41st IEEE International Conference on Data Engineering
HONG KONG SAR, CHINA | MAY 19 – 23, 2025

KAIST AI
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Simple yet Effective Node Property Prediction on Edge Streams under Distribution Shifts


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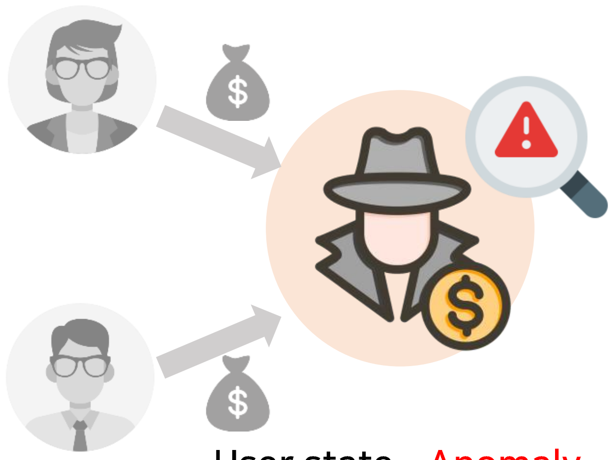
Node Properties in Real-world Networks

Various characteristics of entities can be represented as node properties

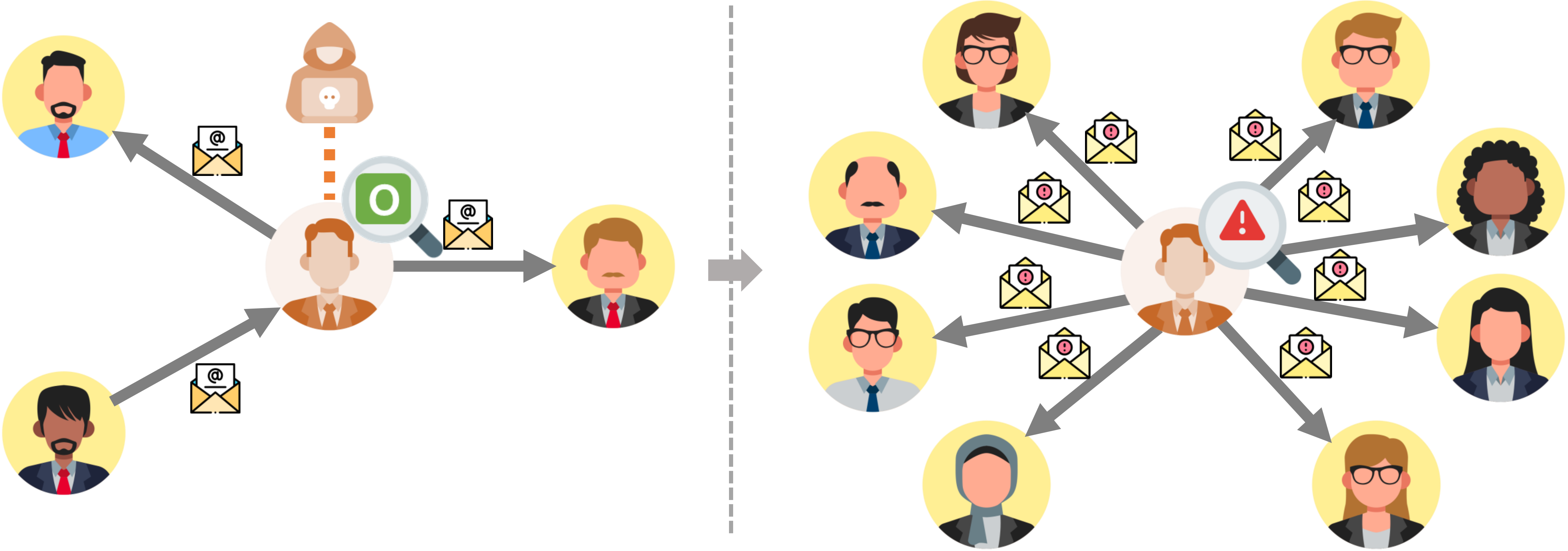
- Predicting these properties can be valuable for many real-world applications
  - Anomalous states in financial networks (anomaly detection)
  - Users' preferred song categories for next week on a streaming site (recommendation)



Challenges in Predicting Node Properties

Node properties dynamically change in real-world networks

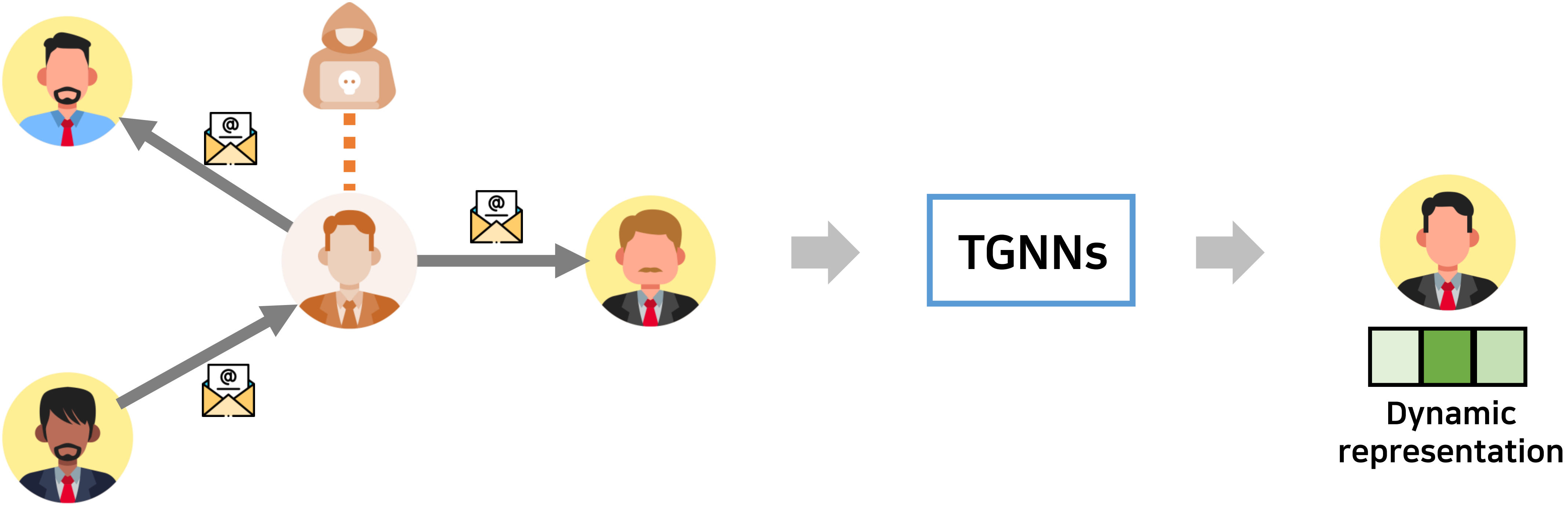
- Many real-world networks evolve over time, with emerging interactions
  - Previous methods based on static graphs become less effective and efficient in such a case



Challenges in Predicting Node Properties

Temporal Neural Networks (TGNNs) can be used for node property prediction

- These models can predict dynamically changing node properties by incrementally update node representations that capture complex temporal and structural patterns



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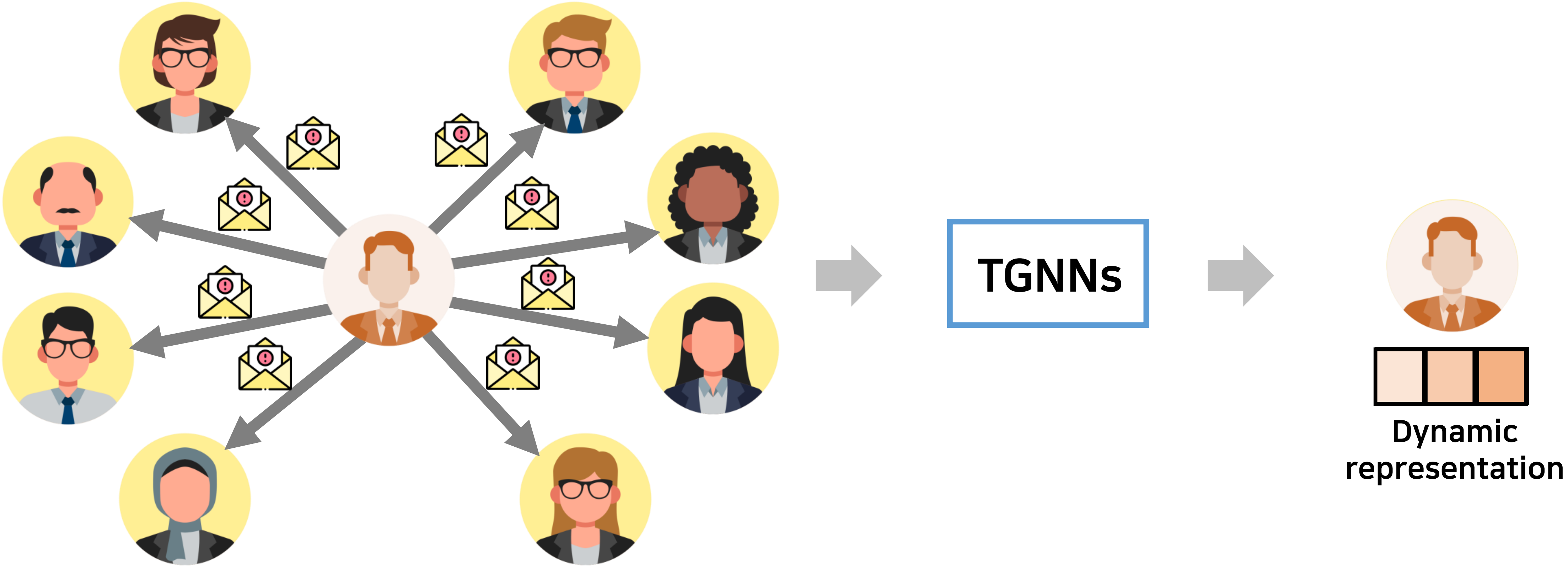
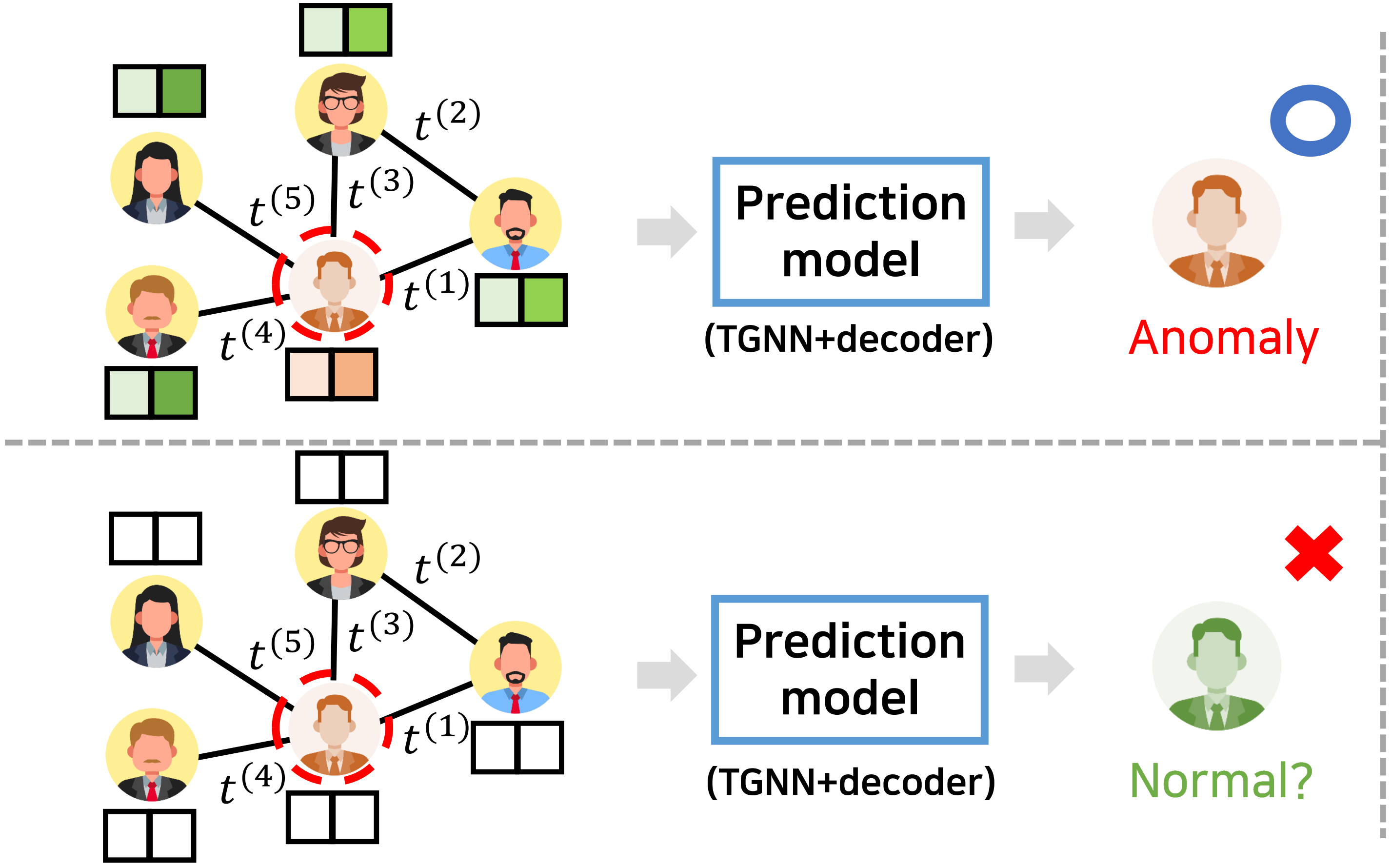
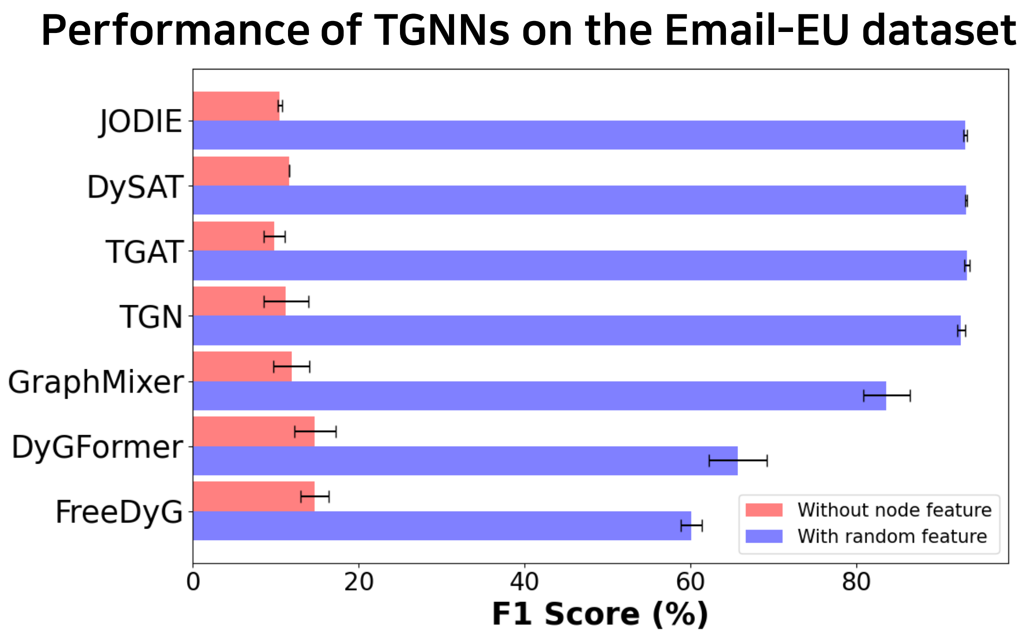


