Continually-Adaptive Representation Learning Framework for Time-Sensitive Healthcare Applications

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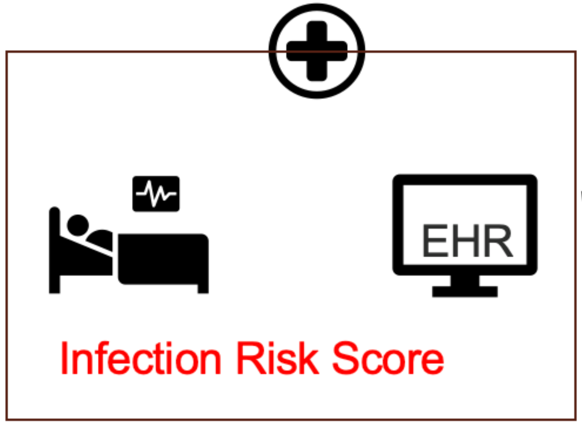
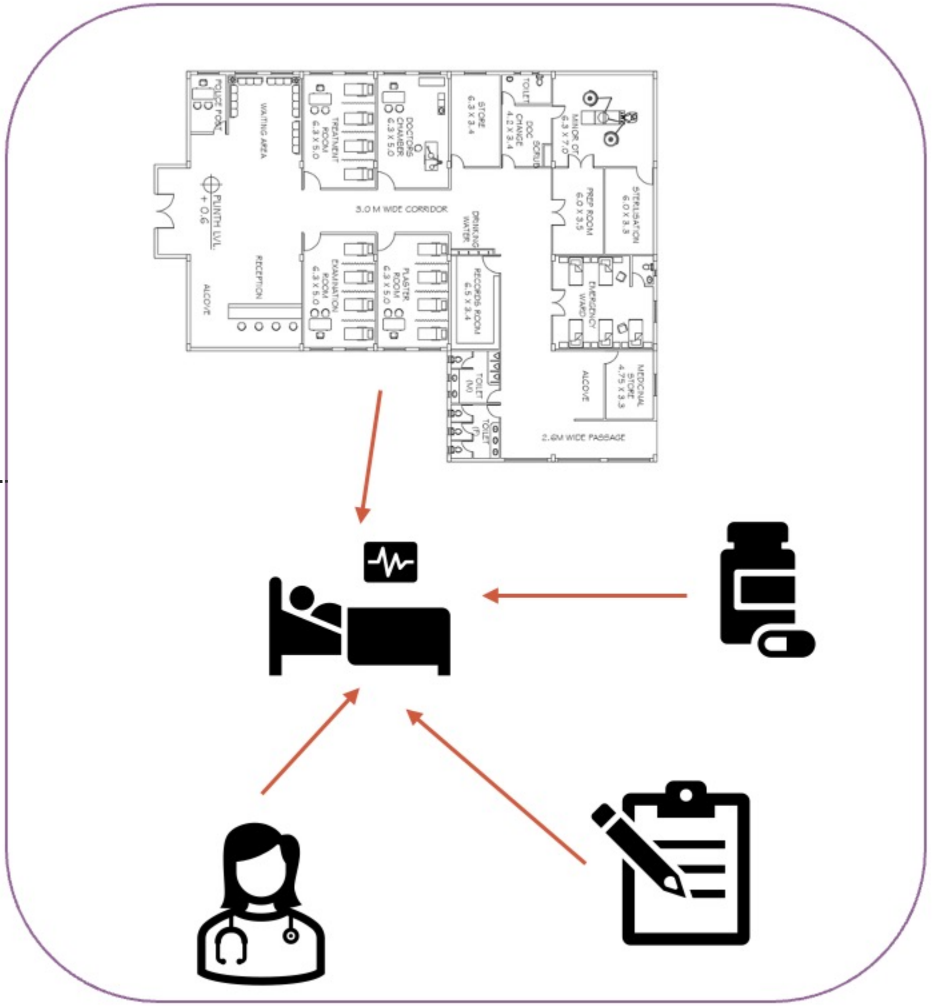
Motivation 1: Learning representations of Patients

