A Deep Learning Program Prototype to Predict Acute Kidney Injury

livvddcc@gmail.com [a,1]
[a] *MSc. Medicine Informatics, Heidelberg University, Heidelberg Germany*
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[1] Corresponding Author E-mail: livvddcc@gmail.com

Abstract. Acute kidney injury is a dangerous and sometime fatal clinical situation which can cause irreversible damage. If we can predict it earlier and make appropriate prevention before its outbreak, kidney injury or other critical consequence e.g. organ failure could be avoided. Thanks progress in AI algorithm such as deep learning, we have a chance to approach acute kidney injury prediction via new big data analyzing technology. This purpose of this study is to make a prototype program to predict the development of acute kidney injury. We use recurrent neural network to make data mining on laboratory results of patients ICU stays. The results show that this method is possible to forecasting some important criteria of acute kidney injury such as serum creatinine.

Keywords. Artificial intelligence, acute kidney injury, Prediction, Neural network, deep learning, RNN, LSTM

1. Introduction

AKI (Acute kidney injury) is one of a number of conditions that affect kidney structure and function.

AKI is defined as any of the following (Not Graded)[1]:

1. Increase in SCr (Serum creatinine) by >=0.3 mg/dl (>=26.5 lmol/l) within 48 hours; or
2. Increase in SCr to >=1.5 times baseline, which is known or presumed to have occurred within the prior 7 days; or
3. Urine volume <0.5 ml/kg/h for 6 hours.

A recent clinical practice assessment concluded that only 50% of patients with AKI were considered to have received a ‘‘good’’ overall standard of care. There was an unacceptable delay in recognizing AKI in 43% of those that developed the condition after admission, and that in a fifth of such patients its development was predictable and avoidable[4].

2. Mathematical methodology of this study

This study focuses on creating a program prototype to predict acute kidney injury by using the deep learning algorithm. Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks (RNN) and convolutional neural networks have been applied to many fields, where they have produced results comparable to and in some cases surpassing human expert performance[2].

Bayesian network is used in this study to calculate the conditional possibility. We use the neural network to predict real value (e.g., serum creatinine in this study), so we rescale the possibility results of activation function at last.

The details of our mathematical methodology of this study are as following:

$$
\begin{aligned}
P(C_1|x) &= \frac{P(C_1,x)}{P(x)} \\
&= \frac{P(x|C_1)P(C_1)}{p(x|C_1)P(C_1)+P(x|C_2)P(C_2)} \\
&= \frac{1}{1+\frac{P(x|C_2)P(C_2)}{p(x|C_1)P(C_1)}} \\
&= \frac{1}{1+e^{-a}} \qquad [sigmoid]
\end{aligned}
$$

Where:

$$a = In\frac{P(x|C_1)P(C_1)}{P(x|C_2)P(C_2)}$$

We use Gaussian distribution:

$$P(x|C_1) \sim N(x|\mu_1,\Sigma) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{1/2}}exp\{-\frac{1}{2}(x-\mu_1)^T\Sigma^{-1}(x-\mu_1)\}$$

$$P(x|C_2) \sim N(x|\mu_2,\Sigma) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{1/2}}exp\{-\frac{1}{2}(x-\mu_2)^T\Sigma^{-1}(x-\mu_2)\}$$

$$InP(x|C_1) = -\frac{D}{2}In(2\pi) - \frac{1}{2}In|\Sigma| - \frac{1}{2}(x-\mu_1)^T\Sigma^{-1}(x-\mu_1)$$

$$InP(x|C_2) = -\frac{D}{2}In(2\pi) - \frac{1}{2}In|\Sigma| - \frac{1}{2}(x-\mu_2)^T\Sigma^{-1}(x-\mu_2)$$

So we get:

$$
\begin{aligned}
a(x) &= InP(x|C_1) - InP(x|C_2) + In\frac{P(C_1)}{P(C_2)} \\
&= (\mu_1-\mu_2)^T\Sigma^{-1}x - \frac{1}{2}\mu_1^T\Sigma^{-1}\mu_1 + \frac{1}{2}\mu_2^T\Sigma^{-1}\mu_2 + In\frac{P(C_1)}{P(C_2)} \\
&= w^Tx + w_0
\end{aligned}
$$