Challenges in Predicting Node Properties

However, performance of TGNNs drops when node features are absent

- TGNNs can be less effective without proper node features in node property prediction



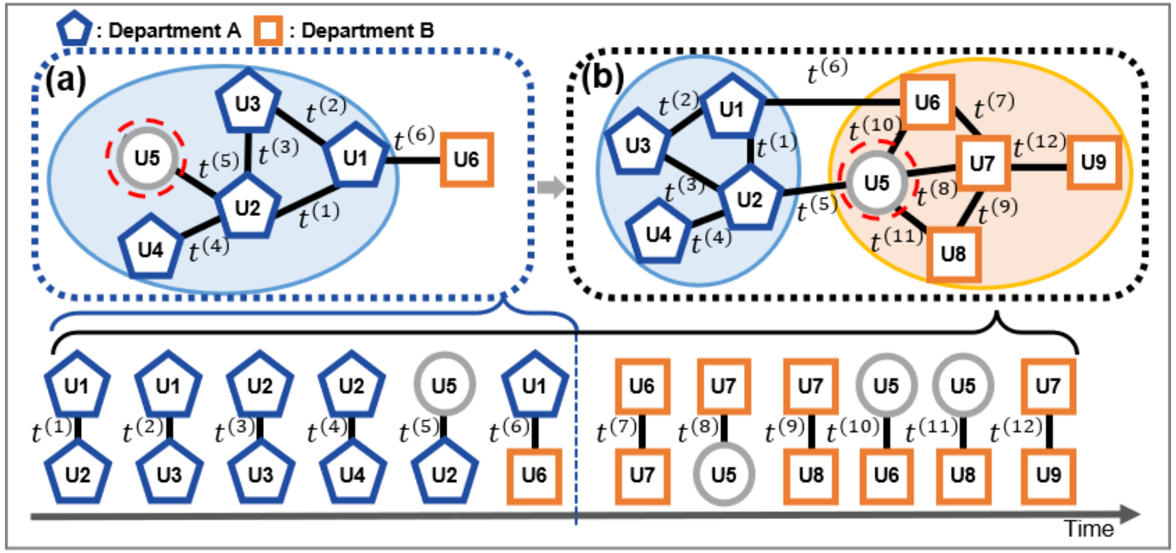


Challenges in Predicting Node Properties

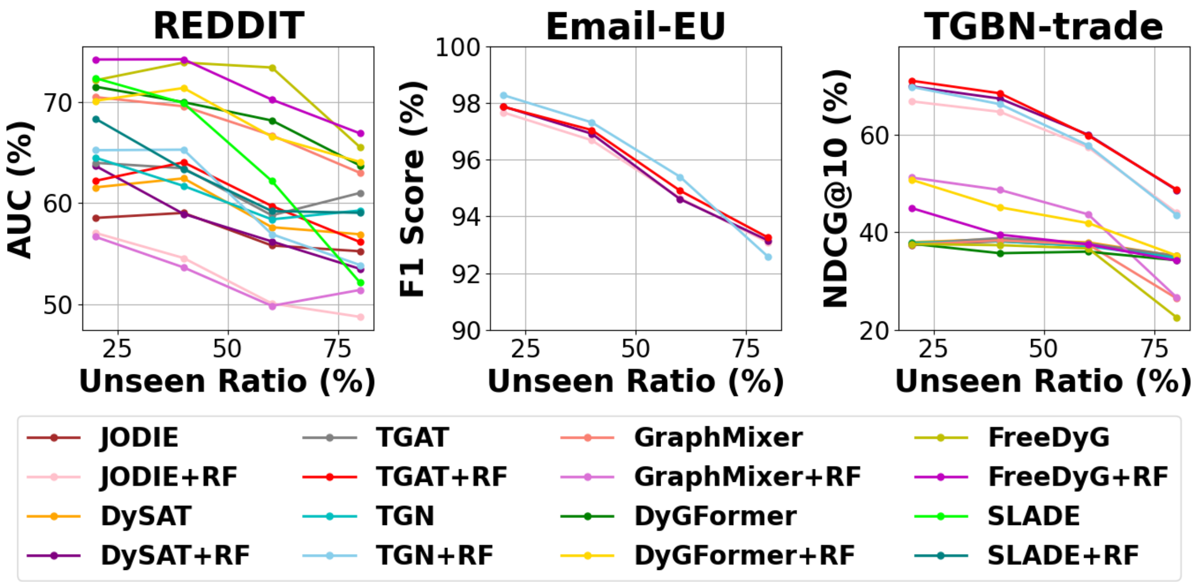
TGNNs are vulnerable to distribution shifts in real-world networks

- Many TGNN models employ complex architectures such as RNNs and attention modules
- However, complex model architectures can be vulnerable to distribution shifts

Example of distribution shifts in a collaboration network



Performance degradations of TGNNs under distribution shift



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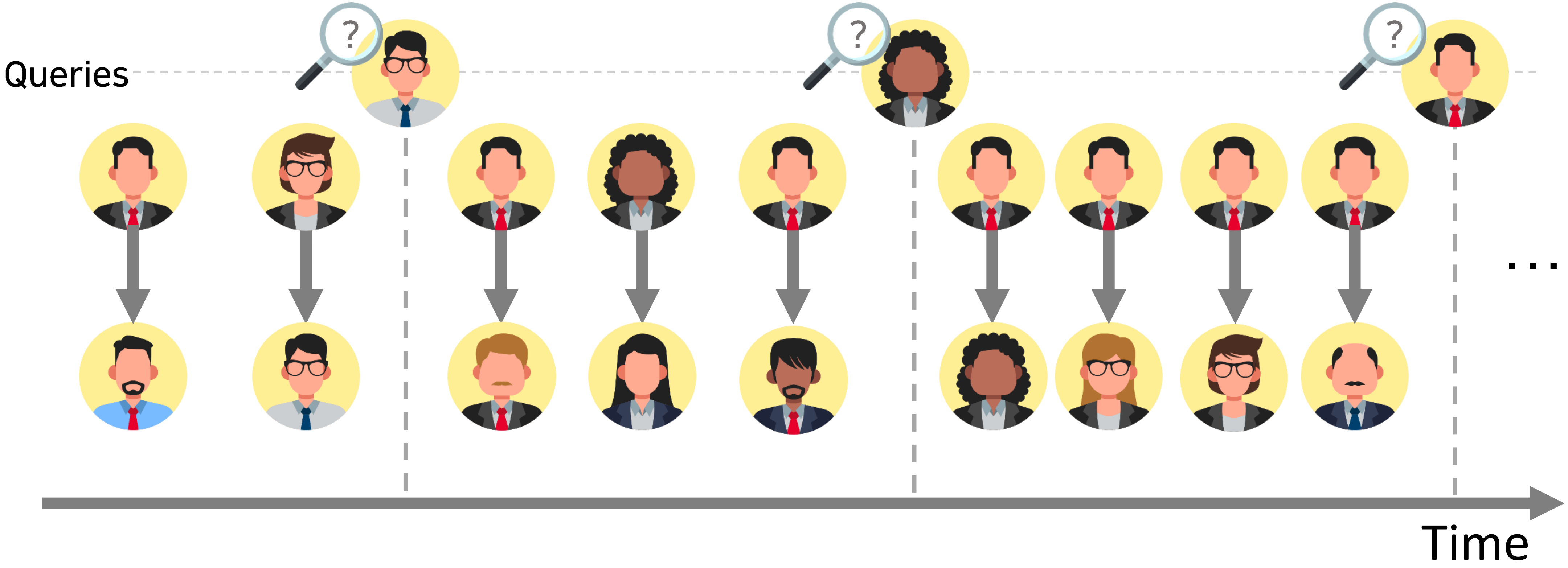
Problem Definition

Node Property Prediction in Edge Streams

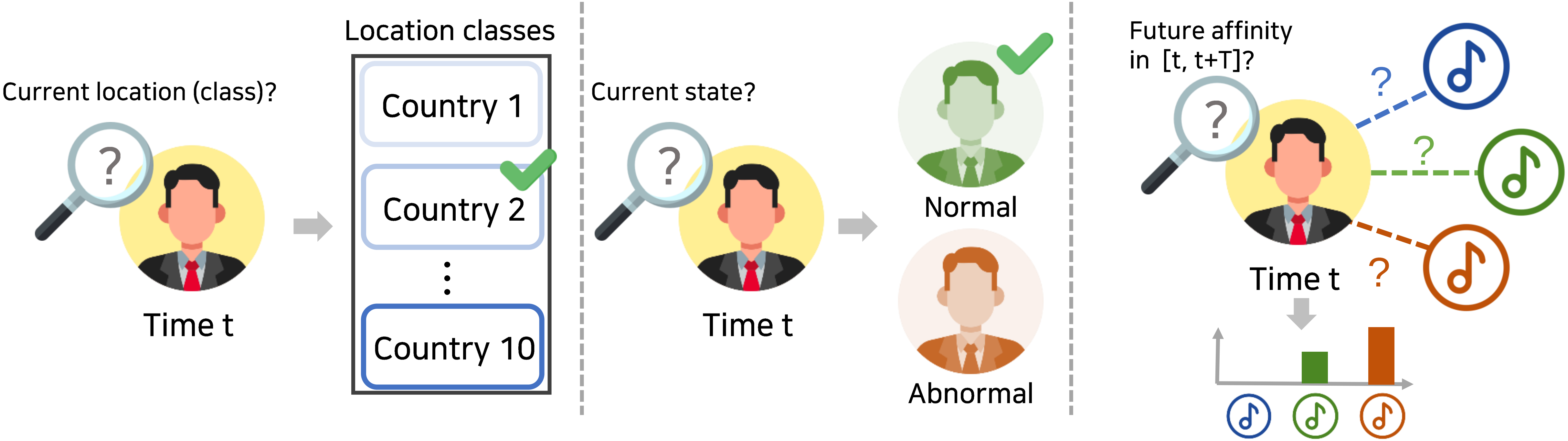
- To predict the node property of each query node in edge streams
- Only past edges can be utilized for predicting the current node properties



