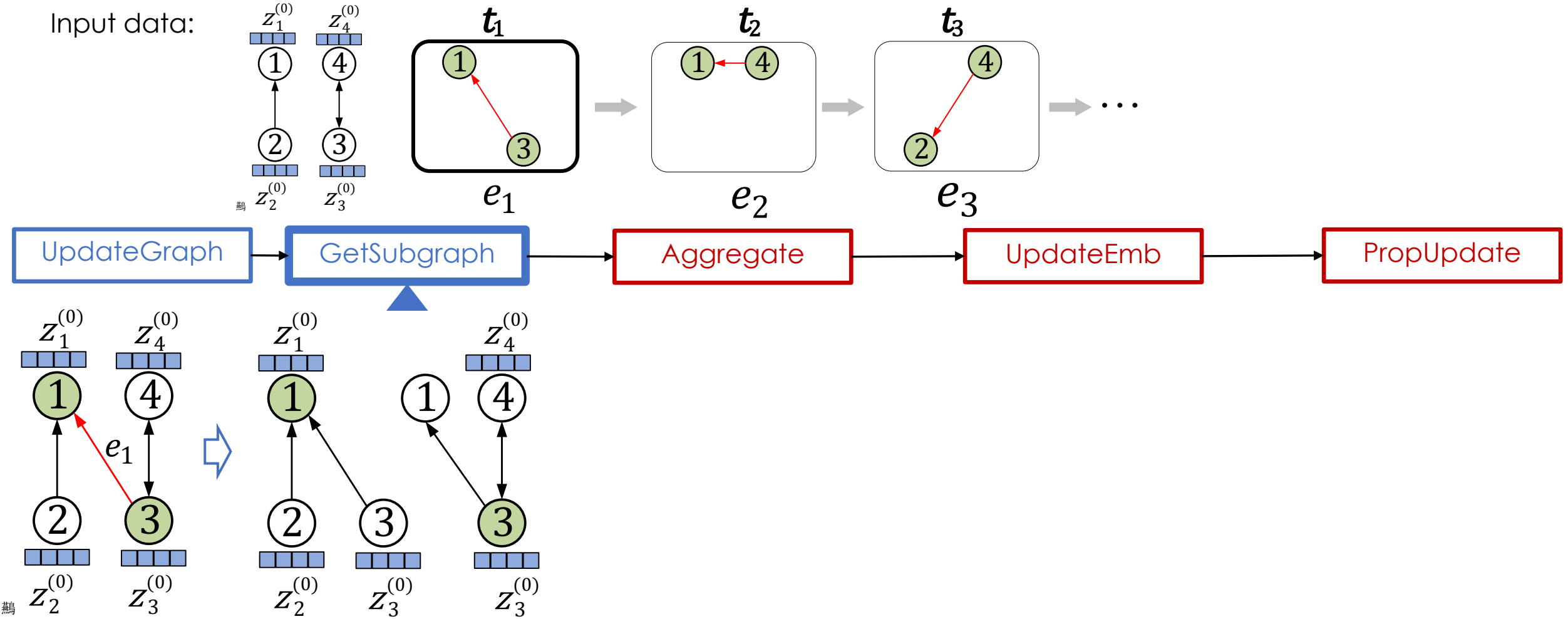

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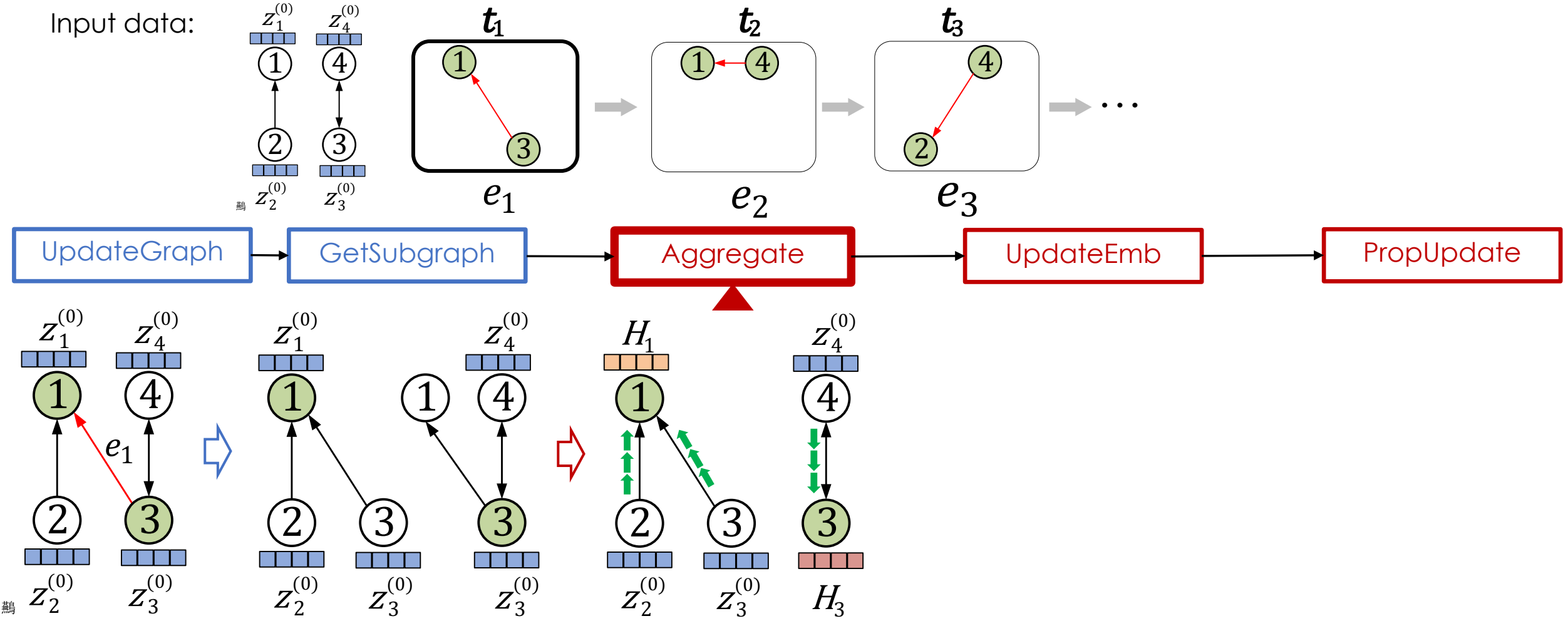

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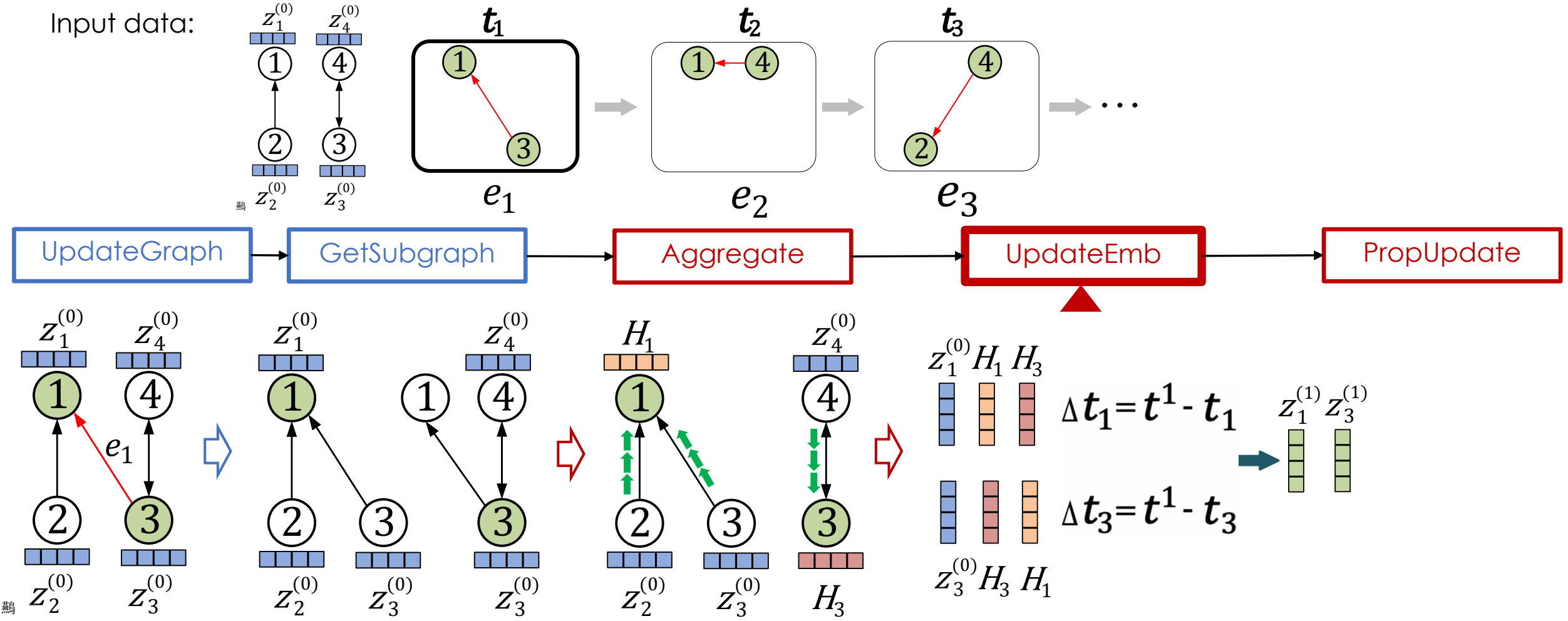

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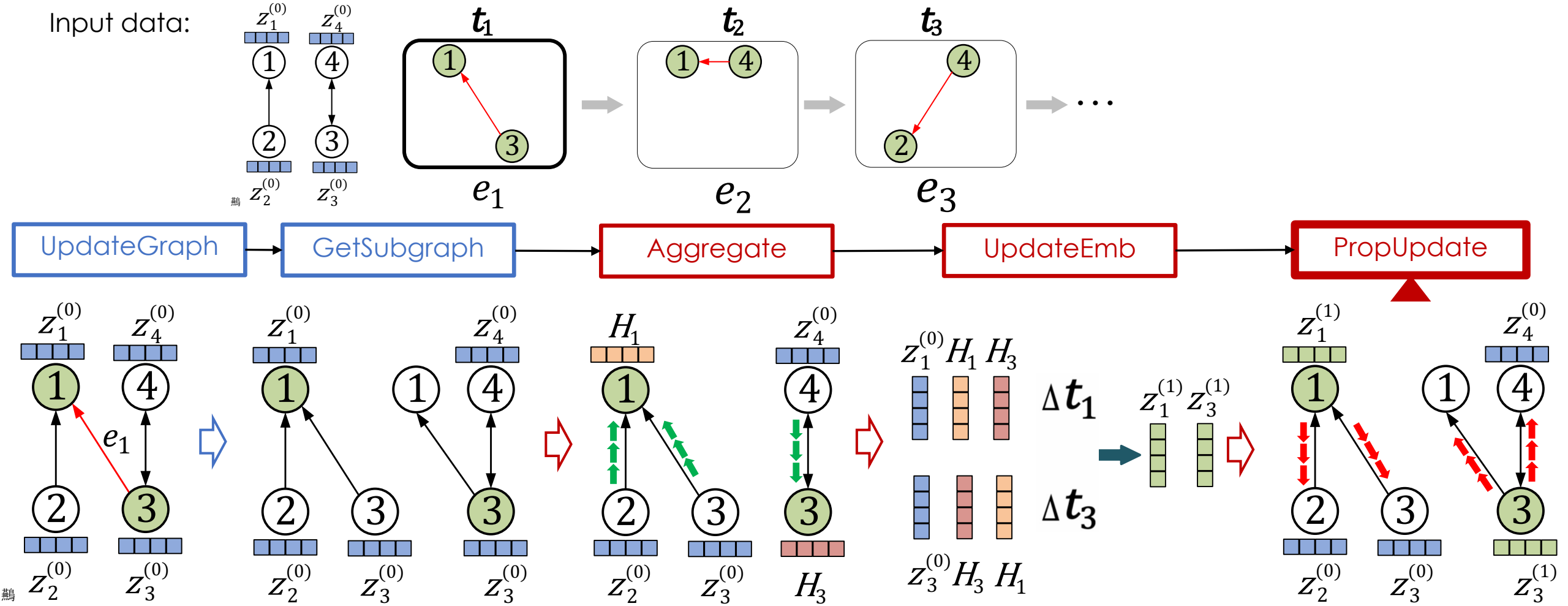
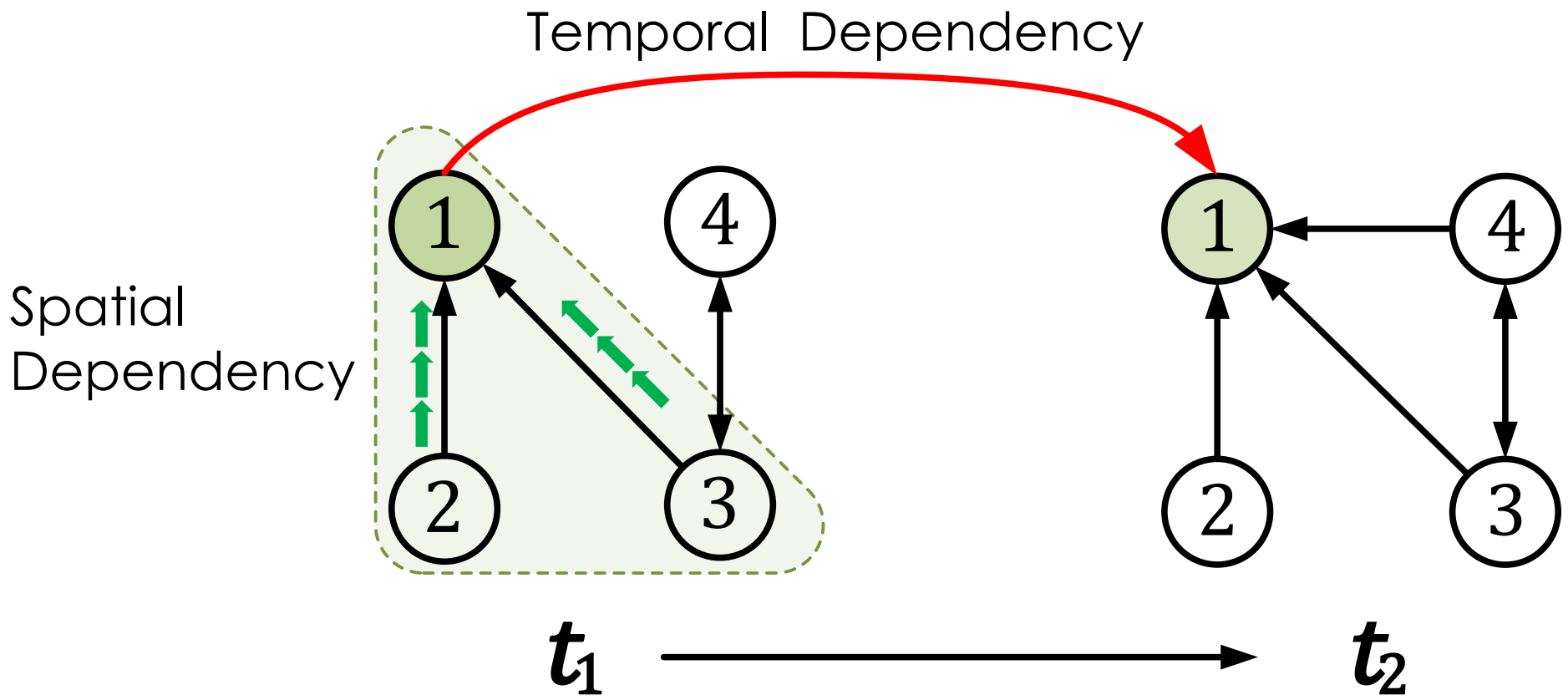


