

Domain Knowledge Augmented Contrastive Learning on Dynamic Hypergraphs for Improved Health Risk Prediction

Akash Choudhuri, Hieu Vu, Kishlay Jha, Bijaya Adhikari

University of Iowa

Overview

- Motivation
- Problem Formulation
- Our Approach
- Experiments
- Conclusion

Patient Risks in Hospitals

- In 2022, there were 6,120 hospitals in the US with 33,679,935 admissions^[1]
- Patients admitted to hospitals have several risks:
 - Risk of getting Healthcare Associated Infections (HAIs)
 - Risk of Medication/ diagnosis errors
 - Risk of worsening physical health leading to admission in critical care units
- **This risks sometimes even lead to death!**



[1] <https://www.aha.org/statistics/fast-facts-us-hospitals>

How big are the costs?

- Patient risks are costly:
 - About 4% of patients in the US are diagnosed with an infection during their hospitalization^[1]
 - ICU costs per day in 2010 were estimated to be \$4300, a 61% increase since the 2000 cost per day of \$2669^[2]
- In the 2021 annual report published by CDC^[3], acute care hospitals in USA have:
 - **14%** increase in MRSA cases
 - **12%** increase in ventilator-associated events
 - **11%** increase in surgical site infections following abdominal hysterectomy
- **Forecasting these risks before they take place is crucial to prevent them**

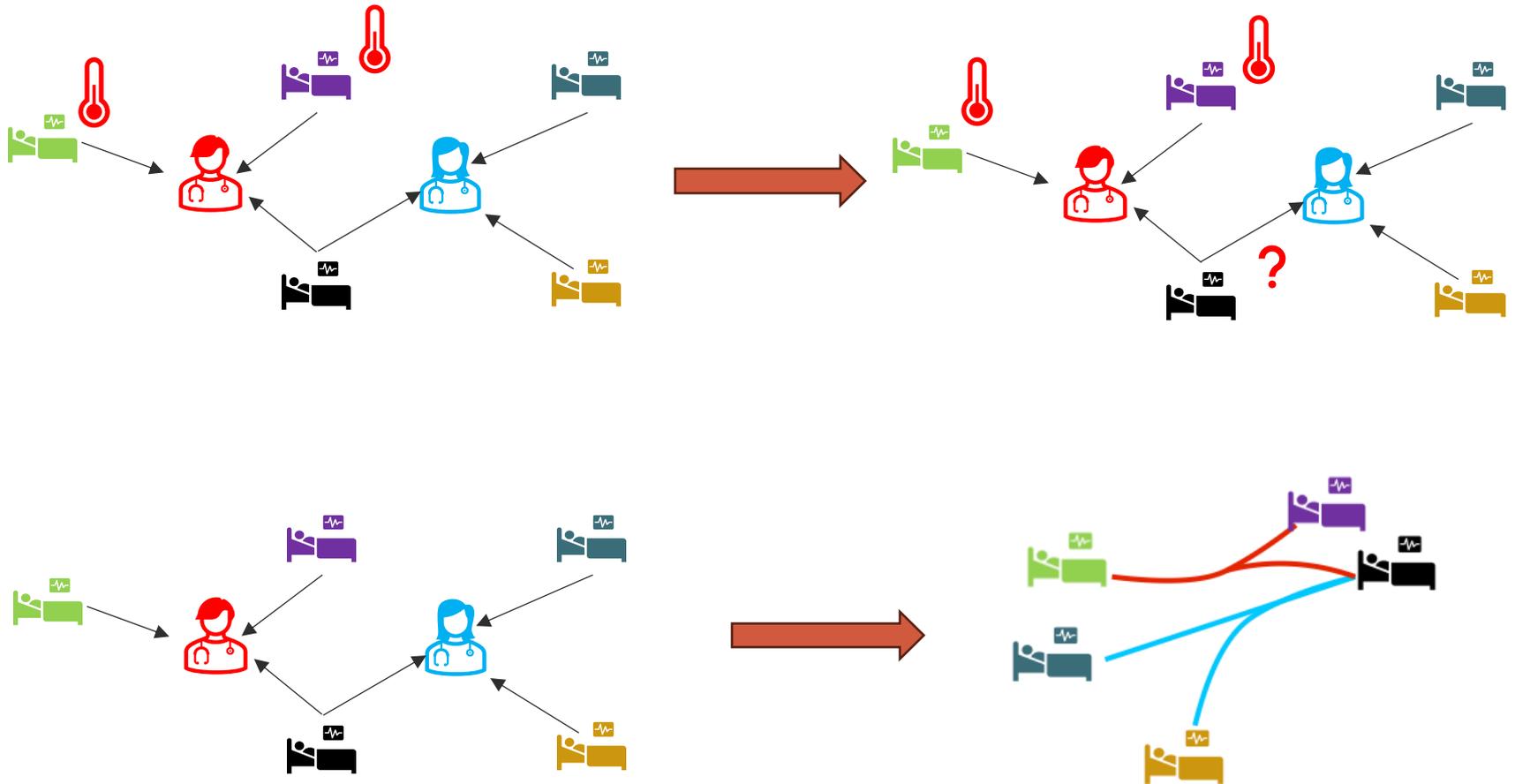


[1] Magill, Shelley S., et al. "Multistate point-prevalence survey of health care-associated infections." *New England Journal of Medicine* 370.13 (2014): 1198-1208.