Motivations and Principle

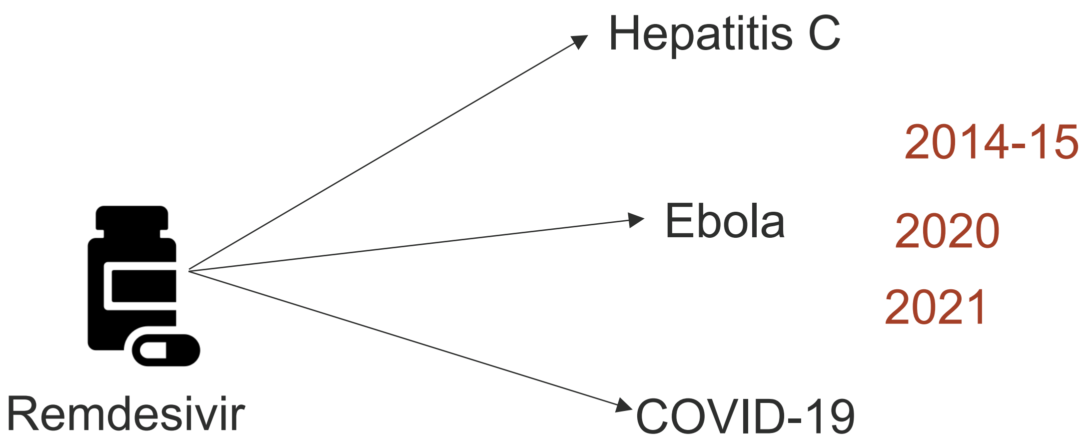


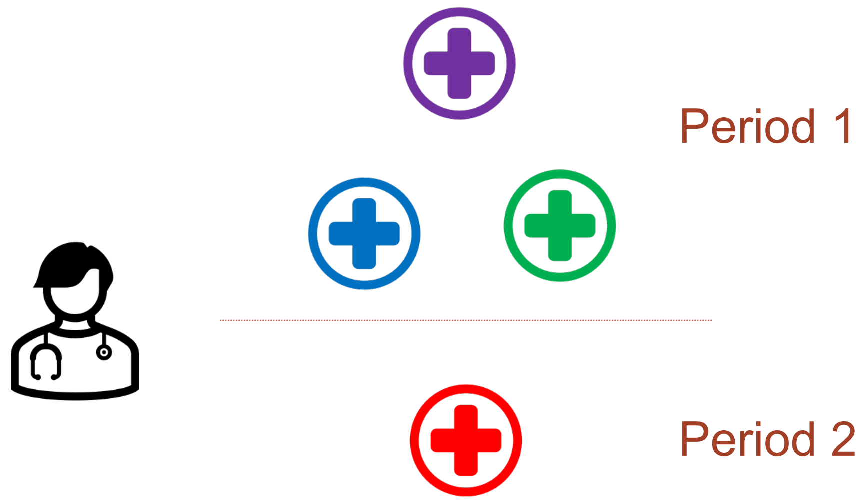
Patient Features	Outcome



Motivation 2: Incremental Incorporation of New Information

Motivations and Principle



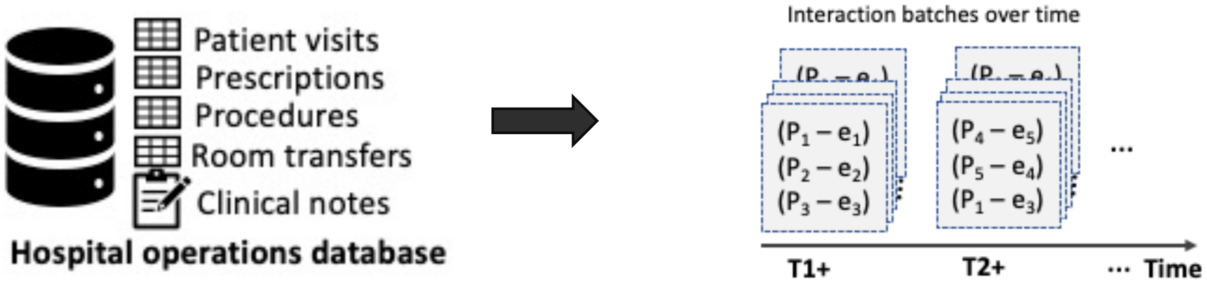


Faster Training!