Characteristic: Spatial-Temporal Dependency

- **Spatial Dependency**: a node status depends on its neighbors
- **Temporal Dependency**: a node status depends on its previous status



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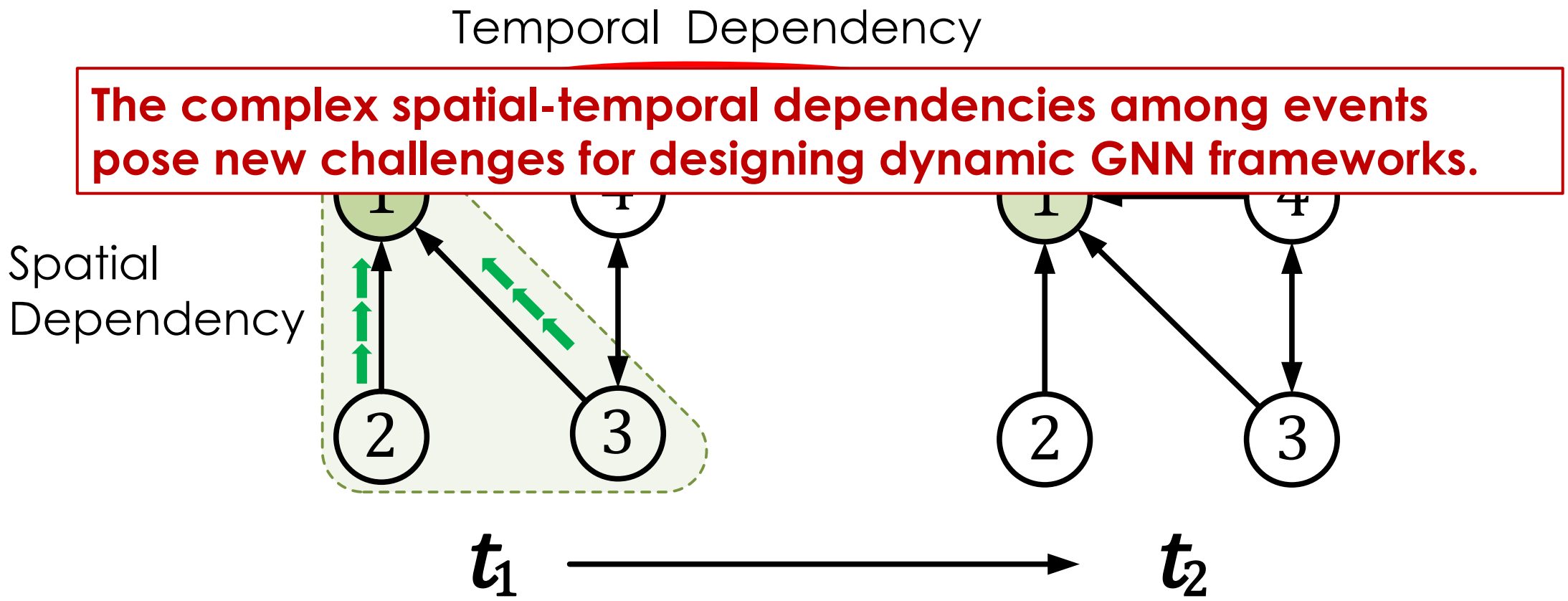
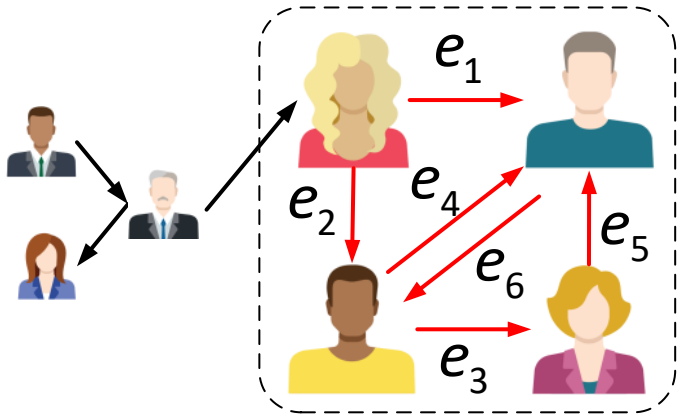


Challenge 1: The training method needs to capture real-time structural information

Key Observations : Events in the same area should update parameters collaboratively to better capture spatial dependencies

Update event stream

e_1 e_2 e_3 e_4 e_5 e_6 ...

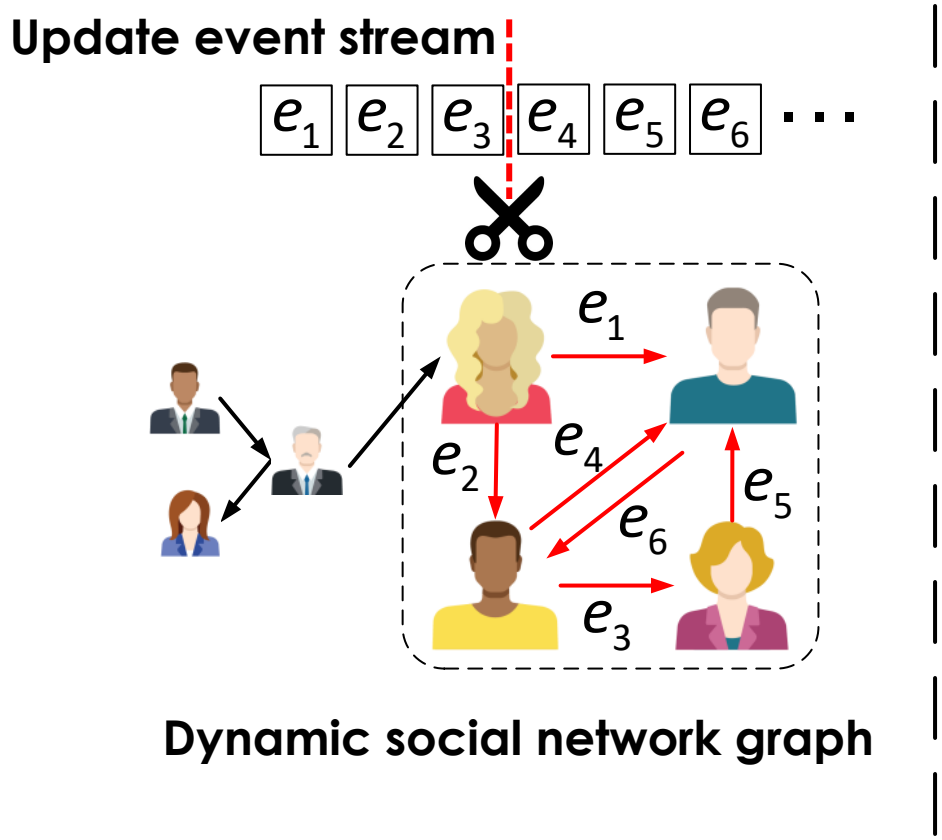


Dynamic social network graph

Six events are concentrated in one area

Challenge 1: The training method needs to capture real-time structural information

The traditional batched training method forcibly cuts off the event stream and ignores the spatial locality between events



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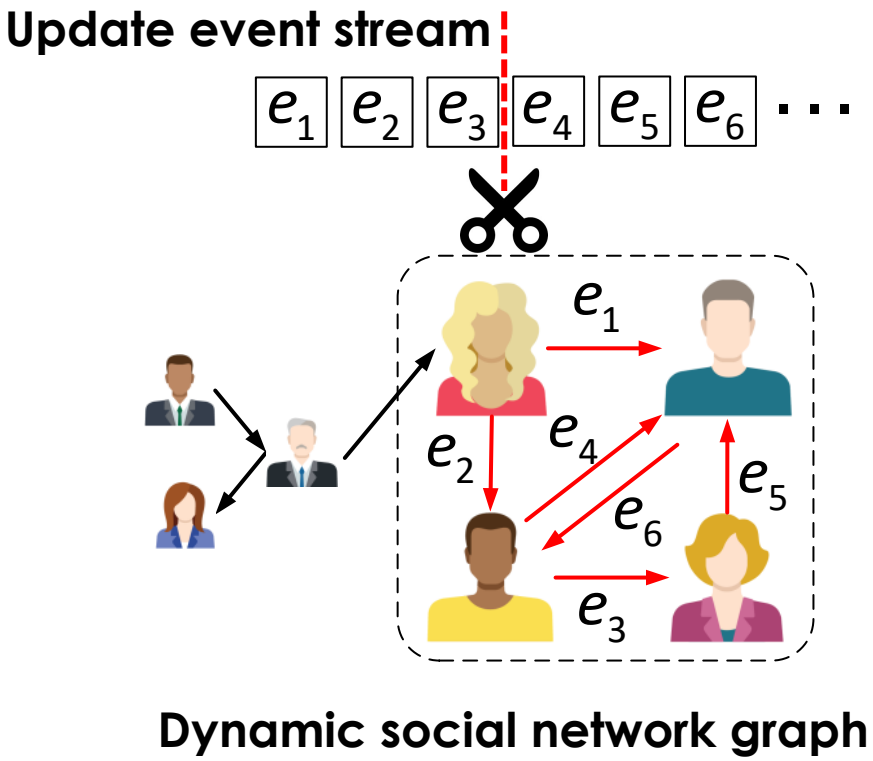