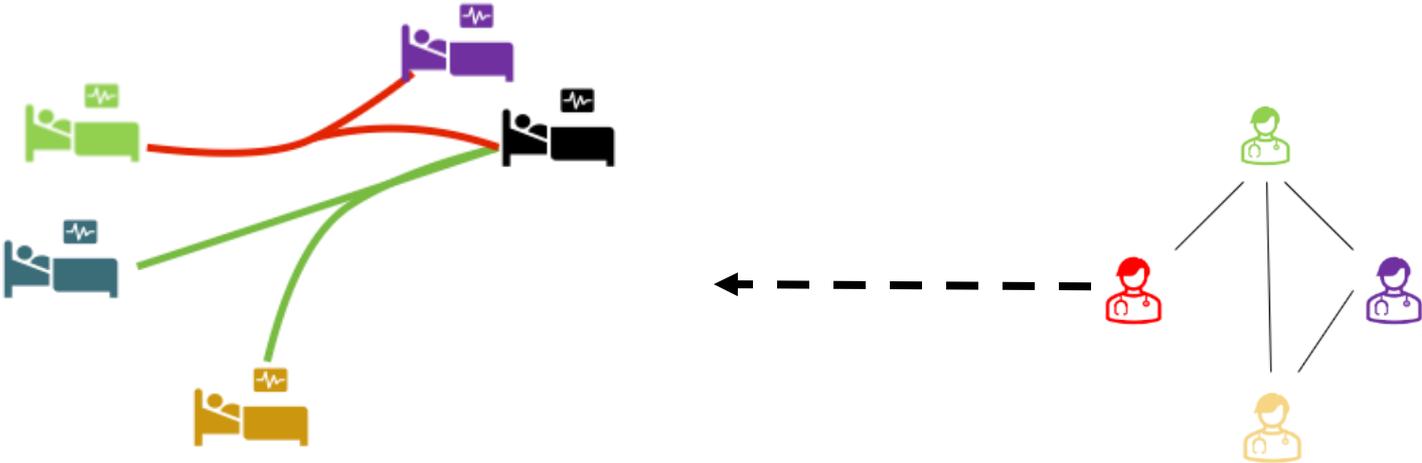
[2] <https://sccm.org/communications/critical-care-statistics>

[3] <https://www.aha.org/news/headline/2022-11-11-cdc-reports-increase-certain-health-care-associated-infections-2021>

Interactions are helpful for Risk Estimation



Incorporating Domain Knowledge

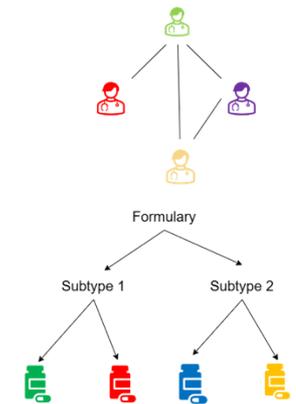
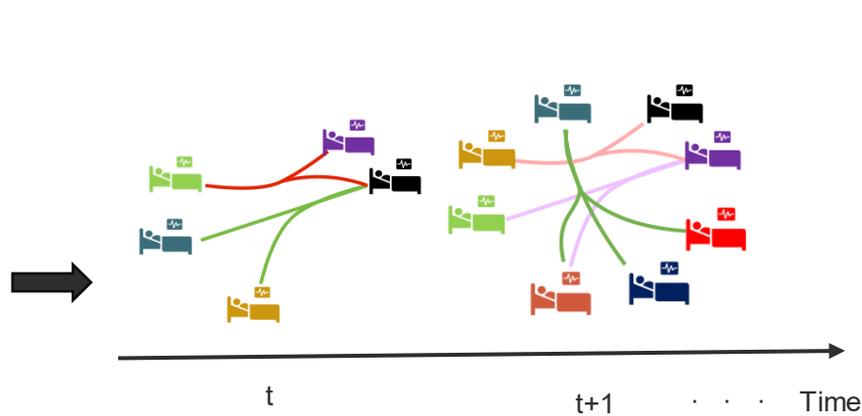


Overview

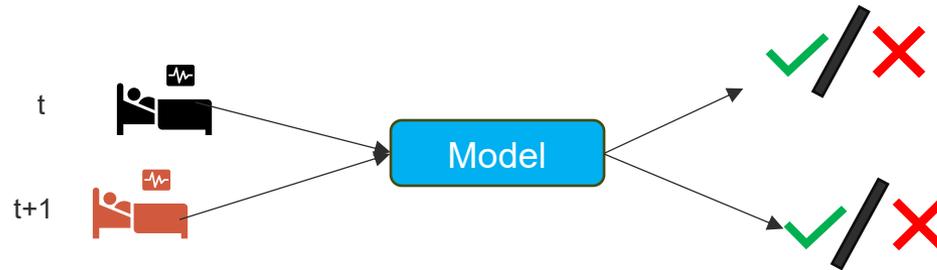
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Problem Formulation

Given:



Learn:



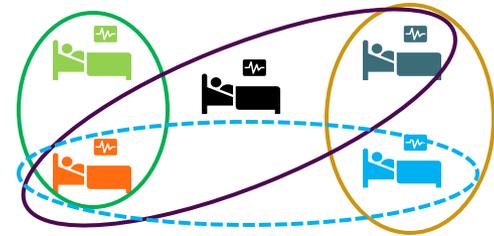
Such That:

A loss function is minimized:

- Across all labeled patients
- Across training timestamps

Challenges

- Missing Data
 - Interaction data is granular
 - Need for robust method
- Alignment to domain knowledge
- Temporal dependencies
 - Patient risk evolves over time
 - The effects of certain interactions are visible later



Existing Works

- **Clinical Literature:**
 - Do not account for high-order interactions^[1]
 - Do not use contact-based interactions ^[2,3]
- **ML Methods:**^[4]
 - Randomly deletes interaction patterns for contrastive augmentations
 - Introduces harmful noise

[1] Oh, Jeeheh, et al. "A generalizable, data-driven approach to predict daily risk of Clostridium difficile infection at two large academic health centers." *infection control & hospital epidemiology* 39.4 (2018): 425-433.

[2] Xu, Ran, et al. "Hypergraph transformers for ehr-based clinical predictions." *AMIA Summits on Translational Science Proceedings* 2023 (2023): 582.

[3] Xu, Ran, et al. "Counterfactual and factual reasoning over hypergraphs for interpretable clinical predictions on ehr." *Machine Learning for Health*. PMLR, 2022.