Problem Definition

Subtasks of Node Property Prediction in Edge Streams

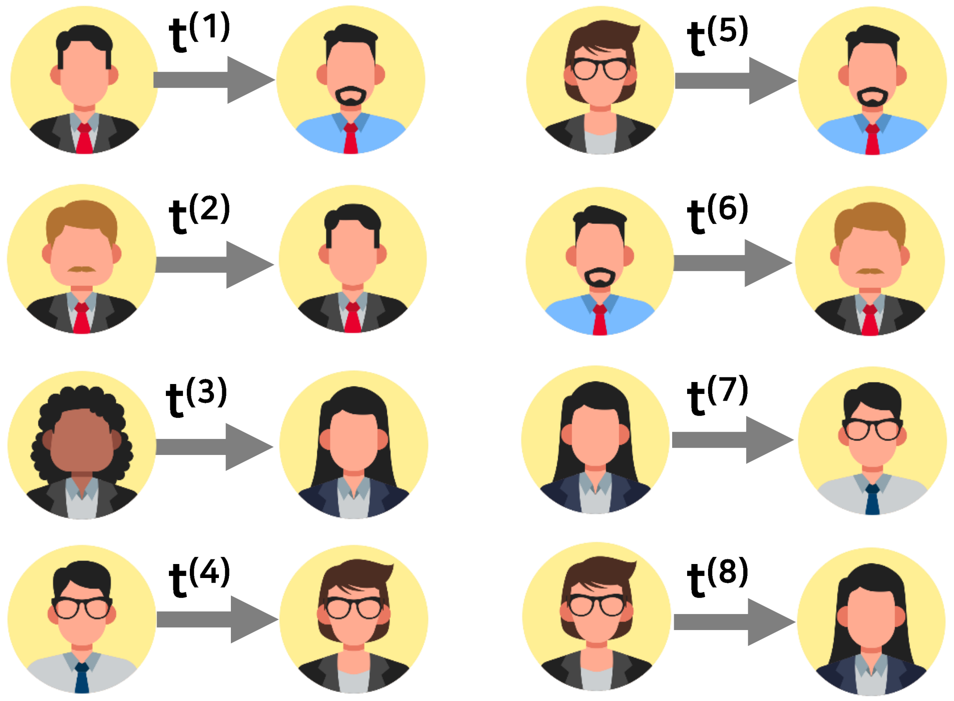
- Dynamic Node Classification
- Dynamic Anomaly Detection
- Node Affinity Prediction



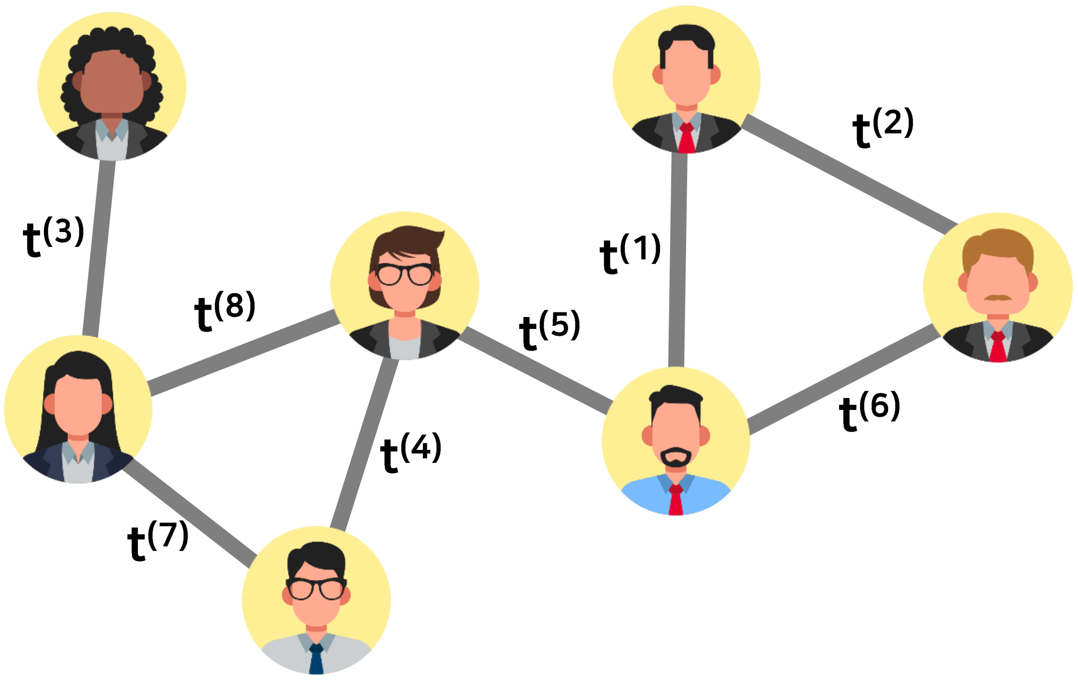
Our Graph Model for Edge Stream: CTDG

CTDG (Continuous Time Dynamic Graph)-based methods

- Incrementally update the graph by adding time information as a new edge arrives
- Allow for incremental algorithms to minimize time delay



Edge Stream

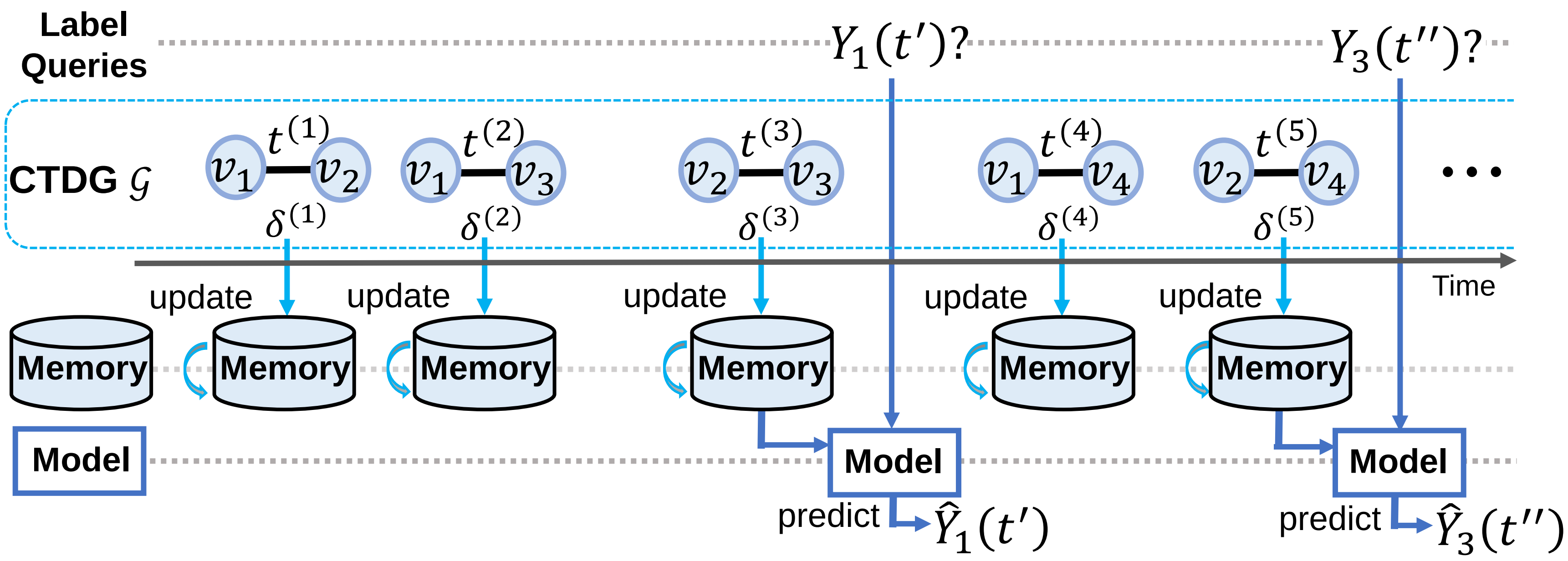


Continuous Time Dynamic Graph

Our Graph Model for Edge Stream: CTDG

Node Property Prediction Process using CTDGs

- Specifically, temporal edges appear over time and are used to update the memory
- Based on the updated memory, the model make predictions for incoming property queries



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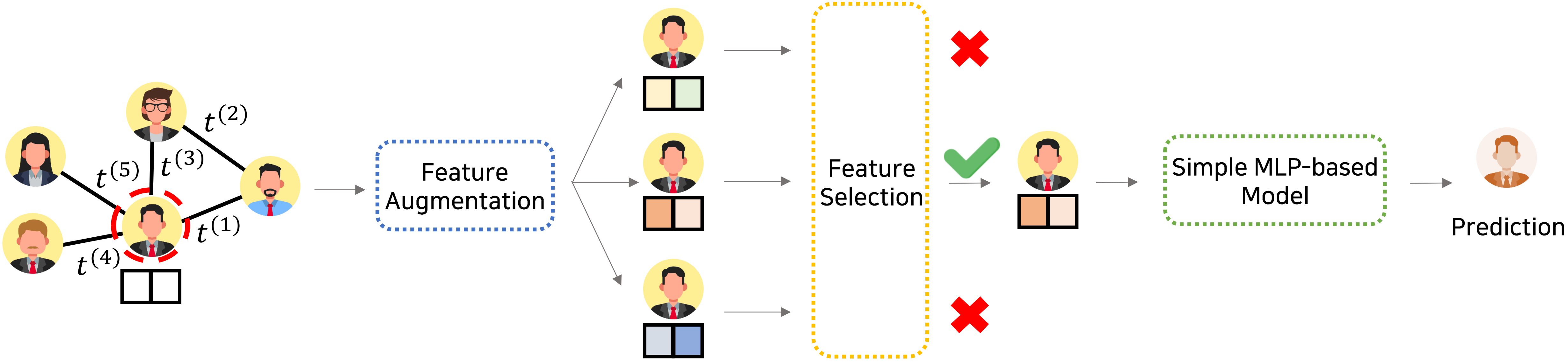
Proposed Method: SPALSH

Simple node Property prediction via representation Learning with Augmented features under distribution SHifts

- Effective in predicting node properties using proposed augmented node features
- Accurately and efficiently select the proper feature augmentation schemes
- Lightweight MLP-based model that is highly efficient and robust under distribution shifts

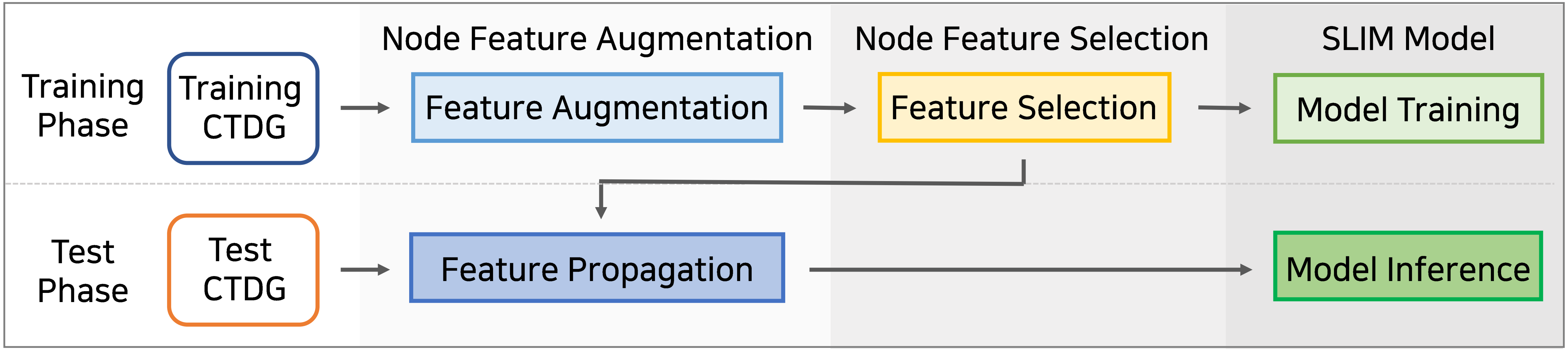


Overview of SPLASH

(1) Node Feature Augmentation

(2) Node Feature Selection

(3) SLIM Model (Our Proposed TGNN Model)