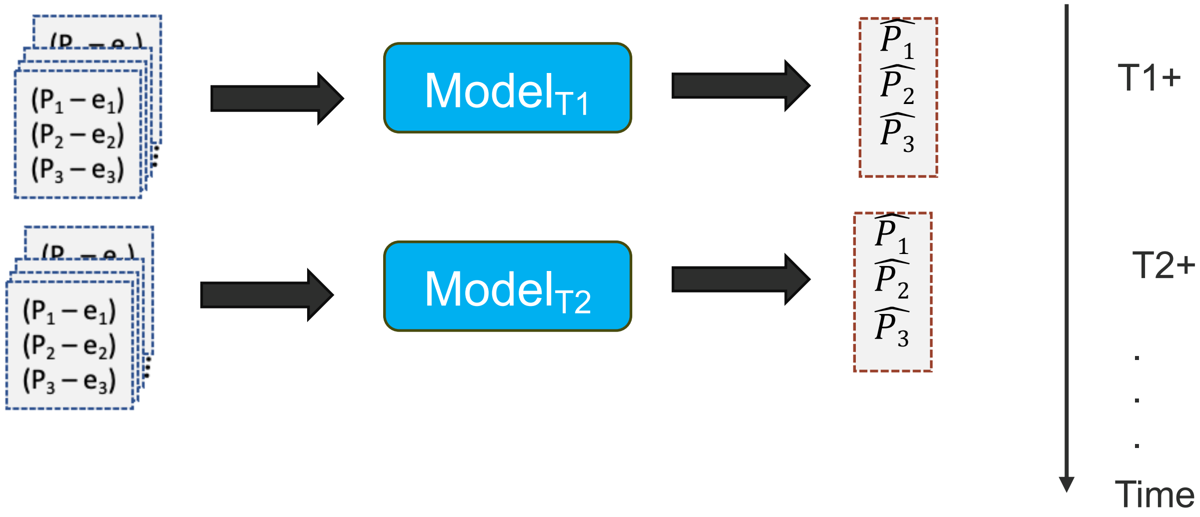
Problem Formulation

Model and Components

Given:



Learn:

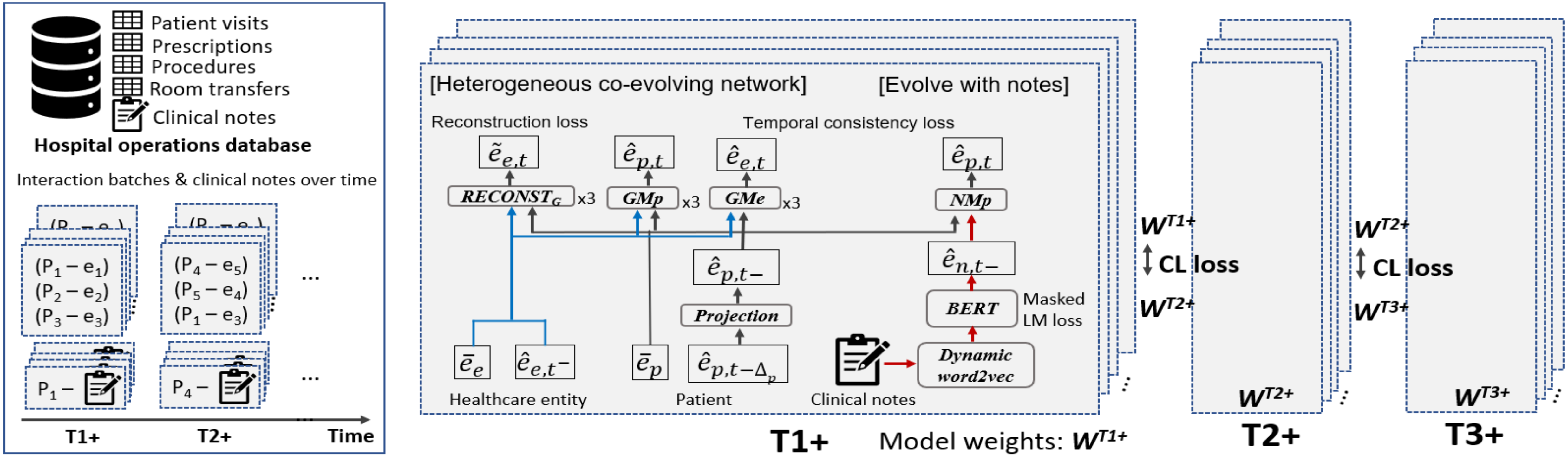


Such That:

- Dynamic patient embeddings encodes information to aid predictions
- The model parameters across periods doesn't drastically change

Model Architecture

Model and Components

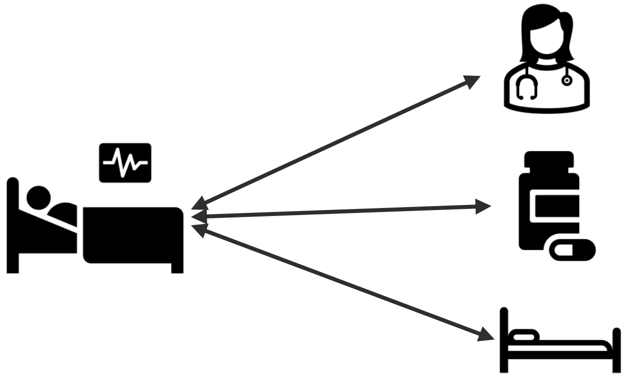


General purpose, unsupervised and continually learning embedding method for dynamic heterogenous interactions

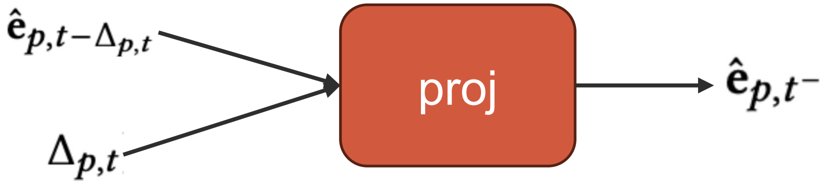
- Preserves information on the interaction via interaction type specific autoencoder
- Continually infuses knowledge across periods to prevent catastrophic forgetting

Dynamic Embedding Update

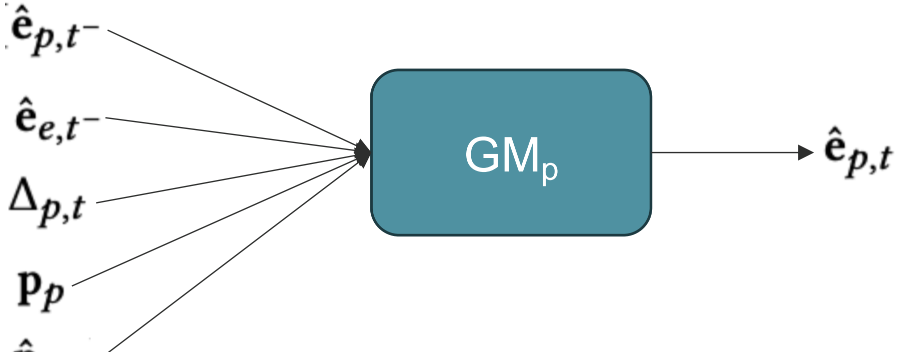
Model and Components

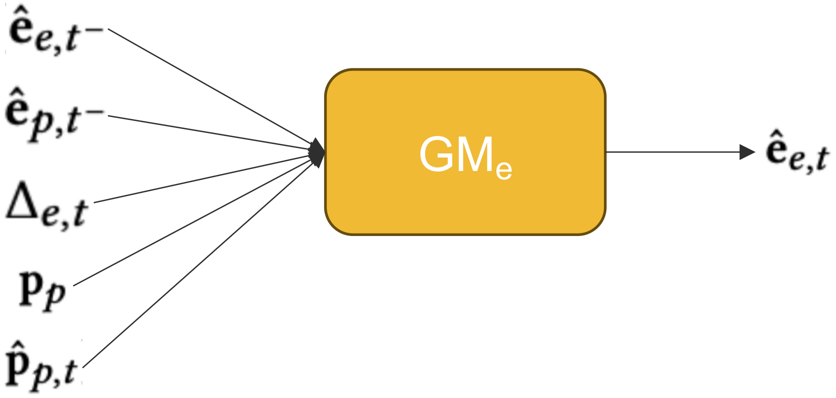


- Projection of Patient embedding (from time $t - \Delta$ to t^-) [1]:



- Update dynamic embeddings of patient and the entity at t via co-evolving neural networks:





$$\mathcal{L}_{temp} = \sum_{(p,e,t)\in S} ||\hat{e}_{p,t} - \hat{e}_{p,t^-}||_2 + ||\hat{e}_{e,t} - \hat{e}_{e,t^-}||_2$$

[1] S. Kumar, X. Zhang, and J. Leskovec, "Predicting dynamic embedding trajectory in temporal interaction networks," in ACM SIGKDD, 2019

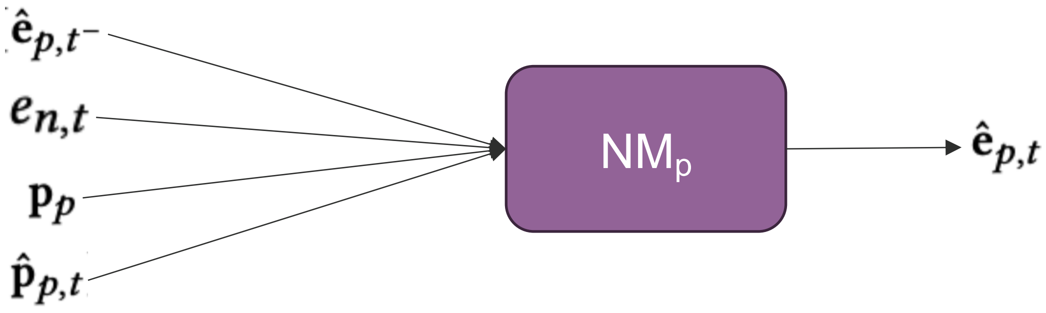
Evolution with Clinical Notes

Model and Components

- Obtaining Clinical Note Embeddings
  - For each clinical note in a period, obtain learned word embeddings using DynamicWord2Vec[1]
  - Use learned word vector embeddings to pre-train BERT[2] on Masked Language Loss:

$$\mathcal{L}_{LM} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

- Update Dynamic Patient embeddings:

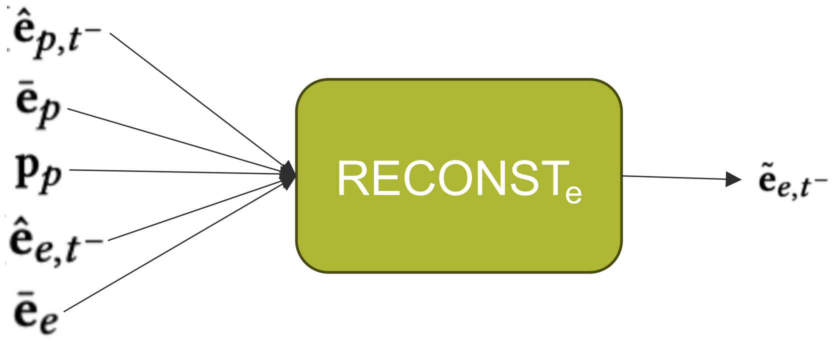


[1] Z. Yao, Y. Sun, W. Ding, N. Rao, H. Xiong, “Dynamic Word Embeddings for Evolving Semantic Discovery” in ACM WSDM, 2018
[2] J. Devlin, M. Chang, K. Lee, K. Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding” in arXiv, 2019

Reconstruction and Continual Knowledge Infusion

Model and Components

- We reconstruct the original entity dynamic and static embeddings via a reconstruction autoencoder:



- For each period, we prevent ‘catastrophic forgetting’ across periods by:
  - Initializing model parameters for a new period with the learned model parameters from the previous period
  - Minimizing the Continual Learning loss:

$$\text{Model}_{T1} \approx \text{Model}_{T2} \approx \text{Model}_{T3} \quad \ldots$$

$$\mathcal{L}_{CL} = \lambda||\theta_i - \theta_{i-1}||_2$$

Data

- Hospital Operations Data was obtained from University of Iowa Hospitals and Clinics (UIHC) data on:
  - **Electronic Health Records**
  - **Admission- Discharge-Transfer (ADT) logs**
- Hospital Operations was divided into 3 periods:

Period	Start Date	End Date	No. of D,M,R Interactions	No. of N Interactions
Period 1	5/4/2008	6/25/2008	245,043	149,685
Period 2	6/13/2008	8/7/2008	252,089	152,037
Period 3	7/10/2008	8/31/2008	257,994	163,158

- **Assumption:** No new entities are added across the periods

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CDI Incidence Prediction

Results

- Clostridioides difficile infection (CDI) is one of a common HAI, increases mortality risk of patients with weakened immune system
- 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
- 3- fold cross validation with 30 repetitions

Period	Method	LR	SVM	RF
Period 1	DOMAIN	0.49 ± 0.20	0.52 ± 0.07	0.34 ± 0.07
	JODIE	0.44 ± 0.12	0.36 ± 0.09	0.52 ± 0.03
	DECENT	0.62 ± 0.07	0.57 ± 0.01	0.61 ± 0.06
	Ours	$\mathbf{0.65 \pm 0.05}$	$\mathbf{0.60 \pm 0.04}$	$\mathbf{0.73 \pm 0.07}$
Period 2	DOMAIN	0.60 ± 0.11	0.54 ± 0.13	0.76 ± 0.19
	JODIE	0.50 ± 0.05	0.47 ± 0.06	0.52 ± 0.18
	DECENT	0.71 ± 0.02	0.59 ± 0.16	0.77 ± 0.04
	Ours	$\mathbf{0.74 \pm 0.08}$	$\mathbf{0.62 \pm 0.06}$	$\mathbf{0.78 \pm 0.19}$
Period 3	DOMAIN	0.67 ± 0.19	0.56 ± 0.09	0.71 ± 0.18
	JODIE	0.61 ± 0.08	0.55 ± 0.14	0.59 ± 0.03
	DECENT	0.68 ± 0.12	0.63 ± 0.04	0.71 ± 0.19
	Ours	$\mathbf{0.69 \pm 0.14}$	$\mathbf{0.66 \pm 0.07}$	$\mathbf{0.72 \pm 0.23}$

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[1] M. Monsalve, S. Pemmaraju, S. Johnson, and P. M. Polgreen, “Improving risk prediction of clostridium difficile infection using temporal event-pairs,” in IEEE ICHI, 2015

MICU Transfer Prediction

Results

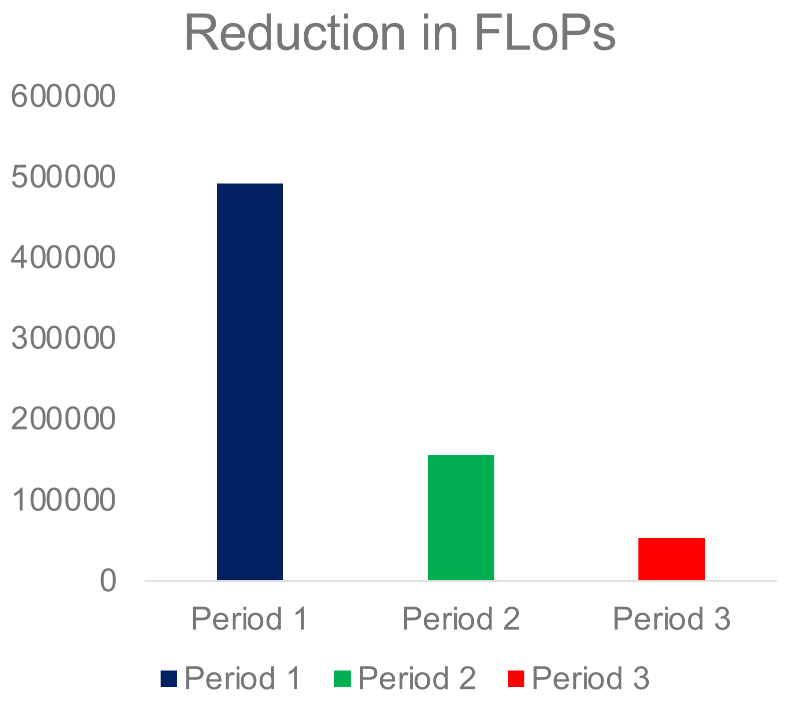
- Forecast whether a patient is at risk of transfer to a Medical Intensive Care Unit (MICU)
- Binary Classification Problem:
  - Instance: Patient at time t and features at that time
  - Label: Binary indicator of MICU transfer in the next day
- Evaluation Metric: ROC-AUC Score
- 3- fold cross validation with 30 repetitions

