Programa de Pós-Graduação em Ciência da Computação
Universidade Federal de Minas Gerais

# DYNAMIC PREDICTION OF ICU MORTALITY RISK USING DOMAIN ADAPTATION

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February 28, 2018

# Content

- An Intensive Care Unit (ICU) is a department of a hospital in which patients who are dangerously ill are kept under constant observation.
- Monitoring patients in ICU can become a complex task as data becomes larger.
- Systems that learn from this data are playing a significant role in the decision making process [McNeil and Bryden, 2013].

Stanford ML Group

### Improving Palliative Care with Deep Learning

Anand Avati*, Kenneth Jung, Stephanie Harman, Lance Downing, Andrew Ng, Nigam Shah

We build a program using Deep Learning to automatically identify hospitalized patients having palliative needs

While 80% of Americans prefer to spend their final days in their home, only 20% actually do. More than 60% of deaths in the US happen in an accute care hospital, most of the patients receiving aggressive care in their final days. We build a program using Deep Learning to identify hospitalized patients with a high risk of death in the next 3-12 months by only inspecting their Electronic Health Record data. Such patients are automatically brought to the attention of the Palliative Care team with notifications. This helps the Palliative Care team to be engaged early enough to ensure patients have their Goals of Care recorded, and provide their services while it is still meaningful.

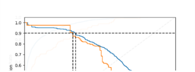
READ OUR PAPER

Our paper wins the Best Student Paper Award at IEEE International Conference on Bioinformatics and Biomedicine 2017!

IEEE BIBM 2017

Our model is an 18-layer Deep Neural Network that inputs the EHR data of a patient, and outputs the probability of death in the next 3-12 months.

We train the model on the historic data from the Stanford Hospital EHR data base, which contains data of over 2 million patients. The model is trained to predict



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**Rewriting Life**

# Machine Learning and Risk Prediction in the ICU

A Boston startup wants to bring smart analytics to critical care in order to help doctors spot and treat at-risk patients.

by Susan Young Rojahn June 5, 2013

Machine learning and predictive algorithms could help doctors make sense of the overload of data that streams out of the many patient-monitoring machines in an ICU.

**The intensive care unit (ICU) is one of the most data-intense rooms in a** hospital, but the information streaming out of heart monitors, ventilators, and pressure sensors is generally not integrated and analyzed to enable a deeper understanding of the patient's condition. To change this, Boston-area startup Etiometry is building a clinical-decision support system that can interpret large volumes of real-time patient data and provide doctors with a snapshot view of actionable information.

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## Google is using 46 billion data points to predict the medical outcomes of hospital patients


Chinese markets reopen, Newsweek goes rogue, eyebrow indicators. All this and more in today's Daily Brief.

- Accurate models can help intensivists prioritize their patients better.
- Early predictions can lead to early diagnostics.
- A single ICU may not have enough data for a robust model.
- General models don't capture domain related particularities.

- A method that explores the differences between ICU through domain adaptation to improve robustness.
- A study of patients within different ICU domains.
- A deep learning end-to-end model that captures local and temporal features.
- A dynamic representation to help gain insights into the patient's treatment.

## PhysioNet ICU Mortality Challenge 2012

- Robust Support Vector Machine (SVM) classifier [Citi and Barbieri, 2012].
- Logistic Regression with Hidden Markov Model [Vairavan et al., 2012].
- Shallow neural networks and boosting [Xia et al., 2012].

## Imbalanced data

- Classification Algorithm for Imbalanced Datasets Applied to Mortality Prediction [Bhattacharya et al., 2017].

## Time series prediction

- Recurrent Neural Networks for Mortality Prediction [Che et al, 2016]

## Domain adaptation

- Deep Learning Domain Adaptation [Glorot et al., 2011]

- PhysioNet 2012 Challenge dataset [Silva et al., 2012].
- Records from 4000 patients.
- Age, gender, height, weight and 37 time-stamped physiological parameters.
- First 48 hours of ICU stay.
- Target is in-hospital death.