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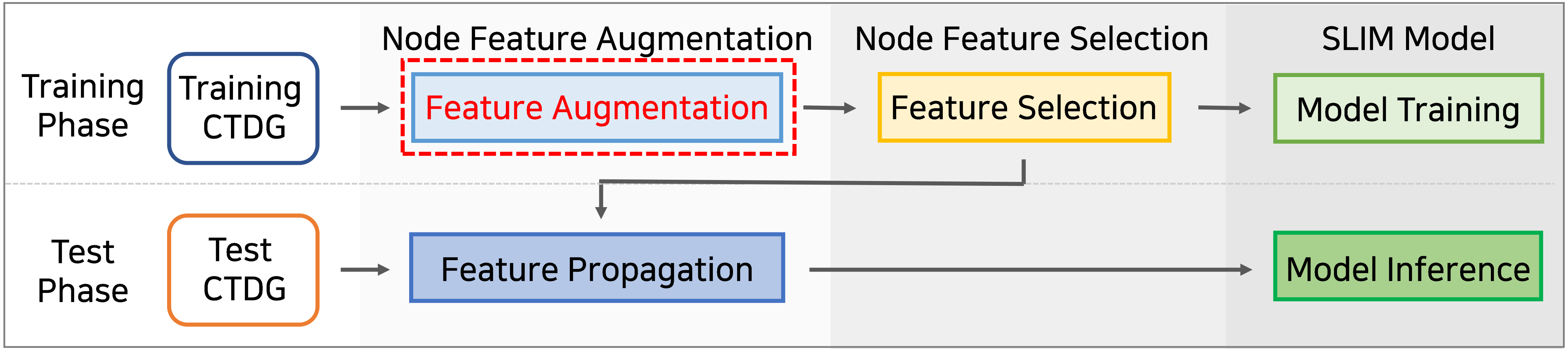
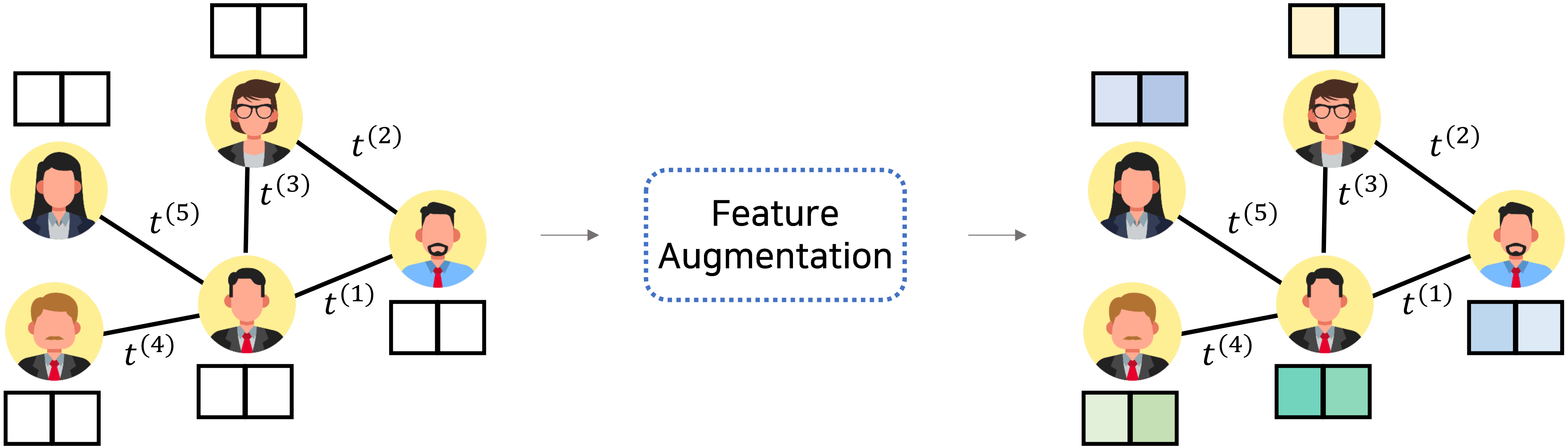


Feature Augmentation (Training Phase)

Goal: to augment the node features of seen nodes within the training graph

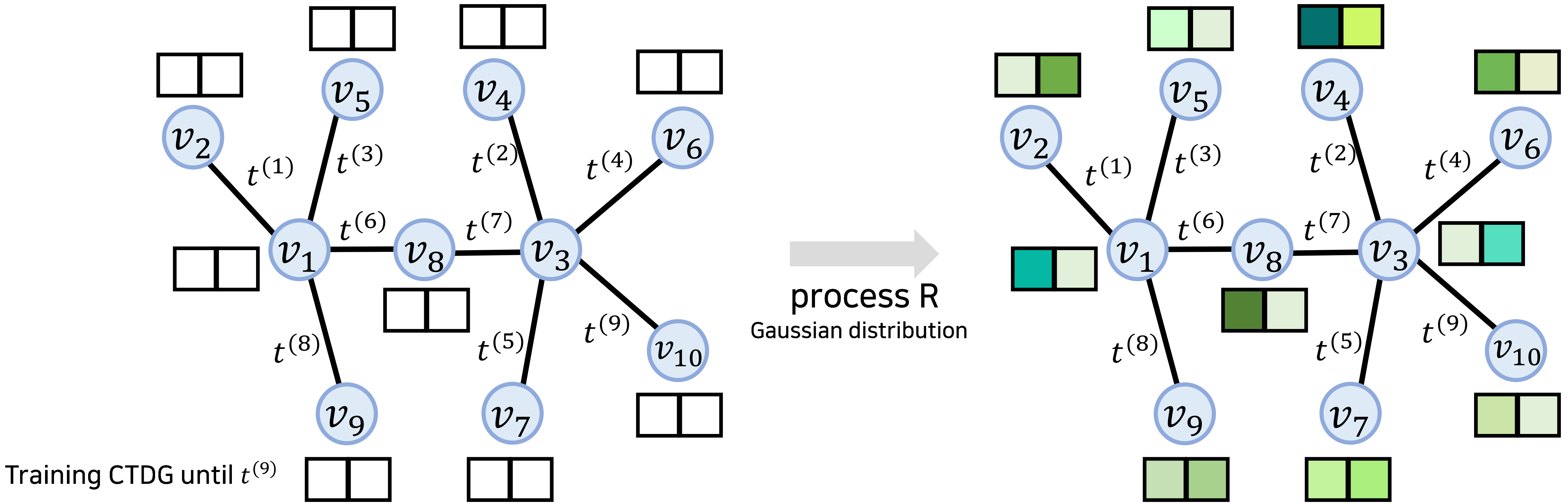

: Seen Nodes



Feature Augmentation (Training Phase)

Random Feature Augmentation

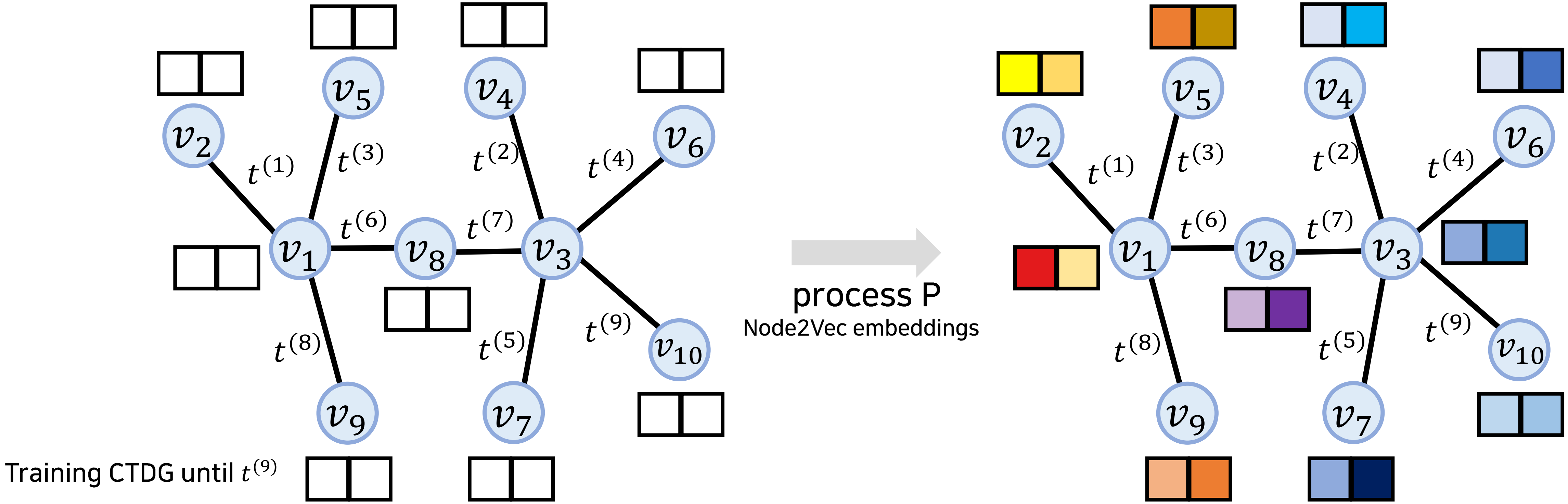
- This process aims to encode stable and absolute positions of seen nodes



Feature Augmentation (Training Phase)

Positional Feature Augmentation

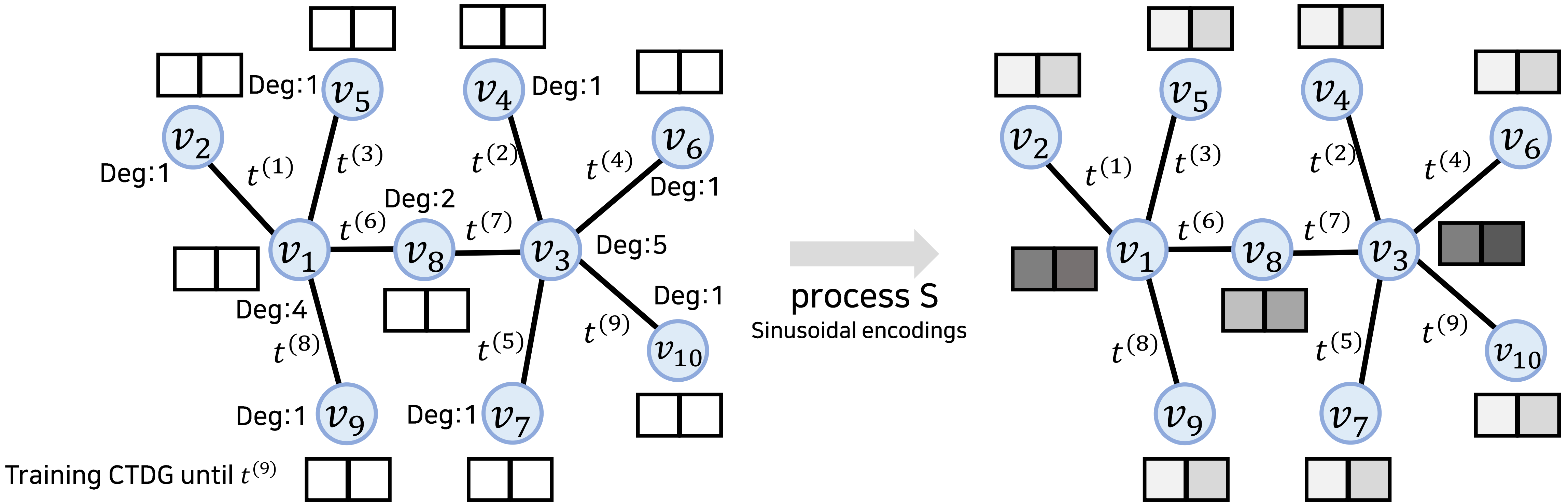
- This process aims to encode stable and relative positions of seen nodes



Feature Augmentation (Training Phase)

