IEEE Big Data 2018
Computer Science Department at UFMG & Kunumi

Dynamic Prediction of ICU Mortality Risk Using Domain Adaptation

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Motivation

- Intensive Care Unit (ICU) is a special hospital area to treat patients that need constant attention.
- Data from patients in the ICU are complex, extensive.
- Monitoring patients in ICU can become a complex task as data becomes larger.

- Use of machine learning models.

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- Models often lacks generalization as we change the population.

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- Model's explanation

- PhysioNet 2012 Challenge dataset [Silva et al., 2012].

Dataset and Domains
Methodology

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- Age, gender, height, weight and 37 time-stamped physiological parameters.
- First 48 hours of ICU stay.
- Target is in-hospital death.

4 Different ICU

- Cardiac Surgery Recovery Unit
- Coronary Care Unit
- Medical ICU
- Surgical ICU

Average patient physiological data.

	Cardiac	Coronary	Medical	Surgical
N	874	577	1,481	1,067
Age	67.91	69.22	62.83	60.50
Mortality Rate	4.9%	14.0%	18.6%	14.5%

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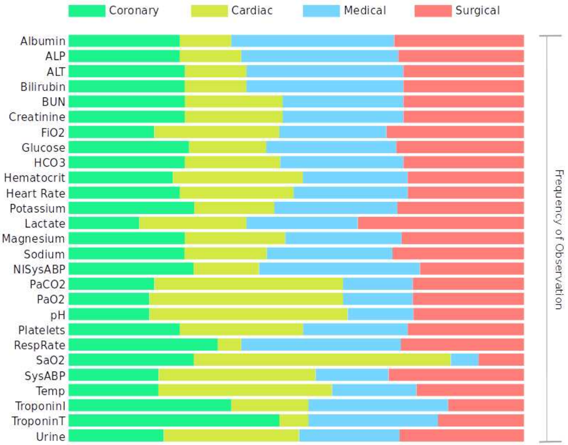
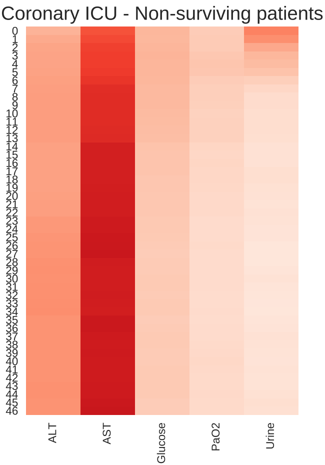
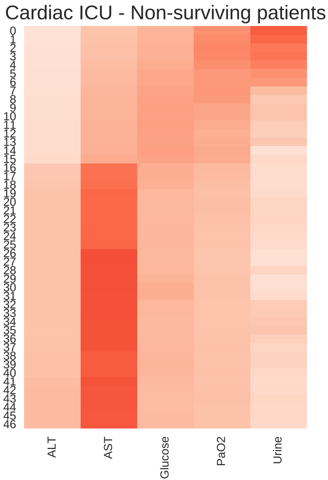
Relative frequency in which physiological parameters are measured in different ICU domains.



Mean value for non-surviving patients at the Coronary ICU through time.



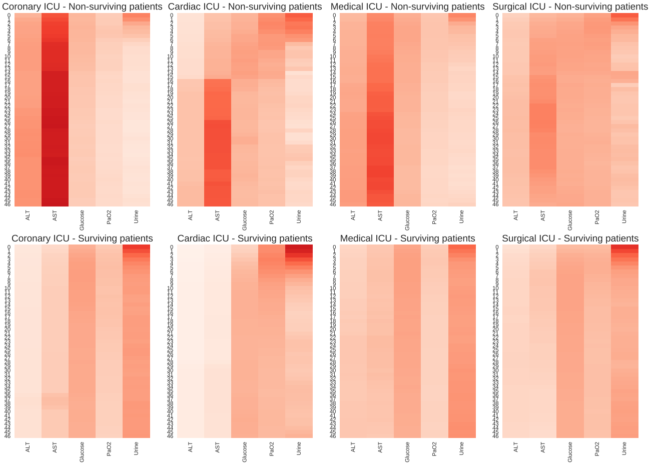
Mean value for non-surviving patients at the Cardiac ICU through time.