Where:

$$w = \Sigma^{-1}(\mu_1-\mu_2)$$

$$w_0 = \frac{1}{2}\mu_2^T\Sigma^{-1}\mu_2 - \frac{1}{2}\mu_1^T\Sigma^{-1}\mu_1 + In\frac{P(C_1)}{P(C_2)}$$

$$P(C_2|x) = 1 - P(C_1|x)$$

At last we get:

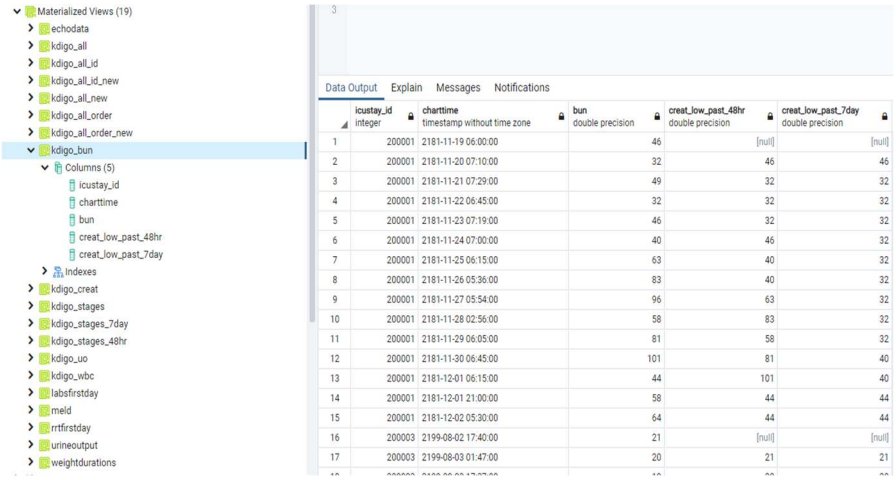
$$P(C_k|x) = \frac{P(x|C_k)P(C_k)}{\sum_j P(x|C_j)P(C_j)} = \frac{exp(a_k)}{\sum_j exp(a_j)}$$

3. Date-set of this study

The quality of data determinates the top limit of neural network. MIMIC-III Database is used for this study. MIMIC-III (Medical Information Mart for Intensive Care III) is a database comprising de-identified health-related data associated with over forty thousand patients who stayed in critical care units of the Beth Israel Deaconess Medical Center between 2001 and 2012[3].

The data preprocessing is made in this study for standardization and data cleaning. The patient data used in our study contains approximately 60000 admissions of patients included information such as patient demographics, vital signs, laboratory test results. In this prototype we consider laboratory test results e.g. SCr (Serum creatinine), bicarbonate, blood urea nitrogen (BUN), chloride, international normalized ratio (INR), white blood count (WBC) as features, because these indicators are related to AKI according to the past studies[4]. We use unsupervised learning algorithm, so in this study the patient data is not necessary to be labeled manually. The test results of each sample during ICU-stay are collected with different time interval, the number of tests of each sample are also different. But if the amount of samples is big enough, such training data-set can represent the real world data. Therefore after training the neural network is suitable for predict AKI with different patient data.

The data-sets are rescaled to fit the neural network activation function. PostgreSQL is used as database engine. The relevant data is selected in different views for analyzation by neural network.



	icustay_id integer	charttime timestamp without time zone	bun double precision	creat_low_past_48hr double precision	creat_low_past_7day double precision
1	200001	2181-11-19 06:00:00	46	[null]	[null]
2	200001	2181-11-20 07:10:00	32	46	46
3	200001	2181-11-21 07:29:00	49	32	32
4	200001	2181-11-22 06:45:00	32	32	32
5	200001	2181-11-23 07:19:00	46	32	32
6	200001	2181-11-24 07:00:00	40	46	32
7	200001	2181-11-25 06:15:00	63	40	32
8	200001	2181-11-26 05:36:00	83	40	32
9	200001	2181-11-27 05:54:00	96	63	32
10	200001	2181-11-28 02:56:00	58	83	32
11	200001	2181-11-29 06:05:00	81	58	32
12	200001	2181-11-30 06:45:00	101	81	40
13	200001	2181-12-01 06:15:00	44	101	40
14	200001	2181-12-01 21:00:00	58	44	44
15	200001	2181-12-02 05:30:00	64	44	44
16	200003	2199-08-02 17:40:00	21	[null]	[null]
17	200003	2199-08-03 01:47:00	20	21	21