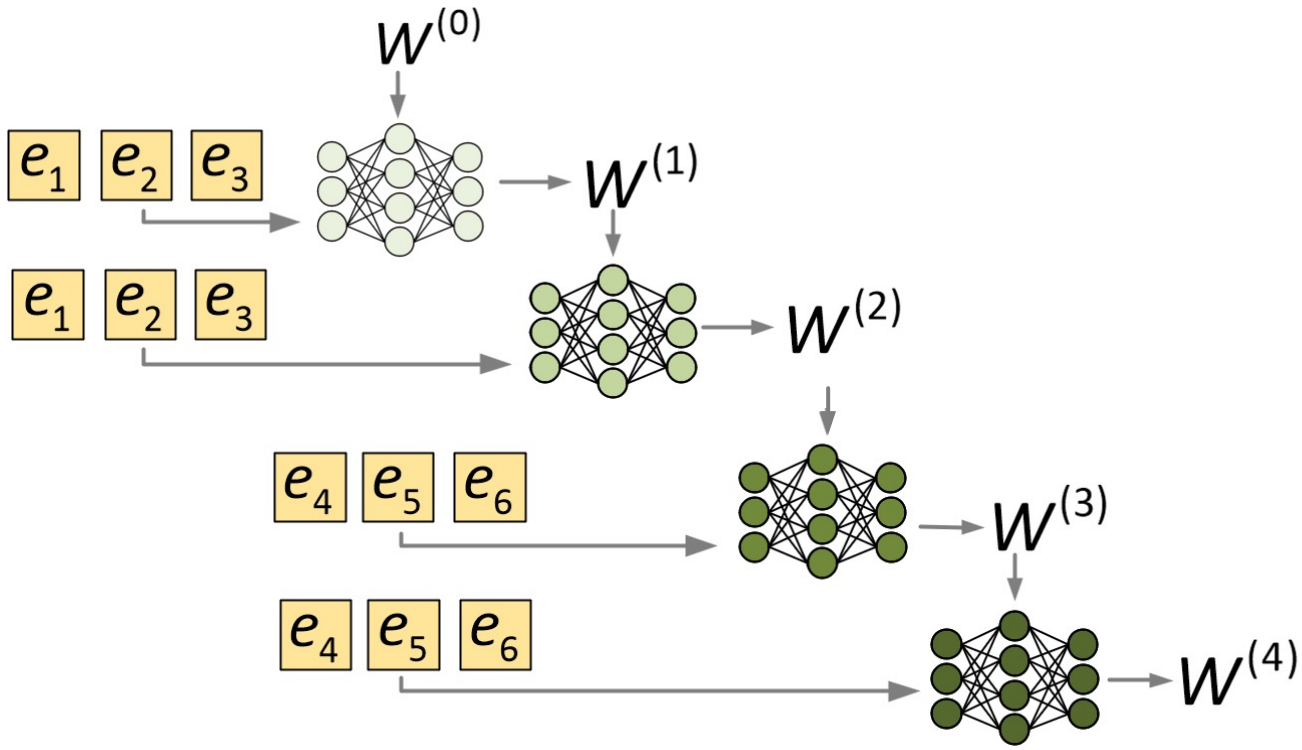

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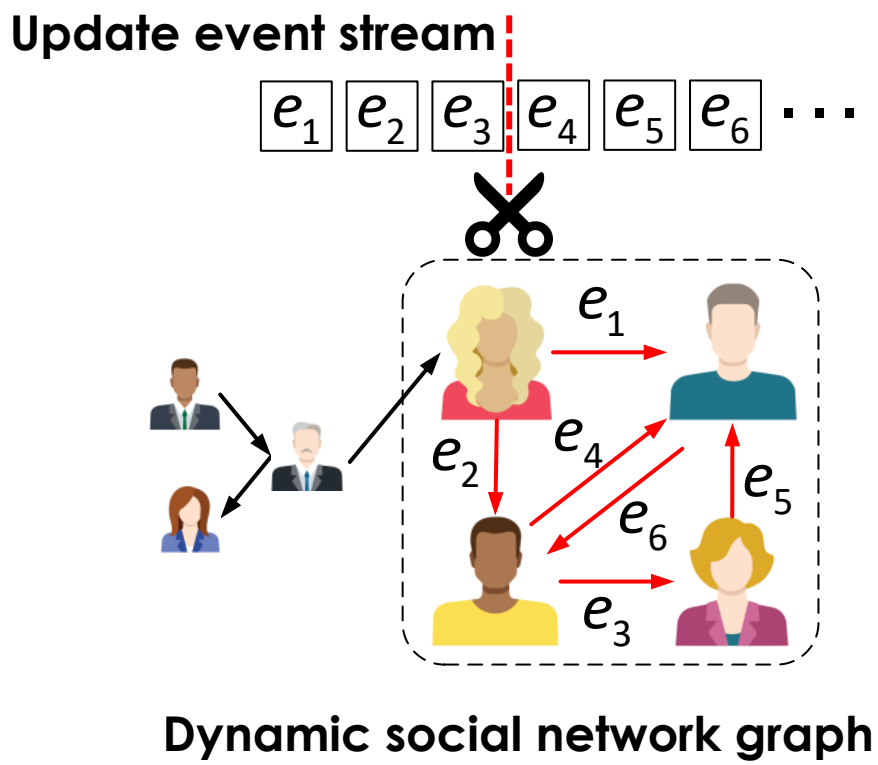
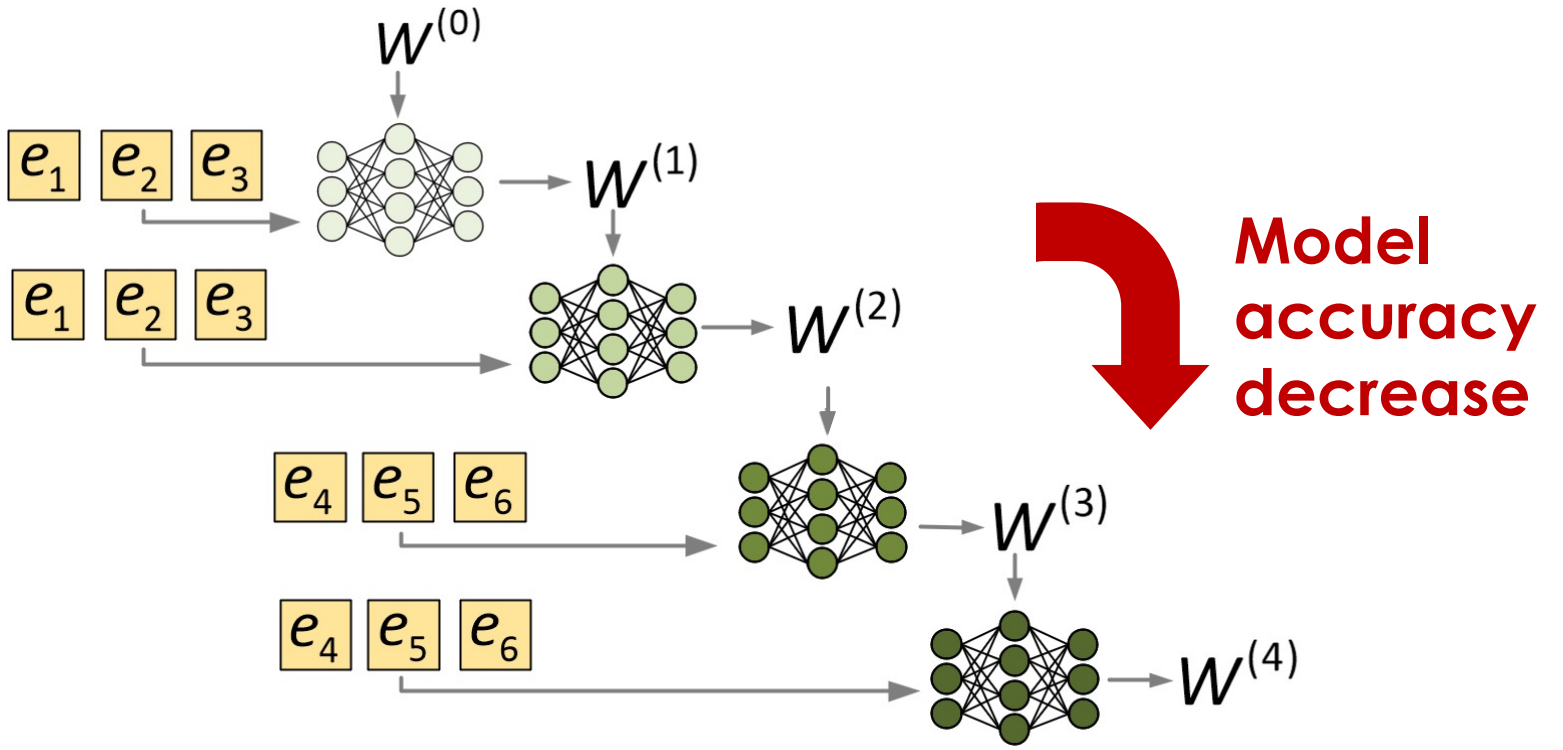




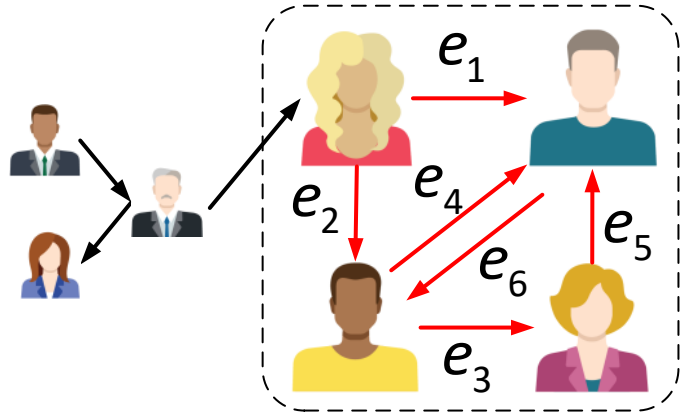
Challenge 2: The temporal dependency nature makes parallelism optimization hard to design

- **Temporal Dependency: a node status depends on its previous status**

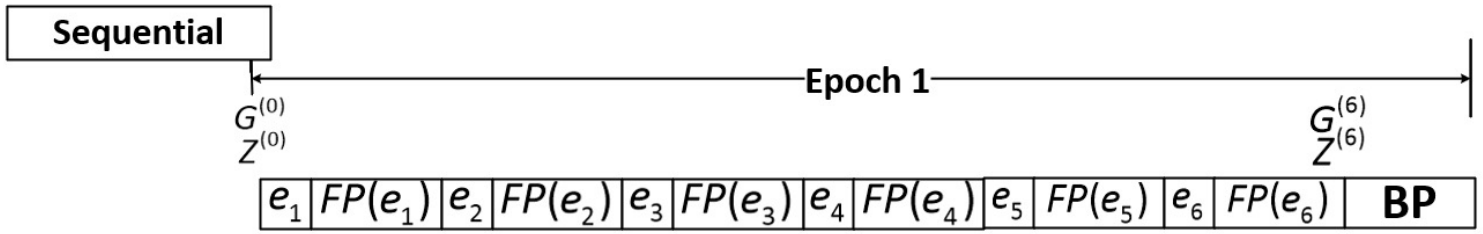
Existing frameworks sequential iterative processing

Update event stream

e_1 e_2 e_3 e_4 e_5 e_6 ...



Dynamic social network graph



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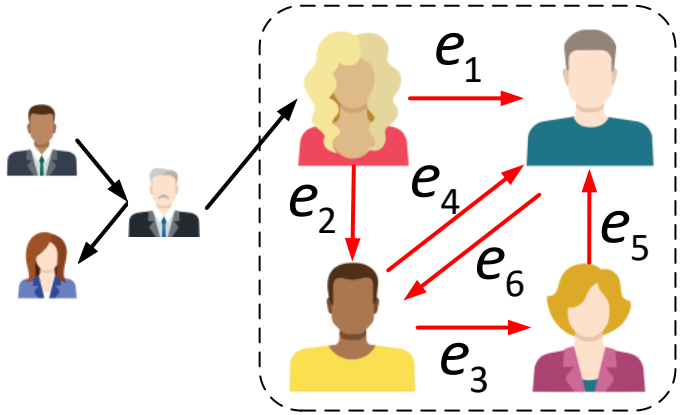

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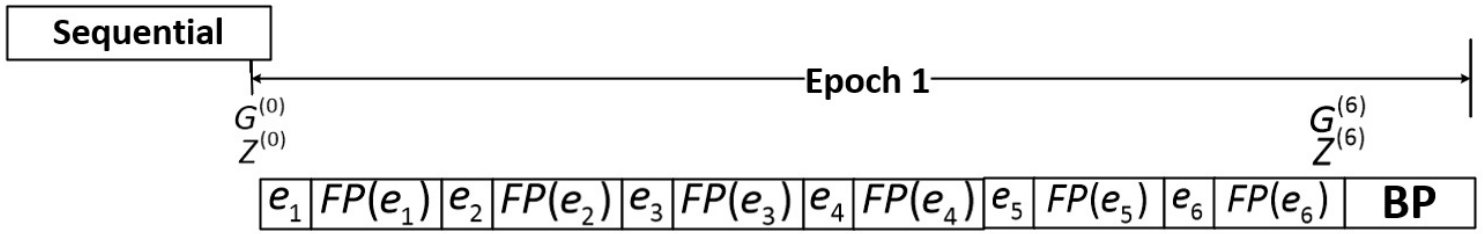
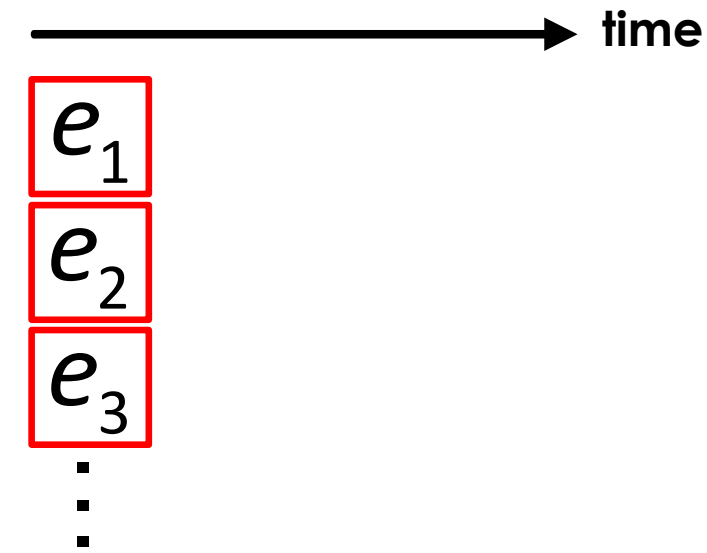


DyRep on GitHub dataset

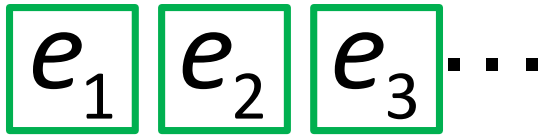
- **Single thread for an epoch : 60.45s**
- **20 threads for an epoch : 60.89s**

Challenge 2: The temporal dependency nature makes parallelism optimization hard to design

- **Without Temporal Dependency** : Ignore time, execute events in parallel
- **With Temporal Dependency** : Keep time, execute events chronologically



(a) Without Temporal Dependency



(b) With Temporal Dependency

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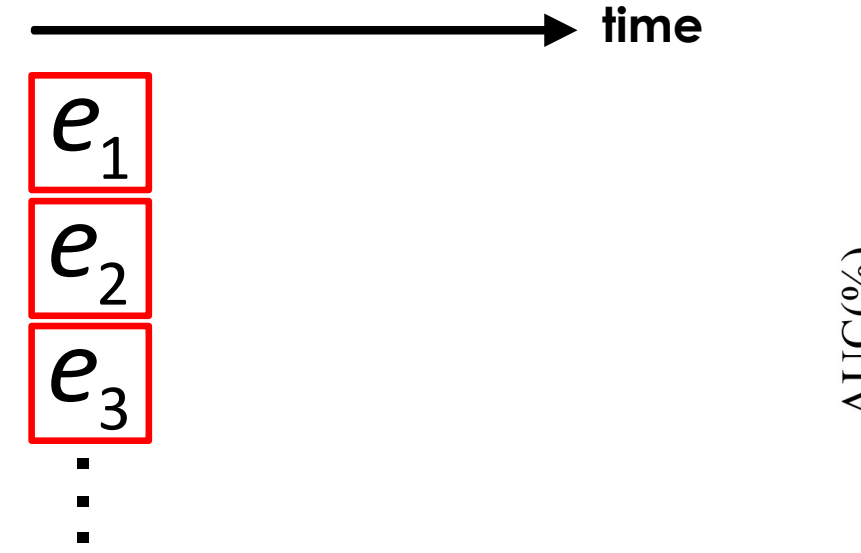
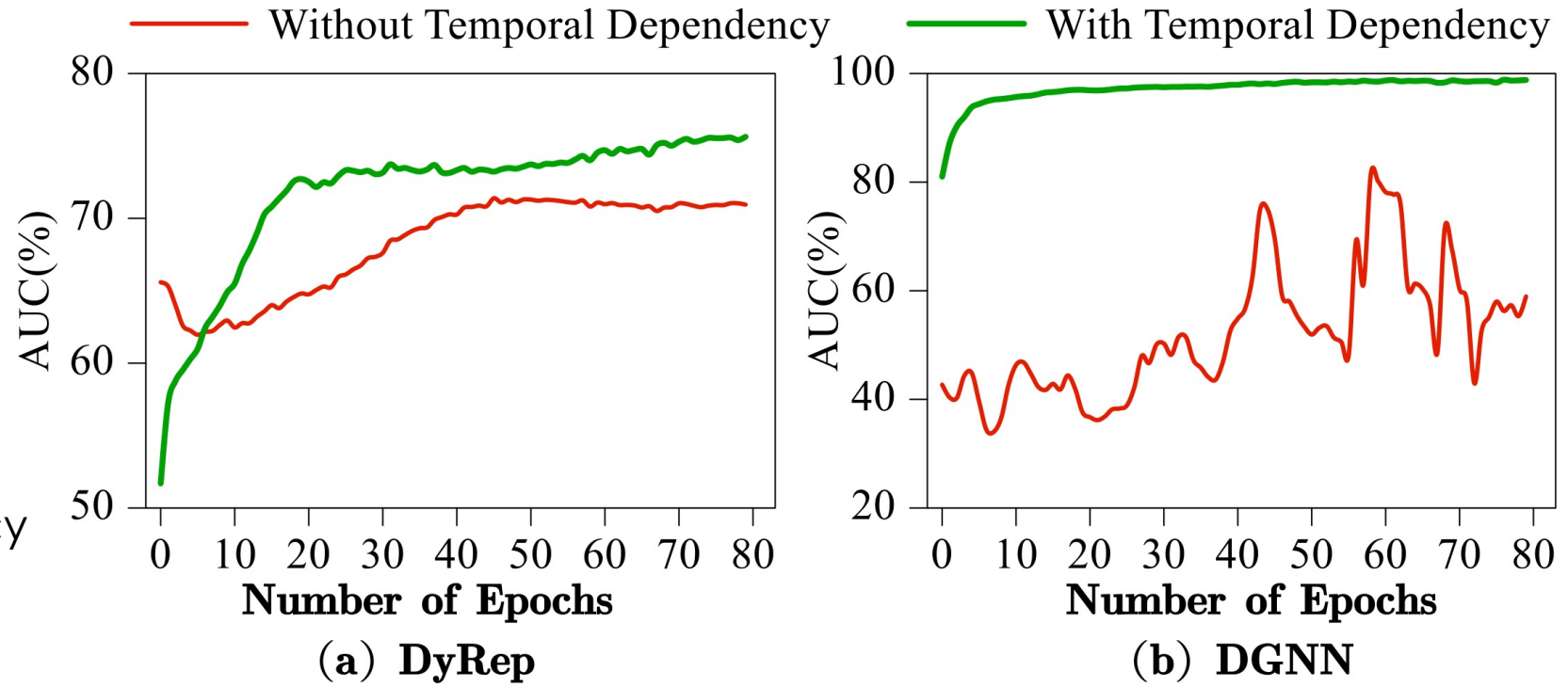