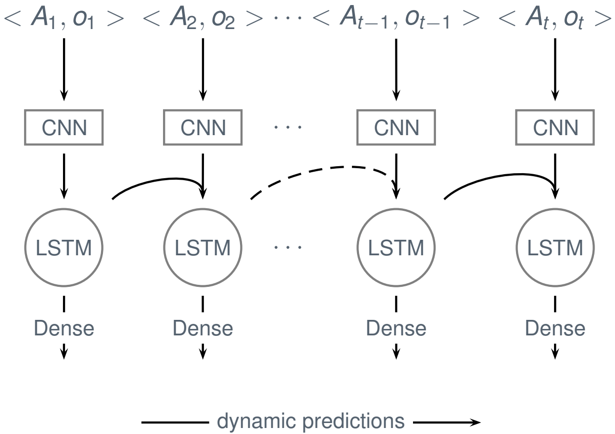
Dataset and Domains

Methodology

Mean value by ICU and outcome through time.



Network architecture for predicting patient outcomes over time.



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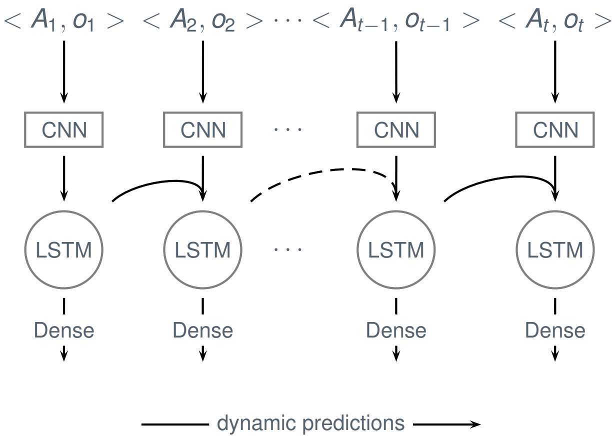
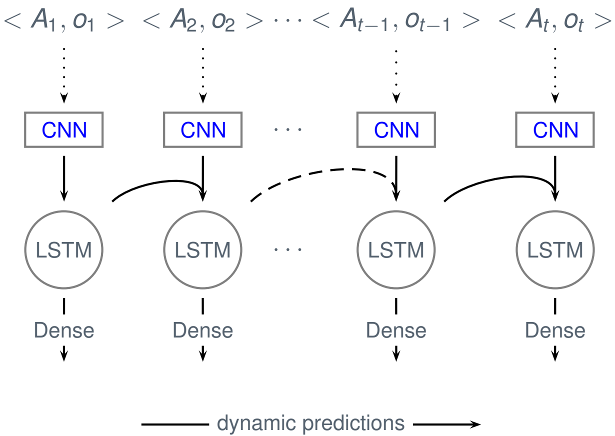
- First layers extract more general features

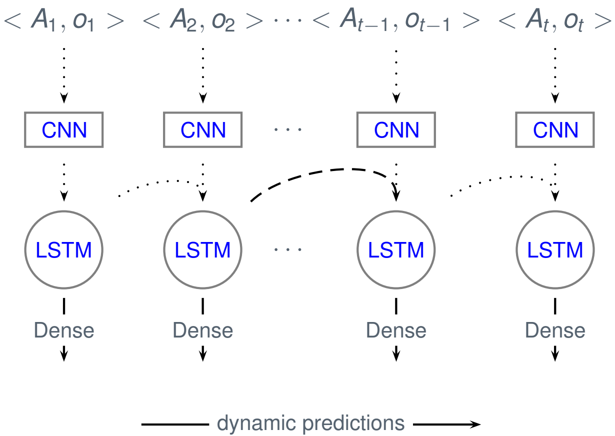
NF: No layers are frozen during fine-tuning.