Structural Feature Augmentation

- This process aims to encode dynamic structural patterns of seen nodes



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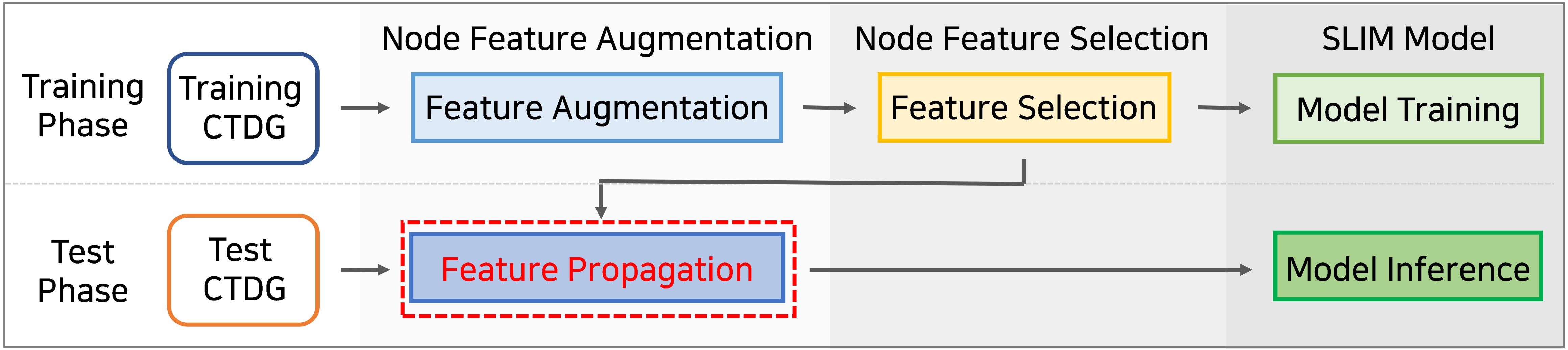
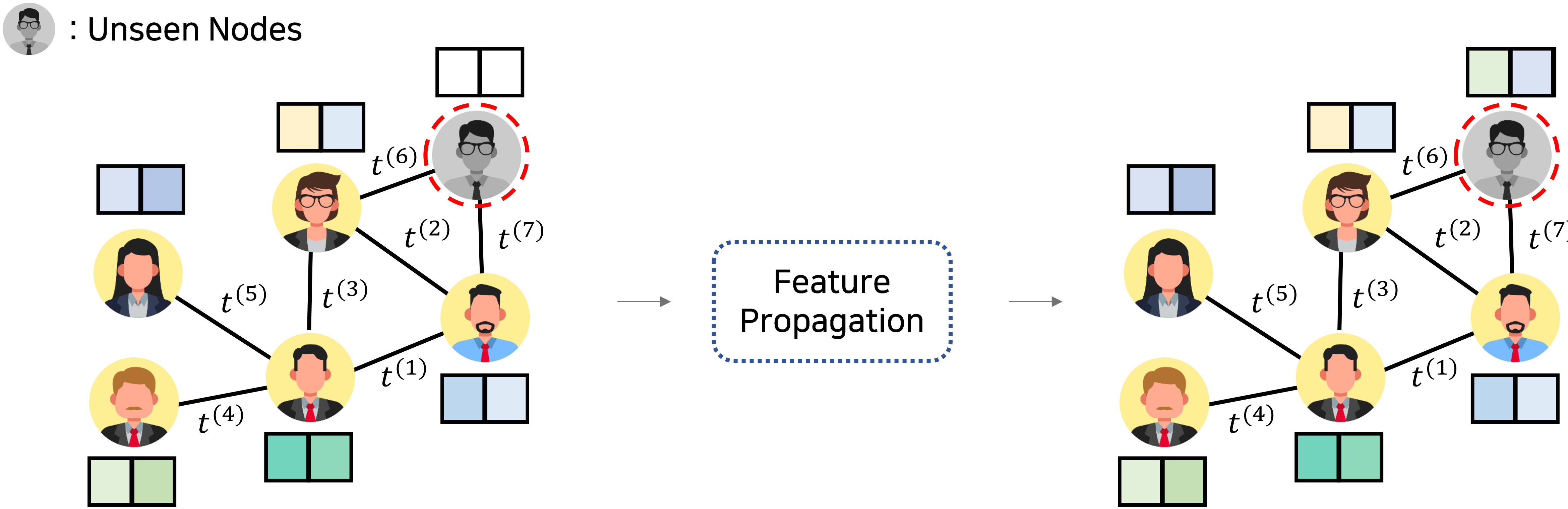


Feature Propagation (Test Phase)

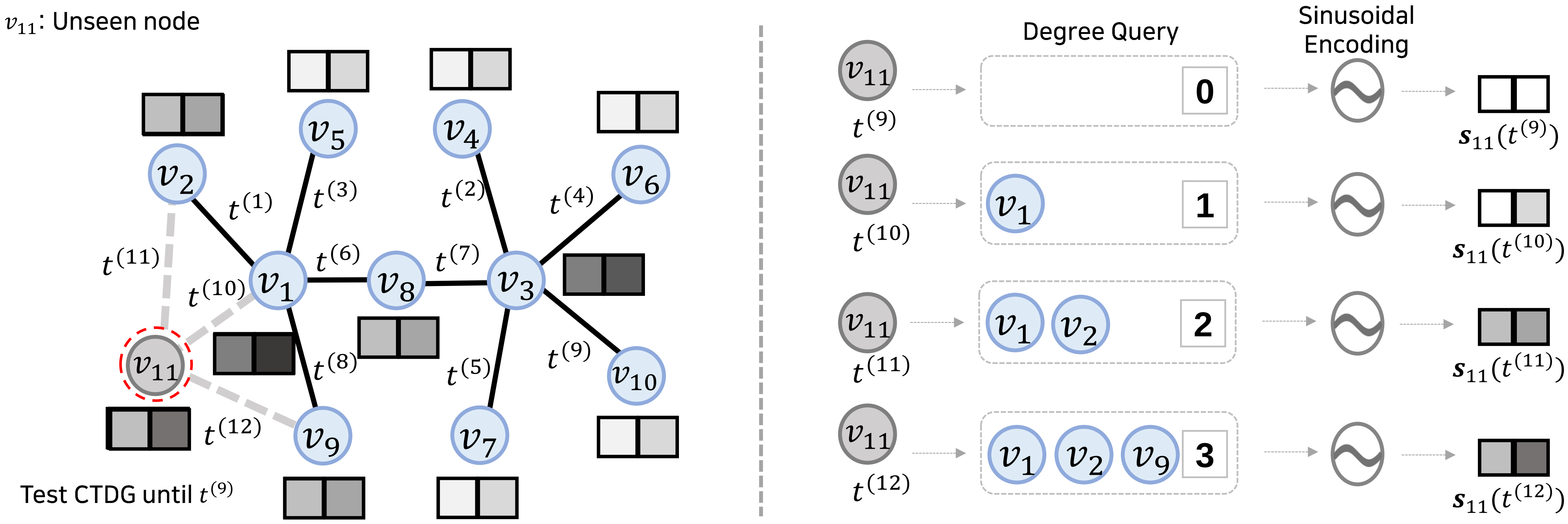
Goal: to generate the node features of unseen nodes in the test phase



Feature Propagation (Test Phase)

Structural Feature Augmentation for Unseen Nodes

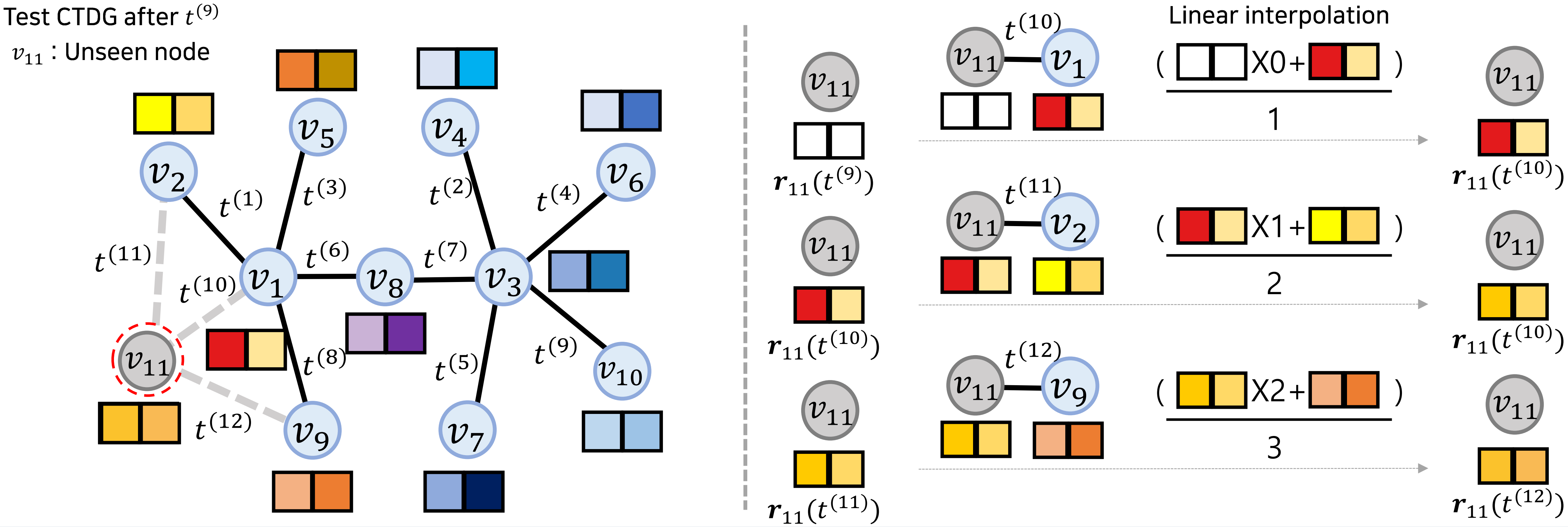
- The same process S used in the training phase is applied to unseen nodes



Feature Propagation (Test Phase)

Positional Feature Augmentation for Unseen Nodes

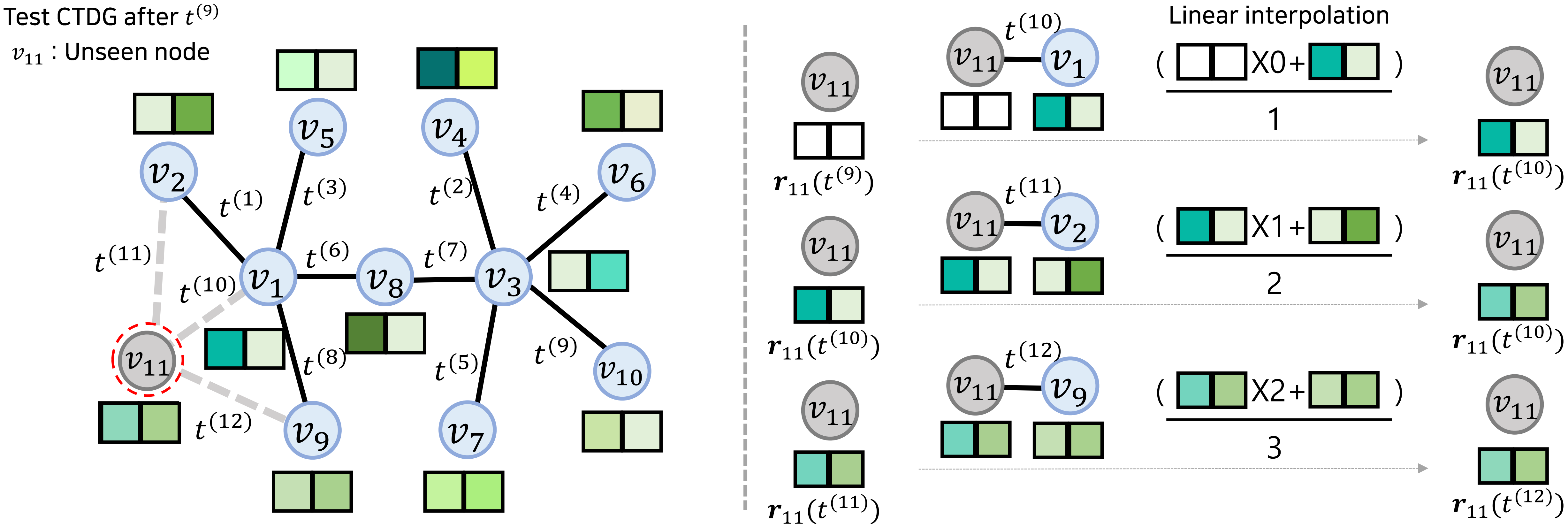
- This process aims to represent the node feature for the unseen node using a simple linear interpolation of neighboring nodes' features



Feature Propagation (Test Phase)

Random Feature Augmentation for Unseen Nodes

- As the random features assigned to unseen nodes cannot be trained, the same linear interpolation is used instead for unseen nodes