Figure 1. MIMIC-III Dataset Example

4. Prototype programming

4.1. Programming

Mining all the information from raw Data and dimensionality reduction are 2 main targets of data processing for neural network. Deep learning such as LSTM is algorithm to decide how to mine information and reduce dimension through training neural network with big data. Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning[5]. It can not only process single data points, but also entire sequences of data. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series.

We use the ICU case data as multi-Case multivariate time series. At first, we transfer the case data into Pandas DataFrame of series framed for supervised learning. As example of this prototype, this program predicts the next serum creatinine values (SCr), which is the most important indicator of AKI, based on the last laboratory test results after emergency admissions, including SCr (Serum creatinine), bicarbonate, blood urea nitrogen (BUN), chloride, international normalized ratio (INR), and white blood count (WBC).

We use 3 timesteps for 1 prediction, i.e we use the laboratory results of 3 timesteps of one case to predict the next SCr value of next time step. The prediction of one case is as follow:

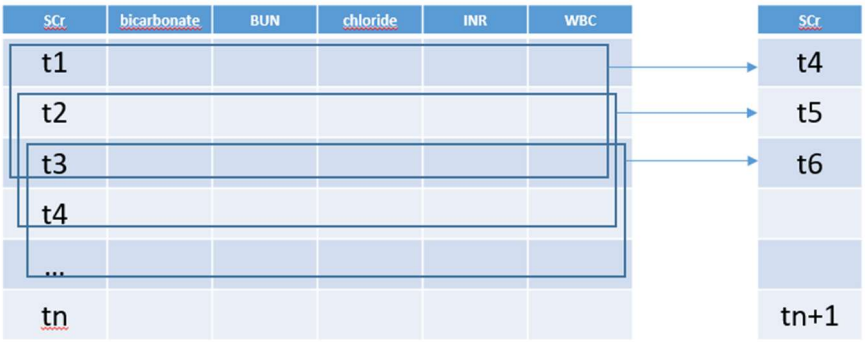


Figure 2. Serum creatinine (SCr.) Prediction of one case

For multi-cases predictions, the data-structure is as follow:

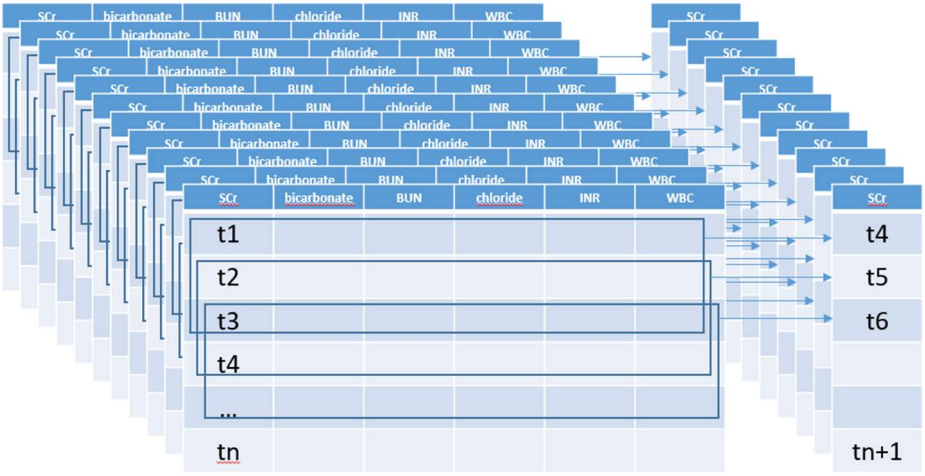


Figure 3. SCr. Prediction of multi-cases

4.2. Training of neural network

Keras API is used to train the dataset. Keras is a deep learning API written in Python, running on top of the machine learning platform TensorFlow[6], which is installed on CUDA GPU. GRU is also used and compared with LSTM to get better results and performance. 60% dataset is used for training and 40% for test.