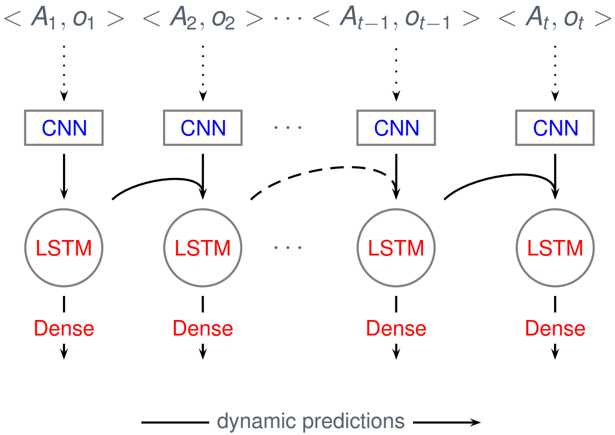
FC: Freeze CNN layers during fine-tunning.



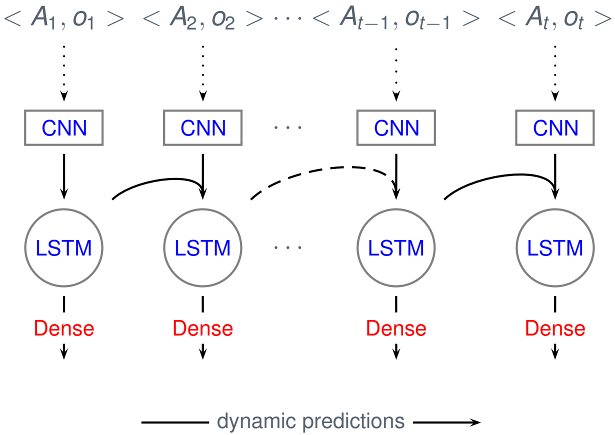
FCL: Freeze CNN and LSTM layers during fine-tunning.



FCR: Freeze CNN layer and all other layers have their weights randomly initialized during fine-tunning.



FCLR: Freeze CNN and LSTM layers and all other layers have their weights randomly initialized during fine-tunning.



AUC numbers for different feature transference approaches

Target	NF	FC	FCL	FCR	FCLR
Cardiac	0.852	**0.885**	0.829	0.849	0.858
Coronary	**0.848**	0.812	0.807	0.793	0.784
Medical	0.754	0.763	**0.782**	0.759	0.736
Surgical	0.822	**0.827**	0.808	0.818	0.788
Overall	0.819	**0.822**	0.806	0.804	0.791

AUC numbers for baselines and approaches

Model	Cardiac	Coronary	Medical	Surgical	Avg
SVM	0.627	0.572	0.503	0.532	0.558
LR	0.629	0.601	0.510	0.517	0.564
RF	0.610	0.578	0.587	0.623	0.599
TT	0.821	0.769	0.722	0.727	0.759
LSTM	0.812	0.807	0.742	0.769	0.782
CNN	0.866	0.802	0.747	0.812	0.807
NT^{-}	0.876	0.833	0.737	0.801	0.812
NT	0.876	0.837	0.757	0.812	0.820
[Che *et al., 2015*]	0.853	0.802	0.760	0.785	0.800
[Che *et al., 2018*]	0.868	0.824	0.775	**0.823**	0.823
CNN–LSTM	**0.885**	**0.848**	**0.782**	**0.827**	**0.836**

