Predicting Diagnoses Using Patient EMRS

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Background

Electronic medical records (EMRs) are the main form of storing patient information in clinical settings. Previous work has used EMRs to establish links between hospital stay duration and mortality[1]. In this project, I predict the diagnosis of the patient and compare different prediction methods in their accuracy. My models output categorical code probabilities.

Data Collection

The data is from the MIMIC-III[2] (Medical Information Mart for Intensive Care III) dataset: aggregated EMRs from Beth Israel Deaconess Medical Center's ICU. I merged on SUBJECT_ID as the common pivot column.

I one-hot encoded all of the categorical variables while using a label binarizer to clean the ICD9_CODE (diagnosis code) column for use as my output set. I split the dataset 80/20 for train and test in all of these methods.

Features

SUBJECT_ID	ETHNICITY	ICD9_CODE	LABEL	212	HEF
1	Cuban	280	heart rate	80	0

Fig. 1 Sample example of inputs and the output, ICD9_CODE.

Feature	Description
ROW_ID	Unique Data Linker
SUBJECT_ID	Admission/Patient ID
HADM_ID	Admission ID
ADMITTIME	Admission Time
DISCHTIME	Discharge Time
DEATHTIME	Time of Death
ADMISSION_TYPE	Elective, Urgent, Newborn, Emergency
ADMISSION_LOCATION	Pre-admit location: Categorical Var.
DISCHARGE_LOCATION	Categorical Var.
INSURANCE	Categorical Var.
LANGUAGE	Categorical Var.
RELIGION	Categorical Var.
MARITAL_STATUS	Categorical Var.
ETHNICITY	Categorical Var.
EDREGTIME	ED Entry
EDOUTTIME	ED Out
DIAGNOSIS	Free text notes
HOSPITAL_EXPIRE_FLAG	Did patient survive to discharge?
HAS_CHARTEVENTS_DATA	Chart populated?
SEQ_NUM	Priority order of ICD9
ICD9_CODE	Patient diagnosis

Models

This was modeled as a reflex-based problem. Since I had several columns of related data, it was evident that these would need to be the features and the output would be the ICD9_CODES or the columns that I wanted to predict. Specifically, I used three primary types of classifiers and each classifier with different feature sets.

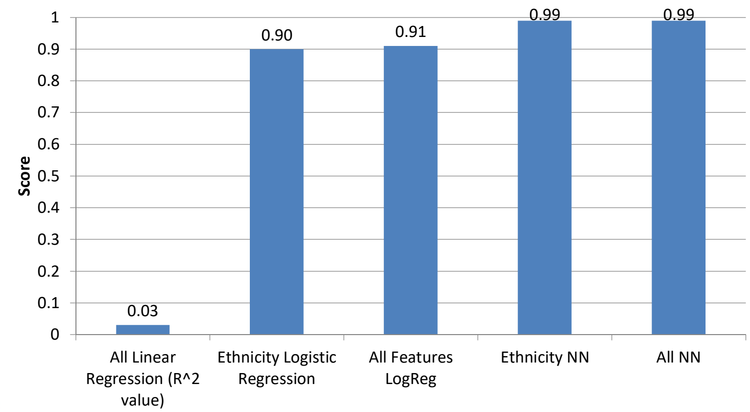
Linear Regression
This is a basic regressor model where the feature vector is given and a dot function is performed with a weight vector to classify using a score.

$$log\frac{p(x)}{1-p(x)} = \beta_0 + x \cdot \beta$$

Logistic Regression
This is a classification model which uses the function identified below. Y=1 when the probability is greater than 0.5.

Multilayer Perceptron Classifier
This is composed of hidden and input layers feeding into a softmax layer. I used hidden layer sizes (5,2)

Results and Discussion



Key Takeaways

- Linear Regression is not optimal
- Due to the high scores of the NN and logistic regression, especially when comparing a single feature to all features, there is likely overfitting occuring
- Why Overfitting?: One theory is that while there are nearly 1.1 million patients in this data, the feature vectors for many of the ICD9_CODES are extremely sparse while others are overrepresented

Future Research

- Use NLP on the free text diagnoses and see if mortality can be predicted
- Use NLP on free text notes to predict ICD9_CODE

References

1. Pirracchio, R., Petersen, M. L., Carone, M., Rigon, M. R., Chevret, S., \& van der Laan, M. J. (2015). Mortality prediction in intensive care units with the Super ICU Learner Algorithm (SICULA): a population-based study. The Lancet Respiratory Medicine, 3(1), 42-52.
2. MIMIC-III, a freely accessible critical care database. Johnson AEW, Pollard TJ, Shen L, Lehman L, Feng M, Ghassemi M, Moody B, Szolovits P, Celi LA, and Mark RG. Scientific Data (2016). DOI: 10.1038/sdata.2016.35. Available from: www.nature.com/articles/sdata201635
3. Previous work done by me