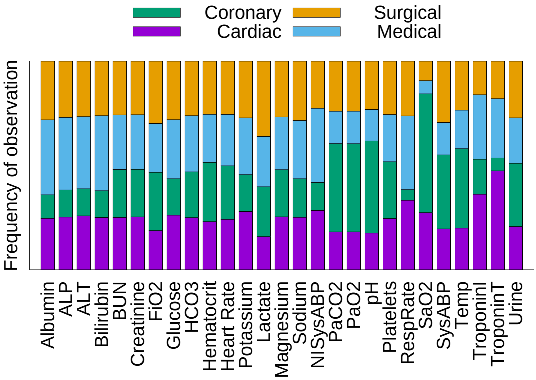
## 4 Different ICU

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

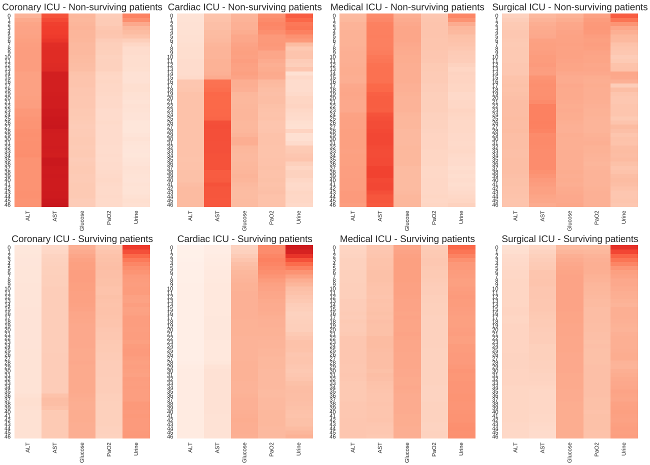
Average patient physiological data. Mean, first and third quartiles within each physiological parameter.

| | Cardiac | Coronary | Medical | Surgical |
|---|---|---|---|---|
| N | 874 | 577 | 1,481 | 1,067 |
| Age | 67.91 (56–79) | 69.22 (59–81) | 62.83 (51–78) | 60.50 (48–76) |
| Male | 530 (60.6%) | 333 (57.7%) | 753 (50.8%) | 630 (59.0%) |
| Mortality Rate | 4.9% (7.8%) | 14.0% (14.6%) | 18.6% (49.6%) | 14.5% (28.0%) |
| Albumin (g/dL) | 2.92 (2.4–3.5) | 3.31 (2.9–3.6) | 2.92 (2.5–3.3) | 2.99 (2.5–3.5) |
| Alkaline phosphatase (IU/L) | 74.93 (46–83) | 92.44 (59–102) | 126.15 (64–138) | 91.43 (52–96) |
| Serum glucose (mg/dL) | 129.28 (103–145) | 165.74 (114–191) | 155.02 (104–175) | 148.85 (114–167) |
| Heart rate (bpm) | 85.43 (79–91) | 84.32 (69–97) | 95.61 (80–110) | 87.83 (74–100) |
| Invasive mean press. (mmHg) | 78.86 (69–86) | 86.14 (73–99) | 86.58 (68–96) | 87.13 (73–98) |
| Partial press. of art. O2 (mmHg) | 295.46 (218–387) | 181.58 (89–248) | 147.68 (78–185) | 188.24 (101–250) |
| Troponin-I ($\mu$g/L) | 6.77 (0.8–10.1) | 10.05 (0.8–12.4) | 5.59 (0.8–7) | 7.02 (0.4–6.7) |
| Urine output (mL) | 497.92 (120–615) | 365.62 (100–500) | 255.39 (70–325) | 389.29 (100–500) |

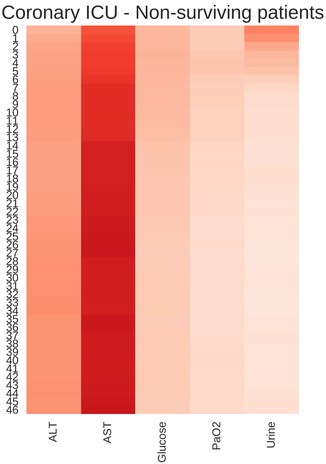
Relative frequency in which physiological parameters are measured in different ICU domains.



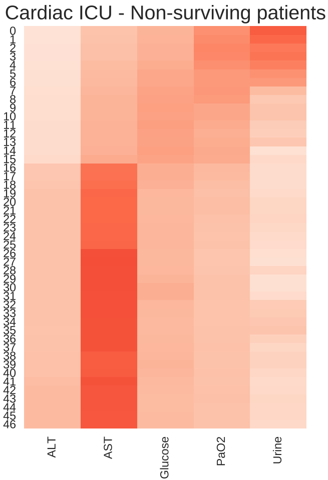
Mean value by ICU and outcome through time.