(a) Without Temporal Dependency

(b) With Temporal Dependency



AUC Comparison with dependency and without dependency

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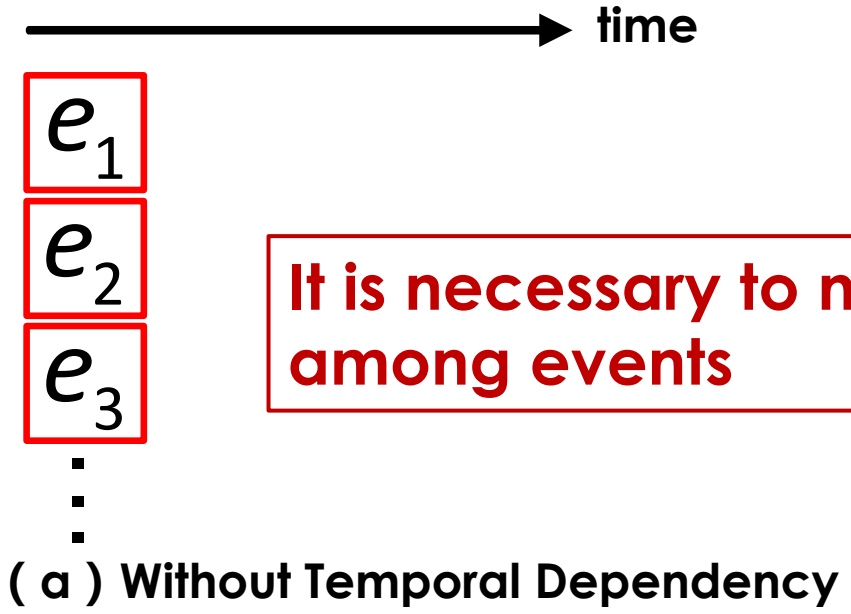
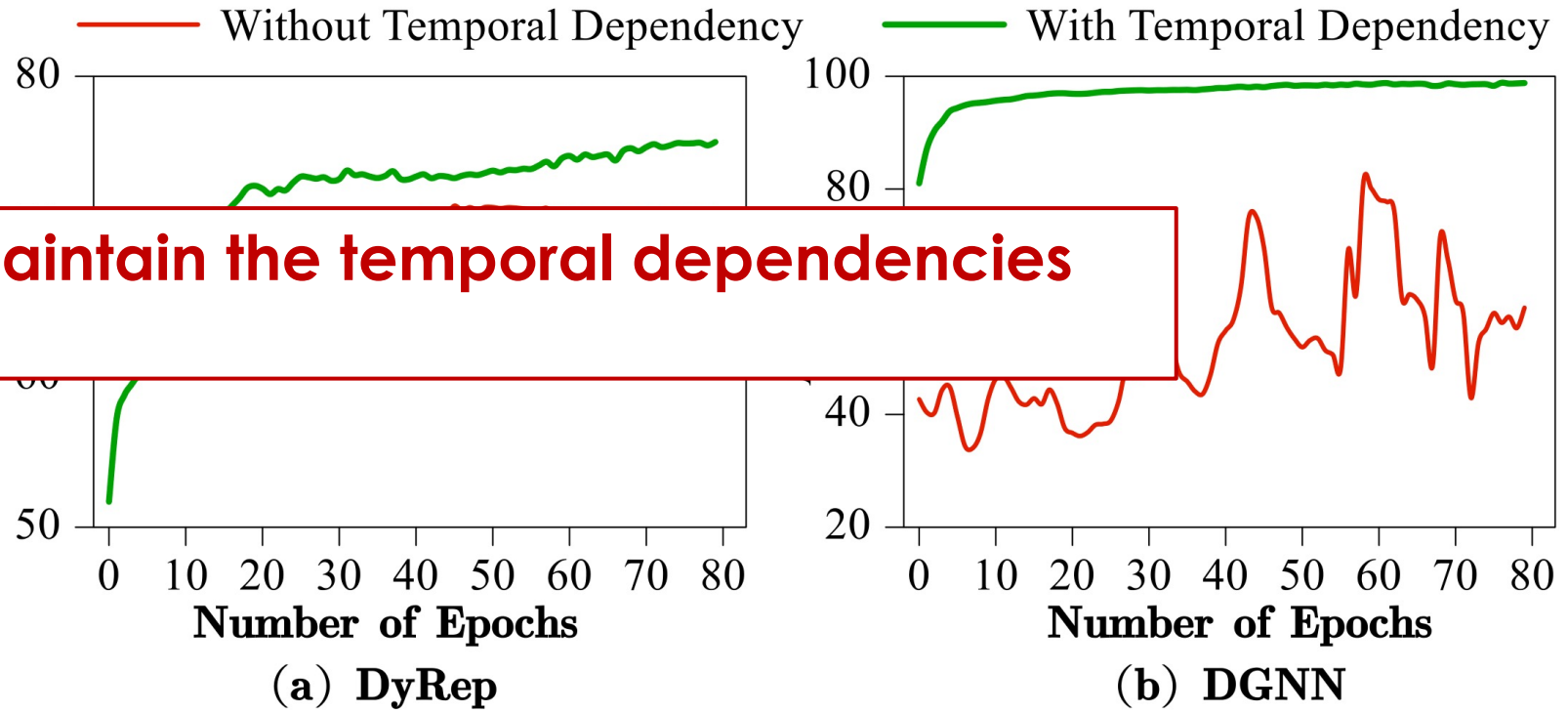


(a) Without Temporal Dependency

(b) With Temporal Dependency

It is necessary to maintain the temporal dependencies among events



AUC Comparison with dependency and without dependency

Summary

- **Challenge 1:** The traditional batched training mode fail to capture the real-time structural evolution information

Model accuracy decrease

- **Challenge 2:** The temporal dependency nature makes parallelism optimization hard to design

Training performance decrease

Our Contributions

We propose NeutronStream, a high-performance Dynamic GNN framework

- **Solution 1:** Propose a new incremental learning mode with a sliding window for training on graph streams → Challenge 1 → Model accuracy improve

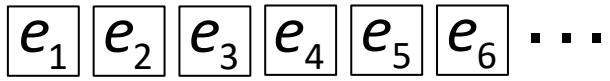
- **Solution 2:** Propose a fine-grained event parallel execution scheme → Challenge 2 → Training performance improve

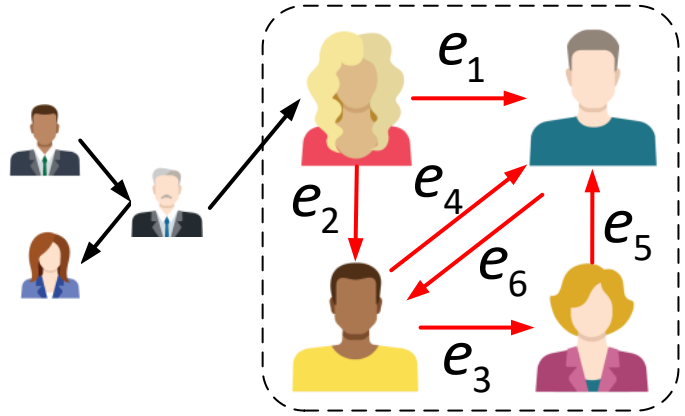
Solution 1: Sliding-window-based Training Method

Incremental Mode with Sliding Window (denoted as **NS-Slide)**

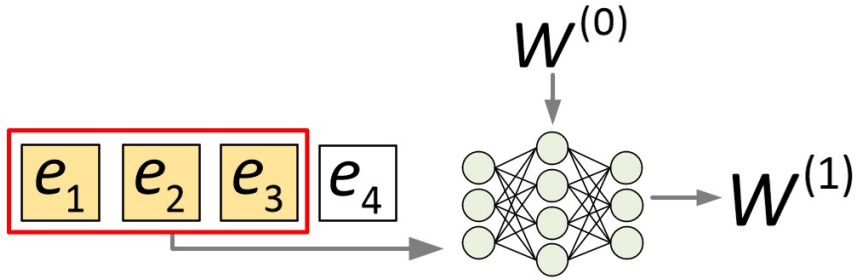
We design a sliding window to select consecutive events from the input event stream

Update event stream





Dynamic social network graph



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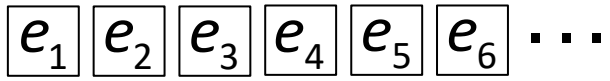

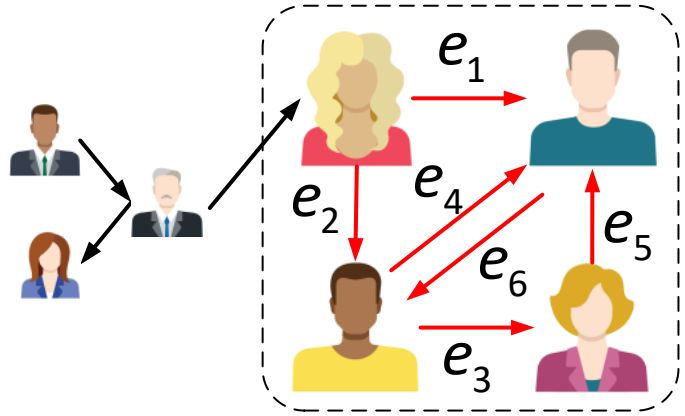

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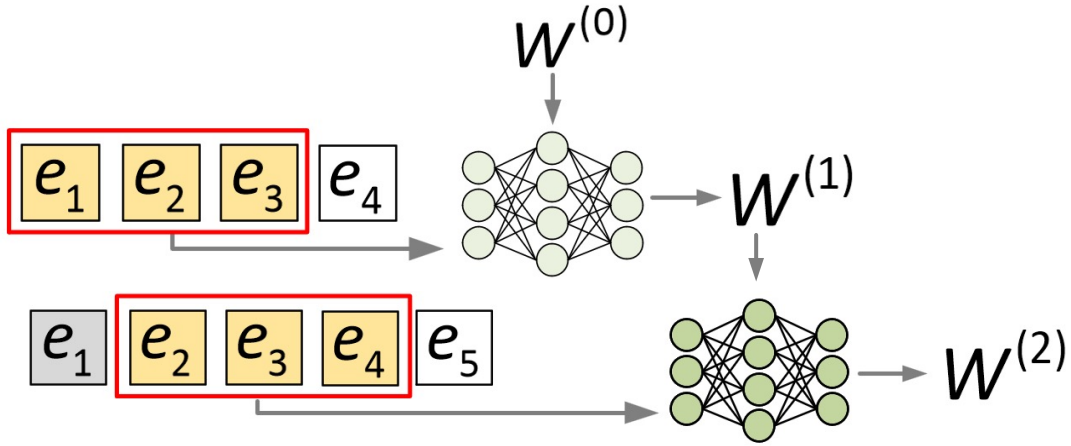

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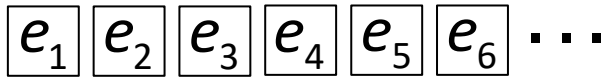

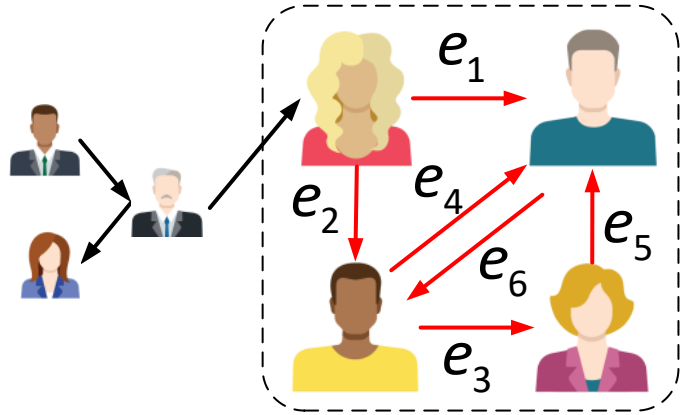

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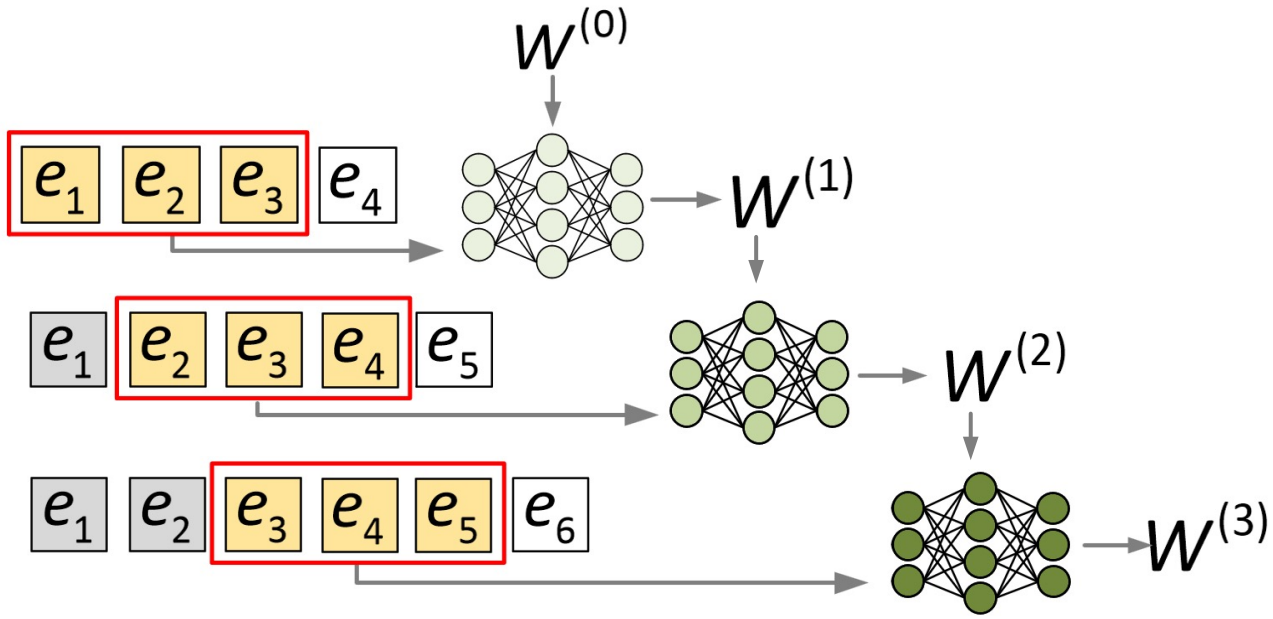

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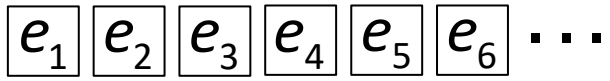

