A Deep Learning Program Prototype to Predict Acute Kidney Injury

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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 AKI prediction via new big data analyzing technology. This purpose of this study is to make a prototype program to predict the development of AKI. 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 AKI such as serum creatinine.

Introduction

AKI (Acute kidney injury) is one of a number of conditions that affect kidney structure and function. AKI is defined by an abrupt decrease in kidney function that includes, but is not limited to, ARF (Acute renal failure). It is a broad clinical syndrome encompassing various etiologies, including specific kidney diseases (e.g., acute interstitial nephritis, acute glomerular and vasculitic renal diseases); non-specific conditions (e.g., ischemia, toxic injury); as well as extrarenal pathology (e.g., prerenal azotemia, and acute postrenal obstructive nephropathy). More than one of these conditions may coexist in the same patient and, more importantly, epidemiological evidence supports the notion that even mild, reversible AKI has important clinical consequences, including increased risk of death. Thus, AKI can be thought of more like acute lung injury or acute coronary syndrome. Furthermore, because the manifestations and clinical consequences of AKI can be quite similar (even indistinguishable) regardless of whether the etiology is predominantly within the kidney or predominantly from outside stresses on the kidney, the syndrome of AKI encompasses both direct injury to the kidney as well as acute impairment of function.

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

- 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.

Stages of AKI are defined by KDIGO as following:

	ıcute kidney injury	
Stage	Creatinine Criteria	Urine Output Criteria
1	Cr 1.5-1.9 times baseline, OR Cr increase >0.3 mg/dL	< 0.5 ml/kg/hr x 6-12 hours
2	Cr 2-2.9x baseline	<0.5 ml/kg/hr for > 12 hours
3	Cr > 3x baseline, OR Cr > 4 mg/dL, OR Initiation of dialysis	<0.3 ml/kg/hr for >24 hours, OR Anuria > 12 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. Risk assessment for AKI should be part of the initial evaluation of emergency admissions, along with appropriate serum biochemistry on admission and at frequent intervals thereafter.

This study focuses on creating a program prototype to predict acute kidney injury by using the deep learning algorithm. Deep learning (also known as deep structured learning or differential programming) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Deep learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to many fields including computer vision, bioinformatics, drug design, medical image analysis etc., where they have produced results comparable to and in some cases surpassing human expert performance. With deep learning we can analyse multi-dimensional vector more easily than other statistical methods.

The overall cost function in neural network can be defined as following:

$$J(W,b) = \left[\frac{1}{m} \sum_{i=1}^{m} J(W,b;x^{(i)},y^{(i)})\right] + \frac{\lambda}{2} \sum_{l=1}^{n_l-1} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} \left(W_{ji}^{(l)}\right)^2$$

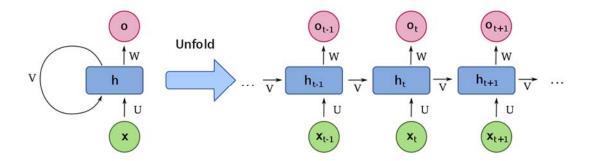
$$= \left[\frac{1}{m} \sum_{i=1}^{m} \left(\frac{1}{2} \left\|h_{W,b}(x^{(i)}) - y^{(i)}\right\|^2\right)\right] + \frac{\lambda}{2} \sum_{l=1}^{n_l-1} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} \left(W_{ji}^{(l)}\right)^2$$

Data Set

The patient data used in our study contains approximately 60000 admissions of patients who stayed in critical care units of the Beth Israel Deaconess Medical Center between 2001 and 2012. In particular, this database included information such as patient demographics, vital signs, laboratory test results. The collection dataset is passive and de-identified, which is in compliance with the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule and does not produce significant impacts on patient safety. In this prototype we consider laboratory test results e.g. bicarbonate, blood urea nitrogen (BUN), chloride, creatinine, international normalized ratio (INR), white blood count (WBC) as features, because these indicators are more likely related to AKI according to the past studies.

Algorithm

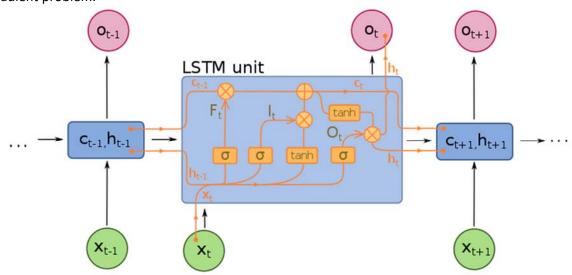
A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior.



Unlike feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. The term "recurrent neural network" is used indiscriminately to refer to two broad classes of networks with a similar general structure, where one is finite impulse and the other is infinite impulse. Both classes of networks exhibit temporal dynamic behavior. A finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced with a strictly feedforward neural network, while an infinite impulse recurrent network is a directed cyclic graph that cannot be unrolled.

Prototype Programming

We use the ICU case data as multi-Case multivariate time series. A time series is a sequence of numbers that are ordered by a time index. At first, we transfer the case data into Pandas DataFrame of series framed for supervised learning. As a simplified modeling prototype, this program predicts the next serum creatinine values based on the last laboratory test results after emergency admissions. In this study we use long short-term memory (LSTM) system to avoid the vanishing gradient problem.



Results

We use epoch=10 and batch_size=10 in the first training as an example to show the back-propagation process in our program.

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Epoch 1/10

- 0s - loss: 0.2215 - val_loss: 0.2118

Epoch 2/10

- 0s - loss: 0.2222 - val_loss: 0.2057

Epoch 3/10

- 0s - loss: 0.2211 - val_loss: 0.1972

Epoch 4/10

- 0s - loss: 0.2186 - val_loss: 0.1865

Epoch 5/10

- 0s - loss: 0.2148 - val_loss: 0.1739

Epoch 6/10

- 0s - loss: 0.2099 - val loss: 0.1594

Epoch 7/10

- 0s - loss: 0.2039 - val_loss: 0.1434

Epoch 8/10

- 0s - loss: 0.2005 - val_loss: 0.1302

Epoch 9/10

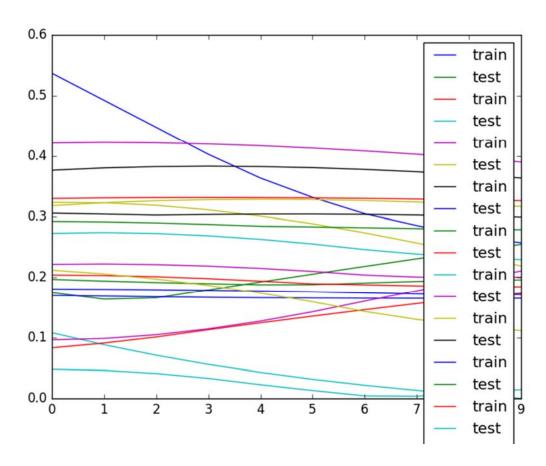
- 0s - loss: 0.2006 - val_loss: 0.1197

Epoch 10/10

- 0s - loss: 0.2002 - val_loss: 0.1117

inv_yhat: [1.07766474]

inv_y: [1.1] Test RMSE: 0.022



At last, we train the RNN on whole dataset. As the result shown, this prototype can be extended to predict criteria of AKI.

Discussion

Following points can be considered to further improve the precision of AKI prediction:

- 1. Prediction should be grouped by demographics to avoid Simpson's paradox.
- 2. Influence of medications and comorbidities should be considered.
- 3. More data are needed to avoid overfitting in RNN.
- 4. Vital signs measured at the bedside such as ECG, SpO2, and respiration rate could also be helpful for AKI development prediction.