Period	Method	LR	SVM	RF
Period 1	DOMAIN	0.63 ± 0.20	0.52 ± 0.03	0.86 ± 0.13
	JODIE	0.54 ± 0.15	0.51 ± 0.02	0.66 ± 0.04
	DECENT	0.85 ± 0.07	0.71 ± 0.05	0.83 ± 0.05
	Ours	**0.89 ± 0.05**	**0.77 ± 0.08**	**0.87 ± 0.03**
Period 2	DOMAIN	0.68 ± 0.12	0.57 ± 0.13	0.71 ± 0.07
	JODIE	0.59 ± 0.05	0.52 ± 0.10	0.55 ± 0.01
	DECENT	0.72 ± 0.07	0.65 ± 0.10	0.86 ± 0.03
	Ours	**0.76 ± 0.02**	**0.72 ± 0.03**	**0.89 ± 0.09**
Period 3	DOMAIN	0.67 ± 0.13	0.56 ± 0.02	0.81 ± 0.03
	JODIE	0.61 ± 0.08	0.52 ± 0.18	0.62 ± 0.12
	DECENT	**0.85 ± 0.07**	0.67 ± 0.01	**0.87 ± 0.18**
	Ours	0.84 ± 0.12	**0.71 ± 0.01**	**0.87 ± 0.08**

Empirical Verification of Continual Adaptation

Results

- The model training is very resource intensive
- We used the continual learning formulation to reduce training time without costing too much on the quality of embeddings
- Our model will require more operations to train for the first period. But it will require much less operations to train on the data for the subsequent periods
- We validate this intuition by profiling the proxy of FLoPs (MACs) required to train the model to construct dynamic embeddings across periods
- Note that the number of FLoPs required to pre-train our BERT model is excluded from our analysis



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Conclusion

- The learned patient embeddings incorporate both the interactions and the clinical notes
- We use continual learning to reduce the time for training incoming heterogenous and dynamic batches of interactions and notes
- We evaluate the performance of the learned embeddings over the predictive tasks:
  - CDI Incidence Prediction
  - MICU Transfer Prediction
- Our proposed model outperforms state-of-the-art baselines across both the tasks
- Our continual learning formulation leads to faster training of model parameters in subsequent batches

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Special Thanks

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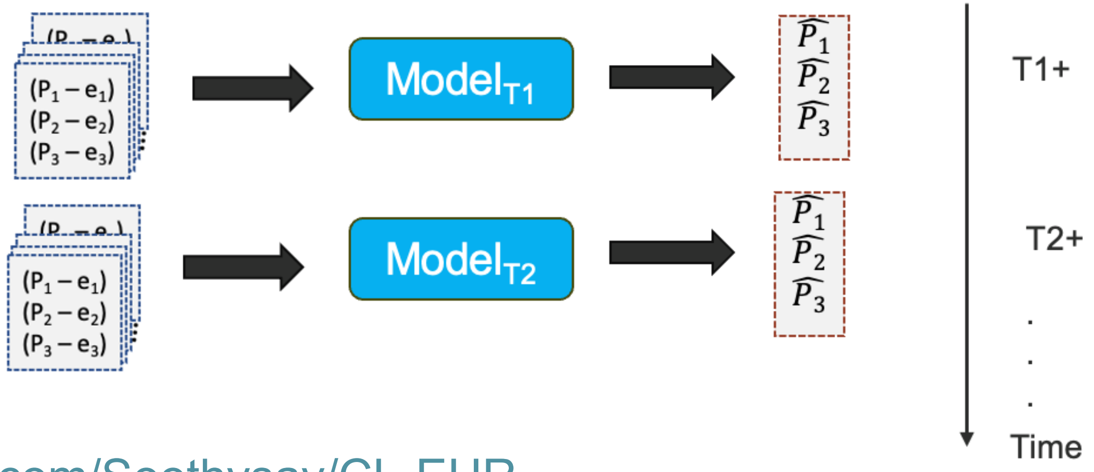

Code: https://github.com/Soothysay/CL-EHR

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