Predicting Trauma Inpatient Disposition through Graph Convolutional Networks

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Objective
It has been recognized that efficient resource allocation can improve patient care quality and reduce health care expenditure, especially in a trauma setting, where inpatient resource consumption is extremely high. Predicting patient discharge disposition early can help healthcare organizations allocate an appropriate amount of resources for an estimated number of inpatient stays. Concurrently, early prediction of discharge disposition can help providers to schedule subsequent post-trauma care to ensure continuity of care. With patient overcrowding being a widespread issue in hospitals across the US, proper allocation of resources and early coordination of post-trauma care can alleviate this issue. The objective of our study is to apply graph convolutional networks (GCN) on electronic health records (EHRs) to predict discharge dispositions one day after patient admissions.

Methods
Our data samples were pulled from the National Trauma Data Bank. Since our aim was to predict trauma inpatient discharge dispositions one day after admission, we excluded samples whose length of stay (LOS) was less than one day. Each sample includes a patient’s demographics, comorbidities, vital signs, and cause of injury prior to admission, and one-day inpatient data (e.g., procedure codes and injury severity scores) in the trauma center. Our data consists of 5,085 samples, presenting an average age of 54, with 59.4% male and 40.6% female patients. The samples were discharged to 13 unique locations, 57.3% of which were sent home and 42.7% being sent to 12 other locations (e.g., nursing facility, inpatient rehab, etc.). We assume patients sharing similar contextual information should be discharged to the similar places. Therefore, we measure patient similarities through cosine similarity and leverage GCN to train disposition prediction models based on the created patient similarity network. To measure similarity between patients, we represent each patient sample as a numeric vector which is learned via feature engineering approaches including Doc2Vec and Term-Frequency-Inverse-Document-Frequency (TF-IDF). GCN aims to amplify relationships between patients with high similarity and weaken relations of patients whose similarities are low. At the same time, GCN can build non-linear associations between neighborhood of a patient sample and the patient discharge disposition, which will be used to predict dispositions of new patients. We divided our cohort into training (80%) and test sets (20%). To train the models, we used 5-fold cross validation. To compare the performances of GCN models, we also trained several baseline models using logistical regression (LR).

Results
Table 1. Performance of GCN vs. Logistic Regression

<table>
<thead>
<tr>
<th>Model</th>
<th>TF-IDF + GCN</th>
<th>Doc2Vec + GCN</th>
<th>TF-IDF + LR</th>
<th>Doc2Vec + LR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>70.98%</td>
<td>69.33%</td>
<td>70.32%</td>
<td>64.34%</td>
</tr>
</tbody>
</table>

The performances of GCN and baseline models are depicted in Table 1. Through the table, it is evident that the accuracy of GCN models have a miniscule improvement over LR. TF-IDF is better than Doc2Vec to characterize each patient sample and create patient similarity network.

Discussion
A potential reason that GCN failed to achieve a high performance may be due to the high dimensionalities and complexities of the patient records, which are insufficiently to be characterized by using TF-IDF or Doc2Vec. In future, we will create a network (graph) of features for each patient sample rather than a single patient similarity network. In that case, GCN can deal with similarities between patient samples via their corresponding networks. Such a strategy will rely on similarities between patient networks (each node is a feature) to predict dispositions.

Conclusions
Despite the small improvement of GCN, we believe that it has the potential of high performance with further experimentation and learning strategy (networks of features). Furthermore, we will conduct a comparative study between human intelligence (guidelines in clinical practice) and artificial intelligence (GCN models) to predict discharge disposition.