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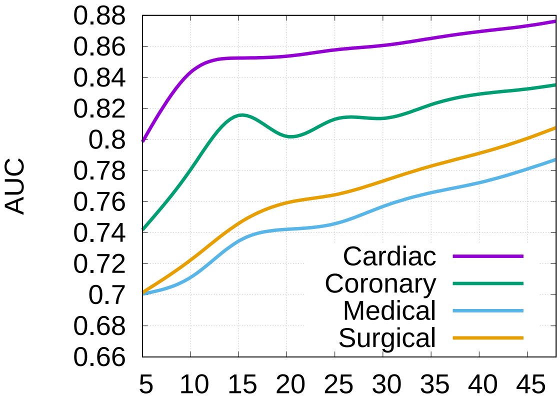
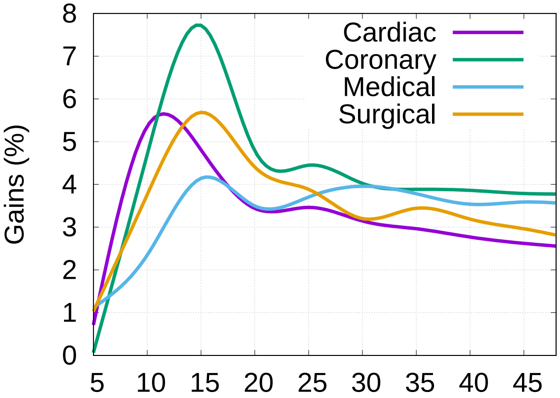
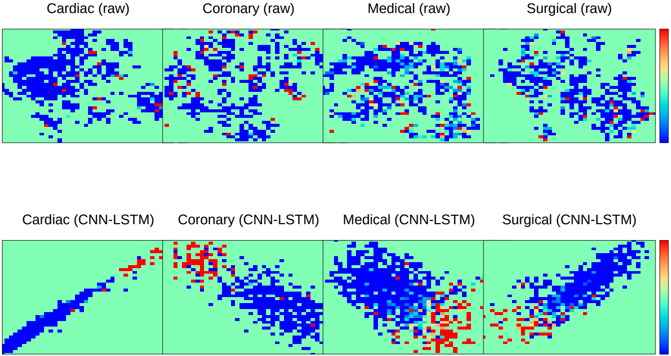
CNN-LSTM AUC within the first y hours ($5 \leq y \leq 48$).

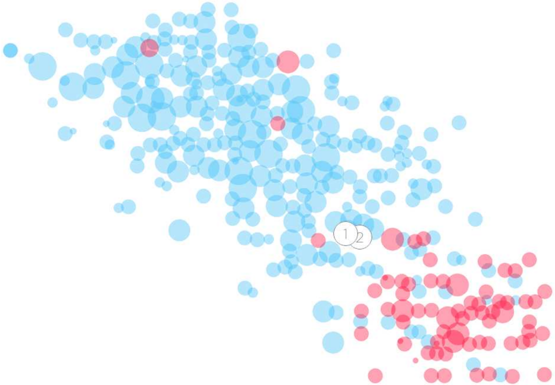


Gains over [Che et al., 2015] at different prediction times ($5 \leq y \leq 48$).



Mortality risk space for different ICU domains. Regions in red are risky.

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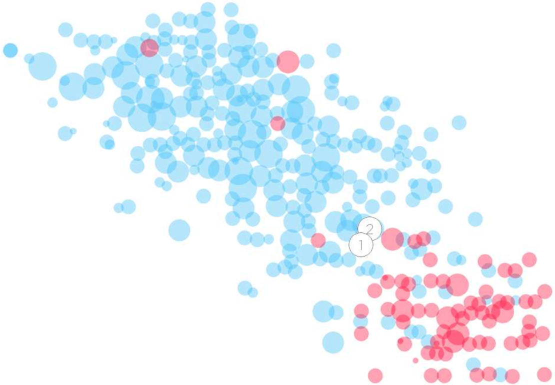

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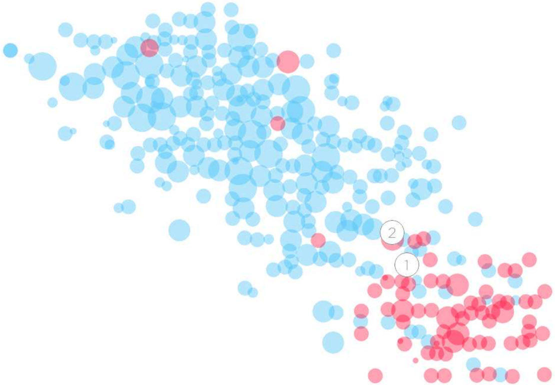
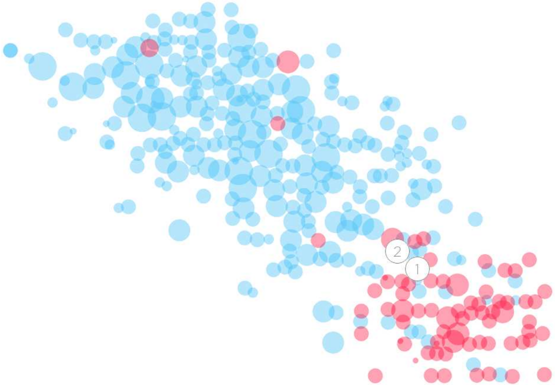