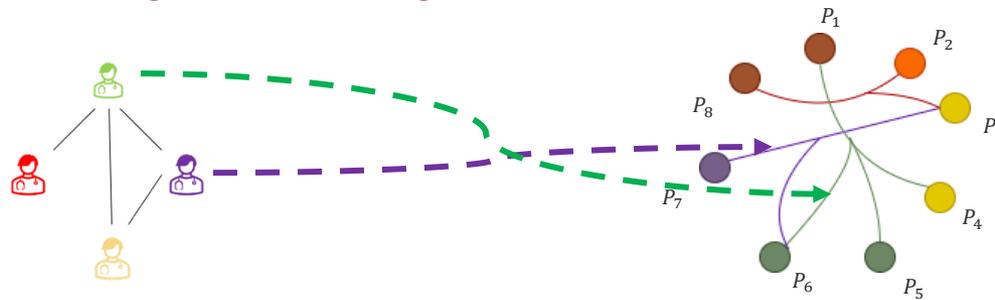
[4] Ma, Tianyi, et al. "Hypergraph contrastive learning for drug trafficking community detection." *2023 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2023.

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Our Ideas

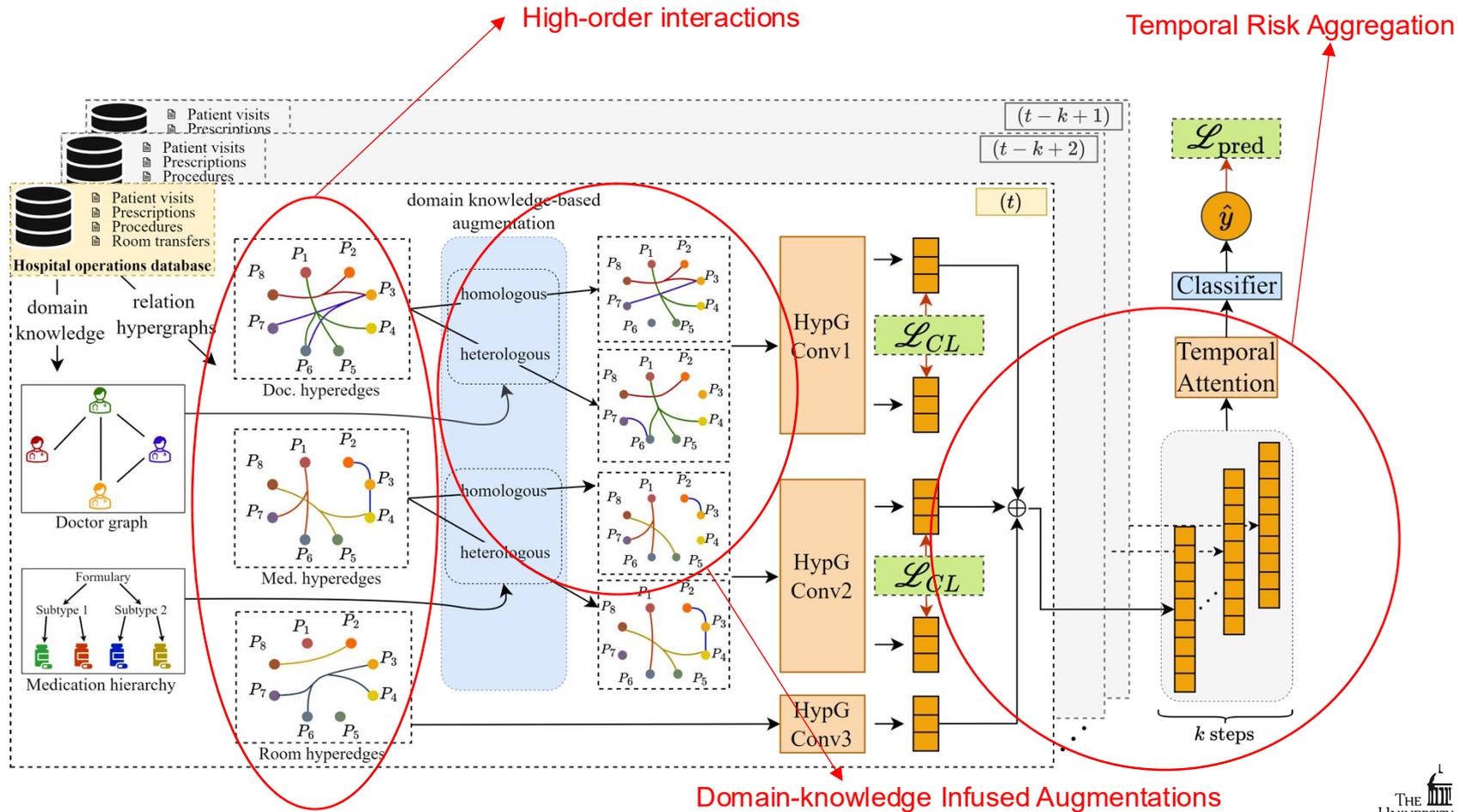
- Domain-Knowledge Infused Augmentations



