Learning Score Systems for ICU Mortality Prediction via Orthogonal Matching Pursuit

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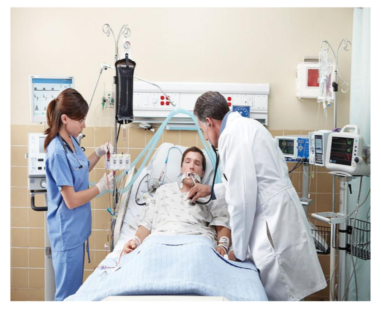
ICU Patient Mortality Prediction



Estimating probability of patient survival/death in ICUs

- Monitoring quality of care
- Resource allocation
- Comparing ICUs across demographics
- …

ICU Score systems widely used in the US and Europe for this purpose

St. John's ICU data: A Case Study

St. John's Medical College Hospital, Bangalore, India

ICU patient data (2006-2014)

- 3499 patients
- 29 clinical observations

	AUC
APACHE-II	66%
LODS	63%

APACHE-II Score System

Features / Intervals / Scores

SCORE	4	3	2	1	0	1	2	3	4
Rectal Temp, °C	=41	39.0–40.9		38.5–38.9	36.0–38.4	34.0–35.9	32.0–33.9	30.0–31.9	=29.9
Mean blood pressure, mmHg	=160	130-159	110-129		70-109		50-69		=49
Heart rate	=180	140–179	[illegible]	[illegible]	[illegible]		55–69	40–54	=39
Respiratory rate	=50	35–49	[illegible]	25–34	12–24	10–11	6–9		=5
Arterial pH	=7.70	7.60–7.69		7.50–7.59	7.33–7.49		7.25–7.32	7.15–7.24	<7.15
Oxygenation									
If FIO2 > 0.5, use (A – a) DO2	=500	350–499	200–349		<200				
If FIO2 0.5, use PaO2					>70	61–70		55–60	<55
Serum sodium, meq/L	=180	160–179	155–159	150–154	130–149		120–129	111–119	=110
Serum potassium, meq/L	=7.0	6.0–6.9		5.5–5.9	3.5–5.4	3.0–3.4	2.5–2.9		<2.5
Serum creatinine, mg/dL	=3.5	2.0–3.4	1.5–1.9		0.6–1.4		<0.6		
Hematocrit	=60		50–59.9	46–49.9	30–45.9		20–29.9		<20
WBC count, 10^3/mL	=40		20–39.9	15–19.9	3–14.9		1–2.9		<1

Drawbacks of Score Systems

Not Adaptive!

- Often handcrafted by domain experts
- Tailored to a specific population
- Become suboptimal over time

Fixed set of clinical observations

- Not all observations available in a hospital

Standard ML methods

- Logistic Regression
- Support Vector Machine (+ Platt Scaling)
- Decision Trees
- …

Representation different from what clinicians prefer!

Our Contribution

A ML method for learning score system type prediction models for ICU mortality prediction:

- Adaptive!
- Easily interpreted by clinicians

Problem Setup

ICU Mortality Rate Prediction

Patient Training Sample: $((\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N))$

Probability of death: $\hat{\eta}(\mathbf{x}) = \mathbf{P}(y = 1 \,|\, \mathbf{x})$

Computing Patient Mortality using Score Systems

Score Table

Feature Intervals

Feature i	$(a_1^i, a_2^i]$	$(a_2^i, a_3^i]$	$(a_3^i, a_4^i]$	…	$(a_m^i, a_{(m+1)}^i]$
	α_1^i	α_2^i	α_3^i	…	α_m^i

Scores

Severity score for a patient:

$$f_{\text{severity}}(\mathbf{x}) = \sum_{j=1}^{d} \sum_{k=1}^{m_j} \alpha_k^j \mathbf{1}(x_j \in (a_k^j, a_{k+1}^j])$$

Estimated patient mortality:

Parameters learnt using logistic regression

$$\hat{\eta}(\mathbf{x}) = \text{sigmoid}(\boxed{c} f_{\text{severity}}(\mathbf{x}) + \boxed{d})$$

Popular Score Systems: APACHE, SAPS, MPM, LODS, SOFA, etc…

Reformulation of Score Tables

Reformulated Score Table

Thresholds

Feature i	$(-\infty, a_1^i]$	$(-\infty, a_2^i]$	$(-\infty, a_3^i]$	…	$(-\infty, a_m^i]$
	α_1^i	α_2^i	α_3^i	…	α_m^i

Severity score for a patient:

Number of intervals / Scores / Thresholds

$$f_{\text{severity}}(\mathbf{x}) = \sum_{j=1}^{d} \sum_{k=1}^{\boxed{m_j}} \boxed{\alpha_k^j} \mathbf{1}(x_j \le \boxed{a_k^j})$$

Goal: Find a score table that minimizes logistic loss on training sample

Sparse Learning in a Blown-up Space

Cluster each feature into 'm' intervals

$$\underbrace{\mathbf{1}(x_1 \le a_1^1) \ldots \mathbf{1}(x_1 \le a_1^m)}_{\text{Original Feature 1}} \;\ldots\; \underbrace{\mathbf{1}(x_d \le a_d^1) \ldots \mathbf{1}(x_d \le a_d^m)}_{\text{Original Feature d}}$$

Sparse Logistic Regression!

Orthogonal Matching Pursuit Based Method

Iterate:

- Compute residual difference between estimated mortalities and true outcomes
- (Greedily) pick feature in blow-up space that best explains this difference
- Solve logistic regression problem over chosen features

Experimental Results

Data sets:

- St. John's data (3449 patients, 29 features)
- CinC data / MIMIC-II (4000 patients, 42 features)

Methods	AUC	Brier Score
LogitOMP-SS	70.15	0.1639
LOD	63.19	0.1724
Linear Logistic Regression	68.15	0.1664
Kernel Logistic Regression	69.00	0.1600
RankSVM + Platt Scaling	68.92	0.1668

Comparison with LOD on St. John's Data

Methods	AUC	Brier Score
LogitOMP-SS	70.47	0.1599
APACHE-II	66.07	0.1673
Linear Logistic Regression	70.47	0.1593
Kernel Logistic Regression	70.69	0.1582
RankSVM + Platt Scaling	70.67	0.1597

Comparison with APACHE-II on St. John's Data

Methods	AUC	Brier Score
LogitOMP-SS	94.32	0.0620
SAPS-II	88.02	0.0860
Linear Logistic Regression	91.20	0.0732
Kernel Logistic Regression	93.01	0.0688
RankSVM + Platt Scaling	93.13	0.0692

Comparison with SAPS-II on Cinc Data

Methods	AUC	Brier Score
LogitOMP-SS	86.67	0.0876
SOFA	81.19	0.0994
Linear Logistic Regression	84.53	0.0946
Kernel Logistic Regression	85.27	0.0921
RankSVM + Platt Scaling	85.49	0.0923

Comparison with SOFA on Cinc Data

Conclusion

	Interpretable by Clinicians?	Adaptive?
Static Score Systems	✓	✗
Standard ML Methods	✗	✓
LogitOMP-SS	✓	✓

References

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