4.3. Result

The back-propagation process in this program as example:

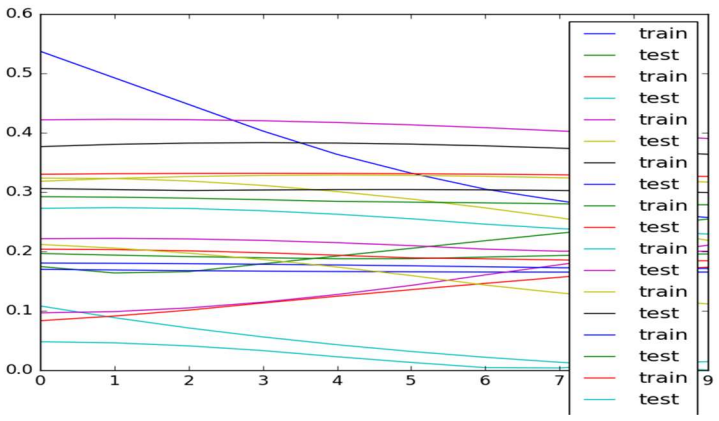


Figure 4. RNN training progress sample

We train the RNN on whole dataset (i.e. multi-cases prediction). As the result shown, this prototype can predict criteria (SCr) of AKI with a RMSE (Root Mean Square Error) of 0.017.

5. Conclusion and Discussion

Because of the complexity of the clinical data, it is difficultly to precisely analyze the features manually by using statistical methods such as linear regression. Our purpose of feature engineering is keeping the original information of data and dimension reduction at same time, the deep learning algorithm can achieve these goals automatically, it can be used to predict the curve of some important laboratory test results of AKI, such as serum creatinine. This study shows that using deep learning algorithm for AKI prediction is possible in theory and praxis.

The prediction of AKI is very challenging, therefore this study is only try to make a prototype of a prediction approach, following points can be considered for further improvement of the prediction's precision:

- Prediction should be grouped by demographics to avoid Simpson's paradox. E.g. using data of same age/sex group for prediction is better than mixed data.
- Influence of medications and comorbidities should be considered. Vital signs measured at the bedside such as ECG, SpO2, and respiration rate could also be helpful for AKI development prediction. But because our activation function of neural network is based on Bayesian theorem, the conditional independence of features should be further analyzed and managed before we can use them to minimize overfitting.

References

[1] KDIGO Clinical Practice Guideline for Acute Kidney Injury. Kidney International Supplements (2012) 2, 2; doi:10.1038/kisup.2012.2 https://kdigo.org/

[2] Andrew Ng, Jiquan Ngiam, Chuan Yu Foo, Yifan Mai, Caroline Suen, Adam Coates, Andrew Maas, Awni Hannun, Brody Huval, Tao Wang, Sameep Tandonhttp://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

[3] MIMIC-III, Johnson AEW, Pollard TJ, Shen L, Lehman LH, Feng M, Ghassemi M, Moody B, Szolovits P, Celi LA, and Mark RG. Scientific Data (2016). DOI: 10.1038/sdata.2016.35. Available at: http://www.nature.com/articles/sdata201635

[4] Predictive Modeling of the Risk of Acute Kidney Injury in Critical Care: A Systematic Investigation of The Class Imbalance Problem. Zhenxing Xu, Yujuan Feng, Yun Li, Anand Srivastava, Prakash Adekkanattu, Jessica S. Ancker, Guoqian Jiang, Richard C. Kiefer, Kathleen Lee, Jennifer A. Pacheco, Luke V. Rasmussen, Jyotishman Pathak, Yuan Luo, and Fei Wang

[5] Sepp Hochreiter; Jürgen Schmidhuber (1997). "Long short-term memory". Neural Computation. 9 (8): 1735–1780. doi:10.1162/neco.1997.9.8.1735. PMID 9377276. S2CID 1915014.

[6] Tomašev, N., Glorot, X., Rae, J.W. et al. A clinically applicable approach to continuous prediction of future acute kidney injury. Nature 572, 116–119 (2019). https://doi.org/10.1038/s41586-019-1390-1