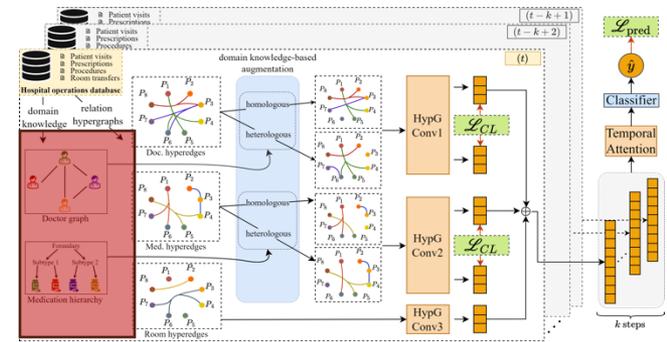
- Temporal Aggregation of Risk



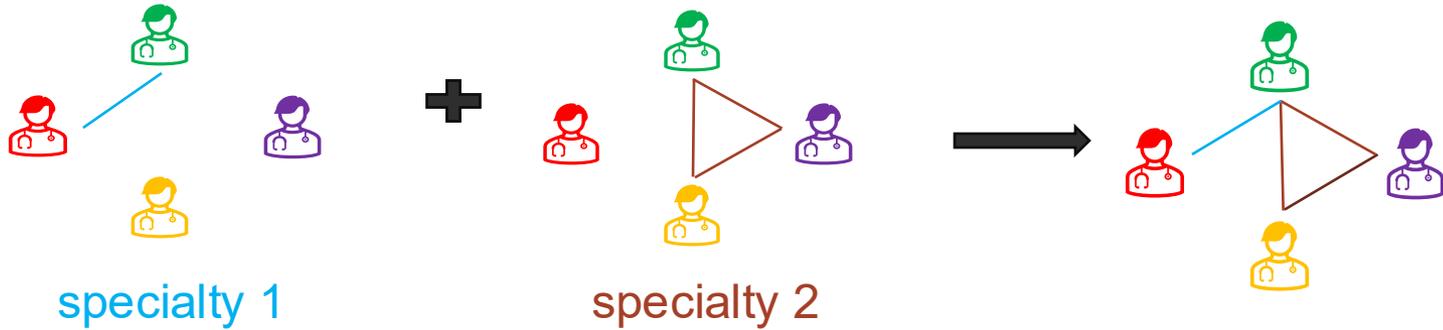
Our Approach: Overview



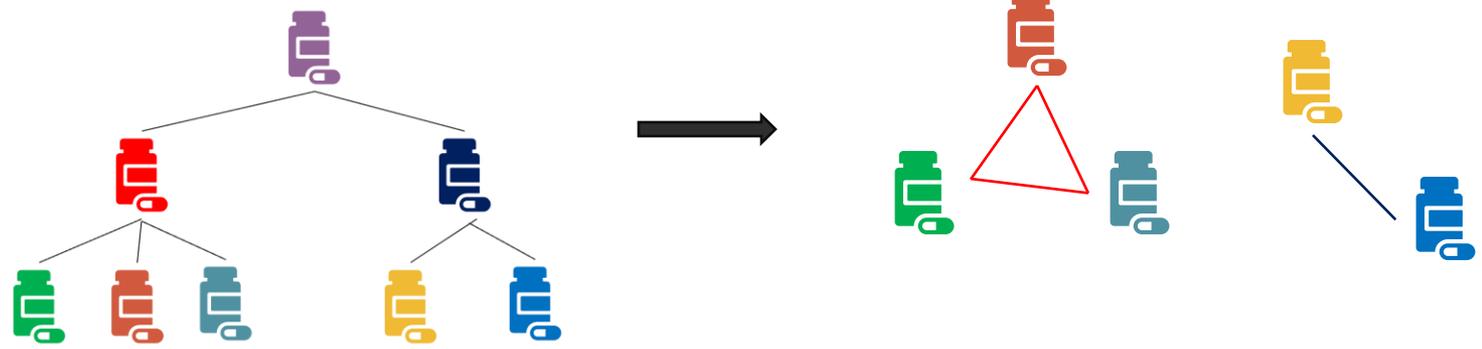
Domain Graph Construction



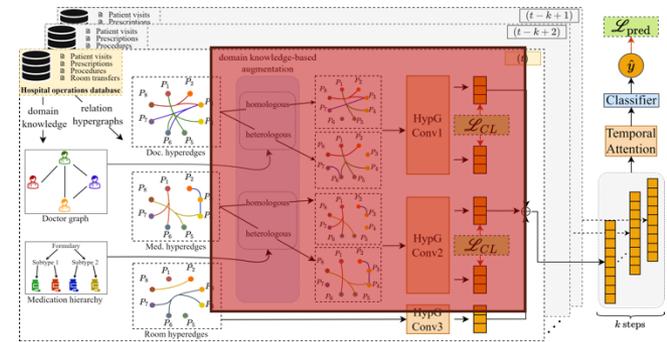
- Doctor Graph:



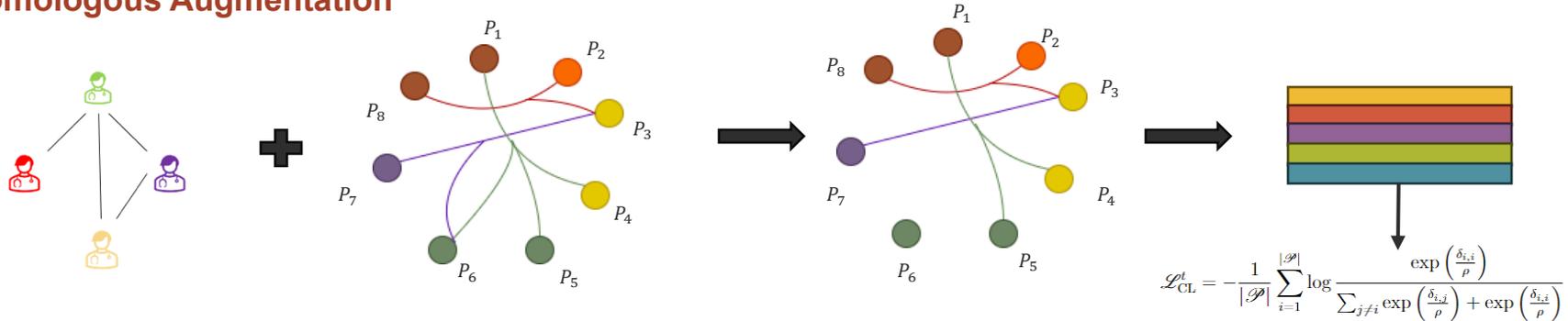
- Medication Graph:



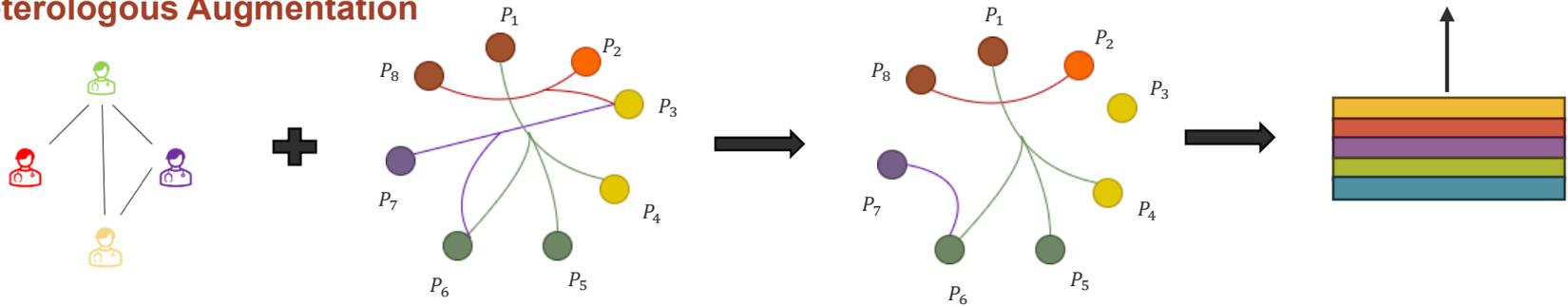
Contrastive Augmentations



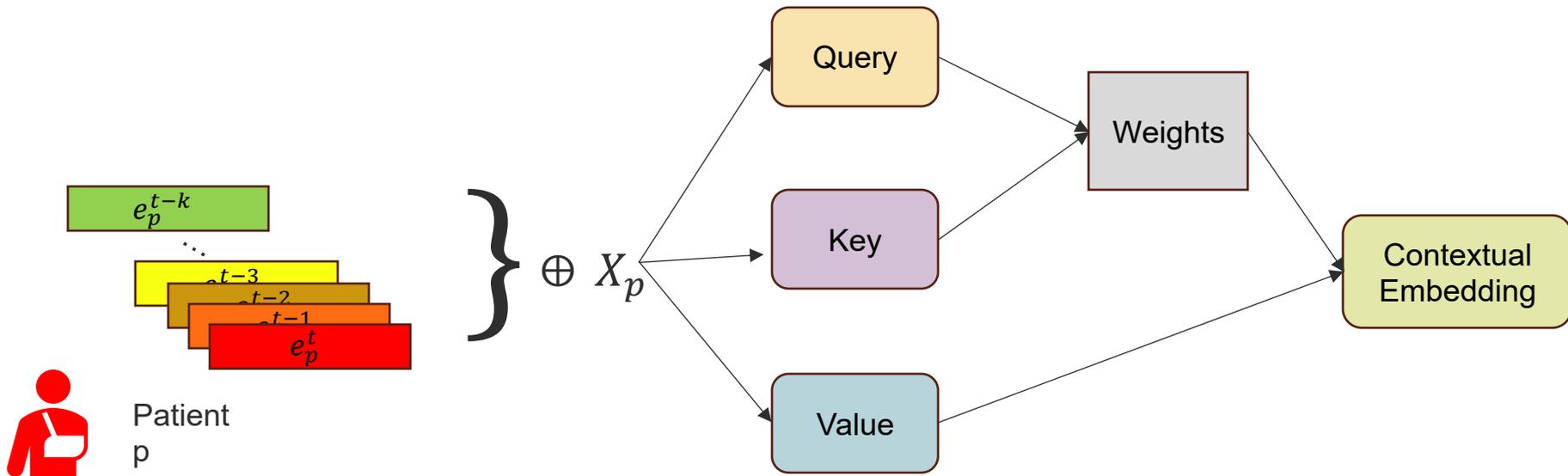
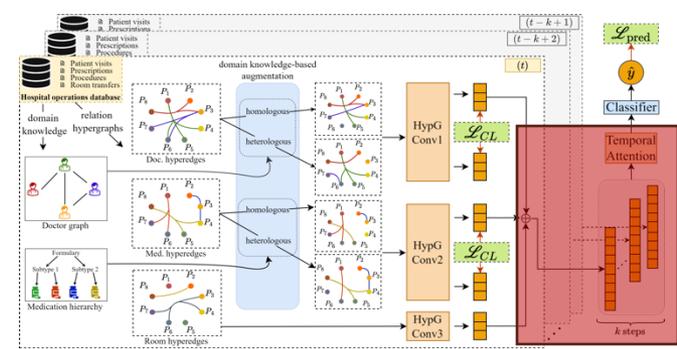
Homologous Augmentation



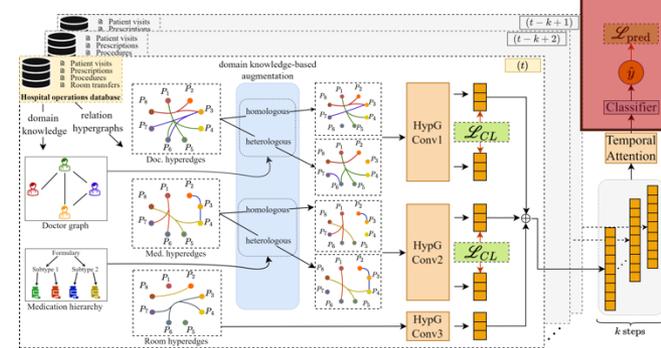
Heterologous Augmentation



Temporal Aggregation



Training



- After obtaining temporal embedding for each patient, predicted label \hat{y} is obtained by passing it through a Feed-Forward Layer
- For each binary prediction label, the loss is:

$$\mathcal{L}_{\text{pred}}^t = -[y_p^t \log(\hat{y}_p^t) + (1 - y_p^t) \log(1 - \hat{y}_p^t)]$$

- The overall objective function to be minimized over training timestamps τ is:

$$\mathcal{L} = \sum_{t \in \tau} (\gamma \mathcal{L}_{CL}^t + (1 - \gamma) \mathcal{L}_{\text{pred}}^t)$$