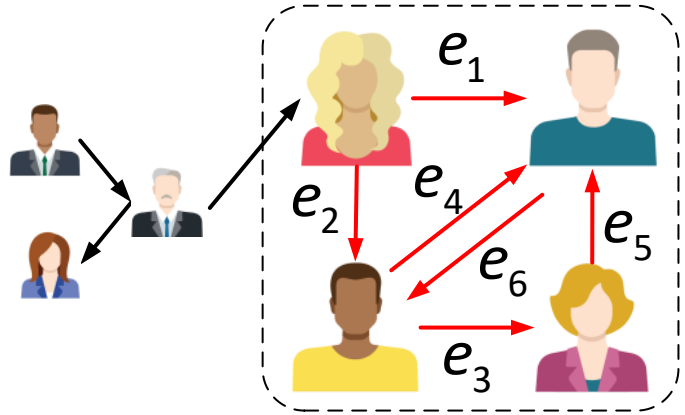

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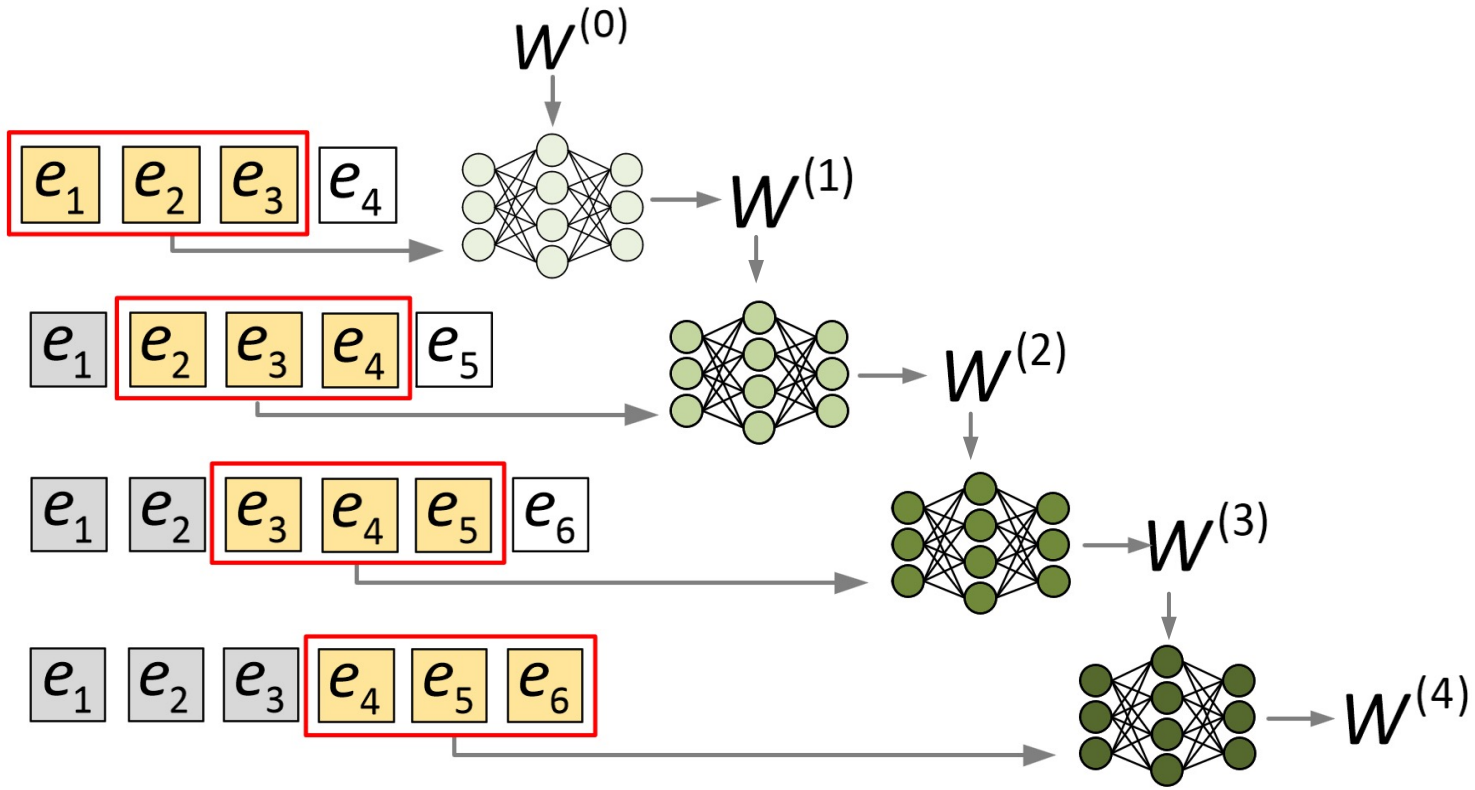

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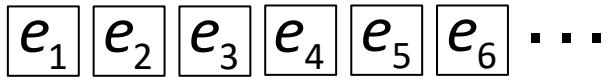

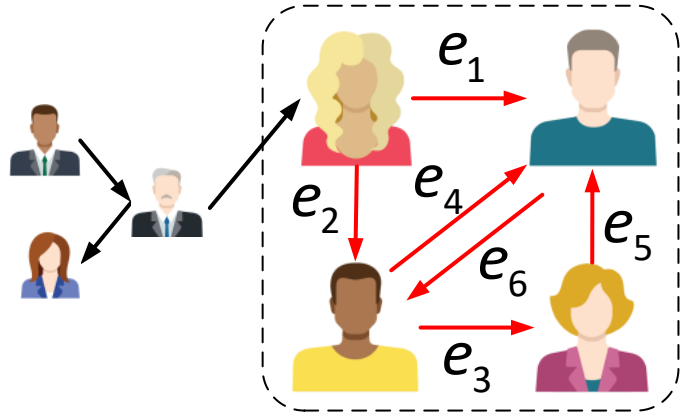

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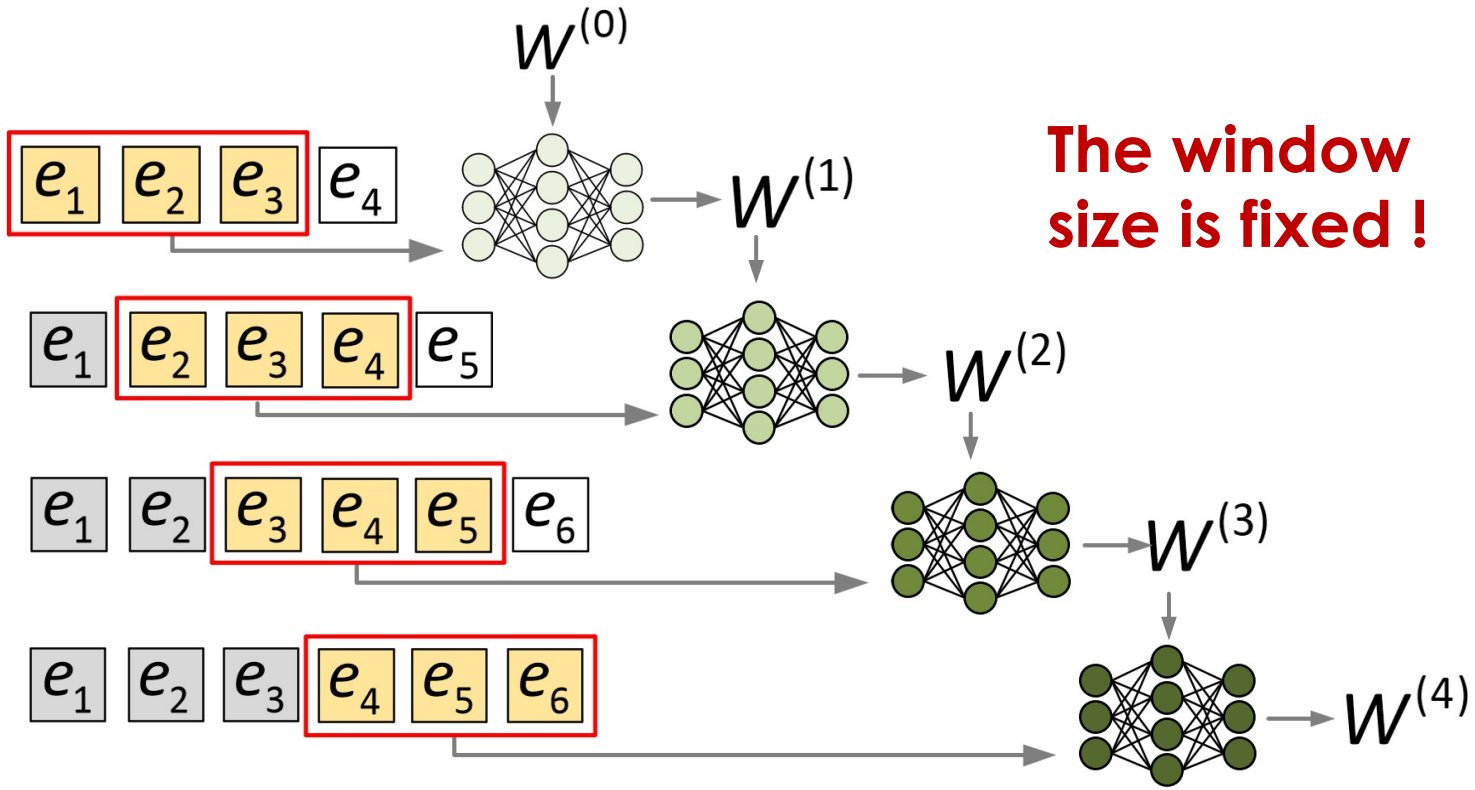
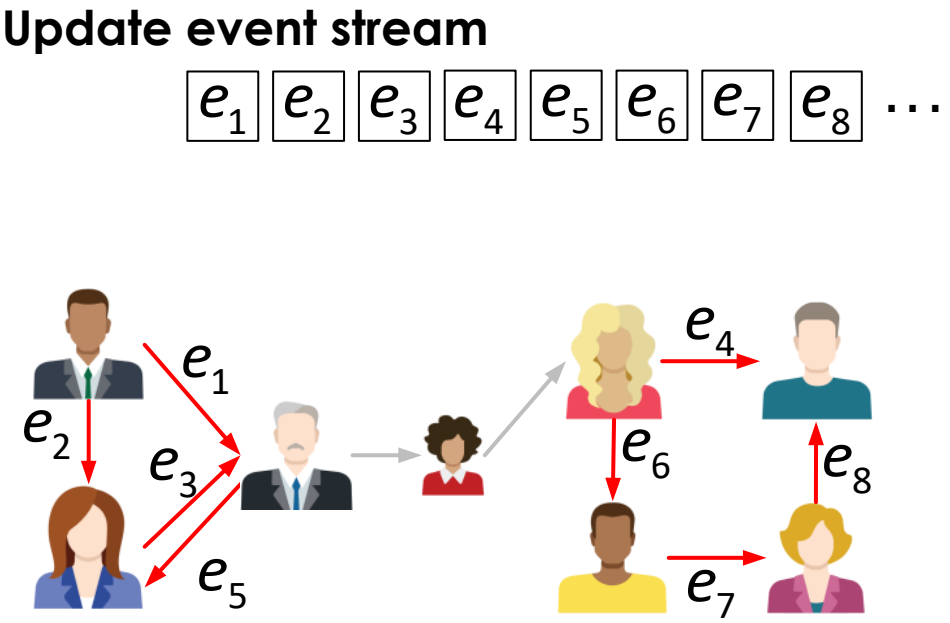


The window size is fixed !

Solution 1: Sliding-window-based Training Method

The window size determines how much data can be fed into the model

Key Observations : A continuous segment of events is usually concentrated in a local area in the graph



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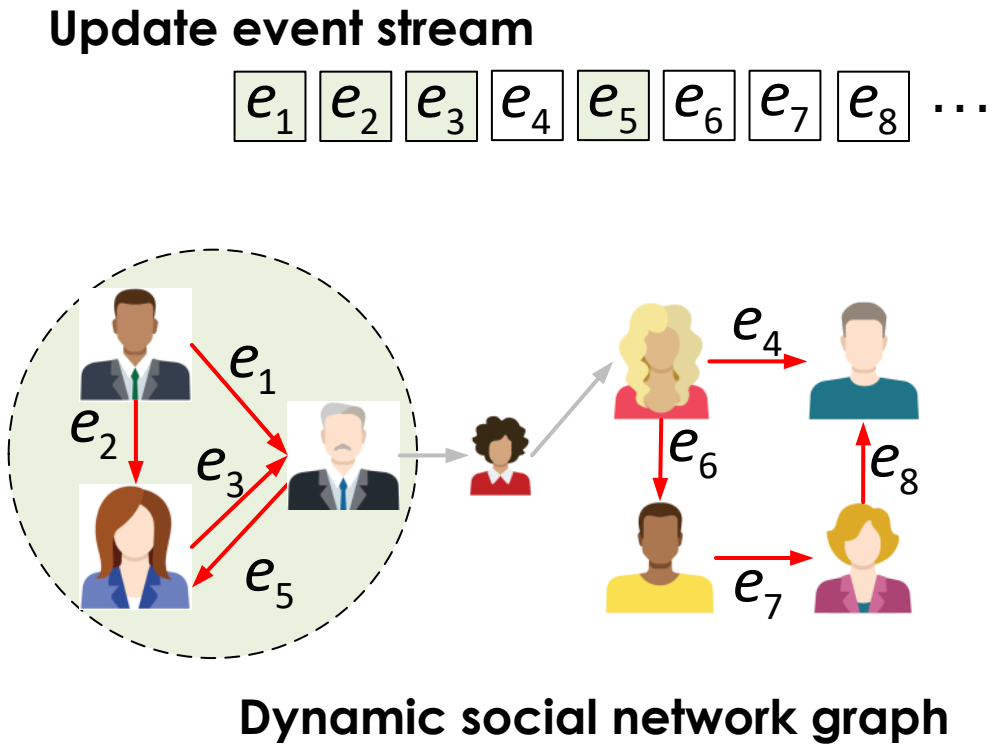

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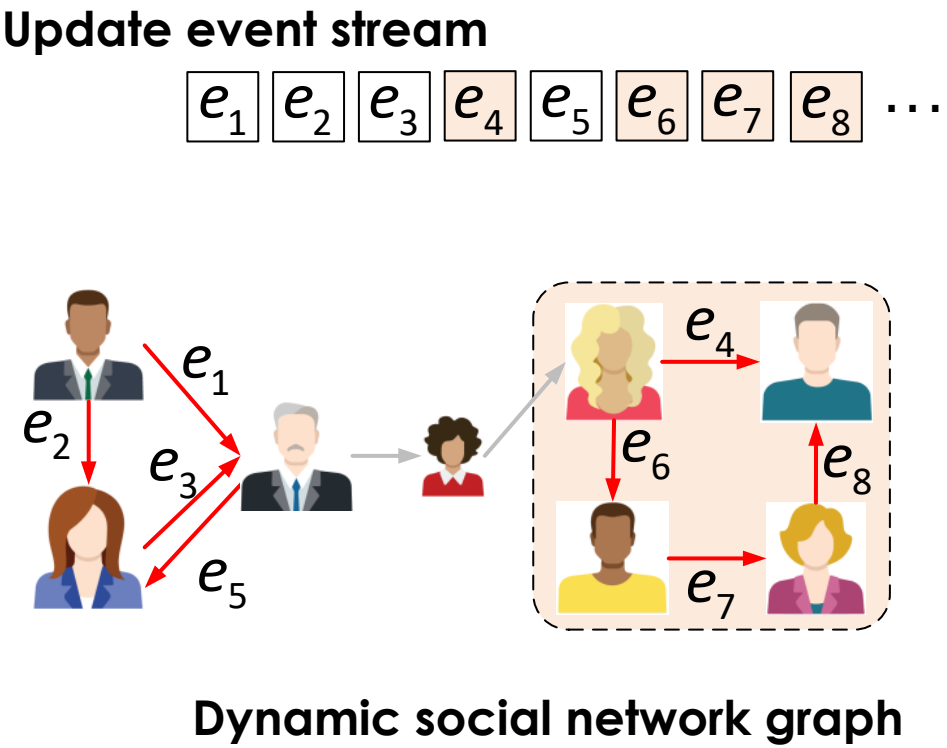