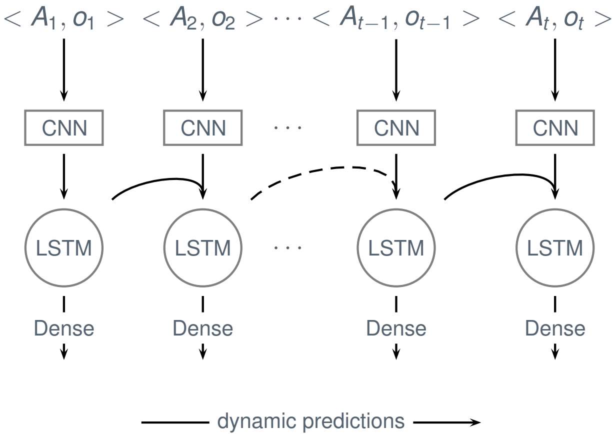
Mean value for non-surviving patients at the Coronary ICU through time.



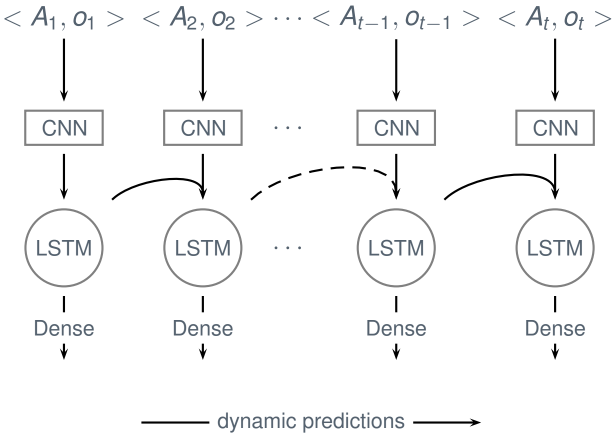
Mean value for non-surviving patients at the Cardiac ICU through time.



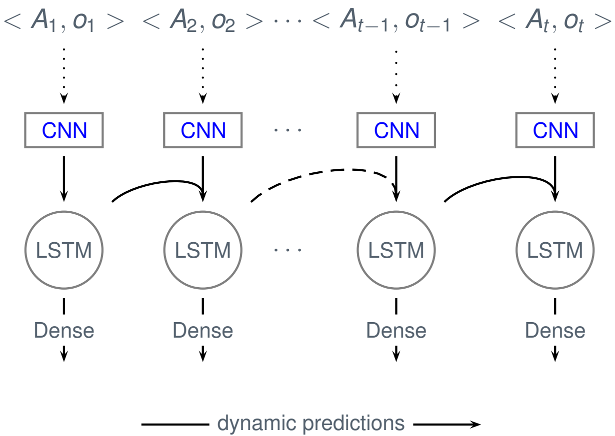
Network architecture for predicting patient outcomes over time.



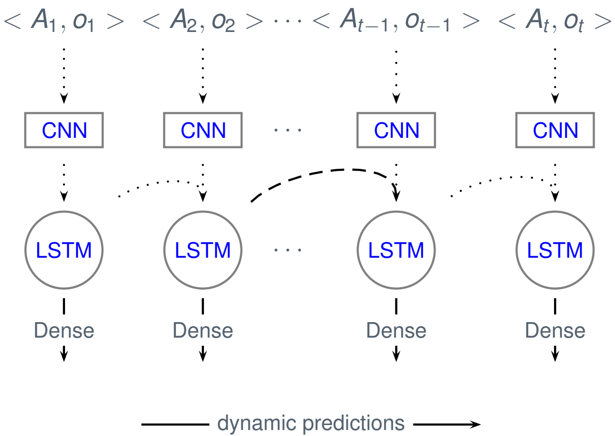
A1: No layers are frozen during fine-tuning.



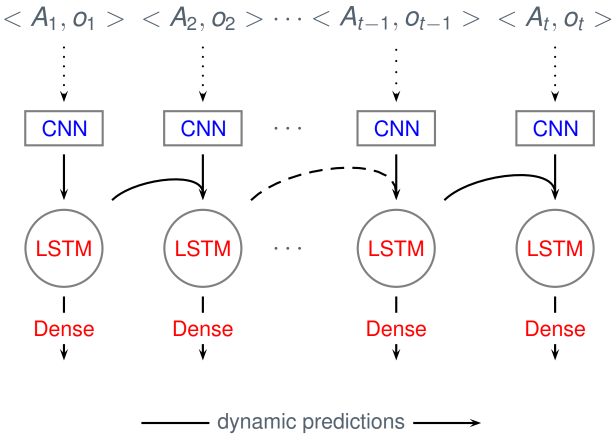
A2: Freeze CNN layers during fine-tunning.