- We used Adaptive Moment Estimation Optimization (ADAM) algorithm for optimization

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Data

- Hospital Operations Data was obtained from:
 - The University of Iowa Hospitals and Clinics (**UIHC**)
 - Beth Israel Deaconess Medical Center (**MIMIC-IV**)
- The resultant patient-hospital interaction data statistics are:

Interaction Type	UIHC	MIMIC-IV
Patient-Doctor/HCW	23,085	8,046
Patient- Medication	349,345	34,857
Patient-Room/Unit	16,771	3,334

- Tasks:
 - CDI Incidence Prediction
 - MICU Transfer Prediction

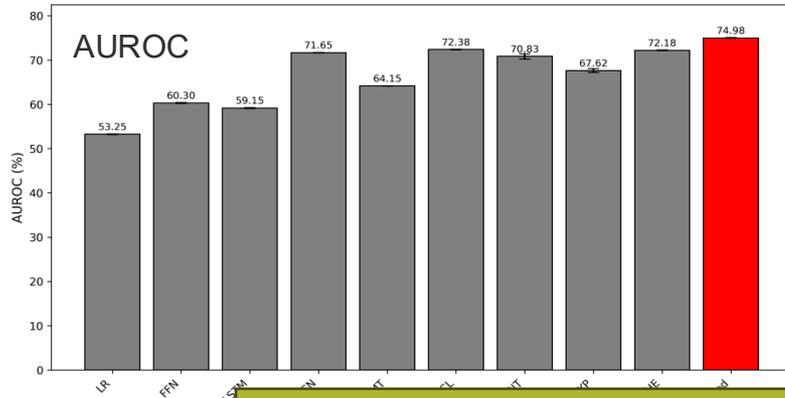
CDI Incidence Prediction

- **Clostridioides difficile infection (CDI)** is a common HAI, increasing the mortality risk of patients with weakened immune systems
- Binary Classification Problem:
 - Instance: Patient at time t and features at that time
 - Label: Binary indicator of getting infection in next 3 days^[1]
- Evaluation Metric:
 - ROC-AUC Score
 - AUPRC Score
- Averaged across 3 independent runs

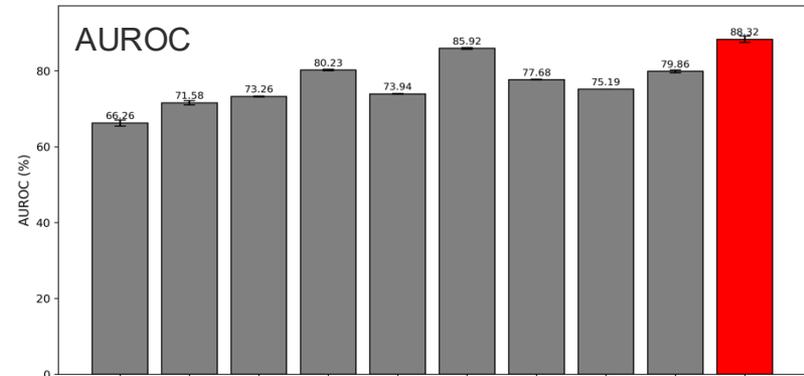


Results: CDI Incidence Prediction

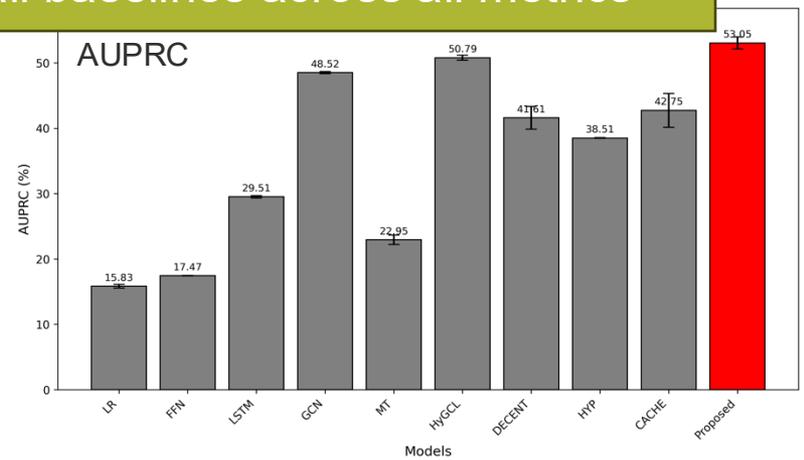
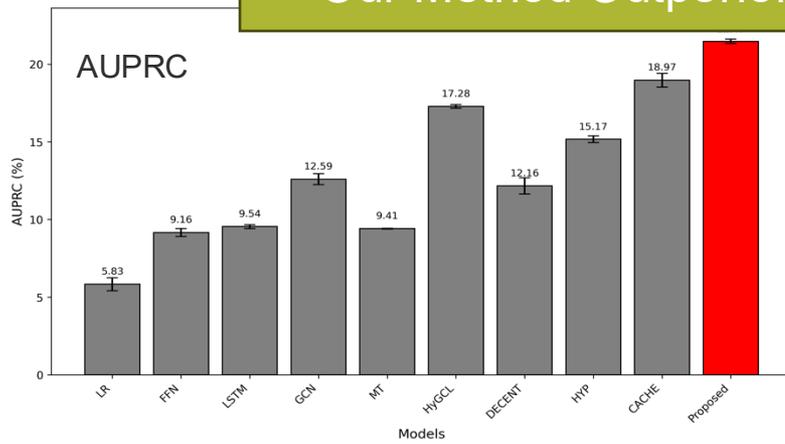
- UIHC:



- MIMIC-IV:



Our Method Outperforms all baselines across all metrics



MICU Transfer Prediction

- Forecast whether a patient is at risk of transfer to a **Medical Intensive Care Unit (MICU)**
- Binary Classification Problem:
 - Instance: Patient at time t and features at that time
 - Label: Binary indicator of MICU transfer in the next k days
- Evaluation Metric:
 - ROC-AUC Score
 - AUPRC Score
- Averaged across 3 independent runs