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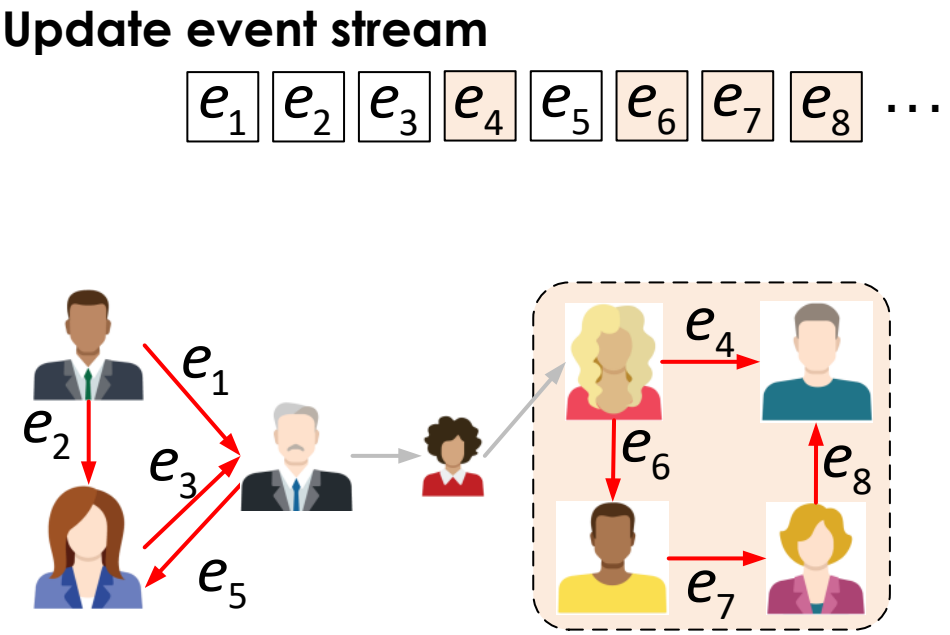


The window size should be dynamically adjustable

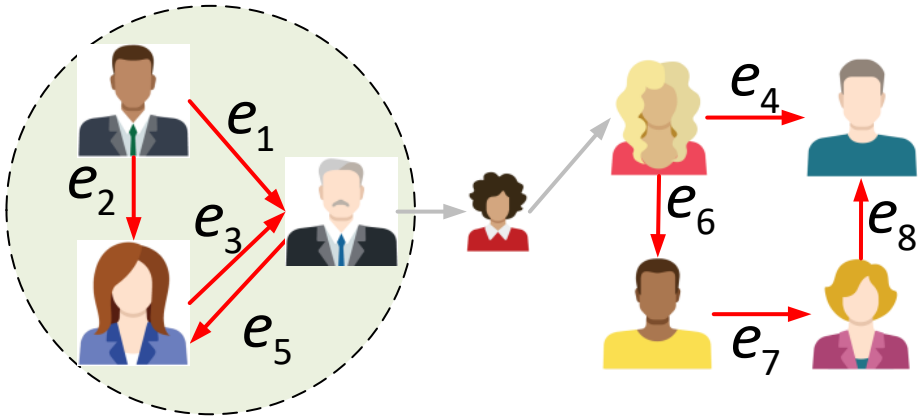
Solution 1: Sliding-window-based Training Method

Adaptive Adjustment of Window Size (denoted as **NS-AdaSlide)**

The window size can be adaptively adjusted for capturing the **complete spatial dependencies**

Update event stream

e_1 e_2 e_3 e_4 e_5 e_6 e_7 e_8 …



Dynamic social network graph

e_1 e_2 e_3 e_4 e_5

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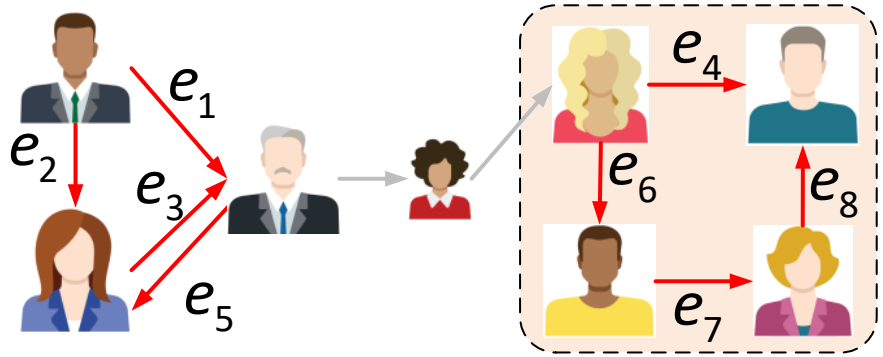

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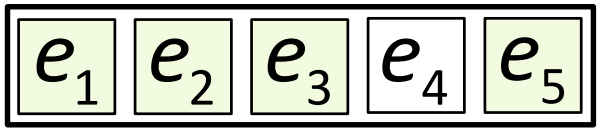
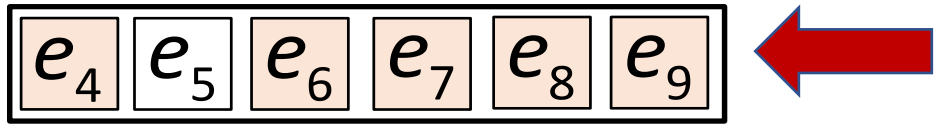
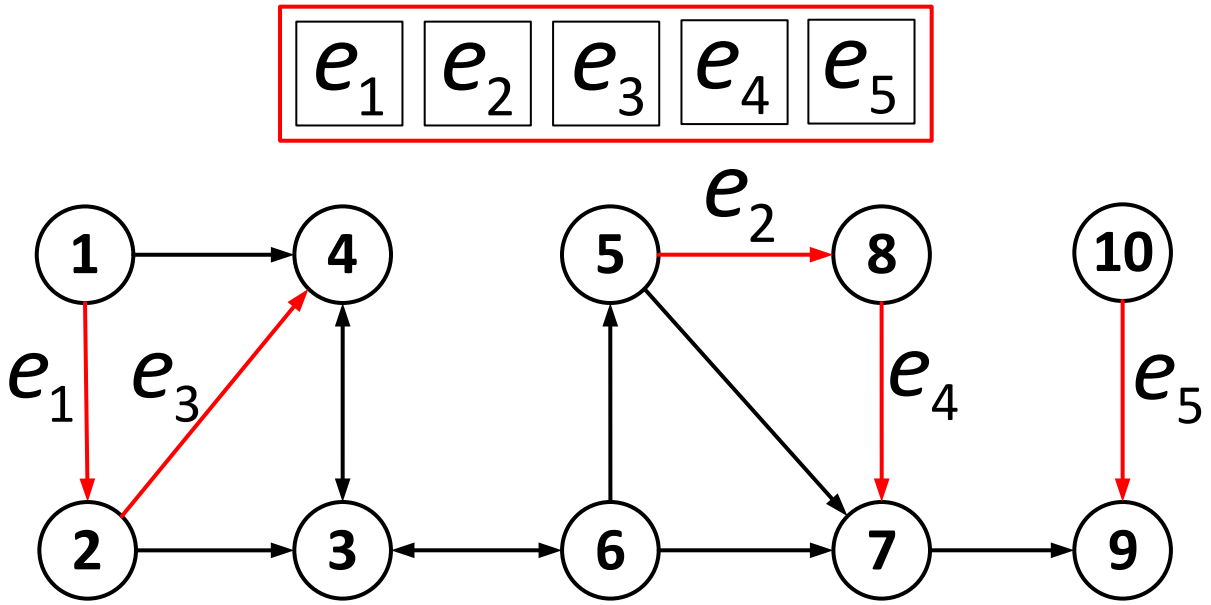




Solution 2: Dependency-Graph-Driven Event Parallelizing

Key Observations : An event only involves a subgraph. If there are no read-write conflicts between two events, they can be executed in parallel.



A subgraph consists of event nodes and their neighbors, where

- **Event nodes are write sets**
- **Event nodes and their neighbors are read sets**

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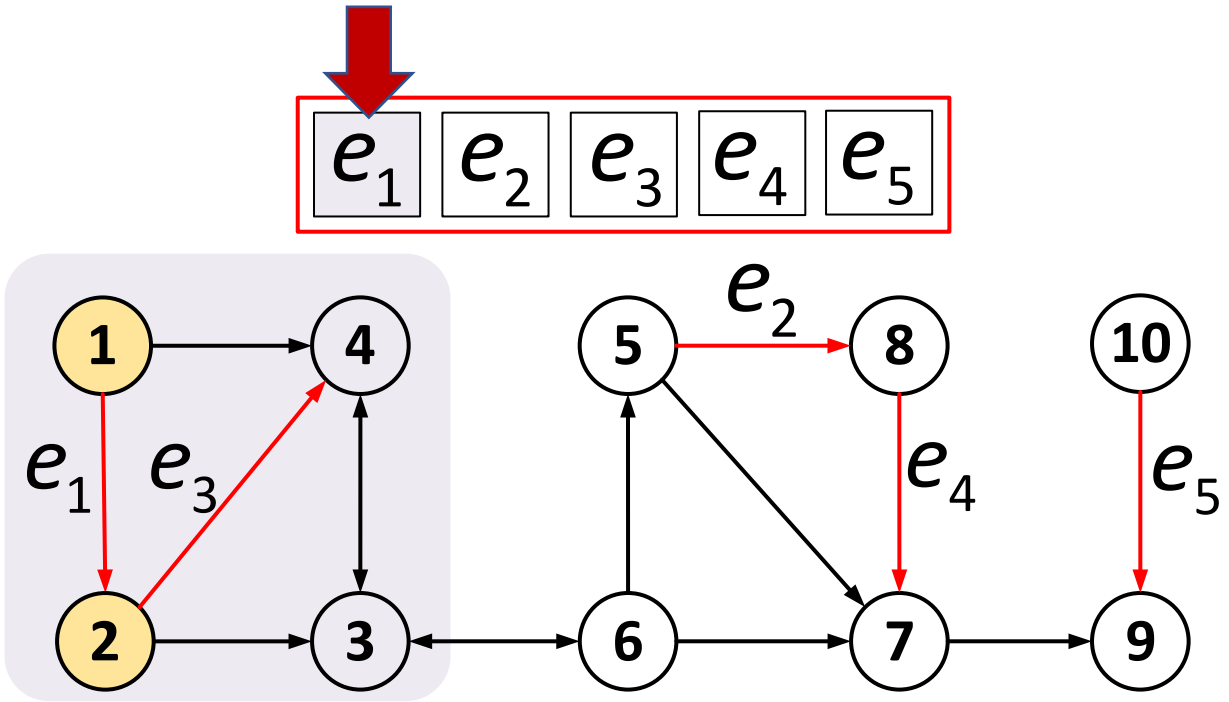

The purple area is the subgraph of events e_1

- Write set: {**1**, **2**}
- Read set: {**1**, **2**, **3**, **4** }

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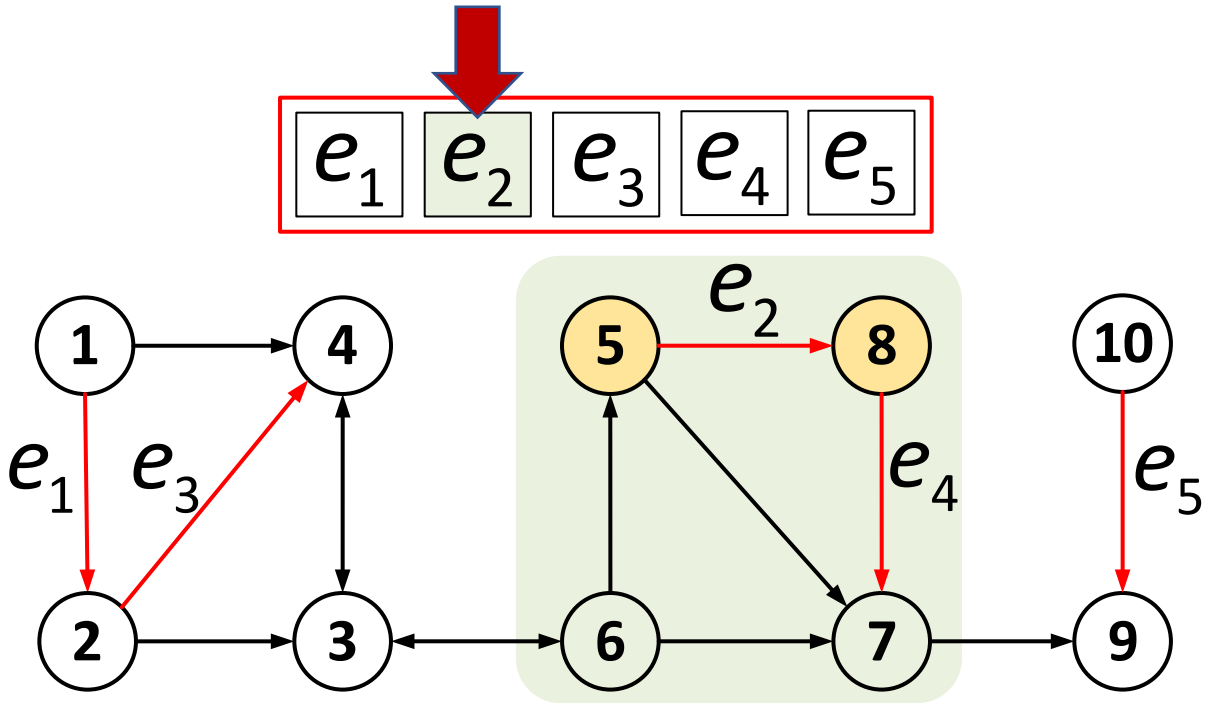

The green area is the subgraph of events e_2

- Write set: {**5**, **8**}
- Read set: {**5**, **8**, **6**, **7** }

Solution 2: Dependency-Graph-Driven Event Parallelizing

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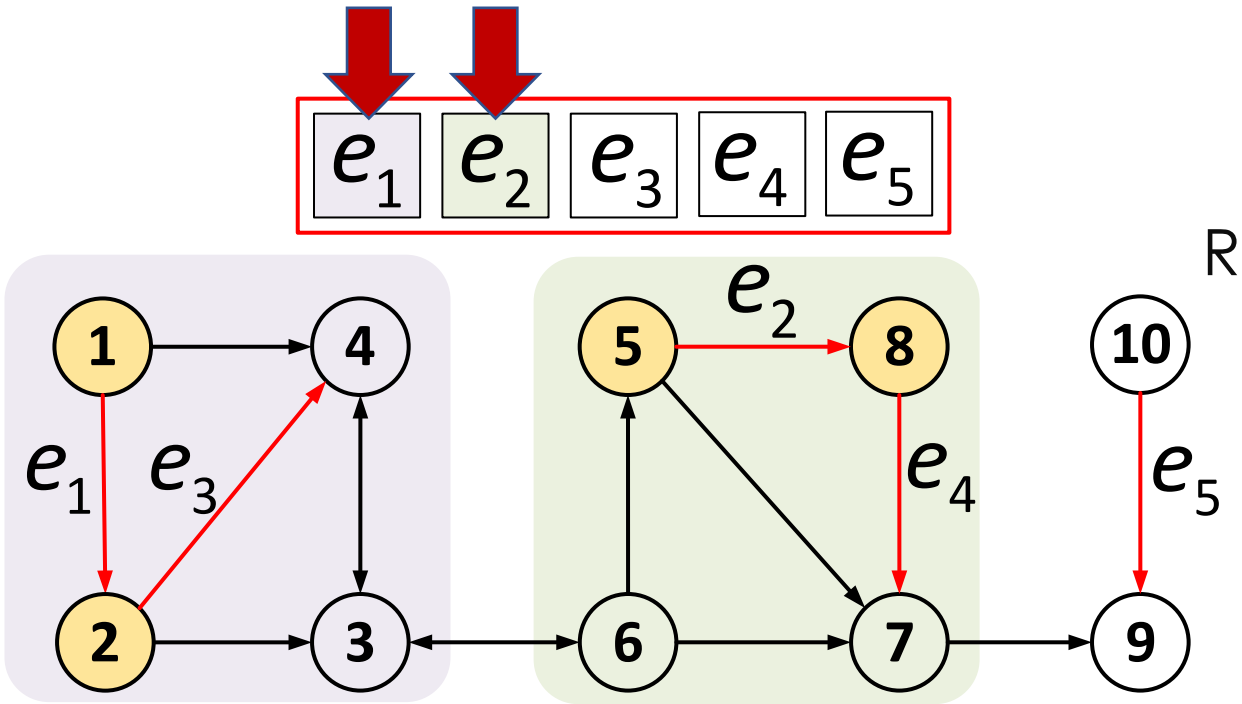