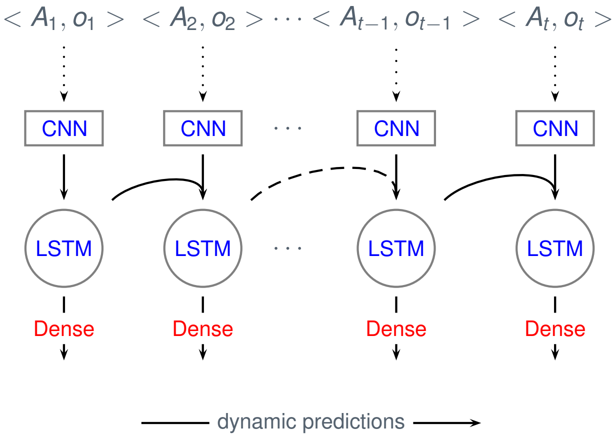
A3: Freeze CNN and LSTM layers during fine-tunning.



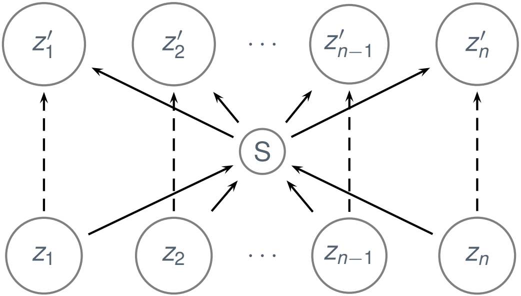
A4: Freeze CNN layer and all other layers have their weights randomly initialized during fine-tunning.



A5: Freeze CNN and LSTM layers and all other layers have their weights randomly initialized during fine-tunning.



Switch Layer. Each circle is a neuron, each full arrow is a trainable weight, and each dashed arrow is a constant weight.




- Seeks to create dense internal representations and group similar patients.
- Applies the learned representation to the receiving features.

## Metric

- Area Under ROC Curve (AUC)
- Sensitivity and Specificity

## Training Approaches

TT Train on Target, where only the target ICU is trained

GT General training, where all ICU are trained together

DA Domain Adaptation training

AUC comparison between Convolutional, Recurrent and CNN-LSTM models.

| | CNN | | | LSTM | | | CNN-LSTM | | |
|---|---|---|---|---|---|---|---|---|---|
| ICU Domain | DA | TT | GT | DA | TT | GT | DA | TT | GT |
| Cardiac | 0.828 | 0.737 | 0.866 | 0.786 | 0.740 | 0.812 | 0.833 | 0.773 | **0.876** |
| Coronary | 0.771 | 0.742 | 0.802 | 0.785 | 0.731 | 0.807 | 0.809 | 0.744 | **0.833** |
| Medical | 0.754 | 0.739 | 0.747 | 0.732 | 0.714 | 0.742 | **0.757** | 0.732 | 0.737 |
| Surgical | **0.813** | 0.787 | 0.812 | 0.752 | 0.753 | 0.769 | 0.807 | 0.791 | 0.801 |
| Average | 0.791 | 0.751 | 0.807 | 0.764 | 0.735 | 0.782 | 0.802 | 0.760 | **0.812** |

AUC Scores for Models With and Without Switch Layer.

| | Without Switch | | | With Switch | | |
|---|---|---|---|---|---|---|
| ICU Domain | Model | Mode | Score | Model | Mode | Score |
| Cardiac | CNN-LSTM | GT | 0.876 | CNN-LSTM | DA | **0.881** |
| Coronary | CNN-LSTM | GT | 0.833 | CNN-LSTM | GT | **0.837** |
| Medical | CNN-LSTM | DA | 0.757 | CNN | DA | **0.762** |
| Surgical | CNN | DA | 0.812 | CNN | DA | **0.827** |
| Average | | | 0.818 | | | **0.827** |

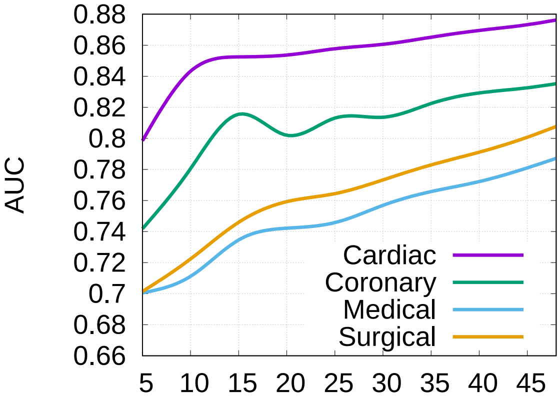
AUC numbers for shallow and deep models. Numbers in bold indicate the best models for each ICU domain.

