Deep Learning from Heterogeneous Sequences of Sparse Medical Data for Early Prediction of Sepsis

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Sepsis, At A Glance

□ A life-threatening complication to infections

One of the most serious forms of healthcare associated infections
 A leading cause of hospital morbidity and mortality

- Survival is dependent on initiating appropriate antimicrobial treatment as early as possible
- Mortality from septic shock increases by 7.6% for every hour that antimicrobial treatment is delayed after the onset





Early prediction of sepsis in the non-ICU (intensive care units) setting from electronic health records (EHRs)

Performance analysis of long short-term memory based recurrent neural network (RNN-LSTM)

Investigating temporality and sequence length

□ Investigating missingness



HEALTH BANK - Swedish Health Record Research Bank

- □ Unique research resource containing a large sets of electronic patient records
- Used in a number of research projects carried out by the Clinical Text Mining Group, Department of Computer and Systems Sciences, Stockholm University
- Contains data from over 512 clinical units from Karolinska University Hospital (2006–2014) over two million patients.
- Structured information contains, a serial number (de-identified) for each patient, age, gender, ICD-10 diagnosis codes, drugs, ab and blood values, admission and dicharge time, and date
- Unstructured data contains text written under different headings





Patients > 18 years admitted to the hospital between July 2010 and June 2013

- □ Followed until first sepsis onset, discharge or death
- Excluded if admitted to an obstetric ward and censored during ICU-care
- □ Encompasses 124,054 patients and 198,638 care episodes
- □ Sepsis in the cohort is **8.9%**



Care Episode



Input Feature Selection





Care Episode Representation



When **multiple values** are present in a time window, the **"worst"** value is chosen



Handling Missing Values, Without Imputation

When data is assumed to be missing not at random

Imputation is not carried out

Missing values are simply assigned an integer value which is not present in the data

The idea is that the model may learn to treat missingness as a distinct feature



Q

Handling Missing Values, With Imputation

When data is assumed to be **missing at random**

When a value exists for a given feature in the care episode, it is carried forward to subsequent windows until another present value is encountered, which is then in turn carried forward and so on

- When there is no value for a given feature in a care episode, it is imputed globally
 - For categorical features, the most frequent value is chosen, while mean imputation is carried out for numeric features

For SOFA, qSOFA, and NEWS2, missing values are not mean-imputed; instead, the score is assumed to be 0 - if missing - at the start of an episode and then carried forward

Care Episode Distribution





RNN (Recurrent Neural Network) Architecture



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LSTM (Long Short-Term Memory)-RNN Architecture



Experiments

1. Different time window sizes

2. Handling missing values

3. Performance at different time points

4. Evaluation of earliness

5. Performance with different sequence lengths



Evaluation Metrics: F₁-Score

relevant elements



Precision =
$$\frac{TP}{TP + FP}$$

Recall (or Sensitivity or **True Positive Rate**) = $\frac{TP}{TP + FN}$ Specificity = $\frac{TN}{TN + FP}$

False Positive Rate(or 1 - Specificity) = $\frac{FP}{TN + FP}$

 $F_1 Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$



Evaluation Metrics : AUPRC & AUROC



Area Under the Precision-Recall Curve (**AUPRC** or **AP**)-

Average of precision across all recall values



Area Under the Receiver Operating Characteristics (**AUROC** or **AUC**)-

Probability with which the classifier will assign a larger score to the positive than to the negative data point 16



Predictive Performance At Different Time Points



Earliness Performance In Median Hours Before Sepsis Onset Combined With F₁-score

Window	Without Imputation						With Imputation					
Size	<2	4h	<4	8h	A	11	<2	4h	<4	8h	A	1
5120	Med.	F ₁	Med.	F ₁	Med.	F ₁	Med.	F ₁	Med.	F ₁	Med.	F ₁
1	6.00	0.65	7.37	0.53	11.79	0.28	5.90	0.61	7.77	0.48	10.78	0.25
2	7.24	0.73	8.00	0.57	12.68	0.33	7.02	0.74	8.00	0.57	13.43	0.32
3	12.45	0.77	12.57	0.65	14.34	0.38	7.78	0.75	8.33	0.65	13.00	0.42
4	7.13	0.73	7.92	0.63	14.22	0.41	11.22	0.79	10.00	0.67	13.36	0.41
6	10.09	0.76	11.00	0.68	14.00	0.46	8.43	0.74	8.48	0.65	14.00	0.44
8	8.73	0.74	9.82	0.67	14.75	0.46	6.58	0.70	8.00	0.64	24.28	0.44

Allowing true positives only **<24h** or **<48h** before sepsis onset, as well **as any time** (**All**)



Earliness Distribution





Episode-Wise Earliness

Two-hour time window and without imputation of missing values





Length-Wise Performance Evaluation

Two-hour time window and without imputation of missing values

Each bin contains at least 1000 test instances



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Discussion

- Dividing the temporal EHR data into hourly time windows and prediction times
- Treating missing values in the care episodes as missing at random
- Early detection of sepsis in the non-ICU setting with sparse data
- Model performance on care episodes of different (sequence) lengths



Future works

- Predicting sepsis should be divided into multiple stages to emulate the actual condition of sepsis
- We will investigate modifications to the neural architecture to make it more task-specific
- We will use additional natural language processing technique by incorporating free text data to provide additional important features to our model
- □ We also plan to investigate the interpretability of the models



Questions?