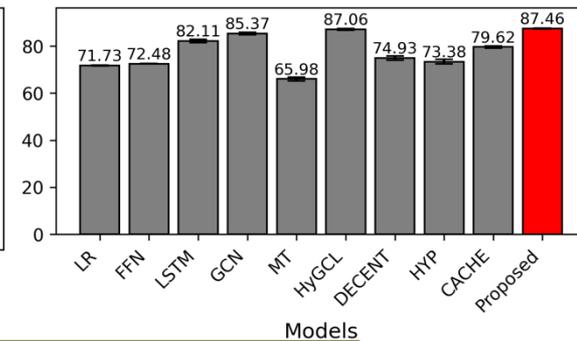
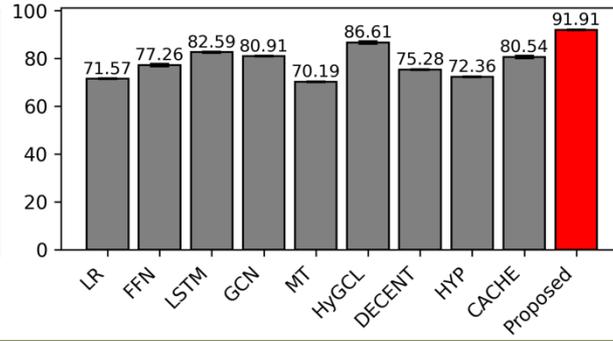
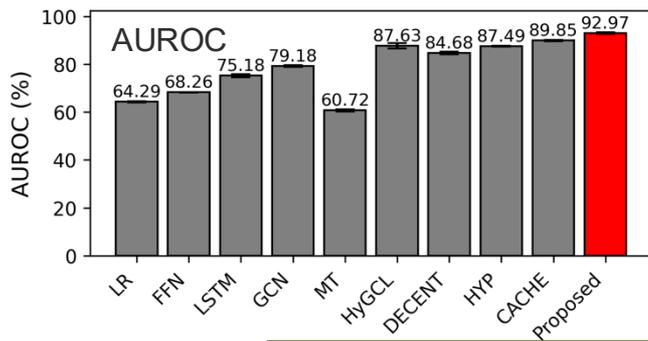


MICU Transfer: UIHC

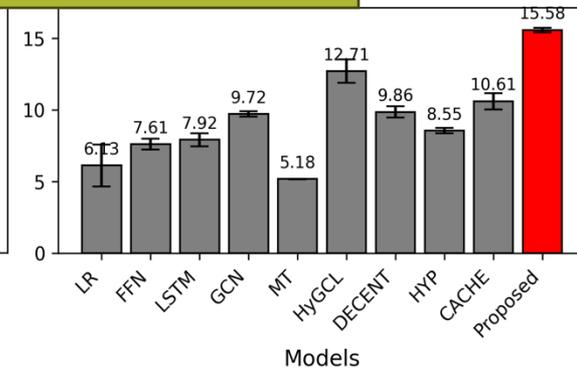
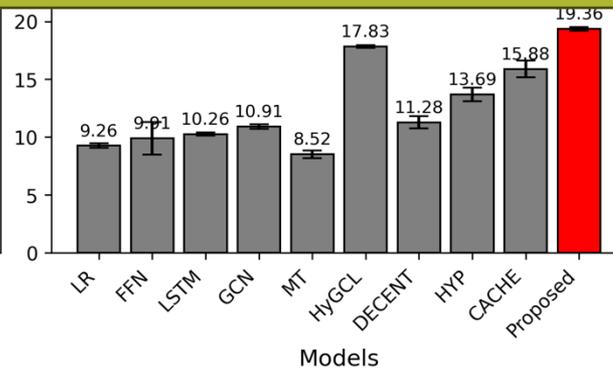
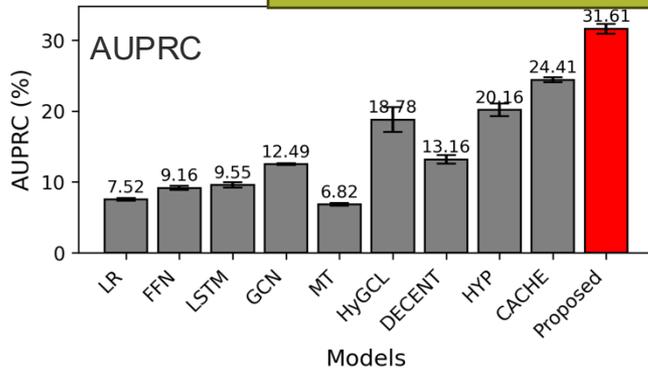
• 1- day ahead

• 2- day ahead

• 3- day ahead



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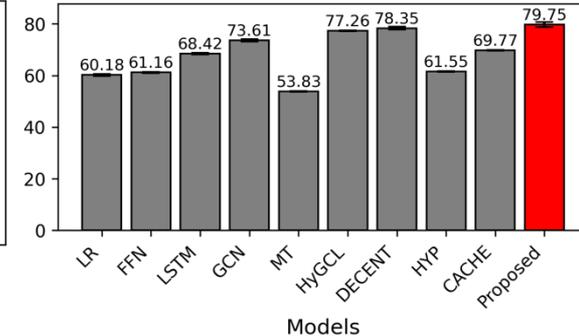
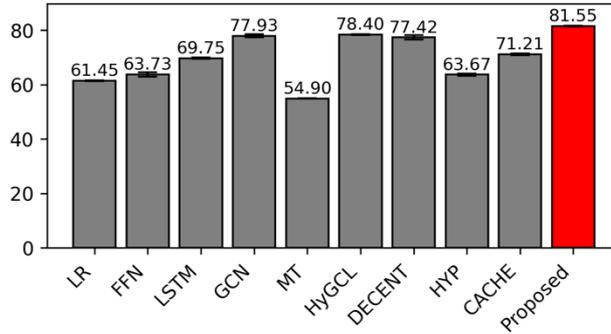
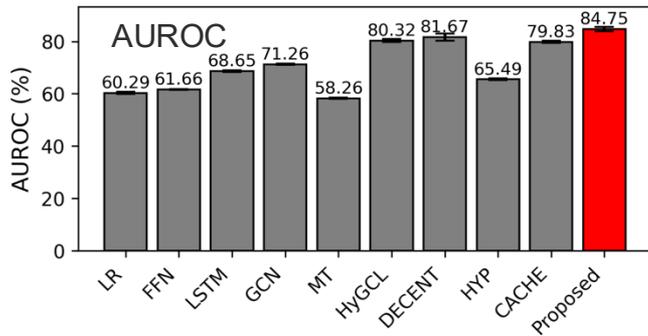