Read set: {**5**, **8**, **6**, **7** } ⋂ Write set: {**1**, **2**} = ∅

e_1 **and** e_2 **can be executed in parallel**

Solution 2: Dependency-Graph-Driven Event Parallelizing

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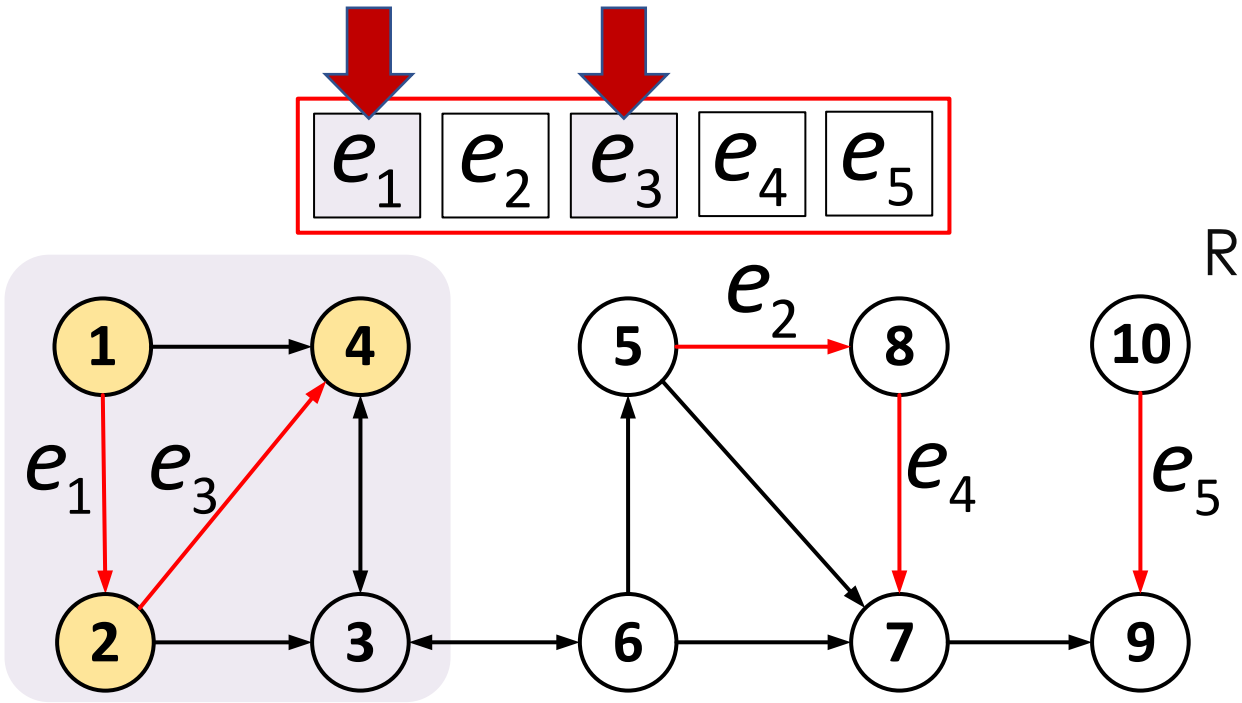


Read set: {**1**, **2**, **3**, **4** } ⋂ Write set: {**1**, **2**} ≠ ∅

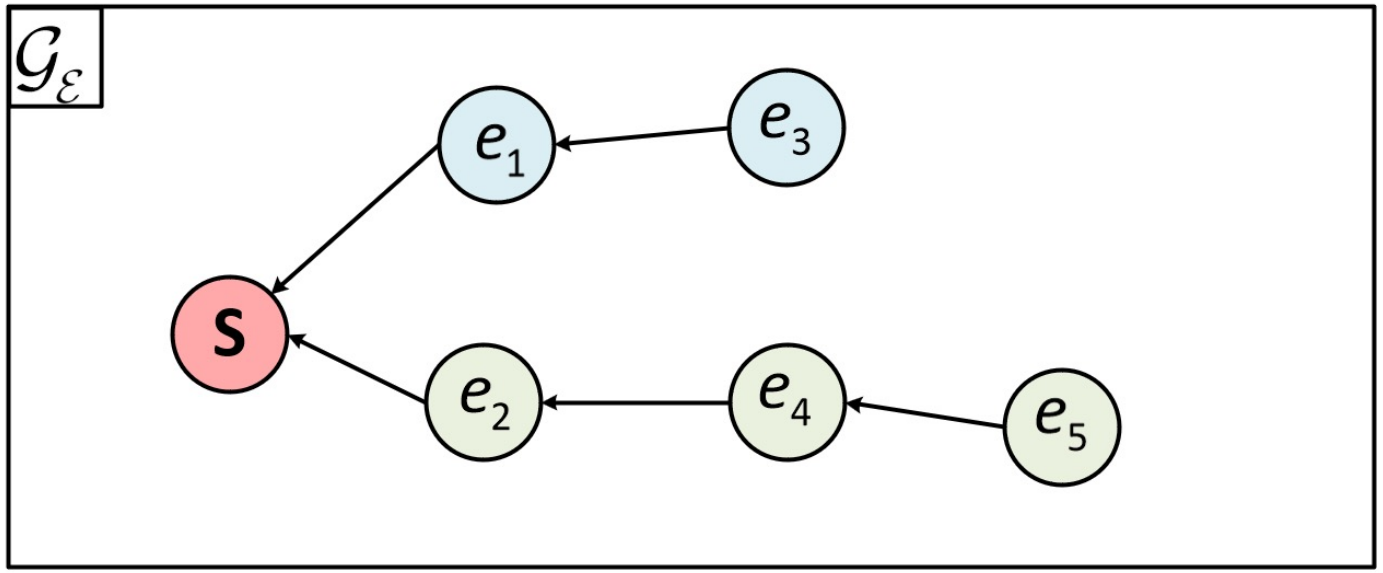
e_1 **and** e_3 **cannot be executed in parallel**

$$e_3 \Rightarrow e_1$$

Solution 2: Dependency-Graph-Driven Event Parallelizing

Event Dependency Graph $\mathcal{G}_{\mathcal{E}} = (\mathcal{V}, \mathcal{E})$

Each node represents an event. Each edge represents a dependency.



Event dependency graph

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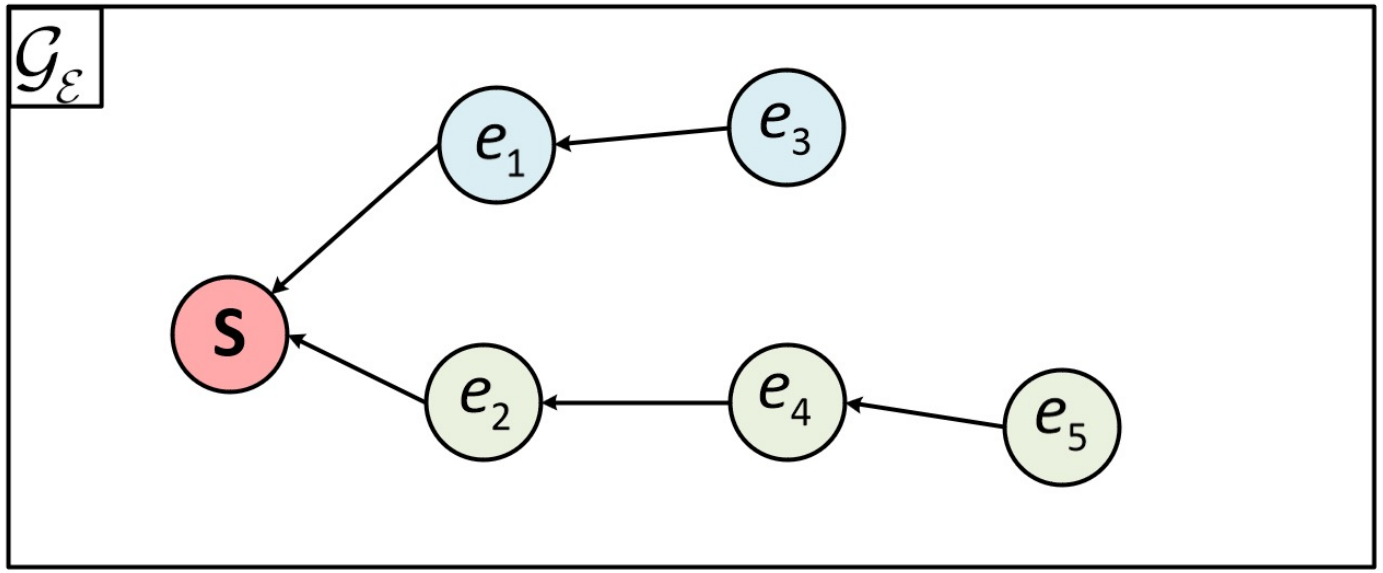
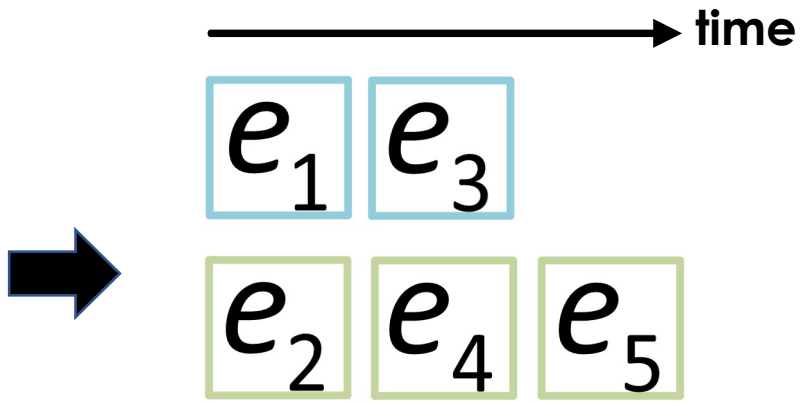


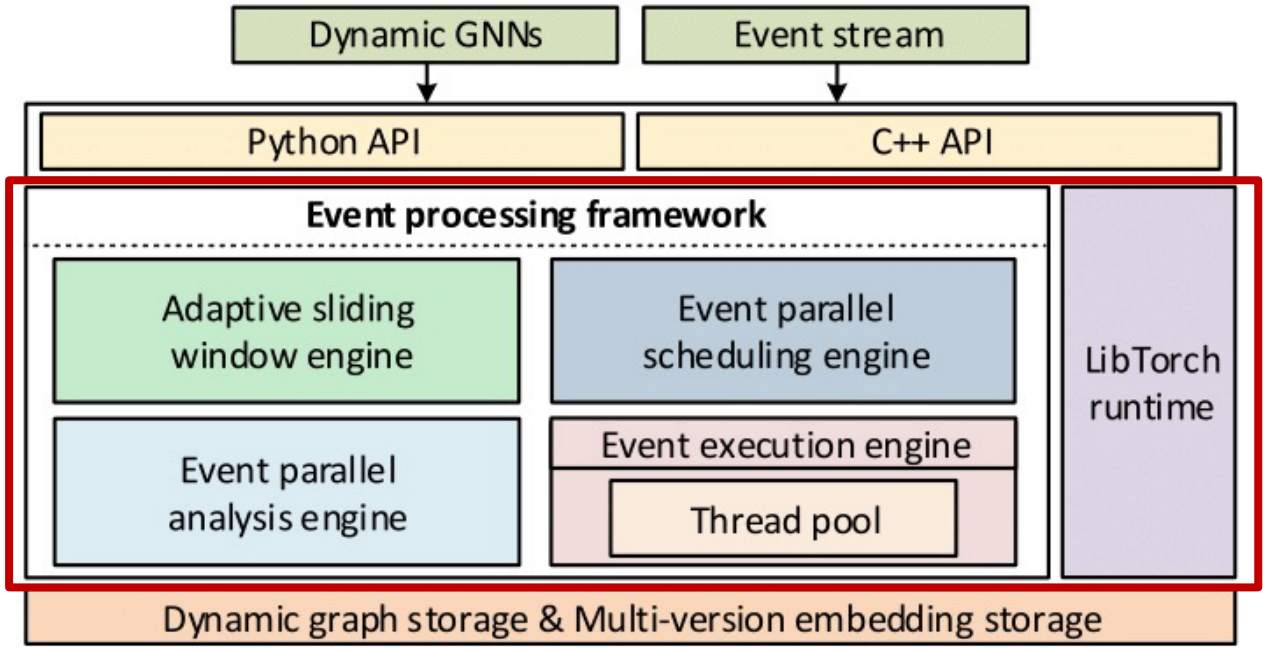
Event dependency graph



Parallel plan

NeutronStream

We deliver a dynamic GNN training framework NeutronStream , which consists of 10,336 LoC