2
1

Patient Dynamics
Experimental Results



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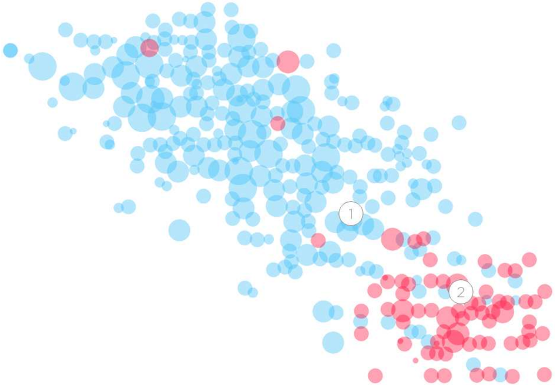
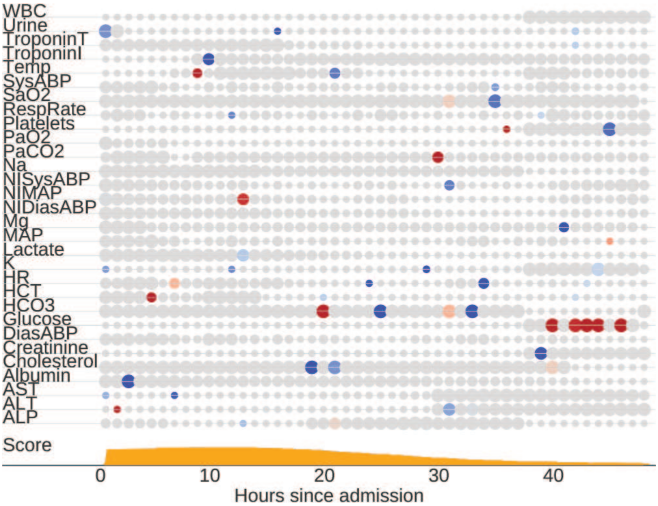
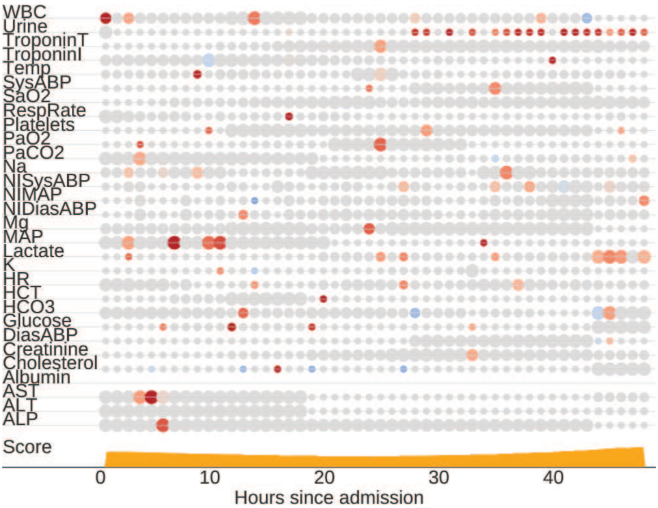


Explanations for a surviving patient instance



Explanations for a non-surviving patient instance



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- Deep learning models can employ local and temporal feature extractors to perform dynamic predictions, potentially leading to earlier diagnosis.
- Specific models built with domain adaptation outperforms the general models.

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