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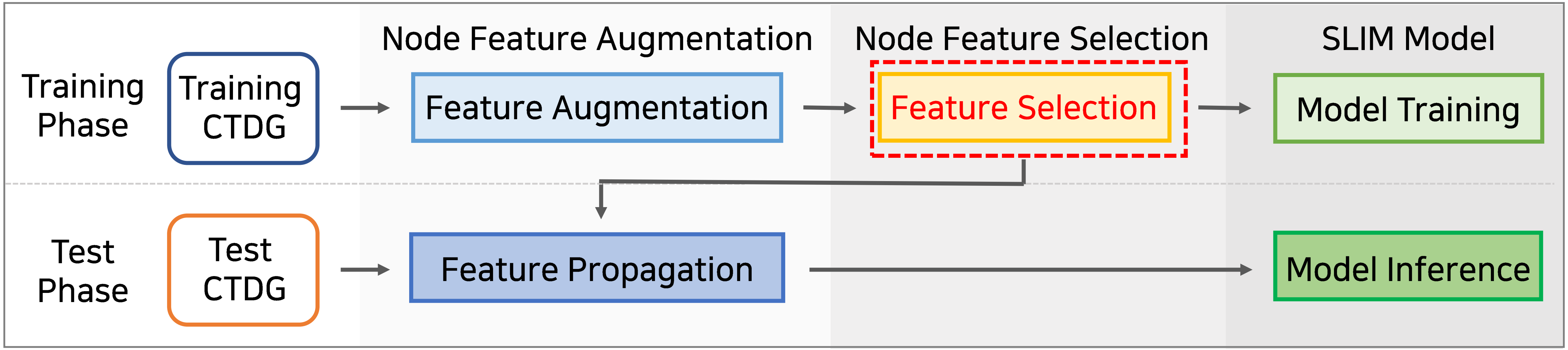
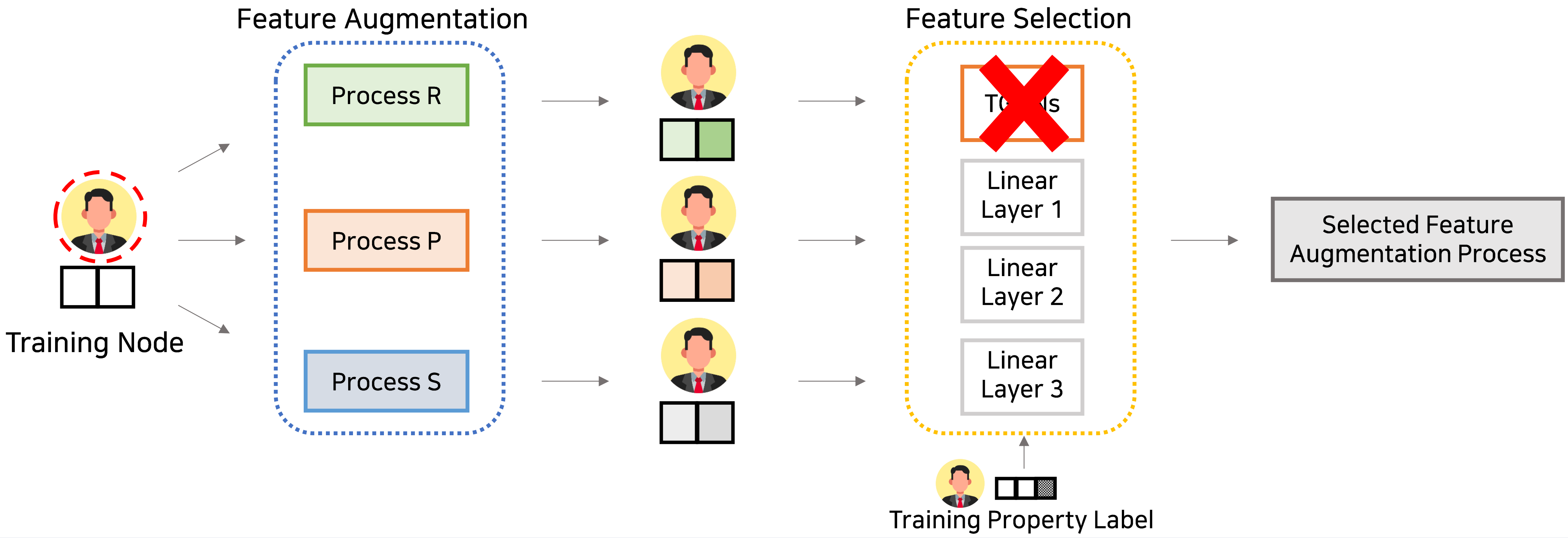


Node Feature Selection

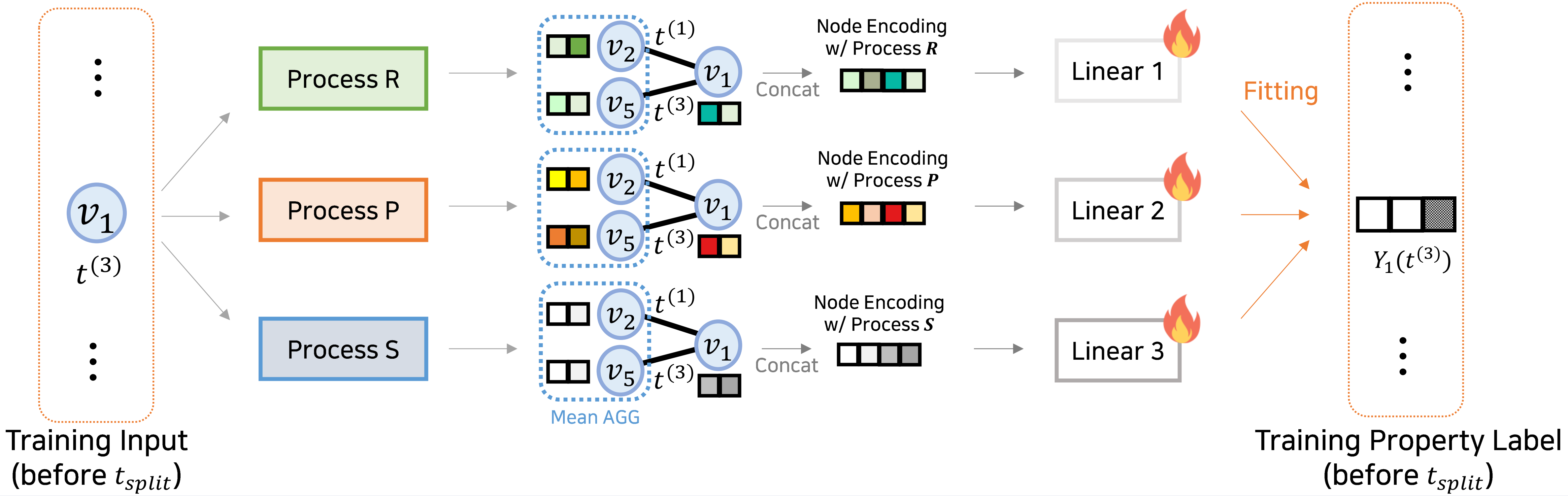
Goal: to efficiently identify a feature augmentation process that is effective for property label prediction



Node Feature Selection

Fitting with Node Encodings

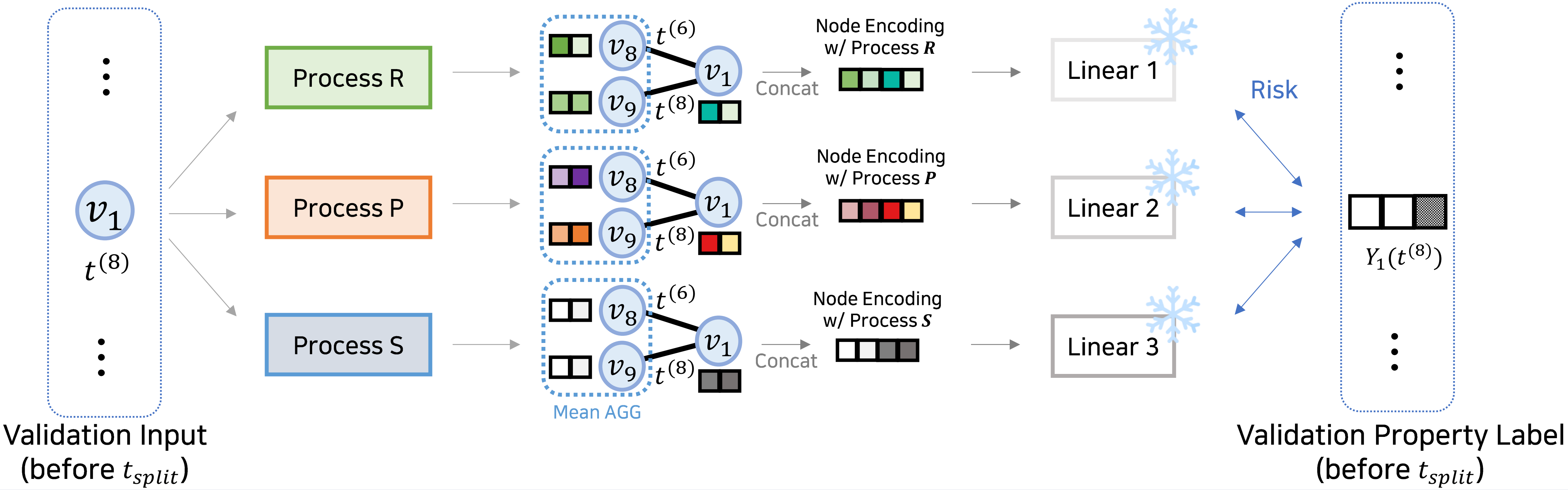
- Each augmentation process generates node encodings using recent neighbors, followed by training the corresponding linear model to fit the property labels



Node Feature Selection

Evaluation Using the Validation Set

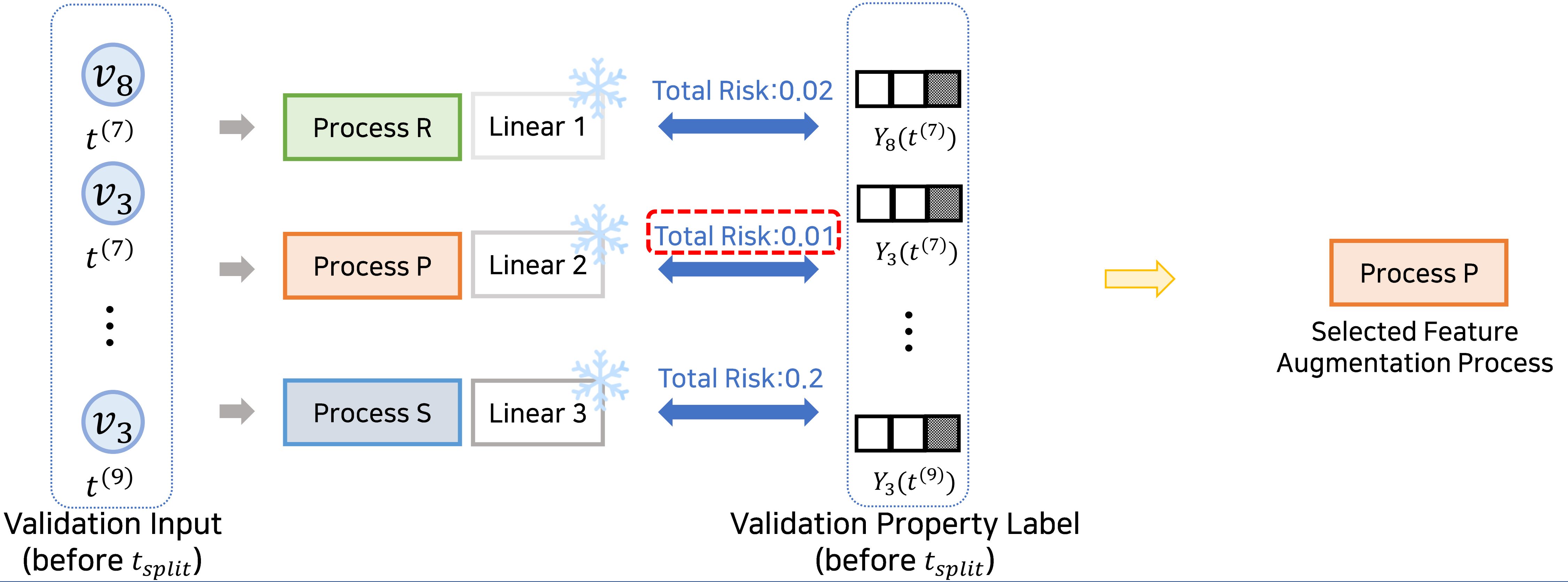
- The risk of each augmentation process with the trained linear model is evaluated on the validation set



Node Feature Selection

Augmentation Process Selection

- The feature augmentation process with the lowest sum of risks on the validation set is selected