MICU Transfer: MIMIC-IV

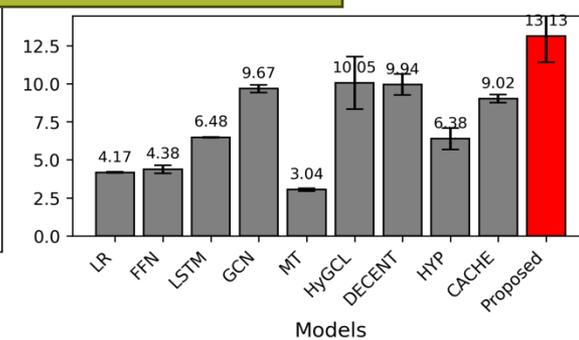
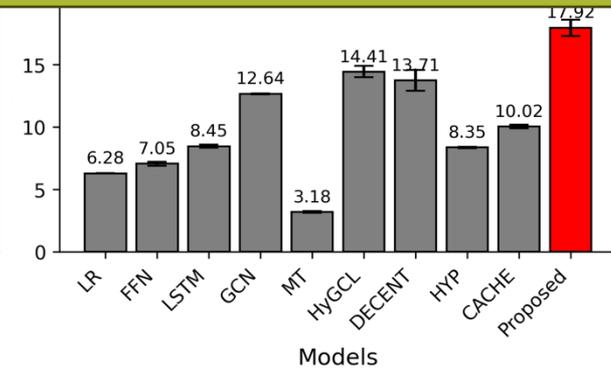
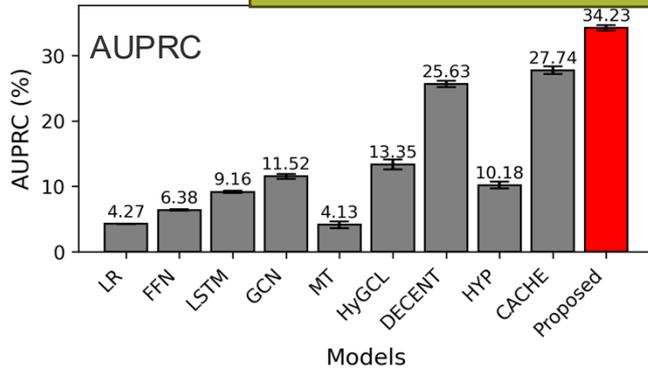
• 1- day ahead

• 2- day ahead

• 3- day ahead



Our Method Outperforms all baselines across all metrics



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Conclusion

- Leveraging high-order spatio-temporal mobility interactions is an effective way to estimate patient risk when prior visit information is unavailable. We use:
 - Patient-HCW/Doctor interaction
 - Patient-Medication interaction
 - Patient-Room interaction
- To exploit the domain information and account for missing interaction data, we propose a new hypergraph contrastive augmentation strategy that is aligned with domain information
- We evaluate the performance of the learned embeddings over the predictive tasks:
 - CDI Incidence Prediction
 - Short and Long Term MICU Transfer Prediction
- Our proposed model outperforms state-of-the-art baselines across both tasks

Thank You



Akash Choudhuri



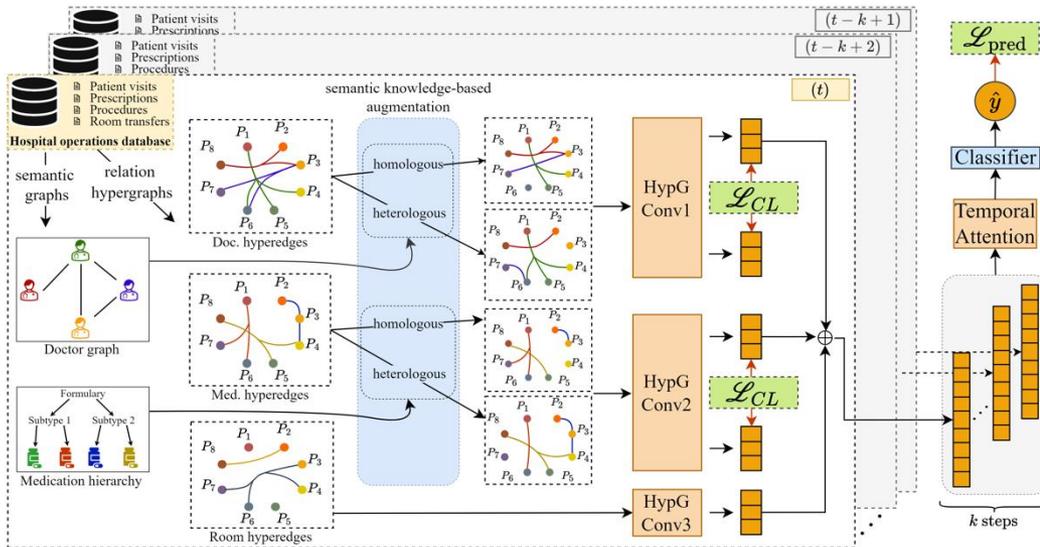
Hieu Vu



Kishlay Jha



Bijaya Adhikari



Code: <https://github.com/Soothysay/HyperHA>

More Results in the Paper!

Contact:
akash-choudhuri@uiowa.edu