| Model | Cardiac | Coronary | Medical | Surgical |
|---|---|---|---|---|
| AdaBoost | 0.572 | 0.551 | 0.510 | 0.531 |
| SVM | 0.627 | 0.572 | 0.503 | 0.532 |
| LR | 0.629 | 0.601 | 0.510 | 0.517 |
| LDA | 0.632 | 0.602 | 0.516 | 0.513 |
| RF | 0.610 | 0.578 | 0.587 | 0.623 |
| QDA | 0.689 | 0.668 | 0.567 | 0.610 |
| Che et al., 2015 | 0.853 | 0.802 | 0.760 | 0.785 |
| CNN-LSTM | **0.881** | **0.837** | **0.762** | **0.827** |

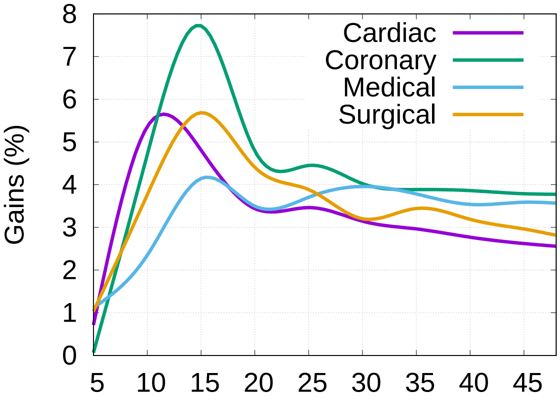
AUC numbers for different feature transference approaches. Numbers in bold indicate the best transference approach for each target ICU domain.

| | TT | No D.A. | A1 | A2 | A3 | A4 | A5 |
|---|---|---|---|---|---|---|---|
| Cardiac | 0.821 | 0.876 | 0.852 | **0.881** | 0.829 | 0.849 | 0.858 |
| Coronary | 0.769 | **0.837** | 0.800 | 0.823 | 0.798 | 0.817 | 0.786 |
| Medical | 0.722 | 0.757 | 0.754 | **0.763** | 0.744 | 0.759 | 0.736 |
| Surgical | 0.727 | 0.812 | 0.821 | **0.827** | 0.778 | 0.818 | 0.788 |
| Average | 0.746 | 0.802 | 0.792 | **0.804** | 0.774 | 0.798 | 0.770 |

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



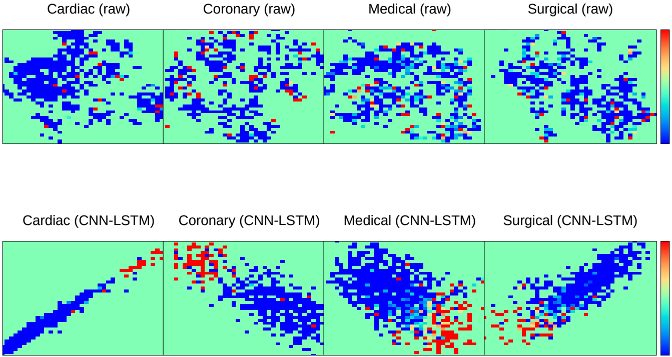
Gains over [Che et al., 2015] at different prediction times ($5 \leq y \leq 48$).

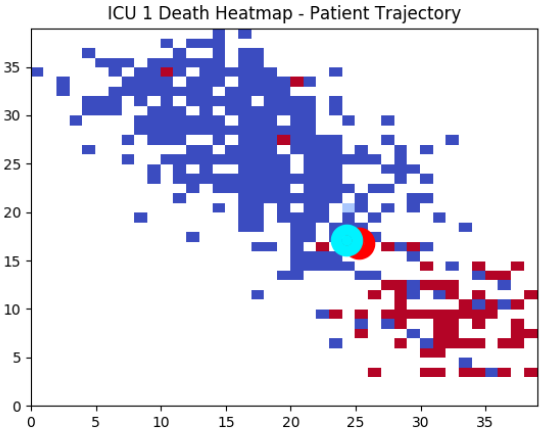


# Experimental Results
## Patient Dynamics



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





ICU 1 Death Heatmap - Patient Trajectory
35
30
25
20
15
10
5
0
0
5
10
15
20
25
30
35

# Conclusion



- Patients within a specific ICU domain are epidemiologically and physiologically different from patients within other domains.
- 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 in three of the four ICU.
- The switch layer brings improvements despite the domain.

# Future Work



- Provide means to explain the models' output.
- Suggest which interventions should be made.
- Predict diagnosis.
- Predict targets beyond in-hospital death.

Dynamic Prediction of ICU Mortality Risk Using Domain Adaptation
Submitted on Jan. 28th

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