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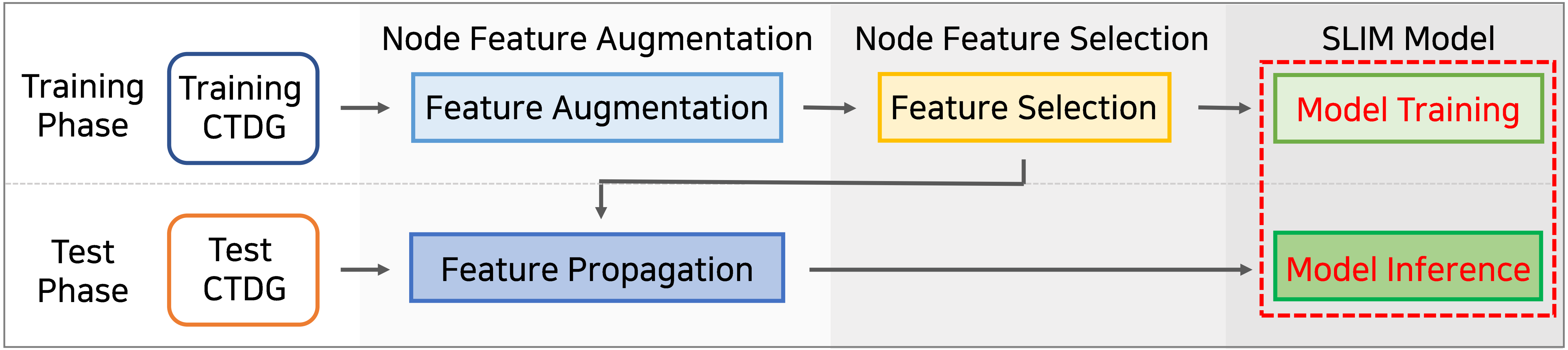
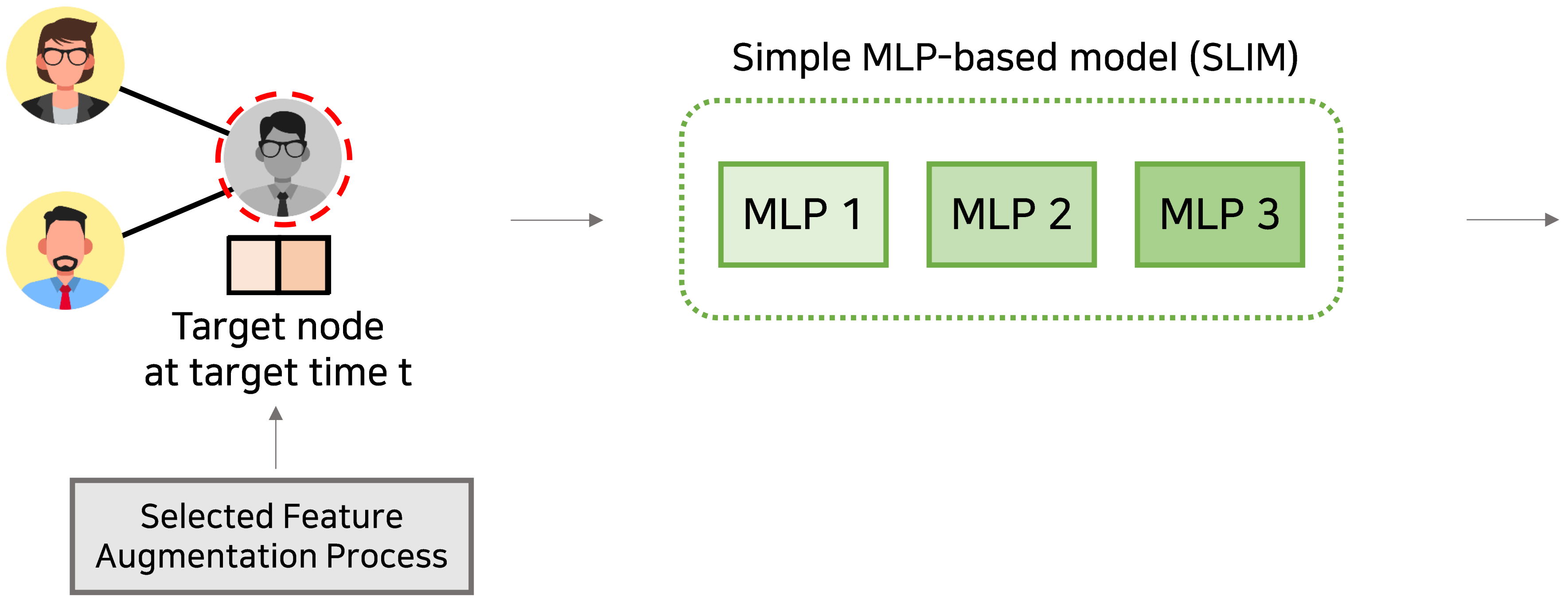


SLIM Model

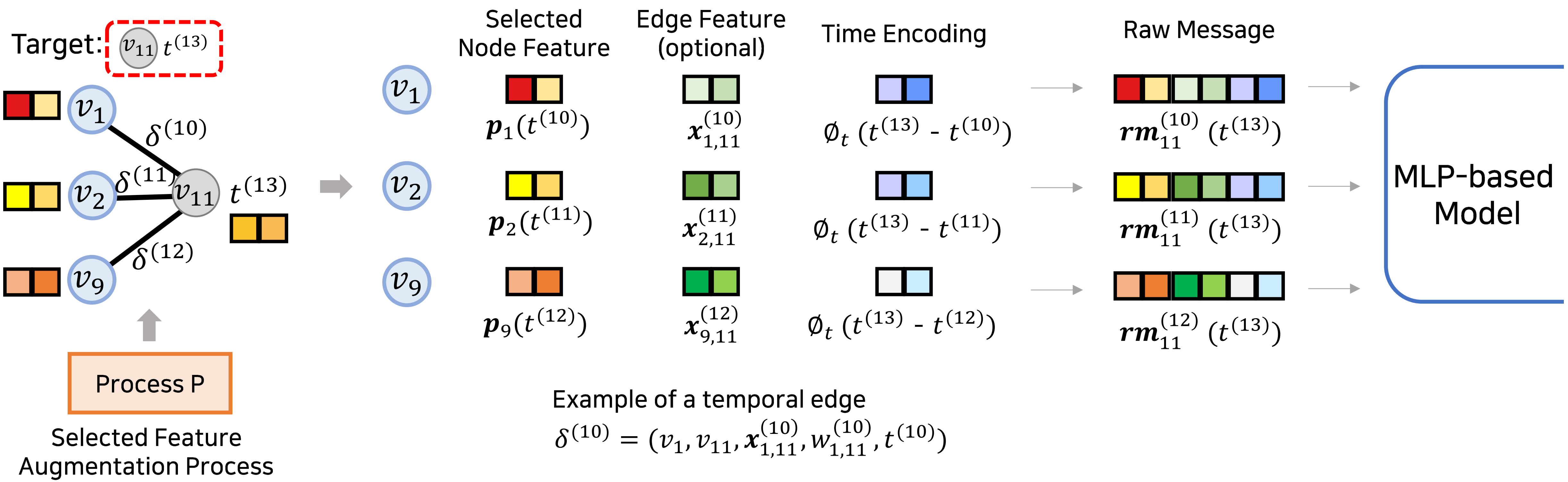
Goal: to efficiently and effectively predict node properties using a simple MLP-based model with augmented node features



SLIM Model

Message Encoding Module

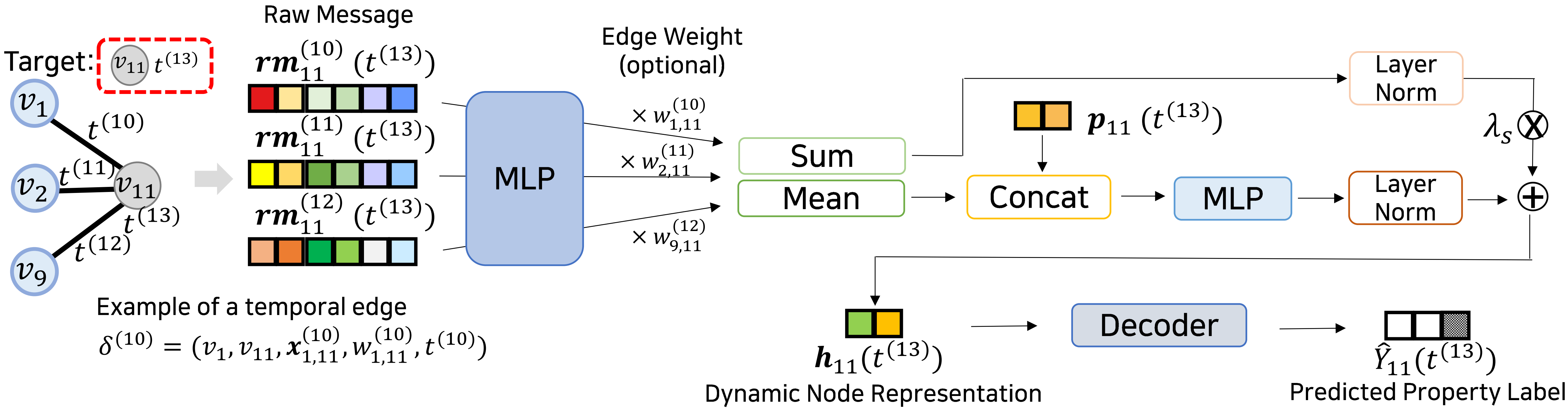
- SLIM first generates messages from recent temporal edges using selected augmentation process and MLPs



SLIM Model

Proposed SLIM Model Architecture

- SLIM computes the latest representation of a given target node by aggregating the messages in the previous module and predicts its property label



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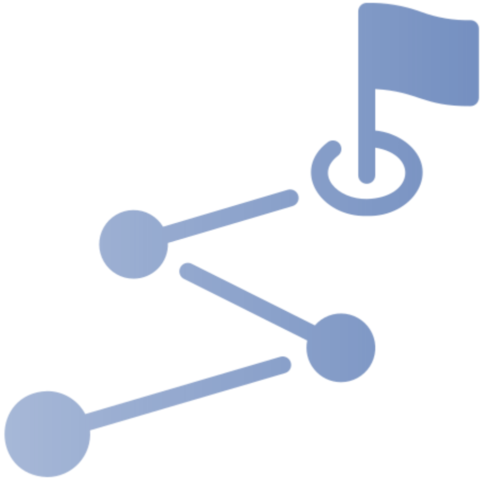


Research Questions

RQ1) Accuracy & Generalization

- ✓ How accurately does SPLASH predict node properties under distribution shifts?

RQ2) Efficiency & Scalability

- ✓ How efficient and scalable is SPLASH?

RQ3) Qualitative Analysis

- ✓ Does SPLASH outperform other baselines in qualitative evaluation?

Experimental Settings

Datasets

- ✓ 3 social networks (Wikipedia, Reddit, MOOC) for dynamic anomaly detection
- ✓ Email network (Email-EU) and event network (GDELT) for dynamic node classification
- ✓ Trade network (tgbn-trade) and music platform network (tgbn-genre) for node affinity prediction

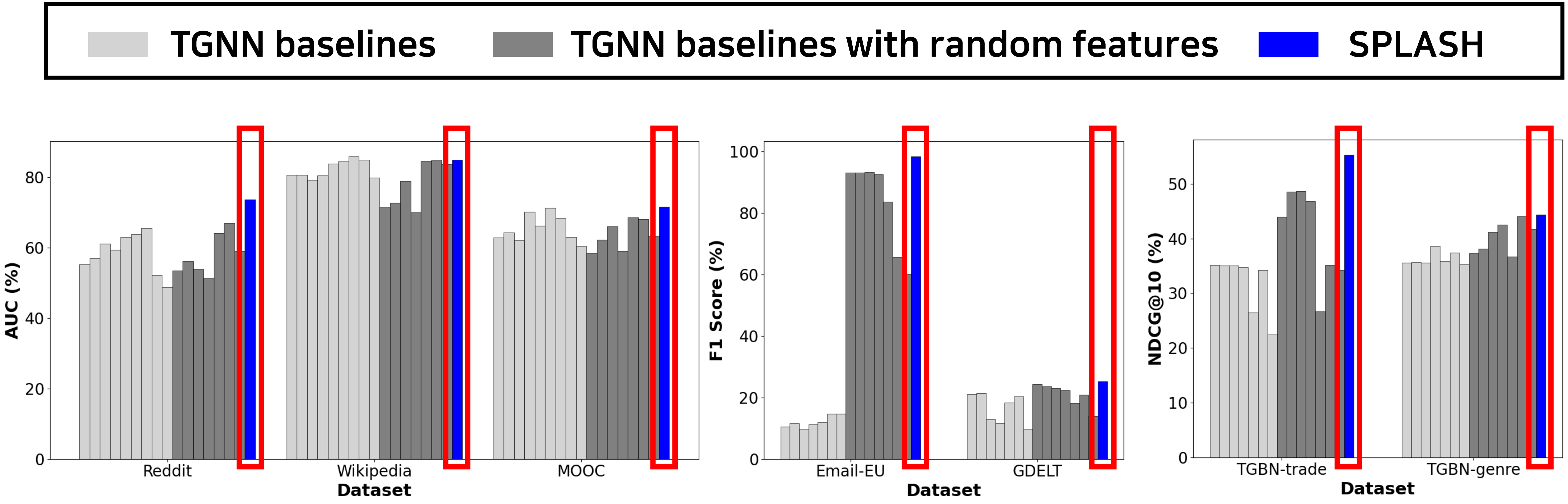
Baselines

- ✓ 8 TGNNs: JODIE, DySAT, TGAT, TGN, GraphMixer, DyGFormer, FreeDyG, SLADE
- ✓ 8 TGNNs with random features: JODIE+RF, DySAT+RF, TGAT+RF, TGN+RF, GraphMixer+RF, DyGFormer+RF, FreeDyG+RF, SLADE+RF