Image Source

[1] http://colah.github.io/posts/2015-08-Understanding-LSTMs/
[2] https://en.wikipedia.org/wiki/Precision_and_recall
[3] https://stackoverflow.com/questions/53772249/how-to-evaluateaccuracy-on-highly-unbalanced-data-using-naive-bayes-model
[4] https://riptutorial.com/machine-learning/example/14446/areaunder-the-curve-of-the-receiver-operating-characteristic--auroc-



Backup Slides



Neural Network Parameters

Name	Values / Range			
alpha	0, 10 ⁻⁴			
beta one	0, 1 - 10^{-1}			
beta two	0, 1 - 10 ⁻³			
hidden layers	2, 3, 4			
neurons	64, 128, 256			
drop out	0, 10, 20, 30, 40, 50, 60, 70			
epochs	1, 2			
mini-batch	100			
classification function	log-softmax			
optimizer	Adam optimizer			



NEWS2, National Early Warning Score 2

Chart 1: The NEWS scoring system

Physiological	Score								
parameter	3	2	1	0	1	2	3		
Respiration rate (per minute)	≤8		9–11	12–20		21–24	≥25		
SpO ₂ Scale 1 (%)	≤91	92–93	94–95	≥96					
SpO ₂ Scale 2 (%)	≤83	84–85	86–87	88–92 ≥93 on air	93–94 on oxygen	95–96 on oxygen	≥97 on oxygen		
Air or oxygen?		Oxygen		Air					
Systolic blood pressure (mmHg)	≤90	91–100	101–110	111–219			≥220		
Pulse (per minute)	≤40		41–50	51–90	91–110	111–130	≥131		
Consciousness				Alert			CVPU		
Temperature (°C)	≤35.0		35.1–36.0	36.1–38.0	38.1–39.0	≥39.1			

https://www.rcplondon.ac.uk/projects/outputs/national-early-warningscore-news-2



NEWS2, National Early Warning Score 2

Chart 2: NEWS thresholds and triggers

NEW score	Clinical risk	Response		
Aggregate score 0–4	Low	Ward-based response		
Red score Score of 3 in any individual parameter	Low-medium	Urgent ward-based response*		
Aggregate score 5–6	Medium	Key threshold for urgent response*		
Aggregate score 7 or more	High	Urgent or emergency response**		

* Response by a clinician or team with competence in the assessment and treatment of acutely ill patients and in recognising when the escalation of care to a critical care team is appropriate.

**The response team must also include staff with critical care skills, including airway management.

https://www.rcplondon.ac.uk/projects/outputs/national-early-warningscore-news-2



Sequential Organ Failure Assessment (SOFA) score

The SOFA Score^{*}

<i>Organ System,</i> Measurement					
	0	1	2	3	4
Respiration	Normal	<400	<300	<200	<100
PaO ₂ /FiO ₂ ,				(with respiratory	(with respiratory
mmHg				support)	support)
Coagulation	Normal	<150	<100	<50	<20
Platelets					
x10³/mm³					
Liver	Normal	1.2-1.9	2.0-5.9	6.0-11.9	>12.0
Bilirubin, mg/dL		(20-32)	(33-101)	(102-204)	(<204)
(µmol/l)					
Cardiovascular	Normal	MAP<70	Dopamine ≤5 or	Dopamine >5 or	Dopamine >15 or
Hypotension		mmHg	dobutamine (any	epinephrine ≤0.1 or	epinephrine >0.1 or
			dose)**	norepinephrine <0.1	norepinephrine >0.1
Central Nervous	Normal	13-14	10-12	6-9	<6
System					
Glasgow Coma					
Score					
Renal	Normal	1.2-1.9	2.0-3.4	3.5-4.9	>5.0
Creatinine,		(110-170)	(171-299)	(300-440)	(>440)
mg/dL (µmol/l)				or <500 mL/day	or <200 mL/day
or					
Urine output					

* Source: Vincent et al., 1996.

re.pdf

**Adrenergic agents administered for at least 1 hour (doses given are in mcg/kg/min).

http://www.iccueducation.org.uk/uploads/2/3/1/0/23109338/sofa_sco

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quick Sepsis related Organ Failure Assessment (qSOFA)

Assessment	qSOFA score
Respiratory rate ≥22/min	1
Altered mentation*	1
Systolic blood pressure ≤100 mm Hg	1

*Glasgow Coma Scale (GCS)<=14

https://jamanetwork.com/journals/jama/fullarticle/2492881 https://www.glasgowcomascale.org/



Sepsis Definition, Sepsis-3 clinical criteria

Suspected infection in combination with organ dysfunction

Sepsis onset time is the first time window when both organ dysfunction and suspected infection criteria are met (time zero)



Sepsis Definition, Suspected Infection



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Sepsis Definition, Organ Dysfunction

- □ **SOFA score** >= 2 compared to the baseline
- Measured 48 hours before to 24 hours after the onset of suspected infection
- Baseline SOFA score is defined as the latest value measured before the 72-hour time window and is assumed to be 0 in patients not known to have a pre-existing organ dysfunction