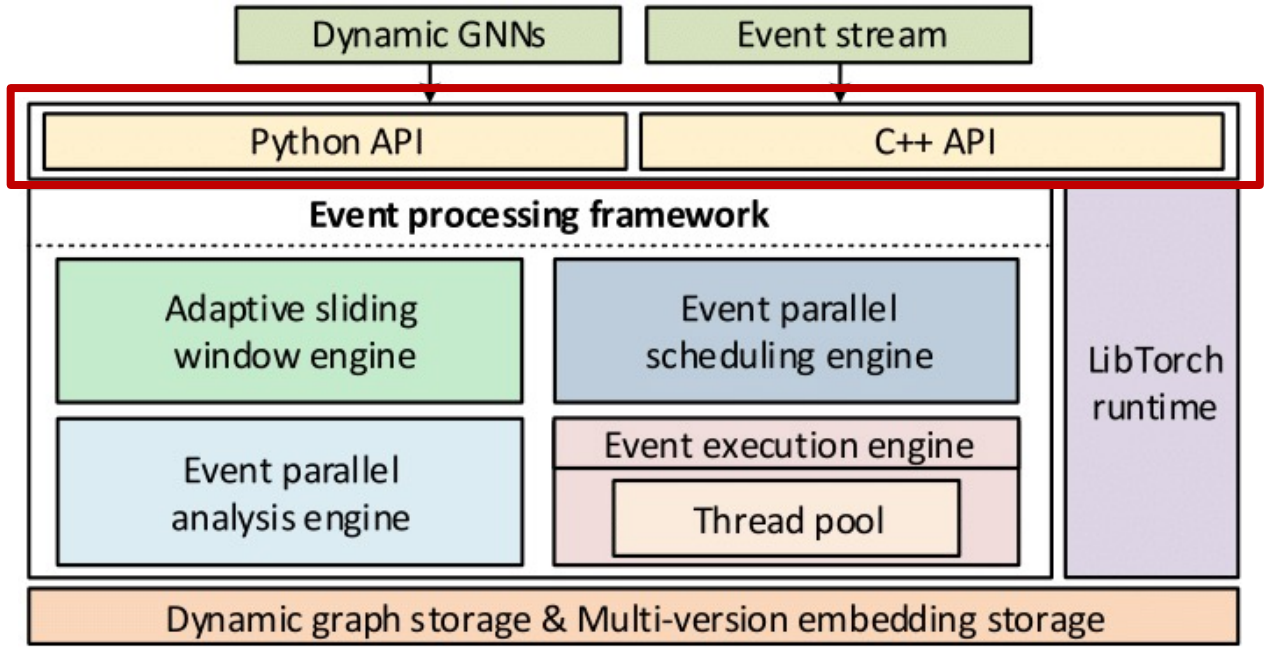


NeutronStream architecture

1. Sliding-window-based Training Method
2. Dependency-Graph-Driven Event Parallelizing

NeutronStream

We provides a set of easy-to-use APIs



NeutronStream architecture

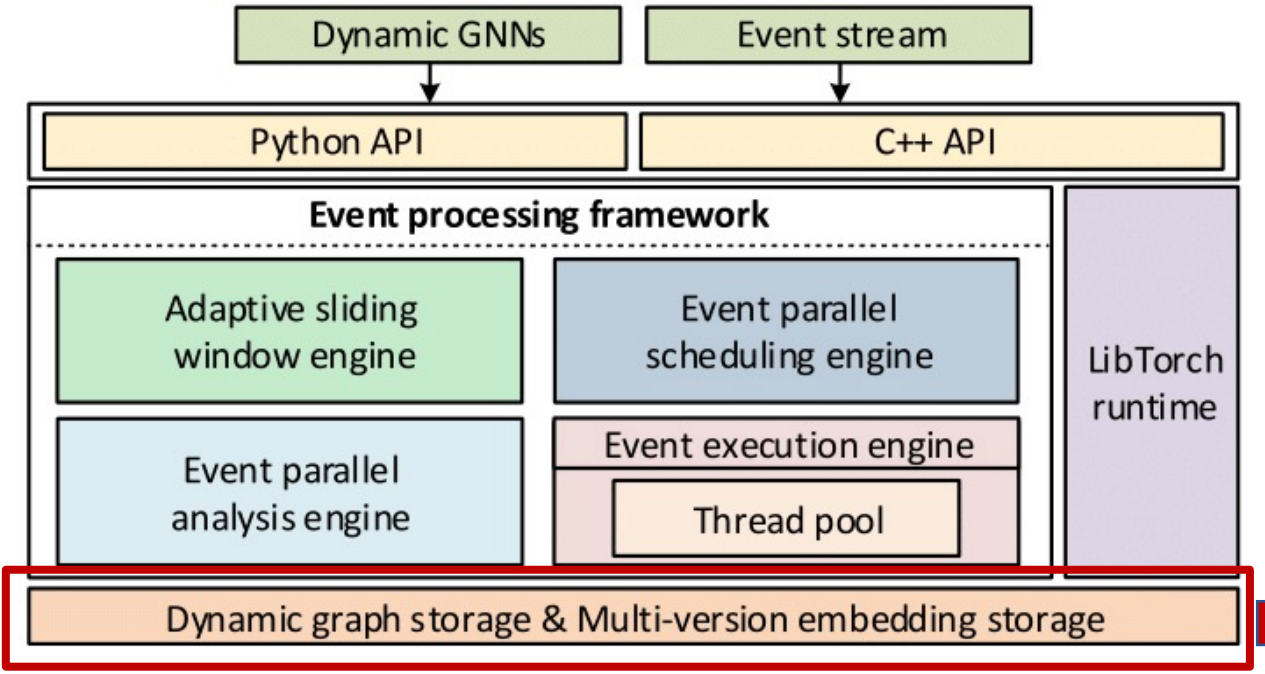
```
Class DyRep(nn.module):
   def __init__(self, h_dim):
      # initial parameters include W_h, W_struct, W_rec, W_t
and attention martix S

# update graph structure based an event
   def UpdateGraph(evt, dynGraph):
        # compute intensity
        # update attention matrix self.S
        if evt.type == 'Association'
           dynGraph.add_edge(evt.u,evt.v, undir=True)
        return dynGraph.get_subgraph(evt)
# compute aggregated neighbor information of an event node
   def Aggregate(dynSubgraph, dynEmb, nid):
        nbr = dynSubgraph.get_nbr(nid, dir='in')
        nbr_emb = self.W_h(dynEmb.index(nbr))
        q_ni = torch.exp(self.S[nid, nbr])
        q_ni = q_ni/(torch.sum(q_ni) + 1e-7)
        agg = torch.max(nn.sigmoid(q_ni.view(1,1)*nbr_emb),dim=0)[0]
        return self.W_struct(agg)
# compute updated embedding of an event node
   def UpdateEmb(dynSubgraph, dynEmb, nid, h_agg, time):
        delta_time = time - dynSubgraph.query_time(nid)
        h_exogenous = self.W_t(delta_time)
        h_self = self.W_rec(dynEmb.index(nid))
        upd_emb = nn.sigmoid(h_agg + h_self + h_exogenous)
        dynEmb.update(nid, upd_emb)
# forward function
   def forward(evt_list, dynGraph, dynEmb):
        for evt in evt_list:
           dynSubgraph = UpdateGraph(evt, dynGraph)
           h_u_agg = Aggregate(dynSubgraph, dynEmb, evt.u)
           h_v_agg = Aggregate(dynSubgraph, dynEmb, evt.v)
           UpdateEmb(dynGraph, dynEmb, evt.u, h_v_agg, evt.time)
           UpdateEmb(dynGraph, dynEmb, evt.v, h_u_agg, evt.time)
```

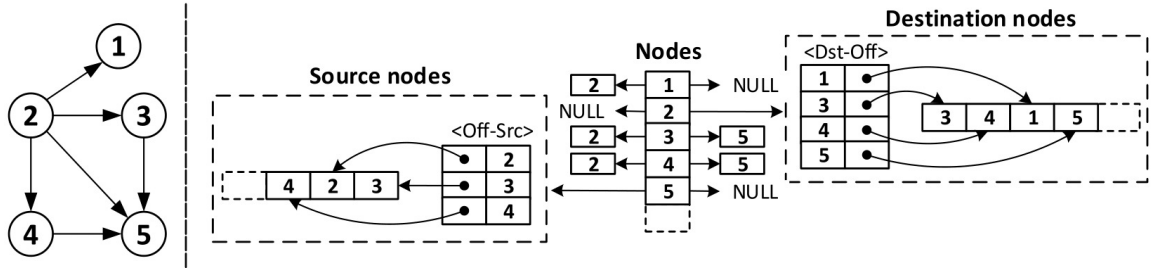
DyRep implementation with NeutronStream APIs

NeutronStream

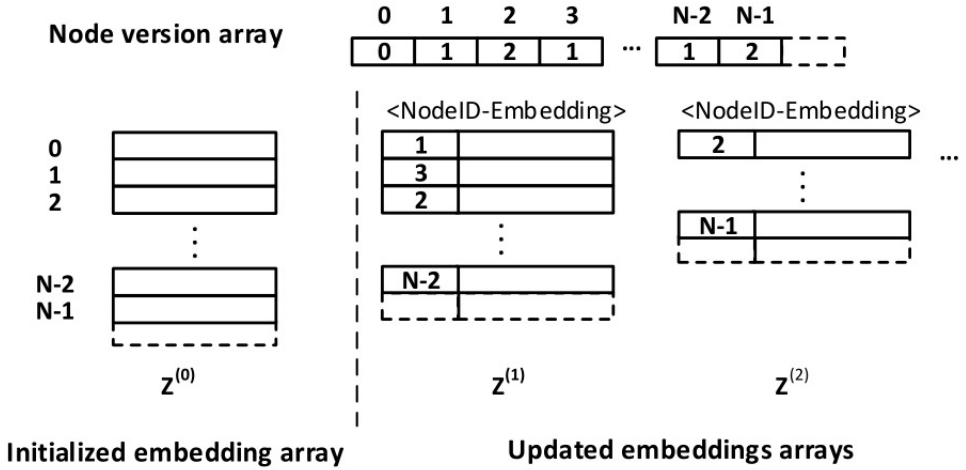
We design a built-in graph storage structure that supports efficient dynamic updates



NeutronStream architecture



(a) In-out-edge-separated indexed adjacency lists



(b) Multi-version node embedding storage

Dynamic graph storage design

Experimental Setups

Baseline: **Torch-Batch**, **NS-Batch** (NeutronStream), **NS-Slide** (NeutronStream) and **NS-AdaSlide** (NeutronStream).

Platforms:

An Aliyun ECS cluster (ecs.g5.6xlarge instance, 24 vCPUs, 96GB RAM)

Models and datasets:

- 3 Dynamic GNN DyRep, LDG, DGNN
- 6 real-world graphs.

Environment

- Ubuntu 18.04 LTS
- PyTorch 1.12.1

Table 2: Dataset statistics

Dataset	$\|V\|$	$\|E\|$.init	$\|E\|$.final	$evt.num$
Social Evolution [29]	84	575	794	54,369
Github [4]	284	298	4,131	20,726
DNC [21]	2,029	0	5,598	39,264
UCI [21]	1,899	0	20,296	59,835
Reality [7]	6,809	0	9,484	52,052
Slashdot [12]	51,083	0	131,175	140,778

AUC Comparison

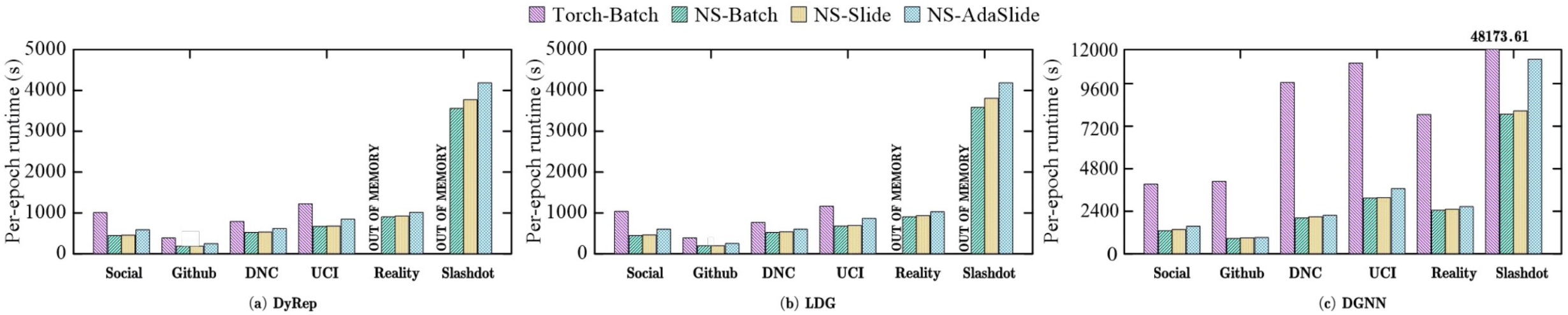
Table 3: AUC comparison of three training methods

Model	Dataset	Training Method			
		Torch-Batch	NS-Batch	NS-Slide	NS-AdaSlide
DyRep	Social	83.01%	83.01%	86.15%	**89.32%**
	Github	73.46 %	73.46%	77.54%	**79.28%**
	DNC	63.15%	63.15%	63.49%	**66.18%**
	UCI	62.46%	62.46%	63.53%	**65.68%**
LDG	Social	87.07%	87.07%	88.52%	**92.98%**
	Github	74.34%	74.34%	78.10%	**79.16%**
	DNC	64.62%	64.62%	66.50%	**69.41%**
	UCI	62.16%	62.16%	64.38 %	**66.57%**
DGNN	Social	97.21%	97.21%	97.61%	**97.67%**
	Github	81.94%	81.94%	82.54%	**84.45%**
	DNC	86.04%	86.04 %	87.72%	**88.81%**
	UCI	78.45%	78.45%	81.14 %	**82.09%**

(1) The batch method (**Torch-Batch** and **NS-Batch**) has the **lowest AUC** because it cuts off the data stream, resulting in the loss of training information.

(2) The adaptive sliding method (**NS-AdaSlide**) achieves the **highest AUC** by effectively capturing the spatial-temporal locality between events.

Runtime Comparison



Compared with the **Torch-Batch**, **NS-Batch** achieves **1.48x – 5.87x** on 3 Dynamic GNNs and six real datasets.

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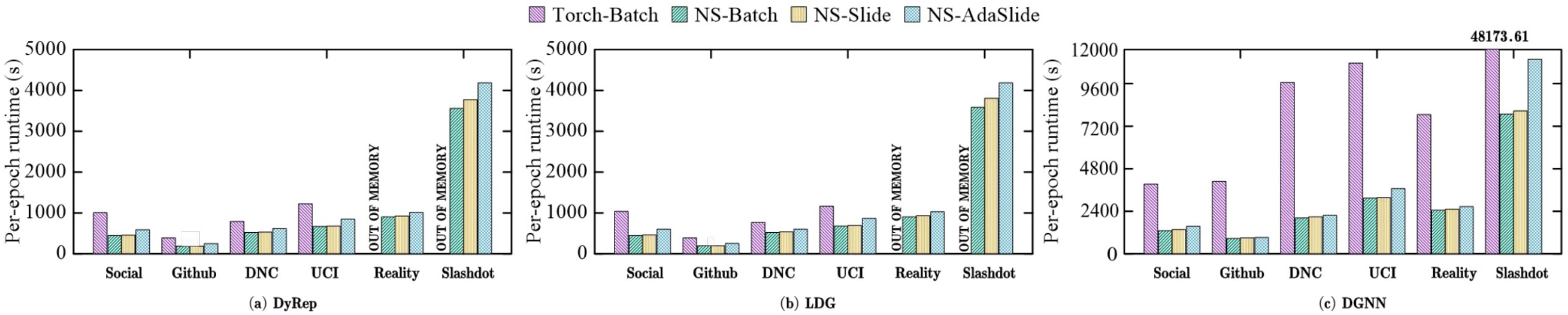

Compared with the **Torch-Batch**, **NS-AdaSlide** have lowest parallelism. However, thanks to our system optimization, **NS-AdaSlide** can achieve **1.27X-4.44X** speedups on 3 Dynamic GNNs and six real datasets.

Summary

NeutronStream: A Dynamic GNN Training Framework with Sliding Window for Graph Streams.

- **Proposing a new incremental learning mode with a sliding window for training on graph streams**

  We design a sliding-window-based method to incrementally train models for capturing the spatial-temporal dependency of events.

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  We build a dependency graph analysis method that identifies the events having no node-updating conflicts and processes them in parallel.

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- **The codes are publicly available on github**

https://github.com/iDC-NEU/NeutronStream