RQ1) Accuracy & Generalization

SPLASH outperforms other baselines in node property prediction

- Including TGNNs without node features and TGNNs using random features

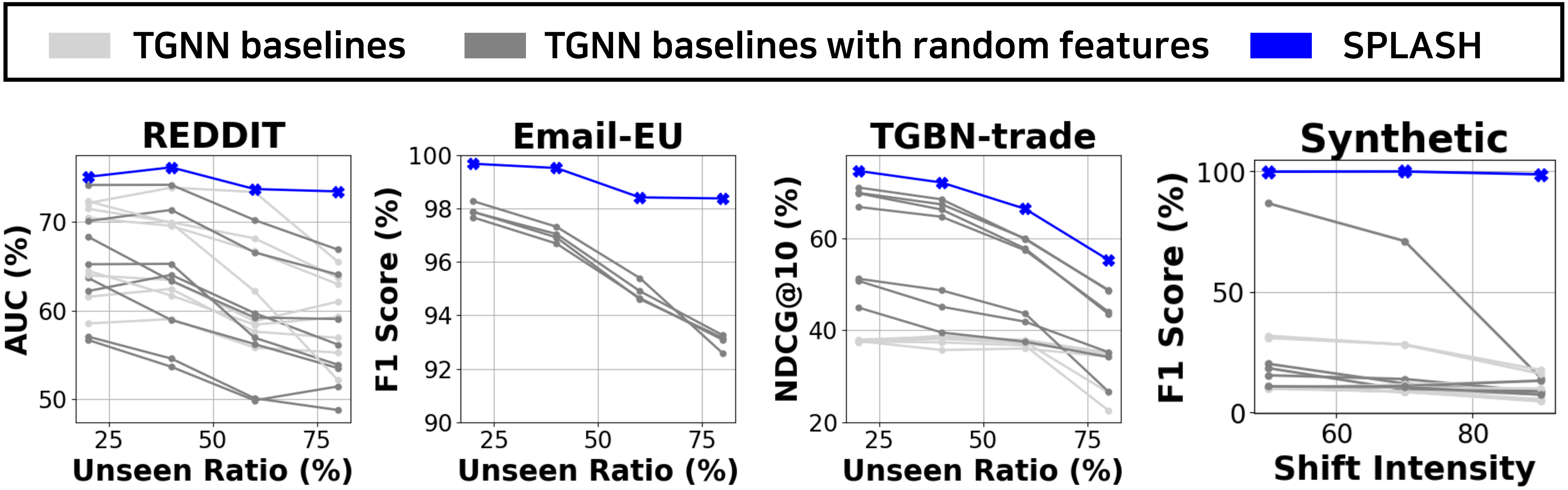


Dynamic anomaly detection Dynamic node classification Node affinity prediction

RQ1) Accuracy & Generalization

SPLASH shows better generalization capabilities compared to other baselines

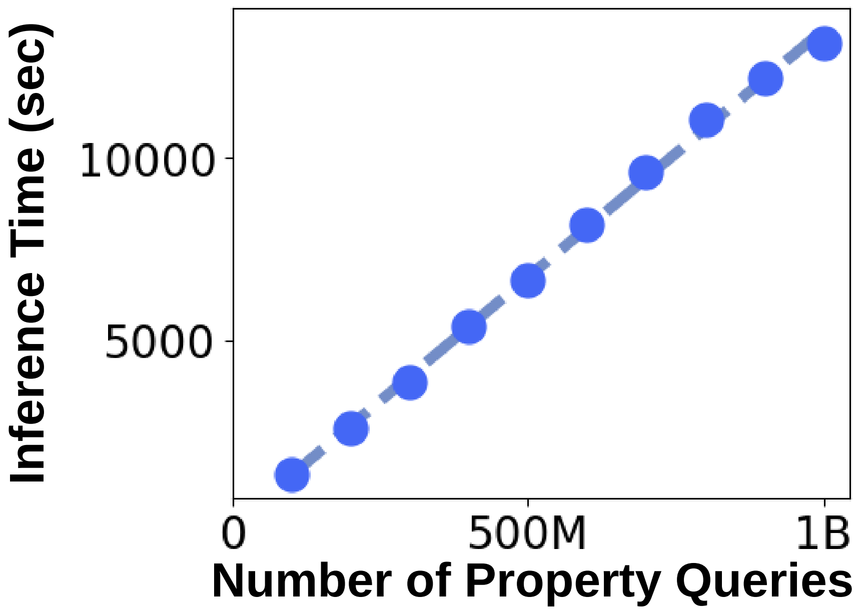
- As the distribution shift becomes more severe, the performance gap widens

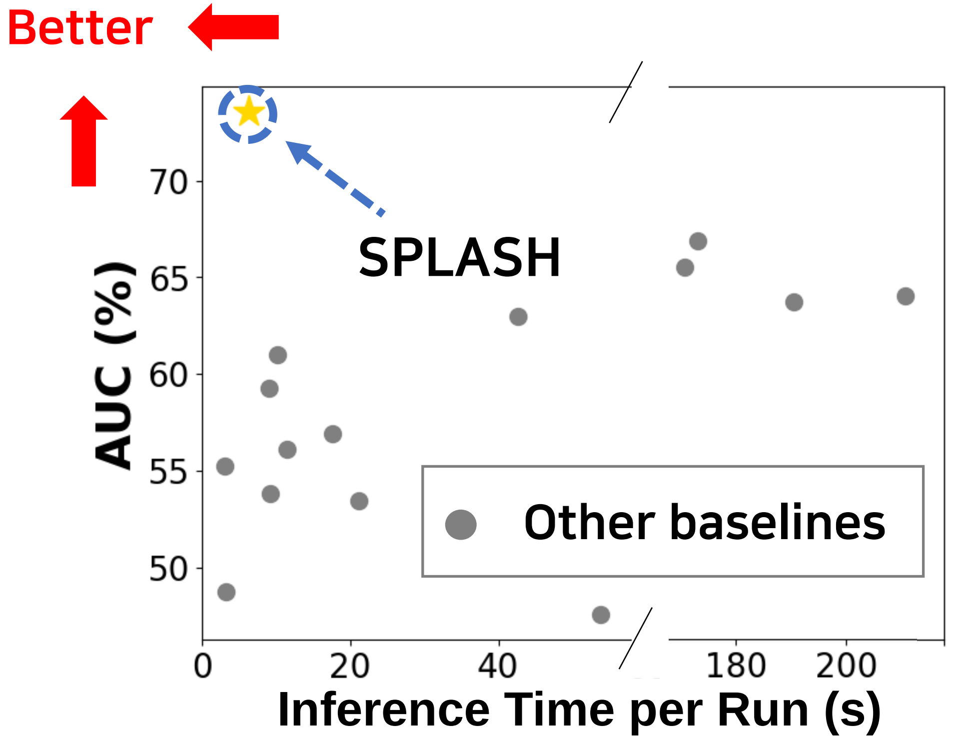


RQ2) Efficiency & Scalability

SPLASH enables efficient and scalable node property prediction

- Maintains a constant inference time per property query regardless of graph size
- Offers the best trade-off between performance and inference time

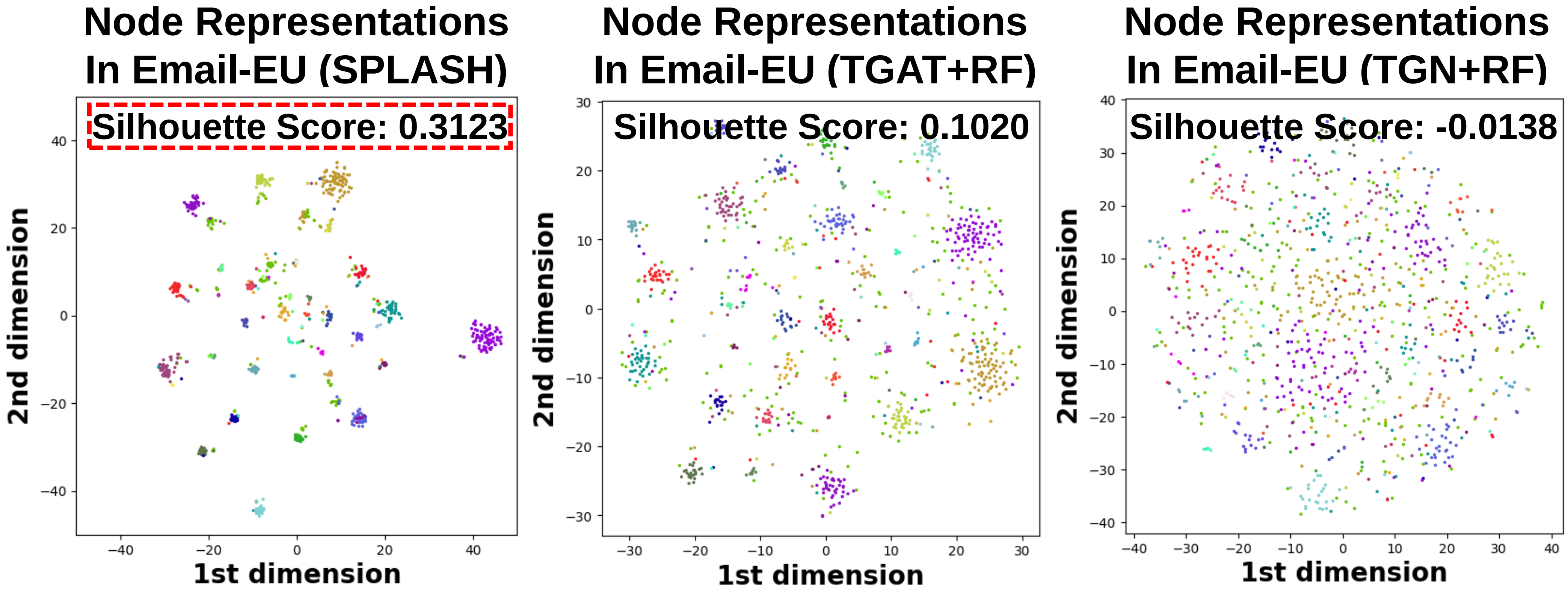




RQ3) Qualitative Analysis

SPLASH shows qualitatively better performance than other baselines

- In the Email EU dataset, which has a static class property, SPLASH generates the most cohesive clusters for each class compared to other baselines



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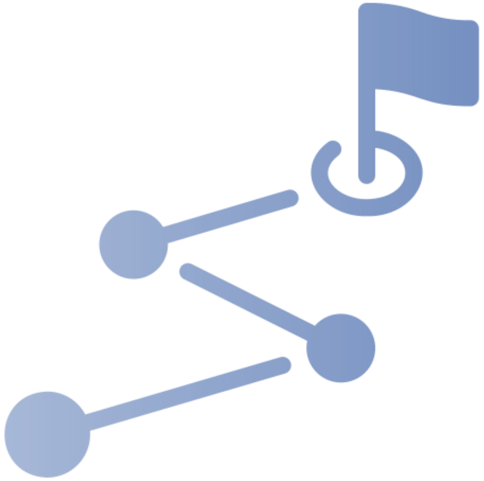

Conclusion

Github: https://github.com/jhsk777/SPLASH

- We propose SPLASH, a simple yet effective method for node property prediction in edge streams under distribution shifts
  - ✓ Fast & Lightweight: SPLASH uses only MLP layers, enabling fast inference
  - ✓ Effective: SPLASH outperforms other baselines in node property prediction
  - ✓ Robust: SPLASH shows the smallest performance drop as the distribution shift intensifies